# CO650

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# 1 Minimum-cost Spanning Trees

What's a spanning tree?

### **Definition 1**

Given a graph G = (V, E), a subgraph T is a spanning tree of G if:

- V(T) = V(G)
- T is connected
- T is acyclic (contains no cycle)

# Theorem 2

Let G=(V,E) be connected graph, T be a subgraph of G, with V(T)=V, then the following are equivalent (TFAE)

- T is a spanning tree of G.
- T is minimally connected (T will be disconnected if any edge is dropped).
- T is maximally acyclic (Add any edge between vertices of T makes it cyclic).
- $\forall u, v \in V$ , there exists a unique u v path in T (call it  $T_{u,v}$ ).

#### **Theorem 3**

A graph G = (V, E) is connected if and only if  $\forall A \subseteq V$  with  $\emptyset \neq A \neq V$ , we have  $\delta(A) \neq \emptyset$  ( $\delta(A) := \{e \in E : |e \cap A| = 1\}$ , the set of edges with exactly one edge in A).

# 1.1 Minimum Spanning Tree Problem

Input:

- Connected graph G = (V, E).
- Costs  $C_e, \forall e \in E$ .

Output: A spanning tree T of G of minimum cost  $C(T) := \sum_{e \in E(t)} C_e$ .

#### Theorem 4

Let G = (V, E), connected,  $C : E \mapsto \mathbb{R}$ , T is a spanning tree of G, then TFAE:

- a) T is a MST (minimum spanning tree).
- b)  $\forall uv \in E \setminus E(T)$ , all edges e on  $T_{u,v}$  have  $C_e \leqslant C_{uv}$ .
- c)  $\forall e \in E(T)$ , let  $T_1, T_2$  be the two connected components obtained from T when removing e, then e is a min cost edge in  $\delta(T_1)$  (of G).

# Proof.

- $a) \implies b$ ). Suppose  $\exists uv \in E \setminus E(T)$  and  $e \in T_{u,v}$  such that  $C_e > C_{uv}$ , consider T' = T + uv e. Since we don't change delete any vertices, V(T') = V(T) = V(G). If we write  $T_{u,v} = u, v_1, \ldots, v_n, v$  and say  $v_i, v_{i+1}$  are the ends of e. Then, for any two vertices of G, if they are not on  $T_{u,v}$ , they are still connected. If at least one of them is on  $T_{u,v}$ , say  $k_2$  is on  $T_{u,v}$ , WLOG, say the unique path is  $k_1, \ldots, u, \ldots, k_2$ , if e is not in the path, we are good, if it is, then we take  $k_1, \ldots, u, v, \ldots, k_2$  on T'. Hence, T' is connected. That is, T' is connected and |E(T')| = |E(T)| = |V| 1, so by theorem 2, we know T' is a spanning tree of G. And since  $C_{uv} < C_e$ , C(T') < C(T), T is not a MST, contradiction, so no such uv exists.
- b)  $\implies$  c). Suppose  $\exists e \in T, uv \in \delta(T_1)$  such that  $C_{uv} < C_e$ . First,  $uv \notin E(T)$ , otherwise, since  $v \in T_2$  and  $T_1, T_2$  are connected, so there is a cycle including uv and e in T, contradiction. Also,  $e \in T_{uv}$ , because we have  $u \in T_1$ , and  $v \in T_2$ , and  $T_1, T_2$  are separated by e, so any path from  $T_1$  to  $T_2$  will include e. Then this contradicts to b), contradiction, no such e exists, e0 is true.
- $c) \implies a$ ). Let T satisfy c). Let  $T^*$  be a MST with largest  $k := |E(T) \cap E(T^*)|$ . If k = n 1 = |V| 1, we are done.

Else, there is  $e \in E(T) \setminus E(T^*)$  (note T is also a spanning tree). Let  $T_1, T_2$  be connected component of T - e, there exists  $e^* \in E(T^*) \cap \delta(T_1)$ .

First  $e^* \notin E(T)$  because otherwise, we have e and  $e^*$  connecting  $T_1$  and  $T_2$  in T (note  $e \neq e^*$ ).

Also,  $T' = T^* - e^* + e$  is also a spanning tree, because all vertices stay connected and the number of edges stay the same (as above proof).

By c),  $C_e \leq C_{e^*}$ , so  $C(T) \leq C(T^*)$ . So T' is a MST, and  $|E(T) \cap E(T')| = k + 1 > k$ , contradiction. So k = n - 1,  $T = T^*$  which is a MST.

# 1.2 Kruskal's Algorithm

# Algorithm 1 Kruskal's Algorithm for MST

```
Require: G be a connected graph, n = |V|, m = |E| H = (V, \emptyset) while H is not a spanning tree do

Find the cheapest edge whose endpoints are in different components of H H \leftarrow H + e end while
```

We also have an equivalent version:

### **Algorithm 2** Equivalent

```
Sort edges so that C_{e_1} \leqslant \ldots \leqslant C_{e_m}.

for i=1,\ldots,m do

if endpoints u,v of e_i are in different components of H then

H \leftarrow H + e_i

end if

end for
```

Implementation:

- Keep array comp, with  $comp[v] \leftarrow v, \forall v \in V$  initially.
- The if step in algorithm 2 can be done by checking if comp[u] == comp[v], for e = uv. O(1).
- When the assignment step in alg2 is executed, go through comp[t],  $\forall t \in V$ , if comp[t] = comp[v], set comp[t] = comp[u]. That is, make sure u, v and the vertices they are connected to are in the same component. O(n).
- Sort step  $O(m \log m)$ .
- For loop step O(m) in total.

Overall, we have  $O(m \log m) + O(mn) = O(mn)$ , which is a polynomial time. At the end, H will be a spanning tree.

# Q: Can alg1 get stuck?

- The e we need to find always exists. Since H is not a spanning tree, either it is not connected, or it has a cycle in it. However, if H has a cycle, the last edge added to that cycle will not be added because its two endpoints are already in H. Hence, H is disconnected, so we can find an edge connecting different components of H.
- Everytime  $H \leftarrow H + e$  is executed, two different components are connected, so the number of different connected components of H minus 1. Also, since H is acyclic before the assignment, and e connects two different components, there is no cycle.

• Every iteration, the number of components minus 1, and we have n components at the beginning, so we do O(n) iterations, during the time, we keep the H acyclic.

### Q: Does it return a MST?

Suppose not, there exists  $uv \in E \setminus E(H)$  and  $e \in H_{uv}$  with  $C_{uv} < C_e$  by theorem4, so  $C_{uv}$  will be considered before  $C_e$  in the first step of alg2. When  $C_{uv}$  is being tested in alg2's third step, there is no path from u to v, so they are in different components, so uv will be added to H, not e, contradiction.

# 1.3 Correctness via LP

- Show techniques that can be used in other settings
- Lead to "good" approaches for more challenging problems

### 1.3.1 Integer Programming Formulation

- Let  $x_e \in \{0, 1\}$  to indicate if edge e is in the MST
- Spanning tree: acylic, n-1 edges (n:=|v|)

$$\min \sum_{e \in E} c_e x_e \ c^T x$$

$$s.t. \ x(E) = n - 1 \text{ ,where } x(F) := \sum_{e \in F} x_e$$

$$x(F) \leqslant n - \kappa(F), \forall F \subseteq E$$

$$x \in \{0, 1\}^E$$

## For Acyclic:

Consider  $F \subseteq E$ . How many edges of F can a spanning tree have?

Let  $\kappa(F)$  be the number of connected components of (V,F), then our answer is  $n-\kappa(F)$ . Since if we consider every connected components of (V,F), we can find a spanning tree in it and have at most the number of vertices in that component minus one edges. So, sum over all components, we have n-k(F) at most without forming a cycle.

Note: If  $F = \{e\}$ , then  $\kappa(F) = n - 1$ , so  $x(F) \leq n - \kappa(F)$  becomes  $x_e \leq 1$ , so our problem becomes

$$\min \sum_{e \in E} c_e x_e$$

$$s.t. \ x(E) = n - 1$$

$$x(F) \leqslant n - \kappa(F), \forall F \subseteq E$$

$$x \geqslant 0, x \in \mathbb{Z}^E$$

#### 1.3.2 LP relaxation:

$$(P_{ST}), \ \zeta_{P_{ST}}^* := \min \sum_{e \in E} c_e x_e$$
 
$$s.t. \ x(E) = n - 1$$
 
$$x(F) \leqslant n - \kappa(F), \forall F \subseteq E$$
 
$$x \geqslant 0$$

It has optimal solutions. Since G is connected, it has feasible solutions (just find a spanning tree) and its feasible regions is bounded, so it has optimal solutions.

# Proof Idea:

- Any spanning tree T corresponds to a feasible solution to  $(P_{ST}) \implies c(T) \geqslant \zeta_{P_{ST}}^*$ .
- Shows that spanning tree produced by Kruskal is optimal for  $(P_{ST})$  (using Complementary Slackness).

$$\min c^{T} x$$

$$s.t. \ x(E) = n - 1$$

$$x(F) \leqslant n - \kappa(F), \forall F \subseteq E$$

$$x \geqslant 0$$

note that  $n-1=n-\kappa(E)$ . Then we find the dual

Dual 
$$(D_{ST})$$
: 
$$\max \sum_{F \subseteq E} (n - \kappa(F)) y_F$$
$$s.t. \sum_{F:e \in F} y_F \leqslant c_e, \forall e \in E$$
$$y_F \leqslant 0, \forall F \subset E$$
$$y_E \text{ is free.}$$

Let  $E = \{e_1, \dots, e_m\}$ , with  $c_{e_1} \le c_{e_2} \le \dots \le c_{e_m}$ . Let  $E_i = \{e_1, \dots, e_i\}$ ,

- $\overline{y}_{E_i} = c_{e_i} c_{e_{i+1}} \leq 0, \forall i = 1, \dots, m-1$
- $\overline{y}_E = c_{e_m}, \overline{y}_F = 0, \forall$  other F.

Now, we want to show that  $\overline{y}$  is feasible for  $(D_{ST})$  and all constraints are satisfied at equality (except the  $y_F \leq 0$  ones). For each  $e_i \in E$ , we know  $e_i \in E_i, \dots, E_m$  and some other non- $E_i$  edge subsets. Hence,

$$\sum_{F:e_i \in F} y_F = \sum_{j=i}^m y_{E_j} + \sum_{F \neq E_j, j \geqslant i:e_i \in F} y_F$$

$$= c_{e_i} - c_{e_m} + c_{e_m} + 0$$

$$= c_{e_i}$$

So the Complementary Slackness condition for Dual constraints are satisfied, we only need to check either  $\overline{y}_i = 0$  or  $\overline{x}_{E_i}$  constraint is tight.

Now, let  $\overline{x}$  be the incidence vector of tree T constructed by Krustal. Note:  $\overline{x}(E_i) = \sum_{e \in E_i} \overline{x}_e = |E(T) \cap E_i|$ .

- $T_i = (V, E_i \cap E(T))$  is a maximally acyclic subgraph of  $H_i = (V, E_i)$ . Suppose not, then we can add an edge  $e_k$  of  $E_i \setminus E(T)$  to  $T_i$ , and it's still acyclic. This edge  $e_k$  connects two component of  $T_i$ , otherwise, since  $e_k \notin E(T)$ , its endpoints are in the same component in T, so there is a path between its endpoints in  $E_k \cap E(T) \subseteq E_i \cap E(T)$ , contradiction. Since it connects two components of  $T_i$ , it will added be to T at  $k^{th}$  iteration, so it will be in E(T), contradiction.
- As argued before,  $n \kappa(E_i)$  is the largest number of edges we can choose from  $E_i$  without forming a cycle in  $H_i = (V, E_i)$ , that is, by previous point,  $n \kappa(E_i) = |E_i \cap E(T)| = \overline{x}(E_i)$ .
- Now we argue the Complementary Slackness conditions are satisfied. For each  $F \subseteq E$ , if  $F \in \{E_1, \dots, E_m\}$ , then by the previous point, the equality is tight; otherwise,  $y_F = 0$ . For each  $e \in E$ , we showed that all constraints of the dual problem are tight. So  $\overline{x}, \overline{y}$  are optimal for  $P_{ST}, D_{ST}$  respectively.
- Hence,  $c^T\overline{x}=c(T)=\zeta_{P_{ST}}^*$  by Complementary Slackness Theorem.

Consequence of Proof:

- $\zeta_{P_{ST}}^* = c(T^*)$ , where  $T^*$  is MST.
- Solving the above LP can give us an integral solution (under mild assumptions), which rarely happens.

Alternative Formulation for  $P_{ST}$ :

$$\zeta_{P_{ST}}^* := \min c^T x$$

$$s.t. \ x(E) = n - 1$$

$$x(E(S)) \leqslant |S| - 1, \forall \emptyset \subsetneq S \subsetneq V$$

$$x \geqslant 0$$

where  $E(S) = \{e \in E : |e \cap S| = 2\}.$ 

### 1.3.3 Greedy and Max Cost Forest

- MST Algorithms are greedy (best decision based only on local structure).
- Ex: Max weight independent set. Given G = (V, E),  $S \subseteq V$  is an independent set if  $\forall u, v \in S$ ,  $uv \notin E$ . Then given  $C_v$ ,  $\forall v \in V$ , find independent set S, which maximize  $c(S) := \sum_{v \in S} c_v$ .

Maximum Forest Problem:

Given G = (V, E), a <u>forest</u> is a subgraph (V, F) with  $F \subseteq E$  that is acyclic. (We refer to a forest by its set of edges). Then we want

Given G = (V, E),  $c_e, \forall e \in E$ , find a forest F maximizing  $c(F) := \sum_{e \in F} c_e$ .

#### USE MST:

- Compute MST with respect to  $c'_e = -c_e$ .
- Delete from MST all edges with  $c_e \leqslant 0$ .

*Remark.* If G is not connected, add edges to it with cost -M, where M > 0 is large.

- The above algorithm will compute a max cost forest: Consider any two components of the computed forest. By the definition of MST algorithm, the edge deleted from the computed spanning tree has the smallest cost in the edges between the two components (w.r.t.  $-c_e$ ), so all edges between this two components have negative costs. Also, for any edges e not connecting two components of the forest, if it has a positive cost, then it will be added to the computed spanning tree, hence a contradiction. Similar for the case when an edge is between two vertices of a component of the forest.
- We should have M greater than the largest absolute value of the negative  $c_e$ , so that when we are computing the MST, the "added" edges will never be selected.

#### 1.3.4 Kruskal for Maximum Cost Forest

# **Algorithm 3**

 $H=(V,\emptyset).$  **while**  $\exists e: c_e>0$ , with endpoints in different connected components of H **do** e= highest cost edge whose endpoints are in different components of H.  $H\leftarrow H+e$  **end while** 

return H

To solve MST (alternatively):

- Add -M to  $c_e$ ,  $\forall e$  such that  $c_e M < 0$
- Solve maximum cost forest w.r.t.  $c_e' = -(c_e M)$

If G is connect, and with all costs  $c'_e > 0$ , the above algorithm will find a spanning tree with the largest cost w.r.t.  $c'_e$ , that is, a spanning tree with the smallest cost w.r.t  $c_e$ .

# 2 Matroids

Look at edge setes of forests, i.e. instead of finding H = (V, F), we just refer to F.

# Algorithm 4 Generic Greedy

```
F \leftarrow \emptyset.

while \exists e : F \cup \{e\} \in I \text{ and } c_e > 0 \text{ do}

choose such e with largest c_e;

F \leftarrow F \cup \{e\}

end while

return F
```

where *I* here represents the set of all forests.

# 2.1 Matroid 1

### **Definition 5: Matroids**

Let S be a ground set. Let  $I\subseteq 2^S$  (the set of all subsets of S). M=(S,I) is called a Matroid if it satisfies the following:

- (M1)  $\emptyset \in I$
- (M2) If  $F \in I$ ,  $F' \subseteq F$ , then  $F' \in I$ .
- (M3) For all  $A \subseteq S$ , every inclusionwise maximal element of I that is contained in A (definition of the basis of A) has the same cardinality. That is,  $B \in I$  is a subset of A and no other subsets of A in I is a strict superset of B, then B is a basis of A.

# Example 6

- Let G = (V, E). Set  $S = E, I = \{$  all forest $\}$ . We get a **Graphical/Forest Matroid**.
- Let  $S = \{1, ..., n\}$ . Let  $r \in \{0, ..., n\}$ , I = set of all subsets of S with at most r elements. We have

$$U_n^r = (S, I) \implies$$
 Uniform matroid of rank  $r$ 

Q1: Is  $U_n^r$  a matroid?

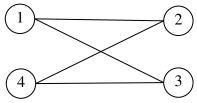
- (M1)  $|\phi| = 0 \leqslant r$
- (M2) If  $A \in I$  and  $B \subseteq A$ , then  $|B| \leqslant |A| \leqslant r \implies B \in I$ .
- (M3) If there are two basis  $B_1, B_2$  of A and  $|B_1| < |B_2| \leqslant \min\{r, |A|\}$ , then let  $e \in B_2 \setminus B_1$ . Then  $B_1 \cup \{e\} \subseteq A$  and  $|B_1 \cup \{e\}| \leqslant |B_2| \leqslant \min\{r, |A|\}$ . So  $B_1$  is not a basis, contradiction.
- Let N be an  $m \times n$  matrix of real numbers. Let  $S = \{1, \ldots, n\}$ .  $I = \{A \subseteq S : \text{columns indexed by } A \text{ are linearly independent.}\}$ . We call this a **Linear Matroid**. e.g.:

$$N = \begin{pmatrix} 2 & 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 3 & 0 \\ 0 & 0 & 1 & 0 & 2 & 0 \end{pmatrix}$$

, then 
$$I = \{\emptyset, \{1\}, \dots, \{5\}, \{1, 2\}, \{1, 3\}, \{1, 5\}, \{2, 3\}, \{2, 4\}, \{2, 5\}, \dots\}.$$

- (M1)  $\emptyset \in I$ .
- (M2) If a set of vectors is linearly independent, then any subset of it is also linearly independent.
- (M3) Follows from linear algebra. (Note: basis of a vector space transalte to basis of A).

# Example 7



Let S=V,  $I=\{A\subseteq V: A \text{ is a stable set}\}.$ 

- (M1)  $\emptyset \in I$
- (M2) A subset of a stable set is also stable set.
- (M3) Maximal (inclusionwise) subsets of S:  $\{1,4\},\{2,3\}$  which has the same cardinality. So is this example a matroid? **NO!**.  $A = \{1,2,3\}$ , then both  $\{1\},\{2,3\}$  are the maximal subsets of A that are in I but they have different cardinality.

# **Definition 8: nomenclature of matroids**

- Elements of *I* are called independent sets.
- Minimal dependent sets are called circuit (in the forest sense, cycle are circuits).
- If M = (S, I) satisfies (M1), (M2), it's called an independence system.
- The rank of A:  $r(A) := \max\{|B|: B \subseteq A, B \in I\}$
- The basis of M = the basis of S.
- r(S) is the rank of M (matroid or independent system).
- $\rho(A) := \min\{|B|: B \text{ is a basis of } A\}$ . Note:

$$M$$
 is a matroid  $\iff \rho(A) = r(A), \forall A \subseteq S$ 

# 2.2 Matroid 2

Maximum Weight independent Set (for independent systems):

Given M=(S,I) independence system,  $c_e\in\mathbb{R}_+$  (I can always delete the ones with  $c_e<0$ , so assume  $c_e\geqslant 0$ ), for all  $e\in S$ , find  $A\in I$  maximizing  $c(A):=\sum_{e\in A}C_e$ .

```
F \leftarrow \emptyset
while \exists e : F \cup \{e\} \in I \text{ and } c_e > 0 \text{ do}:
Choose such e with largest c_e;
F \leftarrow F \cup \{e\}
end while
return F
```

#### Theorem 9: Rado, Edmonds

Let M be a matroid,  $c \in \mathbb{R}_+^S$ . Then greedy algorithm above finds Maximum Weight Independent Set.

*Proof.* Later □

#### Theorem 10: Rado, Edmonds

Let M=(S,I) be an independence system. Then greedy finds an optimal independent set  $\forall c \in \mathbb{R}^S_+$  if and only if M is a matroid.

Proof.

