Institut für Kartographie und Geoinformatik | Leibniz Universität Hannover

Data Analysis: Trajectories and VGI Data

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Outline

- Exploiting „new“ data sources (Trajectories, Social Media)
- Different applications areas: analysis of traffic, football, disaster
- Trajectory acquisition and interpretation
- Trajectory analysis
- VGI-data analysis

Deep Learning of Behavioural Models in Shared Spaces

Hao Cheng

Motivation

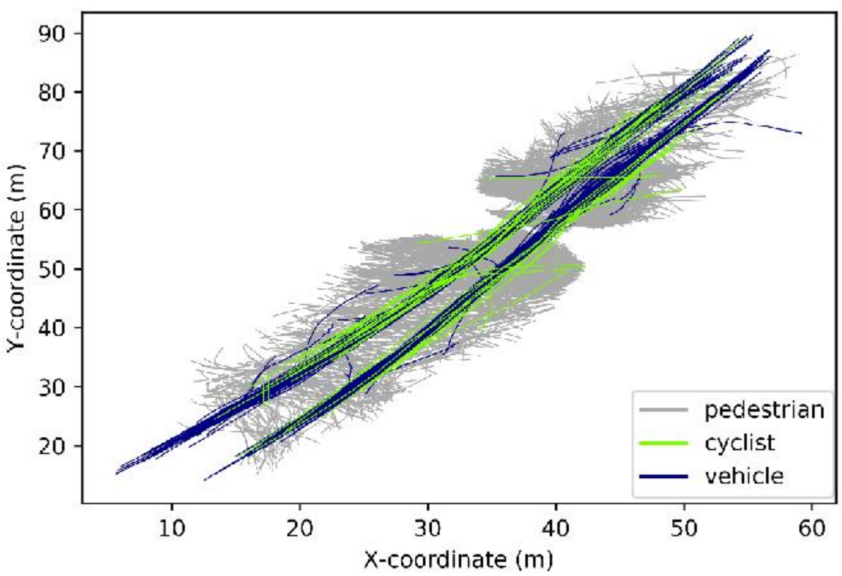
- The behavior of road users in shared spaces need to be investigated for mixed traffic trajectory prediction and management
- Established models lack flexibility (e.g. w.r.t. different user types and constellations)

How to build flexible and robust models using real-world data for mixed traffic trajectory prediction with collision avoidance in shared space?

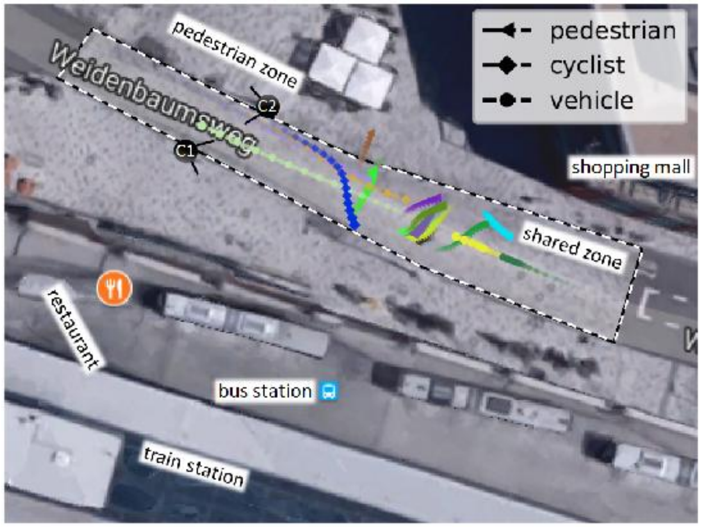
Data

- Shared space dataset

Accumulated mixted traffic trajectories

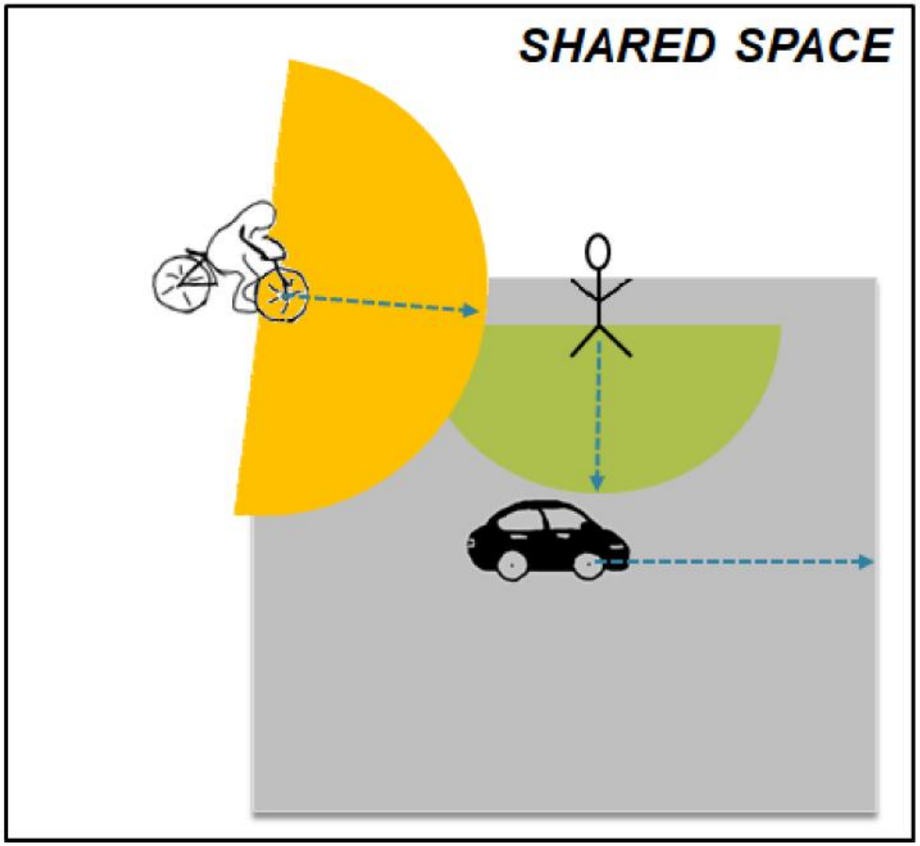


Layout of a shared space



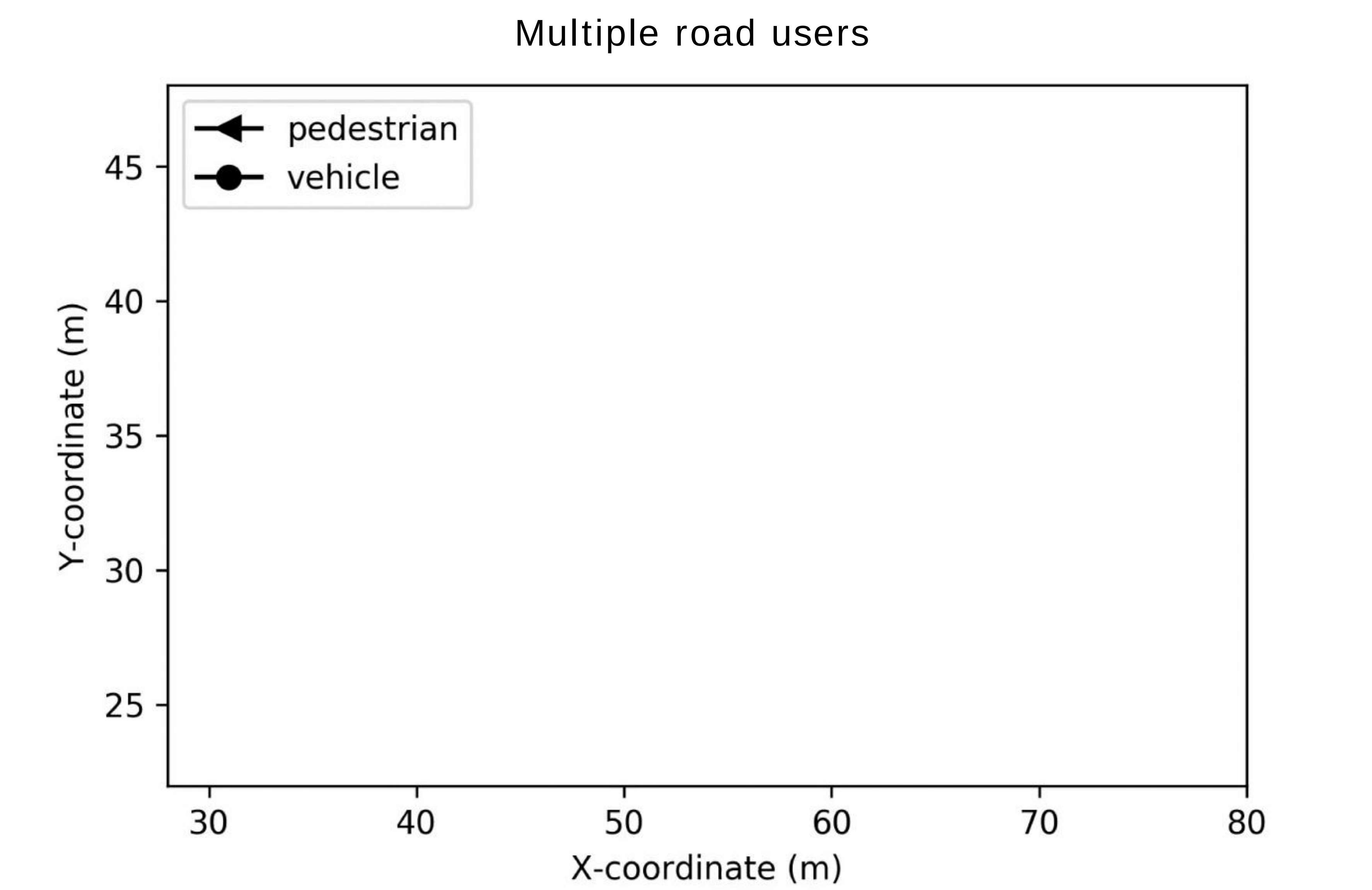
Feature Incorporation for Long Short-Term Memory

- Incorporate user type and/or sight of view with spatio-temporal features as input for Long Short-Term Memory models (Cheng and Sester 2018)

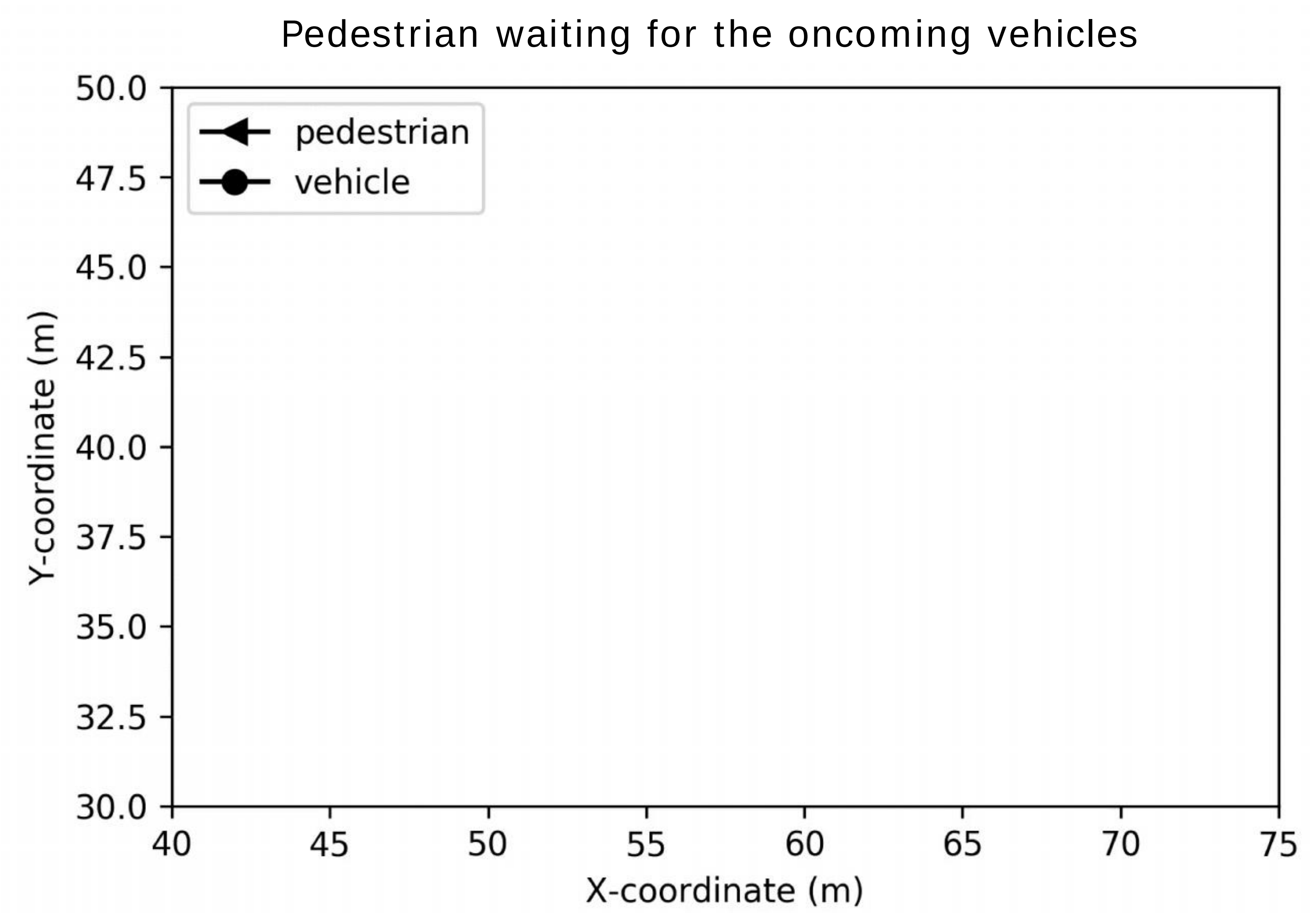


Plus: probability of a collision (PDM)

Prediction by LSTM-PDM—Qualitative Analysis



Prediction by LSTM-PDM—Qualitative Analysis



Current research

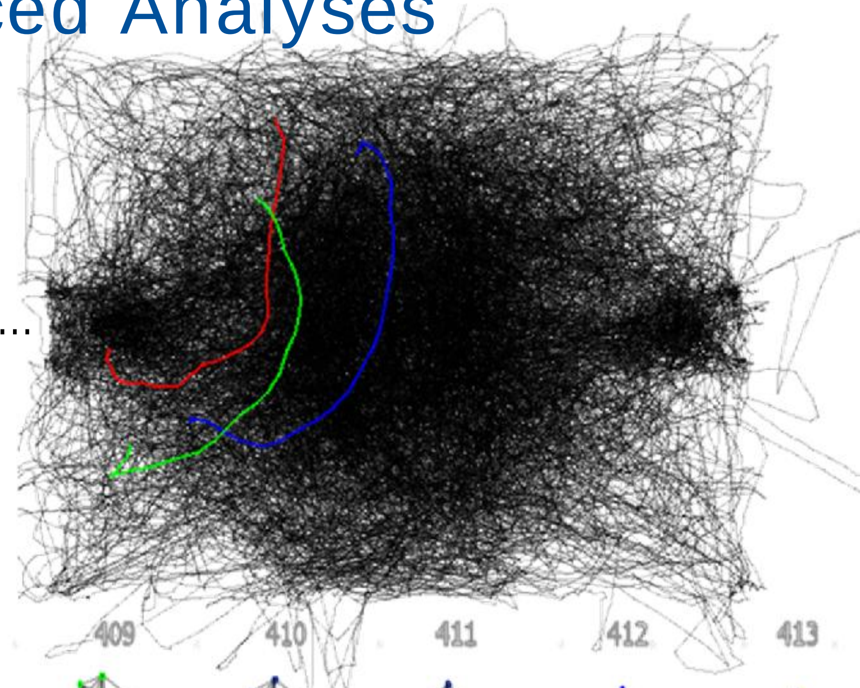
- Include groups and group behaviour
- To this end: evaluation of data set and determination of groups (using clustering approach)
- Questions:
  - How do car drivers behave with respect to a group of people (and vice versa)?
  - When do groups split in order to give way to other traffic participants?

