Institute of Cartography and Geoinformatics | Leibniz Universität Hannover

Monitoring cities with modern sensors and analysis methods

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Smart City – Internet of Things (IoT)

- Data about objects and processes in the city are recorded and observed with sensors and made generally available.

- Citizens are also part of this structure (as actors and sensors).

- Interaction between citizens and the technology that surrounds them

Monitoring traffic violations in China

Smart City – Vision

Political framework

- Horizon Europe: Mission: Climate Neutral and Smart Cities;
- relevant aspects:
  - Climate change, air quality
  - Spatial planning and development, energy-efficient buildings
  - urban infrastructures and networks, including transport and logistics systems, energy, water, etc.

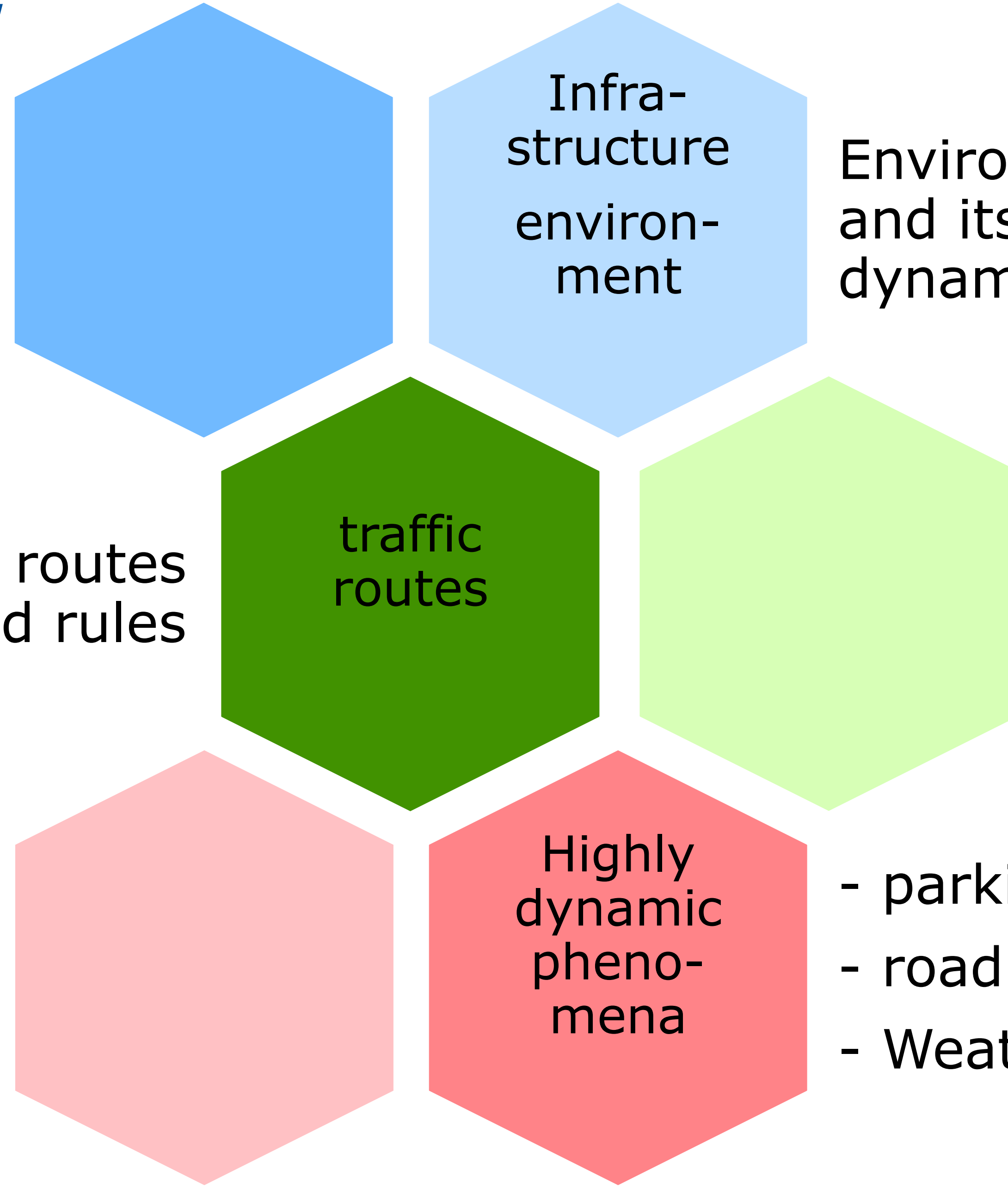
- Germany: Digital Cabinet of the Federal Government: "Digital Sovereignty”
  - to use, link and evaluate data responsibly and autonomously
  - “The basis for technological innovation, knowledge generation and social cohesion".
  - "Key resource for social prosperity and participation, for a prosperous economy and the protection of the environment and climate, for scientific progress and for government action".

City monitoring

- Observe and document processes that take place in a city:
- Static:
  - Buildings, infrastructure
- Dynamic:
  - Traffic, fine dust, solar radiation, weather, use of a park, energy consumption, noise, odours, overcrowded trash cans, open-air concert, delivery traffic, height of trees/grass

- Many things can be captured with modern sensor technology or crowd sourcing –> we will see examples
- Much is relevant and interesting for city administration
- Much is interesting for the citizen
- Much is interesting for autonomous traffic

Overview



Environment and its dynamics

- Traffic routes and rules

- parking spaces
- road users
- Weather

Detection of changes in the environment

Julia Schachtschneider, Claus Brenner

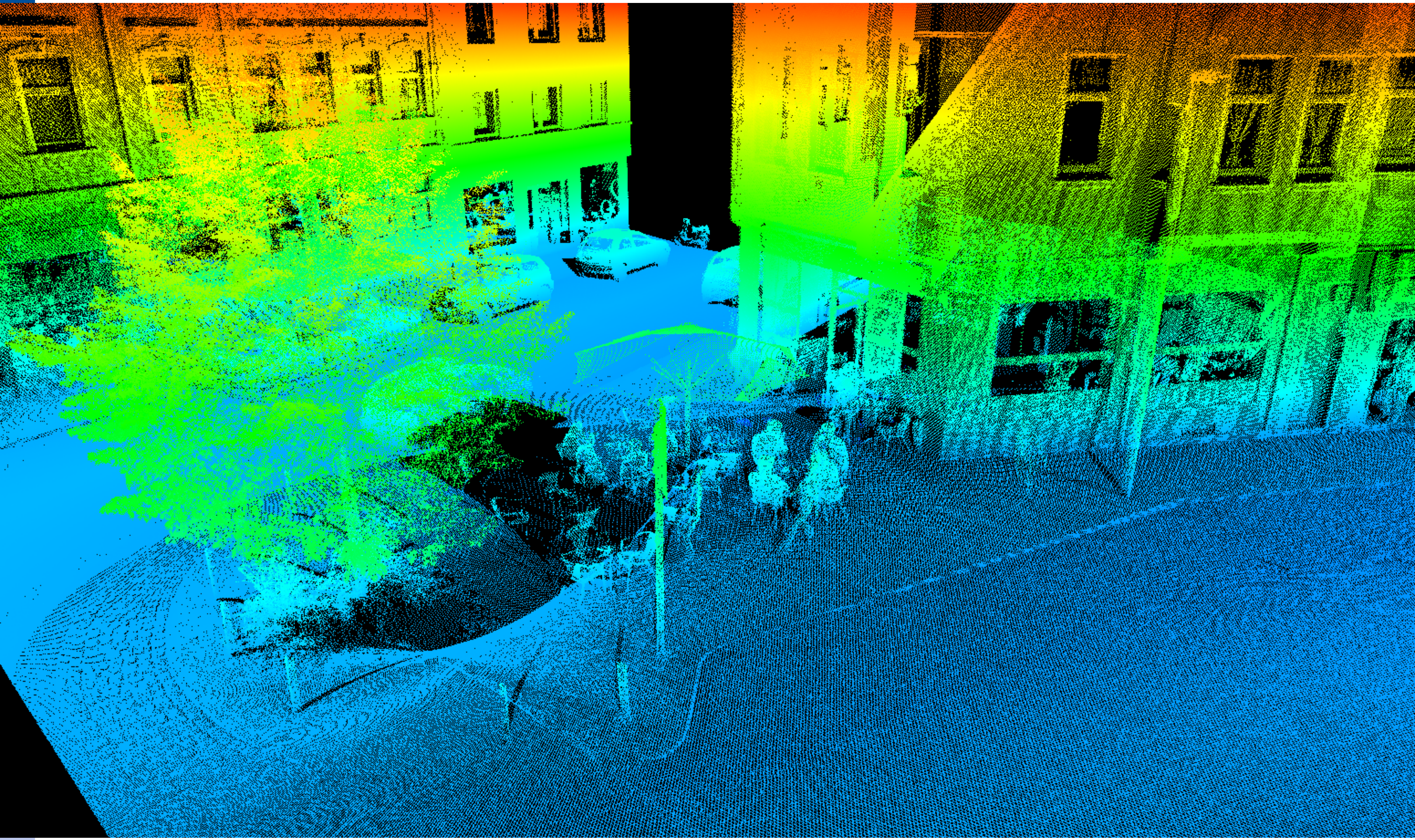
DFG-Graduiertenkolleg i.c.sens

Important information for autonomous vehicles or assistance systems

- Changes in the environment (especially in the transport sector)
  - day and night
  - Summer and winter, rain and sunshine
  - School (morning / afternoon / evening)
  - construction site
  - New construction, renovation
- humans have an expectation about how a (familiar or unfamiliar) environment looks like in another temporal context – autonomous vehicles do not have this per se.
  - -> we have to equip them with this information, then they can "understand" their environment better and react faster
  - -> they also need to know which objects in the environment can be used reliably for positioning
- -> therefore required: **dynamic map**

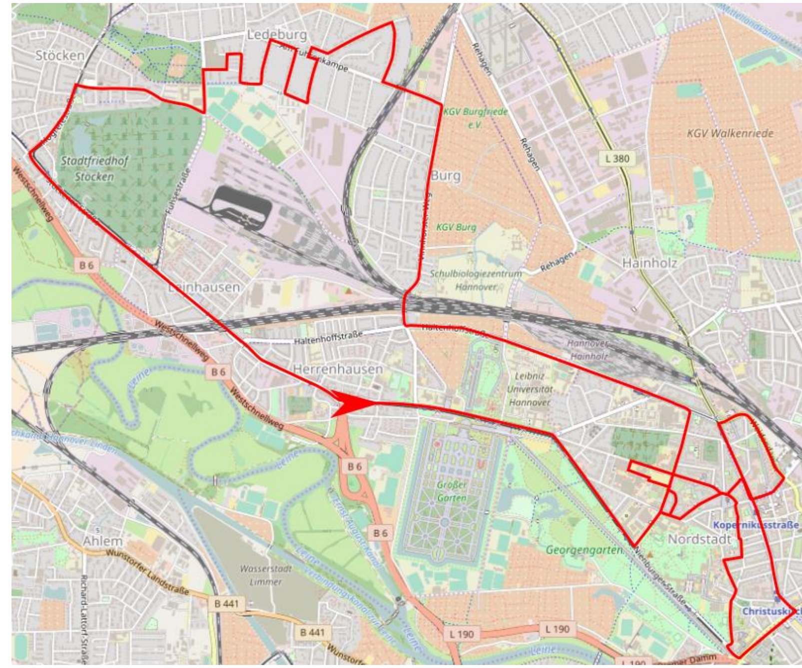
Mobile Mapping Van

- Riegl VMX-250, 600k points/s



Data capture

- ~20 km route in Hannover
  - Nordstadt
  - Stöcken
  - Leinhausen
  - Herrenhausen

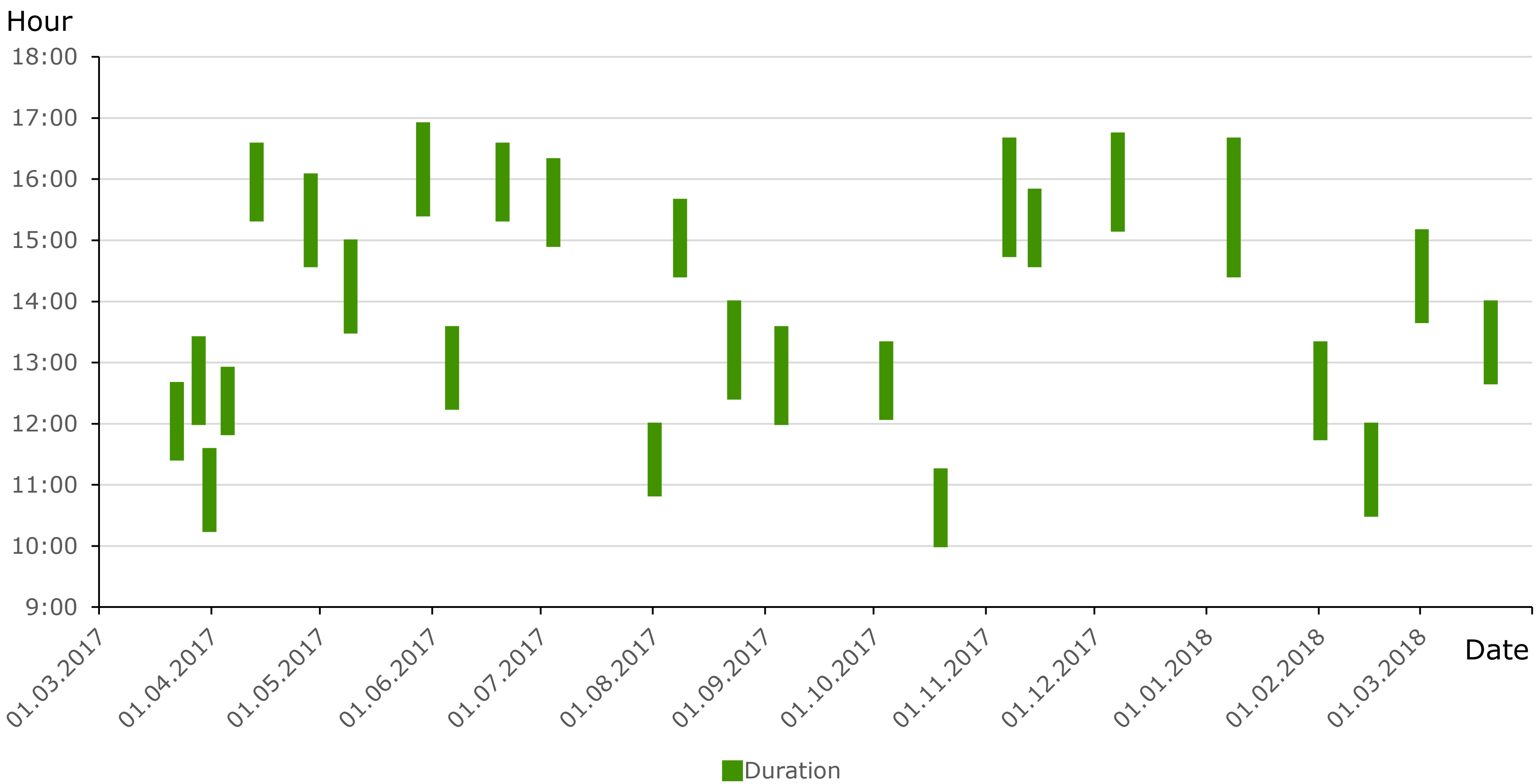


20 km Route for biweekly measurements

- One year bi-weekly measurement runs

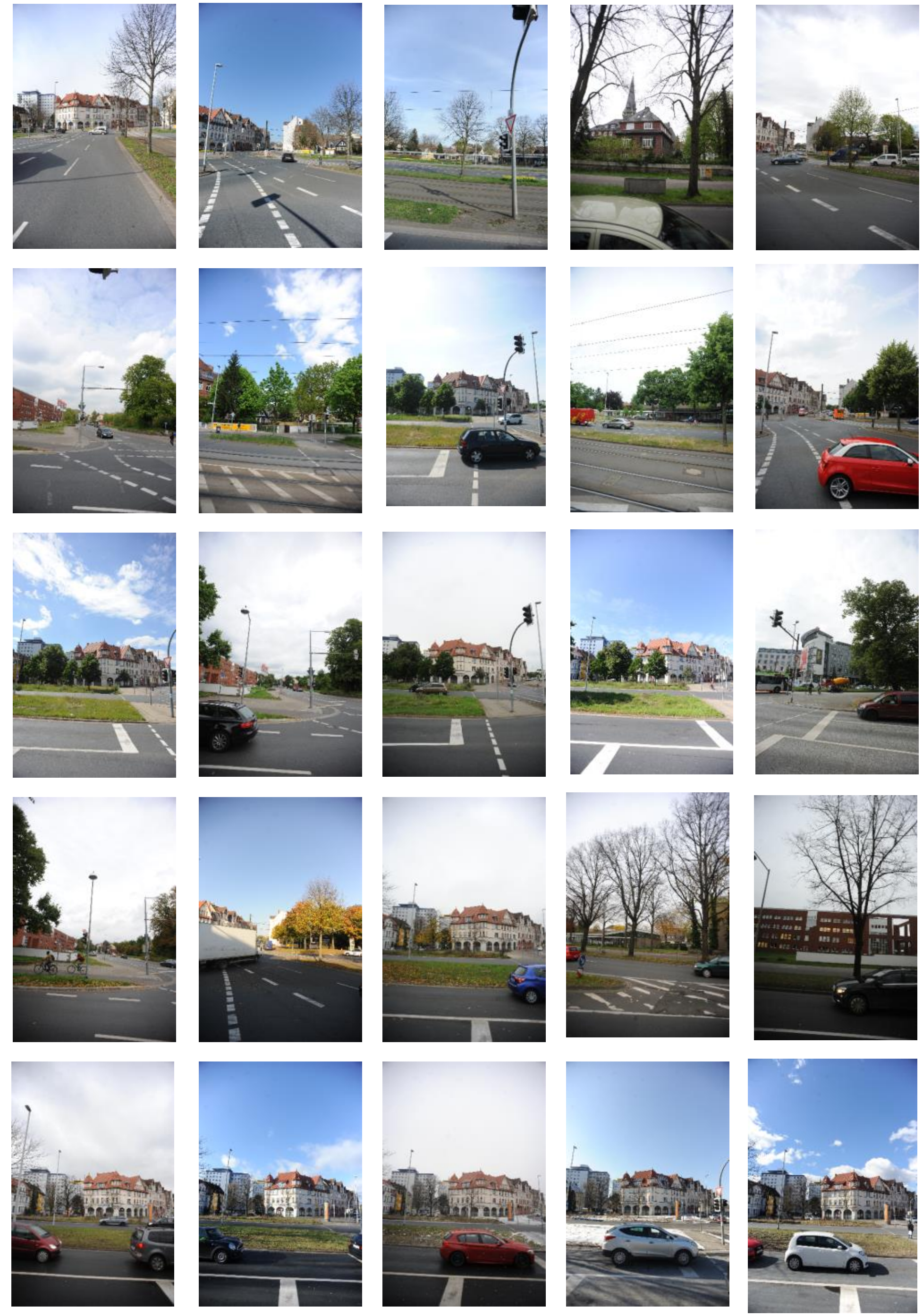
Data

- A total of 25 measurement runs
- March 2017 to March 2018,
- Different times of day/days of the week

