On the Real-time Vehicle Placement Problem

Abhinav Jauhri, Carlee Joe-Wong, John Paul Shen

ECE Department
Carnegie Mellon University

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Background

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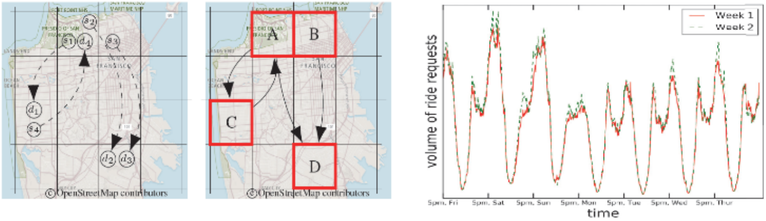
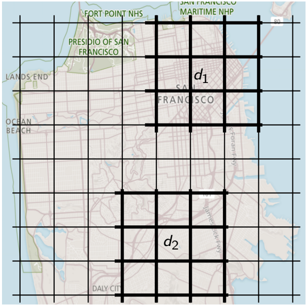
Space-Time Graph Modeling of Ride Requests Based on Real-World Data

Abhinav Jauhri,[1] Brian Foo,[2] Jérôme Berclaz,[2] Chih Chi Hu,[1]
Radek Grzeszczuk,[2] Vasu Parameswaran,[2] John Paul Shen[1]
[1]Carnegie Mellon University, USA; [2]Uber Technologies, Inc., USA
{ajauhri, chihhu, jpshen}@cmu.edu; {bfoo, jrb, radek, vasu}@uber.com



Problem Definition



- d_i - dropoffs at time snapshot t

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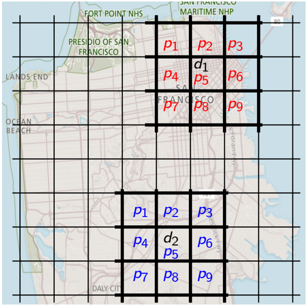
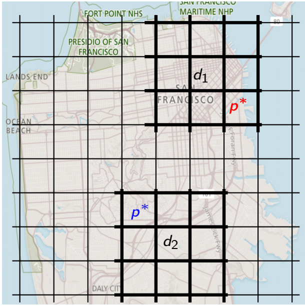


- d_i - dropoffs at time snapshot t
- p_i - possible placements for d_1 by time snapshot $t+1$
- p_i - possible placements for d_2 by time snapshot $t+1$



- d_i - dropoffs at time snapshot t
- p^* - placement for d_1 by time snapshot $t + 1$
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Two placements are made using some algorithm.

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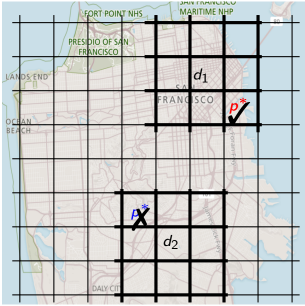

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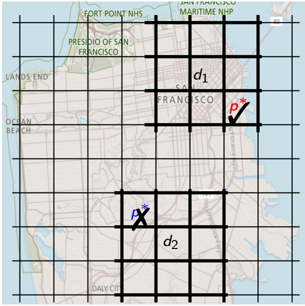

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Reward R is computed for every time snapshot:

$$R(t+1) = \frac{\#\text{good placements}}{\#\text{total placements}}$$

For the example above:

$$R(t+1) = \frac{1}{2}$$

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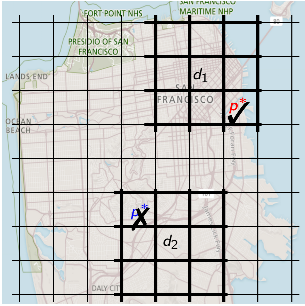

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Objective: Maximize the reward R over multiple time snapshots.

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4. $|(t+1)-t| < \tau_{epsilon}$ (usually a few minutes).

Potential Algorithms

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2. Follow the Leader with Complete History (FTL-CH).
3. Assume each cell follows a Poisson Process for ride requests (PP-LH).

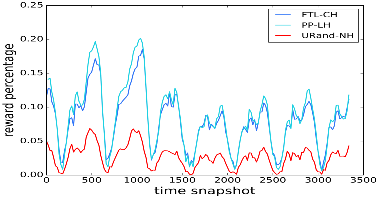
Experimental Setup

1. Looked at ≈ 10 million real ride requests for over a week in four US cities. Each ride request is defined by:
   - Pickup
   - Dropoff
   - Time of pickup
   - Time of dropoff

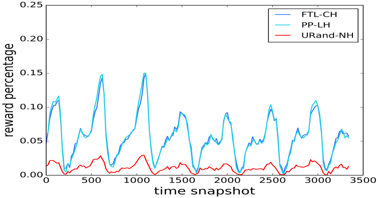
2. Each time snapshot is 3 minutes long.

