Incidentdetektering för Proaktiv TrafikLedning (IPTL)

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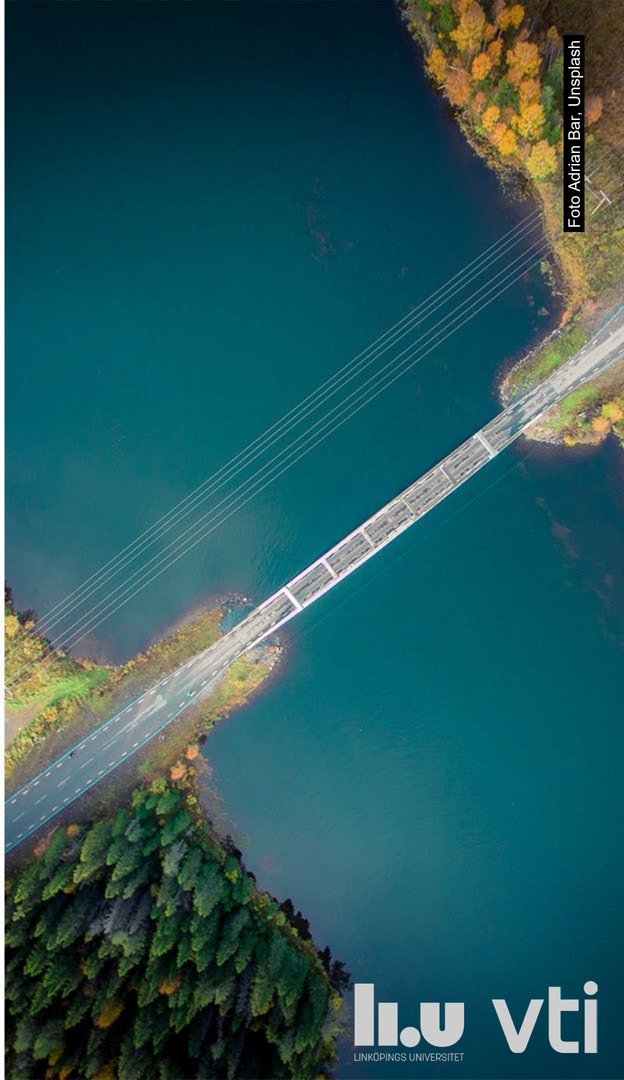
AGENDA

- Introduction
- Literature Review
- Preliminary Data Analysis
- Next Steps



Introduction

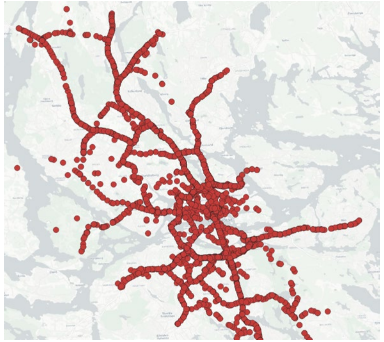
- Around 20 000 incidents yearly in Stockholm. Early detection is important to
  - Fast initiation of appropriate action plans
  - Inform and (if possible) control traffic and road users to minimize the impact of the incident on the traffic system

- Background: Workshop about Traffic managment in 2023
  - False alarms of incidents in existing systems
  - New data sources available (vehicle-by-vehicle data, GPS-data)
  - The SAP-HANA-plattform
- The purpose of this project is to due a **state-of-the-art literature review** in the field of incident detection, **identify suitable algorithms** for use under Swedish conditions, and **evaluate** one or two algorithms for a selected test area.

