# Introduction to Approximation Algorithms

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Friday 13:20 – 15:10

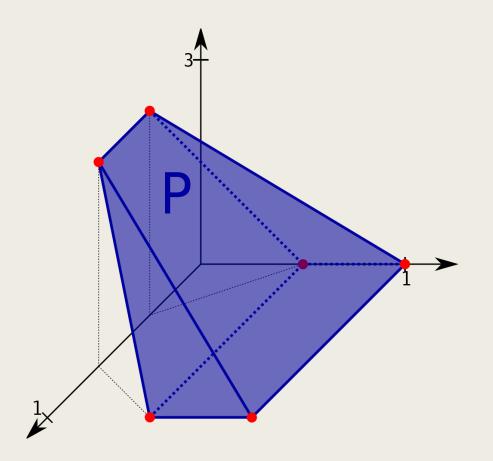
### Outline

- Extreme Point Structure of LPs
- Half-Integrality of Vertex Cover
- Unrelated Machine Scheduling
  - A strengthened LP (\*) and parametric search
  - Extreme point structure of (\*)
  - A 2-approximation algorithm

# Extreme Point Structure of LPs

# Extreme Points of a Polytope

■ Consider the convex polytope Q defined by  $Ax \leq b$ , where  $x \in \mathbb{R}^n$ .



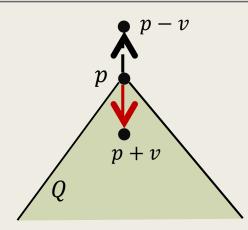
## Extreme Points of a Polytope

■ Consider the convex polytope Q defined by  $Ax \leq b$ , where  $x \in \mathbb{R}^n$ .

#### **Definition.** (Extreme Point)

A point  $p \in Q$  is an *extreme point* if for any (vector)  $v \in \mathbb{R}^n$ ,  $p + v \in Q$  implies that  $p - v \notin Q$ .

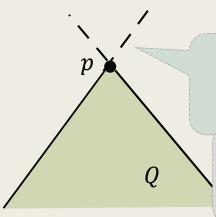
- Such a point is also called a <u>vertex</u> of Q, or, a <u>basic feasible</u> solution for  $Ax \le b$ .
- An equivalent definition is that,  $p \in Q$  is an extreme point if  $\nexists q, r \in Q$  such that p = (q + r)/2.



### **Extreme Points Structure**

- Let p be an extreme point for  $Ax \leq b$ , where  $x \in \mathbb{R}^n$ .
  - The point p lies in **the hyperplanes** defined by some of the constraints in  $Ax \le b$ , with the inequality <u>holds with equality</u>.
  - Let A'x = b' be the system formed by these constraints, i.e., those in  $Ax \le b$  that hold with equality at p.
  - To <u>uniquely define</u> p,
     the matrix A' must have
     a rank of n.

For any extreme point p, there exists a set of n linearly independent constraints in  $Ax \le b$  that hold with equality at p.

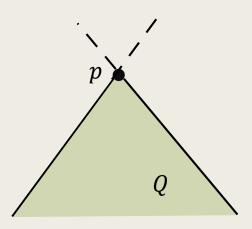


The set of *hyperplanes* that uniquely define p.

The set of constraints in  $Ax \le b$  that hold with equality at p.

# Obtaining Optimal Extreme Point Solutions

- Most LP solvers compute optimal extreme point solutions for the considered LP.
  - This includes the simplex method, interior-point method, and Ellipsoid method.
  - So, simply apply the solvers and you get an optimal extreme point solution for the LP.



## Why Extreme Point Solutions?

■ Let's consider the *simple one-edge example* for vertex cover, and the *linear constraints* for it.

$$x_1 + x_2 \ge 1,$$

$$x_1, x_2 \ge 0.$$

$$v_1$$

$$v_2$$

$$0.3$$

$$v_1$$

$$v_2$$

$$v_1$$

$$0.4$$

$$0.6$$

- For small  $\epsilon > 0$ ,  $(0.3 + \epsilon, 0.7 \epsilon)$  and  $(0.3 \epsilon, 0.7 + \epsilon)$  are both feasible solutions. So, (0.3, 0.7) is not extreme.
- The only extreme point solutions are (0,1) and (1,0).

