# Two-Commodity Flow (2CF) is equivalent to Linear Programming (LP)

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# Problem definition -- Linear Programs (LP)

Optimization problem with linear objective and linear constraints

### Given

- a matrix  $A \in \mathbb{R}^{m \times n}$ ,
- a vector  $\boldsymbol{b} \in \mathbb{R}^m$ , a vector  $\boldsymbol{c} \in \mathbb{R}^n$ ,

find  $x \in \mathbb{R}^n$  s.t.

$$\max c^{T}x$$
s.t.  $Ax \le b$ 

$$x \ge 0$$

### Polynomially-bounded assumption

- 1. magnitude:  $||A, b, c||_{max} \leq X$
- 2. polytope radius:  $||x||_1 \le R$

$$X, R = poly(nnz(A))$$

SOTA LP solver runtime [Cohen-Lee-Song'19,

Jiang-Song-Weinstein-Zhang'20]

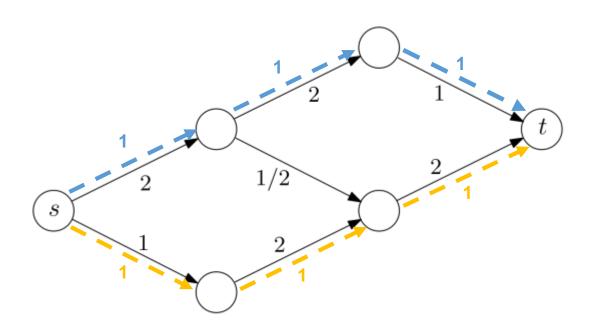
$$\tilde{O}(nnz(\mathbf{A})^{\max\{\omega, 2.055\}})$$
,  $\omega \approx 2.37$ 

# (Single-commodity) maxflow problem (1CF)

#### Given

- a directed graph G = (V, E),
- a source-sink pair (s, t),
- edge capacity  $u \in \mathbb{R}^{|E|}_{\geq 0}$

Find a **feasible** flow  $f \in \mathbb{R}^{|E|}$  s.t. the amount of flow routed from s to t is maximized.



maxFlow = 2

SOTA maxflow solver runtime [Chen-Kyng-Liu-Peng-Probst-Sachdeva'22]

$$\tilde{O}(|E|^{1+o(1)})$$

### 1CF as LP

• f is a feasible flow if it satisfies

#### 1. Flow conservation constraints

$$\sum_{incoming} f(\cdot, v) - \sum_{outgoing} f(v, \cdot) = 0, \quad \forall v \in V \setminus \{s, t\}$$

$$\sum_{outgoing} f(s, \cdot) = \sum_{incoming} f(\cdot, t) = F$$

### 2. Capacity constraints

$$f(e) \le u(e), \quad \forall e \in E$$

### 3. Direction constraints

$$f(e) \ge 0$$
,  $\forall e \in E$ 

max 
$$F$$
s.t.  $Bf = Fd$ 
 $f \le u$ 
 $f \ge 0$ 

LP solver:  $\tilde{O}(|E|^{\max\{\omega, 2.055\}})$ 

(since  $nnz = \Theta(|E|)$ )

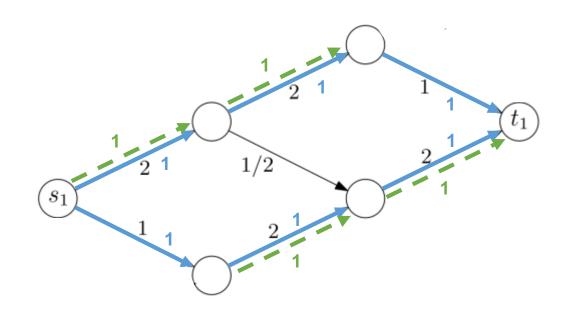
1CF solver:  $\tilde{O}(|E|^{1+o(1)})$ 

### Two-commodity maxflow problem (2CF)

### Given

- a directed graph G = (V, E),
- two source-sink pairs  $(s_1, t_1, s_2, t_2)$ ,
- edge capacity  $u \in \mathbb{R}^{|E|}_{\geq 0}$

Find a pair of **feasible** flow  $f_1, f_2 \in \mathbb{R}^{|E|}$  s.t. the sum of the amount of flow routed from  $s_1$  to  $t_1$  and from  $s_2$  to  $t_2$  is maximized.



