Early detection of bearing degradation

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Abstract

Prognostics is an engineering discipline that applies data science and machine learning techniques to predict when part or machine maintenance is needed before fault or failure occurs. These techniques can be applied to bearings, a critical machine component with wide industrial applications. Bearing vibration signal can be measured using accelerometer sensors to determine states of deterioration and failure. Until now, most research has focused on labeling bearing status as functional or failed, a binary classification problem. Using multi-class classification techniques, it may be possible to detect early stages of bearing fault before failure occurs.

First, I define three bearing life stages – healthy, faulty, and failed – and identify two time series measures from the literature that are predictive of failure. I then discuss an attempt to apply a semi-supervised learning approach developed by Juodelyte, et. al.[1] to new data from three run-to-failure experiments published by the Center for Intelligent Maintenance Systems (IMS) in 2007 and accessed via the open-source NASA Prognostics Data Repository. Finally, I identified a new unsupervised time series segmentation approach to detect phase change from the healthy to faulty states, allowing early detection before failure occurs. This approach detects meaningful change in the bearing's signal, on average 85% of the way through the bearing's lifetime, and with sensitivity of 50% and specificity of 83%. This approach is simple, reliable, and accurate. This analysis shows that early detection of bearing degradation is possible and has implications for improved predictive maintenance.

Background

Maintenance

All assets require periodic maintenance to ensure smooth operation. Maintenance costs money in terms of tools, parts, and labor. However, lack of proper maintenance also incurs costs and risks from unscheduled downtime, production disruption, shorter asset lifespan (improper maintenance of a single component can cause the entire machine to wear out sooner), customer dissatisfaction, physical danger, reputational damage, and increased insurance costs, among others. Catastrophic failure can have far-reaching costs to the wider society – consider, for instance, the 1986 NASA Challenger Space Shuttle explosion became a national disaster.

[1] Juodelyte, et. al., also referred to as the "ITUC team" since all 4 authors are from the IT University of Copenhagen.

Businesses have adopted three common approaches to maintenance. The choice of maintenance strategy depends on the specific part or asset and the level of management sophistication.

1. **Corrective (Run-to-failure).** Parts are only repaired or replaced after they fail. This strategy requires little planning and monitoring. However, part failure causes unpredicted, unscheduled downtime, which can stop production until the component is fixed or replaced. Waiting until part failure occurs can be incur high costs and risks catastrophic failure.

2. **Preventative (Scheduled).** Maintenance is conducted on a regular, scheduled cadence, based on the amount of time or amount of usage since the last revision. Maintenance frequency can be optimized to balance the cost and risk of part failure against the cost of maintenance. This increases reliability, reduces disruptions, allows businesses to budget maintenance costs in advance, and increases asset lifespan. But it also is costly and risks over-maintenance, resulting in over-spending and the opportunity cost of foregoing other projects.

3. **Predictive (On demand)**. Maintenance occurs only when needed, as determined by continuous monitoring of performance and the use of data analytics, to predict in advance when repair or replacement are needed. This promises cost savings from reduced maintenance frequency while also reducing the costs and risks of failure.

A fourth maintenance strategy, **reliability-centered maintenance (RCM)**, goes beyond predictive maintenance to create a customized maintenance plan for each asset based on the unique characteristics and criticality of the asset (i.e., quantify the likelihood and consequences of each potential failure mode). RCM is beyond the scope of this paper because it relies on custom analysis of each individual asset.

Maintenance costs are not trivial and can be prohibitively expensive in the case of expensive industrial machines which require skilled technicians to repair specialized parts. Many such machines depend on moving parts, particularly rotation.

Bearings

Bearings are commonly used in machines that require rotation, because they minimize friction (rolling resistance) while bearing weight. A classic example is a bicycle wheel, which has an axle that rotates as the wheel rolls. A bearing carries the weight of the machine and rider (radial load) while the axle shaft rotates forward (axial load). Bearings are placed on the wheel axle to support the load and minimize rolling resistance. A bearing is composed of two concentric rings (races), with grooved interiors to hold the rolling elements (e.g., balls). As the axle shaft turns, the inner race rotates with it, causing the balls to rotate, while the outer race remains stationary. The rotation of the rolling elements within the bearing has far less friction than two flat surfaces sliding against one another.

