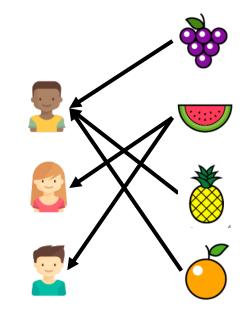
Prophet Inequalities

Part 3: Online combinatorial auctions and balanced prices

Paul Dütting, Google Research duetting@google.com ADFOCS 2024 Summer School August 2024

The basic set-up:

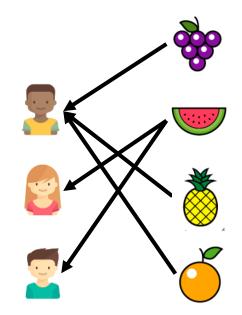
- *n* buyers with valuation functions $v_i \sim D_i$, $v_i: 2^{[m]} \rightarrow \mathbb{R}_{\geq 0}$ arriving one-by-one
- *m* items



n bidders *m* items

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- *n* buyers with valuation functions $v_i \sim D_i$, $v_i: 2^{[m]} \rightarrow \mathbb{R}_{\geq 0}$ arriving one-by-one
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- Upon arrival of buyer *i*:
- Immediately and irrevocably assign a subset X_i of the (not yet) allocated items [m] \ (U_{i'<i}X_i)



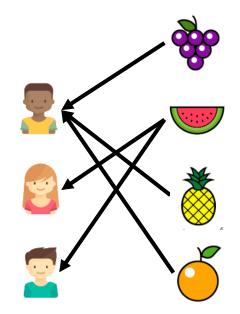
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Goal: Maximize $\mathbb{E}[\sum_{i} v_i(X_i)]$ (a.k.a. "expected welfare")

Benchmark ("prophet"): $\mathbb{E}[\sum_{i} v_i(OPT_i(v))]$

= items buyer *i* receives in optimal allocation

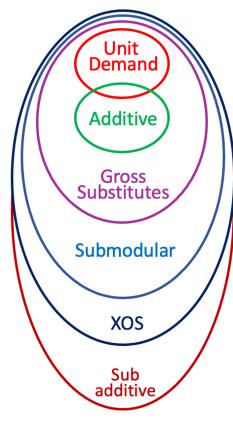
Hierarchy of Valuations

We will always assume monotonicity:

- Valuation function $v_i: 2^{[m]} \to \mathbb{R}_{\geq 0}$ is monotone if
 - $v_i(S) \le v_i(T)$ for $S \subseteq T$

We will also impose some structure, e.g.,

- Valuation function v_i is unit demand if
 - $v_i(S) = \max_{j \in S} v_{ij}$
- Valuation function v_i is subadditive if
 - $v_i(S \cup T) \le v_i(S) + v_i(T)$



"hierarchy of complementfree valuations"

[Lehman Lehman Nisan 2006]

Posted-Price Mechanism

Particularly desirable solution:

- Post (static, anonymous) item prices p_j for $j \in [m]$
- Buyer *i* buys set of still available items X_i that maximizes

$$u_i(X_i, p) = v_i(X_i) - \sum_{j \in X_i} p_j$$

buyer *i*'s value for set X_i sum of the prices of the items in X_i

(is simple and has nice economic properties)



High-Level Intuition

Prices serve two purposes:

- They should be high enough
 - This is to ensure that items are protected from being snapped away by low-value buyers
- They should be low enough
 - This is to ensure that high-value buyers, when they come along, actually buy these items

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 - This is to ensure that items are protected from being snapped away by low-value buyers
- They should be low enough
 - This is to ensure that high-value buyers, when they come along, actually buy these items
- \implies we want prices to "balance" these two forces

Plan for Part 3

- Alternative "economic" proof of classic single-choice prophet inequalities via "balanced prices"
- The balanced prices framework and its main extension theorem
 - Proof for known valuations that extends to Bayesian setting
 - Simplifies problem to the problem of finding balanced prices for known valuations
- In particular: Factor 2 prophet inequality / posted-price mechanism for XOS combinatorial auctions

