Multimodal Traffic Management

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Collaboration between LiU, KTH and Stockholm Traffic Management Center

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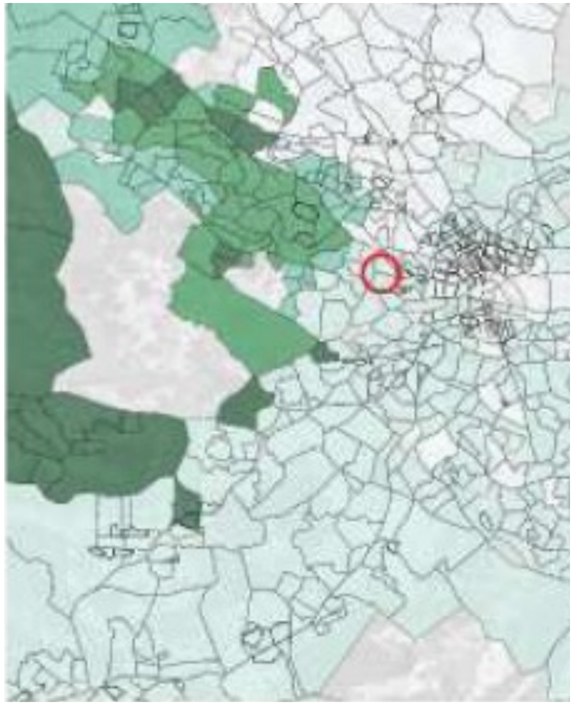
Multimodal Traffic Management

- Research targets
  - Better understanding of multimodal travel patterns
  - New methods for multimodal demand estimation and prediction
  - New methods for predicting route and mode choice
  - Synergies of multimodal traffic management

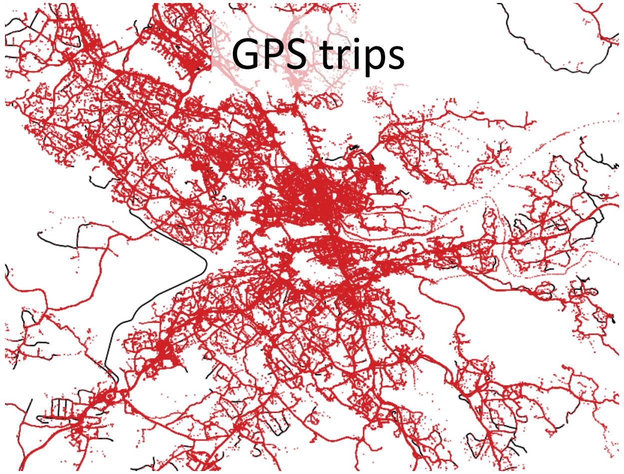
- Incident decision support
  - State prediction during incidents (including effects on route and mode choice)
  - Which traveller flows are affected most by the incident (and affect the incident the most)?
  - Which multimodal rerouting altenatives are available for these traveller flows?
  - How does the rerouting affect the future traffic state?

