TECHNISCHE UNIVERSITÄT DRESDEN

DRESDEN concept

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Unsupervised Machine Learning for Anomaly Detection using an Autoencoder

Profilprojekt Anwendungsforschung in der Informatik

xx.03.2020

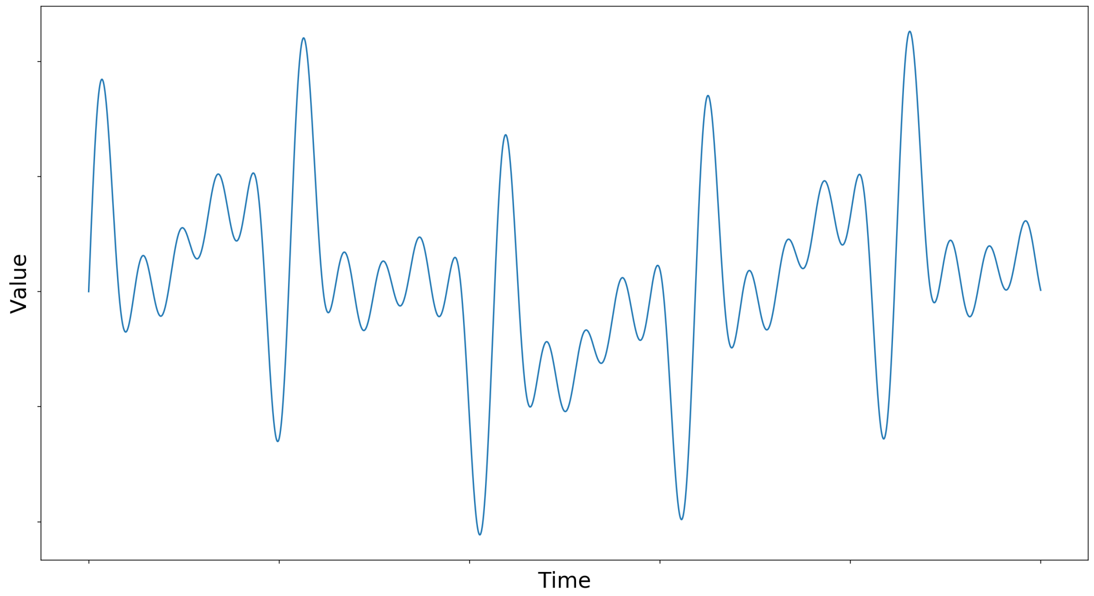
Agenda

1. Motivation - Anomaly Detection
2. Available Data
3. Task
4. Classical Approaches
    1. Autocorrelation
    2. Mean Absolute Change
5. Machine Learning Approach
    1. Autoencoder Concept
    2. Architecture
6. Results
    1. Qualitatively
    2. Quantitively
    3. Latent Spaces
    4. Reduced Model
7. Conclusion, Outlook and Problems

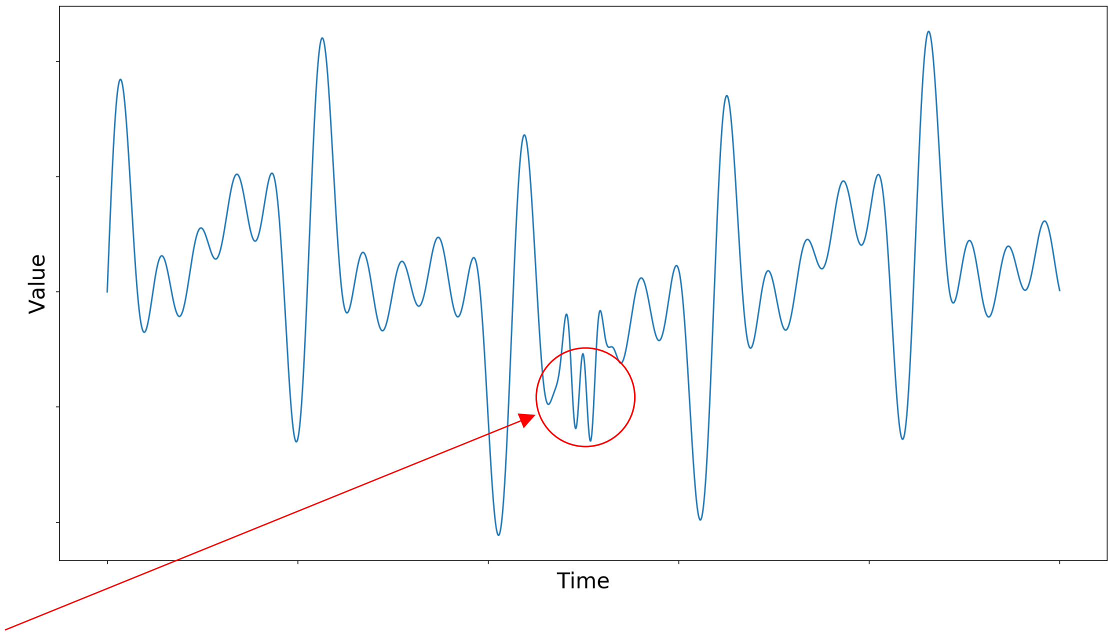
Motivation - Anomaly Detection

- Detect abnormal behaviour/patterns of measurements of a machine
- **Catch:** It is unknown how the anomaly manifests itself in the measurement data (think nuclear power plant)

Normal behaviour



Possible error behaviour

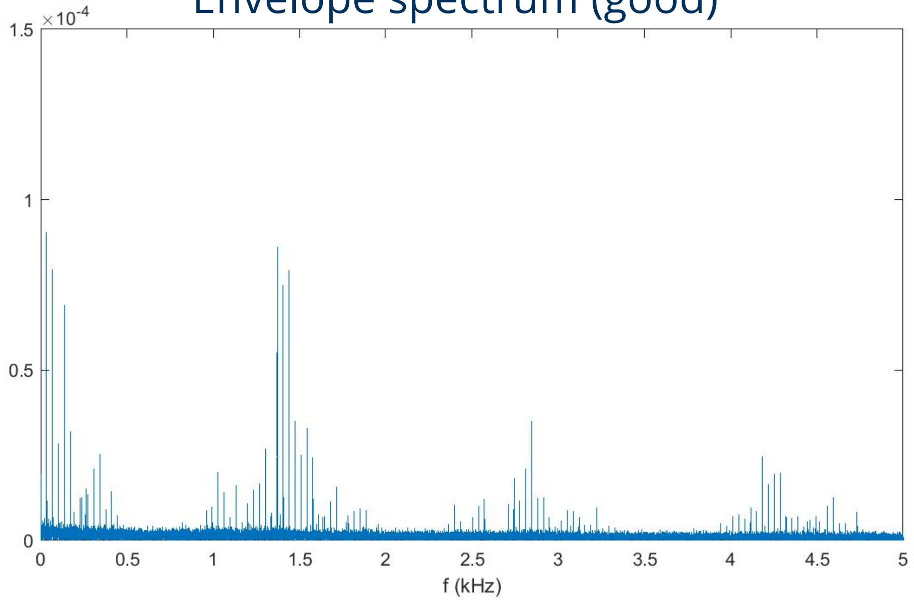


Previously unknown behaviour. Is this an error or just noise/measurement error?

