Activity-based Travel Demand Forecasting: Extensions to the SBB Nationwide Model

nextRail19

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EPFL

Travel demand forecasting at SBB – big picture

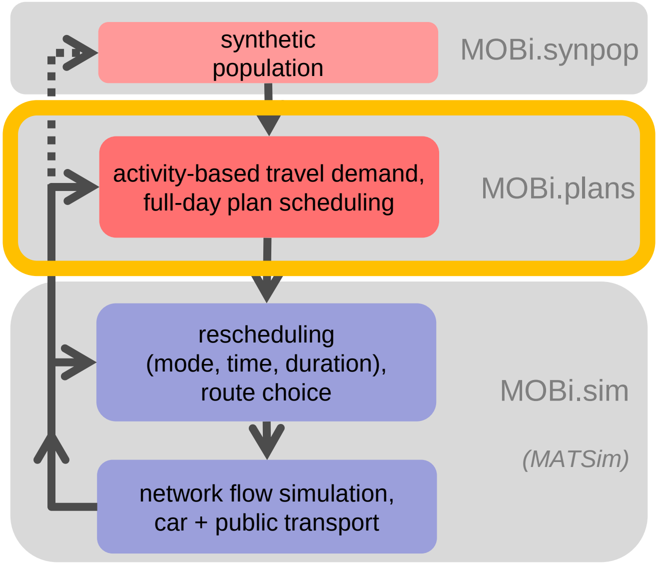
→ SBB is currently developing a **multimodal** and **microscopic** transport model as an extension of the existing rail model

→ Model requirements:

- ability to simulate long-term forecasting scenarios (2040+)
- representation of transport modes that are **competing with the railway**
- **door-to-door** simulation of travel (e.g. access to train stations)
- **future transport modes** (e.g. autonomous vehicles and ridesharing services from and to the rail stations)
- detailed representation of **demographic shifts** and **disruptive policies**

→ Pioneers in this field, need for more research on various topics

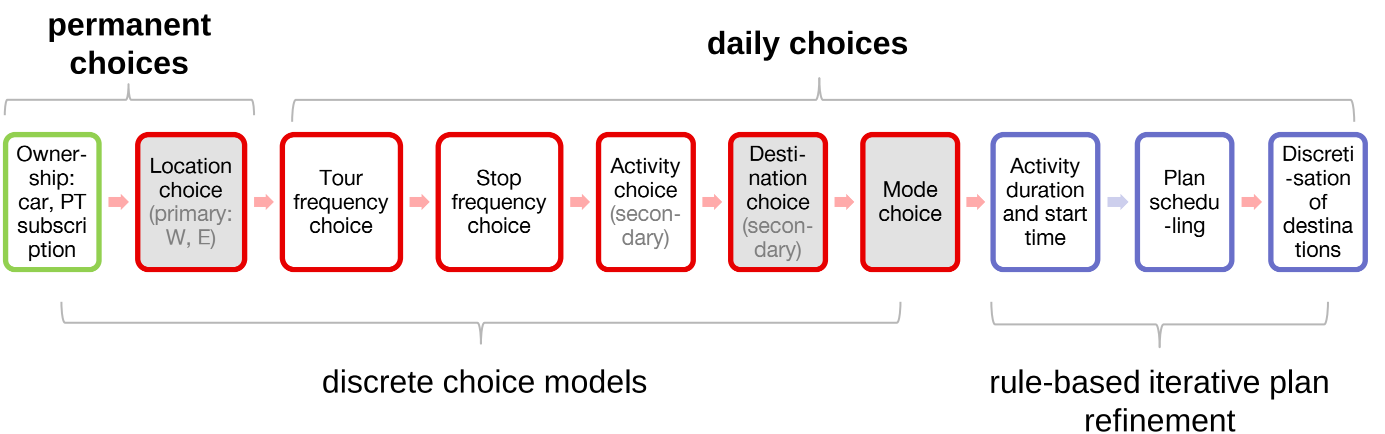
SIMBA MOBi: microscopic travel simulation of Switzerland