- (  $\iff$  ) By Theorem 9 above.
- ( $\Longrightarrow$ ) Suppose M is not a matroid. Let  $A\subseteq S$ ,  $A_1$  and  $A_2$  be bases of A with  $|A_1|<|A_2|$ . Let

$$c_e = \begin{cases} v_1, & \forall e \in A_1 \\ v_2, & \forall e \in A_2 \setminus A_1 \\ 0, & \forall e \notin A_1 \cup A_2 \end{cases}$$

Choose  $v_1>0$  and  $v_1>v_2>\frac{|A_1|}{|A_2|}v_1$ . Then since all other elements have cost zero, the greedy algorithm only considers the elements in  $A_1\cup A_2$ . Since  $v_1>v_2$ , the algorithm will select  $A_1$  first, since  $A_1$  is a basis of A, the algorithm can't add more elements to it, so it stops and output  $A_1$ . Then  $A_2$  has cost  $v_1|A_1\cap A_2|+v_2|A_2\setminus A_1|\geqslant v_2|A_2|>v_1|A_1|$ . So the greedy algorithm does not output an optimal solution when all  $c\in\mathbb{R}_+^S$ , contradiction.

Theorem 11: Jenkyns 176

Let (S, I) be an independent system. Let  $gr_{S,I}$  be the total weight of the independent set formed by the greedy algorithm and  $opt_{S,I}$  be the optimal solution weight. Then

$$gr_{S,I} \geqslant q(S,I)opt_{S,I}$$

where  $q(S, I) = \min_{A \subseteq S, r(A) \neq 0} \frac{\rho(A)}{r(A)}$  (rank quotient).

*Proof.* Let  $S = \{e_1, \dots, e_n\} : c_{e_1} \ge \dots \ge c_{e_n}$ . Let  $S_j := \{e_1, \dots, e_j\}$  and  $S_0 := \emptyset$ . Let  $G \in I$  be solution obtained by greedy,  $\sigma \in I$  be the optimal solution and  $G_j = G \cap S_j$ ;  $\sigma_j = \sigma \cap S_j$ .

$$c(G) = \sum_{j \in G} c_j = \sum_{j=1}^n c_{e_j} (|G_j| - |G_{j-1}|) = \sum_{j=1}^n |G_j| (\underbrace{c_{e_j} - c_{e_{j+1}}}_{\Delta_i \geqslant 0})$$

note that if  $e_j \in G$ , then  $|G_j| - |G_{j-1}| = 1$ , otherwise,  $|G_j| - |G_{j-1}| = 0$  and  $c_{e_{n+1}} := 0$ . Greedy computes a maximum independent subset of  $S_j$  implies  $G_j$  is a basis of  $S_j$  implies

$$c(G) = \sum_{j=1}^{n} |G_j| \Delta_j$$

$$\geqslant \sum_{j=1}^{n} \rho(S_j) \Delta_j$$

$$\geqslant \sum_{j=1}^{n} q(S, I) r(S_j) \Delta_j$$

$$\geqslant \sum_{j=1}^{n} q(S, I) |\sigma_j| \Delta_j$$

$$= q(S, I) \sum_{j=1}^{n} |\sigma_j| (c_{e_j} - c_{e_{j+1}})$$

$$= q(S, I) \sum_{j=1}^{n} c_{e_j} (|\sigma_j| - |\sigma_{j-1}|)$$

$$= q(S, I) \sum_{j \in \sigma} c_j$$

$$= q(S, I) c(\sigma)$$

Hence, by Jenkyn's results, we have if M is a matroid, greedy gets an optimal solution. And **Theorem 9 is proved by it**.

How fast is Greedy? Hence a total O(|S|) times executed.

```
F \leftarrow \emptyset \ \ O(1)
while \exists e: F \cup \{e\} \in I and c_e > 0 do:
\text{can be checked in time } Poly(|S|)?
Choose such e with largest c_e; O(|S|)
F \leftarrow F \cup \{e\} \ O(1)
end while
\text{return } F \ O(1)
```

# 2.3 Matroid 3

#### **Theorem 12**

Let M=(S,I) independent system. Then  $(M3)\iff (M3'): \forall X,Y\in I,|X|>|Y|,\exists x\in X\setminus Y:Y\cup\{x\}\in I.$ 

Proof.

- $(M3') \implies (M3)$  trivial.
- $(M3) \implies (M3')$ . Let  $X,Y \in I$  and |X| > |Y|. Consider  $A = X \cup Y$ . Then Y is not a basis of A because by (M3), and |X| > |Y|, we have |Y| < r(A). Then there exists  $x \in A \setminus Y = X \setminus Y : Y \cup \{x\} \in I$ .

# Example 13

Let  $G=(V,E), W\subseteq V$  a stable set. Let  $k_v\in\mathbb{Z}_+, \forall v\in W, S=E, I=\{F\subseteq E: |\delta(v)\cap F|\leqslant k_v, \forall v\in W\}$ . Clearly (M1), (M2) hold. (M3') Let  $X,Y\subseteq E, X,Y\in I, |X|>|Y|$ . Let  $W_Y=\{v\in W: |\delta(v)\cap Y|=k_v\}$ . Also,  $2|X|=\sum_{v\in V}|X\cap\delta(v)|$ . then

$$2|X| = \sum_{v \in W_Y} \underbrace{|X \cap \delta(v)|}_{\leqslant k_v} + \sum_{v \in W \setminus W_Y} |X \cap \delta(v)| + \sum_{v \in V \setminus W} |X \cap \delta(v)|$$
$$2|Y| = \sum_{v \in W_Y} \underbrace{|Y \cap \delta(v)|}_{=k_v} + \sum_{v \in W \setminus W_Y} |Y \cap \delta(v)| + \sum_{v \in V \setminus W} |Y \cap \delta(v)|$$

Since |X| > |Y|, there exists  $x \in X \setminus Y$ :  $x \in \delta(v)$  only for some  $v \notin W_Y$ . Otherwise, all  $x \in X$  are either in Y or incident to  $W_Y$ , then |X| is the number of edges in X incident to  $W_Y$  and the rest. While the rest part of X are all in Y but not incident to  $W_Y$  which are in the set of edges in Y but not incident to  $W_Y$ , and the number of edges in X incident to  $W_Y$  is less than or equal to number of edges in Y incident to  $W_Y$ . Mathematically, say  $K_X$  is subset of X such that  $x \in K_X \iff x \in \delta(v)$  for some  $v \in W_Y$ .  $K_Y$  is the subset such that  $y \in K_Y \iff y \in \delta(v)$  for some  $v \in W_Y$ . And  $|K_X| \leqslant |K_Y|$  by the definition of  $W_Y$ . Then,  $X \setminus K_X \subseteq Y \setminus K_Y$ . Hence,  $|X| \leqslant |Y|$ , contraction. Then  $Y \cup \{x\}$  satisfies the condition.

#### 2.3.1 Circuit characterization

#### **Theorem 14: Circuit**

If instead of describing I, you are given the set of circuits (min. dependent set) ( $\mathcal{C}$ ) of M, then  $A \in I \iff \nexists c \in \mathcal{C} : c \subseteq A$ .

Proof.

- $\implies$ : by (M2), any subset of A should be in I, so it has no subset in  $\mathcal{C}$ .
- $\Leftarrow$ : Suppose A is not in I, then its dependent, keep deleting elements from A till it's in C, then we have a subset of A which is in C, contradiction.

# Example 15

$$S = \{1, 2, 3, 4\}, C = \{\{4\}, \{1, 2, 3\}\}, I = \{\emptyset, \{1\}, \{2\}, \{3\}, \{1, 2\}, \{1, 3\}, \{2, 3\}\}.$$

Q: When is  $\mathcal{C} \subseteq 2^S$  the set of circuits of a matroid?

#### **Theorem 16**

Let M = (S, I) be a matroid. Then  $\forall A \in I, \forall e \in S, A \cup \{e\}$  contains at most 1 circuit.

*Proof.* Let A be smallest set so that

- $A \in I$
- $\exists e : A \cup \{e\}$  has two distinct circuits  $C_1, C_2$ .

Note  $e \in C_1 \cap C_2$ , otherwise, A has a circuit then it can't be in I.

By the choice of A, we have  $A \cup \{e\} = C_1 \cup C_2$  (otherwise there exists  $u \in A \setminus (C_1 \cup C_2)$ , then  $A \setminus \{u\}$  is a smaller set satisfying the properties above).

Since  $C_1 \nsubseteq C_2$ ,  $C_2 \nsubseteq C_1$  (if  $C_1 \subset C_2$ , then  $C_2$  is not a circuit), let  $e_1 \in C_1 \setminus C_2$  and  $e_2 \in C_2 \setminus C_1$ . Consider  $A' = (C_1 \cup C_2) \setminus \{e_1, e_2\}$ , if A' has a circuit C, then

- $C \neq C_1$ ,  $C \neq C_2$  because  $C \cap \{e_1, e_2\} = \emptyset$ .
- Since  $e_1 \notin C_2, C_2 \subseteq \{A \setminus e_1\} \cup \{e\}$ , similarly, C is also a subset of it.
- Then  $A \setminus \{e_1, e_2\}$  will be a set satisfying the properties, contradicts to the minimality of A, so A' has no circuit, so  $A' \in L$ .

so A, A' are bases of  $C_1 \cup C_2$ , with |A'| < |A| which contradicts to M being a matroid.

#### **Theorem 17**

Let  $\mathcal{C} \subseteq 2^S$ . Then  $\mathcal{C}$  is the set of circuits of a matroid iff

- (C1)  $\emptyset \notin \mathcal{C}$
- (C2) If  $C_1, C_2 \in \mathcal{C}, C_1 \subseteq C_2$ , then  $C_1 = C_2$ .
- (C3) If  $C_1, C_2 \in \mathcal{C}, C_1 \neq C_2$  and  $e \in C_1 \cap C_2$ , then there exists  $C \in \mathcal{C}$  with  $C \subseteq (C_1 \cup C_2) \setminus \{e\}$ .

Proof.

- ( $\Longrightarrow$ ):  $(C_1), (C_2)$  are trivial to prove. Suppose  $(C_3)$  not true, then  $A := (C_1 \cup C_2) \setminus \{e\} \in I$  by  $\nexists c \in \mathcal{C}$  such that  $C \subseteq A$ . This implies  $A \cup \{e\}$  has two distinct circuits, contradicts to the previous theorem.
- Define  $I = \{A \subseteq S : \nexists C \in \mathcal{C} \text{ with } C \subseteq A\}$ . Let M = (S, I), then (M1), (M2) clearly hold

Suppose (M3) is false, let  $A_1, A_2$  be the bases of  $A \subseteq S$  with  $|A_1| < |A_2|$ , choose  $A_1, A_2$  with largest  $|A_1 \cap A_2|$ . Let  $e \in A_1 \setminus A_2$  (it exists because  $A_1 \not\subseteq A_2$ ) and  $A_2 \cup \{e\}$  contains a circuit C. If  $A_2 \cup \{e\}$  contains  $C' \neq C$  (note  $e \in C \cap C'$ ), then  $(C3) \Longrightarrow A_2$  contains a circuit, but  $A_2 \in I$ . Hence C is a unique circuit in  $A_2 \cup \{e\}$ . Let  $f \in C \setminus A_1 \Longrightarrow \underbrace{(A_2 \cup \{e\}) \setminus \{f\}}_{A_2} \in I$ ,

but  $|A_3 \cap A_1| > |A_2 \cap A_1|$ ,  $|A_3| = |A_2| > |A_1|$ , contradiction. Note: we can make  $A_3$  a basis by adding elements, but the inequalities above still hold.

# 2.4 Matroid 4

# **Theorem 18: Bases characterization**

Instead of giving I, we are given  $\mathbb{B}$ , the set of bases of M, then  $A \in I \iff A \subseteq B$ , for some  $B \in \mathbb{B}$ .

### **Theorem 19**

Let  $\mathbb{B}\subseteq 2^S.$   $\mathbb{B}$  is the set of bases of a matroid (S,I) if and only if

- (B1)  $\mathbb{B} \neq \emptyset$
- (B2)  $\forall B_1, B_2 \in \mathbb{B}, x \in B_1 \setminus B_2$ , there exists  $y \in B_2 \setminus B_1$  such that  $(B_1 \setminus \{x\}) \cup \{y\} \in \mathbb{B}$ .

#### Theorem 20

Let  $\mathbb{B} \subseteq 2^S$ .  $\mathbb{B}$  is the set of bases of a matroid (S, I) if and only if

- (B1)  $\mathbb{B} \neq \emptyset$
- (B2)  $\forall B_1, B_2 \in \mathbb{B}, y \in B_2 \setminus B_1$ , there exists  $x \in B_1 \setminus B_2$  such that  $(B_1 \setminus \{x\}) \cup \{y\} \in \mathbb{B}$ .

# 2.5 Polymatroids

Let M=(S,I) be a matroid,  $c\in\mathbb{R}_+^S$ . Let  $x\in\mathbb{R}^S$  be decision variables.

$$(P_M) \quad \max c^T x$$
$$(x_M) \leq x(A) \leq r(A), \forall A \subseteq S$$
$$x \geq 0$$

Note: If  $J \in I$ , then  $x^J$  (incidence vector) is feasible for  $(P_M)$ .

### **Theorem 21**

Let M = (S, I) be a matroid, and let G be the solution returned by the greedy algorithm. Then  $x^G$  is optimal for  $(P_M)$ .

### **Definition 22**

A function  $f: 2^S \mapsto \mathbb{R}$  is called submodular if  $\forall A, B \subseteq S$ ,

$$f(A) + f(B) \geqslant f(A \cap B) + f(A \cup B)$$

# **Proposition 23**

Let M = (S, I). Then r(A) is submodular.

*Proof.* Let  $A, B \subseteq S$ . Let  $J_{\cap}$  be a basis of  $A \cap B$  (i.e.  $|J_{\cap}| = r(A \cap B)$ ). Extend  $J_{\cap}$  to a basis  $J_B$  of B (i.e.  $|J_B| = r(B)$ ) (by keep adding elements of B to  $J_{\cap}$  until we get a maximal independent set contained in B). Similarly, extend  $J_B$  to a basis  $J_{\cup}$  of  $A \cup B$  (i.e.  $|J_{\cup}| = r(A \cup B)$ ). Let  $J' = J_{\cup} \setminus (J_B \setminus J_{\cap})$ 

- Since  $J' \subseteq J_{\cup}$ , we have  $J' \in I$ .
- Suppose there exists  $v \in J' \setminus A$ , then  $v \in J_{\cup} \setminus A$  and  $v \notin J_{B} \setminus J_{\cap}$ . Since  $v \notin A$ , we have  $v \notin J_{\cap}$ . so  $v \notin J_{B}$ , and  $v \in B$ . Since  $J_{\cup}$  is a basis,  $J_{B} \cup \{v\} \in I$ , then  $J_{B}$  is not a basis of B, contradiction. So  $J' \subseteq A$ .

Thus:

$$r(A) + r(B) \ge |J'| + |J_B| = |J_{\cup} - (|J_B| - |J_{\cap}|) + |J_B| = |J_{\cup}| + |J_{\cap}| = r(A \cup B) + r(A \cap B)$$

#### **Definition 24**

Let  $f: 2^S \mapsto \mathbb{R}_+$  be submodular, then

$$\left\{x \in \mathbb{R}^S : \substack{x(A) \leqslant f(A) \\ x \geqslant 0}, \forall A \subseteq S\right\}$$

is called a Polymatroid.

Note: May assume  $f(\emptyset) = 0$ , f is monotone (i.e.  $X \subseteq Y \subseteq S \iff f(X) \leqslant f(Y)$ ). Consider (where f monotone and  $f(\emptyset) = 0$ )

$$\max_{C} c^{T} x$$

$$(P_f) \quad s.t. \ x(A) \leqslant f(A), \forall A \subseteq S$$

$$x \geqslant 0$$

$$\min \sum_{A \subseteq S} f(A)y_A$$

$$(D_f) \quad s.t. \sum_{A:e \in A} y_A \geqslant c_e, \forall e \in S$$

$$y \geqslant 0$$

# **Primal Greedy**

$$S = \{e_1, \dots, e_n\}, c_{e_1} \geqslant \dots \geqslant c_{e_k} \geqslant 0 \geqslant c_{e_{k+1}} \geqslant \dots \geqslant c_{e_n}, S_j = \{e_1, \dots, e_j\}$$
 and

$$x_{e_j} = \begin{cases} f(S_j) - f(S_{j-1}), & \forall j = 1, \dots, k \\ 0, & \forall j > k \end{cases}$$

If  $f(S_j) = r(S_j)$ , for M = (S, I) matroid. Let G be a greedy solution,  $G_j := G \cap S_j$ . If  $G_{j-1}$  is a basis of  $S_{j-1}$ , then when  $r(S_j) = r(S_{j-1})$ , we have  $x_{e_j} = 0$ , so  $e_j \notin G_j$ . Then  $G_j = G_{j-1}$ , so  $G_{j-1}$  is also a basis of  $S_j$ . When  $r(S_j) > r(S_{j-1})$ ,  $x_{e_j} = 1$ , so  $e_j \in G \implies G_j = G_{j-1} \cup \{e_j\} \implies G_j$  is a basis of  $S_j$ .

# **Dual Greedy**

$$y_{S_j} = c_{e_j} - c_{e_{j+1}}, \forall j = 1, \dots, k-1$$
  
 $y_{s_k} = c_{e_k}$   
 $y_A = 0$ , for all other  $A$ 

We can show that x, y above are optimal solutions by Complementary Slackness conditions.

#### **Corollary 25**

Let M = (S, I),  $c \in \mathbb{R}^S$ ,  $J \in I$ . Then J is an inclusionwise minimal, max weight independent set if and only if

(a) 
$$e \in J \implies c_e > 0$$

(b) 
$$e \notin J, J \cup \{e\} \in I \implies c_e \leqslant 0$$

(c) 
$$e \notin J, f \in J, (J \cup \{e\}) \setminus \{f\} \in I \implies c_e \leqslant c_f$$
.

Proof.

- $\Longrightarrow$  : trivial
- $\Leftarrow$ : Consider  $(P_r)$ , where r is the rank function of M which is monotone, submodular and  $r(\emptyset) = 0$ . (note J is independent, so J is feasible for  $P_r$ ). Let y be the solution from greedy. Let  $x^J$  be the characteristic vector of J. Then

$$\sum_{A: e_j \in A} y_A = c_{e_j}, \forall j \leqslant k$$

and

$$a) \implies x^J e_j = 0, \forall j > k$$

Thus for all  $j \in \{1, \dots, n\}$ , we have  $x_{e_j}^J = 0$  OR  $\sum_{A:e_j \in A} y_A = c_{e_j}$ .

Pick  $y_A > 0$ . By construction,  $A = S_j$  for  $j \le k$ . Note  $x^J(S_j) = |J \cap S_j| = |J_j|$ . Suppose  $|J_j| < r(S_j)$ , then  $J_j$  is not a basis of  $S_j$ , but it's an independent set so there exists  $e \in S_j \setminus J$  such that  $J_i \cup \{e\} \in I$ .

Case 1  $J \cup \{e\} \in I$ , then  $b \implies c_e \leq 0$ , but  $e \in S_j \implies c_e > 0$ , contradiction.

Case 2  $J \cup \{e\} \notin I$ . Extend  $J_j \cup \{e\}$  to a basis J' of  $J \cup \{e\}$ . Note J is a basis of  $J \cup \{e\}$ . Hence, |J'| = |J| by both being basis of  $J \cup \{e\}$ .

Then there exists  $f \in J \setminus S_j$  such that  $J' = (J \cup \{e\}) \setminus \{f\} \in I$ . This f exists because  $e \in J' \setminus J$ , so there is  $f \in J \setminus J'$ , and  $J_j \subseteq J \cap J'$ , so  $f \notin J_j$ , which implies  $f \notin S_j$ . Then by c),  $c_e \leqslant c_f$ .

By  $y_{S_j} = c_{e_j} - c_{e_{j+1}} > 0 \implies c_{e_j} > c_{e_{j+1}}$  and  $f \notin S_j \implies c_{e_{j+1}} \geqslant c_f \geqslant c_e$ , we have  $c_{e_j} > c_{e_{j+1}} \geqslant c_f \geqslant c_e$ , but  $e \in S_j$ , so  $c_e \leqslant c_{e_j}$ , contradiction.

Hence,  $x^J(S_j) = r(S_j)$ .

Hence, Complementary Slackness conditions hold, so  $x^J$  is optimal for  $(P_r)$  which implies J is a maximal weight independent set. And a) implies the inclusionwise minimality.

