

# Cooperation in Multi-Organization Matching

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# Outline

1. Presentation of the problem
  - Definition
  - Applications
  - Advantages and limits of the cooperation
2. Complexity
3. Approximation
4. Generalization : relaxing the selfishness

# Presentation of the problem

Given:

- a set of  $k$  organizations  $O_1, \dots, O_k$  (agencies)
- a bipartite graph  $G=(V1,V2,E)$  where each vertex belongs to an organization.

Cost of edge  $e$ :  $w(e)$  (price the buyer can pay)

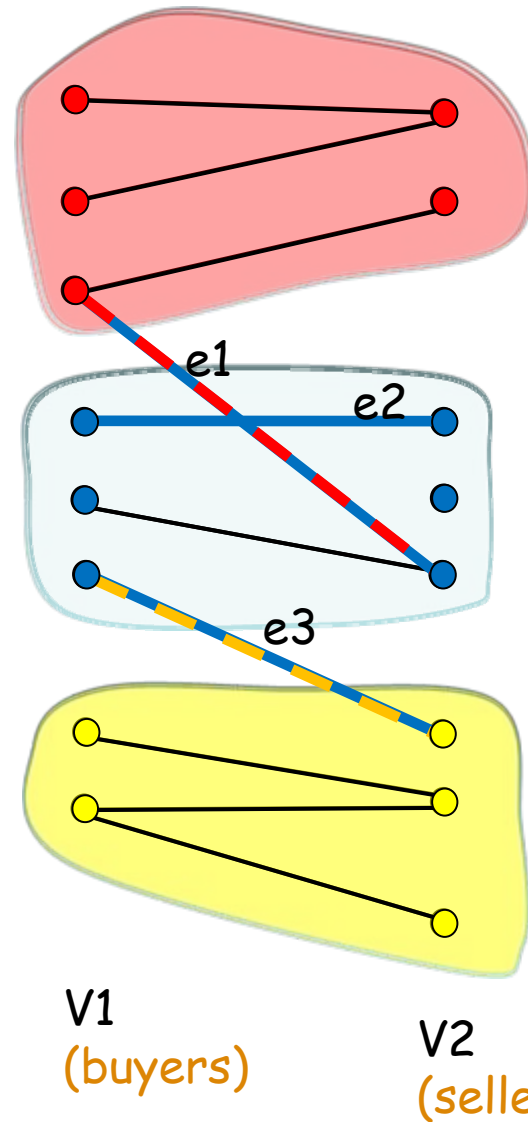
Aim of an organization: maximize its gain.  
(percentage on the amount of transactions done)

- $p_1$  and  $p_2$  s.t.  $0 \leq p_1 \leq p_2 \leq 1$  and  $p_1 + p_2 = 1$ .

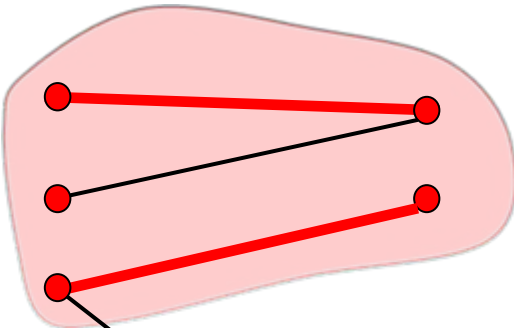
Profit of  $O_i$  in a matching  $M$ :

$$\text{Gain}(O_i, M) = p_1 \sum_{e \in (M \cap V1) \cap O_i} w(e) + p_2 \sum_{e \in (M \cap V2) \cap O_i} w(e)$$

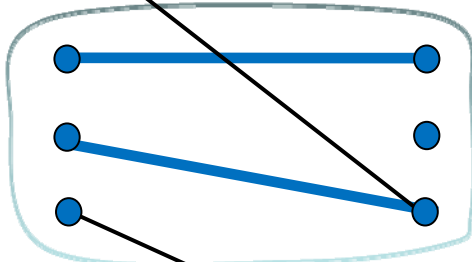
Example:  $\text{Gain}(O_2, M) = w(e2) + p_1 w(e3) + p_2 w(e1)$



# Presentation of the problem



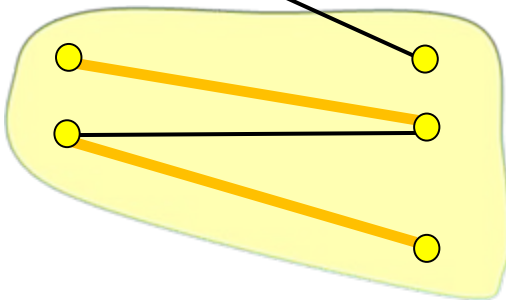
Let  $\text{GainAlone}(O_i)$  be the max. weight of a matching induced by the edges of  $O_i$ .