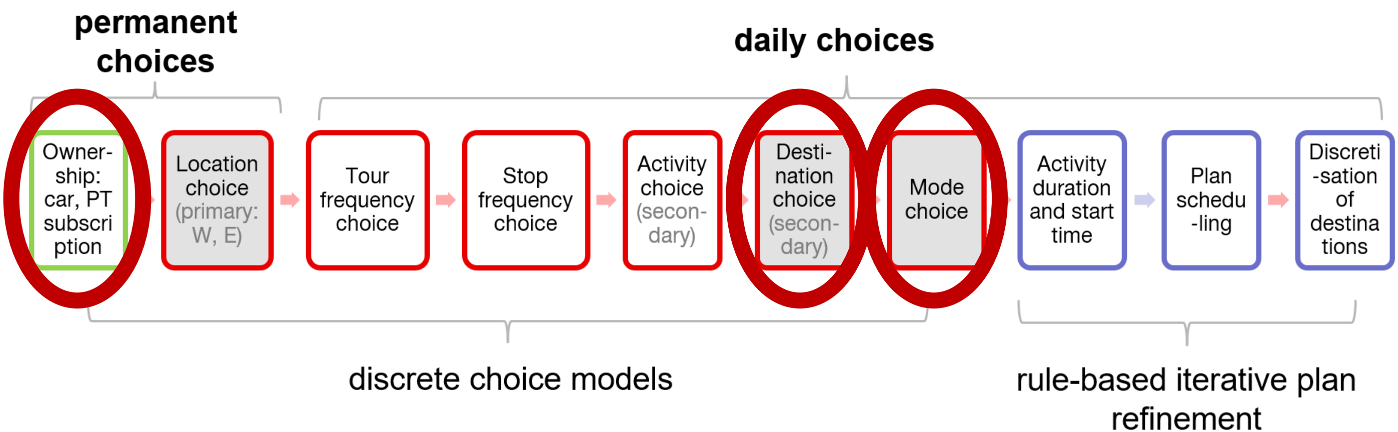
MOBi.plans' output: individual full-day plans

MOBi.Plans: microscopic travel demand

→ A sequence of steps to construct individual day plans



EPFL Research – Model extensions



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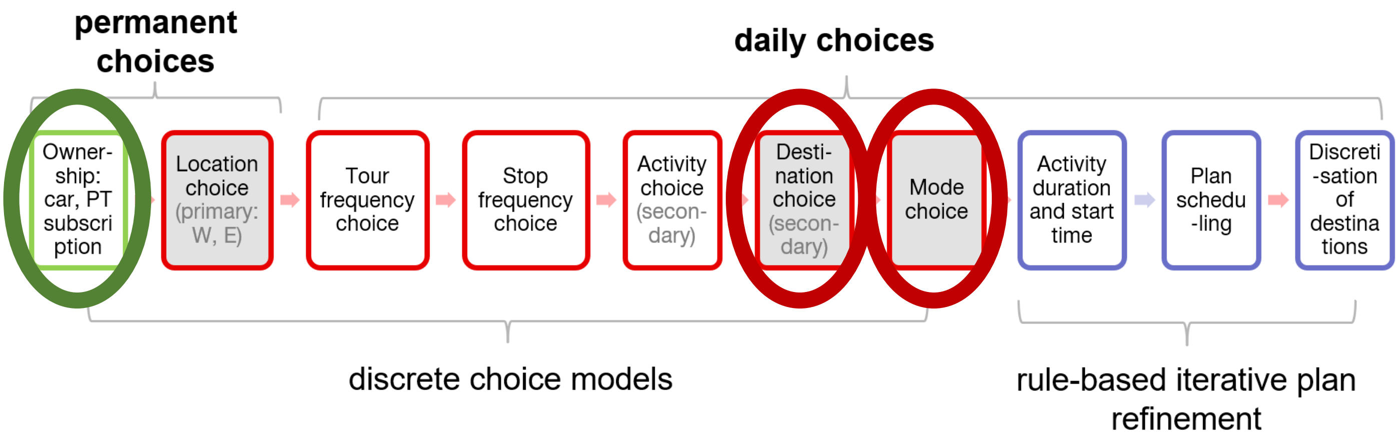
EPFL Research – Model extensions



