Research Statement

Yingkai Li

Our economy is formed by the interactions of strategic agents. The behavior of the agents is sophisticated and the environment they interact with each other in may not be well structured. My research focused on models with plausible real-world implications that capture this sophistication of strategic interaction under the natural assumption that not all underlying information is well known. Designing and analyzing the mechanisms that mediates these strategic interactions have numerous applications such as ride-sharing and the AdWords auction. While there is a huge literature building theoretical foundations for designing optimal and approximately optimal mechanisms, while there is still a gap in applying the theories to practice. My goal is to identify and narrow critical gaps between theory and practice.

Currently, my specific interests lie in the mechanism design, online algorithms, and their intersection. For example, one of my contributions is to show that simple mechanisms are approximately optimal for a broad class of non-linear agents, which justifies the popularity of simple mechanisms in rich environments, e.g., when in practice agents are risk-averse or have budget constraints. Moreover, motivated by the observation that in some situations the mechanism designer may lack crucial information to implement the desirable optimal mechanism in practice, whether due to the fact that the prior distribution is not available to the mechanism designer or the fact that agents arrive online, I design simple and robust mechanisms that optimize the worst case performance under uncertainty. In the following paragraphs, I discuss my research agenda and a few central open questions. My publications are denoted in italics, while the important related work in literature is denoted in plain text.

Simple Mechanisms for Non-linear Agents. The revenue-optimal mechanism for single-dimensional agents with linear utility is complex and requires competition and simultaneous implementation of the mechanism, while simple mechanisms such as anonymous pricings are widely used in practice. As indicated in a long series of work, simple mechanisms are approximately optimal for single-dimensional agents with linear utility (e.g., Yan, 2011; Alaei et al., 2018). A natural question is whether this philosophy of simple versus optimal holds in richer environments. It is well understood that the optimal mechanism is more complex and in general has no closed-form characterization when agents have non-linear utilities. In *Feng et al. (2019a,b)*, for non-linear agents, we show that if posted pricing is approximately optimal for the single-agent problem with any supply constraint, then simple pricing based mechanisms (e.g., sequential posted pricings) are approximately optimal for multiple non-linear agents for any feasibility environment where simple pricing based mechanisms are approximately optimal for linear agents. If in addition a certain concavity property holds for each agent, anonymous pricings are approximately optimal as well. Our results indicate that the existing approximate optimality of simple mechanisms for linear agents can be greatly extended to non-linear agents. The reduction also applies to other objectives such as welfare maximization. As instantiations of our reduction framework, we show that for public budgeted agents, private budgeted agents with independent and monotone hazard rate (MHR) budget distribution, and a special case of risk-averse agents, posted pricing is indeed approximately optimal for the single-agent problem with any supply constraint. One immediate open question is to have a broader application of our reduction framework. For example, whether posting pricing is approximately optimal for a risk-averse agent is still unknown. We can even go beyond the von Neumann-Morgenstern expected utility model, and instead consider the prospect theory model or consider the case when the world is ambiguous to the agents and they have max-min utility for the outcome (Gilboa and Schmeidler, 1989). A more important open question is whether the philosophy of simple versus optimal can be extended beyond mechanism design problems. Recently the community has achieved success in extending this idea to contract theory. In principle, any problem where the optimal solution is too complex to be applicable in practice such as optimal taxation is worth making effort to find justification for the phenomenon that we only adopt simple mechanisms in practice.

Benchmark Design and Prior-independent Optimization. For revenue maximization problems, the knowledge of the prior distribution is crucial for designing the Bayesian optimal mechanism, which contrasts with welfare maximization problems where the optimal can be guaranteed using the VCG mechanism for each realization of the valuation without knowing the prior distribution. In the environments where the prior distribution is unknown to the seller, there are two standard approaches in the literature that provide guidance for identifying good mechanisms. Prior-independent mechanism design assumes that the prior distribution for different agents are independent and identical, and the Bayesian optimal mechanism minimizes the maximum approximation ratio to the optimal revenue for a large family of distributions. Prior-free mechanism design specifies a prior-free benchmark and the optimal mechanism minimizes the maximum approximation ratio to the performance of the benchmark for any realization of the valuation profile. A question we want to ask in prior-free mechanism design is how to design the optimal benchmark. A good benchmark should have at least the expected performance of the optimal mechanism with access to the distribution, and it should minimize the approximation of the optimal prior-free mechanism so that it can distinguish good mechanisms from bad mechanisms (Hartline, 2016).

