RESEARCH STATEMENT

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On-demand transportation is one of the major success stories of the sharing economy. Surprisingly, the rapid growth of ride-sharing platforms like Lyft and Uber or bike-sharing platforms like Citi Bike (NYC) and Divvy (Chicago) has been possible even though many of their operational challenges remain unsolved. This provides ample opportunities for operations management research on impactful real-world problems. My own research tackles these problems by leveraging data through stochastic modeling and optimization techniques.

A particular complication in operating on-demand transportation systems arises from intricate supply externalities. For example, each Lyft ride not only causes a decrease in supply (available drivers) at the origin, but also a future increase in supply at the destination. In a dock-based bike-sharing system, such as Citi Bike, these supply externalities are even more pronounced, since the decrease in the supply of bikes at the origin of a trip is accompanied by an increase in the supply of available docks at the origin (and vice-versa at the destination).

Beyond the supply externalities present, on-demand transportation platforms also vary with respect to their objectives and the exact operational levers at their disposal. For example, in our collaboration with Motivate International, the operator of America’s largest bike-sharing systems (NYC, Bay Area, Chicago, DC, Boston, etc.), we aim to minimize the number of out-of-stock events that its customers experience, i.e., the number of times customers arrive at a bike-sharing station to rent/return a bike and find themselves unable to do so because the station is empty/full. At Motivate’s disposal are various operational tools [3] ranging from customer incentives (Bike Angels) to motorized rebalancing (trucks and vans transporting bikes) and valets (artificial station capacity enhancement). However, due to existing agreements with local governments, Motivate cannot use pricing to alleviate operational hardships. In contrast, at Lyft and Uber pricing is a key part of the operational toolkit; however, the objectives in ride-sharing are somewhat more multidimensional. Rather than merely maximizing the number of passengers served, Lyft and Uber also need to take into account other metrics such as revenue, driver satisfaction, and low ETAs (estimated arrival times of dispatched drivers to passengers). Given these differences, there is no one-size-fits-all solution for optimizing operations on such platforms.

Below, I describe some of the projects I work on within this space. On the practical side, the ones related to bike-sharing involved implementations by Motivate International. I highlight these at the end of each paragraph. On the theoretical side, contributions from three of the projects have been submitted to Management Science, Operations Research, and Mathematics of Operations Research; the other two are ongoing work. While the methodological approach varies among these works, they all aim to fulfill the same goal: improving on-demand services through data-driven tools and insights.

1. CURRENT RESEARCH

1.1. Pricing and Matching in Ride-sharing. Optimal pricing decisions in ride-sharing systems necessarily need to consider the supply externalities described above. In joint work with Siddhartha Banerjee and Thodoris Lykouris [1], we investigated a natural queueing-model that tracks the local supplies (number of drivers/vehicles) over time and thus accounts for these externalities. In the model, customer arrivals are modeled as Poisson processes, each with a randomly drawn (unknown) value and a randomly drawn destination. If a vehicle is present and the customer’s value exceeds a price that the platform offers, then the customer takes a trip to the destination and the supply at the origin/destination decreases/increases by 1. Else, the customer is turned away. In various extensions, we allowed for controls beyond pricing, such as determining which driver to dispatch or when to incentivize drivers to relocate to better locations after ending a trip. The basic model, as well as its extensions, create a closed queueing network. Attempts to find controls for the steady-state of closed networks go back to Whitt [7]; however, since XYZ, the existing literature tends to focus on either open networks (non-constant number of drivers) or limiting regimes (diffusion/fluid limits). Instead, we developed a convex relaxation the solution of which gives rise to a stochastic control and an upper bound on the optimal objective. The performance of this control can be bounded parametrically, making it optimal in the limiting regimes and near-optimal in finite regimes of interest.

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After obtaining these results, I interned on Lyft’s pricing team (summer 2017). There, the results of this project proved tremendously helpful in developing new pricing algorithms that are now part of Lyft’s toolbox.

1.2. Pooling in Ride-sharing. In August 2014, Lyft and Uber announced services (Lyft Line and Uber-Pool) that allow customers to be served at a lower price, enabled by the platform potentially pooling numerous customers together. Though the potential advantage to all parties involved is easily apparent, from an operational point of view, carpooling can lead to computationally harder decision-making problems. In fact, it even begs the question whether drivers should take longer routes in order to increase the probability of pooling a passenger through a new request. As a follow-up to our work on pricing and matching, I am currently working with Siddhartha Banerjee, Varun Gupta, and Sanitha Samaranayake on a related question that extends the above approach to pooling. Interestingly, despite the added complexity, our preliminary results show that very simple pooling policies, including ones that always take the shortest route for every passenger, can be optimal.