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Ownership model – current approach

- Individual-level DCM (MNL) with 10 alternatives:

	GA	Regional ticket	Half fare	RT + HF	None
Car	1	2	3	4	5
No-car	6	7	8	9	10

- Individual-level input features from travel survey data – manual specification (arbitrary utility functions)

Mobility resources in Switzerland in 2015, Danalet & Mathys (STRC2018)

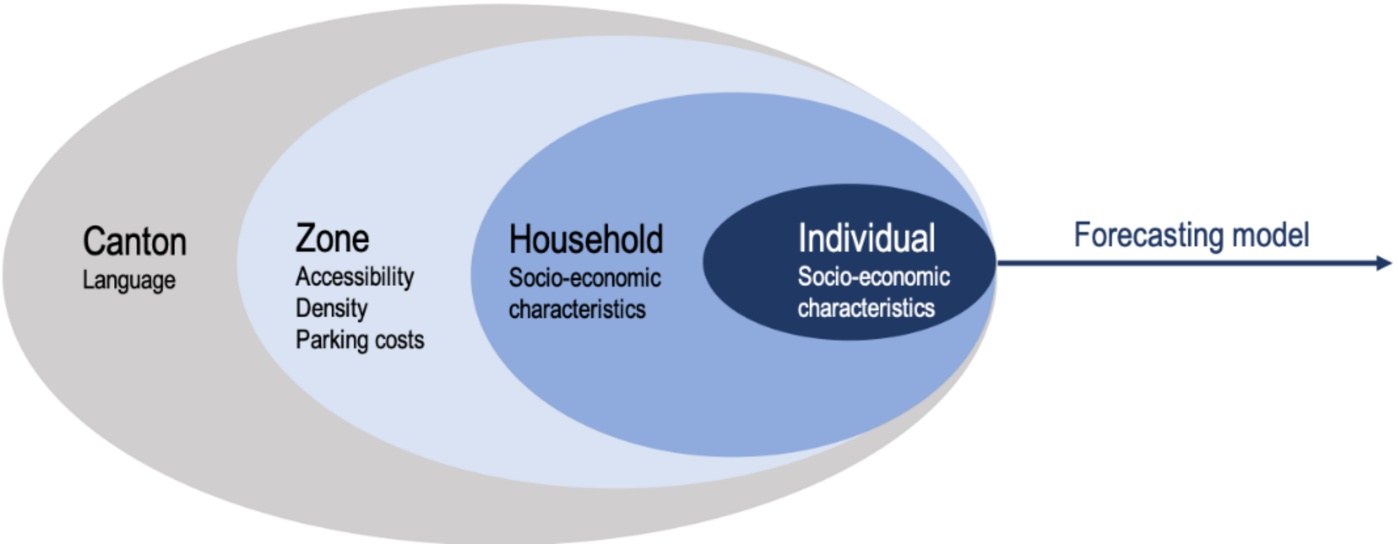
Improvements

1. **Data**
   - Augment travel survey with network-level data - individual, household, zonal, and canton level input features

2. **Structure**
   - Sequential individual-household-individual decision structure

