Validation of timeseries anomaly detection methods in noise and vibration testing

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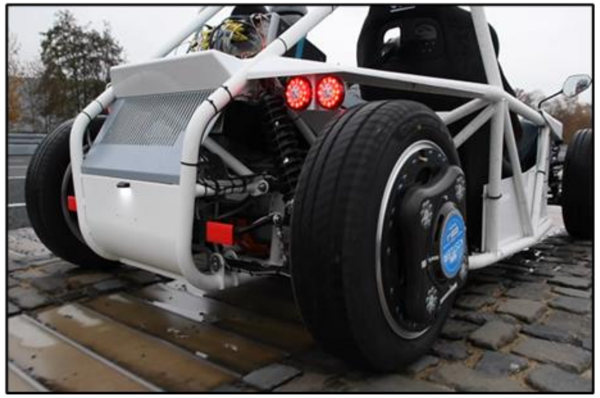
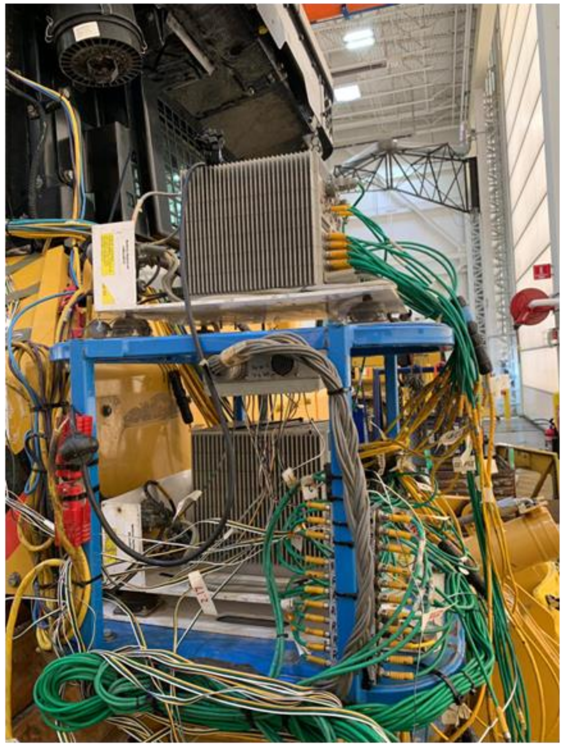
Introduction

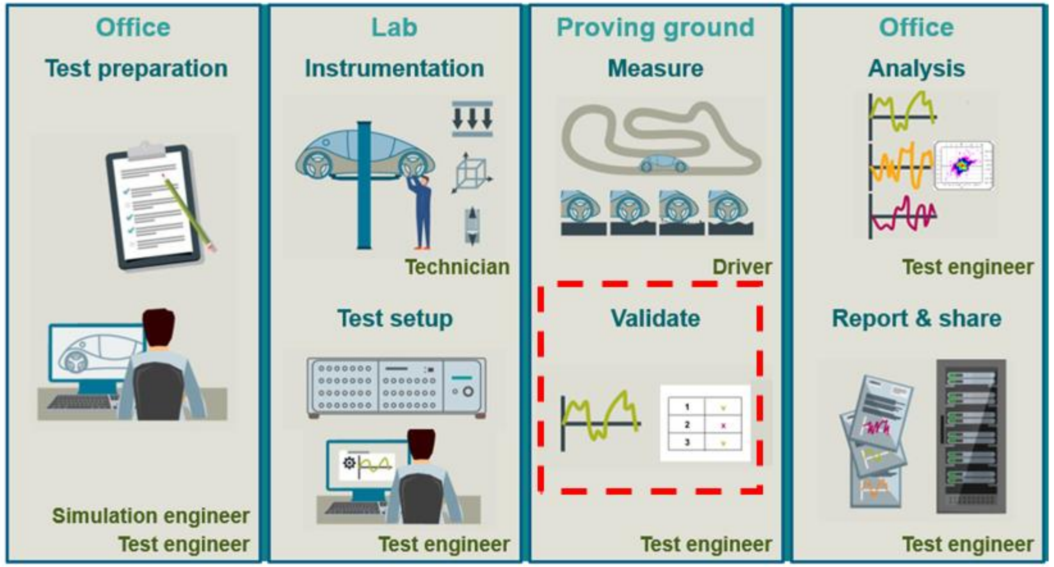
Acoustic measurements in a wind tunnel (typical configurations include a few 100 channels)



