

Algorithmic Game Theory and Applications

Bayesian Games and First-Price Auctions

First-price auctions (FPA)

Houses in Scotland are sold via *sealed-bid first-price auctions*.

Each bidder submits their bid independently, without seeing the bids of the other bidders.

The winner is the bidder with the **highest bid**.

If there are multiple such bidders, one is chosen **at random**.

The **winner** needs to **pay their bid**, all **other bidders do not pay anything**.



First-Price Auction

There are n bidders from a set $N = \{1, \dots, n\}$.

There is **one item** for sale.

Every bidder has a value v_i for the item - this is the bidder's **willingness to buy** it.

Each bidder chooses a bid $b_i = \beta(v_i)$ according to some function β .

Let $W = \{i : b_i \geq b_j, \forall j\}$ be the set of **possible winners** of the auction (those with the highest bid).

The **utility** of bidder i is

- $(v_i - b_i) \cdot \frac{1}{|W|}$ if $i \in W$.

- 0 , otherwise.

How should you bid in the FPA?

“I should bid lower than the amount I am willing to spend, to win the item on sale for a smaller price.”

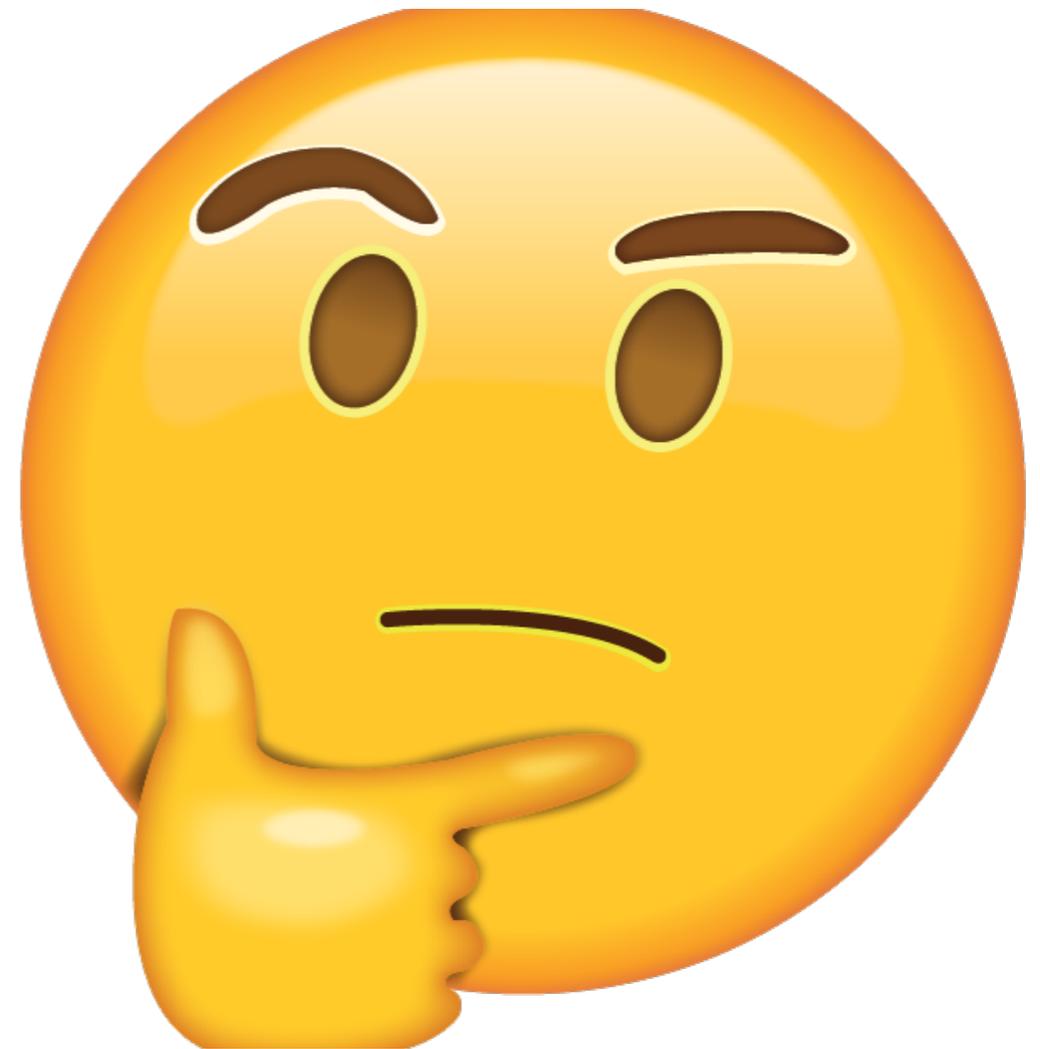
“I shouldn’t bid too low though, because that increases the chances of not winning the item at all.”

“How low should I bid?”

Before we attempt to answer this question, let’s ask another one first:

Could we design a **different auction** that does not require us to engage in such considerations?

i.e., can we define a **truthful** auction?



Auctions

Auction: A mechanism for buying or selling goods or services by means of eliciting bids from interested parties.

Classic example: Auction of a painting, or art in general.

Most prominent example nowadays: Ad auctions

Selling advertising space (ad impressions) on online market places (ad exchanges).

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Actually, virtually all of these Ad exchanges use the first-price auction!

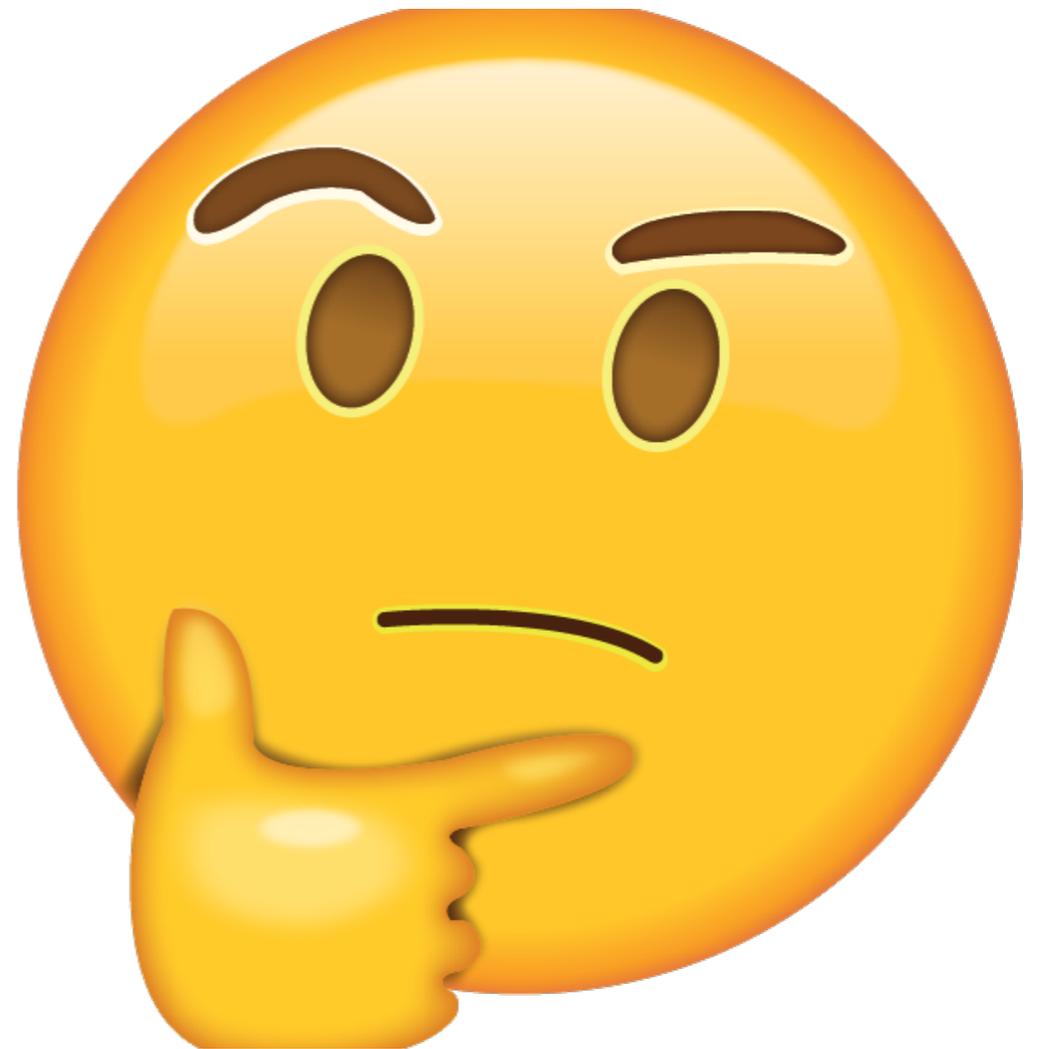
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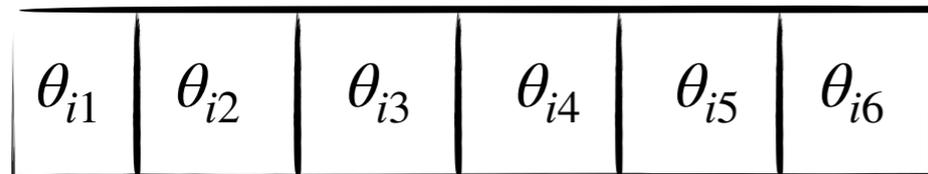
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We write $U_i(s_i, s_{-i}; \theta_i)$.

