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Chernoff Bound; Randomized Rounding

Routing to minimize congestion.

Given $G = (V, E)$ [directed]

src-destination pairs $\{(s_i, t_i)\}_{i=1}^k$ $s_i, t_i \in V$.

edge capacities $c_{uv} \in \mathbb{N}$. $\forall (u, v) \in E$.

Goal: Choose a routing path P_i connecting s_i to t_i for all i .

Define $\text{load}(u, v) = \#\{i \mid P_i \text{ contains } (u, v)\}$.
minimize $\max_{(u, v) \in E} \left\{ \frac{\text{load}(u, v)}{c_{uv}} \right\}$.

This is NP-Hard.

The following relaxation is solvable in poly time:

Choose a prob distrib. f_i over paths P_i joining s_i to t_i .

Define $\text{load}(u,v) = \sum_{i=1}^k \Pr((u,v) \text{ belongs to } P_i \text{ sampled from } f_i)$

minimize $\max_{(u,v) \in E} \left\{ \frac{\text{load}(u,v)}{c_{uv}} \right\}$.

Why easy? f_i (prb distrib over paths) can be summarized by

$$\phi_i(u,v) = \Pr((u,v) \in P_i \text{ sampled from } f_i) - \Pr((v,u) \in P_i \text{ samp from } f_i).$$

Then ϕ_i is a flow of value 1 from s_i to t_i .

This reduces to solving a poly-size LP. Variables are $\{\phi_i(u,v)\} \forall i, u, v$.

minimize r

s.t. $\phi_i(u,v) = -\phi_i(v,u) \quad \forall i, u, v.$

$$\sum \phi_i(u,v) = \begin{cases} 1 & \text{if } u=s_i \\ -1 & \text{if } u=t_i \\ \emptyset & \text{if } u \notin \{s_i, t_i\} \end{cases} \quad \forall i, u$$

$$\sum_i \phi_i(u,v) \leq r \cdot c_{uv} \quad \forall (u,v) \in E.$$

Solve this LP. Obtain flows ϕ_1, \dots, ϕ_k .
Decompose each ϕ_i as prob distrib^{ns}
over s_i - t_i paths, $f_{i,j}$.

Draw one random sample, P_i ,
from each distribution f_i ,
independently. } indep.
randomised
rounding

Output (P_1, \dots, P_k) .

For any (u,v) ,

$$\mathbb{E}[\text{load}(u,v) \text{ from } P_1, \dots, P_k]$$

$$= \sum_{i=1}^k \mathbb{E}[\text{load}(u,v) \text{ from } P_i]$$

$$= \sum_{i=1}^k \Pr((u,v) \in P_i)$$

$$= \sum_i \phi_i(u,v) \quad (\text{assuming wlog, } \Pr((u,v) \in P_i) = 0)$$

$$\leq r \cdot C_{uv}$$

Chebyshev Bound: If X_1, \dots, X_N are independent $[0, 1]$ -valued rand vars, and if $X = X_1 + \dots + X_N$
 $\mu = E[X]$.

then $\Pr(X > (1+\epsilon)\mu)$ and $\Pr(X < (1-\epsilon)\mu)$

are both $< \exp(-\psi(\epsilon) \cdot \mu)$.

where $\psi(\epsilon) > 0$ for $\epsilon > 0$,

$\psi(\epsilon) > \frac{1}{3} \epsilon^2$ for $\epsilon < 1$.

"The tail probability, i.e. $\Pr(X > (1+\epsilon)\mu)$ or $\Pr(X < (1-\epsilon)\mu)$ is exponentially small when the expectation of the sum, μ , is much bigger than the max possible value of any constituent of the sum."

