PUTTING DATA in the DRIVER'S SEAT

Optimizing Earnings for On-Demand Ride-Hailing

Harshal Chaudhari John Byers Evimaria Terzi

BOSTON UNIVERSITY

Problem Motivation

The Washington Post

Democracy Dies in Darkness

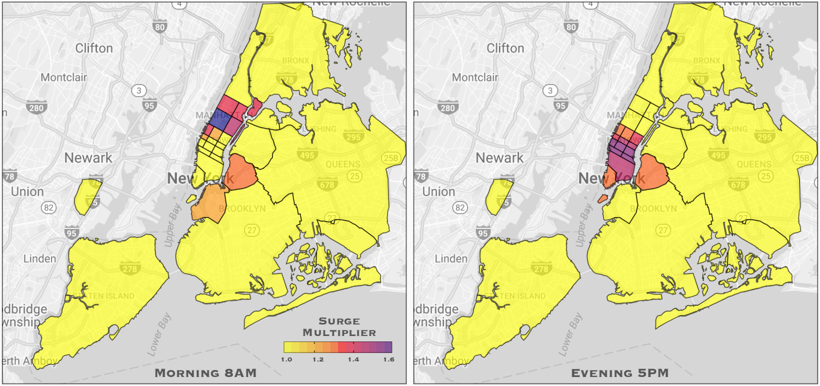
The Switch

How much Uber drivers actually make per hour

By Jacob Bogage June 27, 2016 Email the author

‘ … about half of the hours logged into the app in New York City are spent without passengers in the car. And that’s in one of Uber’s busiest markets in the country. ’

Spatio-Temporal Demand Variation in NYC



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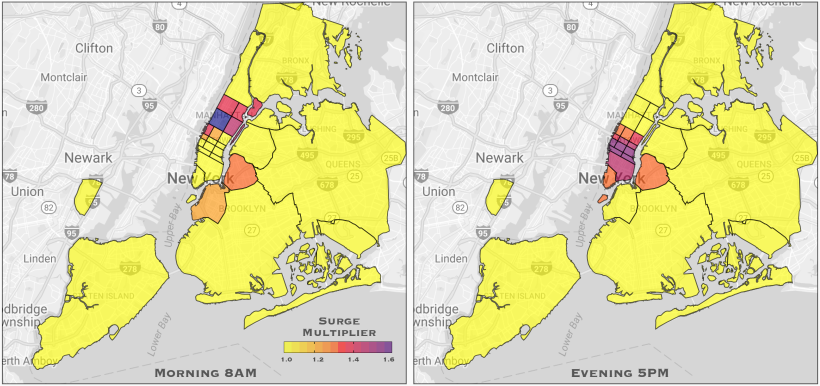

As an Uber driver, how do you maximize earnings?

Silicon Valley Steps In ...

#1 Supporting Platform For On-Demand Workers

Get Access **SherpaShare** Suite
Dashboard + **Tracker** + **Pulse** + **Heatmap** + ...

SherpaShare provides ‘myopic’ guide to drivers in form of heat-maps. No predictions!

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We focus on earnings of individual, self-interested drivers empowered by data.

Modeling a Strategic Driver

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  - **Edges**: Rides between each pair of zones.
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- Rewards Matrix (R):
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In general, all these matrices are time-dependent, their entries change throughout the day.

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Naive Uber Driver

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- **Driver Policy (π):**
  - Time and location dependent actions takes by driver.
  - Let Π denote entire policy space of size $\left|n \times N \times B \times \mathcal{A}\right|$.

Problem Definition

MaxEarnings Problem: Given a set of time-evolving F, T and R matrices, as well as the driver's budget B, find a policy π^* such that:

$$\pi^* = \arg\max_{\pi \in \Pi} \mathcal{E}(\pi, F, T, R, B)$$

where $\mathcal{E}(.)$ denotes total expected earnings.

