

5.1: Amortized Analysis

Frank Stajano

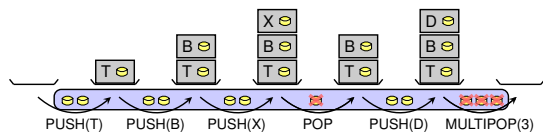
Thomas Sauerwald

Lent 2016



UNIVERSITY OF
CAMBRIDGE

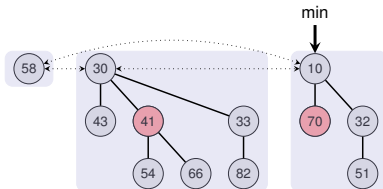
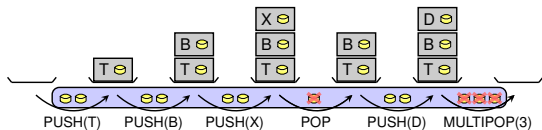
Use of Amortized Analysis



Amortized Analysis



Use of Amortized Analysis



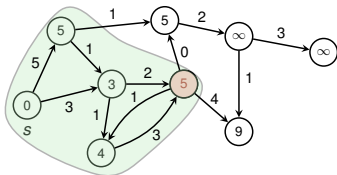
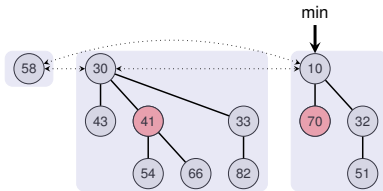
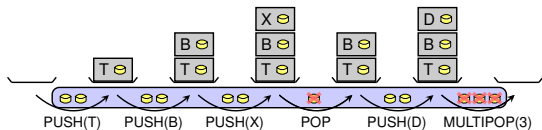
Amortized Analysis

next week

Fibonacci Heaps



Use of Amortized Analysis



Amortized Analysis

next week

Fibonacci Heaps

≈ two weeks

Finding Shortest Paths



Motivating Example: Stack

Stack Operations



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Stack Operations

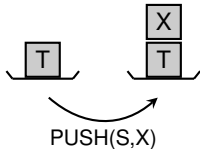
- **PUSH (S, x)**



Motivating Example: Stack

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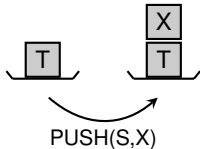
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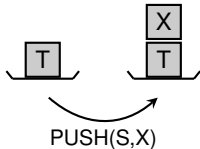
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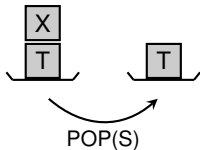
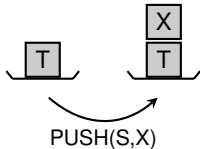
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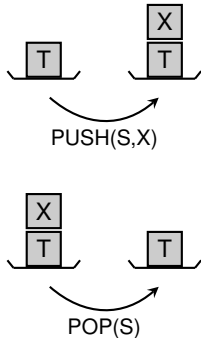
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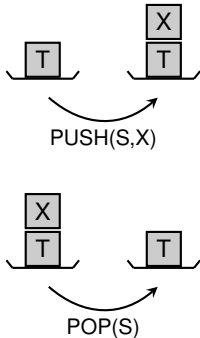
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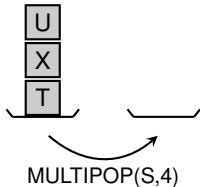
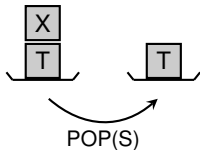
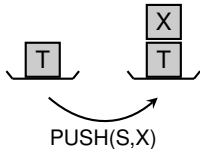
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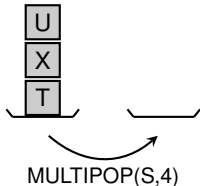
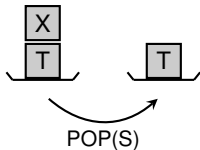
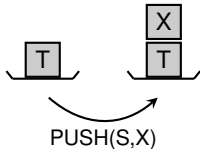
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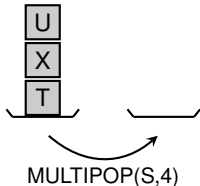
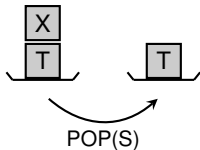
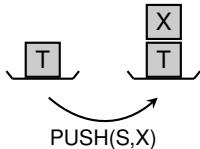


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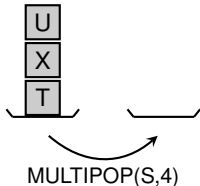
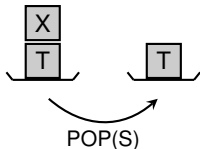
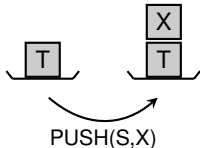
```
0: MULTIPOP (S, k)
1: while not S.empty() and k > 0
2:     POP (S)
3:     k = k - 1
```



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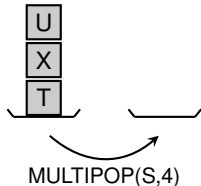
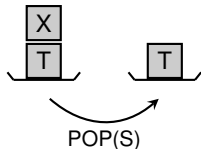
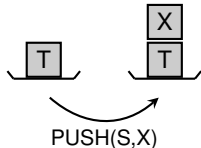
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Simple Worst-Case Bound (stack is initially empty):

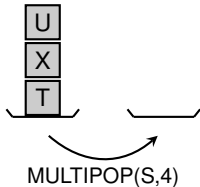
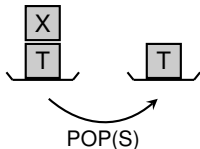
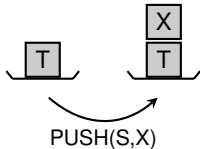
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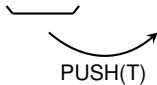


Sequence of Stack Operations

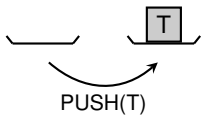
⌋



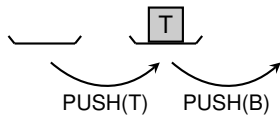
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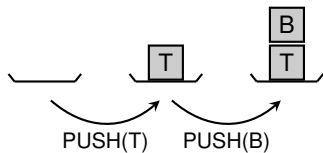
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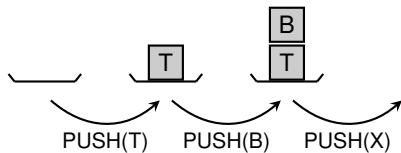
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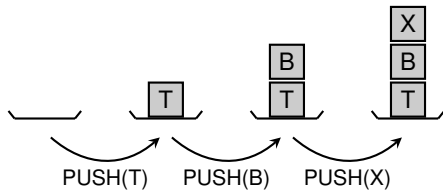
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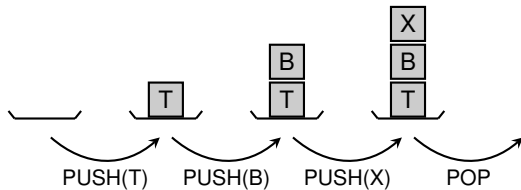
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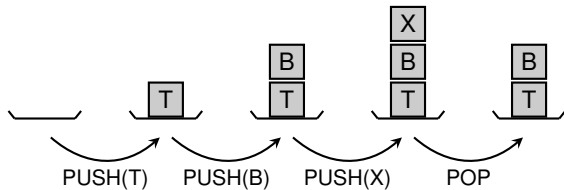
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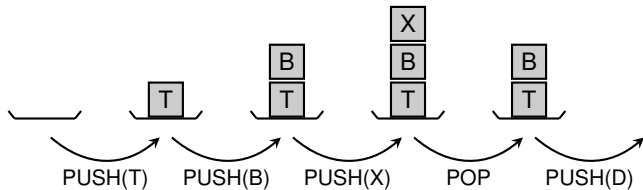
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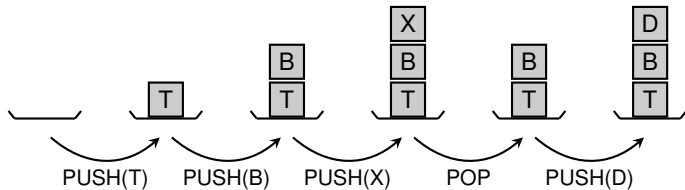
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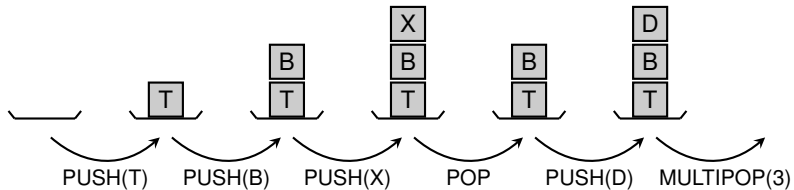
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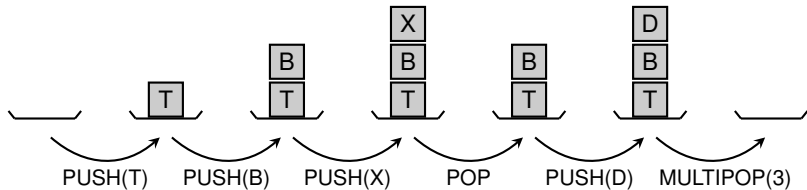
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Sequence of Stack Operations



A new Analysis Tool: Amortized Analysis

Amortized Analysis



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Amortized Analysis

- analyse a **sequence** of operations



A new Analysis Tool: Amortized Analysis

Data structure operations (Heap, Stack, Queue etc.)

Amortized Analysis

- analyse a **sequence** of operations



A new Analysis Tool: Amortized Analysis

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- analyse a **sequence** of operations
- show that **average cost** of an operation is small



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This is **not** average case analysis!



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- concrete techniques
 - Aggregate Analysis
 - Potential Method



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Aggregate Analysis

- Determine an upper bound $T(n)$ for the total cost of any **sequence** of n operations
- **amortized cost** of each operation is the **average** $\frac{T(n)}{n}$



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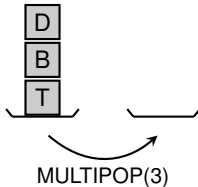
Even though operations may be of different types/costs



Stack: Aggregate Analysis

Simple Worst-Case Bound:

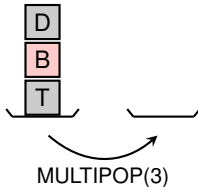
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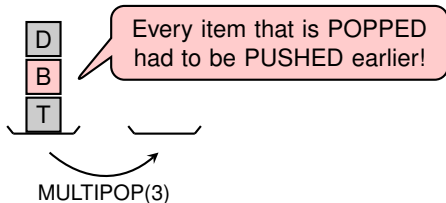
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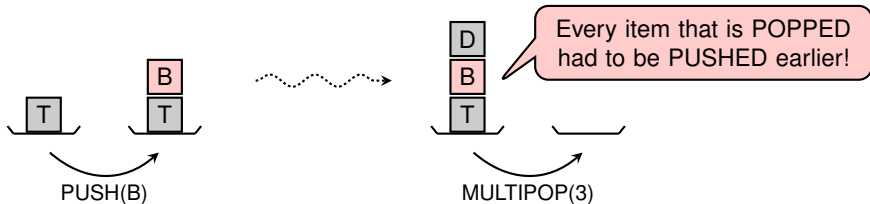
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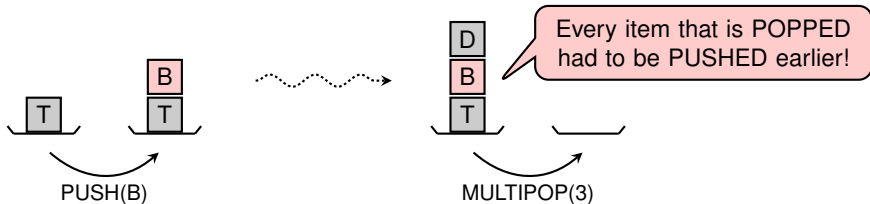
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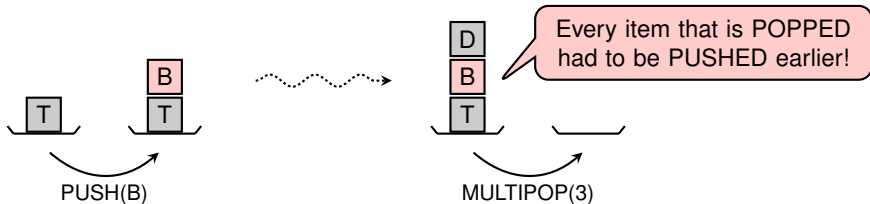
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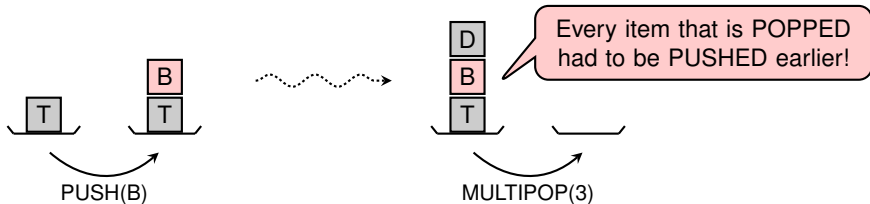
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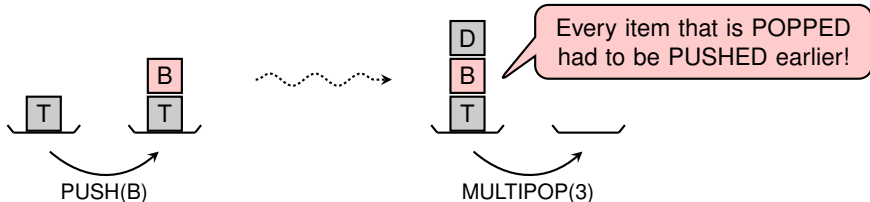
$$T(n) \leq T_{POP}(n) + T_{PUSH}(n)$$



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$\text{MULTIPOP}(k)$ contributes $\min\{k, |S|\}$ to $T_{\text{POP}}(n)$

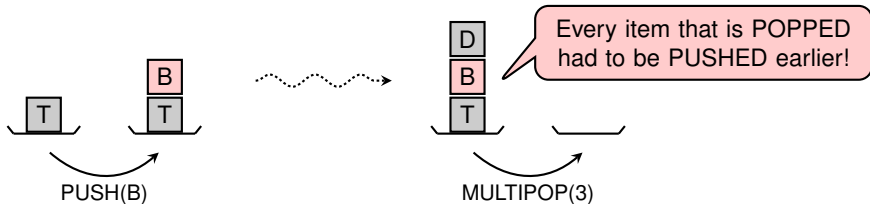
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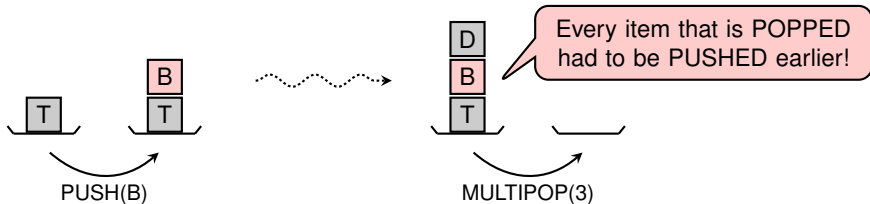
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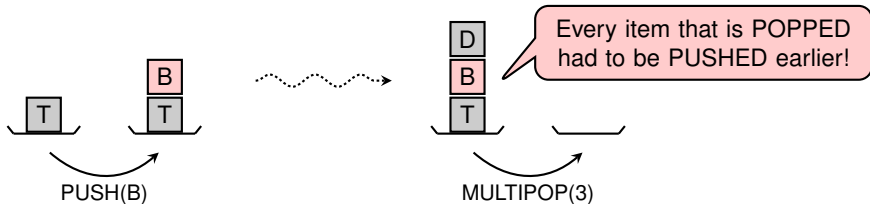
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$$T(n) \leq T_{POP}(n) + T_{PUSH}(n) \leq 2 \cdot T_{PUSH}(n) \leq 2 \cdot n.$$

Aggregate Analysis: The amortized cost per operation is $\frac{T(n)}{n} \leq 2$



Second Technique: Potential Method

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- ↪ store **(fictitious)** credit in the data structure to cover up for expensive operations



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Potential of a data structure can be also thought of as

- amount of potential energy stored
- distance from an ideal state



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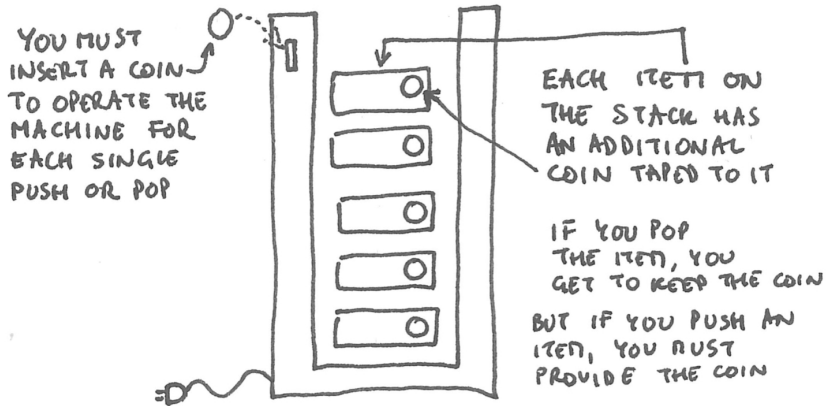
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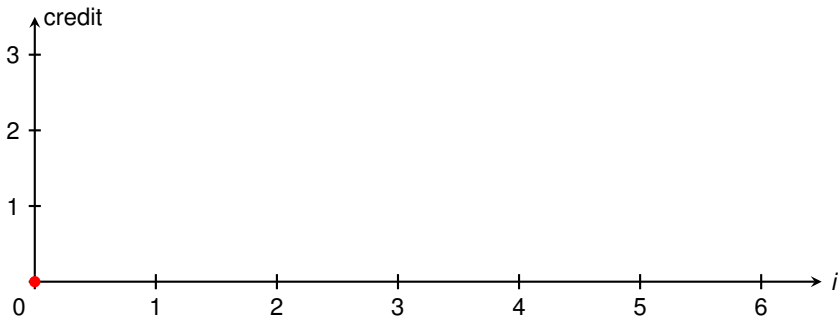
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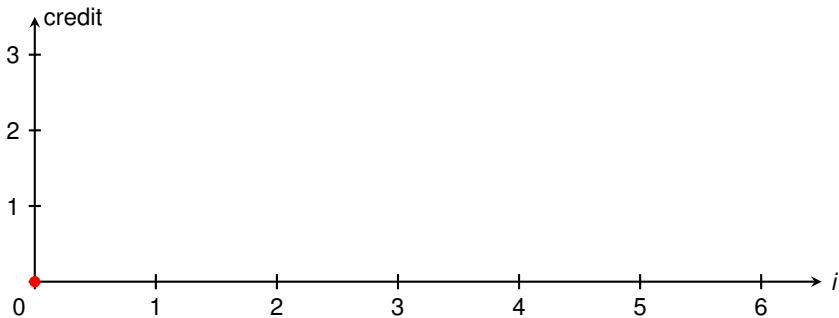
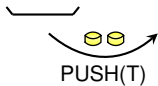
Stack as a coin-operated machine (p. 83)



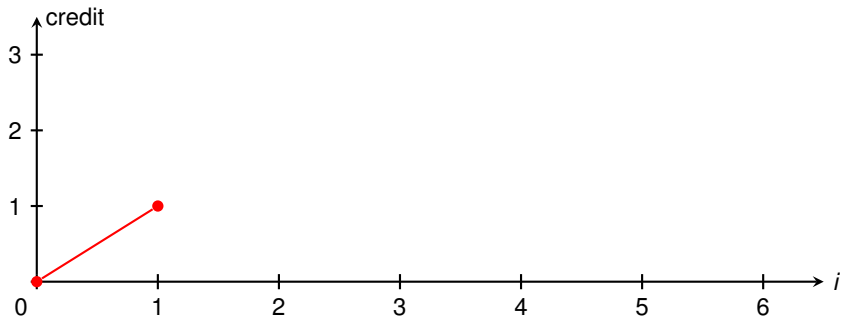
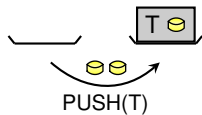
Stack and Coins



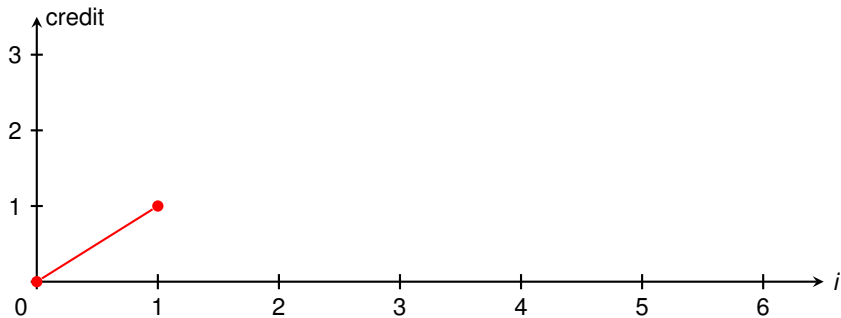
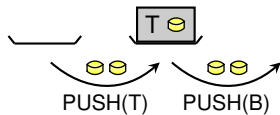
Stack and Coins



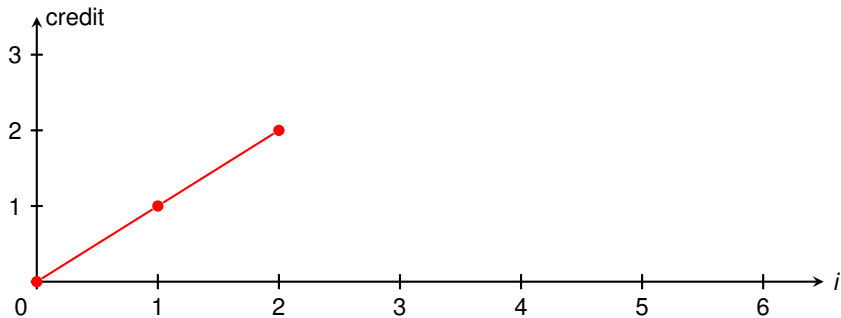
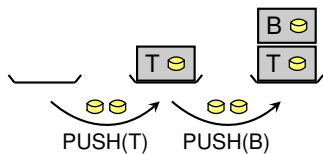
Stack and Coins



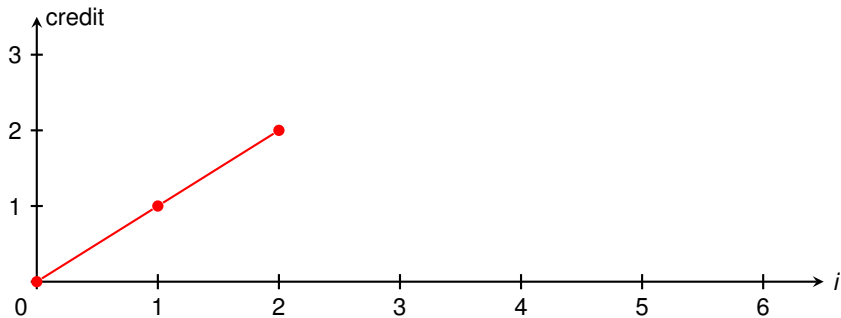
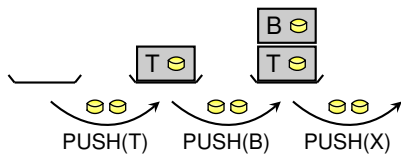
Stack and Coins



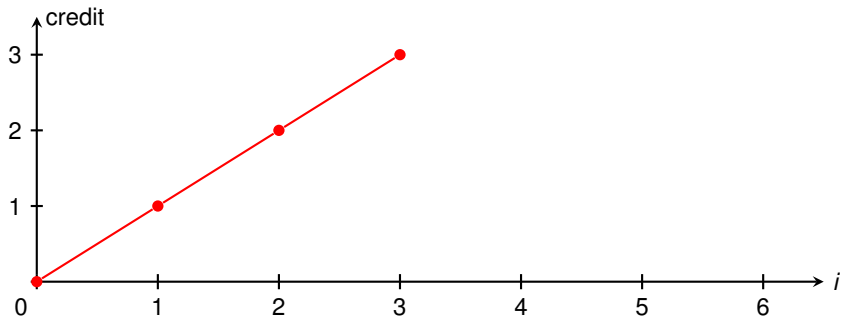
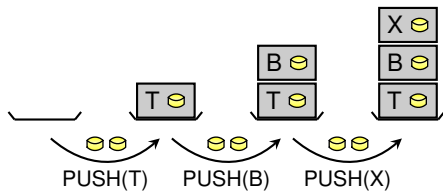
Stack and Coins



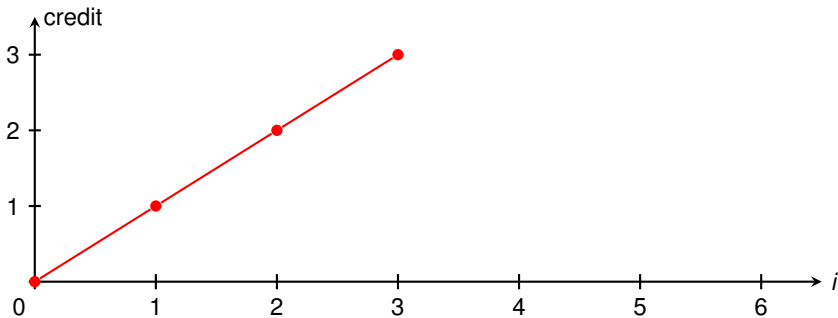
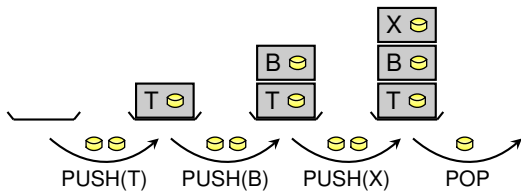
Stack and Coins



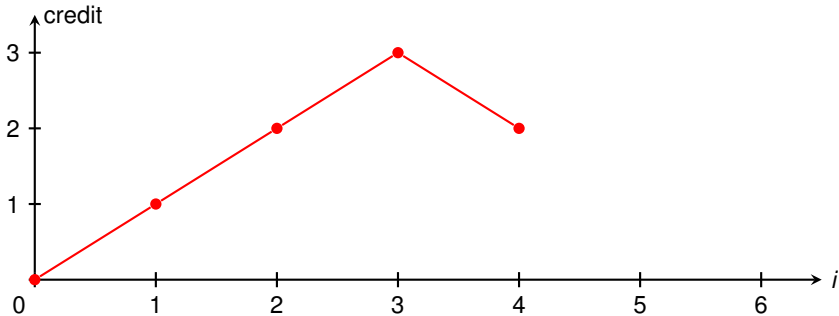
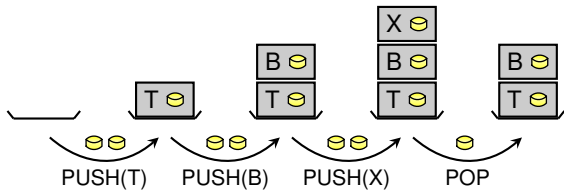
Stack and Coins



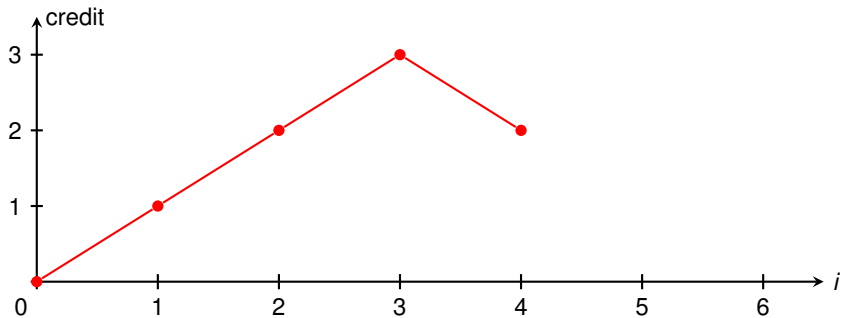
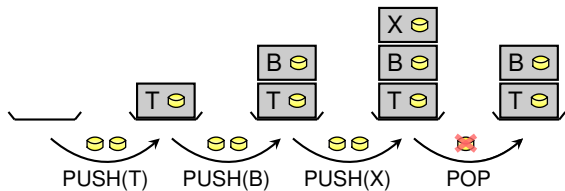
Stack and Coins



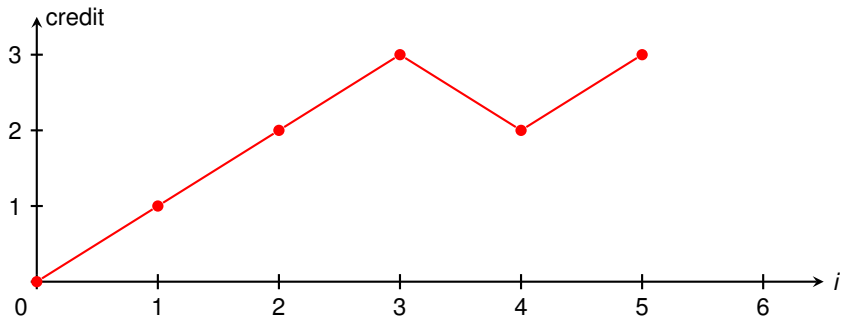
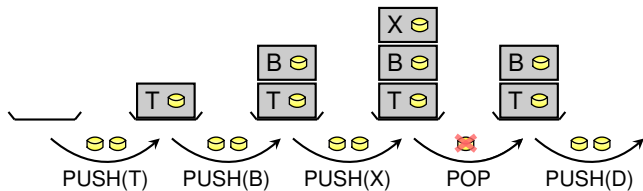
Stack and Coins



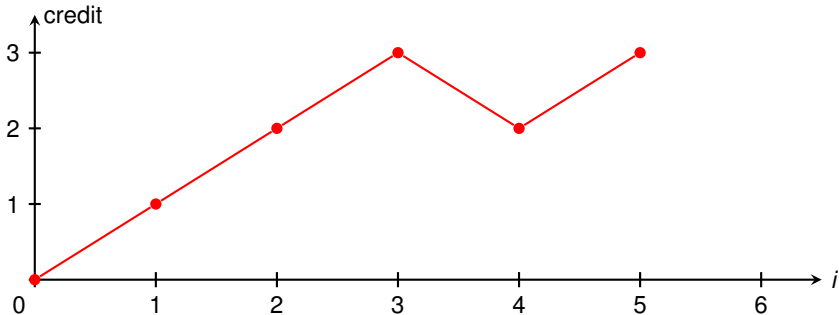
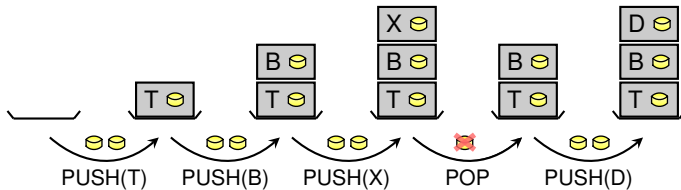
Stack and Coins



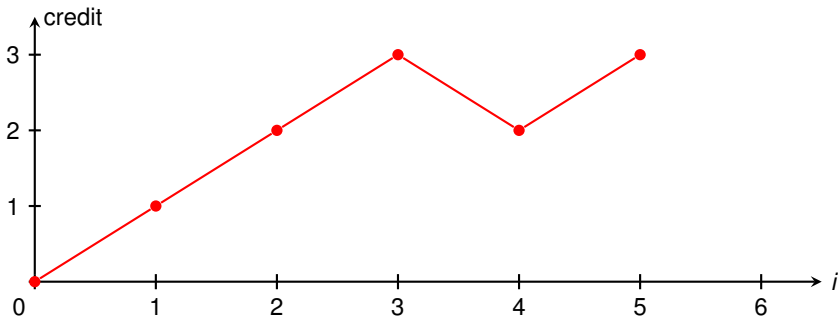
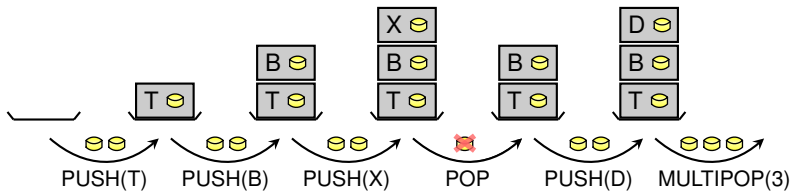
Stack and Coins



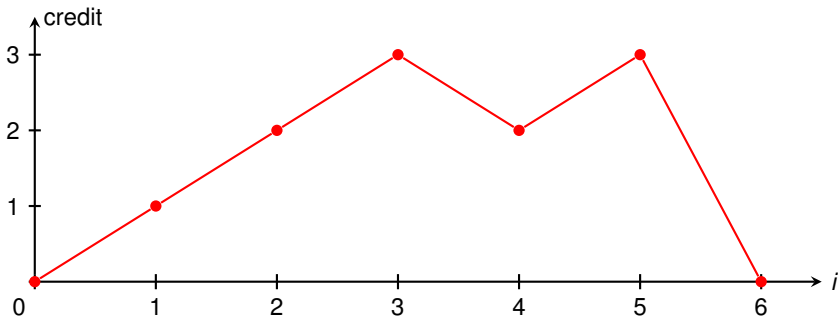
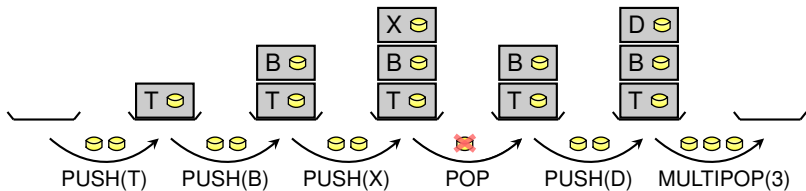
Stack and Coins



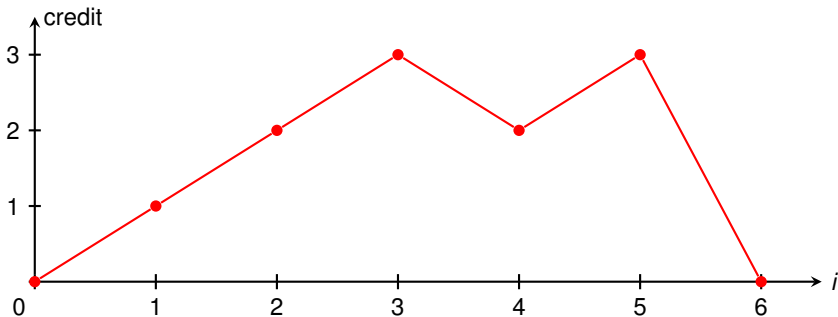
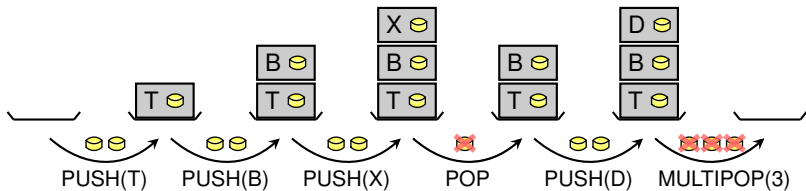
Stack and Coins



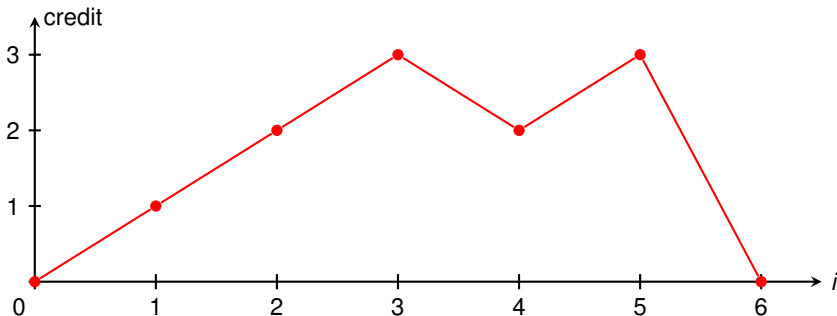
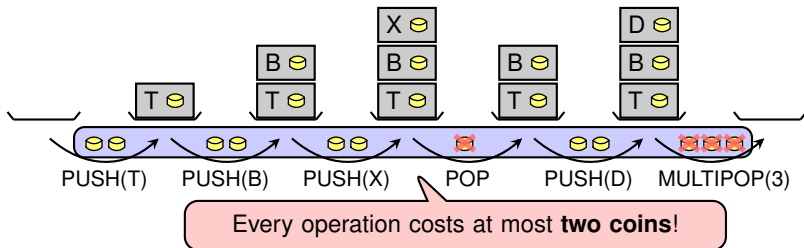
Stack and Coins



Stack and Coins



Stack and Coins



Potential Method in Detail

- c_i is the actual cost of operation i



Potential Method in Detail

- c_i is the **actual cost** of operation i
- \hat{c}_i is the **amortized cost** of operation i



Potential Method in Detail

- c_i is the **actual cost** of operation i
- \hat{c}_i is the **amortized cost** of operation i

$c_i < \hat{c}_i$, $c_i = \hat{c}_i$ or
 $c_i > \hat{c}_i$ are all possible!



Potential Method in Detail

- c_i is the **actual cost** of operation i
- \hat{c}_i is the **amortized cost** of operation i
- Φ_i is the **potential** stored after operation i ($\Phi_0 = 0$)



Potential Method in Detail

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Function that maps states of the data structure to some value



Potential Method in Detail

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$$\hat{c}_i = c_i + (\Phi_i - \Phi_{i-1})$$



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$$\hat{c}_i = c_i + (\Phi_i - \Phi_{i-1})$$

- PUSH(): $c_i = 1$
- POP: $c_i = 1$

- PUSH(): $\Phi_i - \Phi_{i-1} = 1$
- POP: $\Phi_i - \Phi_{i-1} = -1$



Potential Method in Detail

- c_i is the **actual cost** of operation i
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$$\hat{c}_i = c_i + (\Phi_i - \Phi_{i-1})$$

$$\sum_{i=1}^n \hat{c}_i = \sum_{i=1}^n (c_i + \Phi_i - \Phi_{i-1}) =$$



Potential Method in Detail

- c_i is the **actual cost** of operation i
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$$\sum_{i=1}^n \hat{c}_i = \sum_{i=1}^n (c_i + \Phi_i - \Phi_{i-1}) = \sum_{i=1}^n c_i + \Phi_n - \Phi_0$$



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$$\sum_{i=1}^n \hat{c}_i = \sum_{i=1}^n (c_i + \Phi_i - \Phi_{i-1}) = \sum_{i=1}^n c_i + \Phi_n$$

If $\Phi_n \geq 0$ for all n , sum of amortized costs is an upper bound for the sum of actual costs!



Stack: Analysis via Potential Method

$$\Phi_j =$$



Stack: Analysis via Potential Method

$\Phi_i = \#$ objects in the stack after i th operation (= # coins)



Stack: Analysis via Potential Method

$\Phi_i = \#$ objects in the stack after i th operation (= # coins)

PUSH

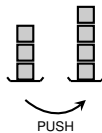


Stack: Analysis via Potential Method

$\Phi_i = \#$ objects in the stack after i th operation (= # coins)

PUSH

- actual cost: $c_i = 1$

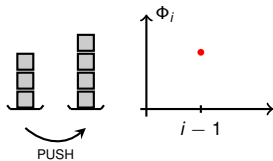


Stack: Analysis via Potential Method

$\Phi_i = \#$ objects in the stack after i th operation ($= \#$ coins)

PUSH

- actual cost: $c_i = 1$
- potential change: $\Phi_i - \Phi_{i-1} =$

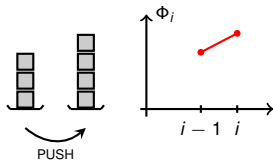


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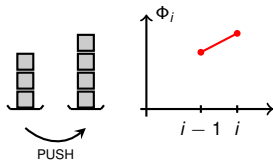


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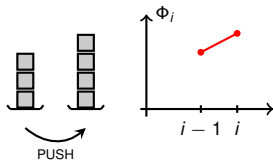


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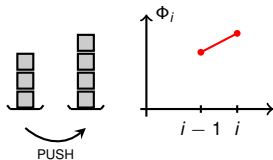


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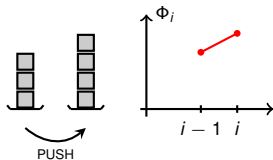


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POP

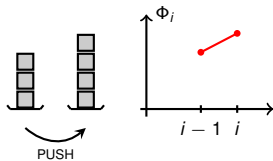


Stack: Analysis via Potential Method

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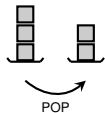
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POP

- $c_i = 1$

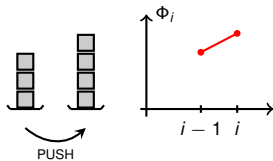


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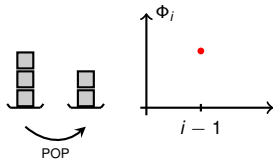
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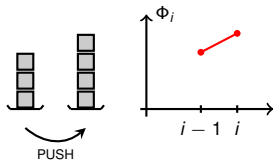


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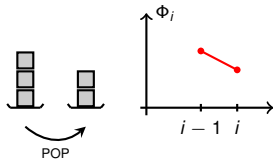
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POP

- $c_i = 1$
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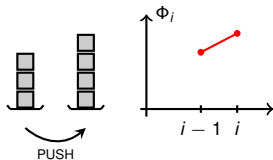


Stack: Analysis via Potential Method

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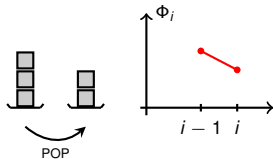
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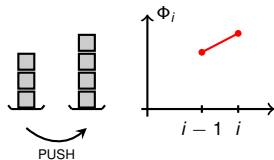


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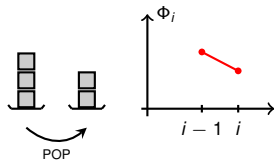
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POP

- $c_i = 1$
- $\Phi_i - \Phi_{i-1} = -1$
- $\hat{c}_i = c_i + (\Phi_i - \Phi_{i-1}) = 1 - 1 = 0$

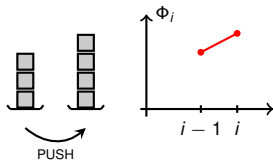


Stack: Analysis via Potential Method

$\Phi_i = \#$ objects in the stack after i th operation (= # coins)

PUSH

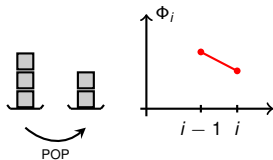
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POP

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- $\hat{c}_i = c_i + (\Phi_i - \Phi_{i-1}) = 1 - 1 = 0$

Stack is non-empty!

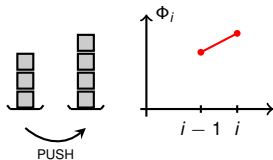


Stack: Analysis via Potential Method

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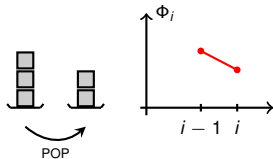
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MULTIPOP(k)

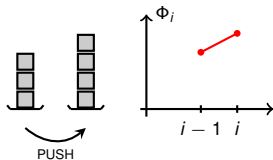


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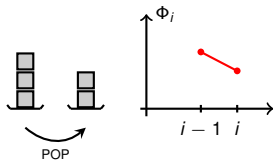
PUSH

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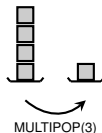
POP

- $c_i = 1$
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- $\hat{c}_i = c_i + (\Phi_i - \Phi_{i-1}) = 1 - 1 = 0$



MULTIPOP(k)

- $c_i = \min\{k, |S|\}$

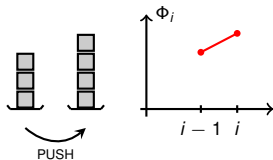


Stack: Analysis via Potential Method

$\Phi_i = \#$ objects in the stack after i th operation (= # coins)

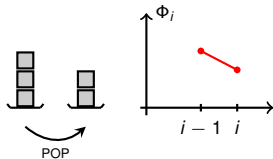
PUSH

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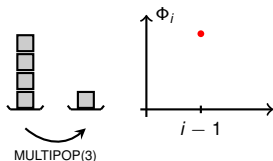
POP

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- $\Phi_i - \Phi_{i-1} = -1$
- $\hat{c}_i = c_i + (\Phi_i - \Phi_{i-1}) = 1 - 1 = 0$



MULTIPOP(k)

- $c_i = \min\{k, |S|\}$
- $\Phi_i - \Phi_{i-1} =$

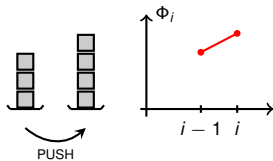


Stack: Analysis via Potential Method

$\Phi_i = \#$ objects in the stack after i th operation (= # coins)

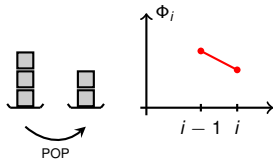
PUSH

- actual cost: $c_i = 1$
- potential change: $\Phi_i - \Phi_{i-1} = 1$
- amortized cost: $\hat{c}_i = c_i + (\Phi_i - \Phi_{i-1}) = 1 + 1 = 2$



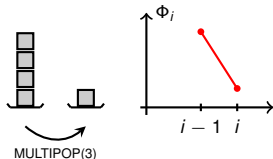
POP

- $c_i = 1$
- $\Phi_i - \Phi_{i-1} = -1$
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MULTIPOP(k)

- $c_i = \min\{k, |S|\}$
- $\Phi_i - \Phi_{i-1} = -\min\{k, |S|\}$

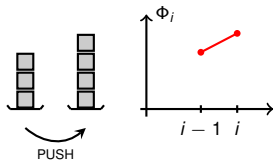


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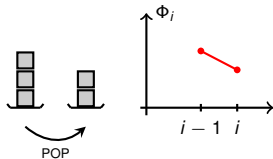
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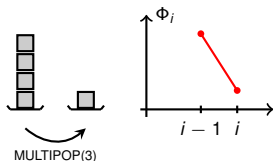
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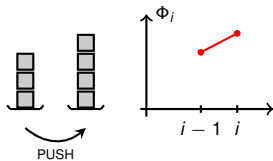


Stack: Analysis via Potential Method

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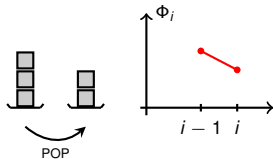
PUSH

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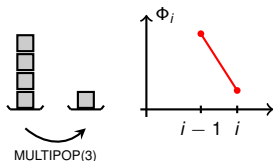
POP

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MULTIPOP(k)

- $c_i = \min\{k, |S|\}$
- $\Phi_i - \Phi_{i-1} = -\min\{k, |S|\}$
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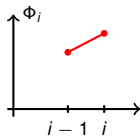
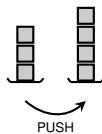


Stack: Analysis via Potential Method

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PUSH

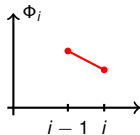
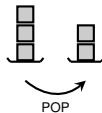
- actual cost: $c_i = 1$
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POP

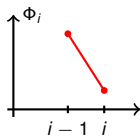
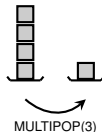
- $c_i = 1$
- $\Phi_i - \Phi_{i-1} = -1$
- $\hat{c}_i = c_i + (\Phi_i - \Phi_{i-1}) = 1 - 1 = 0$

Amortized Cost $\leq 2 \Rightarrow T(n) \leq 2n$



MULTIPOP(k)

- $c_i = \min\{k, |S|\}$
- $\Phi_i - \Phi_{i-1} = -\min\{k, |S|\}$
- $\hat{c}_i = c_i + (\Phi_i - \Phi_{i-1}) = \min\{k, |S|\} - \min\{k, |S|\} = 0$

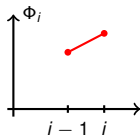
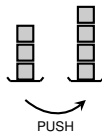


Stack: Analysis via Potential Method

$\Phi_i = \#$ objects in the stack after i th operation (= # coins)

PUSH

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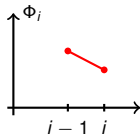
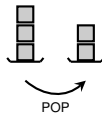


POP

- $c_i = 1$
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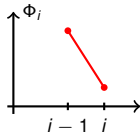
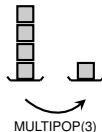
Amortized Cost $\leq 2 \Rightarrow T(n) \leq 2n$

$n/2$ PUSH, $n/2$ POP $\Rightarrow T(n) \leq n$



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Second Example: Binary Counter

Binary Counter

- Array $A[k - 1], A[k - 2], \dots, A[0]$ of k bits
- Use array for counting from 0 to $2^k - 1$



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$A[3] A[2] A[1] A[0]$

1 0 1 1

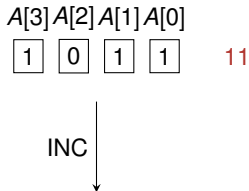
11



Second Example: Binary Counter

Binary Counter

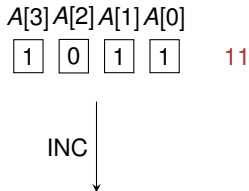
- Array $A[k - 1], A[k - 2], \dots, A[0]$ of k bits
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- only operation: **INC**



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- Array $A[k - 1], A[k - 2], \dots, A[0]$ of k bits
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Binary Counter

- Array $A[k - 1], A[k - 2], \dots, A[0]$ of k bits
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 - increases the counter by one

A[3] A[2] A[1] A[0]
1 0 1 1 11

INC
↓

A[3] A[2] A[1] A[0]
1 1 0 0 12



Second Example: Binary Counter

Binary Counter

- Array $A[k - 1], A[k - 2], \dots, A[0]$ of k bits
- Use array for counting from 0 to $2^k - 1$
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 - increases the counter by one

```
0: INC(A)
1: i = 0
2: while i < k and A[i]==1
3:     A[i] = 0
4:     i = i + 1
5: A[i] = 1
```

A[3]	A[2]	A[1]	A[0]	
1	0	1	1	11

INC
↓

A[3]	A[2]	A[1]	A[0]	
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Second Example: Binary Counter

Binary Counter

- Array $A[k - 1], A[k - 2], \dots, A[0]$ of k bits
- Use array for counting from 0 to $2^k - 1$
- only operation: **INC**
 - increases the counter by one
 - total cost: ??

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A[3]	A[2]	A[1]	A[0]	
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Second Example: Binary Counter

Binary Counter

- Array $A[k - 1], A[k - 2], \dots, A[0]$ of k bits
- Use array for counting from 0 to $2^k - 1$
- only operation: **INC**
 - increases the counter by one
 - total cost: $\leq k$

A[3] A[2] A[1] A[0] 11
1 0 1 1

INC
↓

A[3] A[2] A[1] A[0] 12
1 1 0 0



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- Array $A[k-1], A[k-2], \dots, A[0]$ of k bits
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INC
↓

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1 1 0 0

What is the total cost of a sequence of n INC operations?



Second Example: Binary Counter

Binary Counter

- Array $A[k - 1], A[k - 2], \dots, A[0]$ of k bits
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1	0	1	1	11

INC

A[3]	A[2]	A[1]	A[0]	
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What is the total cost of a sequence of n INC operations?

Simple Worst-Case Bound:

- largest cost of an operation: k
- cost is at most $n \cdot k$



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- Array $A[k - 1], A[k - 2], \dots, A[0]$ of k bits
- Use array for counting from 0 to $2^k - 1$
- only operation: **INC**
 - increases the counter by one
 - total cost: $\leq k$

A[3]	A[2]	A[1]	A[0]	
1	0	1	1	11

INC
↓

A[3]	A[2]	A[1]	A[0]	
1	1	0	0	12

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- largest cost of an operation: k
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Second Example: Binary Counter

Binary Counter

- Array $A[k - 1], A[k - 2], \dots, A[0]$ of k bits
- Use array for counting from 0 to $2^k - 1$
- only operation: **INC**
 - increases the counter by one
 - total cost: ~~$\times k$~~
number of flips (smallest index of a zero)

A[3]	A[2]	A[1]	A[0]	
1	0	1	1	11

INC

A[3]	A[2]	A[1]	A[0]	
1	1	0	0	12

What is the total cost of a sequence of n INC operations?

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Incrementing a Binary Counter

Counter Value	A[7]	A[6]	A[5]	A[4]	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0	0	0	0	0



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Counter Value	A[7]	A[6]	A[5]	A[4]	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0	0	0	0	0



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Counter Value	A[7]	A[6]	A[5]	A[4]	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	1	1



Incrementing a Binary Counter

Counter Value	A[7]	A[6]	A[5]	A[4]	A[3]	A[2]	A[1]	A[0]	Total Cost
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1	0	0	0	0	0	0	0	1	1



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Counter Value	A[7]	A[6]	A[5]	A[4]	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	1	1
2	0	0	0	0	0	0	1	0	3



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Counter Value	A[7]	A[6]	A[5]	A[4]	A[3]	A[2]	A[1]	A[0]	Total Cost
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1	0	0	0	0	0	0	0	1	1
2	0	0	0	0	0	0	1	0	3



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Counter Value	A[7]	A[6]	A[5]	A[4]	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	1	1
2	0	0	0	0	0	0	1	0	3
3	0	0	0	0	0	0	1	1	4



Incrementing a Binary Counter

Counter Value	A[7]	A[6]	A[5]	A[4]	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	1	1
2	0	0	0	0	0	0	1	0	3
3	0	0	0	0	0	0	1	1	4



Incrementing a Binary Counter

Counter Value	A[7]	A[6]	A[5]	A[4]	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	1	1
2	0	0	0	0	0	0	1	0	3
3	0	0	0	0	0	0	1	1	4
4	0	0	0	0	0	1	0	0	7



Incrementing a Binary Counter

Counter Value	A[7]	A[6]	A[5]	A[4]	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	1	1
2	0	0	0	0	0	0	1	0	3
3	0	0	0	0	0	0	1	1	4
4	0	0	0	0	0	1	0	0	7



Incrementing a Binary Counter

Counter Value	A[7]	A[6]	A[5]	A[4]	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	1	1
2	0	0	0	0	0	0	1	0	3
3	0	0	0	0	0	0	1	1	4
4	0	0	0	0	0	1	0	0	7
5	0	0	0	0	0	1	0	1	8



Incrementing a Binary Counter

Counter Value	A[7]	A[6]	A[5]	A[4]	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	1	1
2	0	0	0	0	0	0	1	0	3
3	0	0	0	0	0	0	1	1	4
4	0	0	0	0	0	1	0	0	7
5	0	0	0	0	0	1	0	1	8



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Counter Value	A[7]	A[6]	A[5]	A[4]	A[3]	A[2]	A[1]	A[0]	Total Cost
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3	0	0	0	0	0	0	1	1	4
4	0	0	0	0	0	1	0	0	7
5	0	0	0	0	0	1	0	1	8
6	0	0	0	0	0	1	1	0	10



Incrementing a Binary Counter

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0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	1	1
2	0	0	0	0	0	0	1	0	3
3	0	0	0	0	0	0	1	1	4
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5	0	0	0	0	0	1	0	1	8
6	0	0	0	0	0	1	1	0	10



Incrementing a Binary Counter

Counter Value	A[7]	A[6]	A[5]	A[4]	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	1	1
2	0	0	0	0	0	0	1	0	3
3	0	0	0	0	0	0	1	1	4
4	0	0	0	0	0	1	0	0	7
5	0	0	0	0	0	1	0	1	8
6	0	0	0	0	0	1	1	0	10
7	0	0	0	0	0	1	1	1	11



Incrementing a Binary Counter

Counter Value	A[7]	A[6]	A[5]	A[4]	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	1	1
2	0	0	0	0	0	0	1	0	3
3	0	0	0	0	0	0	1	1	4
4	0	0	0	0	0	1	0	0	7
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6	0	0	0	0	0	1	1	0	10
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Counter Value	A[7]	A[6]	A[5]	A[4]	A[3]	A[2]	A[1]	A[0]	Total Cost
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2	0	0	0	0	0	0	1	0	3
3	0	0	0	0	0	0	1	1	4
4	0	0	0	0	0	1	0	0	7
5	0	0	0	0	0	1	0	1	8
6	0	0	0	0	0	1	1	0	10
7	0	0	0	0	0	1	1	1	11
8	0	0	0	0	1	0	0	0	15



Incrementing a Binary Counter

Counter Value	A[7]	A[6]	A[5]	A[4]	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	1	1
2	0	0	0	0	0	0	1	0	3
3	0	0	0	0	0	0	1	1	4
4	0	0	0	0	0	1	0	0	7
5	0	0	0	0	0	1	0	1	8
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3	0	0	0	0	0	0	1	1	4
4	0	0	0	0	0	1	0	0	7
5	0	0	0	0	0	1	0	1	8
6	0	0	0	0	0	1	1	0	10
7	0	0	0	0	0	1	1	1	11
8	0	0	0	0	1	0	0	0	15
9	0	0	0	0	1	0	0	1	16



Incrementing a Binary Counter

Counter Value	A[7]	A[6]	A[5]	A[4]	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	1	1
2	0	0	0	0	0	0	1	0	3
3	0	0	0	0	0	0	1	1	4
4	0	0	0	0	0	1	0	0	7
5	0	0	0	0	0	1	0	1	8
6	0	0	0	0	0	1	1	0	10
7	0	0	0	0	0	1	1	1	11
8	0	0	0	0	1	0	0	0	15
9	0	0	0	0	1	0	0	1	16



Incrementing a Binary Counter

Counter Value	A[7]	A[6]	A[5]	A[4]	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	1	1
2	0	0	0	0	0	0	1	0	3
3	0	0	0	0	0	0	1	1	4
4	0	0	0	0	0	1	0	0	7
5	0	0	0	0	0	1	0	1	8
6	0	0	0	0	0	1	1	0	10
7	0	0	0	0	0	1	1	1	11
8	0	0	0	0	1	0	0	0	15
9	0	0	0	0	1	0	0	1	16
10	0	0	0	0	1	0	1	0	18



Incrementing a Binary Counter

Counter Value	A[7]	A[6]	A[5]	A[4]	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	1	1
2	0	0	0	0	0	0	1	0	3
3	0	0	0	0	0	0	1	1	4
4	0	0	0	0	0	1	0	0	7
5	0	0	0	0	0	1	0	1	8
6	0	0	0	0	0	1	1	0	10
7	0	0	0	0	0	1	1	1	11
8	0	0	0	0	1	0	0	0	15
9	0	0	0	0	1	0	0	1	16
10	0	0	0	0	1	0	1	0	18



Incrementing a Binary Counter

Counter Value	A[7]	A[6]	A[5]	A[4]	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	1	1
2	0	0	0	0	0	0	1	0	3
3	0	0	0	0	0	0	1	1	4
4	0	0	0	0	0	1	0	0	7
5	0	0	0	0	0	1	0	1	8
6	0	0	0	0	0	1	1	0	10
7	0	0	0	0	0	1	1	1	11
8	0	0	0	0	1	0	0	0	15
9	0	0	0	0	1	0	0	1	16
10	0	0	0	0	1	0	1	0	18
11	0	0	0	0	1	0	1	1	19



Incrementing a Binary Counter

Counter Value	A[7]	A[6]	A[5]	A[4]	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	1	1
2	0	0	0	0	0	0	1	0	3
3	0	0	0	0	0	0	1	1	4
4	0	0	0	0	0	1	0	0	7
5	0	0	0	0	0	1	0	1	8
6	0	0	0	0	0	1	1	0	10
7	0	0	0	0	0	1	1	1	11
8	0	0	0	0	1	0	0	0	15
9	0	0	0	0	1	0	0	1	16
10	0	0	0	0	1	0	1	0	18
11	0	0	0	0	1	0	1	1	19



Incrementing a Binary Counter

Counter Value	A[7]	A[6]	A[5]	A[4]	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	1	1
2	0	0	0	0	0	0	1	0	3
3	0	0	0	0	0	0	1	1	4
4	0	0	0	0	0	1	0	0	7
5	0	0	0	0	0	1	0	1	8
6	0	0	0	0	0	1	1	0	10
7	0	0	0	0	0	1	1	1	11
8	0	0	0	0	1	0	0	0	15
9	0	0	0	0	1	0	0	1	16
10	0	0	0	0	1	0	1	0	18
11	0	0	0	0	1	0	1	1	19
12	0	0	0	0	1	1	0	0	22



Incrementing a Binary Counter

Counter Value	A[7]	A[6]	A[5]	A[4]	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	1	1
2	0	0	0	0	0	0	1	0	3
3	0	0	0	0	0	0	1	1	4
4	0	0	0	0	0	1	0	0	7
5	0	0	0	0	0	1	0	1	8
6	0	0	0	0	0	1	1	0	10
7	0	0	0	0	0	1	1	1	11
8	0	0	0	0	1	0	0	0	15
9	0	0	0	0	1	0	0	1	16
10	0	0	0	0	1	0	1	0	18
11	0	0	0	0	1	0	1	1	19
12	0	0	0	0	1	1	0	0	22



Incrementing a Binary Counter

Counter Value	A[7]	A[6]	A[5]	A[4]	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	1	1
2	0	0	0	0	0	0	1	0	3
3	0	0	0	0	0	0	1	1	4
4	0	0	0	0	0	1	0	0	7
5	0	0	0	0	0	1	0	1	8
6	0	0	0	0	0	1	1	0	10
7	0	0	0	0	0	1	1	1	11
8	0	0	0	0	1	0	0	0	15
9	0	0	0	0	1	0	0	1	16
10	0	0	0	0	1	0	1	0	18
11	0	0	0	0	1	0	1	1	19
12	0	0	0	0	1	1	0	0	22
13	0	0	0	0	1	1	0	1	23



Incrementing a Binary Counter

Counter Value	A[7]	A[6]	A[5]	A[4]	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	1	1
2	0	0	0	0	0	0	1	0	3
3	0	0	0	0	0	0	1	1	4
4	0	0	0	0	0	1	0	0	7
5	0	0	0	0	0	1	0	1	8
6	0	0	0	0	0	1	1	0	10
7	0	0	0	0	0	1	1	1	11
8	0	0	0	0	1	0	0	0	15
9	0	0	0	0	1	0	0	1	16
10	0	0	0	0	1	0	1	0	18
11	0	0	0	0	1	0	1	1	19
12	0	0	0	0	1	1	0	0	22
13	0	0	0	0	1	1	0	1	23



Incrementing a Binary Counter

Counter Value	A[7]	A[6]	A[5]	A[4]	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	1	1
2	0	0	0	0	0	0	1	0	3
3	0	0	0	0	0	0	1	1	4
4	0	0	0	0	0	1	0	0	7
5	0	0	0	0	0	1	0	1	8
6	0	0	0	0	0	1	1	0	10
7	0	0	0	0	0	1	1	1	11
8	0	0	0	0	1	0	0	0	15
9	0	0	0	0	1	0	0	1	16
10	0	0	0	0	1	0	1	0	18
11	0	0	0	0	1	0	1	1	19
12	0	0	0	0	1	1	0	0	22
13	0	0	0	0	1	1	0	1	23
14	0	0	0	0	1	1	1	0	25



Incrementing a Binary Counter

Counter Value	A[7]	A[6]	A[5]	A[4]	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	1	1
2	0	0	0	0	0	0	1	0	3
3	0	0	0	0	0	0	1	1	4
4	0	0	0	0	0	1	0	0	7
5	0	0	0	0	0	1	0	1	8
6	0	0	0	0	0	1	1	0	10
7	0	0	0	0	0	1	1	1	11
8	0	0	0	0	1	0	0	0	15
9	0	0	0	0	1	0	0	1	16
10	0	0	0	0	1	0	1	0	18
11	0	0	0	0	1	0	1	1	19
12	0	0	0	0	1	1	0	0	22
13	0	0	0	0	1	1	0	1	23
14	0	0	0	0	1	1	1	0	25



Incrementing a Binary Counter

Counter Value	A[7]	A[6]	A[5]	A[4]	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	1	1
2	0	0	0	0	0	0	1	0	3
3	0	0	0	0	0	0	1	1	4
4	0	0	0	0	0	1	0	0	7
5	0	0	0	0	0	1	0	1	8
6	0	0	0	0	0	1	1	0	10
7	0	0	0	0	0	1	1	1	11
8	0	0	0	0	1	0	0	0	15
9	0	0	0	0	1	0	0	1	16
10	0	0	0	0	1	0	1	0	18
11	0	0	0	0	1	0	1	1	19
12	0	0	0	0	1	1	0	0	22
13	0	0	0	0	1	1	0	1	23
14	0	0	0	0	1	1	1	0	25
15	0	0	0	0	1	1	1	1	26



Incrementing a Binary Counter

Counter Value	A[7]	A[6]	A[5]	A[4]	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	1	1
2	0	0	0	0	0	0	1	0	3
3	0	0	0	0	0	0	1	1	4
4	0	0	0	0	0	1	0	0	7
5	0	0	0	0	0	1	0	1	8
6	0	0	0	0	0	1	1	0	10
7	0	0	0	0	0	1	1	1	11
8	0	0	0	0	1	0	0	0	15
9	0	0	0	0	1	0	0	1	16
10	0	0	0	0	1	0	1	0	18
11	0	0	0	0	1	0	1	1	19
12	0	0	0	0	1	1	0	0	22
13	0	0	0	0	1	1	0	1	23
14	0	0	0	0	1	1	1	0	25
15	0	0	0	0	1	1	1	1	26



Incrementing a Binary Counter

Counter Value	A[7]	A[6]	A[5]	A[4]	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	1	1
2	0	0	0	0	0	0	1	0	3
3	0	0	0	0	0	0	1	1	4
4	0	0	0	0	0	1	0	0	7
5	0	0	0	0	0	1	0	1	8
6	0	0	0	0	0	1	1	0	10
7	0	0	0	0	0	1	1	1	11
8	0	0	0	0	1	0	0	0	15
9	0	0	0	0	1	0	0	1	16
10	0	0	0	0	1	0	1	0	18
11	0	0	0	0	1	0	1	1	19
12	0	0	0	0	1	1	0	0	22
13	0	0	0	0	1	1	0	1	23
14	0	0	0	0	1	1	1	0	25
15	0	0	0	0	1	1	1	1	26
16	0	0	0	1	0	0	0	0	31



Incrementing a Binary Counter

Counter Value	A[7]	A[6]	A[5]	A[4]	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	1	1
2	0	0	0	0	0	0	1	0	3
3	0	0	0	0	0	0	1	1	4
4	0	0	0	0	0	1	0	0	7
5	0	0	0	0	0	1	0	1	8
6	0	0	0	0	0	1	1	0	10
7	0	0	0	0	0	1	1	1	11
8	0	0	0	0	1	0	0	0	15
9	0	0	0	0	1	0	0	1	16
10	0	0	0	0	1	0	1	0	18
11	0	0	0	0	1	0	1	1	19
12	0	0	0	0	1	1	0	0	22
13	0	0	0	0	1	1	0	1	23
14	0	0	0	0	1	1	1	0	25
15	0	0	0	0	1	1	1	1	26
16	0	0	0	1	0	0	0	0	31



Incrementing a Binary Counter: Aggregate Analysis

Counter Value	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0
1	0	0	0	1	1
2	0	0	1	0	3
3	0	0	1	1	4
4	0	1	0	0	7
5	0	1	0	1	8
6	0	1	1	0	10
7	0	1	1	1	11



Incrementing a Binary Counter: Aggregate Analysis

Counter Value	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0
1	0	0	0	1	1
2	0	0	1	0	3
3	0	0	1	1	4
4	0	1	0	0	7
5	0	1	0	1	8
6	0	1	1	0	10
7	0	1	1	1	11



Incrementing a Binary Counter: Aggregate Analysis

Counter Value	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0
1	0	0	0	1	1
2	0	0	1	0	3
3	0	0	1	1	4
4	0	1	0	0	7
5	0	1	0	1	8
6	0	1	1	0	10
7	0	1	1	1	11



Incrementing a Binary Counter: Aggregate Analysis

Counter Value	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0
1	0	0	0	1	1
2	0	0	1	0	3
3	0	0	1	1	4
4	0	1	0	0	7
5	0	1	0	1	8
6	0	1	1	0	10
7	0	1	1	1	11



Incrementing a Binary Counter: Aggregate Analysis

Counter Value	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0
1	0	0	0	1	1
2	0	0	1	0	3
3	0	0	1	1	4
4	0	1	0	0	7
5	0	1	0	1	8
6	0	1	1	0	10
7	0	1	1	1	11



Incrementing a Binary Counter: Aggregate Analysis

Counter Value	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0
1	0	0	0	1	1
2	0	0	1	0	3
3	0	0	1	1	4
4	0	1	0	0	7
5	0	1	0	1	8
6	0	1	1	0	10
7	0	1	1	1	11

- Bit $A[i]$ is only flipped every 2^i increments



Incrementing a Binary Counter: Aggregate Analysis

Counter Value	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0
1	0	0	0	1	1
2	0	0	1	0	3
3	0	0	1	1	4
4	0	1	0	0	7
5	0	1	0	1	8
6	0	1	1	0	10
7	0	1	1	1	11

- Bit $A[i]$ is only flipped every 2^i increments
- In a sequence of n increments from 0, bit $A[i]$ is flipped $\lfloor \frac{n}{2^i} \rfloor$ times



Incrementing a Binary Counter: Aggregate Analysis

Counter Value	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0
1	0	0	0	1	1
2	0	0	1	0	3
3	0	0	1	1	4
4	0	1	0	0	7
5	0	1	0	1	8
6	0	1	1	0	10
7	0	1	1	1	11

- Bit $A[i]$ is only flipped every 2^i increments
- In a sequence of n increments from 0, bit $A[i]$ is flipped $\lfloor \frac{n}{2^i} \rfloor$ times

$$T(n) \leq$$



Incrementing a Binary Counter: Aggregate Analysis

Counter Value	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0
1	0	0	0	1	1
2	0	0	1	0	3
3	0	0	1	1	4
4	0	1	0	0	7
5	0	1	0	1	8
6	0	1	1	0	10
7	0	1	1	1	11

- Bit $A[i]$ is only flipped every 2^i increments
- In a sequence of n increments from 0, bit $A[i]$ is flipped $\lfloor \frac{n}{2^i} \rfloor$ times

$$T(n) \leq \sum_{i=0}^{k-1} \left\lfloor \frac{n}{2^i} \right\rfloor$$



Incrementing a Binary Counter: Aggregate Analysis

Counter Value	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0
1	0	0	0	1	1
2	0	0	1	0	3
3	0	0	1	1	4
4	0	1	0	0	7
5	0	1	0	1	8
6	0	1	1	0	10
7	0	1	1	1	11

- Bit $A[i]$ is only flipped every 2^i increments
- In a sequence of n increments from 0, bit $A[i]$ is flipped $\lfloor \frac{n}{2^i} \rfloor$ times

$$T(n) \leq \sum_{i=0}^{k-1} \left\lfloor \frac{n}{2^i} \right\rfloor \leq \sum_{i=0}^{k-1} \frac{n}{2^i}$$



Incrementing a Binary Counter: Aggregate Analysis

Counter Value	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0
1	0	0	0	1	1
2	0	0	1	0	3
3	0	0	1	1	4
4	0	1	0	0	7
5	0	1	0	1	8
6	0	1	1	0	10
7	0	1	1	1	11

- Bit $A[i]$ is only flipped every 2^i increments
- In a sequence of n increments from 0, bit $A[i]$ is flipped $\lfloor \frac{n}{2^i} \rfloor$ times

$$T(n) \leq \sum_{i=0}^{k-1} \left\lfloor \frac{n}{2^i} \right\rfloor \leq \sum_{i=0}^{k-1} \frac{n}{2^i} = n \cdot \left(1 + \frac{1}{2} + \frac{1}{4} + \dots + \frac{1}{2^{k-1}} \right)$$



Incrementing a Binary Counter: Aggregate Analysis

Counter Value	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0
1	0	0	0	1	1
2	0	0	1	0	3
3	0	0	1	1	4
4	0	1	0	0	7
5	0	1	0	1	8
6	0	1	1	0	10
7	0	1	1	1	11

- Bit $A[i]$ is only flipped every 2^i increments
- In a sequence of n increments from 0, bit $A[i]$ is flipped $\lfloor \frac{n}{2^i} \rfloor$ times

$$T(n) \leq \sum_{i=0}^{k-1} \left\lfloor \frac{n}{2^i} \right\rfloor \leq \sum_{i=0}^{k-1} \frac{n}{2^i} = n \cdot \left(1 + \frac{1}{2} + \frac{1}{4} + \dots + \frac{1}{2^{k-1}} \right) \leq 2 \cdot n.$$



Incrementing a Binary Counter: Aggregate Analysis

Counter Value	A[3]	A[2]	A[1]	A[0]	Total Cost
0	0	0	0	0	0
1	0	0	0	1	1
2	0	0	1	0	3
3	0	0	1	1	4
4	0	1	0	0	7
5	0	1	0	1	8
6	0	1	1	0	10
7	0	1	1	1	11

- Bit $A[i]$ is only flipped every 2^i increments
- In a sequence of n increments from 0, bit $A[i]$ is flipped $\lfloor \frac{n}{2^i} \rfloor$ times

Aggregate Analysis: The amortized cost per operation is $\frac{T(n)}{n} \leq 2$.

$$T(n) \leq \sum_{i=0}^{k-1} \left\lfloor \frac{n}{2^i} \right\rfloor \leq \sum_{i=0}^{k-1} \frac{n}{2^i} = n \cdot \left(1 + \frac{1}{2} + \frac{1}{4} + \dots + \frac{1}{2^{k-1}} \right) \leq 2 \cdot n.$$



Binary Counter: Analysis via Potential Function

$$\Phi_i =$$



Binary Counter: Analysis via Potential Function

$\Phi_i = \# \text{ ones in the binary representation of } i$



Binary Counter: Analysis via Potential Function

$$\Phi_0 = 0 \checkmark \quad \Phi_i \geq 0 \checkmark$$

$\Phi_i = \#$ ones in the binary representation of i



Binary Counter: Analysis via Potential Function

$$\Phi_0 = 0 \checkmark \quad \Phi_i \geq 0 \checkmark$$

$\Phi_i = \#$ ones in the binary representation of i

Increment without Carry-Over



Binary Counter: Analysis via Potential Function

$$\Phi_0 = 0 \checkmark \quad \Phi_i \geq 0 \checkmark$$

$\Phi_i = \#$ ones in the binary representation of i

Increment without Carry-Over

- actual cost: $c_i = 1$

1 1 0 0



Binary Counter: Analysis via Potential Function

$$\Phi_0 = 0 \checkmark \quad \Phi_i \geq 0 \checkmark$$

$\Phi_i = \#$ ones in the binary representation of i

Increment without Carry-Over

- actual cost: $c_i = 1$

1	1	0	0
			↓ INC
1	1	0	1



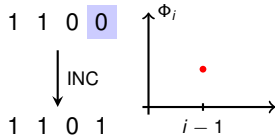
Binary Counter: Analysis via Potential Function

$$\Phi_0 = 0 \checkmark \quad \Phi_i \geq 0 \checkmark$$

$\Phi_i = \# \text{ ones in the binary representation of } i$

Increment without Carry-Over

- actual cost: $c_i = 1$
- potential change: $\Phi_i - \Phi_{i-1} =$



Binary Counter: Analysis via Potential Function

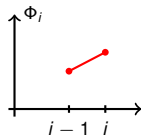
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1 1 0 0
↓ INC
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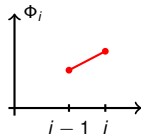
Increment without Carry-Over

- actual cost: $c_i = 1$
- potential change: $\Phi_i - \Phi_{i-1} = 1$
- amortized cost: $\hat{c}_i =$

1 1 0 0

↓ INC

1 1 0 1



Binary Counter: Analysis via Potential Function

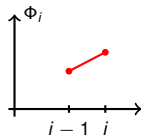
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- actual cost: $c_i = 1$
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- amortized cost: $\hat{c}_i = c_i + (\Phi_i - \Phi_{i-1}) =$

1 1 0 0
↓ INC
1 1 0 1



Binary Counter: Analysis via Potential Function

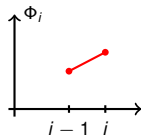
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- actual cost: $c_i = 1$
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- amortized cost: $\hat{c}_i = c_i + (\Phi_i - \Phi_{i-1}) = 1 + 1 = 2$

1 1 0 0
↓ INC
1 1 0 1



Binary Counter: Analysis via Potential Function

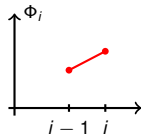
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1 1 0 0
↓ INC
1 1 0 1



Increment with Carry-Over



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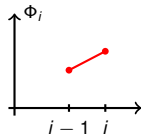
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1 1 0 0

↓ INC

1 1 0 1



Increment with Carry-Over

- $c_i = x + 1$, (x lowest index of a zero)

0 1 1 1



Binary Counter: Analysis via Potential Function

$$\Phi_0 = 0 \checkmark \quad \Phi_i \geq 0 \checkmark$$

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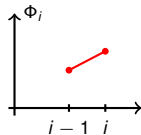
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1 1 0 0

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Binary Counter: Analysis via Potential Function

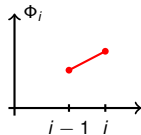
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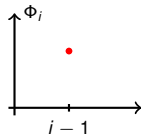
1 1 0 0
↓ INC
1 1 0 1



Increment with Carry-Over

- $c_i = x + 1$, (x lowest index of a zero)
- $\Phi_i - \Phi_{i-1} =$

0 1 1 1
↓ INC
1 0 0 0



Binary Counter: Analysis via Potential Function

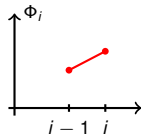
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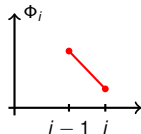
1 1 0 0
↓ INC
1 1 0 1



Increment with Carry-Over

- $c_i = x + 1$, (x lowest index of a zero)
- $\Phi_i - \Phi_{i-1} = -x + 1$

0 1 1 1
↓ INC
1 0 0 0



Binary Counter: Analysis via Potential Function

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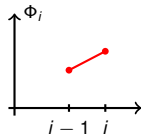
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1 1 0 0

↓ INC

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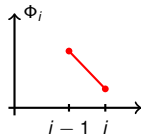
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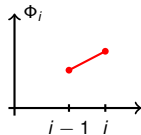
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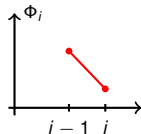
1 1 0 0
↓ INC
1 1 0 1



Increment with Carry-Over

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- $\Phi_i - \Phi_{i-1} = -x + 1$
- $\hat{c}_i = c_i + (\Phi_i - \Phi_{i-1}) = 1 + x - x + 1$

0 1 1 1
↓ INC
1 0 0 0



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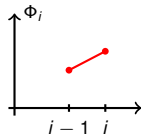
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1 1 0 0

↓ INC

1 1 0 1



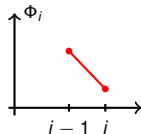
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0 1 1 1

↓ INC

1 0 0 0



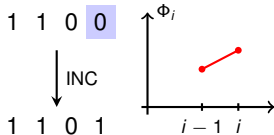
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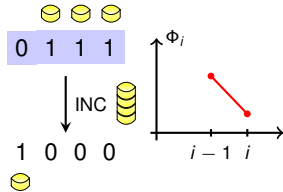
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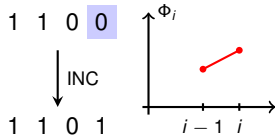
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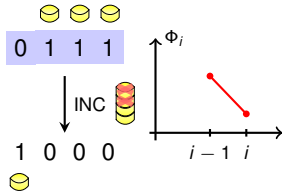
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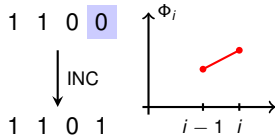
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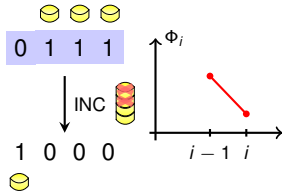
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Amortized Cost = 2 $\Rightarrow T(n) \leq 2n$

Increment with Carry-Over

- $c_i = x + 1$, (x lowest index of a zero)
- $\Phi_i - \Phi_{i-1} = -x + 1$
- $\hat{c}_i = c_i + (\Phi_i - \Phi_{i-1}) = 1 + x - x + 1 = 2$



Amortized Analysis

- Average costs over a sequence of n operations
- overcharge cheap operations and undercharge expensive operations
- no probability/average case analysis involved!



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Aggregate Analysis



Amortized Analysis

- Average costs over a sequence of n operations
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Aggregate Analysis

- Determine an absolute upper bound $T(n)$



Amortized Analysis

- Average costs over a sequence of n operations
- overcharge cheap operations and undercharge expensive operations
- no probability/average case analysis involved!

E.g. by bounding the number of expensive operations

Aggregate Analysis

- Determine an absolute upper bound $T(n)$



Summary

Amortized Analysis

- Average costs over a sequence of n operations
- overcharge cheap operations and undercharge expensive operations
- no probability/average case analysis involved!

Aggregate Analysis

- Determine an absolute upper bound $T(n)$
- every operation has amortized cost $\frac{T(n)}{n}$

$$T(n) \quad \boxed{} \boxed{} \boxed{} \boxed{} \boxed{} \boxed{}$$



Summary

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Potential Method



Summary

Amortized Analysis

- Average costs over a sequence of n operations
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Aggregate Analysis

- Determine an absolute upper bound $T(n)$
- every operation has **amortized** cost $\frac{T(n)}{n}$

$$T(n) \quad \boxed{} \boxed{} \boxed{} \boxed{} \boxed{} \boxed{}$$

Potential Method

- use **savings** from cheap operations to compensate for expensive ones



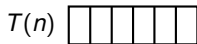
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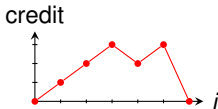
Aggregate Analysis

- Determine an absolute upper bound $T(n)$
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Potential Method

- use **savings** from cheap operations to compensate for expensive ones



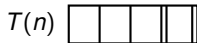
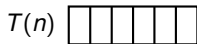
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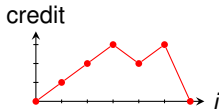
Aggregate Analysis

- Determine an absolute upper bound $T(n)$
- every operation has **amortized** cost $\frac{T(n)}{n}$



Potential Method

- use **savings** from cheap operations to compensate for expensive ones
- operations may have different **amortized** cost



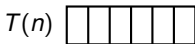
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Aggregate Analysis

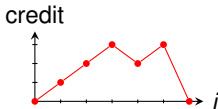
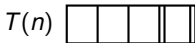
- Determine an absolute upper bound $T(n)$
- every operation has **amortized** cost $\frac{T(n)}{n}$



Full power of this method will become clear later!

Potential Method

- use **savings** from cheap operations to compensate for expensive ones
- operations may have different **amortized** cost



Next Lecture: Fibonacci Heap

Operation	Binomial heap worst-case cost
MAKE-HEAP	$\mathcal{O}(1)$
INSERT	$\mathcal{O}(\log n)$
MINIMUM	$\mathcal{O}(\log n)$
EXTRACT-MIN	$\mathcal{O}(\log n)$
UNION	$\mathcal{O}(\log n)$
DECREASE-KEY	$\mathcal{O}(\log n)$
DELETE	$\mathcal{O}(\log n)$

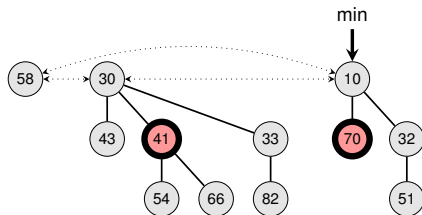


Next Lecture: Fibonacci Heap

Operation	Binomial heap worst-case cost	Fibonacci heap amortized cost
MAKE-HEAP	$\mathcal{O}(1)$	$\mathcal{O}(1)$
INSERT	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$
MINIMUM	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$
EXTRACT-MIN	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$
UNION	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$
DECREASE-KEY	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$
DELETE	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$

Crucial for many applications including shortest paths and minimum spanning trees!





5.2 Fibonacci Heaps

Frank Stajano

Thomas Sauerwald

Lent 2016



UNIVERSITY OF
CAMBRIDGE

Priority Queues Overview

Operation	Linked list	Binary heap	Binomial heap
MAKE-HEAP	$\mathcal{O}(1)$	$\mathcal{O}(1)$	$\mathcal{O}(1)$
INSERT	$\mathcal{O}(1)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$
MINIMUM	$\mathcal{O}(n)$	$\mathcal{O}(1)$	$\mathcal{O}(\log n)$
EXTRACT-MIN	$\mathcal{O}(n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$
MERGE	$\mathcal{O}(n)$	$\mathcal{O}(n)$	$\mathcal{O}(\log n)$
DECREASE-KEY	$\mathcal{O}(1)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$
DELETE	$\mathcal{O}(1)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$



Priority Queues Overview

Operation	Linked list	Binary heap	Binomial heap	Fibon. heap
MAKE-HEAP	$\mathcal{O}(1)$	$\mathcal{O}(1)$	$\mathcal{O}(1)$	$\mathcal{O}(1)$
INSERT	$\mathcal{O}(1)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$
MINIMUM	$\mathcal{O}(n)$	$\mathcal{O}(1)$	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$
EXTRACT-MIN	$\mathcal{O}(n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$
MERGE	$\mathcal{O}(n)$	$\mathcal{O}(n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$
DECREASE-KEY	$\mathcal{O}(1)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$
DELETE	$\mathcal{O}(1)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$



Binomial Heap vs. Fibonacci Heap: Costs

Operation	Binomial heap	Fibonacci heap
MAKE-HEAP	$\mathcal{O}(1)$	$\mathcal{O}(1)$
INSERT	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$
MINIMUM	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$
EXTRACT-MIN	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$
MERGE	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$
DECREASE-KEY	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$
DELETE	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$



Binomial Heap vs. Fibonacci Heap: Costs

Operation	Binomial heap actual cost	Fibonacci heap amortized cost
MAKE-HEAP	$\mathcal{O}(1)$	$\mathcal{O}(1)$
INSERT	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$
MINIMUM	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$
EXTRACT-MIN	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$
MERGE	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$
DECREASE-KEY	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$
DELETE	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$



Binomial Heap vs. Fibonacci Heap: Costs

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EXTRACT-MIN	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$
MERGE	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$
DECREASE-KEY	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$
DELETE	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$

n is the number of items in the heap when the operation is performed.



Binomial Heap vs. Fibonacci Heap: Costs

Operation	Binomial heap actual cost	Fibonacci heap amortized cost
MAKE-HEAP	$\mathcal{O}(1)$	$\mathcal{O}(1)$
INSERT	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$
MINIMUM	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$
EXTRACT-MIN	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$
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Binomial Heap: $k/2$ DECREASE-KEY
+ $k/2$ INSERT



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- $c_1 = c_2 = \dots = c_k = \mathcal{O}(\log n)$



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+ $k/2$ INSERT

$$\blacksquare c_1 = c_2 = \dots = c_k = \mathcal{O}(\log n)$$

$$\Rightarrow \sum_{i=1}^k c_i = \mathcal{O}(k \log n)$$



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Binomial Heap: $k/2$ DECREASE-KEY
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Fibonacci Heap: $k/2$
DECREASE-KEY + $k/2$ INSERT

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Binomial Heap: $k/2$ DECREASE-KEY
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$$\begin{aligned} & \blacksquare c_1 = c_2 = \dots = c_k = \mathcal{O}(\log n) \\ \Rightarrow & \sum_{i=1}^k c_i = \mathcal{O}(k \log n) \end{aligned}$$

Fibonacci Heap: $k/2$
DECREASE-KEY + $k/2$ INSERT

$$\blacksquare \hat{c}_1 = \hat{c}_2 = \dots = \hat{c}_k = \mathcal{O}(1)$$



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Binomial Heap: $k/2$ DECREASE-KEY
+ $k/2$ INSERT

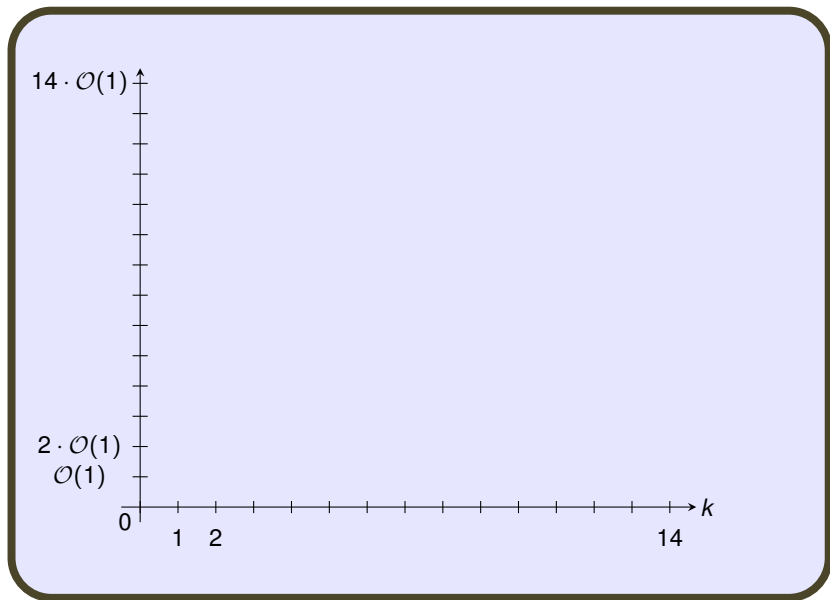
$$\begin{aligned} & \blacksquare c_1 = c_2 = \dots = c_k = \mathcal{O}(\log n) \\ \Rightarrow & \sum_{i=1}^k c_i = \mathcal{O}(k \log n) \end{aligned}$$

Fibonacci Heap: $k/2$
DECREASE-KEY + $k/2$ INSERT

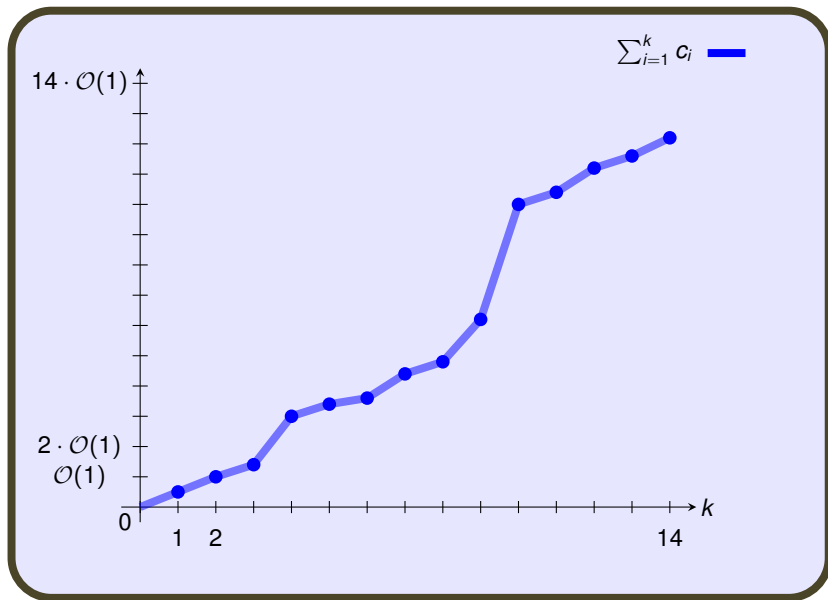
$$\begin{aligned} & \blacksquare \hat{c}_1 = \hat{c}_2 = \dots = \hat{c}_k = \mathcal{O}(1) \\ \Rightarrow & \sum_{i=1}^k c_i \leq \sum_{i=1}^k \hat{c}_i = \mathcal{O}(k) \end{aligned}$$



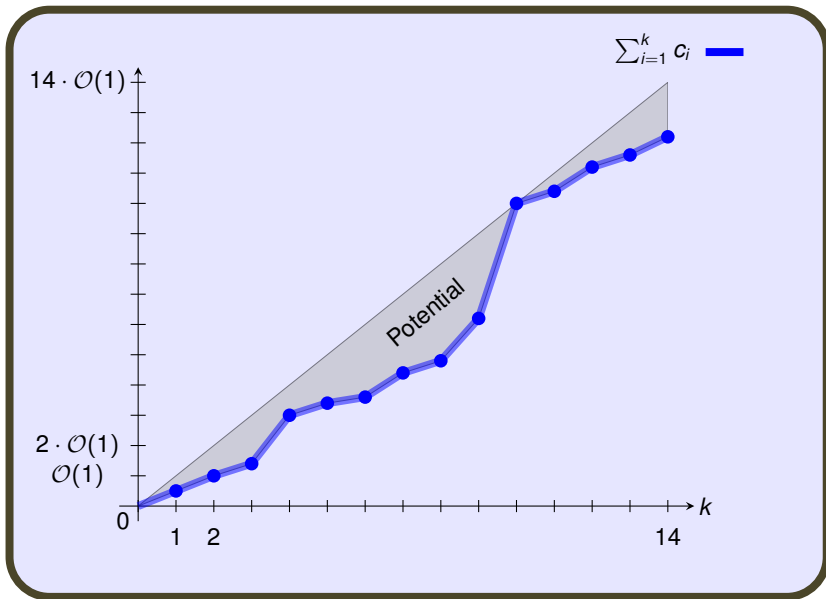
Actual vs. Amortized Cost



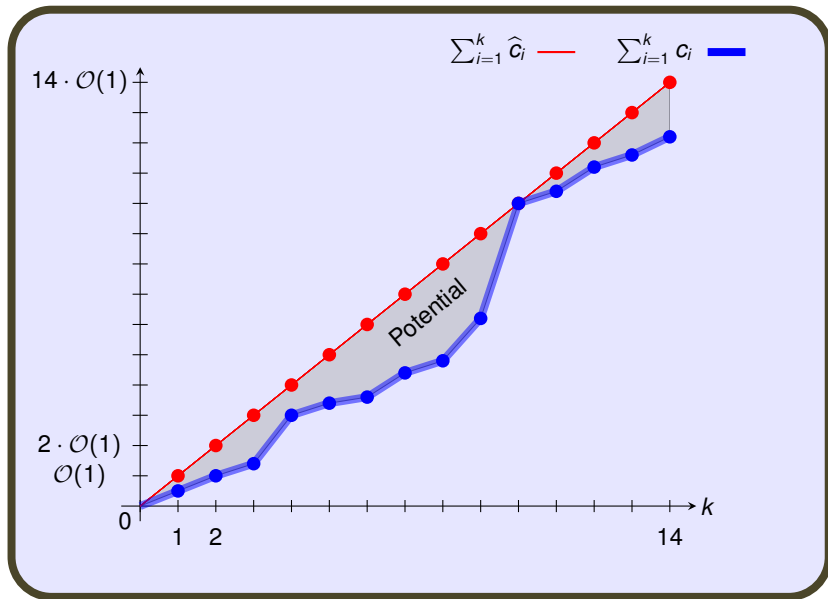
Actual vs. Amortized Cost



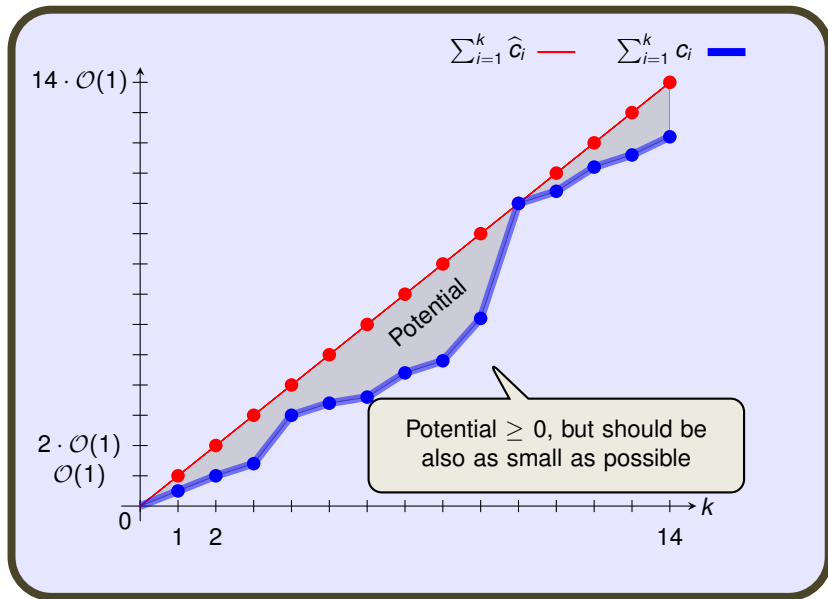
Actual vs. Amortized Cost



Actual vs. Amortized Cost



Actual vs. Amortized Cost



Outline

Structure

Operations

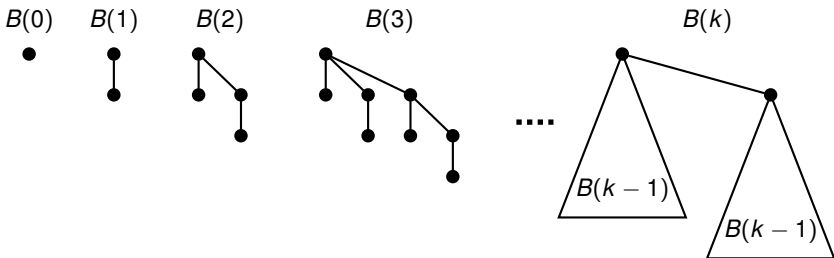
Glimpse at the Analysis

Amortized Analysis



Reminder: Binomial Heaps

Binomial Trees



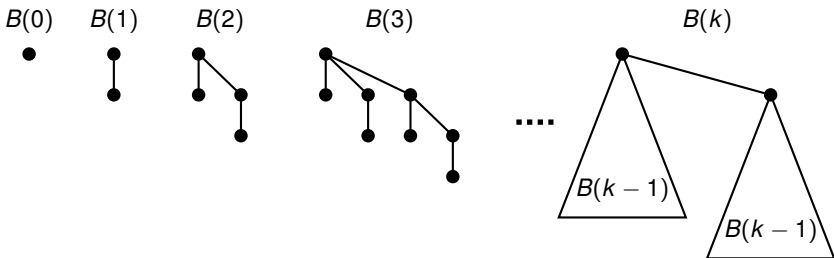
Binomial Heaps

- Binomial Heap is a collection of binomial trees of **different orders**, each of which obeys the **heap property**



Reminder: Binomial Heaps

Binomial Trees



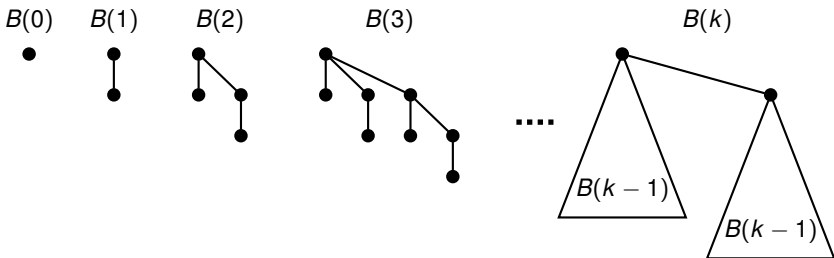
Binomial Heaps

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- **Operations:**



Reminder: Binomial Heaps

Binomial Trees

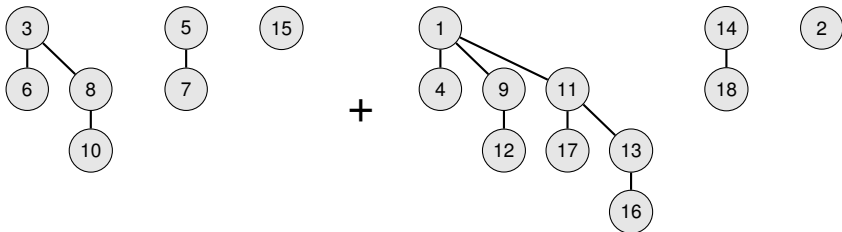


Binomial Heaps

- Binomial Heap is a collection of binomial trees of **different orders**, each of which obeys the **heap property**
- Operations:**
 - MERGE:** Merge two binomial heaps using **Binary Addition Procedure**
 - INSERT:** Add $B(0)$ and perform a **MERGE**
 - EXTRACT-MIN:** Find tree with minimum key, cut it and perform a **MERGE**
 - DECREASE-KEY:** The same as in a binary heap



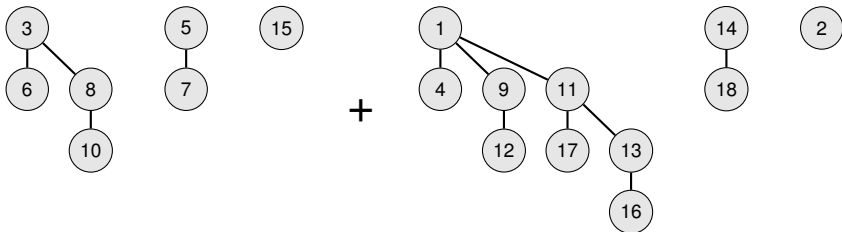
Merging two Binomial Heaps



$$\begin{array}{r} 0 \ 0 \ 1 \ 1 \ 1 \ = 7 \\ 0 \ 1 \ 0 \ 1 \ 1 \ = 11 \\ \hline 1 \ 1 \ 1 \ 1 \\ 1 \ 0 \ 0 \ 1 \ 0 \ = 18 \end{array}$$



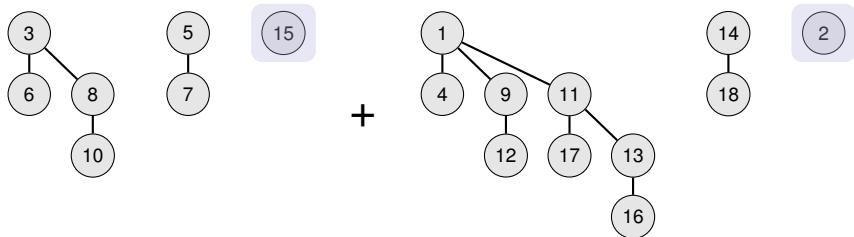
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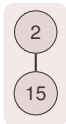
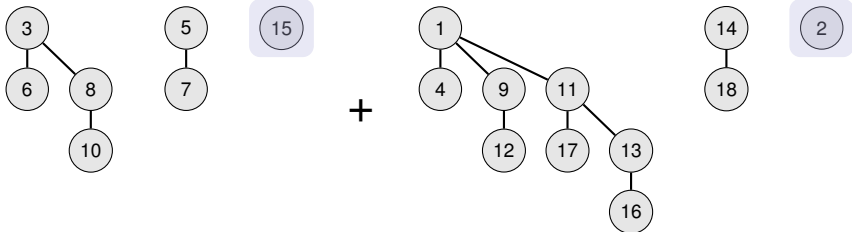
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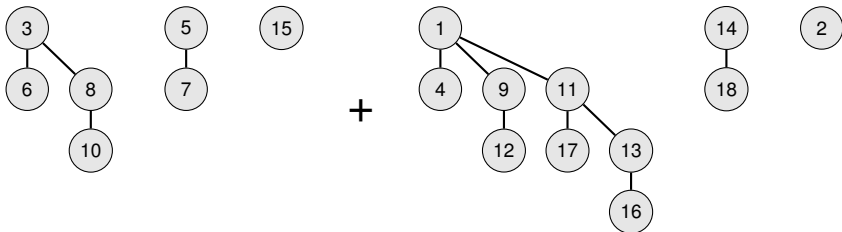
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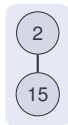
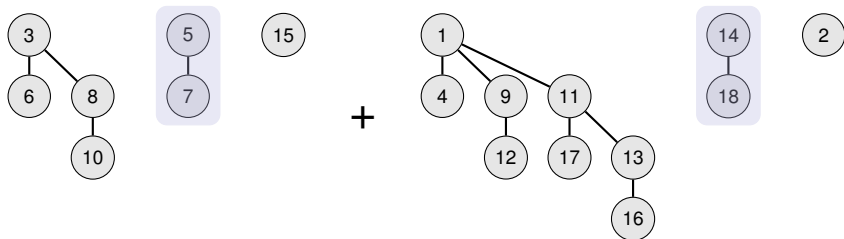
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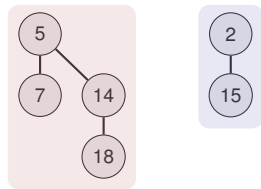
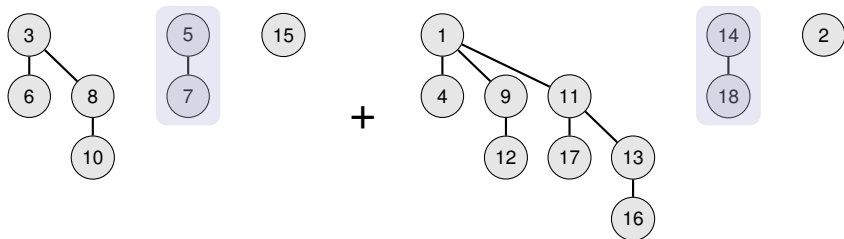
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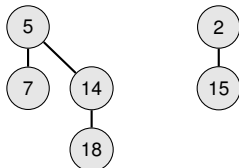
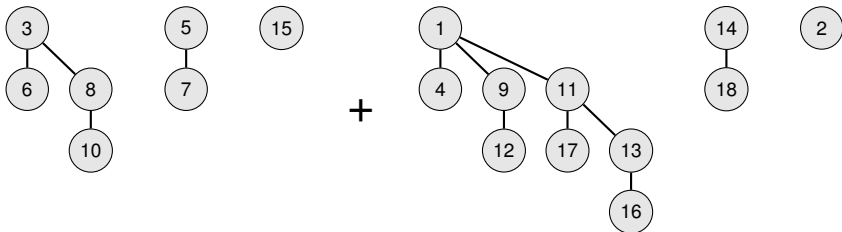
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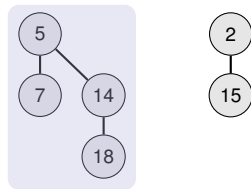
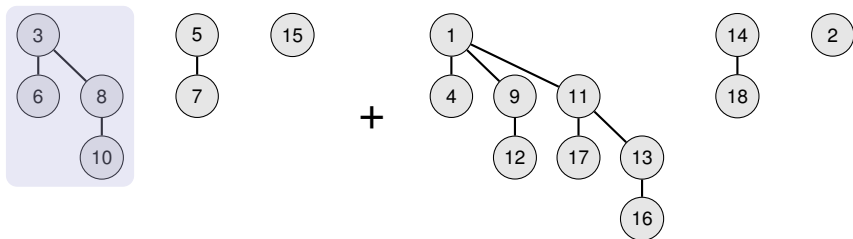
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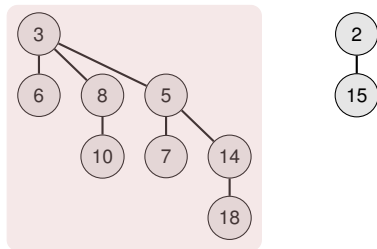
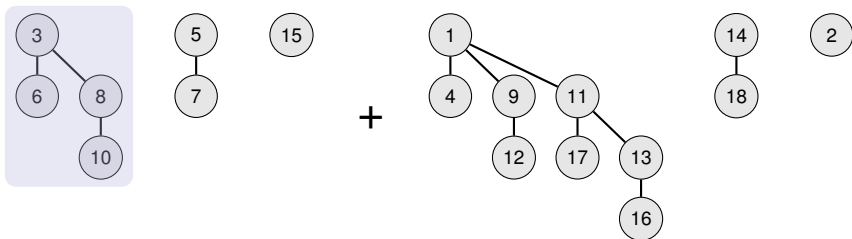
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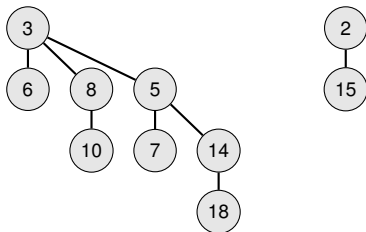
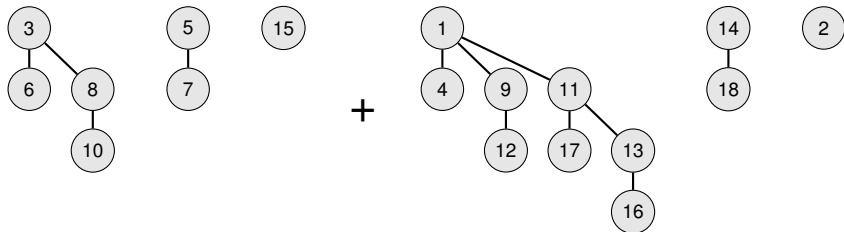
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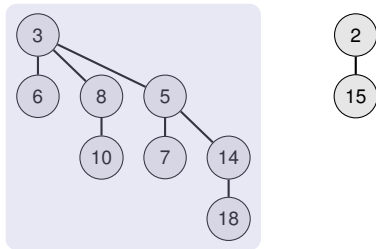
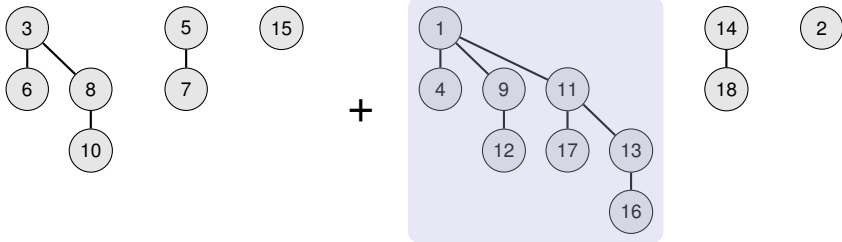
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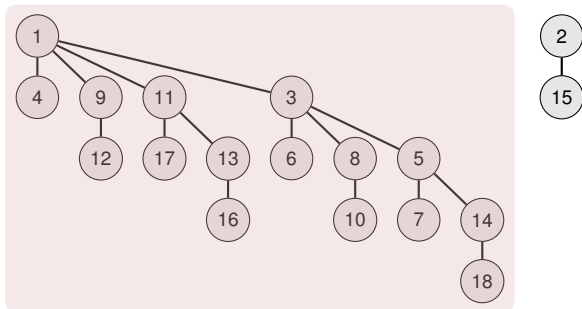
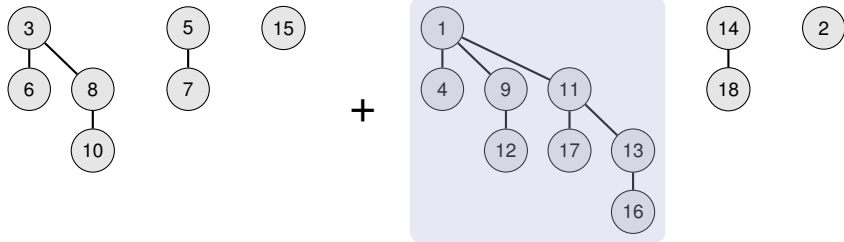
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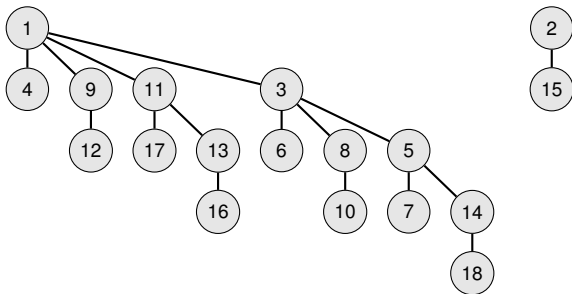
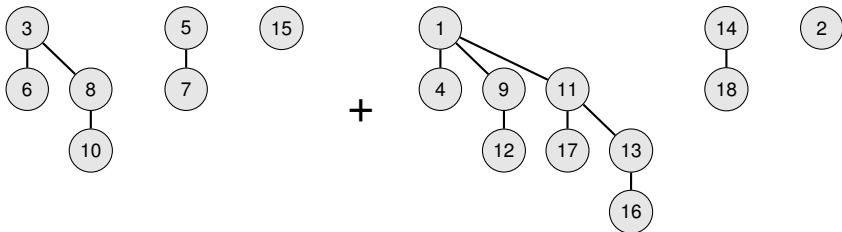
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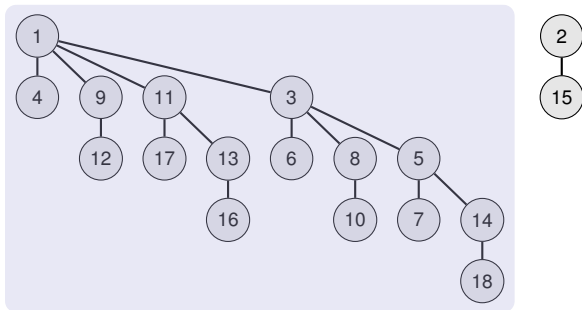
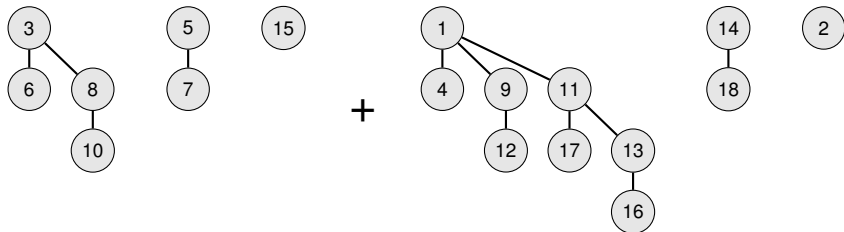
Merging two Binomial Heaps



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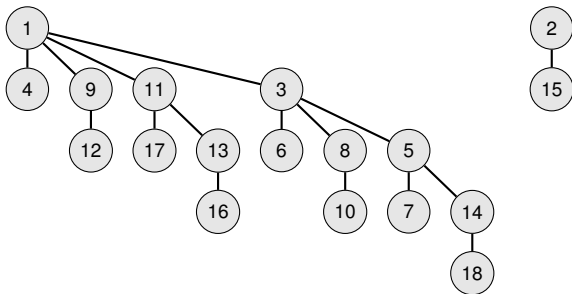
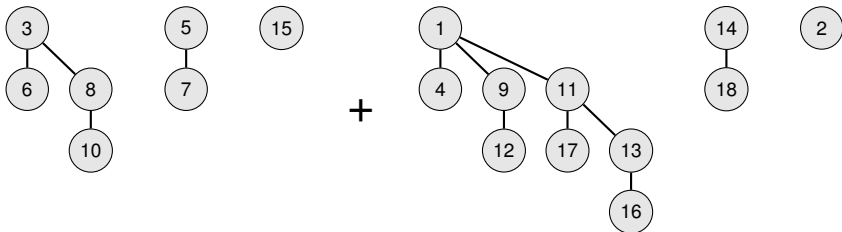
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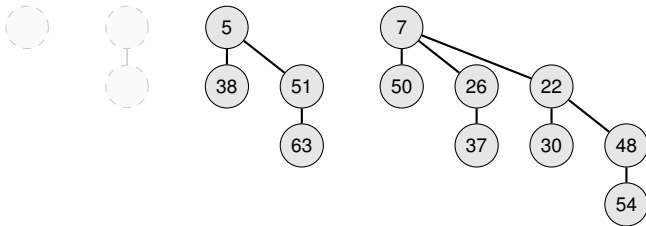
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Binomial Heap vs. Fibonacci Heap: Structure

Binomial Heap:

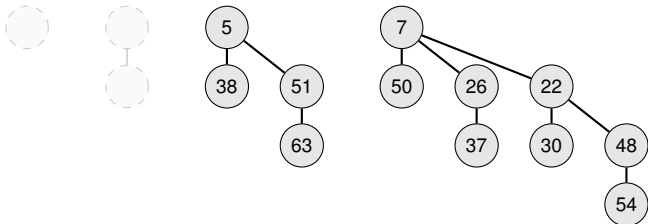
- consists of **binomial trees**, and every order appears at most once
- **immediately tidy up** after INSERT or MERGE



Binomial Heap vs. Fibonacci Heap: Structure

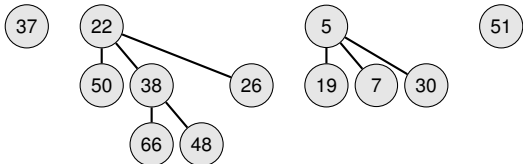
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Fibonacci Heap:

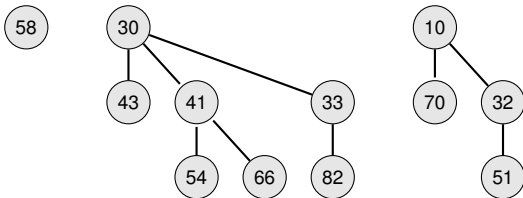
- forest of MIN-HEAPs
- **lazily** defer tidying up; do it on-the-fly when search for the MIN



Structure of Fibonacci Heaps

Fibonacci Heap

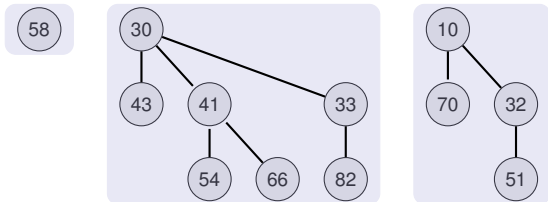
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Structure of Fibonacci Heaps

Fibonacci Heap

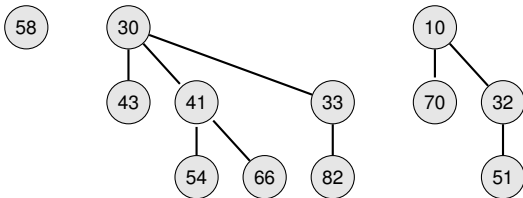
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Structure of Fibonacci Heaps

Fibonacci Heap

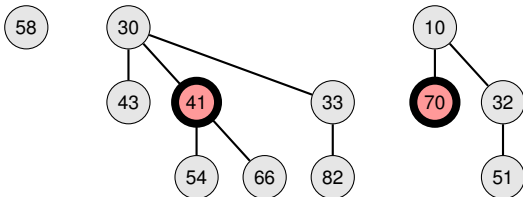
- Forest of MIN-HEAPs
- Nodes can be marked (roots are always unmarked)



Structure of Fibonacci Heaps

Fibonacci Heap

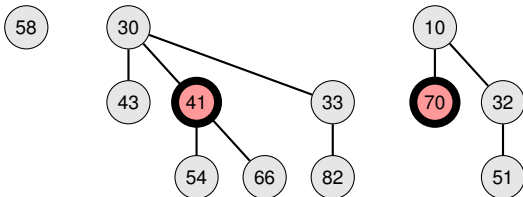
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Structure of Fibonacci Heaps

Fibonacci Heap

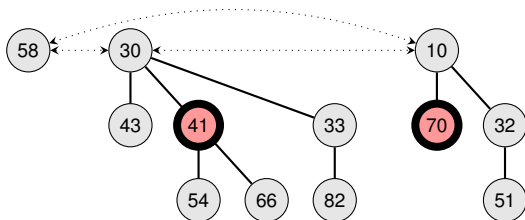
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- Tree roots are stored in a circular, doubly-linked list



Structure of Fibonacci Heaps

Fibonacci Heap

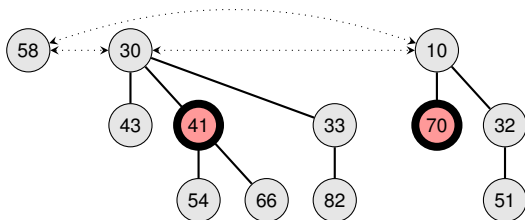
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Structure of Fibonacci Heaps

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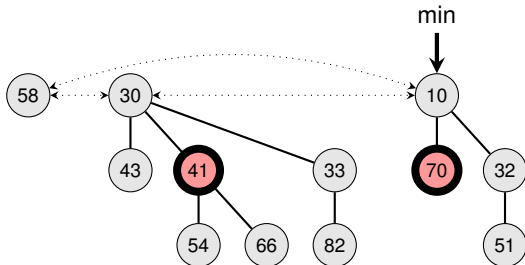
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Structure of Fibonacci Heaps

Fibonacci Heap

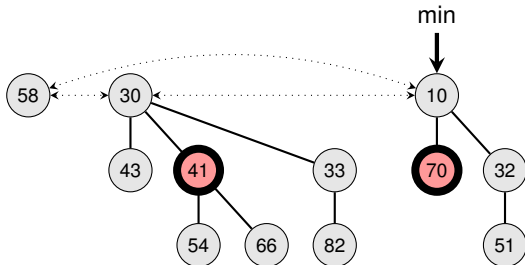
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Structure of Fibonacci Heaps

Fibonacci Heap

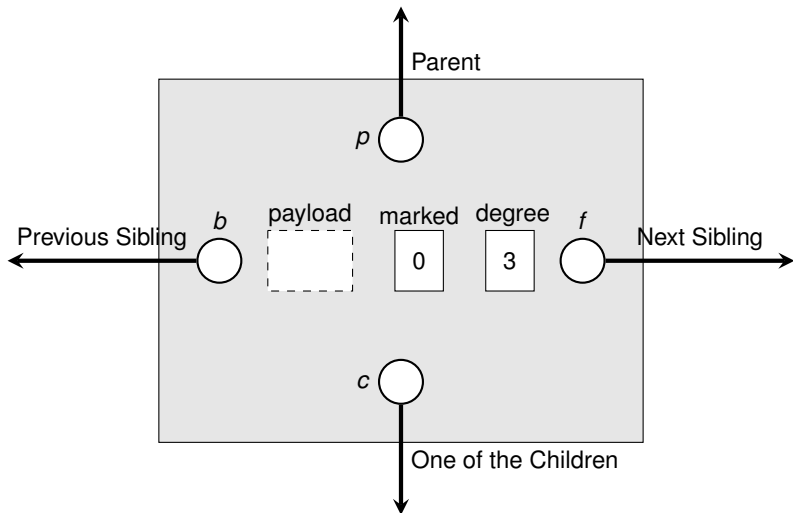
- Forest of MIN-HEAPs
- Nodes can be marked (roots are always unmarked)
- Tree roots are stored in a circular, doubly-linked list
- Min-Pointer pointing to the smallest element



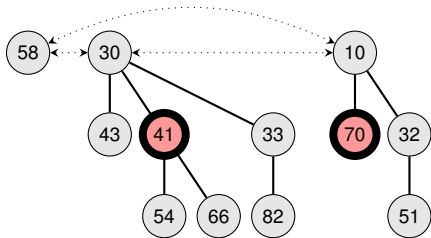
How do we implement a Fibonacci Heap?



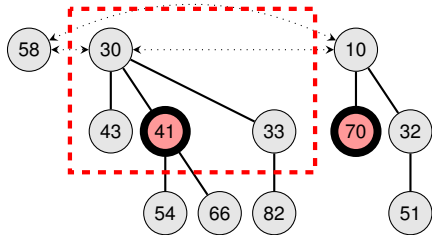
A single Node



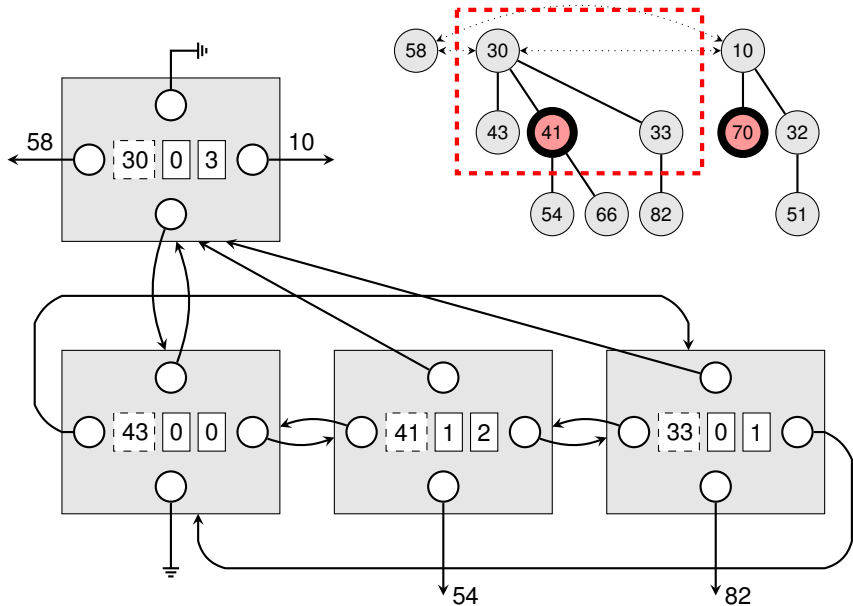
Magnifying a Four-Node Portion



Magnifying a Four-Node Portion



Magnifying a Four-Node Portion



Outline

Structure

Operations

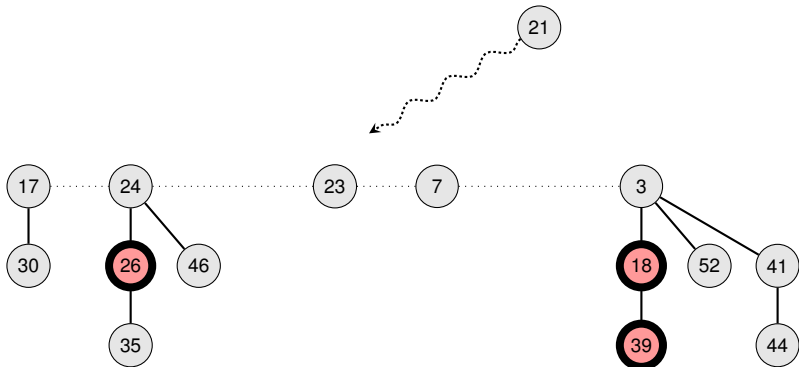
Glimpse at the Analysis

Amortized Analysis



Fibonacci Heap: INSERT

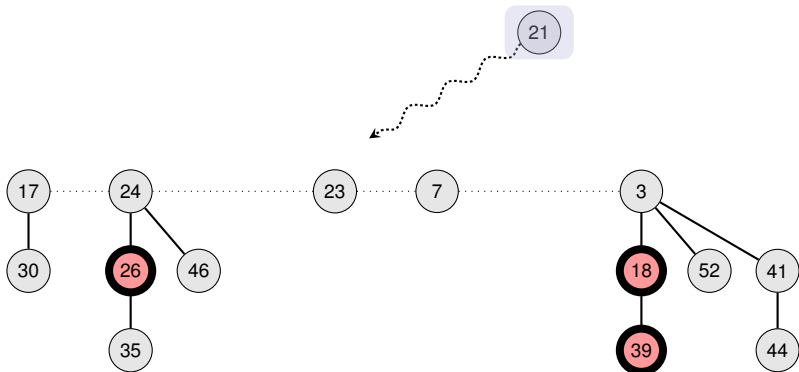
INSERT



Fibonacci Heap: INSERT

INSERT

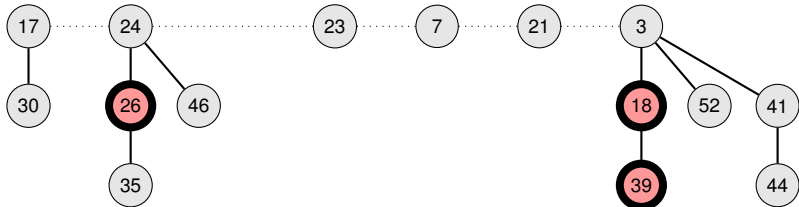
- Create a singleton tree



Fibonacci Heap: INSERT

INSERT

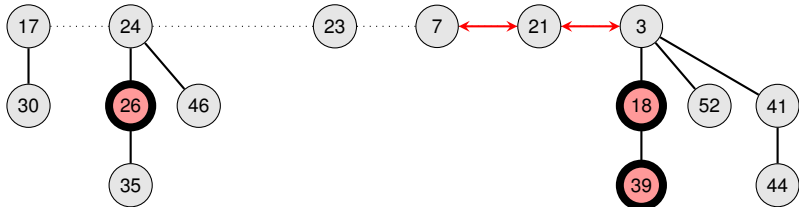
- Create a singleton tree
- Add to root list



Fibonacci Heap: INSERT

INSERT

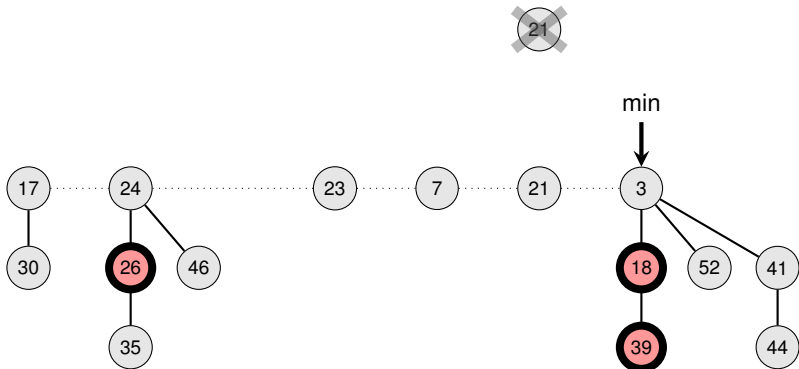
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Fibonacci Heap: INSERT

INSERT

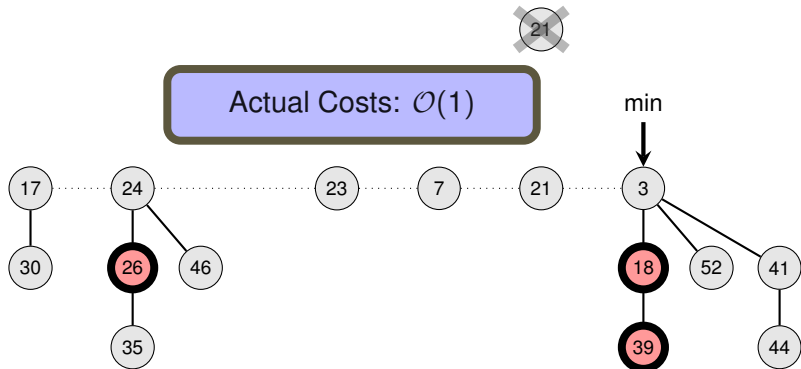
- Create a singleton tree
- Add to root list and update min-pointer (if necessary)



Fibonacci Heap: INSERT

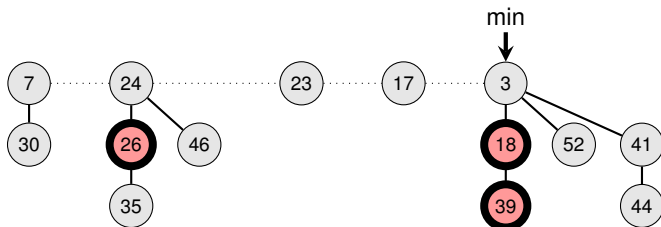
INSERT

- Create a singleton tree
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Fibonacci Heap: EXTRACT-MIN

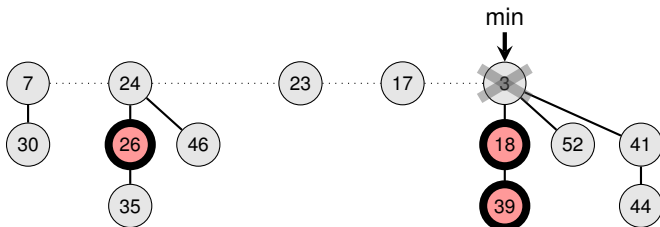
EXTRACT-MIN



Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

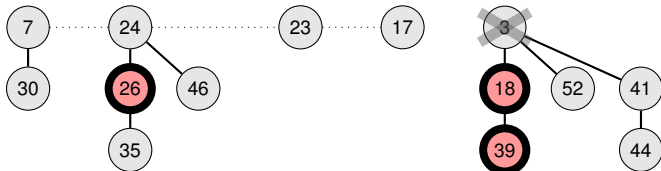
- Delete min



Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

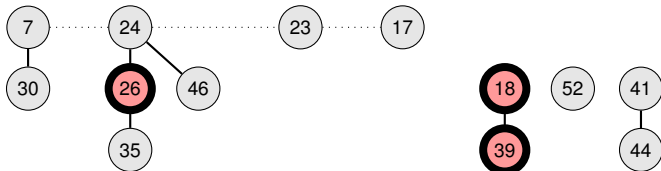
- Delete min ✓



Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

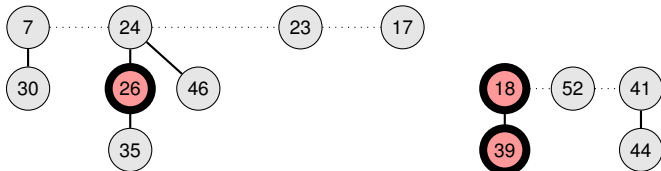
- Delete min ✓
- Meld children into root list and unmark them



Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

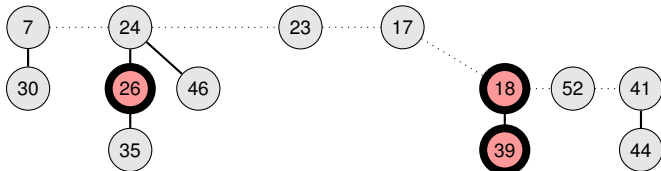
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Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

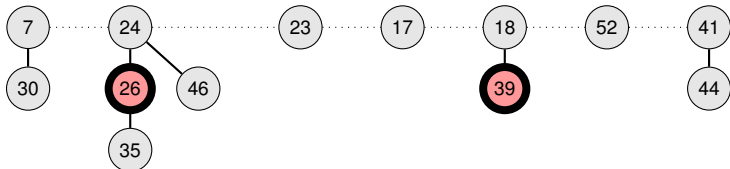
- Delete min ✓
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Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

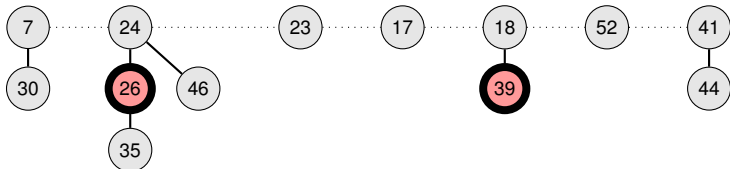
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Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

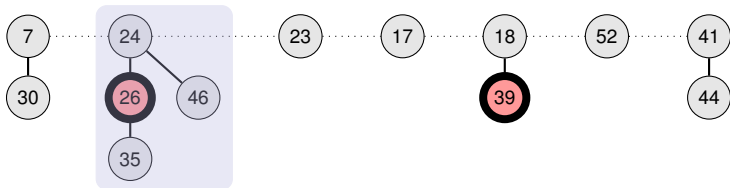
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- **Consolidate** so that no roots have the same degree



Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

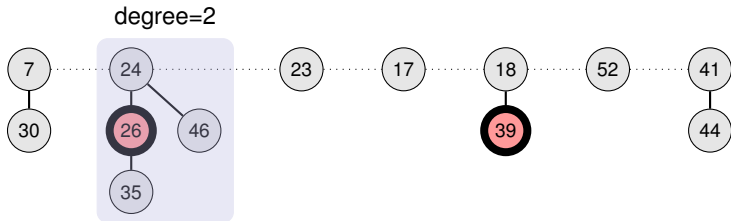
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Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

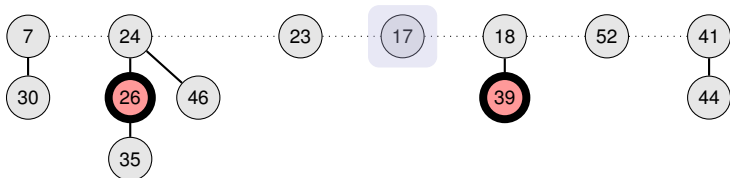
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Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

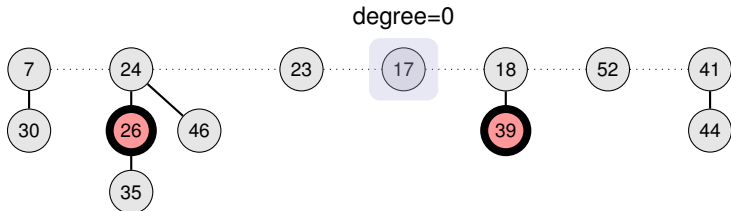
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Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

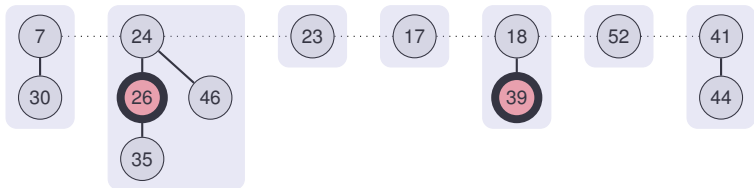
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Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

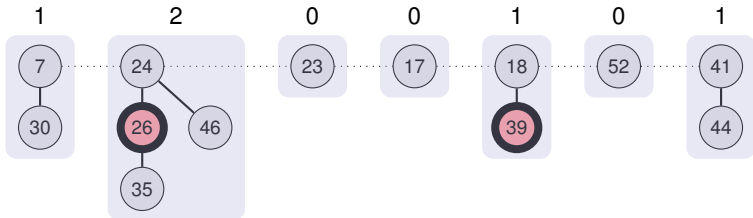
- Delete min ✓
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Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

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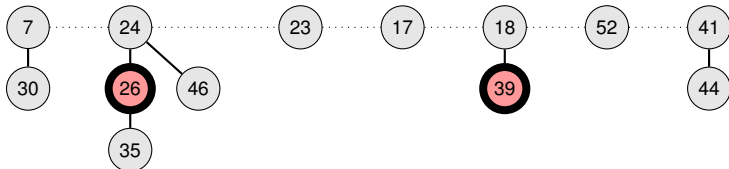
Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

- Delete min ✓
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degree

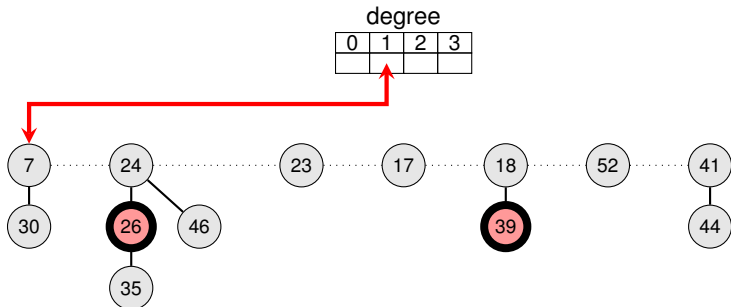
0	1	2	3



Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

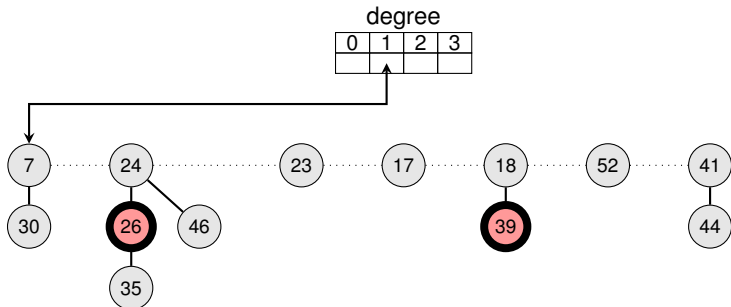
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Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

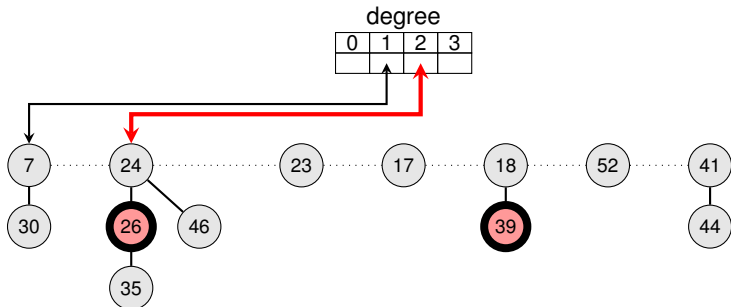
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EXTRACT-MIN

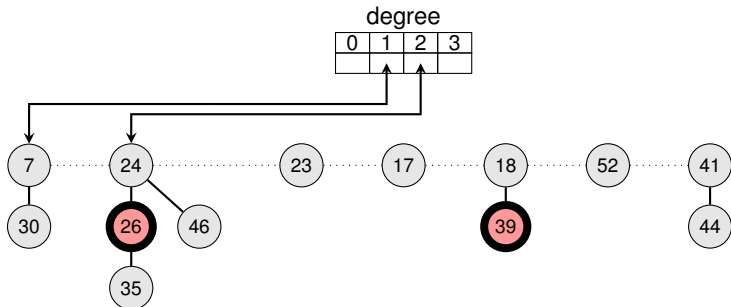
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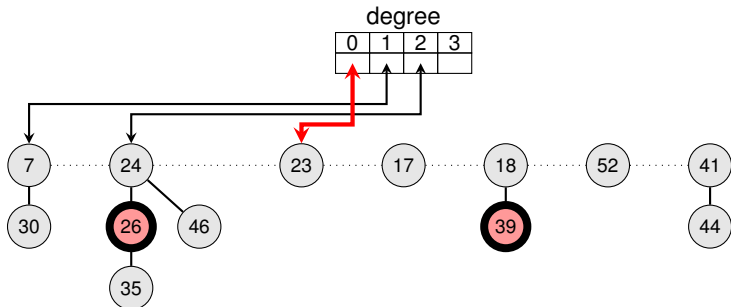
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Fibonacci Heap: EXTRACT-MIN

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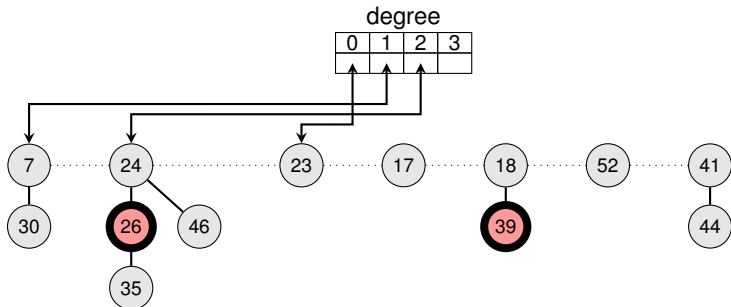
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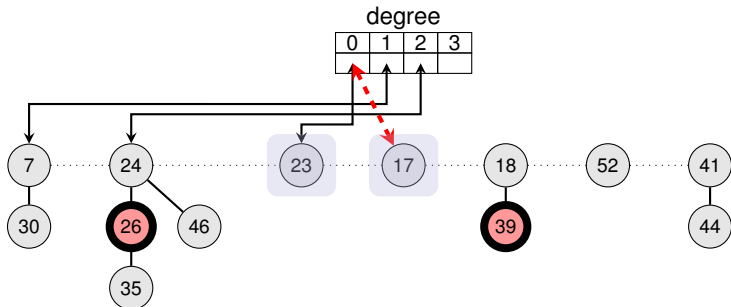
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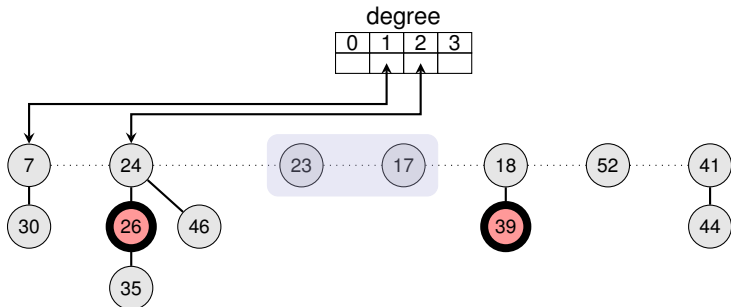
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Fibonacci Heap: EXTRACT-MIN

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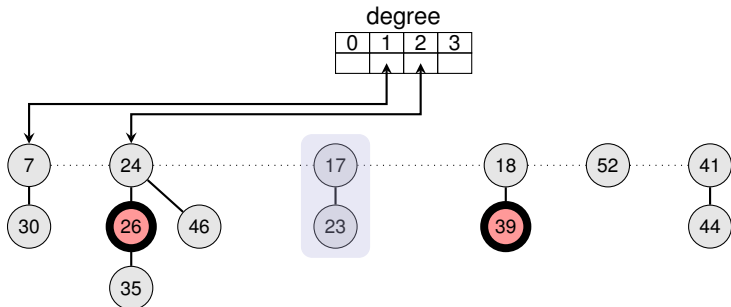
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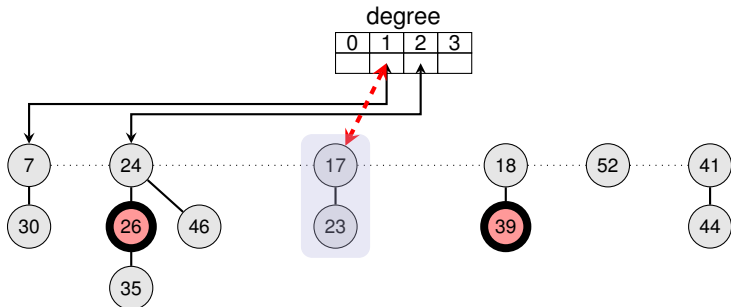
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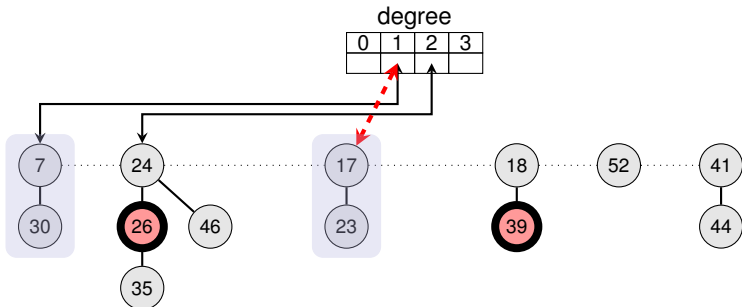
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EXTRACT-MIN

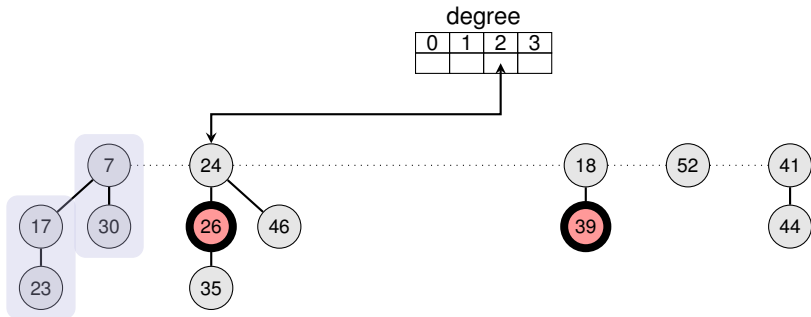
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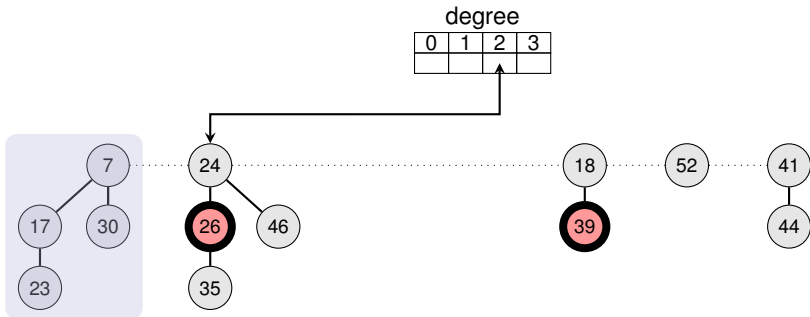
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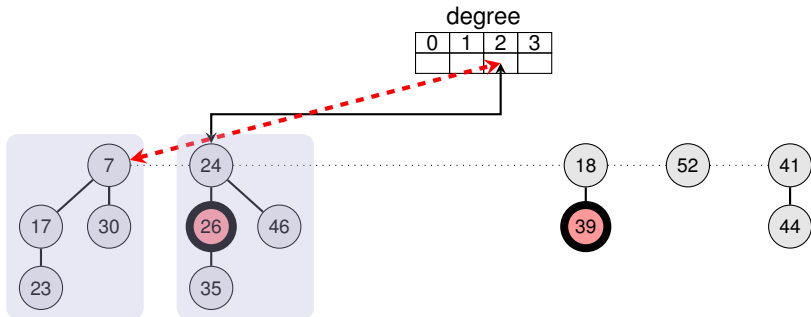
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Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

- Delete min ✓
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degree

0	1	2	3



Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

- Delete min ✓
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- **Consolidate** so that no roots have the same degree (# children)

degree

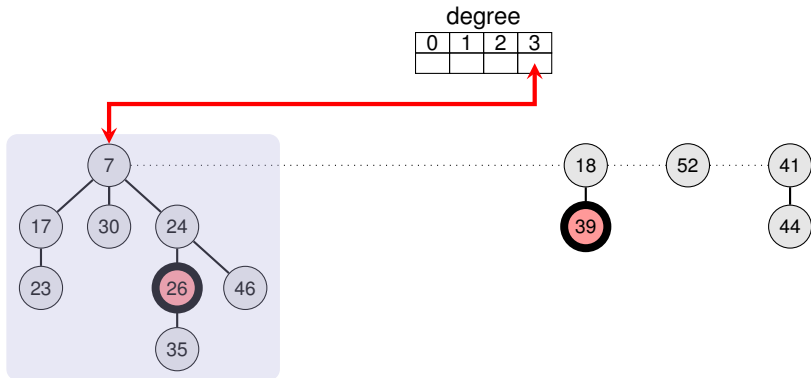
0	1	2	3



Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

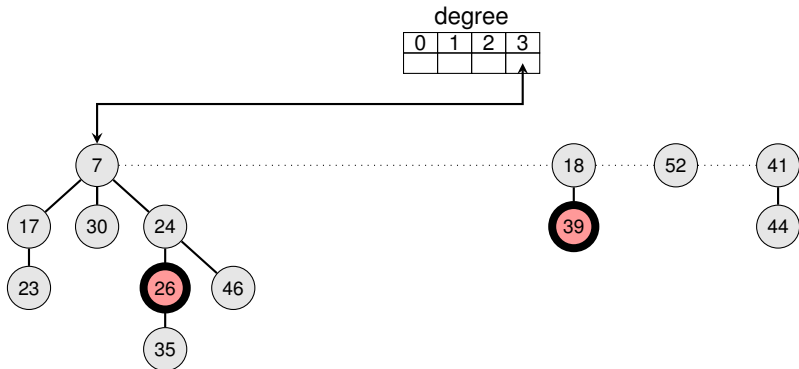
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Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

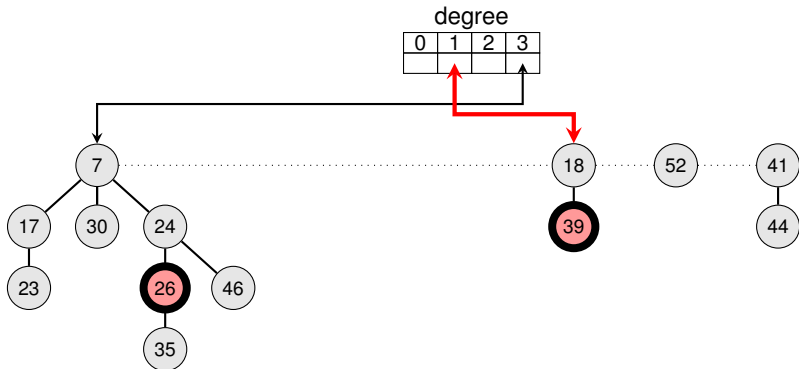
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Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

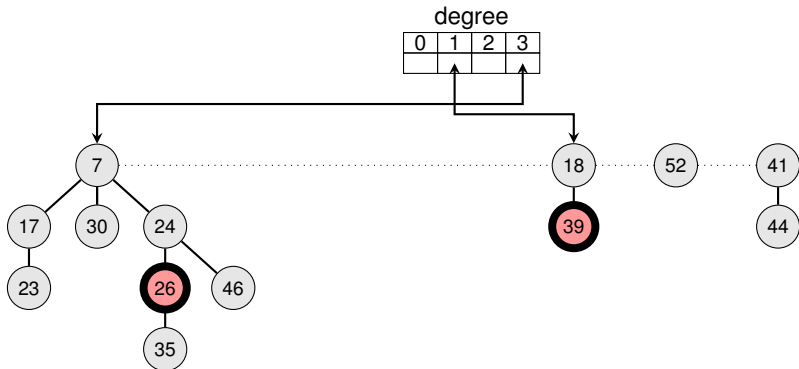
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Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

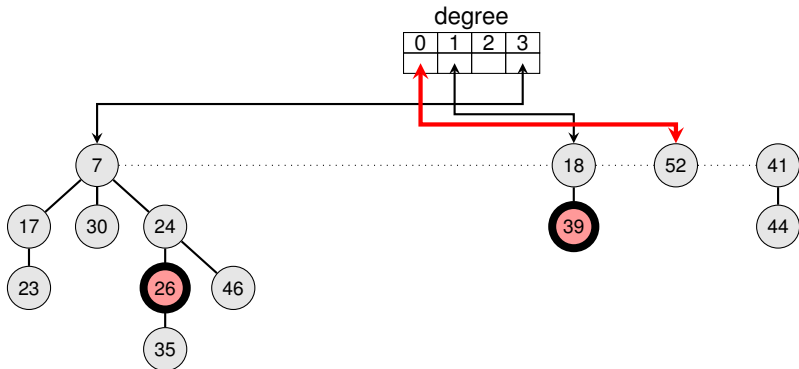
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EXTRACT-MIN

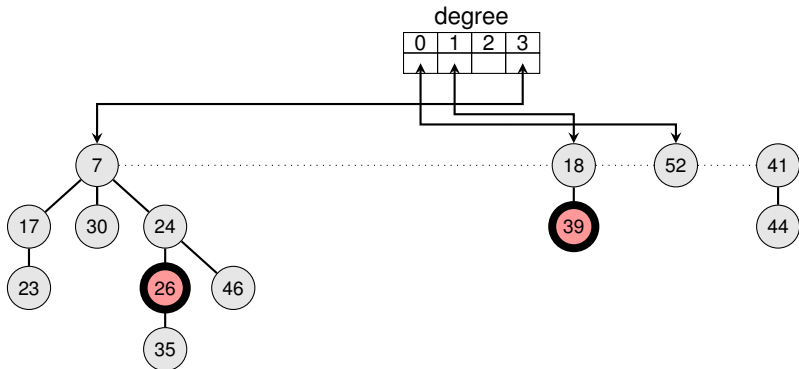
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Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

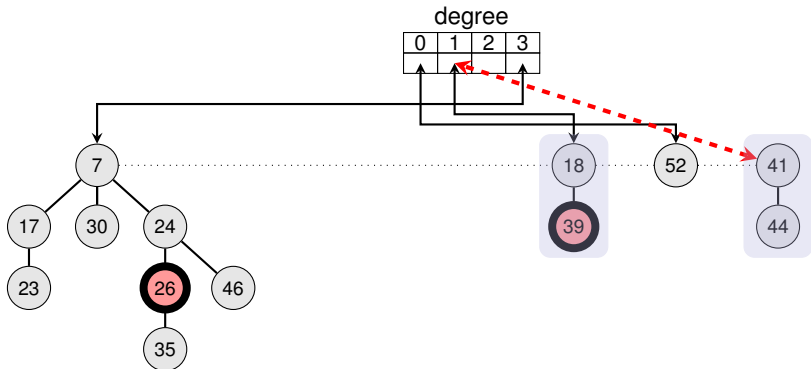
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Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

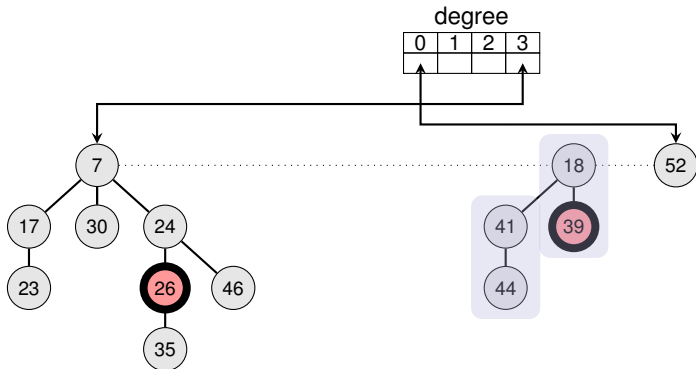
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Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

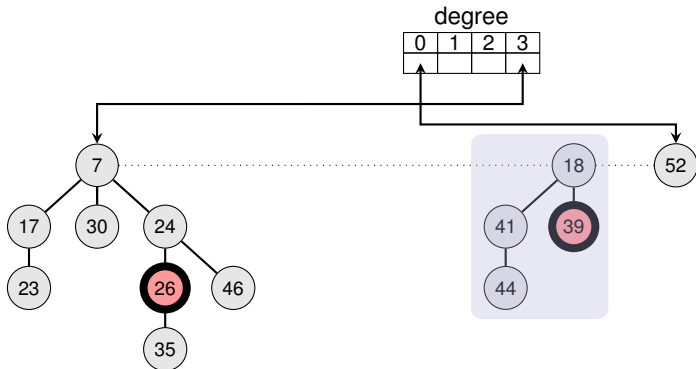
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Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

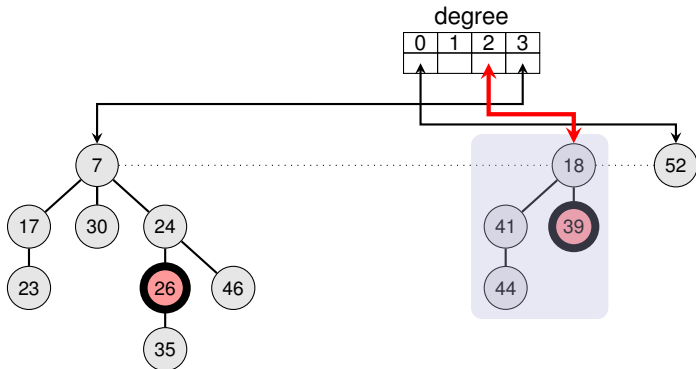
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Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

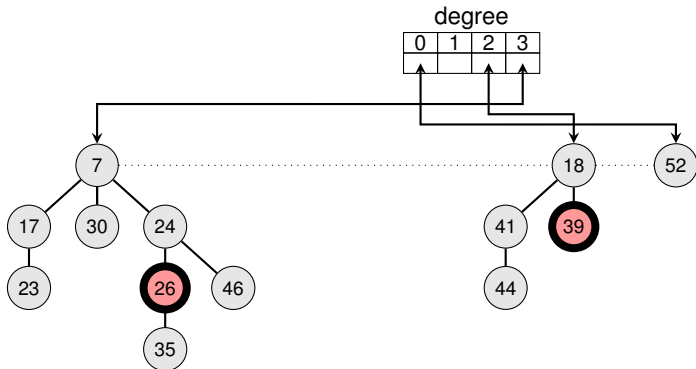
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EXTRACT-MIN

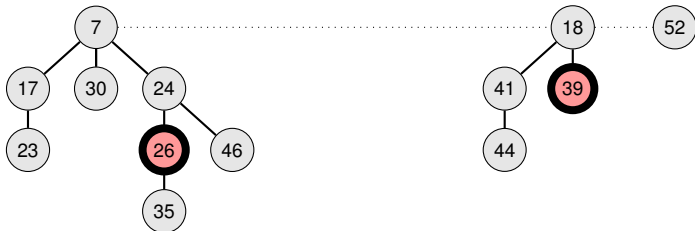
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Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

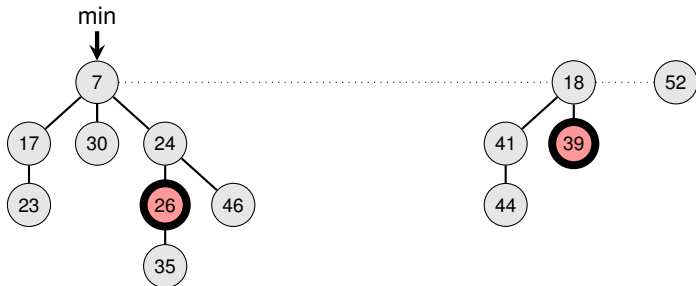
- Delete min ✓
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- Update minimum



Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

- Delete min ✓
- Meld children into root list and unmark them ✓
- **Consolidate** so that no roots have the same degree (# children) ✓
- Update minimum ✓

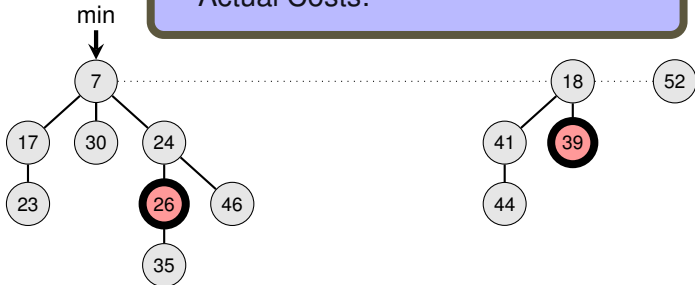


Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

- Delete min ✓
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- Update minimum ✓

Actual Costs:



Fibonacci Heap: EXTRACT-MIN

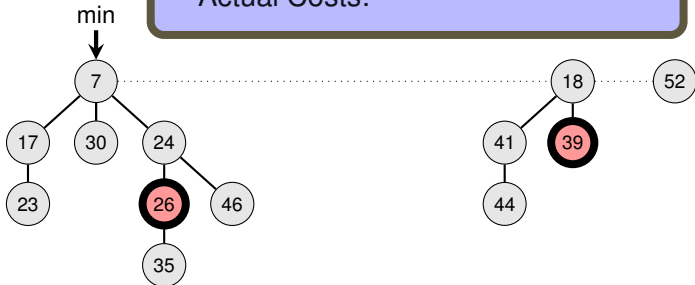
EXTRACT-MIN

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- Update minimum ✓

Every root becomes child of another root at most once!

