BEUTH HOCHSCHULE FÜR TECHNIK BERLIN
University of Applied Sciences

Spatio-temporal traffic flow forecasting on a city-wide sensor network

GIS Ostrava 2017

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About me

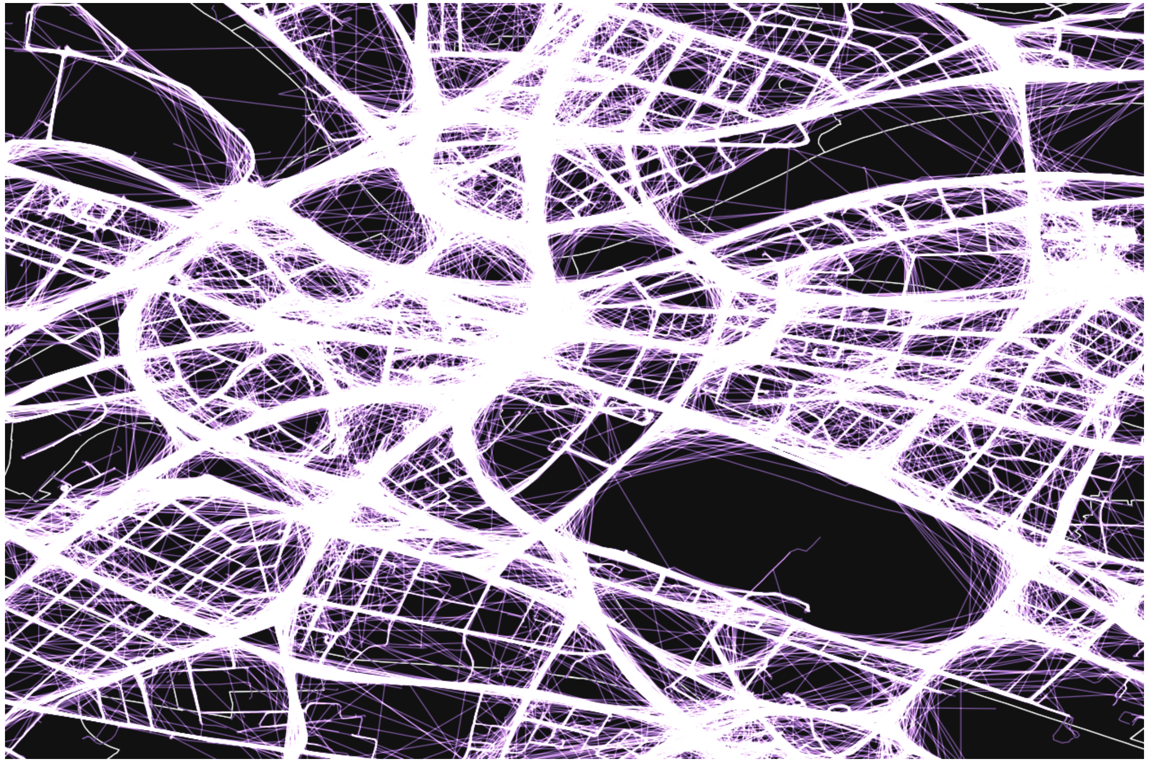
- Research assistant @BeuthHS
- Geography/GIS background
- Last 5yrs focus on spatial databases
- Core contributor to OS projects 3D City Database (CityGML) and pgMemento (Postgres versioning)
- Member of German Foss4g community
- Twitter: @FlxKu , GitHub: FxKu

Outline of this talk

- **Context:** Transportation research
- **Task:** Traffic forecasting
- **Problem:** Hardly used in the field
- **Question:** What works best?
- **My interest:** Spatio-temporal correlations
- **Methods:** Machine learning on time series
- **Results:** Where and when do we get a good prediction?
- **Discussion:** What can we tell / not tell from the results?

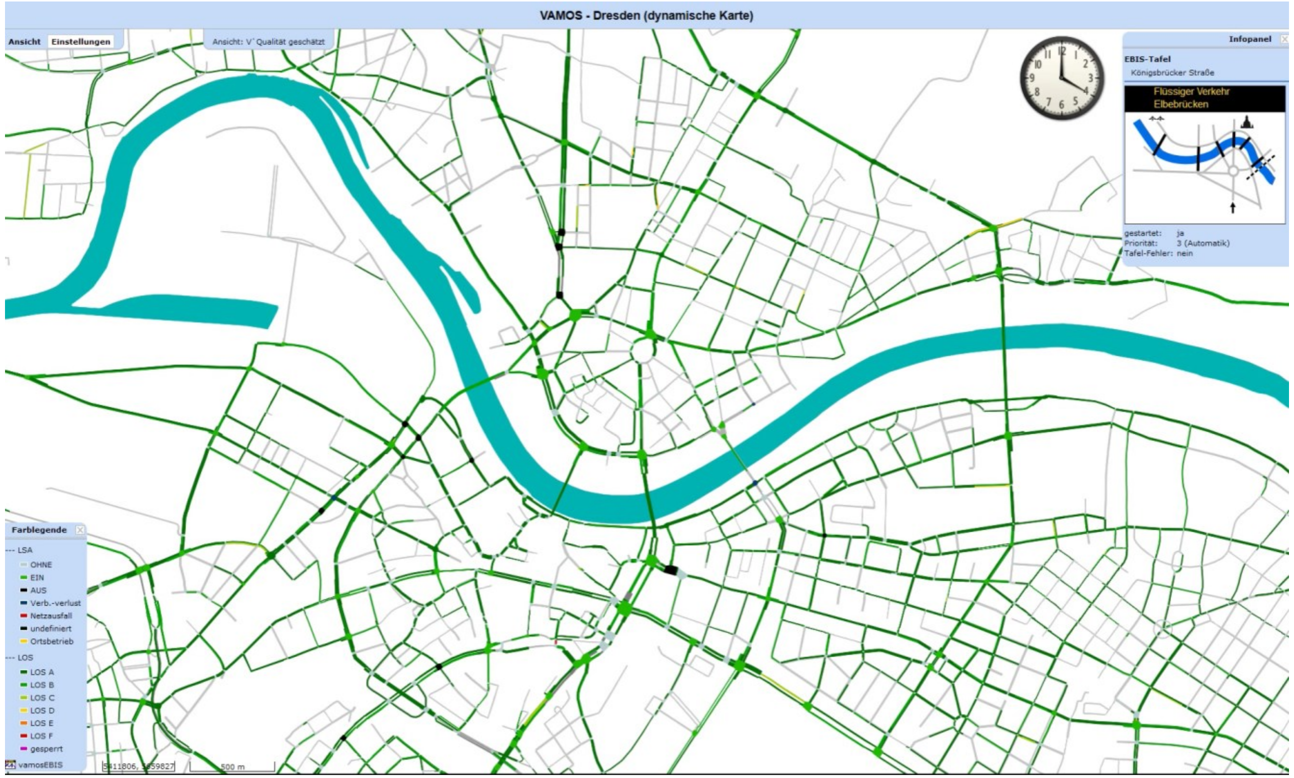
Context: ITS and Smart Mobility

- An Intelligent Transportation System (ITS) plays a crucial role in **optimizing the traffic flow** in a city
- Aims to recreate a most **realistic image of the current traffic** from **limited sample data** (static and floating sensors)
- Adopt **traffic theory to real-world** scenarios. Create programs to manage traffic flow (switching signs etc.)
- More data is always better (see Google, HERE) but usually it's **not available** to an ITS of the public sector

