Incentivizing Shared Rides in e-hailing Systems: Dynamic Discount Pricing

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1 INTRODUCTION

Transportation Network Companies (TNCs) such as Uber, Didi and Lyft have emerged and grown explosively over the past decade. Those TNCs offer e-hailing platforms to provide point to point on-demand mobility services, and one of the most common services provided is ridesourcing. However, it has been shown by various studies that ridesourcing has deteriorated traffic conditions as it increases the number of unoccupied vehicles on the road (Schaller, 2017), which subsequently lead to more crashes, pollution and congestion (Anair *et al.*, 2020, Barrios *et al.*, 2020). Ridesharing is another service also often provided by TNCs and is enabled by the real-time matching nature of e-hailing platforms, where passengers with similar itineraries may be pooled together in a combined trip. Though less popular among passengers (Xu *et al.*, 2021), ridesharing could counteract some of the negative externalities of ridesourcing, as it might increase the number of passengers on board and enables a smaller fleet to service the same number of passenger requests. The lower popularity of ridesharing can be attributed to the potentially longer waiting time and detour, and the inconvenience of sharing with a stranger. Therefore, the passengers in shared trips are generally compensated with a price discount. Higher discount offered makes ridesharing more appealing to passengers but irrevocably lowers the profit generated per trip and vice versa. Ergo, the price discount is a crucial variable a platform has control over. In this paper, we formulate a dynamic ridesharing discount pricing strategy for a profit maximizing TNC and the ramifications of such strategy are evaluated.

2 Methodology

We construct a dynamic model of the on-demand mobility market, where we consider a single platform in the market, that offers both ridesourcing and ridesharing services with a fleet of vehicles with drivers whose wage has to be paid for offering the service to passengers. The majority of the studies on ridesharing assume all passengers are willing to share irrespective of service quality and price. However, in this study we explicitly consider the passengers to be cost and service quality sensitive, impatient, and have a choice to decline services offered by the platform. We use utility choice models to predict the passenger's decision (Section 2.1). We propose a dynamic discount pricing strategy for the platform. The strategy is integrated in the matching algorithm which maximizes the profit with given batches of waiting passengers and idle vehicles, and strategically offers shared trips to *selected* passengers with varying price discount levels (Section 2.2).

2.1 Passenger Choice

Consider an individual passenger p_i. Once a request is made with origin and destination, the platform will attempt to match p_i to a suitable trip. If successfully matched, the service *offered* to p_i could *either* be a solo trip or a shared-trip at the will of the platform (with the overall objective of maximizing the platform profit, see Section 2.2). However, p_i may or may not be pleased with the service offered by the platform, and therefore they could choose to reject the offer. If p_i is matched in a shared trip, they make a choice between accepting it or they would rather be in a solo trip. If p_i is matched in a solo trip, they make a choice between accepting or leaving the platform for other modes of travel. We consider two binary choice models for these two scenarios. To facilitate the choice modeling, we assume p_i perceives the utilities of different modes of travel as follows:

$$\text{Solo Trip}: u_i^{\mathrm{s}} = \beta_i^{\mathrm{s}} - \beta_i^{\mathrm{t}} w_i^{\mathrm{s}} - \beta_i^{\mathrm{f}} f_i^{\mathrm{s}} \tag{1a}$$

$$\text{Shared Trip}: u_i^{\mathrm{h}} = \beta_i^{\mathrm{h}} - \beta_i^{\mathrm{t}} (w_i^{\mathrm{h}} + \delta_i) - \beta_i^{\mathrm{f}} [f_i^{\mathrm{s}}(1-\theta_i)] \tag{1b}$$

$$\text{Other Modes}: u_i^{\mathrm{o}} = \beta_i^{\mathrm{o}} \tag{1c}$$

Where β_i^{s}, β_i^{h}, β_i^{o} are the utility constants for the three travel modes. β_i^{t} is the utility coefficient per unit time, w_i^{s} and w_i^{h} are the waiting times for the solo and shared trips respectively, and δ_i is the detour time for the shared trip. The waiting time and detour time are negatively correlated with the quality of the service, which are reflected in the utilities. β_i^{f} is the utility coefficient per unit cost, f_i^{s} is the solo trip fare where we assume that the fare structure consists of a fixed cost and a variable cost that depends on trip distance/duration, and θ_i is the discount level for the shared trip. Similarly, the utilities are negatively correlated with the cost of fare.

2.2 Dynamic Discount Pricing

The platform establishes matching between a set of unmatched passengers, $\mathcal{P} = \{p_1, ..., p_n\}$, and a set of idle vehicles, $\mathcal{V} = \{v_1, ..., v_v\}$ every Δ seconds. The dynamic discount pricing strategy is designed to determine (i) the profit maximizing matching between the two sets that consists of solo and shared trips, and simultaneously (ii) the profit maximizing price discount for every passenger in shared trips.