In *Hartline et al. (2019)*, we show that prior-independent mechanism design is equivalent to the prior-free benchmark design in the sense that the optimal benchmark is the scaled up optimal prior-independent mechanism. We also optimally solved the prior-independent mechanism for two i.i.d. agents with regular distribution, which is a central problem in the area which has been open for several years. However, a negative interpretation is that the optimal benchmark designed in this manner is not more robust compared to the optimal prior-independent mechanism. For example, in the expert learning problem, the scaled prior-independent benchmark is not comparable to the widely used best-in-hindsight benchmark for certain inputs. So a main open question that we would like to understand in the expert learning problem is how to design the benchmark that minimizes the approximation ratio of the optimal prior-free mechanism subject to the constraint that the designed benchmark approximates the best-in-hindsight benchmark for all inputs.

Non-revelation Mechanism Design. In the previous paragraph, we only considered designing the optimal revelation prior-independent mechanism. It is known that in general there exists a gap between the optimal revelation mechanism and non-revelation mechanism for prior-independent mechanism design, which is referred to as the revelation gap (Feng and Hartline, 2018). Understanding the revelation gap in various models is a new and interesting question. The previous approach for showing the revelation gap utilizes the gap between the optimal dominant strategy incentive compatible (DSIC) mechanism and the optimal Bayesian incentive compatible (BIC) mechanism, which is not applicable here since the optimal DSIC mechanism is the optimal BIC mechanism for linear agents. For this problem, since we already have the characterization for the optimal revelation mechanism, the goal is to show that there exists a constant revelation gap by directly comparing the performance of an all-pay mechanism with the performance of the optimal revelation mechanism. Similarly, for the digital good environment with two i.i.d. buyers, or the single-item environment with a single buyer and the seller has access to a single sample, we can ask the same question and show whether the optimal non-revelation mechanism has strictly better worst case performance. As a work in progress, we already show that for the single-item environment with single sample access, when the distribution for the buyer satisfies the monotone hazard rate assumption, the revelation gap is at least 1.19, but numerous questions remain open.

Online Algorithms. Another line of work I am interested in is online algorithms. I have made some preliminary progress in designing online dispersion *(Chen et al., 2019)* and bandit learning algorithms *(Li et al., 2019a,b)*. My current interests lie in the intersection between online algorithms and mechanism design problems. Specifically, there are three areas that attract me the most.

The first is mechanism design in repeated environments. For example, for welfare maximization without monetary transfer, without the repeated environment, implementing the welfare maximization mechanism is not possible. In the repeated environment, the mechanism designer can incentivize the agents to truthfully report by linking their decisions across different periods to approximate the first best solution. However, without monetary transfer, the objective of welfare may not be appropriate since the scale of the utility should not matter in this case, and a possible direction is to extend the objective to Nash welfare maximization.

Another problem is the dynamic assortment problem. In this model, the seller has multiple items to sell and each item generates different revenue for the seller. A single stochastic myopic agent arrives on each day, and this agent will purchase the utility maximization item available to her on that day. The choice of the seller on each day is to choose the set of items available to the buyer to optimize revenue. As normal for online problems, we compare the performance of the algorithm to the optimal choice in hindsight and minimize the additive regret. This problem is closely related to the contextual bandit problem and the main challenge here is to find an efficient algorithm that achieves sublinear regret with time polynomial in the number of items. In general, this is not possible so we need to impose weak assumptions on the preference of the agents. One of the classical choice models I would like to consider here is the mixed logit model (Rusmevichientong et al., 2014). The task is to show that the classical UCB algorithm combined with the maximum likelihood estimator will achieve the desired result.

The last question is to consider the bandit learning with strategic agents. In this setting, the actions are not taken by the principle but by strategic agents, and the principle needs to reward the agents so that they will follow the suggestion of the principle. This area recently attracts great attention from both the algorithmic game theory community and the economics community. However, current models in many papers in this area do not capture the real-world scenarios perfectly. For example, some papers assume that the reward is a constant for all time periods in order to characterize the optimal online policy (Kremer et al., 2014). It remains open what should be a reasonable model to consider here to discuss the trade-off between exploration-exploitation and incentivizing the strategic agents.

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