Automotive Proving Ground Testing
Rough roads, non-stationarity (e.g. run-ups),



Instrumentation example



Large # of sensors, sensor types, cables, conditions

Sensor failures and instrumentation mistakes

Labor-intensive measurement & analysis process

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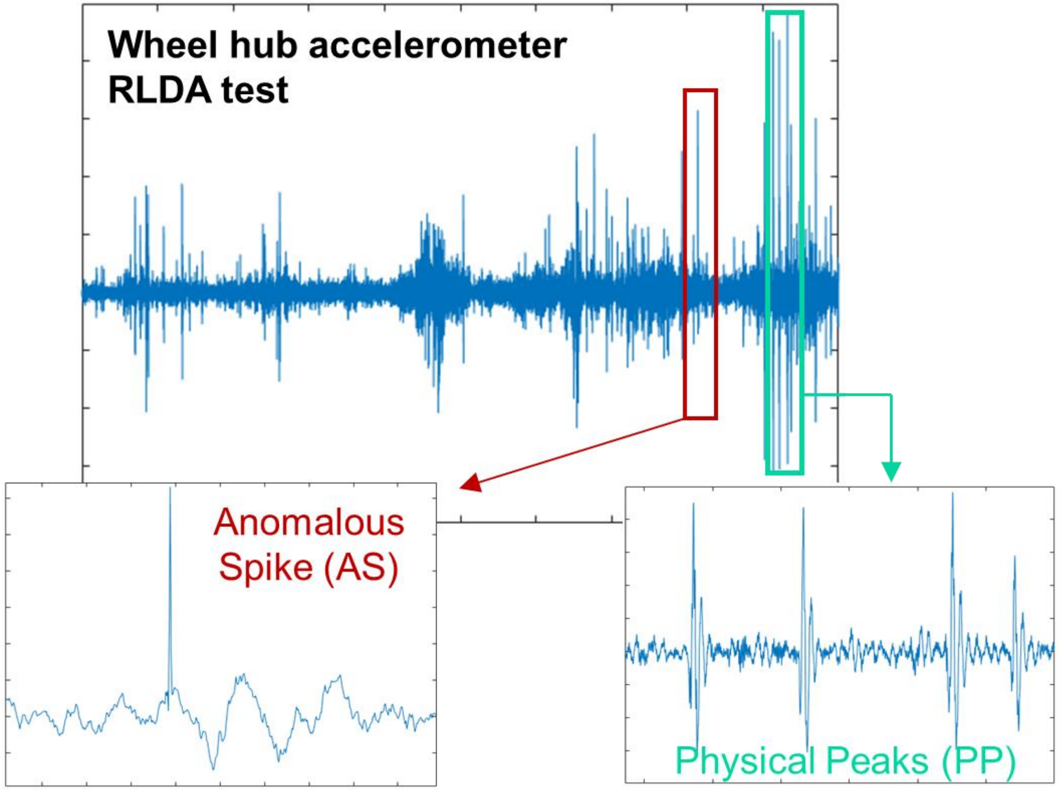
Introduction
Previous work and current goal

Previous works: detect specific anomalies which happen often (e.g. spikes)



Current goal: achieve a "universal" anomaly detection for a large variety of anomalies, also for anomalies that has never been encountered previously

- Cornelis, Bram & Deuschle, Federico & Gryllias, Konstantinos. (2023). Performance study of DTW-based spike measurement anomaly detection in sensors on real world tests.
- Cornelis, Bram & Peeters, Bart. (2014). Online Bayesian spike removal algorithms for structural health monitoring of vehicle components.

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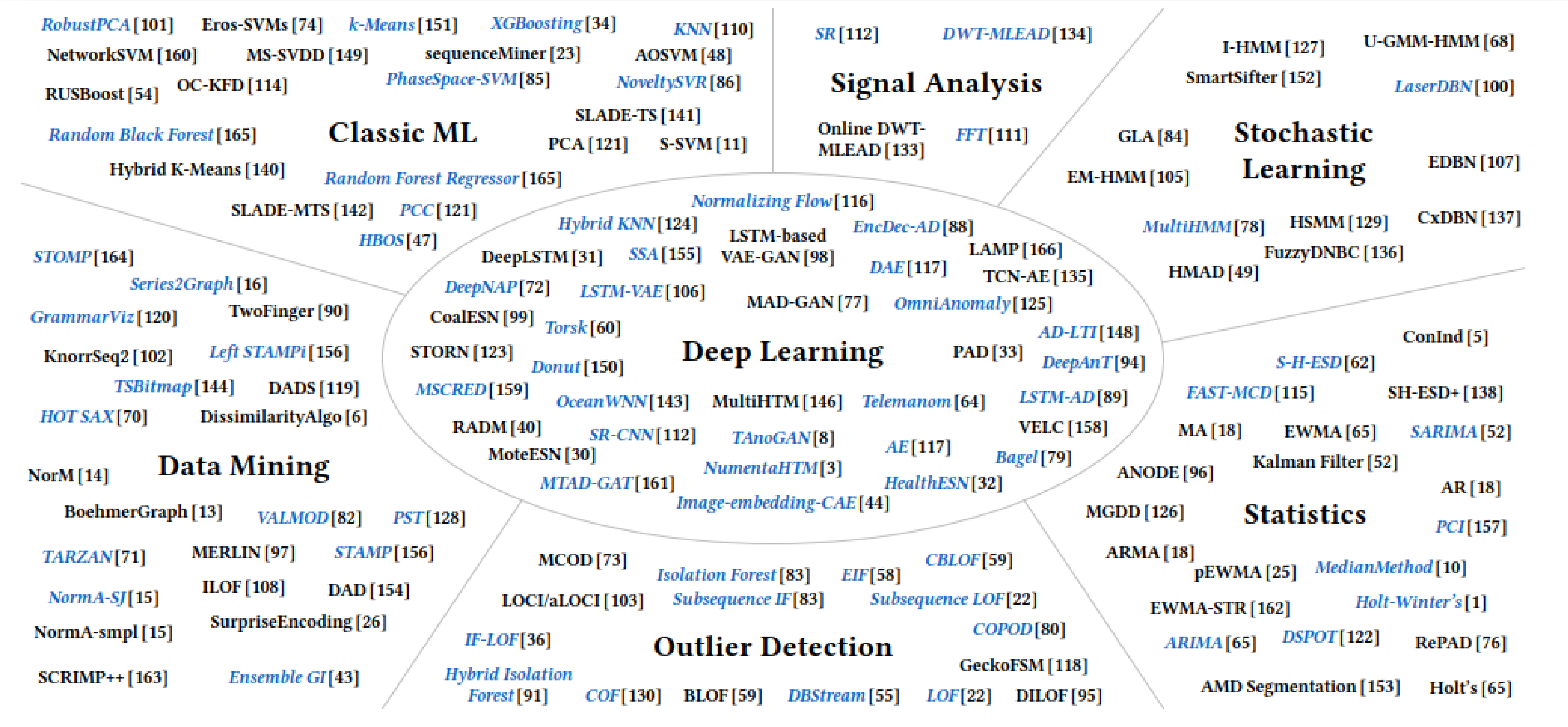
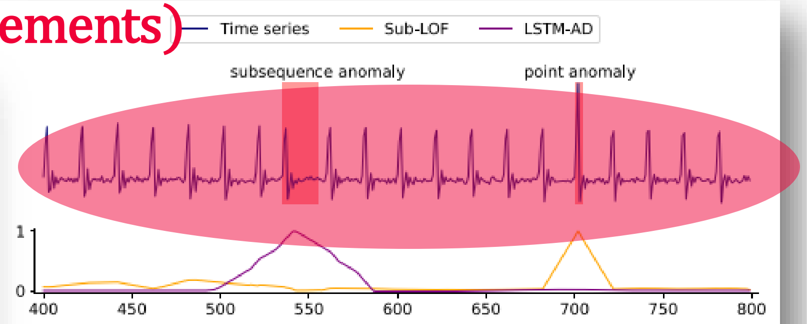
Methodology

