

Max flow: using MW. (unit capacity graph).

we want to solve the problem $\left\{ \begin{array}{l} \sum_p f_p = \text{our guess for the max flow.} \\ \sum_{p \in e} f_p \leq 1 = u_e \quad \forall \text{ edges } e. \\ f_p \geq 0. \end{array} \right.$

Given weights $\{p_e\} \in \Delta_m$ we get the problem: find a solution to the

problem $\left\{ \begin{array}{l} \sum_p f_p = F \\ \sum_{p \in e} p_e \sum_p f_p \leq \sum p_e = 1. \Leftrightarrow \sum_p f_p \cdot p(P) \leq 1 \\ f_p \geq 0. \end{array} \right.$

This is an "unconstrained" problem essentially, we should find the shortest path P^* under the edge lengths p_e , and set $f_{P^*} = F$ for that path. (if $\exists$ no solution to this problem then $\exists$ no solⁿ to original problem as well.) // this means, length of S.P $\leq \frac{1}{\text{OPT}}$.

Now once we find this path, we return this solⁿ $f_p \rightarrow$ transformed as an assignment of values $\{f_e\}_{e \in E}$. Note that $f_e \leq F$ $\forall$ edges. Now we know that

Use one-sided guarantee $\rightarrow \frac{1}{T} \sum_t \langle f^t, p^t \rangle \geq \frac{1}{T} \sum_t \langle f^t, \bar{e}_{\text{edge } e_i} \rangle - \epsilon \quad \text{for } T \geq \frac{\theta(f \ln m)}{\epsilon^2}$

If the flow $\hat{f} = \frac{1}{T} \sum f^t$, then RHS = $\max_{e \in E} \langle \hat{f}, e_e \rangle - \epsilon$

And $\sum_K \frac{\langle \hat{f}, p^t \rangle}{T} \leq 1. \Rightarrow$ the edge congestion $\leq \frac{(1+\epsilon)}{(1-\epsilon)} \leq (1+\epsilon)^2$

Note: Since the losses/gains are only positive, we can reduce the dependence on the oracle width (f) to f instead of f^2 . [use AKK analysis of MW]

But the runtime now is: $T \times$ shortest path

$\Rightarrow O\left(\frac{F \log m}{\epsilon^2} \times m \log n\right)$ at most $O(m^2)$ or $\tilde{O}(mF)$

Like FF: Not very impressive! $\therefore$ But the idea has potential.

②

If only we could find a solution of low width. (f). We know $\exists$ an ideal solution (namely the flow itself) that has width $f = \max_{e \in E} f_e = 1$.
But that is what we seek!

Here's a way to get width $O(\sqrt{m})$ and still find the flow in time $\tilde{O}(m)$.
Electrical flows!

Suppose we set the voltage (potential) of source s at some value V_s and sink t at $V_t = 0$. Then you set electrical current through the network that minimizes the total energy dissipated, which is $\sum f_e^2 \cdot R_e$, where R_e is resistance of the edge. Recall also that $\Delta\phi$ across the edge $= f_e \cdot R_e$.

$$\text{Energy} = \sum_e f_e^2 R_e = \sum_{u,v} \frac{(\phi_u - \phi_v)^2}{R_e}.$$

How do we find this flow: -

L = Laplacian of the graph = $\text{Deg}(\text{degrees}) - A$. (unweighted).

Note: Laplacian of an edge $(u,v) = \begin{matrix} u & v \\ \begin{pmatrix} 1 & -1 \\ -1 & 1 \end{pmatrix} \end{matrix}$ or with resistance R_e $\begin{pmatrix} 1 & -1 \\ -1 & 1 \end{pmatrix} \times \frac{1}{R_e}$.

Laplacian of graph = $\sum_{\text{edges}} \text{Laplacian of the edge} \cdot \left(\frac{1}{R_e}\right)$.

$$\text{So } Lx = \sum_{u,v} \frac{L_{uv} \cdot x}{R_e} \quad \cancel{\frac{1}{R_e} (x_u - x_v)} \Rightarrow \left(\sum_{v \sim u} \frac{(x_u - x_v)}{R_e} \right)_{u \in V}$$

$(Lx)_u$: this should be total current being pushed into u .