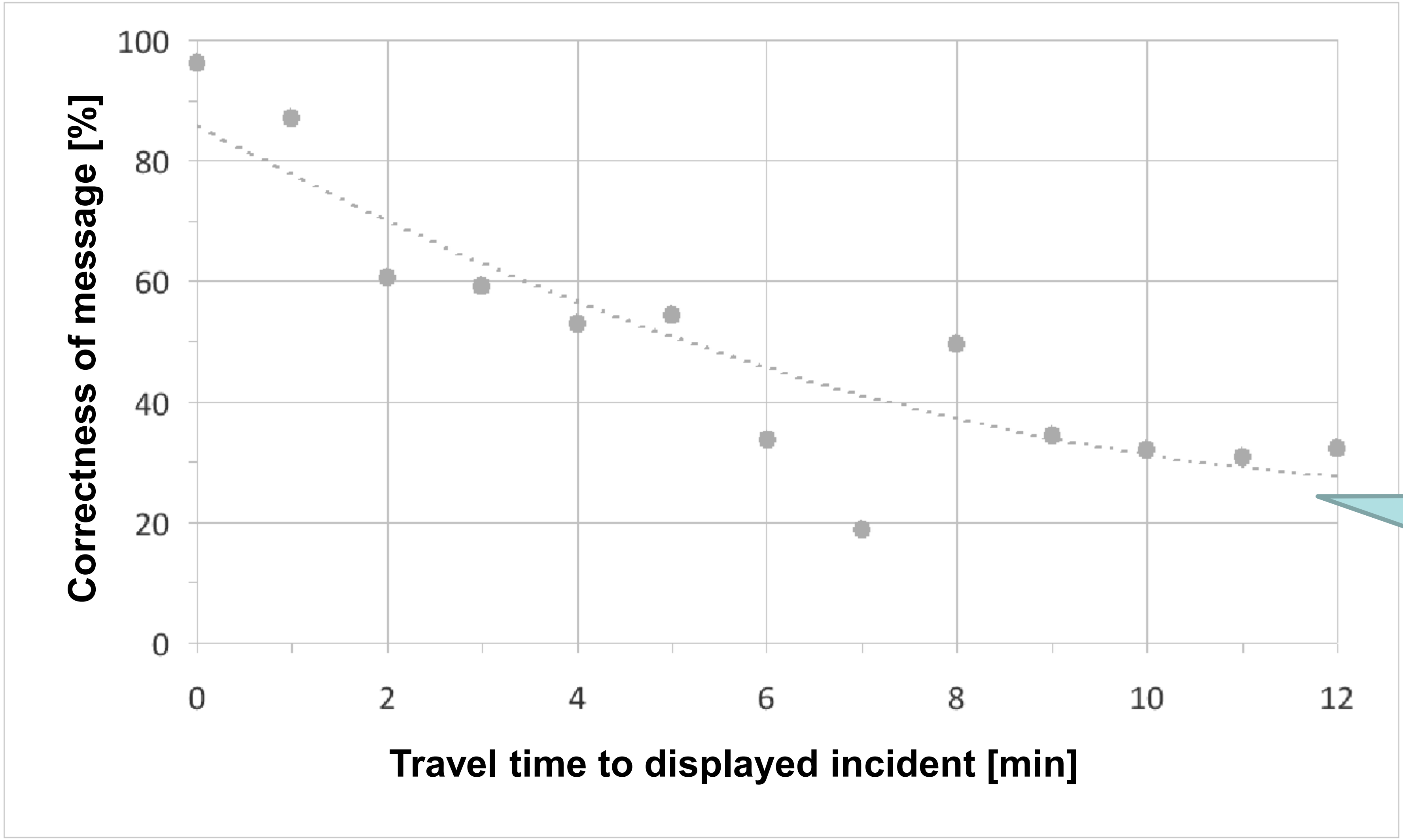


Problem: Adoption

- Sophisticated forecasting methods are not used most ITS (in Germany)
- Data aggregation and fusion is only done for monitoring reasons
- Trigger rule-based systems which are based empirical studies



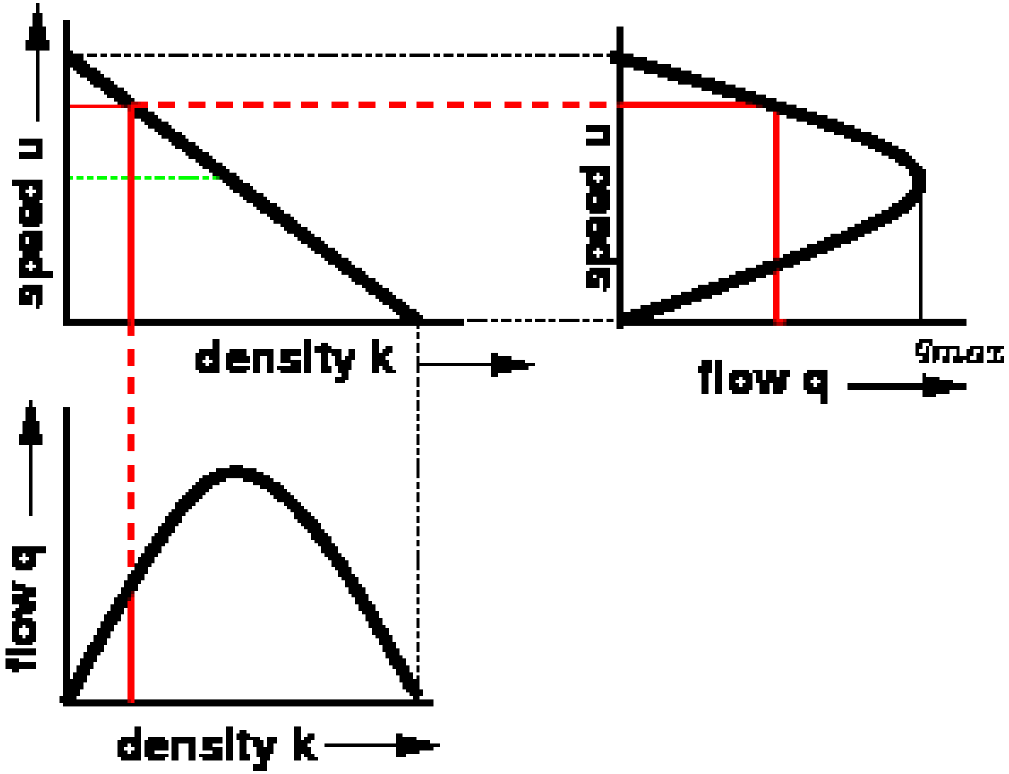
Problem: Forecasting in the field



Great uncertainty in traffic messages!

