

Recurring Themes in Auction Theory and Mechanism Design

Part I: Virtual Value and Revenue

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February 13, 2023
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Overview

- ♦ Goal: highlight a few ideas that help us understand lots of results in auction theory/mechanism design
- ♦ Today:

The expected revenue from any sales mechanism is the expected value of the **virtual value** of the buyer who receives the good.

(one interpretation of Myerson (1981), “Optimal Auction Design”)

- ♦ What does this mean? Why is it true?
- ♦ Why does it “make sense”?
- ♦ Several other results that follow from it



**What's the best way
to sell a thing?**



Model

- ♦ Single object to sell
- ♦ Fixed set of n risk-neutral buyers, with valuations v_i
- ♦ v_i are independent random variables $v_i \sim F_i$ on $[a_i, b_i]$
- ♦ Seller can specify (and commit to) any game for buyers to play, subject to two constraints:
 - ♦ Participation is voluntary
 - ♦ Players will understand the game and play equilibrium
- ♦ What outcomes can seller achieve?
What game maximizes expected revenue?

max $E(\text{revenue})$

literally all
possible games

s.t. participation, equilibrium

- ♦ For any game the seller could design, let
 - ♦ $p_i(v_1, v_2, \dots, v_n)$ be equilibrium probability buyer i gets object
 - ♦ $x_i(v_1, v_2, \dots, v_n)$ be expected payment buyer i makes to seller
- ♦ What if instead of playing the game, seller...
 - ♦ asked buyers their valuations
 - ♦ committed to implementing allocation $p(\cdot)$ and payments $x(\cdot)$
- ♦ “Revelation principle”
 - ♦ any outcome implemented by any game can be implemented by “direct revelation mechanism”
 - ♦ WLOG, maximize revenue only over DRMs

\max E(revenue) direct revelation mechanisms s.t. participation, truth-telling

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 - ♦ WLOG, maximize revenue only over DRMs
 - ♦ Constraints: voluntary participation and truth-telling

max E(revenue)

direct revelation
mechanisms

s.t. participation, truth-telling

♦ Truth-telling requires two things:

- ♦ Allocation rule p must be “monotone” $(E_{v_{-i}} p_i(v_i, v_{-i})) \uparrow v_i$
- ♦ Each bidder’s equilibrium expected payoff $U_i(v_i)$ must satisfy

$$U_i(v_i) = U_i(a_i) + \int_{a_i}^{v_i} E_{v_{-i}} p_i(s, v_{-i}) ds$$

♦ Voluntary participation requires $U_i(v_i) \geq 0$

- ♦ $U_i(\cdot)$ is increasing, so $U_i(a_i) \geq 0$ suffices

♦ Now...

- ♦ If p determines each buyer’s chance of winning given v_i ...
- ♦ ...and p and $U_i(a_i)$ together determine i ’s expected payoff...
- ♦ ...then p and $\{U_i(a_i)\}_i$ determine seller’s expected revenue!

$\max E(\text{revenue})$ p monotone, $\{U_i(a_i)\} \geq 0$ s.t. participation, truth-telling

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$$\begin{array}{ll} \max & E(\text{revenue}(p, \{U_i(a_i)\})) \\ \text{s.t.} & p \text{ monotone,} \\ & \{U_i(a_i)\} \geq 0 \\ & \text{participation, truth-telling} \end{array}$$

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$$\max E(\text{revenue}(p, \{U_i(a_i)\}))$$

p monotone,

$$\{U_i(a_i)\} \geq 0$$

$$\text{Expected Revenue} = \text{Gross Surplus from Allocating Object} - \text{Expected Surplus Earned by Bidders}$$

$$= E_v \sum_i v_i p_i(v) - \sum_i E_{v_i} \left(U_i(a_i) + \int_{a_i}^{v_i} E_{v_{-i}} p_i(s, v_{-i}) ds \right)$$

- ♦ After a bunch of algebra, this is

$$\text{Expected Revenue} = E_v \sum_i p_i(v) \left[v_i - \frac{1 - F_i(v_i)}{f_i(v_i)} \right] - \cancel{\sum_i U_i(a_i)}$$