$d(n)$ is the maximum degree of a root in any Fibonacci heap of size n

Actual Costs:



Fibonacci Heap: EXTRACT-MIN

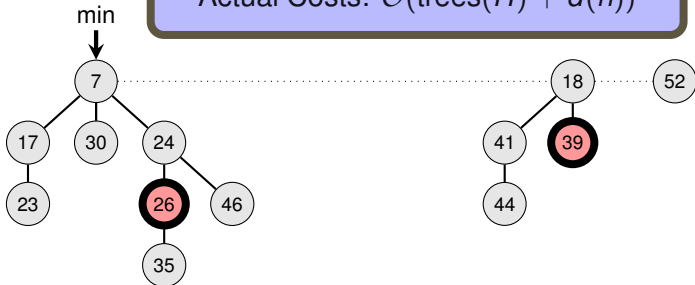
EXTRACT-MIN

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$d(n)$ is the maximum degree of a root in any Fibonacci heap of size n

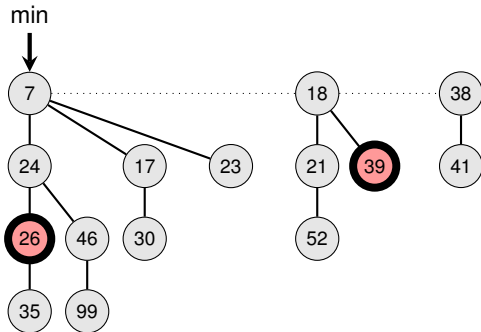
Actual Costs: $\mathcal{O}(\text{trees}(H) + d(n))$



Fibonacci Heap: DECREASE-KEY (First Try)

DECREASE-KEY of node x

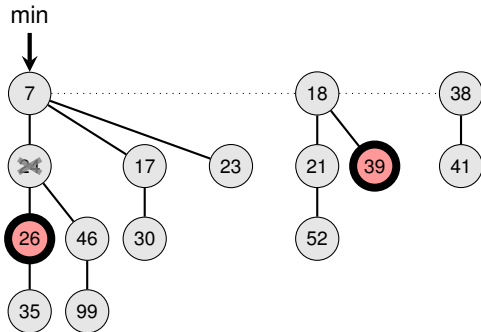
- Decrease the key of x (given by a pointer)



Fibonacci Heap: DECREASE-KEY (First Try)

DECREASE-KEY of node x

- Decrease the key of x (given by a pointer)



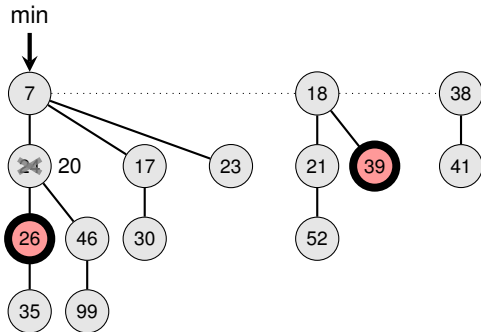
1. DECREASE-KEY 24 \rightsquigarrow 20



Fibonacci Heap: DECREASE-KEY (First Try)

DECREASE-KEY of node x

- Decrease the key of x (given by a pointer)



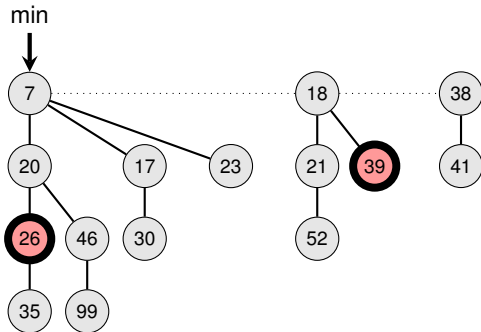
1. DECREASE-KEY 24 \rightsquigarrow 20



Fibonacci Heap: DECREASE-KEY (First Try)

DECREASE-KEY of node x

- Decrease the key of x (given by a pointer)
- Check if heap-order is violated



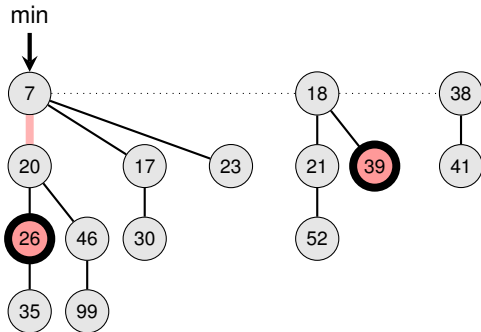
1. DECREASE-KEY 24 \rightsquigarrow 20



Fibonacci Heap: DECREASE-KEY (First Try)

DECREASE-KEY of node x

- Decrease the key of x (given by a pointer)
- Check if heap-order is violated



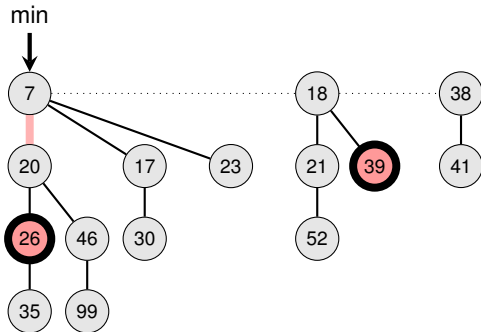
1. DECREASE-KEY 24 \rightsquigarrow 20



Fibonacci Heap: DECREASE-KEY (First Try)

DECREASE-KEY of node x

- Decrease the key of x (given by a pointer)
- Check if heap-order is violated
 - If not



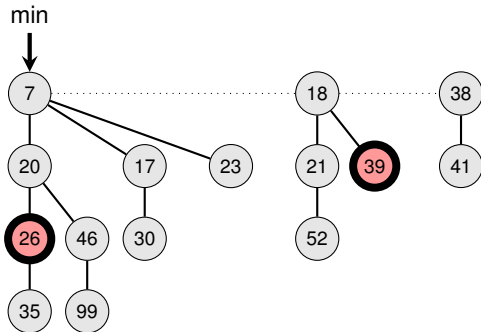
1. DECREASE-KEY 24 \rightsquigarrow 20



Fibonacci Heap: DECREASE-KEY (First Try)

DECREASE-KEY of node x

- Decrease the key of x (given by a pointer)
- Check if heap-order is violated
 - If not, then done.



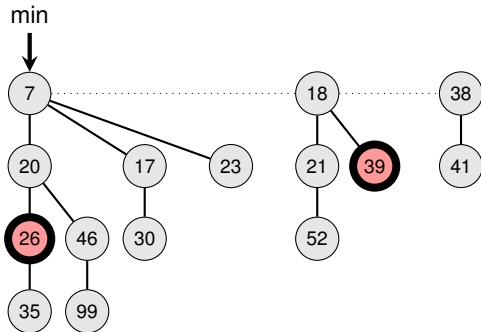
1. DECREASE-KEY 24 \rightsquigarrow 20



Fibonacci Heap: DECREASE-KEY (First Try)

DECREASE-KEY of node x

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 - If not, then done.
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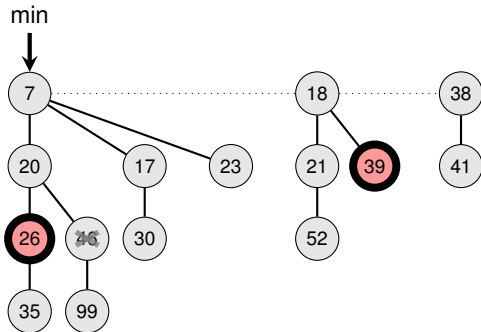
1. DECREASE-KEY 24 \rightsquigarrow 20



Fibonacci Heap: DECREASE-KEY (First Try)

DECREASE-KEY of node x

- Decrease the key of x (given by a pointer)
- Check if heap-order is violated
 - If not, then done.
 - Otherwise,



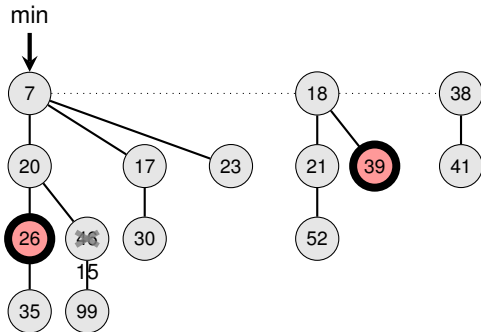
1. DECREASE-KEY 24 \rightsquigarrow 20
2. DECREASE-KEY 46 \rightsquigarrow 15



Fibonacci Heap: DECREASE-KEY (First Try)

DECREASE-KEY of node x

- Decrease the key of x (given by a pointer)
- Check if heap-order is violated
 - If not, then done.
 - Otherwise,



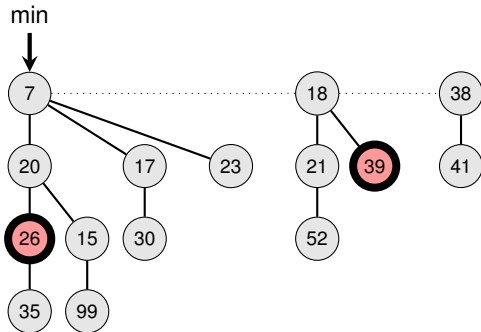
1. DECREASE-KEY 24 \rightsquigarrow 20
2. DECREASE-KEY 46 \rightsquigarrow 15



Fibonacci Heap: DECREASE-KEY (First Try)

DECREASE-KEY of node x

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- Check if heap-order is violated
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 - Otherwise,



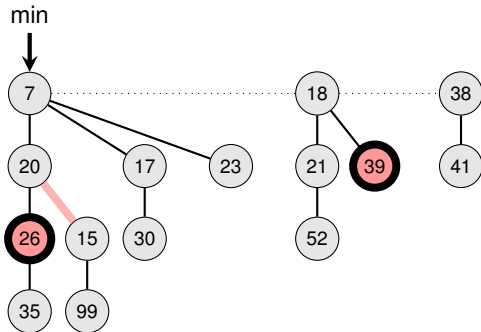
1. DECREASE-KEY 24 \rightsquigarrow 20
2. DECREASE-KEY 46 \rightsquigarrow 15



Fibonacci Heap: DECREASE-KEY (First Try)

DECREASE-KEY of node x

- Decrease the key of x (given by a pointer)
- Check if heap-order is violated
 - If not, then done.
 - Otherwise,



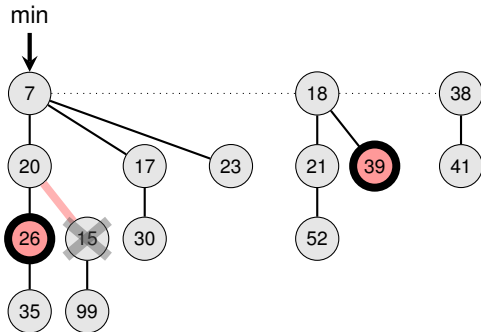
1. DECREASE-KEY 24 \rightsquigarrow 20
2. DECREASE-KEY 46 \rightsquigarrow 15



Fibonacci Heap: DECREASE-KEY (First Try)

DECREASE-KEY of node x

- Decrease the key of x (given by a pointer)
- Check if heap-order is violated
 - If not, then done.
 - Otherwise, cut tree rooted at x and meld into root list (update min).



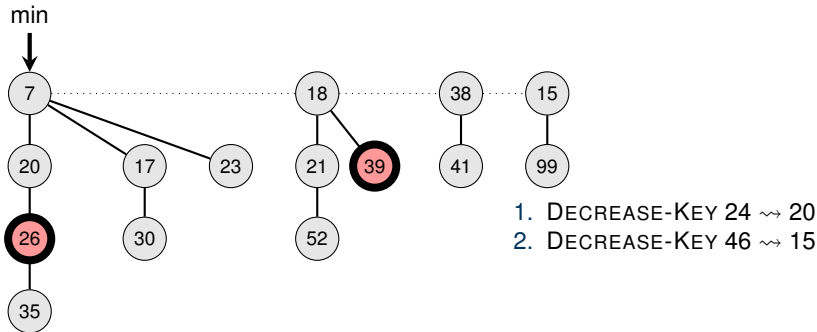
1. DECREASE-KEY 24 \rightsquigarrow 20
2. DECREASE-KEY 46 \rightsquigarrow 15



Fibonacci Heap: DECREASE-KEY (First Try)

DECREASE-KEY of node x

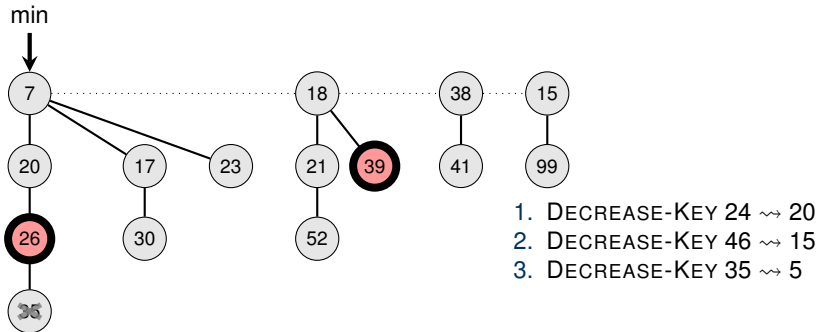
- Decrease the key of x (given by a pointer)
- Check if heap-order is violated
 - If not, then done.
 - Otherwise, cut tree rooted at x and meld into root list (update min).



Fibonacci Heap: DECREASE-KEY (First Try)

DECREASE-KEY of node x

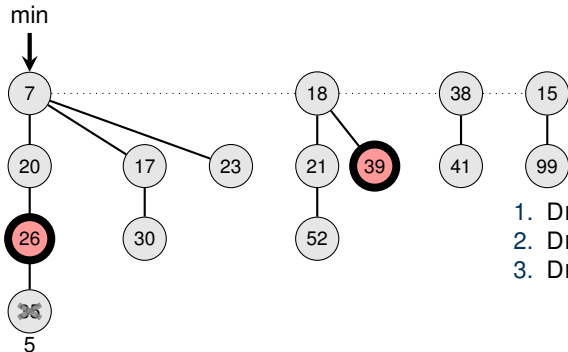
- Decrease the key of x (given by a pointer)
- Check if heap-order is violated
 - If not, then done.
 - Otherwise, cut tree rooted at x and meld into root list (update min).



Fibonacci Heap: DECREASE-KEY (First Try)

DECREASE-KEY of node x

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- Check if heap-order is violated
 - If not, then done.
 - Otherwise, cut tree rooted at x and meld into root list (update min).



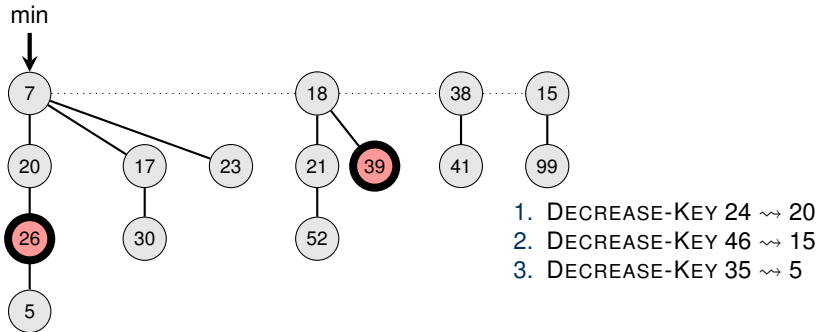
1. DECREASE-KEY 24 \rightsquigarrow 20
2. DECREASE-KEY 46 \rightsquigarrow 15
3. DECREASE-KEY 35 \rightsquigarrow 5



Fibonacci Heap: DECREASE-KEY (First Try)

DECREASE-KEY of node x

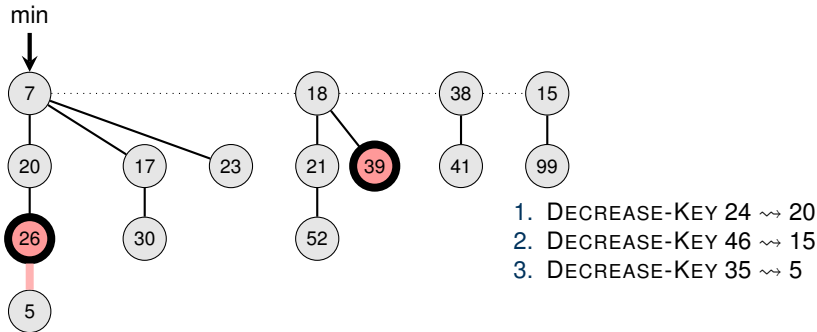
- Decrease the key of x (given by a pointer)
- Check if heap-order is violated
 - If not, then done.
 - Otherwise, cut tree rooted at x and meld into root list (update min).



Fibonacci Heap: DECREASE-KEY (First Try)

DECREASE-KEY of node x

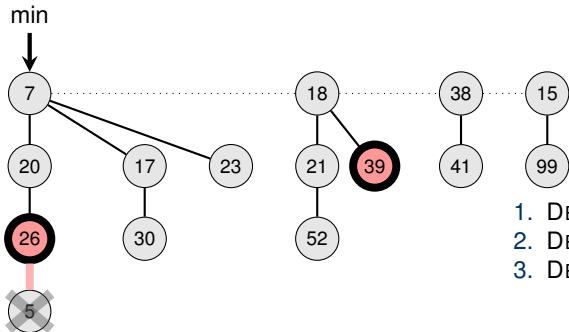
- Decrease the key of x (given by a pointer)
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 - If not, then done.
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Fibonacci Heap: DECREASE-KEY (First Try)

DECREASE-KEY of node x

- Decrease the key of x (given by a pointer)
- Check if heap-order is violated
 - If not, then done.
 - Otherwise, cut tree rooted at x and meld into root list (update min).



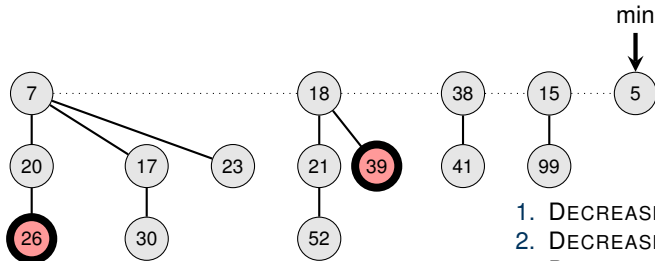
1. DECREASE-KEY 24 \rightsquigarrow 20
2. DECREASE-KEY 46 \rightsquigarrow 15
3. DECREASE-KEY 35 \rightsquigarrow 5



Fibonacci Heap: DECREASE-KEY (First Try)

DECREASE-KEY of node x

- Decrease the key of x (given by a pointer)
- Check if heap-order is violated
 - If not, then done.
 - Otherwise, cut tree rooted at x and meld into root list (update min).



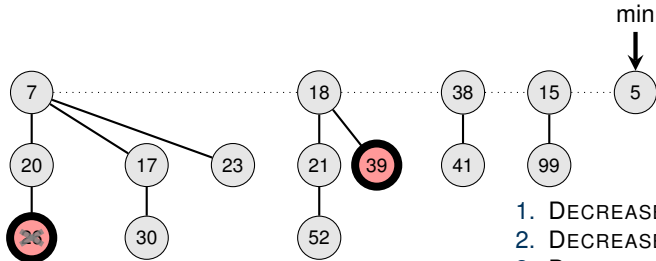
- DECREASE-KEY 24 \rightsquigarrow 20
- DECREASE-KEY 46 \rightsquigarrow 15
- DECREASE-KEY 35 \rightsquigarrow 5



Fibonacci Heap: DECREASE-KEY (First Try)

DECREASE-KEY of node x

- Decrease the key of x (given by a pointer)
- Check if heap-order is violated
 - If not, then done.
 - Otherwise, cut tree rooted at x and meld into root list (update min).



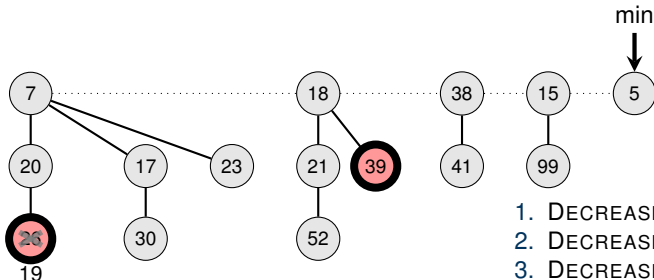
1. DECREASE-KEY 24 \rightsquigarrow 20
2. DECREASE-KEY 46 \rightsquigarrow 15
3. DECREASE-KEY 35 \rightsquigarrow 5
4. DECREASE-KEY 26 \rightsquigarrow 19



Fibonacci Heap: DECREASE-KEY (First Try)

DECREASE-KEY of node x

- Decrease the key of x (given by a pointer)
- Check if heap-order is violated
 - If not, then done.
 - Otherwise, cut tree rooted at x and meld into root list (update min).



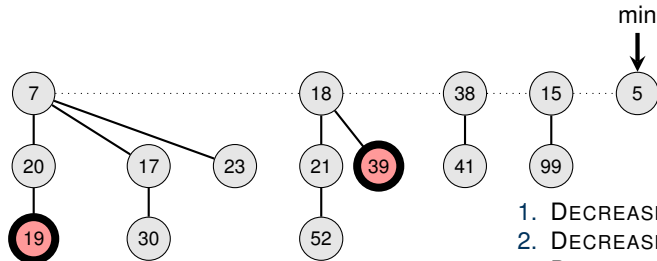
1. DECREASE-KEY 24 \rightsquigarrow 20
2. DECREASE-KEY 46 \rightsquigarrow 15
3. DECREASE-KEY 35 \rightsquigarrow 5
4. DECREASE-KEY 26 \rightsquigarrow 19



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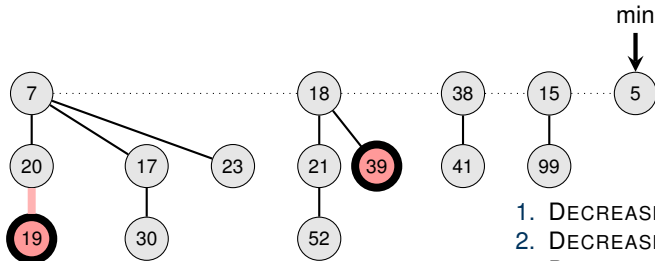
- DECREASE-KEY 24 \rightsquigarrow 20
- DECREASE-KEY 46 \rightsquigarrow 15
- DECREASE-KEY 35 \rightsquigarrow 5
- DECREASE-KEY 26 \rightsquigarrow 19



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- Check if heap-order is violated
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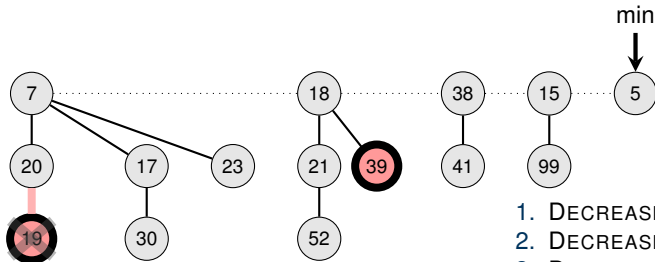
1. DECREASE-KEY 24 \rightsquigarrow 20
2. DECREASE-KEY 46 \rightsquigarrow 15
3. DECREASE-KEY 35 \rightsquigarrow 5
4. DECREASE-KEY 26 \rightsquigarrow 19



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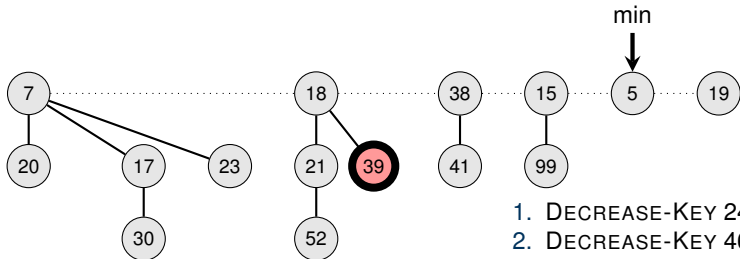
- DECREASE-KEY 24 \rightsquigarrow 20
- DECREASE-KEY 46 \rightsquigarrow 15
- DECREASE-KEY 35 \rightsquigarrow 5
- DECREASE-KEY 26 \rightsquigarrow 19



Fibonacci Heap: DECREASE-KEY (First Try)

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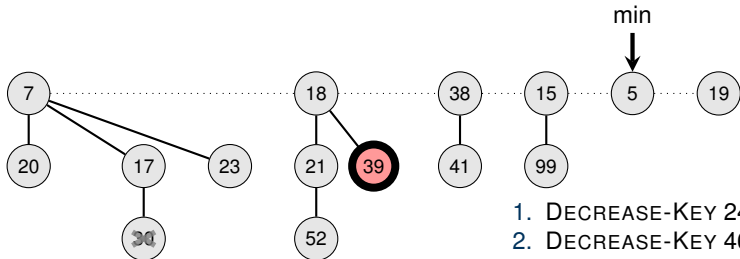
- DECREASE-KEY 24 \rightsquigarrow 20
- DECREASE-KEY 46 \rightsquigarrow 15
- DECREASE-KEY 35 \rightsquigarrow 5
- DECREASE-KEY 26 \rightsquigarrow 19



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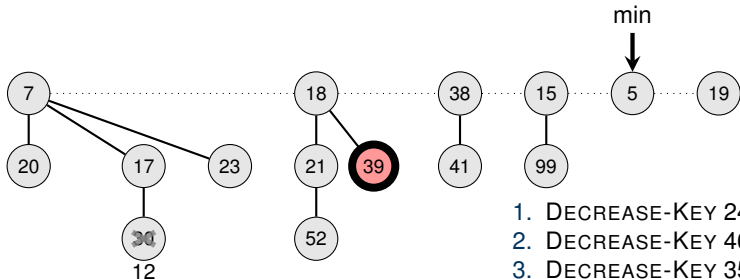
- DECREASE-KEY 24 \rightsquigarrow 20
- DECREASE-KEY 46 \rightsquigarrow 15
- DECREASE-KEY 35 \rightsquigarrow 5
- DECREASE-KEY 26 \rightsquigarrow 19
- DECREASE-KEY 30 \rightsquigarrow 12



Fibonacci Heap: DECREASE-KEY (First Try)

DECREASE-KEY of node x

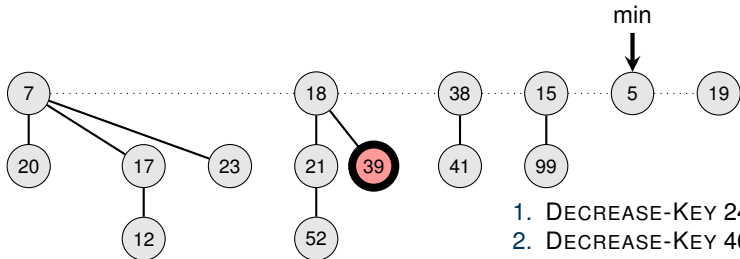
- Decrease the key of x (given by a pointer)
- Check if heap-order is violated
 - If not, then done.
 - Otherwise, cut tree rooted at x and meld into root list (update min).



Fibonacci Heap: DECREASE-KEY (First Try)

DECREASE-KEY of node x

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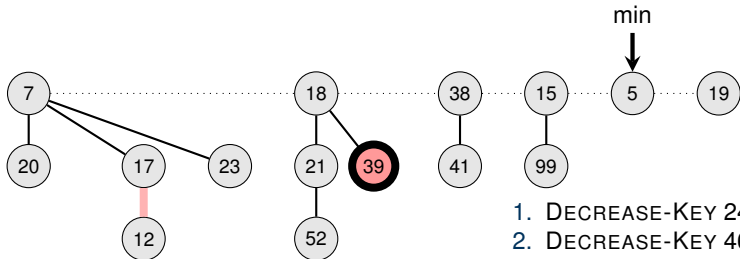
- DECREASE-KEY 24 \rightsquigarrow 20
- DECREASE-KEY 46 \rightsquigarrow 15
- DECREASE-KEY 35 \rightsquigarrow 5
- DECREASE-KEY 26 \rightsquigarrow 19
- DECREASE-KEY 30 \rightsquigarrow 12



Fibonacci Heap: DECREASE-KEY (First Try)

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- Check if heap-order is violated
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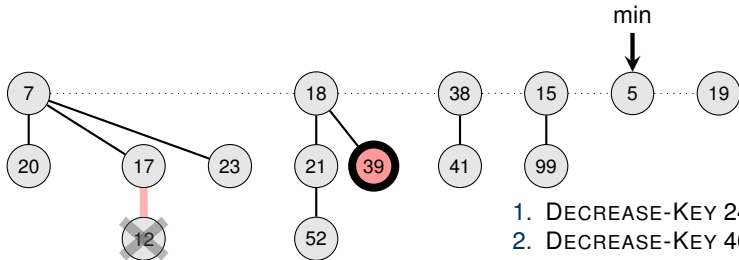
- DECREASE-KEY 24 \rightsquigarrow 20
- DECREASE-KEY 46 \rightsquigarrow 15
- DECREASE-KEY 35 \rightsquigarrow 5
- DECREASE-KEY 26 \rightsquigarrow 19
- DECREASE-KEY 30 \rightsquigarrow 12



Fibonacci Heap: DECREASE-KEY (First Try)

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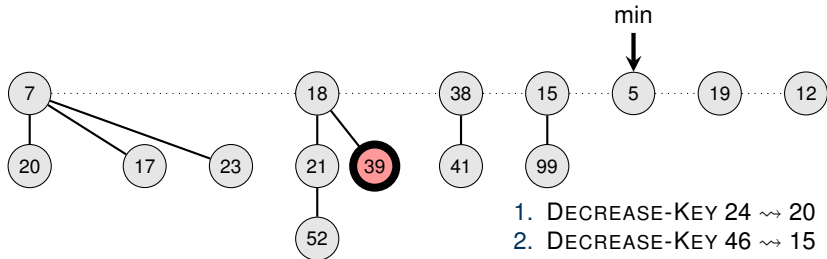
1. DECREASE-KEY 24 \rightsquigarrow 20
2. DECREASE-KEY 46 \rightsquigarrow 15
3. DECREASE-KEY 35 \rightsquigarrow 5
4. DECREASE-KEY 26 \rightsquigarrow 19
5. DECREASE-KEY 30 \rightsquigarrow 12



Fibonacci Heap: DECREASE-KEY (First Try)

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- Check if heap-order is violated
 - If not, then done.
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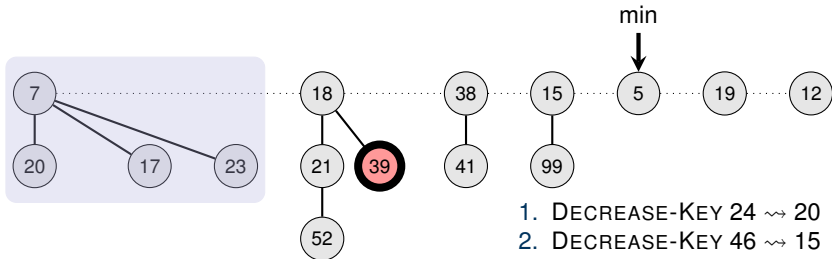
1. DECREASE-KEY 24 \rightsquigarrow 20
2. DECREASE-KEY 46 \rightsquigarrow 15
3. DECREASE-KEY 35 \rightsquigarrow 5
4. DECREASE-KEY 26 \rightsquigarrow 19
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Fibonacci Heap: DECREASE-KEY (First Try)

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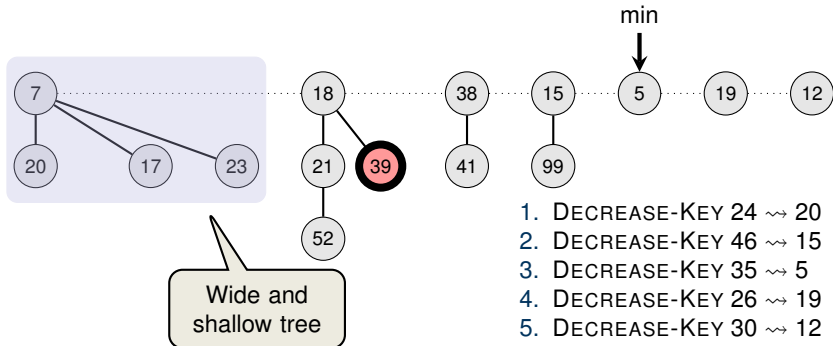
1. DECREASE-KEY 24 \rightsquigarrow 20
2. DECREASE-KEY 46 \rightsquigarrow 15
3. DECREASE-KEY 35 \rightsquigarrow 5
4. DECREASE-KEY 26 \rightsquigarrow 19
5. DECREASE-KEY 30 \rightsquigarrow 12



Fibonacci Heap: DECREASE-KEY (First Try)

DECREASE-KEY of node x

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- Check if heap-order is violated
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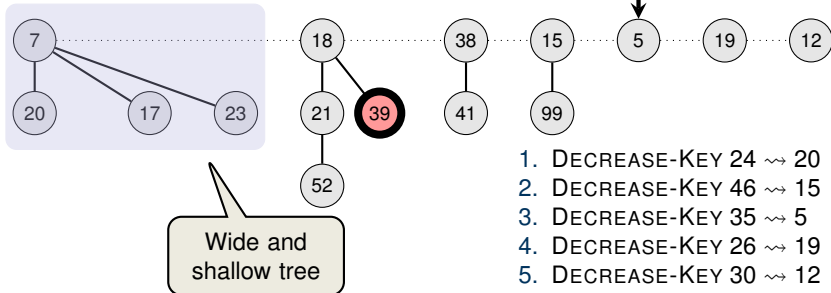


Fibonacci Heap: DECREASE-KEY (First Try)

DECREASE-KEY of node x

- Decrease the key of x (given by a pointer)
- Check if heap-order is violated
 - If not, then done.
 - Otherwise, cut tree rooted at x and meld into root list (update min).

Degree = 3,
Nodes = 4

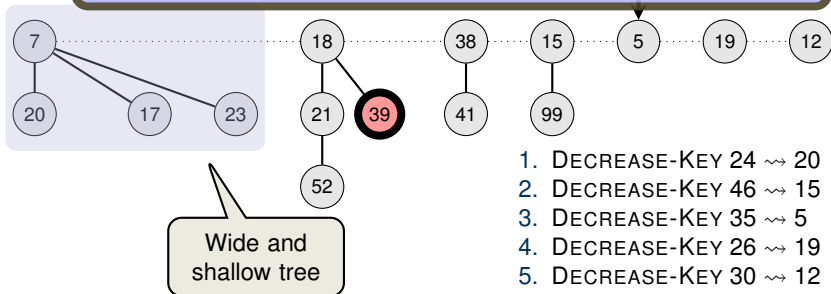


Fibonacci Heap: DECREASE-KEY (First Try)

DECREASE-KEY of node x

- Decrease the key of x (given by a pointer)
- Check if heap-order is violated
 - If not, then done.
 - Otherwise, cut tree rooted at x and meld into root list (update min).

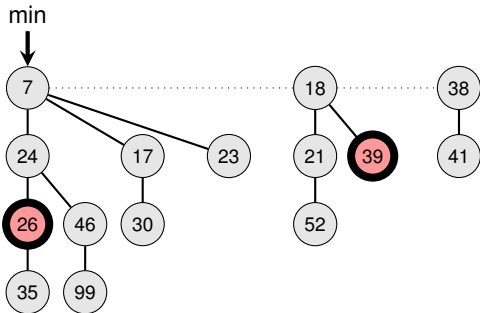
Peculiar Constraint: Make sure that each non-root node loses at most one child before becoming root



Fibonacci Heap: DECREASE-KEY

DECREASE-KEY of node x

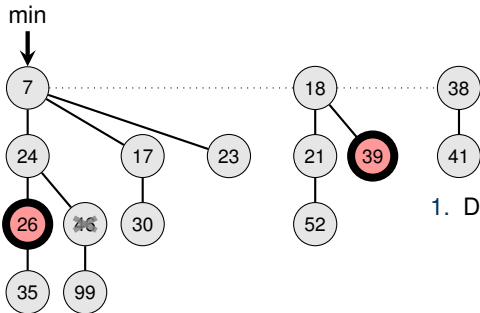
- Decrease the key of x (given by a pointer)



Fibonacci Heap: DECREASE-KEY

DECREASE-KEY of node x

- Decrease the key of x (given by a pointer)
- (Here we consider only cases where heap-order is violated)



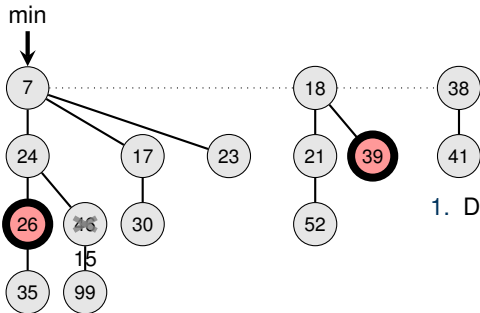
1. DECREASE-KEY 46 \rightsquigarrow 15



Fibonacci Heap: DECREASE-KEY

DECREASE-KEY of node x

- Decrease the key of x (given by a pointer)
 - (Here we consider only cases where heap-order is violated)
- ⇒ Cut tree rooted at x , unmark x , meld into root list



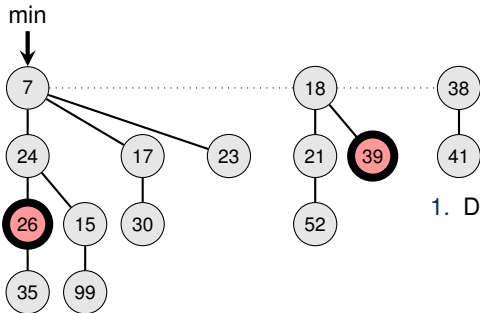
1. DECREASE-KEY 46 \rightsquigarrow 15



Fibonacci Heap: DECREASE-KEY

DECREASE-KEY of node x

- Decrease the key of x (given by a pointer)
 - (Here we consider only cases where heap-order is violated)
- ⇒ Cut tree rooted at x , unmark x , meld into root list



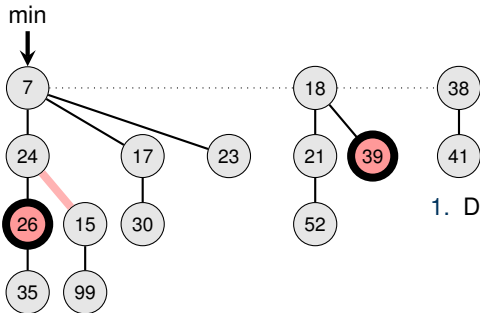
1. DECREASE-KEY 46 \rightsquigarrow 15



Fibonacci Heap: DECREASE-KEY

DECREASE-KEY of node x

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 - (Here we consider only cases where heap-order is violated)
- ⇒ Cut tree rooted at x , unmark x , meld into root list



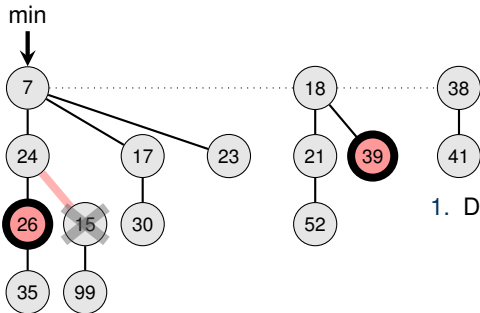
1. DECREASE-KEY 46 \rightsquigarrow 15



Fibonacci Heap: DECREASE-KEY

DECREASE-KEY of node x

- Decrease the key of x (given by a pointer)
 - (Here we consider only cases where heap-order is violated)
- ⇒ Cut tree rooted at x , unmark x , meld into root list



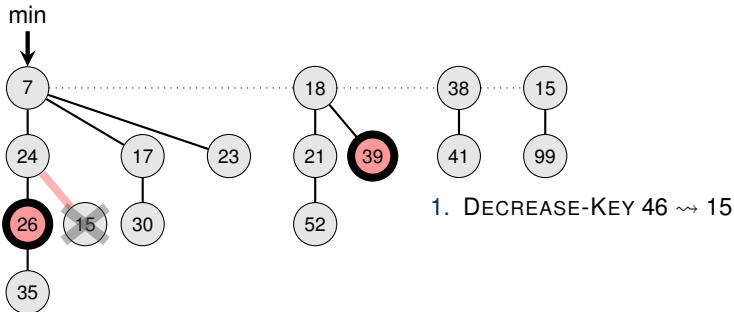
1. DECREASE-KEY 46 \rightsquigarrow 15



Fibonacci Heap: DECREASE-KEY

DECREASE-KEY of node x

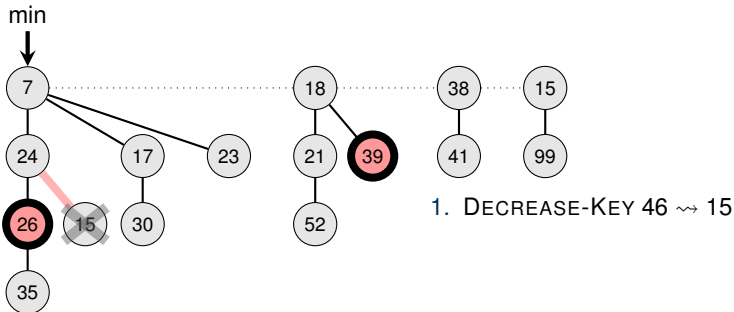
- Decrease the key of x (given by a pointer)
 - (Here we consider only cases where heap-order is violated)
- ⇒ Cut tree rooted at x , unmark x , meld into root list **and**:



Fibonacci Heap: DECREASE-KEY

DECREASE-KEY of node x

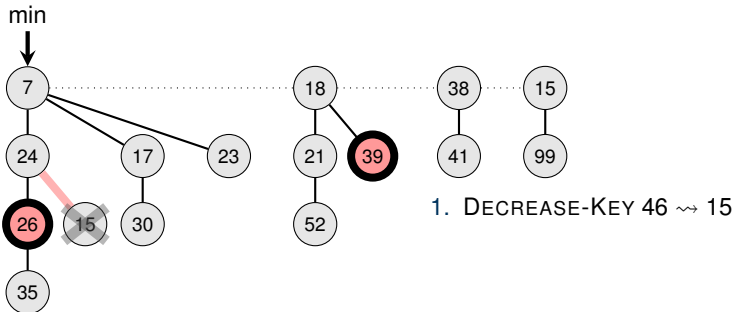
- Decrease the key of x (given by a pointer)
 - (Here we consider only cases where heap-order is violated)
- ⇒ Cut tree rooted at x , unmark x , meld into root list **and**:
- Check if parent node is marked



Fibonacci Heap: DECREASE-KEY

DECREASE-KEY of node x

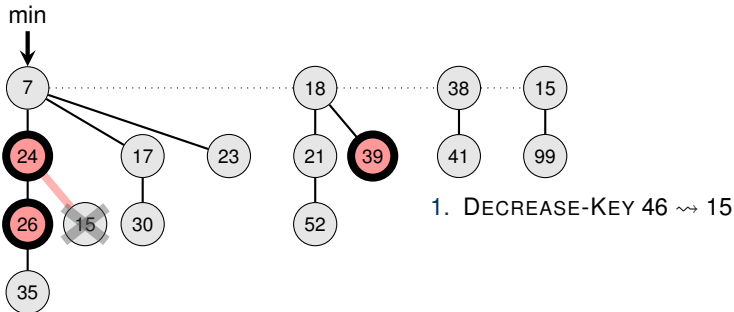
- Decrease the key of x (given by a pointer)
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- ⇒ Cut tree rooted at x , unmark x , meld into root list **and**:
- Check if parent node is marked
 - If unmarked, mark it (unless it is a root)



Fibonacci Heap: DECREASE-KEY

DECREASE-KEY of node x

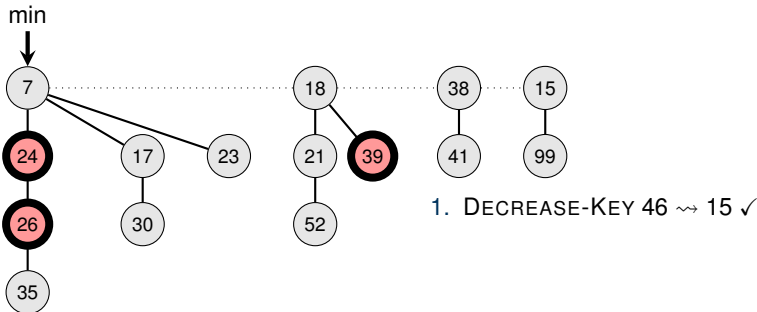
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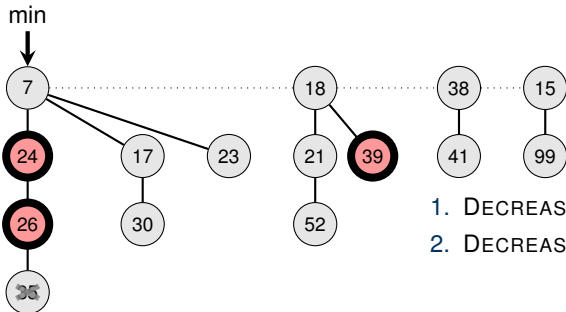
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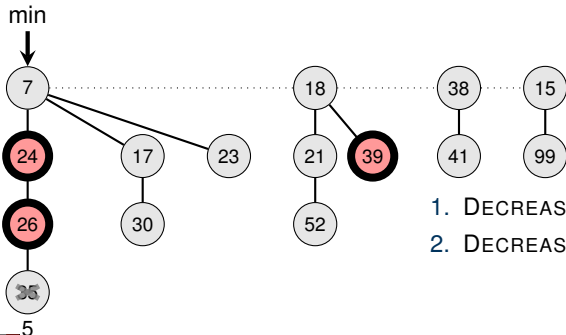
1. DECREASE-KEY 46 \rightsquigarrow 15 ✓
2. DECREASE-KEY 35 \rightsquigarrow 5



Fibonacci Heap: DECREASE-KEY

DECREASE-KEY of node x

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2. DECREASE-KEY 35 \rightsquigarrow 5

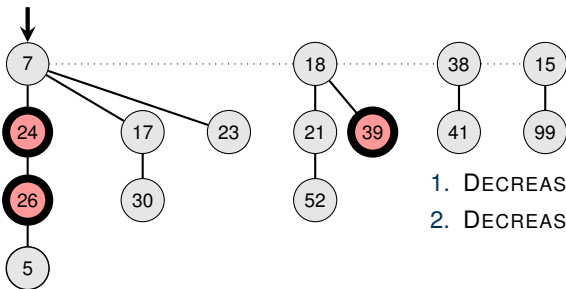


Fibonacci Heap: DECREASE-KEY

DECREASE-KEY of node x

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min



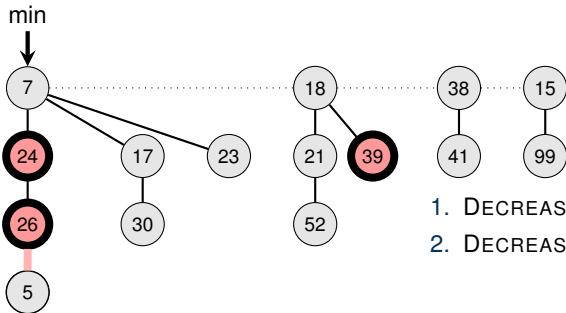
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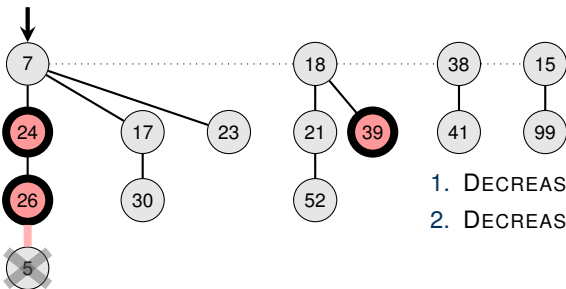


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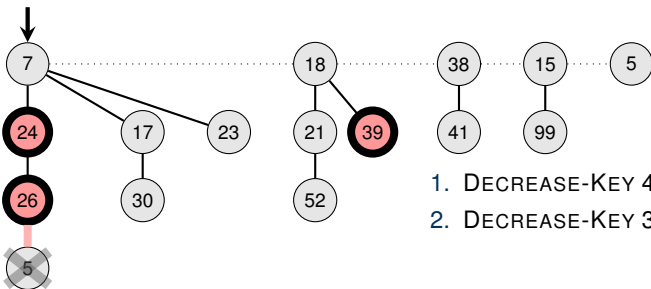


Fibonacci Heap: DECREASE-KEY

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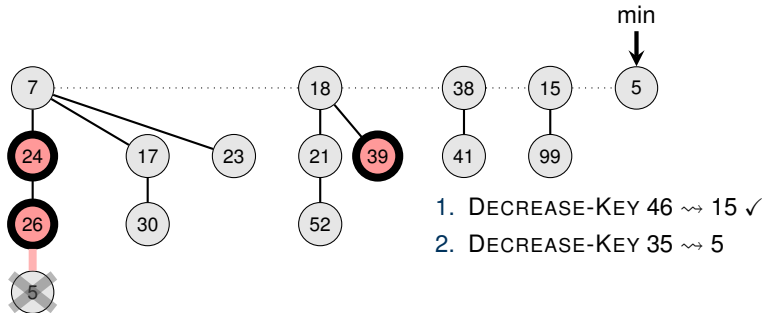
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Fibonacci Heap: DECREASE-KEY

DECREASE-KEY of node x

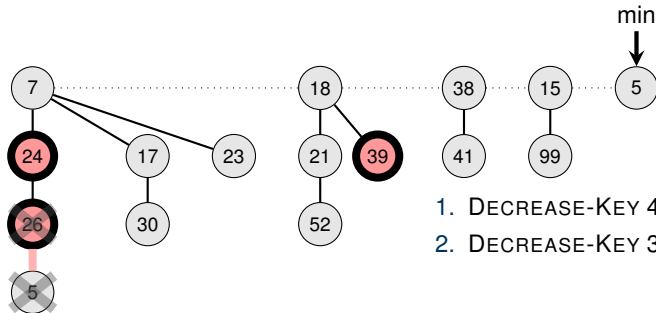
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 - If marked, unmark and meld it into root list and recurse (**Cascading Cut**)



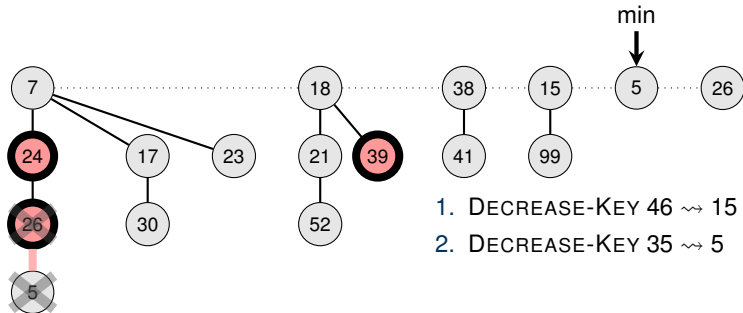
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Fibonacci Heap: DECREASE-KEY

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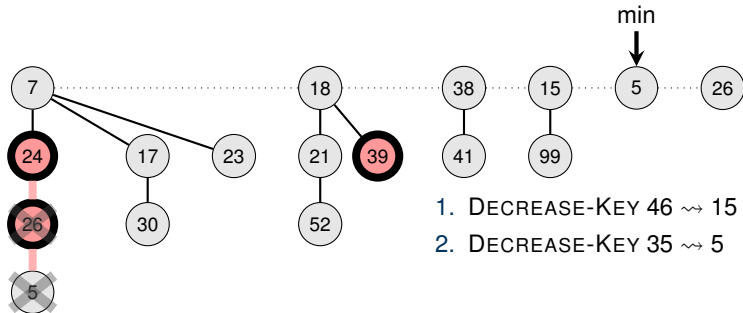
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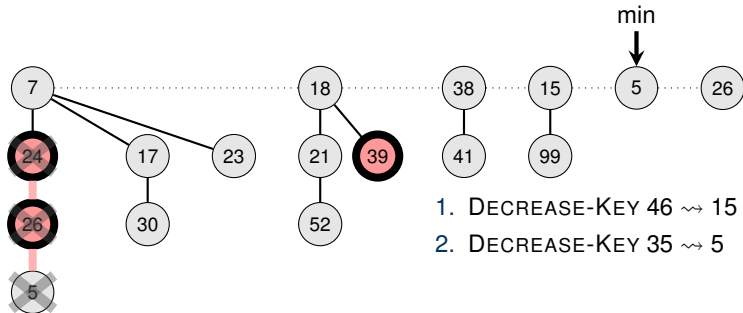
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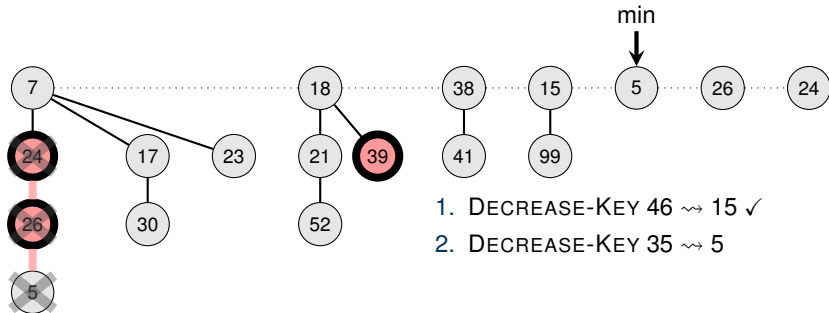
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Fibonacci Heap: DECREASE-KEY

DECREASE-KEY of node x

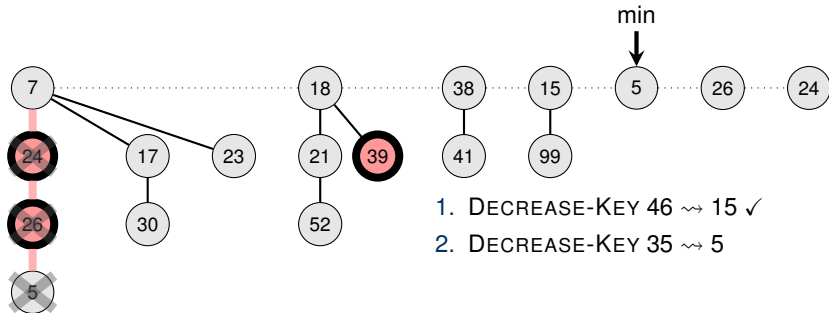
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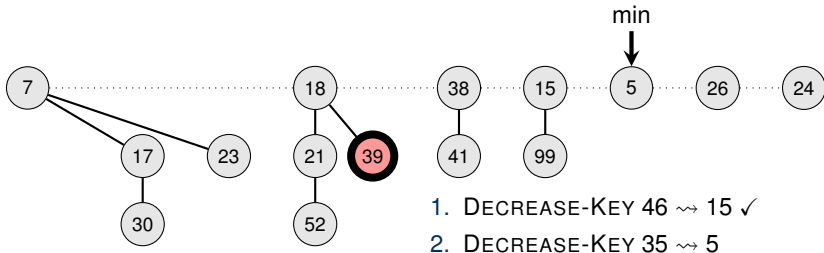
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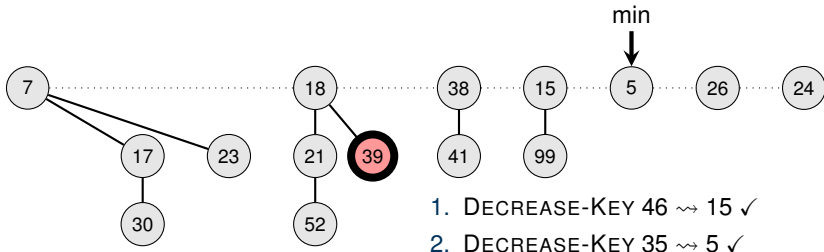
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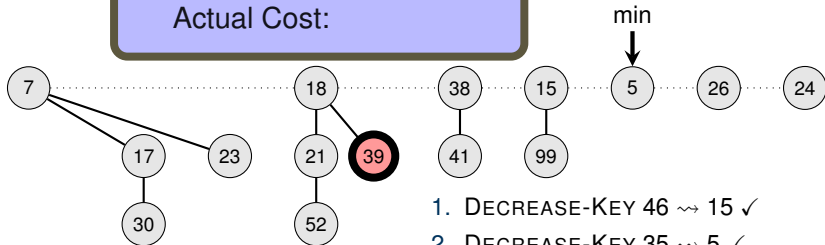


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Actual Cost:

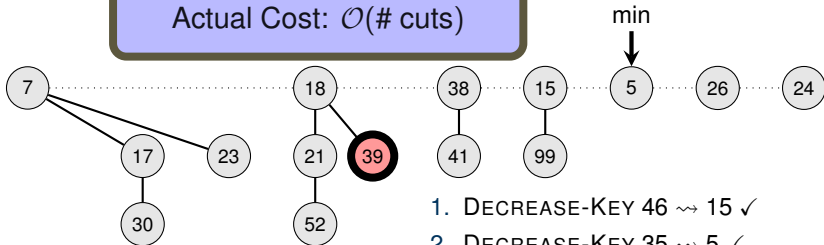


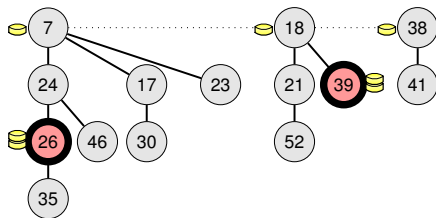
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Actual Cost: $\mathcal{O}(\# \text{ cuts})$





5.2 Fibonacci Heaps (Analysis)

Frank Stajano

Thomas Sauerwald

Lent 2016



UNIVERSITY OF
CAMBRIDGE

Outline

Structure

Operations

Glimpse at the Analysis

Amortized Analysis



Amortized Analysis via Potential Method

- INSERT: actual $\mathcal{O}(1)$
- EXTRACT-MIN: actual $\mathcal{O}(\text{trees}(H) + d(n))$
- DECREASE-KEY: actual $\mathcal{O}(\# \text{ cuts}) \leq \mathcal{O}(\text{marks}(H))$



Amortized Analysis via Potential Method

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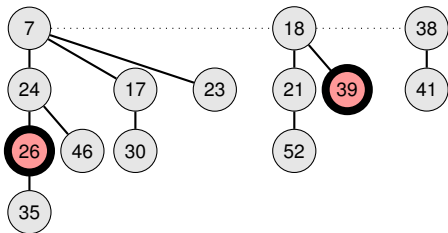
$$\Phi(H) = \text{trees}(H) + 2 \cdot \text{marks}(H)$$



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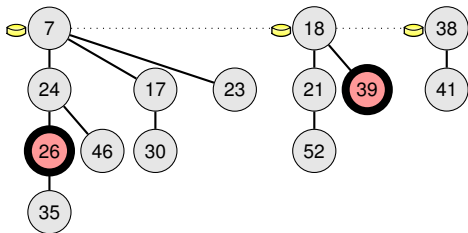
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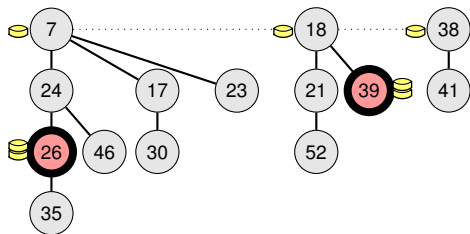
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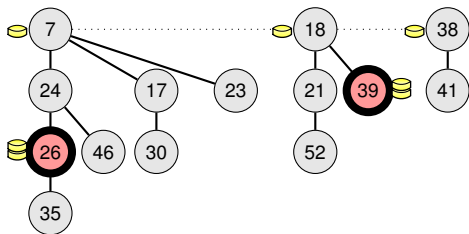
$$\Phi(H) = \text{trees}(H) + 2 \cdot \text{marks}(H)$$



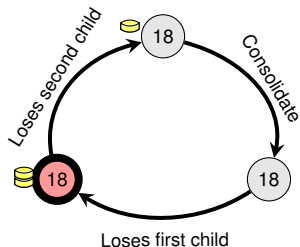
Amortized Analysis via Potential Method

- INSERT: actual $\mathcal{O}(1)$ amortized $\mathcal{O}(1)$
- EXTRACT-MIN: actual $\mathcal{O}(\text{trees}(H) + d(n))$ amortized $\mathcal{O}(d(n))$
- DECREASE-KEY: actual $\mathcal{O}(\# \text{ cuts}) \leq \mathcal{O}(\text{marks}(H))$ amortized $\mathcal{O}(1)$

$$\Phi(H) = \text{trees}(H) + 2 \cdot \text{marks}(H)$$



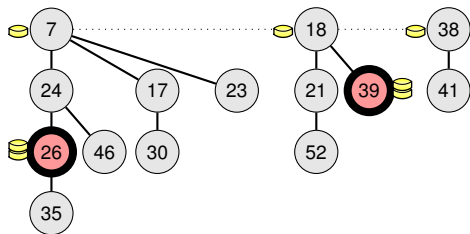
Lifecycle of a node



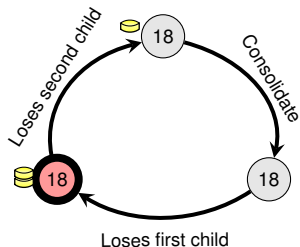
Amortized Analysis via Potential Method

- INSERT: actual $\mathcal{O}(1)$ amortized $\mathcal{O}(1)$ ✓
- EXTRACT-MIN: actual $\mathcal{O}(\text{trees}(H) + d(n))$ amortized $\mathcal{O}(d(n))$?
- DECREASE-KEY: actual $\mathcal{O}(\# \text{ cuts}) \leq \mathcal{O}(\text{marks}(H))$ amortized $\mathcal{O}(1)$?

$$\Phi(H) = \text{trees}(H) + 2 \cdot \text{marks}(H)$$



Lifecycle of a node



Outline

Structure

Operations

Glimpse at the Analysis

Amortized Analysis



Amortized Analysis of DECREASE-KEY

Actual Cost

- DECREASE-KEY: $\mathcal{O}(x + 1)$, where x is the number of cuts.



Amortized Analysis of DECREASE-KEY

Actual Cost

- DECREASE-KEY: $\mathcal{O}(x + 1)$, where x is the number of cuts.

$$\Phi(H) = \text{trees}(H) + 2 \cdot \text{marks}(H)$$



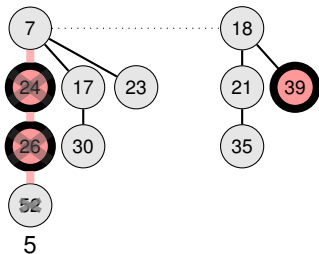
Amortized Analysis of DECREASE-KEY

Actual Cost

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$$\Phi(H) = \text{trees}(H) + 2 \cdot \text{marks}(H)$$

Change in Potential



Amortized Analysis of DECREASE-KEY

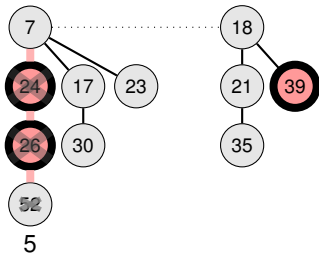
Actual Cost

- DECREASE-KEY: $\mathcal{O}(x + 1)$, where x is the number of cuts.

$$\Phi(H) = \text{trees}(H) + 2 \cdot \text{marks}(H)$$

Change in Potential

- $\text{trees}(H') =$



Amortized Analysis of DECREASE-KEY

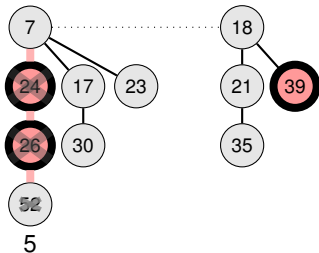
Actual Cost

- DECREASE-KEY: $\mathcal{O}(x + 1)$, where x is the number of cuts.

$$\Phi(H) = \text{trees}(H) + 2 \cdot \text{marks}(H)$$

Change in Potential

- $\text{trees}(H') = \text{trees}(H) + x$



Amortized Analysis of DECREASE-KEY

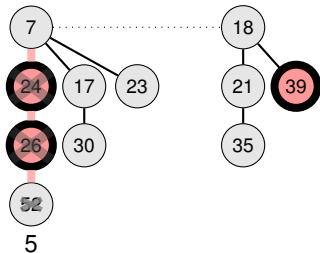
Actual Cost

- DECREASE-KEY: $\mathcal{O}(x + 1)$, where x is the number of cuts.

$$\Phi(H) = \text{trees}(H) + 2 \cdot \text{marks}(H)$$

Change in Potential

- $\text{trees}(H') = \text{trees}(H) + x$
- $\text{marks}(H') \leq$



Amortized Analysis of DECREASE-KEY

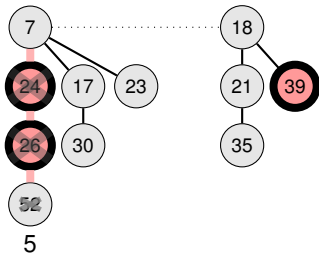
Actual Cost

- DECREASE-KEY: $\mathcal{O}(x + 1)$, where x is the number of cuts.

$$\Phi(H) = \text{trees}(H) + 2 \cdot \text{marks}(H)$$

Change in Potential

- $\text{trees}(H') = \text{trees}(H) + x$
- $\text{marks}(H') \leq \text{marks}(H) - x + 2$



Amortized Analysis of DECREASE-KEY

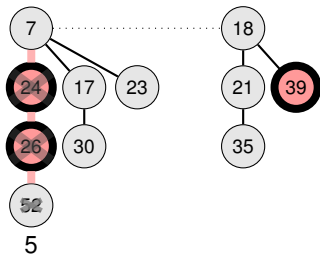
Actual Cost

- DECREASE-KEY: $\mathcal{O}(x + 1)$, where x is the number of cuts.

$$\Phi(H) = \text{trees}(H) + 2 \cdot \text{marks}(H)$$

Change in Potential

- $\text{trees}(H') = \text{trees}(H) + x$
 - $\text{marks}(H') \leq \text{marks}(H) - x + 2$
- $$\Rightarrow \Delta\Phi \leq x + 2 \cdot (-x + 2) = 4 - x.$$



Amortized Analysis of DECREASE-KEY

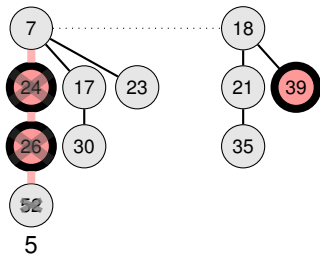
Actual Cost

- **DECREASE-KEY**: $\mathcal{O}(x + 1)$, where x is the number of cuts.

$$\Phi(H) = \text{trees}(H) + 2 \cdot \text{marks}(H)$$

Change in Potential

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- $\Rightarrow \Delta\Phi \leq x + 2 \cdot (-x + 2) = 4 - x.$



Amortized Cost

$$\hat{c}_i = c_i + \Delta\Phi$$



Amortized Analysis of DECREASE-KEY

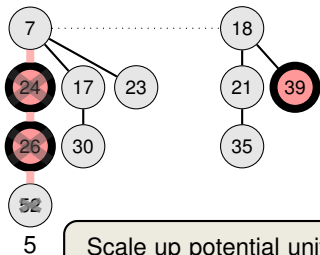
Actual Cost

- **DECREASE-KEY**: $\mathcal{O}(x + 1)$, where x is the number of cuts.

$$\Phi(H) = \text{trees}(H) + 2 \cdot \text{marks}(H)$$

Change in Potential

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Amortized Cost

$$\hat{c}_i = c_i + \Delta\Phi \leq \mathcal{O}(x + 1) + 4 - x$$



Amortized Analysis of DECREASE-KEY

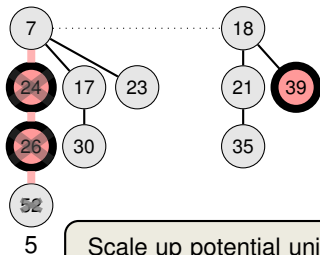
Actual Cost

- **DECREASE-KEY**: $\mathcal{O}(x + 1)$, where x is the number of cuts.

$$\Phi(H) = \text{trees}(H) + 2 \cdot \text{marks}(H)$$

Change in Potential

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Amortized Cost

$$\hat{c}_i = c_i + \Delta\Phi \leq \mathcal{O}(x + 1) + 4 - x = \mathcal{O}(1)$$



Amortized Analysis of DECREASE-KEY

Actual Cost

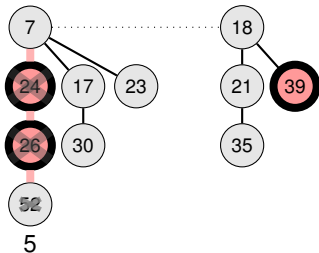
- **DECREASE-KEY**: $\mathcal{O}(x + 1)$, where x is the number of cuts.

$$\Phi(H) = \text{trees}(H) + 2 \cdot \text{marks}(H)$$

First Coin \rightsquigarrow pays cut
Second Coin \rightsquigarrow increase of $\text{trees}(H)$

Change in Potential

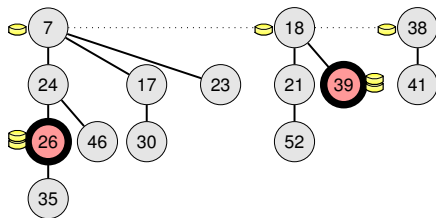
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Amortized Cost

$$\hat{c}_i = c_i + \Delta\Phi \leq \mathcal{O}(x + 1) + 4 - x = \mathcal{O}(1)$$





5.2 Fibonacci Heaps (Analysis)

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Thomas Sauerwald

Lent 2016



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Recap of INSERT, EXTRACT-MIN and DECREASE-KEY

Glimpse at the Analysis

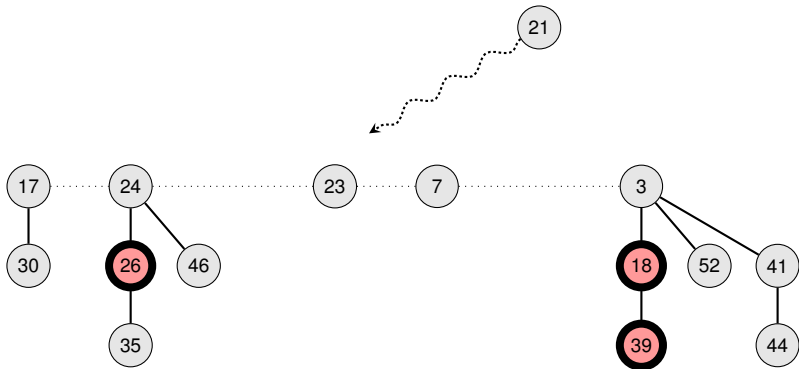
Amortized Analysis

Bounding the Maximum Degree



Fibonacci Heap: INSERT

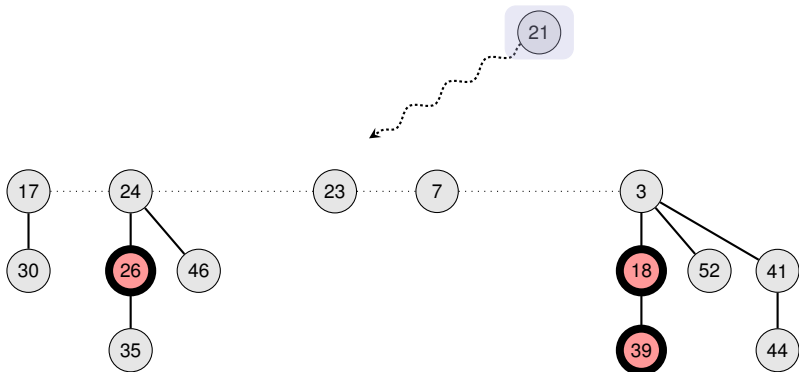
INSERT



Fibonacci Heap: INSERT

INSERT

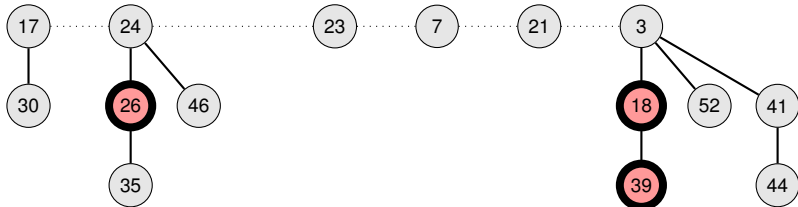
- Create a singleton tree



Fibonacci Heap: INSERT

INSERT

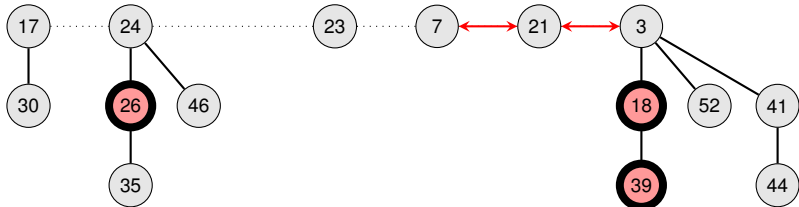
- Create a singleton tree
- Add to root list



Fibonacci Heap: INSERT

INSERT

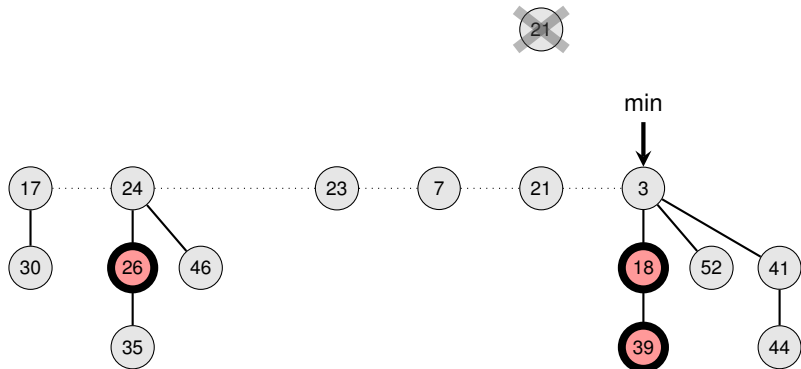
- Create a singleton tree
- Add to root list



Fibonacci Heap: INSERT

INSERT

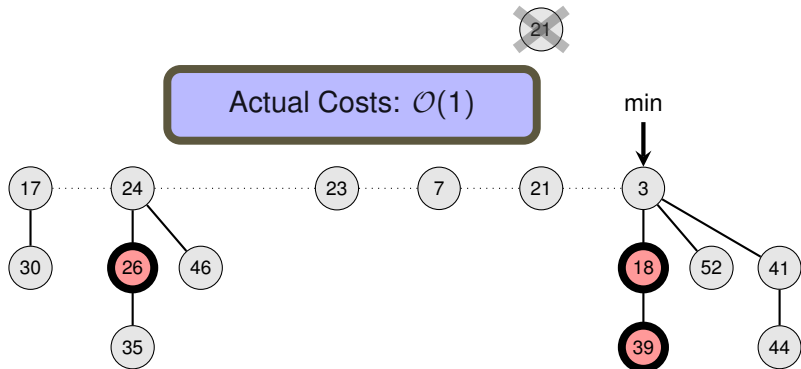
- Create a singleton tree
- Add to root list and update min-pointer (if necessary)



Fibonacci Heap: INSERT

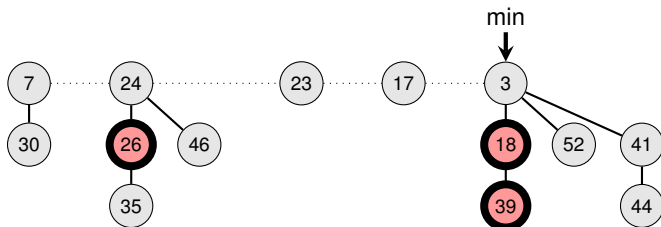
INSERT

- Create a singleton tree
- Add to root list and update min-pointer (if necessary)



Fibonacci Heap: EXTRACT-MIN

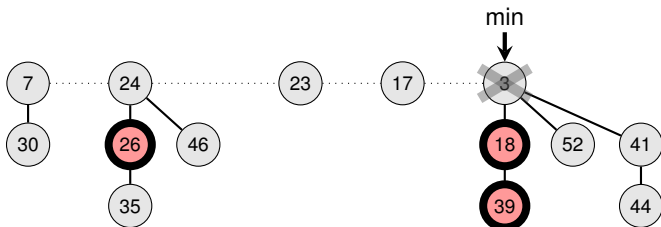
EXTRACT-MIN



Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

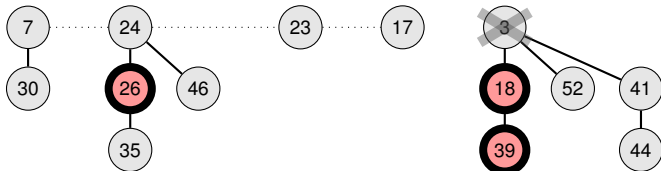
- Delete min



Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

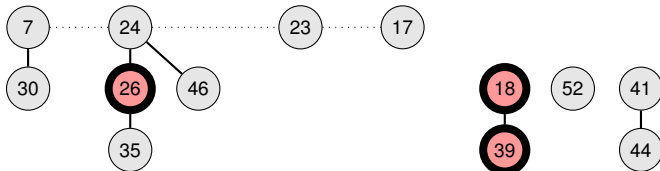
- Delete min ✓



Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

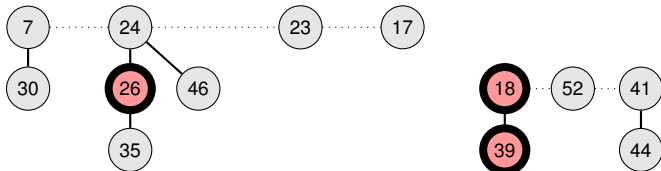
- Delete min ✓
- Meld children into root list and unmark them



Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

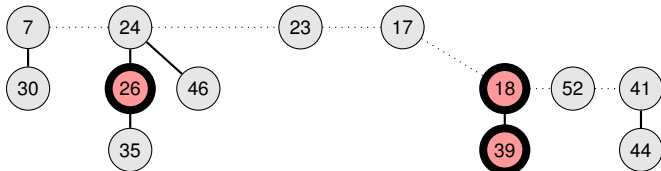
- Delete min ✓
- Meld children into root list and unmark them



Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

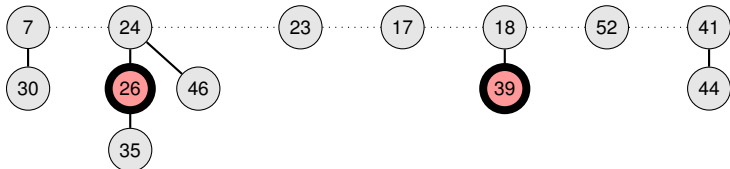
- Delete min ✓
- Meld children into root list and unmark them



Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

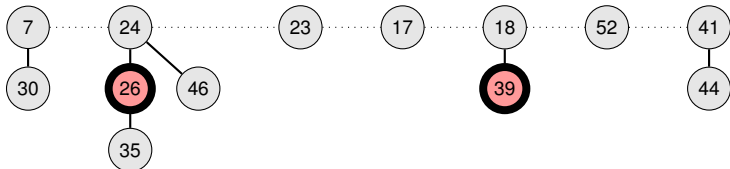
- Delete min ✓
- Meld children into root list and unmark them ✓



Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

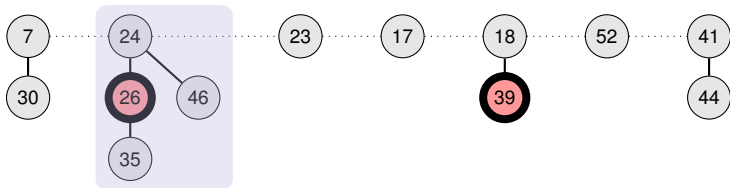
- Delete min ✓
- Meld children into root list and unmark them ✓
- **Consolidate** so that no roots have the same degree



Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

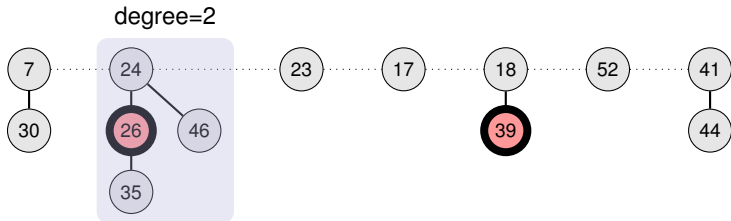
- Delete min ✓
- Meld children into root list and unmark them ✓
- **Consolidate** so that no roots have the same degree (# children)



Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

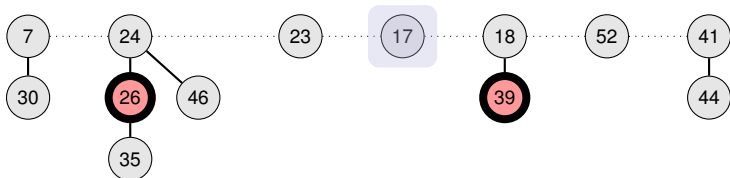
- Delete min ✓
- Meld children into root list and unmark them ✓
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Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

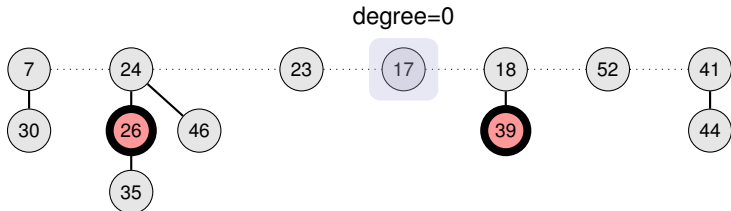
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Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

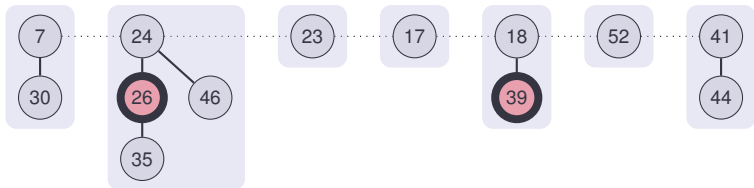
- Delete min ✓
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Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

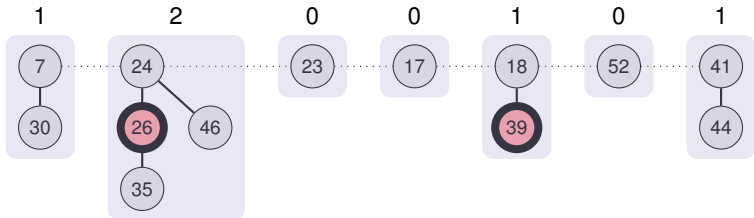
- Delete min ✓
- Meld children into root list and unmark them ✓
- **Consolidate** so that no roots have the same degree (# children)



Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

- Delete min ✓
- Meld children into root list and unmark them ✓
- **Consolidate** so that no roots have the same degree (# children)



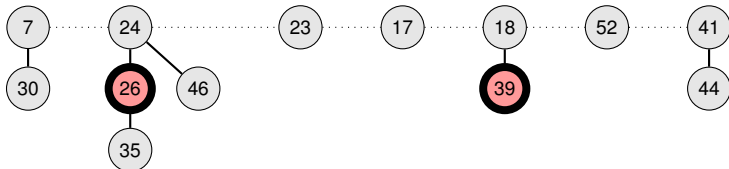
Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

- Delete min ✓
- Meld children into root list and unmark them ✓
- **Consolidate** so that no roots have the same degree (# children)

degree

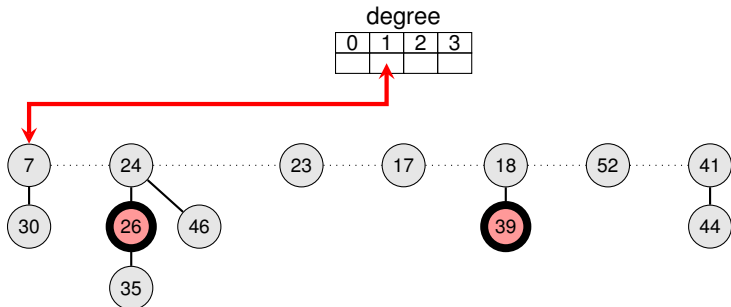
0	1	2	3



Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

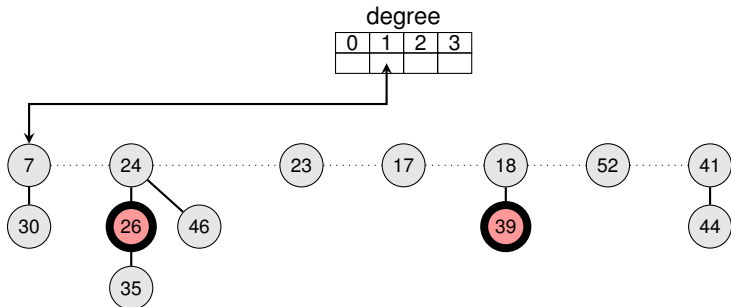
- Delete min ✓
- Meld children into root list and unmark them ✓
- **Consolidate** so that no roots have the same degree (# children)



Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

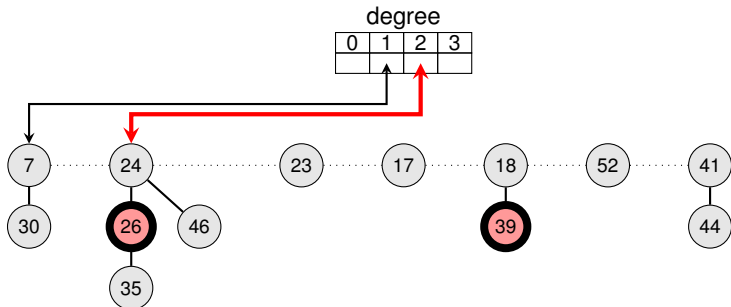
- Delete min ✓
- Meld children into root list and unmark them ✓
- **Consolidate** so that no roots have the same degree (# children)



Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

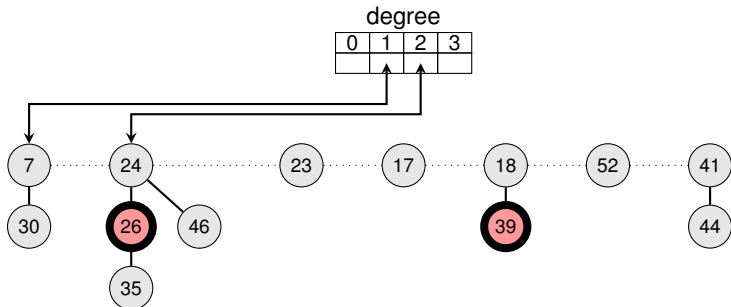
- Delete min ✓
- Meld children into root list and unmark them ✓
- **Consolidate** so that no roots have the same degree (# children)



Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

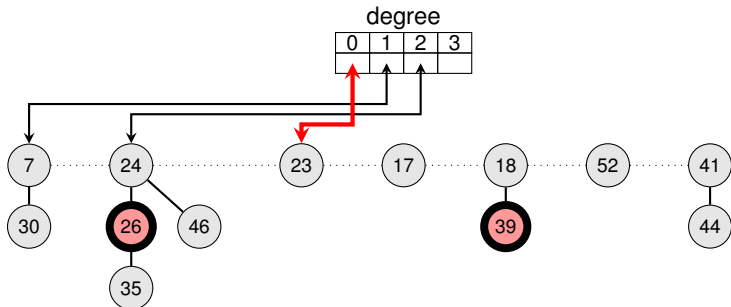
- Delete min ✓
- Meld children into root list and unmark them ✓
- **Consolidate** so that no roots have the same degree (# children)



Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

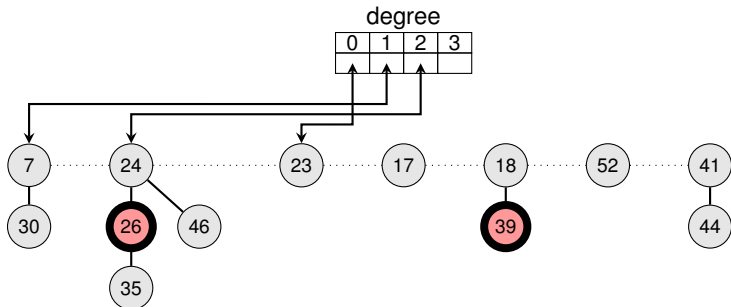
- Delete min ✓
- Meld children into root list and unmark them ✓
- **Consolidate** so that no roots have the same degree (# children)



Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

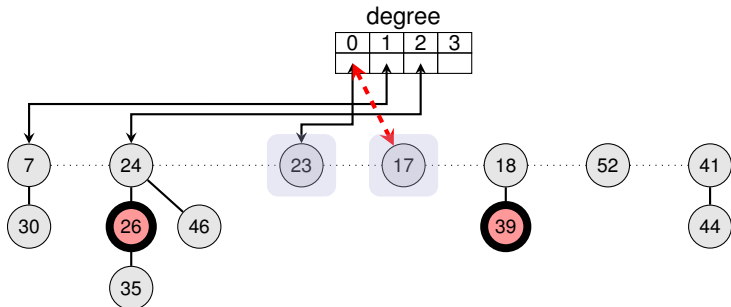
- Delete min ✓
- Meld children into root list and unmark them ✓
- **Consolidate** so that no roots have the same degree (# children)



Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

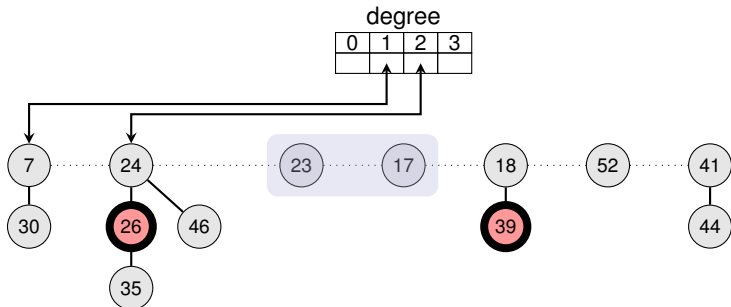
- Delete min ✓
- Meld children into root list and unmark them ✓
- **Consolidate** so that no roots have the same degree (# children)



Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

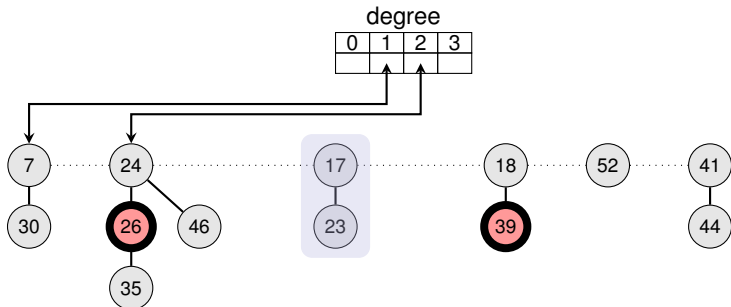
- Delete min ✓
- Meld children into root list and unmark them ✓
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Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

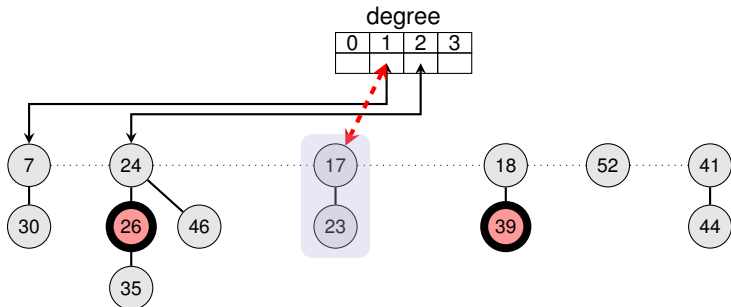
- Delete min ✓
- Meld children into root list and unmark them ✓
- **Consolidate** so that no roots have the same degree (# children)



Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

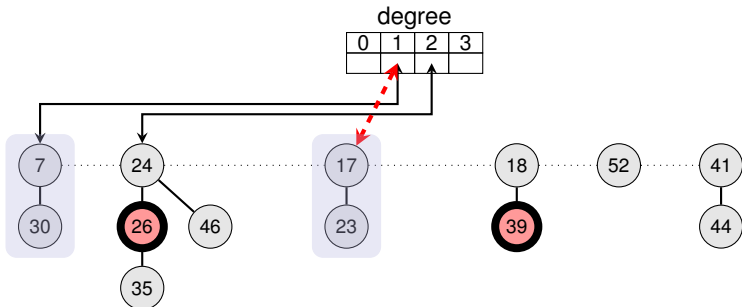
- Delete min ✓
- Meld children into root list and unmark them ✓
- **Consolidate** so that no roots have the same degree (# children)



Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

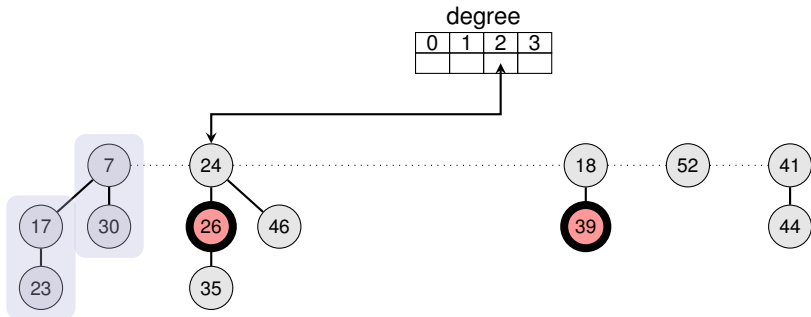
- Delete min ✓
- Meld children into root list and unmark them ✓
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Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

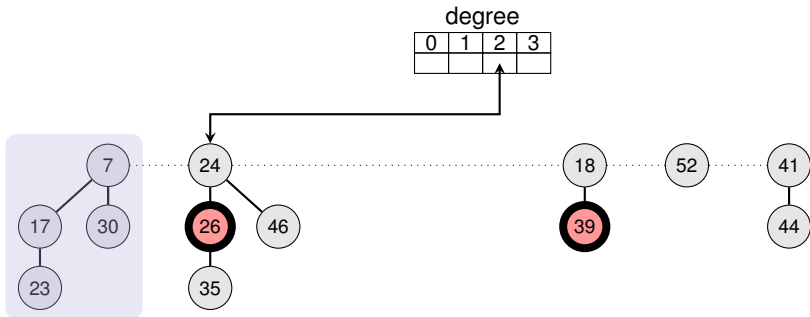
- Delete min ✓
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Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

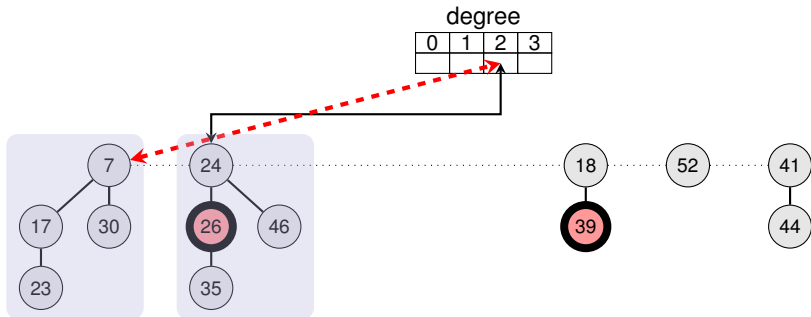
- Delete min ✓
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Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

- Delete min ✓
- Meld children into root list and unmark them ✓
- **Consolidate** so that no roots have the same degree (# children)

degree

0	1	2	3



Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

- Delete min ✓
- Meld children into root list and unmark them ✓
- **Consolidate** so that no roots have the same degree (# children)

degree

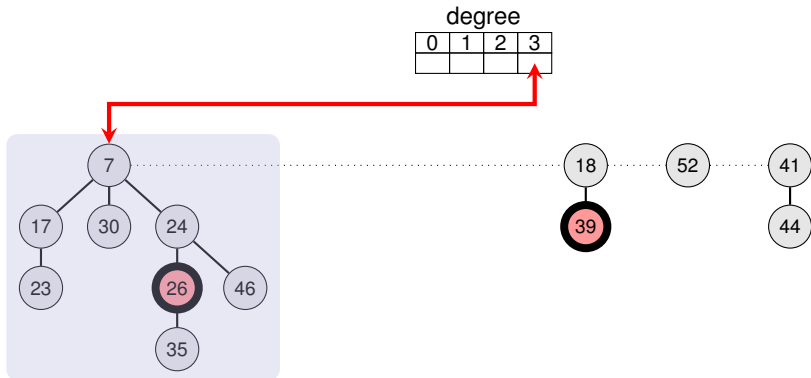
0	1	2	3



Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

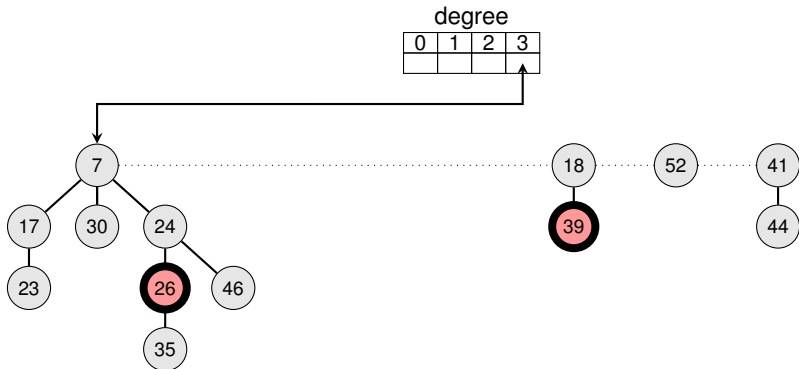
- Delete min ✓
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- **Consolidate** so that no roots have the same degree (# children)



Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

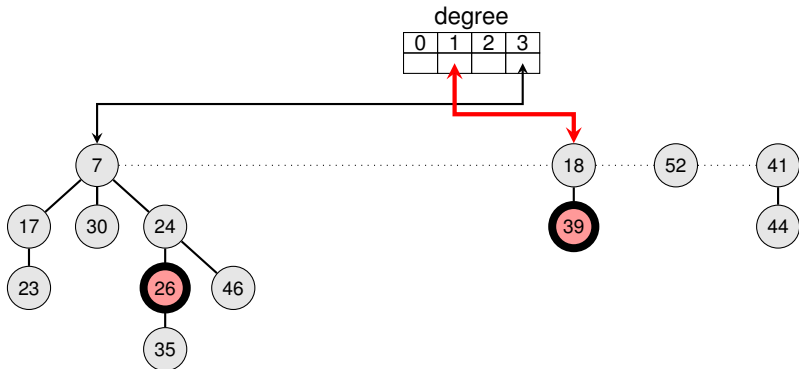
- Delete min ✓
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Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

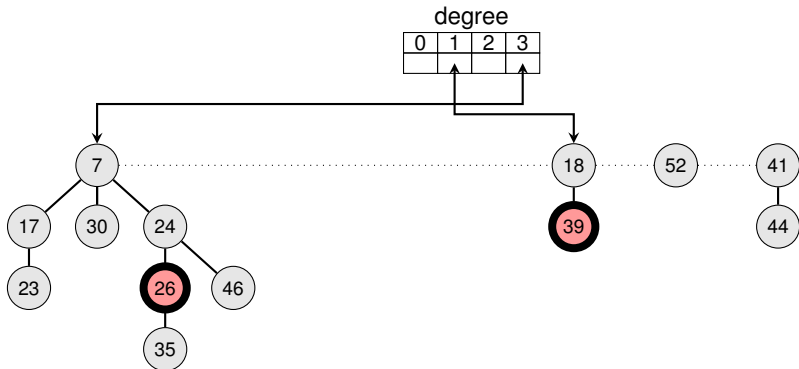
- Delete min ✓
- Meld children into root list and unmark them ✓
- **Consolidate** so that no roots have the same degree (# children)



Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

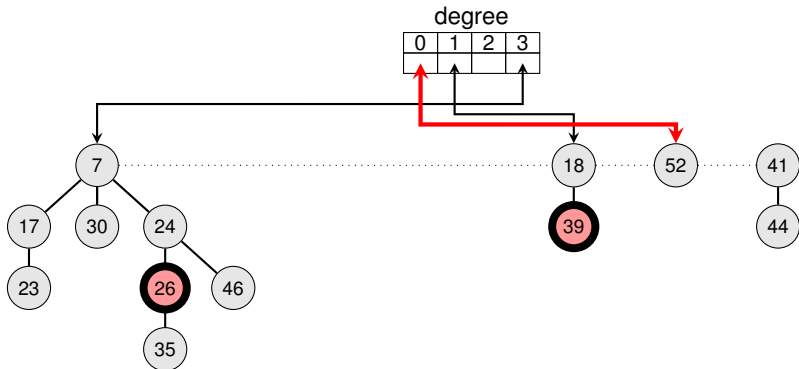
- Delete min ✓
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Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

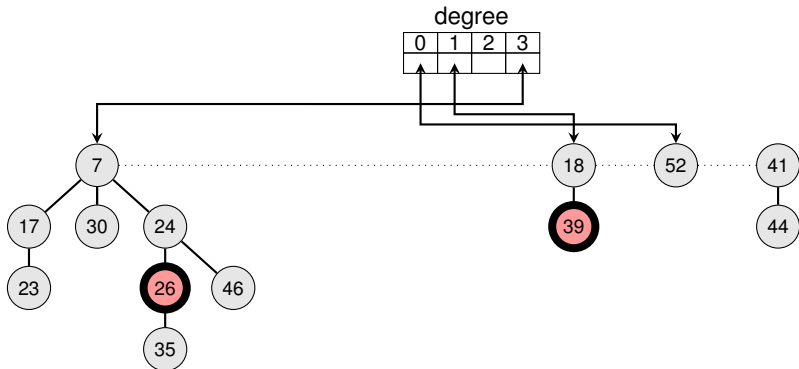
- Delete min ✓
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Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

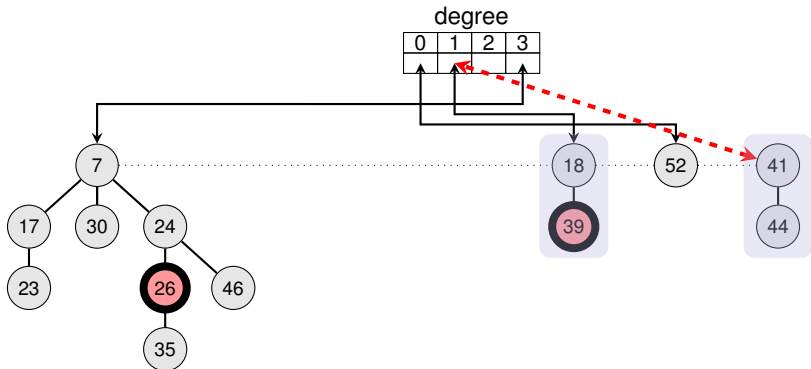
- Delete min ✓
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Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

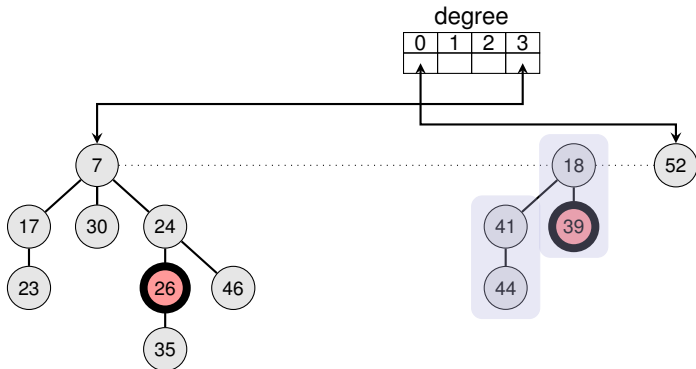
- Delete min ✓
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Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

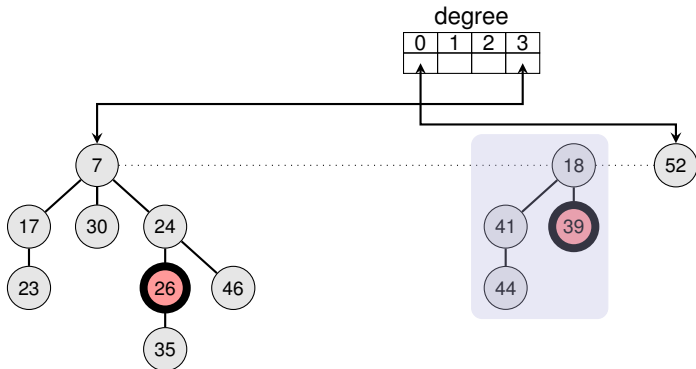
- Delete min ✓
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Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

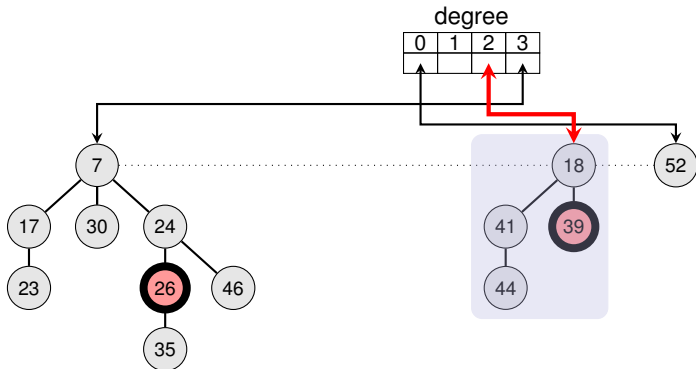
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Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

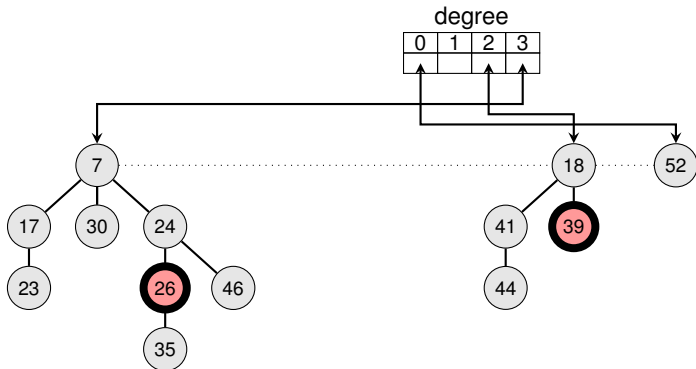
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Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

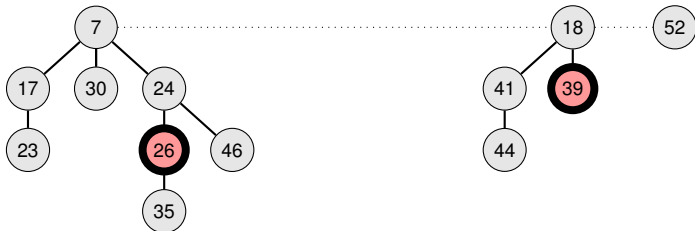
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Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

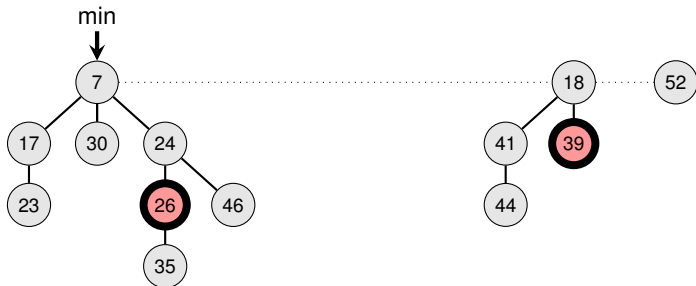
- Delete min ✓
- Meld children into root list and unmark them ✓
- **Consolidate** so that no roots have the same degree (# children) ✓
- Update minimum



Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

- Delete min ✓
- Meld children into root list and unmark them ✓
- **Consolidate** so that no roots have the same degree (# children) ✓
- Update minimum ✓

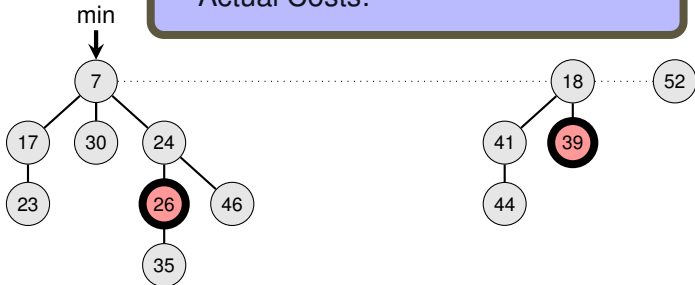


Fibonacci Heap: EXTRACT-MIN

EXTRACT-MIN

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Actual Costs:



Fibonacci Heap: EXTRACT-MIN

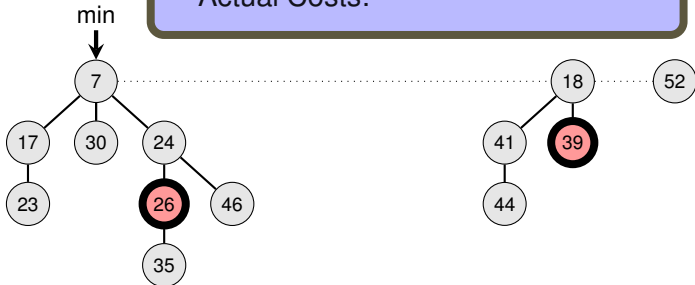
EXTRACT-MIN

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Every root becomes child of another root at most once!

$d(n)$ is the maximum degree of a root in any Fibonacci heap of size n

Actual Costs:



Fibonacci Heap: EXTRACT-MIN

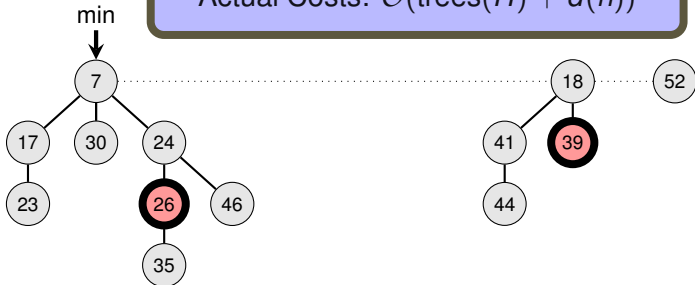
EXTRACT-MIN

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$d(n)$ is the maximum degree of a root in any Fibonacci heap of size n

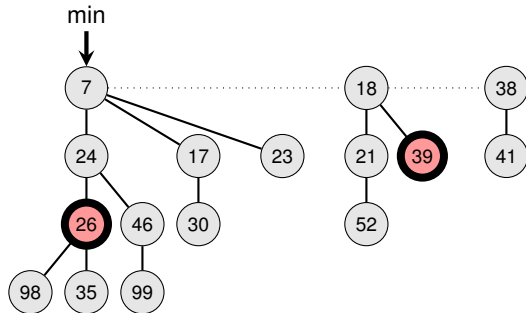
Actual Costs: $\mathcal{O}(\text{trees}(H) + d(n))$



Fibonacci Heap: DECREASE-KEY

DECREASE-KEY of node x

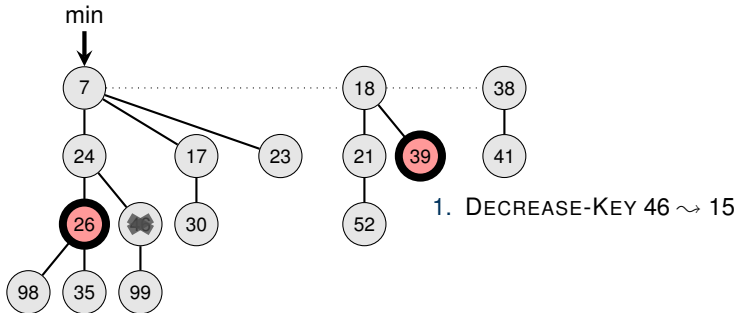
- Decrease the key of x (given by a pointer)



Fibonacci Heap: DECREASE-KEY

DECREASE-KEY of node x

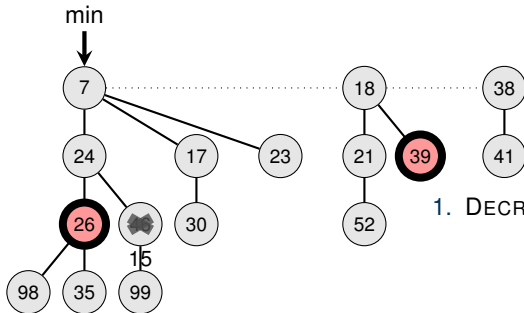
- Decrease the key of x (given by a pointer)
- (Here we consider only cases where heap-order is violated)



Fibonacci Heap: DECREASE-KEY

DECREASE-KEY of node x

- Decrease the key of x (given by a pointer)
 - (Here we consider only cases where heap-order is violated)
- ⇒ Cut tree rooted at x , unmark x , meld into root list



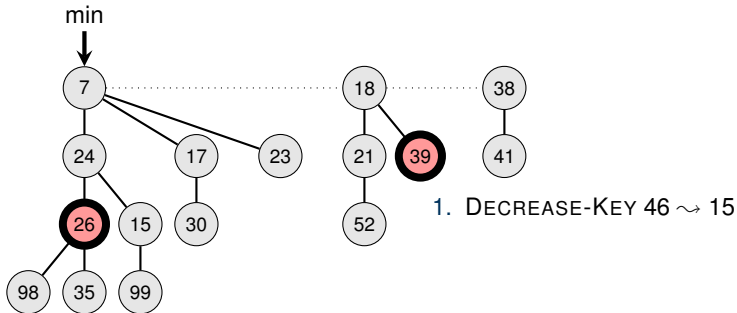
1. DECREASE-KEY 46 \rightsquigarrow 15



Fibonacci Heap: DECREASE-KEY

DECREASE-KEY of node x

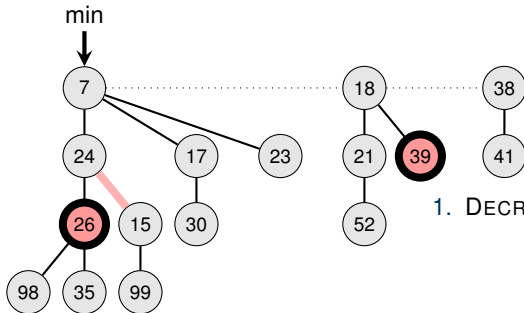
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Fibonacci Heap: DECREASE-KEY

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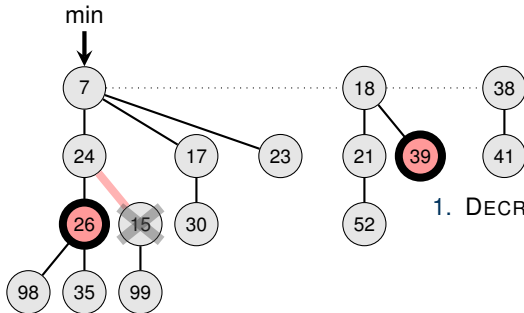
1. DECREASE-KEY 46 \rightsquigarrow 15



Fibonacci Heap: DECREASE-KEY

DECREASE-KEY of node x

- Decrease the key of x (given by a pointer)
 - (Here we consider only cases where heap-order is violated)
- ⇒ Cut tree rooted at x , unmark x , meld into root list



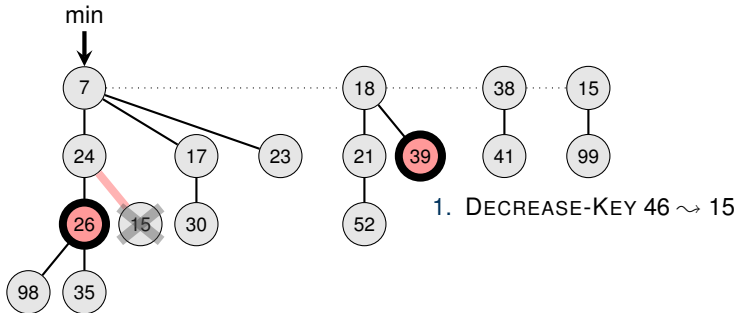
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Fibonacci Heap: DECREASE-KEY

DECREASE-KEY of node x

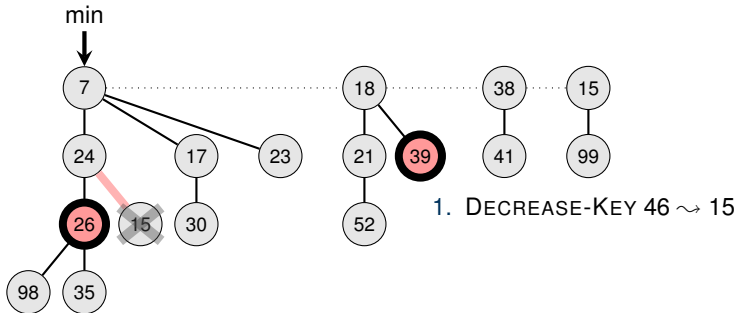
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Fibonacci Heap: DECREASE-KEY

DECREASE-KEY of node x

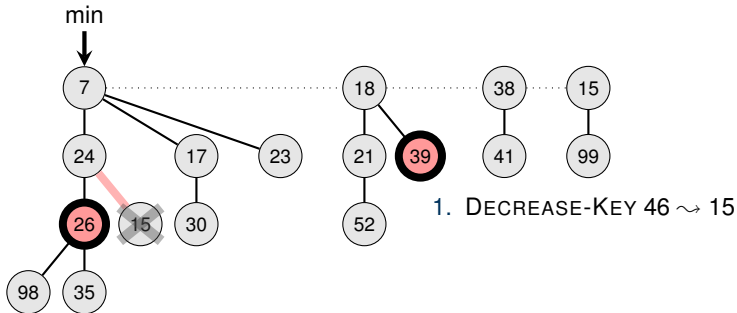
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Fibonacci Heap: DECREASE-KEY

DECREASE-KEY of node x

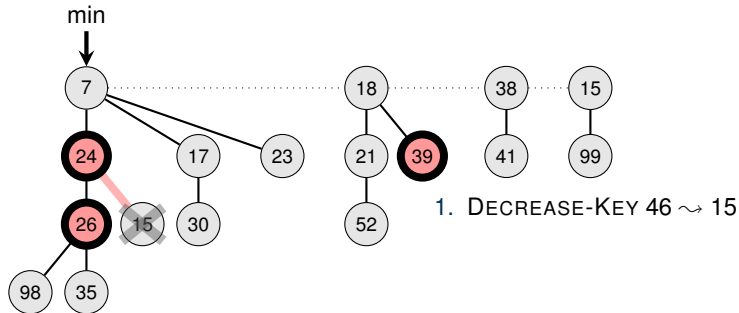
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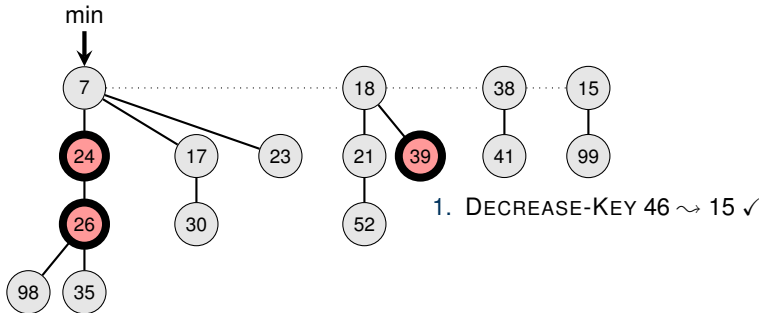
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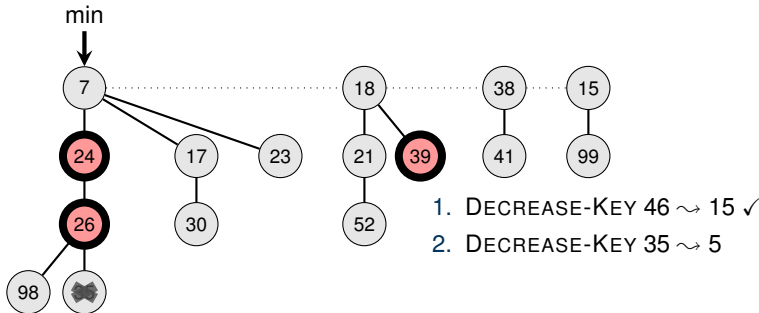
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Fibonacci Heap: DECREASE-KEY

DECREASE-KEY of node x

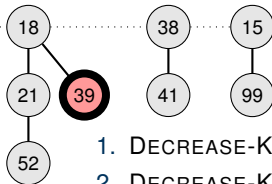
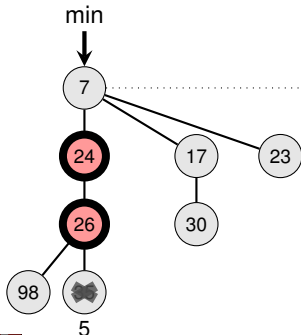
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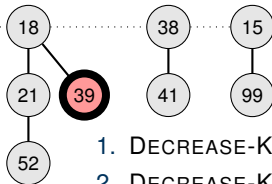
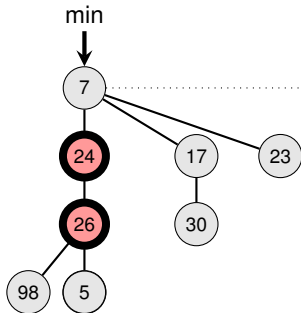
- DECREASE-KEY 46 \rightsquigarrow 15 ✓
- DECREASE-KEY 35 \rightsquigarrow 5



Fibonacci Heap: DECREASE-KEY

DECREASE-KEY of node x

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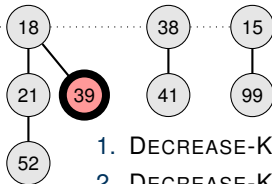
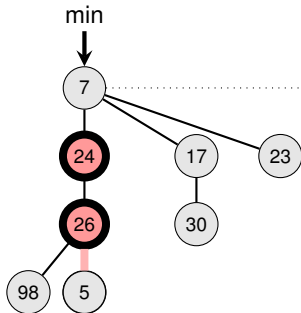
1. DECREASE-KEY 46 \rightsquigarrow 15 ✓
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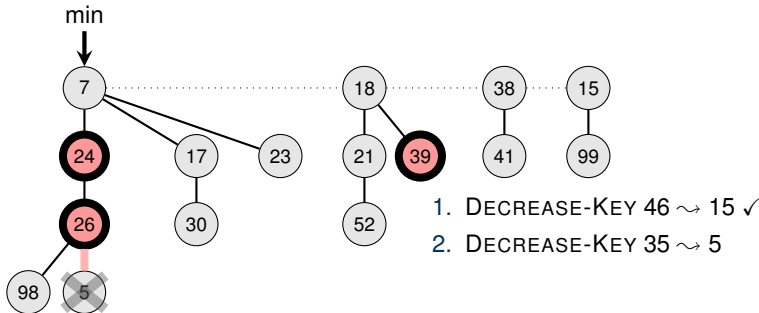
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Fibonacci Heap: DECREASE-KEY

DECREASE-KEY of node x

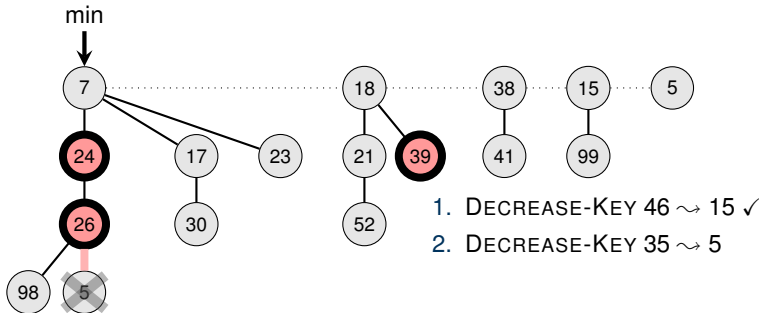
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Fibonacci Heap: DECREASE-KEY

DECREASE-KEY of node x

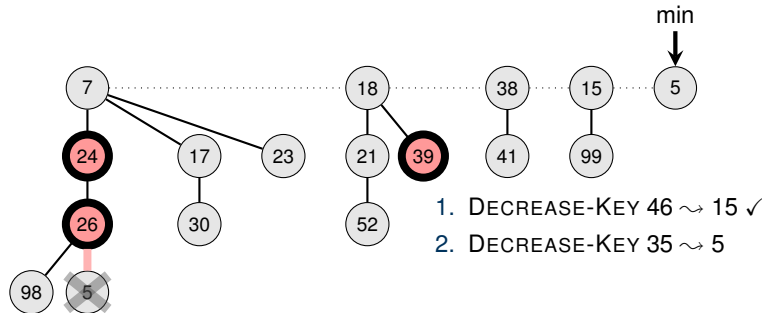
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Fibonacci Heap: DECREASE-KEY

DECREASE-KEY of node x

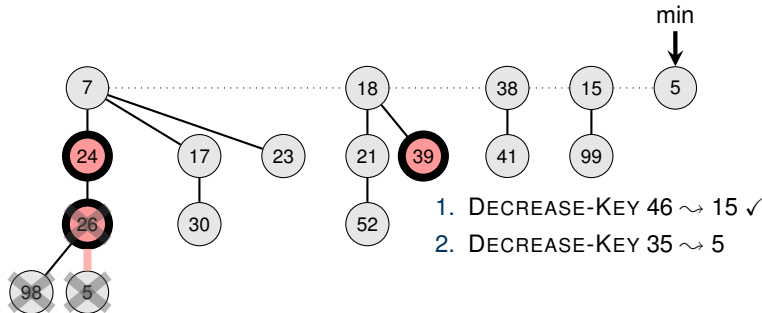
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Fibonacci Heap: DECREASE-KEY

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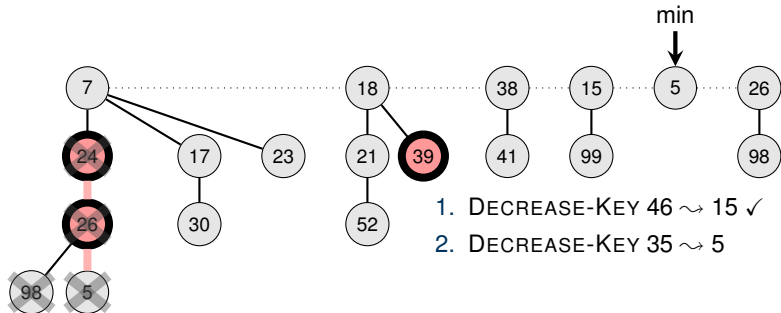
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Fibonacci Heap: DECREASE-KEY

DECREASE-KEY of node x

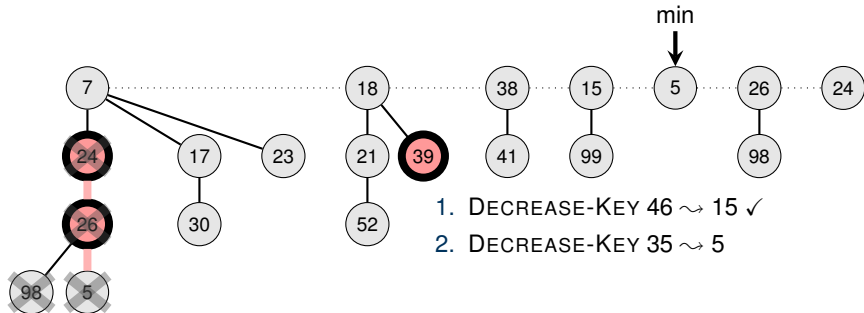
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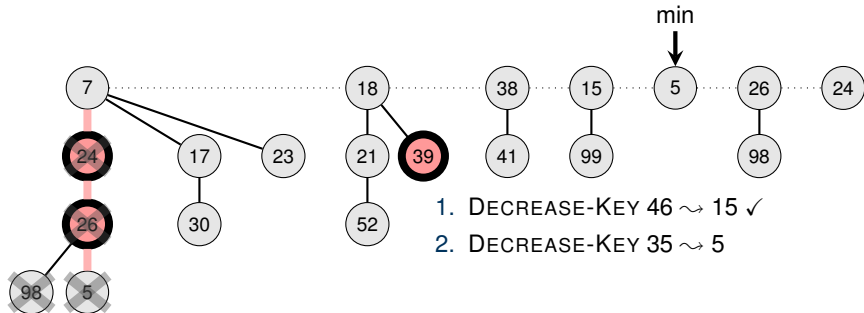
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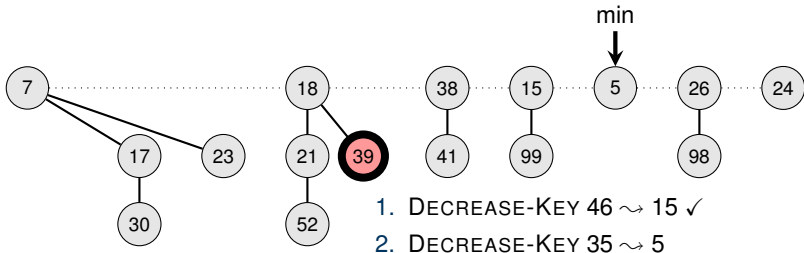
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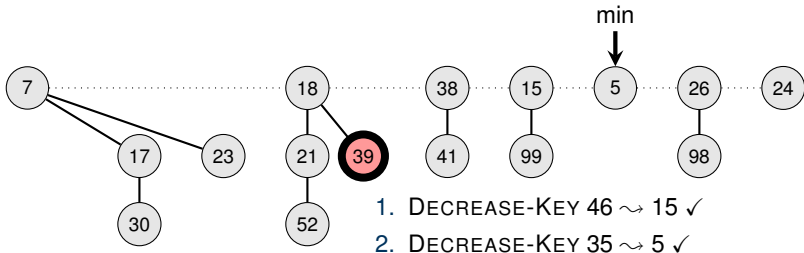
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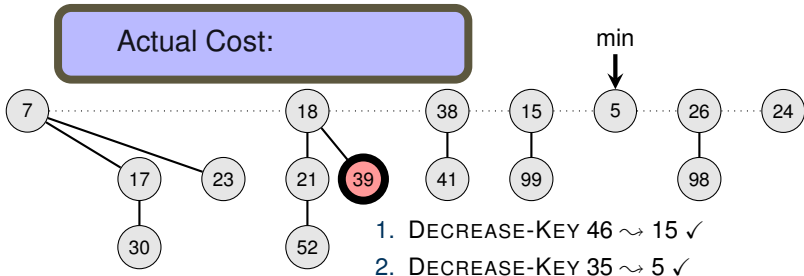
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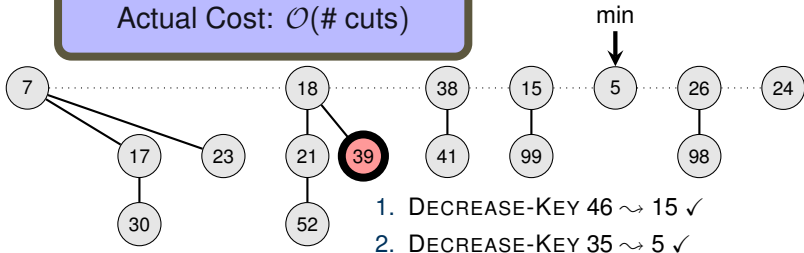


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Actual Cost: $\mathcal{O}(\# \text{ cuts})$



Recap of INSERT, EXTRACT-MIN and DECREASE-KEY

Glimpse at the Analysis

Amortized Analysis

Bounding the Maximum Degree



Amortized Analysis via Potential Method

- INSERT: actual $\mathcal{O}(1)$
- EXTRACT-MIN: actual $\mathcal{O}(\text{trees}(H) + d(n))$
- DECREASE-KEY: actual $\mathcal{O}(\# \text{ cuts}) \leq \mathcal{O}(\text{marks}(H))$



Amortized Analysis via Potential Method

- INSERT: actual $\mathcal{O}(1)$
- EXTRACT-MIN: actual $\mathcal{O}(\text{trees}(H) + d(n))$
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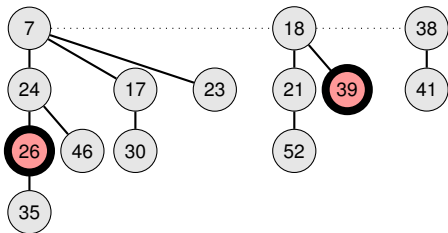
$$\Phi(H) = \text{trees}(H) + 2 \cdot \text{marks}(H)$$



Amortized Analysis via Potential Method

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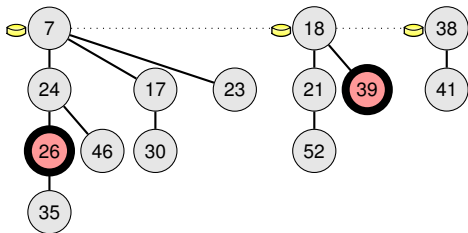
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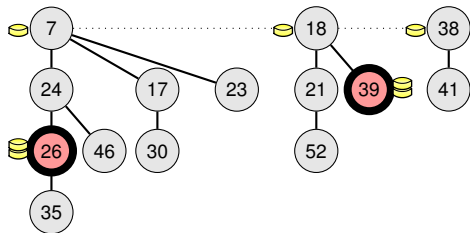
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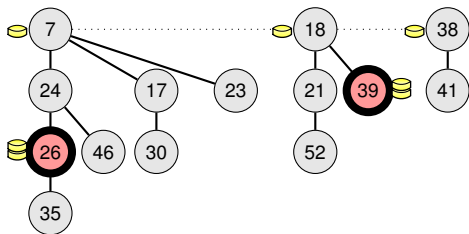
$$\Phi(H) = \text{trees}(H) + 2 \cdot \text{marks}(H)$$



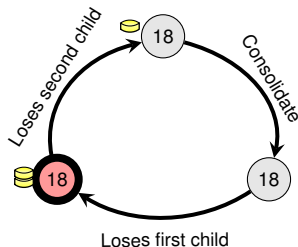
Amortized Analysis via Potential Method

- INSERT: actual $\mathcal{O}(1)$ amortized $\mathcal{O}(1)$
- EXTRACT-MIN: actual $\mathcal{O}(\text{trees}(H) + d(n))$ amortized $\mathcal{O}(d(n))$
- DECREASE-KEY: actual $\mathcal{O}(\# \text{ cuts}) \leq \mathcal{O}(\text{marks}(H))$ amortized $\mathcal{O}(1)$

$$\Phi(H) = \text{trees}(H) + 2 \cdot \text{marks}(H)$$



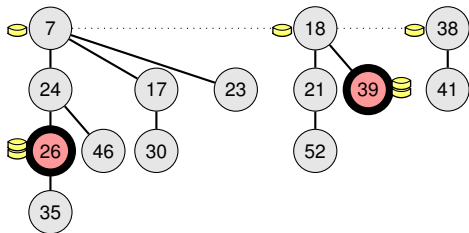
Lifecycle of a node



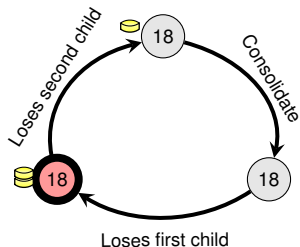
Amortized Analysis via Potential Method

- INSERT: actual $\mathcal{O}(1)$ amortized $\mathcal{O}(1)$ ✓
- EXTRACT-MIN: actual $\mathcal{O}(\text{trees}(H) + d(n))$ amortized $\mathcal{O}(d(n))$?
- DECREASE-KEY: actual $\mathcal{O}(\# \text{ cuts}) \leq \mathcal{O}(\text{marks}(H))$ amortized $\mathcal{O}(1)$?

$$\Phi(H) = \text{trees}(H) + 2 \cdot \text{marks}(H)$$



Lifecycle of a node



Recap of INSERT, EXTRACT-MIN and DECREASE-KEY

Glimpse at the Analysis

Amortized Analysis

Bounding the Maximum Degree



Amortized Analysis of DECREASE-KEY

Actual Cost

- DECREASE-KEY: $\mathcal{O}(x + 1)$, where x is the number of cuts.



