

MAXIMUM k -COVERAGE

Vasilis Margonis

Combinatorial Optimization

$\infty \wedge \mu \nabla$

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Definition

Input:

- A universe of m elements: $\mathcal{U} = \{e_1, e_2, \dots, e_m\}$.
- n subsets of \mathcal{U} : $\mathcal{S} = \{S_1, S_2, \dots, S_n\}$.
- An integer k .

Goal:

- Find a subset S' of \mathcal{S} , such that $|S'| \leq k$ and the number of covered elements $\left| \bigcup_{S_i \in S'} S_i \right|$ is maximized.

ILP Formulation

$$\begin{aligned} \text{Maximize} \quad & \sum_{e_j \in \mathcal{U}} y_j \\ \text{Subject to} \quad & \sum_{S_i \in \mathcal{S}} x_i \leq k \\ & \sum_{e_j \in S_i} x_i \geq y_j, \quad \forall e_j \in \mathcal{U} \\ & y_j \in \{0, 1\}, \quad \forall e_j \in \mathcal{U} \\ & x_i \in \{0, 1\}, \quad \forall S_i \in \mathcal{S} \end{aligned}$$

Greedy Algorithm

Algorithm 1 GREEDY COVERING $(\mathcal{U}, \mathcal{S}, k)$

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1:  $C \leftarrow \emptyset$ 
2: while  $|C| \leq k$  do
3:   Select  $S_i \in \mathcal{S}$  such that  $|S_i \cap \mathcal{U}|$  is maximized
4:    $\mathcal{U} \leftarrow \mathcal{U} - S_i$ 
5:    $C \leftarrow C \cup \{S_i\}$ 
6: end while
7: return  $C$ 
```

Approximation Ratio

Theorem (1)

GREEDY COVERING is a $(1 - \frac{1}{e}) \simeq 0.632$ -approximation for MAXIMUM k -COVERAGE.

- OPT := The value of an optimal solution.
- x_i := Number of elements covered in the i -th iteration.
- $y_i := \sum_{j=1}^i x_j$.
- $z_i := OPT - y_i$.
- $y_k = SOL$:= Number of elements covered by GREEDY COVERING.

Analysis

Lemma (2)

For every $i = 1, \dots, k$, $x_i \geq \frac{z_{i-1}}{k}$.

Proof:

- At each iteration, GREEDY COVERING selects the subset S_j which covers the maximum number of uncovered elements.
- The optimal solution uses k sets to cover OPT elements.
- Then, in the i -th iteration, there is a set that covers at least $\frac{z_{i-1}}{k}$ elements.
- Hence, $x_i \geq \frac{z_{i-1}}{k}$. □

Analysis

Lemma (3)

For every $i = 0, \dots, k$, $z_i \leq \left(1 - \frac{1}{k}\right)^i \cdot OPT$.

Proof:

- The claim holds for $i = 0$, since $z_0 = OPT$.
- Inductively, we assume that $z_{i-1} \leq \left(1 - \frac{1}{k}\right)^{i-1} \cdot OPT$, $i > 1$. Then

$$\begin{aligned} z_i &\leq z_{i-1} - x_i \stackrel{(2)}{\leq} z_{i-1} - \frac{z_{i-1}}{k} \\ &\leq z_{i-1} \cdot \left(1 - \frac{1}{k}\right) \\ &\leq \left(1 - \frac{1}{k}\right)^i \cdot OPT \quad \square \end{aligned}$$

Analysis

Proof of Theorem (1).

- From lemma (3), it follows that $z_k \leq \left(1 - \frac{1}{k}\right)^k \cdot OPT$.
- Also, for every $k \geq 1$, $\left(1 - \frac{1}{k}\right)^k \leq 1/e$.
- Hence, $z_k \leq \frac{1}{e} \cdot OPT$.
- Then

$$SOL = y_k = OPT - z_k \geq OPT - \frac{1}{e} \cdot OPT = \left(1 - \frac{1}{e}\right) \cdot OPT \quad \square$$

Theorem (Feige, 1998)

For every $\varepsilon > 0$, there is no $\left(1 - \frac{1}{e} + \varepsilon\right)$ -approximation algorithm for MAXIMUM k -COVERAGE, unless $\mathbf{P} = \mathbf{NP}$.