Call this buyer i 's
virtual value
Optimizing seller
will set to 0

- ♦ Expected revenue from any sales mechanism is
EV of winning bidder's virtual value

$$\max_{\substack{p \text{ monotone,} \\ \{U_i(a_i)\} \geq 0}} E_v \sum_i p_i(v) \left[v_i - \frac{1 - F_i(v_i)}{f_i(v_i)} \right]$$

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Optimizing seller will set to 0

- ♦ Expected revenue from any sales mechanism is **EV of winning bidder's virtual value**

$$\max_{p \text{ monotone}} E_v \sum_i p_i(v) \left[v_i - \frac{1 - F_i(v_i)}{f_i(v_i)} \right]$$

- ♦ Recapping the main takeaways:
 - ♦ Any *allocation* can be implemented as equilibrium of some sales game as long as it's monotone
 - ♦ An allocation is implemented by essentially unique payment rule, so equilibrium allocation uniquely* determines expected revenue
 - ♦ **The expected revenue from any sales mechanism is the expected value of virtual value of buyer who gets the object**
- ♦ Rest of today: why does this make sense?
and what does this buy us?

**Is there any nice intuition
for “virtual value”?**

Expected revenue is $E_v \sum_i p_i(v) \left[v_i - \frac{1 - F_i(v_i)}{f_i(v_i)} \right]$

- ◆ Consider a monopolist facing measure 1 of consumers with willingness-to-pay distributed F

- ◆ At price p , demand is $q = 1 - F(p)$, revenue is $p(1 - F(p))$
- ◆ To sell to “one more buyer,” seller must cut price by

