Toward Simple and Robust Auctions for Revenue Maximization

Abstract: Auctions that aim to maximize the seller's profit tend to be complex, and their revenue guarantees are closely tied to the assumption that the seller has precise knowledge about the bidders. **I will design near-optimal auctions that are simple and do not depend on such assumptions, bringing auction theory more in line with what is desired in practice.**

Motivation: Mechanism design, also known as "incentive engineering," is concerned with the design of protocols such that rational participants, motivated solely by their self-interest, will end up achieving the designer's goals. The applications of mechanism design in the age of the internet are vast: scheduling tasks in the cloud, routing traffic in a network, buying and selling goods in electronic marketplaces, assigning ad-slots on search engines, etc. Nowadays, most algorithm problems are in fact mechanism design problems. Solving these problems requires merging ideas from computer science with ideas from game theory and economics. One of the most important goals in this domain is the design of auctions to maximize seller revenue.

My work aims to address two fundamental issues with existing auction formats for optimizing revenue: complexity and sensitivity to information. Optimal auctions tend to be *computationally complex* for a seller to both determine and implement. Moreover, in an optimal auction, a buyer might be presented with an infinite menu of randomized allocations [3], and determining how to bid in such auctions is highly nontrivial. For this reason, there has been a major push in recent years to design mechanisms that are simultaneously *simple*—for both buyers and sellers to implement and "play"—and still yield near-optimal revenue.

The second major issue concerns *robustness* to a lack of exact knowledge about the buyers. Optimal Bayesian mechanism design assumes that each buyer's *valuation*—how much he is willing pay for any set of items—is drawn according to some prior distribution, and moreover, that the auctioneer has full knowledge of what this prior distribution is for each agent. These assumptions are unrealistic. Because the buyer population is dynamic, a seller is unlikely to have precise information about these prior distributions. An auction tailored to a specific input may perform poorly if the seller's knowledge of this information is noisy or flat-out wrong. In practice, sellers want an auction format that they can use successfully every time, including on different populations. **To align auction theory with the sort of auctions we can implement in practice, I will design mechanisms that, independent of the distributions of the bidders, still have strong guarantees on the revenue produced.**

Proposal: I propose to design *simple* and *robust* auctions that guarantee near-optimal seller revenue. I will explore a range of settings where an auctioneer sells multiple types of items, and the buyers have values for every subset of items. For example, consider a seller that can segment his market by providing *k* types of service, each increasing in quality and price. The seller could be an Internet Service Provider providing various network bandwidth plans, or FedEx providing different guarantees on package delivery time. Each buyer seeks to buy the level that maximizes his utility, trading off between his preference for higher quality and lower price.

This is only one example from a large class of problems. The general multiple-item setting lacks structure that would help us to gain traction, so instead, I will focus on specific settings with respect to buyer valuations and seller supply. For example, buyers might want one type of service (this FedEx problem), have additive value per item (ad-slots per keyword), or have some more nuanced structure. Sellers might have unlimited supply (like an mp3) or limited supply (three ad-slots per keyword). **For any such problem, I will take the following approach**:

1. Characterize the optimal auction when the seller knows the prior distributions of the buyers precisely, if possible.

2. Explore the space of mechanisms that trade off optimality of revenue for simplicity.
3. Determine a way to use the bids of some buyers to estimate the parameters of a simple auction. That is, use a small number of bids to approximately understand the unknown priors.
4. Choose a benchmark for comparison. It should have properties that we desire, serving as a goal to design toward in Step 5, and a natural point of evaluation for the resulting auction.
5. Design a simple, near-optimal auction that compares well to the benchmark on every input.

The FedEx Problem: This level-of-service problem is a good candidate because it is more general than the solved case of positively correlated items [2], but likely to be easier than the unsolved unit-demand setting. I will describe my ideas for each step of this problem in the context of my success applying them to a more restricted case: suppose each buyer has a private value v for obtaining any of the top j highest quality levels of service. When their pairs (v,j) are drawn from a "nice" class of prior distributions, with my advisor and others from the Simons Institute, I have characterized the optimal mechanism using a dynamic program to produce increasing prices, and we know how to efficiently design simple auctions for this setting. I will work to expand our characterizations to any class of distributions. Moreover, we have built on results from digital goods auctions [1] to design *prior-free* auctions that achieve a constant fraction of a natural benchmark on *every* bid input. The key idea is to partition the bidders into two sets and use one set to understand and set payments for the other. Going forward, I will apply my intuition from our preliminary results together with established techniques for the unit-demand setting to the more challenging and general level-of-service domain.

Additive Buyers: Consider when there are m items to sell, and n buyers, each valuing any set of items as the sum of its parts. The optimal mechanism here is extremely complex, but a recent breakthrough shows that there is a simple mechanism that achieves a constant fraction of the optimal revenue [4]. However, this result relies on detailed knowledge of the buyers' prior distributions. **In recent work with my advisor, I have shown how to implement this auction *without* knowledge of the priors** by using some of the submitted bids as samples from the buyers' priors. These samples are then fed into a procedure for computing prices for other buyers. We have shown that this can be done while preserving near-optimality of profit. I am working to characterize and extend the class of distributions for which this technique works.

Intellectual Merit and Broader Impacts: We see combinatorial auctions all the time in practice: Google sells keyword ad-slots to advertisers; Amazon sells EC2's cloud computing resources. Our preliminary results give the first known near-optimal auctions for selling multiple types of items that are 1) prior-independent for additive buyers and 2) prior-free for unit-demand buyers who want at least the j-highest level of service. But optimal and near-optimal auctions depend significantly on the seller's supply and the buyers' valuation structure, so our techniques and the form of optimal, robust, or simple auctions will vary widely depending on the setting. ***Simple* auctions benefit everyone, buyer and seller alike**, as they are straightforward to determine, implement, and bid in. Following the plan of attack described above, I will study a range of settings over the course of the next three years, **producing *simple* and *robust* mechanisms that can be used in practice**, and the analytical tools to understand them.

References:

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