Outline Other Parts

Part 1: Introduction

Part 2: Online matching and contention resolution

Part 3: Online combinatorial auctions and balanced prices

Part 4: Data-driven prophet inequalities

Recall: The Classic Prophet Inequality

The Problem

- Given known distributions $\mathcal{D}_1, \mathcal{D}_2, \dots, \mathcal{D}_n$ over (non-negative) values:
 - A gambler gets to see realizations $v_i \sim D_i$ one-by-one, and needs to immediately and irrevocable decide whether to accept v_i
 - The prophet sees the entire sequence of values v_1, v_2, \dots, v_n at once, and can simply choose the maximum value
- Question: What's the worst-case gap between E[value accepted by gambler] and E[value accepted by prophet]?
 =: E[ALG]

 $= \mathbb{E}[\max_i v_i]$

Prophet Inequality

Theorem [Samuel-Cahn '84]

For all distributions $\mathcal{D}_1, \mathcal{D}_2, ..., \mathcal{D}_n$, there is a threshold algorithm ALG_{τ} such that $\mathbb{E}[ALG_{\tau}] \geq \frac{1}{2} \mathbb{E}[\max_i v_i]$.

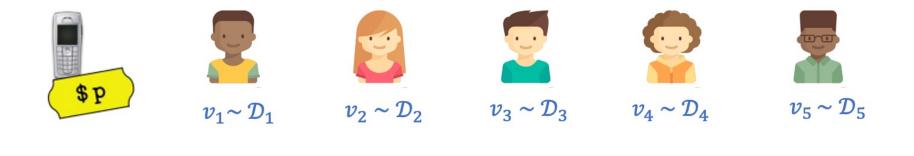
Threshold algorithm: set threshold/price τ , accept first $v_i \ge \tau$



Samuel-Cahn (from Gil Kalai's Blog)

Proof via Balanced Prices

Economic Interpretation



- There are *n* buyers with values $v_i \sim D_i$, and a single item with price *p*
- Buyer *i* has a utility of $v_i p$ for buying the item
 - If the item is still available when it's buyer *i*'s turn, she will buy if $v_i p \ge 0$

Bottom line: One-to-one correspondence between online algorithm with threshold $\tau = p$ and rational economic desicisions of the buyers

Economic Terminology

For (fixed) values $\boldsymbol{v} = (v_1, \dots, v_n)$:

- We will write $\operatorname{utility}_i(v)$ (or $u_i(v)$ for shory) for buyer *i*'s utility
- We will write revenue(v) for the revenue
 - The revenue is *p* if the item is sold, 0 otherwise
- We will write welfare(v) for the welfare
 - This is the value v_i of the buyer that buys the item (0 if the item is not sold)
- Note that: welfare(\boldsymbol{v}) = \sum_{i} utility_i(\boldsymbol{v}) + revenue(\boldsymbol{v})

Our goal: Want to show that there exists a price p such that $\mathbb{E}[\text{welfare}(v)] \ge \frac{1}{2} \mathbb{E}[\max_{i} v_{i}]$

An Argument for <u>Known</u> Valuations



Price $p = \frac{1}{2} \max_{i} v_i$ is "balanced": Let $v_{i^*} = \max_{i} v_i$.

