KP LABS

Antelope: Towards on-board anomaly detection in telemetry data using deep learning

Jakub Nalepa, Michal Myller, Pawel Benecki, Jacek Andrzejewski, and Daniel Kostrzewa

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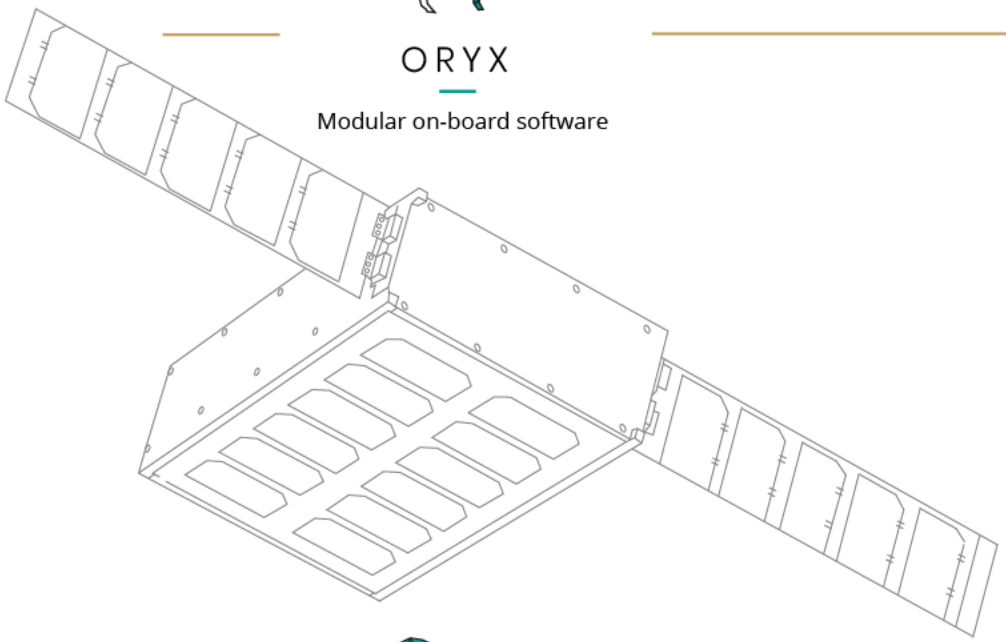
Smart Mission **Ecosystem** by KP LABS

HARDWARE, SOFTWARE AND AI-POWERED ALGORITHMS DESIGNED TO COMPLETE YOUR MISSION

ORYX

Modular on-board software



ANTELOPE

On-board computer with predictive maintenance

LEOPARD

High-performance data processing unit for AI applications

THE HERD

AI-powered algorithms for Earth Observation

OASIS

Electrical Ground Support Equipment created to test satellite on the Earth

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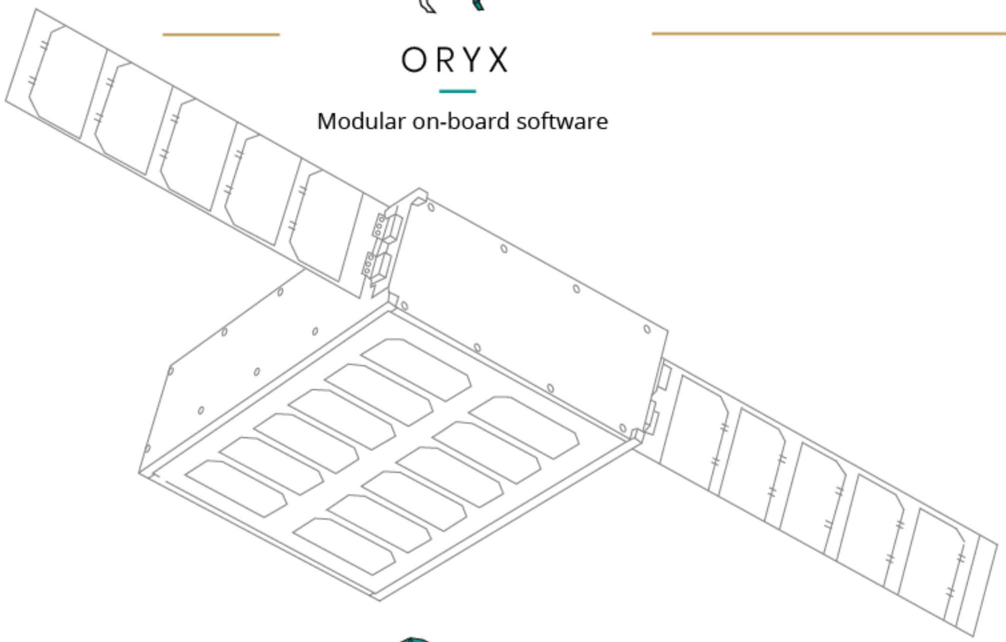

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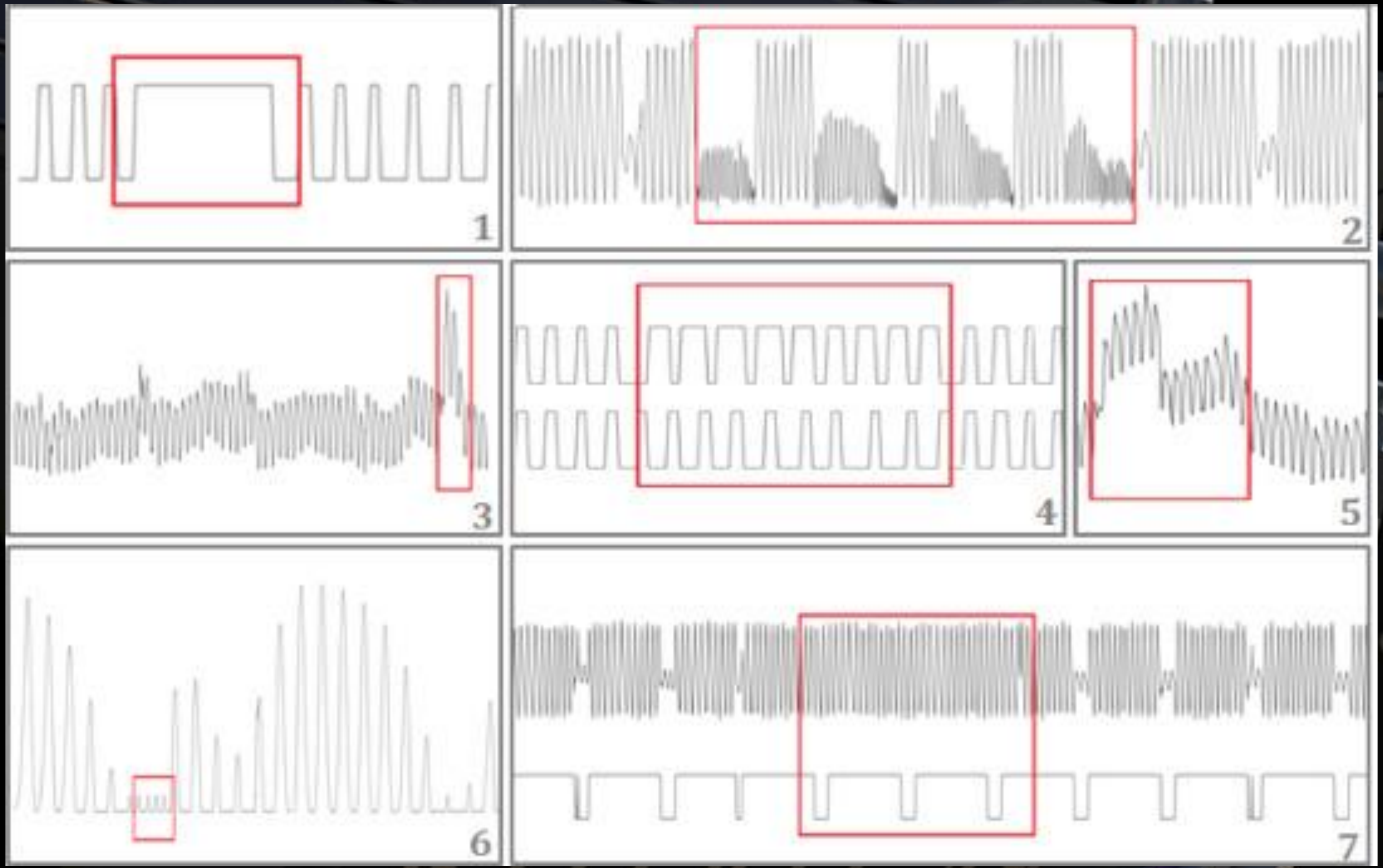
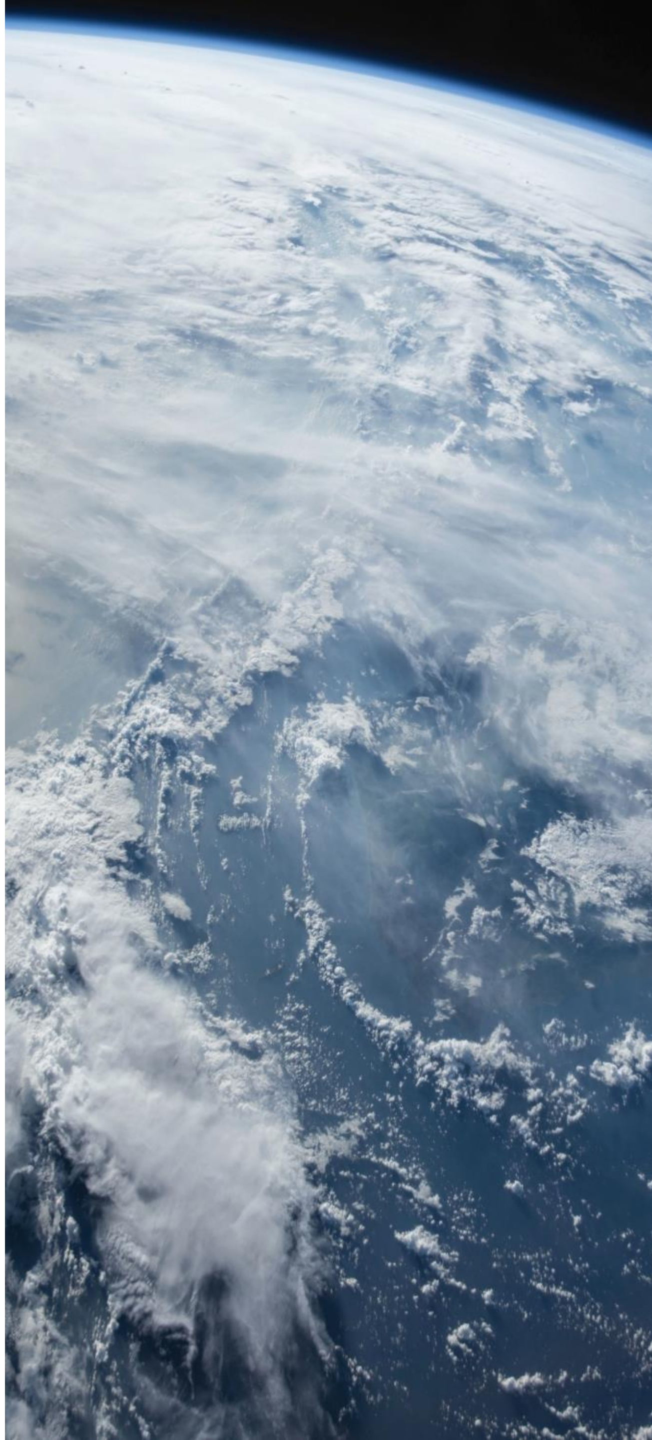


