

Revenue Maximization in Multi-Object Auctions

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- Manelli, A and Vincent, D. (2007): "Multidimensional Mechanism Design: Revenue Maximization and the Multiple-Good Monopoly", *Journal of Economic Theory* **137**, 153-185.

Multi-Object Auction Model

- n agents and m objects. Value of object j to agent i is $v_i^j \in R_+$.
- Value of a bundle of objects is the sum of the values of the objects in the bundle.
- The utility of agent i who obtains set of objects S and makes monetary transfer t is

$$\sum_{j \in S} v_i^j - t.$$

- Auctioneer maximize revenues = maximize the sum of monetary transfers made by agents.

Information

- Each agent i knows $\mathbf{v}_i = (v_i^1, \dots, v_i^m)$ but regards \mathbf{v}_k , $k \neq i$, as being a random draw from a compact and convex set $V_k \subset \mathbb{R}_+^m$.
- \mathbf{v}_k independent of \mathbf{v}_l , $l \neq k$.
- Distribution F_k with density $f_k > 0$ is common knowledge
- Auctioneer regards all values as random variables.

Mechanisms

- In a *direct revelation mechanism* (DRM) each agent i reports \mathbf{v}_i (not necessarily truthfully!), and the mechanism determines a physical and monetary allocation.
- Formally, a mechanism consists of:
- 1 $\forall i, j, p_i^j(\mathbf{v}_1, \dots, \mathbf{v}_n) \in [0, 1]$ is the probability that agent i gets object j when the reports are $(\mathbf{v}_1, \dots, \mathbf{v}_n)$. Feasibility requires that

$$\forall j, \mathbf{v}_1, \dots, \mathbf{v}_n, \sum_{i=1}^n p_i^j(\mathbf{v}_1, \dots, \mathbf{v}_n) \leq 1$$

- 2 $\forall i, t_i(\mathbf{v}_1, \dots, \mathbf{v}_n) \in R$ is the monetary transfer made by agent i to the auctioneer when reports are $(\mathbf{v}_1, \dots, \mathbf{v}_n)$.

The Revelation Principle

- In a Bayes-Nash equilibrium, each agent optimizes given his expectation about the actions of others and expectations are correct.
- The Bayes-Nash equilibrium of **any** possible selling scheme can be replicated by a DRM where it is a Bayes-Nash equilibrium for each agent to truthfully reveal his values.
- Thus, in order to find the revenue maximizing selling scheme it is enough to restrict attention to truthful (or incentive compatible) DRM's

Incentive Compatibility

- Fix a DRM (\mathbf{p}, \mathbf{t}) and define:

$$q_i^j(\widehat{\mathbf{v}}_i) = \int_{V_{-i}} p_i^j(\mathbf{v}_{-i}, \widehat{\mathbf{v}}_i) f_{-i}(\mathbf{v}_{-i}) d\mathbf{v}_{-i}$$

$$T_i(\widehat{\mathbf{v}}_i) = \int_{V_{-i}} t_i(\mathbf{v}_{-i}, \widehat{\mathbf{v}}_i) f_{-i}(\mathbf{v}_{-i}) d\mathbf{v}_{-i}$$

Agent i 's expected utility is given by :

$$U_i(\mathbf{v}_i, \widehat{\mathbf{v}}_i) = \mathbf{q}_i(\widehat{\mathbf{v}}_i) \cdot \mathbf{v}_i - T_i(\widehat{\mathbf{v}}_i)$$

- Truthful telling requires then that for all i , and for all $\mathbf{v}_i, \widehat{\mathbf{v}}_i \in V_i$ we have:

$$S_i(\mathbf{v}_i) := U_i(\mathbf{v}_i, \mathbf{v}_i) = \sup_{\widehat{\mathbf{v}}_i \in V_i} U_i(\mathbf{v}_i, \widehat{\mathbf{v}}_i)$$

Consequences of IC

- The function $S_i(\mathbf{v}_i) = U_i(\mathbf{v}_i, \mathbf{v}_i)$ is the supremum of linear functions, hence it is continuous and convex, and $\nabla S_i = \mathbf{q}_i$ a.e.
- \mathbf{q}_i is cyclically monotone and

$$S_i(\mathbf{v}_i) = S_i(\underline{\mathbf{v}}_i) + \int_{\underline{\mathbf{v}}_i}^{\mathbf{v}_i} \mathbf{q}_i(\mathbf{w}_i) \cdot d\mathbf{w}_i$$

where $\underline{\mathbf{v}}_i$ is an arbitrary vector in V_i , and where the integral does not depend on the path of integration.

