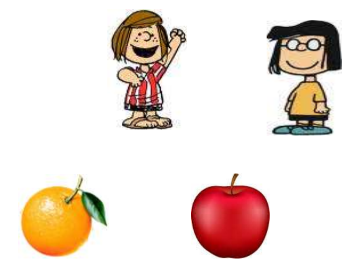
Lecture 3: Computation of CE

CS 580

Instructor: Ruta Mehta

ILLINOIS
UNIVERSITY OF ILLINOIS AT URBANA-CHAMPAIGN

(Recall) Fisher's Model



- Set A of n agents.
- Set G of m divisible goods.

- Each agent i has
  - budget of B_i dollars
  - valuation function $V_i: R_+^m \to R_+$

  Linear: for bundle $x_i = (x_{i1}, \dots, x_{im})$,

$$V_i(x_i) = \sum_{j \in G} V_{ij} x_{ij}$$

- **Supply of every good is one.**

(Recall) Competitive Equilibrium

Pirces $p = (p_1, \dots, p_m)$ and allocation $X = (x_1, \dots, x_n)$

x_{ij}: Amount of good j agent i gets

- Optimal bundle: Agent i demands

$$x_i \in \operatorname*{argmax}_{x \in R_m^+ :\, p \cdot x \le B_i} V_i(x)$$

$\sum_j p_j \cdot x_{ij}$

- Market clears: For each good j, demand = supply

$$\sum_i x_{ij} = 1$$

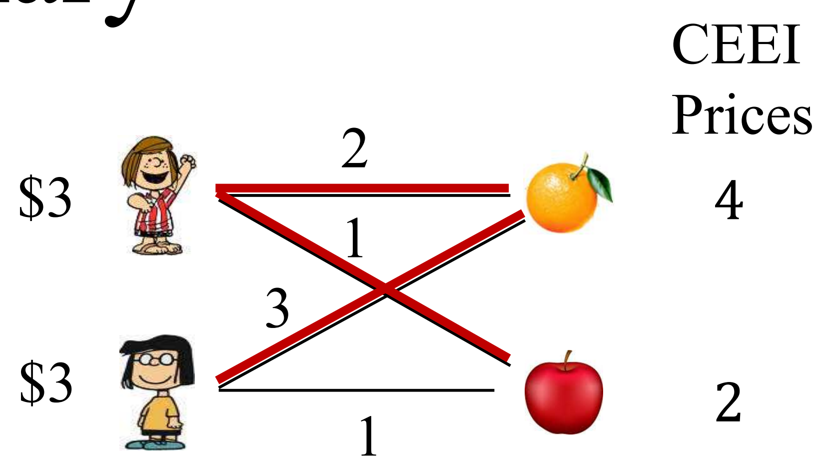
CEEI Properties: Summary

CEEI ($B_i = 1, \forall i$) allocation is

- Pareto optimal (PO)
- Envy-free
- Proportional

Next…

- Nash welfare maximizing



CEEI Allocation:

$X_1 = \left(\frac{1}{4}, 1\right), X_2 = \left(\frac{3}{4}, 0\right)$

$V_1(X_1) = \frac{3}{2},\ V_2(X_2) = \frac{9}{4}$

$V_1(X_2) = \frac{3}{2},\ V_2(X_1) = \frac{7}{4}$

Social Welfare

$$\sum_{i \in A} V_i(X_{i1}, \dots, X_{im})$$

Utilitarian

Issues: May assign 0 value to some agents.
Not scale invariant!

Max Nash Welfare

$$\max: \prod_{i \in A} V_i(X_{i1}, \ldots, X_{im})$$

$$\text{s.t.} \quad \sum_{i \in A} X_{ij} \leq 1, \ \forall j \in G$$

$$X_{ij} \geq 0, \qquad \forall i, \forall j$$

Feasible allocations

Max Nash Welfare (MNW)

$$\text{max: } \color{red}{\log}\left(\prod_{i\in A} V_i(X_{i1},\dots,X_{im})\right)$$

$$\text{s.t.} \quad \textstyle\sum_{i\in A} X_{ij} \le 1, \ \forall j \in G$$

$$X_{ij} \ge 0, \qquad \forall i, \forall j$$

Feasible allocations

Max Nash Welfare (MNW)

$$\max: \sum_{i \in A} \log V_i(X_{i1}, \ldots, X_{im})$$

$$\text{s.t.} \quad \sum_{i \in A} X_{ij} \leq 1, \ \forall j \in G$$

$$X_{ij} \geq 0, \qquad \forall i, \forall j$$

Feasible allocations

Eisenberg-Gale Convex Program '59

$$\max: \quad \sum_{i \in A} \log V_i(\bar{X}_i)$$

Dual var.

$$\text{s.t.} \quad \textstyle\sum_{i \in A} X_{ij} \le 1, \ \forall j \in G \longrightarrow p_j$$

$$X_{ij} \ge 0, \qquad \forall i, \forall j$$

Theorem. Solutions of EG convex program are exactly the CEEI (p, X).

Proof.

Consequences: CEEI

- **Exists**
- Forms a convex set
- Can be *computed* in polynomial time
- Maximizes Nash Welfare

Theorem. Solutions of EG convex program are exactly the CEEI (p, X).

Proof. $\Rightarrow$ (Using KKT)

Recall: CEEI Characterization

Pirces $p = (p_1, \dots, p_m)$ and allocation $X = (X_1, \dots, X_n)$

- Optimal bundle: For each buyer i
  - $p \cdot X_i = 1$
  - $X_{ij} > 0 \Rightarrow \frac{V_{ij}}{p_j} = \max_{k \in M} \frac{V_{ik}}{p_k}$, for all good j
- Market clears: For each good j,

$$\sum_i X_{ij} = 1.$$

Theorem. Solutions of EG convex program are exactly the CEE.

$$\max: \sum_{i \in A} \log(V_i(\bar{X}_i)) \quad \longrightarrow \sum_j V_{ij} X_{ij}$$

Dual var.

$$\text{s.t.} \quad \sum_{i \in A} X_{ij} \le 1, \ \forall j \in G \longrightarrow p_j \ge 0$$

$$X_{ij} \ge 0, \qquad \forall i, \forall j$$

Proof. ⇒ (Using KKT)

$$\forall j,\ p_j > 0 \Rightarrow \sum_i X_{ij} = 1$$

Dual condition to X_{ij}:

$$\frac{V_{ij}}{V_i(X_i)} \le p_j \Rightarrow \frac{V_{ij}}{p_j} \le V_i(X_i) \Rightarrow p_j > 0 \Rightarrow \text{market clears}$$

