

# Introduction to **Approximation Algorithms**

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# Outline

- The Set Cover Problem
  - An  $H_n$ -approximation via greedy approach
    - The cost-efficiency of the choices
    - A tight example for the algorithm analysis
  - An  $O(\log n)$ -Approximation via randomized LP-rounding

# The Set Cover Problem

# The Set Cover Problem

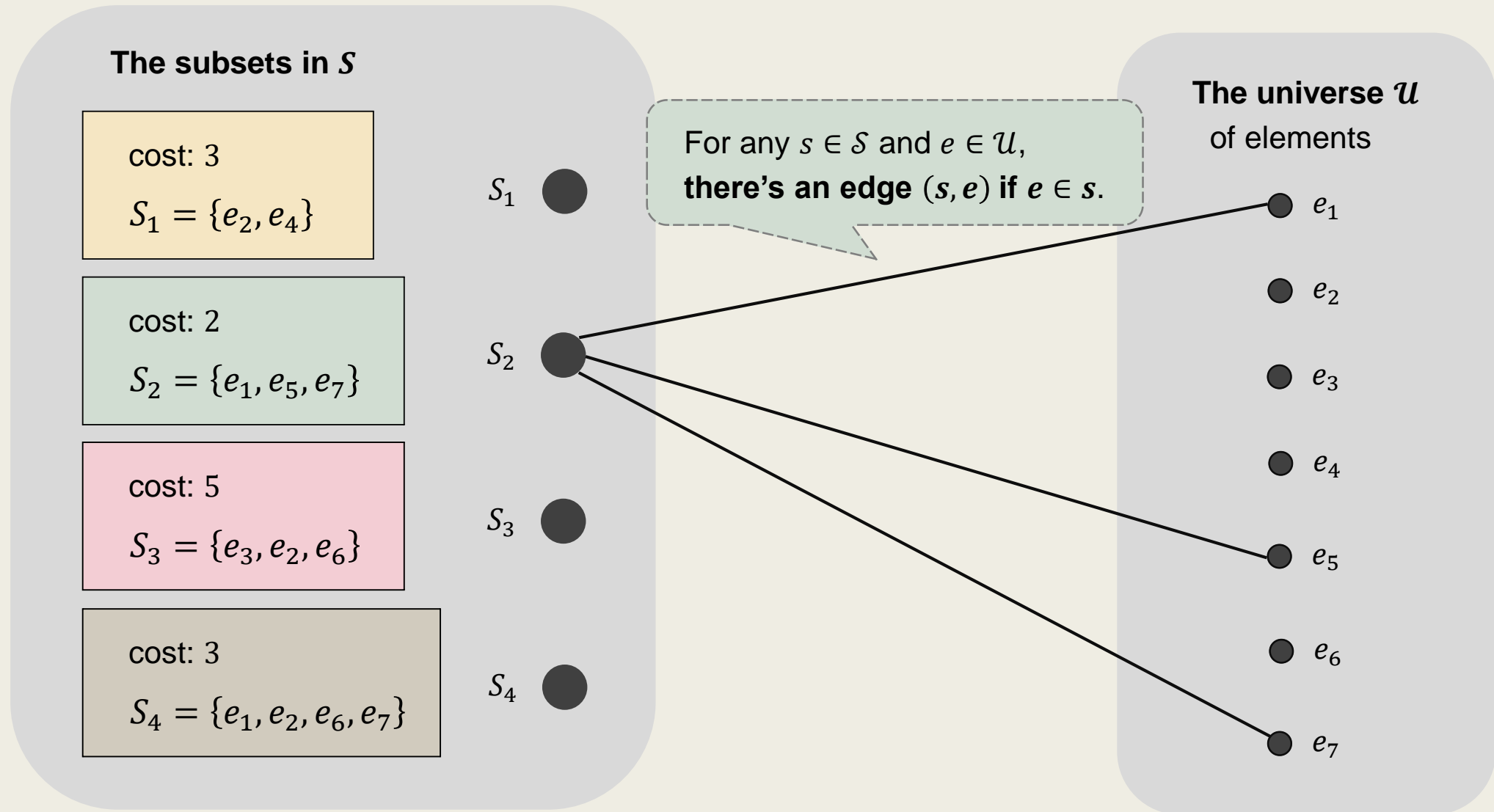
- Given a universe  $\mathcal{U}$  of  $n$  elements, a collection of subsets of  $\mathcal{U}$ ,  $\mathcal{S} = \{ S_1, S_2, \dots, S_k \}$ , and a cost function  $c : \mathcal{S} \rightarrow \mathbb{Q}^+$ ,

the set cover problem is to *compute a minimum cost subcollection of  $\mathcal{S}$  that covers all the elements of  $\mathcal{U}$ .*

- i.e., to pick a collection of subsets  $\mathcal{A} \subseteq \mathcal{S}$  such that

$\bigcup_{s \in \mathcal{A}} s = \mathcal{U}$  and **the total cost,  $\sum_{s \in \mathcal{A}} c(s)$ , is minimized.**

# An Intuitive Way to View the Set Cover Problem



Pick a minimum cost vertex subset from the left, such that  
*every vertex on the right is adjacent to at least one chosen vertex on the left.*