$$\frac{1}{-dq/dp} = \frac{1}{f(p)}$$

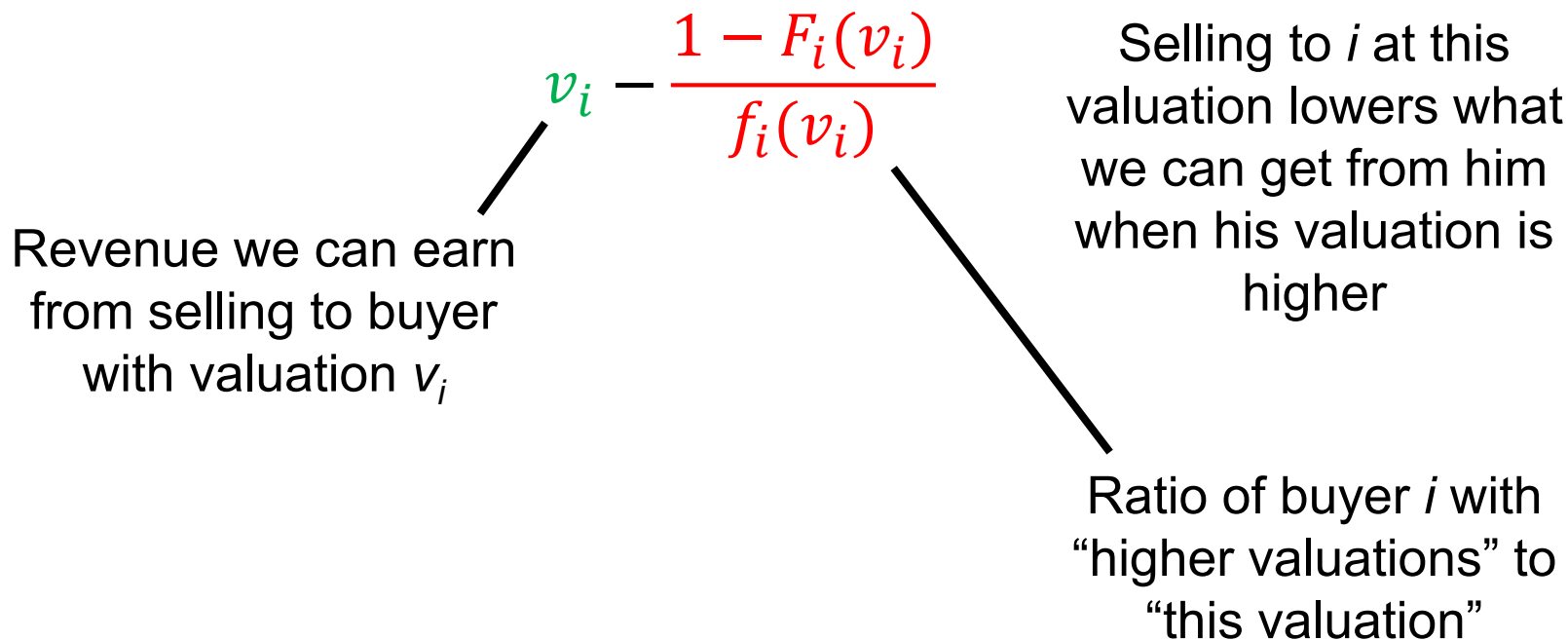
- ◆ Effect on revenue is

$$-\frac{1}{f(p)} \frac{d}{dp} [p(1 - F(p))] = -\frac{1}{f(p)} [1 - F(p) - pf(p)] = p - \frac{1 - F(p)}{f(p)}$$

- ◆ So $p - \frac{1 - F(p)}{f(p)}$ is **marginal revenue** from selling to one more buyer, when that buyer has valuation p !

Expected revenue is $E_v \sum_i p_i(v) \left[v_i - \frac{1 - F_i(v_i)}{f_i(v_i)} \right]$

- ♦ Think of virtual value as the incremental revenue from selling to buyer i when he has valuation v_i



**What do we get from this
formulation of expected revenue?**

Expected revenue is $E_v \sum_i p_i(v) \left[v_i - \frac{1 - F_i(v_i)}{f_i(v_i)} \right]$

- ♦ Corollary 1: revenue equivalence
 - ♦ If p and $\{U_i(a_i)\}$ determine expected revenue...
 - ♦ ...then any two games with same p and $\{U_i(a_i)\}$ have same expected revenue

- ♦ Usually stated as:
 - ♦ “Suppose bidders have symmetric, independent private values.
 - ♦ Define a *standard auction* as any auction where
 - (i) the bidder with the highest valuation wins in equilibrium, and
 - (ii) a bidder with their lowest possible valuation gets 0 payoff
 - ♦ All standard auctions have the same expected revenue.”

$$\max_{p \text{ monotone}} E_v \sum_i p_i(v) \left[v_i - \frac{1 - F_i(v_i)}{f_i(v_i)} \right]$$

♦ Corollary 2: solution to seller's problem

- ♦ Without “monotone p ” constraint, maximize pointwise: for each v , give object to whoever has the highest virtual value (if ≥ 0)
- ♦ If $v_i - \frac{1 - F_i(v_i)}{f_i(v_i)}$ is increasing in v_i (F_i is “regular”) for each i , this allocation rule is monotone \rightarrow feasible \rightarrow optimal
- ♦ In symmetric case, “highest value wins” – optimal mechanism is a second price auction with reserve price!
- ♦ Reserve price is set such that $0 = r - \frac{1 - F(r)}{f(r)}$
- ♦ (Prevents sale when winner's *virtual value* is negative)
- ♦ (Note that optimal reserve does not depend on n !)
- ♦ If distributions not regular, optimal mechanism more complicated

**What else is this
formulation good for?**

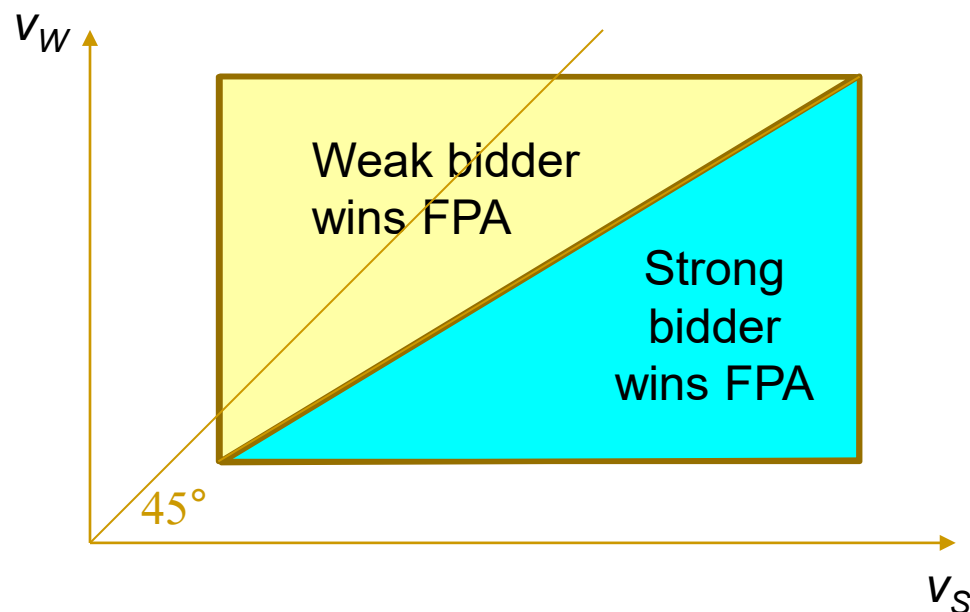
Revenue rankings of asymmetric auction formats

