

## Seminar Approximation Algorithms

# Approximating Nash Social Welfare under Submodular Valuations through (Un)Matchings

Based on a paper of the same name by Garg, Kulkarni and Kulkarni

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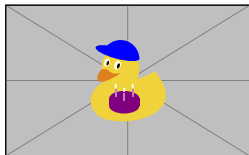
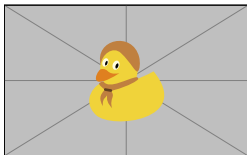
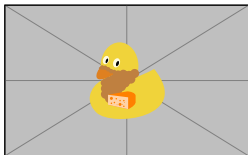
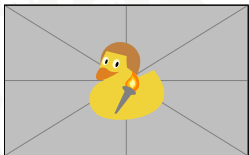
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# What is the issue?

We need to distribute goods amongst recipients *fast*, *efficient* and *fairly*.

Where is this encountered?

- industrial procurement
- mobile edge computing
- satellites
- water withdrawal



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# 1

## Preliminaries



Setting:

- goods: set  $\mathcal{G}$  of  $m$  items
  - unsharable
  - indivisible
- recipients: set  $\mathcal{A}$  of  $n$  agents

### Definition (1)

An *allocation* is a tuple  $\mathbf{x} = (\mathbf{x}_i)_{i \in \mathcal{A}}$  of bundles  $\mathbf{x}_i \subset \mathcal{G}$  such that each item is element of precisely one bundle.

Item  $j$  is *assigned* to agent  $i$  if  $j \in \mathbf{x}_i$ .

But how to measure its efficiency and fairness?

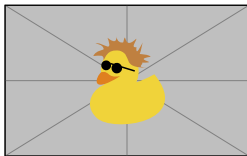
# Valuation Functions

Requirements:

- monotonically non-decreasing:  $v_i(\mathcal{S}_1) \leq v_i(\mathcal{S}_2) \quad \forall \mathcal{S}_1 \subset \mathcal{S}_2 \subset \mathcal{G}$
- normalised:  $v_i(\emptyset) = 0$
- non-negative:  $v_i(\mathcal{S}) \geq 0 \quad \forall \mathcal{S} \subset \mathcal{G}$

Types:

- additive:  $v_i(\mathcal{S}) := \sum_{j \in \mathcal{S}} v_i(j) \quad \forall \mathcal{S} \subset \mathcal{G}$
- submodular:  $v_i(\mathcal{S}_1 \mid \mathcal{S}_2) := v_i(\mathcal{S}_1 \cup \mathcal{S}_2) - v_i(\mathcal{S}_2) \quad \forall \mathcal{S}_1, \mathcal{S}_2 \subset \mathcal{G} \text{ with } \mathcal{S}_1, \mathcal{S}_2 \text{ disjoint}$ 
  - more general (encompasses additivity)
  - diminishing returns



# Asymmetric Maximum Nash Social Welfare Problem

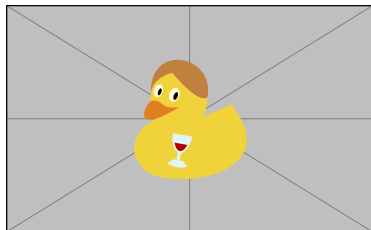
## Problem (2)

$$\mathbf{x}^* \stackrel{!}{=} \arg \max_{\mathbf{x} \in X_{\mathcal{A}}(\mathcal{G})} \{\text{NSW}(\mathbf{x})\} \quad \text{with } \text{NSW}(\mathbf{x}) := \left( \prod_{i \in \mathcal{A}} v_i(\mathbf{x}_i)^{\eta_i} \right)^{1 / \sum_{i \in \mathcal{A}} \eta_i}$$

- $X_{\mathcal{A}}(\mathcal{G})$ : all possible allocations
- $\eta_i$ : agent weight
- middle ground between efficiency and fairness

## Challenge

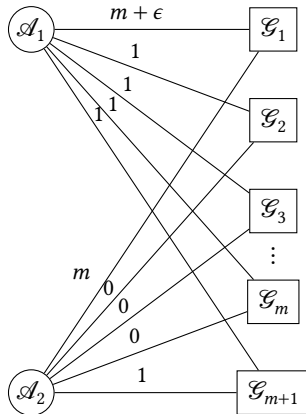
Algorithm with approximation factor *independent from m!*



# RepReMatch







What are the items of lowest valuation?

