Revenue Maximization

Yingkai Li

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Single-item Auctions

Auctions: a single item, n agents.

- each agent i has value $v_i \sim F_i$;
- each agent i has utility $u_i = v_i x_i p_i$.

Revenue maximization: maximize $\sum_i p_i$.

Incentives

Given any v > v':

$$v \cdot x(v) - p(v) \ge v \cdot x(v') - p(v')$$

$$v' \cdot x(v') - p(v') \ge v' \cdot x(v) - p(v)$$

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Combining inequalities:

$$v' \cdot (x(v) - x(v')) \le p(v) - p(v') \le v \cdot (x(v) - x(v')) \Rightarrow x(v) - x(v') \ge 0.$$

In any incentive compatible mechanism, allocation must be weakly increasing in values.

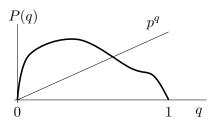
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Revenue Optimal Mechanisms

Revenue Curves: Single-agent Analysis

Price posting revenue curve P(q): expected revenue from selling the item using market clearing price p^q .

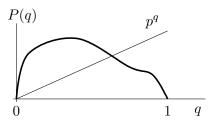
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- p^q : per-unit price that sells the item with total demand q;
- \bar{P} : concave hull of P.



Pricing-based Mechanisms

Quantile space: let $q = \Pr_{t' \sim F}[t' \geq t]$ be the quantile for type t.

- ullet $q \sim U[0,1]$ (assuming continuous type distribution)
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Pricing-based mechanism in quantile space: thresholds $\{Q_i\}_{i\in[n]}$

- threshold $\hat{q}_i = Q_i(q_{-i})$ on quantiles for agent i;
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For each agent i, given Q_i , the distribution over thresholds \hat{q}_i does not depend on the type distribution of other agents.

Expected revenue from pricing-based mechanisms:

$$\begin{split} \sum_{i \in N} \mathbf{E}_{\forall j \neq i, q_j \sim U[0,1]} [P_i(Q_i(q_{-i}))] &= \sum_{i \in N} \mathbf{E}_{\forall j, q_j \sim U[0,1]} \big[P_i'(q_i) x_i(q_i, q_{-i}) \big] \\ &= \mathbf{E}_{\forall j, q_j \sim U[0,1]} \Bigg[\sum_{i \in N} P_i'(q_i) x_i(q_i, q_{-i}) \Bigg] \,. \end{split}$$

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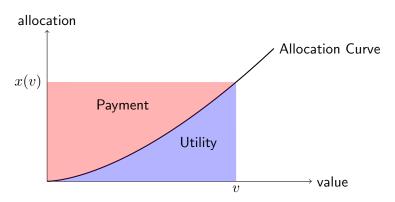
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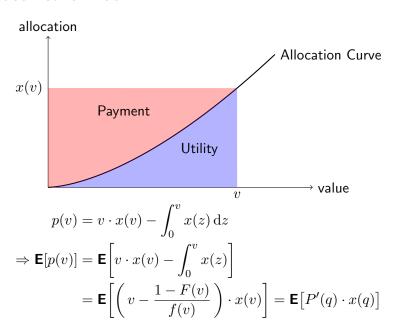
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Marginal revenue maximization is optimal among all possible mechanisms.

Alternative Geometric Proof



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Revenue Equivalence

The marginal revenue $P'_i(q_i)$ for value $v_i(q_i)$ sometimes is also referred to as the virtual value for $v_i(q_i)$ [Myerson'81].

Lemma

Given any mechanism M with allocation rule x, the expected revenue of the mechanism equals the expected marginal revenue / virtual value. That is,

$$\operatorname{Rev}(M) = \mathbf{E}_{\forall j, q_j \sim U[0, 1]} \left[\sum_{i \in N} P'_i(q_i) x_i(q_i, q_{-i}) \right].$$

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Expected ironed marginal revenue is an upper bound for expected marginal revenue, and they have the same maximizer.

• ironed marginal revenue is always weakly decreasing.

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Remark: the optimal reserve price v^* does not depend on the number of agents.

• it is also the optimal price in the single agent problem.

Approximation Under Linear Utilities

Posted Pricing

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Question: is posted pricing mechanisms also approximately optimal for revenue maximization?

Recap: Prophet Inequality

Online Selection Problem: n items arriving online.

- item i has value $v_i \sim F_i$;
- the agent knows F_1, \ldots, F_n at time 0.
- at time $i \leq n$, the agent observes value v_i and decides whether to select item i (if the selection has not been made).