Udo Feuerhake

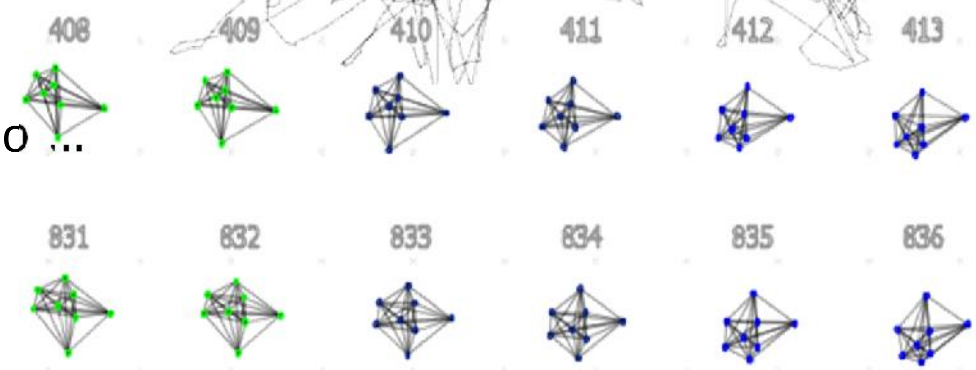
Football Analysis

Football Analysis – Advanced Analyses

- Recognition of Patterns in ...
  - ... individual player movements to ...
    - ... characterize players
    - ... predict player movements



  - ... team (group) movements to ...
    - ... identify team tactics

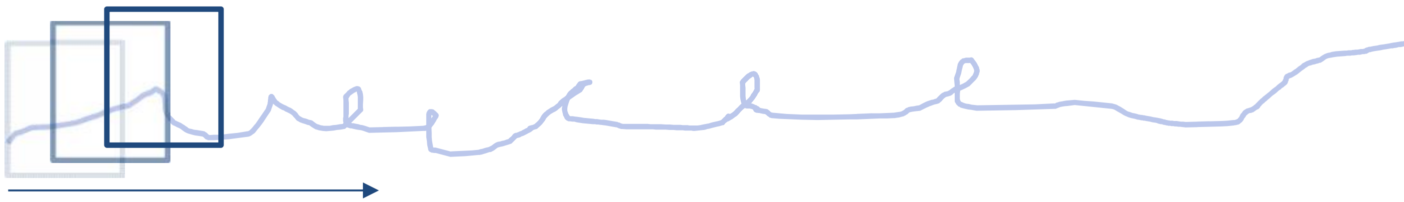


  - ... pass sequences to ...
    - ... predict next passes

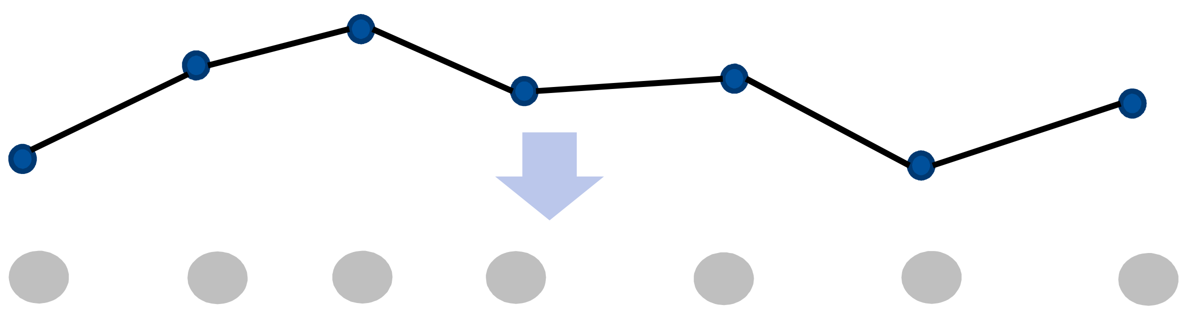
Recognition of Individual Movement Patterns

- Movement pattern = frequent repetitive movement

- Approach without segmentation step is required
  - moving window algorithm

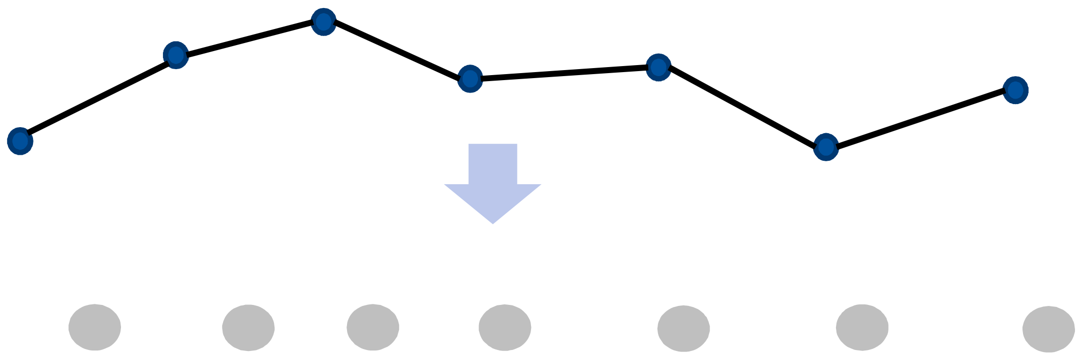


  - Transformation to a sequence mining problem
    - Trajectory as a sequence of movements/positions/...



Recognition of Individual Movement Patterns

- Transforming a trajectory to a sequence



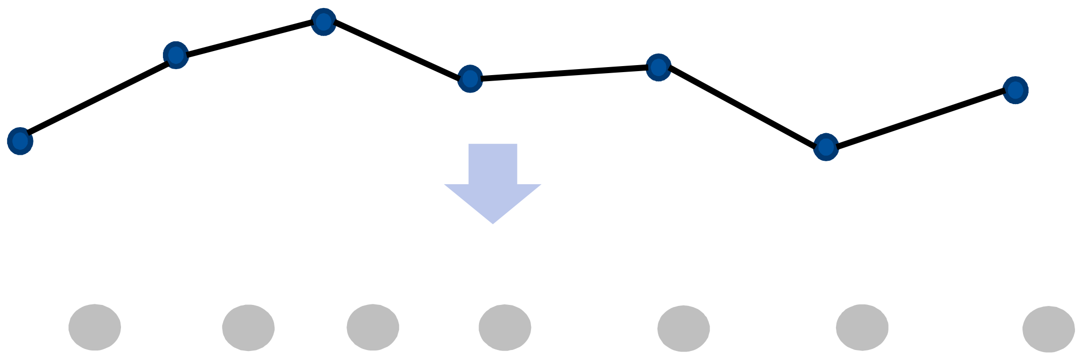
  - Points as sequence items

$$= \left\{ \left(\quad \right), \ldots, \left(\quad \right) \right\}$$

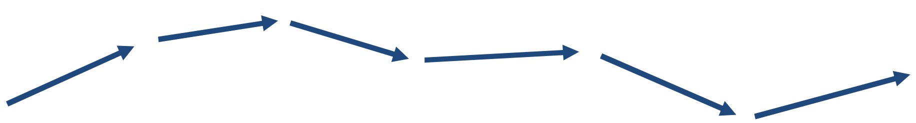
→ No invariances (only exact reproduction)

Recognition of Individual Movement Patterns

- Transforming a trajectory to a sequence



  - Movements/movement vectors as sequence items



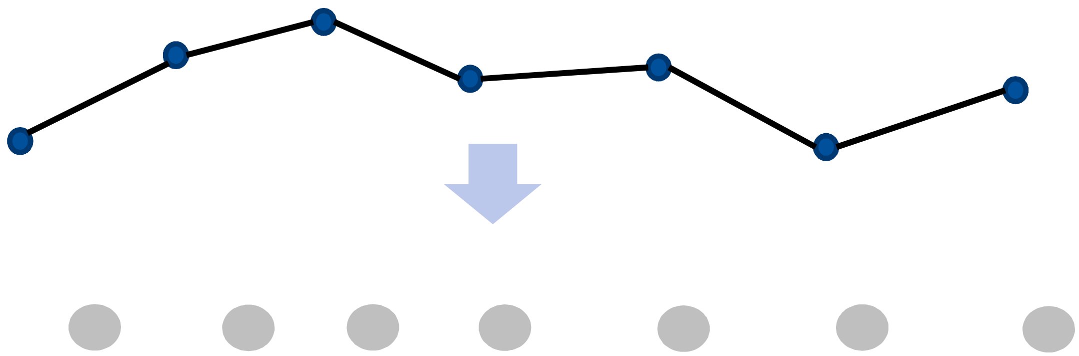
$$ = \left\{ \left(\quad \right), \ldots, \left(\quad \right) \quad \right\} \text{ or}$$

$$ = \left\{ \left(\quad \right), \ldots, \left(\quad \right) \quad \right\}$$

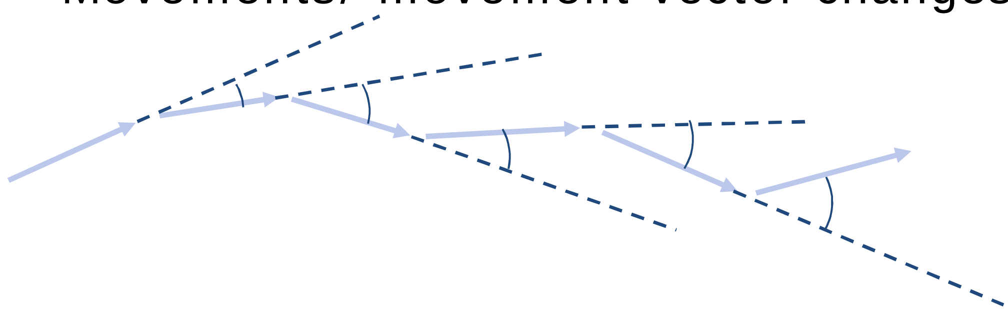
  - Translation invariances

Recognition of Individual Movement Patterns

- Transforming a trajectory to a sequence



  - Movements/ movement vector changes as sequence items



$$. = \{(\quad), \ldots, (\quad) \quad \}$$

  - Translation & rotation invariances

Recognition of Individual Movement Patterns

- Problem of continuous data/attributes

→Sequence will consist of non repetitive elements (as all data will be nearly unique!)

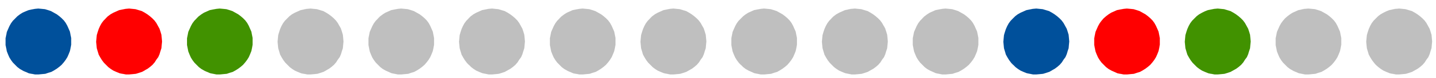
→No patterns will be found at all

- Solution?
  - Determine item similarities to deal with variances

→ Clustering of items

Recognition of Individual Movement Patterns

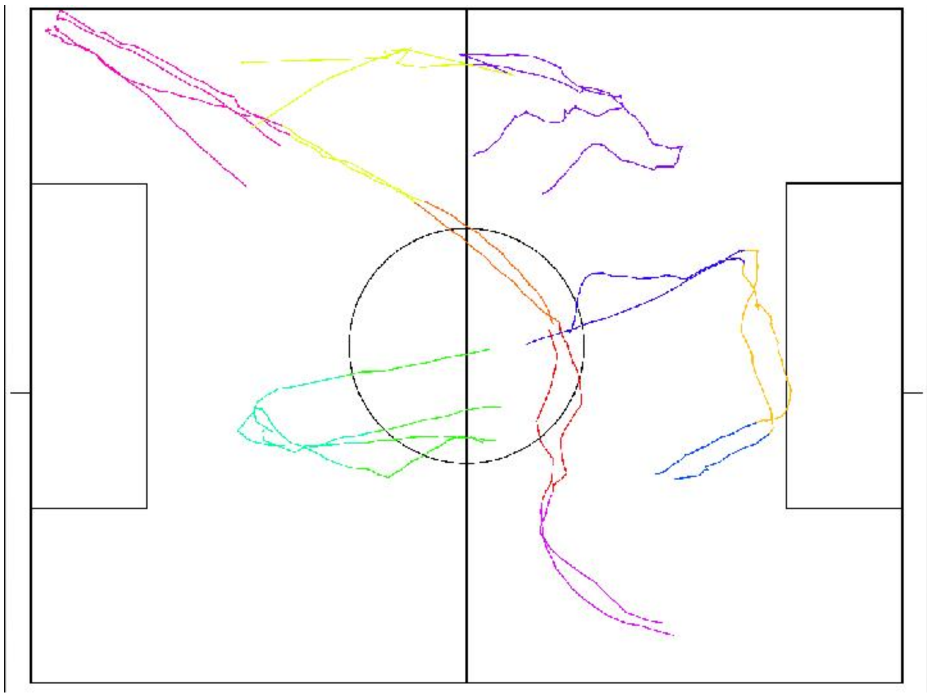
- Use of sequence mining algorithm to extract patterns from the sequence of clusters (clustered items)
  - Algorithm to find repetitive subsequences in long supersequence



