

Algorithmic Game Theory and Applications

Optimal Auctions

Single-Item Auctions: Quick Refresher

Model: Single-Item Auctions $[0, \infty)$

- **Bidders** $i = 1, 2, \dots, n$
- Each bidder i has **value** $v_i \in \mathbb{R}_+$ for the item
 - Submits a **bid** $b_i \in \mathbb{R}_+$
- An **mechanism** $\mathcal{M} = (\mathbf{a}, \mathbf{p})$ consists of
 - **allocation** rule $\mathbf{a} = (a_1, a_2, \dots, a_n) : \mathbb{R}_+^n \longrightarrow [0, 1]^n$, where $\sum_{i=1}^n a_i(\mathbf{b}) \leq 1$,
 - **payment** rule $\mathbf{p} = (p_1, p_2, \dots, p_n) : \mathbb{R}_+^n \longrightarrow \mathbb{R}_+^n$
- Bidder **utility**: $u_i(\mathbf{b}; v_i) := a_i(\mathbf{b}) \cdot v_i - p_i(\mathbf{b})$
- Mechanism \mathcal{M} is **truthful** (DSIC) if: $u_i(v_i, \mathbf{b}_{-i}; v_i) \geq u_i(b_i, \mathbf{b}_{-i}; v_i) \quad \forall i \quad \forall \mathbf{b}_{-i} \quad \forall v_i, b_i$
 - + Individual rationality (IR): $u_i(v_i, \mathbf{b}_{-i}; v_i) \geq 0 \quad \forall i \quad \forall \mathbf{b}_{-i} \quad \forall v_i$

Myerson's Characterization



Roger Myerson (1951 -)



Nobel prize in Economics
(2007)

Myerson's Characterization [1981]

A mechanism $\mathcal{M} = (a, b)$ is truthful if and only if, for any bidder i and all bid profiles \mathbf{b}_{-i} :

- $a_i(b_i, \mathbf{b}_{-i})$ is a *nondecreasing* function of b_i , and

- payments are given by $p_i(\mathbf{b}) = a_i(\mathbf{b}) \cdot b_i - \int_0^{b_i} a_i(t, \mathbf{b}_{-i}) dt$.

- The second-price auction (i.e., VCG) is truthful *and* welfare maximizing!
- What if our goal is to maximize the seller's *revenue* instead?
 - Shall we still *always* sell to the *highest* bidder?

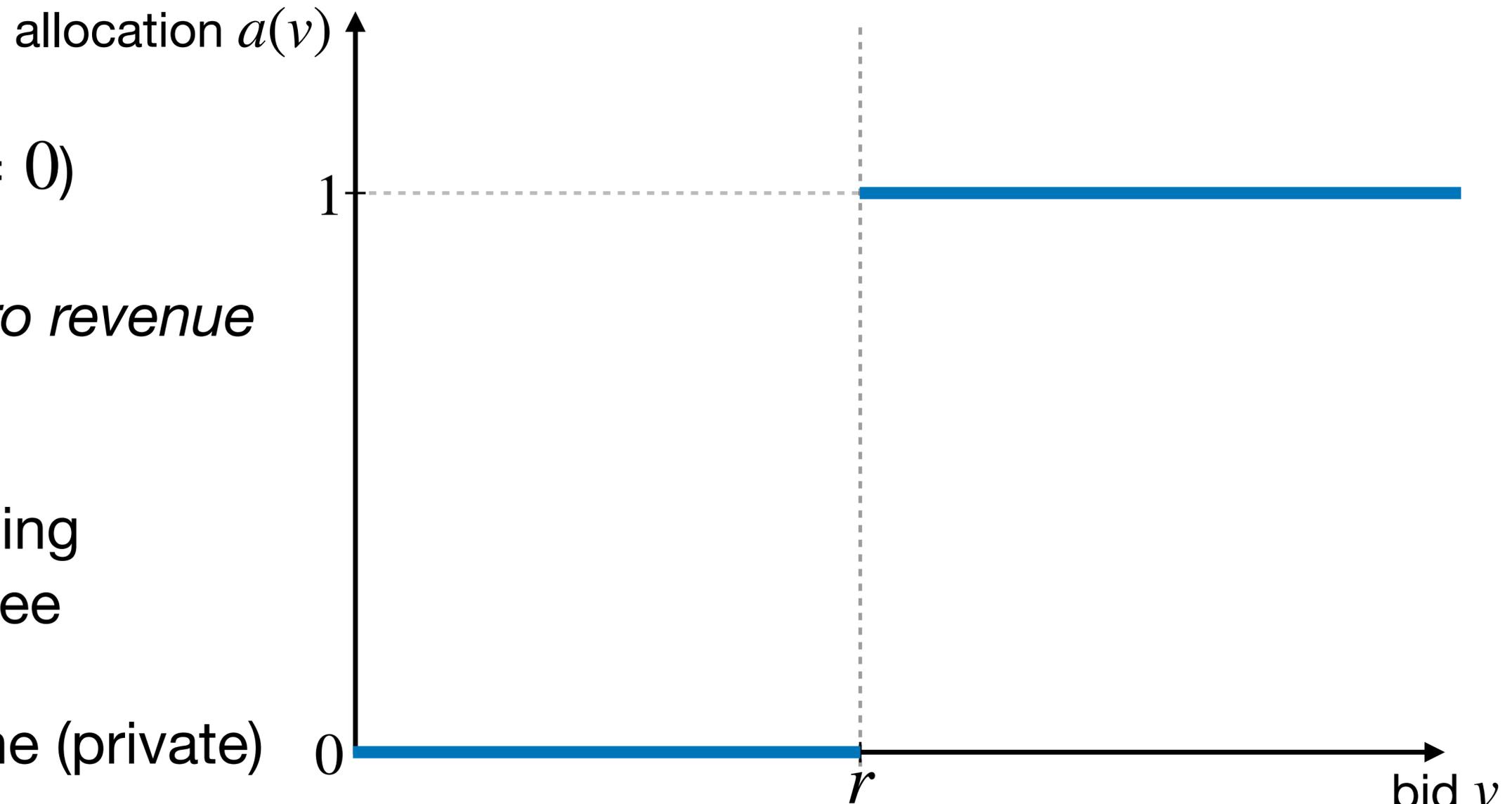


Roger Myerson

Welfare vs Revenue

Example: *Single-Bidder Deterministic Auctions*

- Always selling for free ($r = 0$) maximizes the welfare
 - However: this gives *zero revenue* to the seller!
- Where shall we set the selling price r , in order to guarantee “good” revenue?
 - *Highly* dependent on the (private) value v of the bidder.