This study focuses on bearings due to their:

- **Ubiquity** – wide use in commercial and industrial applications, including aircraft.
- **Criticality** – bearing part failure can lead to catastrophic machine failure.
- **Complexity** – many factors influence bearing lifespan, and bearings have multiple failure modes. This results in a large variance in bearing lifespan and complicates modeling.

- **Ease of monitoring** – bearing vibration signal can be measured with accelerometer sensors.
- **Ease of maintenance** – bearings can be replaced or maintained via proper cleaning, lubrication, and loading.

Fig. 1: Diagram of a ball bearing.

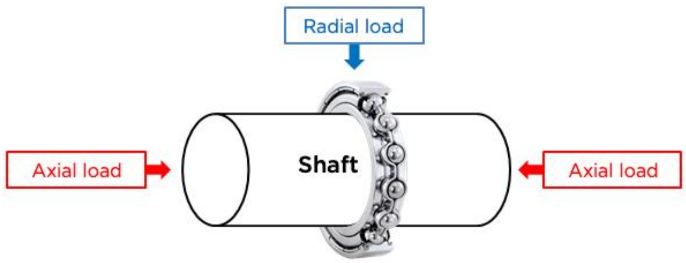


Image source: JTekt.

Can we predict when bearings require maintenance?

Prognostics

Prognostics is an engineering discipline focused on predicting when a machine or component will no longer perform as intended. In other words, prognostics is concerned with predictive maintenance.

Predictive maintenance is particularly suitable for data analysis and machine learning because of the proliferation of cheap, ubiquitous sensors that can be embedded directly into machinery and enable real-time monitoring.

Existing data science and machine learning methods can be applied to high-frequency sensor data to classify the status of components (functioning or malfunctioning), to predict the probability of failure, and to predict the remaining time before failure (remaining useful life, or RUL).

Data

NASA maintains an open-source Prognostics Data Repository of time-series data on time-to-failure for a variety of devices, components, and machines.

For this study I used experimental bearing data published in 2007 by the Center for Intelligent Maintenance Systems (IMS) at the University of Cincinnati. (Lee, et. al. 2007).

Researchers at IMS conducted three run-to-failure experiments between October 2003 and April 2004. Each experiment included four bearings and was run until one or more bearings failed. Three different failure modes are represented in the data – inner race defect, roller element defect, and outer race failure. All three experiments exceeded the bearings' designed lifespan of 100 million revolutions.

The experimental design included four bearings installed on a shaft. The shaft was rotated at 2,000 rpm with a radial load of 6,000 pounds. High-sensitivity accelerometers were installed on the bearings' housing – two accelerometers in the first experiment (measuring x- and y-axis vibration), while only one accelerometer was installed in the second and third experiments (one-dimensional vibration).

Each experiment consisted of one-second vibration signal snapshots (acceleration measured at 20,480 Hz), recorded from the accelerometers at intervals of 5- and 10-minutes. Data were recorded over multiple days, with experiments lasting between one week and one month in duration.[2]

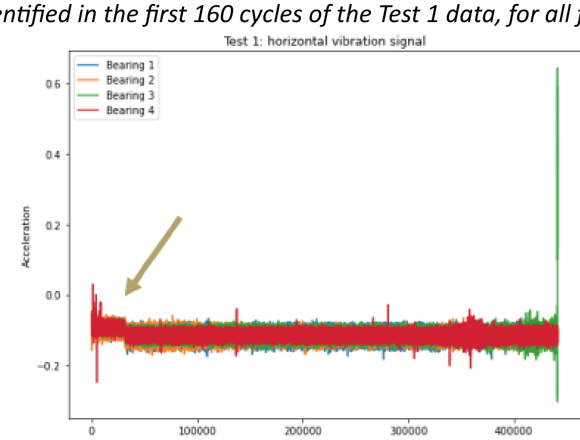
Data are un-labelled, meaning that we do not know bearings' status at each observation – only the measured acceleration values.

