Application of the MRI framework to a large network: Québec city

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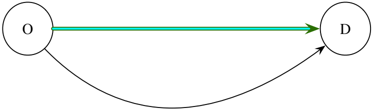
Agenda

1. Preamble
2. Modeling
3. Results
4. Conclusion

Agenda

Route choice

Identify the route that a traveler would choose to go from the origin (O) to the destination (D).



- Key travel demand model.
- At the core of traffic assignment.
- Off-line and real time services and applications:
  - Decision-aid tools and transportation policies.
  - Real time operations and *route guidance*.

$\rightarrow$ **Random utility models**

- Understand, describe and predict route choice behavior.

Towards aggregate route choice

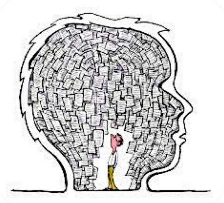
How can we represent a route in a behaviorally realistic way without increasing the model complexity?

→ Model the strategic decisions of people.

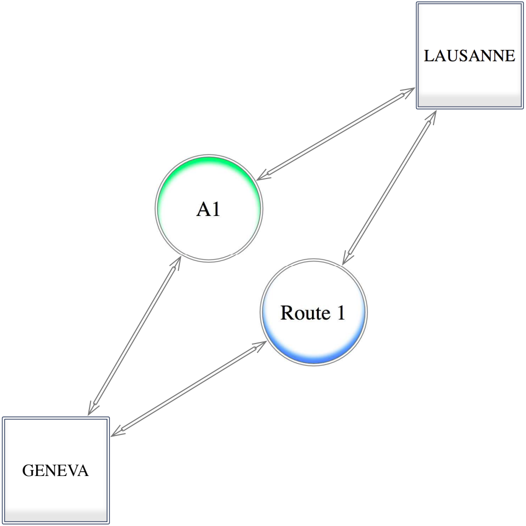
⋆ **Mental Representation Item (MRI)**

1. Kazagli, E., Bierlaire, M., and de Lapparent, M. (2017). Operational route choice methodologies for practical applications. Technical report TRANSP-OR, ENAC, EPFL.

2. Kazagli, E., Bierlaire, M., and Flötteröd, G. (2016). Revisiting the Route Choice Problem: A Modeling Framework Based on Mental Representations, Journal of Choice Modelling 19:1-23.



A trivial example of a `MRI` model



Objective

Application of the MRI framework to a large network.

1. Additional complexity in the definition of the model due to the size of the city of interest.
2. Lack of a detailed disaggregate network model.

Goals

Conceptual model that is realistic and meaningful.

1. Operationalization using simple techniques.
    1. Definition and operationalization of the aggregate graph.
    2. Concrete specifications: compatible with the standard estimation procedures.
2. Application to aggregate route choice analysis.
    1. Québec city.
    2. Prediction of flows on the major segments of the network.

Agenda

Considerations

Operational aspects of the aggregate model

1. Path-based specification of utilities
   1. Representative points $\rightarrow$ representative paths.
   2. Sensitivity of model parameters.
2. “Path-free” approach
   1. Elimination of representative points/ paths.
   2. Less dependent on detailed network data.
   3. Low structural model complexity and computational times.

Dataset

- Québec city.
- Montrajet smartphone application (McGill university)[1],[2]
- Data collection: April 25 to May 16, 2014.
- GPS trajectories of more around 4000 individuals.
- More than 20000 trips.

- Trip purpose.
- Departure time.

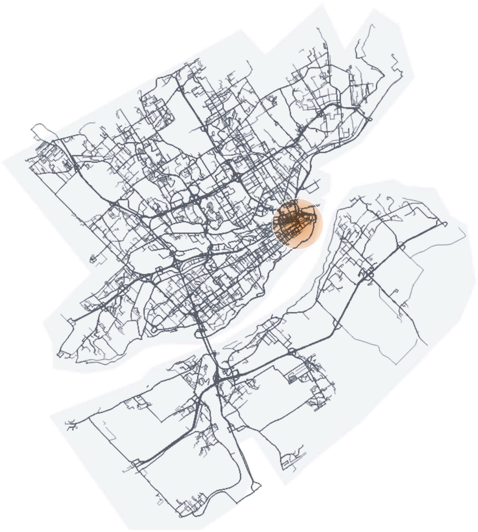
[1] Mirando-Moreno L.F., Chung C., Amyot D., Chappon H. (2014), A system for collecting and mapping traffic congestion in a network using GPS smartphones from regular drivers.

