

# Maximizing Revenue in Expectation

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- ▶ What does that mean? What is our benchmark?
- ▶ This lecture: a case study for single item auctions.

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- ▶ Consider a single bidder, single item auction. Offering a fixed price  $p$  is always dominant strategy truthful.
- ▶ Revenue is  $p$  if  $v_i \geq p$ , 0 otherwise.
- ▶ So *ex-post*, the revenue-optimal auction sets  $p = v_i$ ... But *ex-ante*, we don't have enough information.

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$$\text{Rev}(p) = p \cdot (1 - F(p))$$

Where  $F(p) = \Pr_{v \sim D}[v \leq p]$ .

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Where  $F(p) = \Pr_{v \sim D}[v \leq p]$ .

- ▶ E.g. if  $D$  is uniform on  $[0, 1]$ , then  $F(p) = p$  and:

$$\max_p Rev(p) = \frac{1}{2} \cdot \left(1 - \frac{1}{2}\right) = \frac{1}{4}$$

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- ▶ For truthfulness, we need  $X$  to be monotone non-decreasing...
- ▶ And we know:

$$P_i(v) = v_i \cdot X_i(v) - \int_0^{v_i} X_i(z, v_{-i}) dz$$

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$$\mathbb{E}_{v \sim D^n} \left[ \sum_{i=1}^n P_i(v) \right] = \sum_{i=1}^n \mathbb{E}_{v_{-i} \sim D^{n-1}} [\mathbb{E}_{v_i \sim D} [P_i(v_i, v_{-i})]]$$

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- ▶ Notation:  $f(p)$  is the pdf of  $D$ .

$$F(p) = \Pr_{v \sim D} [v \leq p] = \int_0^p f(v) dv$$

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Consider the inner term:

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So: We want to maximize

$$\mathbb{E}_{v \sim D^n} \left[ \sum_{i=1}^n \phi(v_i) \cdot X(v) \right] \quad \underbrace{\phi(v_i) = \left( v_i - \frac{(1 - F(v_i))}{f(v_i)} \right)}_{\text{"Virtual Value"}}$$

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- ▶ (Pointwise) optimal allocation rule: Give the item to the bidder  $i$  with highest  $\phi(v_i)$  if it's positive. Otherwise give the item to nobody.
- ▶ This is a monotone allocation rule if  $D$  is *regular*:  $\phi(v_i)$  is monotone.
  - ▶ e.g. if  $D$  is uniform,  $\phi(v_i) = v_i - (1 - v_i) = 2v_i - 1$
  - ▶ Note that  $\phi^{-1}(0)$  recovers the optimal  $p = 1/2$  for a single bidder.

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- ▶ i.e. its just a Vickrey auction with a reserve price of  $\phi^{-1}(0)$ !
- ▶ Remarkable — Simple eBay style auction is *the best possible*.

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- ▶ Doesn't extend beyond single parameter domains...
- ▶ Requires knowledge of  $D$ ...

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- ▶ What about a Vickrey auction with 2 bidders?



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$$Rev(VA) = E_{v_1, v_2 \sim D}[\min(v_1, v_2)] = 1/3$$

- ▶ So we might be better off maximizing welfare with more bidders...



# The Bulow/Klemperer Theorem

## Theorem

*Consider bidders drawn i.i.d. from a regular distribution  $D$ . For any  $n \geq 1$ , the Vickrey auction with  $n + 1$  bidders has higher expected revenue than the revenue optimal auction with  $n$  bidders.*

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So recruiting just *one* extra bidder is worth more than optimizing revenue for the current population.

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## Observations:

1. The revenue of  $A$  is exactly equal to the optimal revenue obtainable from  $n$  bidders.
2.  $A$  *always* allocates the item.

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- ▶ Recall that  $E_v[\sum_i P_i(v)] = E[\sum_i \phi_i(v_i) \cdot X_i(v)]$ .
- ▶ We can maximize the RHS (subject to always allocating the item) by always allocating to  $\arg \max_i \phi(v_i)$ .



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- ▶ We can maximize the RHS (subject to always allocating the item) by always allocating to  $\arg \max_i \phi(v_i)$ .
- ▶ Since  $D$  is regular,  $\phi$  is monotone: this is  $\arg \max_i v_i$  — the Vickrey allocation!
- ▶ So: The Vickrey-auction with  $n + 1$  bidders has only higher revenue than the optimal  $n$  bidder auction.

# Thanks!

See you next class — stay healthy!