Pape, S.; Körner, M. (2016): Verkehrslageprognose unter Berücksichtigung der dynamischen Kapazitäten an LSA-abhängigen Knotenpunkten zur qualitativen Aufwertung der Verkehrslageinformation im Verkehrsmanagementsystem VAMOS

- Macroscopic properties
  - **Speed** = Avg. speed of cars per time per location / trajectory
  - **Traffic flow** = Number of cars per time per location / trajectory
  - Max traffic flow = **Road capacity** / lane / hour
  - **Traffic density** = Flow / Speed (simplified)

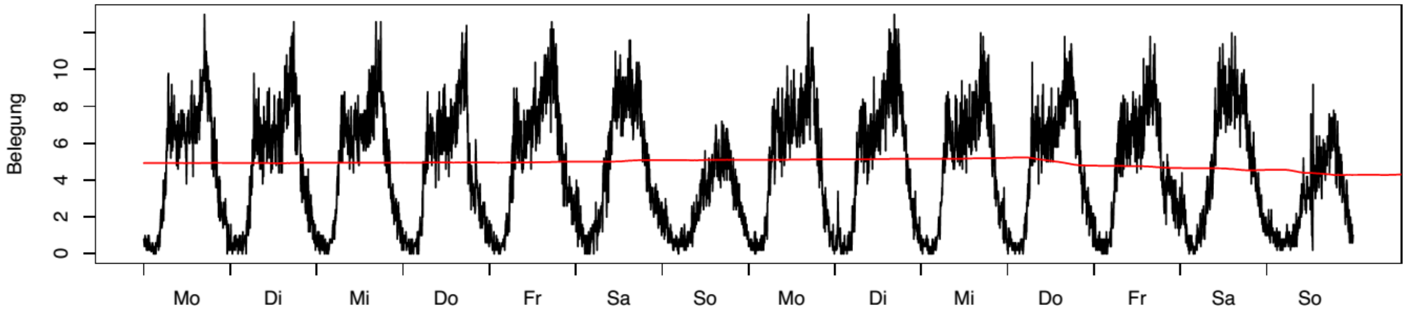


Source: https://www.civil.iitb.ac.in/tvm/1111_nptel/512_FundRel/plain/plain.html

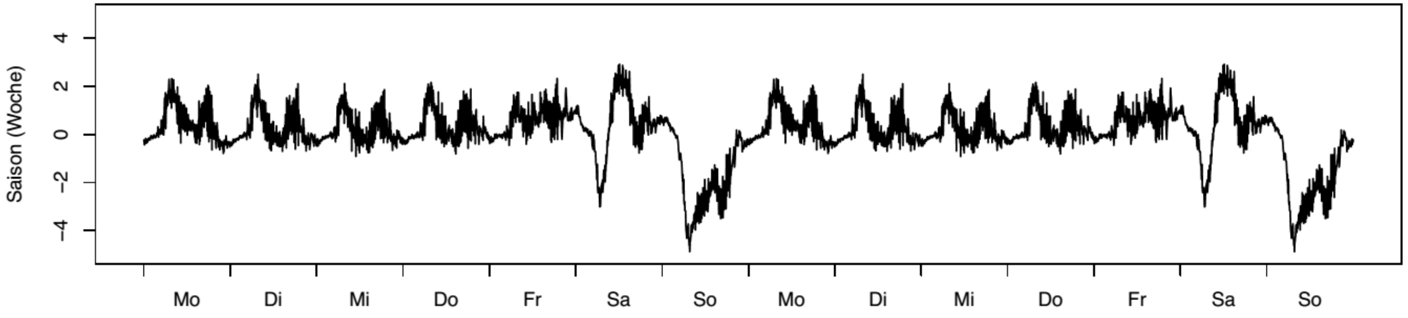
Treiber, M.; Kesting, A. (2013): Traffic Flow Dynamics – Data, Models and Simulation

Task: Traffic Forecasting – Dependencies

- Temporal dependencies
  - Many time-series analysis methods require **stationarity** = no trend or seasonal dependency (rarely given but can be reached)
  - **Autocorrelation**
  - How to deal with **missing data**? How does data imputation affect the **statistical characteristics** of the time series?



Measured occupancy (with MA 5 minutes) and global trend



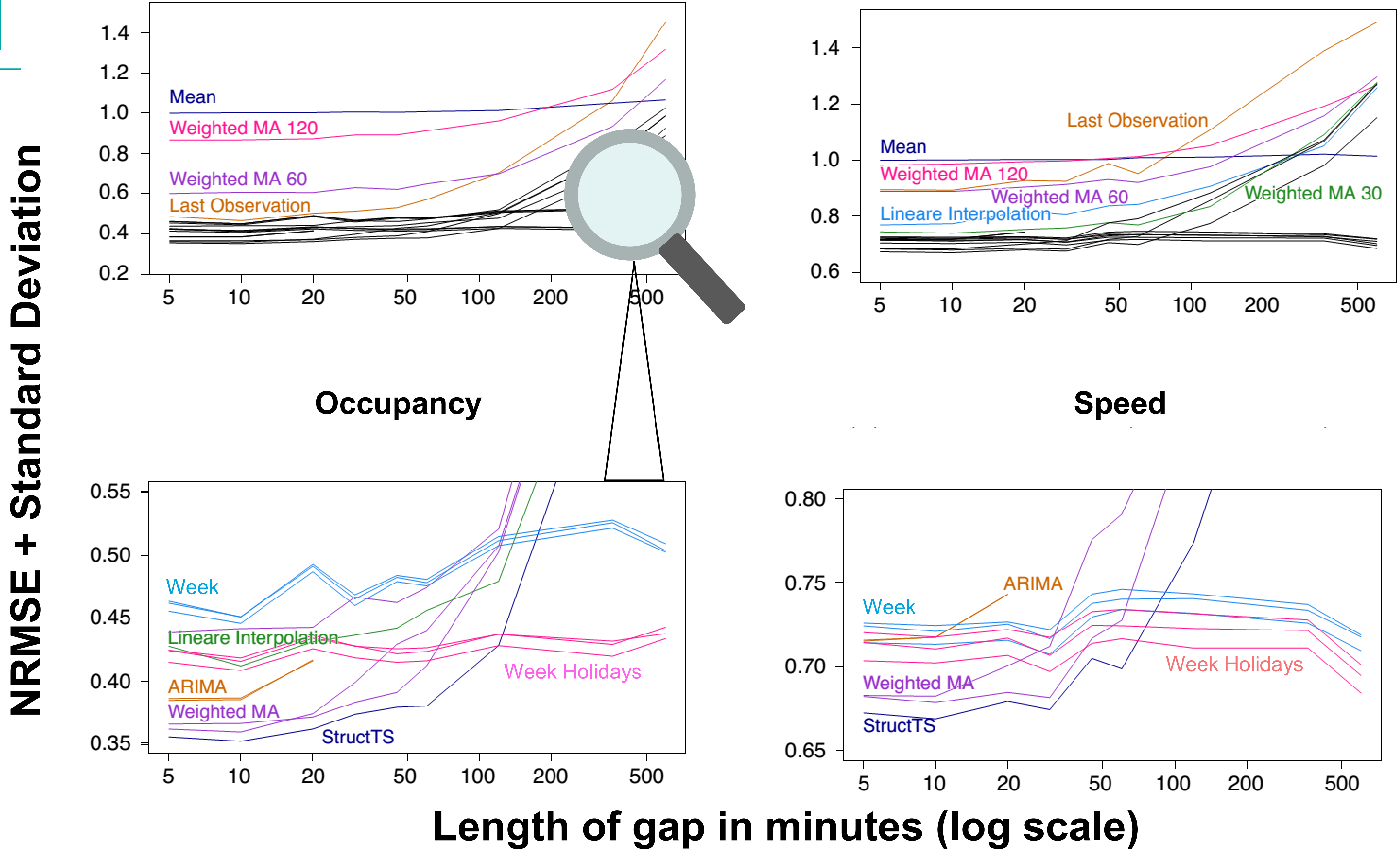
Extracted weekly season

Waterloo, S. (2017): Analyse und Bereinigung unvollständiger und fehlerhafter Messreihen von Verkehrssensoren. Bachelor Thesis.

