Detection and Mitigation of Jamming, Meaconing, and Spoofing based on Machine Learning and Multi-Sensor Data

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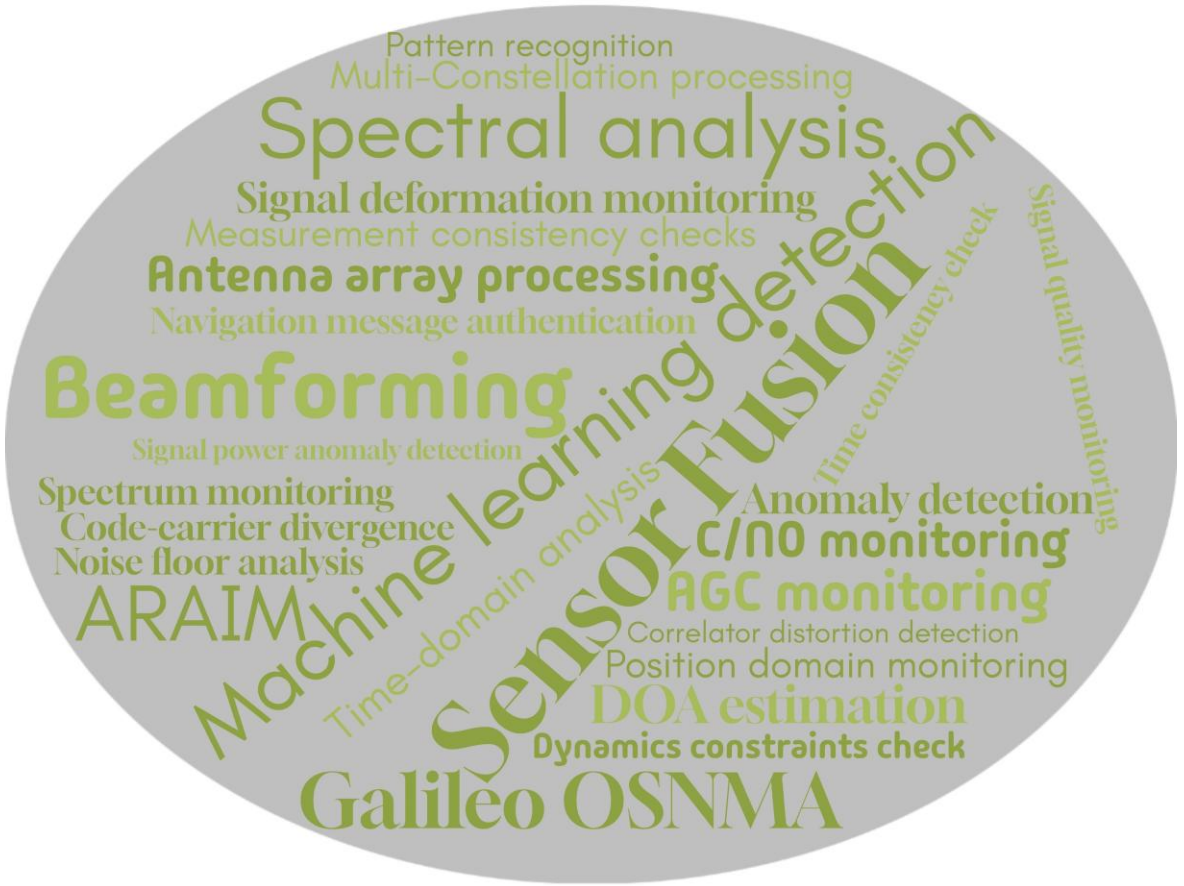
ION GNSS+ 2025
B4a: Navigation Resilience to Interference and Cyber-Attacks

How to Become Robust Against GNSS Interference

- Detection of GNSS interference can be tackled at different stages
- Our Approach: contribute to the stage after tracking with **Machine Learning for GNSS interference detection** based on GNSS observables, signal strength monitoring and IMU data
- ANavS positioning solutions already include
  - Propagate the GNSS receiver's capabilities
  - Consistency checks across different carriers due to **multi-frequency + multi-constellation** processing
  - **Multi-sensor** positioning solutions to bridge GNSS outages (INS, wheel-based odometry, LiDAR, Camera, LPS)
  - **Galileo** Open Service Navigation Message Authentication (**OSNMA**)



ANavS® – Advanced Navigation Solutions

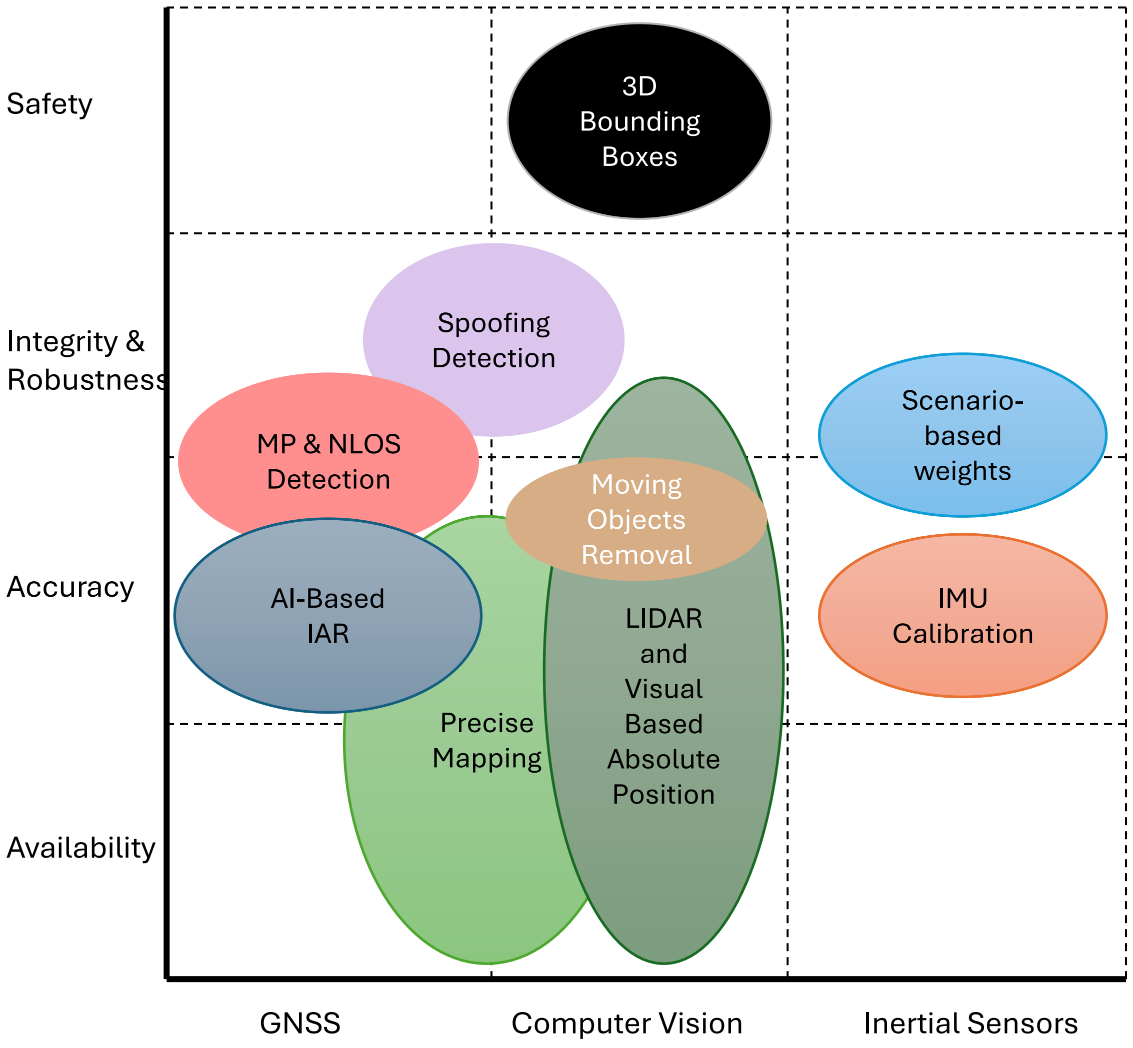
- Leading company in the development of high-precision positioning systems.
- ANavS® positioning system is a modular and flexibly configurable sensor fusion of **GNSS, inertial, odometry, camera** and **lidar measurements**.
- The innovative positioning algorithms have been developed and patented by ANavS® and incorporate the latest **RTK / PPP** technologies (including compatibility with Galileo HAS) as well as state-of-the-art **SLAM** algorithms and **object detection & tracking**.