# Looking into the Future? Changing the Past!

Under submodular valuations, the set of lowest valuation is approximable only by  $\Omega(\sqrt{m/\ln m})$ . ⚡

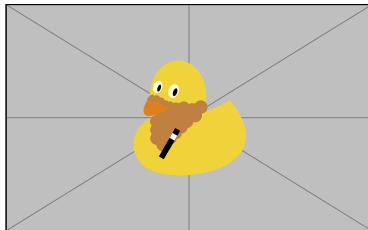


We need change the past in three phases:

**Phase I** Assign enough high-value items temporarily.

**Phase II** Assign the remaining items definitely.

**Phase III** Re-assign the items of phase I definitely.



A  $2n(\log_2 n + 3)$ -approximation is possible!

# The Algorithm

## Phase I

- 1** repeat  $\lceil \log_2 n \rceil + 1$  times or until  $\mathcal{G} = \emptyset$ 
  - 1** create bipartite graph  $G = (\mathcal{A}, \mathcal{G}, E)$  with edge weights  $w(i, j) = \eta_i \log v_i(j)$
  - 2** compute maximum weight matching  $\mathcal{M}$
  - 3** update bundles  $\mathbf{x}_i^I$  according to matching  $\mathcal{M}$  and remove assigned items

## Phase II

- 2** repeat until  $\mathcal{G} = \emptyset$ 
  - 1** create bipartite graph  $G = (\mathcal{A}, \mathcal{G}, E)$  with edge weights  $w(i, j) = \eta_i \log(v_i(\mathbf{x}_i^I \cup \{j\}))$
  - 2** compute maximum weight matching  $\mathcal{M}$
  - 3** update bundles  $\mathbf{x}_i^I$  according to matching  $\mathcal{M}$  and remove assigned items

## Phase III

- 3** create bipartite graph  $G = (\mathcal{A}, \bigcup_{i \in \mathcal{A}} \mathbf{x}_i^I, E)$  with edge weights  $w(i, j) = \eta_i \log(v_i(\mathbf{x}_i^I \cup \{j\}))$
- 4** compute maximum weight matching  $\mathcal{M}$
- 5** create bundles  $\mathbf{x}_i^I$  according to matching  $\mathcal{M}$  and previous bundles  $\mathbf{x}_i^I$

# Analysing Phase II (1/5)

## Definition (9)

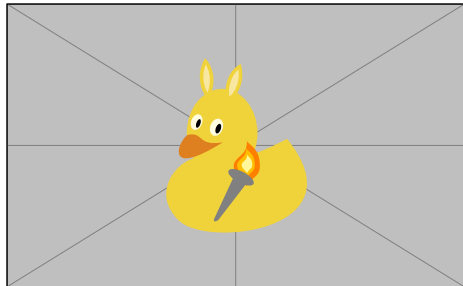
The set  $\mathcal{L}_{i,r}$  of *lost items* is the set of all optimal items  $j \in \mathbf{x}_i^*$  assigned to other agents  $i' \neq i$  in round  $r$ .

## Definition (10)

Let  $\mathbf{x}_i^{\Pi} = \{a_i^1, a_i^2, \dots\}$  be the bundle of agent  $i$ . The set of *optimal and attainable items* is defined as

$$\bar{\mathbf{x}}_{i,r}^* := \begin{cases} \mathbf{x}_i^* \setminus \bigcup_{i' \in \mathcal{A}} \mathbf{x}_{i'}^1 & \text{in round } r = 0, \\ \bar{\mathbf{x}}_{i,0}^* \setminus \mathcal{L}_{i,1} & \text{in round } r = 1, \\ \bar{\mathbf{x}}_{i,r-1}^* \setminus (\mathcal{L}_{i,r} \cup \{a_i^{r-1}\}) & \text{in round } r \geq 2. \end{cases}$$

⇒ What is the valuation of the remaining items?