So if we set $(Lx)_s = \text{OPT} = -(Lx)_t$ And solve for x , we get the potentials.
 $(Lx)_u = 0 \quad \forall u \notin \{s, t\}$

And hence the f_e 's.

③

Good: the best part is: we can solve $Lx=b$ for Laplacian matrices in time $O(m \text{ poly}(\log n))$. [Spielman Teng, Miller Koutis Peng ...] In fact in time $O(m \sqrt{\log n})$ now. [Check: is linear doable already?].

Why is this Electrical flow better than just the shortest path flow?

Intuitively, does not overload any edge, since the energy dissipated is f_e^2 .

So will try to spread it out a little more

Formally: Suppose we set resistances $R_e = \frac{1}{p_e} + \frac{\epsilon}{m}$ then get electrical flow f_e

with $\sum p_e f_e \leq (1+\epsilon) \leftarrow$ instead of 1, but no real big deal.

$\max_e f_e \leq \tilde{O}(\sqrt{m}) \leftarrow$ width!

Pf: Since $\exists$ a feasible flow f^* with $f^*(e) \leq 1 \forall e$, it has energy at most $\text{Energy}(f^*) \leq \sum R_e (f_e^*)^2 \leq \sum (\frac{1}{p_e} + \frac{\epsilon}{m}) \leq 1+\epsilon$.

$$\Rightarrow (\sum p_e f_e)^2 \leq (\sum p_e f_e^2) (\sum p_e) \leq (1+\epsilon).$$

$$\Rightarrow \sum p_e f_e \leq \sqrt{1+\epsilon} \leq 1+\epsilon \quad \checkmark$$

also $\forall e \quad \frac{f_e^2 \cdot \epsilon}{m} \leftarrow$ at least this much energy burn on edge e

$$\Rightarrow f_e \leq \sqrt{\frac{m(1+\epsilon)}{\epsilon}} \approx \sqrt{m}.$$

$\leq (1+\epsilon)$ total energy burn on min-energy flow

Plugging this in, get an $\tilde{O}(m^{3/2})$ runtime algorithm.

Even for sparse graphs, ~~not~~ as good as Even-Tarjan but no better.

How can we do better?

[Christiano Kelner Madry Spielman Teng 2011].

One Sided Guarantee:

[Amotz Hazan Kale Thm 2.1]

Thm 1: $\forall \epsilon \leq \frac{1}{2}$, The MW(ϵ) algorithm achieves the following guarantee:-
for any sequence of loss vectors $\ell^t \in [-1, 1]^N$, $\forall T, \forall i$,

$$\sum_t \langle \ell^t, p^t \rangle \leq \sum_t \langle \ell^t, e_i \rangle + \epsilon \sum_t |\ell_i^t| + \frac{\ln N}{\epsilon}.$$

Now translating to gains, and scaling by φ , (ie. setting $\ell^t = -\frac{g^t}{\varphi}$) we set

Thm 2: $\forall \epsilon \leq \frac{1}{2}$, the MW(ϵ) algorithm achieves, for all sequence of gain
vectors $g^t \in [-\varphi, \varphi]^N$, $\forall T, \forall i$

$$\sum_t \langle g^t, p^t \rangle \geq \sum_t g_i^t - \epsilon \sum_t |g_i^t| - \varphi \frac{\ln N}{\epsilon} \quad (*)$$

What if the gains are only positive? then (*) simplifies to
in $[0, \varphi]$

$$\sum_t \langle g^t, p^t \rangle \geq \left(\sum_t g_i^t \right) (1 - \epsilon) - \frac{\varphi \ln N}{\epsilon}$$

Now setting T large enough, we get that (ie. $T \geq \frac{\varphi \ln N}{\epsilon^2}$)

$$\text{Average gain} = \frac{1}{T} \sum_t \langle g^t, p^t \rangle$$

$$\geq \frac{(\text{Gain of expert } i)}{T} (1 - \epsilon) - \left(\frac{\varphi \ln N}{\epsilon} \cdot \frac{1}{T} \right)$$

$$= (\text{Average gain of expert } i) (1 - \epsilon) - \epsilon$$

■