- **Case 1:** Some buyer $i' < i^*$ buys the item:
 - \Rightarrow revenue $(\boldsymbol{v}) \ge p \ge \frac{1}{2} \max_{i} v_i$
- **Case 2:** No buyer $i' < i^*$ buys the item:
 - $\Rightarrow \sum_{i} \text{utility}_{i}(\boldsymbol{v}) \ge u_{i^{\star}}(\boldsymbol{v}) \ge v_{i^{\star}} p = \frac{1}{2} \max_{i} v_{i}$

In either case:

welfare(\boldsymbol{v}) = \sum_{i} utility_i(\boldsymbol{v}) + revenue(\boldsymbol{v}) $\geq 1/2 \cdot \max_{i} v_{i}$

Q.E.D. (w/ compl. info)

Let $\hat{\boldsymbol{v}} \sim \mathcal{D}$ denote an independent sample

Consider price $p = \mathbb{E}\left[p^{\hat{v}}\right]$, where $p^{\hat{v}} = \frac{1}{2} \cdot \max_{i} \hat{v}_{i}$

Define $SOLD_i(v) \coloneqq$ item is sold to buyers 1, ..., *i* when values are v

Define $OPT(v) \coloneqq$ bidder that receives the item in the optimal (welfare-maximizing) allocation for values v

To establish a bound on the expected welfare, we will again establish bounds on the expected revenue and the expected sum of utilities.

Revenue:

 $\mathbb{E}[\text{revenue}(\boldsymbol{v})] = \mathbb{E}[p \cdot 1_{\text{SOLD}_n(\boldsymbol{v})}]$ $= p \cdot \mathbb{E}[1_{\text{SOLD}_n(\boldsymbol{v})}]$ $= \frac{1}{2} \mathbb{E}[\max_i \hat{v}_i] \cdot \mathbb{E}[1_{\text{SOLD}_n(\boldsymbol{v})}]$ $= \frac{1}{2} \mathbb{E}[\max_i v_i] \cdot \mathbb{E}[1_{\text{SOLD}_n(\boldsymbol{v})}]$

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 - the item has not been sold to buyers $1, \ldots, i-1$

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 $\implies \mathbb{E}[u_i(\boldsymbol{v})] \ge \mathbb{E}[(v_i - p) \cdot 1_{OPT(v_i, v_{-i}^{(i)}) = i} \cdot 1_{\neg \text{ SOLD}_{i-1}(\boldsymbol{v})}]$

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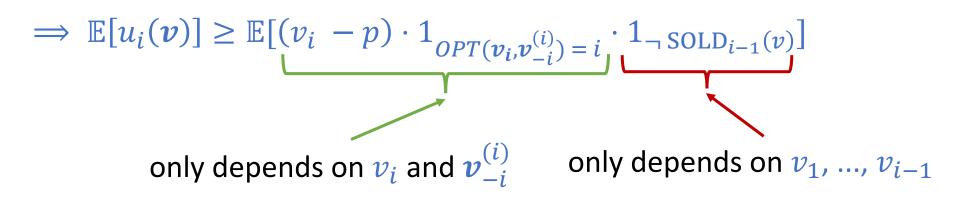
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$$= \mathbb{E}[(v_{i} - p) \cdot 1_{OPT(v_{i}, \boldsymbol{v}_{-i}) = i}] \geq \mathbb{E}[1_{\neg \text{ SOLD}_{n}(\boldsymbol{v})}]$$
since $\boldsymbol{v}_{-i}^{(i)}$ and \boldsymbol{v}_{-i} are identically distributed since $\neg \text{ SOLD}_{n}(\boldsymbol{v}) \Rightarrow \neg \text{ SOLD}_{i-1}(\boldsymbol{v})$

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• Summing over all buyers $i \in [n]$, we thus obtain

 $\mathbb{E}[\sum_{i} u_{i}(\boldsymbol{v})] \geq \sum_{i} \mathbb{E}[(v_{i} - p) \cdot 1_{OPT(\boldsymbol{v})=i}] \cdot \mathbb{E}[1_{\neg \text{ SOLD}_{n}(\boldsymbol{v})}]$ $= (\mathbb{E}[\max_{i} v_{i}] - p) \cdot \mathbb{E}[1_{\neg \text{ SOLD}_{n}(\boldsymbol{v})}]$ $= \frac{1}{2} \mathbb{E}[\max_{i} v_{i}] \cdot \mathbb{E}[1_{\neg \text{ SOLD}_{n}(\boldsymbol{v})}]$