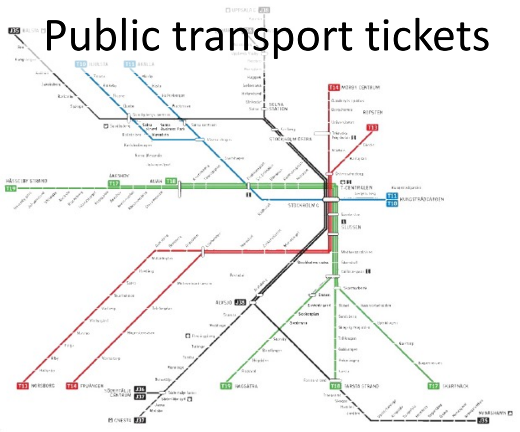


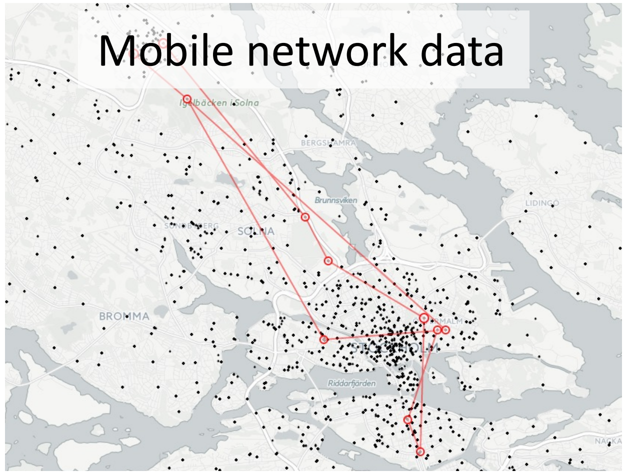
Overview of computational modules

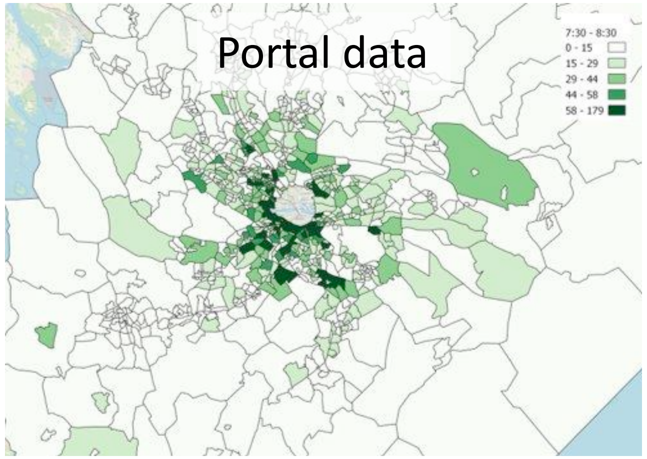
- Explorative analysis of multimodal data
- Data-driven route and mode choice modeling
- MMTM
- Multimodal demand estimation
- Scenario evaluation and analytics

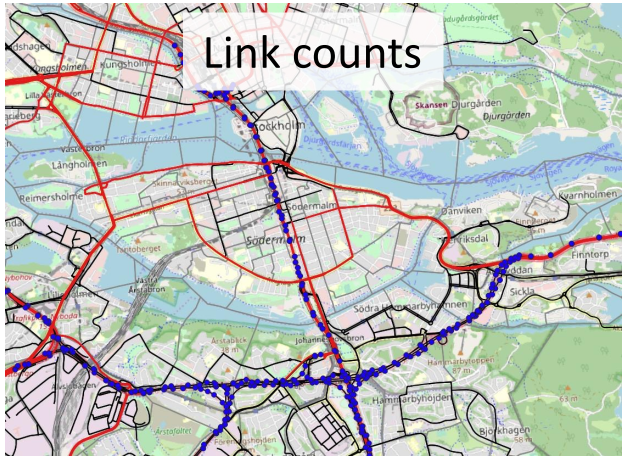
Stockholm Dataset











Data-driven route choice modeling

Anna Danielsson

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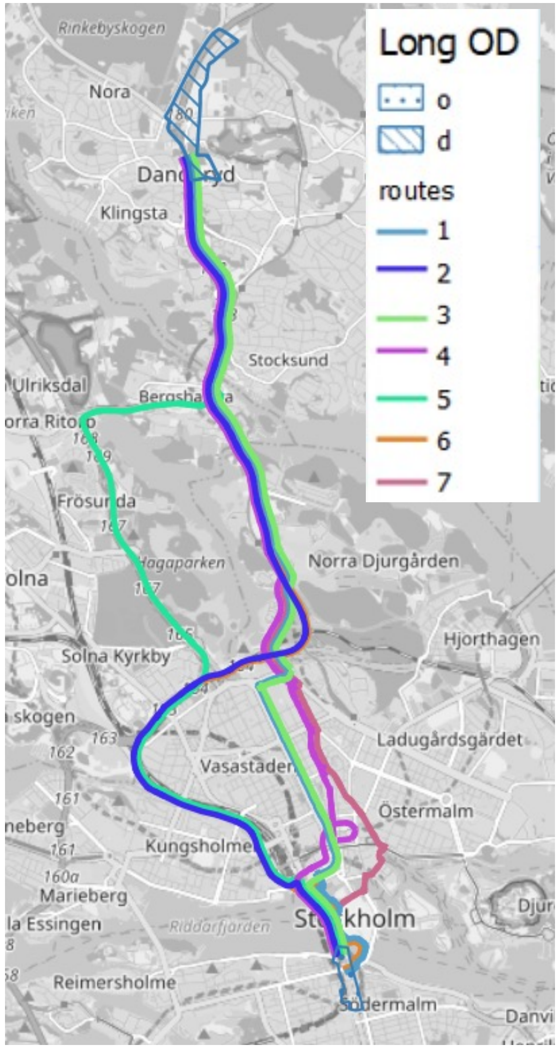
Data-driven route choice modeling