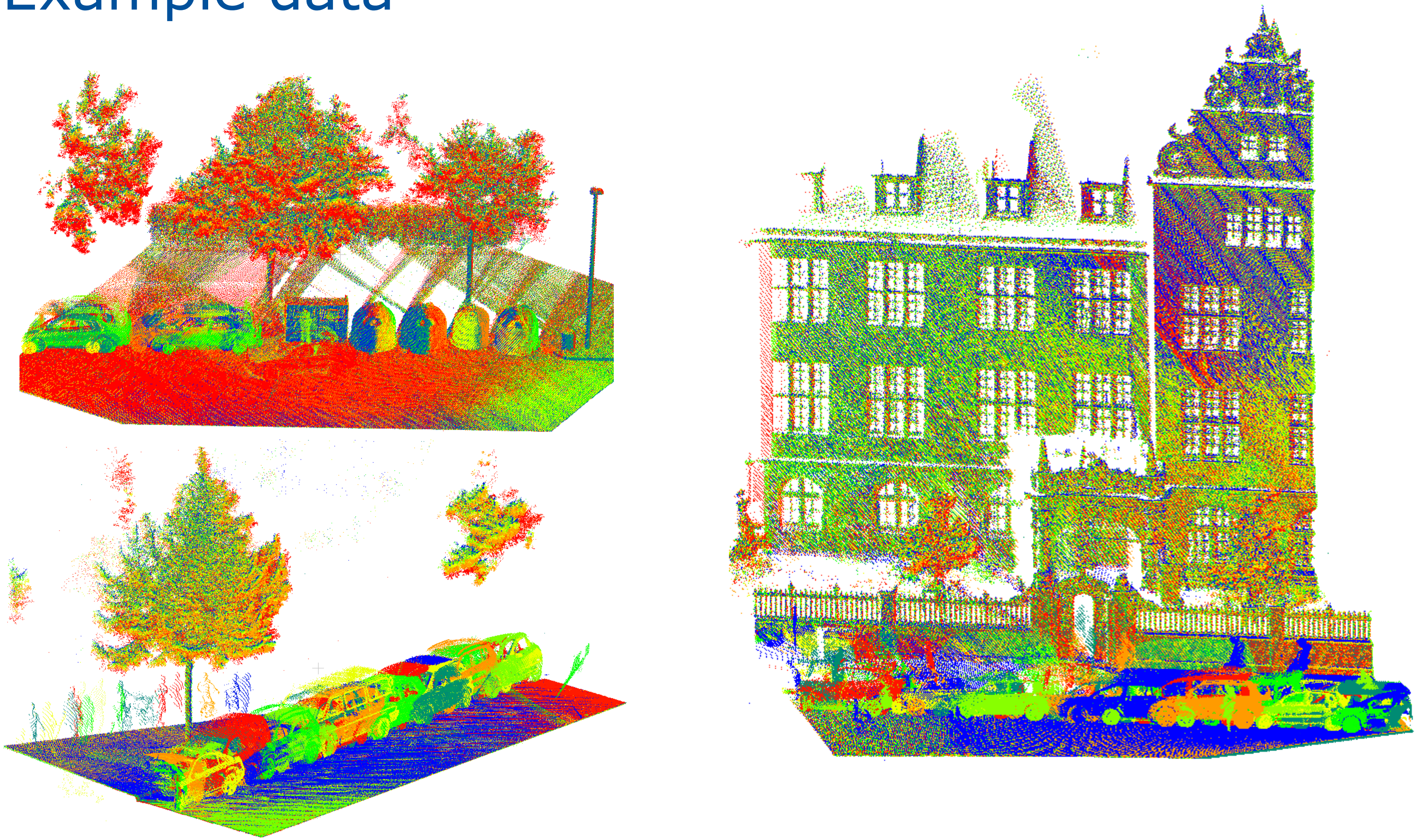


Data

- Various
  - seasons
  - weather conditions
  - traffic situations



Example data

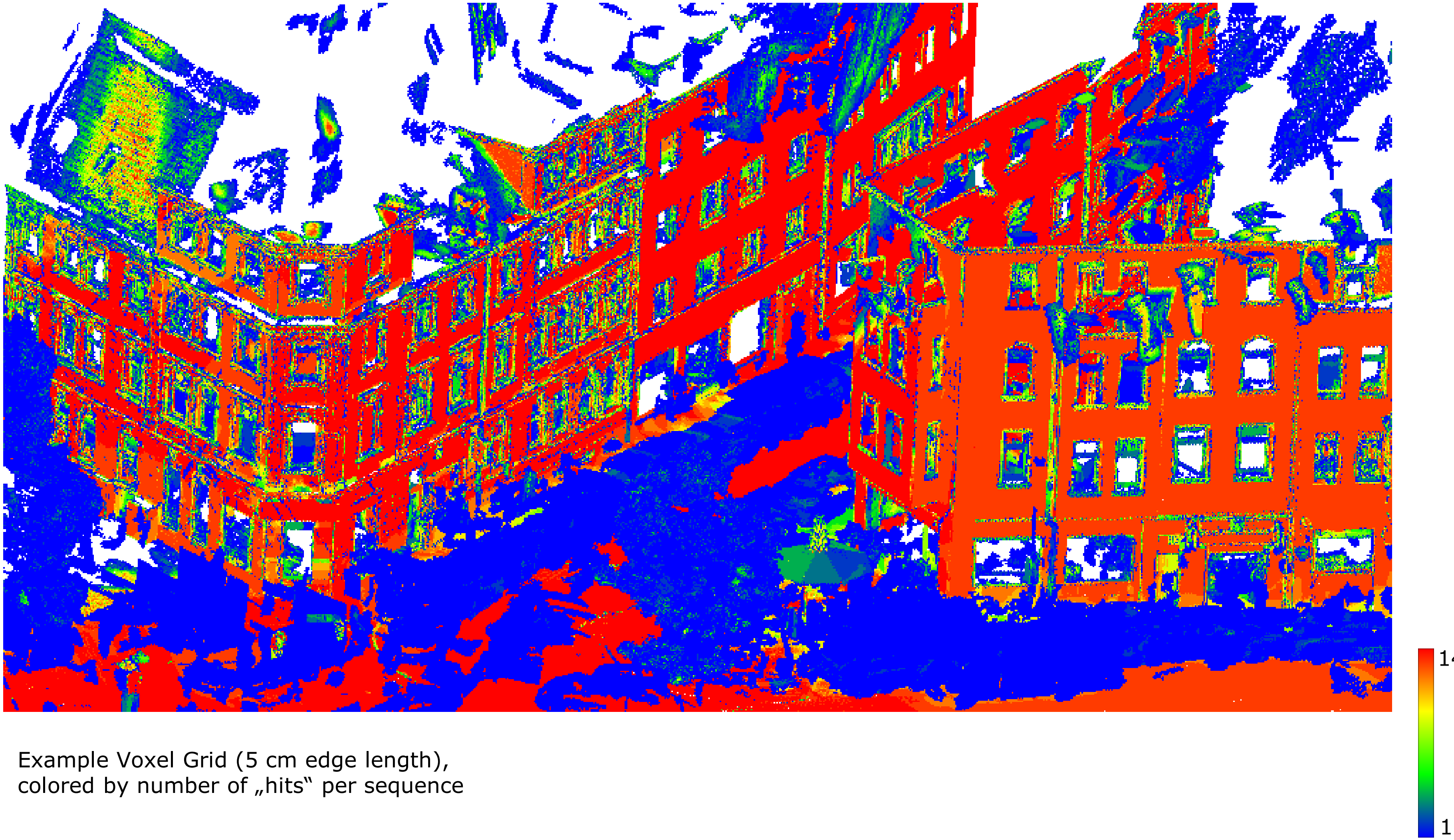


Example point clouds from seven measurement, colored by run id

Analysis of Changes – Ray tracing

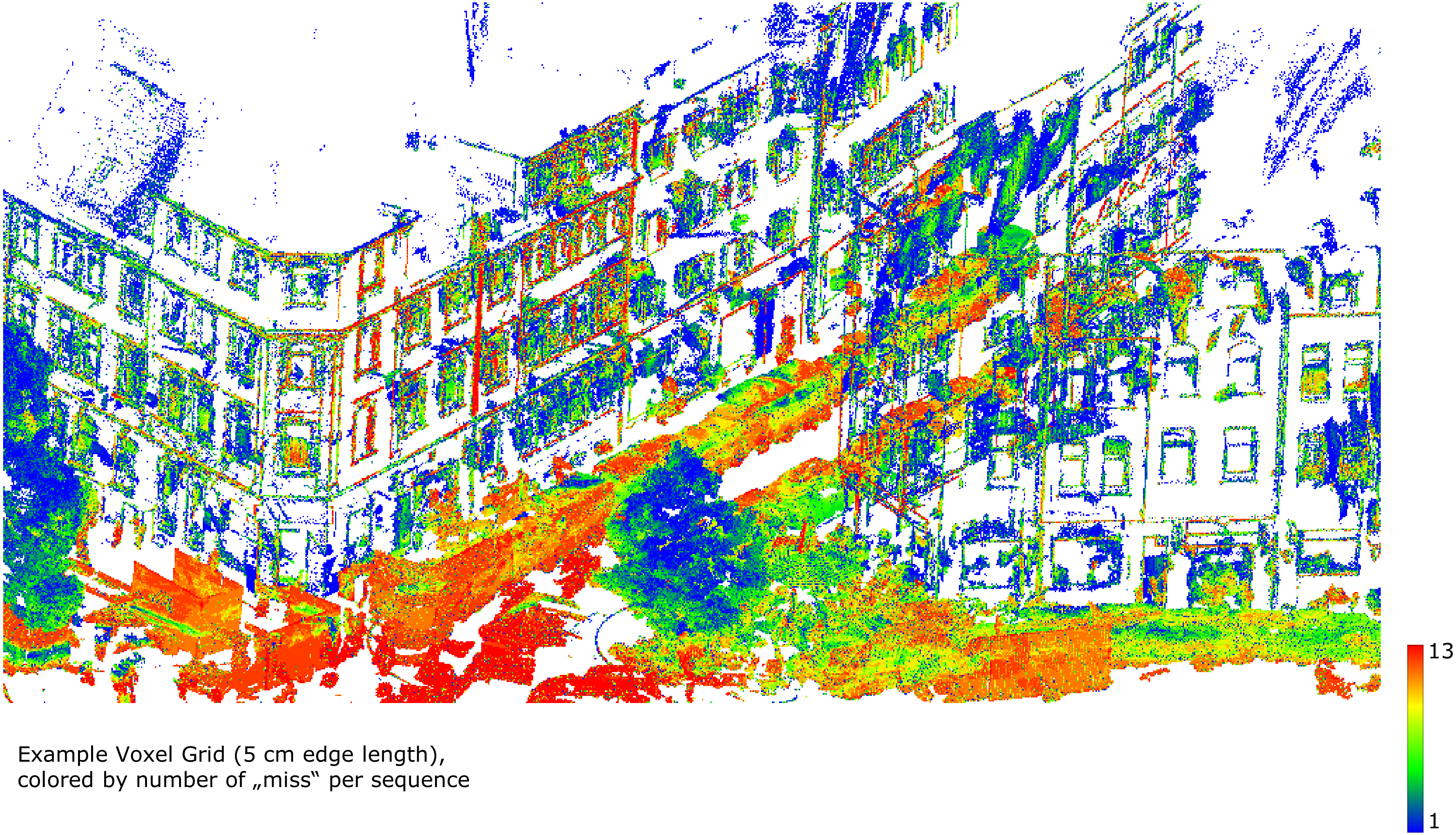
- Alignment of all runs based on adjustment (C. Brenner)
- Sorting the 14 billion points into voxel grid:
  - beam hits object in voxel ("hit")
  - beam passes through voxel ("miss")

Voxel „Hit“ Count

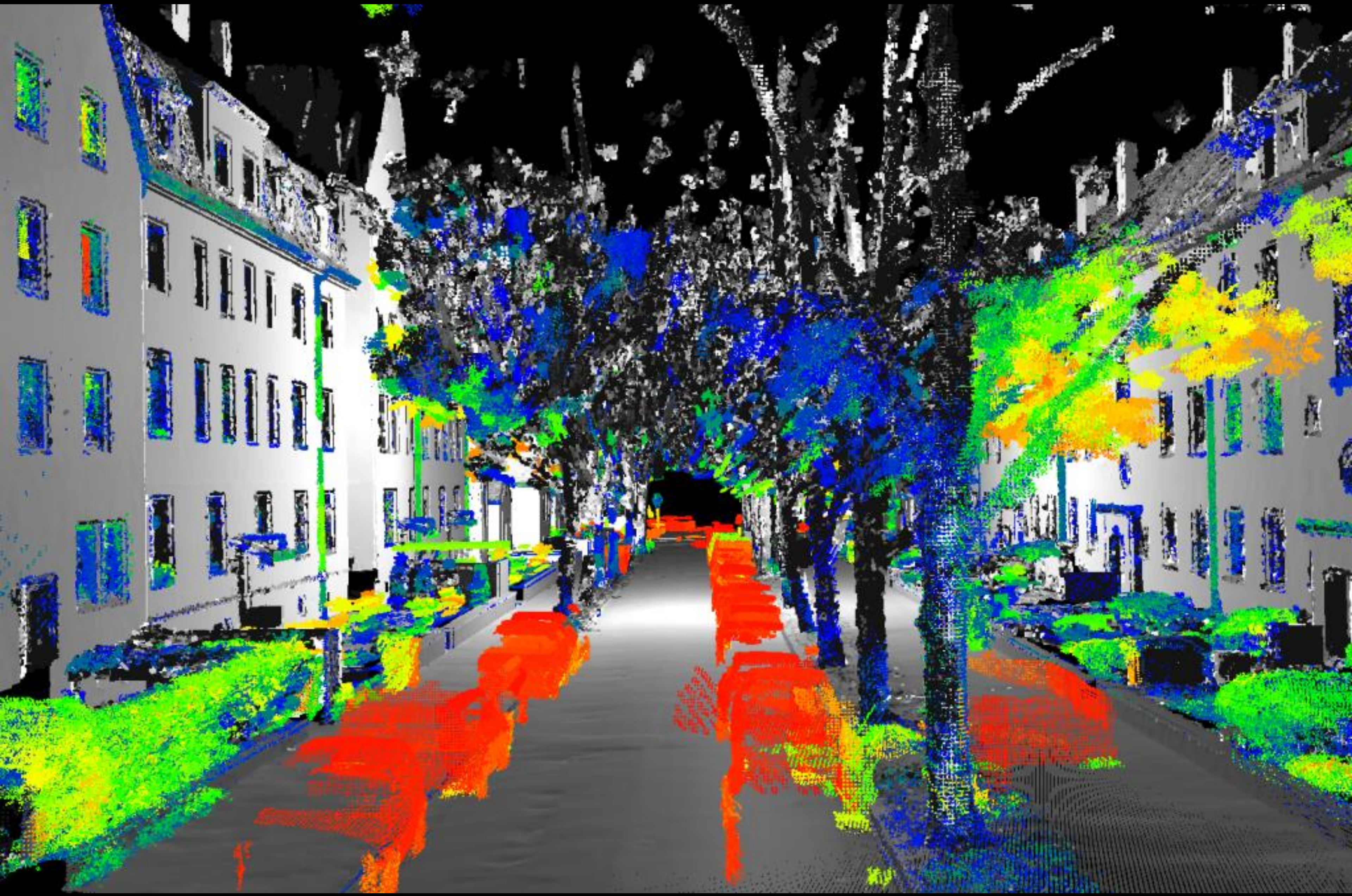


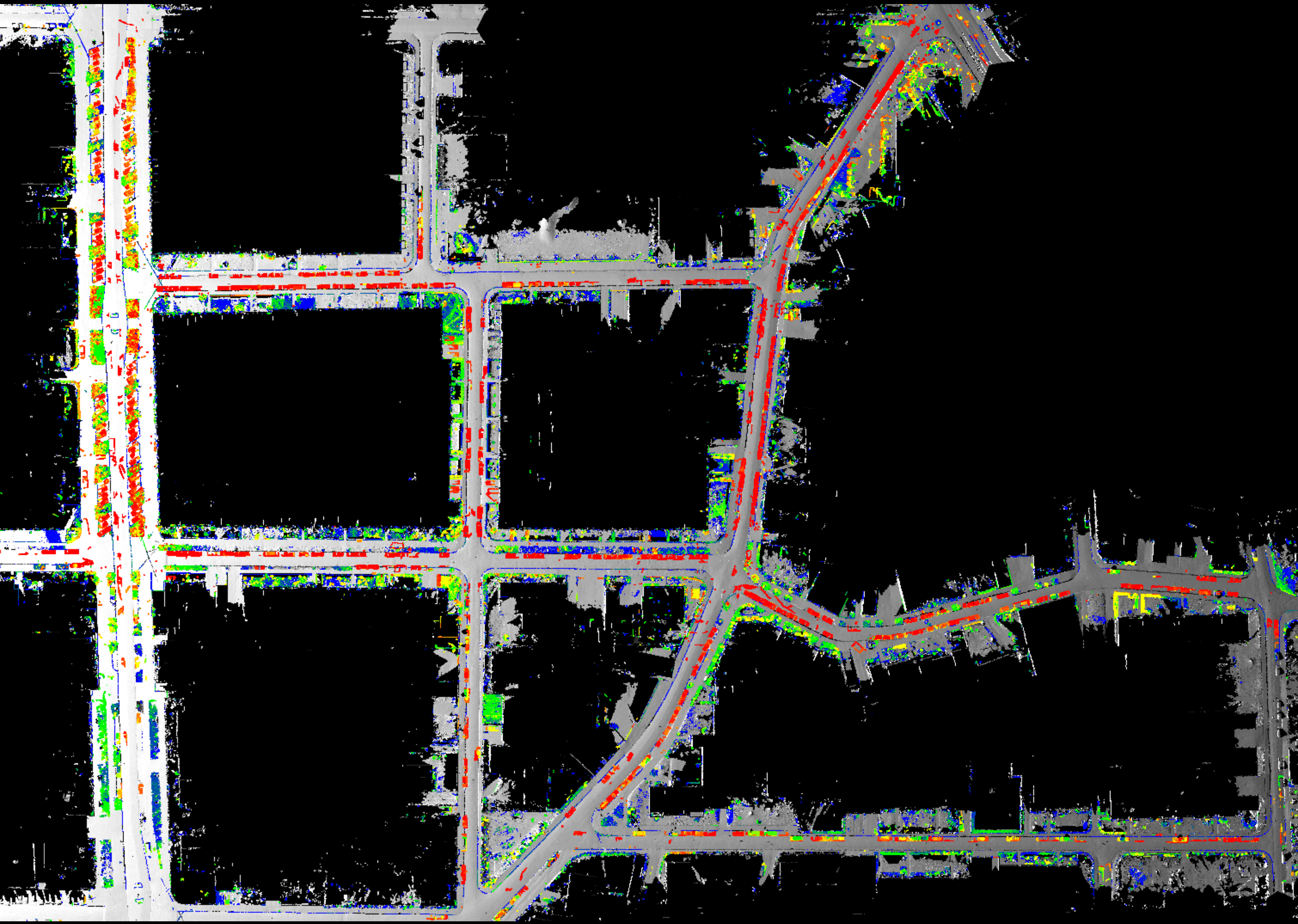
Example Voxel Grid (5 cm edge length),
colored by number of „hits“ per sequence

Voxel „Miss“ Count



Example Voxel Grid (5 cm edge length),
colored by number of „miss“ per sequence





Maps for autonomous driving (2cm):
- Static information
- Dynamic information including its temporal behaviour

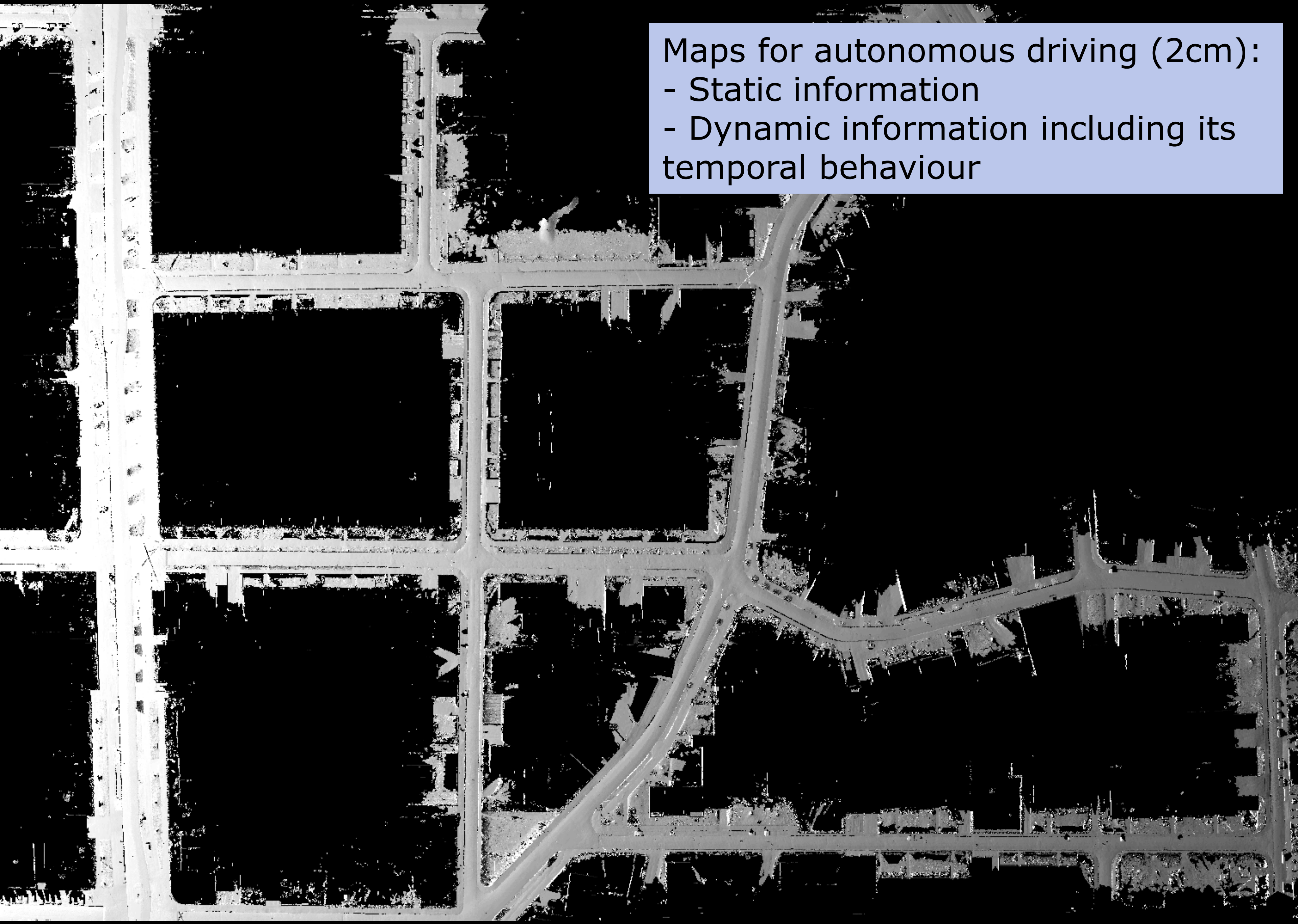


Photo-realistic visualization of Point Clouds

Torben Peters, Claus Brenner

DFG-Graduiertenkolleg i.c.sens

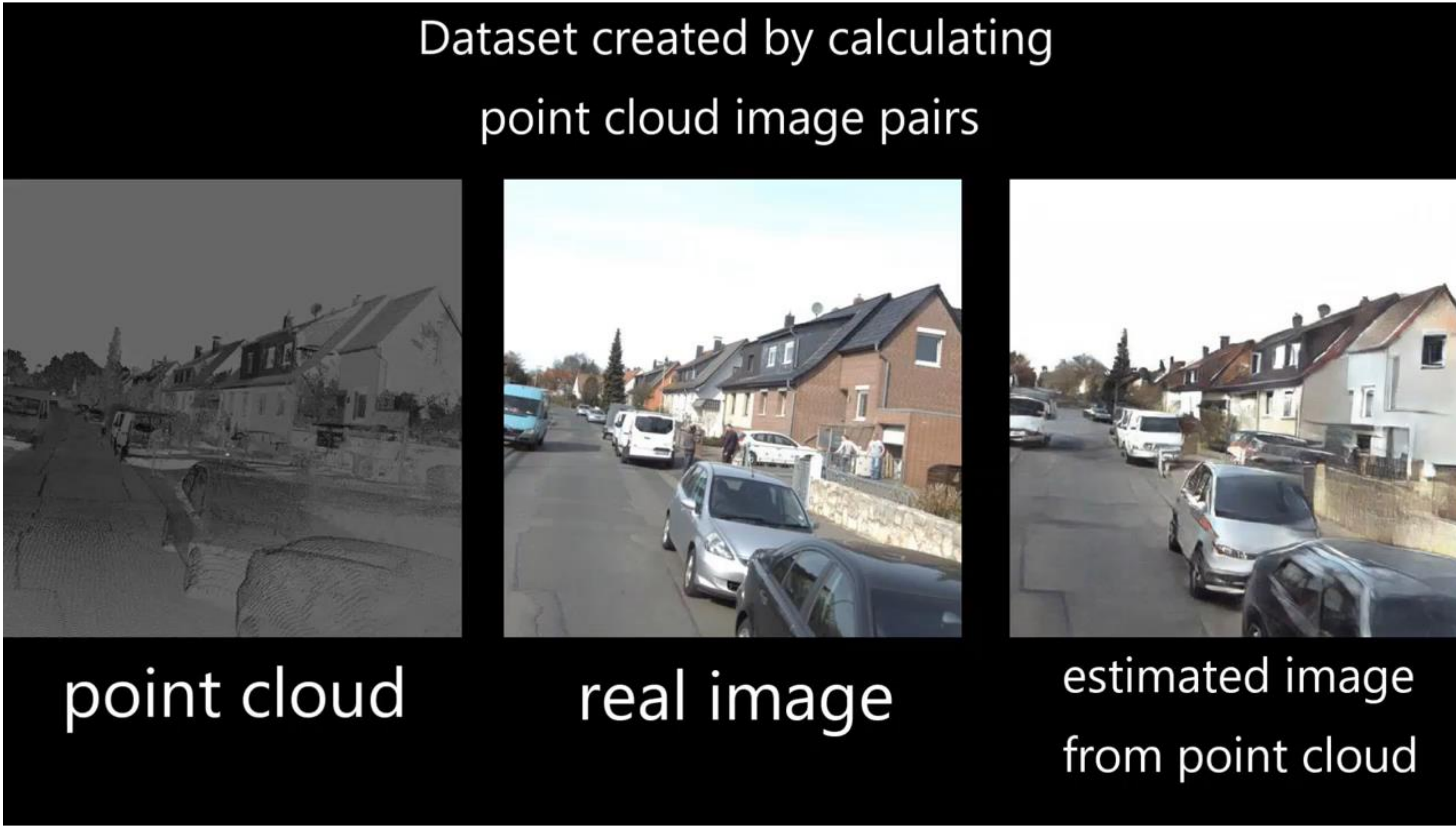
GANs (generative adversarial networks) -> Synthesis of images from point clouds

Input
3D-point cloud

Real image

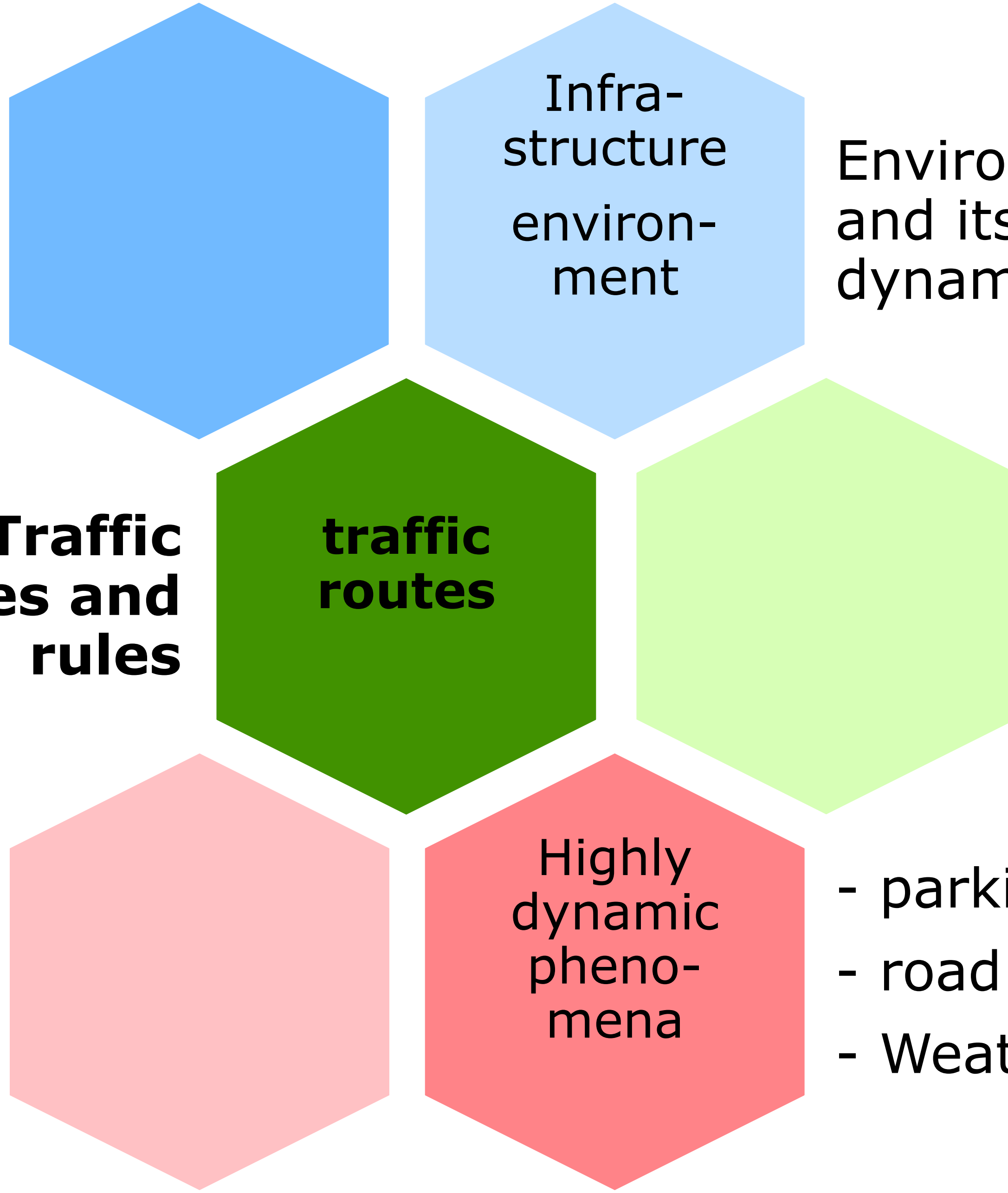
Synthesized image

Synthesis of seasonal images



https://www.fbg.uni-hannover.de/fileadmin/fbg/Geodaesie/Geowerkstatt/2019_04_GAN/Peters_Brenner_GAN.mp4