Products Lines:

- **A-ROX:** GNSS-INS tightly coupled positioning for dynamic automotive, railway and maritime applications.
- **V-ROX:** A-ROX + powerful 128-channel LiDAR + stereo camera, enabling e.g., SLAM-based localization for indoor or GNSS-denied environments
- **G-ROX** RTK reference station + cloud based RTCM service.

DREAM Project

- More information: slides of Session C1 (Wed, 11:03): AI-assisted Multi-Sensor Fusion for Enhanced Autonomous Vehicle Navigation
- DREAM aims to address the stringent requirements of **ADAS** systems in challenging urban environments by developing advanced AI solutions.
- **AI** techniques to detect **spoofing**, **multipath** and NLOS situations and ensuring correct **ambiguity resolution**
- Multi-sensor: **IMU calibration and denoising**, **LiDAR/Visual SLAM** (with moving objects removal)
- **3D bounding boxes** for object detection and **geo-referenced maps**



Data from Jammertest 2024

Tests

- On Andøya, Norway, 9th – 13th of September 2024
- Interference types: **Low-power & high-power Jamming, Meaconing, Spoofing**
- 3 test areas: Both **static** antenna in the main test area (1) and **dynamic test drives** with our (rented) test vehicle (all test sites)

Data collection

- Different Multi-frequency Multi-Sensor Modules:
  - Single GNSS receiver + IMU
  - VROX Multiple-GNSS-receivers + Multi-Sensor Fusion (GNSS+IMU+LiDar+Camera)
- Features for interference detection (see on the following slides)
- Overall, **more than 50 hours of labeled data**

Jamming & Spoofing Detection - Concept

- Use combination of input features which are well-known to show typical characteristics in GNSS interference scenarios + unaffected multi-sensor data (see next slide)
- Learn the reaction to different types of interference with Machine Learning (CNN + LSTM)
- Multi-Label classification: 16 signal types and 3 interference types (J- Jamming, S- Spoofing, M- Meaconing)
- Optimizing the cross-entropy-loss function

$$Loss = -\sum_{i=1}^{C} w_i y_i log(f(s_i)) + (1 - y_i) log(1 - f(s_i)),\ f(s_i) = \frac{1}{1+e^{-s_i}}$$

- Weight samples based on the frequency of the specific label to account for unbalanced labelling (logarithmic adjustment)

Input Features and Data Labelling

Input features

Signal Characteristics

Gain + Average CN/0

\+

GNSS Measurements

Carrier-ratio + Double differenced Phase Measurements

\+

Multi-Sensor Information

Raw angular rate & acceleration (IMU) + [optionally]: Odometry

Data Labelling:

- Generated labels for each GNSS epoch (@5 Hz) and for each type (J- Jamming, S- Spoofing and M- Meaconing) and signal based on the Transmission log and information about the vehicle's / modules' location(s)
- Example: combination of ['B2a', 'B2b', 'B3I', 'E5a', 'E5b', 'E6', 'G2', 'G3', 'L2', 'L5'] signals are jammed Label vector is as shown:

Signal	B1C	B1I	B2I	B2a	B2b	B3I	E1	E5a	E5b	E6	G1	G2	G3	L1	L2	L5
Type	J S M	J S M	J S M	J S M	J S M	J S M	J S M	J S M	J S M	J S M	J S M	J S M	J S M	J S M	J S M	J S M
Example	0 0 0	0 0 0	0 0 0	1 0 0	1 0 0	1 0 0	0 0 0	1 0 0	1 0 0	1 0 0	0 0 0	1 0 0	1 0 0	0 0 0	1 0 0	1 0 0

Challenges for Data Labelling

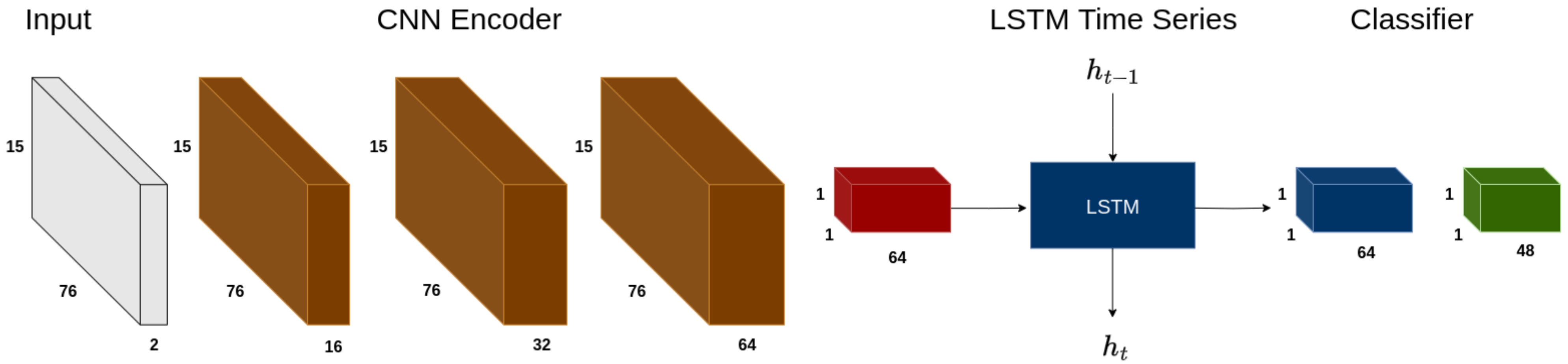
!

