

# **Fair Allocation of indivisible goods with externalities**

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# Externalities

# Fair division problem

There are objects to be distributed among agent,  
where each agent gains a **utility**,  
when an object is allocated to her.

$$V_i(\{b\})$$

# Fair division problem

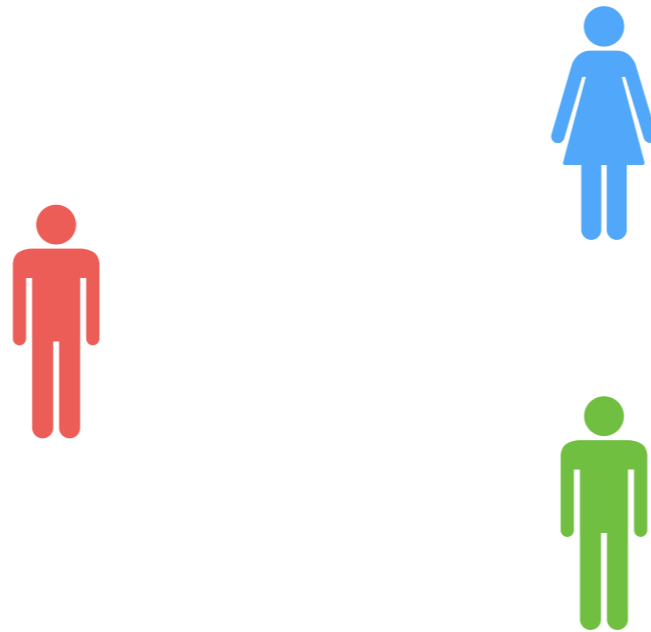
With externalities

There are objects to be distributed among agent,  
where each agent gains a **utility**,  
when an object is allocated to anyone.

**items allocated to other agents is important for each agent.**

# Fair division problem

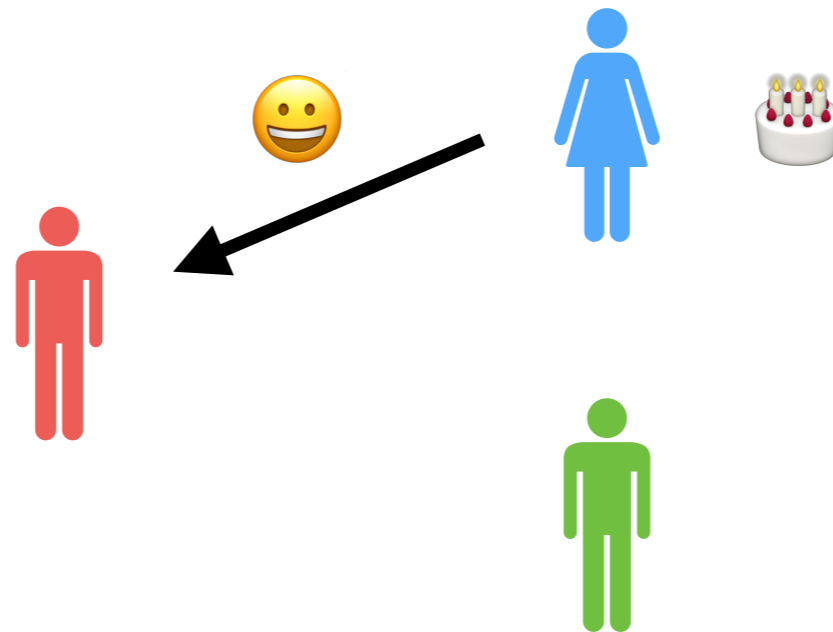
With externalities



items allocated to other agents is important for each agent.

# Fair division problem

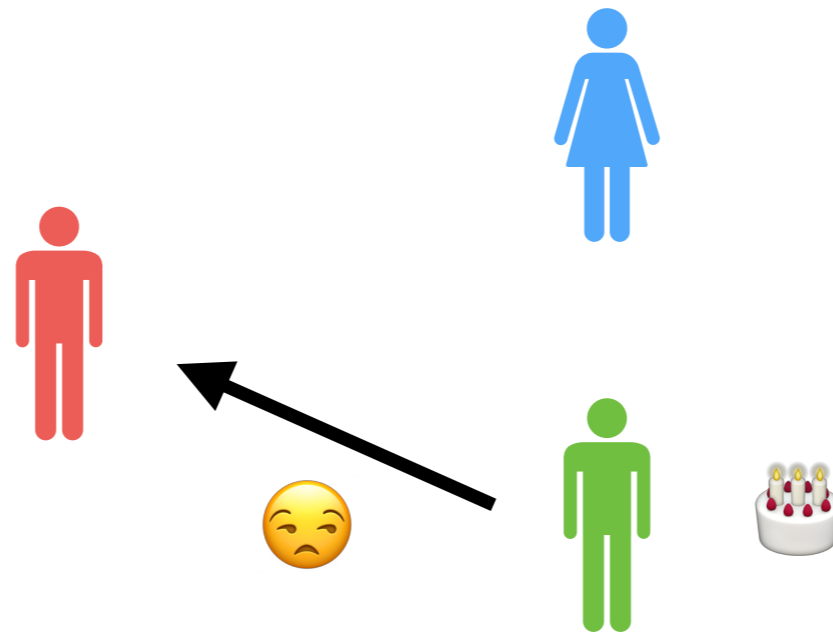
With externalities



items allocated to other agents is important for each agent.

# Fair division problem

With externalities



items allocated to other agents is important for each agent.

**Model**



# General Externalities Model

Suppose set **S** is allocated to agent **j**,  
then agent **i** gains utility of

$$V_{j,i}(S)$$

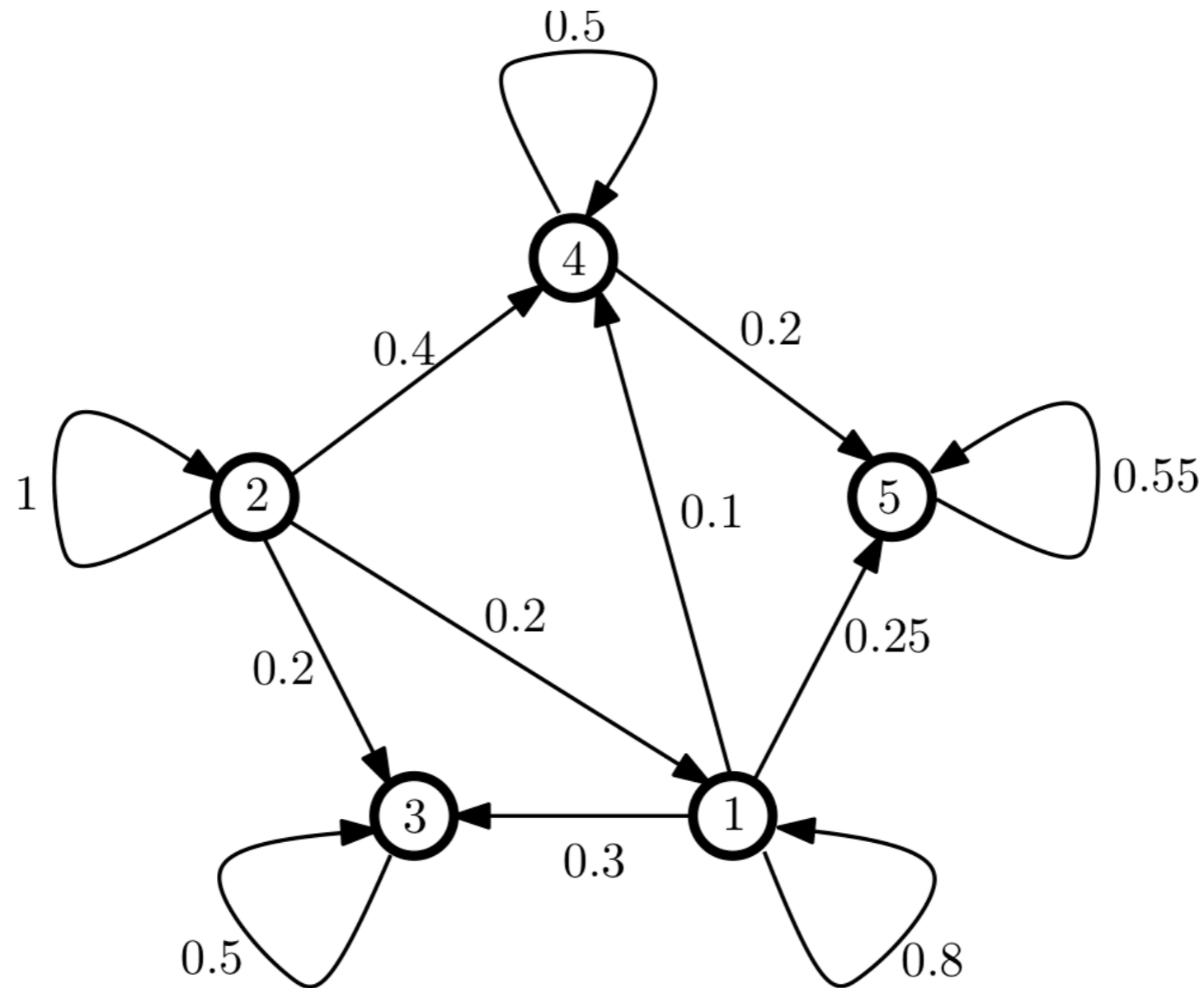
# General Externalities Model

Suppose set **S** is allocated to agent **j**,  
then agent **i** gains utility of

