Prediktions- och Scenariobaserad Trafikledning (POST)

- Clustering for Scenario Evaluation

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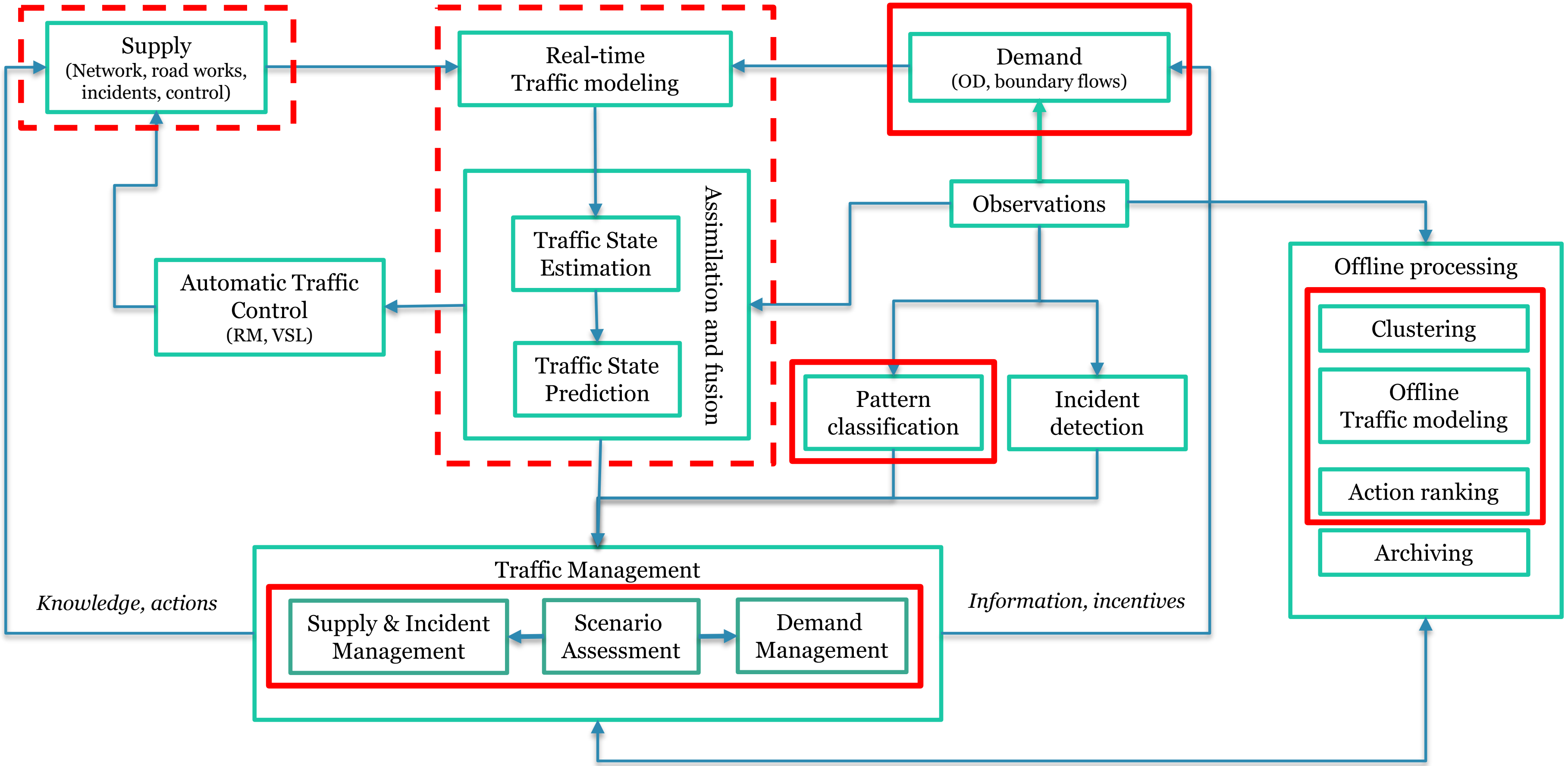
Project Background

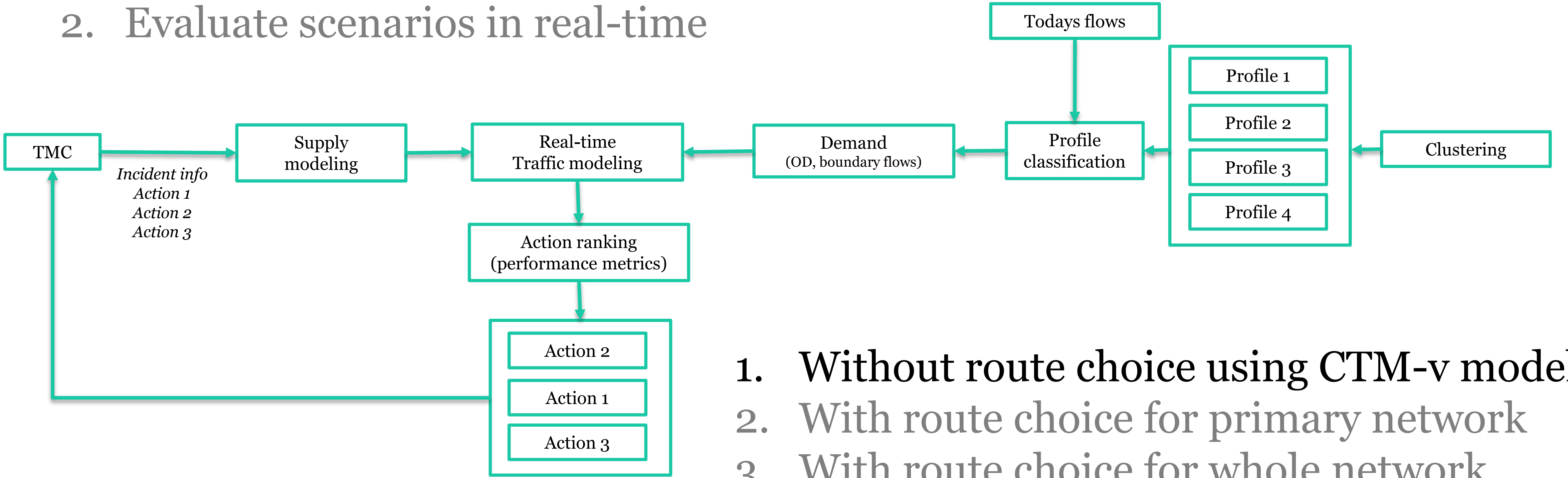
- Predict demand and route choice for scenario evaluation and action ranking
  - Offline processes for demand prediction and scenario evaluation
  - Online processes for classification of traffic situation and choice of control measure
- Example
  - Tow directly or after peak
  - Early information to travelers of severe incidents (i.e. do not use car)
- In this presentation focus on clustering methods for demand prediction

POST - Overview



Framework for Scenario-based Traffic Management

1. Offline för historical events
2. Evaluate scenarios in real-time



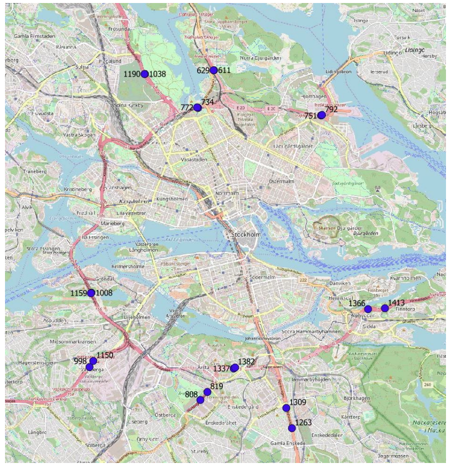
1. Without route choice using CTM-v model
2. With route choice for primary network
3. With route choice for whole network