The extreme point solution moves the value *greedily* towards some direction.

# The Half-Integrality of Vertex Cover

# Half-Integrality of Vertex Cover

Consider the natural LP relaxation for the vertex cover problem.

$$\min \sum_{v \in V} x_v \qquad (*)$$
 s.t.  $x_u + x_v \ge 1$ ,  $\forall (u, v) \in E$ ,  $x_v \ge 0$ ,  $\forall v \in V$ .

- We will show that, any extreme point solution for (\*) will set the value of each variable to be either 0, 1/2, or 1.
  - i.e., it will be *half-integral*.

■ Consider any feasible solution x for (\*) that is not half-integral, i.e.,  $\exists v \in V$  such that  $x_v \notin \left\{0, \frac{1}{2}, 1\right\}$ .

$$\min \sum_{v \in V} x_v \qquad (*)$$
s.t.  $x_u + x_v \ge 1$ ,  $\forall (u, v) \in E$ ,  $x_v \ge 0$ ,  $\forall v \in V$ .

- $\blacksquare$  We will show that x is not an extreme point solution.
  - The idea is to show that,  $\exists p \text{ such that, both } x + p \text{ and } x - p \text{ are feasible for } LP(*).$
  - Let

$$V^{+} = \left\{ v \in V : \frac{1}{2} < x_{v} < 1 \right\}, \text{ and } V^{-} = \left\{ v \in V : 0 < x_{v} < \frac{1}{2} \right\}$$

be the set of large / small vertices that are not half-integrally set.

Let

$$V^+ = \left\{ v \in V : \frac{1}{2} < x_v < 1 \right\}$$
, and  $V^- = \left\{ v \in V : 0 < x_v < \frac{1}{2} \right\}$ 

be the set of large / small vertices that are not half-integrally set.

- Pick a *sufficiently small*  $\epsilon > 0$ , and define

$$y_{v} \coloneqq \begin{cases} x_{v} + \epsilon, & \text{if } v \in V^{+}, \\ x_{v} - \epsilon, & \text{if } v \in V^{-}, \\ x_{v}, & \text{otherwise,} \end{cases} \quad z_{v} \coloneqq \begin{cases} x_{v} - \epsilon, & \text{if } v \in V^{+}, \\ x_{v} + \epsilon, & \text{if } v \in V^{-}, \\ x_{v}, & \text{otherwise.} \end{cases}$$

Intuitively, for any  $v \in V^-$ ,



 $u \in N(v)$ 

Any  $u \in N(v)$  must belong to  $V^+$ .

Hence, the adjustment in y keeps the constraints satisfied, and y is feasible.

$$\min \sum_{v \in V} x_v \tag{*}$$

s.t. 
$$x_u + x_v \ge 1$$
,  $\forall (u, v) \in E$ ,  $x_v \ge 0$ ,  $\forall v \in V$ .

Let

$$V^+ = \left\{ v \in V : \frac{1}{2} < x_v < 1 \right\}$$
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Both y and z are feasible for (\*), and x = (y + z)/2.

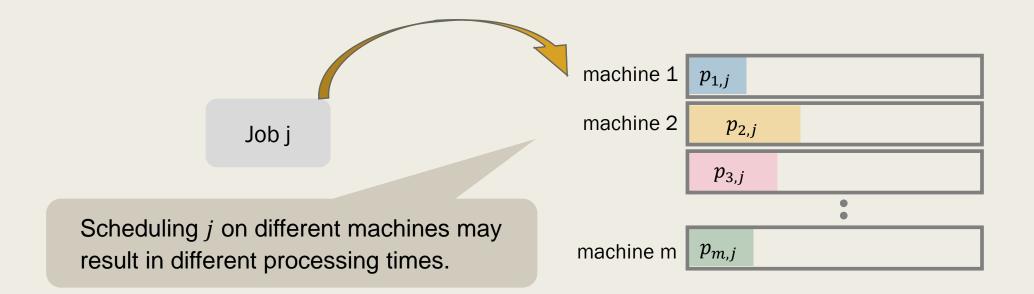
Hence, x is not extreme for (\*).

min 
$$\sum_{v \in V} x_v$$
 (\*)  
s.t.  $x_u + x_v \ge 1$ ,  $\forall (u, v) \in E$ ,  $x_v \ge 0$ ,  $\forall v \in V$ .