The multi-organization assignment problem (MOA):

Find a **maximum weight matching**  $M$  such that for each  $O_i$  :

$$\text{Gain}(O_i, M) \geq \text{GainAlone}(O_i).$$



Notation:  $\text{Gain}(M) = \bigcup_{1 \leq i \leq k} \text{Gain}(O_i, M)$

V1

V2

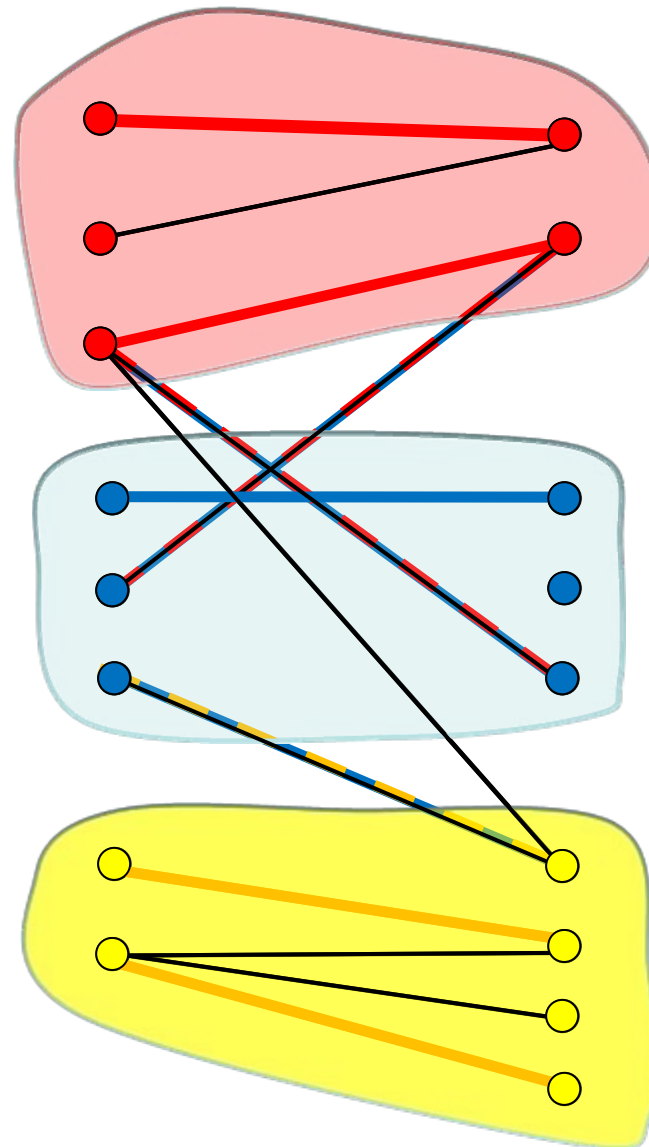
# Presentation of the problem

Example:  
(all the weights  
are equal to 1,  
 $p_1=p_2=0,5$ )

