

Seminar Approximation Algorithms

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

Based on a paper of the same title by J. Garg, P. Kulkarni, and R. Kulkarni

Zeno Adrian Weil Supervised by Dr Giovanna Varricchio

27th July 2023 · Algorithms and Complexity (Prof. Dr Martin Hoefer)

What is the issue?



What is the issue?



We need to distribute goods amongst recipients

What is the issue?



We need to distribute goods amongst recipients efficiently

What is the issue?



We need to distribute goods amongst recipients *efficiently* and *fairly*.

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We need to distribute goods amongst recipients *efficiently* and *fairly*.

Where is this encountered?



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We need to distribute goods amongst recipients efficiently and fairly.

Where is this encountered?

industrial procurement



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- industrial procurement
- satellites





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We need to distribute goods amongst recipients efficiently and fairly.

Where is this encountered?

- industrial procurement
- satellites
- water withdrawal







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Allocations



Allocations



Setting:

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■ recipients: set \mathcal{A} of n agents

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- goods: set \mathcal{G} of m items

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Item *j* is *assigned* to agent *i* if $j \in x_i$.

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Item *j* is assigned to agent *i* if $j \in x_i$.

But how to measure its efficiency and fairness?

Valuation Functions



Valuation Functions



Requirements:

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■ monotonically non-decreasing: $v_i(\mathcal{S}_1) \leq v_i(\mathcal{S}_2)$ if $\mathcal{S}_1 \subset \mathcal{S}_2$

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Valuation Functions

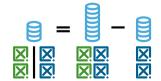


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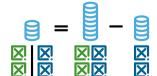


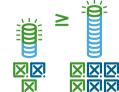
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 - diminishing returns







Asymmetric Maximum Nash Social Welfare Problem





Asymmetric Maximum Nash Social Welfare Problem

Problem

$$x^* \stackrel{!}{=} \underset{x \in X_{\mathscr{A}}(\mathscr{G})}{\operatorname{arg max}} \{ \operatorname{NSW}(x) \}$$

■ $X_{\mathcal{A}}(\mathcal{G})$: all possible allocations

Asymmetric Maximum Nash Social Welfare Problem

Problem

$$x^* \stackrel{!}{=} \arg \max \{ \text{NSW}(x) \}$$

 $x \in X_{\mathscr{A}}(\mathscr{E})$

- $X_{\mathcal{A}}(\mathcal{G})$: all possible allocations
- η_i : agent weight

Asymmetric Maximum Nash Social Welfare Problem

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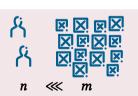
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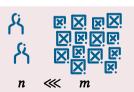
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- ... independent from *m*?





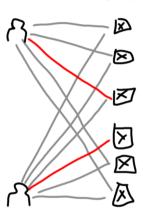


Naïve Approach

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Naïve approach:

- repeatedly use maximum matchings
- fails because of missing foresight
 - additive valuations: sort items by valuation ⇒ 2*n*-approximation (SMatch)
 - submodular valuations: lowest valuation approximable only by $\Omega(\sqrt{m/\ln m})$ \$\frac{1}{2}\$



Key Ideas of the Algorithm



We need change the past in three phases:

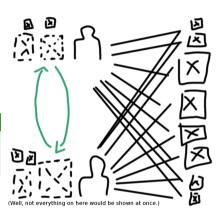
Phase I Assign enough high-value items temporarily.

Phase II Assign the remaining items definitely.

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

Theorem

RepReMatch guarantees a $2n(\log_2 n + 3)$ -approximation under submodular valuations.



The Algorithm



Phase I:

- **1** repeat $\lceil \log_2 n \rceil + 1$ times
 - **1** create bipartite graph $(\mathcal{A}, \mathcal{G}, E)$ with edge weights $\log v_i(j)^{\eta_i}$
 - 2 compute maximum weight matching
 - 3 update bundles x_i^{I} & remove assigned items

Phase II:

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

Phase III:

- **3** create bipartite graph $(\mathcal{A}, \bigcup_{i \in \mathcal{A}} \mathbf{x}_i^{\mathrm{I}}, E)$ with edge weights $\log v_i(\mathbf{x}_i^{\mathrm{II}} \cup \{j\})^{\eta_i}$
- 4 compute maximum weight matching
- **5** create bundles x_i^{III}

Analysing Phases I & III (1/2)



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Phase I reserves 'high-value' items.

