Shortest Path

$$\begin{array}{llll} \min & & \sum_{e} c(e) x_{e} \\ \text{s.t.} & \forall S \in S & \sum_{e \in \delta(S)} x_{e} & \geq & 1 \\ & \forall e \in E & x_{e} & \in & \{0,1\} \end{array}$$

S is the set of subsets that separate s from t.

The Dual:

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s.t. $\forall e \in E \ \sum_{S:e \in \delta(S)} y_{S} \le c(e)$
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The Separation Problem for the Shortest Path LP is the Minimum Cut Problem

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Suppose that ℓ_e -values are solution to Minimum Cut LP.

- We can view ℓ_e as defining the length of an edge.
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Let B(s,r) be the ball of radius r around s (w.r.t. metric d). Formally:

$$B = \{ v \in V \mid d(s, v) \le r \}$$

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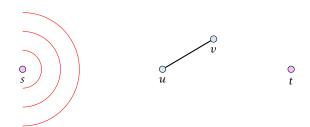


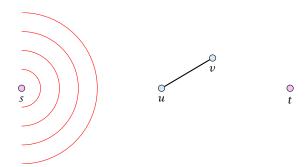


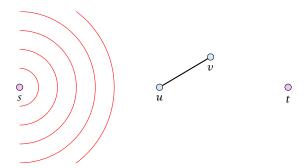


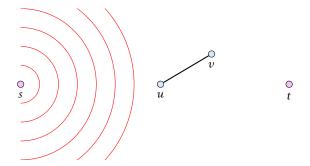


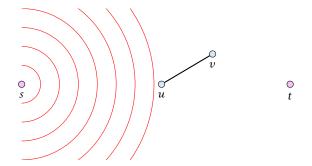


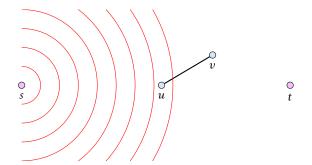


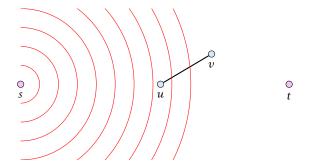


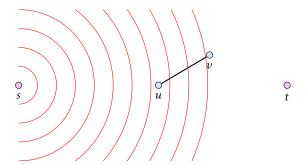




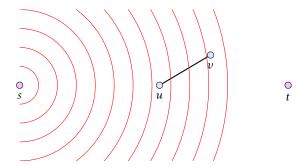




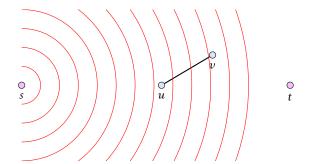




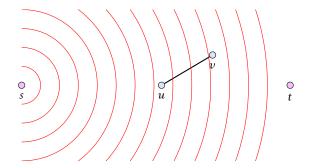


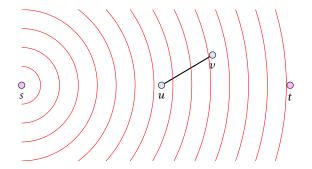


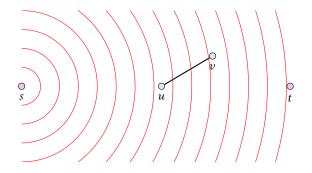






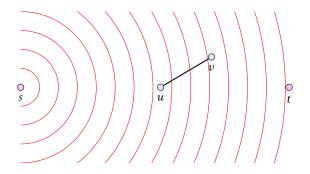






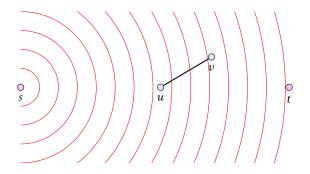
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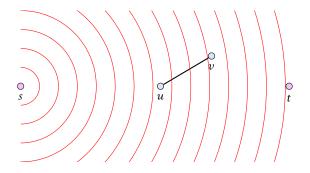
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Given a graph G=(V,E), together with source-target pairs s_i,t_i , $i=1,\ldots,k$, and a capacity function $c:E\to\mathbb{R}^+$ on the edges. Find a subset $F\subseteq E$ of the edges such that all s_i - t_i pairs lie in different components in $G=(V,E\setminus F)$.