1.3. Inventory Management in Bike-sharing. Out-of-stock events in bike-sharing systems occur when customers try to return bikes to full or rent bikes from empty stations. Surveys have shown that these events, especially the first type in which customers are unable to return bikes, are the main cause of user dissatisfaction. While most of the academic literature has dealt, usually through heuristics, with the question of how trucks or vans can move bikes within the system to reduce such dissatisfaction, my work with David B. Shmoys and Shane G. Henderson [2] deals with an underlying design question: how to optimally manage the dock inventory within the system, i.e., what is the optimal allocation of dock capacity? A standard demand model, widely used in the academic literature on truck routing in bike-sharing systems, was defined by [6]. It considers the demand at each bike-sharing station as given by independent Poisson arrivals of rentals and returns. A continuous-time Markov chain tracks the number of bikes, and thus implicitly the number of empty docks, at a station over a finite time interval. Whenever a rental/return occurs when there are no bikes/docks available, an out-of-stock event occurs. We discovered that the number of out-of-stock events in this model as a function of capacity and initial number of bikes exhibits discrete convexity properties; more specifically, it is multimodular, which captures properties of diminishing marginal returns in multidimensional space. This allowed for a local-search algorithm to efficiently find the optimal allocation of docks within the system. Using tools from simulation optimization, I then verified, in joint work with Nanjing Jian, Holly Wiberg, and Shane G. Henderson [4], that even though the discrete convexity properties necessarily rely on the assumption that the arrivals at different stations are independent, the optimal solution identified under that assumption remains close to optimal even when allowing for network effects within the system.

Our analysis now forms the basis for negotiations between operators and city officials in New York City, Chicago, and Boston, all of which can greatly benefit from reallocating docks within their system. In particular, our results indicate that operators could provide better service quality at significantly lower rebalancing costs if they reallocated even 1% of the docks within the system.

1.4. Incentives in Bike-sharing. In 2015, during my internship at Citi Bike, I was part of the team that set up an incentive program (Bike Angels) to help reduce out-of-stock events. A pilot version of the program statically designated stations as drop-off or pick-up stations; each return at the former and each rental at the latter earned participants points towards rewards. This approach was chosen for its simplicity, even though we knew that the static labels could cause points to be awarded for rides with undesirable supply externalities. In ongoing work with Cornell undergraduate Hangil Chung and David B. Shmoys, we use a proprietary data-set to study the impact the program has had on out-of-stock events. To do so, we first investigated for each incentivized ride the change it caused in the objective of the continuous-time Markov chain model described above [6]. Then, we applied machine learning techniques to estimate the probability of a ride having happened due to the incentive program. Our work both informs managerial decisions related to when and where Citi Bike should incentivize rentals/returns and relates to fundamental questions related to the trade-offs between static and dynamic decision-making. With regard to the former, it contributed to Citi Bike’s decision to adopt a partially dynamic incentive system, in which a real-time map indicates whether or not rentals/returns at stations are incentivized.

1.5. Prize-Collecting TSP. The frustration about out-of-stock events in bike-sharing systems is amplified by defective docks, at which it is hard or impossible to return a bike even though the docks are empty. To avoid such situations, operators aim to identify and fix defective docks as soon as possible. Based on a data-set Citi Bike provided us with, David B. Shmoys and I developed analytics to determine when docks within the system are likely broken. This led to a natural theoretical question: given the probability that each dock in the system is broken, find the optimal route of a Citi Bike maintenance crew that wants to reduce the expected number of such out-of-stock events by repairing as many defective docks as possible within the time allocated to one shift. In joint work with Alice Paul, David P. Williamson, and Cornell
undergraduate Aaron Ferber, we developed an approximation algorithm for this optimization problem [5], a budgeted version of the prize-collecting TSP. While the analytics we developed are still in place, our contribution is primarily of theoretical interest as improving results in a line of prize-collecting problems in combinatorial optimization.

2. Research Plans

In the near future, I intend to continue my investigations of operational problems related to on-demand transportation. The advent of autonomous driving will play a key role in that space, providing a range of new opportunities for operations management. Such questions relate for example to incentive design: whereas Lyft and Uber currently pay drivers various incentives beyond surge pricing (Guaranteed Prime Time, Quests, etc.) to increase supply, in the future it will be car (or fleet) owners that need to be incentivized. Setting such incentives appropriately, in particular in a market with competing platforms, is necessary for platforms to succeed. A more strategic issue arises in the context of empty autonomous vehicles ("zombie cars"). To avoid such cars congesting streets, cities will need hubs at which cars wait outside of peak rush hours. Finding the right locations for such hubs will be of key importance to reduce traffic congestion.

Beyond the realm of transportation, there are many small and medium-sized companies in the sharing economy that face hard, non-standard, challenges in their operations. My experience in working with Motivate International in an early stage of their development highlighted for me the opportunities present in collaborations with an enterprise of such scale and character. As an academic in operations management, I view my role as bringing advanced mathematical tools to these real-world problems.

REFERENCES