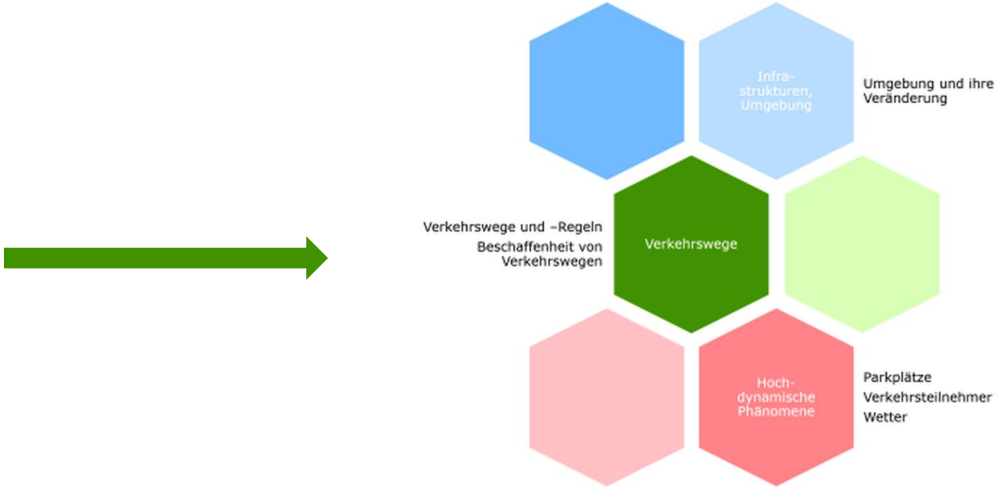
Overview



Environment and its dynamics

- **Traffic routes and rules**

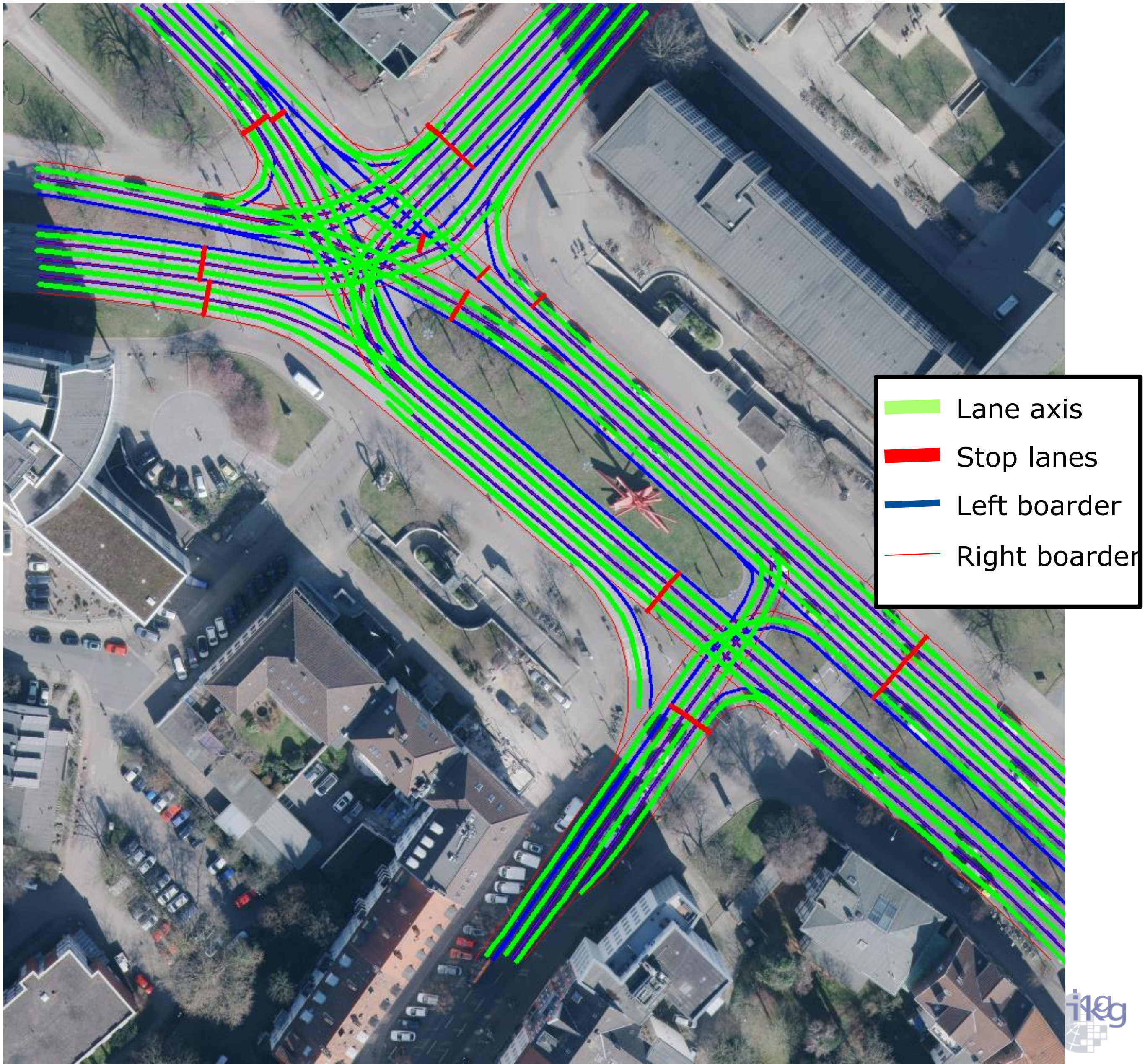
- parking spaces
- road users
- Weather



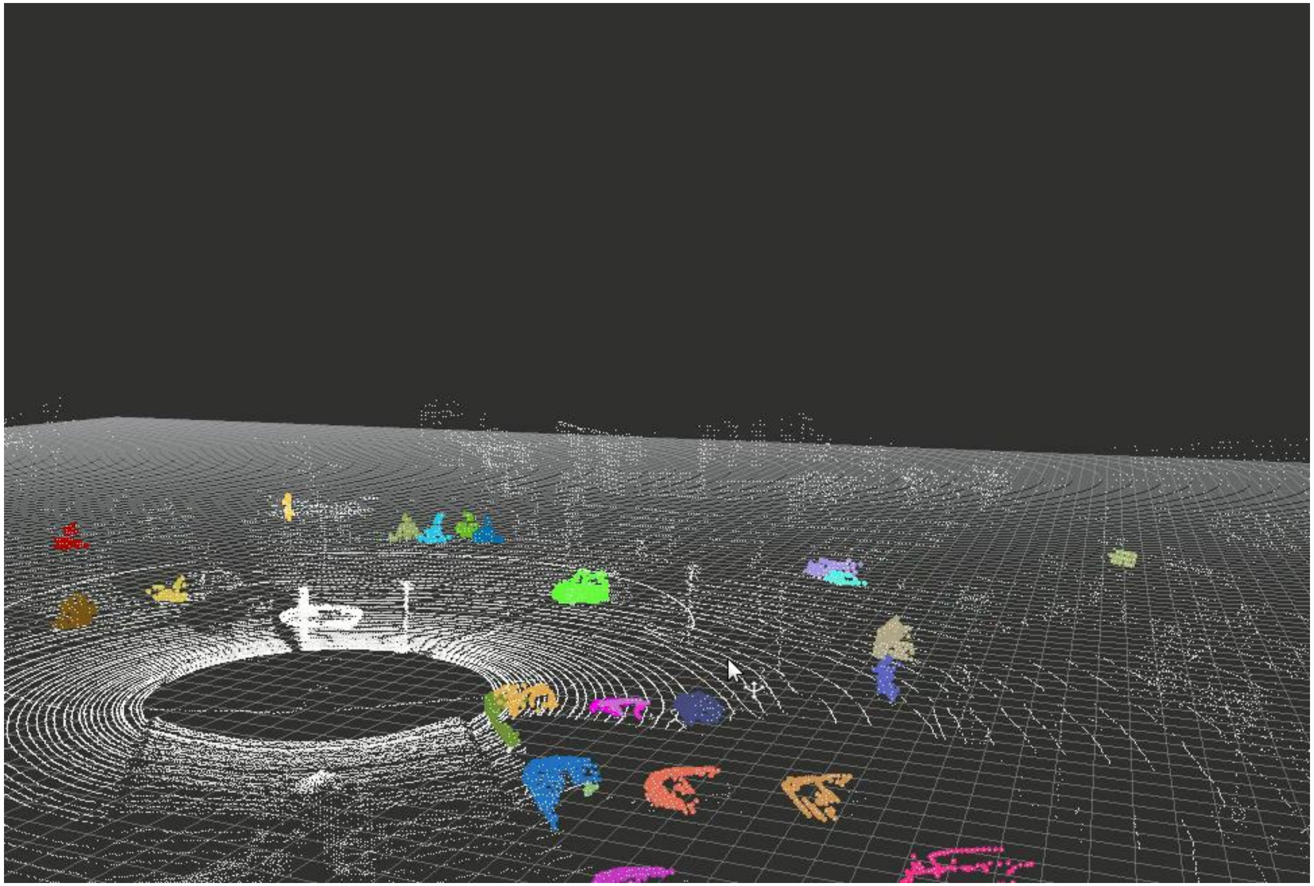
High definition maps from laser scanning

Steffen Busch

Derive road geometry from vehicle trajectories

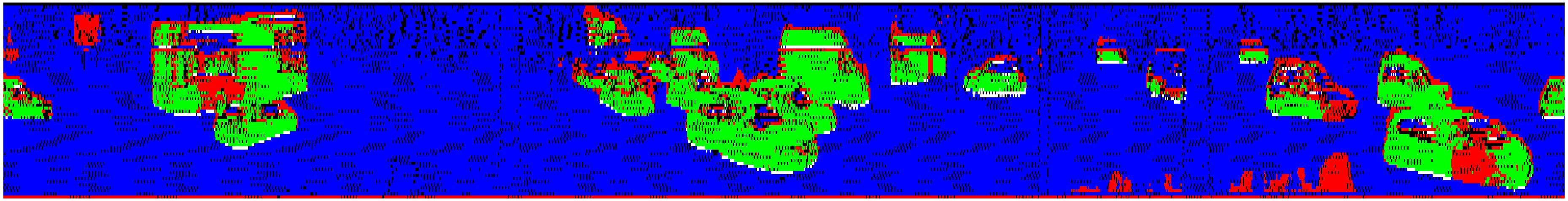


Experiment: Velodyne scanner at a junction



Neural Network Detection & Tracking

- Segmentation by neural network



True positive
True negative
False negative
False positive

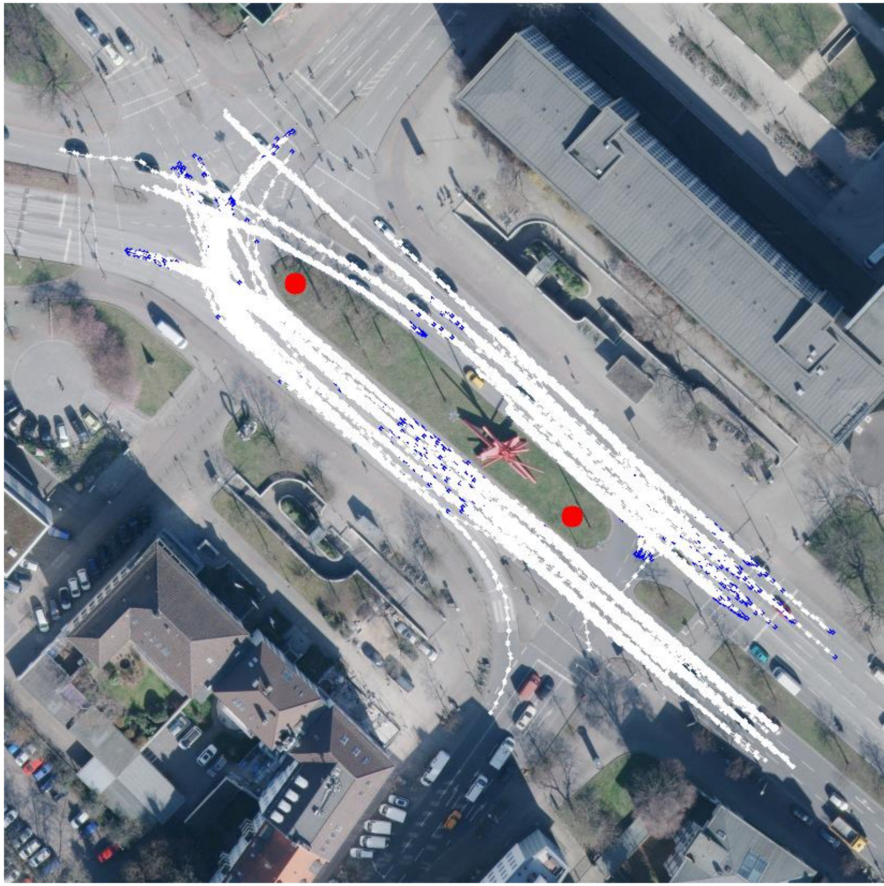
- 200,000 images (depth and intensity values, labels)
  - ~4h scans
  - 6 intersections in Hannover
  - Labels of road users
  - Target: Cars

Data assessment
Trajectories

- Cars

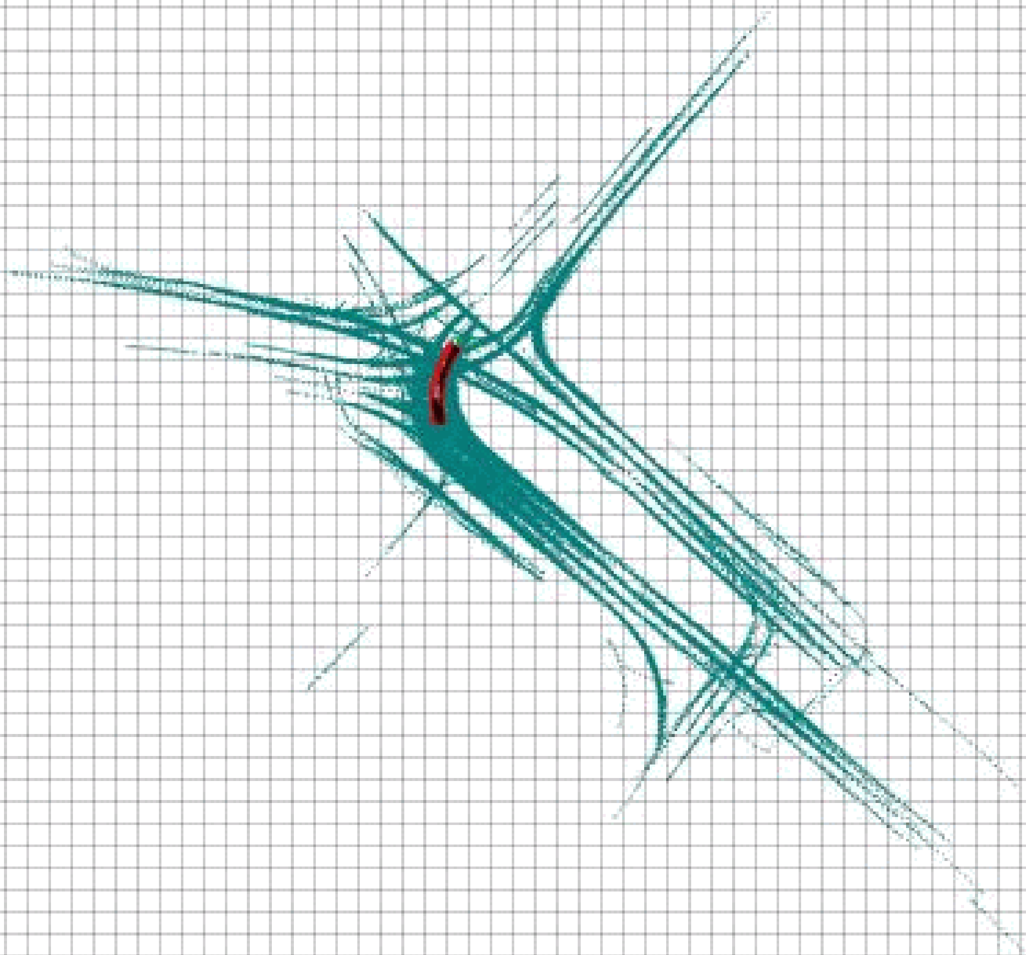
Trajektorien Königswortherplatz

- Iterative extended Kalman filter
  - Connected points -> trajectories



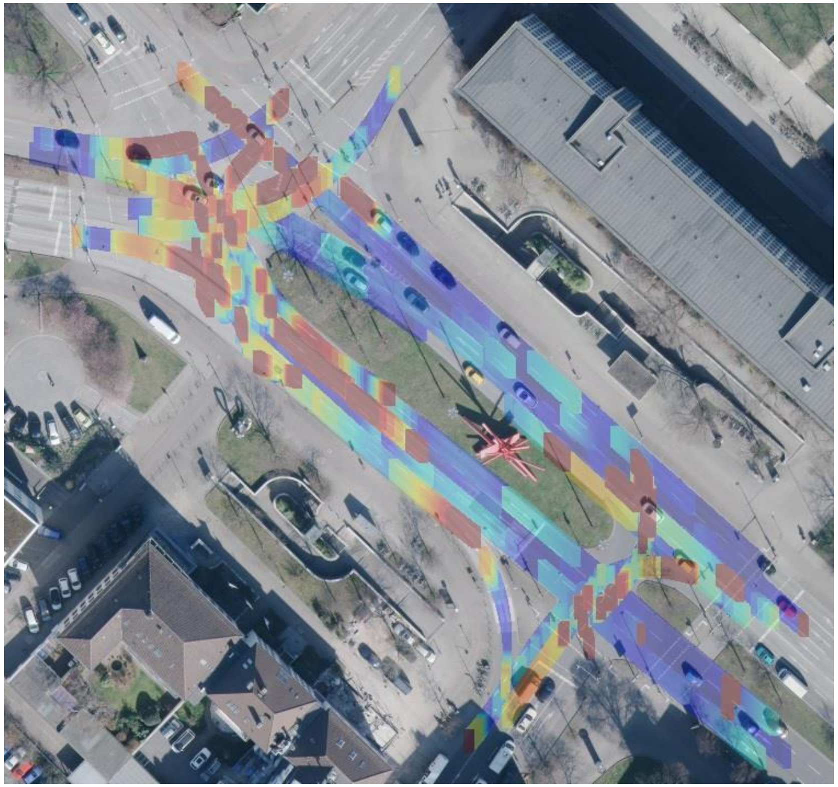
- Target:
  - cluster trajectories corresponding to a lane
  - Approach: MonteCarlo Optimization

High Definition Mapping
Markov Chain Monte Carlo Optimization

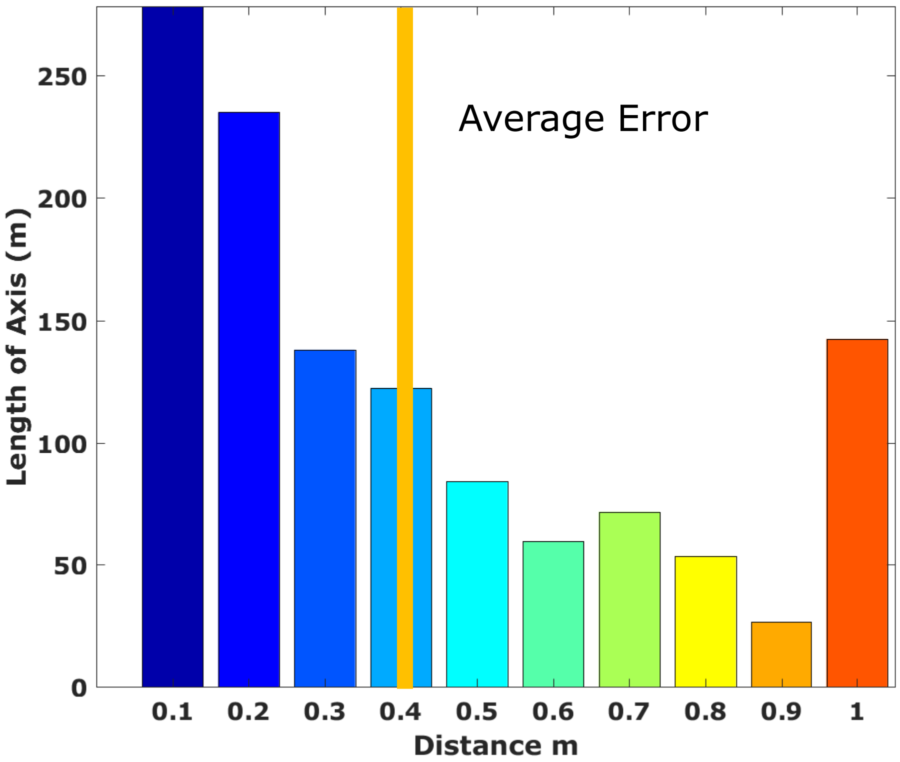


Evaluation

Reconstructed lane axis



Error to Reference

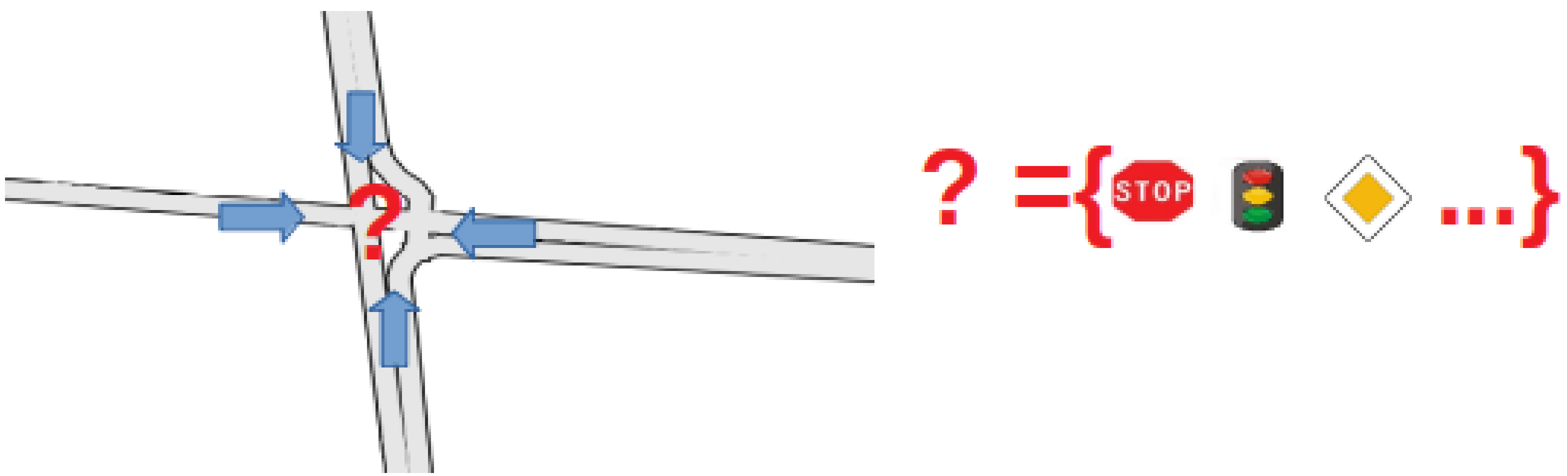


Recognition of traffic rules from trajectories

Stefania Zourlidou

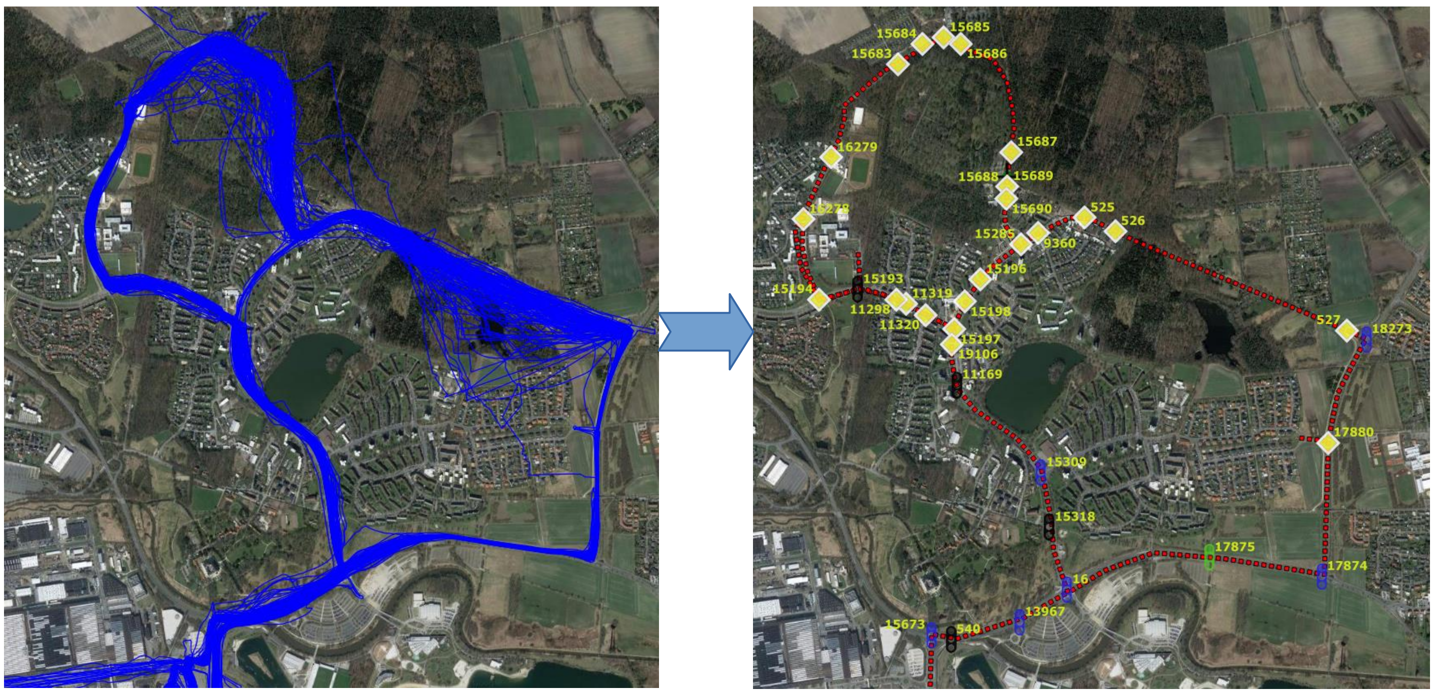
Recognition of traffic rules from GPS trajectories