Barbara Pilastre, Loïc Boussouf, Stéphane D'Escrivan, Jean-Yves Tourneret; Anomaly detection in mixed telemetry data using a sparse representation and dictionary learning; Signal Processing, Volume 168, 2020

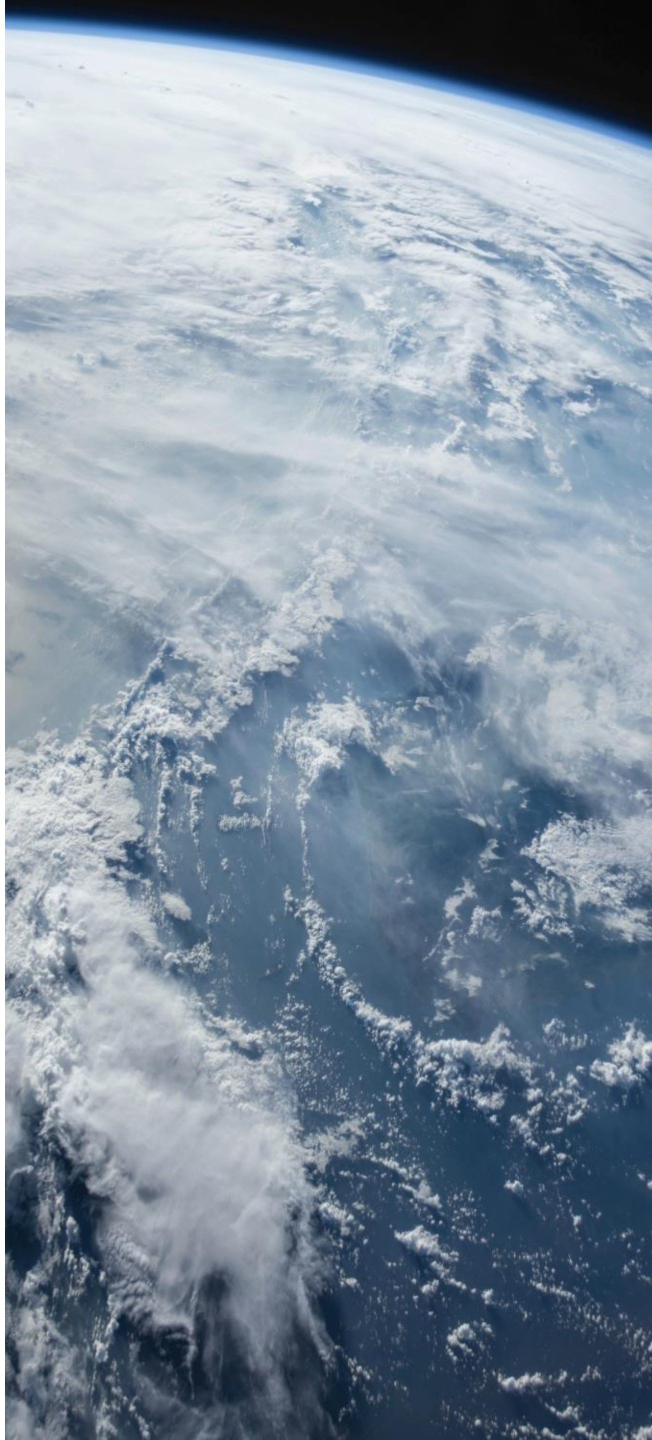
Anomaly detection in FDIR

- Failure Detection Isolation and Recovery: on-board systems dedicated for discovery of anomalies and entering safe state
- Current state of the art
    - **Out-of-limit checks**
    - **Machine learning algorithms, expert systems**
    - **Detailed analysis on the ground**



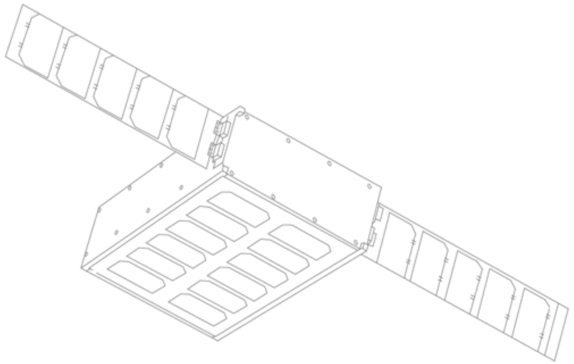
Anomaly detection in FDIR

- Failure Detection Isolation and Recovery: on-board systems dedicated for discovery of anomalies and entering safe state
- Current state of the art
  - **Out-of-limit checks** (How about periodic signals? Inter-parameter relations?)
  - **Machine learning algorithms, expert systems** (Training data? Parameterization? On-board implementation, e.g., FPGA?)
  - **Detailed analysis on the ground**
    - Need access to communication window
    - Human analysis and reaction necessary
    - Problem for small satellites with small teams and non-continuous communication
    - Data transfer (cost & time; which part of data is „relevant"?)



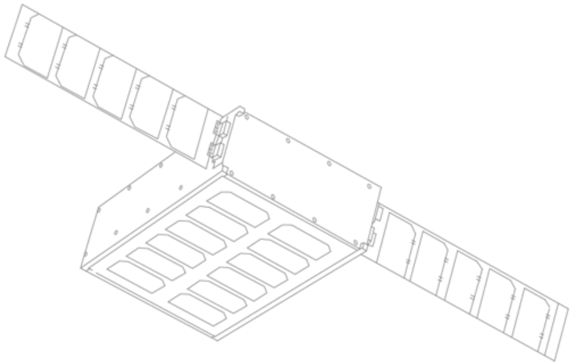
Towards on-board anomaly – why?

- Traditional out-of-limit FDIR systems often **detect point anomalies only**
- **Entering safe mode earlier** after failure undetectable by basic out-of-limits methods
- **Smaller amount of telemetric data** sent to Earth – more bandwidth available to other data

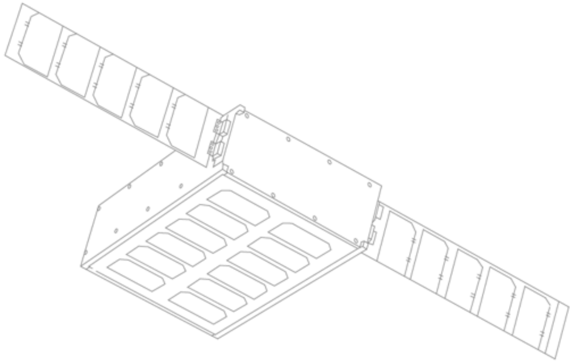


Towards on-board anomaly – why?