Data Processing

Data were downloaded in a >1GB zipped folder and were stored in text files (2,156 files in Test 1; 984 files in Test 2; and 6,324 files in Test 3). Each file represents one second of data (20,480 observations, corresponding to 20,480 Hz). File names indicate the measurement timestamp. Files were read into memory and concatenated in Python. Data processing included:

- **Dropping data**:
    - Vertical (y-axis) signal data in Test 1 were excluded for consistency given that Tests 2 and 3 only included horizontal (x-axis) accelerometers.
    - Visual inspection identified an unusual discontinuity in the early stage of the Test 1 data. This may be due to measurement error or to a change in the experimental approach. It corresponds with a known change from taking measurements at 5-minute intervals (for the first 43 cycles) to 10-minute intervals. I excluded the first 160 cycles of Test 1.
- **Sampling**: down-sampled by a factor of 10 from 20 kHz to ~2 kHz to reduce the volume of data.
- **Time-domain features**: calculated 22 measures (e.g., mean, RMS, kurtosis, etc.) for each obs.
- **Frequency-domain features**: converted signal from time to frequency domain via Fast Fourier Transform.

Fig. 2: Discontinuity in the data identified in the first 160 cycles of the Test 1 data, for all four bearings.



[2] Source: Metadata document provided in the IMS data download.

Methodology

Multi-class Classification

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

In either approach, “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.)” (Mathworks 2024).

The scope of this project, per sponsor Sandia National Laboratories, was to build a signal classifier. Classifiers can include:

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

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

- **Multi-class**: a model is trained on data segmented into multiple states (e.g., healthy, faulty, and failed) corresponding to the bearing’s degradation stage.

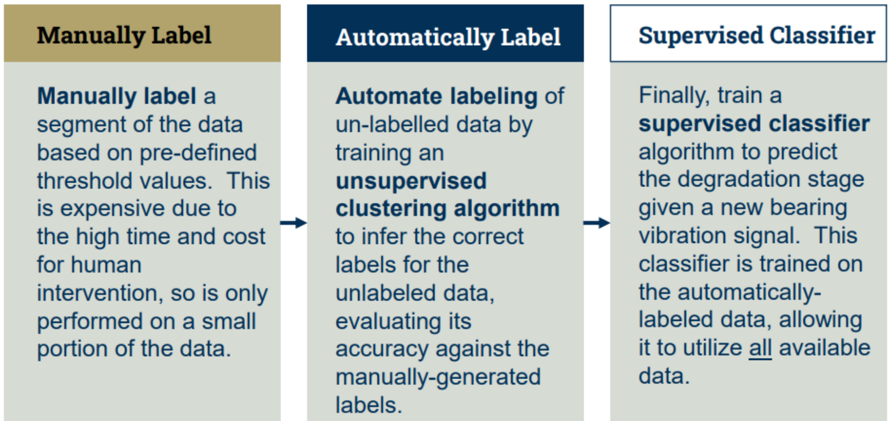
Multi-class classification has advantages over other traditional prognostics approaches:

- **Single-class and Binary classification** lack detail on the health condition of bearings. By the time a predictive model classifies a bearing to be at a high probability of failure, it may be too late for preventative maintenance.

- **Continuous degradation** approaches rely on regression models that predict time-to-failure based on when a bearing’s signals will exceed a pre-defined threshold value. Setting the threshold value is difficult and arbitrary, however, bearings have highly variable lifespans, and bearing degradation may not degrade in a consistent manner (e.g., linear, or exponential degradation) (Juodelyte, et. al. 2022).

For this project I attempted **multi-class classification** using two different approaches. I initially attempted a **semi-supervised learning approach** developed by researchers at the IT University of Copenhagen (ITUC) for use in bearing degradation classification on the open-source FEMTO bearing data set (Juodelyte, et. al. 2022). I then switched to a new **unsupervised time series segmentation** approach that uses time series segmentation (TSS) for change detection (Ermshaus, et. al. 2023).