**The subsets in  $S$**

cost: 3

$$S_1 = \{e_2, e_4\}$$

cost: 2

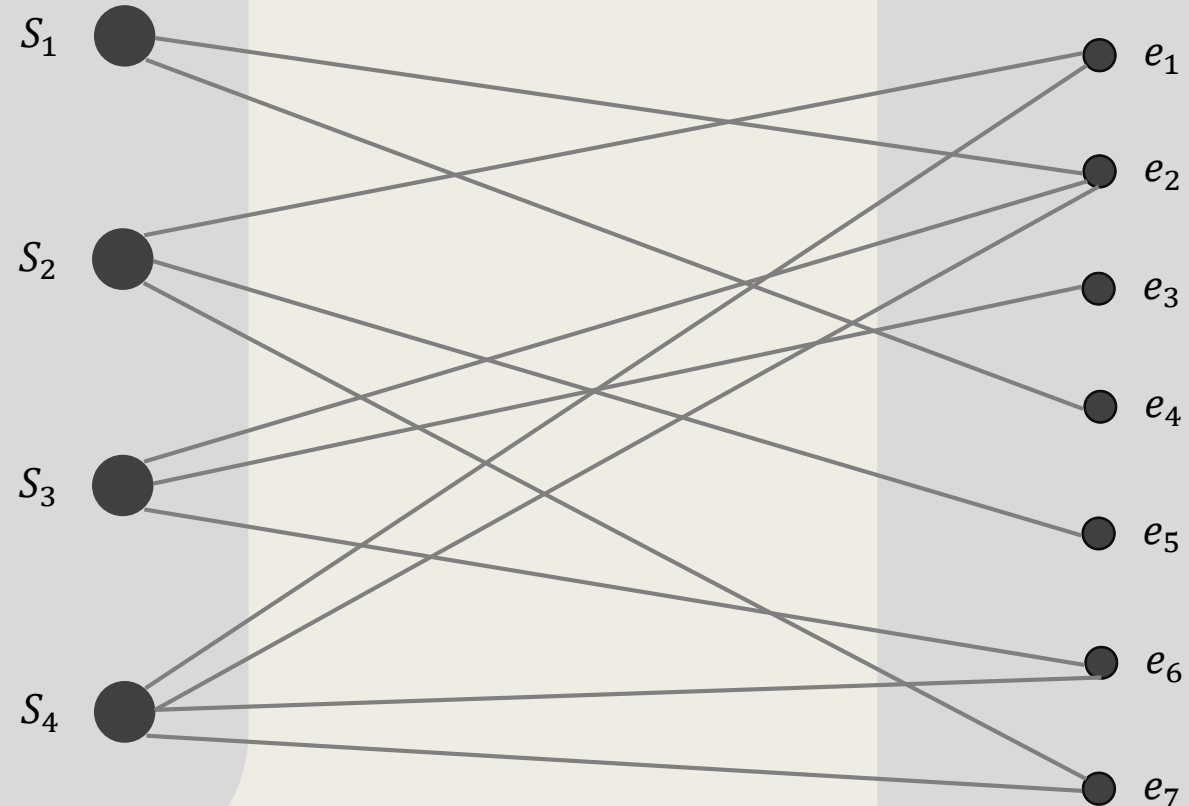
$$S_2 = \{e_1, e_5, e_7\}$$

cost: 5

$$S_3 = \{e_3, e_2, e_6\}$$

cost: 3

$$S_4 = \{e_1, e_2, e_6, e_7\}$$



**The universe  $\mathcal{U}$   
of elements**

Pick a minimum cost vertex subset from the left, such that  