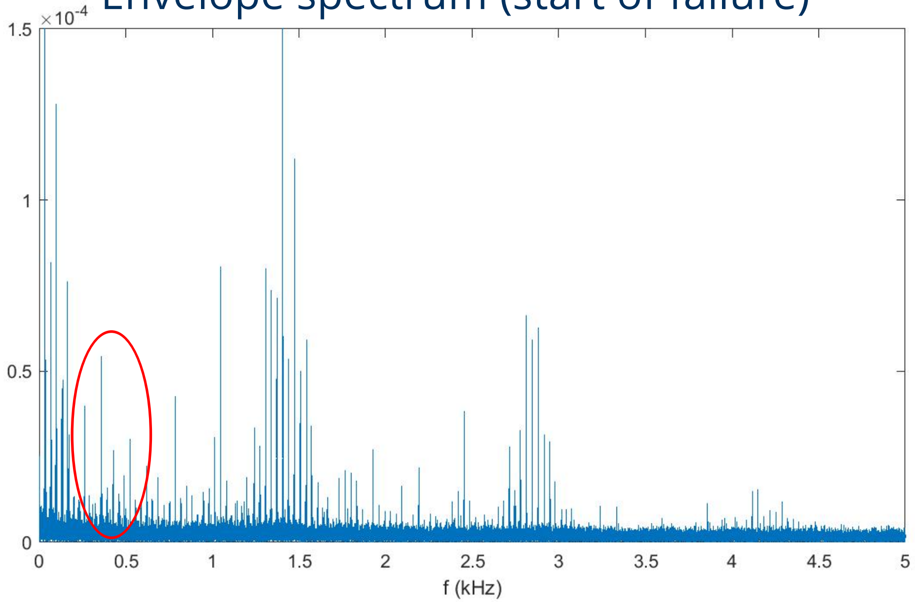
Available Data

- Bearings running until they break → 2 datasets available (**"Lager 4"** and **"Lager 5"**)
- Every 2 minutes 4 separate measurements from 4 ultrasonic sensors
- Available "ground truth" data: Raw signal, amplitude spectrum, spectrogram, **envelope spectrum**

Envelope spectrum (good)



Envelope spectrum (start of failure)

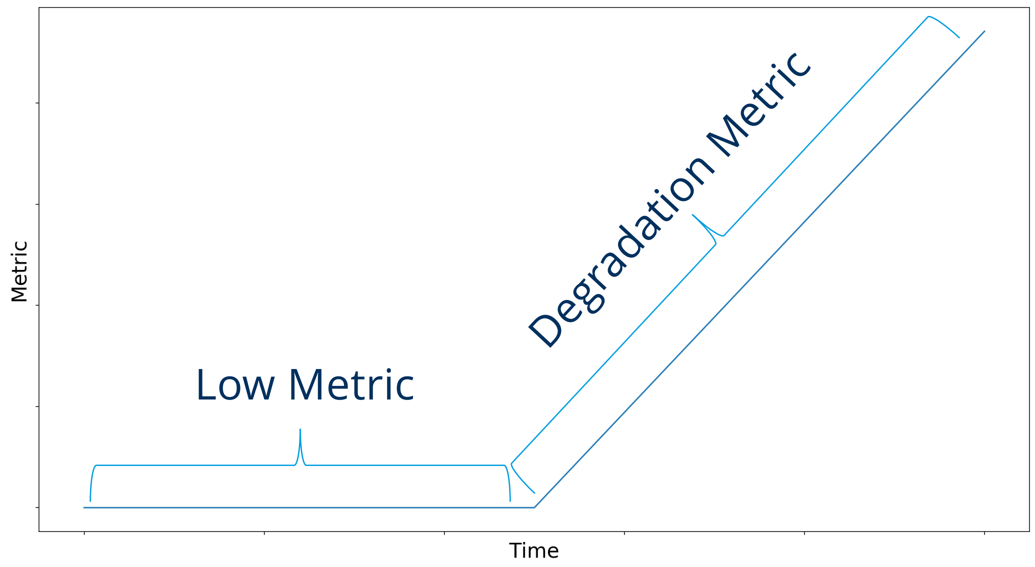


- **Expert Feature:** Specific area in envelope spectrum that shows more noise as bearing is breaking
- Knowledge of expert feature is very problem specific

Task

Raw audio bearing should contain all the necessary information to detect the starting point of the degradation.

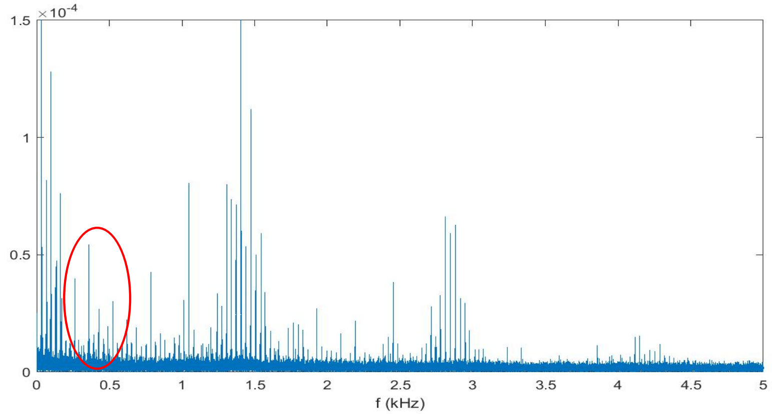
Use an appropriate machine learning scheme to map non pre-processed audio recording to an error plot.



