

Estimation of choice models in dynamic traffic simulations

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Outline

Introduction

A macroscopic path flow estimator

A microscopic behavioral estimator

Application to DRACULA

Application to MATSim

Summary, outlook

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A macroscopic path flow estimator

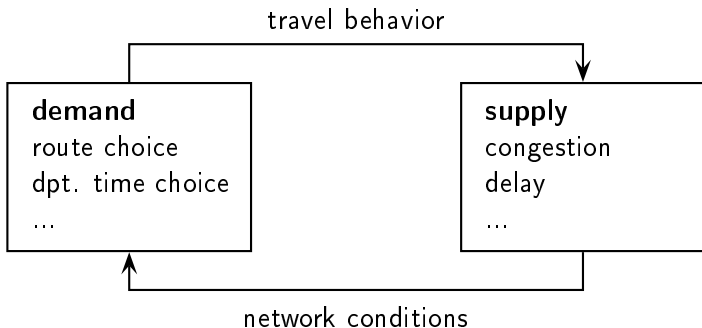
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Summary, outlook

Iterated DTA microsimulations



- account for arbitrary demand dimensions
- capture arbitrary demand heterogeneity
- handle complex and large systems

Calibration of iterated DTA microsimulations

- OD matrix / path flow estimation is of limited use
 - cannot estimate all demand dimensions
 - hardly accounts for demand heterogeneity
 - computationally involved
- supply calibration: not the topic of this talk

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Prior path flows

- a minimum of notation

n origin/destination (OD) pair, $n = 1 \dots N$
 d_n number of trips between OD pair n
 C_n set of available routes for OD pair n
 d_{ni} number of trips on route $i \in C_n$

- path flows $\mathbf{d} = (d_{ni})$ are consistent with network conditions

$$d_{ni} = P_n(i|\mathbf{d})d_n \quad \forall n, i \in C_n$$

where $P_n(i|\mathbf{d})$ is the congestion-dependent route choice model

Derivation of estimator

1. consistent path flows maximize **prior entropy function**

$$W(\mathbf{d}) = \sum_{n=1}^N \sum_{i \in C_n} d_{ni} \ln \frac{P_n(i|\mathbf{d})}{d_{ni}}$$

2. relate traffic counts \mathbf{y} to path flows \mathbf{d} through likelihood $p(\mathbf{y}|\mathbf{d})$
3. path flows given counts maximize **posterior entropy function**

$$W(\mathbf{d}|\mathbf{y}) = \ln p(\mathbf{y}|\mathbf{d}) + W(\mathbf{d})$$

4. evaluate optimality conditions...

Posterior path flows

- route choice model given the traffic counts \mathbf{y} fulfills

$$P_n(i|\mathbf{d}, \mathbf{y}) \sim \exp\left(\frac{\partial \ln p(\mathbf{y}|\mathbf{d})}{\partial d_{ni}}\right) P_n(i|\mathbf{d})$$

- replace iterative optimization by path flow distribution scaling
- apart from local linearizability, no modeling assumptions

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Reinterpretation of the macroscopic setting

- notation, revisited

n individual traveler, $n = 1 \dots N$

d_n number of repeated choice situations

C_n set of available **travel plans** for individual n

d_{ni} number of times traveler n chooses plan $i \in C_n$

$P_n(i|\mathbf{d})$ congestion-dependent plan choice distribution

- estimation: select plans from **posterior choice distribution**

$$P_n(i|\mathbf{d}, \mathbf{y}) \sim \exp\left(\frac{\partial \ln p(\mathbf{y}|\mathbf{d})}{\partial P_n(i|\mathbf{d}, \mathbf{y})}\right) P_n(i|\mathbf{d})$$

...as before!

