

# Fair Division of Indivisible Items

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# Maximin Share (MMS) [B11]

- Suppose we allow agent  $i$  to propose a partition of items into  $n$  bundles with the condition that  $i$  will choose at the end
- Clearly,  $i$  partitions items in a way that **maximizes** the value of her **least preferred bundle**
- $\mu_i :=$  Maximum value of  $i$ 's least preferred bundle
- $\Pi :=$  Set of all partitions of items into  $n$  bundles
- $\mu_i := \max_{A \in \Pi} \min_{A_k \in A} v_i(A_k)$
- **MMS Allocation:**  $A$  is called MMS if  $v_i(A_i) \geq \mu_i, \forall i$

# What is Known?

- Finding MMS value is NP-hard
  - PTAS for finding MMS value [W97]

## Existence (MMS allocation)?

- $n = 2$  : YES 
- $n > 2$  : NO [PW14]
- $\alpha$ -MMS allocation:  $v_i(A_i) \geq \alpha \cdot \mu_i$ 
  - 2/3-MMS exists [PW14, AMNS17, BK17, KPW18, G.MT18]
  - 3/4-MMS exists [GHSSY18]
  - $(3/4 + 1/(12n))$ -MMS exists [G.T20]

# Properties

- **Normalized valuations**

- **Scale free:**  $v_{ij} \leftarrow c \cdot v_{ij}, \forall j \in M$

- $\sum_j v_{ij} = n \Rightarrow \mu_i \leq 1$

- **Ordered Instance:** We can assume that agents' order of preferences for items is same:  $v_{i1} \geq v_{i2} \geq \dots v_{im}, \forall i \in N$

- **Valid Reduction ( $\alpha$ -MMS):** If there exists  $S \subseteq M$  and  $i^* \in N$

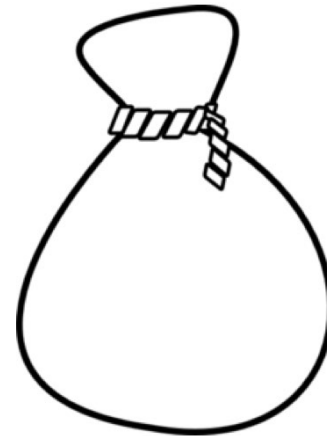
- $v_{i^*}(S) \geq \alpha \cdot \mu_{i^*}^n(M)$

- $\mu_i^{n-1}(M \setminus S) \geq \mu_i^n(M), \forall i \neq i^*$

$\Rightarrow$  We can reduce the instance size!

# Challenge

- Allocation of **high-value items!**
- If for all  $i \in N$ 
  - $v_i(M) = n \Rightarrow \mu_i \leq 1$
  - $v_{ij} \leq \epsilon, \forall i, j$



**Bag Filling Algorithm** for  $(1 - \epsilon)$ -MMS allocation:

Repeat until every agent is assigned a bag

- Start with an empty bag  $B$
- Keep adding items to  $B$  until some agent  $i$  values it  $\geq (1 - \epsilon)$
- Assign  $B$  to  $i$  and remove them