- **Mean average error (MAE)** for imputing estimated values in gaps of 5 minutes
- **Conservation of standard deviation** using different estimation methods in R (0 worst, 1 best)

Method	Occupancy (MAE)	Occupancy (SD)	Speed (MAE)	Speed (SD)
StructTS (na.kalman)	**0,84**	0,95	**5,38 km/h**	0,66
Average week incl. holidays	0,95	0,93	5,64 km/h	0,58
Weighted Moving Average (25 min before and after gap)	**0,86**	0,93	**5,49 km/h**	0,66
ARIMA	0,90	0,97	5,71 km/h	0,65
Linear Interpolation	0,98	0,97	6,08 km/h	**0,85**
Last Observation Carried Foreward	**1,13**	**1,0**	**7,00 km/h**	**0,97**
Overall Mean	**3,32**	**0**	**10,84 km/h**	**0**

Waterloo, S. (2017): Analyse und Bereinigung unvollständiger und fehlerhafter Messreihen von Verkehrssensoren. Bachelor Thesis.



Waterloo, S. (2017): Analyse und Bereinigung unvollständiger und fehlerhafter Messreihen von Verkehrssensoren. Bachelor Thesis.

Task: Traffic Forecasting – Dependencies

- Spatial dependencies
  - **Spatio-temporal autocorrelation** in time series at different locations (e.g. STARIMA)
  - General assumption: Neighbours are having a higher impact on the target than distant detectors, but **how to select neighbours**? (geometrical, physical, mathematical)

Pfeifer, P.E. & Deutsch, S.J. (1981): Seaosonal Space-Time ARIMA Modeling.

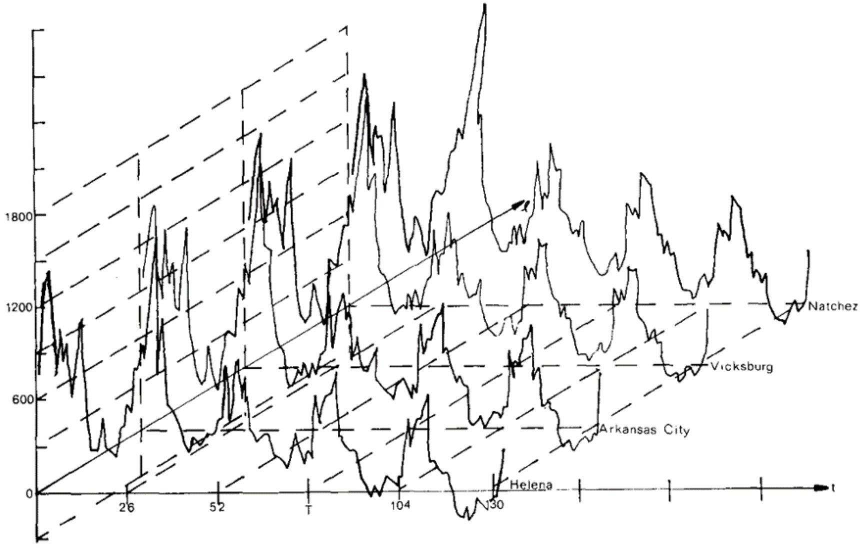
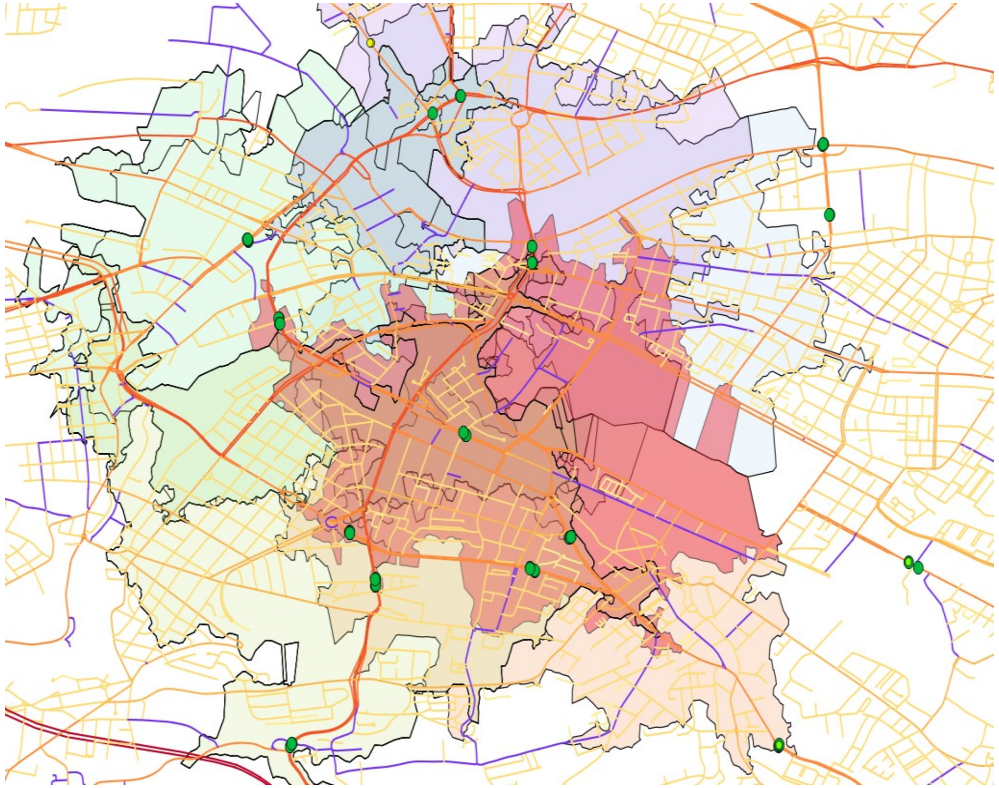


FIG. 7. Past Observations and STARIMA $(2_{11}, 0, 0) \times (0, 1, 1_0)_{26}$ Forecasts Made from $T = 79$

- Consider underlying **road network**
  - Travel times for trajectories
  - **Temporal dynamics** of neighbourhoods (see Cheng et al. 2014)

- **Spatial Weight Matrix** specifying existence and strength of spatial neighbours

	s1	s2	s3	s4	s5	s6	s7	s8	...
s1	1	1	0	0	1	1	0	0	...
s2	1	1	1	0	0	0	0	0	...
s3	0	1	1	0	0	0	0	0	...
s4	0	0	1	1	0	1	0	1	...
s5	1	0	0	0	1	0	1	0	...
s6	1	1	0	1	0	1	0	1	...
s7	0	0	0	0	1	0	1	0	...
s8	0	0	0	1	0	1	0	1	...
...	...	...	...	...	...	...	...	...	...