Fig. 3: A semi-supervised learning approach as described by Juodelyte, et. al. (2022)

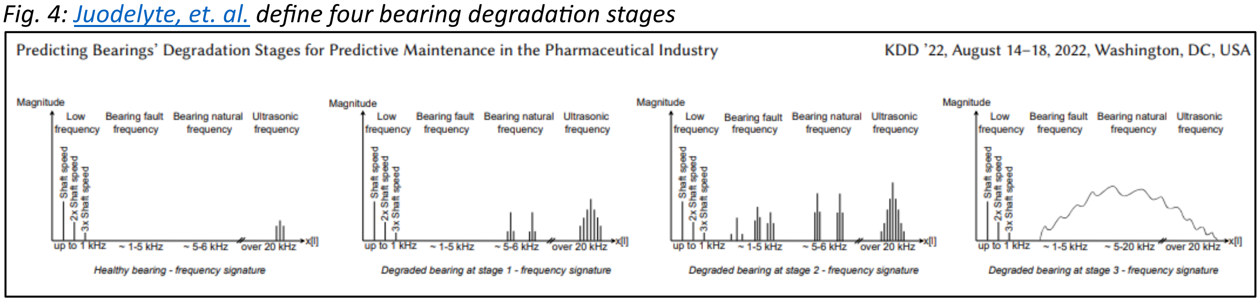


Bearing Degradation Stages

Multi-class classification involves classifying data into more than two classes. In this case, I defined three bearing degradation stages – healthy, faulty, and failed – based on review of the data and the literature.

The ITUC team used domain knowledge to define five bearing life stages, of which four are identifiable via frequency signal (the first two stages are both considered healthy). In reviewing the IMS data, I was not able to accurately distinguish between the "healthy" and "degraded" stages in the signal – using a variety of time series metrics – and so defined **three bearing life stages: healthy, faulty, and failed**.

Fig. 4: Juodelyte, et. al. define four bearing degradation stages



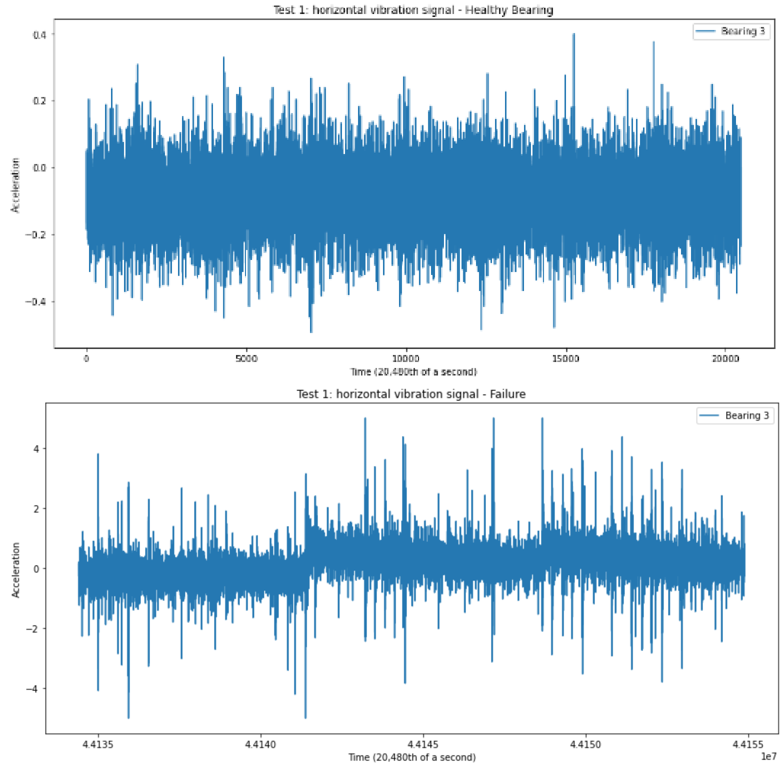
Manual Labeling

Any attempt at classifying data requires comparing the predicted classes against a set of known labels. However, the IMS data are unlabeled, meaning that we do not know bearings' state at each observation – only the measured acceleration value.

Therefore, I produced my own class labels ("manual labeling") before doing unsupervised learning. Manual labeling is an inherently arbitrary and subjective process but is required to obtain a "ground truth" against which to evaluate the unsupervised learning output.

Manual labeling requires visualizing the frequency- and time-domain features to identify patterns that may indicate a change in the bearing state. Healthy vs. failed bearing states can be visually identified by charting the acceleration. Note the irregular acceleration pattern and large magnitude in Fig. 5 below (the y-axis is 10x larger in the bottom chart vs. in the top chart). It is also apparent that the acceleration data is very noisy, which is why frequency- and time-based feature extraction is required.