buy only MBB goods

$$X_{ij} > 0 \Rightarrow \frac{V_{ij}}{p_j} = V_i(X_i)$$

$$\sum_j V_{ij} X_{ij} = \left(\sum_j p_j X_{ij}\right) V_i(X_i)$$

$$\Rightarrow \sum_j p_j X_{ij} = 1$$

⇒ optimal bundle

Efficient (Combinatorial) Algorithms

Polynomial time

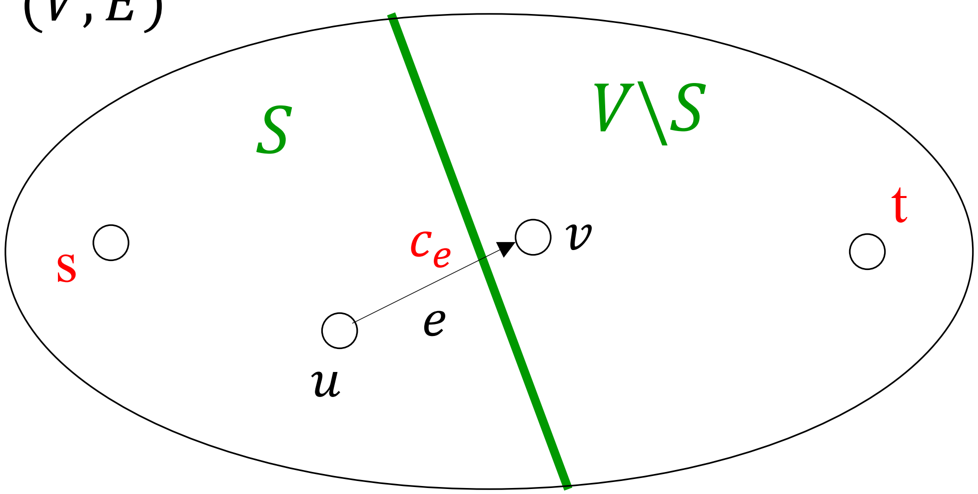
- Flow based [DPSV'08]
  - General exchange model (barter system) [DM'16, DGM'17, CM'18]
- Scaling + Simplex-like path following [GM.SV'13]

Strongly polynomial time

- Scaling + flow [O'10, V'12]
  - Exchange model (barter system) [GV'19]

Max Flow (One slide overview)

Directed Graph (V, E)



Theorem: Max-flow = Min-cut
s-t *s-t*

s-t cut: $S \subset V,\ s \in S,\ t \notin S$

cut-value: $C(S) = \sum_{\substack{(u,v) \in E: \\ u \in S, v \notin S}} c_{(u,v)}$

Min s-t cut: $\min_{\substack{S \subset V: \\ s \in S, t \notin S}} C(S)$

Given $s, t \in V$. Capacity c_e for each edge $e \in E$.

Find maximum flow from s to t: $(\boldsymbol{f_e})_{e \in E}$ s.t.

- Capacity constraint

  $f_e \leq c_e,\ \forall e \in E$

- Flow conservation: at every vertex $u \neq s, t$

  total in-flow = total out-flow

Can be solved in *strongly* polynomial-time

CE Characterization

Pirces $p = (p_1, \dots, p_m)$ and allocation $X = (x_1, \dots, x_n)$

- Optimal bundle: Agent i demands $x_i \in \underset{x:\, p\cdot x \le B_i}{\operatorname{argmax}} V_i(x)$
  - $p \cdot x_i = B_i$
  - $x_{ij} > 0 \Rightarrow \frac{V_{ij}}{p_j} = \max_{k \in G} \frac{V_{ik}}{p_k}$, for all good j

- Market clears: For each good j, demand = supply

$$\sum_i x_{ij} = 1.$$

Competitive Equilibrium → Flow

Pirces $p = (p_1, \dots, p_m)$ and allocation $F = (f_1, \dots, f_n)$

$f_{ij} = x_{ij} p_j$ (money spent by agent i on good j)

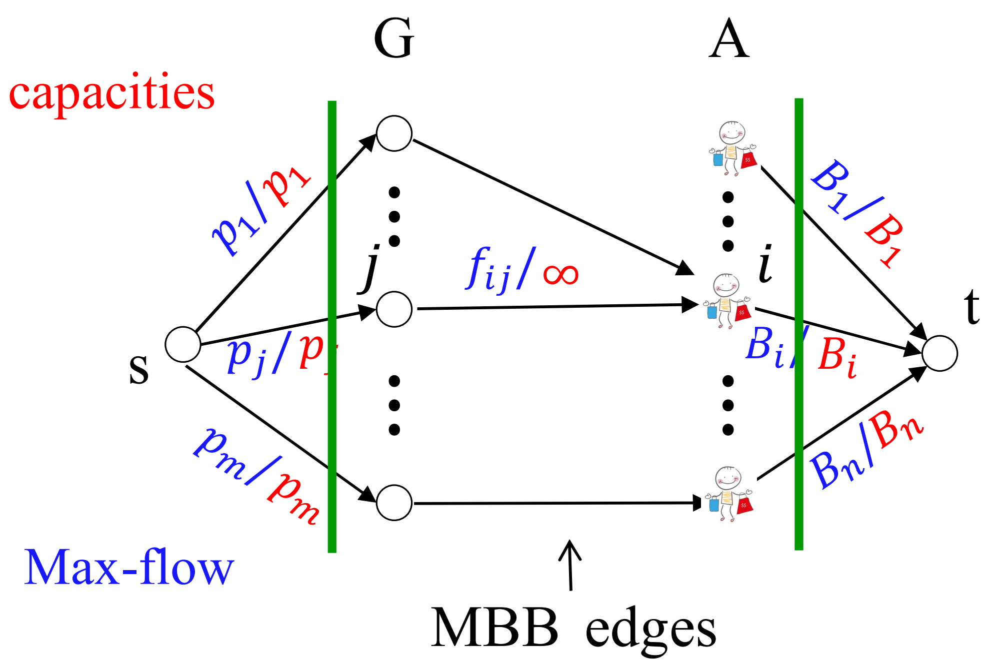
- Optimal bundle: Agent i demands $x_i \in argmax_{x:\, p \cdot x \leq B_i} v_i(x)$
  - $\sum_{j \in G} f_{ij} = B_i$
  - $f_{ij} > 0 \Rightarrow \frac{V_{ij}}{p_j} = \max_{k \in G} \frac{V_{ik}}{p_k}$ for all good j

    → Maximum bang-per-buck (MBB)

- Market clears: For each good j, demand = supply

$$\sum_{i \in N} f_{ij} = p_j$$

Competitive Equilibrium → Flow



CE: (p, F) s.t.

Opt. Bundle: $\sum_{j \in M} f_{ij} = B_i$, $f_{ij} > 0$ on MBB edges

Market clears: $\sum_{i \in N} f_{ij} = p_j$

Max-flow = min-cut

$= \sum_{j \in G} p_j = \sum_{i \in A} B_i$

Issue: Eq. prices and hence also MBB edges not known!

Fix [DPSV'08]: Start with low prices, keep increasing.