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Putting everything together:

 $\mathbb{E}[\text{welfare}(\boldsymbol{v})] = \mathbb{E}[\sum_{i} u_{i}(\boldsymbol{v})] + \mathbb{E}[\text{revenue}(\boldsymbol{v})]$ $\geq \frac{1}{2} \mathbb{E}[\max_{i} v_{i}] \cdot (\mathbb{E}[1_{\neg \text{ SOLD}_{n}(\boldsymbol{v})}] + \mathbb{E}[1_{\text{ SOLD}_{n}(\boldsymbol{v})}]) \qquad \textbf{Q.E.D.}$ = 1

Prophet Inequalities via Balanced Prices

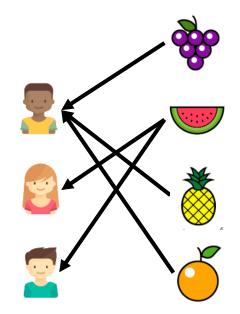
[Weinberg Kleinberg 2012, Feldman Gravin Lucier 2015, Dütting Feldman Kesselheim Lucier 2017]

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Goal: Maximize $\mathbb{E}[\sum_{i} v_i(X_i)]$ (a.k.a. "expected welfare")

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= items buyer *i* receives in optimal allocation

XOS Valuations

Definition. A valuation function $v_i: 2^{[m]} \to \mathbb{R}_{\geq 0}$ is fractionally subadditive (XOS) if there are $v_{ij}^{\ell} \in \mathbb{R}_{\geq 0}$ such that

$$v_i(S) = \max_{\ell} \sum_{j \in S} v_{ij}^{\ell}$$
.

1

XOS Valuations

Definition. A valuation function $v_i: 2^{[m]} \to \mathbb{R}_{\geq 0}$ is fractionally subadditive (XOS) if there exist additive functions v_i^{ℓ} with $\ell \in [k]$ such that

$$v_i(S) = \max_{\ell} v_i^{\ell}(S) = \max_{\ell} \sum_{j \in S} v_{ij}^{\ell}$$

Examples:

- Additive: $v_i(S) = \sum_{j \in S} v_{ij}$
- Unit demand: $v_i(S) = \max_{j \in S} v_{ij}$
- Budget additive: $v_i(S) = \min\{\sum_{j \in S} v_{ij}, B\}$
- Submodular: $v_i(S \cup \{j\}) v_i(S) \ge v_i(T \cup \{j\}) v_i(T)$ for $S \subseteq T$

The FGL 15 Result

Definition. [Feldman Gravin Lucier 2015]

For any distributions $\mathcal{D}_1, \mathcal{D}_2, \dots, \mathcal{D}_n$ over XOS valuation functions, there exist (static, anonymous) item prices such that for the resulting allocation X_1, \dots, X_n :

 $\mathbb{E}[\sum_{i} v_{i}(X_{i})] \geq \frac{1}{2} \mathbb{E}[\mathsf{OPT}]$

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Generalizes the classic prophet inequality (and is tight).

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Main technique: Balanced prices.

Balanced Prices

Definition. [Dütting Feldman Kesselheim Lucier 2017] A valuation function $v_i: 2^{[m]} \to \mathbb{R}_{\geq 0}$ admits balanced prices if for every set of items $U \subseteq [m]$ there exist item prices p_j for $j \in U$ such that for all $T \subseteq U$: (1) $\sum_{j \in T} p_j \ge v_i(U) - v_i(U \setminus T)$ (2) $\sum_{j \in U \setminus T} p_j \le v_i(U \setminus T)$

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Known fact (implicit in [FGL 15]): XOS valuation functions admit balanced prices. (See exercise!)

