Research Statement

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I study various topics in microeconomic theory with a particular interest in mechanism design, information design, and rational inattention. My works are motivated by, but not restricted to, understanding how data is generated, used and monetized, and designing markets for and regulations over data. Inspired by this, I am currently working on two broad categories: markets for and regulation over data and discrimination.

I. Market for and Regulation over Data

My job market paper, "**Optimal Recommender System Design**," is motivated from an observation that consumers often rely on intermediaries' recommendations in deciding which product to purchase; but at the same time, sellers of products pay to the intermediaries in exchange for recommending their products. Intermediaries such as Amazon and Google have an immeasurable amount of consumer data from which they can infer which products are a good match for consumers. They use this information to give consumers recommendations, but at the same time, to collect payments from sellers. This is a major, but understudied, business model of monetizing data. I consider a problem of a monopolistic intermediary that designs a pair of a recommendations rule and a transfer rule to maximize the revenue it collects from sellers. An auction with bonuses and penalties implements the optimal recommender system: if products are good for the consumer, then sellers of the products get bonuses in that for them to win the auction to be recommended to the consumer, they can still win the auction even if their bids are somewhat lower than what their competitors bid. This is the key principle behind auction systems of real-world intermediaries such as Amazon and Google.

Using this characterization, I explore regulatory issues on these intermediaries. The main issue I explore is whether the intermediaries should be allowed to use data about sellers. When selling through intermediaries, sellers leave immeasurable data about their products, target consumers, sales, and margins. Intermediaries use sellers' data to raise more revenue is no secret that regulatory bodies suspect as anti-competitive. The key question to this concern is whether the data necessarily harms consumers and sellers. The answer I provide is that additional information does not necessarily harms consumers and sellers, and therefore, these regulations need to carefully think about benefits and harms of additional data before executing them. I provide sufficient conditions under which additional information is beneficial or harmful, and discuss what kind of additional information are beneficial or harmful. Beside the additional information, I also explore welfare-maximizing recommendations rule and find that, relative to the revenue-maximizing, it decreases the intermediary's revenue, but increases consumer surplus and sellers' profits. I hope to extend this framework to study further regulatory issues, including regulations regarding private-label products and search engine services.

II. Discrimination

One of the main concerns in economics is to understand how discrimination arises and can be reduced. With the increasing availability of data, algorithms and predictive tools are proposed to reduce group disparities. For example, predictive policing algorithms are proposed to inform police where to patrol independent of their prior bias; hiring algorithms are proposed to decide whom to hire independently of genders. These algorithms, however, often resulted in widening the disparities: police patrolling neighborhoods of darker skins more often; hiring algorithms disproportionately favoring men over women. Central to this issue is how algorithms interact with human decision-makers. I use economic theory to understand the interactions and their implications on designing fair algorithms to reduce group disparities.

My paper "**Outcome Test for Policies**" (with Mallesh Pai and Rakesh Vohra) proposes a statistical test for identifying whether a policy, or an algorithm, is designed by a principal with discriminatory tastes. The test can be used for identifying, for example, whether predictive policing algorithms are discriminatory against neighborhoods of darker skin. We also argue that the marginal outcome test (Becker (2010)), a 'go-to test' of taste-based discrimination, fails for policies. We consider a canonical setup where the principal designs a policy (algorithm) that maps signals (data) to decisions for each group, say, whether to patrol or not for each area. The principal commits to the policy, which in turn affects on agents' incentives to take action, say, whether to commit a crime. In such environment, the marginal outcome test fails because the principal not only cares marginal benefit of patrolling and catching a criminal, but also incentive effect of how patrolling affects on agents' incentive to commit a crime and hence on crime rate. We propose a new statistical test that deviates away from the marginal outcome test precisely as much as the incentive effect.

Another paper of mine "**Fair Prediction with Endogenous Behavior**" (with Christopher Jung, Sampath Kannan, Mallesh Pai, Aaron Roth and Rakesh Vohra) explores what notions of fairness should we require policies, or algorithms, to satisfy when an algorithm tries to achieve a social goal and interact with humans in that agents' behaviors are endogenously determined as a response to the algorithm chosen. In a simple setup where a principal designs a policy (algorithm) that maps signals (data) to decisions for each group in order to minimize aggregate crime rates, we find that the most effective policy equalizes false positive and negative rates across groups. This is in sharp contrast to the previous literature that abstracts away from the interaction and finds equalizing thresholds on well-calibrated risk scores are advocated to be the only policy that is both fair and the most effective. These results combined show it is essential to consider human interactions in designing fair algorithms - in other words, fair algorithms designed in the absence of human-algorithms interactions can be misleading. One of our ultimate goals is to develop economics-based design principles for fair algorithms.