Task: Traffic Forecasting

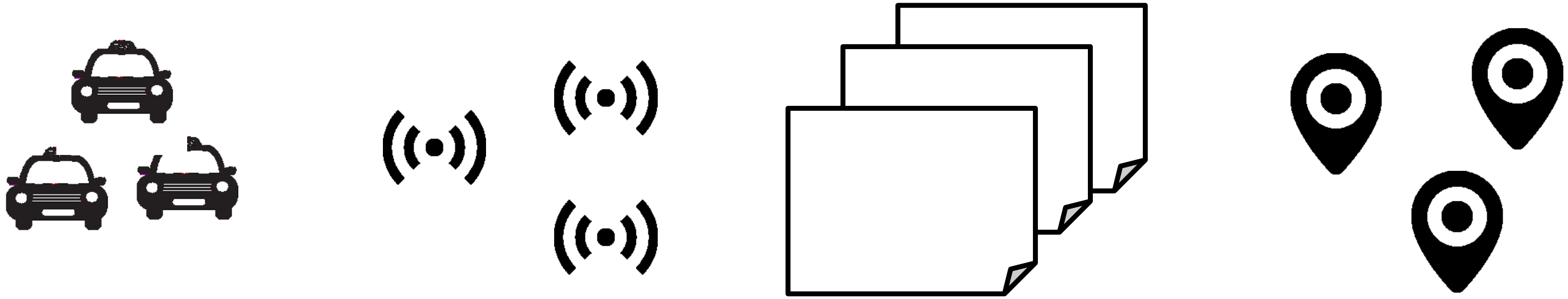
- **Trivial**: Take current value, seasonal average, random walk etc.
- **Simple**: Exponential Smoothing, Moving Average (MA)
- **Autoregressive**: ARIMA, SARIMA, VARMA etc.
- **kNN**: Past scenarios closest to recent one
- **Graphical models:** Decision Trees, Bayesian Networks, Markov Chains
- **Machine Learning**: Support Vector Machines (SVM), Artificial Neural Networks (ANN)

- What works best?

Research questions

- In the papers, usually, **only one method is engineered exhaustively** and only **compared to rather simple baseline methods** from other algorithmic families
- Non parametric approaches (SVM, ANN etc.) are regarded as superior in predicting **non-linear traffic patterns**. How big is the gap to parametric models?
- Simplified scenarios (freeway setting, low number of sensors, fixed spatial dependencies)
- **Performance and scalability** is often neglected. Would it work with >1000 sensors?
- Do we need a **combination of different methods**?

- What data do we have?



Floating Car Data from Dresden (1 year)

Sensor Data from Dresden (8 years)

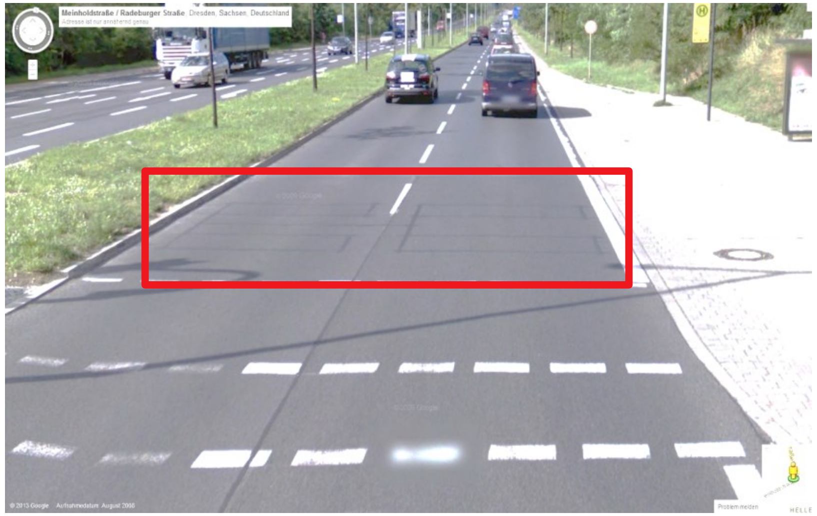
Protocol Data from Dresden (1 year)