Two conditions:

(1) $\sum_{j \in T} p_j \ge v_i(U) - v_i(U \setminus T)$ ($\forall T \subseteq U$) and (2) $\sum_{i \in S} p_i \leq v_i(S)$

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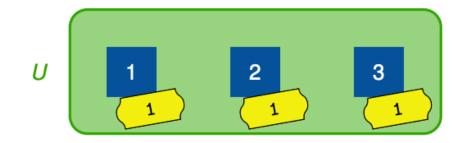


Example 1: Additive $v_i(S) = |S|$

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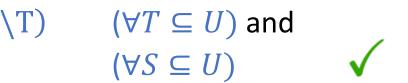
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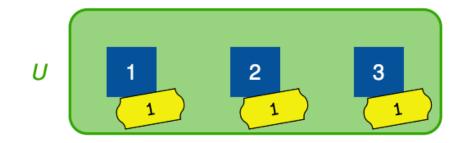


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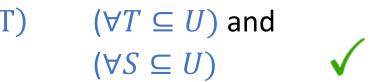


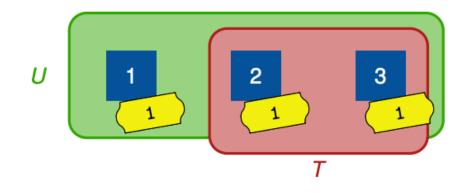


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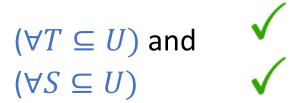


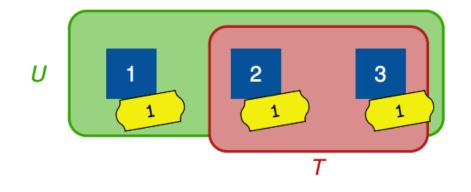
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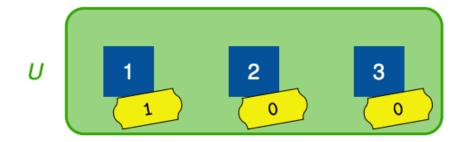


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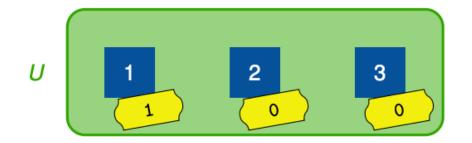


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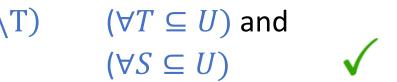


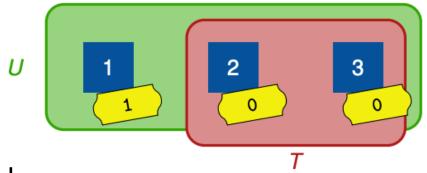


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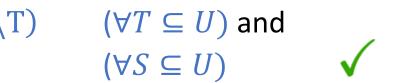


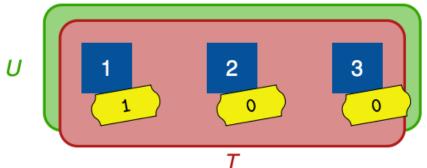


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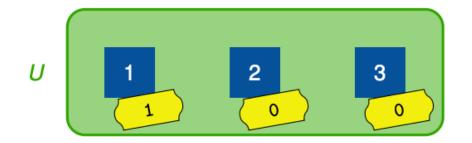


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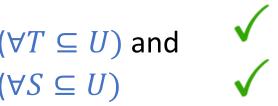


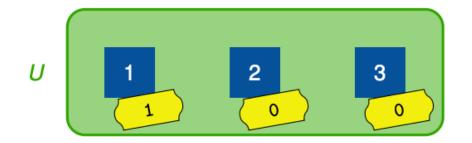


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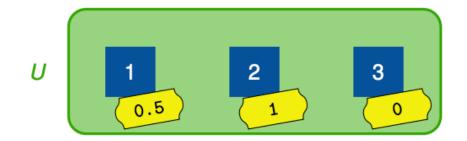
Example 3: Budget additive