$$\text{GainAlone}(O_1) = 2$$

$$\text{GainAlone}(O_2) = 1$$

$$\text{GainAlone}(O_3) = 2$$



$$\text{Gain}(O_1, M) = 2$$

$$\text{Gain}(O_2, M) = 2,5$$

$$\text{Gain}(O_3, M) = 2,5$$

# A scheduling example

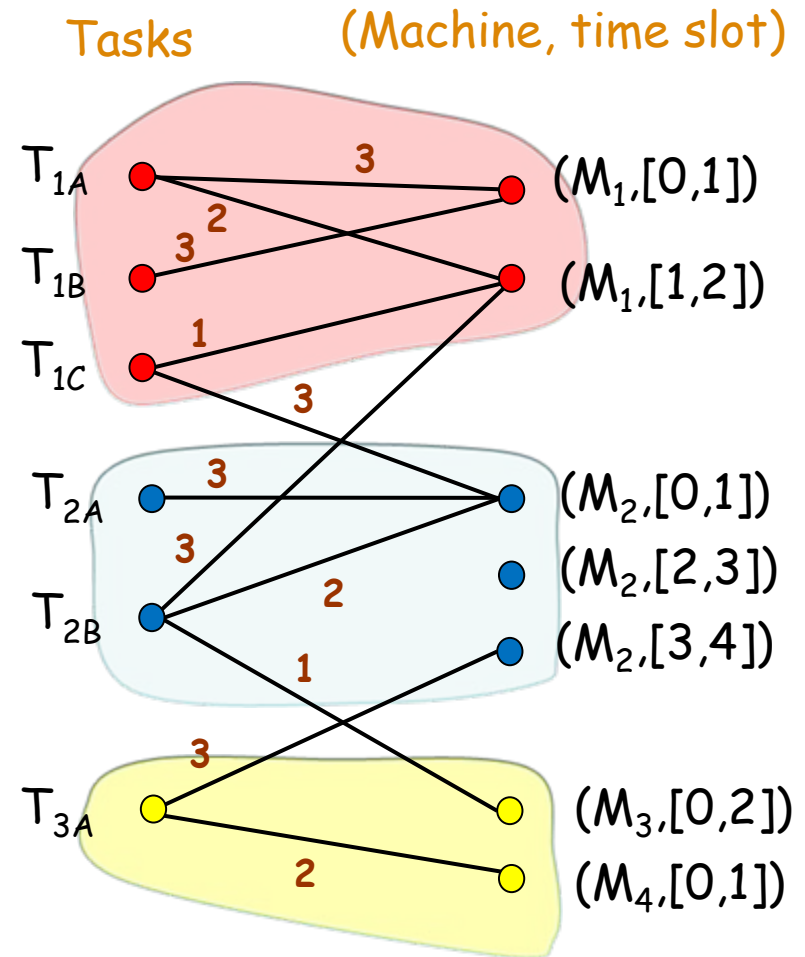
Each organization owns:

- Machines (which may be different)
- Users : each user wants to execute a unit task on a machine, and gives its preferences (integer between 1 and B).

**Aim of each organization :** maximize the average satisfaction of its users.

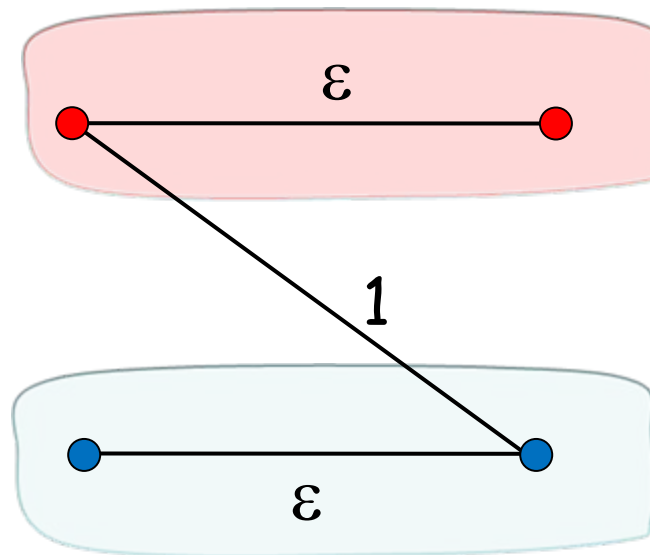
**Global aim :** maximize the average total satisfaction.

➔ MOA problem with  $p_1 = 1$  and  $p_2 = 0$ .



# Cooperation can help a lot

Cooperation allows much better solutions.