Analysing Phases I & III (1/2)



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Let $\mathbf{x}_i^* = \{o_i^1, o_i^2, ...\}$ be an optimal bundle.

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

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⇒ Are enough outstanding items reserved?

Analysing Phases I & III (2/2)



Lemma

Each agent can be matched with an outstanding item in phase ${\rm III.}$

Analysing Phases I & III (2/2)



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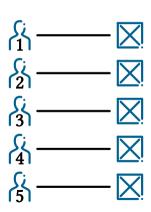
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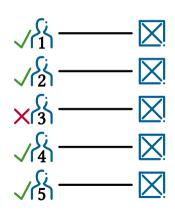
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Base Case: In round 1 of phase I, either

■ $\geq n/2$ many agents matched with an outstanding item



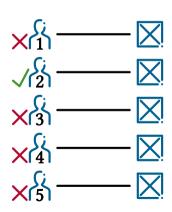


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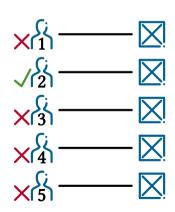


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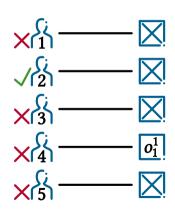


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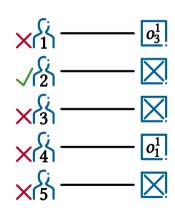


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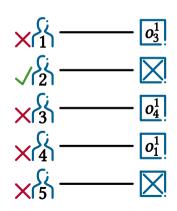


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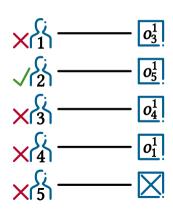


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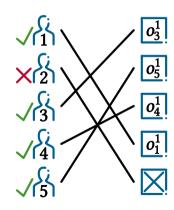


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 - > n/2 many agents matched upon release in phase III



Analysing Phase II (1/2)



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Let $x_i^{\text{II}} = \{a_i^1, a_i^2, ...\}$ be the bundle of agent *i*. The set of *optimal and attainable items* is defined as

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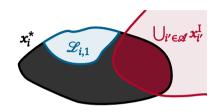
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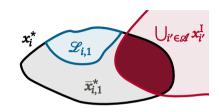
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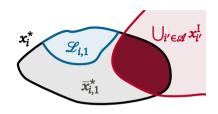
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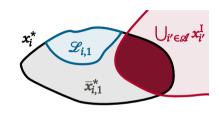
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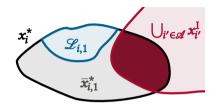


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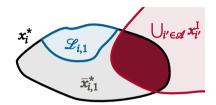


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The set $\mathcal{L}_{i,r}$ of *lost items* is the set of all optimal items $j \in x_i^*$ matched with other agents $i' \neq i$ in round r.

Definition

$$\overline{\boldsymbol{x}}_{i,r}^{\star} := \begin{cases} \boldsymbol{x}_{i}^{\star} \setminus \left(\bigcup_{i' \in \mathscr{A}} \boldsymbol{x}_{i'}^{\mathrm{I}} \cup \mathscr{L}_{i,1}\right) & \text{in round } r = 1, \\ & \text{in round } r \geq 2. \end{cases}$$





Analysing Phase II (1/2)

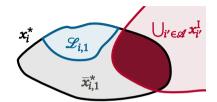


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Analysing Phase II (1/2)

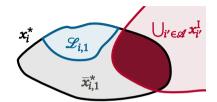


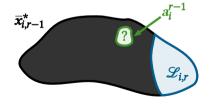
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Analysing Phase II (1/2)

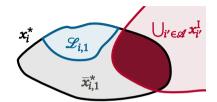


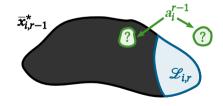
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Analysing Phase II (1/2)