# Unrelated Machine Scheduling

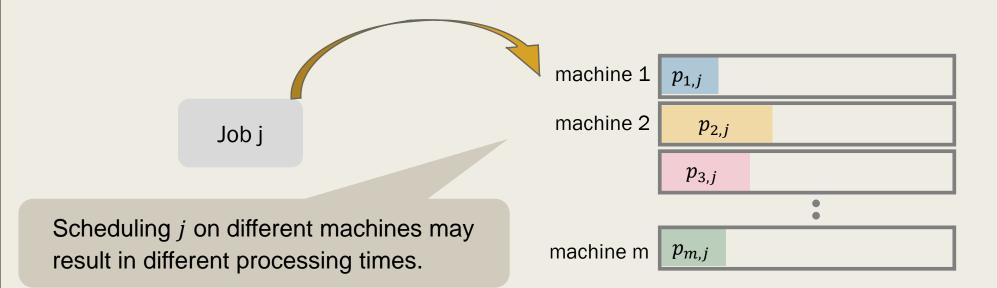
# Scheduling on Unrelated Parallel Machines

- Let J be a set of n jobs, M be a set of m machines, and  $p_{i,j} \in \mathbb{Z}^+$  for each  $j \in J, i \in M$  be the time it takes to process job j on machine i.
  - The



## Scheduling on Unrelated Parallel Machines

Given a set J of n jobs, a set M of machines, and for each  $j \in J$ ,  $i \in M$ ,  $p_{i,j} \in \mathbb{Z}^+$  which is the time it takes to process job j on machine i, the goal of this problem is to schedule the jobs on the machines so as to *minimize* the *maximum processing time of any machine*, i.e., to minimize the *makespan* of the schedule.



### The Natural LP has an Unbounded Integrality Gap

- We can formulate the problem in the following natural way.
  - For each  $i \in M, j \in J$ , we have a variable  $x_{i,j} \in \{0,1\}$ . The constraints for feasibility of the schedule:

$$\sum_{i \in M} x_{i,j} = 1, \qquad \forall j \in J.$$

- To model the objective value, we have a variable  $t \in \mathbb{Z}^{\geq 0}$ .

The constraints for modeling the objective value:

$$\sum_{j\in J} p_{i,j} \cdot x_{i,j} \le t, \qquad \forall i \in M.$$

We obtain a natural LP for this problem.
 However, this LP has an unbounded integrality gap.

Consider the following example.

Suppose that we have m machines and one job j with  $p_{i,j} = m$  for all  $1 \le i \le m$ .

The optimal fractional solution for (\*)

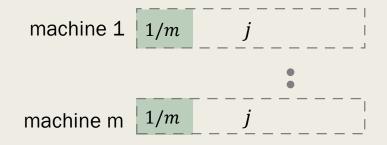
 $\sum_{j \in J} p_{i,j} \cdot x_{i,j} \le t, \qquad \forall i \in M,$   $t \ge 0,$   $x_{i,j} \ge 0, \qquad \forall i \in M, j \in J.$ 

(\*)

 $\forall j \in J$ ,

min

will set  $x_{i,j} = 1/m$  for all  $1 \le i \le m$ , which results in a makespan of 1, while the optimal integral solution has a makespan of m.



The problem is that, we allow jobs to be assigned to machines which has <u>strictly less completion time</u> than the job's processing time on that machine.

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machine 1	1/m	j
		•
machine m	1/m	j

The problem is that, we allow jobs to be assigned to machines which has <u>strictly less completion time</u> than the job's processing time on that machine.

