Asset Monitoring and Predictive Maintenance

CMPINF 2100 Final Project

Sponsored by FPoliSolutions, LLC

FPoliSolutions, LLC

- Pittsburgh based consulting company supporting the global energy sector.

- FPoliSolutions collaborates with global clients to develop data-driven and methodically-based solutions for complex technical, regulatory, and operational challenges.

- Please see the FPoliSolutions website to learn more about the company, its mission, and services.

FPoliSolutions, LLC

- FPoliSolutions creates software tools that rely on data science and machine learning to bring value to their clients.
- FPoliSolutions must properly validate models to ensure results are appropriate, trustworthy, and high quality.
- This project gives you experience working on a challenging application where validation is of paramount importance.

Asset Monitoring and Predictive Maintenance

- Large engineered systems such as nuclear power plants consist of thousands of interconnected components.
- Components eventually wear out over time which may lead to strange anomalies, faults, and system failures.
- Failures may force shutdowns and are expensive to repair. Worst case scenarios endanger public health and safety.
- It is therefore critical to monitor components and understand when they must be repaired BEFORE a failure occurs.

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- Components are monitored many ways. One common approach is to record vibrations.
- Vibrations give insights into the dynamic response of the component.
- Vibrations can tell you if the component characteristics change over time.
- Certain changes may mean the component is wearing out and should be repaired before it fails.

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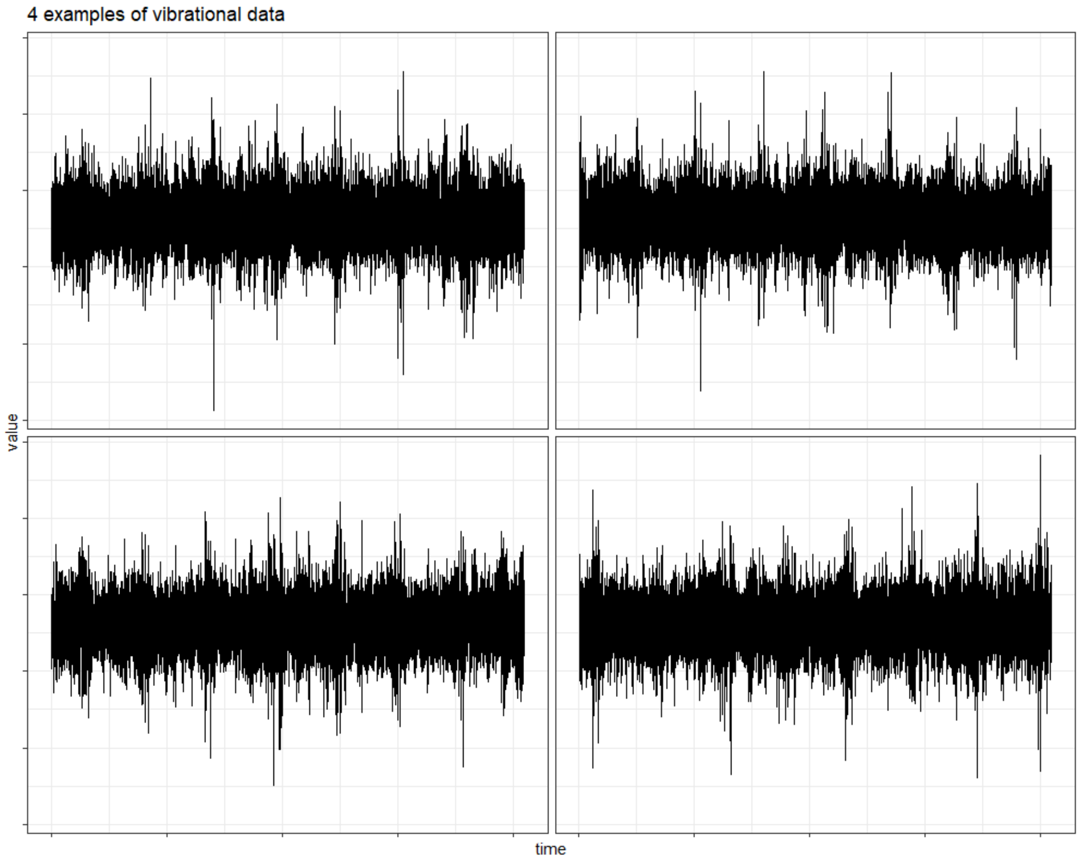
- However, vibrational data are challenging to work with.
- Examples of vibrational data are shown to the right.
- They are high frequency time series signals.
- Patterns are hidden in the signals.