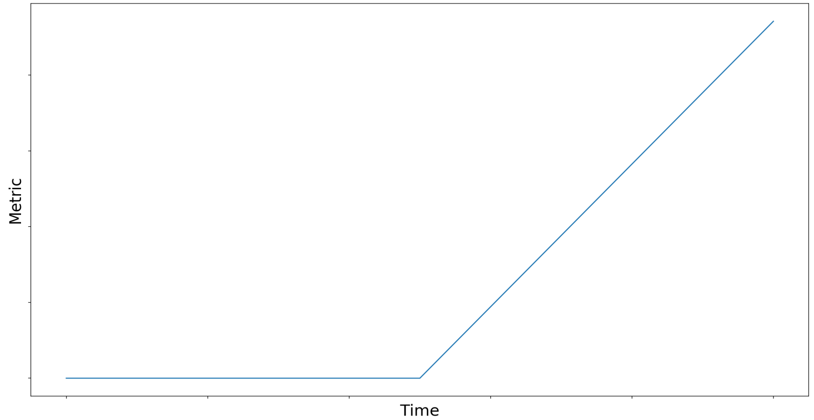
Main Idea:

- Use a metric that increases when bearing degrades → Change point visible
- Unsupervised approach possible without knowing labels beforehand
- Reduction of expert feature possibilities to universal metric plot
- Evaluation using ROC and AUC

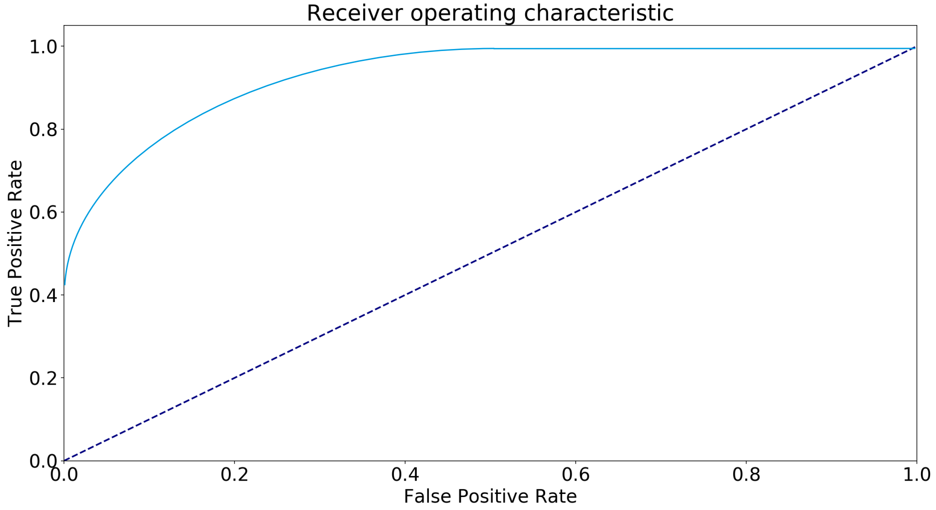
Main Idea



Determine ground truth changepoint time



Create metric

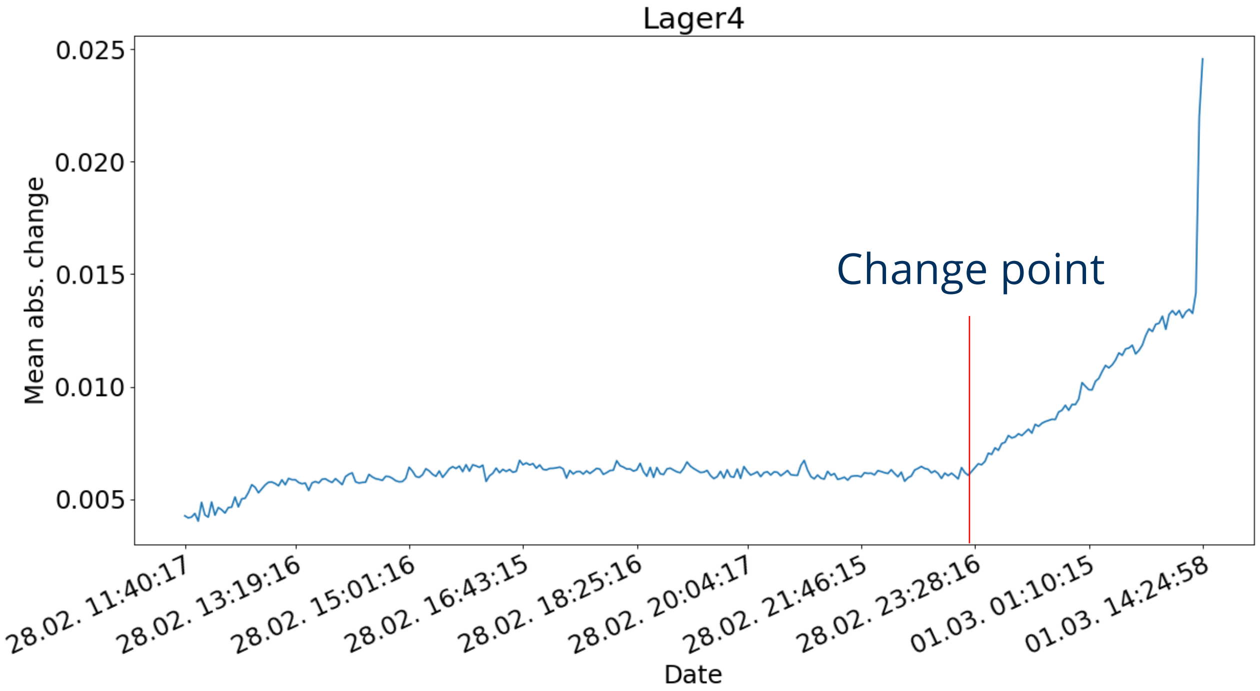


- Evaluate metric based on separability using a threshold with AUC-ROC curve
- We compare all methods based on AUC score

Classical Approaches (non machine learning)

- We calculate 65 classical statistical features and search for a separability threshold
- This includes: autocorrelation, kurtosis, linear trend, mean, median, skewness, variance, …

