

Analysis of Greedy for Vertex Cover

APPROX-VERTEX-COVER(G)

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2  $E' = G.E$ 
3 while  $E' \neq \emptyset$ 
4   let  $(u, v)$  be an arbitrary edge of  $E'$ 
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6   remove from  $E'$  every edge incident on either  $u$  or  $v$ 
7 return  $C$ 
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→ A "vertex-based" Greedy-Alg. which adds one vertex at each iteration does not achieve approx. ratio of 2 (Exercise 18)

Theorem 35.1

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



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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: $|C^*| \geq |A|$

- Every edge in A contributes 2 vertices to $|C|$: $|C| = 2|A| \leq 2|C^*|$. □



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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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Key idea: A is a maximal matching

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Solving Special Cases

Strategies to cope with NP-complete problems

1. If inputs are small, an algorithm with exponential running time may be satisfactory.
2. Isolate important special cases which can be solved in polynomial-time.
3. Develop algorithms which find near-optimal solutions in polynomial-time.



Solving Special Cases

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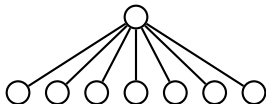
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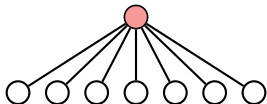
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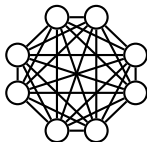
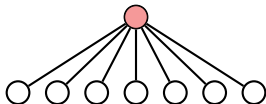
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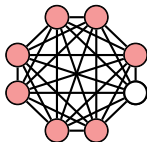
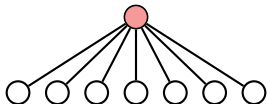
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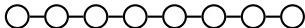
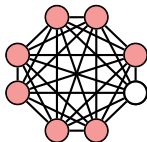
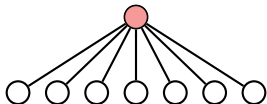
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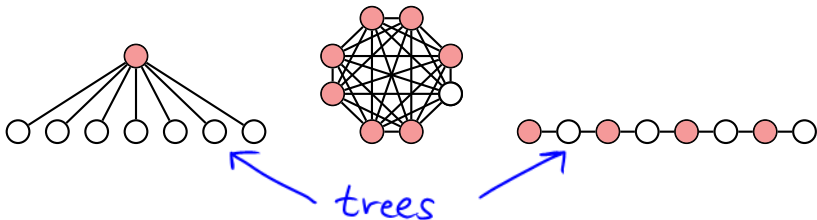
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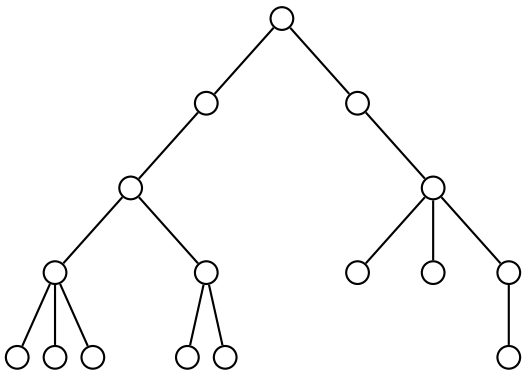
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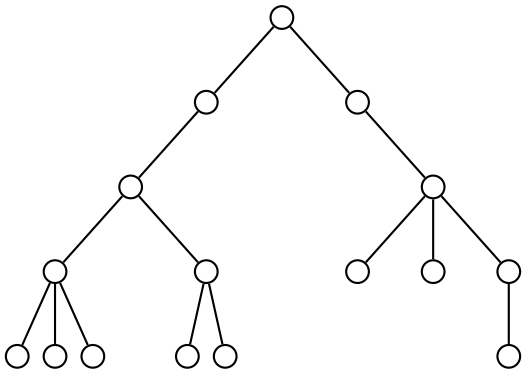
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Vertex Cover on Trees



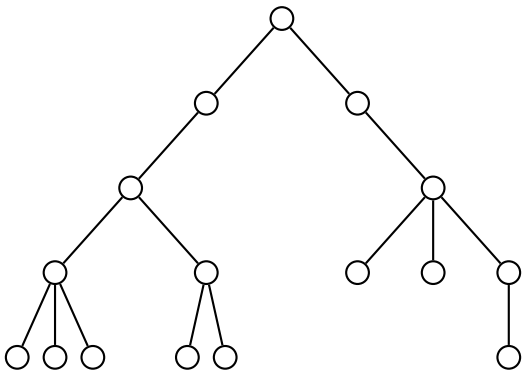
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There exists an **optimal vertex cover** which does not include any **leaves**.