# 2.6 Matroid Construction

Let  $M = (S, \mathcal{I})$  be a matroid.

- 1. Deletion: Let  $B \subseteq S$ ,  $M \setminus B := (S', \mathcal{I}')$  is a matroid, where  $S' := S \setminus B$ ,  $\mathcal{I}' := \{A \subseteq S \setminus B : A \in \mathcal{I}\}.$
- 2. Truncation: Let  $k \in \mathbb{Z}_+$ , define  $\mathcal{I}' := \{A \in \mathcal{I} : |A| \leqslant k\}$ . Then  $M' = (S, \mathcal{I}')$  is a matroid.
- 3. Disjoint Union: Let  $M_i = (S_i, \mathcal{I}_i), \forall i \in \{1, \dots, k\}$  be matroids, with  $S_i \cap S_j = \emptyset, \forall i \neq j$ . Then  $M_1 \oplus \ldots \oplus M_k = (S, \mathcal{I})$ , with  $S = \bigcup_{i=1}^k S_i$ . And  $\mathcal{I} = \{A \subseteq S : A \cap S_i \in \mathcal{I}_i, \forall i = 1, \dots, k\}$  is a matroid.

Proof.

- (M1) hold
- (M2) hold
- (M3) Let B be a basis of  $A \subseteq S$ . Let  $B_i = B \cap S_i$ ,  $\forall i$ . Then  $B_i \in \mathcal{I}$ , but also, it is a basis of  $A \cap S_i$ . (otherwise, we can add  $\alpha \in A \cap S_i$  to  $B_i$ , hence to B, then B is not a basis of A). This implies  $|B| = \sum_{i=1}^k |B_i| = \sum_{i=1}^k r_i(A \cap S_i)$ , thus all basis of A have the same size.

Example: Partition Matroid: Let  $S = S_1 \dot{\cup} S_2 \dots \dot{\cup} S_k$ ,  $b_1, \dots, b_k \in \mathcal{Z}_+$ .  $M = (S, \mathcal{I})$  where  $I = \{A \subseteq S : |A \cap S_i| \leqslant b_i, \forall i = 1, \dots, k\}$ . Then  $M_i = (S_i, \mathcal{I}_i), \mathcal{I}_i = \{J \subseteq S_i : |J| \leqslant b_i\}$  is the uniform matroid. And  $M = M_1 \oplus \dots \oplus M_k$ .

4. Contraction: Let  $B \subseteq S$ , let J be a basis of B. Then  $M/B = (S', \mathcal{I}')$  where  $S' = S \setminus B$ ,  $\mathcal{I}' = \{A \subseteq S' : A \cup J \in \mathcal{I}\}.$ 

# **Proposition 26**

If M is forest matroid of G = (V, E),  $B \subseteq E$ , then M/B is a forest matroid of G/B (contraction in graph theory).

#### **Theorem 27**

M/B is a matroid independent from choice of J, and its rank fcn is  $r_{M/B}(A) = r_M(A \cup B) - r_M(B)$ .

*Proof.* (M1), (M2) clearly hold. (M3): Let  $A \subseteq S' = S \setminus B$ , let J' be an M/B basis of  $A \implies J \cup J' \in \mathcal{I}$ .

Claim.  $J \cup J'$  is an M-basis of  $A \cup B$ .

*Proof.* Suppose not, then there is  $e \in A \cup B \setminus J \cup J'$  and  $J \cup J' \cup \{e\} \in \mathcal{I}$ . If  $e \in B$ , then  $J \cup \{e\} \in \mathcal{I}$  and it's a subset of B, contradicts to J being a basis of B. If  $e \notin B$  then  $e \in A \setminus B$ , then  $(J' \cup \{e\}) \cup J \in \mathcal{I} \implies J' \cup \{e\} \in \mathcal{I}'$ , contradicts to J' being a basis of A.

By the claim,  $|J \cup J'| = r_M(A \cup B) \implies |J| + |J'| = r_M(A \cup B) \implies |J'| = r_M(A \cup B) - |J| = r_M(A \cup B) - r_M(B)$ . Thus,  $A \in \mathcal{I}'$  if and only if  $|A| = r_{M/B}(A) = r_M(A \cup B) - r_M(B)$  which doesn't depend on J.

5. Duality:  $M^* = (S, \mathcal{I}^*)$ ,  $\mathcal{I}^* = \{A \subseteq S : S \setminus A \text{ has a basis of } M\} = \{A \subseteq S : r_M(S \setminus A) = r_M(S)\}$ . Note here the basis of M means the basis of S. Example:  $M = U_n^r$ ,  $A \subseteq S = \{1, \ldots, n\}$ ,  $A \in \mathcal{I}^* \iff |A| \leqslant n - r \implies M^* = U_n^{n-r}$ .

#### **Theorem 28**

 $M^*$  is a matroid with rank function  $r^*(A) = |A| + r_M(S \setminus A) - r_M(S)$ .

*Proof.* Clearly (M1), (M2) hold. For (M3), let  $A \subseteq S$ , let  $J^*$  an  $M^*$ -basis of A. Let J be an M-basis of  $S \setminus A$ . Extend J to an M-basis J' of  $S \setminus J^*$ . By definition, we know J' is an M-basis of S.

Claim.  $A \setminus J^* \subseteq J'$ 

*Proof.* Suppose 
$$e \in (A \setminus J^*) \setminus J' \implies J' \subseteq S \setminus (J^* \cup \{e\})$$
, and since  $J'$  is an  $M$ -basis of  $S, J^* \cup \{e\} \in I^*$ , contradiction.  $\square$ 

Then

$$|J'| = |A \setminus J^*| + |J| = |A| - |J^*| + |J| \iff |J^*| = |A| - |J'| + |J| = |A| - r_M(S) + r_M(S \setminus A)$$

# 3 Matchings

# 3.1 Matchings 1

#### **Definition 29**

Given a graph G = (V, E), a subset  $M \subseteq E$  is a matching if  $|\delta(v) \cap M| \leqslant 1, \forall v \in V$ ; i.e., every vertex incident to at most one edge in M.

Given a matching M, a vertex v is called  $\underline{M}$ -covered if  $|\delta(v) \cap M| = 1$ , and it's called M-exposed otherwise.

Note: There are 2|M| M-covered vertices and |V|-2|M| M-exposed vertices.

- A matching is perfect if there are no M-exposed vertices.
- The size of the largest cardinality matching in G will be denoted as  $\nu(G)$ . ( M is a perfect matching if and only  $\nu(G) = \frac{|V(G)|}{2}$ .)
- Given G = (V, E), and a matching M, a path  $P = (v_1, \dots, v_k)$  is called  $\underline{M}$ -alternating if  $\{v_{i-1}, v_i\} \in M \iff \{v_i, v_{i+1}\} \notin M, \forall i = 2, \dots, k-1.$
- An M-alternating path is called M-augmenting if  $v_1, v_k$  are exposed.
- Given  $F_1, F_2 \subseteq E$ , the symmetric difference between  $F_1, F_2$  is defined as

$$F_1 \triangle F_2 = \{e \in E : e \text{ is in exactly one of } F_1, F_2\}$$

#### Theorem 30

Let M be a matching of G=(V,E). Then M is a max cardinality matching if and only if there does not exist an M-augmenting path.

# Proof.

• ( $\Longrightarrow$ ) Suppose there exists an M-augmenting path  $P = \{v_0, \ldots, v_k\}$ . Let  $e_i = \{v_{i-1}, v_i\}$ ,  $\forall i = 1, \ldots, k$ . Let  $M' = M \triangle E(P)$ . Note since P is M-augmenting, we know  $v_0, v_k$  are M-exposed, so  $e_1, e_k \notin M$ , so k is odd. That is  $|M'| = |(E(P) \setminus M) \cup (M \setminus E(P))| = |M| - |(E(P) \cap M)| + |(E(P) \cap M)| + 1 = |M| + 1$ . Suppose M' is not a matching. Then there are two edges in M' incident to one vertex. If both edges are in M, then M is not a matching, contradiction. Hence, at lease one of them is in  $M' \setminus M$ , call it e. Then e is in  $E(P) \setminus M$ . If we have  $v_i v_{i+1} e v_{i+2} v_{i+3}$ . Then  $v_i v_{i+1}$  and  $v_{i+2} v_{i+3}$  are not in M' by they are in both M and E(P), so  $v_{i+1}, v_{i+2}$  are not M'-exposed, contradiction. If one end of e is  $v_0(v_k)$ , then if  $v_1$  incident to another egde in e', we know  $e' \neq v_1 v_2$  by  $v_1 v_2 \in M \implies v_1 v_2 \notin M'$ , so  $e' \notin E(P)$ , so  $e' \in M$ , then  $v_1$  incidence to e' and  $v_1 v_2$  in M, contradiction. Hence,  $v_0$  is incidence to another e' in M', then  $e' \notin E(P) \implies e' \in M$ , but  $v_0$  is M-exposed, contradiction. Hence, M' is a matching, and |M'| > |M|, contradiction, so not such P exists.

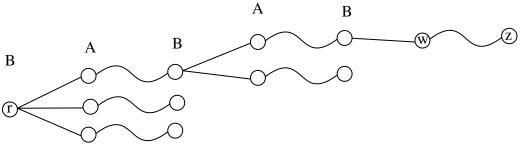
• (  $\iff$  ) Suppose M' is a matching of G with |M'| > |M|. Consider  $G' = (V, M \triangle M')$ . Note  $|\delta_{G'}(v)| \leqslant 2, \forall v \in V$ , because if  $|\delta_{G'}(v)| = 3$  for some  $v \in V$ , then there are three edges incident to it, so there are at least two edges in the same matching incident to it, contradiction. Also  $|\delta_{G'}(v)| \leqslant 2 \implies G'$  is a (edge) disjoint union of paths and cycles, and all of them are alternating (w.r.t. M and M'). Also note if C is a cycle in G',  $|E(C) \cap M| = |E(C) \cap M'|$ , otherwise C is an odd cycle and there will be a vertex incident to two edges in M or M', contradiction. Hence, there exists a path P with  $|E(P) \cap M'| > |E(P) \cap M|$ , then P is the desired M-augmenting path in G, contradiction.

- Q: Does there exist a path from a vertex u to a vertex v?
   A: Use Breadth First Search.
- Q: Does there exist an M-alternating path from an M-exposed vertex u to an M-exposed vertex v?

A: Similar, keep the path you are looking for alternating. Instead of constructing a Breadth First Search Tree, we construct an "alternating" trees. It can keep track of nodes at odd/even distance from the tree root.

# Tentative Algorithm:

Input: G = (V, E), M is a matching,  $r \in V$  is M-exposed.  $T \leftarrow (\{r\}, \emptyset)$ ,  $A(T) \leftarrow \emptyset$ ,  $B(T) \leftarrow \{r\}$ , where A represents the node at odd distance from the tree root, and B represents the node at even distance from the tree root.



In the tree, we use tilde lines to represent the edges in M and straight lines otherwise. Also, we can see that each path from the root r to a node in T is an M-alternating path in G.

Case 1: If we can find  $vw \in E$ :  $v \in B(T), w \notin V(T)$ , and w is M-covered. We can extend T using vw.

Let  $z \in V: wz \in M$ , since every vertex in T, v is either incident to another edge in M or M-exposed,  $z \notin V(T)$ . Then update  $V(T) \leftarrow V(T) \cup \{w,z\}$ ,  $B(T) \leftarrow B(T) \cup \{z\}$ ,  $A(T) \leftarrow A(T) \cup \{w\}$ ,  $E(T) \leftarrow E(T) \cup \{vw,wz\}$ .

Case 2: If we find  $vw \in E : v \in B(T), w \notin V(T)$  and w is M-exposed, then we find an M-augmenting path from r to w, which is P' = P + vw, where P is the M-alternating path from r to v in T,  $M \leftarrow M \triangle P'$ .

Hence, the tentative algorithm can be written as

# **Algorithm 5** Tentative Algorithm for Matchings

```
G = (V, E), M \text{ is a matching, } r \in V \text{ and it's } M\text{-exposed. } T \leftarrow (\{r\}, \emptyset), A(T) \leftarrow \emptyset, B(T) \leftarrow \{r\} \text{ (initialized } T \text{ with } r).
\mathbf{while} \ \exists vw \in E : v \in B(T), w \notin V(T) \ \mathbf{do}:
\mathbf{if } w \text{ is } M\text{-covered } \mathbf{then}
Use \ vw \text{ to extend } T
\mathbf{else}
Use \ vw \text{ to augment } M;
\mathbf{if } \exists \ M\text{-exposed vertex } r \in V \ \mathbf{then}
Initialize \ T \text{ with } r
\mathbf{else}
Stop
\mathbf{end if}
\mathbf{end if}
\mathbf{end while}
\mathbf{return } M
```

This does not always work (e.g. G is not connected).

# 3.2 Matching 2

### **Definition 31**

A graph is <u>bipartite</u> if there exists a partition (A, B) of V such that  $\forall e \in E, |e \cap A| = |e \cap B| = 1$ .

# Theorem 32: Hall's Theorem

Let G=(V,E) be bipartite, with bipartition  $V=A\dot{\cup}B$ . Then there exists a matching covering A if and only if  $|N(X)|\geqslant |X|, \forall X\subseteq A$ , where  $N(X):=\{v\in V\setminus X:\exists u\in X \text{ with } \{u,v\}\in E\}$ .

Proof.

- ( $\Longrightarrow$ ) If there exists  $X \subseteq A: |X| > |N(X)|$ , then since vertices only matched to vertices in N(X), no matching can cover all vertices in X (there is a vertex in X having no neighbors).
- (  $\iff$  ) By induction, cases |A|=0, |A|=1 are trivial. If  $|N(X)|-|X|>0, \forall X\subset A, X\neq\emptyset$ , pick  $uv\in E$  with  $u\in A, v\in B$ , and consider  $G'=G\setminus\{u,v\}$ , bipartite with bipartition  $A'=A\setminus\{u\}, B'=B\setminus\{v\}$ . Now,  $\forall X\subseteq A'$ ,  $|N_{G'}(X)|\geqslant |N_G(X)|-1\implies |N_{G'}(X)|-|X|\geqslant 0, \forall X\subseteq A'$ . By induction, there exist a matching M' covering A', then  $M'\cup\{u,v\}$  covers A.

If |N(X)| = |X|, for some  $X \subset A, X \neq \emptyset$ . By induction, there exist a matching  $M_1$  in  $G[X \cup N(X)]$  covering X. Now consider  $G' = G[(A \setminus X) \cup (B \setminus N(X))]$ . Note  $\forall Y \subseteq A \setminus X$ ,

$$|N_{G'}(Y)| = |N_G(Y) \setminus N_G(X)| = |N_G(X \cup Y)| - \underbrace{|X|}_{=|N_G(X)|} \geqslant |X \cup Y| - |X| = |Y|$$

Hence, there exists a matching in G' covering  $A \setminus X$ , combine it with  $M_1$ , there is a matching covering A.

#### **Corollary 33**

Let G = (V, E) be bipartite with bipartition  $V = A \dot{\cup} B$ . Then G has a perfect matching if and only if |A| = |B| and  $|X| \leq |N(X)|, \forall X \subseteq A$ .

# Algorithm 6 Algorithm for Perfect Matchings of bipartite graphs

```
G=(V,E) be bipartite, initialize T with r.

while \exists vw \in E: v \in B(T), w \notin V(T) do:

if w is M-covered then

Use vw to extend T

else

Use vw to augment M;

if \exists M-exposed vertex r \in V then

Initialize T with r

else

Stop, output perfect matching M

end if

end while

Output No Perfect Matchings exists. (*)
```

If algorithm reaches (\*), then G has no perfect matching.

*Proof.* If the algorithm reaches (\*), then

- N(B(T)) = A(T). First,  $A(T) \subseteq N(B(T))$ , and if there exist a vertex  $u \in N(B(T)) \setminus A(T)$  which is a neighbor of  $v \in B(T)$ , then  $u \notin B(T)$ , because otherwise, both u, v are at even distance from the root, and by G being bipartite, that means both u, v are in the same partition of G, and they are incident, contradiction.
- |B(T)| > |A(T)|. Suppose the tree has a leaf in A(T), then by our algorithm, if it's M-exposed, we augment M, otherwise, we extend T, so all leaves of T are in B(T). That is, for every vertex in A(T), it has a neighbor in B(T) in the tree with one larger height from the root, and since  $T \in B(T)$ , we have |B(T)| > |A(T)|.

• By what's above, we know |B(T)| > |N(B(T))|, by the Corollary above, G has no perfect matching.

**Definition 34** 

 $U\subseteq V$  is a vertex cover if  $\forall e\in E, |e\cap U|\geqslant 1$ . We let  $\tau(G)$  be the size of the smallest cardinality vertex cover. Fact:  $\nu(G)\leqslant \tau(G)$ . Otherwise, consider the max cardinality matching, you need at least |M| vertice to cover the M-covered vertices because for each edge in M, you need one of the ends in the vertex cover.

# Theorem 35: König's Theorem

Let G be bipartite, then  $\nu(G) = \tau(G)$ .

# 3.3 Matching 3

Recall  $\nu(G) \leqslant \tau(G)$  and equality holds for bipartite graph. Suppose  $A \subseteq V$ , let  $H_1, \ldots, H_k$  be odd connected components of  $G \setminus A$ .

Q: How many M-exposed vertices can there be?

If  $H_i$  has no M-exposed vertices, then there exists at least on edge in M from  $H_i$  to A (becasue there are odd number of vertices in  $H_i$ ). But there are at most |A| such edges, implies there are at least k - |A| M-exposed vertices for all matching M.

Recall: there are |V|-2|M| M-exposed vertices in any matching, which implies  $|V|-2|M| \ge k - |A|, \forall M$ . It is equivalent to  $|M| \le \frac{1}{2}(|V|-k+|A|)$ . Then, let  $k = oc(G \setminus A)$  (number of odd components of  $G \setminus A$ ),

$$\nu(G) \leqslant \frac{1}{2}(|V| - oc(G \setminus A) + |A|), \forall A \subseteq V$$

We also note that if A is a vertex cover, then  $G \setminus A$  is a graph with no edges, so  $oc(G \setminus A) = |V| - |A|$ , then the bound above becomes |A|.

### Theorem 36: Tutte-Berge Formula

Let G = (V, E) be a graph. Then

$$\max\{|M|\colon \ M \text{ is a matching}\} = \frac{1}{2}\min\{|V| - oc(G\setminus A) + |A|\colon A\subseteq V\}$$

# **Theorem 37: Tutte's Matching Theorem**

G has a perfect matching  $\iff oc(G\setminus A)\leqslant |A|, \forall A\subseteq V.$ 

*Proof.* If oc(G) > 0, then G has no perfect matching and  $A = \emptyset$  violates  $oc(G \setminus A) \leq |A|$ .

If oc(G) = 0, then

G has a perfect matching

$$\iff \nu(G) = \frac{n}{2}$$
 
$$\iff n = \min\{n - oc(G \setminus A) + |A| \colon A \subseteq V\}$$
 
$$\iff \min\{|A| - oc(G \setminus A) \colon A \subseteq V\} = 0$$

But for  $A = \emptyset$ ,  $|A| - oc(G \setminus A) = 0$ , so 0 can be obtained, that is,

$$\min\{|A| - oc(G \setminus A) : A \subseteq V\} = 0 \iff oc(G \setminus A) \leqslant |A|, \forall A \subseteq V$$

So Tutte's Matching Theorem is proved by using Tutte-Berge Formula, which is what we want to prove now. Before that, we say  $u \in V$  is essential if u is M-covered in <u>EVERY</u> maxmimum cardinality matching M; otherwise, it is inessential.

Proof. of Tutte-Berge Formula.

Goal: Show a matching M and  $A \subseteq V$  with exactly  $oc(G \setminus A) - |A|$  vertices (which is saying  $oc(G \setminus A) - |A| = |V| - 2|M|$ ). If such M, A are found, then the Tutte-Berge formula is proved. As we have shown before,  $\nu(G) \leqslant \frac{1}{2}(|V| - oc(G \setminus A) + |A|)$ ,  $\forall A \subseteq V$ , so  $\nu(G) \leqslant \frac{1}{2}\min\{|V| - oc(G \setminus A) + |A| +$ 

$$\nu(G)\geqslant |M|=\frac{1}{2}(|V|-oc(G\setminus A)+|A|)\leqslant \frac{1}{2}\min\{|V|-oc(G\setminus A)+|A|\colon A\subseteq V\}$$

so the Tutte-Berge Formula holds.