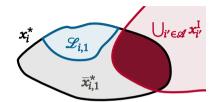


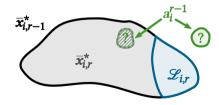
Definition

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

Definition

$$\overline{x}_{i,r}^{\star} := \begin{cases} x_i^{\star} \setminus \left(\bigcup_{i' \in \mathscr{A}} x_{i'}^{\mathrm{I}} \cup \mathscr{L}_{i,1} \right) & \text{in round } r = 1, \\ & \text{in round } r \geq 2. \end{cases}$$





Analysing Phase II (1/2)

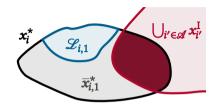


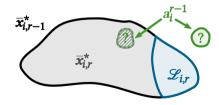
Definition

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Definition

$$\overline{\mathbf{x}}_{i,r}^{\star} := \begin{cases} \mathbf{x}_{i}^{\star} \setminus \left(\bigcup_{i' \in \mathscr{A}} \mathbf{x}_{i'}^{\mathrm{I}} \cup \mathscr{L}_{i,1}\right) & \text{in round } r = 1, \\ \overline{\mathbf{x}}_{i,r-1}^{\star} \setminus \left(\mathscr{L}_{i,r} \cup \left\{a_{i}^{r-1}\right\}\right) & \text{in round } r \geq 2. \end{cases}$$





Analysing Phase II (1/2)



Definition

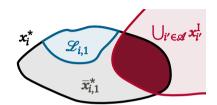
The set $\mathcal{L}_{i,r}$ of *lost items* is the set of all optimal items $j \in x_i^*$ matched with other agents $i' \neq i$ in round r.

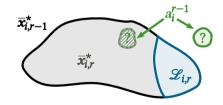
Definition

Let $x_i^{\text{II}} = \{a_i^1, a_i^2, ...\}$ be the bundle of agent *i*. The set of *optimal and attainable items* is defined as

$$\overline{x}_{i,r}^* := \begin{cases} x_i^* \setminus \left(\bigcup_{i' \in \mathscr{A}} x_{i'}^{\mathrm{I}} \cup \mathscr{L}_{i,1} \right) & \text{in round } r = 1, \\ \overline{x}_{i,r-1}^* \setminus \left(\mathscr{L}_{i,r} \cup \left\{ a_i^{r-1} \right\} \right) & \text{in round } r \ge 2. \end{cases}$$

 \Rightarrow What is the valuation of the remaining items?





Analysing Phase II (2/2)

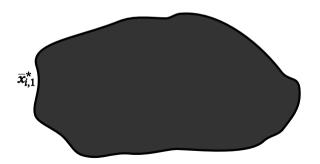


$$v_i\big(\overline{x}_{i,r}^*\mid a_i^1,\dots,a_i^{r-1}\big)$$

Analysing Phase II (2/2)



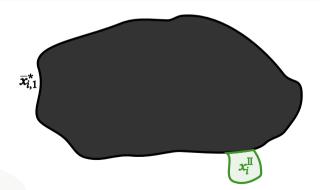
$$v_i\big(\overline{x}_{i,r}^*\mid a_i^1,\dots,a_i^{r-1}\big)$$



Analysing Phase II (2/2)



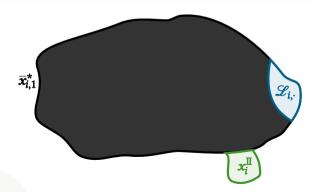
$$v_i\big(\overline{x}_{i,r}^{\star}\mid a_i^1,\dots,a_i^{r-1}\big)$$



Analysing Phase II (2/2)



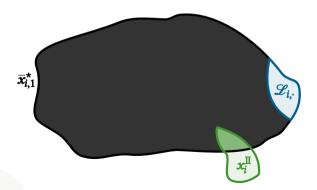
$$v_i\big(\overline{x}_{i,r}^{\star}\mid a_i^1,\dots,a_i^{r-1}\big)$$



Analysing Phase II (2/2)



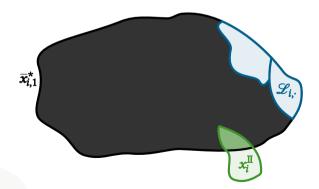
$$v_i\big(\overline{\boldsymbol{x}}_{i,r}^{\star}\mid a_i^1,\dots,a_i^{r-1}\big)$$



