Where did you come from? Where did you go? Robust policy relevant evidence from mobile network big data

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CPRsouth 2015
Taipei, Taiwan
26 August 2015

This work was carried out with the aid of a grant from the International Development Research Centre, Canada and the Department for International Development UK.
Policy implication

• Mobile Network Big Data (MNBD) can support urban transport planning as a continuous exercise
  – Greater spatio-temporal detail than corresponding traditional output
  – Negligible incremental cost of generating forecasts
  – Single source for understanding different aspects of mobility

• Inherent limitations mean MNBD cannot replace traditional process entirely
Transport forecasting in developing countries are based on infrequent surveys

- These are done on an as-needed basis
  - The Colombo transport master plan (COMTRANS) survey in 2013 in Sri Lanka, funded by JAICA
- Expensive
  - COMTRANS 2013 survey cost approximately $400,000\(^1\)
- Time consuming
  - By the time the results are ready, they are often already outdated
- Cannot support continuous monitoring of transport patterns
- Not very useful to help evaluate impact of policies

\(^1\) Estimated based on interviews
Mobility insights from MNBD need to be aligned with the traditional process

- MNBD based insights provide greater temporal and spatial resolution
- MNBD cannot replace the diverse data collected by the traditional survey
- MNBD insights need to be aligned with different stages of traditional process familiar to planners
The data: historical and anonymized Call Detail Records (CDRs) from Sri Lanka

• Call Detail Record (CDR):
  – Records of all calls made and received by a person created mainly for the purposes of billing
  – Similar records exist for all SMS-es sent and received as well as for all Internet sessions

<table>
<thead>
<tr>
<th>Calling Party Number</th>
<th>Called Party Number</th>
<th>Caller Cell ID</th>
<th>Call Time</th>
<th>Call Duration</th>
</tr>
</thead>
<tbody>
<tr>
<td>A24BC1571X</td>
<td>B321SG141X</td>
<td>3134</td>
<td>13-04-2013 17:42:14</td>
<td>00:03:35</td>
</tr>
</tbody>
</table>

  – The Cell ID in turn has a lat-long position associated with it

• CDR data for 13 contiguous months in 2012-2013
  – Nearly million 10 SIMs
  – Over 25 billion records
Origin – Destination Matrices

- Key intermediate output of the traditional forecasting process
- Estimated people/vehicle flows between regions
  - E.g.: DSD (3rd level administrative division) level O-D matrix for the Western Province of Sri Lanka
- Used in traffic studies, identifying key transport corridors, etc.
Multiple methods exist for extracting O-D matrices from MNBD

• We extracted O-D matrices for the Western Province of Sri Lanka using 3 methods:
  – Stay based method
  – Transient Trip method
  – Frequent Trip method

• Methods have two stages:
  – Identify individual movement as a sequence of trips (varies across methods)
  – Aggregate individual trips across the origin and destination locations of the trips (same for all methods)
Stay based approach

- Identify instances when a user has been stationary - **Stays**
  - Geographical location with the associated time period
- With CDR a Stay is contiguous series of records such that,
  - Any two records in the series are less than a distance $D$ apart, where $D = 1km$
  - The entire series of records should span a period of more than 10 minutes
  - Two contiguous records are separated by a time interval $T$ such that $T \leq 1 hour$
- Each pair of consecutive stays for a person is taken as origin and destination of a trip
- Built on prior work
Transient trip approach

- A trip is identified from the CDRs by a consecutive pair of records such that,
  - The records indicate a displacement, i.e. the BTS-es utilized for each record is different
  - The records are separated by a time interval $T_{\text{Interval}}$ where, $10 \text{ minutes} \leq T_{\text{Interval}} \leq 1 \text{ hour}$
- Maximizes amount of extracted mobility information by capturing intermediate points in trips
- Extracted trips likely to correspond to segments of real trips
- Built on prior work
Frequent trip approach

• Frequent trip approach attempts to capture regular travel
  – Identify frequent sequences of two locations in the daily trajectories of a person (Frequent Sequence Mining)
  – A sequence can be non-contiguous.
  – A sequence is frequent if it occurs at least on 10% of the days a person is observed
  – A frequent sequence defines the endpoints of a frequent trip

• Estimate the likelihood of making a frequent trip during a period of a given day

\[
P(Trip_i|D_j, Period_k) \approx \frac{\text{Frequency of Trip}_i \text{ during } D_j \text{ and } Period_k}{\# \text{ of times I had at least 1 record during } D_j \text{ and } Period_k}
\]

\[k = \{\text{Morning, Afternoon, Evening, Night}\}\]
\[D_j = \text{day of the week, } j = \{0,6\}\]

• Built on prior work
Each method has strengths/weaknesses

<table>
<thead>
<tr>
<th></th>
<th>Stay based</th>
<th>Transient trips</th>
<th>Frequent trips</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amount of mobility</td>
<td>Low</td>
<td>High</td>
<td>Regular mobility</td>
</tr>
<tr>
<td>Sensitivity to noise</td>
<td>Low</td>
<td>High</td>
<td>Low</td>
</tr>
<tr>
<td>Bias towards active users</td>
<td>High</td>
<td>Moderate</td>
<td>Low</td>
</tr>
<tr>
<td>Use</td>
<td>Identifies congregations of people</td>
<td>Suitable for short term mobility analysis</td>
<td>Aligns best with outputs from traditional process</td>
</tr>
</tbody>
</table>
Validation with traditional output

- Compared with best available traditional forecast
  - Number of trips generated by region at the DSD level, from COMTRANS 2013

- Constructed weighted linear models for all three methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Intercept</th>
<th>MNBD estimate</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stay based</td>
<td>35,516***</td>
<td>76.41***</td>
<td>0.819</td>
</tr>
<tr>
<td>Transient trip</td>
<td>25,460**</td>
<td>2.66***</td>
<td>0.903</td>
</tr>
<tr>
<td>Frequent Trips</td>
<td>14,770</td>
<td>1.16***</td>
<td>0.909</td>
</tr>
</tbody>
</table>
MNBD insights within a traditional transport forecasting process

- MNBD insights have inherent limitations
  - Sampling biases: high activity users, mobile phone penetration in different regions
  - Sparsity of data: less than 25 records per day for 90% of the users
  - Lack of socioeconomic, demographic, travel motivation

- Solutions exist to mitigate these issues to some extent
  - Adjust for penetration and operator market share by scaling flows
  - Associating demographic parameters from travel surveys with MNBD insights using machine learning techniques to match mobility variables in both
  - Probabilistic models (E.g: Hidden Markov Models) to estimate locations for people where no records exist, can improve mobility estimates
Policy implication

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  – Negligible incremental cost of generating forecasts
  – Single source for understanding different aspects of mobility
  – Inherent limitations mean cannot replace traditional process entirely
Thank you.