Theorem

There exists a threshold policy that achieves a 2-approximation, i.e., it achieves expected value at least $\frac{1}{2}\mathbf{E}[\max_i v_i]$.

Connection to Revenue Maximization

Prophet inequality: n items

- value distributions $F = F_1 \times \cdots \times F_n$;
- threshold τ for each item;
- arrival order π .

Posted pricing mechanism: n agents

- marginal revenues $F = F_1 \times \cdots \times F_n$;
- threshold τ for each agent i;
- tie breaking rule π .

Any threshold τ in the marginal revenue space corresponds to a price p_i in the value space.

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Given any valuation profile $v=(v_1,\ldots,v_n)$, the selected value and the optimal value in both problems are the same.

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expected marginal revenue = expected revenue

 \Rightarrow posted pricing mechanism has a 2-approximation to the expected revenue.

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Example: n agents. For agent $i \leq n$, $v_i = 2^i$ w.p $\frac{1}{2^{i+1}}$, and $v_i = 0$ w.p $1 - \frac{1}{2^{i+1}}$.

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Third-degree price discrimination is crucial for revenue maximization.

• competition and simultaneous implementation is not.

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Theorem (Yan '11)

Sequential posted pricing mechanism has an $\frac{e}{e-1}$ -approximation to the expected revenue.

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A non-negative real-valued set function f over subsets S of an n element ground set $N = \{1, \dots, n\}$ and a distribution over subsets given by \mathcal{D} .

- \hat{q}_i : ex ante probability that element i is in the random set $S \sim \mathcal{D}$
- \mathcal{D}^I : distribution over subsets induced by independently adding each element i to the set with probability equal to its ex ante probability \hat{q}_i .

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The correlation gap is the ratio of the expected value of the set function for the (correlated) distribution \mathcal{D} to that with independent distribution \mathcal{D}^I , i.e.,

$$\frac{E_{S \sim \mathcal{D}}[f(S)]}{E_{S \sim \mathcal{D}^I}[f(S)]}.$$

Definition

A set function $f: 2^S \to \mathbb{R}$ defined on the subsets of a finite set S is called submodular if for all $A \subseteq B \subseteq S$ and $x \notin B$, the following inequality holds:

$$f(A \cup \{x\}) - f(A) \ge f(B \cup \{x\}) - f(B).$$

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Theorem

If the set function f is submodular, the correlation gap for function f is at most $\frac{e}{e-1}$.

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Under independent distribution \mathcal{D}^I :

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As
$$n \to \infty$$
, $\frac{E_{S \sim \mathcal{D}}[f(S)]}{E_{S \sim \mathcal{D}^I}[f(S)]} = \frac{e}{e-1}$.

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Ex ante relaxation: consider the relaxed problem where the sum of ex ante probabilities of receiving an item is at most 1.

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EAR is an upper bound on the optimal revenue.

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- $E_{S \sim \mathcal{D}^I}[f(S)]$: expected revenue from sequential posted pricing;
- $E_{S \sim \mathcal{D}}[f(S)]$: EAR.

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Correlation gap implies that

$$\frac{E_{S \sim \mathcal{D}}[f(S)]}{E_{S \sim \mathcal{D}^I}[f(S)]} \le \frac{e}{e - 1}.$$

Extension of Approximations Under Non-linear Utilities

Two options, which one would you choose:

- get \$10M;
- draw a lottery, with probability $\frac{1}{2}$, get \$20M, and get nothing otherwise.

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Risk aversion: $t_i = (v_i, \varphi_i)$ where $v_i \in \mathbb{R}_+$, φ_i is an increasing concave function, and

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Private budgets: $t_i = (v_i, B_i)$ where $v_i, B_i \in \mathbb{R}_+$, and

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Are simple mechanisms approximately optimal for non-linear utilities?

In single-agent environments, a mechanism is posting a per-unit price p if the agent can purchase any lottery x with price $x \cdot p$ for any $x \in [0,1]$.

• agent pays price $x \cdot p$ even if the realized allocation is 0.

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The demand of the agent $d^u(t,p)$ is the optimal lottery of the agent given per-unit price p.

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Assumption (Ordinary Goods)

 $d^u(t,p)$ is non-increasing in p for all $t \in T$.

Excludes Giffen goods or Veblen goods.

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Demand of an agent with a private budget given per-unit pricing:

	$t_1: (v=5, B=1)$	$t_2: (v=2, B=2)$
$p_1 = 4$	0.25	0
$p_2 = 2$	0.5	1

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There isn't a simple deterministic and consistent way of ordering types for a non-linear agent.