Analysing Phase II (2/2)



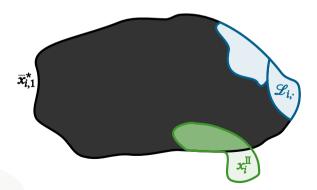
$$v_i\big(\overline{x}_{i,r}^{\star}\mid a_i^1,\dots,a_i^{r-1}\big)$$



Analysing Phase II (2/2)



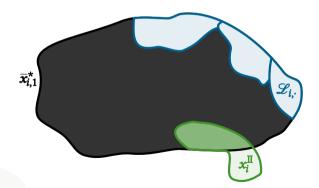
$$v_i\big(\overline{x}_{i,r}^{\star}\mid a_i^1,\dots,a_i^{r-1}\big)$$



Analysing Phase II (2/2)



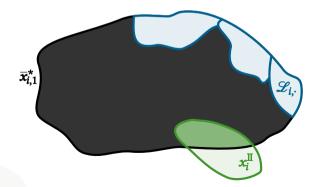
$$v_i\big(\overline{x}_{i,r}^*\mid a_i^1,\dots,a_i^{r-1}\big)$$



Analysing Phase II (2/2)



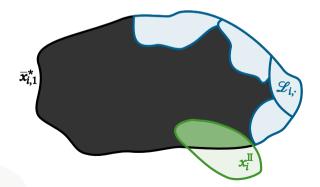
$$v_i\big(\overline{\boldsymbol{x}}_{i,r}^{\star}\mid a_i^1,\dots,a_i^{r-1}\big)$$



Analysing Phase II (2/2)



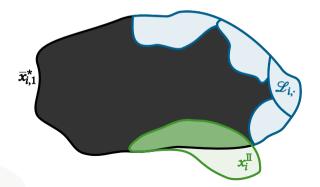
$$v_i\big(\overline{\boldsymbol{x}}_{i,r}^{\star}\mid a_i^1,\dots,a_i^{r-1}\big)$$



Analysing Phase II (2/2)



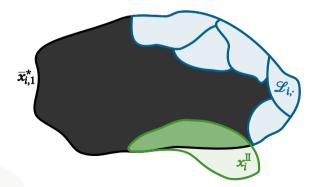
$$v_i\big(\overline{x}_{i,r}^*\mid a_i^1,\dots,a_i^{r-1}\big)$$



Analysing Phase II (2/2)



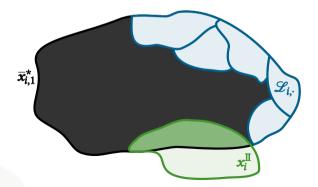
$$v_i(\overline{\mathbf{x}}_{i,r}^* \mid a_i^1, \dots, a_i^{r-1})$$



Analysing Phase II (2/2)



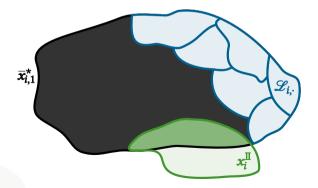
$$v_i\big(\overline{x}_{i,r}^{\star}\mid a_i^1,\dots,a_i^{r-1}\big)$$



Analysing Phase II (2/2)



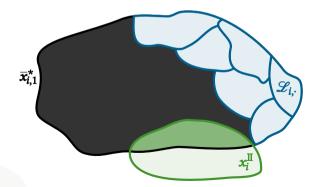
$$v_i\big(\overline{x}_{i,r}^*\mid a_i^1,\dots,a_i^{r-1}\big)$$



Analysing Phase II (2/2)



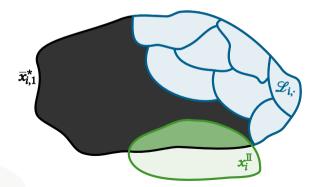
$$v_i\big(\overline{\boldsymbol{x}}_{i,r}^{\star}\mid a_i^1,\dots,a_i^{r-1}\big)$$



Analysing Phase II (2/2)