 $maxFlow_1 = 2$  $maxFlow_2 = 2$ 

### 2CF as LP

- $(f_1, f_2)$  is a pair of feasible flow if it satisfies
  - 1. Flow conservation constraints: for  $i \in \{1,2\}$

$$\sum_{incoming} f_i(\cdot, v) - \sum_{outgoing} f_i(v, \cdot) = 0, \quad \forall v \in V \setminus \{s_i, t_i\}$$

$$\sum_{outgoing} f_{i}(s,\cdot) = \sum_{incoming} f_{i}(\cdot,t) = F_{i}$$

2. Capacity constraints

$$f_1(e) + f_2(e) \le u(e), \quad \forall e \in E$$

3. Direction constraints

$$f_1(e), f_2(e) \ge 0, \quad \forall e \in E$$

$$\begin{array}{ll} \max & F_1 + F_2 \\ \text{s.t.} & \pmb{B} \pmb{f}_1 = F_1 \pmb{d}_1 \\ & \pmb{B} \pmb{f}_2 = F_2 \pmb{d}_2 \\ & \pmb{f}_1 + \pmb{f}_2 \leq \pmb{u} \\ & \pmb{f}_1, \pmb{f}_2 \geq \pmb{0} \end{array}$$

LP solver:  $\tilde{O}(|E|^{\max\{\omega, 2.055\}})$ 

(since  $nnz = \Theta(|E|)$ )

1CF solver:  $\tilde{O}(|E|^{1+o(1)})$ 

2CF solver: No faster algorithms

known for 2CF beyond general LPs!

[D.-Kyng-Zhang'22] LP can be reduced to 2CF!

# Optimization version -> Feasibility version

LP

2CF

# Optimization version

$$\begin{array}{ll}
\text{max} & c^{\top} x \\
\text{s.t.} & Ax \leq b \\
& x \geq 0
\end{array}$$

max 
$$F_1 + F_2$$
  
s.t.  $Bf_1 = F_1d_1$   
 $Bf_2 = F_2d_2$   
 $f_1 + f_2 \le u$   
 $f_1, f_2 \ge 0$ 

### Equivalent hardness



Binary search over K,  $R^{2cf}$ 



# Feasibility version

$$c^{\mathsf{T}}x \ge K - \epsilon^{lp}$$

$$Ax \le b + \epsilon^{lp}\mathbf{1}$$

$$x \ge \mathbf{0}$$

$$(\boldsymbol{A}, \boldsymbol{b}, \boldsymbol{c}, K, \epsilon^{lp})$$

$$F_1 + F_2 \ge R^{2cf} - \epsilon^{2cf}$$

$$\|\mathbf{B}f_1 - F_1\mathbf{d}_1\|_{\infty} \le \epsilon^{2cf}$$

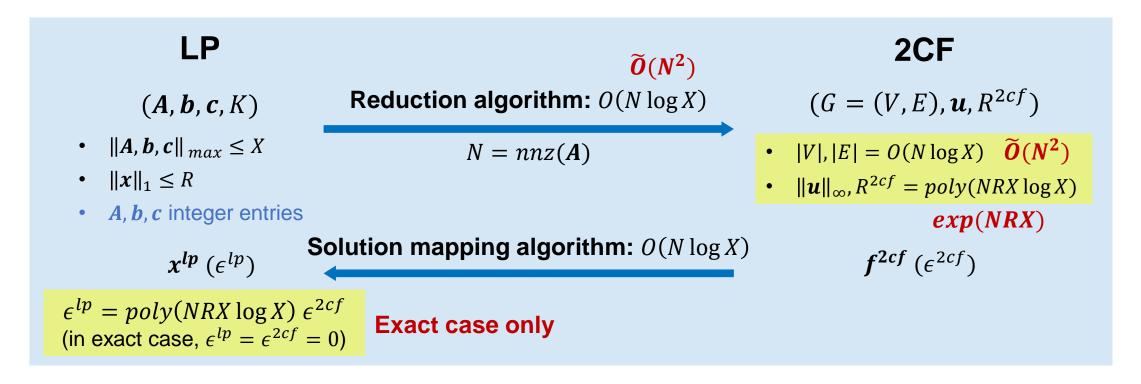
$$\|\mathbf{B}f_2 - F_2\mathbf{d}_2\|_{\infty} \le \epsilon^{2cf}$$

$$f_1 + f_2 \le u + \epsilon^{2cf} \mathbf{1}$$

$$f_1, f_2 \ge \mathbf{0}$$

$$(G = (V, E), \boldsymbol{u}, R^{2cf}, \epsilon^{2cf})$$

### Main results



### An immediate implication

If we can solve 2CF in  $\tilde{O}(|E|^c)$  time,  $c \ge 1$ , then it can be translated to an LP solver with runtime  $\tilde{O}(N^c)$ , where  $|E| = \tilde{O}(N)$ 

### Comparison to [Itai'78]

Our proof builds upon Itai's polynomial-time reduction, but we made several improvements