- What traffic signs?
- Idea: the nature of the rule is reflected in the way the intersection is used by (many) road users



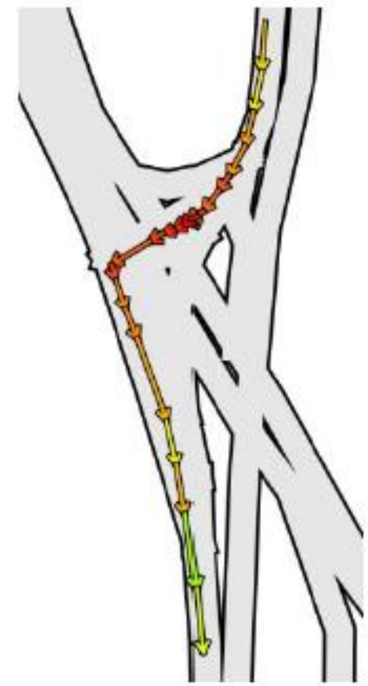
Data

- A series of opportunistically collected GPS tracks (1Hz sampling rate)



Learning the traffic regulation context

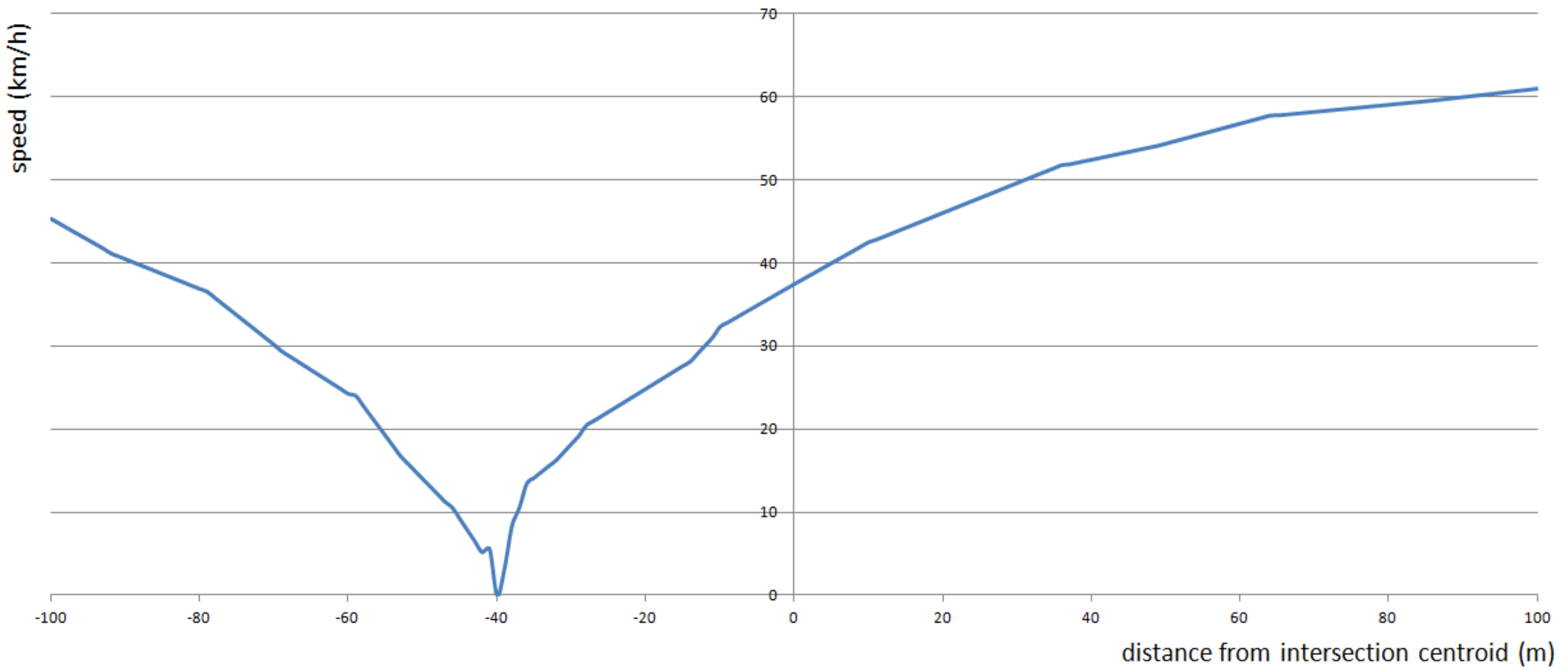
- Different traffic regulators cause vastly different driving behaviour, e.g. :
  - **Traffic lights**: vehicles have to come to a full stop (traffic light is red) or they cross the junction with no impediment.
  - **Priority control**: vehicles cross the junction mostly unhindered
  - **Yield control**: vehicles stop to give way to other cars at irregular times



- Speed profiles as classification features
  - Supervised approach

Supervised approach: Speed profiles

- Assumption: intersections show characteristic speed profiles
  - e.g. stop at stop sign, speed decrease to give way at ordinary intersections, etc.
  - Multiple occurrences reinforce statement about intersection (type)

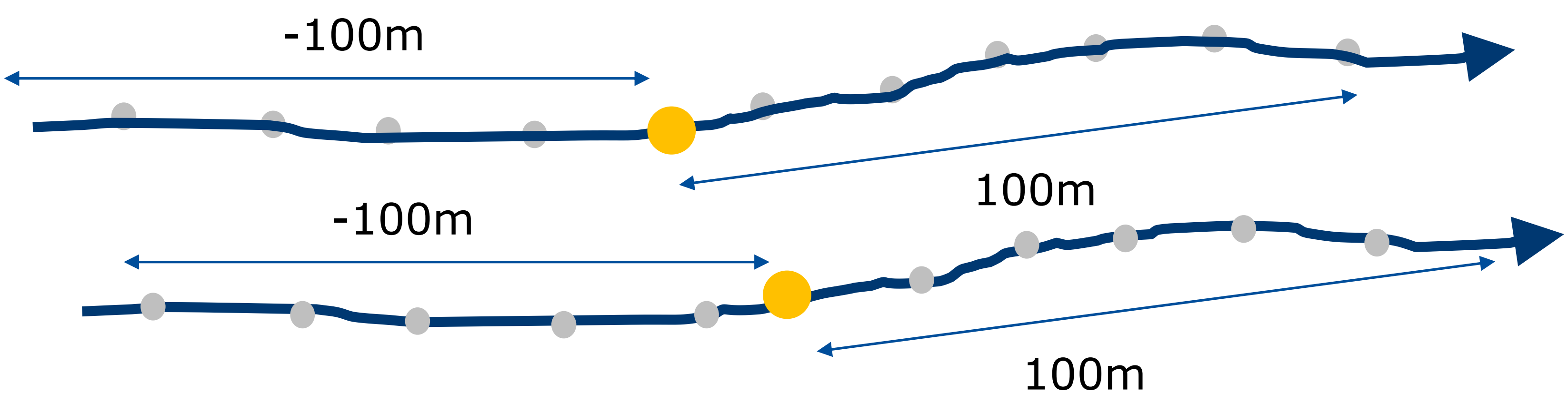


Approach

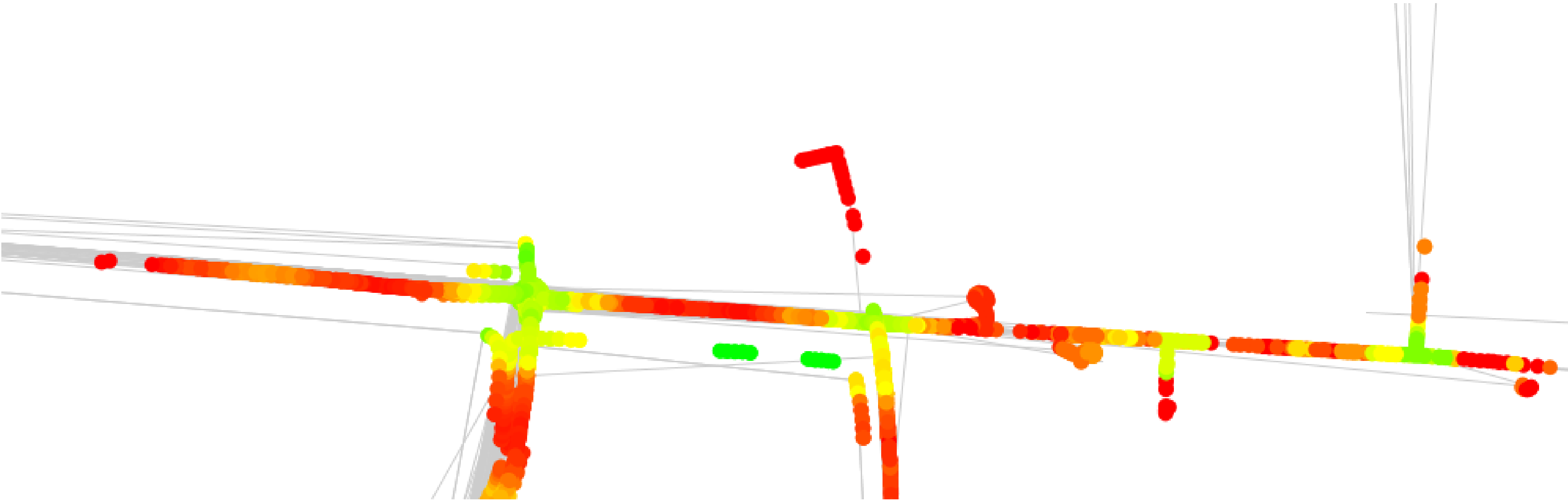
- Application of classification methods
  - e.g. C4.5, Logistic Regression or Random Forest

Input vector=[v_{-100}, v_{-199},..., v_{0}, v_{1}, v_{100}]

[$v_{i:}$ Speed value i meters before(-)/ after (+) the]



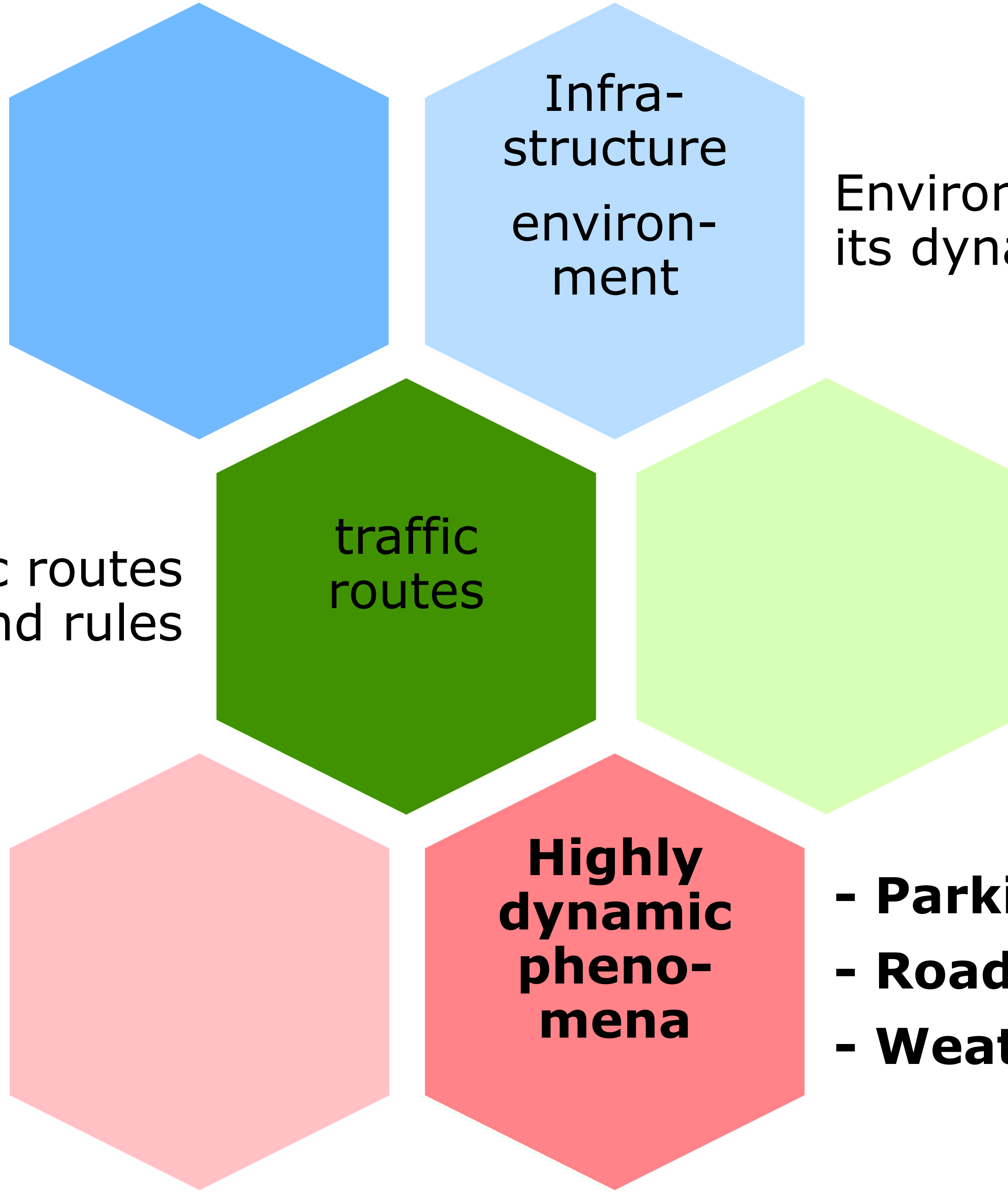
Detected locations



- Results of the aggregation after individual trajectory classification. Colours encode consensus levels for detected intersections
  - red: low consensus, i.e. outliers/false classifications due to e.g. traffic congestions
  - green: high consensus.
- Peaks in classification confidence correspond to actual intersection locations.

Traffic signal controlled intersection

Overview



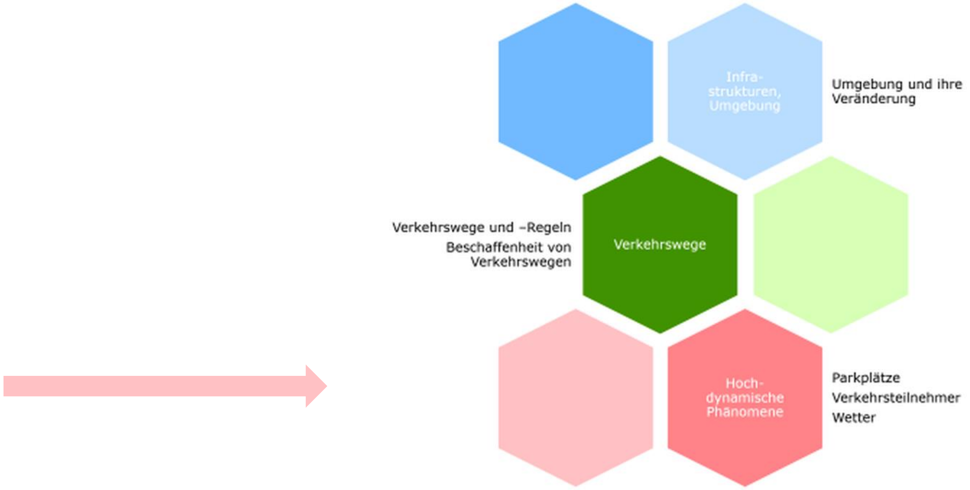
Environment and its dynamics

- Traffic routes and rules

- Parking spaces

- Road users

- Weather

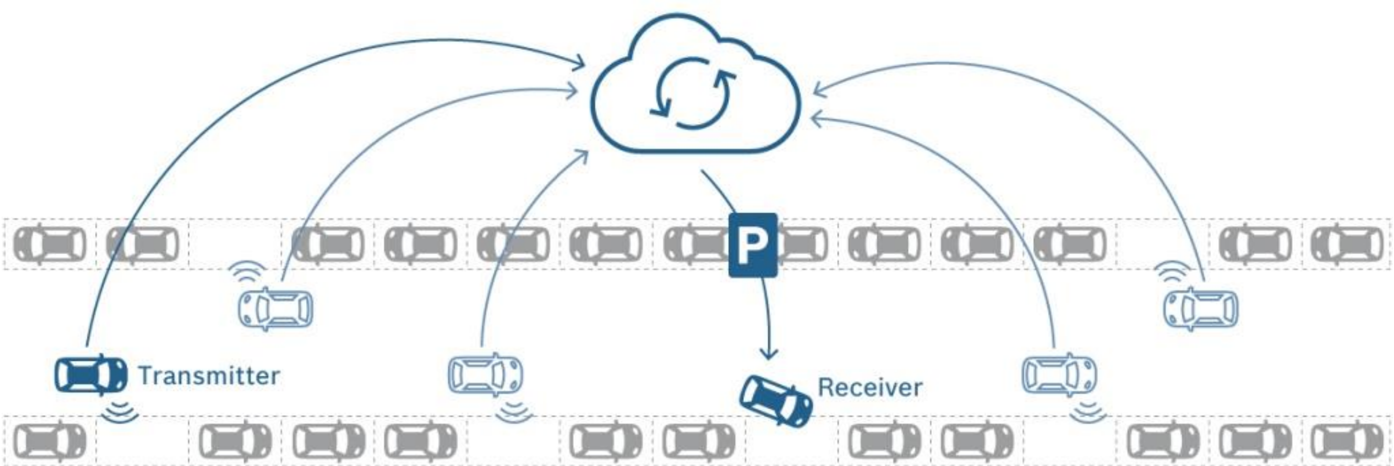


Dynamic parking maps through crowd sensing

Fabian Bock

Generation of dynamic parking lot maps by crowd sensing

- **30%** of the traffic is parking search traffic
- Dynamic parking map includes street sections with parking permission and an estimate of current parking availability
- Numerous mobile sensors (e.g. vehicles with sensors, smartphones) record parking data irregularly



Quelle: bosch-mobility-solutions.com/

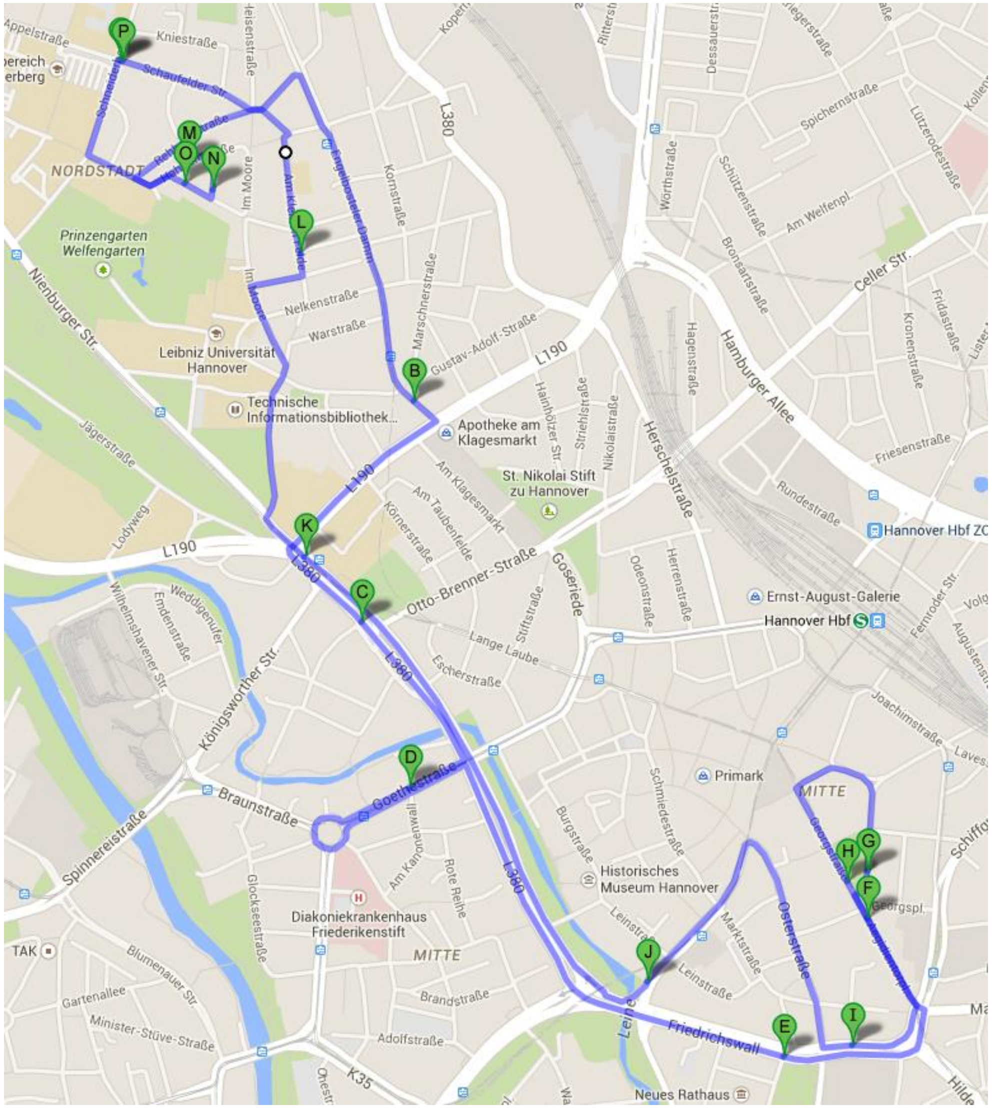
Steps for detection by crowd sensing

- Determination of parking space occupancy
  - Detection of parked vehicles at the edge of the roadway
  - Mobile Mapping System (Laserscanning)