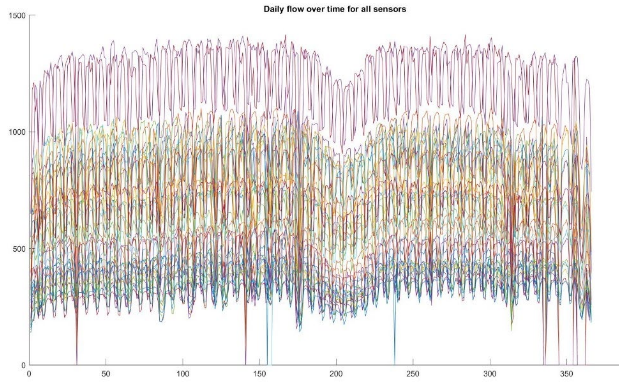
Demand Prediction

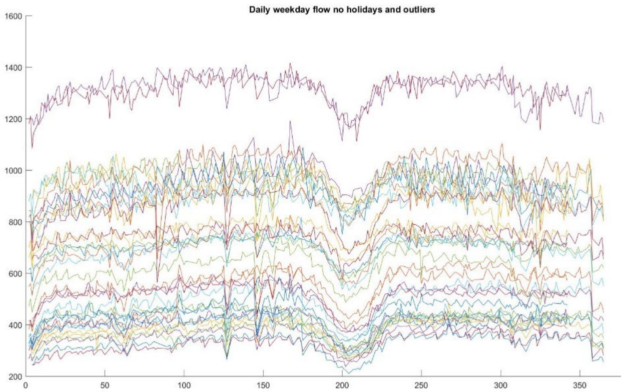
- To enable evaluation of traffic control measures we need to estimate (offline evaluation) and predict (online evaluation) demand
- Clustering + Classification VS Time series analysis
  - Important component to get an understanding of traffic patterns
  - With distinct traffic patterns we can determine how control measures perform for different scenarios patterns
- 1) Clustering
  - What type of data shall we cluster and at which aggregation level?
  - Which method shall we use for clustering?
  - How many clusters should we have?
- 2) How well does clustering-based demand prediction work?

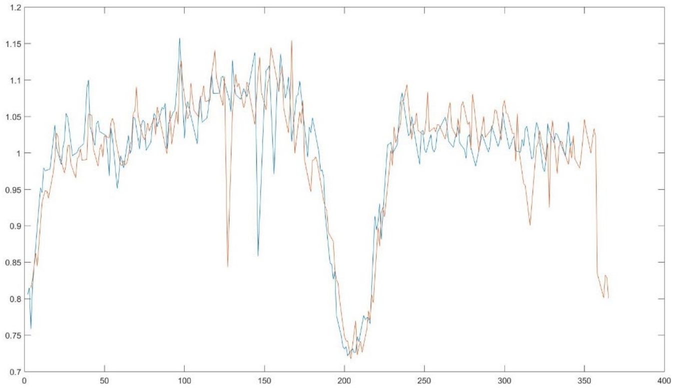
Datasets and Preprocessing

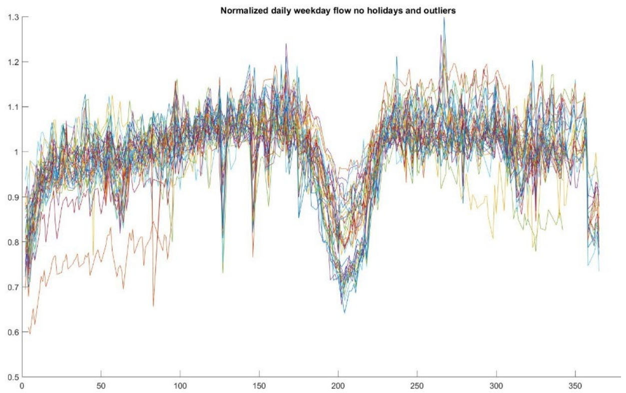
- Special days
  - Nyårsdagen
  - Trettondagen
  - Skärtorsdag
  - Långfredag
  - Påskafton
  - Påskdagen
  - Annandag påsk
  - Valborg
  - Kristi himmelsfärd
  - Klämdagar
  - Nationaldagen
  - Skolavslutning
  - Studenten
  - Midsommarafton
  - Midsommardagen
  - Midsommarsöndag
  - Julafton
  - Juldagen
  - Annandag jul
  - Nyårsafton
- Special periods
  - Januaridagar
  - Sportlov
  - Påsklov
  - Sommar/semester
  - Juli
  - Höstlov
  - Mellandagar











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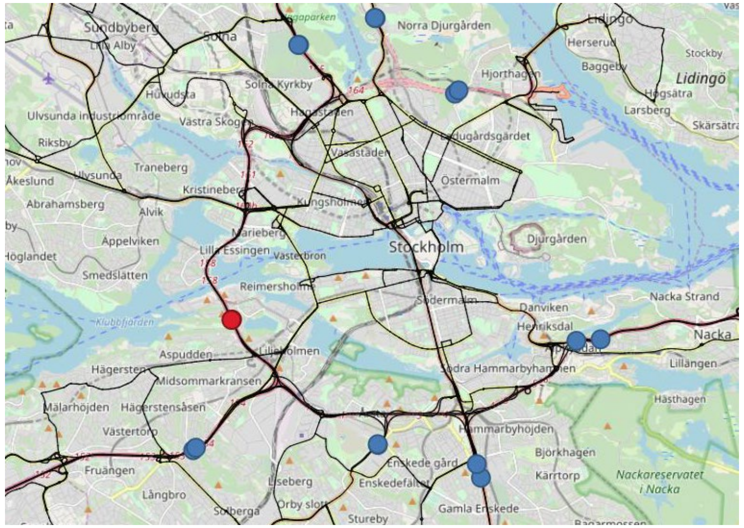
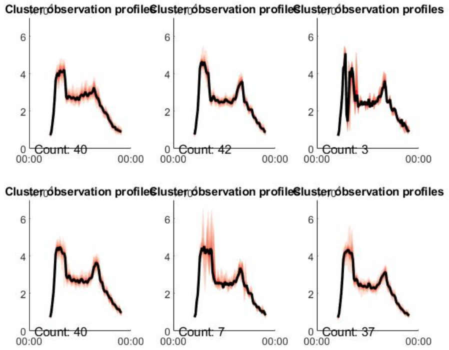
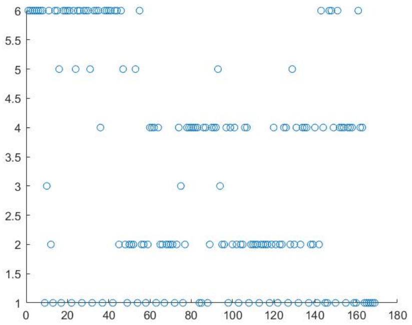
Datasets and Preprocessing

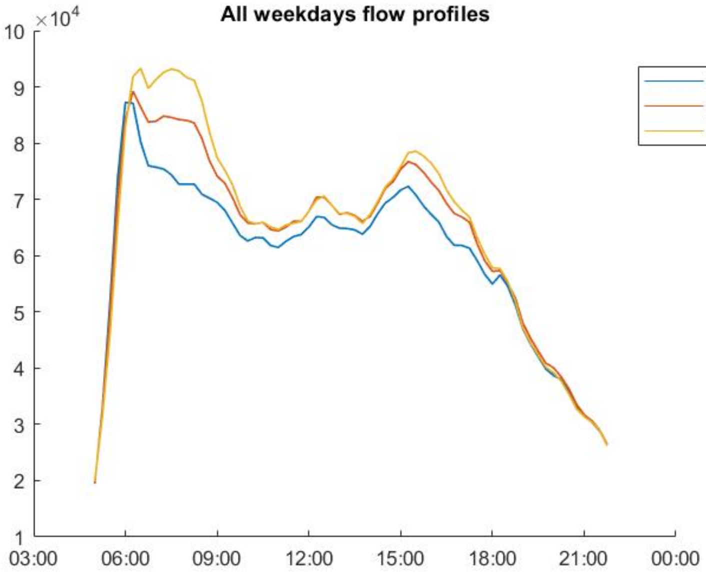
- 14 selected sensors on 7 major roads in Stockholm
- 2 sensors on each direction of Essingeleden
- Speed and flow aggregated to 15 minute intervals from 05-22
- Days with missing time intervals removed
- Special days, weekends and holiday periods removed
- Days with incidents are (still) included
- Remaining: 169 regular weekdays

