# 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

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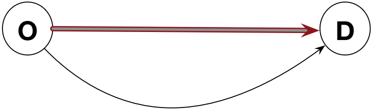
# Route choice (RC)

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.

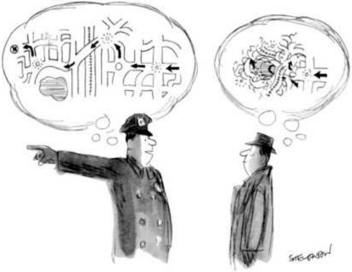
# Motivation

*Estimation of RUMs[1] with RP[2] data and path assumption is challenging*

## Operational limitations

- Data
- Choice set
- Structural correlation


## Behavioral limitations



[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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# Backbone of the framework

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.

$\rightarrow$ 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 $\mathcal{C}_n$
    2. Explanatory variables $x_{in}, z_n$
    3. Specification of the deterministic utility function $V_{in}$
    4. Assumption about the error terms $\varepsilon_{in}$

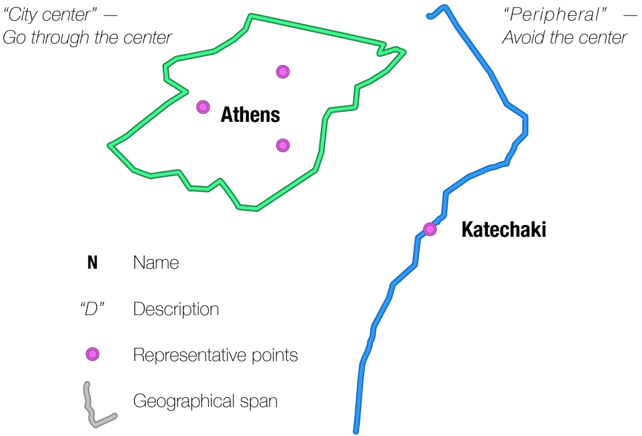
# Mental Representation Item (*MRI*)

- *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*



# 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.

$\rightarrow$ 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:

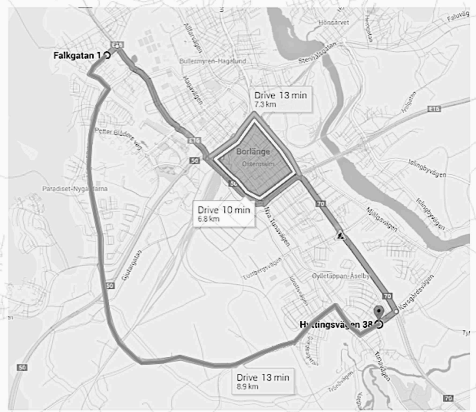
1. 3077 nodes and 7459 unidirectional links
2. Link travel times
3. Clear choices

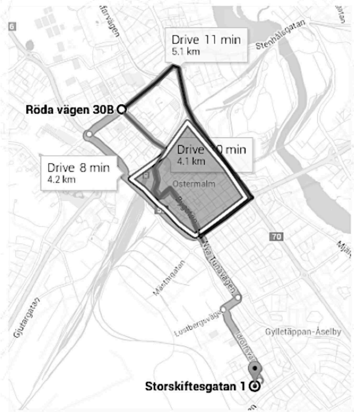
- We use a sample of 139 observations.
- We present one possible way to operationalize the model, taking advantage of the available network model.

# Borlänge road network

# Borlänge *MRI* CS

$$\mathcal{C} = \{ \begin{array}{ll} \mathit{1:} & \mathit{through\ the\ city\ center\ (CC),} \\ \mathit{2:} & \mathit{clockwise\ movement\ around\ the\ CC,} \\ \mathit{3:} & \mathit{counter\text{-}clockwise\ movement\ around\ the\ CC,} \\ \mathit{4:} & \mathit{avoid\ the\ CC} \end{array} \}$$



