A Route Choice Model Based on Mental Representations

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Agenda

1. Introduction
2. Methodology
3. Case study
4. Application
5. Conclusion
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Route choice (RC)

Predict the route that a traveler would choose to go from the origin (O) to the destination (D) of her trip.

- One of the key travel demand models.
- Core of traffic assignment for planning and real-time operations.
- Need to go beyond the shortest/fastest path models.
Random utility models (RUMs) for route choice

1. Decision maker \( n \)

2. Alternatives
   - **Choice set** \( C_n \)
   - Route representation: path \( p \)
   - Paths as link sequences \( p \in C_n \)

3. Attributes of alternatives \( x_{pn} \)
   - Usually link additive (travel time, length, etc.), but also path based.

4. Characteristics of decision maker \( z_n \)
   - Usually missing.

5. Decision rule \( P(p|C_n) \)
   - Utility maximization
   - \( P(p|C_n) = Pr(U_{pn} \geq U_{qn} \forall q \in C_n) \)
Motivation

Estimation of RUMs with RP\textsuperscript{1} data and path assumption is challenging

Operational limitations

- Data
- Choice set
- Structural correlation

Behavioral limitations

\textsuperscript{1}Revealed preference.
State-of-the-art

- Path based models
  1. Complex;
  2. Fail to capture observed behavior.

- No realistic, yet simple model, based on RP data has been proposed.

- Few attempts to use abstract elements related to perceptions
  1. [Ben-Akiva et al., 1984] path generation and sampling;
  2. [Frejinger and Bierlaire, 2007] capturing correlation.
Proposed framework

1. Simple model exploiting RP data
2. Not based on paths
3. Key feature: *mental representations*
4. The general framework may be network-free, yet applicable to traffic assignment.
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A *path* is solely the manifestation of the route choice – the way the traveler implements her decision to take a specific route.

How can we represent a route in a behaviorally realistic way without increasing the model complexity?

- Choice takes place at a higher conceptual level.

  \[ \text{Mental Representation Item (MRI) = main modeling element} \]
Outline of the methodology

1 Definition of the \textit{MRI}:
   1. Empirical evidence through simple qualitative analyzes
   2. Literature review in relevant fields

2 Definition of a RUM model based on \textit{MRI}:
   1. Choice set \( C_n \)
   2. Explanatory variables \( x_{in}, z_n \)
   3. Specification of the deterministic utility function \( V_{in} \)
   4. Assumption about the error terms \( \varepsilon_{in} \)
Mental Representation Item (MRI)

- MRIs are associated with mental representations used in daily language to describe a route.

- An MRI is an item characterising the mental representation of an itinerary:

  E.g. a highway, the city center or a bridge.
The MRI components

Perceptual: a name and a description; Tangible: a point and an area

"City center" — Go through the center

"Peripheral" — Avoid the center

N  Name

"D"  Description

Representative points

Geographical span
The exact definition of the MRI is context dependent, and must be designed such that:

1. It has a meaningful behavioral interpretation, and
2. Its level of aggregation is high enough for the model to be simple and operational, and low enough for the model to be useful.
Definition of the alternatives

A route is either one-\textit{MRI} or a sequence-of-\textit{MRIs}.

The number of \textit{MRIs} should be kept low so that the number of sequences-of-\textit{MRIs} is also low and can be enumerated.

Issues:

1. How to relate available data to \textit{MRI} alternatives; and
2. How to specify the utility function for the abstract alternatives.

→ Different heuristics can be considered and evaluated.
From data to *MRIs*

- Interviews and surveys.
- GPS devices and smartphones.

**Maximum likelihood estimation:**

Obtain the contribution of each piece of data to the likelihood function. Let $i$ be an alternative of the MRI model, and $y$ an observation, then:

$$\sum_i P(y|i) \cdot P(i|C, x_{in}, z_n)$$

where $P(y|i)$ is the measurement model, $P(i|C, x_{in}, z_n)$ is the choice model.

Associating each piece of data to a single alternative, so that $P(y|i)$ takes values 0 and 1 only, is convenient. For more complex measurement models, we refer to [Bierlaire and Frejinger, 2008] and [Chen and Bierlaire, 2013].
Specification of the utility function

Probably the most complex part. We need to go from abstract back to specific.