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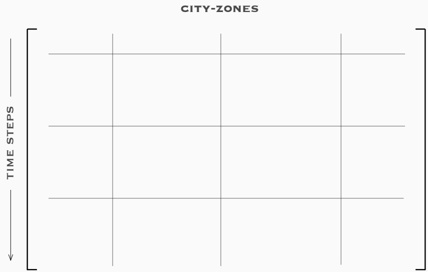

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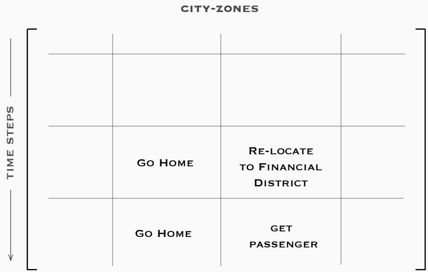

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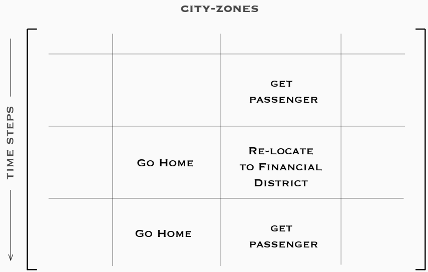

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- Methodology:

2016

1st Sunday of January
1 pm
Brooklyn to Williamsburg

NYC Taxi Ride

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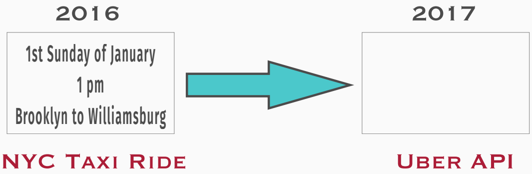

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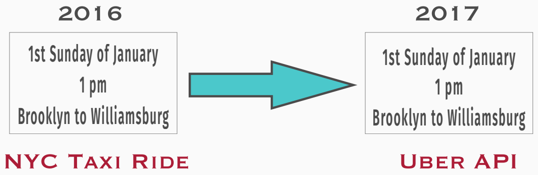

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- Generation of input matrices:
  - Discretize time into 10 minute steps i.e. $N = 144$ for a day long strategy.
  - For time-evolving matrices $F^{(t)}$, $R^{(t)}$ and $T^{(t)}$, aggregate observations within a 30-minute sliding window centered around time step t.
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Better data can be easily incorporated!

Performance of Strategies

- 100 simulated drivers for each strategy.
  - Random home zone.
  - 8 hour work-day i.e. $B = 48$.
  - Non-flexible strategy drivers work from 9AM-5PM.
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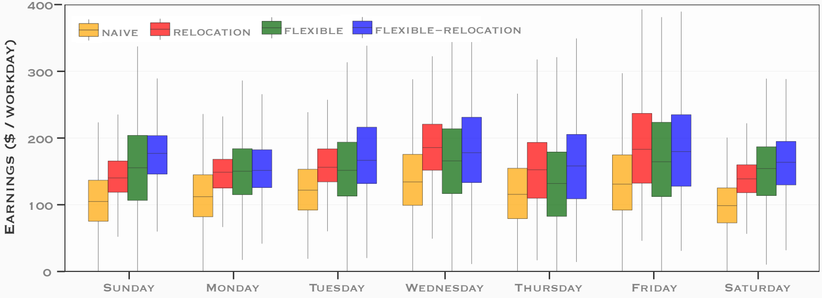
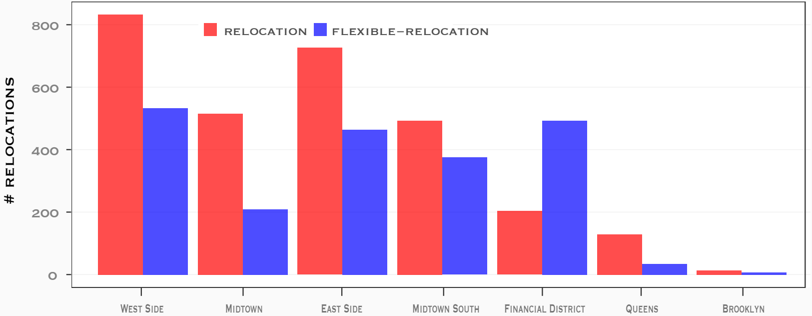
Average 47% increase in median earnings per day!