[2] Stipancic, J., Miranda-Moreno, L. and Saunier, N. (2017). The impact of congestion and traffic flow on crash frequency and severity: An application of smartphone-collected gps travel data, Technical report.

Québec city

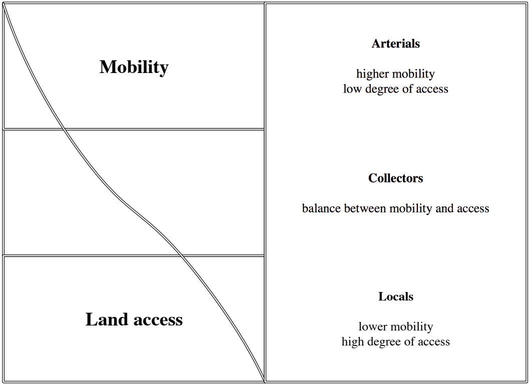
Origins and destinations in the data sample (2321 trips)

Observed trajectories

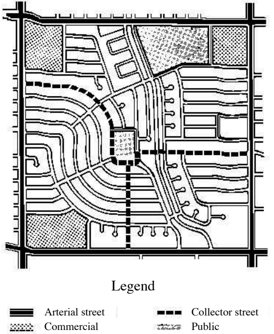


Most visited segments

Mobility vs accessibility

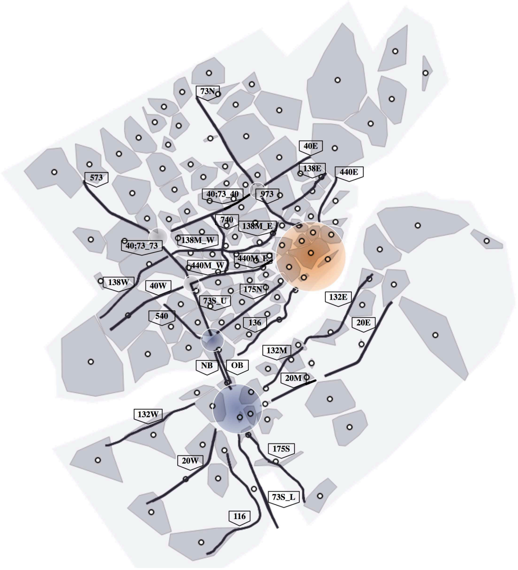


Schematic of a Portion
of an
Urban Street Network

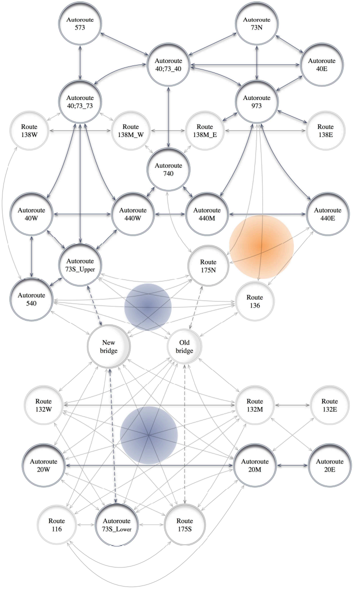


Source: Grant Benjamin, *"Grand Reductions: 10 Diagrams That Changed City Planning"*, The Urbanist, Issue 518, November 2012, SPUR Ideas + Action for a Better City