### Remark

Our hardness result only rules out possibilities of fast 2CF algorithms for

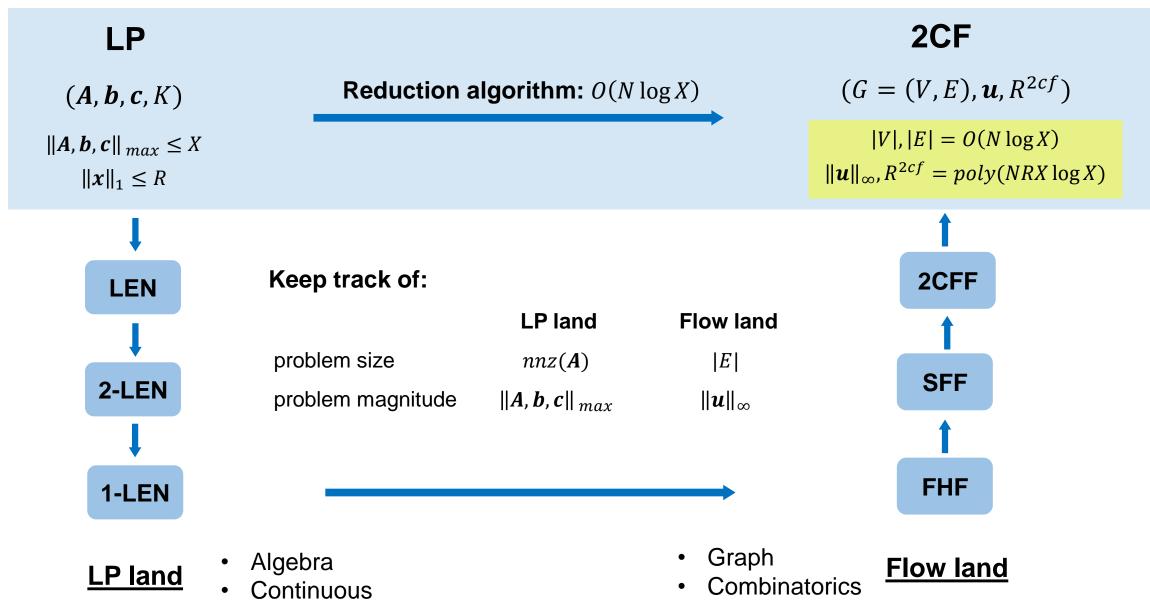
- 1. Directed graph:  $f \ge 0$
- 2. Sparse graph: m = O(n), where |E| = m, |V| = n
- 3. High-accuracy regime: polylog dependences on  $\epsilon$

Outside of the settings, there indeed exists some fast multi-commodity flow solvers:

	Undirected k-CF	Directed k-CF
Low accuracy $(poly(1/\epsilon))$	[She17] $\tilde{O}(mk\epsilon^{-1})$	[Mad10] $\tilde{O}((m+k)n\epsilon^{-2})$
High accuracy $(poly \log(1/\epsilon))$	[CY23] $ \tilde{O}_{q,p} \left( m^{1+o(1)} k^2 \right) $ smoothed $k\text{-CF}$	[BZ23] $ \tilde{O}(k^{2.5}\sqrt{m}n^{\omega-1/2}) $ faster than LP solver for dense graphs

# Reduction Algorithm

# Overview of reduction algorithm



### LP land

LP

$$c^{\top}x \ge K$$
$$Ax \le b$$
$$x \ge 0$$

O(N) Add slack variables  $\alpha$ , s

#### LEN

(Linear Equations with Nonnegative variables)

$$c^{\top}x - \alpha = K$$

$$Ax + s = b$$

$$x, s, \alpha \ge 0$$

 $O(N \log X)$  Bitwise decomposition

#### 2-LEN

$$\overline{A}_{ij} \in \{0, \pm 1, \pm 2\}$$

$$\overline{A}\overline{x} = \overline{b}$$

$$\overline{x} \ge 0$$

O(N log X) Add auxiliary variables 
$$\begin{cases} 2x_i \leftarrow x_i + x_{i'} \\ x_i - x_{i'} = 0 \end{cases}$$

1-LEN

$$\widehat{A}_{ij} \in \{-1,0,1\}$$

$$\widehat{A}\widehat{x} = \widehat{b}$$

$$\widehat{x} \ge 0$$

 $\|\widehat{A}, \widehat{b}\|_{max} \le poly(NRX \log X)$ 

 $\|\widehat{\mathbf{x}}\|_1 \leq poly(NRX\log X)$ 

$$5x_1 + 3x_2 = -1$$

$$2^0 + 2^2 2^0 + 2^1 -2^0$$

$$2^0 \cdot (x_1 + x_2) + 2^1 \cdot x_2 + 2^2 \cdot x_1 = -2^0 \cdot 1$$

$$x_1 + x_2 = -1$$

$$x_2 = 0$$

$$x_1 = 0$$

 $x_2 = 0$  Add carry terms

$$x_1 + x_2 - 2c_0 = -1$$
  

$$x_2 + c_0 - 2c_1 = 0$$
  

$$x_1 + c_1 = 0$$

$$\begin{array}{c}
c_i \leftarrow d_i - e_i, \\
d_i, e_i \ge 0
\end{array}$$

$$x_1 + x_2 - 2(d_0 - e_0) = -1$$

$$x_2 + (d_0 - e_0) - 2(d_1 - e_1) = 0$$

$$x_1 + (d_1 - e_1) = 0$$

$$d_i, e_i \le 2XR$$

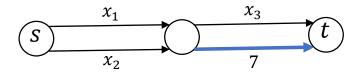
### LP land → Flow land

#### 1-LEN

 $\widehat{A}_{ij} \in \{-1,0,1\}$ 

$$x_1 + x_2 - x_3 = 7$$

Encode flow conservation constraint

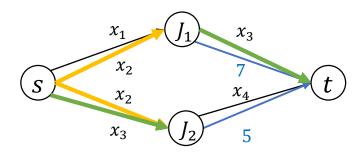


# 1. Fixed flow constraint f(e) = u(e) = RHS

### $|E| = O(N \log X)$

 $\|\boldsymbol{u}\|_{\infty} = \|\widehat{\boldsymbol{b}}\|_{max} \le poly(NRX \log X)$ 