The situation can be avoid, if we add the constraint to the relaxation:

$$\forall i \in M, j \in J : \text{ if } p_{i,j} > t, \text{ then } x_{i,j} = 0.$$

However, this is not a linear constraint.

# Parametric Search for Machine Scheduling

- In the following, we develop a parametric search process for this problem.
- Let  $t^*$  denote the optimal makespan and  $T \in \mathbb{Z}^+$  be a guess for  $t^*$ .
  - Then, we know that, for any  $T \ge t^*$ , no assignments will be made between any  $i \in M, j \in J$  with  $p_{i,j} > T$  in the optimal schedule.
  - Let

$$S_T := \left\{ (i,j) : i \in M, j \in J, \quad p_{i,j} \leq T \right\}$$

denote the pairs between which the assignments are allowed w.r.t. the guess T.

- Let  $t^*$  denote the optimal makespan and  $T \in \mathbb{Z}^+$  be a guess for  $t^*$ .
  - Let  $S_T \coloneqq \{ (i,j) : i \in M, j \in J, p_{i,j} \le T \}$ denote the pairs between which the assignments are allowed w.r.t. the guess T.
- Then we have the modified feasibility LP defined *for each possible T*.
  - Any integral solution is contained as a feasible solution in one of these LPs.
  - For any T ≥ t\*,
     LP-(T) is guaranteed to be feasible.
    - Conversely, whenever LP-(T) is infeasible, then  $T < t^*$  must hold.

$$\sum_{i:(i,j)\in S_T} x_{i,j} = 1, \quad \forall j \in J, \quad \text{LP-}(T)$$

$$\sum_{j:(i,j)\in S_T} p_{i,j} \cdot x_{i,j} \leq T, \quad \forall i \in M,$$

$$x_{i,j} \geq 0, \quad \forall (i,j) \in S_T.$$

- Then we have the modified feasibility LP defined *for each possible T*.
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  - For any T ≥ t\*, LP-(T) is guaranteed to be feasible.
     Conversely, whenever LP-(T) is infeasible, then T < t\* must hold.</li>
  - Under the *parametric search framework*, it suffices to show that,
     whenever LP-(T) is feasible,
     we can always round the solution
     properly.

$$\sum_{i:(i,j)\in S_T} x_{i,j} = 1, \quad \forall j \in J, \quad \text{LP-}(T)$$

$$\sum_{j:(i,j)\in S_T} p_{i,j} \cdot x_{i,j} \leq T, \quad \forall i \in M,$$

$$x_{i,j} \geq 0, \quad \forall (i,j) \in S_T.$$

# Parametric Search for Machine Scheduling

- We will derive a rounding process for LP-(T) such that the resulting makespan is at most 2T.
  - Then, we can apply binary search to find the smallest T for which LP-(T) is feasible, and it follows that  $T \le t^*$ .

Then applying the rounding process gives us a 2-approximation.

$$\sum_{i:(i,j)\in S_T} x_{i,j} = 1, \quad \forall j \in J, \quad \text{LP-}(T)$$

$$\sum_{j:(i,j)\in S_T} p_{i,j} \cdot x_{i,j} \leq T, \quad \forall i \in M,$$

$$x_{i,j} \geq 0, \quad \forall (i,j) \in S_T.$$

# The Extreme Point Structure for LP-(T)

# Extreme Point Solutions for LP-(T)

- The intuition here is that, although  $x_{i,j}$  LP-(T) may have a number of variables, it has only a linear number of nontrivial constraints.
  - i.e., it has only |J| + |M| constraints bounding the variables in a nontrivial way.
  - Hence, only a linear number of non-trivial variables can be defined at the extreme points of this LP.
    - In other words, most of the variables must be set zero there.
  - Let n = |J| and m = |M|.

$$\sum_{i:(i,j)\in S_T} x_{i,j} = 1, \qquad \forall j \in J, \qquad \text{LP-}(T)$$

$$\sum_{j:(i,j)\in S_T} p_{i,j} \cdot x_{i,j} \le T, \qquad \forall i \in M,$$

$$x_{i,j} \geq 0, \quad \forall (i,j) \in S_T.$$

#### Lemma 3.

Any extreme point solution to LP-(T) has at most n + m nonzero variables.