Amortized Analysis of DECREASE-KEY

Actual Cost

- DECREASE-KEY: $\mathcal{O}(x + 1)$, where x is the number of cuts.

$$\Phi(H) = \text{trees}(H) + 2 \cdot \text{marks}(H)$$



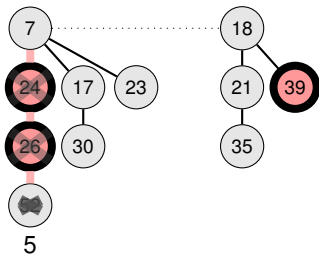
Amortized Analysis of DECREASE-KEY

Actual Cost

- DECREASE-KEY: $\mathcal{O}(x + 1)$, where x is the number of cuts.

$$\Phi(H) = \text{trees}(H) + 2 \cdot \text{marks}(H)$$

Change in Potential



Amortized Analysis of DECREASE-KEY

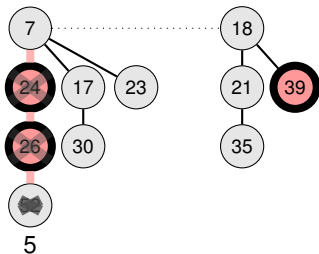
Actual Cost

- DECREASE-KEY: $\mathcal{O}(x + 1)$, where x is the number of cuts.

$$\Phi(H) = \text{trees}(H) + 2 \cdot \text{marks}(H)$$

Change in Potential

- $\text{trees}(H') =$



Amortized Analysis of DECREASE-KEY

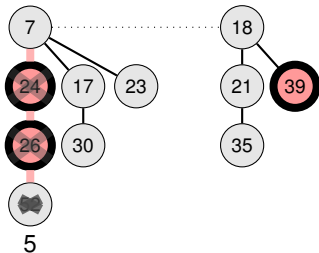
Actual Cost

- DECREASE-KEY: $\mathcal{O}(x + 1)$, where x is the number of cuts.

$$\Phi(H) = \text{trees}(H) + 2 \cdot \text{marks}(H)$$

Change in Potential

- $\text{trees}(H') = \text{trees}(H) + x$



Amortized Analysis of DECREASE-KEY

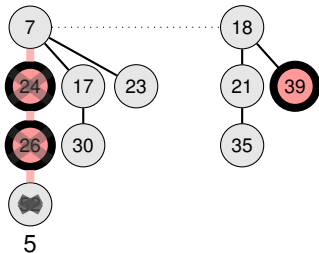
Actual Cost

- DECREASE-KEY: $\mathcal{O}(x + 1)$, where x is the number of cuts.

$$\Phi(H) = \text{trees}(H) + 2 \cdot \text{marks}(H)$$

Change in Potential

- $\text{trees}(H') = \text{trees}(H) + x$
- $\text{marks}(H') \leq$



Amortized Analysis of DECREASE-KEY

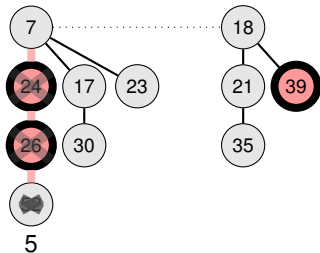
Actual Cost

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$$\Phi(H) = \text{trees}(H) + 2 \cdot \text{marks}(H)$$

Change in Potential

- $\text{trees}(H') = \text{trees}(H) + x$
- $\text{marks}(H') \leq \text{marks}(H) - x + 2$



Amortized Analysis of DECREASE-KEY

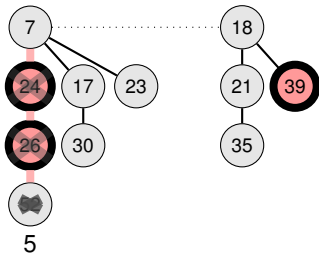
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$$\Phi(H) = \text{trees}(H) + 2 \cdot \text{marks}(H)$$

Change in Potential

- $\text{trees}(H') = \text{trees}(H) + x$
 - $\text{marks}(H') \leq \text{marks}(H) - x + 2$
- $$\Rightarrow \Delta\Phi \leq x + 2 \cdot (-x + 2) = 4 - x.$$



Amortized Analysis of DECREASE-KEY

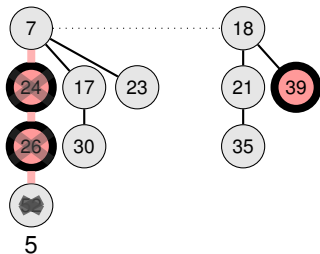
Actual Cost

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$$\Phi(H) = \text{trees}(H) + 2 \cdot \text{marks}(H)$$

Change in Potential

- $\text{trees}(H') = \text{trees}(H) + x$
 - $\text{marks}(H') \leq \text{marks}(H) - x + 2$
- $\Rightarrow \Delta\Phi \leq x + 2 \cdot (-x + 2) = 4 - x.$



Amortized Cost

$$\tilde{c}_i = c_i + \Delta\Phi$$



Amortized Analysis of DECREASE-KEY

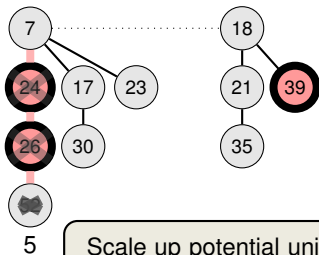
Actual Cost

- **DECREASE-KEY**: $\mathcal{O}(x + 1)$, where x is the number of cuts.

$$\Phi(H) = \text{trees}(H) + 2 \cdot \text{marks}(H)$$

Change in Potential

- $\text{trees}(H') = \text{trees}(H) + x$
 - $\text{marks}(H') \leq \text{marks}(H) - x + 2$
- $$\Rightarrow \Delta\Phi \leq x + 2 \cdot (-x + 2) = 4 - x.$$



Amortized Cost

$$\tilde{c}_i = c_i + \Delta\Phi \leq \mathcal{O}(x + 1) + 4 - x$$



Amortized Analysis of DECREASE-KEY

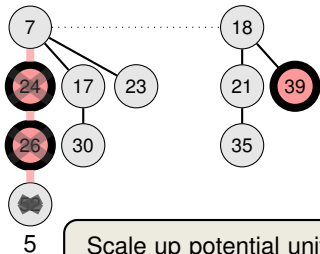
Actual Cost

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$$\Phi(H) = \text{trees}(H) + 2 \cdot \text{marks}(H)$$

Change in Potential

- $\text{trees}(H') = \text{trees}(H) + x$
 - $\text{marks}(H') \leq \text{marks}(H) - x + 2$
- $\Rightarrow \Delta\Phi \leq x + 2 \cdot (-x + 2) = 4 - x.$



Amortized Cost

$$\tilde{c}_i = c_i + \Delta\Phi \leq \mathcal{O}(x + 1) + 4 - x = \mathcal{O}(1)$$



Amortized Analysis of DECREASE-KEY

Actual Cost

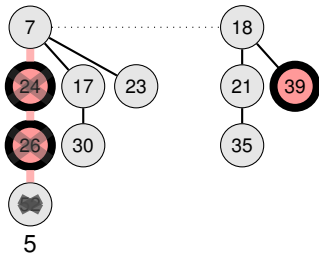
- **DECREASE-KEY**: $\mathcal{O}(x + 1)$, where x is the number of cuts.

$$\Phi(H) = \text{trees}(H) + 2 \cdot \text{marks}(H)$$

First Coin \sim pays cut
Second Coin \sim increase of $\text{trees}(H)$

Change in Potential

- $\text{trees}(H') = \text{trees}(H) + x$
 - $\text{marks}(H') \leq \text{marks}(H) - x + 2$
- $$\Rightarrow \Delta\Phi \leq x + 2 \cdot (-x + 2) = 4 - x.$$



Amortized Cost

$$\tilde{c}_i = c_i + \Delta\Phi \leq \mathcal{O}(x + 1) + 4 - x = \mathcal{O}(1)$$



Amortized Analysis of EXTRACT-MIN

Actual Cost

- EXTRACT-MIN: $\mathcal{O}(\text{trees}(H) + d(n))$



Amortized Analysis of EXTRACT-MIN

Actual Cost

- EXTRACT-MIN: $\mathcal{O}(\text{trees}(H) + d(n))$

$$\Phi(H) = \text{trees}(H) + 2 \cdot \text{marks}(H)$$



Amortized Analysis of EXTRACT-MIN

Actual Cost

- EXTRACT-MIN: $\mathcal{O}(\text{trees}(H) + d(n))$

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Change in Potential



Amortized Analysis of EXTRACT-MIN

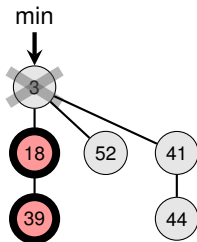
Actual Cost

- EXTRACT-MIN: $\mathcal{O}(\text{trees}(H) + d(n))$

$$\Phi(H) = \text{trees}(H) + 2 \cdot \text{marks}(H)$$

Change in Potential

- $\text{marks}(H') ? \text{marks}(H)$



Amortized Analysis of EXTRACT-MIN

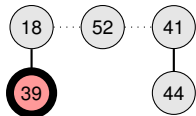
Actual Cost

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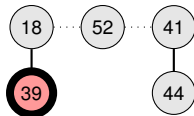
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$$\Phi(H) = \text{trees}(H) + 2 \cdot \text{marks}(H)$$

Change in Potential

- $\text{marks}(H') \leq \text{marks}(H)$



Amortized Analysis of EXTRACT-MIN

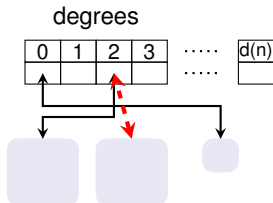
Actual Cost

- EXTRACT-MIN: $\mathcal{O}(\text{trees}(H) + d(n))$

$$\Phi(H) = \text{trees}(H) + 2 \cdot \text{marks}(H)$$

Change in Potential

- $\text{marks}(H') \leq \text{marks}(H)$
- $\text{trees}(H') \leq$



Amortized Analysis of EXTRACT-MIN

Actual Cost

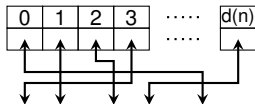
- EXTRACT-MIN: $\mathcal{O}(\text{trees}(H) + d(n))$

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Change in Potential

- $\text{marks}(H') \leq \text{marks}(H)$
- $\text{trees}(H') \leq$

degrees



Amortized Analysis of EXTRACT-MIN

Actual Cost

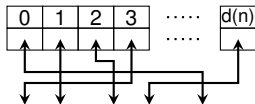
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Change in Potential

- $\text{marks}(H') \leq \text{marks}(H)$
- $\text{trees}(H') \leq d(n) + 1$

degrees



Amortized Analysis of EXTRACT-MIN

Actual Cost

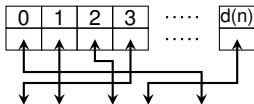
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Change in Potential

- $\text{marks}(H') \leq \text{marks}(H)$
 - $\text{trees}(H') \leq d(n) + 1$
- $\Rightarrow \Delta\Phi \leq d(n) + 1 - \text{trees}(H)$

degrees



Amortized Analysis of EXTRACT-MIN

Actual Cost

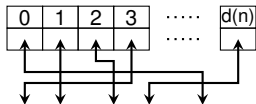
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degrees



Amortized Cost

$$\tilde{c}_i = c_i + \Delta\Phi$$



Amortized Analysis of EXTRACT-MIN

Actual Cost

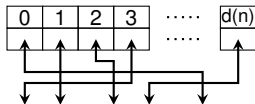
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degrees



Amortized Cost

$$\tilde{c}_i = c_i + \Delta\Phi \leq \mathcal{O}(\text{trees}(H) + d(n)) + d(n) + 1 - \text{trees}(H)$$



Amortized Analysis of EXTRACT-MIN

Actual Cost

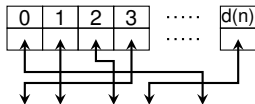
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degrees



Amortized Cost

$$\tilde{c}_i = c_i + \Delta\Phi \leq \mathcal{O}(\text{trees}(H) + d(n)) + d(n) + 1 - \text{trees}(H) = \mathcal{O}(d(n))$$



Amortized Analysis of EXTRACT-MIN

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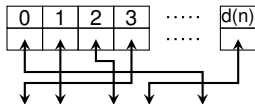
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degrees



Amortized Cost

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How to bound $d(n)$?



Recap of INSERT, EXTRACT-MIN and DECREASE-KEY

Glimpse at the Analysis

Amortized Analysis

Bounding the Maximum Degree



Bounding the Maximum Degree

Binomial Heap

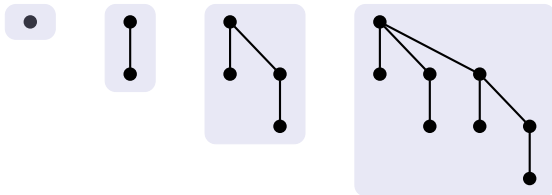
Every tree is a binomial tree $\Rightarrow d(n) \leq \log_2 n$.



Bounding the Maximum Degree

Binomial Heap

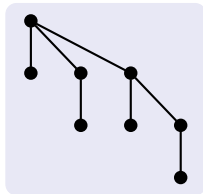
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Bounding the Maximum Degree

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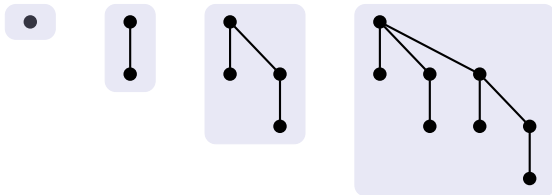
$$d = 3, n = 2^3$$



Bounding the Maximum Degree

Binomial Heap

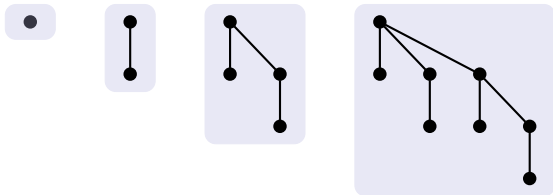
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Bounding the Maximum Degree

Binomial Heap

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Fibonacci Heap

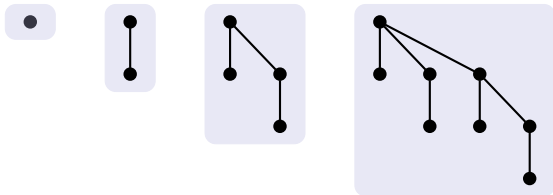
Not all trees are binomial trees, but still $d(n) \leq \log_{\varphi} n$, where $\varphi \approx 1.62$.



Bounding the Maximum Degree

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Fibonacci Heap

Not all trees are binomial trees, but still $d(n) \leq \log_{\varphi} n$, where $\varphi \approx 1.62$.

► Skip Analysis



Lower Bounding Degrees of Children

$$d(n) \leq \log_{\varphi} n$$



Lower Bounding Degrees of Children

We will prove a stronger statement:
Any tree with degree k contains at least φ^k nodes.

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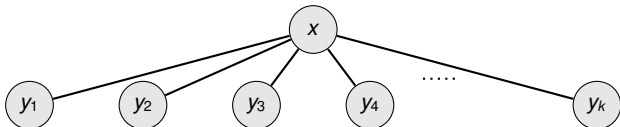


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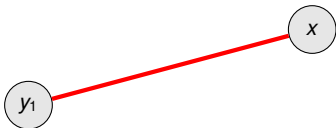


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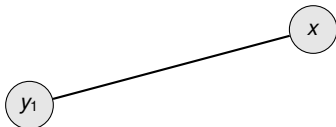


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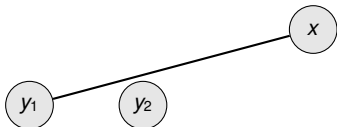


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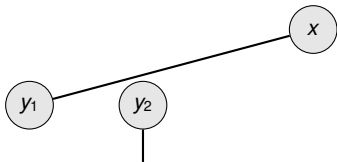


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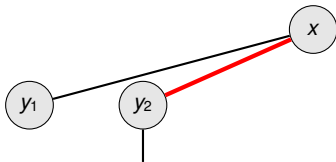


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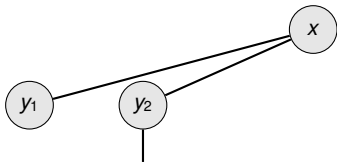


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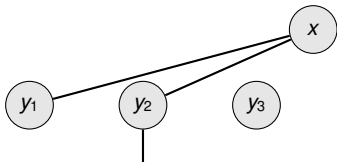


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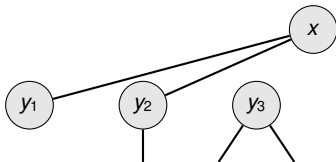


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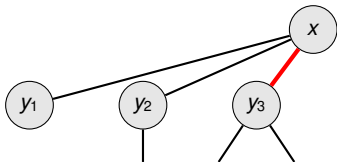


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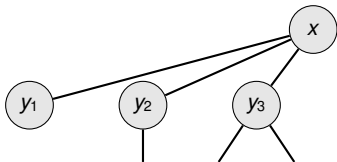


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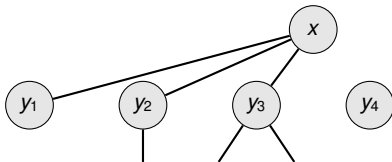


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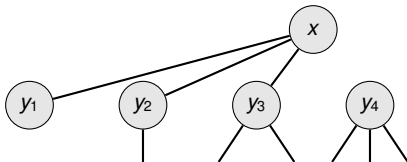


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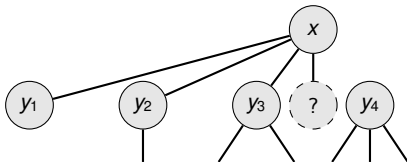


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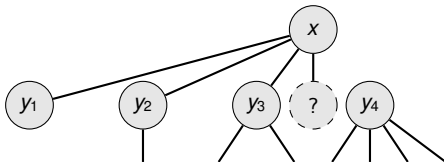


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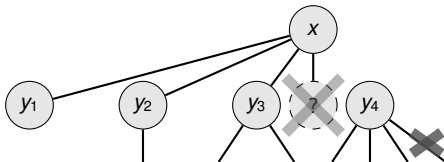


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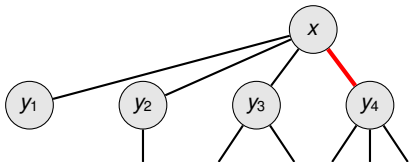


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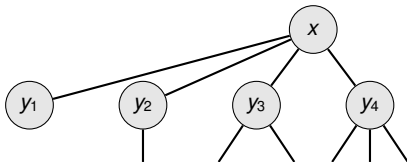


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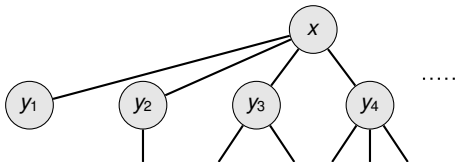


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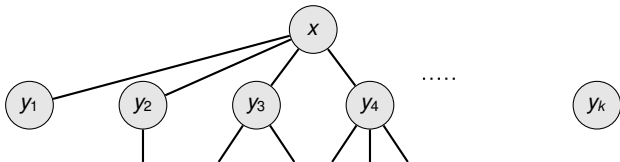


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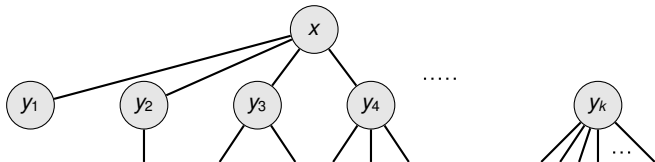


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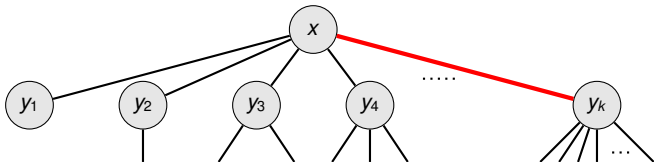


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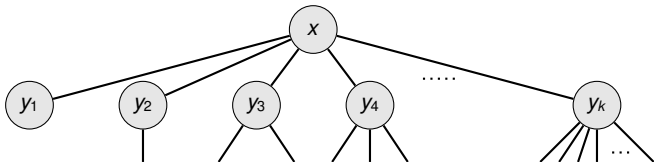


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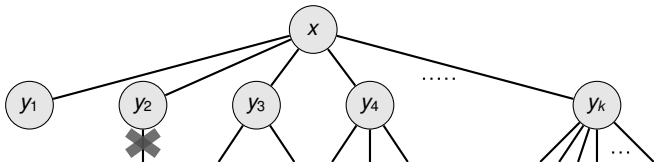


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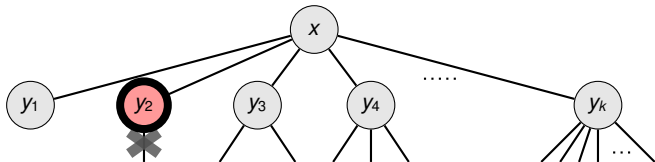


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$$d(n) \leq \log_{\varphi} n$$

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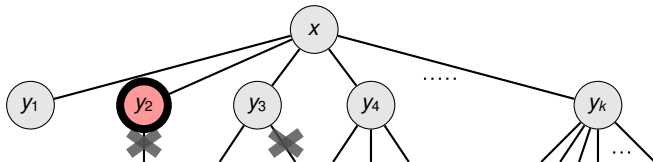


Lower Bounding Degrees of Children

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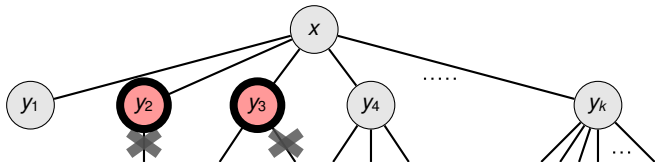


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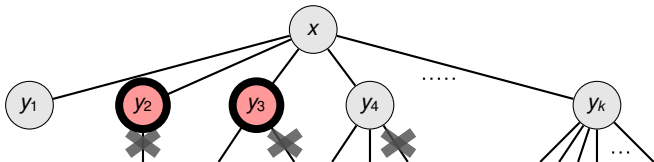


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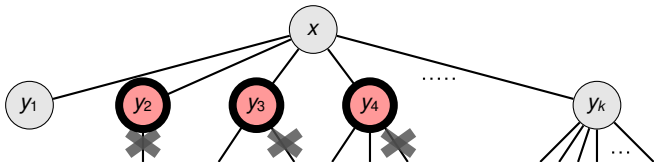


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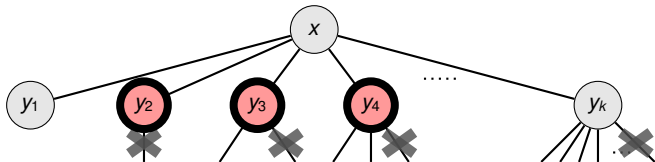


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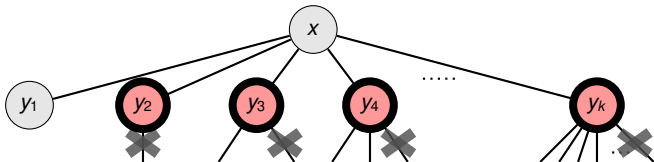


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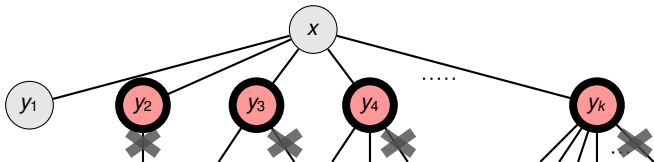


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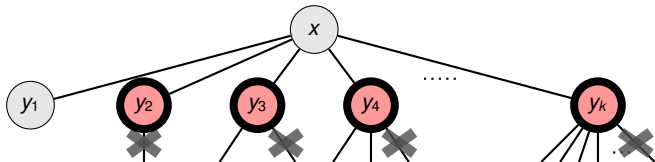
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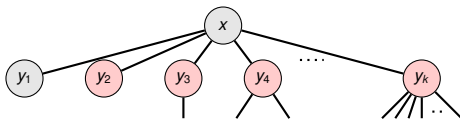
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$$\Rightarrow \forall 1 \leq i \leq k: d_i \geq i - 2$$



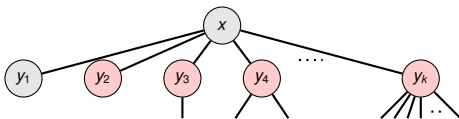
From Degrees to Minimum Subtree Sizes



$$\forall 1 \leq i \leq k: d_i \geq i - 2$$



From Degrees to Minimum Subtree Sizes



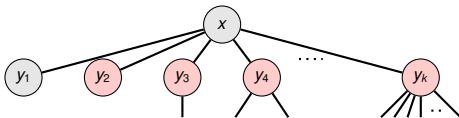
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Definition

Let $N(k)$ be the **minimum possible number of nodes** of a subtree rooted at a node of degree k .



From Degrees to Minimum Subtree Sizes



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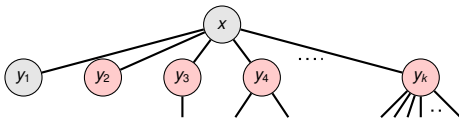
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$N(0)$



From Degrees to Minimum Subtree Sizes



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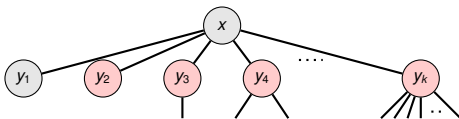
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From Degrees to Minimum Subtree Sizes



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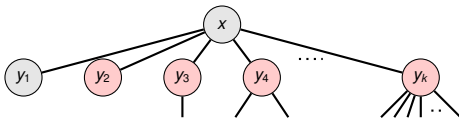
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From Degrees to Minimum Subtree Sizes



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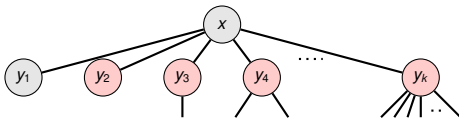
• 0

$N(1)$

• 1



From Degrees to Minimum Subtree Sizes



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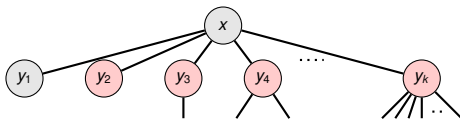
• 0

$N(1)$

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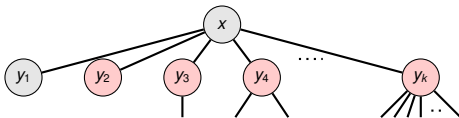
$N(1)$

• 1
|
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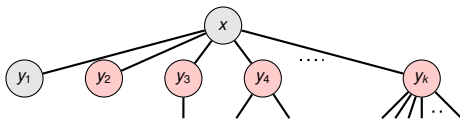
• 1
|
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• 2



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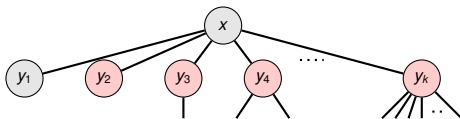
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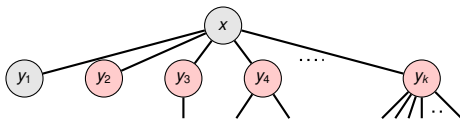
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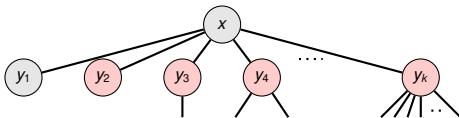
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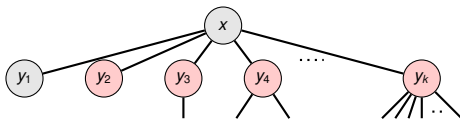
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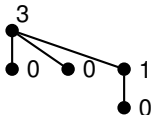
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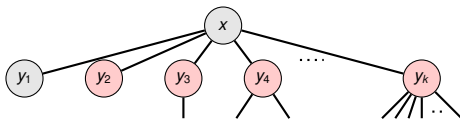
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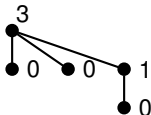
$N(1)$



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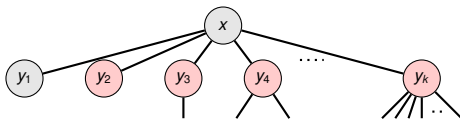
$N(3)$



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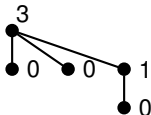
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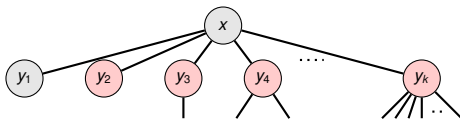
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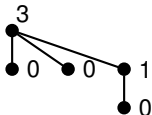
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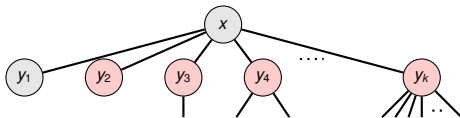
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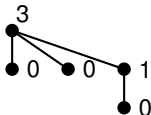
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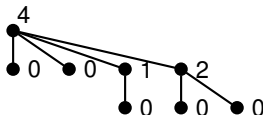
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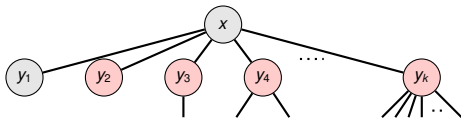
$N(3)$



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From Degrees to Minimum Subtree Sizes



$$\forall 1 \leq i \leq k: d_i \geq i - 2$$

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$N(0) = 1$



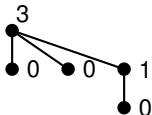
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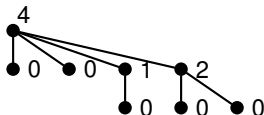
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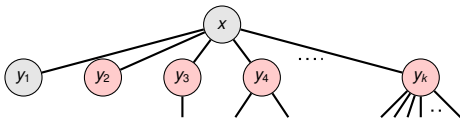
$N(3)$



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From Degrees to Minimum Subtree Sizes



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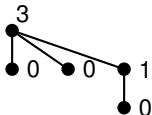
$$N(1) = 2$$



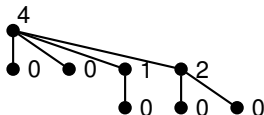
$$N(2)$$



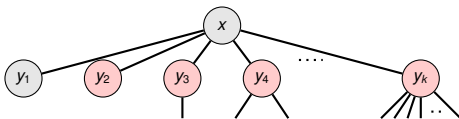
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From Degrees to Minimum Subtree Sizes



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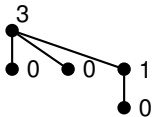
$$N(1) = 2$$



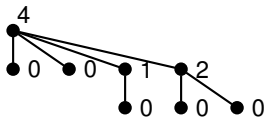
$$N(2) = 3$$



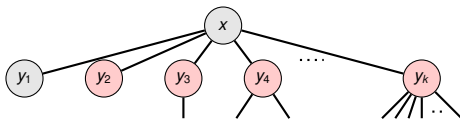
$$N(3)$$



$$N(4)$$



From Degrees to Minimum Subtree Sizes



$$\forall 1 \leq i \leq k: d_i \geq i - 2$$

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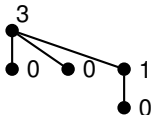
$$N(1) = 2$$



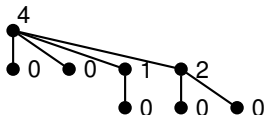
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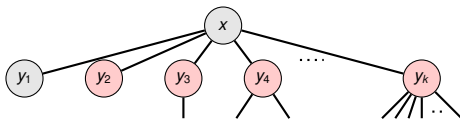
$$N(3) = 5$$



$$N(4)$$



From Degrees to Minimum Subtree Sizes



$$\forall 1 \leq i \leq k: d_i \geq i - 2$$

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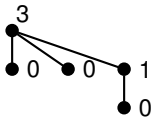
$$N(1) = 2$$



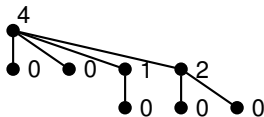
$$N(2) = 3$$



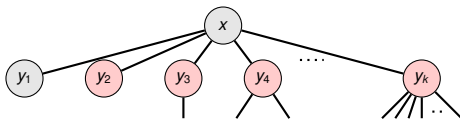
$$N(3) = 5$$



$$N(4) = 8$$



From Degrees to Minimum Subtree Sizes



$$\forall 1 \leq i \leq k: d_i \geq i - 2$$

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$$N(1) = 2$$



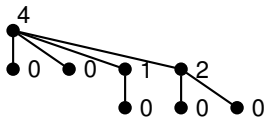
$$N(2) = 3$$



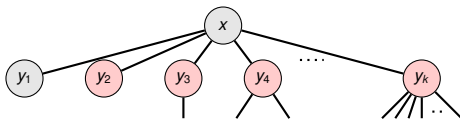
$$N(3) = 5$$



$$N(4) = 8$$



From Degrees to Minimum Subtree Sizes



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$$N(1) = 2$$



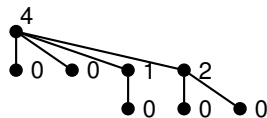
$$N(2) = 3$$



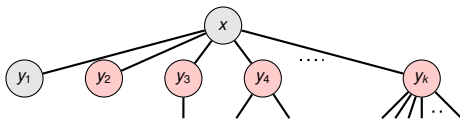
$$N(3) = 5$$



$$N(4) = 8$$



From Degrees to Minimum Subtree Sizes



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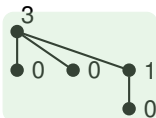
$$N(1) = 2$$



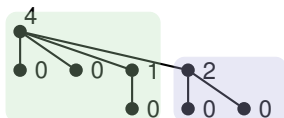
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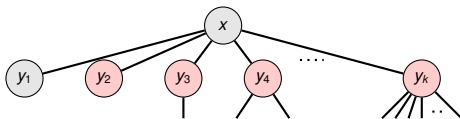
$$N(3) = 5$$



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From Degrees to Minimum Subtree Sizes



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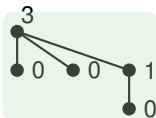
$$N(1) = 2$$



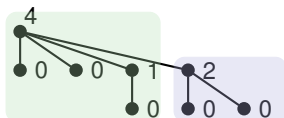
$$N(2) = 3$$



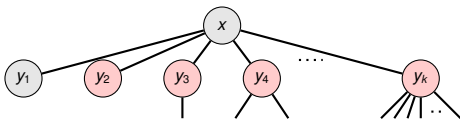
$$N(3) = 5$$



$$N(4) = 8 = 5 + 3$$



From Degrees to Minimum Subtree Sizes



$$\forall 1 \leq i \leq k: d_i \geq i - 2$$

Definition

Let $N(k)$ be the minimum possible number of nodes of a subtree rooted at a node of degree k .

$$N(k) = F(k + 2)?$$

$$N(0) = 1$$



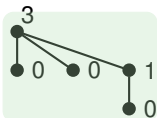
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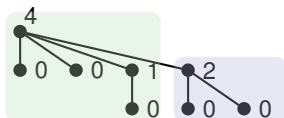
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From Minimum Subtree Sizes to Fibonacci Numbers

$$\forall 1 \leq i \leq k: d_i \geq i - 2$$

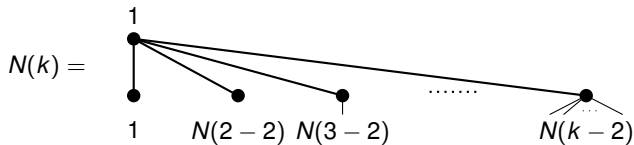
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$$\forall 1 \leq i \leq k: d_i \geq i - 2$$

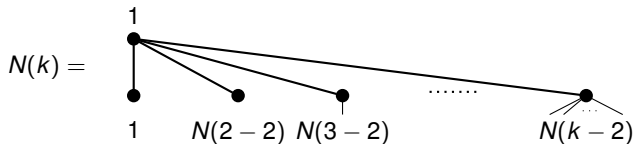
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From Minimum Subtree Sizes to Fibonacci Numbers

$$\forall 1 \leq i \leq k: d_i \geq i - 2$$

$$N(k) = F(k + 2)?$$



$$N(k) = 1 + 1 + N(2-2) + N(3-2) + \dots + N(k-2)$$

$$= 1 + 1 + \sum_{\ell=0}^{k-2} N(\ell)$$

$$= 1 + 1 + \sum_{\ell=0}^{k-3} N(\ell) + N(k-2)$$

$$= N(k-1) + N(k-2)$$

$$= F(k+1) + F(k) = F(k+2) \quad \square$$



Exponential Growth of Fibonacci Numbers

Lemma 19.3

For all integers $k \geq 0$, the $(k+2)$ nd Fib. number satisfies $F(k+2) \geq \varphi^k$, where $\varphi = (1 + \sqrt{5})/2 = 1.61803\dots$



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Fibonacci Numbers grow at least exponentially fast in k .



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- Base $k = 0$: $F(2) = 1$ and $\varphi^0 = 1 \checkmark$



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Proof by induction on k :

- Base $k = 0$: $F(2) = 1$ and $\varphi^0 = 1 \checkmark$
- Base $k = 1$: $F(3) = 2$ and $\varphi^1 \approx 1.619 < 2$



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$$\begin{aligned} F(k+2) &= F(k+1) + F(k) \\ &\geq \varphi^{k-1} + \varphi^{k-2} \end{aligned} \quad \text{(by the inductive hypothesis)}$$



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$$\begin{aligned} F(k+2) &= F(k+1) + F(k) \\ &\geq \varphi^{k-1} + \varphi^{k-2} && \text{(by the inductive hypothesis)} \\ &= \varphi^{k-2} \cdot (\varphi + 1) \\ &= \varphi^{k-2} \cdot \varphi^2 && (\varphi^2 = \varphi + 1) \\ &= \varphi^k \quad \square \end{aligned}$$



Amortized Analysis

- INSERT: amortized cost $\mathcal{O}(1)$
- EXTRACT-MIN: amortized cost $\mathcal{O}(d(n))$
- DECREASE-KEY: amortized cost $\mathcal{O}(1)$



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$N(k)$



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- INSERT: amortized cost $\mathcal{O}(1)$
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$$N(k) = F(k + 2)$$



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$$N(k) = F(k + 2) \geq \varphi^k$$



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$$n \geq N(k) = F(k + 2) \geq \varphi^k$$



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$$\Rightarrow \quad n \geq N(k) = F(k+2) \geq \varphi^k$$
$$\log_{\varphi} n \geq k$$



Amortized Analysis

- INSERT: amortized cost $\mathcal{O}(1)$
- EXTRACT-MIN: amortized cost ~~$\mathcal{O}(d(n))$~~ $\mathcal{O}(\log n)$
- DECREASE-KEY: amortized cost $\mathcal{O}(1)$

$$\begin{aligned} n \geq N(k) = F(k+2) &\geq \varphi^k \\ \Rightarrow \log_{\varphi} n &\geq k \end{aligned}$$



What if we don't have marked nodes?

- INSERT: actual $\mathcal{O}(1)$
- EXTRACT-MIN: actual $\mathcal{O}(\text{trees}(H) + d(n))$
- DECREASE-KEY: actual $\mathcal{O}(1)$



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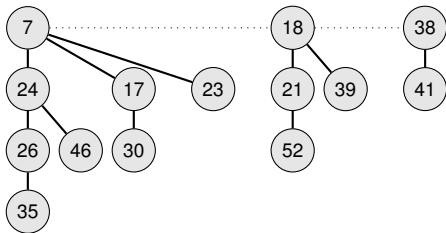
$$\Phi(H) = \text{trees}(H)$$



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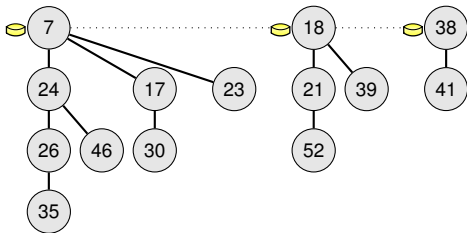
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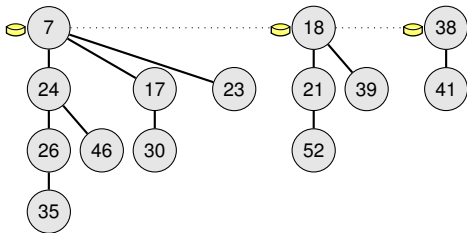
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What if we don't have marked nodes?

- INSERT: actual $\mathcal{O}(1)$ amortized $\mathcal{O}(1)$
- EXTRACT-MIN: actual $\mathcal{O}(\text{trees}(H) + d(n))$ amortized $\mathcal{O}(d(n))$
- DECREASE-KEY: actual $\mathcal{O}(1)$ amortized $\mathcal{O}(1)$

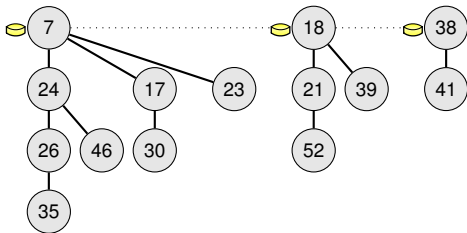
$$\Phi(H) = \text{trees}(H)$$



What if we don't have marked nodes?

- INSERT: actual $\mathcal{O}(1)$ amortized $\mathcal{O}(1)$
- EXTRACT-MIN: actual $\mathcal{O}(\text{trees}(H) + d(n))$ amortized $\mathcal{O}(d(n)) \neq \mathcal{O}(\log n)$
- DECREASE-KEY: actual $\mathcal{O}(1)$ amortized $\mathcal{O}(1)$

$$\Phi(H) = \text{trees}(H)$$



Summary

Operation	Linked list	Binary heap	Binomial heap	Fibon. heap
MAKE-HEAP	$\mathcal{O}(1)$	$\mathcal{O}(1)$	$\mathcal{O}(1)$	$\mathcal{O}(1)$
<u>INSERT</u>	$\mathcal{O}(1)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$
MINIMUM	$\mathcal{O}(n)$	$\mathcal{O}(1)$	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$
<u>EXTRACT-MIN</u>	$\mathcal{O}(n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$
UNION	$\mathcal{O}(n)$	$\mathcal{O}(n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$
<u>DECREASE-KEY</u>	$\mathcal{O}(1)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$
DELETE	$\mathcal{O}(1)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$



Summary

Can we perform EXTRACT-MIN in $o(\log n)$?

Operation	Linked list	Binary heap	Binomial heap	Fibon. heap
MAKE-HEAP	$\mathcal{O}(1)$	$\mathcal{O}(1)$	$\mathcal{O}(1)$	$\mathcal{O}(1)$
<u>INSERT</u>	$\mathcal{O}(1)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$
MINIMUM	$\mathcal{O}(n)$	$\mathcal{O}(1)$	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$
<u>EXTRACT-MIN</u>	$\mathcal{O}(n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$
UNION	$\mathcal{O}(n)$	$\mathcal{O}(n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$
<u>DECREASE-KEY</u>	$\mathcal{O}(1)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$
DELETE	$\mathcal{O}(1)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$



Summary

If this was possible, then there would be a sorting algorithm with runtime $o(n \log n)$!

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Operation	Linked list	Binary heap	Binomial heap	Fibon. heap
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MINIMUM	$\mathcal{O}(n)$	$\mathcal{O}(1)$	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$
<u>EXTRACT-MIN</u>	$\mathcal{O}(n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$
UNION	$\mathcal{O}(n)$	$\mathcal{O}(n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$
<u>DECREASE-KEY</u>	$\mathcal{O}(1)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$
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MAKE-HEAP	$\mathcal{O}(1)$	$\mathcal{O}(1)$	$\mathcal{O}(1)$	$\mathcal{O}(1)$
<u>INSERT</u>	$\mathcal{O}(1)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$
MINIMUM	$\mathcal{O}(n)$	$\mathcal{O}(1)$	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$
<u>EXTRACT-MIN</u>	$\mathcal{O}(n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$
UNION	$\mathcal{O}(n)$	$\mathcal{O}(n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$
<u>DECREASE-KEY</u>	$\mathcal{O}(1)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$
DELETE	$\mathcal{O}(1)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$



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Operation	Linked list	Binary heap	Binomial heap	Fibon. heap
MAKE-HEAP	$\mathcal{O}(1)$	$\mathcal{O}(1)$	$\mathcal{O}(1)$	$\mathcal{O}(1)$
<u>INSERT</u>	$\mathcal{O}(1)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$
MINIMUM	$\mathcal{O}(n)$	$\mathcal{O}(1)$	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$
<u>EXTRACT-MIN</u>	$\mathcal{O}(n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$
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<u>DECREASE-KEY</u>	$\mathcal{O}(1)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$
DELETE	$\mathcal{O}(1)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$

DELETE = DECREASE-KEY + EXTRACT-MIN



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MAKE-HEAP	$O(1)$	$O(1)$	$O(1)$	$O(1)$
<u>INSERT</u>	$O(1)$	$O(\log n)$	$O(\log n)$	$O(1)$
MINIMUM	$O(n)$	$O(1)$	$O(\log n)$	$O(1)$
<u>EXTRACT-MIN</u>	$O(n)$	$O(\log n)$	$O(\log n)$	$O(\log n)$
UNION	$O(n)$	$O(n)$	$O(\log n)$	$O(1)$
<u>DECREASE-KEY</u>	$O(1)$	$O(\log n)$	$O(\log n)$	$O(1)$
DELETE	$O(1)$	$O(\log n)$	$O(\log n)$	$O(\log n)$

DELETE = DECREASE-KEY + EXTRACT-MIN

EXTRACT-MIN = MIN + DELETE



Summary

Operation	Linked list	Binary heap	Binomial heap	Fibon. heap
MAKE-HEAP	$\mathcal{O}(1)$	$\mathcal{O}(1)$	$\mathcal{O}(1)$	$\mathcal{O}(1)$
<u>INSERT</u>	$\mathcal{O}(1)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$
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DELETE	$\mathcal{O}(1)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$

Crucial for many applications including shortest paths and minimum spanning trees!



Recent Studies

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- pointer-based heap implementation similar to Fibonacci Heaps
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- Queries to **marked bits** are intercepted and responded with a **random bit**
 - several lower bounds on the amortized cost in terms of the size of the heap **and** the number of operations
- ⇒ less efficient than the original Fibonacci heap
- ⇒ **marked bit** is not redundant!



Outlook: A More Efficient Priority Queue for fixed Universe

Operation	Fibonacci heap amortized cost	Van Emde Boas Tree actual cost
<u>INSERT</u>	$\mathcal{O}(1)$	$\mathcal{O}(\log \log u)$
MINIMUM	$\mathcal{O}(1)$	$\mathcal{O}(1)$
<u>EXTRACT-MIN</u>	$\mathcal{O}(\log n)$	$\mathcal{O}(\log \log u)$
MERGE/UNION	$\mathcal{O}(1)$	-
<u>DECREASE-KEY</u>	$\mathcal{O}(1)$	$\mathcal{O}(\log \log u)$
DELETE	$\mathcal{O}(\log n)$	$\mathcal{O}(\log \log u)$
SUCC	-	$\mathcal{O}(\log \log u)$
PRED	-	$\mathcal{O}(\log \log u)$
MAXIMUM	-	$\mathcal{O}(1)$

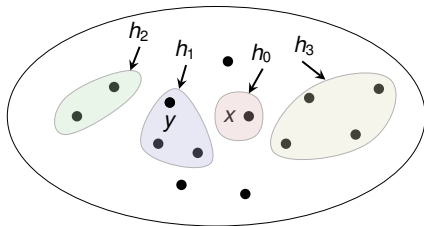


Outlook: A More Efficient Priority Queue for fixed Universe

Operation	Fibonacci heap amortized cost	Van Emde Boas Tree actual cost
<u>INSERT</u>	$\mathcal{O}(1)$	$\mathcal{O}(\log \log u)$
MINIMUM	$\mathcal{O}(1)$	$\mathcal{O}(1)$
<u>EXTRACT-MIN</u>	$\mathcal{O}(\log n)$	$\mathcal{O}(\log \log u)$
MERGE/UNION	$\mathcal{O}(1)$	-
<u>DECREASE-KEY</u>	$\mathcal{O}(1)$	$\mathcal{O}(\log \log u)$
DELETE	$\mathcal{O}(\log n)$	$\mathcal{O}(\log \log u)$
SUCC	-	$\mathcal{O}(\log \log u)$
PRED	-	$\mathcal{O}(\log \log u)$
MAXIMUM	-	$\mathcal{O}(1)$

all this requires key values to be in a universe of size u !





5.3: Disjoint Sets

Frank Stajano

Thomas Sauerwald

Lent 2016



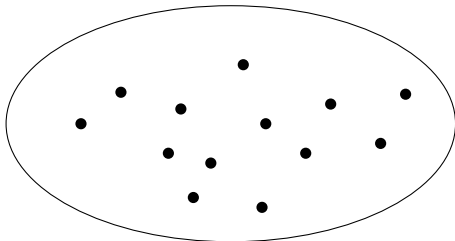
UNIVERSITY OF
CAMBRIDGE

Disjoint Sets



Disjoint Sets (aka Union Find)

Disjoint Sets Data Structure



Disjoint Sets (aka Union Find)

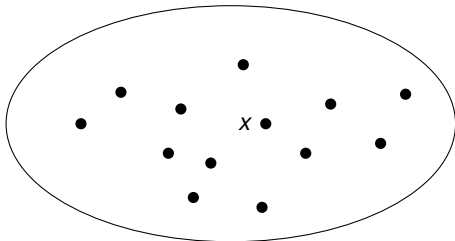
Disjoint Sets Data Structure

- **Handle MakeSet (Item x)**

Precondition: none of the existing sets contains x

Behaviour: create a new set $\{x\}$ and return its handle

$h_0 = \text{MakeSet}(x)$



Disjoint Sets (aka Union Find)

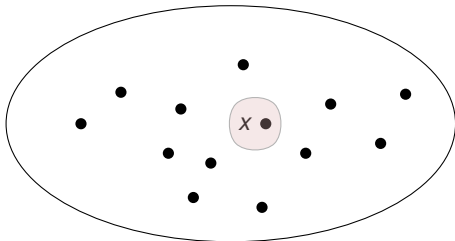
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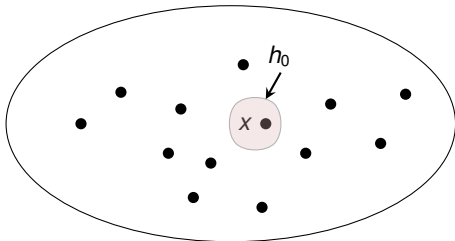
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Disjoint Sets (aka Union Find)

Disjoint Sets Data Structure

- **Handle MakeSet (Item x)**

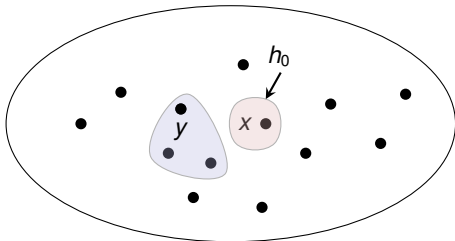
Precondition: none of the existing sets contains x

Behaviour: create a new set $\{x\}$ and return its handle

- **Handle FindSet (Item x)**

Precondition: there exists a set that contains x (given pointer to x)

Behaviour: return the handle of the set that contains x

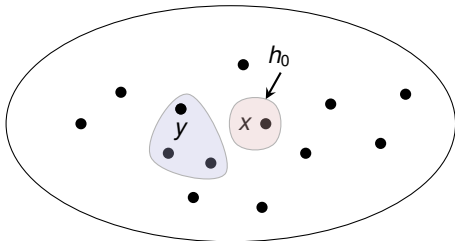


Disjoint Sets (aka Union Find)

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$h_1 = \text{FindSet}(y)$

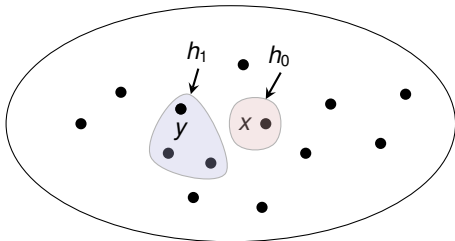


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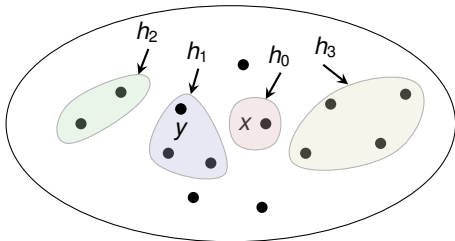
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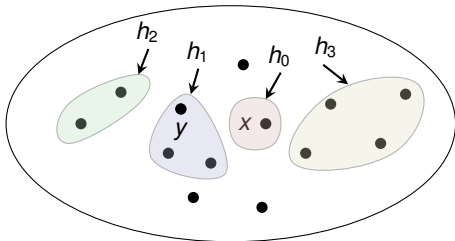


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$$h_4 = \text{Union}(h_0, h_3)$$

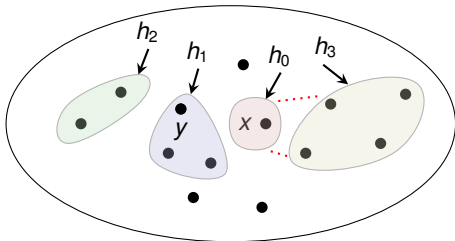


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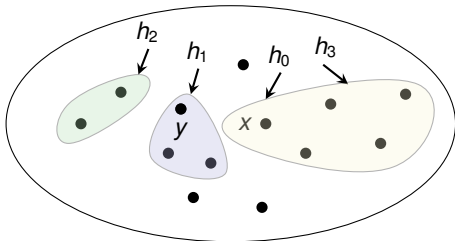


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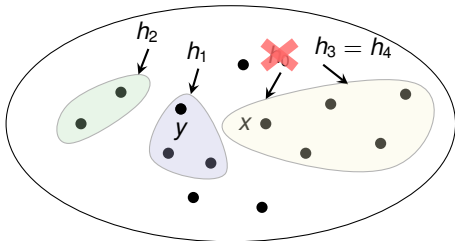


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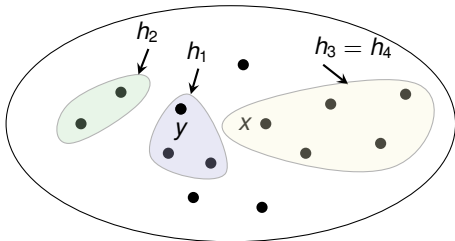
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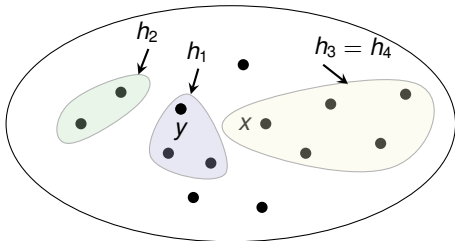


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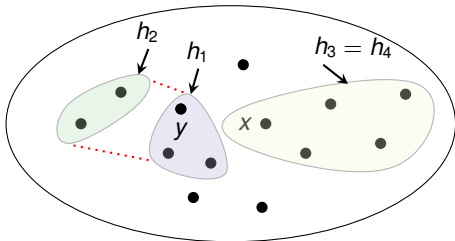


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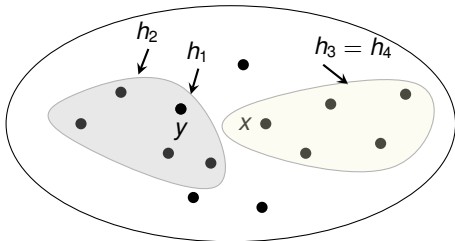


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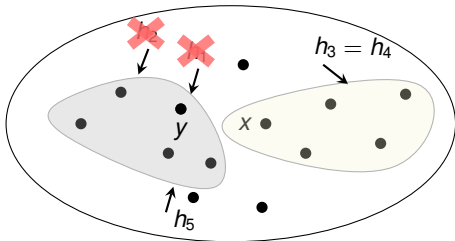


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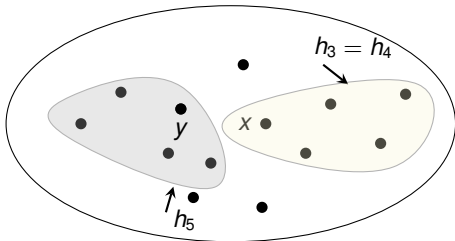


Disjoint Sets (aka Union Find)

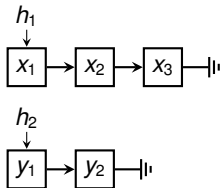
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First Attempt: List Implementation

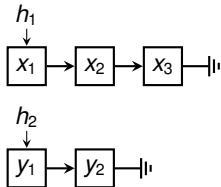


First Attempt: List Implementation

UNION-Operation



Union(h_1, h_2)



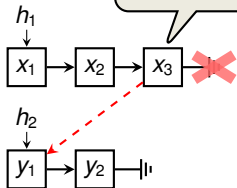
First Attempt: List Implementation

UNION-Operation



Union(h_1, h_2)

Need to find last element!



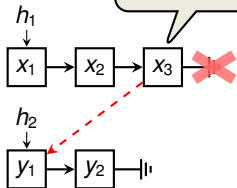
First Attempt: List Implementation

UNION-Operation

- Add **extra pointer** to the last element in each list

Union(h_1, h_2)

Need to find last element!



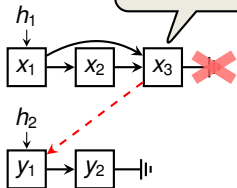
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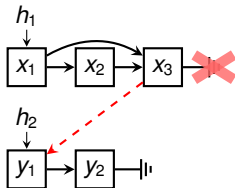


First Attempt: List Implementation

UNION-Operation

- Add **extra pointer** to the last element in each list
- ⇒ UNION takes constant time

Union(h_1, h_2)



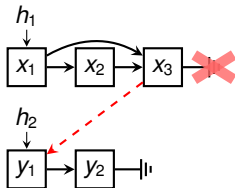
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UNION-Operation

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FINDSET-Operation

Union(h_1, h_2)



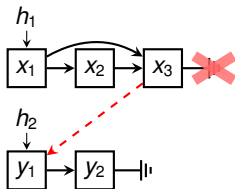
First Attempt: List Implementation

UNION-Operation

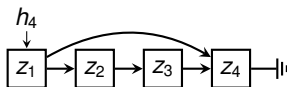
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FINDSET-Operation

Union(h_1, h_2)



FindSet(z_3)



First Attempt: List Implementation

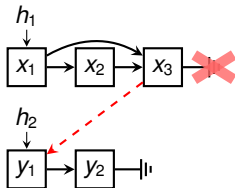
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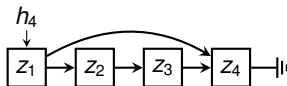
FINDSET-Operation

- Add **backward pointer** to the list head from everywhere

Union(h_1, h_2)



FindSet(z_3)



First Attempt: List Implementation

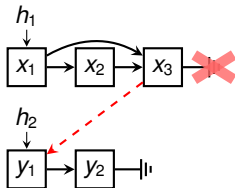
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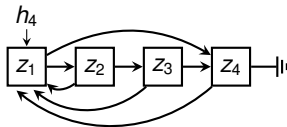
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FindSet(z_3)



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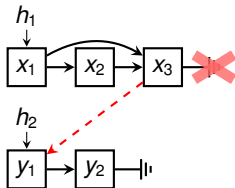
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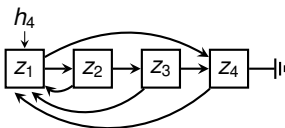
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Union(h_1, h_2)



FindSet(z_3)

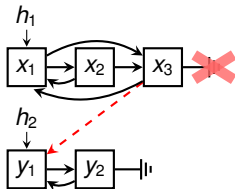


First Attempt: List Implementation

UNION-Operation

- Add **extra pointer** to the last element in each list
- ⇒ UNION takes constant time

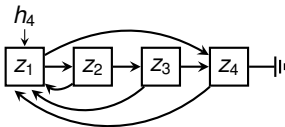
Union(h_1, h_2)



FINDSET-Operation

- Add **backward pointer** to the list head from everywhere
- ⇒ FINDSET takes constant time

FindSet(z_3)



First Attempt: List Implementation

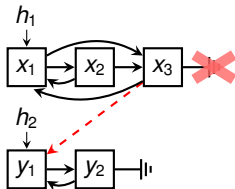
UNION-Operation

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FINDSET-Operation

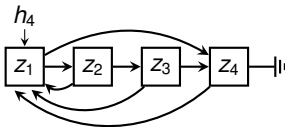
- Add **backward pointer** to the list head from everywhere
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Union(h_1, h_2)



Need to update all backward pointers!

FindSet(z_3)



First Attempt: List Implementation

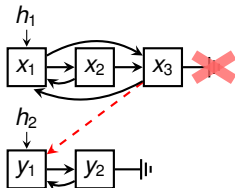
UNION-Operation

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- ⇒ ~~UNION takes constant time~~

FINDSET-Operation

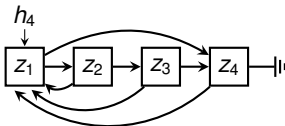
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First Attempt: List Implementation (Analysis)

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First Attempt: List Implementation (Analysis)

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$h_0 = d.\text{MakeSet}(x_0)$



First Attempt: List Implementation (Analysis)

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$h_1 = d.\text{MakeSet}(x_1)$



First Attempt: List Implementation (Analysis)

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$h_0 = d.\text{Union}(h_1, h_0)$



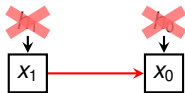
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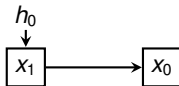
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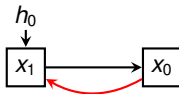
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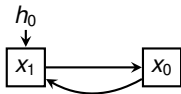
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First Attempt: List Implementation (Analysis)

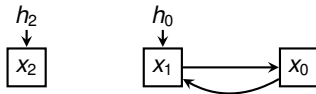
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$h_0 = d.\text{MakeSet}(x_0)$

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$h_0 = d.\text{Union}(h_1, h_0)$

$h_2 = d.\text{MakeSet}(x_2)$



First Attempt: List Implementation (Analysis)

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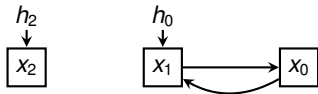
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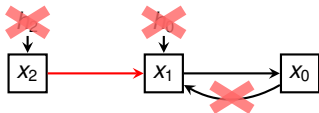
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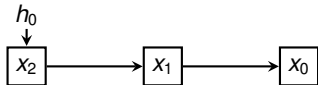
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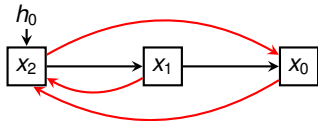
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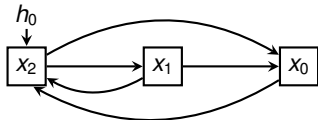
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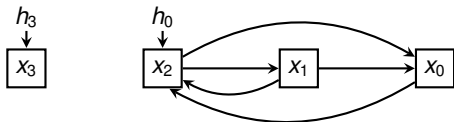
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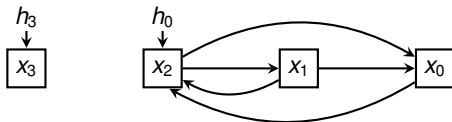
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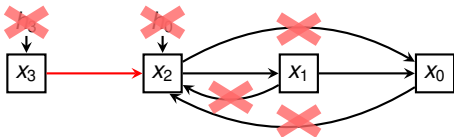
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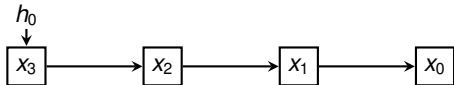
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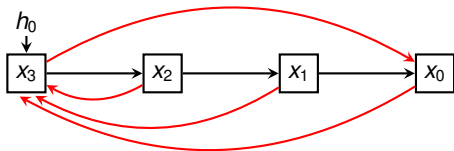
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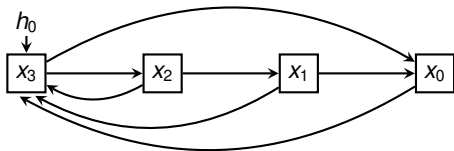
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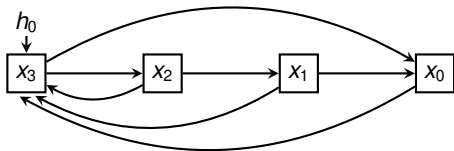
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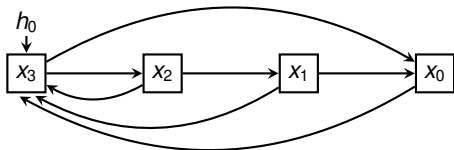
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better to append shorter list to longer \rightsquigarrow Weighted-Union Heuristic

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- Keep track of the length of each list



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- Keep track of the **length of each list**
- Append **shorter list** to the **longer list** (breaking ties arbitrarily)



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Using the **Weighted-Union heuristic**, any sequence of m operations, n of which are MAKESET operations, takes $\mathcal{O}(m + n \cdot \log n)$ time.



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Amortized Analysis: Every operation has amortized cost $\mathcal{O}(\log n)$, but there may be operations with total cost $\Theta(n)$.



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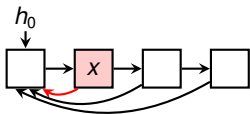
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Analysis of Weighted-Union Heuristic



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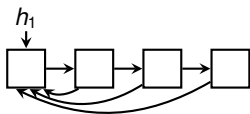
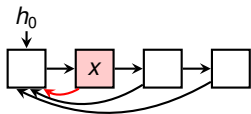
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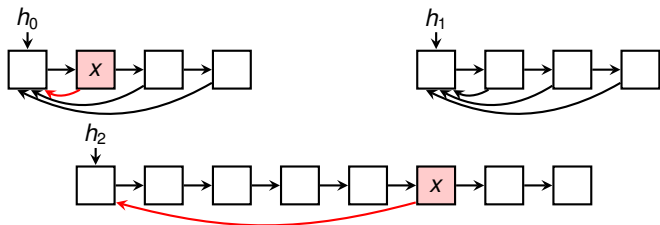
Using the [Weighted-Union heuristic](#), any sequence of m operations, n of which are MAKESET operations, takes $\mathcal{O}(m + n \cdot \log n)$ time.

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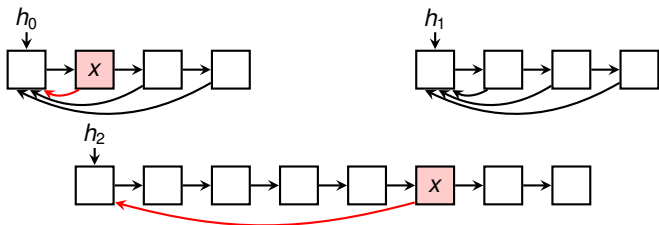
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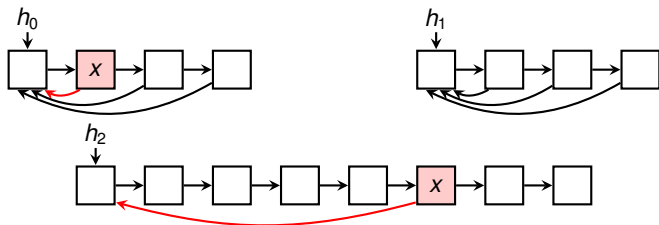
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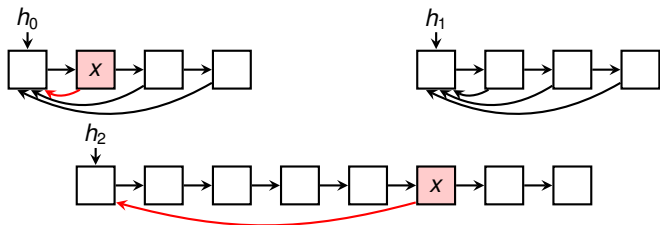
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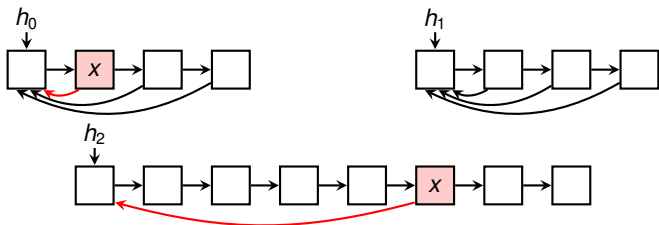
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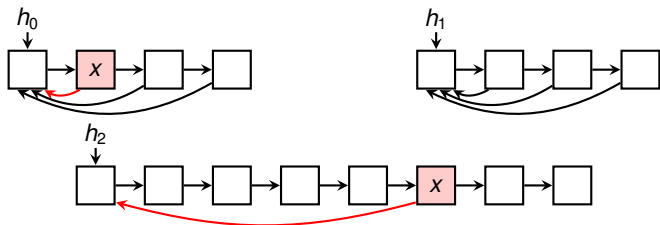
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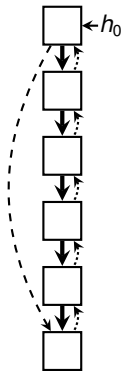
Proof:

Can we improve on this further?

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How to Improve?

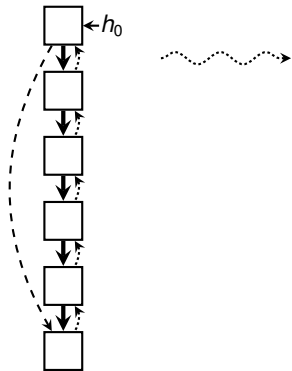


Doubly-Linked List

- MAKESET: $\mathcal{O}(1)$
- FINDSET: $\mathcal{O}(n)$
- UNION: $\mathcal{O}(1)$

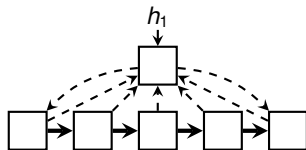


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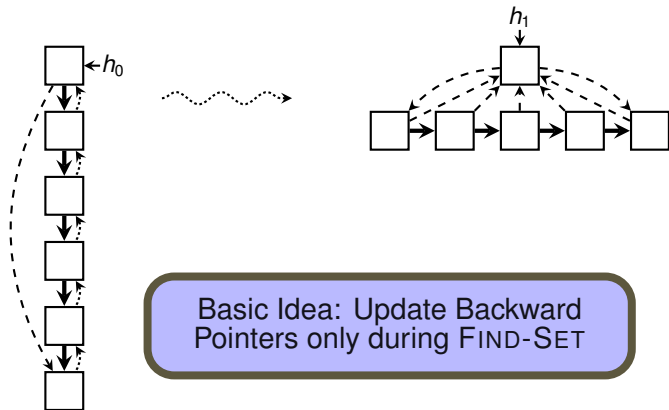


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- MAKESET: $\mathcal{O}(1)$
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- UNION: $\mathcal{O}(\log n)$ (amortized)



How to Improve?



Basic Idea: Update Backward Pointers only during FIND-SET

Doubly-Linked List

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Weighted-Union Heuristic

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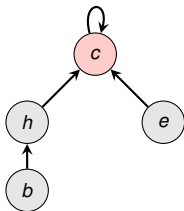
Forest Structure

- Set is represented by a **rooted tree** with root being the representative
- Every node has **pointer** $.p$ to its parent (for root x , $x.p = x$)



Disjoint Sets via Forests

$\{b, c, e, h\}$



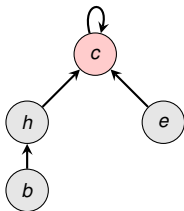
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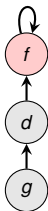
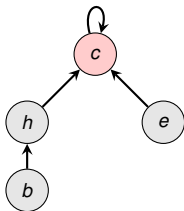
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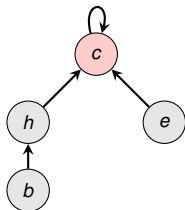
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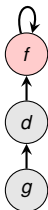


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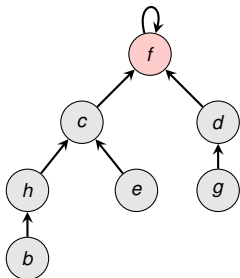
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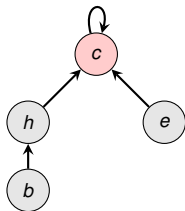
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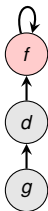


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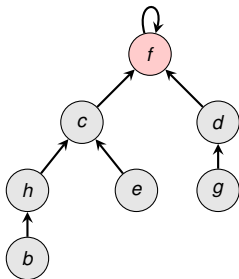
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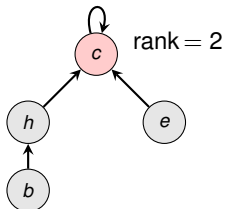
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Append tree of smaller height \rightsquigarrow Union by Rank

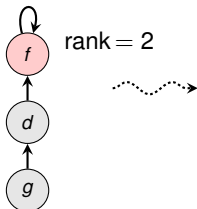


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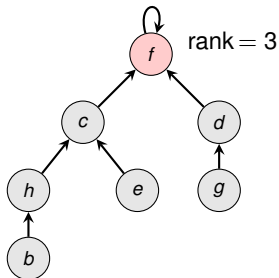
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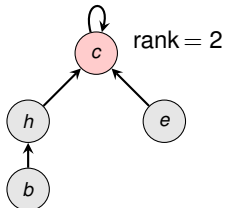
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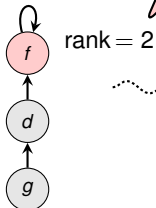


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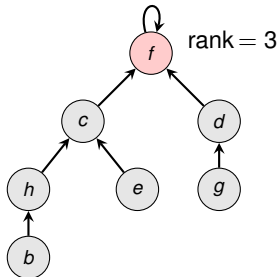


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Rank may be just an upper bound on the height!

$\{b, c, d, e, f, g, h\}$



Forest Structure

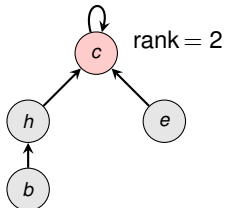
- Set is represented by a **rooted tree** with root being the representative
- Every node has **pointer** $.p$ to its parent (for root x , $x.p = x$)
- **UNION**: Merge the two trees

Append tree of smaller height \rightsquigarrow Union by Rank

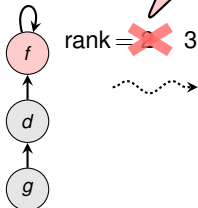


Disjoint Sets via Forests

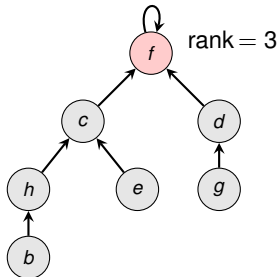
$\{b, c, e, h\}$



$\{d, f, g\}$



$\{b, c, d, e, f, g, h\}$



Rank may be just an upper bound on the height!

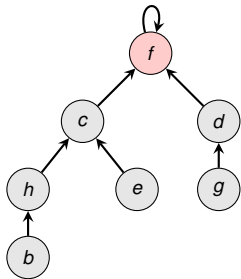
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FindSet (*b*) :

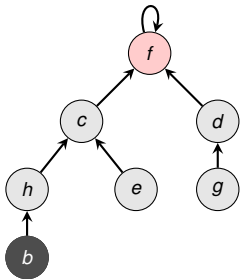


```
0: FindSet (x)  
1:   if  $x \neq x.p$   
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3:   return  $x.p$ 
```



FindSet (*b*):

b

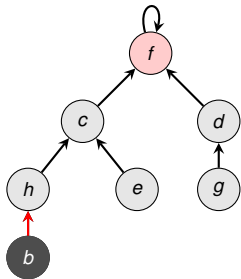


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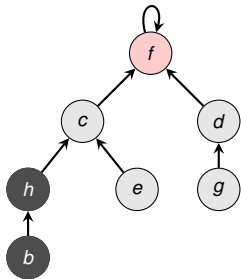
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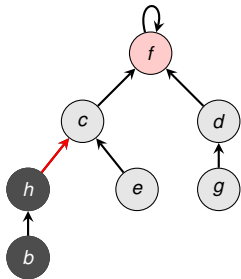
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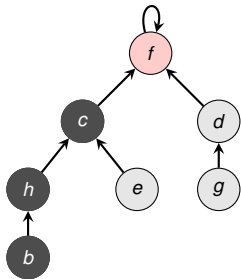
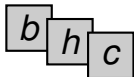
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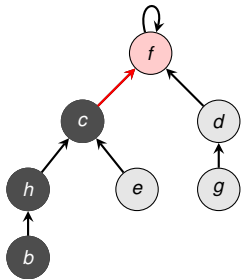
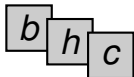
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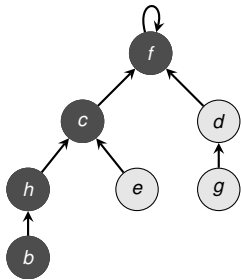
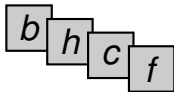
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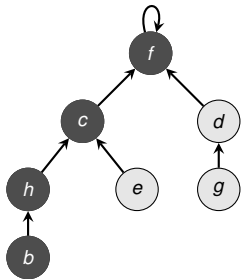
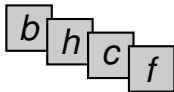
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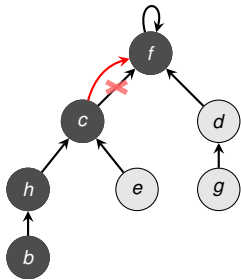
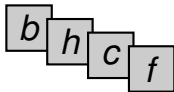
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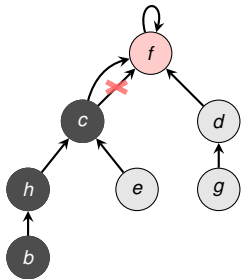
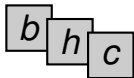
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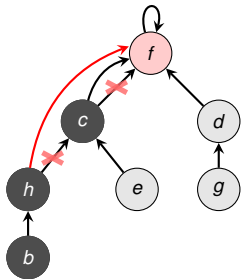
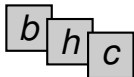
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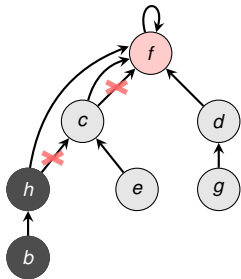
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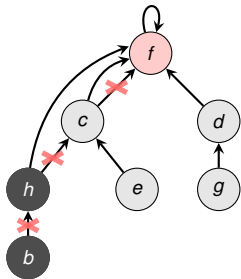
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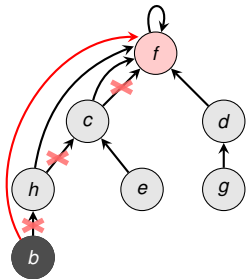


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b

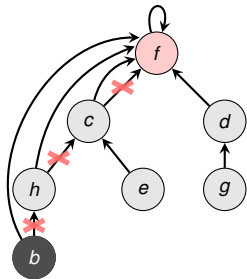


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b

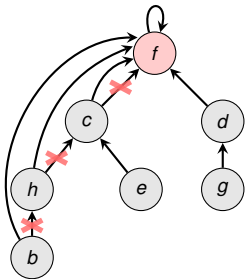


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FindSet (b):

b

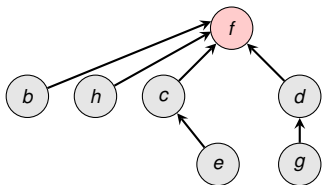


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FindSet (b):

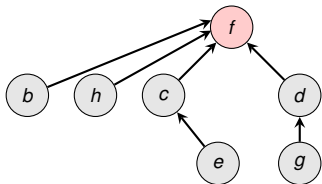
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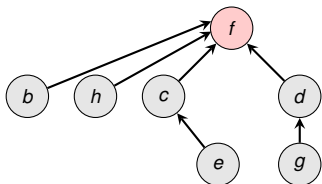
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FindSet (b):



Maintaining the exact height would be costly, hence rank is only an **upper bound**!

```
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Theorem 21.14

Any sequence of m MAKESET, UNION, FINDSET operations, n of which are MAKESET operations, can be performed in $\mathcal{O}(m \cdot \alpha(n))$ time.



Combining Union by Rank and Path Compression

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$$\alpha(n) = \begin{cases} 0 & \text{for } 0 \leq n \leq 2, \\ 1 & \text{for } n = 3, \\ 2 & \text{for } 4 \leq n \leq 7, \\ 3 & \text{for } 8 \leq n \leq 2047, \\ 4 & \text{for } 2048 \leq n \leq 10^{80} \end{cases}$$



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More than the
number of atoms
in the universe!



Combining Union by Rank and Path Compression

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$\log^*(n)$, **the iterated logarithm**, satisfies $\alpha(n) \leq \log^*(n)$, but still $\log^*(10^{80}) = 5$.



Combining Union by Rank and Path Compression

Theorem 21.14

Any sequence of m MAKESET, UNION, FINDSET operations, n of which are MAKESET operations, can be performed in $\mathcal{O}(m \cdot \alpha(n))$ time.

In practice, $\alpha(n)$ is a small constant

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Combining Union by Rank and Path Compression

Data Structure is essentially optimal! (for more details see CLRS)

Theorem 21.14

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Simulating the Effects of Union by Rank and Path Compression



Simulating the Effects of Union by Rank and Path Compression

Experimental Setup

1. Initialise singletons $1, 2, \dots, 300$
2. For every $1 \leq i \leq 300$, pick a random $1 \leq r \leq 300, r \neq i$ and perform $\text{UNION}(\text{FINDSET}(i), \text{FINDSET}(r))$



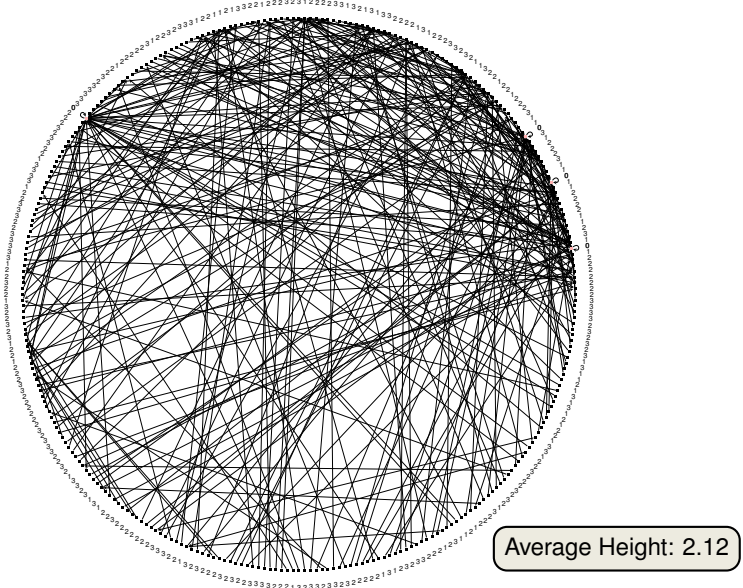
Simulating the Effects of Union by Rank and Path Compression

Experimental Setup

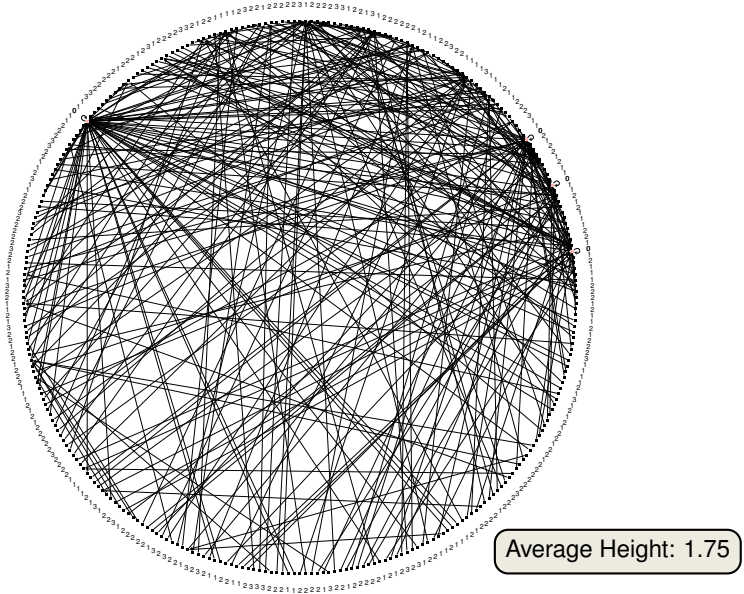
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3. Perform $j \in \{0, 100, 200, 300, 600, 900, 1200, 1500, 1800\}$ many additional $\text{FINDSET}(r)$, where $1 \leq r \leq 300$ is random



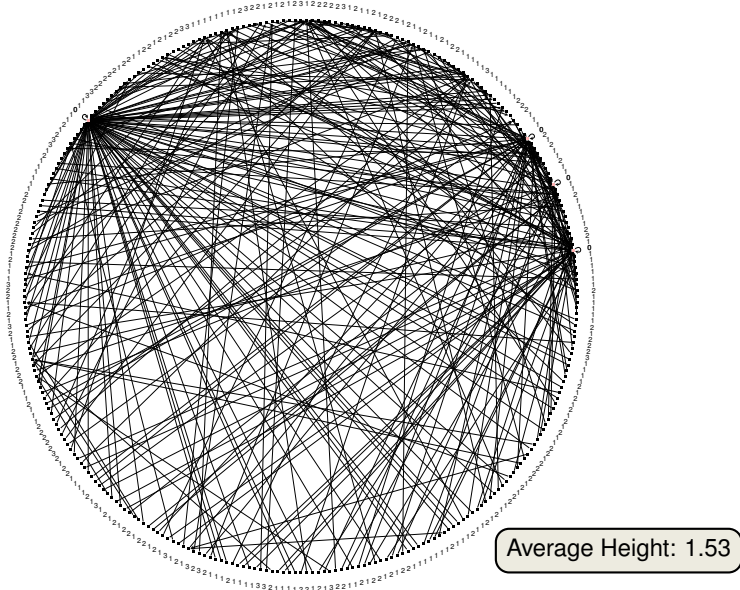
Union by Rank without Path Compression



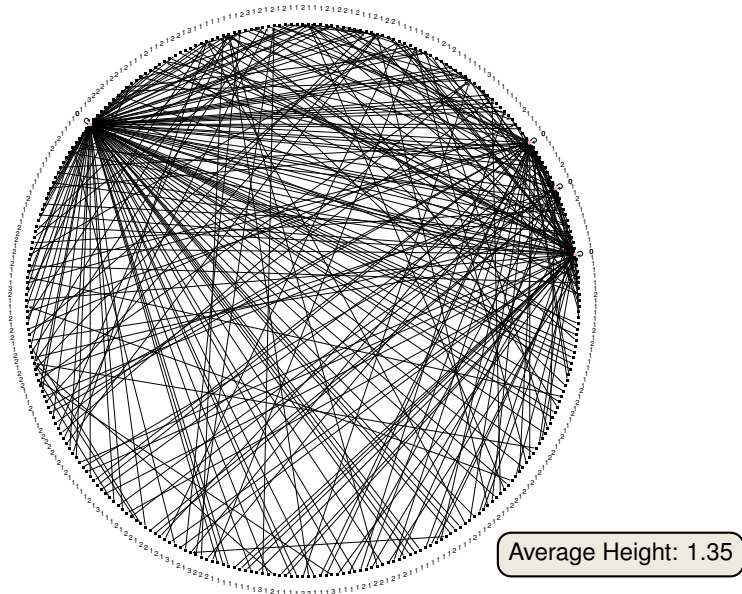
Union by Rank with Path Compression



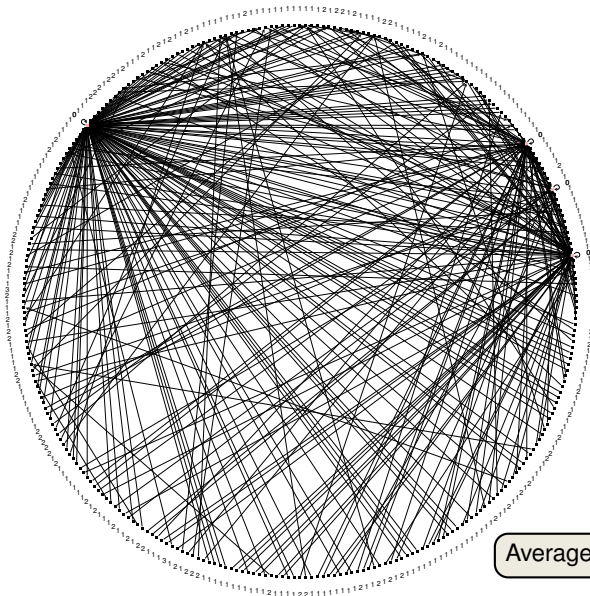
Union by Rank with Path Compression (100 additional FINDSET)



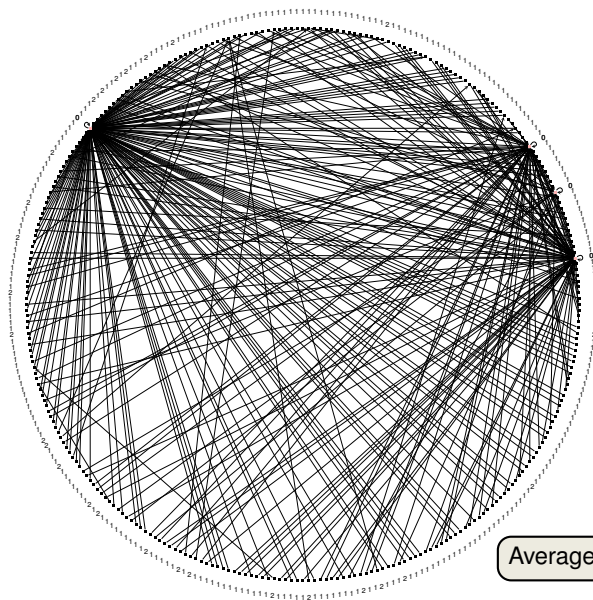
Union by Rank with Path Compression (200 additional FINDSET)



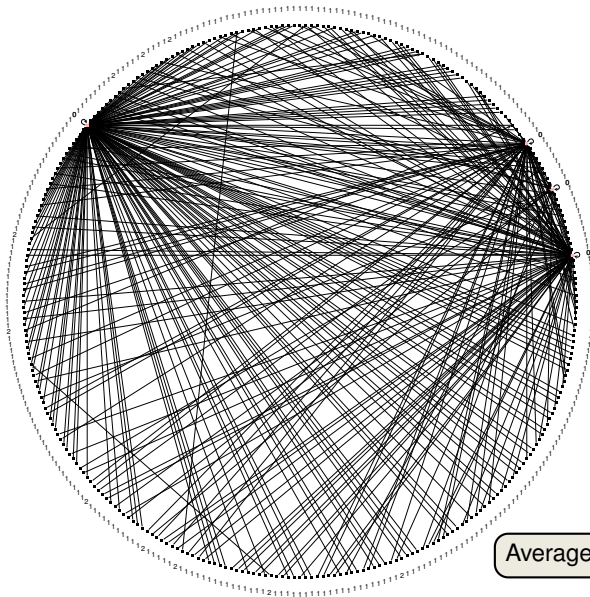
Union by Rank with Path Compression (300 additional FINDSET)



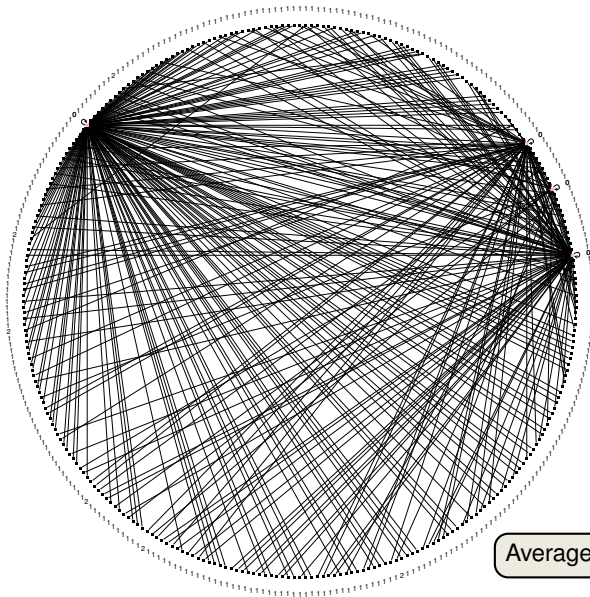
Union by Rank with Path Compression (600 additional FINDSET)



Union by Rank with Path Compression (900 additional FINDSET)



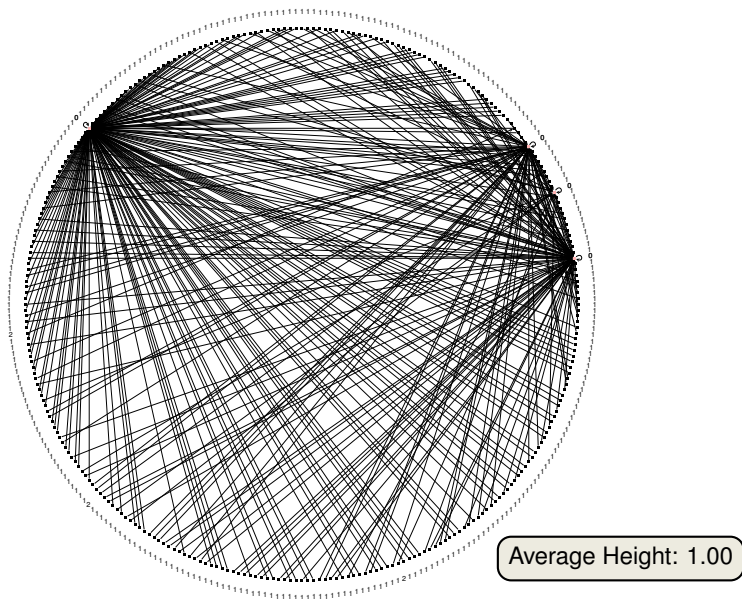
Union by Rank with Path Compression (1200 additional FINDSET)



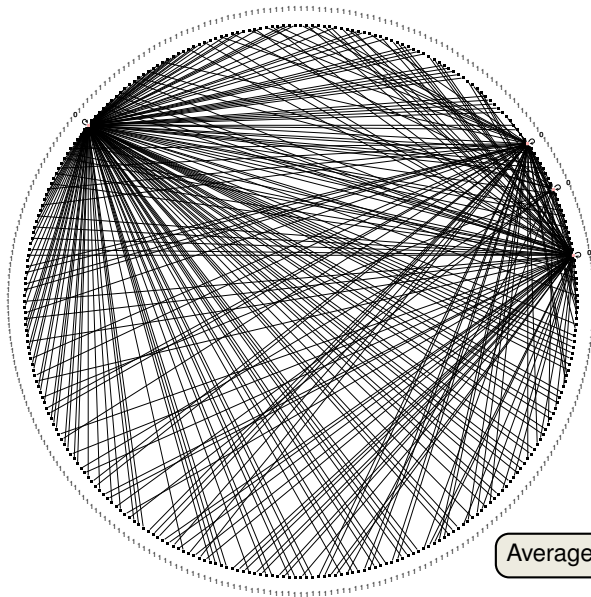
Average Height: 1.01



Union by Rank with Path Compression (1500 additional FINDSET)

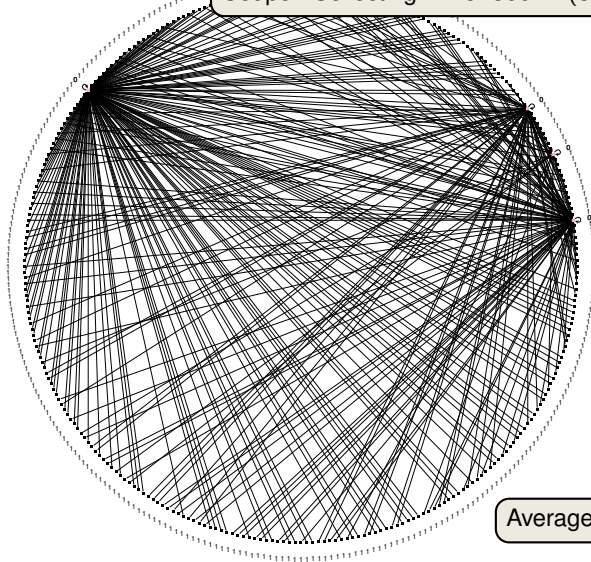


Union by Rank with Path Compression (1800 additional FINDSET)



Union by Rank with Path Compression (1800 additional FINDSET)

Coupon Collecting Time: $300 \cdot \ln(300) \approx 1711$



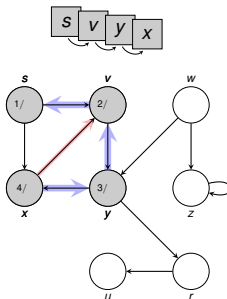
Average Height: 0.98



Overview

	Union by Rank	Union by Rank & Path Compression
300 MAKESET & 300 UNION	2.12	1.75
100 extra FINDSET	2.12	1.53
200 extra FINDSET	2.12	1.35
300 extra FINDSET	2.12	1.22
600 extra FINDSET	2.12	1.08
900 extra FINDSET	2.12	1.02
1200 extra FINDSET	2.12	1.01
1500 extra FINDSET	2.12	1.00
1800 extra FINDSET	2.12	0.98





6.1 & 6.2: Graph Searching

Frank Stajano

Thomas Sauerwald

Lent 2016



UNIVERSITY OF
CAMBRIDGE

Introduction to Graphs and Graph Searching

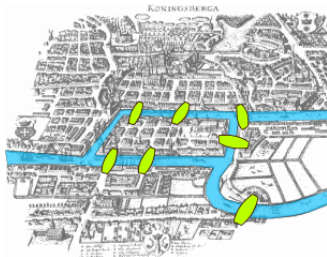
Breadth-First Search

Depth-First Search

Topological Sort



Origin of Graph Theory

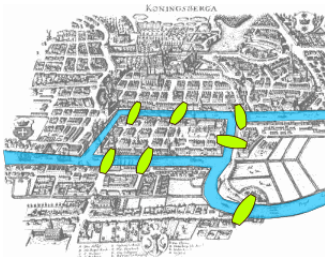


Source: Wikipedia

Seven Bridges at Königsberg 1737



Origin of Graph Theory



Source: Wikipedia

Seven Bridges at Königsberg 1737



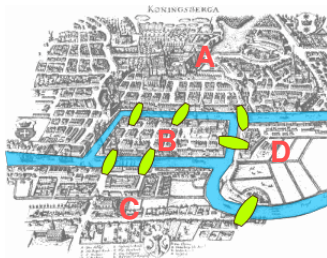
Source: Wikipedia

Leonhard Euler (1707-1783)

Is there a tour which crosses each bridge **exactly once**?



Origin of Graph Theory



Source: Wikipedia

Seven Bridges at Königsberg 1737



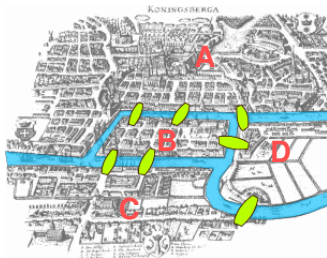
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Source: Wikipedia



Source: Wikipedia

Seven Bridges at Königsberg 1737

Leonhard Euler (1707-1783)

A

B

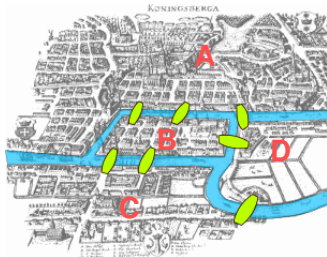
D

C

Is there a tour which crosses each bridge **exactly once**?



Origin of Graph Theory



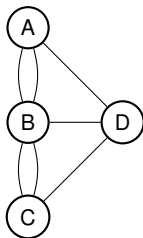
Source: Wikipedia



Source: Wikipedia

Seven Bridges at Königsberg 1737

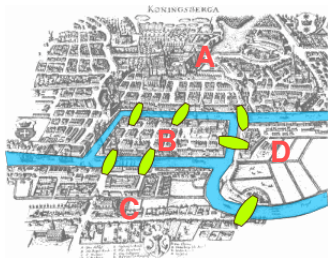
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Origin of Graph Theory



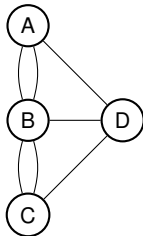
Source: Wikipedia



Source: Wikipedia

Seven Bridges at Königsberg 1737

Leonhard Euler (1707-1783)

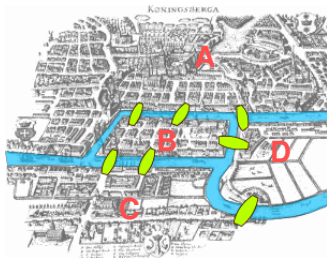


Is there a tour which crosses each bridge **exactly once**?

Is there a tour which visits every island **exactly once**?



Origin of Graph Theory



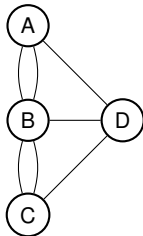
Source: Wikipedia



Source: Wikipedia

Seven Bridges at Königsberg 1737

Leonhard Euler (1707-1783)



Is there a tour which crosses each bridge **exactly once**?

Is there a tour which visits every island **exactly once**?
↪ 1B course: Complexity Theory



What is a Graph?

Directed Graph

A graph $G = (V, E)$ consists of:

- V : the set of vertices
- E : the set of edges (arcs)

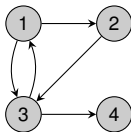


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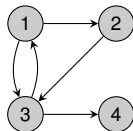


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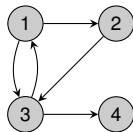
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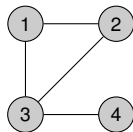
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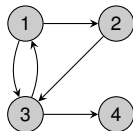
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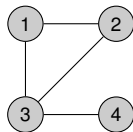
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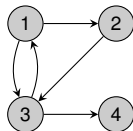


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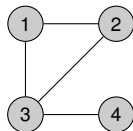
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Paths and Connectivity

- A sequence of edges between two vertices forms a **path**



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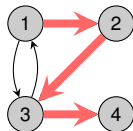
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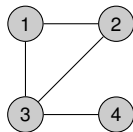
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Path $p = (1, 2, 3, 4)$



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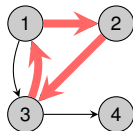
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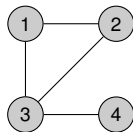
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Path $p = (1, 2, 3, 1)$, which is a cycle



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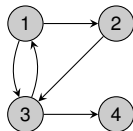


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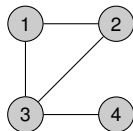
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Paths and Connectivity

- A sequence of edges between two vertices forms a **path**
- If each pair of vertices has a path linking them, then G is **connected**



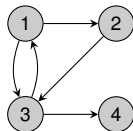
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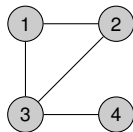
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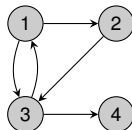
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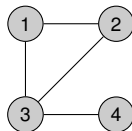
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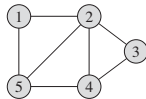
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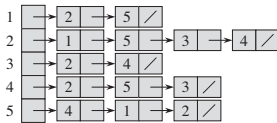
Later: edge-weighted graphs $G = (V, E, w)$



Representations of Directed and Undirected Graphs



(a)



(b)

	1	2	3	4	5
1	0	1	0	0	1
2	1	0	1	1	1
3	0	1	0	1	0
4	0	1	1	0	1
5	1	1	0	1	0

(c)

Figure 22.1 Two representations of an undirected graph. (a) An undirected graph G with 5 vertices and 7 edges. (b) An adjacency-list representation of G . (c) The adjacency-matrix representation of G .



Representations of Directed and Undirected Graphs

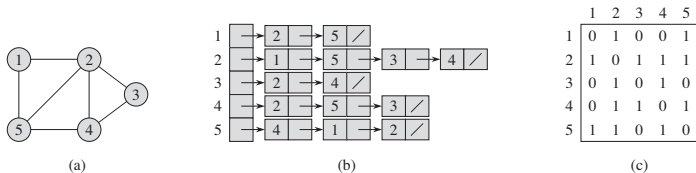


Figure 22.1 Two representations of an undirected graph. (a) An undirected graph G with 5 vertices and 7 edges. (b) An adjacency-list representation of G . (c) The adjacency-matrix representation of G .

Most times we will use the adjacency-list representation!

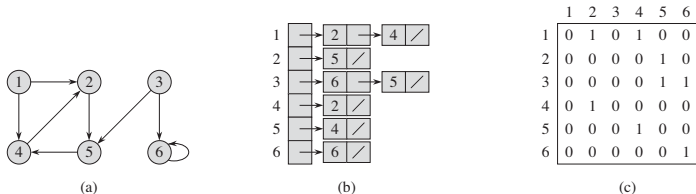



Figure 22.2 Two representations of a directed graph. (a) A directed graph G with 6 vertices and 8 edges. (b) An adjacency-list representation of G . (c) The adjacency-matrix representation of G .



Overview



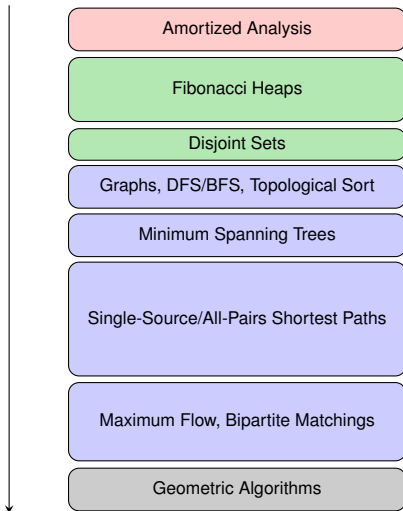
Amortized Analysis

Fibonacci Heaps

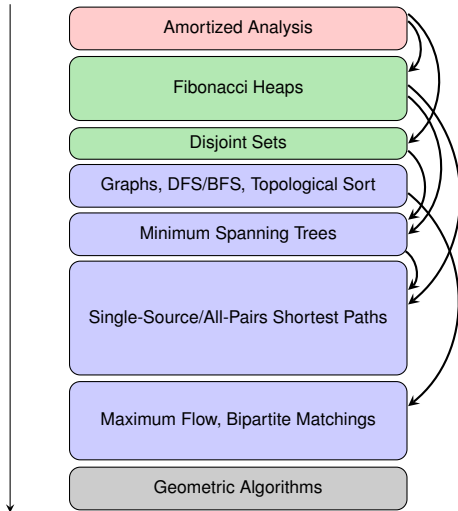
Disjoint Sets



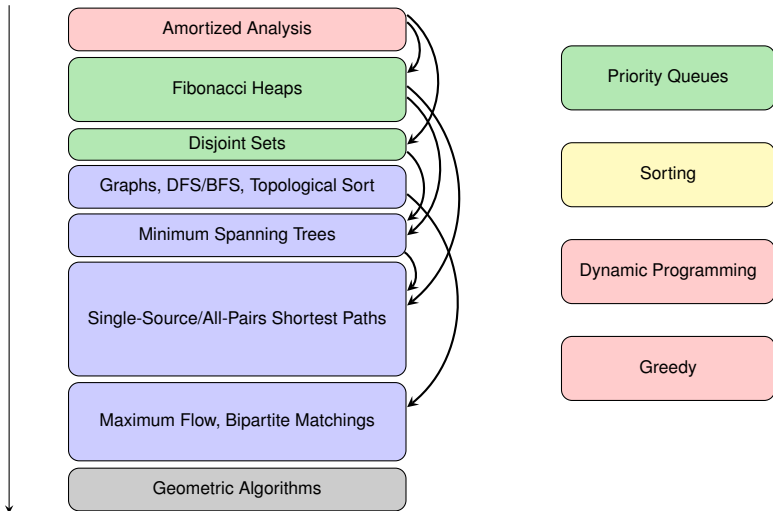
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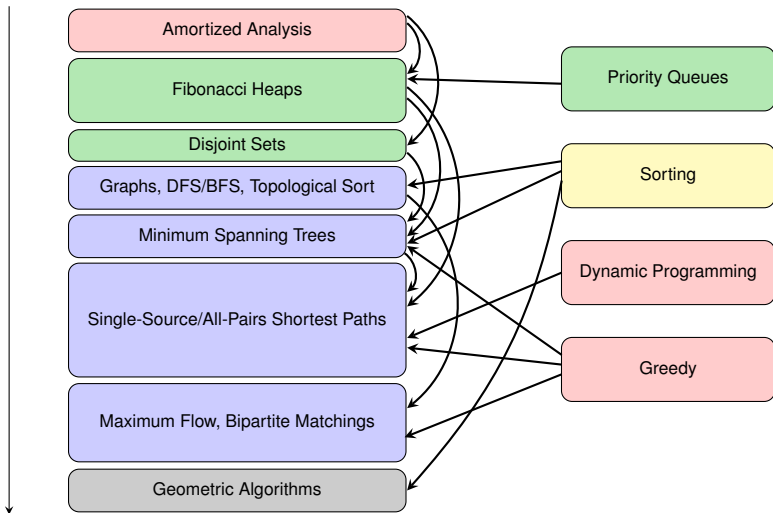
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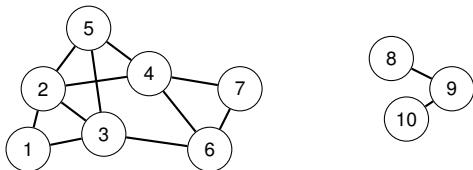
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Overview



Graph Searching

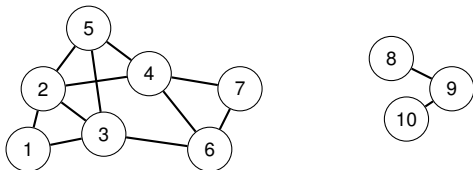


Overview

- **Graph searching** means traversing a graph via the edges in order to visit all vertices
- useful for identifying connected components, computing the diameter etc.



Graph Searching

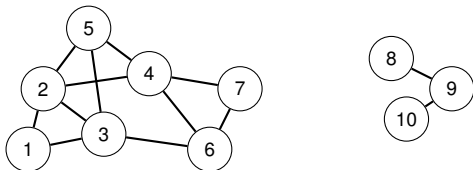


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- Two strategies: **Breadth-First-Search** and **Depth-First-Search**



Graph Searching



Overview

- **Graph searching** means traversing a graph via the edges in order to visit all vertices
- useful for identifying connected components, computing the diameter etc.
- Two strategies: **Breadth-First-Search** and **Depth-First-Search**

Measure time complexity in terms of the size of V and E
(often write just V instead of $|V|$, and E instead of $|E|$)



Outline

Introduction to Graphs and Graph Searching

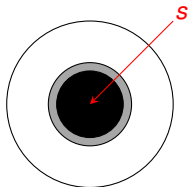
Breadth-First Search

Depth-First Search

Topological Sort



Breadth-First Search: Basic Ideas

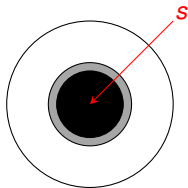


Basic Idea

- Given an undirected/directed graph $G = (V, E)$ and source vertex s



Breadth-First Search: Basic Ideas

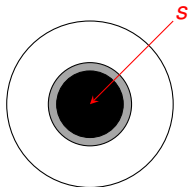


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- BFS sends out a **wave** from $s \rightsquigarrow$ compute distances/shortest paths



Breadth-First Search: Basic Ideas



Basic Idea

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- BFS sends out a **wave** from $s \rightsquigarrow$ compute distances/shortest paths
- **Vertex Colours:**

White = Unvisited

Grey = Visited, but not all neighbors (=adjacent vertices)

Black = Visited and all neighbors



Breadth-First-Search: Pseudocode

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4:   assert(s in G.vertices())
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Assuming that all executions of the FOR-loop for u takes $O(|u.adj|)$ (**adjacency list model!**)

$$\sum_{u \in V} |u.adj| = 2|E|$$



Breadth-First-Search: Pseudocode

```
0: def bfs(G,s)
1:   Run BFS on the given graph G
2:   starting from source s
3:
4:   assert(s in G.vertices())
5:
6:   # Initialize graph and queue
7:   for v in G.vertices():
8:     v.predecessor = None
9:     v.d = Infinity # .d = distance from s
10:    v.colour = "white"
11:   Q = Queue()
12:
13:   # Visit source vertex
14:   s.d = 0
15:   s.colour = "grey"
16:   Q.insert(s)
17:
18:   # Visit the adjacents of each vertex in Q
19:   while not Q.isEmpty():
20:     u = Q.extract()
21:     assert (u.colour == "grey")
22:     for v in u.adjacent()
23:       if v.colour == "white"
24:         v.colour = "grey"
25:         v.d = u.d+1
26:         v.predecessor = u
27:         Q.insert(v)
28:     u.colour = "black"
```

- From any vertex, visit all adjacent vertices before going any deeper

- Vertex Colours:

White = Unvisited

Grey = Visited, but not all neighbors

Black = Visited and all neighbors

- Runtime $O(V + E)$

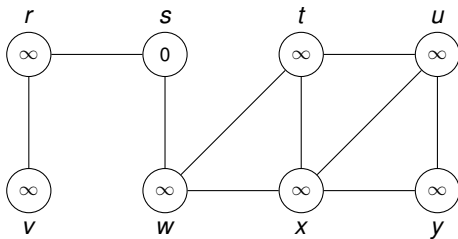
Assuming that all executions of the FOR-loop for u takes $O(|u.adj|)$ (**adjacency list model!**)

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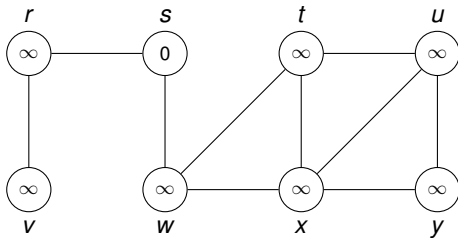
Execution of BFS (Figure 22.3)

Queue:



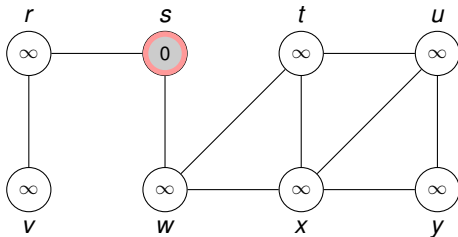
Execution of BFS (Figure 22.3)

Queue: *s*



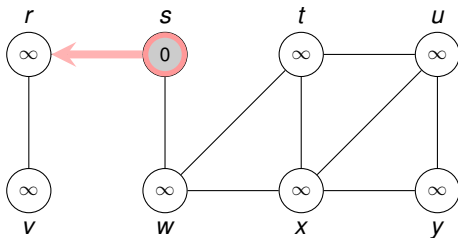
Execution of BFS (Figure 22.3)

Queue: ~~s~~



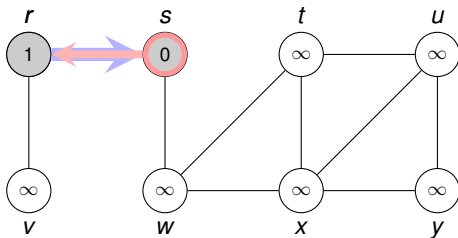
Execution of BFS (Figure 22.3)

Queue: ~~s~~



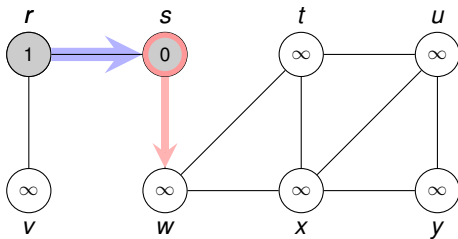
Execution of BFS (Figure 22.3)

Queue: ~~s~~ r



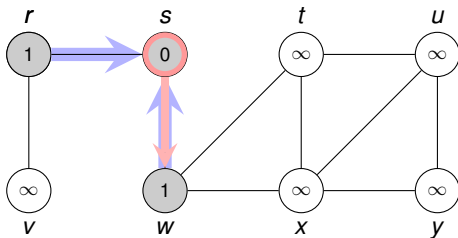
Execution of BFS (Figure 22.3)

Queue: ~~s~~ r



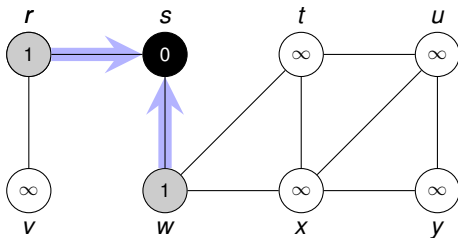
Execution of BFS (Figure 22.3)

Queue: ~~s~~ r w



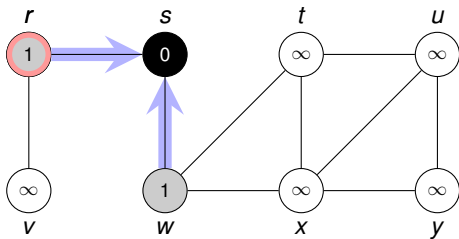
Execution of BFS (Figure 22.3)

Queue: ~~s~~ r w



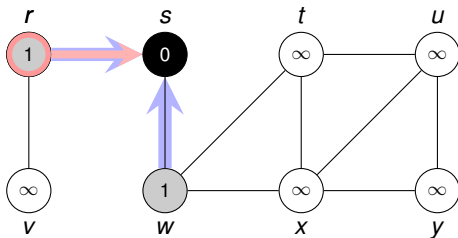
Execution of BFS (Figure 22.3)

Queue: ~~s~~ ~~x~~ w



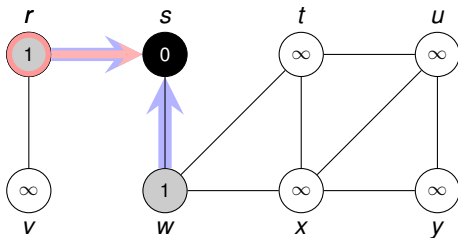
Execution of BFS (Figure 22.3)

Queue: ~~s~~ ~~x~~ w



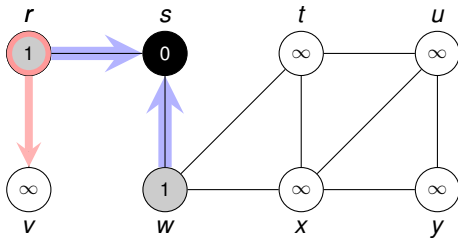
Execution of BFS (Figure 22.3)

Queue: ~~s~~ ~~x~~ w



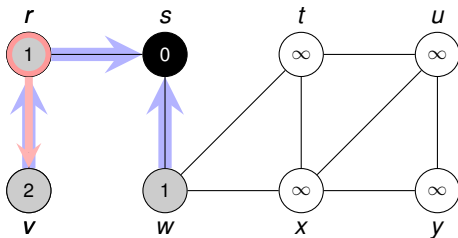
Execution of BFS (Figure 22.3)

Queue: ~~s~~ ~~x~~ w



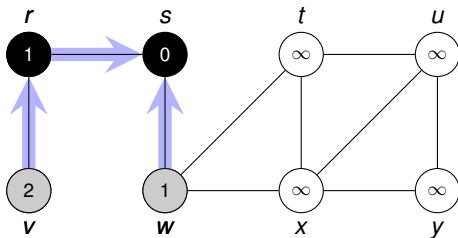
Execution of BFS (Figure 22.3)

Queue: ~~s~~ ~~r~~ w v



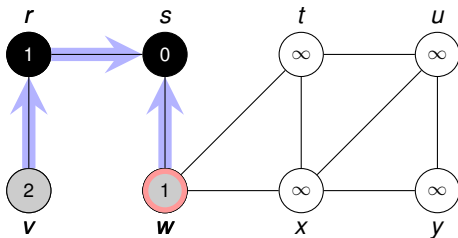
Execution of BFS (Figure 22.3)

Queue: ~~s~~ ~~r~~ w v



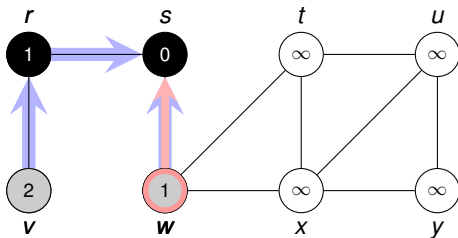
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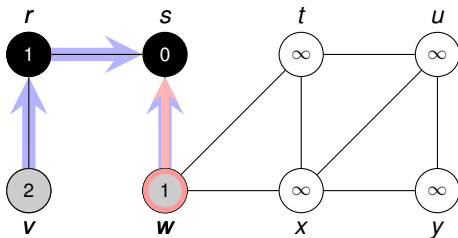
Execution of BFS (Figure 22.3)

Queue: ~~s~~ ~~r~~ ~~w~~ v



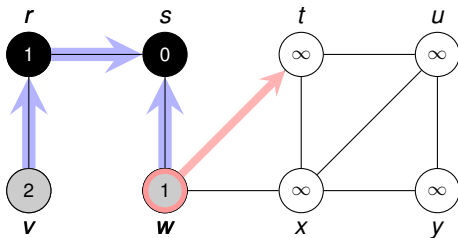
Execution of BFS (Figure 22.3)

Queue: ~~s~~ ~~r~~ ~~w~~ v



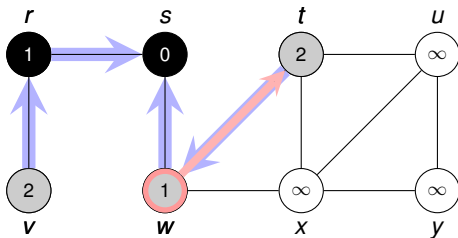
Execution of BFS (Figure 22.3)

Queue: ~~s~~ ~~r~~ ~~w~~ v



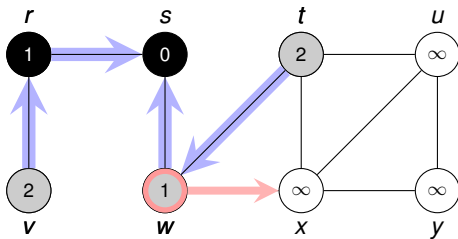
Execution of BFS (Figure 22.3)

Queue: ~~s~~ ~~r~~ ~~w~~ v t



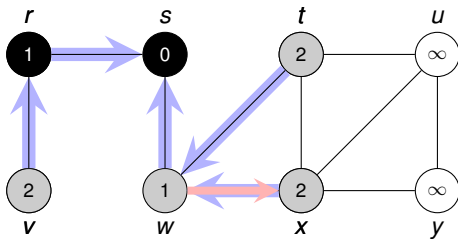
Execution of BFS (Figure 22.3)

Queue: ~~s~~ ~~r~~ ~~w~~ v t



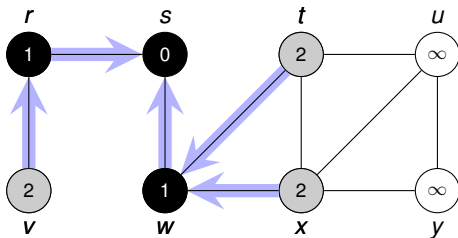
Execution of BFS (Figure 22.3)

Queue: ~~s~~ ~~r~~ ~~w~~ v t x



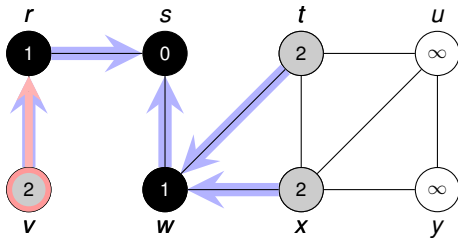
Execution of BFS (Figure 22.3)

Queue: ~~s~~ ~~r~~ ~~w~~ v t x



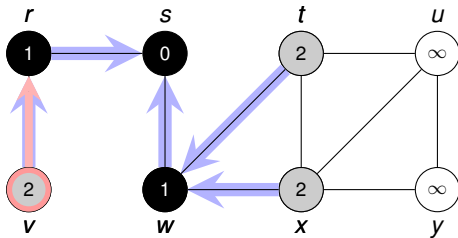
Execution of BFS (Figure 22.3)

Queue: ~~s~~ ~~r~~ ~~w~~ ~~v~~ t x



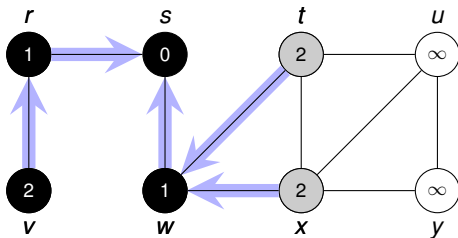
Execution of BFS (Figure 22.3)

Queue: ~~s~~ ~~r~~ ~~w~~ ~~v~~ t x



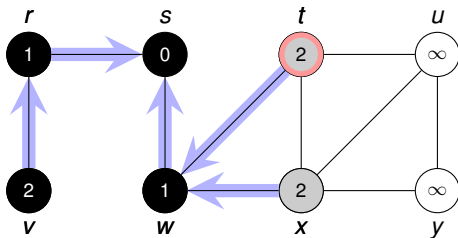
Execution of BFS (Figure 22.3)

Queue: ~~s~~ ~~r~~ ~~w~~ ~~v~~ t x



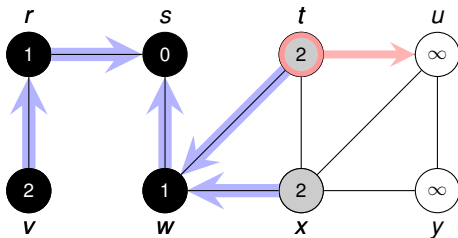
Execution of BFS (Figure 22.3)

Queue: ~~s~~ ~~r~~ ~~w~~ ~~v~~ ~~t~~ x



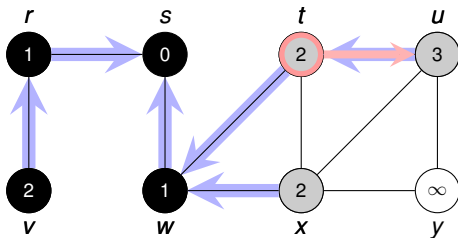
Execution of BFS (Figure 22.3)

Queue: ~~s~~ ~~r~~ ~~w~~ ~~v~~ ~~t~~ x



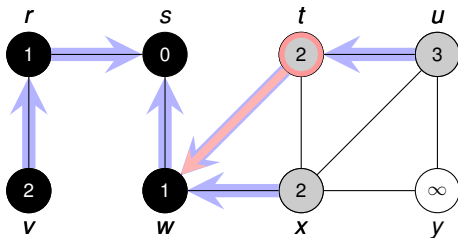
Execution of BFS (Figure 22.3)

Queue: ~~s~~ ~~r~~ ~~w~~ ~~x~~ ~~t~~ x u



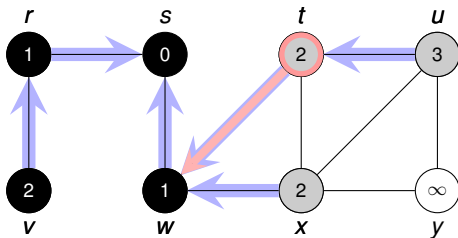
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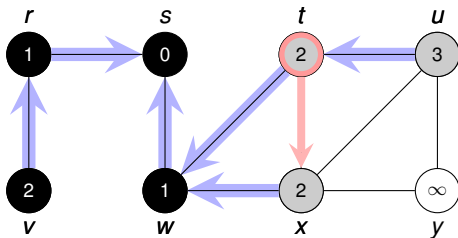
Execution of BFS (Figure 22.3)

Queue: ~~s~~ ~~r~~ ~~w~~ ~~v~~ ~~t~~ x u



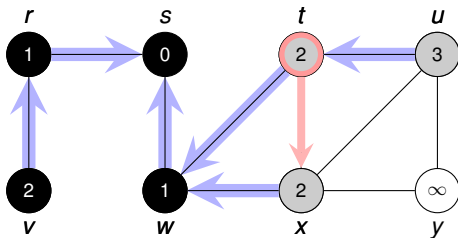
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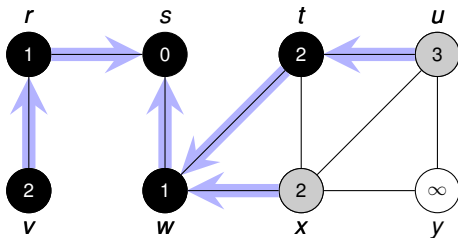
Execution of BFS (Figure 22.3)

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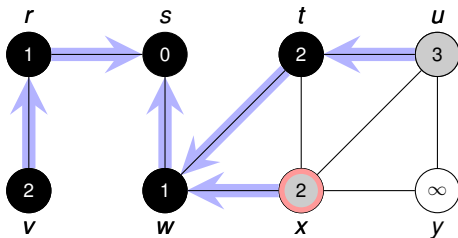
Execution of BFS (Figure 22.3)

Queue: ~~s~~ ~~r~~ ~~w~~ ~~v~~ ~~t~~ x u



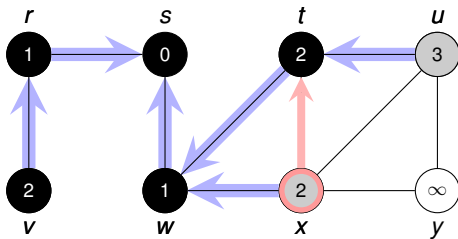
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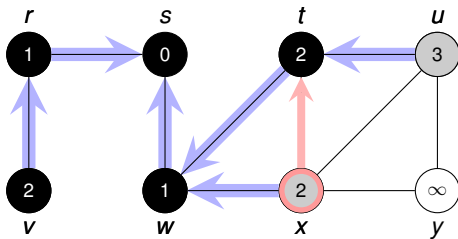
Execution of BFS (Figure 22.3)

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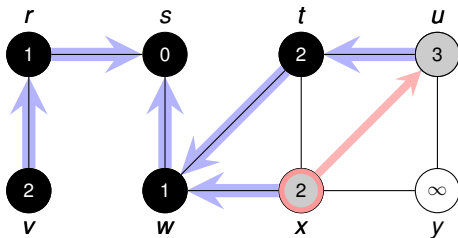
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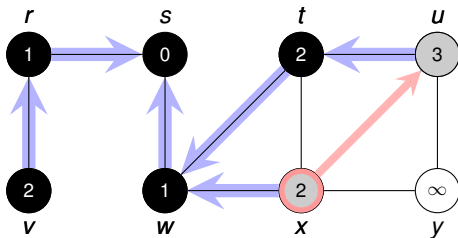
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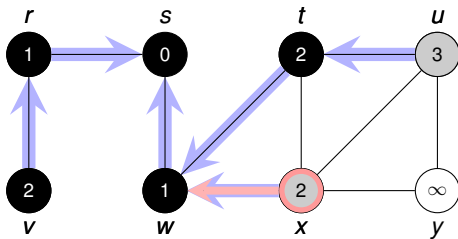
Execution of BFS (Figure 22.3)

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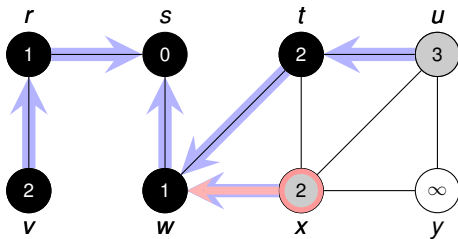
Execution of BFS (Figure 22.3)

Queue: ~~s~~ ~~r~~ ~~w~~ ~~v~~ ~~t~~ ~~x~~ ~~y~~ u



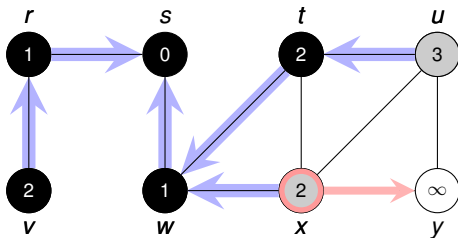
Execution of BFS (Figure 22.3)

Queue: ~~s~~ ~~r~~ ~~w~~ ~~v~~ ~~t~~ ~~x~~ ~~y~~ u



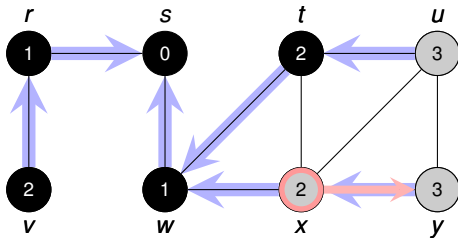
Execution of BFS (Figure 22.3)

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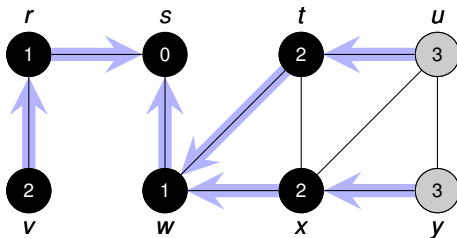
Execution of BFS (Figure 22.3)

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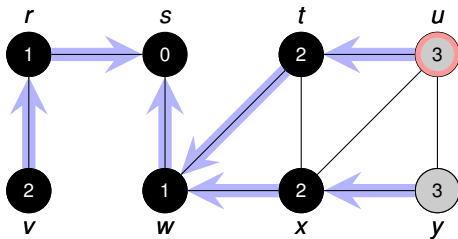
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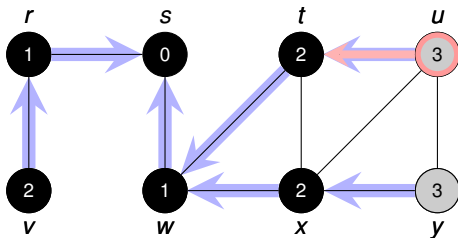
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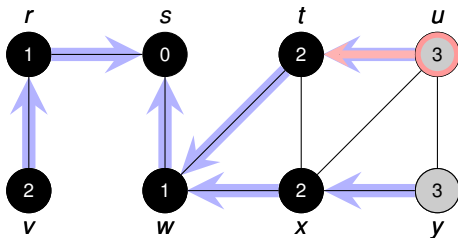
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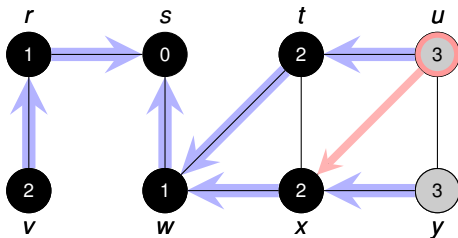
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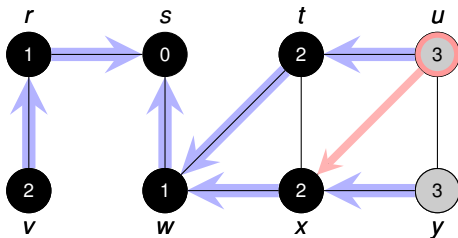
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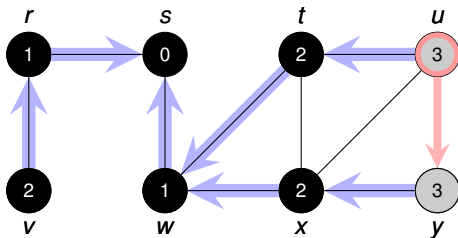
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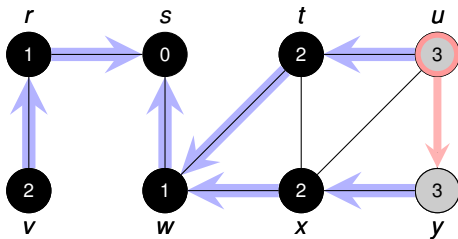
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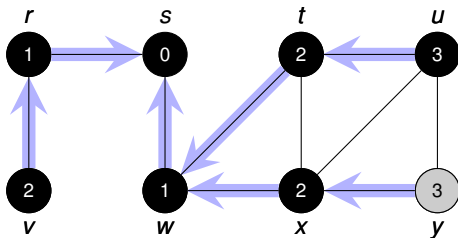
Execution of BFS (Figure 22.3)

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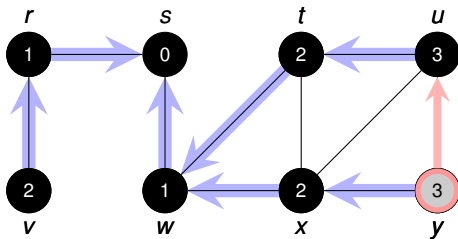
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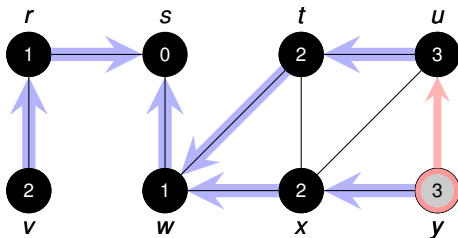
Execution of BFS (Figure 22.3)

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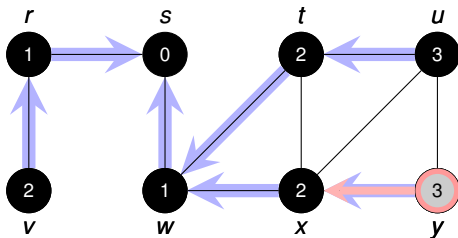
Execution of BFS (Figure 22.3)

Queue: ~~s~~ ~~r~~ ~~w~~ ~~v~~ ~~t~~ ~~x~~ ~~y~~ ~~u~~



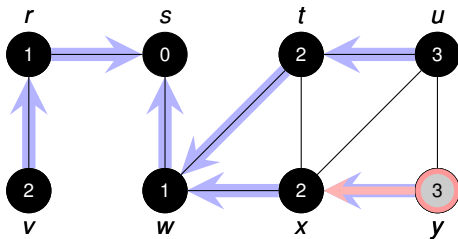
Execution of BFS (Figure 22.3)

Queue: ~~s~~ ~~r~~ ~~w~~ ~~v~~ ~~t~~ ~~x~~ ~~y~~ ~~u~~



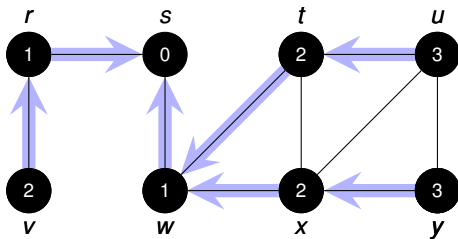
Execution of BFS (Figure 22.3)

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Execution of BFS (Figure 22.3)

Queue: ~~s~~ ~~r~~ ~~w~~ ~~v~~ ~~t~~ ~~x~~ ~~y~~ ~~u~~



Outline

Introduction to Graphs and Graph Searching

Breadth-First Search

Depth-First Search

Topological Sort



Basic Idea

- Given an undirected/directed graph $G = (V, E)$ and source vertex s



Depth-First-Search: Pseudocode

```
0: def dfs(G,s):
1:   Run DFS on the given graph G
2:   starting from the given source s
3:
4:   assert(s in G.vertices())
5:
6:   # Initialize graph
7:   for v in G.vertices():
8:     v.predecessor = None
9:     v.colour = "white"
10:  dfsRecurse(G,s)
```

```
0: def dfsRecurse(G,s):
1:   s.colour = "grey"
2:   s.d = time() # .d = discovery time
3:   for v in s.adjacent()
4:     if v.colour = "white"
5:       v.predecessor = s
6:       dfsRecurse(G,v)
7:   s.colour = "black"
8:   s.f = time() # .f = finish time
```



Depth-First-Search: Pseudocode

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6:       dfsRecurse(G,v)
7:   s.colour = "black"
8:   s.f = time() # .f = finish time
```

- We always go deeper before visiting other neighbors



Depth-First-Search: Pseudocode

```
0: def dfs(G,s):
1:   Run DFS on the given graph  $G$ 
2:   starting from the given source  $s$ 
3:
4:   assert( $s$  in  $G.vertices()$ )
5:
6:   # Initialize graph
7:   for  $v$  in  $G.vertices()$ :
8:      $v.predecessor = \text{None}$ 
9:      $v.colour = \text{"white"}$ 
10:  dfsRecurse( $G,s$ )
```

```
0: def dfsRecurse( $G,s$ ):
1:    $s.colour = \text{"grey"}$ 
2:    $s.d = \text{time()}$  #  $.d = \text{discovery time}$ 
3:   for  $v$  in  $s.adjacent()$ :
4:     if  $v.colour = \text{"white"}$ :
5:        $v.predecessor = s$ 
6:       dfsRecurse( $G,v$ )
7:    $s.colour = \text{"black"}$ 
8:    $s.f = \text{time()}$  #  $.f = \text{finish time}$ 
```

- We always go deeper before visiting other neighbors
- Discovery and Finish times, $.d$ and $.f$



Depth-First-Search: Pseudocode

```
0: def dfs(G,s):
1:   Run DFS on the given graph G
2:   starting from the given source s
3:
4:   assert(s in G.vertices())
5:
6:   # Initialize graph
7:   for v in G.vertices():
8:     v.predecessor = None
9:     v.colour = "white"
10:  dfsRecurse(G,s)
```

```
0: def dfsRecurse(G,s):
1:   s.colour = "grey"
2:   s.d = time() # .d = discovery time
3:   for v in s.adjacent():
4:     if v.colour = "white"
5:       v.predecessor = s
6:       dfsRecurse(G,v)
7:   s.colour = "black"
8:   s.f = time() # .f = finish time
```

- We always go deeper before visiting other neighbors
- **Discovery** and **Finish times**, $.d$ and $.f$
- **Vertex Colours**:

White = Unvisited

Grey = Visited, but not all neighbors

Black = Visited and all neighbors



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Depth-First-Search: Pseudocode

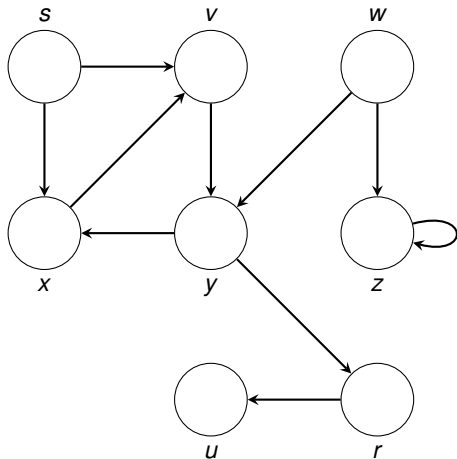
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0: def dfsRecurse(G,s):
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- We always go deeper before visiting other neighbors
- **Discovery** and **Finish times**, $.d$ and $.f$
- **Vertex Colours:**
 - White = Unvisited
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 - Black = Visited and all neighbors
- **Runtime** $O(V + E)$

