Examples of Smooth Auctions (Part 1)

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Last lecture, we defined smoothness of auctions as following:

Definition 1. An auction game is (λ, μ) smooth if $\exists s^*$, s.t, $\sum_i u_i(s_i^*, s_{-i}) \ge \lambda OPT - \mu \sum_i p_i(s)$. Where o(s) is the outcome at strategy vector s, $V_i(o(s))$ is the value of player i at outcome o(s), $p_i(s)$ is the payment of player i given strategy vector s, and $u_i(s) = V_i(o(s)) - p_i(s)$, $OPT = \max_o \sum_i V_i(o)$.

Using smoothness, we also had the following two theorems on PoA bounds for full info. game and Bayesian game (respectively).

Theorem 1. For a full information game, (λ, μ) smooth implies for any Nash s, $SW(s) \geq \frac{\lambda}{\max(1,\mu)}OPT$.

Theorem 2. For a Bayesian game, (λ, μ) smooth with s_i^* depends only on v_i for all *i*, implies for any Nash s, $E[SW(s)] \ge \frac{\lambda}{\max(1,\mu)} E[OPT]$.

In this lecture and next lecture, we will look at examples of smooth games.

Example 1: First Price Auction of a single item

- Players $1, \ldots, n$.
- Values of getting the item (v_1, \ldots, v_n) , and value = 0 if not getting it.
- Bids (b_1, \ldots, b_n) .

We use the following simple argument to show that the game is $(\frac{1}{2}, 1)$ smooth if we let $s_i^* = \frac{v_i}{2}$ for all *i*.

Proof. If $j = \arg \max_i v_i$, then $u_j(s_j^*, s_{-j}) \ge \frac{1}{2}v_j - \sum_i p_i(s)$ because

- If j wins, $u_j = v_j s_j^*(v_j) = \frac{v_j}{2} \ge \frac{1}{2}v_j \sum_i p_i(s)$.
- If j loses, $u_j = 0$, and $\max_i b_i > \frac{1}{2}v_j$. Notice that $\sum_i p_i(s) = \max_i b_i$ because the maximum bid person pays his bid, and others pays 0. Therefore, $u_j = 0 > \frac{1}{2}v_j \sum_i p_i(s)$.

If $i \neq \arg \max_i v_i$, then $u_i(s_i^*, s_{-i}) \ge 0$ because if wins, utility is half of his value which is positive, and if loses, utility is 0.

Sum up over all players we get

$$\sum_{i} u_i(s_i^*, s_{-i}) \ge \frac{1}{2} v_j - \sum_{i} p_i(s) = \frac{1}{2} OPT - \sum_{i} p_i(s)$$

Thus the game is $(\frac{1}{2}, 1)$ smooth.

Thus, according to Theorem 1 and Theorem 2, (notice Theorem 2 applies because here s_i^* only depends on v_i), we have $SW(s) \ge \frac{1}{2}OPT$ for full info game and $E[SW(s)] \ge \frac{1}{2}E[OPT]$ for Bayesian game.

In fact, we can get a tighter bound on PoA as follows.

Theorem 3. For the single item first price auction defined above, the game is $(1 - \frac{1}{e}, 1)$ smooth.

Proof. Let b_i be randomly chosen according to probability distribution $f(x) = \frac{1}{v_i - x}$ from the interval $[0, (1 - \frac{1}{e}v_i)]$. This probability distribution is well defined because $\int_0^{v_i(1 - \frac{1}{e})} \frac{1}{v_i - x} dx = [-\ln(v_i - x)]_0^{v_i(1 - \frac{1}{e})} = -\ln(\frac{v_i}{e}) + \ln(v_i) = \ln(\frac{v_i}{v_i/e}) = 1.$

We use the similar technique as above, that

- If $i \neq \arg \max_i v_i$, then $u_i(s_i^*, s_{-i}) \ge 0$.
- If $i = \arg \max_i v_i$. Then $v_i = OPT$. Let $p = \max_{j \neq i} b_j$, then $u_j(s_j^*, s_{-j}) = \int_p^{v_i(1-\frac{1}{e})} f(x)(v_i x)dx = v(1-\frac{1}{e}) p = v_i(1-\frac{1}{e}) \max_{j \neq i} b_j \ge v_i(1-\frac{1}{e}) \max_j b_j = (1-\frac{1}{e})OPT \sum_j p_j$.

Sum up over all i we get

$$\sum_{i} u_i(s_i^*, s_{-i}) \ge (1 - \frac{1}{e})OPT - \sum_{i} p_i(s)$$

Therefore the game is $(1 - \frac{1}{e}, 1)$ smooth.

Similarly, according to Theorem 1 and Theorem 2, we have $SW(s) \ge \frac{e-1}{e}OPT$ for full info game and $E[SW(s)] \ge \frac{e-1}{e}E[OPT]$ for Bayesian game.

Comments:

- 1. For $s_i^* = \frac{v_i}{2}$, $o(s^*) = OPT$ because bid is monotone in value, so the maximum value player is always getting the item.
- 2. For s_i^* random in interval $[0, (1 \frac{1}{e}v_i)]$, it is possible that $o(s^*) \neq OPT$, because there's possibility even for the max value player to bid close to 0. So in this case the max value person not always get the item.
- 3. So far we analyzed single item auction. We will talk about how to generalize to multiple item auction next time.