Personalised pricing in ride pooling to maximise expected profit

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Short summary

Perception of the ride-pooling service highly depends on individual preferences. Fitting a proper discount for a ride endorses its attractiveness for travellers and increases the profit of the operator. We analyse a scenario where individual heterogeneous behavioural traits remain latent. We introduce the individual pricing strategy, which balances ride's profit with its attractiveness perceived by the travellers. Our method finds optimal sharing discounts individually tailored at the ride level such that the product of platform's profit and traveller's satisfaction (i.e. acceptance probability) is maximised.
To understand the potential impact of personalised pricing on pooling systems' performance we run NYC experiment answering the questions on: the optimal sharing discounts, their impact on travellers perception and operator's profit. Our method outperforms flat discount strategy from both perspectives: travellers are more satisfied with the service and the operator increases own profit.
Keywords: personalised pricing, probabilistic ride-pooling, ride-pooling

1 Introduction

Ride-pooling service offers travellers shared rides. It is a door-to-door service similar to standard ride-hailing with a caveat that, if the requested trips have similar paths and are at the similar time, they are pooled together and travellers share parts of their trips. To compensate for delays, detours and discomfort of sharing a ride, travellers are offered with a monetary incentive (lower fare) referred to as a sharing discount. The service is appreciated thanks to vehicle and congestion reduction, parking spots and money savings, etc (Ke et al. (2021), Zhang & Nie (2021)). The trip compatibility is a relative term, it depends not only on spatio-temporal similarity but also on the value of time and penalty for sharing (alternatively willingness to share) among other behavioural characteristics. In contrast to the popular approach to applying (discounted) sharing discounts in ride-pooling (Ke et al. (2020), Yan et al. (2020)), where the flat discount is proposed, we introduce personalised pricing. For each combination of travellers, we tailor individual discounts that maximise the expected profit for the operator.
While Zhou et al. (2023) offered discount proportional to the trip characteristics (distance shared, delay, detour, etc.), it does not express the operators interests. In our study, we propose a different approach focused on the operator. We assume a heterogeneous population where travellers accept a shared ride only if it is appealing to them. Hence, operator who aims to maximise profit must not only account for a high revenue of the ride but also ensure that travellers will indeed choose proposed service. We introduce the expected profit expected profit as a product of probability that a ride will be accepted and the ride's profit.
Our proposed approach is a preliminary study of the topic where a traveller makes a probabilistic decision based on her unknown behavioural preferences. Here, we confine our analysis to whether the traveller chooses the ride-pooling service or not (which reflects operators perspective) evaluated against the private ride baseline. We assume the traveller is offered only a single ride (shared or non-shared), which she either accepts or rejects. If any of the co-travellers reject a ride, they all find different modes/operators to serve the requested trip (nullified profit).
The perfect knowledge of ones preferences is both costly and ethically questionable (Obermiller et al. (2012)). However, we can operate on the cumulative distribution of the population, which is estimated by recent studies (Alonso-González et al. (2021), Lavieri & Bhat (2019)). Hence, in the study, to assess attractiveness perceived by individual travellers, we assume their behavioural traits follow population distributions of those traits.

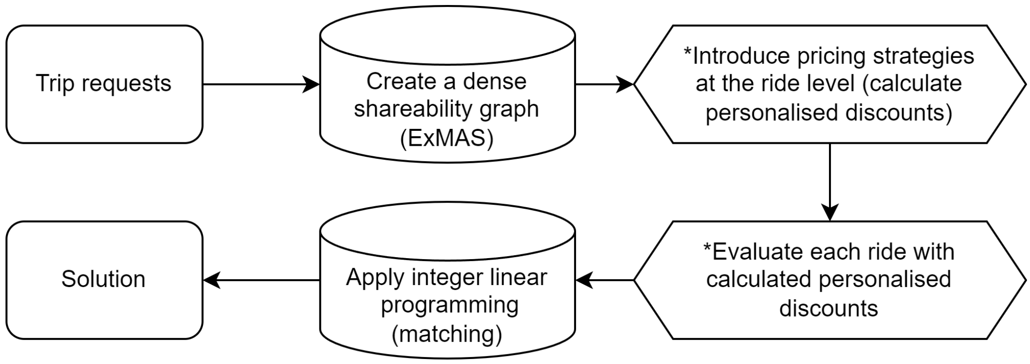

Figure 1: Overview of methodology. Asterisks represent blocks introduced in the study.

