Early detection of bearing degradation

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Predictive maintenance

Prognostics

- Apply data science and machine learning techniques to predict in advance when maintenance or replacement will be needed via the detection of failure modes and modeling of degradation.[1]
  - Identify components that need replacing or machines that need servicing before fault or failure occurs.
  - Find the optimal balance between maximizing component lifetime and reducing downtime due to malfunction.

Project scope

- **Classify high-frequency bearing vibration signal data** into 4 stages (healthy, worn, faulty, failed), for early degradation detection.
  - Utilize open-source bearing data from the NASA Prognostics Data Repository.

Method

- Common predictive maintenance problems include modeling **continuous degradation** (e.g., predicting the Remaining Useful Life of a bearing), a regression problem, and **discrete degradation** (e.g. identifying discrete stages of bearing degradation), a classification problem.

- In both approaches, "typical features for bearing diagnostics and prognostics include time-domain features (root mean square, peak value, signal kurtosis, etc.) or frequency-domain features (peak frequency, mean frequency, etc.)" [6].

- Project scope, per sponsor Sandia National Laboratories, is to build a **signal classifier**. Classifiers can include:

  - **Single-class:** model trained using only healthy bearing data, and faults are detected when the signal deviates significantly from the healthy signal.

  - **Two-class (binary):** model trained on data from the beginning (healthy) and end (faulty) from a run-to-failure experiment.

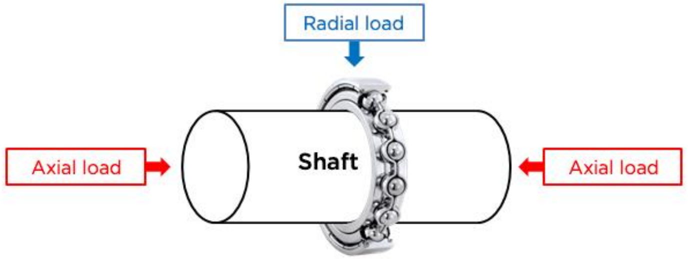
  - **Multi-class:** model trained on data segmented into healthy, degraded, faulty, and failed states, corresponding to the bearing's degradation stage.

- I initially attempted a **semi-supervised learning approach** developed by researchers at the IT University of Copenhagen (ITUC) for use in bearing degradation classification (Juodelyte, et. al. 2022) [3]. I then switched to a new **unsupervised time series segmentation** approach that uses time series segmentation (TSS) for change detection (Ermshaus, et. al. 2023) [11].

*For numbered references, see Appendix.

IMS Bearing Data

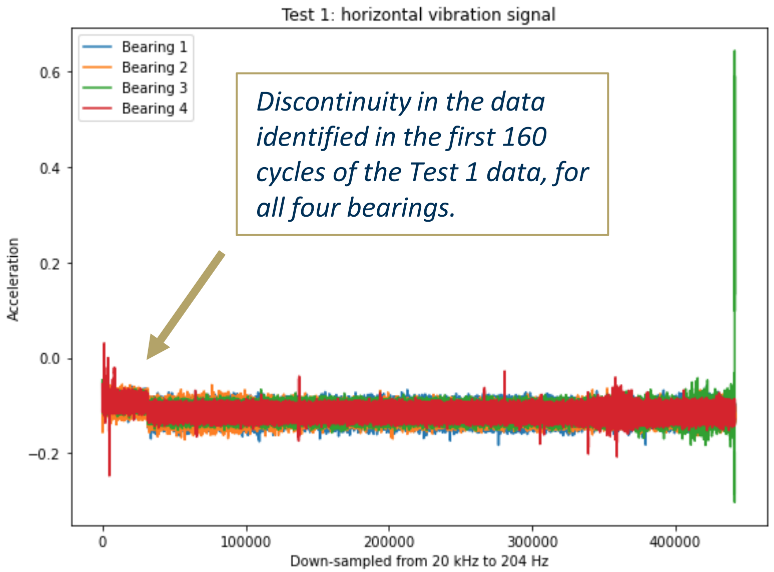
- Data comprised of three run-to-failure experiments, each with four bearings. Experiments were run until one or more bearings failed.
- Files were provided in a >1GB zipped folder. File names indicate the measurement timestamp.
- Each file is a **1-second snapshots of vibration signal (acceleration)** recorded at 5- or 10-minute intervals across multiple days and contains 20,480 observations per second (sampling rate of **20,480 Hz**).
- Experiment #1 included two accelerometers (horizontal and vertical vibration). Experiments #2 and #3 included only one accelerometer.
- Data is **un-labelled**, meaning that we do not know bearings' status at each observation – only the measured acceleration.
- **Data Source:** Center for Intelligent Maintenance Systems (IMS), University of Cincinnati (2007).[12]



Bearing diagram. Source: JTekt.

