IV. Approximation Algorithms: Covering Problems

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UNIVERSITY OF CAMBRIDGE

Outline

Introduction

Vertex Cover

The Set-Covering Problem

Motivation

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2. Isolate important special cases which can be solved in polynomial-time.
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We will call these **approximation algorithms**.

Performance Ratios for Approximation Algorithms

Approximation Ratio

An algorithm for a problem has approximation ratio $\rho(n)$, if for any input of size n, the cost C of the returned solution and optimal cost C^* satisfy:

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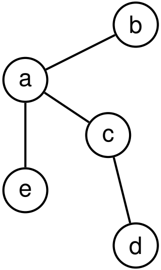
Vertex Cover Problem

- Given: Undirected graph $G = (V, E)$
- Goal: Find a minimum-cardinality subset $V' \subseteq V$ such that if $(u, v) \in E(G)$, then $u \in V'$ or $v \in V'$.



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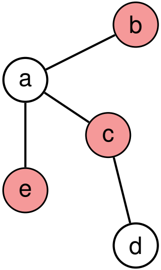

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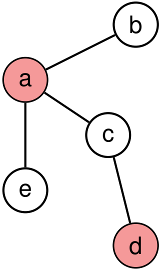

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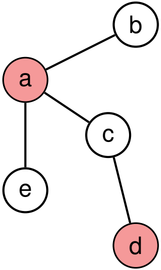

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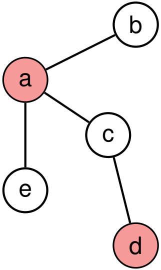

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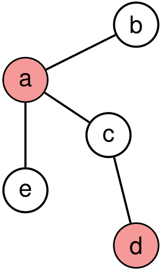

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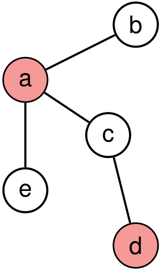

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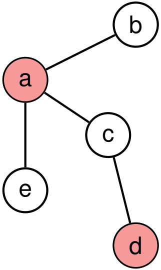

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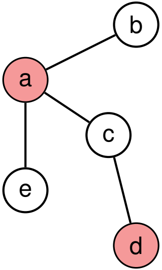

Applications:

- Every edge forms a task, and every vertex represents a person/machine which can execute that task
- Perform all tasks with the minimal amount of resources
- Extensions: weighted vertices or hypergraphs ($\rightsquigarrow$ Set-Covering Problem)

An Approximation Algorithm based on Greedy

APPROX-VERTEX-COVER(G)

$C = \emptyset$
$E' = G.E$
while $E' \neq \emptyset$
    let (u, v) be an arbitrary edge of E'
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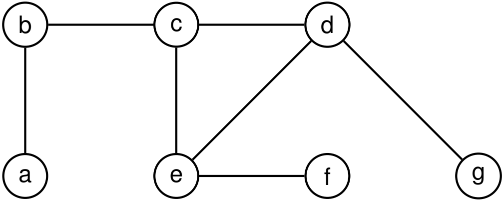

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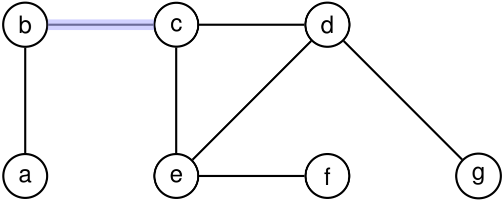

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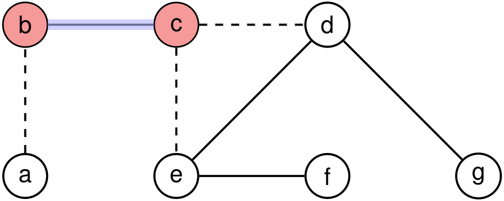

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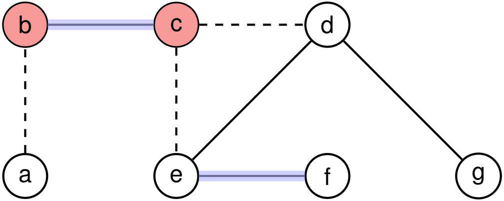

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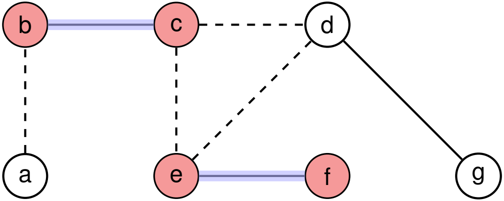

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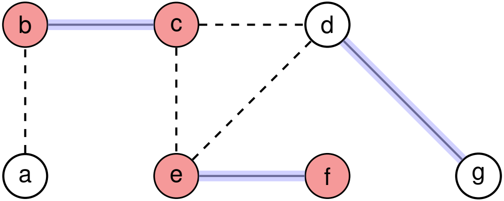

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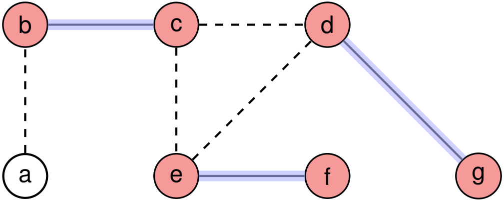

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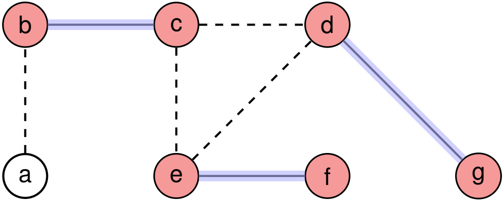

APPROX-VERTEX-COVER produces a set of size 6.