Our method combines two perspectives: operators and travellers. Maximising profitability, controlled via sharing discount, while guaranteeing attractiveness is challenging. The method aims to find the golden mean. We analyse optimal personalised discounts and their contribution to the system performance. Profitability depends both on revenues and on costs. We assume the operator bears costs proportional to vehicle distance. While it is not under control, we analyse our pricing strategy in settings with different operating costs. Hence, we analyse ride-pooling scenario with different operating cost factors.
Optimising personalised discounts to maximise the expected profit sheds a new light on the ride-pooling studies. It explains both sparsity of the service (offered in a small fraction of locations where the ride-hailing is present) and current pricing policies (Uber offers up to only 20% sharing discount (*UberPool*, 2024)).
In the study, we answer the following research questions:

(RQ1) What are the optimal sharing discounts when we apply personalised pricing?

(RQ2) Does personalized pricing improve travellers perception of shared rides?

(RQ3) Does personalized pricing improve operator's profit compared to a flat discount?

(RQ4) How profitable is ride-pooling in the probabilistic scenario with personalized pricing?

2 Methodology

In the ride-pooling service, we distinguish the following steps. First, we collect trip requests, i.e. where and at what time clients want to be picked-up and what is their travel destination. Second, we apply certain criteria (such as maximum delay, attractiveness constraints) to create a set of all feasible combinations of travellers into shared rides. We often refer to this set as a *shareability graph*. Lastly, from the set of all rides, we choose an optimal subset such that it maximises our objective function and satisfies marginal requirements: every traveller is served exactly once and a shared ride must be assigned to all its participants. We refer to this step as *matching*.
In our study, we apply utility-driven (people share a ride only if it is perceived attractive by each of them) ExMAS algorithm (Kucharski & Cats, 2020) to create a dense shareability graph. We obtain its density by applying high sharing discount, low value of time and willingness to share. We reevaluate each feasible ride (i.e. ride in the shareability graph) separately. Ride's attractiveness (utility) strongly depends on individual behavioural traits. For a travellers utility baseline, we choose a ride-hailing private ride. We assume it sets a level at which a person participates with 50% probability. Probability that a person will opt for the shared service is the probability that he will perceive it as more attractive than the baseline.
In this study, we focus on the operational challenge for the service provider to set optimal prices for shared (pooled) ride services. The goal is to maximise the operator's (platform) profit. However, the profit is only received if all travellers comprising the ride are satisfied with it (opt to participate). Otherwise, they reject the ride and find another commute. Along this thought, we introduce the *expected profit*. For each feasible ride we evaluate our measure. For a ride comprising k travellers, the expected profit Γ is a function of personalised sharing discounts $\lambda_1, \ldots, \lambda_k$ (set at the ride level).

$$\Gamma(\lambda_1, \ldots, \lambda_k) = \Xi(\lambda_1, \ldots, \lambda_k)\Pi_{j=1,\ldots,k}\mathbb{P}(\Delta U_j(\lambda_j)), \tag{1}$$

where the first term Ξ denotes profit and the second - probability that the ride will be accepted. Low sharing discounts improve the profit but reduce the ride's attractiveness, while high discounts yield opposite effects. Hence, the main challenge is to find the golden mean in this concave function. The profit of a ride Ξ is a difference between the revenues and costs. The revenue is calculated as $\sum_{1 \leq i \leq k} \rho \lambda_i l_i$, where l_i is distance of the trip requested by traveller i and ρ is the fare (in \$/km). The cost of a ride is a total distance multiplied by the fare and by the operating cost factor. The cost that the operator bears is paid per vehicle kilometre and expressed as a fraction of the fare paid by travellers (also in \$/km). Finally we obtain

$$\Xi(\lambda_1, \ldots, \lambda_k) = \sum_{i=1}^{k} \rho \lambda_i l_i - d_v c_o \rho, \tag{2}$$

where d_v denotes the vehicle distance and c_o is operating cost factor. Note that the operational cost depends on the vehicle kilometres, not on the distance of requested trips. To calculate system-wise values, we sum all profit and subtract all costs of selected rides (matched).