$$x_1 + x_2 - x_3 = 7$$
$$x_2 + x_3 - x_4 = 5$$

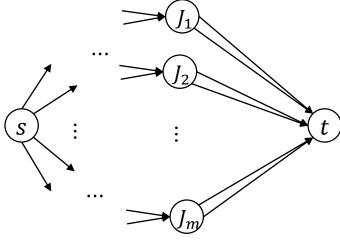


# 2. Homologous flow constraint $f(e_1) = \cdots = f(e_k)$

#### FHF

(Fixed Homologous Flow problem)

$$\widehat{A}x = \widehat{b}$$



$$|E| = O(nnz(\widehat{A}))$$

$$\|\boldsymbol{u}\|_{\infty} = \max\{\|\widehat{\boldsymbol{A}}, \widehat{\boldsymbol{b}}\|_{max}, \|\widehat{\boldsymbol{x}}\|_{1}\}$$
  
  $\leq poly(NRX \log X)$ 

### Flow land

### **Target constraints (2CF):**

1. Flow conservation constraints

$$Bf_i = F_i d_i, i \in \{1,2\}$$

2. Capacity constraints

$$f_1 + f_2 \leq u$$

3. Direction constraints:  $f_1, f_2 \ge 0$ 

drop extra
constraints
step by step

### FHF constrains:

- Target constraints 1, 2, 3
- 4. Fixed flow constraints

$$f(e) = u(e)$$

5. Homologous flow constraints

$$f(e_1) = \cdots = f(e_k)$$