# Example of observed routes (1)

*Around the CC movements*

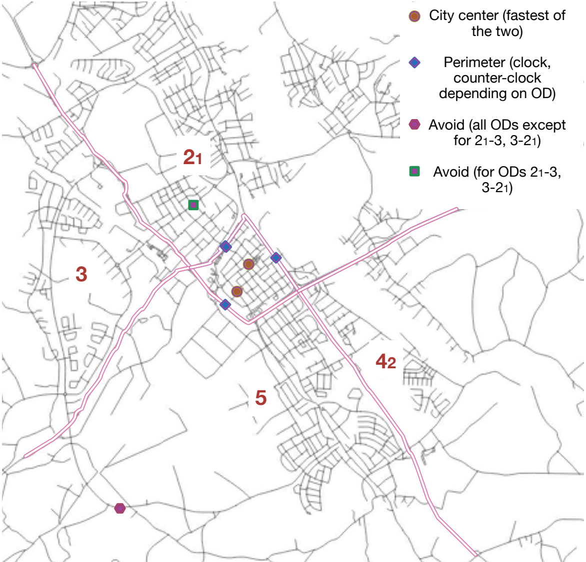
# Example of observed routes (2)

*Avoid the CC alternatives*

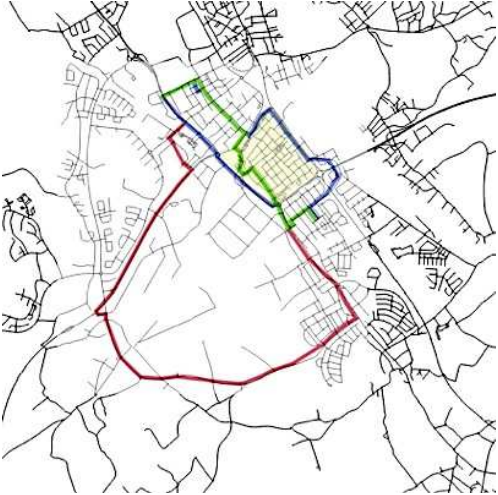
# Example of observed routes (3)

*Through the CC movements*

# Representative nodes



# 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:

$$\mathcal{P}_n(i|\mathcal{C}) = \frac{e^{\mathcal{V}_{ni}}}{\sum_{j \in C} e^{\mathcal{V}_{jn}}}$$

# Estimation results

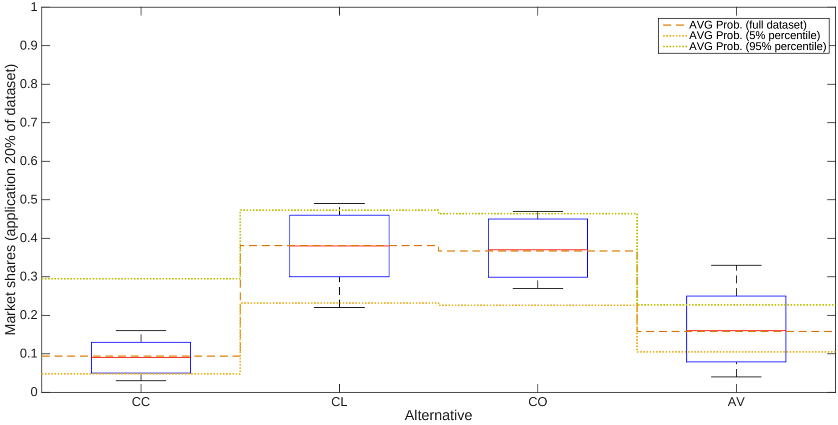
| Parameters | **Model** 1<br>Parameter value; Rob. Std<br>(Rob. $t$-test 0) | **Model** 2<br>Parameter value; Rob. Std<br>(Rob. $t$-test 0) |
|---|---|---|
| $ASC_{AROUND}$ | **-2.11**; 1.44; **(-1.47)** | **-0.975**; 1.67; **(-0.58)** |
| $ASC_{AVOID}$ | **1.87**; 2.09; **(0.89)** | **0.307**; 1.70; **(0.18)** |
| $\beta\, TIME_{CC}$ | **-0.772**; 0.274; **(-2.82)** | |
| $\beta\, TIME_{AROUND}^{(0-10min)}$ | **-0.286**; 0.165; **(-1.74)** | |
| $\beta\, TIME_{AROUND}^{(>10min)}$ | **-0.616**; 0.216; **(-2.86)** | |
| $\beta\, TIME_{AVOID}$ | **-0.583**; 0.187; **(-3.11)** | |
| $\beta\, LENGTH$ | | **-0.871**; 0.173; **(-5.03)** |
| $\beta\, LENGTH_{CC}$ | | **-1.48**; 0.493; **(-2.99)** |
| $\beta\, LEFT$ | **-0.288**; 0.130; **(2.22)** | **-0.270**; 0.143; **(-1.89)** |
| $\beta\, IS$ | **-0.0474**; 0.022; **(-2.16)** | **-0.063**; 0.018; **(-3.42)** |
| **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.