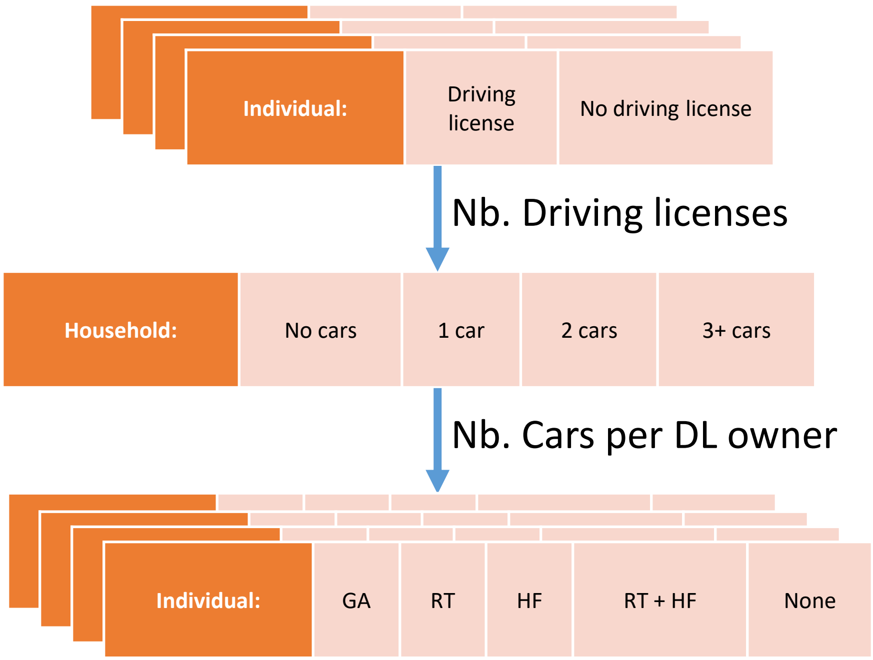
3. **Machine learning**
   - Assisted specification DCMs using Ensemble Learning (EL)

Data



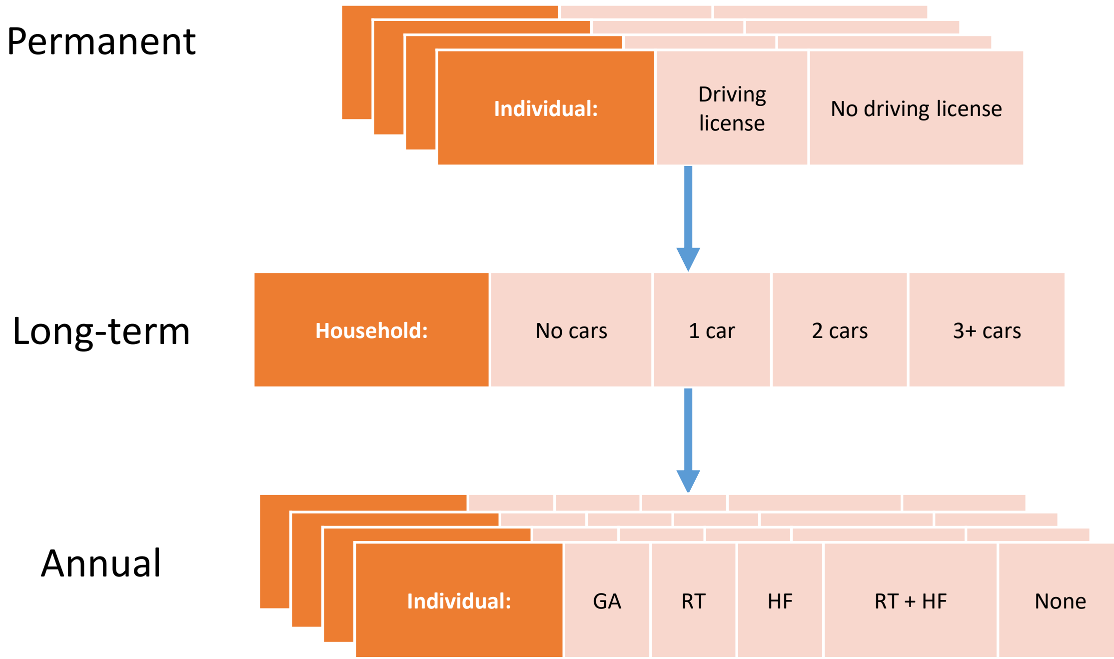
Augmenting traditional travel surveys with network-level data for predicting ownership of mobility instruments: A case study of Switzerland (ISCTSC2020, submitted)