Bayesian (Single-Item) Auctions

Model: Bayesian Single-Item Auctions

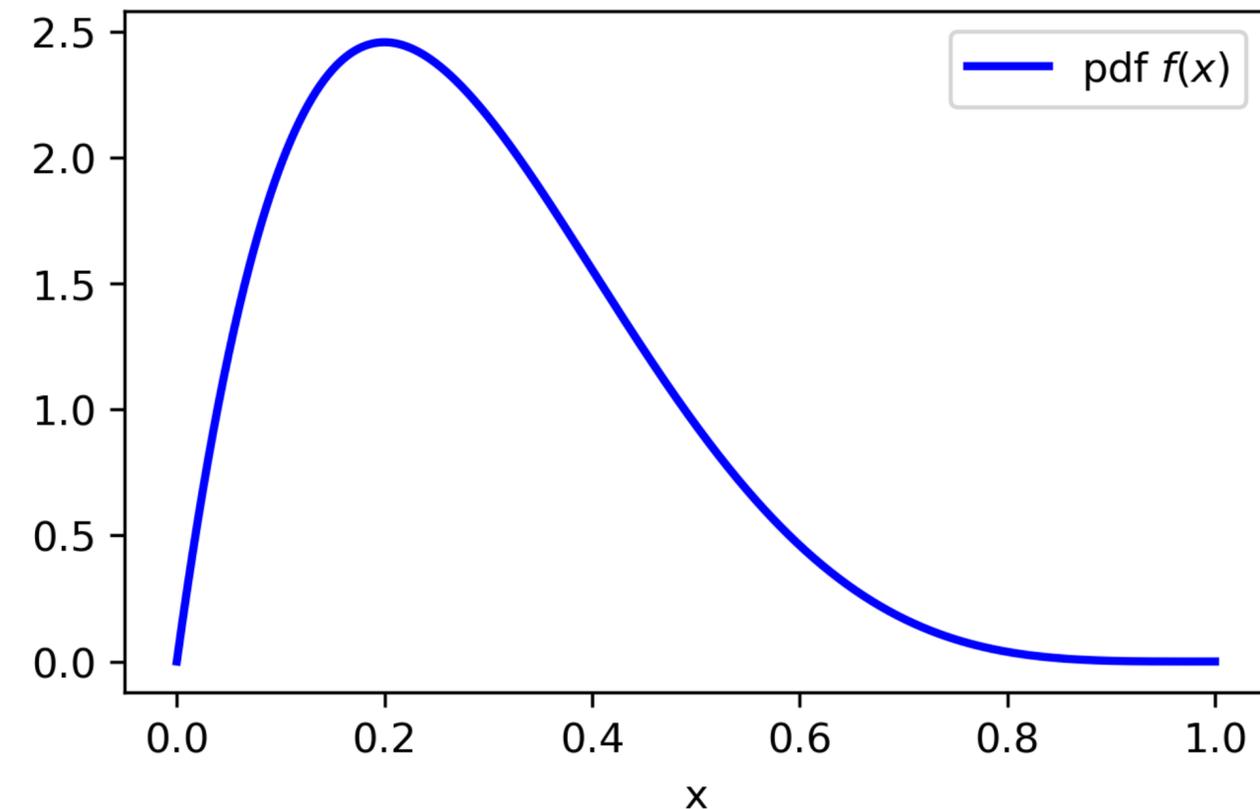
- The seller/auction-designer has *incomplete knowledge* of the bidder values v_i :
 - v_1, v_2, \dots, v_n are independent random variables
 - drawn from **distributions** (“priors”) F_1, F_2, \dots, F_n supported over $[0, 1]$

Continuous Probability Distributions

Quick Mathematical Detour

- Probability density function (pdf) $f : \mathbb{R}_+ \longrightarrow \mathbb{R}_+$
- Cumulative distribution function (cdf) $F : \mathbb{R}_+ \longrightarrow [0,1]$
 - The cdf is *continuous* and *nondecreasing*
 - It is given by