The main modeling element is a mental representation. This has implications for the specification of the utility functions:

- The attributes are fuzzy and based on perceptions rather than objective measurements.
- Possibilities to investigate the impact of perception on behavior:
  1. Model perceptions — e.g. using latent variables;
  2. Network-free approach — e.g. using the level of service of the MRIs;
  3. Use network data to generate attributes for each MRI and specify the utility functions — what we do in the case study.
Operational approach using network data

We propose two heuristics assuming that a network model is available:

✓ Deterministic approach.
   → Unique representative path for each MRI.

✗ Expected maximum utility (EMU).
   → Path enumeration and logsum.
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Borlänge data

✓ GPS data → map-matched trajectories

✓ Borlänge road network:

1. 3077 nodes and 7459 unidirectional links
2. Link travel times
3. Clear choices

- We use a sample of 139 observations.
- We focus on the simplest possible case where each route is described my one-\textit{MRI} and a common choice set $C$ for all travelers.
Borlänge road network
Borlänge MRI CS

\[ C = \{ 1: \text{through the city center (CC)}, \]
\[ 2: \text{clockwise movement around the CC}, \]
\[ 3: \text{counter-clockwise movement around the CC}, \]
\[ 4: \text{avoid the CC} \} \]
## Definition of the MRIs in Borlänge

<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
<th>Geographical span</th>
<th>Representative node</th>
</tr>
</thead>
<tbody>
<tr>
<td>City center (CC) of Borlänge</td>
<td>Go through the CC inside the perimeter</td>
<td>Every link</td>
<td>See Fig. on slide 21</td>
</tr>
<tr>
<td>Street name</td>
<td>Around the center on the perimeter</td>
<td>Every link</td>
<td>See Fig. on slide 21</td>
</tr>
<tr>
<td>Street name</td>
<td>Around the center on the perimeter</td>
<td>Every link</td>
<td>See Fig. on slide 21</td>
</tr>
<tr>
<td>Street name</td>
<td>Avoid the center (Peripheral)</td>
<td>Every other link</td>
<td>See Fig. on slide 21</td>
</tr>
</tbody>
</table>
Representative nodes

- City center (fastest of the two)
- Perimeter (clock, counter-clock depending on OD)
- Avoid (all ODs except for 21-3, 3-21)
- Avoid (for ODs 21-3, 3-21)
Example of observed routes (1)

*Around the CC movements*
Example of observed routes (2)

Avoid the CC alternatives
Example of observed routes (3)

*Through the CC movements*
Example of MRI choice set

- green line: chosen alternative (through CC)
- blue line: around CC alternatives (clock and counter-clockwise)
- red line: avoid CC alternative
Specification of utility functions and attributes of the alternatives

**Deterministic approach**

1. For each MRI determine a representative node $m$ (OD dependent).
2. Calculate the fastest path from $O$ to $m$.
3. Calculate the fastest path from $m$ to $D$.
4. Use the attributes of the generated path for the MRI.
Choice model

For high levels of aggregation, logit can be assumed:

\[ P_n(i|C) = \frac{e^{\nu_{ni}}}{\sum_{j \in C} e^{\nu_{jn}}} \]
### Specification table of model 1

**Piecewise linear travel time for the around alternatives**

<table>
<thead>
<tr>
<th>Parameter name</th>
<th>Through CC</th>
<th>Around clock CC</th>
<th>Around counter CC</th>
<th>Avoid CC</th>
</tr>
</thead>
<tbody>
<tr>
<td>$ASC_{CC}$</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$ASC_{AROUND}$</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>$ASC_{AVOID}$</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>$\beta_{TIME_{CC}}$</td>
<td>$TT$ (min)</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$\beta_{TIME_{AROUND}}^{(0-10\text{ min})}$</td>
<td>0</td>
<td>$TT$ (min)</td>
<td>$TT$ (min)</td>
<td>0</td>
</tr>
<tr>
<td>$\beta_{TIME_{AROUND}}^{(&gt;10\text{ min})}$</td>
<td>0</td>
<td>$TT$ (min)</td>
<td>$TT$ (min)</td>
<td>0</td>
</tr>
<tr>
<td>$\beta_{TIME_{AVOID}}$</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>$TT$ (min)</td>
</tr>
<tr>
<td>$\beta_{LEFT}$</td>
<td># left turns</td>
<td># left turns</td>
<td># left turns</td>
<td># left turns</td>
</tr>
<tr>
<td>$\beta_{IS}$</td>
<td># intersections</td>
<td># intersections</td>
<td># intersections</td>
<td># intersections</td>
</tr>
</tbody>
</table>
### Specification table of model 2

