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Iterated transport microsimulations

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Outline

Intuition

Modeling

Example

Summary



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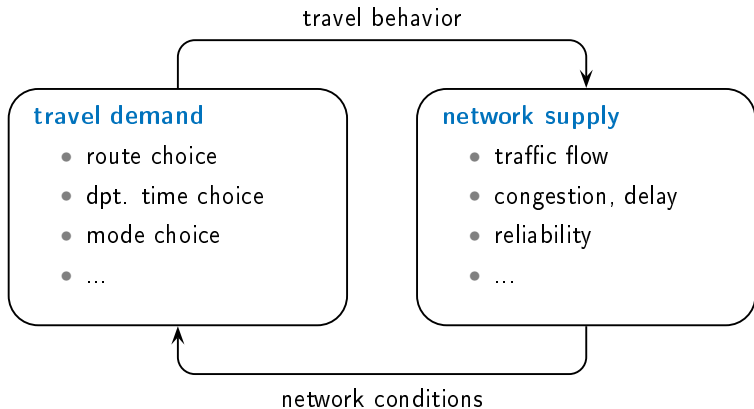
Activities and traveling

The morning question, What good shall I do this day?	5	Rise, wash, and address <i>Powerful Goodness</i> ; contrive day's business and take the resolution of the day; prosecute the present study; and breakfast.
	6	
	7	
	8	
	9	
	10	
	11	
	12	
	1	
	2	
Evening question, What good have I done today?	3	Read or overlook my accounts, and dine.
	4	
	5	
	6	
	7	
	8	
	9	
	10	
	11	
	12	
	1	Put things in their places, supper, music, or diversion, or conversation; examination of the day.
	2	
	3	
	4	
	1	Work.
	2	
	3	
	4	
	1	Sleep.
	2	
	3	
	4	

Network flows



Transport model system



Multi-agent simulation

- create a synthetic population of individual travelers (“agents”)
- resolve the demand/supply dependency iteratively
- in every iteration (simulated day):
 1. every traveler chooses some planned travel behavior
 2. all travelers execute their plans (i.e., they travel)
 3. all travelers observe the resulting network conditions



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Discrete choice modeling



- decision maker n faces choice set C_n of discrete alternatives
- each alternative $i \in C_n$ is given a real-valued utility U_{ni}
- decision maker selects alternative of maximum utility

$$n \text{ selects } i \iff U_{ni} = \max_{j \in C_n} U_{nj}$$

- choice dimensions in transportation
 - ▶ **living:** activities (type, sequence, location)
 - ▶ **traveling:** route, departure time, mode
 - ▶ **driving:** gap acceptance, lane changing

Discrete choice modeling



- fundamental modeling assumption: utility maximization
- decompose utility into systematic and stochastic term:

$$U_{ni} = V_{ni}(\mathbf{x}_{ni}; \beta) + \varepsilon_{ni}$$

- ▶ $V_{ni}(\mathbf{x}_{ni}; \beta)$ depends on attributes \mathbf{x}_{ni} and parameters β
- ▶ random term ε_{ni} captures uncertainty in the modeling
- random utility leads to probabilistic choice model

$$\Pr(n \text{ selects } i) = \Pr(U_{ni} = \max_{j \in C_n} U_{nj})$$

Discrete choice modeling



- some term distributions imply closed-form solutions, e.g.

$$P_n(i | C_n) = \frac{e^{V_{ni}(\mathbf{x}_{ni}; \beta)}}{\sum_{j \in C_n} e^{V_{nj}(\mathbf{x}_{nj}; \beta)}}$$

- general distributions require to resort to simulation

$$\text{draw from } P_n(i | C_n) \Leftrightarrow \begin{cases} 1. \text{ draw error terms } \varepsilon_{ni} \\ 2. \text{ select } \operatorname{argmax}_{i \in C_n} V_{ni}(\mathbf{x}_{ni}; \beta) + \varepsilon_{ni} \end{cases}$$



