

Bayesian and Worst-Case Revenue-Maximizing Auctions [Part I]

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Goal: prove results of the form (e.g., for revenue):

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Auction model: first focus on multi-unit auctions

- n bidders, k identical \vec{x} goods, unit demand
- allocation rule: b_i 's \rightarrow x_i 's
- payment rule: b_i 's \rightarrow p_i 's [all i : $p_i \leq b_i$]
- truthful (i.e., truthful bidding [$b_i = v_i$] dominant)

 - each i faces bid-independent posted price ³³

On Truthful Auctions

Easy Lemma: a multi-unit auction is truthful if and only if it is equivalent to the following:

- separately for each $i=1,2,\dots,n$:
 - choose (possibly randomized) "take-it-or-leave-it" offer at price $t_i(b-i)$ ["posted price"]

Example: the Vickrey auction (with $k=1$) corresponds to $t_i(b-i) = \max_{j \neq i} b_j$ for each i

Fact: [Myerson 81] these assumptions are "WLOG".

-
- "Revelation Principle" + "Revenue Equivalence Thms"

Bayesian Profit Maximization

Example: 1 bidder, 1 item, $v \sim$ known distribution F

- truthful auctions = posted prices p
- expected revenue of p : $p(1-F(p))$
 - given F , can solve for optimal p^*
 - e.g., $p^* = 1/2$ for $v \sim \text{uniform}[0,1]$
- but: what about $k, n > 1$ (with i.i.d. v_i 's)?

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Theorem: [Myerson 81] auction with max expected revenue is Vickrey with above reserve p^* .

-
- note p^* is *independent of k and n*

Two Definitions

- Implementable Allocation Rule:** is a function x (from bids to winners/losers) that admits a payment rule p such that (x,p) is truthful.
- i.e., truthful bidding $[b_i := v_i]$ always maximizes a bidder's (expected) utility

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Monotone Allocation Rule: for every fixed bidder i , fixed other bids b_{-i} , probability of winning only increases in the bid b_i .

- example: highest bidder wins
- non-example: 2nd-highest bidder wins

Myerson's Lemma

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Moreover: for every monotone allocation rule x , there is a unique payment rule p such that (x, p) is truthful and losers always pay 0.

Explicit formula for $p_i(b)$:

- keep b_i fixed, increase z from 0 to b_i
- consider breakpoints y_1, \dots, y_q at which x_i jumps
- set $p_i(b) := \sum_j y_j \bullet [\text{jump in } x_i \text{ at } y_j]$

Digression: Sponsored Search

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Example - Sponsored search:

- n bidders with valuations v_i per click
- k slots, worth $\alpha_1 \geq \alpha_2 \geq \dots \geq \alpha_k$ clicks
- note: "rank by bid" is monotone allocation rule
- total payment from i th ranked bidder:

$$p_i(b) := \sum_{j>i} v_j \bullet [\alpha_j - \alpha_{j+1}]$$

Myerson's Lemma (Proof)

Proof: let x be monotone, fix i and $b-i$. Write $x(z)$, $p(z)$ for $x_i(z, b-i)$, $p_i(z, b-i)$.

Swapping trick: if (x, p) is truthful, p satisfies:

- [take true value = z , false bid = $z + \epsilon$]:
$$z \circ x(z) - p(z) \geq z \circ x(z + \epsilon) - p(z + \epsilon)$$
- [take true value = $z + \epsilon$, false bid = z]:
$$(z + \epsilon) \circ x(z + \epsilon) - p(z + \epsilon) \geq (z + \epsilon) \circ x(z) - p(z)$$

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Thus: $p(z + \epsilon) - p(z)$ lies between $z \circ [x(z + \epsilon) - x(z)]$ and $(z + \epsilon) \circ [x(z + \epsilon) - x(z)]$

Myerson's Lemma (Proof con'd)

The story so far: $p(z + \varepsilon) - p(z)$ lies between

$$z \circ [x(z + \varepsilon) - x(z)] \text{ and } (z + \varepsilon) \circ [x(z + \varepsilon) - x(z)]$$

So: dividing by ε and taking ε to zero, get

- $p'(z) = z \circ x'(z)$ [if x differentiable at z] or
- jump in p at $z = z \circ [\text{jump in } x \text{ at } z]$

Integrating from 0 to b_i , get:

$$p_i(b) := \sum_j y_j \bullet [\text{jump in } x_i \text{ at } y_j]$$

Myerson's Revenue Formula

Step 2: formula for revenue via "virtual valuations".