$$V_{j,i}(S) = \sum_{b \in S} V_{j,i}(\{b\})$$

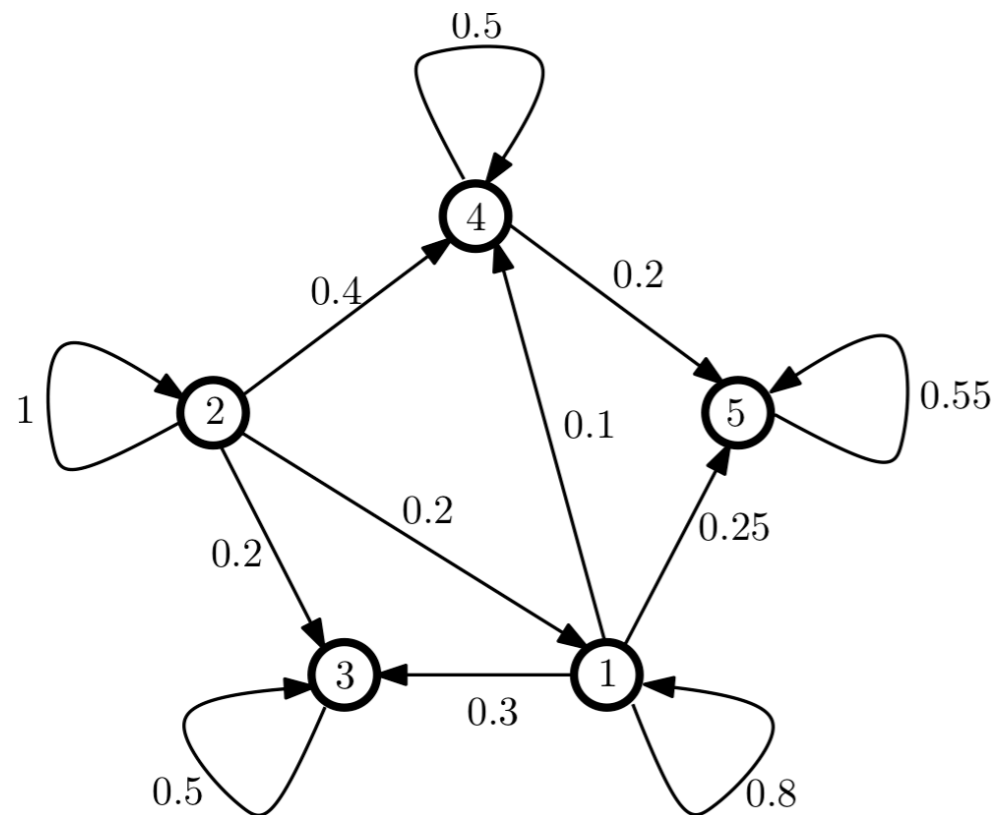
Suppose the valuations are **additive**

# Network Externalities Model



Modeling the externalities based on an **influence graph**

# Network Externalities Model

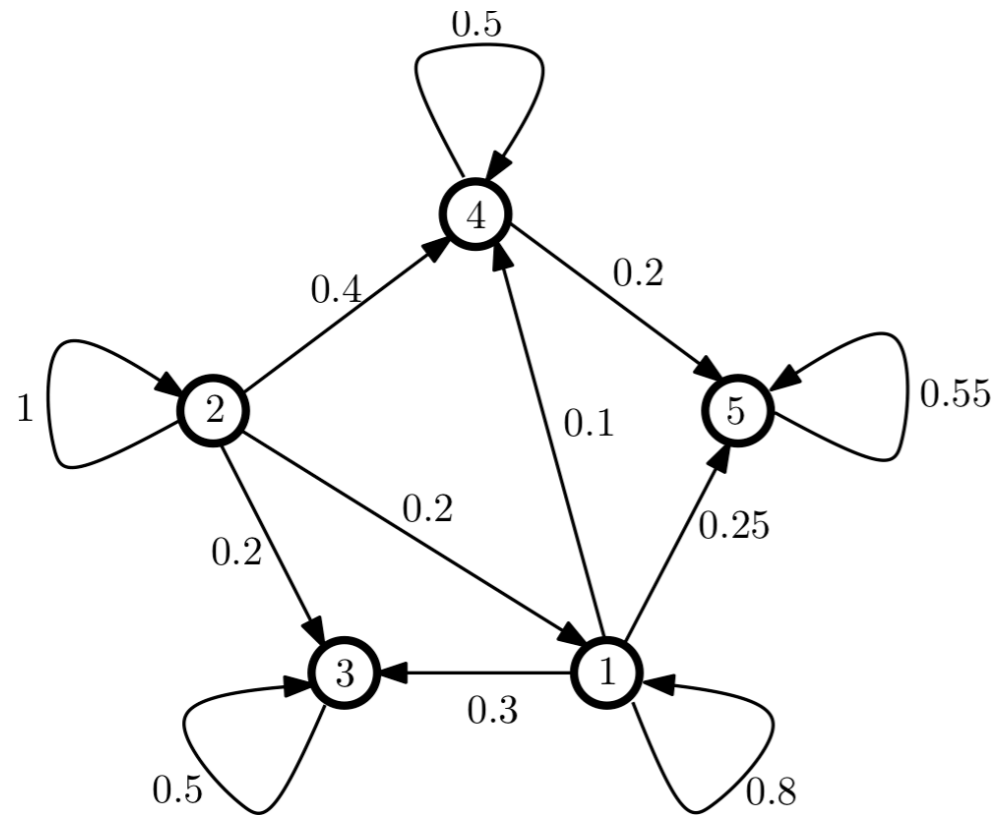


The utility of each agent is based on the edge weights,

$$V_{j,i}(S) = \sum_{b \in S} V_i(\{b\}) \cdot w_{j,i}$$

Modeling the externalities based on an **influence graph**

# Network Externalities Model



The weights of the edges are normalized,

$$\sum_j w_{j,i} = 1$$

Modeling the externalities based on an **influence graph**

# Normalized weights

Why is it ok to normalize the weights?

- We can scale the weights and define a fairness criteria independent of the absolute value of the weights.

# Normalized weights

What do normalized weights mean?

- Normalized weights could be interpreted as the **probability** that agent **j** borrows his allocated items to agent **i**.

# Fairness Criteria



# Common Criteria

The most common criteria could be extended for the case with externalities, namely

- **Proportionality**
- **Envy-freeness**
- **Maximin Share**

# Extended Proportionality

Branzei et al. (2013)

Consider the maximum utility agent  $i$  gains by allocating each item to the right agent,

$$\hat{V}_i = \sum_{b \in \mathcal{M}} \max_{j \in \mathcal{N}} V_{j,i}(\{b\})$$

# Extended Proportionality

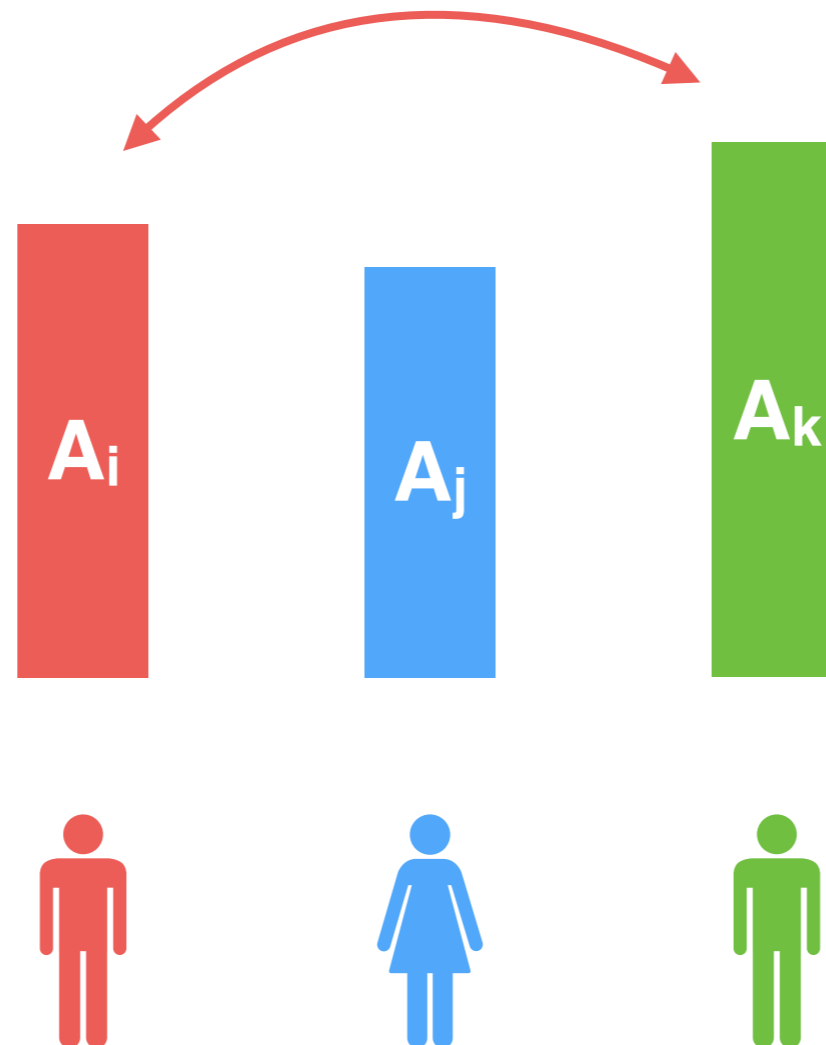
Branzei et al. (2013)