We obtain such strategy by solving a *modified* maximum weighted bipartite matching problem. We first construct the set of all ordered passenger pairs, $\mathcal{Q} = \{p_{1,2}, p_{1,3}, ..., p_{1,n}, p_{2,1}, p_{2,3}, ..., p_{2,n}, ..., p_{n,1}, p_{n,2}, .., p_{n,n-1}\}$. Let $\mathcal{R} = \mathcal{P} \cup \mathcal{Q}$, if for consistency, we denote $\mathcal{P} = \{p_{1,1}, ..., p_{n,n}\}$, then $\mathcal{R} = \{p_{1,1}, ..., p_{1,n}, ..., p_{n,1}, ..., p_{n,n}\}$. Let $\mathcal{E}$ be the set of edges connecting each element of $\mathcal{R}$ and $\mathcal{V}$, where an edge $(p_{i,j}, v_k) \in \mathcal{E}$ connects $p_{i,j} \in \mathcal{R}$ and $v_k \in \mathcal{V}$. The *modified* maximum weighted bipartite matching can be formulated as follows:

$$\underset{x_{ijk}, \theta_{i,ijk}, \theta_{j,ijk}}{\text{Max}} \quad \sum_{(p_{i,j}, v_k) \in \mathcal{E}} g_{ijk} x_{ijk} \tag{2a}$$

$$\text{where}: \quad g_{ijk} = \begin{cases} E(\pi_{ik}) & \text{if } i = j \\ E(\pi_{ijk}) = F(\theta_{i,ijk}, \theta_{j,ijk}) & \text{if } i \neq j \end{cases} \tag{2b}$$

$$\text{s.t.} \quad \sum_{j=1}^{n} \sum_{k=1}^{v} x_{\hat{i}jk} + \sum_{i=1}^{n} \sum_{k=1}^{v} x_{i\hat{j}k} - \sum_{k=1}^{v} x_{\hat{i}\hat{j}k} \leq 1 \;\; \forall \, \hat{i} = \hat{j} \tag{2c}$$

$$\sum_{i=1}^{n} \sum_{j=1}^{n} x_{ijk} \leq 1 \;\; \forall k \tag{2d}$$

$$x_{ijk} \in \{0,1\} \tag{2e}$$

$$\theta_{i,ijk}, \theta_{j,ijk} \in [0,1] \tag{2f}$$

In Equation 2a, x_{ijk} is a binary decision variable on the edge $(p_{i,j}, v_k) \in \mathcal{E}$, with $x_{ijk} = 1$ indicating that the solo passenger p_i (if $i = j$), or the passenger pair p_i and p_j (if $i \neq j$) are matched to v_k. Whereas, g_{ijk} is the weight of the edge, as shown in 2b, we let it be the expected profit made by the platform under this particular arrangement. Thus, for a shared trip, g_{ijk} is a function of $\theta_{i,ijk}$ and $\theta_{j,ijk}$. Contrary to most maximum weighted bipartite matching problems, where the weights of the edges are known, we formulated our problem such that each edge weight of shared arrangements is dependent on a set of decision variables, $\theta_{i,ijk}$ and $\theta_{j,ijk}$. Note that the discount level has range between 0 and 1, as we assume the platform cannot charge more for the shared trip than the original price, and it cannot give money to customers in shared trips. Equation 2c and 2d are constraints that ensure each idle vehicle and unmatched passenger are matched at most once.