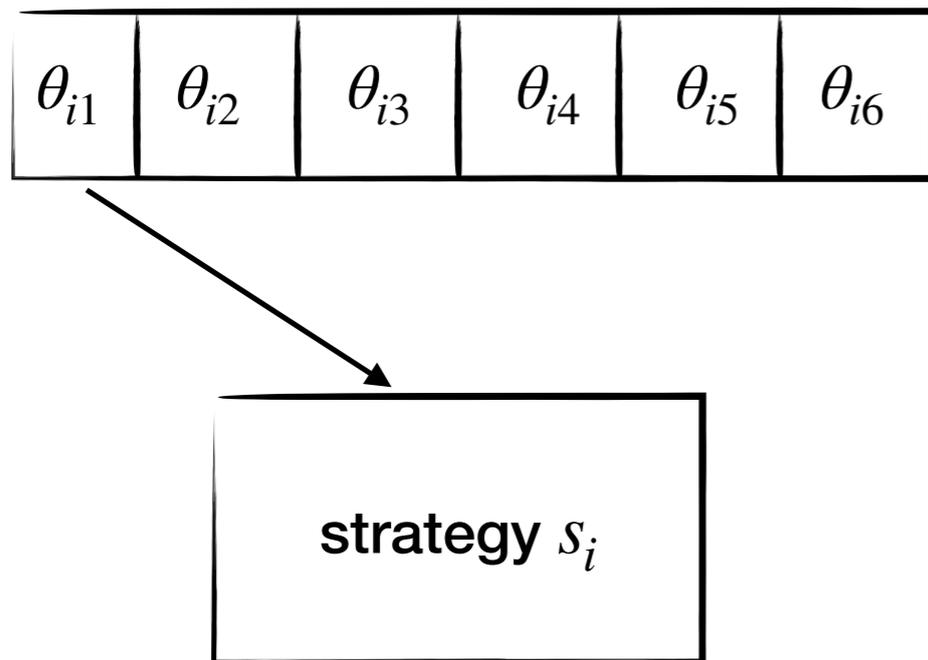
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θ_{i1}	θ_{i2}	θ_{i3}	θ_{i4}	θ_{i5}	θ_{i6}
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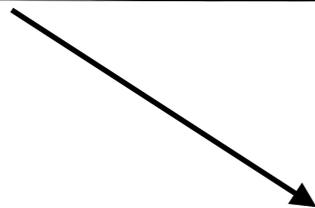
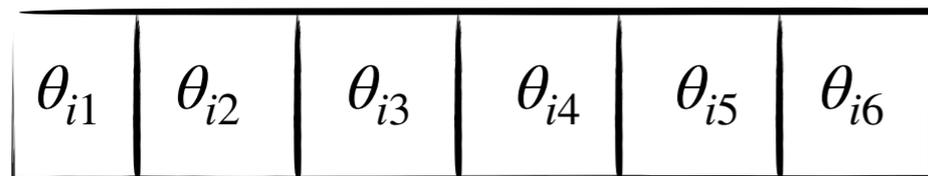
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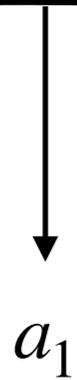
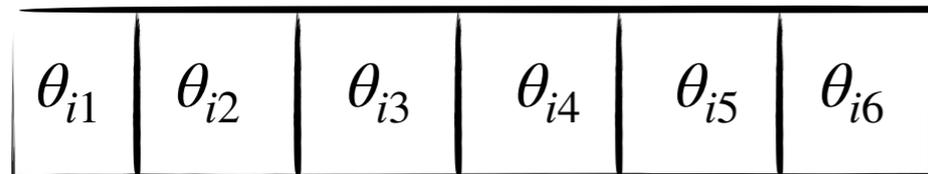


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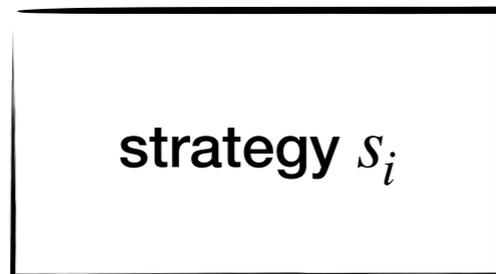
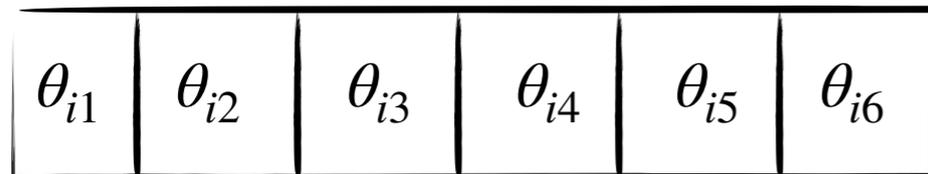
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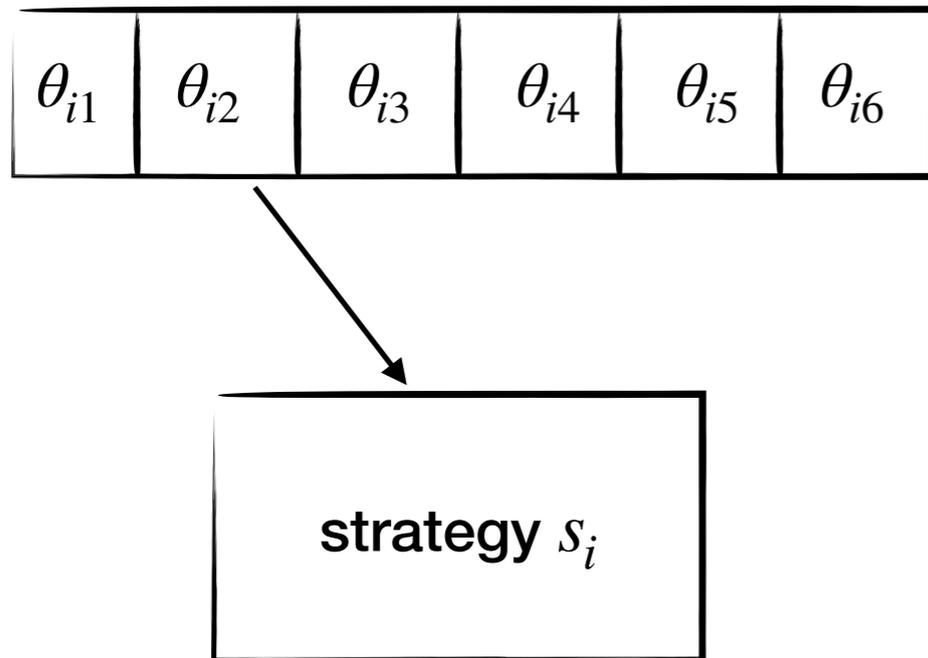
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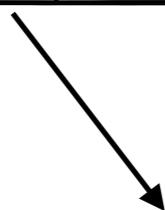
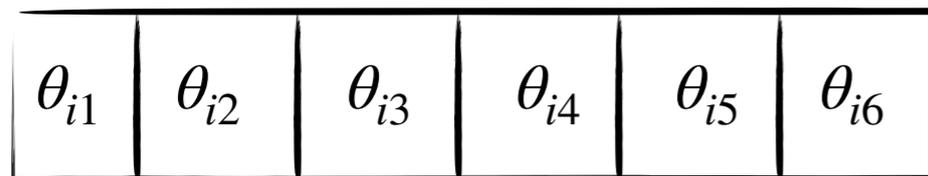
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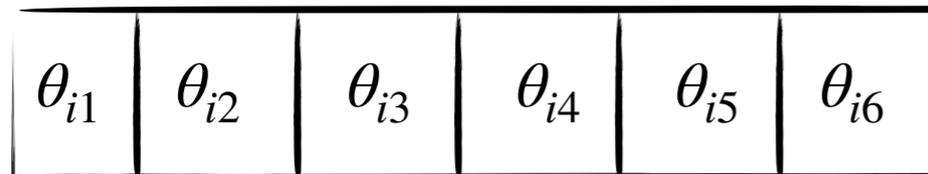


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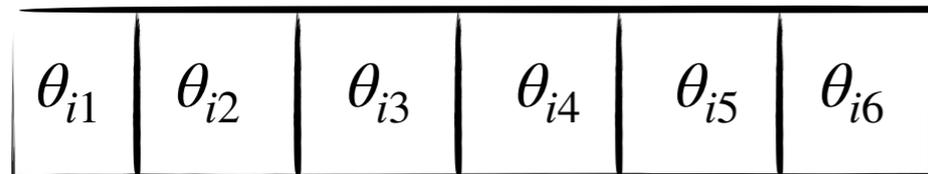
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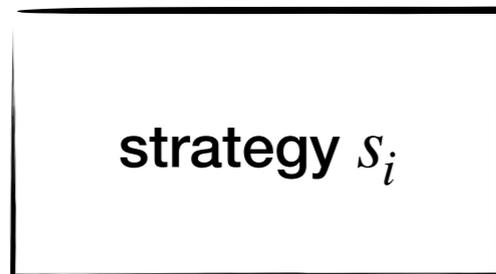
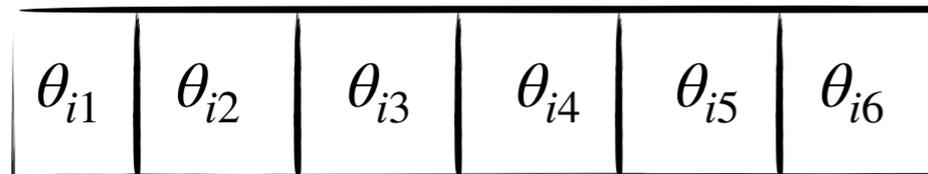
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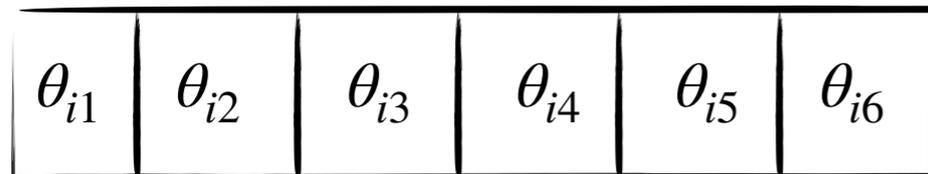