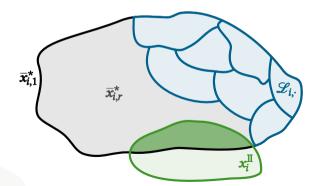


$$v_i\big(\overline{\boldsymbol{x}}_{i,r}^{\star}\mid a_i^1,\dots,a_i^{r-1}\big)$$



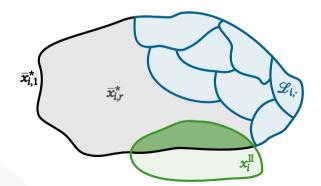


$$v_i\big(\overline{x}_{i,r}^*\mid a_i^1,\dots,a_i^{r-1}\big)$$



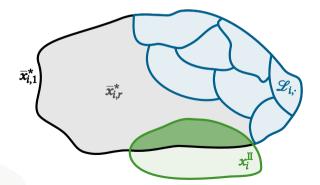


$$v_i\big(\overline{x}_{i,r}^{\star}\mid a_i^1,\dots,a_i^{r-1}\big)=v_i\big(\overline{x}_{i,r}^{\star}\cup\big\{a_i^1,\dots,a_i^{r-1}\big\}\big)-v_i\big(a_i^1,\dots,a_i^{r-1}\big)$$



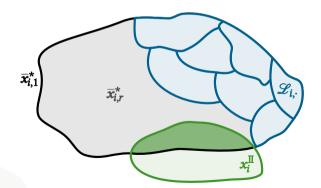


$$v_i\big(\overline{\boldsymbol{x}}_{i,r}^{\star}\mid a_i^1,\ldots,a_i^{r-1}\big)=v_i\big(\overline{\boldsymbol{x}}_{i,r}^{\star}\cup\big\{a_i^1,\ldots,a_i^{r-1}\big\}\big)-v_i\big(a_i^1,\ldots,a_i^{r-1}\big)$$



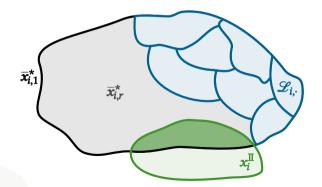


$$v_i(\overline{x}_{i,r}^* \mid a_i^1, \dots, a_i^{r-1}) = -v_i(\underline{a_i^1, \dots, a_i^{r-1}}) + v_i(\overline{x}_{i,r}^* \cup \{a_i^1, \dots, a_i^{r-1}\})$$



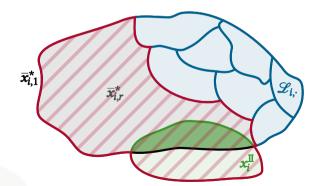


$$v_i(\overline{\mathbf{x}}_{i,r}^* \mid a_i^1, \dots, a_i^{r-1}) = -v_i(a_i^1, \dots, a_i^{r-1}) + v_i(\overline{\mathbf{x}}_{i,r}^* \cup \{a_i^1, \dots, a_i^{r-1}\})$$



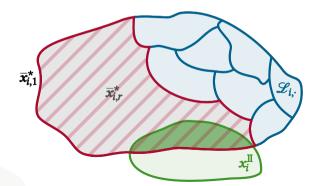


$$v_i(\bar{x}_{i,r}^* \mid a_i^1, \dots, a_i^{r-1}) = -v_i(a_i^1, \dots, a_i^{r-1}) + v_i(\bar{x}_{i,r}^* \cup \{a_i^1, \dots, a_i^{r-1}\})$$



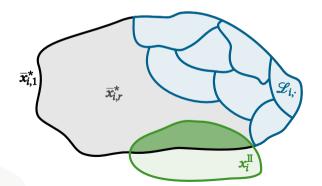


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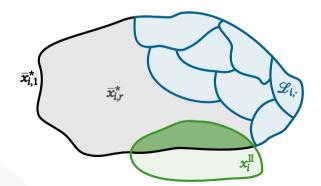


$$v_i\big(\overline{x}_{i,r}^*\mid a_i^1,\dots,a_i^{r-1}\big) \geq -v_i\big(a_i^1,\dots,a_i^{r-1}\big) + v_i\big(\overline{x}_{i,1}^*\big)$$