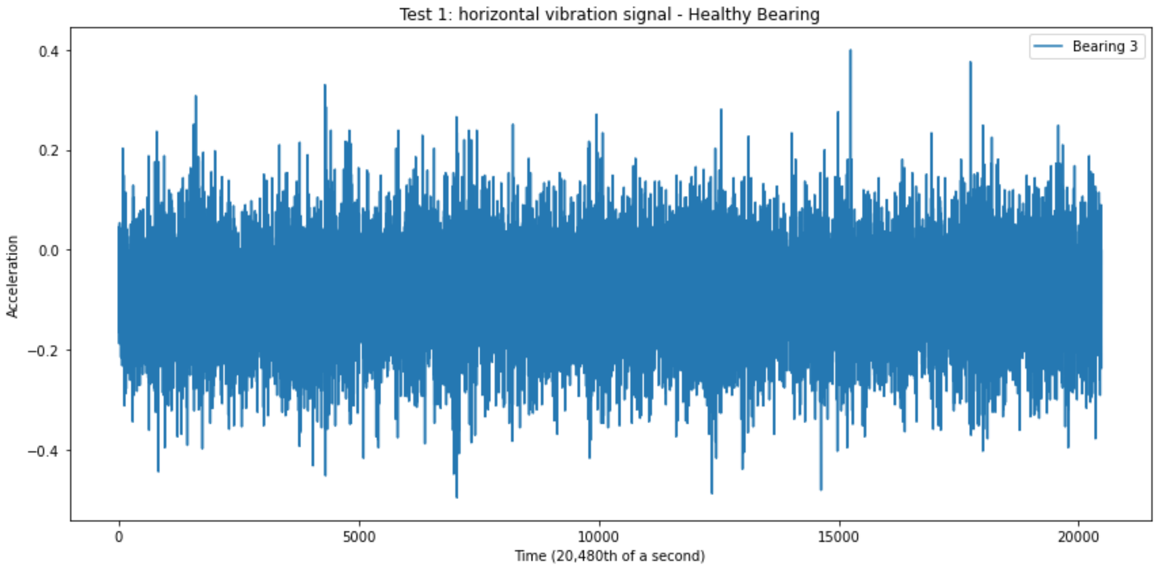
Data Processing

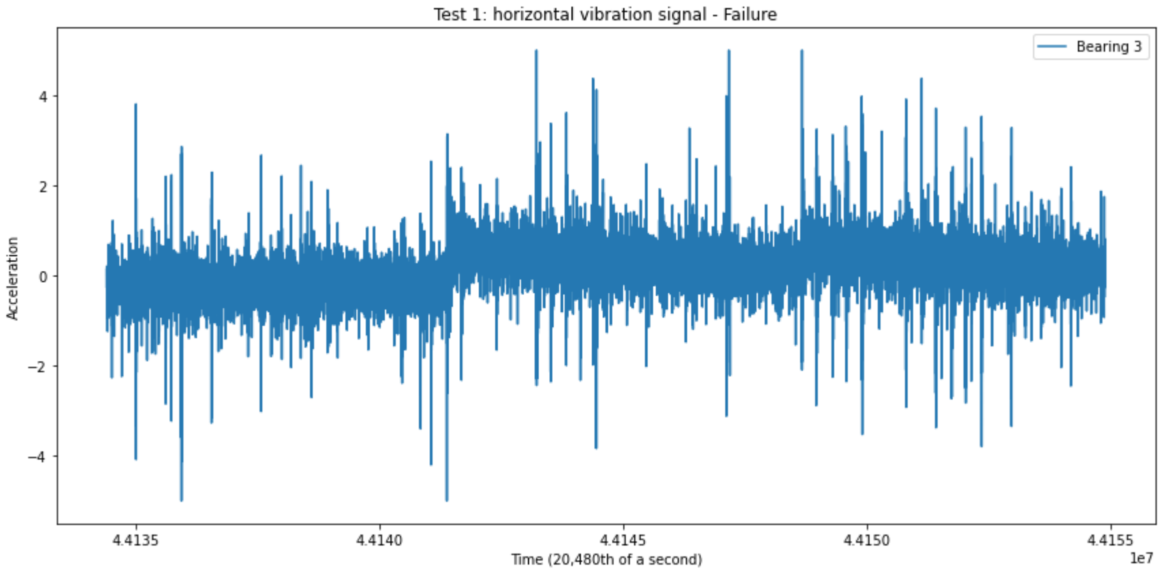
- Data stored in text files (2,156 files in Test 1, each represents a 1-second snapshot of signal data sampled at 20,480 Hz). Files are read into memory and concatenated in Python. Processing included:
    - **Filtering**: excluded vertical (y-axis) signal data in Test 1 because it was not measured in Tests 2 and 3. Excluded the
    - **Sampling**: down-sampled by a factor of 10 from 20 kHz to ~2 kHz to reduce volume of data.
    - **Time-domain features**: calculated 22 measures (e.g., mean, RMS, kurtosis, etc.) for each obs.
    - **Frequency-domain features**: converted signal to the frequency domain via Fast Fourier Transform.