#### Introduce

- 2<sup>nd</sup> commodity
- Selective flow constraints

$$f_{\bar{\imath}}(e) = 0, \quad \bar{\imath} \neq i$$

2CF

Drop fixed

**2CFF** fixed

Drop selective

#### SFF

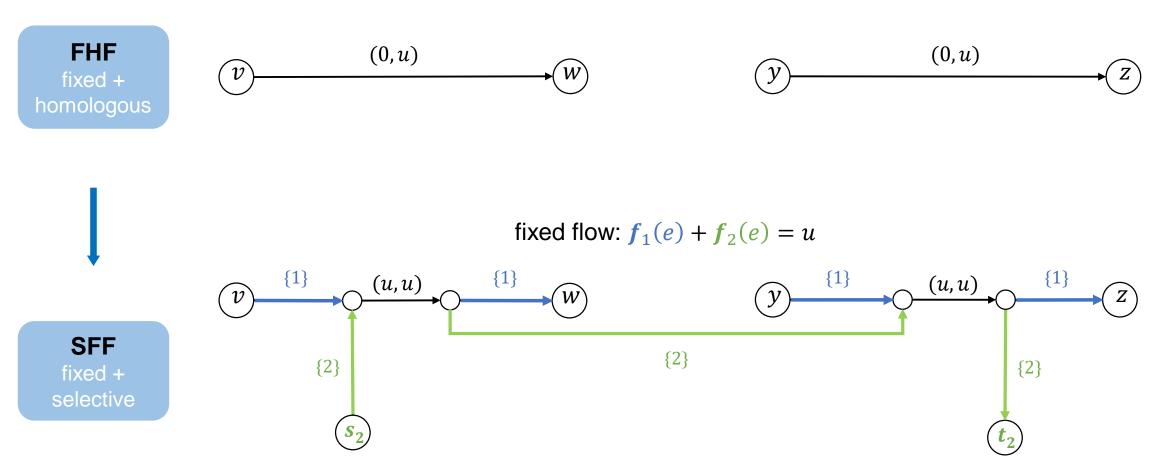
fixed + selective

Drop homologous

FHF

fixed + homologous

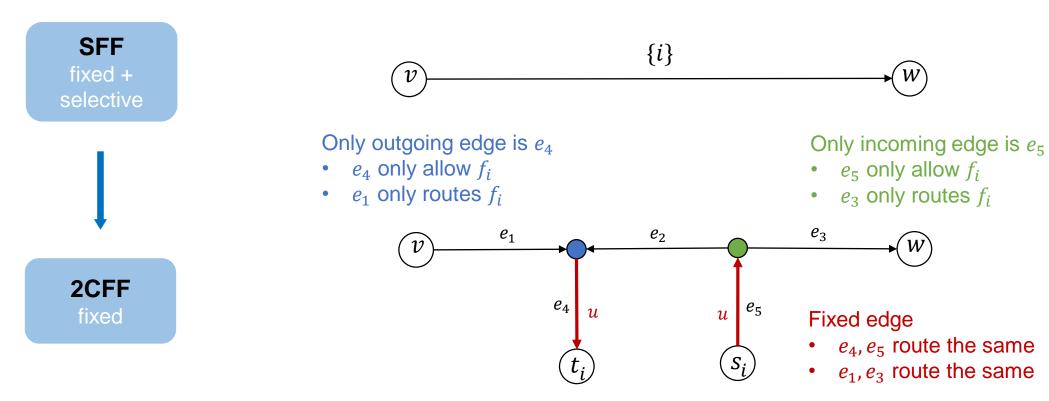
# Drop homologous



selective for commodity 1:  $f_2(e) = 0$ 

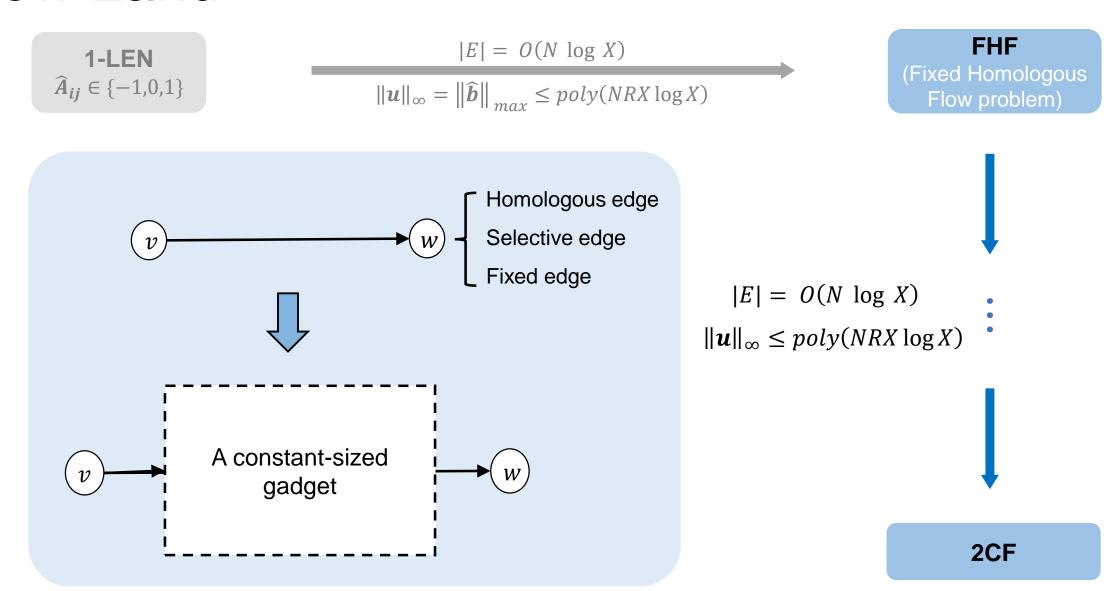
selective for commodity 2:  $f_1(e) = 0$ 

# Drop selective



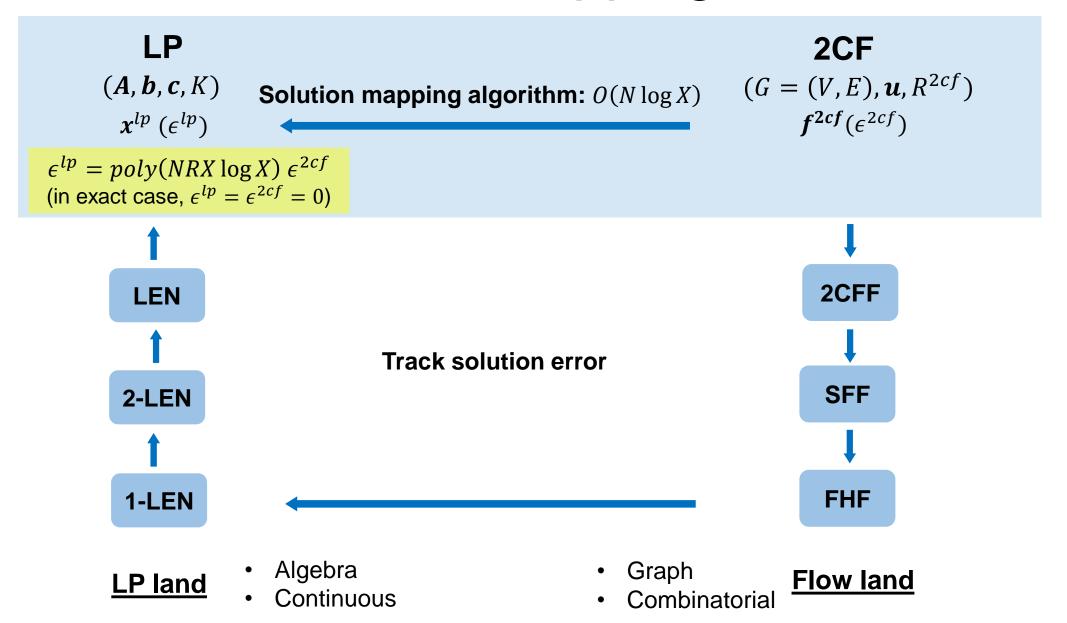
- Only fixed flow constraint remains
- High-level idea of dropping fixed flow constraint (needs several steps)
  - Fixed flow edge = saturated edge
  - In feasibility 2CF, with a carefully chosen  $R^{2cf}$ , use  $F_1 + F_2 \ge R^{2cf}$  to force fixed flow edges to get saturated automatically