$$F(x) = \int_0^x f(t) dt.$$

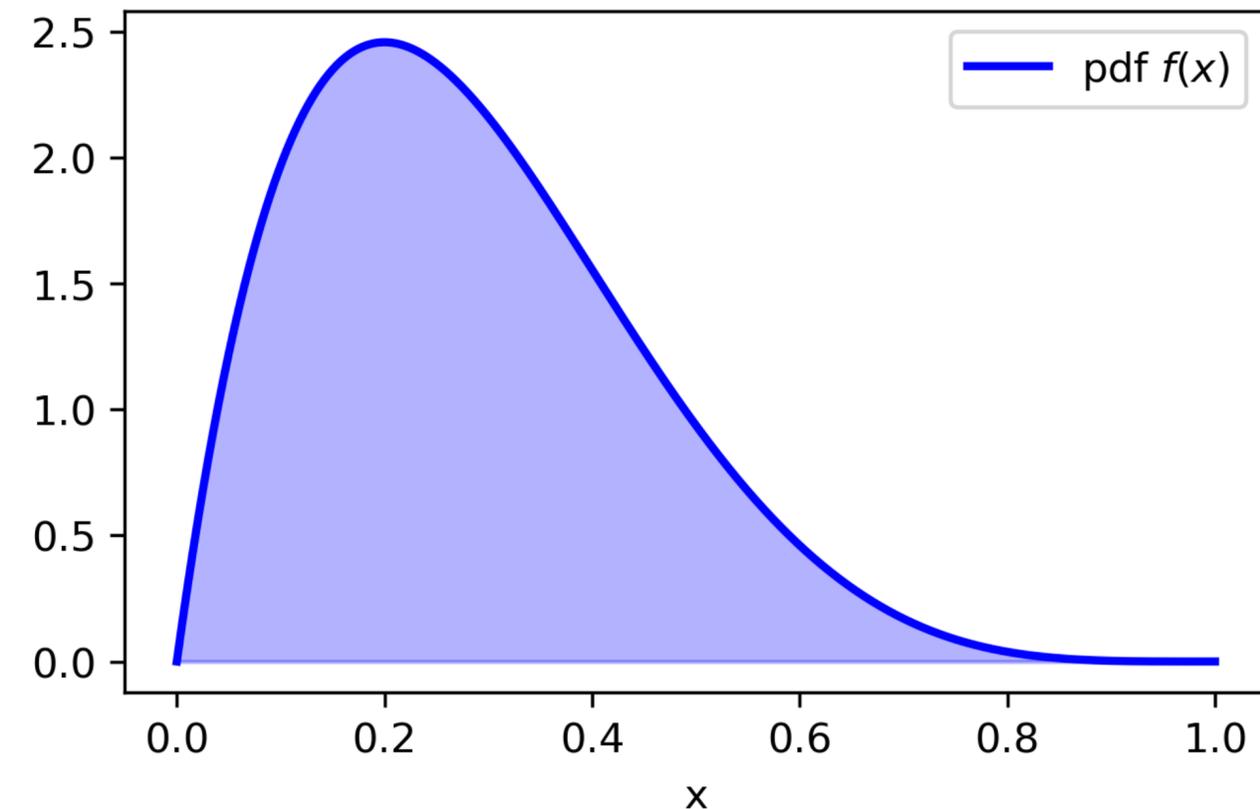


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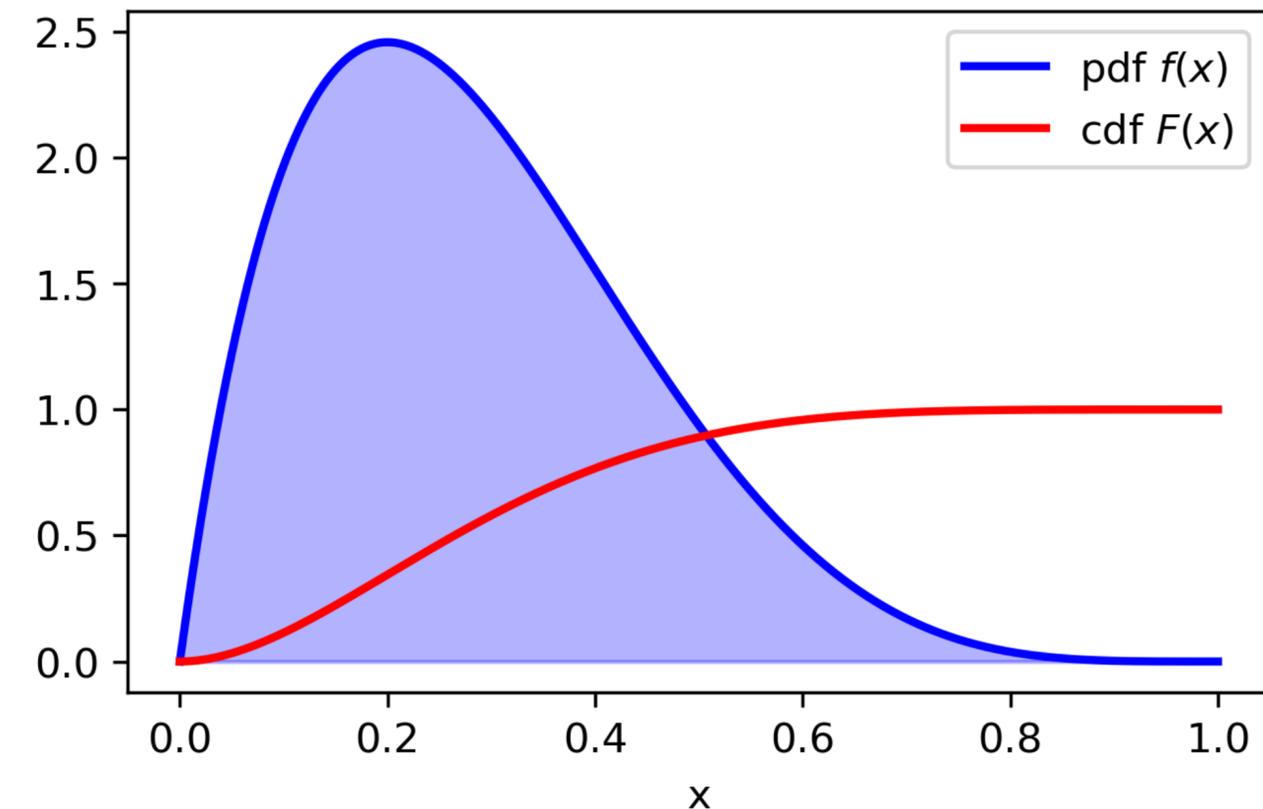


