

# Approximate Max Flow in Near-linear Time

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## 1 Recall some terminology

- Let  $G = (V, E)$  be an undirected graph with edge capacities  $c \in \mathbb{R}_{\geq 0}^E$  (with  $n$  vertices and  $m$  edges).
- A **flow**  $f : V \times V \rightarrow \mathbb{R}$  satisfies  $f(u, v) = -f(v, u)$  and  $f(u, v) = 0$  for  $\{u, v\} \notin E$ .
  - The notation  $f(u, v) > 0$  means that **mass** is routed in the direction from  $u$  to  $v$ .
  - The **congestion** of  $f$  is  $\max_{\{u, v\} \in E} \frac{|f(u, v)|}{c(u, v)}$ . If the congestion is at most 1, we say that  $f$  is **feasible** or **respects capacities**.
  - The **net flow going out of  $u$**  is  $f_{out}(u) = \sum_{v \in V} f(u, v)$ .
- Let  $d : V \rightarrow \mathbb{R}$  be a **demand function**.
  - We say that flow  $f$  **satisfies demand  $d$**  if  $d(u) = f_{out}(u)$  for all  $u \in V$ .
  - For any  $S \subseteq V$ , let  $d(S) = \sum_{v \in S} d(v)$  be the **total demand** on  $S$ .
  - Assume  $d(V) = 0$ .

**Fact 1.1.**  $|d(S)| \leq \epsilon \cdot \delta(S)$  for all  $S \subseteq V$  iff there is a flow with congestion  $\epsilon$  satisfying  $d$ .

- We say  $d$  is **feasible** if  $|d(S)| \leq \delta(S)$  for all  $S \subseteq V$  (i.e. there is a feasible flow satisfying the demand).

## 2 The Approximate Max Flow Problem

- The  $(1 + \epsilon)$ -**approximate max flow problem**:
  - given a capacitated graph  $G = (V, E, c)$  and a demand  $d$ ,
  - output either
    - \* a cut  $S$  where  $\delta(S) < d(S)$
    - \* a flow  $f \in \mathbb{R}^E$  with congestion  $(1 + \epsilon)$  satisfying  $d$

**Exercise 2.1** (Routing through maximum spanning tree). Show how to solve the  $O(m)$ -approximate max flow problem in  $O(m \log n)$  time using maximum spanning trees.

- One of the key idea for solving this problem is to change the problem a bit...

## 2.1 “Almost Route” demand instead

- For a flow  $f$  and a demand function  $\mathbf{d}$ , define **excess** or **residual demand**  $\mathbf{d}^f(v) = \mathbf{d}(v) - f_{out}(v)$  for every  $v \in V$ .
- We say that  $f$   $\epsilon$ -**satisfies**  $\mathbf{d}$  if  $|\mathbf{d}^f(S)| \leq \epsilon\delta(S)$  for all  $S \subseteq V$ 
  - That is, there exists  $f_{aug}$  with congestion  $\epsilon$  where  $f + f_{aug}$  satisfies  $\mathbf{d}$ .
- **The  $\epsilon$ -almost-route problem:** output either
  - a cut  $S$  where  $\delta(S) < |\mathbf{d}(S)|$
  - a feasible flow  $f \in \mathbb{R}^E$  that  $\epsilon$ -satisfies  $\mathbf{d}$ .

**Lemma 2.2.** *We can solve the approximate max flow problem by solving the almost-route problem  $O(\log n)$  time plus  $O(m)$  additional time.*

*Proof.* Given graph  $G$  and demand  $\mathbf{d}_0$ , call almost-route on  $(G, \mathbf{d}_0)$ .