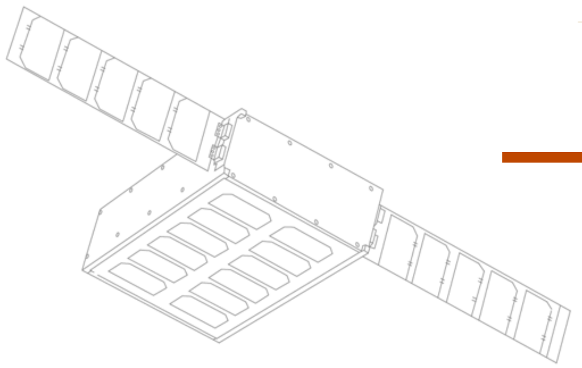
- Traditional out-of-limit FDIR systems often **detect point anomalies only**
- **Entering safe mode earlier** after failure undetectable by basic out-of-limits methods
- **Smaller amount of telemetric data** sent to Earth – more bandwidth available to other data
- Can we **predict** that something bad is about to happen?



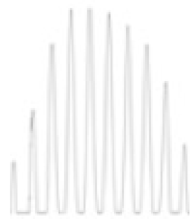
Machine (deep) learning in anomaly detection



Machine (deep) learning in anomaly detection



Reconstruct („predict”) the signal



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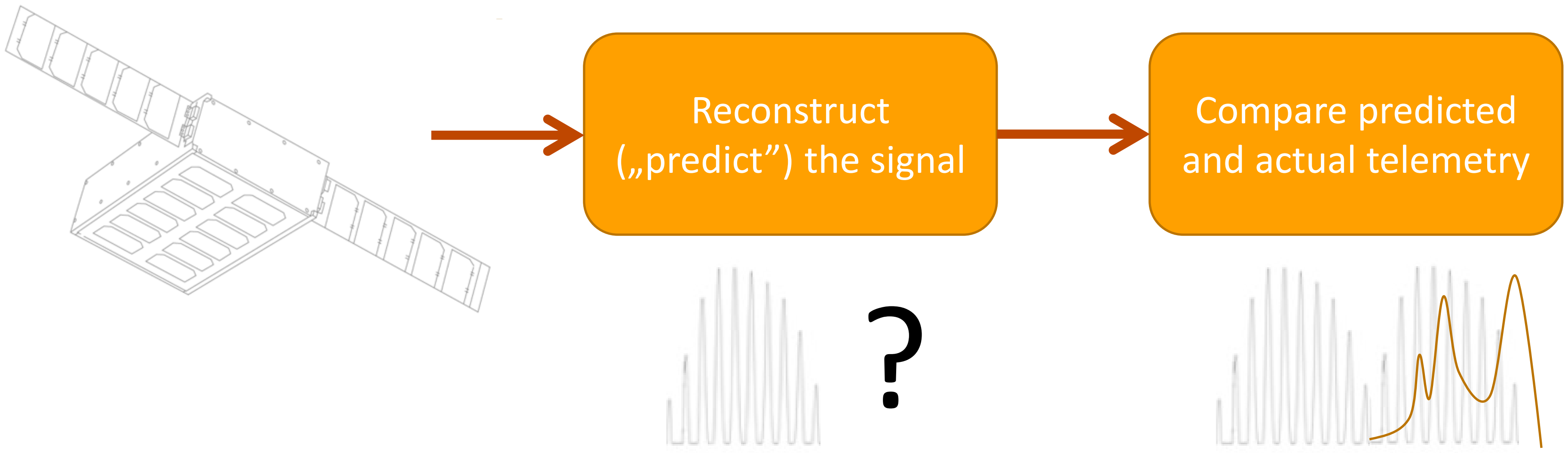
Machine (deep) learning in anomaly detection



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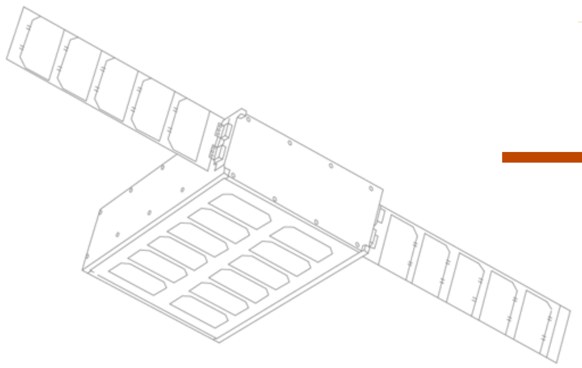
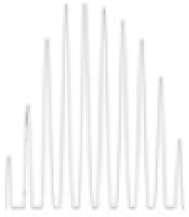


Reconstruct („predict") the signal

Compare predicted and actual telemetry

Correct signal

Anomaly



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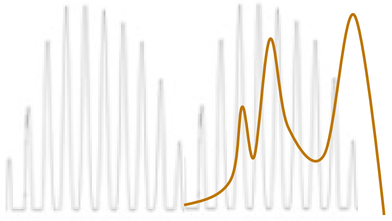
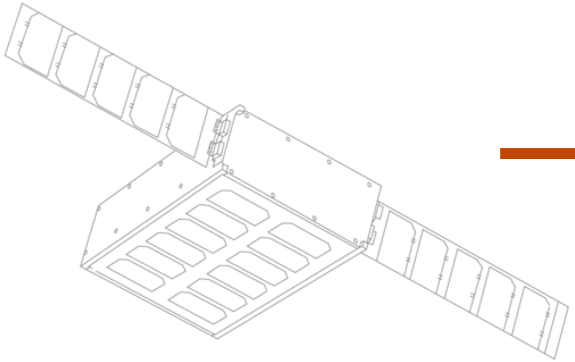
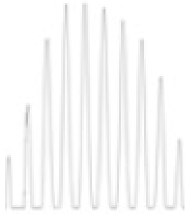


Machine (deep) learning in anomaly detection



Reconstruct („predict”) the signal → Compare predicted and actual telemetry → Correct signal / Anomaly



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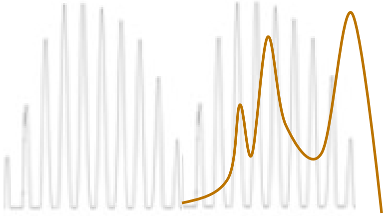
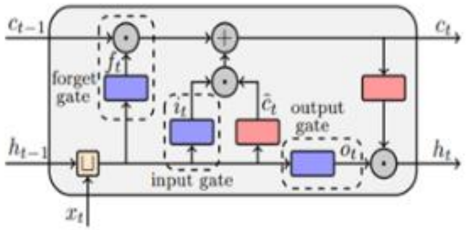
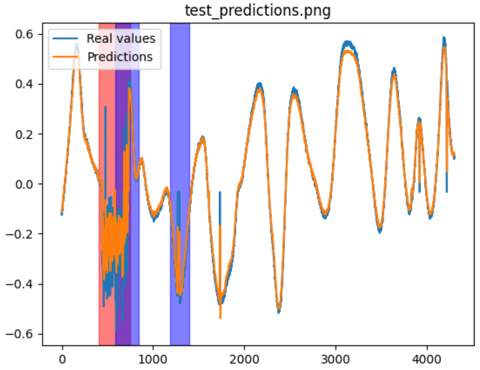
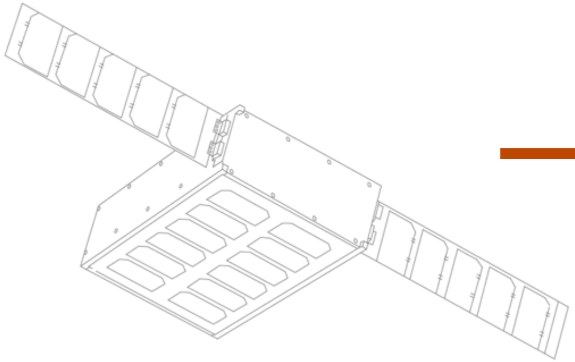


Deep recurrent neural network-based detector





Machine (deep) learning in anomaly detection



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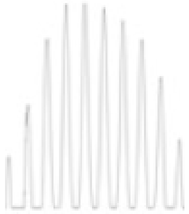

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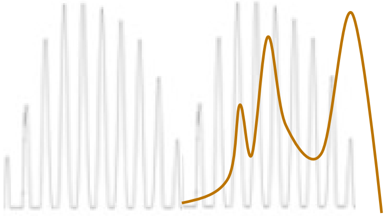
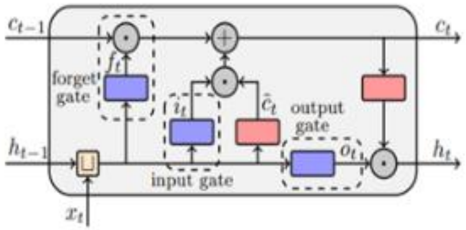
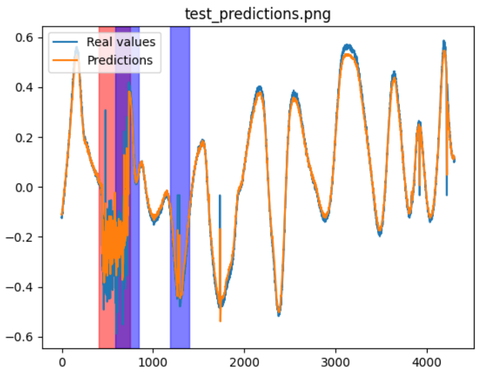


How to objectively assess the detectors?

