

# Lecture 3: linear programming for bipartite matching

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## Outline

- (Recap) Augmenting path algorithm with the alternating tree procedure.
- Maximum weight bipartite matching.
- Linear programming-based method.
- (If time allows) Perfect matching and Hall's marriage theorem.

## Augmenting paths

- Let  $G = (V, E)$  be a bipartite graph, and let  $M$  be a matching of  $G$ .
- We say that a vertex  $v \in V$  is  **$M$ -exposed** if  $v$  is not connected to an edge in  $M$ .
- We say that a path with a sequence of edges  $e_1, \dots, e_k$  is  **$M$ -alternating** if for every two consecutive edges  $e_i$  and  $e_{i+1}$ , either  $e_i \in M, e_{i+1} \notin M$  or  $e_i \notin M, e_{i+1} \in M$  holds.

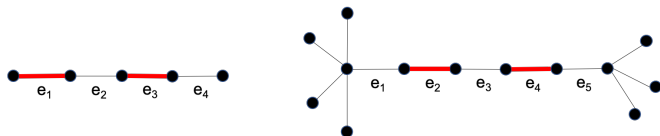


Figure: an  $M$ -alternating path and an  $M$ -augmenting path

- An  **$M$ -augmenting path** is an  $M$ -alternating path if the first and last vertices are  $M$ -exposed.

## Augmenting paths

- The key idea is that if there is an  $M$ -augmenting path, we can improve the matching.

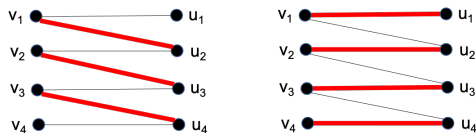


Figure: improving the matching by an augmenting path

- On the augmenting path, we switch the role of the matching edges and that of the edges not in the matching.

## Augmenting paths

- Given a matching  $M$  and an  $M$ -augmenting path  $P$ , their **symmetric difference**  $M \oplus P$  is obtained from  $M$  after augmenting the edges of  $P$ .

### Lemma

Let  $G = (V, E)$  be a graph, not necessarily bipartite. Let  $M$  be a matching, and let  $P$  be an  $M$ -augmenting path. Then  $M \oplus P$  is a matching of  $G$  with  $|M \oplus P| = |M| + 1$ .

### Theorem

Let  $G = (V, E)$  be a graph, not necessarily bipartite, and let  $M$  be a matching. Then  $M$  is a maximum matching if and only if there is no  $M$ -augmenting path in  $G$ .

## Augmenting path algorithm

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**Algorithm 1** Augmenting path algorithm for maximum bipartite matching

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Initialize  $M = \emptyset$ .

**while** there is an  $M$ -augmenting path **do**

    Find an  $M$ -augmenting path  $P$

    Update  $M$  as  $M = M \oplus P$

**end while**

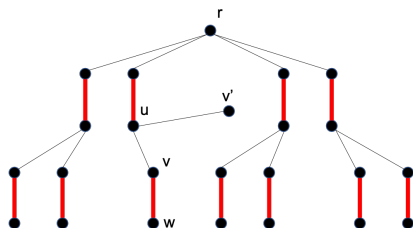
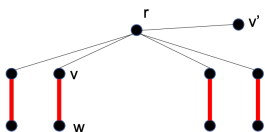
Return  $M$

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- As an augmenting path increases the matching size by 1, the algorithm finds at most  $|V|/2$  augmenting paths.

## Alternating tree procedure

- The algorithm builds a tree structure starting from an  $M$ -exposed vertex as its root.



- We call such a tree an  $M$ -alternating tree.

## Alternating tree procedure

### Theorem

Let  $G = (V, E)$  be a bipartite graph, and let  $M$  be a matching. If ?? does not return an  $M$ -augmenting path, then  $G$  contains no  $M$ -augmenting path as a subgraph.