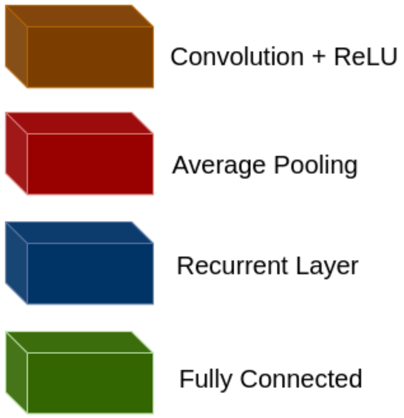
Accurate (1-second-wise) labelling of GNSS interference data
≠ Time where receiver measurements are affected and positioning performance is degraded

Reasons:

- GNSS interference might take a while to have an effect (e.g., in power ramps)
- Vehicle is not always in the affected zone
  - Due to occlusion by buildings etc. (planned to analyze visual data)
  - In specific test cases: Due to limited time handheld receivers are strong enough when passing the “parked” vehicle
- Even tough already good performance: not all wrong classification is really an issue. Thus, even better performance as in metrics

Network Architecture





Input (fixed size with zero padding and masking)

C/N0 (22 values)	CR (22 values)	PRN (22 values)	Constellation, Constellation Freq (2 values)	Gain (1 value)	Sample Variance (1 value)	IMU data (6 values)

⋮ feature vector per GNSS signal

15 (GNSS signals)

76 (input features per signal)

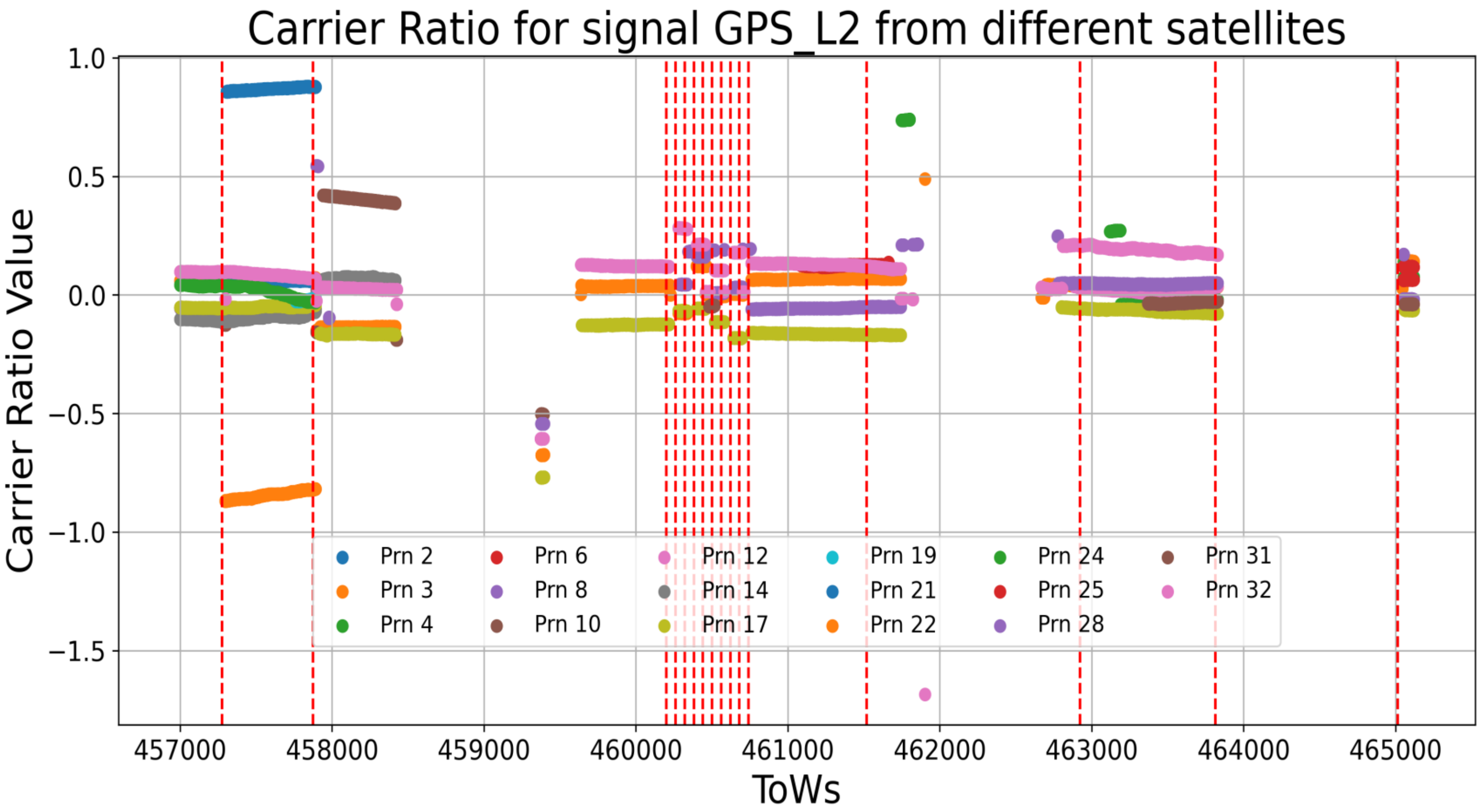
Validation Approach

- Dataset ~ 688k samples
  - 75% for training ~ 516k samples
  - 15% for validation ~ 103k samples
  - 10% for testing ~ 68k samples
- Imbalanced dataset ~ 10-15 % positive samples
- Positive weights with higher value for extremely rare labels are used to handle label imbalances in the training data
- Model trained on random sequences of 10 seconds duration
- Model validated and thresholds selected based on per label threshold rendering higher f1-scores
- Model tested for metrics: Precision, F1-score, Recall and Accuracy