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Discrete choice modeling



- estimating the model parameters β requires Monte Carlo evaluation of $P_n(i | C_n)$ and $\nabla_{\beta} P_n(i | C_n)$: simulated Maximum Likelihood, Bayesian techniques ...
- choice sets C_n get intractably large (all possible travel behaviors)
 - ▶ (importance) sampling of alternatives
 - ▶ correct simulated behavior using sampling probabilities
- example: Metropolis-Hastings sampling of paths



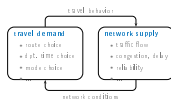
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Traffic flow modeling



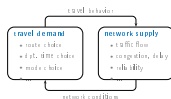
- **microscopic:** car-following models
 - ▶ driver selects acceleration based on immediate environment
 - ▶ see talk of Vincenzo and Biaggio
- **macroscopic:** continuum models, incompatible with agents
- **mesoscopic:** middle ground between micro and macro
 - ▶ move individual vehicles based on aggregate velocity fields
 - ▶ fairly realistic and compatible with the agent-based approach

Iterations



- represent a **day-to-day learning process**
 - ▶ very intuitive, easy to communicate
 - ▶ implicitly assumes a learning process
 - ▶ actual “learning model” is *very ad hoc*
- are **computational means to an end**
 - ▶ stationary process distribution is model solution
 - ▶ stationarity = consistency between demand and supply
 - ▶ justified if travelers learn *expected* network conditions

Iterations



- iterations (hopefully) attain a unique, stationary distribution
- very limited understanding of this distribution
- continuous limit perspective sometimes helps
 - ▶ assume continuum of travelers
 - ▶ approximate network flow dynamics with smooth equations
 - ▶ obtain analytical approximations of stationary mean values



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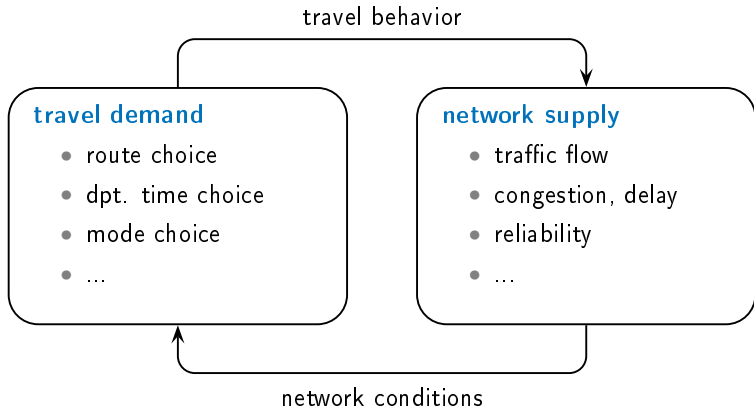
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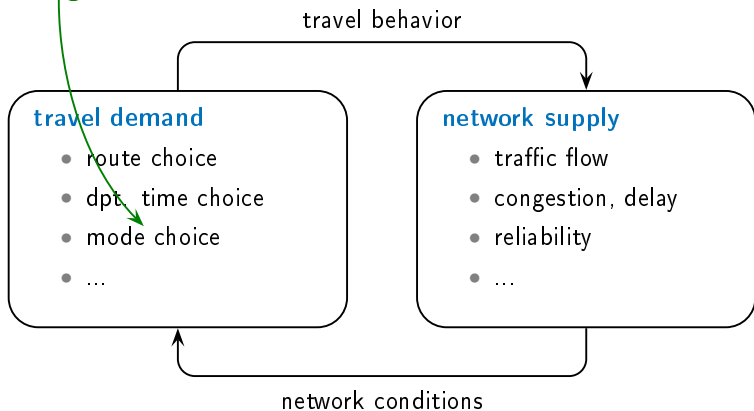
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Behavioral calibration from network data