Structure



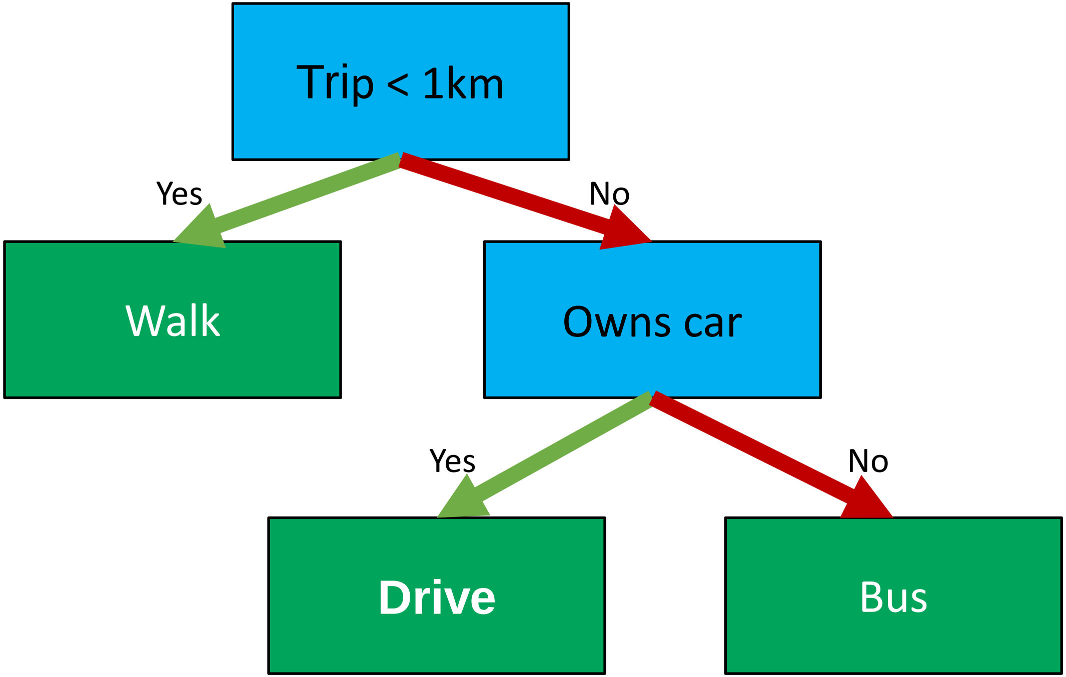
Individual:
Driving license
No driving license
Nb. Driving licenses
Household:
No cars
1 car
2 cars
3+ cars
Nb. Cars per DL owner
Individual:
GA
RT
HF
RT + HF
None