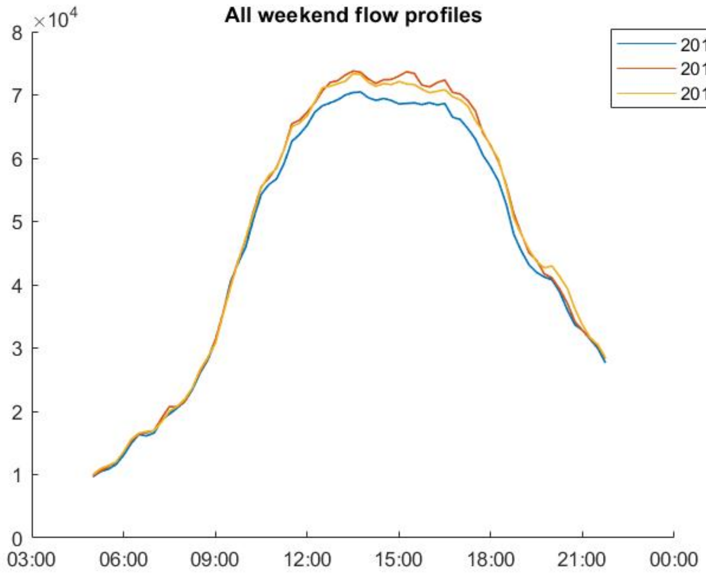


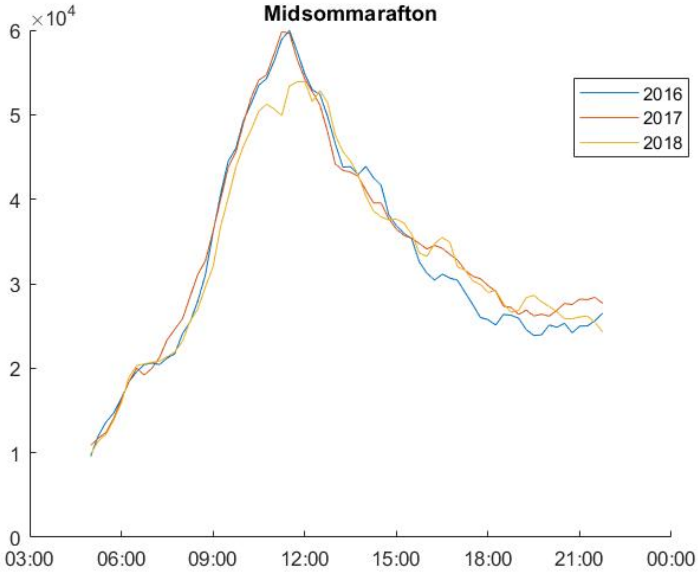


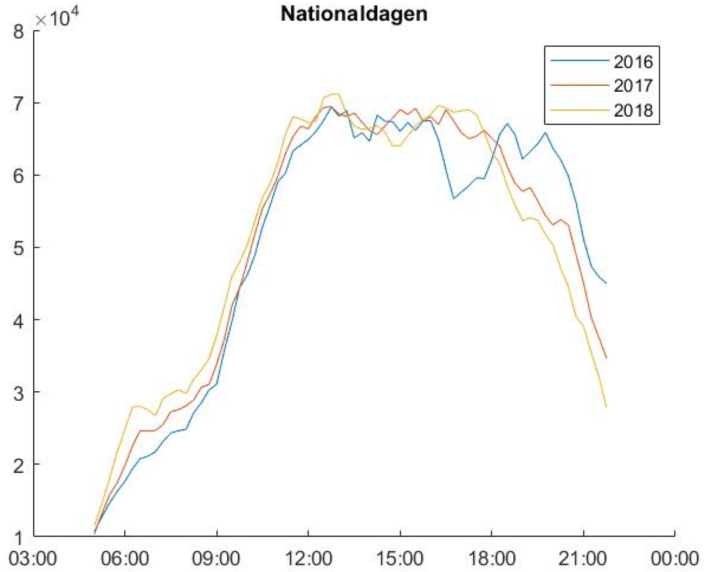


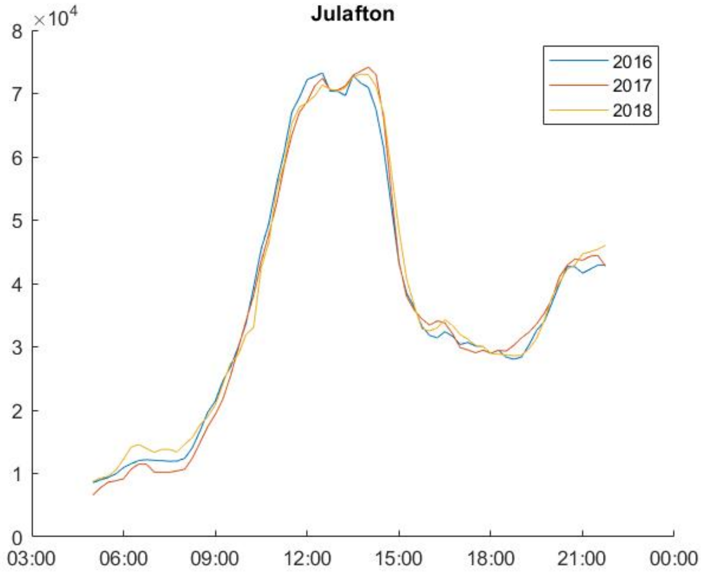
Special days, Weekends and Holidays

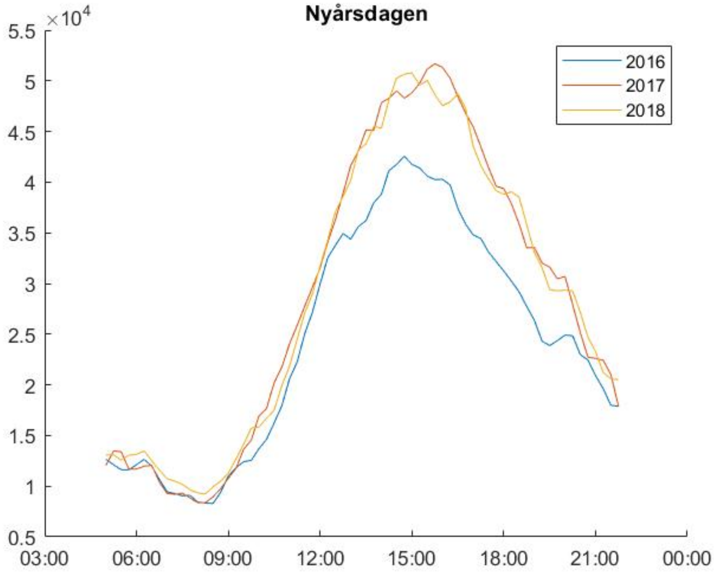






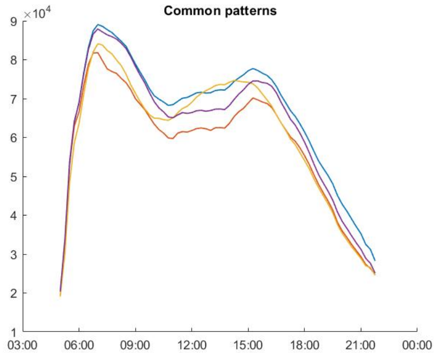


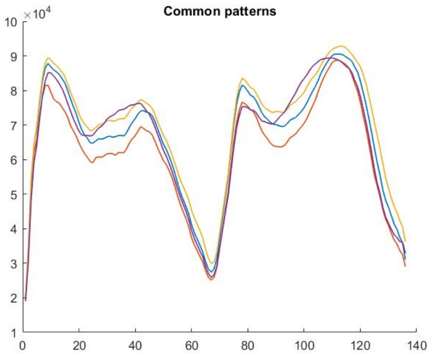


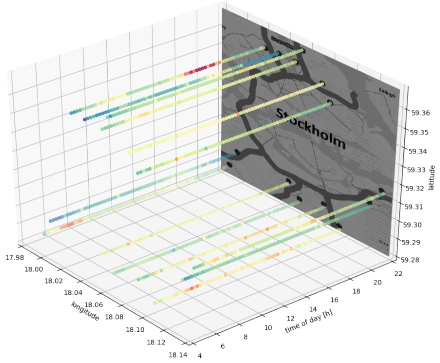


Clustering Methods

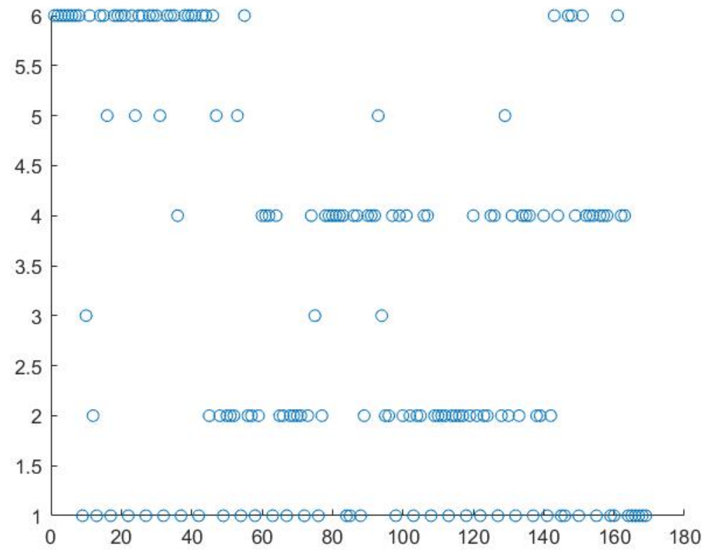
- Standard K-means per sensor (KmeanSensors)
  - Local pattern for each sensor
- K-means jointly for several sensors (KmeanVector)
  - Network effects, but no location clustering
- 3D speed maps (3Dmap)
  - Network effects and location included in clustering
- Median observation vector (MOV)
  - Hybrid between 3D speed map and joint K-means (2-dimensional)