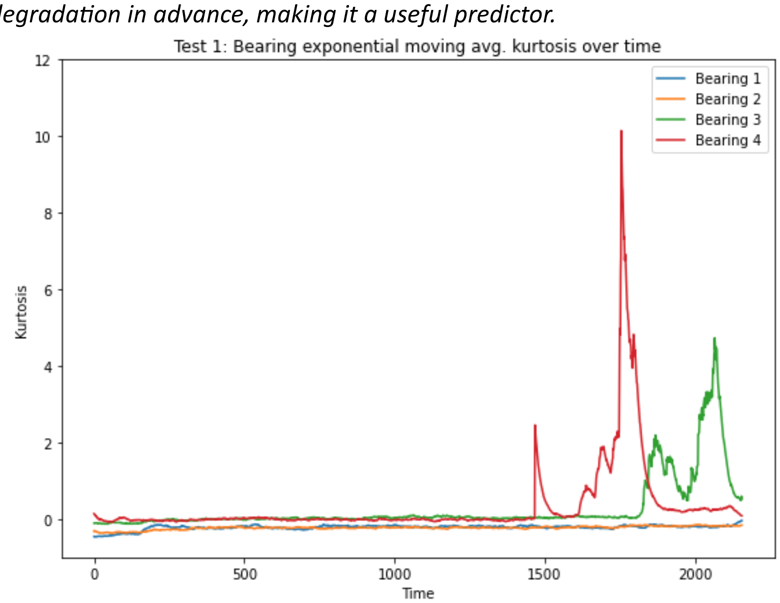
Fig. 5: Healthy vs. failed bearing signal



Existing research was helpful in identifying which features to focus on for manual labeling:

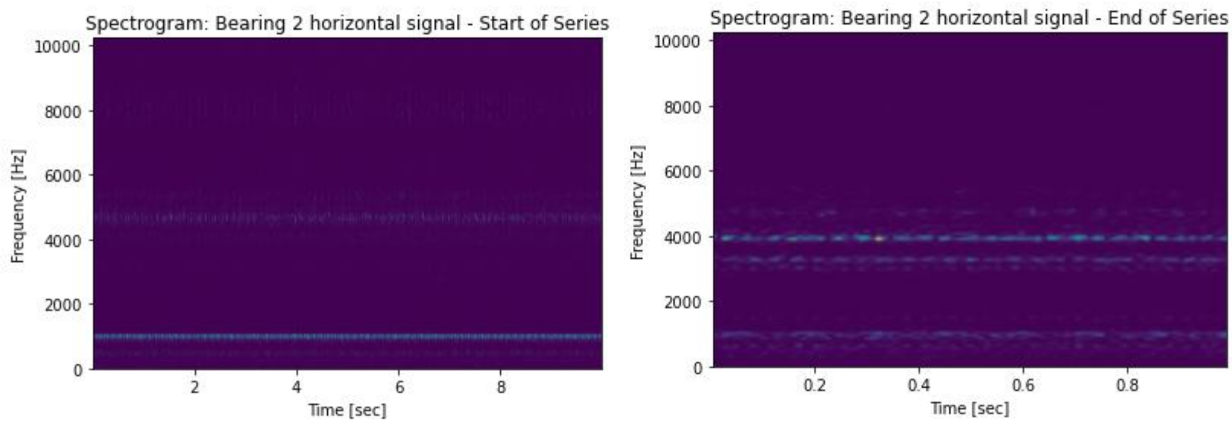
1. Sutrisno, Oh, et. al. (2012), find that the **exponential moving average of kurtosis** (EMA kurtosis) of the bearing increases roughly monotonically over time, making it a good feature for prognostics and therefore for manual labeling.

Fig 6. Bearing EMA kurtosis over the duration of Test 1. Bearings 3 and 4 failed by the end of the experiment, and this measure identified their degradation in advance, making it a useful predictor.



2. 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.

Fig. 7: Spectrogram analysis shows concentration of low frequency (~1,000 Hz) at the beginning of Test 1 and increased high-frequency signal (~4,000 Hz) at the end of the experiment. This suggest that features such as mean peak frequencies can be used as a measure of bearing degradation (Mathworks 2024).



I used both EMA kurtosis and smoothed maximum acceleration time-domain measures to apply manual labels to the IMS bearing data.

