



Chapter 8

Approximation Algorithms

Algorithm Theory
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Minimum (Weighted) Set Cover

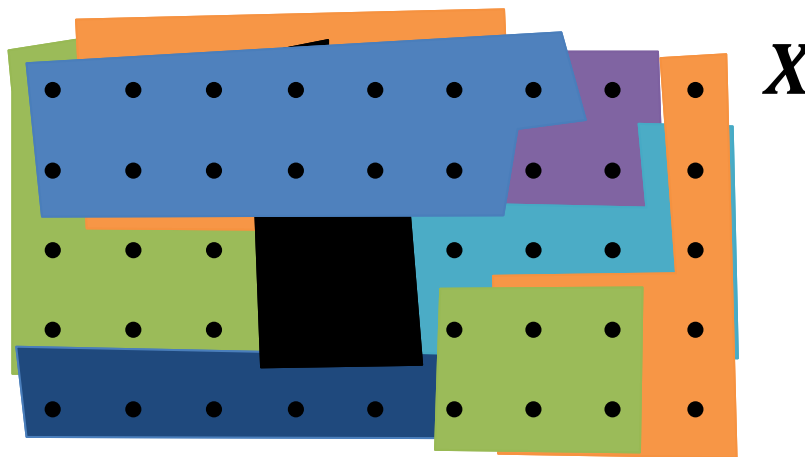
Minimum Set Cover:

- **Goal:** Find a set cover \mathcal{C} of smallest possible size
 - i.e., over X with as few sets as possible

Minimum Weighted Set Cover:

- Each set $S \in \mathcal{S}$ has a **weight** $w_S > 0$
- **Goal:** Find a set cover \mathcal{C} of minimum weight

Example:

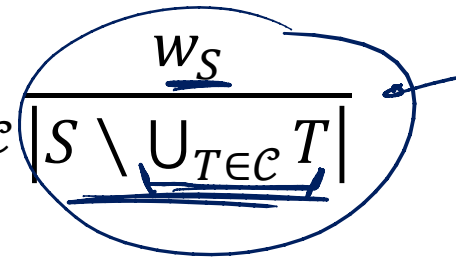


$$X, \mathcal{S} \subseteq 2^X$$

Weighted Set Cover: Greedy Algorithm

Greedy Weighted Set Cover Algorithm:

- Start with $\mathcal{C} = \emptyset$
- In each step, add set $S \in \mathcal{S} \setminus \mathcal{C}$ with the best weight per newly covered element ratio (set with best efficiency):

$$S = \arg \min_{S \in \mathcal{S} \setminus \mathcal{C}} \frac{w_S}{|S \setminus \bigcup_{T \in \mathcal{C}} T|}$$


Analysis of Greedy Algorithm:

- Assign a **price** $p(x)$ to **each element** $x \in X$:
The efficiency of the set when covering the element
- If covering x with set S , if partial cover is \mathcal{C} before adding S :

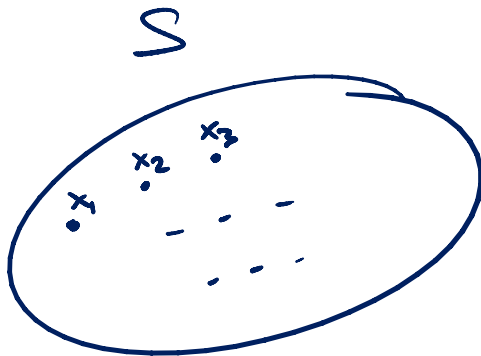
$$\underline{p(x)} = \frac{w_S}{|S \setminus \bigcup_{T \in \mathcal{C}} T|}$$


Weighted Set Cover: Greedy Algorithm

Corollary: The total price of a set $S \in \mathcal{S}$ of size $|S| = k$ is

$$\sum_{x \in S} p(x) \leq w_S \cdot H_k, \quad \text{where } H_k = \sum_{i=1}^k \frac{1}{i} \leq 1 + \ln k$$

Theorem: The approximation ratio of the greedy minimum (weighted) set cover algorithm is at most $H_s \leq 1 + \ln s$, where s is the cardinality of the largest set ($s = \max_{S \in \mathcal{S}} |S|$).