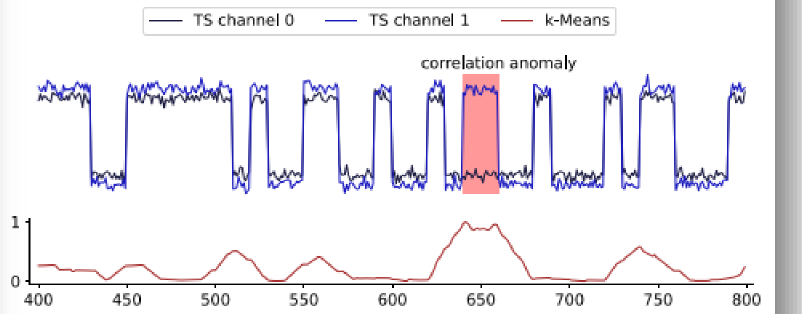
Surveys on time series anomaly detection methods

not for our kind of signals (noise and vibration measurements)





(a) Synthetic *univariate* time series resembling an ECG signal with a subsequence anomaly (pattern shift), a point anomaly (extremum), and the scorings of LSTM-AD and Sub-LOF.



(b) Synthetic *multivariate* time series with a correlation anomaly and the scoring of k-Means.

S. Schmidl, P. Wenig, and T. Papenbrock, "Anomaly detection in time series: a comprehensive evaluation", Proceedings of the VLDB Endowment, 2022, 15(9), pp.1779-1797.

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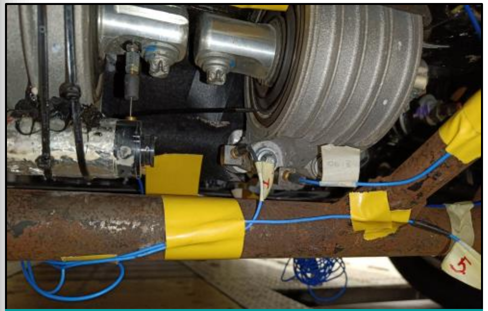
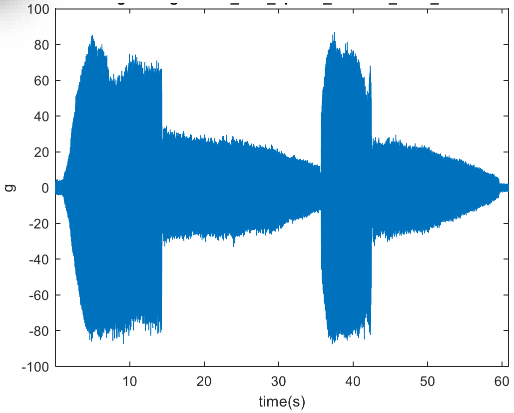
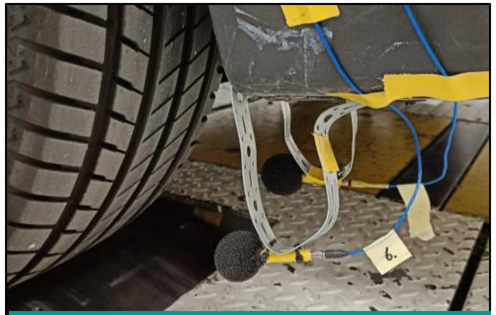
Methodology
Create a benchmark dataset

Real NVH measurements to serve as “healthy” base oscillation
- **Test vehicle:** BMW iX3
- **Run-up condition** @ Chassis dynamometer
- **Reference channels: 3** Channels (3 sensors)
- **Sampling frequency:** 51200 Hz