Approach

I initially replicated the ITUC team's semi-supervised learning approach and ran the frequency data for a selected bearing[3] through an unsupervised AutoEncoder neural network to reduce the dimensionality from 1,025 columns down to only 8 after encoding.[4] I used the exact same AutoEncoder architecture as the ITUC team as detailed in their code repository. I then trained a k-means clustering algorithm on the AutoEncoder output.

Challenges

The k-means algorithm generated cluster labels that were almost entirely overlapping and thus did not distinguish between subsequent bearing life stages (see Fig. 8 below).

To validate this outcome, I tested multiple variations:

1. Truncated the final 20% of the data to remove the failure stage.

2. Applied k-means clustering on the raw frequency data before embedding via the AutoEncoder.

3. Tested other clustering algorithms, specifically hierarchical clustering and DBScan.

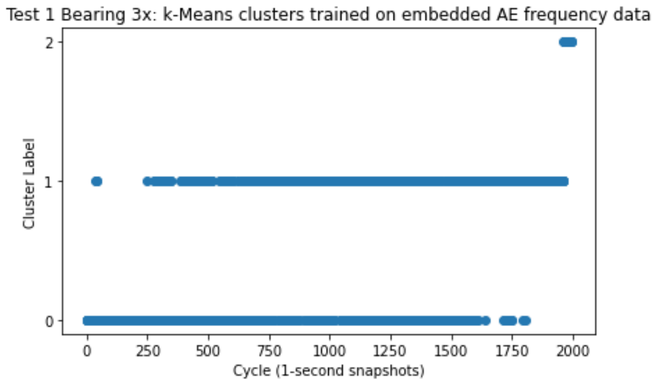
[3] I selected Bearing 3 (x-axis accelerometer) from the Test 1 data because it included the final failure stage.
[4] Frequency data was stored in a matrix of shape n*p, where n is the number of observations in each Test and p = ((f*s)/2) + 1. f is the frequency (20,480 Hz) and s is the sampling rate (0.1, meaning down-sampling by a factor of 10). ((20480*0.1)/2) + 1 == 1025.

4. Tested including a time series trend component (a row counter) in the input frequency data. This did produce sequential, non-overlapping cluster labels, but each cluster was exactly equal in size (an equal number of obs.), meaning that cluster labels were assigned solely based on the time component rather than based on any of the other information encoded in the frequency features.

5. Test training the clustering algorithm on the time-domain features instead of the frequency-domain features.

6. Tested another bearing from the IMS dataset.

Fig. 8: 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.



None of these attempts was successful – all produced overlapping cluster labels. Fig. 8 above shows that the cluster labels have little coherent meaning *over time*. My objective was to output **sequential** bearing states using unsupervised clustering. Once a bearing's state transition from healthy to faulty, it should not revert to a healthy state.

Inability to replicate the ITUC team's unsupervised learning approach may be due to underlying differences between the IMS data I used and the FEMTO bearing data they used – or else it may be due to programming error or lack of understanding on my part. In any case, the setback led me to rethink the merits of the semi-supervised learning approach.

Risks and Limitations of Semi-Supervised Learning

As described previously in Fig. 3, a semi-supervised learning approach includes three stages – manual labeling, unsupervised learning, and a supervised classifier. This requires three models – manual labeling *is* a model, albeit a heuristic one, meant to represent the underlying process of bearing degradation.

This introduces the risk of **"amplification" of error**. If manual labels are improperly set, then no matter how accurate, the unsupervised clustering algorithm will not produce a representation that reflects the underlying degradation process. Likewise, no matter how accurately the supervised classification algorithm can predict its target variable (the clustering labels), it will not produce useful predictions if the clustering labels themselves lack meaning.

This realization led me to redouble efforts to set meaningful manual labels as well as to search for a simpler and more robust solution to early bearing degradation detection.