Geographical span and *OD* zones

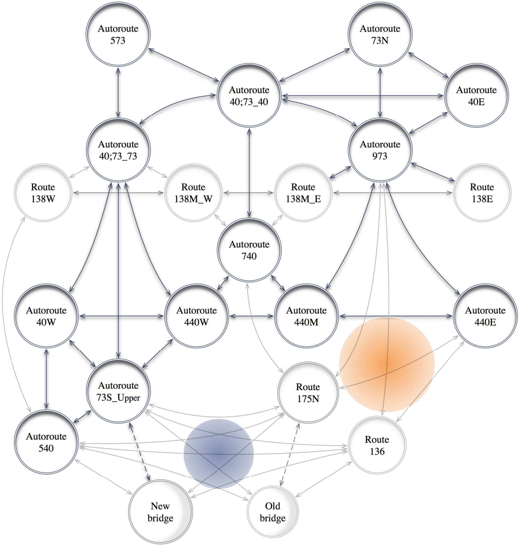


The $G^{\mathcal{M}}$ of Québec city as a dual graph



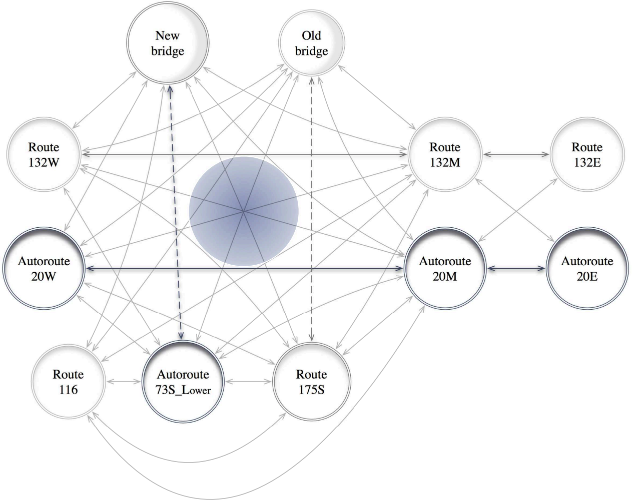
Québec city: upper side

Dual graph



Québec city: lower side

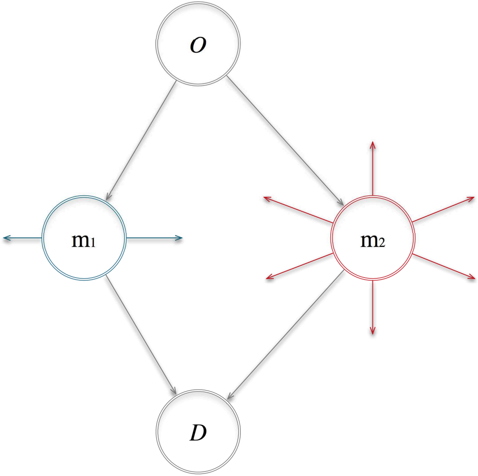
Dual graph



The MRIs attributes

MRI	travel time [min]	motorway	primary	# of connections c_m	measure of entropy $log_2(c_m)$	measure of entropy $log_2(c_m - 1)$
40E	1.83	1	0	3	1.58	1.00
40W	2.87	1	0	4	2.00	1.58
73N	3.53	1	0	3	1.58	1.00
73S_Upper	2.04	1	0	8	3.00	2.81
4073_40	2.15	1	0	6	2.58	2.32
4073_73	1.46	1	0	7	2.81	2.58
573	2.86	1	0	2	1.00	0.00
440E	1.78	1	0	4	2.00	1.58
440M	1.38	1	0	4	2.00	1.58
440W	1.22	1	0	5	2.32	2.00
740	2.43	1	0	6	2.58	2.32
540	1.89	1	0	7	2.81	2.58
973	2.54	1	0	9	3.17	3.00
175N	5.46	0	1	7	2.81	2.58
138E	3.17	0	1	2	1.00	0.00
138M_E	3.15	0	1	4	2.00	1.58
138M_W	2.63	0	1	4	2.00	1.58
138W	4.49	0	1	3	1.58	1.00
136	5.31	0	1	6	2.58	2.32
NB	1.55	1	0	11	3.46	3.32
OB	2.38	0	1	11	3.46	3.32
20E	3.52	1	0	2	1.00	0.00
20M	1.39	1	0	9	3.17	3.00
20W	3.65	1	0	6	2.58	2.32
132E	7.06	0	1	2	1.00	0.00
132M	3.78	0	1	9	3.17	3.00
132W	4.77	0	1	6	2.58	2.32
73S_Lower	3.86	0	1	8	3.00	2.81
175S	4.60	0	1	8	3.00	2.81
116	6.81	0	1	6	2.58	2.32

Illustration of a simple (m_1) and a complex (m_2) node



Gallotti, R., Porter, M. A. and Barthelemy, M. (2016). Lost in transportation: Information measures and cognitive limits in multilayer navigation, Science Advances 2(2).