Exploratory Data Analysis (EDA)

- Healthy vs. failed bearing states can be visually identified by charting the vibration signal (acceleration). Note the **irregular acceleration pattern** and **large magnitude** (the y-axis 10x larger in left vs. right chart).
- Bearing failure modes and lifespan are highly variable, complicating accurate classification.





Manual Labeling

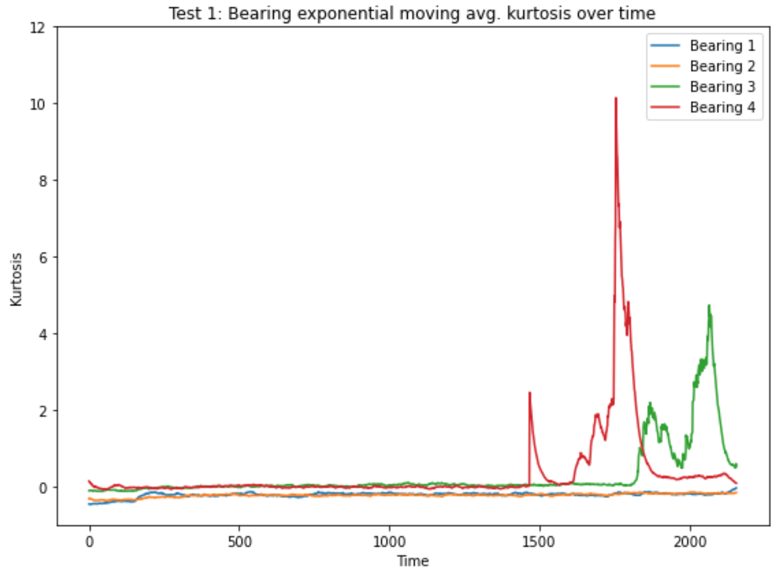
- Healthy vs. failed bearing states can be visually identified by charting the vibration signal.

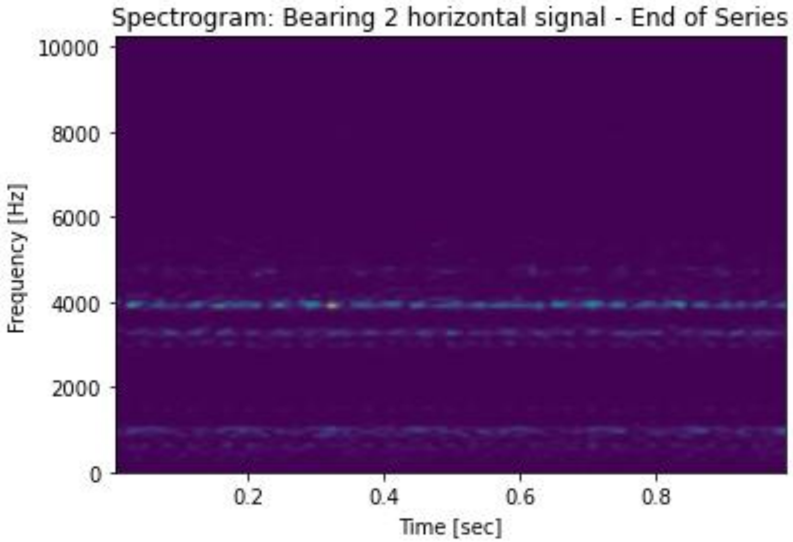
- Bearing failure modes and lifespan are highly variable, complicating accurate classification.