- If we get a cut  $S$  where  $\delta(S) < |\mathbf{d}_0(S)|$ , done.
- If we get a feasible flow  $f_0$   $\epsilon$ -satisfying  $\mathbf{d}_0$ , we will show how to construct  $f$  satisfying  $\mathbf{d}_0$  with congestion  $(1 + O(\epsilon))$ .
  - Let  $\mathbf{d}_1 \leftarrow \mathbf{d}_0^{f_0}$  be the residual demand. Call almost-route on  $(\epsilon \cdot G, \mathbf{d}_1)$ .
  - Can we get a cut? No.
    - \* We knew that  $|\mathbf{d}_1(S)| \leq \epsilon \cdot \delta(S)$  for all  $S \subseteq V$  (as  $f_0$   $\epsilon$ -satisfies  $\mathbf{d}_0$ ).
  - We must get a feasible flow  $f_1$  on  $\epsilon \cdot G$  that  $\epsilon$ -satisfies  $\mathbf{d}_1$ .
    - \*  $f_1$  has congestion  $\epsilon$  on  $G$ .
    - \*  $|\mathbf{d}_1^{f_1}(S)| \leq \epsilon^2 \delta(S)$  for all  $S \subseteq V$ .
  - Let  $\mathbf{d}_2 \leftarrow \mathbf{d}_1^{f_1}$ . Call almost-route on  $(\epsilon^2 \cdot G, \mathbf{d}_2)$  and get a feasible flow  $f_2$  on  $\epsilon^2 \cdot G$  that  $\epsilon$ -satisfies  $\mathbf{d}_2$ .
    - \*  $f_2$  has congestion  $\epsilon^2$  on  $G$ .
    - \*  $|\mathbf{d}_2^{f_2}(S)| \leq \epsilon^3 \delta(S)$  for all  $S \subseteq V$ .
  - Repeat until we call almost-route on  $(\epsilon^L \cdot G, \mathbf{d}_L)$  we get  $f_L$  where  $L = O(\log m)$ .

**Lemma 2.3.** *Consider  $f = f_0 + f_1 + \dots + f_L$ . We have*

1.  $f$  has congestion at most  $1 + \epsilon + \dots + \epsilon^L = 1 + O(\epsilon)$ , and
2.  $f$   $(\epsilon^{L+1})$ -satisfies  $\mathbf{d}_0$ .

*Proof.* For the first statement, this is because each  $f_i$  has congestion at most  $\epsilon^i$  on  $G$ .

For the second statement, for any  $S$ , we have

$$\begin{aligned}\mathbf{d}_0^f(S) &= \mathbf{d}_0(S) - f_0(S) - f_1(S) - \dots - f_L(S) \\ &= \mathbf{d}_1(S) - f_1(S) - \dots - f_L(S) \\ &= \mathbf{d}_L(S) - f_L(S) \\ &= \mathbf{d}_L^{f_L}(S)\end{aligned}$$

but  $|\mathbf{d}_L^{f_L}(S)| \leq \epsilon^{L+1} \delta(S)$

□

□

- The residual demand  $\mathbf{d}_0^f$  can be satisfied with a flow with congestion  $\epsilon^{L+1}$ .
- We can find a flow  $f_{final}$  satisfying  $\mathbf{d}_0^f$  with congestion  $O(m) \cdot \epsilon^{L+1} \leq 1/\text{poly}(m)$ .
  - How? Route through maximum spanning tree, see Exercise 2.1.
- We just return  $f + f_{final}$  which has  $1 + O(\epsilon)$  congestion and exactly satisfies  $\mathbf{d}_0$

### 3 First Ingredient: Congestion Approximator

- Motivation:
  - How can we guarantee that  $f$   $\epsilon$ -satisfies  $\mathbf{d}$ ?
  - There are  $2^n$  many constraints  $|\mathbf{d}^f(S)| \leq \epsilon \delta(S)$  for all  $S \subseteq V$ .

**Definition 3.1** (Congestion Approximator). An **congestion approximator of  $G$  with quality  $q$**  is a family of cuts  $\mathcal{C}$  such that, for any demand vector  $\mathbf{d} \in \mathbb{R}^V$  we have that if  $|\mathbf{d}(S)| \leq \delta(S)$  for all  $S \in \mathcal{C}$ , then  $|\mathbf{d}(S)| \leq q \cdot \delta(S)$  for all  $S \subseteq V$ .

**Exercise 3.2.** Let  $T$  be a tree. Let  $\mathcal{C}$  contains all  $n - 1$  cuts defined by each tree edge. Show that  $\mathcal{C}$  is a congestion approximator of  $T$  with quality 1.

**Exercise 3.3.** Let  $G$  be a  $\phi$ -expander. Let  $\mathcal{C} = \{\{v\}\}_{v \in V}$  contains all  $n$  singleton cuts. Show that  $\mathcal{C}$  is a congestion approximator of  $T$  with quality  $1/\phi$ .