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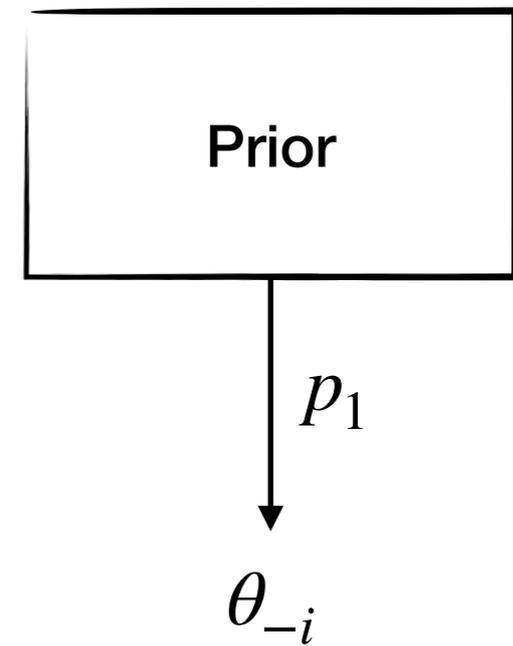
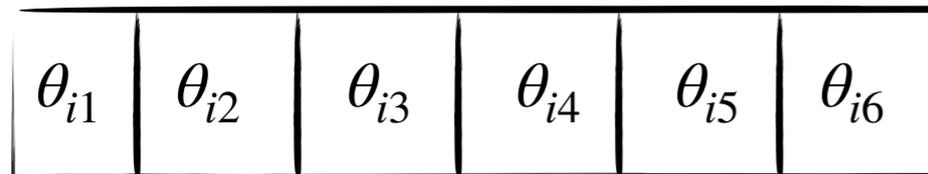
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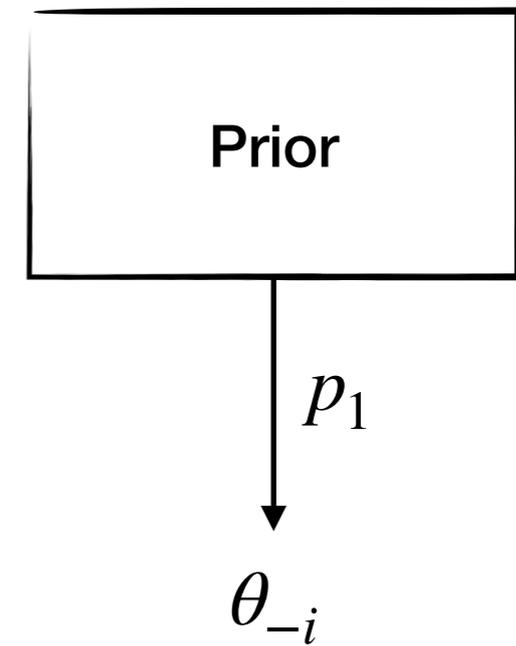
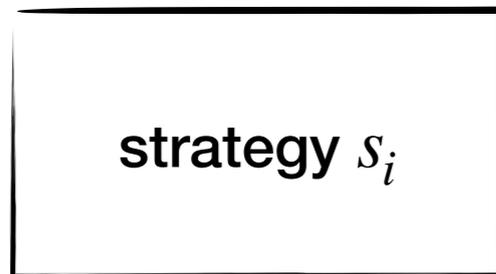
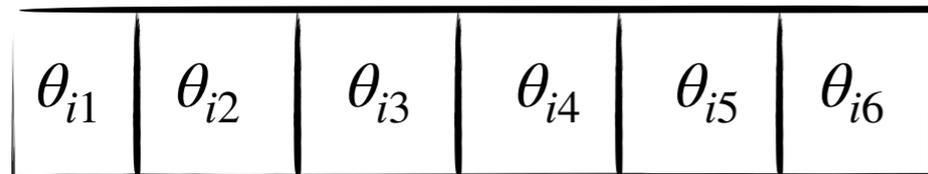
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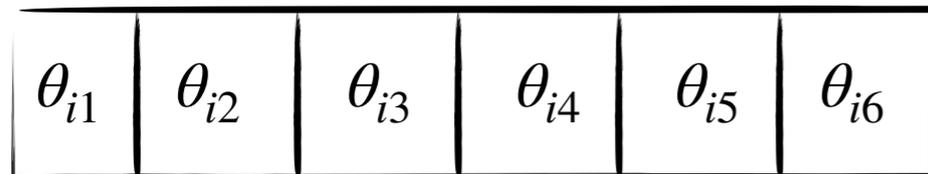


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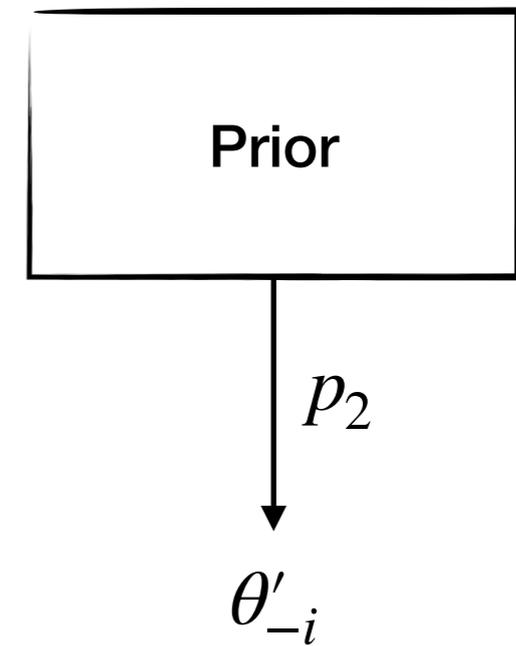
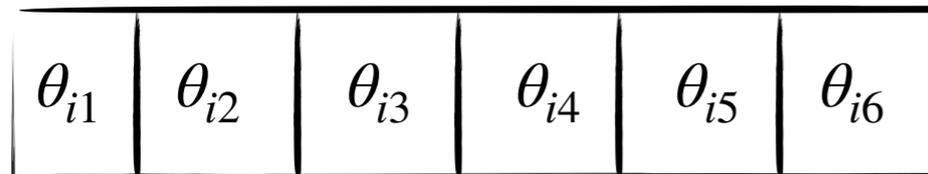
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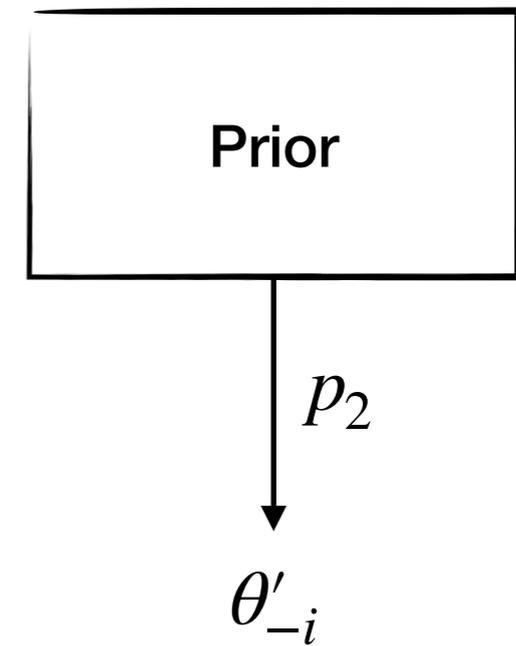
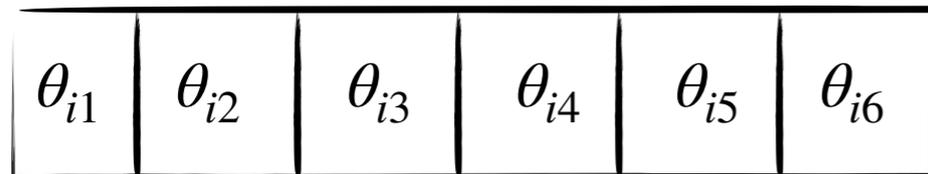
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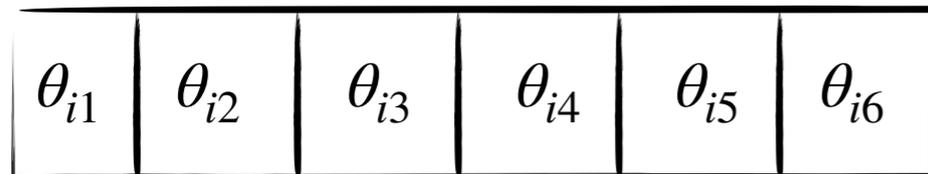
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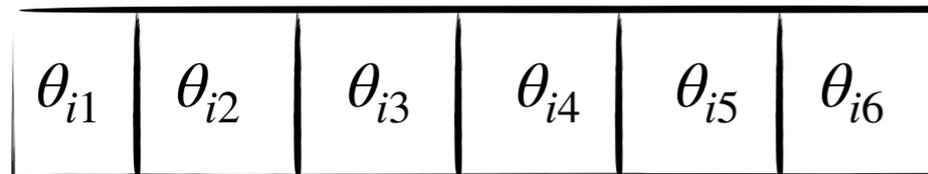
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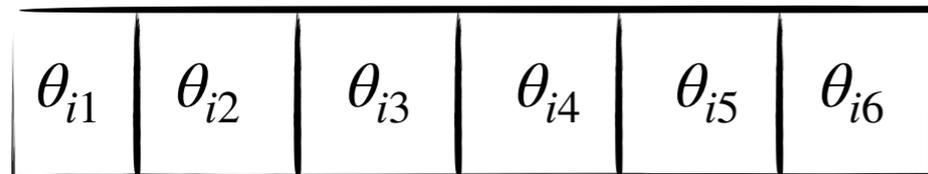
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One can also similarly define **mixed Bayes-Nash equilibria**.