- Sutrisno, Oh, et. al. (2012), find that the **exponential moving average of kurtosis** of the bearing increases roughly monotonically over time, making it a good feature for prognostics and therefore for manual labeling.[5]

- Sahoo and Mohanty (2022) identify two measures as predictive – the highest magnitude frequency (frequency domain) and the **smoothed maximum acceleration** (the average of the five highest absolute acceleration measurements, time domain). Of these two, only smoothed maximum acceleration had predictive value for the IMS data.[4]

Both EMA kurtosis and smoothed maximum acceleration time-domain measures were used to apply manual labels.





(1) Semi-Supervised Learning

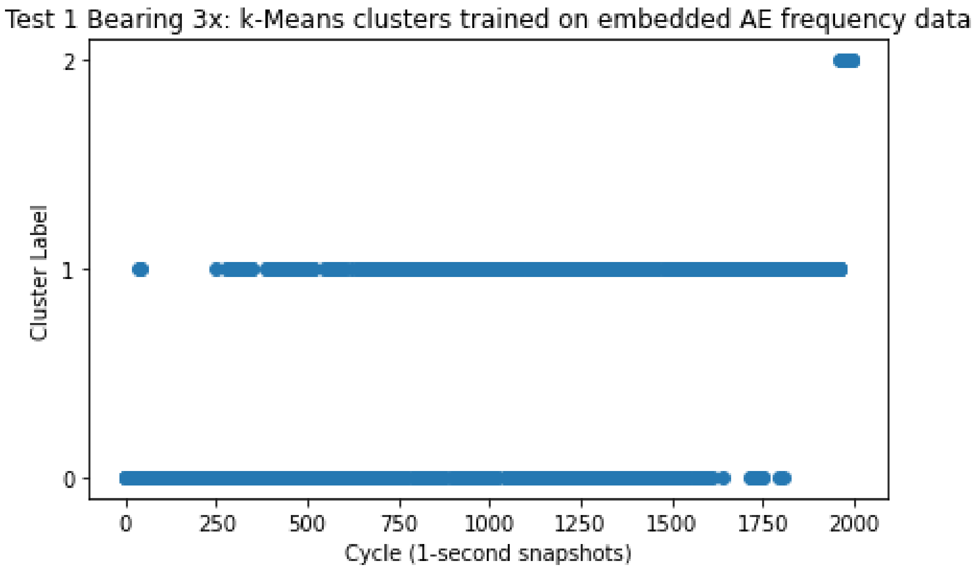
Given desire to classify a large amount of un-labeled data, **semi-supervised learning** can provide a solution.

Manually Label	Automatically Label	Supervised Classifier
Manually label a segment of the data based on pre-defined threshold values. This is expensive due to the high time and cost for human intervention, so is only performed on a small portion of the data.	**Automate labeling** of un-labelled data by training an **unsupervised clustering algorithm** to infer the correct labels for the unlabeled data, evaluating its accuracy against the manually-generated labels.	Finally, train a **supervised classifier** algorithm to predict the degradation stage given a new bearing vibration signal. This classifier is trained on the automatically-labeled data, allowing it to utilize <u>all</u> available data.

Challenges

- Initially attempted to replicate the ITUC team's semi-supervised learning approach.
  - Inputted frequency data to an unsupervised AutoEncoder neural network to reduce dimensionality from 1,025 columns to only 8 after encoding.
  - Used the exact same AutoEncoder architecture as the ITUC team from their code repository.
  - Trained a k-means clustering algorithm on the AutoEncoder output.
- K-means generated cluster labels that were almost entirely overlapping and thus did not distinguish between subsequent bearing life stages.
- As a result, changed strategy to a new time series segmentation approach.

K-means clustering output. Note the near-total overlap between cluster 0 and cluster 1 over time (x-axis). Consecutive, non-overlapping cluster labels could provide information about the bearing's life stage over time.