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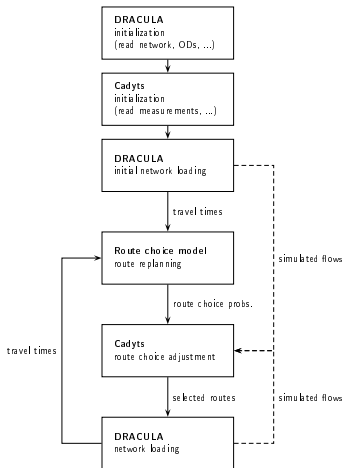
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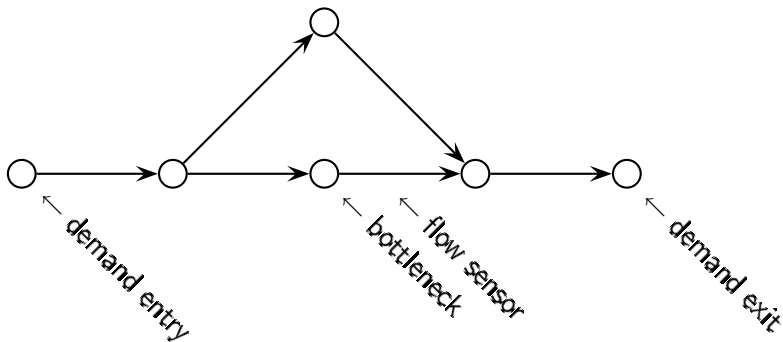
Application to DRACULA



- file-based interaction via Python script
- in every iteration
 1. route choice model computes choice probs.
 2. Cadyts^a writes chosen routes
 3. DRACULA writes travel times

^a“Calibration of dynamic traffic simulations”, see transp-or2.epfl.ch/cadyts/

Test case: network



- route length difference is 1 km
- free-flow travel time difference is 23 s

Test case: choice model

- choice model:
 - stay at home with prob. P_0 (used $\approx 0.091 \Rightarrow$ little variability)
 - otherwise, choose route according to logit model
- formally:

$$P(\text{stay at home}) = P_0$$

$$P(\text{take route } i) = (1 - P_0) \frac{\exp(\beta t_i)}{\sum_j \exp(\beta t_j)}$$

where

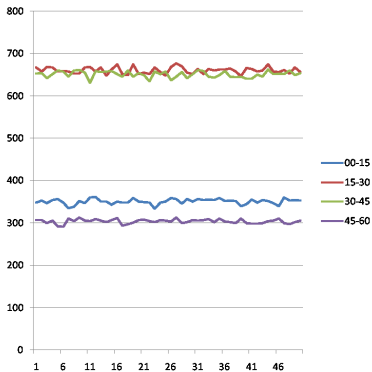
- β captures sensitivity to travel time (used $-0.01 \text{ s}^{-1} \Rightarrow$ fair variability)
- t_i is travel time along route i in previous iteration

Results in numbers

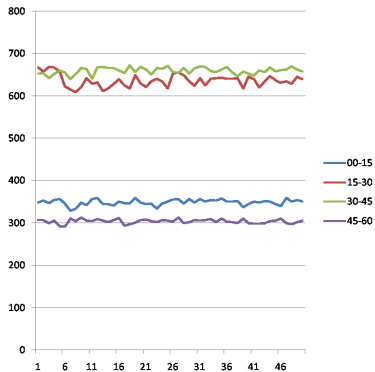
flow[veh] \ time	0:00-0:15	0:15-0:30	0:30-0:45	0:45-1:00
sim. demand	351	659	653	303
sim. sensor flow	164	297	321	212
“real” sensor data	–	200	450	–
estim. demand	350	639	662	303
estim. sensor flow	164	188	331	225

- all values averaged over 15 iterations
- for now, replace significance test by visual inspection ...