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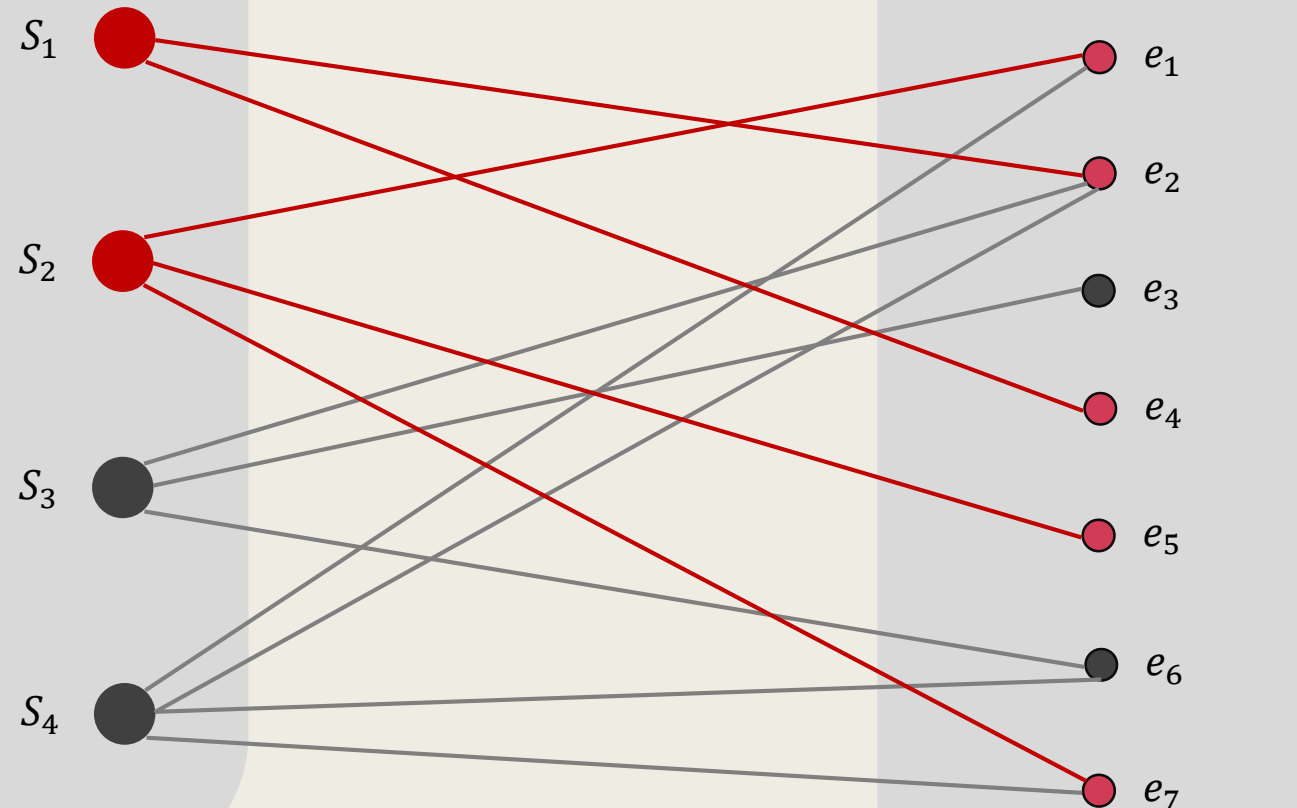
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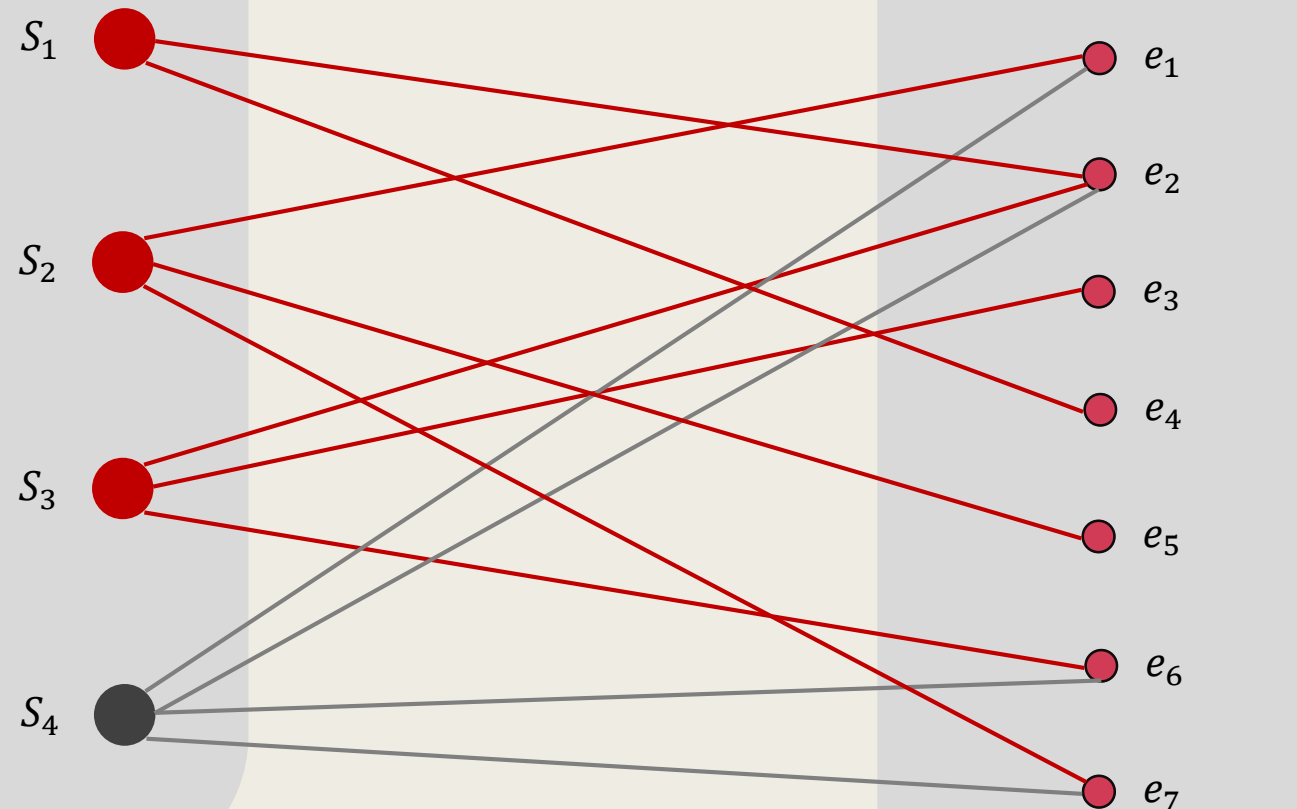
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# Common Parameters for Set Cover