### Flow Land

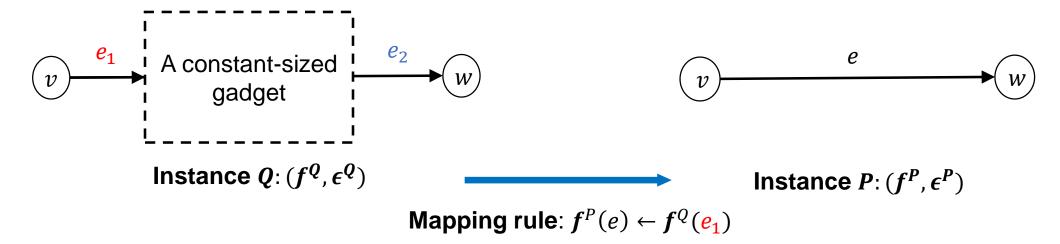


# Solution Mapping & Error Analysis

# Overview of solution mapping



### Flow land



### **Error analysis**

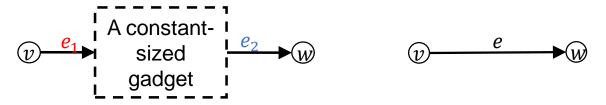
$$\epsilon^P = O(|E^P|) \, \epsilon^Q$$

Intuition: we map the flow of a gadget to a single edge

- error accumulates in an additive manner
  - → per gadget error blows up by a constant
- At most  $|E^P|$  gadgets
  - $\rightarrow$  the **total** error blows up by  $O(|E^P|)$

# Solution Mapping

### Flow land



Instance  $Q: (f^Q, \epsilon^Q)$  Instance  $P: (f^P, \epsilon^P)$ 

Mapping rule:  $f^{P}(e) \leftarrow f^{Q}(e_{1})$ 

#### **Error analysis**

$$\epsilon^P = O(|E^P|) \epsilon^Q$$

Intuition: we map the flow of a gadget to a single edge

- error accumulates in an additive manner
  - → error blows up by a constant per gadget
- At most  $|E^P|$  gadgets
  - $\rightarrow$  the total error blows up by  $O(|E^P|)$

### LP land

$$x^Q = \begin{pmatrix} x^P \\ x^{new} \end{pmatrix}$$

Instance  $Q: (x^Q, \epsilon^Q)$  Instance  $P: (x^P, \epsilon^P)$ Direct mapping

### 2...661.........................

#### **Error analysis**

$$\epsilon^P = \text{poly}(N^P, X^P) \cdot \epsilon^Q$$

Simple algebra

# Summary

$$\begin{array}{ll} \max & F_{1} + F_{2} \\ \text{s.t. } & \boldsymbol{B}\boldsymbol{f}_{1} = F_{1}\boldsymbol{d}_{1} \\ & \boldsymbol{B}\boldsymbol{f}_{2} = F_{2}\boldsymbol{d}_{2} \\ & \boldsymbol{f}_{1} + \boldsymbol{f}_{2} \leq \boldsymbol{u} \\ & \boldsymbol{f}_{1}, \boldsymbol{f}_{2} \geq \boldsymbol{0} \end{array}$$

$$(A, b, c, K)$$

$$\begin{cases} ||A, b, c||_{max} \leq X \\ ||x||_{1} \leq R \\ A, b, c \text{ integer entries} \end{cases}$$