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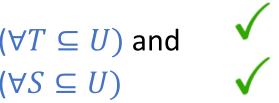


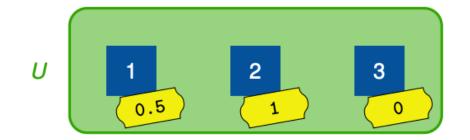
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Main Theorem

Theorem. [Dütting Feldman Kesselheim Lucier 2017]

If a class of valuations admits balanced prices, then for any distributions $\mathcal{D}_1, \mathcal{D}_2, \dots, \mathcal{D}_n$ there exist (static, anonymous) item prices such that for the resulting allocation X_1, \dots, X_n :

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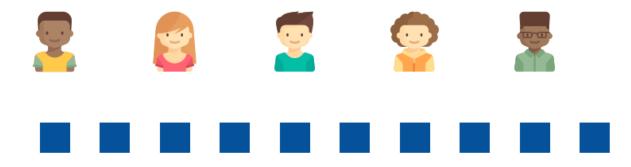
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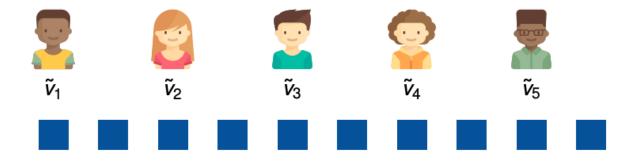
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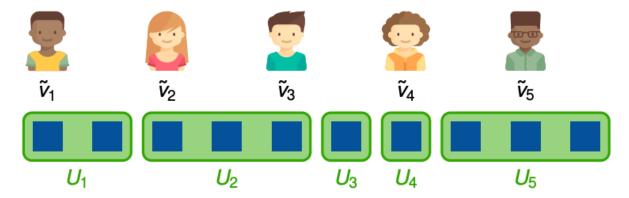
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Up next: How we set prices & the argument for complete information.

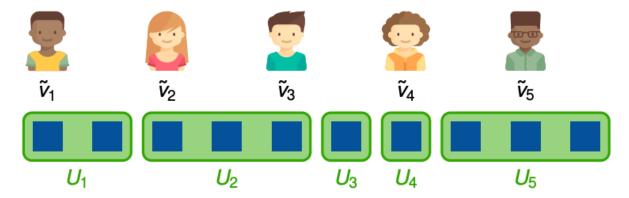




Fix $\hat{v}_1, \ldots, \hat{v}_n$.

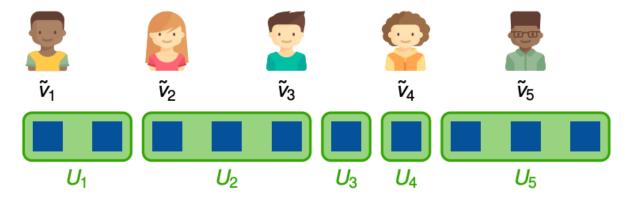


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Price for item *j*: $\bar{p}_j = \frac{1}{2} \cdot \mathbb{E}_{\hat{v} \sim \mathcal{D}}[p_j^{\hat{v}}]$.

(Complete Information)

Let $U_i = \{j \mid i \text{ gets } j \text{ in } OPT(v)\}$ (for all $i \in [n]$) Set price $\bar{p}_j = \frac{p_j}{2}$ for $j \in U_i$. $(p_j = \text{balanced price for } v_i, U_i)$ Let $T_i = \{j \mid j \in U_i \text{ sold to } i' \neq i\}$.