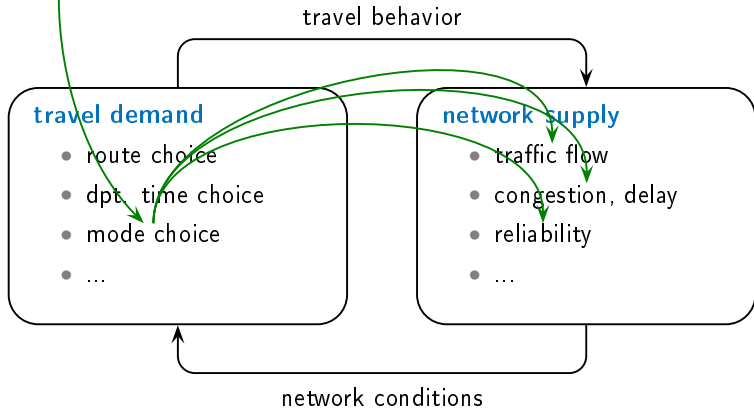
Behavioral calibration from network data

modeling error



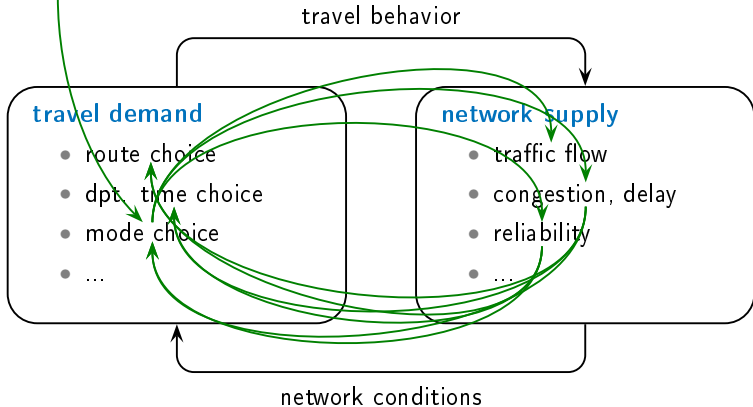
Behavioral calibration from network data

modeling error



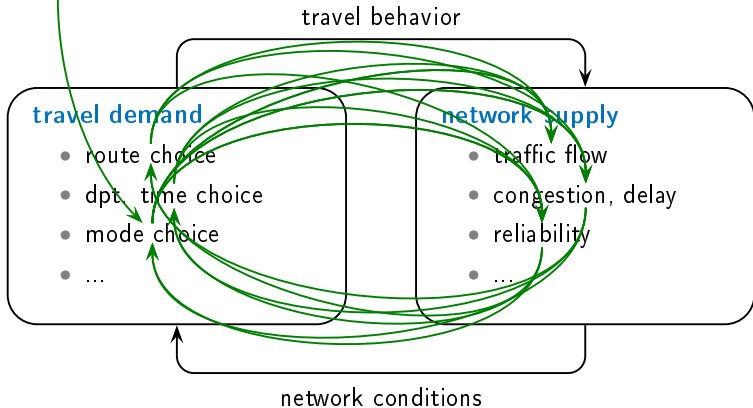
Behavioral calibration from network data