- Route choice modeling for traffic management
  - Estimate and predict traffic state
  - Estimate and predict traffic demand
  - Give relevant and targeted traveler information

- First approach using GPS probe data for estimation of a Logit-based discrete choice model
  - Which features xik affects the route choice?
    - Travel time, distance, capacity, #turns, #traffic lights…



Data-driven route set

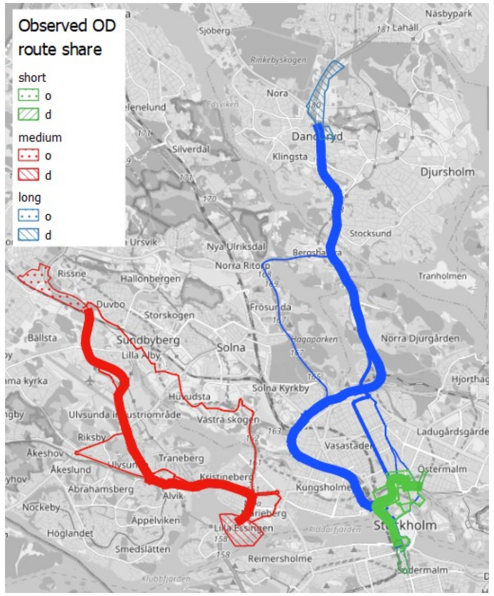
- Choice set (set or routes considered by the traveller) constructed from the set of all observed alternatives
- The first two weeks constritutes a training data set (blue) and the next two weeks a test data set (orange).

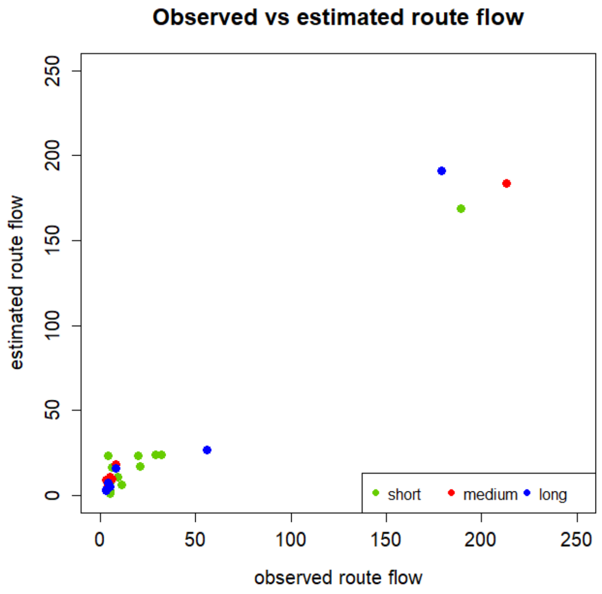
Route attribute statistics

Attribute	Exaplanation	Unit	Average value of all routes in data set	Difference within OD pairs			
				min diff	max diff	average diff	s.d. diff
ttmean	observed mean traveltime	min	1.24	0.06	28.63	3.40	4.30
ttfree	free flow traveltime	min	0.80	0	10.52	1.63	1.92
delay	relative delay (ttmean-ttfree)/ttfree	share	0.57	0	13.79	1.69	2.06
rlength	length of route	km	0.78	0	7.23	1.16	1.41
numlinks	number of links in route (proxy for number of intersections)		5.42	0	129	14.43	18.52
p_city	percentage of route within the city center	share	0.33	0	1	0.07	0.20
p_major_roads	percentage of route using major roads	share	0.75	0	1	0.46	0.43
cf	commonality factor indicating how similar to the alternatives the route is		0.74	0	2.62	0.84	0.64