First Price vs Second Price Auctions

- ♦ If $F_i = F_j = F$ for all bidders, revenue equivalence
 - ♦ FP and SP auctions “equally good”
- ♦ If F_i vary across bidders, no longer true
 - ♦ Neither is optimal (but optimal auction never used)
 - ♦ Which is better?
- ♦ Suppose two bidders, $F_S \geq_{FOSD} F_W$
 - ♦ SP auction: still a dominant strategy to bid valuation
 - ♦ FP auction: equilibrium bids solve pair of diff eq's
 - ♦ Strong bidder prefers SP auction, weak bidder prefers FP
 - ♦ General revenue ranking is not available

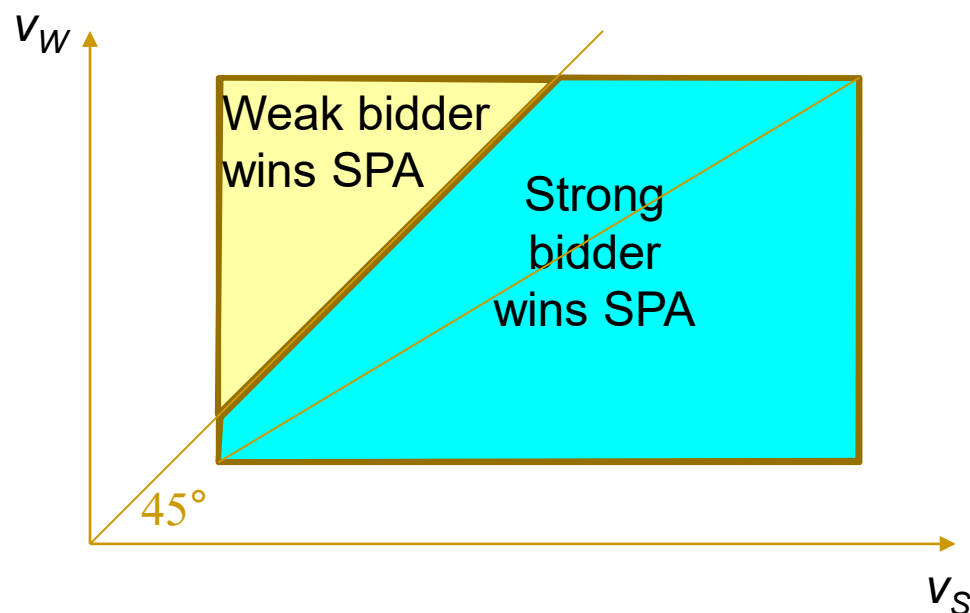
Expected revenue is $E_v \sum_i p_i(v) \left[v_i - \frac{1-F_i(v_i)}{f_i(v_i)} \right]$

- ◆ In FP auction with asymmetric bidders, strong bidder “shades bid more” than weak
- ◆ So weak bidder sometimes wins with lower valuation