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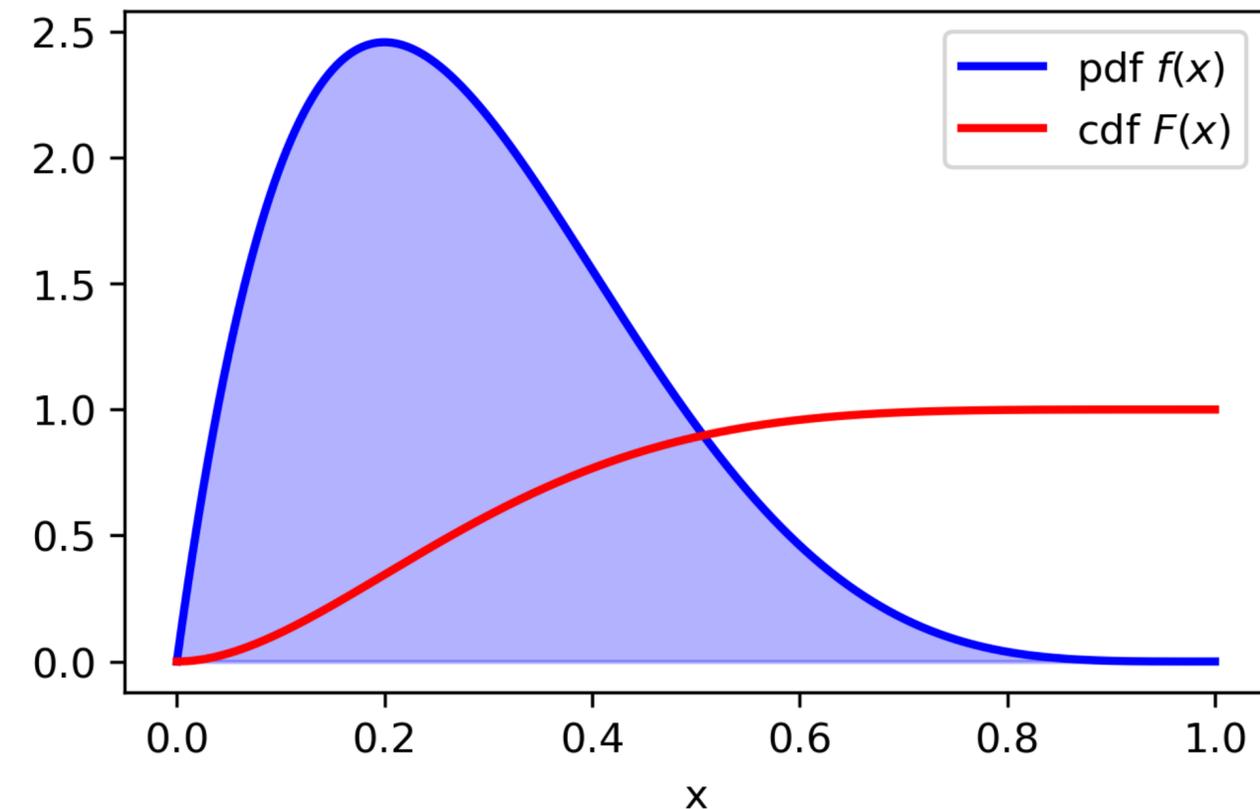
$X \sim F$

$$F(x) = \int_0^x f(t) dt.$$

- If X is a random variable with distribution F , then:

- ▶ $\text{Prob}[a \leq X \leq b] = \int_a^b f(x) dx = F(b) - F(a)$

- ▶ Expectations: $\mathbb{E}[g(X)] = \int_0^\infty g(x) \cdot f(x) dx$



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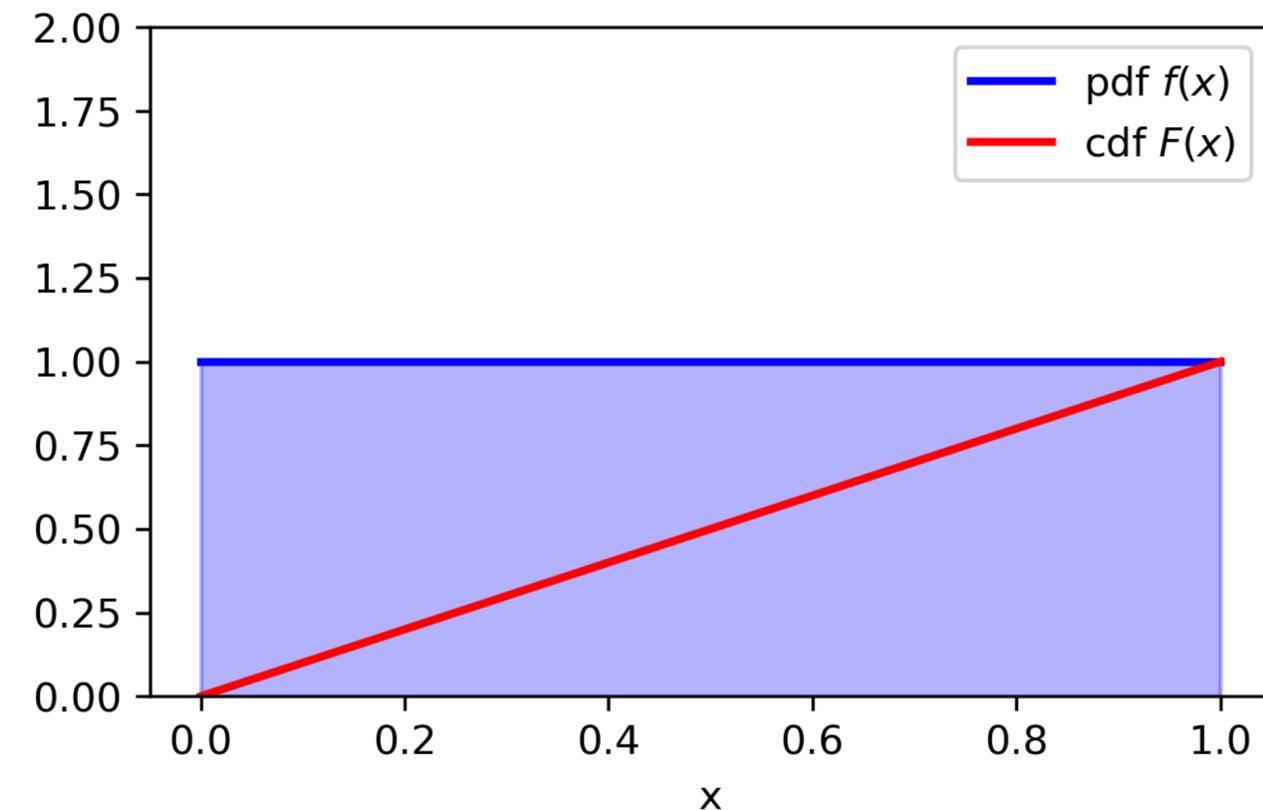
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Example