An allocation  $\mathbf{A}$  is extended-proportional  
if for each  $i$  we have

$$U_i(\mathcal{A}) \geq \frac{\hat{V}_i}{n}$$

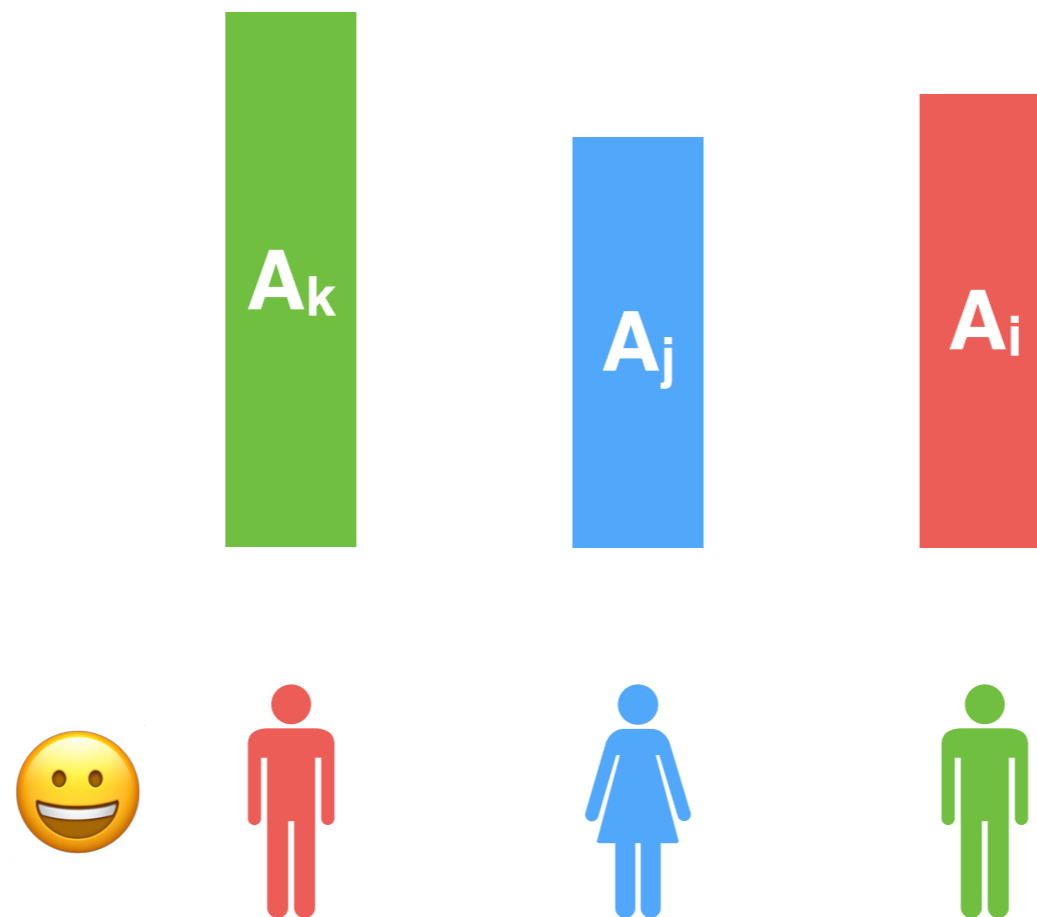
# Swap envy-freeness

Velez (2011)



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Velez (2011)



# Swap envy-freeness

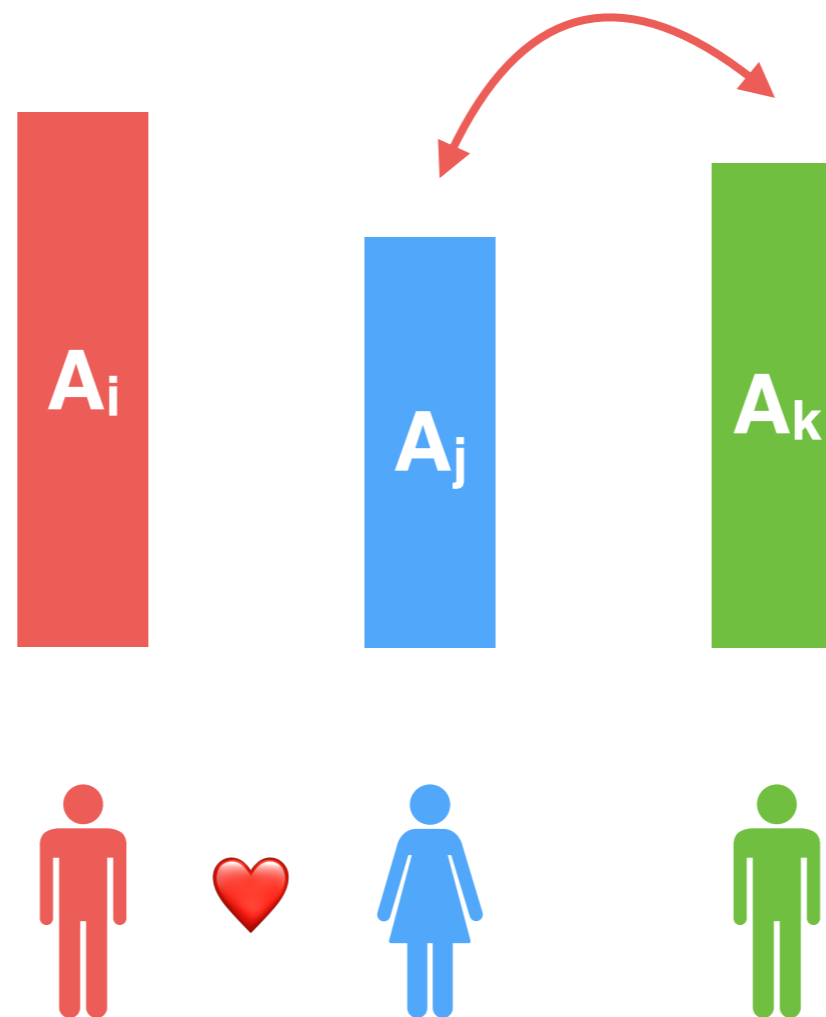
Velez (2011)

An allocation  $\mathbf{A}$  is swap envy-free if for every pair of agents  $\mathbf{i}$  and  $\mathbf{j}$  we have

$$V_{i,i}(\mathcal{A}_i) + V_{j,i}(\mathcal{A}_j) \geq V_{i,i}(\mathcal{A}_j) + V_{j,i}(\mathcal{A}_i)$$