Structure

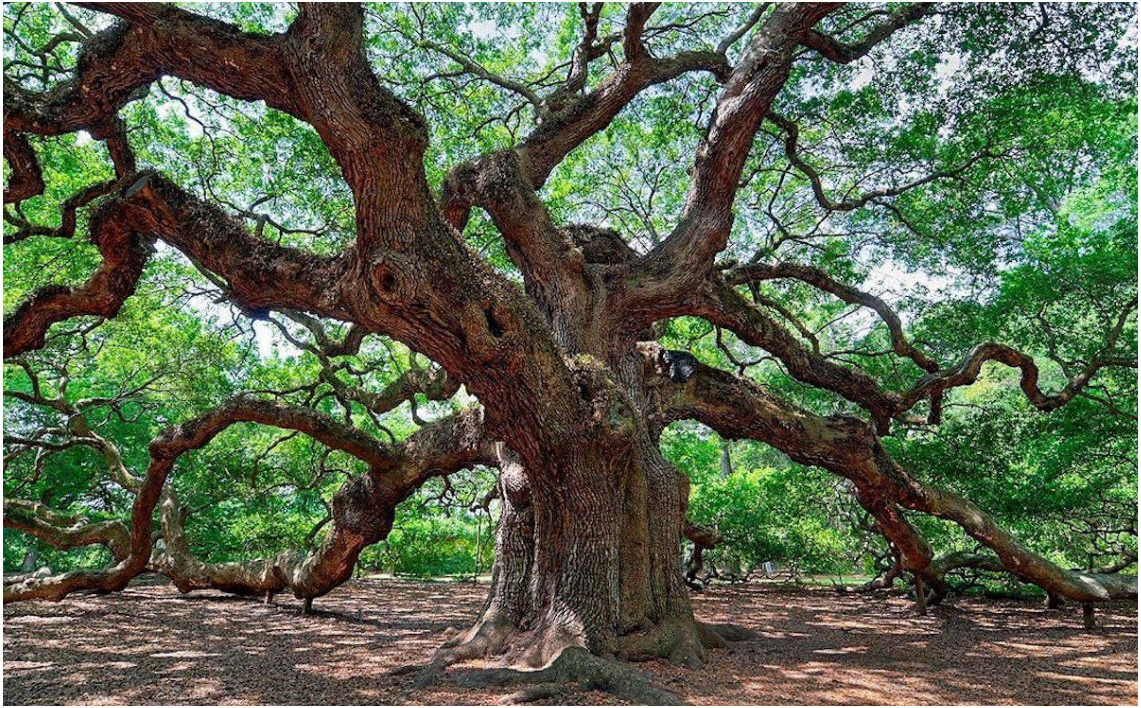


Permanent
Individual:
Driving license
No driving license
Long-term
Household:
No cars
1 car
2 cars
3+ cars
Annual
Individual:
GA
RT
HF
RT + HF
None

Machine learning - Decision trees



Ensemble learning



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Ensemble learning

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Assisted specification approach

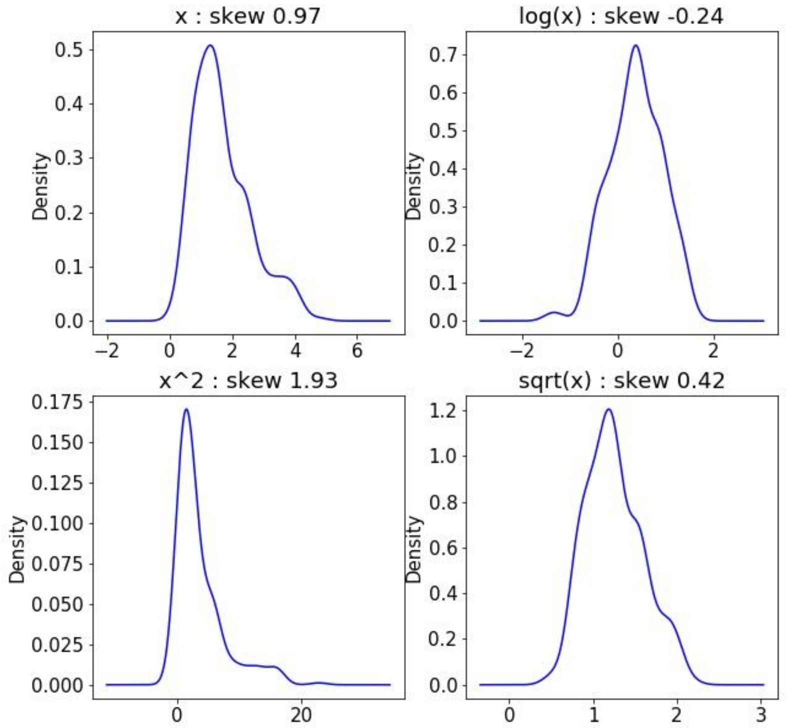
1. Train ensemble learning model on dataset
2. Investigate structure of ensemble learning model, using it to inform utility specifications for DCM
3. Simplify DCM by combining parameters where necessary

Assisted specification inferences

- Feature importances – sum gain over all splits for each features
- Feature interactions – sum gain for each hierarchical combination of n features
- Non-linear interactions of input features – investigate distribution of split values over all splits for each feature

Weak teachers: Assisted specification of discrete choice models using ensemble learning
(hEART 2019)