Estimation approach: link-based formulation

Recursive Logit (RL) (Fosgerau et al., 2013)

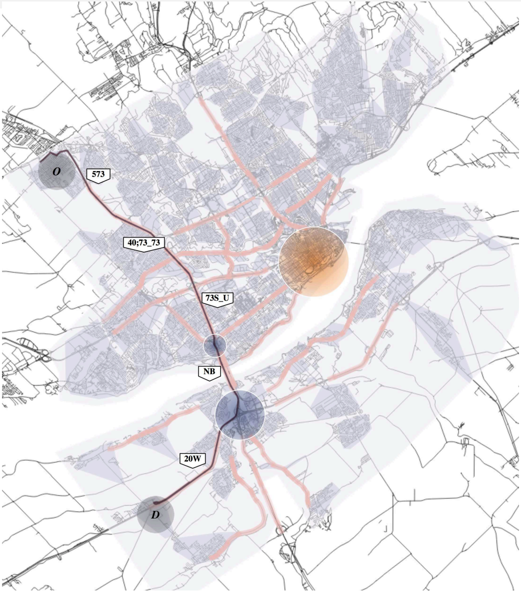
1. Sequential link choice in a dynamic framework.
2. Consistently and efficiently estimated on the full choice set of paths without sampling of alternatives.
3. Equivalent to a multinomial logit.
4. Directly applicable to compute link flows.

Overview of the RL model

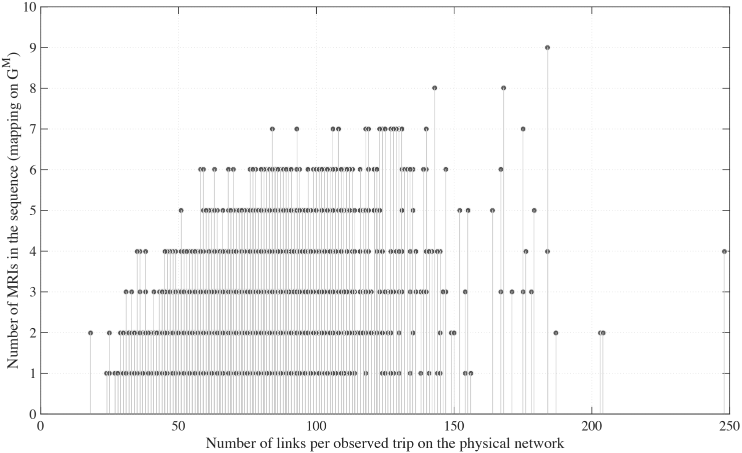
A state corresponds to a node m in $G^{\mathcal{M}}$

1. At each state m the traveler chooses the next state ν that maximizes the sum of the instantaneous utility $u_n(\nu \mid m)$ and the expected downstream utility $V^{D'}(m)$ to the destination D, where:
   1. $u_n(\nu \mid m) = v_n(\nu \mid m) + \mu\varepsilon_n(\nu)$, and
   2. $V^{D'}(m) = \mu ln \sum_{\nu \in \mathcal{M}} \delta(\nu \mid m) e^{\frac{1}{\mu}(v_n(\nu \mid m) + V^{D'}(\nu))} \forall m \in \mathcal{M}$.
2. Output: *destination specific* state transition probabilities $P^{D'}(\nu \mid m)$.
3. Choice probabilities given by the logit model.
4. `MRI` element flows: $F(\nu) = G(\nu) + \sum_{m \in \mathcal{M}} P^{D'}(\nu \mid m) \cdot F^{D'}$, computed by solving $(I - P^T)F = G$.