Uniform distribution on $[0,1]$:

$$f(x) = 1, \quad F(x) = x$$



Model: Bayesian Single-Item Auctions

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 - v_1, v_2, \dots, v_n are independent random variables
 - drawn from **distributions** (“priors”) F_1, F_2, \dots, F_n supported over $[0,1]$
- **Optimization** objectives are defined **in expectation**:

$$W(\mathcal{M}) := \mathbb{E}_{\mathbf{v} \sim F} \left[\sum_{i=1}^n a_i(\mathbf{v}) v_i \right]$$

Welfare

$$R(\mathcal{M}) := \mathbb{E}_{\mathbf{v} \sim F} \left[\sum_{i=1}^n p_i(\mathbf{v}) \right]$$

Revenue

- Goal: find a **revenue-maximizing** truthful mechanism

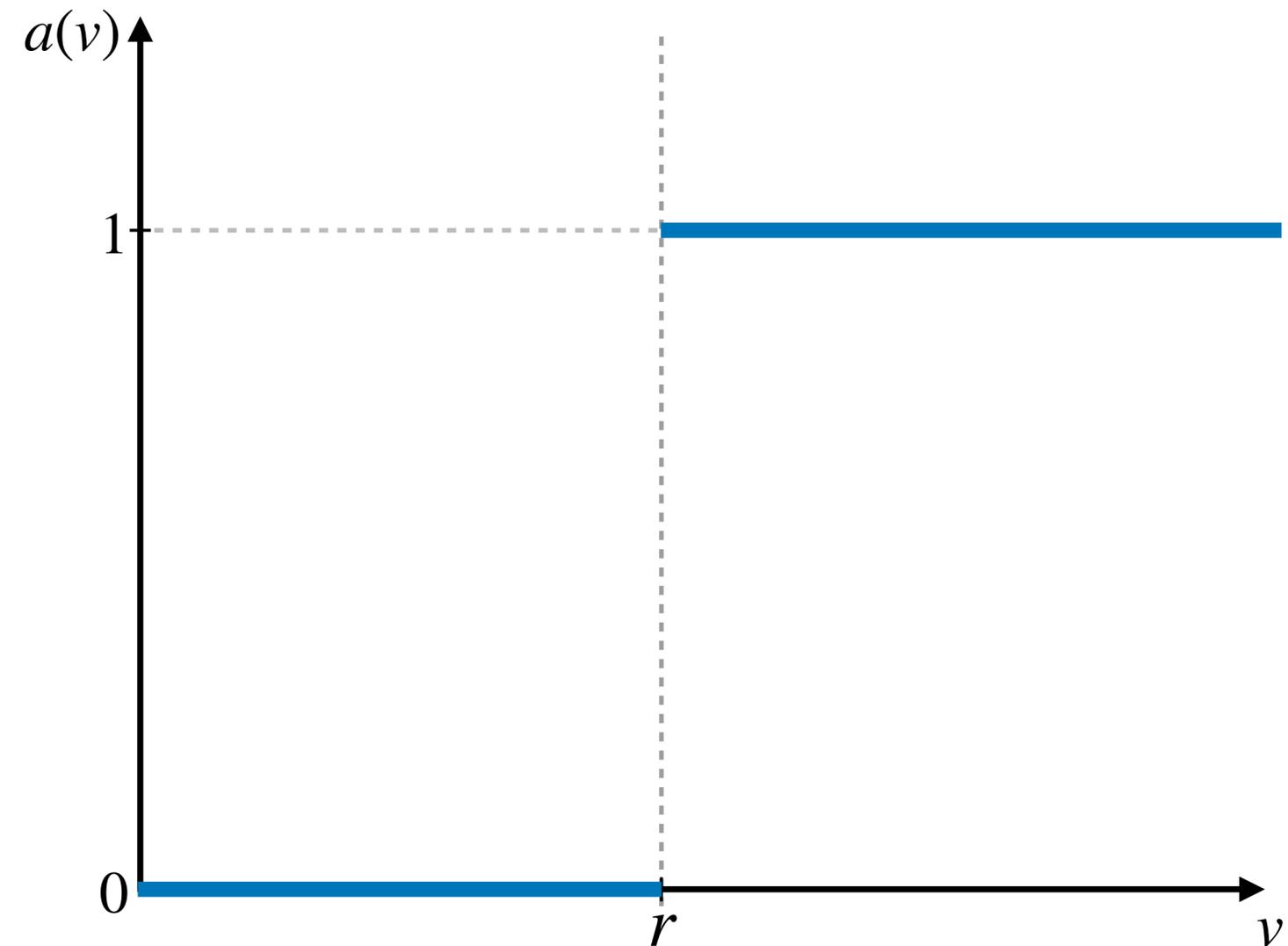
$$\max_{\text{truthful } \mathcal{M}} R(\mathcal{M}) = \max_{\text{monotone } a} \mathbb{E} \left[\sum_{i=1}^n \left(a_i(\mathbf{v}) v_i - \int_0^{v_i} a_i(t, \mathbf{v}_{-i}) dt \right) \right]$$