**Length**

<table>
<thead>
<tr>
<th>Parameter name</th>
<th>Through CC</th>
<th>Around clock CC</th>
<th>Around counter CC</th>
<th>Avoid CC</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASC&lt;sub&gt;CC&lt;/sub&gt;</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>ASC&lt;sub&gt;AROUND&lt;/sub&gt;</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>ASC&lt;sub&gt;AVOID&lt;/sub&gt;</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>β&lt;sub&gt;LENGTH&lt;/sub&gt;&lt;sub&gt;CC&lt;/sub&gt;</td>
<td>Length (km)</td>
<td>0</td>
<td>Length (km)</td>
<td>0</td>
</tr>
<tr>
<td>β&lt;sub&gt;LENGTH&lt;/sub&gt;</td>
<td>0</td>
<td>Length (km)</td>
<td>Length (km)</td>
<td>Length (km)</td>
</tr>
<tr>
<td>β&lt;sub&gt;LEFT&lt;/sub&gt;</td>
<td># left turns</td>
<td># left turns</td>
<td># left turns</td>
<td># left turns</td>
</tr>
<tr>
<td>β&lt;sub&gt;IS&lt;/sub&gt;</td>
<td># intersections</td>
<td># intersections</td>
<td># intersections</td>
<td># intersections</td>
</tr>
</tbody>
</table>
## Estimation results

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Model 1 Parameter value; Rob. Std (Rob. t-test 0)</th>
<th>Model 2 Parameter value; Rob. Std (Rob. t-test 0)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$ASC_{AROUND}$</td>
<td>-2.11; 1.44; (-1.47)</td>
<td>-0.975; 1.67; (-0.58)</td>
</tr>
<tr>
<td>$ASC_{AVOID}$</td>
<td>1.87; 2.09; (0.89)</td>
<td>0.307; 1.70; (0.18)</td>
</tr>
<tr>
<td>$\beta_{TIME_{CC}}$</td>
<td>-0.772; 0.274; (-2.82)</td>
<td></td>
</tr>
<tr>
<td>$\beta_{TIME_{(0-10min)_{AROUND}}}$</td>
<td>-0.286; 0.165; (-1.74)</td>
<td></td>
</tr>
<tr>
<td>$\beta_{TIME_{(&gt;10min)_{AROUND}}}$</td>
<td>-0.616; 0.216; (-2.86)</td>
<td></td>
</tr>
<tr>
<td>$\beta_{TIME_{AVOID}}$</td>
<td>-0.583; 0.187; (-3.11)</td>
<td></td>
</tr>
<tr>
<td>$\beta_{LENGTH}$</td>
<td></td>
<td>-0.871; 0.173; (-5.03)</td>
</tr>
<tr>
<td>$\beta_{LENGTH_{CC}}$</td>
<td></td>
<td>-1.48; 0.493; (-2.99)</td>
</tr>
<tr>
<td>$\beta_{LEFT}$</td>
<td>-0.288; 0.130; (2.22)</td>
<td>-0.270; 0.143; (-1.89)</td>
</tr>
<tr>
<td>$\beta_{IS}$</td>
<td>-0.0474; 0.022; (-2.16)</td>
<td>-0.0631; 0.018; (-3.42)</td>
</tr>
</tbody>
</table>

| Number of observations     | 139                                              | 139                                              |
| Number of parameters       | 8                                                | 6                                                |
| $\overline{\rho}$         | 0.375                                            | 0.416                                            |
| $\mathcal{L}(0)$           | -183.201                                         | -183.201                                         |
| $\mathcal{L}(\hat{\beta})$| -106.563                                         | -101.064                                         |
Forecasting results (Model 1)

1. Randomly select 80% of the data for estimation.
2. Apply the model in the rest 20%.
3. Repeat 100 times.

→ Check market shares (MS), predicted probabilities, elasticities.
Boxplot of MS from the application in 20% of the data and CI from the estimation with the full dataset
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Metropolis-Hastings (MH) algorithm [Flötteröd and Bierlaire, 2013] to sample paths given the OD and $C$.