#### 3.1 Construction via Tree Flow Sparsifier

**Lemma 3.4.** Let  $T$  be a tree flow sparsifier of  $G$  with quality  $q$ . For every  $u \in V(T)$ , let  $S_u \subseteq V$  denote the set of leaves in the subtree rooted at  $u$ . Let

$$\mathcal{C}_T = \{S_u \mid u \in V(T)\}.$$

Then  $\mathcal{C}_T$  is a congestion approximator of  $G$  with quality  $q$ .

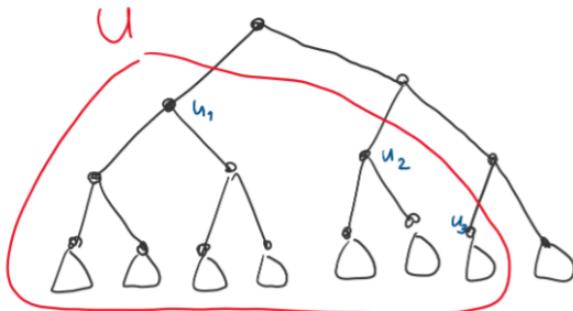
*Proof.* Given a demand  $\mathbf{d} \in \mathbb{R}^{V(G)}$  on  $V(G)$ , we will prove two things

1. If  $|\mathbf{d}(S)| \leq \delta(S)$  for all  $S \in \mathcal{C}_T$ , then  $\mathbf{d}$  is feasible in  $T$ .
2. If  $\mathbf{d}$  is feasible in  $T$ , then  $\mathbf{d}$  can be routed with congestion  $q$  in  $G$  (and so  $|\mathbf{d}(S)| \leq q \cdot \delta(S)$  for all  $S \subseteq V$ ).

□

For the first step, suppose for contradiction that there is  $\mathbf{d}$  is infeasible.

- There is a cut  $U \subseteq V(T)$  where  $|\mathbf{d}(U)| > \delta_T(U)$ .



- But then there must exists  $u \in V(T)$  where  $|\mathbf{d}(S_u)| > c_T(u, \text{parant}(u)) \geq \delta(S_u)$

For the second step, suppose  $\mathbf{d}$  is feasible in  $T$ .

- Let  $f_T$  be the feasible flow in  $T$  that routes  $\mathbf{d}$ .
- Let  $F_T$  be a set of flow-paths in the decomposition of  $f_T$ . Think of  $F_T$  as a multi-commodity flow.
- Let  $D$  be the multi-commodity demand that  $F_T$  routes. In particular,  $D$  is routable in  $T$ .
- But then  $D$  is routable in  $G$  with congestion  $q$ , because  $T$  has is a flow sparsifier with quality  $q$ .
- So  $\mathbf{d}$  is routable in  $G$  with congestion  $q$ .
  - For more details, let  $F_G$  be a multi-commodity flow that routes  $D$  in  $G$ .
  - Let  $f_G$  be obtained from  $F_G$  by treating  $F_G$  as a single-commodity flow (i.e. allow flow cancellation).
  - We have that  $f_G$  routes  $\mathbf{d}$  in  $G$ .

Using the state-of-the-art algorithm for tree-flow sparsifiers, we have:

**Corollary 3.5.** *A congestion approximator  $\mathcal{C}$  of  $G$  with quality  $\text{polylog}(n)$  and  $|\mathcal{C}| \leq 2n$  can be constructed in  $\tilde{O}(m)$  time.<sup>1</sup> Moreover, each vertex is contained in at most  $O(\log n)$  sets from  $\mathcal{C}$ .*

We can also use the expander hierarchy from the previous class. But the quality would be  $n^{o(1)}$  and the construction time would be  $m^{1+o(1)}$ .

### 3.2 Reduce the problem further...

- So we now reduce our problem to the following:
- Given a congestion approximator  $\mathcal{C}$  with quality  $q$  and  $|\mathcal{C}| = O(n)$ , output either
  - a cut  $S$  where  $\delta(S) < |\mathbf{d}(S)|$
  - a feasible flow  $f \in \mathbb{R}^E$  such that for all  $S \in \mathcal{C}$

$$|\mathbf{d}^f(S)| \leq \frac{\epsilon}{q} \delta(S)$$

because this implies that  $f$   $\epsilon$ -satisfies  $\mathbf{d}$ .

