Background

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

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Problem Definition

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- \( p_i \) - possible placements for \( d_1 \) by time snapshot \( t + 1 \)
- \( p_i \) - possible placements for \( d_2 \) by time snapshot \( t + 1 \)
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Two placements are made using some algorithm.
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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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**Objective:** Maximize the reward $R$ over multiple time snapshots.
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3. Each cell covers a small geographical area (like $100 \times 100 \text{m}^2$).
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4. $| (t + 1) - t | < \tau_{\text{epsilon}}$ (usually a few minutes).
1. Pick a cell uniformly at random, and no history (URand-NH).
Potential Algorithms

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

1. Looked at $\approx 10$ 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 100$m$. 
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

(a) Chicago
(b) Los Angeles
(c) New York
(d) San Francisco

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.
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(b) **Our contribution:** Self-similarity for ride requests in Bay Area.
[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 $\epsilon'$ follow a power law:

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

Same can be said for ride requests.
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Same can be said for ride requests.

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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Conclusion

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