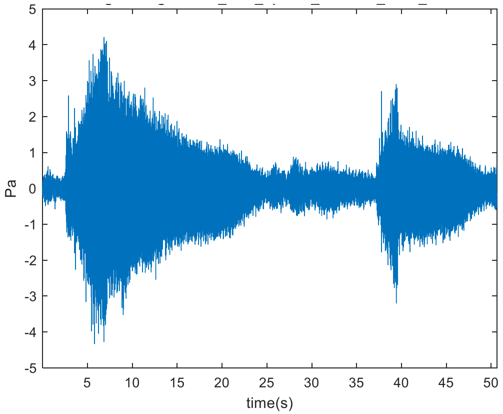


ENG:MTrr

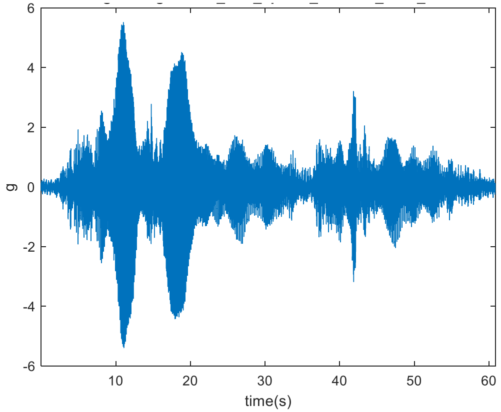




TIRE:RELE_B



STWL:Bott



Test campaign from Deuschle, Federico

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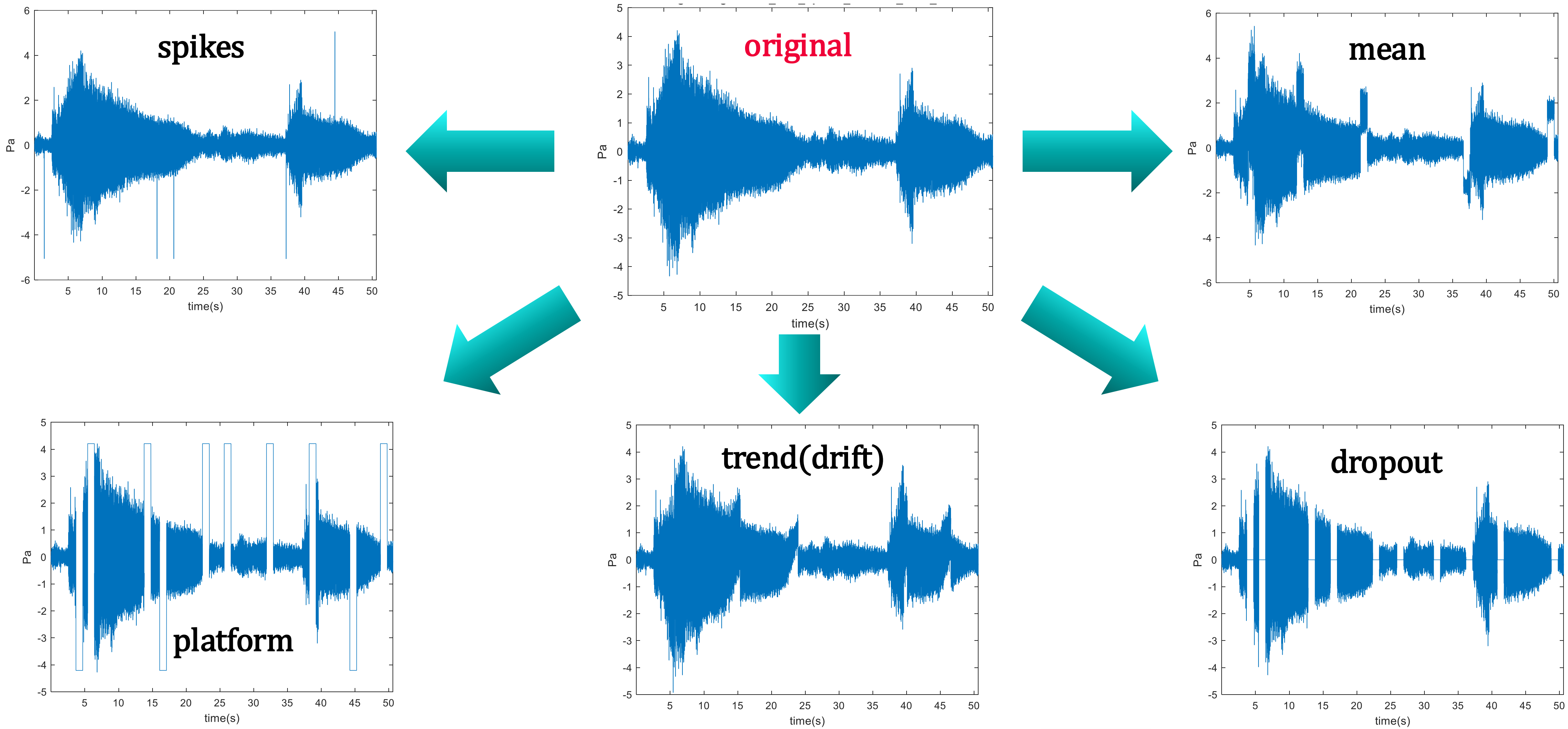
Methodology

Create a benchmark dataset: add synthetic anomalies



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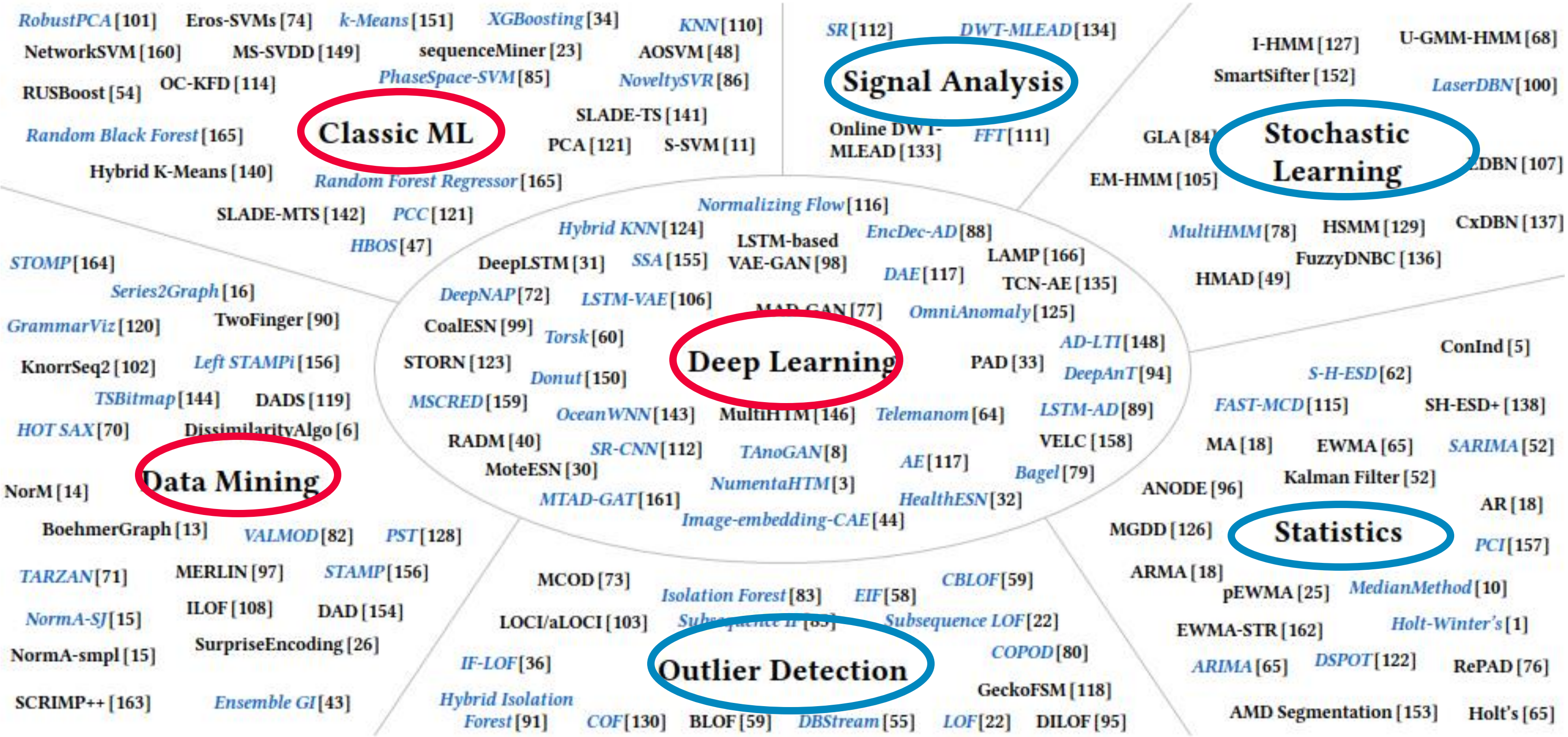
Anomaly Detection Algorithms