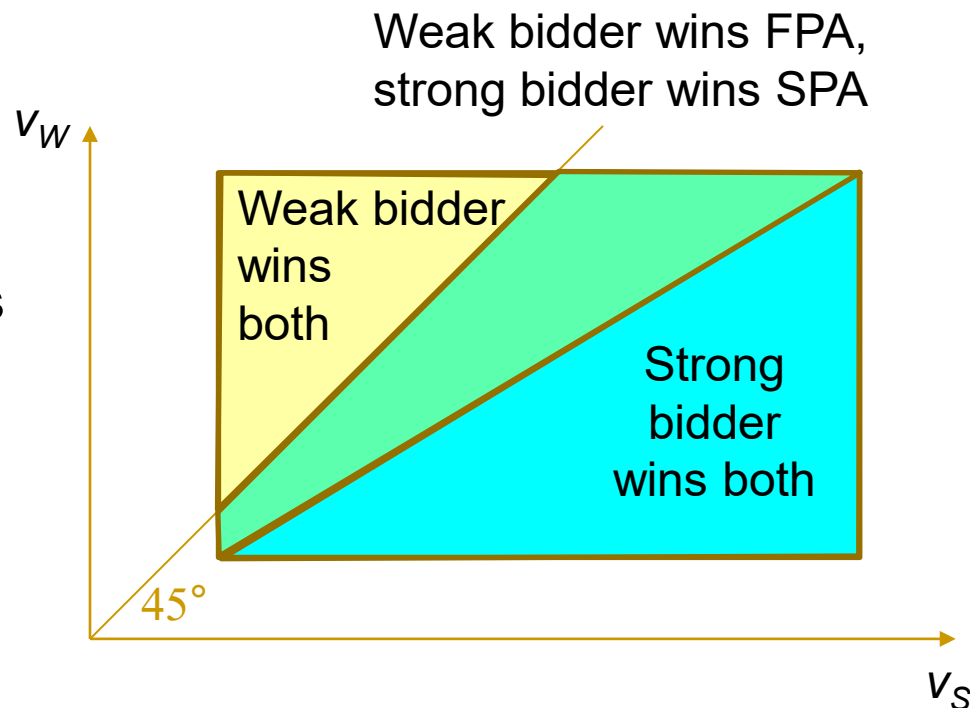
Expected revenue is $E_v \sum_i p_i(v) \left[v_i - \frac{1-F_i(v_i)}{f_i(v_i)} \right]$

- ◆ In SP auction, bidders bid their valuations
- ◆ So bidder with higher valuation wins



Expected revenue is $E_v \sum_i p_i(v) \left[v_i - \frac{1-F_i(v_i)}{f_i(v_i)} \right]$

- ◆ Since revenue is EV of winner's VV...
- ◆ ...revenue ranking depends on who has higher average virtual value in middle region
- ◆ (Lets us better understand known special cases, prove some new ones)



Optimal search auctions

“Search auctions”

- ♦ Suppose seller needs to search for buyers
 - ♦ Instead of “ n buyers ready to go”...
 - ♦ ...there are n *potential* buyers
 - ♦ Costs seller c_i to find buyer i and educate them about object
 - ♦ Buyer i then learns their v_i and can participate in auction
- ♦ Seller knows $\{c_i, F_i\}$ for each of n potential buyers
- ♦ What should seller do?

J. Crémer, Y. Spiegel, and C.Z. Zheng (2007), Optimal Search Auctions, *Journal of Economic Theory* 134

Without private information, optimal search is a solved problem

- ♦ “Pandora’s problem” (Weitzman 1979)
 - ♦ n boxes
 - ♦ Box i has cost c_i to open, contains prize worth $v_i \sim F_i$
 - ♦ You know (c_i, F_i) for each box, can open as many as you want in any order, claim any one opened box’s prize at any time
 - ♦ Solution: calculate index for each box

$$a_i = E \max\{a_i, v_i\} - c_i$$

$$c_i = \int_{a_i}^{\infty} (v_i - a_i) f_i(v_i) dv_i$$

- ♦ Open boxes in decreasing index order
- ♦ Stop when best prize so far $>$ highest remaining index

M.L. Weitzman (1979), Optimal Search for the Best Alternative, *Econometrica* 47

J.C. Gittins and D. Jones (1974), A Dynamic Allocation Index for the Sequential Design of Experiments, in *Progress In Statistics*, Ed. J. Gani, North Holland