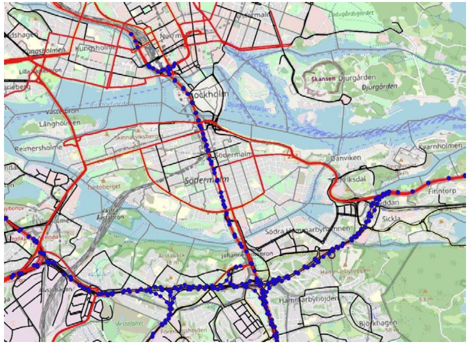
Målområde FOI-plan:

- Möjliggöra: Effektivare hantering av störningar

Ytradar (Navtech)

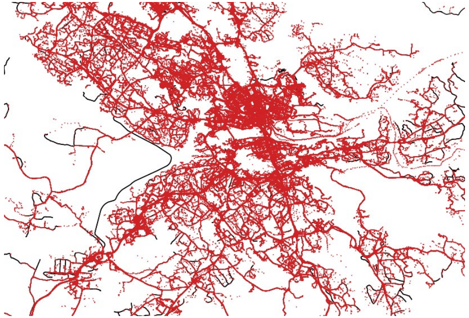


Incidentdata

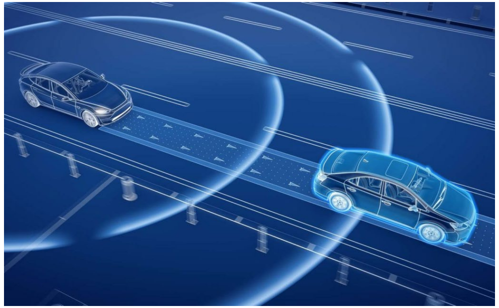


MCS (vehicle-by-vehicle)

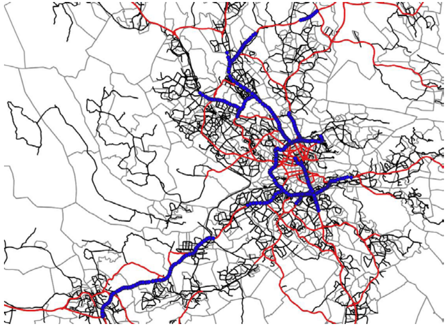
Data sources



Detailed GPS-data



Data from connected vehicles



Travel times from GPS-data

Literature Review

CATEGORIES OF ALGORITHM

1. **Pattern recognition/ Comparative**: Collected traffic flow parameters (speed, occupancy, flow, etc.) are compared against predefined thresholds.
2. **Catastrophe theory**: Sudden changes in the traffic conditions are identified.
3. **Statistical**: Estimate traffic characteristics and compare with observed traffic data. Statistical differences indicates incidents.
4. **Artificial intelligence**: Learn based on historical data when an incident occur by training the algorithm based on incident and non-incident conditions.
5. **Video-image processing**: Tracking objects and determine spatio-temporal characteristics of traffic variables, divide into incident and non-incident conditions.
6. **Hybrid**: Combination of algorithms

Performance Measures

- Common metrics are:
  - Detection Rate (DR)
  - False-Alarm Rate (FAR)
  - Mean Time to Detect (MTTD)
  - Accuracy, Precision, Recall, F1-score
  - AUC-PR, AUC – ROC

- There is a need to determine what is most important?
  - MTTD?
  - High DR may lead to low FAR and vice-versa