$$\sum_{x \in S} p(x) \leq w_S \cdot H_{|S|}$$

↑
price for covering S

$$= 1 + \frac{1}{2} + \frac{1}{3} + \dots + \frac{1}{|S|}$$

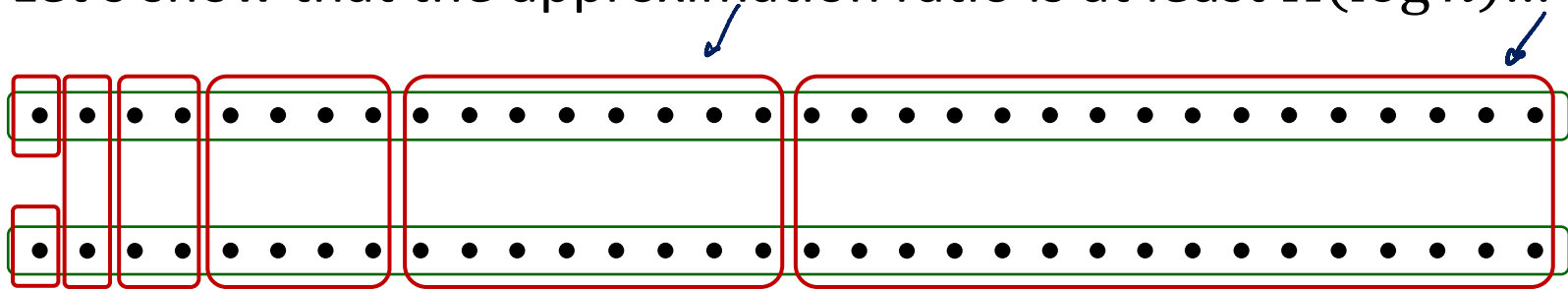
Set Cover Greedy Algorithm

Can we improve this analysis?

No! Even for the unweighted minimum set cover problem, the **approximation ratio** of the **greedy algorithm** is $\geq (1 - o(1)) \cdot \ln s$.

- if s is the size of the largest set... (s can be linear in n)

Let's show that the approximation ratio is at least $\Omega(\log n)$...



OPT = 2

GREEDY $\geq \log_2 n$

Set Cover: Better Algorithm?

An approximation ratio of $\ln n$ seems not spectacular...

Can we improve the approximation ratio?

No, unfortunately not, unless $P \approx NP$

$$\begin{array}{cc} o(1) & o\left(\frac{n}{\log n}\right) \\ \downarrow & \downarrow \\ n & n \end{array}$$

Feige showed that unless NP has deterministic $n^{O(\log \log n)}$ -time algorithms, minimum set cover cannot be approximated better than by a factor $(1 - o(1)) \cdot \ln n$ in polynomial time.

- Proof is based on the so-called PCP theorem
 - PCP theorem is one of the main (relatively) recent advancements in theoretical computer science and the major tool to prove approximation hardness lower bounds
 - Shows that every language in NP has certificates of polynomial length that can be checked by a randomized algorithm by only querying a constant number of bits (for any constant error probability)

Connection to Linear Programming

Linear Programming:

- minimize/maximize a linear function (over \mathbb{R})
- subject to linear side constraints

$$\min a_1 x_1 + a_2 x_2 + \dots + a_n x_n$$

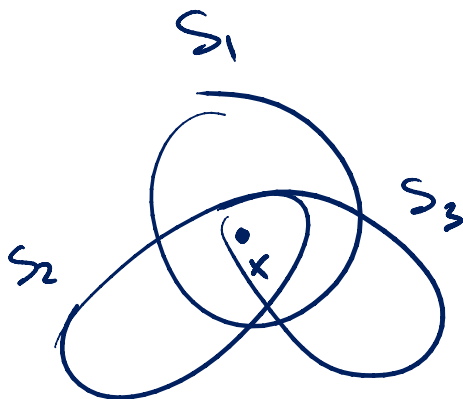
$$2x_1 - 3x_3 + x_5 \leq 7$$

$$x_i \in \mathbb{R}$$

$$x_i \in \mathbb{Z}$$

Set Cover as an Integer Linear Program (LP):

- Given elements X and sets $\mathcal{S} \subseteq 2^X$
- Define a variable $\alpha_S \in \{0,1\}$ for each set $S \in \mathcal{S}$



$$\min \sum_{S \in \mathcal{S}} w_S \cdot \alpha_S$$

$$\sum w_S \alpha_S^* \leq |C^*|$$

$$\forall x \in X : \sum_{S \in \mathcal{S} : x \in S} \alpha_S \geq 1$$

$$\forall S \in \mathcal{S} : \alpha_S \geq 0$$

LP relaxation

$$\alpha_S = 0.5$$

LP Duality

Strong LP Duality: Every linear program (LP) has a dual LP with the same optimal value of the objective function.

LP:

$$\begin{array}{ll} \min & \underline{c^T x} \\ \text{s.t.} & \left. \begin{array}{l} A \cdot x \geq b \\ x \geq 0 \end{array} \right\} \end{array}$$

variables

x, y feasible:

x^*, y^* optimal sol.