Now we do induction on m = |E|

Base: m = 0, let  $A = \emptyset$ , we are done. Now assume  $m \ge 1$  and pick  $uv \in E$ :

Case 1: v is essential. Let  $G' = G \setminus v$ , then  $\nu(G') < \nu(G)$ . By induction, there exists matching M' in G' and  $A' \subseteq V \setminus \{v\}$  with

$$|M'| = \frac{1}{2}(n - 1 - oc(G' \setminus A') + |A'|)$$

Let M be a matching of G with  $|M| = \nu(G)$ . Pick  $e \in \delta(v) \cap M$  (it exists by v being essential). Then  $\overline{M} = M \setminus e$  is a matching in G' which implies  $|\overline{M}| = |M| - 1 \leqslant |M'|$ . Now, suppose |M| - 1 < |M'|, then  $|M| \leqslant |M'|$ , then since M' is also a matching in G, we have  $|M| \geqslant |M'|$ , so |M| = |M'|, then M' is a maximum cardinality matching in G without v, so v is not essential, contradiction. Hence, |M| - 1 = |M'|. Then let  $A = A' \cup \{v\}$ , then |A| = |A'| + 1 and  $G \setminus A = G' \setminus A'$ , so

$$|M| = |M'| + 1 = \frac{1}{2}(n + 1 - oc(G' \setminus A') + |A'|) = \frac{1}{2}(n - oc(G \setminus A) + |A|)$$

we are done.

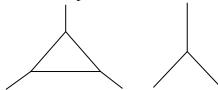
Case 2: u, v both are inessential. Later.

Let C be an odd cycle, let G' = G/C (contracting C). That is  $V'(G) = V(G) \setminus V(C) \cup \{C\}$ ;  $E(G') = \{e \in E(G) : e \cap C = \emptyset\} \cup \{vC : \exists uv \in E(G), u \in V(C), v \notin V(C)\}$ . Note from this point, we allow parallel edges. The idea is that a matching in G' can be extend to a matching in G with the same number of exposed vertices. The process is, let all edges in the matching of G' be in the matching of G, then let one vertex in G to represent the G' in G', and G' has even number of vertices left, then choose edges so they are all G'-covered.

# **Proposition 38**

Let G = (V, E), C an odd cycle, G' = G/C. Let M' a matching in G'. Then there exists a matching M of G such that the number of M-exposed vertices in G equals the number of M'-exposed vertices in G'.

Note we add  $\frac{|C|-1}{2}$  new edges to M' to get M. Therefore,  $\nu(G) \geqslant \nu(G') + \frac{c-1}{2}$ , but the equality does not necessarily hold, for example



where the left graph G has  $\nu(G)=3$ , the right one has  $\nu(G')=1$  and  $\frac{|C|-1}{2}=1$ . An odd cycle is tight if  $\nu(G)=\nu(G')+\frac{|C|-1}{2}$ .

Now back to the proof, we pick a tight cycle C containing uv and where C is inessential in G' = G/C. Then there exist M' matching of G',  $A' \subseteq V(G')$ :

$$|M'| = \frac{1}{2}(|V(G') - oc(G' \setminus A') + |A'|)$$

If  $\mathcal{C} \notin A'$ , then any component of  $G' \setminus A'$  containing  $\mathcal{C}$  will be a component of  $G \setminus A$  of same pairing after extending back (that is, if the component in G' is odd, then the component in G will also be odd because there are even number of vertices if deleting  $\mathcal{C}$ , and G has odd number of vertices, same if the component in G' is even). Hence, there are

$$oc(G' \backslash A') - |A'| = oc(G \backslash A) - |A| = |V| - |C| + 1 - 2|M'| = |V| - |C| + 1 - 2\left(|M| - \frac{|C| - 1}{2}\right) = |V| - 2|M|$$

many M-exposed vertices.

Q: But why does such C exist? What if  $C \in A'$ ?

# 3.4 Matching 4

#### Lemma 39

Let  $uv \in E$ . If u, v are inessential, then there is a tight odd cycle C containing the edge uv, such that C is inessential in G' = G/C.

*Proof.* Let  $M_u, M_v$  be maximum cardinality matchings exposing u, v respectively. (Note1:  $uv \notin M_u \cup M_v$ ; Note 2: Mu, Mv covers v, u respectively by the maximality). Then

- Degree of u, v is 1 in  $M_u \triangle M_v := F((V, F))$  is a vertex disjoint union of  $M_u, M_v$  alternating paths/cycles).
- There exists an alternating path P starting at u and the other end z is  $M_v$ -exposed. Suppose the other end is  $M_u$ -exposed, then the path P is an M-augmenting path, contradicts to the maximality of M in G. If  $z \neq v$ , then vu + P is an  $M_v$  augmenting path in G, contradiction. Hence, P is an alternating path from u to v, let C = uv + P, note C is an odd cycle because P has even length (by v = z is  $M_v$  exposed).
  - $\delta(C) \cap M_u = \emptyset$ . Since the path is alternating, the only vertex in C not incident to a  $M_u$  edge in C is u, but since u is  $M_u$ -exposed,  $\delta(u) \cap M_u = \emptyset$ .
  - $M_u \setminus C$  is a maximum cardinality matching in  $G \setminus C$ . Suppose not, then there is a larger matching M' in  $G \setminus C$ . And consider  $M' \cup \{M_u \cap E(C)\}$ , it is a matching in G because  $\delta(C) \cap M_u = \emptyset$ . And it is larger matching in G than  $M_u$  because

$$|M_u| = |M_u \cap E(G \setminus C)| + |M_u \cap E(C)| < |M'| + |M_u \cap E(C)| = |M' \cup \{M_u \cap E(C)\}|$$

contradiction. Hence, C is inessential in G'.

- Hence,  $M_u \setminus C$  is a maximum cardinality matching in G/C without including C, so C is inessential in G/C. Since there are  $\frac{|C|-1}{2}$  many  $M_u$  vertices in C, we know

$$\nu(G) = |M_u| = |M_u \setminus C| + |M_u \cap E(C)| = \nu(G/C) + \frac{|C|-1}{2}$$

so C is a tight odd cycle containing uv, as required.

### Lemma 40

Let M be a matching,  $A \subseteq V$  such that  $|M| = \frac{1}{2}(|V| - oc(G \setminus A) + |A|)$ . Then all vertices in A are essential.

*Proof.* Let  $v \in A$ . Let  $A' = A \setminus \{v\}, V' = V \setminus \{v\}, G' = G \setminus \{v\}$ . Since the components of  $G \setminus A$  are the same as the components of  $G' \setminus A'$ , we know

$$oc(G \setminus A) = oc(G' \setminus A')$$

$$\nu(G') \leqslant \frac{1}{2} (|V'| - oc(G' \setminus A') + |A'|)$$

$$= \frac{1}{2} (|V| - 1 - oc(G \setminus A) + |A| - 1)$$

$$= |M| - 1$$

so v is essential.

Then answer our question,  $C \in A'$  reaches a contradiction because C is inessential. Hence, such C exists, and  $C \notin A'$ .

# 3.5 Matching 5

We say an M-alternating tree T is <u>frustrated</u> if  $\forall uv \in E, u \in B(T)$ , we have  $v \in A(T)$ .

# Proposition 41

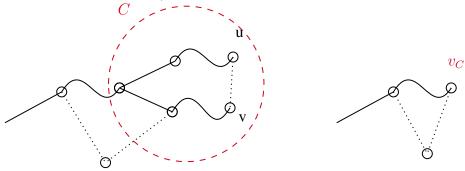
If T is frustrated, then G has no perfect matching.

*Proof.* Since all neighbors of vertices in B(T) are in A(T), we know  $G \setminus A(T)$  has at least |B(T)| many odd components, because each vertex in B(T) in  $G \setminus A(T)$  is an odd component. Hence,

$$|oc(G \setminus A(T))| \geqslant |B(T)| > |A(T)|$$

then by Tutte's Matching Theorem, we know G has no perfect matching.

Let  $u, v \in B(T)$  such that  $uv \in E$ , then T + uv has a unique odd cycle C (called Blossom). Srhink the Blossom and let G' = G/C.



Note:

- Edges in  $M \setminus E(C)$  form a matching M' in G'.
- Shrunken Tree T' is M'-alternating in G'.
- Psuedonode  $v_C$  is in the set B(T') for the tree T.

Note: One may need to shrink multiple times.

We say the graph obtained after shrinking (sequentially) Blossoms is a derived graph. S(v) will represent the set of vertices that have been shrunk into  $v \in V(G')$ , then

$$\forall v \in V(G'), S(v) = \begin{cases} v, & \text{if } v \in V(G) \\ \cup_{w \in C} S(w), & \text{if } v = v_C, \text{ for some Blossom } C \end{cases}$$

Note: |S(v)| is odd,  $\forall v \in V(G')$  by definition |S(v)| = 1 or it's a sum of odd many odd numbers.

# **Proposition 42**

Let G' be a derived graph from G, M' a matching of G', T' an M'-alternating frustrated tree of G' with all pseudonode in B(T'), then G has no perfect matching.

*Proof.* If G has a perfect matching M, then for any Blossom C, G/C also has a perfect matching  $M \setminus C$ , hence, G' will have a perfect matching, but G' has an M'-alternating frustrated tree, contradiction.

# **Proposition 43**

```
Let G' be derived graph from G, M' an matching of G', T' an M'-alternating tree, uv \in E(G') with u,v \in B(T'), C' unique cycle (Blossom) in T'+uv. Then M'' = M' \setminus E(C') is a matching for G'' = G'/C' and T'' = (V(T') \setminus V(C') \cup \{v_{C'}\}, E(T') \setminus E(C')) is an M''-alternating tree in G'' with v_{C'} \in B(T'').
```

# **Algorithm 7** Blossom Algorithm for Perfect Matching

```
Input graph G and matching M of G
Set M' = M, G' = G
Choose an M'-exposed node r of G' and put T = (\{r\}, \emptyset)
while there exists vw \in E' with v \in B(T), w \notin A(T) do
   if w \notin V(T), w is M'-exposed then
       Use vw to augment M'
       Extend M' to a matching M of G
       Replace M' by M and G' by G
       if there is no M'-exposed node in G' then
           Return the perfect matching M' and stop
       else
           Replace T by (\{r\}, \emptyset) where r is M'-exposed.
   else if w \notin V(T), w is M'-covered then
       Use vw to extend T
   else if w \in B(T) then
       Use vw to shrink and update M' and T
   end if
end while
return G', M', T and stop; G has no perfect matching.
```

#### Theorem 44

Blossom algorithm does O(n) augmentation,  $O(n^2)$  shrinks,  $O(n^2)$  tree extensions and correctly determines if G has perfect matchings.

*Proof.* Each augmentation increase |M'| by 1, implies O(n) augmentation. Between two augmentation steps, shrink reduces size of G' by at least 2 vertices implies O(n) shrinks, so total  $O(n^2)$  shirnks. Similar for tree extensions.

# Algorithm 8 Blossom Algorithm for Maximum Cardinality Matching

```
Input graph G and matching M of G
Set M' = M, G' = G, \mathcal{T} = \emptyset
(\star) Choose an M'-exposed node r of G' and put T=(\{r\},\emptyset)
while there exists vw \in E' with v \in B(T), w \notin A(T) do
    if w \notin V(T), w is M'-exposed then
        Use vw to augment M'
        Extend M' to a matching M of G
        Replace M' by M and G' by G
        if there is no M'-exposed node in G' then
            Return the perfect matching M' and stop
        else
            Replace T by (\{r\}, \emptyset) where r is M'-exposed.
    else if w \notin V(T), w is M'-covered then
        Use vw to extend T
    else if w \in B(T) then
        Use vw to shrink and update M' and T
    end if
end while
\mathcal{T} \leftarrow \mathcal{T} \cup \{T\}; G' \leftarrow G' \setminus V(T); M' \leftarrow M' \setminus E(T)
if There exists an M'-exposeed node in G' then
    go back to (\star)
else
return M = \bigcup_{T \in \mathcal{T}} M_T
end if
```

*Proof.* Let  $T_1, \ldots, T_k$  be the trees in T; M be the final matching. For each  $T_i$ , there exists only one M-exposed vertex in  $T_i$  because each  $T_i$  is an  $M_{T_i}$ -alternating tree, so the only M-exposed vertex in  $T_i$  is its root, so there are k M-exposed vertices in total. Let  $A = \bigcup_{i=1}^k A(T_i)$ . Each vertex in  $B(T_i)$  is an odd component of  $G \setminus A$  because each  $T_i$  is frustrated, all neighbors of vertices in  $B(T_i)$  are in A. Hence,

$$oc(G \setminus A) \geqslant \sum_{i=1}^{k} |B(T_i)| \geqslant \sum_{i=1}^{k} (|A(T_i)| + 1) = |A| + k$$

which implies

$$|M| = \frac{|V| - k}{2} \geqslant \frac{1}{2}(|V| - oc(G \setminus A) + |A|)$$

so M is a maximum cardinality matching.

# 3.6 Matching 6

# **Definition 45: Gallai-Edmonds Decomposition**

Let G = (V, E), B be the set of inessential vertices,  $C := \{v \in V \setminus B : v \in N_G(B)\}$ ,  $D := V \setminus (C \cup B)$ . (B, C, D) is called the Gallai-Edmonds partition/decomposition of G.

# **Proposition 46**

Let  $T_i$ , i = 1, ..., k be the frustrated trees found in Blossom algorithm. Then

$$C = \bigcup_{i=1}^{k} A(T_i), \ B = \bigcup_{i=1}^{k} (\bigcup_{v \in B(T_i)} S(v)), \ D = V \setminus (B \cup C)$$

Note.

- This implies all components of G[B] are odd and C is a minimizer of Tutte-Berge Formula.
- This also implies that Gallai-Edmonds decomposition can be computed in polytime.
- Implies G[D] only has even components. (every vertex in D is M-covered, and it's not matched to A nor B).

*Proof.* We saw all vertices in  $\bigcup_{i=1}^k A(T_i)$  are essential (by the proof of correctness of the Blossom Algorithm, we know A is the minimizer of Tutte-Berge Formula hence all vertices in it is essential). For all  $v \in \bigcup_{i=1}^k \left( \bigcup_{v \in B(T_i)} S(v) \right)$ , there exists an even M-alternating path from an M-exposed vertex u to it. Pick such path P, and then  $M' = M \triangle E(P)$  is a matching with |M'| = |M|, and v is M'-exposed which implies that v is inessential.

• Consider  $v \in V \setminus \underbrace{\left(\bigcup_{i=1}^k A(T_i) \cup \left(\bigcup_{i=1}^k \left(\bigcup_{v \in B(T_i)} S(v)\right)\right)\right)}_{D'}$ , and consider  $G' = G \setminus v$ . Since

D' only has even components, we know  $oc(G' \setminus C) = oc(G \setminus C \setminus v) > oc(G \setminus C)$ , not D is not connected to B, so we removing v will not increas the number of components in B, but only D. Hence

$$\nu(G') \leqslant \frac{1}{2} \left( |V| - 1 - oc(G' \setminus C) + |C| \right) < \frac{1}{2} \left( |V| - oc(G \setminus C) + |C| \right) = \nu(G)$$

• Hence, v is essential.

Note.

- $v \in D'$  is not adjacent to a vertex in B, otherwise, if v is M-covered, we can extend M, if it's M-exposed, we can augment M.
- $v \in C$  is adjacent to a vertex in B by the definition of the alternating trees.

# 4 Weighted Matching

# 4.1 Weighted Matching 1

Minimum Weight Perfect Matching

Given G = (V, E),  $c_e \in \mathbb{R}$ ,  $\forall e \in E$ , find a perfect matching M of G minimizing  $c(M) = \sum_{e \in M} c_e$ . Idea:

$$\min \sum_{e \in E} c_e x_e$$

$$s.t. \quad x(\delta(v)) = 1, \forall v \in V$$

$$x \ge 0, x \in \mathbb{Z}^E$$

and we can have the relaxation as

$$(P_M): min \sum_{e \in E} c_e x_e$$
  
s.t.  $x(\delta(v)) = 1, \forall v \in V,$   
 $x \ge 0$ 

$$(D_M): max \sum_{v \in V} y_v$$
 s.t.  $y_u + y_v \leqslant c_{uv}, \forall uv \in E$ 

Note:  $Z_{P_M}$  := optimal value of  $(P_M)$ , so  $Z_{P_M} \leq c(M)$ ,  $\forall$  perfect matching M. (Notice that every perfect matching's indicator vector is a feasible solution for  $P_M$ ). Q: Can we solve our problem by solving  $(P_M)$ ?



Every perfect matching has at least one edge with cost 1. However, the optimal value of  $P_M$  is 0 because we can give 0.5 to those edges of the triangles.

#### Theorem 47: Birkhoff

Let G=(V,E) be bipartite,  $c\in\mathbb{R}^E$ , then G has a perfect matching if and only if  $(P_M)$  is feasible. Moreover, if  $(P_M)$  is feasible, then let  $M^*$  be a minimum cost perfect matching, then we have  $Z_{P_M}=c(M^*)$ .

Proof.

G has a perfect matching 
$$\iff P_M$$
 is feasible (SKIPPED)

Remaining statement: Algorithmic Proof.

Construct a matching H that corresponds to a optimal solution to  $(P_M)$  using Complementary Slackness:

- Let  $\overline{y}$  be feasible for  $(D_M)$ .
- Let  $E^{=}:=\{uv\in E: \overline{y}_u+\overline{y}_v=c_{uv}\}$
- If  $G^{=} := (V, E^{=})$  has a perfect matching M, then  $x^{M}, \overline{y}$  satisfy Complementary Slackness conditions, so we are done, we know M is a minimum weighted perfect matching.
- Else, update  $\overline{y}$ .

But how should we update  $\overline{y}$ ?

Recall at the end of the algorithm for perfect matching on  $G^{=}$ , we will be in one of the two situations

- a) Found a perfect matching M, and it's the min weighted perfect matching in G.
- b) It finds a frustrated tree in  $G^{=}$ .

<u>Idea:</u> Update  $\overline{y}'_v s$  to get  $E^=_{new}$  such that

- $\overline{y}$  is still feasible for  $(D_M)$ .
- Current  $M \subseteq E_{new}^=$ .
- Current  $E(T) \subseteq E_{new}^=$ .
- At least one edge  $uv \in E \setminus E_{old}^{=} : u \in B(T), v \in V(T)$  is in  $E_{new}^{=}$ .

$$\text{Let } \epsilon = \min\{c_{uv} - \overline{y}_u - \overline{y}_v : u \in B(T), v \notin V(T)\}, \text{ and let } \overline{y}_u^* = \begin{cases} \overline{y}_u + \epsilon, & \forall u \in B(T) \\ \overline{y}_u - \epsilon, & \forall u \in A(T) \\ \overline{y}_i, & \forall u \notin V(T) \end{cases}$$

•  $\overline{y}^*$  is still feasible for  $(P_M)$ . Since the graph is bipartite, no  $uv \in E$  such that  $u,v \in B(T)$ . If  $u \in B(T), v \in A(T)$ , then  $\overline{y}_u^* + \overline{y}_v^* = \overline{y}_u + \overline{y}_v$ . If  $u \in A(T), v \notin V(T)$ , then  $\overline{y}_u^* + \overline{y}_v^* = \overline{y}_u + \overline{y}_v - \epsilon \leqslant \overline{y}_u + \overline{y}_v \leqslant c_{uv}$ . If  $u \in B(T), v \notin V(T)$ , then

$$\overline{y}_u^* + \overline{y}_v^* = \overline{y}_u + \overline{y}_v + \epsilon \leqslant \overline{y}_u + \overline{y}_v + c_{uv} - (\overline{y}_u + \overline{y}_v) = c_{uv}$$

If  $u, v \notin V(T)$ , then  $\overline{y}_u^* + \overline{y}_v^* = \overline{y}_u + \overline{y}_v$ .

•  $M \subseteq E_{new}^=$ . Consider any edge uv in E(T), then it has one end in A(T) and the other end in B(T), so we know  $\overline{y}_u^* + \overline{y}_v^* = \overline{y}_u + \overline{y}_v = c_{uv}$ , so  $uv \in E_{new}^=$ . That is,  $M \subseteq E(T) \subseteq E_{new}^=$ .