Maintain:

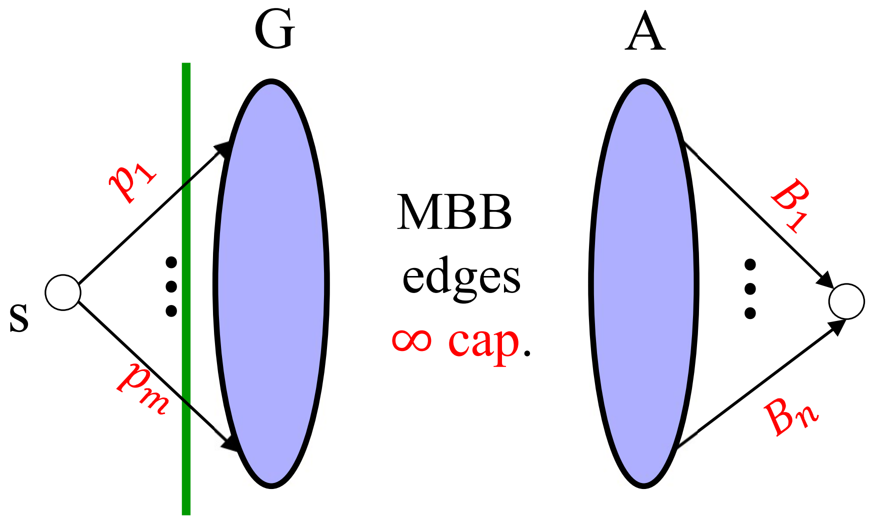
1. Flow only on MBB edges
2. Min-cut $= \{s\}$ (goods are fully sold)

⫴ demand ≥ supply

Algorithm (Pictorial)

Invariants

1. Flow only on MBB edges
2. Min-cut = $\{s\}$ (goods are sold)

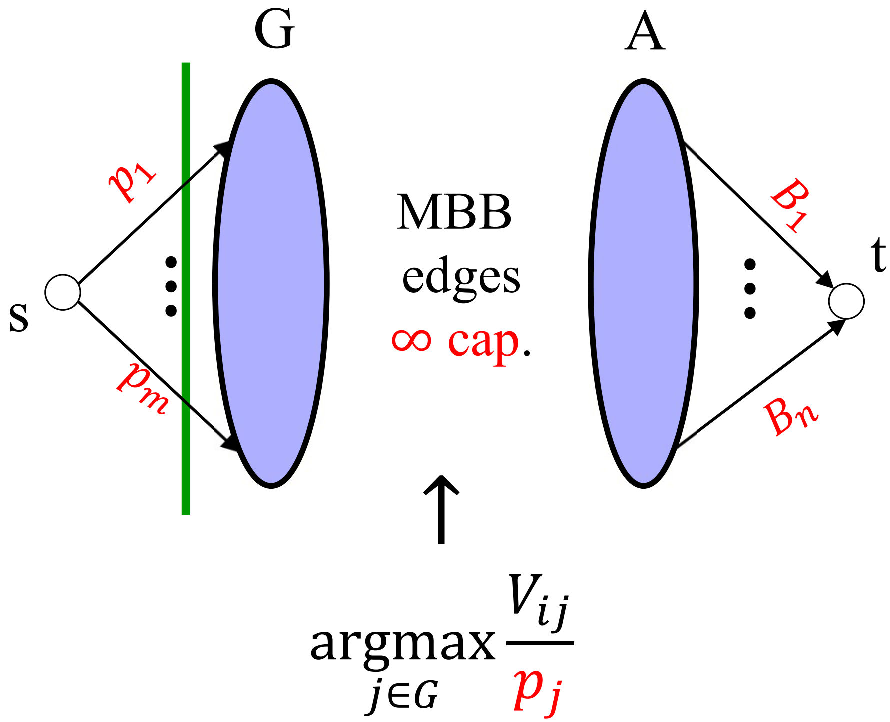


Init: $\forall j \in \mathrm{G},\ p_j < \min_i \frac{B_i}{m}$, and at least one MBB edge to j

Algorithm (Pictorial)

Invariants

1. Flow only on MBB edges
2. Min-cut = $\{s\}$ (goods are sold)



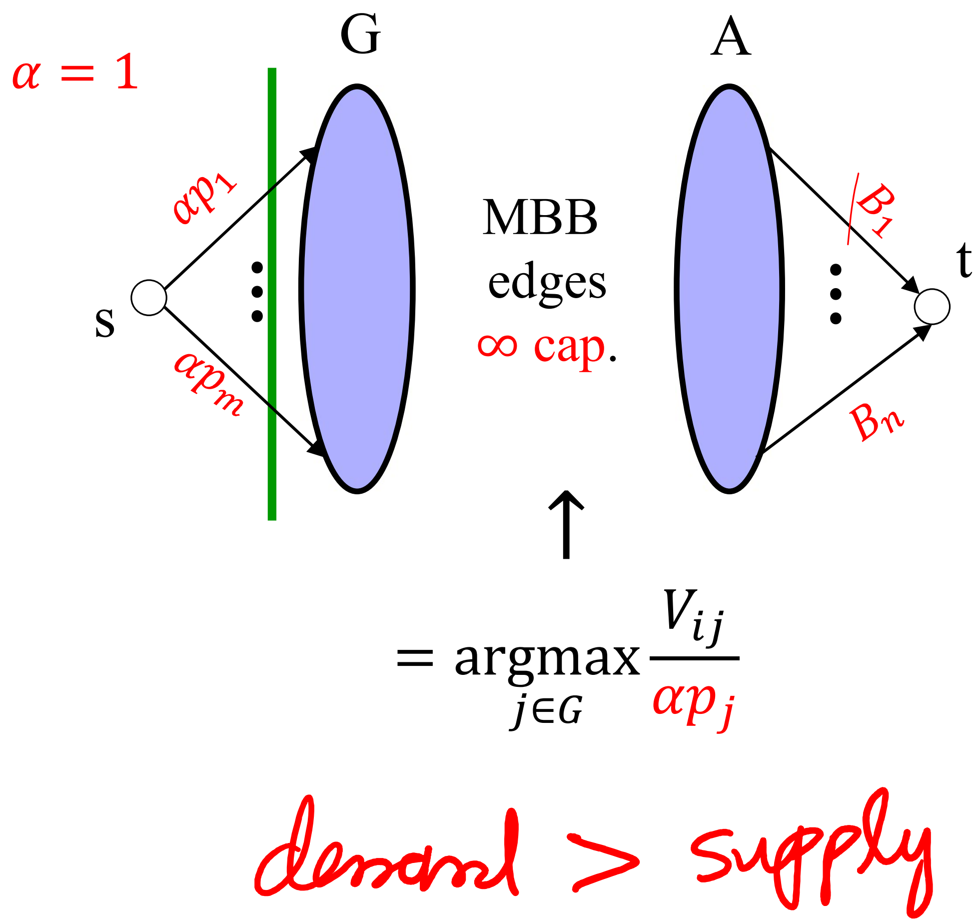
Init: $\forall j \in G,\ p_j < \min_i \frac{B_i}{m}$, and at least one MBB edge to j

Increase $\boldsymbol{p}$**:**

Algorithm (Pictorial)