Statistical / signal processing methods VS machine learning methods

machine learning methods: higher implementation complexity

evaluate if statistical / signal processing methods could already be sufficient



S. Schmidl, P. Wenig, and T. Papenbrock, "Anomaly detection in time series: a comprehensive evaluation", Proceedings of the VLDB Endowment, 2022, 15(9), pp.1779-1797.

Anomaly Detection Algorithms

- AR model

$$y[n] = \sum_{k=1}^{K} a_k y[n-k]$$

- ARMA

$$y[n] = \sum_{k=1}^{K} a_k y[n-k] + \sum_{m=1}^{M} b_m x[n-m]$$

- Median Method

To compare the difference between the median of a neighborhood and the observed data value with a threshold value.

- FFT

Use Fast Fourier Transform to highlight the areas with high frequency change.

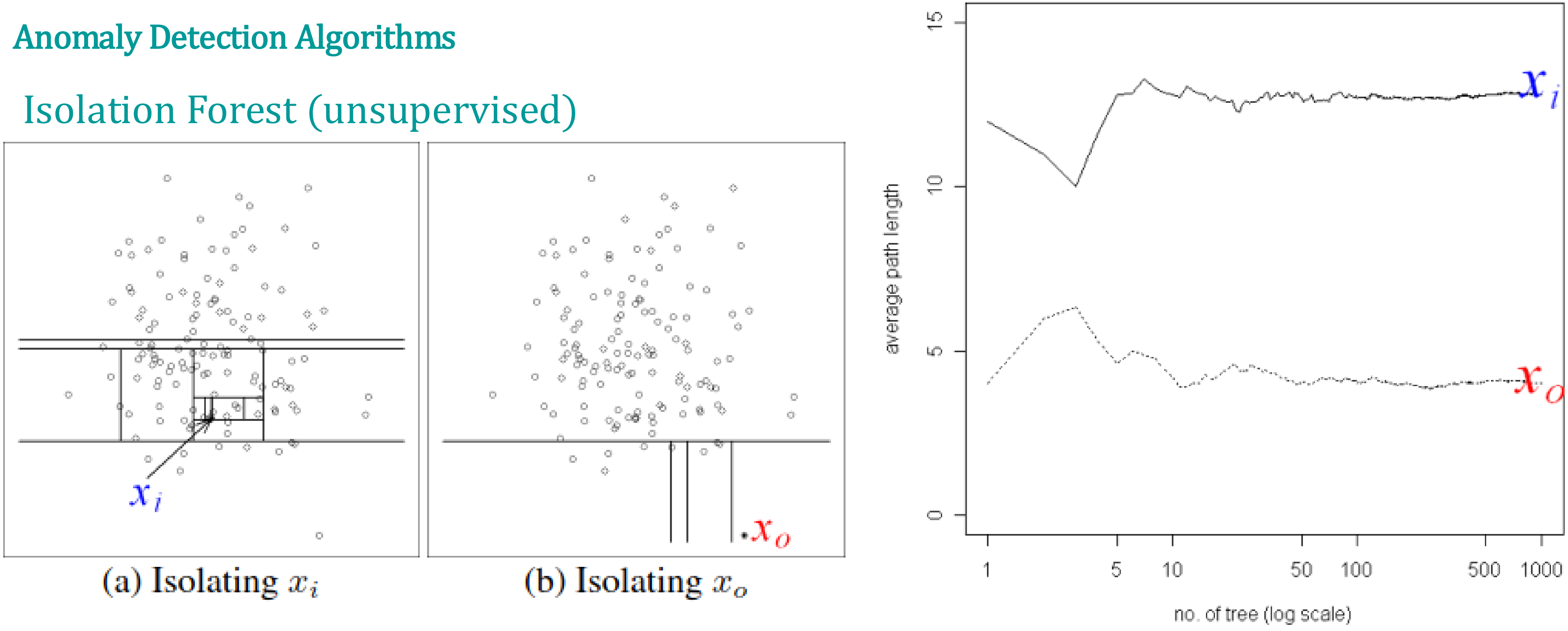
- AbsMean

Compare each data point with the $abs(mean(y_{neighborhood}))$

- Tunnicliffe Wilson, Granville. (2016). Time Series Analysis: Forecasting and Control,5th Edition, by George E. P. Box, Gwilym M. Jenkins, Gregory C. Reinsel and Greta M. Ljung, 2015. Published by John Wiley and Sons Inc., Hoboken, New Jersey, pp. 712. ISBN: 978-1-118-67502-1. Journal of Time Series Analysis. 37. n/a-n/a. 10.1111/jtsa.12194.
- Basu, Sabyasachi & Meckesheimer, Martin. (2007). Automatic outlier detection for time series: An application to sensor data. Knowl. Inf. Syst.. 11. 137-154. 10.1007/s10115-006-0026-6.
- Rasheed, Faraz & Peng, Peter & Alhajj, Reda & Rokne, Jon. (2009). Fourier Transform Based Spatial Outlier Mining. 317-324. 10.1007/978-3-642-04394-9_39.