“Critical” value: Myerson’s lemma

Revenue Maximization

Example: *Single-Bidder, Deterministic Auctions*

- Bidder wins if and only if $v \geq r$
 - And then pays r
- Expected revenue:
 $r \cdot \text{Prob}[v \geq r] = r(1 - F(r))$
- Optimal “**monopoly reserve**”:
 $r^* = \arg \max_{r \in [0,1]} r(1 - F(r))$
- Example: Uniform distribution
 - $r(1 - F(r)) = r(1 - r)$
 - $r^* = 1/2$; optimal revenue $1/4$



Virtual Values



Roger Myerson

- The **virtual value** function of bidder i is defined by

$$\phi_i(v_i) := v_i - \frac{1 - F_i(v_i)}{f_i(v_i)}$$

- If ϕ_i is (strictly) increasing, we will call distribution F_i **(strictly) regular**.

revenue

“virtual” social welfare

THEOREM (R. Myerson [1981])

For any *truthful* mechanism (\mathbf{a}, \mathbf{p}) it holds that

$$\mathbb{E}_{\mathbf{v} \sim F} \left[\sum_{i=1}^n p_i(\mathbf{v}) \right] = \mathbb{E}_{\mathbf{v} \sim F} \left[\sum_{i=1}^n a_i(\mathbf{v}) \phi_i(v_i) \right].$$

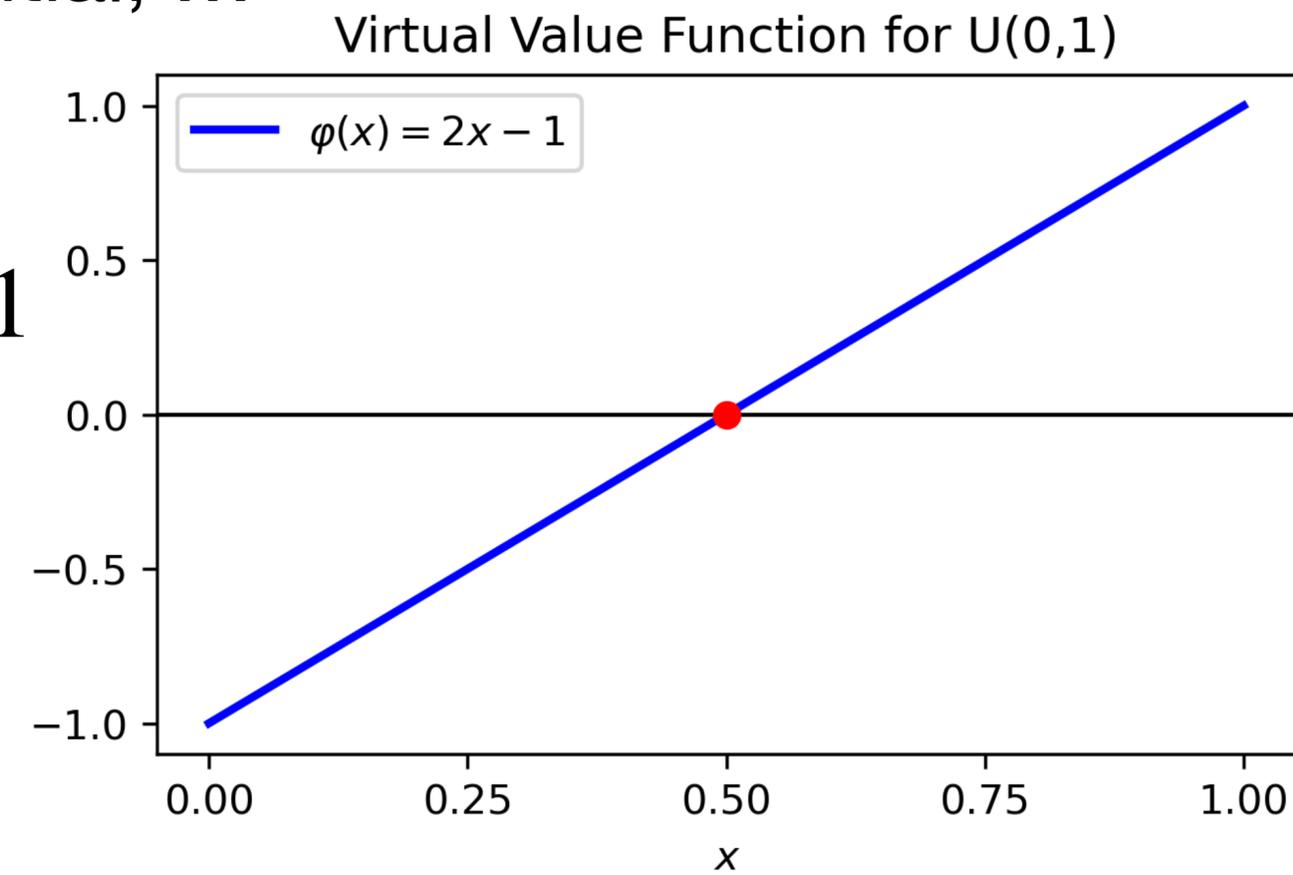
Regular Distributions

Examples

- Most “common” probability distributions in economic theory are strictly regular.
- Intuition: no “thick tails”
- Examples: uniform, (truncated) normal, exponential, ...