Observed trajectory and its mapping on $G^{\mathcal{M}}$



Observed number of links in G vs number of nodes in $G^{\mathcal{M}}$



Agenda

Model specifications

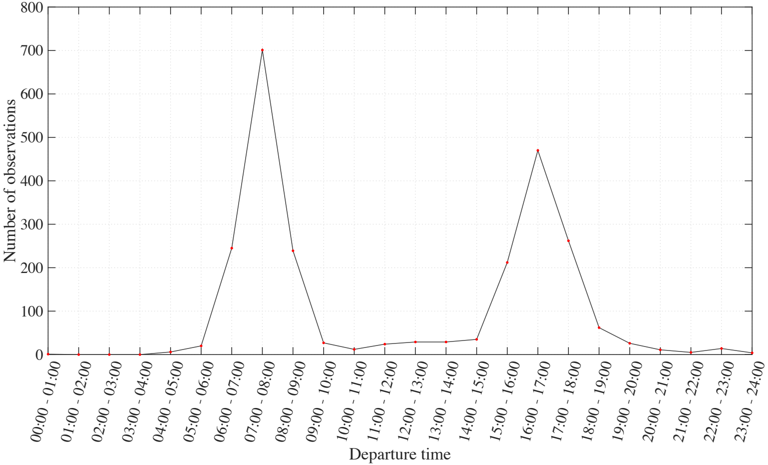
$$v(\nu \mid m) = \beta_{time}\ \text{Time}(\nu) + \beta_{TransferTime}\ \text{TransferTime}(\nu \mid m). \tag{1}$$

$$\begin{aligned} v(\nu \mid m) = \beta_{time,Motor}\ \text{Time}(\nu)\ \text{Motorway}(\nu) + \beta_{time,Prim}\ \text{Time}(\nu)\ \text{Primary}(\nu) + \\ +\beta_{TransferTime}\ \text{TransferTime}(\nu \mid m). \end{aligned} \tag{2}$$

$$\begin{aligned} v(\nu \mid m) = \beta_{time,Motor}\ \text{Time}(\nu)\ \text{Motorway}(\nu) + \beta_{time,Prim}\ \text{Time}(\nu)\ \text{Primary}(\nu) + \\ +\beta_{TransferTime}\ \text{TransferTime}(\nu \mid m) + \beta_{Load}\ \text{CognitiveLoad}(\nu). \end{aligned} \tag{3}$$

$$\begin{aligned} v(\nu \mid m) = \beta_{time,Motor,Off}\ \text{Time}(\nu)\ \text{Motorway}(\nu)\ \text{OffPeak}_n + \\ +\beta_{time,Motor,Peak}\ \text{Time}(\nu)\ \text{Motorway}(\nu)\ \text{Peak}_n + \\ +\beta_{time,Prim,Off}\ \text{Time}(\nu)\ \text{Primary}(\nu)\ \text{OffPeak}_n + \\ +\beta_{time,Prim,Peak}\ \text{Time}(\nu)\ \text{Primary}(\nu)\ \text{Peak}_n + \\ +\beta_{TransferTime}\ \text{TransferTime}(\nu \mid m) + \\ +\beta_{Load}\ \text{CognitiveLoad}(\nu). \end{aligned} \tag{4}$$