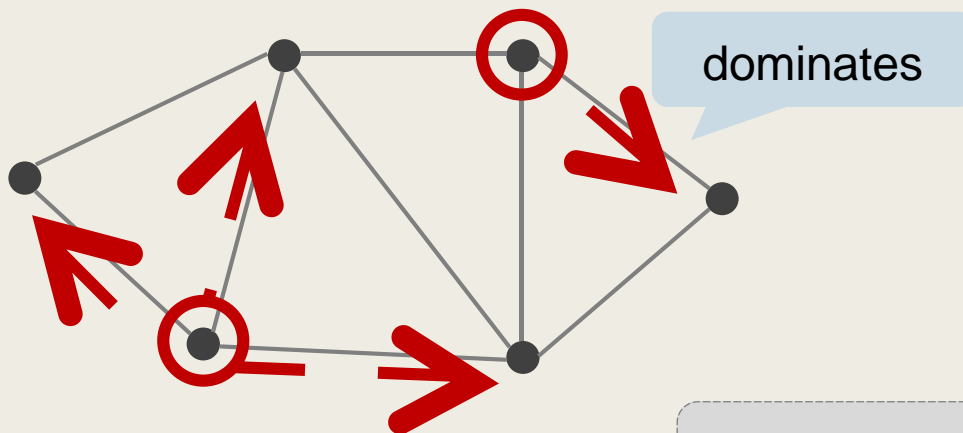
- Let  $\Pi = (\mathcal{U}, \mathcal{S}, c)$  be an instance of the set cover problem.
  - For each  $u \in \mathcal{U}$ , we define the frequency of  $u$  to be the number of sets in  $\mathcal{S}$  to which  $u$  belongs, i.e., the number of sets  $u$  is in.
  - We will use  $f$  to denote ***the maximum frequency of the elements.***
    - It turns out that,  
*the maximum frequency is a useful parameter* when approximating the set cover problem.

# Related Variations

# The Dominating Set Problem

- Given a graph  $G = (V, E)$  and a vertex weight function  $w : V \rightarrow Q^+$ , compute a minimum-weight vertex subset  $U \subseteq V$  such that, for any  $v \in V$ , either

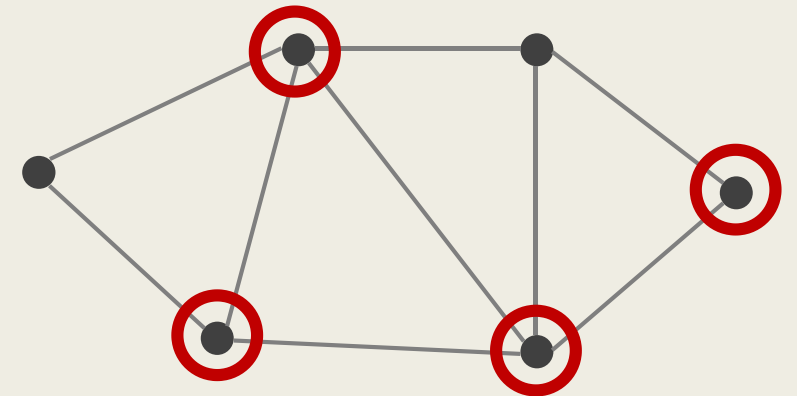
$v \in U$  or  $v$  has a neighbor that does.



Intuitively, we are covering the vertices using the vertices.

# The Vertex Cover Problem

- Given a graph  $G = (V, E)$  and a vertex weight function  $w : V \rightarrow Q^+$ , compute a minimum-weight vertex subset  $U \subseteq V$  such that, for any edge  $e \in E$ , at least one endpoint of  $e$  is in  $U$ .
  - The vertex cover problem is a special case of set cover for which  $f = 2$ .
  - When hypergraphs are considered, vertex cover is equivalent to set cover.



Intuitively, we are covering the edges using the vertices.

(Brief)

# Status of the Set Cover Problem

# The Set Cover Problem

- The set cover problem is a classic NP-hard problem that is studied in many fields.
- The set cover problem can be approximated to a ratio of
  - $H_n$  by simple greedy approach, where  $H_n$  is the  $n^{th}$ -harmonic number.
  - $f$  by the “layering” algorithm, where  $f$  is the maximum frequency of the elements.

# The Set Cover Problem

- The set cover is NP-hard to approximate to  $(1 - o(1)) \cdot \ln n$  unless  $P=NP$ .
- If we assume the Unique Game Conjecture (UGC), then approximating set cover to a ratio better than  $f - \epsilon$  for any  $\epsilon > 0$  is NP-hard.