- Lemma 3 is a formal statement of the intuitions in the previous slide.
- The proof is straightforward.
  - Consider any extreme point solution of LP-(T) and the invertible matrix obtained from LP-(T) at that point.
  - At most |J| + |M| = n + m nontrivial constraints can be selected to form the invertible matrix.
     Hence, the remaining constraints are from x<sub>i,j</sub> ≥ 0 and will set the corresponding variables to zero.

$$\sum_{i:(i,j)\in S_T} x_{i,j} = 1, \quad \forall j \in J, \quad \text{LP-}(T)$$

$$\sum_{i:(i,j)\in S_T} p_{i,j} \cdot x_{i,j} \leq T, \quad \forall i \in M,$$

$$j:(i,j)\in S_T$$

$$x_{i,j} \geq 0, \quad \forall (i,j) \in S_T.$$

■ The following is a direct corollary of Lemma 3.

### **Corollary 4.**

Any extreme point solution to LP-(T) must assign at least n-m jobs integrally.

$$\sum_{i:(i,j)\in S_T} x_{i,j} = 1, \quad \forall j \in J, \quad \text{LP-}(T)$$

$$\sum_{j:(i,j)\in S_T} p_{i,j} \cdot x_{i,j} \leq T, \quad \forall i \in M,$$

$$x_{i,j} \geq 0, \quad \forall (i,j) \in S_T.$$

- Intuitively, Corollary 4 says that, at most *m* jobs are fractionally assigned.
  - The integrally-assigned jobs have a makespan of at most T.
  - Each of the fractionally-assigned jobs will contribute a makespan of at most T. (Since  $x_{i,j} > 0$  implies that  $p_{i,j} \le T$ .)

We will show that, *there exists a matching* from the fractionally-assigned jobs to the machines, and hence, those jobs can be properly assigned.

■ The following is a direct corollary of Lemma 3.

#### **Corollary 4.**

Any extreme point solution to LP-(T) must assign at least n-m jobs integrally.

■ The proof of Corollary 4 is also simple.

See the lecture note for the details.

$$\sum_{(i,j)\in S_T} x_{i,j} = 1, \qquad \forall j \in J, \qquad \text{LP-}(T)$$

$$\sum_{j:(i,j)\in S_T} p_{i,j} \cdot x_{i,j} \le T, \qquad \forall i \in M,$$

$$x_{i,j} \geq 0, \quad \forall (i,j) \in S_T.$$

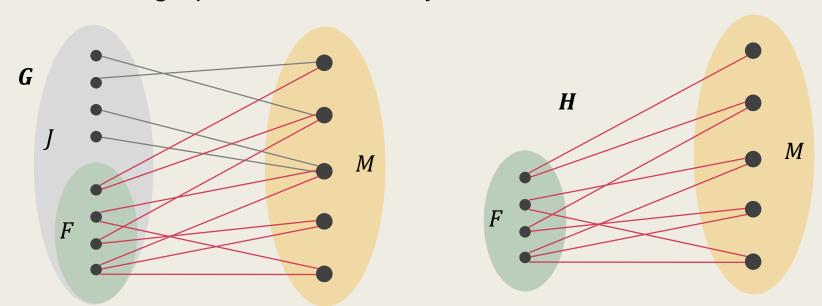
# The Assignment Graphs and Properties

# The Assignment Graph G and H

■ Let x be an extreme point solution for LP-(T).

Define the bipartite graph G = (J, M, E) with partite set J and M such that  $(j, i) \in E$  if and only if  $x_{i,j} \neq 0$ .

Let  $F \subseteq J$  be the set of jobs that are fractionally assigned in x, and H be the subgraph of G induced by  $F \cup M$ .