modeling error

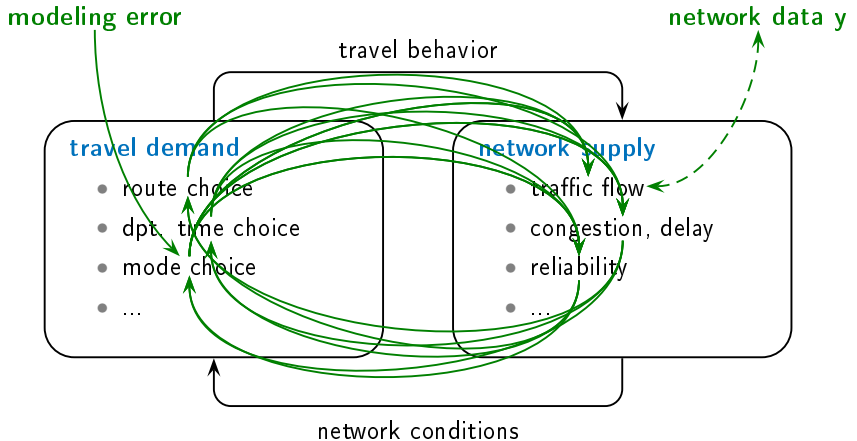


Behavioral calibration from network data

modeling error



Behavioral calibration from network data



Some notation

- population of synthetic individuals $n = 1 \dots N$
- individual n has a choice set C_n of travel plans
- Π_{ni} is probability that person n chooses travel plan $i \in C_n$
- $\mathbf{x}(\boldsymbol{\Pi})$ are average network conditions resulting from $\boldsymbol{\Pi} = (\Pi_{ni})$
- individual n chooses plan i according to model $P_n(i|\mathbf{x})$

Continuous limit approximation

- iterative simulation is maximizer of **prior entropy**

$$W(\mathbf{\Pi}) = \sum_{n=1}^N \sum_{i \in C_n} [\Pi_{ni} \ln P_n(i|\mathbf{x}(\mathbf{\Pi})) - \Pi_{ni} \ln \Pi_{ni}]$$

- interpretation: the system attains its most likely state

Calibration of simulated behavior

- objective: condition simulated behavior $\boldsymbol{\Pi}$ on network data \mathbf{y}
- approach: maximize **posterior entropy**

$$W(\boldsymbol{\Pi}|\mathbf{y}) = \mathcal{L}(\mathbf{y}|\mathbf{x}(\boldsymbol{\Pi})) + W(\boldsymbol{\Pi})$$

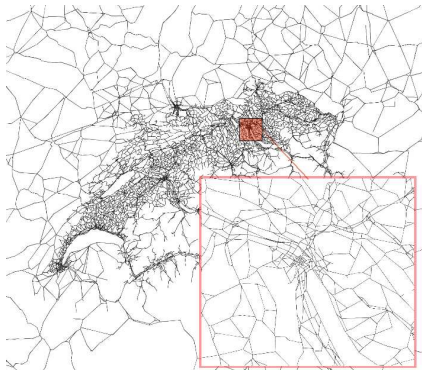
where $\mathcal{L}(\mathbf{y}|\mathbf{x}(\boldsymbol{\Pi}))$ is log-likelihood of \mathbf{y}

- this can be solved analytically:

$$\Pi_{ni} \sim \exp\left(\frac{\partial \mathcal{L}(\mathbf{y}|\mathbf{x}(\boldsymbol{\Pi}))}{\partial \Pi_{ni}}\right) P_n(i|\mathbf{x}(\boldsymbol{\Pi}))$$

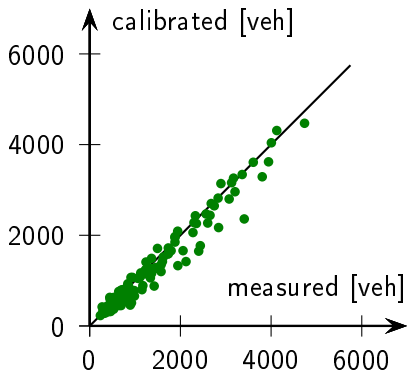
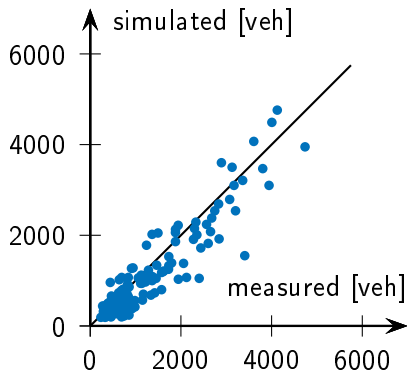
- implemented at *individual* level, *within* simulation loop

Zurich case study: setting



- 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

Zurich case study: evening peak





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- there exist credible models of human travel behavior
- these can be put into models of the physical environment
- the resulting model system is iteratively solved (“learning”)
- MCMC ... one *realization* from this model takes *one day*