- Virtual value function for uniform distribution

$$\triangleright \phi(x) = x - \frac{1 - F(x)}{f(x)} = x - \frac{1 - x}{1} = 2x - 1$$

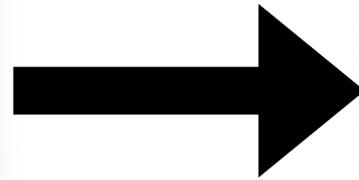


*ties occur with zero probability

Myerson's Optimal Auction

For any *truthful* mechanism $\mathcal{M} = (a, p)$:

$$R(\mathcal{M}) = \mathbb{E}_{\mathbf{v} \sim F} \left[\sum_{i=1}^n a_i(\mathbf{v}) \phi_i(v_i) \right]$$



Optimal revenue $\leq \mathbb{E}_{\mathbf{v} \sim F} \left[\max_{i \in [n]} \phi_i(v_i)^+ \right]$

Notation: $z^+ = \max\{z, 0\}$

Assuming strictly regular priors:

- Selling the item to the bidder with the **highest* nonnegative virtual value**
 1. is monotone (i.e., **truthful**)
 2. maximizes the seller's revenue (i.e., is **optimal**)
- If, furthermore, the priors are identical (aka "**iid**"), then the optimal auction is simply a **second-price auction with reserve price**

Equal to monopoly reserve
 $r^* = \arg \max_{x \in [0,1]} x(1 - F(x))$

$$r := \phi^{-1}(0)$$

Proof of Myerson's Theorem

$$\text{For any } \textit{truthful} \text{ mechanism } (\mathbf{a}, \mathbf{p}): \quad \mathbb{E}_{\mathbf{v} \sim F} \left[\sum_{i=1}^n p_i(\mathbf{v}) \right] = \mathbb{E}_{\mathbf{v} \sim F} \left[\sum_{i=1}^n a_i(\mathbf{v}) \phi_i(v_i) \right].$$

PROOF

- It is enough to prove it “per-bidder”
 - i.e., we will show that, for *any* bidder i and *all* bid/value profiles \mathbf{v}_{-i} of the others:
$$\mathbb{E}_{v_i \sim F_i} [p_i(\mathbf{v})] = \mathbb{E}_{v_i \sim F_i} [a_i(\mathbf{v}) \phi_i(v_i)].$$
 - This is enough, due to the “linearity of expectation”.
- So, from now on let's fix a bidder $i \in [n]$ and values $\mathbf{v}_{-i} \in [0, 1]^{n-1}$.
- Simplify notation: $v := v_i$, $a(v) := a_i(v, \mathbf{v}_{-i})$, $p(v) := p_i(v, \mathbf{v}_{-i})$, $F(v) := F_i(v)$, ...

$$\mathbb{E}_{v_i \sim F_i} [p_i(\mathbf{v})] = \mathbb{E}_{v_i \sim F_i} [a_i(\mathbf{v}) \phi_i(v_i)]$$

Proof of Myerson's Theorem (cont'd)

$$\begin{aligned} \mathbb{E}_{v \sim F} [p(v)] &= \int_0^1 p(v) \cdot f(v) \, dv \\ &= \int_0^1 \left(v \cdot a(v) - \int_0^v a(z) \, dz \right) \cdot f(v) \, dv \end{aligned}$$

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*exchanging the order
of integration*

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exchanging the order of integration

Interchanging Sums & Integrals

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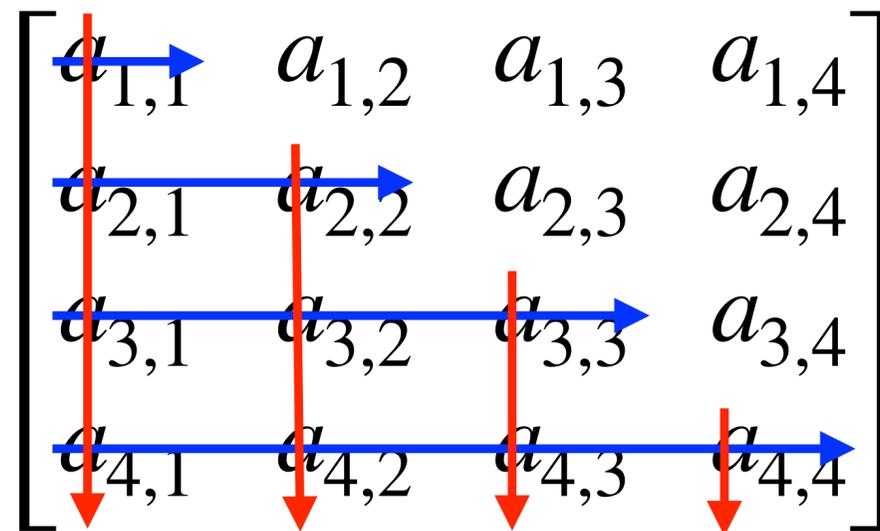
$$\sum_{i=1}^n \sum_{j=1}^i a_{i,j}$$

$$\begin{bmatrix} a_{1,1} & a_{1,2} & a_{1,3} & a_{1,4} \\ a_{2,1} & a_{2,2} & a_{2,3} & a_{2,4} \\ a_{3,1} & a_{3,2} & a_{3,3} & a_{3,4} \\ a_{4,1} & a_{4,2} & a_{4,3} & a_{4,4} \end{bmatrix}$$

Interchanging Sums & Integrals

Quick Mathematical Detour

$$\sum_{i=1}^n \sum_{j=1}^i a_{i,j} = \sum_{j=1}^n \sum_{i=j}^n a_{i,j}$$



$$\mathbb{E}_{v_i \sim F_i} [p_i(\mathbf{v})] = \mathbb{E}_{v_i \sim F_i} [a_i(\mathbf{v})\phi_i(v_i)]$$

Proof of Myerson's Theorem (cont'd)

$$\begin{aligned}\mathbb{E}_{v \sim F}[p(v)] &= \int_0^1 v \cdot a(v)f(v) \, dv - \int_0^1 \int_z^1 a(z)f(v) \, dv \, dz \\ &= \int_0^1 v \cdot a(v)f(v) \, dv - \int_0^1 a(z) \int_z^1 f(v) \, dv \, dz \\ &= \int_0^1 v \cdot a(v)f(v) \, dv - \int_0^1 a(z)(1 - F(z)) \, dz \\ &= \int_0^1 v \cdot a(v)f(v) - a(v)(1 - F(v)) \, dv\end{aligned}$$