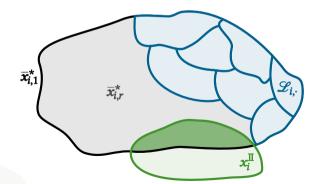


$$v_i(\bar{x}_{i,r}^* \mid a_i^1, \dots, a_i^{r-1}) \ge -v_i(a_i^1, \dots, a_i^{r-1}) + v_i(\bar{x}_{i,1}^*) - v_i(\mathcal{L}_{i,2} \mid a_i^1)$$



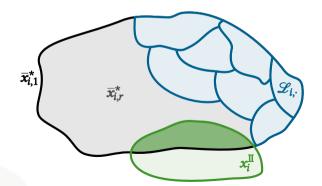


$$v_i\big(\bar{x}_{i,r}^{\star} \mid a_i^1, \dots, a_i^{r-1}\big) \geq -v_i\big(a_i^1, \dots, a_i^{r-1}\big) + v_i\big(\bar{x}_{i,1}^{\star}\big) - v_i\big(\mathcal{L}_{i,2} \mid a_i^1\big) - v_i\big(\mathcal{L}_{i,3} \mid a_i^1, a_i^2\big)$$



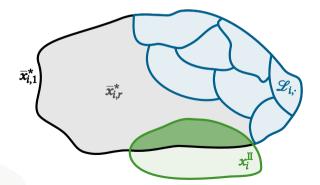


$$v_i\big(\overline{x}_{i,r}^{\star} \mid a_i^1, \dots, a_i^{r-1}\big) \geq -v_i\big(a_i^1, \dots, a_i^{r-1}\big) + v_i\big(\overline{x}_{i,1}^{\star}\big) - v_i\big(\mathcal{L}_{i,2} \mid a_i^1\big) - v_i\big(\mathcal{L}_{i,3} \mid a_i^1, a_i^2\big) - \dots$$



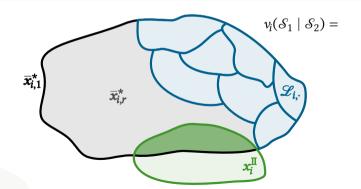


$$v_i(\bar{x}_{i,r}^* \mid a_i^1, \dots, a_i^{r-1}) \ge -v_i(a_i^1, \dots, a_i^{r-1}) + v_i(\bar{x}_{i,1}^*) - \sum_{l=2}^r v_i(\mathcal{L}_{i,l} \mid a_i^1, \dots, a_i^{l-1})$$



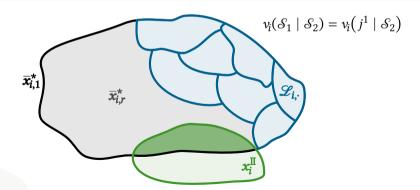


$$v_i(\bar{x}_{i,r}^* \mid a_i^1, \dots, a_i^{r-1}) \ge -v_i(a_i^1, \dots, a_i^{r-1}) + v_i(\bar{x}_{i,1}^*) - \sum_{l=2}^r v_i(\mathcal{L}_{i,l} \mid a_i^1, \dots, a_i^{l-1})$$



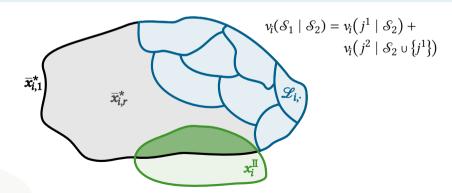


$$v_{i}(\overline{x}_{i,r}^{*} \mid a_{i}^{1}, \dots, a_{i}^{r-1}) \geq -v_{i}(a_{i}^{1}, \dots, a_{i}^{r-1}) + v_{i}(\overline{x}_{i,1}^{*}) - \sum_{l=2}^{r} v_{i}(\mathcal{L}_{i,l} \mid a_{i}^{1}, \dots, a_{i}^{l-1})$$