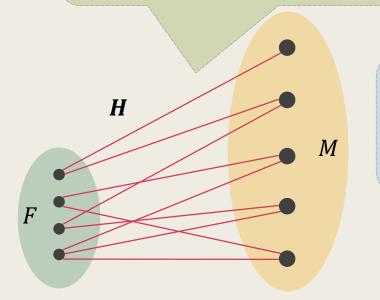
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Let  $F \subseteq J$  be the set of jobs that are fractionally assigned in x, and H be the subgraph of G induced by  $F \cup M$ .

Jobs in J – F have degree 1 in G and contribute a total makespan of  $\leq T$ .

Each edge (j,i) in H satisfies  $p_{i,j} \leq T$ . Provided that there exists a matching to M exists, they will contribute a total makespan of  $\leq T$ .



We will show that, there is a **matching** from jobs in *F* to *M*.

Then, we get a schedule with makespan  $\leq 2T$ .

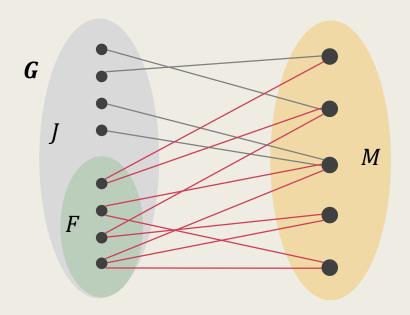
### G and H are Pseudo-Forests.

- We say that a connected graph with vertex set V is a pseudo-tree if it has at most |V| edges.
  - i.e., it is either a tree, or a tree plus one edge.
- We say that a graph is a pseudo-forest if each of its connected components is a pseudo-tree.

#### Lemma 5.

*G* is a pseudo-forest.

- $\blacksquare$  Consider each connected component in G.
  - We will argue that it's a pseudo-tree.



#### Lemma 5.

*G* is a pseudo-forest.

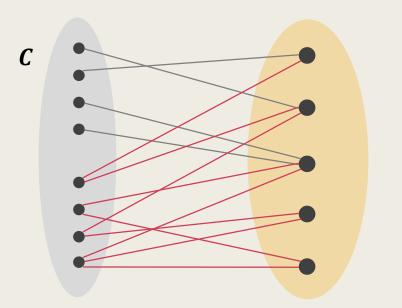
- Consider any connected component, say, C, in G.
  - Consider the variables and constraints to which C corresponds.

Denote the sub-LP by LP- $(T)_C$ .

Clearly,

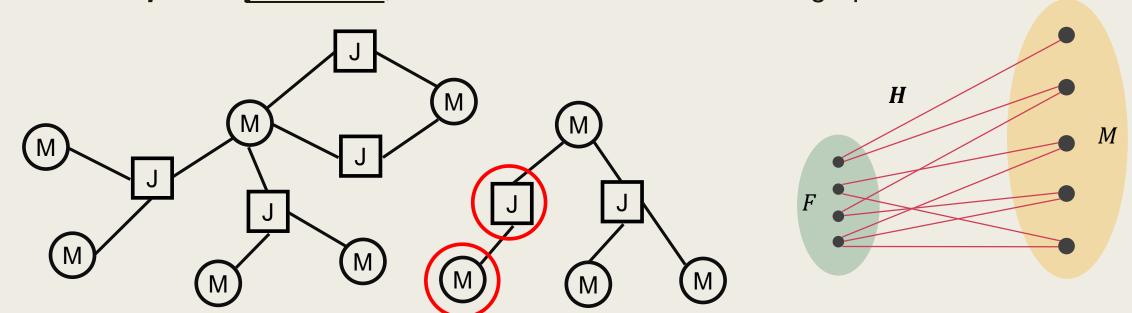
the solution x restricted to C,  $x|_C$ , must also be extreme for LP- $(T)_C$ .

- Hence, C has an equal number of vertices and edges and is a pseudo-tree.
- Since H is obtained by removing some degree-1 vertices from G, it is also a pseudo-forest.