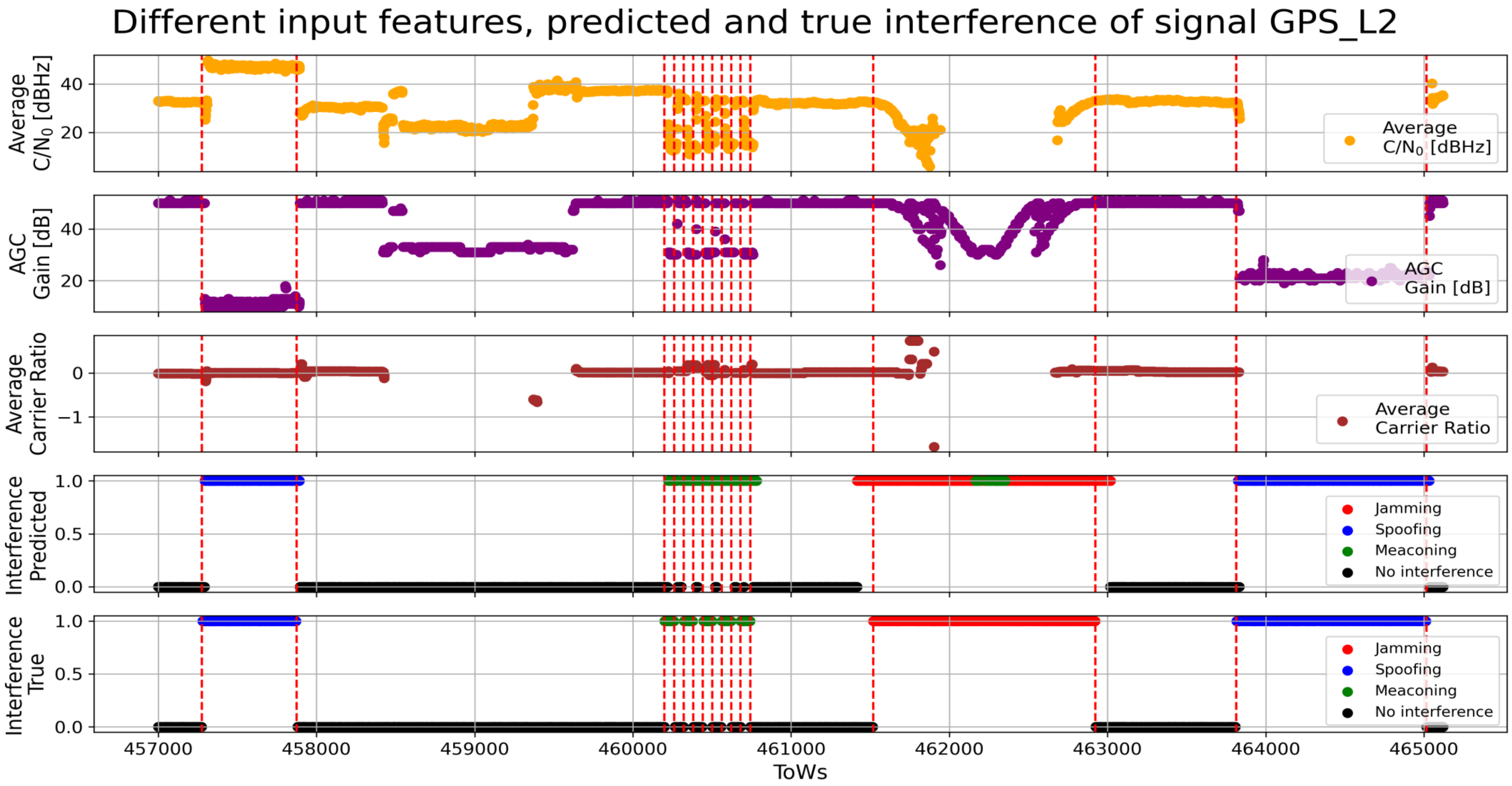
Visualization of Input Features: Carrier Ratio

- The carrier ratio (CR) is
  - very **stable under nominal conditions**
  - **Reacting well to GNSS interference**
- Network uses the CR on a **PRN-basis**, upcoming plots contain average only for easier visualization
- The **modified CR values** (satellite k, signal m) is used to have an easier inspectable range:

$$\mathrm{CR}_m^{\mathrm{k}} = 10^6\left(\frac{\lambda_1 \phi_1^k}{\lambda_m \phi_m^k} - 1\right)$$

