Going beyond path flow estimation – calibration of arbitrary demand dimensions from traffic counts

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Calibration of iterated DTA microsimulations[1]

- why bother? DTA microsimulations
  - equilibrate more than route choice (e.g., dpt. time, mode)
  - capture arbitrary demand heterogeneity
  - handle complex and large systems
- what method? OD matrix estimation / PFE of limited use
  - cannot estimate all demand dimensions
  - hardly accounts for demand heterogeneity
  - computationally involved

[1] aka "doubly dynamic traffic assignment"

Outline

A macroscopic path flow estimator

Microsimulation perspective

Case study

Summary, outlook

Outline

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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 in stochastic user equilibrium (SUE) if

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

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

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Derivation of Bayesian estimator

1. SUE 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 optimization by scaling of path flow distributions

Outline

Reinterpretation of the macroscopic setting

- notation, revisited

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

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

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

...as before!

How to implement the calibration

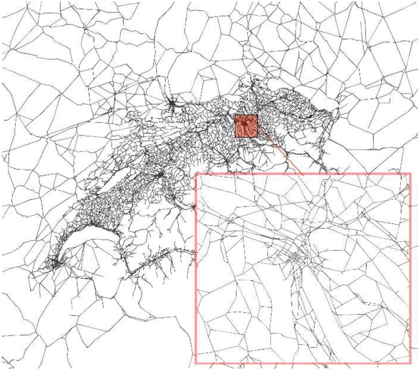
Algorithm

1. choose initial network conditions
2. repeat until stationarity
    2.1 linearize log-likelihood function in given network conditions[2]
    2.2 select plans for all agents from scaled choice distributions[3]
    2.3 load all agents on the network

[2] analytically, based on proportional assignment or regression
[3] by actual prob. scaling, adjustment of ASCs, rejection sampling, ...

Outline

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

	reproduction $(\cdot)^2$ error	validation $(\cdot)^2$ error	comp. time until stationarity
plain simulation	103.6	103.6	$18^1/_2$ h
calibrated simulation	20.9	75.1	$20^1/_4$ h
relative difference	- 80 %	- 28 %	+ 9 %

Outline

Summary, outlook

- disaggregate and dynamic calibration of arbitrary choice dimensions from traffic counts
- freely available calibration toolbox: `transp-or2.epfl.ch/cadyts`
- current work: calibration of choice model *parameters*
- future work: supply calibration to avoid biases