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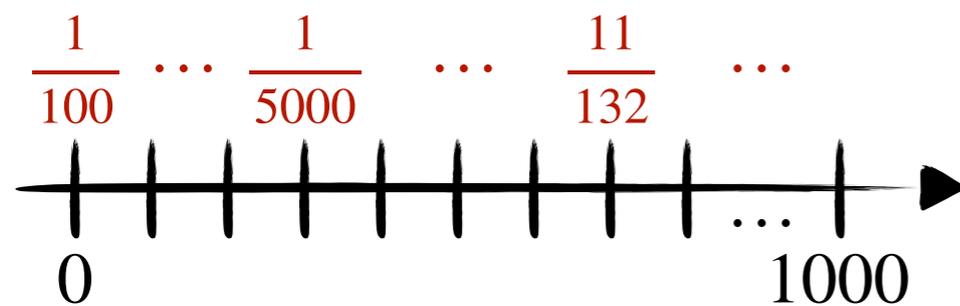
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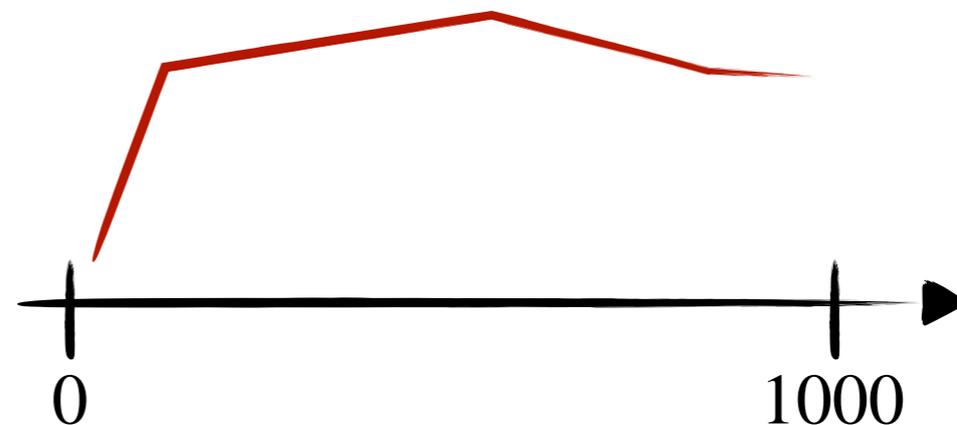
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A Bayesian game is a tuple (N, A, Θ, p, u) where

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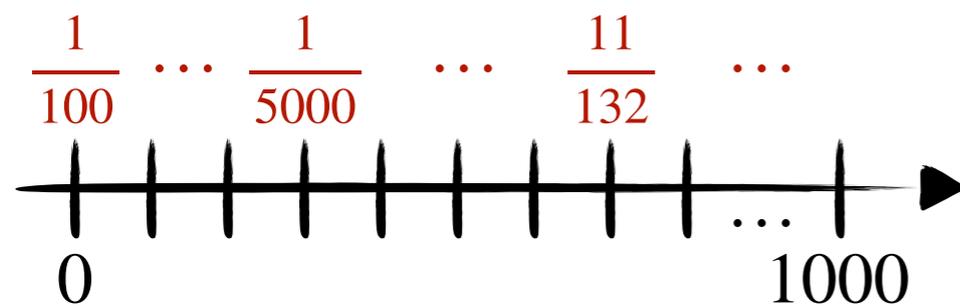
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A function β mapping values to bids.

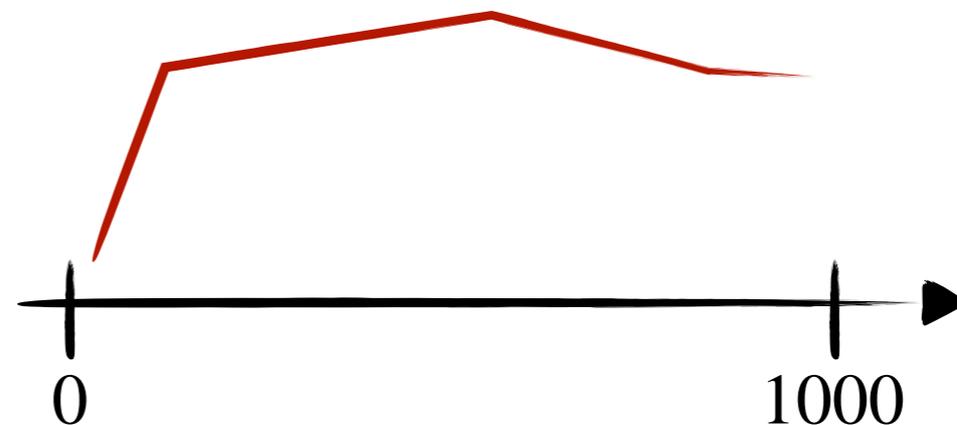
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The values of all bidders come from the same distribution, i.e.,

$$F_i = F_j \quad \forall i, j \quad (\text{symmetric beliefs})$$

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maximises the expected utility of the bidder

$$\mathbb{E}_{v_j \sim F_{ij}, \forall j \neq i} \left[(v_i - \beta(v_i)) \cdot \frac{1}{W(\beta_1(v_1), \dots, \beta_n(v_n))} \right]$$

Nash Equilibrium Existence

Does a **mixed** Nash equilibrium always exist?

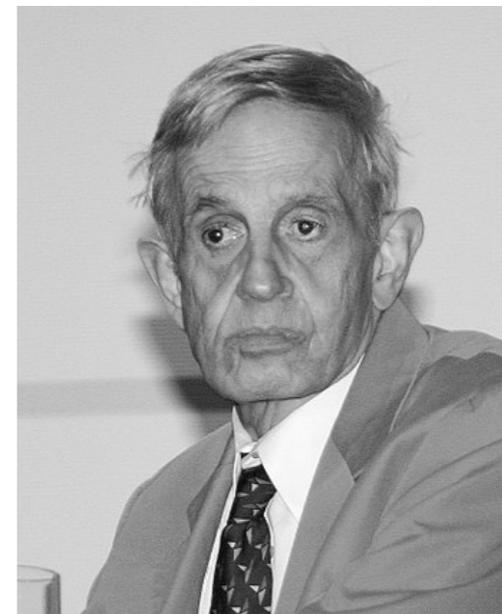
Solution Concept:

Mixed Nash Equilibrium

Introduced by Nash in 1951 (in his PhD dissertation).

MNE: “I won’t change unless the others change”, hence a *stable* outcome.

It is *universal*!



Theorem (Nash 1951): Every (finite normal-form) game has at least one mixed Nash equilibrium.

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Idea: Transform the Bayesian game into a (standard) extensive form or normal form game.

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Not necessarily, even when we have finite type and action spaces.

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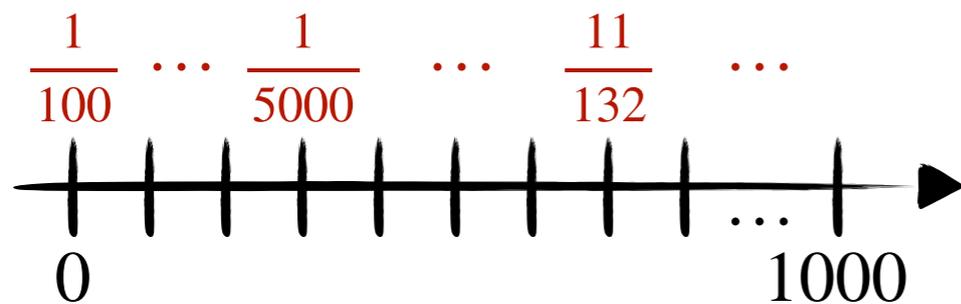
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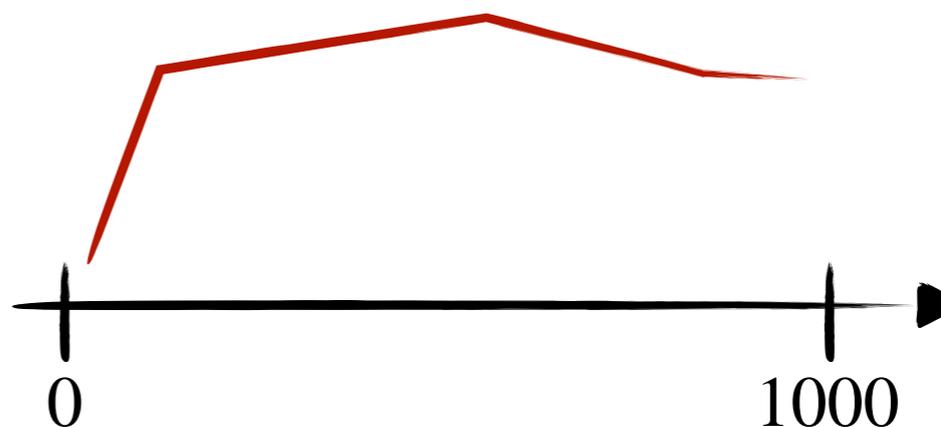
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Athey's proof using **Kakutani**, [F., Giannakopoulos, Hollender, Lazos, and Poças 2023] provide a proof that used **Brouwer's** fixed point theorem.

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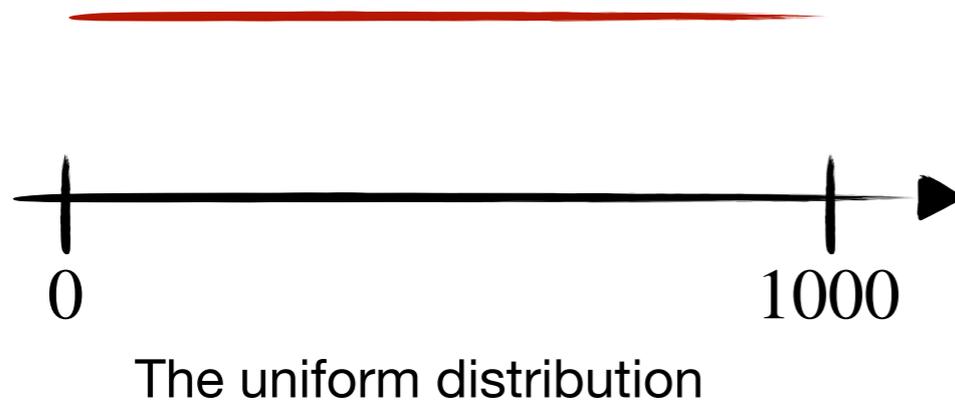
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PBNE in the FPA

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Theorem (Vickrey 1961): Consider a first-price auction with n bidders whose values are drawn independently from the uniform distribution on $[0,1]$. Then the unique symmetric equilibrium is for each bidder to bid $\frac{n-1}{n} \cdot v_i$.

Proof for $n = 2$

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In the other case, bidder 1 loses and has utility zero.

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$$\text{Derivative: } 2v_1 - s_1 = 0 \Rightarrow v_1 = s_1/2$$

Revenue of the second price auction

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COROLLARY (OF THE BULOW-KLEMPERER THEOREM)

For n bidders with uniform iid priors, the second-price auction achieves at least a $(n - 1)/n$ -fraction of the optimal expected revenue (in equilibrium).

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Is this a coincidence?

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But *theoretically*, in equilibrium, it does not!

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What Vickrey provided is called a “*closed form solution*”.

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... and often we cannot even get those!

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Before we even attempt such an algorithm, we need to think about how to *represent* the *inputs* and *outputs* of our problem.

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Each F_{ij} is given explicitly as pairs (v_{jk}^i, p_{jk}^i) (in binary) for every possible value v_{jk}^i (from the perspective of bidder i).