Without cooperation :  
 $\text{Gain} = 2\epsilon \ll 1$

With cooperation:  
 $\text{Gain} = 1$

# Limits of cooperation

- Non-cooperating game:
  - **Players** = organizations
  - **Strategies** = {accept the proposed solution; compute its own maximum matching}

- **Price of stability** =

$$\max_{\text{instances}} \frac{\text{Gain in the best Nash equilibrium}}{\text{Gain in the best solution}}$$

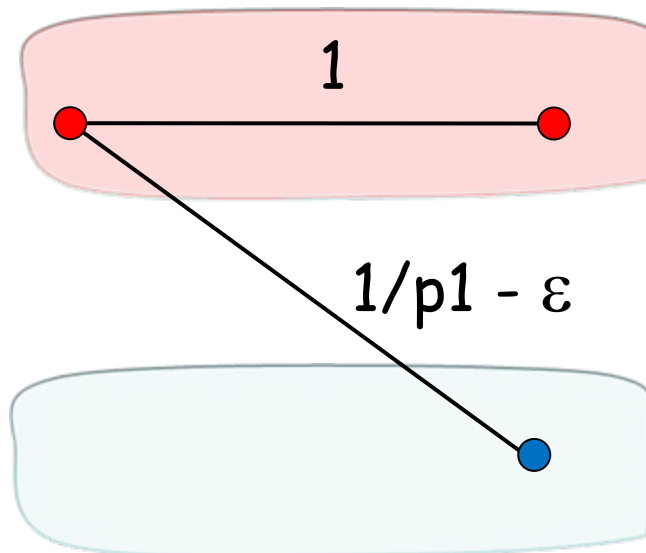
$$\max_{\text{instances}} \frac{\text{Gain}(\text{MOAopt})}{\text{Gain}(M^*)}$$

( $M^*$  is a max. weight matching of  $G$ )

# Limits of cooperation

- Proposition : The price of stability is  $p_1$ .

$p_1 > 0$ :



$GainAlone(O_1) = 1$

$$\text{Price of stability} \geq \frac{\text{Gain}(MOA_{opt})}{\text{Gain}(M^*)} = \frac{1}{1/p_1 - \epsilon} = \frac{p_1}{1 - (p_1 \epsilon)}$$

# Outline

## 1. Presentation of the problem

- Definition
- Applications
- Advantages and limits of the cooperation

## 2. Complexity

- A polynomial case
- General case

## 3. Approximation

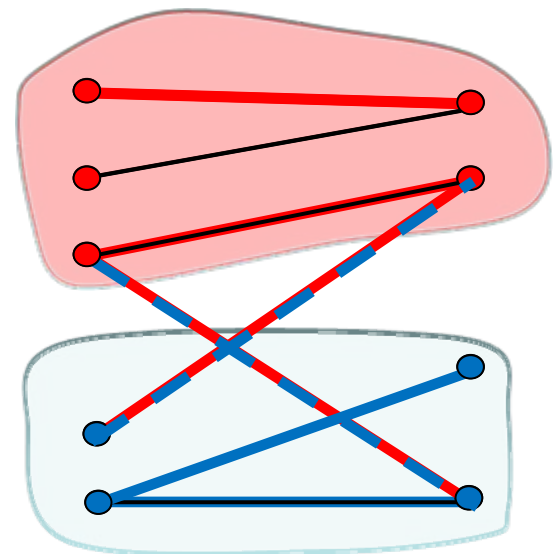
## 4. Generalization : relaxing the selfishness

# A polynomial case

- **Proposition:** If the graph is unweighted, then the MOA problem is polynomial time solvable.

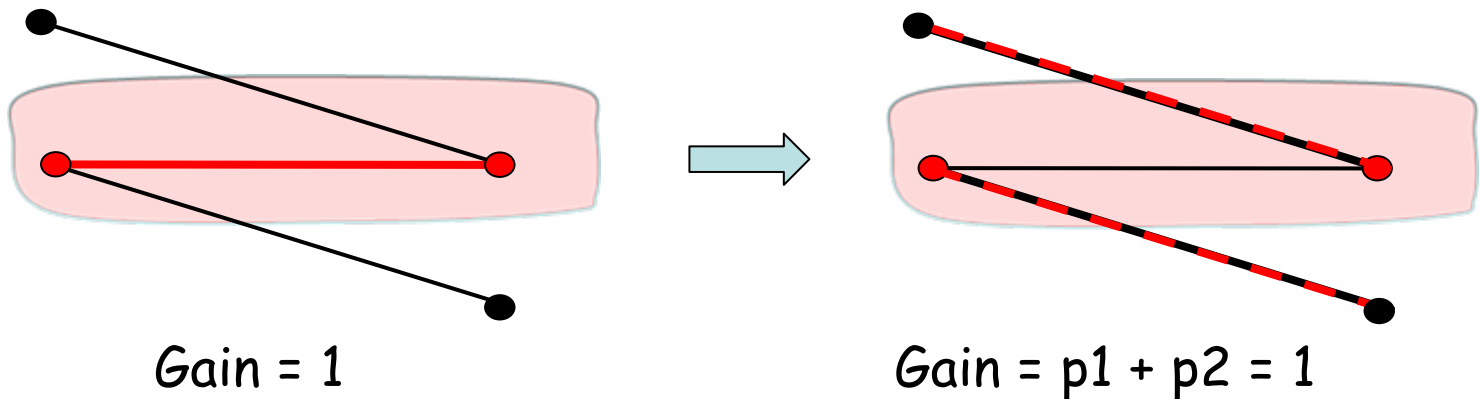
## Algorithm:

- Compute a maximum weight matching for each organization.
- Increase the size of the matching of  $G$  by augmenting its paths while it is possible.



# A polynomial case

- This algorithm returns an optimal solution:
  - Improving the matching via an augmenting an alternating path does not diminishate the gain of any organization.



- The resulting matching is feasible and of max. cardinality since no more augmenting path exists.

# General case

- Proposition:

The MOA problem is **NP-hard** if  $k \geq 2$ .

**Proof:** Reduction from the Partition problem.

- Proposition:

The MOA problem is **strongly NP-hard** if  $k$  is not fixed.

**Proof:** Reduction from the 3-Partition problem.

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1. Presentation of the problem
2. Complexity
3. Approximation
  - Approximate algorithm
  - Inapproximability
4. Generalization : relaxing the selfishness

# Approximation algorithms

- An algorithm  $A$  is  **$x$ -approximate** if

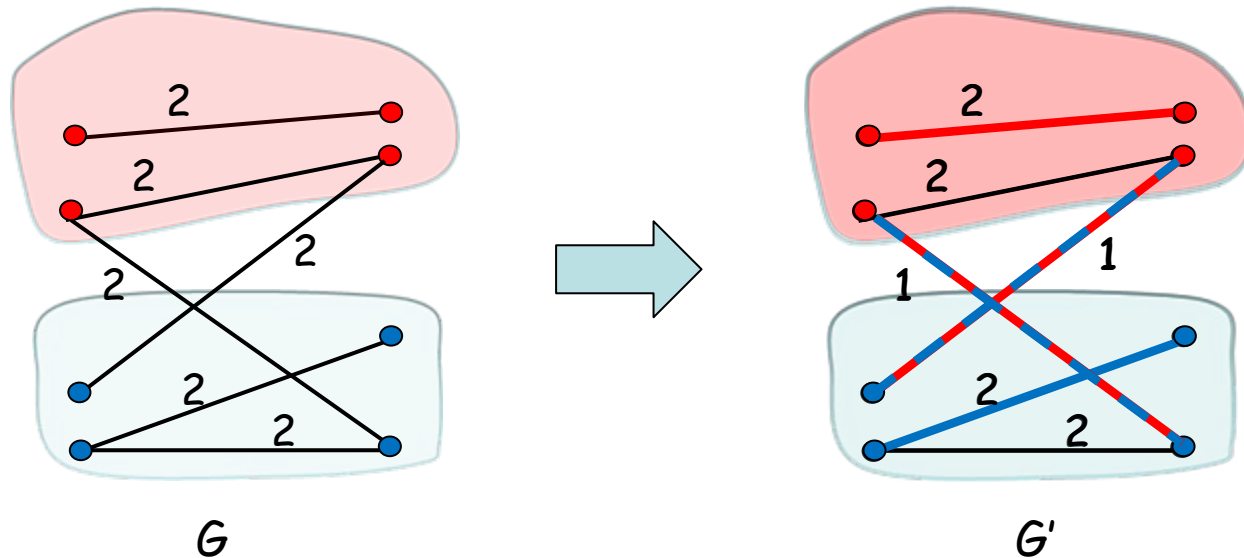
$$\max_{\text{instances}} \frac{\text{Gain in the solution returned by } A}{\text{Gain in the best solution}} \geq x$$

=> Algorithm  $\frac{1}{2}$ -approximate : returns a matching whose gain is at least  $\frac{1}{2}$  the gain of an optimal solution of the MOA problem.

