# Fair Allocation of indivisible goods

with externalities

Hamed Saleh

#### **Externalities**

There are objects to be distributed among agent,

where each agent gains a utility,

when an object is allocated to her.

 $V_i(\{b\})$ 

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 tor each agent.

With externalities



items allocated to other agents is important for each agent.

With externalities



items allocated to other agents is important for each agent.

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 Mode

Modeling the externalities based on an influence graph

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

The utility of each agent is based on the edge weights



# Network Externalities Mode

Modeling the externalities based on an influence graph



are normalized,

The weights of the edges



Network Externalities Mode

## 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?

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

### 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,

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

# **Extended** Proportionality

Branzei et al. (2013)

An allocation A is extended-proportional

if for each we have

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

### Swap envy-freeness

Velez (2011)



### Swap envy-freeness

Velez (2011)



### Swap envy-treeness

Velez (2011)

An allocation **A** is swap envy-free if for every pair of agents i and j we have

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

### Swap Stability

Branzei et al. (2013)



### Swap Stability

Branzei et al. (2013)



### Swap Stability

Branzei et al. (2013)

An allocation  $\mathbf{A}$  is swap stable if for every

three agents i, j, and k we have

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

# Relationship between criteria



# Relationship between criteria



But is extended proportionality the best extension of proportionality?

### Average Share

Ghodsi et al. (2018)

Consider the average utility agent i gains by

allocating item **b** to each agent,

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

### Average Share

Ghodsi et al. (2018)

Average Share of agent i equals the sum of these

average values for all items,

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

### Average Share

Ghodsi et al. (2018)

An allocation  $\mathbf{A}$  is average if for each agent we have

 $U_i(\mathcal{A}) \geq \overline{V_i}$ 

# Average Share vs Extended Proportionality

It is easy to observe that in network externalities

model, we have the following:

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

# Average Share vs Extended Proportionality



comparison to Extended Proportionality.

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





Ghodsi 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.

Ghodsi et al. (2018)

# Cut and choose is consisted of two parts:

- 1. Division
- 2. Allocation

Ghodsi 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.

Ghodsi et al. (2018)

- 1. Division
- 2. Allocation:

An adversary allocates the bundles to agents in

a way that the utility of agent i minimizes.

Ghodsi 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>.

adversary

 $\mathcal{W}_i(P) = \operatorname{arg\,min}_{\mathcal{A} \in \Omega_P} U_i(\mathcal{A})$ 

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

Maximin Share, if for each agent we have

An allocation A guarantees Extended

**Extended** Maximin Share

Ghodsi et al. (2018)





### Computation Aspects of EMMS in Network Externalities mode

We can observe that computing **EMMS** is

equivalent to the following problem:

bundles where vector x is the sorted values of the bundles in increasing order. 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

$$v \cdot x = \sum_{i=1}^{n} W_i \cdot x_i$$

bundles where vector x is the sorted values of the bundles in increasing order. 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

$$x = \sum_{i=1}^{n} W_i \cdot X_i$$

Z.

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

The most common partitioning schemes are

the special cases of this problem:

- 1. Maximin partition
- 2. Minimax partition
- 3. Leximin partition

$$w_{1} = 1, w_{2} = 0, \dots, w_{n} = 0$$
$$w_{1} = \frac{1}{n-1}, \dots, w_{n-1} = \frac{1}{n-1}, w_{n} = 0$$
$$w_{1} = 1 - \epsilon, w_{2} = \epsilon - \epsilon^{2}, \dots, w_{n} = \epsilon^{n-1} - \epsilon^{n}$$

The most common partitioning schemes are

the special cases of this problem:



#### minimax





0.5

0.5

0



Computing EMMS







#### maximin

#### minimax



Computing EMMS

 $\wedge$ 



0

0



#### maximin

### Greedy Approach

A simple greedy algorithm would achieve

a 1/2-approximation of the optimum answer.





G













ယ	
ω	
ယ	
ω	



ယ	
ω	
ω	



ယ ယ



ω



**Optimal partition** 





ω ω 4 4

#### **Regardless of the weights**

approximates EMMS by a factor of 1/2.

**Theorem 4.3.** The **LPT** algorithms provides a partition which

### Computing EMMS

Ghodsi et al. (2018)

#### in Network Externalities model Fair Allocation

#### Self Reliance

We say an agent i is β-self-relient if

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

#### Main result

**Theorem 5.2.** If all the agents are **β-self-relient**, then there exists an allocation that guarantees β/2EMMS.

Ghodsi et al. (2018)

Fair allocation

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

find an allocation that guarantees β/4EMMS.

Corollary 5.6. If all the agents are β-self-relient, then we can

Fair allocation

Ghodsi et al. (2018)

#### Thank you!