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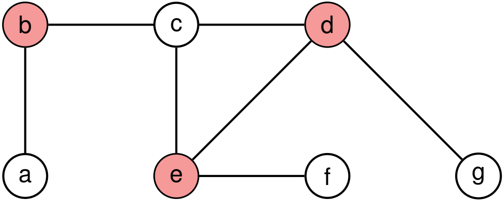

The optimal solution has size 3.

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Theorem 35.1

APPROX-VERTEX-COVER is a poly-time 2-approximation algorithm.

Proof:

- Running time is $O(V + E)$ (using adjacency lists to represent E')
- Let $A \subseteq E$ denote the set of edges picked in line 4
- Every optimal cover C^* must include at least one endpoint of edges in A, and edges in A do not share a common endpoint: $\boxed{|C^*| \geq |A|}$
- Every edge in A contributes 2 vertices to $|C|$: $\boxed{|C| = 2|A| \leq 2|C^*|.}$

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We can bound the size of the returned solution without knowing the (size of an) optimal solution!

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A "vertex-based" Greedy that adds **one** vertex at each iteration fails to achieve an approximation ratio of 2 (Exercise)!

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Solving Special Cases

Strategies to cope with NP-complete problems

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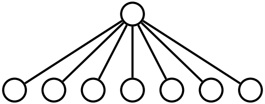

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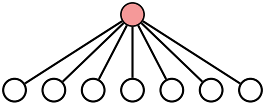

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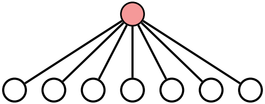

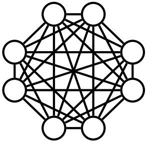

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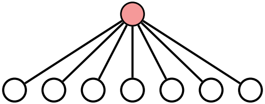

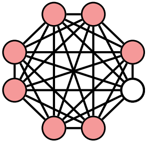

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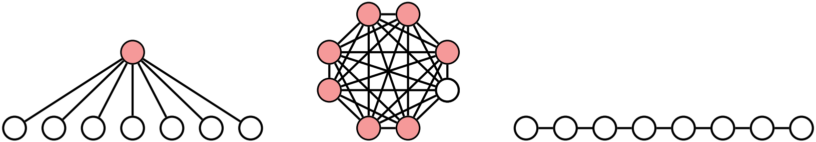

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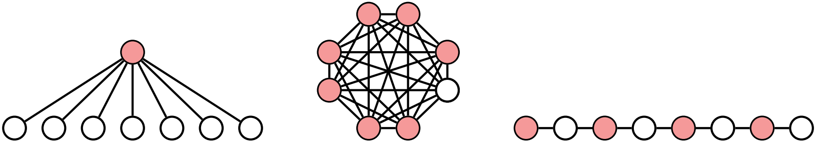
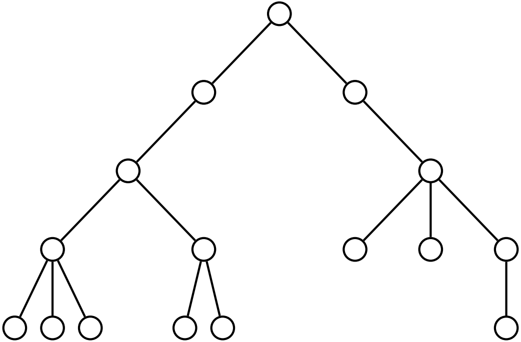


Vertex Cover on Trees



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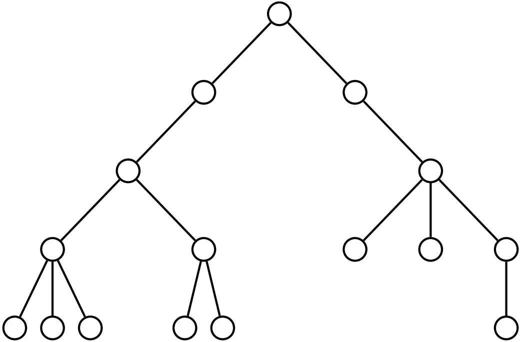

There exists an optimal vertex cover which does not include any leaves.

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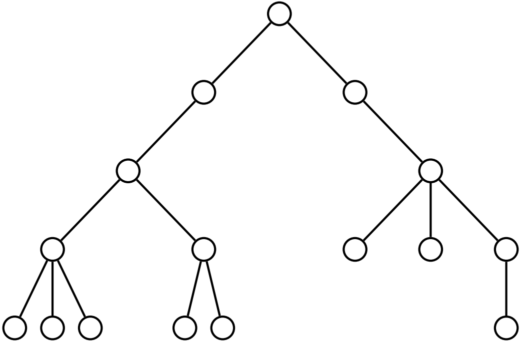

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Exchange-Argument: Replace any leaf in the cover by its parent.