- In other words, either
  - find a violating cut, or
  - make sure that the total excess on every set  $S \in \mathcal{C}$  is small (instead of all sets  $S \subseteq V$ ).

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<sup>1</sup><https://arxiv.org/pdf/1411.7631.pdf>

## 4 Second Ingredient: Multiplicative Weights Update

Here, we state how the multiplicative weight update (MWU) framework can be used for solving *general* LPs.

- Given a following linear program (LP):

$$(LP) \quad \begin{aligned} & \text{Find } x \text{ s.t.} \\ & Ax \geq b \\ & x \in \Delta \end{aligned}$$

where  $A \in \mathbb{R}^{n \times m}$ ,  $b \in \mathbb{R}^n$ ,  $x \in \mathbb{R}^m$ ,  $\Delta$  is convex (e.g.  $x \geq 0$ ).

- Define:

- $Ax \geq b$  as a set of “hard” constraints
- $x \in \Delta$  as an “easy” constraint

- Our goal is to find  $\bar{x}$  that approximately satisfies the LP, i.e.,

$$\begin{aligned} A\bar{x} &\geq b - \epsilon\mathbf{1} \\ \bar{x} &\in \Delta \end{aligned}$$

- The MWU allows us to find  $\bar{x}$  if we can solve the problem “average” problem for a few rounds.

- More precisely,

- In each round  $t = 1, 2, \dots$ , the framework will fix some  $p_t \in \mathbb{R}_{\geq 0}^n$  (i.e. “weights” of hard constraints).
  - \*  $p_1$  is initially the all-one vector.
- We need to solve the following “average” LP:

$$\begin{aligned} & \text{Find } x \text{ s.t.} \\ & p_t^\top Ax \geq p_t^\top b \\ & x \in \Delta \end{aligned}$$

Note that, the hard constraint are not average into just one constraint!

- Suppose we can compute a feasible solution  $x_t$  of the average problem (i.e.  $p_t^\top Ax_t \geq p_t^\top b$  and  $x_t \in \Delta$ ) such that  $x_t$  has **width** at most  $\rho$ , i.e.

$$|A_i x_t - b_i| \leq \rho \forall i \in [n]$$

That is,  $x_t$  does not violate or over-satisfy each constraint by more than  $\rho$ .

- Given  $x_t$ , the MWU framework will adaptively update  $p_{t+1}$  based on  $x_t$  as follows:

$$(p_{t+1})_i = (p_t)_i \cdot \exp\left(\frac{\epsilon}{\rho} \cdot (b_i - A_i x_t)\right)$$

and proceed to the next round.

- \* Intuition: If the  $i$ -th constraint is violated a lot by  $x_t$  ( $A_i x_t \ll b_i$ ), then the weight  $(p_{t+1})_i$  increases a lot. So in the next round, the  $i$ -th constraint should be satisfied.
- \* From the way we update weights, this give the name *multiplicative weight update* framework.
- After  $T = O(\rho^2 \log n / \epsilon^2)$  rounds, the MWU framework guarantees that  $\bar{x} = (\sum_{t=1}^T x_t)/T$  satisfies

$$\begin{aligned} A\bar{x} &\geq b - \epsilon\mathbf{1} \\ \bar{x} &\in \Delta \end{aligned}$$

- It is quite an amazing framework: reducing a worst-case problem to an average problem.

## 5 The Algorithm

Recall our goal: either find

- a violating cut  $S$  where  $\delta(S) < |\mathbf{d}(S)|$ , or
- a feasible  $f$  where  $|\mathbf{d}^f(S)| \leq \epsilon/q \cdot \delta(S)$  for all  $S \in \mathcal{C}$ .

To formulate this goal as an LP (so that we can apply MWU), let's define some notations.