$H_n$ -approximation by

Simple Greedy Approach on Cost-Efficiency



# Greedy towards Cost-Efficiency

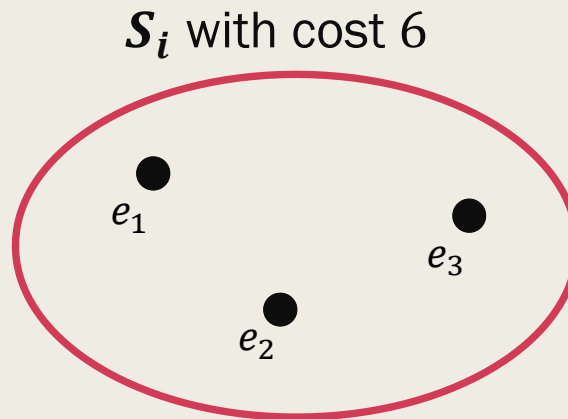
- For problems of this kind, a very natural approach is to consider the ***cost-effectiveness / cost-efficiency*** of the choices, and to *always* pick the most cost-efficient one.
  - This is likely fail for most of the times, if our goal is to solve the optimization problem for an optimal solution.
    - For example, this can perform arbitrarily bad for the knapsack problem.
  - However, this intuitive approach yields a good approximation for the set cover problem, *provably* the best one.

# How is Cost-Efficiency Defined?

- One natural question is that,

How should the **cost-efficiency** of the sets be defined?

- It may seem that...



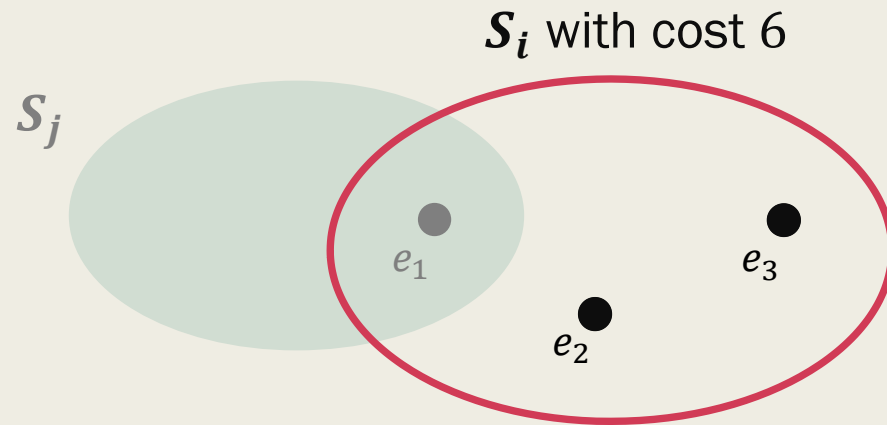
Selecting  $S_i$  can cover 3 elements with a cost of 6.

The **average price** of  $S_i$  is  $6/3 = 2$ .

This may seem correct, but...

# How is Cost-Efficiency Defined?

- The **cost-efficiency** of the sets can change as the algorithm proceeds.
  - Suppose that, prior to picking  $S_i$ , some sets were already picked...



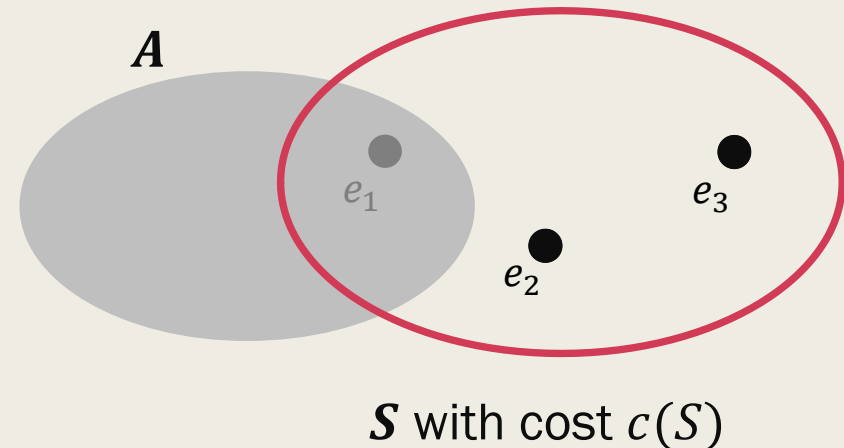
Selecting  $S_i$  can cover only 2 elements.

The **average price** of  $S_i$  is now  $6/2 = 3$ , instead of 2.

# How is Cost-Efficiency Defined?

- Let  $A$  be the set of elements that have already been covered.
  - We define the average covering price of a set  $S$ , subject to a prior coverage of  $A$ , to be

$$\text{Aprice}(S, A) := \frac{c(S)}{|S - A|}.$$



# The Algorithm Description

# The algorithm

- The algorithm **picks the *most cost-efficient subset*** in each iteration *until all the elements are covered.*

- While  $\mathcal{C}$  is not yet a cover,  
Pick the most cost-efficient subset from  $\mathcal{S}$  and add it to  $\mathcal{C}$ .