Algorithm 9 Min Weight Perfect Matching Algorithm for Bipartite Graphs

```
Let y be a feasible solution to (P_M), M a matching of G^=
If M is a perfect matching of G, return M and stop
Set T \leftarrow (\{r\}, \emptyset) where r is an M-exposed node of G
while not stopped do
    while there exists vw \in E^{=} with v \in B(T), w \notin V(T) do
        if w is M-exposed then
            Use vw to augment M
            if there is no M-exposed node in G then
                Return the perfect matching and stop
            else
                Replace T by (\{r\},\emptyset) where r is M-exposed
            end if
        else
            Use vw to extend T
        end if
    end while
    if every vw \in E with v \in B(T) has w \in A(T) then
        Stop, G has no perfect matching
    else
        Let \epsilon = \min\{c_{vw} - y_v - y_w : v \in B(T), w \notin V(T)\}
        Replace y_v by y_v + \epsilon for v \in B(T), y_v - \epsilon for v \in A(T).
   end if
end while
```

Note.

- $M \subseteq E^{=}$  all the time, so if we find a perfect matching, it will be a min weight one.
- Stopping points: either we find a perfect matching in G or we find a frustrated tree in G (not  $G^{=}$ ), so there is no perfect matching.
- The loop can only run polynomially many times because for every iteration, one more egde will be added to T, so the algorithm will terminate in polynomial time.

# 4.2 Weighted Matching Two

Rather than the  $P_M$  we used in the previous subsection, we now consider the fact that if  $S \subseteq V$  and |S| is odd and  $|S| \ge 3$ , any perfect matching must use at least one edge in  $\delta(S)$  because if we pick the pairs of two from S, there is always one left, and we let  $|S| \ge 3$  because if |S| = 1, then the

condition is necessary for having a perfect matching. Let  $\vartheta = \{S : S \subseteq V, |S| \text{ is odd and } |S| \geqslant 3\}$ . We introduce the new problem

$$(P'_{M}) \min \sum_{e \in E} c_{e} x_{e}$$
s.t. 
$$x(\delta(v)) = 1, \forall v \in V,$$

$$x(\delta(S)) \geqslant 1, \forall S \in \vartheta,$$

$$x \geqslant 0$$

$$(D'_{M}) \max \sum_{v \in V} y_{v} + \sum_{S \in \vartheta} y_{S}$$
s.t. 
$$y_{u} + y_{v} + \sum_{S \in \vartheta: uv \in \delta(S)} y_{S} \leqslant c_{uv}, \forall uv \in E,$$

$$y_{S} \geqslant 0 , \forall S \in \vartheta$$

*Note.* When needed, will use  $P'_M(G)$ ,  $D'_M(G)$  to explicitly refer to which graph is being used.

Define  $\overline{c}_{uv} = c_{uv} - \sum_{S \in \vartheta: uv \in \delta(S)} y_S - y_u - y_v$ . Complementary Slackness Conditions:

- $x(\delta(v)) = 1$  which is satisfied by any perfect matching
- $x(\delta(S)) = 1 \text{ or } y_S = 0$
- $x_{uv} = 0$  or  $\overline{c}_{uv} = 0$ .

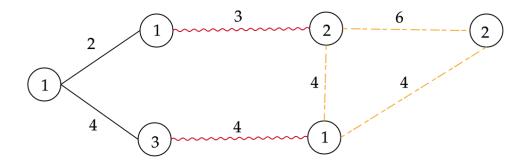
We want to construct perfect matching M with

$$\overbrace{M \subseteq E^{=} = \{e \in E : \overline{c}_{e} = 0\}}^{(*)} \text{ AND } \underbrace{|M \cap \delta(S)| = 1, \forall S \in \vartheta : y_{S} > 0}_{(**)}.$$

when needed, we use  $E^{=}(G, \overline{y})$ . Basic Algorithm Sketch

- Start with  $\overline{y}: \overline{y}_S = 0, \forall S \in \vartheta$ , feasible for  $(D_M')$ .
- If found a perfect matching M in  $G^=$ , we are done.
- Else, look at the frustrated tree T in  $G^=$  and update  $\overline{y}$  so that more vertices can be added to T.

Let's look at the example below. Assume  $y_S = 0, \forall S \in \vartheta$  and the value of  $y_v$  is given for every  $v \in V$ .



where red curved lines means the edges in M and the yellow dashed ones means the edges in E but not in  $E^{=}$ .

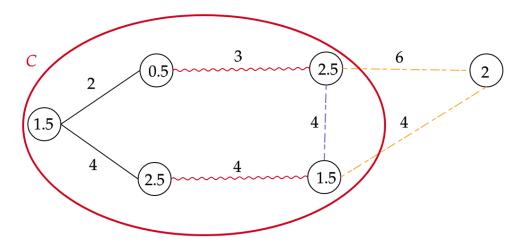
If we let  $\epsilon_1 = \min\{\overline{c}_{uv} : u \in B(T), v \notin V(T)\}$ , then we have  $\epsilon_1 = \min\{6-2-2, 4-2-1\} = 1$ . However, if we update  $\overline{y}_u$  by

$$\overline{y}_u = \begin{cases} \overline{y}_u + \epsilon_1, & \forall u \in B(T) \\ \overline{y}_u - \epsilon_1, & \forall u \in A(T) \\ \overline{y}_i, & \forall u \notin V(T) \end{cases}$$

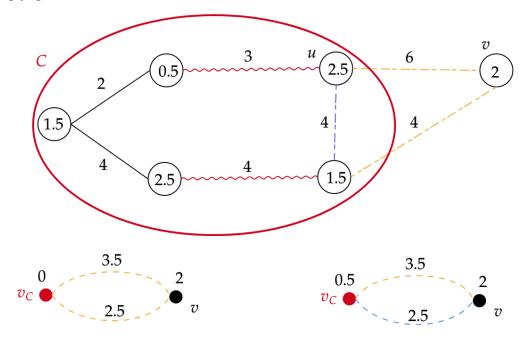
, we realized we have  $\overline{c}_{uv}=4-3-2=-1$  for the  $u,v\in B(T)\setminus r$ . So we also introduce  $\epsilon_2=\min\{\overline{c}_{uv}/2:u\in B(T),v\in B(T)\}$  and  $\epsilon=\min\{\epsilon_1,\epsilon_2\}$ . Then update

$$\overline{y}_u = \begin{cases} \overline{y}_u + \epsilon, & \forall u \in B(T) \\ \overline{y}_u - \epsilon, & \forall u \in A(T) \\ \overline{y}_i, & \forall u \notin V(T) \end{cases}$$

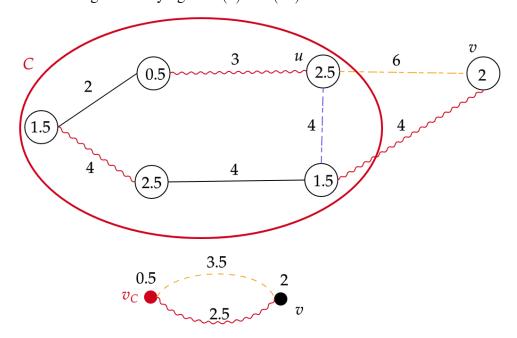
In the above example,  $\epsilon=\epsilon_2=1/2.$  Now we have



Notice the blue dashed edge means the edge is in  $E^=$ . Then, we realize that we find a blossom in  $G^=$ . If we find a perfect matching in  $G^=/C$ , then it can be extended to a perfect matching of  $G^=$  satisfying (\*\*). But how to shrink? Notice that  $\overline{c}_{uv} = c_{uv} - y_u - y_v - \sum_{S \in \vartheta: uv \in \delta(S)} y_S$ , so we can change  $y_S$  (here,  $y_C$ ). And define the parallel edges as  $c_{v_cv} = c_{uv} - y_u$ . Then adjust  $y_{v_C}$  accordingly, get



Then we find a matching M satisfying both (\*) and (\*\*).



# Shrinking a blossom C:

We say G', C' is **derived** from G, C by shrinking blossom C if G', C' are defined as:

- $V(G') = (V(G) \setminus C) \cup \{v_c\}$
- For every  $uv \in E$ ,
  - If  $u, v \notin V(C)$ , add uv to E(G'), let  $c'_{uv} = c_{uv}$ .
  - If  $u \in V(C)$ ,  $v \notin V(C)$ , add  $v \notin V(C)$ , add  $v_c v$  to E(G') with cost  $c'_{v_c v} = c_{uv} y_u$ .

### Now we have Basic Algorithm Sketch:

- Start with  $\overline{y}: \overline{y}_S = 0, \forall S \in \vartheta$ , feasible for  $(D'_M)$ .
- If found a perfect matching M in  $G^{=}$ , we are done.
- Else, look at the frustrated tree T in  $G^=$  and update  $\overline{y}$  so that more vertices can be added to T. If update allows to find blossom C, with  $E(C) \subseteq E^=$ , shrink it, set  $y_{v_c} = 0$ .

### **Proposition 48**

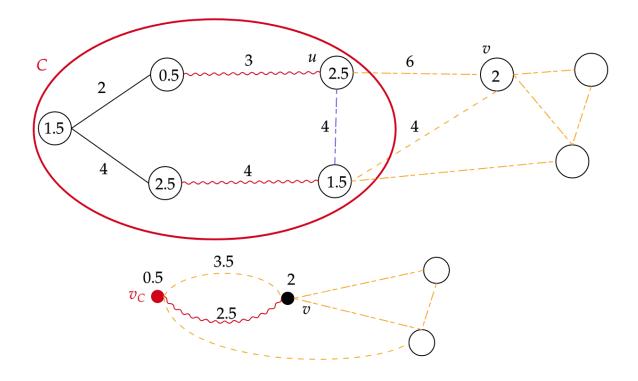
Let  $\overline{y}$  be feasible for  $D'_M(G)$ , with  $\overline{y}_S=0, \forall S\in \vartheta(G)$ . Let G',c' be derived from G,c by shrinking blossom C with  $E(C)\subseteq E^=(G,\overline{y})$ . Let M' be a perfect matching of G' and y' feasible for  $D'_M(G')$ , where M',y' satisfy (\*),(\*\*) and  $y'_{v_c}\geqslant 0$ . Then extend M' tp a perfect matching  $\hat{M}$  of G and define  $\hat{y}$  as

- $\hat{y}_v = \overline{y}_v, \forall v \in V(C)$ .
- $\hat{y}_v = y'_v, \forall v \in V(G') \setminus v_c$ .
- $\bullet \hat{y}_{S(v_c)} = y'_{v_c}$
- $\hat{y}_{S(D)} = y'_D, \forall D \in \vartheta(G')$
- $\hat{y}_S = 0$ , for every other  $S \in \vartheta$ .

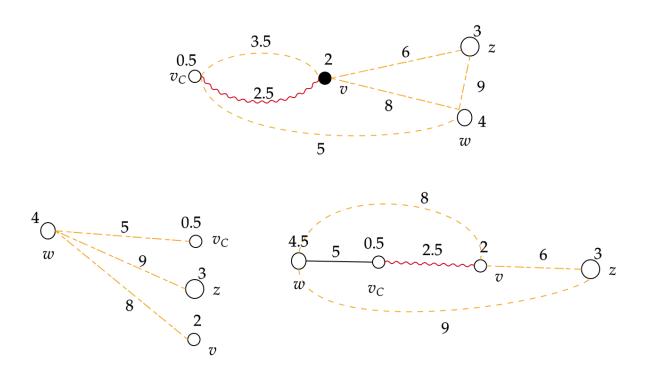
Then  $\hat{y}$  is feasible for  $D_M'(G)$  and  $\hat{M}, \hat{y}$  satisfy (\*), (\*\*).

# 4.3 Weighted Matching Three

Now, what if we don't find a perfect matching in G'?



If we start working back in G, we need to keep track of all  $y_S > 0$ , that's not good. Instead, we keep working on G'!



Note we pick w as r and change  $y_w$ . Now we have

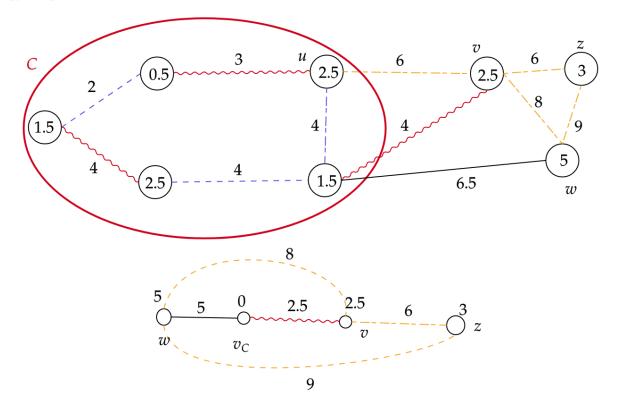
$$\epsilon_{1} = \min\{\overline{c}_{uv} : u \in B(T), v \notin V(T)\}$$

$$\epsilon_{2} = \min\{\overline{c}_{uv}/2 : u \in B(T), v \notin V(T)\}$$

$$\epsilon = \min\{\epsilon_{1}, \epsilon_{2}\}$$

$$\overline{y}_{u} = \begin{cases} \overline{y}_{u} + \epsilon, & \forall u \in B(T) \\ \overline{y}_{u} - \epsilon, & \forall u \in A(T) \\ \overline{y}_{i}, & \forall u \notin V(T) \end{cases}$$

In the example, we see that  $\epsilon_1=1$  and  $\epsilon_2=0.75$ , so  $\epsilon=0.75$ . But then if we update with  $\epsilon$ , we have  $\overline{y}_{v_c}=-0.25$ , so it's infeasible for  $D_M'$ . So we also define  $\epsilon_3=\min\{\overline{y}_u:u\in A(T) \text{ and } u \text{ is a pseudonode}\}$ . And  $\epsilon=\min\{\epsilon_1,\epsilon_2,\epsilon_3\}$ . So the new  $\epsilon=0.5$ , update  $\overline{y}$ , we are stuck, so expand the  $v_C$  back and for each edge uv with  $u\in V(C), v\notin V(C)$  replace  $c_{uv}'$  by  $c_{uv}'+\overline{y}_u$ .



Now let's consider the algorithm

## Algorithm 10 Blossom Algorithm for Minimum-Weight Perfect Matching

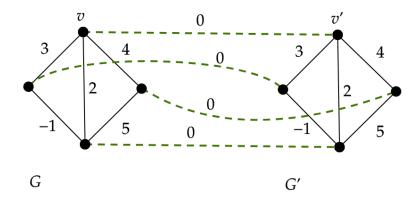
```
Let y be a feasible solution to (D'_M), M' a matching of G^=, G' = G.
If M' is a perfect matching of G, return M' and stop
Set T \leftarrow (\{r\}, \emptyset) where r is an M'-exposed node of G
while not stopped do
     while there exists vw \in E^{=} with v \in B(T), w \notin V(T) do
         if w is M'-exposed then
              Use vw to augment M
              if there is no M'-exposed node in G then
                   Return the perfect matching and stop
              else
                   Replace T by (\{r\}, \emptyset) where r is M'-exposed
              end if
         else
              Use vw to extend T
         end if
     end while
    if There exists uv \in E^= then
         Use uv to shrink and update M', T and c'
     else if every vw \in E with v \in B(T) has w \in A(T) and A(T) contains no pseudonode then
          Stop, G has no perfect matching
    else if There is a pseudonode v_c \in A(T) with y_{v_c} = 0 then
         Expand v and update M', T, and c'
     else
                 \epsilon_1 = \min\{\overline{c}_{uv} : u \in B(T), v \notin V(T)\}
                 \epsilon_2 = \min\{\bar{c}_{uv}/2 : u \in B(T), v \notin V(T)\}
                 \epsilon_3 = \min\{\overline{y}_u : u \in A(T) \text{ and } u \text{ is a pseudonode}\} \epsilon = \min\{\epsilon_1, \epsilon_2, \epsilon_3\}
               \overline{y}_u = \begin{cases} \overline{y}_u + \epsilon, & \forall u \in B(T) \\ \overline{y}_u - \epsilon, & \forall u \in A(T) \\ \overline{y}_i, & \forall u \notin V(T) \end{cases}
    end if
end while
```

Correctness can be shown by argueing each step preserves matching  $\subseteq E^=$ . Polytime: Bound number of steps while keeping same matching. Note: Shrink and unshrink may lead to infinite loop.

# 4.4 Maximum Weight Matching

Find matching M maximizing c(M). We can use max. weighted perfect matching problem. Let G = (V, E),  $c : E \mapsto \mathbb{R}$ . Let G' be a copy of G with exact same edge costs (if  $v \in V(G)$ , v' is corresponding copy). Let  $\overline{G}$  be graph with vertices  $V(G) \cup V(G')$  edges  $E(G) \cup E(G') \cup V(G')$ 

$$\{\underbrace{vv':v\in V(G)}_{c(vv')=0,\forall v\in V(G)}\}.$$



Clearly,  $\overline{G}$  has a perfect matching.

## **Proposition 49**

Let  $\overline{M}$  be a max. weighted perfect matching in  $\overline{G}$ . Then  $M=\overline{M}\cap E(G)$  is a max. weighted matching in G.

*Proof.* It is clear that M is a matching of G. Let  $M^*$  be a max weighted matching of G. Let U =set of  $M^*$ -exposed vertices in G.

- First, we can construct a perfect matching M'' in  $\overline{G}$  by copying  $M^*$  in G', and for  $v \in U$ , we include  $vv' \in M''$ , so  $c(M'') = 2c(M^*) + c(E(U,U')) = 2c(M^*) + 0$ .
- Let  $M' = \overline{M} \cap E(G')$ , we know c(M) = c(M') because if say c(M) > c(M'), then by previous point, we create a perfect matching with larger weight, contradiction.
- So  $2c(M^*)=c(M'')\leqslant c(\overline{M})=2c(M)$  implies  $c(M^*)\leqslant c(M)$ , and by definition,  $c(M)\leqslant c(M^*)$ , so  $c(M)=c(M^*)$ , we are done.

# 5 Matroid Intersection

### 5.1 Matroid Intersection One

### **Definition 50**

Let  $M_1 = (S, \mathcal{I}_1)$ ,  $M_2 = (S, \mathcal{I}_2)$  be two matroids over the same ground set S.

- Matroid Intersection Problem (unweighted):
  - Find  $A \in \mathcal{I}_1 \cap \mathcal{I}_2$  maximizing |A|.
- Matroid Intersection Problem (weighted):
  - Given  $c \in \mathbb{R}_+^S$ , find  $A \in \mathcal{I}_1 \cap \mathcal{I}_2$  maximizing the cots c(A).

#### Example 51

Let G = (V, E) be bipartite with bipartition  $V_1, V_2$ , let

$$\mathcal{I}_1 = \{ A \subseteq E : |A \cap \delta(v)| \leqslant 1, \forall v \in V_1 \}$$

$$\mathcal{I}_2 = \{ A \subseteq E : |A \cap \delta(v)| \leqslant 1, \forall v \in V_2 \}$$

In Example 13, we showed that  $(E, \mathcal{I}_1)$  and  $(E, \mathcal{I}_2)$  are both matroids. Then the problem of finding  $A \in \mathcal{I}_1 \cap \mathcal{I}_2$  maximizing |A| is the same as finding the maximum cardinality matching in G.

We first find the upper bound for the set we can find in the matroid intersection. Let  $J \in \mathcal{I}_1 \cap \mathcal{I}_2$  and let  $A \subseteq S$  be arbitrary.

**Goal:** Try to account for size of J by splitting it into an  $M_1$  component and an  $M_2$  component.

$$|J| = |\underbrace{J \cap A}_{\in \mathcal{I}_1}| + |\underbrace{J \cap \overline{A}}_{\in \mathcal{I}_2}| \leqslant r_1(A) + r_2(A)$$

where  $\overline{A}$  represents the compliment of A in S. Note  $J \cap A \in \mathcal{I}_1$  because  $J \in \mathcal{I}_1 \cap \mathcal{I}_2$ , so its subset is also in  $\mathcal{I}_1$ , same for the  $\mathcal{I}_2$  one.