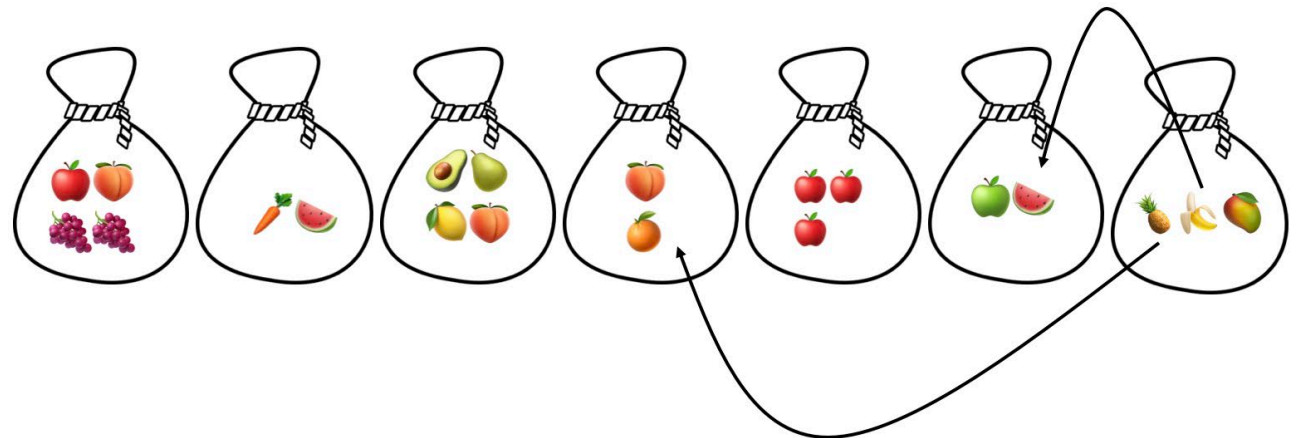
# 1/2-MMS Allocation

- **Assume** that  $\mu_i$  is known for all  $i$ 
  - Scale valuations so that  $\mu_i = 1 \Rightarrow v_i(M) \geq n$

## Step 1: Valid Reductions

- If  $v_{i1} \geq 1/2$  then assign item 1 to  $i$

## Step 2: Bag Filling



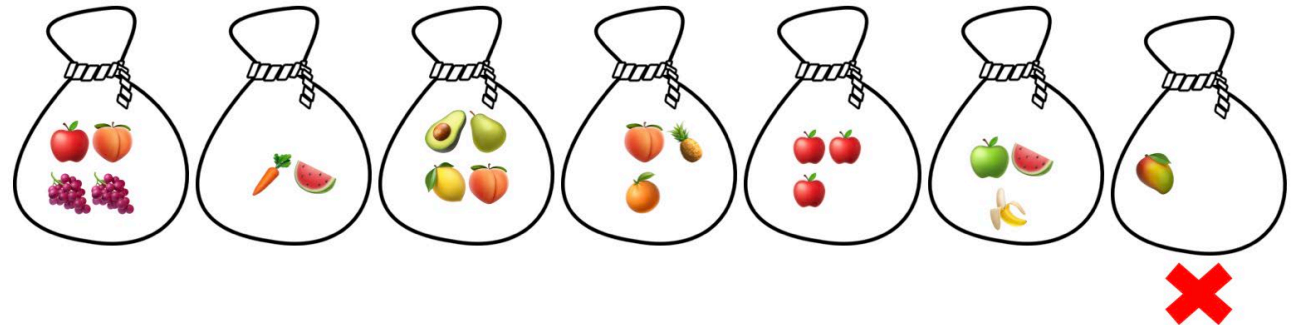
# 1/2-MMS Allocation

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## Step 1: Valid Reductions

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## Step 2: Bag Filling



# 1/2-MMS Allocation

- $\mu_i$  is not known

**Step 0: Normalize Valuations:**  $\sum_j v_{ij} = n \Rightarrow \mu_i \leq 1$

**Step 1: Valid Reductions**

- If  $v_{i1} \geq 1/2$  then assign item 1 to  $i$
- After every valid reduction, normalize valuations

**Step 2: Bag Filling**



# 2/3-MMS Allocation [G.MT19]

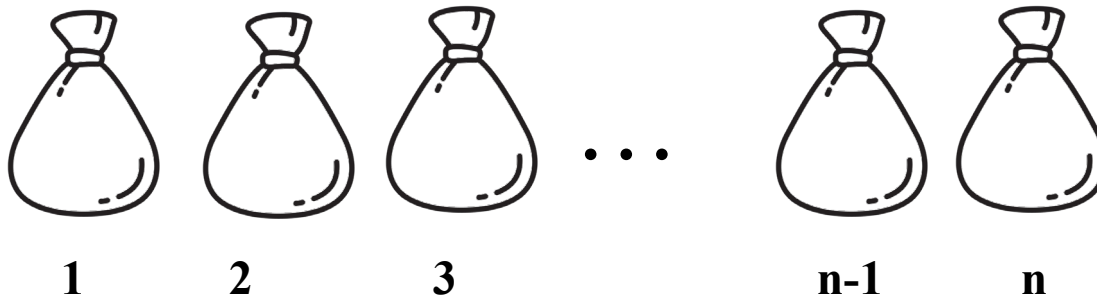
- **Assume** that  $\mu_i$  is known for all  $i$ 
  - Scale valuations so that  $\mu_i = 1 \Rightarrow v_i(M) \geq n$
- If all  $v_{ij} \leq 1/3$  then ?