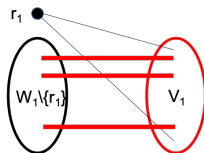


Figure: the first  $M$ -alternating tree



## Alternating tree procedure

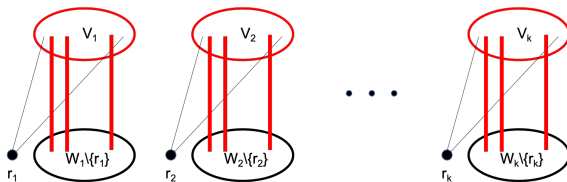


Figure: a partition of  $V$  with  $M$ -alternating trees

## Alternating tree procedure

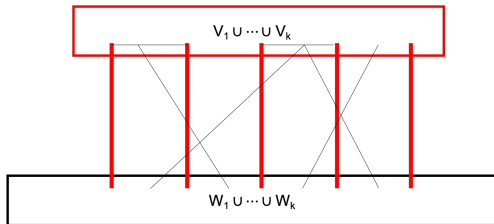


Figure: another illustration of the partition

## Maximum weight matching

- Maximum matching seeks to **maximize the number of edges** in a matching, in which individual edges are treated equally.
- Some edges can be more important than others, captured by **edge weights**.
- With the edge weights, an alternate objective is to find a matching that **maximizes the total weight sum of its edges**.

- New objective:

$$\text{maximize } \sum_{e \in M} \underbrace{w_e}_{\text{the weight of edge } e} .$$

- This is referred to as the **maximum weight bipartite matching** problem.
- One may extend the augmenting path algorithm to the weighted case, let us discuss another method that has a slightly different flavor.

# Formulating as an optimization problem

## Variables

- For each edge  $e \in E$ , use **variable**  $x_e$  to indicate whether  $e$  is picked for our matching  $M$  or not, i.e.,

$$x_e = \begin{cases} 1 & \text{if } e \text{ is included in matching } M, \\ 0 & \text{otherwise.} \end{cases}$$

- In this case,  $x \in \{0, 1\}^{|E|}$  is the **incidence vector**, or the **characteristic vector**, of matching  $M$  given by

$$M = \{e \in E : x_e = 1\}.$$

- Then we have

$$\sum_{e \in M} w_e = \sum_{e \in E} w_e x_e.$$

# Formulating as an optimization problem

## Constraints

- However, not all  $x \in \{0, 1\}^{|E|}$  corresponds to a matching.
- What we know is that a vertex  $u \in V$  is incident to at most one edge of a matching.
- We may impose the condition by setting

$$\sum_{v \in V: uv \in E} x_{uv} \leq 1 \quad (\text{degree})$$

where the sum is taken over the neighbors of  $u$ .

## Lemma

Let  $G = (V, E)$  be a graph, not necessarily bipartite, and let  $x \in \{0, 1\}^{|E|}$ . Then  $x$  satisfies (degree) for all  $u \in V$  if and only if  $x$  is the incidence vector of some matching  $M$  of  $G$ .

# Formulating as an optimization problem

## Optimization problem

- Then the following computes a maximum weight matching:

$$\begin{aligned} & \text{maximize} && \sum_{e \in E} w_e x_e \\ & \text{subject to} && \sum_{v \in V: uv \in E} x_{uv} \leq 1 \quad \text{for all } u \in V, \\ & && x_e \in \{0, 1\} \quad \text{for all } e \in E. \end{aligned} \tag{IP}$$

- This is to select a vector  $x$  that achieves the maximum value of  $\sum_{e \in E} w_e x_e$  among the vectors satisfying (**degree**) for all  $u \in V$  and  $x \in \{0, 1\}^{|E|}$ .
- For (IP), constraint (**degree**) is referred to as the **degree constraint**.
- Constraint  $x \in \{0, 1\}^{|E|}$  is called the **binary constraint**.

## Formulating as an optimization problem

$$\begin{aligned} &\text{maximize} && \sum_{e \in E} w_e x_e \\ &\text{subject to} && \sum_{v \in V: uv \in E} x_{uv} \leq 1 \quad \text{for all } u \in V, \\ &&& x_e \in \{0, 1\} \quad \text{for all } e \in E. \end{aligned} \tag{IP}$$

### Proposition

Let  $G = (V, E)$  be a graph, not necessarily bipartite, and let  $w \in \mathbb{R}^{|E|}$ . Then solving the optimization problem (IP) computes a maximum weight matching in  $G$ .