#### **Theorem 52: Matroid Intersection Theorem (Edmonds 71)**

Let  $M_i = (S, \mathcal{I}_i), i = 1, 2$  be matroids, then

$$\max\{|J|: J \in \mathcal{I}_1 \cap \mathcal{I}_2\} = \min\{r_1(A) + r_2(\overline{A}): A \subseteq S\}$$

Now back to Example 51 above. Let M be an maximum cardinality matching of G. By Matroid Intersection Theorem, there exist  $A \subseteq E$  such that  $|M| = r_1(A) + r_2(\overline{A})$ . Let  $B_1$  be an  $M_1$ -basis of A,  $B_2$  be an  $M_2$  basis of  $E \setminus A = \overline{A}$ . Let  $U_i = V(B_i) \cap V_i$ , i = 1, 2.

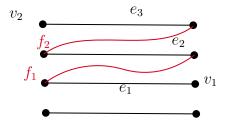
- Since  $|B_1| = r_1(A)$ , and  $B_1 \subseteq A$ , we know for every  $e \in B_1$ , it must be incident to one vertex in  $V_1$  and no two edges in  $B_1$  incident to the same vertex in  $V_1$ , that is,  $r_1(A) = |B_1| = |B_1 \cap V_1| = |U_1|$ , similarly,  $|U_2| = r_2(E \setminus A)$ .
- Consider any edge  $uv \in E$ , say  $u \in V_1, v \in V_2$ . Suppose  $u \notin U_1, v \notin U_2$ , then  $uv \notin B_1 \cup B_2$ . Notice that if  $uv \in A$ , then  $uv \notin B_1$  implies that there is an edge in  $B_1$  which is incident to u, so  $u \in B_1 \cap V_1$ , contradiction. That is,  $uv \in E \setminus A$ , similarly,  $uv \notin B_2$  implies that there is an edge in  $B_2$  incident to v, so  $v \in U_2$ , contradiction. Hence,  $U_1 \cup U_2$  is a vertex cover of G.

## Theorem 53: König's Theorem

If G is bipartite,

 $\max\{|M|: M \text{ is a matching}\} = \min\{|U|: U \text{ is a vertex cover}\}$ 

#### **5.1.1** Matroid Intersection Algorithm:



We see that J (the red curly part) is a matching, and  $P = e_1 f_1 e_2 f_2 e_3$  is an augmenting path. Note  $e_i \notin J, \forall i = 1, 2, 3$  and  $f_i \in J, \forall i = 1, 2$ .

How can I write the condition  $v_1, v_2$  are J-exposed, only based on  $M_1, M_2$ ?

$$J \cup \{e_1\} \in \mathcal{I}_1, J \cup \{e_2\} \in \mathcal{I}_2$$

because  $e_1$  is incident to  $v_1$ ,  $J \cup \{e_1\} \in \mathcal{I}_1$  implies that  $J \cup \{e_1\} \cap \delta(v_1) \leq 1$ , and if  $J \cap \delta(v_1) > 0$ , then the above inequality does not hold, same for  $v_2$ .

How can we make sure it is still a matching after symmetric difference between J and P?

- $J \cup \{e_i\} \setminus \{f_i\} \in \mathcal{I}_1$
- $J \cup \{e_{i+1}\} \setminus \{f_i\} \in \mathcal{I}_2$

Since  $e_i$ ,  $f_i$  share a vertex in  $V_1$ , then  $J \cup \{e_i\} \setminus \{f_i\} \in \mathcal{I}_1$  makes sure no two edgs sharing a vertex in  $V_1$  after symmetric difference; similar for  $e_{i+1}$ ,  $f_i$  who share a vertex in  $V_2$ .

Let  $J \in \mathcal{I}_1 \cap \mathcal{I}_2$ . Suppose I find  $P = \{e_1, f_1, \dots, e_m, f_m, e_{m+1}\}$ :

(**\***)

- $e_i \notin J, \forall i = 1, \dots, m+1$
- $f_i \in J, \forall i = 1, \dots, m$

- $J \cup \{e_1\} \in \mathcal{I}_2$
- $J \cup \{e_{m+1}\} \in \mathcal{I}_1$
- $J \cup \{e_i\} \setminus \{f_i\} \in \mathcal{I}_1, \forall i = 1, \dots, m$
- $J \cup \{e_{i+1}\} \setminus \{f_i\} \in \mathcal{I}_2, \forall 1, \dots, m+1$

(That is, P is an augmenting path with respect to P), then define  $J' = J \triangle P = J \cup \{e_1, \dots, e_{m+1}\} \setminus \{f_1, \dots, f_m\}$ .

#### Lemma 54

If P is the smallest subset of S satisfying  $(\star)$ , then  $J' \in \mathcal{I}_1 \cap \mathcal{I}_2$ .

Proof.

Claim.  $J \cup \{e_i\} \notin \mathcal{I}_1, \forall i = 1, \dots, m$ .

*Proof.* If  $J \cup \{e_i\} \in \mathcal{I}_1$ , pick  $\{e_1, f_1, \dots, e_{i-1}, f_{i-1}, e_i\}$  also satisfies  $(\star)$  and smaller than P.  $\square$ 

Let  $A = J \cup \{e_1, \dots, e_{m+1}\}$ , let  $A_i = A \setminus \{f_m, \dots, f_i\}$  (note  $A_{m+1} = A$ ,  $A_1 = J'$ ). Let  $C_i$  be the  $M_1$ -circuit in  $J \cup \{e_i\}$ ,  $\forall i = 1, \dots, m$  ( $C_i$  exists by  $J \cup \{e_i\} \notin \mathcal{I}_1$  from the claim).

Claim.  $C_i \subseteq A_{i+1}$ 

*Proof.* Otherwise, by  $C_i \subseteq J \cup \{e_i\} \subseteq A$ , we have  $C_i \not\subseteq A_{i+1}$  implies there exist  $f_k \in C_i \subseteq A$  but not in  $A_{i+1}$ , so  $f_k \in \{f_m, \ldots, f_{i+1}\}$ . So there exist k > i such that  $J \cup \{e_i\} \setminus \{f_k\} \in \mathcal{I}_1$  because  $J \cup \{e_i\}$  has a unique circuit  $C_i$  (by theorem 16), and  $f_k \in C_i$ . Then  $\{e_1, f_1, \ldots, e_i, f_k, e_{k+1}, \ldots, f_m, e_{m+1}\}$  also satisfies  $(\star)$ , we find a smaller P, contradiction.  $\square$ 

Note

$$C_i \subseteq A_{i+1} = A_i \cup \{f_i\} \implies C_i \setminus \{f_i\} \subseteq A_i$$

Since  $C_i$  is an  $M_1$ -circuit in  $J \cup \{e_i\}$ , we know  $C_i \setminus \{f_i\} \in \mathcal{I}_1$  by definition. Extend it to an  $M_1$ -basis of  $A_i$ , call it  $B_i$ . But  $B_i \cup \{f_i\} \supseteq C_i$  and  $B_i \subseteq A_i \subseteq A_{i+1} = A_i \cup \{f_i\}$ . Hence,  $B_i$  is an  $M_1$ -basis of  $A_{i+1}$  which implies that  $r_1(A_i) = r_1(A_{i+1}) \implies r_1(J') = r_1(A)$ .

Then by  $(\star)$ , we know  $J \cup \{e_{m+1}\} \in \mathcal{I}_1$ , which implies

$$r_1(A) \geqslant |J| + 1$$

because  $J \cup \{e_{m+1}\} \subseteq A$ . And |J|+1 = |J'| by definition. Hence

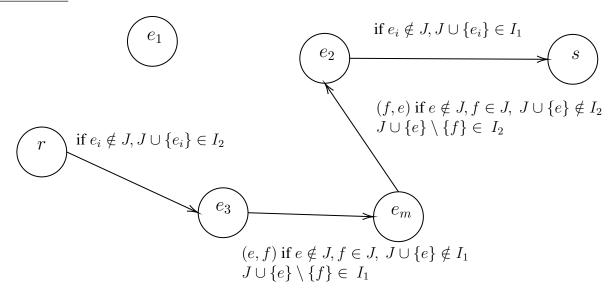
$$r_1(J') = r_1(A) \geqslant |J| + 1 = |J'| \geqslant r_1(J')$$

that is,  $|J'| = r_1(J')$ , so  $J' \in \mathcal{I}_1$ . Similarly, we can prove  $J' \in \mathcal{I}_2$ , then we are done.

## 5.2 Matroid Intersection Two

Recall that in last subsection, we consider the conditions  $(\star)$ , and we look for a P satisfying  $(\star)$ , but how to find P?

Finding  $P: S = \{e_1, \ldots, e_m\}, J \in \mathcal{I}_1 \cap \mathcal{I}_2$ .



According to the plot above, we treat each edge as a vertex, and add two more vertices r, s. If there is an edge  $e_i \notin J, J \cup \{e_i\} \in \mathcal{I}_2$ , then we add a directional edge from r to  $e_i$ . Similar for all other cases, then, if there is a directional path from r to s, by definition, the vertices on the directional path forms a P satisfying  $(\star)$  in the original graph G.

#### Lemma 55

If there does not exist P satisfying  $(\star)$ , then J is a maximum cardinality element of  $\mathcal{I}_1 \cap \mathcal{I}_2$ .

Proof. Let U be elements of S reachable from r by directional path. If  $U=\emptyset$ , then for every  $e_i\notin J,\ J\cup\{e_i\}\notin \mathcal{I}_2$ . Then suppose there is a J' with larger cardinality, consider  $e\in J'\setminus J$ . Since  $J\cup\{e\}\notin \mathcal{I}_2$ , we know there exist  $e'\in J$  such that e' and e share the same end in  $\mathcal{I}_2$ . That also implies that  $e'\notin J'$ . That is, for every  $e\in J'\setminus J$ , there exist a unique  $e'\in J\setminus J'$ , that is,  $|J|\geqslant |J'|$ , contradiction. Then by the definition of U, we know there exist an edge  $e\in U\setminus J$ . Since (e,s) is not an arc (otherwise we find P), then  $J\cup\{e\}\notin \mathcal{I}_1$ . Let C be  $M_1$ -circuit of  $J\cup\{e\}$ . Since (e,f) with  $f\in S\setminus U$  (otherwise f is reachable from f,  $f\in U$ ), we know f (otherwise, f is reachable from f,  $f\in U$ ), we know f (otherwise, f is f is reachable from f, f is no circuit, so f (otherwise) f is an f in f

$$|J| = |J \cap U| + |J \cap \overline{U}| = r_1(U) + r_2(\overline{U})$$

implies J is optimal by Matroid Intersection Theorem.

#### A few notes:

- The lemma above leads to poyltime algorithm or solving matroid intersection (assuming checking independence can also be done in polytime).
- Weighted version also can be solved in polytime.
- Can also be solved using the LP:

$$max \quad c^T x$$
  
s.t.  $x(A) \leqslant r_1(A), \forall A \subseteq S,$   
 $x(A) \leqslant r_2(A), \forall A \subseteq S,$   
 $x \geqslant 0$ 

• Solving  $\max |A|$ :  $A \in \mathcal{I}_1 \cap \mathcal{I}_2 \cap \mathcal{I}_3$  is NP-hard (no known polynomial time algorithms for this, and most people believe there does not exist any).

## 5.2.1 Matroid Partitioning

Let  $M_i = (S, \mathcal{I}_i)$  matroids for all i = 1, ..., k. Call  $J \subseteq S$  partitionable if

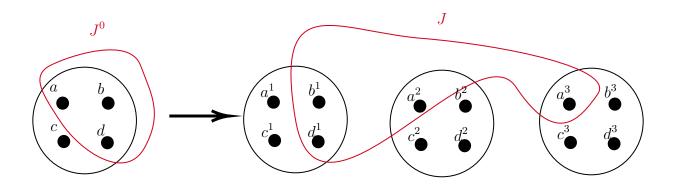
$$J = J_1 \dot{\cup} \dots \dot{\cup} J_k$$
, with  $J_i \in \mathcal{I}_i, \forall i = 1, \dots, k$ 

## Theorem 56: Matroid Partitioning; Edmonds&Fulkerson

$$\max\{|J|\colon J \text{ partitionable}\} = \min_{A\subseteq S} |\overline{A}| + \sum_{i=1}^k r_i(A)$$

*Proof.* Let  $S = \{e_1, \dots, e_n\}$ . Let  $S^i$  be a copy of S (i.e.  $S^i = \{e_1^i, \dots, e_n^i\}$ ), for every  $i = 1, \dots, k$ . For  $J \subseteq \bigcup_{i=1}^k S^i$ , let  $J^0$  be corresponding set of elements in S:

$$J^0 = \{e \in S : \exists i \in \{1, \dots, k\} \text{ such that } e^i \in J\}$$



Define  $M_i'=(S^i,\{J\subseteq S^i:J^0\in\mathcal{I}_i\})$ . Let  $N_a=M_1'\oplus\ldots\oplus M_k'$ . Let  $S'=\cup_{i=1}^kS_i,\,\mathcal{I}_b=\{A\subseteq S^i\}$  $S': A \text{ has at most one copy of } e, \forall e \in S \}, N_b = (S', \mathcal{I}_b).$ 

Suppose there exist  $J \in \mathcal{I}_a \cap \mathcal{I}_b$ . Then  $J^0$  is partitionable and  $|J^0| = |J|$ . The reason is, since  $J^0 \in \mathcal{I}_a$ , we partition  $J^0$  with respect to each  $M_i'$ ; since  $J^0 \in \mathcal{I}_b$ , for every  $e^i \in J$ ,  $e \in J^0$  and there exists at most one i such that  $e^i \in J$ , so  $|J^0| \ge |J|$ , and by definition  $|J^0| \le |J|$ , so  $|J^0| = |J|$ . Thus

$$\max\{|J|: J \in \mathcal{I}_a \cap \mathcal{I}_b\} \leq \max\{|J^0|: J^0 \text{ is partitionable}\}$$

Conversely, suppose some set K is partitionable, then we can put each partition of it into  $M'_i$ , then we create  $K' \in \mathcal{I}_a \cap \mathcal{I}_b$  such that |K'| = |K| and  $K = (K')^0$ . Thus,

$$\max\{|J|: J \in \mathcal{I}_a \cap \mathcal{I}_b\} \geqslant \max\{|J^0|: J^0 \text{ is partitionable}\}$$

Then by Matroid Intersection Theorem,

$$\max\{|J^0|: J^0 \text{ is partitionable}\} = \min_{B \subseteq S'} \{r_a(B) + r_b(S' \setminus B)\}$$

We may assume the minimizer B is in the form:  $\bigcup_{e \in B^0} \{e^1, \dots, e^k\}$ . The reason is, suppose there exists  $e^j \in B$ , and  $e^k \in S' \setminus B$ . Consider  $B' = B \setminus \{e^j\}$ . Let D be  $N_b$ -basis of  $S' \setminus B$ , and note  $D \subseteq S' \setminus B'$ . If  $D \cup \{e^j\} \in \mathcal{I}_b$ , then  $e^k \notin D$  (otherwise  $D \cup \{e^j\}$  has two copies of e), so  $D \cup \{e^k\} \in \mathcal{I}_b$ , D is not an  $N_b$ -basis of  $S' \setminus B$ , contradiction. Hence, D is an  $M_b$  basis of  $S' \setminus B'$ . So  $r_b(S' \setminus B') = r_b(S' \setminus B)$ . Moreover,  $r_a(B') \leq r_a(B)$ , so B' is also a minimizer. Then, we have  $r_a(B) = \sum_{i=1}^k r_i(B^0)$  and  $r_b(S' \setminus B) = |S \setminus B^0|$ , we are done.

Then, we have 
$$r_a(B) = \sum_{i=1}^k r_i(B^0)$$
 and  $r_b(S' \setminus B) = |S \setminus B^0|$ , we are done.

# 6 T-Join

# 6.1 T-Join One

### **Definition 57: Euler Tours**

Given a connected graph G=(V,E) (potentially having parallel edges), an <u>Euler Tour</u> is a closed walk visiting every edge (not necessary every vertex) exactly once.

#### **Theorem 58**

A connected graph G has an Euler tour if and only if every vertex has even degree.

# **Definition 59: Postman Tour**

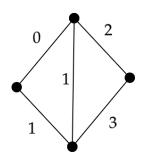
A <u>postman tour</u> is a closed walk traversing every edge at least (not necessary to be exactly) once.

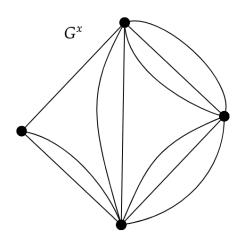
Consider the situation that  $c_e \geqslant 0, \forall e \in E$ , every time e is traversed, it incurs cost  $c_e$ .

Goal: Find minimum cost postman tour.

Note if G has an Euler tour, it is optimal.

Let  $x_e \in Z, x_e \geqslant 0, \forall e \in E$ . Let  $G^x$  be obtained by making  $1 + x_e$  copies of e (all with cost  $c_e$ ).





Idea:Find x so that  $G^x$  has Euler tour.

$$min \quad \sum_{e \in E} c_e x_e$$
s.t. 
$$\sum_{e \in \delta(v)} (1 + x_e) \equiv 0 \mod 2, \forall v \in V,$$

$$x_e \geqslant 0,$$

$$x \in Z^E$$

which is equivalent to

$$\begin{aligned} \min & & \sum_{e \in E} c_e x_e \\ \text{s.t.} & & x(\delta(v)) \equiv |\delta(v)| \mod 2, \forall v \in V, \\ & & x_e \geqslant 0, \\ & & & x \in Z^E \end{aligned}$$

*Note.* Since  $c_e \ge 0$ , we may assume  $x_e \in \{0,1\}$ ,  $\forall e \in E$ . If  $x_e \ge 2$ , let  $x'_e \leftarrow x_e - 2$ , then the cost decrease by  $2c_e$ , but the constraints are still satisfied.

So the problem becomes

$$\begin{array}{ll} \min & \sum_{e \in E} c_e x_e \\ \text{s.t.} & x(\delta(v)) \equiv |\delta(v)| \mod 2, \forall v \in V, \\ & x_e \in \{0,1\} & , \forall e \in E \end{array}$$

Want: (Postman set) Set  $J \subseteq E$  such that  $|J \cap \delta(v)| \equiv |\delta(v)| \mod 2$ .

#### **Definition 60: T-joins**

More generally, let  $T\subseteq V$  such that |T| is even.  $J\subseteq E$  is called a <u>T-join</u> if

$$|J \cap \delta(v)| \equiv |T \cap \{v\}| \mod 2, \forall v \in V$$

that is, the vertices of (V, J) with odd degree are precisely T. Also, every vertex in  $V \setminus T$  has even degree in (V, J). That is, you can say  $v \in T$  if and only if  $|J \cap \delta(v)|$  is odd.

#### **6.1.1** Min Cost T-Join

Given  $c \in \mathbb{R}^E$ , G = (V, E),  $T \subseteq V$  with |T| even, find a T-join of G minimizing c(J).

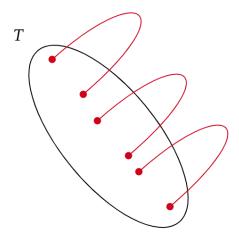
*Note.* Definition does not require connectedness or  $c \ge 0$ .

## Example 61

- Postman sets.
- $T = \emptyset \implies$  every vertex has even degree in (V, J), finding negative cost cycles.
- $T = \{r, s\}$ . Only r, s have odd degree in (V, J), so the solution will be r-s path plus cycles.

## **6.1.2** Min Cost T-Joint when $c \geqslant 0$

There is always an optimal T-join that is minimal (inclusionwise), so we can focus on minimal T-joins. But what does minimal T-joins look like?



### **Proposition 62**

J is a minimal T-join if and only if it is the union of the edges of  $\frac{|T|}{2}$  edge-disjoint paths, joining pairs of vertices in T (all distinct).

*Proof.* Let |T| = 2k,  $k \in \mathbb{Z}_+$ . Induction on k. Base case: k = 0,  $T = \emptyset$ , the only minimal T-join is  $\emptyset$ . Let |T| = 2k,  $k \in \mathbb{Z}_+$ .