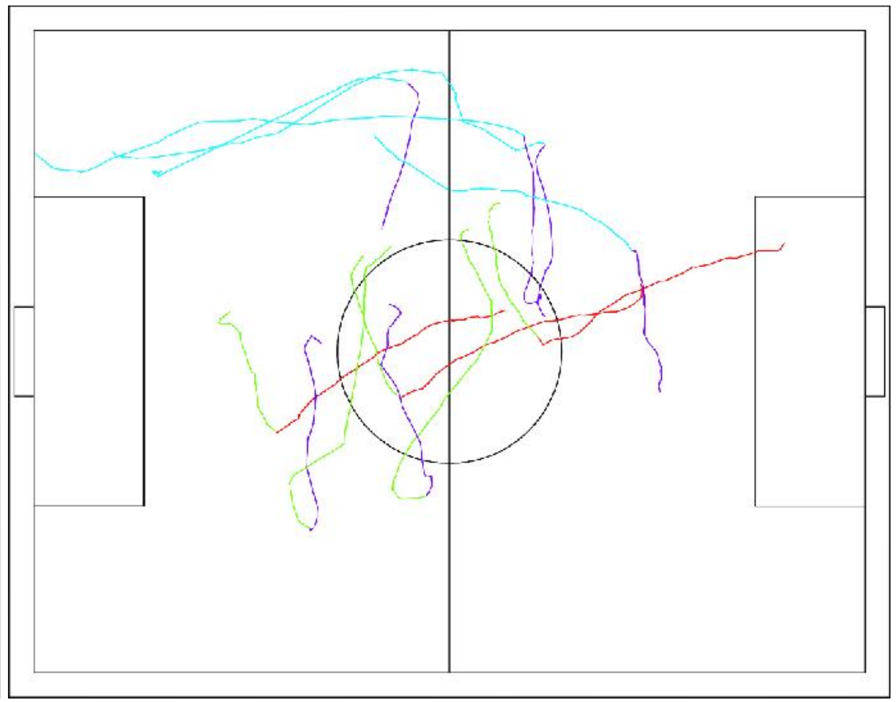
- Application of modified version of Apriori algorithm

Recognition of Individual Movement Patterns

- Results
  - No invariances allowed

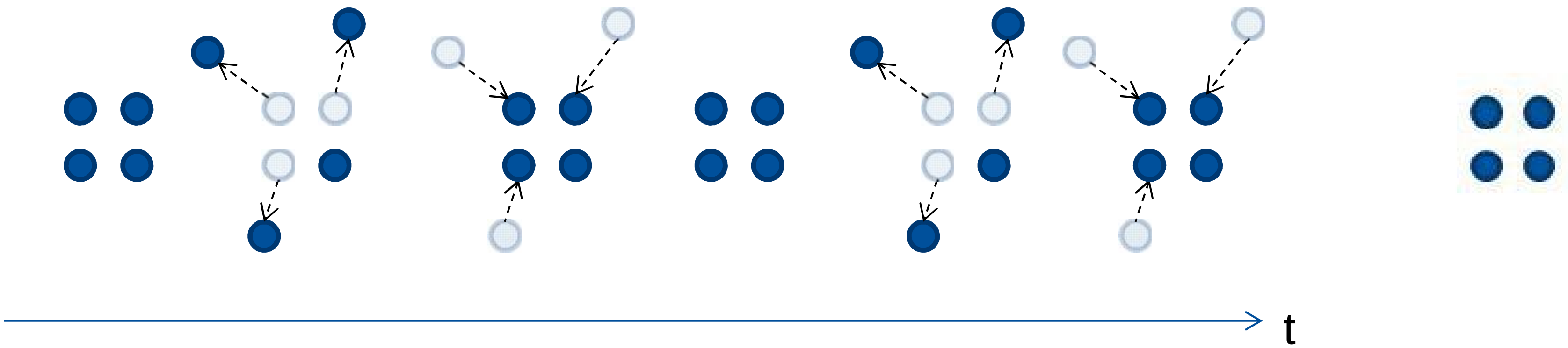


Translation is allowed



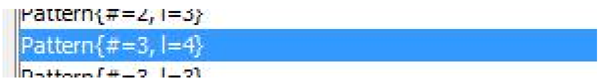
Recognition of Team Movement Patterns

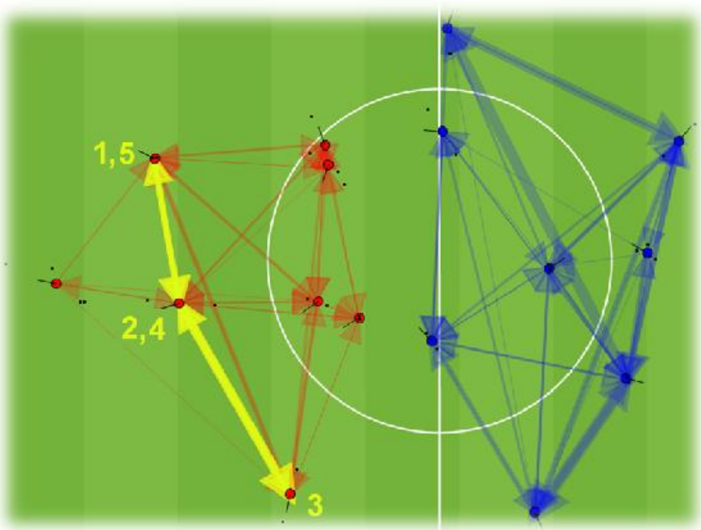
- In general: repetitive relative movements of a group of objects

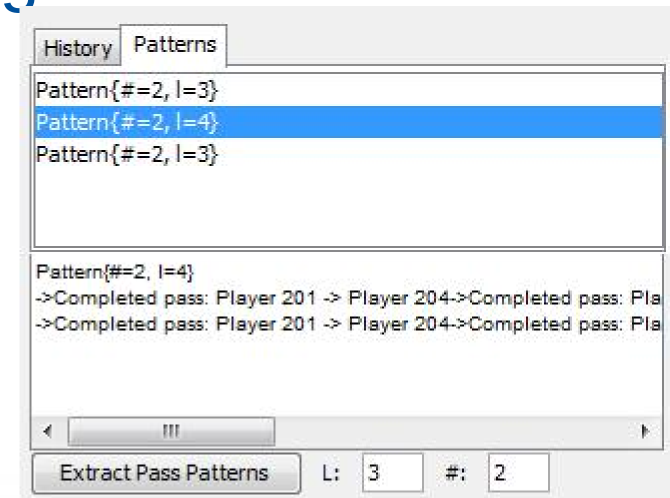


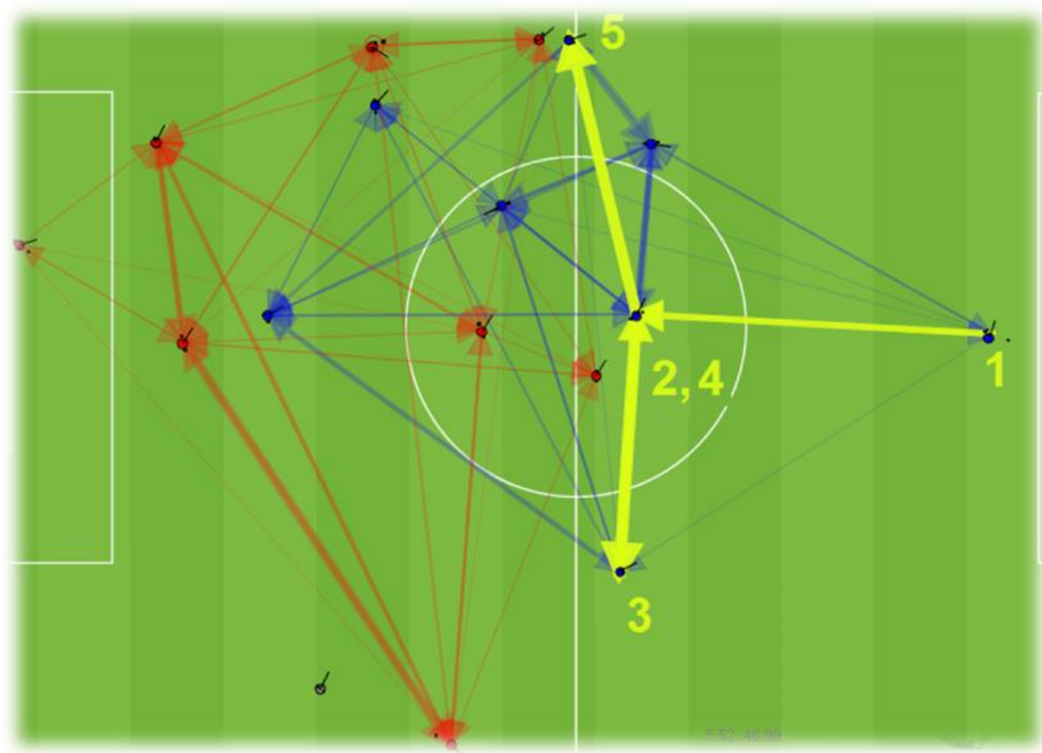
- Requirements:
  - Group members are already known
  - Group size has to be constant over time

Pass Sequence Pattern Mining





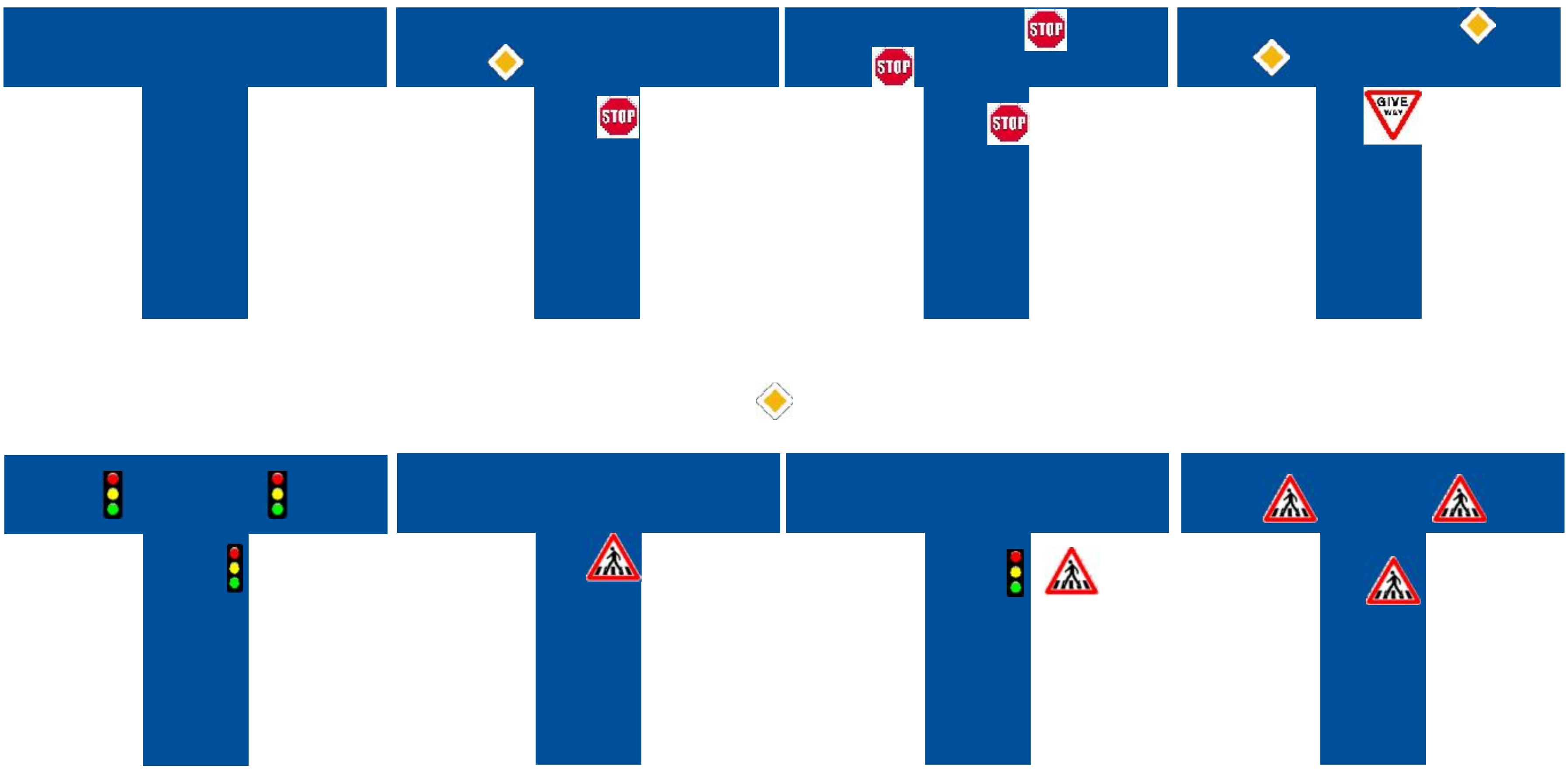




Stefania Zourlidou

Crowd sensing for traffic regulation detection and recognition

Examples of traffic rules: T-junction control systems



Traffic control technology

- Uncontrolled intersections, without signs or signals (or sometimes with a warning sign). Priority (right-of-way) rules may vary by country