Distribution of departure time in the data sample

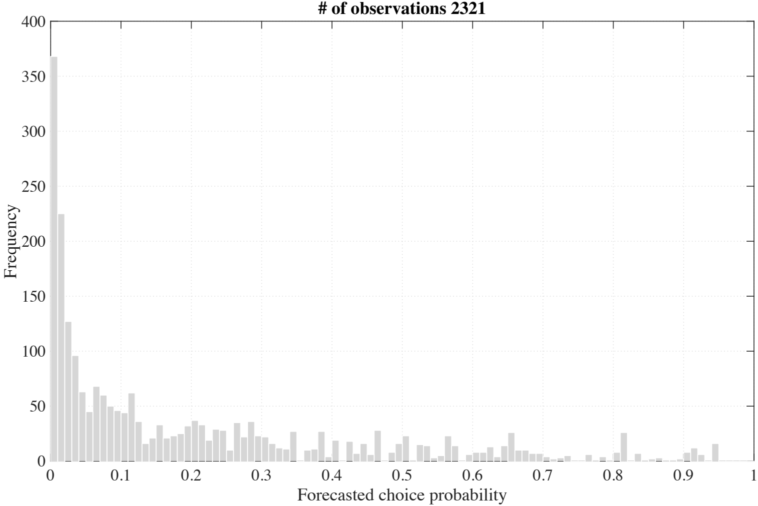


Estimation results

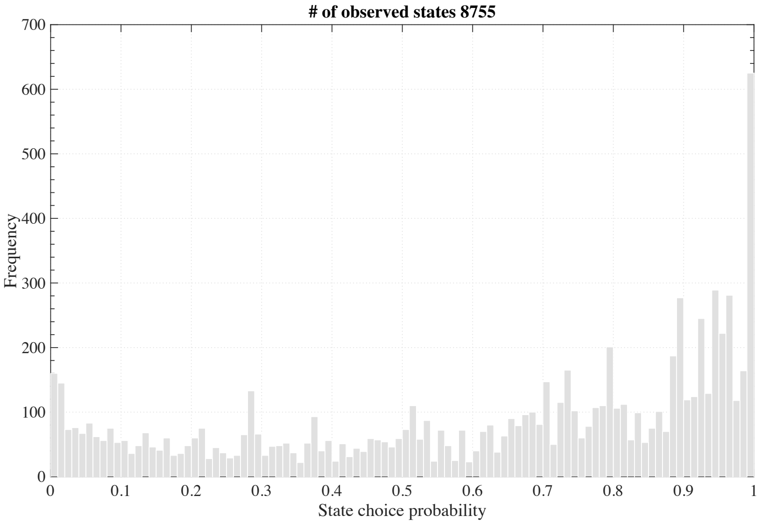
Parameter	Model 1 value (t-test)	Model 2 value (t-test)	Model 3 value (t-test)	Model 4 value (t-test)
$\beta_{TransferTime}$	-0.56 (-72.17)	-0.58 (-78.62)	-0.54 (-72.04)	-0.54 (-72.10)
β_{time}	-1.12 (-152.25)	$\times$	$\times$	$\times$
$\beta_{time,Motor}$	$\times$	-1.24 (-148.41)	-0.50 (-28.94)	$\times$
$\beta_{time,Prim}$	$\times$	-0.85 (-75.39)	-0.52 (-38.37)	$\times$
$\beta_{time,Motor,OffPeak}$	$\times$	$\times$	$\times$	-0.70 (-40.68)
$\beta_{time,Motor,Peak}$	$\times$	$\times$	$\times$	-0.48 (-25.60)
$\beta_{time,Prim,OffPeak}$	$\times$	$\times$	$\times$	-0.51 (-27.78)
$\beta_{time,Prim,Peak}$	$\times$	$\times$	$\times$	-0.54 (-25.28)
β_{Load}	$\times$	$\times$	-0.70 (-40.65)	-0.51 (-32.95)
# observations	2321	2321	2321	2321
# parameters	2	3	4	6
$\mathcal{LL}(\hat{\beta})$	-8145.1	-7593.6	-6935.0	-6930.7
Estimation time (min)	2.5	3.1	4.0	7.2

Forecasted choice probabilities (Model 4)

`20% <= 0.01, 10% <= 0.001`

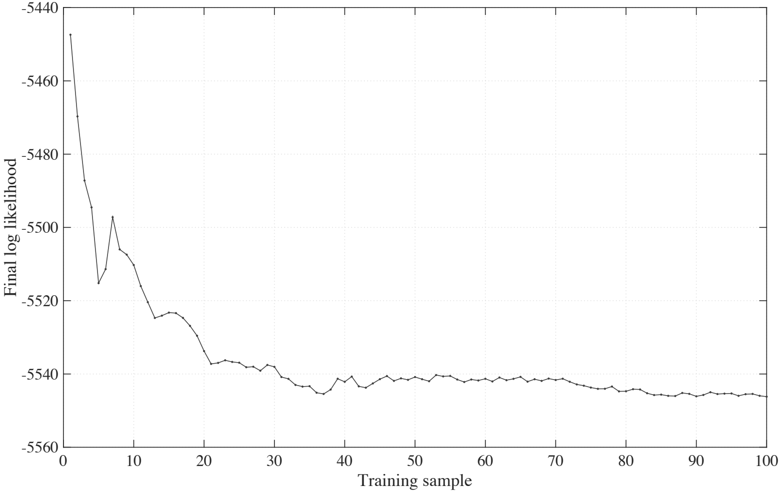


State choice probabilities (Model 4)