To assess the probability that a ride will be accepted, we apply utility formulas founded in Kucharski & Cats (2020). The shared rides attractiveness is expressed as its advantage over the non-shared alternative (U_s vs. U_{ns}). Let U_i^{ns} and U_{i,r_l}^{s} denote (negative) utilities of non-shared and shared ride r_l (comprising k travellers) for traveller i, respectively.

Utilities are given by the equations:

$$U_i^{ns} = -\rho l_i - \beta_t t_i \tag{3}$$

$$U_{i,r_l}^{s} = -(1 - \lambda_{i,r_l}) \rho l_i - \beta_t \beta_{s,k} (\hat{t}_i + \beta_d (\hat{t}_i^p)), \tag{4}$$

where ρ stands for fare (\$/km), λ_{i,r_l} - discount for sharing a ride. β^t, $\beta_{s,k}$ β^d denote individual preferences: value of time, penalty for sharing (discomfort associated with sharing a ride increasing with the number of co-travellers $k-1$) and delay sensitivity, respectively. t_i and $\hat{t}_i$ stand for travel time of non-shared and shared ride, respectively, $\hat{t}_i^p$ is a pick-up delay.

In our setting, the value of time (β_t) and penalty for sharing ($\beta_{s,k}$) are random variables. As a result, the value of $\Delta U_{i,r_l} := U_{i,r_l}^{s} - U_i^{ns}$ is not deterministic. We can rearrange equations (3) and (4) to obtain

$$\Delta U_{i,r_l} = \lambda_j \rho l_j - \beta_t (\beta_{s,k} (t_j^s + \beta_d t_j^p) - t_j). \tag{5}$$

We assume that the β_t and β_s follow multimodal heteroscedastic normal distribution, i.e.

$$\beta_t = \sum_{i \leq n} \alpha_i X_i, \tag{6}$$

where X_i follow normal distributions with mean μ_i and std σ_i; $\alpha_i \in (0, 1)$ and $\sum_{i \leq n} \alpha_i = 1$. Distribution of the product of a two multimodal heteroscedastic normal variables (in our case, $\beta_t \beta_s$ in Equation 5) has no closed analytical formula and, even in much simpler cases, is approximated by numerical methods (Stojanac et al. (2017)). Hence, to evaluate probability that a shared ride r_l will be accepted by i-th traveller (equivalently, $\mathbb{P}(\Delta U_{i,r_l} > 0)$), we resort to the Monte Carlo simulations (via sampling behavioural parameters and measuring frequencies when $\Delta U_{i,r_l} > 0$)).

Solution to our problem is found at individual ride level. We seek a vector $\lambda^* = (\lambda_1^*, \ldots, \lambda_k^*)$ that maximises the expected profit. We can formulate it as:

$$\lambda^* = \underset{\lambda = (\lambda_1, \ldots, \lambda_k) \in \mathbb{R}_+^k}{\operatorname{argmax}} \Gamma(\lambda_1, \ldots, \lambda_k). \tag{7}$$

Our pricing method allows to find optimal discounts for each traveller in each ride. To find the optimal pooling solution (matching), we apply integer linear programming (ILP) techniques with the objective to maximise the cumulative expected profit (sum of Γ of rides in the solution).

The optimal discounts at the ride level are also optimal for the system-wide solution, which can easily be proved by contradiction. While the expected profit depends on the operating cost factor, optimal discounts stay the same (ride's cost is fixed for the optimal route, we maximise revenue). The difference implied by the operating cost factor is pronounced at the matching stage.