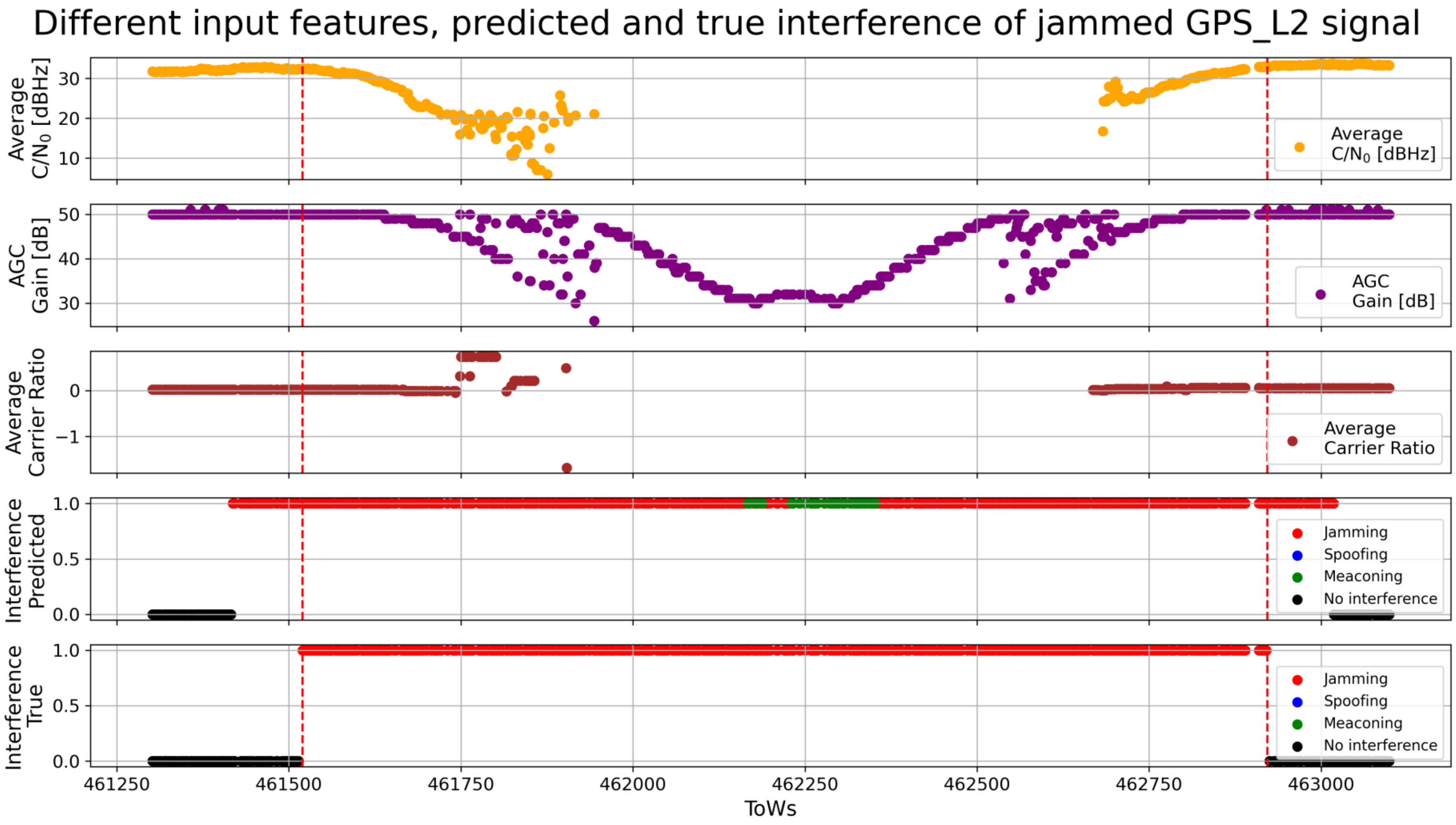


Visualization of Input Features

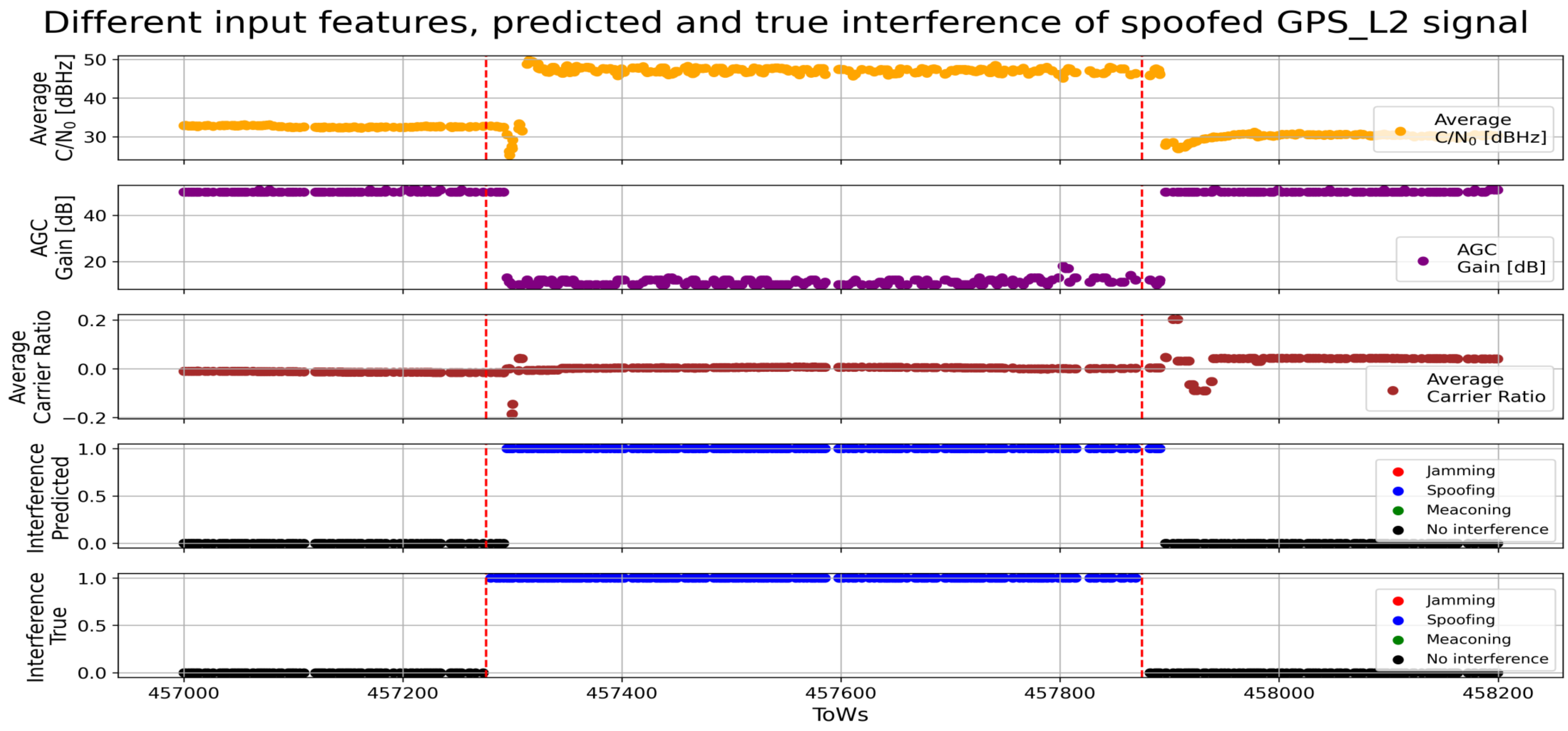


Example for Jamming

- Working Jamming detection
- Sometimes non-critical latency of receiver reaction (see later slide)
- Sometimes conservativeness (false positives)
- Sometimes wrong classification but not critical as other positive classification