## Step 1: Valid Reductions

- If  $v_{i1} \geq 2/3$  then assign item 1 to  $i$
- If  $v_{in} + v_{i(n+1)} \geq 2/3$  then assign  $\{n, n+1\}$  to  $i$

## Step 2: Generalized Bag Filling

- Initialize  $n$  bags  $\{B_1, \dots, B_n\}$  with  $B_k = \{k\}, \forall k$



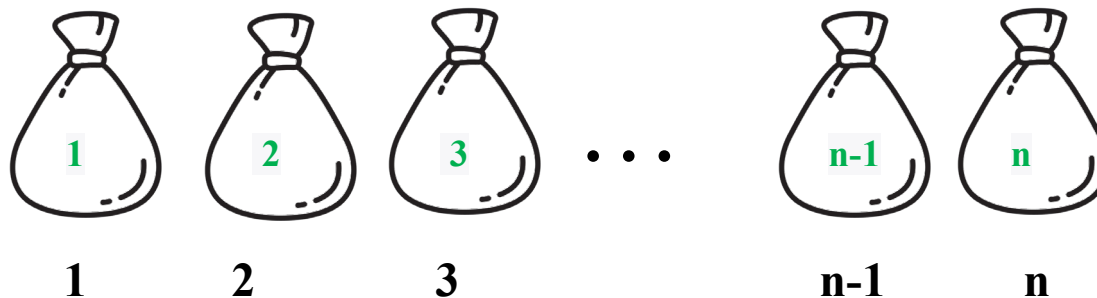
- Assume that  $\mu_i$  is known for all  $i$ 
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# 2/3-MMS Allocation [G.MT19]

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**Step 2: Generalized Bag Filling**

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# New Fairness Notions

- $n$  agents,  $m$  **indivisible** items (like cell phone, painting, etc.)
- Each agent  $i$  has a **valuation** function over **subset of items** denoted by  $v_i : 2^m \rightarrow \mathbb{R}$
- **Goal:** fair and efficient allocation

## Fairness:

Envy-free (EF)

Proportionality (Prop)

## Efficiency:

Pareto optimal (PO)

**Maximum Nash Welfare (MNW)**

|                   |       |                  |
|-------------------|-------|------------------|
| EF1               | EFX   | Lecture 3        |
| MMS               | Prop1 | Lecture 4        |
| <b>Guarantees</b> |       | <b>Lecture 5</b> |

# Objectives

- Maximize the sum of valuations

(**Utilitarian** Welfare):

$$UW(A) = \sum_i v_i(A_i)$$



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(Max-Min-Fairness, **Egalitarian** Welfare):

$$EW(A) = \min_i v_i(A_i)$$



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- Maximize the minimum of valuations

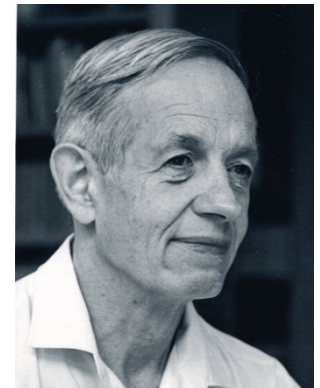
(Max-Min-Fairness, **Egalitarian** Welfare):

$$EW(A) = \min_i v_i(A_i)$$

- Maximize the geometric mean of valuations

( $\approx$  **Efficiency + Fairness**, **Maximum Nash Welfare**):

$$NW(A) = \left( \prod_{i \in A} v_i(A_i) \right)^{1/n} \quad \text{Scale-free}$$



