Dynamic Pricing Provides Robust Equilibria in Stochastic Ride-Sharing Networks

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Ridesharing markets are complex. Drivers are strategic, rider and driver decisions are stochastic, drivers’ locations influence their ability to serve demand and are influenced in turn by the trips they take, and complex city-scale phenomena, like weather, induce correlation across space and time. At the same time, the academic literature on the interplay between strategic driver behaviour and platform control considers only a portion of this complexity at a time. Existing work in this space either assumes that demand is completely deterministic [12], takes a fluid limit in which demand becomes deterministic [1, 3], dramatically simplifies a city’s geography [6, 7, 10, 11], ignores strategic behavior [2, 4, 13], or ignores correlation across time and space [9].

Our paper studies strategic driver behaviour in a model unifying many of the real-world complexities that were previously studied in isolation: stochastic rider demand, stochastic driver availability, strategic driver decisions, all including city-scale phenomena and network structure with spatial and temporal components. We model stochastic supply and demand with a two-level hierarchical distribution. The top level corresponds to macroscopic city-level variation in traffic patterns, such as those caused by changes in weather or large public events, and the second level corresponds to microscopic fine-grained randomness of driver availability and demand. Drivers in our model are strategic across multiple time periods and multiple decision types: when to enter and/or exit the market, whether to accept or reject a dispatch, and where they should relocate in the absence of a passenger.

Our first contribution is an algorithm called the stochastic spatiotemporal pricing (SSP) mechanism, which builds conceptually on a mechanism proposed for deterministic settings by [12]. The SSP mechanism is an approximately incentive-compatible and welfare-maximizing algorithm that recomputes pricing and matching decisions at each time period based on the observed state of the world. This repeated recomputation makes our process approximately subgame perfect for the drivers: following the action-allocations produced by the SSP mechanism is approximately incentive compatible at every time period from any state of the world. In addition, we show that the SSP mechanism satisfies a new and practically important robustness property: every approximate equilibrium is approximately welfare-optimal, when the market is large.

Next, we show that the dynamic nature of the SSP mechanism is essential for achieving good market performance. This insight is derived from comparing the SSP mechanism to a static variant of the SSP mechanism that uses prices derived from only a single computation. While this static mechanism satisfies a weaker non-subgame-perfect notion of incentive compatibility, we observe that the gap between the practical efficacy of both mechanisms is often extremely wide. This has implications for the broader debate on the need for dynamic pricing in ridesharing markets [2, 5, 6, 8, 10].

Our techniques for deriving the SSP mechanism are twofold. First, we consider a fluid market approximation, where the second level of fine-grained randomness in our hierarchical distribution is replaced by a deterministic, continuous fluid approximation. However, the top level randomness governing variation in traffic patterns is retained, as is the underlying spatial and temporal network structure. Second, we formulate the expected-welfare-maximizing movement of drivers across space and time as a stochastic minimum-cost flow convex program. The SSP mechanism re-solves the optimal stochastic flow convex program at each time period.
to produce its pricing and matching decisions. Welfare robustness and subgame-perfect incentive-compatibility are derived from convex duality.

Full paper available at https://arxiv.org/abs/2205.09679.

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