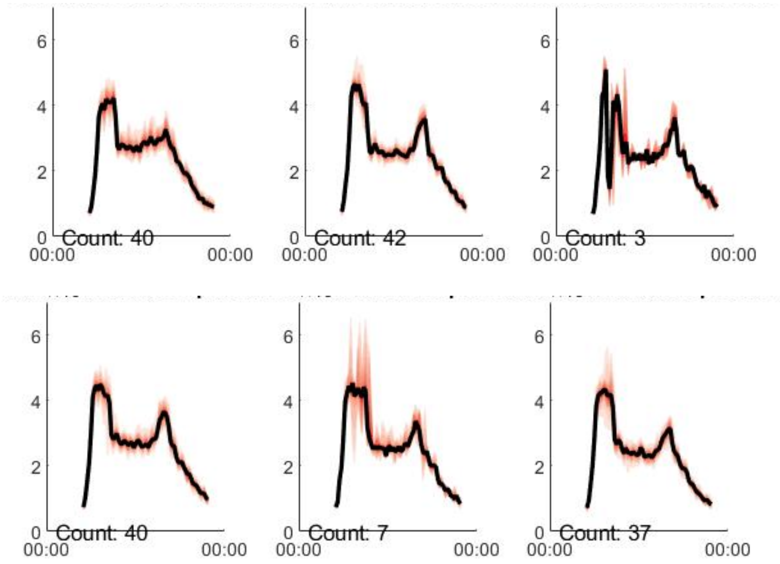


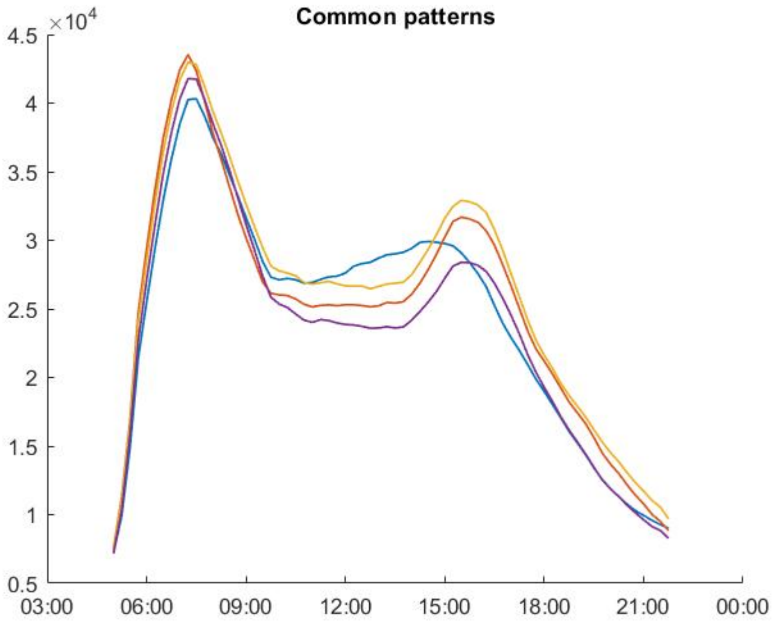


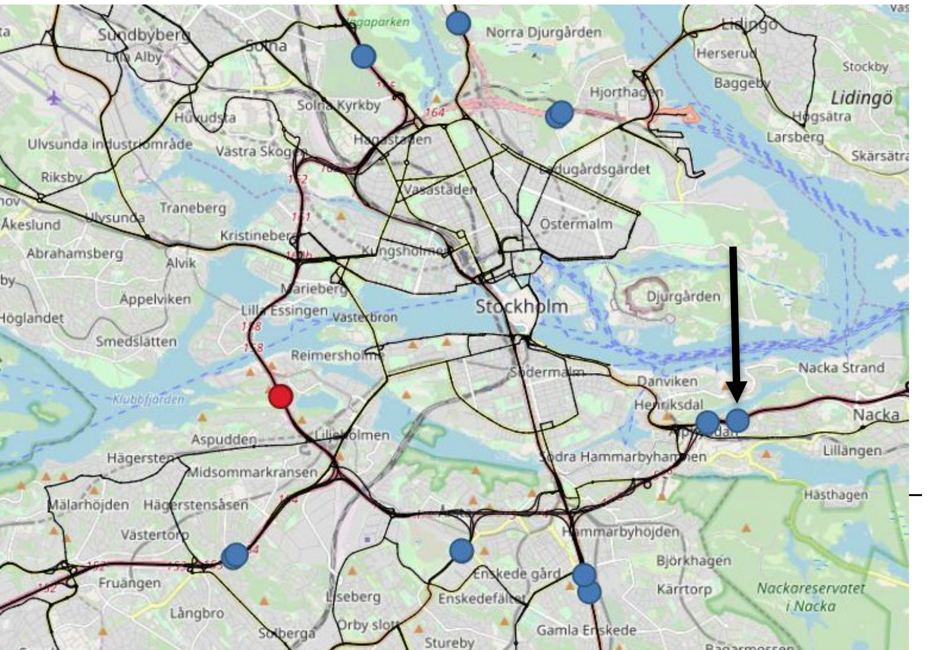


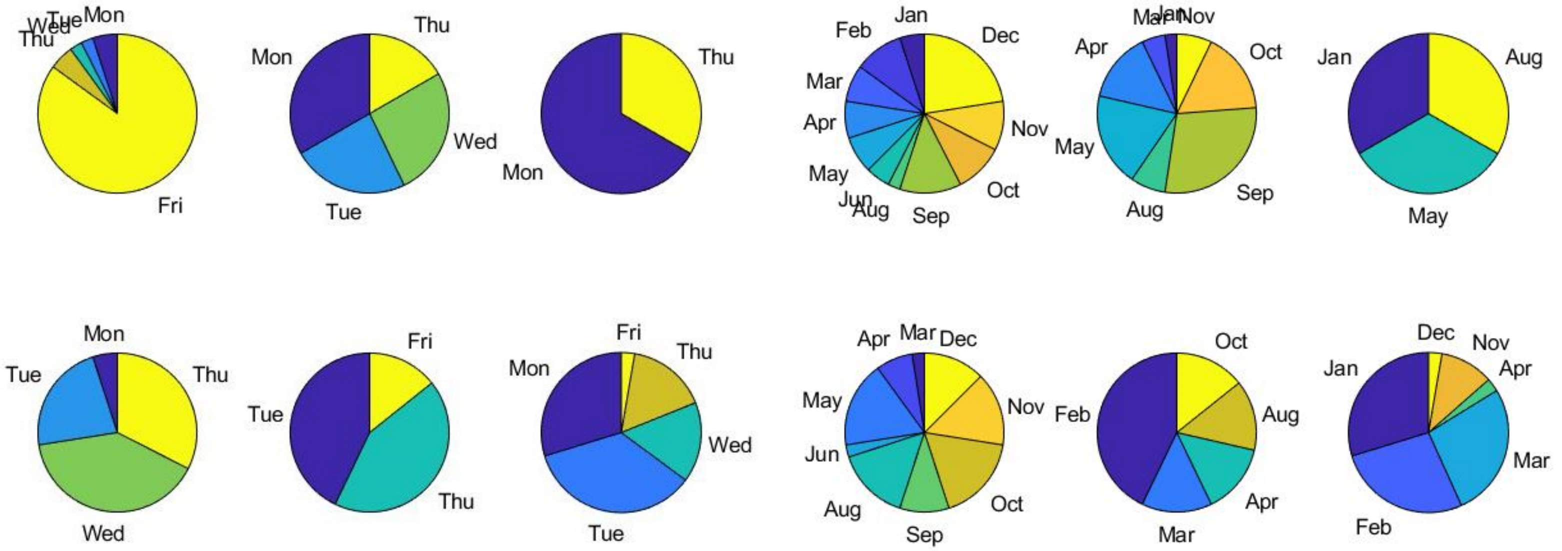
Clustering Results Example



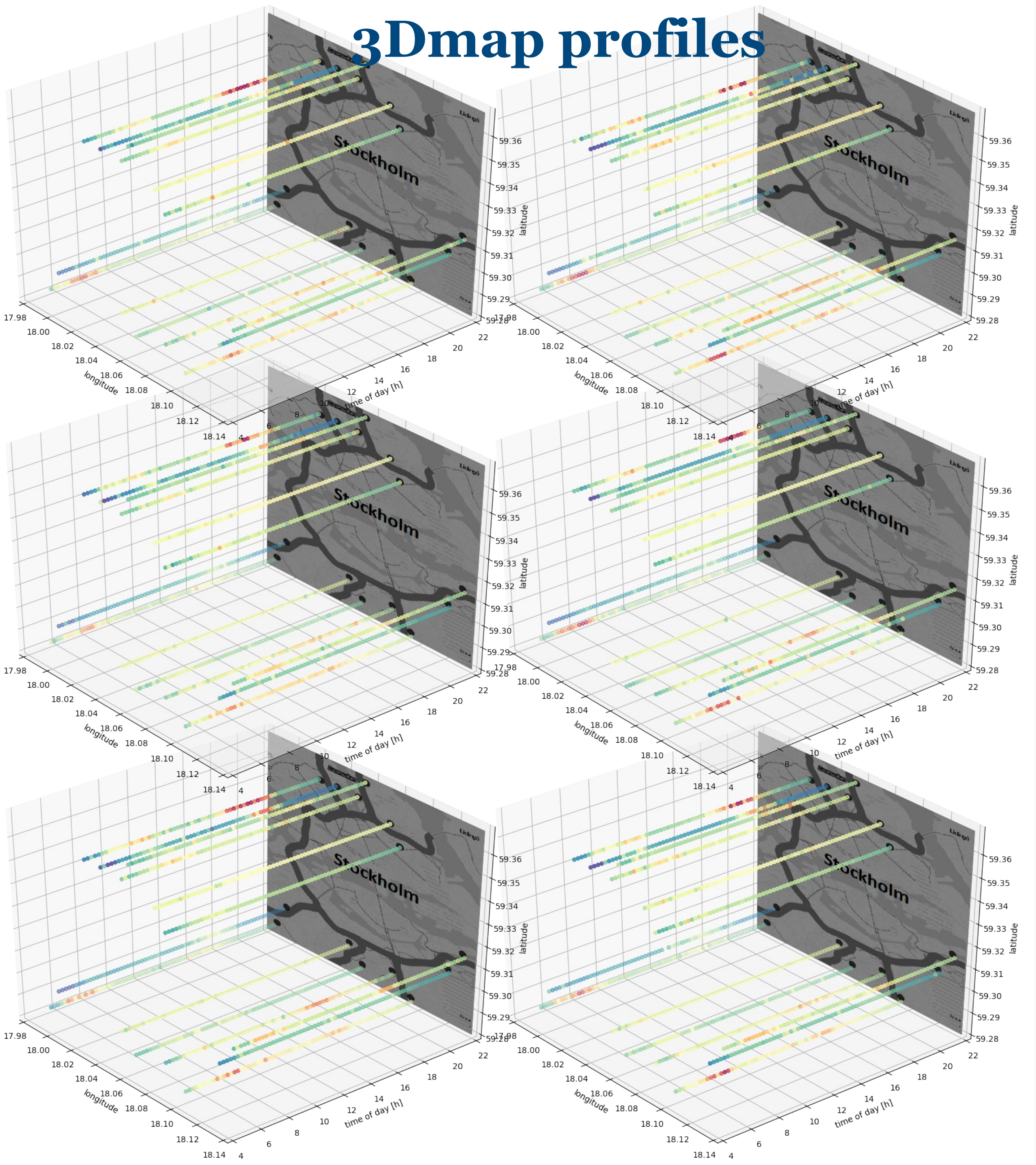




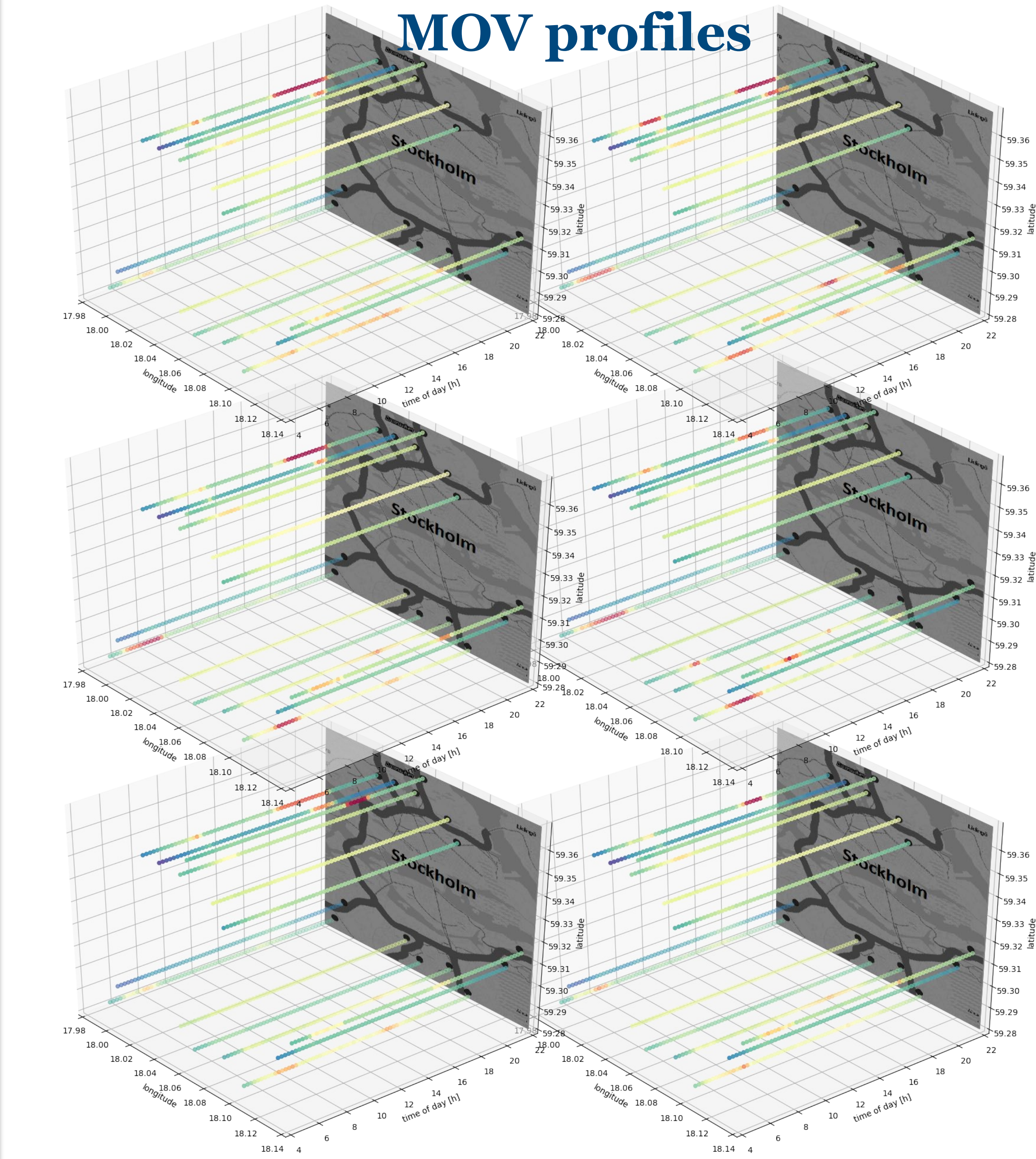




3Dmap profiles



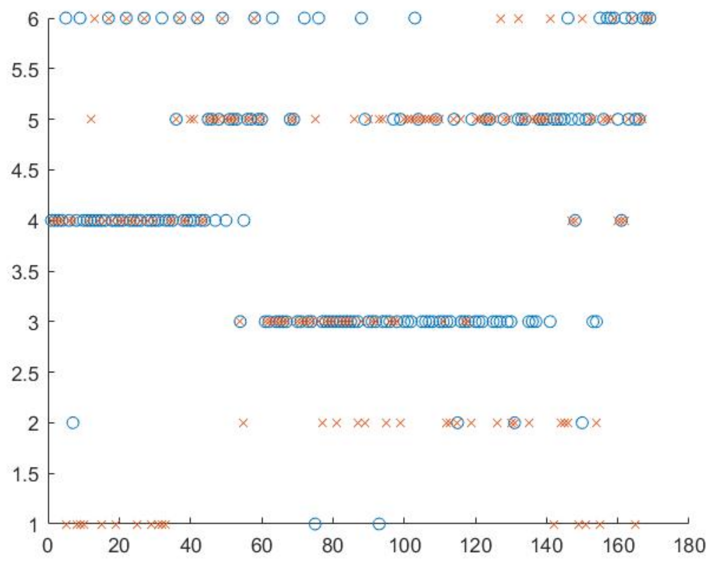
MOV profiles

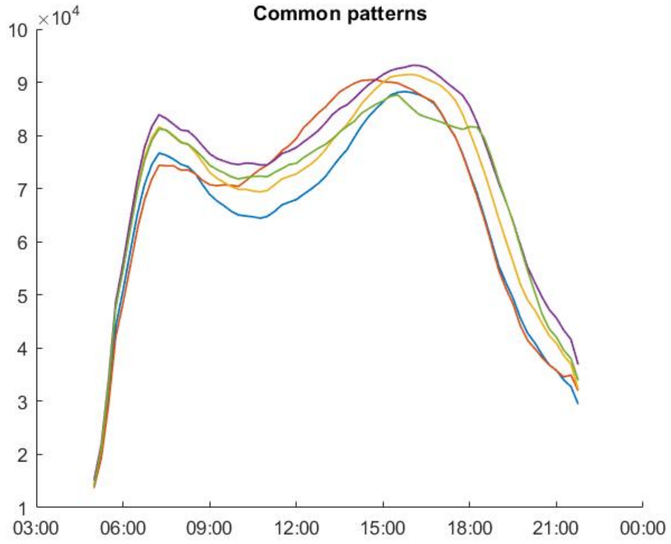


Clustering Similarity

- What matters?
  - Clustering method?
  - Clustering variables?
  - Sensor selection?
- Day clustering similarity
  - Optimum overlap
  - NMI and Rand's index
- Cluster time profile similarity

$$d_{ij} = 1 - \frac{\sum_k^N abs(v_{ik} - v_{jk})}{\sum_k^N max(v_{ik}, v_{jk})}$$





Day Clustering Similarity Results

Adjusted mutual information: 1 – the same / 0 – nothing in common

Speeds

	3Dmap_12	3Dmap_18	3Dmap_6	MOV_12	MOV_18	MOV_6	KmeanVector_12	KmeanVector_18	KmeanVector_6	KmeanSensors
3Dmap_12	1.00	0.41	0.32	0.21	0.26	0.16	0.16	0.25	0.15	0.18
3Dmap_18	0.41	1.00	0.28	0.30	0.36	0.19	0.25	0.33	0.18	0.21