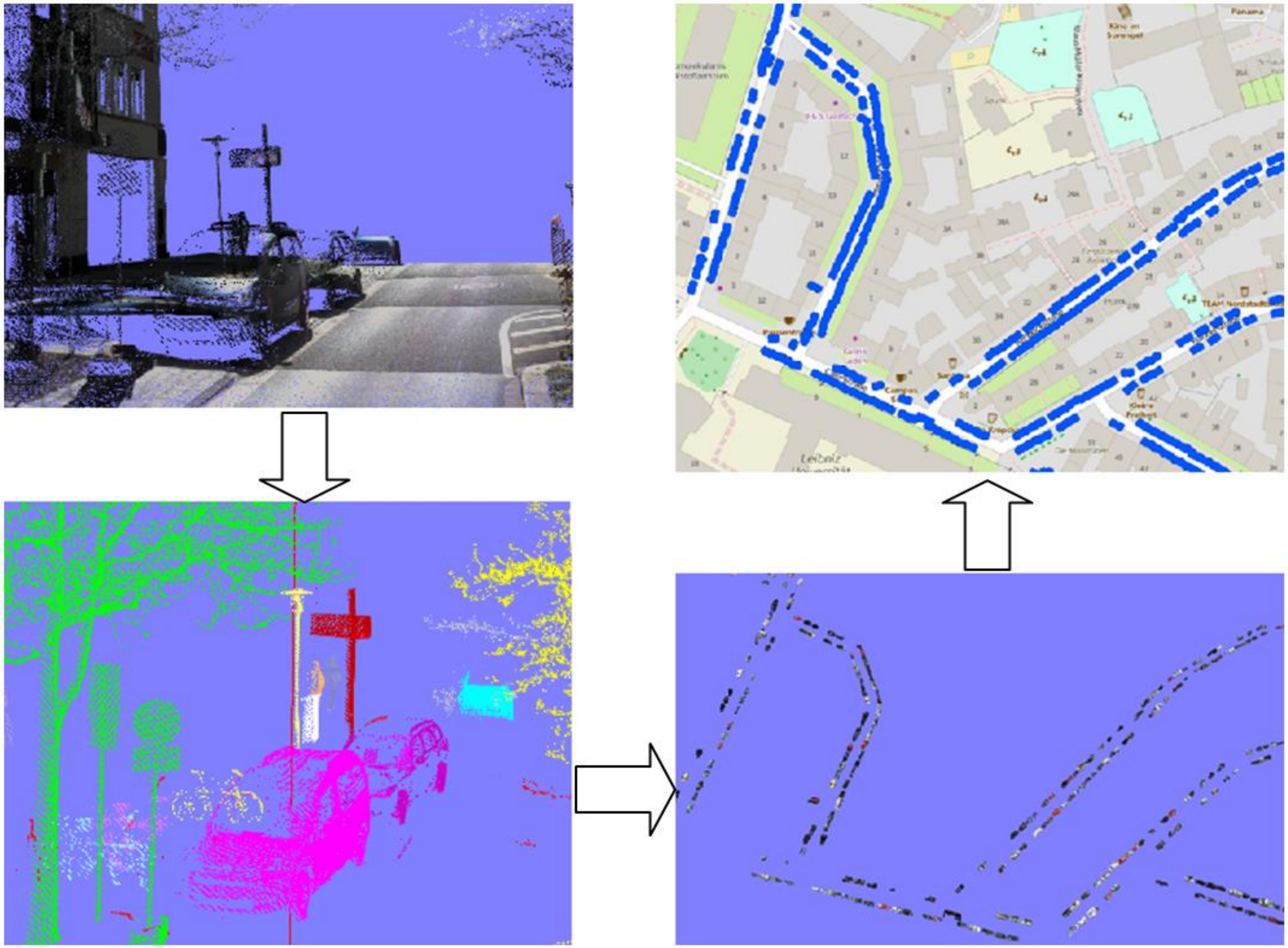
- Methodology:
  - Methods of machine learning (clustering, random forest, ..)

measurement campaign

- Measurements:
  - 11 laps between 8 and 20 o'clock,
  - 35 minutes for each round
  - ~900 GB of data

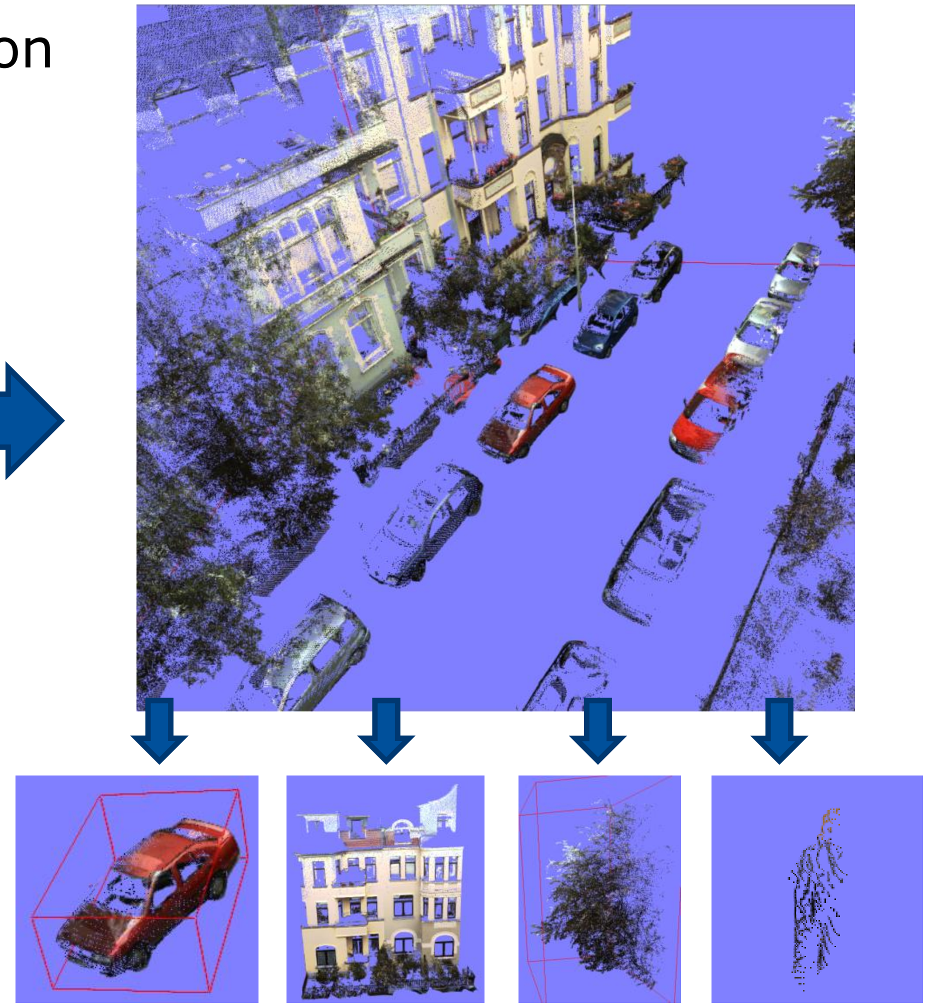


Overview



Processing of point clouds

- Extraction and elimination of the ground
- Point cloud segmentation: region growing
- classification



Object classification

- Training set: 86 cars, 269 other objects
- Test set: 396 cars, 931 other objects

- Confusion matrix:

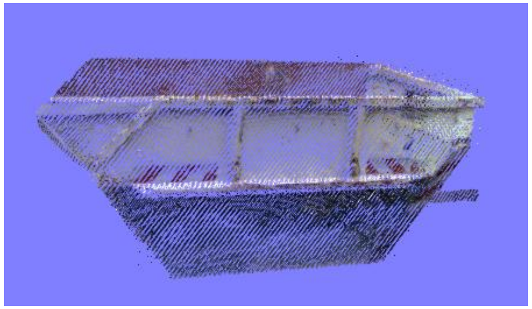
		Predicted class	
True class		Car	Others
	Car	366 (TP)	30 (FN)
	Others	6 (FP)	925 (TN)

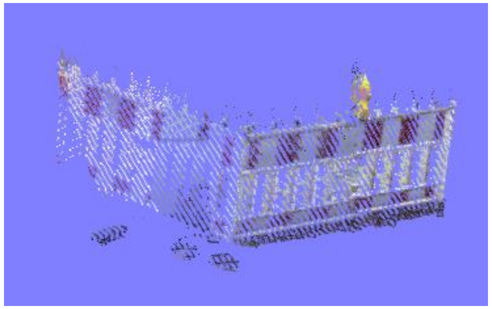
- Precision = TP/(TP+FP) = 98,4%: percentage of correct pred.
- Recall = TP/(TP+FN) = 92,4%: percentage of correctly pred. True cars

TP=True Positives, TN=True Negatives, FP=False Positive, FN=False Negative

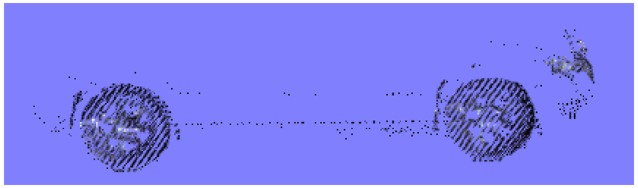
Object classification

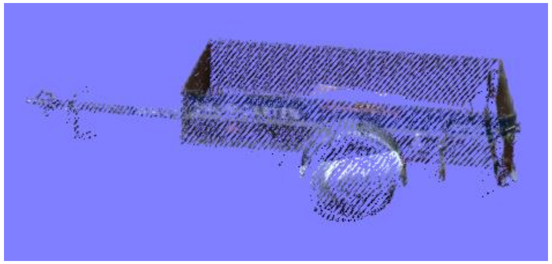
- Examples for False Positives

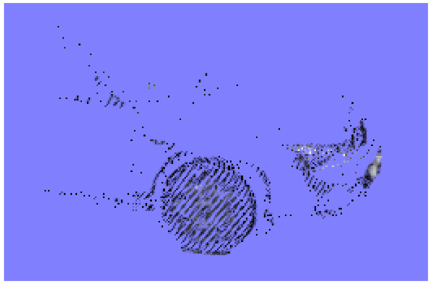




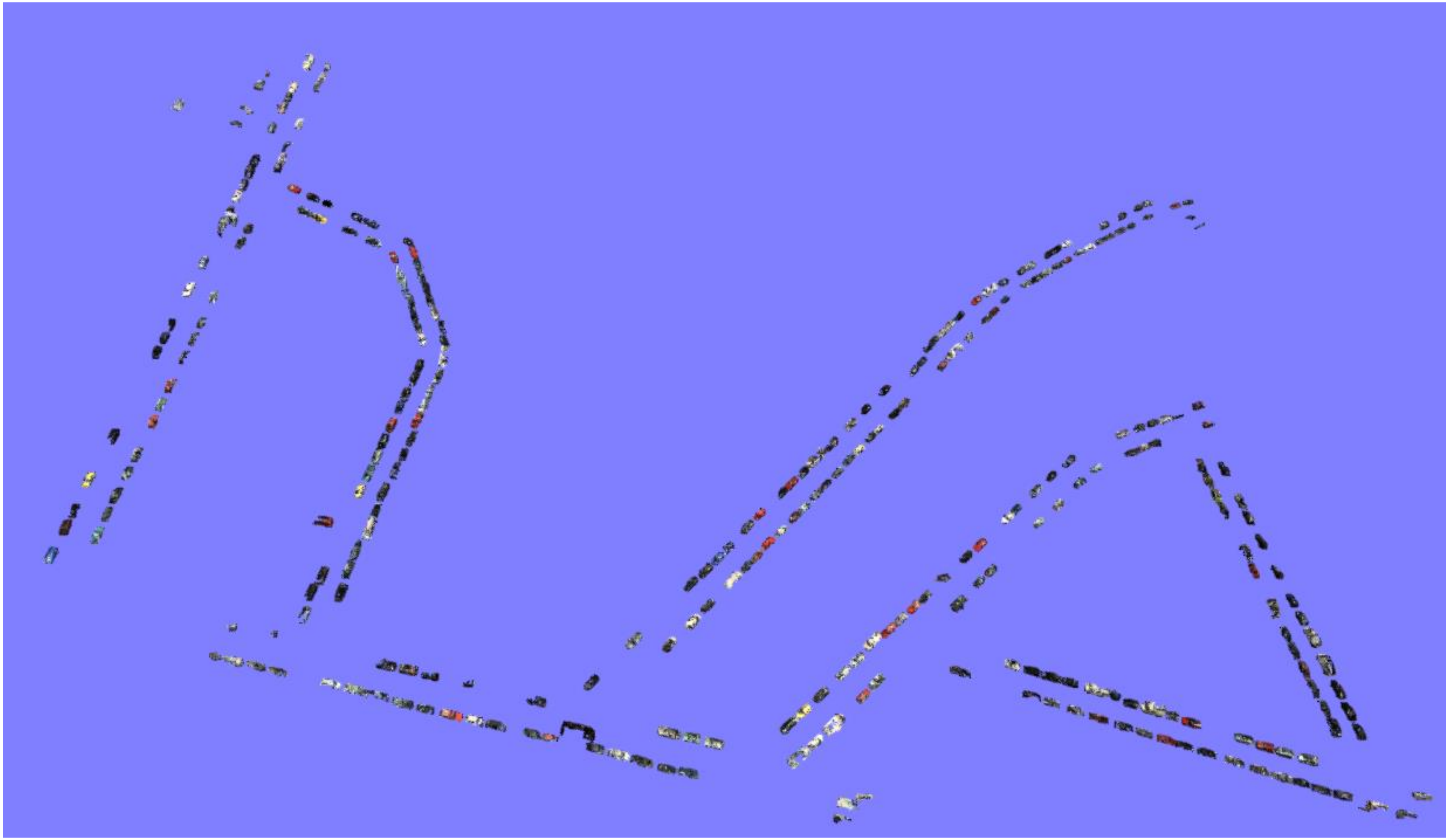
- Examples for False Negatives



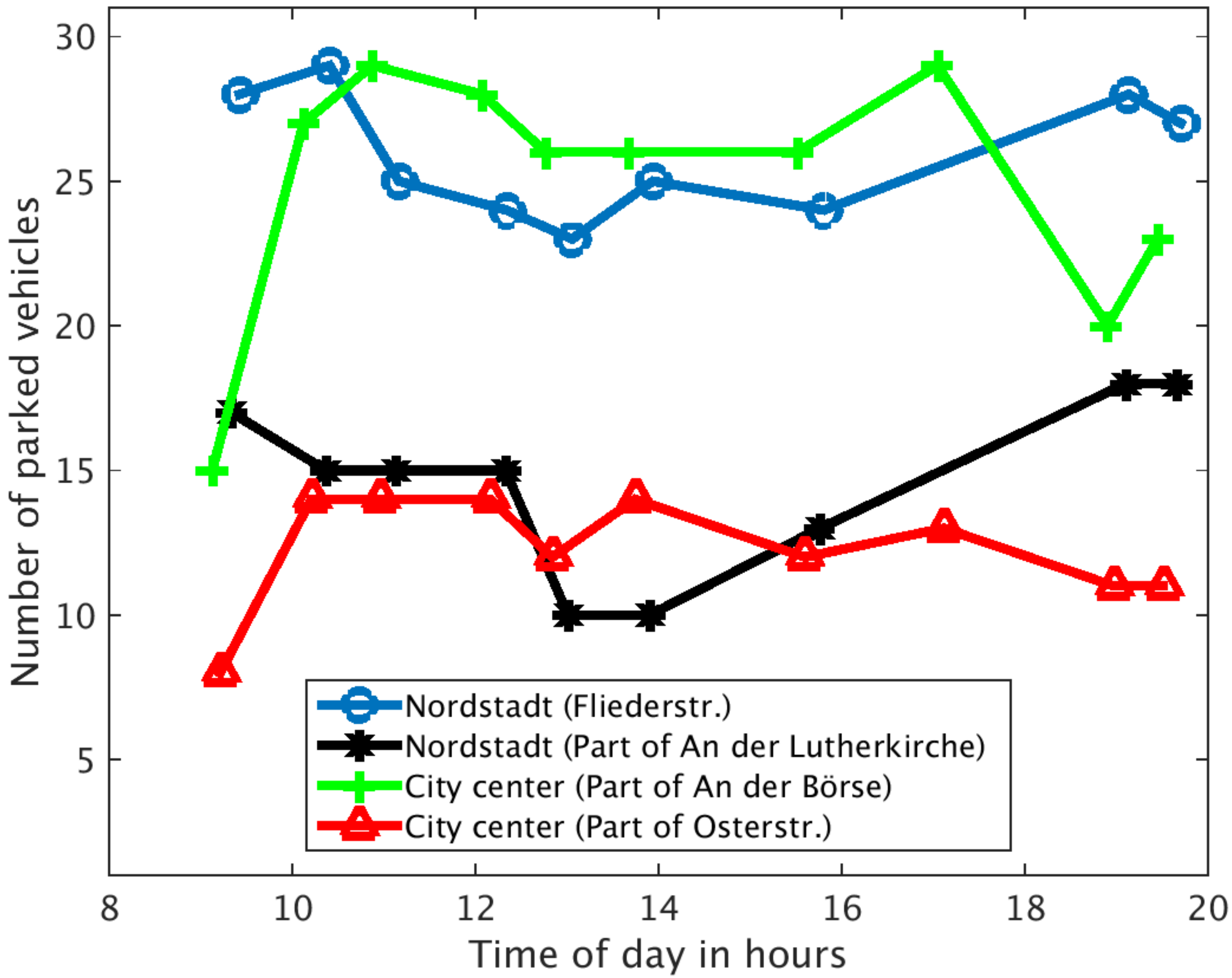




Detected Cars



Day course of street parking occupancy



Adaptive rerouting of taxis for parking crowd sensing

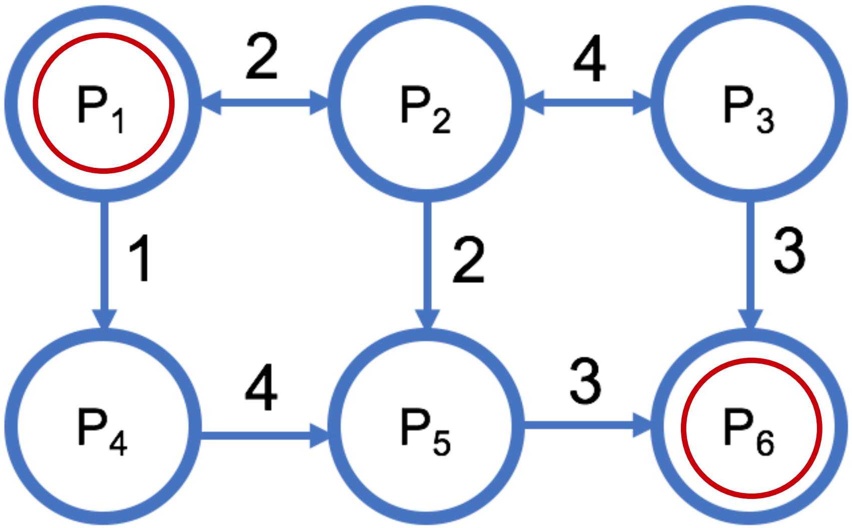
Christian Koetsier

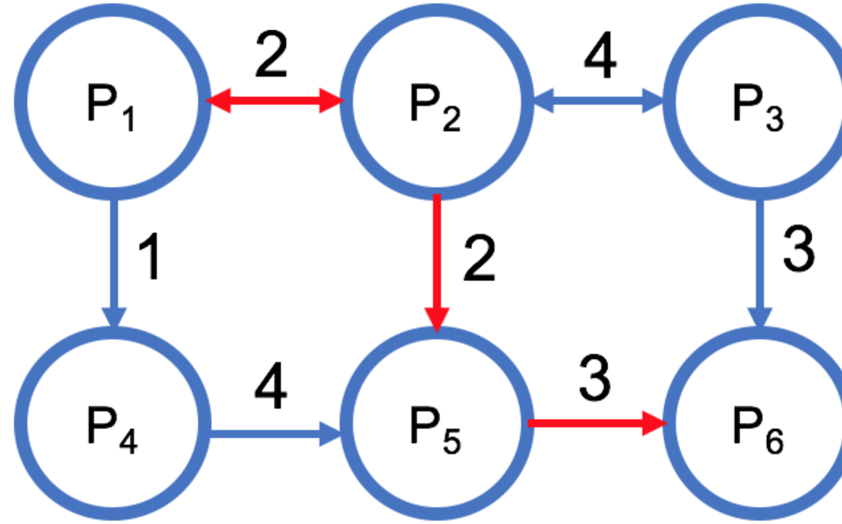
Research Question and Idea

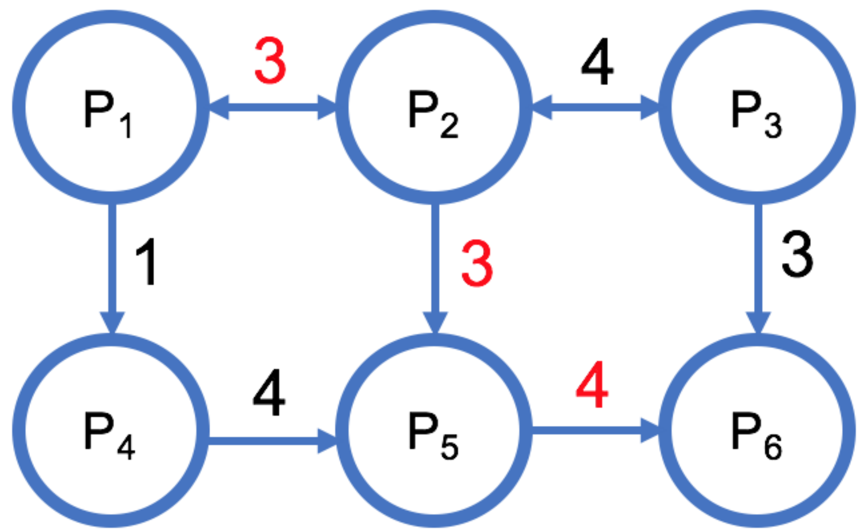
- "What information gain can be achieved by rerouting measuring vehicles, for example taxis, depending on a maximum allowed detour in comparison to the actual and shortest route of the measuring vehicles?

- Approach:
  - Variation of the cost function in routing
  - Once a road has been driven on, its weight is increased so that less efficient roads are normally used later.

DynamicEdgeCosts-Rerouting: P1->P6

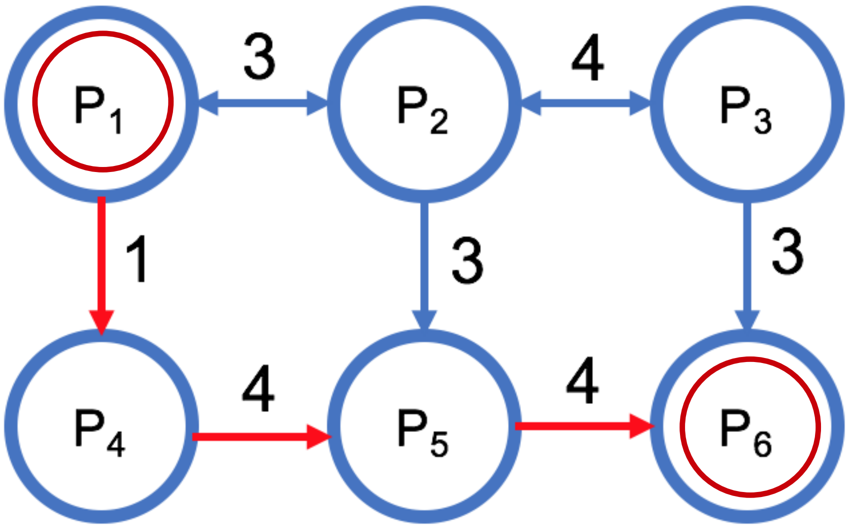


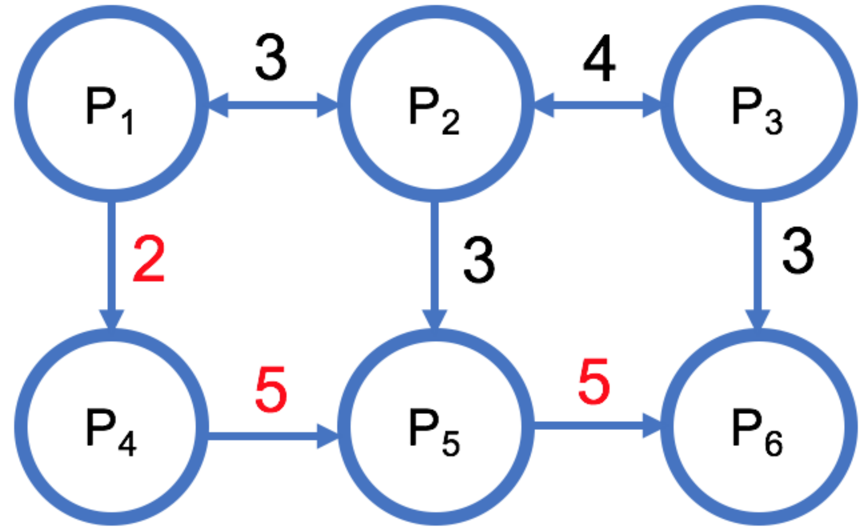




Normal case:
All vehicles that want to go from P1 to P6 use the (shortest) route P1, P2, P5, P6.