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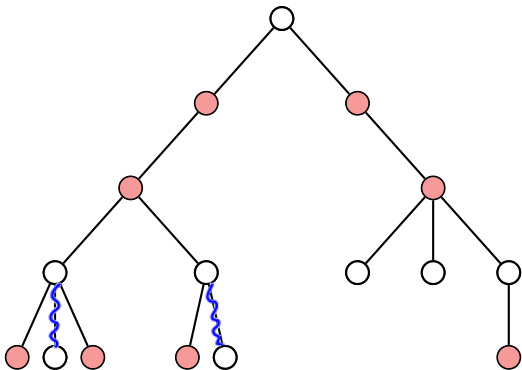


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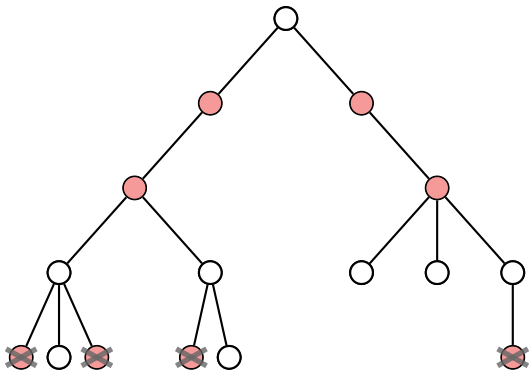


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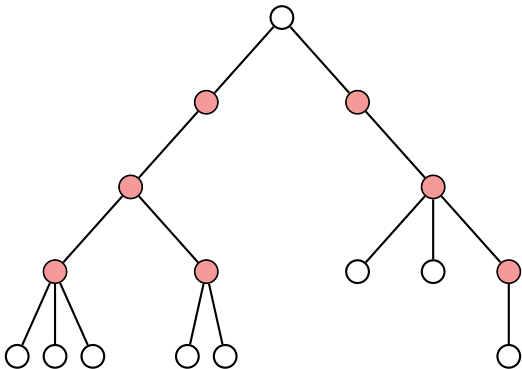


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VERTEX-COVER-TREES(G)

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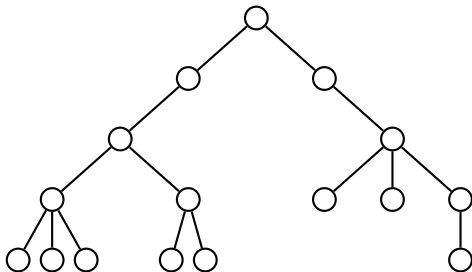
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Solution is also **optimal**. (Use inductively the existence of an optimal vertex cover without leaves)



Execution on a Small Example

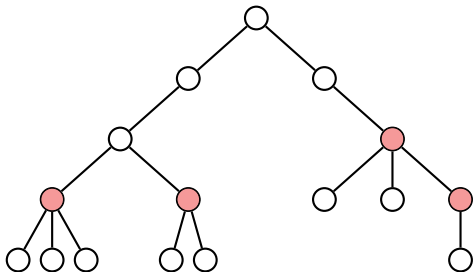


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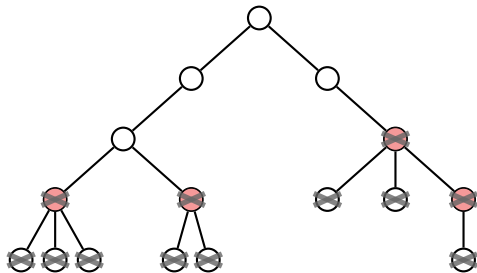


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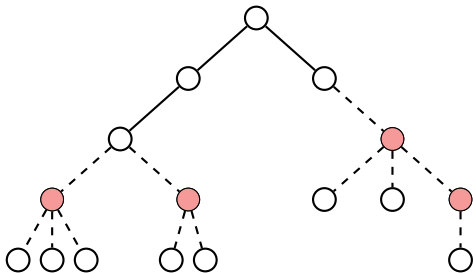


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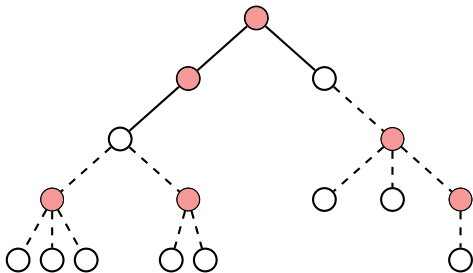


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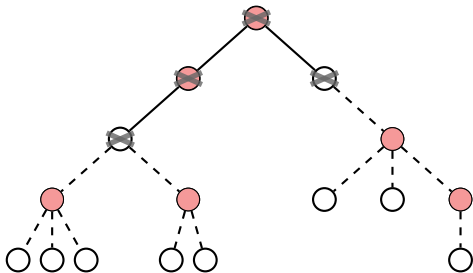


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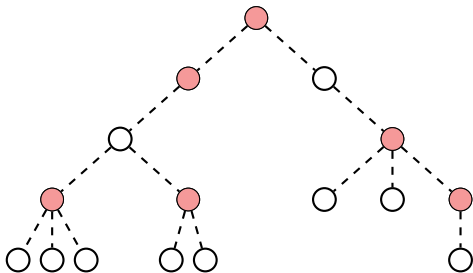


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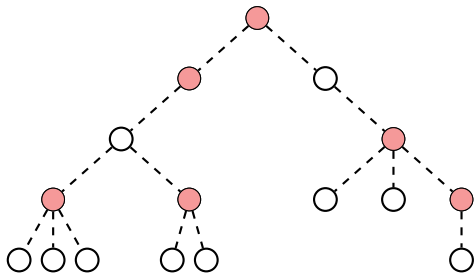


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Problem can be also solved on bipartite graphs, using Max-Flows and Min-Cuts.