How to gather training data?

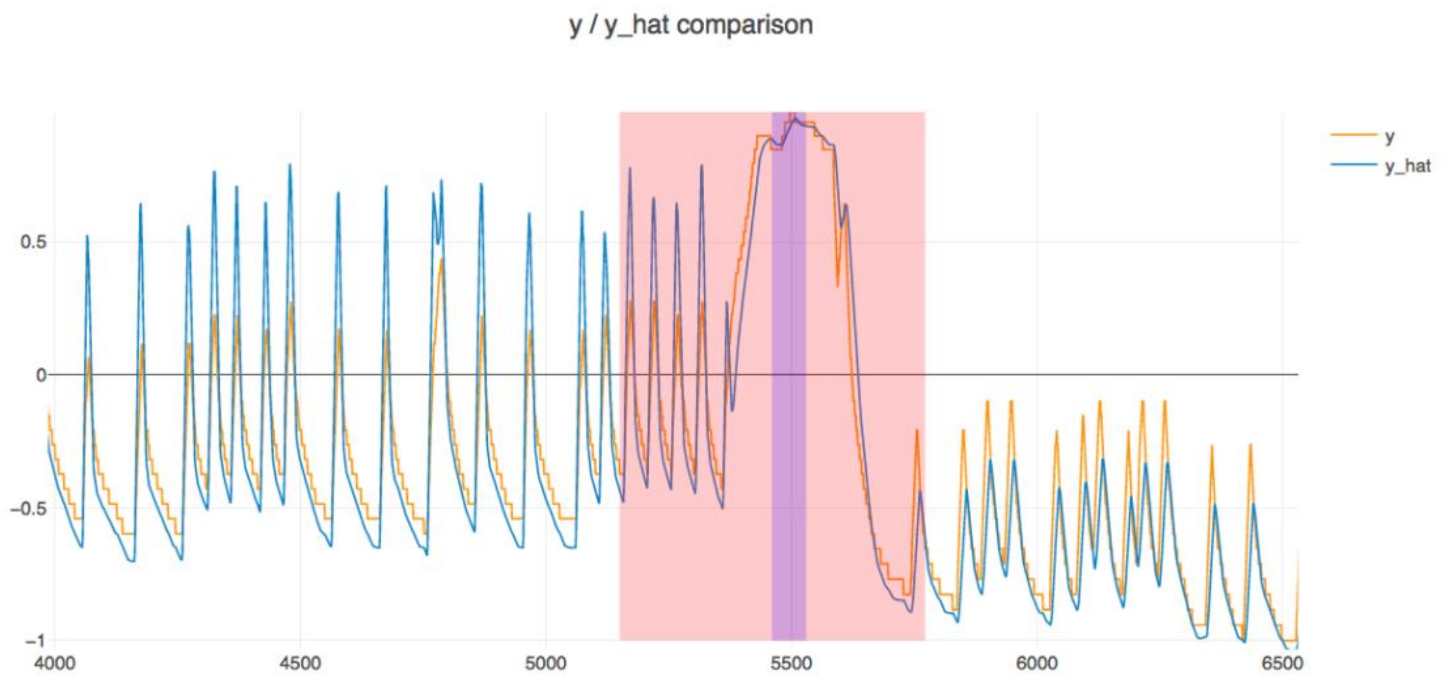
Deep recurrent neural network-based detector





Telemetry „ground-truth” datasets

Telemanom (Detecting Spacecraft Anomalies Using LSTMs and Nonparametric Dynamic Thresholding; Hundman, Constantinou, Laporte, Colwell, Soderstrom; 2018 (NASA Jet Propulsion Laboratory) https://arxiv.org/pdf/1802.04431.pdf)



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Telemetry „ground-truth” datasets

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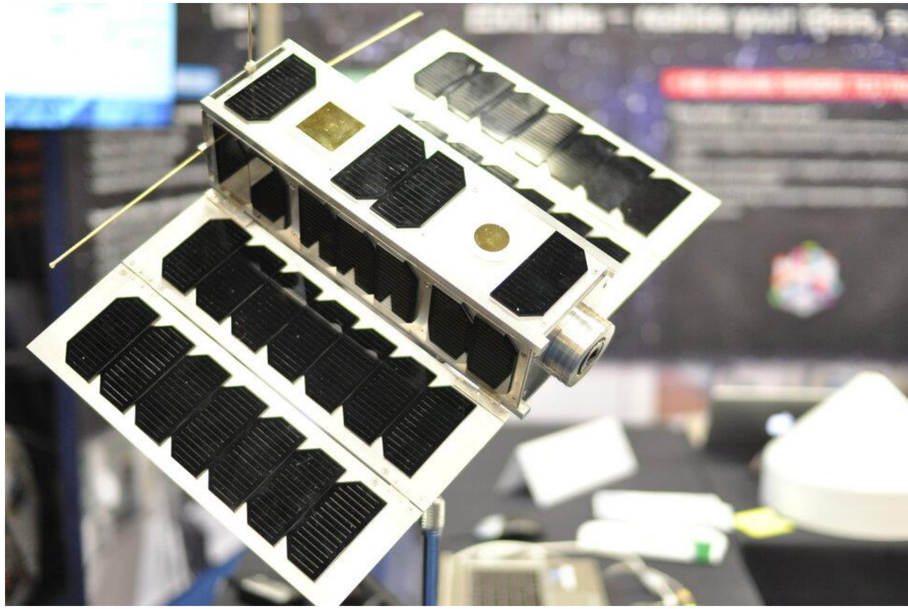
- Few dozens of time series, few thousands of values each, taken from SNAP and MSL NASA's missions
- Each series is split into training (no anomalies) and test parts (with anomalies)
    - Visual inspection shows that training part **may contain** anomalies
    - Data corrupted due to separate train/test normalization
        - Models trained on train parts generate values different that in the original paper
- No more public telemetry datasets

What about using OPS-SAT?

- OPS-SAT is a novel small satellite containing powerful on-board computer
- Available for execution of code and commands by external experimenters
- OPS-SAT's telemetry data is freely available to experimenters



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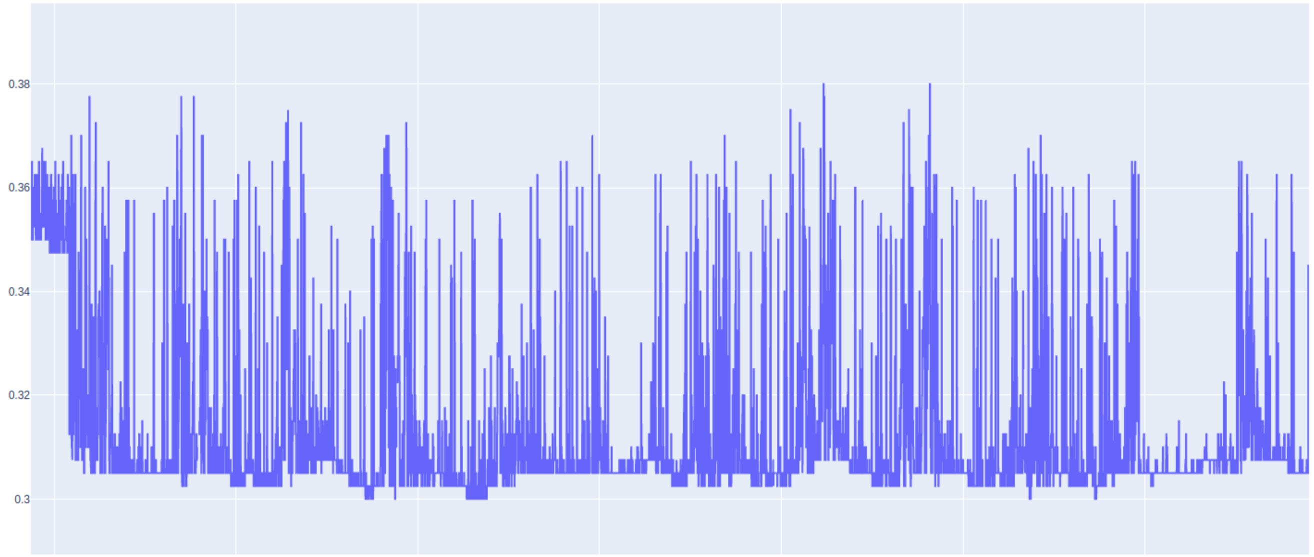
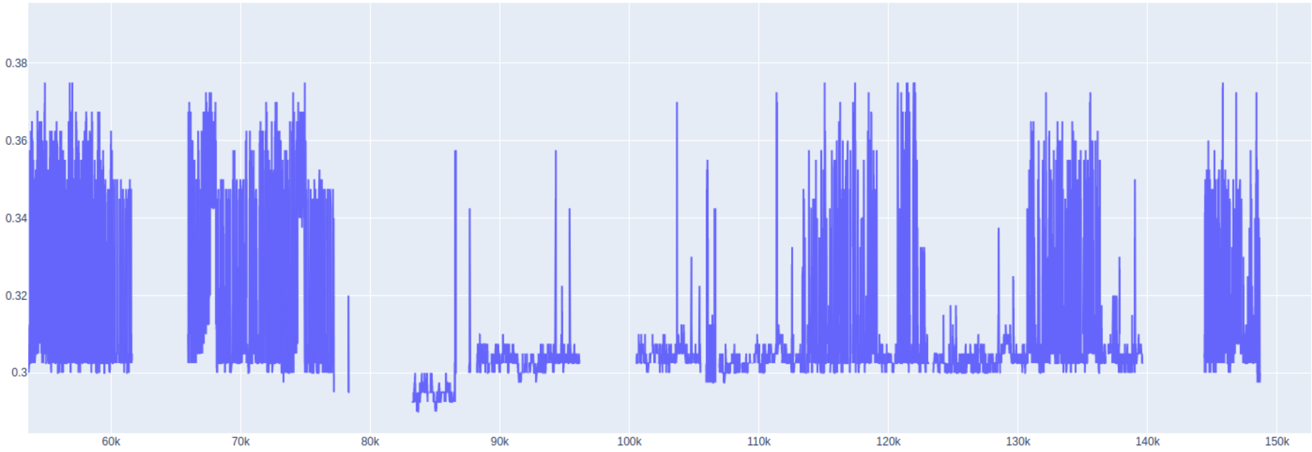
OPS-SAT telemetry