Time Series Segmentation (TSS)

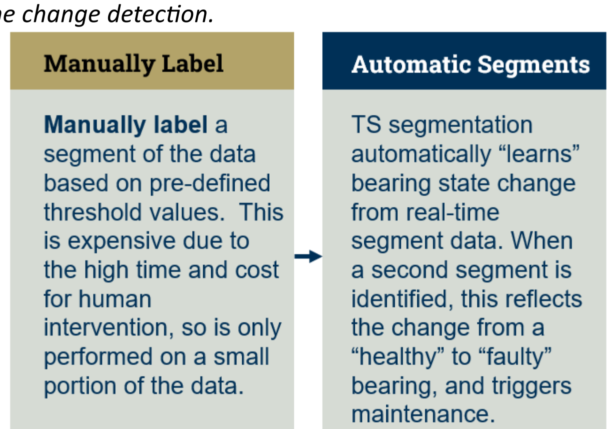
A key insight was that unsupervised clustering does not account for the time dimension of the signal data. Time is a crucial dimension in this analysis because I sought to identify **sequential, non-overlapping bearing states**, from healthy → faulty, and faulty → failed.

Whereas clustering aggregates similar observations based on a distance metric (typically Euclidean distance)[5], **segmentation** takes a time series and splits it into segments.

Classification Score Profile (ClaSP) is a new time series segmentation (TSS) algorithm and associated Python package. It is an "unsupervised learning task applied to large, real-world sensor signals for human inspection, change point detection or as preprocessing for classification and anomaly detection." ClaSP **automatically partitions a time series into sequential, semantically meaningful segments** that are fully interpretable to human inspection. Interpretability is crucial to connect the predicted segment labels back to the visual changes in the underlying time series. ClaSP is also very accurate, found to be the top performer in a benchmark study of seven competitor TSS algorithms. (Ermshaus, et. al. 2023).

TSS could be used within the same semi-supervised learning approach deployed by the ITUC team, replacing the unsupervised learning step – i.e., replace the AutoEncoder + k-means clustering with TSS and then train a supervised classifier on the predicted segments. However, I believe that a supervised classifier is superfluous. Instead, TSS can function as a **standalone change detector** that automatically "learns" a bearing state change from **real-time signal data**. This has the benefits of being simpler (fewer models) while potentially more reliable and accurate.

Fig. 9: A TSS approach for real-time change detection.



Results

Manual labels

Manual labeling identified at least one phase change (i.e., two segments, representing healthy and faulty states) in all 12 bearings, and identified three segments (i.e., failure) in 9 of the 12 bearings. This is greater than the 4 failed bearings reported by the original IMS researchers. Why might that be?

[5]Alex Minnaar makes a convincing case that Euclidean distance (the distance metric used in k-means clustering) is not optimal for comparing similarity between time series for non-linear series, and instead defines a dynamic time warping metric.

Manual labels identified a phase change within the final 3% of the time series for all 12 bearings (and in 6 of 12 bearings, sooner). This is not surprising – these were run-to-failure tests, and even the bearings that did not fail showed significant signs of deterioration by the end of the experiment. Since each experiment included four bearings attached to the same axle, if one bearing failed it likely placed additional and/or atypical load on the remaining bearings, accelerating their failure.[6]

Change Detection with TSS

I trained several TSS variations to obtain optimal results:

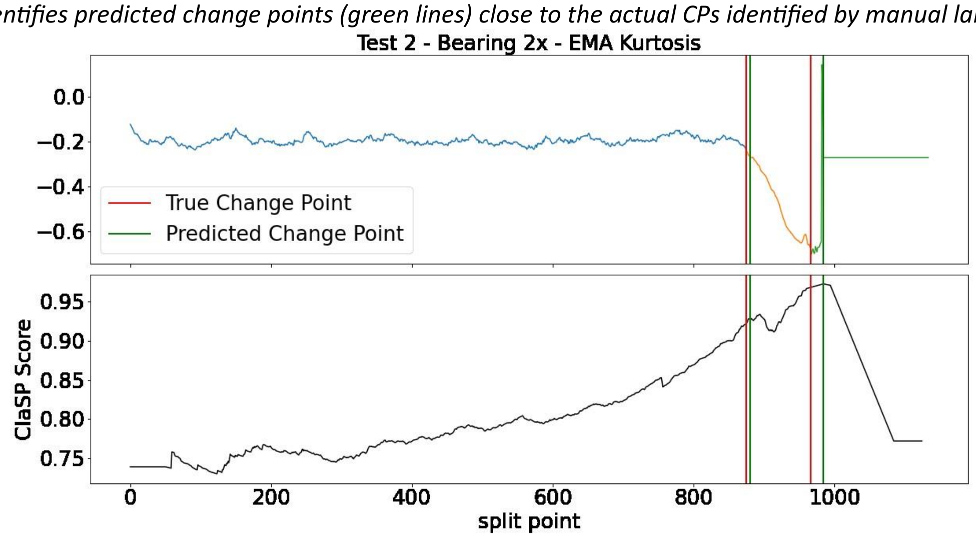
1. Using default ClaSP algorithm settings.