- Let  $\epsilon' = \epsilon/q$ .
- Let  $B \in \{0, -1, 1\}^{V \times E}$  be the incidence matrix of  $G$ .
  - Note that, for every  $v$ , we have  $f_{out}(v) = (Bf)_v$
- For any  $S \subseteq V$ , let  $\mathbf{1}_S \in \mathbb{R}^V$  be the indicator vector of  $S$ .
- We have

$$\begin{aligned} |\mathbf{d}^f(S)| \leq \epsilon' \cdot \delta(S) &\iff \\ \mathbf{1}_S^\top (\mathbf{d} - Bf) \leq \epsilon' \cdot \delta(S) \text{ and } \mathbf{1}_S^\top (\mathbf{d} - Bf) \geq -\epsilon' \cdot \delta(S) &\iff \\ \frac{1}{\delta(S)} \mathbf{1}_S^\top Bf \geq \frac{1}{\delta(S)} \mathbf{1}_S^\top \mathbf{d} - \epsilon' \text{ and } -\frac{1}{\delta(S)} \mathbf{1}_S^\top Bf \geq -\frac{1}{\delta(S)} \mathbf{1}_S^\top \mathbf{d} - \epsilon' & \end{aligned}$$

We can rewrite our goal: either find

- a violating cut  $S$  where  $\delta(S) < \mathbf{d}(S)$ , or
- a flow  $f$  where
  1. for all  $e$ ,  $|f_e|/c_e \leq 1$
  2. for all  $S \in \mathcal{C}$ ,  $\frac{1}{\delta(S)} \mathbf{1}_S^\top Bf \geq \frac{1}{\delta(S)} \mathbf{1}_S^\top \mathbf{d} - \epsilon'$  and  $-\frac{1}{\delta(S)} \mathbf{1}_S^\top Bf \geq -\frac{1}{\delta(S)} \mathbf{1}_S^\top \mathbf{d} - \epsilon'$  for all  $S \in \mathcal{C}$ .

So now, let's write an LP

Find  $f$  s.t.

$$\frac{1}{\delta(S)} \mathbf{1}_S^\top Bf \geq \frac{1}{\delta(S)} \mathbf{1}_S^\top \mathbf{d} \quad \text{for all } S \in \mathcal{C} \quad (1)$$

$$\frac{-1}{\delta(S)} \mathbf{1}_S^\top Bf \geq \frac{-1}{\delta(S)} \mathbf{1}_S^\top \mathbf{d} \quad \text{for all } S \in \mathcal{C} \quad (2)$$

$$|f_e|/c_e \leq 1 \quad \text{for all } e \in E \quad (3)$$

We want to find a violating cut  $S$  or find  $f$  that satisfies the above LP upto  $\epsilon'$  additive factor. We are now ready to apply MWU:

- 1 and 2 are “hard” constraints.
- 3 are “easy” constraints.

In round  $t$  of MWU, the framework sets the weights  $\{p_{S,\circ}\}_{S \in \mathcal{C}, \circ \in \{+, -\}}$  of each hard constraint where  $p_{S,\circ} \geq 0$ .

- Given the weights, we have need to solve the following average LP

Find  $f$  s.t.

$$\sum_{S \in \mathcal{C}} \frac{p_{S,+}}{\delta(S)} \mathbf{1}_S^\top Bf - \sum_{S \in \mathcal{C}} \frac{p_{S,-}}{\delta(S)} \mathbf{1}_S^\top Bf \geq \sum_{S \in \mathcal{C}} \frac{p_{S,+}}{\delta(S)} \mathbf{1}_S^\top \mathbf{d} - \sum_{S \in \mathcal{C}} \frac{p_{S,-}}{\delta(S)} \mathbf{1}_S^\top \mathbf{d}$$

$$|f_e|/c_e \leq 1 \quad \text{for all } e \in E$$

- Define potentials on vertices as

$$\phi = \sum_{S \in \mathcal{C}} \frac{p_{S,+}}{\delta(S)} \mathbf{1}_S - \sum_{S \in \mathcal{C}} \frac{p_{S,-}}{\delta(S)} \mathbf{1}_S \in \mathbb{R}^V.$$

- We need to solve

Find  $f$  s.t.

$$\phi^\top Bf \geq \phi^\top \mathbf{d}$$

$$|f_e|/c_e \leq 1 \quad \text{for all } e \in E$$

- To understand  $\phi$  more intuitively, observe that

$$\phi_v = \sum_{S \ni v} \frac{1}{\delta(S)} (p_{S,+} - p_{S,-})$$

- Each  $v$  is contained in  $O(\log n)$  sets from  $\mathcal{C}$ , so  $\phi$  can be computed  $O(n \log n)$  time.