right of way rule

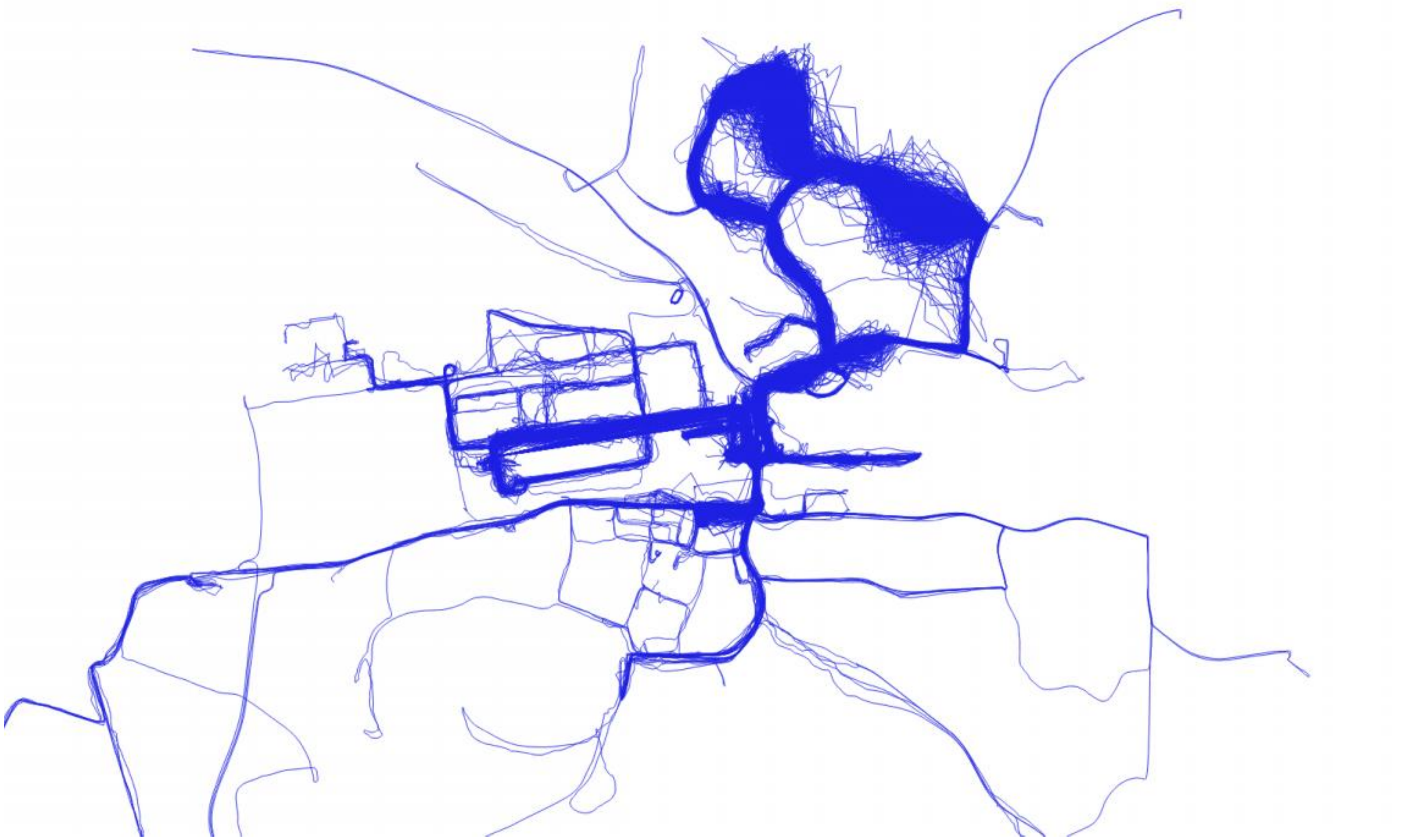
- Yield-controlled intersections may or may not have specific "YIELD" signs (known as "GIVE WAY" signs in some countries).

- Stop-controlled intersections have one or more "STOP" signs. Two-way stops are common, while some countries also employ four-way stops (or multi-way stop control).

- Signal-controlled intersections depend on traffic signals, usually electric, which indicate which traffic is allowed to proceed at any particular time.

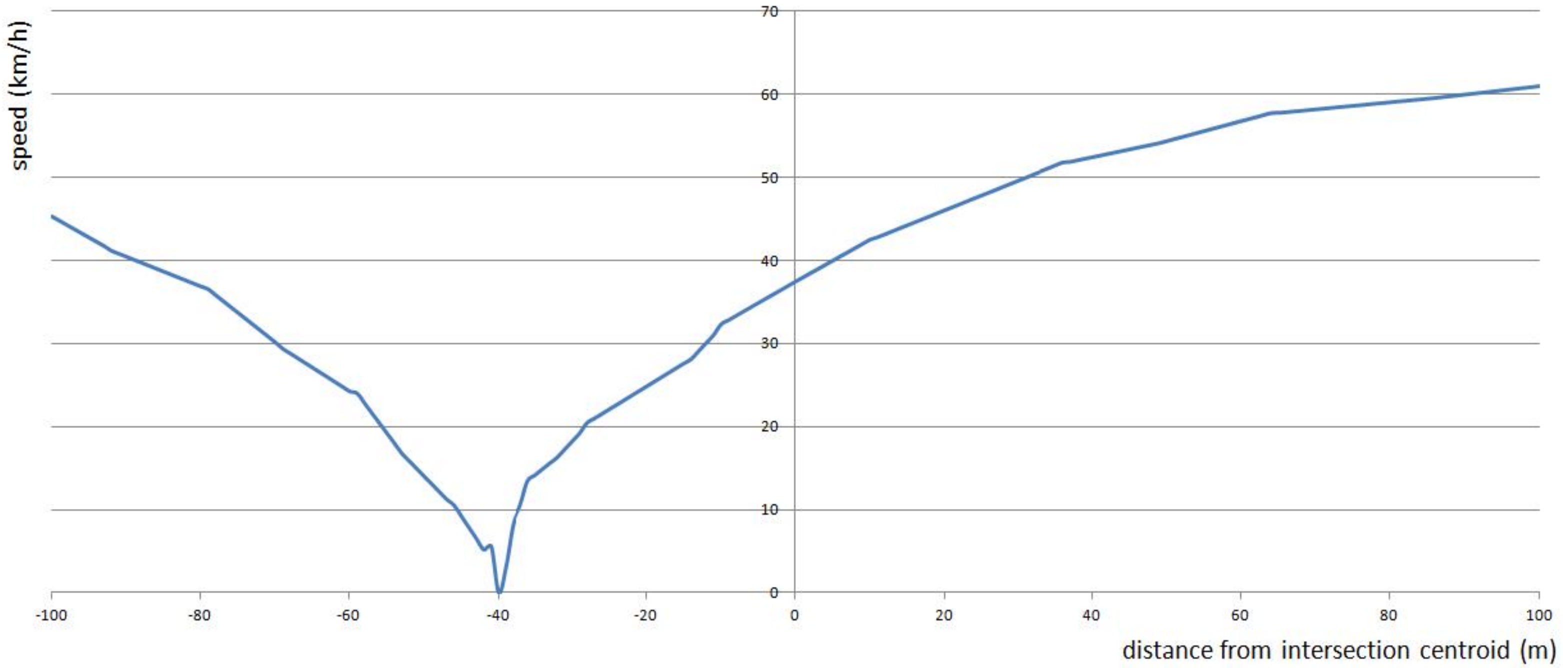
A trajectory-based approach

- Given a large vehicle trajectory data set, how can we infer traffic rules for enriching maps with traffic regulations?



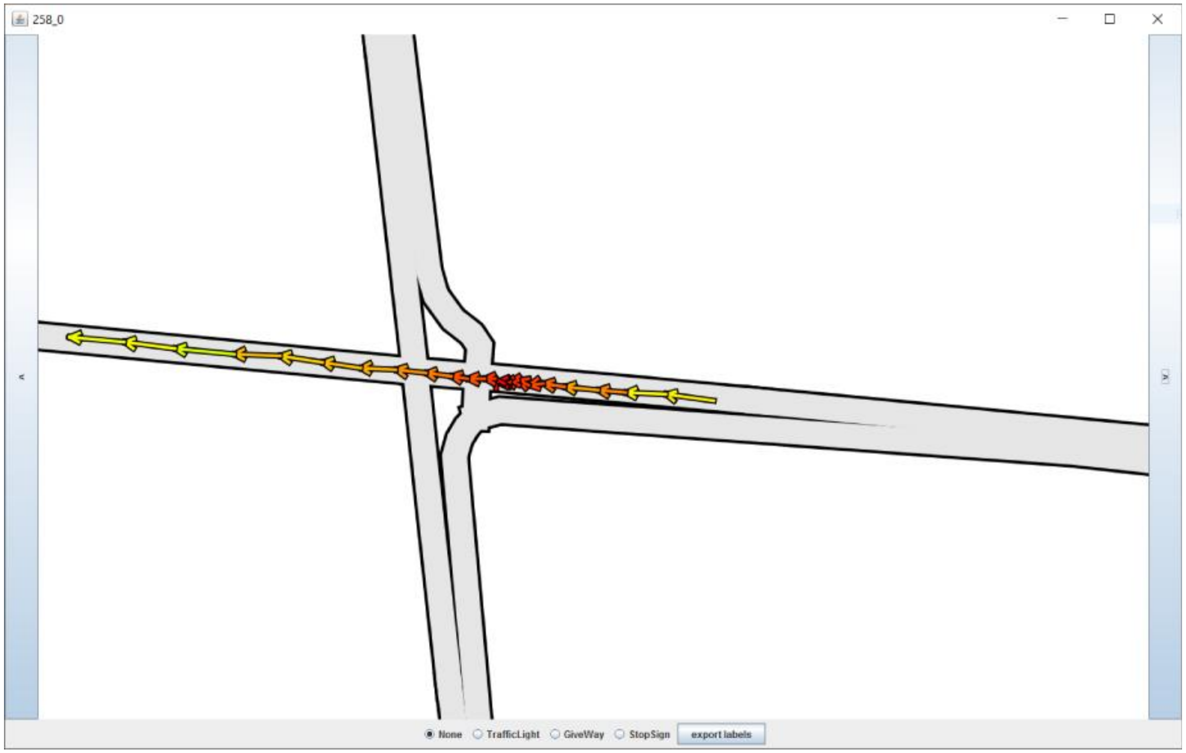
Supervised approach: Speed profiles

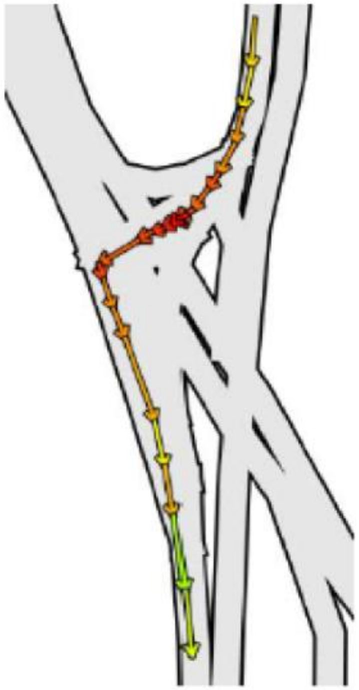
- Assumption: intersections show characteristic speed profiles
  - e.g. stop at stop sign, speed decrease to give way at ordinary intersections, etc.
  - Multiple occurrences reinforce statement about intersection (type)



Supervised approach

- Learning the traffic context of intersections from speed profile data
- Supervised Learning method to classify each tracking point of each trajectory



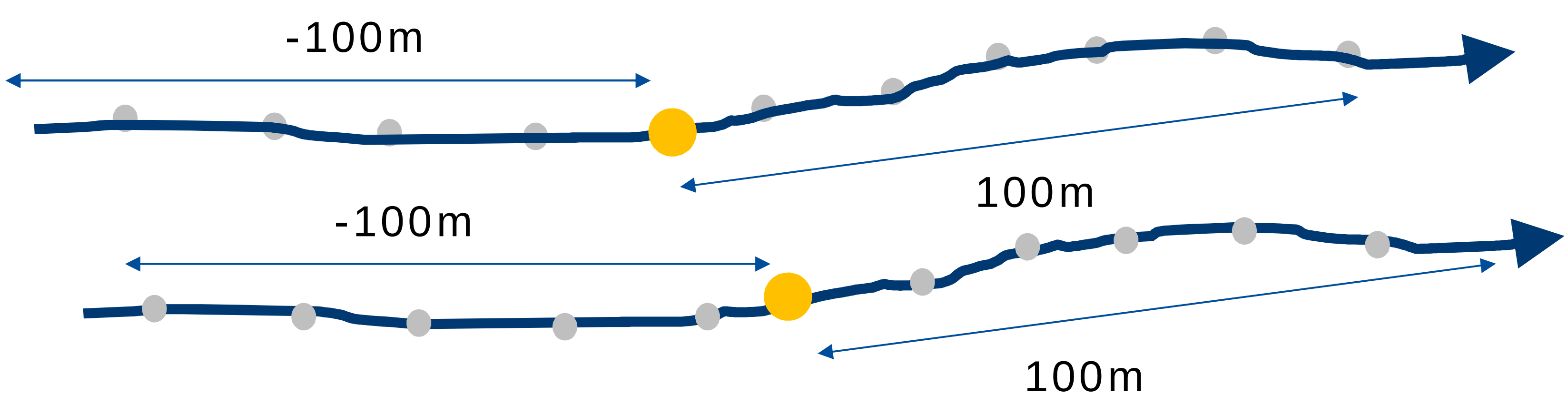


Approach

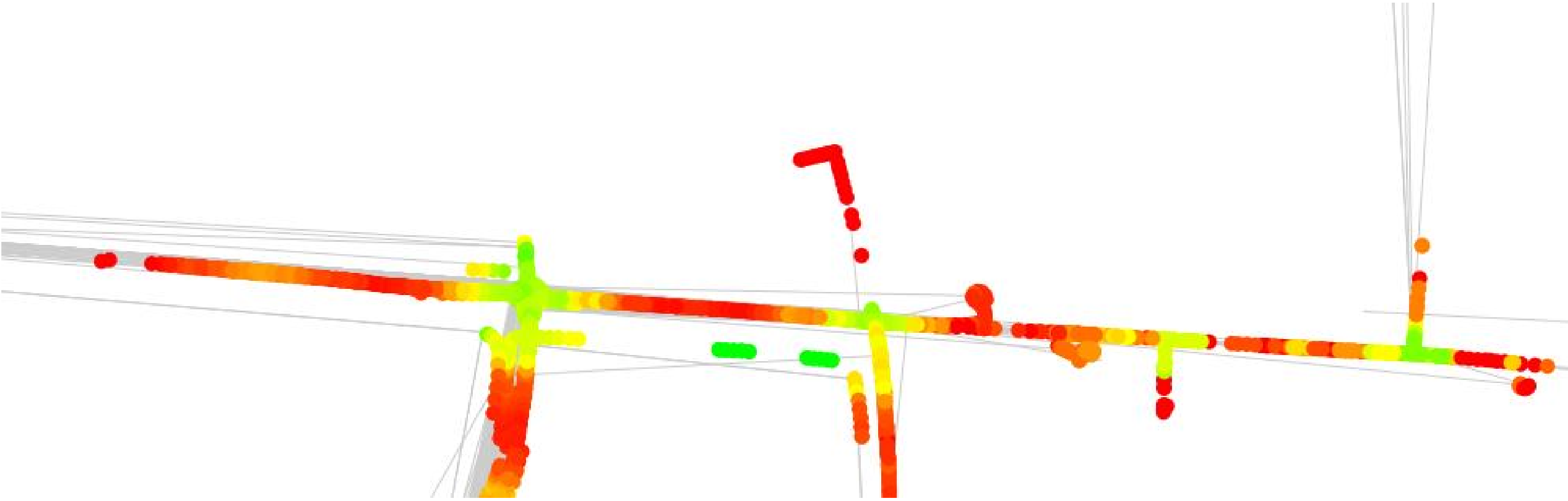
- Application of classification methods
  - e.g. C4.5, Logistic Regression or Random Forest

