Assessing the Potential of Ride-Sharing Using Mobile and Social Data

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Car Usage and Impact

- In USA*:  
  - Commuters: 132.3M  
  - Driving alone: 79.9%

- Impact  
  - Pollution  
  - Lost productivity  
  - High car expenses

Introducing Ride-Sharing
An Old Idea, yet ...

- Challenges:
  - Live/Work close by
  - Similar schedules
  - Avoid strangers

- Opportunities:
  - Smartphones
  - Social media
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- Challenges:
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- Opportunities:
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Full potential of ride-sharing is still unknown
Related Work

Goal: Assess Ride-Sharing Potential

- Q: How many cars can be removed?

- Ideal Data:
  - For all people in a city
  - Full commuting trajectories
  - Willingness to share a ride

- Available Mobile and Social Datasets:
  - Large (but not entire) population
  - Samples of trajectories
  - (Parts of) social media graphs
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Find an upper bound to the ride-sharing potential
Outline

- Introduction
- Datasets
- Algorithms for Matching Users
- Results
Call Description Records (CDRs)

- **Spatio-temporal:**
  - Cell tower coordinates
  - Timestamps

- **Social:**
  - Calls among users

- **Details:**
  - Sept – Dec 2009
  - Madrid: 820M calls, 5M users
  - Barcelona: 465M calls, 2M users
Geo-tagged Tweets

- **Spatio-temporal:**
  - (lat, lng) coordinates
  - Timestamps

- **Social:**
  - Twitter Graph

- **Details:**
  - Nov ‘12 – Feb ‘13
  - New York: 5.20M geotweets, 225K users
  - Los Angeles: 3.23M geotweets, 155K users
Learning from Data 1: Home/Work Locations

- Methodology
  - Based on:
  - Ground truth (known home/work):
    - CDRs: Known industrial and residential areas
    - Geo-tweets: Foursquare
  - Train classifiers to identify home/work

- Home and Work locations inferred:
  - Madrid (CDRs): 272,479
  - NY (Twitter): 71,977

- Home and Work distribution is NOT uniform
  - In contrast to related work:
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- Exploit consecutive Home-Work calls
- Home-Work travel
  - Time: Online maps
- Similar for work departure times
\[ d(v, u) = \begin{cases} 
  h(v, u) + w(v, u), & \text{IF } \max(h(v, u), w(v, u)) \leq \delta \\
  \max(|LH(u) - LH(v)|, |LW(u) - LW(v)|) \leq \tau \\
  \infty, & \text{otherwise} 
\end{cases} \]
Problem Formulation

- Capacitated Facility Location with Unsplittable Demands:
  - Users: \( V \)
    - Drivers: \( S \subseteq V \)
    - Passengers: \( V - S \)
  - Capacity: 4 users/car
  - Find:
    - Assignment \( a: (V - S) \rightarrow S \)
    - Minimize:
      \[
      \sum_{u \in V} d(a(u), u) + \sum_{v \in S} p(v)
      \]
      - driver-passenger distances
      - driver penalties
Algorithm: EndPoints RS

- Heuristic solution:
  - Based on:
  - Initial solution:
    • b-matching
  - Iterative improvements
    • Scalability
      - Fixed local search steps
      - Fixed numbers of iterations
  - Polynomial complexity
    • \( O(n \log n) + O(n) \) for initial solution
    • \( O(n) \) to evaluate solution
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**EndPoint RS for Madrid-CDRs**

- **SD of departure time**: 30 min
- **Distance tolerance**: 1 km
- **Delay tolerance**: 10 min

24% of the cars can be removed!
Algorithm: EnRoute RS

- Home/Work paths:
  - Popular Online Maps

- EnRoute RS:
  - Get the solution of EndPoints RS
  - Iterative improvements
  - Fill empty seats by pick-ups

- Spatio-temporal constr. intermediate points:
  - Same and point constraints
Algorithm: EnRoute RS

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53% of the cars can be removed!
Learning from Data 3: Social Ties

- CDRs graph:
  - Nodes: Users
  - Edges: ≥ 1 call

- Geo-Tweets graph:
  - Nodes: Twitter ids
  - Edges: mutually declared friendship
Social Filtering

- **Friends:**
  - Graph neighbors

- **Sharing rides with:**
  - Friends
  - Friend-of-friends
## Results

- **Ride-sharing parameters:**
  - Time distribution: 30 min
  - Distance tolerance: 1 km
  - Delay tolerance: 10 min

<table>
<thead>
<tr>
<th>City</th>
<th>Friends only</th>
<th>Friends of friends</th>
<th>Anybody</th>
</tr>
</thead>
<tbody>
<tr>
<td>Madrid - CDR</td>
<td>1.1%</td>
<td>19% (31%)</td>
<td>53% (65%)</td>
</tr>
<tr>
<td>NY - Tweets</td>
<td>1.2%</td>
<td>8.2% (26%)</td>
<td>44% (68%)</td>
</tr>
</tbody>
</table>

Green numbers show potential of ride-sharing projected to commuters’ population.
Conclusion

- High potential based on route overlap:
  - E.g. 53% for Madrid-CDR

- Bottleneck:
  - Willingness to ride-share
  - Riding ONLY with friends is too restrictive

- Technology and building trust:
  - Riding with friends of friends: up to 31% potential.

- Other lessons:
  - Lessons from data sets
  - Spatio-temporal constraints
  - Comparisons between cities
Thank You

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