Joint Pricing and Matching for City-Scale Ride-Pooling

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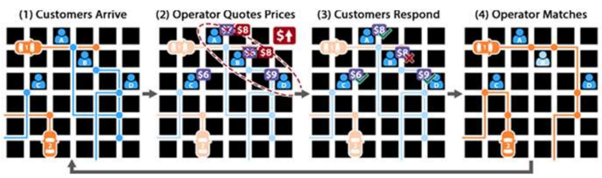
Ride-Pool

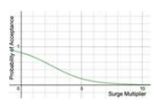


Challenges: (1) Pricing and (2) Matching

Choices and challenges

Choices:

- Single Operator
- Known Price Sensitivity[1]
- **Batched**



Price Sensitivity

Challenges as compared to existing work

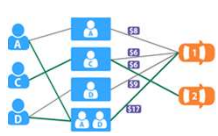
- Pooling
- Complicated Matching[2]
- City-Scale

[1] Ma, Hongyao, Fei Fang, and David C. Parkes. "Spatio-temporal pricing for ridesharing platforms." *ACM EC*. 2019.
[2] Banerjee, Siddhartha, Carlos Riquelme, and Ramesh Johari. "Pricing in ride-share platforms: A queueing-theoretic approach." *Available at SSRN 2568258* (2015).

Matching

- Constraints
  - Delay/Wait Time
- Not bipartite
  - Generalisation of Bipartite Matching

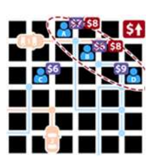
- Weights $weight^t_v = \alpha^t_v \sum_{r \in R_t} \mu_r + \beta^t_v$
- Objective
  - Revenue
  - Profit
  - Fairness



Pricing

- Price such that expected value of matching is maximised

$$\max_{\mu} \mathop{\mathbb{E}}_{R_\mu \sim p(\mu)} \left[\text{Matching}(\mu, R_\mu)\right]$$



Ride-Pooling as an auction

- Seller – Ride-pool operator. Buyer – Customers who want rides
- Single parameter
  - Item sold – Service of being transported from source to destination
- Maximise `Utility' for Seller

$$\max \sum_{\forall t, v} x^t_v \cdot weights^t_v = \max \sum_{\forall t, v} x^t_v \cdot [\alpha^t_v \sum_{r \in R_t} \mu_r + \beta^t_v]$$

- Price sensitivity and intrinsic values
- Auction objective and payment rule

Proposition 1 (Utility Maximising Auction) *We can maximise the expression in Eq 5 by allocating according to:*

$$\max_{X \in C} \sum_{x^t_v \in X} x^t_v \cdot (\alpha^t_v \sum_{r \in R_t} \varphi_r(\nu_r) + \beta^t_v) \quad (6)$$

where $\varphi_r(\nu_r) = \nu_r - \frac{1 - F_r(\nu_r)}{f_r(\nu_r)}$ *denotes the 'virtual value' for a request.*

- Allocation Rule
  - Utility Maximizing Auction - Modified Myerson Theorem

Posted Price Mechanism

- Equivalent to `posted price mechanism'
- Price such that likelihood of acceptance is the same as in an optimal auction

Algorithm 1: Generate Posted Prices

Input: Get number of samples s
Initialise a counter N_r for each request
for $i \in [1, \ldots, s]$ **do**
  Sample a set of intrinsic values $\boldsymbol{\nu} \sim \mathbf{F}$
  Run the optimal auction from Section 4.1 with the sampled intrinsic values $\boldsymbol{\nu}$
  for all $r \in R$ **do**
    Increment N_r if r is assigned a vehicle in the auction.
for all $r \in R$ **do**
  Get the probability $prob_r = \frac{N_r}{s}$ of r being served
  Smooth out this probability by clipping it to the range [MIN_PROB, MAX_PROB]
  Generate the price: $\mu_r = F_r^{-1}(prob_r)$

Algorithm from Chawla et. al.

Chawla, S., Hartline, J. D., Malec, D. L., & Sivan, B. (2010, June). Multi-parameter mechanism design and sequential posted pricing. In *Proceedings of the forty-second ACM symposium on Theory of computing* (pp. 311-320).

Simulator

- Road Network: Manhattan (~4500 locations)
- Ride Requests: NYTaxi Dataset (~300 requests/min)
- Price Sensitivity: (Yan,Zhu,Korolko,Woodard 2020)
- Travel Times: Inferred from trip data

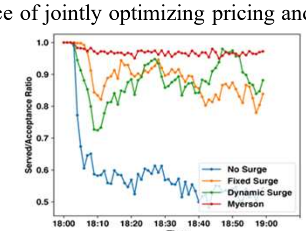
Yan, C., Zhu, H., Korolko, N., & Woodard, D. (2020). Dynamic pricing and matching in ride-hailing platforms. *Naval Research Logistics (NRL)*, *67*(8), 705-724.

Experimental Results

- Max Wait Time: 5 minutes, Maximum Delay: 10 minutes
- Baselines: No Surge, Fixed, Dynamic
- Normalised Revenue

	Variants	No Surge	Fixed Surge	Dynamic Surge	Myerson
Vehicles	2000	1.0000 ± 0.0000	1.0059 ± 0.0032	0.9936 ± 0.0044	$\mathbf{1.0140 \pm 0.0022}$
	1500	1.0000 ± 0.0000	0.9894 ± 0.0044	0.9752 ± 0.0025	$\mathbf{1.0223 \pm 0.0029}$
	1000	1.0000 ± 0.0000	0.9829 ± 0.0035	0.9480 ± 0.0064	$\mathbf{1.0306 \pm 0.0023}$
Capacity	4	1.0000 ± 0.0000	0.9853 ± 0.0031	0.9461 ± 0.0102	$\mathbf{1.0090 \pm 0.0018}$
	2	1.0000 ± 0.0000	0.9894 ± 0.0044	0.9752 ± 0.0025	$\mathbf{1.0223 \pm 0.0029}$
	1	1.0000 ± 0.0000	1.0295 ± 0.0061	1.0349 ± 0.0124	$\mathbf{1.0499 \pm 0.0024}$
Price Sensitivity	Uber	1.0000 ± 0.0000	$\mathbf{1.0138 \pm 0.0025}$	1.0001 ± 0.0007	1.0118 ± 0.0033
	Price Conscious	1.0000 ± 0.0000	0.9894 ± 0.0044	0.9752 ± 0.0025	$\mathbf{1.0223 \pm 0.0029}$
	Very Price Conscious	1.0000 ± 0.0000	0.8634 ± 0.0037	0.8559 ± 0.0126	$\mathbf{1.0025 \pm 0.0033}$

- Looking at `Reliability'
  - Importance of jointly optimizing pricing and matching



1500 vehicles, 2 capacity, Price Conscious

Future Work

- Incorporate Future Value
- Theoretical Guarantees

This research/project is supported by the National Research Foundation, Singapore under its AI Singapore Programme (AISG Award No: AISG2-RP-2020-016). Any opinions, findings and conclusions or recommendations expressed in this material are those of the author(s) and do not reflect the views of National Research Foundation, Singapore.