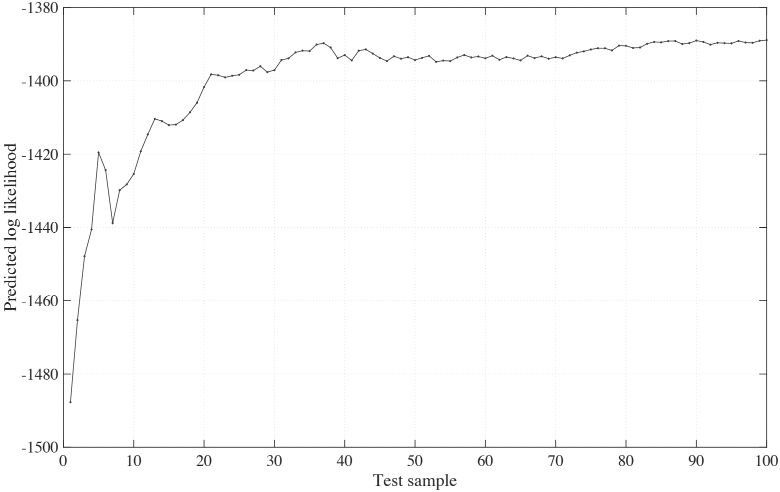
Model validation

Final log likelihood of the training samples



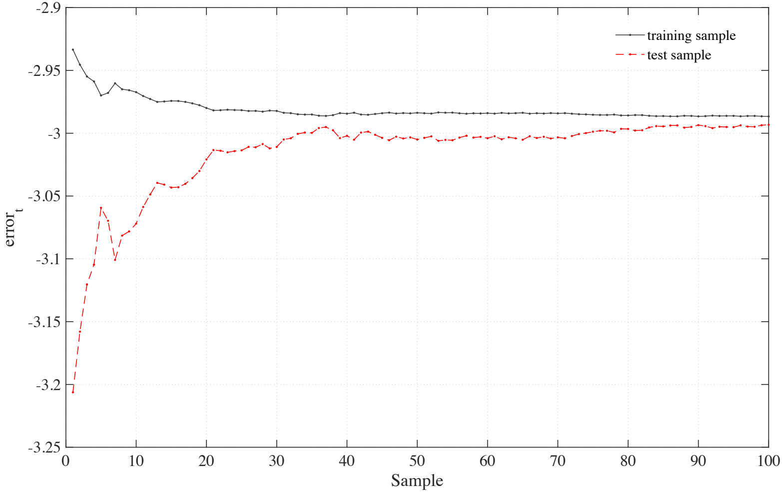
Model validation

Predicted log likelihood of the test samples



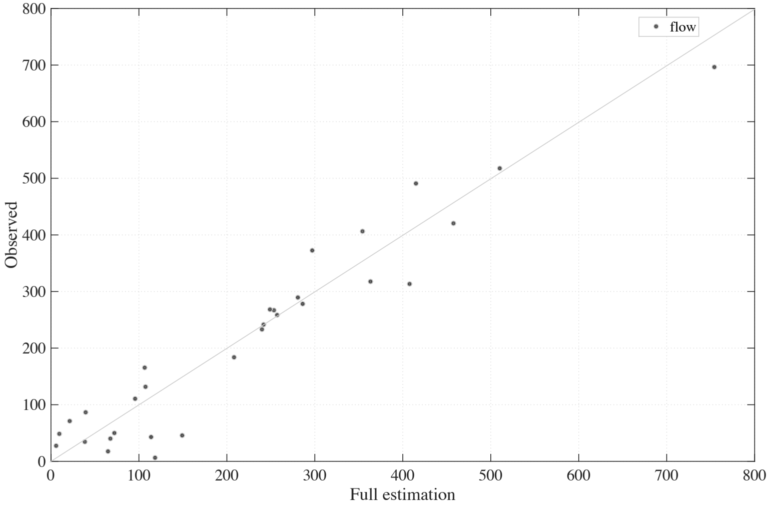
Log likelihood loss

Avg. error over the samples $\overline{err}_t = \frac{1}{t}\sum_{s=1}^{t}\left[\frac{1}{|S_s|}\sum_{i\in S_s} lnP(i,\beta_s)\right]\ \forall\ t = 1,\dots,\ 100$



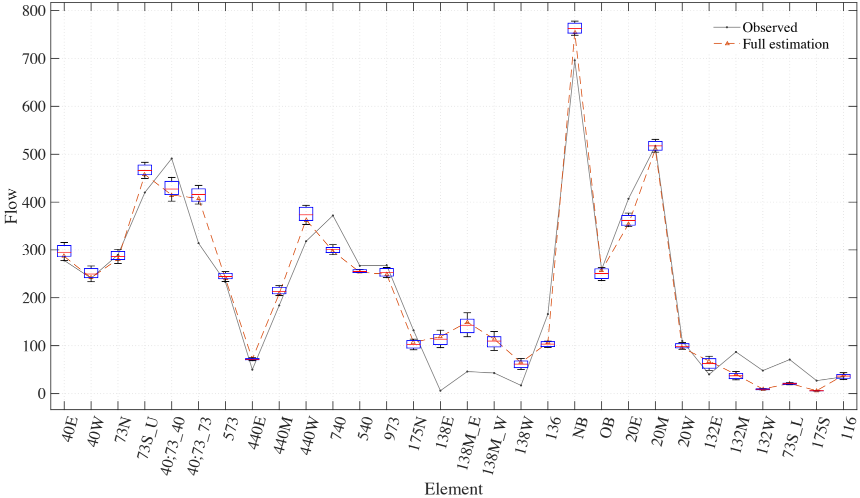
Model application

Aggregate element flows



Model application

Boxplot of aggregate element flows over the samples



Agenda

Conclusion

1. Generalization of the applicability of the `MRI` framework.
2. Operational challenges related to the specification of the utility functions are tackled.
3. Not as simple as the first model, yet of much lower structural complexity in comparison with the disaggregate approach.
4. Insightful understanding and description of the aggregate route choice of individuals.