\* Actually, we can compute  $\phi$  in  $O(n)$  time when  $\mathcal{C}$  is defined from a tree flow sparsifier.  
**(Exercise)**

- To solve this, it suffices to find  $f^t$  that maximizes  $\phi^\top Bf^t$  where  $\max_e |f_e^t|/c_e \leq 1$ . (Then, check if  $\phi^\top Bf^t \geq \phi^\top \mathbf{d}$ ).

- For any  $f$ , we can expand the expression as

$$\phi^\top Bf = \sum_{e=(u,v)} (\phi_v - \phi_u) f_{(u,v)}$$

- To maximize each term, just set  $f_{(u,v)}^t = c_{(u,v)} \operatorname{sgn}(\phi_v - \phi_u)$ .
- We can find the optimal  $f^t$  where  $\phi^\top Bf^t = \sum_{e=(u,v)} c_e |\phi_u - \phi_v|$ .

- There are two cases

- If  $\phi^\top Bf^t < \phi^\top d$ , we claim that we can find a violating cut. Done (to be proved below).
- If  $\phi^\top Bf^t \geq \phi^\top d$ , then the flow  $f^t$  satisfies the average problem in round  $t$ . We can feed  $f^t$  into the MWU framework and proceed to the next round.
- How many round? This depends on the width of  $f^t$ . (How much  $f^t$  violates or over-satisfies the original constraints?)
- **Claim:** the width of  $f^t$  is at most 2.

\* We want to prove that for all  $S \in \mathcal{C}$

$$|\frac{1}{\delta(S)} \mathbf{1}_S^\top Bf - \frac{1}{\delta(S)} \mathbf{1}_S^\top \mathbf{d}| \leq 2.$$

- \* We have  $\mathbf{1}_S^\top Bf = \sum_{e \in E(S, V-S)} f_e \leq \sum_{e \in E(S, V-S)} c_e = \delta(S)$ . So  $|\frac{1}{\delta(S)} \mathbf{1}_S^\top Bf| \leq 1$ .
- \* Also, we have  $|\frac{1}{\delta(S)} \mathbf{1}_S^\top \mathbf{d}| = \frac{\mathbf{d}(S)}{\delta(S)} \leq 1$  because we can actually assume that  $d_S \leq \delta(S)$  for each  $S \in \mathcal{C}$  (this can be easily checked fast from the very beginning), otherwise we obtain a violating cut.
- So there are  $T = O(\log n / \epsilon'^2) = O(\frac{q^2}{\epsilon'^2} \log n) = \tilde{O}(1/\epsilon'^2)$  rounds.
- After  $T$  rounds, we get  $\bar{f} = \frac{f_1 + \dots + f_T}{T}$  where

$$\begin{aligned} \frac{1}{\delta(S)} \mathbf{1}_S^\top B\bar{f} &\geq \frac{1}{\delta(S)} \mathbf{1}_S^\top \mathbf{d} - \epsilon' && \text{for all } S \in \mathcal{C} \\ \frac{-1}{\delta(S)} \mathbf{1}_S^\top B\bar{f} &\geq \frac{-1}{\delta(S)} \mathbf{1}_S^\top \mathbf{d} - \epsilon' && \text{for all } S \in \mathcal{C} \\ |\bar{f}_e|/c_e &\leq 1 && \text{for all } e \in E \end{aligned}$$

- So  $\bar{f}$  is a feasible flow that  $\epsilon$ -satisfies  $\mathbf{d}$ . Done.

- It remains to prove that  $\phi^\top Bf^t < \phi^\top d$ , then there is a violating cut.

**Lemma 5.1.** *If there is  $\phi \in \mathbb{R}^V$  where  $\sum_{e=(u,v)} c_e |\phi_u - \phi_v| < \phi^\top \mathbf{d}$ , then we can find a threshold cut  $S_\tau = \{u \mid \phi_u < \tau\}$  such that  $\delta(S_\tau) < \mathbf{d}(S_\tau)$  in  $O(n)$  time.*

*Proof.* Rearrange the indices so that  $\phi_1 \leq \phi_2 \leq \dots \leq \phi_n$ . □

- We can translate  $\phi_i \leftarrow \phi_i - \phi_1$  so  $\phi_1 = 0$ . Why?