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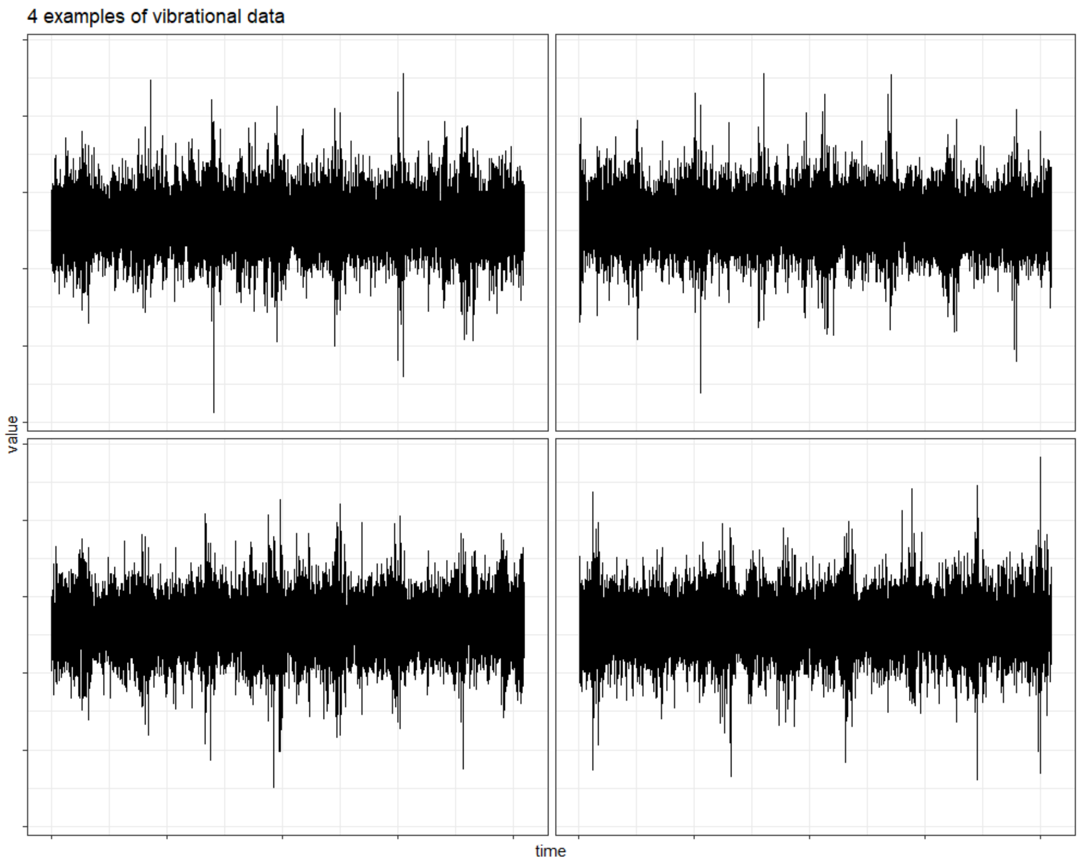
- FPoliSolutions finds the patterns within the signals and monitors how those patterns evolve over time.
- Certain pattern changes are associated with the component wearing out.
- Finding those changes early prevents failure!



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- Finding those changes requires training MODELS. The models are used to PREDICT if the component has worn out and needs replaced.

- However, failures do NOT occur all that often. This leads to significant challenges in properly training the models!
  - The models need to observe failures, but we do NOT want the systems to fail.
  - You will learn why RARE events are so challenging to model later!

- It is therefore difficult to properly collect and assemble training data for predictive maintenance applications.

Computer experiments to study patterns

- Computer simulations can help overcome certain challenges because the simulations are based on physical theory and engineering best practices.
- Simulations are used to generate supplemental data of possible failure states.
- The simulated data can be added to the existing set of real data to help train more accurate models!

You will work with data generated by the computer simulations

- The simulated data consist of higher failure rates compared to real data, because the simulations are specifically designed to induce failures.

- The simulations generate vibrational data consistent with real vibrational measurements. Thus, the simulations generate high frequency time series signals! Patterns can be extracted from those high frequency signals.
  - How those patterns are extracted from the signals are beyond the scope of this course. The patterns are provided to you.

- You will work with the simulated patterns. You will train models to CLASSIFY a simulated failure given the simulated patterns.

The data are provided in a CSV file

- The columns correspond to different patterns extracted from the data.

- The column naming convention indicates the feature extraction approach used to generate the variables.
  - X – Approach 1 at extracting patterns from the signals
  - Z – Approach 2 at extracting patterns from the signals
  - V – Approach 3 at extracting patterns from the signals

- The column letter is followed by a number. Each feature extraction approach includes numerous patterns.
  - Approach 1 has 25 columns: X01 through X25
  - Approach 2 has 9 columns: Z01 through Z09
  - Approach 3 has 29 columns: V01 through V29

The data are provided in a CSV file

- The output is named Y and is a binary variable.

- The output is encoded as:
  - Y = 1 is a FAILURE
  - Y = 0 is NOT a failure

- The models must predict the PROBABILITY of FAILURE given the INPUT patterns (the X, Z, and V columns).

Project instructions

- Specific instructions for all class projects will be shared later after modeling concepts have been introduced.

- However, this project has 2 primary goals:
  - Train a model that accurately classifies failure (Y=1).
  - Identify the most important inputs that influence the failure probability.

- You will need to appropriately explore the inputs BEFORE training models.
  - Make sure you study the RELATIONSHIPS between the inputs!

- You must use an appropriate validation scheme to select the best model!