$$(G = (V, E), u, R^{2cf})$$

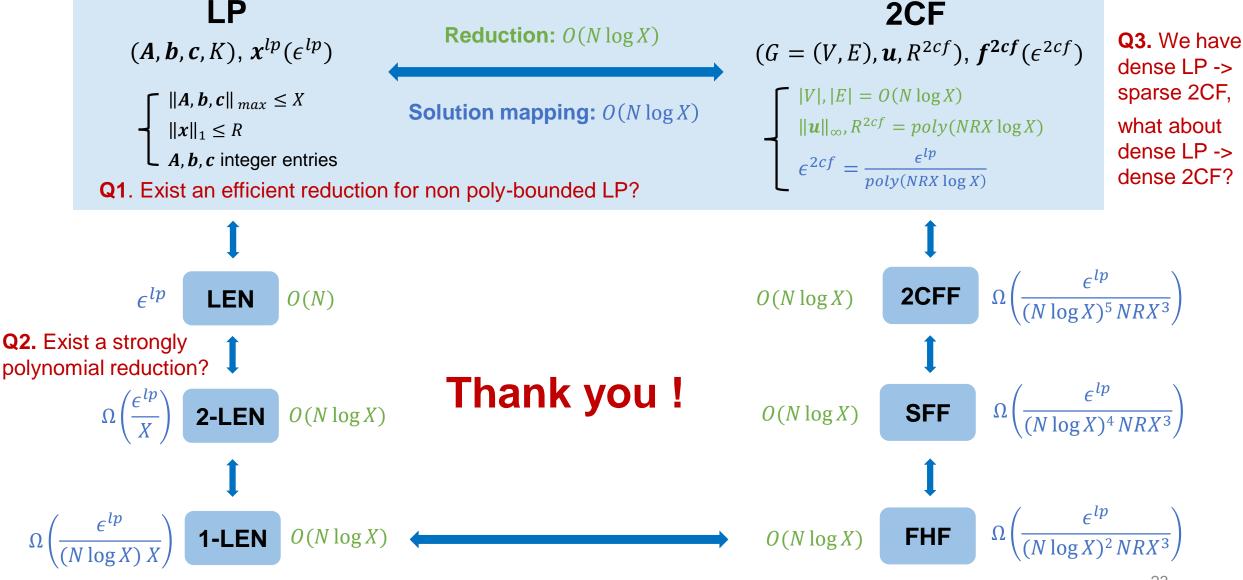
$$\begin{cases} |V|, |E| = O(N \log X) \\ ||u||_{\infty}, R^{2cf} = poly(NRX \log X) \\ \epsilon^{2cf} = \frac{\epsilon^{lp}}{poly(NRX \log X)} \end{cases}$$

$$2CF \leq LP$$

$$LP \leq 2CF$$

$$2CF = LP$$

# Summary & open problems



# Backup slides

# Hardness of two-commodity Laplacians

- State-of-the-art faster algorithms (LPs, maxflow) are Interior-Point-Method-based algorithms
  - Interior Point Methods (IPM): ways of solving convex optimization problems via a sequence of linear systems
- Laplacians linear system: the linear equations that arise in IPM for maxflow
- 2-commodity Laplacians linear system: the linear equations that arise in IPM for 2CF

### **Theorem [Kyng-Zhang'17]**

If we can quickly solve linear systems in **2-commodity Laplacians**, then we can quickly solve linear systems in any matrix.

### Implications:

- Faster 2CF algorithms were unlikely to be IPM-based
- · However, it remains open that if other families of algorithms could succeed

# Integral entry assumption is mild

(A, b, c) is polynomially-bounded

- Magnitude  $||A, b, c||_{max} \le X$
- Polytope radius  $||x||_1 \le R$

$$\begin{array}{ccc}
\text{max} & c^{\top} x \\
\text{s. t.} & Ax \leq b \\
& x \geq 0
\end{array}$$

We round by at most  $\frac{\epsilon}{3R}$ 

- entries of A down to  $\widetilde{A}$
- entries of b, c up to  $\widetilde{b}$ ,  $\widetilde{c}$

If (A, b, c) is feasible, then  $(\widetilde{A}, \widetilde{b}, \widetilde{c})$  is feasible

Since entries of  $(\widetilde{A}, \widetilde{b}, \widetilde{c})$  has a **logarithmic number of bits**, we can **scale** all of them to **polynomially-bounded integers** 

If  $\tilde{x}$  is a solution to  $(\tilde{A}, \tilde{b}, \tilde{c})$  with  $\epsilon/3$  additive error.

Then  $\tilde{x}$  is also a solution to (A, b, c) with  $\epsilon$  additive error.

$$A\widetilde{x} = \widetilde{A}\widetilde{x} + (A - \widetilde{A})\widetilde{x} \le (\widetilde{b} + \frac{\epsilon}{3}\mathbf{1}) + \frac{\epsilon}{3R} \cdot R = \mathbf{b} + \epsilon\mathbf{1}$$

$$\boldsymbol{c}^{\top} \widetilde{\boldsymbol{x}} = \widetilde{\boldsymbol{c}}^{\top} \widetilde{\boldsymbol{x}} + (\boldsymbol{c} - \widetilde{\boldsymbol{c}})^{\top} \widetilde{\boldsymbol{x}} \ge \left( \widetilde{\boldsymbol{c}}^{\top} \widetilde{\boldsymbol{x}}^* - \frac{\epsilon}{3} \right) - \frac{\epsilon}{3R} \cdot R = \widetilde{\boldsymbol{c}}^{\top} \widetilde{\boldsymbol{x}}^* - \frac{2}{3} \epsilon \ge \boldsymbol{c}^{\top} \boldsymbol{x}^* - \frac{2}{3} \epsilon$$

### SFF → FHF

 $\mathsf{FHF} \\ (f^h, \epsilon^h)$ 

 $\begin{array}{ccc}
f^h(e) = f_1^s(e_1) \\
\hline
e & \end{array}$ 

Error in demand: for  $i \in \{1,2\}$ 

 $|f_i^s(e_1) + f_i^s(e_3) - f_i^s(e_4)| \le \epsilon^s$ 

- Error in congestion:  $\leq \epsilon^s$
- Error in demand:  $\leq O(|E^h|)\epsilon^s$
- $\begin{array}{c}
  f^{h}(\hat{e}) = f_{1}^{s}(\hat{e}_{1}) \\
  \hat{e}
  \end{array}$

- Goal: after
- mapping  $f^s$
- with error  $e^s$ ,
- how to bound
  - $\epsilon^h$  of  $f^h$ ?

