Balancing the Tradeoff between Profit and Fairness in Rideshare Platforms During High-Demand Hours

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Rideshare

“...participate in an arrangement in which a passenger travels in a private vehicle driven by its owner, for free or for a fee, especially as arranged by means of a website or app.”

- **Two sided** market: passengers and drivers
- Platforms have control over assigning passengers to drivers
Issues in Rideshare

- Rideshare platforms can allow drivers to reject requests up to a predefined number - exacerbating biases!
- In certain scenarios (e.g., peak hour), drivers have leverage over passengers
-Drivers can choose to reject rides based, e.g., on trip length and starting/ending location
- Can disadvantage those going to “unpopular” destinations

Did Uber Just Enable Discrimination by Destination?

In California, the ride-hailing company is changing a policy used as a safeguard against driver discrimination against low-income and minority riders.
Issues in Rideshare

- UCLA Study (Brown, 2018)
  - Black riders had to wait 1 minute and 43 seconds longer than their white counterparts for rides and were 4 percent more likely to have drivers cancel on them
  - Even worse for taxi service

- Other reported incidents of unfair treatment of passengers

**Woman Says Uber Driver Denied Her Ride Because of Her Wheelchair**

She said she explained to the driver that the chair could be broken down easily and it wasn’t much bigger than a piece of luggage but the driver kept insisting there was no space for it

**Ont. woman says Uber driver rejected her guide dog**
Mitigation by Rideshare Platforms

- Riders’ photo and destination are hidden from the driver until they accept/reject the request
  - Recently, Uber has started showing destination to the drivers before they accept
- Penalty is imposed if drivers cancel a certain number of trips after initially accepting them
  - Eg: temporarily suspending a driver from the platform

Not Enough!

1 wikipedia/uber.com/blog/california/keeping-you-in-the-drivers-seat-1/
Mitigation by Rideshare Platforms - Not Enough!

- Riders’ photo and destination are hidden from the driver until they accept/reject the request
  
  Some drivers start the trip moments before picking up a passenger to see the destination

- Penalty is imposed if drivers cancel a certain number of trips after initially accepting them
  
  In some cases, drivers intentionally delay the pickup, thus forcing the rider to cancel the trip
Profit and Fairness Tradeoffs

● In this work we consider the **peak hour**
  ○ Demand (passengers) >> Supply (drivers)
● Drivers can afford to be selective, thus putting certain groups (eg: those living in “unpopular” parts of a city) in an **unfair** position
● To ensure **fairness**, the platform should aggressively match such trips
● However, this could potentially lead to less profit
  ○ Eg: Drivers leave the platform because it assigns them unfavorable requests

Can we balance these conflicting goals?
Our Contributions

- Formalize a metric of fairness relevant in this setting
- Present a **provably efficient** online matching algorithm
  - Performs better than a reasonable lower bound on both profit and fairness objectives
  - Includes driver’s preference for rides
- Evaluate the proposed algorithm on real-world rideshare data
Setup

Set of driver types (Offline) \( U = \{u_1, u_2, \ldots \} \)

Set of request types (Online) \( V = \{v_1, v_2, \ldots \} \)

Upon arrival of a request \( v \), an immediate and irrevocable assignment must be made.

\[ u_1: \Delta_1 \]
\[ u_2: \Delta_2 \]
\[ u_3: \Delta_3 \]

\[ v_1: \text{start}_1, \text{end}_1, r_v = 2 \]
\[ v_2: \text{start}_2, \text{end}_2, r_v = 1 \]
\[ v_3: \text{start}_3, \text{end}_3, r_v = 3 \]

Total Requests \((T) = 6\)

Fairness Measure: \( \min_{v \in V} \frac{\mathbb{E}[|M_v|]}{r_v} \)

Profit Measure: \( \mathbb{E}[\sum_{e \in M} w_e] \)
Optimal Solution

Consider both sides to be offline

$u_1: \Delta_1$

$u_2: \Delta_2$

$u_3: \Delta_3$

$p_f$

$w_e$

$x_e$?

$\Delta_1$

$\Delta_2$

$\Delta_3$

$r_{v1} = 2$

$r_{v2} = 1$

$r_{v3} = 3$

What are the number of rider to driver assignments for the optimal fair solution ($x_{\text{fair}}^*$) and optimal profit solution ($x_{\text{profit}}^*$) respectively?