Settings of the experiment

We experiment on the New York City open source taxi data (Commission (2023)) with a medium-sized (150 requests) 30-minute batch. We set the price to $1.5\$/km$ in line with NYC Taxi &

Limousine Commission (2022). The operating cost factor (OC) is expressed as a fraction of a fare per kilometre (for OC of 0.2 and fare of 1.5$/km operator bears cost of 0.3$ per vehicle kilometre). We experiment with four values of OC: 0 (profit equals revenue), $0.2, 0.4$ and 0.6.
In our experimental settings, the value of time (β_t) and the penalty for sharing ($\beta_{s,k}$) are random behavioural parameters. Following the findings of Alonso-González et al. (2021), the population is structured into 4 classes (of different size), exhibiting different behavioural patterns. Each class has a certain normal distribution of the value of time and penalty for sharing with parameters presented in Table 1. We directly implement value of time as found in the study and we extrapolate missing data for the penalty for sharing. For penalty for sharing, we present value for two additional passengers. Values for 1, 3 and 4+ additional travellers are scaled by a multiplier of $0.95, 1.1, 1.2, 2$, respectively.

Table 1: Behavioural characteristics of the population based on stated preference study.

Class	**Percentage membership**	**Value of Time**	**Penalty for sharing**
C1	29%	16.98 (0.318)	1.22 (0.082)
C2	28%	14.02 (0.201)	1.135 (0.071)
C3	24%	26.25 (5.77)	1.049 (0.06)
C4	19%	7.78 (1^1)	1.18 (0.076)

3 Results and discussion

RQ1: What are the optimal sharing discounts when we apply personalised pricing? The central point of our study is fitting optimal personalised discounts. From the set of all feasible rides (shareability graph), we find the optimal solution with respect to expected profit with different operating cost factors. Each ride can be included in few, any or none of the solutions. In Figure 2, we present distributions of fitted sharing discounts for all feasible rides, subset selected for solution with a given objective and subset never selected in matching.
The shareability graph is dense (large number of feasible rides) and only a small subset is selected in matching. As a result, distribution of sharing discounts among not selected rides is very close to the distribution for all rides. When we look at the rides that are selected in matching, the range of sharing discount is much smaller, mostly confined to $0.16 - 0.33$ range. Solution maximising revenue occasionally accepts high sharing discounts (up to 0.59) to increase the probability that a ride will be accepted. However, if we assume high operating cost factor, only highly compatible rides are selected. Increasing revenue at the expense of mileage reduction becomes unprofitable. As a result, for the highest operating cost, only shared rides attractive with low discounts are selected.

RQ2: Does personalized pricing improve travellers perception of shared rides? While the exact attractiveness of rides perceived by travellers (as it is a random variable) cannot be calculated, we can compute the probability that a ride will be accepted. It explicitly expresses travellers perceived improvement in attractiveness over the baseline. We calculate the probability for all rides under three discounting scenarios: personalised (our method), flat 0.2 and flat 0.3. Acceptance probability is presented in Figure 3. The improvement from the travellers perspective is clearly observed in our pricing scheme.

RQ3: Does personalized pricing improve operator's profit compared to a flat discount? For a baseline with flat sharing discount, we calculate the average sharing discount in expected revenue maximising scenario and obtain 0.201 (which we round to 0.2). We reevaluate rides with this flat discount and conduct matching with the objective to maximise the expected revenue. We compare the two pricing strategies: personalised pricing and flat discount. Results are presented in Table 2.
Results indicate that our method proves to be more beneficial for the operator (increased expected profit) compared to the flat discount. However, profit maximisation is not perfectly aligned with vehicle distance reduction, which reached higher level with the base scenario.