$\rightarrow$ 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.

# Future steps

1. Traffic assignment.
2. Other model specifications.
3. *MRI* sequences and additional complexity → `Quebec GPS dataset`
4. Extention using a multiple-level representation.

THANK YOU!

# Bibliography I


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Modeling interurban route choice behavior.
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*Transportation Research Part C: Emerging Technologies*, 16(2):187–198.

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*Transportation Research Part B: Methodological*, 41(3):363–378.

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*Normative Pedestrian Flow Behavior, Theory and Applications*.
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# Descriptive statistics of the main variables

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

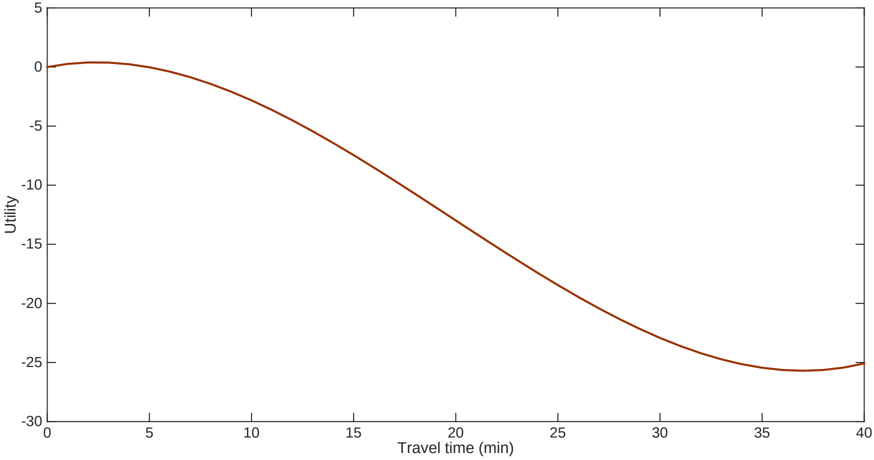
| alternative | # times chosen |
|---|---|
| Through CC | 13 |
| Clockwise | 53 |
| Counter-clockwise | 51 |
| Avoid CC | 22 |

# Specification table of model 1

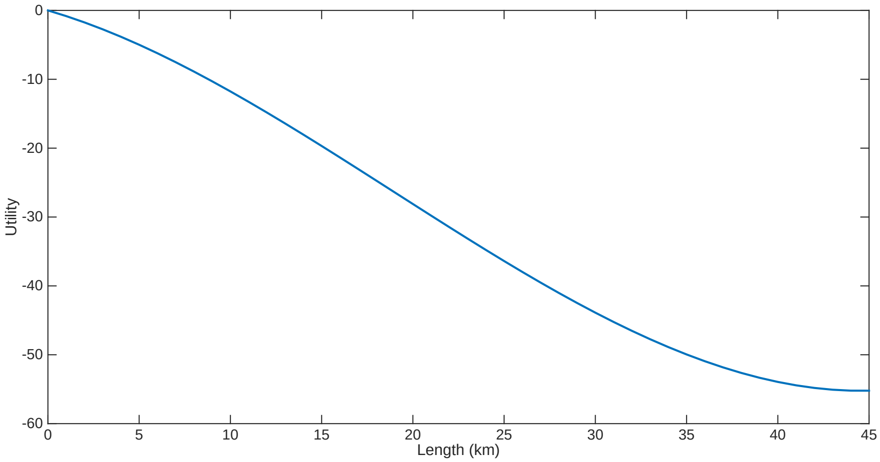
*Piecewise linear travel time for the around alternatives*

