Wheel Health Monitoring Using Onboard Sensors

Brad M. Hopkins, Ph.D.

Project Engineer – Condition Monitoring

Amsted Rail Company, Inc.

Agenda

1. Motivation
2. Overview of Methodology
3. Application: Wheel Flat Detection
4. Application: Wheel Wear Estimation

Agenda

1. **Motivation**
2. Overview of Methodology
3. Application: Wheel Flat Detection
4. Application: Wheel Wear Estimation

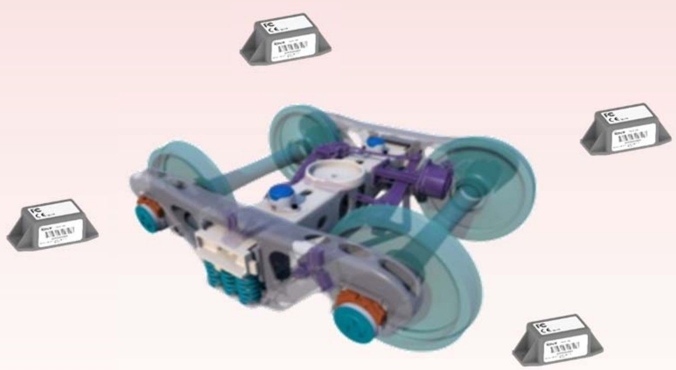
Motivation

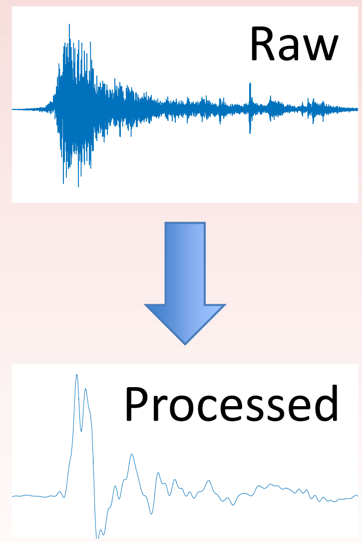
- **Wheel flat spots damage track**
- **Worn wheels affect truck performance and truck wear**
- **~150 Wheel Impact Load Detectors in North America (irregular sampling intervals)**
- **Onboard monitoring provides a solution for monitoring every day, or several times per day**

Agenda

1. Motivation
2. **Overview of Methodology**
3. Application: Wheel Flat Detection
4. Application: Wheel Wear Estimation

Methodology



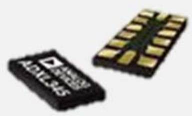


Collect Data

Process Data

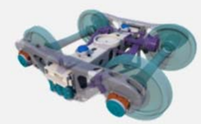
Onboard Data Collection

Sensor Selection



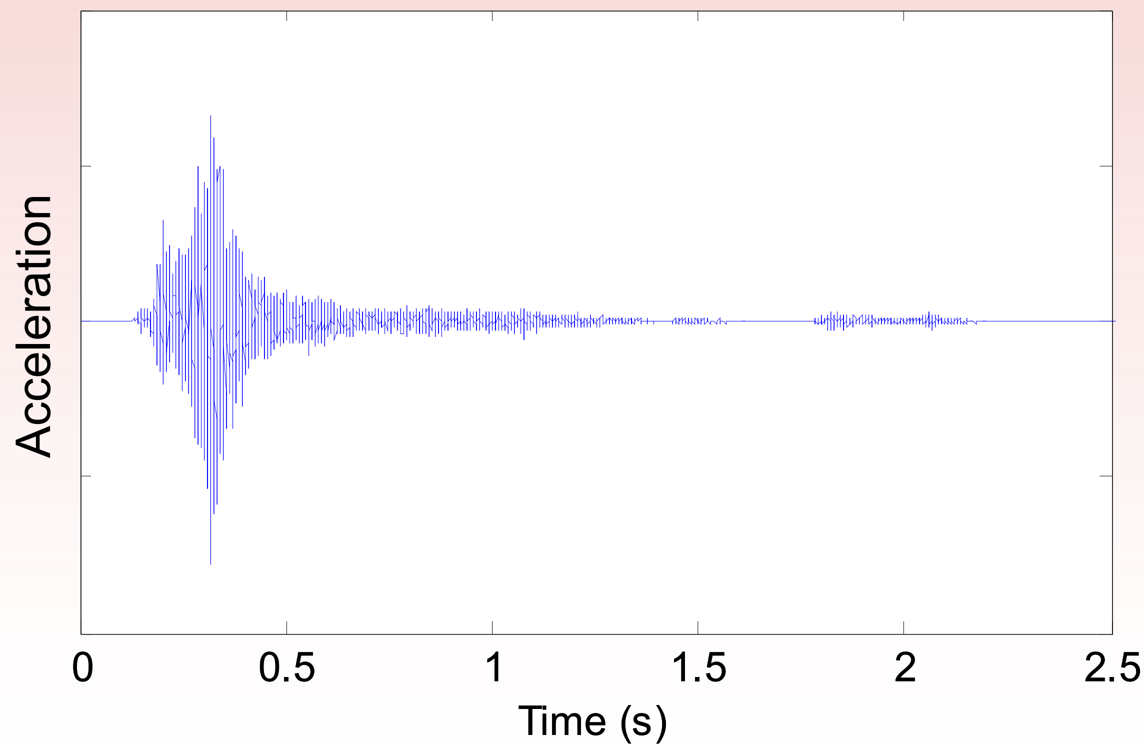
- Low cost
- Low power
- Specs: range, bandwidth, sampling rate, resolution, etc.

Sensor Placement

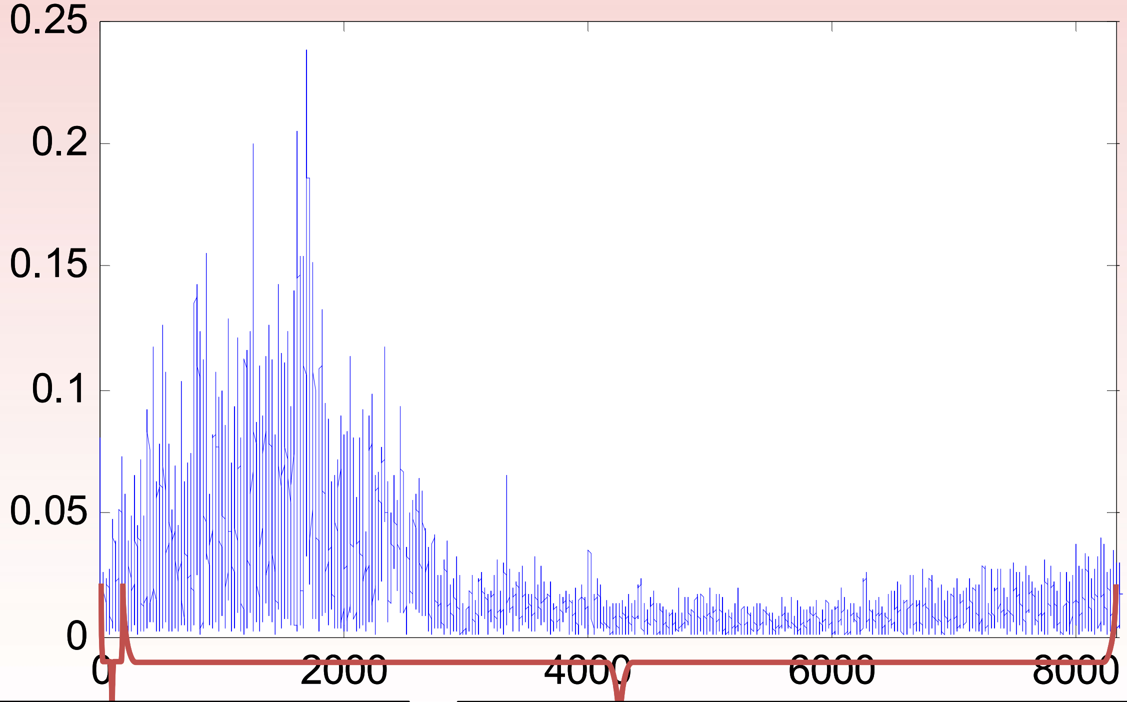


- High sensitivity to vibrations of interest
- Low sensitivity to vibrations that can corrupt signal

Onboard Data Collection



Onboard Data Collection



Range used to characterize event

Range that can corrupt signal

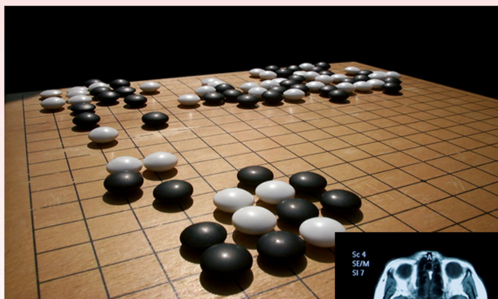
Data Processing

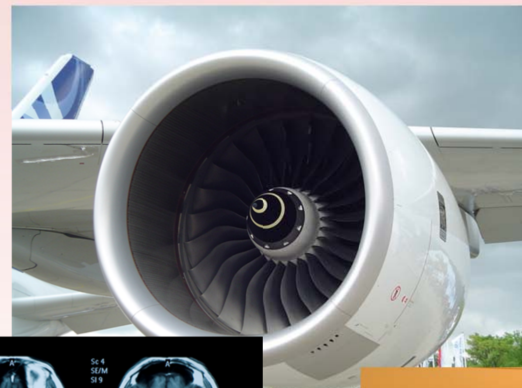
What is Machine Learning?