Strategies to cope with NP-complete problems

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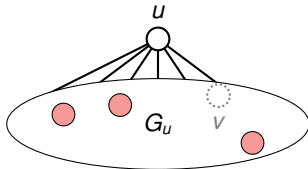
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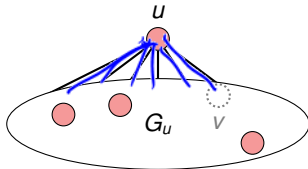
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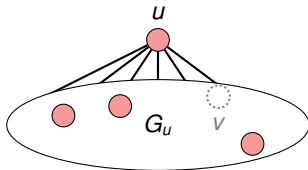
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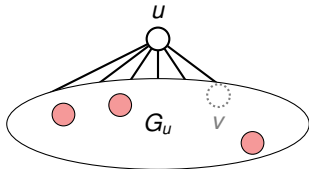
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Removing u from C yields a vertex cover of G_u which is of size $k - 1$. \square



A More Efficient Search Algorithm

VERTEX-COVER-SEARCH(G, k)

- 1: **If $E = \emptyset$ return $\{\perp\}$**
- 2: **If $k = 0$ and $E \neq \emptyset$ return \emptyset**
- 3: Pick an arbitrary edge $(u, v) \in E$
- 4: $S_1 = \text{VERTEX-COVER-SEARCH}(G_u, k - 1)$
- 5: $S_2 = \text{VERTEX-COVER-SEARCH}(G_v, k - 1)$
- 6: **if $S_1 \neq \emptyset$ return $S_1 \cup \{u\}$**
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Correctness follows by the Substructure Lemma and induction.



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Running time:

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Running time:

- Depth k , branching factor 2 \Rightarrow total number of calls is $O(2^k)$



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- $O(E)$ work per recursive call



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- 7: **if** $S_2 \neq \emptyset$ **return** $S_2 \cup \{v\}$
- 8: **return** \emptyset

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)

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

Running time:

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- $O(E)$ work per recursive call
- Total runtime: $O(2^k \cdot E)$.

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 $\mathcal{C} \subseteq \mathcal{F}$

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

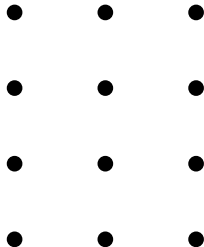


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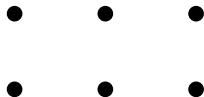
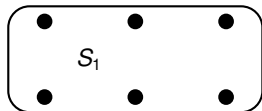


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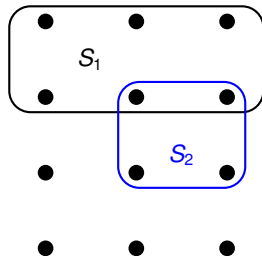


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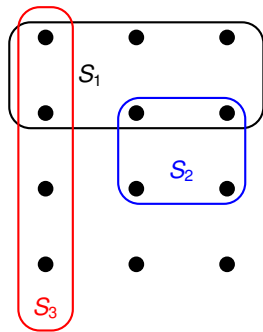


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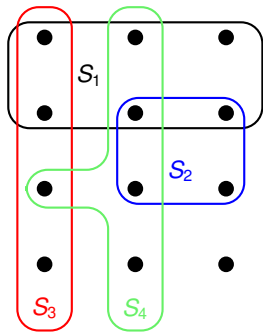


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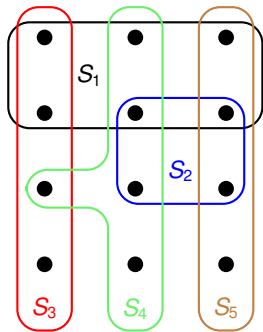


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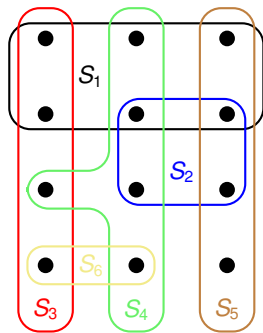