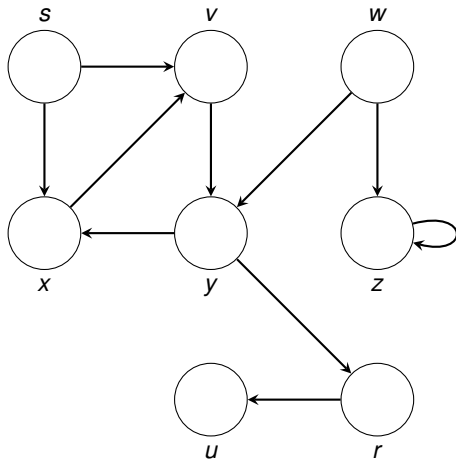


Execution of DFS



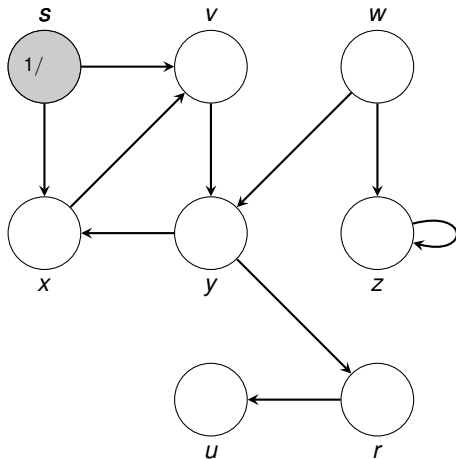
Execution of DFS

S



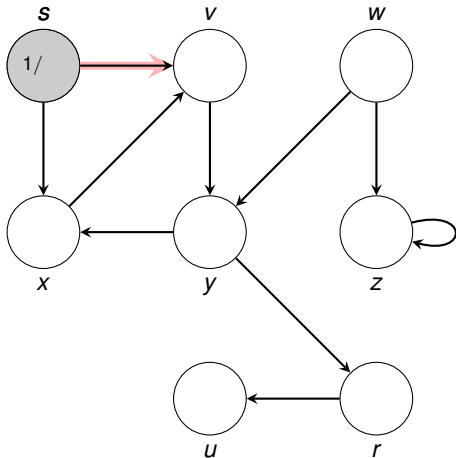
Execution of DFS

S

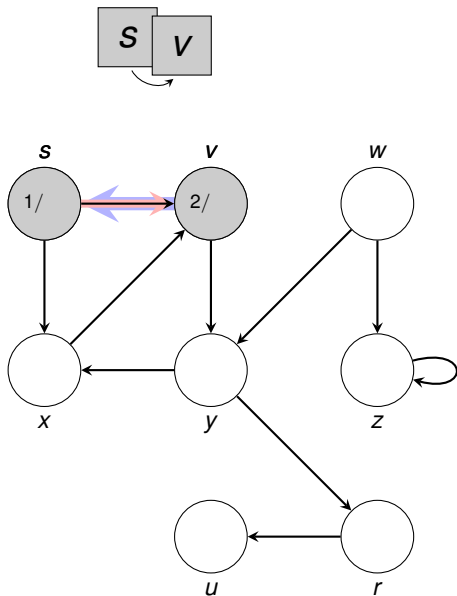


Execution of DFS

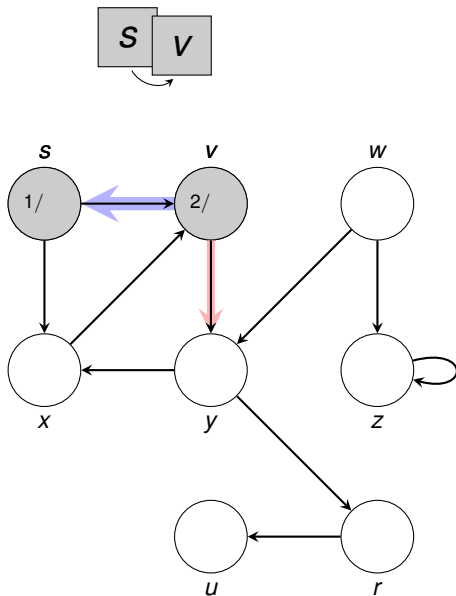
S



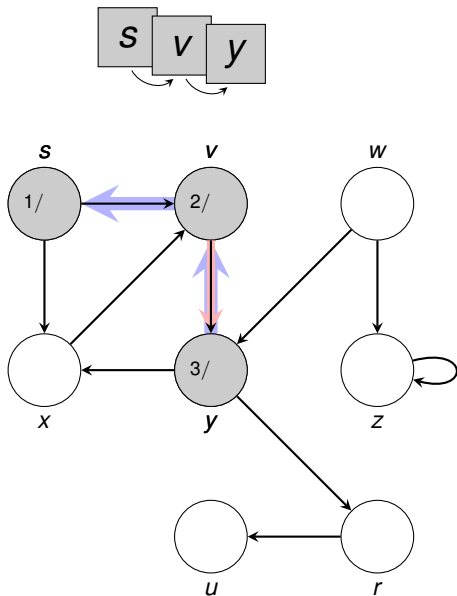
Execution of DFS



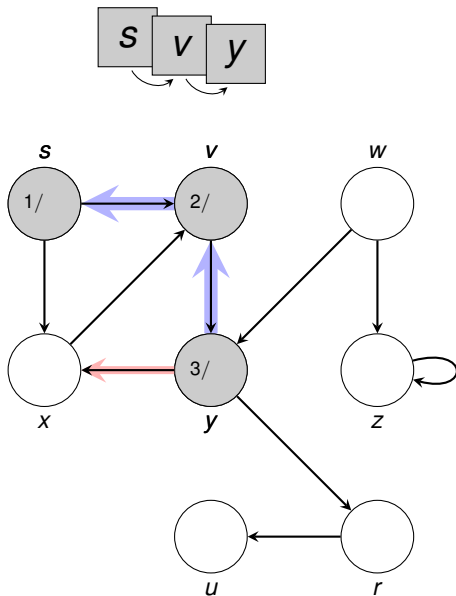
Execution of DFS



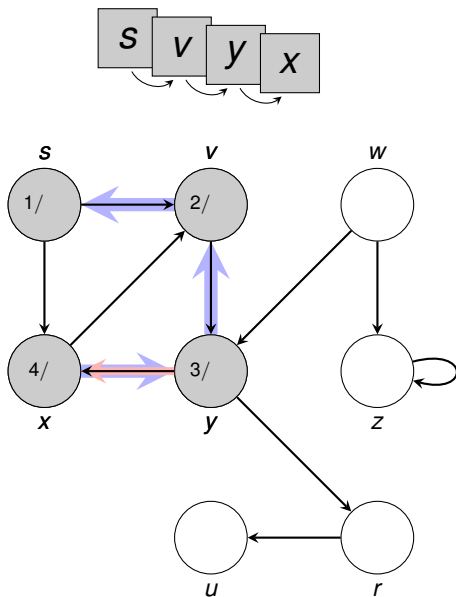
Execution of DFS



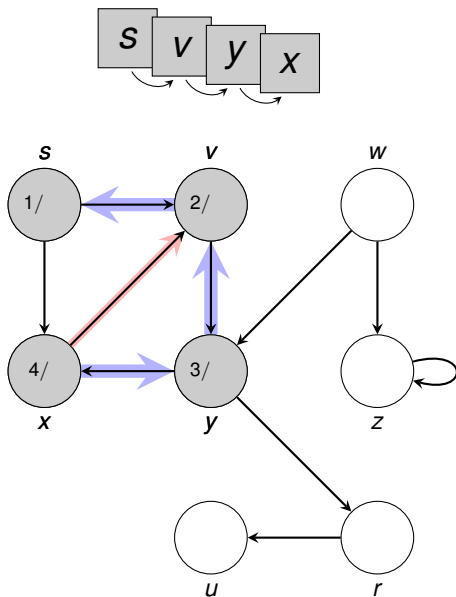
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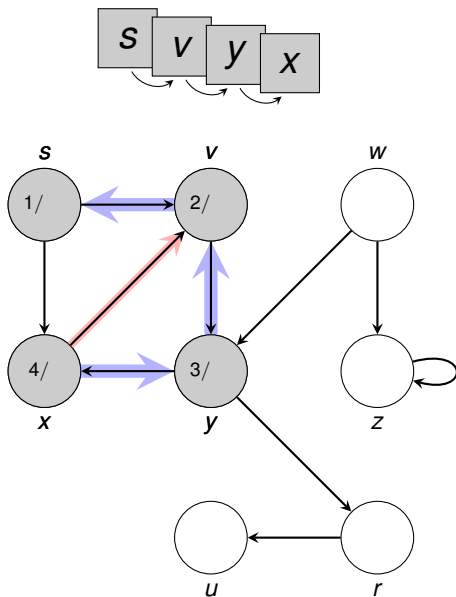
Execution of DFS



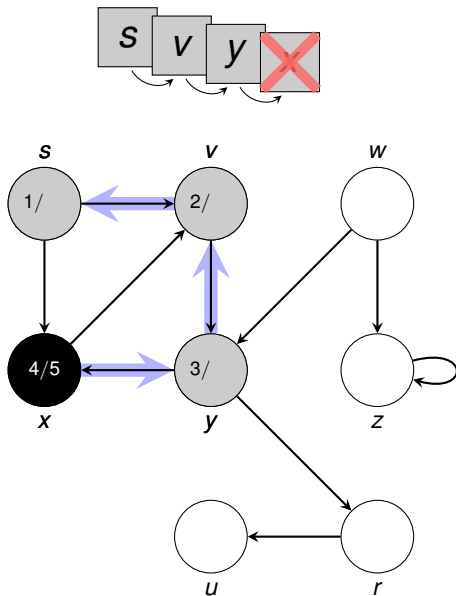
Execution of DFS



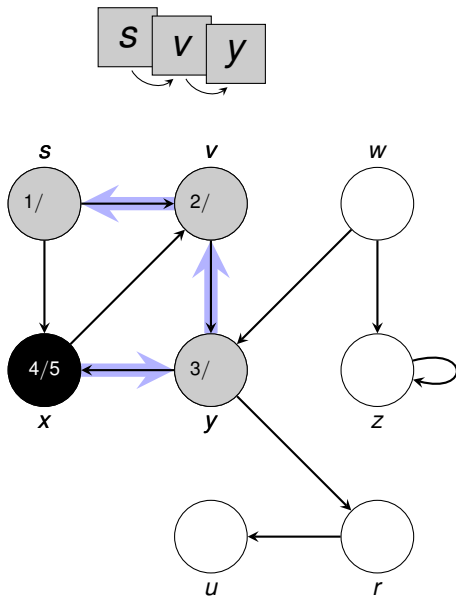
Execution of DFS



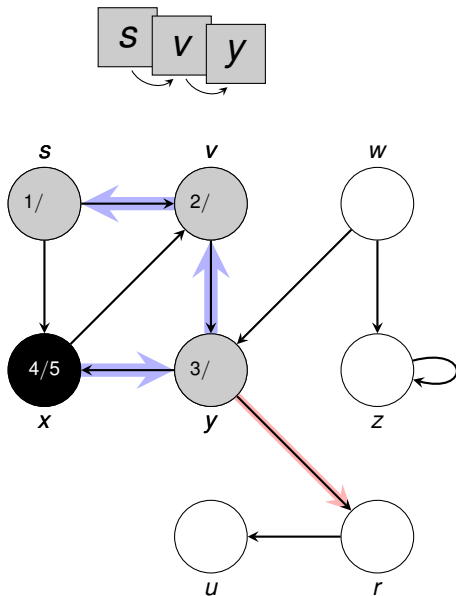
Execution of DFS



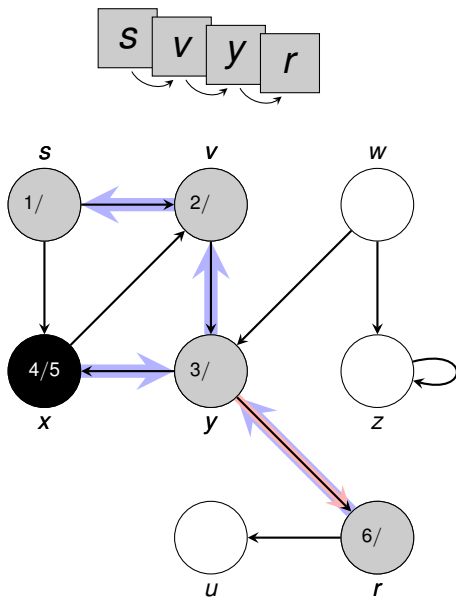
Execution of DFS



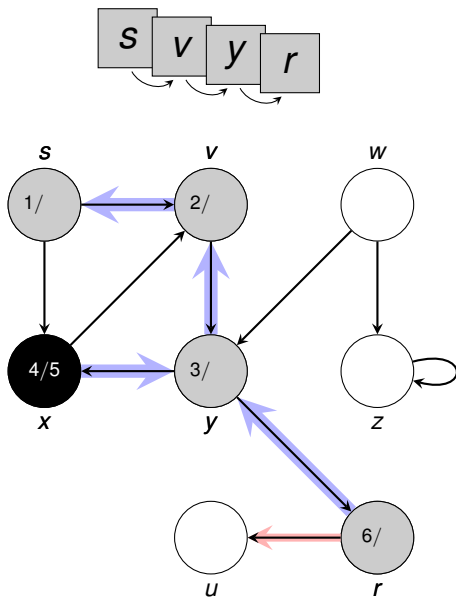
Execution of DFS



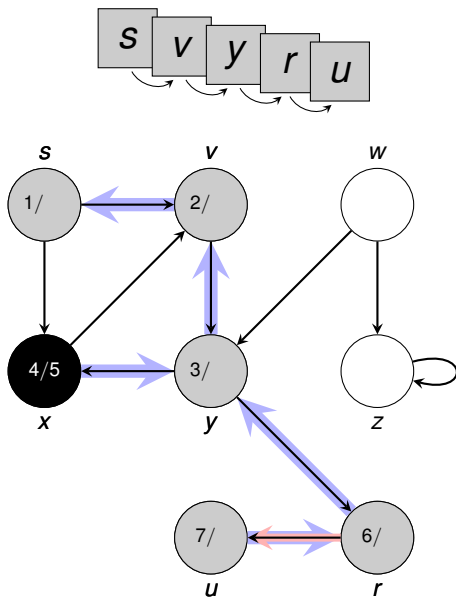
Execution of DFS



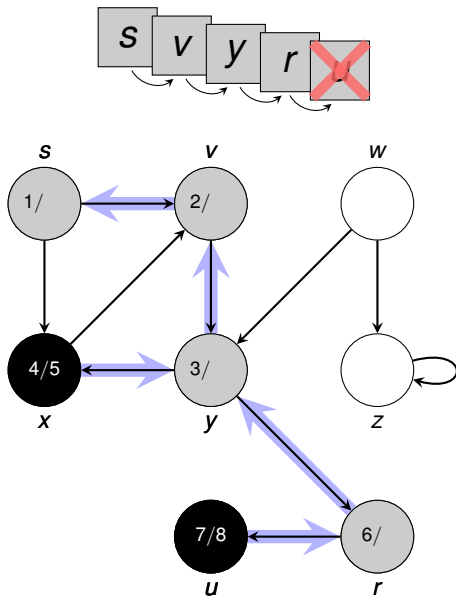
Execution of DFS



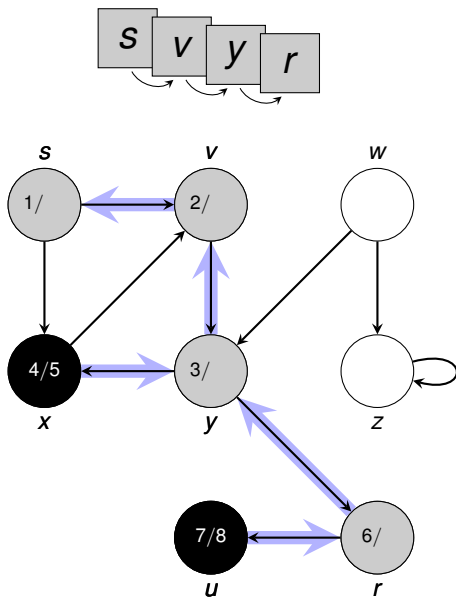
Execution of DFS



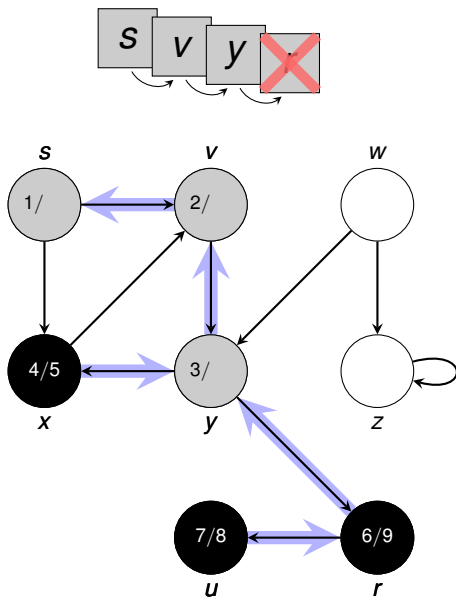
Execution of DFS



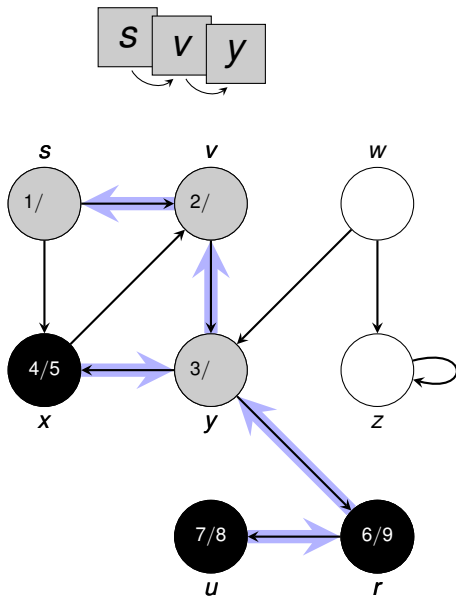
Execution of DFS



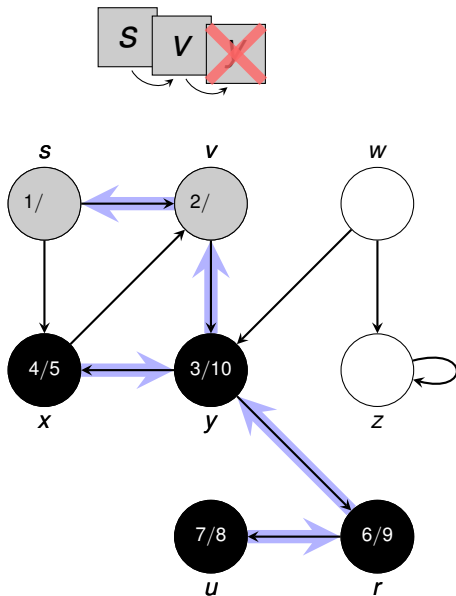
Execution of DFS



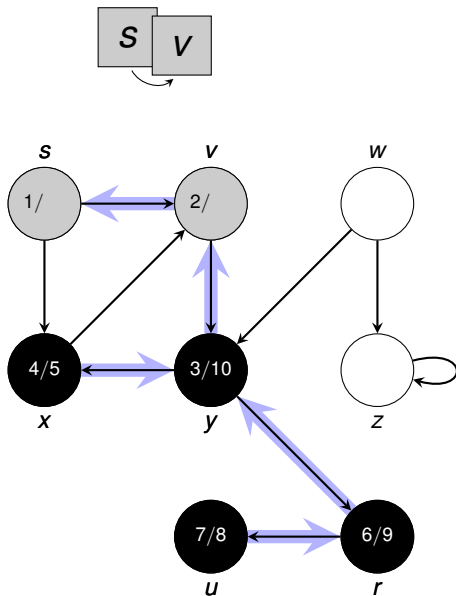
Execution of DFS



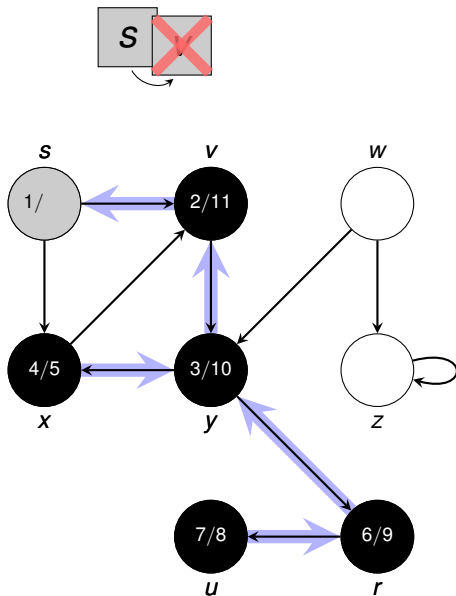
Execution of DFS



Execution of DFS

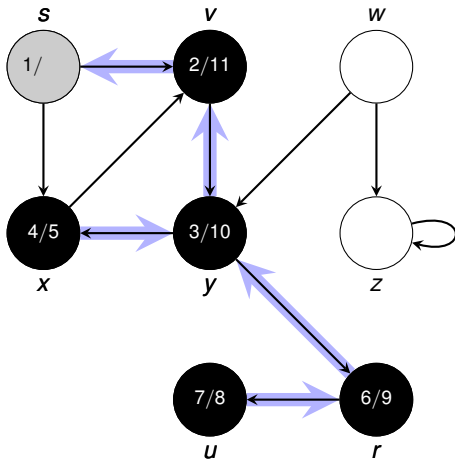


Execution of DFS



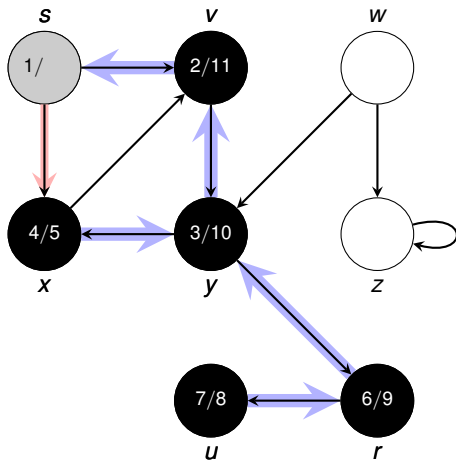
Execution of DFS

S



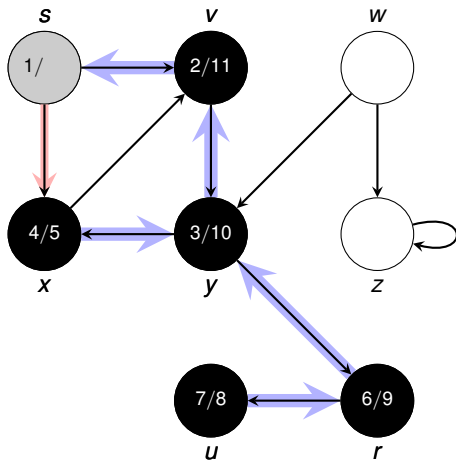
Execution of DFS

S

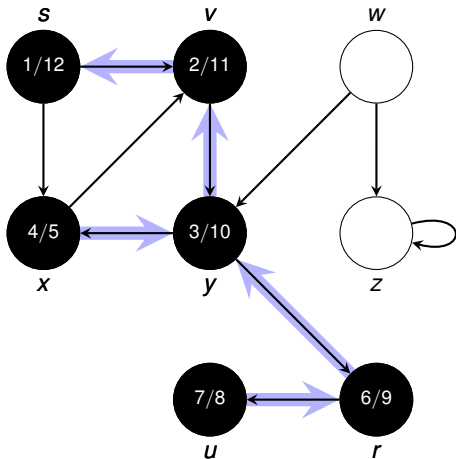


Execution of DFS

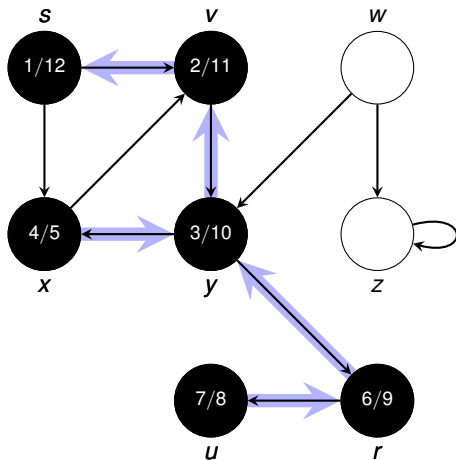
S



Execution of DFS

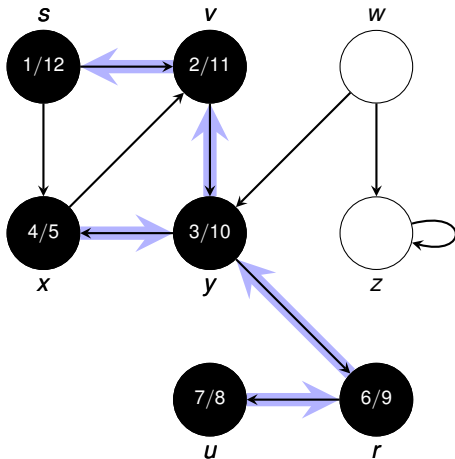


Execution of DFS



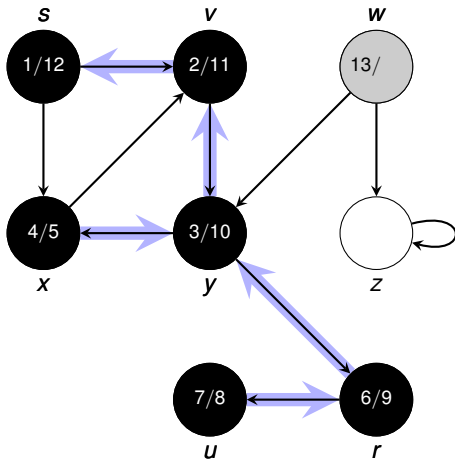
Execution of DFS

W



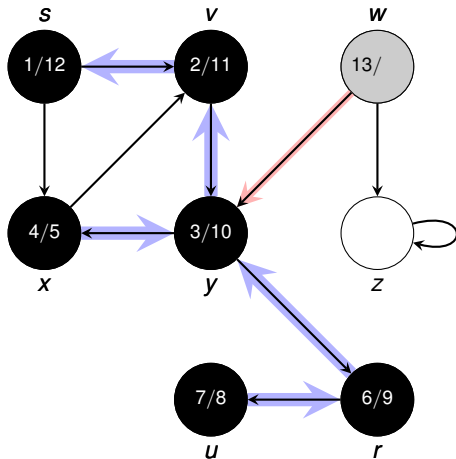
Execution of DFS

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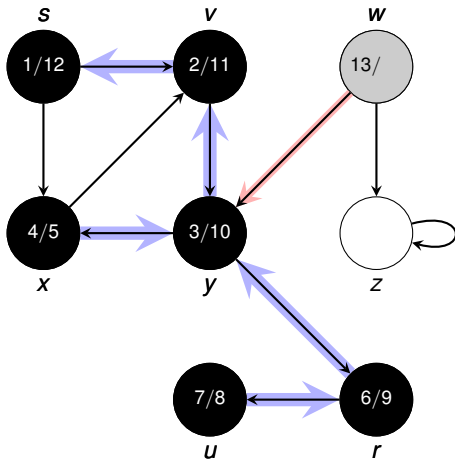
Execution of DFS

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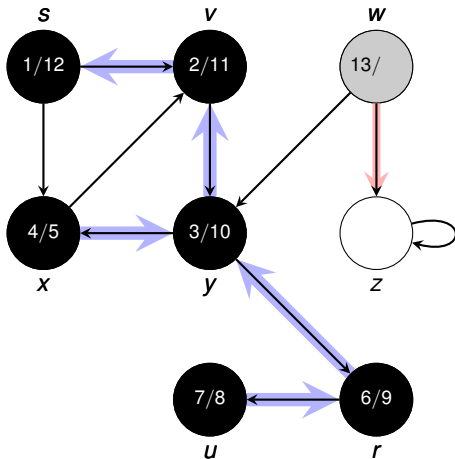
Execution of DFS

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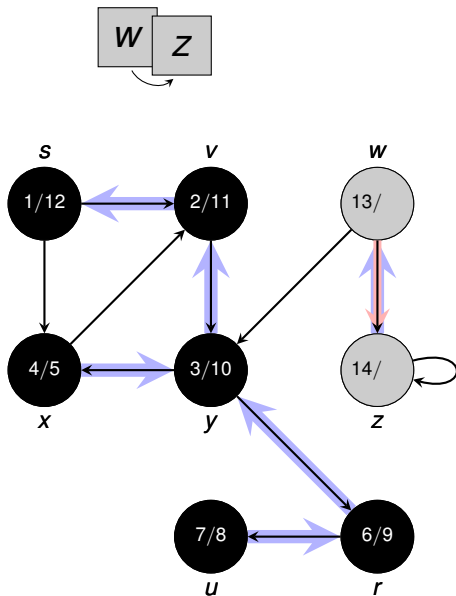


Execution of DFS

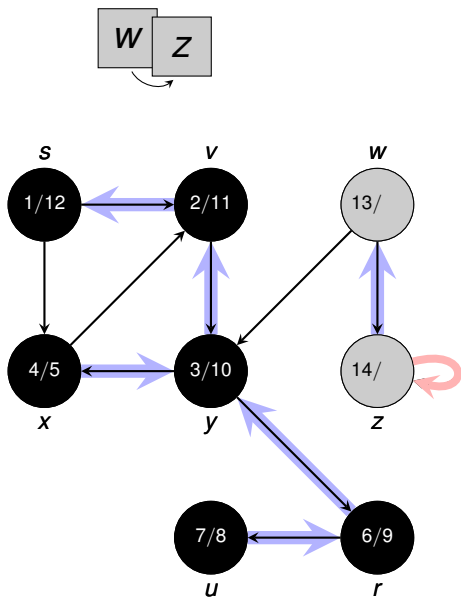
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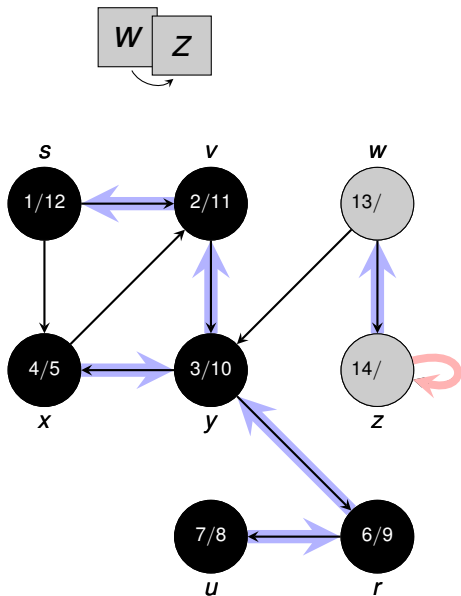
Execution of DFS



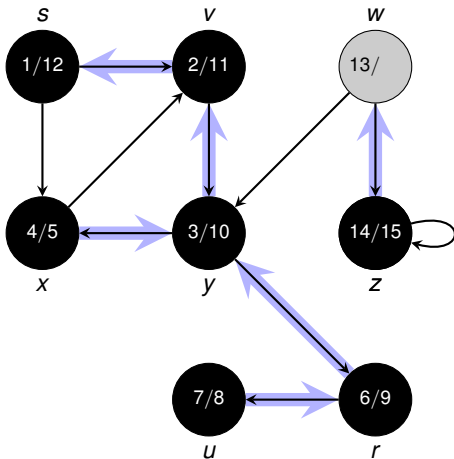
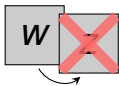
Execution of DFS



Execution of DFS

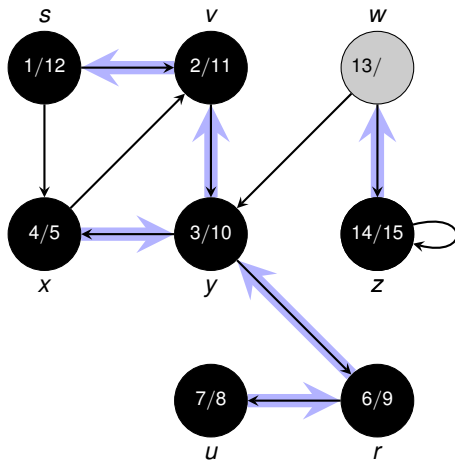


Execution of DFS

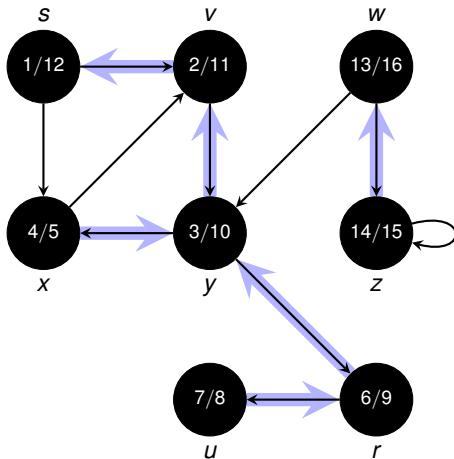


Execution of DFS

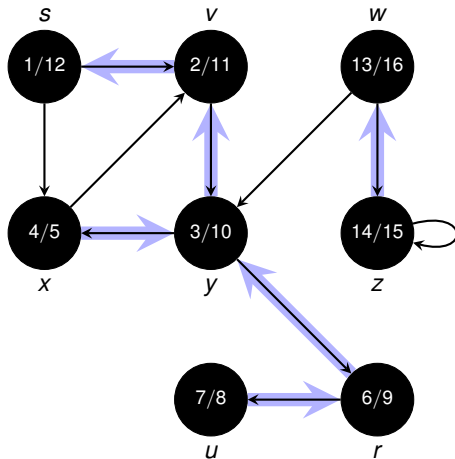
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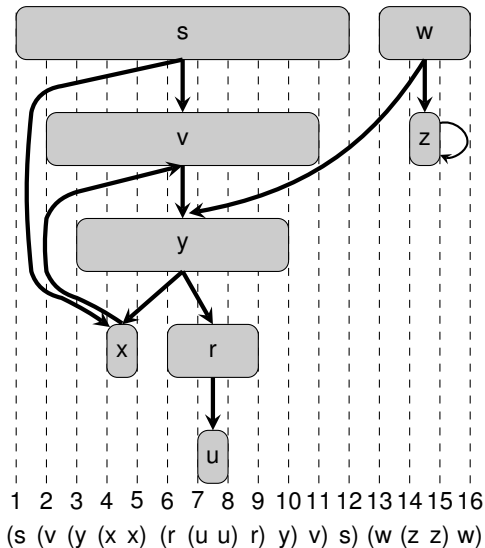
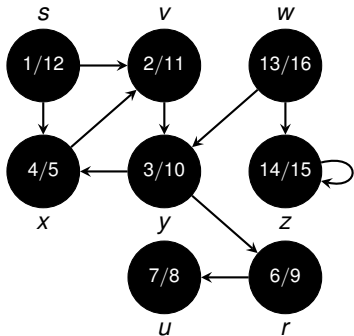
Execution of DFS



Execution of DFS



Paranthesis Theorem (Theorem 22.7)



Outline

Introduction to Graphs and Graph Searching

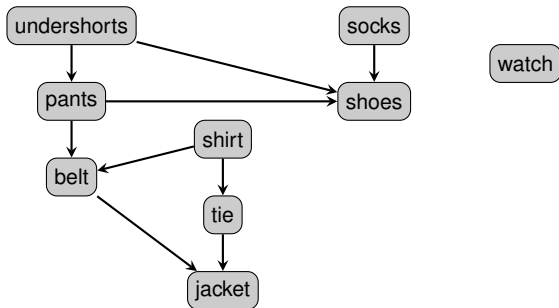
Breadth-First Search

Depth-First Search

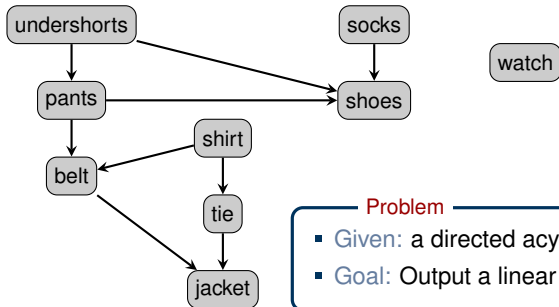
Topological Sort



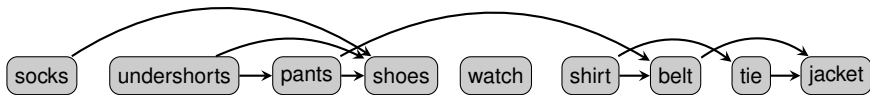
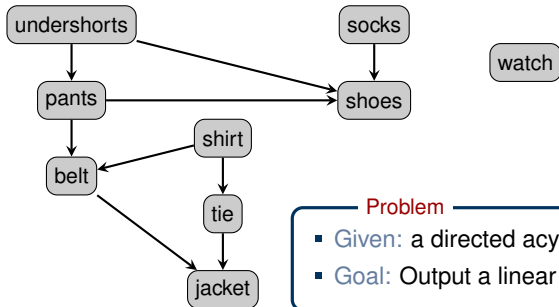
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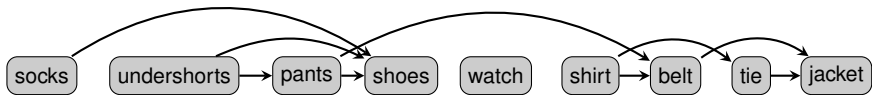
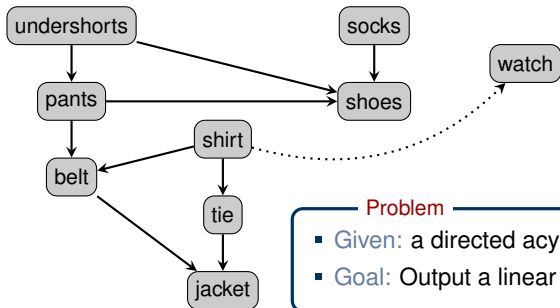
Topological Sort



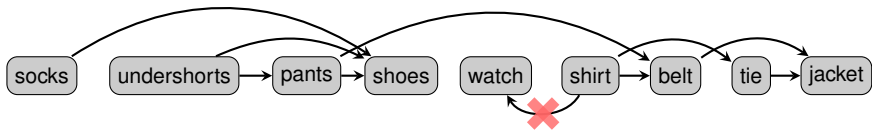
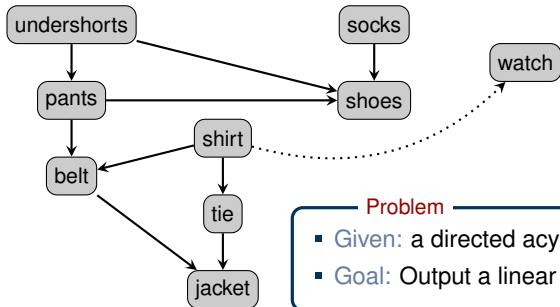
Topological Sort



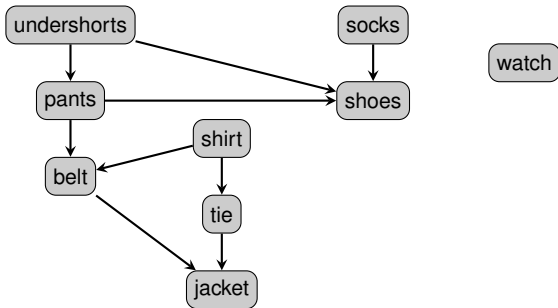
Topological Sort



Topological Sort



Solving Topological Sort

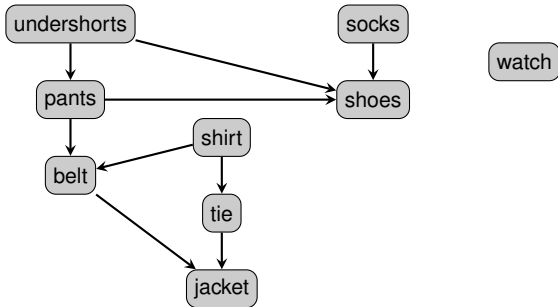


Knuth's Algorithm (1968)

- Perform DFS's so that all vertices are visited
- Output vertices in decreasing order of their finishing time



Solving Topological Sort



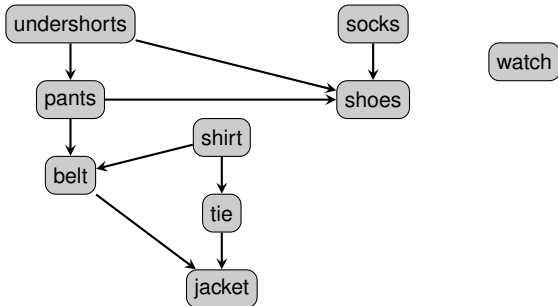
Knuth's Algorithm (1968)

- Perform DFS's so that all vertices are visited
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Runtime $O(V + E)$



Solving Topological Sort



Knuth's Algorithm (1968)

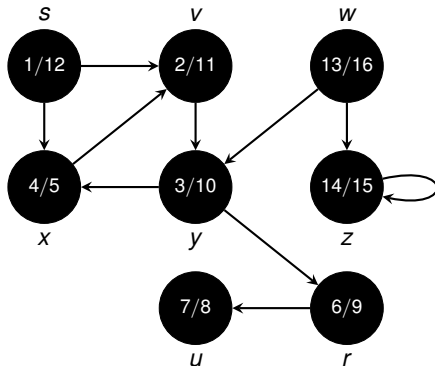
- Perform DFS's so that all vertices are visited
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Runtime $O(V + E)$

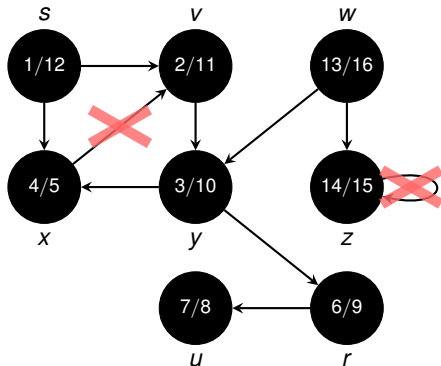
Don't need to sort the vertices – use DFS directly!



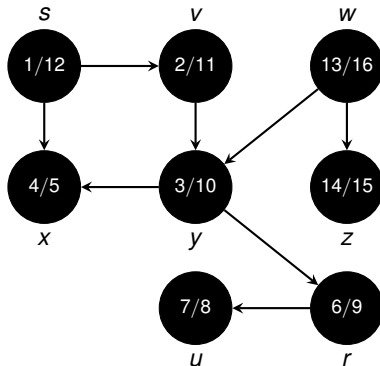
Execution of Knuth's Algorithm



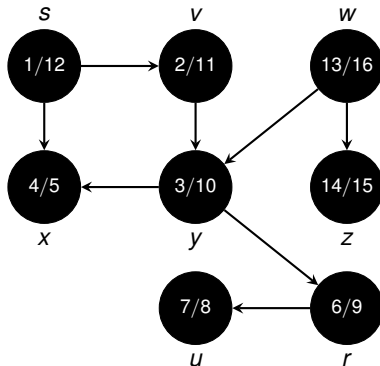
Execution of Knuth's Algorithm



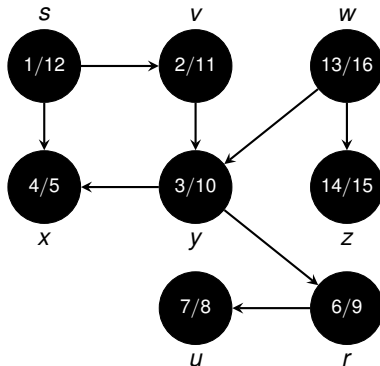
Execution of Knuth's Algorithm



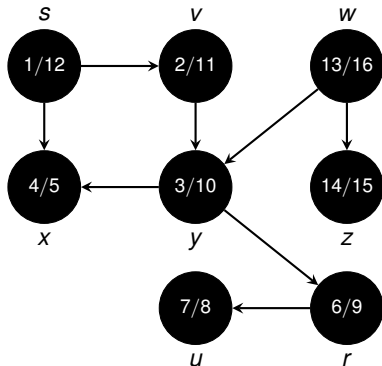
Execution of Knuth's Algorithm



Execution of Knuth's Algorithm



Execution of Knuth's Algorithm



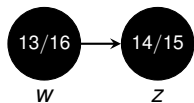
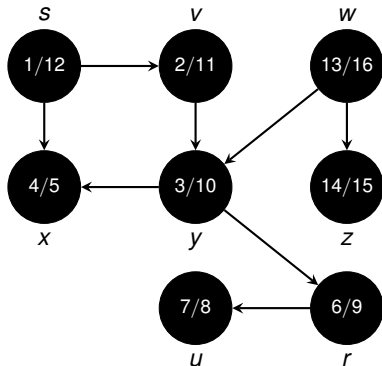
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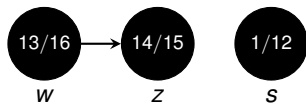
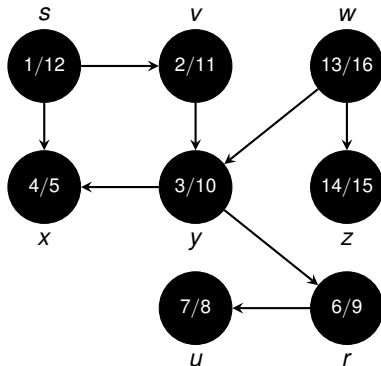
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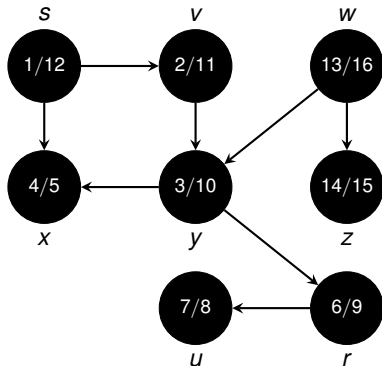
Execution of Knuth's Algorithm



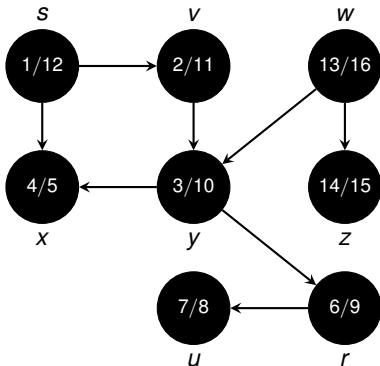
Execution of Knuth's Algorithm



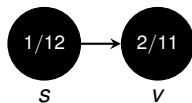
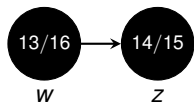
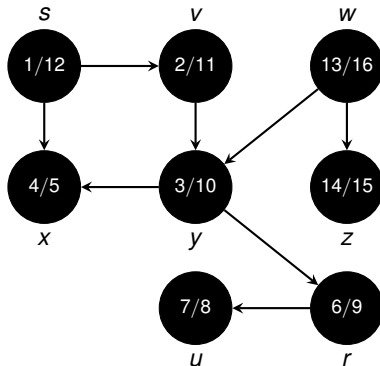
Execution of Knuth's Algorithm



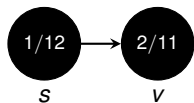
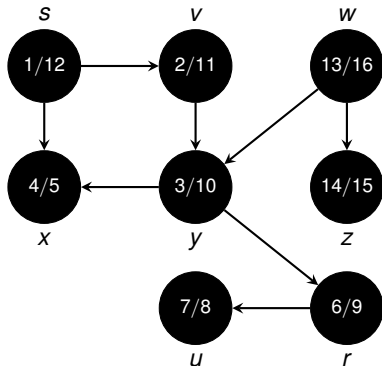
Execution of Knuth's Algorithm



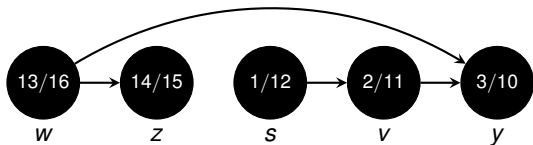
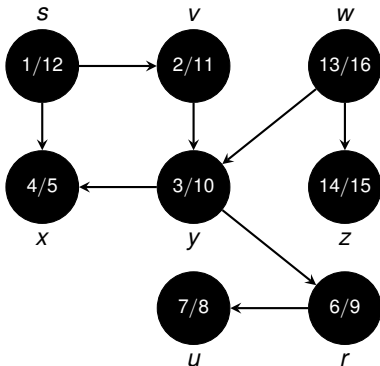
Execution of Knuth's Algorithm



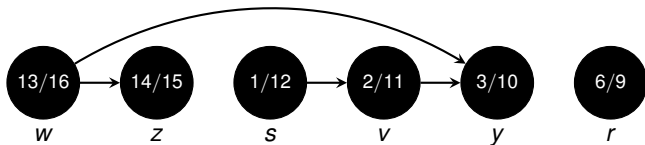
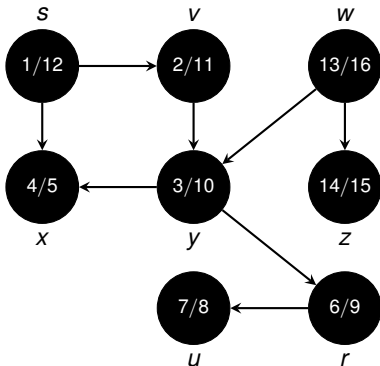
Execution of Knuth's Algorithm



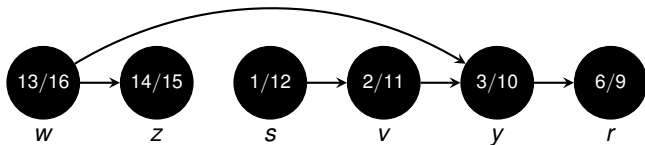
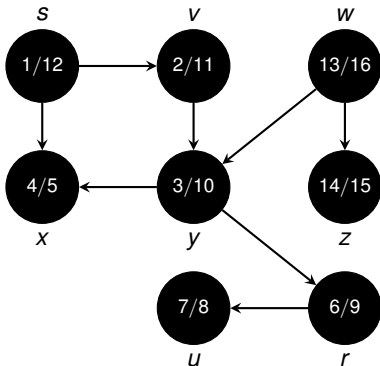
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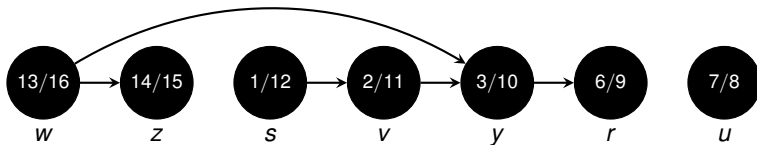
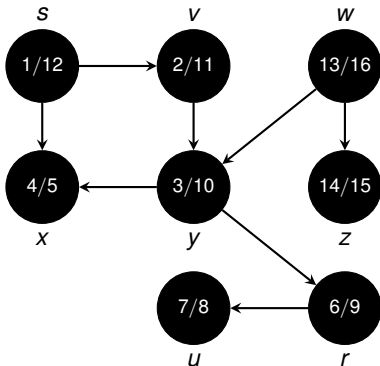
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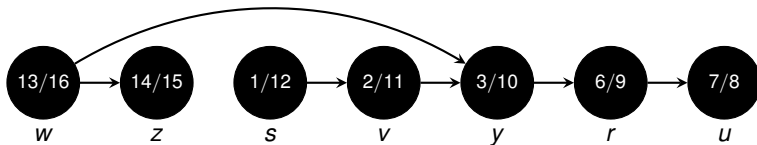
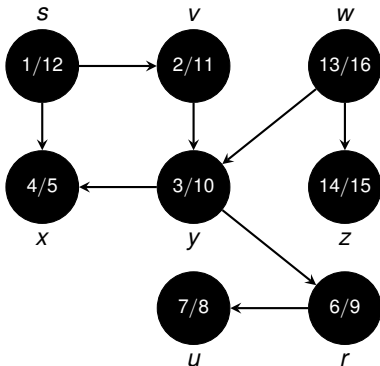
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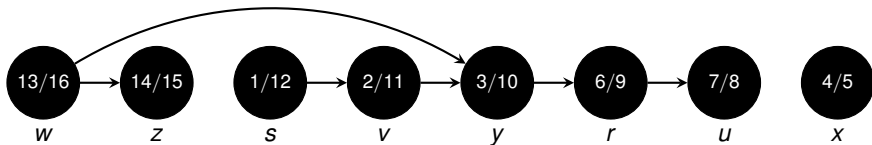
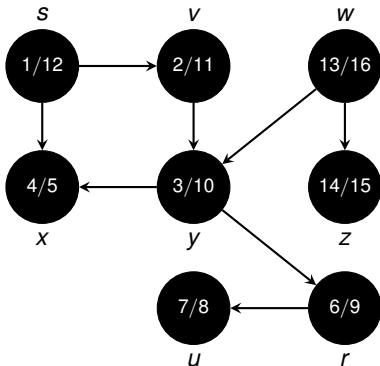
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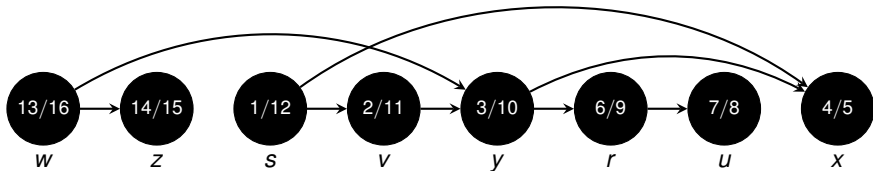
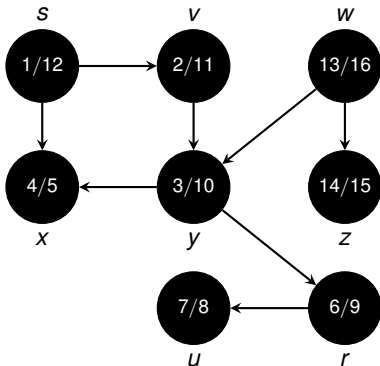
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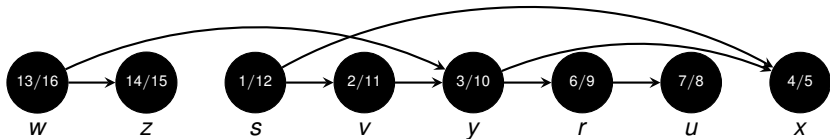
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Correctness of Topological Sort using DFS



Theorem 22.12

If the input graph is a DAG, then the algorithm computes a linear order.



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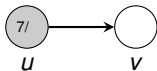
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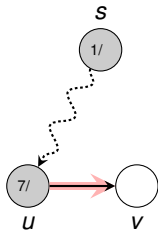
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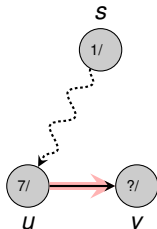
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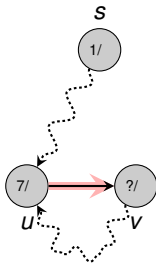
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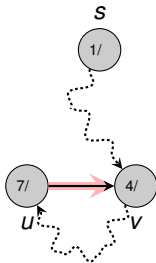
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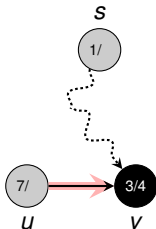
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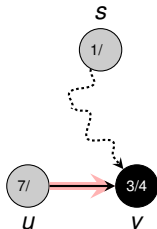
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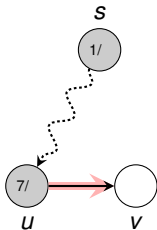
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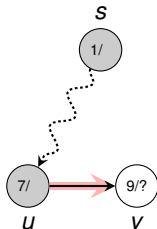
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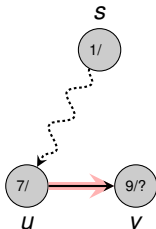
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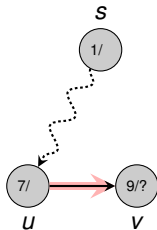
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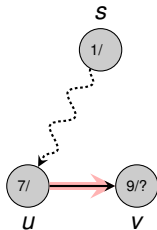
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Breadth-First-Search

- vertices are processed by a **queue**
- computes **distances** and **shortest paths**
~> similar idea used later in Prim's and Dijkstra's algorithm
- Runtime $\mathcal{O}(V + E)$



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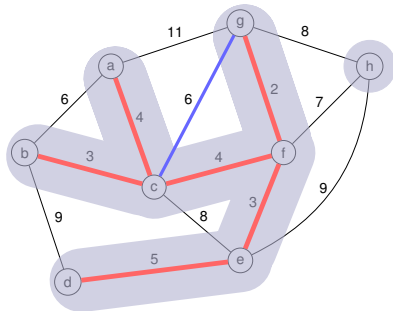
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- Runtime $\mathcal{O}(V + E)$



Depth-First-Search

- vertices are processed by **recursive calls** (\approx stack)
- discovery and finishing times
- application: **Topological Sorting** of DAGs
- Runtime $\mathcal{O}(V + E)$





6.3: Minimum Spanning Tree

Frank Stajano

Thomas Sauerwald

Lent 2016

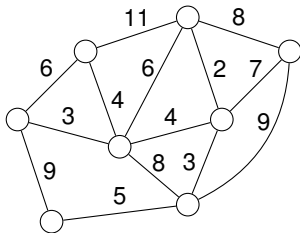


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Minimum Spanning Tree Problem

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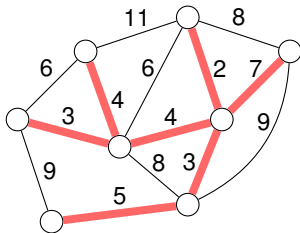
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Minimum Spanning Tree Problem

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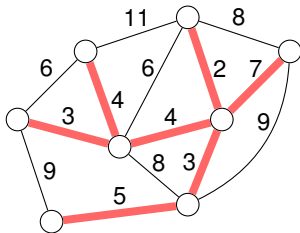


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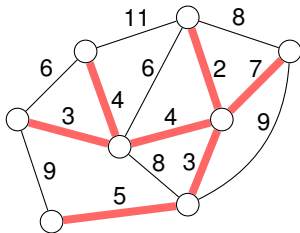
Must be necessarily a tree!



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Applications

- Street Networks, Wiring Electronic Components, Laying Pipes
- **Weights** may represent distances, costs, travel times, capacities, resistance etc.



Generic Algorithm

```
0: def minimum spanningTree(G)
1:   A = empty set of edges
2:   while A does not span all vertices yet:
3:     add a safe edge to A
```



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An edge of G is **safe** if by adding the edge to A , the resulting subgraph is still a subset of a minimum spanning tree.



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How to find a safe edge?



Definitions

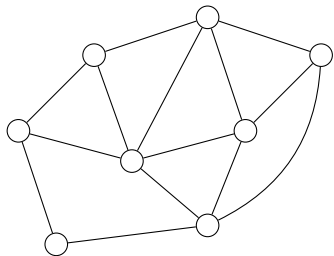
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Finding safe edges

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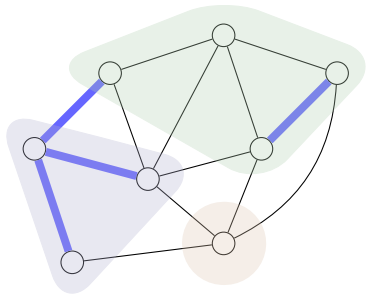
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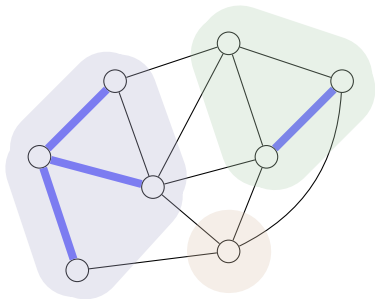
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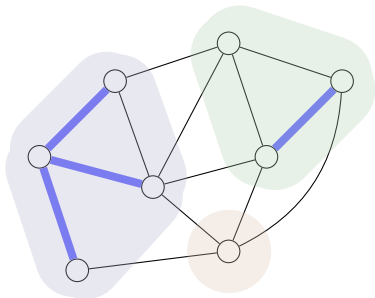
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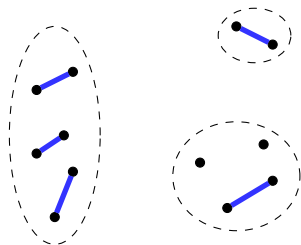


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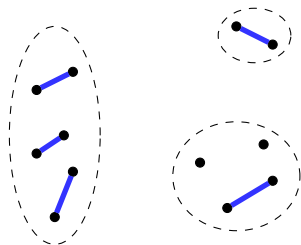
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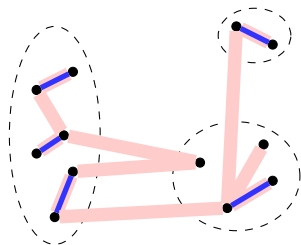
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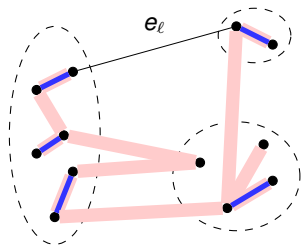
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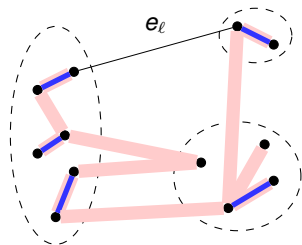
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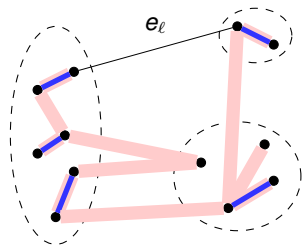
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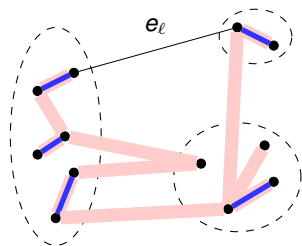
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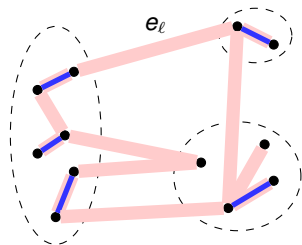
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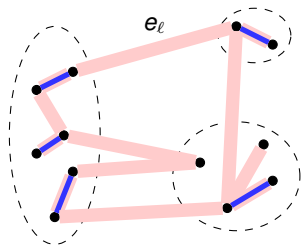
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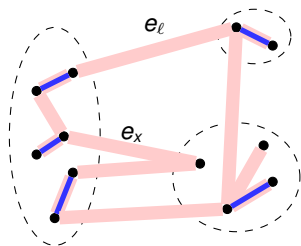
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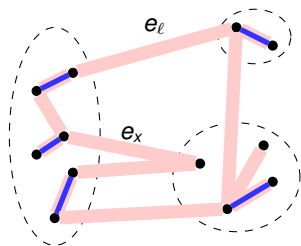
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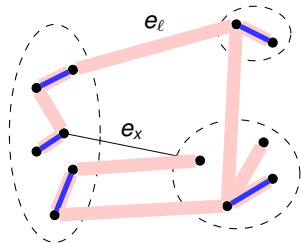
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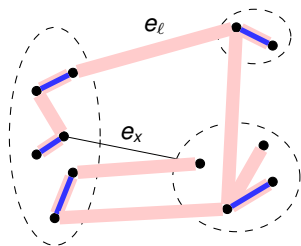
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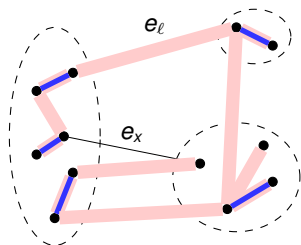
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- Let e_ℓ be the **lightest** edge across the cut
- If $e_\ell \in T$, then we are done
- If $e_\ell \notin T$, then adding e_ℓ to T introduces cycle
- This cycle crosses the cut through e_ℓ and another edge e_x
- Consider now the tree $T \cup e_\ell \setminus e_x$:
 - This tree must be a spanning tree
 - If $w(e_\ell) < w(e_x)$, then this spanning tree has smaller cost than T (**can't happen!**)



Proof of Theorem

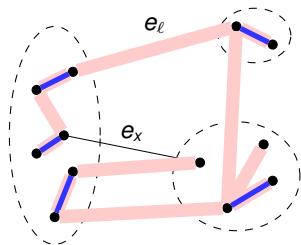
Theorem

Let $A \subseteq E$ be a subset of a MST of G . Then for any cut that respects A , the **lightest edge** of G that goes across the cut is **safe**.

Proof:

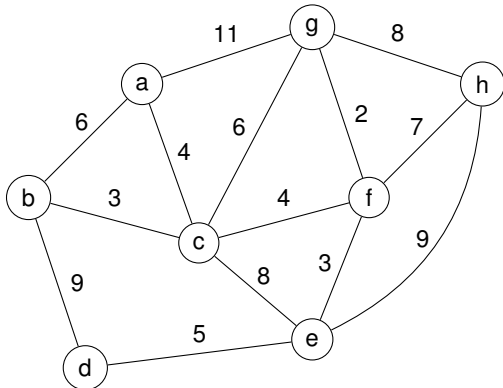
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 - If $w(e_\ell) < w(e_x)$, then this spanning tree has smaller cost than T (**can't happen!**)
 - If $w(e_\ell) = w(e_x)$, then $T \cup e_\ell \setminus e_x$ is a MST.

□



Glimpse at Kruskal's Algorithm

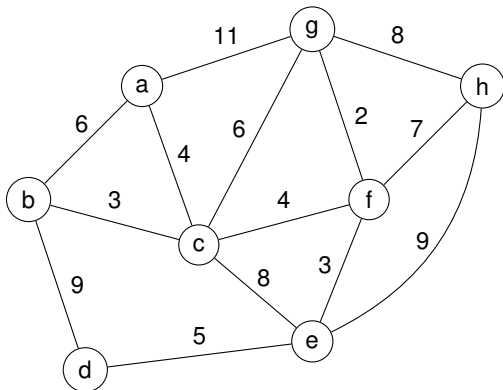
Basic Strategy



Glimpse at Kruskal's Algorithm

Basic Strategy

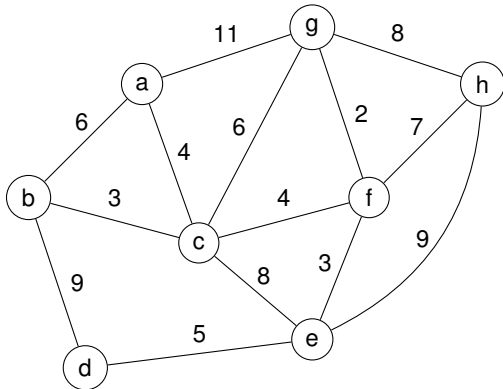
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Glimpse at Kruskal's Algorithm

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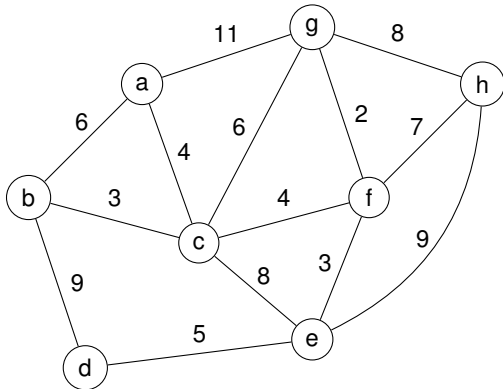
- Let $A \subseteq E$ be a forest, initially empty
- At every step,



Glimpse at Kruskal's Algorithm

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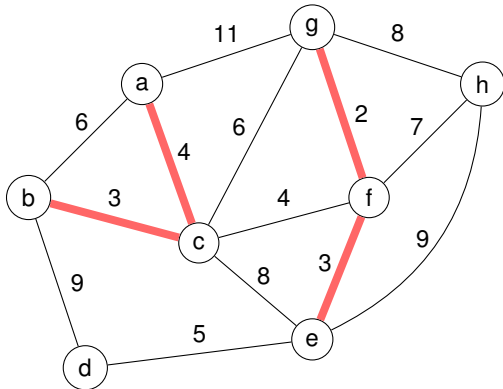
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Glimpse at Kruskal's Algorithm

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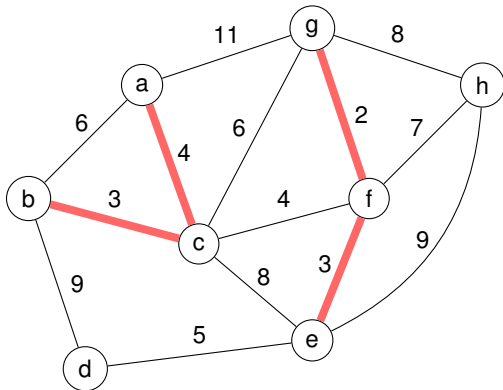
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Glimpse at Kruskal's Algorithm

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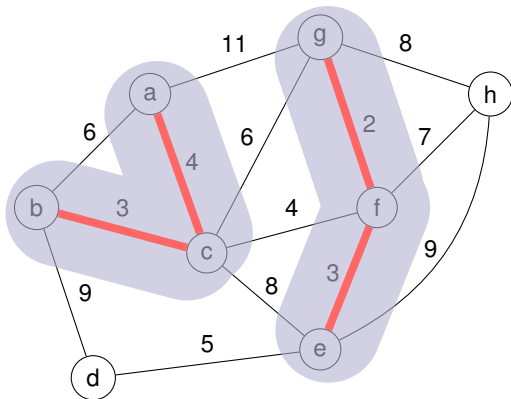
- Let $A \subseteq E$ be a forest, initially empty
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Glimpse at Kruskal's Algorithm

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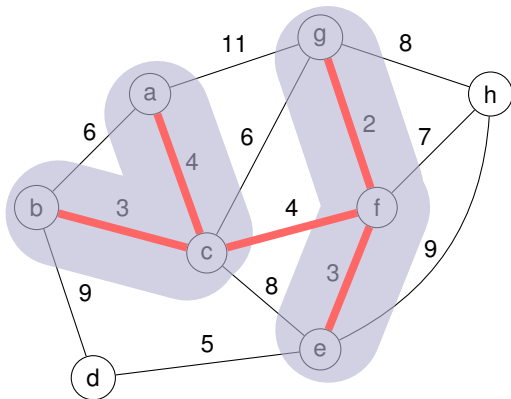
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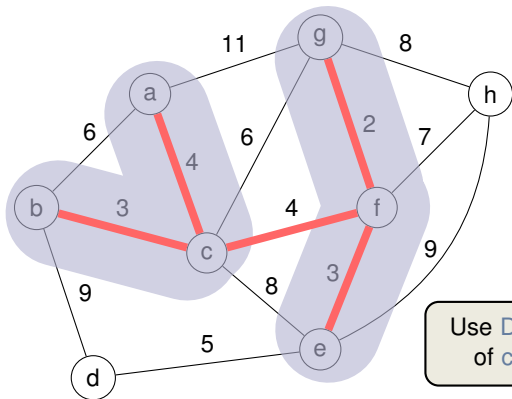
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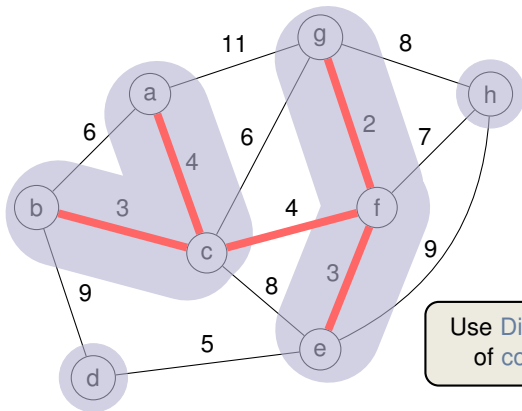
Use Disjoint Sets to keep track of connected components!



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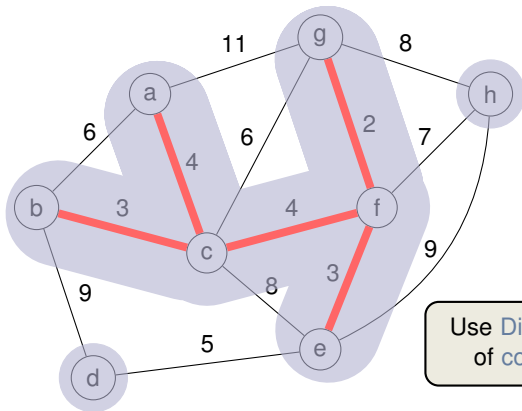
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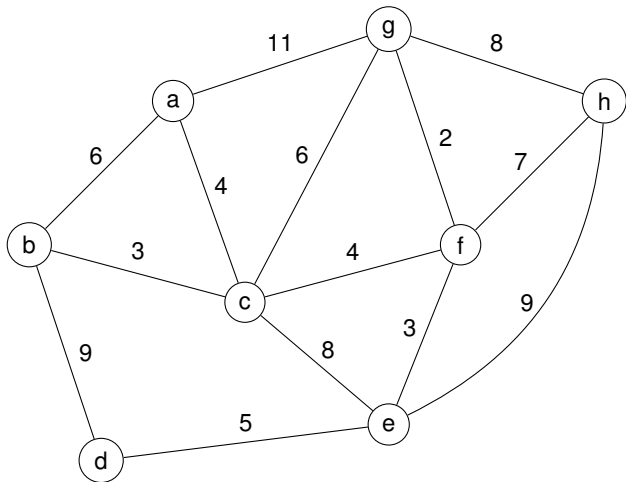
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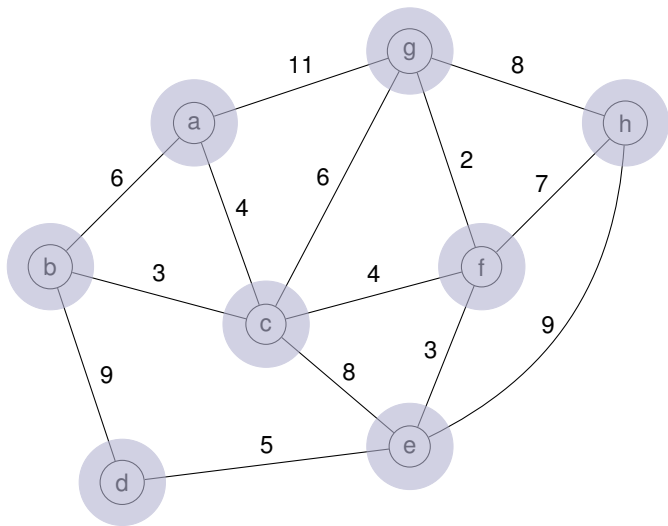
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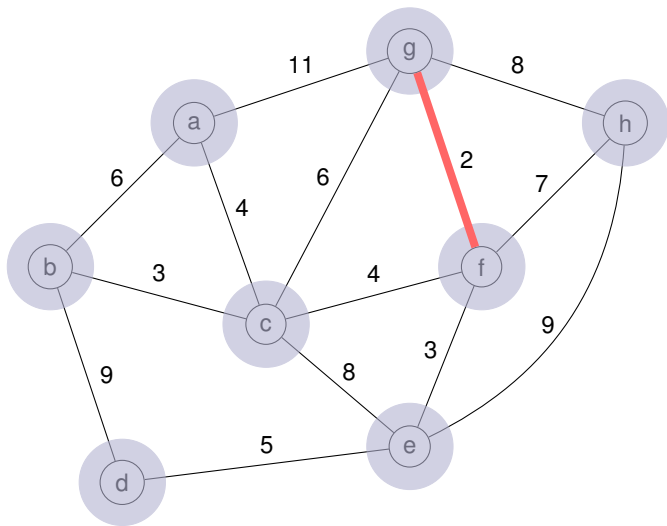
Execution of Kruskal's Algorithm



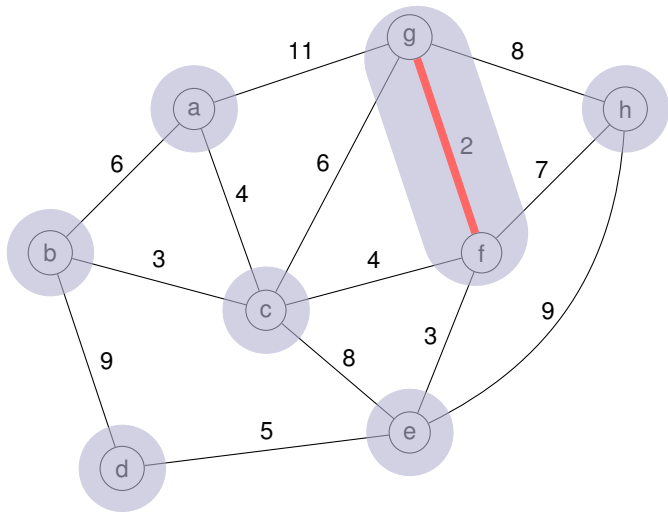
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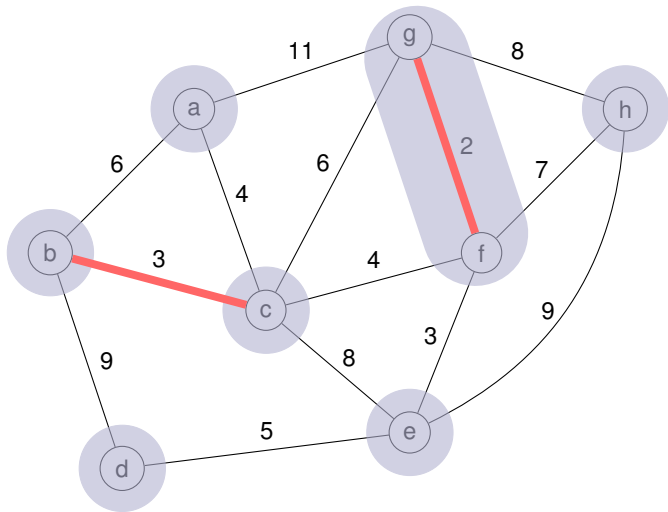
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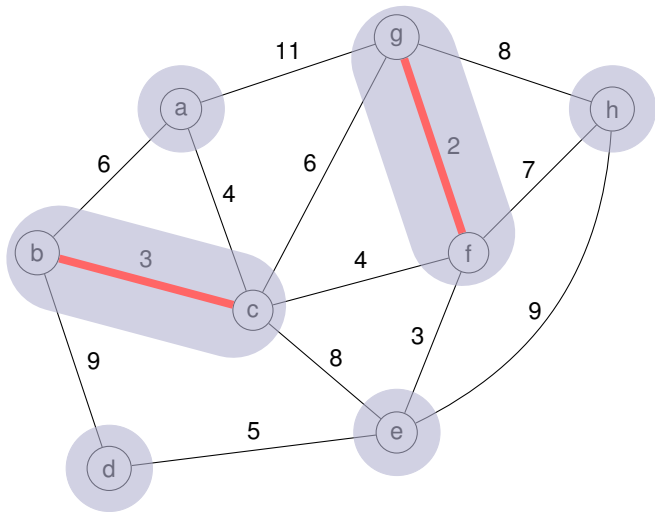
Execution of Kruskal's Algorithm



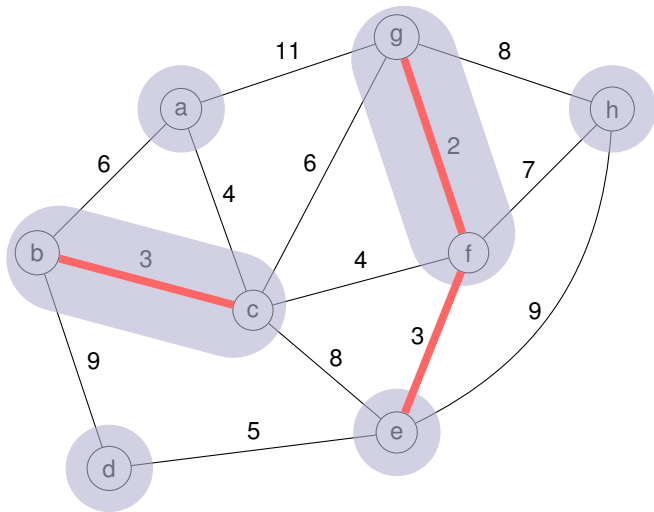
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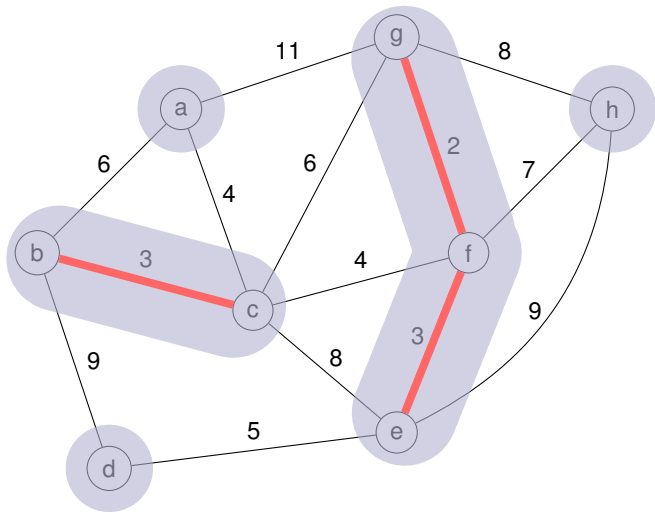
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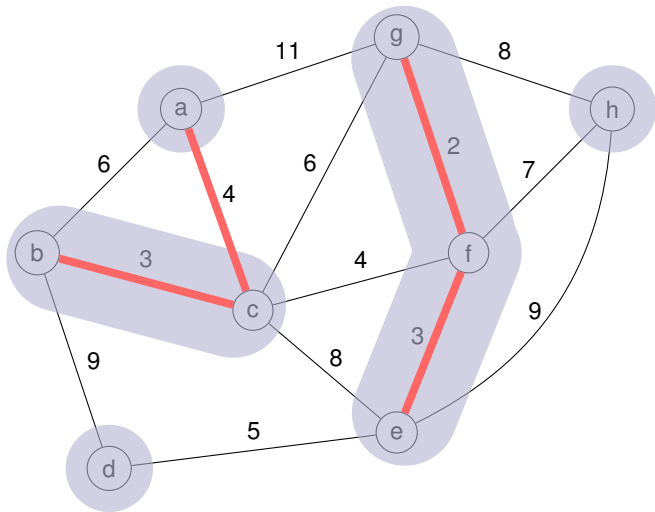
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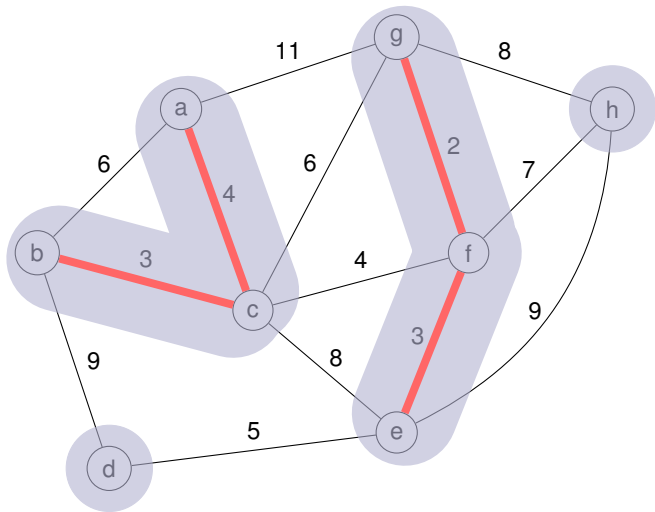
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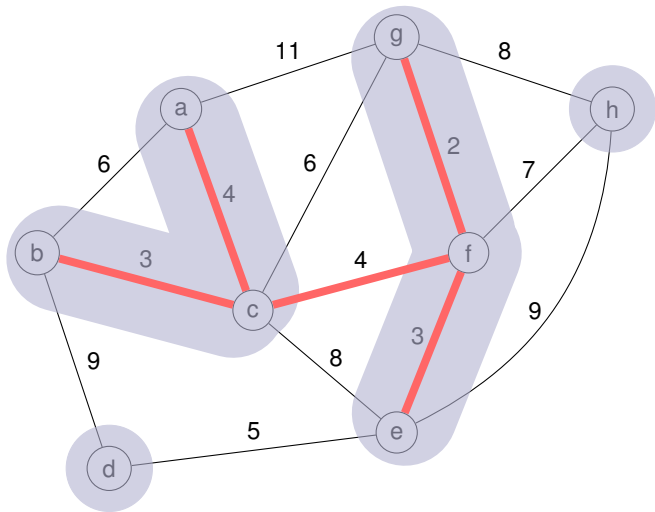
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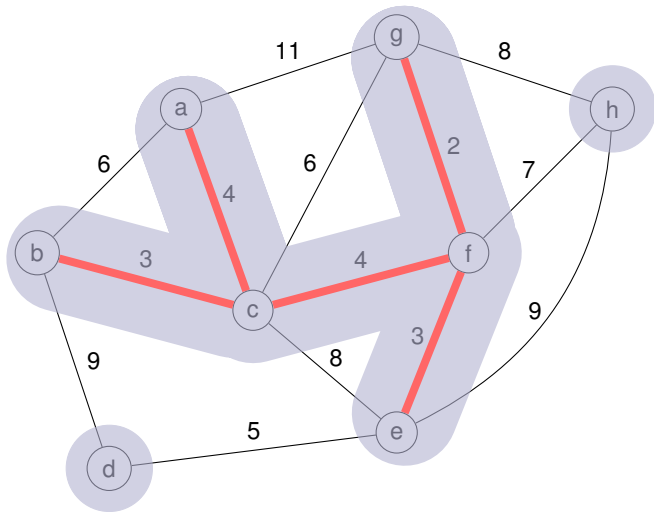
Execution of Kruskal's Algorithm



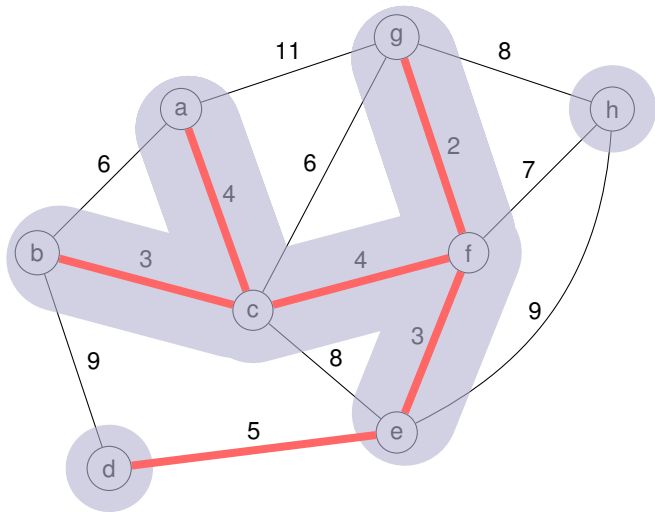
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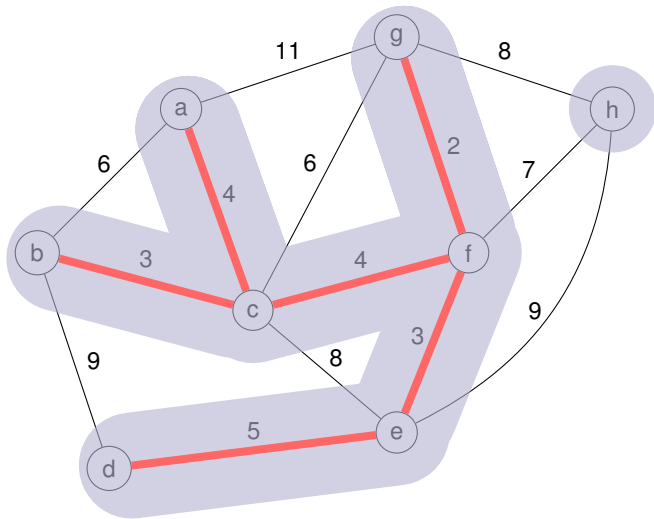
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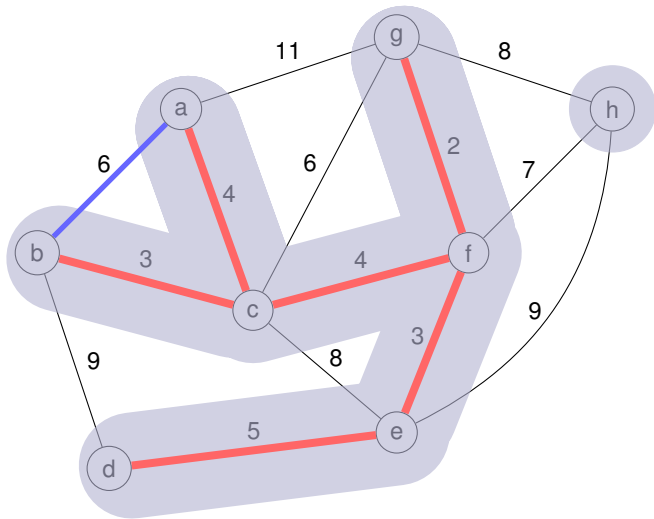
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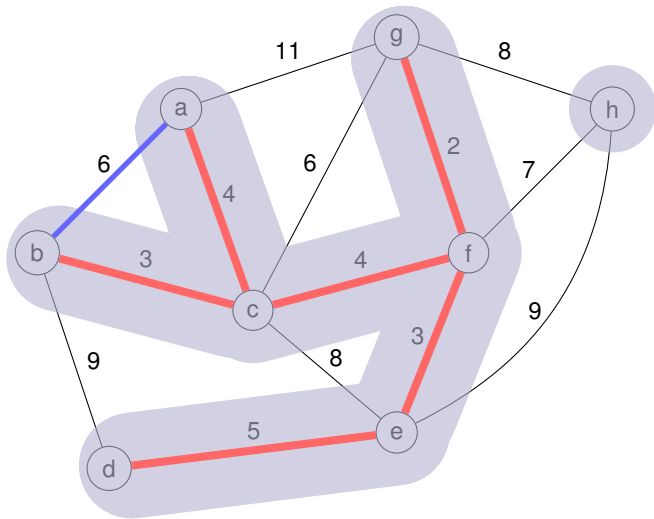
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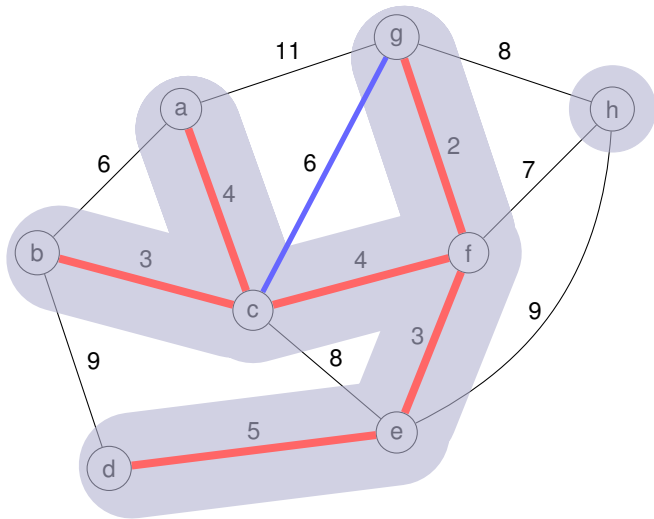
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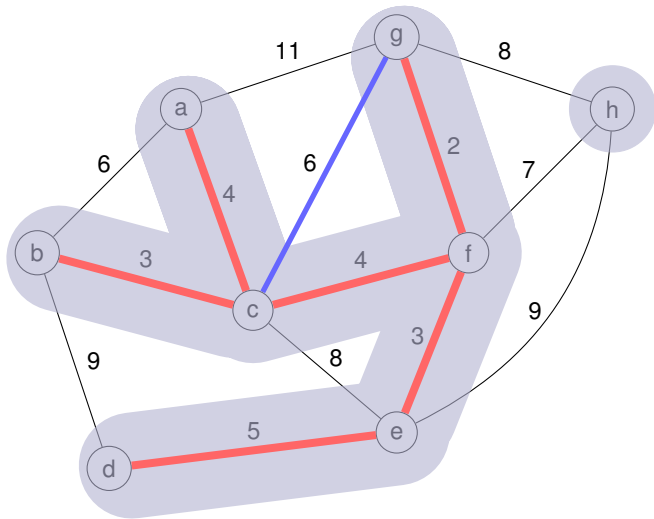
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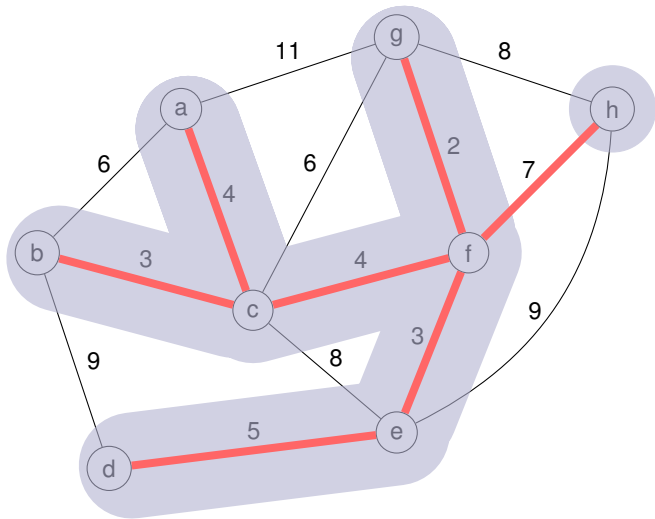
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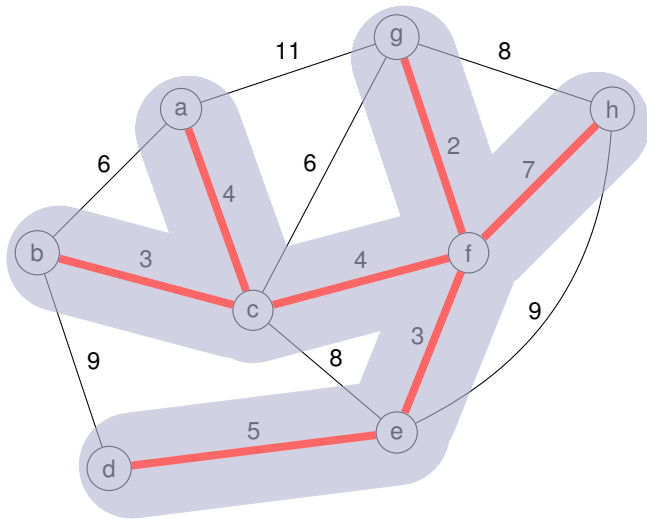
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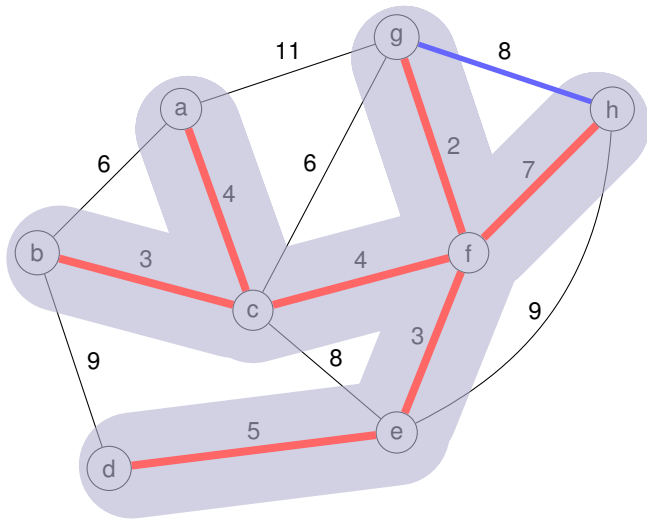
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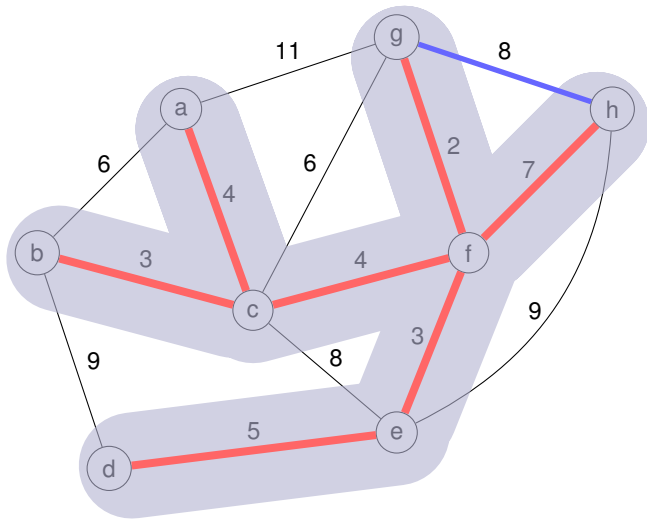
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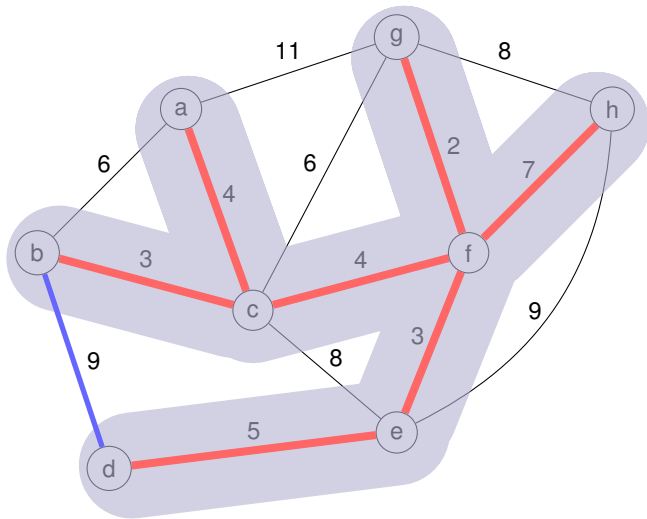
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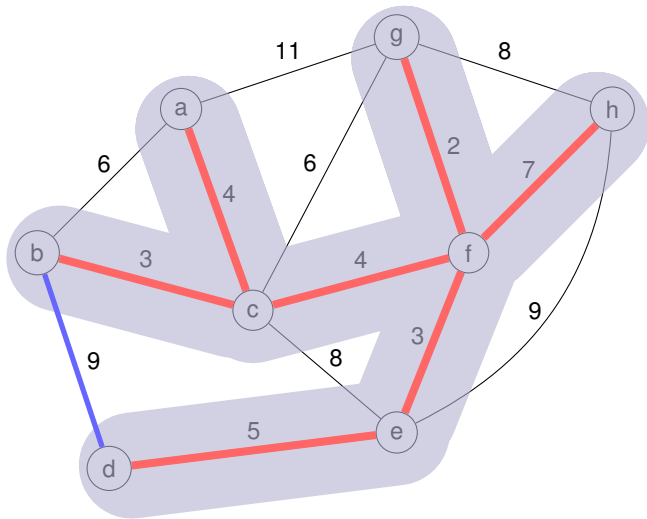
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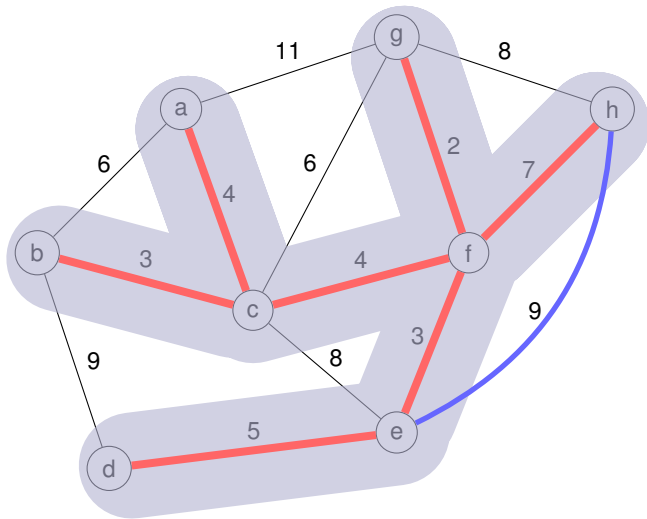
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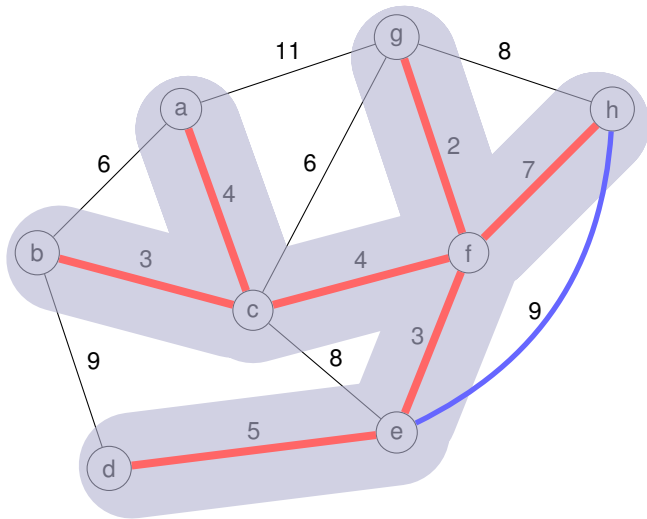
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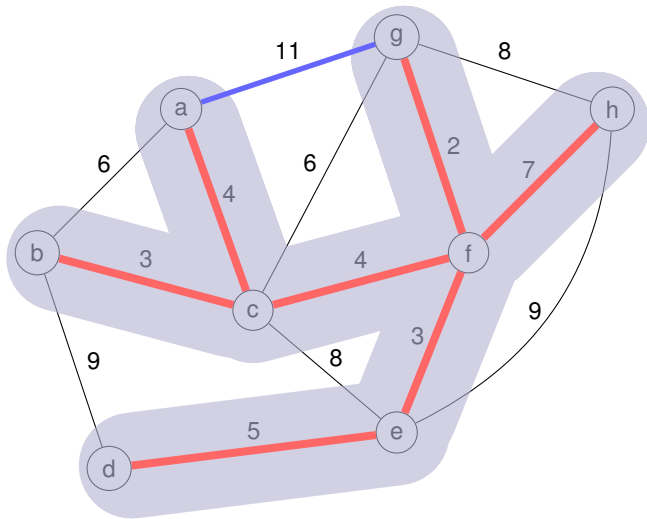
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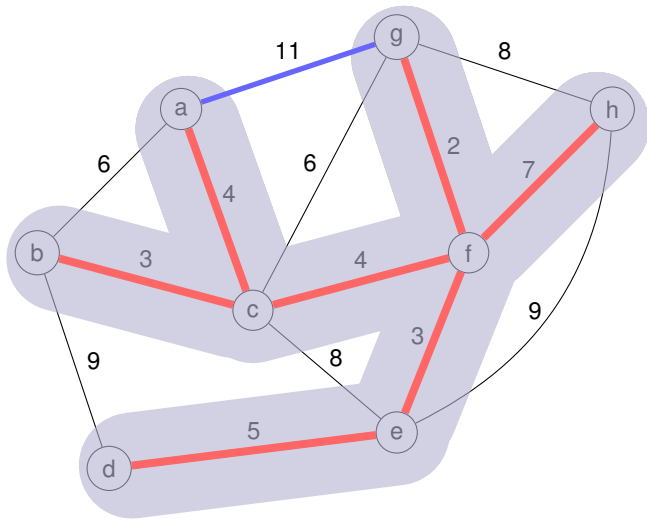
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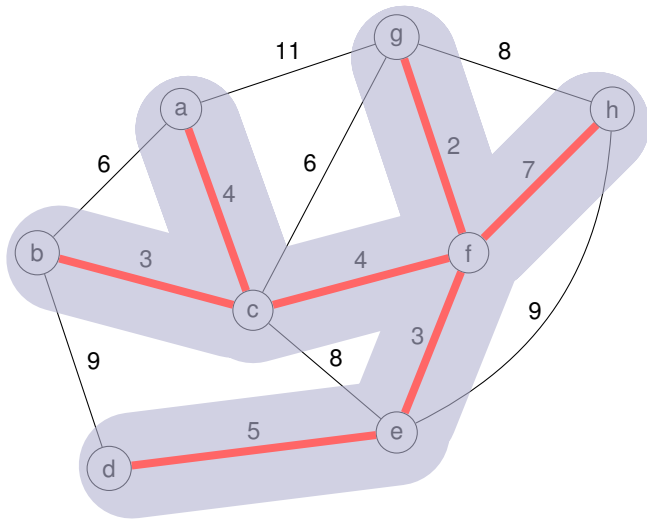
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If edges are already sorted, runtime becomes $\mathcal{O}(E \cdot \alpha(n))!$



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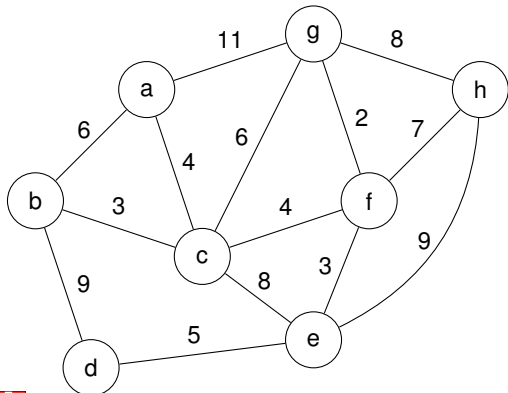
- Consider the **cut** of all connected components (disjoint sets)
- L. 14 ensures that we extend A by an edge that **goes across the cut**
- This edge is also the **lightest edge** crossing the cut (otherwise, we would have included a lighter edge before)



Prim's Algorithm

Basic Strategy

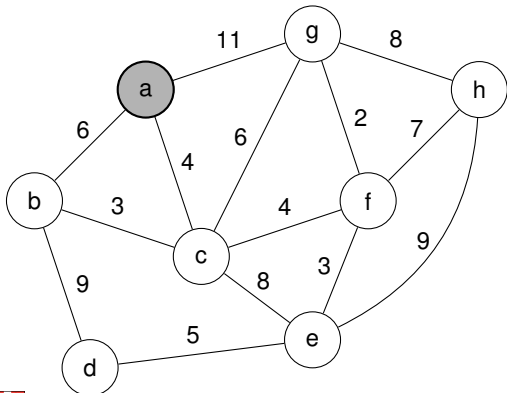
- Start **growing a tree** from a designated root vertex



Prim's Algorithm

Basic Strategy

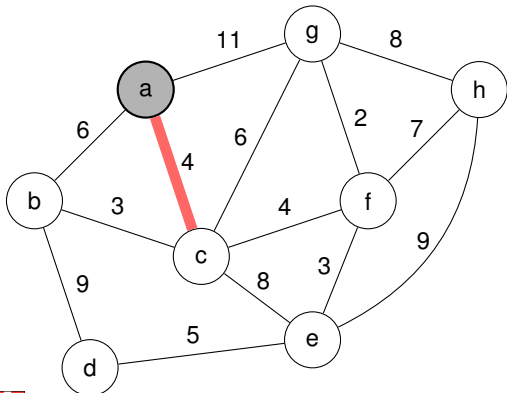
- Start **growing a tree** from a designated root vertex
- At each step, **add lightest edge** linked to A that does not yield cycle



Prim's Algorithm

Basic Strategy

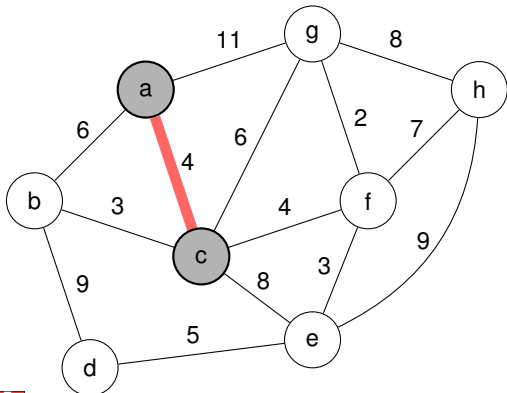
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Prim's Algorithm

Basic Strategy

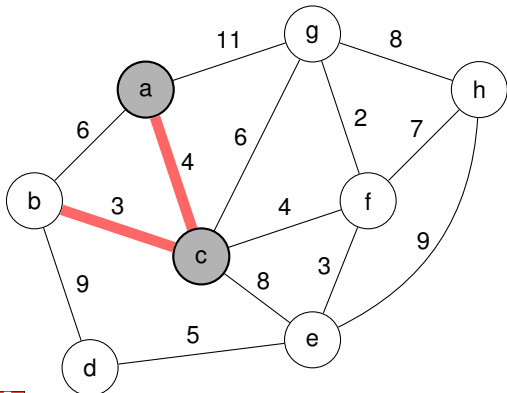
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Prim's Algorithm

Basic Strategy

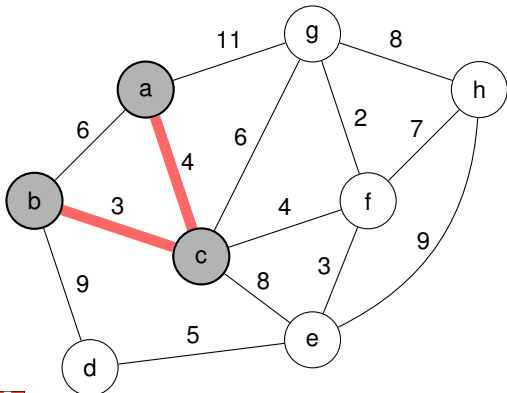
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Prim's Algorithm

Basic Strategy

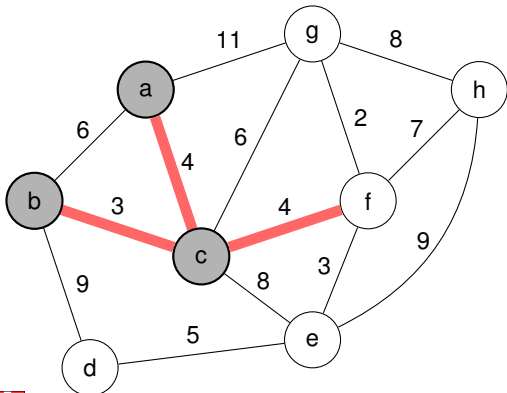
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Prim's Algorithm

Basic Strategy

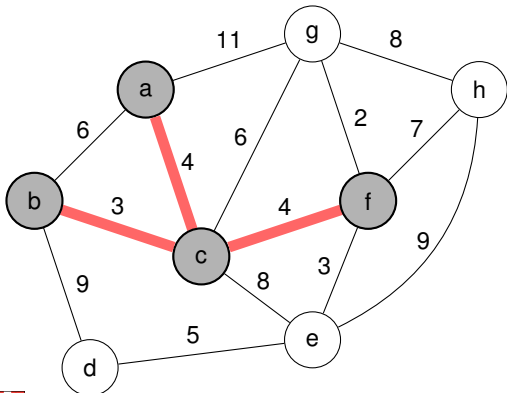
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Prim's Algorithm

Basic Strategy

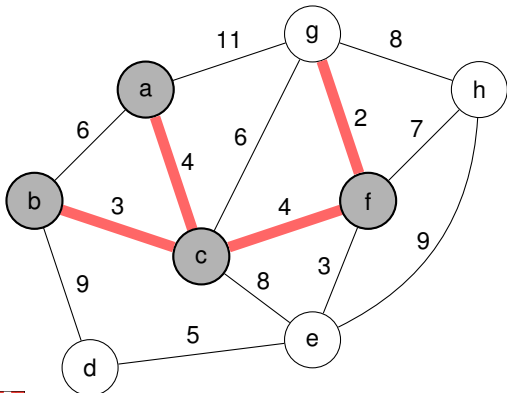
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Prim's Algorithm

Basic Strategy

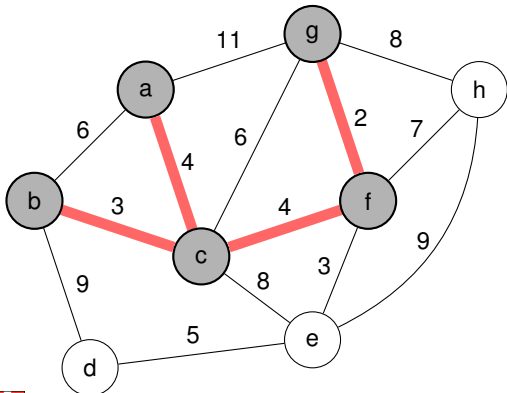
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Prim's Algorithm

Basic Strategy

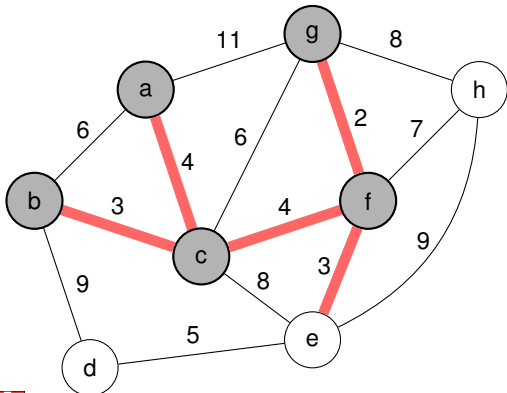
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Prim's Algorithm

Basic Strategy

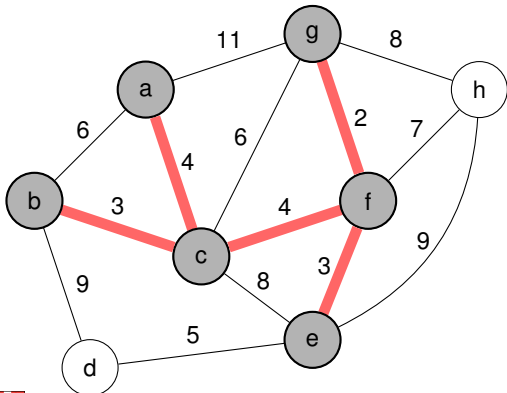
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Prim's Algorithm

Basic Strategy

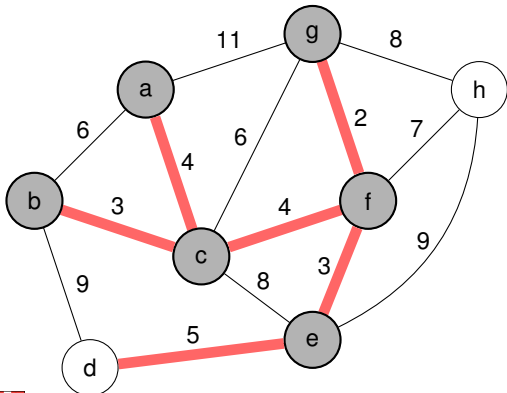
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Prim's Algorithm

Basic Strategy

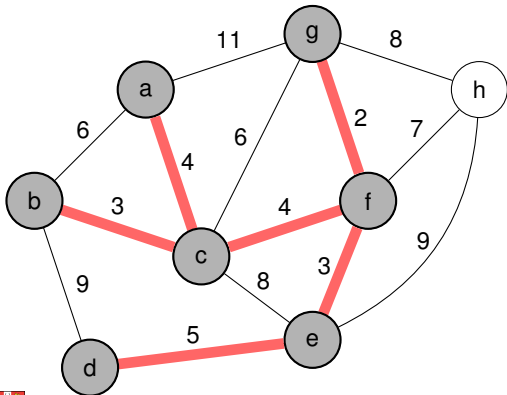
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Prim's Algorithm

Basic Strategy

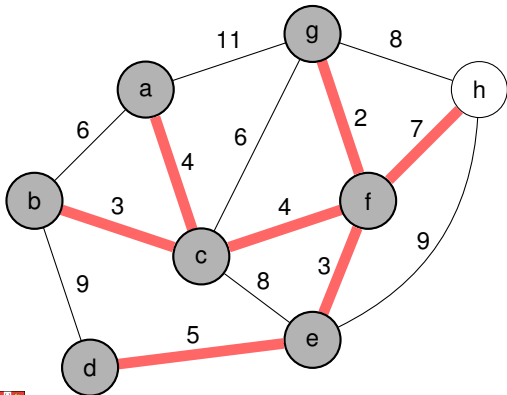
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Prim's Algorithm

Basic Strategy

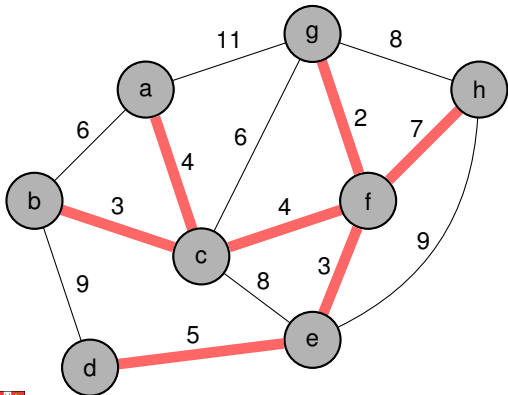
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Prim's Algorithm

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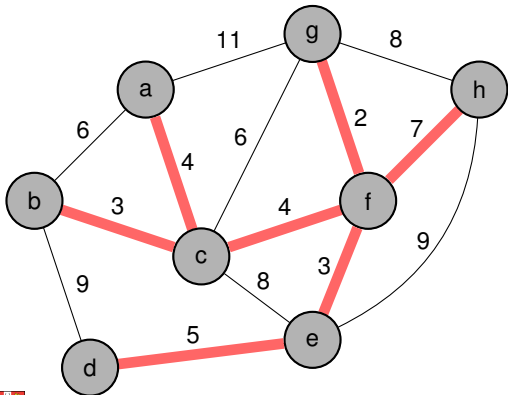


Prim's Algorithm

Basic Strategy

- Start **growing a tree** from a designated root vertex
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Implementation will be based on **vertices!**

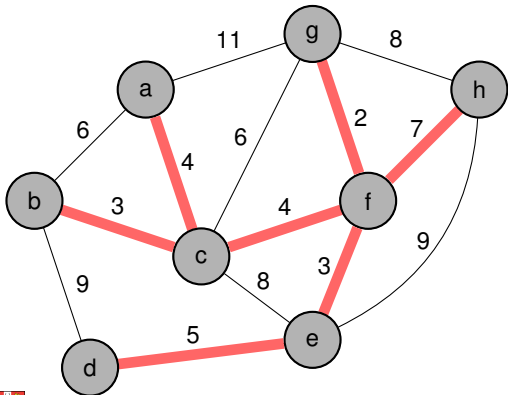


Prim's Algorithm

Basic Strategy

- Start **growing a tree** from a designated root vertex
- At each step, **add lightest edge** linked to A that does not yield cycle

Assign every vertex not in A a **key** which is **at all stages** equal to the smallest weight of an edge connecting to A



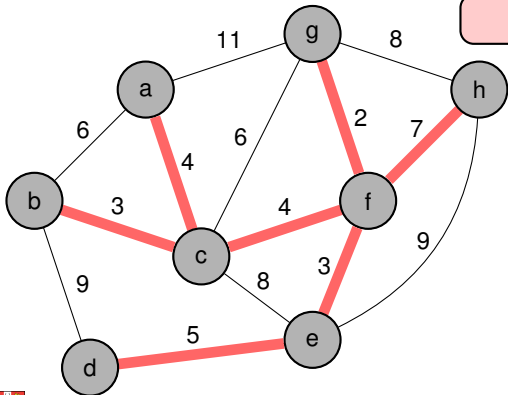
Prim's Algorithm

Basic Strategy

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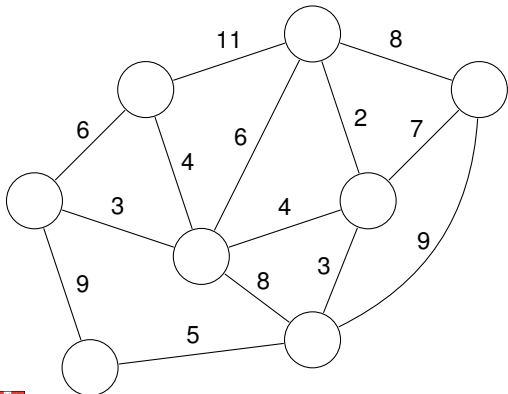
Use a Priority Queue!



Prim's Algorithm

Implementation

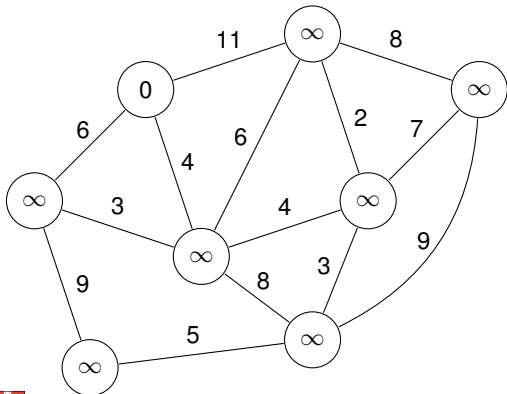
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Prim's Algorithm

Implementation

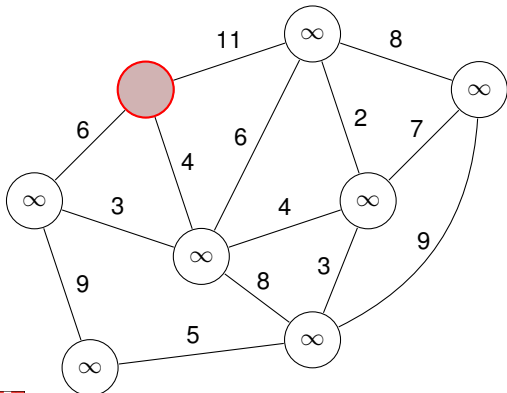
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Prim's Algorithm

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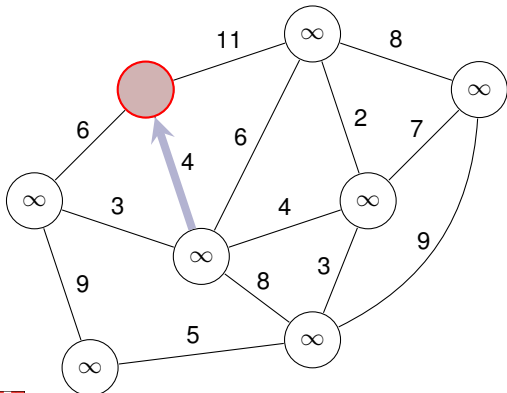
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Prim's Algorithm

Implementation

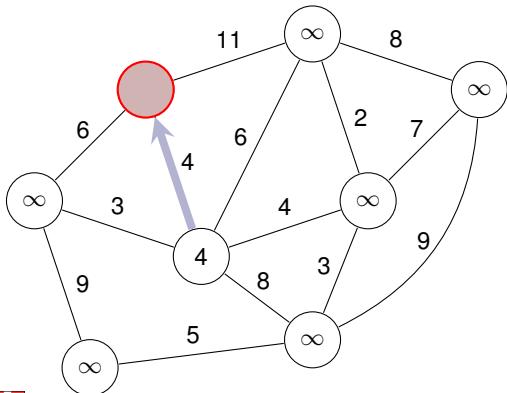
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Prim's Algorithm

Implementation

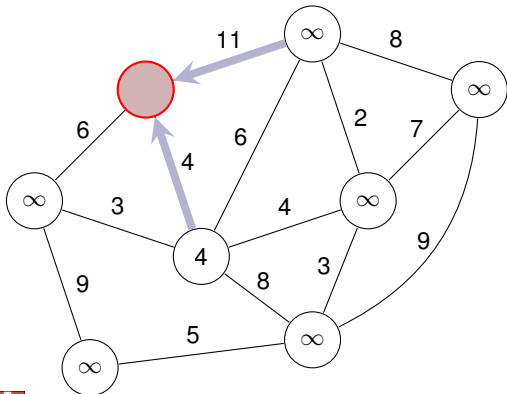
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Prim's Algorithm

Implementation

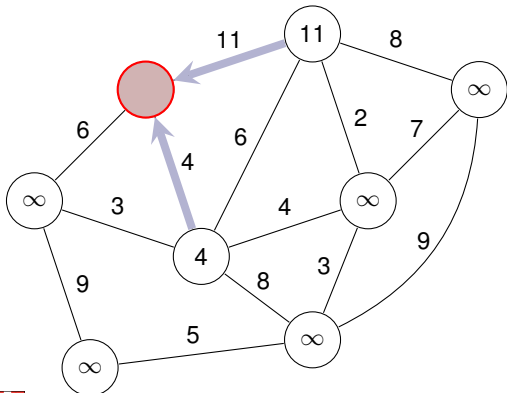
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Prim's Algorithm

Implementation

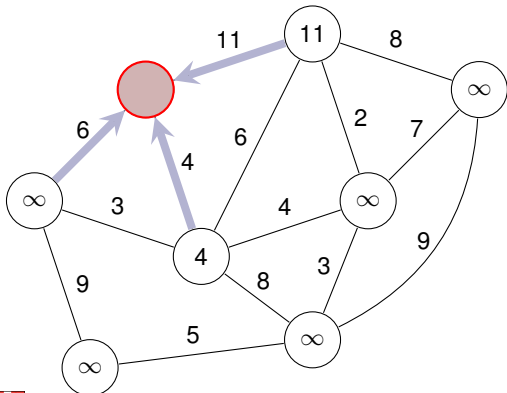
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Prim's Algorithm

Implementation

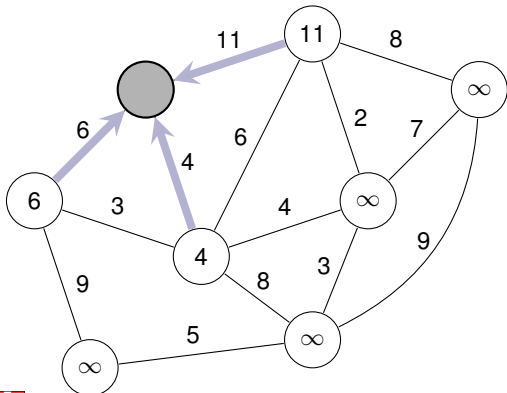
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Prim's Algorithm

Implementation

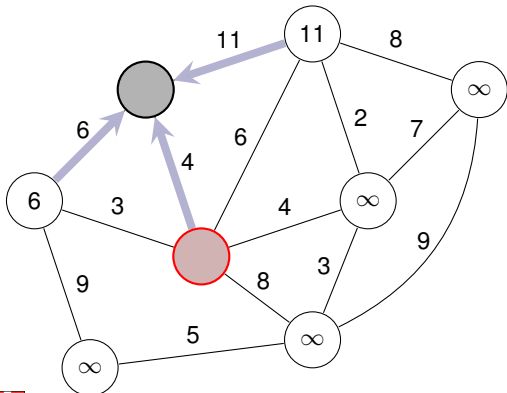
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Prim's Algorithm

Implementation

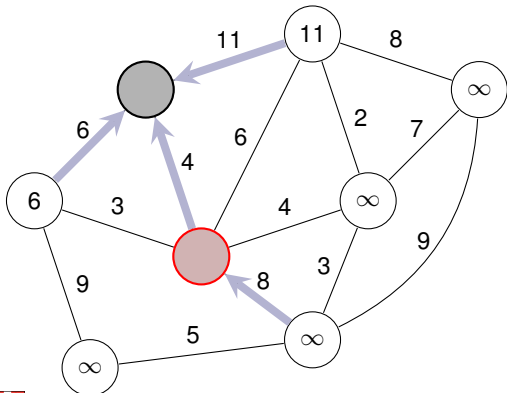
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Prim's Algorithm

Implementation

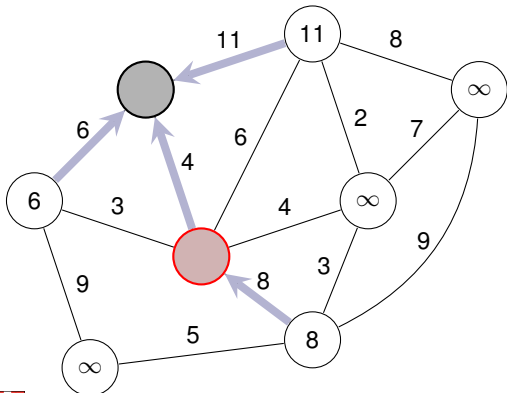
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Prim's Algorithm

Implementation

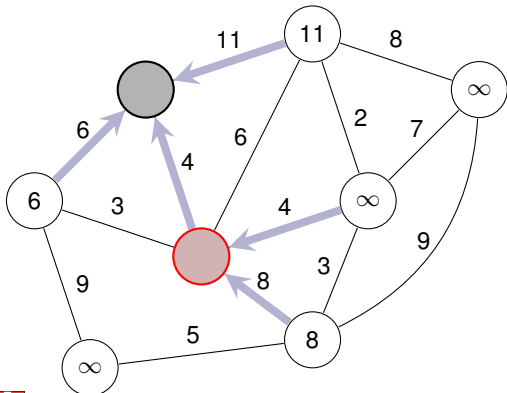
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Prim's Algorithm

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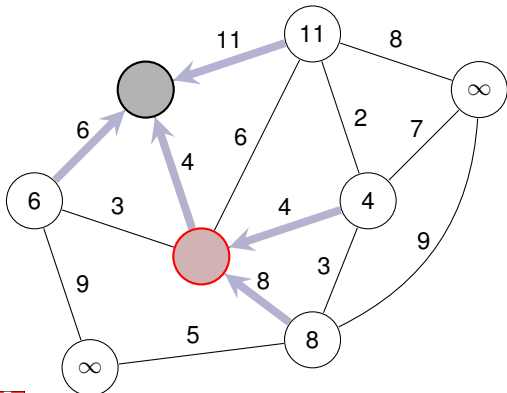
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Prim's Algorithm

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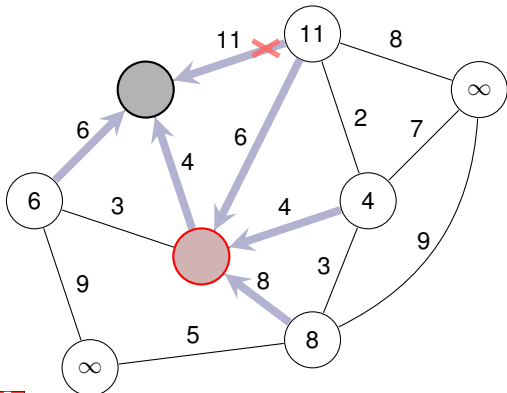
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Prim's Algorithm

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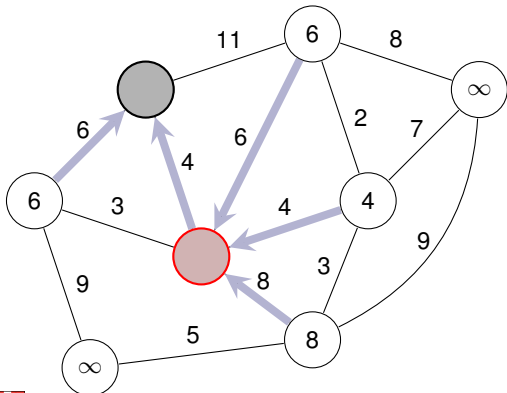
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Prim's Algorithm

Implementation

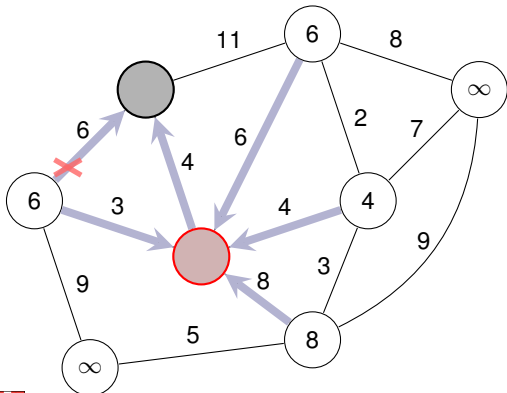
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Prim's Algorithm

Implementation

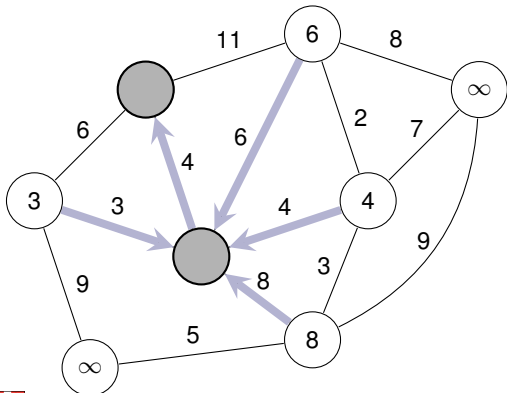
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Prim's Algorithm

Implementation

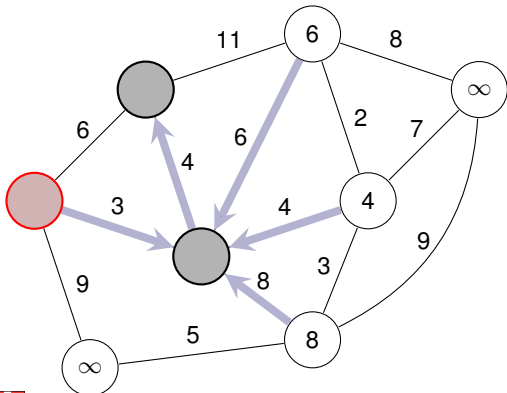
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Prim's Algorithm

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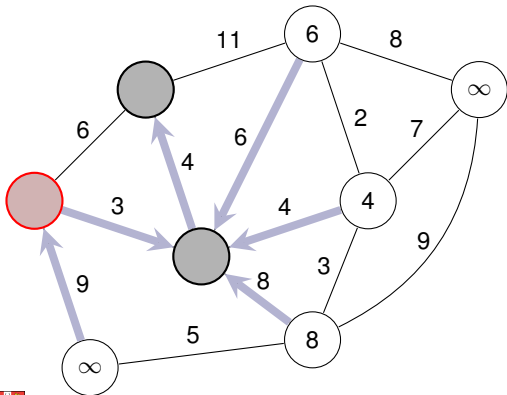
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Prim's Algorithm

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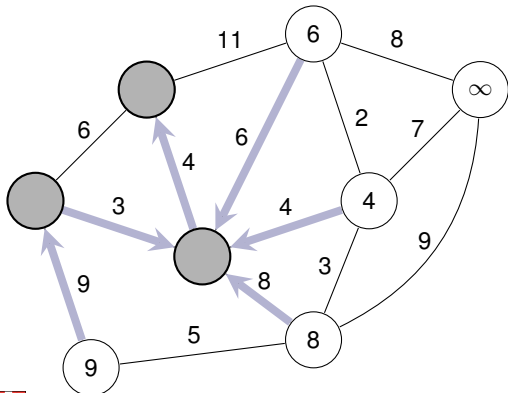
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Prim's Algorithm

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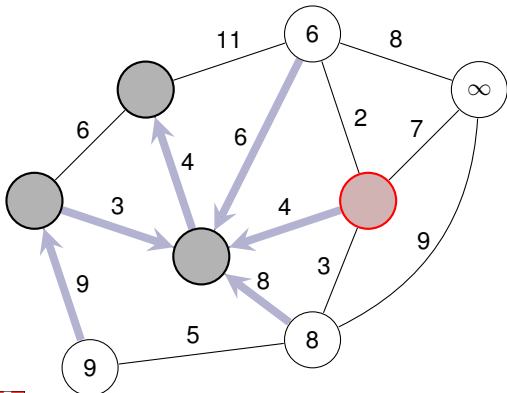
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Prim's Algorithm

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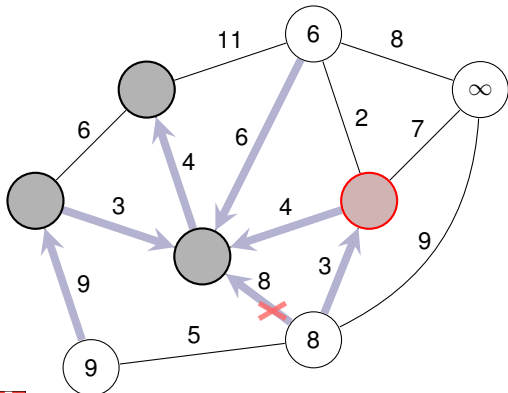
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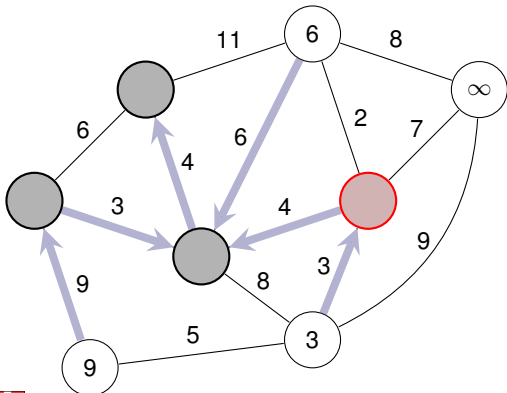
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Prim's Algorithm

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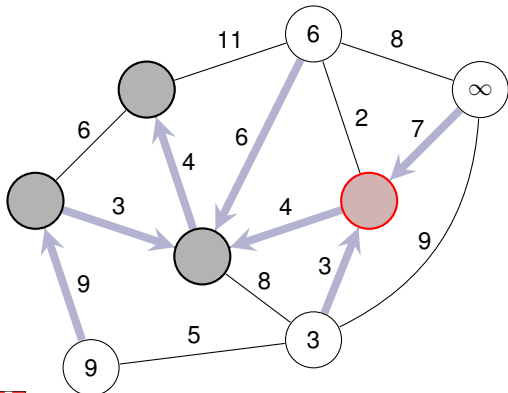
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Prim's Algorithm

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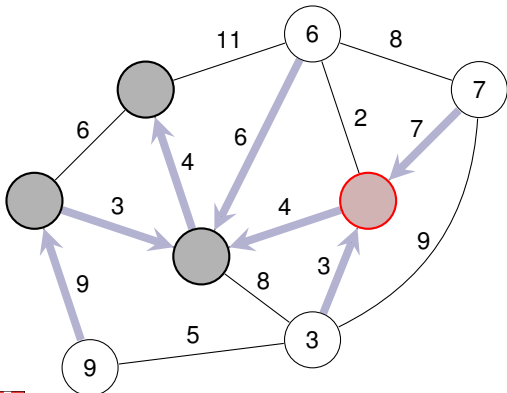
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Prim's Algorithm

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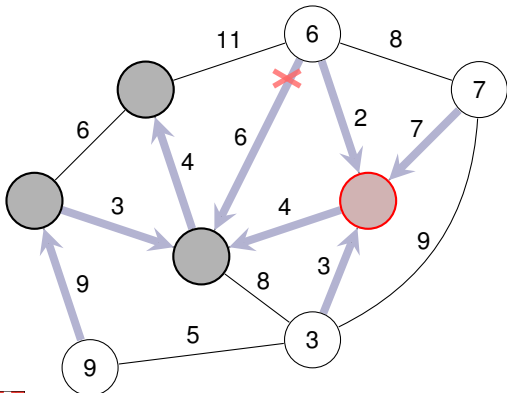
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Prim's Algorithm

Implementation

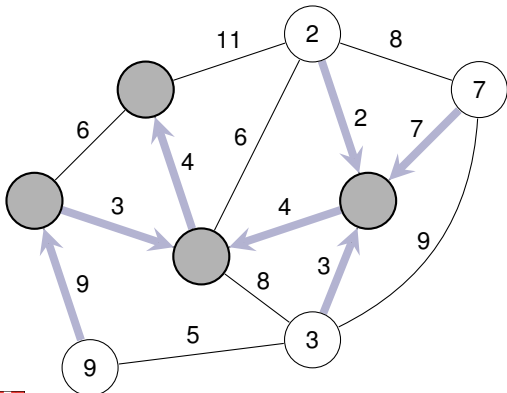
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Prim's Algorithm

Implementation

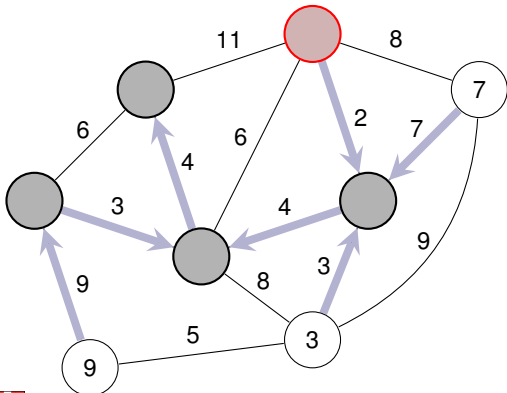
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Prim's Algorithm

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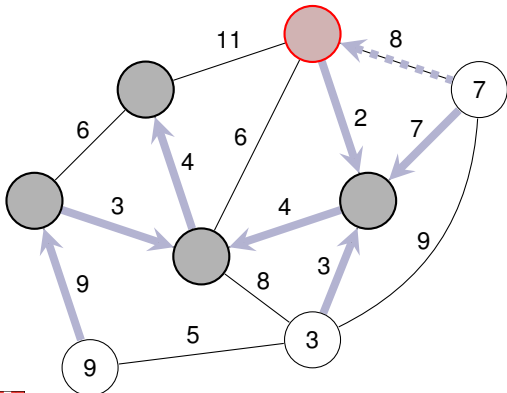
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Prim's Algorithm

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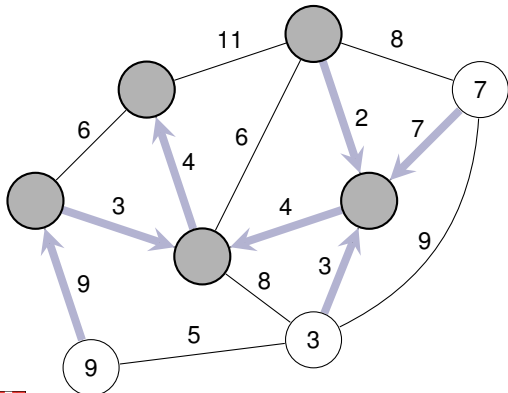
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Prim's Algorithm

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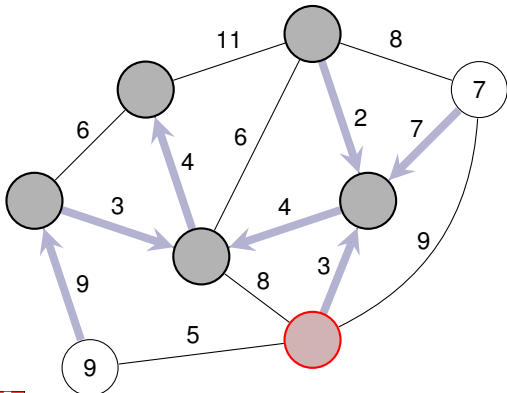
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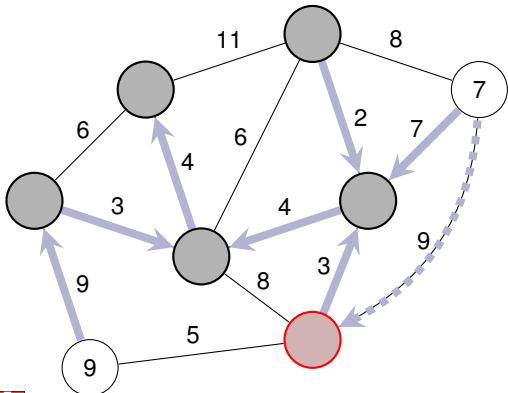
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Prim's Algorithm

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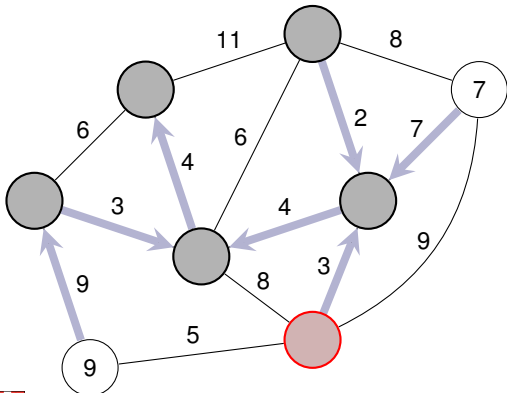
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Prim's Algorithm

Implementation

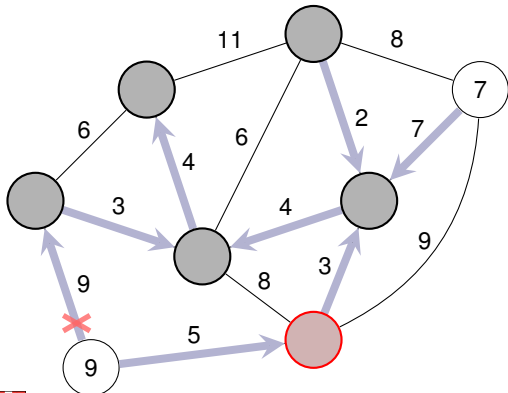
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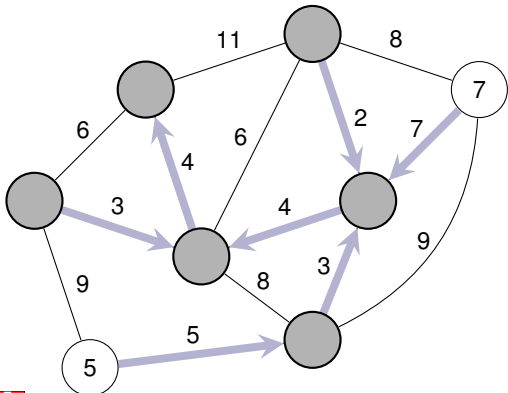
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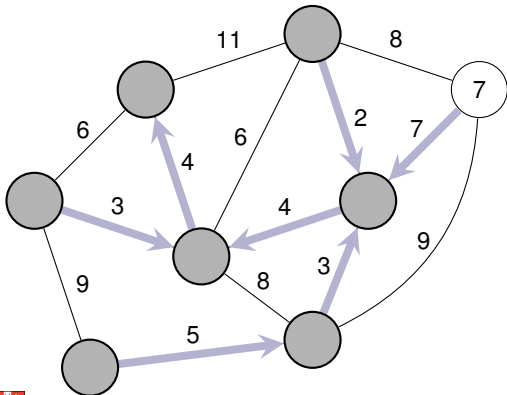
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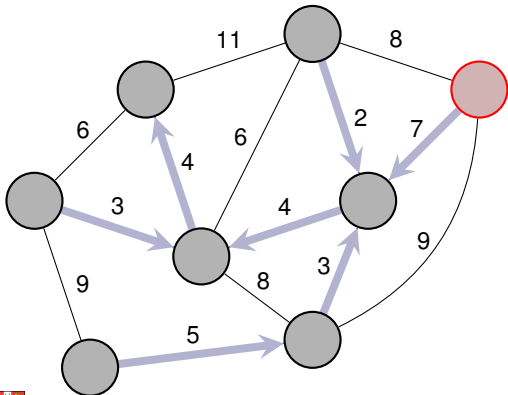
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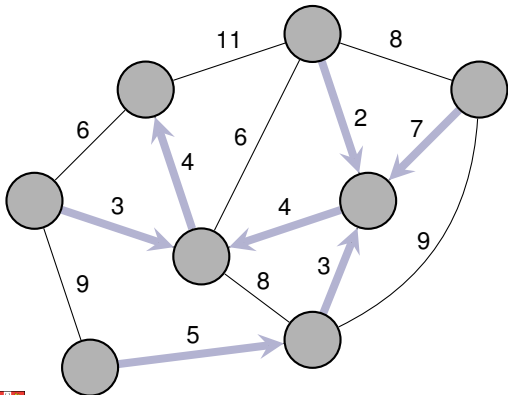
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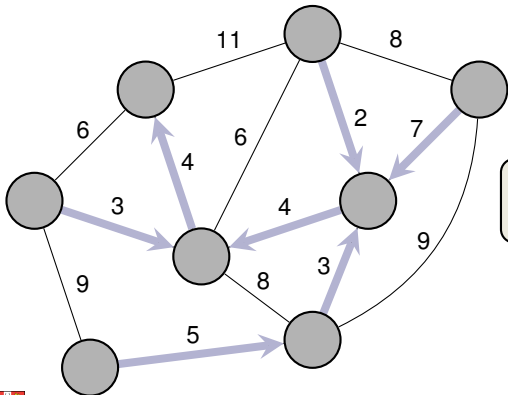
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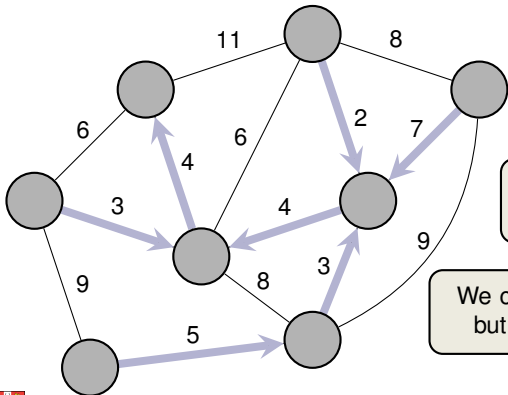
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We computed **same MST** as Kruskal,
but in a completely **different order**!