(2) Time series segmentation (TSS)

- **Key insight**: unsupervised clustering does not account for time dimension of signal data, which is crucial for identifying **sequential, non-overlapping bearing states**, (healthy → faulty and faulty → failed).
  - TSS solves this problem by splitting a time series into segments.
  - New **Classification Score Profile (ClaSP)** TSS implementation with associated Python package. [11]
  - ClaSP automatically partitions a time series into sequential, semantically meaningful segments that are fully interpretable to human inspection.
- TSS can function as a **standalone change detector** that automatically "learns" a bearing state change from **real-time signal data**, without need for a supervised classifier.

Manually Label

Manually label a segment of the data based on pre-defined threshold values. This is expensive due to the high time and cost for human intervention, so is only performed on a small portion of the data.

→

Automatic Segments

Unsupervised TSS automatically "learns" bearing state change from real-time data. When change is detected as a new predicted TS segment, the bearing's status changes from healthy to faulty, triggering maintenance.

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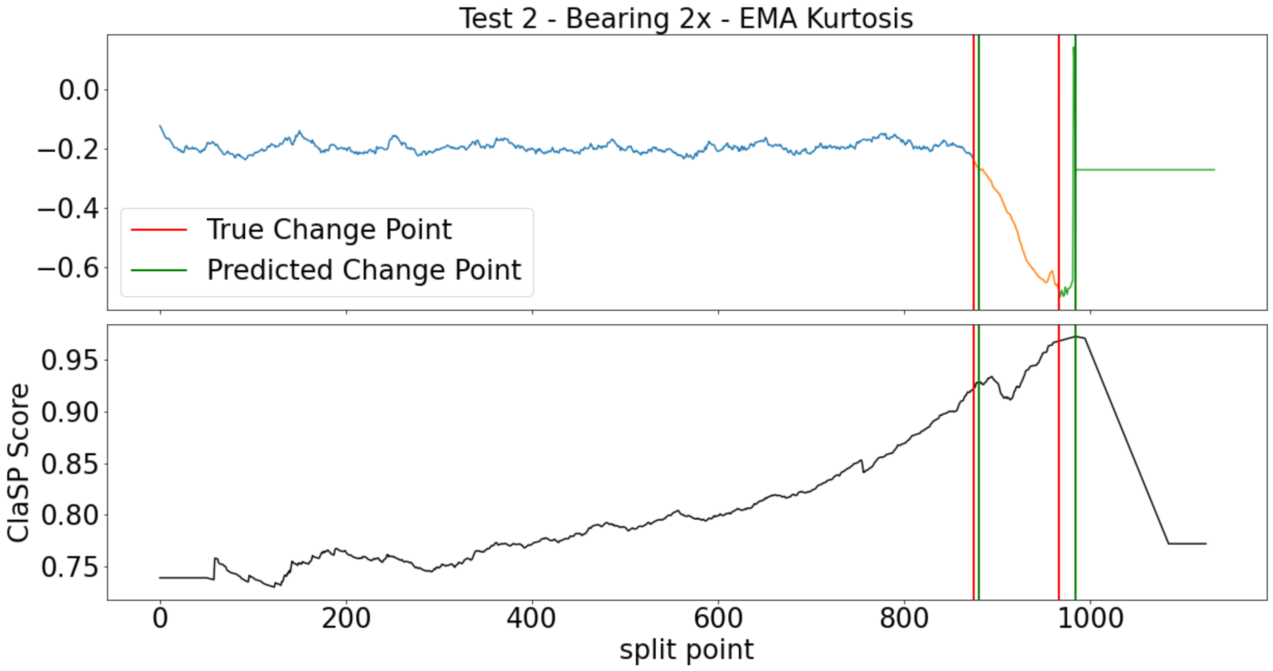
Results

- Change first detected on avg. **85% of the way through the bearing's lifetime**.
- Best result on **full data** with **Smoothed Maximum Acceleration** measure. TSS detected change in 9 bearings, vs. all 12 identified by manual labeling – a **sensitivity rate of 75%**. Correctly detected change in 3 of the 4 bearings that ended in failure.
- Best result on **truncated data** (excl. final 3% failure state in each time series) with **EMA of Kurtosis** measure. Manual labels identified change in 6 of the 12 bearings, and TSS achieved **50% sensitivity and 83% specificity**. Correctly detected change in 2 of the 4 bearings that ended in failure.
- Also **simulate real-world deployment** by training TSS on **successively larger chunks** of data. TSS still detected change but with **higher likelihood of early detection** (too early).

