On the Validity of Geo-Social Mobility Traces

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Understanding Human Mobility

WANT!!
1. Large-scale
2. Accurate
3. Detailed

Traffic Planning

Controlling Infections

Adhoc/vehicular Network Design
Infrastructure Deployment
Getting Real Mobility Data is Hard

- Paying users does not scale
- WiFi registration traces (univ campus)
  - Sparse/incomplete
- Cellular base-station pings
  - Sparse sample, privacy issues
- Getting mobility traces from virtual worlds!
  (mobility traces from SecondLife, WOSN’08)
A New Hope: Geo-Social Traces

- “Check-in” to locations, share with friends
- As of Sept. 2013, Foursquare has 40 million users, 4.5 Billion Checkins, 1.3 million businesses
Is This the Answer?

- Geo-social traces increasing available (e.g. FourSquare)
  - Larger scale datasets, crawl-able or public (Twitter)
  - Researchers use data for:
    - inferring friendships, predicting human movement, urban planning, CDN design
- But is this data representative?
  - Do incentives to check-in cause bias?
  - Are check-ins a small sample of real mobility?
- Our work: try to understand “reality”
  - How representative are Geosocial Location traces?
  - What is the impact of any errors on applications?
  - Can we try to compensate for these errors?
The Rest of This Talk

- Motivation: Why
- Methodology: How
  - Measuring human mobility
  - Getting user participation
- Data Analysis: What
  - (In-)consistencies of geosocial data
  - Application level impact
- Conclusion
The Plan

- Gather simultaneous traces of GPS location and FourSquare check-ins
- Match check-ins to GPS “events” for consistency

GPS Trace: A list of visit events

Checkin Trace: A list of Checkins

Challenge: Collecting parallel GPS and check-in data from the same set of users
Data Collection

- We need: reasonable user size + fine granularity data
  - Data gathering via Android/iOS smartphone apps

- Functionality
  - Record all FourSquare checkins via API
  - Record GPS once per minute → GPS Trace
    - Turn on WiFi/accelerometer when GPS signal is weak
    - An algorithm to detect *visit* events
    - *Visit* event: user stay @ one place for 6min+
  - Reminder feature to attract 4Sq users
    - All checkins from reminders removed from dataset
      (only 10% of check-in events)
Data Collection Continued…

- It’s not easy
  - Getting user participation
  - Challenges: privacy, power consumption

- First thought: crowdsourcing!
  - Pay to install application, leave the rest to user
  - Many did not provide data
  - For the rest: fake checkins dominate user activity

**Surprising result: highly biased data #fail**

- Fallback plan: organic app adoption
  - Boosted awareness with ads on popular websites
  - Slow adoption rate over 5 months
  - A slow wait for users …
Datasets and Processing

- “Primary” dataset
  - Normal Foursquare users who installed our app

- “Baseline” dataset
  - Student volunteers from UCSB Communications Dept.
    - Less likely to be affected by Foursquare incentives

<table>
<thead>
<tr>
<th>Dataset</th>
<th># of users</th>
<th>Avg. days per user</th>
<th># of checkins</th>
<th># of GPS visits</th>
<th>GPS Points</th>
</tr>
</thead>
<tbody>
<tr>
<td>Primary</td>
<td>244</td>
<td>14.2</td>
<td>14K</td>
<td>31K</td>
<td>2.6M</td>
</tr>
<tr>
<td>Baseline</td>
<td>47</td>
<td>20.8</td>
<td>665</td>
<td>6.3k</td>
<td>558K</td>
</tr>
</tbody>
</table>

- “Visit Events” from GPS trace: any stationary location for 6+ mins
- Matching events from two traces
  - Conservative: match check-in to closest GPS event, within 500m in distance, within 30 mins before/after check-in
Limited Data Validation

- Correctness of our GPS event generation
  - 92% of Baseline’s check-ins match GPS events

- Are app users consistent with UCSB students
  - High level consistency in physical mobility patterns

![Graph showing CDF of inter-arrival time]
FourSquare vs. Physical Mobility

75% Checkins are extraneous ("cheating")
89% of visited GPS locations have no checkins
Missing Places / Events

- Routine activities missing from FourSquare check-ins
  - Professional (i.e. work), Shopping, Food (eating out)
  - Intuition: users tend to ignore “boring” or potentially private locations
Extraneous Check-ins

- Behavior prevalent across all users
  - Widespread: for 20% of users, 80+% events are extraneous
  - Not black/white: removing users responsible for 80% of extra events would also remove 50% of legitimate data

![Diagram showing the distribution of extraneous check-ins among users.]

- Types of extraneous check-ins
  - **Drive-by**: check-in while moving at high speed
  - **Superfluous**: checking in nearby locations
  - **Remote**: check-in location >500m away
Are Incentives Responsible?

- Study correlation (Pearson’s) between per-user rate of extra check-ins and FourSquare user features
  - # of badges, # of mayorships, check-ins/day

- High correlation with Foursquare rewards
  - Rate of remote check-ins vs. # of Badges: 0.49
  - Rate of superfluous check-ins vs. # of Mayorships: 0.34
  - Very intuitive

FourSquare incentives have significant correlation to extraneous check-ins
Key Take-aways

- Large discrepancies between GPS trace and check-ins
  - Large amount of FourSquare check-ins are extraneous
  - Majority of real life events missing
- High correlation bet. extra check-ins and FourSquare rewards
- Ongoing work: can we “fix” this?
  - Detecting/removing extraneous check-ins
    - Extract useful features
    - Use machine learning to classify
    - Unsupervised methods?
  - Missing check-in extrapolation
    - Temporal and spatial extrapolation
Thank you!
Questions?