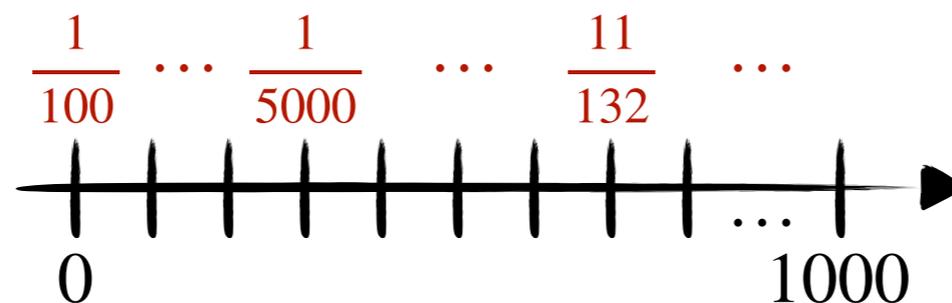
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This is given explicitly as a vector

$(\beta_i(v_{i1}), \beta_i(v_{i2}), \dots, \beta_i(v_{in}))$.

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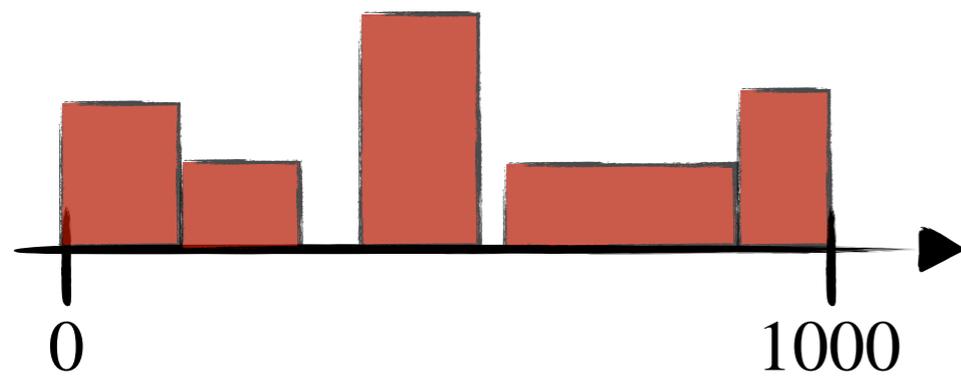
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We will restrict attention to distributions for which there is a natural representation.

Representable Distributions

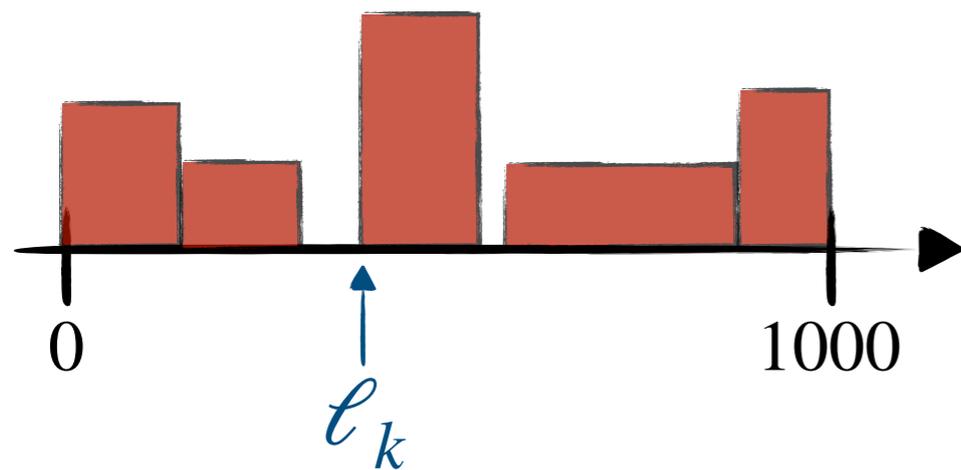
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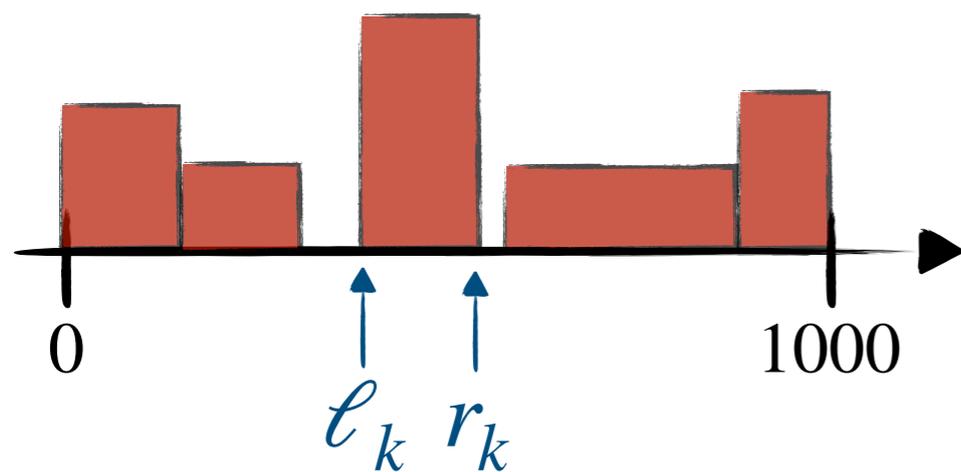
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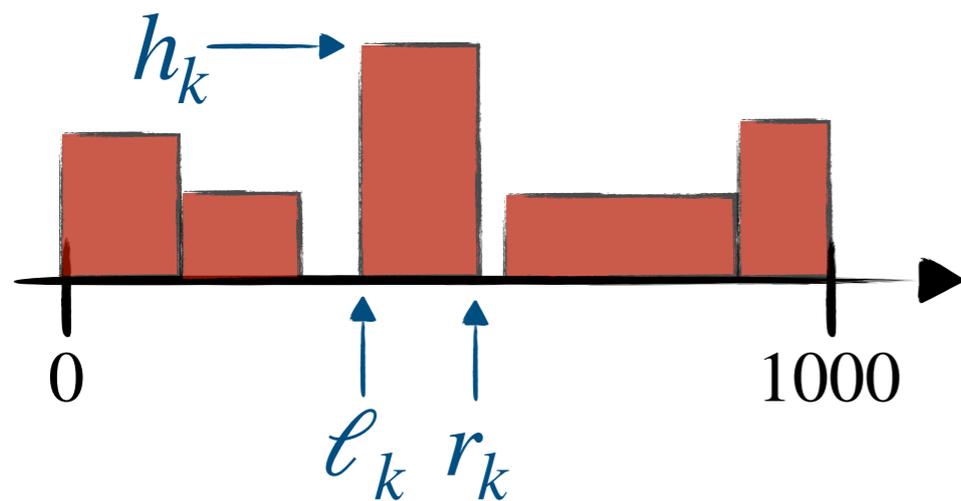
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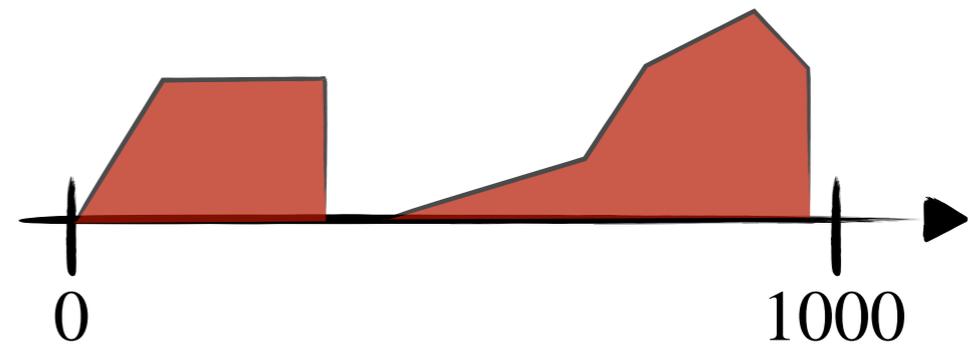
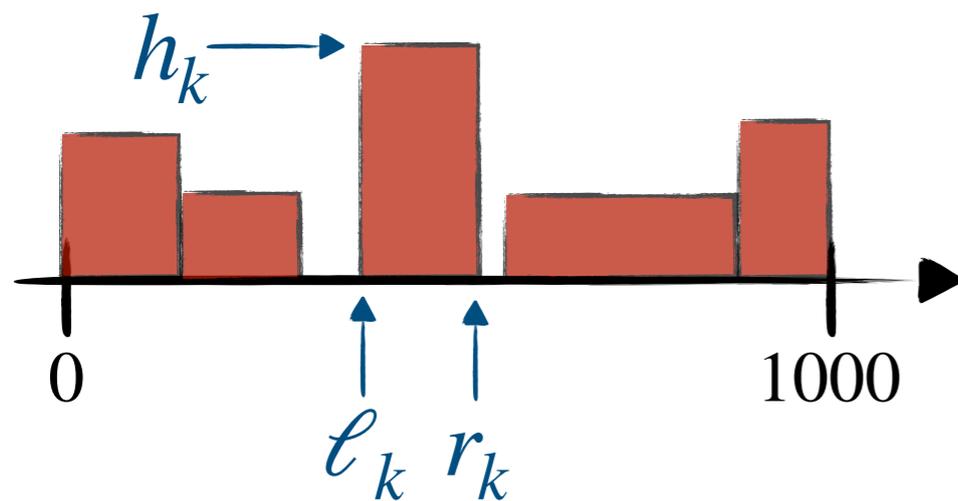
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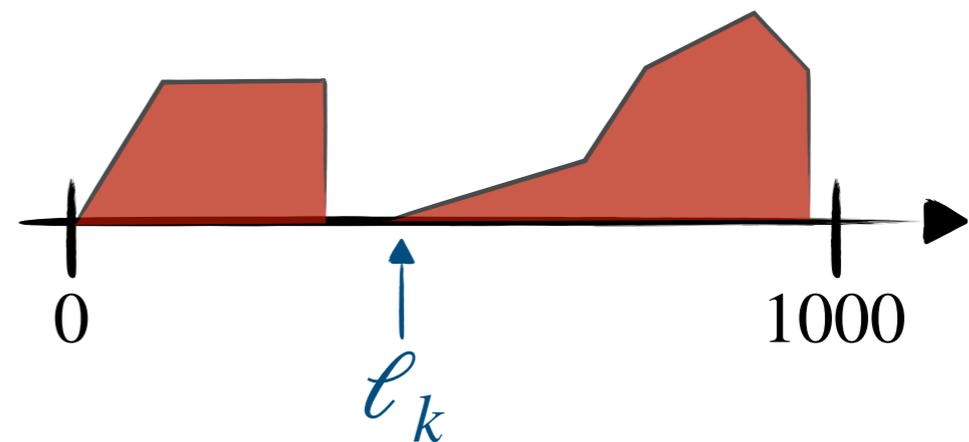
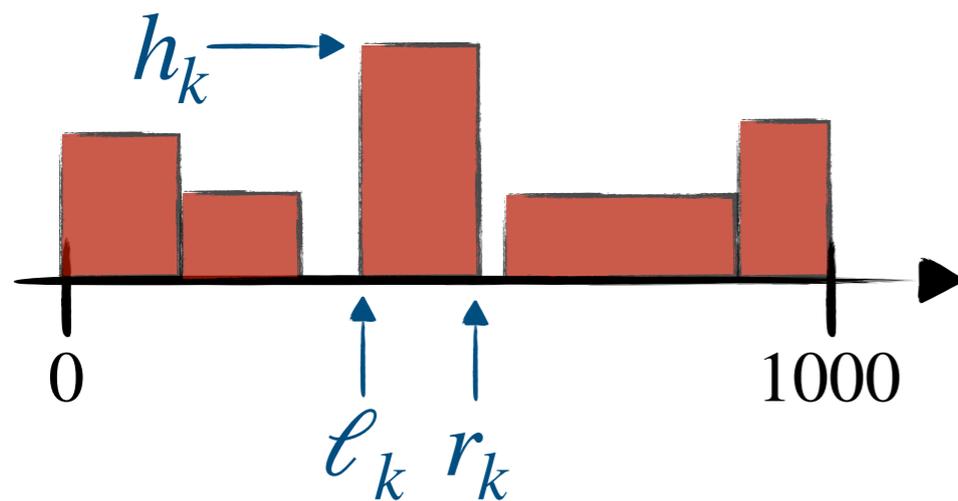
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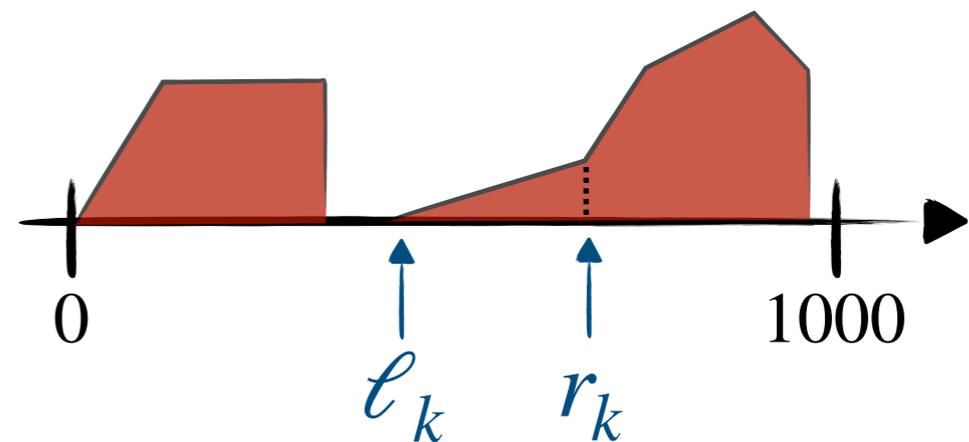
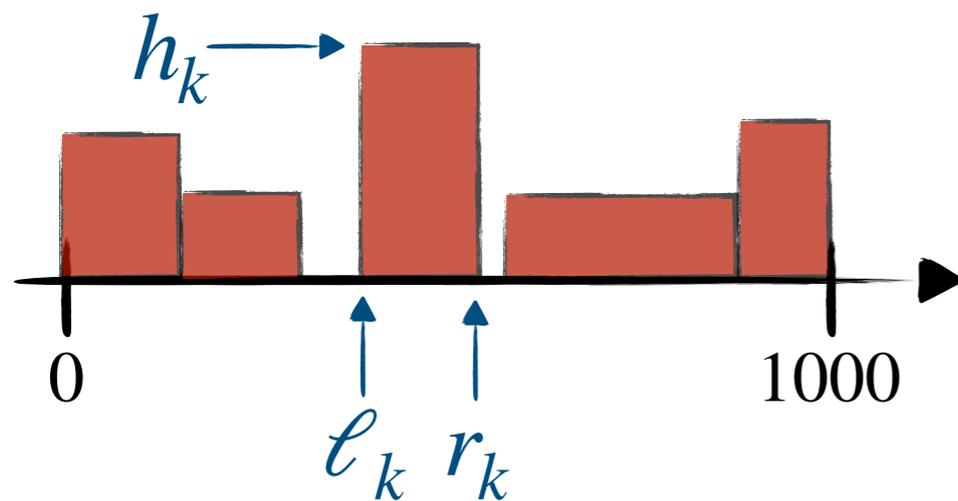
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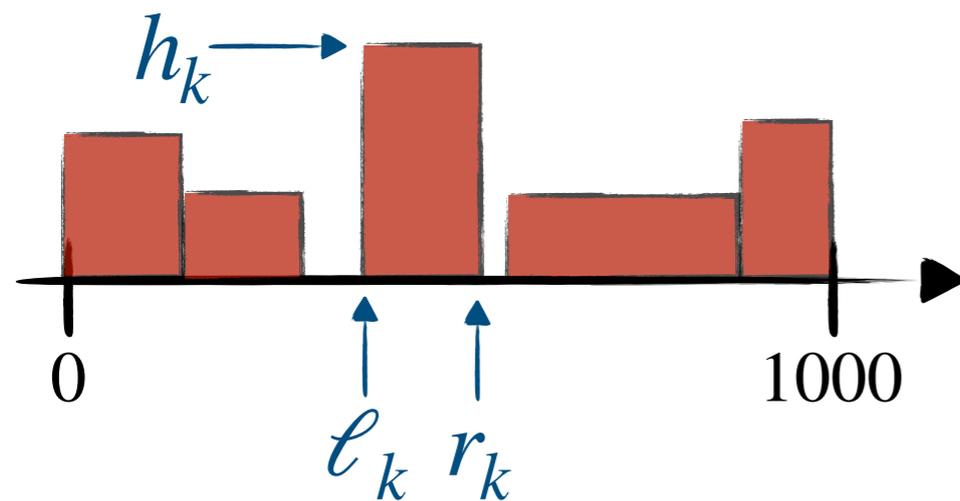
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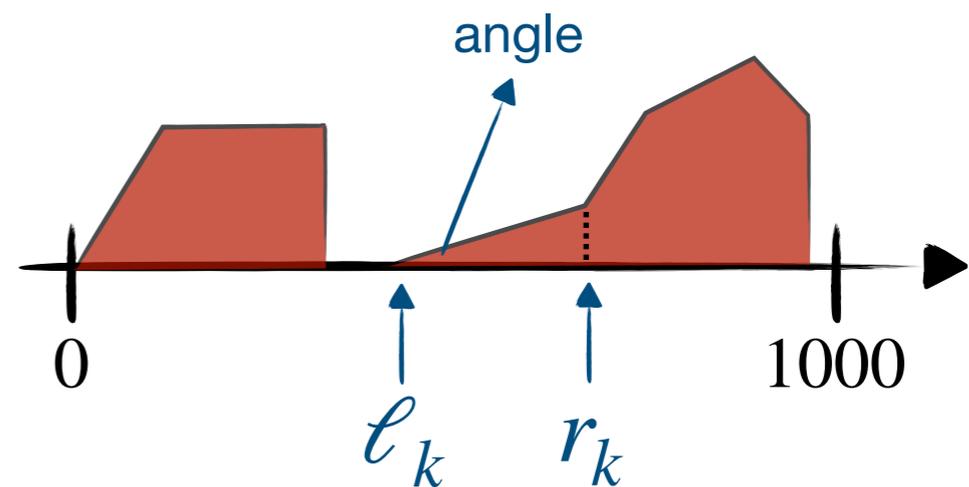