The probability of each path $p$ to be selected, given the OD and $C$, is:

$$P(p|C) = \sum_i P(p|i) \cdot P(i|C)$$

where $P(p|i)$ is the probability of path $p$ to selected given MRI alternative $i$, and $P(i|C)$ is the choice model.

For the assignment we need an indicator function $\delta(p, i)$, which is 1 if the sampled path is consistent with MRI $i$, and 0 otherwise.
Application

Route guidance

Provision of information in an aggregate manner:

1. Guidance on VMS\(^2\)
2. Radio announcements
3. Oral instructions in in-vehicle navigation systems

\(^2\)Variable message signs.
Hierarchical ordering of the decision process

Multi-level hierarchical structure ~ Normative Pedestrian Flow Theory

[Hoogendoorn, 2001]
Model structure

Layer $\ell$
- Choice set: list of MRIs $C_\ell$.
- Choice model:
  \[ P_\ell(i|C_\ell; \beta^\ell) \]

Layer $\ell + 1$
- Choice set: list of MRIs $C_{\ell+1}$.
- Choice model:
  \[ P_{\ell+1}(i|C_{\ell+1}; \beta^{\ell+1}) \]

Behavioral consistency
- All layers refer to the same choice.
- Level of granularity varies.
- Analysis can be performed in any layer.

Structural consistency
\[
\bar{P}_\ell(i|C_\ell; \beta^\ell) = \sum_{j \in C_{\ell+1}} P(i|j, C_\ell; \beta^\ell) P(j|C_{\ell+1}; \beta^{\ell+1})
\]
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Conclusion

It is possible to have a meaningful model even with one-MRI.

Achievements

- Simplification of the choice set and hence the model.
- No need for sampling.
- Behaviorally realistic.
- Flexibility to the analyst.

Challenges

- Involved modeling.
- Data processing.
Future steps

1. Traffic assignment.
2. Generation of attributes $\rightarrow$ EMU
3. Consistency within the hierarchical structure.
4. MRI sequences and additional complexity $\rightarrow$ Quebec GPS dataset
5. Comparison & combination with RL model [Fosgerau et al., 2013]
THANK YOU!
Bibliography I


Bibliography III

### Descriptive statistics of the main variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>mean</th>
<th>median</th>
<th>min</th>
<th>max</th>
<th>std.dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>TT_CC (min)</td>
<td>10.18</td>
<td>8.38</td>
<td>3.88</td>
<td>38.03</td>
<td>6.41</td>
</tr>
<tr>
<td>TT_CL (min)</td>
<td>9.98</td>
<td>8.18</td>
<td>2.86</td>
<td>38.93</td>
<td>6.32</td>
</tr>
<tr>
<td>TT_CO (min)</td>
<td>10.21</td>
<td>8.37</td>
<td>3.81</td>
<td>36.47</td>
<td>6.23</td>
</tr>
<tr>
<td>TT_AV (min)</td>
<td>11.80</td>
<td>13.12</td>
<td>2.66</td>
<td>38.58</td>
<td>11.81</td>
</tr>
<tr>
<td>L_CC (km)</td>
<td>7.65</td>
<td>5.21</td>
<td>1.88</td>
<td>42.91</td>
<td>7.39</td>
</tr>
<tr>
<td>L_CL (km)</td>
<td>7.84</td>
<td>5.47</td>
<td>1.57</td>
<td>43.82</td>
<td>7.30</td>
</tr>
<tr>
<td>L_CO (km)</td>
<td>7.95</td>
<td>5.48</td>
<td>2.33</td>
<td>42.62</td>
<td>7.23</td>
</tr>
<tr>
<td>L_AV (km)</td>
<td>9.18</td>
<td>9.04</td>
<td>1.54</td>
<td>42.29</td>
<td>8.90</td>
</tr>
</tbody>
</table>

### alternative & # times chosen

<table>
<thead>
<tr>
<th>alternative</th>
<th># times chosen</th>
</tr>
</thead>
<tbody>
<tr>
<td>Through CC</td>
<td>13</td>
</tr>
<tr>
<td>Clockwise</td>
<td>53</td>
</tr>
<tr>
<td>Counter-clockwise</td>
<td>51</td>
</tr>
<tr>
<td>Avoid CC</td>
<td>22</td>
</tr>
</tbody>
</table>
Predicted probabilities and elasticity of travel time