5. Readily applied to the prediction of flows on the major segments of the network.

    ⋆ Compatible with route guidance.

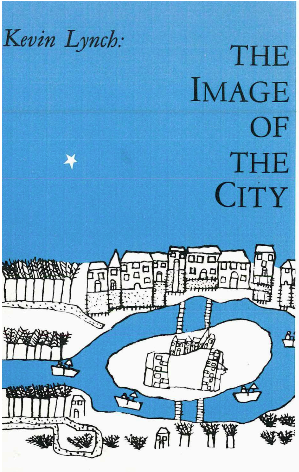
    ⋆ Motivates and can benefit from new data collection approaches.

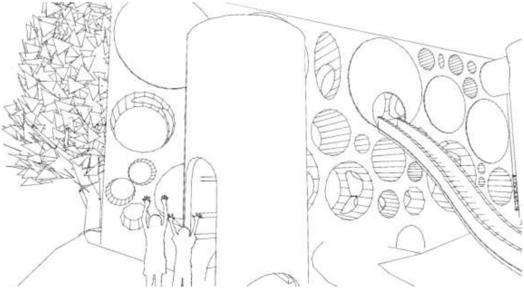
Future work

1. Application to more cities.
2. Application to pedestrian route choice in major hubs.
3. Investigate extensions to macroscopic traffic assignment.

Legibility

"In the process of way-finding, the strategic link is the environmental image, the generalized mental picture of the exterior physical world that is held by the individual. This image is the product both of immediate sensation and of the memory of past experience, and it is used to interpret information and to guide action. The need to recognize and pattern our surroundings is so crucial, and has such long roots in the past, that this image has wide practical and emotional importance to the individual."





Thank you!

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