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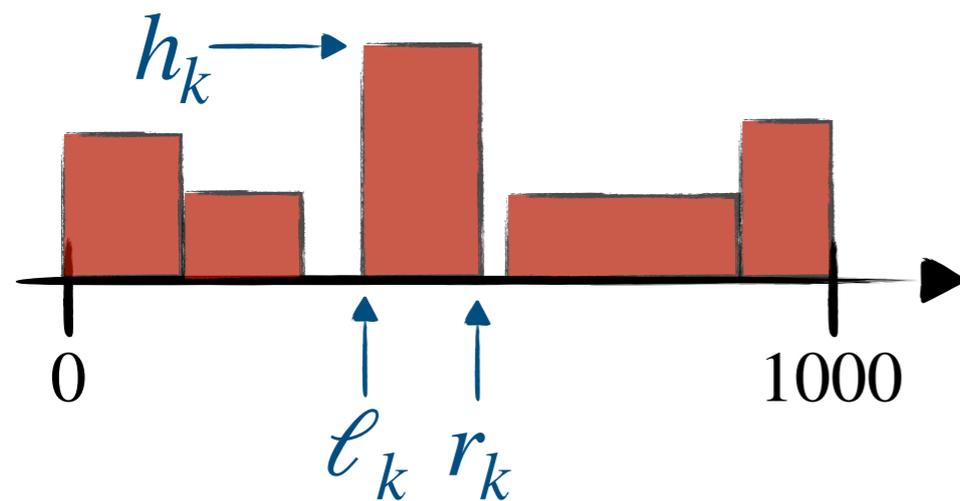