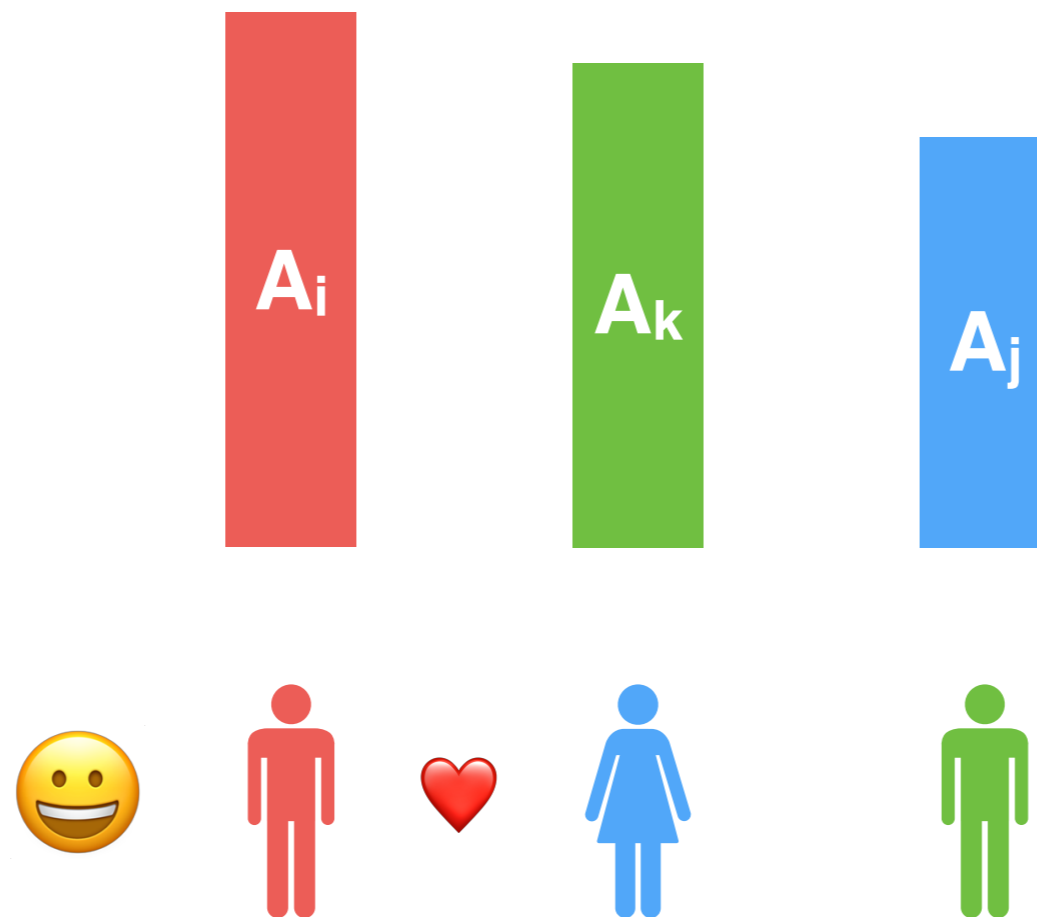
# Swap Stability

Branzei et al. (2013)



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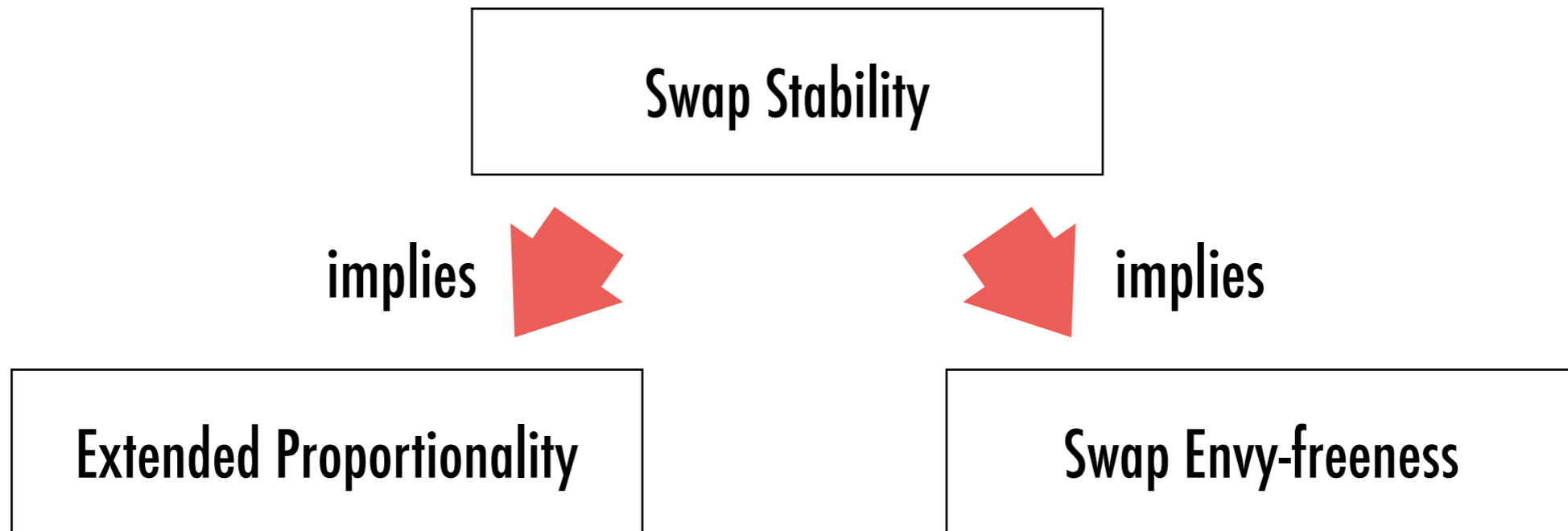
# Swap Stability

Branzei et al. (2013)

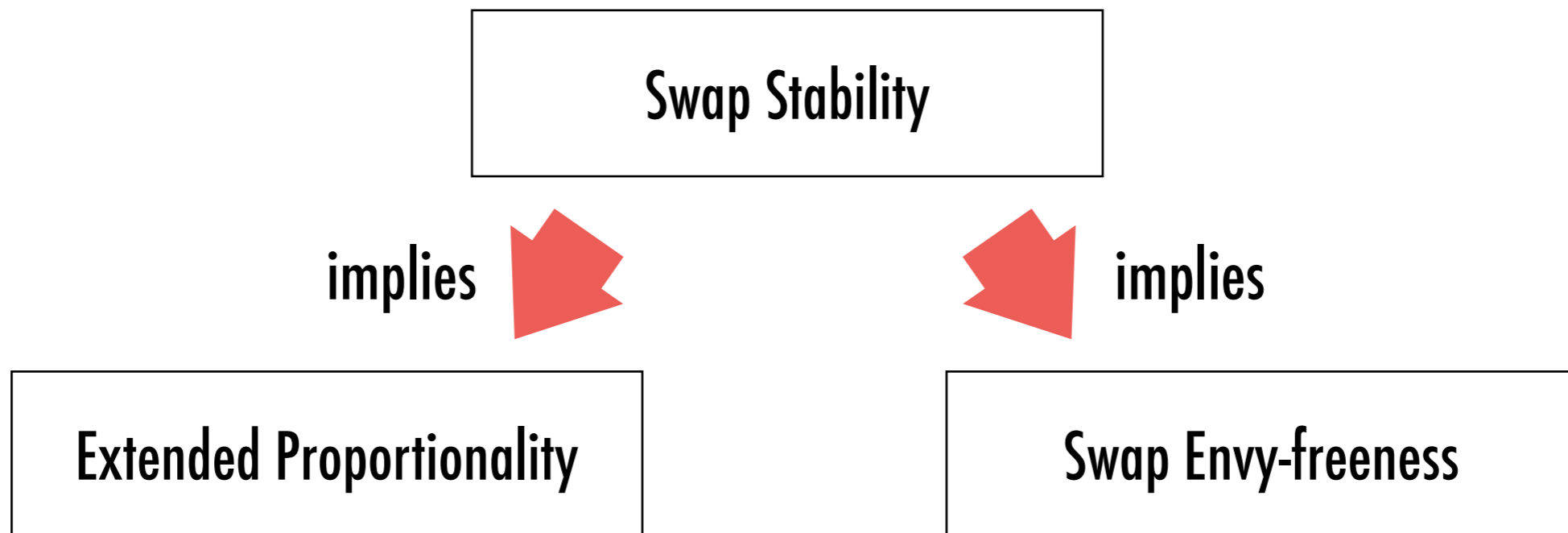
An allocation **A** is swap stable if for every three agents **i**, **j**, and **k** we have

$$V_{j,i}(\mathcal{A}_j) + V_{k,i}(\mathcal{A}_k) \geq V_{j,i}(\mathcal{A}_k) + V_{k,i}(\mathcal{A}_j)$$

# Relationship between criteria



# Relationship between criteria



But is **extended proportionality** the best extension of proportionality?