DynamicEdgeCosts-Rerouting: P1->P6





Comparison of current route with shortest path

- Variation possible without noticeably lengthening the route!

Score

- Measure to express how often/regularly an edge is traversed on average in the road network graph:

$$T = \frac{1}{N_{steps}} \sum_{i=0}^{N_{steps}-1} \left((t_0 + i * \Delta t) - t_{last}(t_0 + i * \Delta t)\right),$$

wobei t_{last}(t) der Zeitstempel des vorherigen Besuches eines Taxis nach der Zeit t und N_{steps} die Anzahl an Zeitschritten mit einem Intervall von Δt ist.

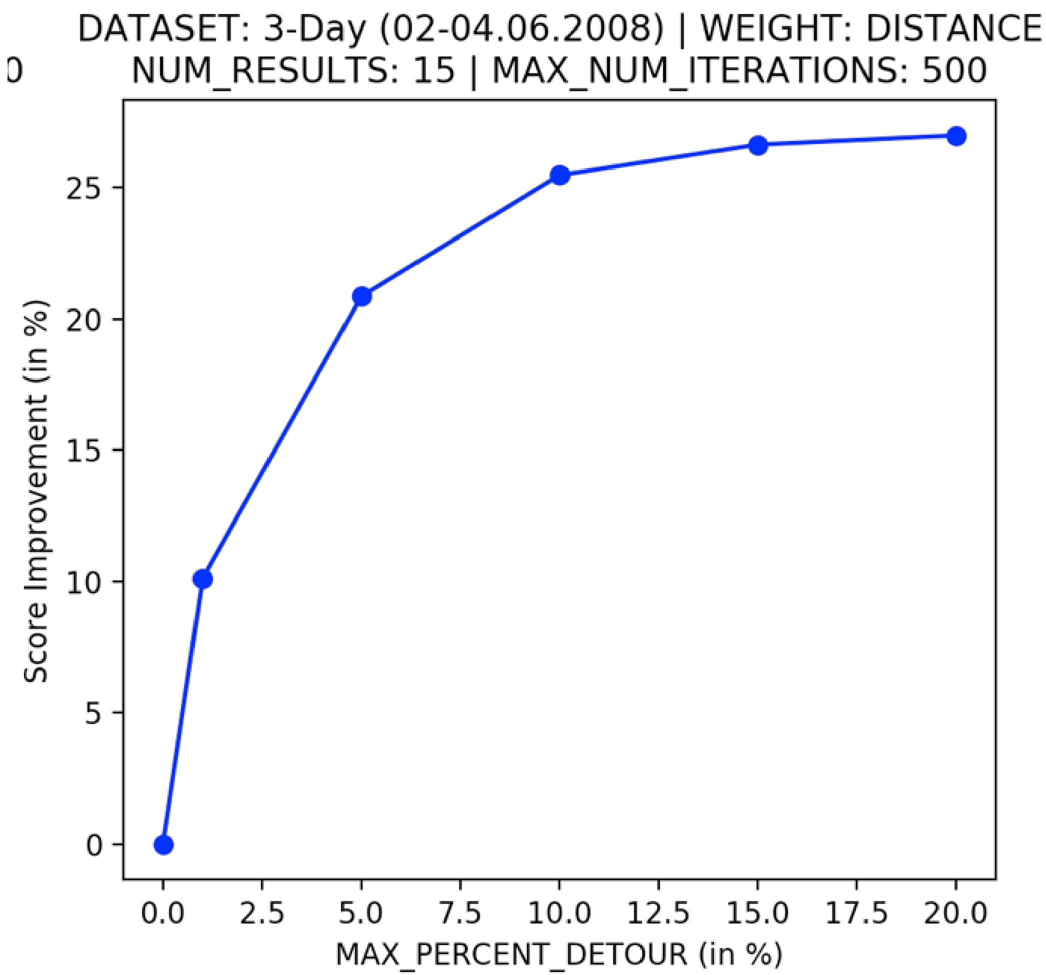
- Visits to an edge: [8:00, 8:03, 8:12] | Time interval: 5min

Zeitpunkt	$t - t_{last}$
8:00	0
8:05	2
8:10	7
8:15	3

- The smaller the value -> the more regularly an edge is visited

Analysis: How does the score grow with the maximum allowed detour?

- Score is given in % improvement to standard situation (i.e. if only exactly the shortest distance is travelled).



Result

- Hypothesis confirmed:

- A rerouting of measuring vehicles leads to a gain in information regarding the parking situation

- The application of the investigated rerouting methods led to an improvement of the score of 27-30% with a maximum permissible detour of 15%.

Shared Space: Automatic recognition and prediction of behaviour with Deep Learning

Hao Cheng
DFG Graduiertenkolleg SocialCars

Motivation

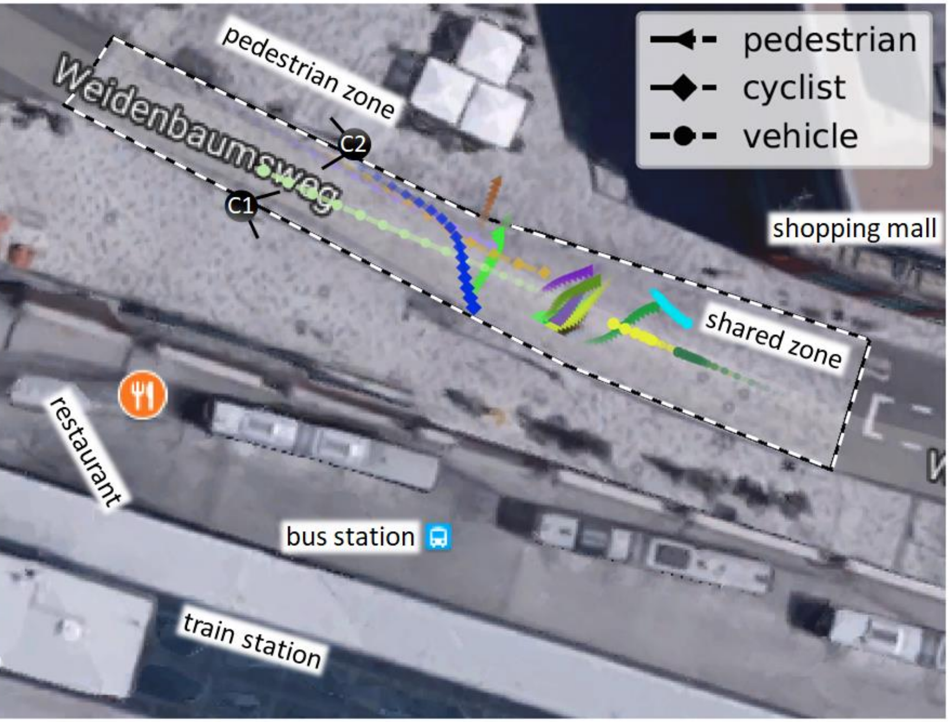
When it is no longer clear who has right of way, the **informal rules of human courtesy** should come into force. Shared Space thus deliberately aims at a certain uncertainty, which should increase actual security (Gerlach et al., 2009).

How can these informal rules be determined?

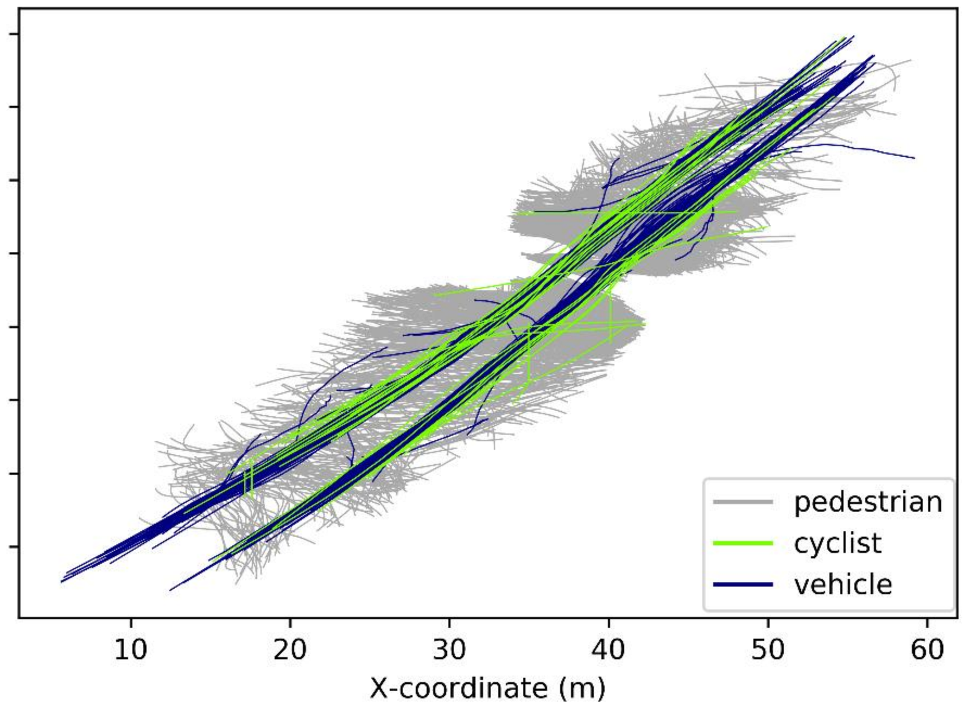
Can they be determined from observations of the behaviour of road users and used for prediction?

Data: Trajectories of road users

- Automatic learning of behavior from data
- LSTM (Long Short-Term Memory): Neural network for recognition of sequence patterns

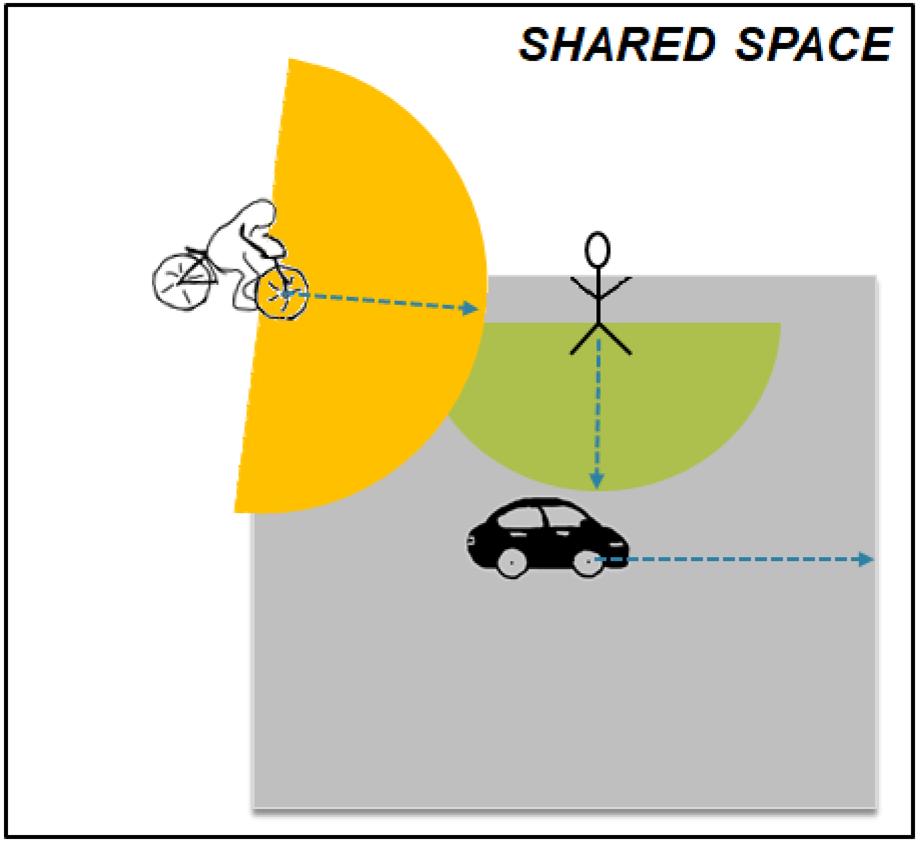


Überlagerung von Trajektorien



Modelling of road users for Long Short-Term Memory (LSTM) network

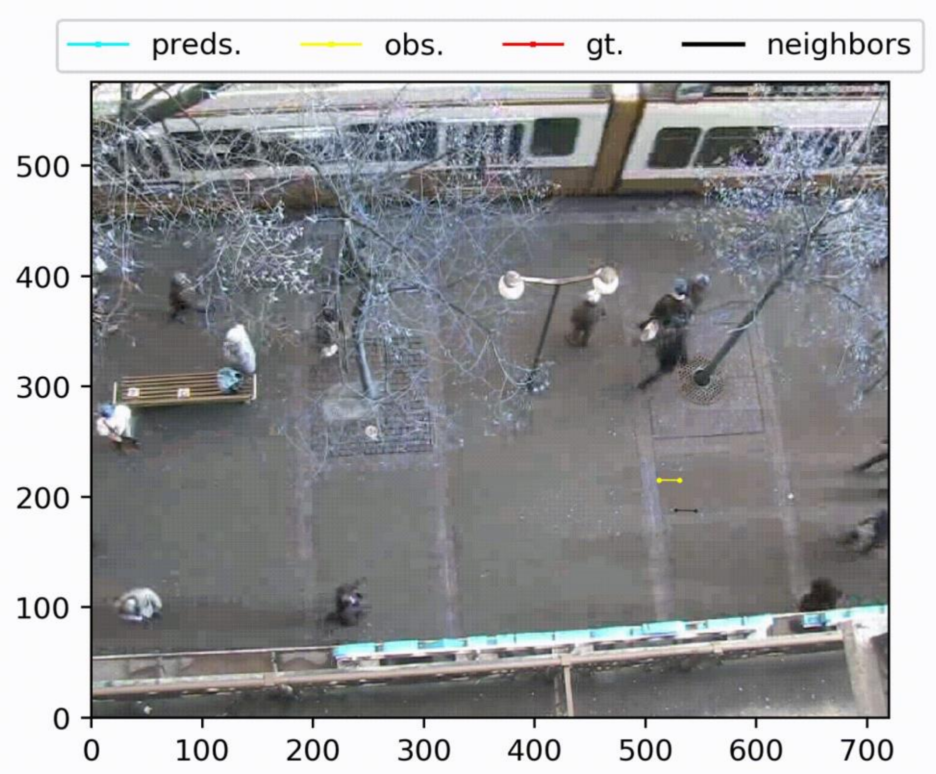
- Modelling of user type, field of view and probability of a collision as input variable for neural network

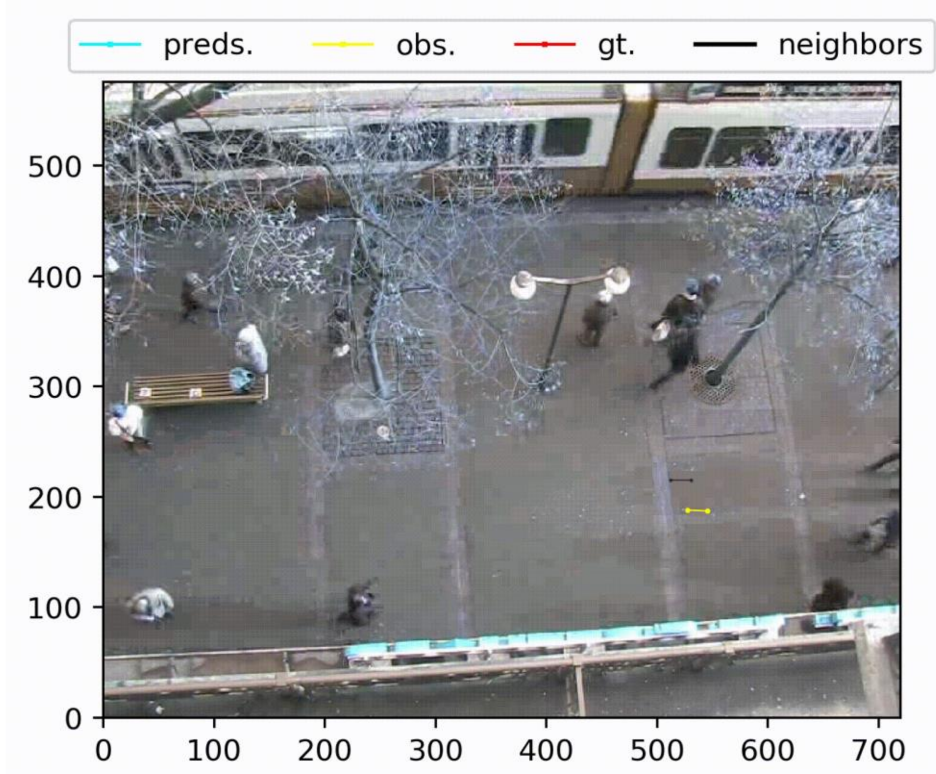


Qualitative Results

- Scenarios on BIWI Hotel dataset

Observing 8 time steps and predicting 8 time steps

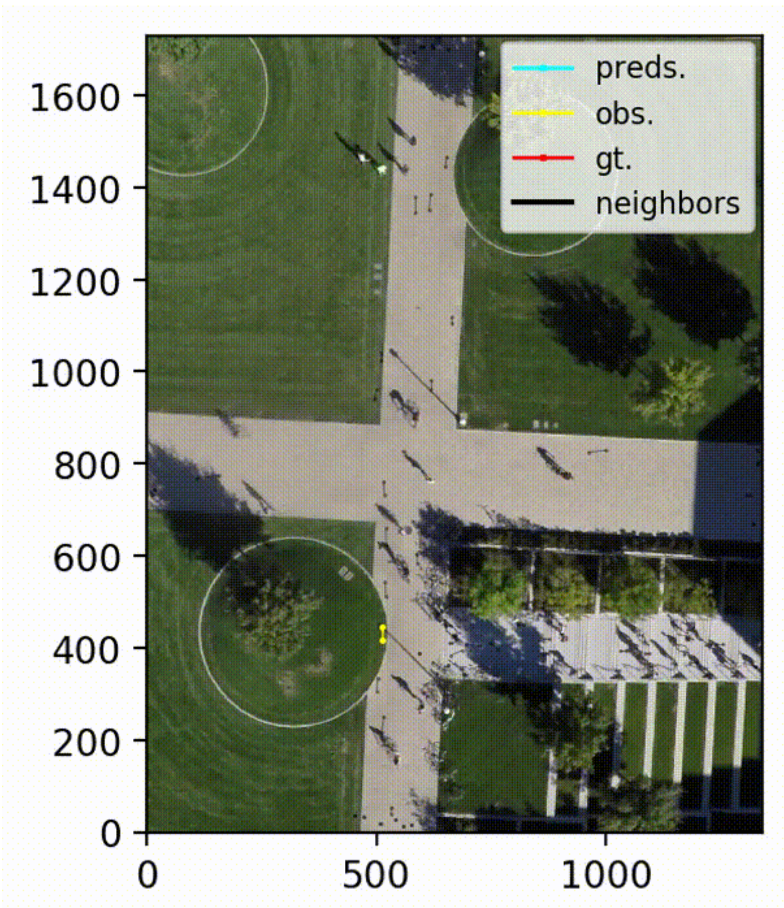


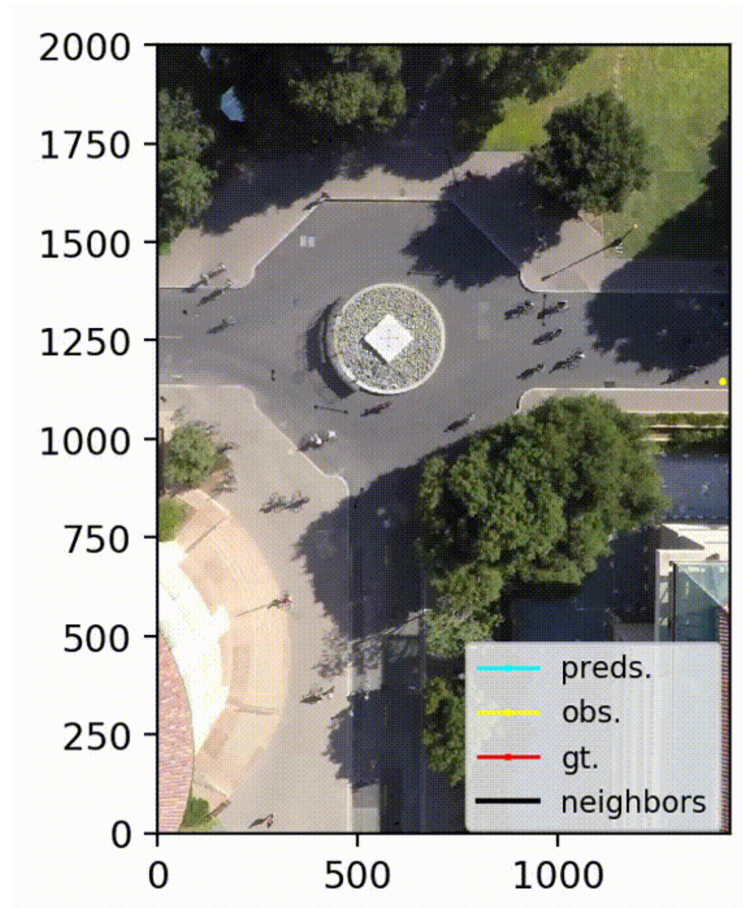


Qualitative Results

- Scenarios from Stanford campus dataset

Observing 8 time steps and predicting 12 time steps





Technische Universität Braunschweig

TU Clausthal

Leibniz Universität Hannover

The **DFG Research Training Group 1931 "SocialCars – cooperative, (de)centralized traffic management"** jointly hosted at Technische Universität Braunschweig, Technische Universität Clausthal and Leibniz Universität Hannover is looking to fill

twelve Ph.D. positions (f/m/d)

SocialCars is a joint collaborative program involving six interdisciplinary research groups representing the areas of **traffic planning, traffic psychology, computer science, business information systems, communications technology, and geodetic science / geo-informatics**. We address challenges that arise when considering the implications of automated mixed traffic scenarios and novel mobility services for dynamic traffic management. Here, the core question is how the interplay of local and global (city-wide) control and coordination strategies should be designed to ensure sustainable, safe, and efficient urban traffic.