- The idea is that,  
since we always pick the “*best choice*” in each iteration,  
its efficiency is ***no worse than that of the optimal solution.***

# The algorithm

- The algorithm **picks the *most cost-efficient subset*** in each iteration *until all the elements are covered.*

```
 $\mathcal{C} \leftarrow \emptyset.$ 
```

```
while  $\bigcup_{s \in \mathcal{C}} s \neq \mathcal{U}$ , do
```

```
    Pick the set  $S' \in \mathcal{S}$  with the minimum  $\text{aprice}(S', \bigcup_{s \in \mathcal{C}} s)$ .
```

```
     $\mathcal{C} \leftarrow \mathcal{C} \cup \{S'\}.$ 
```

```
Return  $\mathcal{C}.$ 
```

# The Analysis



# The Approximation Guarantee

- Let  $e_1, e_2, \dots, e_n$  be the elements in  $\mathcal{U}$ , with indexes labelled by the order they are covered.
  - Define  $\text{price}(e_i)$  to be the price the algorithm uses to cover  $e_i$ , i.e., the average price of the particular set that first makes  $e_i$  covered.
- The following lemma, which bounds the covering price of each element, is the key to establishing the  $H_n$  guarantee.

## Lemma 1.

We have  $\text{price}(e_i) \leq \frac{OPT}{n-i+1}$  for all  $1 \leq i \leq n$ .

# The Approximation Guarantee

## Lemma 1.

We have  $\text{price}(e_i) \leq \frac{OPT}{n-i+1}$  for all  $1 \leq i \leq n$ .

- Suppose that Lemma 1 is true, then it follows that

$$\begin{aligned} c(\mathcal{C}) &:= \sum_{S \in \mathcal{C}} c(S) = \sum_{1 \leq i \leq n} \text{price}(e_i) \leq \sum_{1 \leq i \leq n} \frac{1}{i} \cdot OPT \\ &= H_n \cdot OPT. \end{aligned}$$

The cost of each  $S \in \mathcal{C}$  is *distributed as the prices of the elements it effectively covers*.

So, it suffices to prove Lemma 1.

**Lemma 1.**

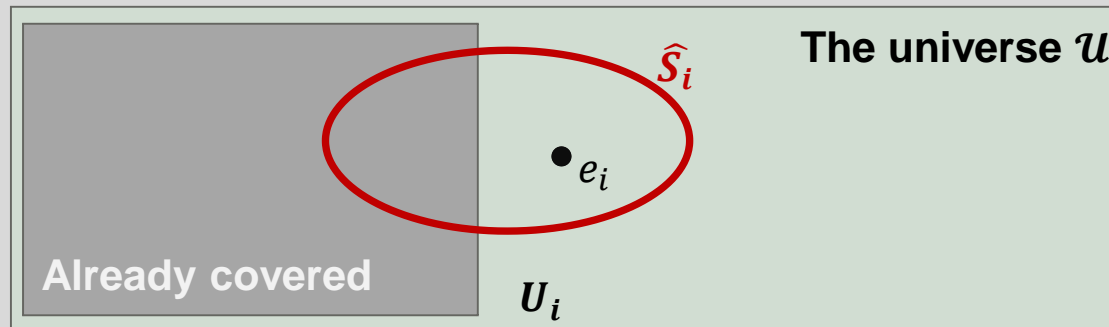
We have  $\text{price}(e_i) \leq \frac{OPT}{n-i+1}$  for all  $1 \leq i \leq n$ .

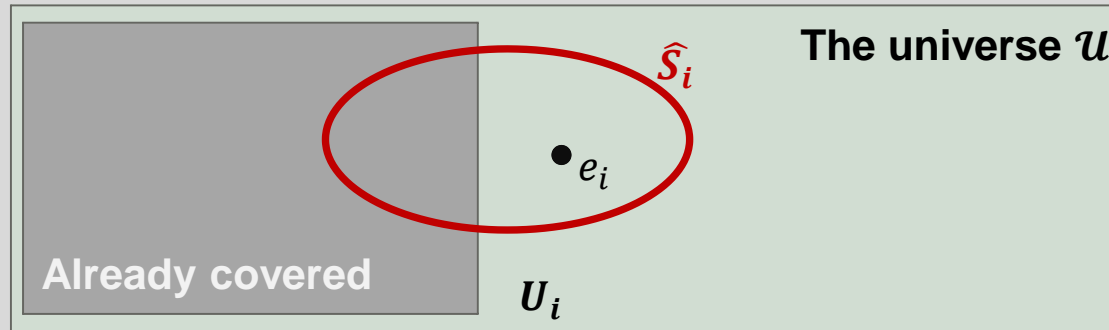
**Proof.**

Consider **the particular iteration** for which  $e_i$  **becomes covered**.

Let  $\hat{S}_i$  denote the set that is picked to cover  $e_i$ , and

$U_i$  denote set of uncovered elements in the beginning of that iteration.





The optimal solution (for  $(\mathcal{U}, \mathcal{S}, c)$ ) can cover  $U_i$  with cost  $OPT$ .

Since  $\hat{S}_i$  is *the **most cost-efficient choice** at that moment*,  
we claim that *its average price is at most  $OPT/|U_i|$ .*

If so, then

$$\text{price}(e_i) \leq \frac{OPT}{|U_i|} \leq \frac{OPT}{n - i + 1}.$$

The average price of the optimal solution at that moment.