# Average Share

Ghods et al. (2018)

Consider the average utility agent  $i$  gains by allocating item  $b$  to each agent,

$$\bar{V}_i(\{b\}) = \frac{1}{n} \sum_{j \in \mathcal{N}} V_{j,i}(\{b\})$$

# Average Share

Ghods et al. (2018)

Average Share of agent  $i$  equals the sum of these average values for all items,

$$\bar{V}_i = \sum_{b \in \mathcal{M}} \sum_{j \in \mathcal{N}} V_{j,i}(\{b\})$$

# Average Share

Ghodsí et al. (2018)

An allocation **A** is average  
if for each agent we have

$$U_i(\mathcal{A}) \geq \bar{V}_i$$


# Average Share **vs** Extended Proportionality

It is easy to observe that in **network externalities** model, we have the following:

$$\hat{V}_i / n = V_i(\mathcal{M}) \cdot (\max_j w_{j,i}) / n$$

$$\bar{V}_i = V_i(\mathcal{M}) \cdot (\sum_j w_{j,i}) / n$$

# Average Share **vs** Extended Proportionality

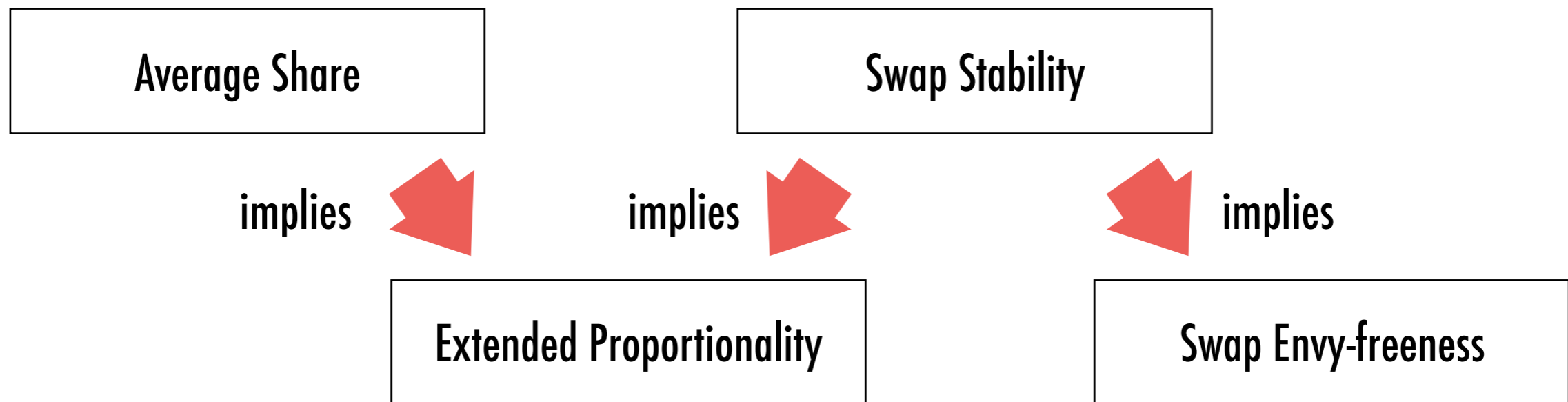
 **Average Share** is more sensitive to externalities in comparison to **Extended Proportionality**.

$$\hat{V}_i / n = V_i(\mathcal{M}) \cdot (\max_j w_{j,i}) / n$$

$$\bar{V}_i = V_i(\mathcal{M}) \cdot (\sum_j w_{j,i}) / n$$



# Relationship between criteria



# Extended Maximin Share

Ghods et al. (2018)

We can utilize the notion of **cut and choose** to find a suitable fairness criterion to capture externalities in fair division of indivisible items.

# Extended Maximin Share

Ghods et al. (2018)

**Cut and choose** is consisted of two parts:

1. Division
2. Allocation

# Extended Maximin Share

Ghodsí et al. (2018)

## 1. Division:

Similar to **Maximin share**, we ask agent ***i*** to divide items into ***n*** bundles in a balanced way.

## 2. Allocation

**Note that the valuations is from the point of view of agent *i*.**

# Extended Maximin Share

Ghodsí et al. (2018)

1. Division

2. Allocation:

An **adversary** allocates the bundles to agents in a way that the utility of agent  $i$  minimizes.

# Extended Maximin Share

Ghods et al. (2018)

1. Division

2. Allocation:

An **adversary** allocates the bundles to agents in a way that the utility of agent  $i$  minimizes.



We call this minimized utility **EMMS <sub>$i$</sub>** .

# Extended Maximin Share

Ghods et al. (2018)

An allocation  $\mathbf{A}$  guarantees Extended Maximin Share, if for each agent we have

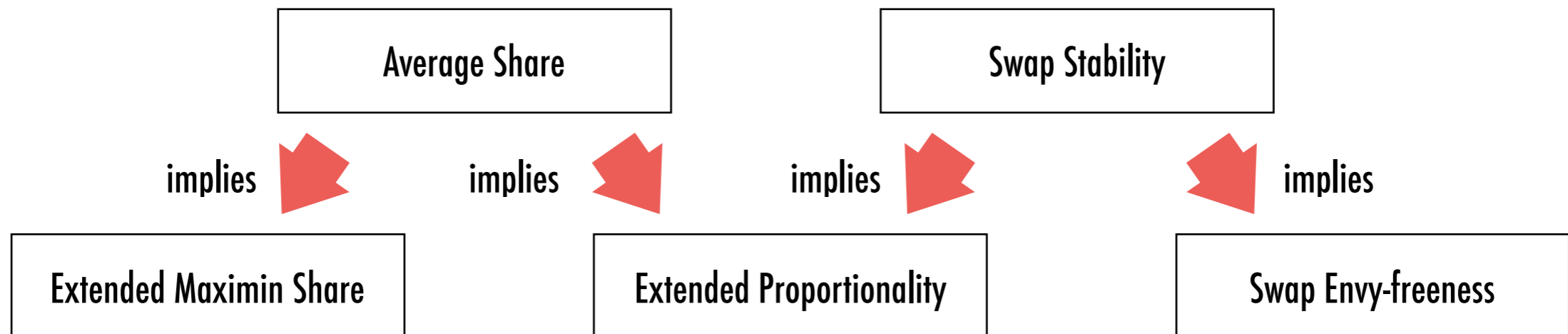
$$U_i(\mathcal{A}) \geq \text{EMMS}_i = \max_{P \in \Pi} U_i(\mathcal{W}_i(P))$$

$$\mathcal{W}_i(P) = \arg \min_{\mathcal{A} \in \Omega_P} U_i(\mathcal{A})$$

adversary



# Relationship between criteria





# Computation Aspects of **EMMS** in Network Externalities model

# Computing **EMMS**

We can observe that computing **EMMS** is equivalent to the following problem:

**Given a set of items  $M$  and a sorted vector of weights  $w$  in decreasing order, what is the maximum value of this function if agent  $i$  partition  $M$  into  $n$  bundles where vector  $x$  is the sorted values of the bundles in increasing order.**

$$w \cdot x = \sum_{i=1}^n w_i \cdot x_i$$

# Computing **EMMS**

Given a set of items  $M$  and a sorted vector of weights  $w$  in decreasing order, what is the maximum value of this function if agent  $i$  partition  $M$  into  $n$  bundles where vector  $x$  is the sorted values of the bundles in increasing order.

$$w \cdot x = \sum_{i=1}^n w_i \cdot x_i$$

This is the utility agent  $i$  gains if an **adversary** allocates the bundles.

# Computing **EMMS**

The most common partitioning schemes are the special cases of this problem:

1. Maximin partition

$$w_1 = 1, w_2 = 0, \dots, w_n = 0$$

2. Minimax partition

$$w_1 = \frac{1}{n-1}, \dots, w_{n-1} = \frac{1}{n-1}, w_n = 0$$

3. Leximin partition

$$w_1 = 1 - \epsilon, w_2 = \epsilon - \epsilon^2, \dots, w_n = \epsilon^{n-1} - \epsilon^n$$

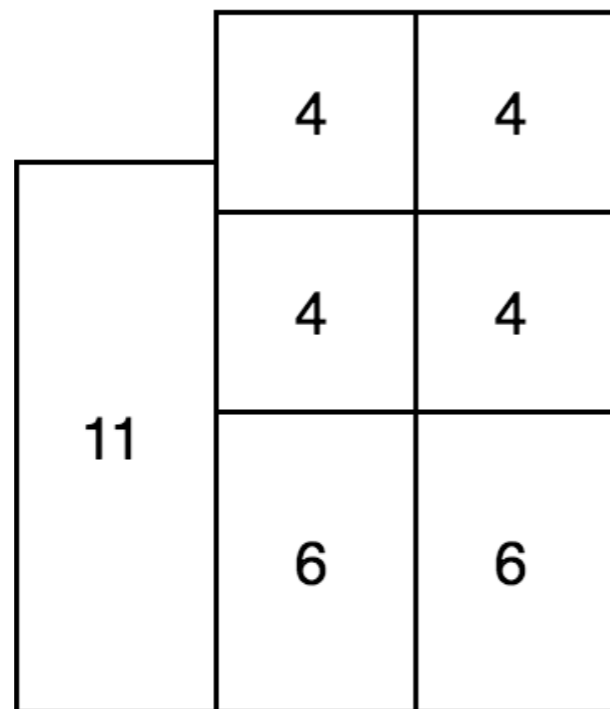
# Computing **EMMS**

The most common partitioning schemes are  
the special cases of this problem:

 It is **NP-hard** to compute the value of **EMMS**.