3 Results

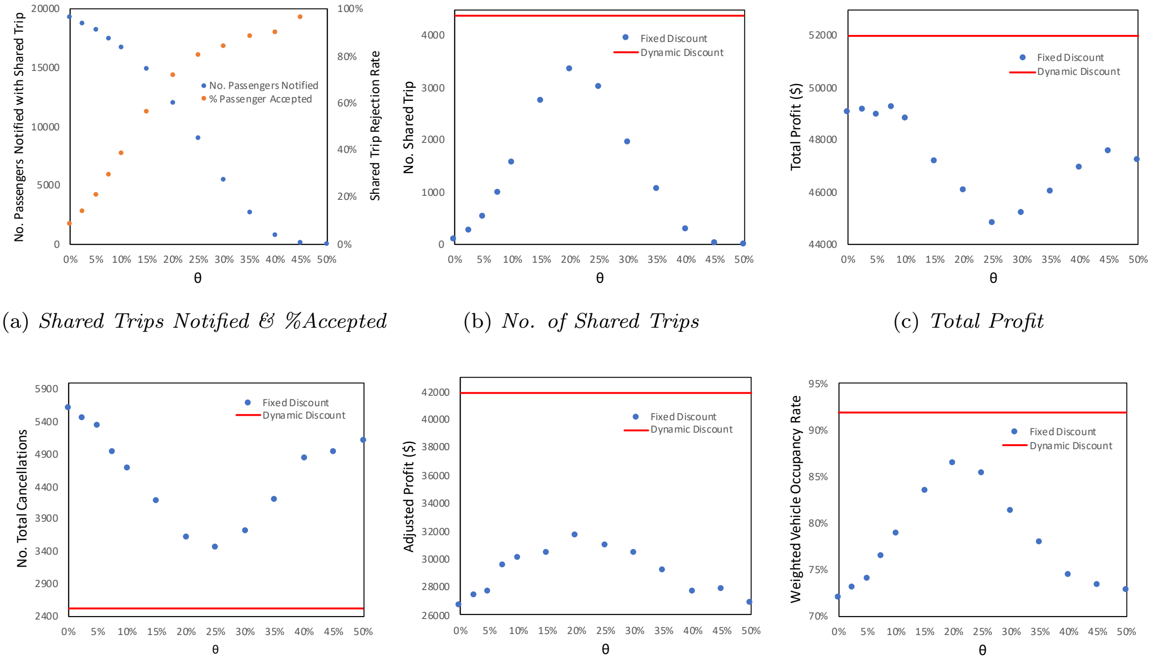
We test the proposed dynamic discount method in an event based simulator. The simulator depicts the road network in Manhattan New York as a directed graph. We use real passenger demand data on a Monday from 7 - 9 am (2 hrs) and we assume there is a fleet of 4200 vehicles.

We consider benchmark scenarios where the platform offers a constant discount level for all passengers matched in shared-trips. That is, for any given sets of unmatched passengers and idle vehicles, we assume $\theta^*_{i,ijk} = \theta^*_{j,ijk} = \theta$, where θ remains constant through each numerical experiment, and instead of using expected profit as edge weight, we use the actual profit in Equation 2b. We conduct experiments for varying θ between the range from 0 to 0.5 (i.e. 0 to 50% discount for sharing). It may be noted that under the benchmark setup, it is illogical for the platform to offer passengers in shared trips at a discount of 50% or above, since it is always more or equally profitable for the platform to just serve a solo trip at full price to one of the passenger in a shared trip. Therefore, for $\theta \geq 0.5$, they are equivalently models of a platform that offers ridesourcing services only. We compare the results of the benchmarks with the dynamic discount pricing strategy in Figure 1.

4 Discussion

Figure 1a shows the total number of passengers that were notified with shared trips at varying benchmark levels of θ, and correspondingly the passengers' acceptance rate. At low levels of discount, the platform is more likely to find shared trips more profitable than solo trips, hence more passengers will be matched in shared trips. However, it is intuitive that when the discount is low, only a small fraction of passengers will accept the shared trips. As the discount level increases, shared trips become less profitable, and thus fewer shared trips will be organized by the platform, but a larger portion of passengers in those shared trips would accept. Consequently, the total number of shared trips are shown in Figure 1b.

Figure 1b - 1f are the performance measures that we compare the benchmarks to the dynamic discount pricing strategy. Figure 1c shows the total profit made by the platform during each experiment. Figure 1d shows the total number of cancellations by the passengers as a result of undesired quality of service. We considered that if a customer cancels, there is a probability they defect to other platforms and thus leading to a long-term loss. Therefore, we deduced that each cancellation translates to roughly \$4 long-term loss (e.g. based on 10-year customer profit) for the platform, and adjusted the total profit in Figure 1e. If we assume that for the benchmark, the platform adopts the constant 20% discount level which maximizes long term profit (see Figure 1e). Then, the dynamic discount pricing strategy generates 12.9% more profit,



(a) *Shared Trips Notified & %Accepted* (b) *No. of Shared Trips* (c) *Total Profit*

(d) *No. Cancellations* (e) *Adjusted Profit* (f) *Weighted Vehicle Occupancy Rate*

Figure 1 – *Results of constant discount scenarios (Blue) and the results of the dynamic discount pricing strategy (Red). The X axis corresponds to the varying benchmark levels of the constant discount, θ, which is not associated with the dynamic discount pricing strategy.*

reduces the number of cancellations by 30.3%, and improves the adjusted profit by 32.6%, while conducting 30.6% more shared trips.

We also introduced a weighted vehicle occupancy rate (WVOR), where the time a vehicle has two passengers on board are weighted twice as when there is only one passenger. The results are shown in Figure 1f, and the dynamic discount pricing strategy increases the WVOR by 6.4%. Therefore, we show that the adoption of the dynamic discount pricing strategy creates substantial economic benefit for the platform in both the short and long term, and improves the fleet efficiency and thus generates positive externalities for the society.

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