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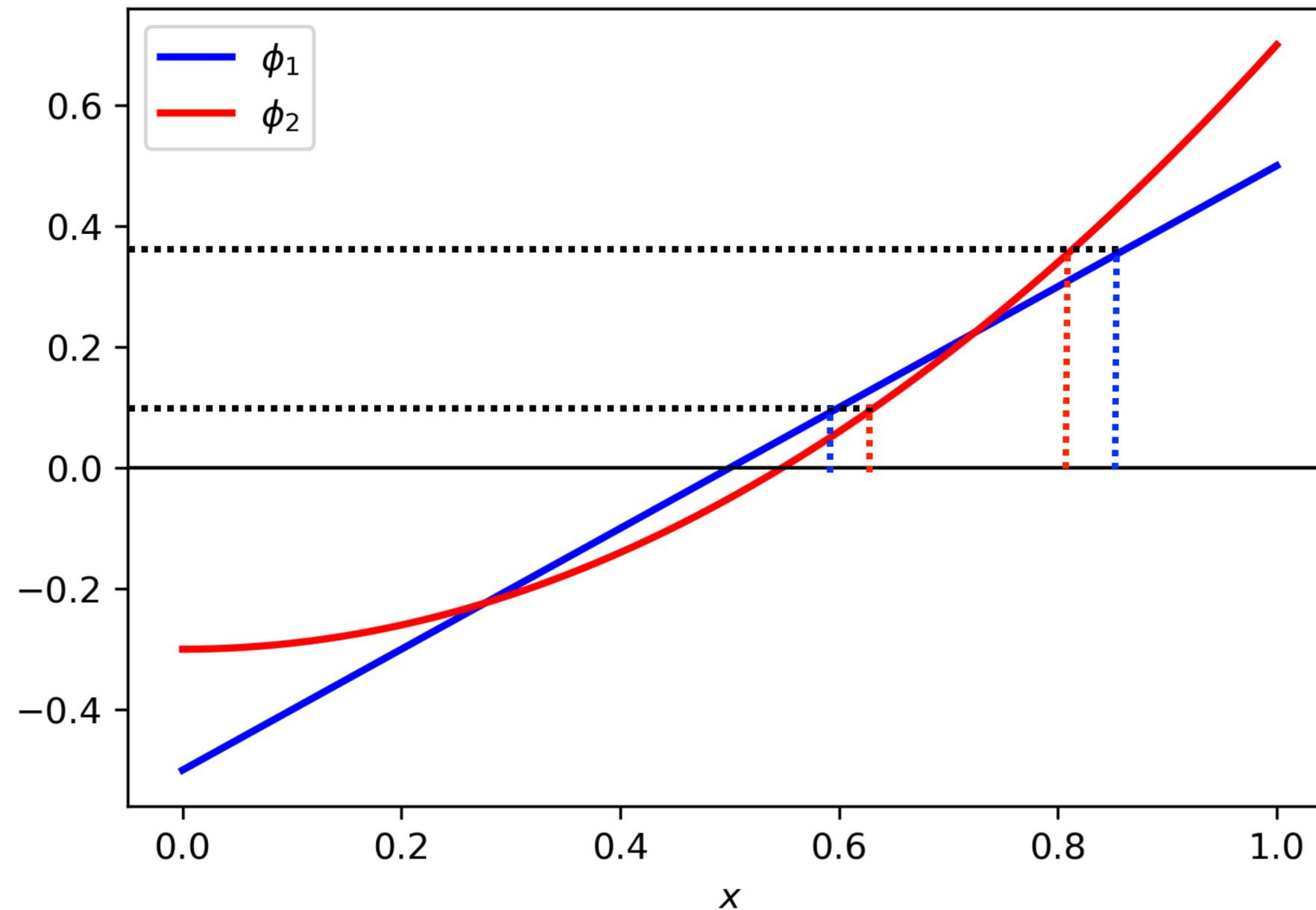
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“Simplicity” vs Optimality

Non-Identical Priors

- The optimal auction might be “complicated”, or even practically infeasible.
 - Higher virtual value does not always correspond to higher value!



Non-Identical Priors

- The optimal auction might be “complicated”, or even practically infeasible
 - Higher virtual value does not always correspond to higher value!

- How much revenue do we lose by restricting to **simple** auction formats? For example:
 - Second-price auction; with reserves or not
 - Posted pricing (“take-it-or-leave-it”)

The Bulow-Klemperer Approximation

Identical Bidders

THEOREM (J. Bulow & P. Klemperer [1996])

For regular iid priors, the expected revenue of the second-price auction (with no reserve) with $n + 1$ bidders is at least the expected revenue of the optimal auction with n bidders.

COROLLARY

For n bidders with regular iid priors, the second-price auction achieves at least a $\frac{n-1}{n}$ -fraction of the optimal expected revenue.

Second-Price with Reserves & Pricing

Optimal Revenue Approximation for Non-Identical Regular Bidders

- Selling the item by posting the *same price* to all bidders, has an approximation ratio of (exactly)

2.6202

- The approximation ratio of the best **second-price** auction with the same (aka “**anonymous**”) **reserve** price for all bidders lies in

[2.1596, 2.6202]

- Selling via a second-price auction with **bidder-specific reserves** achieves an approximation ratio of (exactly)

2

A Small Glimpse Beyond: Multi-item Auctions

Multi-Dimensional Revenue Maximization

Complications

- Fundamental technical obstacles, even for a *single* bidder!
- Randomization is required, in general, for optimality.
- Computational hardness barriers.
- Large constant approximations only (e.g., 8).
- Generally: the exact structure, and key computational properties, of the optimal auctions **still elude us!**
 - Resolved only for a single-bidder, small number of items, and very specific distributions (most notably, uniform).