*ClaSP **predicted change points** close to actual change points identified by **manual labeling**.*



Conclusions

- Further accuracy improvements are likely possible with (1) **additional research** into which time-domain features are most predictive of bearing failure; (2) **ClaSP parameter optimization**, and (3) **more data**.
- Further research required to avoid false positives in a real-world update scenario.
- Ultimately, TSS produced **automatic, interpretable, and accurate** time series segments for change detection.
- This analysis shows that early detection of bearing degradation is possible and that TSS can improve predictive maintenance.

Appendix

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Results

*Fig. 11. TSS results on **full data**: Comparison of predicted change points vs. manually labeled change points.*

				Manual Labels			TS Segmentation: Smoothed Max (5) Acceleration				
Test	Bearing	# Obs.	Failed?	# Segments	Manual Change Points	First Change Detection as % of Total Time*	# Segments	CPs	First Change Detection as % of Total Time*	Classification Outcome**	% in Advance of Manual CP
1	1	1,996	N	2	[1973]	99%	1	[]	N/A	FN	N/A
1	2	1,996	N	2	[1961]	98%	2	[1911]	96%	TP	3%
1	3	1,996	Y	3	[1667, 1905]	84%	2	[1591]	80%	TP	4%
1	4	1,996	Y	3	[1307, 1594]	65%	2	[1307]	65%	TP	0%
2	1	984	Y	2	[975]	99%	1	[]	N/A	FN	N/A
2	2	984	N	3	[875, 966]	89%	2	[939]	95%	TP	-7%
2	3	984	N	3	[860, 981]	87%	2	[984]	100%	TP	-13%
2	4	984	N	3	[861, 982]	88%	3	[769, 910]	78%	TP	9%
3	1	6,324	N	4	[350, 5967, 6323]	6%	1	[]	N/A	FN	N/A
3	2	6,324	N	3	[6174, 6323]	98%	3	[3931, 5608]	62%	TP	35%
3	3	6,324	Y	3	[6174, 6323]	98%	2	[6084]	96%	TP	1%
3	4	6,324	N	3	[6174, 6323]	98%	2	[6125]	97%	TP	1%

*When was state change first detected, as a percentage of the experiment's total duration?

**Classification outcome for the Time Series segmentation models were evaluated against the manual labels.

TP	9
FN	3
FP	0
TN	0
Sensitivity	**75%**
Specificity	N/A

Results, cont'd.

*Fig. 12: TSS results on **truncated data**: Comparison of predicted change points vs. manually labeled change points.*

				Manual Labels			TS Segmentation: Exponential Moving Avg. of Kurtosis			
Test	Bearing	# Obs.	Failed?	# Segments	Manual Change Points	First Change Detection as % of Total Time*	# Segments	CPs	First Change Detection as % of Total Time*	Classification Outcome**
1	1	1,996	N	1	[]	N/A	1	[]	N/A	TN
1	2	1,996	N	1	[]	N/A	1	[]	N/A	TN
1	3	1,996	Y	2	[1667]	84%	1	[]	N/A	FN
1	4	1,996	Y	3	[1307, 1594]	65%	2	[1199]	60%	TP
2	1	984	Y	1	[]	N/A	2	[876]	N/A	FP
2	2	984	N	2	[875]	89%	2	[880]	89%	TP
2	3	984	N	2	[860]	87%	2	[867]	88%	TP
2	4	984	N	2	[861]	88%	1	[]	N/A	FN
3	1	6,324	N	3	[350, 5967]	6%	1	[]	N/A	FN
3	2	6,324	N	1	[]	N/A	1	[]	N/A	TN
3	3	6,324	Y	1	[]	N/A	1	[]	N/A	TN
3	4	6,324	N	1	[]	N/A	1	[]	N/A	TN

*When was state change first detected, as a percentage of the experiment's total duration?

**Classification outcome for the Time Series segmentation models were evaluated against the manual labels.

TP	3
FN	3
FP	1
TN	5
Sensitivity	**50%**
Specificity	**83%**