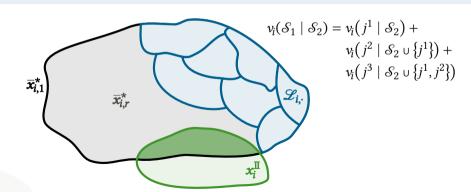


$$v_i(\bar{x}_{i,r}^* \mid a_i^1, \dots, a_i^{r-1}) \ge -v_i(a_i^1, \dots, a_i^{r-1}) + v_i(\bar{x}_{i,1}^*) - \sum_{l=2}^r v_i(\mathcal{L}_{i,l} \mid a_i^1, \dots, a_i^{l-1})$$



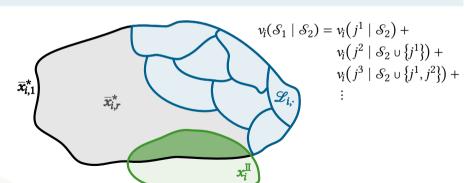


$$v_i(\overline{x}_{i,r}^* \mid a_i^1, \dots, a_i^{r-1}) \ge -v_i(a_i^1, \dots, a_i^{r-1}) + v_i(\overline{x}_{i,1}^*) - \sum_{l=2}^r v_i(\mathcal{L}_{i,l} \mid a_i^1, \dots, a_i^{l-1})$$



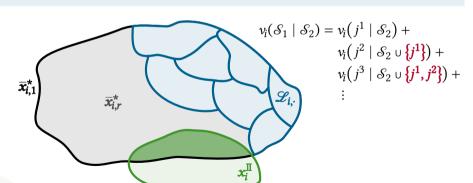


$$v_{i}(\overline{x}_{i,r}^{*} \mid a_{i}^{1}, \dots, a_{i}^{r-1}) \geq -v_{i}(a_{i}^{1}, \dots, a_{i}^{r-1}) + v_{i}(\overline{x}_{i,1}^{*}) - \sum_{l=2}^{r} v_{i}(\mathcal{L}_{i,l} \mid a_{i}^{1}, \dots, a_{i}^{l-1})$$



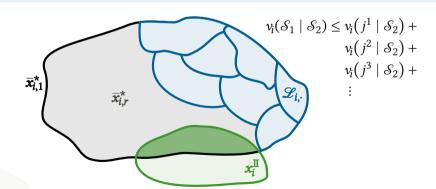


$$v_i(\bar{x}_{i,r}^* \mid a_i^1, \dots, a_i^{r-1}) \ge -v_i(a_i^1, \dots, a_i^{r-1}) + v_i(\bar{x}_{i,1}^*) - \sum_{l=2}^{r} v_i(\mathcal{L}_{i,l} \mid a_i^1, \dots, a_i^{l-1})$$



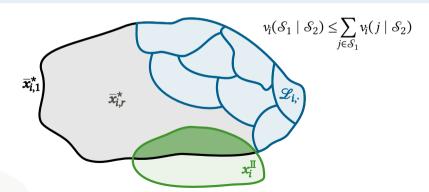


$$v_{i}(\overline{x}_{i,r}^{*} \mid a_{i}^{1}, \dots, a_{i}^{r-1}) \geq -v_{i}(a_{i}^{1}, \dots, a_{i}^{r-1}) + v_{i}(\overline{x}_{i,1}^{*}) - \sum_{l=2}^{r} v_{i}(\mathcal{L}_{i,l} \mid a_{i}^{1}, \dots, a_{i}^{l-1})$$



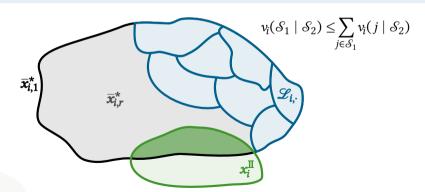


$$v_i(\overline{x}_{i,r}^* \mid a_i^1, \dots, a_i^{r-1}) \ge -v_i(a_i^1, \dots, a_i^{r-1}) + v_i(\overline{x}_{i,1}^*) - \sum_{l=2}^r v_i(\mathcal{L}_{i,l} \mid a_i^1, \dots, a_i^{l-1})$$