Parking cost – household car ownership



Current results – Joint estimation

Model	Features	Fit time	CEL
DCM	33	~10 hours	-1.54
ML (original data)	33	~5 min	- 1.48
ML (new data)	97	~20 min	-1.44

Current results – Sequential estimation

Model	ML		DCM	
	Fit time	CEL	Fit time	CEL
Individual DL	0:46	-0.307	3:22	-0.354
Household car	4:10	-0.84	1:04:03	-0.87
Individual PT	9:19	-1.21	4:04:30	-1.08

Summary

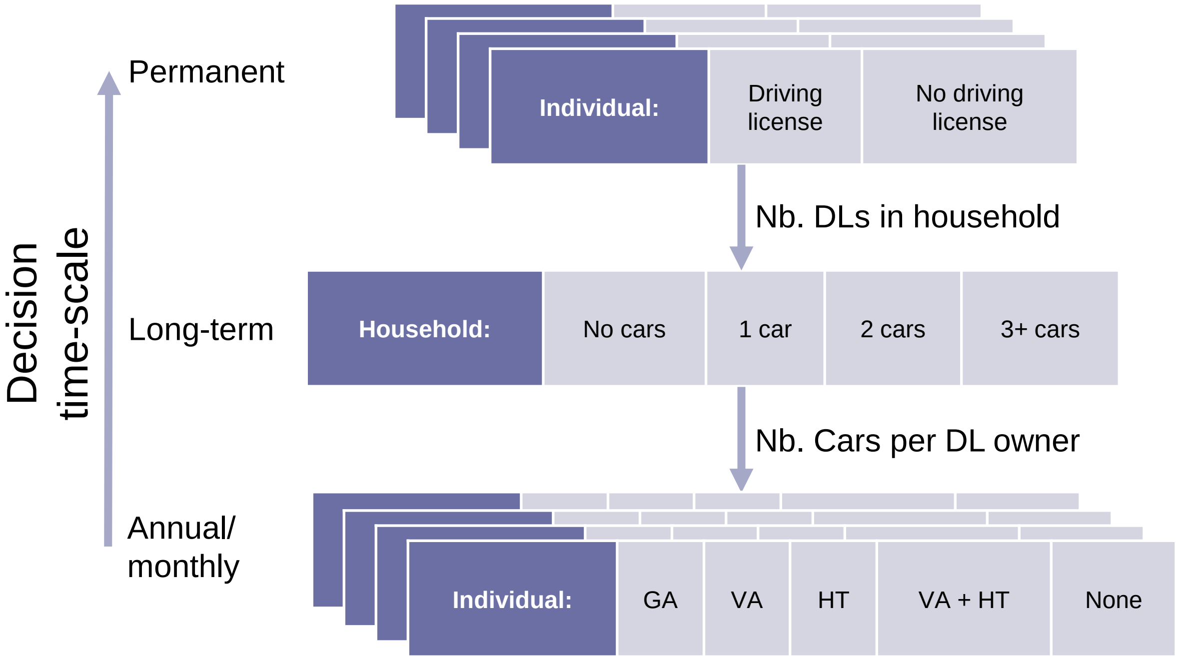
- SBB MOBi.Plans – Activity-based microscopic travel demand
  - A sequence of steps to construct individual day plans
  - Combination of DCMs and Simulation
- Current work to make improvements to:
  - Mobility ownership model
  - Tour based mode-choice
  - Joint estimation of destination and mode choice
- Mobility ownership model improvements
  - Data – Augmented with network level data
  - Structure – sequential modelling structure
  - Machine learning – assisted specification

Further work

- Finalise DCM utility specifications for sequential model

- Validate sequential DCM on synthetic population - MOBi.synpop

- Proceed to further extensions:
  - Tour-based mode-choice
  - Joint destination/mode-choice



Decision time-scale
Permanent
Long-term
Annual/ monthly
Individual:
Driving license
No driving license
Nb. DLs in household
Household:
No cars
1 car
2 cars
3+ cars
Nb. Cars per DL owner
Individual:
GA
VA
HT
VA + HT
None