**SFF**  $(f^s, \epsilon^s)$ 

$$\left| \boldsymbol{f}^h(e) - \boldsymbol{f}^h(\hat{e}) \right| \leq \Theta(\epsilon^s)$$

Error in homology:

Error in congestion (fixed):

$$u - \epsilon^s \le f_1^s(\hat{e}_4) + f_2^s(\hat{e}_4) \le u + \epsilon^s$$

fixed flow: 
$$f_1(e) + f_2(e) = u(e)$$



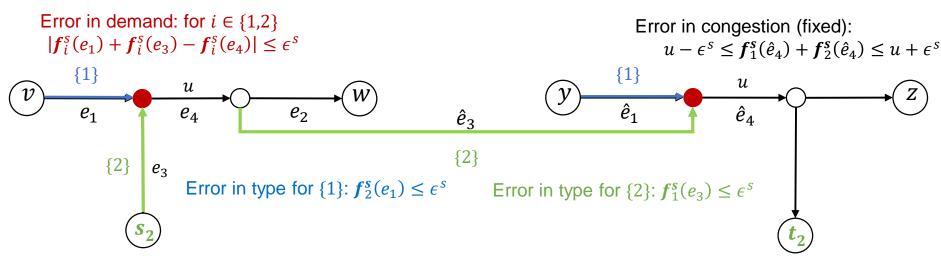
selective for commodity 1:  $f_2(e) = 0$ 

Error in type for  $\{1\}$ :  $f_2^s(e_1) \le \epsilon^s$ 

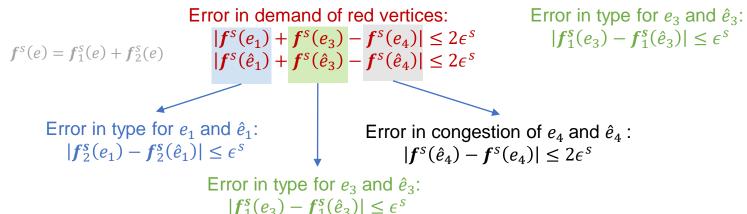
selective for commodity 2:  $f_1(e) = 0$ 

Error in type for  $\{2\}$ :  $f_1^s(e_3) \le \epsilon^s$ 

# Error in homology (SFF → FHF)

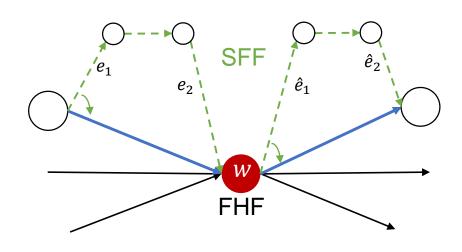


$$\begin{aligned} \left|f^h(e)-f^h(\hat{e})\right| &= |f_1^s(e_1)-f_1^s(\hat{e}_1)| & \text{By solution mapping} \\ &\leq \left|\left(f_1^s(e_1)+f_1^s(e_3)\right)-\left(f_1^s(\hat{e}_1)+f_1^s(\hat{e}_3)\right)\right| + |f_1^s(e_3)-f_1^s(\hat{e}_3)| & \leq \Theta\left(\epsilon^S\right) \end{aligned}$$
 Error in demand of red vertices: Error in type for  $e_3$  and  $\hat{e}_3$ : Constant sized gadget

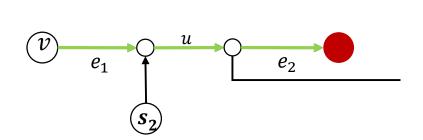


# Error in demand (SFF → FHF)

$$\max_{w \in V^h \setminus \{s,t\}} \left| \sum_{incoming} f^h(\cdot, w) - \sum_{outgoing} f^h(w, \cdot) \right|$$



*H*: set of homologous edges



Solution mapping 
$$\sum_{in \in H} f_1^s(e_1) + \sum_{in \notin H} f_1^s(\cdot, w) = \sum_{out \in H} f_1^s(\hat{e}_1) + \sum_{out \notin H} f_1^s(w, \cdot)$$
Error in demand of  $w$  in SFF 
$$\epsilon^s + \left(\sum_{in \in H} f_1^s(e_2) + \sum_{in \notin H} f_1^s(\cdot, w)\right)$$

$$= \max_{w \in V^h \setminus \{s,t\}} \epsilon^s + \left| \sum_{in \in H} f_1^s(e_1) - \sum_{in \in H} f_1^s(e_2) \right|$$

$$\leq \max_{w \in V^h \setminus \{s,t\}} \epsilon^s + \sum_{in \in H} |f_1^s(e_1) - f_1^s(e_2)| \qquad \leq \Theta(\epsilon^s) \text{ by constant sized gadget}$$

$$\leq \Theta(|E^h|) \cdot \epsilon^s$$
 by at most  $|E^h|$  gadgets