Example for Spoofing

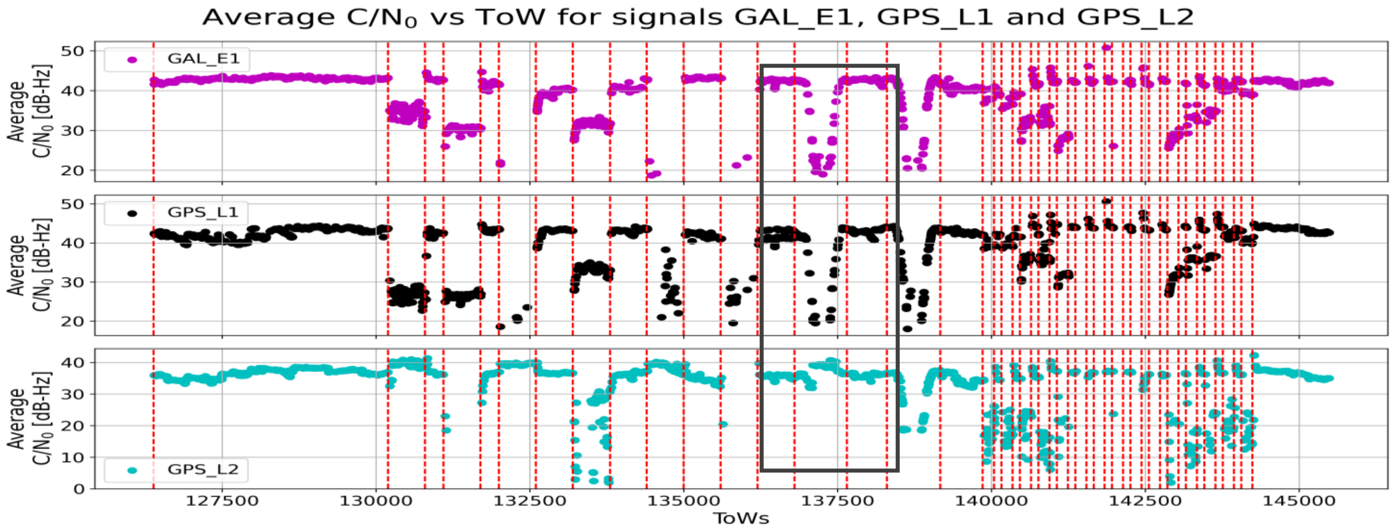


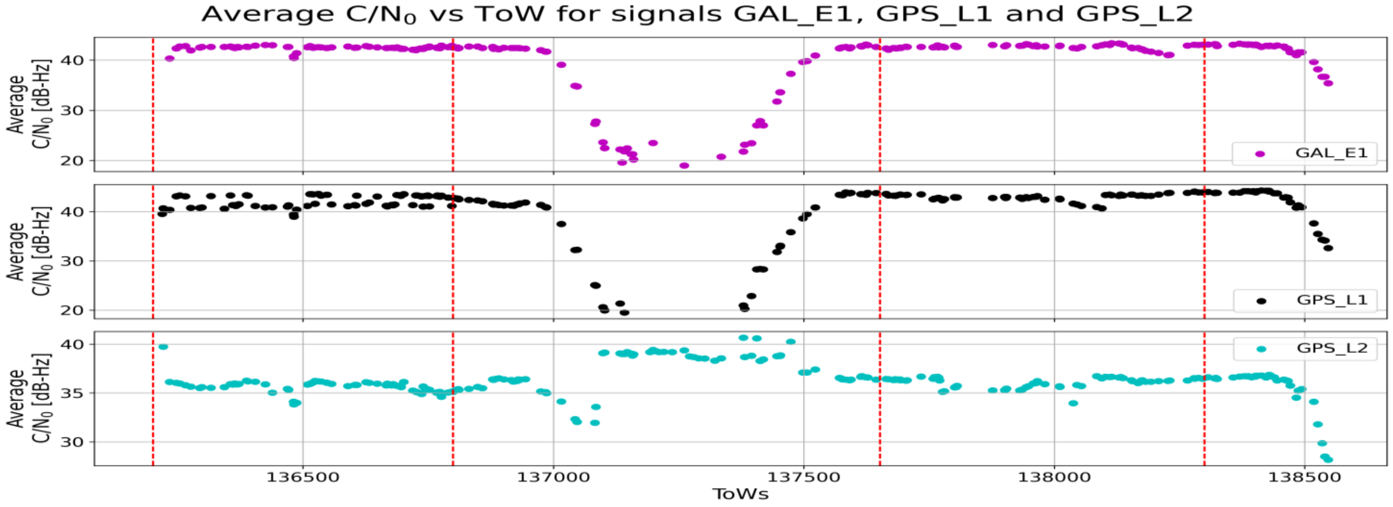
Latency of the Receiver

- Different types of Jamming
- Exemplarily: the reaction of the average C/N_0 for E1, L1, and L2
- **The receiver reacts differently depending on the power and type**:
  - Slow reaction in power ramping (zoomed part): 0.2 µW (-37dBm) to 50 W (47dBm) with 2 dB increments on L1 [power at sending antenna ~2 km away]
  - Faster reactions in burst jamming
  - Different behavior for sweeps

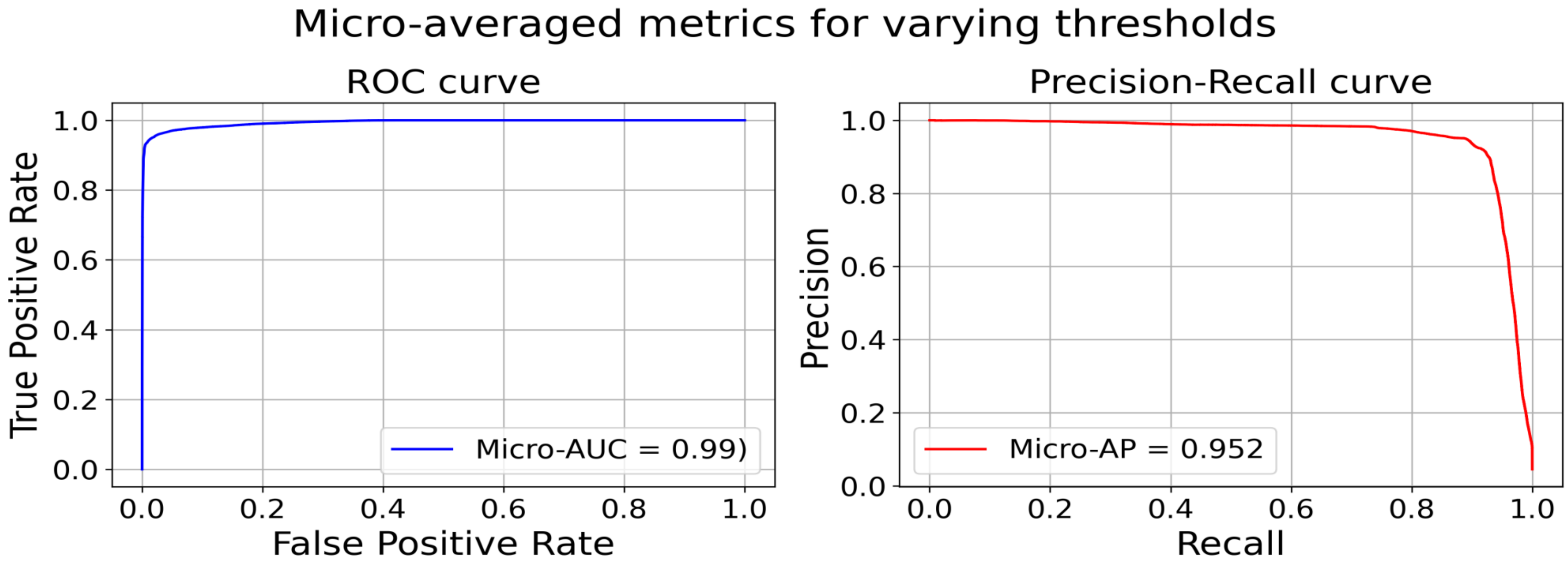
➢ Challenge for labelling and training

➢ Learning and Performance metrics are affected but false positives in the latency period are not critical



