Mechanism Design: Beyond Traditional Models, Beyond Traditional Settings

Kira Goldner

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 on the internet are vast: scheduling tasks in the cloud, routing traffic in a network, and buying and selling goods in electronic marketplaces, to name a few. These days, many algorithmic questions are in fact mechanism design questions. Solving these problems requires merging ideas from computer science, game theory, and economics.

Facebook's goal to make the world more open and connected necessarily involves interacting with many strategic users. Solutions from mechanism design are crucial for achieving these goals: from maximizing revenue from ad assignments, to encouraging individuals to share content, to incentivizing users to try out a new feature.

Beyond Traditional Models in Revenue Maximization. One of the most fundamental goals in mechanism design and a major focus of my own research is profit maximization, e.g., in ad auctions. Consider, for example, an auctioneer selling multiple items to multiple potential buyers, and suppose that the auctioneer has detailed prior knowledge of the distribution from which each buyer's values for items are drawn. What is the revenue-optimal auction that the seller can implement? Unfortunately, despite decades of research on this problem, we are still far from having achieved a full understanding of the answer to this question. In fact, a complete characterization of the optimal auction for selling just two items optimally to a single bidder is still not known! In my research, I have been able to successfully produce results in revenue maximization by studying models that incorporate the uncertainty and specific constraints that mechanisms face in practice.

Beyond Restricted Distributions: Leveraging Structure. The list of known optimal auction formats is very short; almost all known results rely on very simple or specific distributions. In contrast, my work identifies real-world settings where buyer preferences have additional structure that can be leveraged to exactly characterize the optimal auction without placing any restrictions on the distributions. With collaborators, I considered "The FedEx Problem" [EC 2016], the setting where buyers have a package to ship, a deadline d that they want it received by, and a value v for having the package received by its deadline. This setting applies whenever customers require some base level of service. We used techniques from duality to characterize the optimal auction and avoid case analysis. While the optimization problem has infinitely many constraints, the structure of the setting makes the incentive compatibility constraints almost orthogonal in v and d, making the problem tractable to solve. I have identified a number of other settings for future study with sufficient structure, including current work on the setting where buyers value each unit of a good or service up to some demand cap, past which they do not value additional units. In such settings, I believe using our duality approach to characterize optimal auctions is a promising approach.

Beyond Complicated Mechanisms. Optimal mechanisms are often very complicated and involve offering buyers a complex menu of lotteries, rendering them impractical for use. A major focus of recent research in the field has been on understanding the efficacy of *simple* mechanisms that post prices on each service or item that is offered, and then let buyers arrive in any order and take any item they want given the prices. In ongoing work with collaborators, I am working to give an algorithm for setting non-adaptive thresholds for the matroid prophet inequality problem, which would translate to posted pricings that achieve a constant-fraction of the optimal revenue.

Beyond Known Distributions. While the bulk of revenue maximization reasons about buyers with unknown values drawn from known distributions, it is not always realistic to assume that the seller has access to this information. When the buyer population is dynamic, a seller is unlikely to have such precise information. In practice, sellers may want an auction format they can use successfully on different populations. In joint work with Anna Karlin, we constructed a prior-independent mechanism for multiple additive bidders that achieves a constant fraction of the expected profit of the optimal mechanism that is tailored to the prior distributions [WINE 2016]. We do this by using similar buyers as samples for one another to set item prices and entry fees. I plan to investigate remaining key prior-independent mechanism design questions in other settings where simple but prior-dependent approximate auctions have been developed.

Beyond Risk-Neutral. For the most part, revenue maximization focuses on risk-neutral buyers who maximize their expected utility. However, many buyers are actually *risk-averse*: they prefer an outcome that is certain over taking their chances on a lottery, even if their payoff from the certain outcome is slightly less. Imagine the setting where in each stage, there is an ad slot, and advertisers learn how much they value having the ad slot. One could sell the slot each stage separately, or earn more by selling it at a premium now and promising a future discount. In ongoing work with collaborators, I am designing revenue-maximizing mechanisms for risk-averse buyers in this dynamic setting. I am studying the revenue tradeoff: we can earn more revenue because buyers will pay extra for sure outcomes, but less revenue because buyers are less willing to opt for future discounts since their future value is unknown. Another interesting question that I plan to pursue is designing revenue-maximizing mechanisms that are robust to buyers of any risk attitude.

Beyond Trusted Sellers and Centralization. I have also begun work on two other related domains. First, I am looking into designing auctions that give good guarantees and are verifiable from a third-party who may not trust that the seller is implementing the mechanism that he claims. Second, I am working on designing mechanisms for Bitcoin and other blockchain-based systems, a dynamic setting where the auctioneer may change each time step and cannot be trusted.

Beyond Revenue Maximization: Mechanism Design for Social Good. I am also beginning to explore real-world problems where current market and government mechanisms are failing, and where algorithmic mechanism design can help play a role to improve social welfare, mitigate inequality, or disincentive the waste of resources. To this end, I am running a reading group to identify applications in this domain that give rise to interesting theoretical mechanism design questions. Beyond existing work in kidney exchange and school choice, I am focused on a number of research problems in low-income housing, healthcare, income inequality, the online labor market, education, transportation, and climate change/resource conservation.

For example, imagine there are n sick individuals and m hospitals. Individuals have valuations for their treatment, hospitals incur a cost for each treatment specific to that hospital, and some third-party "payer" (such as the government or insurance company) pays for the costs of all of the hospitals, subject to some budget constraint. Wait times are introduced for over-saturated hospitals. Known results maximize social welfare when the budget is relaxed slightly, but they rely on the mechanism designer having full knowledge of the individuals' valuations. I would like to extend these results to incorporate private valuations into the model and to account for individual sensitivities to wait times, which is more accurate as some medical conditions are more dire.

My goal is not only to work on problems in this domain myself, but by formulating interesting questions on fundamental societal problems, I hope to create and kickstart a research community focused on algorithmic and mechanism design problems where the objective is social good.

Conclusion. In social media settings, it is imperative to take incentives of self-interested users into account when designing algorithms. By doing so, we can be sure that the designer's objective, be it generating revenue, promoting the sharing of information, or maximizing social good, will actually be achieved. My work addresses models and settings inspired by problems that arise in practice that have thus far not received enough attention from the theoretical community. The characteristics of the above models — risk-aversion, quality demands, unknown value distributions, and preferences for simple mechanisms — are likely to be found in Facebook's users. Hence, an understanding of mechanism design in the presence of these constraints can be used by Facebook to better align user incentives with Facebook's goals.