- Few thousands of numeric telemetry series
    - Sampling rate 1s - 30s
- Commands sent from ground station

- Discontinuities in data
    - Poses problem while processing with Machine Learning models





Values of SEP8260p: continuous fragment above, gaps visible below

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OPS-SAT, April 2021 – multivariate data example

period_s=5,begin=1617654990,length=3862,count=13.csv

```
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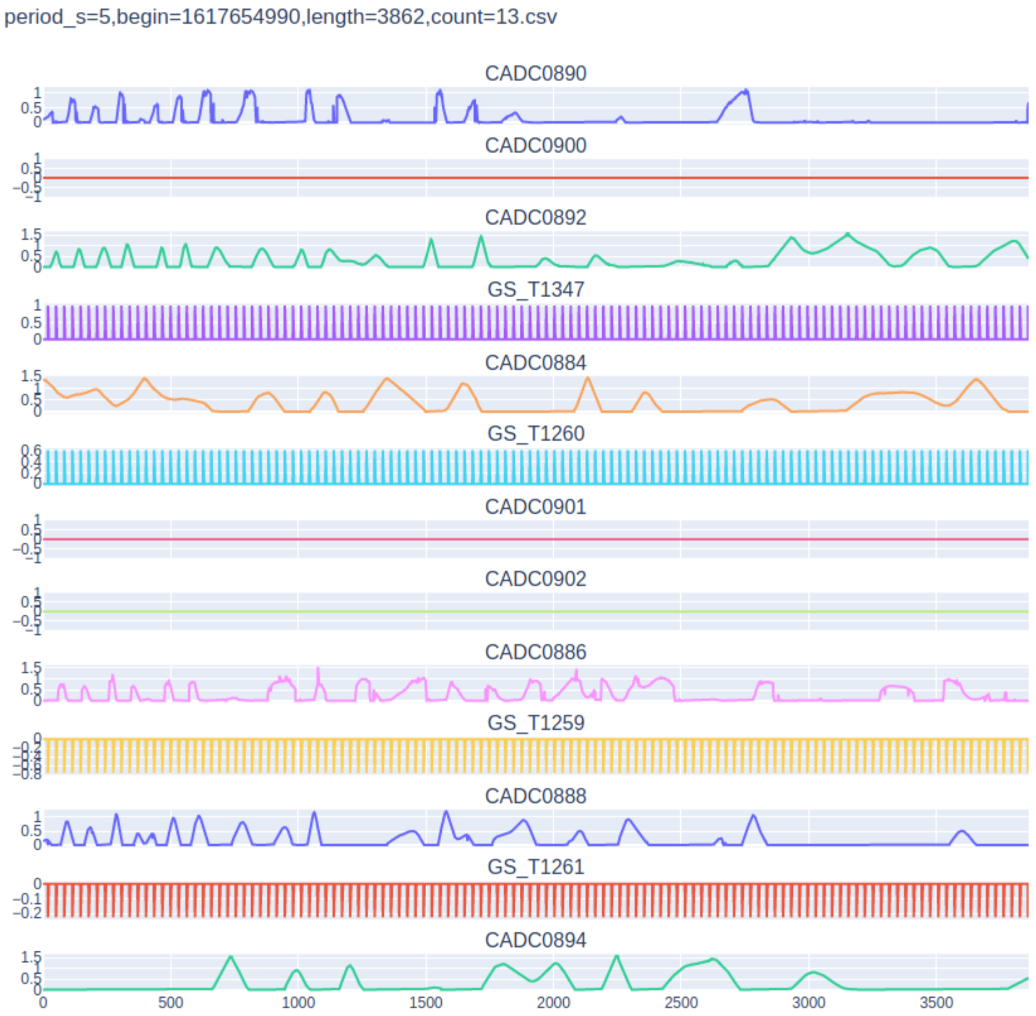
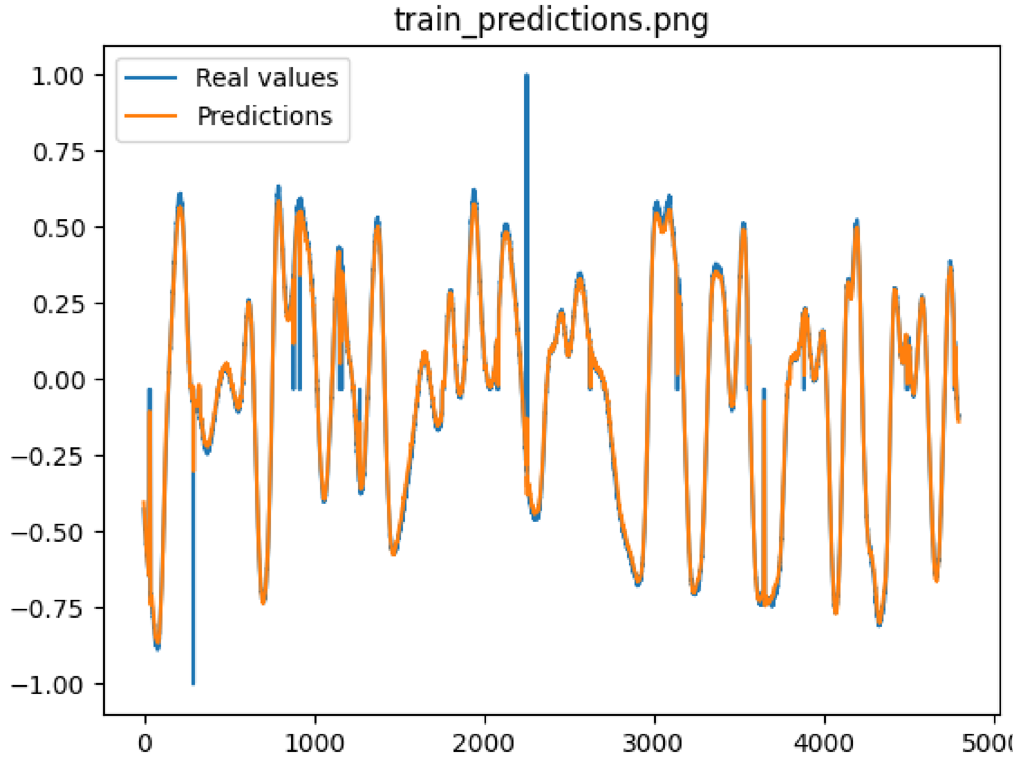
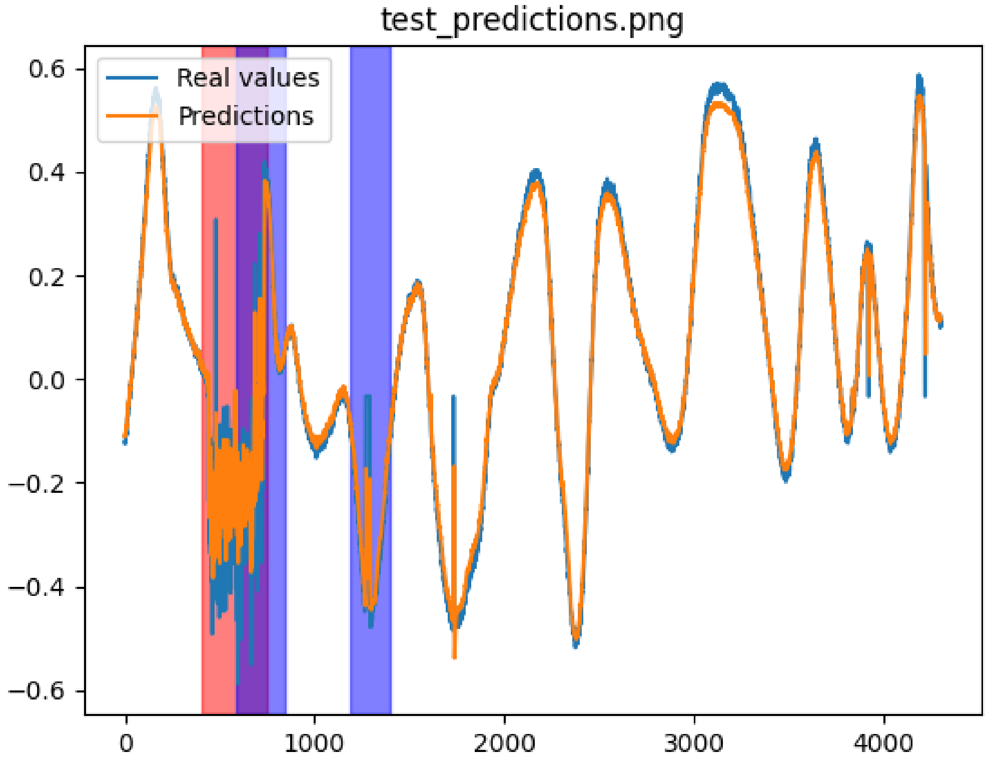


Anomalies (?) in GST1222



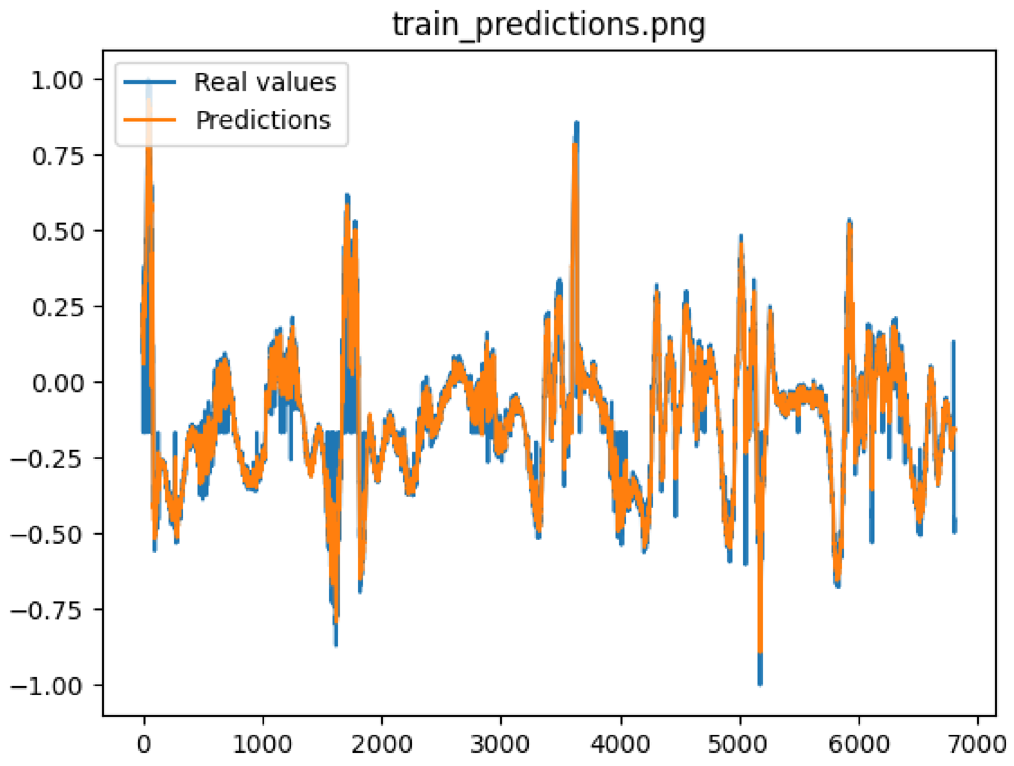
real vs. predictions on the training sequence



test sequence and potential anomalies:

- red – "GT" marked by visual inspection,
- blue & purple – ranges found by our method