# Computing **EMMS**

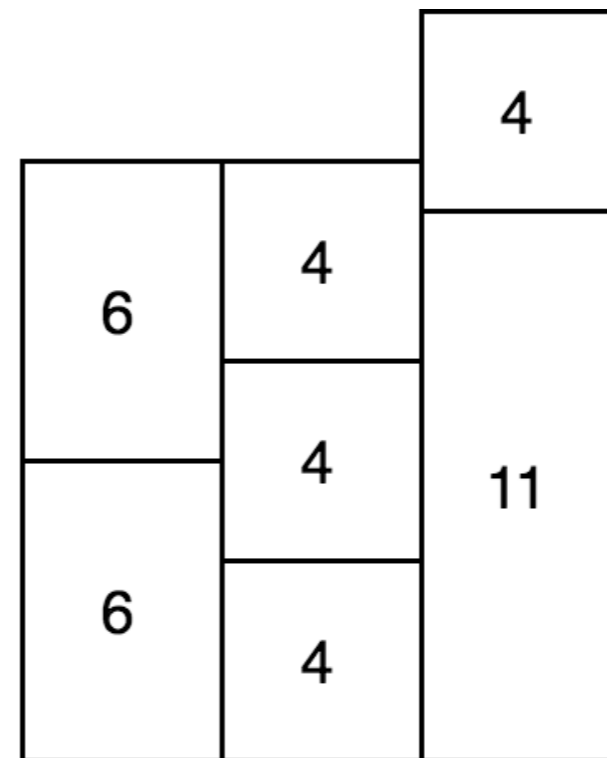
**minimax**



0.5    0.5    0

**=12.5**

**>**



0.5    0.5    0

**=12**

**maximin**

# Computing **EMMS**

minimax

		4	4
		4	4
11		6	6

1 0 0

=11

<

			4
6		4	
		4	
6		4	

1 0 0

=12

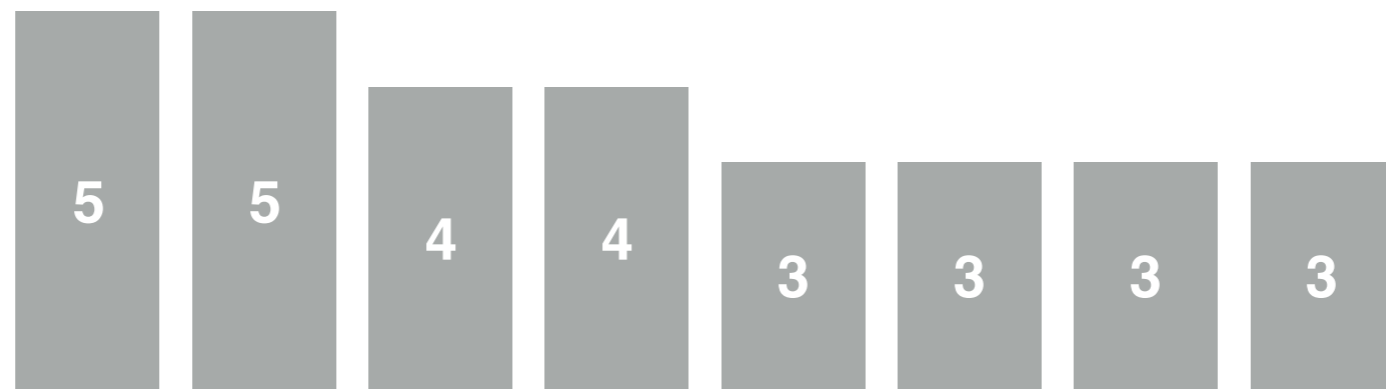
maximin

# Greedy Approach

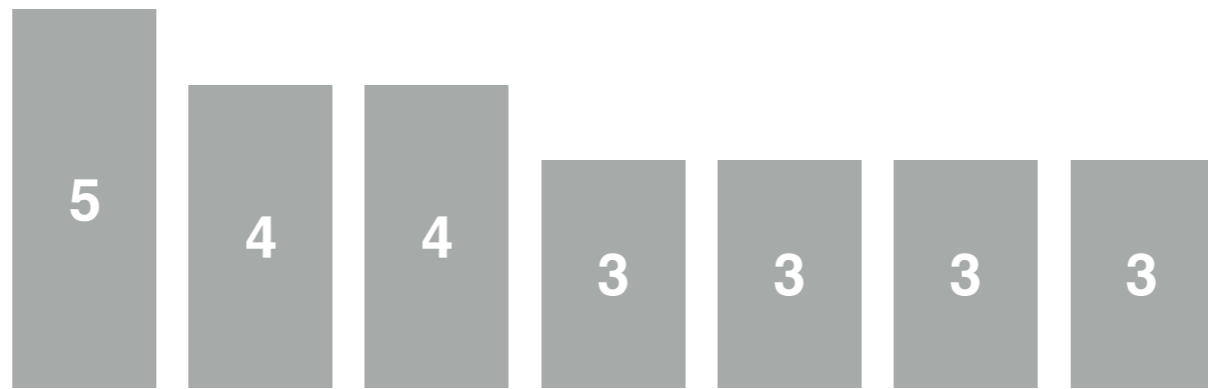
A simple greedy algorithm would achieve a  $1/2$ -approximation of the optimum answer.



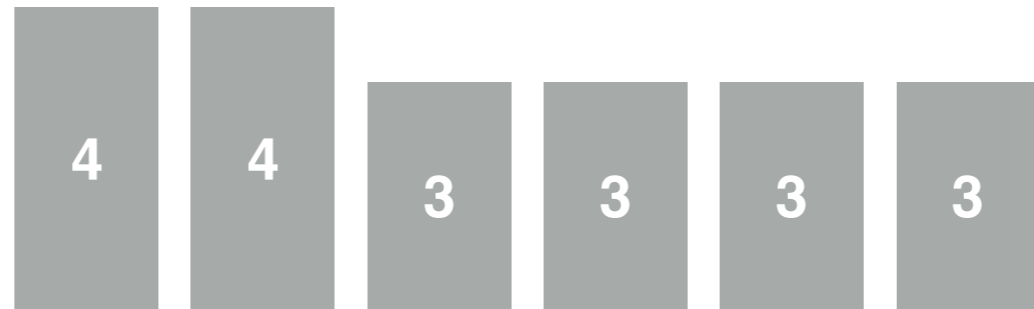
# LPT Algorithm



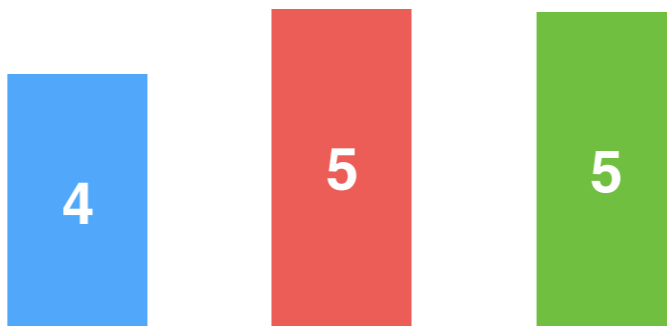
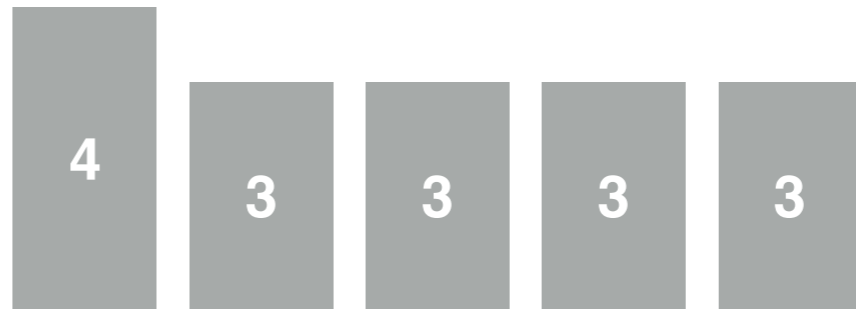
# LPT Algorithm



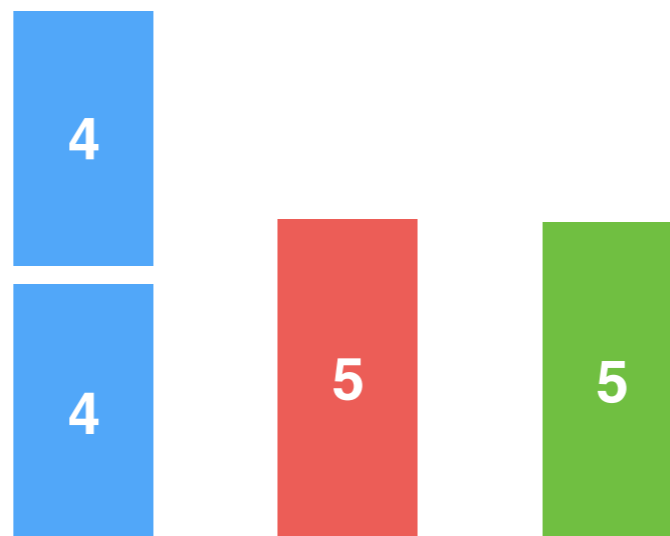
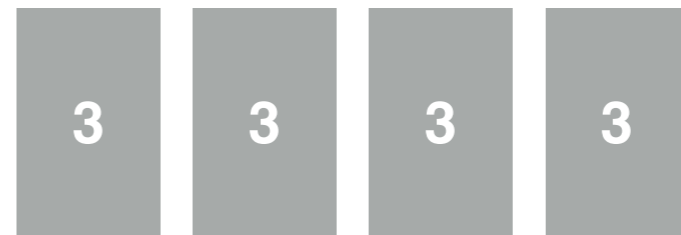
# LPT Algorithm