3Dmap_6	0.32	0.28	1.00	0.18	0.19	0.13	0.15	0.18	0.14	0.14
MOV_12	0.21	0.30	0.18	1.00	0.57	0.43	0.48	0.48	0.40	0.25
MOV_18	0.26	0.36	0.19	0.57	1.00	0.44	0.44	0.52	0.43	0.29
MOV_6	0.16	0.19	0.13	0.43	0.44	1.00	0.48	0.46	0.49	0.23
KmeanVector_12	0.16	0.25	0.15	0.48	0.44	0.48	1.00	0.56	0.63	0.27
KmeanVector_18	0.25	0.33	0.18	0.48	0.52	0.46	0.56	1.00	0.54	0.31
KmeanVector_6	0.15	0.18	0.14	0.40	0.43	0.49	0.63	0.54	1.00	0.24
KmeanSensors	0.18	0.22	0.14	0.27	0.31	0.24	0.28	0.32	0.25	1.00

Flows

	3Dmap_12	3Dmap_18	3Dmap_6	MOV_12	MOV_18	MOV_6	KmeanVector_12	KmeanVector_18	KmeanVector_6	KmeanSensorsl
3Dmap_12	1.00	0.68	0.63	0.55	0.48	0.55	0.63	0.63	0.56	0.45
3Dmap_18	0.68	1.00	0.58	0.55	0.52	0.54	0.62	0.64	0.56	0.47
3Dmap_6	0.63	0.58	1.00	0.57	0.48	0.75	0.71	0.63	0.72	0.43
MOV_12	0.55	0.55	0.57	1.00	0.64	0.55	0.59	0.60	0.60	0.43
MOV_18	0.48	0.52	0.48	0.64	1.00	0.48	0.57	0.59	0.51	0.41
MOV_6	0.55	0.54	0.75	0.55	0.48	1.00	0.68	0.65	0.73	0.42
KmeanVector_12	0.63	0.62	0.71	0.59	0.57	0.68	1.00	0.69	0.77	0.52
KmeanVector_18	0.63	0.64	0.63	0.60	0.59	0.65	0.69	1.00	0.65	0.51