Input vector = [v_{-100}, v_{-199},…, $v_{0,}$ v_1, v_{100}]

[v_i: Speed value i meters before(-)/ after (+) the]

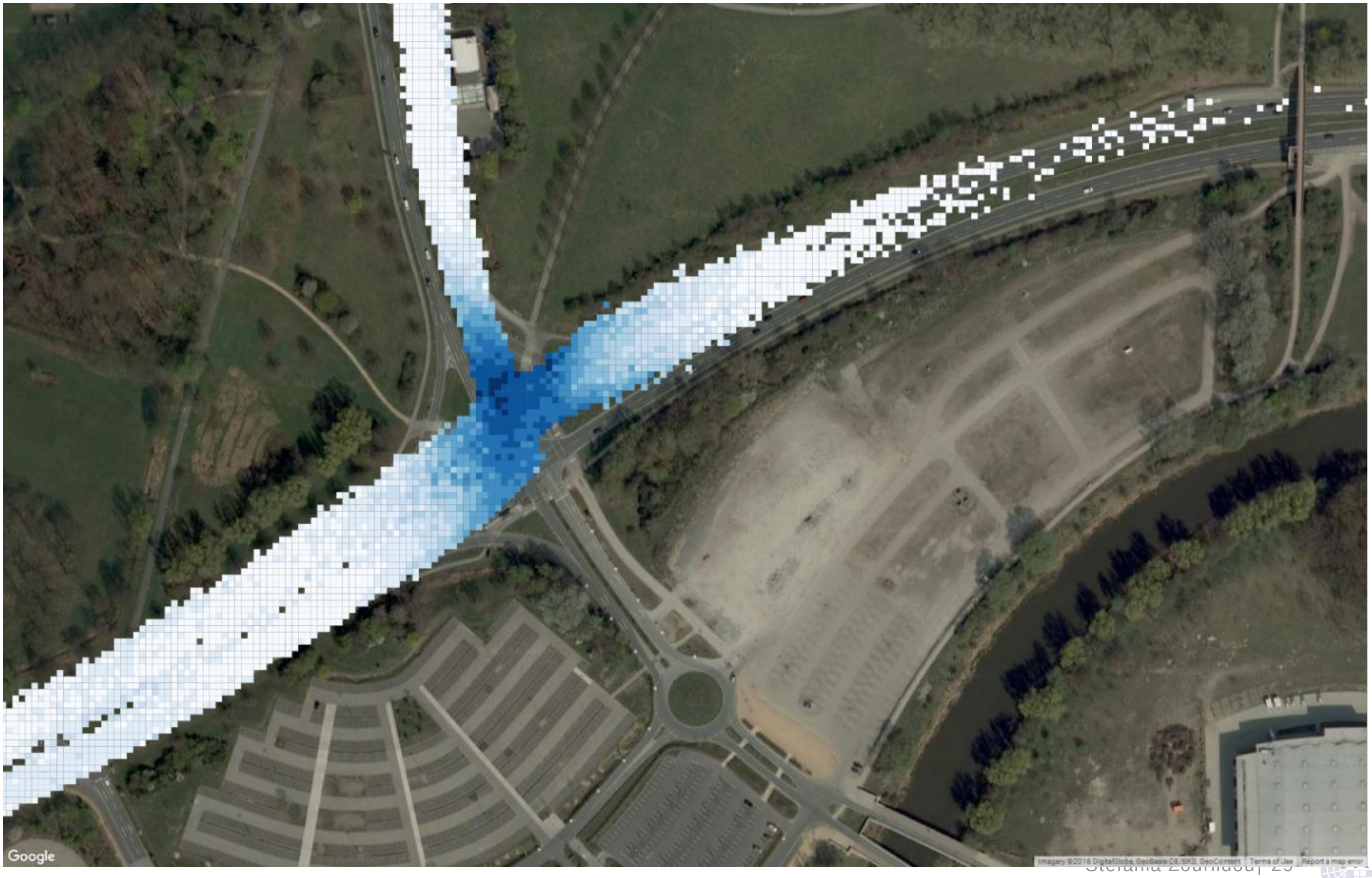


Detected locations



- 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



Extraction of high definition maps from Lidar data

Steffen Busch

Geometric
Detection & Tracking

- Scan to depth image

- Depth image to labels

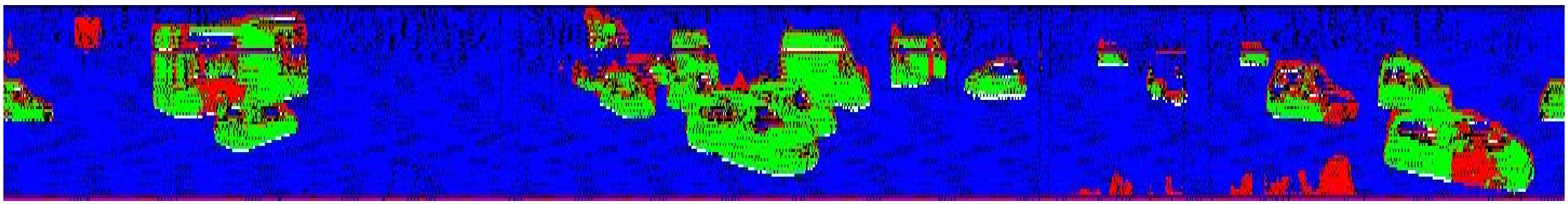
  - Lane projection to point cloud
  - Plane estimation for each lane

- Labels to segments

  - Region Growing

Neural Network
Detection & Tracking

- Segmentation by Neural Network

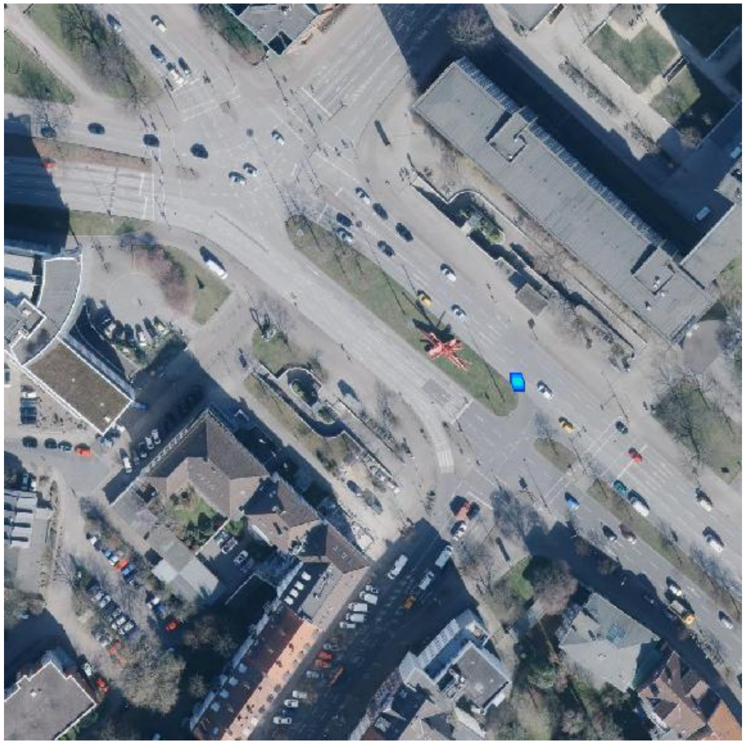


True positive
True negative
False negative
False positive

- 200.000 images (Depth and Intensity values) and labels
  - ~4h scans
  - 6 junctions in Hanover
  - Labelling of traffic participants

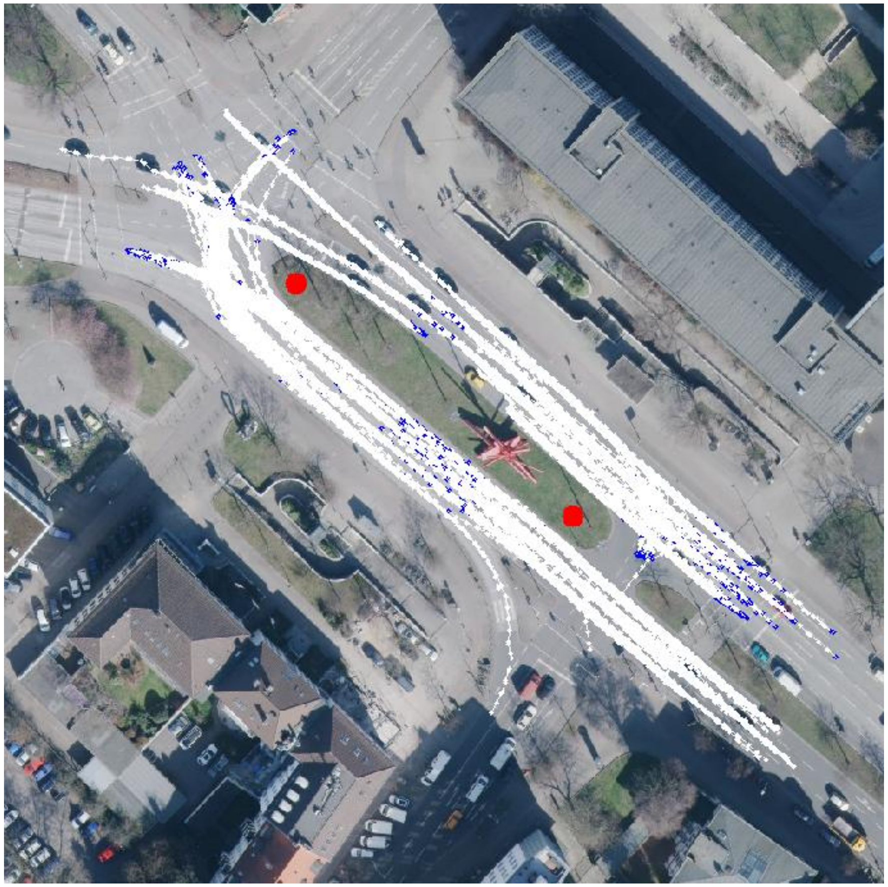
Data assessment
Trajectories

- Detections by ground filtering, lane matching and region growing

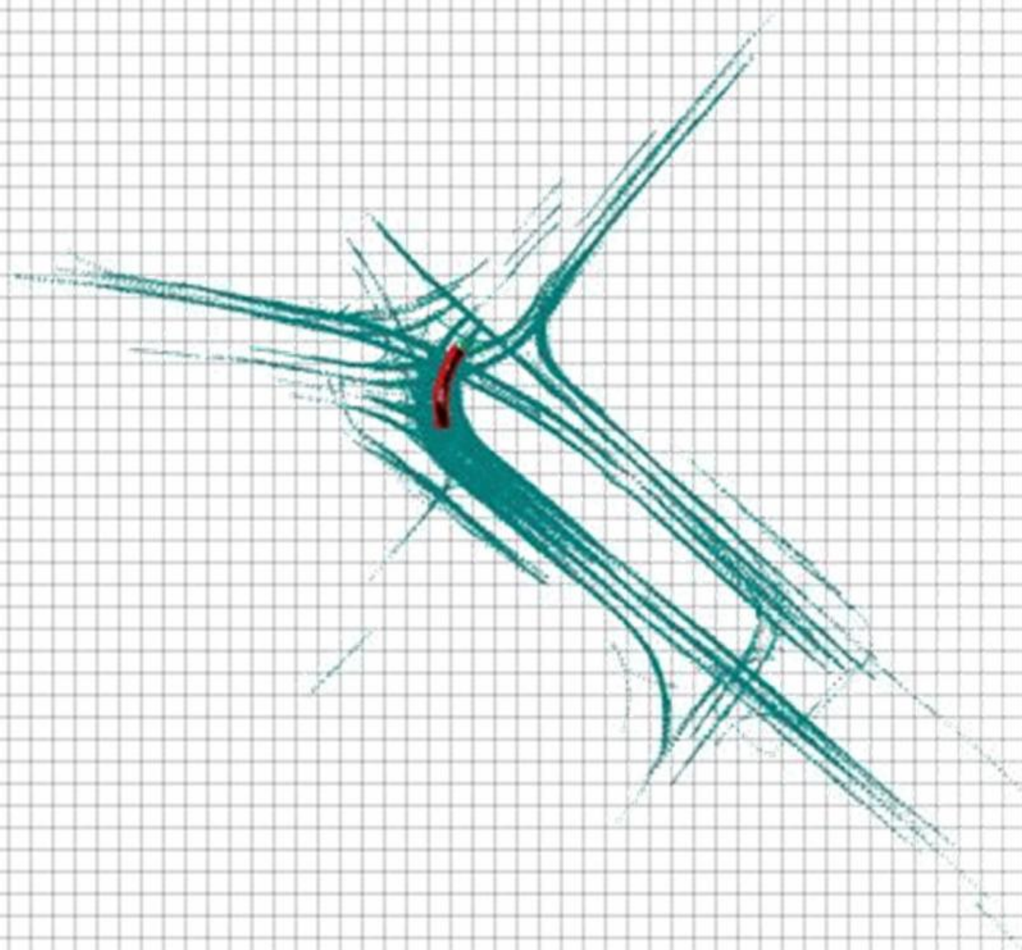


Trajectory Example Königswortherplatz

- Iterative Extended Kalman Filter
- Constant acceleration and yaw rate
- Bicycle model
- Greedy Assignment
  - DB SCAN Detection clustering
  - Hungarian Method per cluster