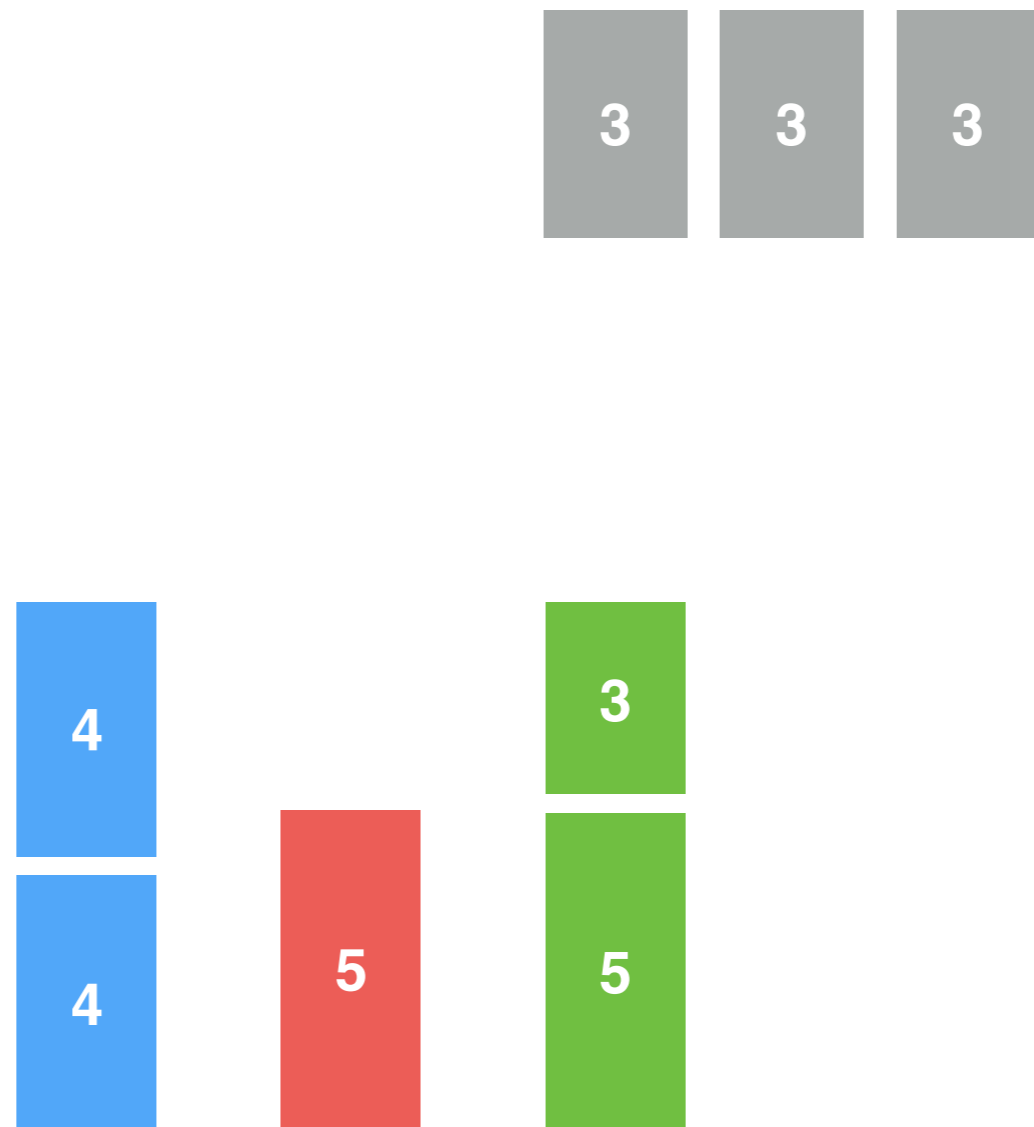
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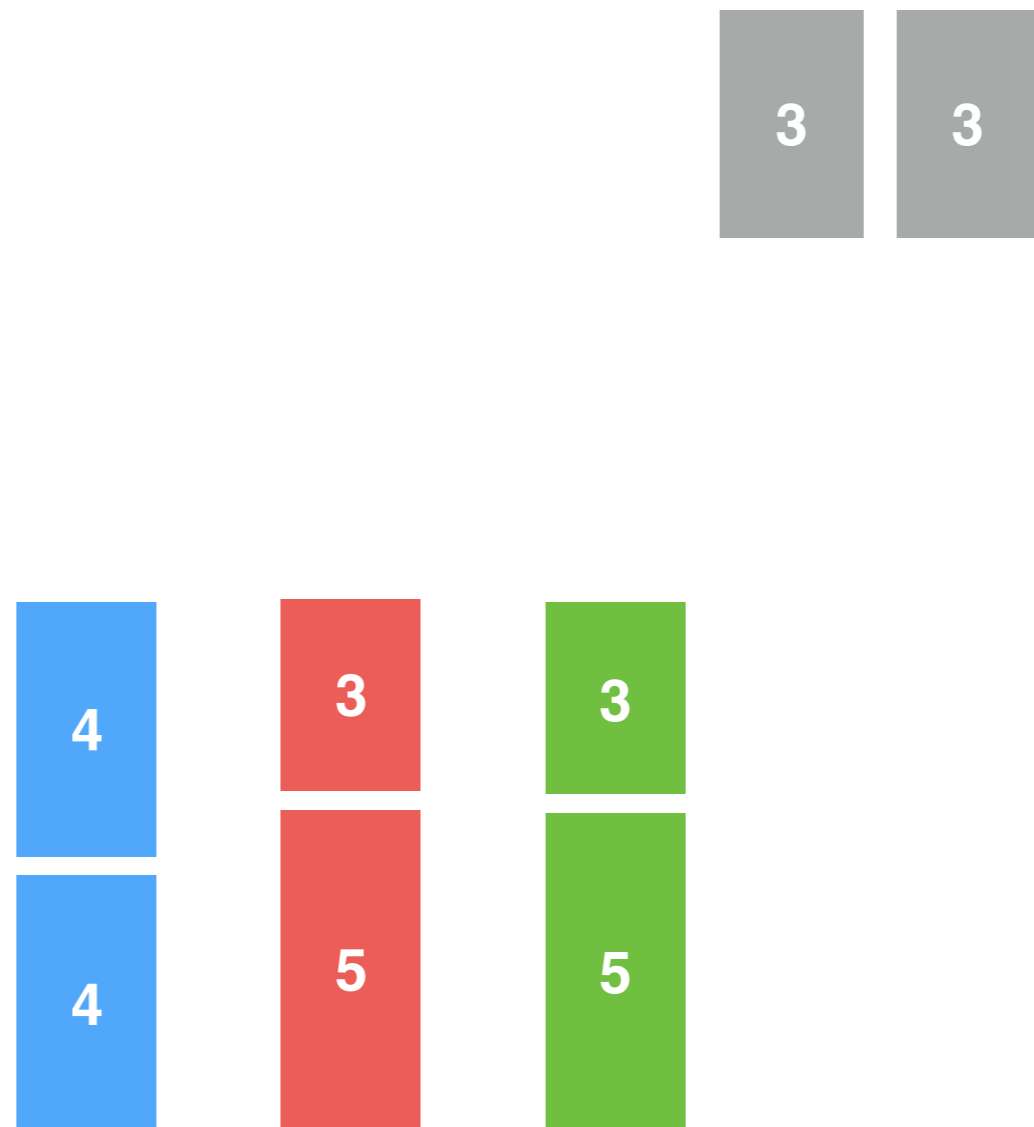
# LPT Algorithm