Anomaly Detection Algorithms

Isolation Forest (unsupervised)



Five features: average, std-dev, energy, kurtosis, and skew.

(c) Average path lengths converge

- Liu, Fei Tony & Ting, Kai & Zhou, Zhi-Hua. (2009). Isolation Forest. 413 - 422. 10.1109/ICDM.2008.17.

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Anomaly Detection Algorithms
Criteria

1. point-wise

2. window-wise
    - Divide the signal in windows of 0.1s (5120 points)
    - IF Window contains ≥ 1 anomaly points: anomaly window
    - IF Window contains no anomaly points at all: normal window

$$\boxed{\begin{aligned} precision &= \frac{tp}{tp + fp} \\ recall &= \frac{tp}{tp + fn} \end{aligned}}$$

- *tp = true anomaly is correctly detected as anomaly*
- *fp = healthy data is incorrectly detected as anomaly (false alarm)*
- *fn = true anomaly is incorrectly indicated as healthy*

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Results
Window-wise performance

	AR	ARMA	Median Method	FFT	AbsMean	Isolation Forest
spike	$precision=1$ $recall=1$	$precision=1$ $recall=1$	$precision=1$ $recall=1$	$precision=0.0088$ $recall=1$	$precision=NaN$ $recall=0$	$precision=0.1667$ $recall=1$
platform	$precision=1$ $recall=0.1515$	$precision=1$ $recall=1$	$precision=1$ $recall=0.9772$	$precision=0.5633$ $recall=0.9820$	$precision=0.6247$ $recall=0.9962$	$precision=1$ $recall=0.1188$
dropout	$precision=1$ $recall=0.1293$	$precision=0.9907$ $recall=0.9507$	$precision=1$ $recall=0.9770$	$precision=0.5049$ $recall=0.9924$	$precision=NaN$ $recall=0$	$precision=NaN$ $recall=0$
mean	$precision=1$ $recall=0.1493$	$precision=0.8282$ $recall=0.1607$	$precision=NaN$ $recall=0$	$precision=0$ $recall=0$	$precision=0.6400$ $recall=0.9846$	$precision=0.6173$ $recall=0.4673$
trend	$precision=1$ $recall=0.0476$	$precision=0.8333$ $recall=0.0556$	$precision=NaN$ $recall=0$	$precision=0.1282$ $recall=0.1111$	$precision=0.9300$ $recall=0.8857$	$precision=0.4660$ $recall=0.4444$

Results

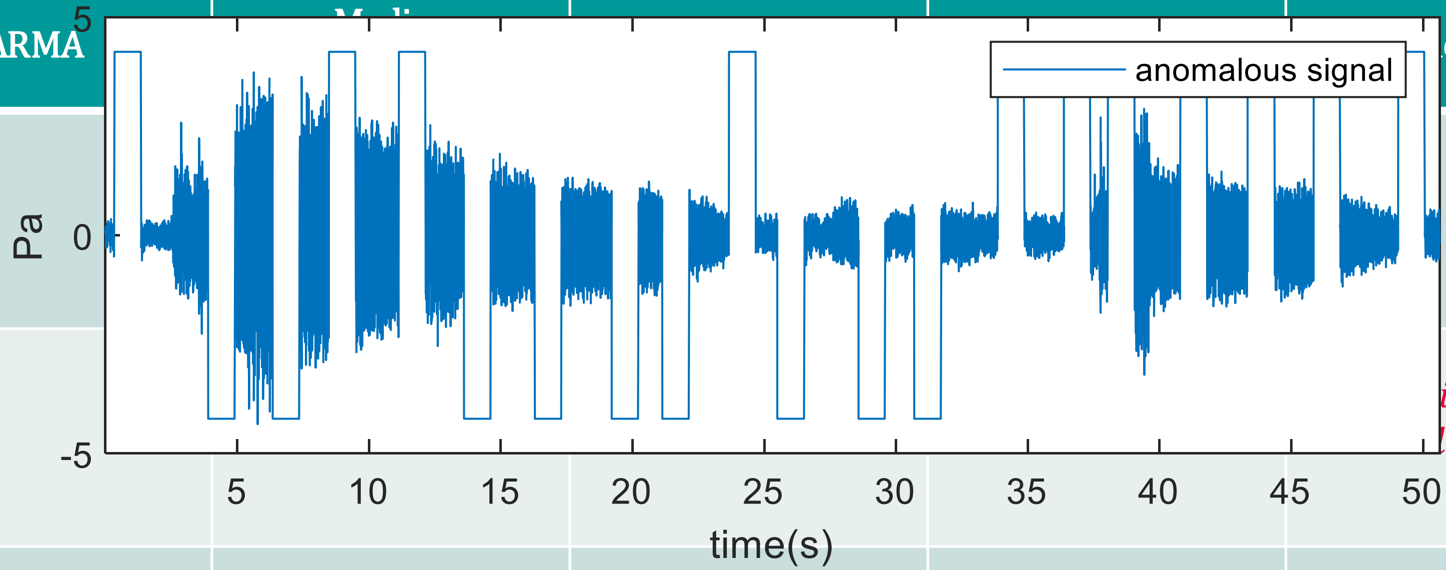
Suitable algorithms for each anomaly type