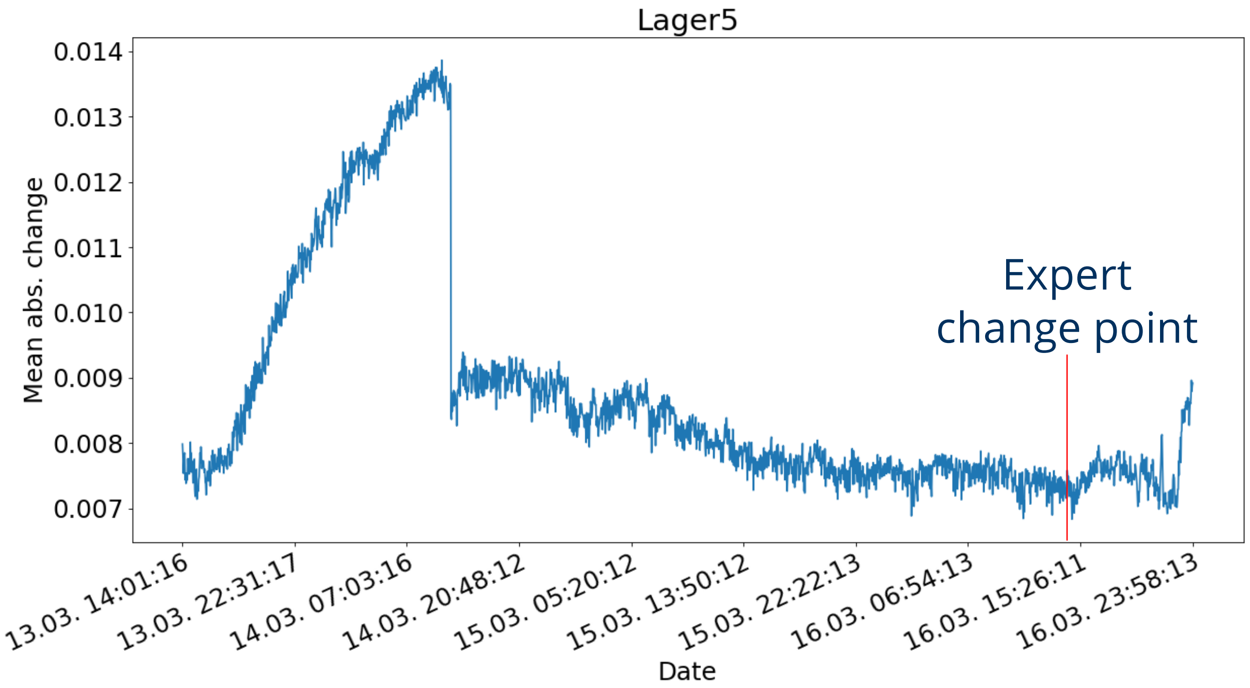
1. **Mean absolute change:**



- Describes the absolute change between two consecutive measurement points
- Error = Mean abs. change
- Error curve looks nearly ideal
- Change point almost perfectly hits the expert opinion
- AUC = 0.99

Problems with mean absolute change

- **Lager 5** does not look so nice …

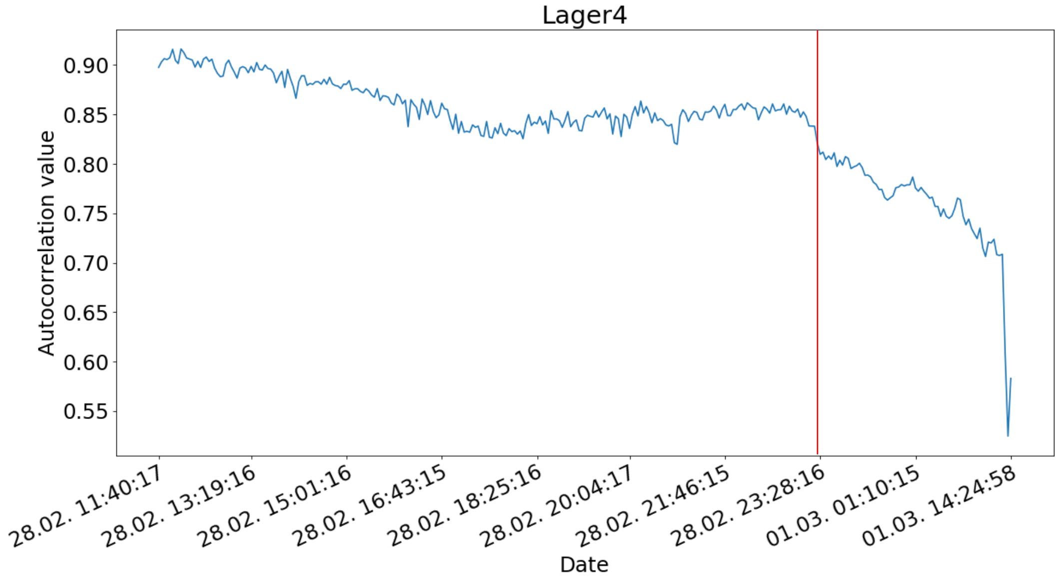


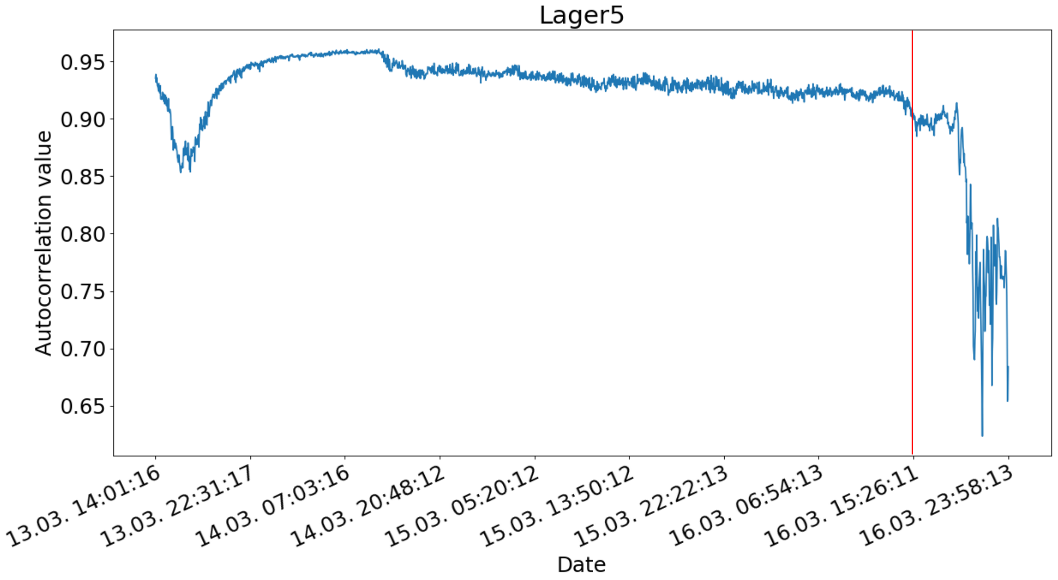
- Error seems to happen right at the start
- Afterwards big drop in error
- Error after change point is not increasing
- AUC = 0.21 (classifier could be reversed)

→ **Does not work universally**

Autocorrelation

- As bearing rotates one full revolution measurement values should correlate with previous revolution
- Using the microphones sampling frequency → 6144 Measurement samples ⟷ one revolution





- **Lager 4** AUC = 1.00
- **Lager 5** AUC = 0.98

Problems with autocorrelation

- We need to specify the autocorrelation lag → we know the exact lag of 6144 thus the results are very good
- What if we don't know the "correct" lag?