- $\sum_{e=(u,v)} c_e |\phi_u - \phi_v|$  is translation invariant.
- $\phi^\top \mathbf{d}$  is changed to  $\phi^\top \mathbf{d} - \phi_0 \mathbf{d}(V) = \phi^\top \mathbf{d}$ .

- We can assume  $\phi_n = 1$  by scaling.
- Now, choose a random threshold  $\tau \in [0, 1]$ . Let  $S_\tau = \{u \mid \phi_u \geq \tau\}$ .

$$\begin{aligned}\mathbb{E}_\tau[\delta(S_\tau)] &= \sum_{e=(u,v) \in E} c_e \Pr[\phi_u \leq \tau < \phi_v] \\ &= \sum_{e=(u,v)} c_e |\phi_u - \phi_v|\end{aligned}$$

and

$$\begin{aligned}\mathbb{E}_\tau[d(S_\tau)] &= \sum_{v \in V} \phi_v d(v) \\ &= \phi^\top d\end{aligned}$$

- So we have

$$\mathbb{E}_\tau[\delta(S_\tau)] < \mathbb{E}_\tau[d(S_\tau)]$$

and so there exists  $\tau$  where  $\delta(S_\tau) < d(S_\tau)$ .

- Let's conclude the algorithm

- In each round, given  $\{p_{S,\circ}\}_{S \in \mathcal{C}, \circ \in \{+,-\}}$ , compute  $\phi$  in  $O(n)$  time.
- for each edge  $(u, v) \in E$ , send flow at full capacity from  $v$  to  $u$  if  $\phi_v > \phi_u$ , and vice versa.  
Total time:  $O(m)$ .
- There are  $O(\frac{q^2}{\epsilon^2} \log n)$  rounds. So total time is  $\tilde{O}(m/\epsilon^2)$ .

- Output: either

- a violating cut  $S$  where  $\delta(S) < |d(S)|$ , or
- a feasible  $f$  where  $|d^f(S)| \leq \epsilon/q \cdot \delta(S)$  for all  $S \in \mathcal{C}$ .
  - \* This implies that  $f$   $\epsilon$ -satisfies  $d$ .

## 6 Intuition: What happen in Expanders?

- Try to interpret this algorithm on  $\phi$ -expanders.
- Here, the congestion approximator is very simple: all singleton cuts give a congestion approximator with quality  $\frac{1}{\phi}$ .
  - Why? See 3.3.
- When all the cuts from the congestion approximator are singletons, this allows us to interpret the algorithm more easily.
- From how MWU works, observe that  $p_{v,+}^{t+1} = p_{v,+}^t \cdot \exp(\frac{\epsilon}{\rho} \cdot \frac{d^{f^t}(v)}{\deg(v)})$  and  $p_{v,-}^{t+1} = p_{v,-}^t \cdot \exp(\frac{\epsilon}{\rho} \cdot \frac{-d^{f^t}(v)}{\deg(v)})$ .  
So

$$\begin{aligned}p_{v,+}^t &= \exp\left(\frac{\epsilon}{\rho} \cdot \sum_{t=1}^t \frac{d^{f^i}(v)}{\deg(v)}\right) \\ p_{v,-}^t &= \exp\left(\frac{\epsilon}{\rho} \cdot \sum_{t=1}^t \frac{-d^{f^i}(v)}{\deg(v)}\right)\end{aligned}$$

- Define  $\bar{f}^t = \frac{f_1 + \dots + f_t}{t}$  as the average flow so far up to time  $t$ . Recall that our algorithm returns  $\bar{f} = \bar{f}^T = \frac{f_1 + \dots + f_T}{T}$  where  $T = O(\frac{\rho^2}{\epsilon^2} \log n)$ .
  - By definition, we have  $\sum_{i=1}^t d^{f^i}(v) = t \cdot d^{\bar{f}^t}(v)$ .
  - $d^{\bar{f}^t}(v)$  has a natural interpretation: it is the average excess at vertex  $v$  up to time  $t$ .
  - Our goal is that the average excess should be close to 0 by time  $T$ . That is,  $d^{\bar{f}^T}(v) \approx 0$ .