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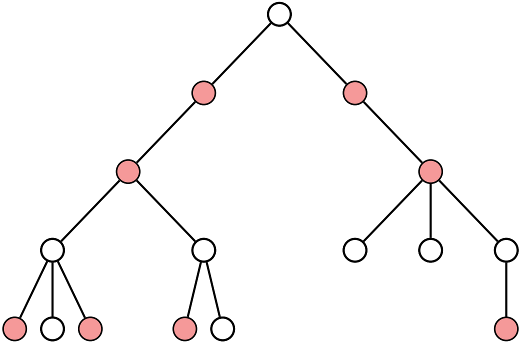

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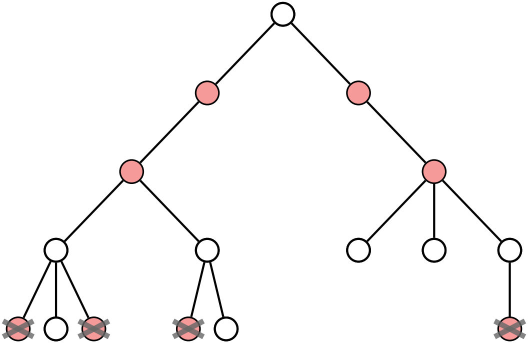

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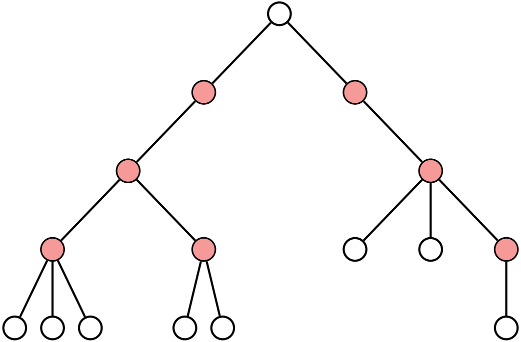

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C = ∅
while ∃ leaves in G
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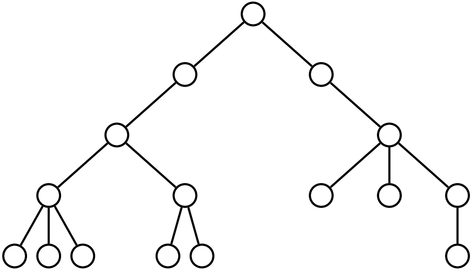
Solution is also optimal. (Use inductively the existence of an optimal vertex cover without leaves)

Execution on a Small Example



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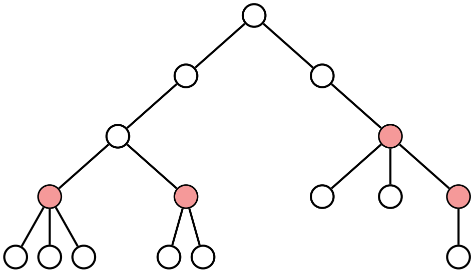

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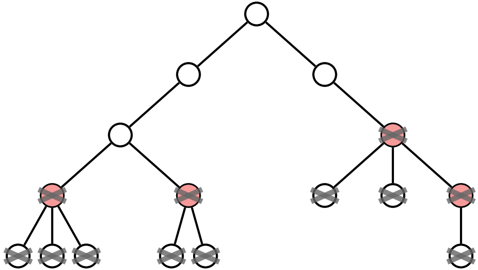

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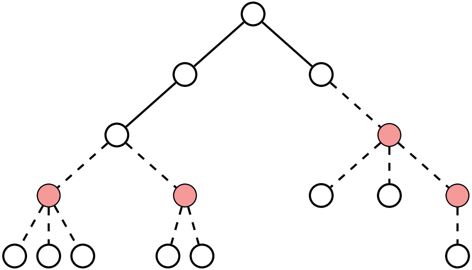

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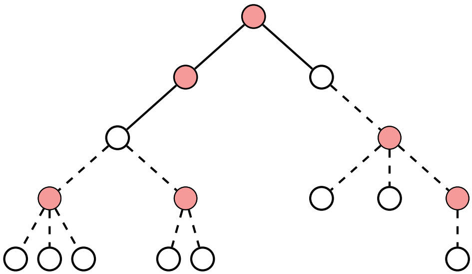

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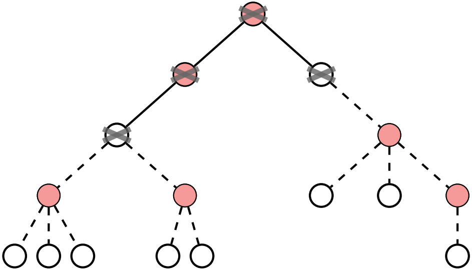

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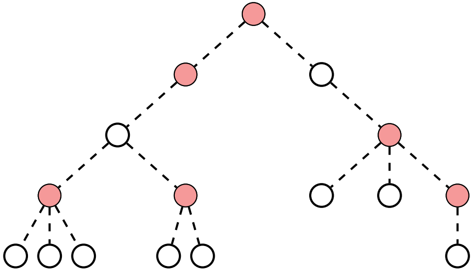

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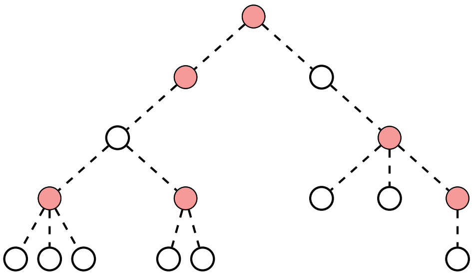

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Problem can be also solved on bipartite graphs, using Max-Flows and Min-Cuts.

Exact Algorithms

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Simple Brute-Force Search would take $\approx \binom{n}{k} = \Theta(n^k)$ time.