High Definition Mapping
Markov Chain Monte Carlo Optimization



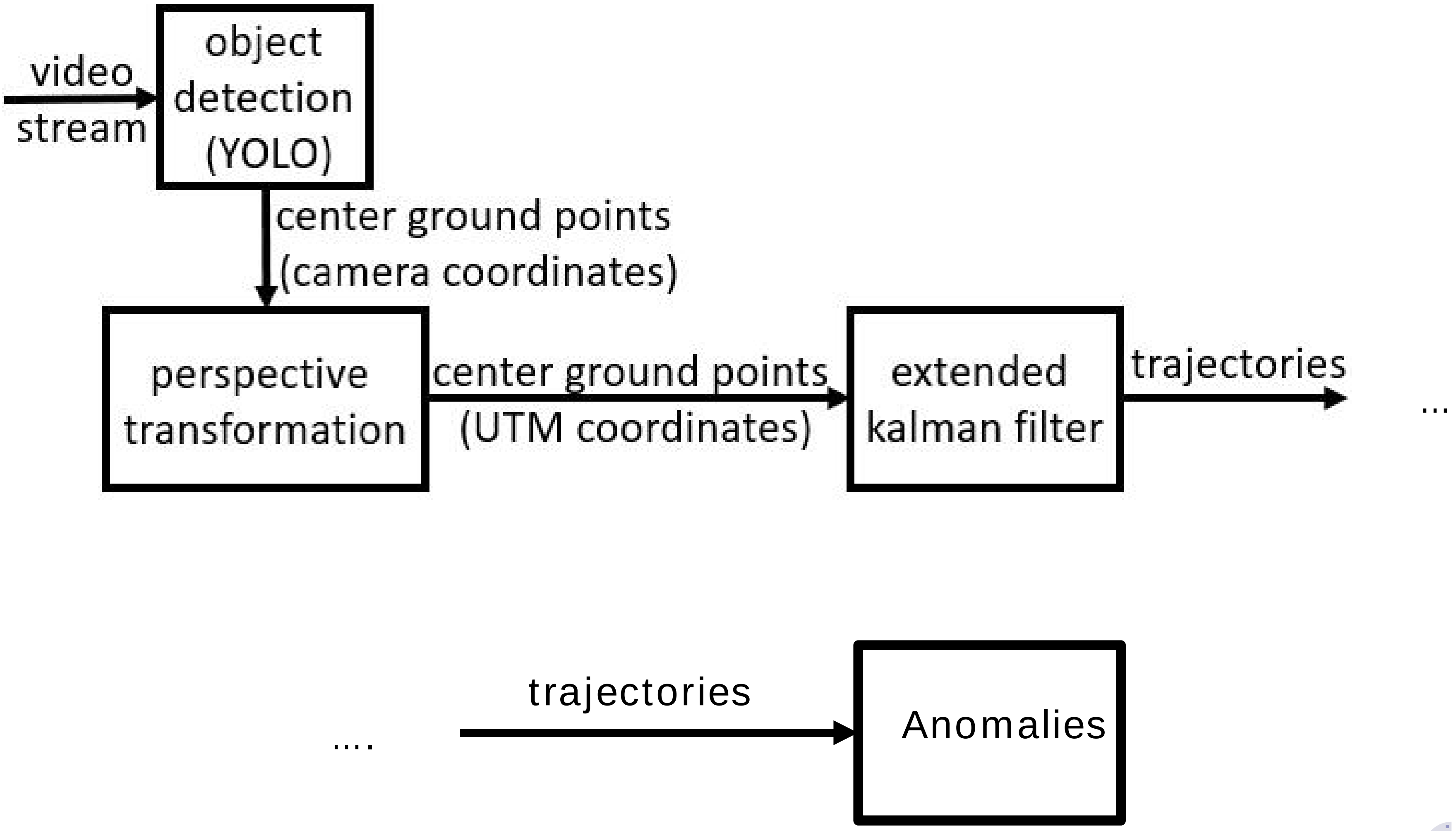
Near accidents from trajectories

Christian Koetsier

Goal

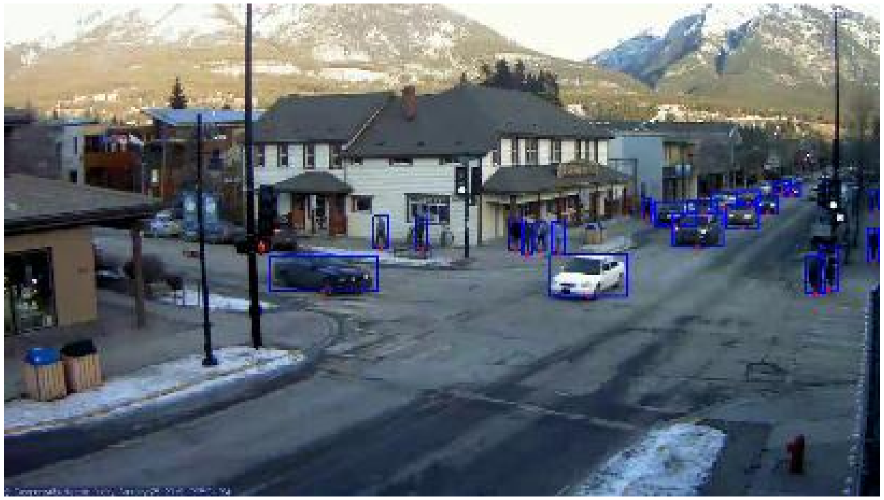
- Automated recognition of “unsafe” driving situations
  - For example: (near) accidents
- Search / Identification of the trigger
  - Other road users (cars, cyclists, pedestrians)
  - The environment (glare, shading, unevenness in the road)
  - Individual (distraction, misbehaviour)
- Include "unsafe" driving situations as well as their triggers in the maps, so that they can be considered in future driving maneuvers.

Surveillance camera pipeline



Detection and trajectories

- Static surveillance camera data

Interpretation of behaviour – a model based approach

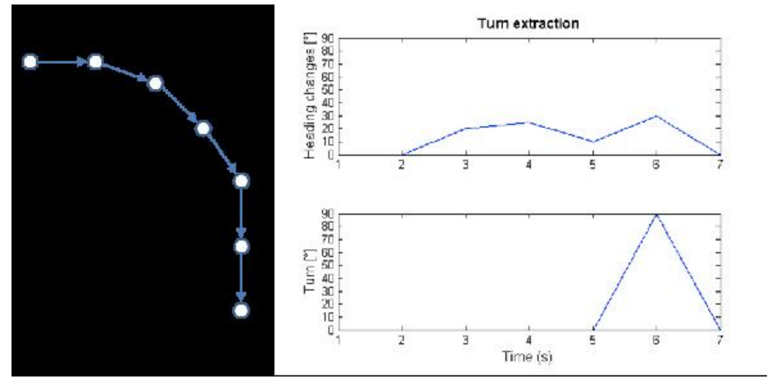
Hai Huang and Lijuan Zhang

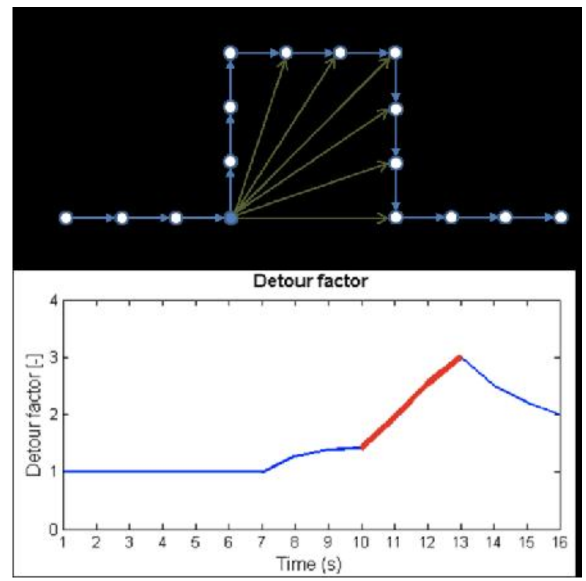
Determination of anomalous behaviour

- Idea: Driver shows specific behaviour when he/she is lost
- -> provide immediate help!

- Components of behaviour:
  - Frequent turns
  - Detour
  - Route repetition

- For these components, typical probabilities for normal behaviour are determined
- Fusion of probabilities via Hidden Markov Modell



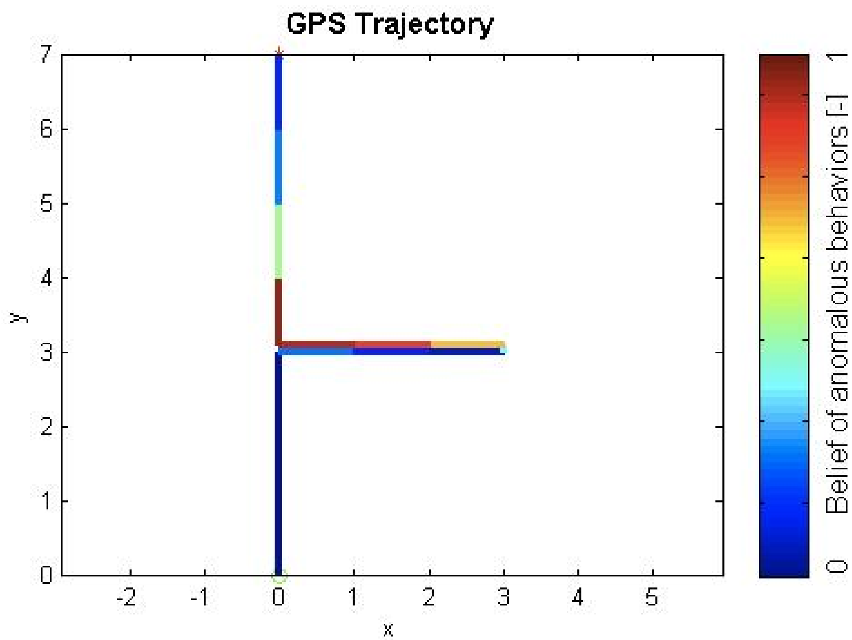


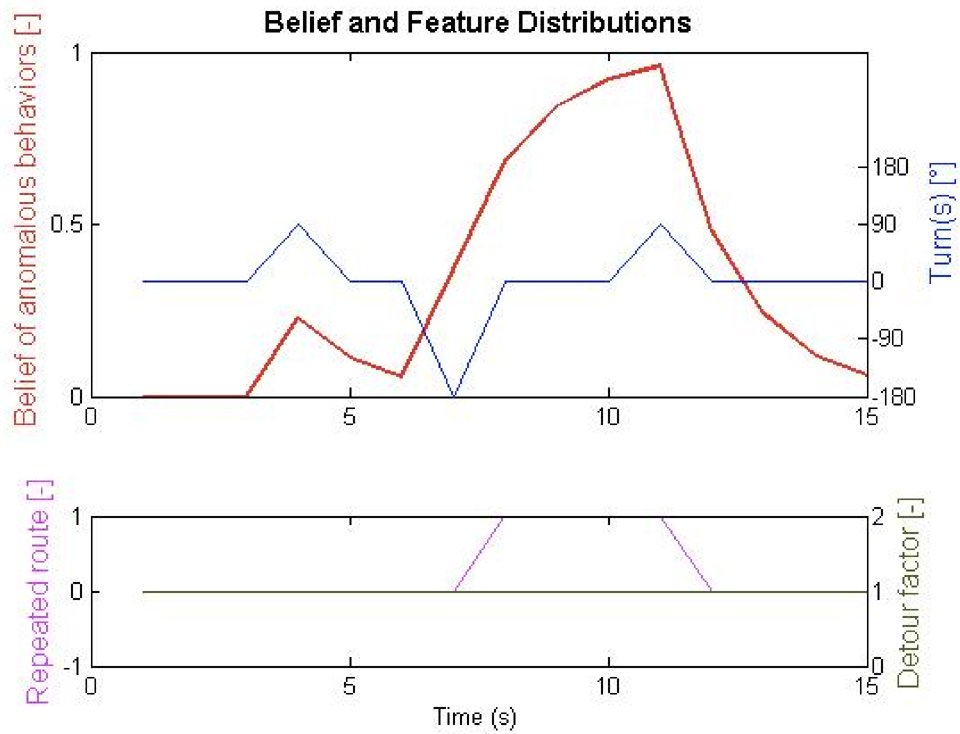
[Huang & Zhang]