- for *any* truthful auction (x,p)

Write: for fixed i, v_{-i} , expected revenue from i :

- integrate over $p_i(v_i, v_{-i})$ w.r.t. v_i (according to F)
- write p_i in terms of x_i , simplify:

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- write p_i in terms of x_i , simplify:

$$= E_{v_i} [\phi(v_i) \cdot x_i(v_i, v_{-i})]$$

where

"virtual valuation" \rightarrow $\phi(v_i) = v_i - \frac{1-F(v_i)}{f(v_i)}$ E.g., $\phi(v_i) = 2v_i - 1$ when $F = \text{Unif}[0,1]$

Proof of Myerson's Theorem

So far: expected revenue of any (x,p) :

$$= E_{\mathbf{v}}[\sum_i \phi(v_i) \cdot x_i(\mathbf{v})]$$

E.g., $\phi(v_i) = 2v_i - 1$ when
 $F = \text{Unif}[0,1]$

- to maximize: for each vector \mathbf{v} , set x_i 's to maximize sum of virtual valuations.
- multi-item auctions: award k items to the top k $\phi(v_i)$'s that are also positive

The Fine Print

So far: to maximize expected revenue
 $E_{\mathbf{v}}[\sum_i \phi(v_i) \cdot x_i(\mathbf{v})]$: for each vector \mathbf{v} , set x_i 's to maximize sum of virtual valuations.

Question: is this allocation rule monotone?

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Question: is this allocation rule monotone?

- yes if ϕ is nondecreasing; otherwise not
- *regular* distribution $F := \phi$ is nondecreasing
 - most prominent non-example: bimodal distributions
- Myerson's theory can be extended to irregular distributions - important but more complicated

Bulow-Klemperer ('96)

Observation: for every F , $E[\phi(v_i)] = 0$.

- proof #1: consider Vickrey with $k = n = 1$
- proof #2: integrate $\phi(v_i) = v_i - (1 - F(v_i)) / f(v_i)$

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Vickrey's revenue

OPT's revenue

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Corollary [BK96]: for $k = 1$, every n , every regular F :

$$\begin{array}{ccc} \text{Vickrey's revenue} & \geq & \text{OPT's revenue} \\ \text{[with } (n+1) \text{ i.i.d. bidders]} & & \text{[with } n \text{ i.i.d. bidders]} \end{array}$$

Interpretation: small increase in market size more important than running optimal auction.

Bulow-Klemperer (Proof)

Proof idea:

- OPT's expected revenue [n bidders]:
$$E v[\max \{ \max_{i \leq n} \phi(v_i), 0 \}]$$
- Vickrey's expected revenue [(n+1) bidders]:
$$E v[\max \{ \max_{i \leq n} \phi(v_i), \phi(v_{n+1}) \}]$$
- condition on $\phi(v_1), \dots, \phi(v_n)$, use observation that $E[\phi(v_i)] = 0$

Application: Search Auctions

Theorem 1: [Dughmi/Roughgarden/Sundararajan EC 09]

The BK theorem extends to multi-unit auctions (add k new bidders); search auctions (ditto); matroid domains (add a new matroid basis).

Theorem 2 [DRS09]: for every regular F and k, n :

Vickrey's revenue $\geq (1 - k/n) \cdot \text{OPT's revenue}$

[with n i.i.d. bidders]

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Interpretation: efficiency and revenue well-aligned with i.i.d. bidders and modest competition.

More General Problems

Downward-closed environment:

- n bidders, independent valuations from F_1, \dots, F_n
- collection C of feasible sets of bidders
- subsets of feasible sets must be again feasible
 - k -unit auction: $C =$ all subsets of at most k bidders

Example: single-minded combinatorial auctions

- set of m different goods
- each bidder i wants a known bundle S_i of goods
- feasible subsets = bidders with disjoint bundles

Myerson still works

In a general downward-closed environment:

- allocation rule still implementable iff monotone
- revenue formula remains valid:
expected revenue under $x = E_{\mathbf{v}}[\sum_i \phi_i(v_i) \cdot x_i(\mathbf{v})]$
- if each F_i is regular, OPT just maximizes total virtual value pointwise (for each \mathbf{v})

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Issue: OPT much more complicated / unintuitive

- single-item auction: might sell to non-highest bidder!
- need detailed information about ϕ_i 's (not just $\phi_i^{-1}(0)$)

Simple vs. Optimal Auctions

Question: is there a simple (+ practically implementable) auction that's almost as good?

Theorem: [Hartline / Roughgarden EC 09] Yes!

Expected revenue of VCG + "monopoly reserve prices" is at least 50% of OPT for:

- all DC environments, if the F_i 's are such that $\frac{1 - F_i(v_i)}{f_i(v_i)}$ nonincreasing in v_i (*monotone hazard rate*)

-
- all matroid environments, if F_i 's are regular

□ $\frac{1 - F_i(v_i)}{f_i(v_i)}$ is

VCG + Monopoly Reserves

- Input:** general DC environment, unknown v_i 's drawn from known regular F_i 's
- set reserve $r_i = \operatorname{argmax}_p p(1-F_i(p))$ [each i]
 - delete all bidders with $v_i < r_i$
 - run "VCG": maximize sum of v_i 's (i.e., welfare) of remaining bidders, subject to feasibility
 - this allocation rule is monotone; charge suitable prices to make truthful (=max{VCG prices, r_i 's})