Towards a more efficient Search

Substructure Lemma

Consider a graph $G = (V, E)$, edge $\{u, v\} \in E(G)$ and integer $k \geq 1$. Let G_u be the graph obtained by deleting u and its incident edges (G_v is defined similarly). Then G has a vertex cover of size k if and only if G_u or G_v (or both) have a vertex cover of size $k - 1$.

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Reminiscent of Dynamic Programming.

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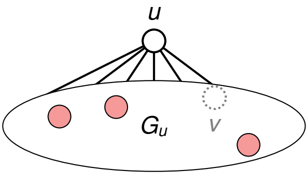

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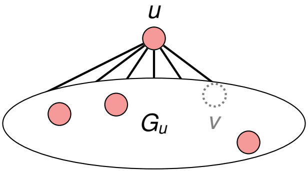

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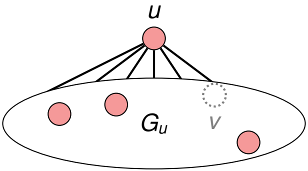

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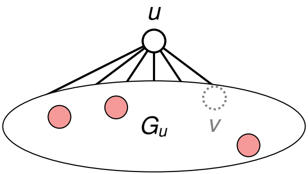
Removing u from C yields a vertex cover of G_u which is of size $k - 1$. □



A More Efficient Search Algorithm

$\textsc{Vertex-Cover-Search}(G, k)$

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If $k = 0$ and $E \neq \emptyset$ **return** $\perp$
Pick an arbitrary edge $(u, v) \in E$
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Correctness follows by the Substructure Lemma and induction.

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- $O(E)$ work per recursive call

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```
If E = ∅ return ∅
If k = 0 and E ≠ ∅ return ⊥
Pick an arbitrary edge (u, v) ∈ E
S_1 = Vertex-Cover-Search(G_u, k − 1)
S_2 = Vertex-Cover-Search(G_v, k − 1)
if S_1 ≠ ⊥ return S_1 ∪ {u}
if S_2 ≠ ⊥ return S_2 ∪ {v}
return ⊥
```

Running time:

- Depth k, branching factor 2 $\Rightarrow$ total number of calls is $O(2^k)$
- $O(E)$ work per recursive call
- Total runtime: $O(2^k \cdot E)$.

A More Efficient Search Algorithm

VERTEX-COVER-SEARCH(G, k)

If $E = \emptyset$ **return** $\emptyset$
If $k = 0$ and $E \neq \emptyset$ **return** $\perp$
Pick an arbitrary edge $(u, v) \in E$
$S_1 =$ VERTEX-COVER-SEARCH$(G_u, k-1)$
$S_2 =$ VERTEX-COVER-SEARCH$(G_v, k-1)$
if $S_1 \neq \perp$ **return** $S_1 \cup \{u\}$
if $S_2 \neq \perp$ **return** $S_2 \cup \{v\}$
return $\perp$

Running time:

- Depth k, branching factor 2 $\Rightarrow$ total number of calls is $O(2^k)$
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exponential in k, but much better than $\Theta(n^k)$ (i.e., still polynomial for $k = O(\log n)$)

Outline

Introduction

Vertex Cover

The Set-Covering Problem

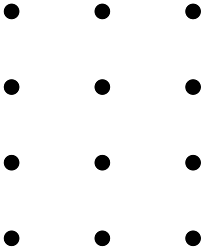
The Set-Covering Problem

Set Cover Problem

- Given: set X of size n and family of subsets $\mathcal{F}$
- Goal: Find a minimum-size subset $\mathcal{C} \subseteq \mathcal{F}$

$$\text{s.t.} \qquad X = \bigcup_{S \in \mathcal{C}} S.$$

The Set-Covering Problem



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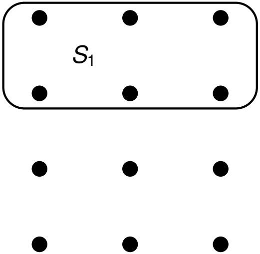

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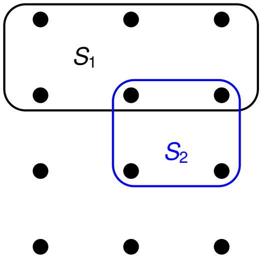

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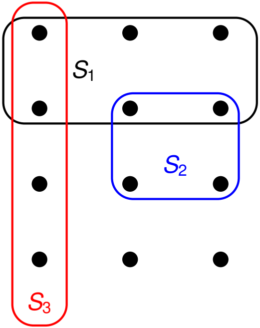

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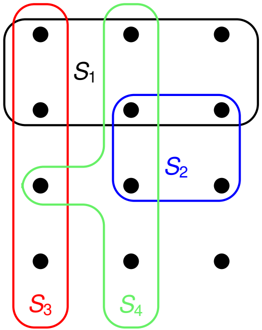

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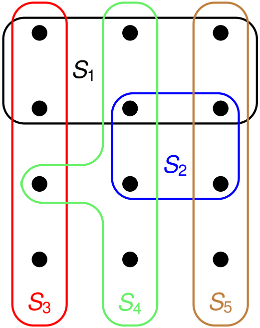

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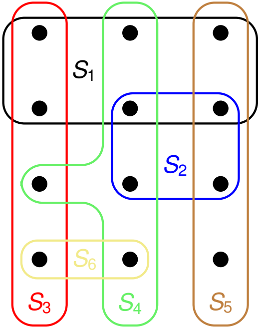

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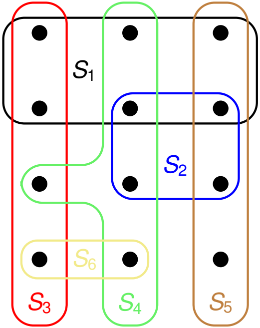

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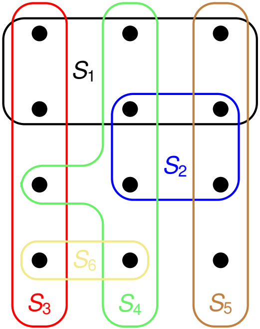

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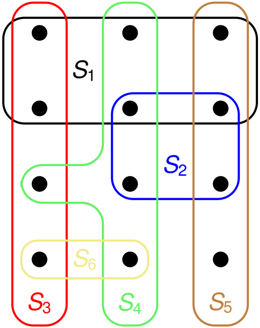

Remarks:

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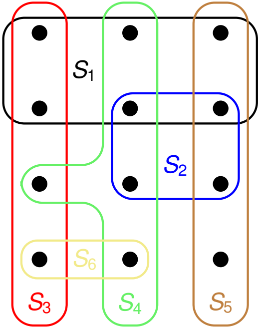

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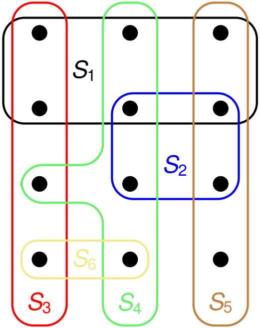

Remarks:

- generalisation of the vertex-cover problem and hence also NP-hard.
- models resource allocation problems

Greedy

Strategy: Pick the set S that covers the largest number of uncovered elements.

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GREEDY-SET-COVER$(X, \mathcal{F})$

$U = X$
$\mathcal{C} = \emptyset$
while $U \neq \emptyset$
    select an $S \in \mathcal{F}$ that maximizes $|S \cap U|$
    $U = U - S$
    $\mathcal{C} = \mathcal{C} \cup \{S\}$
return $\mathcal{C}$

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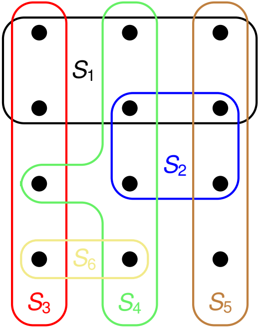

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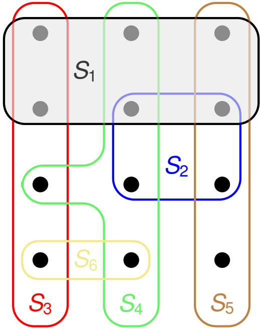

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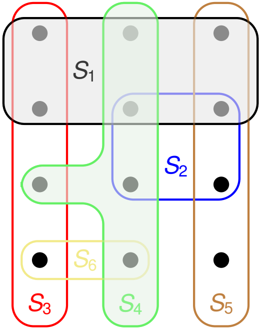
return C
```