Route choice modeling

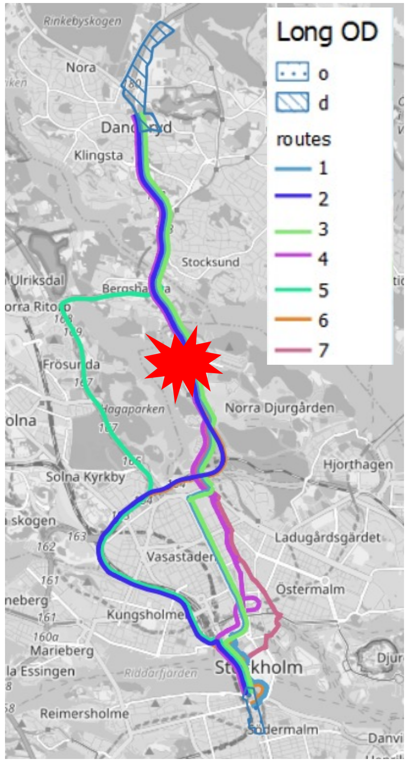
- Attribute selection
  - p_major_roads, numlinks, p_city and rlength are the most important attributes.
- Model estimation
  - Weighting attributes against each other.
- Model evaluation
  - Comparison of estimated and observed route choices.
- Understanding model
  - Analysis of example OD-pairs.

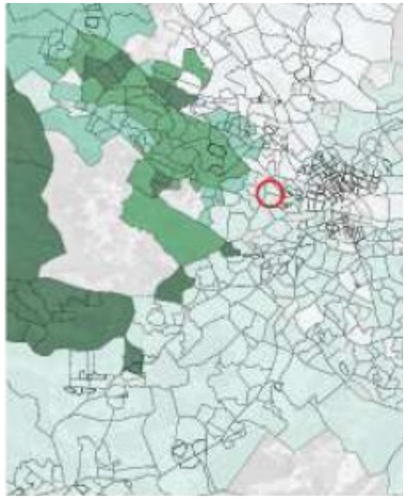




Conclusions so far

- A good route choice model can give important insights for traffic management.
- Insights from the experiments
  - Dataset promising for network-wide analysis and modeling of route choice
  - Route sets in training and test data are similar, thus building up the choice set of the historically observed routes is promising.
  - Attributes seems sufficient for some OD-pairs





Data-driven route choice modeling

Public Transport

Matej Cebecauer

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Public transport OD - routes

- Data

  Anonymized individual travel diaries inferred from smart-card data

- Result

  Dynamic OD matrices from 2015 – 2022 considering routes

- Next

  Data-driven PT route choice modeling

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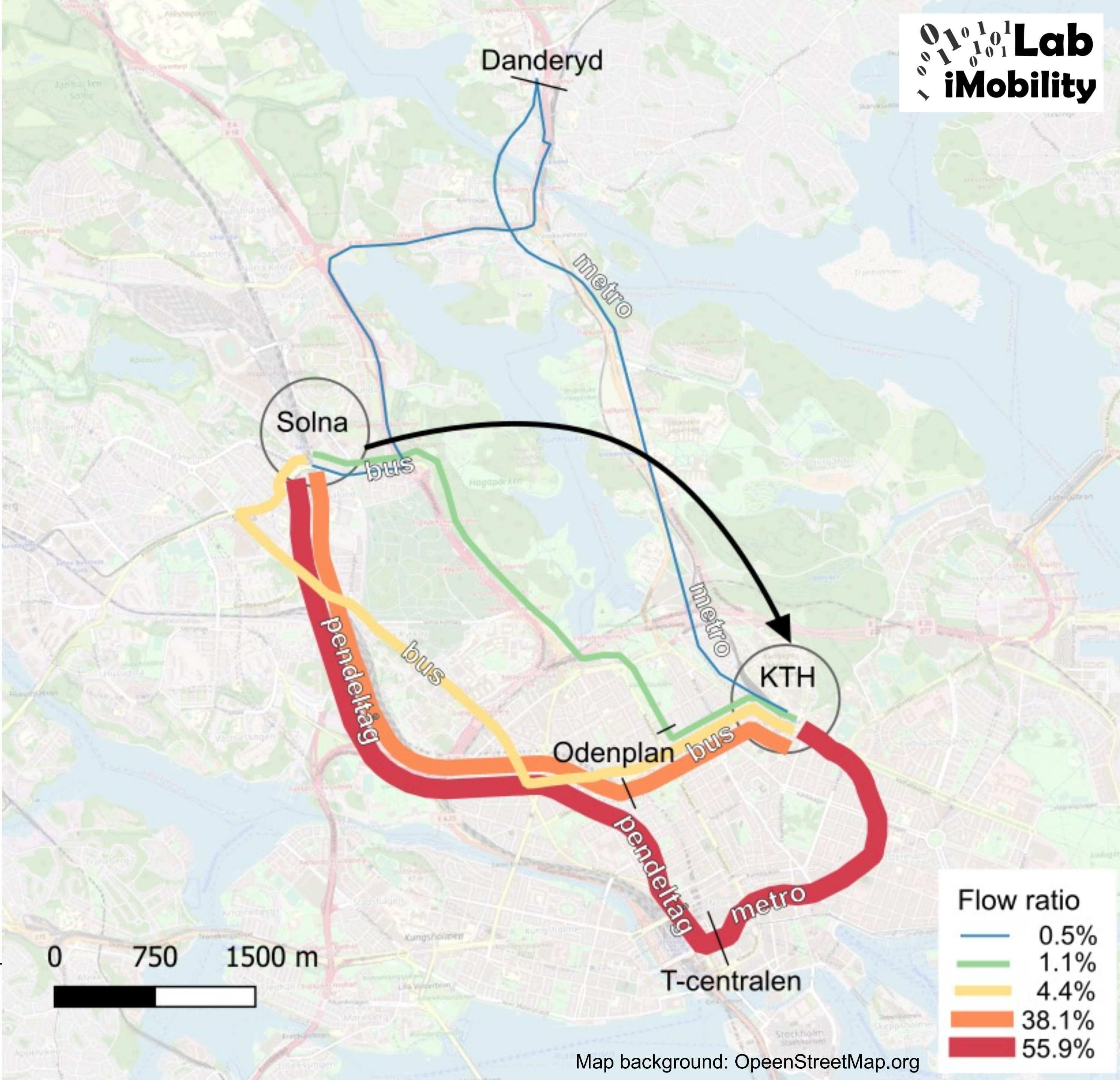