A detailed description of the Ph.D. projects, a list of supervisors as well as further information regarding the application process is available on our website www.socialcars.org/call-for-applications.html

Position

- Carry out independent **research** with emphasis on the **Ph.D. project**
- Participate in **qualification and study program** of the Research Training Group
- **Cooperation with Ph.D. students** of the Research Training Group
- **Presentation** of research results at **(international) conferences** and **publication of scientific papers**
- Enjoy systematic individual **supervision** and **mentoring** throughout the doctoral work

Environmental Phenomenon: Learning a Precipitation Indicator from Traffic Speed Patterns

Yu Feng

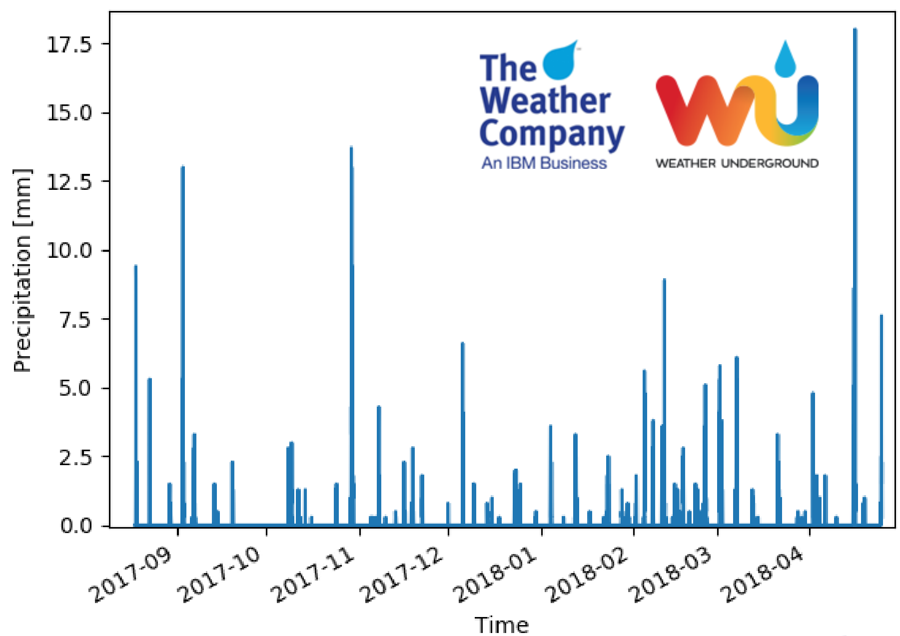
Introduction

- Traffic participants tend to drive slower under rain or snow conditions
  - i.e. weather information improves traffic speed prediction models
- Conversely, to what extent is it possible to derive weather conditions from traffic observations?
- Traffic Speed ⇄ Precipitation
  - Proof of concept: train a binary indicator
- Not intended as a replacement for weather stations, rather an experiment if data that is available anyhow can be used

Source: https://www.toyotaoforlando.com/blog/prep-your-car-for-driving-in-the-rain/

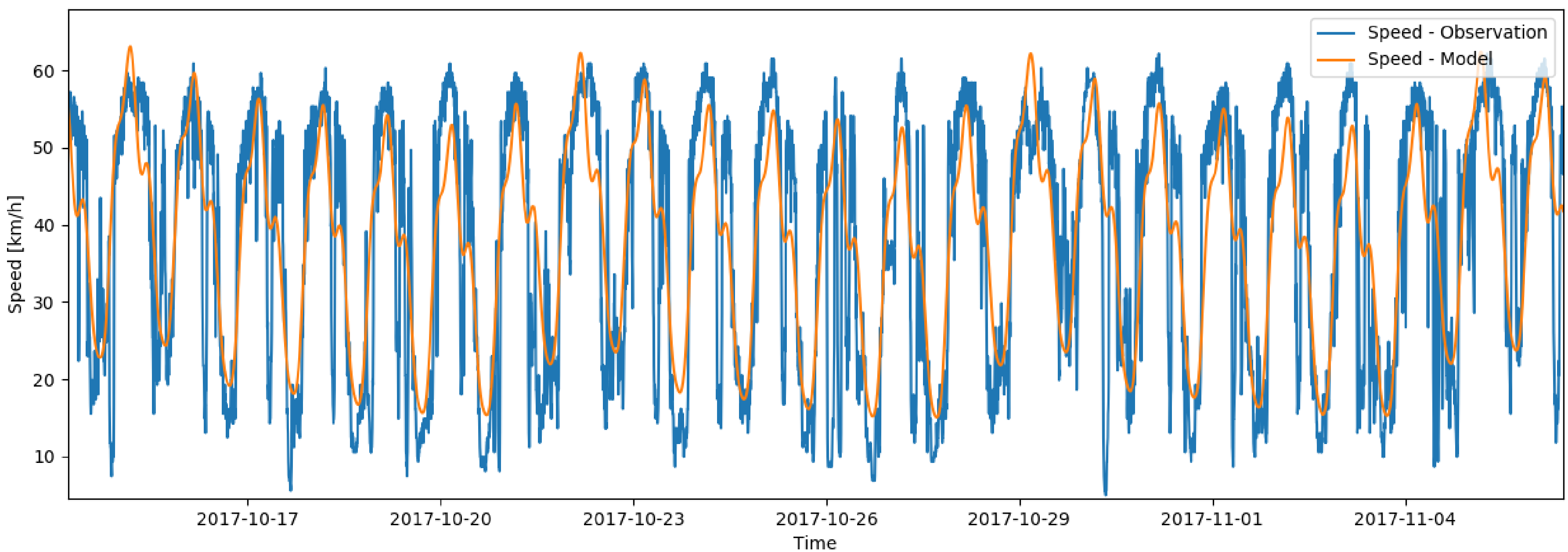
Data

- Real-time traffic speed data in New York City
  - From traffic speed detectors
  - 133 roads with 15-min intervals over a period of 8 months
  - Available at NYC Open Data
- Precipitation data from WeatherUnderground API
  - Unevenly distributed sampling intervals, 10 min to 1 hour
  - Threshold applied: 0.5 mm



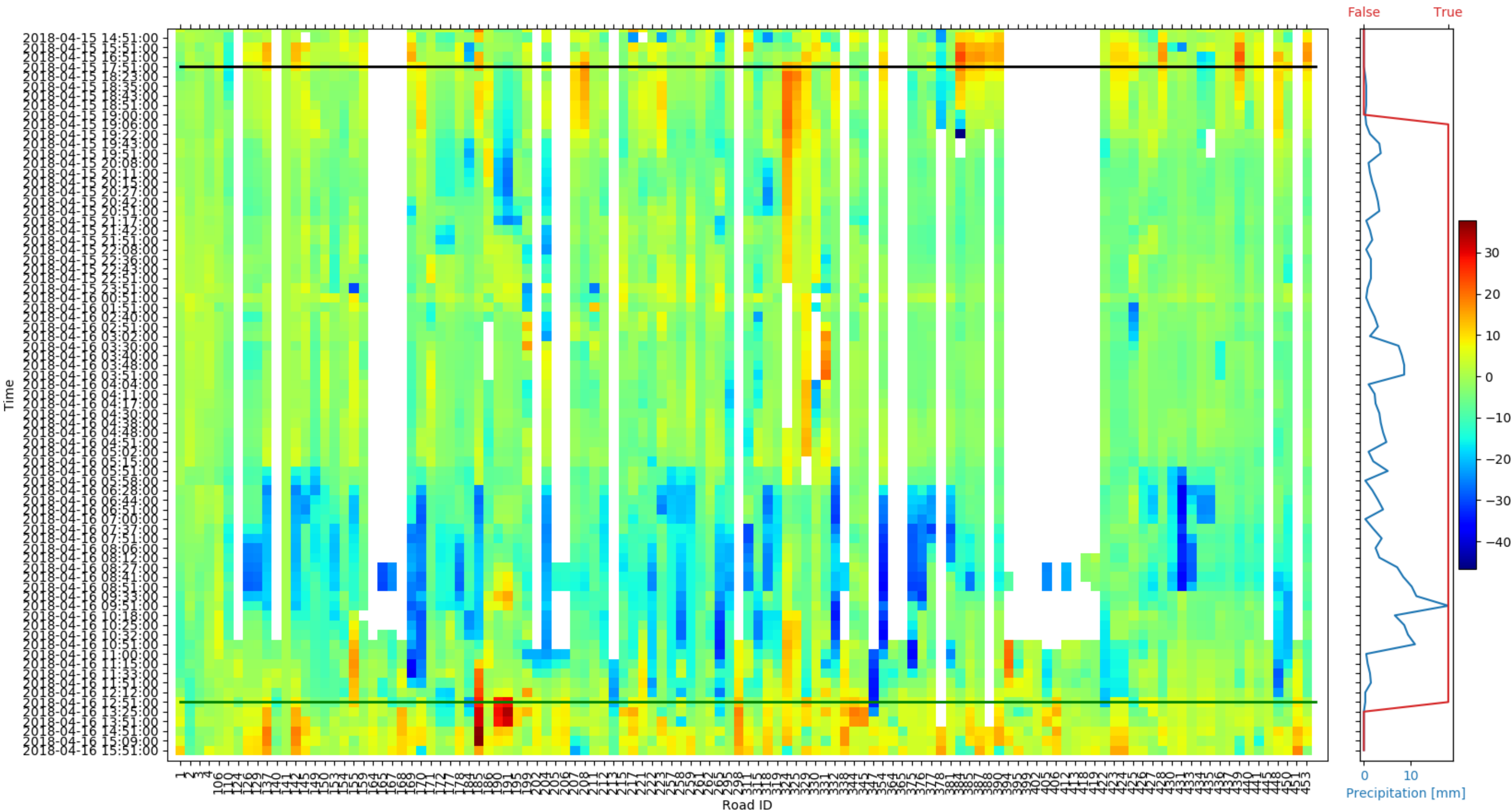
Seasonal Trend Decomposition

- Road speed observations are strongly affected by seasons
- Seasonal trend decomposition
  - Tool: Prophet from Facebook
  - Weekly and daily period considered
  - Residual indicates the level of anomaly



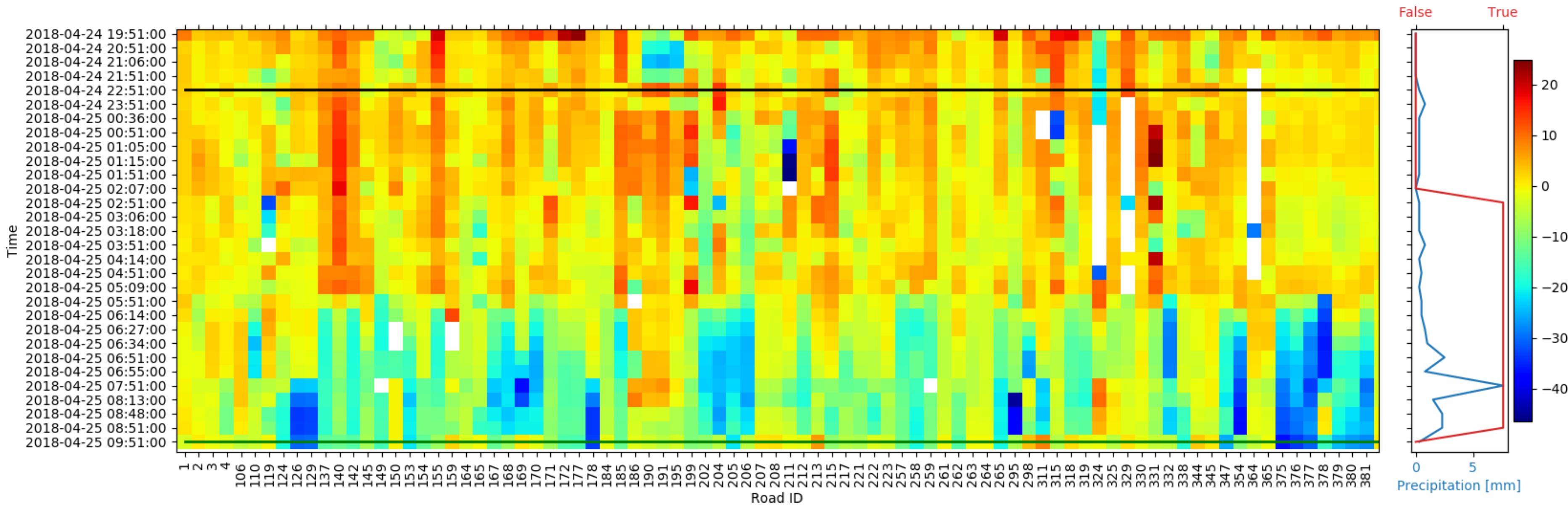
Case Studies

- Example 1 – 15th Apr. 2018



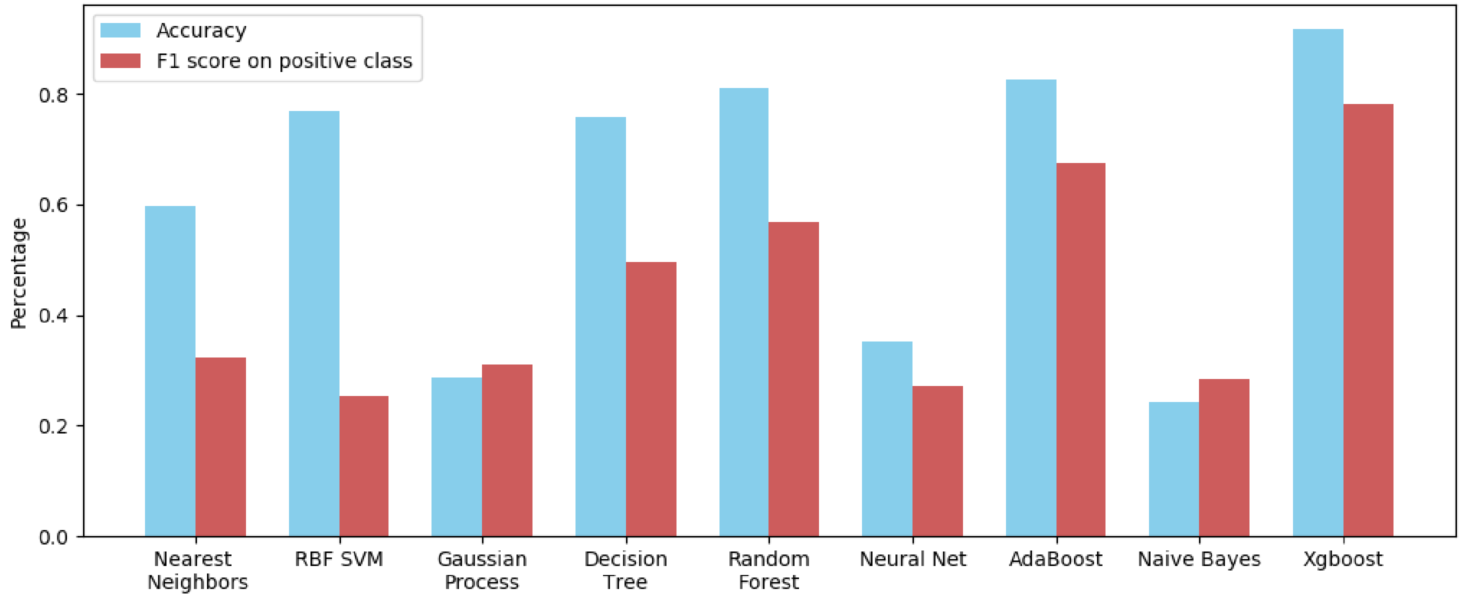
Case Studies

- Example 2 – 25th Apr. 2018



Machine Learning

- Residual between observations and periodic model as features (each timestamp has 133 values, corresponding to roads)
- Train binary classifiers
  - Train on 6 months, and test on the follow-up 2 months
  - Balanced dataset with 408 positive and 408 negative examples
- Comparison of multiple standard machine learning methods

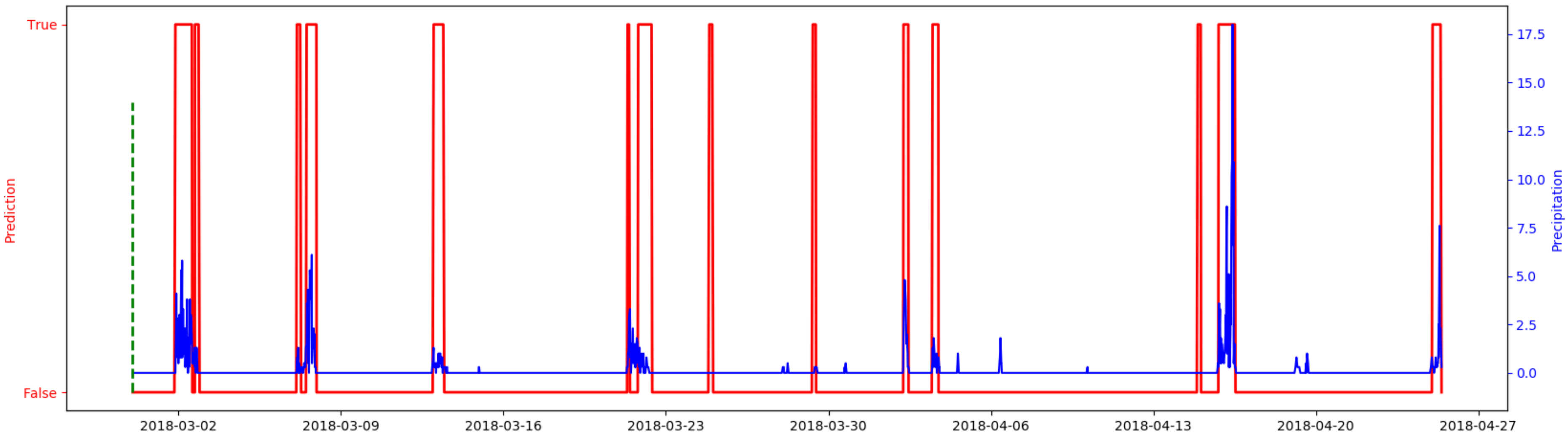


Evaluation

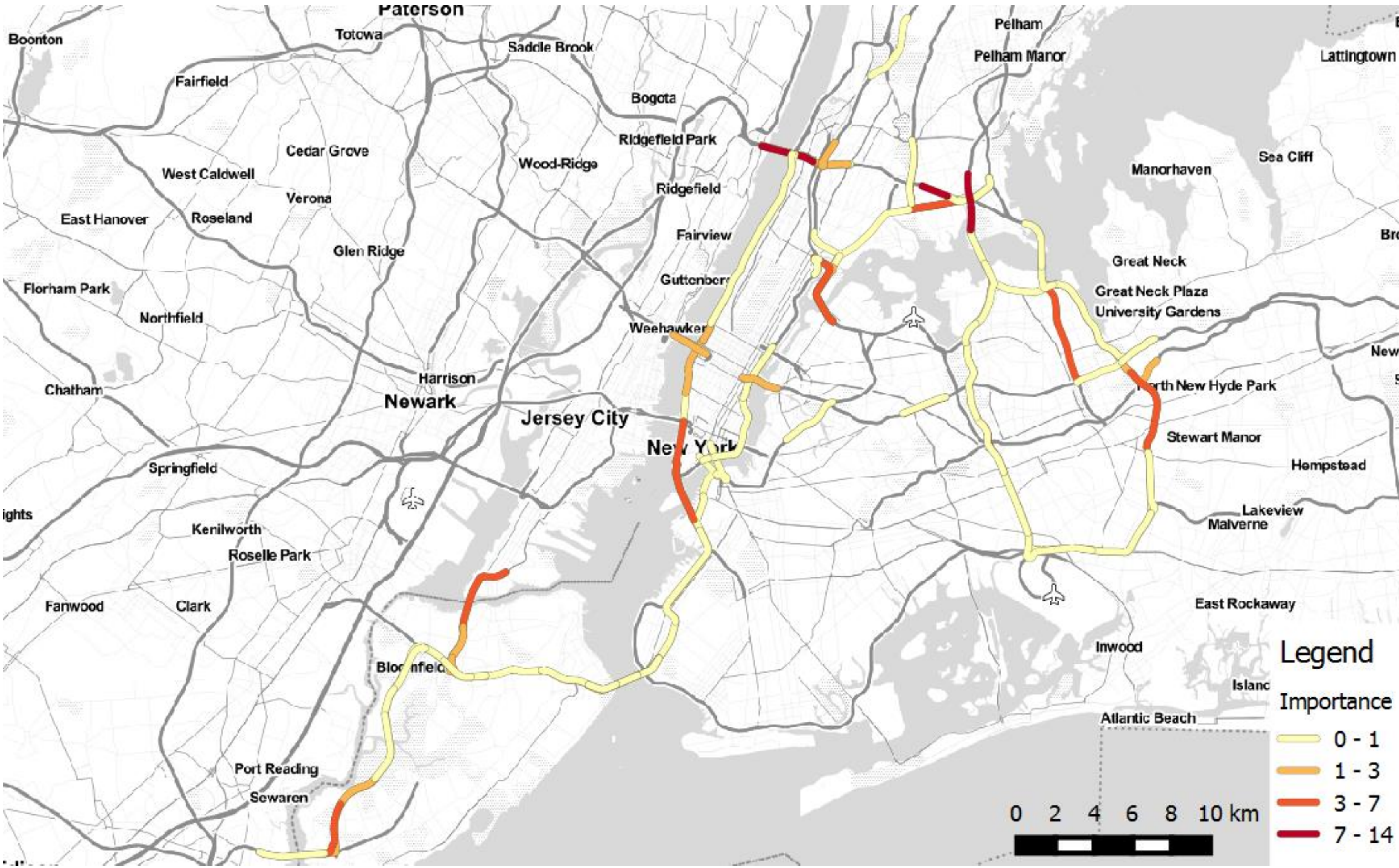
- On 2-month test set using Xgboost
  - Overall accuracy 91.74%

	Precision	Recall	F1-score
No Precipitation	**0.93**	**0.97**	**0.95**
Precipitation	**0.85**	**0.73**	**0.78**

	Pred - 0	Pred - 1
True - 0	**1312**	**45**
True - 1	**96**	**255**



Importance of individual roads, derived from Xgboost classifier



Summary

- Using road speed observations from 133 roads, we trained a binary precipitation indicator.
- Most of the precipitation events were successfully identified
- Side product which can be obtained from massive road speed observations

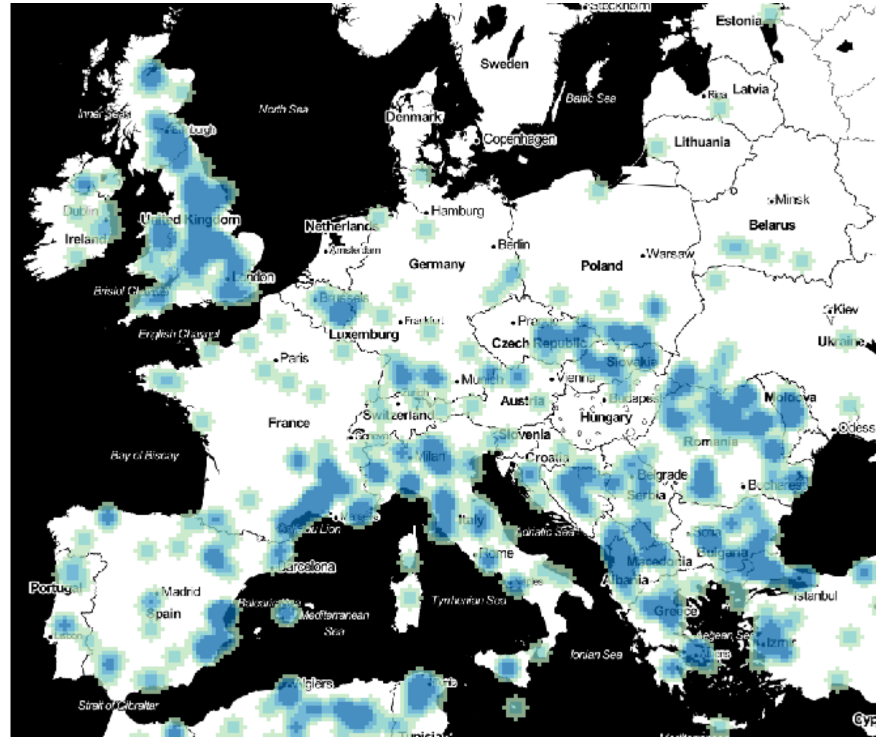
- Outlook:
  - Road speed observations with longer time period → derive precipitation severity?
  - More roads in a city / larger regions → precipitation location?