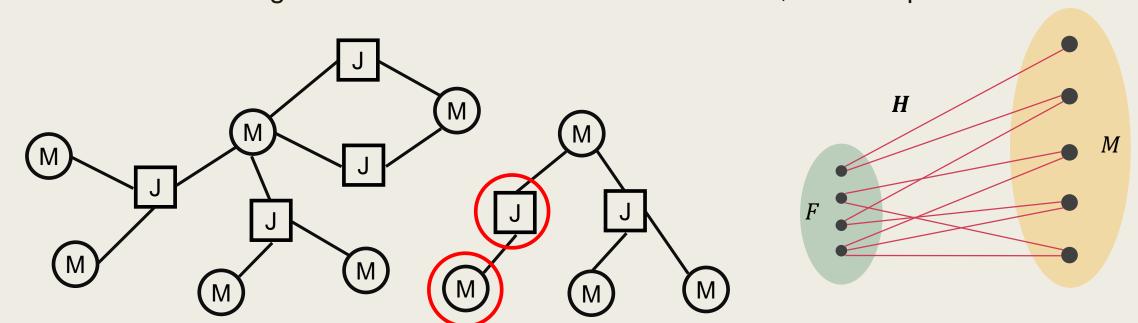


# H has a perfect matching (for F to M).

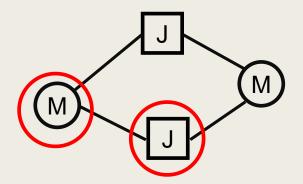
- $\blacksquare$  We have shown that H is a pseudo-forest.
  - Since each job vertex in H has degree at least 2,
     we know that all the leaf vertices in H are machine vertices.
- The idea is to *keep matching* <u>a leaf machine vertex</u> with its parent job vertex, and then remove both from the graph.



- Since each job vertex in H has degree at least 2,
   we know that all the leaf vertices in H are machine vertices.
- We repeat the following process until no more leaf vertex is left.
  - Pick a leaf machine vertex and match it with its parent job vertex.
  - Remove both vertices from the graph.
     Remove isolated vertices.
- Since this process does not change the degree of any other job vertex, the remaining leaf vertices are still machine vertices, *H* is still pseudo-forest.

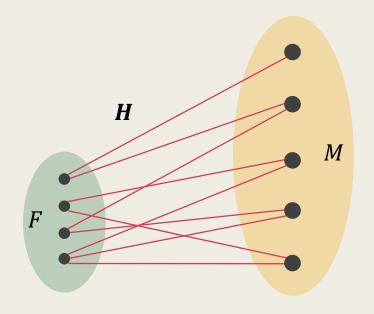


- We repeat the following process until no more leaf vertex is left.
  - Pick a leaf machine vertex and match it with its parent job vertex.
  - Remove both vertices from the graph.
     Remove isolated vertices.
- When this process ends,H is left with even cycles, which can be perfectly matched.



#### Lemma 6.

H has a perfect matching for F to M.



# The Rounding Algorithm $\mathcal{A}$

### Rounding the Extreme Point Solutions for LP-(T)

- The rounding algorithm  $\mathcal{A}$  goes as follows.
  - Input: a basic feasible (extreme point) solution x for LP-(T)
  - Output: a schedule with makespan at most 2T
  - 1. Assign all the jobs in J F according to x.

This contributes a makespan of  $\leq T$ .

- 2. Construct the graph *H* and compute a perfect matching from *F* to *M*. Assign the jobs in *F* according to the matching *M*.
- 3. Output the resulting schedule.

This also contributes a makespan of  $\leq T$ , since each machine gets at most one job with  $p_{i,j} \leq T$ .

The 2-approximation algorithm for

Unrelated Machine Scheduling

### The 2-Approximation Algorithm

The algorithm goes as follows.

This guarantees that  $T \leq t^*$ .

- 1. Apply binary search on  $\left[0, \sum_{i,j} p_{i,j}\right]$  to find the smallest T such that LP-(T) is feasible.
- 2. Compute an extreme point solution x for LP-(T).
- 3. Apply rounding algorithm  $\mathcal{A}$  on x and output the resulting schedule.

The output has a makespan of at most  $2T \leq 2t^*$ .