# Approximate algorithm (APPROX)

- **Construct from  $G$  a graph  $G'$  with the same vertices and edges and s.t. for each  $e$  of  $E$ :**
  - if  $e$  is shared between 2 organizations:  
 $w(e') = p_1 w(e)$ ;
  - otherwise  $w'(e) = w(e)$ .
- **Return a maximum weight matching in  $G'$ .**

$$p_1 = p_2 = \frac{1}{2}:$$



# Approximate algorithm

**Proposition:** APPROX is a  $p_1$ -approximate algorithm for the MOA problem.

**Proof:** ( $p_1=p_2=\frac{1}{2}$ ):

- APPROX is  $\frac{1}{2}$ -approximate:

Gain of the returned solution  $\geq$  Gain( $M^*(G')$ )

In  $G'$ , the weight of each edge has been at most divided by 2.

Thus  $\text{Gain}(M^*(G')) \geq \frac{1}{2} \text{Gain}(M^*(G)) \geq \frac{1}{2} \text{Gain}(\text{MOAopt})$

# Approximate algorithm

- $M$ , the solution returned by APPROX is feasible:
  - $M_{\text{int}}(i)$  : edges of  $M$  whose both endpoints belong to  $O_i$
  - $M_{\text{shared}}(i)$  : edges of  $M$  whose 1 endpoint belongs to  $O_i$

$M$  is a max. weight matching of  $G'$

$\Rightarrow \text{Gain}'(M_{\text{int}}(i)) + \text{Gain}'(M_{\text{shared}}(i)) \geq \text{GainAlone}(i)$

$$\begin{aligned} \text{Gain}(O_i) &= \text{Gain}(M_{\text{int}}(i)) + \frac{1}{2} \text{Gain}(M_{\text{shared}}(i)) \\ &\geq \text{Gain}'(M_{\text{int}}(i)) + \text{Gain}'(M_{\text{shared}}(i)) \\ &\geq \text{GainAlone}(i) \end{aligned}$$

# Inapproximation

**Proposition:** If  $k \geq 3$ , for all  $\varepsilon > 0$ ,  
 $(p_1 + \varepsilon)$ -approximation is NP-hard.

**Proof:** We can map a Partition instance into a MOA instance s.t. there are two possible optimal solutions  $A$  and  $A/p_1$  and so that  
 $\exists \text{Partition} \iff \text{OPT} = A$

$(p_1 + \varepsilon)$ -approximate algorithm can distinguish between the instances with  $\text{OPT} = A$  from instances with  $\text{OPT} = A/p_1$ .

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# Relaxing the selfishness of the organizations

- Each organization accepts to divide its gain by  $\alpha \geq 1$ .
- **MOA( $\alpha$ ) problem**: find a max. weight matching s.t.  $\text{Gain}(O_i, M) \geq \text{GainAlone}(O_i) / \alpha$ .
  - If  $\alpha = 1$  : this is the MOA problem.
  - If  $\alpha \geq 1/p_1$  : a max. weight matching (without taking into account the constraints of the organizations) is feasible.
  - What happens when  $1 > \alpha > 1/p_1$  ?

# Relaxing the selfishness of the organizations

- Complexity:

For all  $1 > \alpha > 1/p_1$ , the  $MOA(\alpha)$  problem is **strongly NP-hard** if  $k \geq 3$ .

- Approximate algorithm:

We slightly modify APPROX: the cost of each shared edge is multiplied in  $G'$  by  $(\alpha p_1)$ .

This is a  **$(\alpha p_1)$ -approximate** algorithm.

# Conclusion

- A study of the incentive to **make agents cooperate** at the algorithmic level, for the assignment problem.
- A problem polynomial in the unweighted case; NP-hard,  $p_1$ -approximable (and not  $(p_1+\varepsilon)$ -approximable when  $k>2$ ) otherwise. It remains hard when we relax the selfishness of the organizations.

# Perspectives

- Is the MOA problem strongly NP-hard when  $k=2$ ? [related to the exact perfect matching problem]
- When we relax the selfishness : is the  $MOA(\alpha)$  problem inapproximable?
- Experimental results
- Fairness issues