# Analysing Phase II (2/5)

## Lemma (11)

$$v_i(\bar{x}_{i,r}^* \mid a_i^1, \dots, a_i^{r-1}) \geq v_i(\bar{x}_{i,1}^*) - \sum_{r'=1}^{r-1} |\mathcal{L}_{i,r'+1}| \cdot v_i(a_i^{r'} \mid a_i^1, \dots, a_i^{r'-1}) - v_i(a_i^1, \dots, a_i^{r-1}) \quad \forall r \geq 2$$

## Proof

- definition of marginal valuation

$$v_i(\bar{x}_{i,r}^* \mid a_i^1, \dots, a_i^{r-1}) = v_i(\bar{x}_{i,r}^* \cup \{a_i^1, \dots, a_i^{r-1}\}) - v_i(a_i^1, \dots, a_i^{r-1})$$

$\Rightarrow$  We need a lower bound on  $v_i(\bar{x}_{i,r}^* \cup \{a_i^1, \dots, a_i^{r-1}\})$ !

# Analysing Phase II (3/5)

## Lemma (11)

$$v_i(\bar{x}_{i,r}^* \mid a_i^1, \dots, a_i^{r-1}) \geq v_i(\bar{x}_{i,1}^*) - \sum_{r'=1}^{r-1} |\mathcal{L}_{i,r'+1}| \cdot v_i(a_i^{r'} \mid a_i^1, \dots, a_i^{r'-1}) - v_i(a_i^1, \dots, a_i^{r-1}) \quad \forall r \geq 2$$

## Proof

- $\bar{x}_{i,r}^* = \bar{x}_{i,r-1}^* \setminus (\mathcal{L}_{i,r} \cup \{a_i^{r-1}\}) \implies (\bar{x}_{i,r}^* \cup \{a_i^{r-1}\}) \supset (\bar{x}_{i,r-1}^* \setminus \mathcal{L}_{i,r})$ 
  - item  $a_i^{r-1}$  perhaps not element of  $\bar{x}_{i,r-1}^*$
- diminishing returns  $\implies v_i(\mathcal{S}_1 \mid \mathcal{S}_2 \cup \mathcal{S}_3) \leq v_i(\mathcal{S}_1 \mid \mathcal{S}_2)$

$$\begin{aligned}
 v_i(\bar{x}_{i,r}^* \cup \{a_i^1, \dots, a_i^{r-1}\}) &\geq v_i(\bar{x}_{i,r-1}^* \setminus \mathcal{L}_{i,r} \cup \{a_i^1, \dots, a_i^{r-2}\}) \\
 &= v_i(\bar{x}_{i,r-1}^* \cup \{a_i^1, \dots, a_i^{r-2}\}) - v_i(\mathcal{L}_{i,r} \mid \bar{x}_{i,r-1}^* \setminus \mathcal{L}_{i,r} \cup \{a_i^1, \dots, a_i^{r-2}\}) \\
 &\geq v_i(\bar{x}_{i,r-1}^* \cup \{a_i^1, \dots, a_i^{r-2}\}) - v_i(\mathcal{L}_{i,r} \mid a_i^1, \dots, a_i^{r-2})
 \end{aligned}$$

# Analysing Phase II (4/5)

## Lemma (11)

$$v_i(\bar{x}_{i,r}^* \mid a_i^1, \dots, a_i^{r-1}) \geq v_i(\bar{x}_{i,1}^*) - \sum_{r'=1}^{r-1} |\mathcal{L}_{i,r'+1}| \cdot v_i(a_i^{r'} \mid a_i^1, \dots, a_i^{r'-1}) - v_i(a_i^1, \dots, a_i^{r-1}) \quad \forall r \geq 2$$

## Proof

- apply inequality recursively

$$\begin{aligned}
 v_i(\bar{x}_{i,r}^* \cup \{a_i^1, \dots, a_i^{r-1}\}) &\geq v_i(\bar{x}_{i,r-1}^* \cup \{a_i^1, \dots, a_i^{r-2}\}) - v_i(\mathcal{L}_{i,r} \mid a_i^1, \dots, a_i^{r-2}) \\
 &\geq v_i(\bar{x}_{i,1}^*) - \sum_{r'=1}^{r-1} v_i(\mathcal{L}_{i,r'+1} \mid a_i^1, \dots, a_i^{r'-2})
 \end{aligned}$$

$\Rightarrow$  We need an upper bound on  $v_i(\mathcal{L}_{i,r'+1} \mid a_i^1, \dots, a_i^{r'-2})$ !

