Revisiting the Route Choice Problem: 
A Modeling Framework based on Mental Representations

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Agenda

1. Introduction
2. Methodology
3. Case study
4. Conclusion
Introduction

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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.
Motivation

Estimation of RUMs\(^1\) with RP\(^2\) data and path assumption is challenging

Operational limitations
- Data
- Choice set
- Structural correlation

Behavioral limitations

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\(^1\) Random Utility Models.
\(^2\) Revealed Preferences.
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.

  → Mental Representation Item (MRI) = *main modeling element*
Outline of the methodology

1. Definition of the *MRI*:
   1. Empirical evidence through simple qualitative analyzes
   2. Literature review in relevant fields

2. Definition of a RUM model based on *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.

- Strategic decisions.
The *MRI* components

**Perceptual**: a name and a description; **Tangible**: a point and a span

“City center” — Go through the center

“Peripheral” — Avoid the center
Definition of the alternatives

A route is either one-MRI or a sequence-of-MRIs.

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

Issues:

1. How to relate available data to 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*

*Geographical span.*

- 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.*

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.
Specification of utility functions

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.
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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 present one possible way to operationalize the model, taking advantage of the available network model.
Borlänge road network
Borlänge MRI CS

\[ C = \{ 1: \text{through the city center (CC)}, \\
2: \text{clockwise movement around the CC}, \\
3: \text{counter-clockwise movement around the CC}, \\
4: \text{avoid the CC} \} \]
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*
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 MRI choice set

- **chosen alternative (through CC)**
- **around CC alternatives (clock and counter-clockwise)**
- **avoid CC alternative**
Choice model

For the present case, logit can be sufficient:

\[ P_n(i|C) = \frac{e^{\nu_{ni}}}{\sum_{j \in C} e^{\nu_{jn}}} \]
### 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\textsubscript{ AROUND}</td>
<td>-2.11; 1.44; (-1.47)</td>
<td>-0.975; 1.67; (-0.58)</td>
</tr>
<tr>
<td>ASC\textsubscript{ AVOID}</td>
<td>1.87; 2.09; (0.89)</td>
<td>0.307; 1.70; (0.18)</td>
</tr>
<tr>
<td>$\beta \text{ TIME}\textsubscript{CC}$</td>
<td>-0.772; 0.274; (-2.82)</td>
<td></td>
</tr>
<tr>
<td>$\beta \text{ TIME}\textsubscript{(0−10min)}$</td>
<td>-0.286; 0.165; (-1.74)</td>
<td></td>
</tr>
<tr>
<td>$\beta \text{ TIME}\textsubscript{(&gt;10min)}$</td>
<td>-0.616; 0.216; (-2.86)</td>
<td></td>
</tr>
<tr>
<td>$\beta \text{ TIME}\textsubscript{AVOID}$</td>
<td>-0.583; 0.187; (-3.11)</td>
<td>-0.871; 0.173; (-5.03)</td>
</tr>
<tr>
<td>$\beta \text{ LENGTH}$</td>
<td></td>
<td>-0.138; 0.493; (-2.99)</td>
</tr>
<tr>
<td>$\beta \text{ LENGTH}\textsubscript{CC}$</td>
<td>-0.288; 0.130; (2.22)</td>
<td>-0.270; 0.143; (-1.89)</td>
</tr>
<tr>
<td>$\beta \text{ LEFT}$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta \text{ IS}$</td>
<td>-0.0474; 0.022; (-2.16)</td>
<td>-0.063; 0.018; (-3.42)</td>
</tr>
</tbody>
</table>

| Number of observations | 139 | 139 |
| Number of parameters | 8 | 6 |
| $\bar{p}$ | 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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Conclusion

It is possible to have a meaningful model using simple heuristics.

Achievements
- Simple and flexible.
- Behaviorally realistic.

Challenges
- Involved modeling.
- Data processing.
Conclusions

Future steps

1. Traffic assignment.
2. Other model specifications.
3. MRI sequences and additional complexity $\rightarrow$ Quebec GPS dataset
4. Extention using a multiple-level representation.
THANK YOU!
Modeling interurban route choice behavior.

Route choice modeling with network-free data.

Probabilistic multimodal map-matching with rich smartphone data.
*Journal of Intelligent Transportation Systems.*


### 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>
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<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>
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<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>
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<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 choices

<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>
## 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>$\text{ASC}_{CC}$</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$\text{ASC}_{AROUND}$</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>$\text{ASC}_{AVOID}$</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>$\beta \text{TIME}_{CC}$</td>
<td>TT (min)</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$\beta \text{TIME}^{(0-10\text{min})}_{AROUND}$</td>
<td>0</td>
<td>TT (min) $\leq$ 10</td>
<td>TT (min) $\leq$ 10</td>
<td>0</td>
</tr>
<tr>
<td>$\beta \text{TIME}^{(&gt;10\text{min})}_{AROUND}$</td>
<td>0</td>
<td>TT (min) $&gt; 10$</td>
<td>TT (min) $&gt; 10$</td>
<td>0</td>
</tr>
<tr>
<td>$\beta \text{TIME}_{AVOID}$</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>TT (min)</td>
</tr>
<tr>
<td>$\beta \text{LEFT}$</td>
<td># left turns</td>
<td># left turns</td>
<td># left turns</td>
<td># left turns</td>
</tr>
<tr>
<td>$\beta \text{IS}$</td>
<td># intersections</td>
<td># intersections</td>
<td># intersections</td>
<td># intersections</td>
</tr>
</tbody>
</table>
Appendix

Power series of degree 3 for the travel time

![Graph showing the utility for different travel times with a power series of degree 3. The x-axis represents travel time in minutes ranging from 0 to 40, and the y-axis represents utility ranging from -30 to 0. The curve descends as travel time increases, indicating a decreasing utility.]
Power series of degree 3 for the length
## 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_{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_{LENGTH_{CC}} )</td>
<td>Length (km)</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>( \beta_{LENGTH} )</td>
<td>0</td>
<td>Length (km)</td>
<td>Length (km)</td>
<td>Length (km)</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>
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 the sum spans the alternatives in the MRI models, $P(i|C)$ is the MRI-choice model, and $P(p|i)$ is the probability of path $p$ to be actually used by a traveler who has chosen the sequence of MRIs $i$. 

Traffics assignment
Application

Route guidance

Provision of information in an aggregate manner:

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

\(^3\text{Variable message signs.}\)
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
\[
\bar{P}_\ell(i|C_\ell; \beta^\ell) = \sum_{j \in C_{\ell+1}} P(i|j, C_\ell; \beta^\ell)P(j|C_{\ell+1}; \beta^{\ell+1})
\]