Explorative analysis of multimodal demand data

Matej Cebecauer

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Multimodal day-types

Day-types:

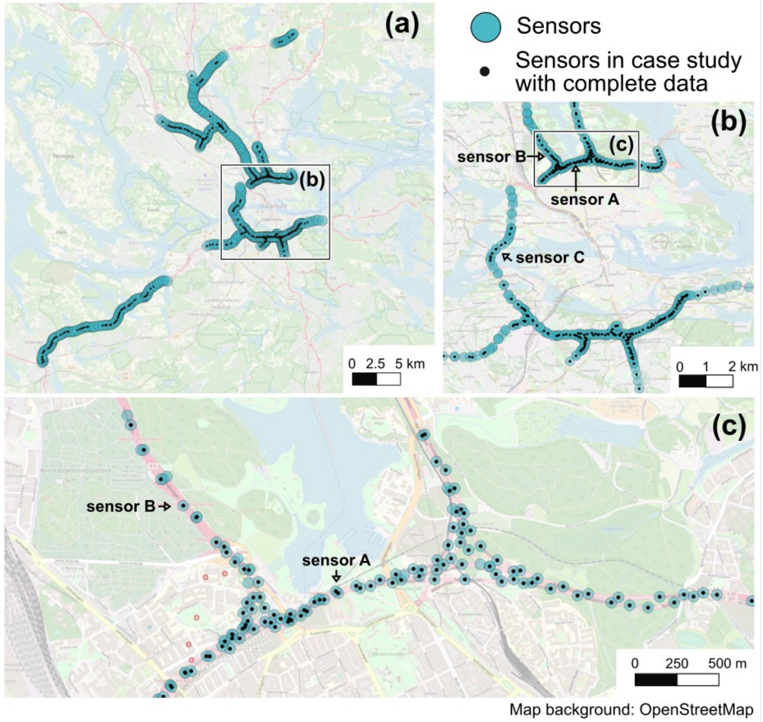
- Representative typical days

How we reveal representative day-types:

1. Clustering / pattern recognition
   - that groups the days based on their similarities, such
     - Minimize the variance/distance/dissimilarity among days in each cluster
     - Maximize the variance/distance/dissimilarity to days in other clusters
2. Representative of the cluster is the recognized day-type
   - Could be an average day of the cluster