Determination of anomalous behaviour

- Example: Route from bottom to top

Goal

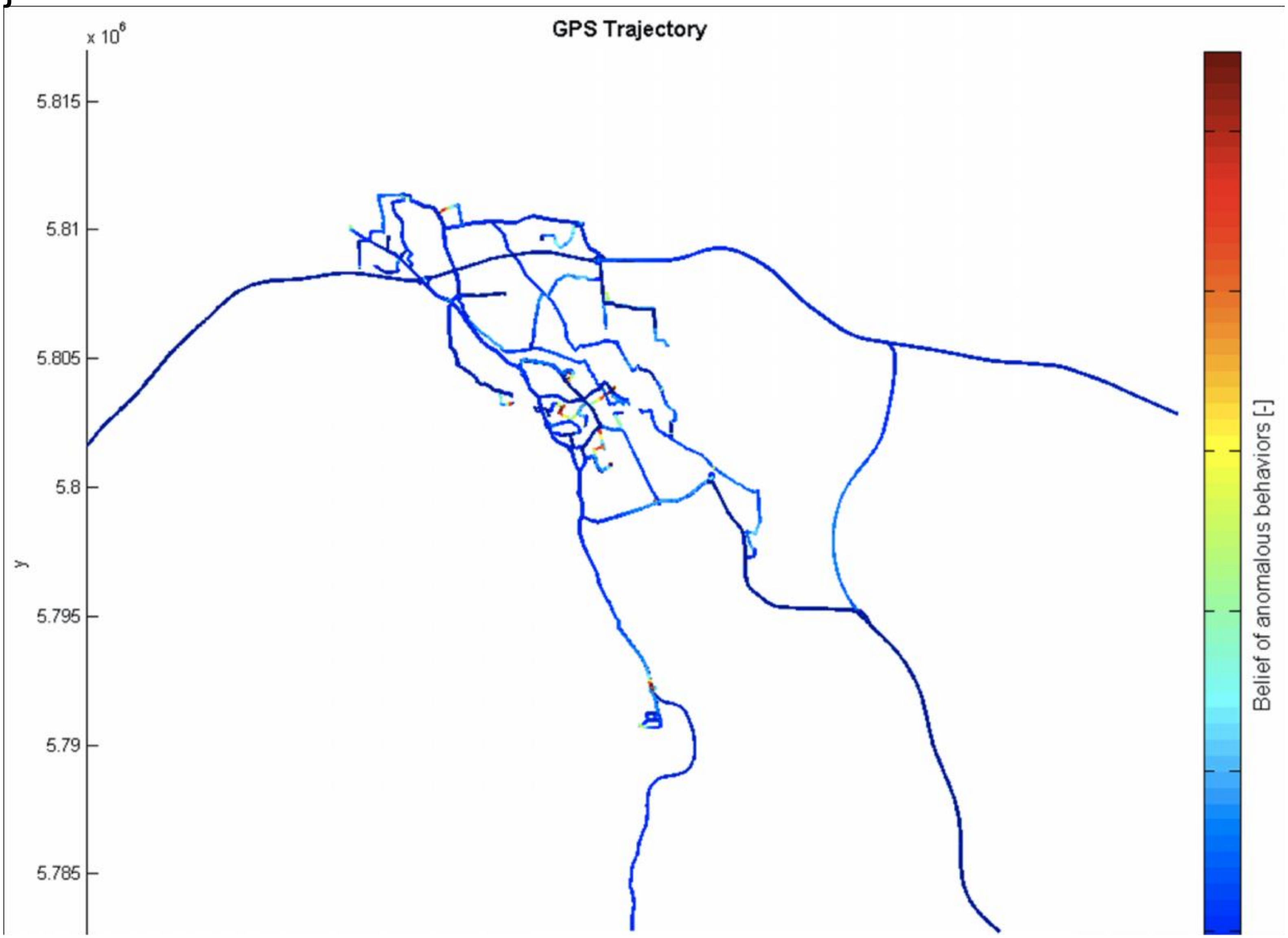




Start

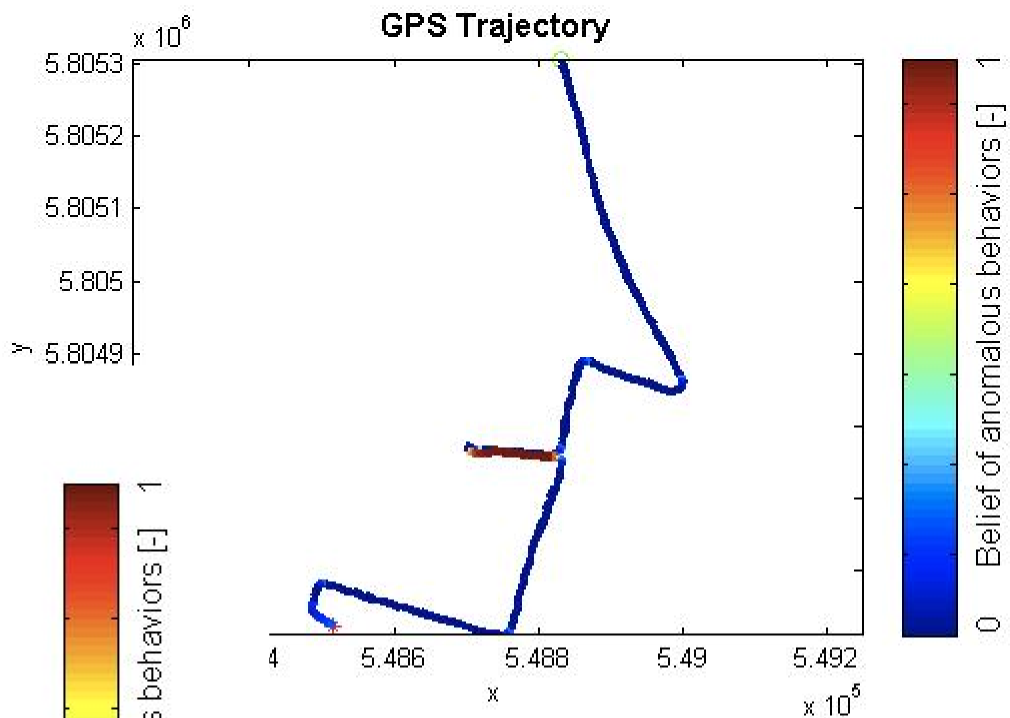
Determination of anomalous behaviour

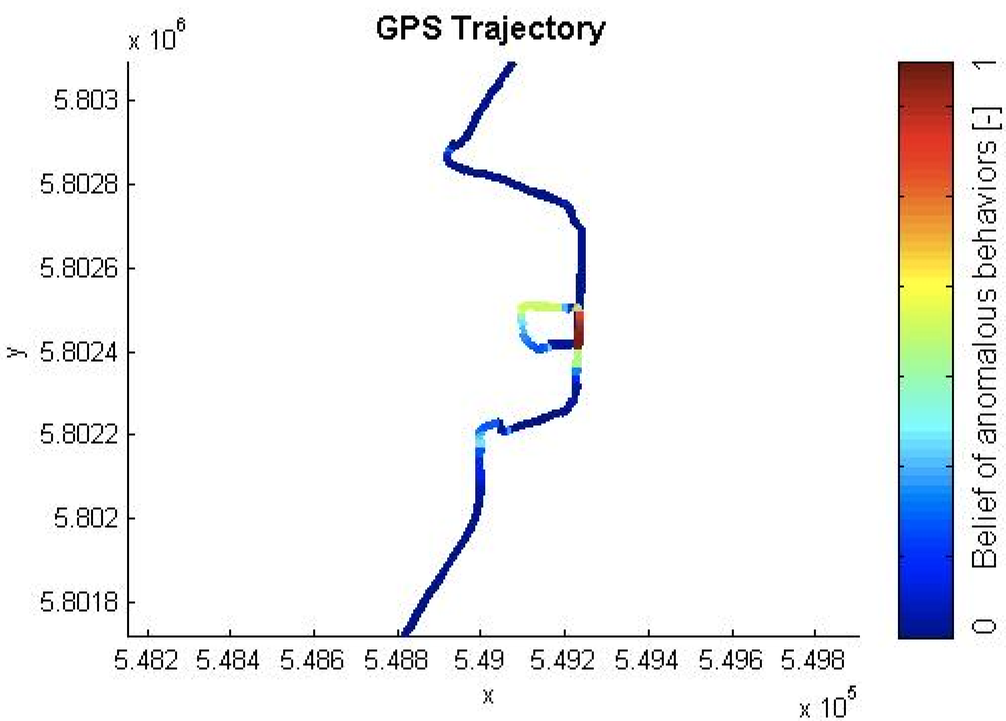
- 100 Trajectories



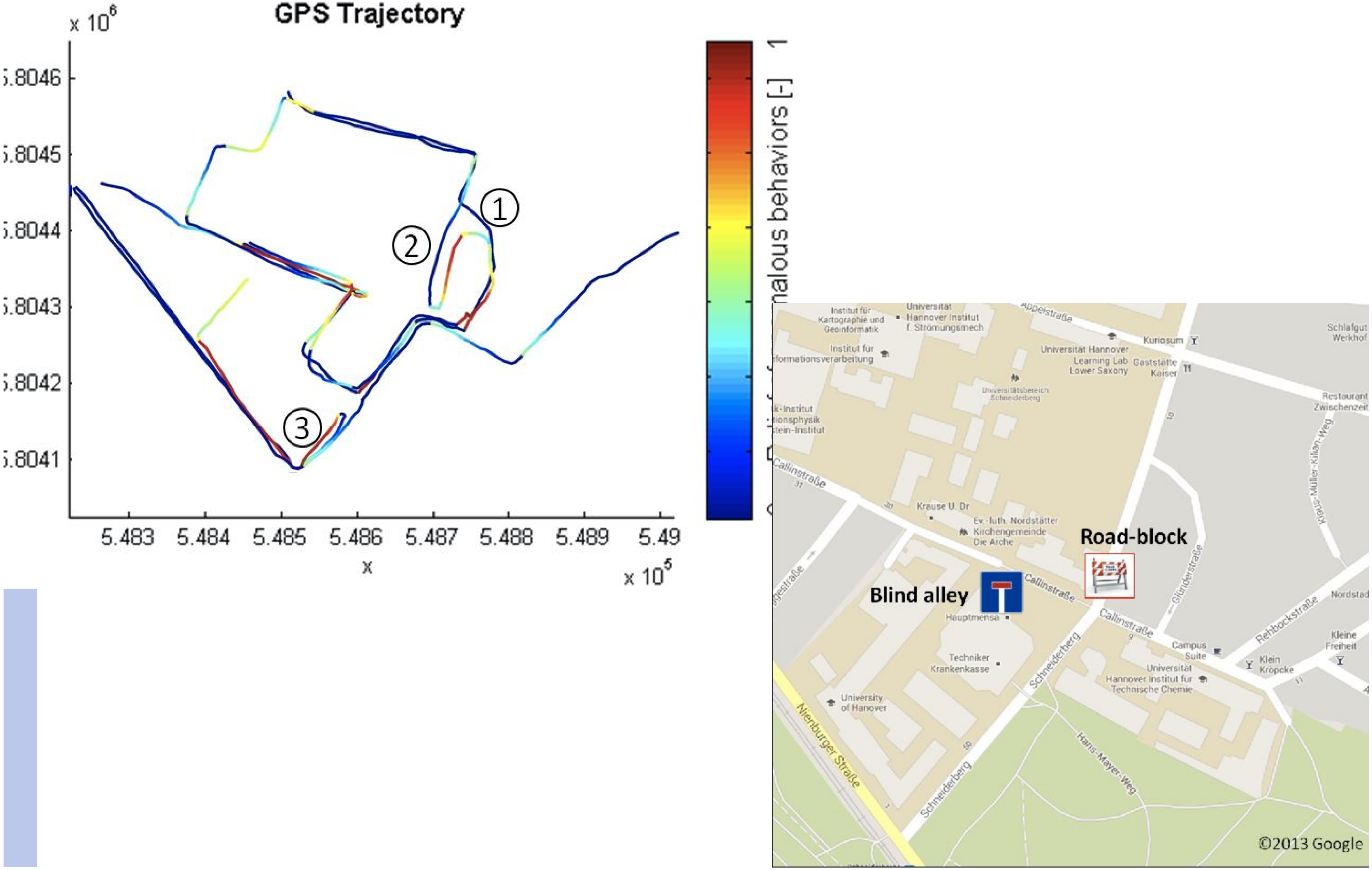
Examples

- Details





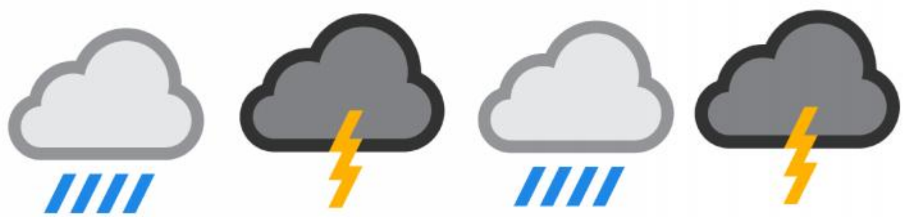
Indication of anomalous traffic situation



Social Media for Pluvial Flood Detection

Yu Feng

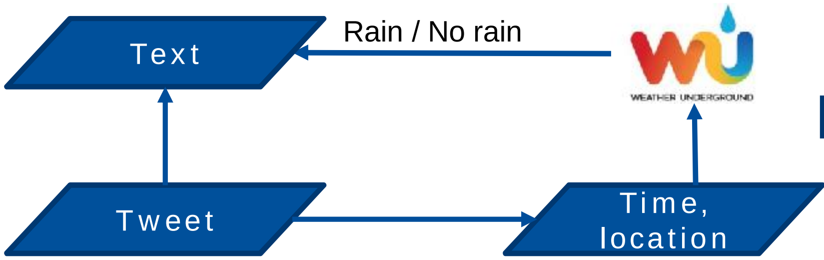
Motivation



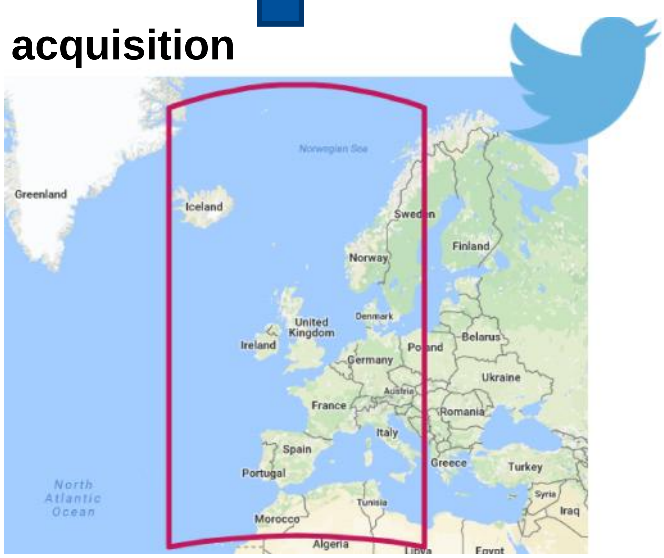
Source: http://blog.yokellocal.com/local-social-media-marketing-twitter

Training of text classifier with ConvNets

Data annotation



Data acquisition



Trainings-Datensatz

Tweets with keywords and marked as positive

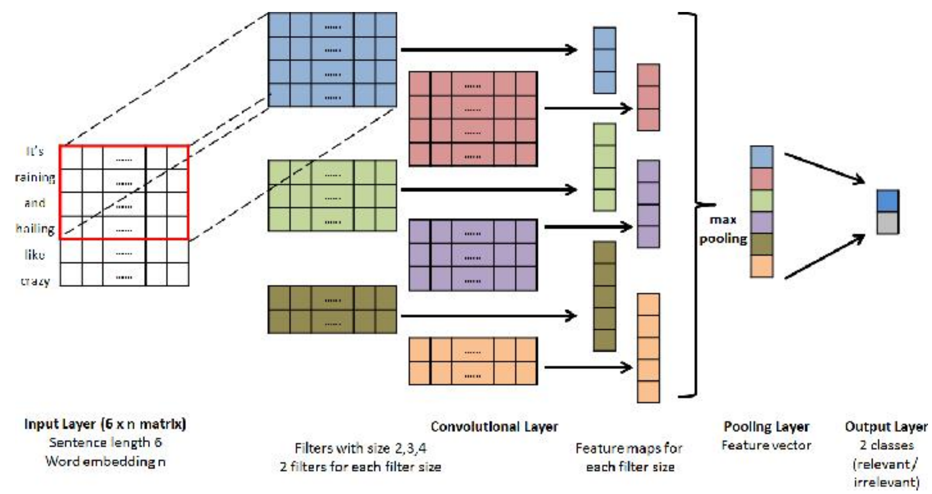
36469 Tweets

15263 Tweets | 21206 Tweets

Tweets with keywords and marked as negative

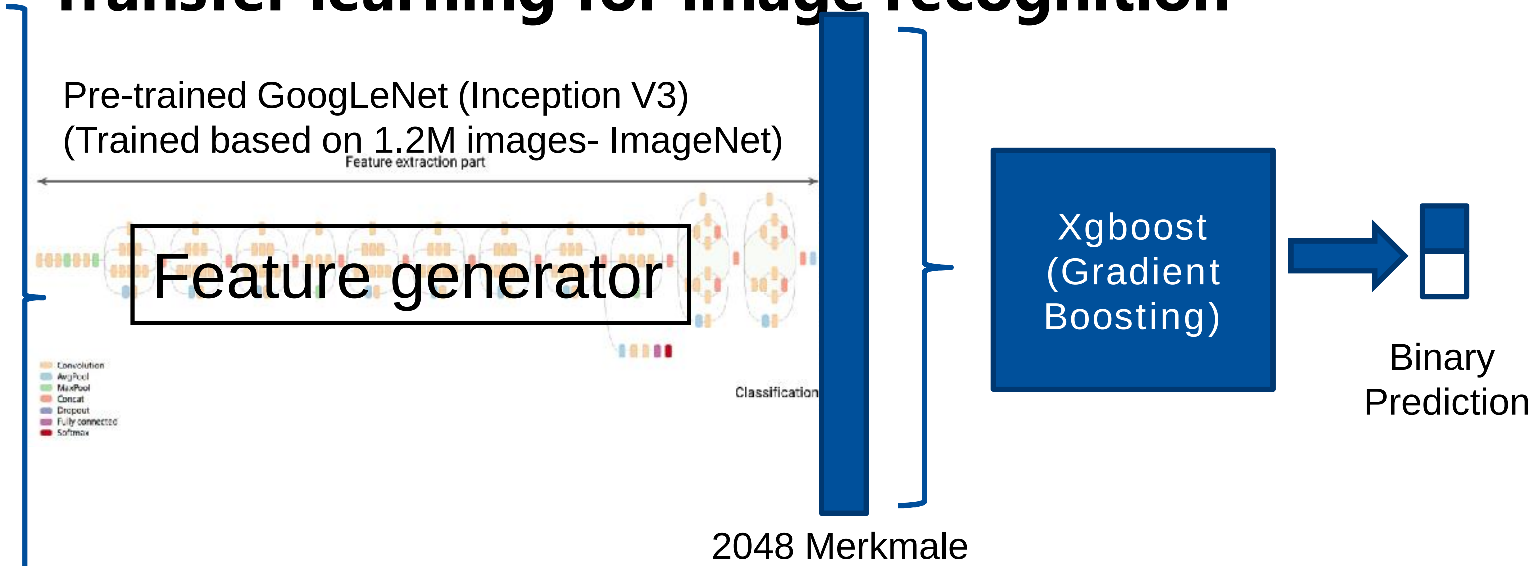
Tweets randomly selected without keywords