Solution: a random mapping from types to quantiles based on demand functions.

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Intuition: given any threshold \hat{q} and any type t, the following two quantities should coincide

- **1** probability the quantile of t is below \hat{q} ;
- 2 the demand of t given market clearing price $p^{\hat{q}}$.

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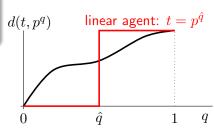
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Definition (Quantiles for Non-linear Agents)

The randomized quantile q for type $t \in T$ is drawn from distribution with CDF $d(t, p^q)$.

- $d(t, p^0) = 0$ and $d(t, p^1) = 1$;
- $d(t, p^q)$ is weakly increasing in q for all type t (ordinary good assumption).



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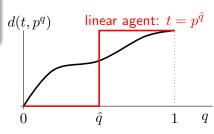
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- $d(t, p^0) = 0$ and $d(t, p^1) = 1$;
- $d(t, p^q)$ is weakly increasing in q for all type t (ordinary good assumption).

Remark: $q \sim U[0,1]$: $\Pr[z \leq q] = \mathbf{E}_{t \sim F}[d(t, p^q)] = q$.



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Pricing-based Mechanisms in Quantile Space

Definition (Pricing-based Mechanisms in Quantile Space)

Given any profile of feasible thresholds $\{Q_i\}_{i\in[n]}$,

- **1** Map type t_i to quantile q_i according to $d(t, p^q)$, and calculate threshold as $\hat{q}_i = Q_i(q_{-i})$.
- ② The allocation of agent i is $x_i = 1$ if and only if $q_i \leq \hat{q}_i$. The payment of agent i is $p_i = p^{\hat{q}_i} \cdot d(t_i, p^{\hat{q}_i})$ regardless of the allocation.

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Price-posting Equivalence Interpretation: Fixing any \hat{q}_i , from perspective of agent i

- wins the item with probability $d(t_i, p^{\hat{q}_i})$;
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Expected revenue: from any pricing-based mechanisms M for non-linear agents,

$$M(P) = \sum_{i} \mathbf{E}_{\forall j \neq i, q_j \sim U[0,1]} [P_i(Q_i(q_{-i}))].$$

For linear agents: $R = \bar{P}$ [Bulow and Robert '89].

For non-linear agents: pricing-based mechanisms in general are not optimal, i.e., $R \neq \bar{P}$.

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- with probability $\frac{1}{2}$, $t_1 : (v = 2, B = 1)$;
- with probability $\frac{1}{2}$, $t_2 : (v = 10, B = 3)$.

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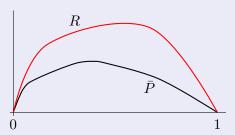
Lottery mechanism:

- offer menu of lotteries $(x_1 = \frac{1}{2}, p_1 = 1)$ and $(x_2 = 1, p_2 = 3)$;
- expected revenue equals 2.

Resemblance: Approximations in Single-agent Settings

Definition (ζ -resemblance)

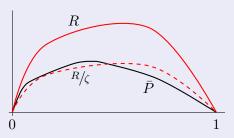
A non-linear agent is ζ -resemblant to a linear agent if given any supply constraint $q \in [0,1]$, there exists a posted pricing mechanism with expected demand $q^\dagger \leq q$ such that $\bar{P}(q^\dagger) \geq \frac{1}{\zeta} R(q)$.



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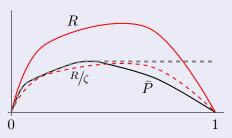
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Reduction from Non-linear to Linear Agents

Theorem

For non-linear agents that are ζ -resemblant to linear agents, pricing-based mechanism M is a γ -approximation to ex ante relaxation for linear agents $\Rightarrow M$ is a $\zeta\gamma$ -approximation to ex ante relaxation for non-linear agents.

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- **3** ζ -resemblance $\Rightarrow \zeta \operatorname{EAR}(\bar{P}) \geq \operatorname{EAR}(R)$ (straightforward)

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Non-linearities are often details that can be dispensed from the model without affecting main economic conclusions.

Economic conclusions for linear agents \Rightarrow economic conclusions for non-linear agents.

ζ -resemblance for Non-linear Agents

	independent private budget*	risk averse*
revenue	3	е
welfare	2	1

Table: Summary of results for ζ -resemblance.

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Corollary

For risk averse agents, sequential posted pricing is an e/(e-1)-approximation to the optimal welfare.