Invariants

1. Flow only on MBB edges
2. Min-cut = $\{s\}$ (goods are sold)



Init: $\forall j \in M,\ p_j < \min_i \frac{B_i}{n}$

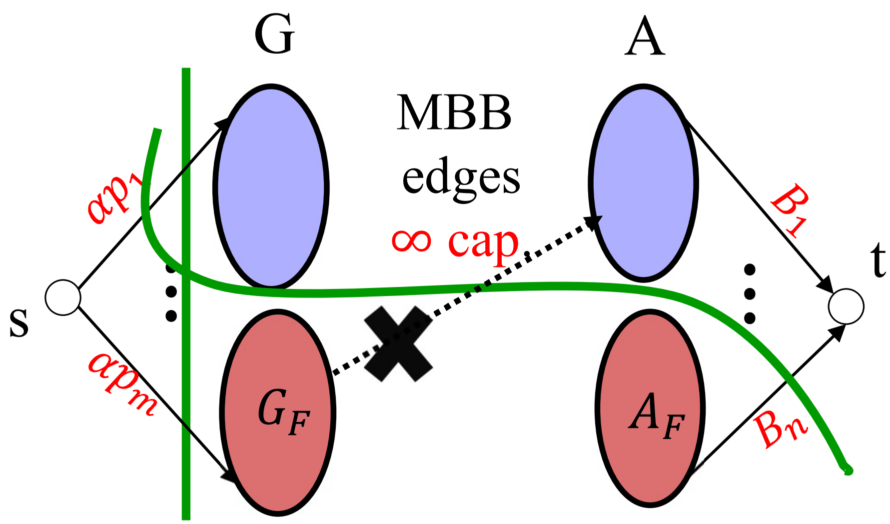
And at least one MBB edge to j

Increase p: $\uparrow \alpha$

Algorithm (Pictorial)

Invariants

1. Flow only on MBB edges
2. Min-cut = $\{s\}$ (goods are sold)



Init: $\forall j \in M,\ p_j < \min_i \frac{B_i}{n}$

And at least one MBB edge to j

Increase p: $\uparrow \alpha$

Event 1: New cross-cutting min-cut

Agents in A_F exhaust all their money.

G_F: Goods that have MBB edges only from A_F.

A tight-set.

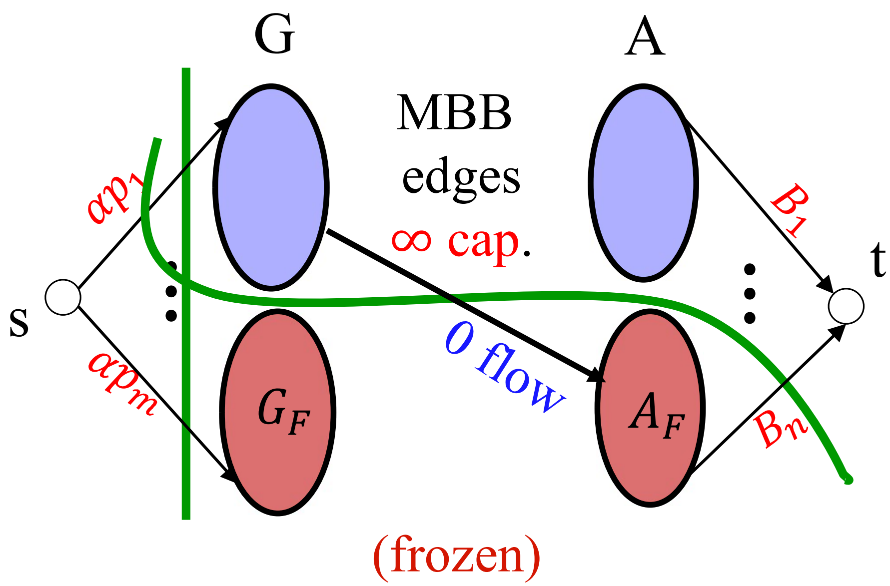
Observation: **Supply = Demand for G_F!** So, if prices of G_F are increased, then these will be under-demanded (supply > demand for G_F). And $\{s\}$ will cease to be a min-cut.

Should freeze prices in G_F.

Algorithm (Pictorial)

Invariants

1. Flow only on MBB edges
2. Min-cut = $\{s\}$ (goods are sold)



Init: $\forall j \in M,\ p_j < \min_i \frac{B_i}{n}$
And at least one MBB edge to j

Increase p: $\uparrow \alpha$

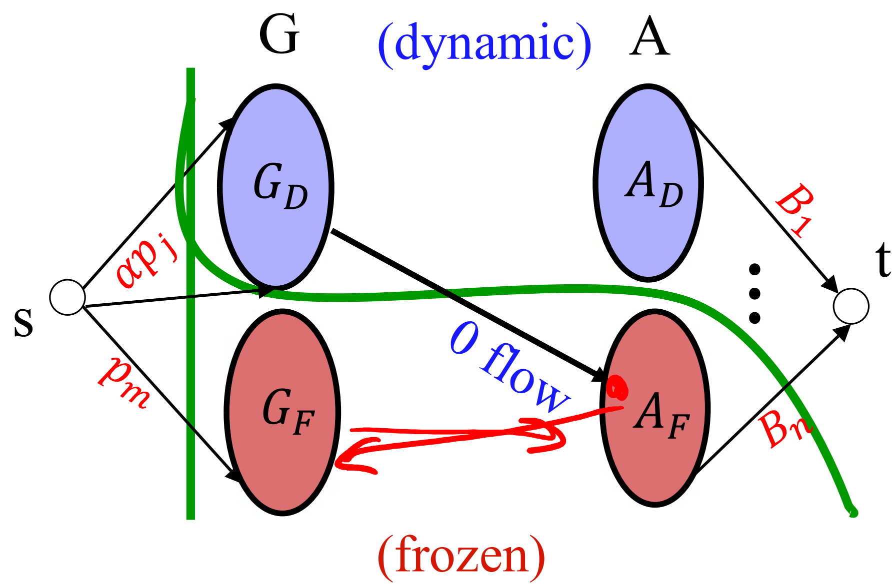
Event 1: A tight subset G_F

Call it *frozen:* (G_F, A_F).

Algorithm (Pictorial)

Invariants

1. Flow only on MBB edges
2. Min-cut = $\{s\}$ (goods are sold)



Init: $\forall j \in M,\ p_j < \min_i \frac{B_i}{n}$

And at least one MBB edge to j

Increase p: $\uparrow \alpha$

Event 1: A tight subset G_F

Call it *frozen:* (G_F, A_F).