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Balancedness:

(1) $\sum_{j \in T_i} p_j \ge v_i(U_i) - v_i(U_i \setminus T_i)$ (2) $\sum_{j \in U_i \setminus T_i} p_j \le v_i(U_i \setminus T_i)$

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Then, for the allocation X_1, \ldots, X_n , we have:

 $u_i(X_i, \overline{p}) + \sum_{j \in T_i} \overline{p}_j$

$$\geq (v_i(U_i \setminus T_i) - \sum_{j \in U_i \setminus T_i} \overline{p}_j) + \sum_{j \in T_i} \overline{p}_j$$

$$\geq (v_i(U_i \setminus T_i) - \frac{1}{2} v_i(U_i \setminus T_i)) + \frac{1}{2} (v_i(U_i) - v_i(U_i \setminus T_i))$$

$$= \frac{1}{2} v_i(U_i)$$

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 $\sum_{i} v_i(X_i) \geq \sum_{i} (u_i(X_i, \overline{p}) + \sum_{j \in T_i} \overline{p}_j)$

$$\geq \sum_{i} [(v_{i}(U_{i} \setminus T_{i}) - \sum_{j \in U_{i} \setminus T_{i}} \overline{p}_{j}) + \sum_{j \in T_{i}} \overline{p}_{j}]$$

$$\geq \sum_{i} [(v_{i}(U_{i} \setminus T_{i}) - \frac{1}{2} v_{i}(U_{i} \setminus T_{i})) + \frac{1}{2} (v_{i}(U_{i}) - v_{i}(U_{i} \setminus T_{i}))]$$

$$= \sum_{i} \frac{1}{2} v_{i}(U_{i})$$
Q.E.D.
(w/ compl. info)

Discussion

- Reduces the problem to finding balanced prices for fixed valuations
 - Often much easier to think about this complete information problem
- The result can be generalized/strengthened in two ways:
 - Prices may be adaptive (required for constant-factor for matroids) [Feldman Svensson Zenklusen 2021]
 - Inequalities can be relaxed
- Captures several known proofs such as [Feldman Gravin Lucier 2015] and [Kleinberg Weinberg 2012] (and leads to new results)

Further Results

- Prices can be computed in poly-time via LP-relaxation (rather than integral optimum) [Dütting Feldman Kesselheim Lucier 2017]
- Techniques also applicable for revenue maximization [Cai Zhao 2017]
- For subadditive combinatorial auctions this approach is limited to Ω(log m) approximation, but O(log log m) possible via relaxation of balancedness [Dütting Kesselheim Lucier 2020]

The $O(\log \log m)$ bound is attained by (static/anonym.) item prices.

Beyond Balanced Prices

Subadditive Buyers

Theorem [Correa Cristi 2023]

For subadditive combinatorial auctions, there exists an O(1)-competitive online algorithm against the prophet benchmark.

For subadditive buyers "simultaneous first-price item auctions" have a constant Price of Anarchy (with respect to Bayes-Nash equilibria) [Feldman Fu Gravin Lucier 2013]

Can view proof as reduction to constant Price of Anarchy of "simultaneous all-pay item auctions with random reserves"

Open question: Via (static/anonym.) pricing?

Cf. reduction in [Banihashem et al. '24] (but adaptive, bundle prices)

Summary

- Alternative "economic" proof of classic single-choice prophet inequalities via "balanced prices"
- The balanced prices framework and its main extension theorem
 - Proof for known valuations that extends to Bayesian setting
 - Simplifies problem to the problem of finding balanced prices for known valuations
- In particular: Factor 2 prophet inequality / posted-price mechanism for XOS combinatorial auctions

Thanks! Coffee!

Additional Slides

Balanced Prices for XOS Valuations

Lemma. For XOS valuation v_i and set U the following prices p_j for $j \in U$ are balanced:

• let v_i^{ℓ} be such that $v_i(U) = \sum_{j \in U} v_{ij}^{\ell}$

• set $p_j = v_{ij}^\ell$

 $(v_i^{\ell} \text{ is also known as the "additive supporting function" of <math>v_i$ on set U)

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Proof: Exercise!

set $p_i = v_{ii}^{\ell}$