# Maximum Nash Welfare (MNW)

- **Maximum Nash welfare (MNW):** An allocation  $A$  that maximizes the Nash welfare among all feasible allocations i.e.,

$$A^* = \arg \max_A (\prod_i v_i(A_i))^{1/n}$$

**Additive Valuations** ( $v_i(A_i) = \sum_{j \in A_i} v_{ij}$ ):

- **Divisible Items:** MNW  $\equiv$  CEEI  $\Rightarrow$  Envy-free + Prop + PO + ...
- **Indivisible Items:** MNW  $\Rightarrow$  EF1 + PO +  $\Omega(\frac{1}{\sqrt{n}})$ -MMS [CKMPSW16]
  - Existence of EF1 + PO allocation



# MNW (additive)

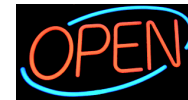
- APX-hard [Lee17]; 1.069-hardness [G.HM18]

## Approximation:

- $\rho$ -approximate MNW allocation  $A$ :  $\rho \cdot \text{NW}(A) \geq \text{MNW}$

- 2 [CG15, CDGJMVY17],  $e$  [AOSS17]

- 1.45 [BKV18] (pEF1 approach)



*Close the gaps!*

- Fairness Guarantees

- Prop1 + PO +  $\frac{1}{2n}$ -MMS + 2-MNW [G.M19]

# MNW: Generalizations

- Non-symmetric Agents (different entitlements/weights)
  - Weighted envy-free, weighted proportionality
  - MNW (weighted geometric mean)

## ■ Beyond Additive Valuations

**Additive**  $\subset$  SC  $\subset$  OXS  $\subset$  Rado  $\subset$  Submodular  $\subset$  Subadditive  
Budget additive

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# The **non-symmetric** MNW Problem

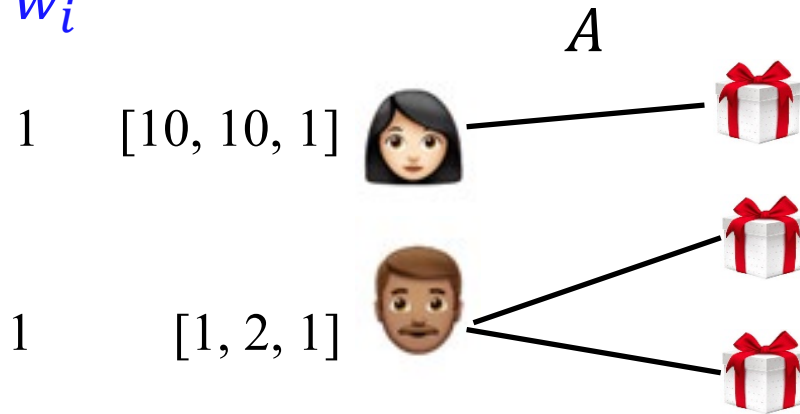
- Non-symmetric MNW was proposed in [HS72, K77] and has been extensively studied and used in many applications
  - Agent  $i$  has a weight of  $w_i$

$$NW(A) = \left( \prod_i v_i(A_i)^{w_i} \right)^{1/\sum_i w_i} \quad \text{weighted geometric mean of agents' valuations}$$

- $MNW = \arg \max_A NW(A)$
- $\rho$ -approximate MNW allocation  $A$ :  $\rho \cdot NW(A) \geq MNW$

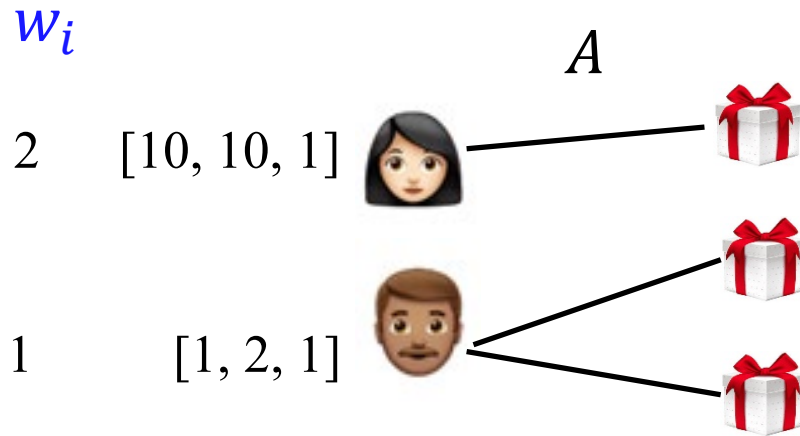
# Example (additive)