Anomalies (?) in CADC0973



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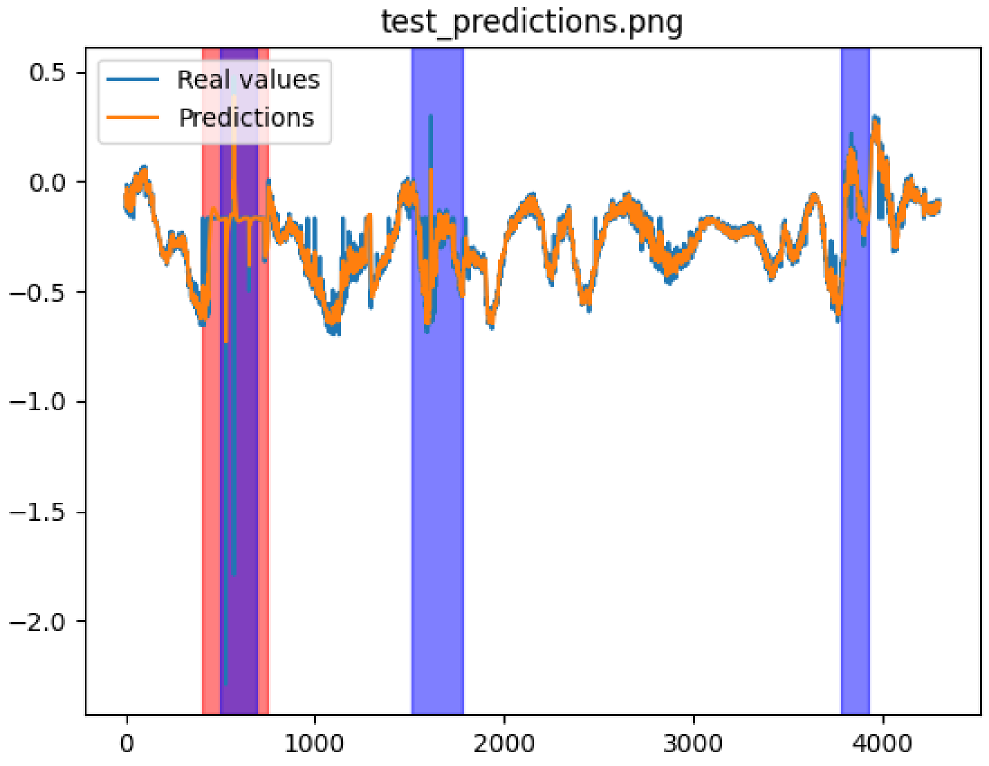

test sequence and potential anomalies:

- red – "GT" marked by visual inspection,
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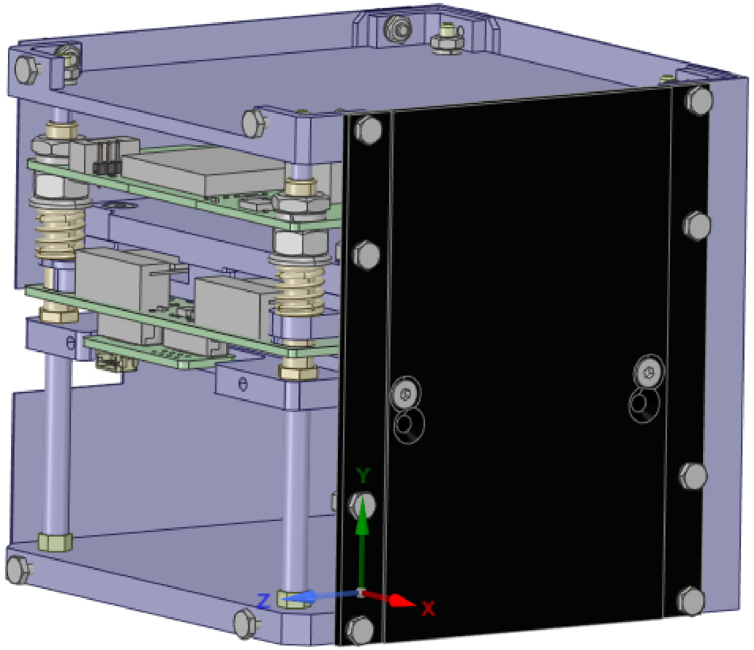
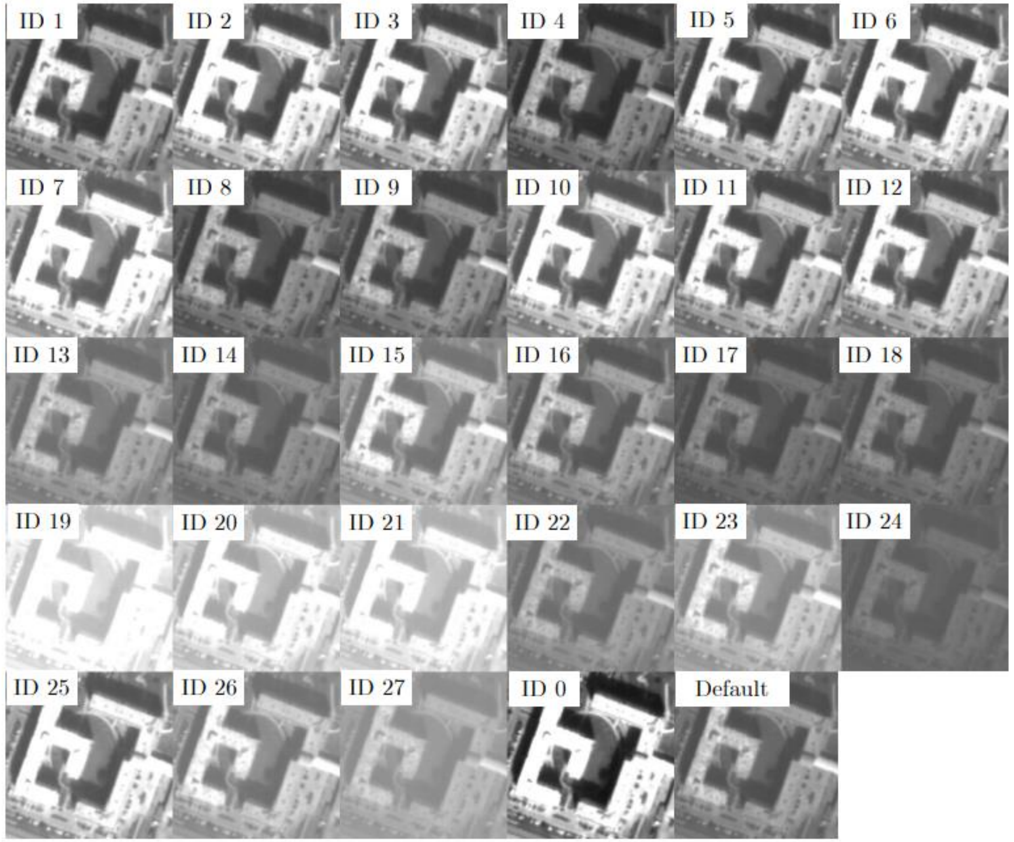
Towards digital twins and simulations…

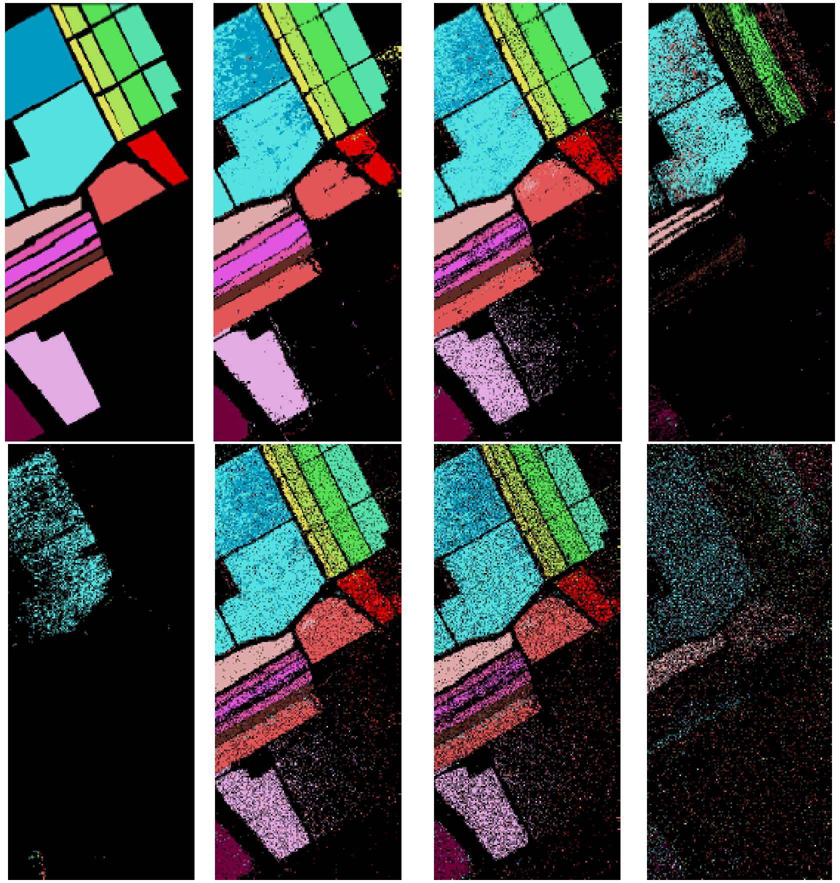


Towards digital twins and simulations…



J. Nalepa et al.: Towards on-board hyperspectral satellite segmentation, Remote Sensing 2021, 13(8), 1532 (https://www.mdpi.com/2072-4292/13/8/1532)

Towards digital twins and simulations…



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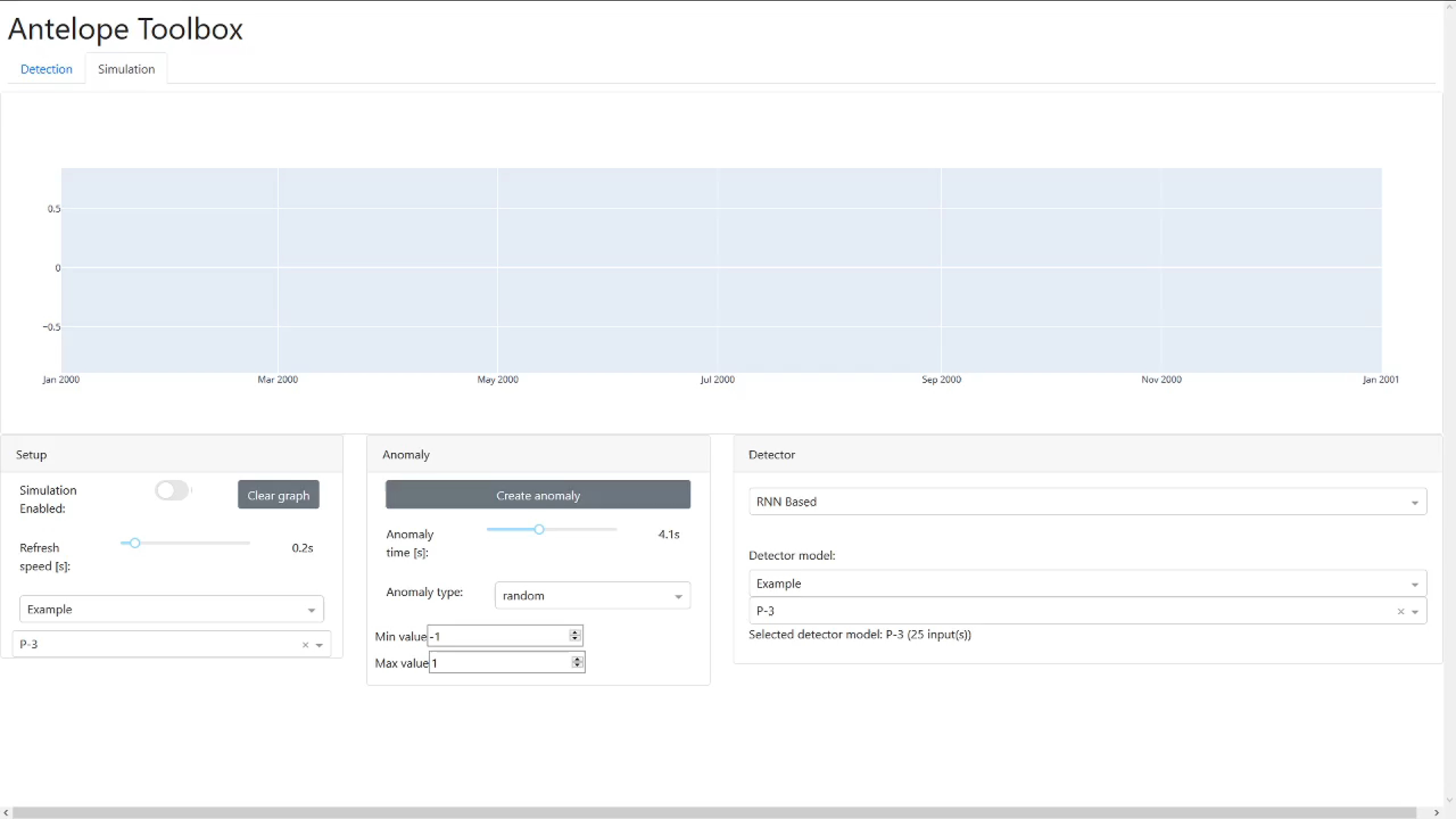
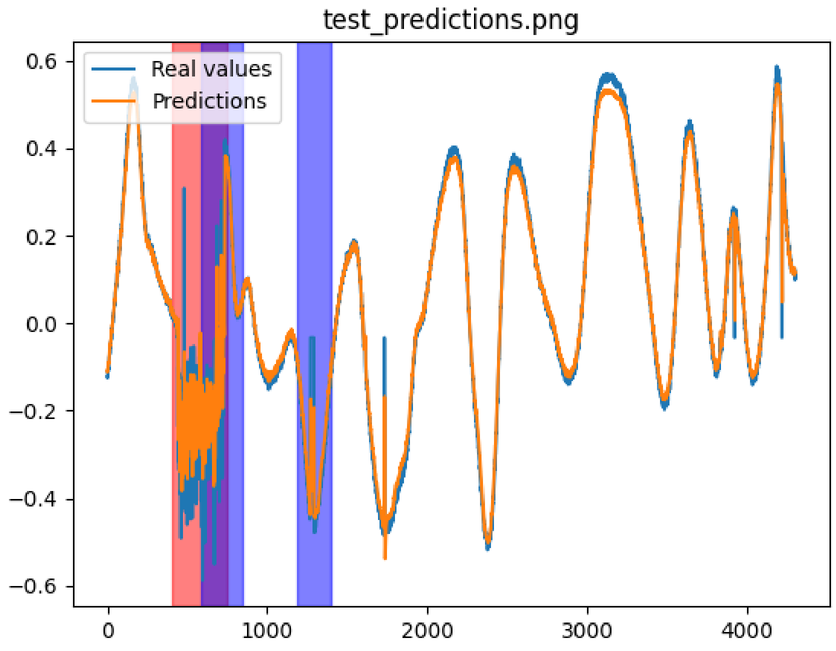
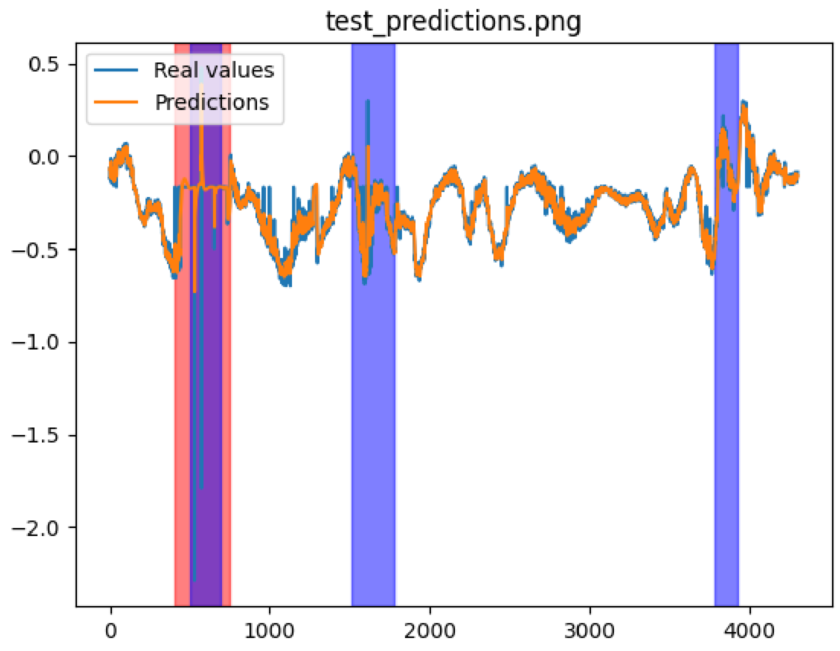