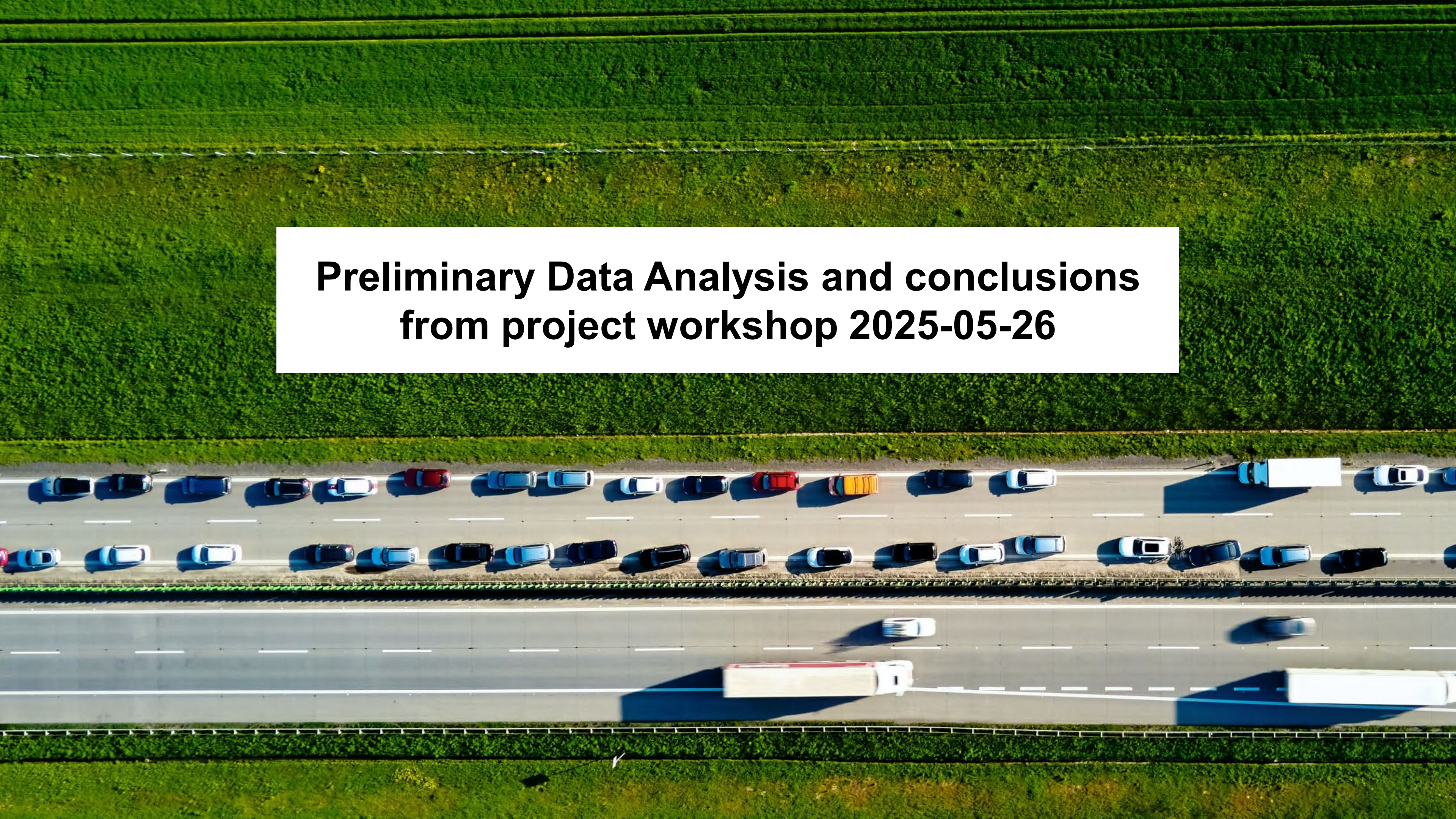
- Sample-bias (very few incident events and very large no. of non-incident events
  - Accuracy may not be a good metric
  - F1-score / AUC may be considered

Comparison

Algorithm	Strengths	Limitations
Pattern Recognition/ Comparative	• Easy to explain • Simple to implement	• Susceptible to false alarms • Limited adaptability • Data dependence
Catastrophe Theory	• Easy to explain • Incorporates historical data • Higher DR and lower MTTD than California algorithm	• Susceptible to weather variations
Statistical	• Can adapt to changing conditions • Incorporates prior knowledge • Computationally efficient	• Sensitive to the quality of data • Model complexity • False alarm potential
AI	• Ability to learn continuously • Real-time processing • Adaptability	• Data dependence • Computational cost • Black box
Video-image processing	• Detection based on direct observation • Versatile • Identification of specific incident types	• Computational cost • Weather dependence • GDPR issues
Hybrid	• Combining data sources improve robustness • Denoising raw data reduces FAR	• Requires data fusion from multiple sources • Computational cost