AUC values for different lags

	128	256	512	1024	2048	4096	8192	16384
Lager 4	0.94	0.78	0.81	0.84	0.59	0.76	0.57	0.60
Lager 5	0.98	0.89	0.95	0.69	0.93	0.92	0.94	0.86

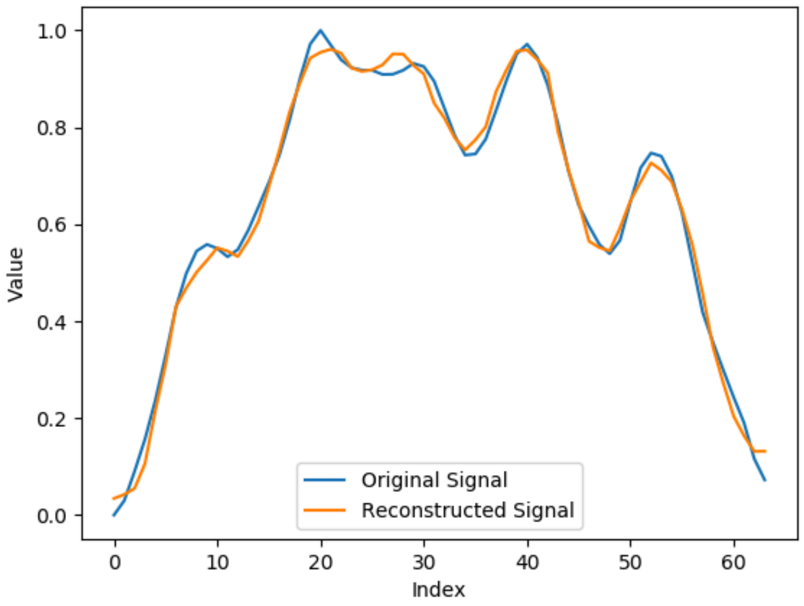
- Guessing the lag gets us random good and bad results

→ We require knowledge of the underlying problem to find optimal lag value

Machine Learning Approach - Autoencoder

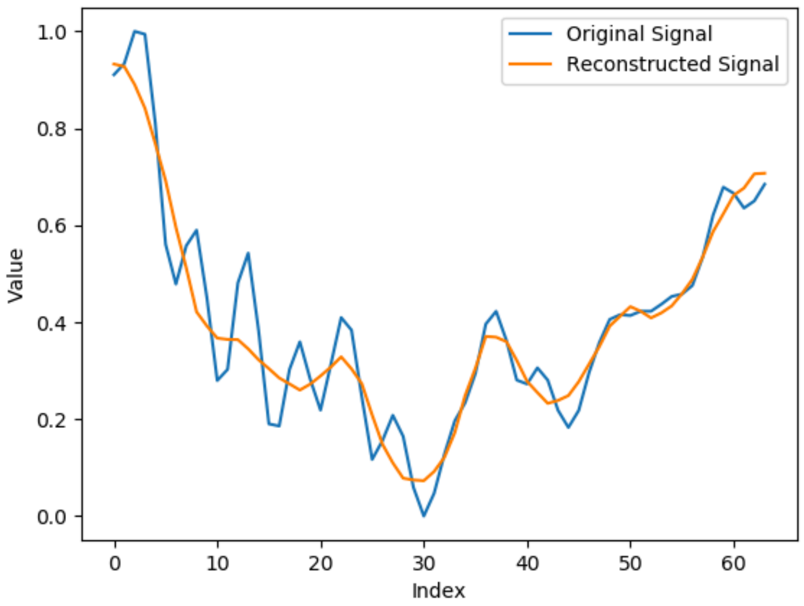
- Reconstruction of the $[0, 1]$ normalized original signal
- We expect the reconstruction of a healthy signal to be better than on a signal showing degradation
- **Evaluation metric:** Sum of the quadratic error of each time step in each measurement

Good reconstruction

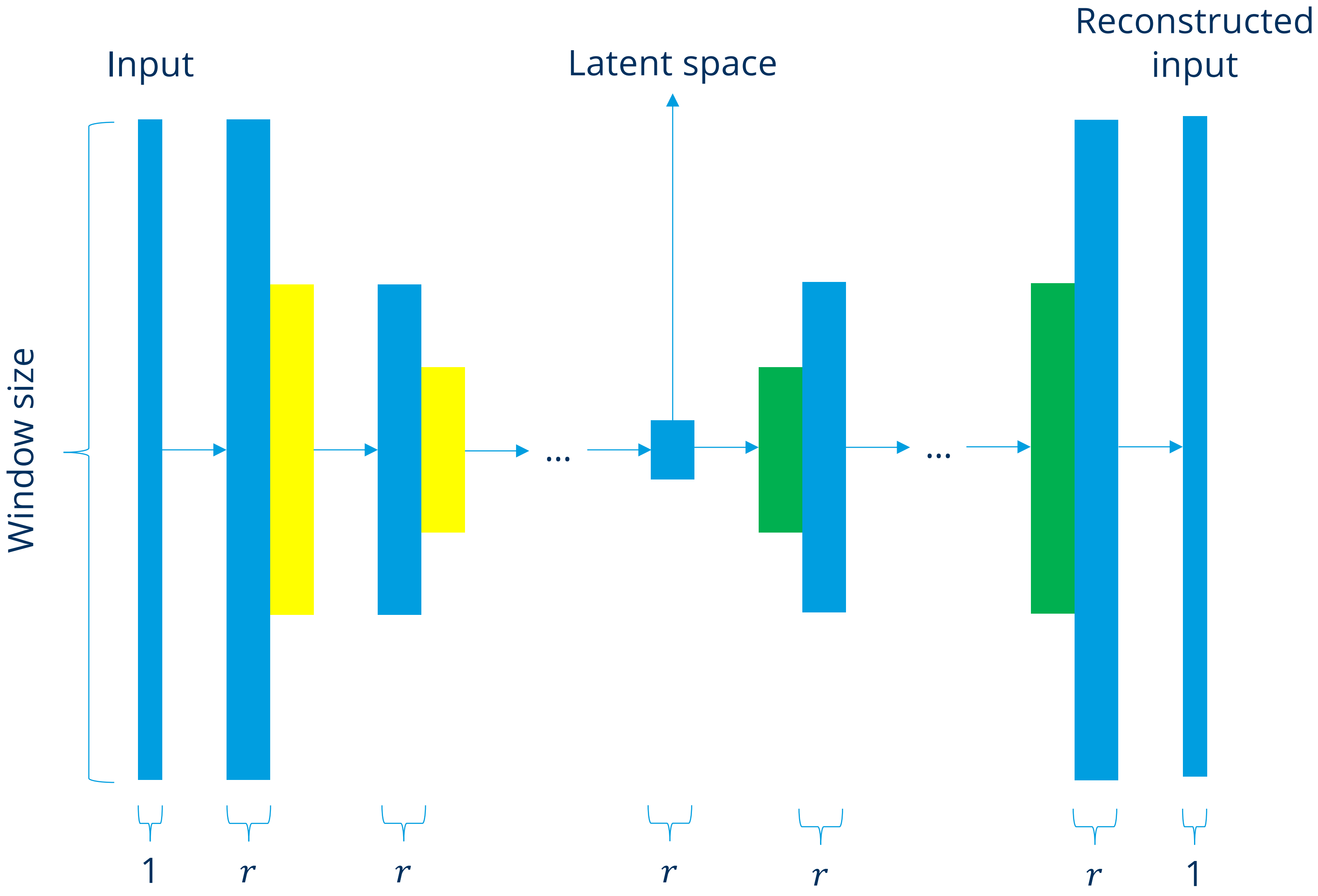


Degradation happens

Bad reconstruction



Autoencoder Architecture



Legend:

- 1D Convolution
- 1D Max pooling (2x)
- 1D Upsampling (2x)

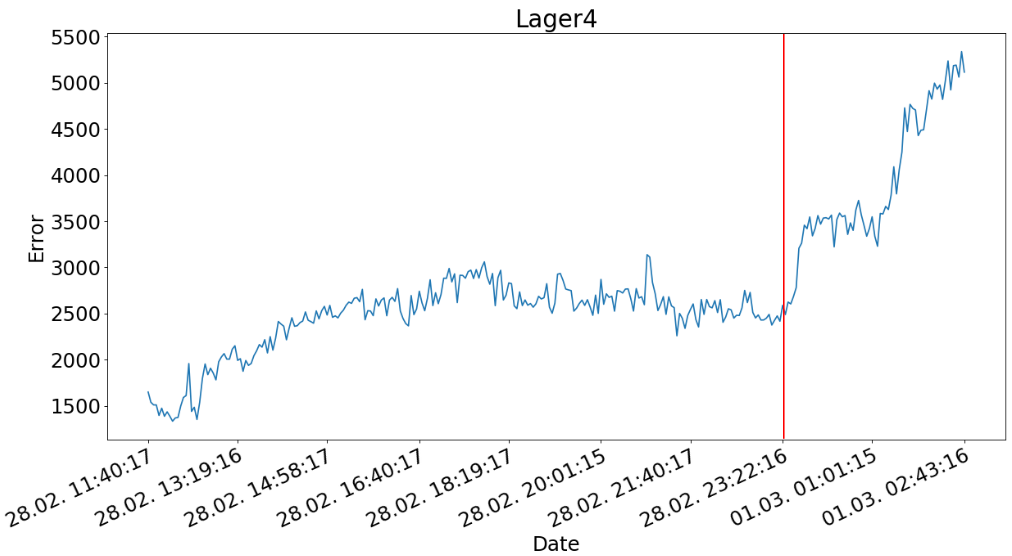
Parameters:

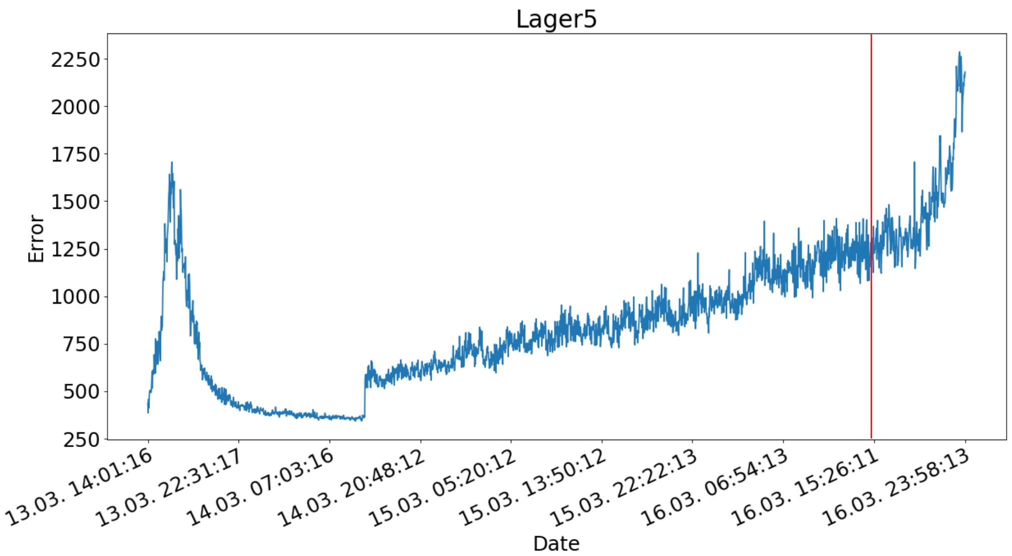
– **Loss:** MSE

– Overall there are 6 pooling stages → 64x reduction

$$r = \frac{64}{l}, \qquad l \in \{2, 4, 8\}$$

Autoencoder Results - Qualitatively





Window size: 128; Latent space size: 50%

- Behaviour of error is as expected: As bearing degrades error goes up (Lager 5 has longer warm-up time)
- Error functions shows signs of steps → indication of different error states
- Error curve is rather smooth thus making finding a threshold easier
- But: This plot is only for window size = 128. How do other window sizes behave?

Autoencoder Results - Quantitatively

Lager 4: AUC depending on window sizes and latent space size

	128	256	512	1024	2048	4096	6144	8192
50%	0.98	0.83	0.64	0.72	0.75	0.80	0.77	0.79
25%	0.82	0.59	0.47	0.57	0.62	0.75	0.73	0.77
12,5%	0.57	0.51	0.45	0.50	0.03 ?	0.67	0.64	0.69

Lager 5: AUC depending on window sizes and latent space size

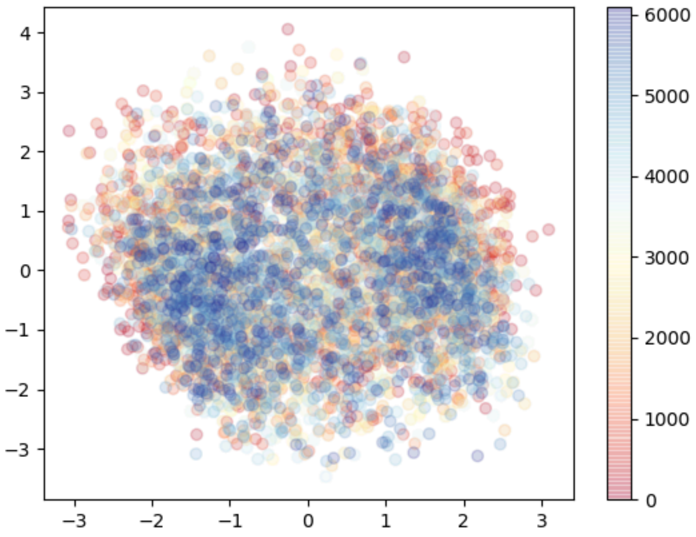
	128	256	512	1024	2048	4096	6144	8192
50%	0.97	0.92	0.91	0.82	0.87	0.70	xxx	0.77
25%	0.94	0.87	0.91	0.93	0.82	0.84	0.71	0.75
12,5%	0.91	0.96	0.72	0.88	0.93	0.84	0.73	0.70

- AUC performance seems to correlate with window size
- Network Lager 4, window size 4096, latent space 12,5%: learned the inverse of the expected behaviour