- (  $\iff$  ) Trivial. First, it is clear that J is a T-join. If it is not minimal, then we know  $J' = J \setminus \{e\}$  is a T-join, but then the two ends of e are in T, contradiction.
- (⇒) Suffices to show J contains such edge set (because if there is an egde in J but not in this set, then J is not minimal since by above, the edge set is always a minimal T-join).
  Let u ∈ T, K be the connected component of (V, J) containing u. There must exists v ∈ T \ u such that v ∈ K, since only vertices in T have odd degree in (V, J). That is, if v not exists, then K only has one odd degree vertex in (V, J), then the sum of degree of K is odd, contradiction. Let P be u-v path in (V, J). Consider J' = J \ E(P). If we show J' is a

T'-join ( $T' = T \setminus \{u, v\}$ ), then by induction we are done. It is not hard to show, for every  $x \in V$ , if  $x \notin P$ , then the number of degree does not change, so  $|J' \cap \delta(v)| = |J \cap \delta(v)|$  which is still odd/even; if  $x \in P$ , then if  $x \notin \{u, v\}$  then  $|J' \cap \delta(v)| = |J \cap \delta(v)| - 2$  which is still odd; if  $x \in \{u, v\}$ , then it has even degree in (V, J'). Hence, J' is a T'-join, and it is minimal, otherwise, we can delete an edge e from J' and it is still a T'-join, then if we delete e from J, it will still be a T-join, contradiction.

### **Proposition 63**

Let J' be a T'-join of G. Then J is a T-join of G if and only if  $J \triangle J'$  is a  $(T \triangle T')$ -join of G.

Proof.

• (  $\Longrightarrow$  ) Let  $\overline{J}=J\triangle J'$ . Let  $v\in V$ . If  $v\in T,v\notin T'$  then  $v\in T\triangle T'$ . We have  $|J\cap\delta(v)|$  being odd and  $|J'\cap\delta(v)|$  being even. Then  $|J\cap\delta(v)|+|J'\cap\delta(v)|$  is odd. But  $J\triangle J'$  removes even number of those, that is

$$|\overline{J} \cap \delta(v)| = |J \cap \delta(v)| + |J' \cap \delta(v)| - 2|J \cap J' \cap \delta(v)|$$

so  $|\overline{J} \cap \delta(v)|$  is odd. Similar argument applies to other cases. Hence,

$$|\overline{J}\cap\delta(v)| \text{being odd} \iff v\in T\triangle T'$$

• ( $\iff$ ) Apply forward implication: with  $J' = J', J'' = J \triangle J'$ , and  $T' = T', T'' = T \triangle T'$ , then by the forward direction

$$(J\triangle J'\triangle J', T\triangle T'\triangle T') = (J\triangle (J'\triangle J'), T\triangle (T'\triangle T')) = (J,T)$$

implies J is a T-join.

Proposition 64

Suppose  $c \geqslant 0$ , then there exists a minimum cost T-join that is the union of |T|/2 edge-disjoint shortest paths joining vertices of T in pairs (all distinct). Here the shortest paths means the paths with least costs.

*Proof.* Let J be a minimal minimum cost T-join. Let P be a u-v path with  $E(P) \subseteq J, u, v \in T$ . Suppose P' is a u-v path with c(E(P')) < c(E(P)). Note E(P), E(P') are  $\{u, v\}$ -joins. Then  $J' = J \triangle E(P) \triangle E(P')$  is a T-join (actually a  $T \triangle \{u, v\} \triangle \{u, v\}$ -join). Then

$$c(J') = c(J \setminus E(P)) + c(E(P')) - 2c((J \setminus E(P)) \cap E(P'))$$
  
$$\leqslant c(J) - c(E(P)) + c(E(P'))$$
  
$$< c(J)$$

contradiction.

#### Can you propose an algorithm to solve min. cost T-join when $c \geqslant 0$ ?

Let d(u, v) be the cost of shortest u-v path. Construct G' with cost d(u, v) for every edge in G', a complete graph with vertex set T.

Claim. Min cost T-join when  $c \ge 0$  can be computed by computed min weight perfect matching in G' (note the weight of edge u, v is d(u, v) and G' has even vertices and complete).

Let M be a min weighted perfect matching in G'. Now let  $\{u_i, v_i\}_{i=1}^{|T|/2}$  be the edges in M. Let  $P_i$  corresponding shortest paths in G,  $\forall i=1,\ldots,\frac{|T|}{2}$ . Then  $E(P_1)\triangle\ldots\triangle E(P_{|T|/2})$  is a T-join of  $\mathrm{cost} \leqslant \sum_{i=1}^{|T|/2} d(u_i,v_i)$ . By proposition, any T-join that is minimal corresponds to a matching in G' and has cost at least  $\sum_{i=1}^{|T|/2} d(u_i,v_i)$ . Hence,  $E(P_1)\triangle\ldots\triangle E(P_2)$  is a min  $\mathrm{cost}\ T$ -join. Note that we keep use minimal T-join because by what we observe previously, when  $c \geqslant 0$ , there exists an optimal T-join that is minimal.

## **6.2** T-Joint Two

#### **6.2.1** Min-Cost T-join for arbitrary costs

Let  $N = \{e \in E : c_e < 0\}$ . Let  $T' = \{v \in V : v \text{ has odd degree in } (V, N)\}$ . Then N is a T'-join. Note by proposition 63 above, we know

$$J$$
 is a  $T$ -join  $\iff J\triangle N$  is a  $(T\triangle T')$ -join

$$c(J) = c(J \setminus N) + c(J \cap N)$$

$$= c(J \setminus N) - \underbrace{c(N \setminus J)}_{c(e) \leqslant 0, \forall e \in N \setminus J} + \underbrace{c(N \setminus J) + c(J \cap N)}_{c(N)}$$

$$= \sum_{e \in J \wedge N} |c_e| + c(N)$$

To minimize c(J), suffices to find min cost  $(T\triangle T')$ -join with respect to costs  $|c_e|\geqslant 0, \forall e\in E$  because c(N) is a constant. Algorithm:

- Find min cost  $(T\triangle T')$ -join with respect to costs  $|c_e|, \forall e \in E$  (call it  $J^*$ ).
- Output min costs T-join  $J^* \triangle N$ .

#### 6.2.2 LP formulations

#### **Definition 65**

A set  $S \subseteq V$  is T-odd if  $|S \cap T|$  is odd. If S is T-odd,  $\delta(S)$  is a T-cut.

Let  $S \subseteq V$  be T-odd; J be a T-join. If  $J \cap \delta(S) = \emptyset$ , then the subgraph of (V, J) induced by S

has an odd number of odd degree vertices (because every vertex in  $S \cap T$  has odd degree in (V, J), and every edge in J incident to v is uv for a  $u \in S$ .), contradiction. Hence,  $|J \cap \delta(S)| \ge 1$ .

(P) 
$$min \sum_{e \in E} c_e x_e$$
  
s.t.  $x(\delta(S)) \ge 1, \forall T\text{-odd set } S,$   
 $x \ge 0$ 

### Theorem 66

Let  $G=(V,E), T\subseteq V, |T|$  even,  $c\in\mathbb{R}^E,\geqslant 0$ . Then the min cost of a T-join is equal to the optimal value of (P).

*Proof.* Let  $J^*$  be an optimal T-join. We've seen that the indicator vector of  $J^*$  is feasible for (P), so  $c(J^*) \geqslant \zeta^*$  ( $\zeta^*$  is the optimal value of (P)). Let  $\vartheta$  be the set of T-odd sets. Then

(P) 
$$min \sum_{e \in E} c_e x_e$$
  
s.t.  $x(\delta(S)) \ge 1, \forall S \in \vartheta,$   
 $x \ge 0$ 

(D) 
$$\max \sum_{S \in \vartheta} \alpha_S$$
  
s.t. 
$$\sum_{S \in \vartheta: e \in \delta(S)} \alpha_S \leqslant c_e, \forall e \in E,$$
$$\alpha > 0$$

<u>Case1</u>: T = V. Let G' = (V, E') be graph used to solve min cost T-join with costs d (min costs from u to v). Then we have the min weighted perfect matching LP:

$$(P_M) \ min \quad \sum_{u,v \in E'} d(u,v) w_{uv}$$
 s.t. 
$$w(\delta(v)) = 1, \forall v \in V,$$
 
$$w(\delta(A)) \geqslant 1, \forall A \subseteq V : |A| \geqslant 3, |A| \text{ odd},$$
 
$$w \geqslant 0$$

Let  $\vartheta_M = \{A \subseteq V : |A| \geqslant 3, |A| \text{ odd}\}.$  Then

$$(D_M) \max \sum_{v \in V} \beta_v + \sum_{A \in \vartheta_M} \gamma_A$$
s.t. 
$$\beta_u + \beta_v + \sum_{A \in \vartheta_M : uv \in \delta(A)} \gamma_A \leqslant d(u, v), \forall u, v \in E',$$

$$\gamma_A \geqslant 0$$

We've shown that  $c(J^*)$  is the optimal value to  $(P_M)$  and  $(D_M)$ .

<u>Idea:</u> Note  $E \subseteq E'$ ,  $d(u,v) \leqslant c_{uv}, \forall u,v \in E$ . From optimal solution to  $(D_M)$ , build optimal solution to (D) of same cost. Then get  $\alpha$  such that  $c(\alpha) = c(J^*) \geqslant \zeta^*$ .

Gneral T: Build  $\hat{G}$  with a copy  $\hat{v}$  of v for all  $v \in V \setminus T$  and add  $v\hat{v}$  edges, with cost 0. Let  $\hat{T} = \hat{V}$  and find min cost  $\hat{T}$ -join of  $\hat{G}$ , call it  $\hat{J}$ .

Note that, since every copied vertex  $\hat{v}$  has degree one in  $\hat{G}$ , and  $\hat{v} \in \hat{T}$ , so it has degree one in  $(\hat{V},\hat{J})$ , that is,  $v\hat{v}$  is in  $\hat{J}$ . Let J be the set deleting all such  $v\hat{v}$ . It is a T-join because, for every  $v \in T$ ,  $\delta(v) \cap T = \delta(v) \cap T'$ , so it has odd degree in (V,T). for every  $v \notin T$ ,  $|\delta(v) \cap T| = |\delta(v) \cap T'| - 1$  which is even. Hence, J is a T-join.

<u>Idea:</u> From dual solution to  $\hat{G}$ , construct dual solution to G.

# 7 Flows and Cuts

#### 7.1 Flows and Cuts One

### **Definition 67**

Consider a directed graph D=(V,A) (where A represents arcs), and  $x\in\mathbb{R}^A$ . Let  $r,s\in V$ . We say x is an r-s flow if

$$x(\delta^{-}(v)) - x(\delta^{+}(v)) = 0, \forall v \in V \setminus \{r, s\}$$

where

$$\delta^{-}(S) = \{(u, v) \in A : u \notin S, v \in S\}$$
  
$$\delta^{+}(S) = \{(u, v) \in A : u \in S, v \notin S\}$$

and we call

$$f_x(v) = x(\delta^-(v)) - x(\delta^+(v))$$

the **Net flow into** v.

#### **Definition 68**

Given capacities  $l \leqslant u, l, u \in \mathbb{R}^A$  (over the arc set A), an r-s flow x is feasible if

$$l_a \leqslant x_a \leqslant u_a, \forall a \in A$$

Given a feasible r-s flow x, its value is  $f_x(s)$  (the flow entering s).

#### **Max-Flow Problem:**

Find feasible r-s flow of maximum value.

#### **Max-Flow Problem:**(integer)

Find feasible integer r-s flow of maximum value.

We will assume l=0,  $\delta^-(r)=\delta^+(s)=\emptyset$ .

#### **Definition 69**

For  $R \subseteq V$ , we call  $\delta^+(R)$  a (directed) cut. Moreover if  $r \in R, s \notin R$ , we say  $\delta^+(R)$  is an  $\underline{r}$ - $\underline{s}$  cut.

#### **Proposition 70**

If x is a feasible r-s flow and  $\delta^+(R)$  is an r-s cut, then

$$x(\delta^+(R)) - x(\delta^-(R)) = f_x(s)$$

*Proof.* x being a feasible r-s flow implies that  $f_x(v) = 0, \forall v \in V \setminus \{r, s\}$ . Proof can be done by adding  $f_x(r) = f_x(s) = 0$ .

### **Corollary 71**

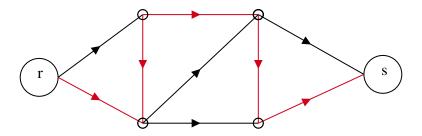
If x is a feasible r-s flow,  $\delta^+(R)$  being an r-s cut implies  $f_x(s) \leq u(\delta^+(R))$ .

Proof.

$$f_x(s) = x(\delta^+(R)) - \underbrace{x(\delta^-(R))}_{\geq 0} \leqslant x(\delta^+(R)) \leqslant u(\delta^+(R))$$

#### **Definition 72**

Suppose P is a path that uses some arcs in "forward" direction, some in "backward" direction. E.g.



We say that P is x-incrementing if

- $x_a < u_a$ , for every a appearing in forward direction.
- $x_a > 0$ , for every a appearing in backward direction.

We say P is x-augmenting if it is an x-incrementing r-s path.

*Note.* If there exists an x-augmenting path, then x is NOT a max flow, because we can

- For every forward arc, increase  $x_a$  by  $\epsilon$ .
- For every backward arc, decreas  $x_a$  by  $\epsilon$ .

Hence, we increase  $f_x(s)$  by  $\epsilon$ .

Let's say we find x and it has an x-augmenting path, and by the operations above, we get  $x^*$ . Then, for every vertex except r, s on the path, if it's incident to two forward or backward arcs, then one is in and the other is out, so net into flow is still 0; if it's incident to one forward and one backward. Either both of them are out or both of them are in arcs for the vertex, so the total net into flow still does not change, so  $x^*$  is feasible.

#### Theorem 73: Max Flow/Min Cut

If there exists a max flow, then

$$\max\{f_x(s): x \text{ is a feasible } r\text{-}s \text{ flow}\} = \min\{u(\delta^+(R)): \delta^+(R) \text{ is an } r\text{-}s \text{ cut}\}$$

*Proof.* Let x be a max-flow. Let  $R = \{v \in V : \exists \text{ an } r\text{-}v \text{ x-incrementing path}\}.$ 

Note:  $r \in R, s \notin R \implies \delta^+(R)$  is an r-s cut. (if  $s \in R$ , then there is an x-augmenting path, x is not a max flow)

Also, let  $(v, w) \in \delta^+(R)$ , then  $x_{vw} = u_{vw}$ ; otherwise  $w \in R$  because r-vw is an r-w incrementing path.

Similarly, let  $(v, w) \in \delta^-(R)$ , then  $x_{vw} = 0$ , becasue otherwise  $v \in R$ . Hence,

$$f_x(s) = x(\delta^+(R)) - \underbrace{x(\delta^-(R))}_{=0} = u(\delta^+(R))$$

and we know  $u(\delta^+(R))$  is the minimum of the RHS by Corollary 71.

*Note.* This can also be shown via LP:

max 
$$f_x(s)$$
  
s.t.  $x(\delta^-(v)) - x(\delta^+(v)) = 0$ ,  $\forall v \in V \setminus \{r, s\}$ ,  
 $0 \le x_a \le u_a$ ,  $\forall x \in A$ 

$$\begin{aligned} & \min & & \sum_{a \in A} u_a \zeta_a \\ & \text{s.t.} & & -y_v + y_w + \zeta_{vw} \geqslant 0, \quad \forall (v,w) \in A : v, w \in V \setminus \{r,s\}, \\ & & -y_r + y_w + \zeta_{rw} \geqslant 0, \quad \forall (r,w) \in A, \\ & & & -y_v + \zeta_{vs} \geqslant 1, \quad \forall (v,s) \in A, \\ & & & \zeta_{rs} \geqslant 1, \quad \text{if } (r,s) \in A, \\ & & & \zeta \geqslant 0 \end{aligned}$$

which can be written as

$$\begin{aligned} \min & & \sum_{a \in A} u_a \zeta_a \\ \text{s.t.} & & -y_v + y_w + \zeta_{vw} \geqslant 0 \quad , \quad \forall (v,w) \in A : v,w \in V \setminus \{r,s\}, \\ & & -y_r + y_w + \zeta_{rw} \geqslant 0 \quad , \quad \forall (r,w) \in A, \\ & & -y_v + y_s + \zeta_{vs} \geqslant 0 \quad , \quad \forall (v,s) \in A, \\ & & -y_r + y_s + \zeta_{rs} \geqslant 0 \quad , \quad \text{if } (r,s) \in A, \\ & & & \zeta \geqslant 0, \\ & & & y_r = 0, \\ & & & y_s = -1 \end{aligned}$$

we can simplify the dual problem as

$$min \quad \sum_{a \in A} u_a \zeta_a$$
s.t. 
$$-y_v + y_w + \zeta_{vw} \ge 0 \quad , \quad \forall (v, w) \in A,$$

$$\zeta \ge 0,$$

$$y_r = 0,$$

$$y_s = -1$$

and we can also add constants to all y because it doesn't violate the constraints nor changing the objective value, so

$$min \quad \sum_{a \in A} u_a \zeta_a$$
s.t. 
$$-y_v + y_w + \zeta_{vw} \ge 0, \quad \forall (v, w) \in A,$$

$$\zeta \ge 0,$$

$$y_r = 1,$$

$$y_s = 0$$

Then we can argue that it has optimal solution with  $y_v = 1$  if  $v \in R$ ;  $y_v = 0$  otherwise AND  $\zeta_{vw} = 1$  if  $vw \in \delta^+(R)$ ;  $\zeta_{vw} = 0$  otherwise.

#### **Theorem 74**

A feasible r-s flow x is maximum if and only if there does not exist an x-augmenting path.

#### **Theorem 75**

If  $u \in \mathbb{Z}_+^A$  and there exists a max flow, then there exists a max flow that is integral.

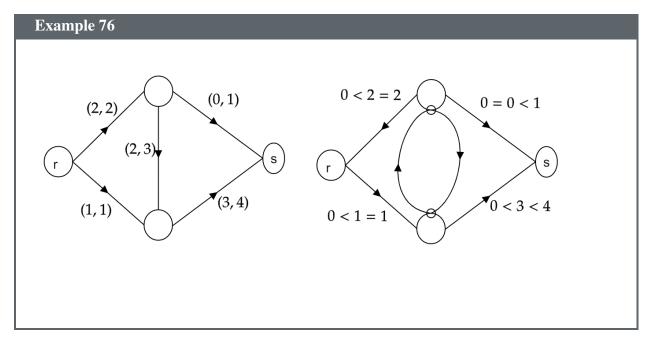
*Proof.* First, it is clear that we can find a max integral flow (that is, an integral flow which is the max among all other integral flow). Let x be a max. integral flow, and assume it is not a max flow. Then, we know there is an x-augmenting path, however, since,  $u \in \mathbb{Z}_+^A$ , we know the  $\epsilon$  we can pick to add/subtract on forward/backward arcs is also an integer, that is, x is not a maximum integral flow, contradiction.

#### 7.1.1 Ford-Fulkerson Algorithm:

<u>Idea</u>:Construct  $D_x = (V, A_x)$  where

- $vw \in A_x$  if  $vw \in A$  and  $x_{vw} < u_{vw}$
- $vw \in A_x$  if  $wv \in A$  and  $x_{wv} > 0$

that is,  $D_x$  consists of arcs that can appear in x-incrementing/x-augmenting paths.

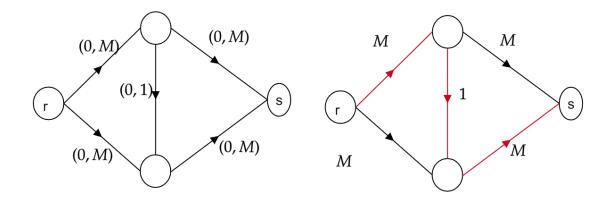


- Let  $u_{vw} x_{vw}$  be residual capacity of forward arcs vw in  $D_x$ .
- Let  $x_{vw}$  be residual capacity of backward arcs wv in  $\mathcal{D}_x$

where in  $D_x$ , if the arc has the same direction as in G, we call it forward, otherwise we call it backward.

There exists x-augmenting path in G if and only if there exists r-s directed path in  $D_x$ .

Moreover, if P is such a path,  $f_x(s)$  can be increased by smallest residual capacity in P. Also, an augmenting path can be found in O(m) time (m = |A|). But how many times do we need to do the augmenting steps to find the max flow?



If we do the augmenting above, and with some choices of the path, we may need 2M iterations to terminate.

### 7.2 Flows and Cuts Two

### Theorem 77: Dinits 70; Edmonds & Karp 72

If P is chosen to be the shortest r-s path in  $D_x$  (shortest w.r.t. the number of arcs), then there are  $\leq nm$  augmentations.

*Proof.* Let  $d_x(v, w)$  be the length of shortest v-w path in  $D_x$ . Let  $P = v_0, \ldots, v_k$  be shortest r-s path in  $D_x$  and x' be feasible r-s flow obtained after augmenting x using P.