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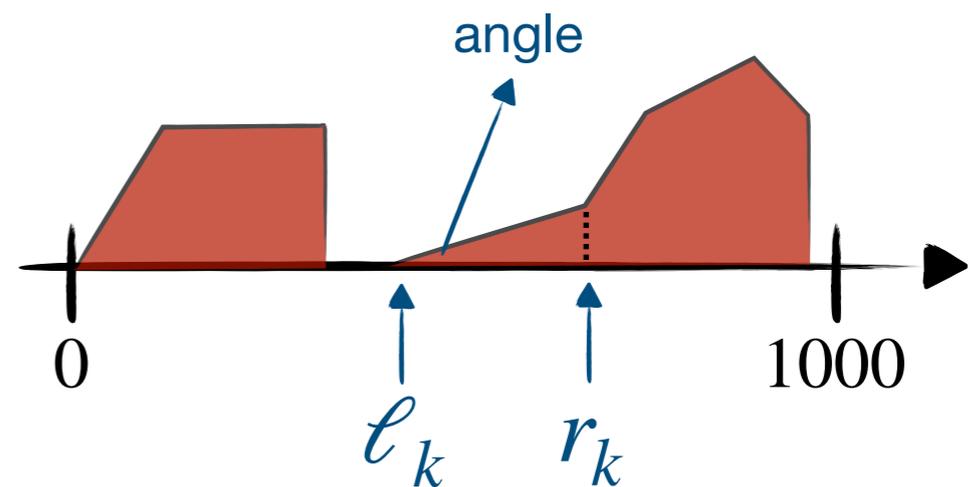


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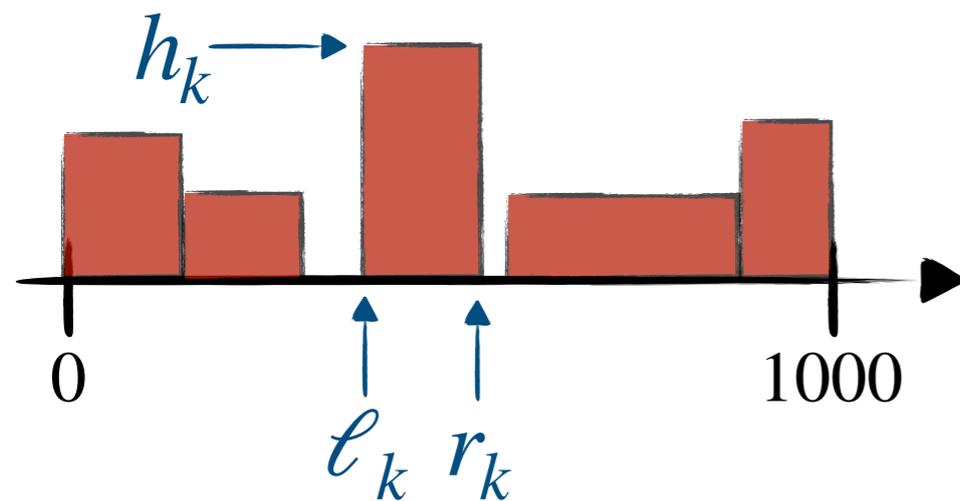
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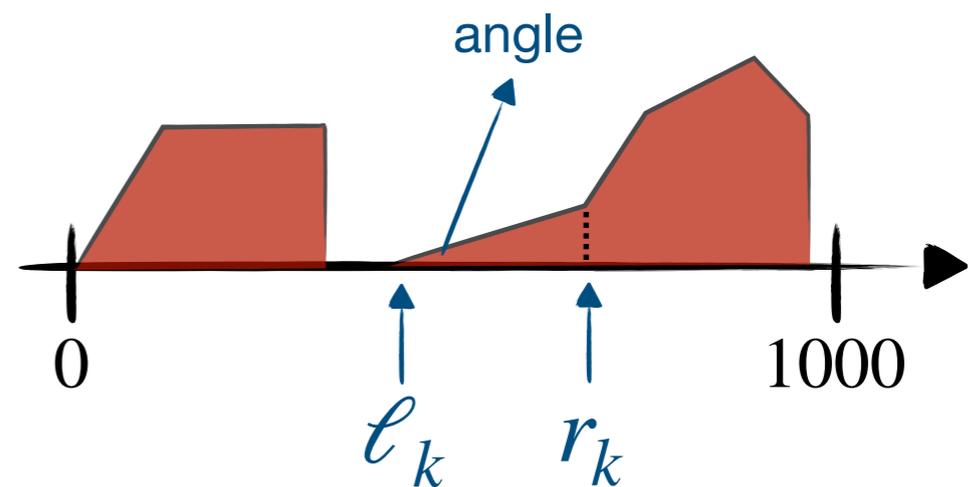
Piece-wise polynomial densities:

Representable Distributions

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For the k -th subinterval $[\ell_k, r_k]$, a list of (rational) coefficients of the polynomial.

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Our functions β_i now have a **continuous domain**.

We cannot simply represent them as a finite map, because we have infinitely many values v_i for which we need to specify

$\beta_i(v_i)$.

Useful observations

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formally, $v_{ij} \geq v_{ik} \Rightarrow \beta_i(v_{ij}) \geq \beta_i(v_{ik})$

Fact (Athey 2001): The continuous FPA has Nash equilibria where all the bidding functions are increasing.

Continuous FPA

In the continuous FPA, the representation requires more thought.

Representation of the output:

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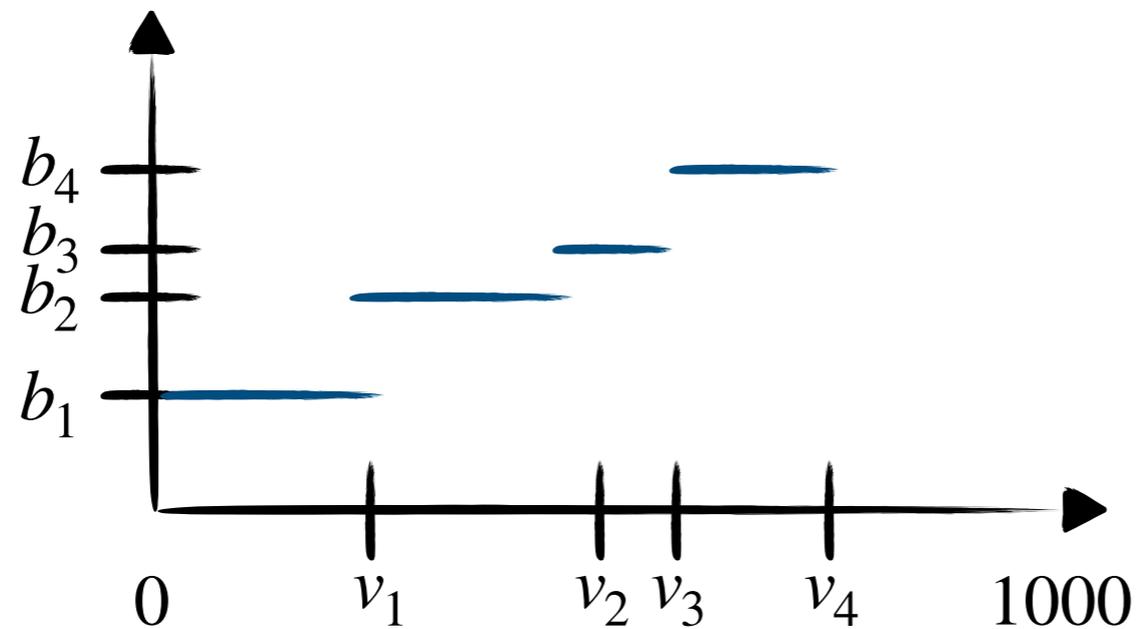
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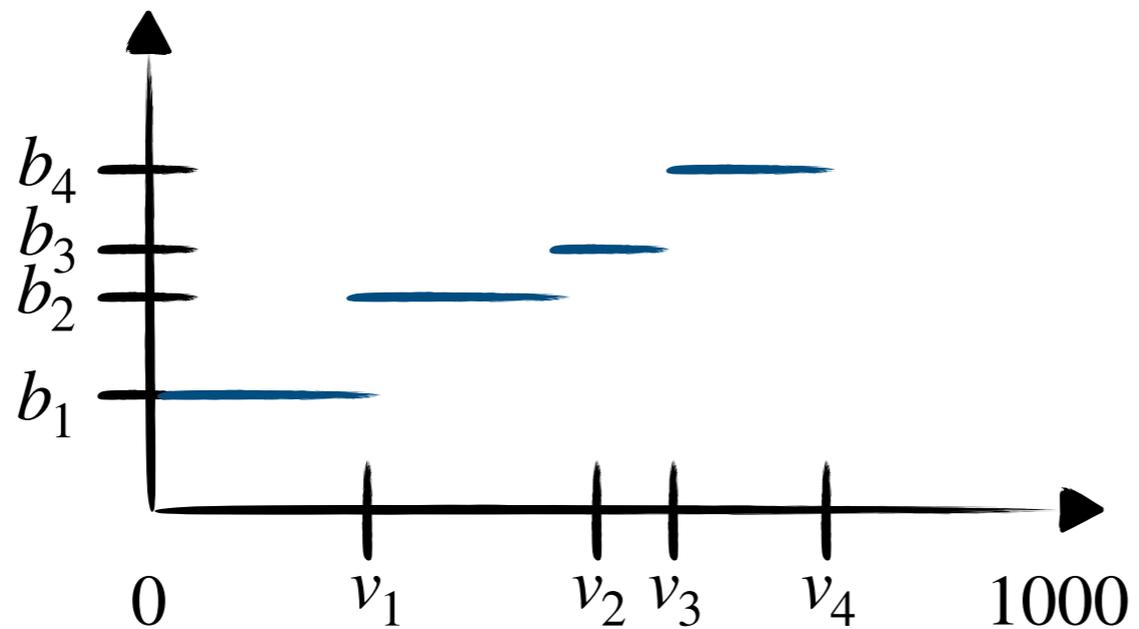
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We call this a “jump point” representation.



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Concrete CS problem: Given a FPA as an input, can we design an efficient algorithm for finding a Nash equilibrium of the auction?

This question is more intricate than it initially looks like.

Vickrey, Myerson, Milgrom, Wilson, and all the other great economists were not thinking about computation.