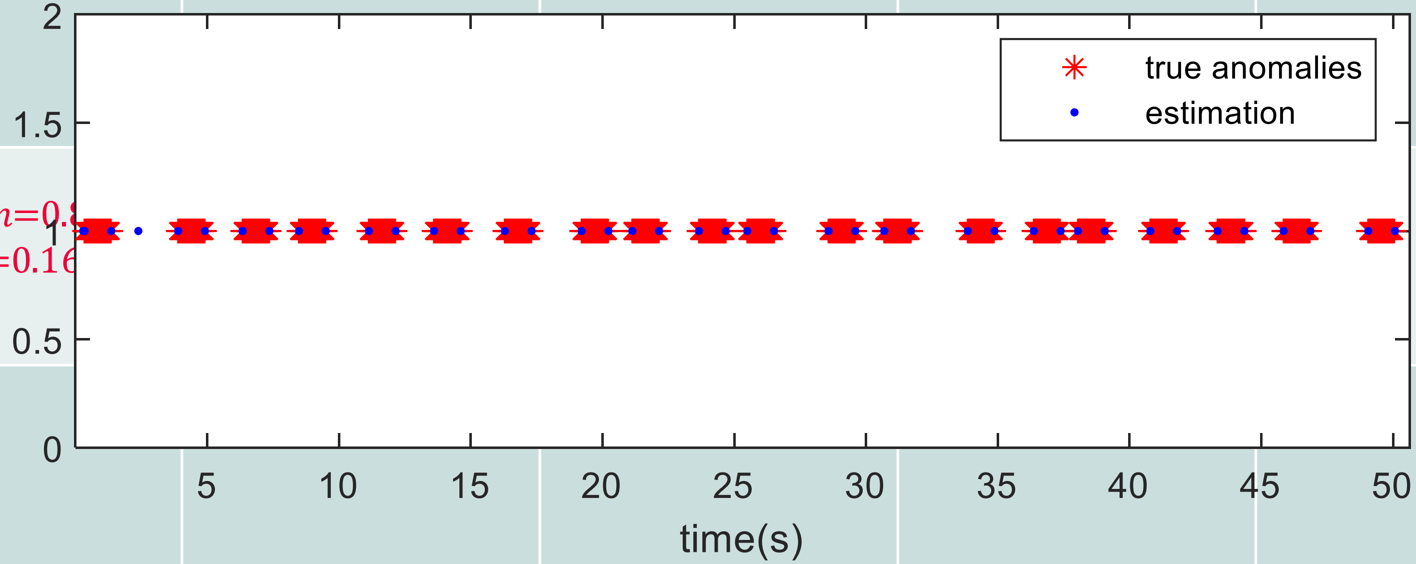
	AR	ARMA	Median Method	FFT	AbsMean	Isolation Forest
spike	$precision=1$ $recall=1$	$precision=1$ $recall=1$	$precision=1$ $recall=1$			
platform		$precision=1$ $recall=1$	$precision=1$ $recall=0.9772$			
dropout		$precision=0.9907$ $recall=0.9507$	$precision=1$ $recall=0.9770$			
mean					$precision=0.6400$ $recall=0.9846$	
trend					$precision=0.9300$ $recall=0.8857$	

Results

high precision & low recall

	AR	ARMA				on Forest
spike						
platform	*precision*=1 *recall*=0.1515					ision=1 =0.1188
dropout	*precision*=1 *recall*=0.1293					
mean	*precision*=1 *recall*=0.1493	*precision*=0. *recall*=0.16				
trend						