But here, buyers have private info

- ◆ Once you contact a buyer, *they* know v_i , you don't
 - ◆ Still need to design a mechanism for them to play
 - ◆ How should seller proceed?
- ◆ Hint: revenue of a mechanism is EV of VV of winner
- ◆ Treat this as a *full-info* search problem, where “prize” is $v_i - \frac{1-F_i(v_i)}{f_i(v_i)}$ rather than v_i
 - ◆ Let G_i be distribution of bidder i 's *virtual* value $v_i - \frac{1-F_i(v_i)}{f_i(v_i)}$
 - ◆ Solve Pandora's problem with (c_i, G_i)
 - ◆ Run dynamic direct-revelation mechanism: each time a buyer is contacted, ask them their valuation
 - ◆ Allocation rule: winner is highest VV when search ends
 - ◆ Payment rule is determined by allocation rule

The importance of n relative to auction format

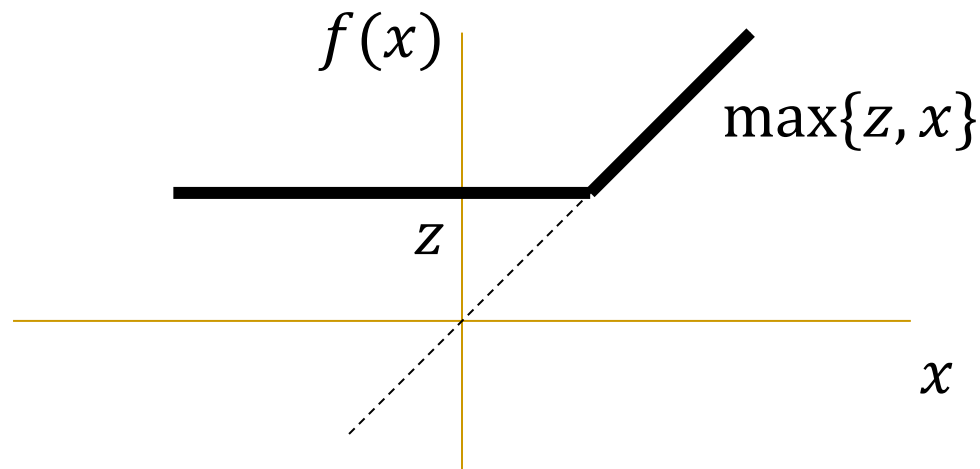
How important is auction choice?

- ♦ We've considered revenue maximization with fixed set of bidders and valuation distributions
- ♦ In some sense, increasing participation matters more than getting the mechanism right
- ♦ Adding *one more bidder* is always more valuable than setting correct reserve price
 - ♦ Optimal auction with n symmetric bidders is lower-revenue than “pure auction” (no reserve price) with $n+1$

Mathematical preliminaries

- ♦ The max operator is convex
 - ♦ For fixed z , $f(x) = \max\{z, x\}$ is a convex function of x
 - ♦ By Jensen, $E_X \max\{z, X\} \geq \max\{z, E(X)\}$
 - ♦ By iterated expectations, if z is a random variable,

$$E_{X,Z} \max\{Z, X\} \geq E_Z \max\{Z, E(X)\}$$



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$$E_{X,Z} \max\{Z, X\} \geq E_Z \max\{Z, E(X)\}$$

- ♦ The expected value of bidder i 's virtual value is a_i

$$E(VV_i) = \int_{a_i}^{b_i} \left[v_i - \frac{1 - F_i(v_i)}{f_i(v_i)} \right] f_i(v_i) dv_i$$

- ♦ (Turns out to be a_i , trust me on this one) ☺

The result

- ♦ Assume symmetric IPV with regular distribution
- ♦ Auction with no reserve price, $n+1$ bidders gives revenue

$$E \max\{VV_1, VV_2, \dots, VV_n, VV_{n+1}\}$$

- ♦ Optimal auction with n bidders gives revenue

$$E \max\{VV_1, VV_2, \dots, VV_n, 0\}$$

- ♦ Just showed $E \max\{Z, X\} \geq E \max\{Z, E(X)\}$, so

$$\begin{aligned}
 & \text{Z } \overline{E \max\{VV_1, VV_2, \dots, VV_n, VV_{n+1}\}} \text{ X} \\
 & \geq E \max\{VV_1, VV_2, \dots, VV_n, E(VV_{n+1})\} \\
 & = E \max\{VV_1, VV_2, \dots, VV_n, a_{n+1}\} \\
 & \geq E \max\{VV_1, VV_2, \dots, VV_n, 0\}
 \end{aligned}$$

- ♦ Adding one bidder is more valuable than learning F and running the optimal mechanism!