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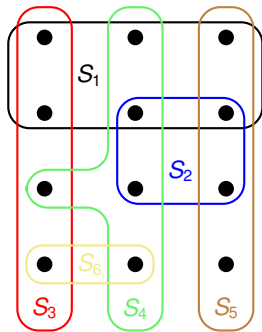
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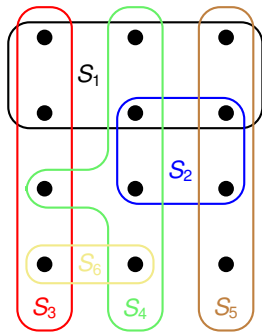
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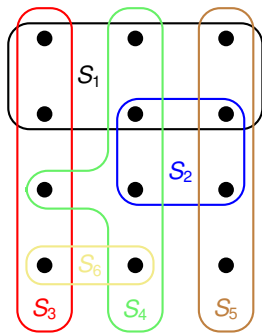
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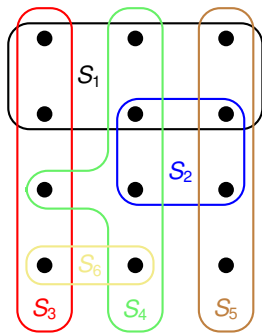
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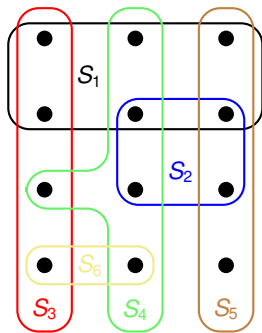
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Remarks:

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



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



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

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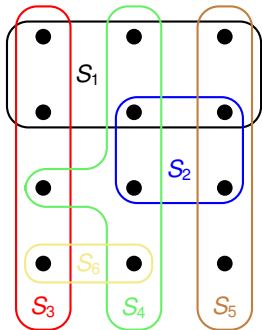


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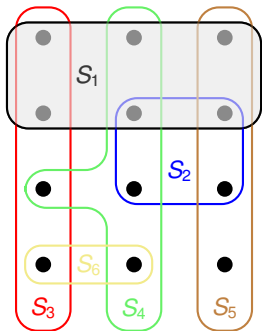


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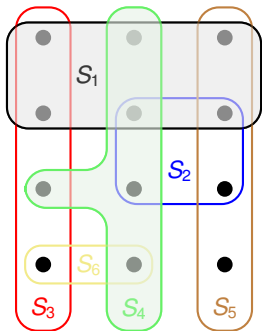


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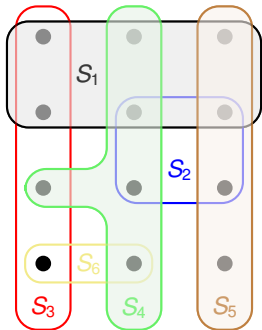


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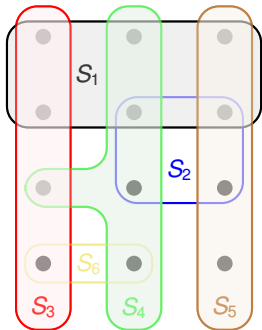


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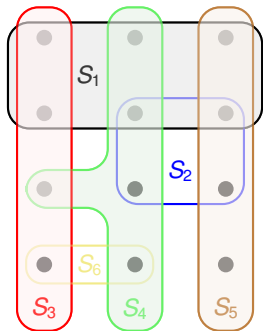


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Greedy chooses S_1, S_4, S_5 and S_3 (or S_6), which is a cover of size 4.

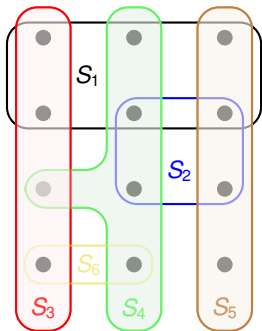


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Optimal cover is $\mathcal{C} = \{S_3, S_4, S_5\}$



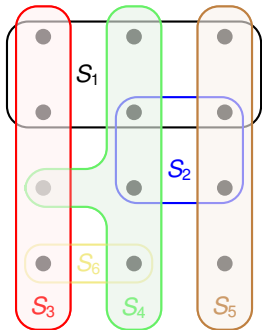
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Can be easily implemented to run
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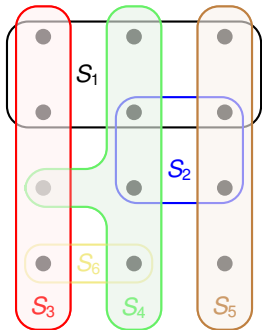
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How good is the approximation ratio?