Results: demand dynamics

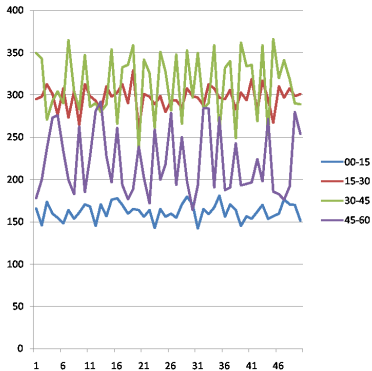


simulated demand over iterations

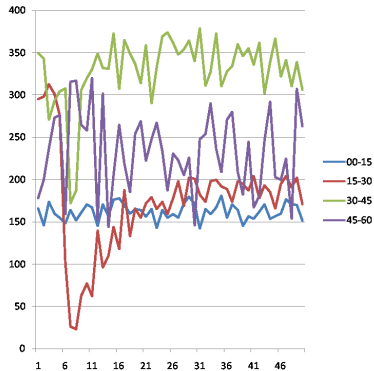


estimated demand over iterations

Results: sensor flow dynamics

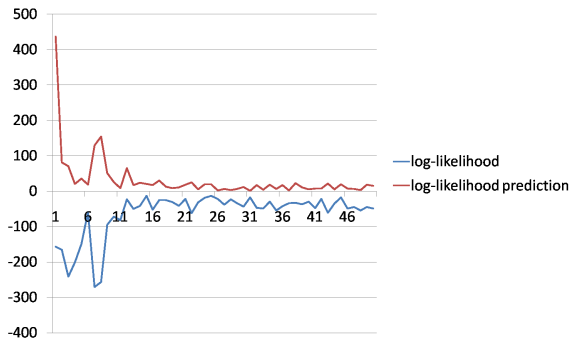


simulated flow over iterations



estimated flow over iterations

Results: dynamics of log-likelihood



(predicted) log-likelihood over iterations

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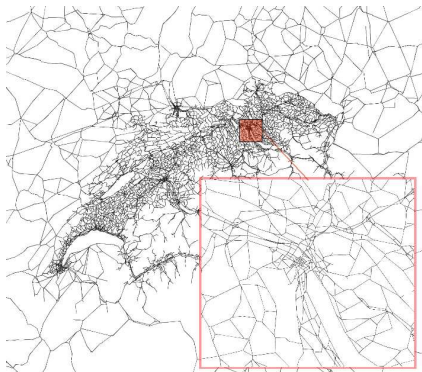
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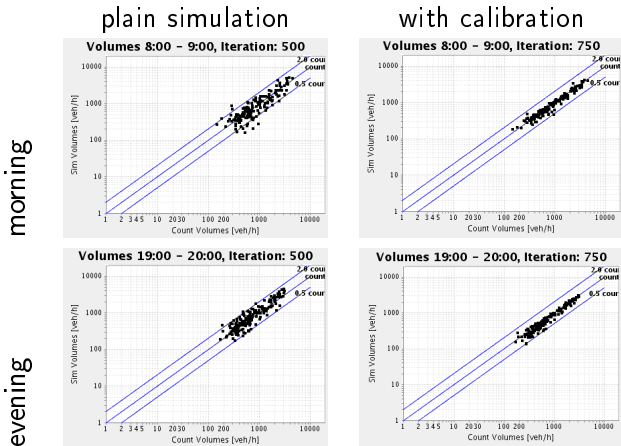
Summary, outlook

Zurich case study



- network with 60 492 links and 24 180 nodes
- 187 484 agents
- hourly counts from 161 counting stations
- jointly estimate route + dpt. time + mode choice

Results: qualitatively



Results: quantitatively

	reproduction (\cdot) ² error	validation (\cdot) ² error	comp. time until stationarity
plain simulation	103.6	103.6	18 ¹ / ₂ h
estimated simulation	20.9	75.1	20 ¹ / ₄ h
relative difference	- 80 %	- 28 %	+ 9 %

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- disaggregate and dynamic calibration of arbitrary choice dimensions from traffic counts
- freely available software: transp-or2.epfl.ch/cadyts
- ongoing work:
 - computation of posterior choice model *parameters*
 - applications: MATSim, DRACULA, SUMO
- future work:
 - disaggregate data sources
 - within-day replanning
 - supply calibration