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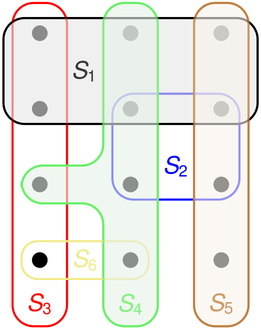

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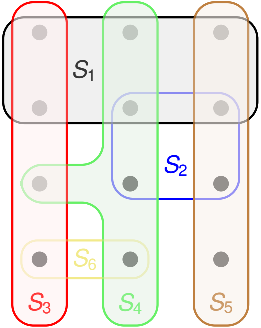

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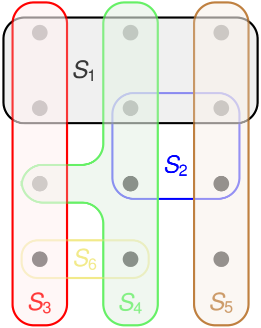

Greedy chooses S_1, S_4, S_5 and S_3 (or S_6), which is a cover of size 4.

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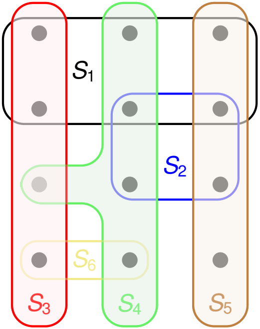

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Optimal cover is $\mathcal{C} = \{S_3, S_4, S_5\}$

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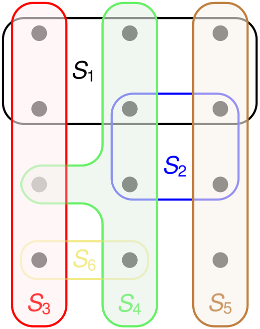
Can be easily implemented to run in time polynomial in $|X|$ and $|\mathcal{F}|$



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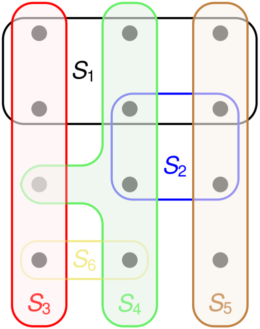

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How good is the approximation ratio?