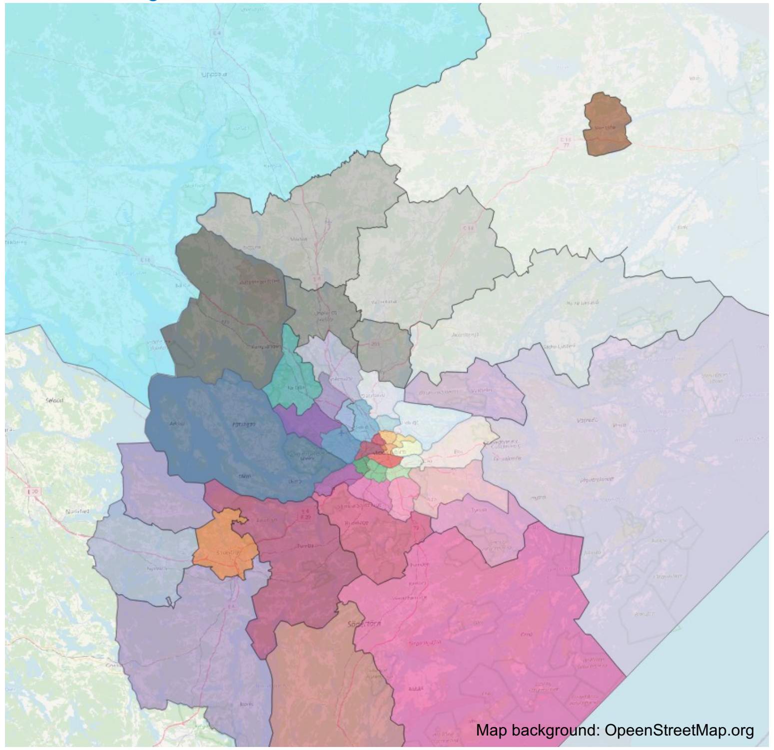
Multimodal day-types

MCS sensors



499 – sensors
66 – 15 minutes intervals

PT dynamic OD matrices

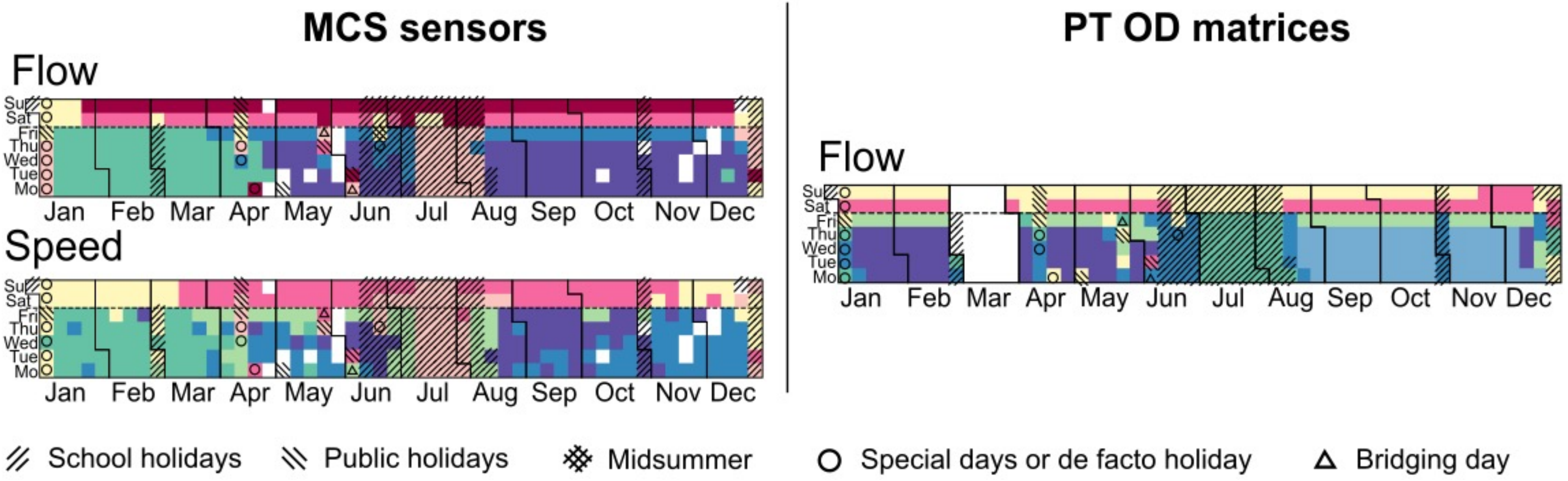


49 – zones (2,400 OD pairs)
38 – 30 minutes intervals

Multimodal day-types

Day-type similarity – calendar evaluation

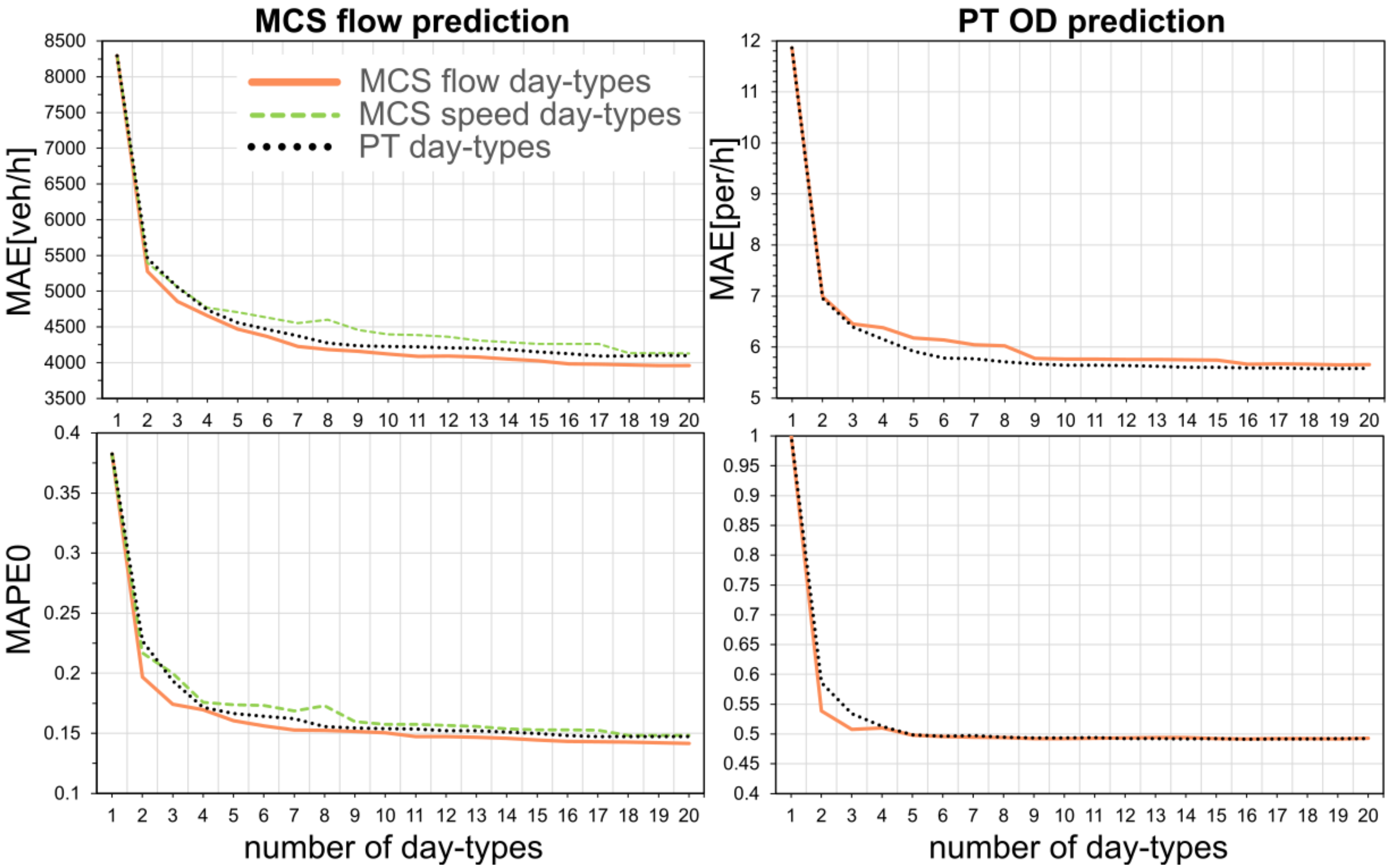
– Clusttering using year 2017



Multimodal day-types

Day-type similarity – external evaluation

- Similarity in short-term prediction application performance
  - Historical mean prediction model
    - Day-types recognized in 2017
    - Predicting for all days in 2018
    - 1 hour into future
    - Past hour to classify day-type for prediction
  - Mean Absolute Error (MAE)
  - Mean Percentage Absolute Error ignoring 0 (MAPE0)



What next?

What next?

- Adding more data sources
- Reveal multimodal day-types
  - Is the robustness of day-types sufficient for traffic management?
- Route choice modeling
  - Route set generation needs to be added to the process to provide better estimates for unseen situations
  - A mode choice component will be added to analyze multimodal traffic management
- Scenario evaluation
  - Simulation Model
  - Support for dynamic changes in network, demand and supply