Approximation Ratio of Greedy

Theorem 35.4

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

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

↓
in general, not a constant



Approximation Ratio of Greedy

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$$c_x := \frac{1}{|S_i \setminus (S_1 \cup S_2 \cup \dots \cup S_{i-1})|}.$$

(in the mathematical analysis, S_i is the set chosen in iteration i - not to be confused with S_1, S_2, \dots, S_6 in the example)



Illustration of Costs

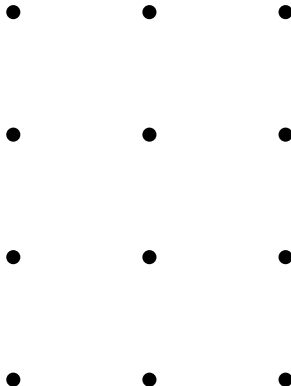


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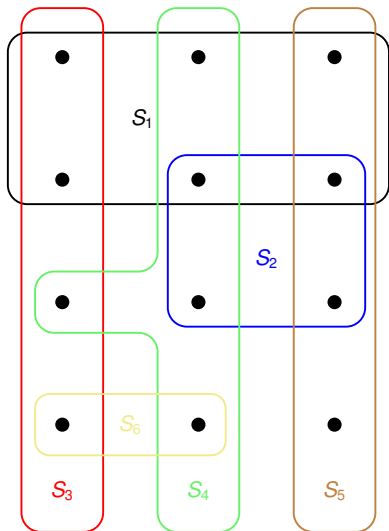


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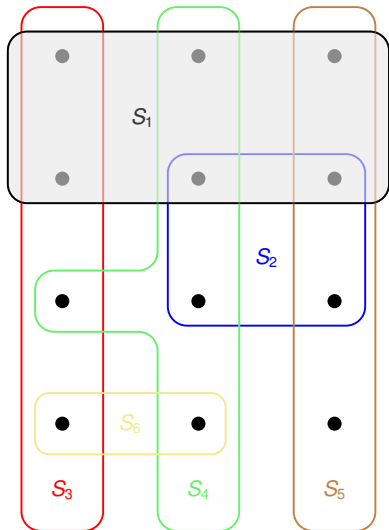


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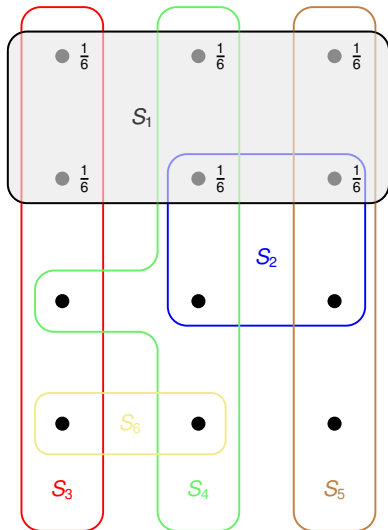


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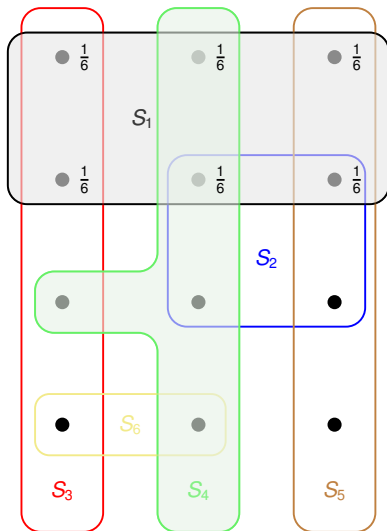


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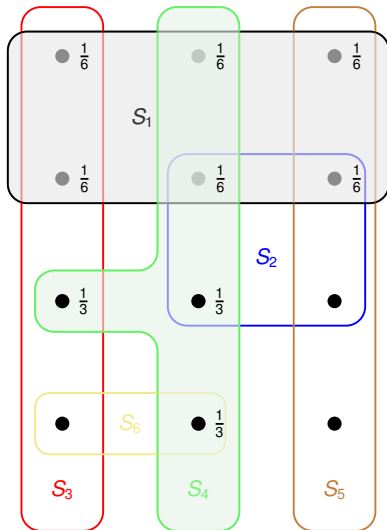


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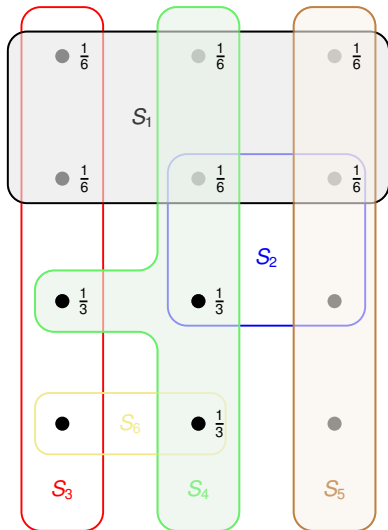


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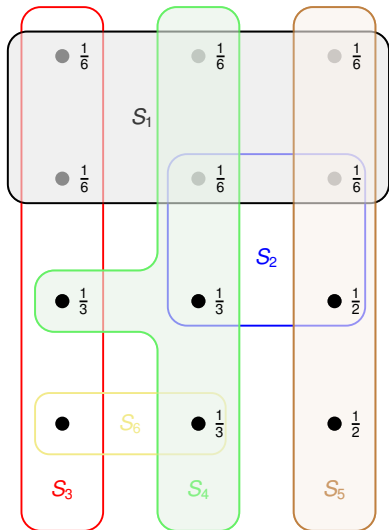