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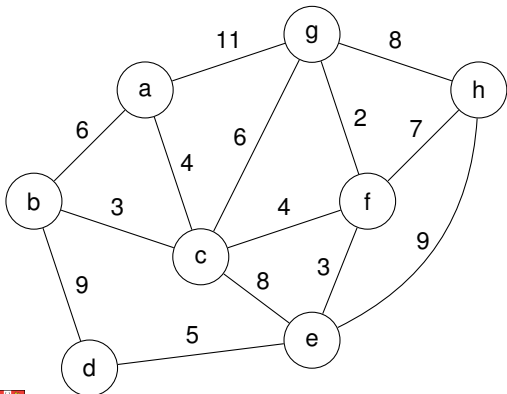
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Outlook: Reverse-Delete Algorithm

Basic Idea

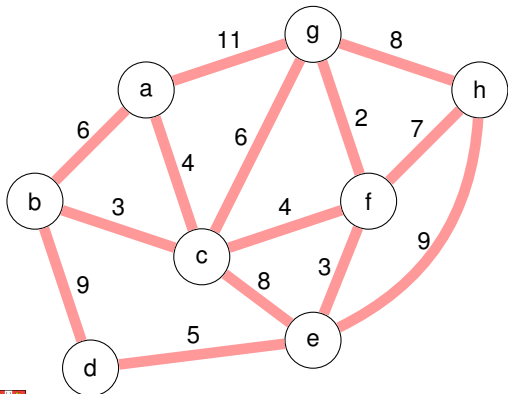
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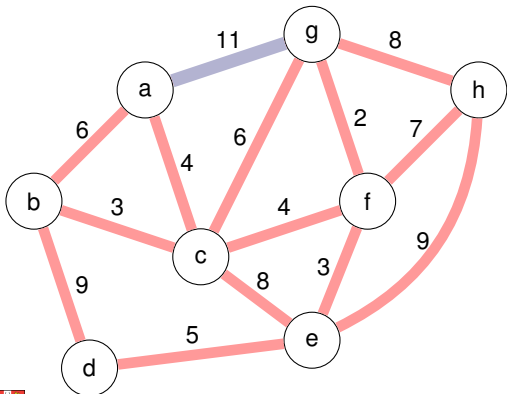
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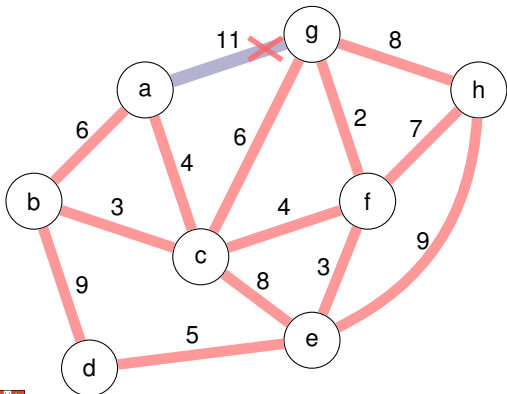
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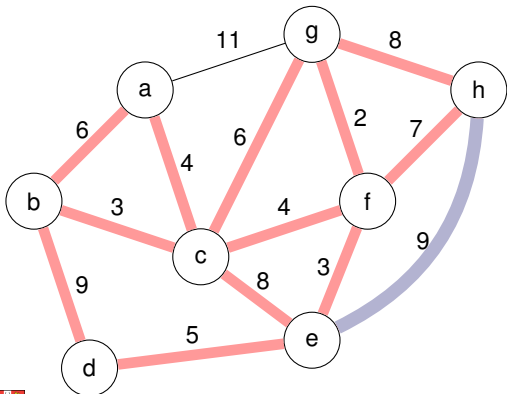
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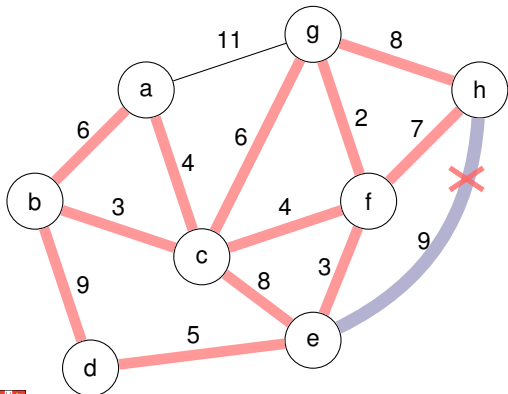
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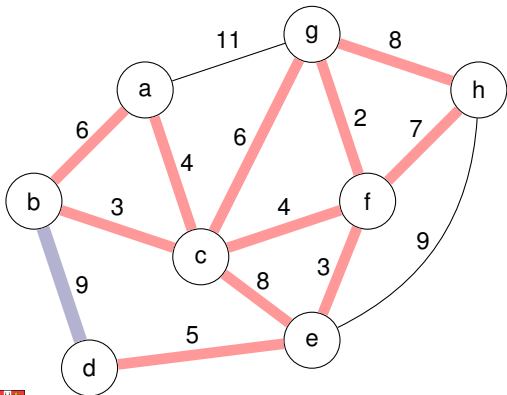
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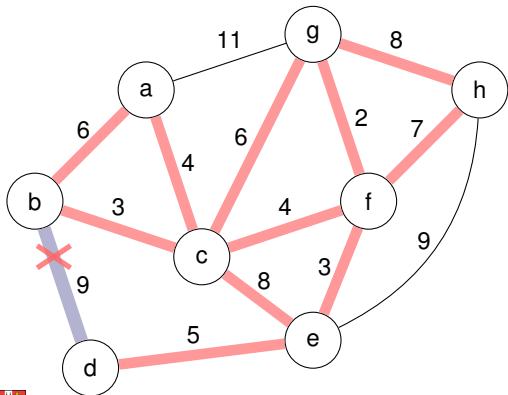
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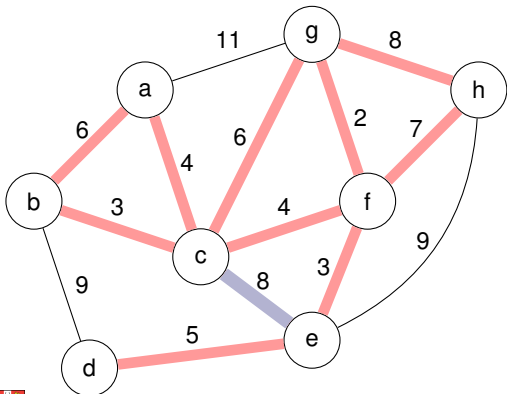
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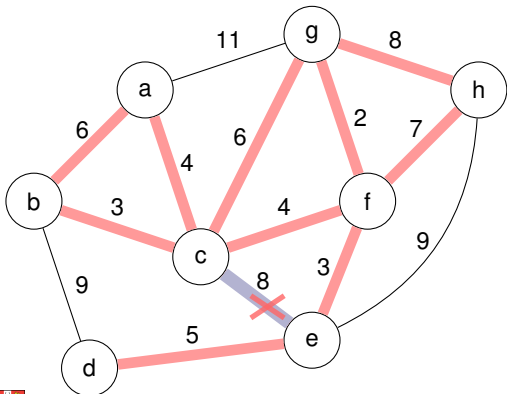
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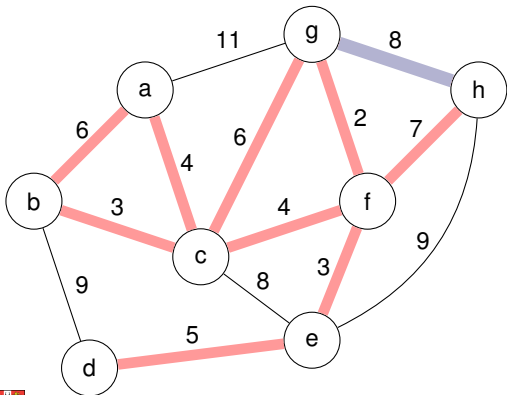
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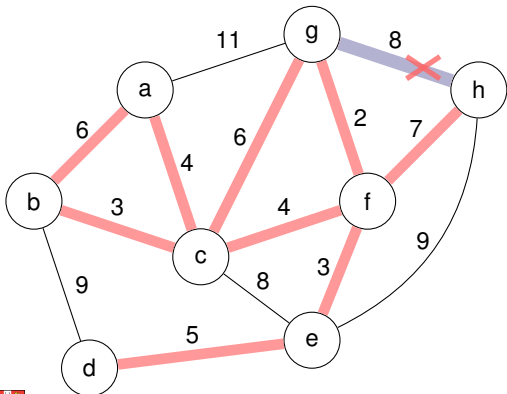
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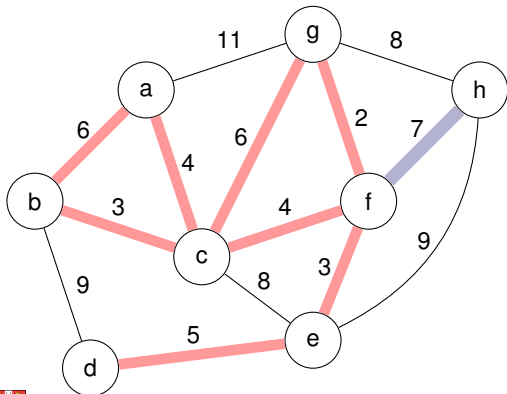
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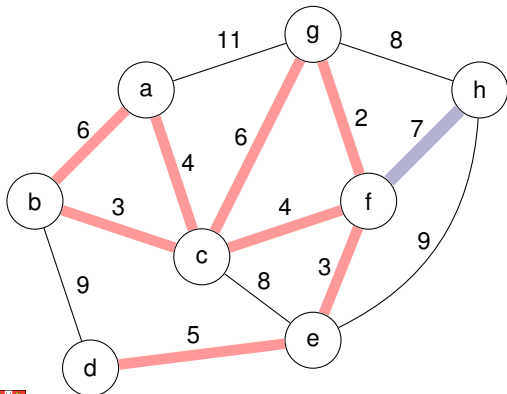
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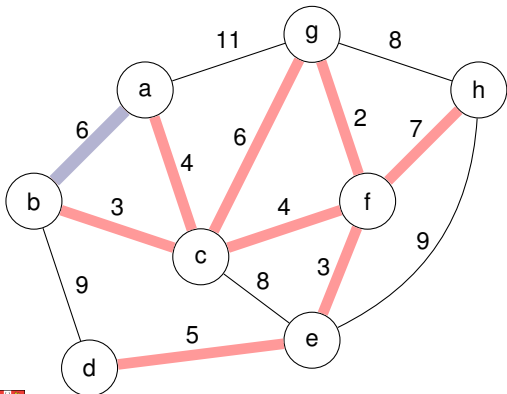
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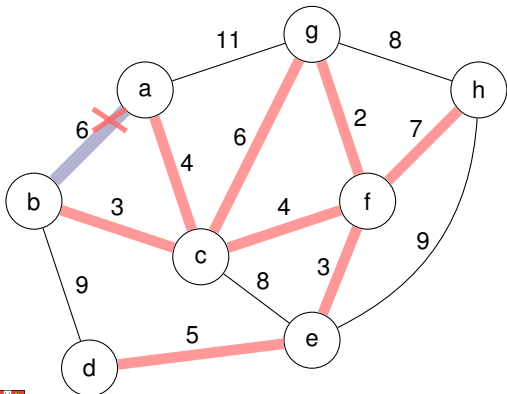
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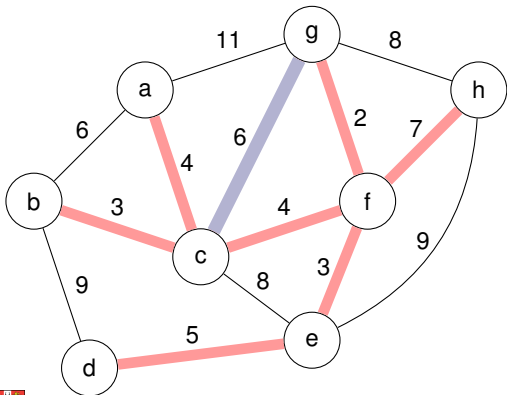
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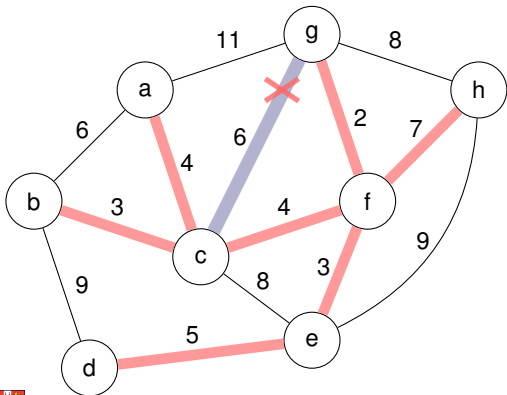
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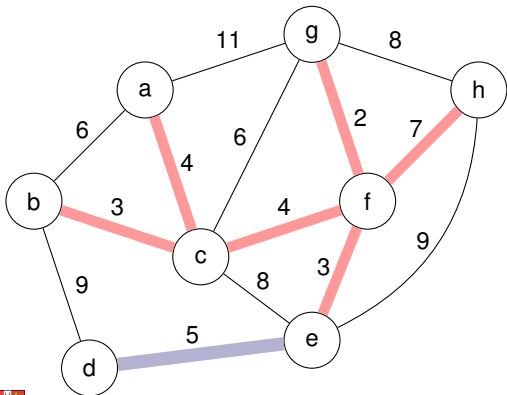
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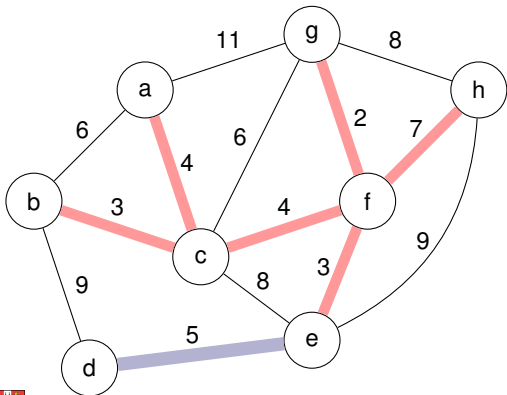
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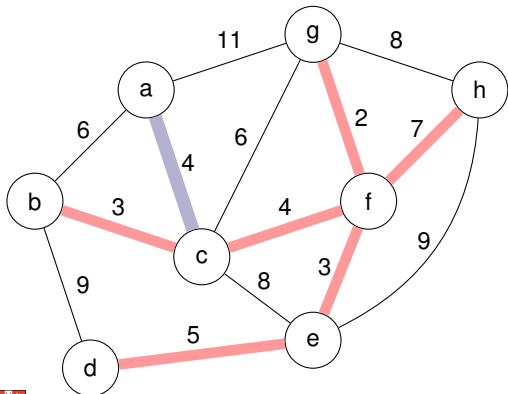
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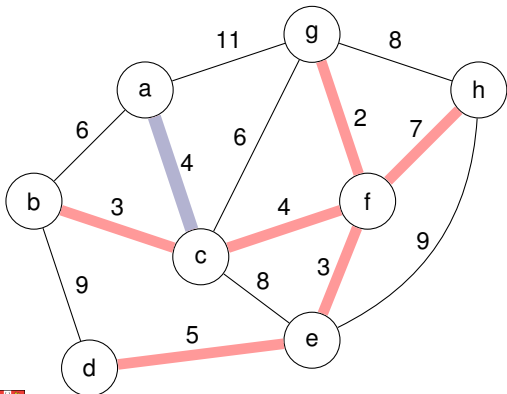
- Let A be initially the set of **all edges**
- Consider all edges in decreasing order of their weight
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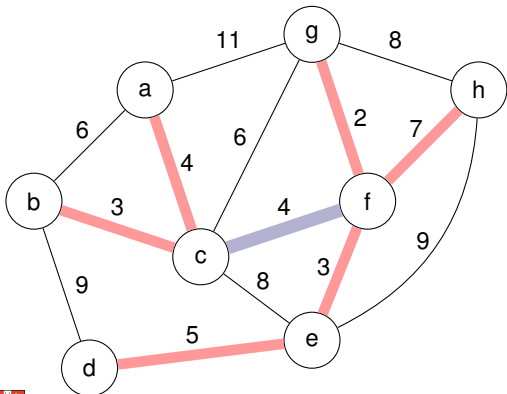
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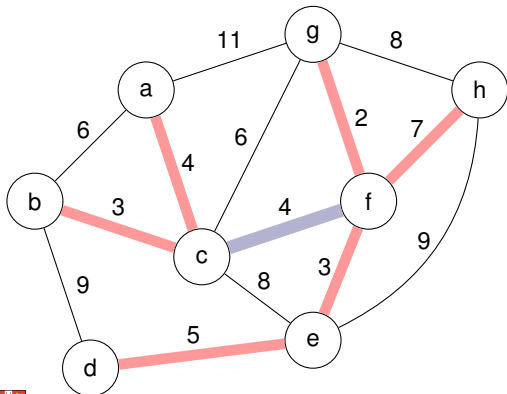
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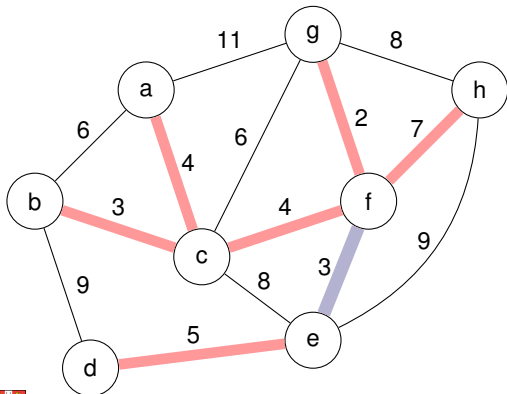
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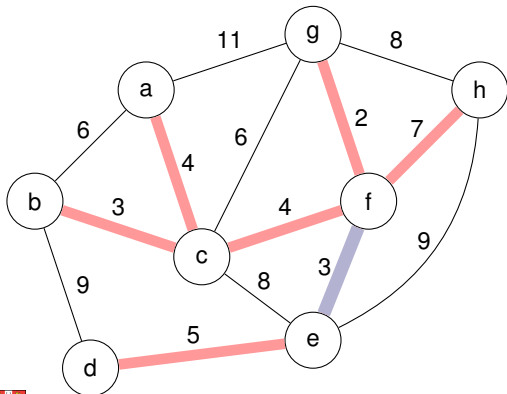
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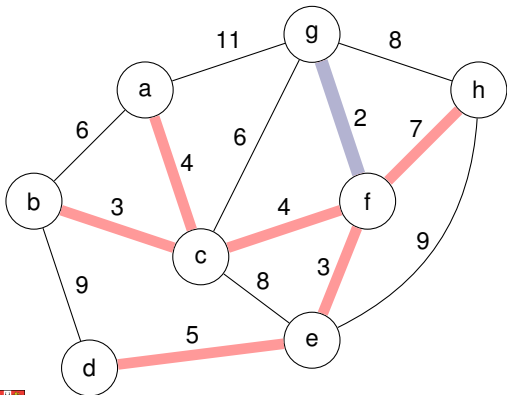
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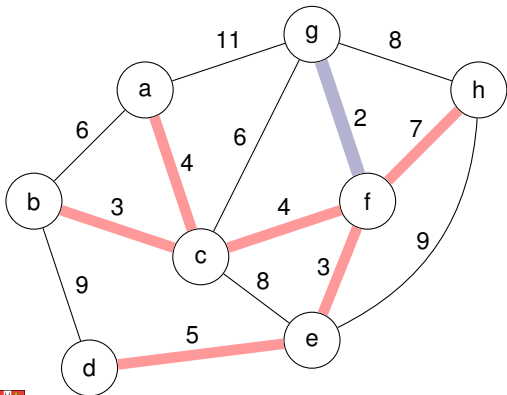
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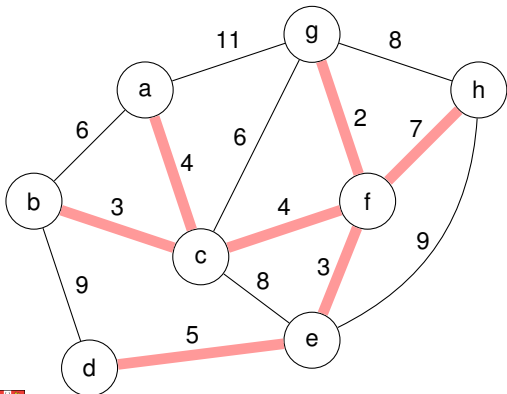
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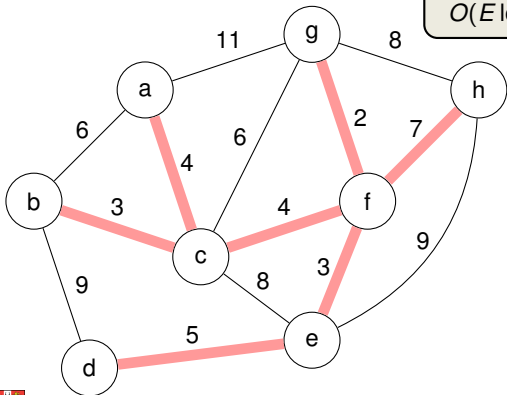


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Can be implemented in time $O(E \log V (\log \log V)^3)$. [Thorup, 2000]



Does a linear-time MST algorithm exist?



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— Karger, Klein, Tarjan, JACM'1995 —

- randomised MST algorithm with expected runtime $O(E)$
- based on Boruvka's algorithm (from 1926)



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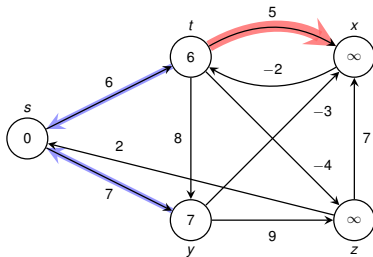
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- **deterministic** MST algorithm with runtime $O(E \cdot \alpha(n))$

— Pettie, Ramachandran, JACM'2002 —

- **deterministic** MST algorithm with **asymptotically optimal runtime**
- however, the runtime itself is not known...





6.4: Single-Source Shortest Paths

Frank Stajano

Thomas Sauerwald

Lent 2016



UNIVERSITY OF
CAMBRIDGE

Introduction

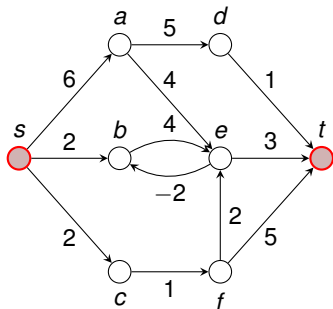
Bellman-Ford Algorithm



Shortest Path Problem

Shortest Path Problem

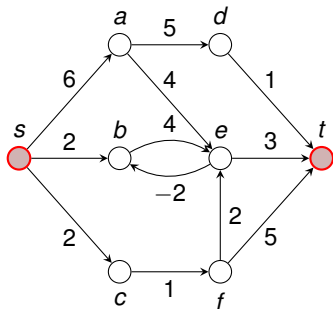
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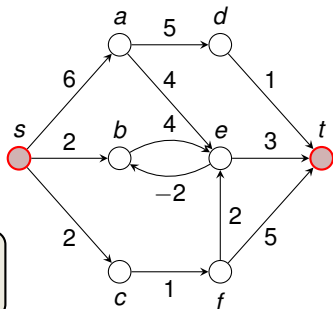


Shortest Path Problem

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$p = (v_0 = s, v_1, \dots, v_k = t)$ such that $w(p) = \sum_{i=1}^k w(v_{k-1}, v_k)$ is minimized.

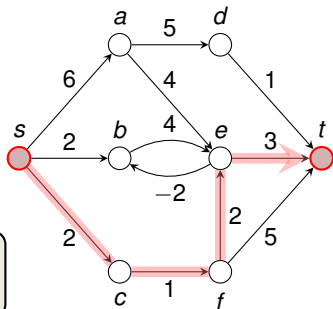


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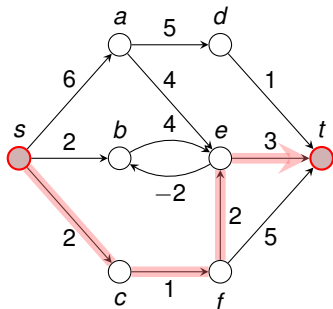
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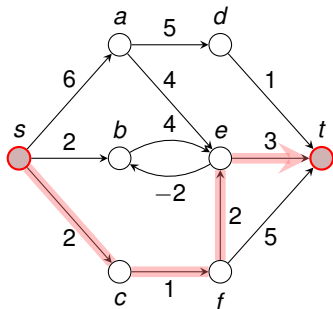
What if G is **unweighted**?



Shortest Path Problem

Shortest Path Problem

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- Goal: Find a path of minimum weight from s to t in G



What if G is **unweighted**?

Two possible answers are:

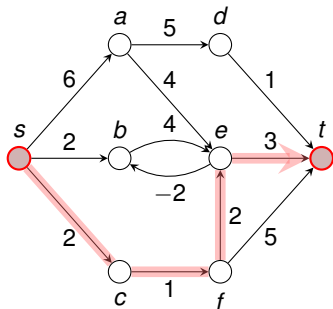
- Run BFS (computes shortest paths in unweighted graphs)
- Set the weight of all edges to 1



Shortest Path Problem

Shortest Path Problem

- Given: directed graph $G = (V, E)$ with edge weights, pair of vertices $s, t \in V$
- Goal: Find a path of minimum weight from s to t in G



Applications

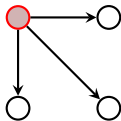
- Car Navigation, Internet Routing, Arbitrage in Concurrency Exchange



Variants of Shortest Path Problems

Single-source shortest-paths problem (SSSP)

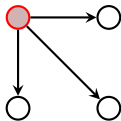
- Bellman-Ford Algorithm
- Dijkstra Algorithm



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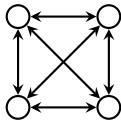
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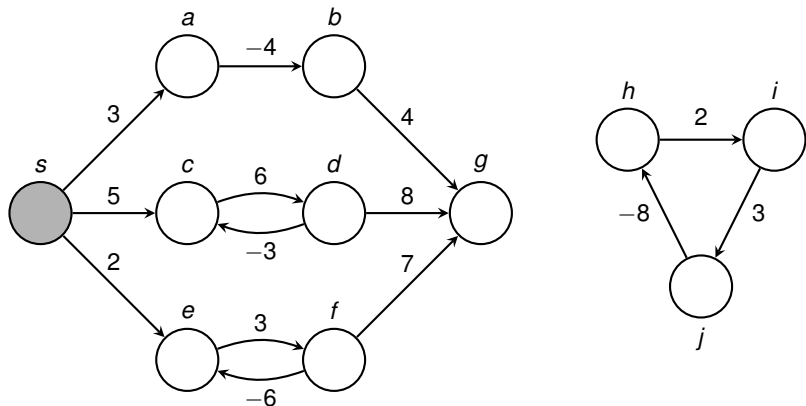


All-pairs shortest-paths problem (APSP)

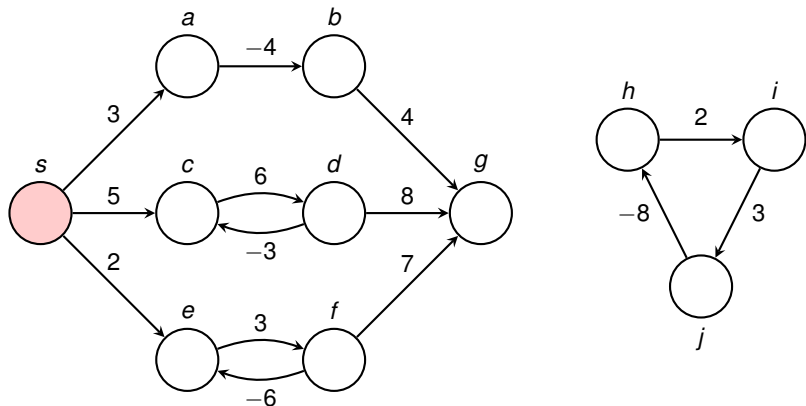
- Shortest Paths via Matrix Multiplication
- Johnson's Algorithm



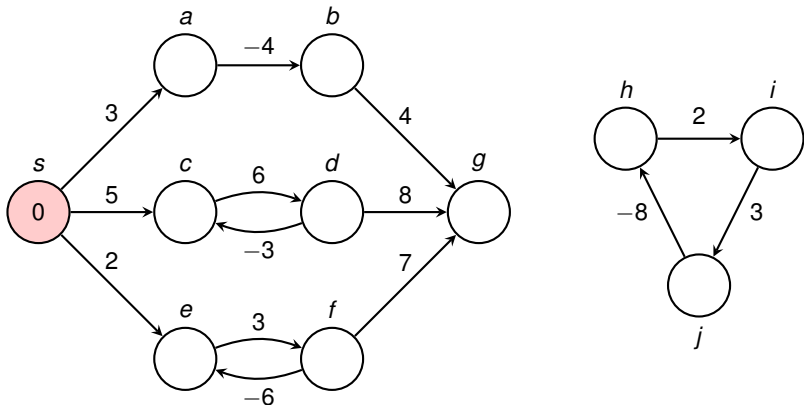
Distances and Negative-Weight Cycles (Figure 24.1)



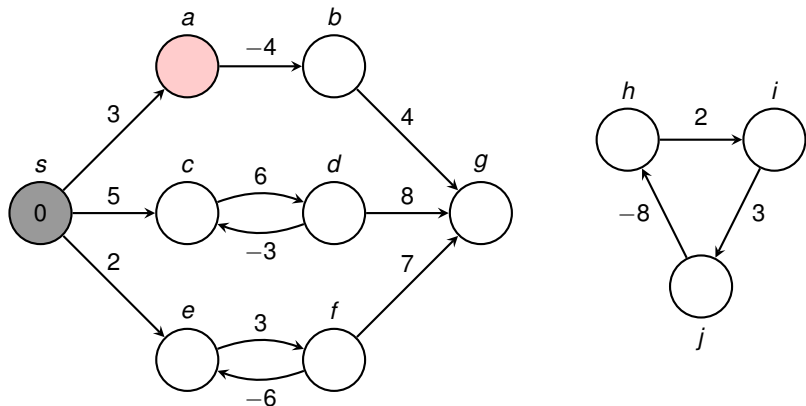
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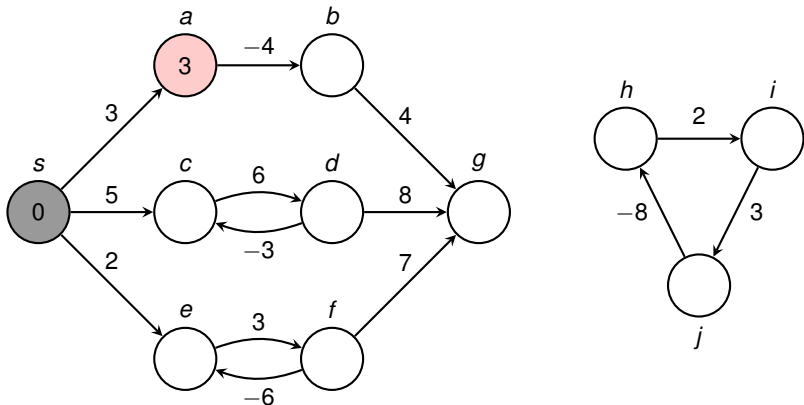
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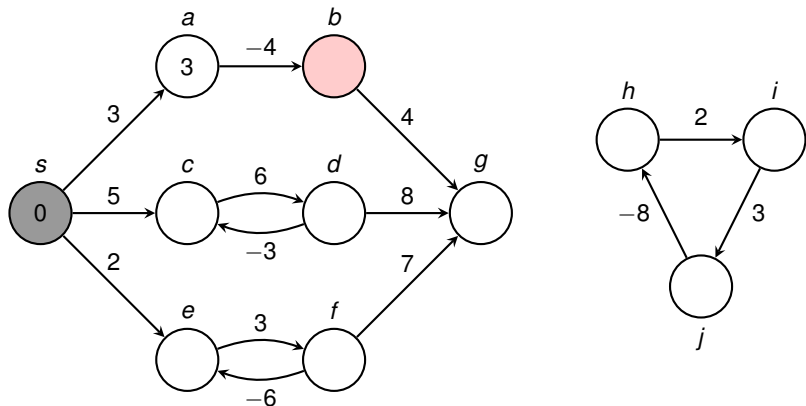
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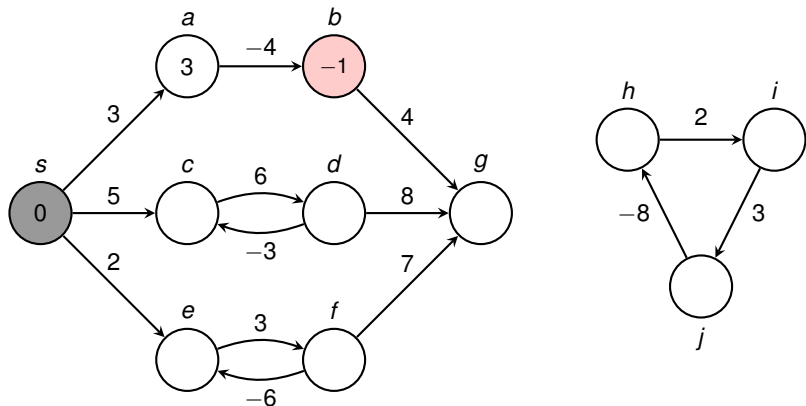
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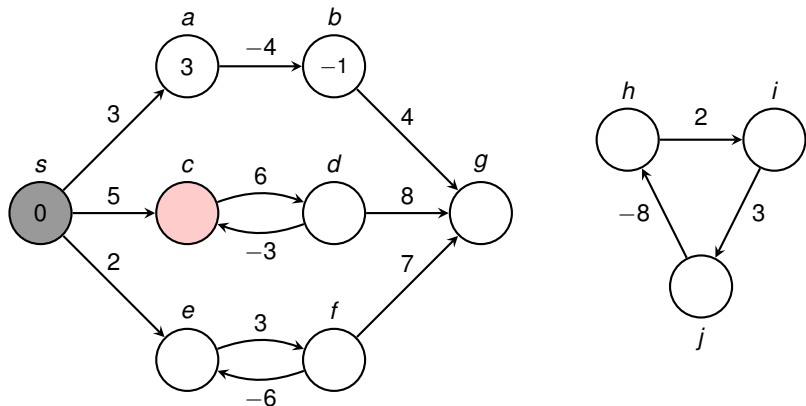
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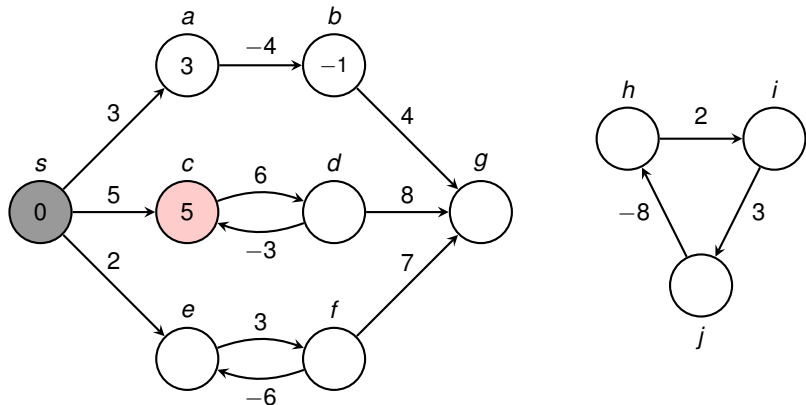
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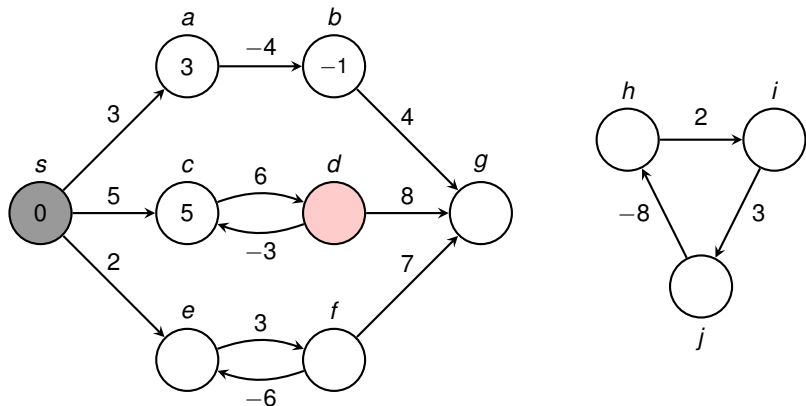
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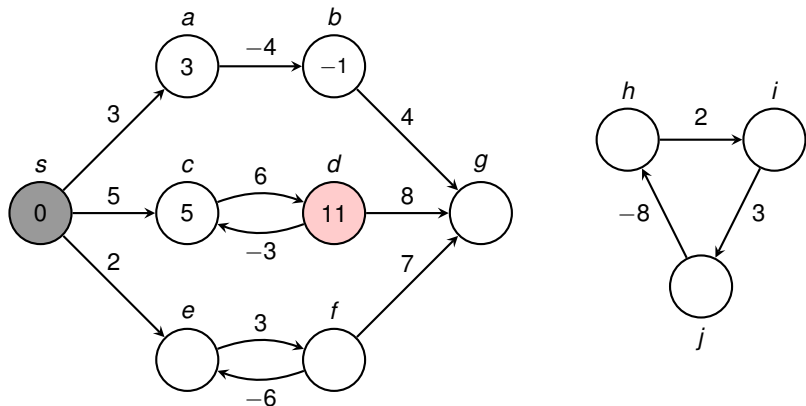
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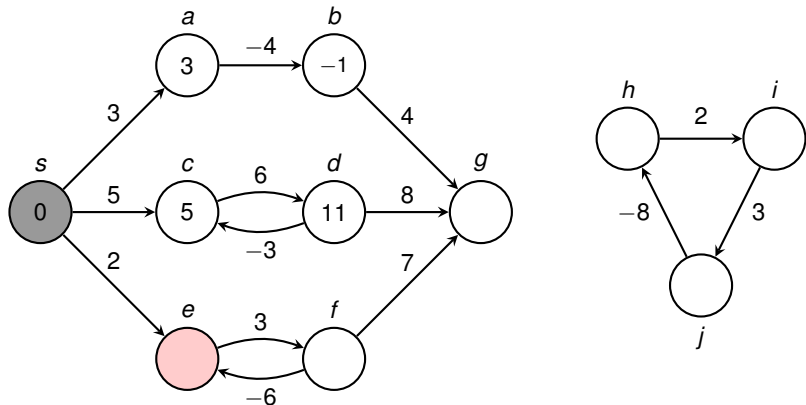
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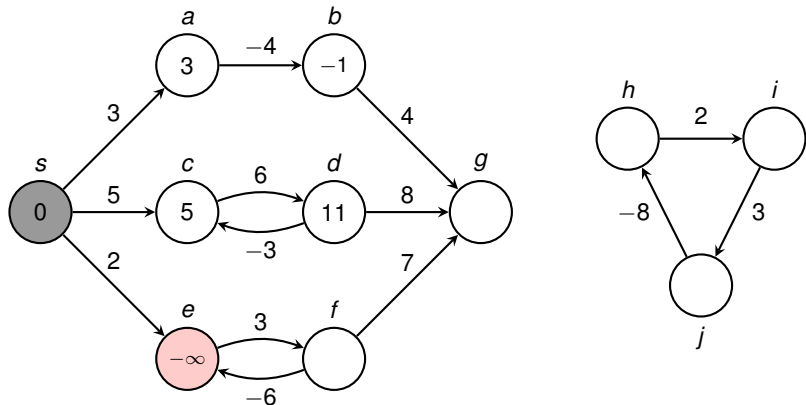
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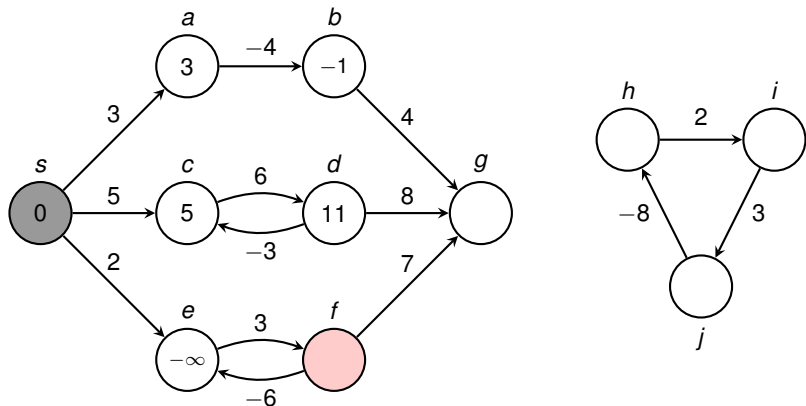
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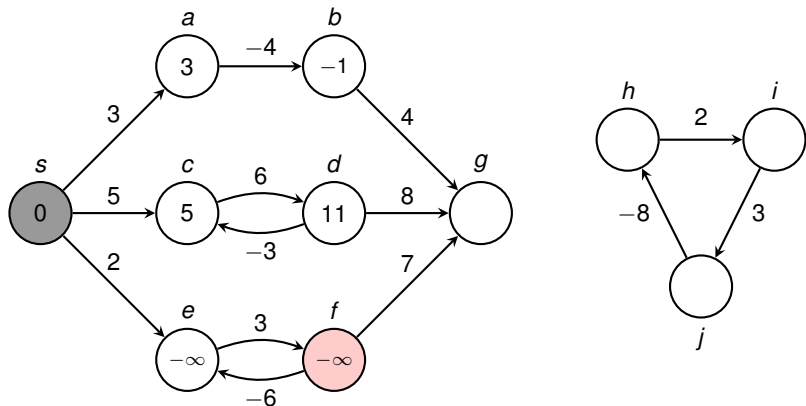
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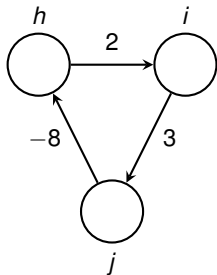
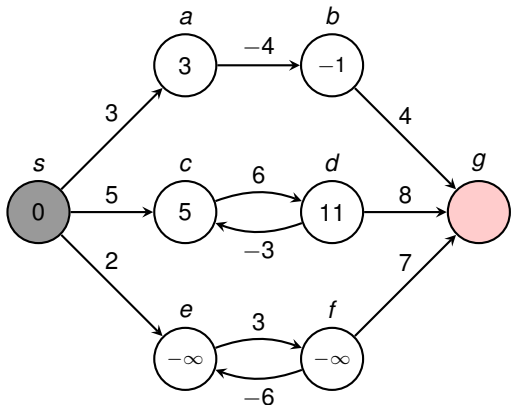
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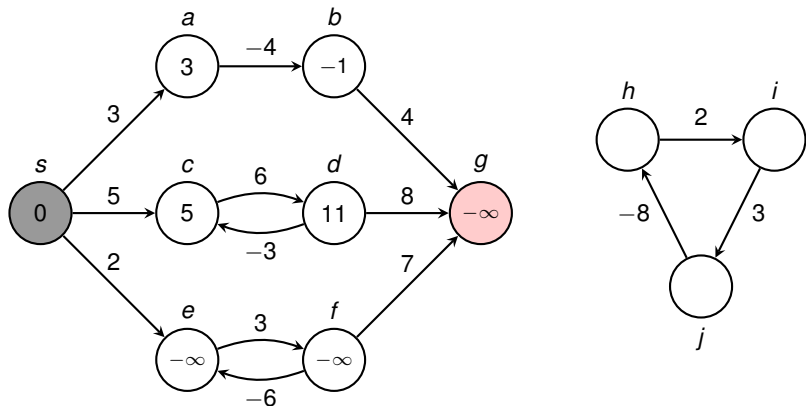
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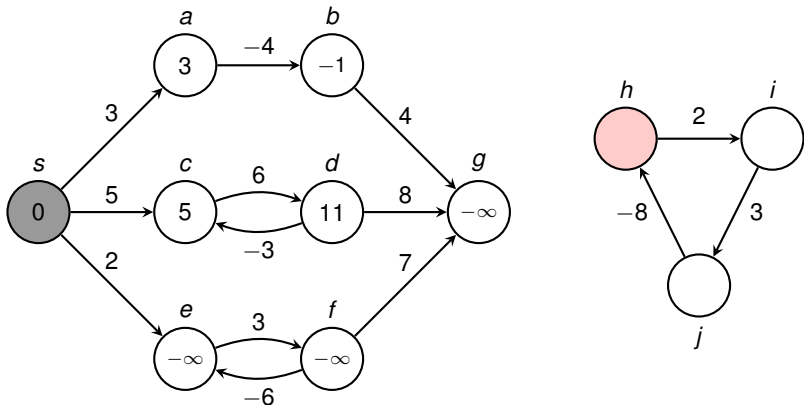
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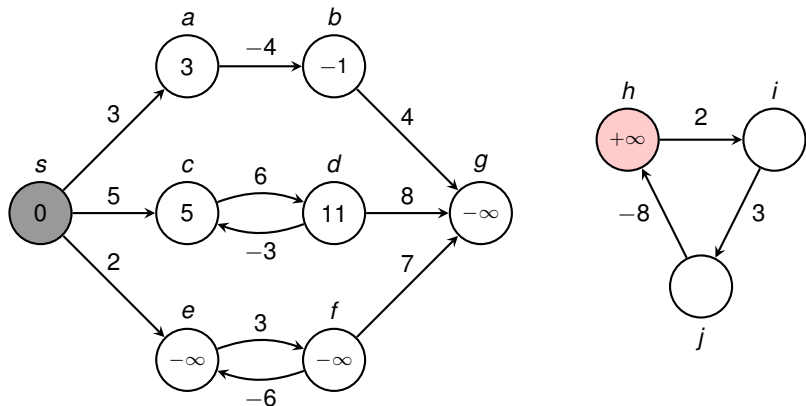
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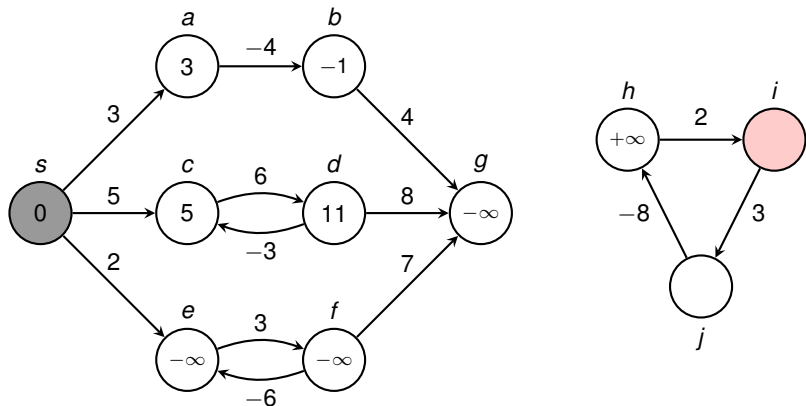
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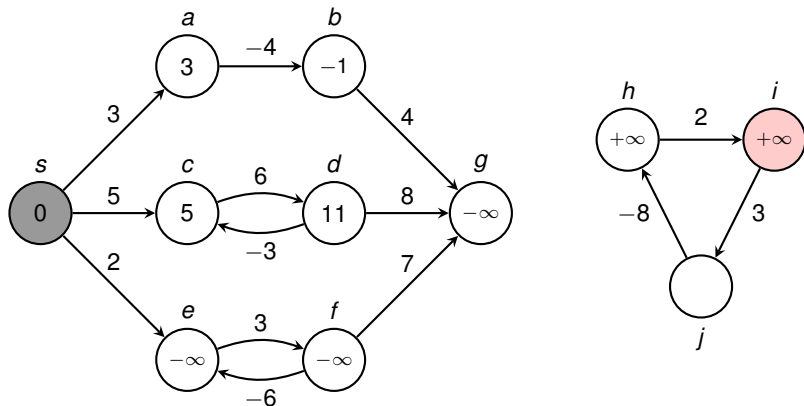
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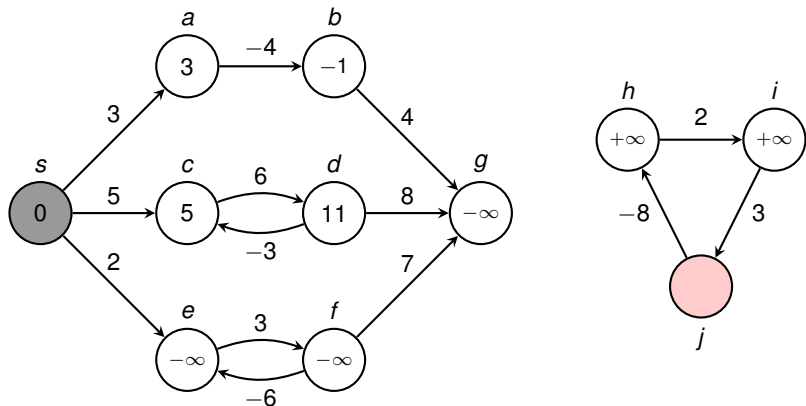
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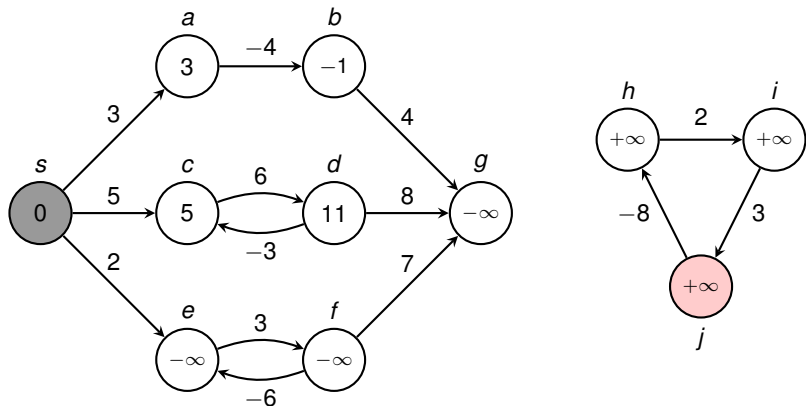
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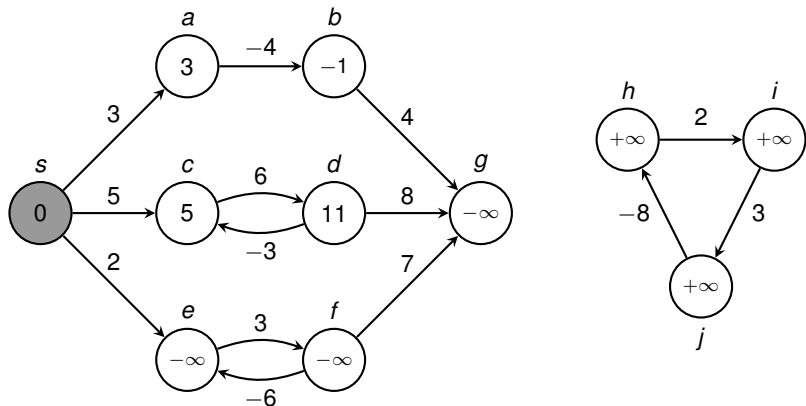
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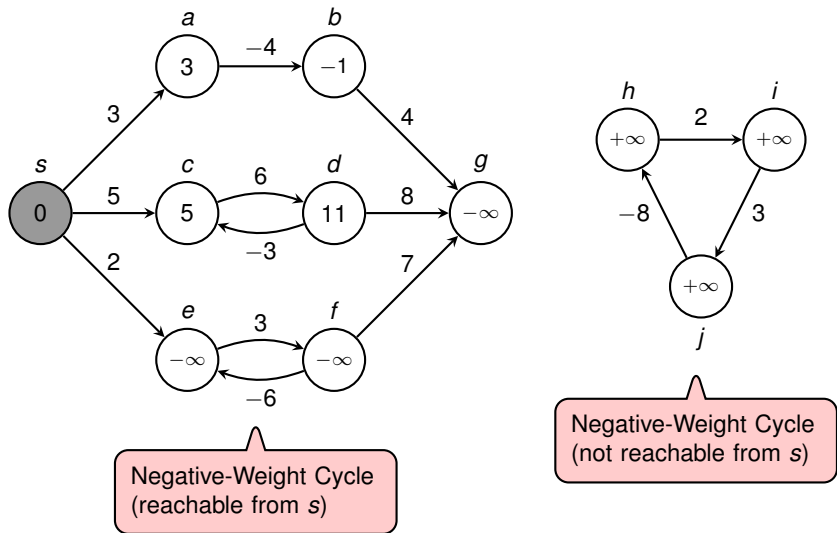
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Introduction

Bellman-Ford Algorithm



Relaxing Edges

Definition

Fix the source vertex $s \in V$

- $v.\delta$ is the length of the shortest path (distance) from s to v
- $v.d$ is the length of the shortest path discovered so far



Relaxing Edges

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Relaxing an edge (u, v)

Given estimates $u.d$ and $v.d$, can we find a better path from v using the edge (u, v) ?



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$$v.d \stackrel{?}{>} u.d + w(u, v)$$



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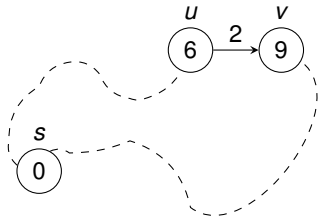
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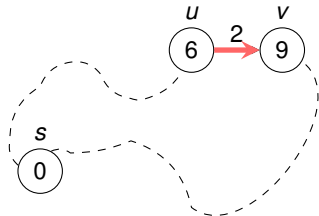
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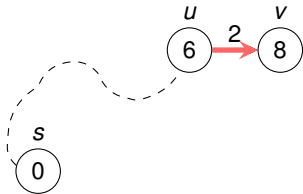
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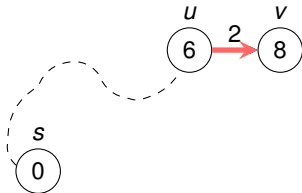
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Given estimates $u.d$ and $v.d$, can we find a better path from v using the edge (u, v) ?

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After relaxing (u, v) , regardless of whether we found a shortcut:
 $v.d \leq u.d + w(u, v)$



Properties of Shortest Paths and Relaxations

Toolkit

Triangle inequality (Lemma 24.10)

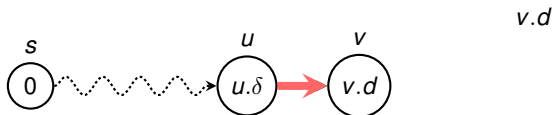
- For any edge $(u, v) \in E$, we have $v.\delta \leq u.\delta + w(u, v)$

Upper-bound Property (Lemma 24.11)

- We always have $v.d \geq v.\delta$ for all $v \in V$, and once $v.d$ achieves the value $v.\delta$, it never changes.

Convergence Property (Lemma 24.14)

- If $s \rightsquigarrow u \rightarrow v$ is a shortest path from s to v , and if $u.d = u.\delta$ prior to relaxing edge (u, v) , then $v.d = v.\delta$ at all times afterward.



Properties of Shortest Paths and Relaxations

Toolkit

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- If $s \rightsquigarrow u \rightarrow v$ is a shortest path from s to v , and if $u.d = u.\delta$ prior to relaxing edge (u, v) , then $v.d = v.\delta$ at all times afterward.



$$v.d \leq u.d + w(u, v)$$



Properties of Shortest Paths and Relaxations

Toolkit

Triangle inequality (Lemma 24.10)

- For any edge $(u, v) \in E$, we have $v.\delta \leq u.\delta + w(u, v)$

Upper-bound Property (Lemma 24.11)

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$$\begin{aligned} v.d &\leq u.d + w(u, v) \\ &= u.\delta + w(u, v) \end{aligned}$$



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Properties of Shortest Paths and Relaxations

Toolkit

Triangle inequality (Lemma 24.10)

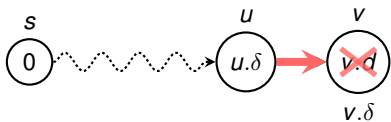
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$$\begin{aligned}v.d &\leq u.d + w(u, v) \\ &= u.\delta + w(u, v) \\ &= v.\delta\end{aligned}$$

Since $v.d \geq v.\delta$, we have $v.d = v.\delta$. \square



Path-Relaxation Property

Path-Relaxation Property (Lemma 24.15)

If $p = (v_0, v_1, \dots, v_k)$ is a **shortest path** from $s = v_0$ to v_k , and we **relax the edges of p** in the order $(v_0, v_1), (v_1, v_2), \dots, (v_{k-1}, v_k)$, then $v_k.d = v_k.\delta$ (regardless of the order of other relaxation steps).



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Proof:

- By induction on i , $0 \leq i \leq k$:
After the i th edge of p is relaxed, we have $v_i.d = v_i.\delta$.



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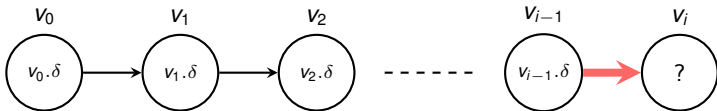
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- Inductive Step ($i - 1 \rightarrow i$):** Assume $v_{i-1}.d = v_{i-1}.\delta$ and relax (v_{i-1}, v_i) .



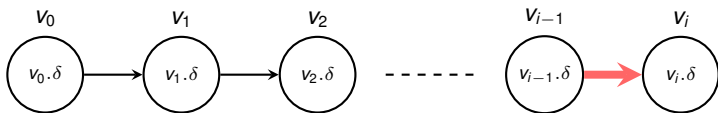
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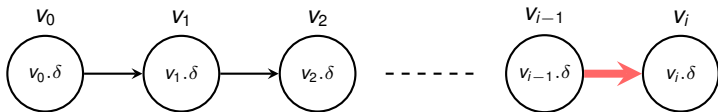
“Propagation”: By relaxing proper edges, set of vertices with $v.\delta = v.d$ gets larger

Path-Relaxation Property (Lemma 24.15)

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The Bellman-Ford Algorithm

```
BELLMAN-FORD(G, w, s)
0: assert(s in G.vertices())
1: for v in G.vertices()
2:     v.predecessor = None
3:     v.d = Infinity
4: s.d = 0
5:
6: repeat |V|-1 times
7:     for e in G.edges()
8:         Relax edge e=(u,v): Check if  $u.d + w(u,v) < v.d$ 
9:             if e.start.d + e.weight.d < e.end.d:
10:                 e.end.d = e.start.d + e.weight
11:                 e.end.predecessor = e.start
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Time Complexity

- A single call of line 9-11 costs $\mathcal{O}(1)$



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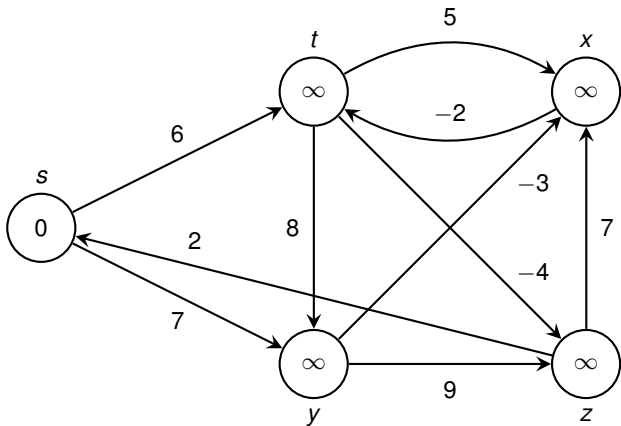
Time Complexity

- A single call of line 9-11 costs $\mathcal{O}(1)$
- In each pass every edge is relaxed $\Rightarrow \mathcal{O}(E)$ time per pass
- Overall $(V - 1) + 1 = V$ passes $\Rightarrow \mathcal{O}(V \cdot E)$ time



Execution of Bellman-Ford (Figure 24.4)

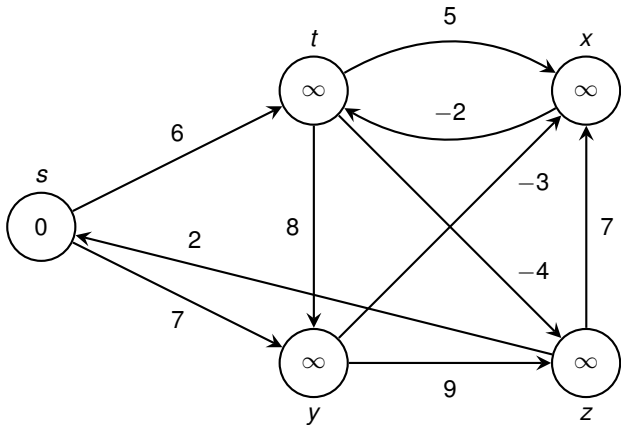
Pass: 1



Execution of Bellman-Ford (Figure 24.4)

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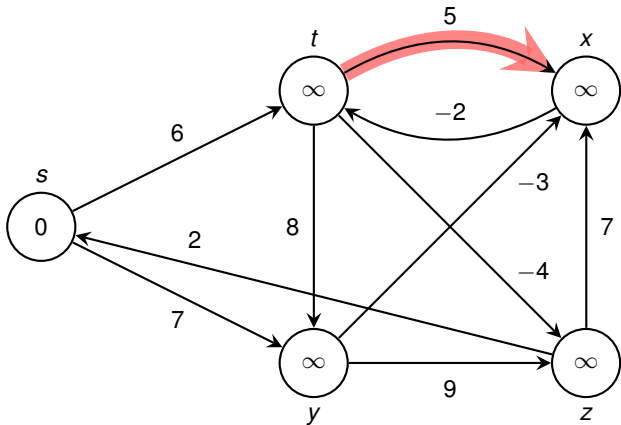
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

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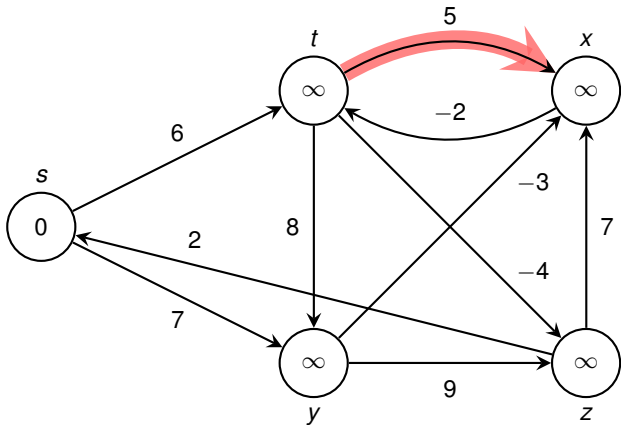
Relaxation Order: (t,x) , (t,y) , (t,z) , (x,t) , (y,x) , (y,z) , (z,x) , (z,s) , (s,t) , (s,y)



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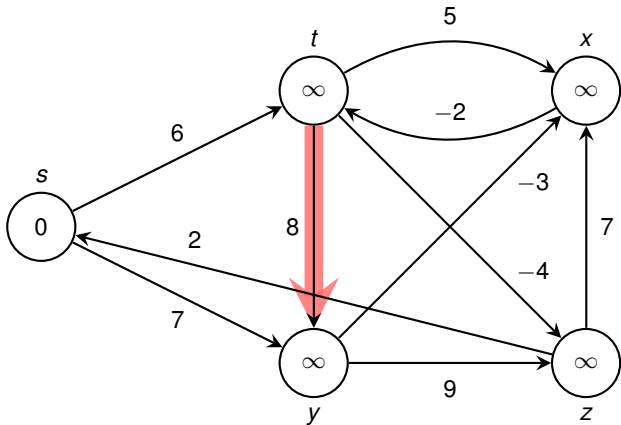
Relaxation Order: (t,x) , (t,y) , (t,z) , (x,t) , (y,x) , (y,z) , (z,x) , (z,s) , (s,t) , (s,y)



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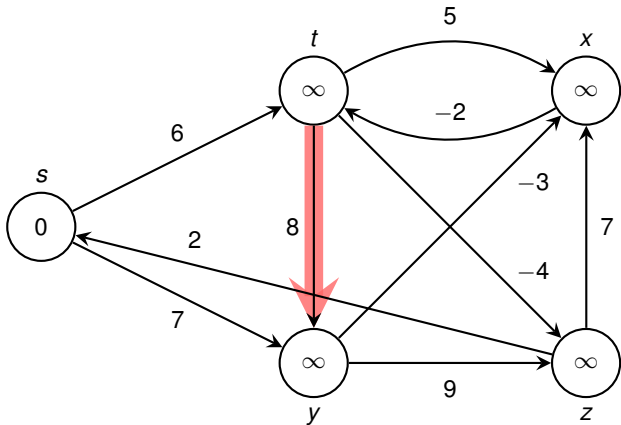
Relaxation Order: (t,x), (t,y), (t,z), (x,t), (y,x), (y,z), (z,x), (z,s), (s,t), (s,y)



Execution of Bellman-Ford (Figure 24.4)

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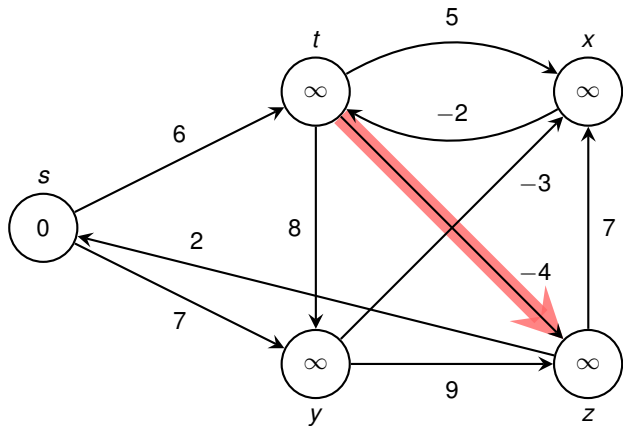
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



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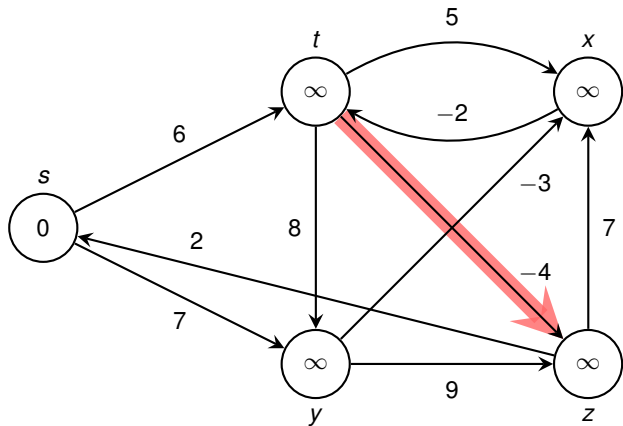
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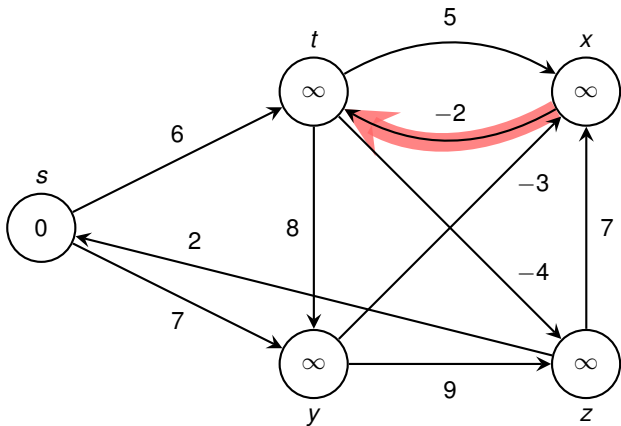
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



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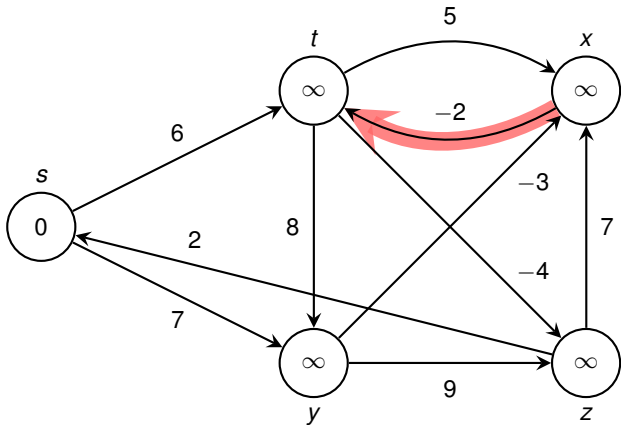
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



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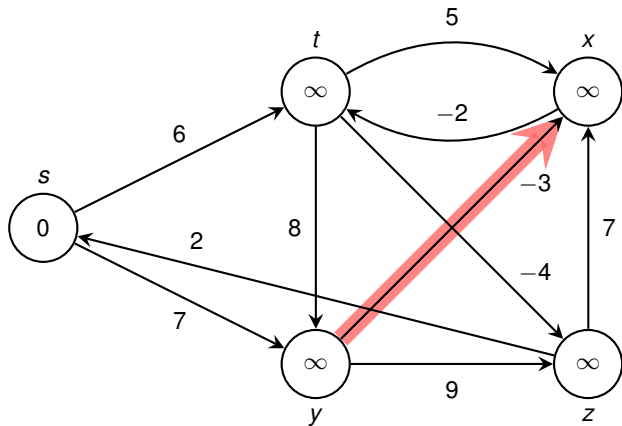
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

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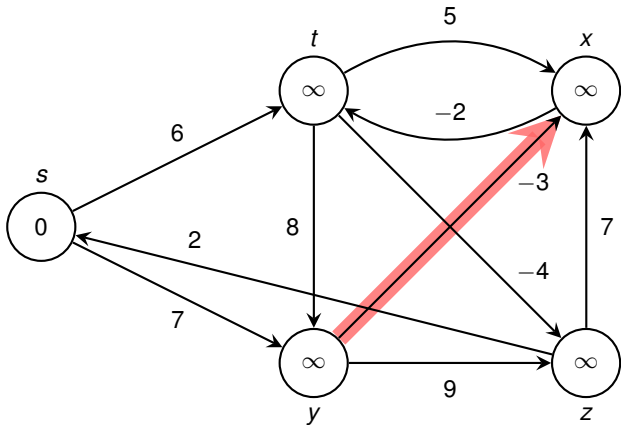
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

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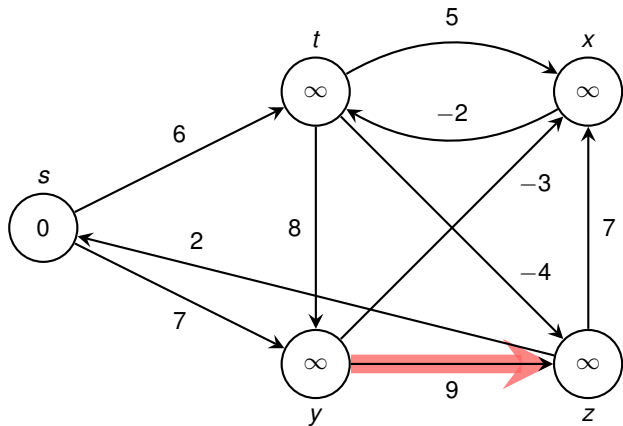
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



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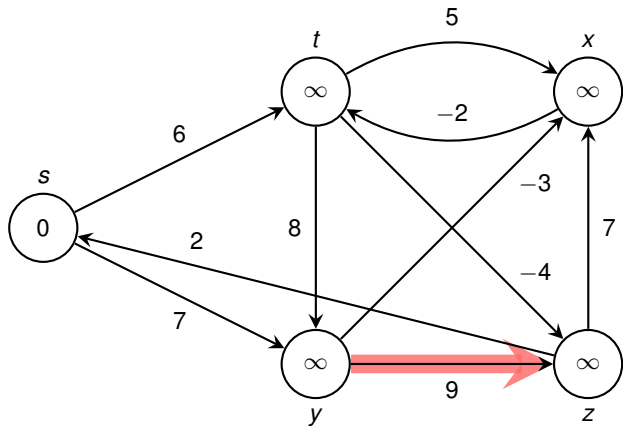
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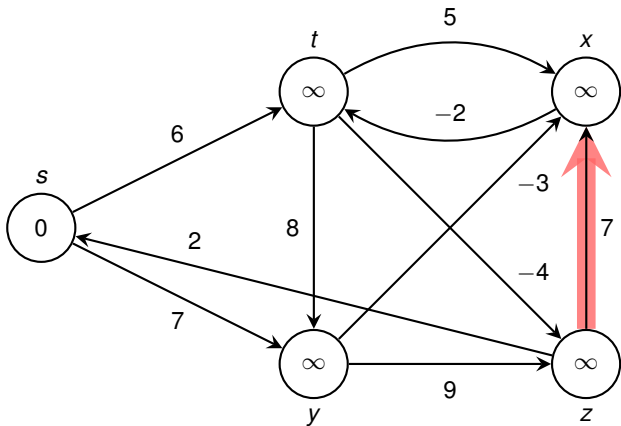
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

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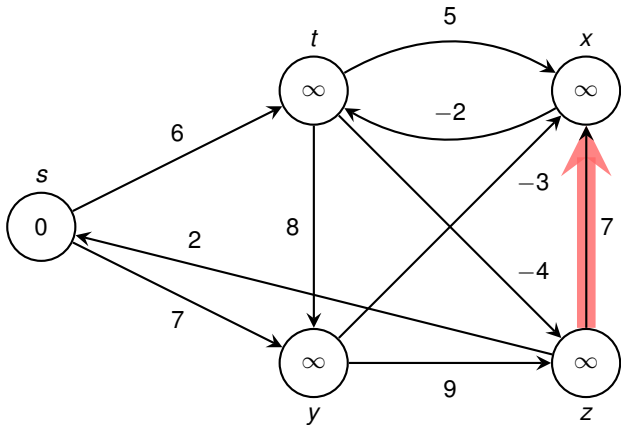
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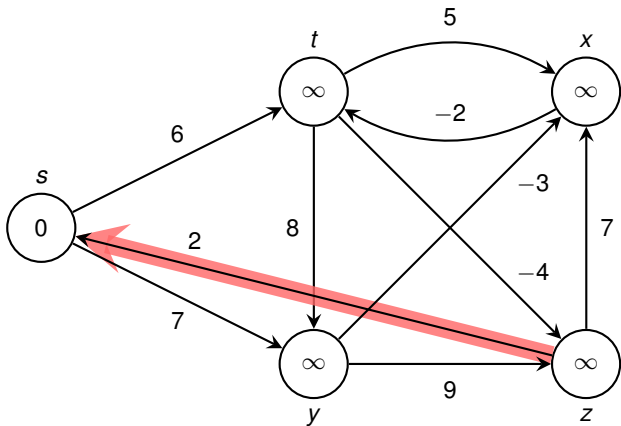
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



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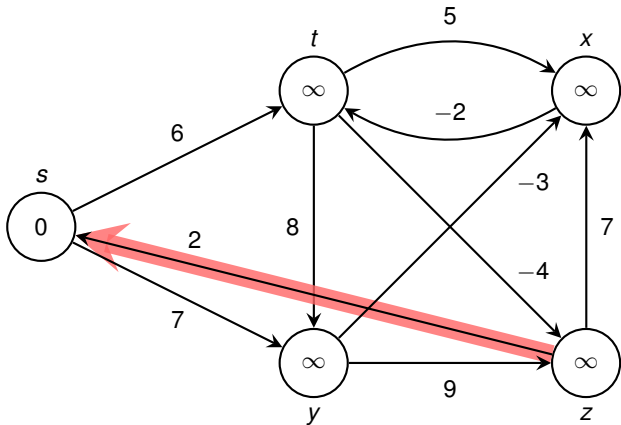
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

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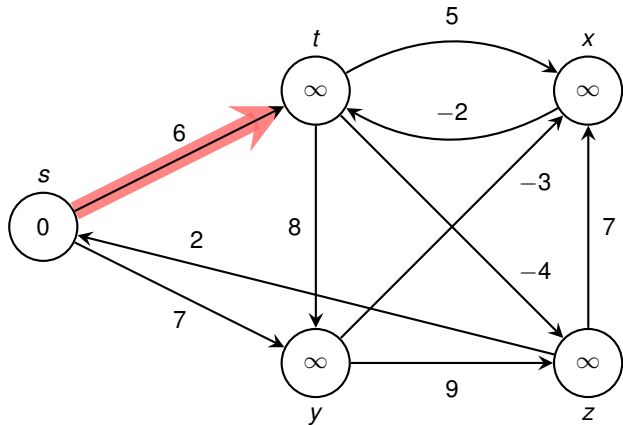
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



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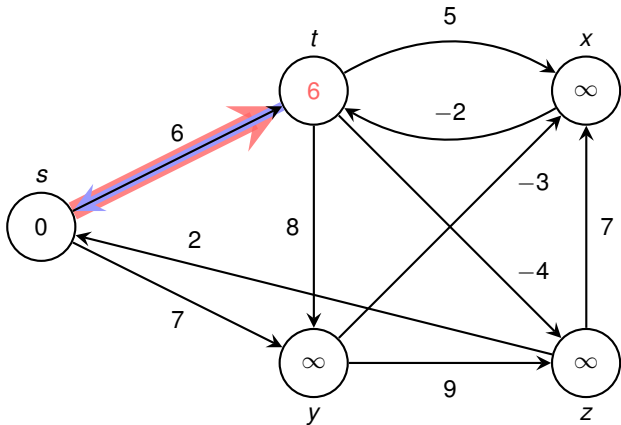
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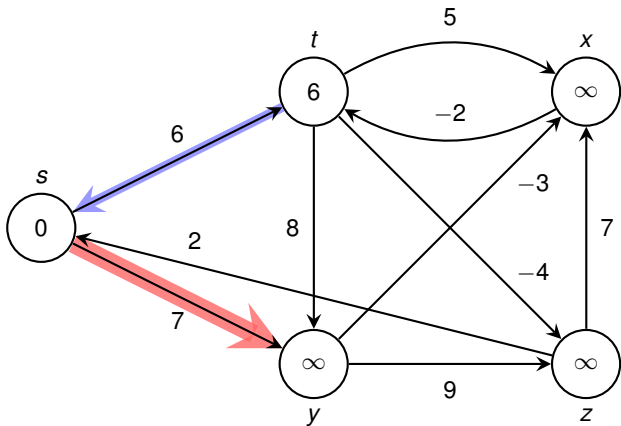
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

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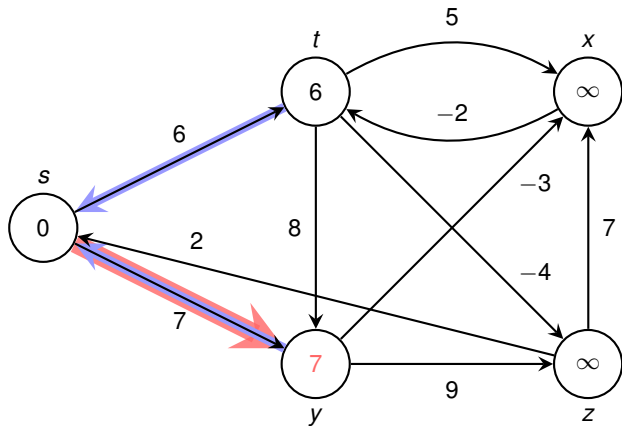
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 1

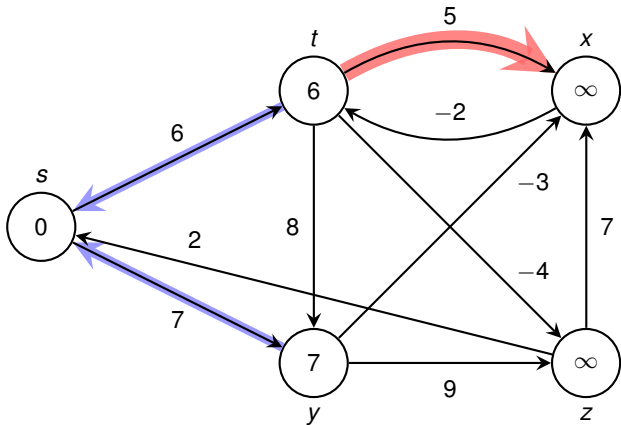
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 2

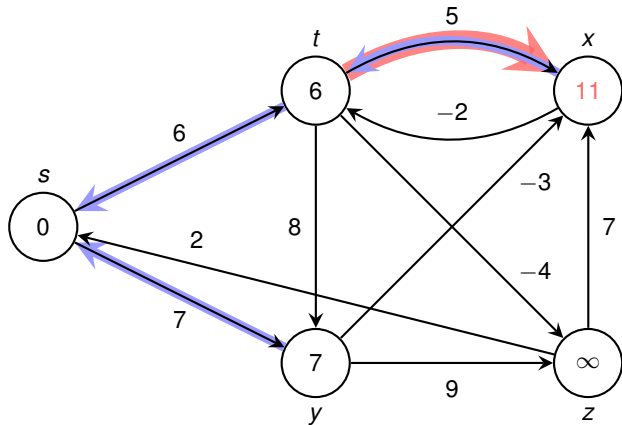
Relaxation Order: (t,x) , (t,y) , (t,z) , (x,t) , (y,x) , (y,z) , (z,x) , (z,s) , (s,t) , (s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 2

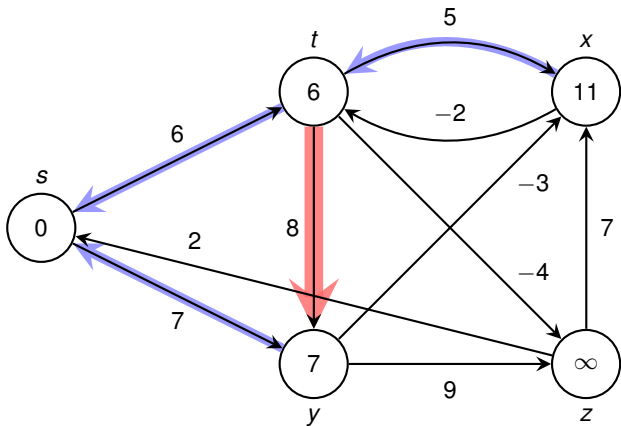
Relaxation Order: (t,x) , (t,y) , (t,z) , (x,t) , (y,x) , (y,z) , (z,x) , (z,s) , (s,t) , (s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 2

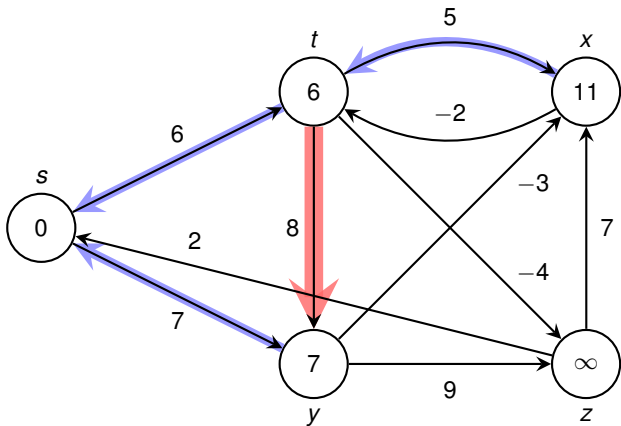
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Pass: 2

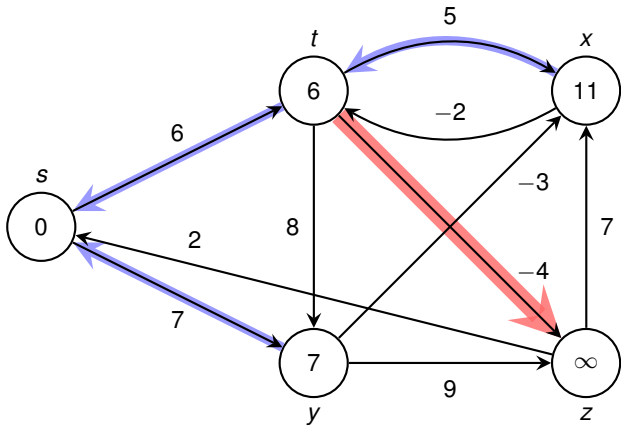
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 2

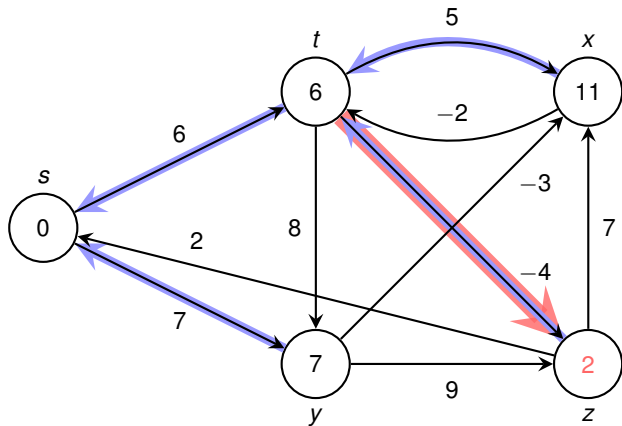
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 2

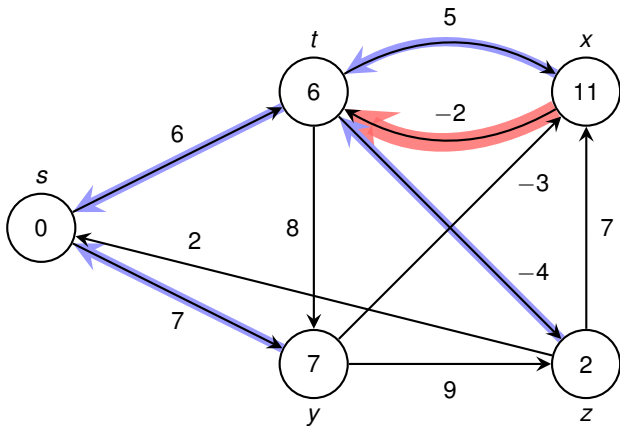
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 2

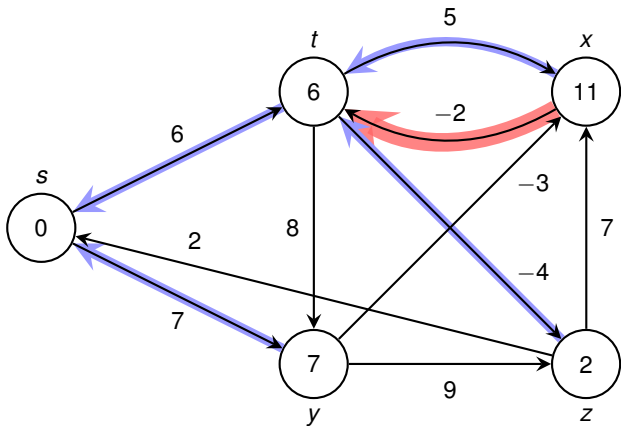
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 2

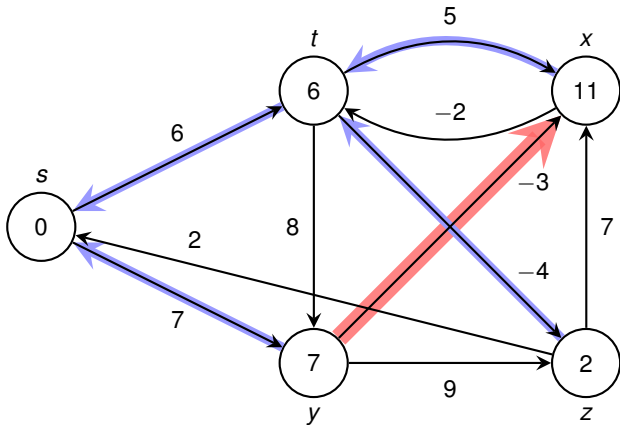
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 2

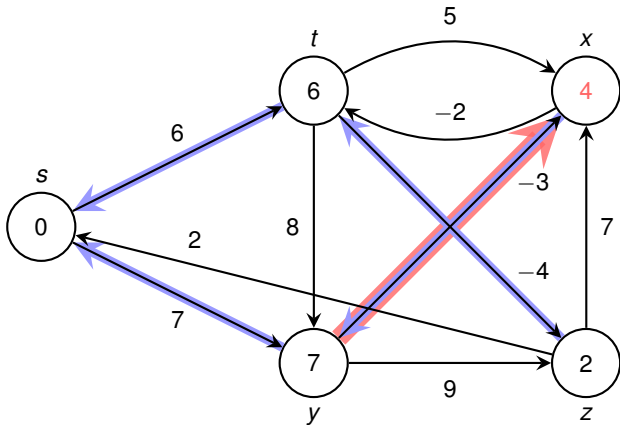
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 2

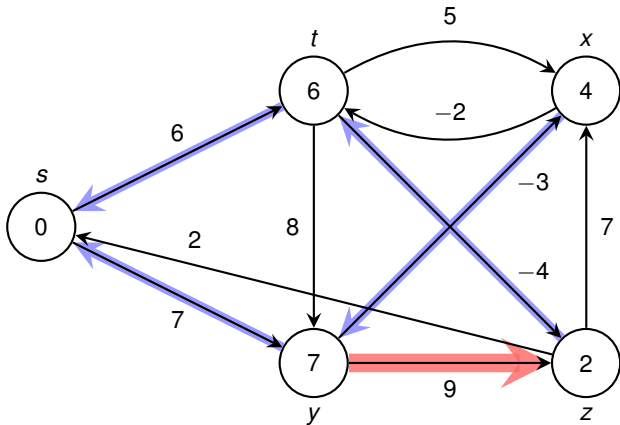
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 2

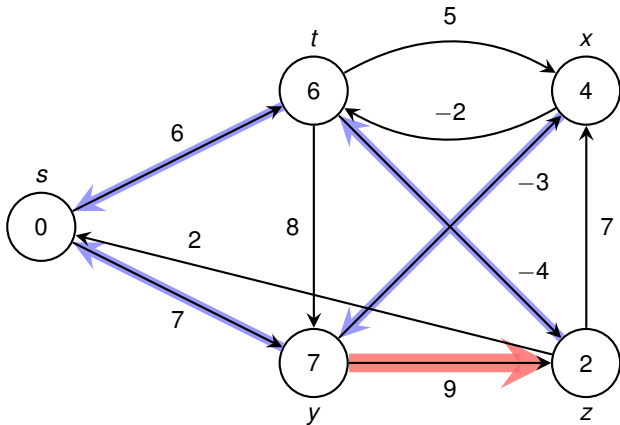
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 2

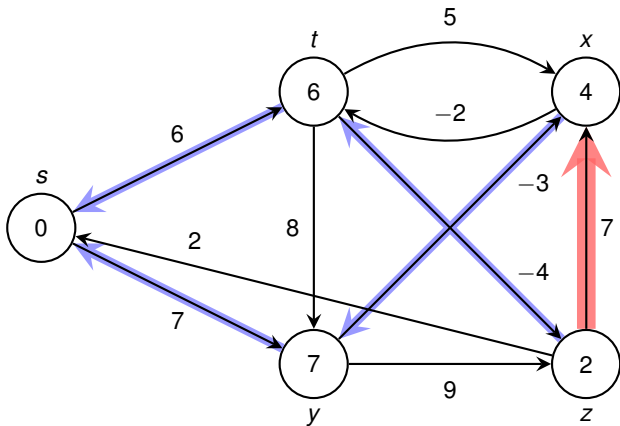
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 2

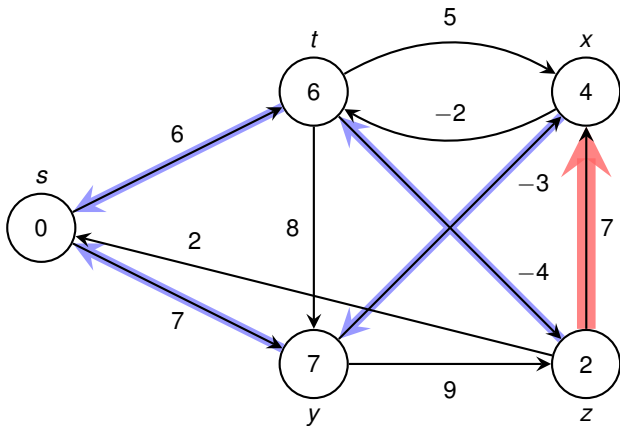
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 2

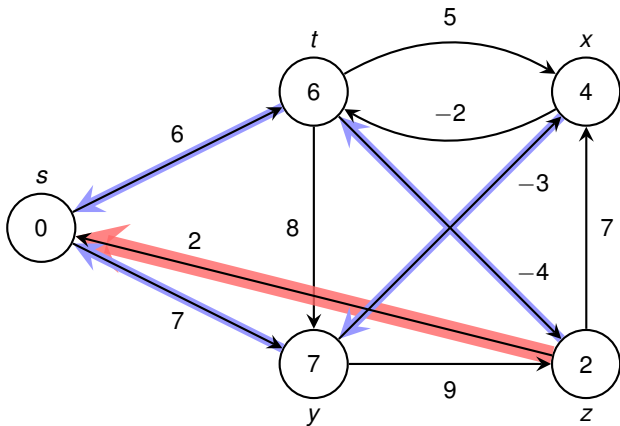
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 2

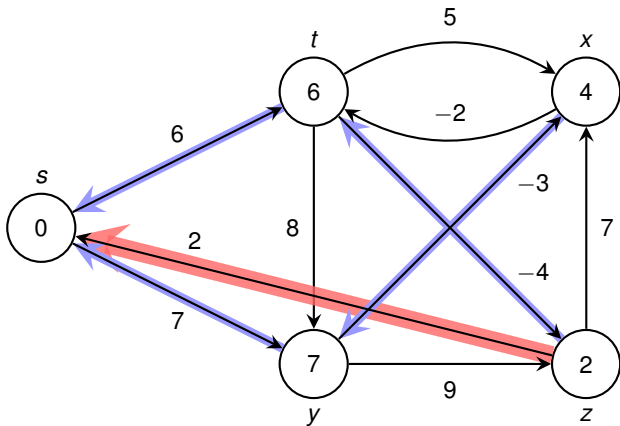
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x), **(z,s)**, (s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 2

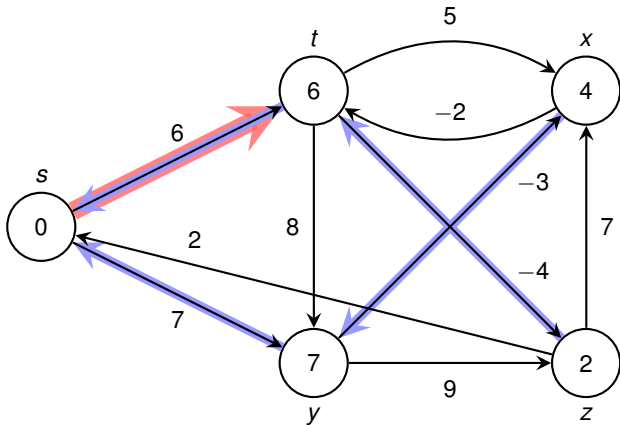
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 2

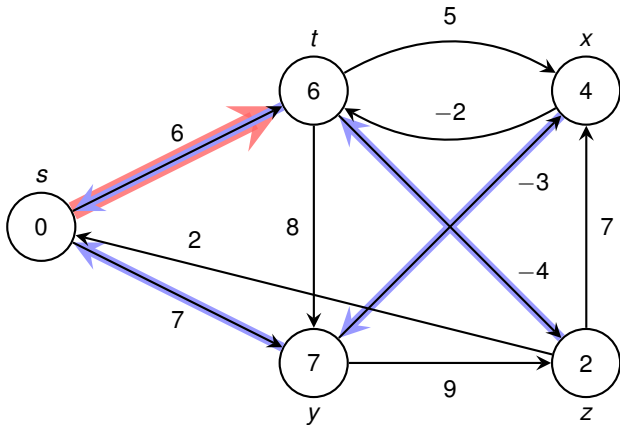
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 2

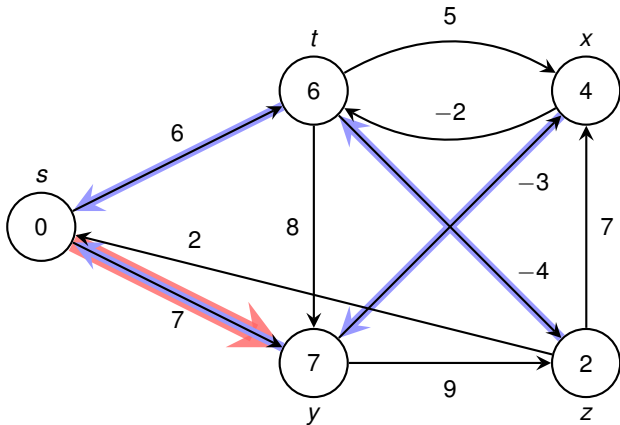
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 2

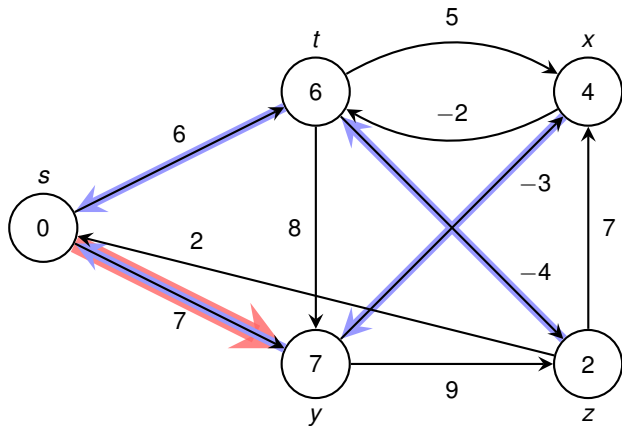
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 2

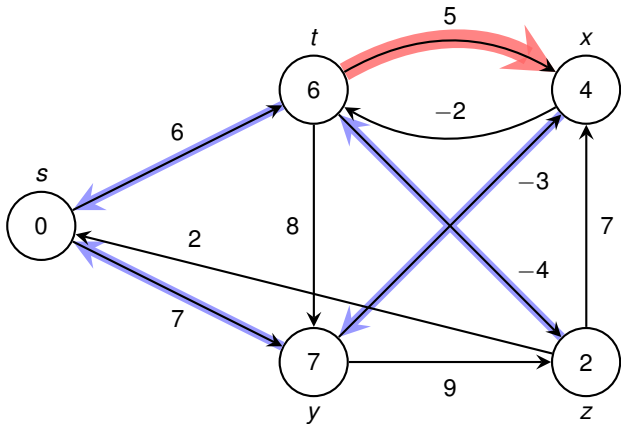
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t), (s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 3

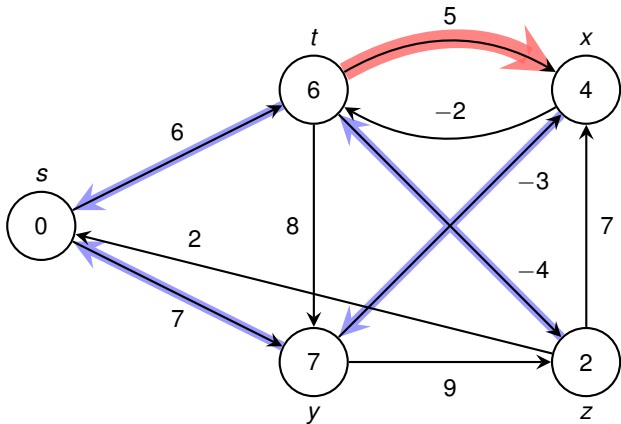
Relaxation Order: (t,x) , (t,y) , (t,z) , (x,t) , (y,x) , (y,z) , (z,x) , (z,s) , (s,t) , (s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 3

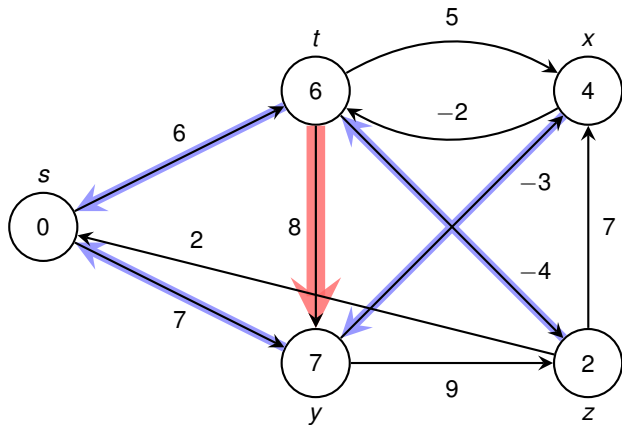
Relaxation Order: (t,x) , (t,y) , (t,z) , (x,t) , (y,x) , (y,z) , (z,x) , (z,s) , (s,t) , (s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 3

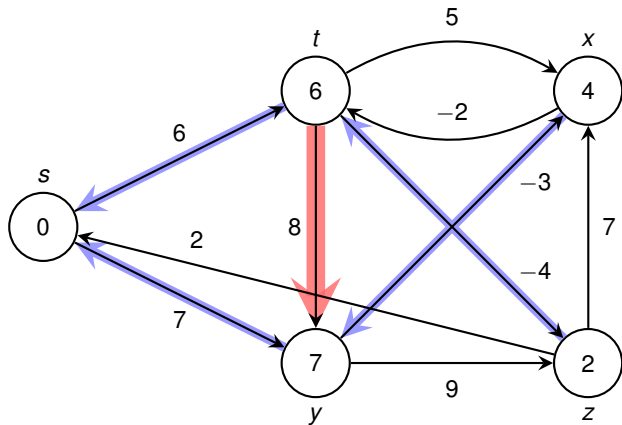
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 3

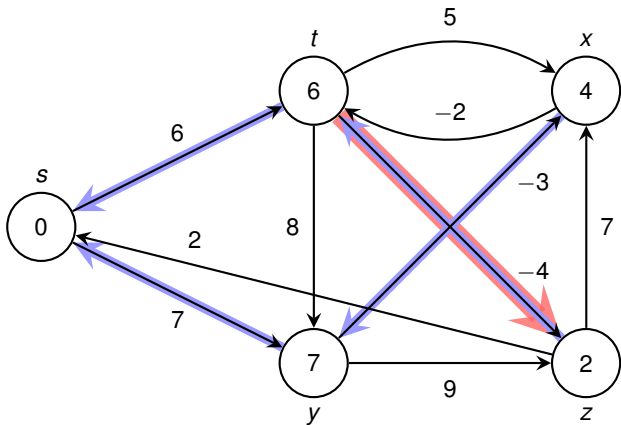
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 3

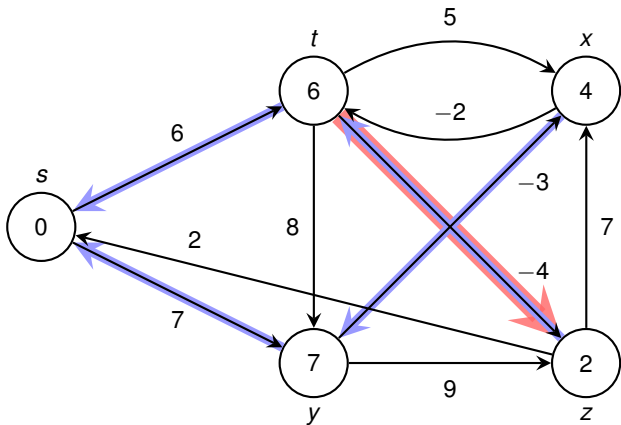
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 3

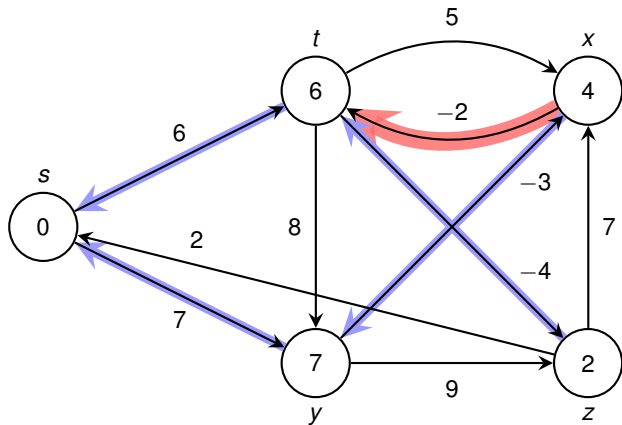
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 3

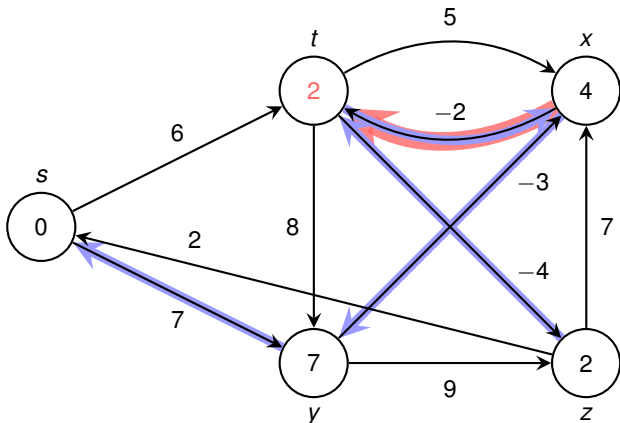
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 3

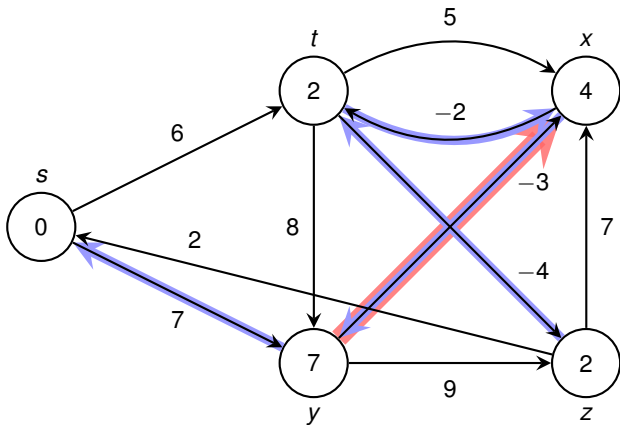
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 3

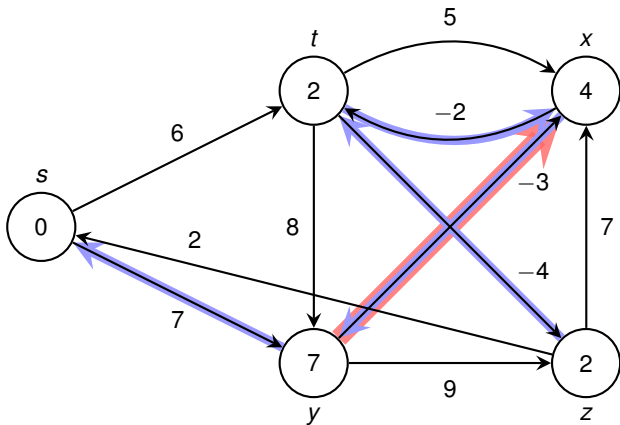
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 3

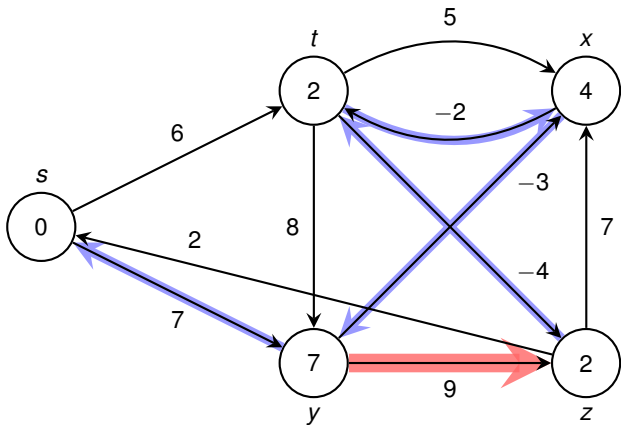
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 3

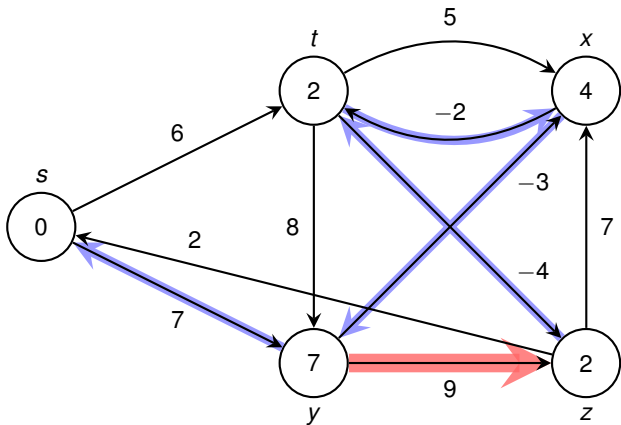
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 3

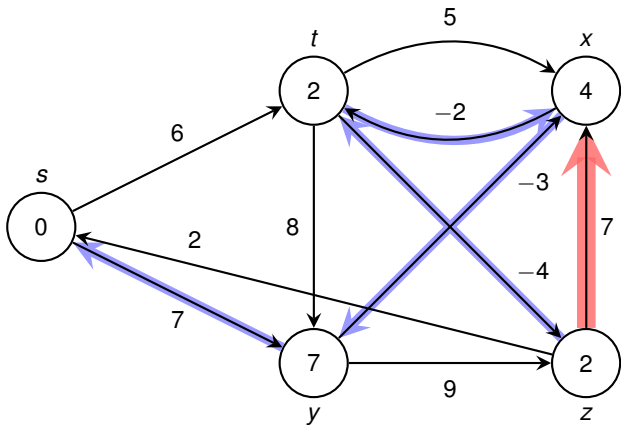
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 3

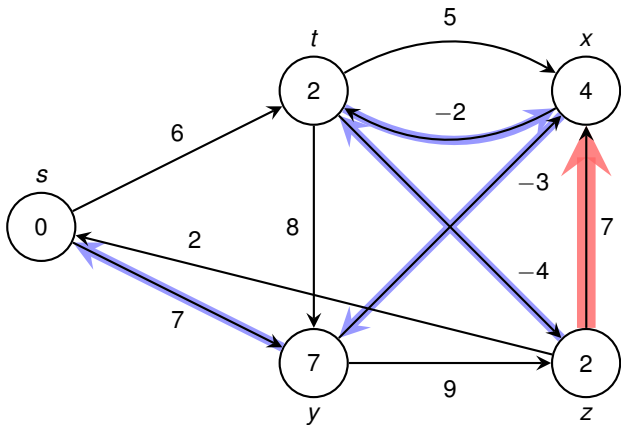
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 3

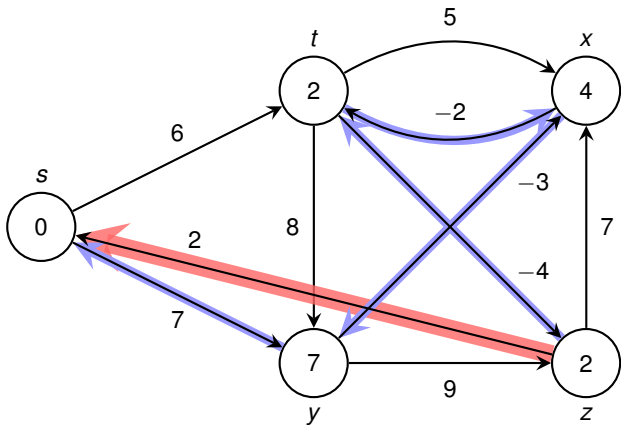
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 3

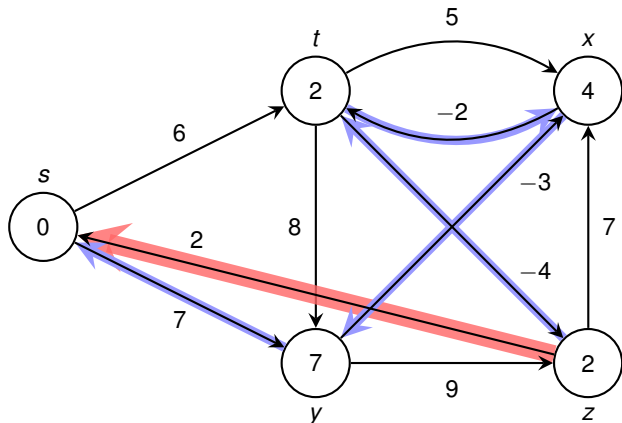
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x), **(z,s)**, (s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 3

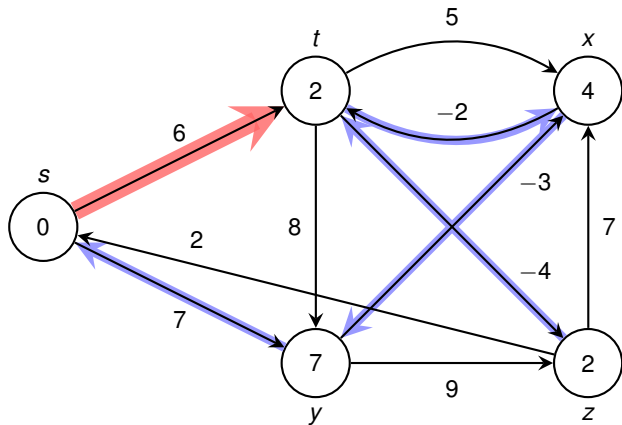
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x), **(z,s)**, (s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 3

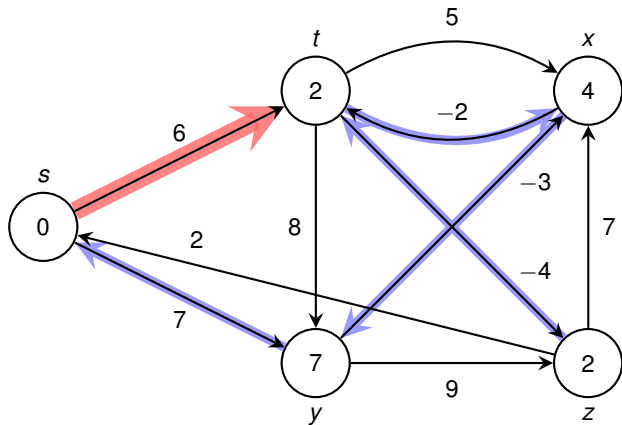
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 3

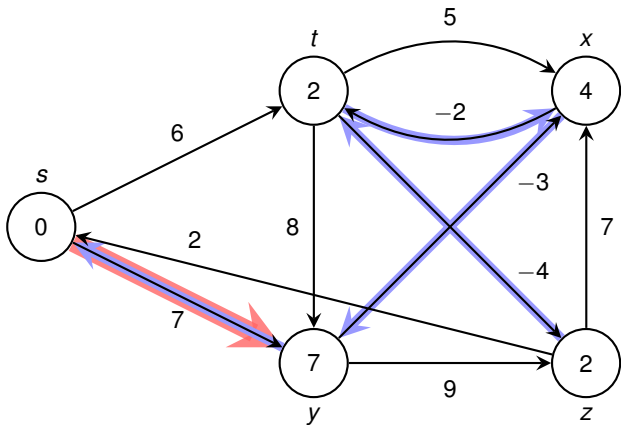
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 3

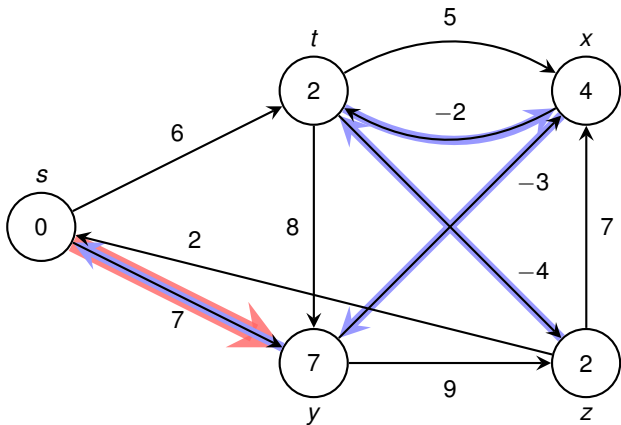
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 3

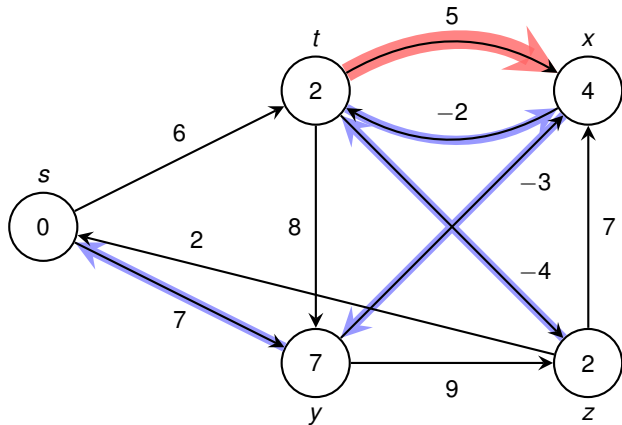
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 4

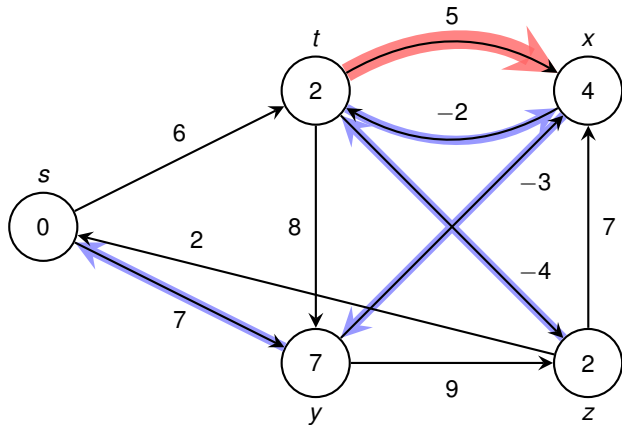
Relaxation Order: (t,x) , (t,y) , (t,z) , (x,t) , (y,x) , (y,z) , (z,x) , (z,s) , (s,t) , (s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 4

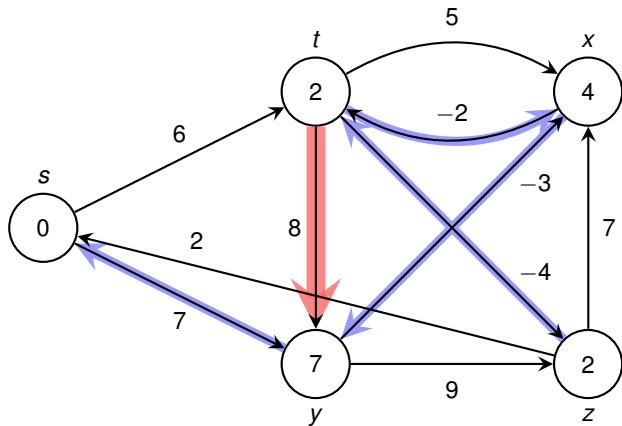
Relaxation Order: (t,x) , (t,y) , (t,z) , (x,t) , (y,x) , (y,z) , (z,x) , (z,s) , (s,t) , (s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 4

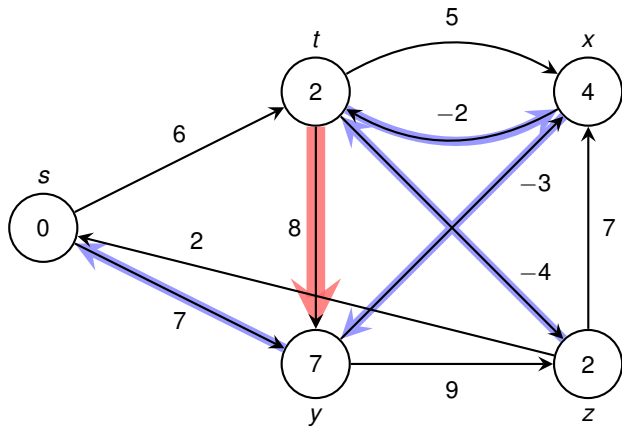
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 4

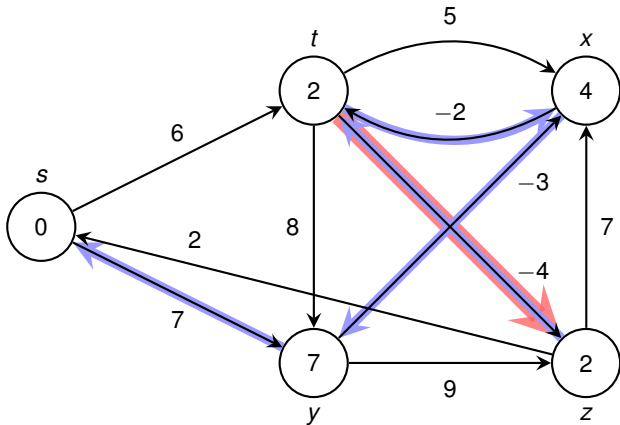
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 4

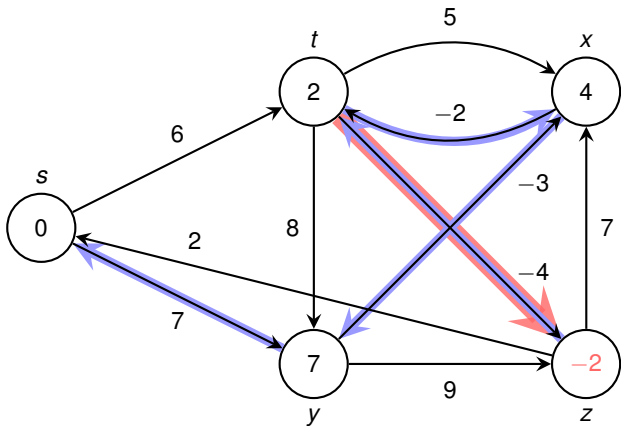
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 4

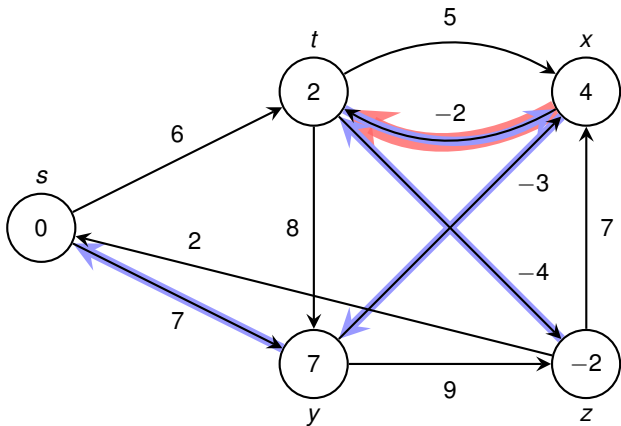
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 4

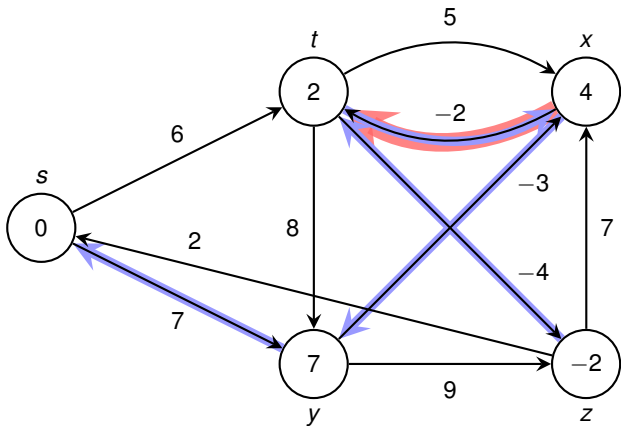
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 4

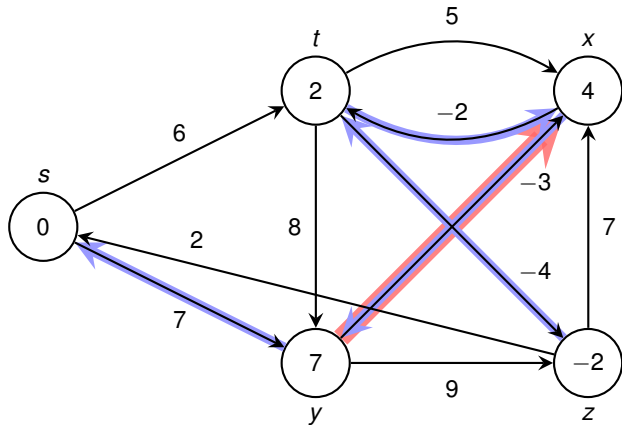
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 4

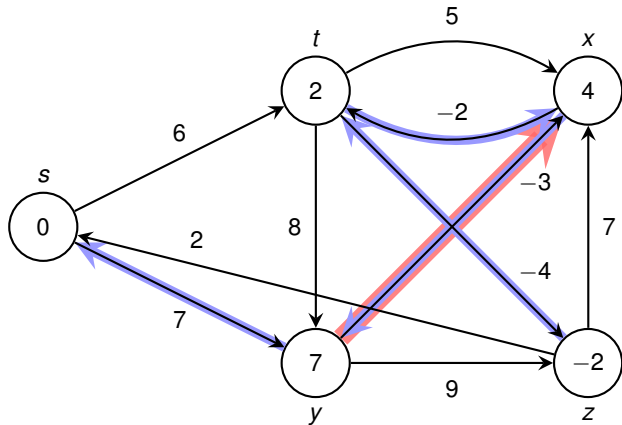
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 4

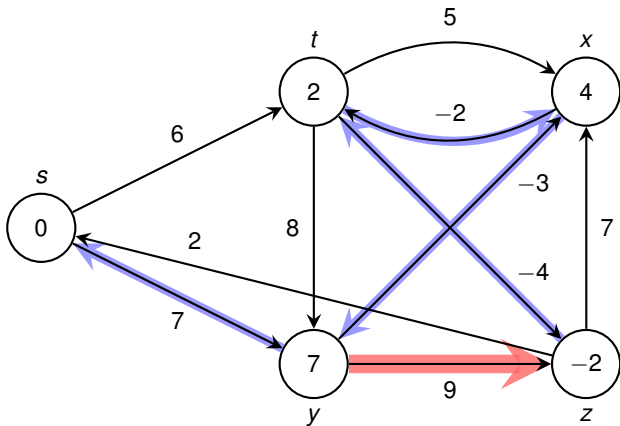
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 4

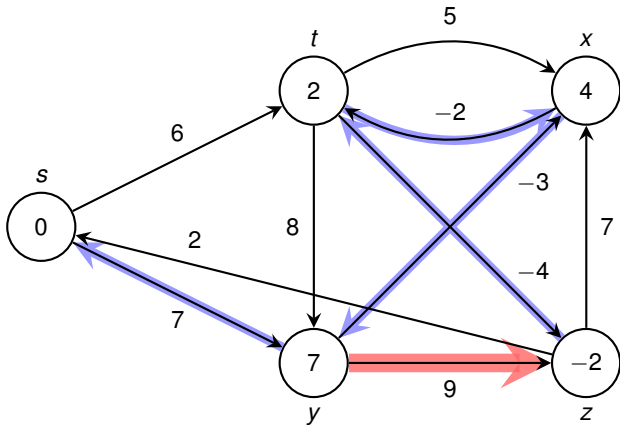
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 4

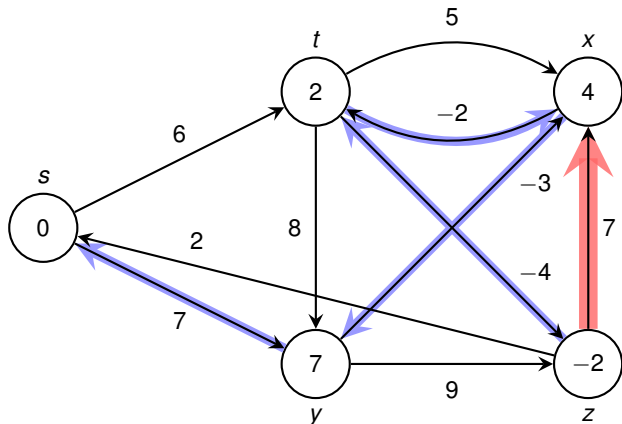
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 4

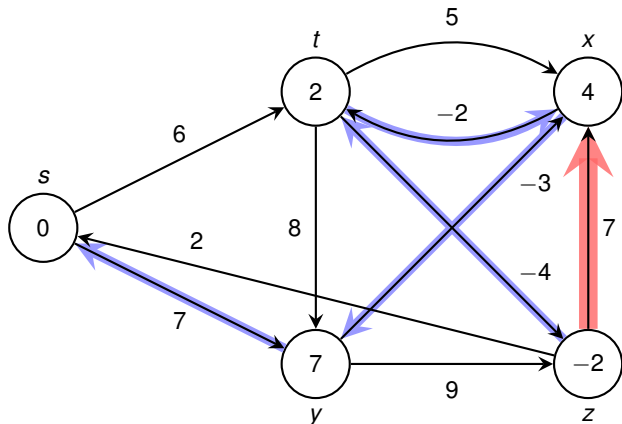
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 4

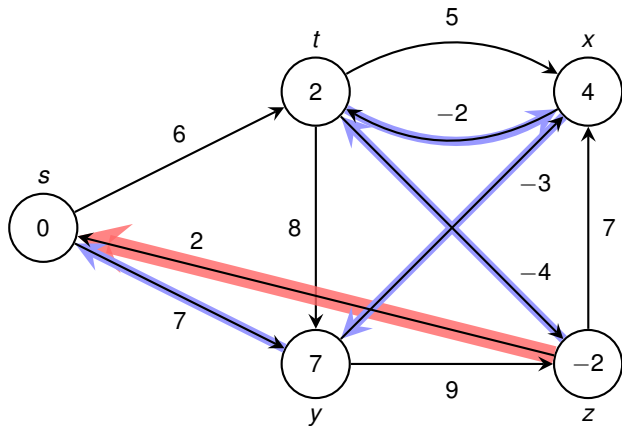
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 4

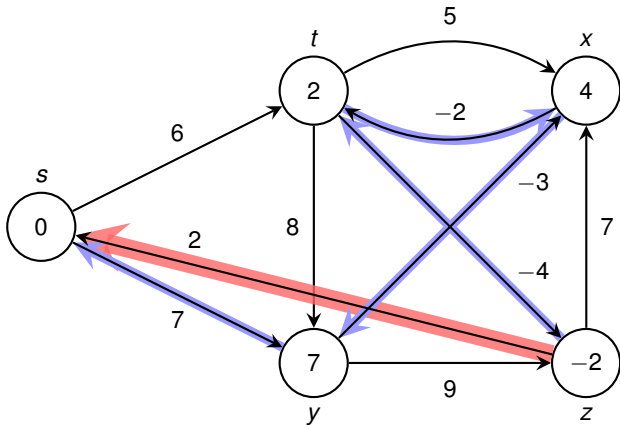
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x), **(z,s)**, (s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 4

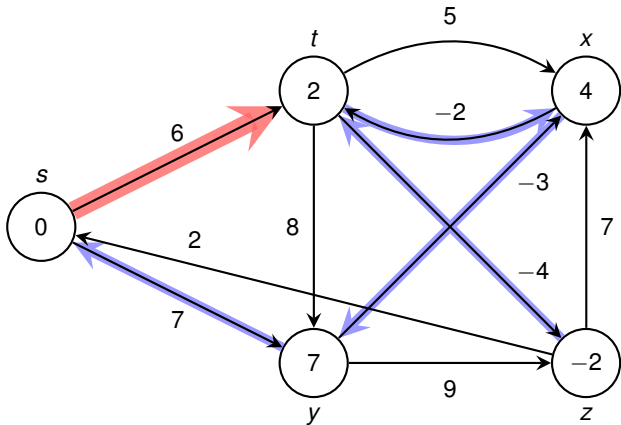
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x), **(z,s)**, (s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 4

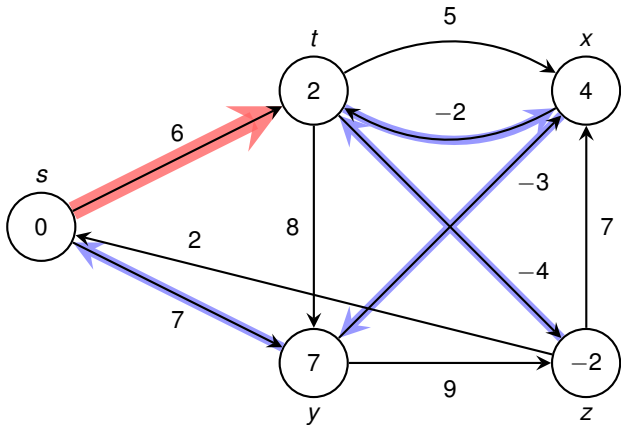
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 4

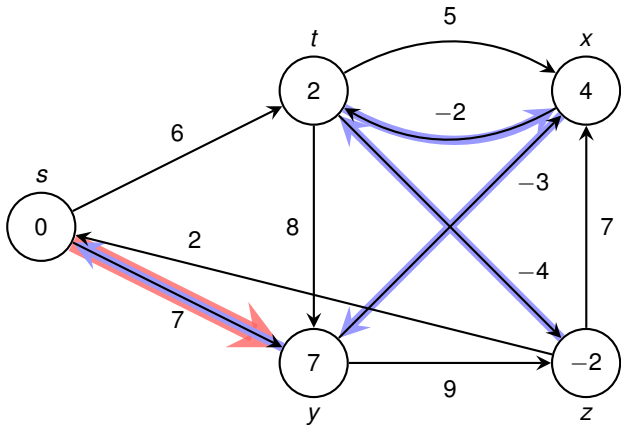
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t),(s,y)



Execution of Bellman-Ford (Figure 24.4)

Pass: 4

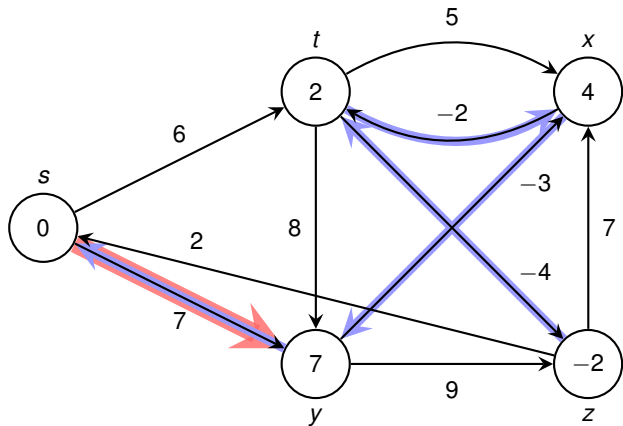
Relaxation Order: (t,x),(t,y),(t,z),(x,t),(y,x),(y,z),(z,x),(z,s),(s,t), (s,y)



Execution of Bellman-Ford (Figure 24.4)

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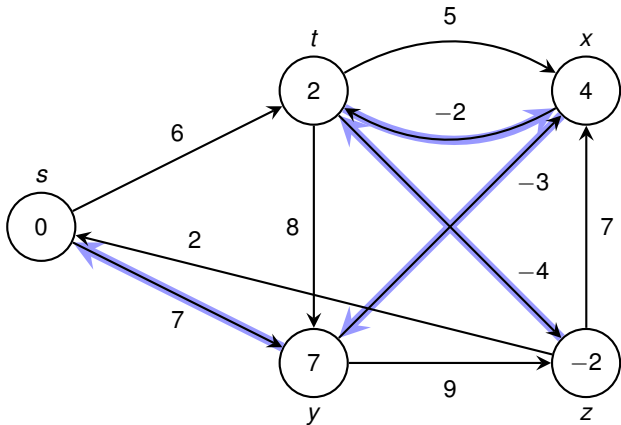
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Execution of Bellman-Ford (Figure 24.4)

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Bellman-Ford Algorithm: Correctness (1/2)

Lemma 24.2/Theorem 24.3

Assume that G contains no negative-weight cycles that are reachable from s . Then after $|V| - 1$ passes, we have $v.d = v.\delta$ for all vertices $v \in V$ (that are reachable) and Bellman-Ford returns TRUE.



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Proof that $v.d = v.\delta$

- Let v be a vertex reachable from s



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- Let v be a vertex reachable from s
- Let $p = (v_0 = s, v_1, \dots, v_k = v)$ be a shortest path from s to v



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- Need to prove: $v.d \leq u.d + w(u, v)$ for all edges



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Triangle inequality (holds even if $w(u, v) < 0!$)



Bellman-Ford Algorithm: Correctness (2/2)

Theorem 24.3

If G contains a negative-weight cycle reachable from s , then Bellman-Ford returns FALSE.



Bellman-Ford Algorithm: Correctness (2/2)

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Proof:

- Let $c = (v_0, v_1, \dots, v_k = v_0)$ be a negative-weight cycle reachable from s
- If Bellman-Ford returns TRUE, then for every $1 \leq i < k$,

$$v_i.d \leq v_{i-1}.d + w(v_{i-1}, v_i)$$



Bellman-Ford Algorithm: Correctness (2/2)

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If G contains a **negative-weight cycle** reachable from s , then Bellman-Ford returns FALSE.

Proof:

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- If Bellman-Ford returns TRUE, then for every $1 \leq i < k$,

$$\begin{aligned}v_i.d &\leq v_{i-1}.d + w(v_{i-1}, v_i) \\ \Rightarrow \sum_{i=1}^k v_i.d &\leq \sum_{i=1}^k v_{i-1}.d + \sum_{i=1}^k w(v_{i-1}, v_i)\end{aligned}$$



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This cancellation is only valid if all $.d$ -values are finite!



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This cancellation is only valid if all $.d$ -values are finite!

- This contradicts the assumption that c is a **negative-weight cycle!** □



The Bellman-Ford Algorithm

```
BELLMAN-FORD (G, w, s)
0: assert(s in G.vertices())
1: for v in G.vertices()
2:     v.predecessor = None
3:     v.d = Infinity
4: s.d = 0
5:
6: repeat |V|-1 times
7:     for e in G.edges()
8:         Relax edge e=(u,v): Check if  $u.d + w(u,v) < v.d$ 
9:             if e.start.d + e.weight.d < e.end.d:
10:                 e.end.d = e.start.d + e.weight
11:                 e.end.predecessor = e.start
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13: for e in G.edges()
14:     if e.start.d + e.weight.d < e.end.d:
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Yes, because if pass i keeps all $.d$ variables, then so does pass $i + 1$.