$e_i$  is the  $i^{th}$ -element that gets covered. So,  $|U_i| \geq n - i + 1$ .

The average price of  $\hat{S}_i$  subject to prior coverage of  $\mathcal{U} - U_i$ .

**Proof. (continue)**

It remains to prove the claim that  $\text{aprice}(\hat{S}_i, \mathcal{U} - U_i) \leq \frac{OPT}{|U_i|}$ .

Let  $\mathcal{O} = \{O_1, O_2, \dots, O_\ell\}$  denote ***an optimal solution for  $(U_i, \mathcal{S}, c)$*** .

- Imagine that,  $O_1, O_2, \dots, O_\ell$  are selected in order.
- For any  $1 \leq j \leq \ell$ , define

$$\text{ap}'(O_j) := \text{aprice}\left(O_j, (U - U_i) \cup \bigcup_{1 \leq k < j} O_k\right).$$

Intuitively,  $\text{ap}'(O_j)$  is the updated average price of  $O_j$ , when  $O_1, O_2, \dots, O_{j-1}$  are selected in prior to  $O_j$ .

### Proof. (continue)

It remains to prove the claim that  $\text{aprice}(\widehat{S}_i, \mathcal{U} - U_i) \leq \frac{OPT}{|U_i|}$ .

Denote by  $\mathcal{O} = \{O_1, O_2, \dots, O_\ell\}$  **an optimal solution for the instance**  $(U_i, \mathcal{S}, c)$ .

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$$\text{ap}'(O_j) := \text{aprice}\left(O_j, (U - U_i) \cup \bigcup_{1 \leq k < j} O_k\right).$$

Then it follows that, for any  $1 \leq j \leq \ell$ , we have

$$\text{aprice}(\widehat{S}_i, \mathcal{U} - U_i) \leq \text{aprice}(O_j, \mathcal{U} - U_i) \leq \text{ap}'(O_j) < \infty.$$

Guaranteed by our greedy choice.

By definition, the effective coverage of  $O_j$  in  $\text{ap}'(O_j)$  is at most that in  $\text{aprice}(O_j, \mathcal{U} - U_i)$ .

### Proof. (continue)

Now we prove the claim that  $\text{aprice}(\widehat{S}_i, \mathcal{U} - U_i) \leq \frac{OPT}{|U_i|}$ .

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Then,

$$\text{aprice}(\widehat{S}_i, \mathcal{U} - U_i) \leq \sum_{1 \leq j \leq \ell} \frac{|O_j - \bigcup_{1 \leq k < j} O_k|}{|U_i|} \cdot \text{ap}'(O_j)$$

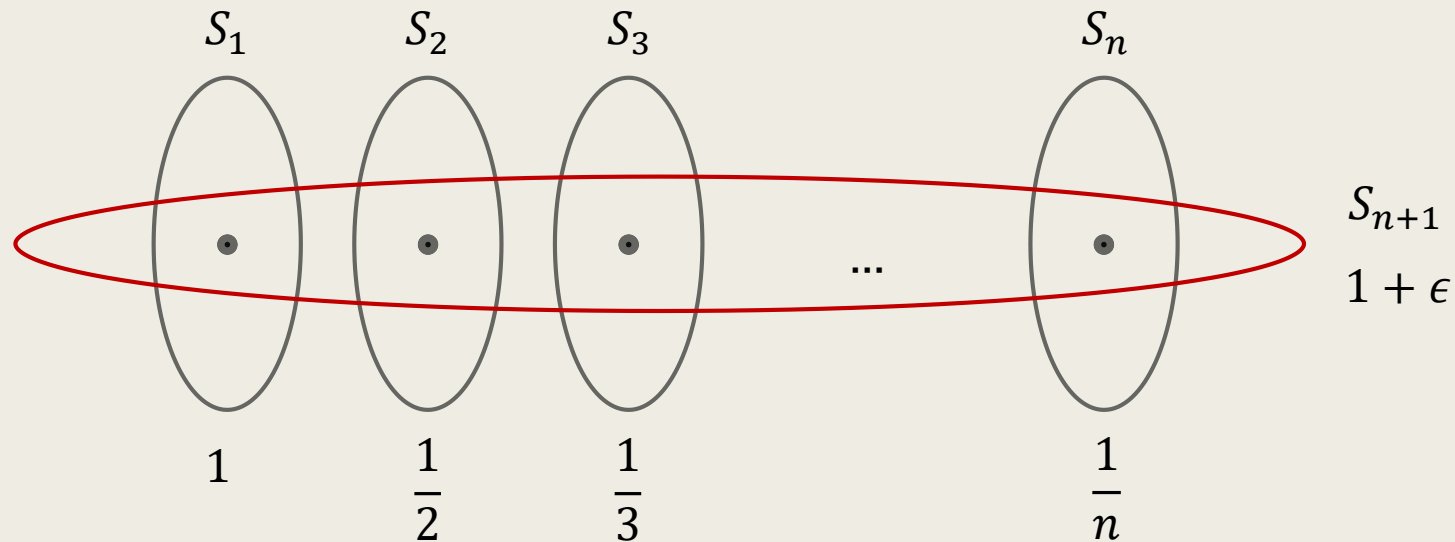
$$= \sum_{1 \leq j \leq \ell} \frac{1}{|U_i|} \cdot c(O_j) = \frac{c(\mathcal{O})}{|U_i|} \leq \frac{OPT}{|U_i|}.$$

By the above inequality, and

$$\sum_{1 \leq j \leq \ell} \frac{|O_j - \bigcup_{1 \leq k < j} O_k|}{|U_i|} = 1.$$

# A Tight Example for the Greedy Algorithm

- The following example shows that,  
the approximation ratio of the greedy algorithm is indeed  $H_n$ .



