Research Proposal

Bayesian Implementation in Crowdsourced Auctions

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May 12, 2012

1 Introduction

From the early days of mankind, the problem of collective decision making in a society where information is dispersed among the members of the society has been a challenging one. Many civilizations have perished, or more recently, governments have taken a downturn due to bad, uninformed policies. Numerous other social, political and economical decisions ranging from voting for political representatives to trading in a market require making decisions collectively. The design of institutions through which individuals interact, play a key role in the decision process. The study of implementation theory deals with the design of specific institutions which bring about socially 'desirable' outcome, given the individual preferences.

In implementation theory, the desirable outcomes are characterized through a set of given properties. For instance, the winner of an election should not be a representative who is less preferred to another representative by all members of the society (Pareto dominated) or should be a representative who wins by majority against any other representative in a pairwise preference of the voters (Condorcet winner). Implementation theory helps establishing the existence and tractability of mechanisms (game forms) which result in outcomes satisfying the given desirable properties. A few examples of implementation questions are:

- Given any possible preference of voters, is there an election procedure such that each equilibrium outcome is Pareto optimal and Condorcet winner?
- How can we design an auction ensuring that the individual who highly values an object (in comparison to other participants) is the winner of the auction?

2 Overview of Implementation in Auctions

The problem of auction design has inspired the growth of implementation theory as it is one of the earliest and most extensively studied problem in game theory. To understand the existing results, we define the generalized auction model as follows:

(Generalized Auction Model)

There is a finite set of *players* $N = \{1, 2, \ldots, n\}$ and a finite set X of *goods* to be auctioned. The set of all *feasible assignments of goods* is denoted by $A = \{(A_0, A_1, A_2, \ldots, A_n) : A_i \subseteq X\}$, where A_i denotes the allocation to the i^{th} player and A_0 denotes the unallocated goods. Each player i has a *valuation function* $\theta_i : 2^X \to \mathbb{R}$. Player i's *utility* of receiving a set A_i and paying a price p_i is $u_i(A_i, p_i) = \theta_i(A_i) - p_i$. A negative price indicates a payment from the mechanism to the player.

$\theta = (\theta_1, \theta_2, \ldots, \theta_n)$ is a *profile* of valuations and Θ is a set of all *possible valuation profiles.* $\mathcal{D}$ is the set of all *probability distributions* over Θ. Let the *true valuation* of players, θ^T, be drawn from the distribution $D \in \mathcal{D}$.

The goal of the auctioneer (seller) is to design an auction game that induces the players to reveal their valuations truthfully (θ^T) and assign goods to players in a way that gives him the highest possible expected revenue.

The celebrated result of Myerson [1], which contributed to his Nobel Prize in Economics, puts forth a mechanism that maximizes revenue for the auctioneer when the participants are truthful. However, this mechanism requires that all the players and the auctioneer know the distribution D associated with the true valuation θ^T (common knowledge). This is equivalent to assuming that the seller (buyer) knows a good estimate of the buyers' (remaining buyers') true valuations.

To obviate the assumption on the seller's end, Caillaud and Robert [2] obtain a optimal mechanism for single-good auctions with independent valuations, assuming that the players have the common knowledge distribution of the true valuation. Choi and Kim [3] extend this result to a setting where each player's distribution is known to someone else. Cremer and Riordan [4] propose an efficient mechanism with the assumption of one expert player (who has knowledge about other players).

The above results involve restrictive settings where players are either allowed to have no information about the valuations of their opponents beyond $D|\theta_i$ [2] or each player's distribution is known perfectly to some player [3, 4]. More recently, Azar, Chen and Micali [5] propose an efficient revenue maximizing mechanism, that they call a crowdsourced mechanism, for multiple-goods auction by removing the common knowledge assumption (only the existence of such a distribution in $\mathcal{D}$ is assumed). Their mechanism uses one of the players to learn his knowledge of the other players' distributions by suitably incentivizing him (crowdsourcing) via scoring rules and achieves a $(1 - \frac{1}{n})$ fraction of the revenue of the optimal mechanism with the remaining $n - 1$ players.

In this project, I aim to investigate this problem in further detail. One of the shortcomings in [5] is that the mechanism has a large communication complexity i.e. the chosen player needs to reveal the entire known distribution which may have very large, even unbounded support. Further, the nature of the mechanism is complex (not transparent, uses other mechanism as black-boxes) and may discourage players from participating. Also, this mechanism allocates nothing (just monetary incentive) to a player picked at random. This might not be favorable for him if he values some goods very highly. For instance, in a rare sale of antiques, any buyer may not wish to go home empty handed. Further, the revenue generated by this mechanism depends on the optimal revenue with $n - 1$ players and could turn out unfavorably if we pick the player who values a majority of goods more than other players. Aiming at a lower bound that is a fraction of the optimal revenue for n players is more reasonable for comparison. Also, the assumption that A satifies a *downward-closure condition* imposes a restriction on the set of feasible assignments. My goal is to find a simpler, more general mechanism for this problem addressing the above shortcomings.

References

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[5] P. Azar, J. Chen and S. Micali, *Crowdsourced Bayesian Auctions*, In Proceedings of the 3rd Innovations in Theoretical Computer Science Conference (ITCS '12), 2012.