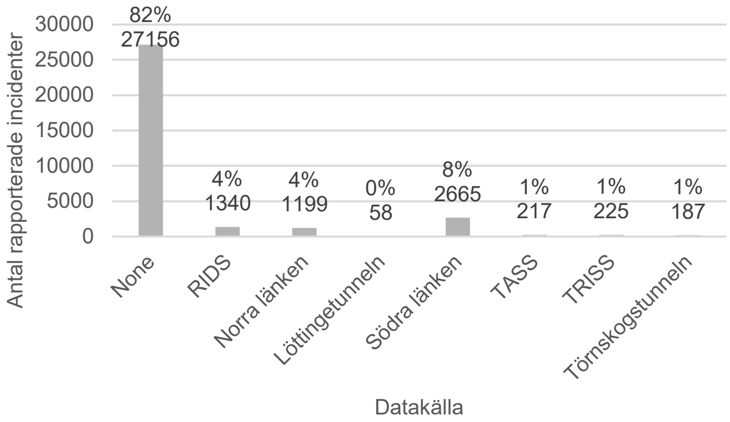
MAIN FINDINGS

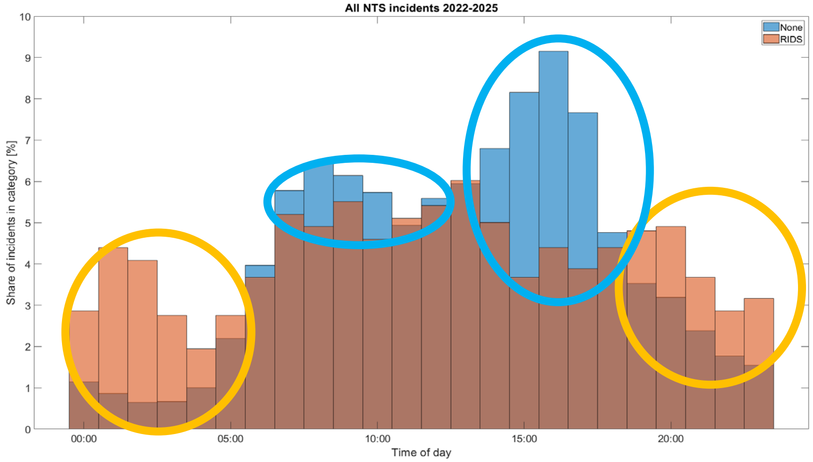
- Recent focus has been on AI-based algorithms.
  - Hybrid algorithms, especially those involved with denoising data as the first step, improve detection performances.
- Incident detection evaluation are usually biased as incident scenarios are rare compared to non-incident scenarios.
  - Recommended to use combined metrics (e.g. F1-score) and/or techniques to make the incident and non-incident sample sizes more comparable (e.g., Generative Adversarial Networks).
- More focus on new data sources, e.g. GPS-traces, Connected Vehicle data, etc.
  - However, very few works on radar (or, vehicle-per-vehicle) data.
  - Most works related to Connected Vehicles consider only speed as the independent variable.
- Most incident detection problems are formulated as binary classification algorithms (incident or no-incident).
  - However, not much effort on further classification of different incident types or spatio-temporal clustering of locations based on same or different incidents.
  - Video-based detections can cover a wide range of classification but restricted by field of view.