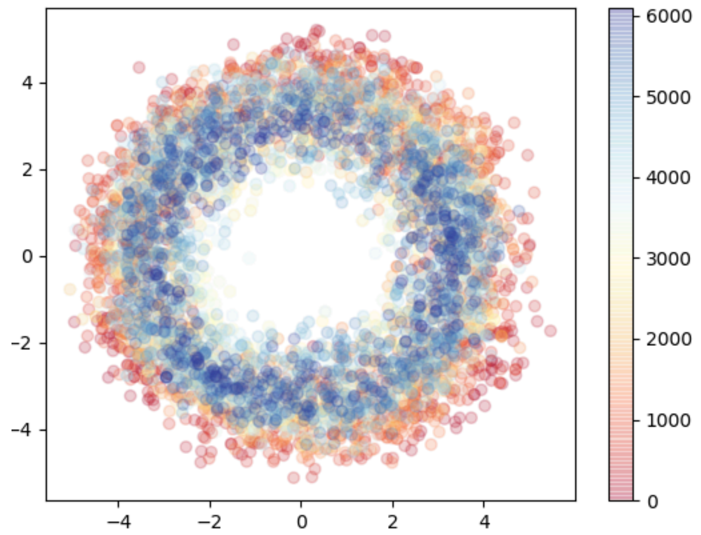
Autoencoder Results - Latent Spaces

- From previous experiments we expect a clustering of latent spaces when applying PCA or TSNE
- We plot latent spaces transformed by PCA into 2D as the bearing runs (from early = red to late = blue)
- TSNE did not yield any useful clustering results

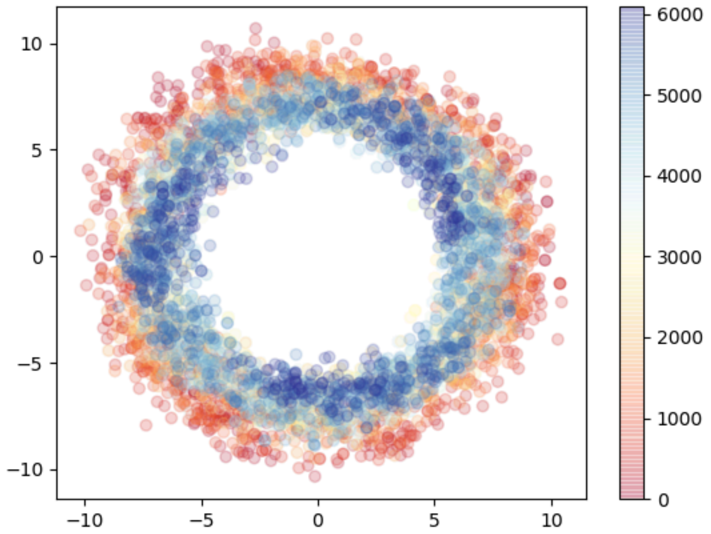
Lager 4; WS 128; Lat. 50%



Lager 4; WS 1024; Lat. 50%



Lager 4; WS 4096; Lat. 50%



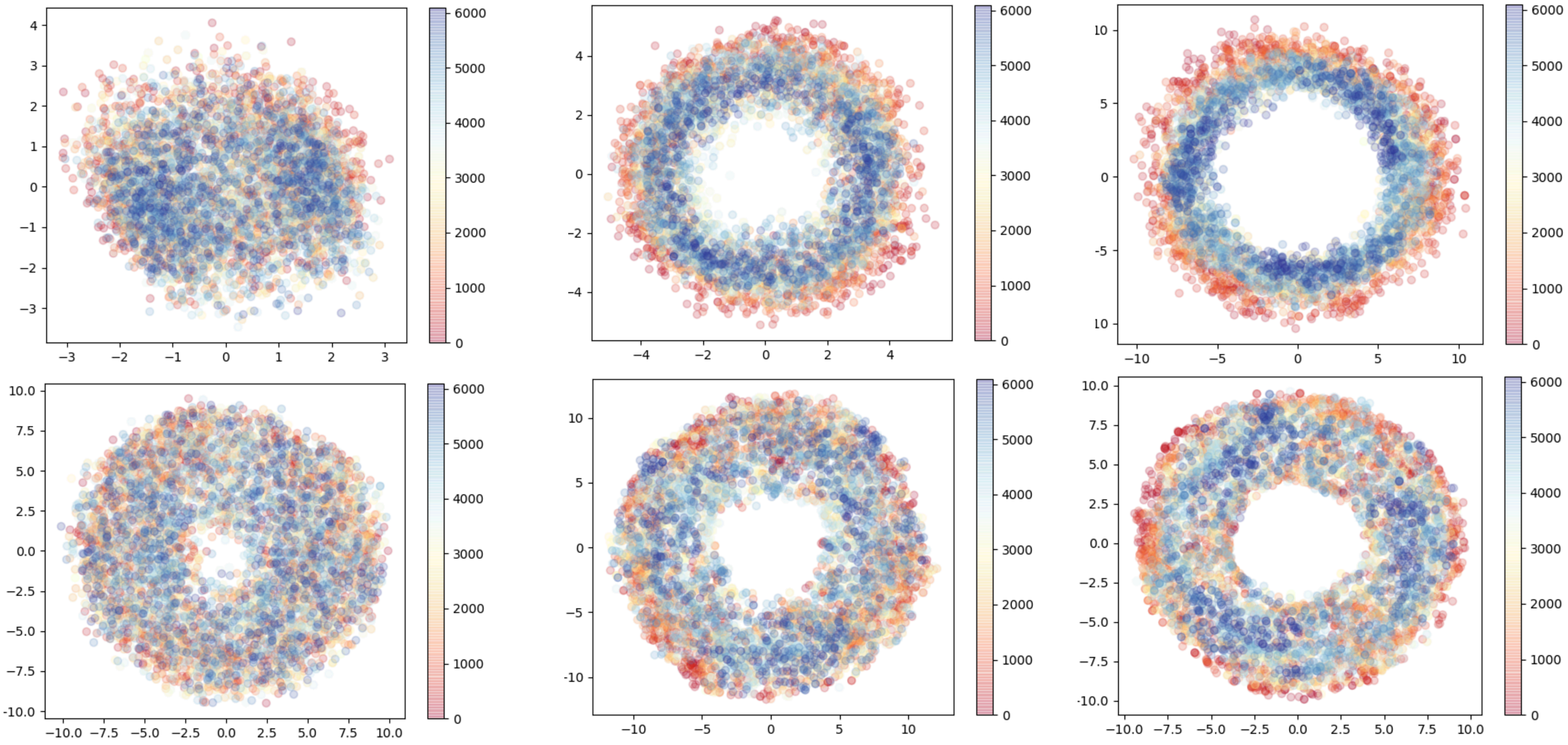
- Clustering is better the bigger the window size is → inverse correlation with AUC results

Autoencoder Results - Latent Spaces

Lager 4; WS 128; Lat. 50% | **Lager 4; WS 1024; Lat. 50%** | **Lager 4; WS 4096; Lat. 50%**

PCA

TSNE



Autoencoder - Reduced Model

- Window size 128 yielded the best results → reduce the window size further to check if this trend continuous
- Reducing the model to 3 down sampling steps to make window size 8 possible