## Formulating as an optimization problem

$$\begin{aligned} & \text{maximize} && \sum_{e \in E} w_e x_e \\ & \text{subject to} && \sum_{v \in V: uv \in E} x_{uv} \leq 1 \quad \text{for all } u \in V, \\ & && x_e \in \{0, 1\} \quad \text{for all } e \in E. \end{aligned} \tag{IP}$$

- In (IP), both the **objective**  $\sum_{e \in E} w_e x_e$  and the constraint  $\sum_{v \in V: uv \in E} x_{uv}$  are **linear functions** in  $x$ .
- Here, a linear function in  $x$  is a function of the form

$$c^T x = \sum_{e \in E} c_e x_e \quad \text{for some } c \in \mathbb{R}^{|E|}.$$

- An optimization problem whose objective and constraints are given by linear functions is called a **linear program**.
- However, the binary constraint in (IP) generates discontinuity and thus cannot be represented by a linear function



## Formulating as an optimization problem

$$\begin{aligned} & \text{maximize} && \sum_{e \in E} w_e x_e \\ & \text{subject to} && \sum_{v \in V: uv \in E} x_{uv} \leq 1 \quad \text{for all } u \in V, \\ & && x_e \in \{0, 1\} \quad \text{for all } e \in E. \end{aligned} \tag{IP}$$

- However, the binary constraint in (IP) generates discontinuity and thus cannot be represented by a linear function.
- When the objective and constraints except for the binary constraint on its variables are given by linear functions, it is called a **binary linear program**.
- In general, a binary linear program is an **integer linear program** which in general can take any integer-valued variables.
- It is known that integer linear programming and binary linear programming are NP-hard.
- Linear programming admits a **polynomial time** algorithm such as the **ellipsoid method** and the **interior-point algorithm**.

## LP relaxation

- A common approach to tackle an integer linear program is to obtain its **linear programming (LP) relaxation**.
- The LP relaxation **relaxes and removes the constraints** to impose that the variables have integer values, and it becomes a linear program.
- The LP relaxation of (IP) is given by

$$\begin{aligned} & \text{maximize} && \sum_{e \in E} w_e x_e \\ & \text{subject to} && \sum_{v \in V: uv \in E} x_{uv} \leq 1 \quad \text{for all } u \in V, && \text{(LP)} \\ & && x_e \geq 0 \quad \text{for all } e \in E \end{aligned}$$

- Any  $x$  satisfying the constraints of (LP) would have  $x_e \leq 1$  for all  $e \in E$ , because  $x_e$  appears in (degree).

## LP relaxation

### Lemma

Let  $G = (V, E)$  be a graph, not necessarily bipartite, and let  $w \in \mathbb{R}^{|E|}$ . Then the optimal value of the LP relaxation (LP) is greater than or equal to the optimal value of (IP).

$$\begin{aligned} & \text{maximize} && \sum_{e \in E} w_e x_e \\ & \text{subject to} && \sum_{v \in V: uv \in E} x_{uv} \leq 1 \quad \text{for all } u \in V, \\ & && x_e \geq 0 \quad \text{for all } e \in E \end{aligned} \tag{LP}$$

- The linear program (LP) provides an upper bound on the maximum size of a matching in any graph that is not necessarily bipartite.
- However, an optimal solution  $x^*$  to (LP) can have fractional parts in  $(0, 1)$  in which case  $x^*$  does not correspond to a matching.
- **Nevertheless, we can prove that bipartite graphs do not have such an issue.**

## Exactness of the LP relaxation for bipartite graphs

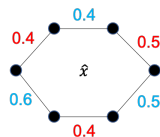
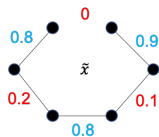
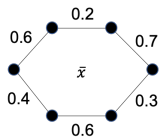
### Theorem

Let  $G = (V, E)$  be a bipartite graph, and let  $w \in \mathbb{R}^{|E|}$ . Then the LP relaxation (LP) has an optimal solution  $x^*$  that satisfies  $x_e^* \in \{0, 1\}$  for all  $e \in E$ . Moreover, one can find a maximum matching in  $G$  by solving the linear program (LP).

- Let  $\bar{x} \in [0, 1]^{|E|}$  be an optimal solution to (LP).
- Consider  $S = \{e \in E : \bar{x}_e > 0\}$  and the subgraph  $H$  of  $G$  obtained by deleting the edges that are not in  $S$ .
- $S$  may have **cycles** and **large trees**.
- We break the cycles and trees to obtain a matching.