Approximation Ratio of Greedy

Theorem 35.4

GREEDY-SET-COVER is a polynomial-time $\rho(n)$-algorithm, where

$$\rho(n) = H(\max\{|S| : |S| \in \mathcal{F}\})$$

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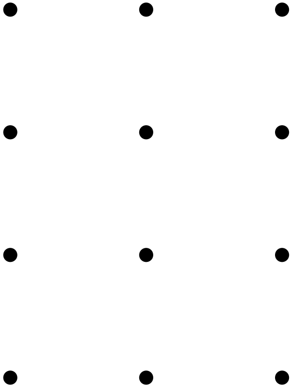
Notice that in the mathematical analysis, S_i is the set chosen in iteration i - not to be confused with the sets $S_1, S_2, \ldots, S_6$ in the example.

Illustration of Costs for Greedy picking S_1, S_4, S_5 and S_3



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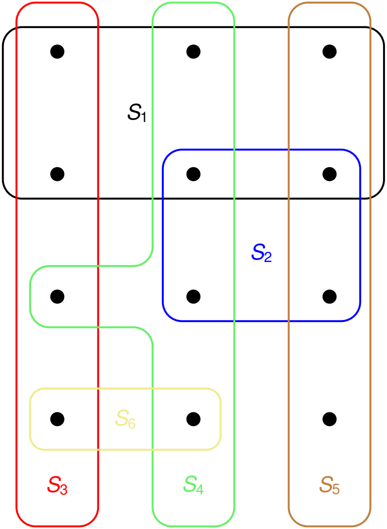

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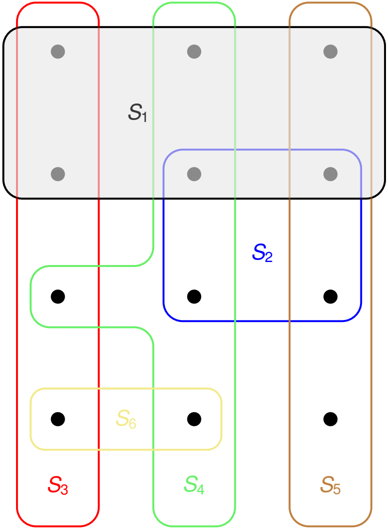

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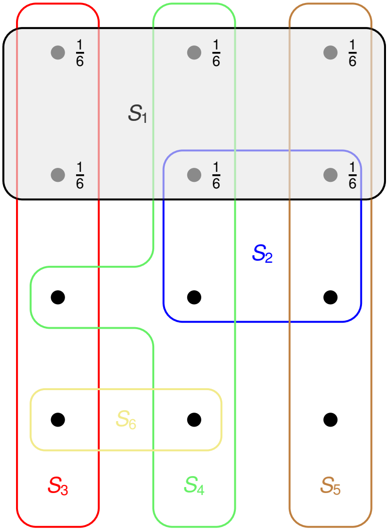

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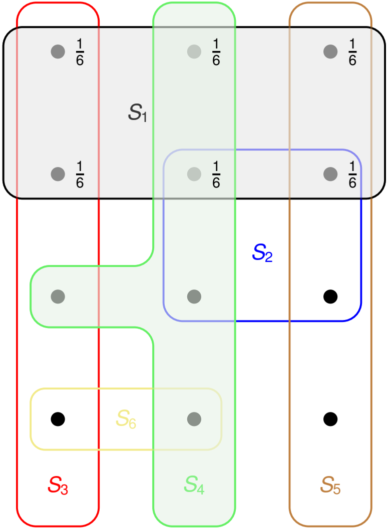

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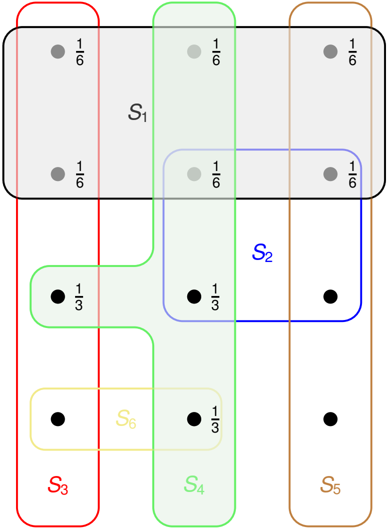

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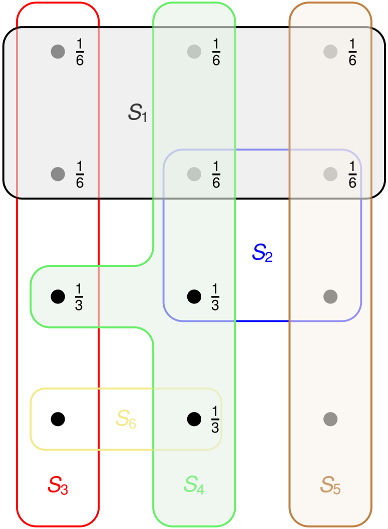

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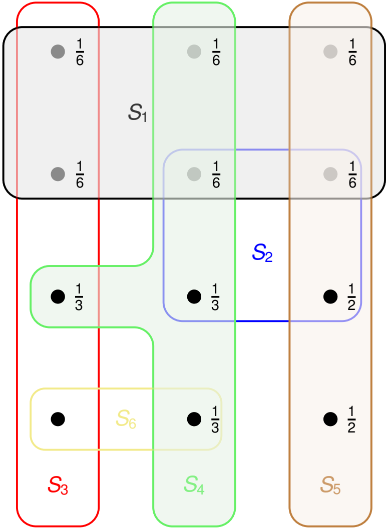