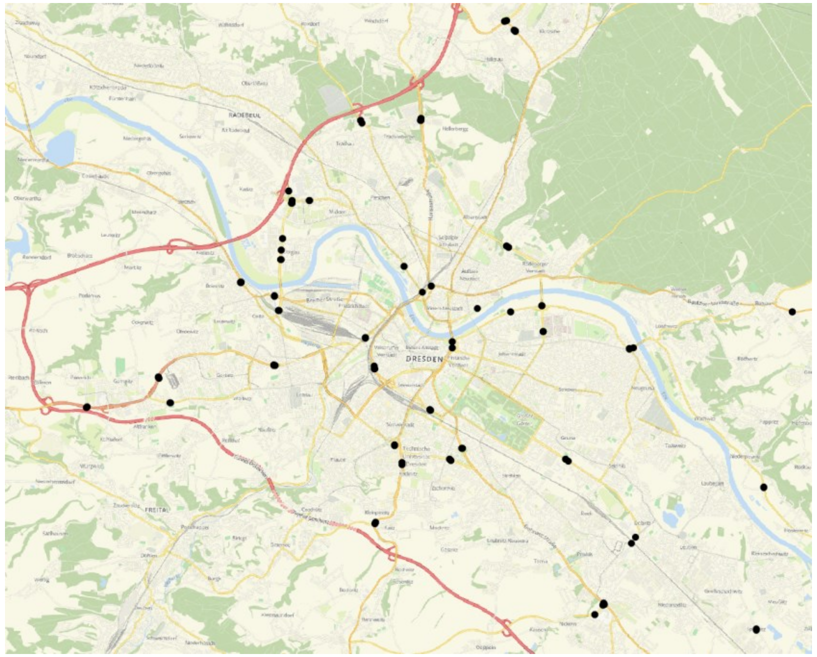
GPS-Tracking Data from ExCELL

Not present here, but you can check:
https://magda-beuthhs.github.io/magdablog/

Experimental Setup: Data selection

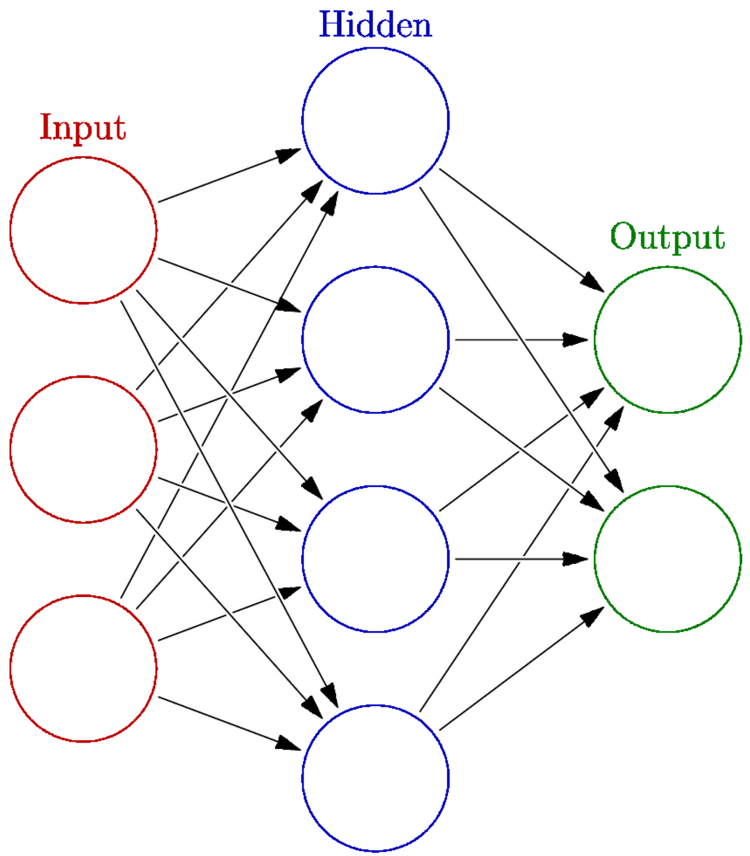
- Take data from **double inductive loops**
  - Installed on main roads with distance to waiting queues at intersections
  - Can capture the speed properly
  - Good distribution across the city
- Task: **Predict future values** (occupancy, speed) at the sensor locations (5, 10, 15, 30, 45 minutes offset)
- **Different inputs** to check spatial relevance for predictions:
  - Only historic values of the target
  - Historic values from the target's neighbours
  - Historic values from the whole data set





Experimatental Setup: FFNN

- **Data**: Occupancy of July 2015, tested against August and September 2015
- **ANN Type**: Feed Forward (FFNN)
- **Layers**: 1 input, 1 hidden, 1 output
- **Activation Function**: Sigmoid
- **Optimization**: Stochastic Gradient Descent
- **Loss Function**: RMSE
- **Other Hyperparameters**:
  - n Neurons = 59 (= number of sensors taken)
  - Learning rate = 0.01
  - Batch Size = 20
  - Iterations = 10000



Experimatental Setup: FFNN

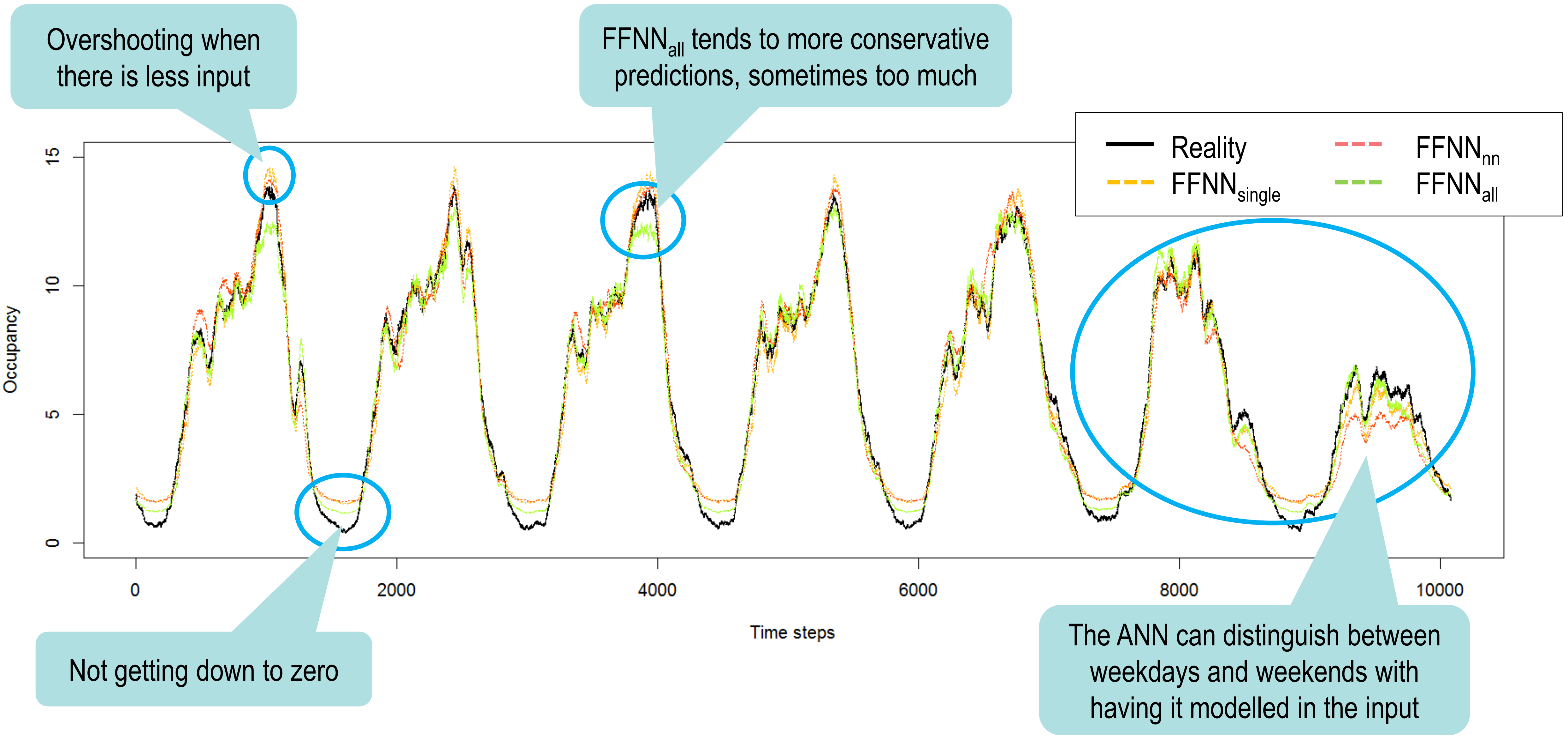
- $\text{FFNN}_{\text{single}}$ fed only **with target** sensor
- FFNN_{NN} fed only **with neighbours** of target sensor
- $\text{FFNN}_{\text{NN+}}$ fed **with neighbours incl. target** itself
- FFNN_{all} fed with values from **all sensors**

$$\begin{bmatrix} x_{s_1,t_0} & \cdots & x_{s_n,t_0} \\ \vdots & \ddots & \vdots \\ x_{s_1,t_n} & \cdots & x_{s_n,t_n} \end{bmatrix} \begin{bmatrix} x_{s_1,t_{0+offset}} & \cdots & x_{s_n,t_{0+offset}} \\ \vdots & \ddots & \vdots \\ x_{s_1,t_{n+offset}} & \cdots & x_{s_n,t_{n+offset}} \end{bmatrix}$$

Input Matrix *Target Matrix*

- Testing environment:
  - **Hadoop Cluster** for SVMs (Apache Spark, LibSVM)
  - **CUDA node** for ANNs (Tensor Flow, DeepLearning4J)
  - **In-Memory DB** node for storing sensor data (Exasol DB)