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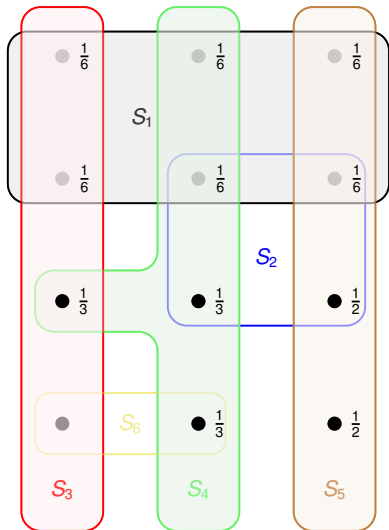


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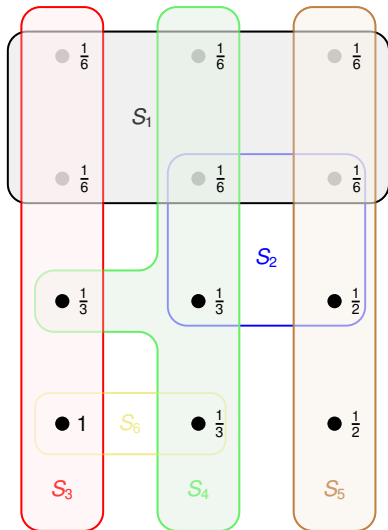
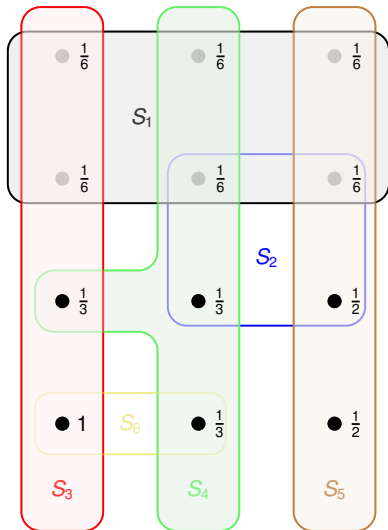


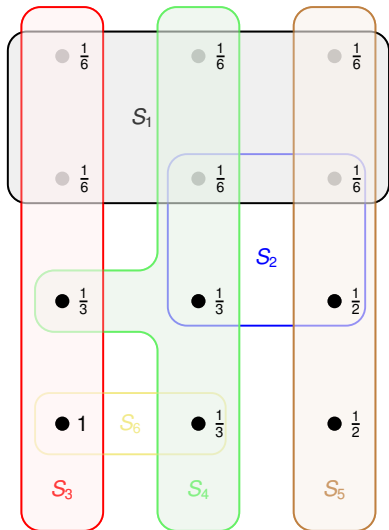
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Proof of Theorem 35.4 (1/2)

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- Each element $x \in X$ is in at least one set in the optimal cover \mathcal{C}^* , so

$$\sum_{S \in \mathcal{C}^*} \sum_{x \in S} c_x \geq \sum_{x \in X} c_x \quad (2)$$

- Combining 1 and 2 gives

$$|\mathcal{C}| \leq \sum_{S \in \mathcal{C}^*} \sum_{x \in S} c_x$$



Proof of Theorem 35.4 (1/2)

Definition of cost

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

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Key Inequality: $\sum_{x \in S} c_x \leq H(|S|)$.



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Proof of Theorem 35.4 (2/2)

Proof of the Key Inequality $\sum_{x \in S} c_x \leq H(|S|)$



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Proof of Theorem 35.4 (2/2)

Proof of the Key Inequality $\sum_{x \in S} c_x \leq H(|S|)$

Remaining uncovered elements in S

- For any $S \in \mathcal{F}$ and $i = 1, 2, \dots, |C| = k$ let $u_i := |S \setminus (S_1 \cup S_2 \cup \dots \cup S_i)|$



Proof of Theorem 35.4 (2/2)

Proof of the Key Inequality $\sum_{x \in S} c_x \leq H(|S|)$

Sets chosen by the algorithm

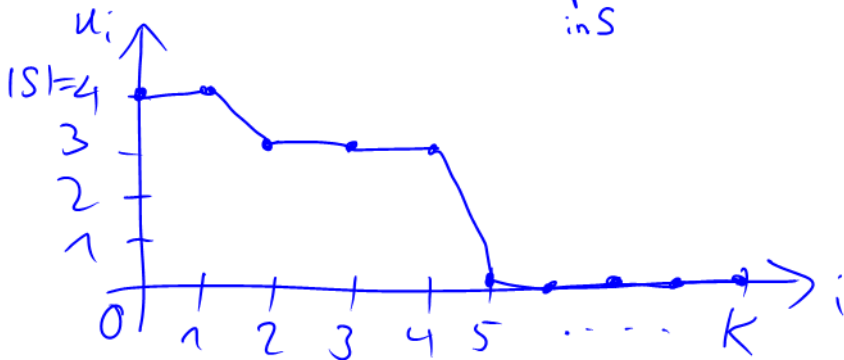
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cost assigned to elements in S
iteration i