KmeanVector_6	0.56	0.56	0.72	0.60	0.51	0.73	0.77	0.65	1.00	0.47
KmeanSensors	0.45	0.47	0.43	0.43	0.41	0.42	0.52	0.51	0.47	1.00

Clustering Profile Similarity Results

$$ps_{IJ} = \frac{1}{|I|}\min\sum_{i}^{I}\sum_{j}^{J} d_{ij}x_{ij}$$

$$\sum_{j}^{J} x_{ij} = 1\,, \qquad \text{for } i \in I$$

$$\sum_{i}^{I} x_{ij} \leq 1\,, \qquad \text{for j} \in J$$

$$x_{ij} \in \{0,1\}$$

I,J – set of profiles

1 – the same profiles

Speed

J/I	3Dmap_12	3Dmap_18	3Dmap_6	MOV_12	MOV_18	MOV_6	KmeanVector_12	KmeanVector_18	KmeanVector_6
3Dmap_12	1.00	0.95	0.96	0.96	0.95	0.96	0.94	0.92	0.96
3Dmap_18	0.95	1.00	0.96	0.96	0.95	0.96	0.95	0.93	0.96
3Dmap_6	0.96	0.96	1.00	0.95	0.94	0.95	0.92	0.90	0.95
MOV_12	0.96	0.96	0.95	1.00	0.96	0.97	0.94	0.92	0.97
MOV_18	0.95	0.95	0.94	0.96	1.00	0.97	0.95	0.93	0.97
MOV_6	0.96	0.96	0.95	0.97	0.97	1.00	0.92	0.90	0.96
KmeanVector_12	0.94	0.95	0.92	0.94	0.95	0.92	1.00	0.91	0.94
KmeanVector_18	0.92	0.93	0.90	0.92	0.93	0.90	0.91	1.00	0.94
KmeanVector_6	0.96	0.96	0.95	0.97	0.97	0.96	0.94	0.94	1.00