**If you face one buyer
and don't know F**

What if seller doesn't know F ?

- ♦ With enough buyers, doesn't really matter
- ♦ But what if $n = 1$?
- ♦ Cool result: if you don't know F but know it's regular, you can get at least $\frac{1}{2}$ the expected revenue of the optimal mechanism if you get *one* sample draw from F
- ♦ How? Set posted price equal to the sample draw!

Guaranteeing half the optimal revenue with one sample draw from F

- ♦ Let v_0 be outcome of sample draw, demand price $p = v_0$
- ♦ You sell whenever actual buyer's valuation v_1 is above v_0
- ♦ Expected revenue is $E\{VV_1 \times 1_{v_1 > v_0}\}$
- ♦ Since F regular, this is $E\{VV_1 \times 1_{VV_1 > VV_0}\}$
- ♦ By symmetry, $= \frac{1}{2}E\{VV_1 \times 1_{VV_1 > VV_0}\} + \frac{1}{2}E\{VV_0 \times 1_{VV_0 > VV_1}\}$
 $= \frac{1}{2}E \max\{VV_1, VV_0\}$
- ♦ Recall $E \max\{VV_1, VV_0\}$ is revenue of a two-bidder auction with no reserve...
- ♦ ...which is more than optimal one-bidder auction
- ♦ So if F regular, revenue is at least half the optimal revenue!

Generalizing to other environments

Generalizing to richer environments

- ♦ “Marginal revenue maximization” is also used in algorithmic mechanism design at the CS/econ junction
 - ♦ “The intuition that profit is optimized by maximizing marginal revenue is a guiding principle in microeconomics.
 - ♦ In the classical auction theory for agents with quasi-linear utility and single-dimensional preferences, Bulow and Roberts show that the optimal auction of Myerson is in fact optimizing marginal revenue.
 - ♦ In particular Myerson’s virtual values are exactly the derivative of an appropriate revenue curve.”

Generalizing to richer environments

- ◆ Now consider a richer setting where...
 - ◆ Seller can “serve” multiple buyers, faces constraint on which sets of buyers can be served
 - ◆ Non-quasilinear preferences (e.g., risk aversion or budget constraints), possible flexibility on other details of “service”
- ◆ For a single buyer, find mechanism that maximizes expected revenue for a fixed ex ante probability of service
 - ◆ This defines “revenue curve” relating revenue to “quantity,” which lets you calculate “marginal revenue” for each buyer at each valuation
 - ◆ “Marginal revenue mechanism” then serves set of buyers that maximizes marginal revenue of those served
- ◆ Paper shows...
 - ◆ condition (“revenue linearity”) under which this mechanism is optimal
 - ◆ that it is approximately optimal when sufficient condition holds approximately

Summing up

Overview

- ◆ “Best” way to sell a single object?
 - ◆ Revenue of any mechanism determined by equilibrium allocation
 - ◆ Any allocation can be implemented if it's monotone
 - ◆ Expected revenue is EV of winner's virtual value
- ◆ Leads to lots of classic results
 - ◆ Revenue equivalence and optimal mechanism
 - ◆ Importance of participation over mechanism choice
 - ◆ Useful tool for comparing non-optimal auction formats, solving sequential search for buyers, doing “well enough” without knowing distribution of valuations...
 - ◆ ...and analogous mechanism can be defined in richer environments

Overview

- ◆ Today: how does a seller optimize given a fixed set of buyers with fixed information and fixed valuations
- ◆ Tomorrow: pre-auction choices
 - ◆ Auctions with endogenous participation...
 - ◆ ...or endogenous buyer information...
 - ◆ ...or endogenous pre-auction investments
 - ◆ Focus on efficiency rather than revenue maximization
 - ◆ **Externalities** give useful lens for simplifying intuition

Thank you!

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