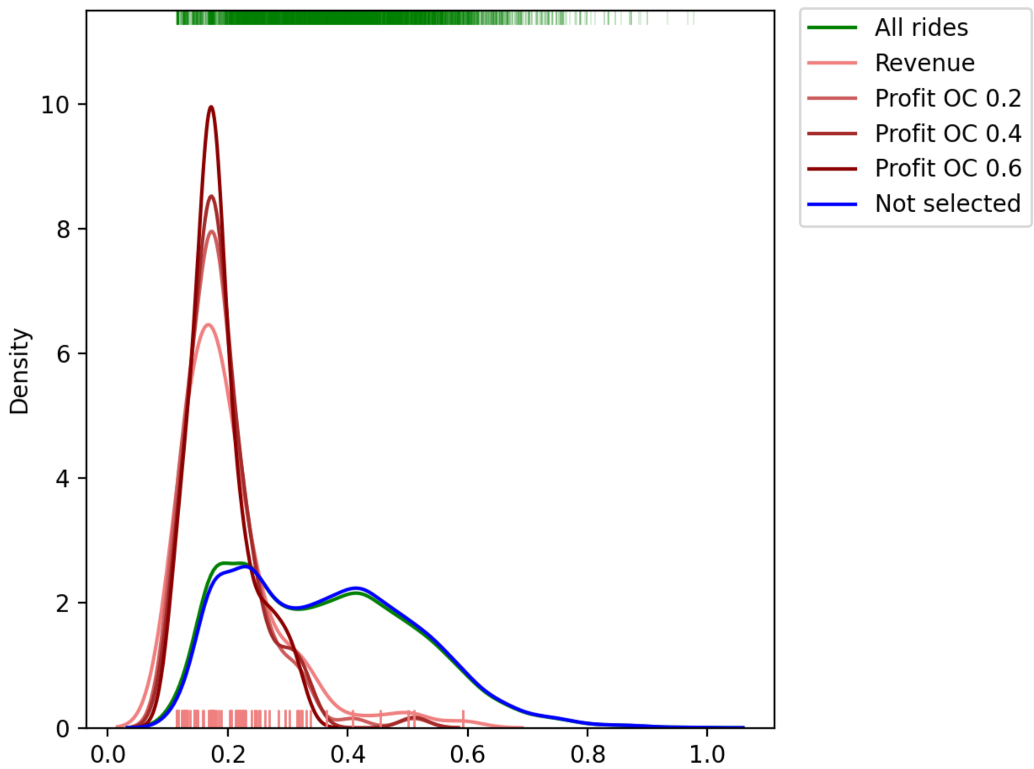

Figure 2: Sharing discount distributions (kernel density estimates) for: all feasible rides; rides selected in matching with the objective of profit maximisation with cost factors of 0 (i.e. max revenue), 0.2, 0.4 and 0.6; rides never selected in matching. Ticks represent observations for all rides (top) and selected for revenue maximisation (bottom).

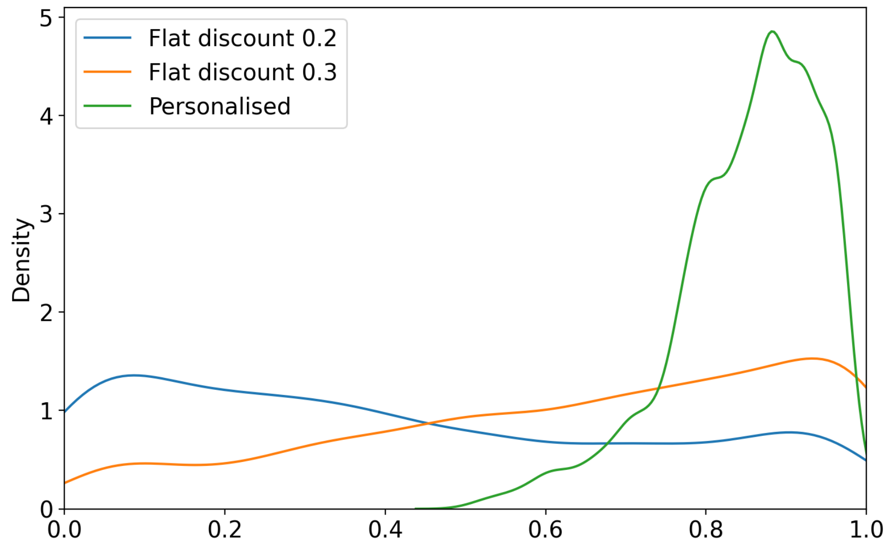

Figure 3: Probability of acceptance of a shared ride in three scenarios: personalised expected profit maximising strategy, flat sharing discounts of 0.2 and of 0.3.

