Multimodal Traffic Management

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Collaboration between LiU, KTH and Stockholm Traffic Management Center
Project Team

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Multimodal Traffic Management

• Research targets
  – Better understanding of multimodal travel patterns
  – New methods for multimodal demand estimation and prediction
  – New methods for predicting route and mode choice
  – Synergies of multimodal traffic management

• Incident decision support
  – State prediction during incidents (including effects on route and mode choice)
  – Which traveller flows are affected most by the incident (and affect the incident the most)?
  – Which multimodal rerouting alternatives are available for these traveller flows?
  – How does the rerouting affect the future traffic state?
Overview of computational modules

- Exploratory analysis of multimodal data
- Data-driven route and mode choice modeling
- Multimodal demand estimation
- Scenario evaluation and analytics

MMTM
Stockholm Dataset

- GPS trips
- Public transport tickets
- Mobile network data
- Portal data
- Link counts
Data-driven route choice modeling

Anna Danielsson
Data-driven route choice modeling

• Route choice modeling for traffic management
  – Estimate and predict traffic state
  – Estimate and predict traffic demand
  – Give relevant and targeted traveler information

• First approach using GPS probe data for estimation of a Logit-based discrete choice model
  – Which features $x_{ik}$ affects the route choice?
    • Travel time, distance, capacity, #turns, #traffic lights...
Data-driven route set

- Choice set (set or routes considered by the traveller) constructed from the set of all observed alternatives

- The first two weeks constitutes a training data set (blue) and the next two weeks a test data set (orange).
# Route attribute statistics

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Explanation</th>
<th>Unit</th>
<th>Average value of all routes in data set</th>
<th>Difference within OD pairs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>min diff</td>
</tr>
<tr>
<td>ttmean</td>
<td>observed mean traveltime</td>
<td>min</td>
<td>1.24</td>
<td>0.06</td>
</tr>
<tr>
<td>ttfree</td>
<td>free flow traveltime</td>
<td>min</td>
<td>0.80</td>
<td>0</td>
</tr>
<tr>
<td>delay</td>
<td>relative delay ((ttmean - ttfree) / ttfree)</td>
<td>share</td>
<td>0.57</td>
<td>0</td>
</tr>
<tr>
<td>rlength</td>
<td>length of route</td>
<td>km</td>
<td>0.78</td>
<td>0</td>
</tr>
<tr>
<td>numlinks</td>
<td>number of links in route (proxy for number of intersections)</td>
<td></td>
<td>5.42</td>
<td>0</td>
</tr>
<tr>
<td>p_city</td>
<td>percentage of route within the city center</td>
<td>share</td>
<td>0.33</td>
<td>0</td>
</tr>
<tr>
<td>p_major_roads</td>
<td>percentage of route using major roads</td>
<td>share</td>
<td>0.75</td>
<td>0</td>
</tr>
<tr>
<td>cf</td>
<td>commonality factor indicating how similar to the alternatives the route is</td>
<td></td>
<td>0.74</td>
<td>0</td>
</tr>
</tbody>
</table>
Route choice modeling

- Attribute selection
  - `p_major_roads`, `numlinks`, `p_city` and `rlength` are the most important attributes.

- Model estimation
  - Weighting attributes against each other.

- Model evaluation
  - Comparison of estimated and observed route choices.

- Understanding model
  - Analysis of example OD-pairs.
Conclusions so far

• A good route choice model can give important insights for traffic management.

• Insights from the experiments
  – Dataset promising for network-wide analysis and modeling of route choice
  – Route sets in training and test data are similar, thus building up the choice set of the historically observed routes is promising.
  – Attributes seems sufficient for some OD-pairs
Data-driven route choice modeling
Public Transport
Matej Cebecauer
Public transport OD - routes

• Data
  Anonymized individual travel diaries inferred from smart-card data

• Result
  Dynamic OD matrices from 2015 – 2022 considering routes

• Next
  Data-driven PT route choice modeling
Explorative analysis of multimodal demand data

Matej Cebecauer
Multimodal day-types

Day-types:
- Representative typical days

How we reveal representative day-types:

1. Clustering / pattern recognition
   - that groups the days based on their similarities, such
     - Minimize the variance/distance/dissimilarity among days in each cluster
     - Maximize the variance/distance/dissimilarity to days in other clusters

2. Representative of the cluster is the recognized day-type
   - Could be an average day of the cluster
Multimodal day-types

MCS sensors

499 – sensors
66 – 15 minutes intervals

PT dynamic OD matrices

49 – zones (2,400 OD pairs)
38 – 30 minutes intervals

Map background: OpenStreetMap.org
Multimodal day-types
Day-type similarity – calendar evaluation
– Clustering using year 2017

Flow

MCS sensors

Speed

PT OD matrices

School holidays  Public holidays  Midsummer  Special days or de facto holiday  Bridging day
Multimodal day-types
Day-type similarity – external evaluation

• Similarity in short-term prediction application performance
  – Historical mean prediction model
    • Day-types recognized in 2017
    • Predicting for all days in 2018
    • 1 hour into future
    • Past hour to classify day-type for prediction
  – Mean Absolute Error (MAE)
  – Mean Percentage Absolute Error ignoring 0 (MAPE0)
What next?
What next?

• Adding more data sources
• Reveal multimodal day-types
  – Is the robustness of day-types sufficient for traffic management?
• Route choice modeling
  – Route set generation needs to be added to the process to provide better estimates for unseen situations
  – A mode choice component will be added to analyze multimodal traffic management
• Scenario evaluation
  – Simulation Model
  – Support for dynamic changes in network, demand and supply