The Bellman-Ford Algorithm (modified)

```
BELLMAN-FORD-NEW(G, w, s)
0: assert(s in G.vertices())
1: for v in G.vertices()
2:     v.predecessor = None
3:     v.d = Infinity
4: s.d = 0
5:
6: repeat |V| times
7:     flag = 0
8:     for e in G.edges()
9:         Relax edge e=(u,v): Check if u.d + w(u,v) < v.d
10:            if e.start.d + e.weight < e.end.d:
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13:                flag = 1
14:     if flag = 0 return TRUE
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The Bellman-Ford Algorithm (modified)

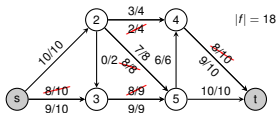
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Can we terminate earlier if there is a pass that keeps all *d* variables?

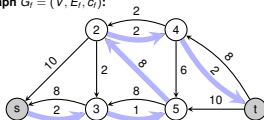
Yes, because if pass *i* keeps all *d* variables, then so does pass *i* + 1.



Graph $G = (V, E, c)$:



Residual Graph $G_r = (V, E_r, c_r)$:



6.6: Maximum flow

Frank Stajano

Thomas Sauerwald

Lent 2016



UNIVERSITY OF
CAMBRIDGE

Outline

Introduction

Ford-Fulkerson

A Glimpse at the Max-Flow Min-Cut Theorem

Analysis of Ford-Fulkerson



History of the Maximum Flow Problem [Harris, Ross (1955)]

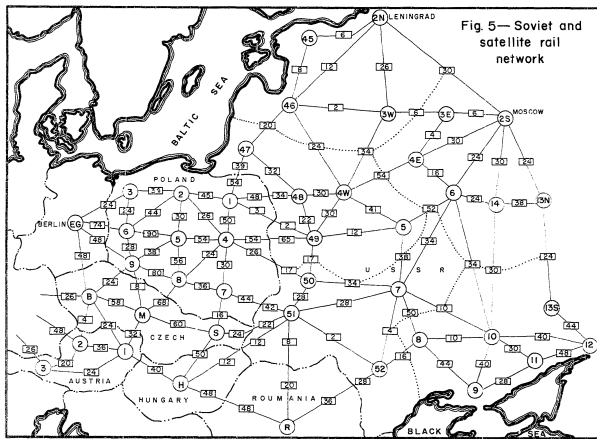


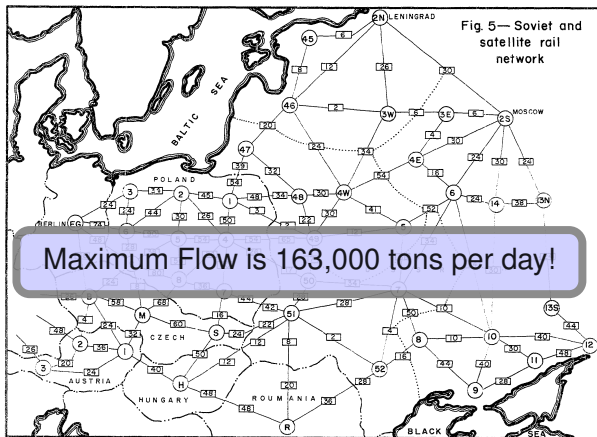
Fig. 5—Soviet and satellite rail network

Legend: — International boundary Regional boundaries of the USSR (they are included as a matter of general information)

⑦ Operating divisions. Those located in Russia are believed to be accurately located. Some Russian divisions (2, 3, 4 and 13) are located in two regions and are so indicated. Divisions shown in the satellites are indicated according to the authors' best judgment, since intelligence reports are unavailable. Train capacities in Russia are for 1000-net-ton trains or their equivalent. Train capacities in Poland are for 666-net tons (or the equivalent). Train capacities in all other satellites are for 400 net tons (or the equivalent) except in East Germany. In East Germany, train capacities are those of entering lines. The numbers shown in boxes are total interdivisional capacities.



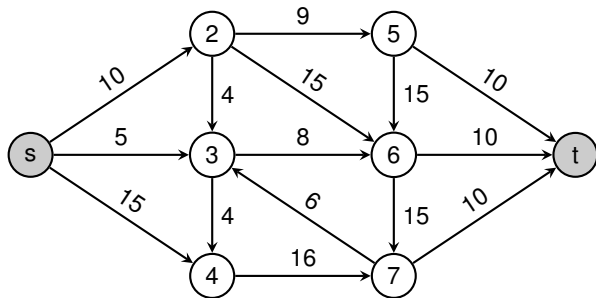
History of the Maximum Flow Problem [Harris, Ross (1955)]



Flow Network

Flow Network

- Abstraction for material (one commodity!) **flowing** through the edges
- $G = (V, E)$ directed graph **without parallel edges**
- distinguished nodes: source s and sink t
- every edge e has a capacity $c(e)$

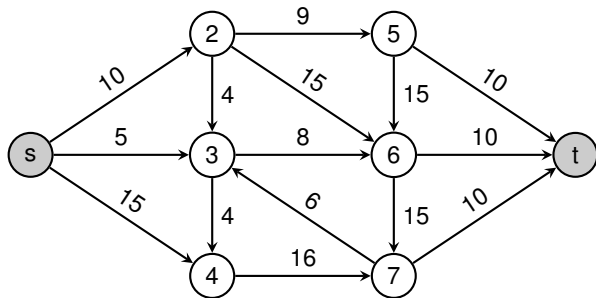


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Capacity function $c : V \times V \rightarrow \mathbb{R}^+$



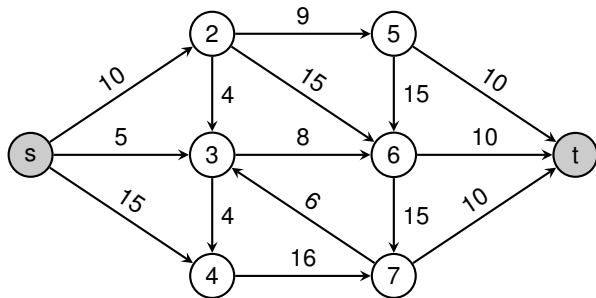
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Capacity function $c : V \times V \rightarrow \mathbb{R}^+$

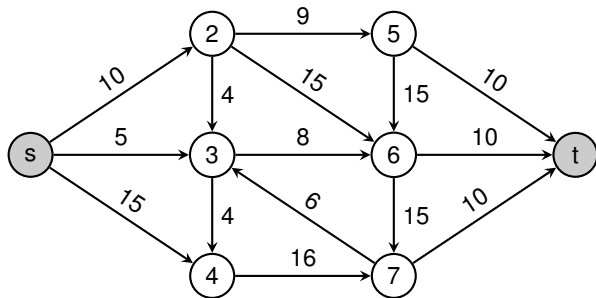
$c(u, v) = 0 \Leftrightarrow (u, v) \notin E$



Flow Network

Flow

A **flow** is a function $f : V \times V \rightarrow \mathbb{R}$ that satisfies:

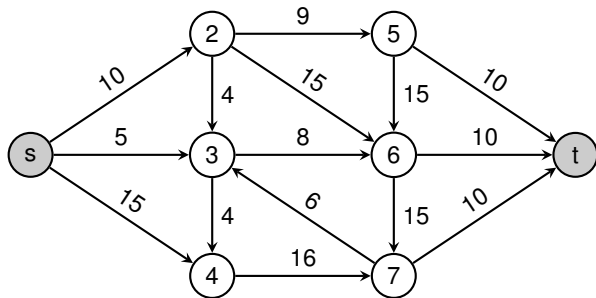


Flow Network

Flow

A **flow** is a function $f : V \times V \rightarrow \mathbb{R}$ that satisfies:

- For every $u, v \in V$, $f(u, v) \leq c(u, v)$

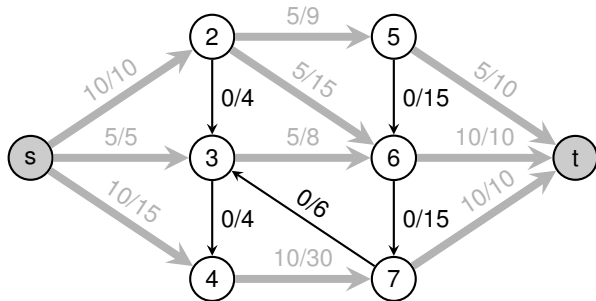


Flow Network

Flow

A **flow** is a function $f : V \times V \rightarrow \mathbb{R}$ that satisfies:

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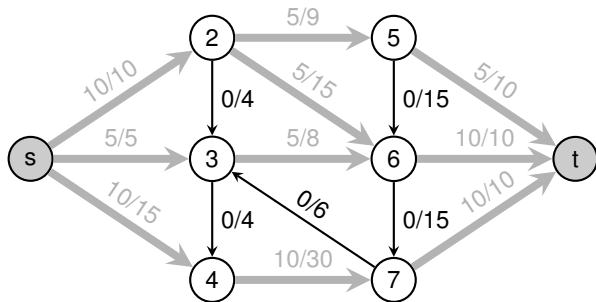


Flow Network

Flow

A **flow** is a function $f : V \times V \rightarrow \mathbb{R}$ that satisfies:

- For every $u, v \in V$, $f(u, v) \leq c(u, v)$
- For every $u, v \in V$, $f(u, v) = -f(v, u)$

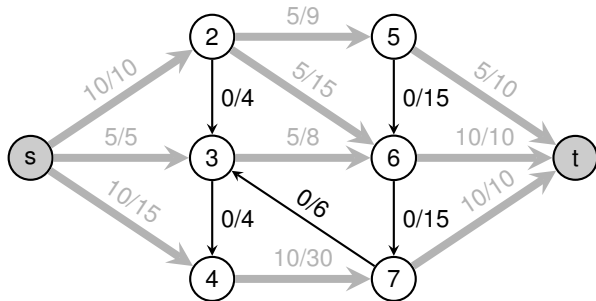


Flow Network

Flow

A **flow** is a function $f : V \times V \rightarrow \mathbb{R}$ that satisfies:

- For every $u, v \in V$, $f(u, v) \leq c(u, v)$
- For every $u, v \in V$, $f(u, v) = -f(v, u)$
- For every $u \in V \setminus \{s, t\}$, $\sum_{v \in V} f(u, v) = 0$



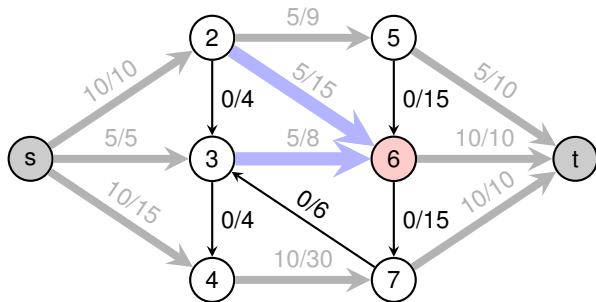
Flow Network

Flow

A **flow** is a function $f : V \times V \rightarrow \mathbb{R}$ that satisfies:

- For every $u, v \in V$, $f(u, v) \leq c(u, v)$
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Flow Conservation



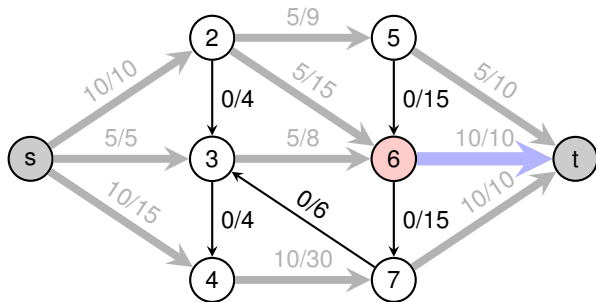
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Flow Conservation



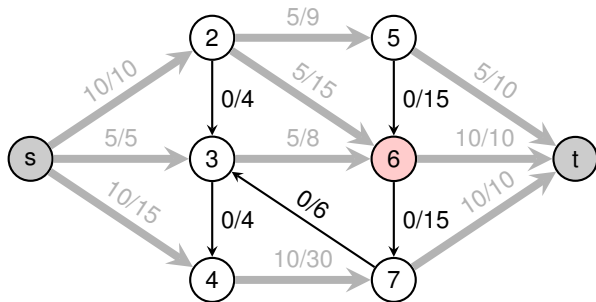
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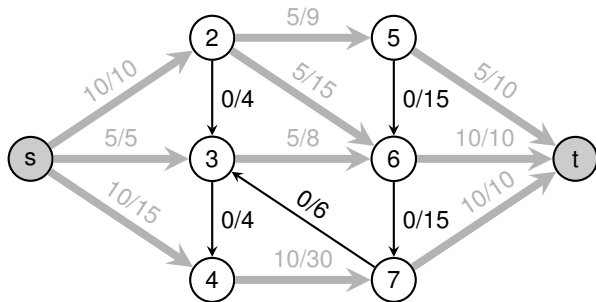
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Flow Conservation



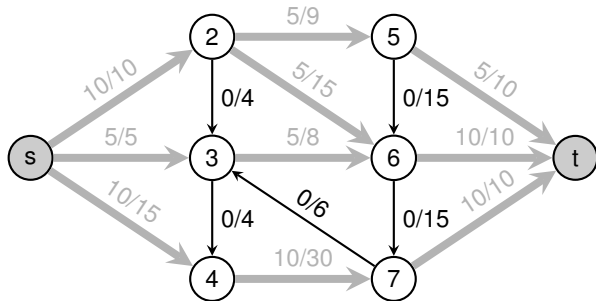
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The **value** of a flow is defined as $|f| = \sum_{v \in V} f(s, v)$



Flow Network

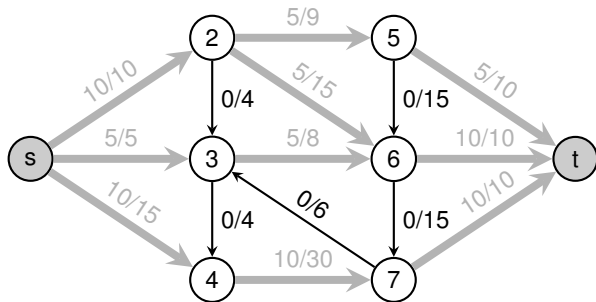
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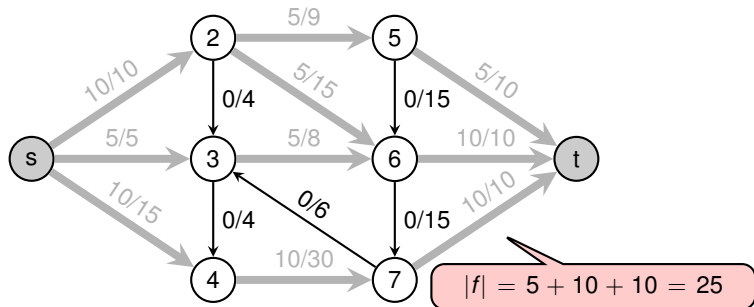
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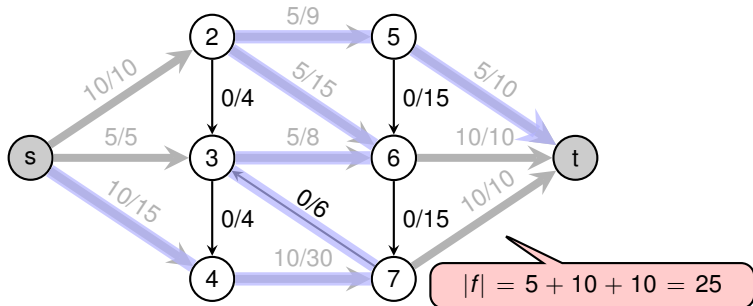
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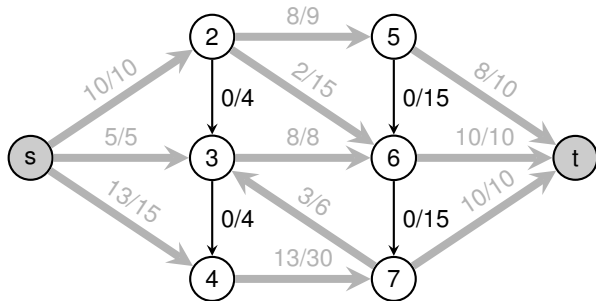
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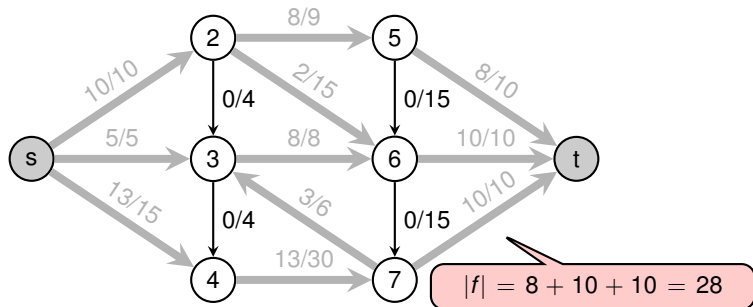
Flow Network

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Flow Network

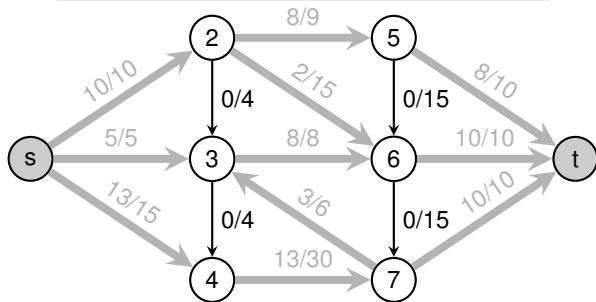
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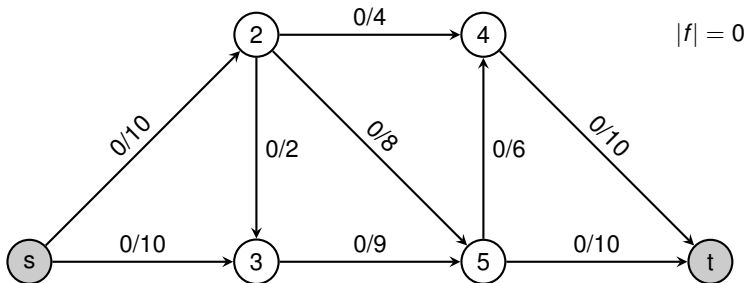
How to find a Maximum Flow?



A First Attempt

Greedy Algorithm

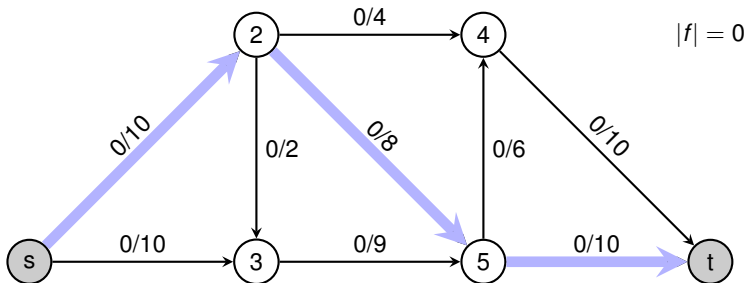
- Start with $f(u, v) = 0$ everywhere
- Repeat as long as possible:
 - Find a (s, t) -path p where each edge $e = (u, v)$ has $f(u, v) < c(u, v)$
 - Augment flow along p



A First Attempt

Greedy Algorithm

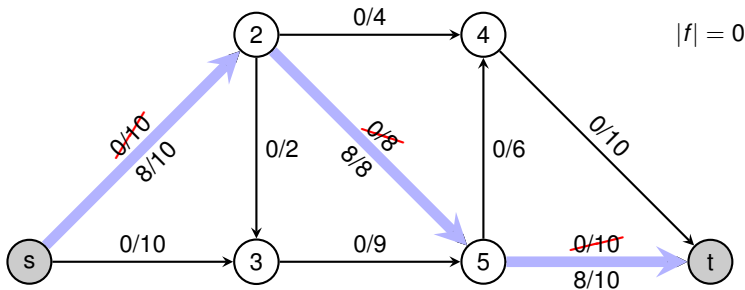
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A First Attempt

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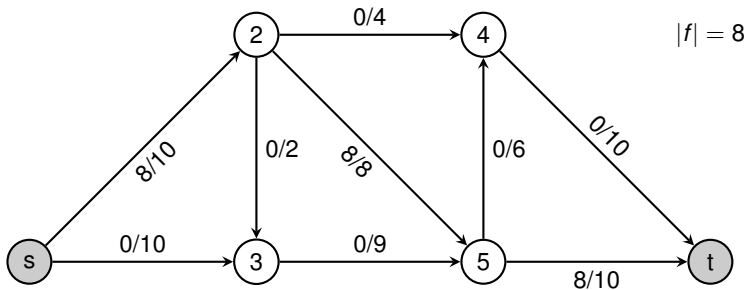
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A First Attempt

Greedy Algorithm

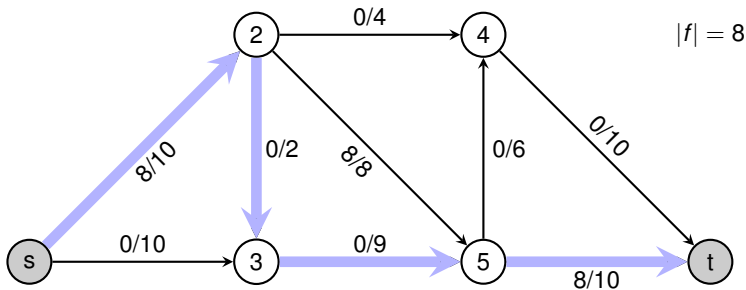
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A First Attempt

Greedy Algorithm

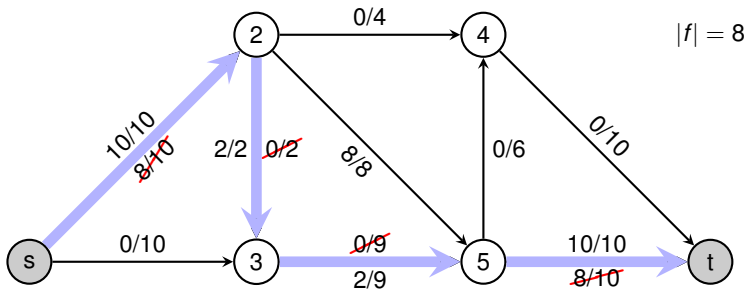
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A First Attempt

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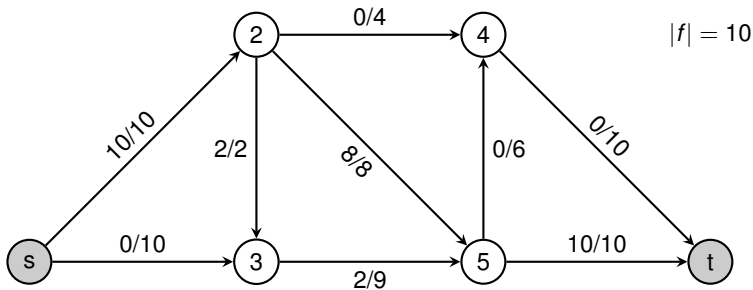
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A First Attempt

Greedy Algorithm

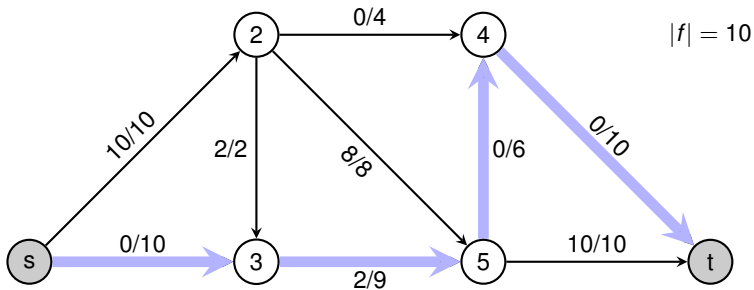
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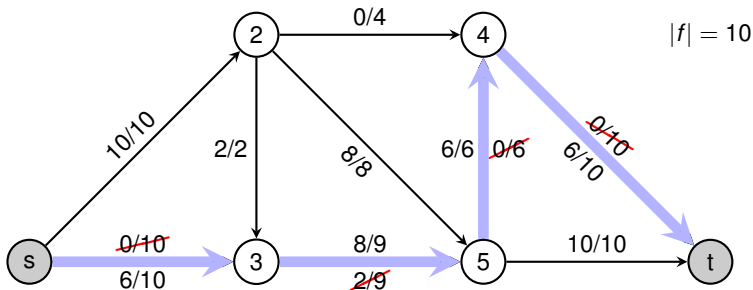
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A First Attempt

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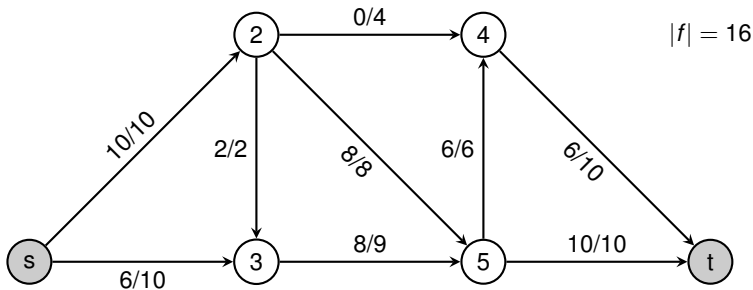
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A First Attempt

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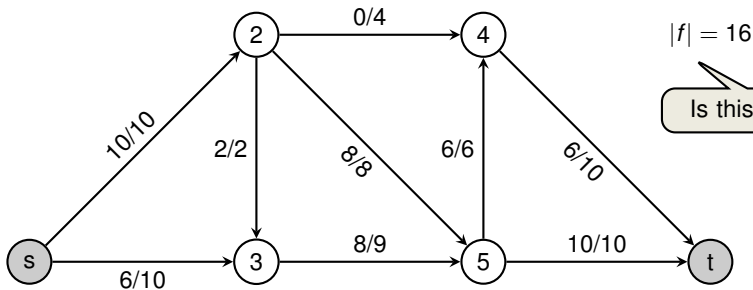
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$$|f| = 16$$

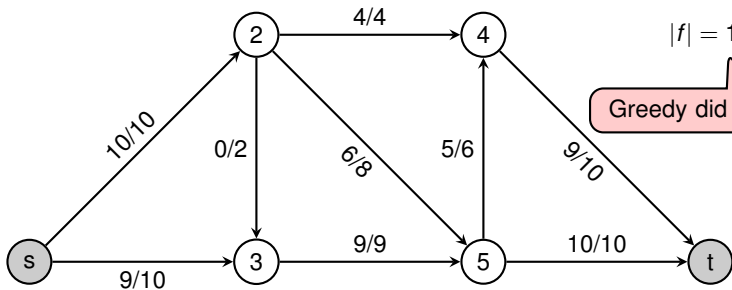
Is this optimal?



A First Attempt

Greedy Algorithm

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$$|f| = 19$$

Greedy did not succeed!



Introduction

Ford-Fulkerson

A Glimpse at the Max-Flow Min-Cut Theorem

Analysis of Ford-Fulkerson



Residual Graph

Original Edge

Edge $e = (u, v) \in E$

- flow $f(u, v)$ and capacity $c(u, v)$



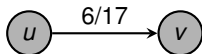
Residual Graph

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Graph G:



Residual Graph

Original Edge

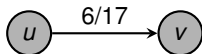
Edge $e = (u, v) \in E$

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Residual Capacity

$$c_f(u, v) = \begin{cases} c(u, v) - f(u, v) & \text{if } (u, v) \in E, \\ f(v, u) & \text{if } (v, u) \in E, \\ 0 & \text{otherwise.} \end{cases}$$

Graph G:



Residual Graph

Original Edge

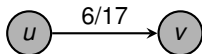
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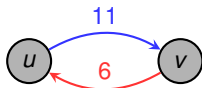
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Graph G :



Residual G_f :



Residual Graph

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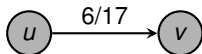
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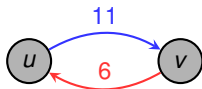
Residual Graph

- $G_f = (V, E_f, c_f)$, $E_f := \{(u, v) : c_f(u, v) > 0\}$

Graph G:



Residual G_f :



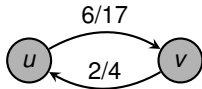
Residual Graph with anti-parallel edges

Original Edge

Edge $e = (u, v) \in E$ (& possibly $e' = (v, u) \in E$)

- flow $f(u, v)$ and capacity $c(u, v)$

Graph G:



Residual Graph with anti-parallel edges

Original Edge

Edge $e = (u, v) \in E$ (& possibly $e' = (v, u) \in E$)

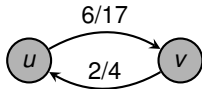
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Residual Capacity

For every pair $(u, v) \in V \times V$,

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Graph G:



Residual Graph with anti-parallel edges

Original Edge

Edge $e = (u, v) \in E$ (& possibly $e' = (v, u) \in E$)

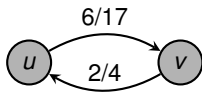
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Residual Capacity

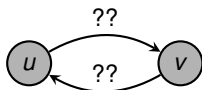
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Graph G :



Residual G_f :



Residual Graph with anti-parallel edges

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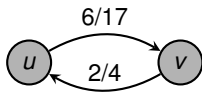
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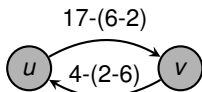
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Residual G_f :



Residual Graph with anti-parallel edges

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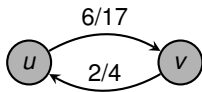
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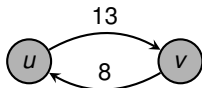
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Graph G :



Residual G_f :



Residual Graph with anti-parallel edges

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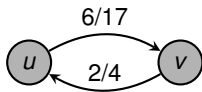
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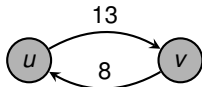
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Graph G:

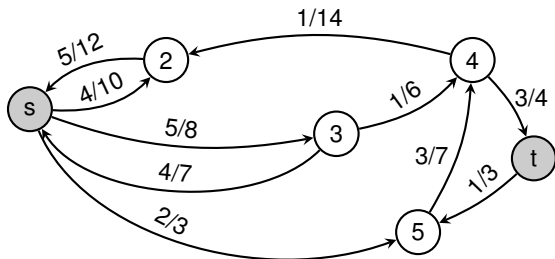


Residual G_f :

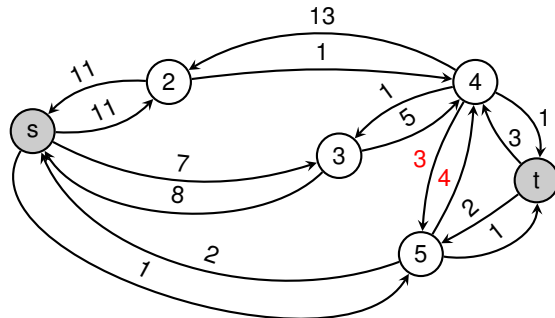


Example of a Residual Graph (Handout)

Flow network G

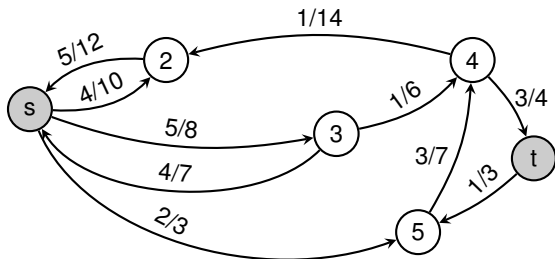


Residual Graph G_f



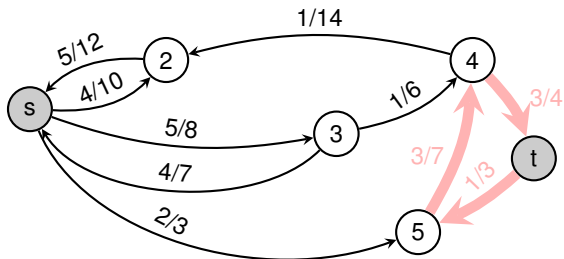
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Flow network G



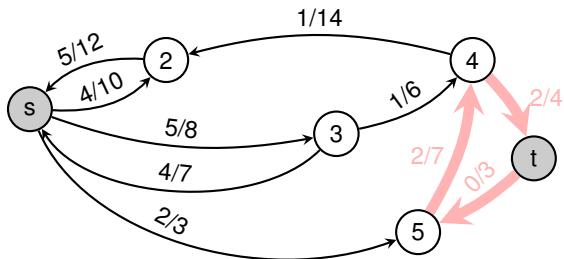
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Flow network G



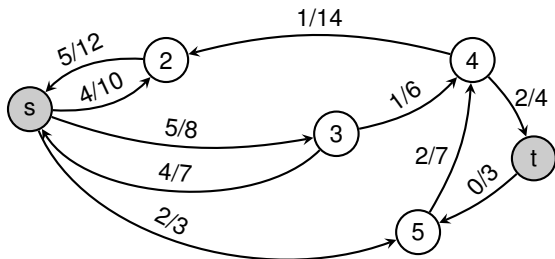
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Flow network G



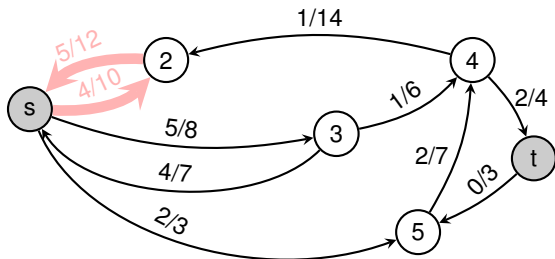
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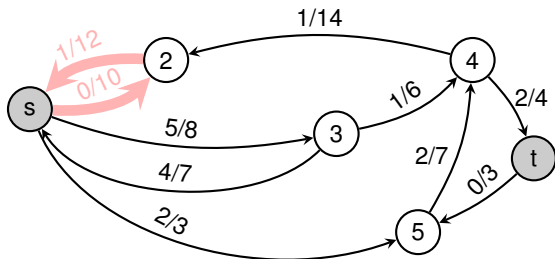
Example of a Residual Graph (Handout)

Flow network G



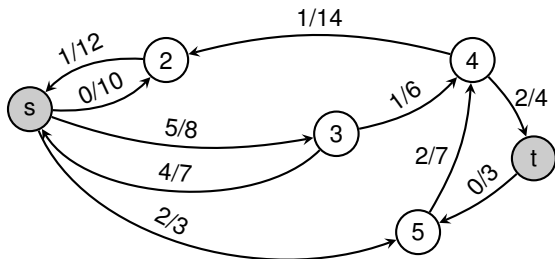
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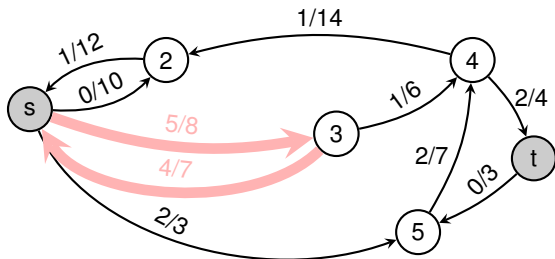
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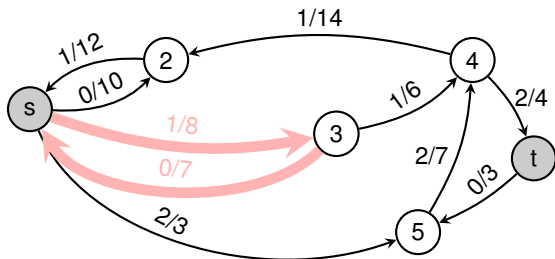
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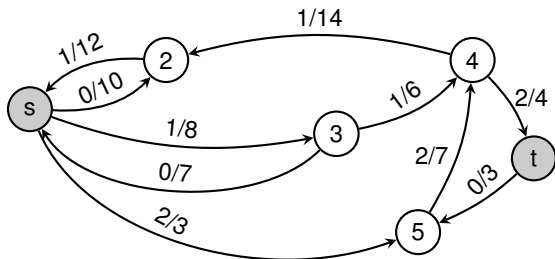
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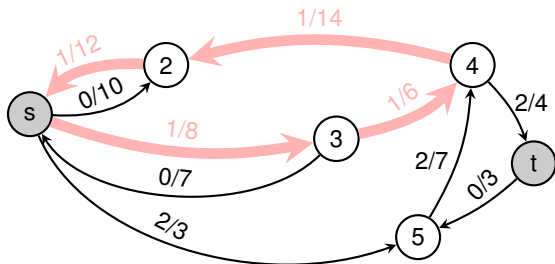
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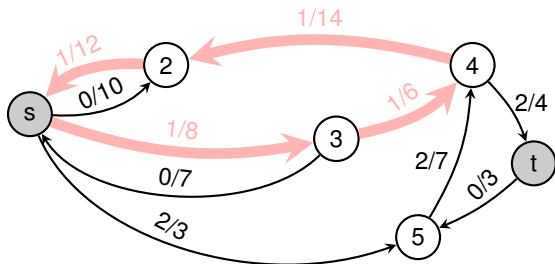
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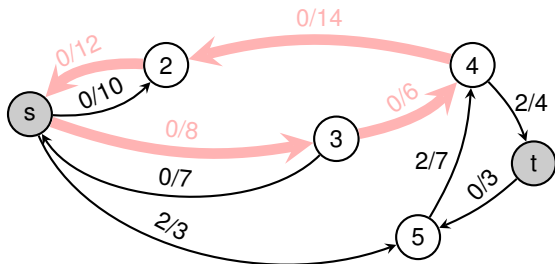
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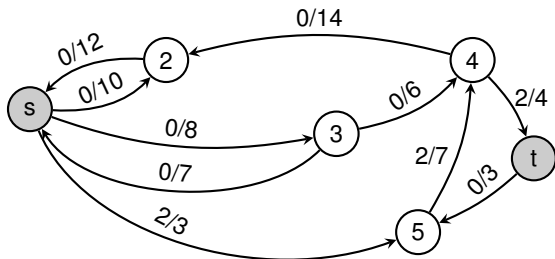
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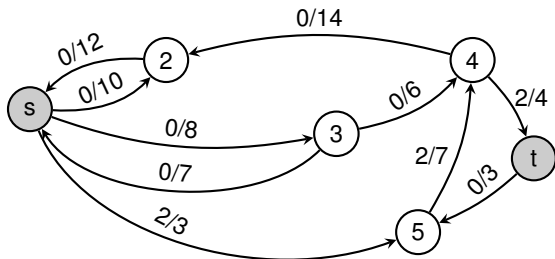
Example of a Residual Graph (Handout)

Flow network G



Example of a Residual Graph (Handout)

Flow network G



By successively eliminating cycles we can simplify and reduce the “transportation” cost of a flow.



The Ford-Fulkerson Method (“Enhanced Greedy”)

```
0: def fordFulkerson(G)
1:   initialize flow to 0 on all edges
2:   while an augmenting path in  $G_f$  can be found:
3:     push as much extra flow as possible through it
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Augmenting path: Path
from source to sink in G_f



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If f' is a flow in G_f and f a flow in G , then $f + f'$ is a flow in G



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Questions:

- How to find an augmenting path?
- Does this method terminate?
- If it terminates, how good is the solution?



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Using BFS or DFS, we can find an augmenting path in $O(V + E)$ time.

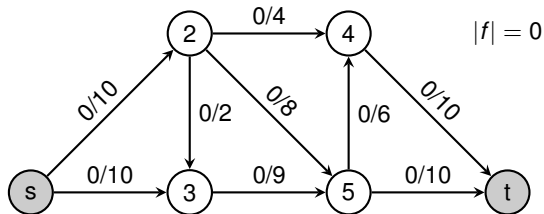
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Illustration of the Ford-Fulkerson Method

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Residual Graph $G_f = (V, E_f, c_f)$:

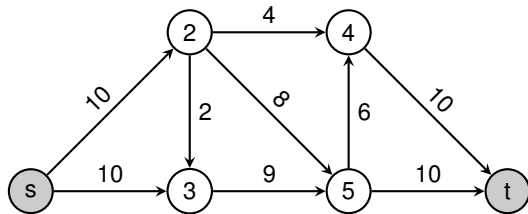
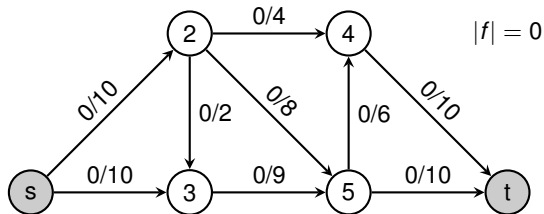


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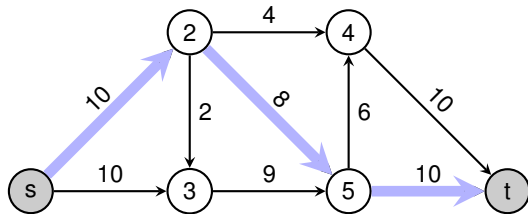
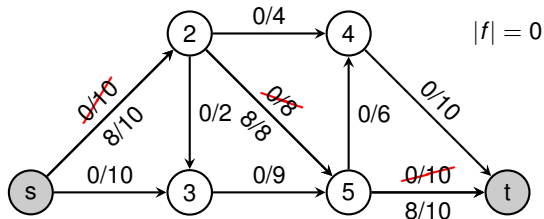


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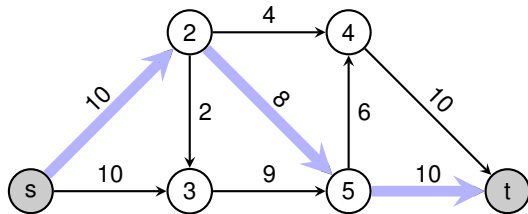
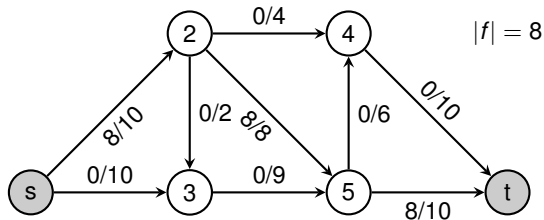


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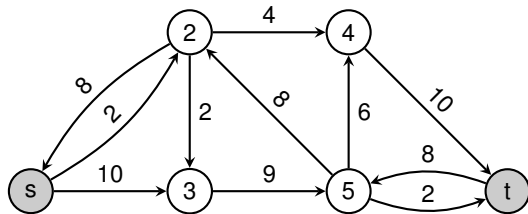
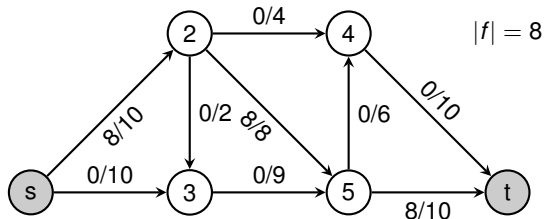


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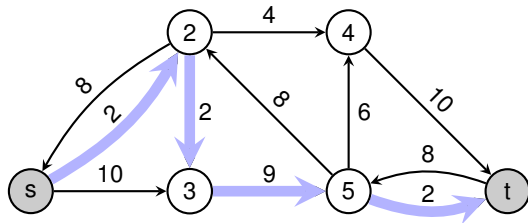
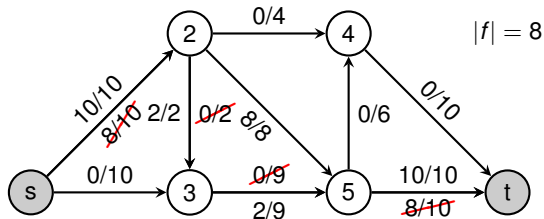


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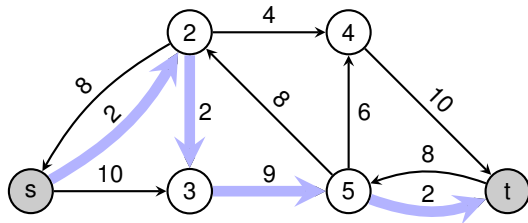
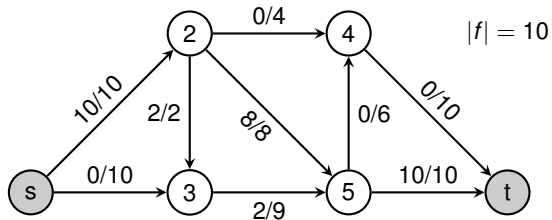


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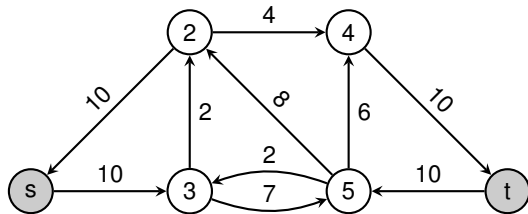
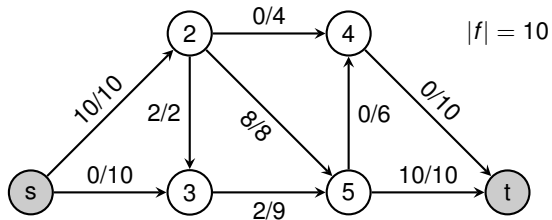


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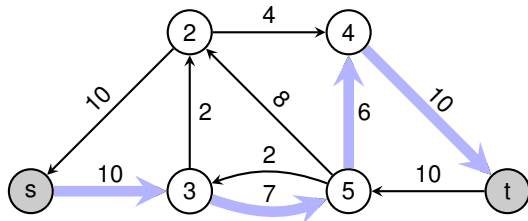
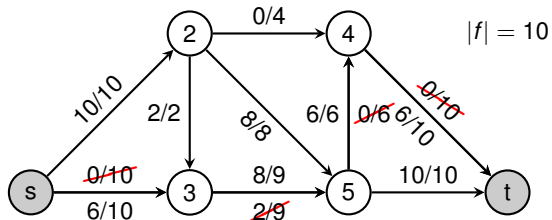


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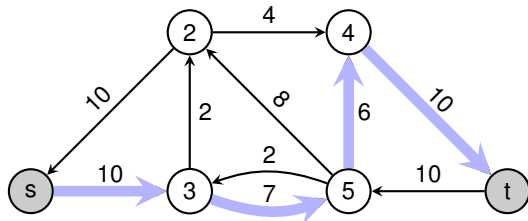
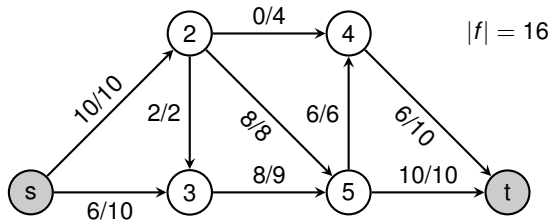


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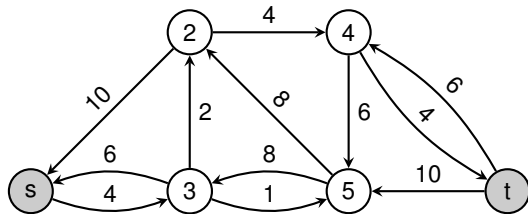
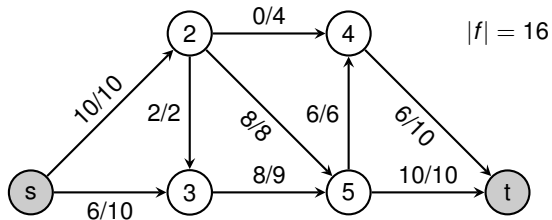


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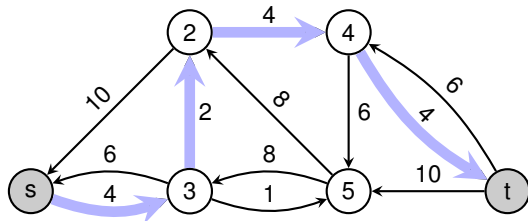
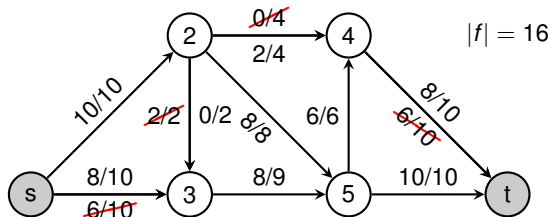


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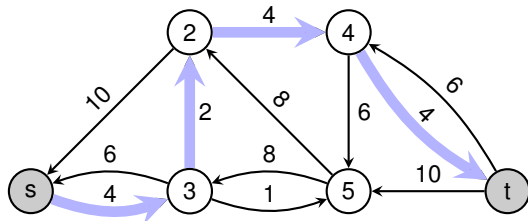
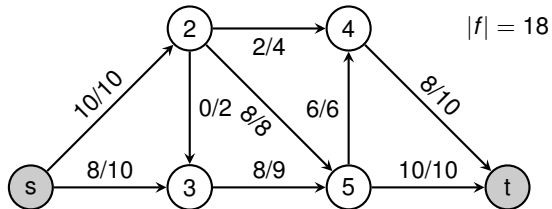


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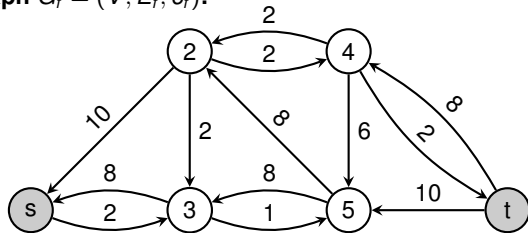
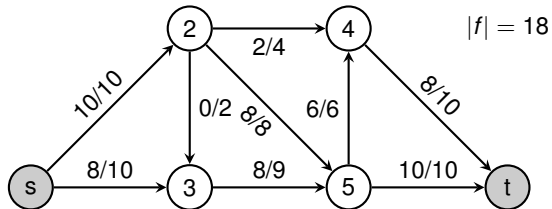


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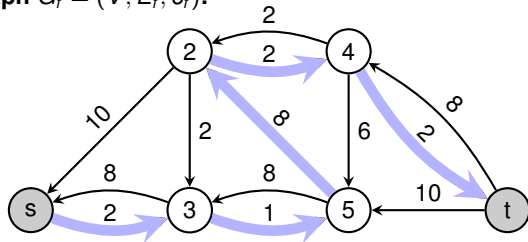
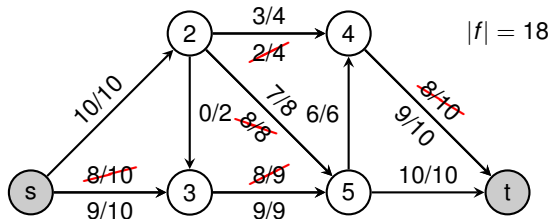


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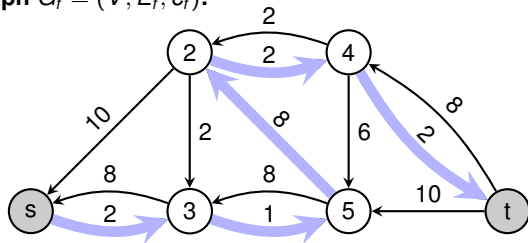
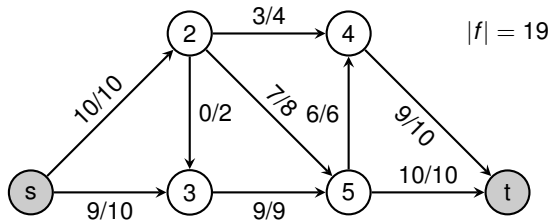


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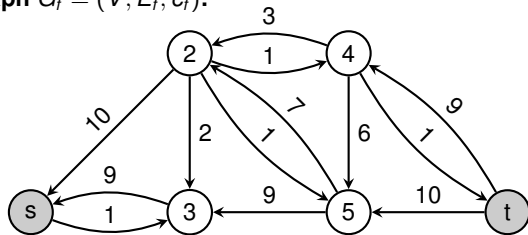
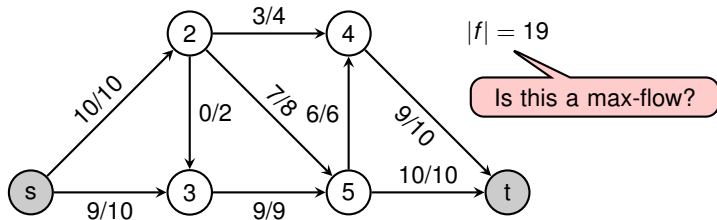


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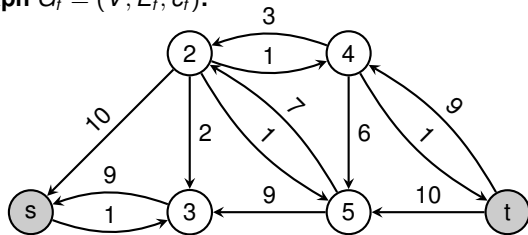
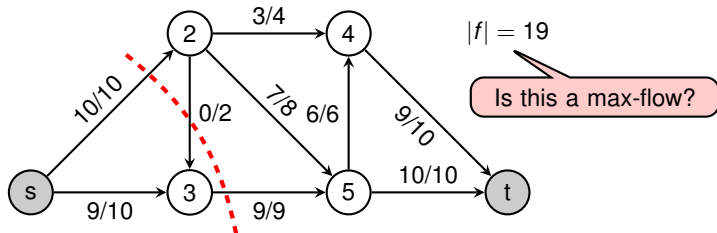


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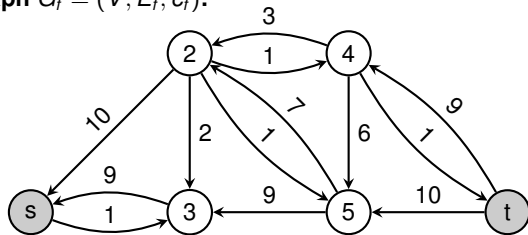
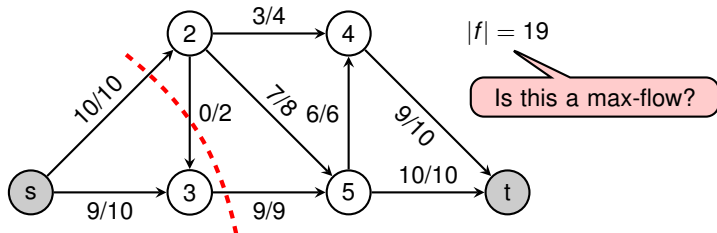
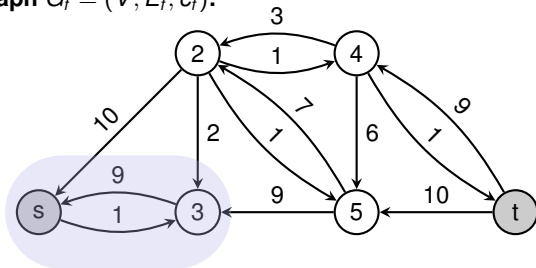


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Outline

Introduction

Ford-Fulkerson

A Glimpse at the Max-Flow Min-Cut Theorem

Analysis of Ford-Fulkerson

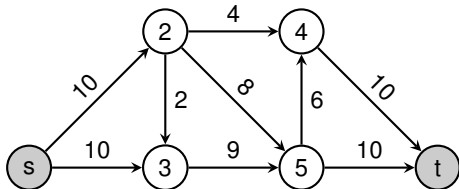


From Flows to Cuts

Cut

- A cut (S, T) is a partition of V into S and $T = V \setminus S$ such that $s \in S$ and $t \in T$.

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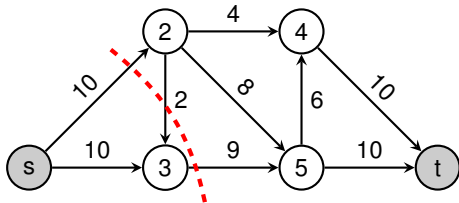


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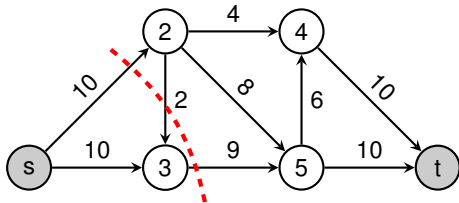
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$$c(S, T) = \sum_{u \in S, v \in T} c(u, v) = \sum_{(u, v) \in E(S, T)} c(u, v)$$

Graph $G = (V, E, c)$:



$$c(\{s, 3\}, \{2, 4, 5, t\}) =$$



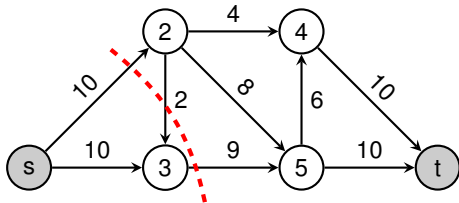
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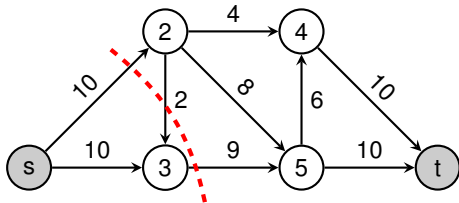
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- A **minimum cut** of a network is a cut whose capacity is minimum over all cuts of the network.

Graph $G = (V, E, c)$:



$$c(\{s, 3\}, \{2, 4, 5, t\}) = 10 + 9 = 19$$



From Flows to Cuts

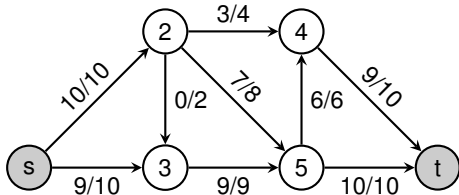
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The value of the max-flow is equal to the capacity of the min-cut, that is

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From Flows to Cuts

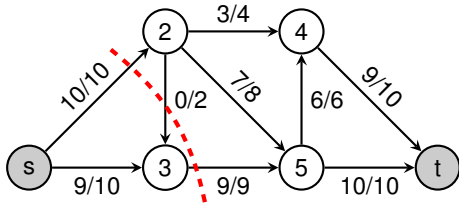
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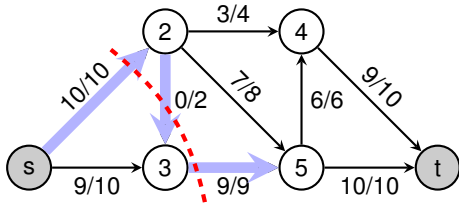
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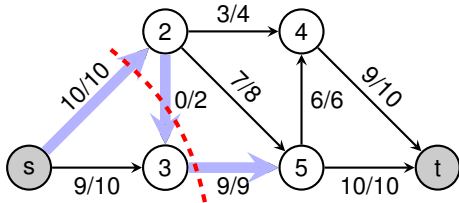
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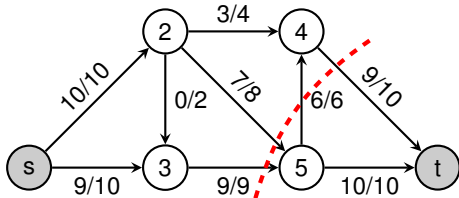
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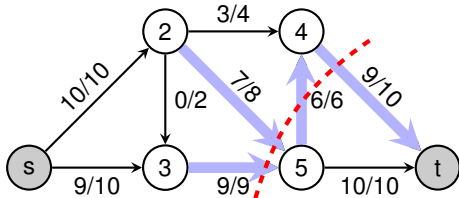
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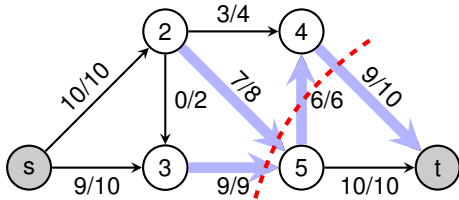
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Flow before iteration integral
& capacities in G_f are integral
 \Rightarrow Flow after iteration integral



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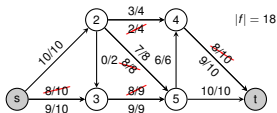
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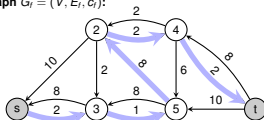
(proof omitted here, see CLRS3)



Graph $G = (V, E, c)$:



Residual Graph $G_r = (V, E_r, c_r)$:



6.6: Maximum flow

Frank Stajano

Thomas Sauerwald

Lent 2016



UNIVERSITY OF
CAMBRIDGE

A Glimpse at the Max-Flow Min-Cut Theorem

Analysis of Ford-Fulkerson

Matchings in Bipartite Graphs

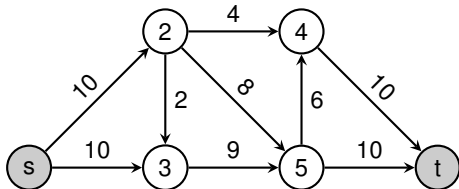


From Flows to Cuts

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- A cut (S, T) is a partition of V into S and $T = V \setminus S$ such that $s \in S$ and $t \in T$.

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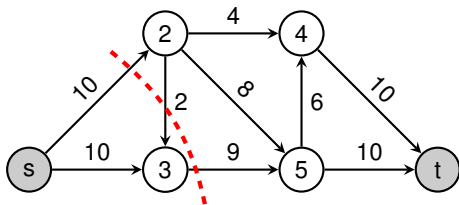


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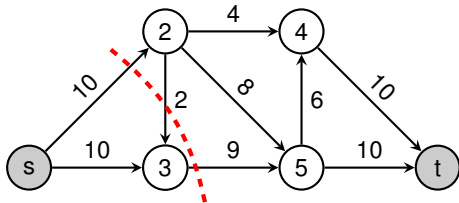
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- A **cut** (S, T) is a partition of V into S and $T = V \setminus S$ such that $s \in S$ and $t \in T$.
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$$c(S, T) = \sum_{u \in S, v \in T} c(u, v) = \sum_{(u, v) \in E(S, T)} c(u, v)$$

Graph $G = (V, E, c)$:



$$c(\{s, 3\}, \{2, 4, 5, t\}) =$$



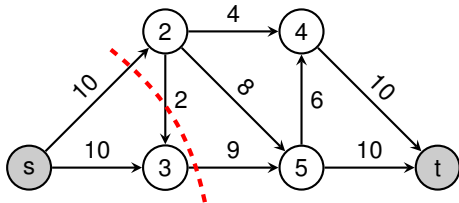
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Graph $G = (V, E, c)$:



$$c(\{s, 3\}, \{2, 4, 5, t\}) = 10 + 9 = 19$$



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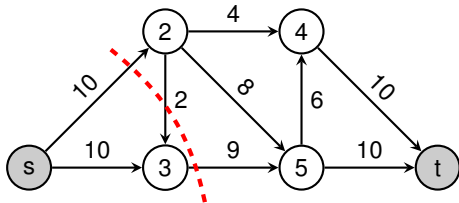
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- A **minimum cut** of a network is a cut whose capacity is minimum over all cuts of the network.

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From Flows to Cuts

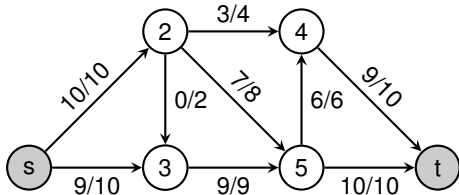
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The value of the max-flow is equal to the capacity of the min-cut, that is

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From Flows to Cuts

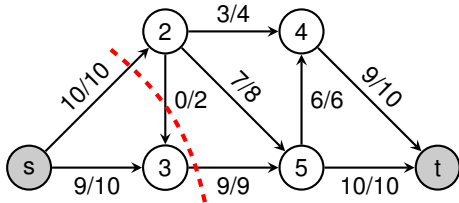
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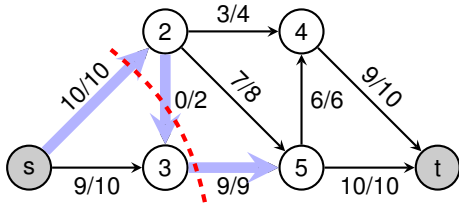
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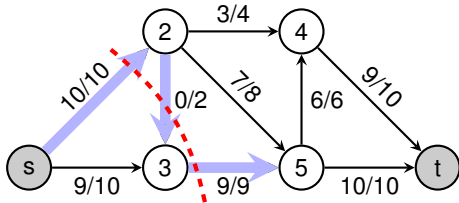
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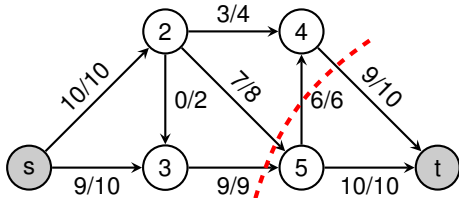
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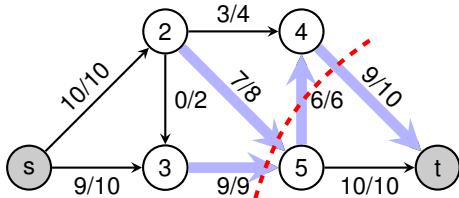
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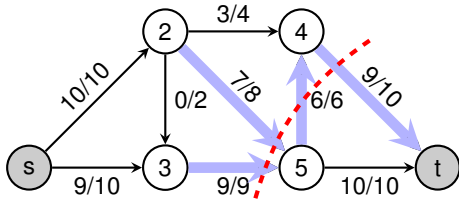
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$$9 + 7 - 6 + 9 = 19$$



Extra: Proof of the Max-Flow Min-Cut Theorem (Easy Direction)

1. For every $u, v \in V$, $f(u, v) \leq c(u, v)$,
 2. For every $u, v \in V$, $f(u, v) = -f(v, u)$,
 3. For every $u \in V \setminus \{s, t\}$, $\sum_{v \in V} f(u, v) = 0$.
- Let f be any flow and (S, T) be any cut:

Flow-Value-Lemma:

For any cut (S, T) ,

$$|f| = \sum_{u \in S} \sum_{v \in T} f(u, v).$$

$$\begin{aligned} |f| &= \sum_{v \in V} f(s, v) \\ &\stackrel{(3)}{=} \sum_{u \in S} \sum_{v \in V} f(u, v) \\ &= \sum_{u \in S} \sum_{v \in S} f(u, v) + \sum_{u \in S} \sum_{v \in T} f(u, v) \\ &\stackrel{(2)}{=} \sum_{u \in S} \sum_{v \in T} f(u, v) \\ &\stackrel{(1)}{\leq} \sum_{u \in S} \sum_{v \in T} c(u, v) \\ &= c(S, T). \end{aligned}$$

- Since this holds for any pair of flow and cut, it follows that

$$\max_f |f| \leq \min_{(S, T)} c(S, T)$$

□



A Glimpse at the Max-Flow Min-Cut Theorem

Analysis of Ford-Fulkerson

Matchings in Bipartite Graphs



Analysis of Ford-Fulkerson

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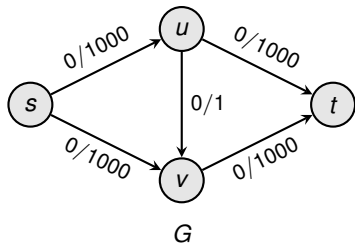
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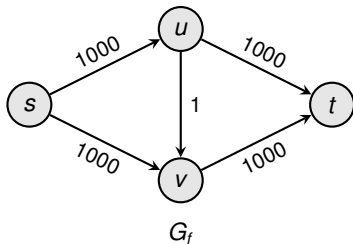
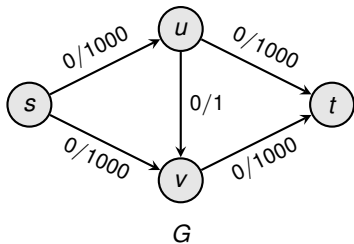
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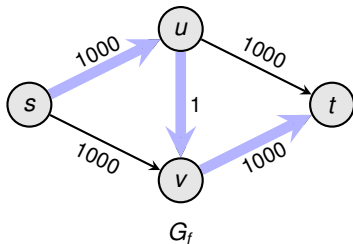
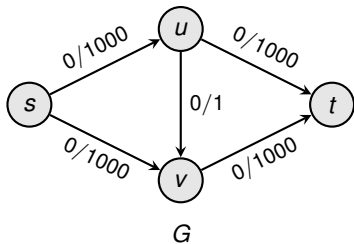
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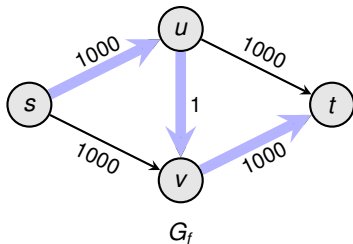
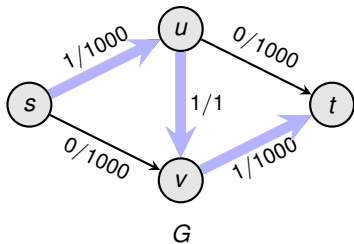
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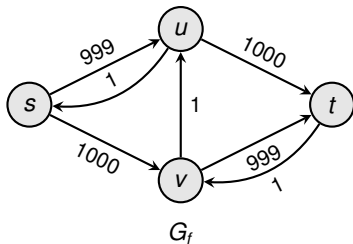
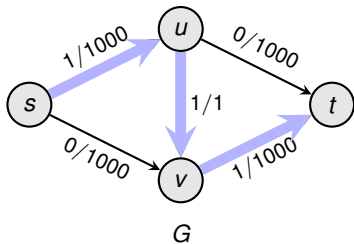
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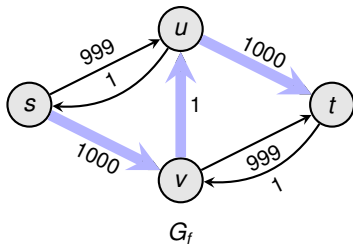
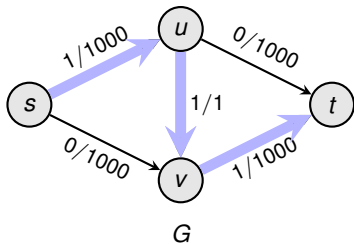
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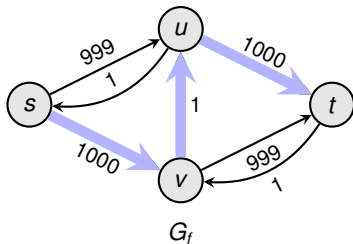
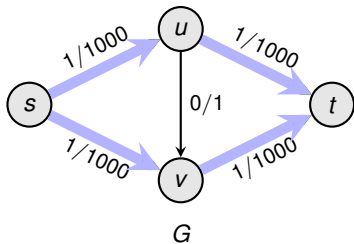
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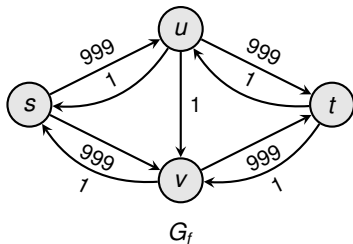
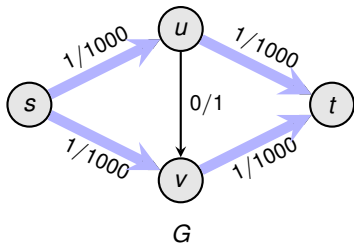
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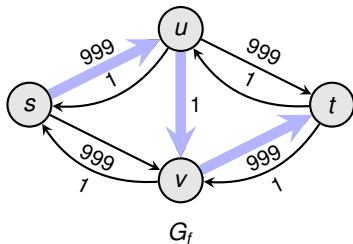
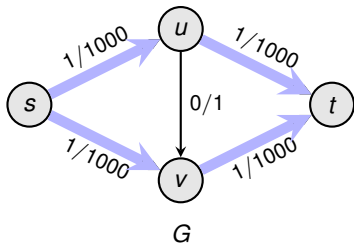
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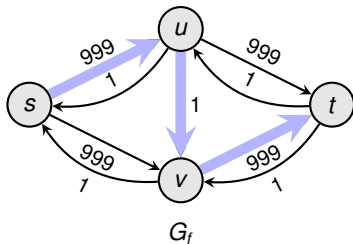
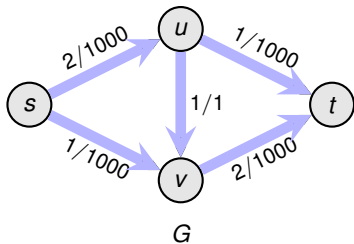
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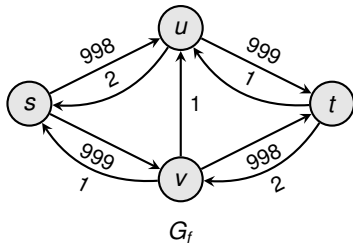
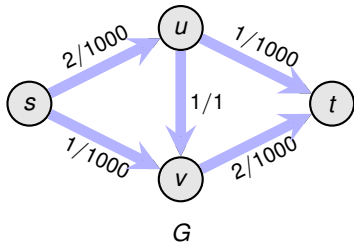
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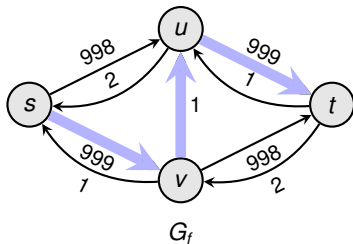
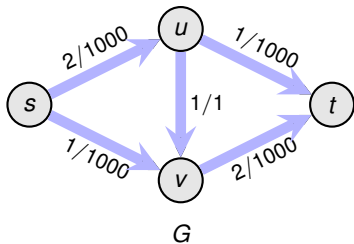
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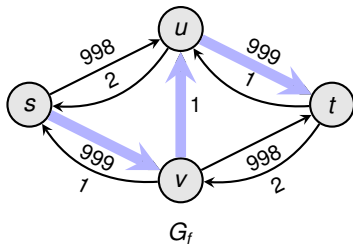
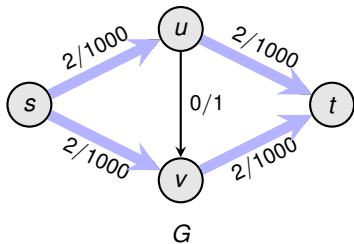
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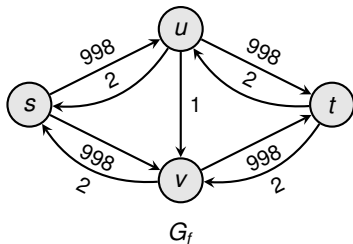
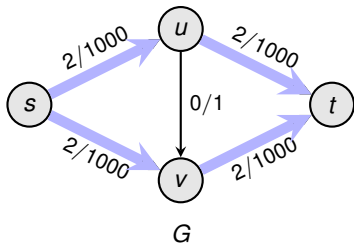
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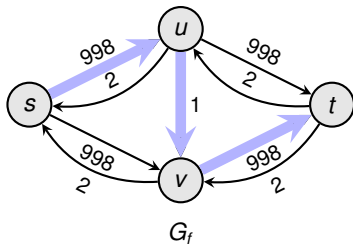
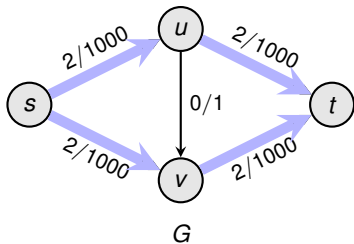
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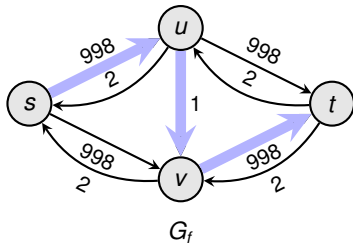
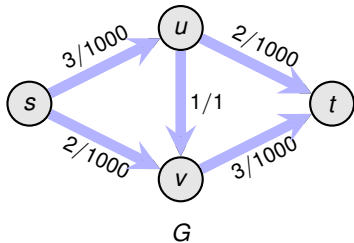
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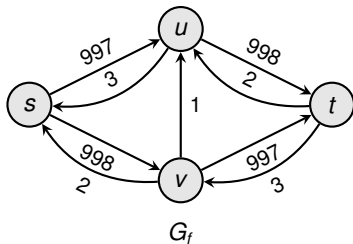
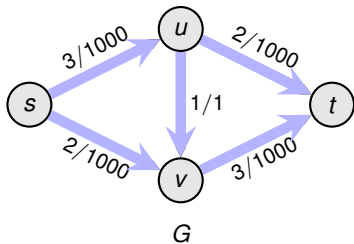
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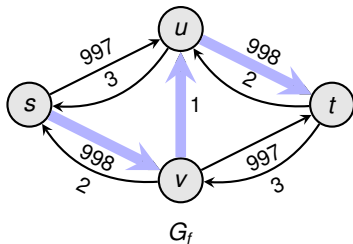
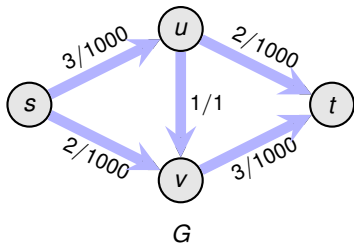
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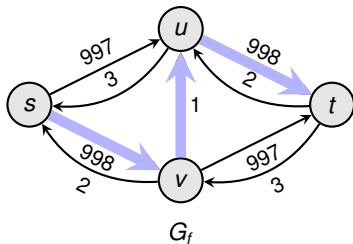
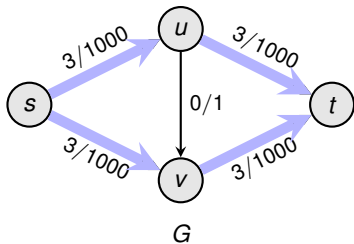
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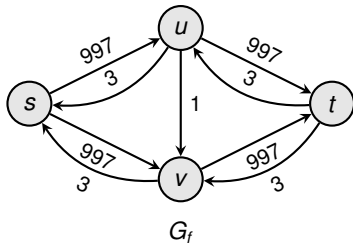
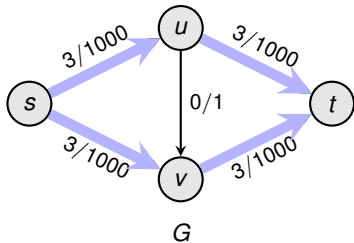
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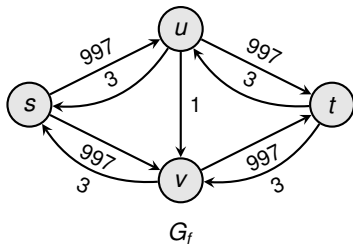
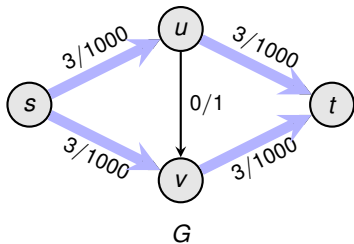
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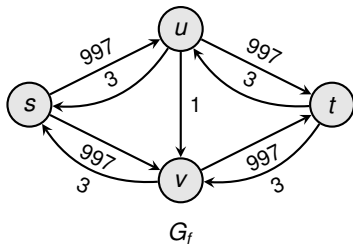
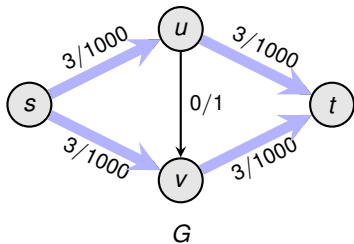
Slow Convergence of Ford-Fulkerson (Figure 26.7)



Number of iterations is $C := \max_{u,v} c(u, v)!$



Slow Convergence of Ford-Fulkerson (Figure 26.7)

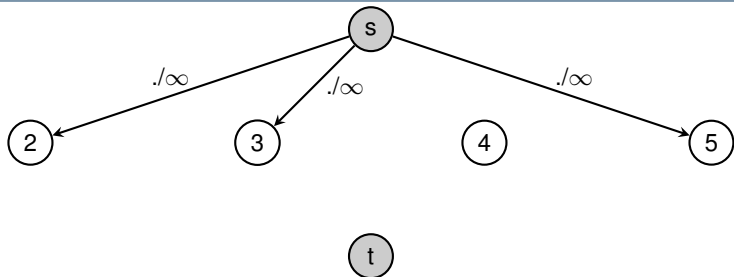


Number of iterations is $C := \max_{u,v} c(u, v)!$

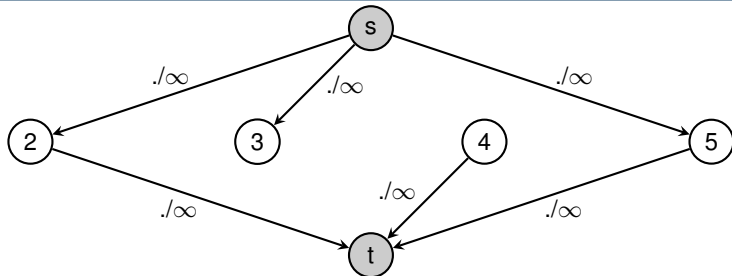
For irrational capacities, Ford-Fulkerson may even fail to terminate!



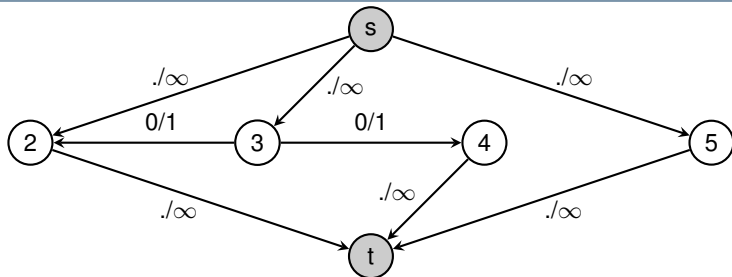
Non-Termination of Ford-Fulkerson for Irrational Capacities



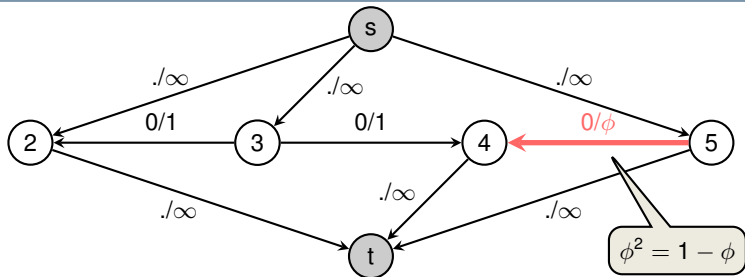
Non-Termination of Ford-Fulkerson for Irrational Capacities



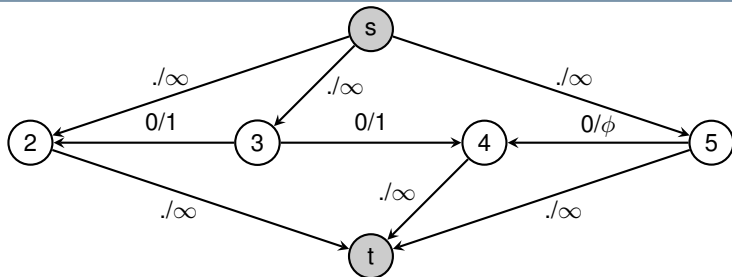
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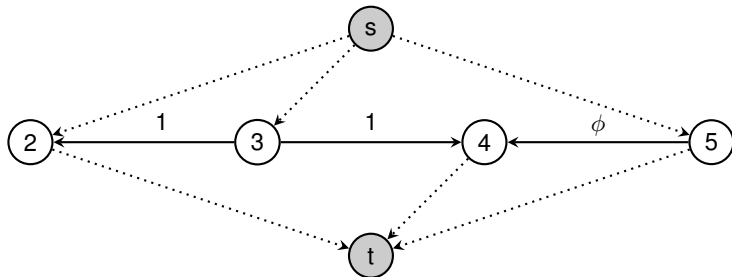
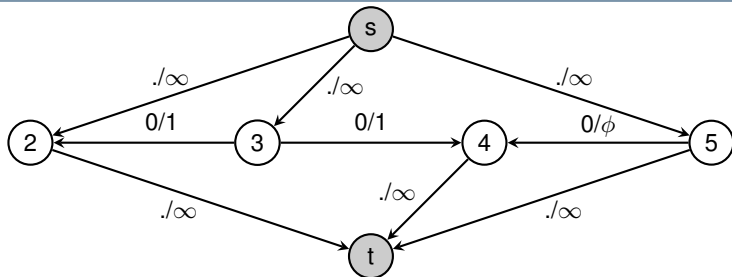
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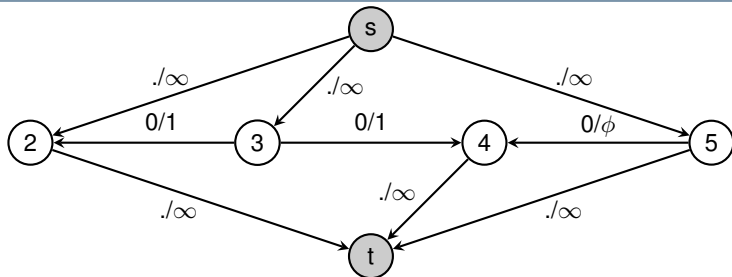
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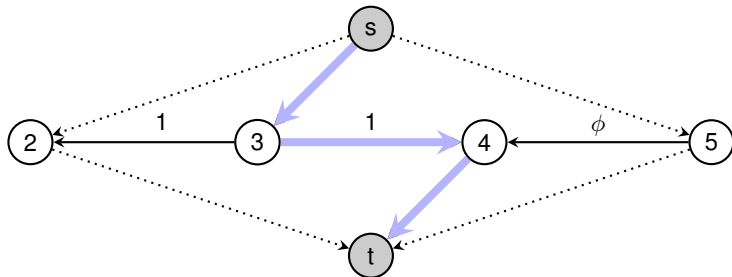
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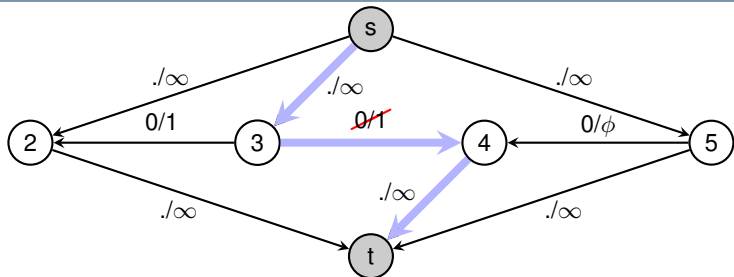
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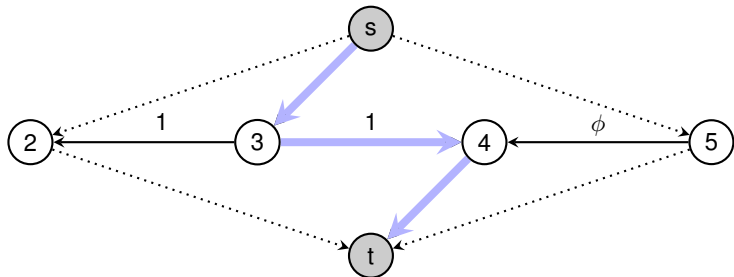
Iteration: 1, $|f| = 0$



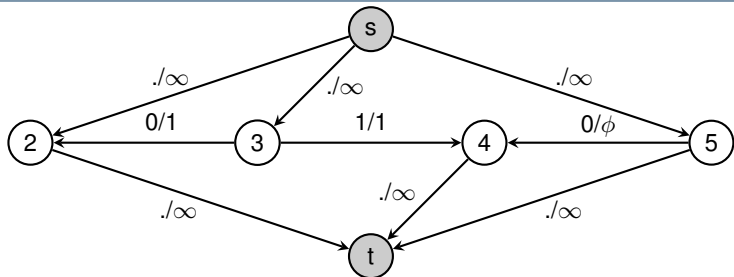
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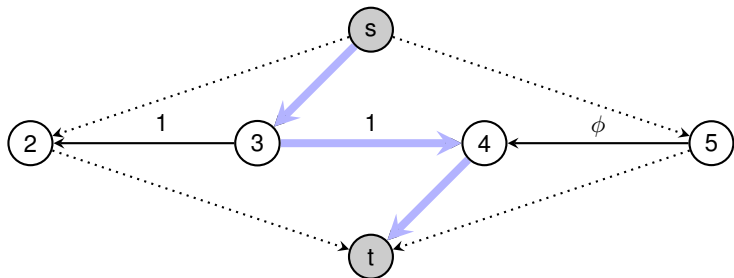
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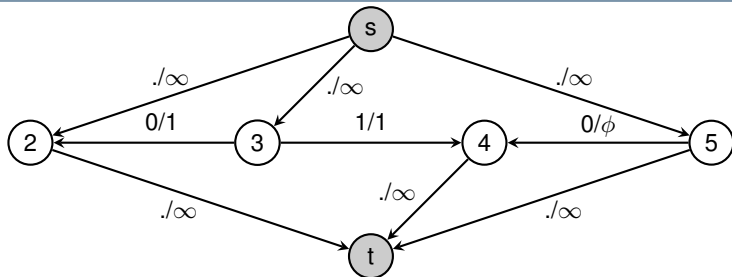
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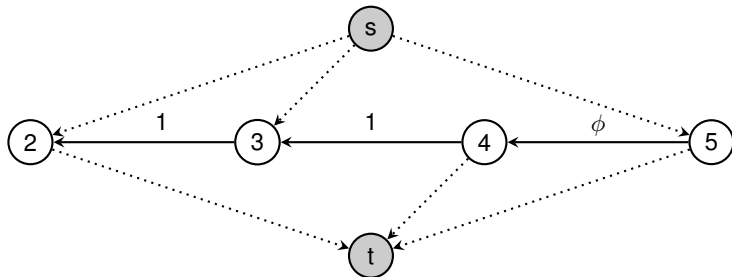
Iteration: 1, $|f| = 1$



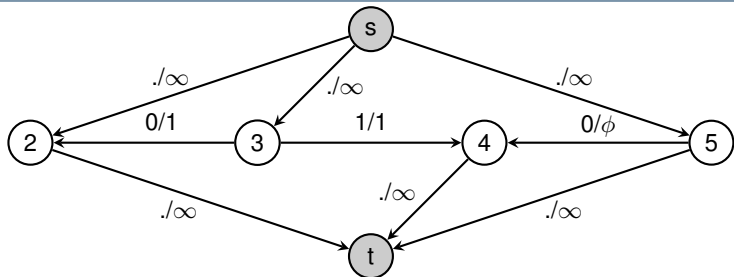
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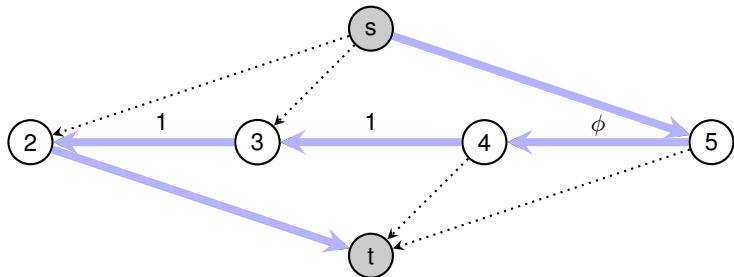
Iteration: 1, $|f| = 1$



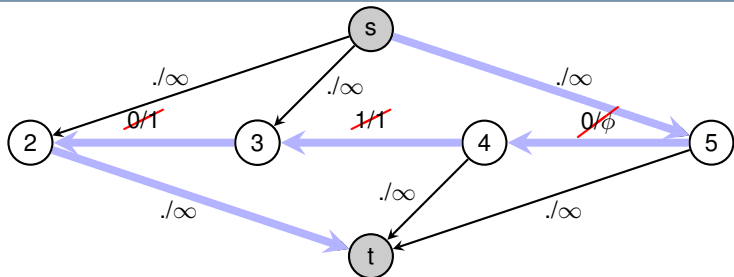
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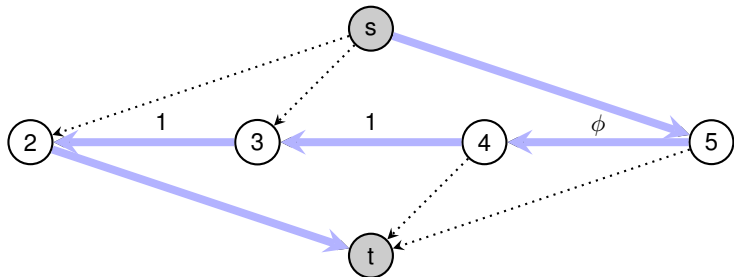
Iteration: 2, $|f| = 1$



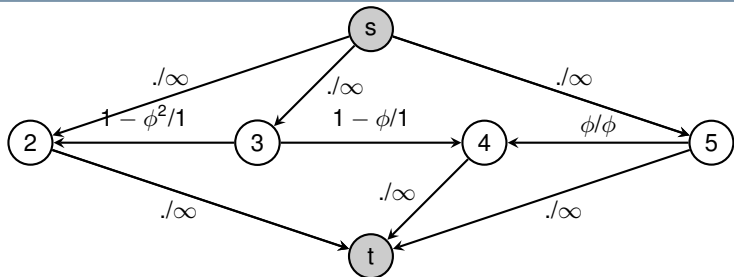
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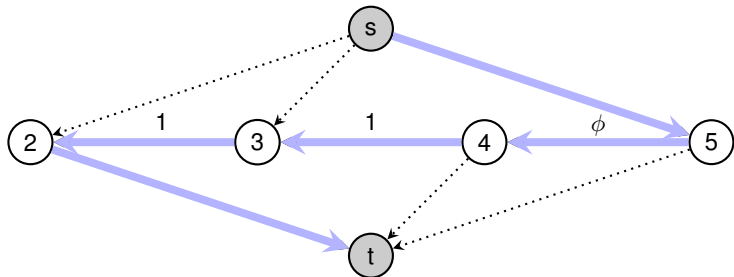
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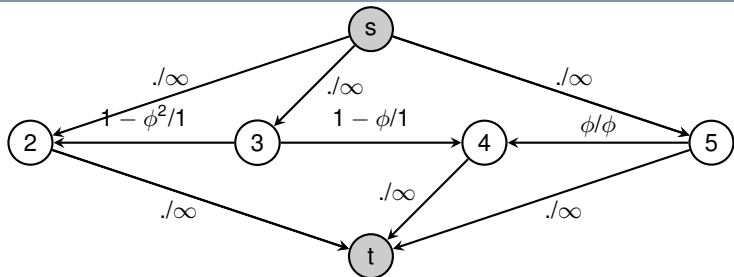
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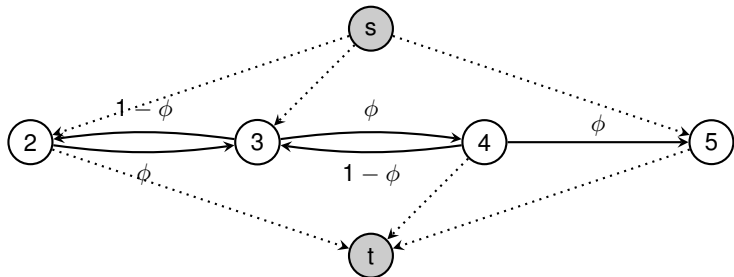
Iteration: 2, $|f| = 1 + \phi$



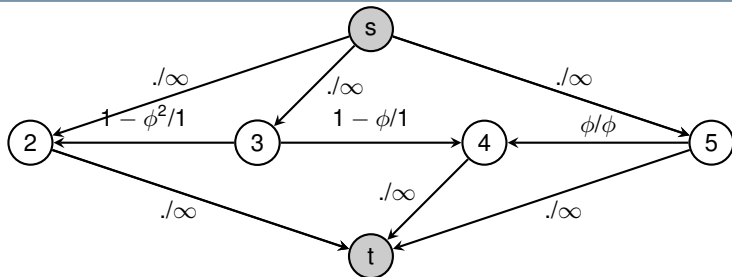
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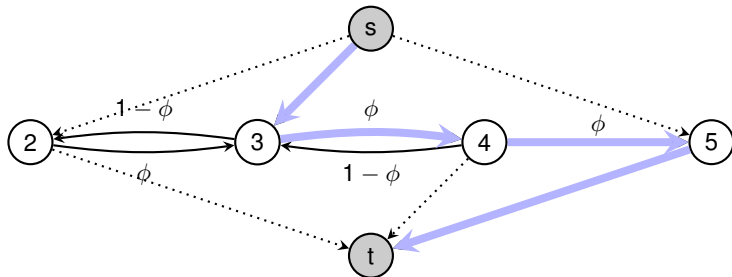
Iteration: 2, $|f| = 1 + \phi$



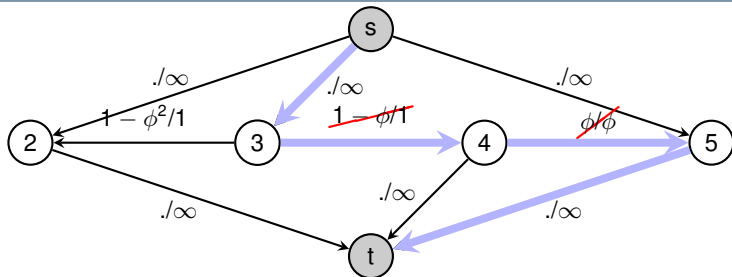
Non-Termination of Ford-Fulkerson for Irrational Capacities



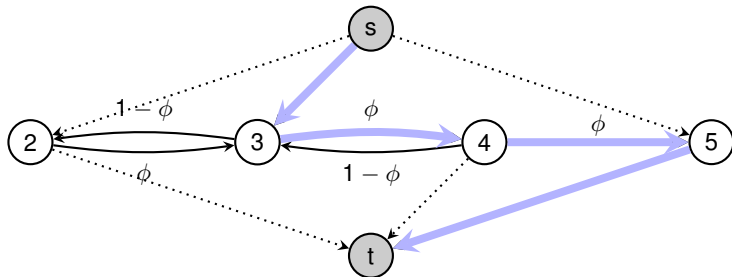
Iteration: 3, $|f| = 1 + \phi$



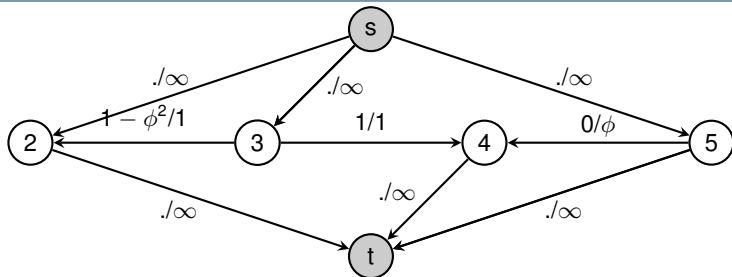
Non-Termination of Ford-Fulkerson for Irrational Capacities



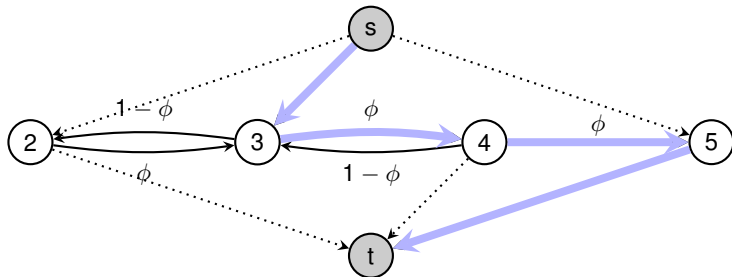
Iteration: 3, $|f| = 1 + \phi$



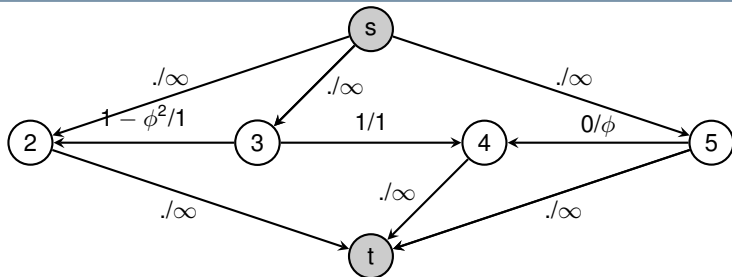
Non-Termination of Ford-Fulkerson for Irrational Capacities



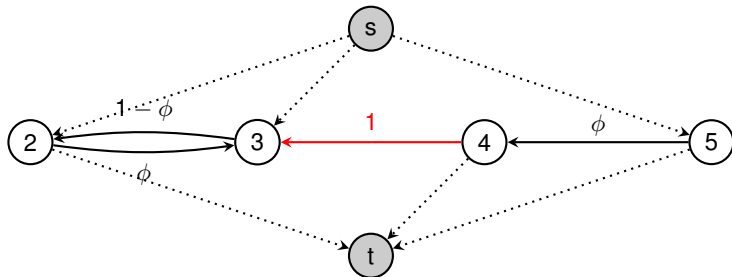
Iteration: 3, $|f| = 1 + 2 \cdot \phi$



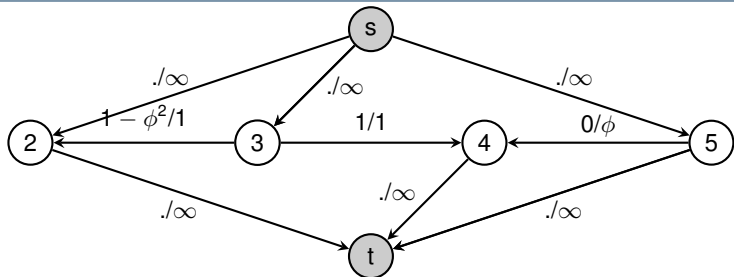
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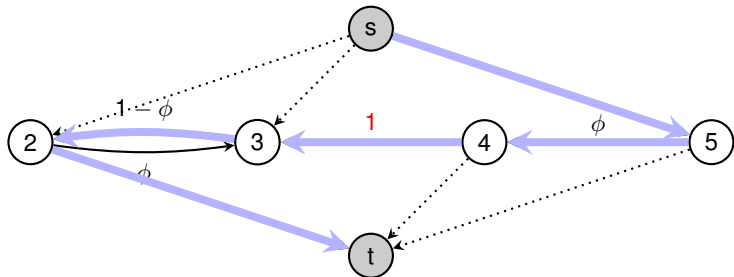
Iteration: 3, $|f| = 1 + 2 \cdot \phi$



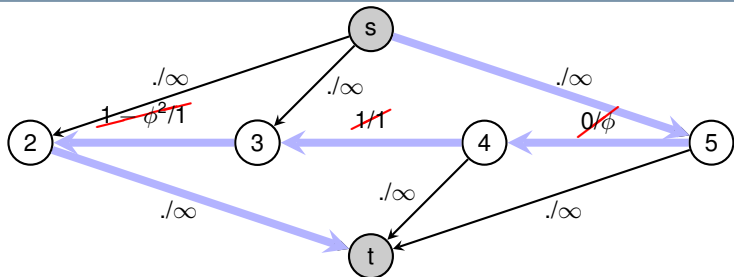
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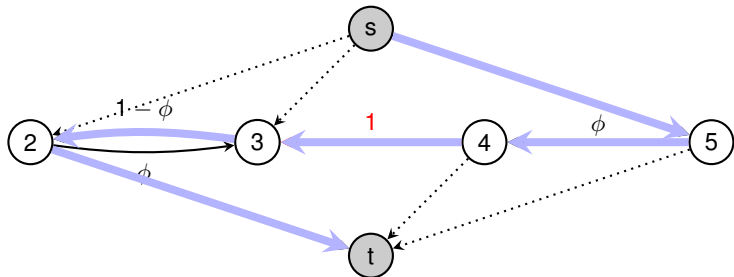
Iteration: 4, $|f| = 1 + 2 \cdot \phi$



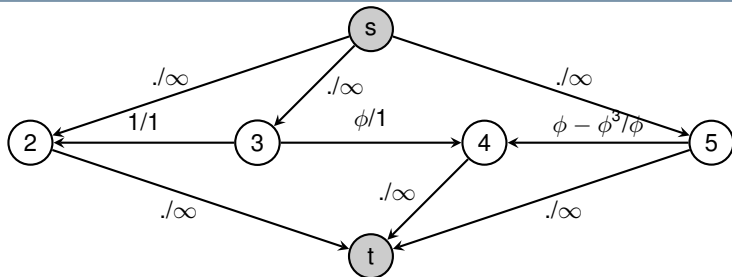
Non-Termination of Ford-Fulkerson for Irrational Capacities



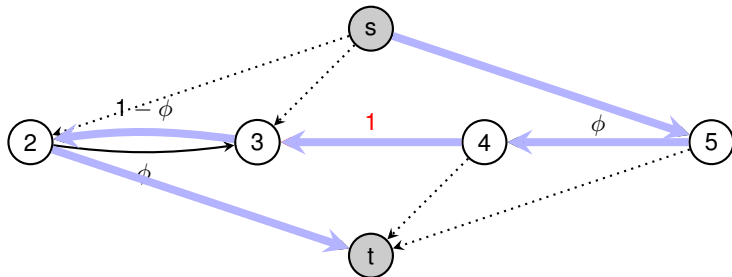
Iteration: 4, $|f| = 1 + 2 \cdot \phi$



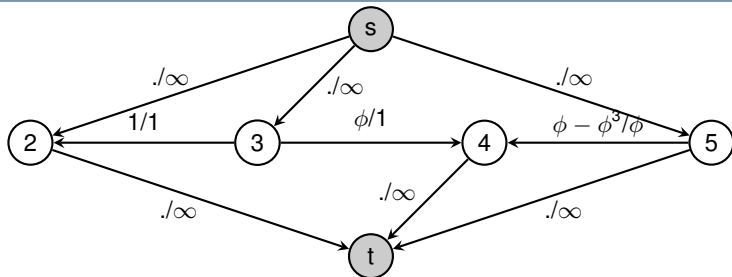
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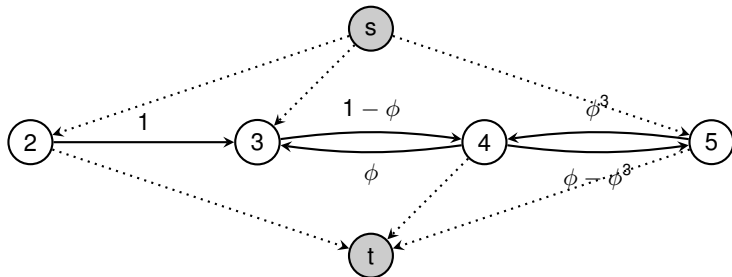
Iteration: 4, $|f| = 1 + 2 \cdot \phi + \phi^2$



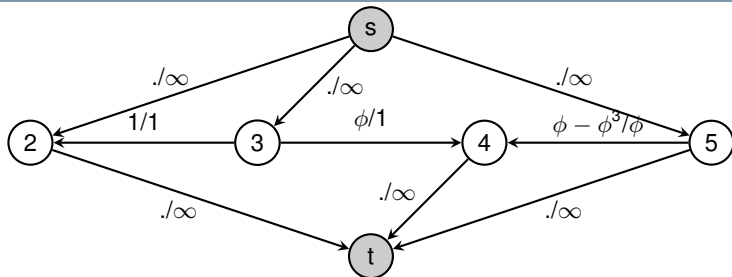
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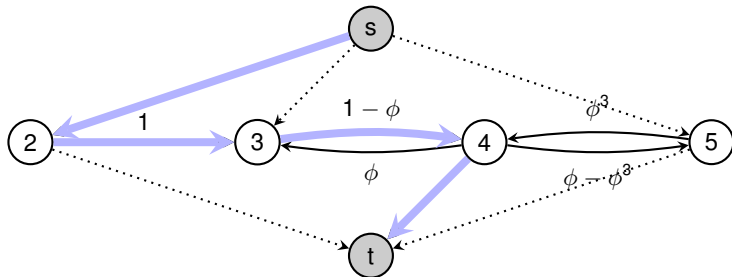
Iteration: 4, $|f| = 1 + 2 \cdot \phi + \phi^2$



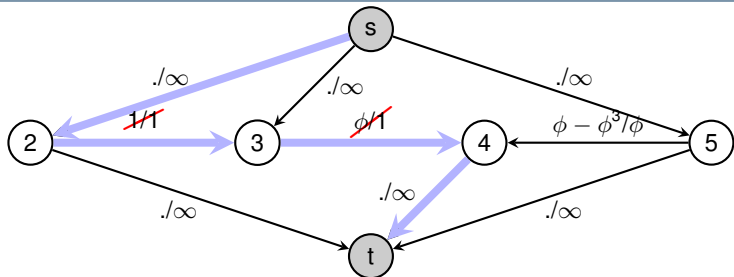
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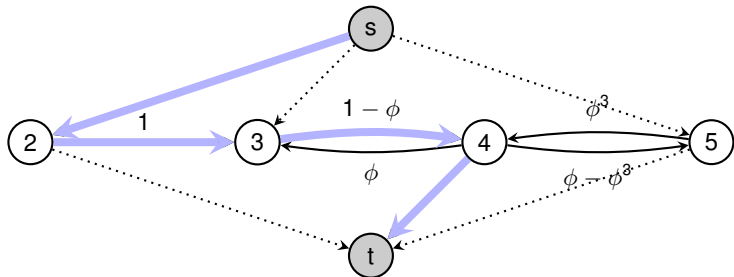
Iteration: 5, $|f| = 1 + 2 \cdot \phi + \phi^2$



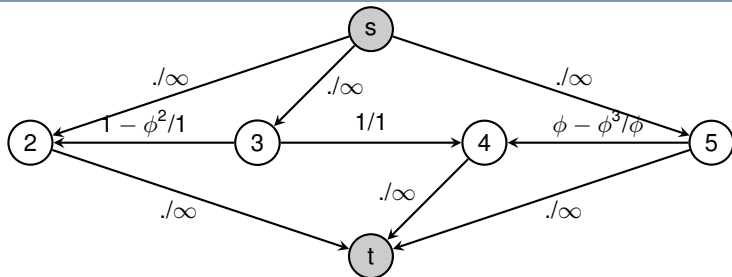
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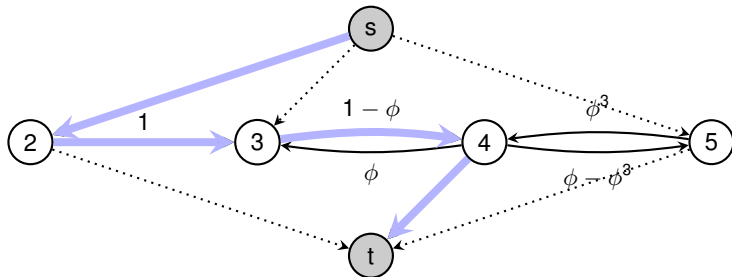
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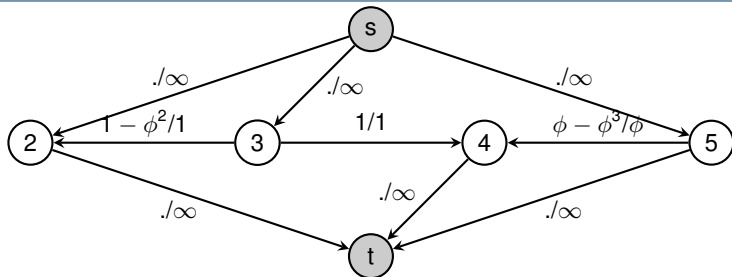
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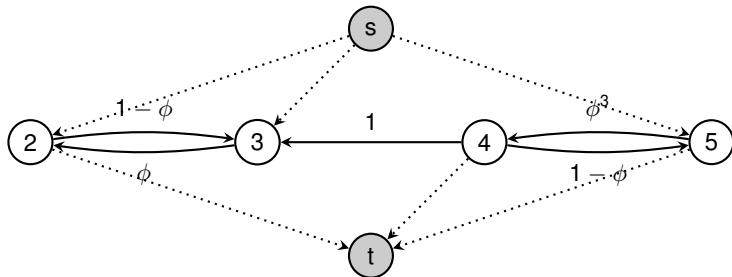
Iteration: 5, $|f| = 1 + 2 \cdot \phi + 2 \cdot \phi^2$



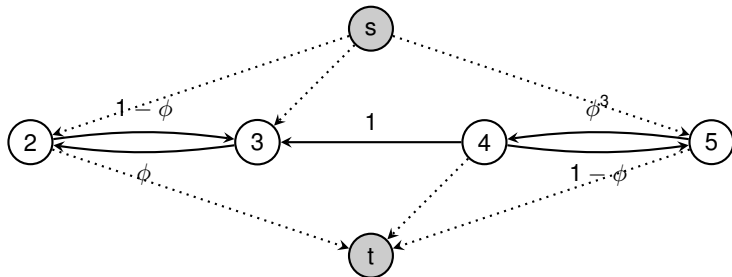
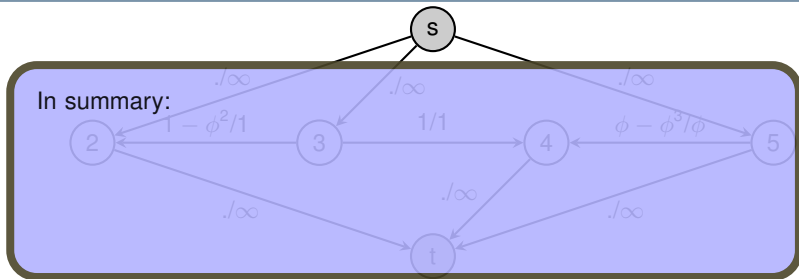
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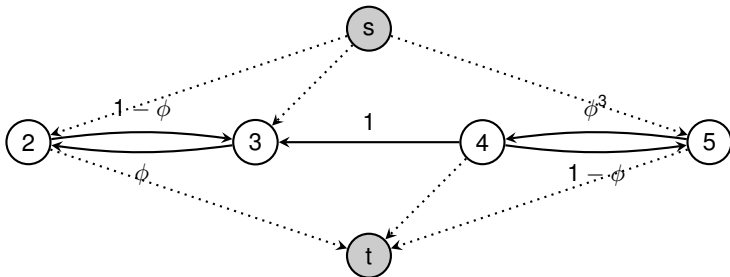
Non-Termination of Ford-Fulkerson for Irrational Capacities



Non-Termination of Ford-Fulkerson for Irrational Capacities

In summary:

- After iteration 1: $\leftarrow \overset{0}{2}, \overset{1}{3}, \overset{0}{4}, |f| = 1 \rightarrow$

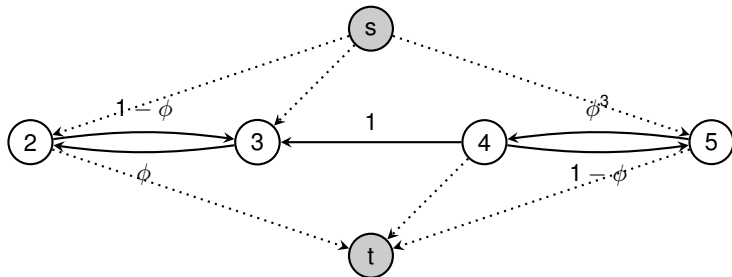


Non-Termination of Ford-Fulkerson for Irrational Capacities

In summary:

- After iteration 1: $\leftarrow \frac{0}{\infty}, \frac{1}{\infty} \rightarrow, \leftarrow \frac{0}{\infty}, \frac{1}{\infty} \rightarrow, |f| = 1$

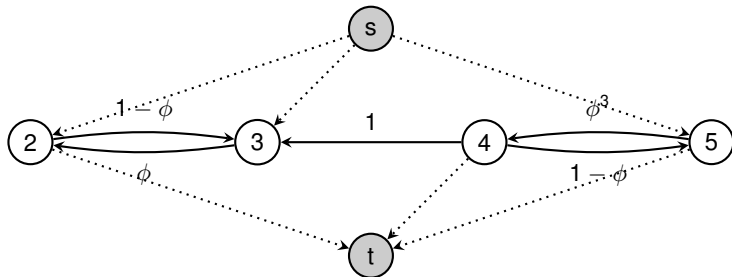
- After iteration 5: $\leftarrow \frac{1-\phi^2}{\infty}, \frac{1}{\infty} \rightarrow, \leftarrow \frac{\phi-\phi^3}{\infty}, \frac{1}{\infty} \rightarrow, |f| = 1 + 2\phi + 2\phi^2$



Non-Termination of Ford-Fulkerson for Irrational Capacities

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- After iteration 9: $\leftarrow \frac{1-\phi^4}{\infty}, \frac{1}{\infty}, \frac{\phi-\phi^5}{\infty}, |f| = 1 + 2\phi + 2\phi^2 + 2\phi^3 + 2\phi^4$

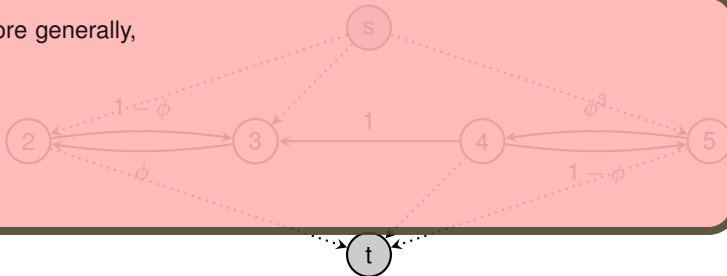


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More generally,



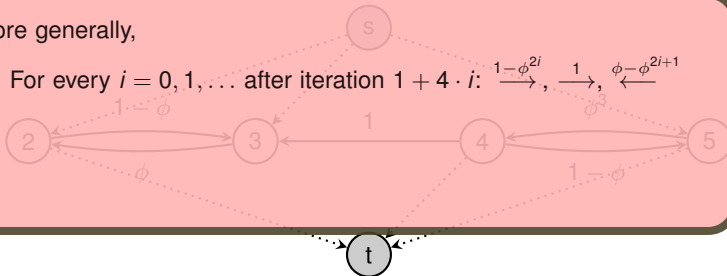
Non-Termination of Ford-Fulkerson for Irrational Capacities

In summary:

- After iteration 1: $\leftarrow \frac{0}{\phi^2/1}, \frac{1}{\phi} \rightarrow, \leftarrow \frac{0}{\phi}, \frac{1}{\phi} \rightarrow, |f| = 1$
- After iteration 5: $\leftarrow \frac{1-\phi^2}{\phi}, \frac{1}{\phi} \rightarrow, \leftarrow \frac{\phi-\phi^3}{\phi}, \frac{1}{\phi} \rightarrow, |f| = 1 + 2\phi + 2\phi^2$
- After iteration 9: $\leftarrow \frac{1-\phi^4}{\phi}, \frac{1}{\phi} \rightarrow, \leftarrow \frac{\phi-\phi^5}{\phi}, \frac{1}{\phi} \rightarrow, |f| = 1 + 2\phi + 2\phi^2 + 2\phi^3 + 2\phi^4$

More generally,

- For every $i = 0, 1, \dots$ after iteration $1 + 4 \cdot i$: $\frac{1-\phi^{2i}}{\phi} \rightarrow, \frac{1}{\phi} \rightarrow, \leftarrow \frac{\phi-\phi^{2i+1}}{\phi}$



Non-Termination of Ford-Fulkerson for Irrational Capacities

In summary:

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- **Ford-Fulkerson does not terminate!**



Non-Termination of Ford-Fulkerson for Irrational Capacities

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- $|f| = 1 + 2 \sum_{i=1}^{\infty} \phi^i \approx 4.23607 < 5$



Non-Termination of Ford-Fulkerson for Irrational Capacities

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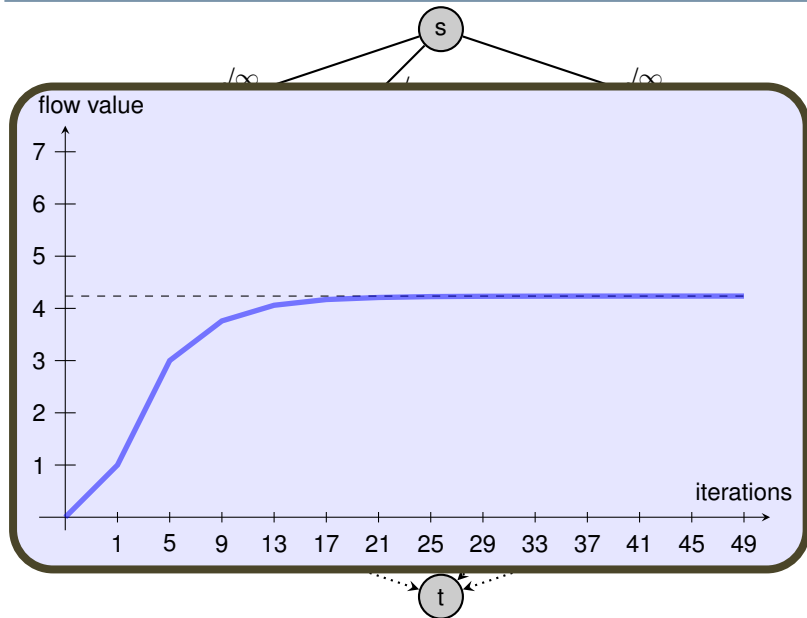
- After iteration 1: $\leftarrow \frac{0}{\infty}, \frac{1}{\infty} \rightarrow, \leftarrow \frac{0}{\infty}, |f| = 1$
- After iteration 5: $\leftarrow \frac{1-\phi^2}{\infty}, \frac{1}{\infty} \rightarrow, \leftarrow \frac{\phi-\phi^3}{\infty}, |f| = 1 + 2\phi + 2\phi^2$
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More generally,

- For every $i = 0, 1, \dots$ after iteration $1 + 4 \cdot i$: $\frac{1-\phi^{2i}}{\infty} \rightarrow, \frac{1}{\infty} \rightarrow, \leftarrow \frac{\phi-\phi^{2i+1}}{\infty}$
- **Ford-Fulkerson does not terminate!**
- $|f| = 1 + 2 \sum_{i=1}^{\infty} \phi^i \approx 4.23607 < 5$
- **It does not even converge to a maximum flow!**



Non-Termination of Ford-Fulkerson for Irrational Capacities



Ford-Fulkerson Method

- works only for integral (rational) capacities
- Runtime: $O(E \cdot |f^*|) = O(E \cdot V \cdot C)$



Summary and Outlook

Ford-Fulkerson Method

- works only for integral (rational) capacities
- Runtime: $O(E \cdot |f^*|) = O(E \cdot V \cdot C)$

Capacity-Scaling Algorithm



Summary and Outlook

Ford-Fulkerson Method

- works only for integral (rational) capacities
- Runtime: $O(E \cdot |f^*|) = O(E \cdot V \cdot C)$

Capacity-Scaling Algorithm

- Idea: Find an augmenting path with high capacity
- Consider subgraph of G_f consisting of edges (u, v) with $c_f(u, v) > \Delta$
- scaling parameter Δ , which is initially $2^{\lceil \log_2 C \rceil}$ and 1 after termination
- Runtime: $O(E^2 \cdot \log C)$



Summary and Outlook

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- Runtime: $O(E^2 \cdot \log C)$

Edmonds-Karp Algorithm

- Idea: Find the shortest augmenting path in G_f
- Runtime: $O(E^2 \cdot V)$



A Glimpse at the Max-Flow Min-Cut Theorem

Analysis of Ford-Fulkerson

Matchings in Bipartite Graphs



Application: Maximum-Bipartite-Matching Problem

Matching

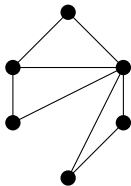
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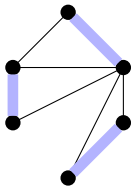
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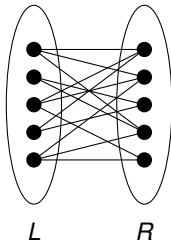
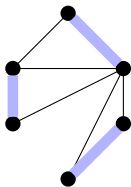
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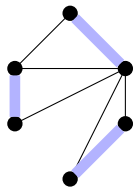
A graph G is **bipartite** if V can be partitioned into L and R so that all edges go between L and R .



Application: Maximum-Bipartite-Matching Problem

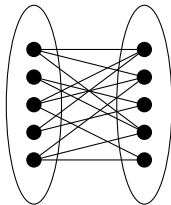
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L

R

Jobs

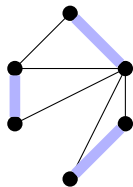
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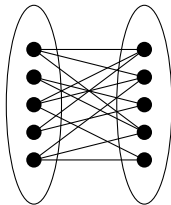
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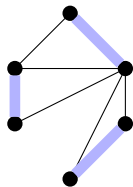
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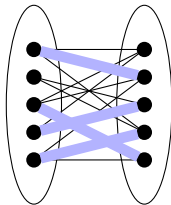
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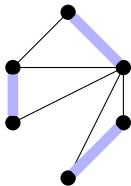
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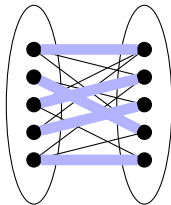
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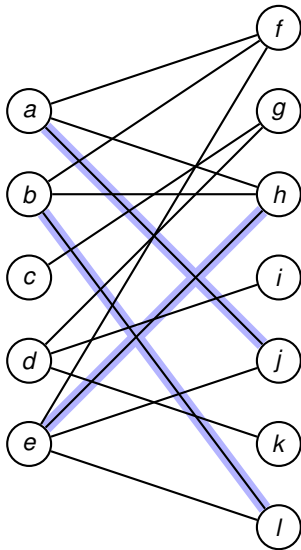
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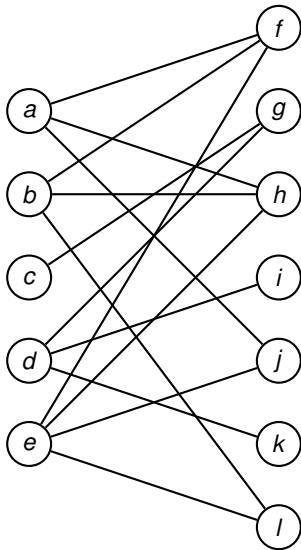
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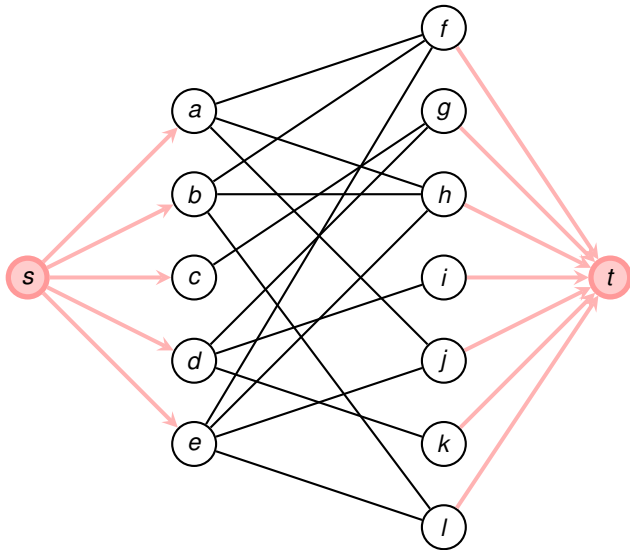
Matchings in Bipartite Graphs via Maximum Flows



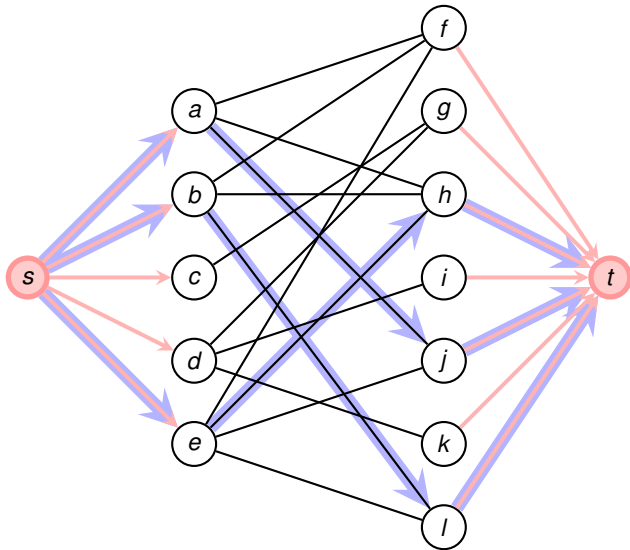
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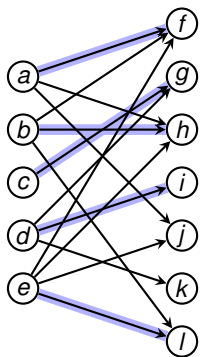
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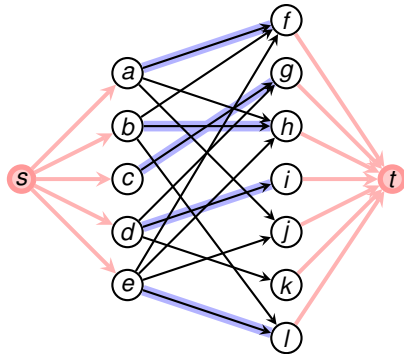
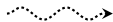
Correspondence between Maximum Matchings and Max Flow

Theorem (Corollary 26.11)

The cardinality of a maximum matching M in a bipartite graph G equals the value of a maximum flow f in the corresponding flow network \tilde{G} .



Graph G

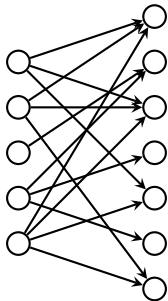


Graph \tilde{G}



From Matching to Flow

- Given a maximum matching of cardinality k

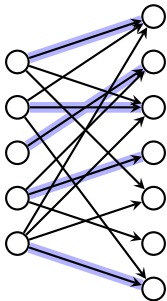


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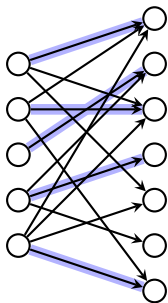


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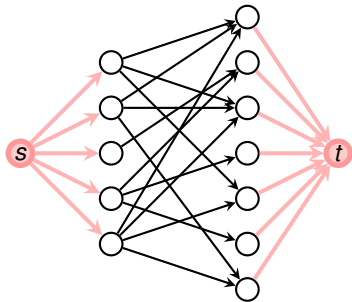
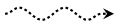


From Matching to Flow

- Given a maximum matching of cardinality k
- Consider flow f that sends one unit along each each of k paths



Graph G

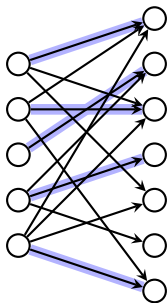


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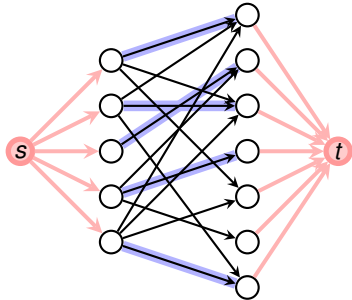
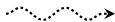


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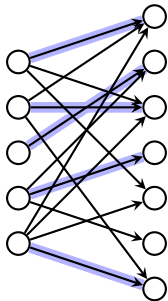


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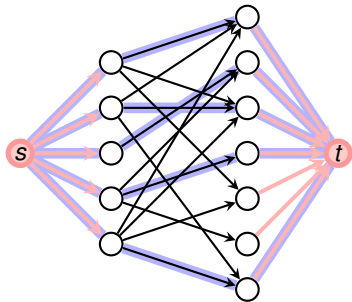
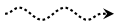


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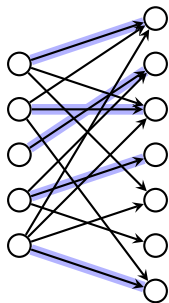


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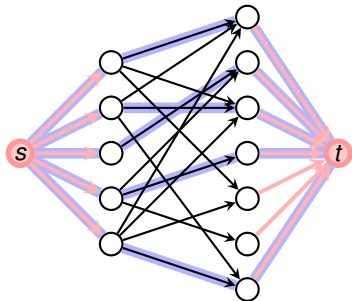
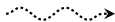


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- Given a maximum matching of cardinality k
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- $\Rightarrow f$ is a flow and has value k



Graph G



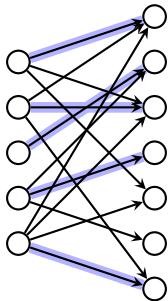
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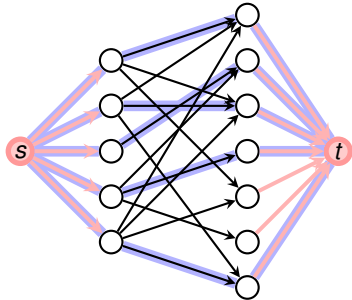
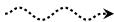
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max cardinality matching \leq value of maxflow



Graph G



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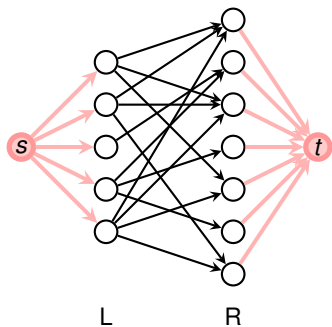
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- Let f be a maximum flow in \tilde{G} of value k



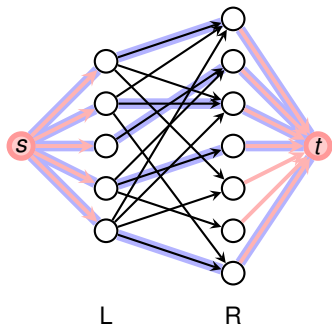
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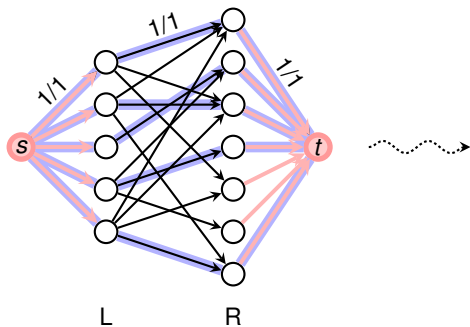
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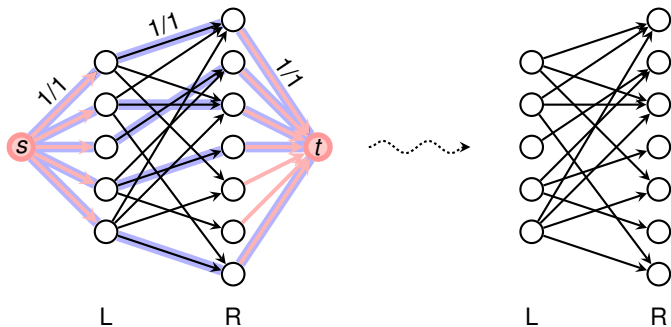
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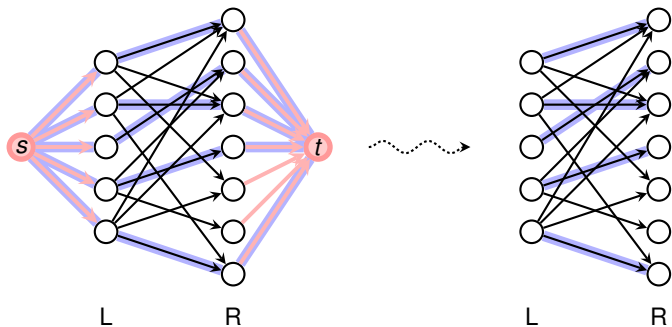
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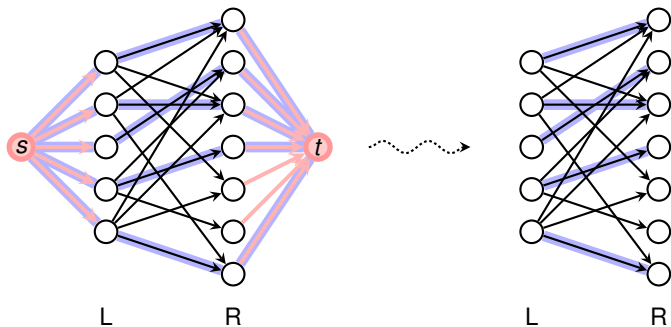
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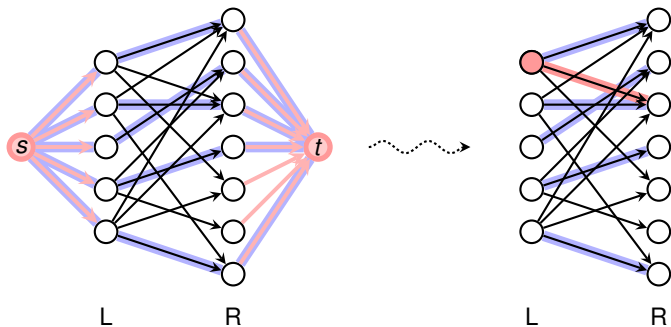
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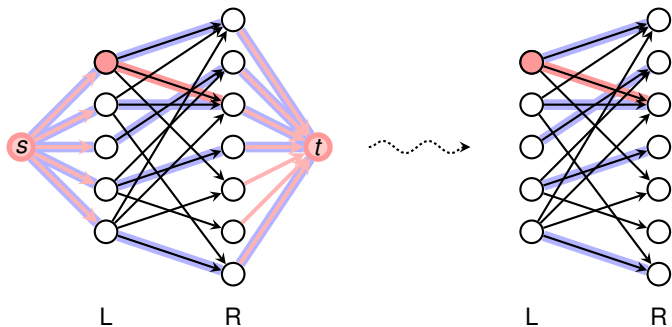
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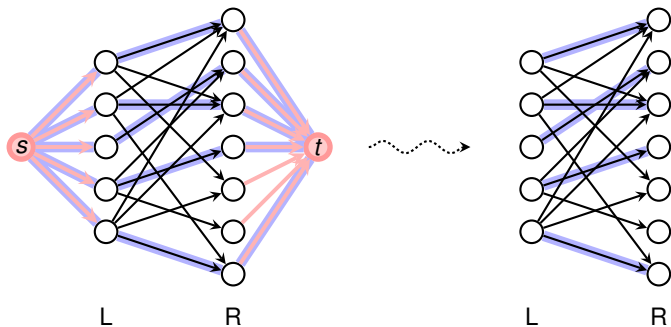
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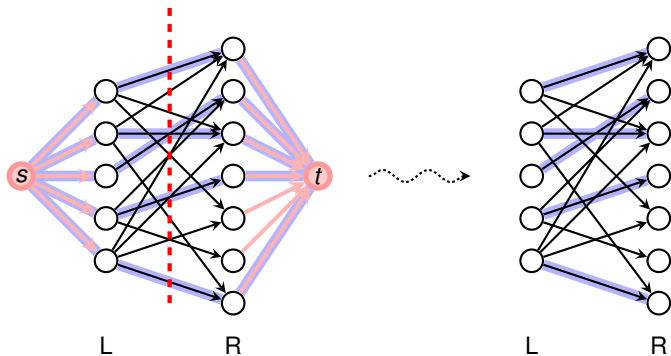
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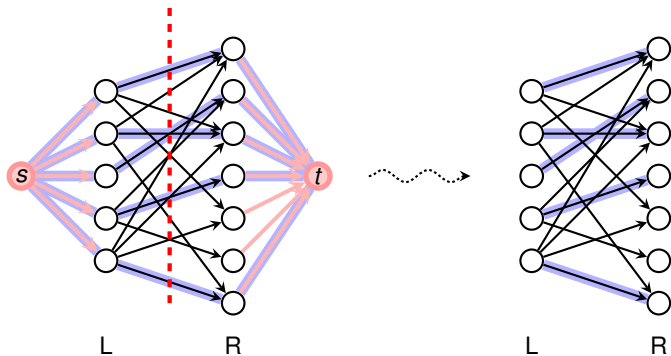
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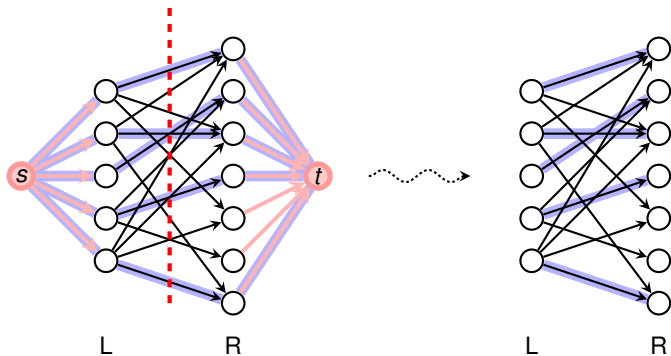
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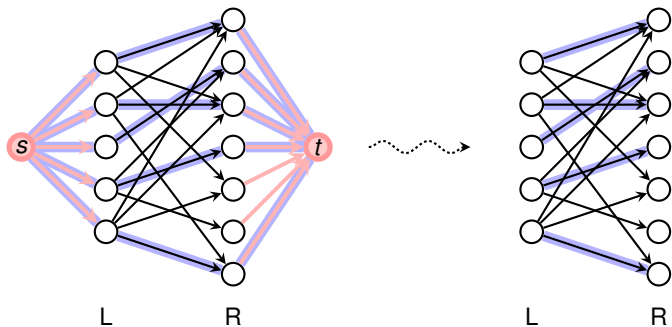
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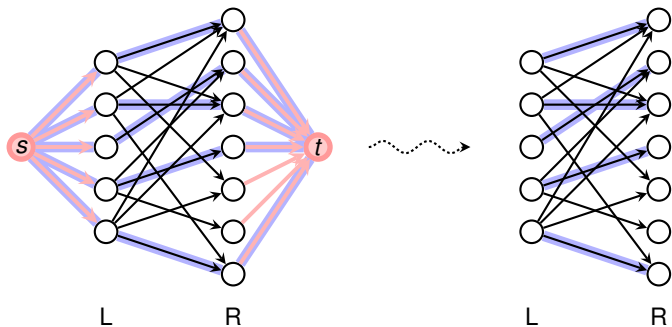
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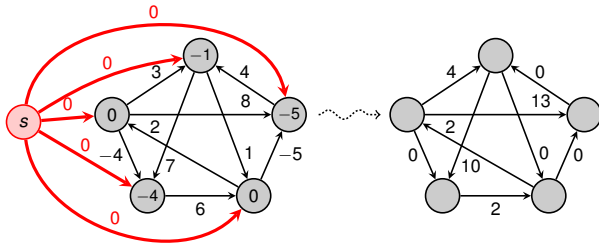


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value of maxflow \leq max cardinality matching





6.5: All-Pairs Shortest Paths

Frank Stajano

Thomas Sauerwald

Lent 2016



UNIVERSITY OF
CAMBRIDGE

All-Pairs Shortest Path

APSP via Matrix Multiplication

Johnson's Algorithm



All-Pairs Shortest Path Problem

- Given: directed graph $G = (V, E)$, $V = \{1, 2, \dots, n\}$, with edge weights represented by a matrix W :

$$w_{i,j} = \begin{cases} \text{weight of edge } (i,j) & \text{for an edge } (i,j) \in E, \\ \infty & \text{if there is no edge from } i \text{ to } j, \\ 0 & \text{if } i = j. \end{cases}$$



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- **Goal:** Obtain a matrix of shortest path weights L , that is

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Here we will only compute the weight of the shortest path without keeping track of the edges of the path!



All-Pairs Shortest Path

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A Recursive Approach



Basic Idea

- Any shortest path from i to j of length $k \geq 2$ is the **concatenation** of a shortest path of length $k - 1$ and an edge



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$$\ell_{i,j}^{(2)} = \min \left(\ell_{i,j}^{(1)}, \min_{1 \leq k \leq n} \ell_{i,k}^{(1)} + w_{k,j} \right)$$



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- How can we obtain $L^{(2)}$ from $L^{(1)}$?

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A Recursive Approach



Basic Idea

- Any shortest path from i to j of length $k \geq 2$ is the **concatenation** of a shortest path of length $k - 1$ and an edge

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Recall that $w_{j,j} = 0!$

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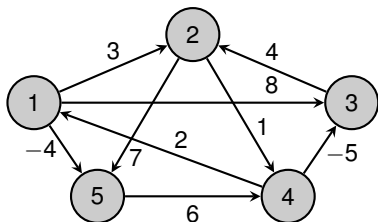
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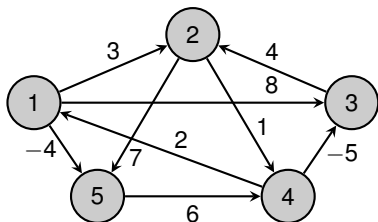
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Example of Shortest Path via Matrix Multiplication (Figure 25.1)



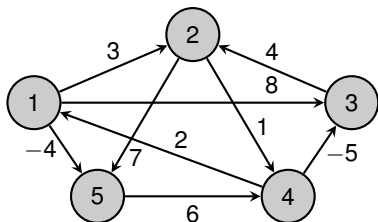
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$$L^{(1)} = W = \begin{pmatrix} 0 & 3 & 8 & \infty & -4 \\ \infty & 0 & \infty & 1 & 7 \\ \infty & 4 & 0 & \infty & \infty \\ 2 & \infty & -5 & 0 & \infty \\ \infty & \infty & \infty & 6 & 0 \end{pmatrix}$$



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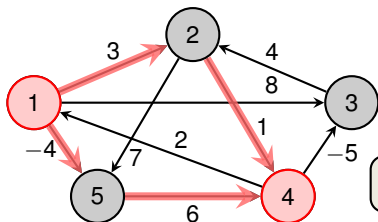


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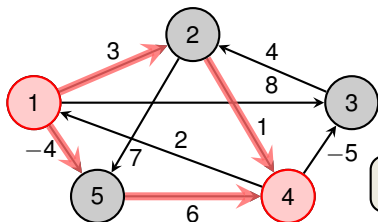
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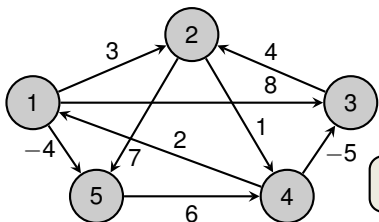
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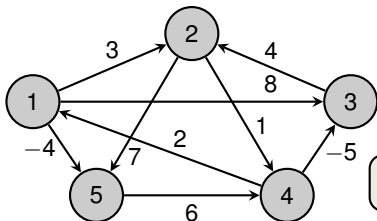
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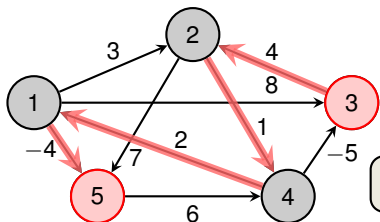
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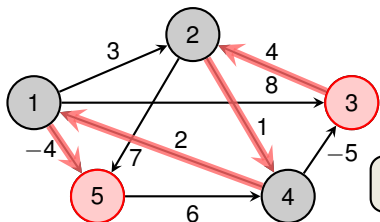
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$L^{(m)}$ can be computed in $\mathcal{O}(n^3)$

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- For, say, $n = 738$, we subsequently compute

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Computing $L^{(n-1)}$ efficiently

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Takes $\mathcal{O}(n \cdot n^3) = \mathcal{O}(n^4)$

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$$L^{(1)}, L^{(2)}, L^{(4)}, \dots, L^{(512)}, L^{(1024)} = L$$



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We need $L^{(4)} = L^{(2)} \cdot L^{(2)} = L^{(3)} \cdot L^{(1)}$! (see Ex. 25.1-4)

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All-Pairs Shortest Path

APSP via Matrix Multiplication

Johnson's Algorithm



Johnson's Algorithm

Overview



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- allow negative-weight edges and negative-weight cycles



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- one pass of Bellman-Ford and $|V|$ passes of Dijkstra



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Adding a constant to every edge doesn't work!

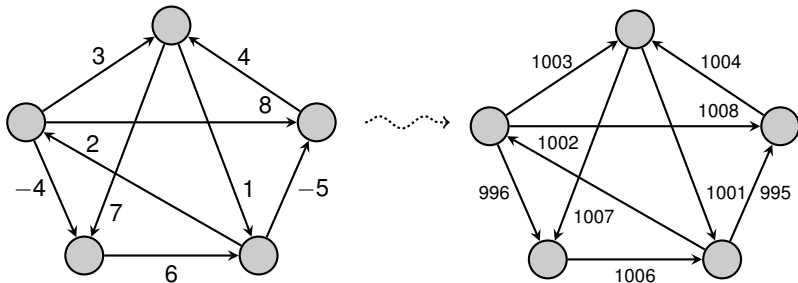


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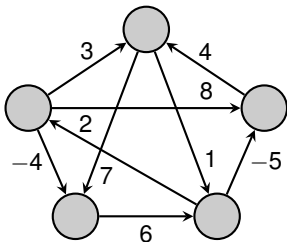
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How Johnson's Algorithm works

Johnson's Algorithm

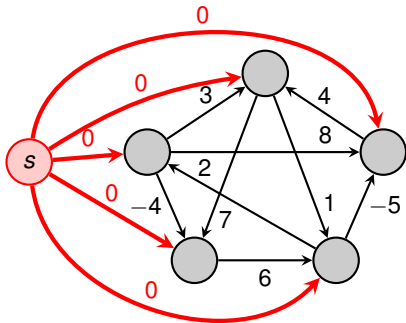
1. Add a new vertex s and directed edges $(s, v), v \in V$, with weight 0



How Johnson's Algorithm works

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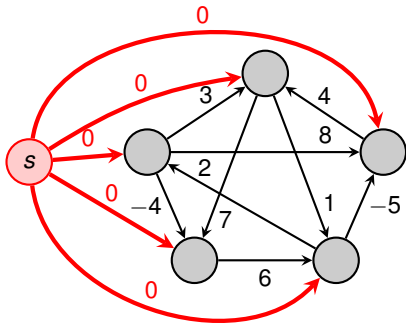
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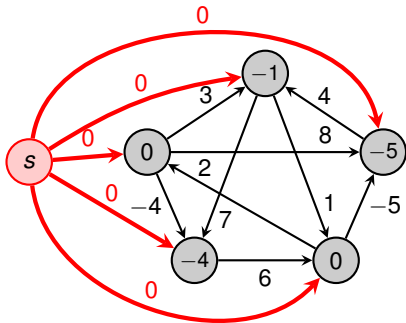
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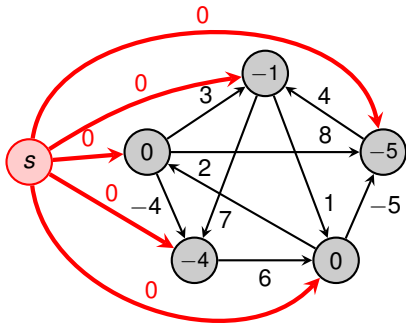
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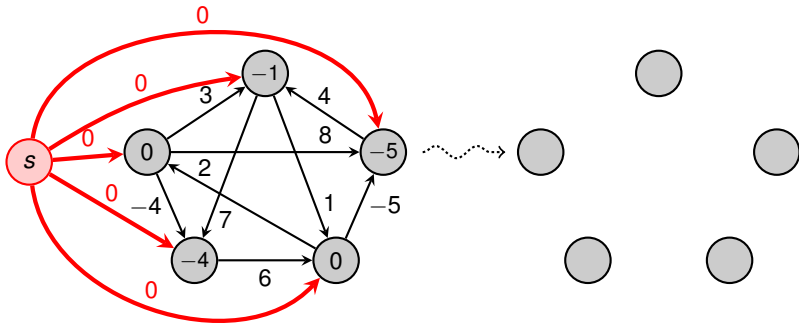
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 - If there are negative weight cycles, abort



How Johnson's Algorithm works

Johnson's Algorithm

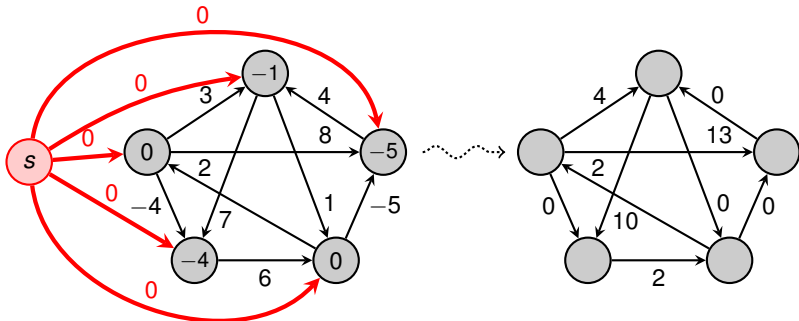
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 - If there are negative weight cycles, abort
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 - 2) Remove vertex s and its incident edges



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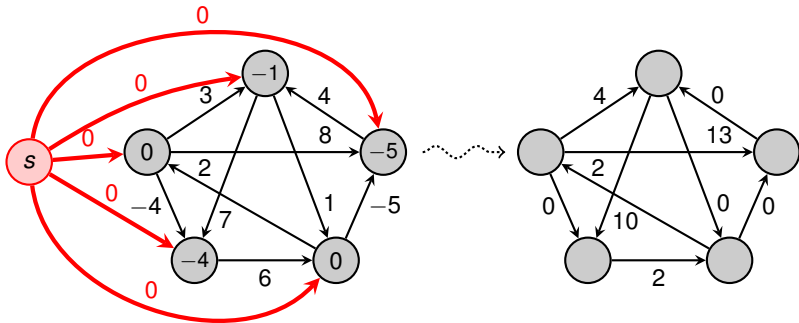
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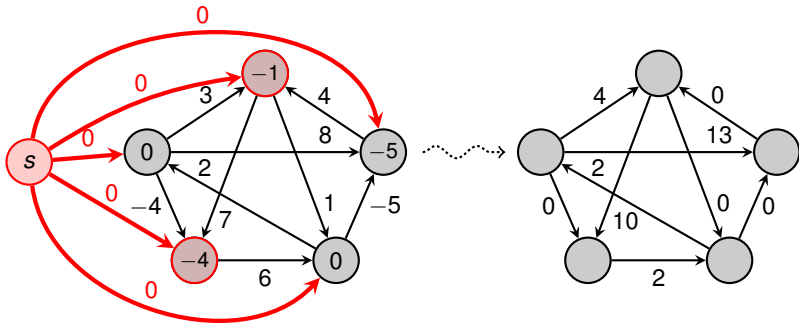
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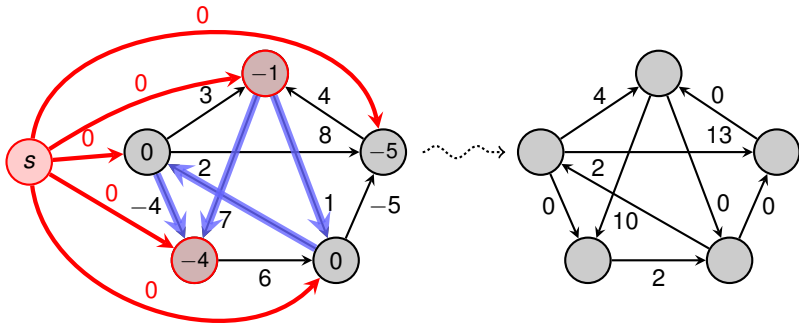
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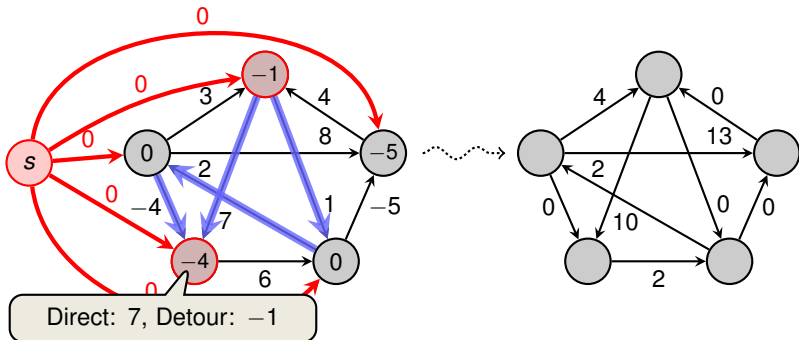
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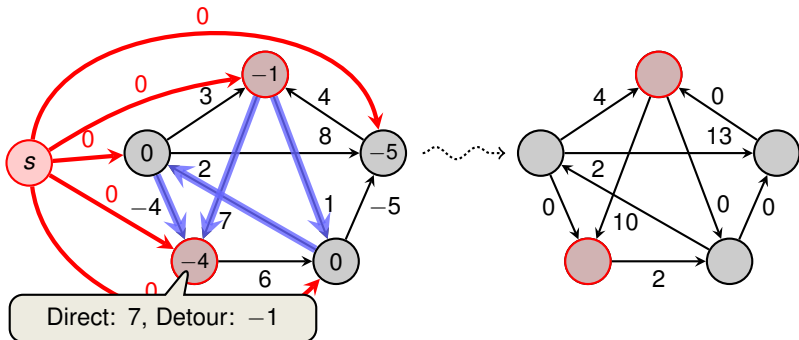
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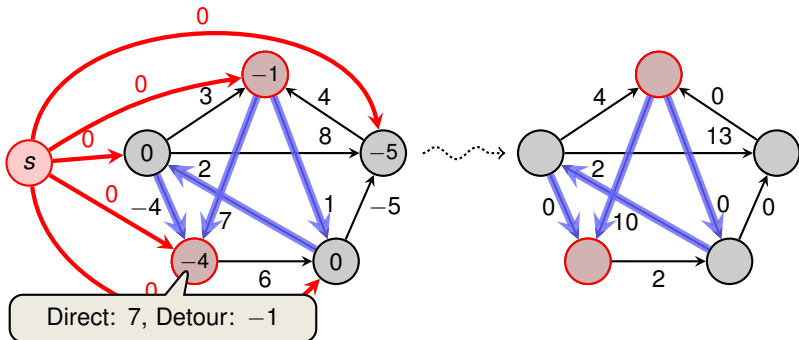
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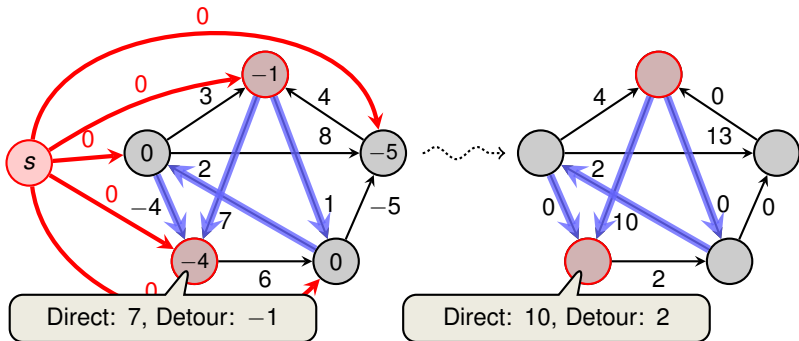
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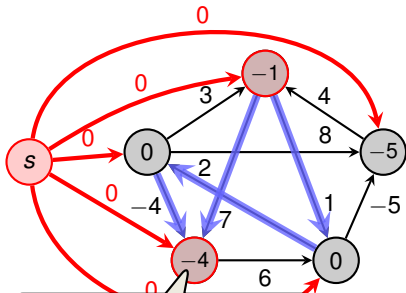


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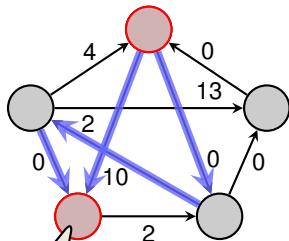
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Runtime: $O(V \cdot E + V \cdot (V \log V + E))$



Direct: 7, Detour: -1



Direct: 10, Detour: 2



Theorem

For any graph $G = (V, E, w)$ without negative-weight cycles:

1. After **reweighting**, all edges are non-negative
2. Shortest Paths are **preserved**



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Proof of 1.



Correctness of Johnson's Algorithm

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$$u.\delta + w(u, v) \geq v.\delta \quad (\text{triangle inequality})$$



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$$\begin{aligned} u.\delta + w(u, v) &\geq v.\delta && \text{(triangle inequality)} \\ \Rightarrow \tilde{w}(u, v) + u.\delta + w(u, v) &\geq w(u, v) + u.\delta - v.\delta + v.\delta \end{aligned}$$



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□



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For any graph $G = (V, E, w)$ without negative-weight cycles:

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Proof of 2.



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Proof of 2.

Let $p = (v_0, v_1, \dots, v_k)$ be **any** path



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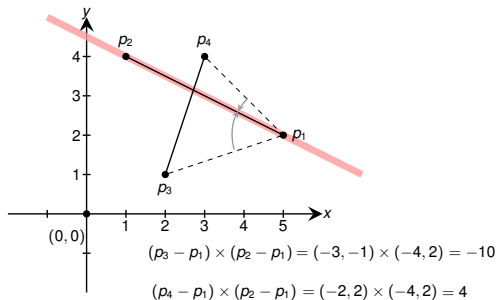


Comparison of all Shortest-Path Algorithms

Algorithm	SSSP		APSP		negative weights
	sparse	dense	sparse	dense	
Bellman-Ford	V^2	V^3	V^3	V^4	✓
Dijkstra	$V \log V$	V^2	$V^2 \log V$	V^3	X
Matrix Mult.	–	–	$V^3 \log V$	$V^3 \log V$	(✓)
Johnson	–	–	$V^2 \log V$	V^3	✓

can handle negative weight edges,
but not negative weight cycles





7: Geometric Algorithms

Frank Stajano

Thomas Sauerwald

Lent 2016



UNIVERSITY OF
CAMBRIDGE

Introduction and Line Intersection

Convex Hull

Glimpse at (More) Advanced Algorithms



Computational Geometry

- Branch that studies algorithms for geometric problems



Computational Geometry

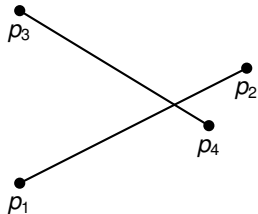
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- typically, input is a set of points, line segments etc.