$w_i$



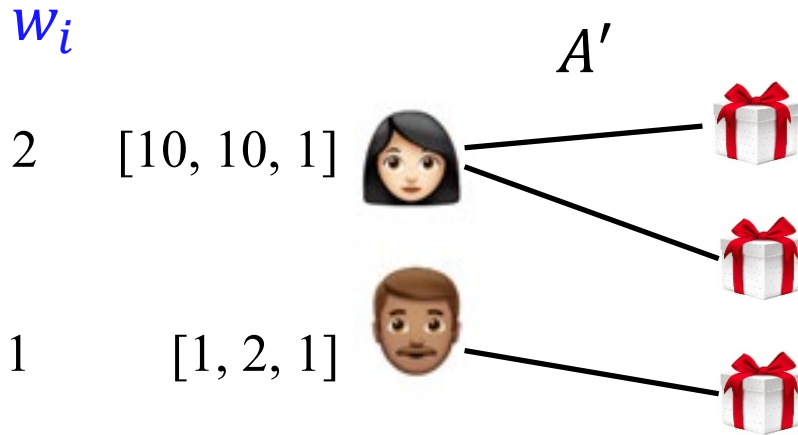
$$\text{MNW} = \text{NW}(A) = (10^1 \cdot 3^1)^{1/2}$$

# Example (additive)



$$NW(A) = (10^2 \cdot 3^1)^{1/3}$$

# Example (additive)



$$NW(A) = (10^2 \cdot 3^1)^{1/3} < (20^2 \cdot 1^1)^{1/3} = NW(A') = MNW$$

# MNW Approximations: Additive

|               | <b>Lower bound</b> | <b>Upper Bound</b> |
|---------------|--------------------|--------------------|
| Symmetric     | 1.069              | 1.45               |
| Non-symmetric | 1.069              | $O(n)$             |

$n$ : # of agents



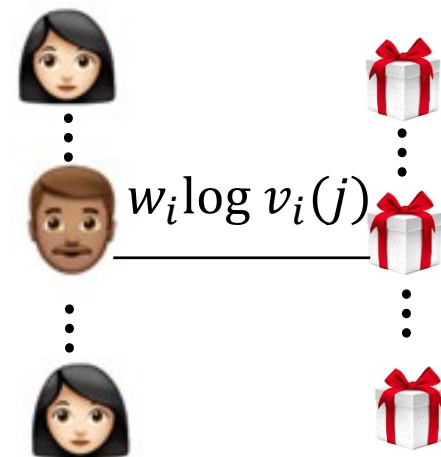
Constant factor? sublinear?



# Matching ( $m = n$ )

$$NW(A) = \left( \prod_i v_i(A_i)^{w_i} \right)^{1/\sum_i w_i}$$

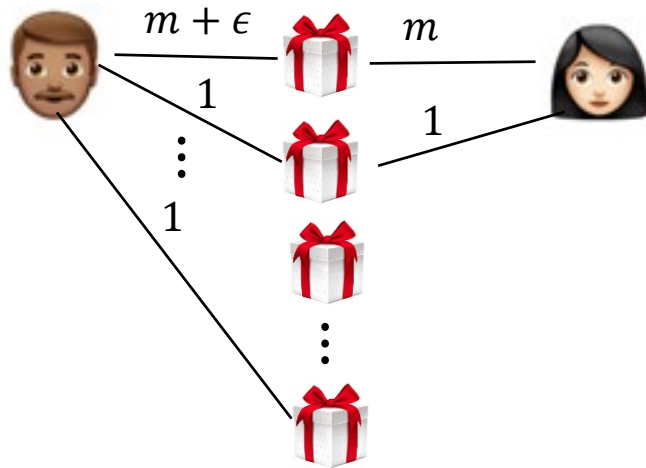
$$MNW = \max_A NW(A) \equiv \max_A \sum_i w_i \log v_i(A_i)$$



**Claim:** If  $m = n$ , then max-weight matching outputs MNW

$$m > n$$

- How good is max-weight matching?



$$\text{NW}(A^*) \simeq m$$

$$\text{NW}(A) \simeq \sqrt{2m}$$

- **Issue:** Allocation of high-value items!