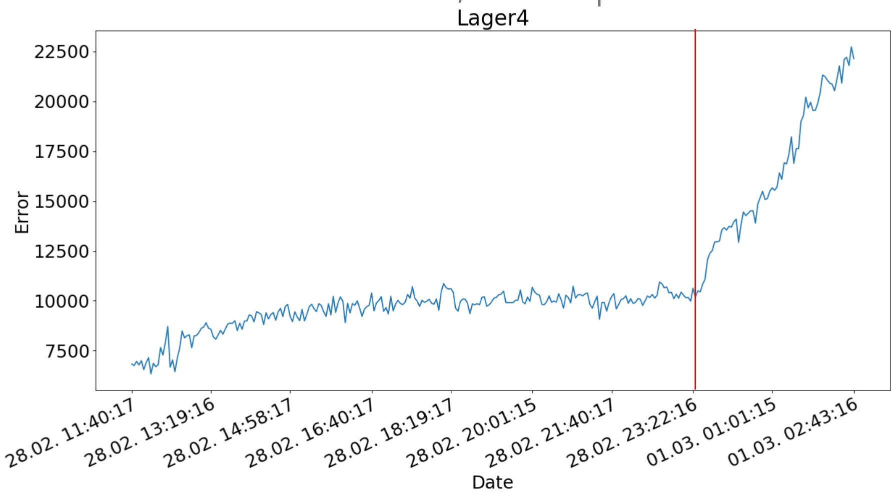
Lager 4: AUC depending on window sizes and latent space size

	8	16	32	64
50%	1.0	0.99	0.98	0.98

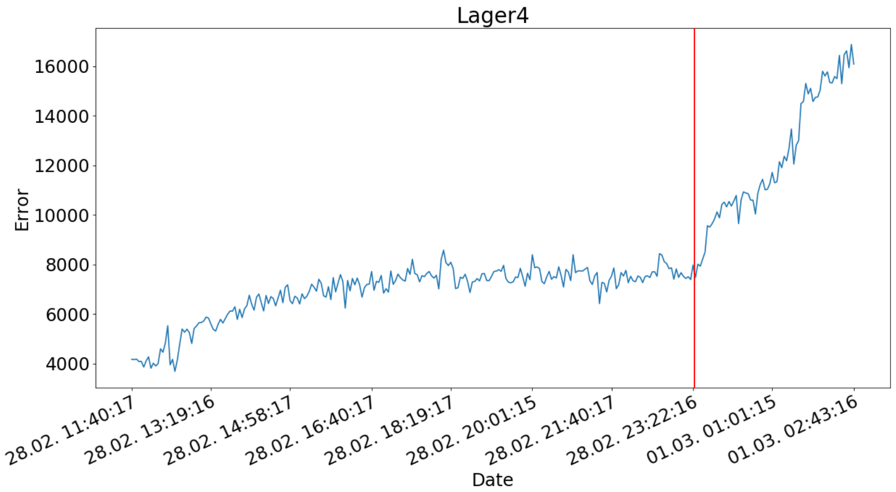
- Although the window size is very small the network behaves as expected
- The error noise caused by the degradation introduces high frequency components into the signal
- These components thus also influence very small window sizes

Autoencoder - Reduced Model

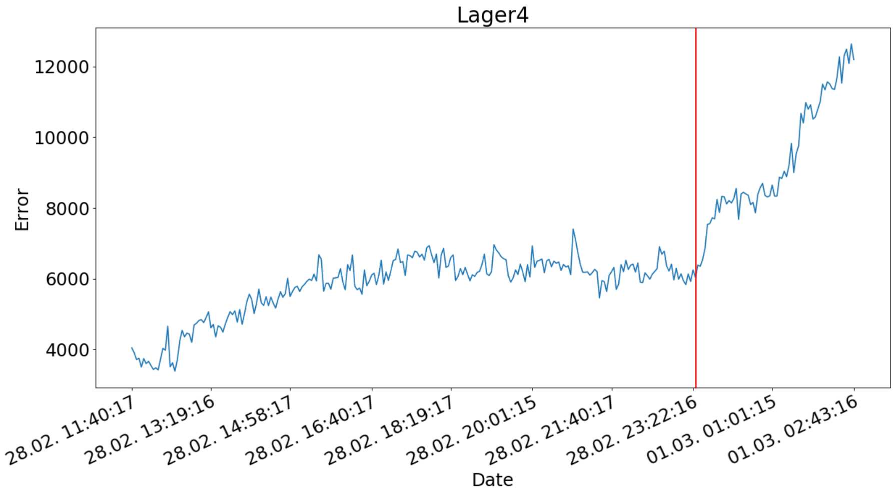
Window Size 8; Latent Space 50%



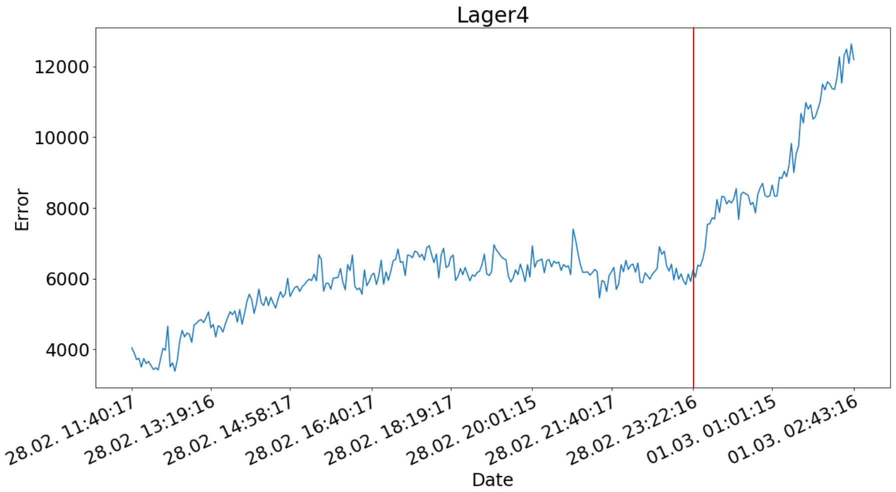
Window Size 16; Latent Space 50%



Window Size 32; Latent Space 50%



Window Size 64; Latent Space 50%



Conclusion, Outlook and Problems

- Degradation starting point can be determined by an expert exactly knowing which feature to look at
- Finding a classical generally applicable feature is very hard

- The application of an autoencoder machine learning model reduces the feature space to 1 error plot
- Some fine tuning parameters remain e.g. the window size making the model not always universal

- We only evaluate the separability of the resulting error plot
- No instructions yet on how to find a good threshold
- Sometimes the network is better in reconstructing erroneous data (reversed classifier) than ”normal” data
- Inverse correlation of latent space clustering and performance