Table 2: Personalised vs flat sharing discount in terms of expected performance.

Scenario \ Performance	Expected Revenue	Expected Vehicle Distance Reduction
Personalised	457	7659
Flat 0.2	451	8700

While our algorithm provides a method for evaluating individual rides, the final results depend on the matching objective. In our case, the objective depends solely on the assumed operating cost factor. We analyse five outputs (results of matching): four of personalised discounts with OC of $0, 0.2, 0.4$ and 0.6 and a flat discount with OC 0. We present the expected performance of those final ride-pooling solutions in Table 3. We observe that the highest vehicle distance reduction is reached when we impose high operating costs.

Table 3: Ride-pooling performance with different operating costs (OC). In rows, we present objectives: four personalised discount strategies with different matching (four levels of OC) and a flat discount with revenue maximisation. In columns, performance measures calculated for the final solution of the matching in each scenario.

Objective \ Value	Expected Profit OC 0 (Revenue)	OC 0.2	OC 0.4	OC 0.6	Distance Reduction
Expected Revenue	**457**	359	260	162	7659
E.Profit OC 0.2	454	**363**	271	180	10395
E.Profit OC 0.4	444	360	**275**	191	12918
E.Profit OC 0.6	426	350	273	**196**	**13847**
E.Rev. Flat Disc.	451	359	267	175	8700

RQ4: How profitable is ride-pooling service in the introduced probabilistic scenario? To make sure that the ride-pooling service is offered, the primary concern is whether

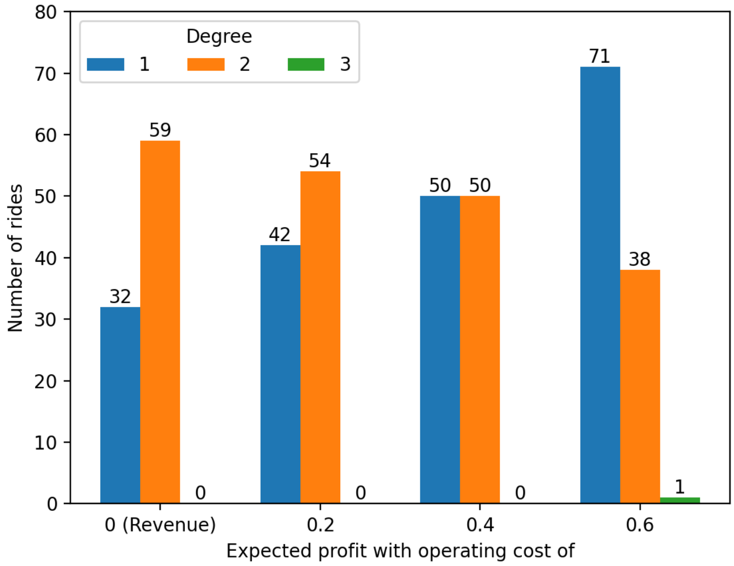

Figure 4: Degree distribution for different matching objectives: expected revenue and expected profits with increasing operational costs.

an operator is interested. In Table 4, we analyse expected profit for the operator in a system with private rides only and for ride-pooling under two pricing strategies.

Table 4: Expected profit: private rides only vs. private and shared rides. Comparison of expected profits at different levels of the cost operating factor with two pricing strategies (personalised discounts and flat discount of 0.2).

Value / Service	Expected profit with operating cost factor			
	0 (Revenue)	0.2	0.4	0.6
Only private	305.12	244.09	183.07	122.05
Private & shared Personalised	**457.38**	**362.71**	**275.42**	**196.17**
Private & shared Flat	451.27	360.35	273.63	187.71

In Figure 4, we present distributions of rides' degrees. With increased cost operating factor, we observe a decrease in the number of shared rides. The underlying reasons are 1) cost of a ride appears only when the ride is accepted, which benefits rides with lower acceptance probability; 2) more co-travellers increase perceived discomfort associated with sharing a ride. However, at an operating cost factor of 0.6, we observe the first triple appears. This ride offered very high vehicle distance reduction, which is most appreciated in the setting with high operating costs.