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Each factor is **at most one.**



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u_i's are integers



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0
||
H(0)
||



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Set-Covering Problem (Summary)

Theorem 35.4

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

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

"Toy" Application:

Vertex Cover for Graphs with maximum degree 3

$$G = (V, E)$$

$$\mathcal{F} = \{S_1, S_2, \dots, S_{|V|}\}$$

$$X = E$$

Apply GREEDY-SET-COVER $\Rightarrow \rho(G) = H(3) = 1 + \frac{1}{2} + \frac{1}{3} < 2$



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Lower Bound

Unless P=NP, there is no $c \cdot \ln(n)$ *polynomial-time* approximation algorithm for set cover for some constant $0 < c < 1$.



Set-Covering Problem (Summary)

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

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Example where Greedy is a $(1/2) \cdot \log_2 n$ factor off

Instance

- Given any integer $k \geq 3$



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- Given any integer $k \geq 3$
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Example where Greedy is a $(1/2) \cdot \log_2 n$ factor off

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- Given any integer $k \geq 3$
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- Sets S_1, S_2, \dots, S_k are pairwise disjoint and each set contains $2, 4, \dots, 2^k$ elements

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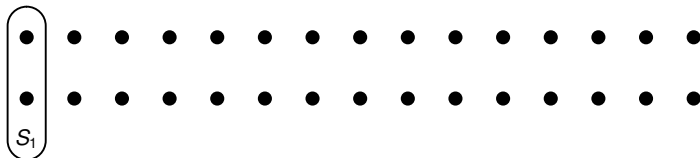


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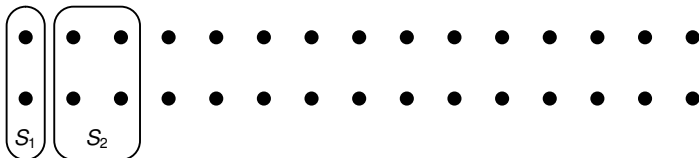


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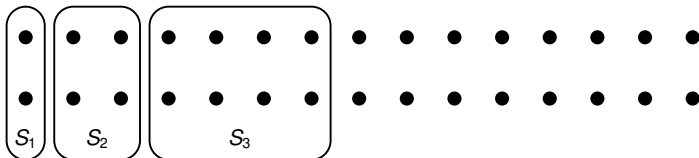


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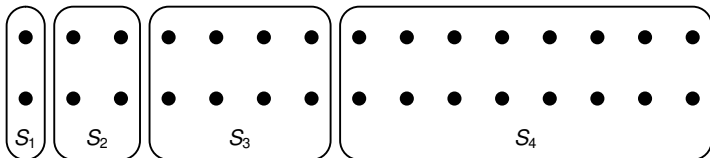


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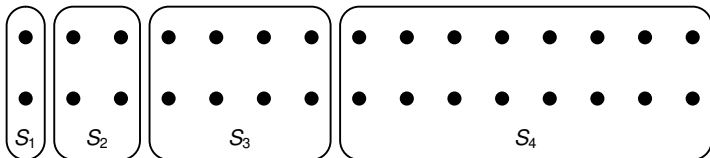


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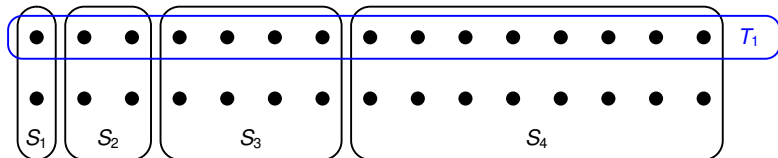


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$k = 4$:

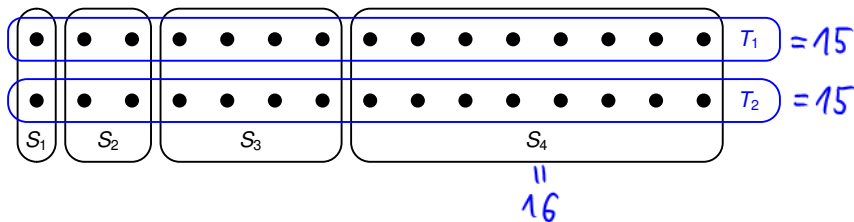


Example where Greedy is a $(1/2) \cdot \log_2 n$ factor off

Instance

- Given any integer $k \geq 3$
- There are $n = 2^{k+1} - 2$ elements overall
- Sets S_1, S_2, \dots, S_k are pairwise disjoint and each set contains $2, 4, \dots, 2^k$ elements
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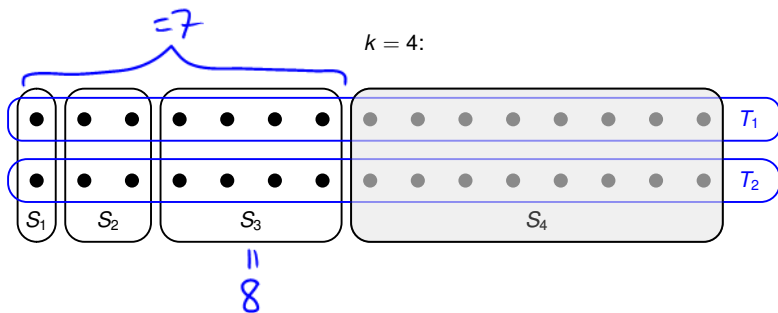
$k = 4:$ $(n = 32 - 2 = 30)$



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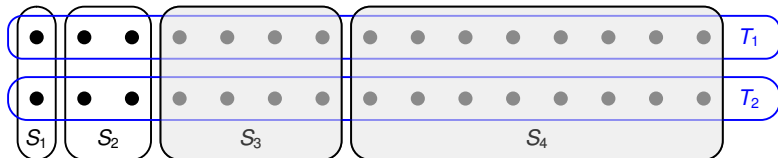


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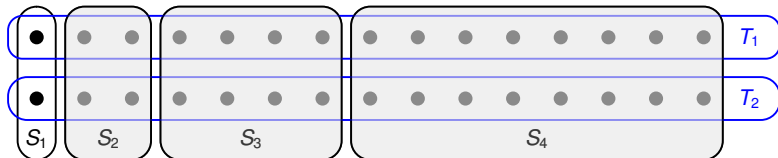


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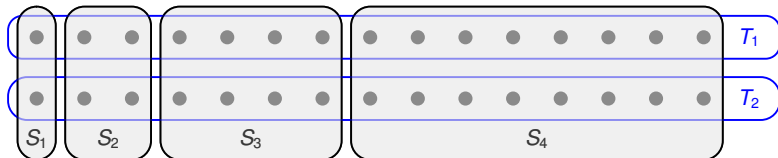


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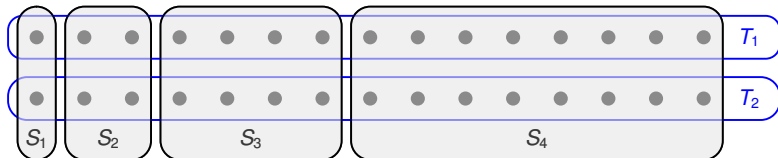


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$k = 4$:



Solution of Greedy consists of k sets.

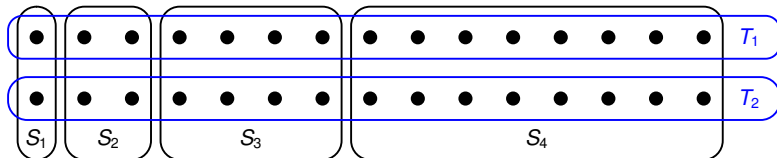


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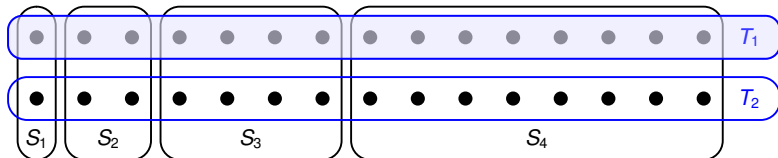


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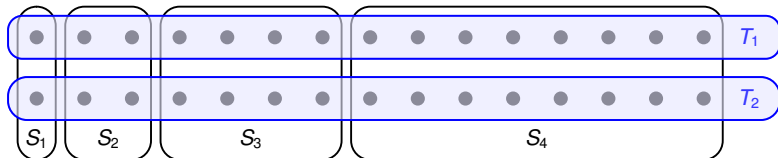


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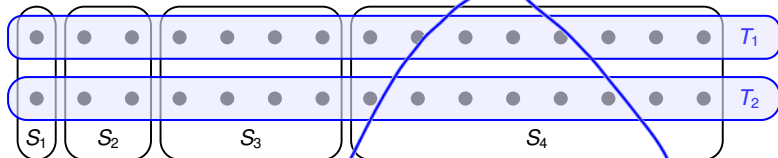


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$$k = 4: p(n) \geq \frac{k}{2} = \frac{\log_2(\frac{n}{2}) - 1}{2} = \frac{\log_2(n) - 2}{2}$$



Solution of Greedy consists of k sets.

Optimum consists of 2 sets.

