Optimal Vehicle Dispatching for Ride-sharing Platforms via Dynamic Pricing
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Introduction
The recently established applications of shared mobility, such as ride-sharing, bike-sharing, and car-sharing, have proven to be an effective way to utilize redundant transportation resources and to optimize social efficiency.

Dispatching problem, intrinsic differences between:

<table>
<thead>
<tr>
<th>Centralized dispatching</th>
<th>Ride-sharing</th>
<th>Traditional Taxi</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dynamic pricing</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Big data &amp; real-time analysis</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Optimal dispatching?</td>
<td>Combined with pricing</td>
<td>Separated with pricing</td>
</tr>
</tbody>
</table>

Contributions:
- Propose a graph model to analyze the vehicle pricing and dispatching problem
- Induce a MDP model and reduce it to a convex problem by randomized pricing and “ironing” technique
- Characterize the optimal solution via primal-dual analysis
- Perform extensive empirical analysis and our algorithm significantly outperforms the other two methods.

Settings & Goal
- Customers send request (s – t) to the platform
- Platform sets a price for each request
- If the customer accepts the price, one driver at will send the customer to
- Platform aims to maximize revenue or other objectives (social welfare, throughput, etc.)

A simple model that is flexible enough to handle the complex problems raised in practice.

A general dynamic environment
- Many drivers and customers (non-atomic model)
- Directed graph for geo-information
- Dynamic demand, supply, and costs.

Throughput-objective tradeoff function \( g(q) \)
- The maximum reward can be collected from edge \( e \) in period \( t \), given the throughput along edge \( e \) is fixed to be \( q \)
- Can be computed
- Theoretically from customer value distribution
- Empirically from past data
- Randomized pricing rules are critical

Two settings
(i) dynamic environment with finite horizon
(ii) static environment with infinite horizon

Randomized Pricing
Randomized pricing rules are critical to:
- Optimality: strictly outperforms deterministic pricing rules
- Tractability: non-convex optimization to convex optimization

Throughput revenue tradeoff curve

Solve via Convex Program

\[
\begin{align*}
\max & \quad \sum_{e} \sum_{t} \tilde{g}(q_{e}) \\
\text{s.t.} & \quad \sum_{e} q_{e} = 1 \\
& \quad \forall e, t \\
& \quad \sum_{c(t,e)} q_{e} \leq q_{c}, & \forall e, t \\
& \quad q_{e} \geq 0, q_{c} \geq 0
\end{align*}
\]

Advantages
- Can be solved efficiently (gradient descent)
- Easy to add/change constraints for practical needs
- Strong duality: optimality verification and approximation

Characterization of optimality via Lagrange dual

\[
\begin{align*}
q_{e}^* + q_{c}^* + \rho_{e} + \lambda = 0, & \quad q_{c}^* = 0 \\
q_{e}^* \text{ driver marginal contribution on edge } e = (v^e, v) \\
\rho_{e} \text{ potential driver contribution at node } v \\
\lambda \text{ global driver marginal contribution}
\end{align*}
\]

Empirical analysis

Dataset
A collection of orders in a city for three consecutive weeks
- \( order = \text{ID} + \text{passenger ID} + \text{driver ID} + \text{origin} + \text{destination} + \text{estimated price} + \text{timestamp} \)
- more than 8.5 millions orders
- 66 major regions and consider 21 (or 5) most popular regions which covers 90% (or 50%) orders

Data preparation

Benchmarks
- FIXED: fixed per-minute pricing
- SURGE: based on FIXED policy, using surge pricing to clear the local market when supply is not enough

Performance

Instantaneous revenue in different environments

In static environment, DYNAM on average outperforms FIXED and SURGE by roughly 24% and 17% respectively

In dynamic environment, DYNAM performs well at “peak times”

DYNAM shows much stronger power in demand-supply balance.