| Parameter name | Through CC | Around clock CC | Around counter CC | Avoid CC |
|---|---|---|---|---|
| $ASC_{CC}$ | 0 | 0 | 0 | 0 |
| $ASC_{AROUND}$ | 0 | 1 | 1 | 0 |
| $ASC_{AVOID}$ | 0 | 0 | 0 | 1 |
| $\beta\,TIME_{CC}$ | TT (min) | 0 | 0 | 0 |
| $\beta\,TIME_{AROUND}^{(0-10min)}$ | 0 | TT (min) $\leq 10$ | TT (min) $\leq 10$ | 0 |
| $\beta\,TIME_{AROUND}^{(>10min)}$ | 0 | TT (min) $> 10$ | TT (min) $> 10$ | 0 |
| $\beta\,TIME_{AVOID}$ | 0 | 0 | 0 | TT (min) |
| $\beta\,LEFT$ | # left turns | # left turns | # left turns | # left turns |
| $\beta\,IS$ | # intersections | # intersections | # intersections | # intersections |

# Power series of degree 3 for the travel time



# Power series of degree 3 for the length



# Specification table of model 2

## *Length*

| Parameter name | Through CC | Around clock CC | Around counter CC | Avoid CC |
|---|---|---|---|---|
| $ASC_{CC}$ | 0 | 0 | 0 | 0 |
| $ASC_{AROUND}$ | 0 | 1 | 1 | 0 |
| $ASC_{AVOID}$ | 0 | 0 | 0 | 1 |
| $\beta LENGTH_{CC}$ | Length (km) | 0 | 0 | 0 |
| $\beta LENGTH$ | 0 | Length (km) | Length (km) | Length (km) |
| $\beta LEFT$ | # left turns | # left turns | # left turns | # left turns |
| $\beta IS$ | # intersections | # intersections | # intersections | # intersections |

# Application

*Traffic assignment*

1. Metropolis-Hastings (MH) algorithm [Flötteröd and Bierlaire, 2013] to sample paths given the OD and $\mathcal{C}$.

2. The probability of each *path* $p$ to be selected, given the OD and $\mathcal{C}$, is:

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

   where the sum spans the alternatives in the *MRI* models, $P(i|\mathcal{C})$ 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* $i$.

# Application

*Route guidance*

Provision of information in an aggregate manner:

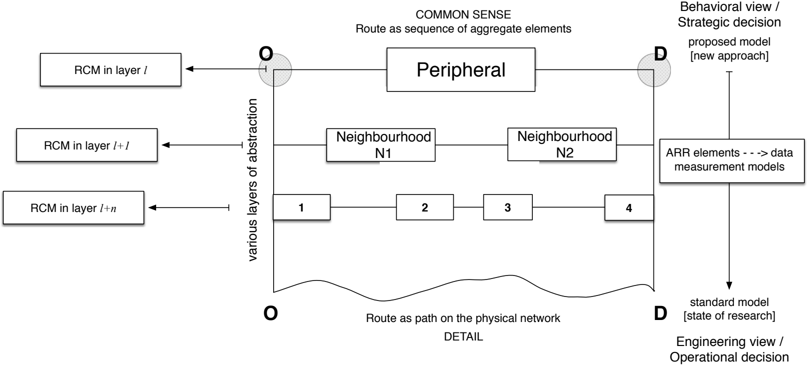
1. Guidance on VMS[3]
2. Radio announcements
3. Oral instructions in in-vehicle navigation systems

[3] 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* $\mathcal{C}_\ell$.
- Choice model:

$$P_\ell(i|\mathcal{C}_\ell; \beta^\ell)$$

### Layer $\ell + 1$

- Choice set: list of *MRIs* $\mathcal{C}_{\ell+1}$.
- Choice model:

$$P_{\ell+1}(i|\mathcal{C}_{\ell+1}; \beta^{\ell+1})$$

### Behavioral consistency

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

### Structural consistency

$$\bar{P}_\ell(i|\mathcal{C}_\ell; \beta^\ell) = \sum_{j \in \mathcal{C}_{\ell+1}} P(i|j, \mathcal{C}_\ell; \beta^\ell) P(j|\mathcal{C}_{\ell+1}; \beta^{\ell+1})$$