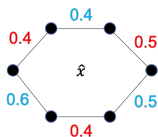
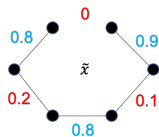
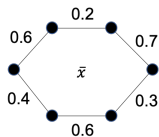
# Exactness of the LP relaxation for bipartite graphs

## Breaking cycles



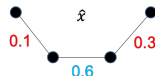
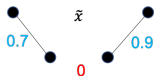
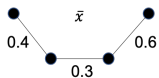
# Exactness of the LP relaxation for bipartite graphs

## Breaking cycles



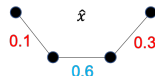
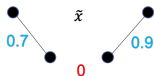
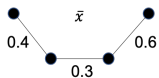
# Exactness of the LP relaxation for bipartite graphs

## Breaking trees



# Exactness of the LP relaxation for bipartite graphs

## Breaking trees





## LP-based algorithm for maximum weight bipartite matching

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**Algorithm 1** LP-based algorithm for maximum weight bipartite matching

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Solve the linear program (LP) and get an optimal solution  $\bar{x}$

Take  $S = \{e \in E : \bar{x}_e > 0\}$  and the corresponding subgraph  $H$

**while**  $H$  contains a cycle **do**

    Find a cycle  $C$  in  $H$

    Break  $C$  by updating  $\bar{x}$  and  $S$

**end while**

**while**  $H$  contains a tree with at least three vertices **do**

    Take a connected component  $T$  of  $H$

    Break  $T$  by updating  $\bar{x}$  and  $S$

**end while**

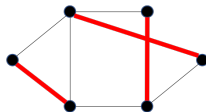
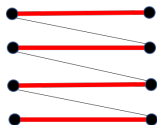
Return  $S$

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- In practice, we may use the **simplex method** for solving the LP relaxation (LP).
- For (LP), we can in fact argue that the simplex method directly finds an optimal solution  $\bar{x}$  with  $\bar{x}_e \in \{0, 1\}$  for all  $e \in E$ .

## Perfect matching

- Given a graph  $G = (V, E)$ , not necessarily bipartite, a matching  $M$  in  $G$  is **perfect** if every vertex  $v \in V$  is incident to an edge in  $M$ .
- In other words, every vertex is attached to a matching edge in a perfect matching.



## Maximum weight perfect matching

- We can compute a perfect matching by solving an optimization problem described as follows.
- As in the previous section, we use  $x_e$  to indicate whether  $e$  is picked for our matching  $M$  or not.
- To guarantee that  $M$  is a perfect matching, we impose the constraint

$$\sum_{v \in V: uv \in E} x_v = 1$$

for any vertex  $u \in V$ .

- Optimization problem:

$$\begin{aligned} & \text{maximize} && \sum_{e \in E} w_e x_e \\ & \text{subject to} && \sum_{v \in V: uv \in E} x_{uv} = 1 \quad \text{for all } u \in V, && \text{(Perfect)} \\ & && x_e \in \{0, 1\} \quad \text{for all } e \in E. \end{aligned}$$

## Maximum weight perfect matching

- A matching always exists as the empty set is trivially a matching.
- However, a perfect matching does not always exist even for a bipartite graph.

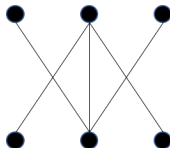


Figure: a bipartite graph that does not admit a perfect matching

## Hall's marriage theorem

- This means that the integer linear program (**Perfect**) may not have a feasible solution.
- For bipartite graphs, we have a simple structural characterization for the existence of a perfect matching.
- The characterization is referred to as **Hall's marriage theorem**.
- Given a subset  $S \subseteq V$ ,  $N(S)$  denotes the set of vertices that are adjacent to any vertex in  $S$ .

### Theorem (Hall's marriage theorem)

*Let  $G = (V, E)$  be a bipartite graph where  $V$  is partitioned into  $V_1$  and  $V_2$ . Then  $G$  has a perfect matching if and only if  $|N(S)| \geq |S|$  for any  $S \subseteq V_1$ .*

## Hall's marriage theorem

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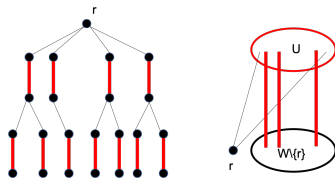


Figure: the  $M$ -alternating tree from an  $M$ -exposed vertex