Dual LP:

$$\begin{array}{ll} \max & \underline{b^T y} \\ \text{s.t.} & \left. \begin{array}{l} A^T \cdot y \leq c \\ y \geq 0 \end{array} \right\} \end{array}$$

$$b^T y \leq c^T x \quad (\text{weak duality})$$

$$\underline{b^T y^* = c^T x^*}$$

Dual Set Cover LP $\frac{1}{H_n} \sum_{p(x)} = \sum \beta_x \leq \sum w_S \alpha_S^* \leq |w(C^*)|$

(Fractional) Set Cover LP: size of greedy solution

(Fractional) Set Cover Dual LP:

$$\min \sum_{S \in \mathcal{S}} w_S \cdot \alpha_S$$

$$\forall x \in X : \sum_{S \in \mathcal{S} : x \in S} \alpha_S \geq 1$$

$$\forall S \in \mathcal{S} : \alpha_S \geq 0$$

$$\max \sum_{x \in X} \beta_x$$

$$\forall S \in \mathcal{S} : \sum_{x \in S} \beta_x \leq w_S$$

$$\forall x \in X : \beta_x \geq 0$$

price
p(x) for each element

we showed:

$$\forall S \in \mathcal{S} : \sum_{x \in S} p(x) \leq w_S \cdot H_{|S|} \leq w_S \cdot H_n$$

dual fitting

$$\beta_x := \frac{p(x)}{H_n}$$

variable for each element $x \in X$
 β_x

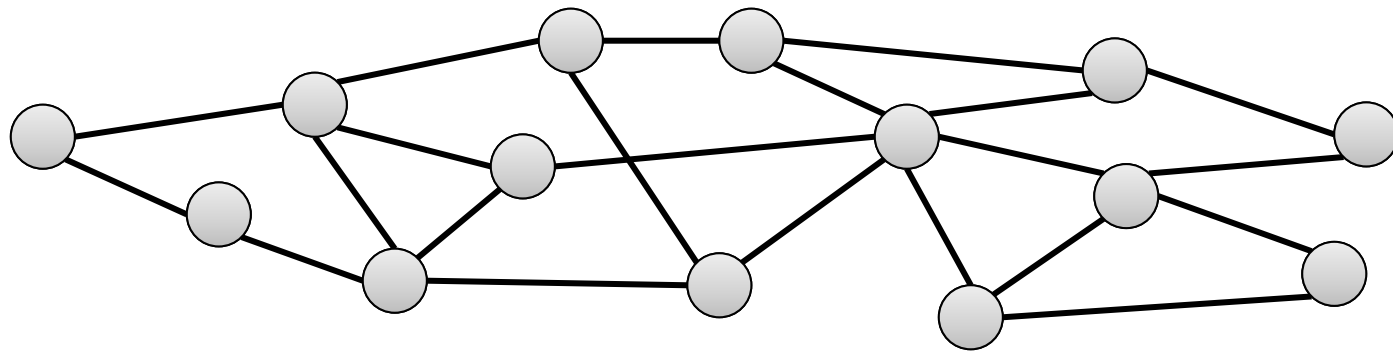
$$\max \sum \beta_x$$

$$\beta_{x_1} \cdot x_1 + \beta_{x_2} \cdot x_2 + \dots \leq w_S$$

feasible dual sol.

Set Cover: Special Cases

Vertex Cover: set $S \subseteq V$ of nodes of a graph $G = (V, E)$ such that
 $\forall \{u, v\} \in E, \quad \{u, v\} \cap S \neq \emptyset.$



2-approx.

Minimum Vertex Cover:

- Find a vertex cover of minimum cardinality

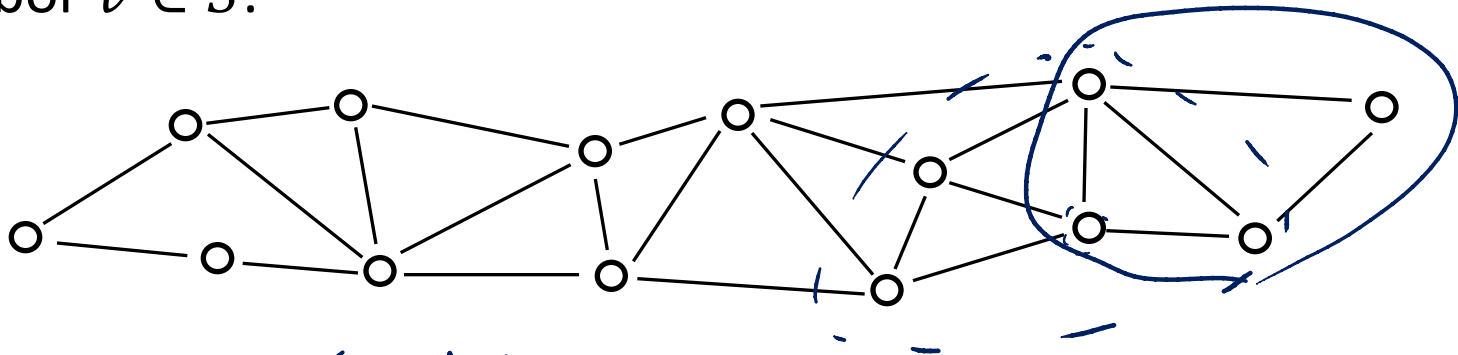
Minimum Weighted Vertex Cover:

- Each node has a weight
- Find a vertex cover of minimum total weight

Set Cover: Special Cases

Dominating Set:

Given a graph $G = (V, E)$, a dominating set $S \subseteq V$ is a subset of the nodes V of G such that for all nodes $u \in V \setminus S$, there is a neighbor $v \in S$.



unweighted / weighted

greedy: approx. ratio: $H_{\Delta+1} \approx \ln \Delta$

Minimum Hitting Set

Given: Set of elements X and collection of subsets $\mathcal{S} \subseteq 2^X$

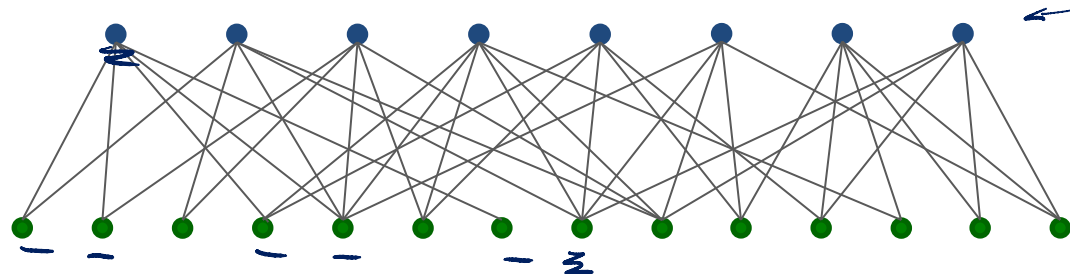
– Sets cover X : $\bigcup_{S \in \mathcal{S}} S = X$

Goal: Find a min. cardinality subset $H \subseteq X$ of elements such that
 $\forall S \in \mathcal{S} : S \cap H \neq \emptyset$

Problem is **equivalent to min. set cover** with roles of sets and elements interchanged

Sets

Elements



Knapsack

- n items $1, \dots, n$, each item has weight $\underline{w}_i > 0$ and value $\underline{v}_i > 0$
- Knapsack (bag) of capacity W
- Goal: pack items into knapsack such that total weight is at most W and total value is maximized:

$$\max \sum_{i \in S} v_i$$

$$S \subseteq \{1, \dots, n\}$$

$$x_i \in \{0, 1\}$$

$$\text{s.t. } \underline{S \subseteq \{1, \dots, n\}} \text{ and } \underline{\sum_{i \in S} w_i \leq W}$$

- E.g.: jobs of length w_i and value v_i , server available for W time units, try to execute a set of jobs that maximizes the total value

Knapsack: Dynamic Programming Alg.

We have shown:

- If all item weights w_i are integers, using dynamic programming, the knapsack problem can be solved in time $O(nW)$
- If all values v_i are integers, there is another dynamic progr. algorithm that runs in time $O(n^2V)$, where V is the max. value.

Problems:

- If W and V are large, the algorithms are not polynomial in n
- If the values or weights are not integers, things are even worse (and in general, the algorithms cannot even be applied at all)

Idea:

- Can we adapt one of the algorithms to at least compute an approximate solution?

Approximation Algorithm

- The algorithm has a parameter $\varepsilon > 0$
- We assume that each item alone fits into the knapsack (w.l.o.g.)
- We define:

$$\underline{V} := \max_{1 \leq i \leq n} v_i, \quad \forall i: \underline{\hat{v}}_i := \left\lfloor \frac{v_i n}{\varepsilon \underline{V}} \right\rfloor, \quad \underline{\hat{V}} := \max_{1 \leq i \leq n} \underline{\hat{v}}_i$$
- We solve the problem with **integer** values $\underline{\hat{v}}_i$ and weights \underline{w}_i using dynamic programming in time $O(\underline{n}^2 \cdot \underline{\hat{V}})$
- If solution value $\leq \underline{V}$, we take item with value \underline{V} instead

Theorem: The described algorithm runs in time $O(n^3 / \varepsilon)$.

Proof:

$$\underline{\hat{V}} = \max_{1 \leq i \leq n} \underline{\hat{v}}_i = \max_{1 \leq i \leq n} \left\lfloor \frac{v_i n}{\varepsilon \underline{V}} \right\rfloor = \left\lfloor \frac{\underline{V} n}{\varepsilon \underline{V}} \right\rfloor = \left\lfloor \frac{n}{\varepsilon} \right\rfloor$$

$\varepsilon = \frac{1}{\text{poly}(n)}$

$\frac{1}{\varepsilon} + 1$