Introduction

Computational Geometry

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Do these lines intersect?

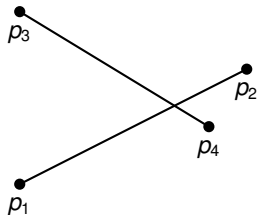


Computational Geometry

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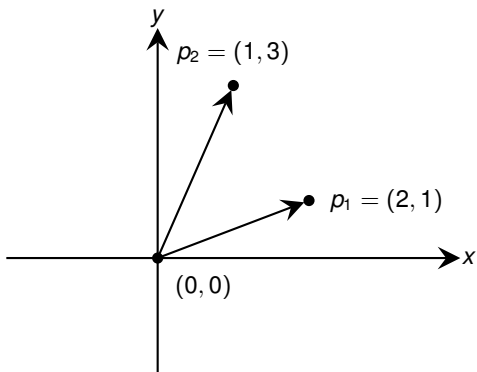
Applications

- computer graphics
- computer vision
- textile layout
- VLSI design
-

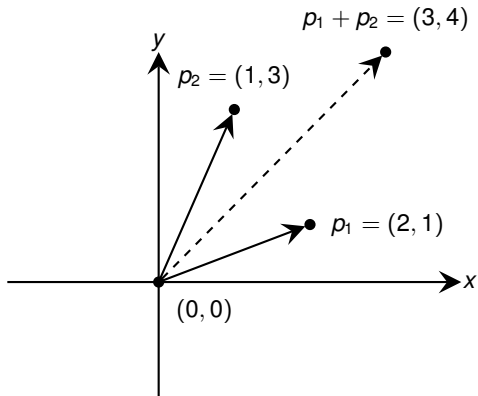


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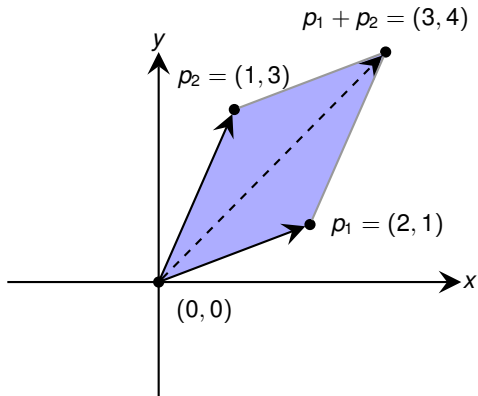
Cross Product (Area)



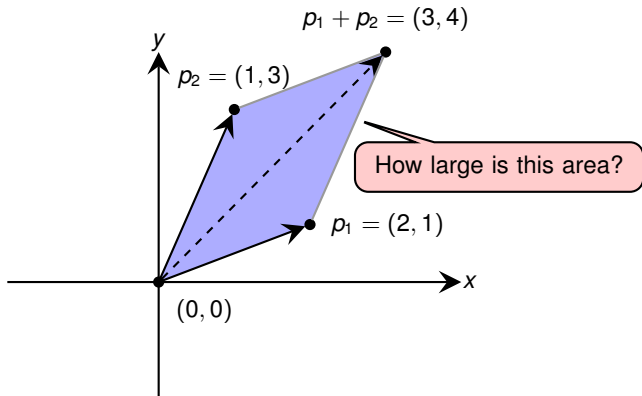
Cross Product (Area)



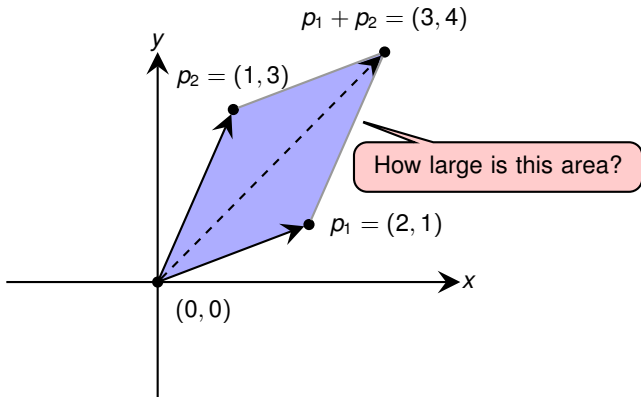
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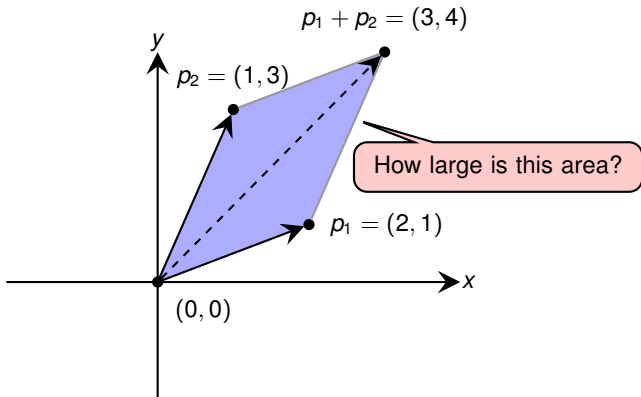
Cross Product (Area)



$$p_1 \times p_2 = \det \begin{pmatrix} x_1 & x_2 \\ y_1 & y_2 \end{pmatrix}$$



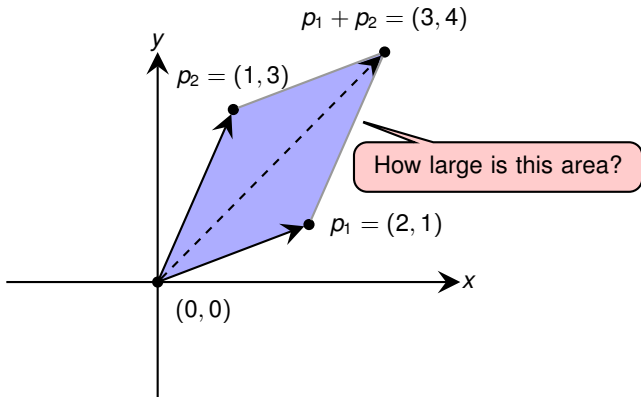
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$$p_1 \times p_2 = \det \begin{pmatrix} x_1 & x_2 \\ y_1 & y_2 \end{pmatrix} = x_1 y_2 - x_2 y_1$$



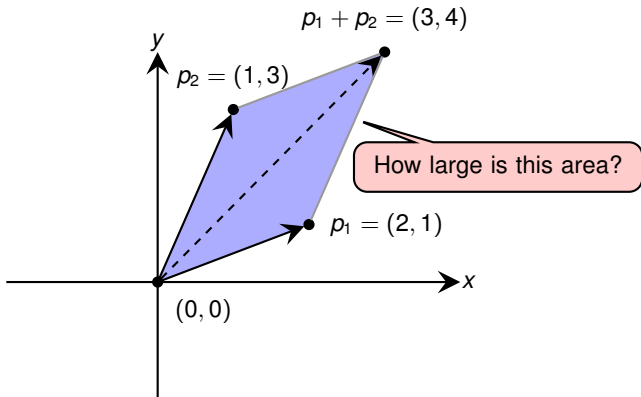
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$$p_1 \times p_2 = \det \begin{pmatrix} x_1 & x_2 \\ y_1 & y_2 \end{pmatrix} = x_1 y_2 - x_2 y_1 = 2 \cdot 3 - 1 \cdot 1$$



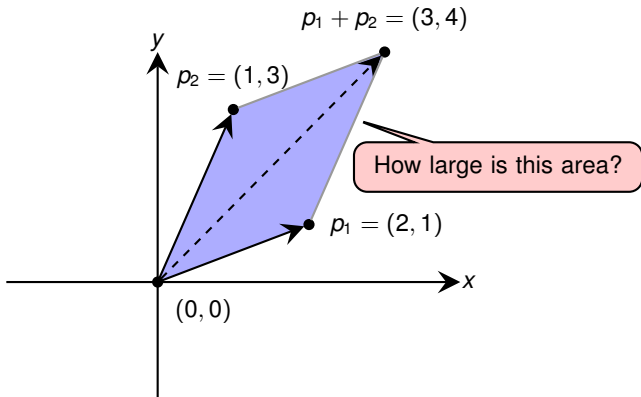
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$$p_1 \times p_2 = \det \begin{pmatrix} x_1 & x_2 \\ y_1 & y_2 \end{pmatrix} = x_1 y_2 - x_2 y_1 = 2 \cdot 3 - 1 \cdot 1 = 5$$



Cross Product (Area)

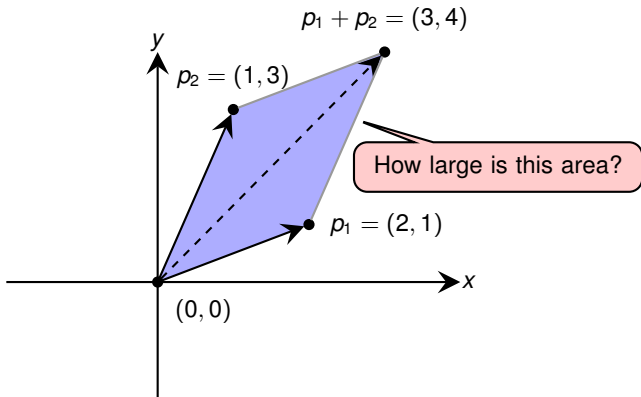


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$$p_2 \times p_1$$



Cross Product (Area)

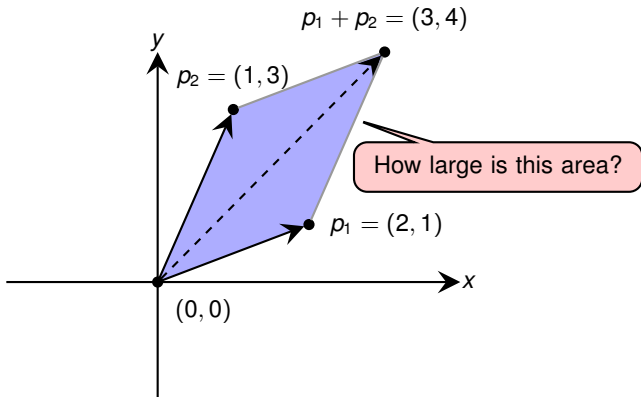


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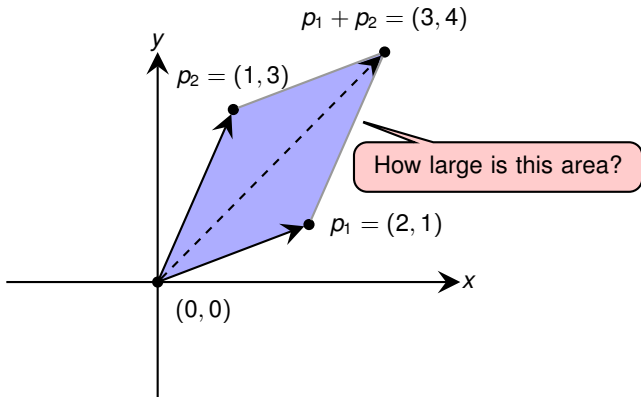


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$$p_2 \times p_1 = y_1 x_2 - y_2 x_1 = -(p_1 \times p_2)$$



Cross Product (Area)

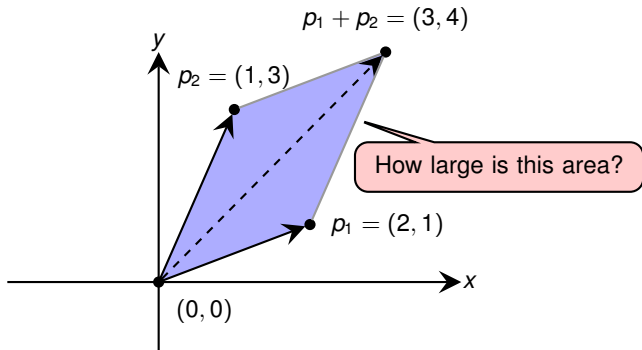


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$$p_2 \times p_1 = y_1 x_2 - y_2 x_1 = -(p_1 \times p_2) = -5$$



Cross Product (Area)



Alternatively, one could take the dot-product (but not used here):

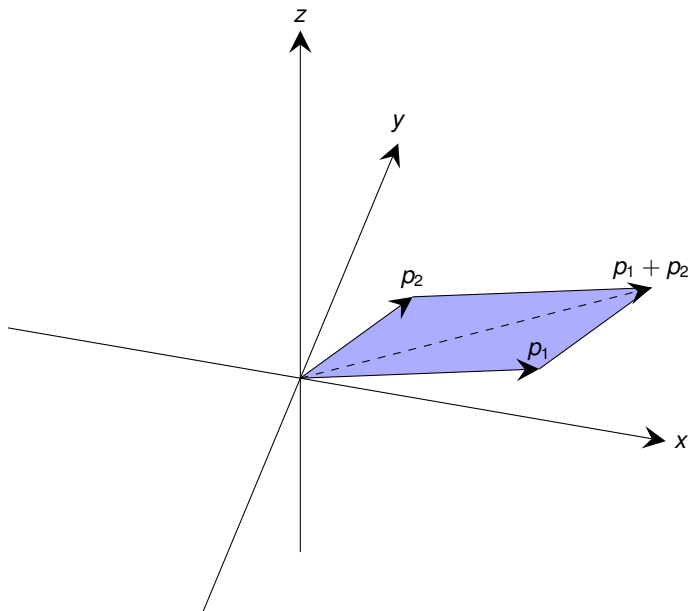
$$p_1 \cdot p_2 = \|p_1\| \cdot \|p_2\| \cdot \cos(\phi).$$

$$p_1 \times p_2 = \det \begin{pmatrix} x_1 & x_2 \\ y_1 & y_2 \end{pmatrix} = x_1 y_2 - x_2 y_1 = 2 \cdot 3 - 1 \cdot 1 = 5$$

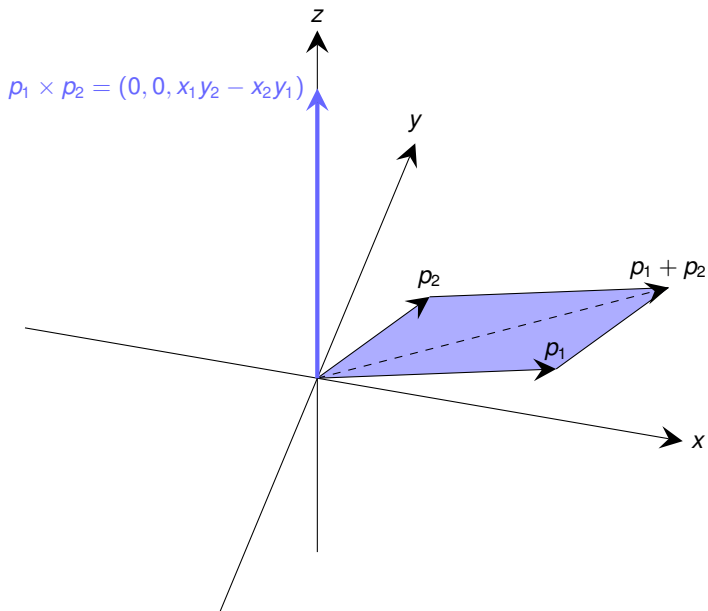
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Cross Product in 3D

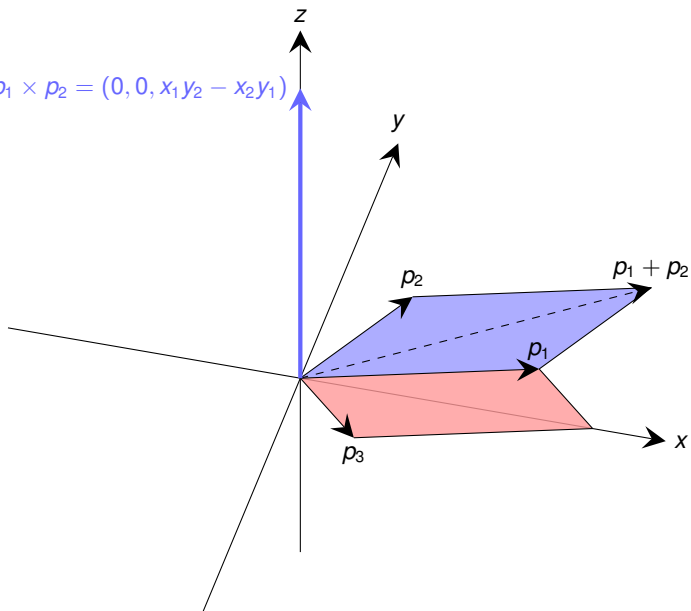


Cross Product in 3D

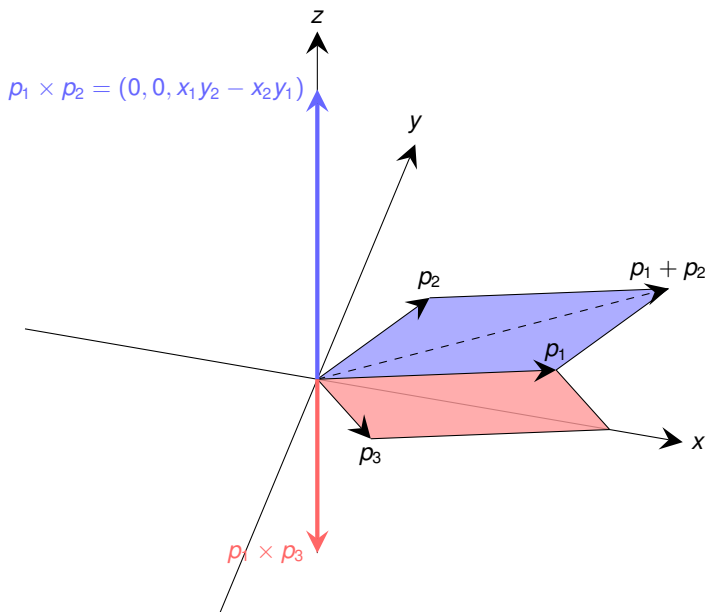


Cross Product in 3D

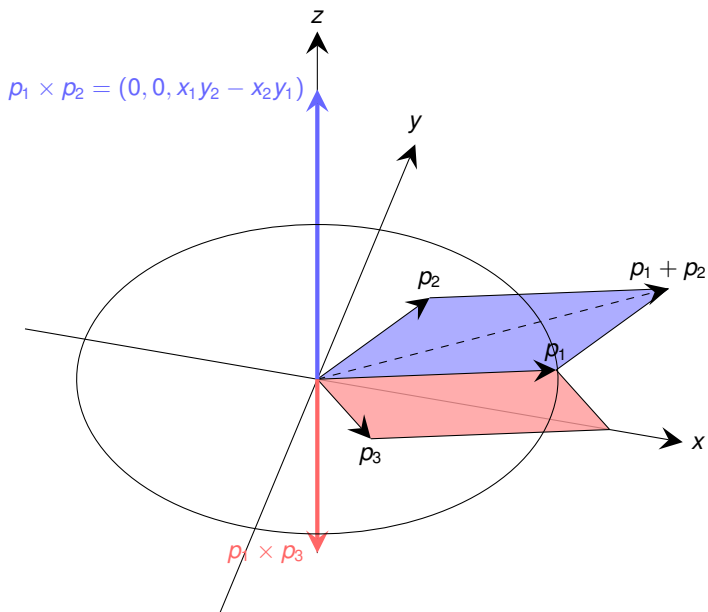
$$p_1 \times p_2 = (0, 0, x_1y_2 - x_2y_1)$$



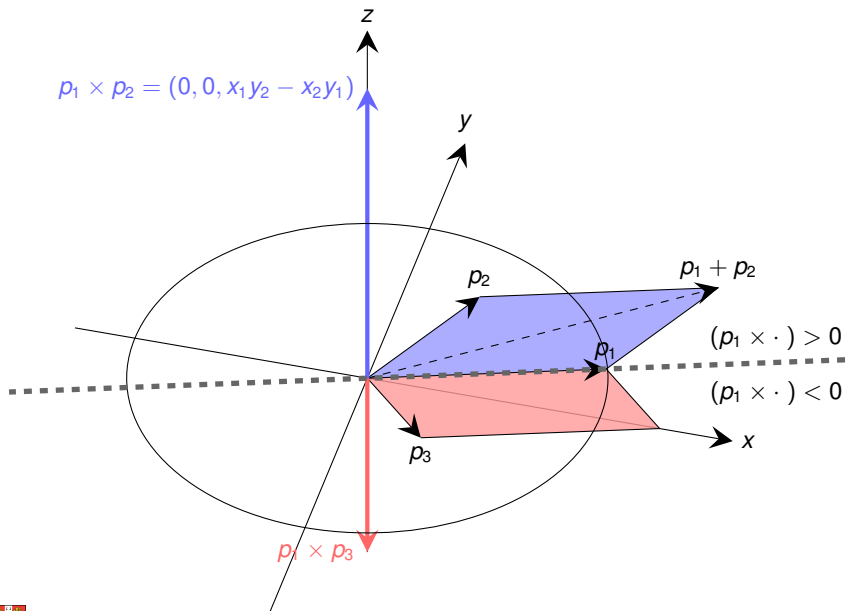
Cross Product in 3D



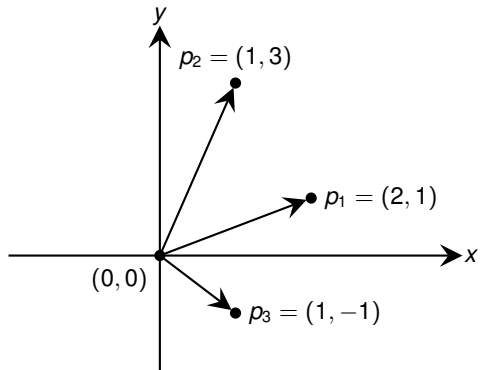
Cross Product in 3D



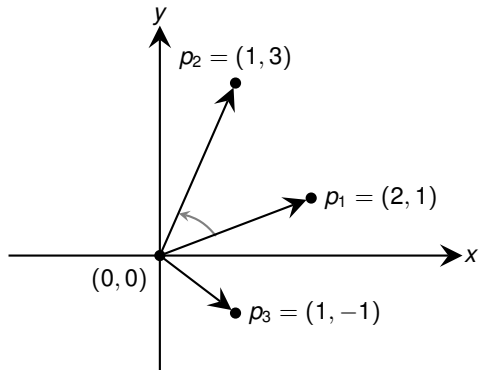
Cross Product in 3D



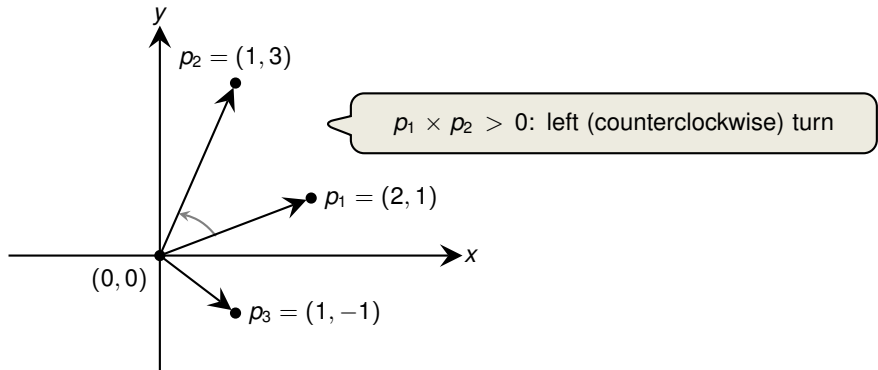
Using Cross product to determine Turns



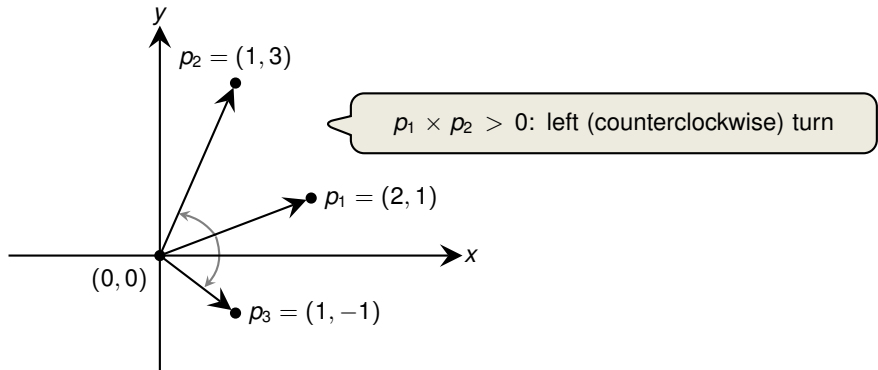
Using Cross product to determine Turns



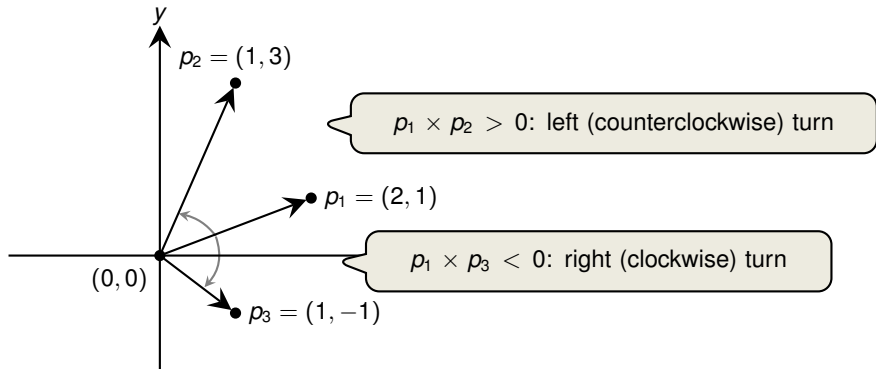
Using Cross product to determine Turns



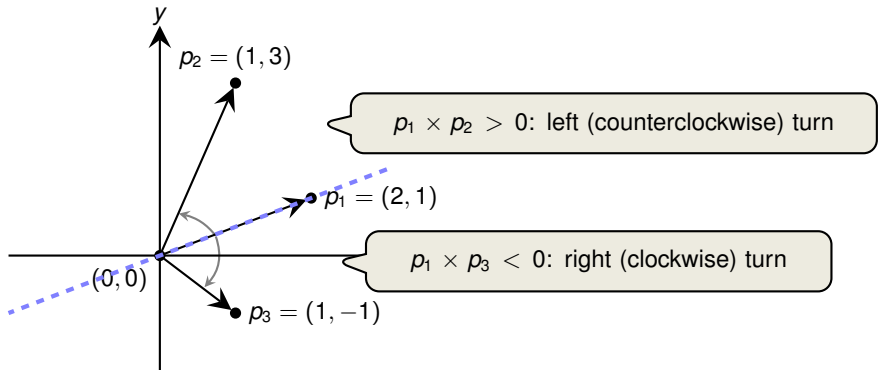
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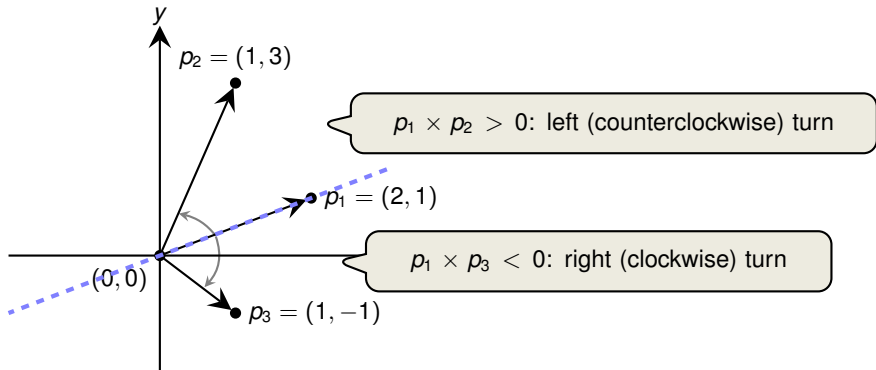
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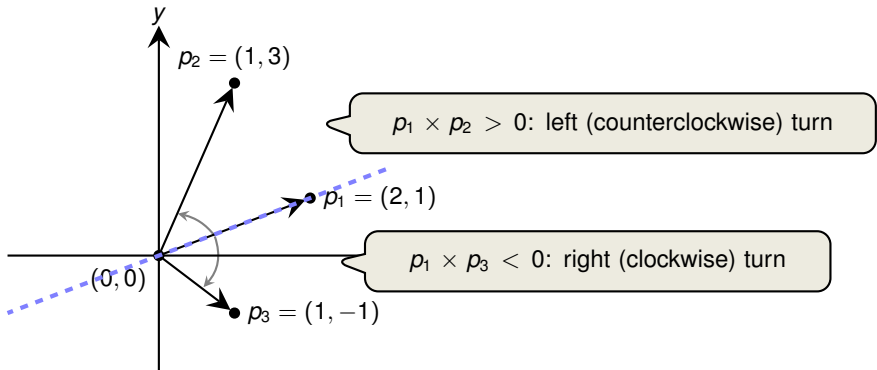
Using Cross product to determine Turns



Sign of cross product determines turn!



Using Cross product to determine Turns

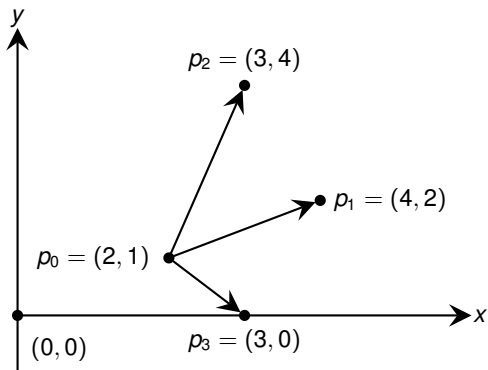


Sign of cross product determines turn!

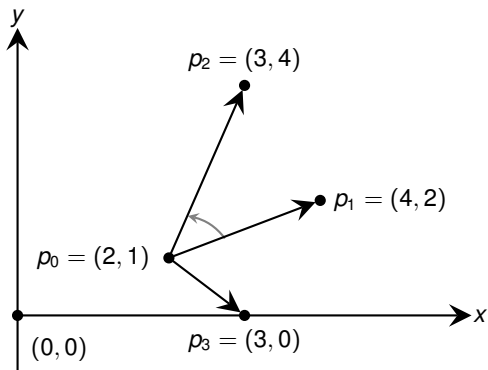
Cross product equals zero iff vectors are colinear



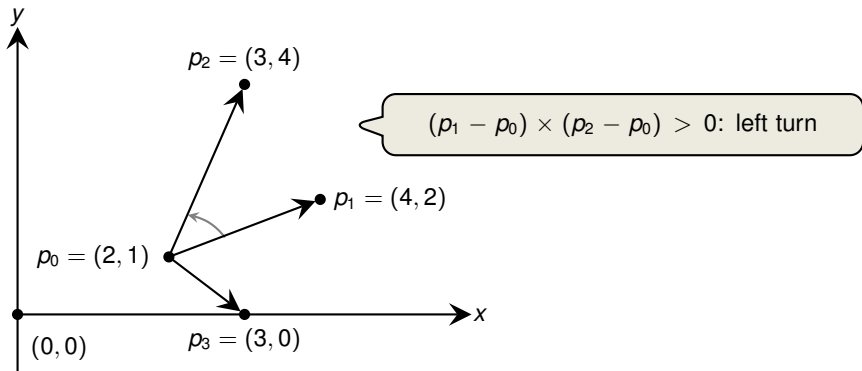
Using Cross product to determine Turns (origin shifted)



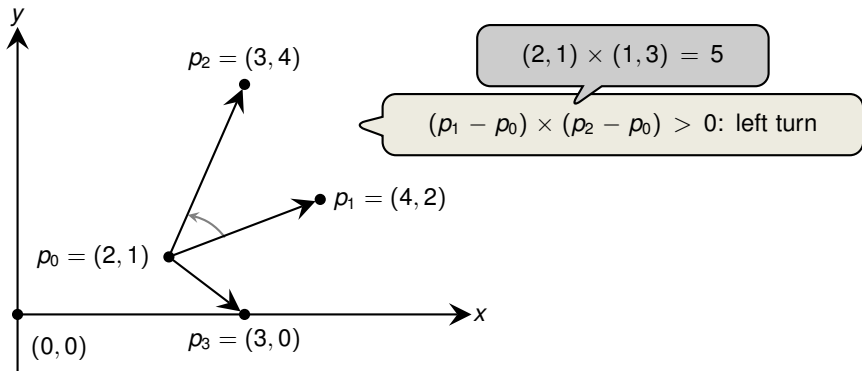
Using Cross product to determine Turns (origin shifted)



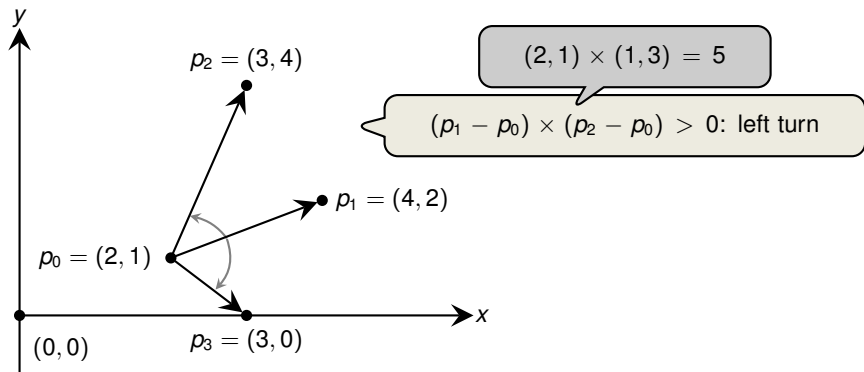
Using Cross product to determine Turns (origin shifted)



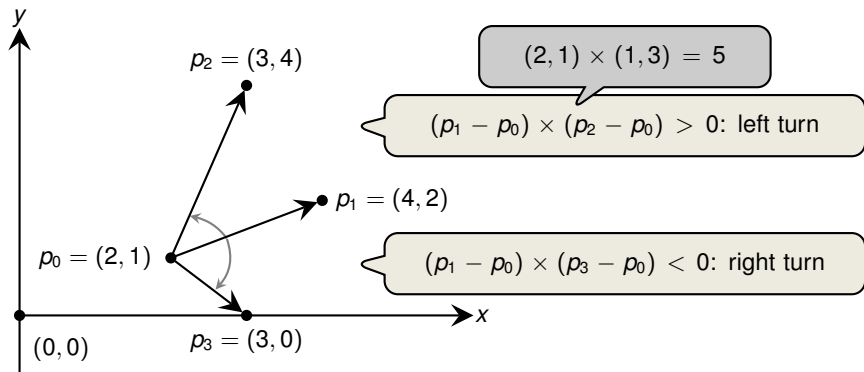
Using Cross product to determine Turns (origin shifted)



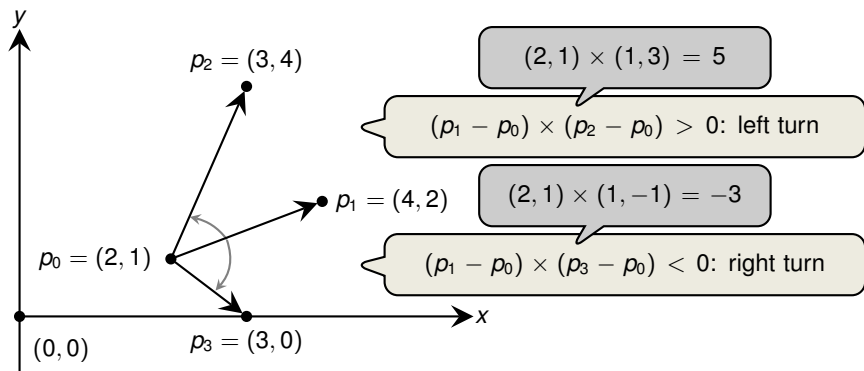
Using Cross product to determine Turns (origin shifted)



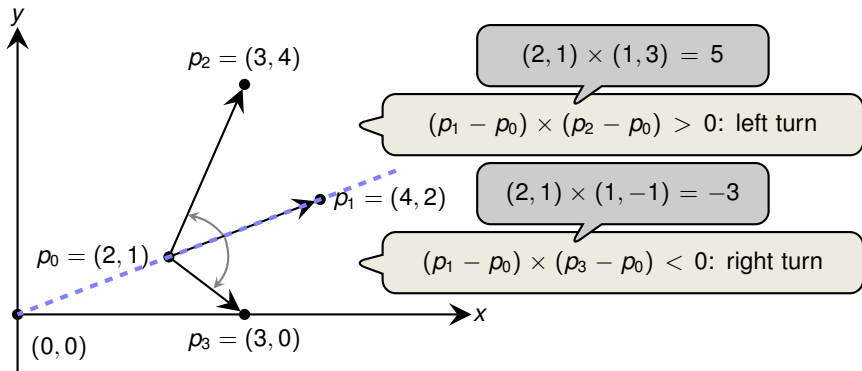
Using Cross product to determine Turns (origin shifted)



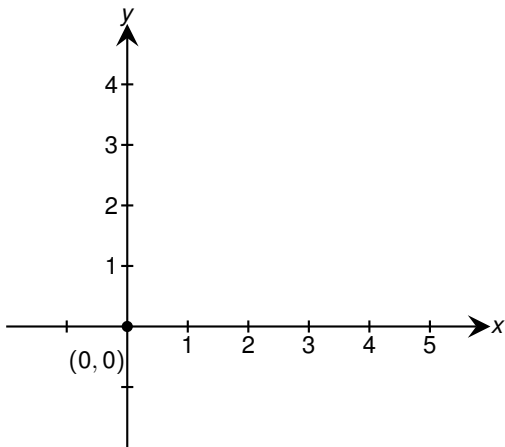
Using Cross product to determine Turns (origin shifted)



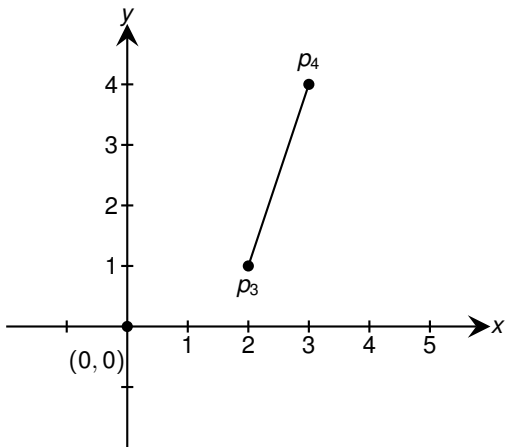
Using Cross product to determine Turns (origin shifted)



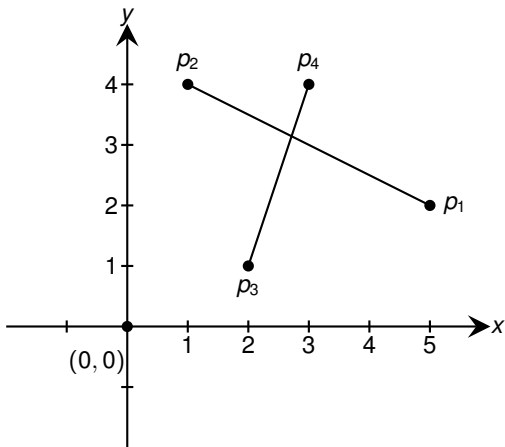
Solving Line Intersection



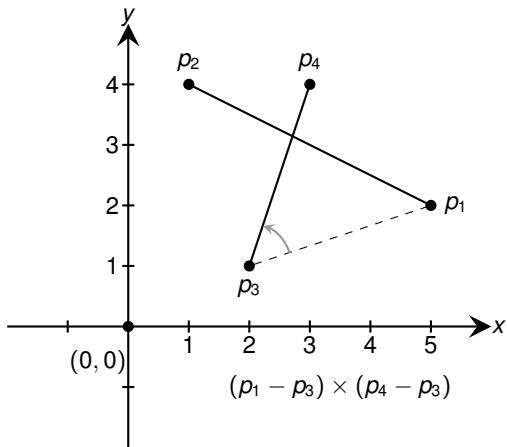
Solving Line Intersection



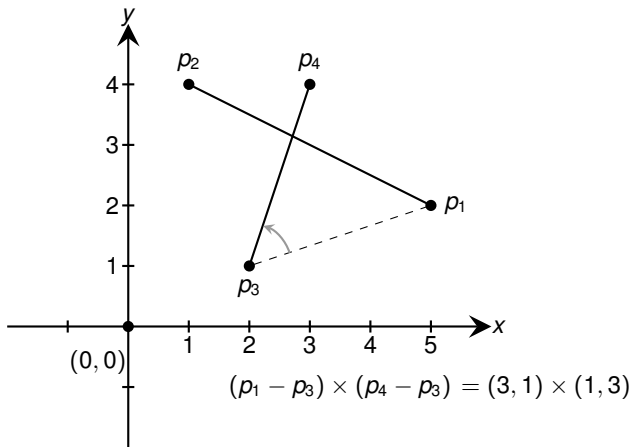
Solving Line Intersection



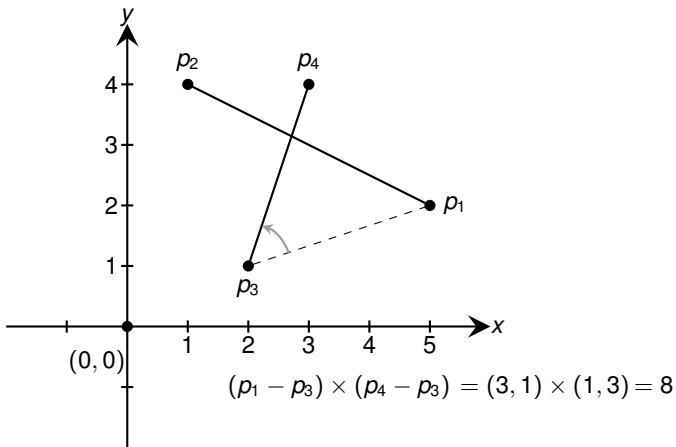
Solving Line Intersection



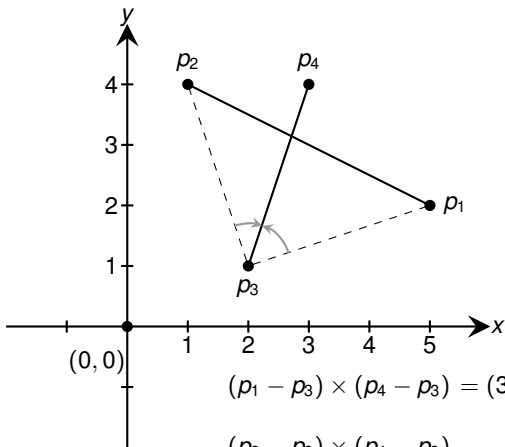
Solving Line Intersection



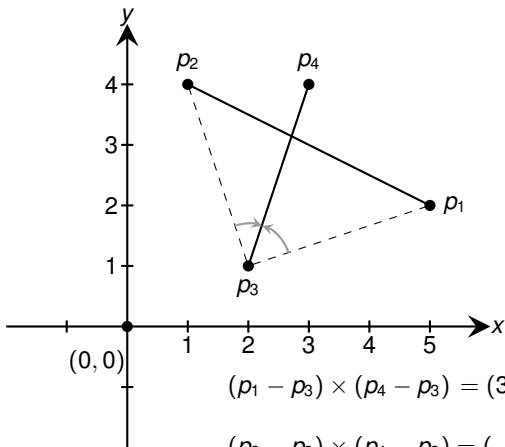
Solving Line Intersection



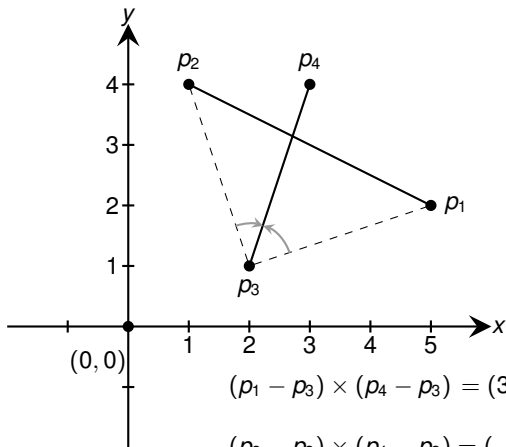
Solving Line Intersection



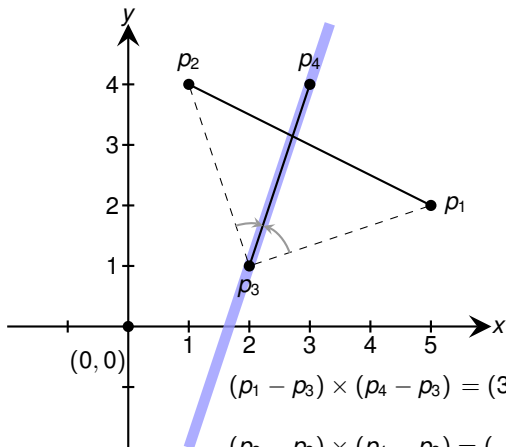
Solving Line Intersection



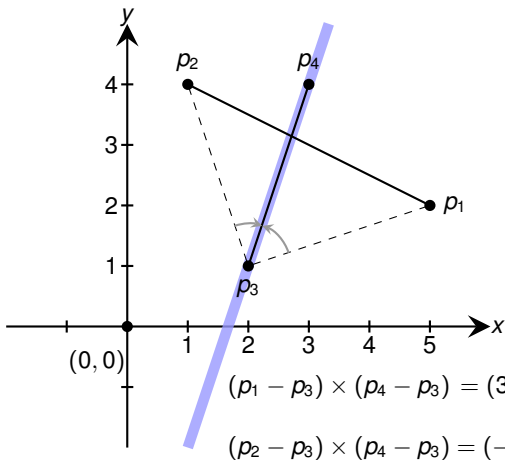
Solving Line Intersection



Solving Line Intersection



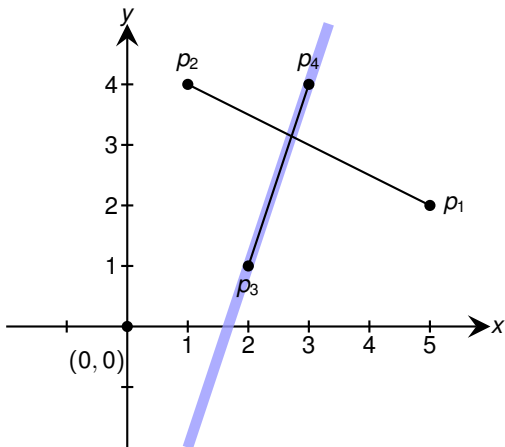
Solving Line Intersection



Opposite signs $\Rightarrow \overline{p_1 p_2}$ crosses
(infinite) line through p_3 and p_4



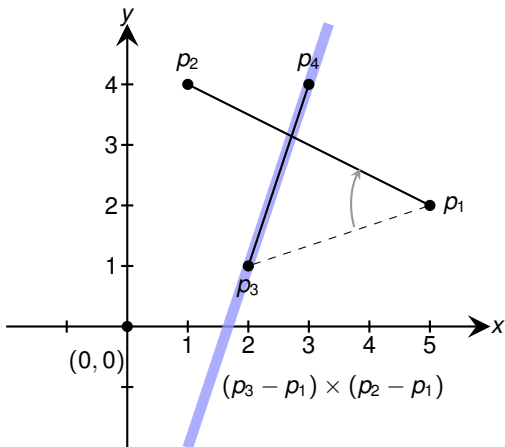
Solving Line Intersection



Opposite signs $\Rightarrow \overline{p_1 p_2}$ crosses
(infinite) line through p_3 and p_4



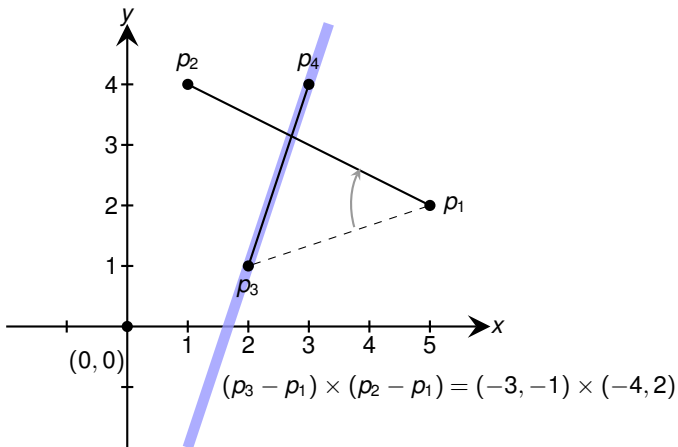
Solving Line Intersection



Opposite signs $\Rightarrow \overline{p_1 p_2}$ crosses
(infinite) line through p_3 and p_4



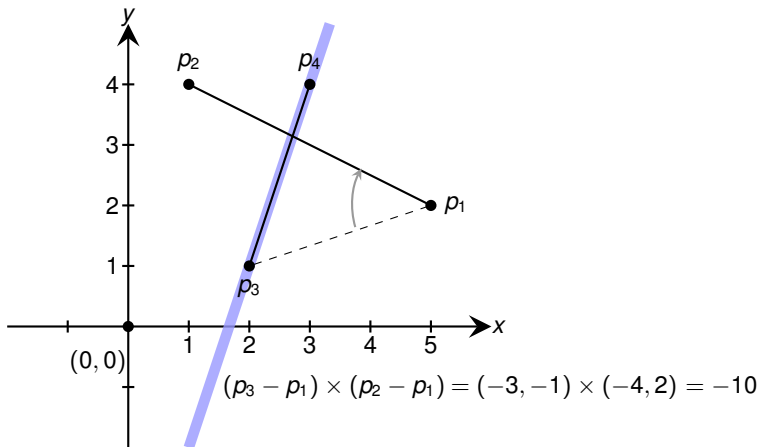
Solving Line Intersection



Opposite signs $\Rightarrow \overline{p_1 p_2}$ crosses
(infinite) line through p_3 and p_4



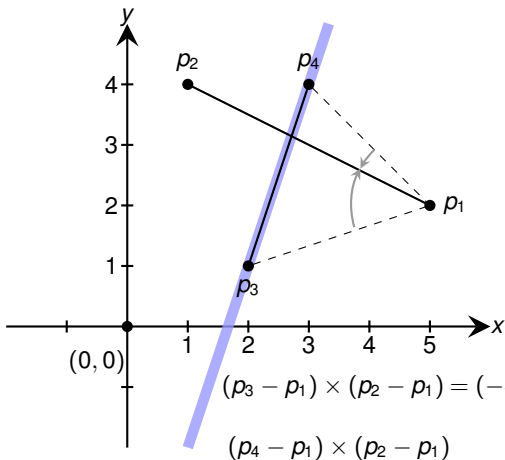
Solving Line Intersection



Opposite signs $\Rightarrow \overline{p_1 p_2}$ crosses
(infinite) line through p_3 and p_4



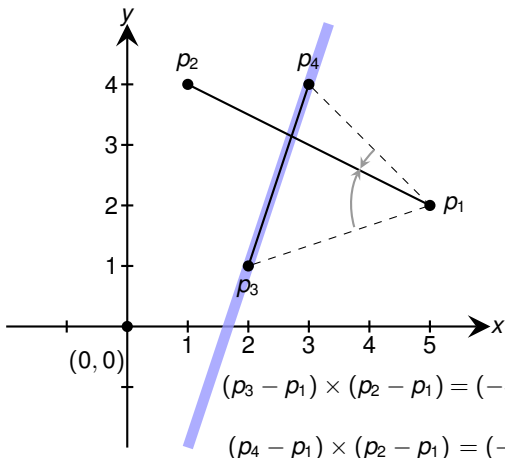
Solving Line Intersection



Opposite signs $\Rightarrow \overline{p_1 p_2}$ crosses
(infinite) line through p_3 and p_4



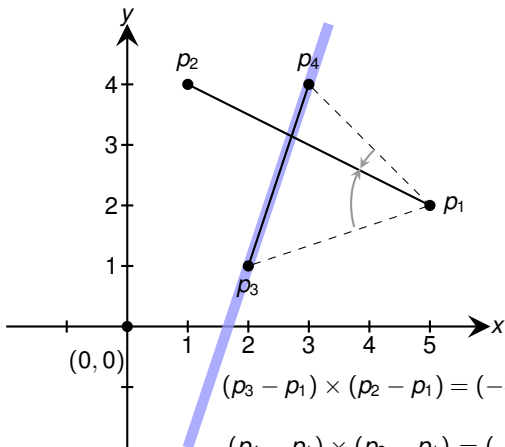
Solving Line Intersection



Opposite signs $\Rightarrow \overline{p_1 p_2}$ crosses
(infinite) line through p_3 and p_4



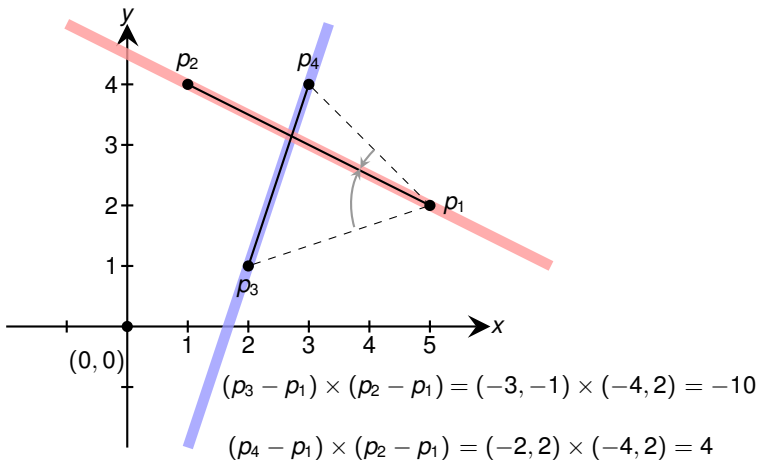
Solving Line Intersection



Opposite signs $\Rightarrow \overline{p_1 p_2}$ crosses
(infinite) line through p_3 and p_4



Solving Line Intersection

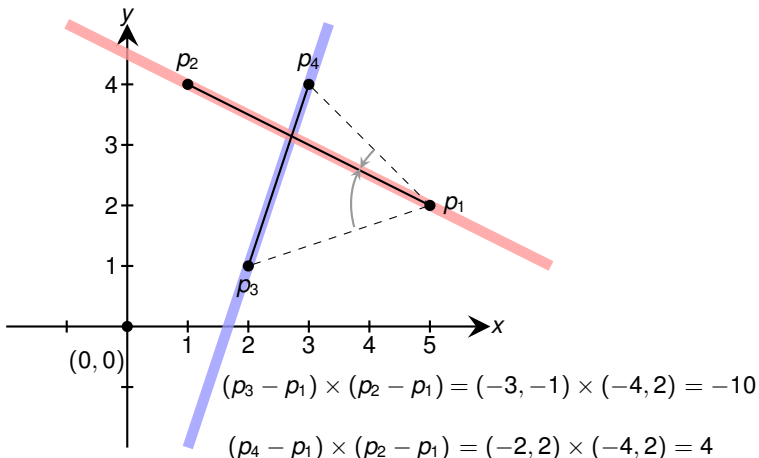


Opposite signs $\Rightarrow \overline{p_1 p_2}$ crosses
(infinite) line through p_3 and p_4

Opposite signs $\Rightarrow \overline{p_3 p_4}$ crosses
(infinite) line through p_1 and p_2



Solving Line Intersection

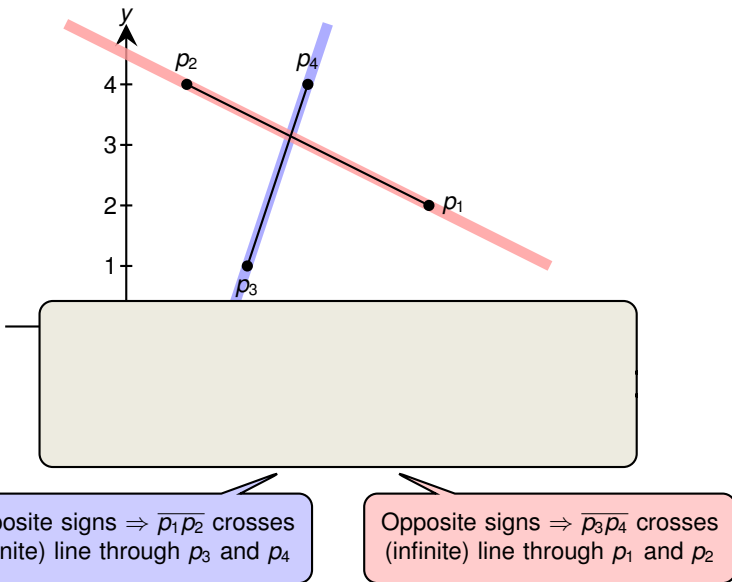


Opposite signs $\Rightarrow \overline{p_1 p_2}$ crosses
(infinite) line through p_3 and p_4

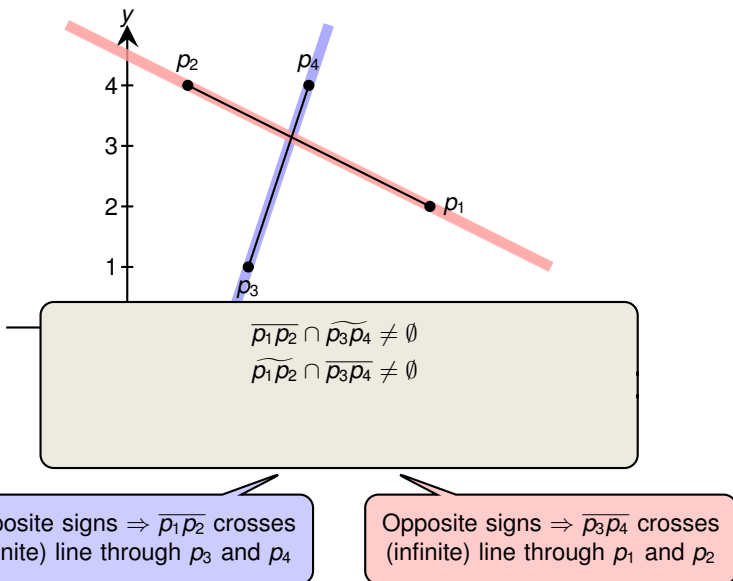
Opposite signs $\Rightarrow \overline{p_3 p_4}$ crosses
(infinite) line through p_1 and p_2



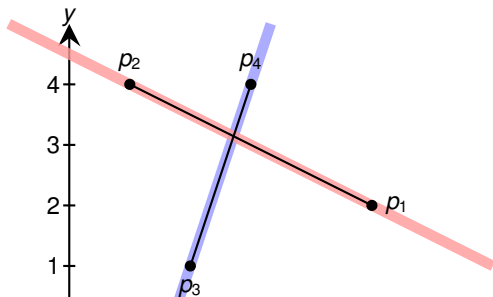
Solving Line Intersection



Solving Line Intersection



Solving Line Intersection



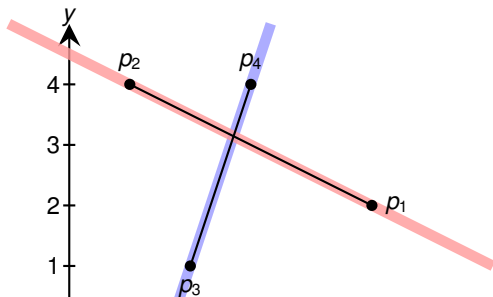
- $\widetilde{p_1 p_2} \cap \widetilde{p_3 p_4} \supseteq \overline{p_1 p_2} \cap \widetilde{p_3 p_4} \neq \emptyset$
- $\widetilde{p_1 p_2} \cap \widetilde{p_3 p_4} \supseteq \widetilde{p_1 p_2} \cap \overline{p_3 p_4} \neq \emptyset$

Opposite signs $\Rightarrow \overline{p_1 p_2}$ crosses
(infinite) line through p_3 and p_4

Opposite signs $\Rightarrow \overline{p_3 p_4}$ crosses
(infinite) line through p_1 and p_2



Solving Line Intersection



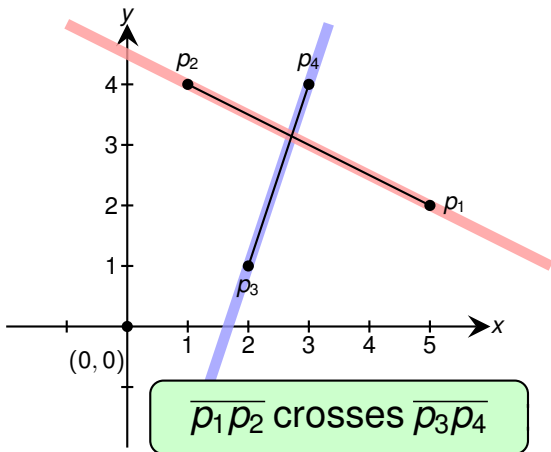
- $\widetilde{p_1 p_2} \cap \widetilde{p_3 p_4} \supseteq \overline{p_1 p_2} \cap \widetilde{p_3 p_4} \neq \emptyset$
- $\overline{p_1 p_2} \cap \widetilde{p_3 p_4} \supseteq \widetilde{p_1 p_2} \cap \overline{p_3 p_4} \neq \emptyset$
- Since $\widetilde{p_1 p_2} \cap \widetilde{p_3 p_4}$ consists of (at most) one point
 $\Rightarrow \overline{p_1 p_2} \cap \overline{p_3 p_4} \neq \emptyset$

Opposite signs $\Rightarrow \overline{p_1 p_2}$ crosses
(infinite) line through p_3 and p_4

Opposite signs $\Rightarrow \overline{p_3 p_4}$ crosses
(infinite) line through p_1 and p_2



Solving Line Intersection

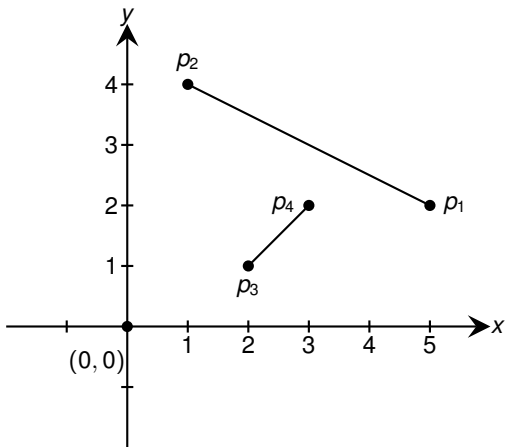


Opposite signs $\Rightarrow \overline{p_1 p_2}$ crosses
(infinite) line through p_3 and p_4

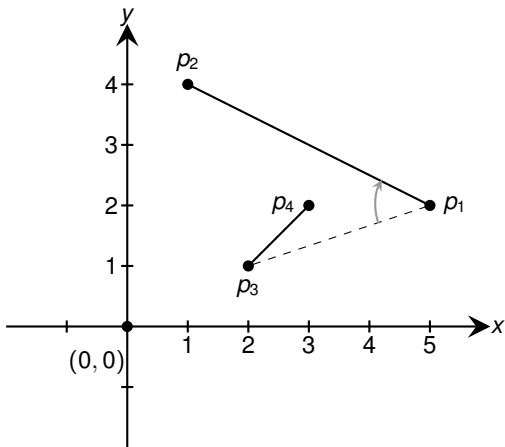
Opposite signs $\Rightarrow \overline{p_3 p_4}$ crosses
(infinite) line through p_1 and p_2



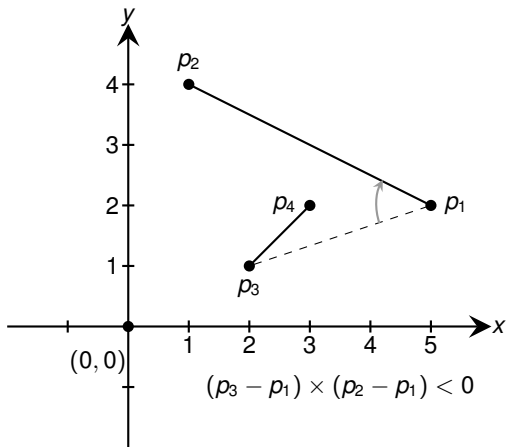
Solving Line Intersection



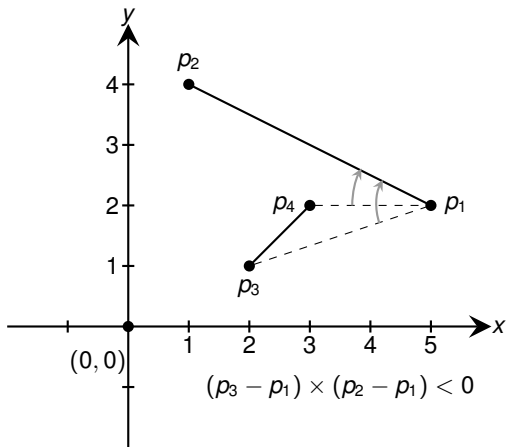
Solving Line Intersection



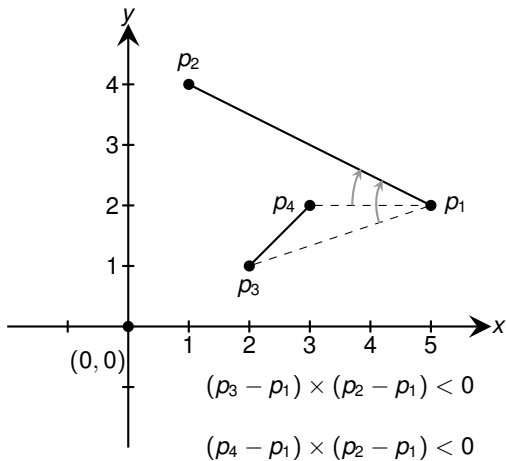
Solving Line Intersection



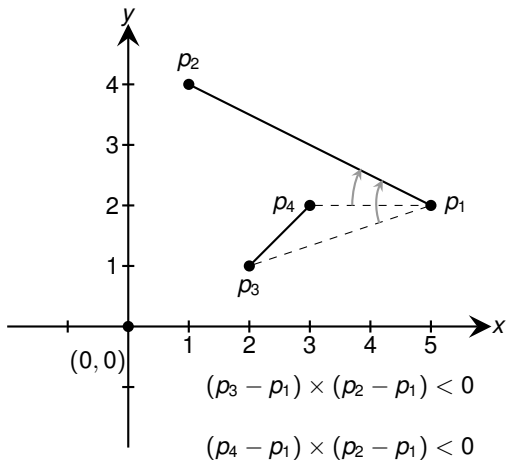
Solving Line Intersection



Solving Line Intersection



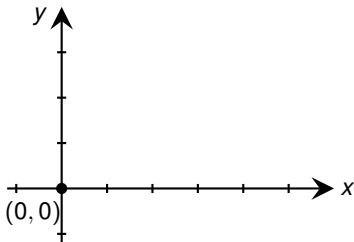
Solving Line Intersection



$\overline{p_1 p_2}$ does **not** cross $\overline{p_3 p_4}$



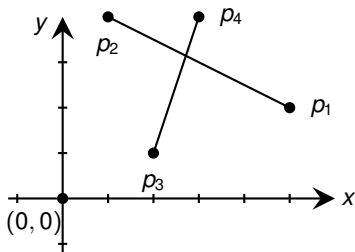
Solving Line Intersection



```
0: DIRECTION( $p_i, p_j, p_k$ )  
1:   return  $(p_k - p_i) \times (p_j - p_i)$ 
```



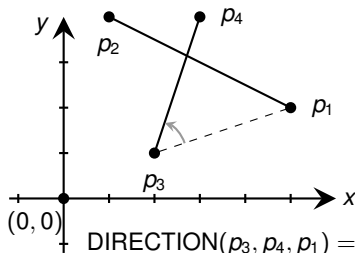
Solving Line Intersection



```
0: DIRECTION( $p_i, p_j, p_k$ )  
1: return  $(p_k - p_i) \times (p_j - p_i)$ 
```



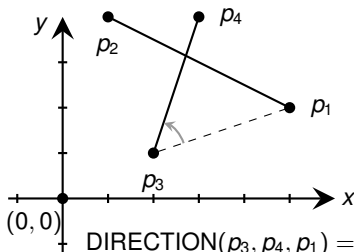
Solving Line Intersection



```
0: DIRECTION( $p_i, p_j, p_k$ )  
1: return  $(p_k - p_i) \times (p_j - p_i)$ 
```



Solving Line Intersection

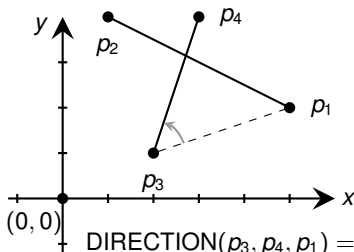


```
0: DIRECTION( $p_i, p_j, p_k$ )  
1:   return  $(p_k - p_i) \times (p_j - p_i)$ 
```

```
0: SEGMENTS-INTERSECT( $p_1, p_2, p_3, p_4$ )  
1:    $d_1 =$  DIRECTION( $p_3, p_4, p_1$ )  
2:    $d_2 =$  DIRECTION( $p_3, p_4, p_2$ )  
3:    $d_3 =$  DIRECTION( $p_1, p_2, p_3$ )  
4:    $d_4 =$  DIRECTION( $p_1, p_2, p_4$ )  
5:   If  $d_1 \cdot d_2 < 0$  and  $d_3 \cdot d_4 < 0$  return TRUE  
6:   ... (handle all degenerate cases)
```



Solving Line Intersection



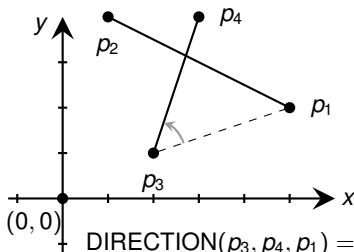
$$\text{DIRECTION}(p_3, p_4, p_1) = (p_1 - p_3) \times (p_4 - p_3)$$

- 0: $\text{DIRECTION}(p_i, p_j, p_k)$
- 1: return $(p_k - p_i) \times (p_j - p_i)$

- 0: $\text{SEGMENTS-INTERSECT}(p_1, p_2, p_3, p_4)$
- 1: $d_1 = \text{DIRECTION}(p_3, p_4, p_1)$
- 2: $d_2 = \text{DIRECTION}(p_3, p_4, p_2)$
- 3: $d_3 = \text{DIRECTION}(p_1, p_2, p_3)$
- 4: $d_4 = \text{DIRECTION}(p_1, p_2, p_4)$
- 5: If $d_1 \cdot d_2 < 0$ and $d_3 \cdot d_4 < 0$ return TRUE
- 6: ... (handle all degenerate cases)



Solving Line Intersection



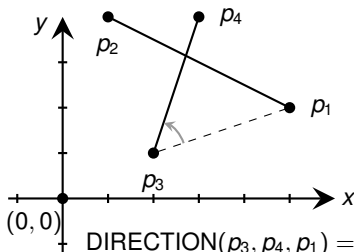
- ```
0: DIRECTION(p_i, p_j, p_k)
1: return $(p_k - p_i) \times (p_j - p_i)$
```

- ```
0: SEGMENTS-INTERSECT( $p_1, p_2, p_3, p_4$ )
1:    $d_1 = \text{DIRECTION}(p_3, p_4, p_1)$ 
2:    $d_2 = \text{DIRECTION}(p_3, p_4, p_2)$ 
3:    $d_3 = \text{DIRECTION}(p_1, p_2, p_3)$ 
4:    $d_4 = \text{DIRECTION}(p_1, p_2, p_4)$ 
5:   If  $d_1 \cdot d_2 < 0$  and  $d_3 \cdot d_4 < 0$  return TRUE
6:   ... (handle all degenerate cases)
```

In total 4 satisfying conditions!



Solving Line Intersection



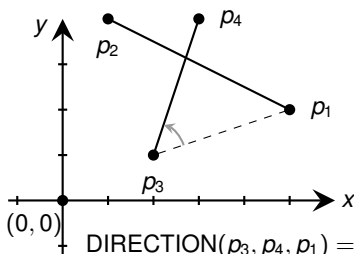
```
0: DIRECTION( $p_i, p_j, p_k$ )  
1:   return  $(p_k - p_i) \times (p_j - p_i)$ 
```

```
0: SEGMENTS-INTERSECT( $p_1, p_2, p_3, p_4$ )  
1:    $d_1 =$  DIRECTION( $p_3, p_4, p_1$ )  
2:    $d_2 =$  DIRECTION( $p_3, p_4, p_2$ )  
3:    $d_3 =$  DIRECTION( $p_1, p_2, p_3$ )  
4:    $d_4 =$  DIRECTION( $p_1, p_2, p_4$ )  
5:   If  $d_1 \cdot d_2 < 0$  and  $d_3 \cdot d_4 < 0$  return TRUE  
6:   ... (handle all degenerate cases)
```

Lines could touch or be colinear

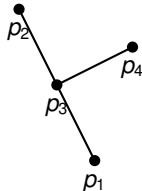


Solving Line Intersection



```
0: DIRECTION( $p_i, p_j, p_k$ )  
1: return  $(p_k - p_i) \times (p_j - p_i)$ 
```

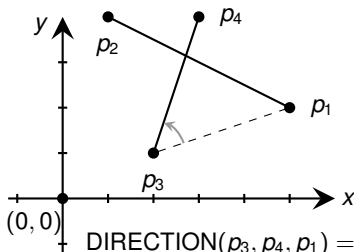
```
0: SEGMENTS-INTERSECT( $p_1, p_2, p_3, p_4$ )  
1:  $d_1 =$  DIRECTION( $p_3, p_4, p_1$ )  
2:  $d_2 =$  DIRECTION( $p_3, p_4, p_2$ )  
3:  $d_3 =$  DIRECTION( $p_1, p_2, p_3$ )  
4:  $d_4 =$  DIRECTION( $p_1, p_2, p_4$ )  
5: If  $d_1 \cdot d_2 < 0$  and  $d_3 \cdot d_4 < 0$  return TRUE  
6: ... (handle all degenerate cases)
```



Lines could touch or be colinear

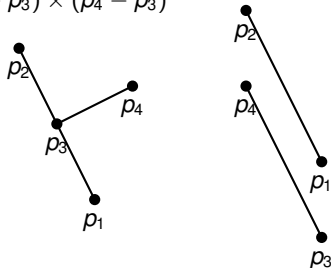


Solving Line Intersection



```
0: DIRECTION( $p_i, p_j, p_k$ )  
1: return  $(p_k - p_i) \times (p_j - p_i)$ 
```

```
0: SEGMENTS-INTERSECT( $p_1, p_2, p_3, p_4$ )  
1:  $d_1 = \text{DIRECTION}(p_3, p_4, p_1)$   
2:  $d_2 = \text{DIRECTION}(p_3, p_4, p_2)$   
3:  $d_3 = \text{DIRECTION}(p_1, p_2, p_3)$   
4:  $d_4 = \text{DIRECTION}(p_1, p_2, p_4)$   
5: If  $d_1 \cdot d_2 < 0$  and  $d_3 \cdot d_4 < 0$  return TRUE  
6: ... (handle all degenerate cases)
```



Lines could touch or be colinear



Outline

Introduction and Line Intersection

Convex Hull

Glimpse at (More) Advanced Algorithms

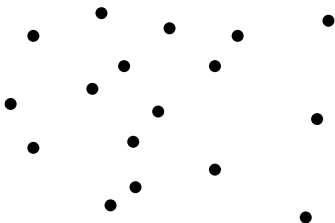


Definition

The **convex hull** of a set Q of points is the **smallest convex polygon** P for which each point in Q is either on the boundary of P or in its interior.



Convex Hull

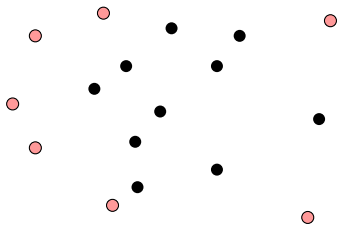


Definition

The **convex hull** of a set Q of points is the **smallest convex polygon** P for which each point in Q is either on the boundary of P or in its interior.



Convex Hull

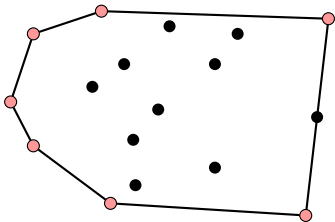


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The **convex hull** of a set Q of points is the **smallest convex polygon** P for which each point in Q is either on the boundary of P or in its interior.



Convex Hull

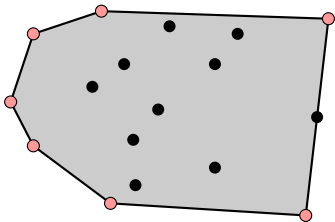


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Convex Hull

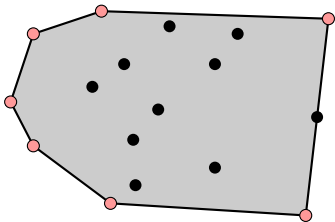


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Convex Hull



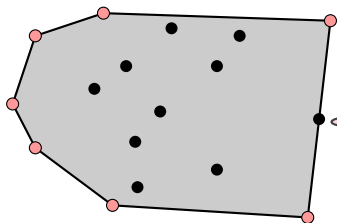
Definition

The **convex hull** of a set Q of points is the **smallest convex polygon** P for which each point in Q is either on the boundary of P or in its interior.

Smallest perimeter fence enclosing the points



Convex Hull



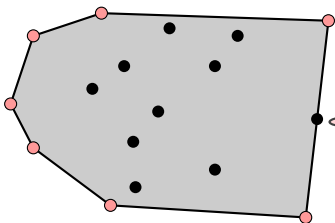
Vertex lies on the convex hull, but is not part of the polygon!

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Convex Hull



Vertex lies on the convex hull,
but is not part of the polygon!

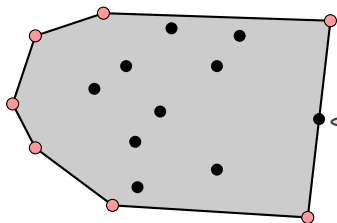
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Convex Hull Problem



Convex Hull



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Definition

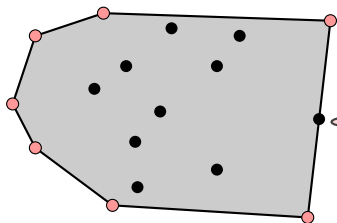
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Convex Hull Problem

- **Input:** set of points Q in the Euclidean space



Convex Hull



Vertex lies on the convex hull, but is not part of the polygon!

Definition

The **convex hull** of a set Q of points is the **smallest convex polygon** P for which each point in Q is either on the boundary of P or in its interior.

Convex Hull Problem

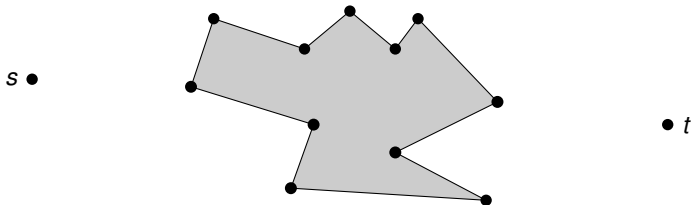
- **Input:** set of points Q in the Euclidean space
- **Output:** return points of the convex hull in counterclockwise order



Application of Convex Hull

Robot Motion Planning

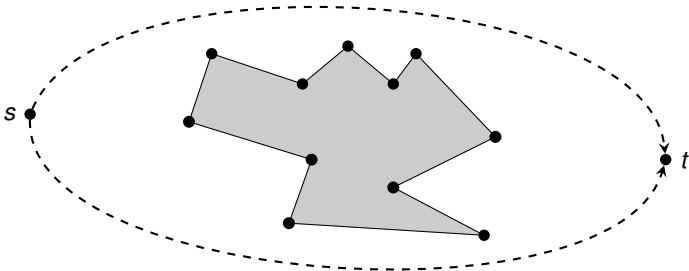
Find shortest path from s to t which avoids a **polygonal obstacle**.



Application of Convex Hull

Robot Motion Planning

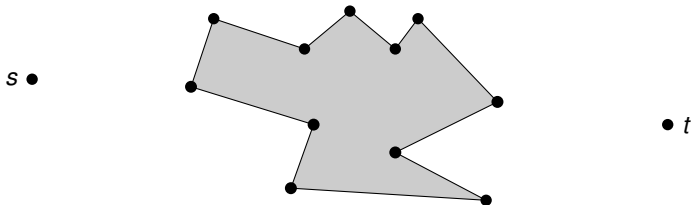
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Application of Convex Hull

Robot Motion Planning

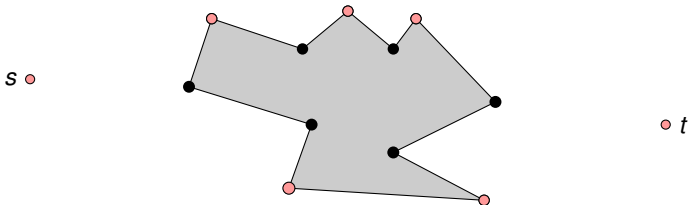
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Application of Convex Hull

Robot Motion Planning

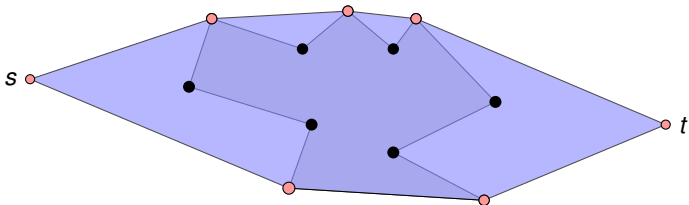
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Application of Convex Hull

Robot Motion Planning

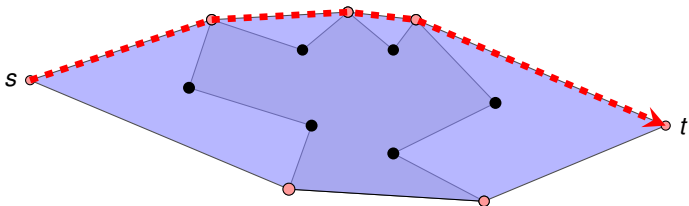
Find shortest path from s to t which avoids a **polygonal obstacle**.



Application of Convex Hull

Robot Motion Planning

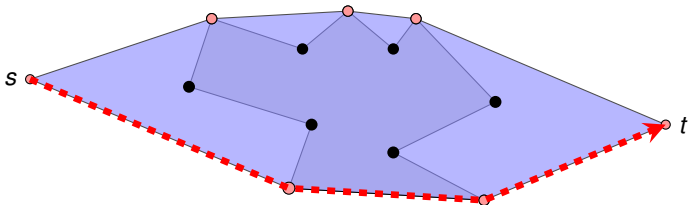
Find shortest path from s to t which avoids a **polygonal obstacle**.



Application of Convex Hull

Robot Motion Planning

Find shortest path from s to t which avoids a **polygonal obstacle**.

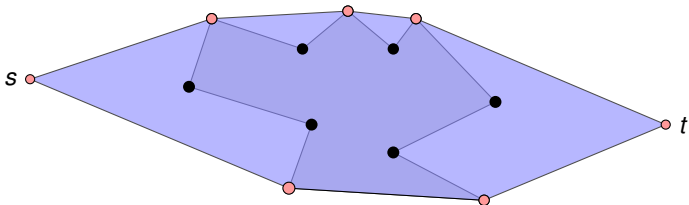


Application of Convex Hull

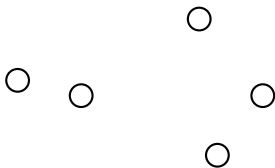
Robot Motion Planning

Find shortest path from s to t which avoids a **polygonal obstacle**.

can be solved by computing the Convex hull!



Graham's Scan

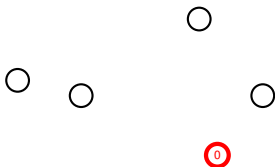


Basic Idea

- Start with the point with smallest y -coordinate



Graham's Scan

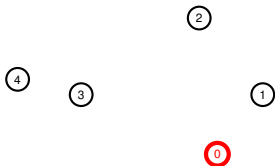


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Graham's Scan

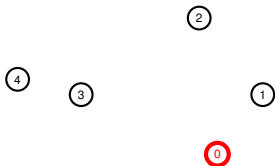


Basic Idea

- Start with the point with smallest y -coordinate
- Sort all points increasingly according to their polar angle



Graham's Scan

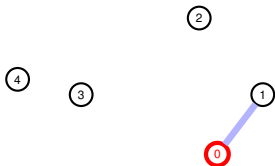


Basic Idea

- Start with the point with smallest y -coordinate
- Sort all points increasingly according to their polar angle
- Try to add next point to the convex hull



Graham's Scan

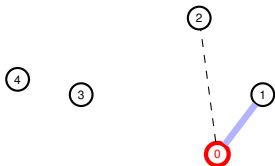


Basic Idea

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Graham's Scan

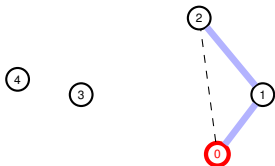


Basic Idea

- Start with the point with **smallest y-coordinate**
- **Sort** all points increasingly according to their **polar angle**
- Try to add **next point** to the convex hull
 - If it does not introduce non-left turn, then fine



Graham's Scan

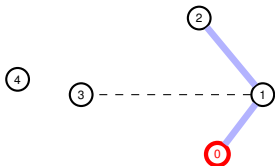


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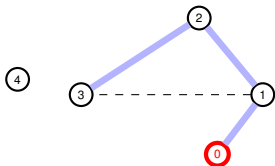


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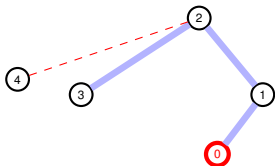


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Graham's Scan

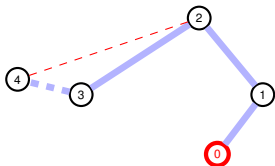


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 - Otherwise,



Graham's Scan

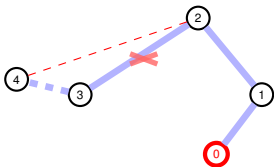


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 - Otherwise, keep on removing recent points until point can be added



Graham's Scan

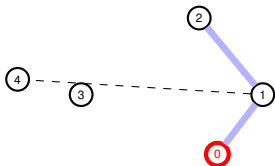


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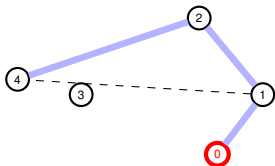


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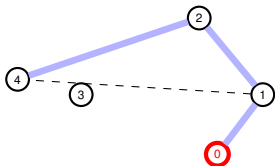


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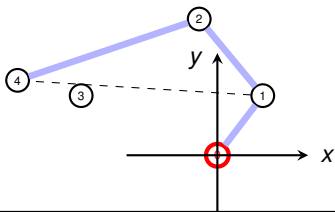
Basic Idea

Efficient Sorting by comparing (not computing!) polar angles

- Start with the point with **smallest y-coordinate**
- Sort all points increasingly according to their **polar angle**
- Try to add **next point** to the convex hull
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Graham's Scan



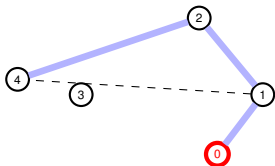
Efficient Sorting by comparing (not computing!) polar angles

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Graham's Scan



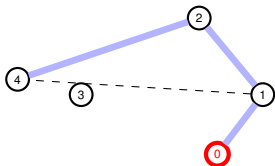
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Graham's Scan



Use Cross Product!

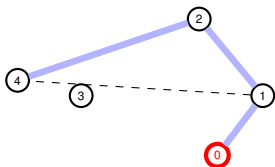
Efficient Sorting by comparing (not computing!) polar angles