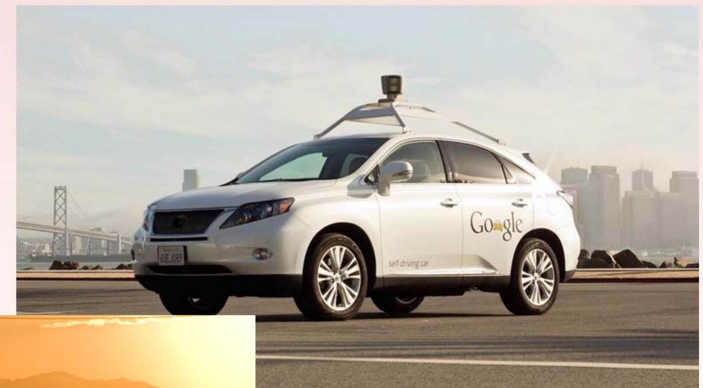
1. Find <u>features of interest</u> that contain information related to the class or state

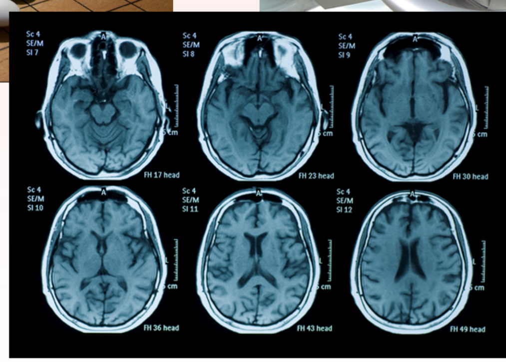
2. <u>Classify the features</u> using a set of rules and/or optimization routines

The Wide Field of Machine Learning





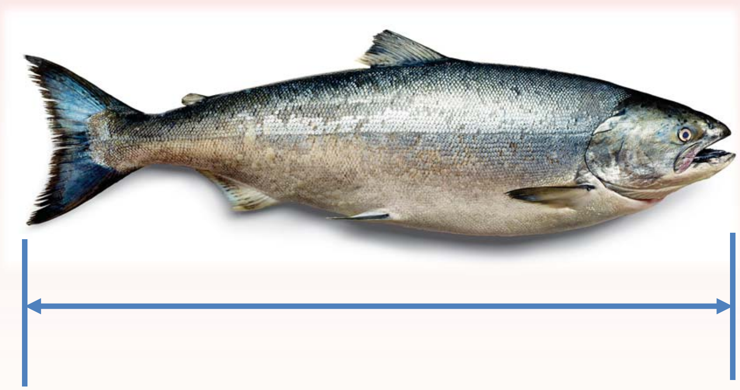




Example: Image Recognition

Salmon or tuna?

Example: Image Recognition

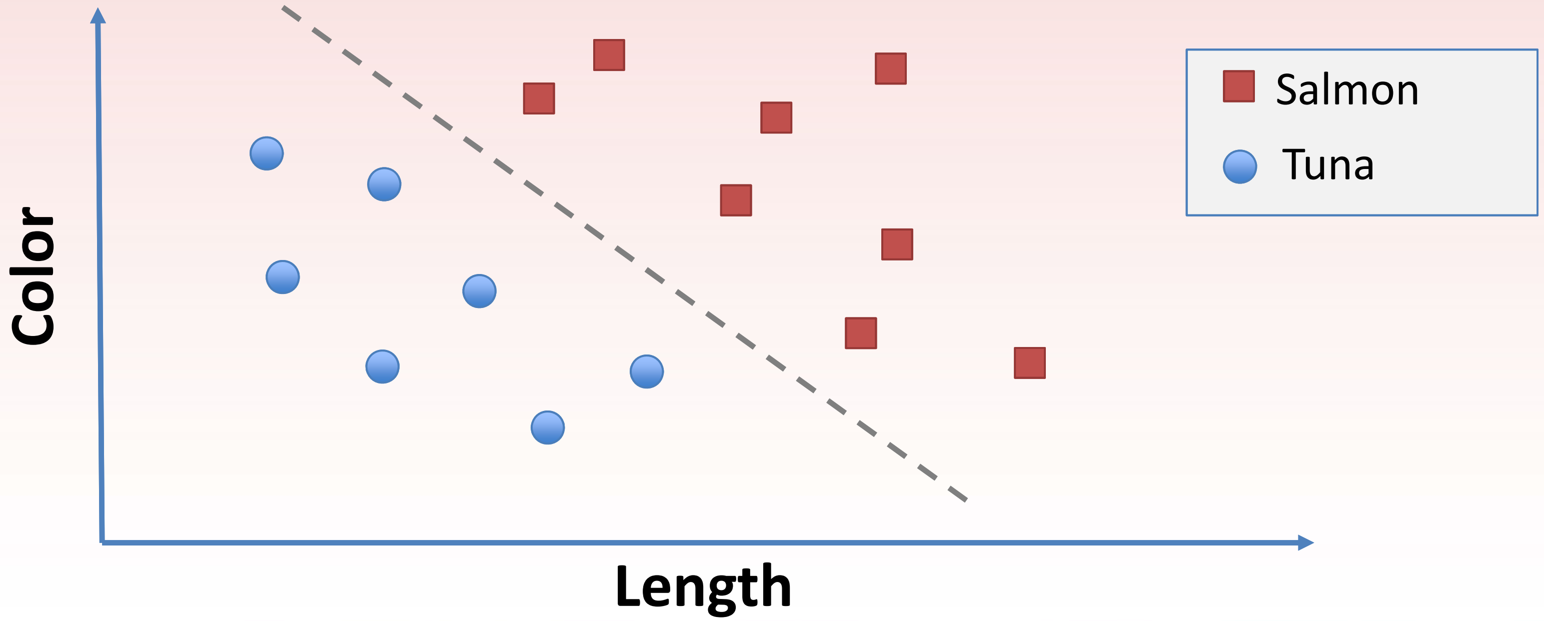


Features:

1. Length (# pixels)
2. Color (pixel intensity)

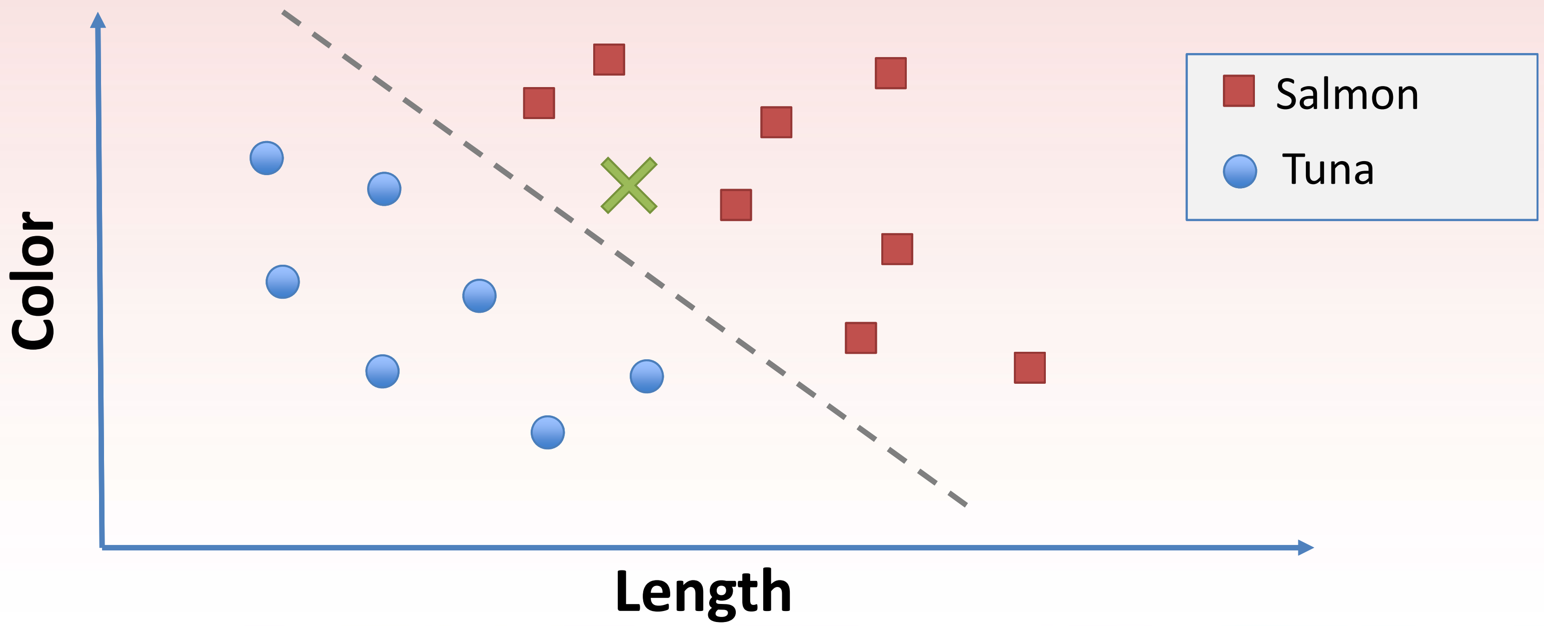
Example: Image Recognition

Train Classifier:

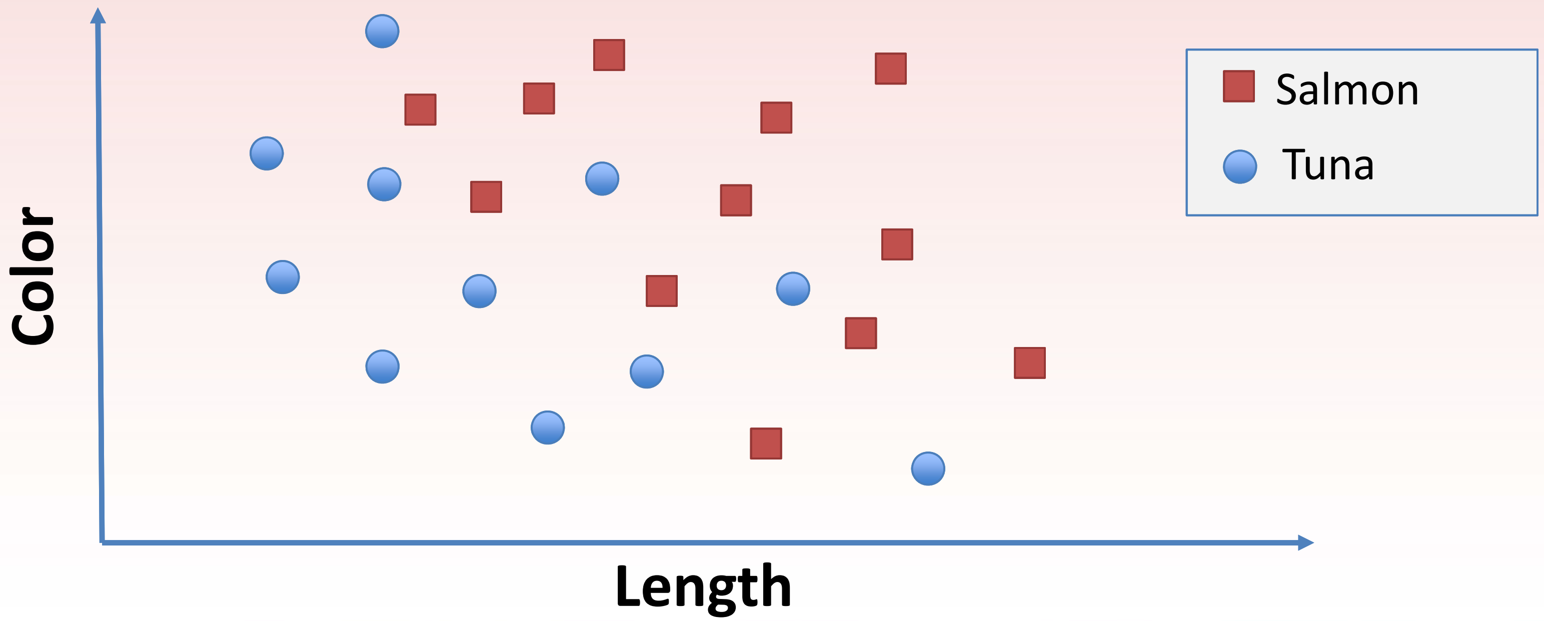


Example: Image Recognition

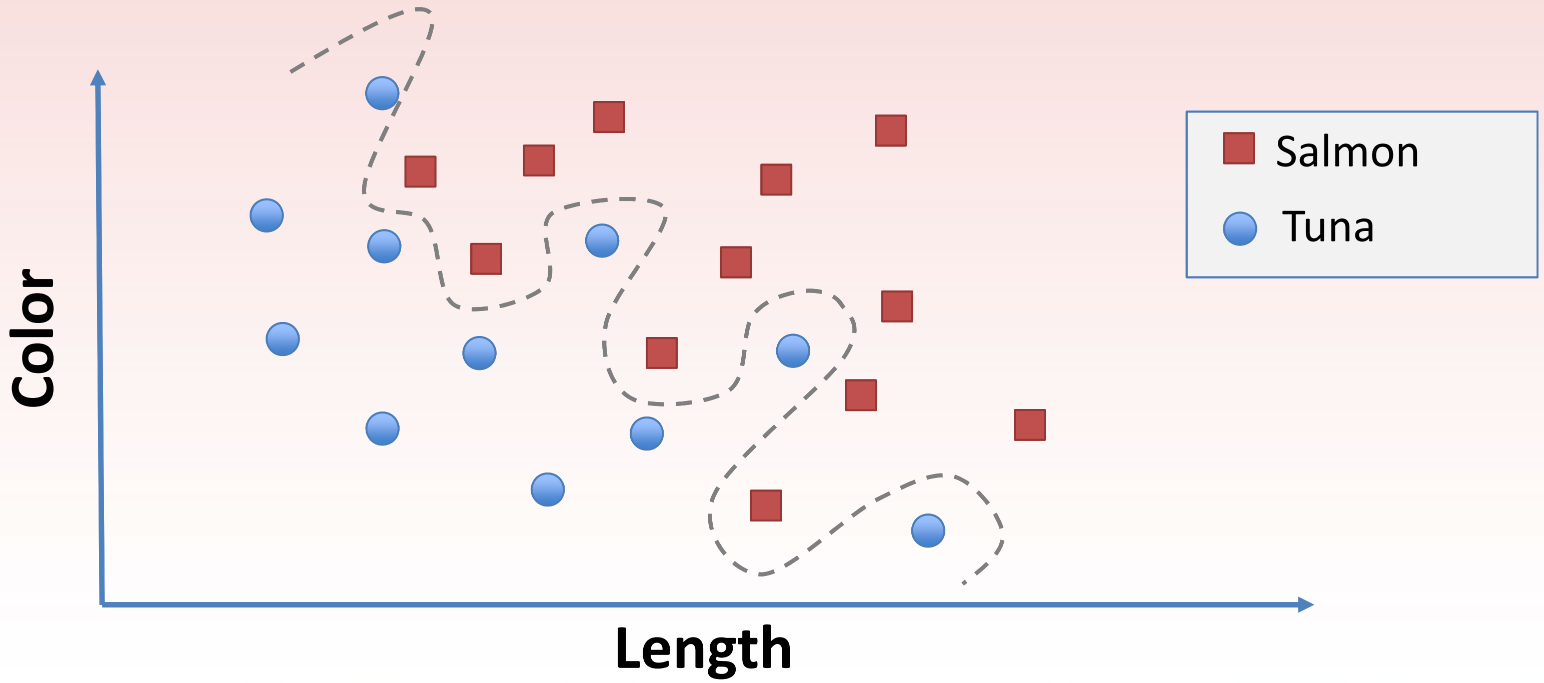
Deploy Classifier:



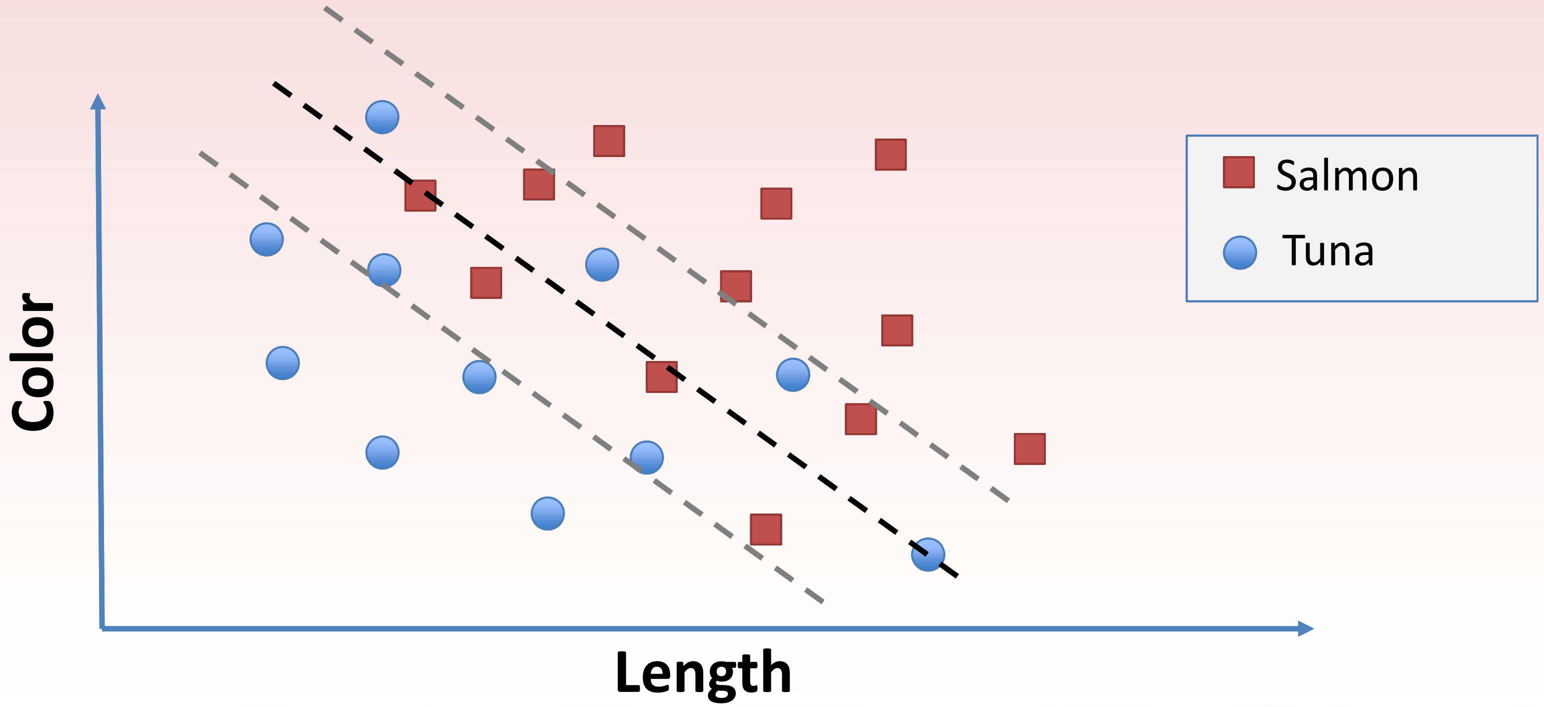
What the data might actually look like in the real world....



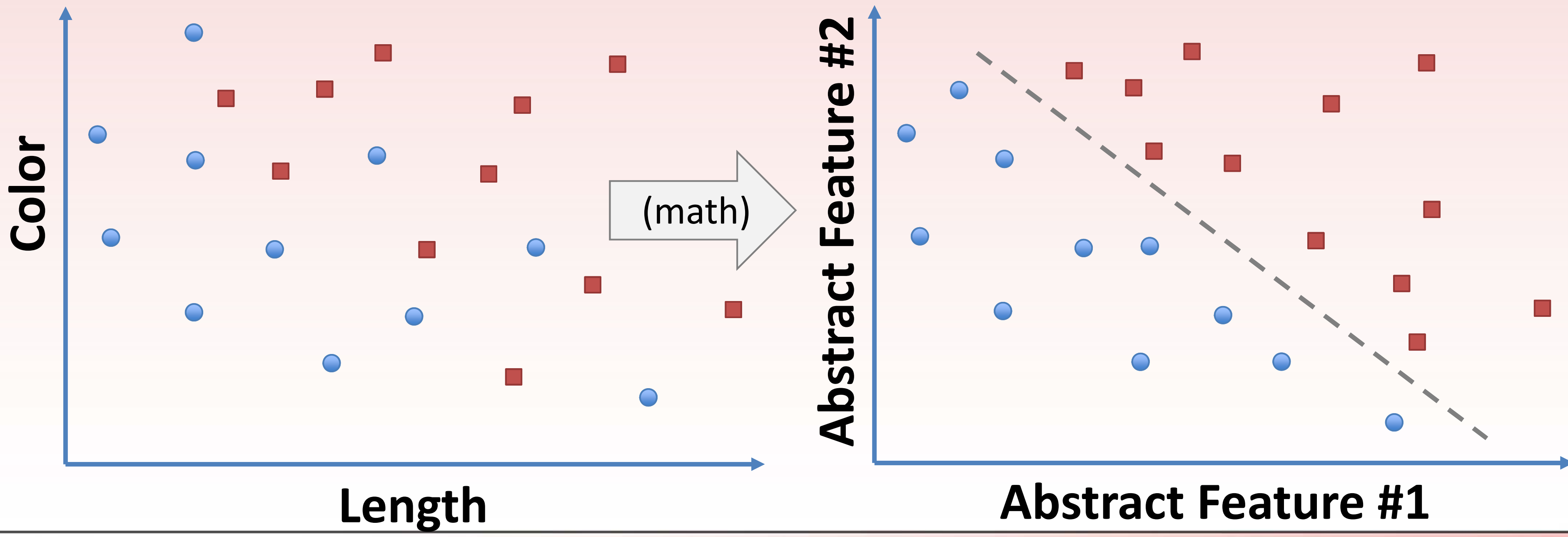
Overfitting the data is a problem!



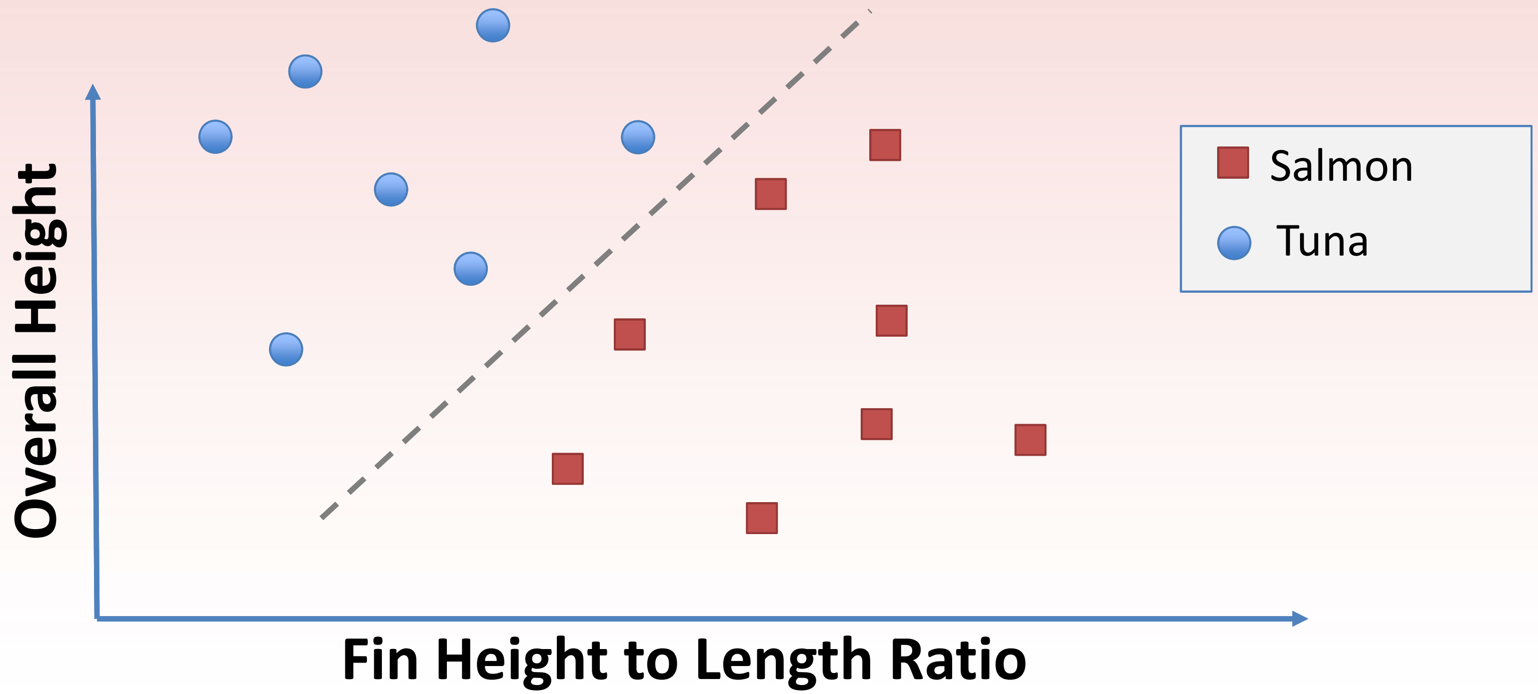
We could linearly separate, and report confidence/ error band:



Or we could transform the features to a new space:



Or we could find new features that work better:

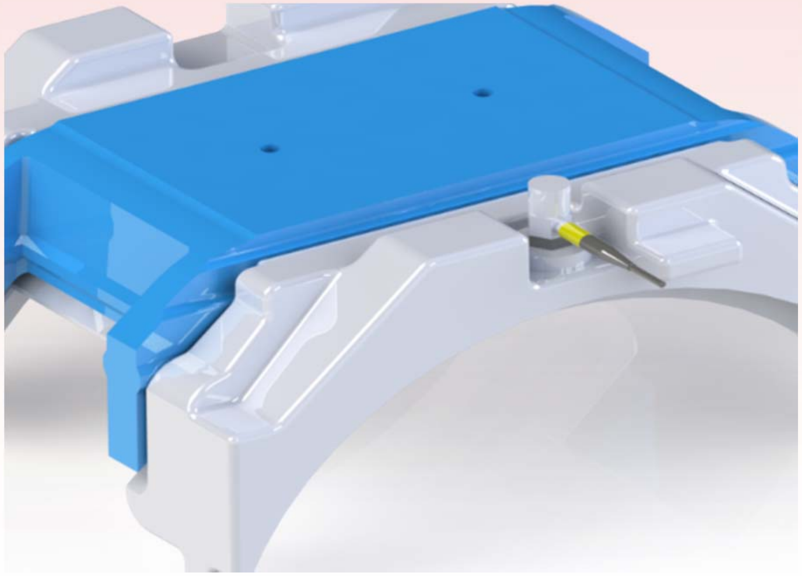


Agenda

1. Motivation
2. Overview of Methodology
3. **Application: Wheel Flat Detection**
4. Application: Wheel Wear Estimation

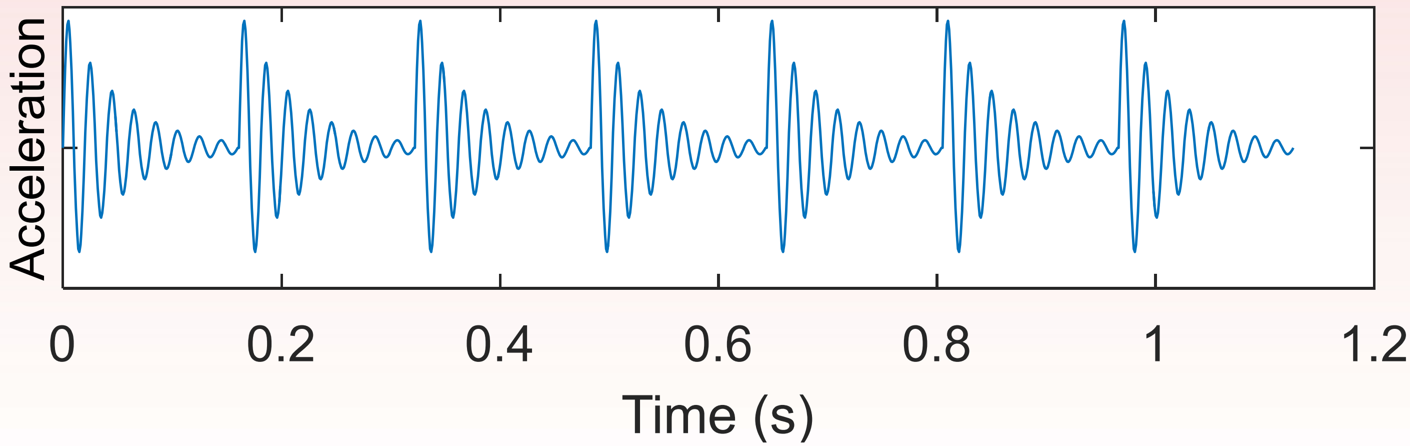
Application: Wheel Flat Detection

Accelerometer mounted to bearing adapter:



Application: Wheel Flat Detection

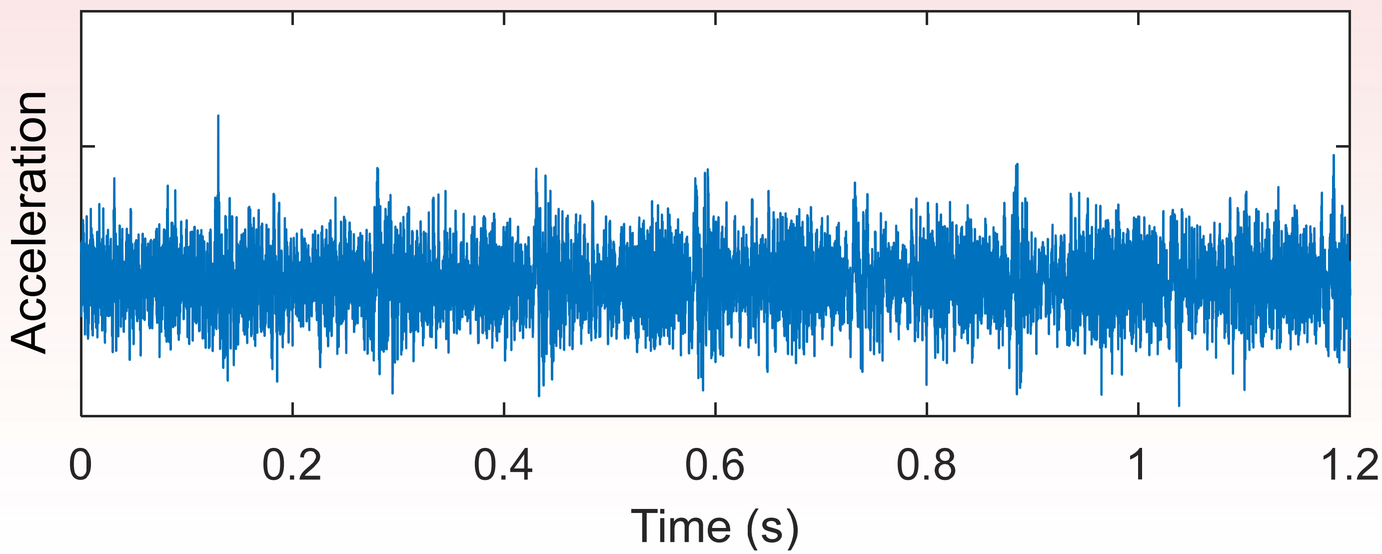
What we *hope* the data will look like:



36 inch wheel would generate a pulse 6.5 times per second traveling at 42 mph

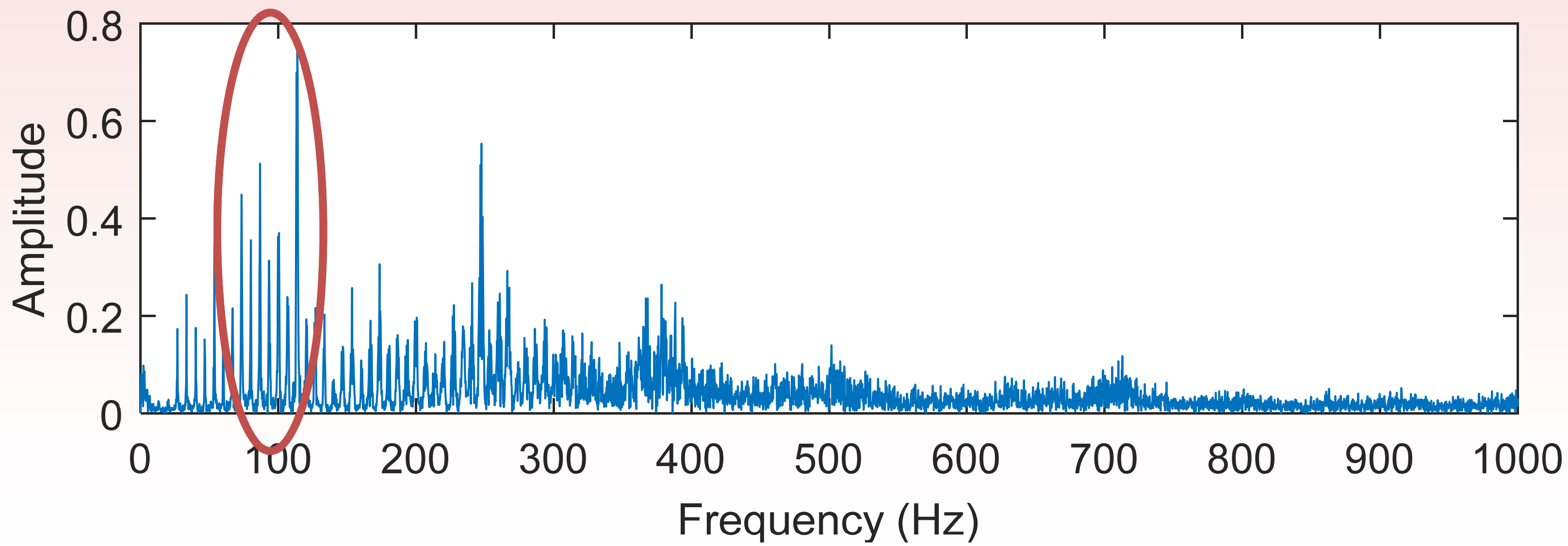
Application: Wheel Flat Detection

What the data really looks like:



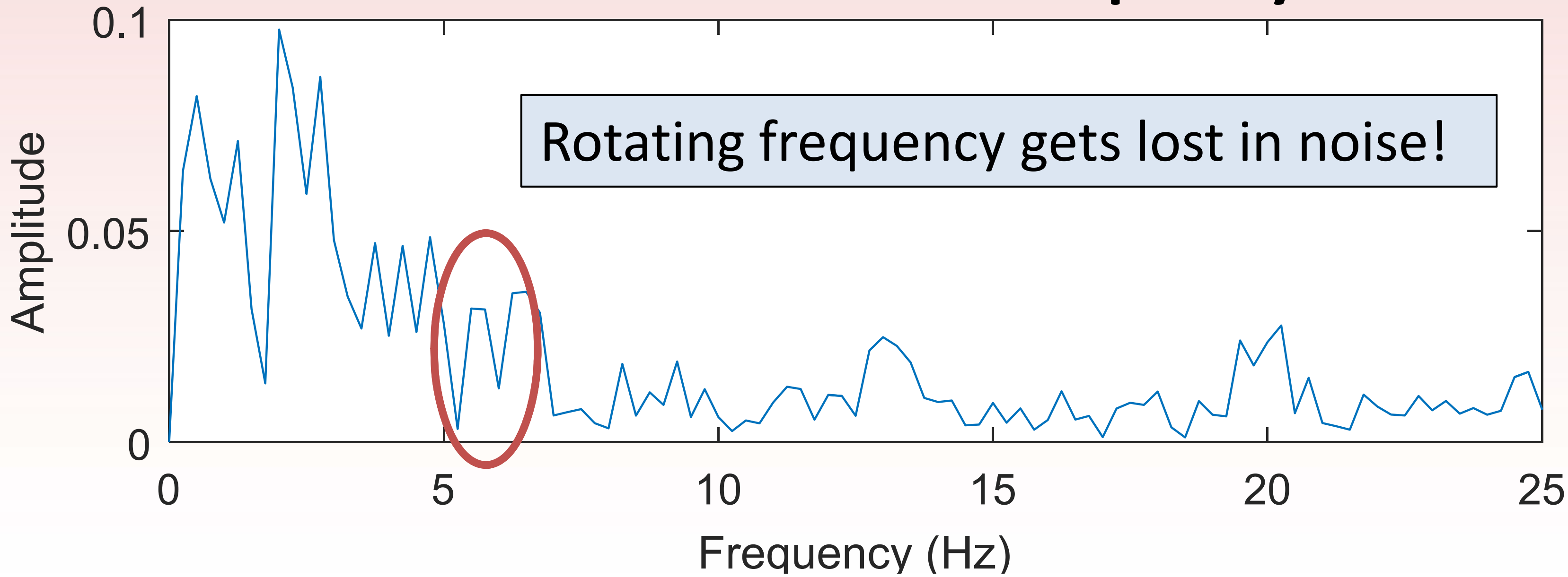
Application: Wheel Flat Detection

Here is what it looks like in the frequency domain:



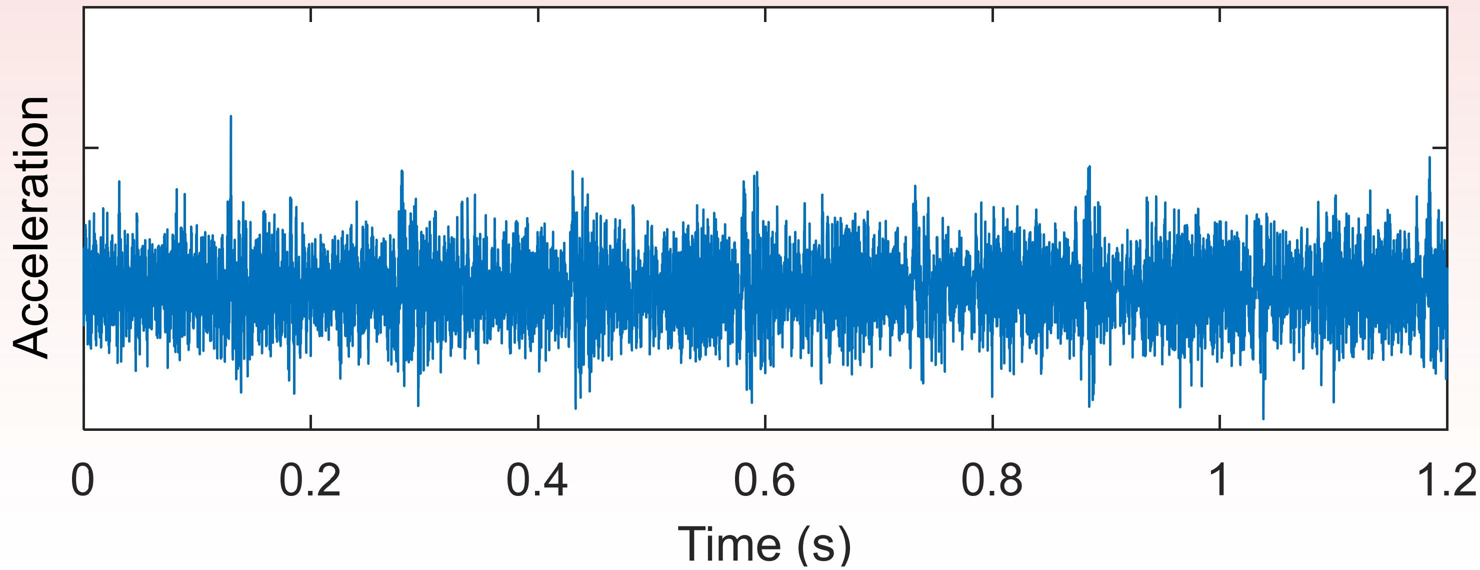
Application: Wheel Flat Detection

Here is what it looks like in the frequency domain:



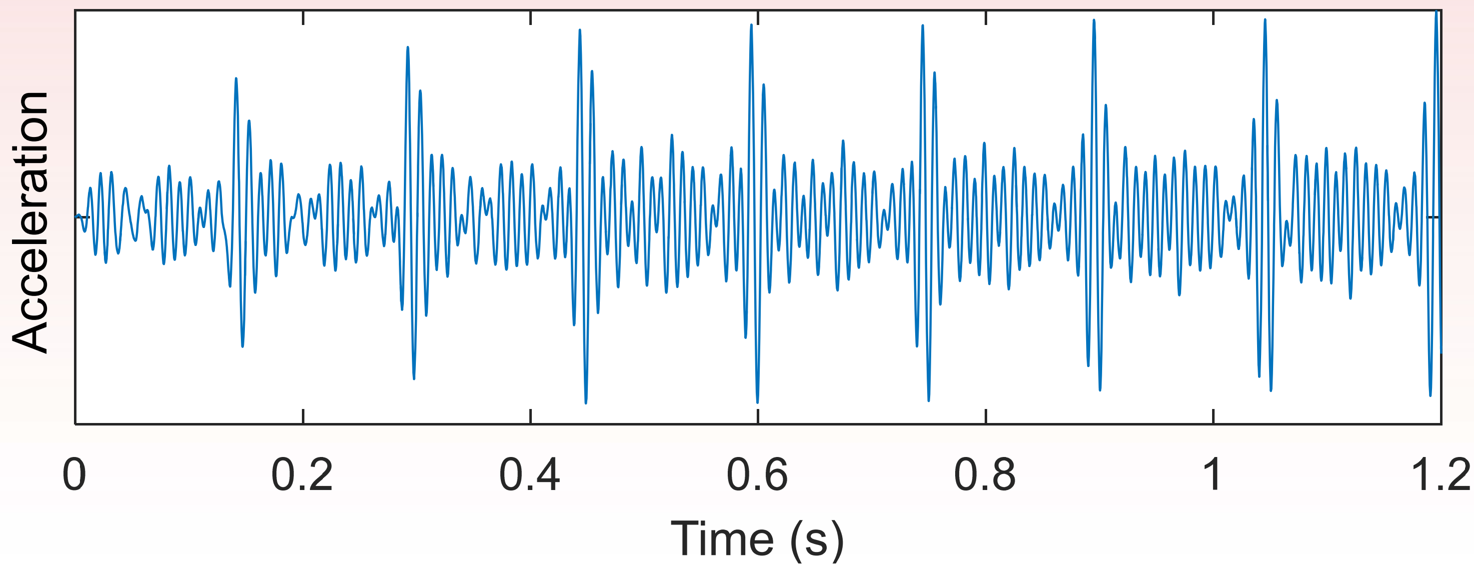
Application: Wheel Flat Detection

Original time domain signal:



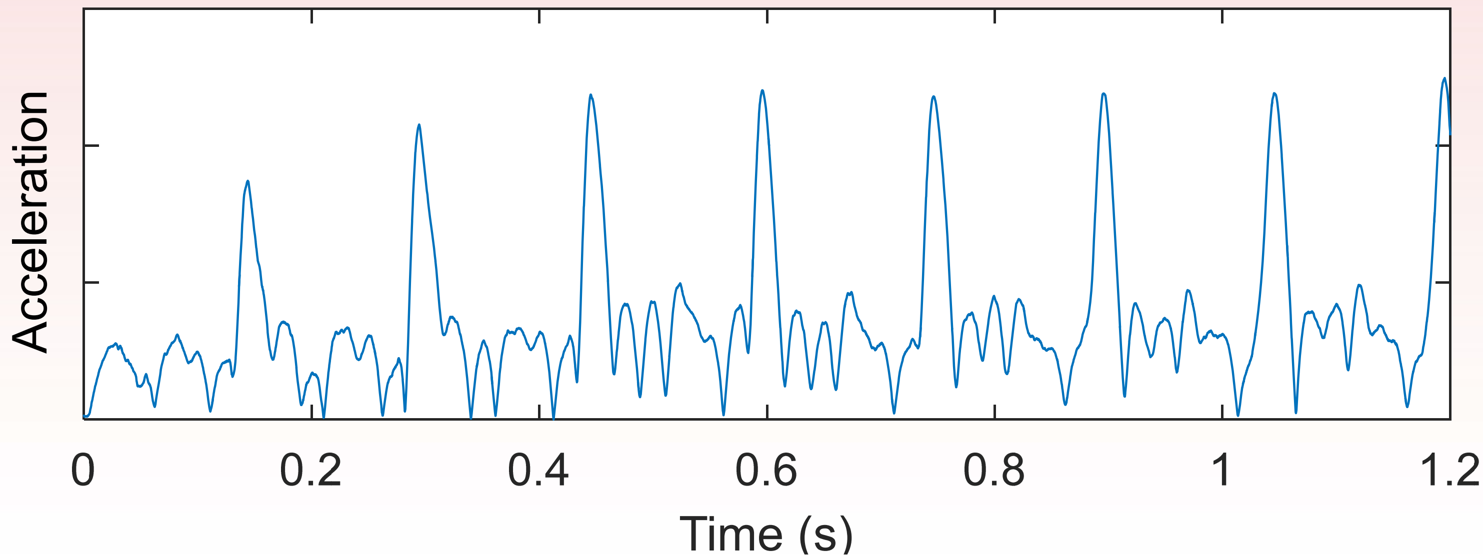
Application: Wheel Flat Detection

Filtered around carrier frequency

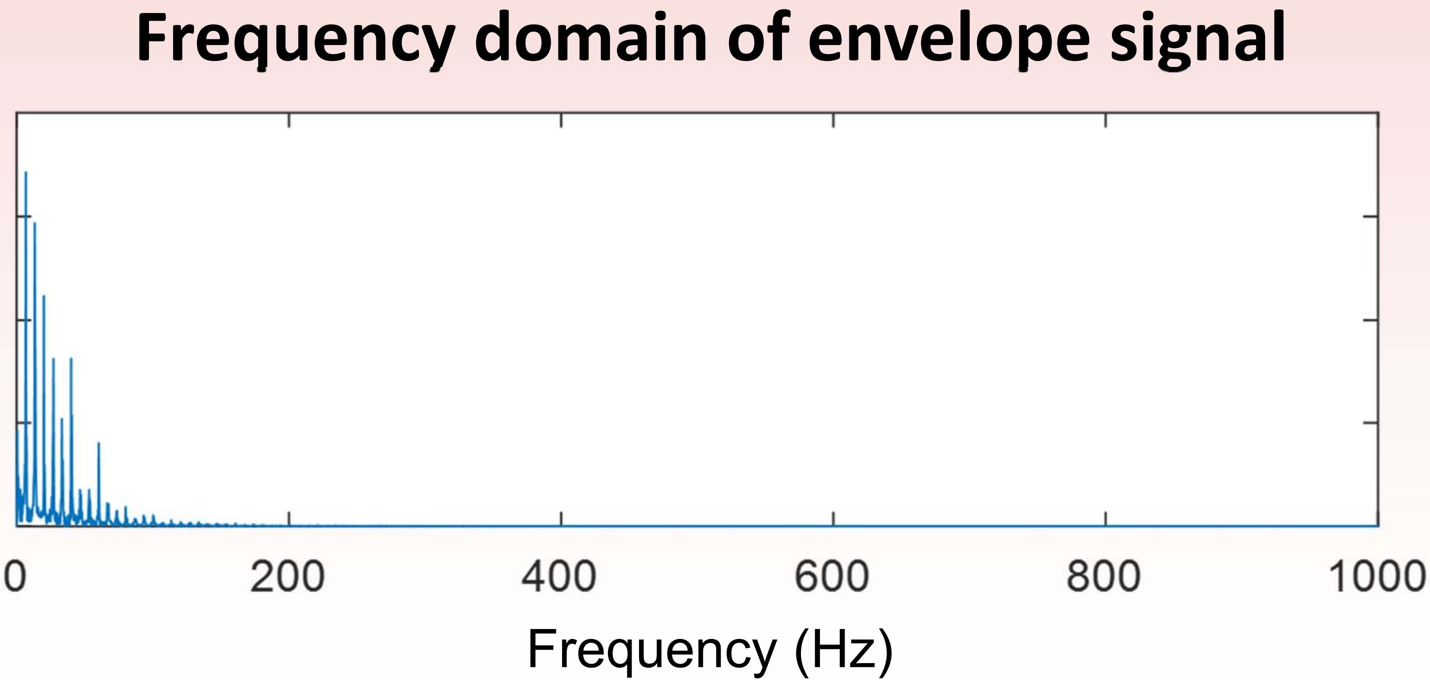


Application: Wheel Flat Detection

Envelope signal

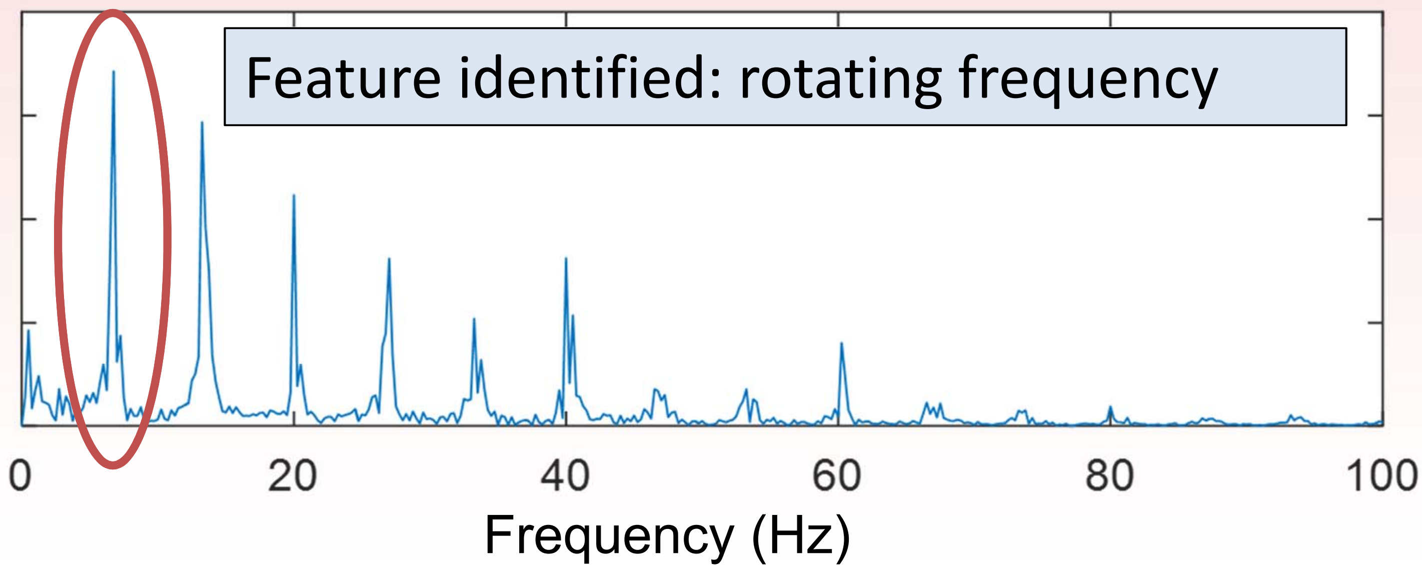


Application: Wheel Flat Detection



Application: Wheel Flat Detection

Frequency domain of envelope signal

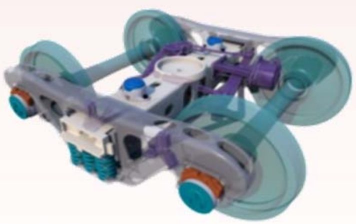


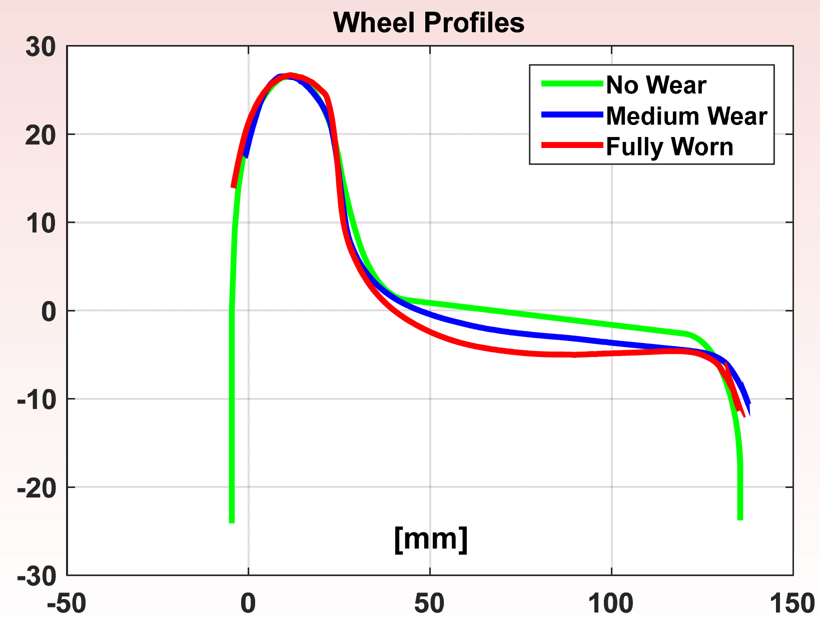
Agenda

1. Motivation
2. Overview of Methodology
3. Application: Wheel Flat Detection
4. **Application: Wheel Wear Estimation**

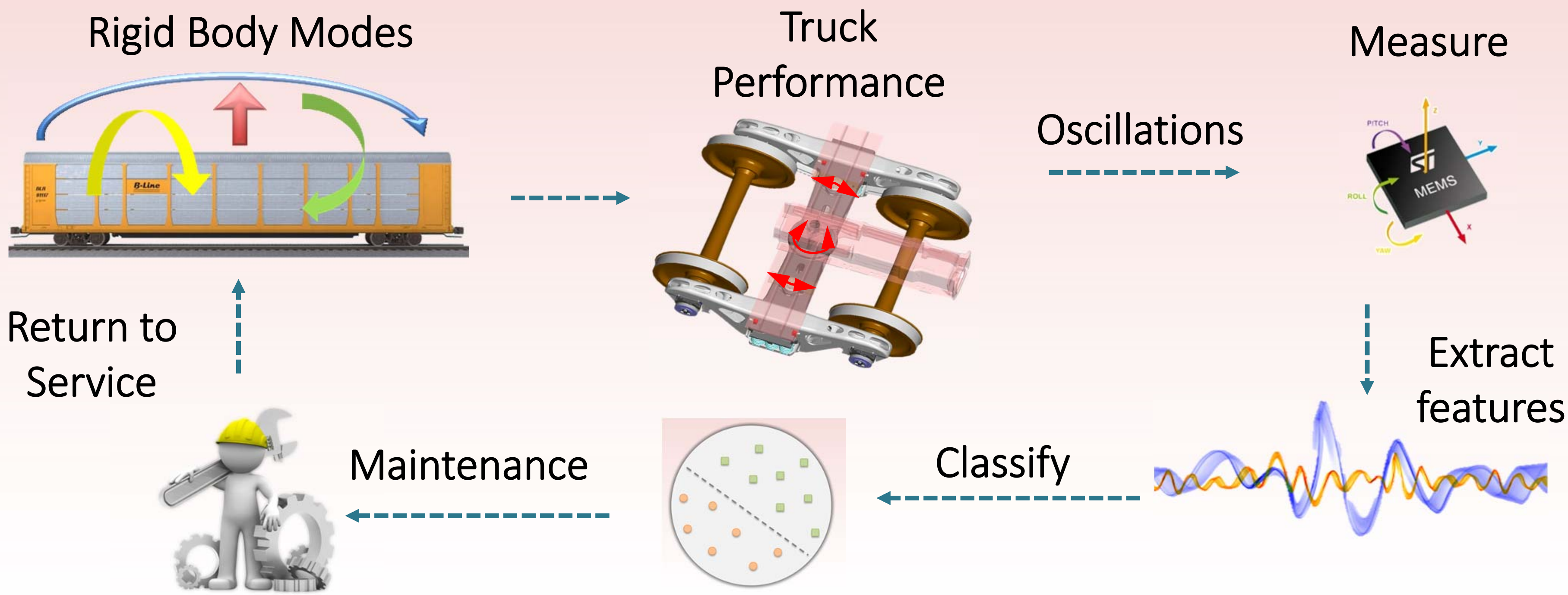
Application: Wheel Wear Estimation

Goal:
determine level of wheel wear using onboard accelerometers





Application: Wheel Wear Estimation



Application: Wheel Wear Estimation

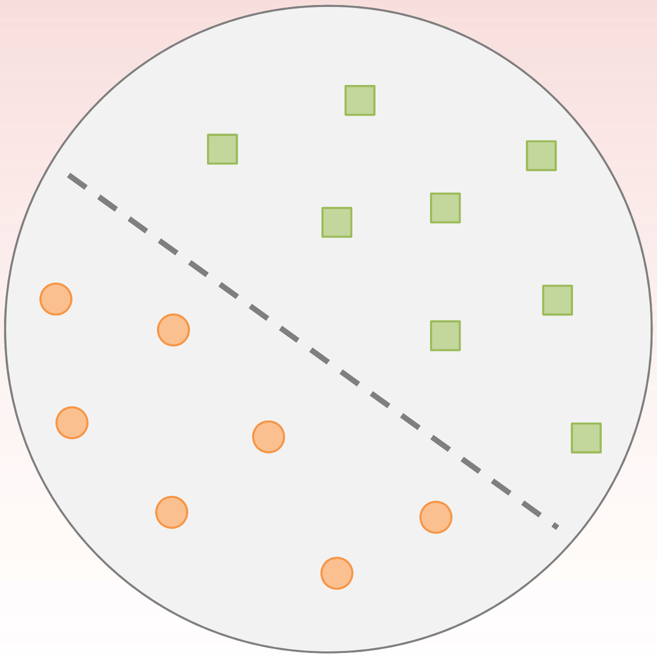
The relevant information is encoded in various time domain, frequency domain, and statistical features

Feature #	Feature Description
1	Band Power (1) 0-5 Hz
2	Band Power (2) 7-12 Hz
3	Band Power (3) 25-50 Hz
4	Magnitude at Fund. Frequency
5	Fundamental Frequency
6	Mean
7	Variance
8	Standard Deviation
9	Peak to Peak

Application: Wheel Wear Estimation

The features are fed into a support vector machine (SVM) to classify

An SVM seeks to maximize the distance between two classes



Application: Wheel Wear Estimation

Results at 50 mph:

Average Classification Accuracy of 79%

Sample Simulation	Predicted Class			
Actual Class		No Wear	Med. Wear	Fully worn
	No Wear	30	0	0
	Med. Wear	0	28	7
	Full Wear	0	14	21

Application: Wheel Wear Estimation

Results at 65 mph:

Average Classification Accuracy of 92%

Classification accuracy using peak to peak and standard deviation: 55%

Sample Simulation	Predicted Class			
Actual Class		No Wear	Med. Wear	Fully worn
	No Wear	29	0	1
	Med. Wear	0	31	4
	Full Wear	1	1	33

Conclusions

- **Sensor selection, placement, and data acquisition are not trivial**
- **Finding the features of interest requires expertise**
- **Machine learning provides a powerful way to classify features for health monitoring**

Questions?