3. Grid length $100m$.

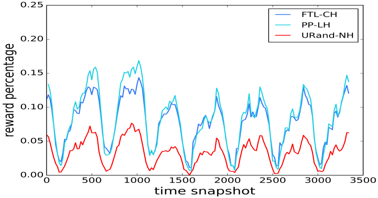
Results



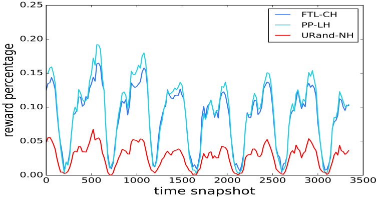
(a) Chicago



(b) Los Angeles



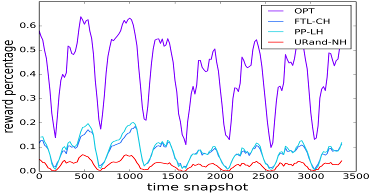
(c) New York



(d) San Francisco

Figure: The PP-LH algorithm out-performs FTL-CH slightly and URand-NH significantly across all four cities in terms of the reward.

Results with OPT



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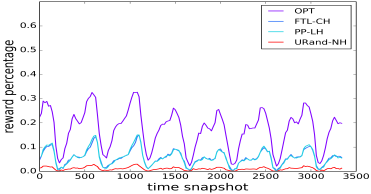

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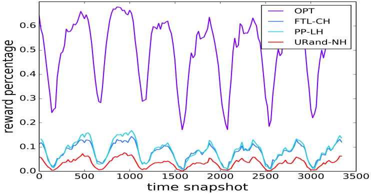

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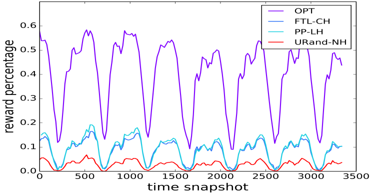

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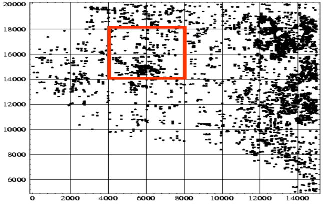
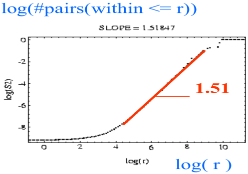
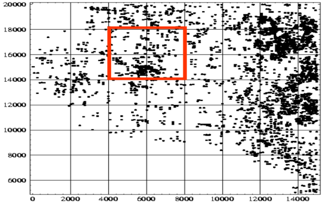
Figure: Comparison of reward percentage plots for 3 algorithms along with optimal (OPT) reward.

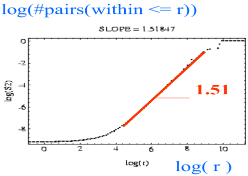




(a) **Known work:** Self-similarity for cross roads of Montgomery county.

Fractals





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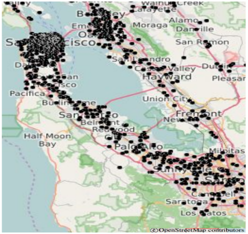

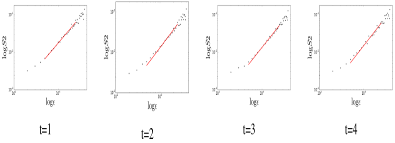

(b) **Our contribution:** Self-similarity for ride requests in Bay Area.

Fractal Dimensionality & Human Mobility Pattern

[Belussi 1998] Given a set of points $\mathbb{P}$ with finite cardinality and D_2, the average number of points within a square of radius ϵ' follow a power law:

$$\overline{nb}(\epsilon') \propto \epsilon'^{D_2} \tag{1}$$

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Expected Performance of FTL-CH is strictly better than URand-NH:

$$\mathbb{E}_{\text{FTL-CH}}[R_t] > \mathbb{E}_{\text{URand-NH}}[R_t] \tag{2}$$

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2. Highlight using real data connection between human mobility and chaos theory (fractals).

3. Propose potential online algorithms with guarantees which could reduce rider wait time, and driver idle time.