The greedy algorithm will pick  $S_1, S_2, \dots, S_n$ , while the optimal solution is to pick  $S_{n+1}$ .



# Randomized $O(\log n)$ -Approximation for Set Cover via LP-rounding

# Randomized Rounding for Set Cover

- We can use a simple & interesting randomized rounding technique to compute an  $O(\log n)$ -approximation for Set Cover.

Consider the following natural ILP for set cover.

$$\begin{array}{ll} \min & \sum_{A \in \mathcal{S}} w_A \cdot x_A \quad (*) \\ \text{s. t.} & \sum_{A \in \mathcal{S}: e \in A} x_A \geq 1, \quad \forall e \in \mathcal{U}, \\ & x_A \in \{0, 1\}, \quad \forall A \in \mathcal{S}. \end{array}$$

# Randomized Rounding for Set Cover

1. Solve LP (\*\*) for an optimal fractional solution  $x^*$ .
2. Let  $\mathcal{C} \leftarrow \emptyset$ .

We will set  $c := 1 + o(1)$ .

Repeat the following process for  $c \cdot \log n$  times.

- For each  $A \in \mathcal{S}$ ,  
include  $A$  into  $\mathcal{C}$  with probability  $x_A^*$ .

3. Output  $\mathcal{C}$ .

$$\begin{aligned} \min \quad & \sum_{A \in \mathcal{S}} w_A \cdot x_A & (**) \\ \text{s.t.} \quad & \sum_{A \in \mathcal{S}: e \in A} x_A \geq 1, & \forall e \in \mathcal{U}, \\ & x_A \geq 0, & \forall A \in \mathcal{S}. \end{aligned}$$

# The Feasibility

- Consider any  $e \in \mathcal{U}$  and the sets  $N(e) := \{ A \in \mathcal{S} : e \in A \}$  that contain  $e$ .
  - Consider *each* of the  $c \cdot \log n$  iterations. We have

$$\begin{aligned} \Pr[ e \text{ does not get covered} ] &= \prod_{A \in N(e)} (1 - x_A^*) \\ &\leq \prod_{A \in N(e)} e^{-x_A^*} = e^{-\sum_{A \in N(e)} x_A^*} \end{aligned}$$

$$1 + x \leq e^x \text{ holds for all } x \in \mathbb{R}.$$

$$\leq e^{-1}.$$

$$\sum_{A \in N(e)} x_A^* \geq 1 \text{ by the feasibility of } x^* \text{ for LP (**).}$$

This process will cover  $\mathcal{U}$  with high probability (w.h.p.).

# The Feasibility

- Consider any  $e \in \mathcal{U}$  and the sets  $N(e) := \{ A \in \mathcal{S} : e \in A \}$  that contain  $e$ .

- Consider each of the  $c \cdot \log n$  iterations.

We have  $\Pr[ e \text{ does not get covered } ] \leq e^{-1}$ .

- Hence,

$$\Pr[ \mathcal{C} \text{ does not cover } e ] \leq (e^{-1})^{c \cdot \log n} \leq \frac{1}{4n}$$

for  $c := 1 + o(1)$  such that  $n^{-c} \leq 1/(4n)$ .

- Applying *union bound*, we get

$$\Pr[ \mathcal{C} \text{ does not cover } \mathcal{U} ] \leq |\mathcal{U}| \cdot \frac{1}{4n} \leq \frac{1}{4}.$$

# The Approximation Guarantee

- The expected cost incurred by each iteration is

$$E[\text{cost of subsets chosen in this iteration}] = \sum_{A \in \mathcal{S}} w_A \cdot x_A^* = OPT_f .$$

Hence, we have  $E[w(\mathcal{C})] = c \cdot \log n \cdot OPT_f$  .

- By Markov's inequality, we get

$$\Pr[w(\mathcal{C}) \geq 4c \cdot \log n \cdot OPT_f] \leq \frac{1}{4} .$$

This cost is bounded with high probability (w.h.p.).

# The Approximation Guarantee

- Combining the two w.h.p (with-high-probability) conclusions, it follows that

$$\Pr[ \mathcal{C} \text{ does not cover } \mathcal{U} \text{ or } w(\mathcal{C}) \geq 4c \cdot \log n \cdot OPT_f ] \leq \frac{1}{2} .$$

- Repeat the entire process  $c'$  times for some constant  $c' \in \mathbb{N}$  sufficiently large and output the best feasible solution.

We get a  $(4c \cdot \log n)$ -approximation with probability at least  $1 - 2^{-c'}$ .

That's all for Set Cover so far.

Let's proceed to our next problem.