# Round Robin Procedure

- $H_i$ : Set of  $n$  highest-valued items for agent  $i$
- $u_i = v_i(M \setminus H_i)$
- Guarantee?

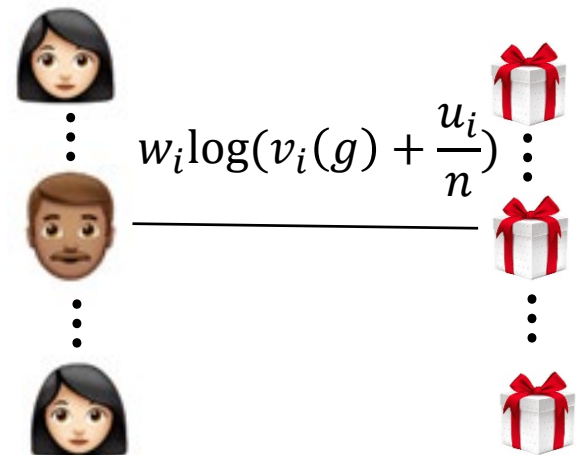
- $H_i$ : Set of  $n$  highest-valued items for agent  $i$
- $u_i = v_i(M \setminus H_i)$
- Round-Robin guarantees  $\geq \frac{u_i}{n}$

### MNW allocation $A^*$ :

- $g_i^*$ : highest-valued item in  $A_i^*$
- $v_i(A_i^*) \leq nv_i(g_i^*) + u_i$   
 $\leq n \left( v_i(g_i^*) + \frac{u_i}{n} \right)$
- If  $v_i(A_i) \geq v_i(g_i^*) + \frac{u_i}{n}$ , then  $A$  is  $O(n)$ -approximation!

# Matching + Round-Robin [G.KK20]

- $H_i$ : Set of  $2n$  highest-valued items for agent  $i$
- $u_i = v_i(M \setminus H_i)$
- Allocate one item to each agent using max-weight matching with weights  $w_i \log(v_i(g) + \frac{u_i}{n})$ :  $y_i^*$  is allocated to  $i$
- $A \leftarrow$  Allocate remaining items using Round Robin



- $H_i$ : Set of  $2n$  highest-valued items for agent  $i$
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- $A \leftarrow$  Allocate remaining items using Round Robin

- $g_i^*$ : highest-valued item in  $A_i^*$

- $v_i(A_i^*) \leq 2nv_i(g_i^*) + u_i \implies \text{MNW} \leq 2n \left( \prod_i \left( v_i(g_i^*) + \frac{u_i}{n} \right)^{w_i} \right)^{1/\sum_i w_i}$

- $v_i(A_i) \geq v_i(y_i^*) + \frac{u_i}{n}$

$$\implies \text{NW}(A) \geq \left( \prod_i \left( v_i(y_i^*) + \frac{u_i}{n} \right)^{w_i} \right)^{\frac{1}{\sum_i w_i}} \geq \left( \prod_i \left( v_i(g_i^*) + \frac{u_i}{n} \right)^{w_i} \right)^{\frac{1}{\sum_i w_i}}$$

**Theorem** [G.KK20]:  $A$  is  $2n$ -MNW + EF1

# Generalizations

- Non-symmetric Agents (different entitlements/weights)
  - Weighted envy-free, weighted proportionality
  - MNW (weighted geometric mean)