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- Assume for simplicity that all edge-length ℓ_e are multiples of $\delta \ll 1$.
- ▶ Replace the graph G by a graph G', where an edge of length ℓ_e is replaced by ℓ_e/δ edges of length δ .
- ▶ Let $B(s_i, z)$ be the ball in G' that contains nodes v with distance $d(s_i, v) \le z\delta$.

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1: z ← 0
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- choose $p = 6 \ln k \cdot \delta$
- we make $\frac{1}{2\delta}$ trials before reaching radius 1/2.
- ▶ we say a Region Growing is not successful if it does not terminate before reaching radius 1/2.

$$\Pr[\mathsf{not}\;\mathsf{successful}] \leq (1-p)^{\frac{1}{2\delta}} = \left((1-p)^{1/p}\right)^{\frac{p}{2\delta}} \leq e^{-\frac{p}{2\delta}} \leq \frac{1}{k^3}$$

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$$\begin{split} E[\text{cutsize} \mid \text{succ.}] &= \frac{E[\text{cutsize}] - Pr[\text{no succ.}] \cdot E[\text{cutsize} \mid \text{no succ.}]}{Pr[\text{success}]} \\ &\leq \frac{E[\text{cutsize}]}{Pr[\text{success}]} &= \frac{1}{1 - \frac{1}{k^2}} 6 \ln k \cdot \text{OPT} \leq 8 \ln k \cdot \text{OPT} \end{split}$$

Note: success means all source-target pairs separated. We assume k > 2.

$$\begin{split} E[\text{cutsize}] &= \text{Pr}[\text{success}] \cdot E[\text{cutsize} \mid \text{success}] \\ &\quad + \text{Pr}[\text{no success}] \cdot E[\text{cutsize} \mid \text{no success}] \end{split}$$

$$\begin{split} \text{E[cutsize \mid succ.]} &= \frac{\text{E[cutsize]} - \text{Pr[no succ.]} \cdot \text{E[cutsize \mid no succ.]}}{\text{Pr[success]}} \\ &\leq \frac{\text{E[cutsize]}}{\text{Pr[success]}} \leq \frac{1}{1 - \frac{1}{k^2}} 6 \ln k \cdot \text{OPT} \leq 8 \ln k \cdot \text{OPT} \end{split}$$

Note: success means all source-target pairs separated. We assume k > 2.



$$\begin{split} E[\text{cutsize}] &= \text{Pr}[\text{success}] \cdot E[\text{cutsize} \mid \text{success}] \\ &\quad + \text{Pr}[\text{no success}] \cdot E[\text{cutsize} \mid \text{no success}] \end{split}$$

$$\begin{split} \text{E[cutsize \mid succ.]} &= \frac{\text{E[cutsize]} - \text{Pr[no succ.]} \cdot \text{E[cutsize \mid no succ.]}}{\text{Pr[success]}} \\ &\leq \frac{\text{E[cutsize]}}{\text{Pr[success]}} \leq \frac{1}{1 - \frac{1}{k^2}} 6 \ln k \cdot \text{OPT} \leq 8 \ln k \cdot \text{OPT} \end{split}$$

Note: success means all source-target pairs separated

We assume V > 2

$$\begin{split} E[\text{cutsize}] &= \text{Pr}[\text{success}] \cdot E[\text{cutsize} \mid \text{success}] \\ &\quad + \text{Pr}[\text{no success}] \cdot E[\text{cutsize} \mid \text{no success}] \end{split}$$

$$\begin{split} \text{E[cutsize \mid succ.]} &= \frac{\text{E[cutsize]} - \text{Pr[no succ.]} \cdot \text{E[cutsize \mid no succ.]}}{\text{Pr[success]}} \\ &\leq \frac{\text{E[cutsize]}}{\text{Pr[success]}} \leq \frac{1}{1 - \frac{1}{k^2}} 6 \ln k \cdot \text{OPT} \leq 8 \ln k \cdot \text{OPT} \end{split}$$

Note: success means all source-target pairs separated

We assume $k \ge 2$.



If we are not successful we simply perform a trivial k-approximation.

This only increases the expected cost by at most $\frac{1}{k^2} \cdot k\text{OPT} \leq \text{OPT}/k$.

Hence, our final cost is $O(\ln k) \cdot OPT$ in expectation.