Basic Idea

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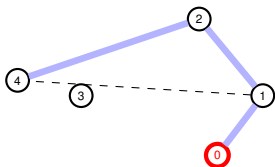
Graham's Scan



```
0: GRAHAM-SCAN(Q)
1:   Let  $p_0$  be the point with minimum  $y$ -coordinate
2:   Let  $(p_1, p_2, \dots, p_n)$  be the other points sorted by polar angle w.r.t.  $p_0$ 
3:   If  $n < 2$  return false
4:    $S = \emptyset$ 
5:   PUSH( $p_0, S$ )
6:   PUSH( $p_1, S$ )
7:   PUSH( $p_2, S$ )
8:   For  $i = 3$  to  $n$ 
9:     While angle of NEXT-TO-TOP( $S$ ), TOP( $S$ ),  $p_i$  makes a non-left turn
10:      POP( $S$ )
11:     End While
12:     PUSH( $p_i, S$ )
13:   End For
14:   Return  $S$ 
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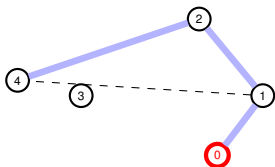
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Graham's Scan

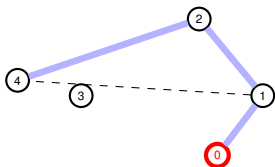


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```

Takes  $O(n \log n)$  time



## Graham's Scan

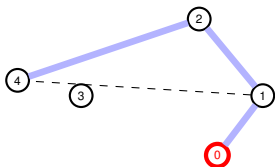


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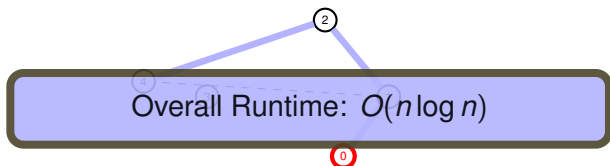
Graham's Scan



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```
- Takes  $O(n \log n)$  time
- Takes  $O(n)$  time, since every point is part of a PUSH or POP at most once.



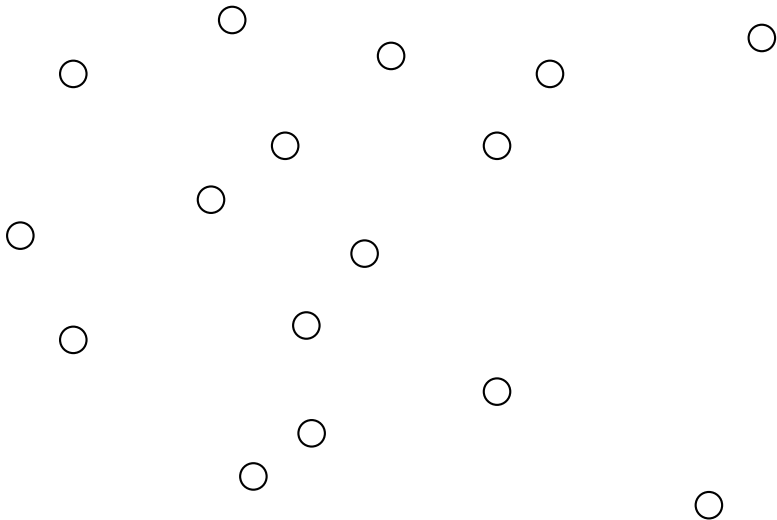
## Graham's Scan



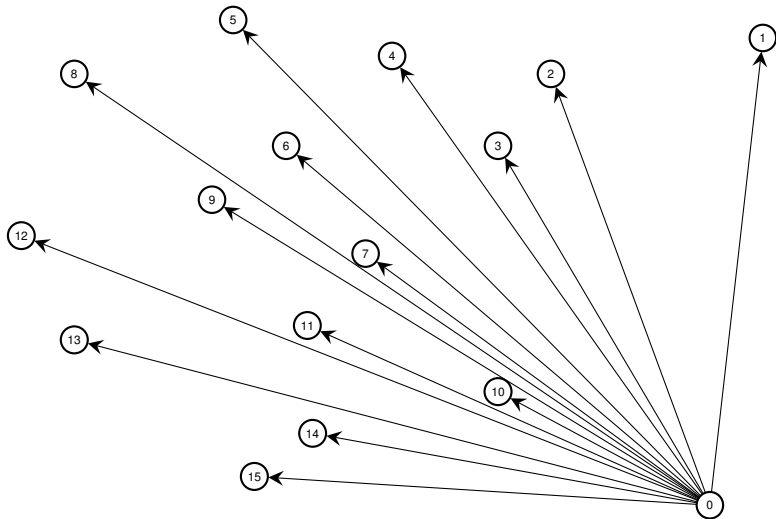
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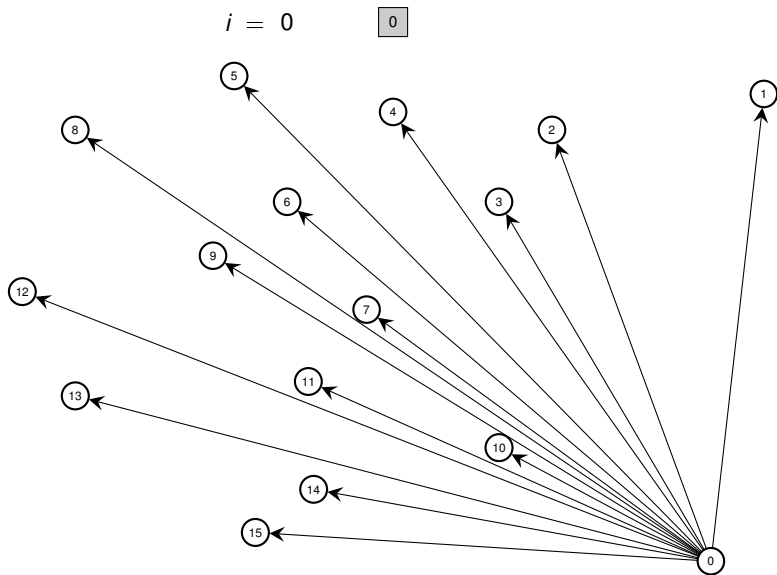
Execution of Graham's Scan



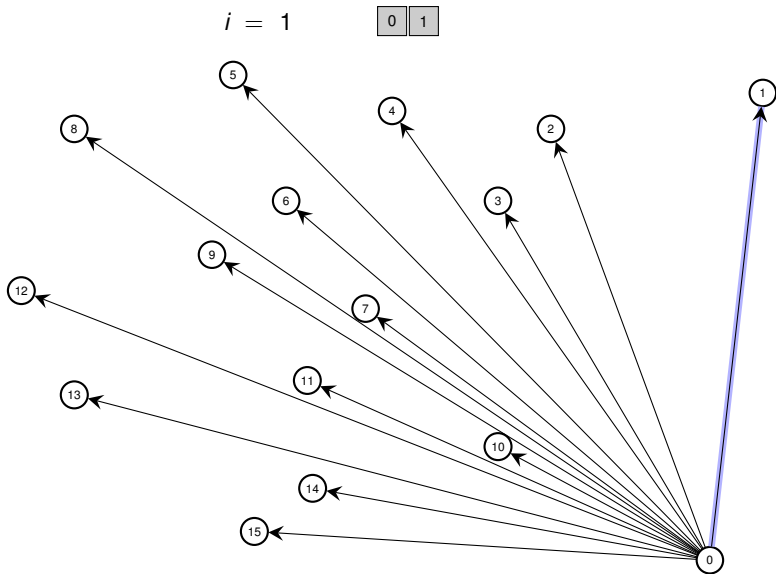
Execution of Graham's Scan



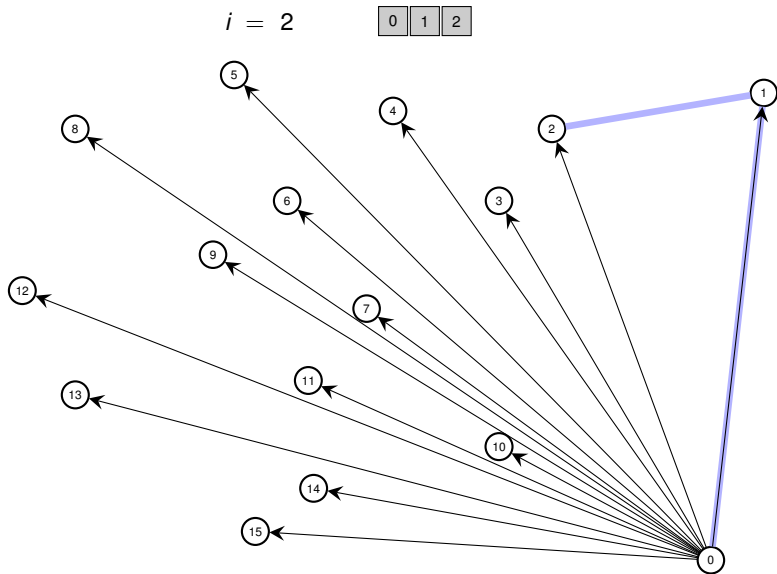
Execution of Graham's Scan



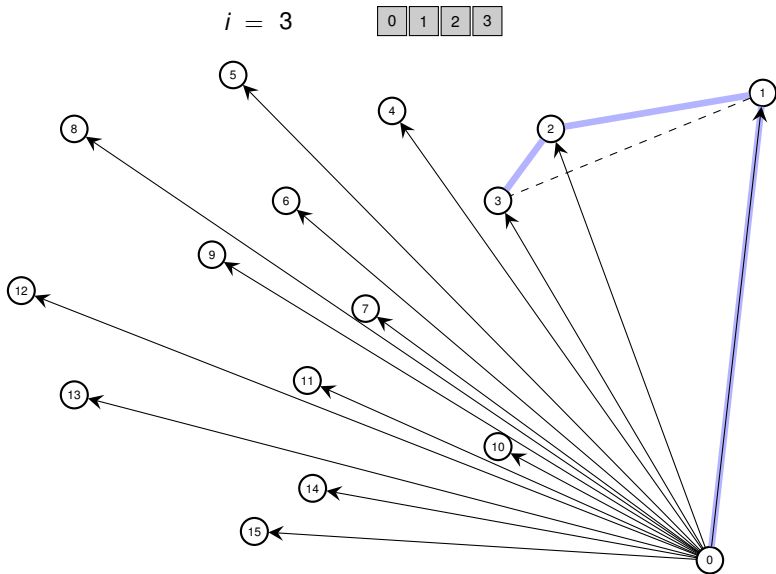
Execution of Graham's Scan



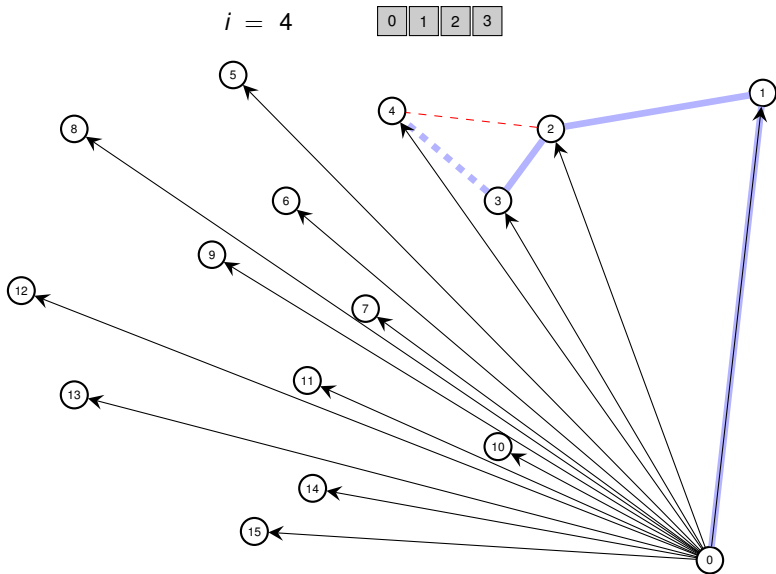
Execution of Graham's Scan



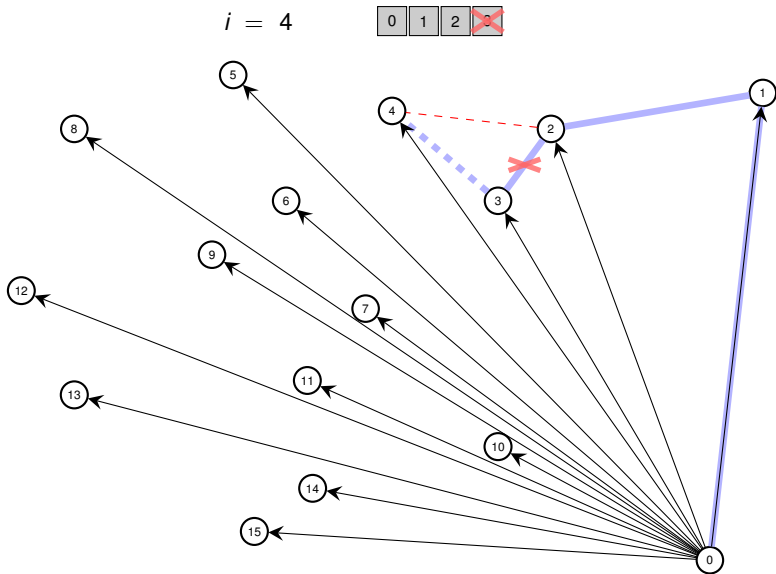
Execution of Graham's Scan



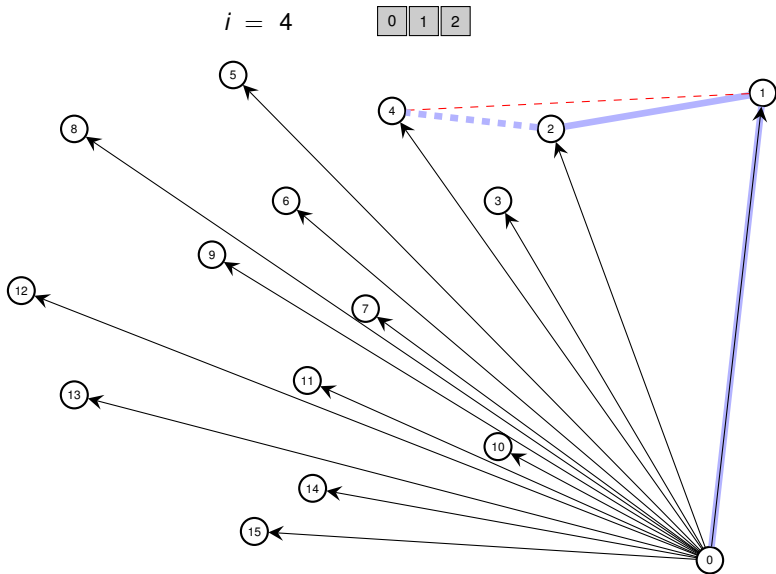
Execution of Graham's Scan



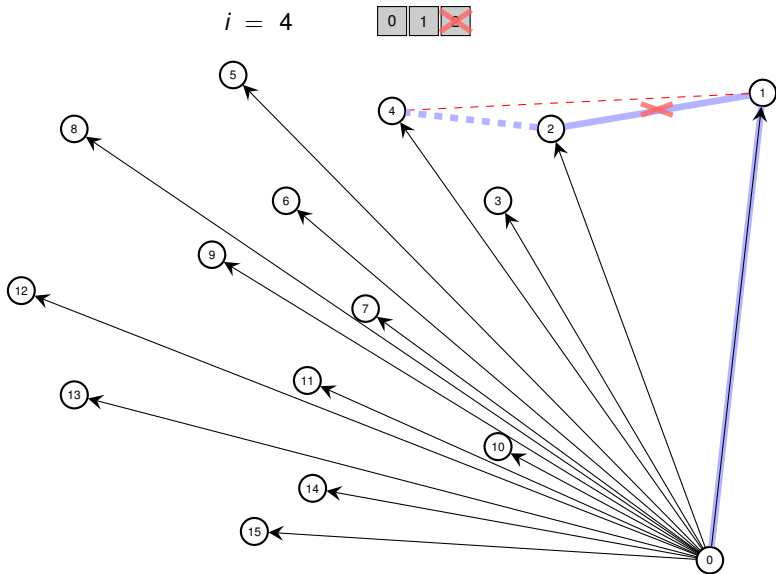
Execution of Graham's Scan



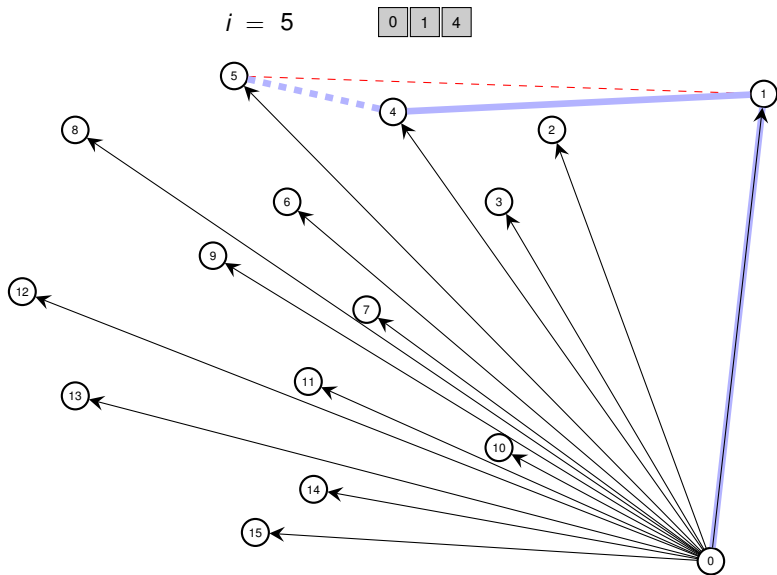
Execution of Graham's Scan



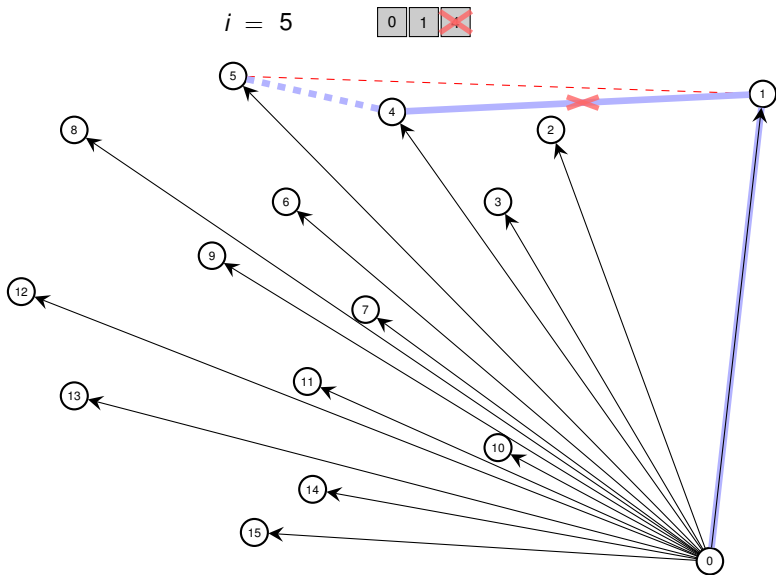
Execution of Graham's Scan



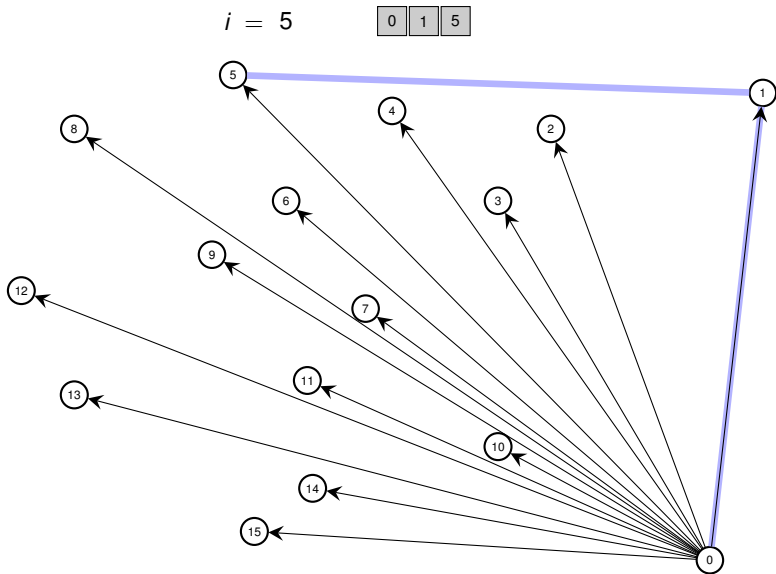
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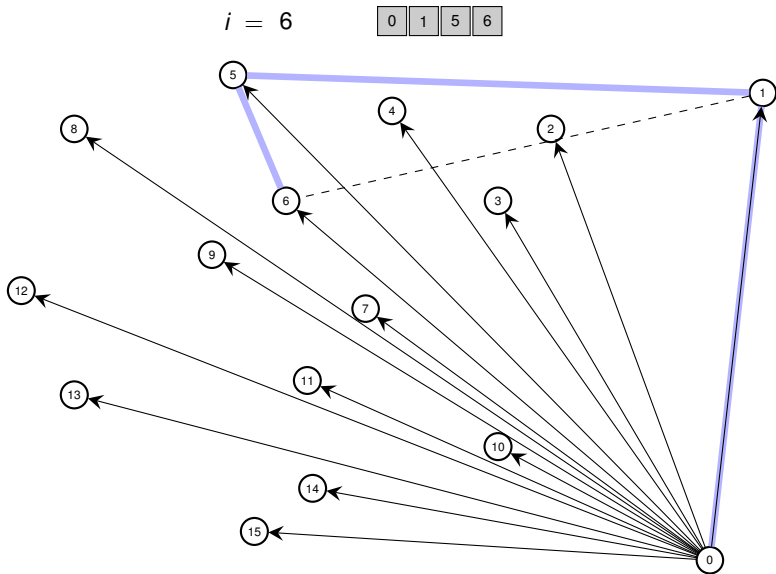
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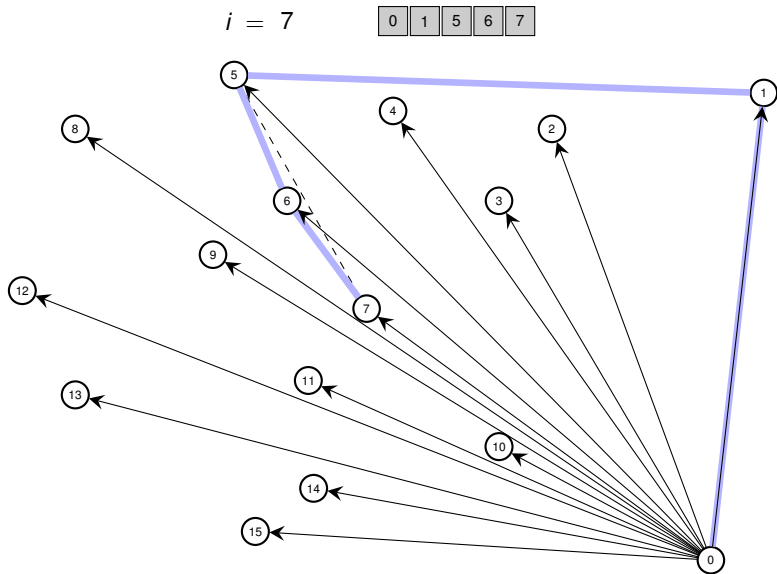
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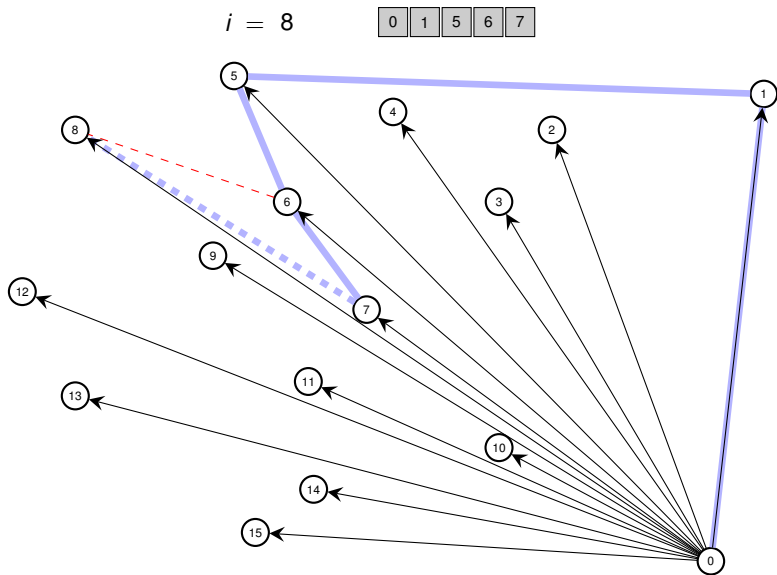
Execution of Graham's Scan



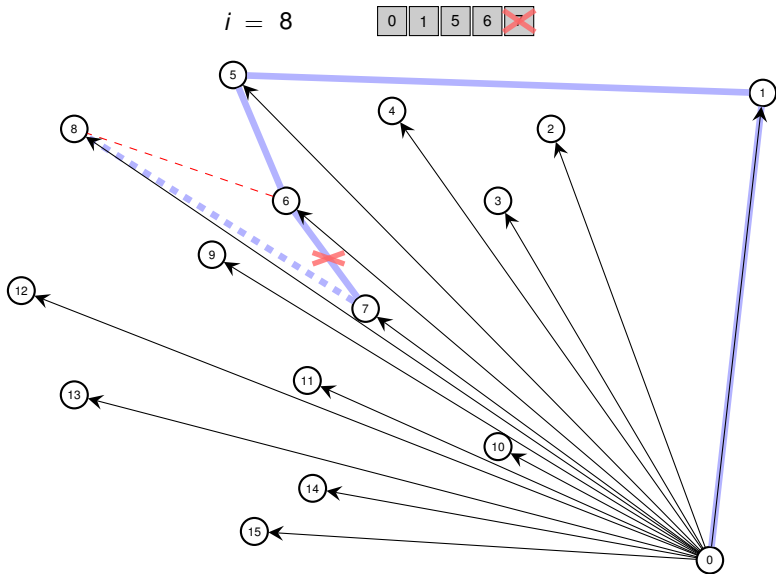
Execution of Graham's Scan



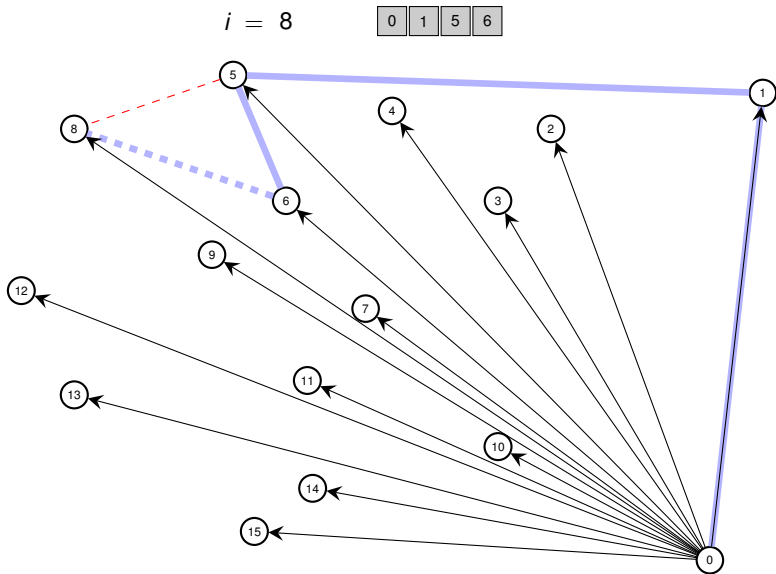
Execution of Graham's Scan



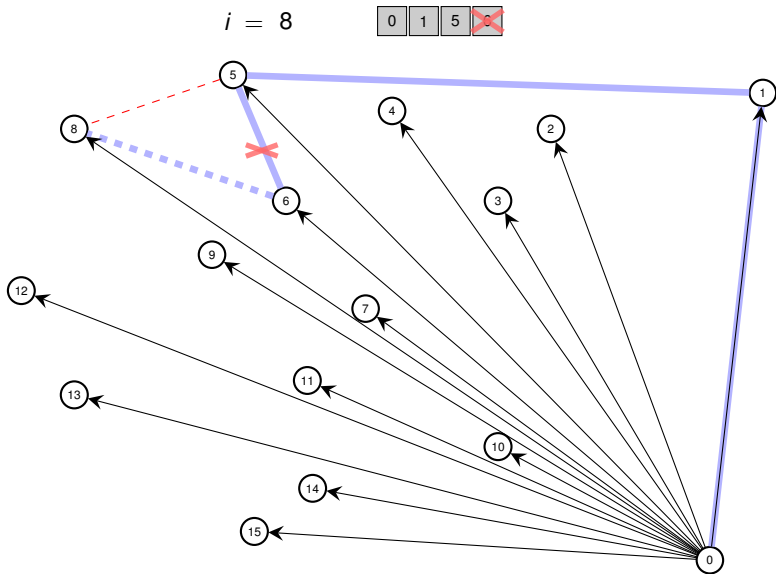
Execution of Graham's Scan



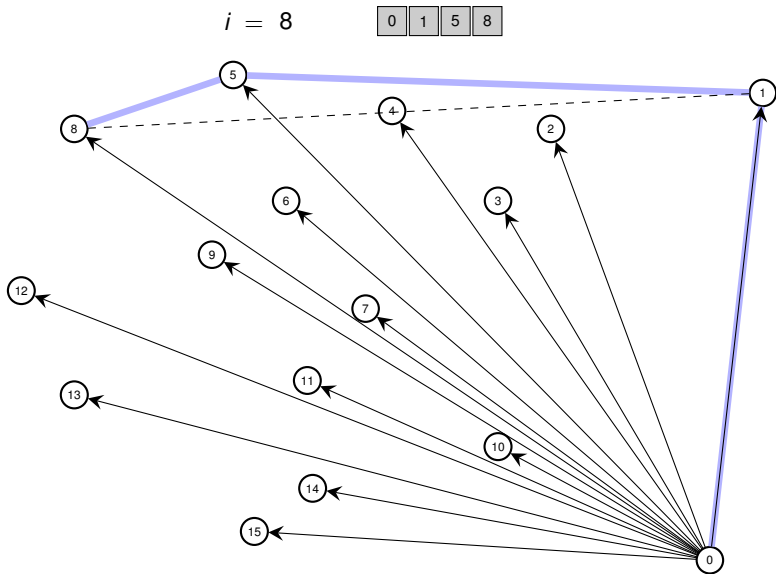
Execution of Graham's Scan



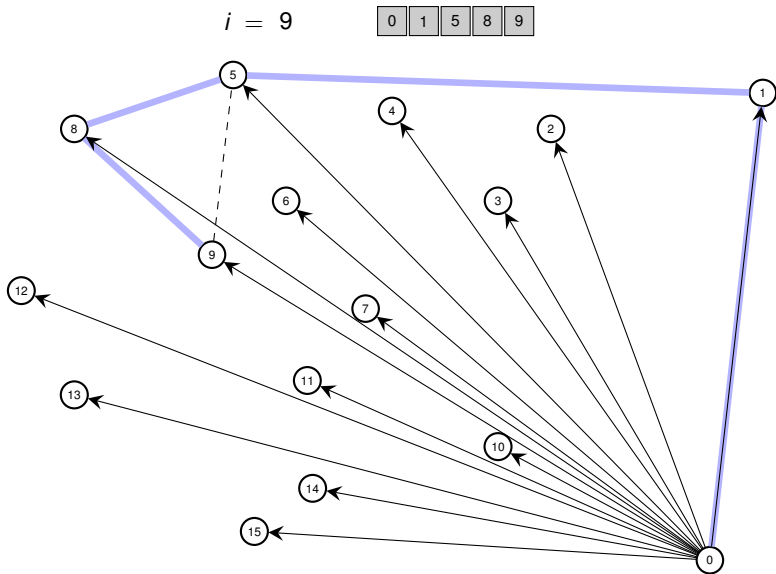
Execution of Graham's Scan



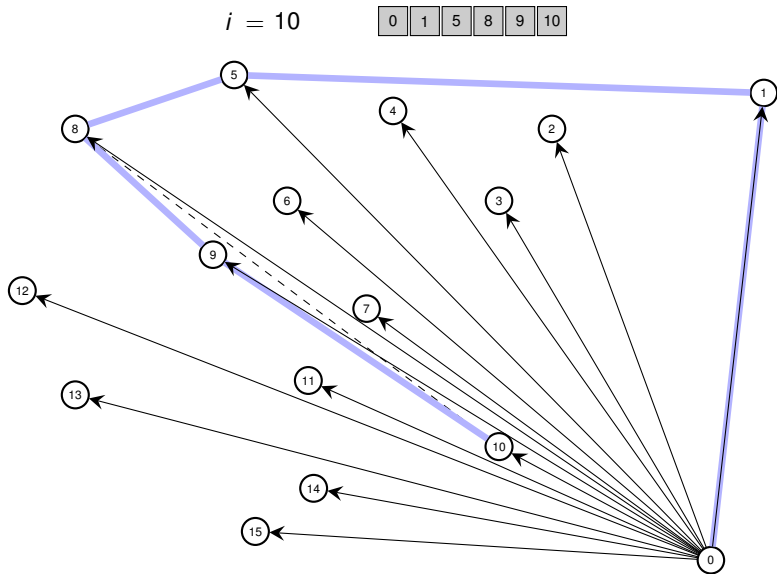
Execution of Graham's Scan



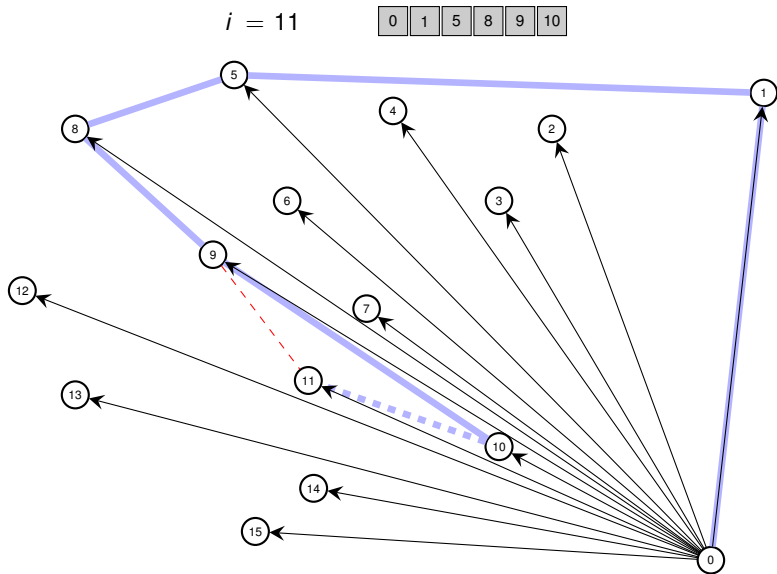
Execution of Graham's Scan



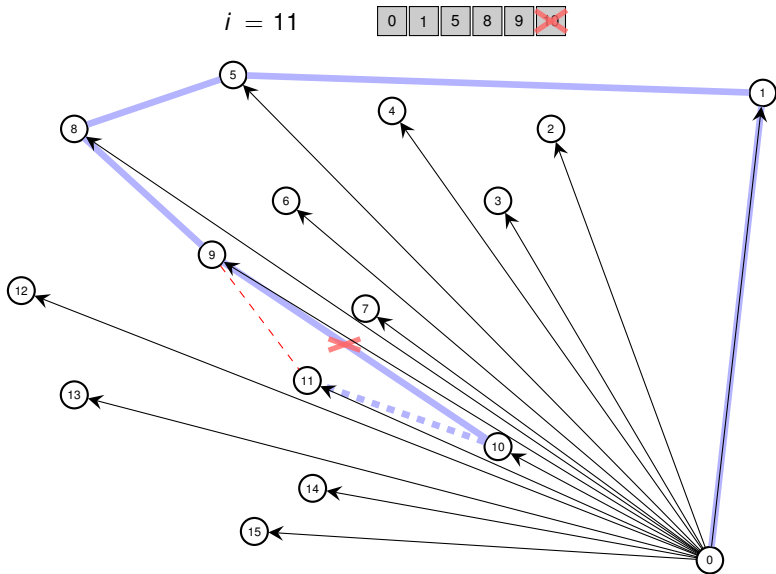
Execution of Graham's Scan



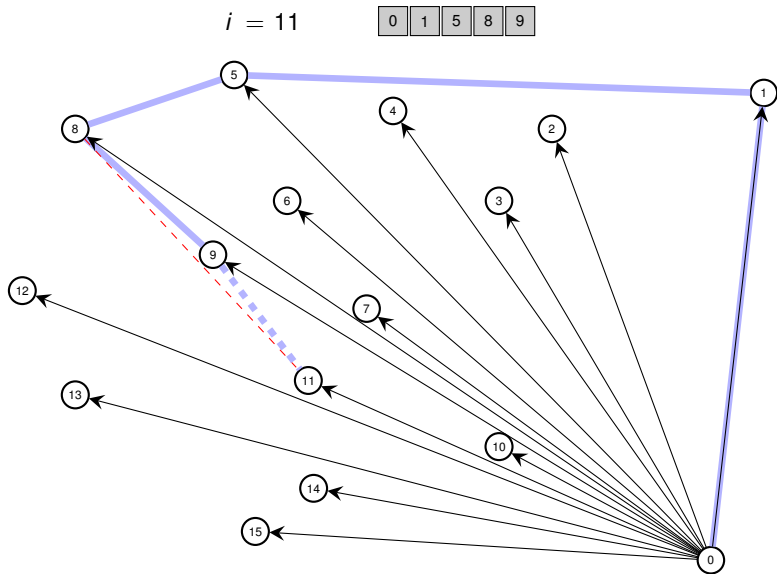
Execution of Graham's Scan



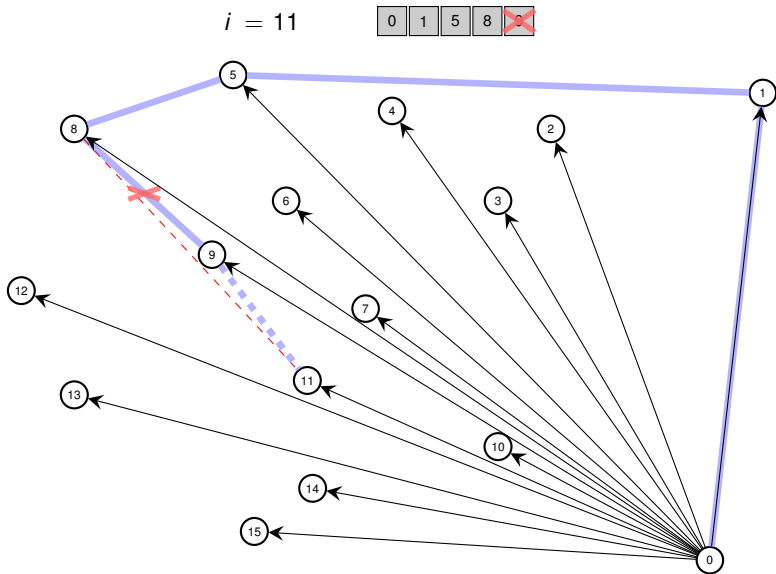
Execution of Graham's Scan



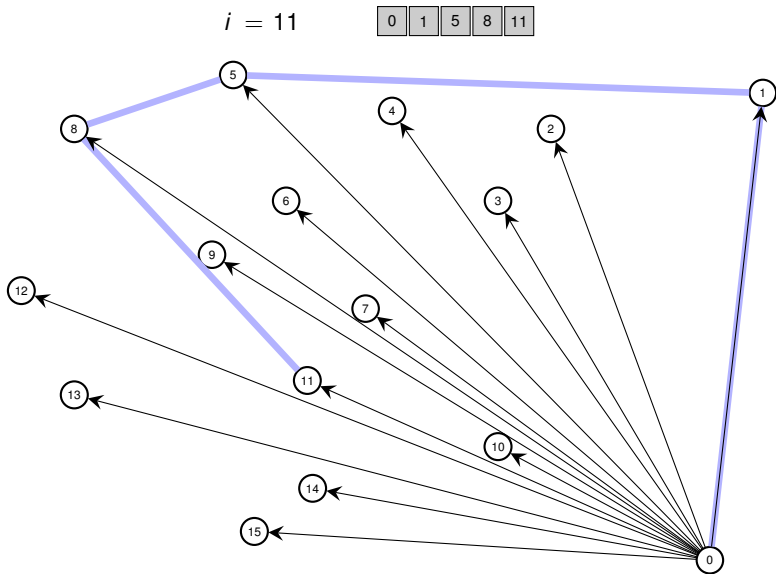
Execution of Graham's Scan



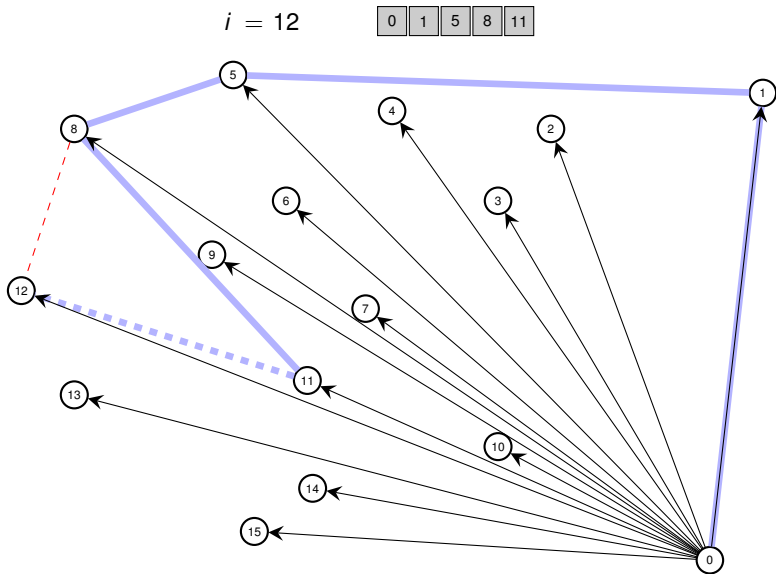
Execution of Graham's Scan



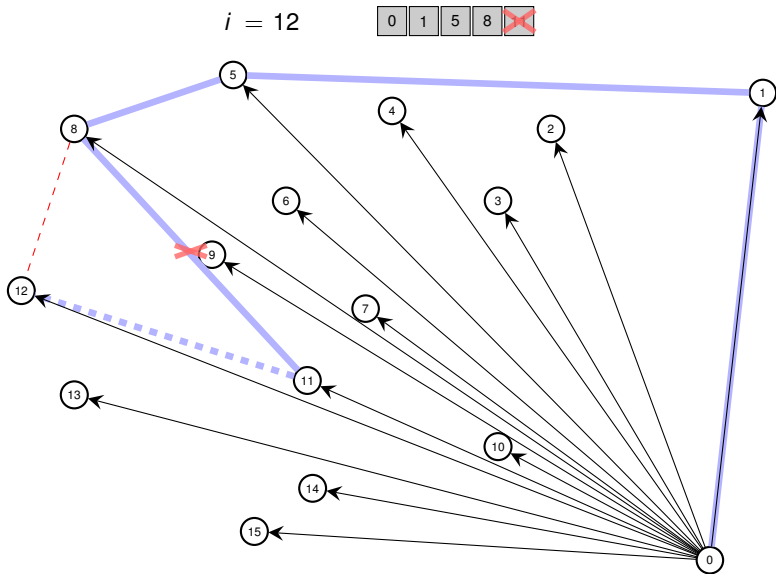
Execution of Graham's Scan



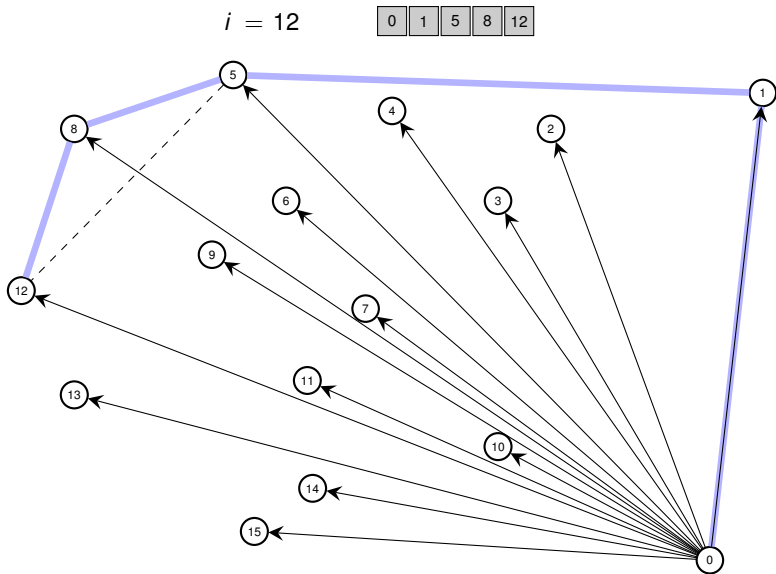
Execution of Graham's Scan



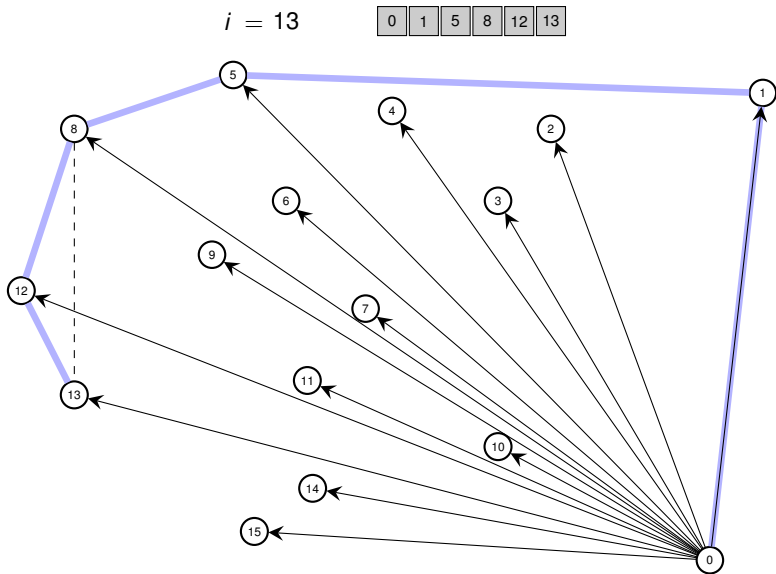
Execution of Graham's Scan



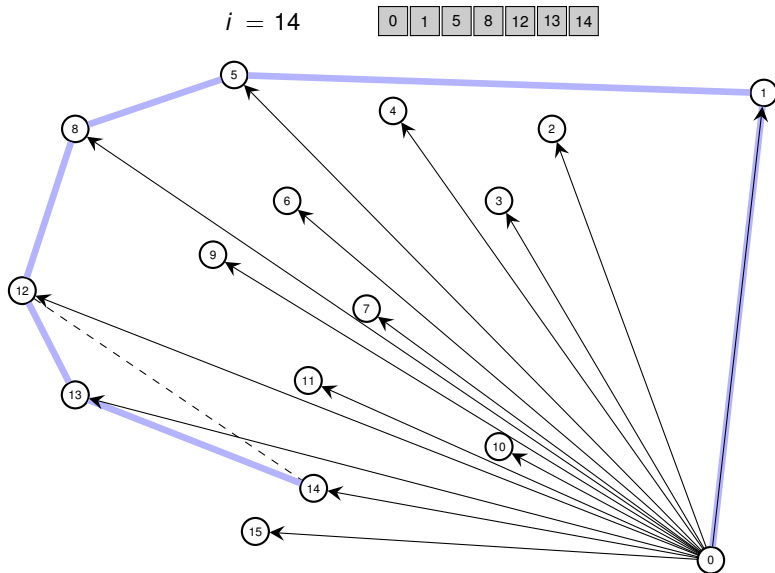
Execution of Graham's Scan



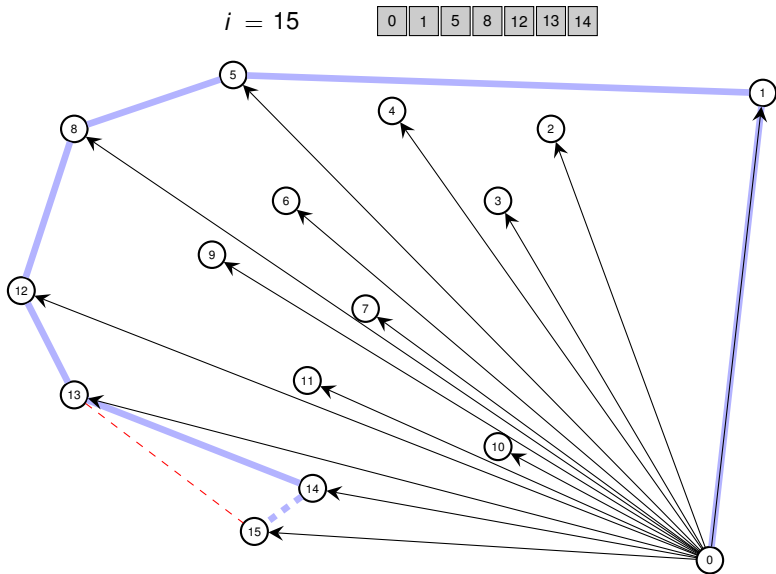
Execution of Graham's Scan



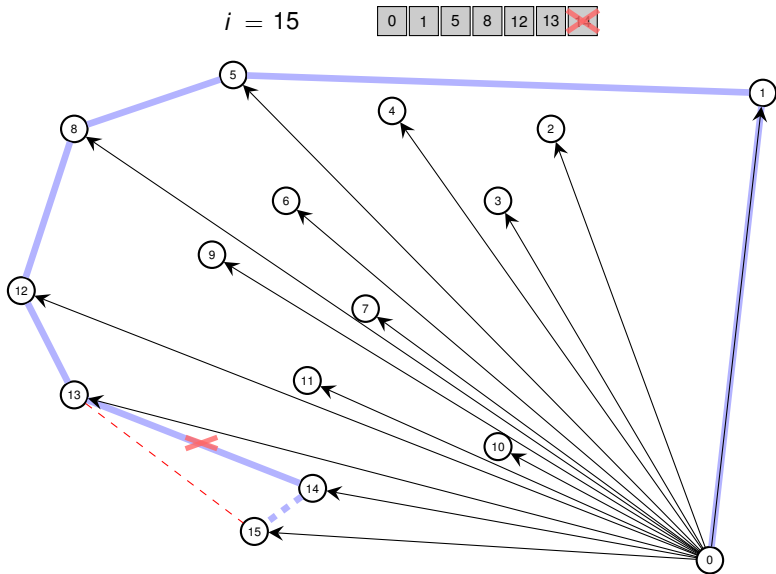
Execution of Graham's Scan



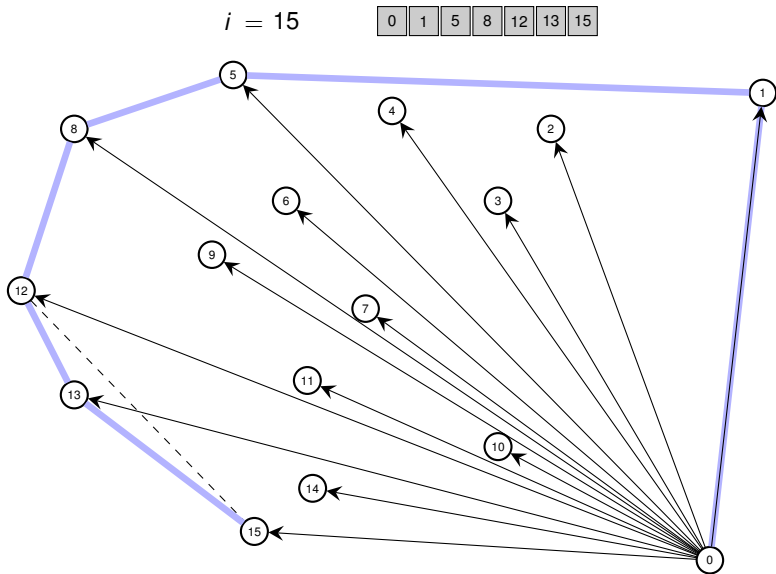
Execution of Graham's Scan



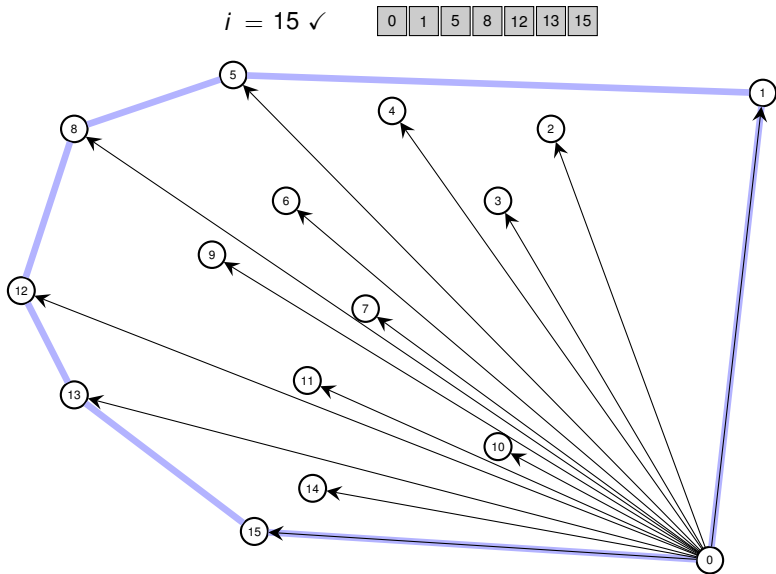
Execution of Graham's Scan



Execution of Graham's Scan



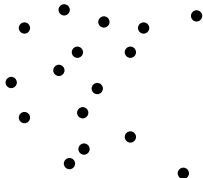
Execution of Graham's Scan



Jarvis' March (Gift wrapping)

Intuition

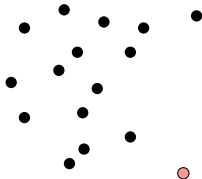
- Wrapping taut paper around the points



Jarvis' March (Gift wrapping)

Intuition

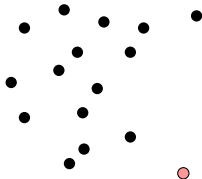
- Wrapping taut paper around the points
 - Tape end of paper at lowest point



Jarvis' March (Gift wrapping)

Intuition

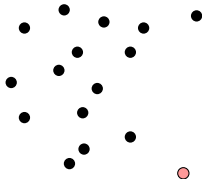
- Wrapping taut paper around the points
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Jarvis' March (Gift wrapping)

Intuition

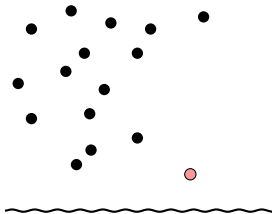
- Wrapping taut paper around the points
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Jarvis' March (Gift wrapping)

Intuition

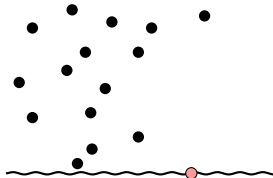
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Jarvis' March (Gift wrapping)

Intuition

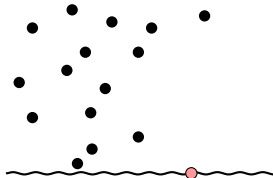
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Jarvis' March (Gift wrapping)

Intuition

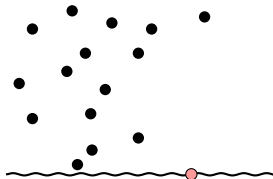
- Wrapping taut paper around the points
 1. Tape end of paper at lowest point
 2. Pull paper to the right until it touches a point



Jarvis' March (Gift wrapping)

Intuition

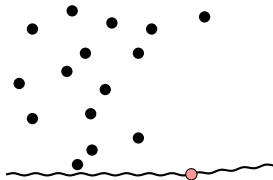
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Intuition

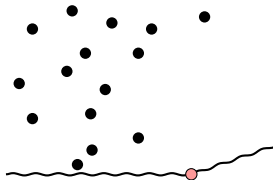
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Jarvis' March (Gift wrapping)

Intuition

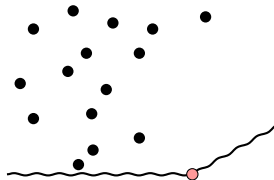
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Intuition

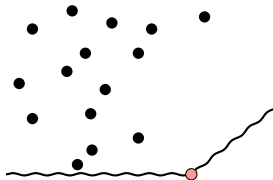
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Jarvis' March (Gift wrapping)

Intuition

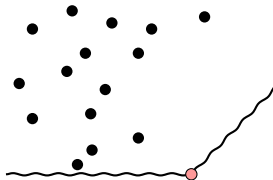
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Jarvis' March (Gift wrapping)

Intuition

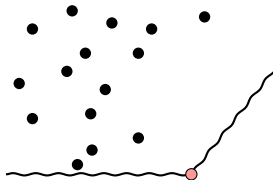
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Jarvis' March (Gift wrapping)

Intuition

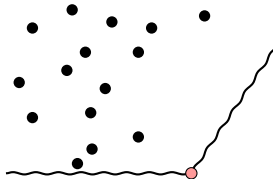
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Jarvis' March (Gift wrapping)

Intuition

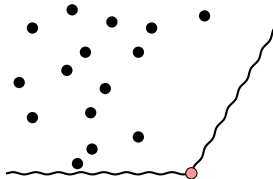
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Intuition

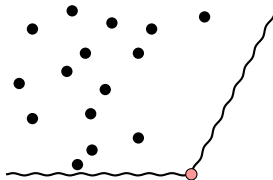
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Intuition

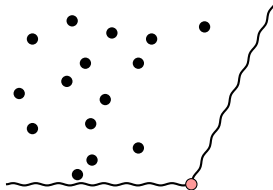
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Jarvis' March (Gift wrapping)

Intuition

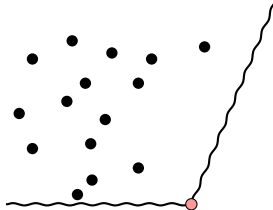
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Jarvis' March (Gift wrapping)

Intuition

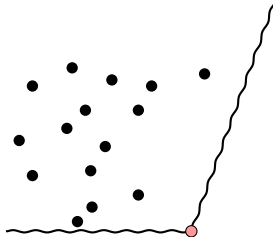
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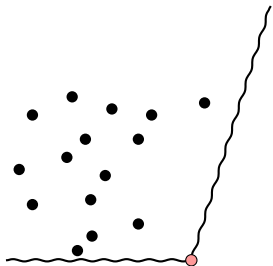
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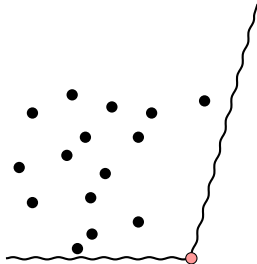
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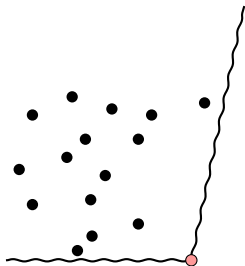
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Jarvis' March (Gift wrapping)

Intuition

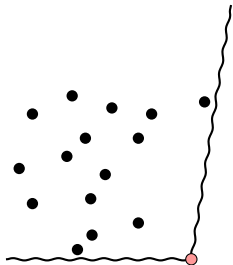
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Jarvis' March (Gift wrapping)

Intuition

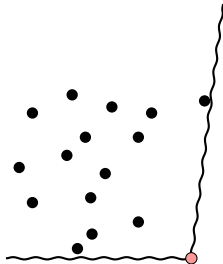
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Jarvis' March (Gift wrapping)

Intuition

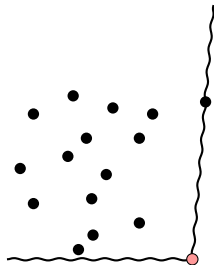
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Jarvis' March (Gift wrapping)

Intuition

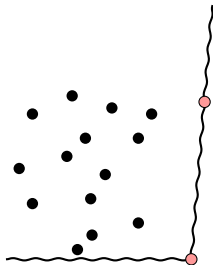
- Wrapping taut paper around the points
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 2. Pull paper to the right until it touches a point



Jarvis' March (Gift wrapping)

Intuition

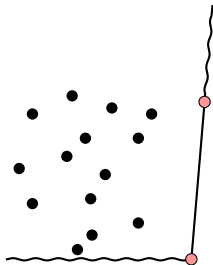
- Wrapping taut paper around the points
 1. Tape end of paper at lowest point
 2. Pull paper to the right until it touches a point
 3. Tape paper and go to 2



Jarvis' March (Gift wrapping)

Intuition

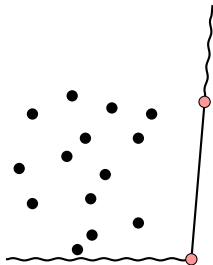
- Wrapping taut paper around the points
 - Tape end of paper at lowest point
 - Pull paper to the right until it touches a point
 - Tape paper and go to 2



Jarvis' March (Gift wrapping)

Intuition

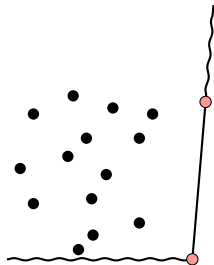
- Wrapping taut paper around the points
 - Tape end of paper at lowest point
 - Pull paper to the right until it touches a point
 - Tape paper and go to 2



Jarvis' March (Gift wrapping)

Intuition

- Wrapping taut paper around the points
 - Tape end of paper at lowest point
 - Pull paper to the right until it touches a point
 - Tape paper and go to 2



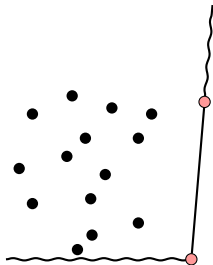
Jarvis' March (Gift wrapping)

Intuition

- Wrapping taut paper around the points
 - Tape end of paper at lowest point
 - Pull paper to the right until it touches a point
 - Tape paper and go to 2

Algorithm

- Let p_0 be the lowest point
- Next point the one with **smallest angle** w.r.t. p_0



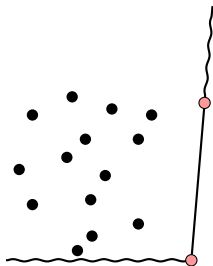
Jarvis' March (Gift wrapping)

Intuition

- Wrapping taut paper around the points
 - Tape end of paper at lowest point
 - Pull paper to the right until it touches a point
 - Tape paper and go to 2

Algorithm

- Let p_0 be the lowest point
- Next point the one with **smallest angle** w.r.t. p_0
- Continue until highest point p_k



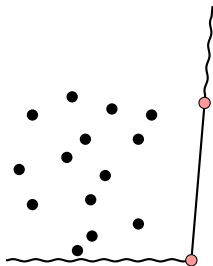
Jarvis' March (Gift wrapping)

Intuition

- Wrapping taut paper around the points
 - Tape end of paper at lowest point
 - Pull paper to the right until it touches a point
 - Tape paper and go to 2

Algorithm

- Let p_0 be the lowest point
- Next point the one with **smallest angle** w.r.t. p_0
- Continue until highest point p_k
- Next point the one with **smallest angle** w.r.t. p_k



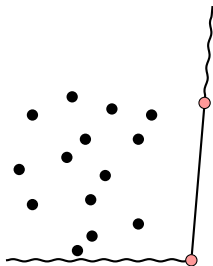
Jarvis' March (Gift wrapping)

Intuition

- Wrapping taut paper around the points
 - Tape end of paper at lowest point
 - Pull paper to the right until it touches a point
 - Tape paper and go to 2

Algorithm

- Let p_0 be the lowest point
- Next point the one with **smallest angle** w.r.t. p_0
- Continue until highest point p_k
- Next point the one with **smallest angle** w.r.t. p_k



Here, we rotate the coordinate system by 180!



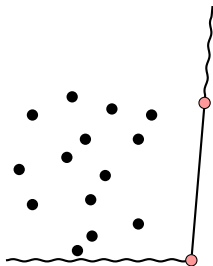
Jarvis' March (Gift wrapping)

Intuition

- Wrapping taut paper around the points
 - Tape end of paper at lowest point
 - Pull paper to the right until it touches a point
 - Tape paper and go to 2

Algorithm

- Let p_0 be the lowest point
- Next point the one with **smallest angle** w.r.t. p_0
- Continue until highest point p_k
- Next point the one with **smallest angle** w.r.t. p_k
- Continue until p_0 is reached



Jarvis' March (Gift wrapping)

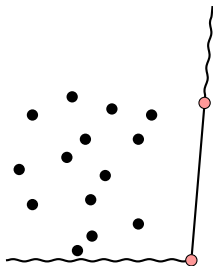
Intuition

- Wrapping taut paper around the points
 - Tape end of paper at lowest point
 - Pull paper to the right until it touches a point
 - Tape paper and go to 2

Algorithm

- Let p_0 be the lowest point
- Next point the one with **smallest angle** w.r.t. p_0
- Continue until highest point p_k
- Next point the one with **smallest angle** w.r.t. p_k
- Continue until p_0 is reached

Runtime: $O(n \cdot h)$, where h is no. points on convex hull.



Jarvis' March (Gift wrapping)

Intuition

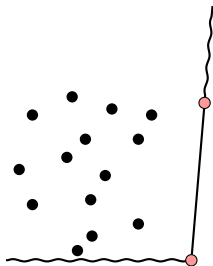
- Wrapping taut paper around the points
 - Tape end of paper at lowest point
 - Pull paper to the right until it touches a point
 - Tape paper and go to 2

Algorithm

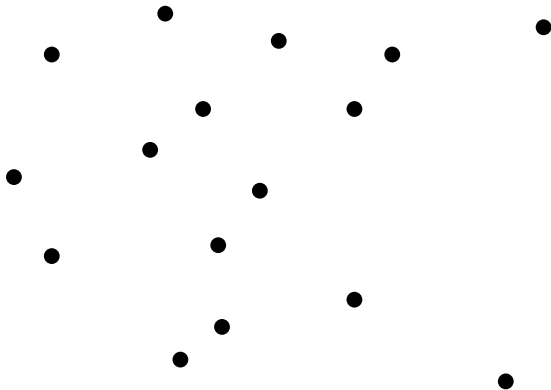
- Let p_0 be the lowest point
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- Continue until highest point p_k
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Runtime: $O(n \cdot h)$, where h is no. points on convex hull.

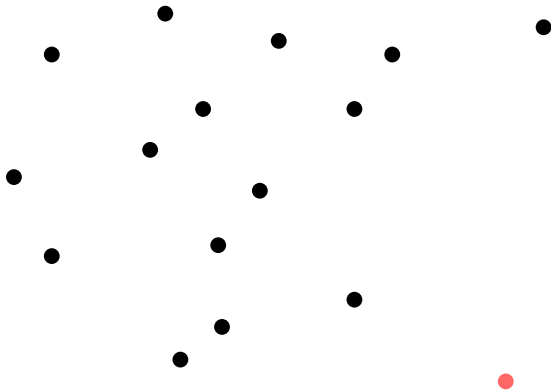
Output sensitive algorithm!



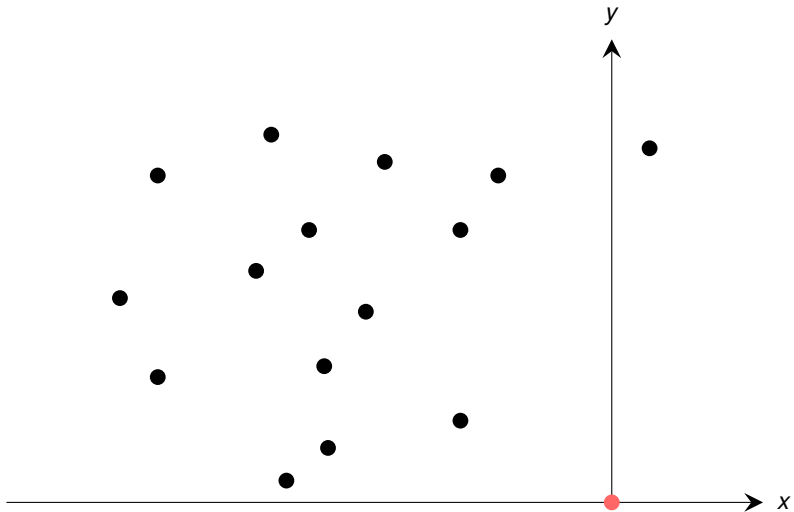
Execution of Jarvis' March



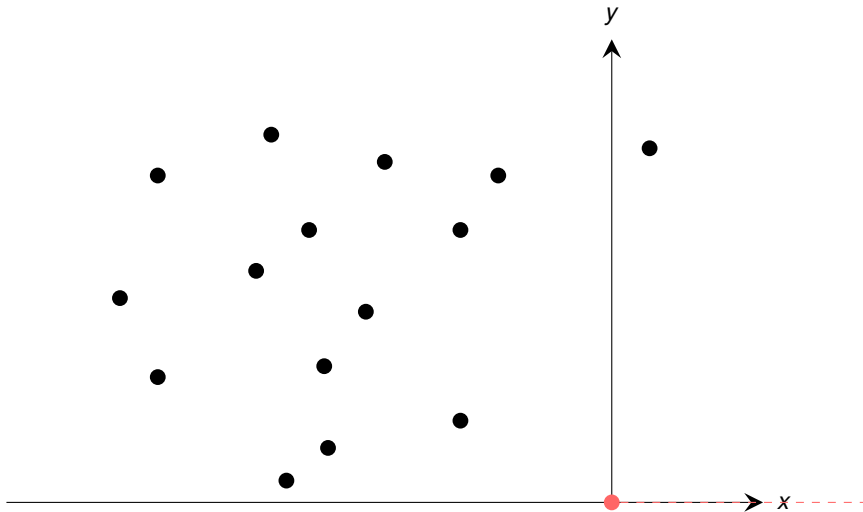
Execution of Jarvis' March



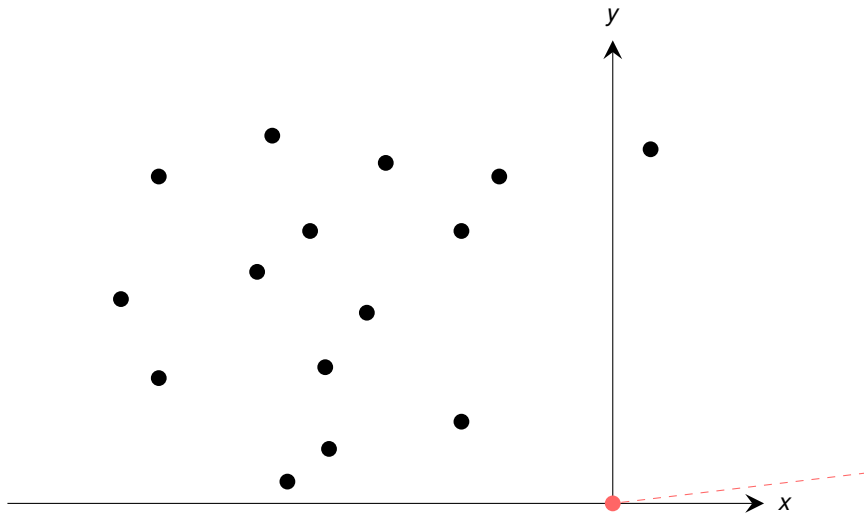
Execution of Jarvis' March



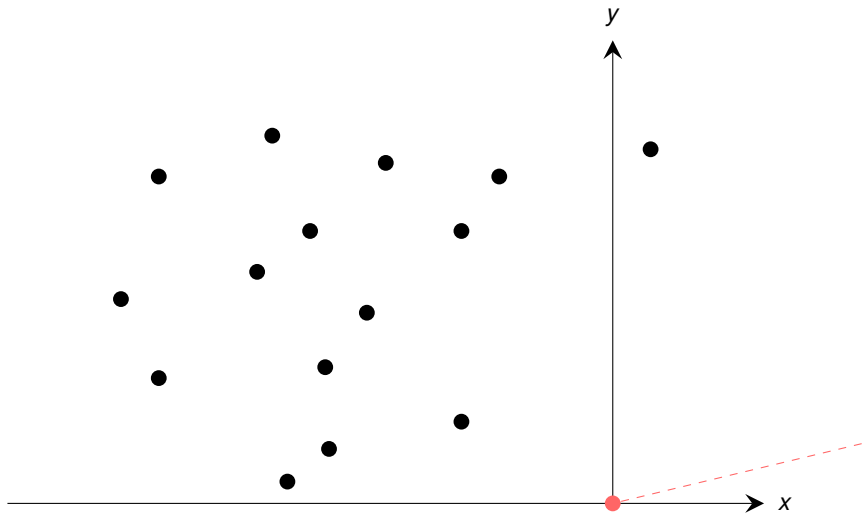
Execution of Jarvis' March



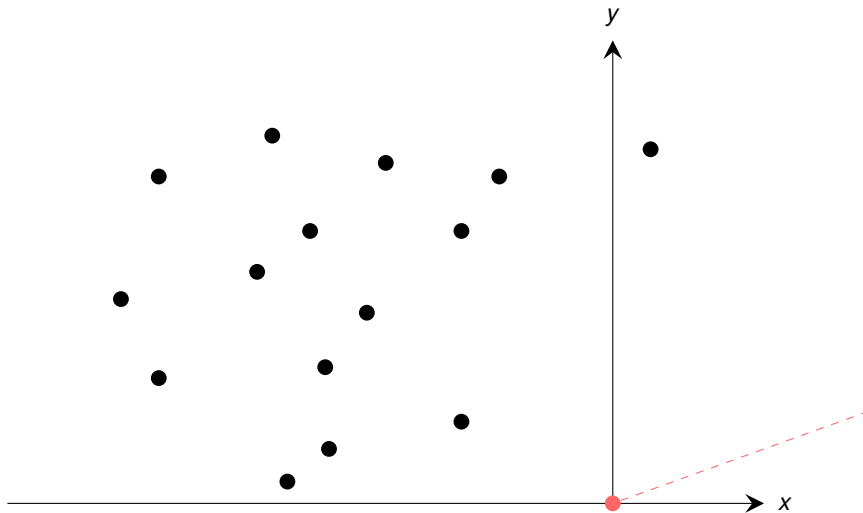
Execution of Jarvis' March



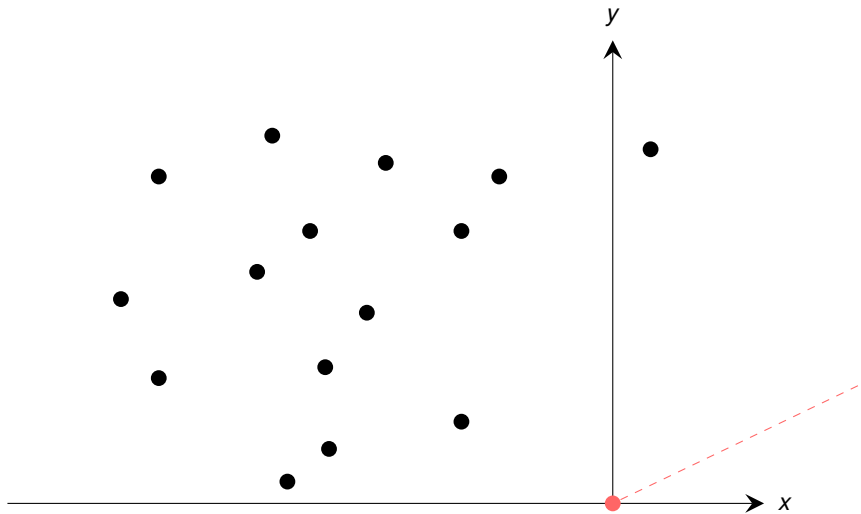
Execution of Jarvis' March



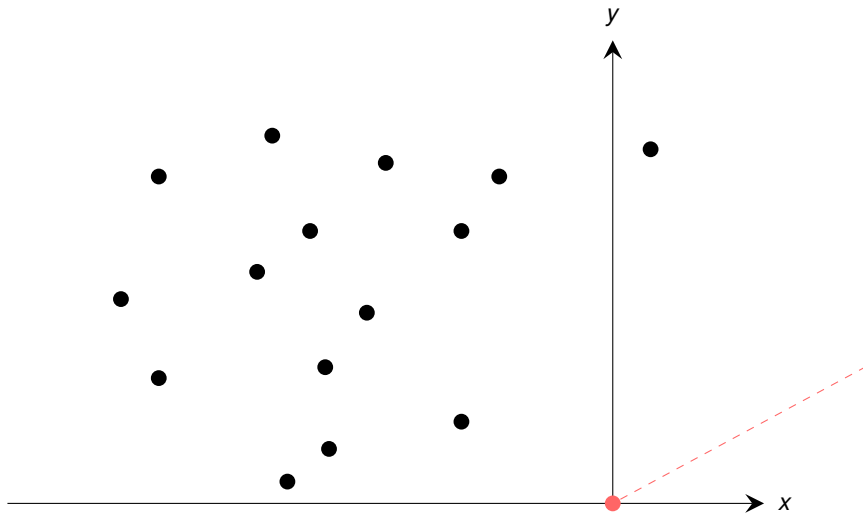
Execution of Jarvis' March



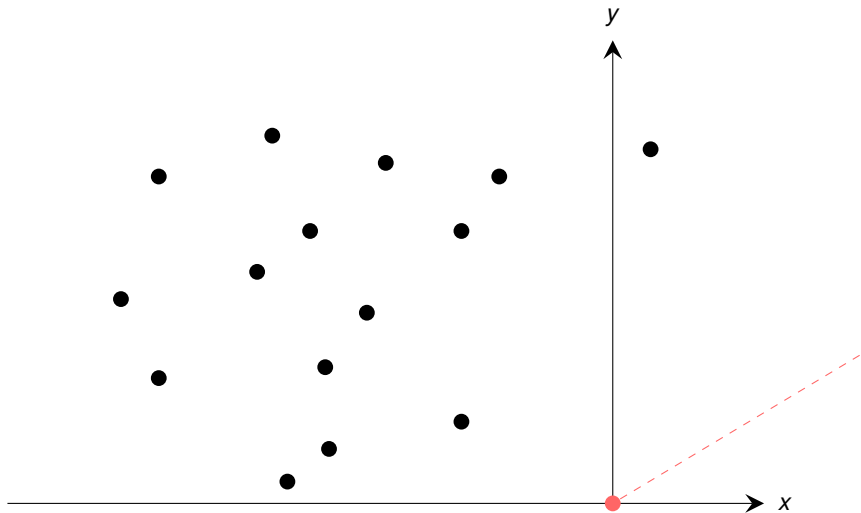
Execution of Jarvis' March



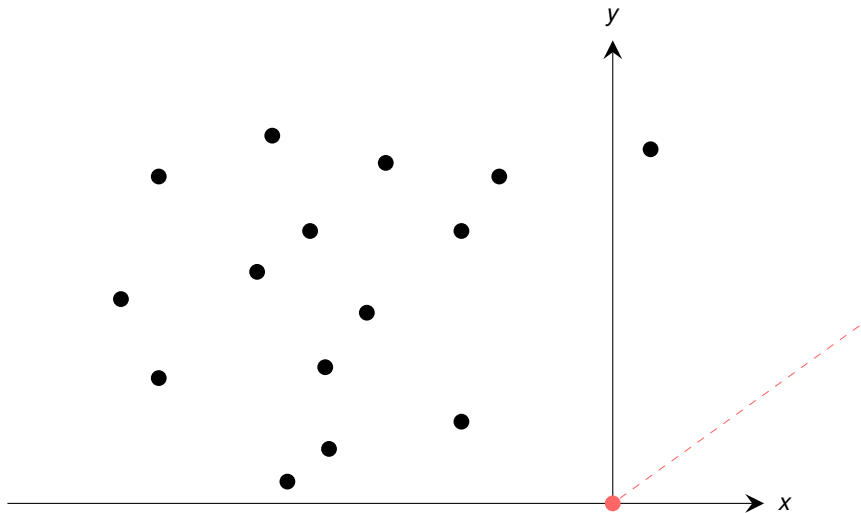
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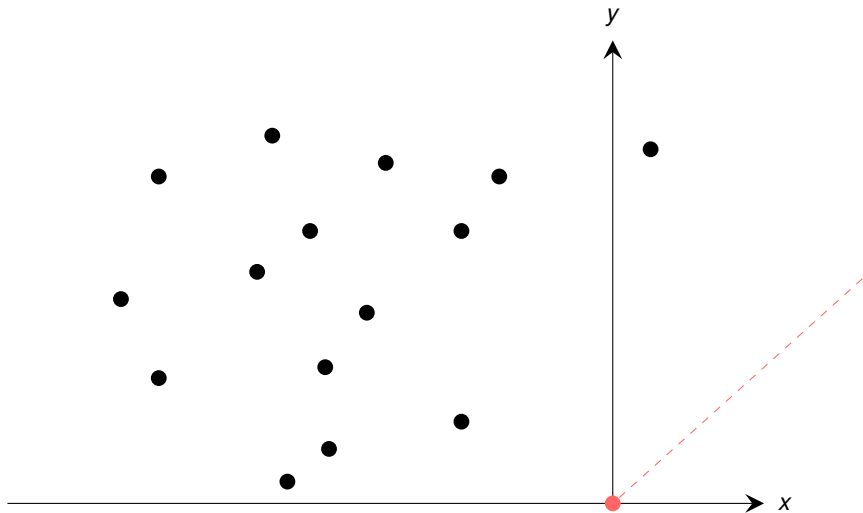
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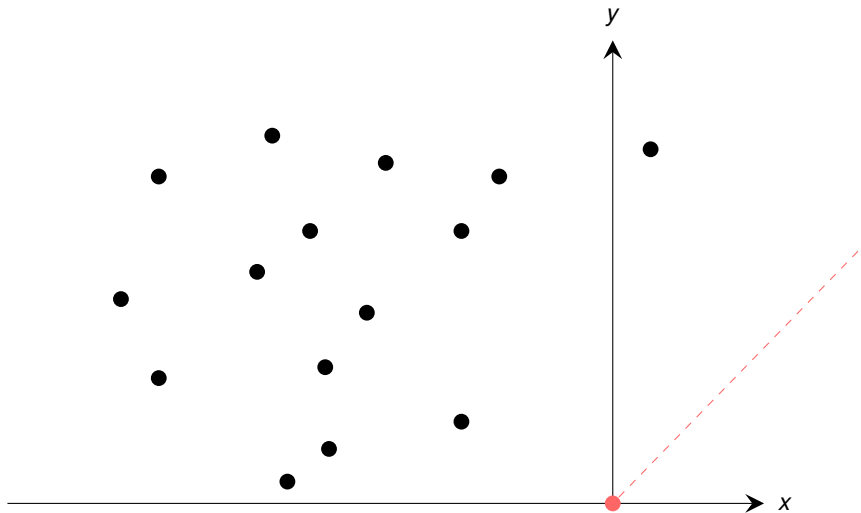
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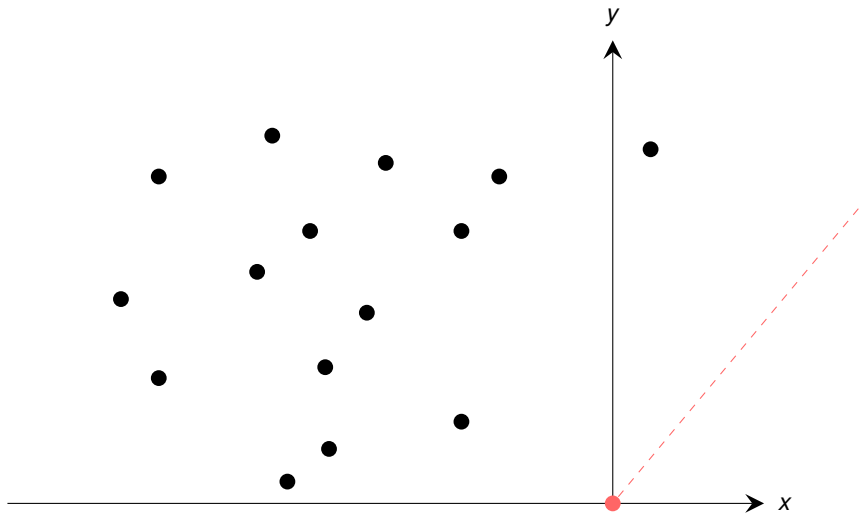
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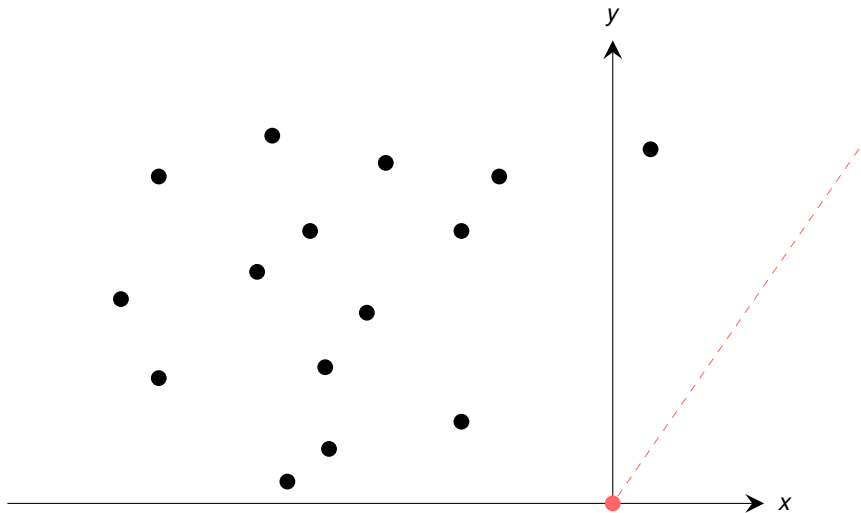
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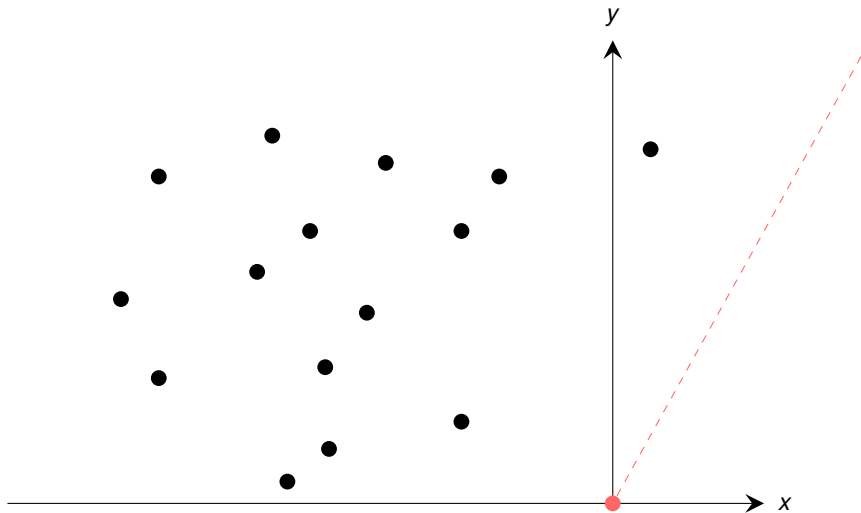
Execution of Jarvis' March



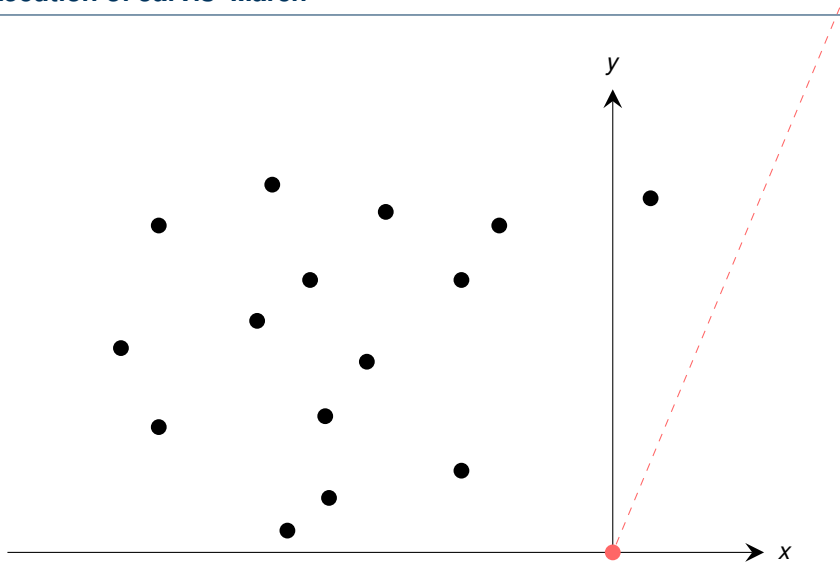
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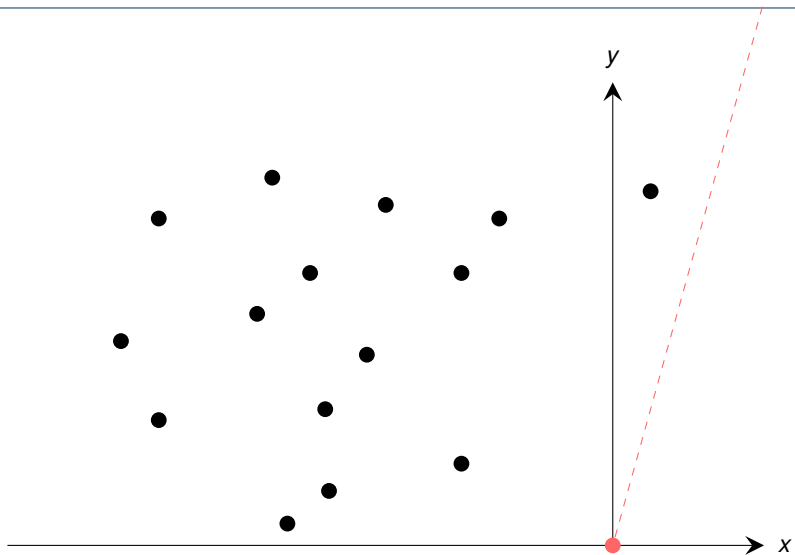
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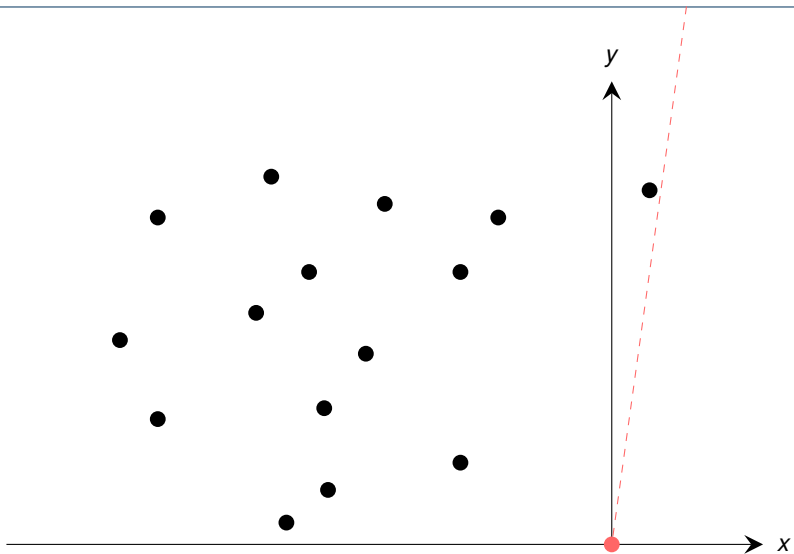
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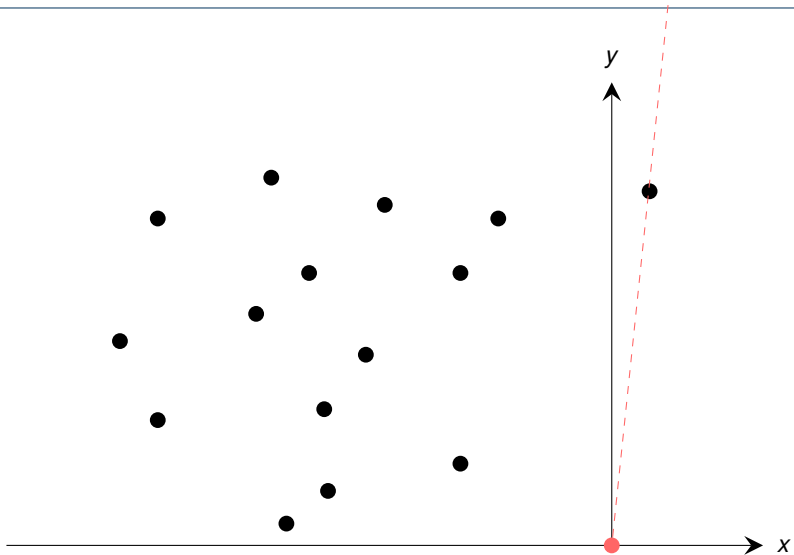
Execution of Jarvis' March



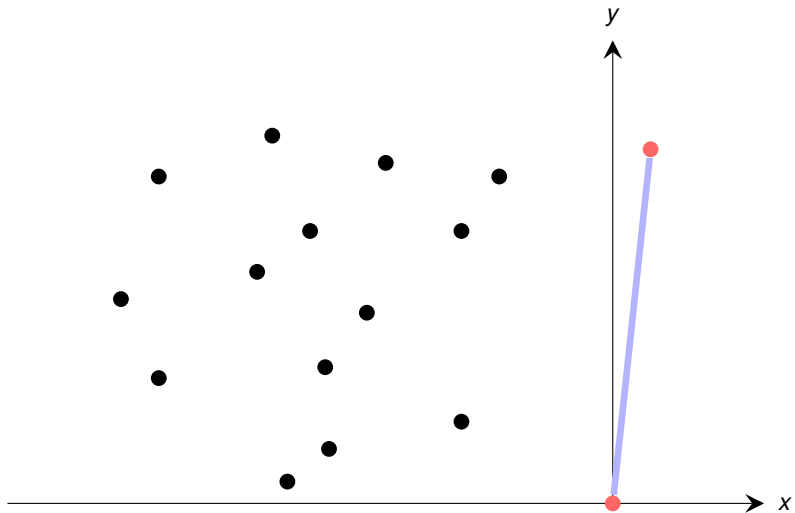
Execution of Jarvis' March



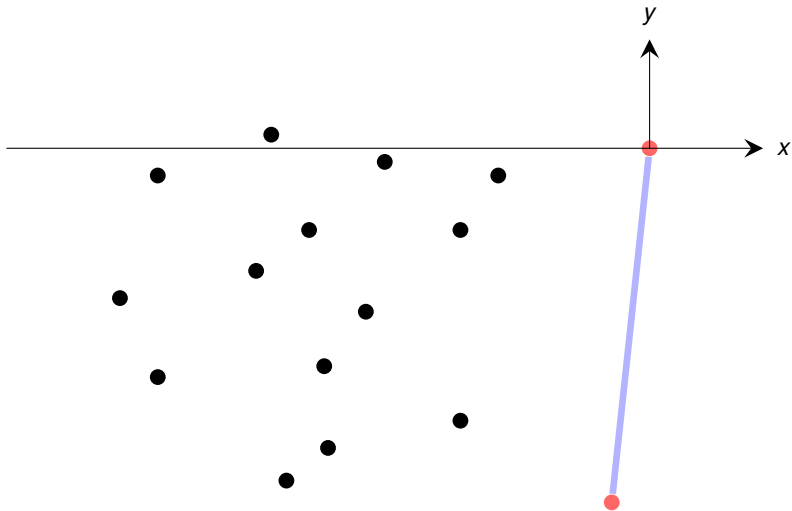
Execution of Jarvis' March



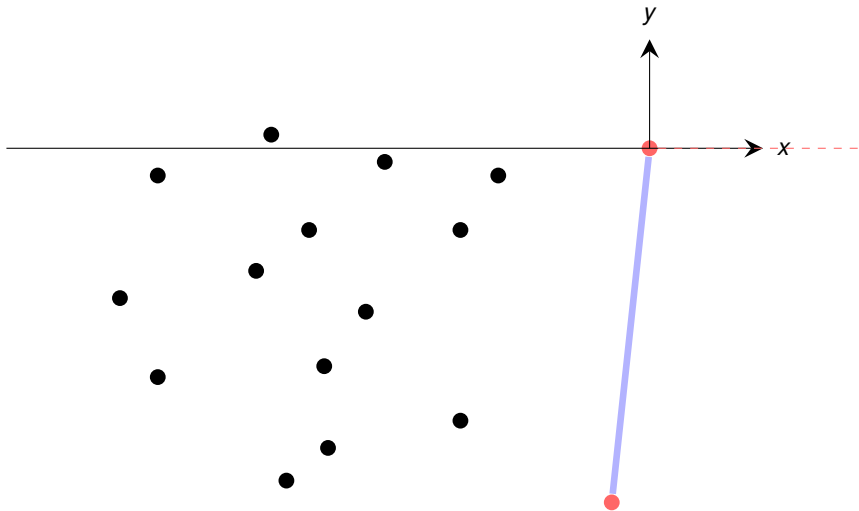
Execution of Jarvis' March



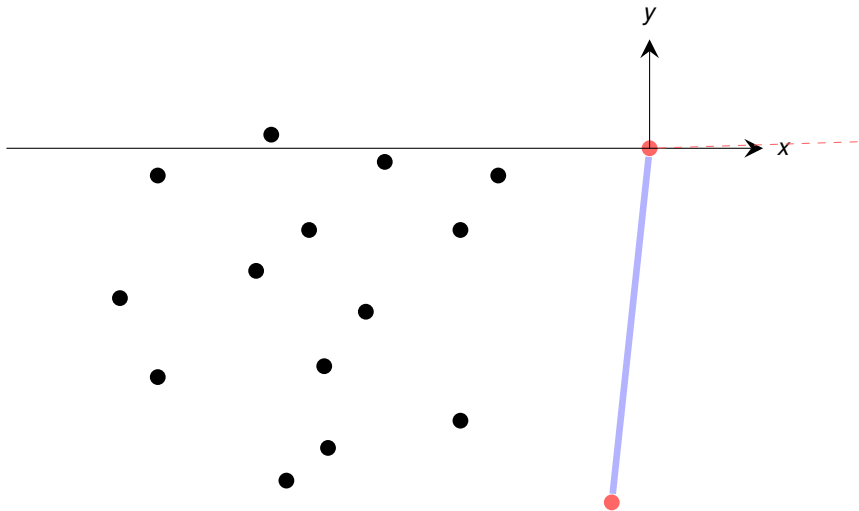
Execution of Jarvis' March



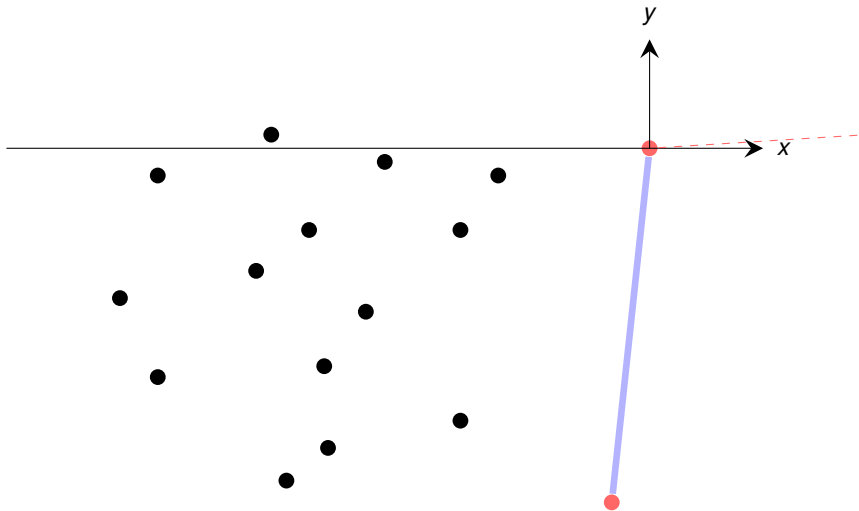
Execution of Jarvis' March



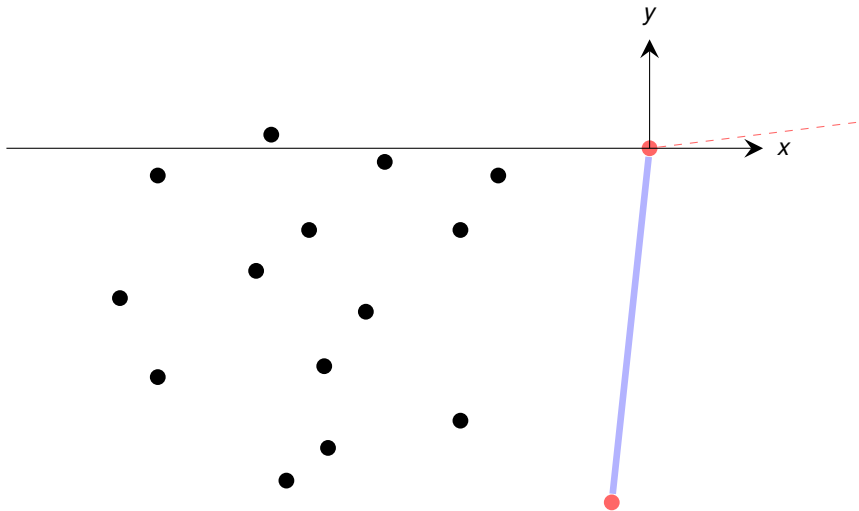
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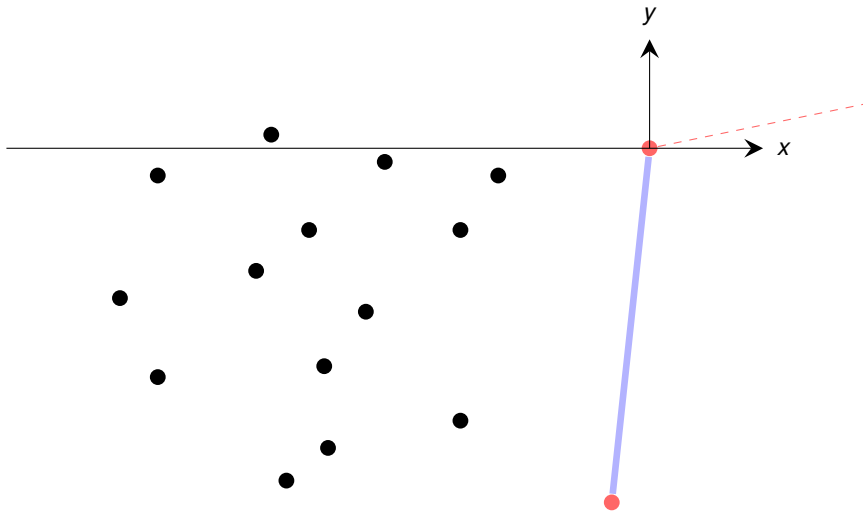
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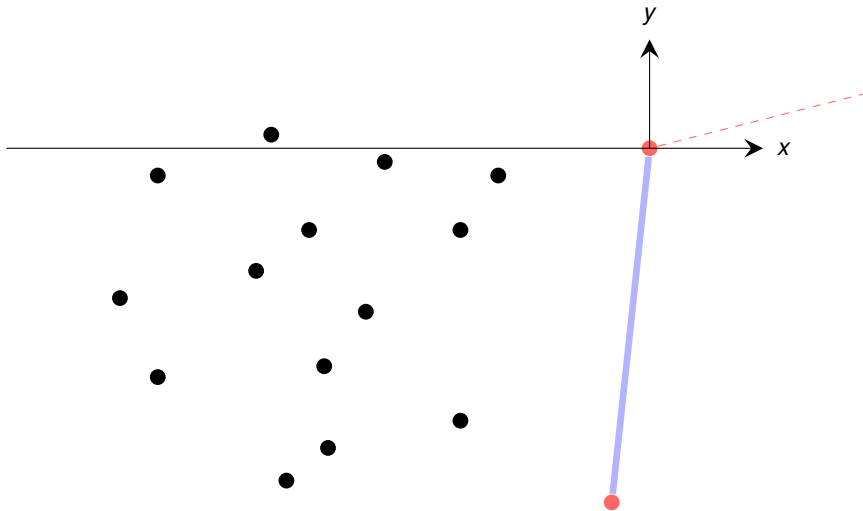
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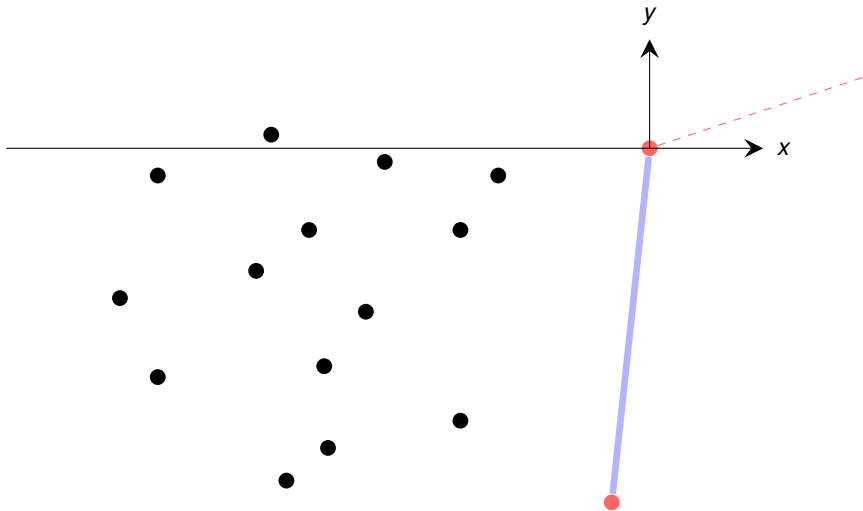
Execution of Jarvis' March



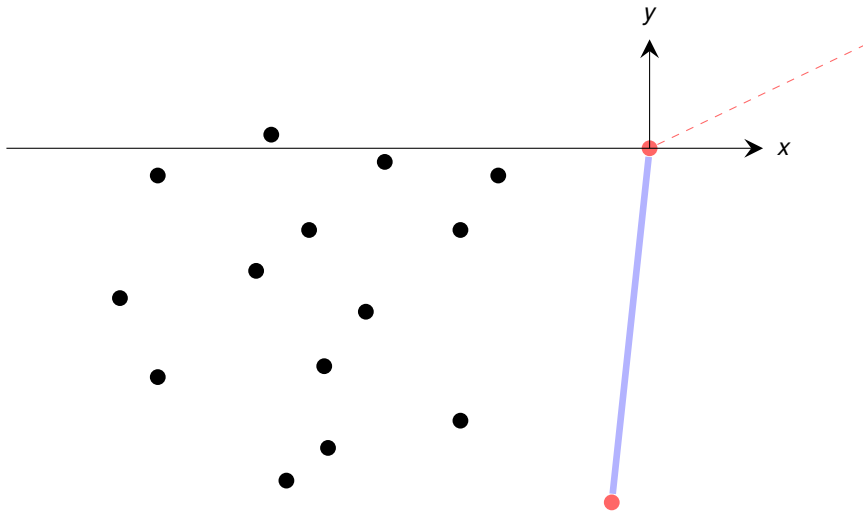
Execution of Jarvis' March



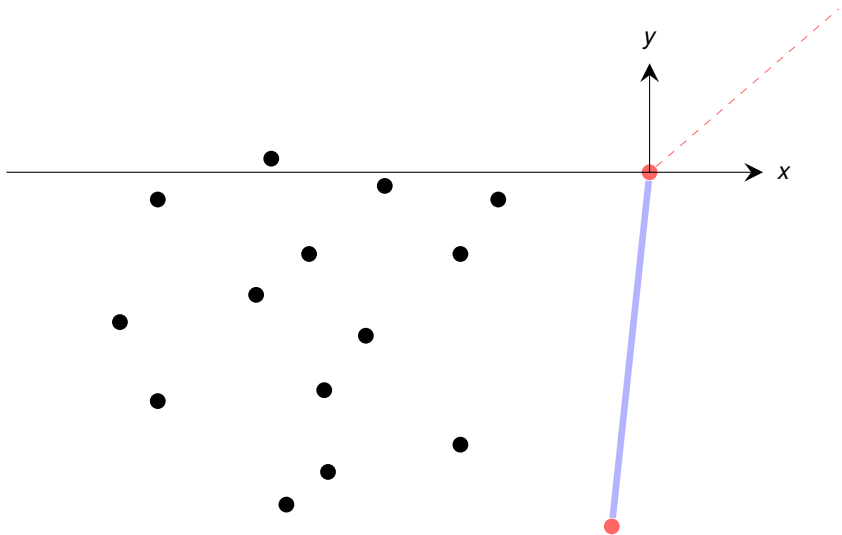
Execution of Jarvis' March



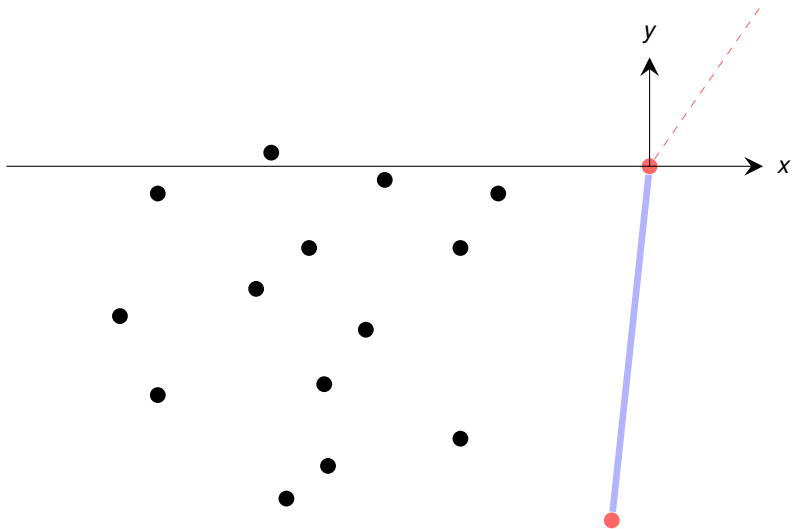
Execution of Jarvis' March



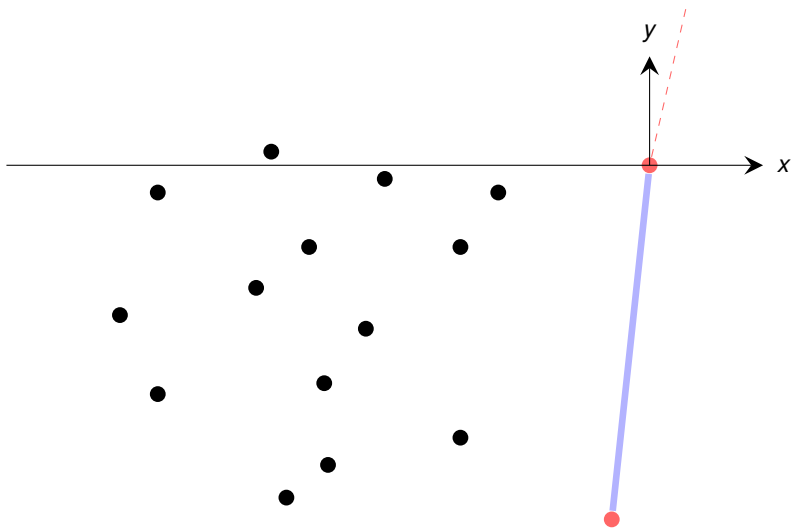
Execution of Jarvis' March



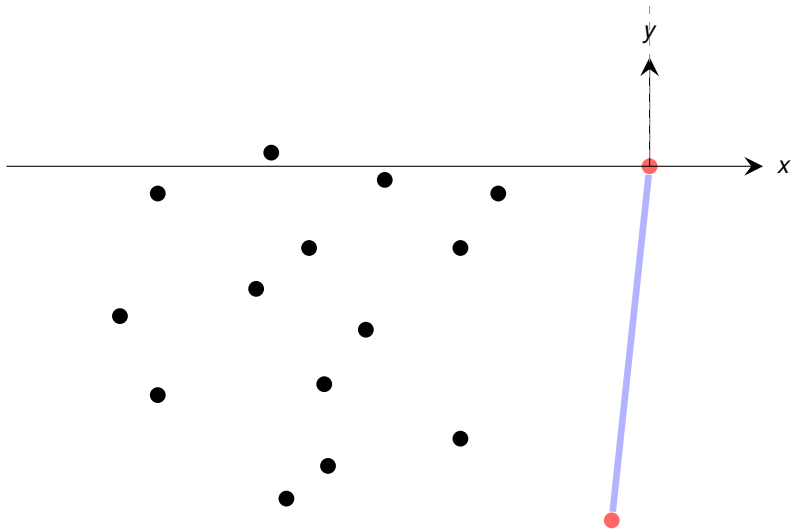
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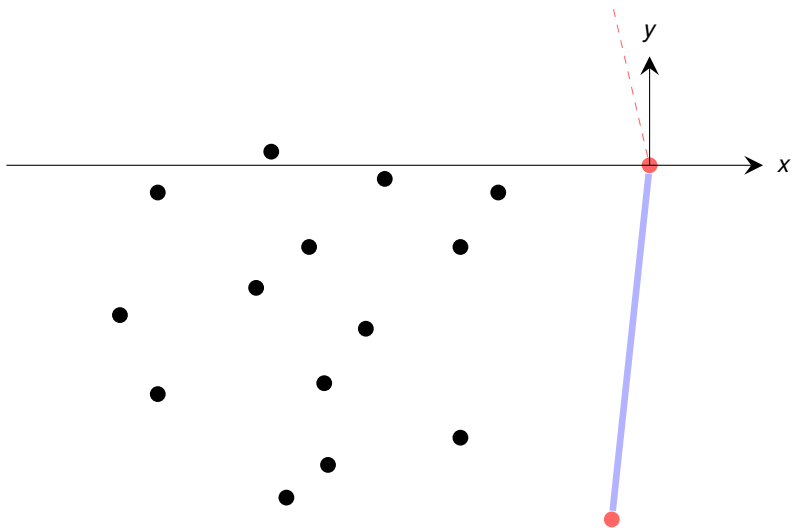
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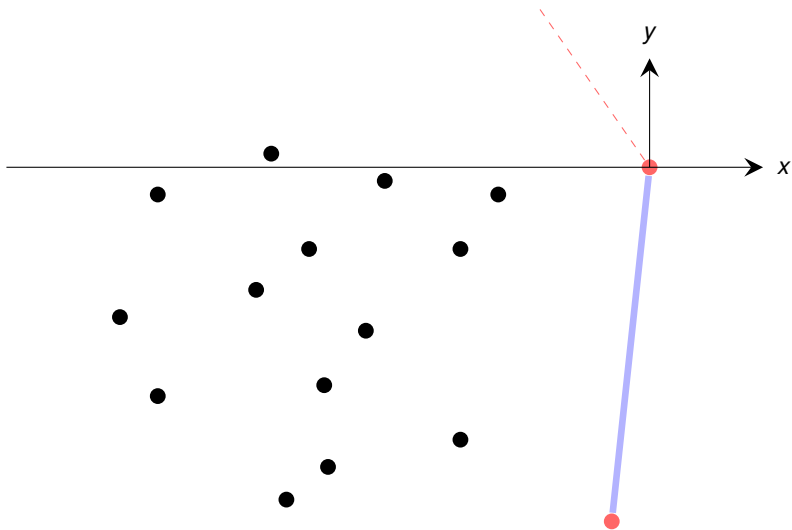
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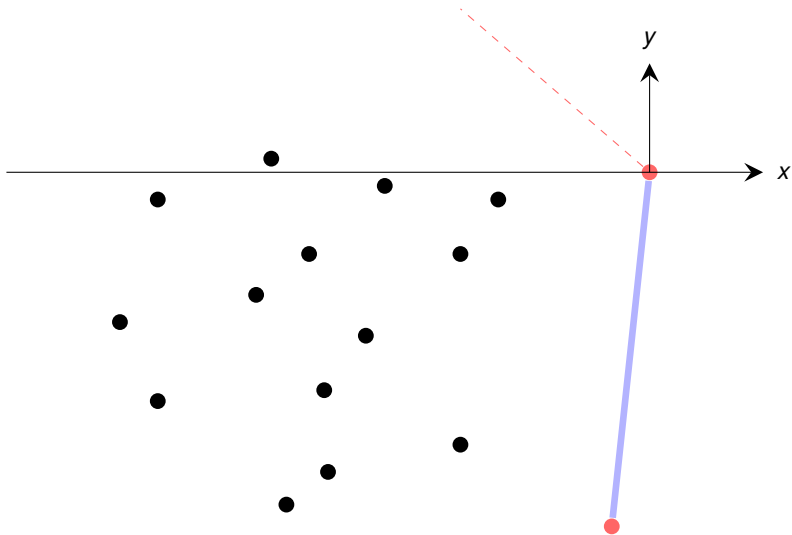
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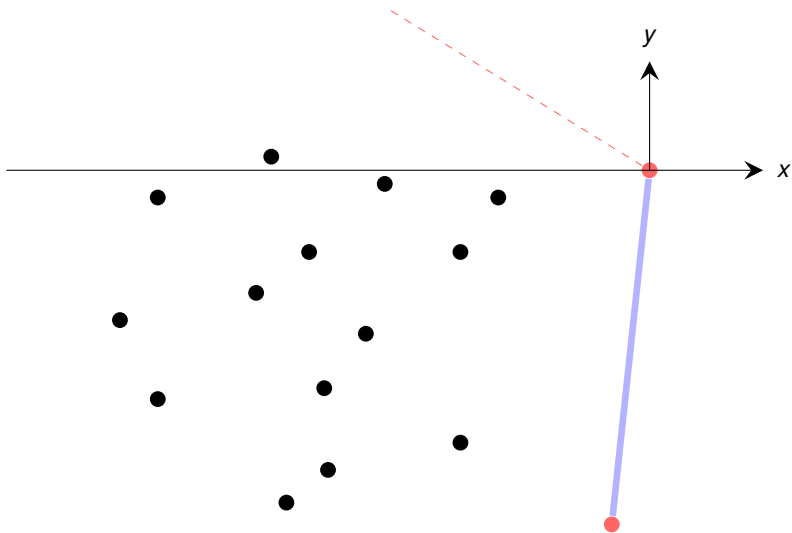
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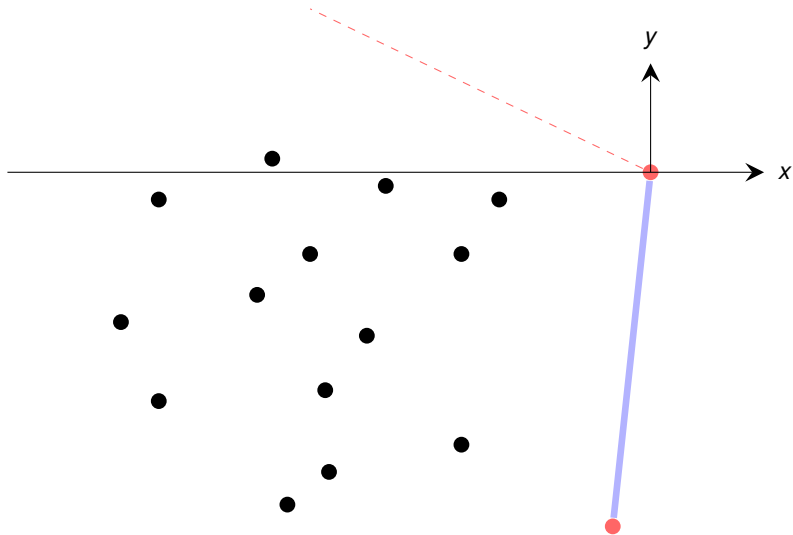
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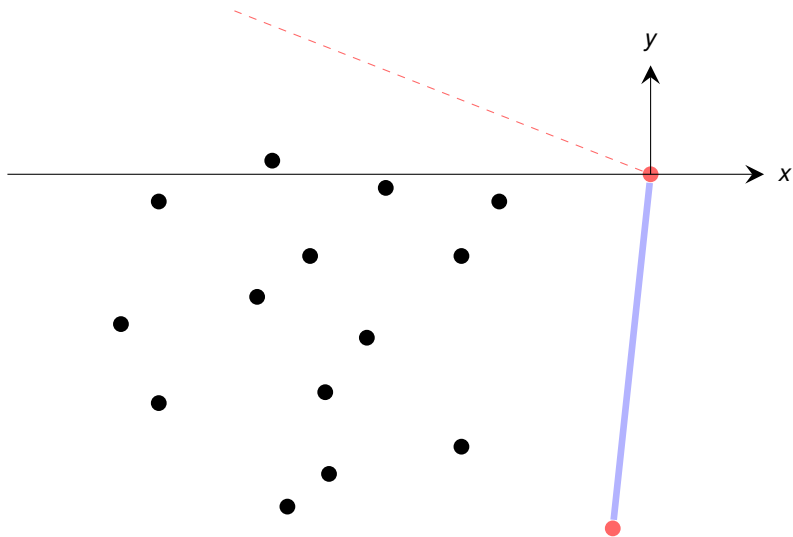
Execution of Jarvis' March



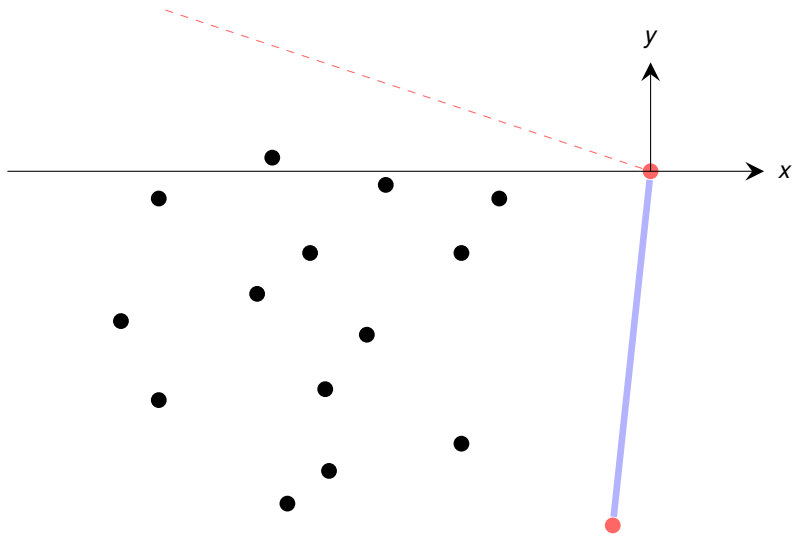
Execution of Jarvis' March



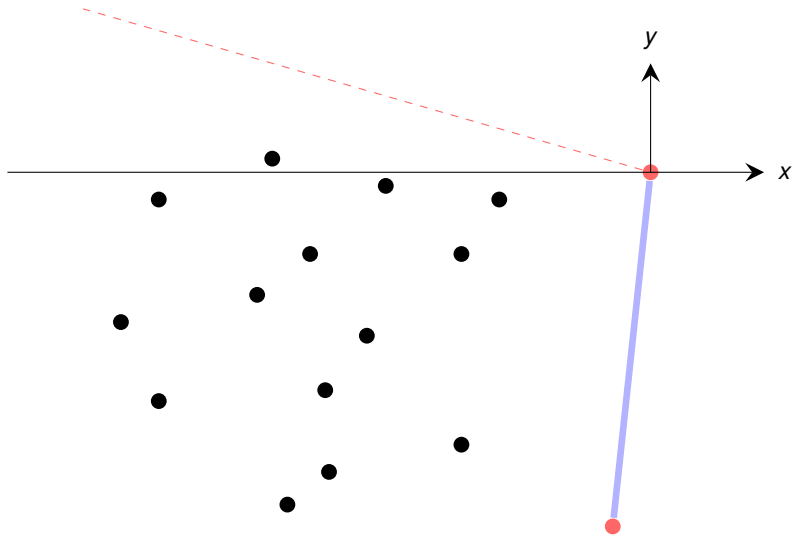
Execution of Jarvis' March



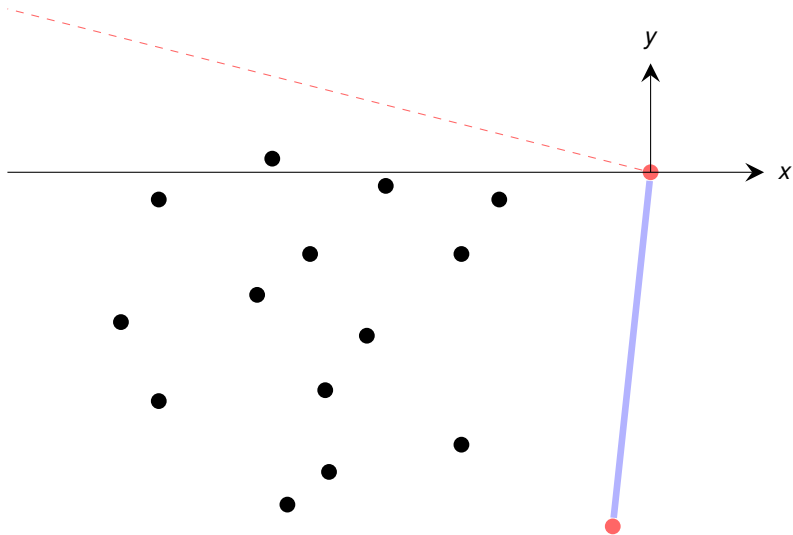
Execution of Jarvis' March



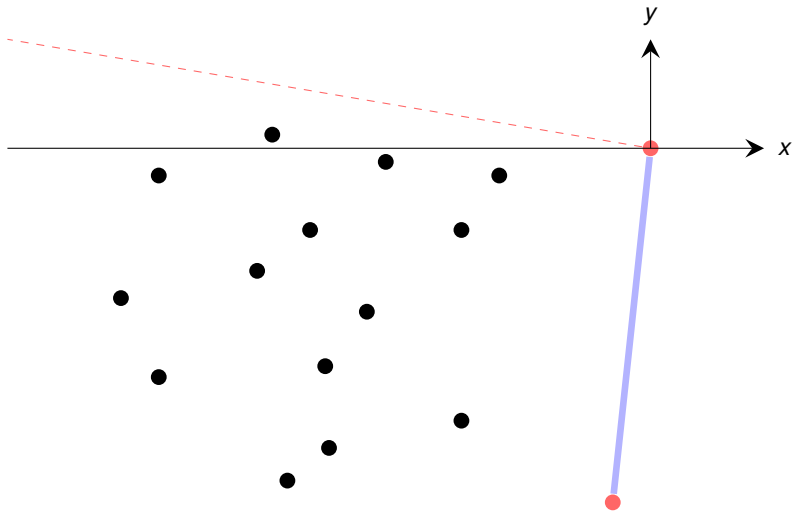
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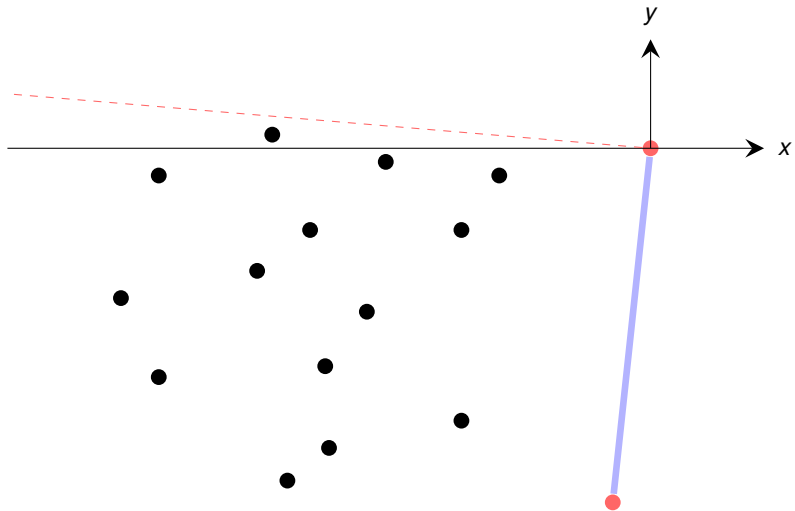
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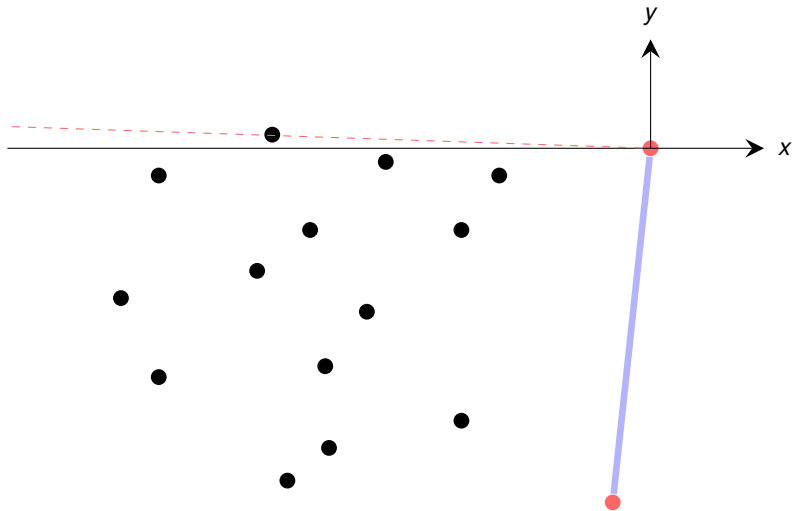
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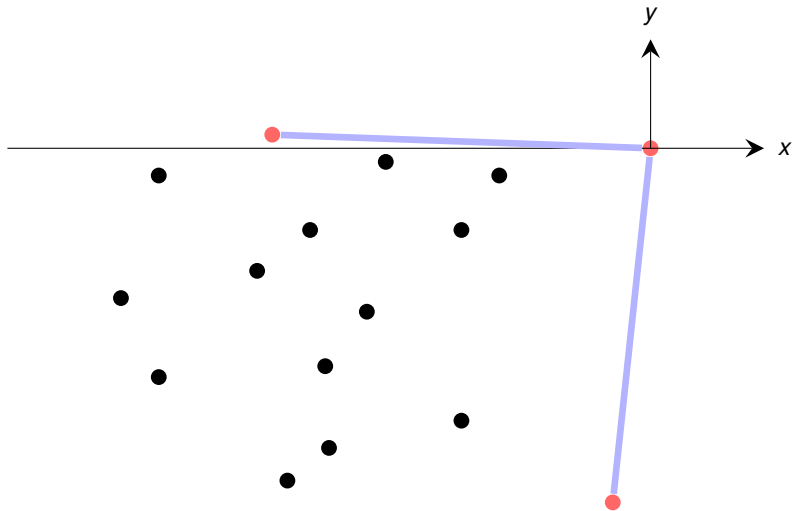
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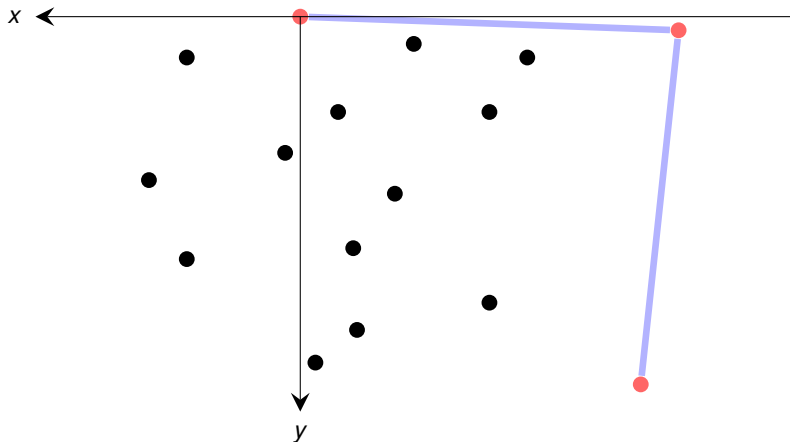
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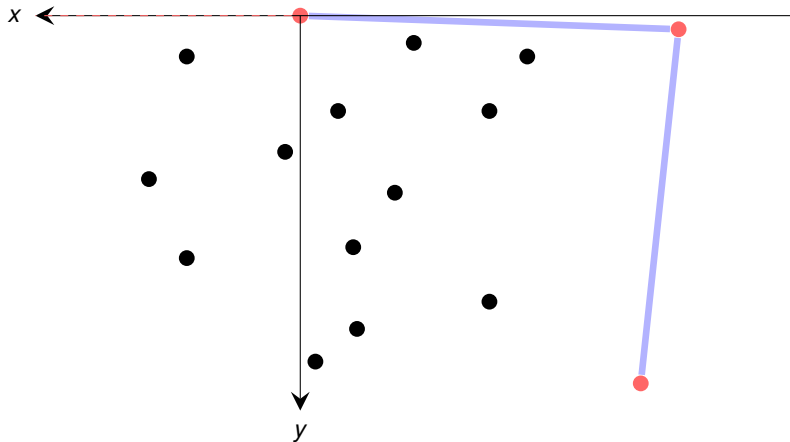
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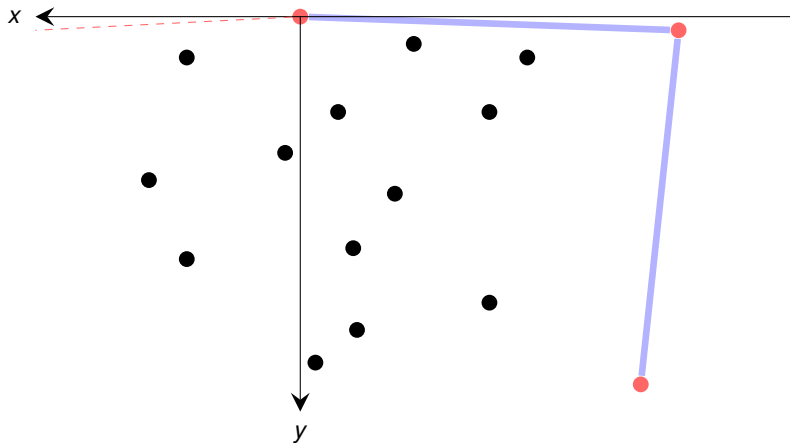
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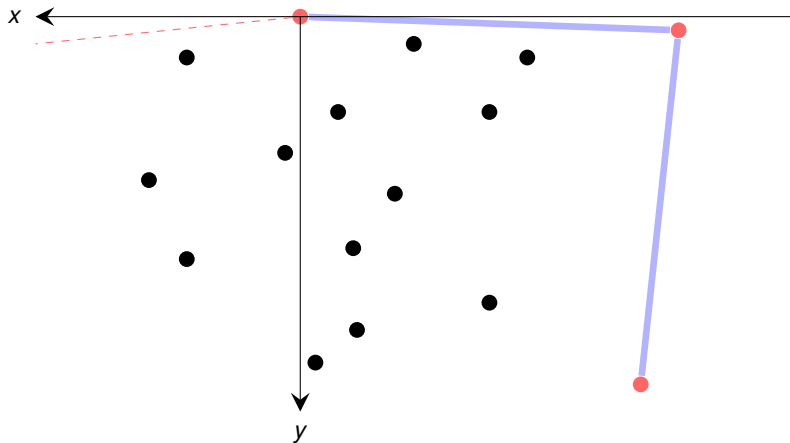
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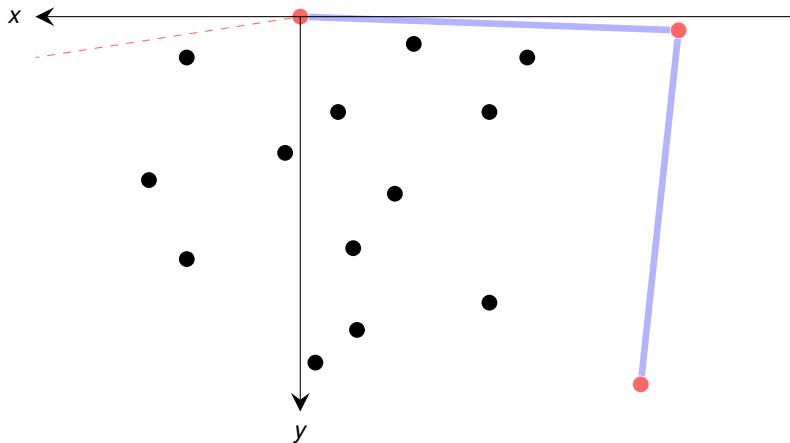
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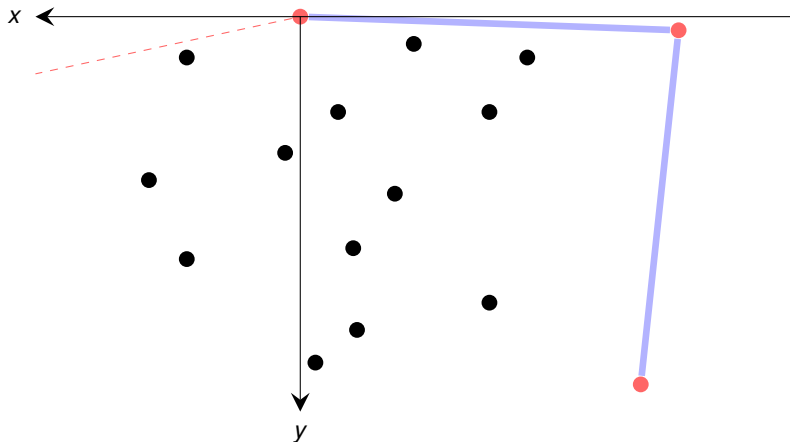
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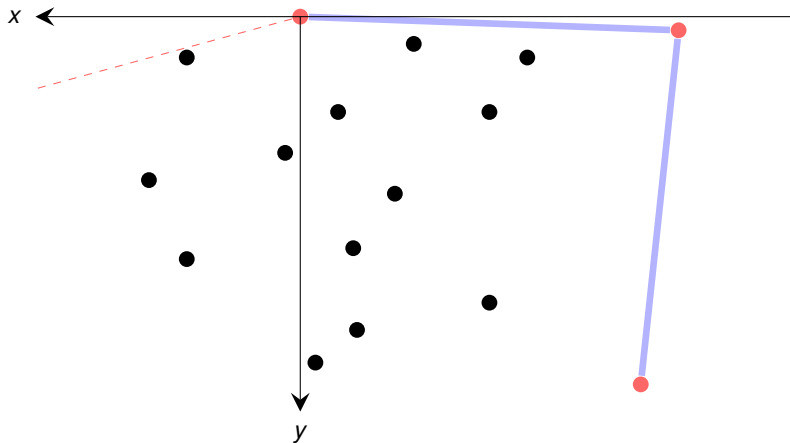
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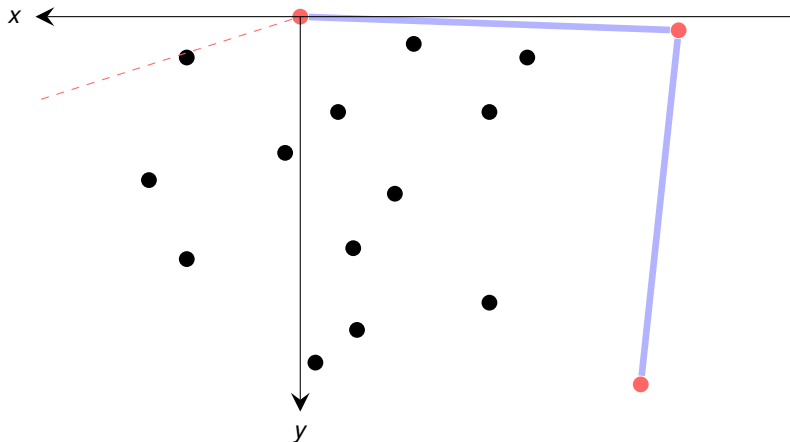
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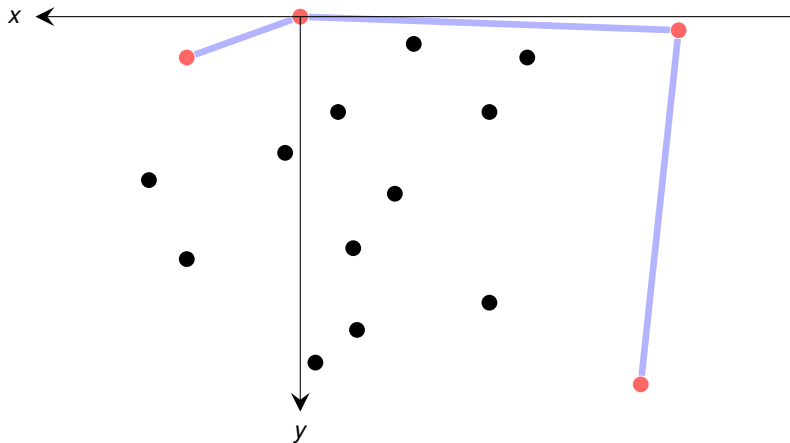
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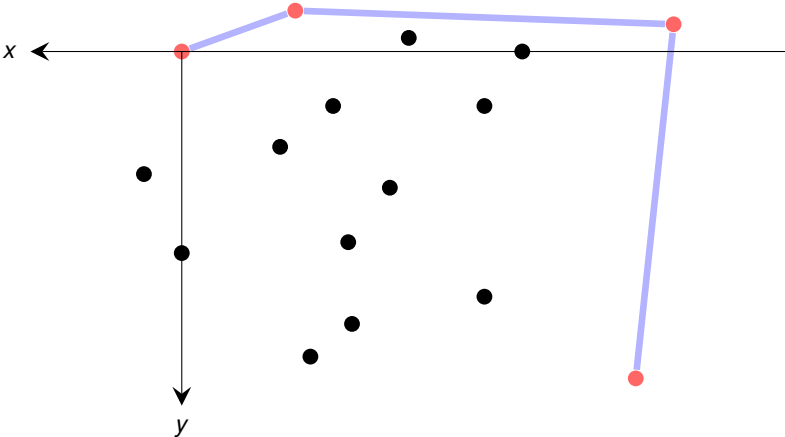
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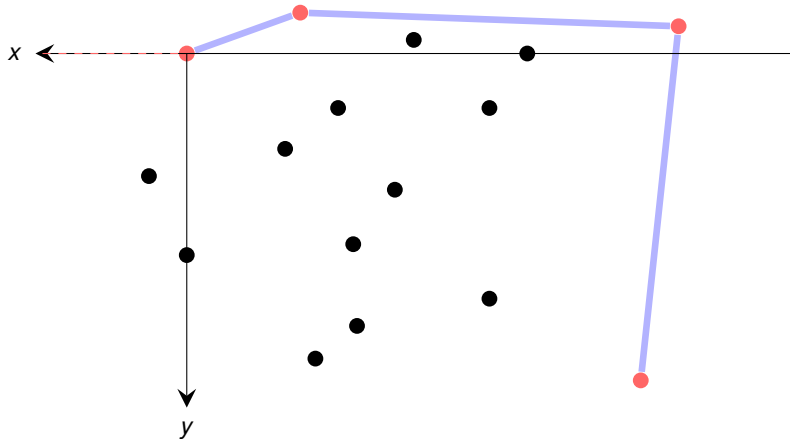
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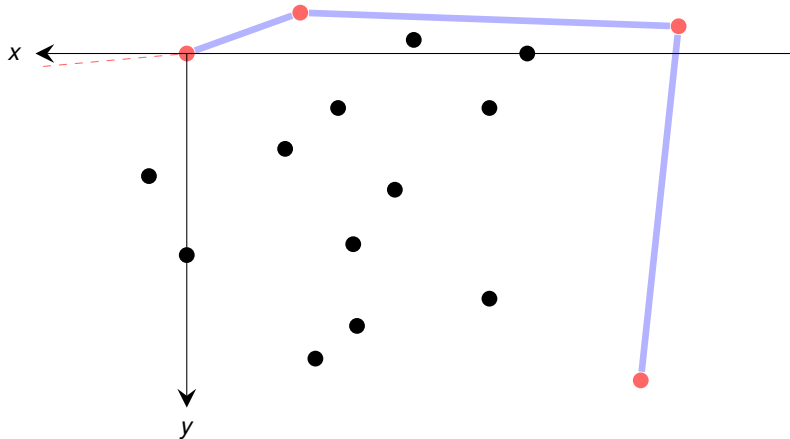
Execution of Jarvis' March



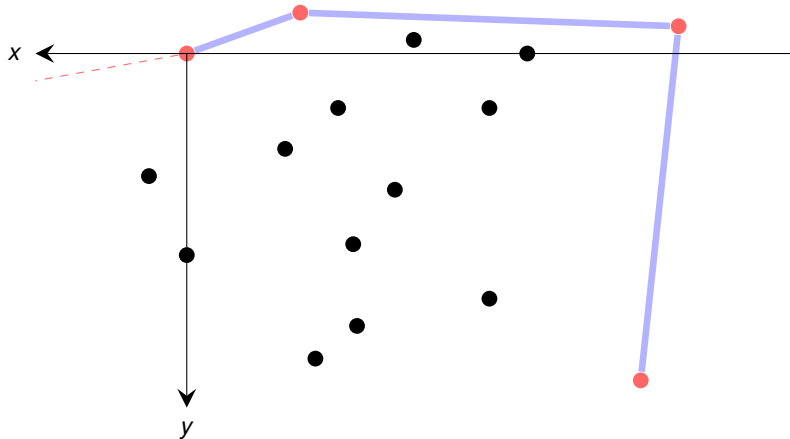
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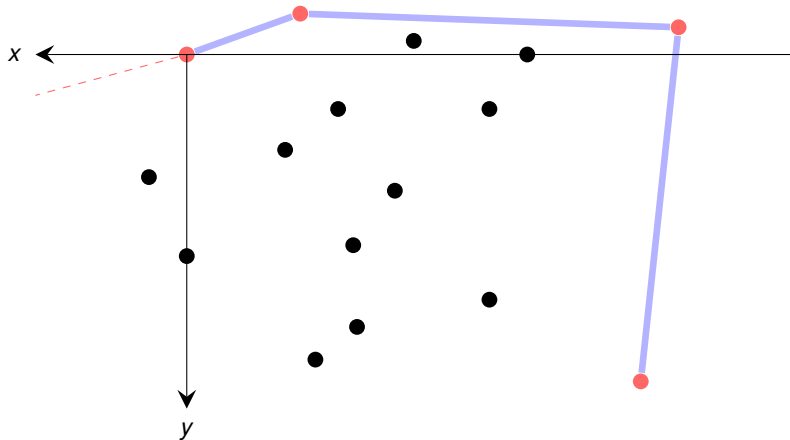
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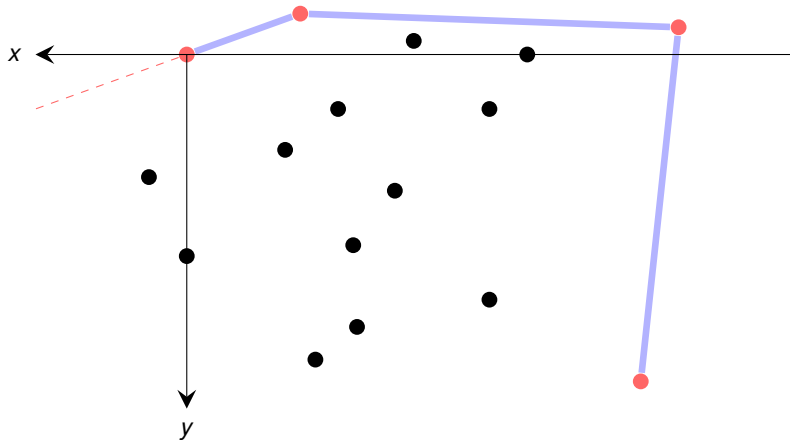
Execution of Jarvis' March



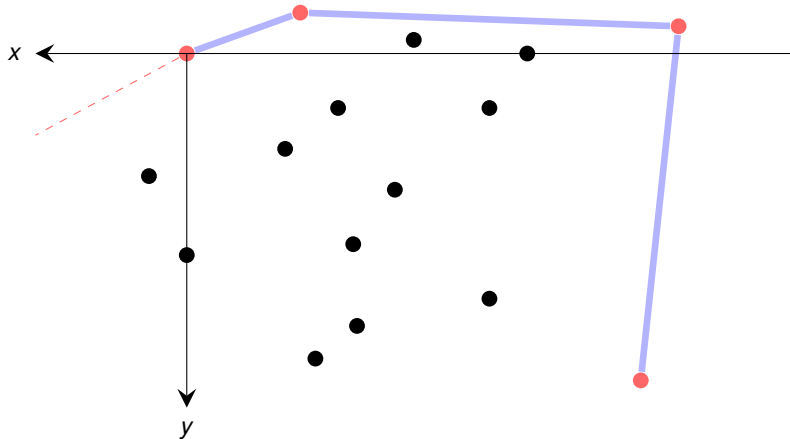
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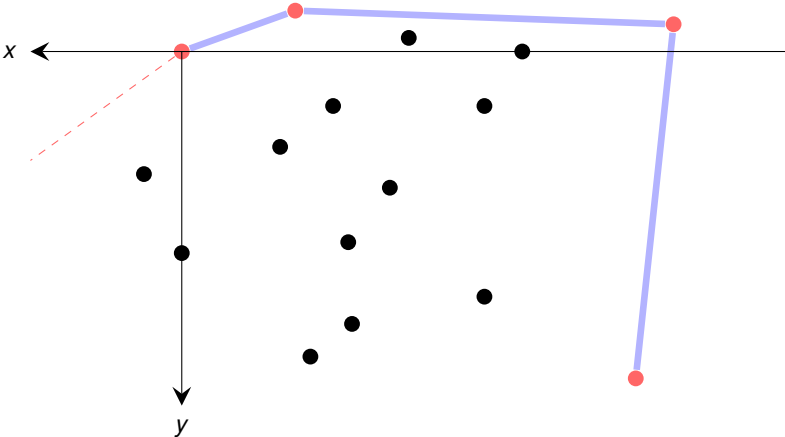
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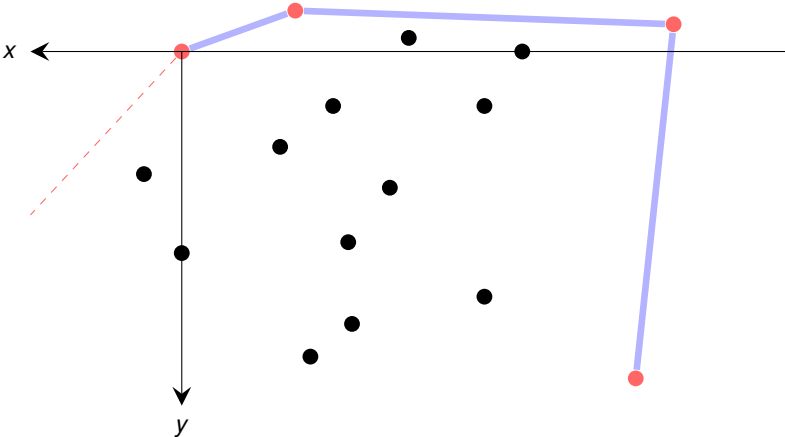
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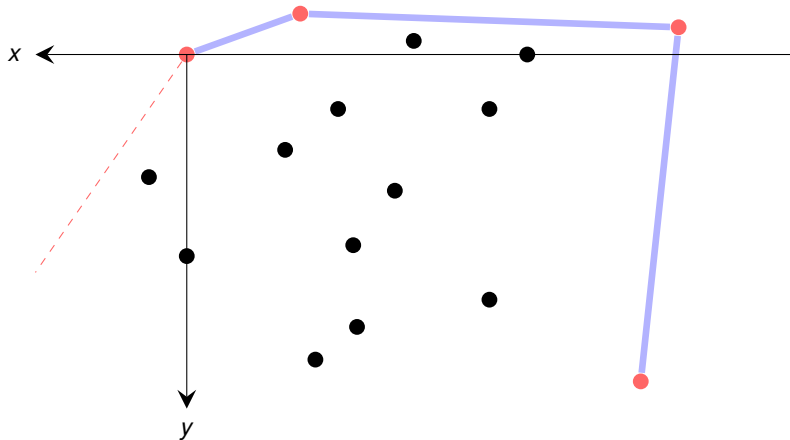
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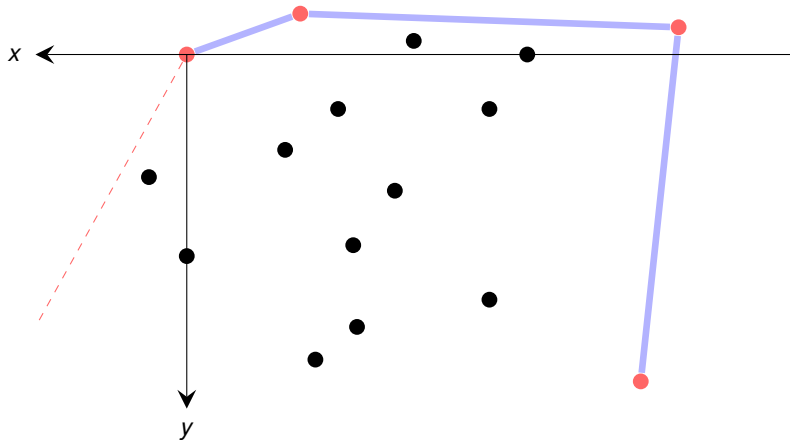
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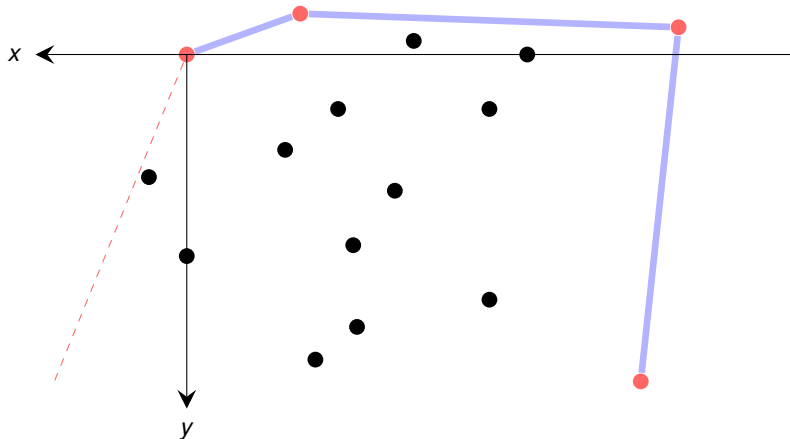
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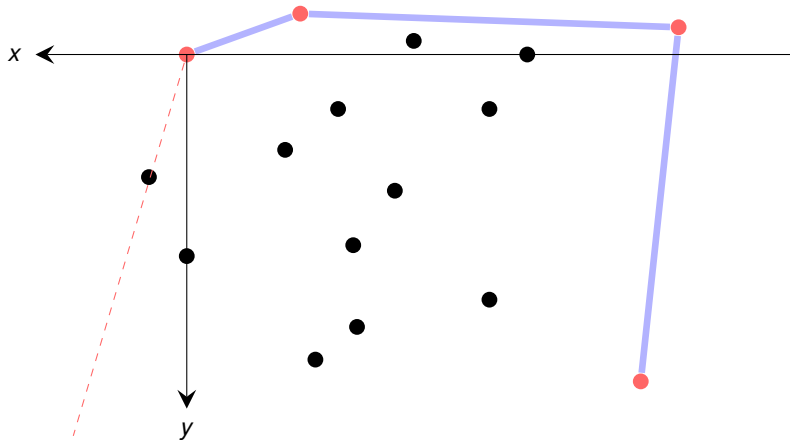
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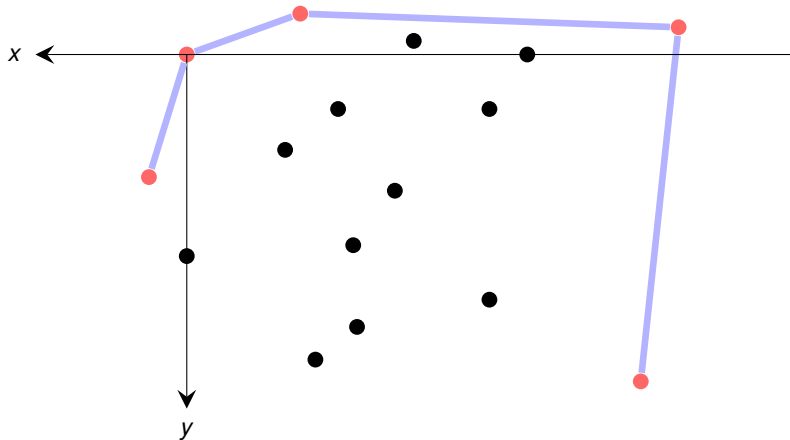
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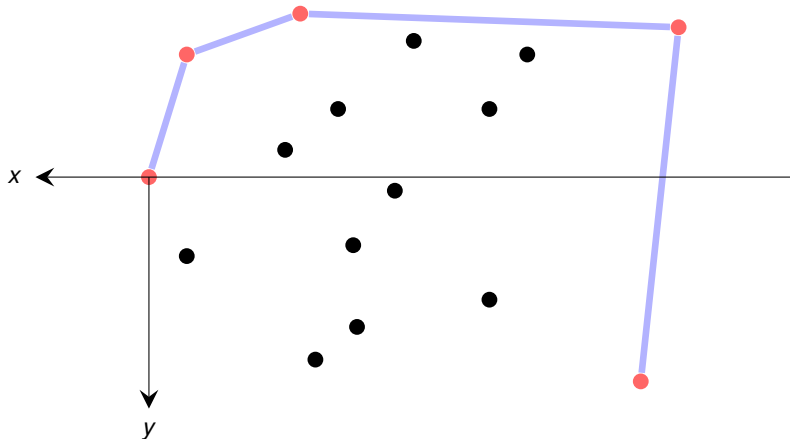
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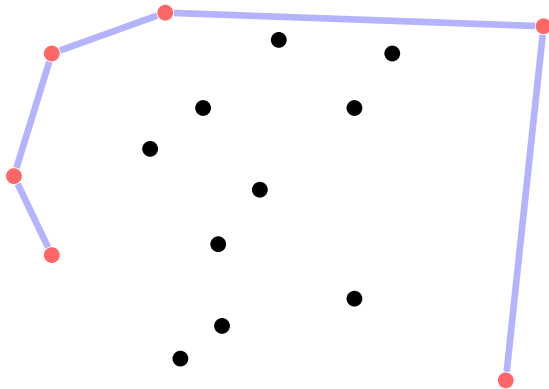
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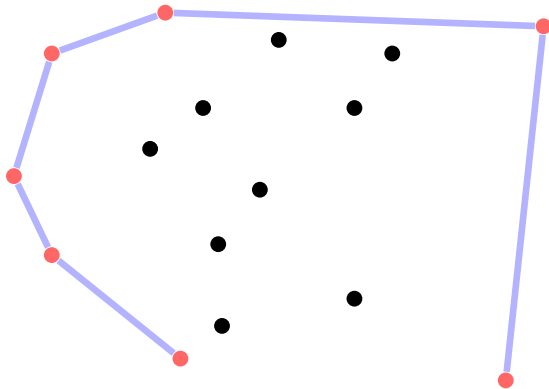
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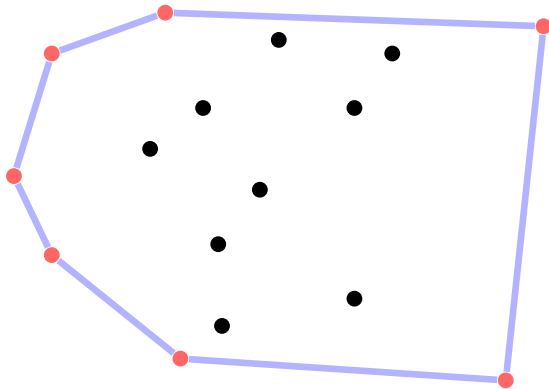
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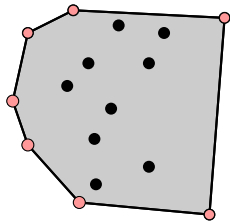
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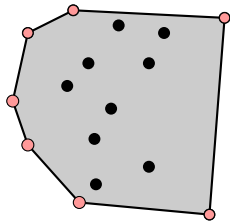


Computing Convex Hull: Summary



Computing Convex Hull: Summary

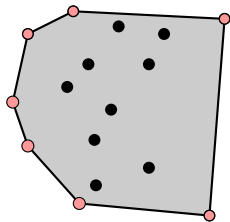
Graham's Scan



Computing Convex Hull: Summary

Graham's Scan

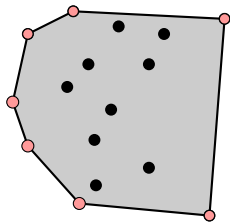
- natural backtracking algorithm



Computing Convex Hull: Summary

Graham's Scan

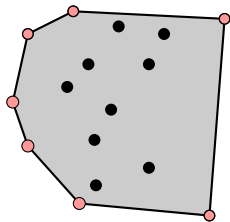
- natural backtracking algorithm
- cross-product avoids computing polar angles



Computing Convex Hull: Summary

Graham's Scan

- natural backtracking algorithm
- cross-product avoids computing polar angles
- Runtime dominated by sorting $\rightsquigarrow O(n \log n)$

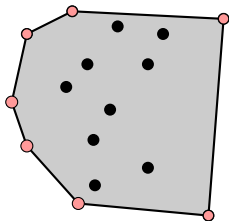


Computing Convex Hull: Summary

Graham's Scan

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Jarvis' March



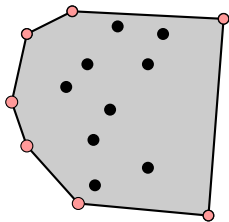
Computing Convex Hull: Summary

Graham's Scan

- natural backtracking algorithm
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Jarvis' March

- proceeds like wrapping a gift



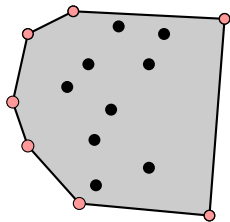
Computing Convex Hull: Summary

Graham's Scan

- natural backtracking algorithm
- cross-product avoids computing polar angles
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Jarvis' March

- proceeds like wrapping a gift
- Runtime $O(nh)$ \rightsquigarrow output-sensitive



Computing Convex Hull: Summary

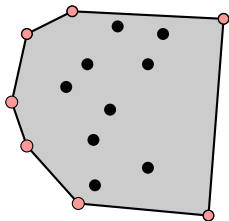
Graham's Scan

- natural backtracking algorithm
- cross-product avoids computing polar angles
- Runtime dominated by sorting $\rightsquigarrow O(n \log n)$

Jarvis' March

- proceeds like wrapping a gift
- Runtime $O(nh)$ \rightsquigarrow output-sensitive

Improves Graham's scan only if $h = O(\log n)$



Computing Convex Hull: Summary

Graham's Scan

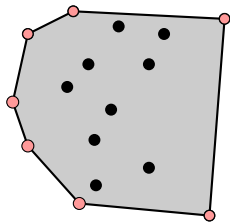
- natural backtracking algorithm
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Jarvis' March

- proceeds like wrapping a gift
- Runtime $O(nh)$ \rightsquigarrow output-sensitive

Improves Graham's scan only if $h = O(\log n)$

There exists an algorithm with $O(n \log h)$ runtime!



Computing Convex Hull: Summary

Graham's Scan

- natural backtracking algorithm
- cross-product avoids computing polar angles
- Runtime dominated by sorting $\rightsquigarrow O(n \log n)$

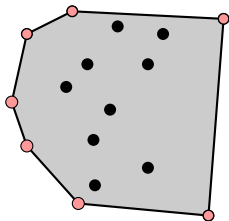
Jarvis' March

- proceeds like wrapping a gift
- Runtime $O(nh)$ \rightsquigarrow output-sensitive

Improves Graham's scan only if $h = O(\log n)$

There exists an algorithm with $O(n \log h)$ runtime!

Lessons Learned



Computing Convex Hull: Summary

Graham's Scan

- natural **backtracking** algorithm
- **cross-product** avoids **computing polar angles**
- Runtime dominated by sorting $\rightsquigarrow O(n \log n)$

Jarvis' March

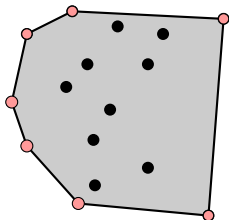
- proceeds like **wrapping a gift**
- Runtime $O(nh)$ \rightsquigarrow **output-sensitive**

Improves Graham's scan only if $h = O(\log n)$

There exists an algorithm with $O(n \log h)$ runtime!

Lessons Learned

- **cross product** very powerful tool
(avoids trigonometry and division!)



Computing Convex Hull: Summary

Graham's Scan

- natural **backtracking** algorithm
- **cross-product** avoids **computing polar angles**
- Runtime dominated by sorting $\rightsquigarrow O(n \log n)$

Jarvis' March

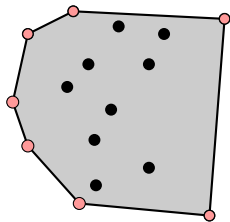
- proceeds like **wrapping a gift**
- Runtime $O(nh)$ \rightsquigarrow **output-sensitive**

Improves Graham's scan only if $h = O(\log n)$

There exists an algorithm with $O(n \log h)$ runtime!

Lessons Learned

- **cross product** very powerful tool (avoids trigonometry and division!)
- take care of **degenerate cases**



Outline

Introduction and Line Intersection

Convex Hull

Glimpse at (More) Advanced Algorithms



Linear Programming and Simplex

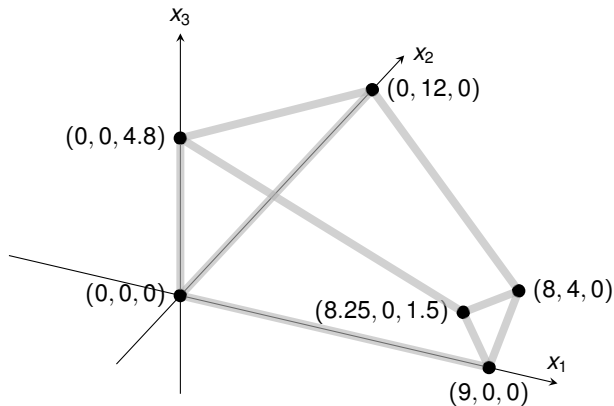
maximize
subject to

$$\begin{array}{rcccccc} 3x_1 & + & x_2 & + & 2x_3 & & \\ x_1 & + & x_2 & + & 3x_3 & \leq & 30 \\ 2x_1 & + & 2x_2 & + & 5x_3 & \leq & 24 \\ 4x_1 & + & x_2 & + & 2x_3 & \leq & 36 \\ & & x_1, x_2, x_3 & & & \geq & 0 \end{array}$$

▶ Go to End



Linear Programming and Simplex



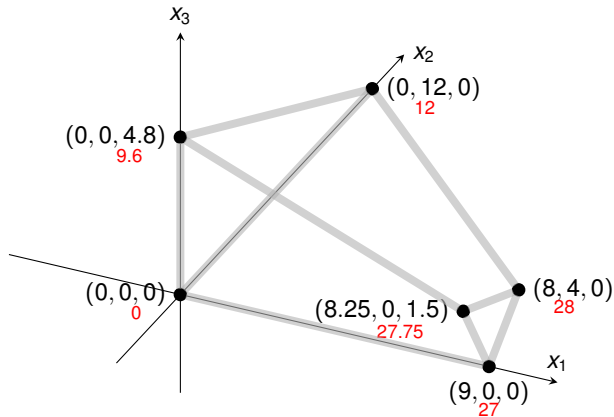
maximize
subject to

$$\begin{array}{rcccccc} 3x_1 & + & x_2 & + & 2x_3 & & \\ x_1 & + & x_2 & + & 3x_3 & \leq & 30 \\ 2x_1 & + & 2x_2 & + & 5x_3 & \leq & 24 \\ 4x_1 & + & x_2 & + & 2x_3 & \leq & 36 \\ & & x_1, x_2, x_3 & & & \geq & 0 \end{array}$$

▶ Go to End



Linear Programming and Simplex



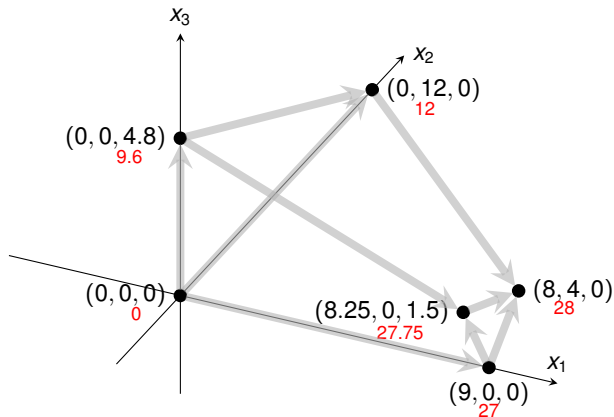
maximize
subject to

$$\begin{array}{rcccccc} 3x_1 & + & x_2 & + & 2x_3 & & \\ x_1 & + & x_2 & + & 3x_3 & \leq & 30 \\ 2x_1 & + & 2x_2 & + & 5x_3 & \leq & 24 \\ 4x_1 & + & x_2 & + & 2x_3 & \leq & 36 \\ & & x_1, x_2, x_3 & & & \geq & 0 \end{array}$$

▶ Go to End



Linear Programming and Simplex



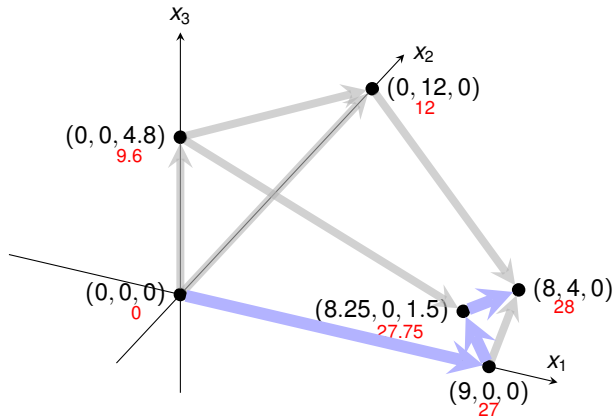
maximize
subject to

$$\begin{array}{rcccccc} 3x_1 & + & x_2 & + & 2x_3 & & \\ x_1 & + & x_2 & + & 3x_3 & \leq & 30 \\ 2x_1 & + & 2x_2 & + & 5x_3 & \leq & 24 \\ 4x_1 & + & x_2 & + & 2x_3 & \leq & 36 \\ & & x_1, x_2, x_3 & & & \geq & 0 \end{array}$$

▶ Go to End



Linear Programming and Simplex



maximize
subject to

$$\begin{array}{rcccccc} 3x_1 & + & x_2 & + & 2x_3 & & \\ x_1 & + & x_2 & + & 3x_3 & \leq & 30 \\ 2x_1 & + & 2x_2 & + & 5x_3 & \leq & 24 \\ 4x_1 & + & x_2 & + & 2x_3 & \leq & 36 \\ & & x_1, x_2, x_3 & & & \geq & 0 \end{array}$$

▶ Go to End



SOLUTION OF A LARGE-SCALE TRAVELING-SALESMAN PROBLEM*

G. DANTZIG, R. FULKERSON, AND S. JOHNSON

The Rand Corporation, Santa Monica, California

(Received August 9, 1954)

It is shown that a certain tour of 49 cities, one in each of the 48 states and Washington, D. C., has the shortest road distance.

THE TRAVELING-SALESMAN PROBLEM might be described as follows: Find the shortest route (tour) for a salesman starting from a given city, visiting each of a specified group of cities, and then returning to the original point of departure. More generally, given an n by n symmetric matrix $D=(d_{IJ})$, where d_{IJ} represents the 'distance' from I to J , arrange the points in a cyclic order in such a way that the sum of the d_{IJ} between consecutive points is minimal. Since there are only a finite number of possibilities (at most $\frac{1}{2}(n-1)!$) to consider, the problem is to devise a method of picking out the optimal arrangement which is reasonably efficient for fairly large values of n . Although algorithms have been devised for problems of similar nature, e.g., the optimal assignment problem,^{3,7,8} little is known about the traveling-salesman problem. We do not claim that this note alters the situation very much; what we shall do is outline a way of approaching the problem that sometimes, at least, enables one to find an optimal path and prove it so. In particular, it will be shown that a certain arrangement of 49 cities, one in each of the 48 states and Washington, D. C., is best, the d_{IJ} used representing road distances as taken from an atlas.



Travelling Salesman Problem: The 42 (49) Cities

1. Manchester, N. H.
2. Montpelier, Vt.
3. Detroit, Mich.
4. Cleveland, Ohio
5. Charleston, W. Va.
6. Louisville, Ky.
7. Indianapolis, Ind.
8. Chicago, Ill.
9. Milwaukee, Wis.
10. Minneapolis, Minn.
11. Pierre, S. D.
12. Bismarck, N. D.
13. Helena, Mont.
14. Seattle, Wash.
15. Portland, Ore.
16. Boise, Idaho
17. Salt Lake City, Utah
18. Carson City, Nev.
19. Los Angeles, Calif.
20. Phoenix, Ariz.
21. Santa Fe, N. M.
22. Denver, Colo.
23. Cheyenne, Wyo.
24. Omaha, Neb.
25. Des Moines, Iowa
26. Kansas City, Mo.
27. Topeka, Kans.
28. Oklahoma City, Okla.
29. Dallas, Tex.
30. Little Rock, Ark.
31. Memphis, Tenn.
32. Jackson, Miss.
33. New Orleans, La.
34. Birmingham, Ala.
35. Atlanta, Ga.
36. Jacksonville, Fla.
37. Columbia, S. C.
38. Raleigh, N. C.
39. Richmond, Va.
40. Washington, D. C.
41. Boston, Mass.
42. Portland, Me.
- A. Baltimore, Md.
- B. Wilmington, Del.
- C. Philadelphia, Penn.
- D. Newark, N. J.
- E. New York, N. Y.
- F. Hartford, Conn.
- G. Providence, R. I.



The (Unique) Optimal Tour (699 Units \approx 12,345 miles)

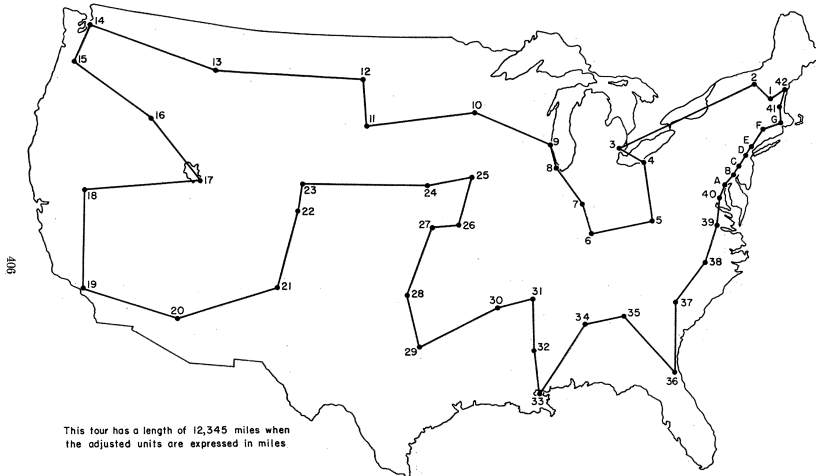
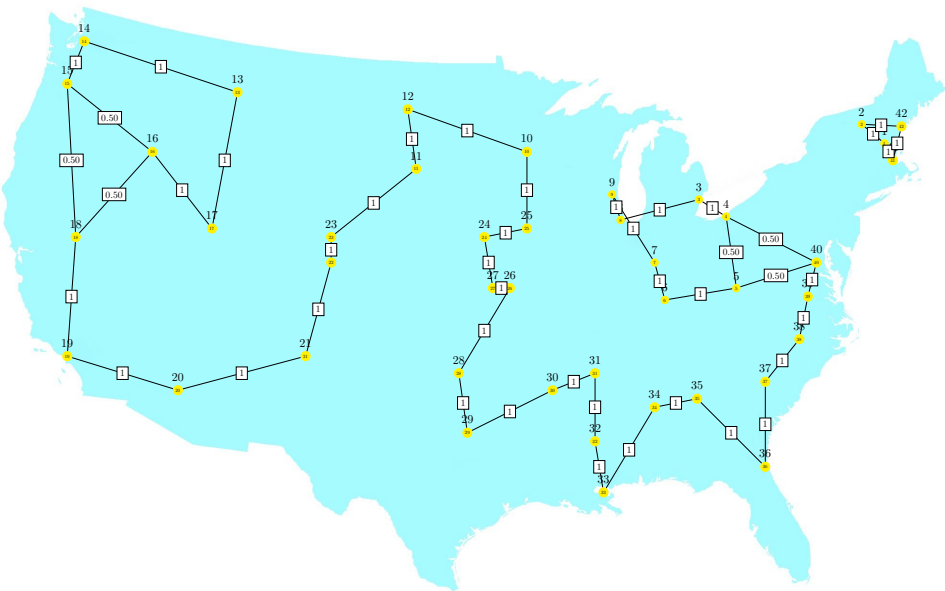


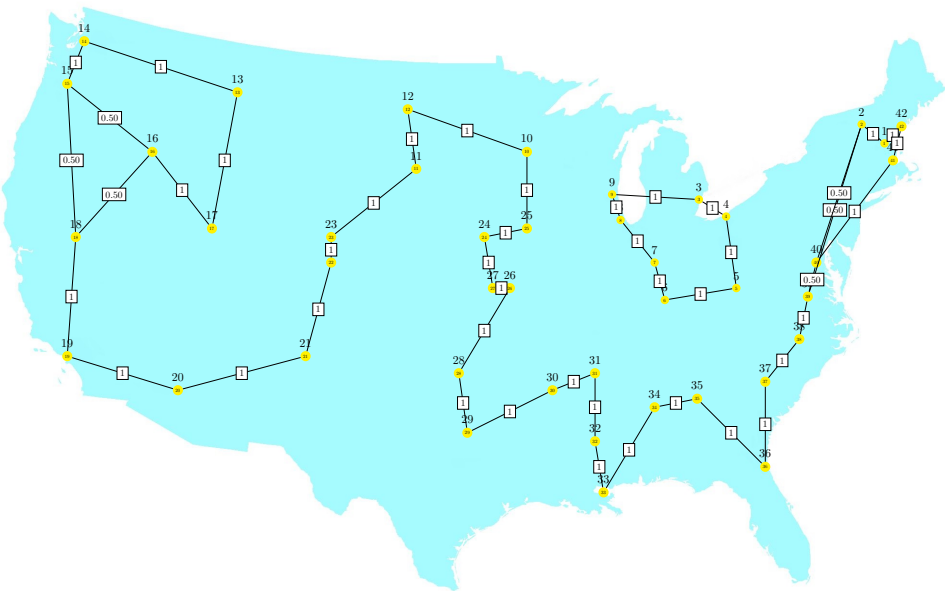
FIG. 16. The optimal tour of 49 cities.



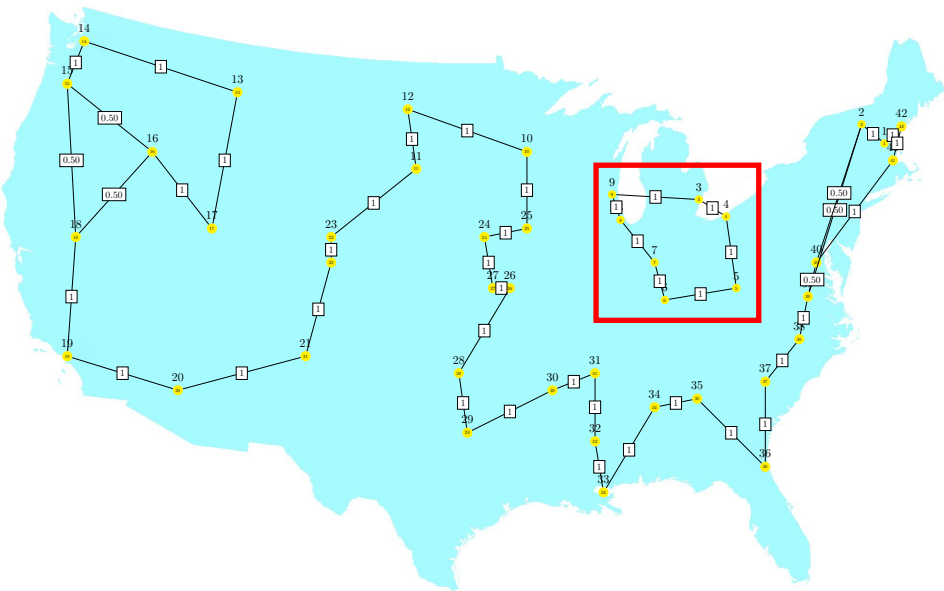
Iteration 1: Objective 641



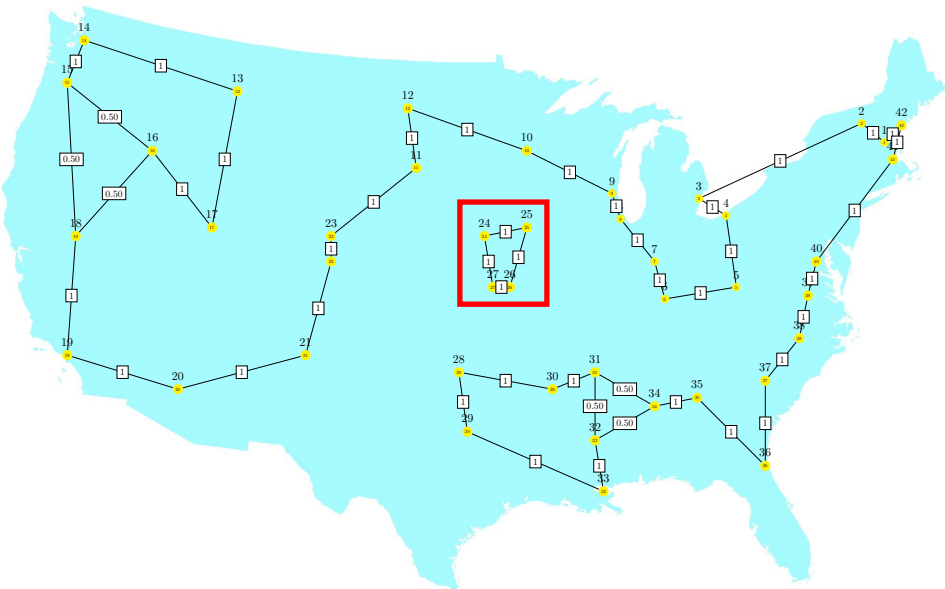
Iteration 2: Objective 676



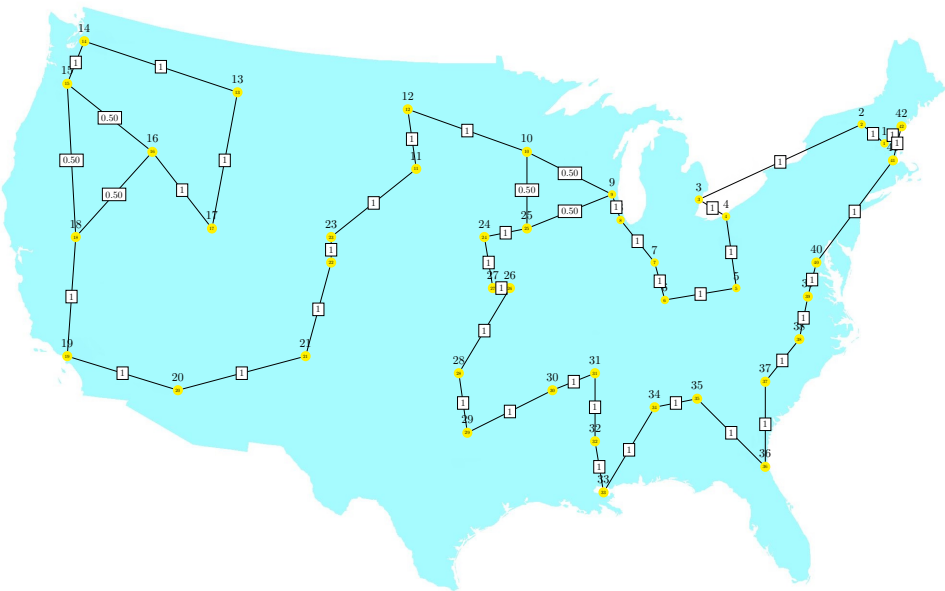
Iteration 2: Objective 676, Eliminate Subtour 3 – 9



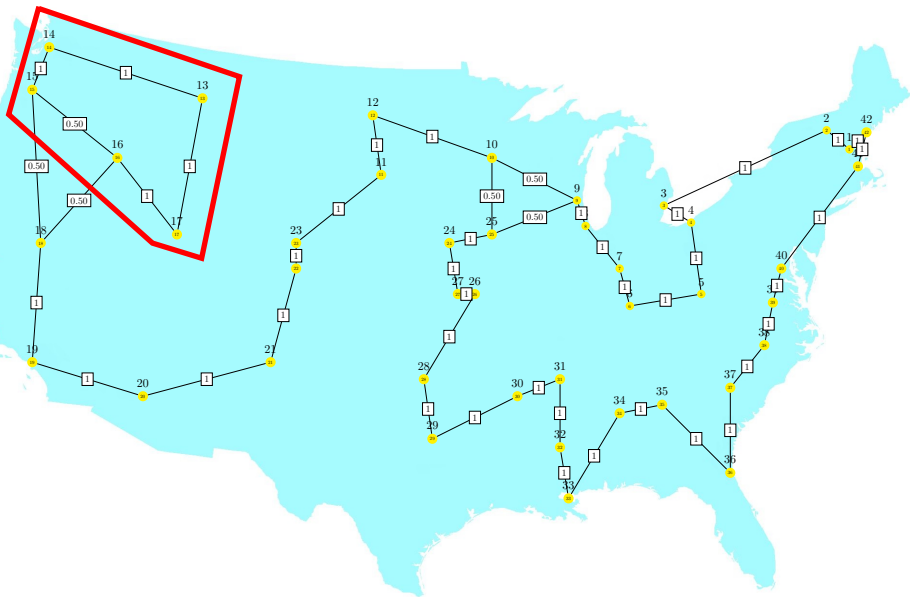
Iteration 3: Objective 681, Eliminate Subtour 24, 25, 26, 27



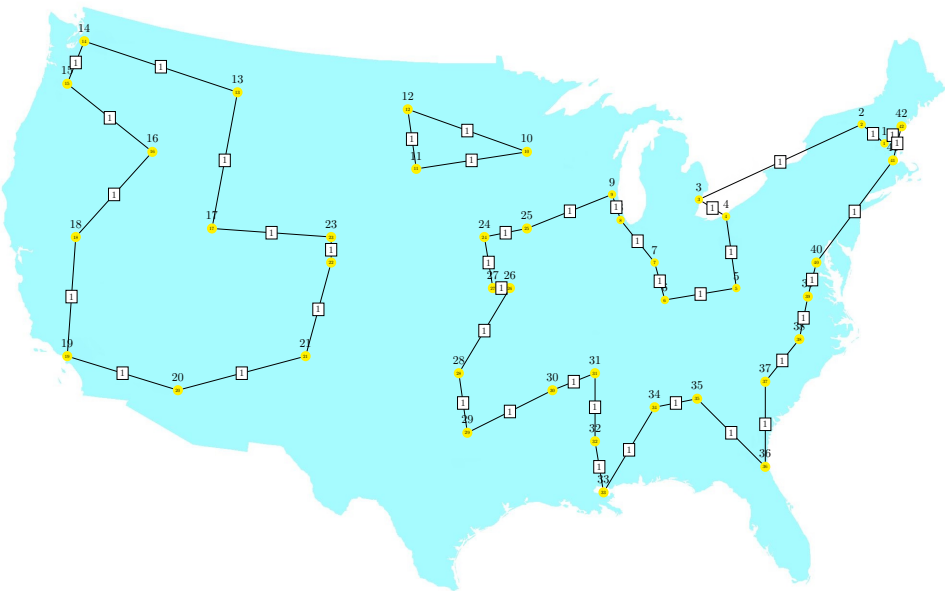
Iteration 4: Objective 682.5



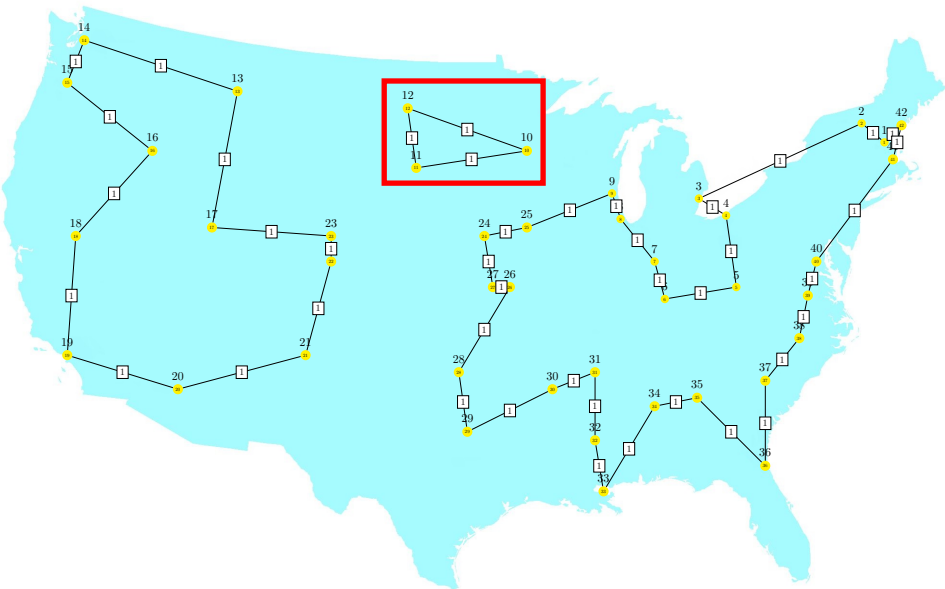
Iteration 4: Objective 682.5, Eliminate Small Cut by 13 – 17



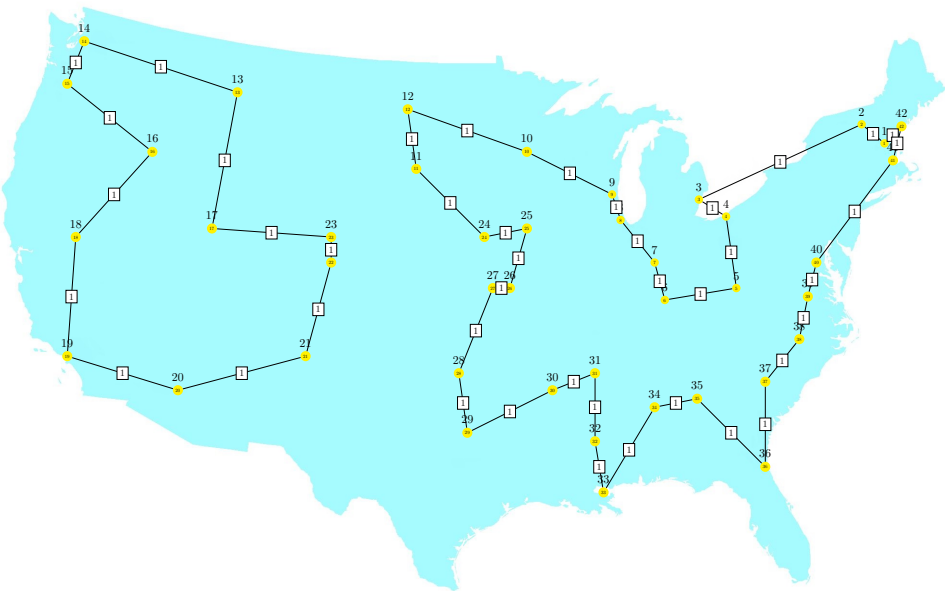
Iteration 5: Objective 686



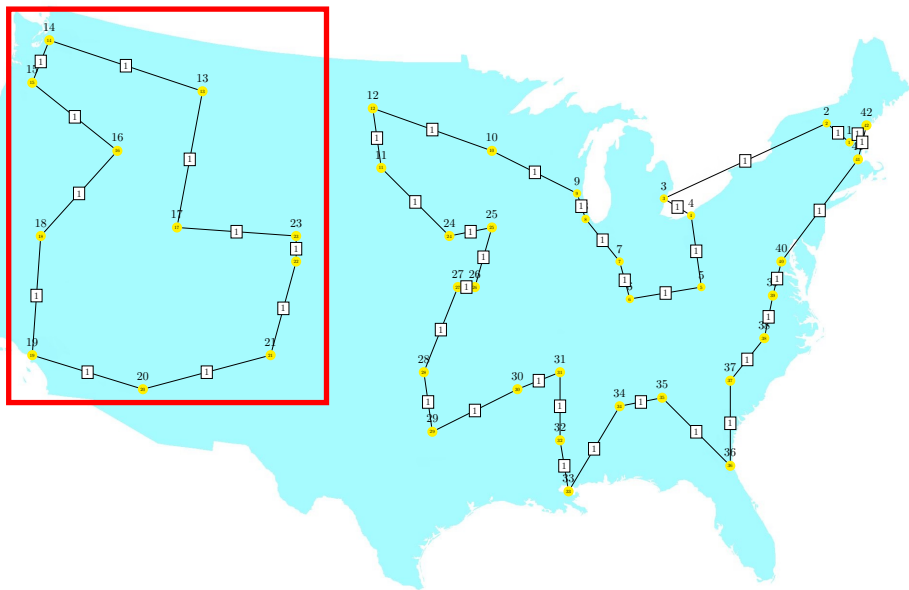
Iteration 5: Objective 686, Eliminate Subtour 10, 11, 12



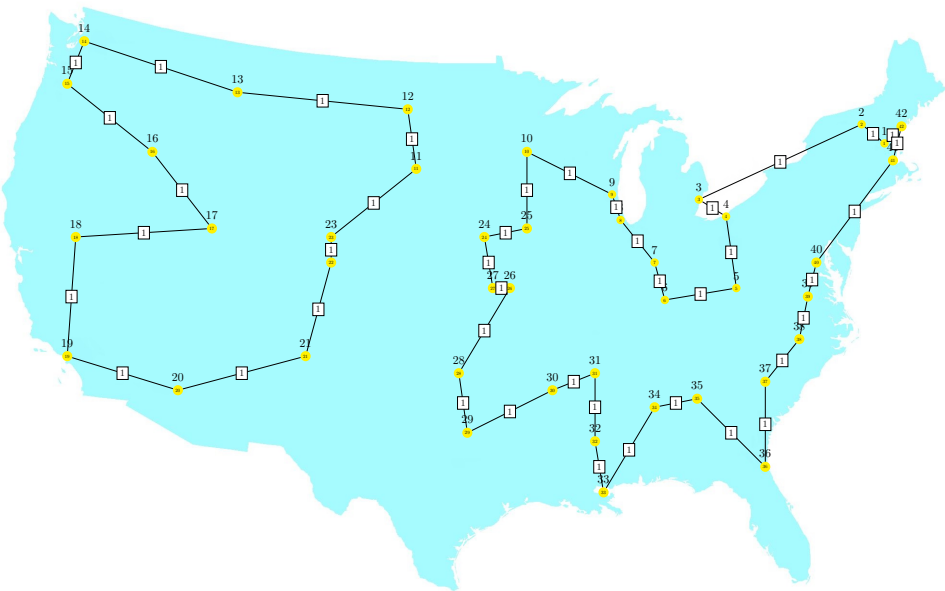
Iteration 6: Objective 686



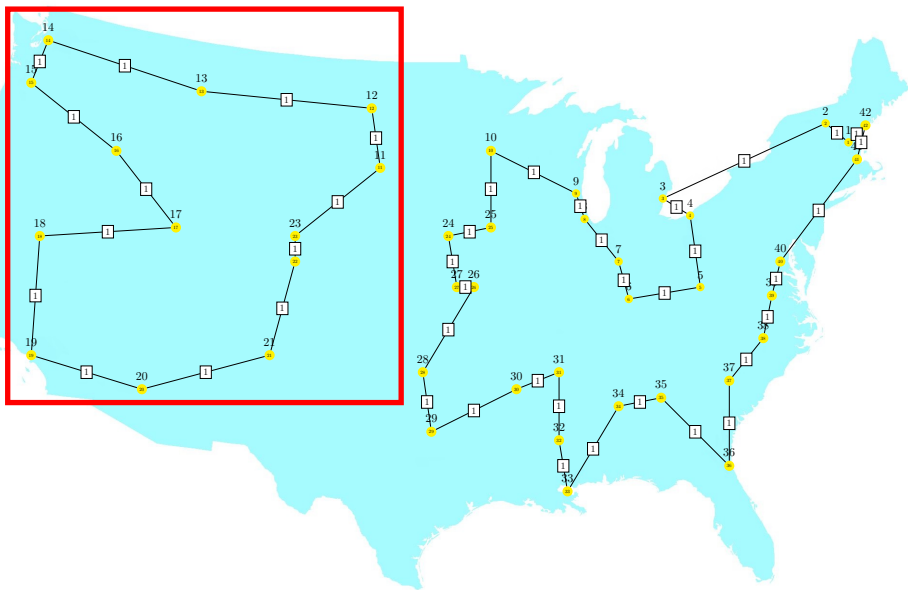
Iteration 6: Objective 686, Eliminate Subtour 13 – 23



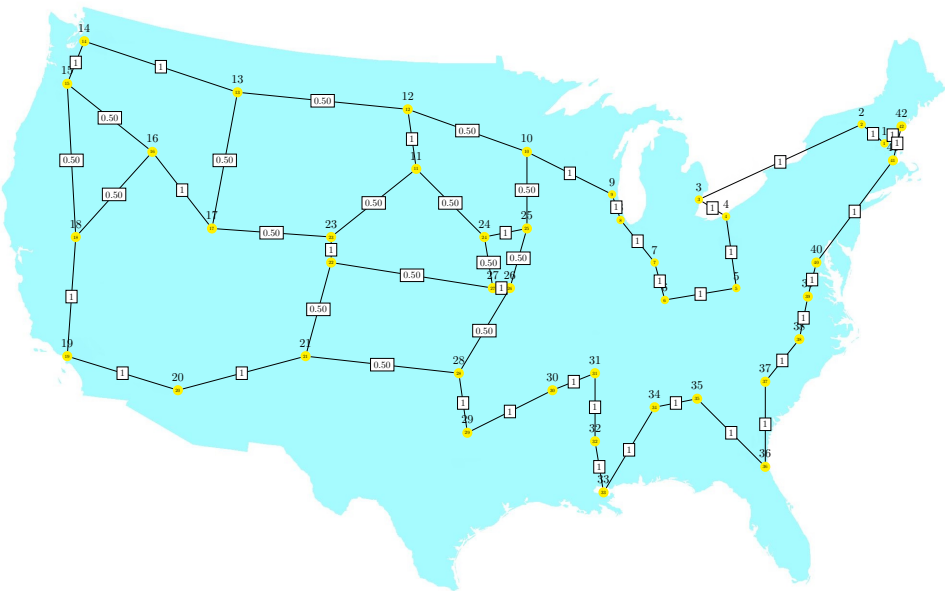
Iteration 7: Objective 688



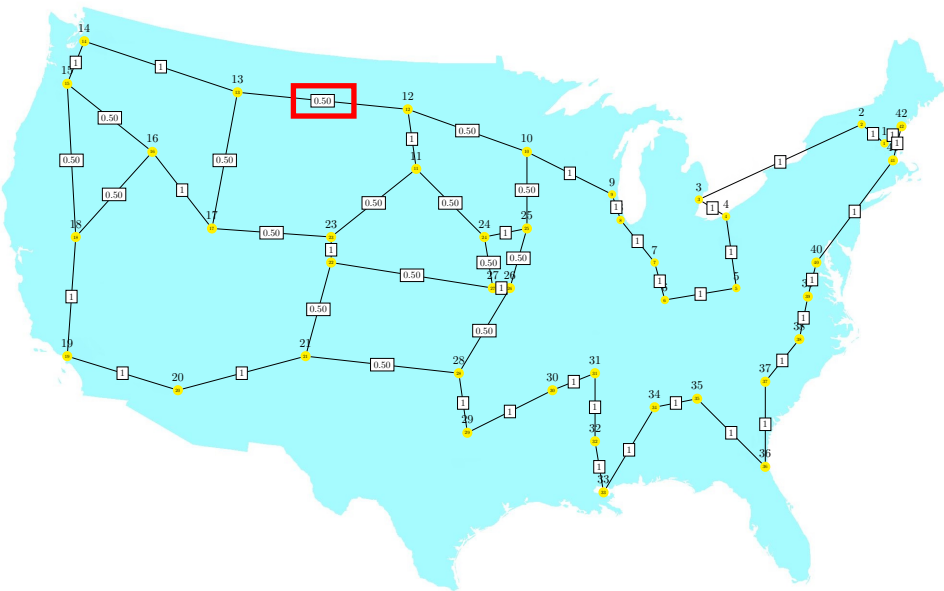
Iteration 7: Objective 688, Eliminate Subtour 11 – 23



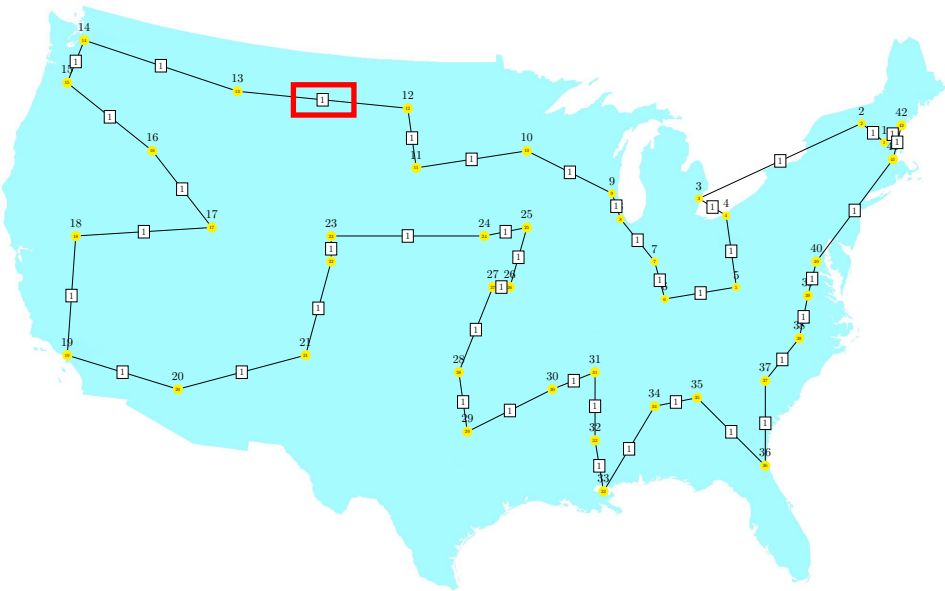
Iteration 8: Objective 697



Iteration 8: Objective 697, Branch on $x(13, 12)$



Iteration 9, Branch a $x(13, 12) = 1$: Objective 699 (Valid Tour)



Welcome to IBM(R) ILOG(R) CPLEX(R) Interactive Optimizer 12.6.1.0
with Simplex, Mixed Integer & Barrier Optimizers
5725-A06 5725-A29 5724-Y48 5724-Y49 5724-Y54 5724-Y55 5655-Y21
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Type 'help' for a list of available commands.
Type 'help' followed by a command name for more
information on commands.

```
CPLEX> read tsp.lp
Problem 'tsp.lp' read.
Read time = 0.00 sec. (0.06 ticks)
CPLEX> primopt
Tried aggregator 1 time.
LP Presolve eliminated 1 rows and 1 columns.
Reduced LP has 49 rows, 860 columns, and 2483 nonzeros.
Presolve time = 0.00 sec. (0.36 ticks)
```

```
Iteration log . . .
Iteration:    1   Infeasibility =          33.999999
Iteration:   26   Objective      =        1510.000000
Iteration:   90   Objective      =          923.000000
Iteration:  155   Objective      =          711.000000
```

```
Primal simplex - Optimal: Objective = 6.9900000000e+02
Solution time =    0.00 sec. Iterations = 168 (25)
Deterministic time = 1.16 ticks (288.86 ticks/sec)
```

CPLEX> █

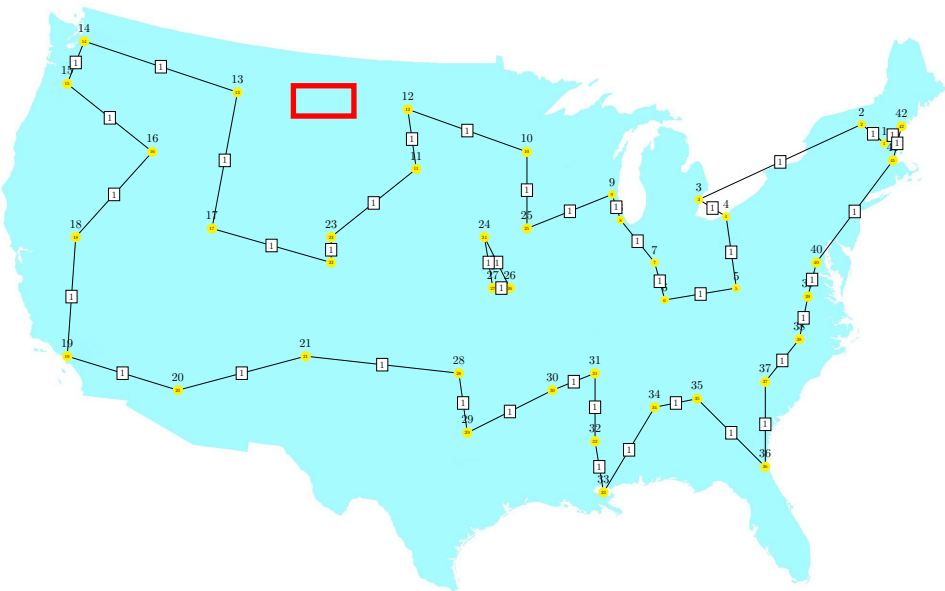


```
CPLEX> display solution variables -
Variable Name      Solution Value
x_2_1              1.000000
x_42_1             1.000000
x_3_2              1.000000
x_4_3              1.000000
x_5_4              1.000000
x_6_5              1.000000
x_7_6              1.000000
x_8_7              1.000000
x_9_8              1.000000
x_10_9             1.000000
x_11_10            1.000000
x_12_11            1.000000
x_13_12            1.000000
x_14_13            1.000000
x_15_14            1.000000
x_16_15            1.000000
x_17_16            1.000000
x_18_17            1.000000
x_19_18            1.000000
x_20_19            1.000000
x_21_20            1.000000
x_22_21            1.000000
x_23_22            1.000000
x_24_23            1.000000
x_25_24            1.000000
x_26_25            1.000000
x_27_26            1.000000
x_28_27            1.000000
x_29_28            1.000000
x_30_29            1.000000
x_31_30            1.000000
x_32_31            1.000000
x_33_32            1.000000
x_34_33            1.000000
x_35_34            1.000000
x_36_35            1.000000
x_37_36            1.000000
x_38_37            1.000000
x_39_38            1.000000
x_40_39            1.000000
x_41_40            1.000000
x_42_41            1.000000
```

All other variables in the range 1-861 are 0.



Iteration 10, Branch b $x(13, 12) = 0$: Objective 701



Thank you for attending this course &
Best wishes for the rest of your Tripos!

- Don't forget to visit the [online feedback](#) page!
- Please send comments on the slides to:
tms41@cam.ac.uk