- Now, the potential of  $v$  at round  $t$  is

$$\phi_v^t = \frac{p_{v,+}^t - p_{v,-}^t}{\deg(v)} = \frac{\exp(\frac{\epsilon}{\rho} \cdot t \cdot \frac{d^{\bar{f}^t}(v)}{\deg(v)}) - \exp(\frac{\epsilon}{\rho} \cdot t \cdot \frac{-d^{\bar{f}^t}(v)}{\deg(v)})}{\deg(v)}$$

- Up to scaling (also in the exponent)

$$\phi_v^t \sim e^{d^{\bar{f}^t}(v)} - e^{-d^{\bar{f}^t}(v)}$$

- Interpretation:

- When  $d^{\bar{f}^t}(v) > 0$ , then  $\phi_v^t$  goes up positively exponentially fast.
- When  $d^{\bar{f}^t}(v) < 0$ , then  $\phi_v^t$  goes down negatively exponentially fast.

- This make sense. Why?

- Recall our we construct the flow in each round. For every edge  $(u, v)$ , if  $\phi_u > \phi_v$ , then send flow at full capacity from  $u$  to  $v$ . Otherwise, do the opposite direction.
- So if  $v$  has excess ( $d^{\bar{f}^t}(v) > 0$ ), then  $\phi_v$  is big. So the algorithm would likely send flow out of  $v$  in the next round.
- So if  $v$  has deficit ( $d^{\bar{f}^t}(v) < 0$ ), then  $\phi_v$  is small. So the algorithm would likely send flow into  $v$  in the next round.

- At the end, we expect  $d^{\bar{f}}(v) \approx 0$  for all  $v$ .

- More precisely,  $|d^{\bar{f}}(v)| \leq \epsilon \deg(v)$  for all  $v \in V$ .
- This implies  $|d^{\bar{f}}(S)| \leq \frac{\epsilon}{\phi} \delta(S)$  for all  $S \subseteq V$ . So  $\bar{f}$   $\frac{\epsilon}{\phi}$ -satisfies  $d$ .

- This intuitively is similar to push-relabel algorithms.

- We maintain levels and flow from higher vertices to lower vertices.

## 7 History and State of the art

- Nice book by David Williamson: <http://www.networkflowalgs.com/>
- 60-70's
  - Ford-Fulkerson
  - $O(mn^2)$  Blocking flow (Dinic)

- $O(m \min\{m^{1/2}, n^{2/3}\})$  time in unit capacity (Even-Tarjan, Karzanov)

- 80's

- $O(mn \log n)$  Blocking flow + dynamic tree (Sleator Tarjan)
- $O(mn \log n)$  Push relabel (Goldberg Tarjan)

- 90's

- $\tilde{O}(m \min\{m^{1/2}, n^{2/3}\})$  in general graph (Goldberg Rao)

- In sparse graphs,  $n^{1.5}$  is the best since 70's... but there was a breakthrough in approximation algorithms in

- Approximation in edge-capacitated graphs

- $\tilde{O}(mn^{1/3})$  Electrical flow + MWU + Arc Boosting (Christiano et al '10<sup>2</sup>)
- $\tilde{O}(m)$  Congestion approximator + MWU (Sherman'13<sup>3</sup>, KLOS'13<sup>4</sup>, Peng'16<sup>5</sup>)

- Approximation in vertex-capacitated graphs

- $O(m^{1+o(1)})$  Dynamic shortest path + MWU (Bernstein Gutenberg S'21<sup>6</sup>)

- Exact (based on Interior Point Method + Dynamic algorithms)

- $\tilde{O}(m + n^{1.5})$  (BLLSSW'21<sup>7</sup>)

- $O(m^{4/3+o(1)})$  unit-capacity [Kathuria'20] [Lui Sidford'20] <https://www.youtube.com/watch?v=VF3EbC>

- My belief:

- Exact max flow in  $\tilde{O}(m)$  time (in 5-10 years).
- Maybe in your PhD thesis.

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<sup>2</sup><https://arxiv.org/abs/1010.2921>

<sup>3</sup><https://arxiv.org/pdf/1304.2338.pdf>

<sup>4</sup><https://arxiv.org/pdf/1304.2077.pdf>

<sup>5</sup><https://arxiv.org/abs/1411.7631>

<sup>6</sup><https://arxiv.org/pdf/2101.07149.pdf>

<sup>7</sup><https://arxiv.org/pdf/2101.05719.pdf>