Fairness Measure: $\min_{v \in V} \frac{\mathbb{E}[|M_v|]}{r_v}$

Profit Measure: $\mathbb{E}[\sum_{e \in M} w_e]$
Optimal Solution

- We model profit and fairness objectives as maximization problems
  - Subject to feasibility constraints!
- We solve these using linear programming to obtain $x^*_{\text{fair}}$ and $x^*_{\text{profit}}$
- Use these optimal solutions to guide the online algorithm
Online Algorithm

- We propose a parameterized matching algorithm $\text{ALG} (\alpha, \beta)$: $\alpha$ controls profit and $\beta$ controls fairness.
- Guided by a linear combination of $x^*_{\text{profit}}$ and $x^*_{\text{fair}}$: $\alpha x^*_{\text{profit}} + \beta x^*_{\text{fair}}$

- We prove that $\text{ALG}$ achieves a competitive ratio of at least $\frac{\alpha}{e}$ for profit and at least $\frac{\beta}{e}$ for fairness (for $\alpha + \beta \leq 1$).
- We also prove that no (non-adaptive) algorithm can achieve $(\alpha, \beta)$ competitive ratio simultaneously on the profit and fairness with $\alpha + \beta > 1 - \frac{1}{e}$.
Online Algorithm

- We propose a parameterized matching algorithm $\text{ALG} (\alpha, \beta)$: $\alpha$ controls profit and $\beta$ controls fairness.
- Guided by a linear combination of $x^\text{profit}$ and $x^\text{fair}$: $\alpha x^\text{profit} + \beta x^\text{fair}$.

<table>
<thead>
<tr>
<th>$u_1$</th>
<th>$u_2$</th>
<th>$p_f$</th>
<th>Ending location</th>
<th>Estimated profit</th>
</tr>
</thead>
<tbody>
<tr>
<td>MAN</td>
<td>MAN</td>
<td>0.5</td>
<td>NP</td>
<td>1</td>
</tr>
<tr>
<td>MAN</td>
<td>MAN</td>
<td>0.5</td>
<td>P</td>
<td>2</td>
</tr>
<tr>
<td>MAN</td>
<td>MAN</td>
<td>0.5</td>
<td>P</td>
<td>10</td>
</tr>
<tr>
<td>MAN</td>
<td>MAN</td>
<td>0.5</td>
<td>P</td>
<td>20</td>
</tr>
</tbody>
</table>
Online Algorithm

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</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
<td></td>
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</tbody>
</table>

Starting location: Manhattan
Ending location: Not-popular
Estimated profit: 2

Starting location: Manhattan
Ending location: Popular
Estimated profit: 10

Starting location: Manhattan
Ending location: Popular
Estimated profit: 20
Online Algorithm

- We propose a parameterized matching algorithm $\text{ALG} (\alpha, \beta)$: $\alpha$ controls profit and $\beta$ controls fairness.
- Guided by a linear combination of $x^*_{\text{profit}}$ and $x^*_{\text{fair}}$: $\alpha x^*_{\text{profit}} + \beta x^*_{\text{fair}}$

### Starting location: Manhattan
### Ending location: Popular
### Estimated profit: 10
Online Algorithm

- We propose a parameterized matching algorithm \( \text{ALG} (\alpha, \beta) \): \( \alpha \) controls profit and \( \beta \) controls fairness.
- Guided by a linear combination of \( x^{\text{profit}} \) and \( x^{\text{fair}} \): \( \alpha x^{\text{profit}} + \beta x^{\text{fair}} \)

### Starting location: Manhattan
### Ending location: Not-popular
### Estimated profit: 1

### Starting location: Manhattan
### Ending location: Not-popular
### Estimated profit: 2

### Starting location: Manhattan
### Ending location: Popular
### Estimated profit: 10

### Starting location: Manhattan
### Ending location: Popular
### Estimated profit: 20
Experiments

\( \beta = 1 - \alpha; \Delta = 3; \text{ Real-world Data} \)

- \text{Competitive Ratios}
- \text{Profit CR}
- \text{Fairness CR}

Legend:
- NAdap (fairness)
- Lower Bound (fairness)
- NAdap (profit)
- Lower Bound (profit)

\( \Delta = 3; \text{ Real-world Data} \)

Points:
- (1.0, 0.0)
- (0.1, 0.9)
Conclusion

- We propose a fairness metric in the setting of peak-hour.
- We propose a provable, efficient and flexible online algorithm that can achieve reasonable performance on both profit and fairness objectives simultaneously.
- We validate our theoretical results with experiments on real world data.

Questions?

Code: tinyurl.com/rideshare-code  Paper: tinyurl.com/rideshare-fairness

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