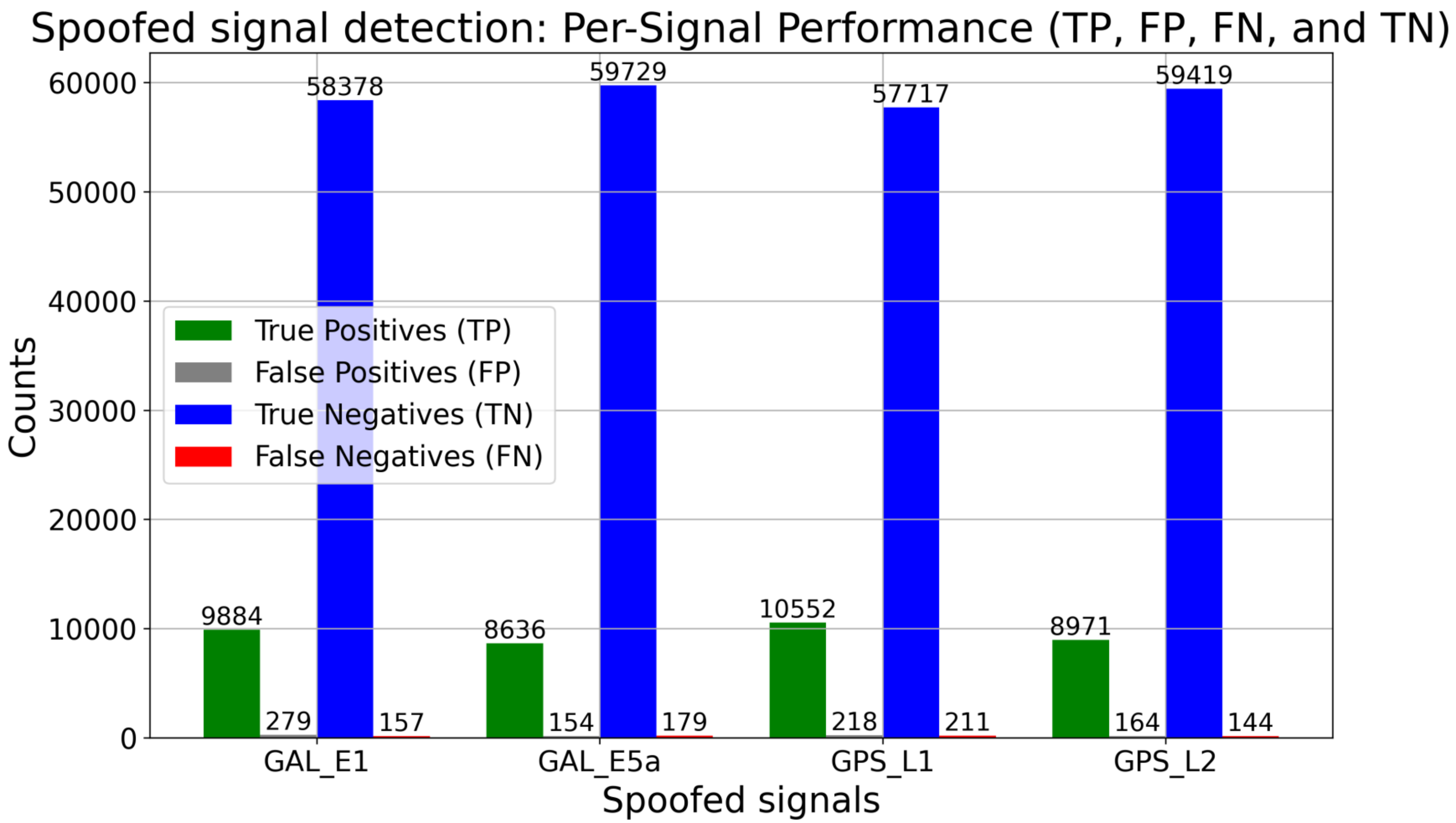


Metrics

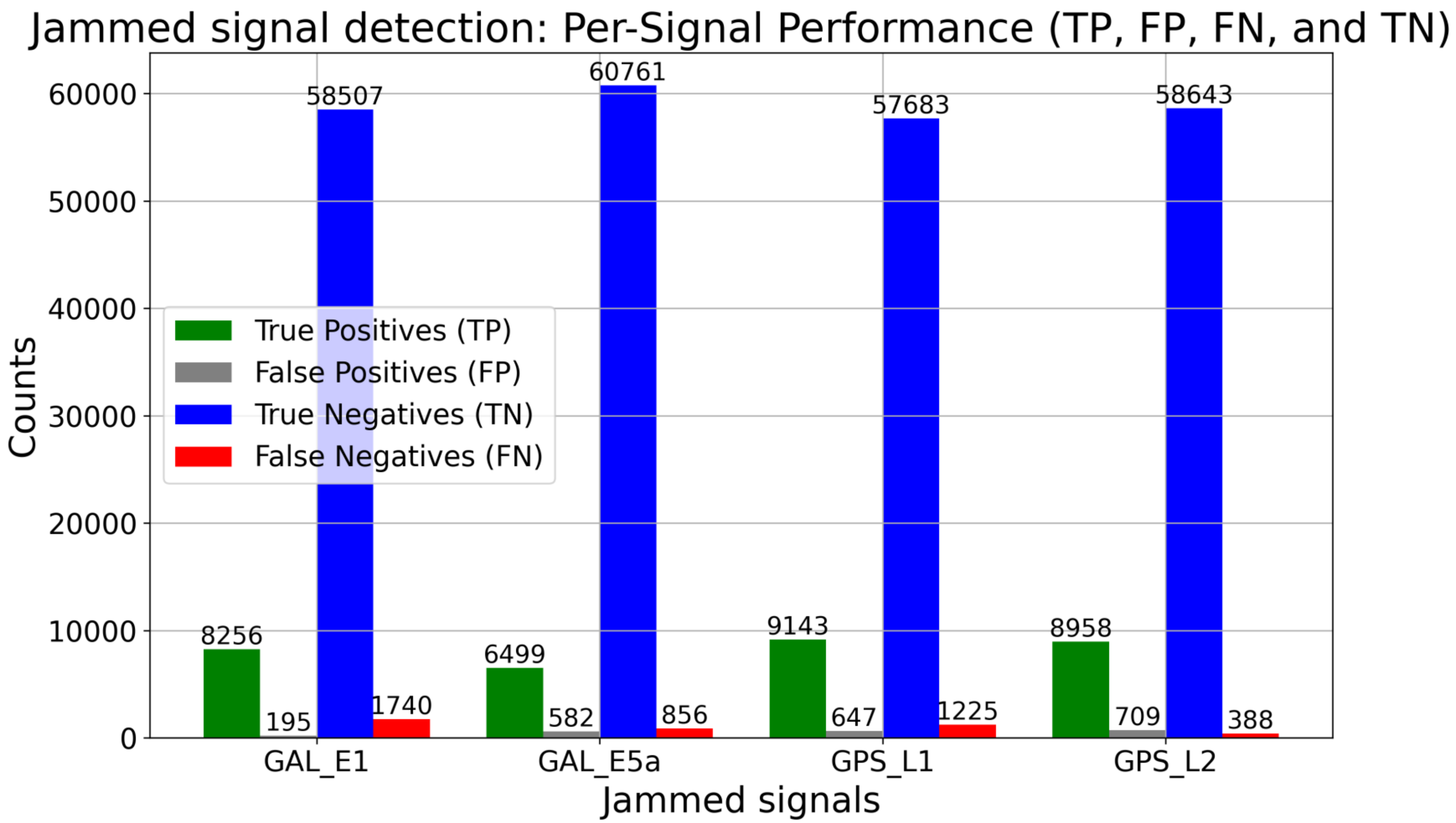


- Micro-AP and Micro-AUC computes overall performance globally across all labels and well suited for imbalanced data
- Models with high micro-AP retrieves true positives well, with high precision and recall across all labels
- Models with high micro-AUC can rank all positive labels higher than negatives globally

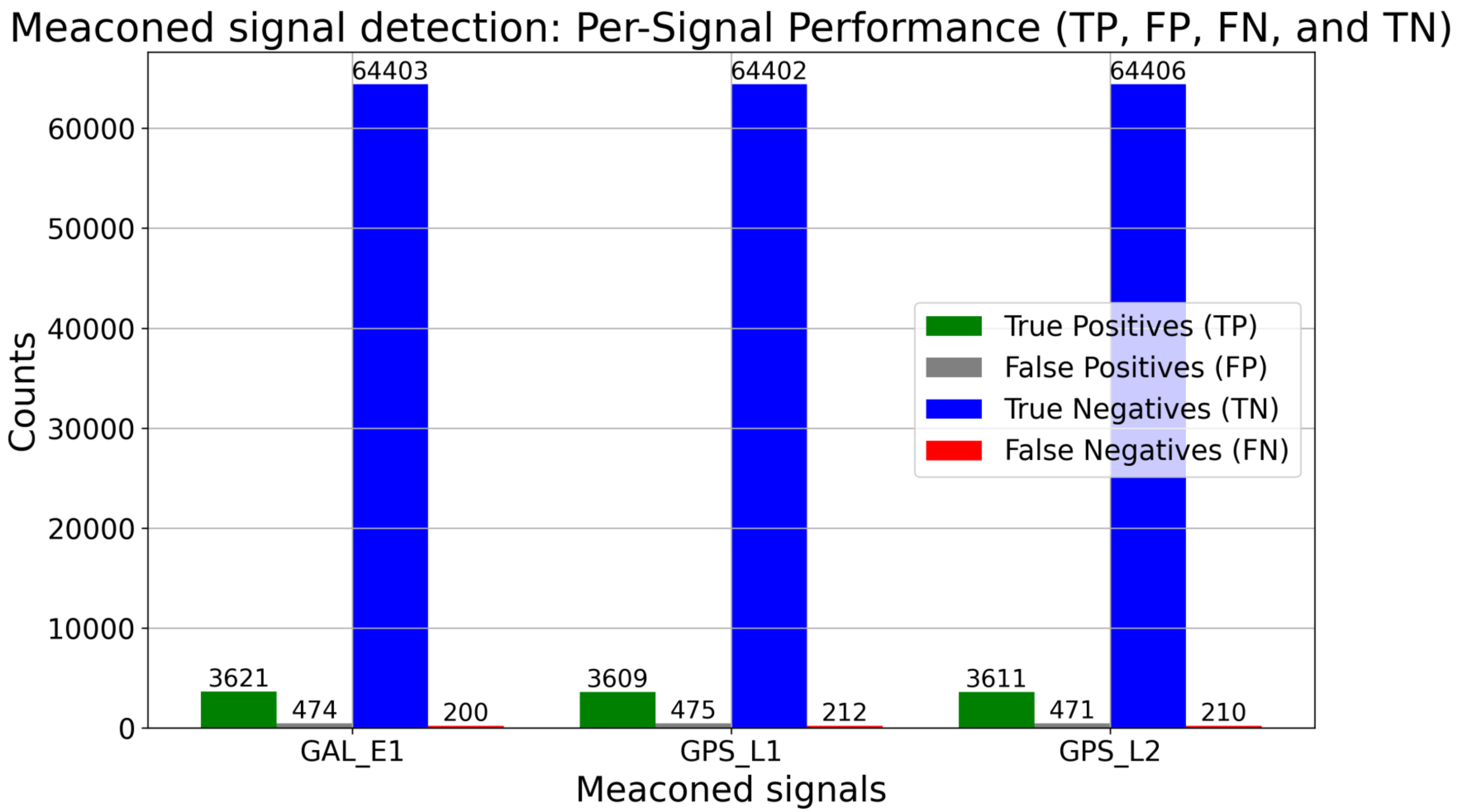
Confusion Matrix - Spoofed signals



Confusion Matrix - Jammed signals



Confusion Matrix - Meaconed signals



Summary & Outlook

- Invaluable multi-sensor data collected for static and dynamic cases and pre-processed for accurate labelling of various types of GNSS interference
- Well-working classification of Jamming, Meaconing and Spoofing (Micro-AUC=0.99, Micro-AP=0.952) even though we
- Baseline work with many identified challenges for upcoming research to improve detection even further
  - Refinement of labels due to latency in the receiver's reaction
  - Refinement of labels due to effects of occlusion and entering/leaving the affected area
  - Increased focus on dynamic data and positioning performance with and without ML-based interference detection
- The network and labelled data will be published at: https://github.com/anavsgmbh/ml-based-jamming-and-spoofing-detection

Contact & Project Information

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DREAM Project

- Funded by the EUSPA as part of the Fundamental Elements Programme
- contract number: EUSPA/GRANT/03/2022.
- https://dream-project-eu.com/

DRIVING AIDS POWERED BY E-GNSS AI AND MACHINE LEARNING