Crowdsourcing for flood monitoring

Yu Feng

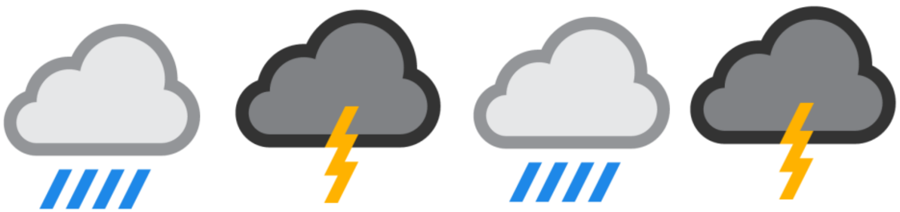
Motivation

- Flood, a global problem
- Demand of Crowdsourcing
  - disaster monitoring
  - verification of hydraulic model
  - loss estimation
- Our solution
  - Interpret information more from text and photos

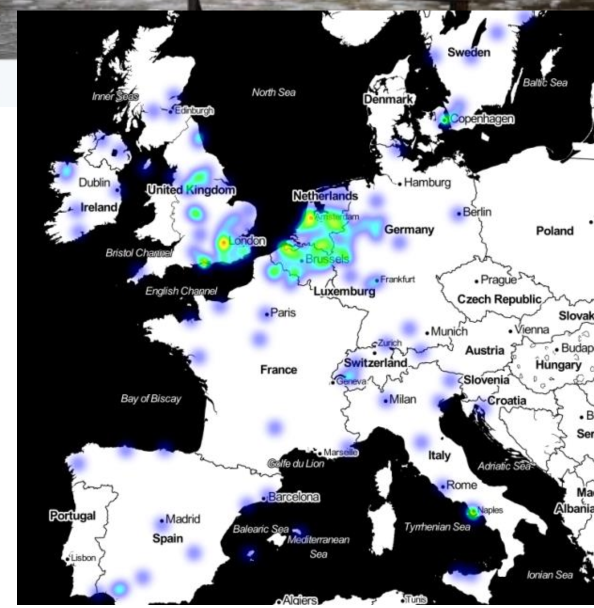


Global hotspot map for the large flood events since 1985
(Data source: http://floodobservatory.colorado.edu)

Motivation

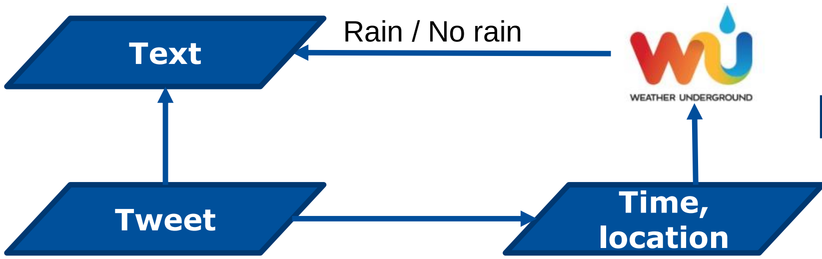


Source: http://blog.yokellocal.com/local-social-media-marketing-twitter



Training of text classifier with ConvNets

Data annotation



Trainings-Datensatz

Tweets with keywords and marked as positive

36469 Tweets

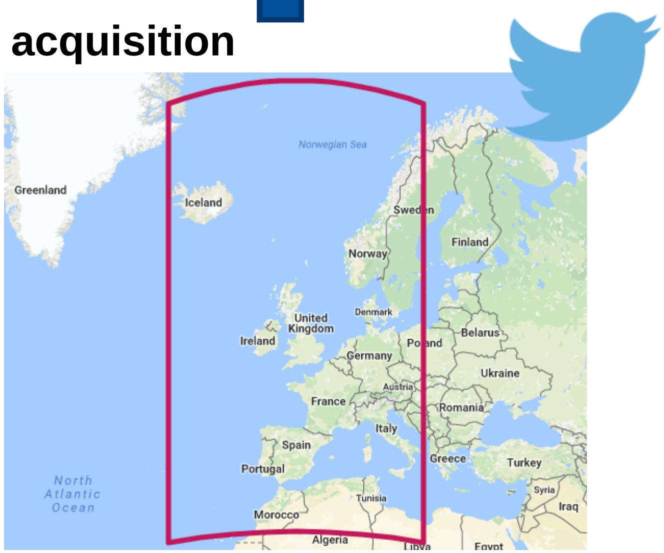
15263 Tweets

Tweets with keywords and marked as negative

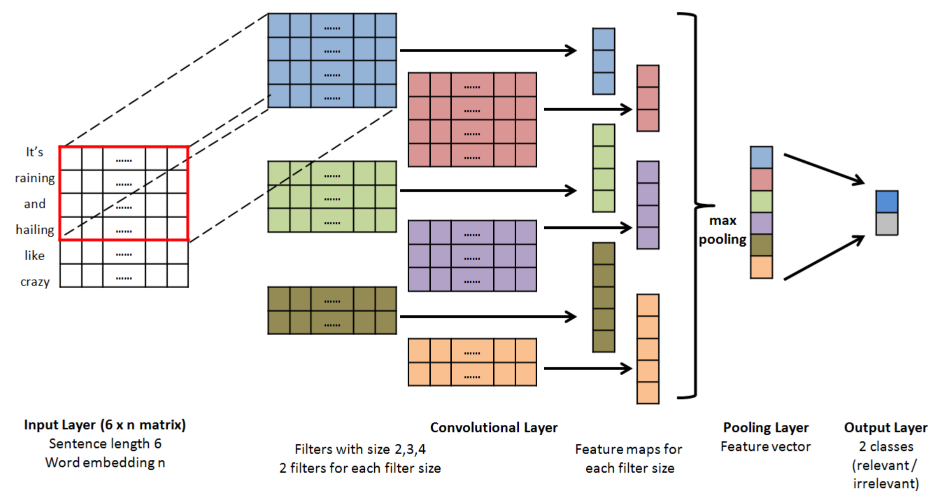
21206 Tweets

Tweets randomly selected without keywords

Data acquisition

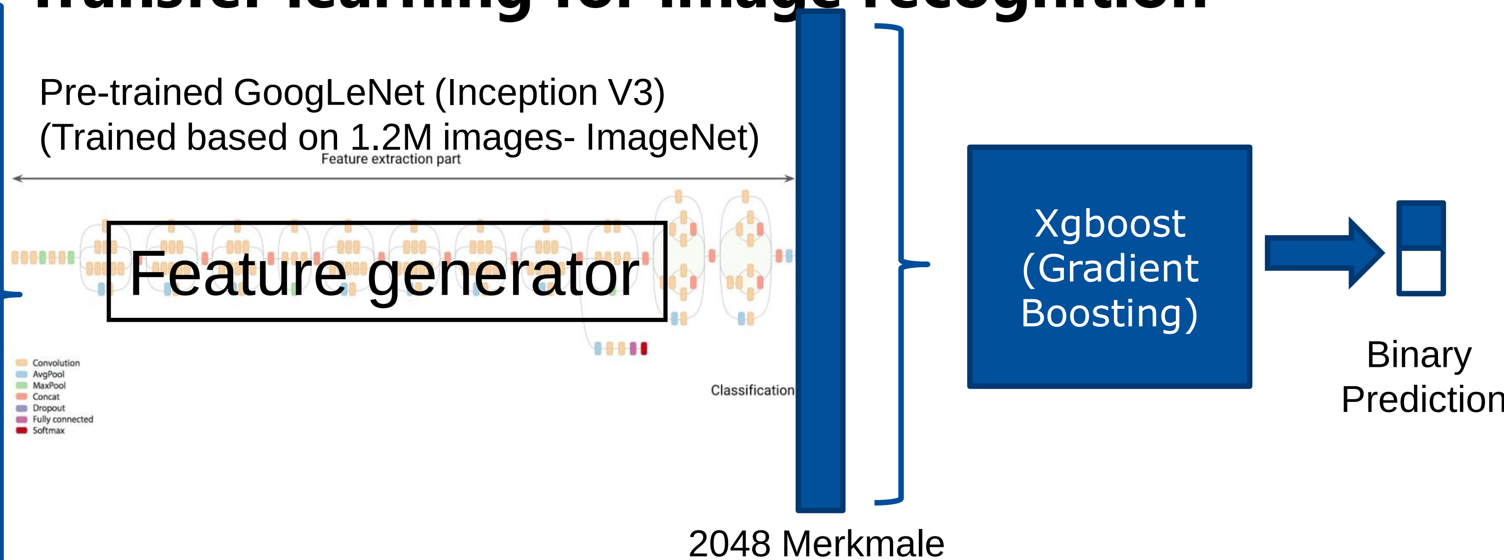


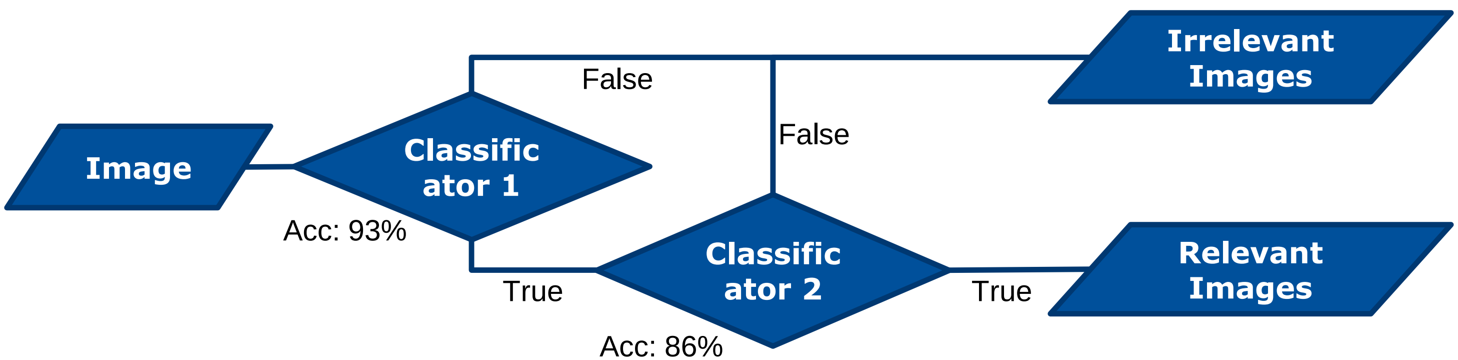
Model for Prediction



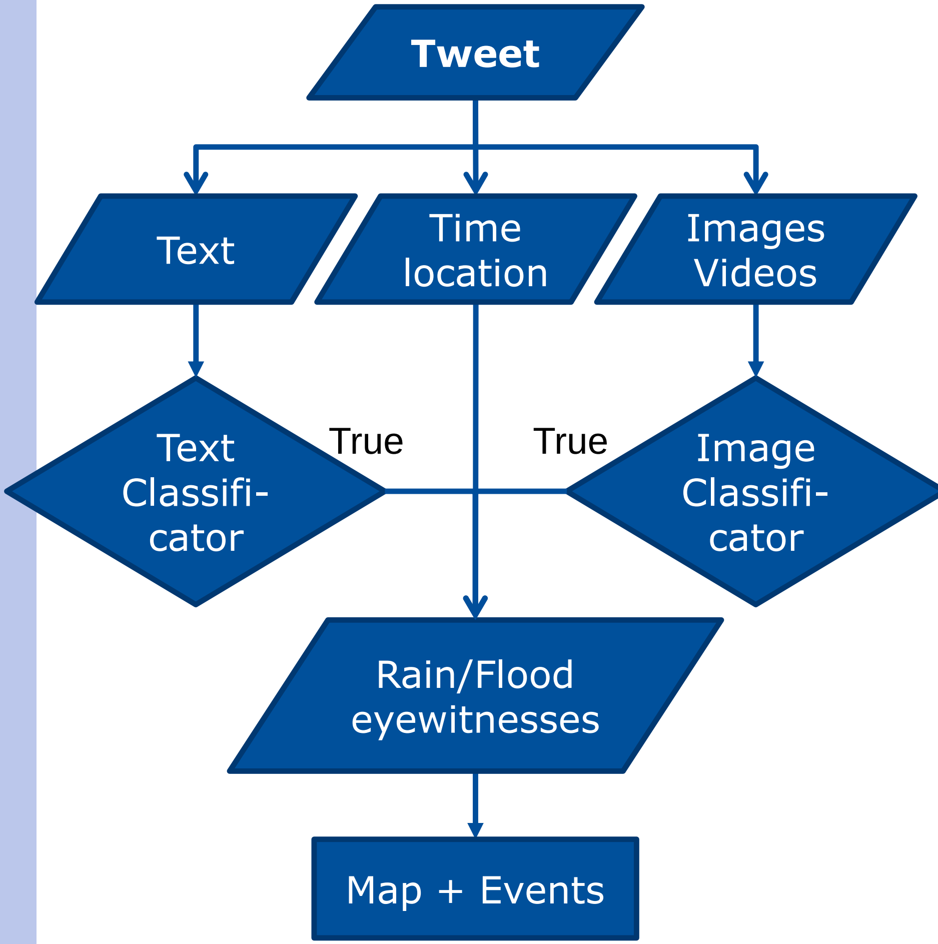
Training of image classifier with transfer learning

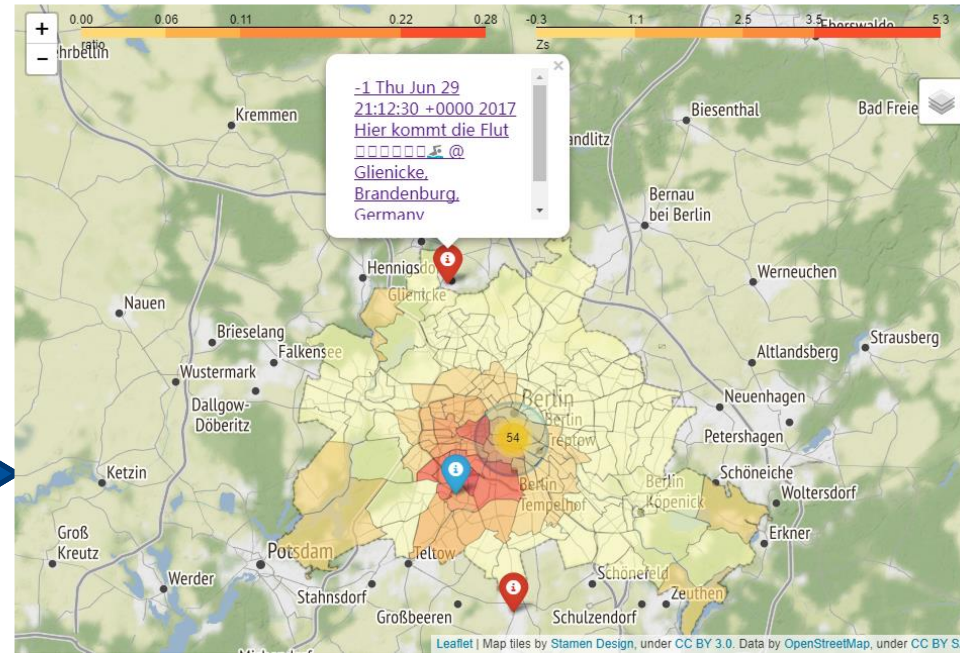
Transfer learning for image recognition





Event Detection

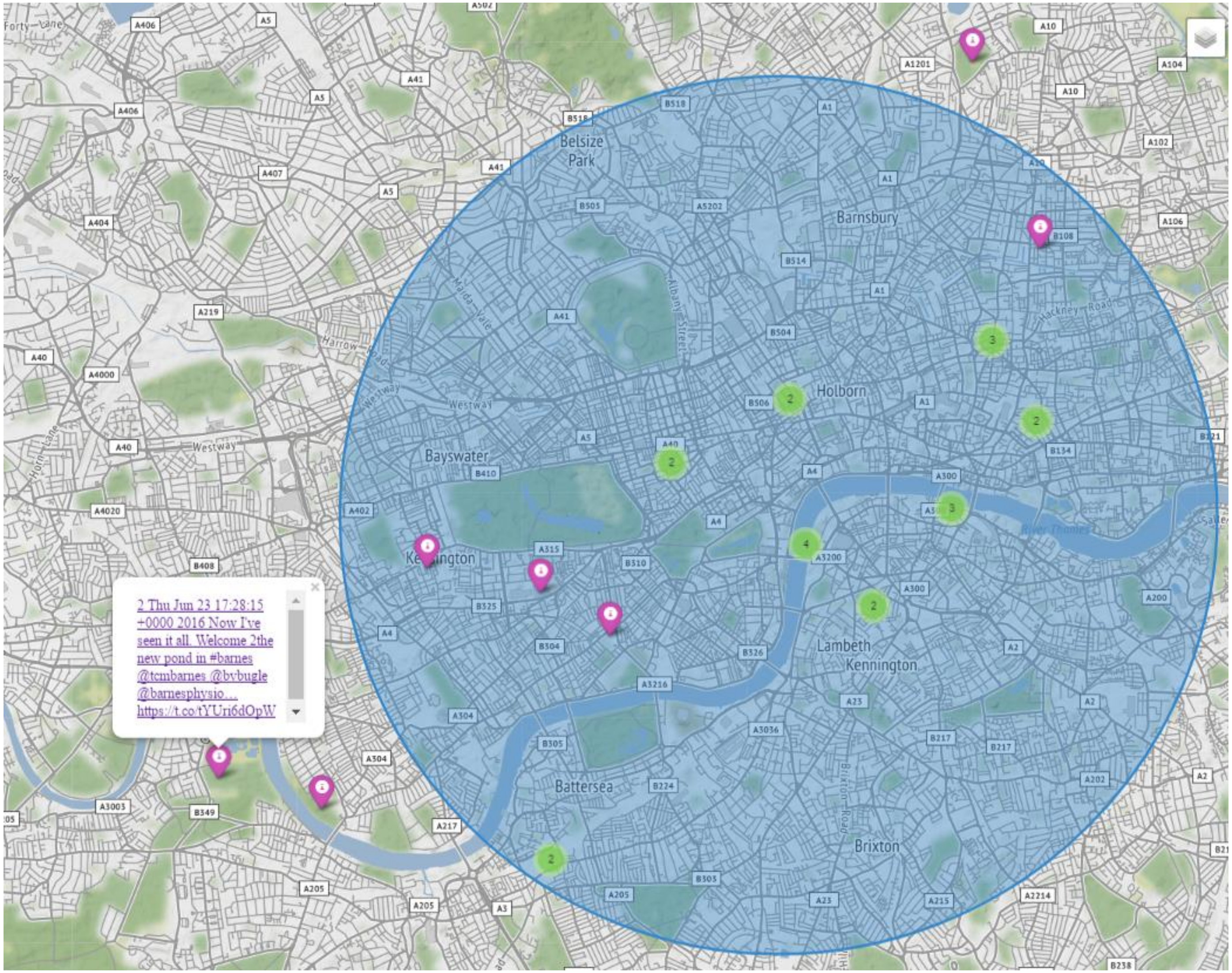




- **Spatiotemporal Analyses**
  - Clustering – ST-DBSCAN
  - Hotspot-Detection – Getis-Ord-Gi*

Urban Flood in London, June 23 2016

London demo

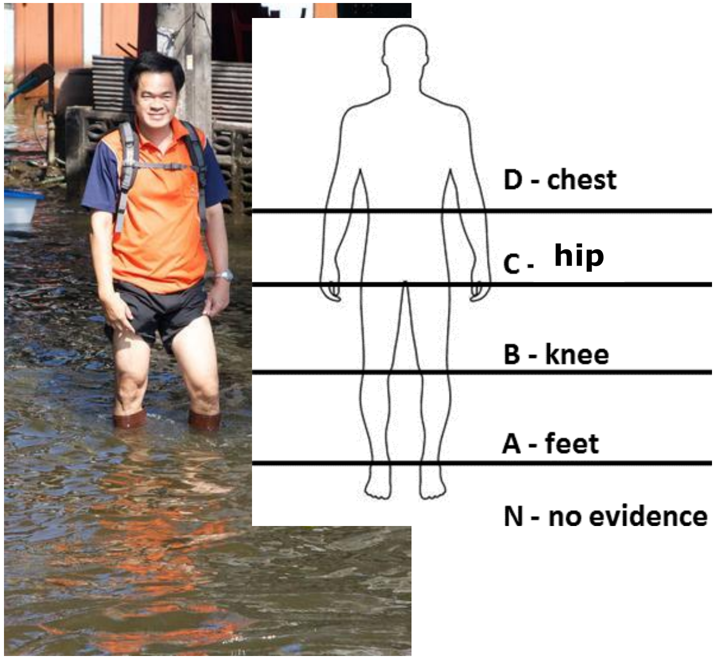


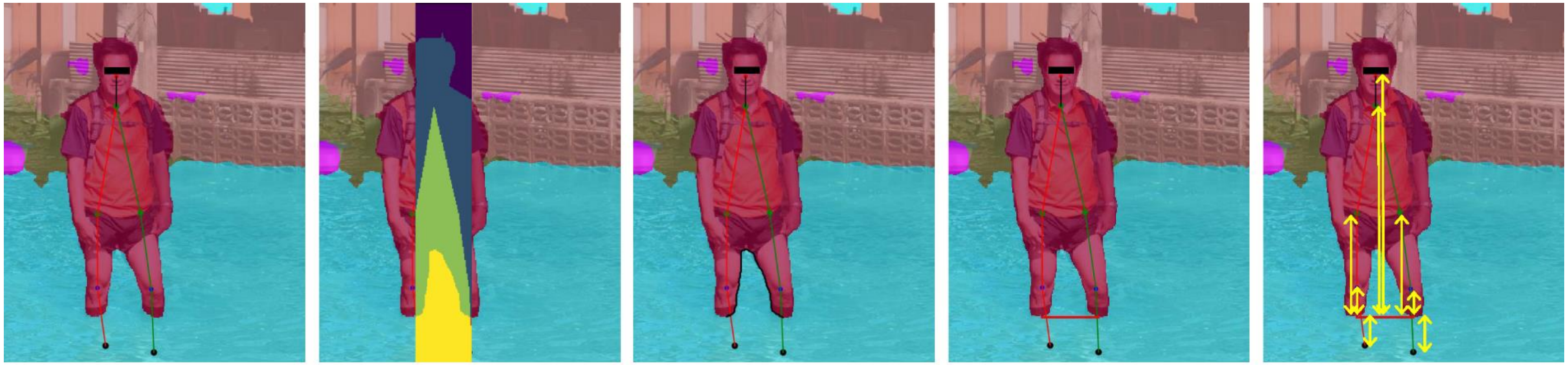
Source: Basemap - OpenStreetMap

Water level estimation

- Fixed size objects in the scene show evidence about water level
  - <u>people</u>
  - cars, bikes…

- Rule-based ML methods for water level classification
  - Extraction of skeleton with OpenPose





(1) Overlay of semantic segmentation and body keypoints

(2) Valid area created by body keypoints and image bottom points using convex hull

(3) Extract valid connecting boundary

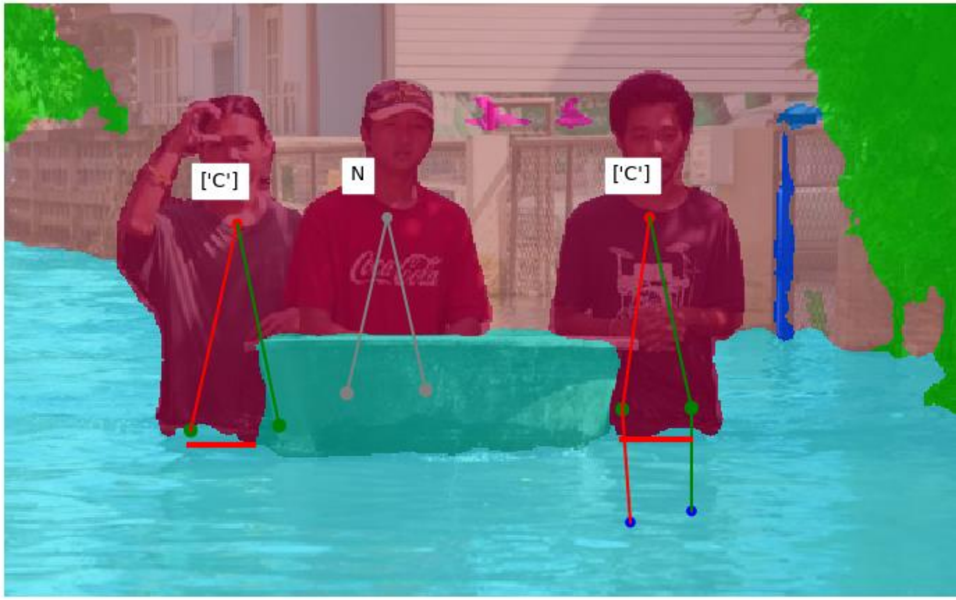
(4) Abstraction with the height of lowest boundary point

(5) Extraction of distance feature

Examples

Input:ap9z5774_6356496275_o.jpg Ground Truth:X

Prediction based on skeleton features:C



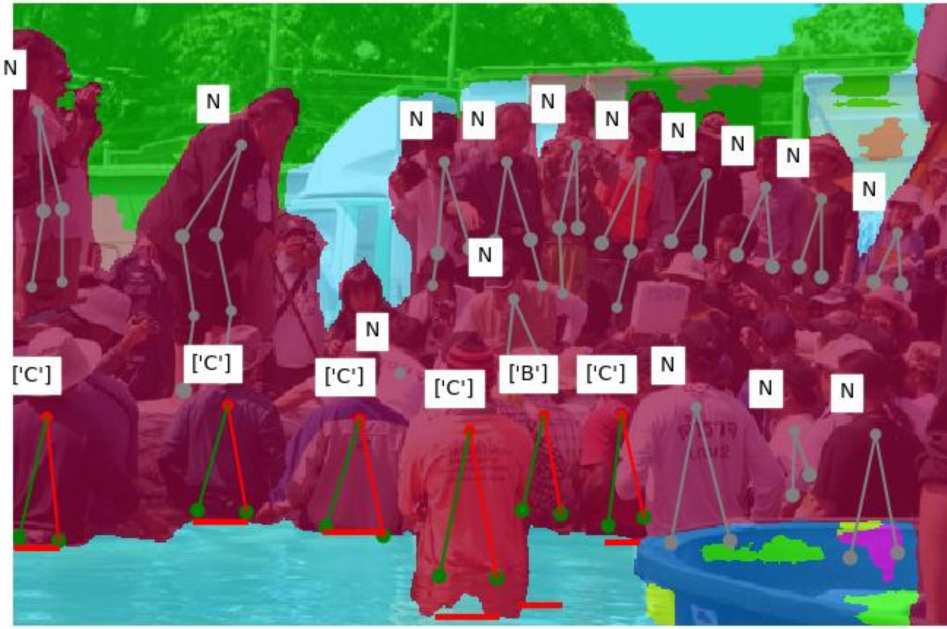
Input:ap9z5901_6356637353_o.jpg Ground Truth:X

Prediction based on skeleton features:D

Examples

Input:ap9z5609_6356390961_o.jpg Ground Truth:X

Prediction based on skeleton features:C



Input:ap9z5527_6356346301_o.jpg Ground Truth:X

Prediction based on skeleton features:C

Summary and outlook

Summary and outlook

- Data can be captured by a variety of existing sensors (incl. human as sensor)
- Data about the city and the environment are highly relevant for many processes in a city.
- Highly dynamic
- **A lot of data** is important to learn from (AI)
- Much of this information is personally identifiable – privacy!

- Challenges - beyond technology
  - How can citizens be motivated to make their data available for important public purposes?
  - Must data be stored - and if so, for how long?
  - How to ensure that personal data is protected or privacy is protected?

More Information

- www.ikg.uni-hannover.de