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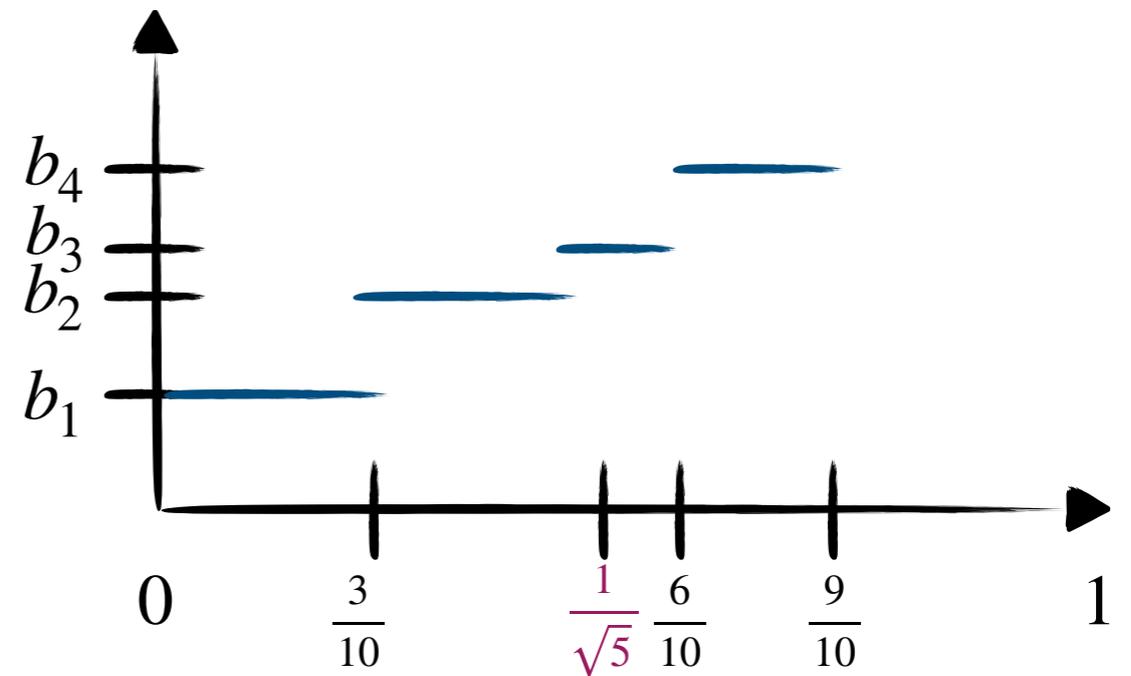
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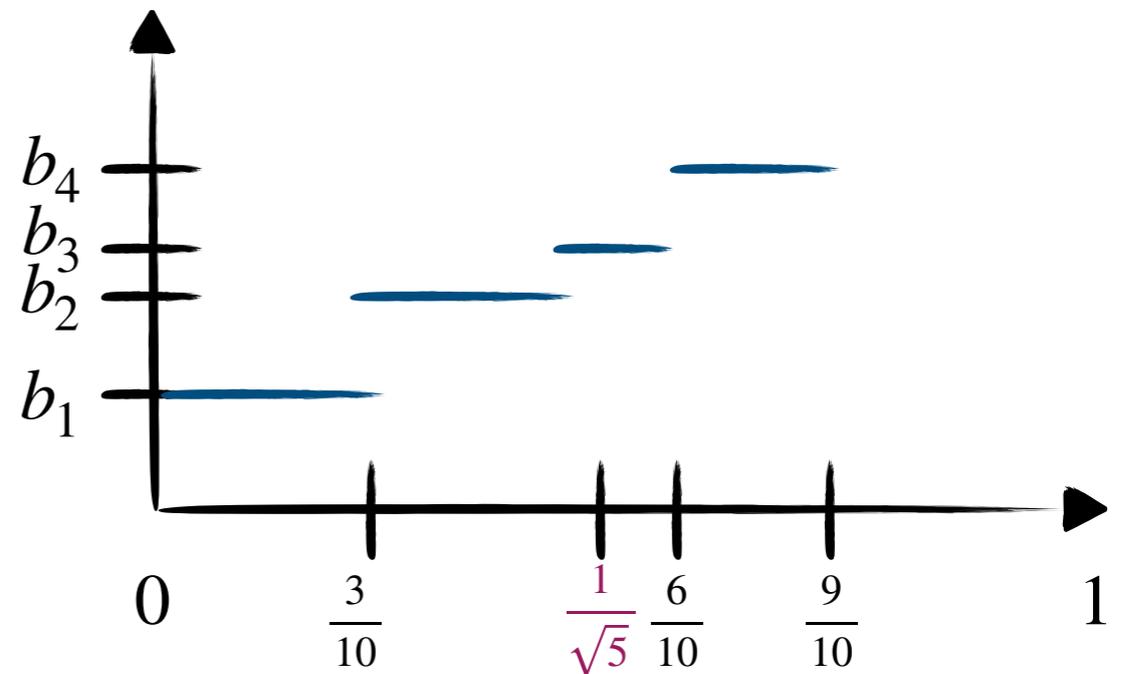


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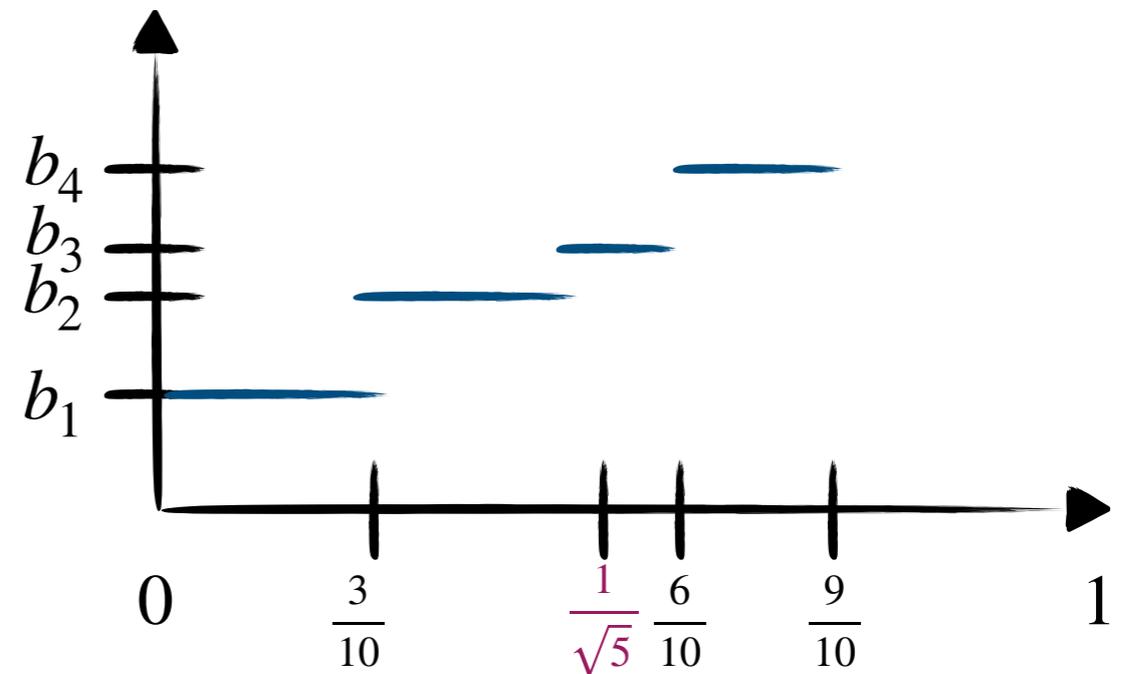
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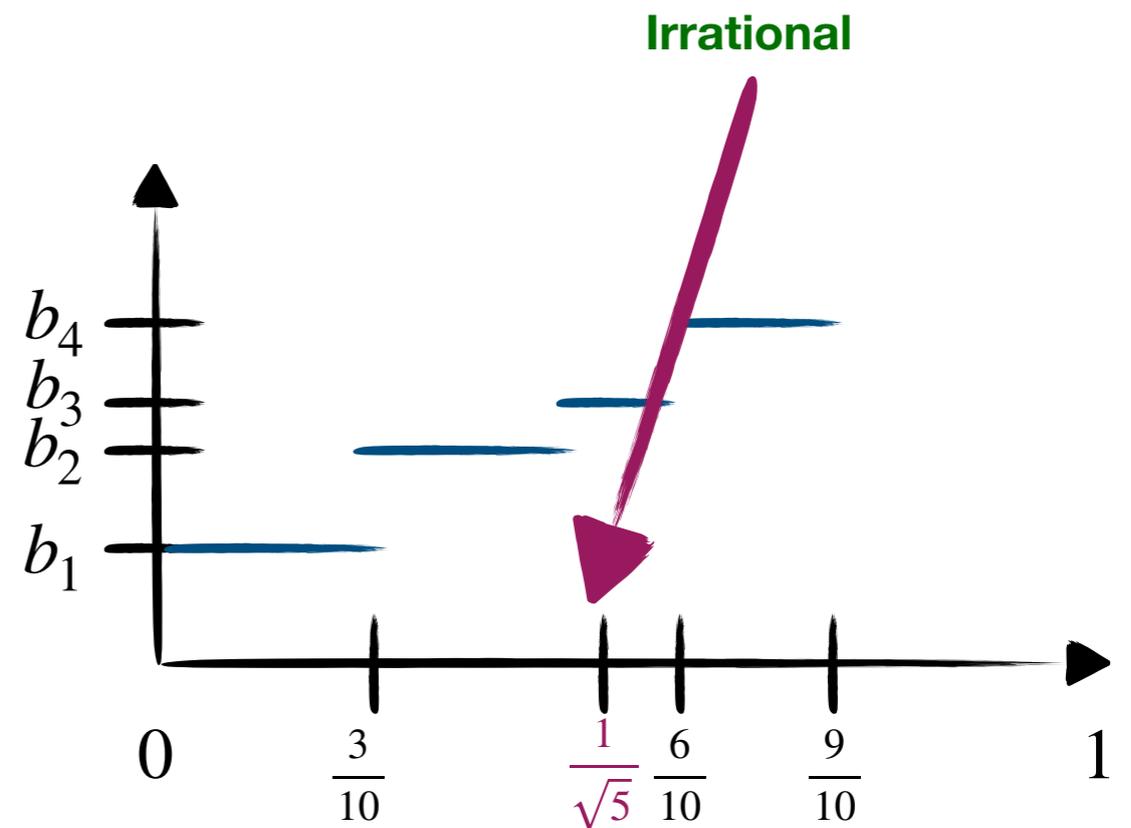
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Discrete FPA problem: Given a discrete FPA and an ε as input, decide if the auction has an ε -approximate Nash equilibrium or not. If it does, return it.

[Theorem \(F., Giannakopoulos, Hollender, and Kokkalis 2024\)](#): The Discrete FPA problem is NP-complete.

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For **symmetric beliefs** ($F_i = F_j$), we have polynomial-time algorithms.
(F. et al. 2023, 2024, 2025, 2026).