## Price of Anarchy for Auction Revenue

Author: Jason Hartline, Darrell Hoy, Sam Taggart May 8, 2023

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After the draw, she will determine a subsequent action according to the strategy  $s_i: V_i \to A_i$ .

## **Definition: Mechanism**

A mechanism M is a pair of two function  $\tilde{x}, \tilde{p} \in (A_1 \times \ldots \times A_n) \to \mathbb{R}^n$  where:

- $\tilde{x}_i(a_1, \ldots, a_n)$  denotes the probability where *i*-th agent gets the item.
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Agent *i*'s utility is  $\tilde{u}_i(a) = v_i \tilde{x}_i(a) - \tilde{p}_i(a)$ .

Simply speaking, it's in the order of Values  $(V_i)$ , Sampling  $(F_i)$ , Strategy  $(S_i)$ , Action  $(A_i)$ , Utility  $(u_i(a))$ , as in the agent perspective.

We want best strategy that works anytime, but even a tiny prison with two rooms don't have such. This is a gargantuan setting. Simply speaking, it's in the order of Values  $(V_i)$ , Sampling  $(F_i)$ , Strategy  $(S_i)$ , Action  $(A_i)$ , Utility  $(u_i(a))$ , as in the agent perspective.

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So we work with **Bayes-Nash equilibrium:** For each agents *i*, the **strategy** is optimal within the **Mechanism** given other agent's **Value**, **Distribution, Actions, Strategies** are fixed.

You can find the correspondence for all five items. Yes, everything except my strategy is fixed.

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Everything is probabilistic BTW, so the profit is expectation of utility according to the distribution  $F_1, \ldots, F_n$ .

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This is the original definition of mechanism in Lecture 2. Throughout the lecture, we will reintroduce some of the concepts in Lecture 2 in a generalized form.

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Question: Why are people interested in maximizing this term?

Myerson introduced the following lemma while introducing the revenue equivalence theorem:

#### Lemma

Let  $f_i$  be the pdf of  $F_i$  and  $F_i$  be the cdf of  $F_i$ . Define the Virtual value  $\phi(v_i) = v_i - \frac{1 - F_i(v_i)}{f_i(v_i)}$ . It follows that  $Rev(M) = E_v[\sum_i p_i(v)] = E_v[\sum_i \phi_i(v_i)x_i(v)]$ 

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The proof for the special case can be found in Lecture 2 notes, I think?

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Price of anarchy is the result of this philosophy. The worst case here is the Nash equilibrium which brings me the minimum profit.

I recommend you to visit the Wikipedia page *Price of anarchy in auctions*. It looks really algorithm-ish.

Let BNE(M, F) be the set of Nash equilibrium strategies per the distribution F. The **Bayesian price of anarchy for revenue** is defined as  $\max_{F \in R, s \in BNE(M, F)} Rev(OPT_F)/Rev(M)$ , where R is the set of regular distributions and  $OPT_F$  is the Bayesian revenue-optimal mechanism for value distribution F.

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I think, the term can be unbounded, though.

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What is the *individual monopoly reserves*? It means the seller can impose a certain threshold where she would not sell if the price is less than the **reserve value**  $r_i$ .

 $r_i$  may be different per agent.

We denote this mechanism  $FPA_r$ .

Now we will present the main theorem.

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## Theorem

For any Bayes-Nash equilibrium strategy,  $Welfare(FPA_r) + Rev(FPA_r) \ge \frac{e-1}{e}Welfare(OPT_r).$  From the theorem we can obtain O(1) PoA for revenue and welfare.

#### Theorem

For any Bayes-Nash equilibrium strategy,  $Rev(OPT_r)/Rev(FPA_r) \leq \frac{2e}{e-1}$ , and  $Welfare(OPT_r)/Welfare(FPA_r) \leq \frac{2e}{e-1}$ . From the theorem we can obtain O(1) PoA for revenue and welfare.

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The proof of these facts is in the paper.

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Model the road as a directed edge with a fixed capacity. If the road exceeds the capacity, it incurs a latency proportional to the traffic flow.

Each driver possesses a mixed strategy where the set of  $s_i - t_i$  paths are selected per certain probability.

They can be modeled as a flow, where each path incurs flow of its own probability.

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On the original problem, there are known bounds of PoA:

Theorem
If a latency function is a linear function the PoA is at most $\frac{4}{3}$ .

#### Theorem

If a latency function is a polynomial of degree at most d, the PoA is at most d + 1.

# Thank you for your attention!