- **Beyond Additive**

Additive  $\subset$  SC  $\subset$  OXS  $\subset$  Rado  $\subset$  Submodular  $\subset$  **Subadditive**  
Budget additive

non-negative monotone:  $v(S) \leq v(T)$ ,  $S \subseteq T$

**Subadditive:**  $v(A \cup B) \leq v(A) + v(B)$ ,  $\forall A, B$

# Additive valuations are restrictive



100



# Additive valuations are restrictive



100



100

# Additive valuations are restrictive



100

+



100

125  $\neq$  100 + 100

# MNW Approximations: Symmetric Agents

Additive  $\subset$  SC  $\subset$  OXS  $\subset$  Rado  $\subset$  Submodular  $\subset$  Subadditive  
 Budget additive

| <b>Valuation</b>                                 | <b>Lower bound</b>  | <b>Upper Bound</b> |
|--|---------------------|--------------------|
| Additive<br>Budget additive<br>Separable concave | 1.069               | 1.45               |
| OXS<br>Rado                                      | 1.069               | $O(1)$             |
| Submodular                                       | 1.58                | $O(n)$             |
| Subadditive                                      | $O(n^{1-\epsilon})$ | $O(n)$             |

$n$ : # of agents

# MNW Approximations: Non-symmetric Agents

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 Budget additive

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| Additive<br>Budget additive<br>Separable concave<br>OXS<br>Rado | 1.069               | $O(n)$      |
| Submodular  | 1.58                | $O(n)$      |
| Subadditive   | $O(n^{1-\epsilon})$ | $O(n)$      |

$n$ : # of agents

# Envy-free (EF) Allocation

**Claim:** An EF allocation  $A$  is  $O(n)$ -approximation

# 1/2-EFX Allocation

- 1/2-EFX allocation  $A$ :  $v_i(A_i) \geq \frac{1}{2} v_i(A_j \setminus g), \forall g \in A_j, \forall i, j$

**Claim:** If  $|A_i| \geq 2, \forall i$ , then  $A$  is  $O(n)$ -approximation

## $O(n)$ Algorithm [CG.M20]

- $H_i$  : Set of  $n$  highest-valued items for agent  $i$
- Allocate one item per agent using max-weight matching with weights  $w_i \log(v_i(g) + \frac{v_i(M \setminus H_i)}{n})$  :  $y_i^*$  is allocated to  $i$
- $A \leftarrow$  Allocate remaining items using  $\frac{1}{2}$ -EFX algorithm

**Claim:**  $A$  is  $O(n)$ -MNW and  $\frac{1}{2}$ -EFX allocation

**Claim:**  $A$  is  $O(n)$ -MNW

**Proof (sketch):**

■  $Y \leftarrow \cup_i y_i^*$ ;  $g_i^*$ : highest-valued item in MNW allocation  $A_i^*$

■ 
$$v_i(A_i^*) \leq n v_i(g_i^*) + v_i(M \setminus H_i) = n \left( v_i(g_i^*) + \frac{v_i(M \setminus H_i)}{n} \right)$$

$$\implies \text{MNW} \leq n \left( \prod_i \left( v_i(g_i^*) + \frac{v_i(M \setminus H_i)}{n} \right)^{w_i} \right)^{1 / \sum_i w_i}$$

■ 
$$v_i(A_i) \geq v_i(y_i^*)$$

■ 
$$v_i(A_i) \geq \frac{v_i(M \setminus Y)}{4n} \geq \frac{v_i(M \setminus H_i) - n v_i(y_i^*)}{4n}$$

EXERCISE 

■ 
$$v_i(A_i) \geq \frac{1}{8} \left( v_i(y_i^*) + \frac{v_i(M \setminus H_i)}{n} \right)$$

$$\text{NW}(A) \geq \frac{1}{8} \left( \prod_i \left( v_i(y_i^*) + \frac{v_i(M \setminus H_i)}{n} \right)^{w_i} \right)^{\frac{1}{\sum_i w_i}} \geq \frac{1}{8} \left( \prod_i \left( v_i(g_i^*) + \frac{v_i(M \setminus H_i)}{n} \right)^{w_i} \right)^{\frac{1}{\sum_i w_i}}$$



# MNW Approximations: Symmetric Agents

$\text{Additive} \subset \text{SC} \subset \text{OXS} \subset \text{Rado} \subset \text{Submodular} \subset \text{Subadditive}$   
 $\text{Budget additive}$

| Valuation  | Lower bound | Upper Bound |
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