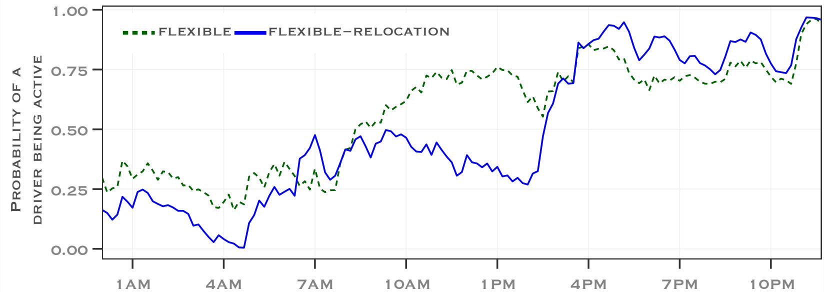


Best zones to re-locate to



Relocation strategy drivers: exploit spatial variation in Manhattan.

Best time to drive



Flexible-Relocation strategy drivers: exploit the temporal variation in Manhattan.

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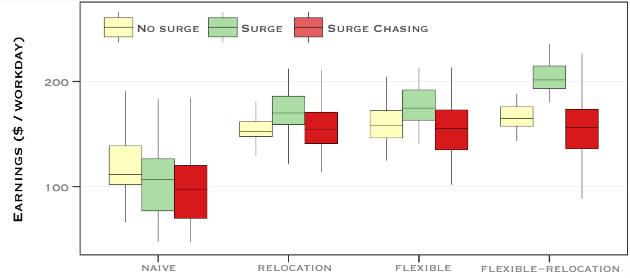
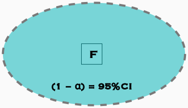


Surge Chasing may lead to lower earnings!

Robustness of Strategies

Robust Earnings Problem



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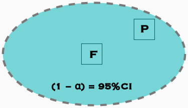

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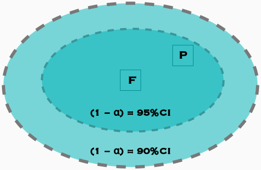

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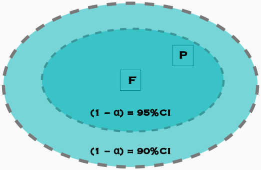

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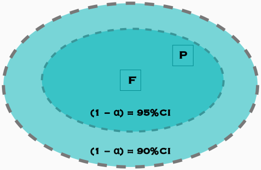

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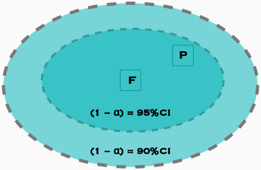

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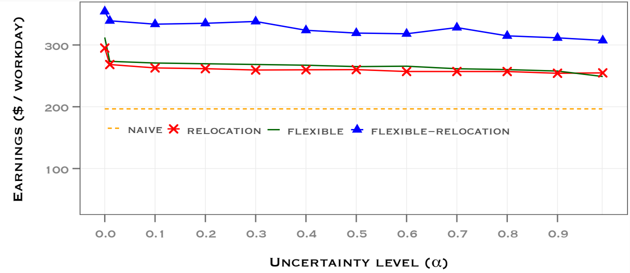
Nilim and El Ghaoui (2004): DP augmented with an optimization step, solvable in polynomial time.

Effect of Uncertainty



Flexible-Relocation Strategy outperforms all other strategies even in presence of high uncertainty!

Conclusion

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- Need for co-ordination when a significant percentage of driver population becomes strategic.

Thank You!

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