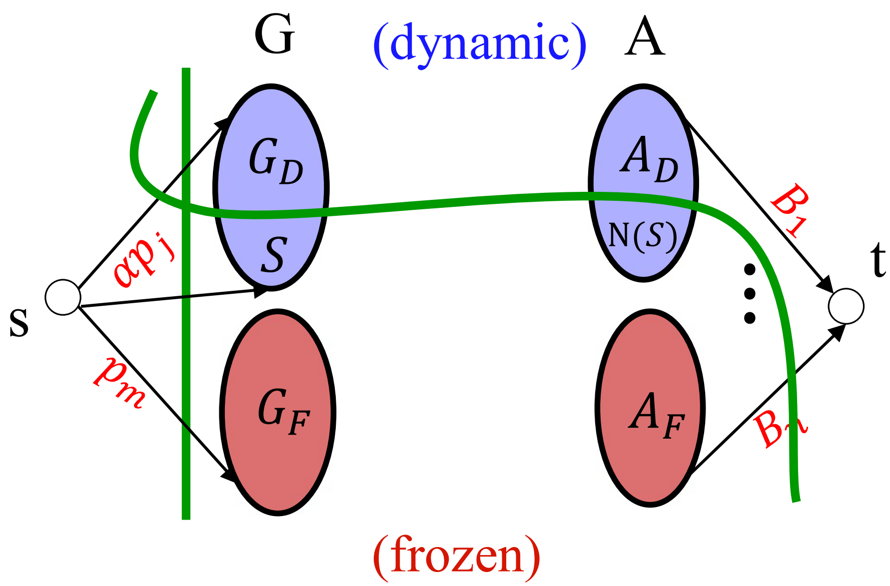
Freeze prices in G_F.

Increase prices in G_D.

Algorithm (Pictorial)

Invariants

1. Flow only on MBB edges
2. Min-cut = $\{s\}$ (goods are sold)



Init: $\forall j \in M,\ p_j < \min_i \frac{B_i}{n}$

And at least one MBB edge to j

Increase p: $\uparrow \alpha$

Event 1: A tight subset $S \subseteq G_D$

$N(S)$: Neighbors of S

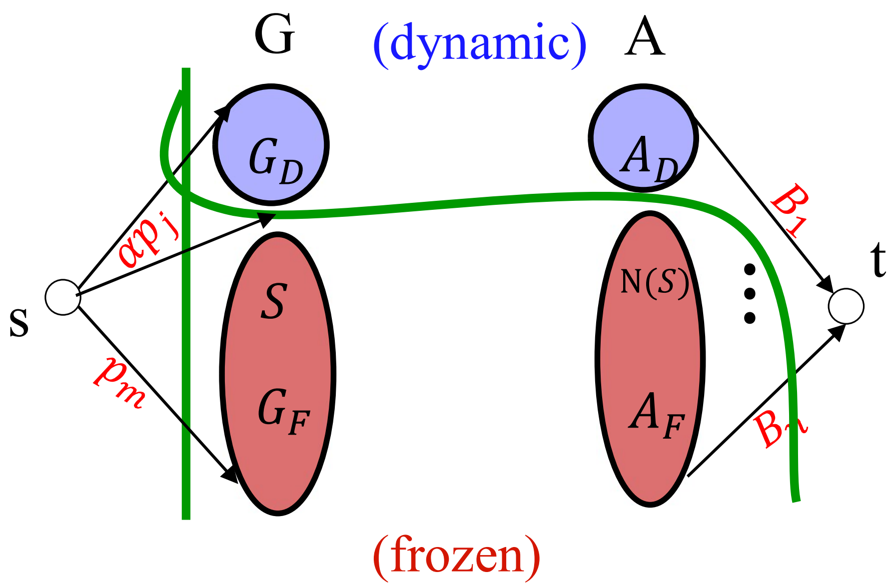
Move $(S, N(S))$ from dynamic to frozen.

Observation: Again, supply=demand for goods in S. If prices of S is increased further, then **S** can not be fully sold. And $\{s\}$ will cease to be a min-cut.

Hence it needs to be moved to the *frozen set.*

Algorithm (Pictorial)

Invariants
1. Flow only on MBB edges
2. Min-cut = $\{s\}$ (goods are sold)



Init: $\forall j \in M,\ p_j < \min_i \frac{B_i}{n}$
And at least one MBB edge to j

Increase p: $\uparrow \alpha$

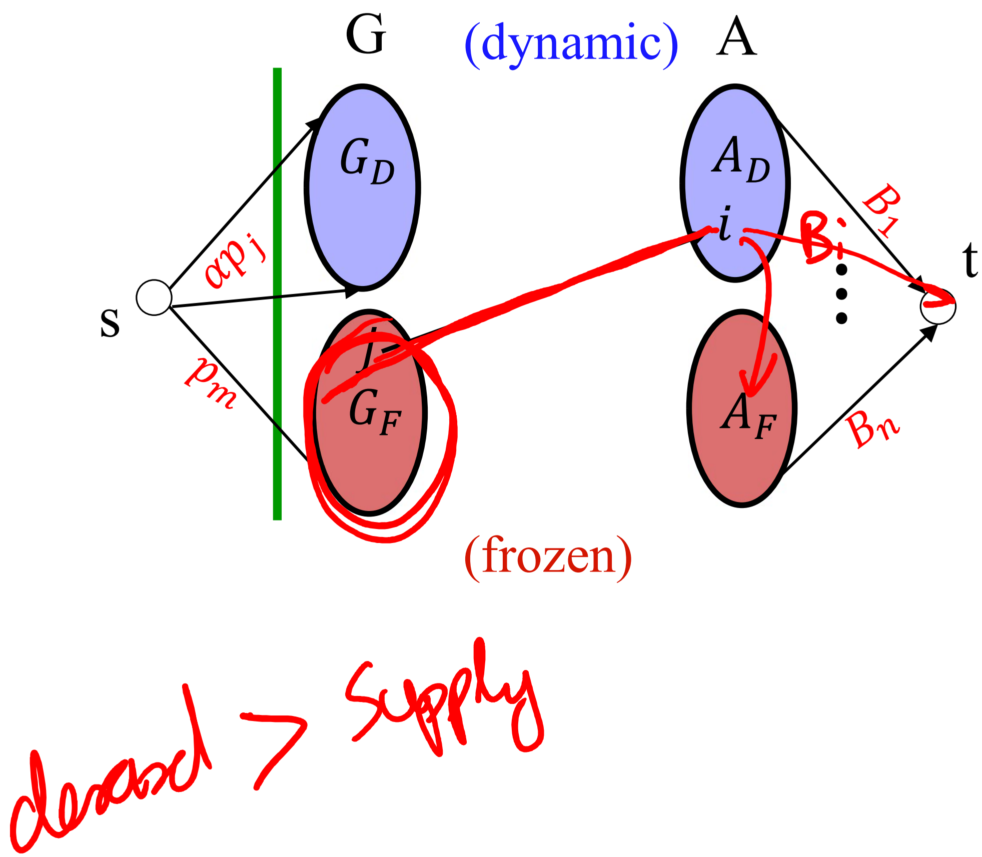
Event 1: A tight subset $S \subseteq G_D$

Move $(S, \mathrm{N}(S))$ to frozen part

Freeze prices in G_F, and increase in G_D.

Algorithm (Pictorial)

Invariants
1. Flow only on MBB edges
2. Min-cut = $\{s\}$ (goods are sold)



Init: $\forall j \in M,\ p_j < \min_i \frac{B_i}{n}$
And at least one MBB edge to j

Increase p: $\uparrow \alpha$

Event 1: A tight subset $S \subseteq G_D$
Move $(S, \mathrm{N}(S))$ from dynamic to frozen
Freeze prices in G_F, and
increase in G_D.

