

## The k-MEDIAN Problem

Lemma 10.5 Primal-dual computes  $S \subseteq F$  with  $\sum_{j \in C} d(S, j) \leq 3(OPT + (k - |S|)\lambda)$ .

Define  $f(S) := \sum_{j \in C} d(S, j)$ . Let  $\alpha = \frac{k - |S_2|}{|S_1| - |S_2|}$ .

Lemma 10.6  $\alpha|S_1| + (1 - \alpha)|S_2| = k$  and  $\alpha f(S_1) + (1 - \alpha)f(S_2) \leq (3 + \varepsilon) \cdot OPT$

$$\text{Proof: } \frac{(k - |S_2|)|S_1|}{|S_1| - |S_2|} + \frac{(|S_1| - |S_2| - k + |S_2|) \cdot |S_2|}{|S_1| - |S_2|} = \frac{k(|S_1| - |S_2|)}{|S_1| - |S_2|}$$

$$\begin{aligned} f(S_1) &\leq 3(OPT + (k - |S_1|)\lambda_1) = 3(OPT + k\lambda_1 - |S_1|(\underbrace{\lambda_1 - \lambda_2 + \lambda_2}_{= \lambda_2})) \\ &\leq 3(OPT + k\lambda_1 - |S_1|\lambda_2) + \frac{\varepsilon \cdot OPT}{3|F|} \end{aligned}$$

$$\begin{aligned} \alpha f(S_1) + (1 - \alpha)f(S_2) &\leq \underbrace{\alpha \varepsilon}_{\leq \varepsilon} OPT + 3\alpha(OPT + k\lambda_1 - |S_1|\lambda_2) \\ &\quad + 3(1 - \alpha)(OPT + k\lambda_2 - |S_2|\lambda_2) \\ &\leq (3 + \varepsilon)OPT + 3(k \cdot \underbrace{(\alpha\lambda_1 + (1 - \alpha)\lambda_2)}_{\leq \lambda_2} - \lambda_2 \underbrace{(\alpha|S_1| + (1 - \alpha)|S_2|)}_{= k}) \\ &\leq (3 + \varepsilon)OPT. \quad \square \end{aligned}$$

Theorem 10.7 The algorithm is a  $(6 + \varepsilon)$ -approximation for k-MEDIAN.

Proof: Case  $\alpha \leq \frac{1}{2}$ :  $|S_2| \leq k$  and  $\frac{1}{2}f(S_2) \leq (1 - \alpha)f(S_2) \leq (3 + \varepsilon)OPT$

Case  $\alpha > \frac{1}{2}$ : "nearest facility": For  $i, j \in F$  define  $d_{ij} := \min \{d_{ij}, d_{i2j} : j \in C\}$ .

Let  $j \in C$ . Let  $i_1 \in S_1$  with  $d_{i_1 j} = d(S_1, j)$  and  $i_2 \in S_2$  with  $d_{i_2 j} = d(S_2, j)$ .

Either  $i_1 \in \bar{S}$  or  $i_1 \in X$  with probability  $\frac{k - |\bar{S}|}{|S_1| - |\bar{S}|} \geq \frac{k - |S_2|}{|S_1| - |S_2|} = \alpha$ .

Furthermore  $d(\bar{S}, j) \leq d_{\phi(i_1), j} \leq d_{i_2 j} + d_{i_2 \phi(i_1)} \leq d_{i_2 j} + d_{i_1 i_2} \leq d_{i_2 j} + d_{i_1 j} + d_{i_2 j}$ .

$\Rightarrow E[d(\bar{S}, X, j)] \leq \alpha d_{i_1 j} + (1 - \alpha)(d_{i_1 j} + 2d_{i_2 j}) \stackrel{\alpha > \frac{1}{2}}{\leq} 2(\alpha d(S_1, j) + (1 - \alpha)d(S_2, j))$

$\Rightarrow E[\sum_{j \in C} d(\bar{S}, X, j)] \leq (6 + 2\varepsilon)OPT \quad \square$

Remark Construction of  $X$  can be derandomized.

# SURVIVABLE NETWORK DESIGN

Lemma 11.1 LP(F) can be solved in polynomial time.

Proof: Separation routine, given  $x \in \mathbb{R}_+^{E \setminus F}$ :

$$\text{Define capacities } u_e := \begin{cases} 1 & \text{if } e \in F \\ x_e & \text{if } e \in E \setminus F \end{cases}$$

For each  $\{v, w\} \subseteq V$ , compute min v-w-cut  $\delta(S)$  w.r.t.  $u_e$ .

If  $\sum_{e \in \delta(S)} u_e < r_{vw}$ , then  $\sum_{e \in \delta(S) \setminus F} x_e < f(S) - |\delta(S) \cap F|$ . That is,

we have found a separating inequality. Otherwise,  $x$  is feasible.  $\square$

Lemma 11.2 The algorithm maintains the following invariant for the optimal solution

$$x \text{ to LP}(F): \quad \frac{1}{2} \sum_{e \in F} d_e + \sum_{e \in E \setminus F} d_e x_e \leq \text{OPT}$$

Proof: By induction on the algorithm. True initially as LP( $\emptyset$ ) is LP relaxation for SND. Now assume claim is true for  $F'$  and opt solution  $x'$  to LP( $F'$ ). Let  $F^+ := \{e \in E \setminus F' : x'_e \geq \frac{1}{2}\}$  and  $F := F' \cup F^+$ .

Let  $x$  be an optimal solution to LP( $F$ ). Observe that  $x'|_{E \setminus F}$  is a feasible solution to LP( $F'$ ), because

$$f(S) - |\delta(S) \cap F'| \leq \sum_{e \in \delta(S) \setminus F'} x'_e \leq \sum_{e \in \delta(S) \setminus F} x'_e + |\delta(S) \cap F'| \quad \forall S \subseteq V.$$

Thus,  $\sum_{e \in E \setminus F} d_e x_e \leq \sum_{e \in E \setminus F} d_e x'_e$  and it follows that

$$\begin{aligned} \frac{1}{2} \sum_{e \in F} d_e + \sum_{e \in E \setminus F} d_e x_e &\leq \frac{1}{2} \sum_{e \in F'} d_e + \frac{1}{2} \sum_{e \in F^+} d_e + \sum_{e \in E \setminus F} d_e x'_e \\ &\leq \frac{1}{2} \sum_{e \in F'} d_e + \sum_{e \in E \setminus F} d_e x'_e \leq \text{OPT}. \quad \square \end{aligned}$$

It remains to show that the algorithm terminates.

→ next lecture