Flow

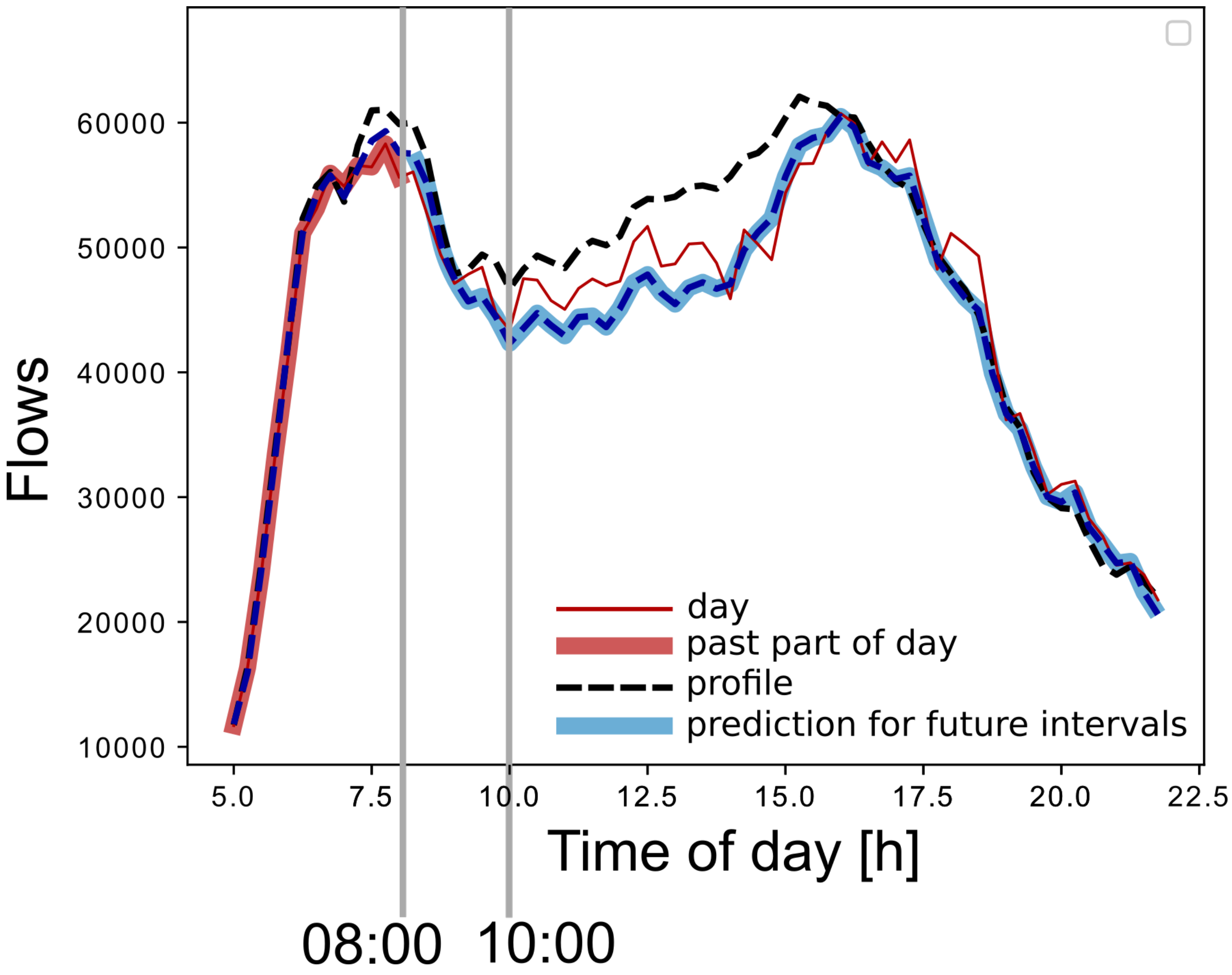
J/I	3Dmap_12	3Dmap_18	3Dmap_6	MOV_12	MOV_18	MOV_6	KmeanVector_12	KmeanVector_18	KmeanVector_6
3Dmap_12	1.00	0.87	0.88	0.89	0.88	0.90	0.84	0.80	0.89
3Dmap_18	0.87	1.00	0.89	0.90	0.89	0.91	0.87	0.83	0.90
3Dmap_6	0.88	0.89	1.00	0.88	0.87	0.89	0.80	0.73	0.88
MOV_12	0.89	0.90	0.88	1.00	0.91	0.93	0.86	0.81	0.92
MOV_18	0.88	0.89	0.87	0.91	1.00	0.93	0.89	0.85	0.93
MOV_6	0.90	0.91	0.89	0.93	0.93	1.00	0.81	0.73	0.91
KmeanVector_12	0.84	0.87	0.80	0.86	0.89	0.81	1.00	0.77	0.87
KmeanVector_18	0.80	0.83	0.73	0.81	0.85	0.73	0.77	1.00	0.86
KmeanVector_6	0.89	0.90	0.88	0.92	0.93	0.91	0.87	0.86	1.00

Demand Prediction

- Prediction for 2 hours (8 x 15 minute time intervals) into the future at the 08:00 and 15:00
- Match the current day with closest profile considering all past intervals to the 08:00 and 15:00

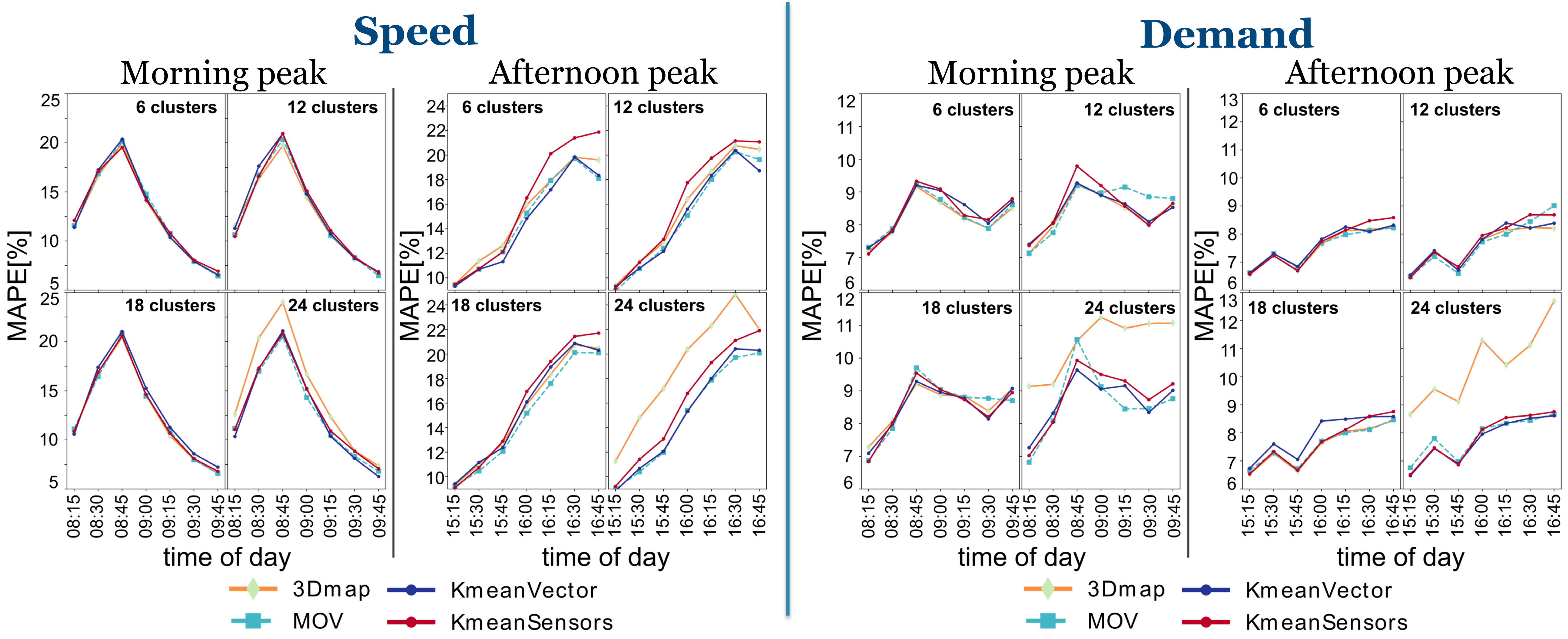
$$\min_i \sum_{k}^{K} abs(v_{ik} - c_k)$$