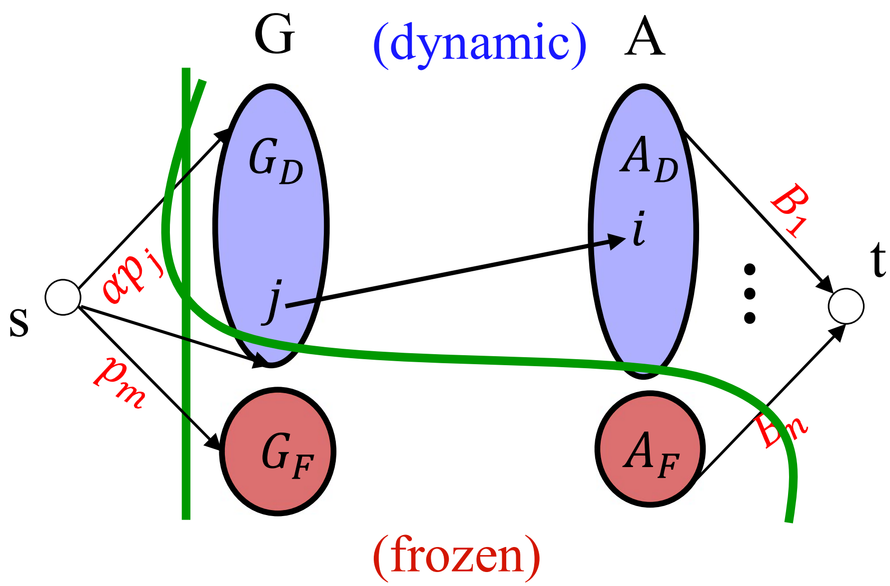
OR

Event 2: New MBB edge
Must be between $i \in A_D$ & $j \in G_F$.
Recompute dynamic and frozen.

Algorithm (Pictorial)

Invariants

1. Flow only on MBB edges
2. Min-cut = $\{s\}$ (goods are sold)



Init: $\forall j \in M,\ p_j < \min_i \frac{B_i}{n}$

And at least one MBB edge to j

Increase $\boldsymbol{p}$: $\uparrow \alpha$

Event 1: A tight subset $S \subseteq G_D$

Move $(S, \mathrm{N}(S))$ from dynamic to frozen

Freeze prices in G_F, and increase in G_D.

OR

Event 2: New MBB edge

Has to be from $i \in A_D$ to $j \in G_F$.

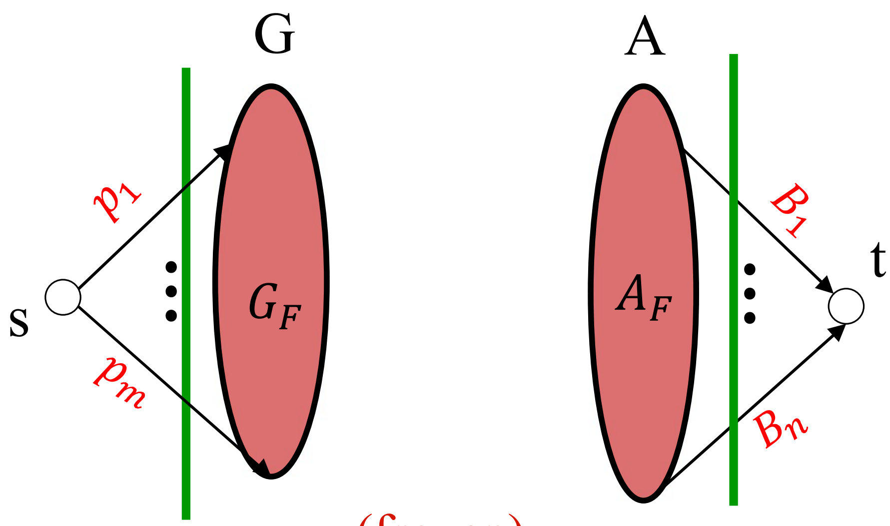
Recompute dynamic and frozen:

Move the component containing good j from frozen to dynamic.

Algorithm (Pictorial)

Invariants

1. Flow only on MBB edges
2. Min-cut = $\{s\}$ (goods are sold)



Init: $\forall j \in M,\ p_j < \min_i \frac{B_i}{n}$

And at least one MBB edge to j

Increase p: $\uparrow \alpha$

Event 1: A tight subset $S \subseteq G_D$

Move $(S, \mathrm{N}(S))$ from dynamic to frozen

Freeze prices in G_F, and increase in G_D.

OR

Event 2: New MBB edge

Must be from $i \in A_D$ to $j \in G_F$.

Recompute dynamic and frozen.

Stop: all goods are frozen.

Observations: Prices only increase.

Each increase can be lower bounded.

Both the events can be computed efficiently.

⇓

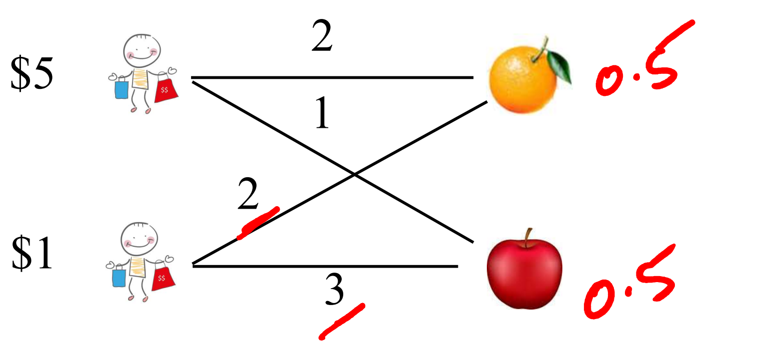
Converges to CE in finite time.