Claim.  $\forall v \in V, d_{x'}(r, v) \geqslant d_x(r, v)$  and  $d_{x'}(v, s) \geqslant d_x(v, s)$ , note the distance might by infinity if no such path.

*Proof.* Suppose there exists  $v: d_{x'}(r, v) < d_x(r, v)$ . Choose such v with the smallest  $d_{x'}(r, v)$ . Let P' be r-v path of  $D_{x'}$  with length  $d_{x'}(r, v)$ . Let w be vertex immediately before v in P'. Then

$$d_x(r,v) > d_{x'}(r,v) = d_{x'}(r,w) + 1 \ge d_x(r,w) + 1 \dots (*)$$

 $d_{x'}(r, w) \geqslant d_x(r, w)$  otherwise we have a contradiction to the choice of v.

If  $wv \in A_x$ , then  $d_x(r, v) \le d_x(r, w) + 1$  because we can go from r to w first then v in  $D_x$ ; if v is on the shortest path from r to w, then  $d_x(r, v) \le d_x(r, w)$ ; so we reach a contradiction.

If  $wv \notin A_x$ ,  $wv \in A_{x'}$  implies that the residual of wv or vw in G is changed which implies wv or vw is an arc in P. But  $E(P) \subseteq A_x \implies vw \in E(P)$  which implies  $v = v_{i-1}, w = v_i$  for some i = 1, ..., k. Then combine with (\*), we have

$$d_x(r, v_{i-1}) \geqslant d_x(r, v_i) + 1$$

since P is the shortest path from r to s in  $D_x$ , if the above is true, we can go to  $v_i$  first and avoid  $v_{i-1}$  in P, contradiction.

This claim shows that the algorithm works in at most n-1 stages (in each stage  $d_x(r,s)$  remains constant).

Claim. If  $d_{x'}(r,s) = d_x(r,s)$ , then  $\tilde{A}_{x'} \subsetneq \tilde{A}_x$ ,

where  $\tilde{A}_x := \{vw \in A : \text{ either } vw \text{ or } wv \text{ are in a shortest } x\text{-augmenting path}\}.$ 

*Proof.* Let  $k = d_x(r, s), vw \in \tilde{A}_{x'}$ . If vw in shortest r-s path  $D_{x'}$ , then there exists i:

$$d_{x'}(r,v) = i - 1, d_{x'}(w,s) = k - i \implies d_{x'}(r,v) + d_{x'}(w,s) = k - 1$$

By previous claim,

$$d_x(r,v) + d_x(w,s) \leqslant k - 1$$

If  $vw \notin \tilde{A}_x$ , then we know it is not in the shortest x-augmenting path of  $A_x$ , so its flow doesn't change; then  $x_{vw} = x'_{vw} \implies vw \in A_x$  because  $vw \in A_{x'}$  and the flow doesn't change. But then there exists r-s path of length at most k (the path r - v - w - s), so  $vw \in \tilde{A}_x$ . Similar in the case wv is in shortest r-s path in  $D_{x'}$ . Hence  $\tilde{A}_{x'} \subseteq \tilde{A}_x$ .

Now let P be the path used to change x to x'. There exists  $vw \in A$ :

•  $vw \in P$  and  $x'_{vw} = u_{vw}$  or

•  $wv \in P$  and  $x'_{vw} = 0$ 

For the first case,  $d_x(r,v)=i-1$ ,  $d_x(w,s)=k-i$ ,  $vw\in \tilde{A}_x$  and  $vw\notin D_{x'}$  because  $x'_{vw}=u_{vw}$ . An x'-augmenting path cannot use vw implies that if  $vw\in \tilde{A}_x$ , then there exists an x'-augmenting path using wv. But  $d_{x'}(r,w)+d_{x'}(v,s)\geqslant d_x(r,w)+d_x(v,s)=(i-1+1)+(k-i+1)=k+1$  by previous claim, so any x'-augmenting path using wv has length at least k+2, so  $vw\notin \tilde{A}_{x'}$ . Similar for the other case. Hence,  $\tilde{A}_{x'}\subsetneq \tilde{A}_x$ .

The first claim shows algorithm works in at most n-1 stages and the second one shows each stage has at most m iterations.

### 7.2.1 Applications

- Bipartite matching/König's Theorem
- Assignment problems
- Flow feasibility

• . . .

For the bipartite matching/König's Theorem, we add r and s to the graph, let (A, B) be the bipartition. Add arcs (r, v) for every  $v \in A$  with capacity 1; add arcs (v, s) for every  $s \in B$  with capacity 1; and add arcs (v, u) for every  $vu \in E(G)$ ,  $v \in A$ ,  $u \in B$  with capacity 1.

For the flow feasibility problem: let  $D=(V,A), u\in\mathbb{R}_+^A, b\in\mathbb{R}^V$  such that b(V)=0, does there exists  $x\in\mathbb{R}^A: f_x(v)=b_v, \forall v\in V$  and  $0\leqslant x_a\leqslant u_a, \forall a\in A$ ? Formally, add r,s to V, add arcs (r,v) with capacity  $-b_v$  if  $b_v<0$ , and (v,s) with capacity  $b_v$  if  $b_v>0$  and compute max flow.

Such a flow we want exists if and only if the max r-s flow is  $\sum_{v:b_v>0} b_v$  which is equivalent to

$$\iff \forall S \subseteq V, u(\delta^{+}(S \cup \{r\})) \geqslant \sum_{v:b_{v}>0} b_{v}$$

$$\iff \sum_{v \notin S:b_{v}>0} b_{v} + \sum_{v \notin S:b_{v}<0} b_{v} \leqslant u(\delta_{D}^{+}(s))$$

$$\iff \forall S \subseteq V, b(s) \leqslant u(\delta_{D}^{+}(\overline{S}))$$

where from the first line to the second, we use  $u(\delta^+(S \cup \{r\})) = \sum_{v \in S: b_v > 0} b_v = \sum_{v \notin S: b_v > 0} (-b_v) + u(\delta_D^+(S))$ ; from the second line to the last line, we use a theorem by Gale (57).

#### 7.3 Flows and Cuts Three

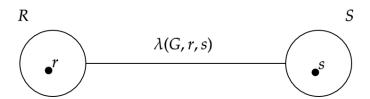
#### Undirected MinCut

Given G=(V,E) undirected,  $u\in\mathbb{R}_+^E$ , find  $S\subseteq V:\emptyset\subsetneq S\subsetneq V$  minimizing  $u(\delta(S))$ . Let  $\lambda(G)$  be the weight of min cut of G.  $\lambda(G,v,w)$  be the weight of min v-w cut (i.e.  $v\in S,w\notin S$ ).

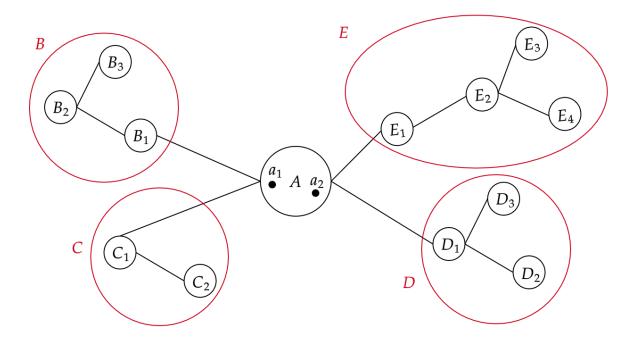
Idea: Direct graph, compute max v-w for every v, w, which takes  $O(n^2)$  max flow computations.

# 7.3.1 Gomory-Hu Trees

Pick  $r,s\in V$  arbitrary and compute min r-s cut. Let R,S be its "shores", i.e.  $\lambda(G,r,s)=u(\delta(R)),S=V\setminus R$ . Treat R and S as two vertices, we create a tree:



where let  $\lambda(G,r,s)$  be the edge label between R and S. In general, suppose our current Gomory-Hu Tree T is:

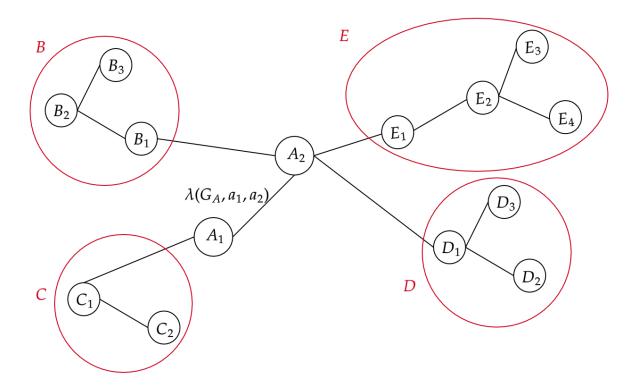


where  $|A| \ge 2$ .

• Pick  $a_1, a_2 \in A$ 

- Contract, in G, the connected component of  $T \setminus A$  and let  $G_A$  be the resulting graph.
- Compute min  $a_1$ - $a_2$  cut in  $G_A$  (say  $\delta(X)$ , and let  $A_1 = X \cap A, A_x = \overline{X} \cap A$ ).
- Split, in T, A into  $A_1$ ,  $A_2$ , edge  $A_1$ - $A_2$  has label  $\lambda(G_A, a_1, a_2)$ .

The resulting graph is



Note  $C_1$  gets connected to  $A_1$  if and only if the contracted  $v_c \in X$ . Same for  $B_1, E_1, D_1$ .

We can keep the process above until every vertex in T represents exactly one vertex in G. Let  $c, d \in V$ , how do I get min c-d cut?

- Get min cost edge  $e^*$  in  $T_{c,d}$  ( $T_{c,d}$  is the only path from c to d in a tree T).
- $\delta(X)$  is a min cost c-d cut where X is one of the component of  $T-e^*$ .

Note. We need n-1 max flow computations (to construct Gomory-Hu Tree) and a nice data structure to store all v-w cuts.

We should prove the correctness.

# Lemma 78

Let  $\delta(S)$  be a min r-s cut, and let  $v,w\in S$ . Then there exists a min v-w cut  $\delta(T)$  such that  $T\subseteq S$ .

*Proof.* Let  $\delta(X)$  be a min v-w cut and note  $S \cap X \neq \emptyset$ ,  $S \cap \overline{X} \neq \emptyset$  by  $v \in X, w \in \overline{X}$ . By replacing X with  $\overline{X}$  and switching r, s if necessary, we may assume  $s, w \in S \cap X$ .

Case  $1 r \in X$ . Then since  $s \in S \cap X$ , we know  $r \in X \cap \overline{S}$ . Since  $u(\delta(A))$  is submodular, we have

$$u(\delta(S)) + u(\delta(\overline{X})) \geqslant u(\delta(S \cap \overline{X})) + u(\delta(S \cup \overline{X}))$$

*Note.*  $u(\delta(A))$  is submodular because,

$$u(\delta(A \cap B)) + u(\delta(A \cup B))$$

$$=u(E(A \cap B, \overline{A \cup B})) + u(E(A \cap B, A \cup B))$$

$$+ u(\delta(A)) - u(E(A, B \setminus A)) + u(\delta(B)) - u(E(B, A \setminus B)) - u(E(A \cap B, \overline{A \cup B}))$$

$$=u(E(A \cap B, B \setminus A)) + u(E(A \cap B, A \setminus B))$$

$$+ u(\delta(A)) - u(E(A, B \setminus A)) + u(\delta(B)) - u(E(B, A \setminus B))$$

$$\leq u(\delta(A)) + u(\delta(B))$$

Notice that  $s \in S \cup \overline{X}$ , so it is a r-s cut. so

$$u(\delta(S)) + u(\delta(\overline{X})) \geqslant u(\delta(S \cap \overline{X})) + u(\delta(S \cup \overline{X})) \geqslant u(\delta(S \cap \overline{X})) + u(\delta(S))$$

implies that  $\delta(S \cap \overline{X})$  is a min v-w cut with  $S \cap \overline{X} \subseteq S$ .

Case2  $r \notin X$ , analogous.

#### Lemma 79

Let  $G=(V,E), u\in\mathbb{R}_+^E, s,t\in V, B\subseteq V$ :  $s,t\notin B$ . If there exists a min s-t cut  $\delta(X)$  with  $X\cap B=\emptyset$ , then

$$\lambda(G,s,t) = \lambda(G/B,s,t)$$

*Proof.* Since  $X \cap B = \emptyset$ ,  $X \subseteq V(G/B)$ .  $\lambda(G, s, t) = u(\delta_G(X)) = u(\delta_{G/B}(X)) \geqslant \lambda(G/B, s, t)$ . But let  $Y \subseteq V(G/B)$  define a min s-t cut in G/B with  $v_B \notin Y$  (if  $v_B \in Y$ , pick  $\overline{Y}$ ). Then we know Y is an s-t cut in G. So

$$\lambda(G/B, s, t) = u(\delta_{G/B}(Y)) = u(\delta_G(Y)) \geqslant \lambda(G, s, t)$$

where  $u(\delta_{G/B}(Y)) = u(\delta_G(Y))$  by  $v_B \notin Y$ . Hence,  $\lambda(G, s, t) = \lambda(G/B, s, t)$ .

#### **Definition 80**

Suppose T is a Gomory-Hu Tree at any point during the algorithm. Let  $f_e$  be its labels for every  $e \in E(T)$ . Let RS be an edge in T. We say RS has a representative if

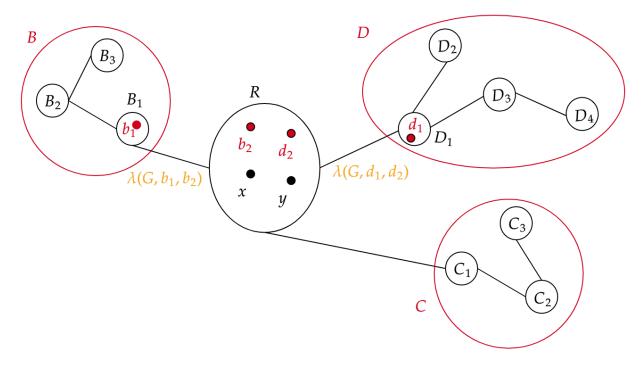
- There exists  $r \in R, s \in S: \lambda(G,r,s) = f_{RS}$  AND
- The connected component of  $T \setminus \{RS\}$  induce the cut of weight  $\lambda(G, r, s)$ .

#### Lemma 81

Every edge in E(T) has a representative at all times.

*Proof.* At first step (when T has only one edge), it is clear, since that is how we create the first edge. Now let  $x, y \in R$ , and X, Y defining a cut in  $G_R$  with  $Y = V(G_R) \setminus X$ ,  $x \in X, y \in Y$  and  $u(\delta_{G_R}(X)) = \lambda(G_R, x, y)$ .

We want to show  $\lambda(G_R, x, y) = \lambda(G, x, y)$ , so then the two conditions are both satisfied.



Since  $B_1$ , R has a representative by our assumption, its label was  $\lambda(G, b_1, b_2) = \lambda(G, b_1, b_2)$ . Then apply Lemma 79 with  $S = \overline{B}$  (where  $\overline{B}$  is a min  $b_1$ - $b_2$  cut). There exists min x-y cut  $\delta_G(U)$  with  $U \subseteq \overline{B}$ . Then by Lemma 81, we have  $\lambda(G, x, y) = \lambda(G/B, x, y)$ .

Since  $D_1$ , R has a representative, its label was  $\lambda(G,d_1,d_2)$  and  $u(\delta_G(D))=\lambda(G,d_1,d_2)$ . Applying Lemma 81, we get  $\lambda(G,d_1,d_2)=\lambda(G/B,d_1,d_2)$  because  $D\cap B=\emptyset$ , so  $D\subseteq \overline{B}$ . Hence,  $\delta_{G/B}(D)$  is still a min  $d_1$ - $d_2$  cut in G/B. Then apply Lemma 79 to get a min x-y cut in G/B, say  $\delta_{G/B}(W)$  with  $W\subseteq \overline{D}$ . Apply Lemma 81 to get

$$\lambda(G,x,y) = \lambda(G/B,x,y) = \lambda((G/B)/D,x,y)$$

Repeat the argument, we get

$$\lambda(G, x, y) = \lambda(G_R, x, y)$$

Let  $X' = X \cap R$ ,  $Y' = Y \cap R$ , then we know X', Y' has a representative.

Also, we can easily show that the edges where vertex sets did not change (like  $C_2, C_3$ ) still has a representative, because actually nothing changes for them.

Now, let's say the label of edge  $B_1$ , R is  $\lambda(G, b, g)$  for a  $b \in B$  and  $g \in R$ . Now, if  $g \in X'$ , then by definition, the edge  $B_1$ , X' still has a representative. But what if  $g \in Y'$ ?

Claim. If  $g \in Y'$ ,  $\lambda(G, b, g) = \lambda(G, b, x)$  (show later) which implies  $B_1, X'$  has a representative.

#### Lemma 82

Let  $G = (V, E), u \in \mathbb{R}_+^E, p, q, r \in V$ . Then

$$\lambda(G, p, q) \geqslant \min\{\lambda(G, q, r), \lambda(G, p, r)\}$$

*Proof.* Let  $\delta(M)$  be the min p-q cut. If  $r \in M$ , then it's also a r-q cut; otherwise, it's a p-r cut, by the definition of  $\lambda$ , we are done.

*Note.* Lemma 82 if and only if Smallest two of  $\lambda(G, p, q), \lambda(G, q, r), \lambda(G, p, r)$  are equal. For the direction, we know the right hand side of Lemma 82 is always the smallest value of the three values, so the inequality holds. For the  $\implies$  direction, let  $\lambda(G, p, q)$  be the smallest, then one of the others must be equal to it, by Lemma 82, done.

Note

$$u(\delta_G(B)) = \lambda(G, b, g) \geqslant \lambda(G, b, x)$$

We've proven  $\lambda(G,x,y)=u(\delta_G(S))$  where  $S=B\cup X'$ . By Lemma 68, there exists a min b-x cut  $\delta_G(W)$  with  $W\subseteq S$ , which means  $W\cap Y'=\emptyset$ . Now let G'=G/Y', then Lemma 69 implies  $\lambda(G,b,x)=\lambda(G',b,x)$ . And  $g\in Y'$  implies any  $v_{Y'}\text{-}b$  cut in G' is a b-g cut in G implies  $\lambda(G',v_{Y'},b)\geqslant \lambda(G,b,g)$ . Also, any  $x\text{-}v_{Y'}$  cut in G' is an x-y cut in G so  $\lambda(G',v_{Y'},x)\geqslant \lambda(G,x,y)$ . Also, the min x-y cut in G is a b-g cut in G by  $b\in X'$ ,  $g\in Y'$  which implies  $\lambda(G,x,y)\geqslant \lambda(G,b,g)$  Then by Lemma 82, we have

$$\lambda(G, b, x) = \lambda(G', b, x) \geqslant \min\{\lambda(G', v_{Y'}, b), \lambda(G', v_{Y'}, x)\}$$
$$\geqslant \min\{\lambda(G, b, g), \lambda(G, x, y)\} = \lambda(G, b, g) \geqslant \lambda(G, b, x)$$

We prove the claim above, hence, we prove the lemma 81.

#### **Theorem 83**

Let T be final Gomory-Hu tree. Then for every  $r, s \in V$ ,  $\lambda(G, r, s)$  is equal to the smallest label of an edge in  $T_{r,s}$ . Also if  $e^*$  is such an edge, then  $\lambda(G, r, s) = u(\delta(H))$ , where H is one of the connected component of  $T \setminus e^*$ .

*Proof.* Let  $T_{r,s} = v_0, e_1, v_1, e_2, \dots, e_k, v_k$ , and let  $f_e$  be labels of edges in T. By previous result,  $\lambda(G, v_{i-1}, v_i) = f_{e_i}, \forall i = 1, \dots, k$ . Show

•  $\lambda(G, r, s) \geqslant \min_{i=1,\dots,k} \{\lambda(G, v_{i-1}, v_i)\}$ , which can be easily proved by Lemma 82

• Then we pick the  $e^*$  as described above and r is in one component of  $T\setminus e^*$  and s is in the other. Thus we find a r-s cut H where

$$\lambda(G,r,s)\leqslant u(\delta(H))=\min_{i=1,\dots,k}\{\lambda(G,v_{i-1},v_i)\}=f_{e^*}$$

Hence,  $\lambda(G, r, s) = u(\delta(H)) = f_{e^*}$  as required.