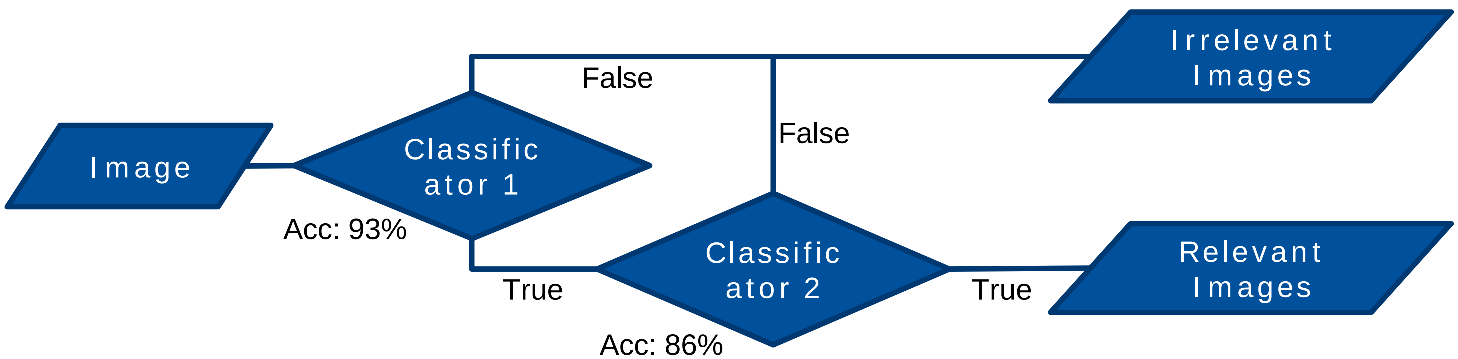
Model for Prediction



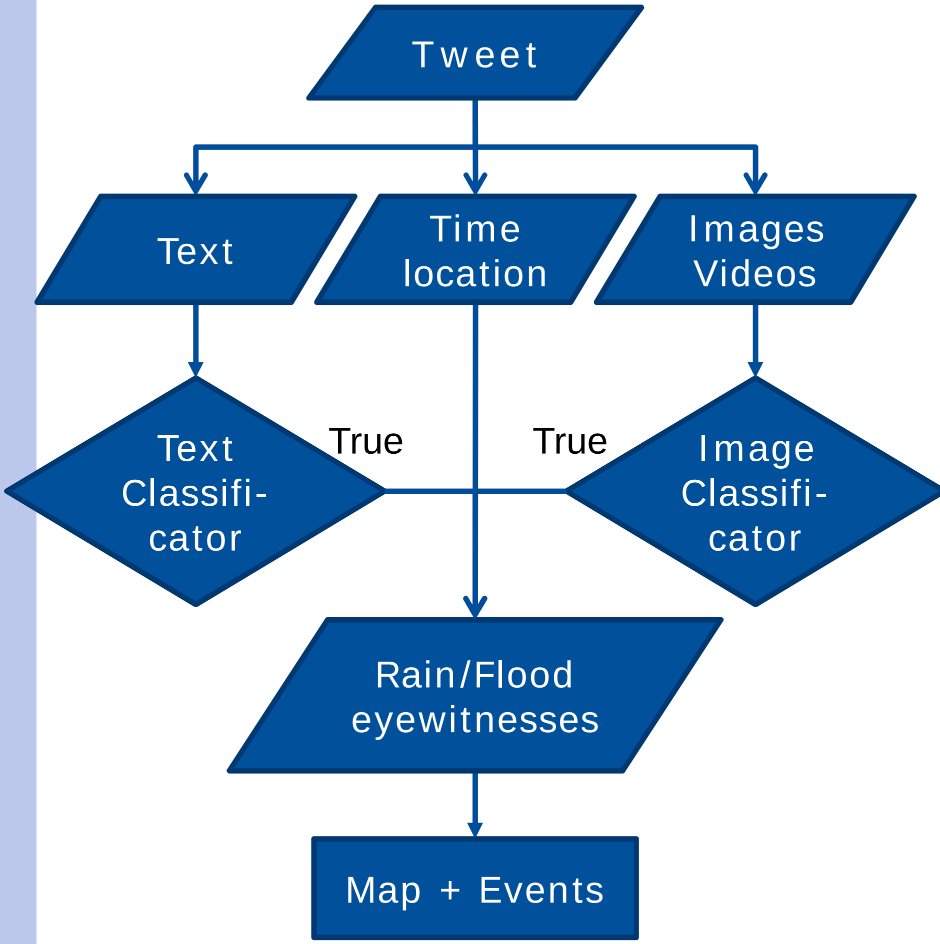
Training of image classifier with transfer learning

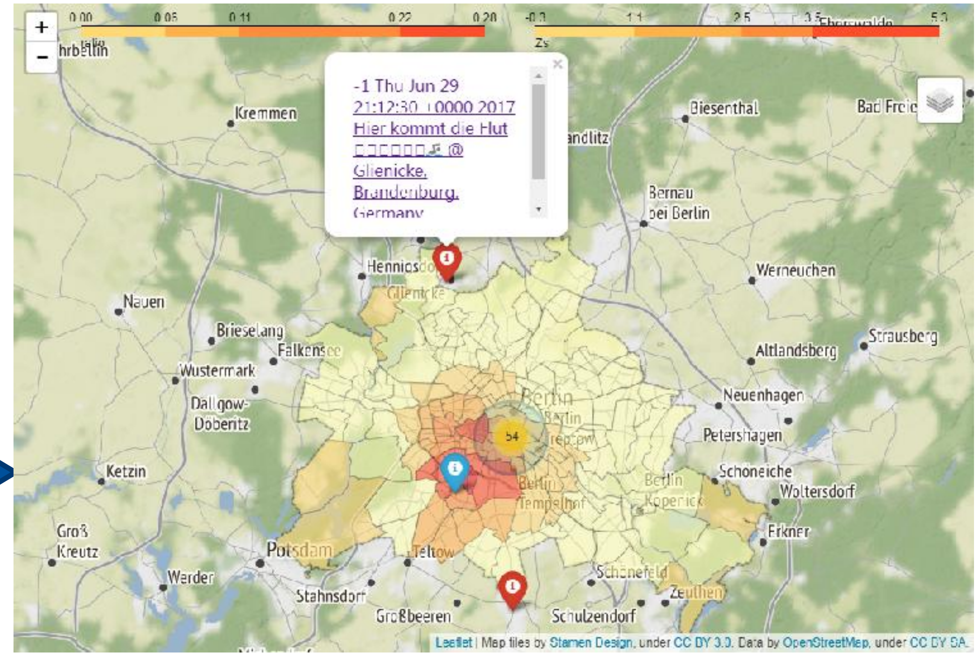
Transfer learning for image recognition





Event Detection





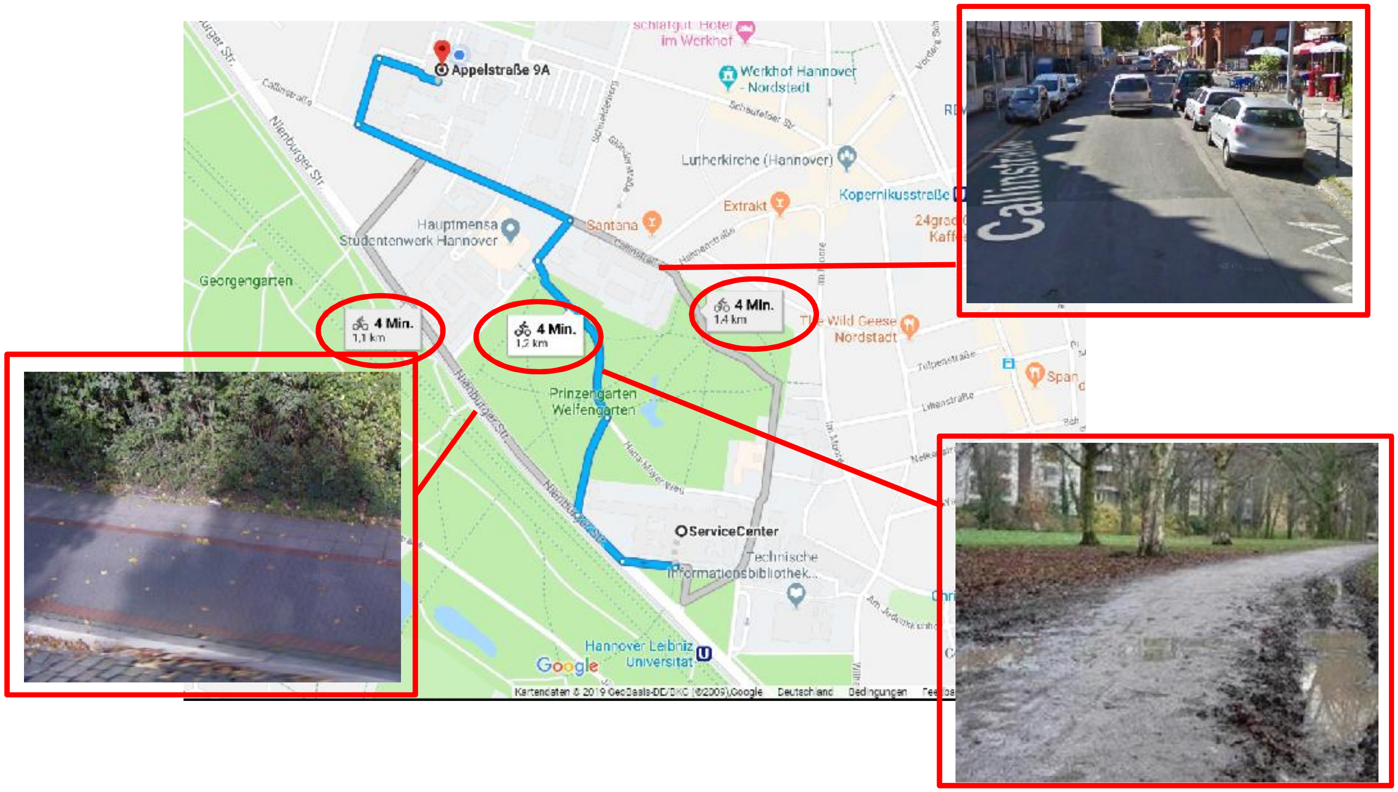
➢ **Spatiotemporal Analyses**

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

Student project

RideVibes

- Scenario: You want to ride from Welfenschloss to ikg by bike



- Which route would you prefer?

RideVibes

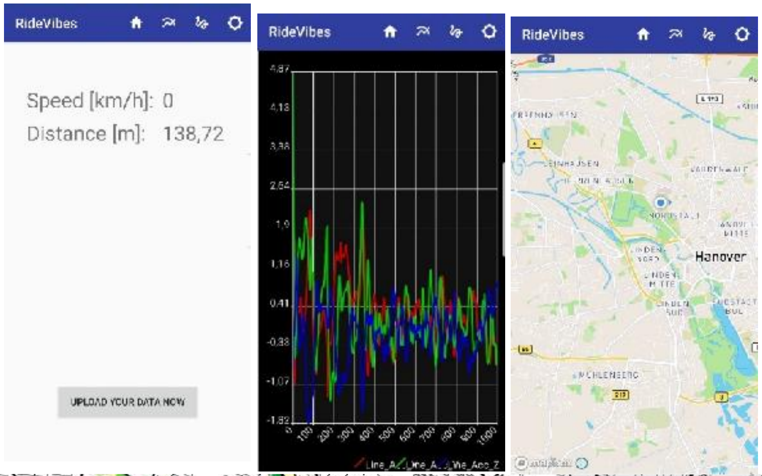
- Mobile app for bike adapted navigation which includes the "comfort factor"

- The "comfort factor" includes the
  - road surface quality (roughness)
  - existence of potholes and curbsides
  - number of unwanted stops (traffic lights, other obstacles)

- Measure, extract and map this factors to extend the common bike routing

RideVibes

- Data acquisition
  - Smartphone-App
  - GPS + sensor data
- Map data
  - Map matching of GPS trajectories
  - Obtain features from trajectories and sensor data
  - Update routing graph
  - [Example]()
- Routing based on additional features



Summary

Summary

- Exploiting „new“ data sources (Trajectories, Social Media)
- Machine Learning (ML), Deep Learning (DL), Optimization approaches

- Cheng: behaviour prediction - DL
- Feuerhake: foodball patterns – ML, association rules
- Zourlidou: traffic regulations - ML
- Busch: High Definition maps – DL and optimization
- Koetsier: near accidents – use of DL + Kalman Filtering
- Huang: Hidden Markov Models
- Feng: strong rainfall events – DL