- Clustering of weekdays 2017
- Prediction of weekdays 2018



Demand Prediction Results

$$MAPE = \frac{100\%}{n} \sum^{n} \frac{observed - predicted}{observer}$$



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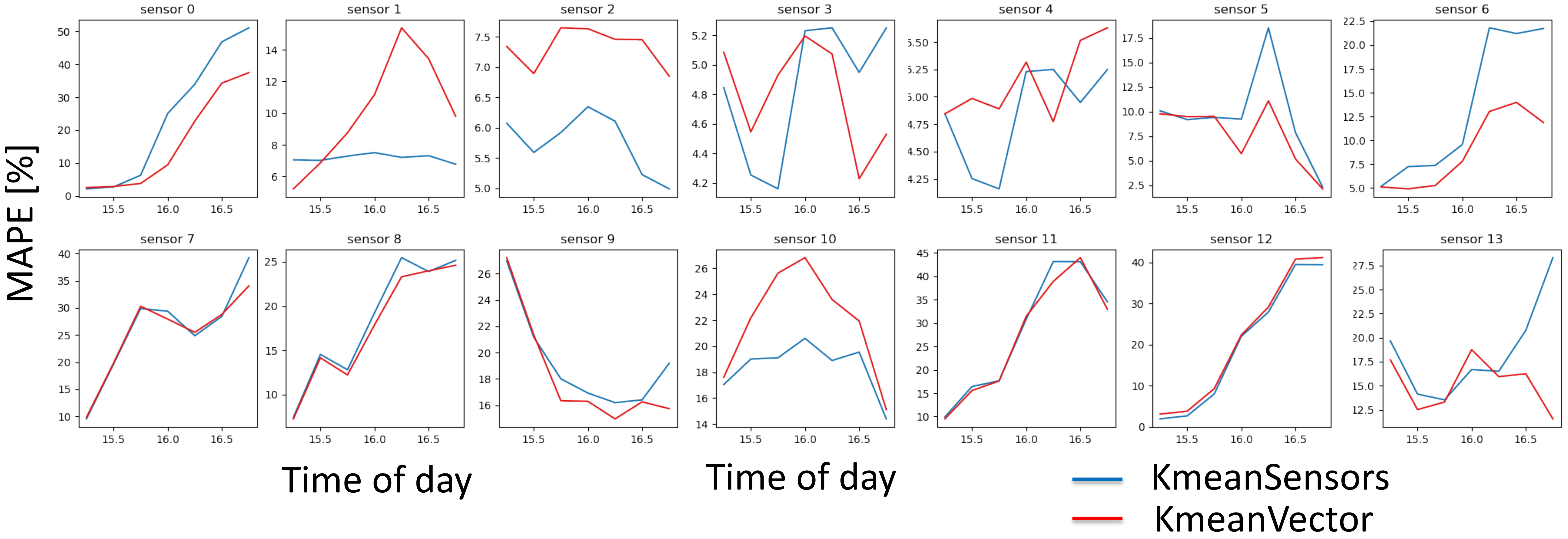
Demand Prediction Results

$$MAPE = \frac{100\%}{n}\sum^{n}\frac{observed - predicted}{observer}$$

KmeanSensors VS KmeanVectors sensor by sensor, speeds and afternoon peak, 6 clusters



Demand Prediction Based on Speed/Travel times?

- Increasing amount of network-wide probe data
- Can we find network-wide demand patterns using travel time / speed data?
  - Cluster link speeds or OD matrix?
- Do we need network-wide clustering?
  - Large-scale actions that affects route choice

Normalized mutual information:
1 – the same / 0 – nothing in common

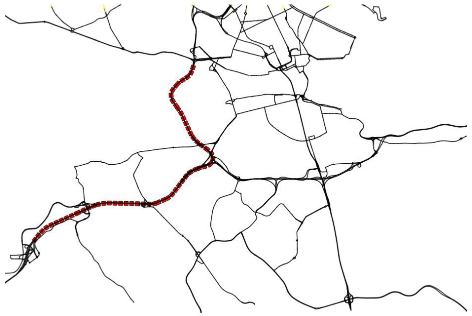
Clustering similarity between flows and speeds clusters [NMI]

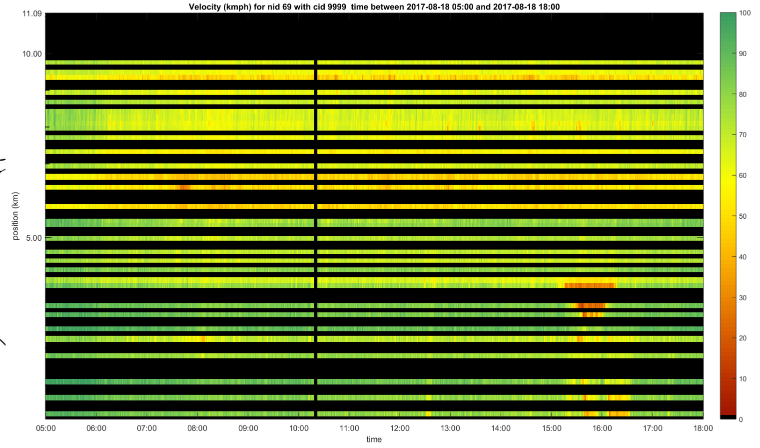
	Number of clusters			
Method	6	12	18	24
3Dmap	0.17	0.23	0.35	0.52
MOV	0.32	0.38	0.46	0.50
KmeanVector	0.41	0.42	0.44	0.54
KmeanSensors	0.27	0.31	0.36	0.42

Scenario Evaluation Example

- 25/8 2017: Malfunctioning bridge splice (”broskarv”) on Essingeleden
  - How to manage lane blocking?
  - What information should be given to travellers and when?

E4N 18/8 2017





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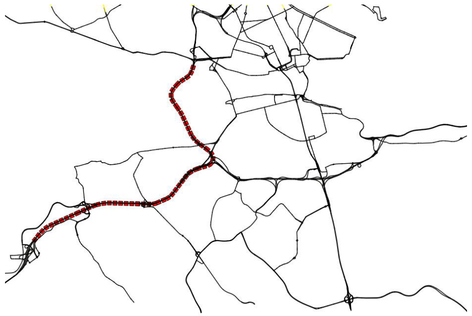
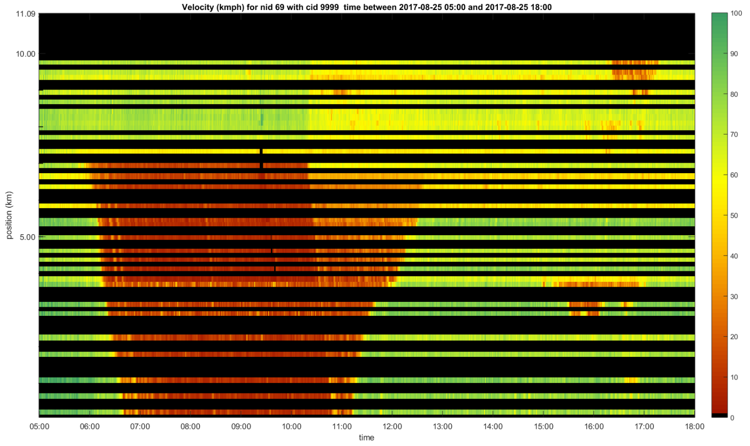
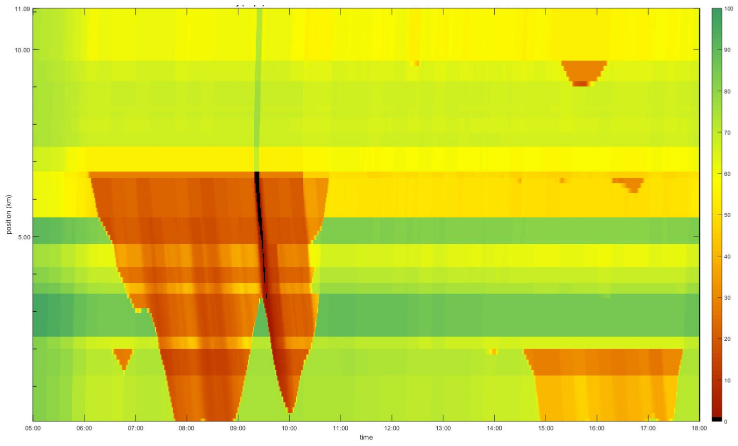


E4N 25/8 2017



E4N 25/8 2017 Model



Conclusions and Future Work

- Is clustering useful for scenario evaluation?
  - Yes, to determine typical days
- Does clustering method/variables matter?
  - Yes, especially for day clustering
  - However, small variations for weekdays and profiles quite similar
- Does cluster-based prediction work?
  - Yes, and tentatively quite little differences between clustering methods
- More work needed
  - To evaluate clustering effects on action ranking
  - To understand network-wide clustering and relationship between speed/flow-based clustering