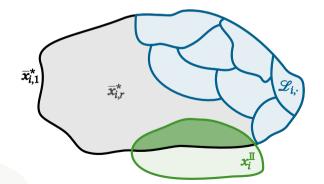


$$v_i(\overline{x}_{i,r}^* \mid a_i^1, \dots, a_i^{r-1}) \ge -v_i(a_i^1, \dots, a_i^{r-1}) + v_i(\overline{x}_{i,1}^*) - \sum_{l=2}^r \sum_{j \in \mathscr{L}_{i,l}} v_i(j \mid a_i^1, \dots, a_i^{l-1})$$



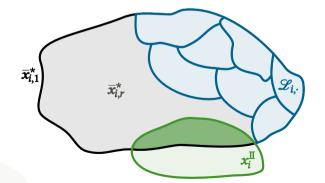


$$v_{i}(\overline{x}_{i,r}^{*} \mid a_{i}^{1}, \dots, a_{i}^{r-1}) \geq -v_{i}(a_{i}^{1}, \dots, a_{i}^{r-1}) + v_{i}(\overline{x}_{i,1}^{*}) - \sum_{l=2}^{r} \sum_{j \in \mathcal{L}_{i,l}} v_{i}(j \mid a_{i}^{1}, \dots, a_{i}^{l-1})$$



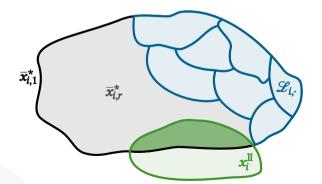


$$v_{i}(\overline{x}_{i,r}^{*} \mid a_{i}^{1}, \dots, a_{i}^{r-1}) \geq -v_{i}(a_{i}^{1}, \dots, a_{i}^{r-1}) + v_{i}(\overline{x}_{i,1}^{*}) - \sum_{l=2}^{r} \sum_{j \in \mathcal{L}_{i,l}} v_{i}(j \mid a_{i}^{1}, \dots, a_{i}^{l-1})$$



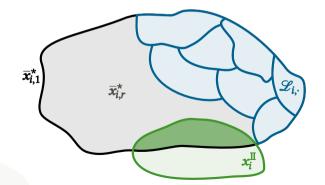


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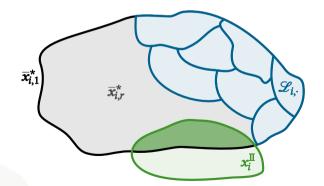


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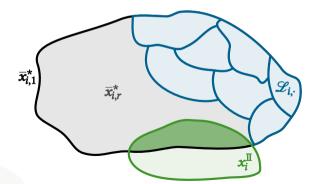


$$v_i(\overline{x}_{i,r}^* \mid a_i^1, \dots, a_i^{r-1}) \ge -v_i(a_i^1, \dots, a_i^{r-1}) + v_i(\overline{x}_{i,1}^*) - \sum_{l=2}^r \sum_{j \in \mathcal{L}_{i,l}} v_i(a_i^{l-1} \mid a_i^1, \dots, a_i^{l-2})$$



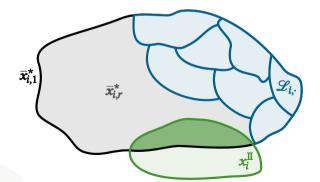


$$v_i\big(\overline{x}_{i,r}^{\star} \mid a_i^1, \dots, a_i^{r-1}\big) \geq -v_i\big(a_i^1, \dots, a_i^{r-1}\big) + v_i\big(\overline{x}_{i,1}^{\star}\big) - \sum_{l=2}^{r} |\mathscr{L}_{i,l}| \cdot v_i\big(a_i^{l-1} \mid a_i^1, \dots, a_i^{l-2}\big)$$





$$v_i\big(\overline{x}_{i,r}^* \mid a_i^1, \dots, a_i^{r-1}\big) \geq -v_i\big(a_i^1, \dots, a_i^{r-1}\big) + v_i\big(\overline{x}_{i,1}^*\big) - \sum_{l=2}^r (n-1) \cdot v_i\big(a_i^{l-1} \mid a_i^1, \dots, a_i^{l-2}\big)$$











Summary & Outlook



■ allocation: partition of items amongst agents

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- bundles valued using submodular valuation functions



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Any Room for Improvement?

Possibly! Lower bound of $\frac{e}{e-1} \approx 1.58$