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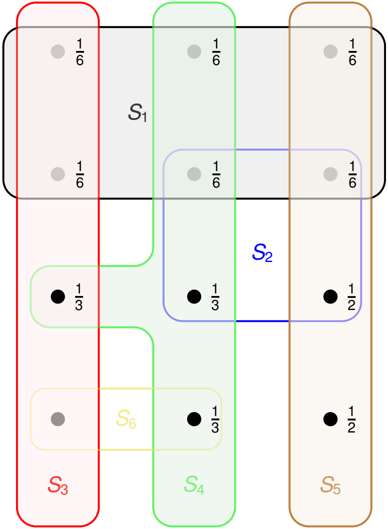

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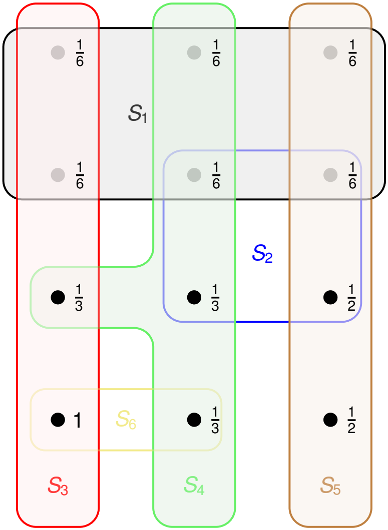

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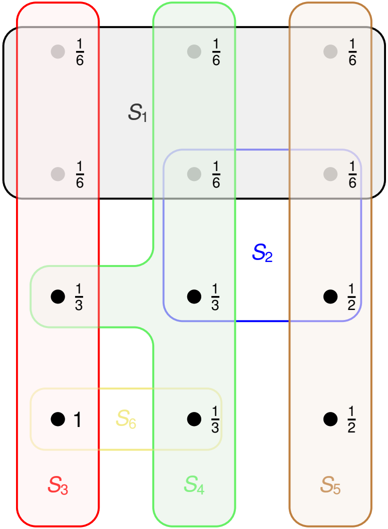

$$\frac{1}{6}+\frac{1}{6}+\frac{1}{6}+\frac{1}{6}+\frac{1}{6}+\frac{1}{6}+\frac{1}{3}+\frac{1}{3}+\frac{1}{3}+\frac{1}{2}+\frac{1}{2}+1 = ??$$

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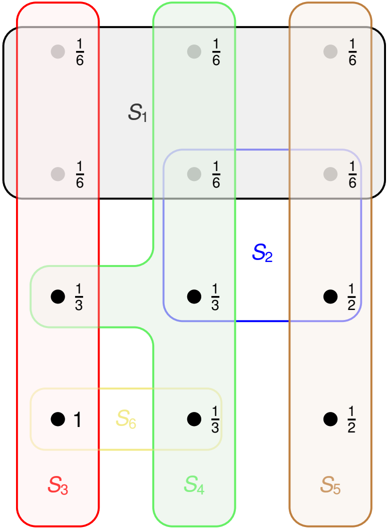

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Proof of Theorem 35.4 (1/2)

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(1)

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$$|\mathcal{C}| = \sum_{x \in X} c_x \tag{1}$$

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If x is covered for the first time by a set S_i, then $c_x := \frac{1}{\left|S_i \setminus (S_1 \cup S_2 \cup \cdots \cup S_{i-1})\right|}$.

Proof.

- Each step of the algorithm assigns one unit of cost, so

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Set-Covering Problem (Summary)

Theorem 35.4

GREEDY-SET-COVER is a polynomial-time $\rho(n)$-algorithm, where

$$\rho(n) = H(\max\{|S| : |S| \in \mathcal{F}\}) \leq \ln(n) + 1.$$

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The same approach also gives an approximation ratio of $O(\ln(n))$ if there exists a cost function $c : S \to \mathbb{Z}^+$

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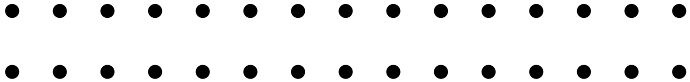

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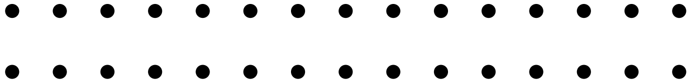

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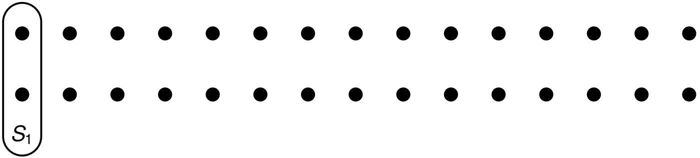
$k = 4, n = 30$:



Example where the solution of Greedy is bad

Instance

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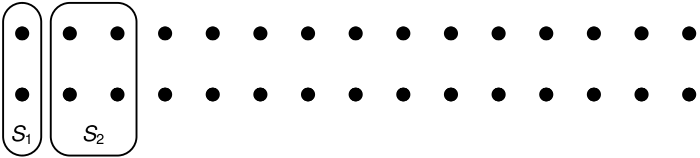

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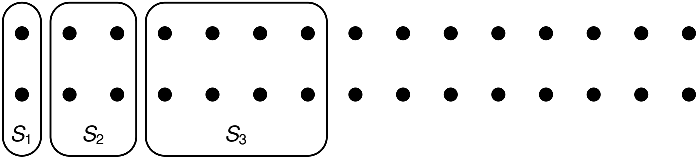