2. Shortened "window size" parameter to make the algorithm more sensitive to changes in the underlying time series. After reviewing the ClaSP documentation, shortening the window size was appropriate for Test 2 because the experiment had fewer observations (984 obs.). The TSS algorithm appears to perform optimally on longer time series (>2,000 observations).[7]

3. Extended the time series by taking the average of the final few observations – the failure state – and copying these values to create 150 additional simulated obs. By default, TSS is slow to pick up on phase changes in the underlying time series. (This is necessary, otherwise the algorithm would generate too many false positives by predicting a new segment for every small perturbation). The IMS experiments terminated upon failure, so the failure state does not have sufficient representation in the data to be detected by the TSS algorithm. Simulating failed bearing signal was gave the algorithm more data to work with.

4. Truncate the end of the time series – the opposite of variant #3 above, I tried training ClaSP on data *excluding* the final 3% of obs., to eliminate the (near) failure state, to see if the algorithm could better detect change from the initial healthy to faulty state.

Fig. 10. ClaSP identifies predicted change points (green lines) close to the actual CPs identified by manual labeling (red lines).



[6] Alternatively, it is also possible that I was too sensitive to changes during the manual labeling process, identifying changes where there were none (i.e., false positives).
[7] Test 1 and 3 data did not need adjustment because they each have >2,000 obs.

Accuracy

Best results on the **full data** were achieved using the **Smoothed Maximum Acceleration** time series measure. ClaSP was able to detect change in 9 of the bearings, vs. all 12 that were identified by manual labeling – a **sensitivity rate of 75%**. This includes correctly detecting changes in 3 of the 4 bearings that ended in failure (the grey rows in Fig. 11 below). Since all 12 bearings were manually detected to have changed, there were no Actual False outcomes to compare against, and thus no specificity metric (see confusion matrix in Fig. 13 below).

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

When training ClaSP on **truncated data** that excluded the final 3% of each time series, manual labels identified change in only 6 of the 12 bearings. TSS, using the **Exponential Moving Average of Kurtosis** measure, achieved **50% sensitivity and 83% specificity**, correctly identifying change in 2 of the 4 bearings that ended in failure.

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%**

Fig. 13: Confusion matrix for binary classification

Confusion Matrix		ACTUAL TRUE	ACTUAL FALSE
PREDICTED	TRUE	TP	FP
PREDICTED	FALSE	FN	TN

These results are based on training TSS with the full time series from a run-to-failure experiment. If deployed for actual predictive maintenance, we would not have the benefit of hindsight to retroactively detect bearing state change. Therefore, I **simulated real-world deployment**, allowing ClaSP to "learn" segments on **successively larger portions** of each bearing's data. Surprisingly, ClaSP performance held up in under real-world conditions – it was still able to detect change but had a **higher likelihood of early detection** (detecting a change too early – before change occurs). If deployed in the real world, further research is required to avoid false positives. For instance, rather than triggering maintenance the first time the TSS detects a state change, the system could require that the change be detected in multiple consecutive samples.

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**.

Ultimately, ClaSP produced automatic, interpretable, and accurate time series segments.

Conclusions

I first attempted, and was unable to replicate, the semi-supervised learning approach developed by Juodelyte, et. al. to classify bearing degradation stages.

I then identified a new unsupervised time series segmentation (TSS) approach to detect change, allowing early detection of bearing degradation. This approach detects change in the bearing's signal, on average 85% of the way through the bearing's lifetime, and with sensitivity of 50% and specificity of 83% on the truncated data. The TSS approach is simple, reliable, accurate, and automated.

Further research and refinement are needed, but this analysis shows that early detection of bearing degradation is possible and can improve predictive maintenance.

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