Results: One exemplary week of August



Results: MAEs of different methods

Table 1. MAE for different prediction horizons for one sensor

FFNN type	t5	t10	t15	t30	t45
$FFNN_{single}$	0,5042	0,5743	0,6679	0,9698	1,2970
$FFNN_{NN}$	0,6255	0,6660	0,7248	0,9831	1,0299
$FFNN_{NN+}$	1,7177	1,7157	1,7236	1,7813	1,8928
$FFNN_{all}$	0,4975	0,4933	0,5262	0,7474	1,0299
$mFFNN_{single}$	0,4324	0,5213	0,6137	0,9360	1,2771
$mFFNN_{NN}$	0,5616	0,6080	0,6667	0,9231	1,2519
$mFFNN_{NN+}$	1,6420	1,6543	1,6862	1,8126	1,9612
$mFFNN_{all}$	**0,3998**	**0,4086**	**0,4521**	**0,6405**	**0,8684**

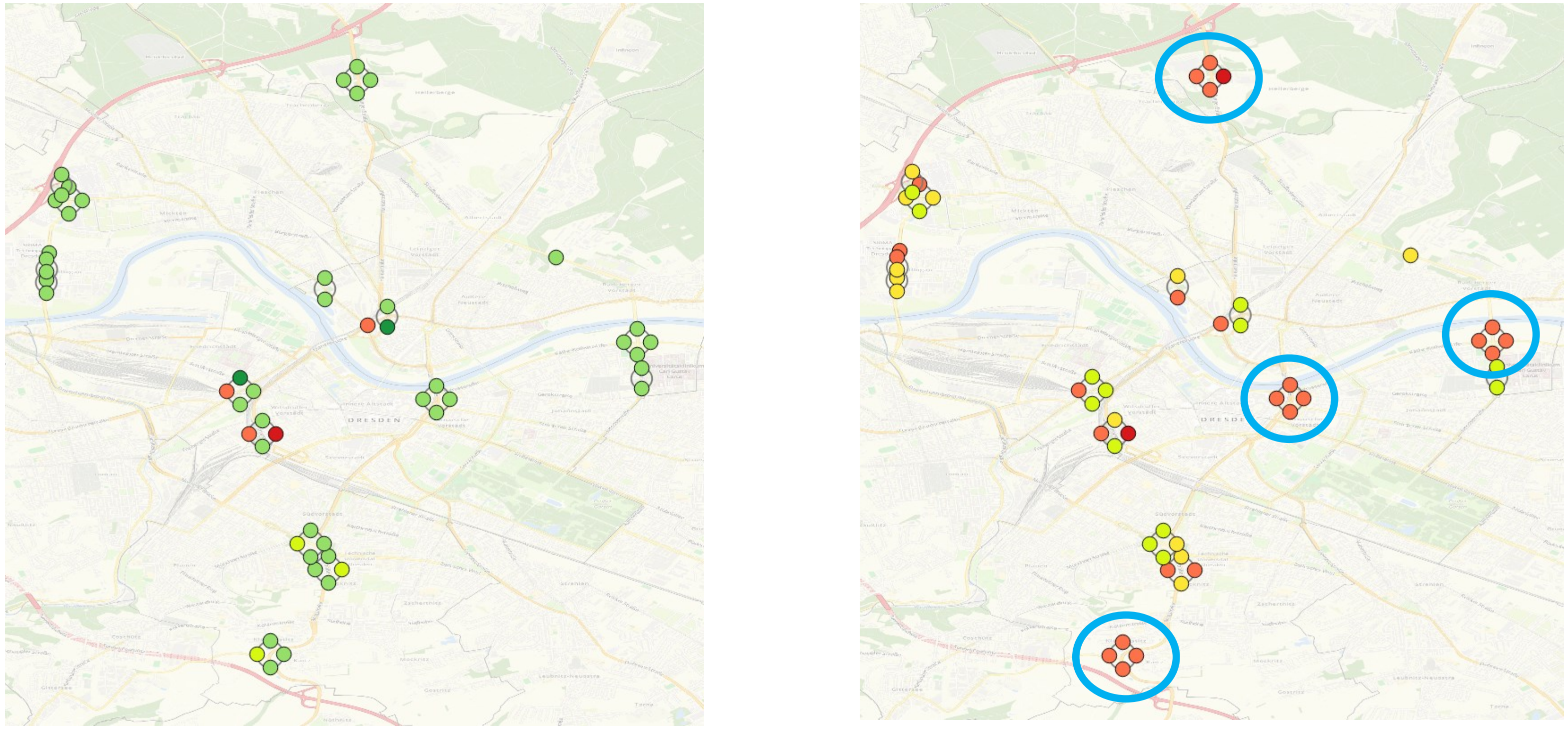
Here, we modelled a sequence into the FFNN input matrix

- Having information about neighbours did **not improve** the predictions compared to $FFNN_{single}$
- For **short-term predictions** the most simplest FFNN is fine enough
- With all sensors (and sequence) the FFNN gives the best predictions