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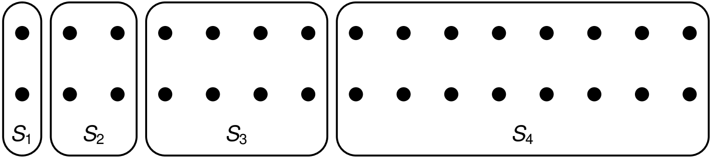

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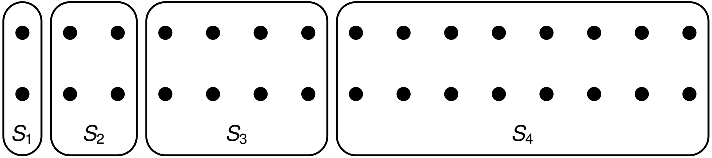

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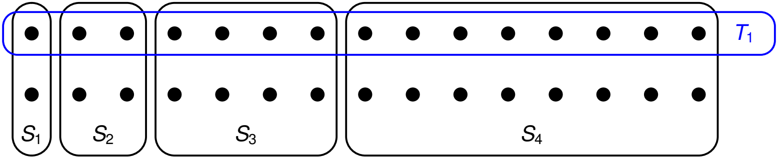

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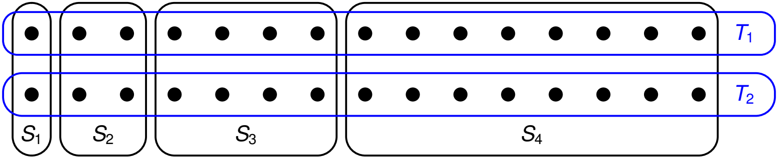

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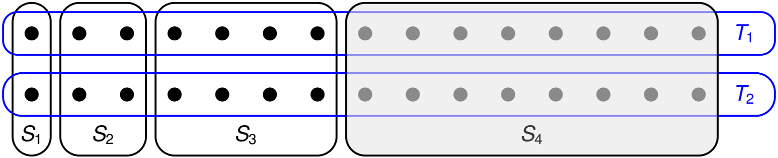

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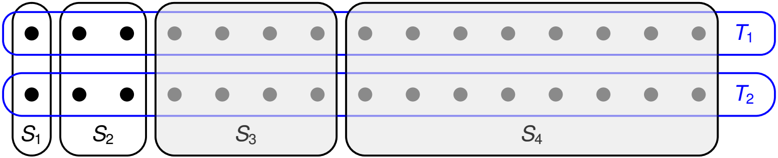

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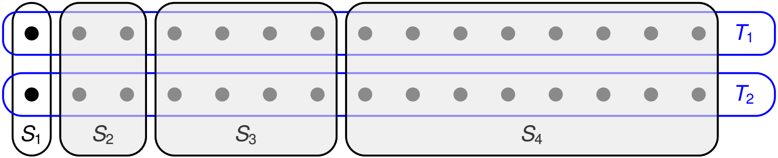

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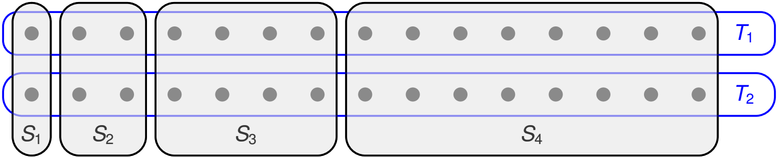

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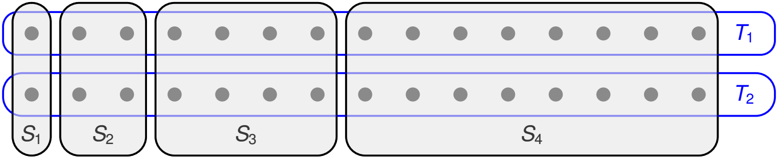

Solution of Greedy consists of k sets.

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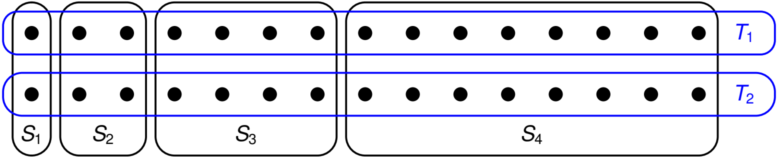

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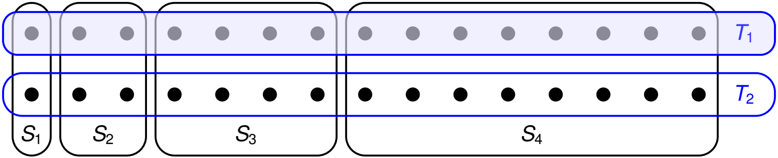

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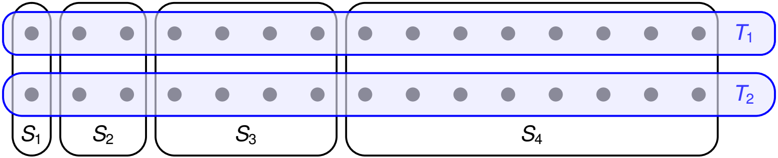

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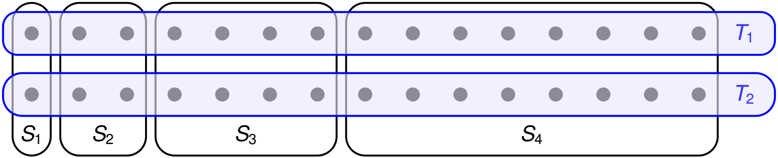

Solution of Greedy consists of k sets.

Optimum consists of 2 sets.