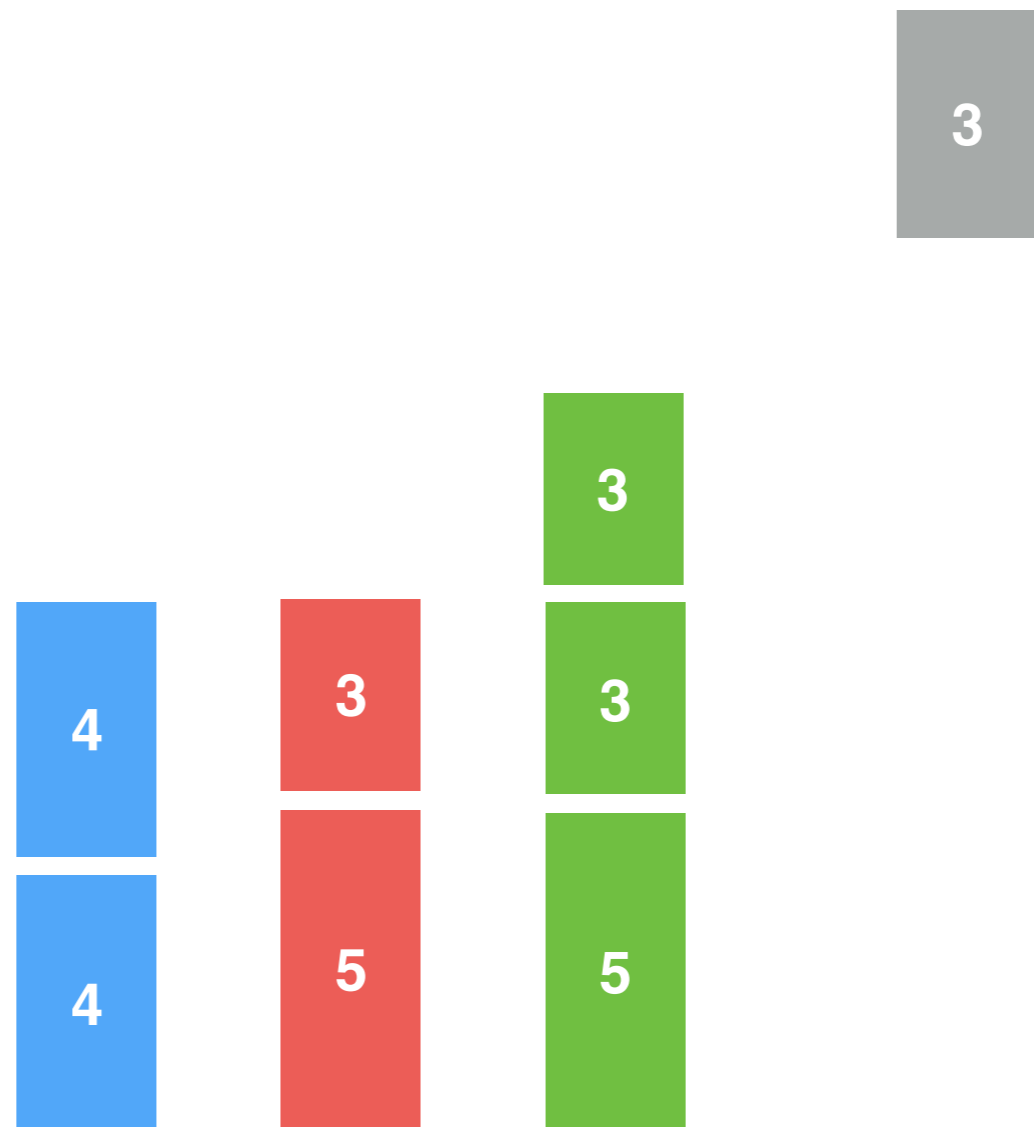
# LPT Algorithm



# LPT Algorithm

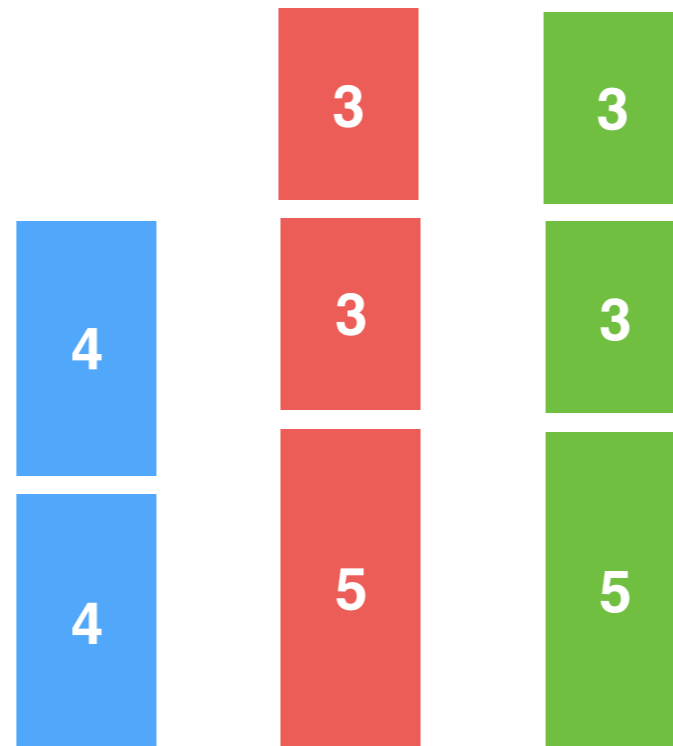


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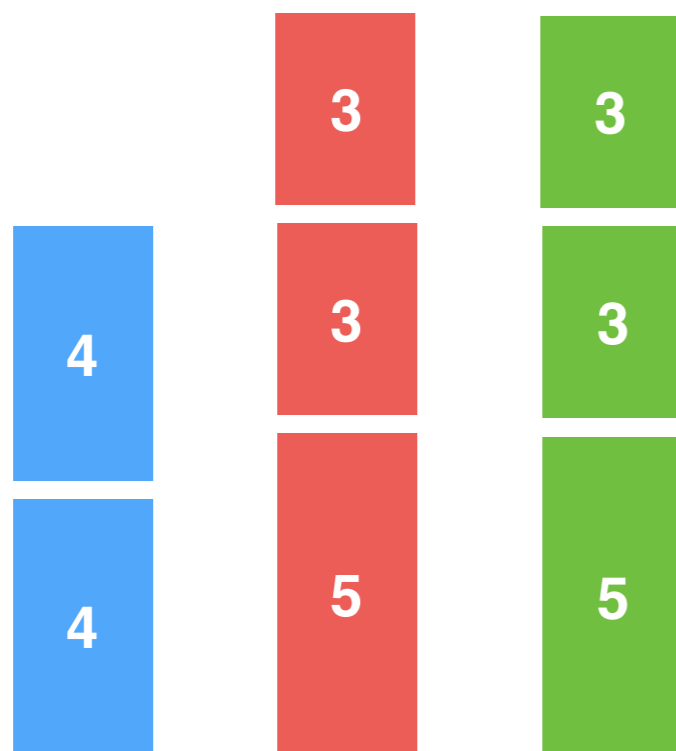




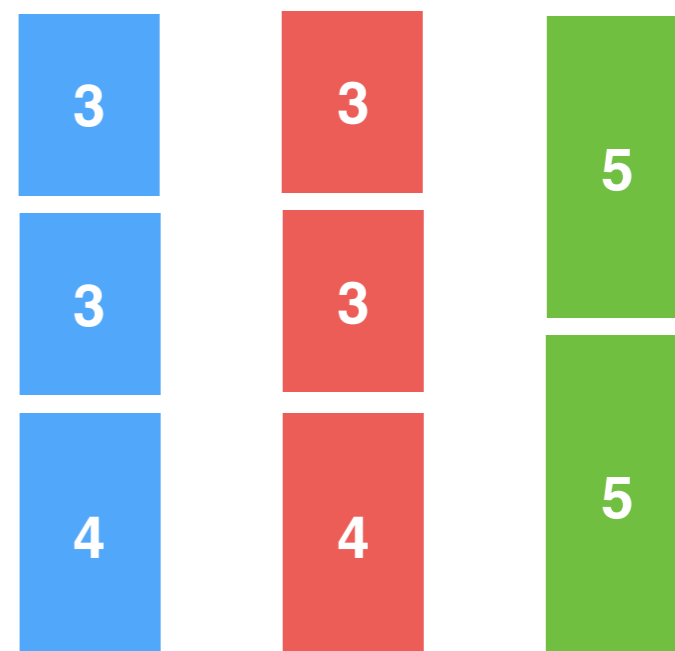
# LPT Algorithm



# LPT Algorithm



**LPT partition**



**Optimal partition**

# Computing **EMMS**

Ghods et al. (2018)

**Theorem 4.3.** The **LPT** algorithm provides a partition which approximates **EMMS** by a factor of  $1/2$ .

Regardless of the weights

# Fair Allocation in Network Externalities model

# Self Reliance

We say an agent **i** is  **$\beta$ -self-reliant** if

$$w_{i,i} \geq \beta$$

# Fair allocation

Ghods et al. (2018)

**Theorem 5.2.** If all the agents are  **$\beta$ -self-reliant**, then there exists an allocation that guarantees  **$\beta/2$ EMMS**.

Main result

# Fair allocation

Ghods et al. (2018)

**Corollary 5.6.** If all the agents are  **$\beta$ -self-reliant**, then we can find an allocation that guarantees  **$\beta/4$ EMMS**.

The algorithm depends on the structure of the **optimal** partition for each agent which we cannot find, but we can use **LPT** partition instead.

**Thank you!**