# Analysing Phase II (5/5)

## Lemma (11)

$$v_i(\bar{x}_{i,r}^* \mid a_i^1, \dots, a_i^{r-1}) \geq v_i(\bar{x}_{i,1}^*) - \sum_{r'=1}^{r-1} |\mathcal{L}_{i,r'+1}| \cdot v_i(a_i^{r'} \mid a_i^1, \dots, a_i^{r'-1}) - v_i(a_i^1, \dots, a_i^{r-1}) \quad \forall r \geq 2$$

## Proof

- diminishing returns  $\implies v_i(\mathcal{S}) \leq \sum_{j \in \mathcal{S}} v_i(j)$  for all  $\mathcal{S}$
- item  $a_i^{r'}$  assigned before any item  $j \in \mathcal{L}_{i,r'+1} \implies v_i(a_i^{r'} \mid a_i^1, \dots, a_i^{r'-1}) \geq v_i(j \mid a_i^1, \dots, a_i^{r'-1})$

$$\begin{aligned}
 v_i(\mathcal{L}_{i,r'+1} \mid a_i^1, \dots, a_i^{r'-2}) &\leq \sum_{j \in \mathcal{L}_{i,r'+1}} v_i(j \mid a_i^1, \dots, a_i^{r'-2}) \\
 &\leq |\mathcal{L}_{i,r'+1}| \cdot v_i(a_i^{r'} \mid a_i^1, \dots, a_i^{r'-1})
 \end{aligned}$$

□



# Analysing Phases I & III (1/2)

## Reminder

**Phase I** Temporary assignments. Valuations of single items as edge weights.

**Phase III** Items of phase I released. Valuations of items and bundles from phase II as edge weights.

Phase I reserves ‘high-value’ items. But what qualifies as ‘high-value’?

## Definition (14)

Let  $\mathbf{x}_i^* = \{o_i^1, o_i^2, \dots\}$  be an optimal bundle. An item  $j \in \mathcal{G}$  is *outstanding* if  $v_i(j) \geq v_i(o_i^1)$ .

⇒ Are enough outstanding items reserved?

# Analysing Phases I & III (2/2)

## Lemma (15)

*Each agent can be matched with an outstanding item in phase III.*

## Sketch Proof

- number of unmatched agents halved with each round of phase I
  - $\lceil \log_2 n \rceil + 1$  rounds in phase I are enough
- induction on number of rounds in phase I

Base Case: In round 1 of phase I, either

- $\geq n/2$  many agents matched with an outstanding item
- $< n/2$  many agents matched with an outstanding item
  - $> n/2$  many items  $o_i^1$  assigned to someone else
  - $> n/2$  many agents matched upon release in phase III

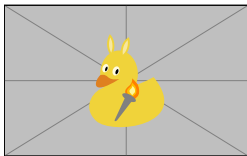
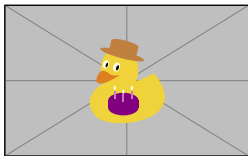
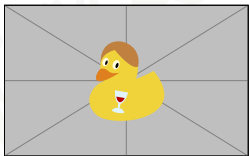


# 3

## Conclusion



- allocation: partition of items amongst agents
- bundles valued using submodular valuation functions
  - diminishing returns
- Nash social welfare: weighted geometric mean of valuations
- wanted: approximation factor independent from  $m$
- naïve, repeated matching fails because of missing foresight
- RepReMatch:  $2n(\log n + 3)$ -approximative
  - Phase I** finding enough outstanding items
  - Phase II** assigning remaining item (lost vs. optimal and attainable)
  - Phase III** assigning outstanding items



# Evaluation and Outlook

An improvement over previous results?

Yes!  $(m - n + 1)$  best known approximation factor before.

Any room for improvement left?

Possibly! Lower bound of 1.72.

Outlook:

- less general valuation functions  $\rightsquigarrow$  better factors
- limits on agent weights  $\rightsquigarrow$  linear and even constant factors
- focus on fairness



**End of Talk**