Example

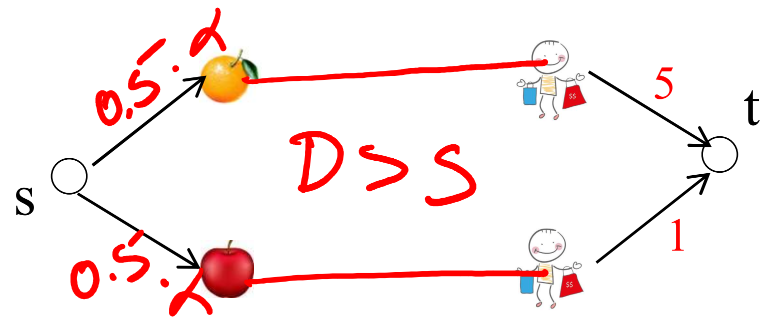
Invariants

1. Flow only on MBB edges
2. Min-cut = $\{s\}$ (goods are sold)

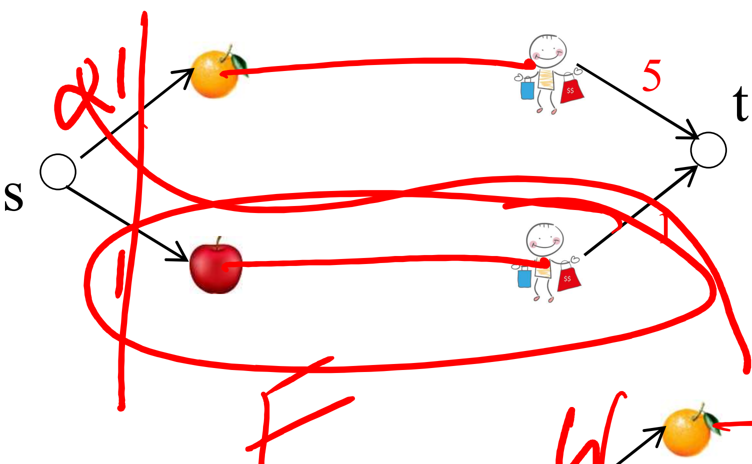
Input



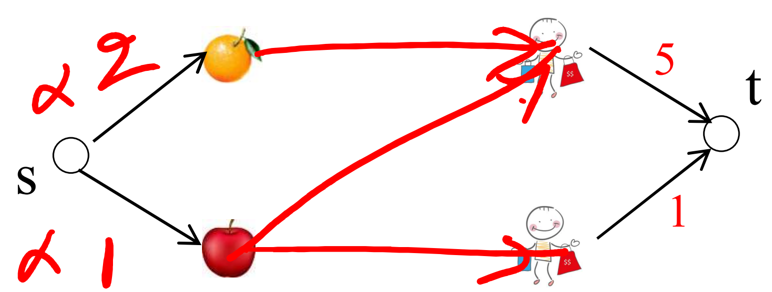
Init.

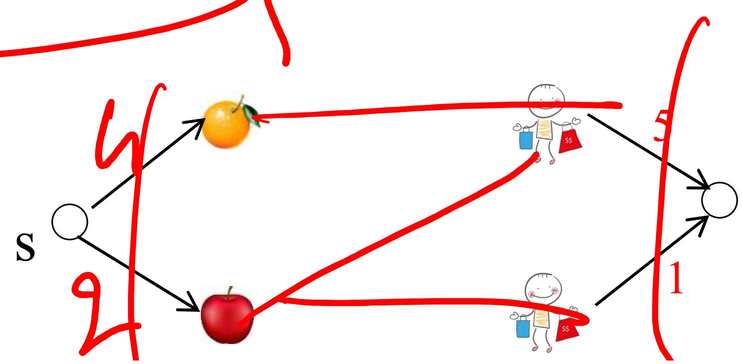


Event 1 α = 2



Event 2 α = 2





Formal Description

- Init: $p \leftarrow$ "low-values" s.t. $\{s\}$ is a min-cut.
  $(G_D, A_D) \leftarrow (G, A),\ (G_F, A_F) \leftarrow (\emptyset, \emptyset)$
- While$(G_D \neq \emptyset)$
  - $\alpha \leftarrow 1,\ p_j \leftarrow \alpha p_j\ \ \forall j \in G_D$. Increase α until

    Event 1: Set $S \subseteq G_D$ becomes tight.

    $\mathrm{N}(S) \leftarrow$ agents w/ MBB edges to S (neighbors of S).

    Move $(\mathrm{S}, \mathrm{N(S)})$ from (G_D, A_D) to (G_F, A_F).

    Event 2: New MBB edge appears between $i \in A_D$ and $j \in G_F$

    Add $(j \rightarrow i)$ edge to graph.

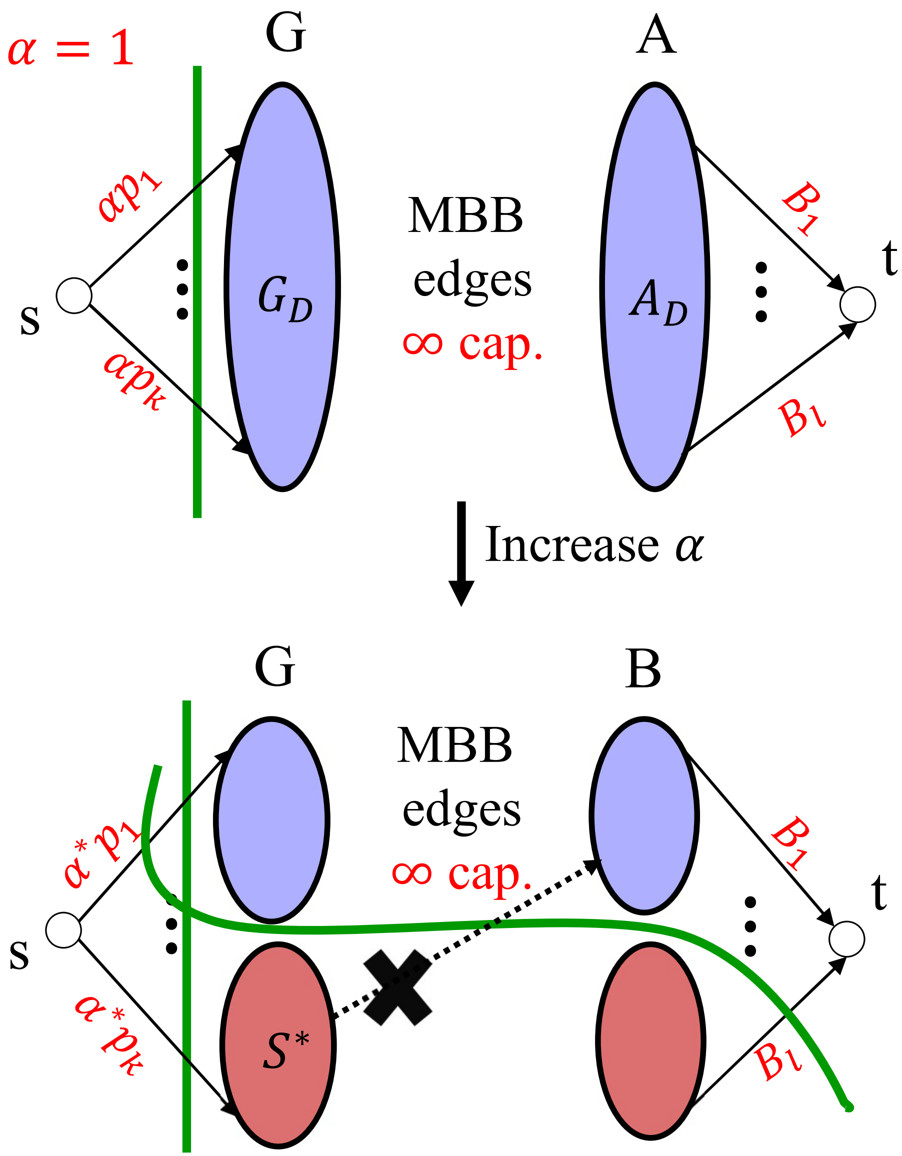
    Move component of j from (G_F, A_F) to (G_D, A_D).
- Output (p, F)