4 Conclusions

In the study, we present a new approach to discounting shared rides in ride-pooling when the operator cannot deterministically predict travellers' decision. We analyse the situation from the operators perspective and aim to maximise the profit and indirectly maximise user's satisfaction (acceptance probability, being a function of utility). In our setting, travellers make independent decisions driven by their behavioural preferences. While individual traits remain latent, we apply population distribution to compute how likely a ride is to be accepted by all travellers at certain discount levels. This probabilistic setting allows us to introduce the expected profit - a product of a rides profit and the probability that the ride is accepted. Via discount individualisation at the ride level, we can significantly increase attractiveness while only slightly decrease the revenue. Our method outperforms flat discount strategy from both perspectives: travellers are more satisfied

with the service and the operator increases his profit. To further validate our method, we analyse ride-pooling performance with different operational costs.
Our results indicate that, in the probabilistic scenario, it is profitable for the operator to make sure that a traveller is satisfied with the service. In the digitalised era, people usually check their commute options and then make informed decision. Hence, the primary concern of the operator is to incentivise potential clients to use their service. The proposed individualisation of sharing discounts accounts for that, as those who experience more pooling-related discomfort are offered a greater monetary incentive. Maximising the probability that a shared ride occurs imposes high discounts if requested trips are not well aligned. Assigning yet another passenger to a combination is always associated with some additional travel time. Even for perfectly aligned trips, there are new pick-ups and drop-offs. As a result, in our setting, we observe only shared rides of degree two with an exception of a single triple when faced with extremely high operating cost factor.

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References

Alonso-González, M. J., Cats, O., van Oort, N., Hoogendoorn-Lanser, S., & Hoogendoorn, S. (2021). What are the determinants of the willingness to share rides in pooled on-demand services? *Transportation*, *48*(4), 1733–1765.

Commission, N. T. L. (2023). *Nyc taxi& limousine commission.* `https://www.nyc.gov/site/tlc/about/tlc-trip-record-data.page`. (Accessed: 2023-10-30)

Ke, J., Yang, H., Li, X., Wang, H., & Ye, J. (2020). Pricing and equilibrium in on-demand ride-pooling markets. *Transportation Research Part B: Methodological*, *139*, 411–431.

Ke, J., Zheng, Z., Yang, H., & Ye, J. (2021). Data-driven analysis on matching probability, routing distance and detour distance in ride-pooling services. *Transportation Research Part C: Emerging Technologies*, *124*, 102922.

Kucharski, R., & Cats, O. (2020). Exact matching of attractive shared rides (exmas) for system-wide strategic evaluations. *Transportation Research Part B: Methodological*, *139*, 285–310.

Lavieri, P. S., & Bhat, C. R. (2019). Modeling individuals willingness to share trips with strangers in an autonomous vehicle future. *Transportation research part A: policy and practice*, *124*, 242–261.

NYC Taxi & Limousine Commission, u. (2022). *Taxi fare.* Retrieved from `https://www1.nyc.gov/site/tlc/passengers/taxi-fare.page`

Obermiller, C., Arnesen, D., & Cohen, M. (2012). Customized pricing: Win-win or end run?

Stojanac, Ž., Suess, D., & Kliesch, M. (2017). On products of gaussian random variables. *arXiv preprint arXiv:1711.10516*.

Uberpool. (2024). `https://www.uber.com/us/en/ride/uberx-share/`. (Accessed: 2024-01-26)

Yan, C., Zhu, H., Korolko, N., & Woodard, D. (2020). Dynamic pricing and matching in ride-hailing platforms. *Naval Research Logistics (NRL)*, *67*(8), 705–724.

Zhang, K., & Nie, Y. M. (2021). To pool or not to pool: Equilibrium, pricing and regulation. *Transportation Research Part B: Methodological*, *151*, 59-90.

Zhou, Z., Roncoli, C., & Sipetas, C. (2023). Optimal matching for coexisting ride-hailing and ridesharing services considering pricing fairness and user choices. *Transportation Research Part C: Emerging Technologies*, *156*, 104326.