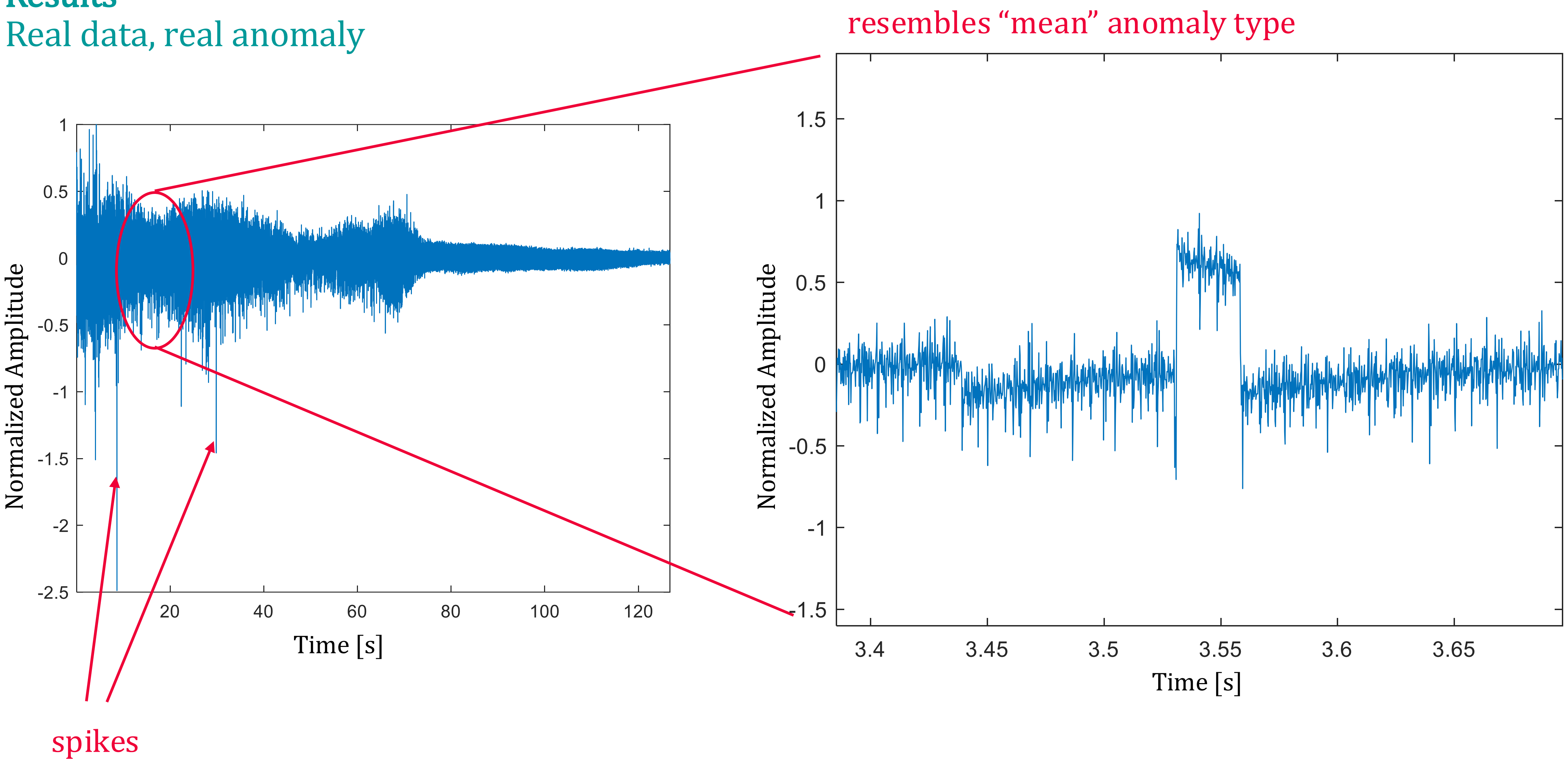




Results
No detections

	AR	ARMA	Median Method	FFT	AbsMean	Isolation Forest
spike					$precision = NaN$ $recall = 0$	
platform						
dropout					$precision = NaN$ $recall = 0$	$precision = NaN$ $recall = 0$
mean						
trend						

Results
Real data, real anomaly



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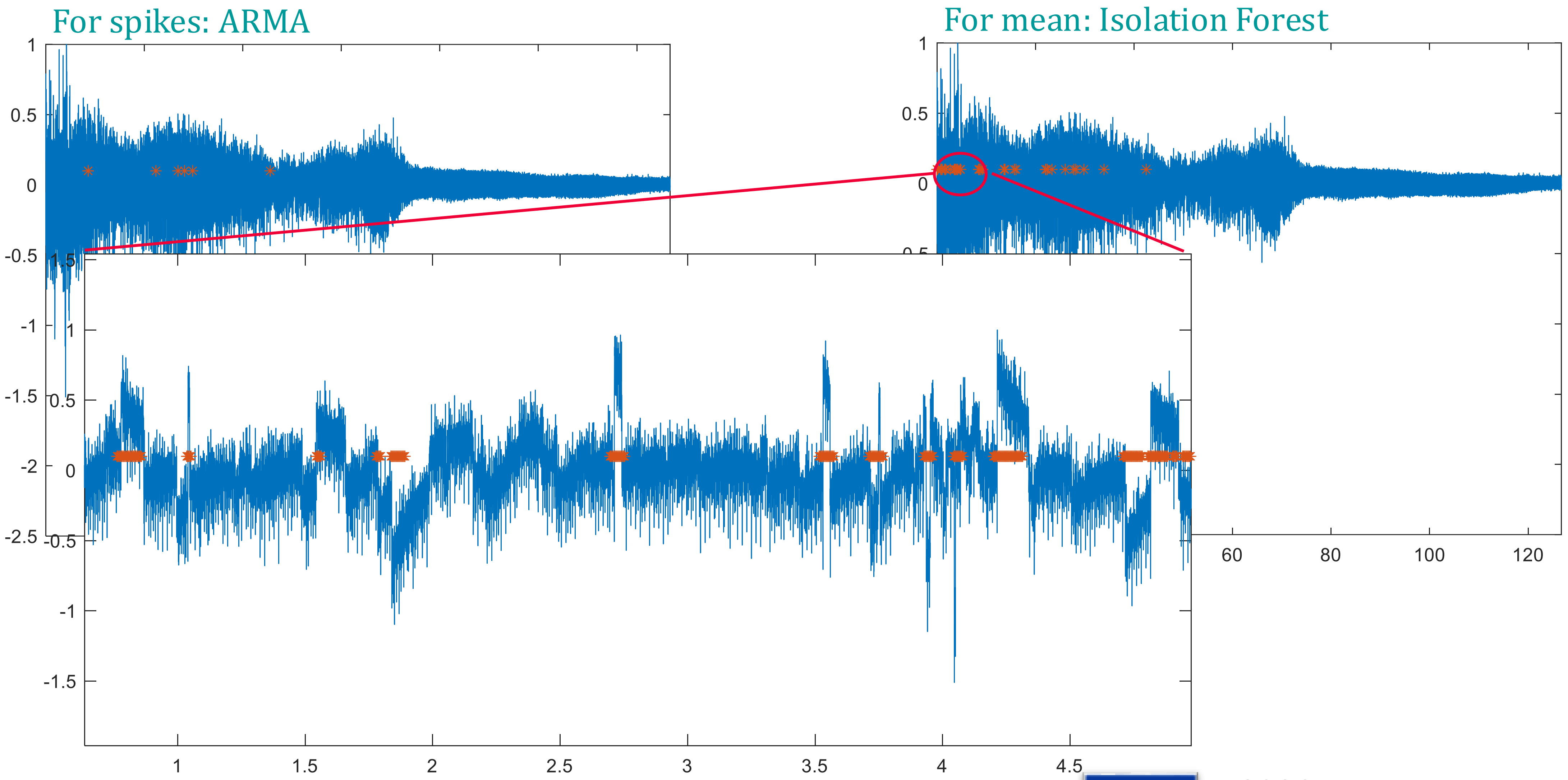
Results

Real data, real anomaly



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Conclusion and Next Steps

- Post-processing of the outputs of the anomaly detection methods is needed, in order to obtain a useful anomaly score to a test engineer
- A one-size-fits-all universal anomaly detection algorithm is not yet found
- Machine learning approaches need to be further investigated
- Next steps: training on a presumed anomaly-free data. Semi-supervised isolation forest (novelty detection) or other semi-supervised methods

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Thank you!

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