

Let I denote the solution obtained by the first rounding algorithm and I' be the solution returned by the second algorithm. Then

$$I \subseteq I' .$$

This means I' is never better than I .

- ▶ Suppose that we take S_i in the first algorithm. I.e., $i \in I$.
- ▶ This means $x_i \geq \frac{1}{f}$.
- ▶ Because of **Complementary Slackness Conditions** the corresponding constraint in the dual must be tight.
- ▶ Hence, the second algorithm will also choose S_i .

Technique 3: The Primal Dual Method

The previous two rounding algorithms have the disadvantage that it is necessary to solve the LP. The following method also gives an f -approximation without solving the LP.

For estimating the cost of the solution we only required two properties.

1. The solution is dual feasible and, hence,

$$\sum_u y_u \leq \text{cost}(x^*) \leq \text{OPT}$$

where x^* is an optimum solution to the primal LP.

2. The set I contains only sets for which the dual inequality is tight.

Of course, we also need that I is a cover.

Technique 3: The Primal Dual Method

Algorithm 1 PrimalDual

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1:  $y \leftarrow 0$ 
2:  $I \leftarrow \emptyset$ 
3: while exists  $u \notin \bigcup_{i \in I} S_i$  do
4:   increase dual variable  $y_i$  until constraint for some
   new set  $S_\ell$  becomes tight
5:    $I \leftarrow I \cup \{\ell\}$ 

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Technique 4: The Greedy Algorithm

Algorithm 1 Greedy

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1:  $I \leftarrow \emptyset$ 
2:  $\hat{S}_j \leftarrow S_j$  for all  $j$ 
3: while  $I$  not a set cover do
4:    $\ell \leftarrow \arg \min_{j: \hat{S}_j \neq \emptyset} \frac{w_j}{|\hat{S}_j|}$ 
5:    $I \leftarrow I \cup \{\ell\}$ 
6:    $\hat{S}_j \leftarrow \hat{S}_j - S_\ell$  for all  $j$ 

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In every round the Greedy algorithm takes the set that covers remaining elements in the most **cost-effective** way.

We choose a set such that the ratio between cost and still uncovered elements in the set is minimized.

Technique 4: The Greedy Algorithm

Lemma 4

Given positive numbers a_1, \dots, a_k and b_1, \dots, b_k then

$$\min_i \frac{a_i}{b_i} \leq \frac{\sum_i a_i}{\sum_i b_i} \leq \max_i \frac{a_i}{b_i}$$

Technique 4: The Greedy Algorithm

Let n_ℓ denote the number of elements that remain at the beginning of iteration ℓ . $n_1 = n = |U|$ and $n_{s+1} = 0$ if we need s iterations.

In the ℓ -th iteration

$$\min_j \frac{w_j}{|\hat{S}_j|} \leq \frac{\sum_{j \in \text{OPT}} w_j}{\sum_{j \in \text{OPT}} |\hat{S}_j|} = \frac{\text{OPT}}{\sum_{j \in \text{OPT}} |\hat{S}_j|} \leq \frac{\text{OPT}}{n_\ell}$$

since an optimal algorithm can cover the remaining n_ℓ elements with cost OPT.

Let \hat{S}_j be a subset that minimizes this ratio. Hence,
 $w_j / |\hat{S}_j| \leq \frac{\text{OPT}}{n_\ell}$.

Technique 4: The Greedy Algorithm

Adding this set to our solution means $n_{\ell+1} = n_\ell - |\hat{S}_j|$.

$$w_j \leq \frac{|\hat{S}_j| \text{OPT}}{n_\ell} = \frac{n_\ell - n_{\ell+1}}{n_\ell} \cdot \text{OPT}$$

Technique 4: The Greedy Algorithm

$$\begin{aligned} \sum_{j \in I} w_j &\leq \sum_{\ell=1}^s \frac{n_\ell - n_{\ell+1}}{n_\ell} \cdot \text{OPT} \\ &\leq \text{OPT} \sum_{\ell=1}^s \left(\frac{1}{n_\ell} + \frac{1}{n_\ell - 1} + \dots + \frac{1}{n_{\ell+1} + 1} \right) \\ &= \text{OPT} \sum_{i=1}^k \frac{1}{i} \\ &= H_n \cdot \text{OPT} \leq \text{OPT}(\ln n + 1) . \end{aligned}$$