Efficiently Computing Event 2

Event 2: New MBB edge appears between $i \in A_D$ and $j \in G_F$

Exercise ☺

Efficiently Computing Event 1



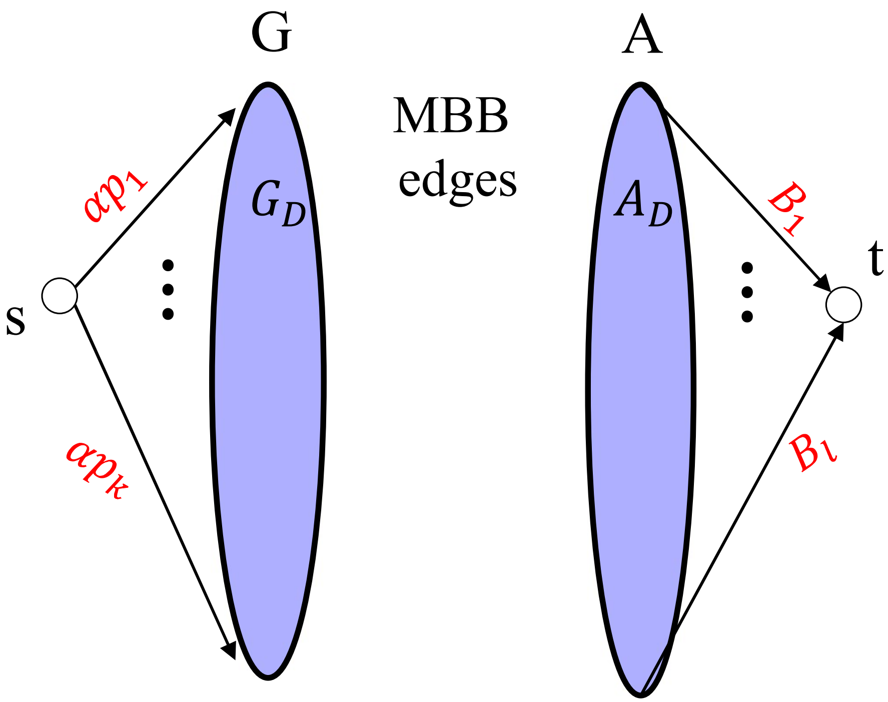
Event 1: Set $S^* \subseteq G_D$ becomes tight.

- $\alpha^* = \frac{\sum_{i \in N(S^*)} B_i}{\sum_{j \in S^*} p_j}$

  $= \min_{S \subseteq G_D} \frac{\sum_{i \in N(S)} B_i}{\sum_{j \in S} p_j}$ — $\alpha(S)$

- Find $S^* = \operatorname{argmin}_{S \subseteq G_D} \alpha(S)$

Efficiently Computing Event 1



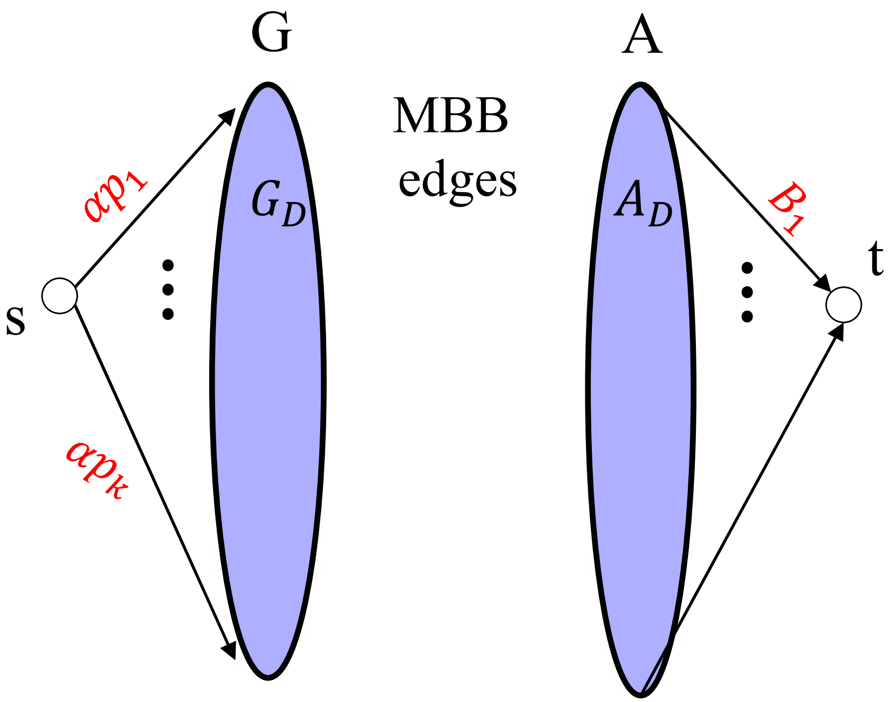
Event 1: Set $S^* \subseteq G_D$ becomes tight.

- $\alpha^* = \frac{\sum_{i \in N(S^*)} B_i}{\sum_{j \in S^*} p_j}$

  $= \min_{S \subseteq G_D} \frac{\sum_{i \in N(S)} B_i}{\sum_{j \in S} p_j}$ — $\alpha(S)$

- Find $S^* = \operatorname{argmin}_{S \subseteq G_D} \alpha(S)$

Efficiently Computing Event 1



Event 1: Set $S^* \subseteq G_D$ becomes tight.

- $\alpha(S) = \frac{\sum_{i \in N(S)} B_i}{\sum_{j \in S} p_j}$

Find $S^* = \underset{S \subseteq G_D}{\operatorname{argmin}}\, \alpha(S)$

Claim. Can be done in O(n) min-cut computations

$(G', A') \leftarrow (G_D, A_D)$
Repeat{
  $\alpha \leftarrow \alpha(G')$. Set $c_{(s,j)} \leftarrow \alpha p_j, \forall j \in G'$
  $(s \cup \{S\} \cup N(S)) \leftarrow$ min-cut in (G', A')
  $(G', A') \leftarrow (S, N(S))$
}Until($\{s\}$ not a min-cut)
Return α

Efficient Flow-based Algorithms

- Polynomial running-time
  - Compute *balanced-flow:* minimizing l_2 norm of agents' surplus [DPSV'08]
- Strongly polynomial: Flow + scaling [Orlin'10]

Exchange model (barter):

- Polynomial time [DM'16, DGM'17, CM'18]
- Strongly polynomial for exchange
  - Flow + scaling + approximate LP [GV'19]

Application to Display Ads: Pacing Eq.

- Google Display Ads
  - Each advertiser has
    - Budget B_i. Value v_{ij} for keyword j
  - Pacing Eq.: $(\lambda_1, \dots, \lambda_n) \in [0,1]^n$ s.t.
    - First price auction with bids $\lambda_i v_{ij}$
    - For each agent i, if $\lambda_i < 1$ then total payment = B_i, else $\leq B_i$
- Equivalent to Fisher market with quasi-linear utilities!

What about chores?

- CEEI exists but may form a non-convex set [BMSY'17]

- Efficient Computation?
  - **Open: Fisher as well as for CEEI**
  - For constantly many agents (or chores) [BS'19, GM'20]
  - *Fast* path-following algorithm [CGMM.'20]

- Hardness result for an exchange model [CGMM.'20]

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THANK YOU