Antelope Toolbox
Detection
Simulation
0.5
0
−0.5
Jan 2000
Mar 2000
May 2000
Jul 2000
Sep 2000
Nov 2000
Jan 2001
Setup
Simulation Enabled:
Clear graph
Refresh speed [s]:
0.2s
Example
P-3
Anomaly
Create anomaly
Anomaly time [s]:
4.1s
Anomaly type:
random
Min value
-1
Max value
1
Detector
RNN Based
Detector model:
Example
P-3
Selected detector model: P-3 (25 input(s))

Measuring the quality of anomaly detection

- Example quality metrics:
  - NAB Score (Numenta Anomaly Benchmark)
  - Dice coefficient: $2 \times |X \cap Y| \,/\, (|X| + |Y|)$
  - F-score and other metrics based on the confusion matrix





Measuring the quality of anomaly detection

- Example quality metrics:
    - NAB Score (Numenta Anomaly Benchmark)
    - Dice coefficient: $2 \times |X \cap Y| \,/\, (|X| + |Y|)$
    - F-score and other metrics based on the confusion matrix

- **Various metrics are used across papers**

- All metrics are designed for **supervised set-ups**

Conclusions

- The community **lacks good anomaly detection datasets**
- **Digital twins and simulations** may help us these issues
- **Our anomaly detection looks promising** in finding potential anomalies (TBV, e.g., in OPS-SAT)
  - The entire process runs in **unsupervised mode**
- **Determining metrics to quantify the anomaly detection** is a (huge) challenge → we need rigorous quantitative, qualitative and statistical validation

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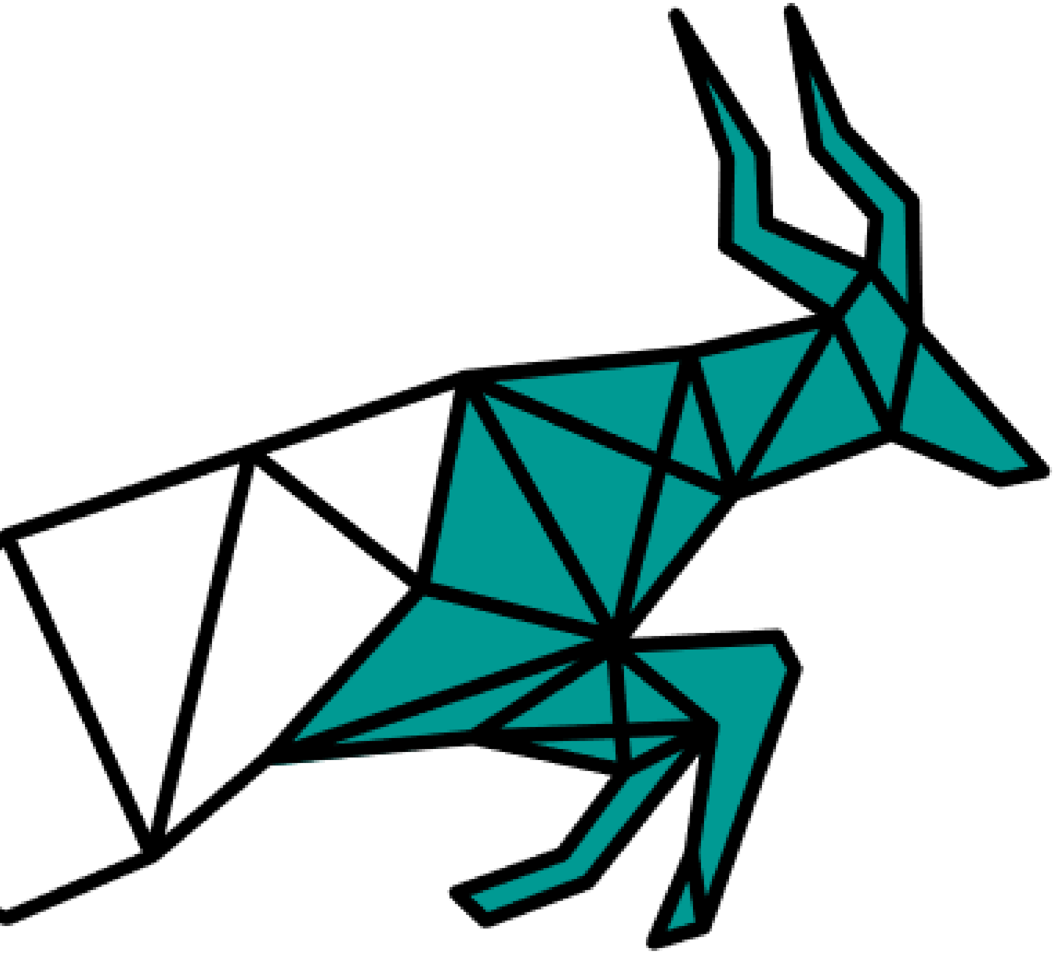

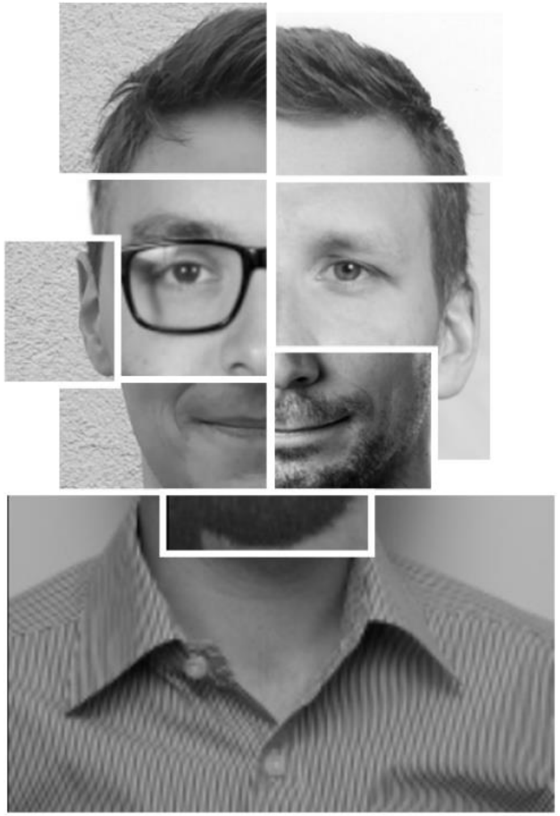

Antelope: Towards on-board anomaly detection in telemetry data using deep learning

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