Preliminary Data Analysis and conclusions
from project workshop 2025-05-26

RIDS vs. manual reporting

- Main data source is manual
- Differences between reported incident over the day for different data sources
  - many false alarms in RIDS during peak-hours (ignored)
  - Hypothesis: RIDS might be better during low traffic flow periods (faster detection than manual)





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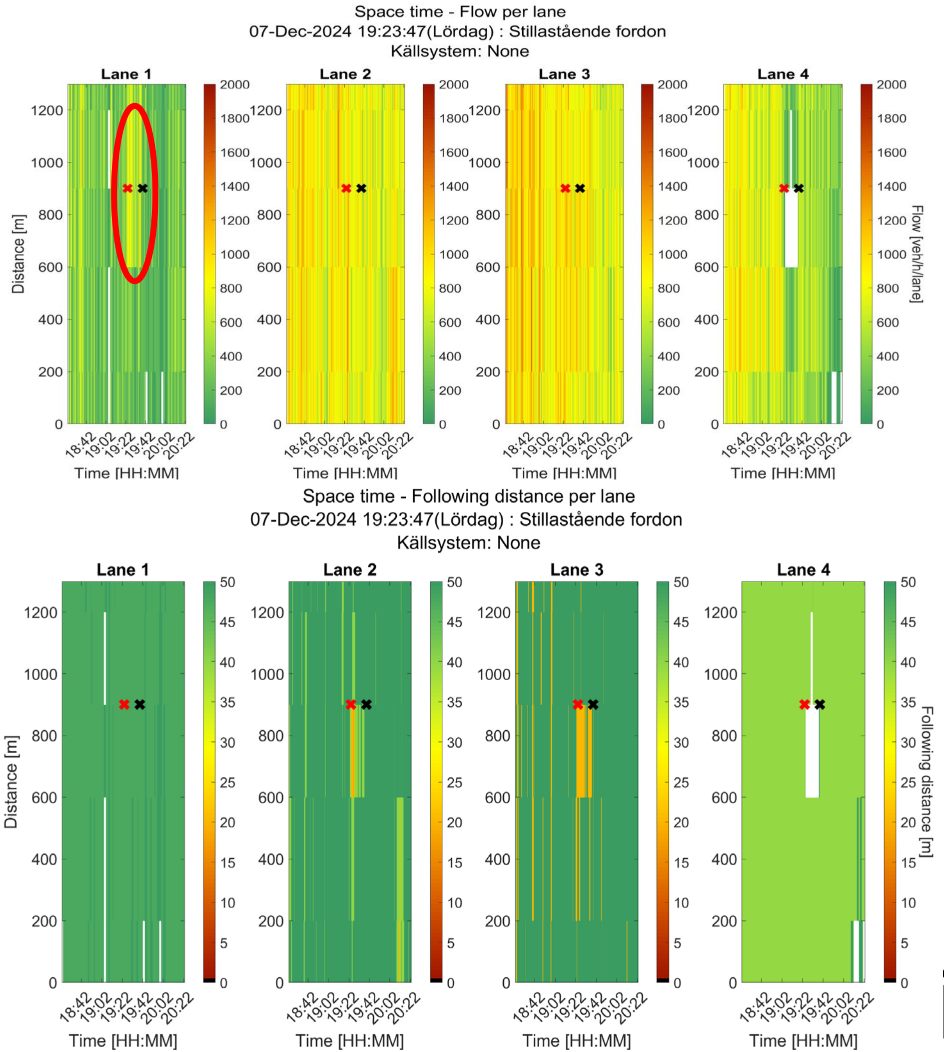
RIDS vs. MCS-data

- RIDS is superior to detect incidents that do not affect traffic flow
  - Possibly interesting to use RIDS for safety perspectives?
- Aggregated measures gives us some indications…
- …but to have fast detection of incidents vehicle-by-vehicle data is promising (following distance and differences between lanes)



Next steps

Important next steps

- Establishing ground truth for the evaluation – which data should we rely on?
  - Possible to use video to verify incident time and location.
- Understand how different types of incidents impact data and how well each type can be detected.
- Definition of the incident stretch: Downstream of one portal and up to the next portal (the event is in front of the sensor).
- Development of algorithms
- Study the role of connected vehicle data

THANK YOU

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