- We can write:

$$\begin{aligned} T_i(v_i) &= -S_i(\mathbf{v}_i) + \mathbf{q}_i(\mathbf{v}_i) \cdot \mathbf{v}_i \\ &= T_i(\underline{\mathbf{v}}_i) - q_i(\underline{\mathbf{v}}_i) \cdot \underline{\mathbf{v}}_i + \mathbf{q}_i(\mathbf{v}_i) \cdot \mathbf{v}_i - \int_{\underline{\mathbf{v}}_i}^{\mathbf{v}_i} \mathbf{q}_i(\mathbf{w}_i) \cdot d\mathbf{w}_i \end{aligned}$$

Payoff Equivalence

- In other words, in a truthful *DRM*, the expected monetary transfer T_i is completely determined, up to a constant, by the expected probabilities of getting the various objects \mathbf{q}_i (and hence by the primitive probabilities p_i^j).
- **This important result is called the payoff-equivalence theorem.**
- Conversely, any mechanism (\mathbf{p}, \mathbf{t}) that satisfies the above conditions is a truthful DRM.

Revenue Maximization: Individual Rationality

- Since $S_i(\mathbf{v}_i) = S_i(\underline{\mathbf{v}}_i) + \int_{\underline{\mathbf{v}}_i}^{\mathbf{v}_i} \mathbf{q}_i(\mathbf{w}_i) \cdot d\mathbf{w}_i$ and \mathbf{q}_i is non-negative we obtain that

$$S_i(\underline{\mathbf{v}}_i) \geq 0 \Rightarrow S_i(\mathbf{v}_i) \geq 0, \forall \mathbf{v}_i.$$

- Let assume now for simplicity that $V_i = [0, 1]^m$, and let us take $\underline{\mathbf{v}}_i = (0, 0, \dots, 0)$. Then, $S_i(\underline{\mathbf{v}}_i) = -T_i(\underline{\mathbf{v}}_i)$, so that

$$S_i(\underline{\mathbf{v}}_i) \geq 0 \Leftrightarrow T_i(\underline{\mathbf{v}}_i) \leq 0.$$

- In other words, the agent with zero values for all objects cannot be asked to make a positive transfer to the auctioneer.
- Thus, in a revenue maximizing mechanism we have $T_i(\underline{\mathbf{v}}_i) = 0$.

Expected Revenue

We have:

$$\begin{aligned}T_i(\mathbf{v}_i) &= \nabla S_i(\mathbf{v}_i) \cdot \mathbf{v}_i - S_i(\mathbf{v}_i) \\ &= \mathbf{q}_i(\mathbf{v}_i) \cdot \mathbf{v}_i - \int_{\underline{\mathbf{v}}_i}^{\mathbf{v}_i} \mathbf{q}_i(\mathbf{w}_i) \cdot d\mathbf{w}_i\end{aligned}$$

The expected revenue is then given by

$$\begin{aligned}R &= \sum_{i=1}^n \left[\int_{V_i} T_i(\mathbf{v}_i) f_i(\mathbf{v}_i) d\mathbf{v}_i \right] \\ &= \sum_{i=1}^n \left[\int_{V_i} \left[\mathbf{q}_i(\mathbf{v}_i) \cdot \mathbf{v}_i - \int_{\underline{\mathbf{v}}_i}^{\mathbf{v}_i} \mathbf{q}_i(\mathbf{w}_i) \cdot d\mathbf{w}_i \right] f_i(\mathbf{v}_i) d\mathbf{v}_i \right]\end{aligned}$$

Constraints

- The above revenue can be written directly in terms of the mechanism's primitive probabilities p_i^j .
- Thus the auctioneer maximizes R over all functions $p_i^j(\mathbf{v}_1, \dots, \mathbf{v}_n)$ such that:

① $\forall i, j, \mathbf{v}_1, \dots, \mathbf{v}_n, \quad p_i^j(\mathbf{v}_1, \dots, \mathbf{v}_n) \in [0, 1].$

② $\forall j, \mathbf{v}_1, \dots, \mathbf{v}_n, \quad \sum_{i=1}^n p_i^j(\mathbf{v}_1, \dots, \mathbf{v}_n) \leq 1.$

③ $\forall i$, the vector field \mathbf{q}_i defined by

$$\mathbf{q}_i^j(\mathbf{v}_i) = \int_{V_{-i}} p_i^j(\mathbf{v}_{-i}, \mathbf{v}_i) f_{-i}(\mathbf{v}_{-i}) d\mathbf{v}_{-i}$$

is the gradient of a convex function.

- Myerson (1981) completely solves the 1-object case.
- Heuristic: ignore constraint 3; solve pointwise; find conditions on the distribution under which constraint 3 is satisfied. Solution is a deterministic allocation.
- Manelli and Vincent (2007) have shown that the extreme points in the multidim. case need not be deterministic