Discussion

MAE 0 – 0.50 | 0.50 – 0.75 | 0.75 – 1.00 | 1.00 – 1.25 | 1.25 – 1.50 | 1.50 – 3.00

$FFNN_{single}$



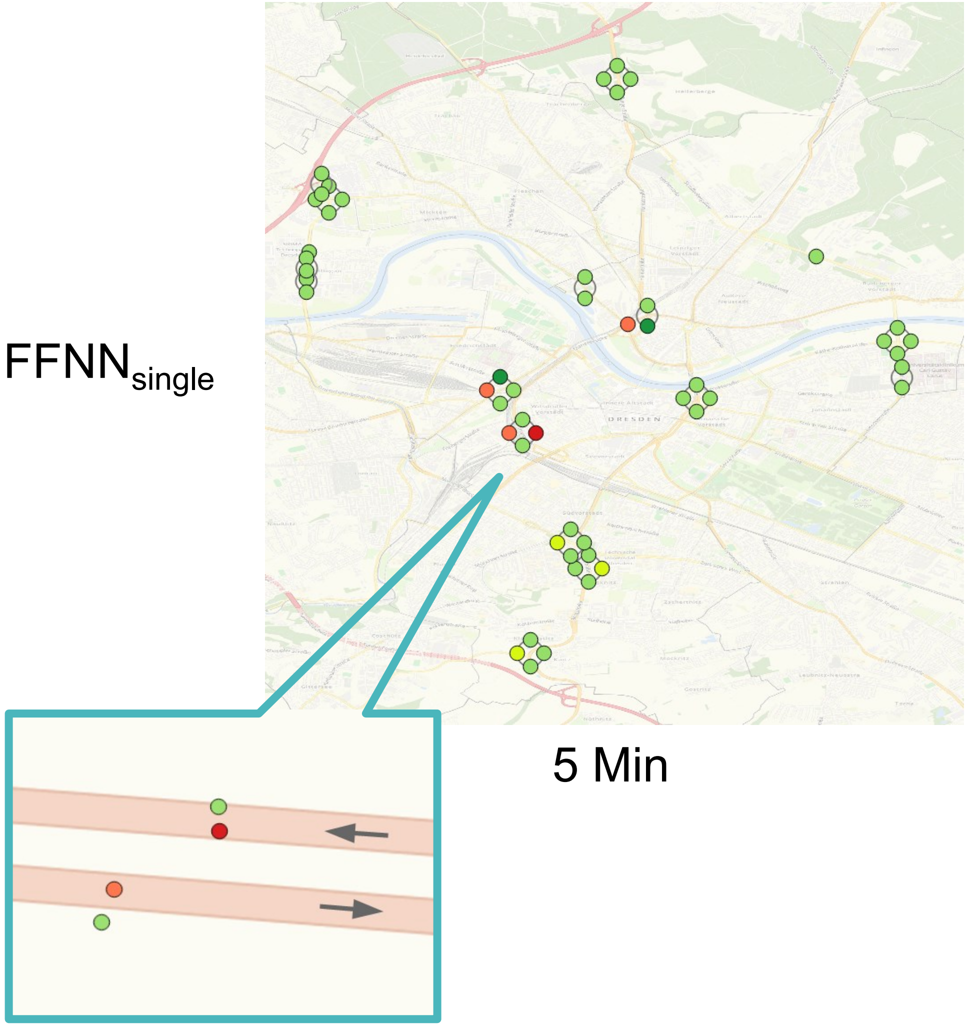
5 Min   45 Min

- Prediction error generally grows with temporal offset (expected)
- It is harder to predict future values (45 min) at locations with more regular traffic flow (main roads closes to highways and bridges)

Discussion

MAE ● 0 – 0.50 ● 0.50 – 0.75 ● 0.75 – 1.00 ● 1.00 – 1.25 ● 1.25 – 1.50 ● 1.50 – 3.00

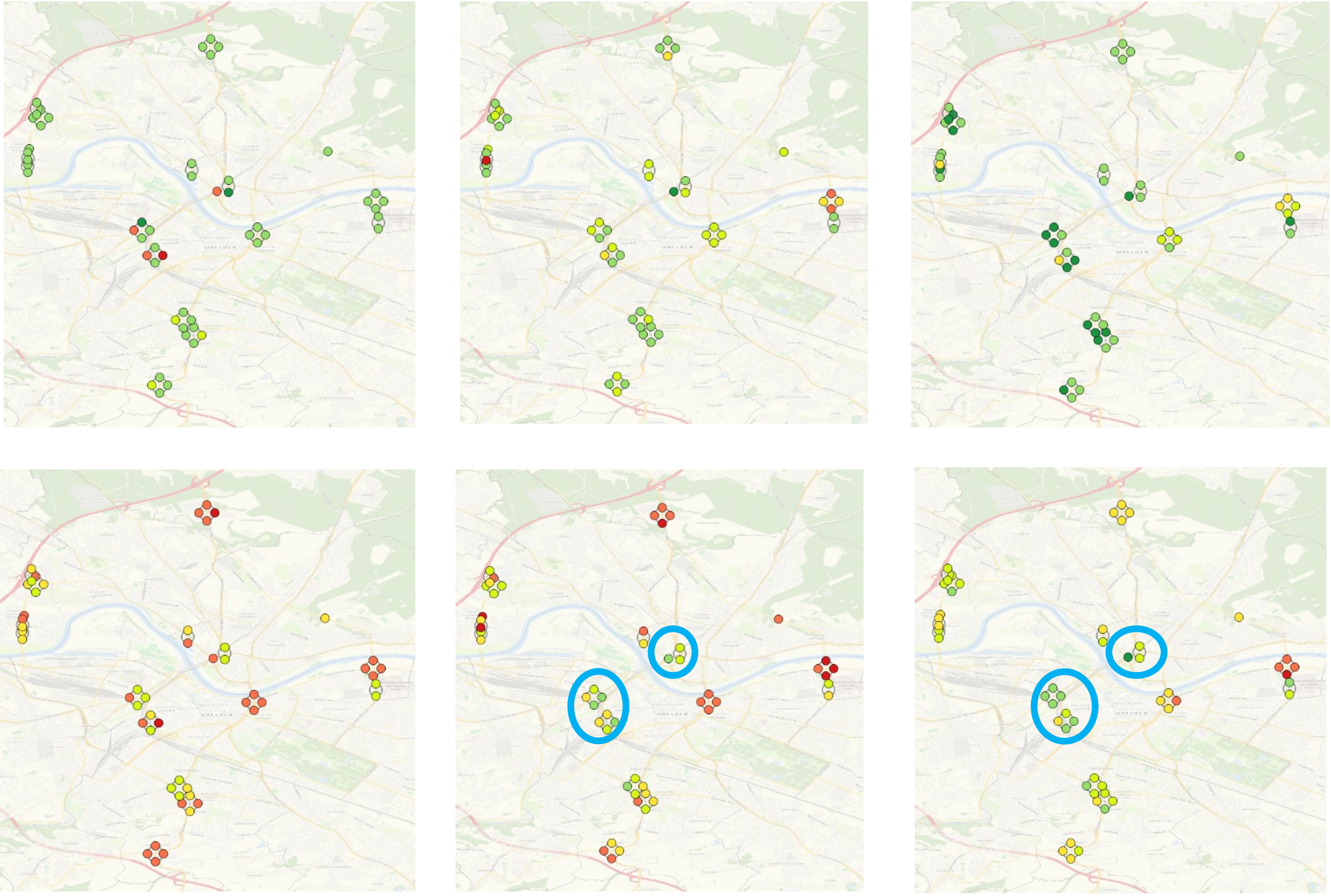
$\text{FFNN}_{\text{single}}$



5 Min

- When only regarding the target itself the error can be higher on the inner lane
- Higher irregularity of road occupancy on the “faster” lane

Discussion



- How is error distributed with other FFNN setups?
- As seen in the results for one sensor (table), adding more information to the inputs vectors, pays off for **long-term predictions**
- Again, higher errors can be seen at the same locations with some exceptions
- Sensors near intersections with potentially more irregular traffic work well with FFNN$_{NN}$ and FFNN$_{all}$

Discussion

- Traffic in Dresden is **very regular** – it is easy to **overfit**
- More **refinement** is necessary, e.g. introduce **more dimensions to the input vectors** (daytime, weekday, holiday, weather conditions etc.)
- Yet, not a strong focus on how good the predictions work at **predicting anomalies** in traffic. Requires a **labeling process** in advance. How much **variance** can be found?
- GIS and ITS specialists want to gain new insights about **spatio-temporal correlations**. Can we define **patterns** with a black box approach such as the ANN represents?
- How to install a **continuous learning** algorithm that adopts to changes in traffic

Future Work

- Extend the forecasting test to compare different approaches
  - **STARIMA** – *WIP*
  - **SVM** – *WIP*
  - Feed Forward Neural Network (**FFNN**) – *first results (see paper)*
  - Long Short-Term Neural Network (**LSTM**) – *WIP*

- Feature engineering to have a labeled input data set for traffic congestion patterns

- Test the developed models in the field against real-time data from the VAMOS ITS

Thank you for your attention!

Questions?

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