

# Predictive Maintenance in MATLAB

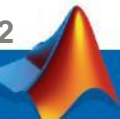
Terasoft

Application Engineer

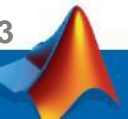
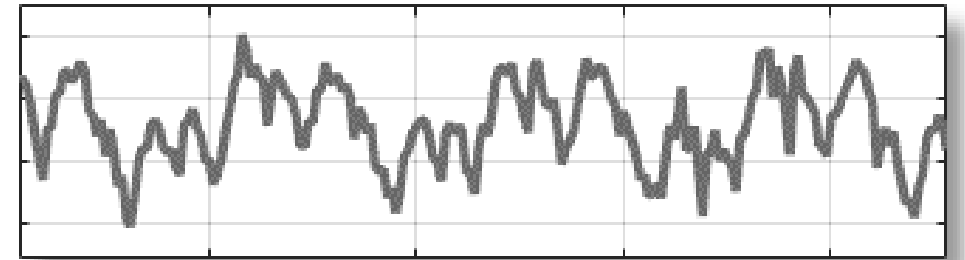
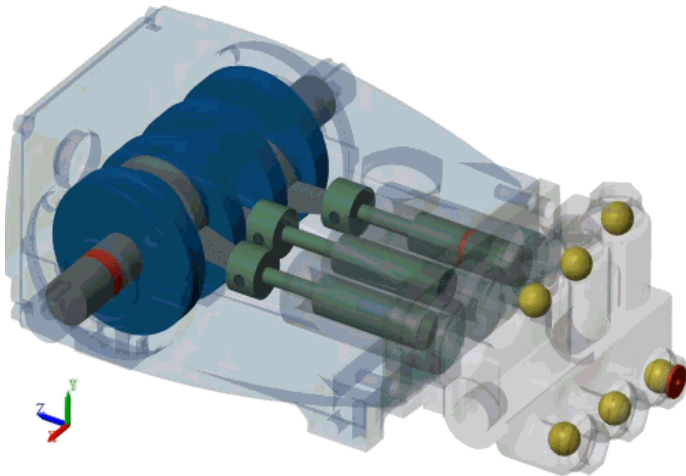
Jeffrey Liu

# Outline

- Predictive Maintenance introduction
- Preprocessing the data (exercise 1)
- Feature extraction using diagnostic feature designer (exercise 2)
- Detecting fault using Classification Learner (exercise 3)
- Predicting remain useful life (exercise 4)
- Deployment



# What is Predictive Maintenance?



# Translate

Turn off instant translation



English

Spanish

French

Pump - detected



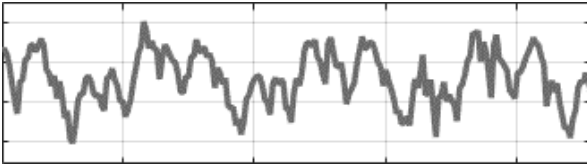
English

Russian

Greek

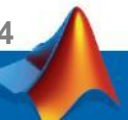


Translate



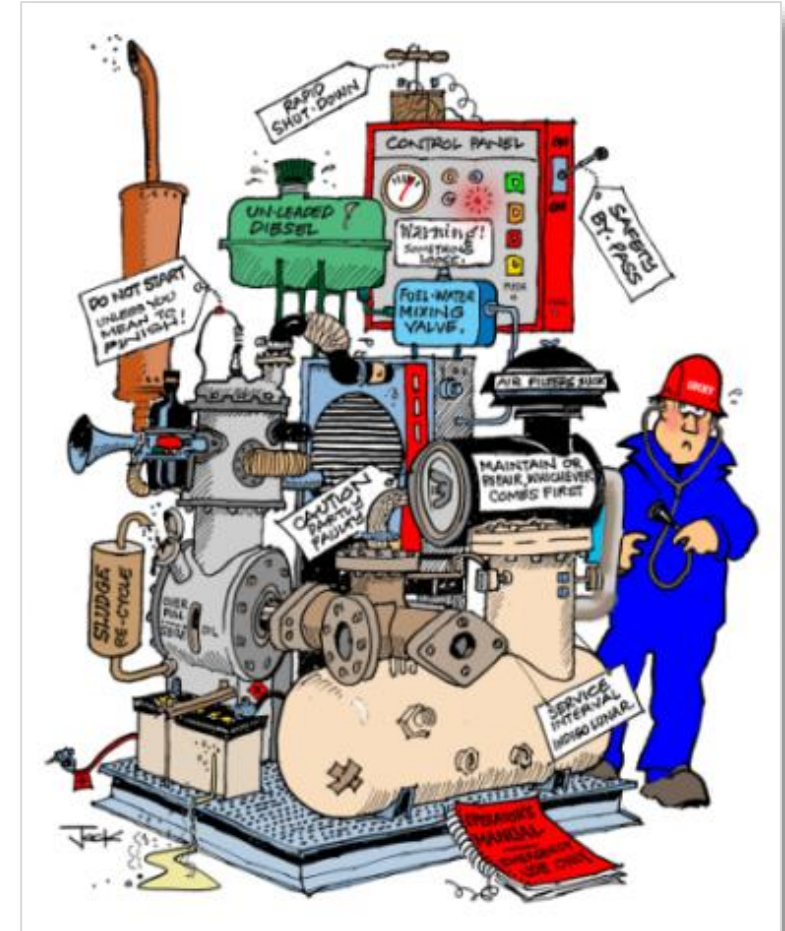
1/5000

**I need help. One of my cylinders is blocked. I will shut down your line in 15 hours.**



# What do you expect from predictive maintenance?

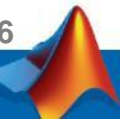
- Maintenance cares about day-to-day operations
  - Reduced downtime
- Operations & IT look at the bigger picture
  - Improved operating efficiency
- Engineering groups get product feedback
  - Better customer experience
- Upper management wants to drive growth
  - New revenue streams



Source: Tensor Systems

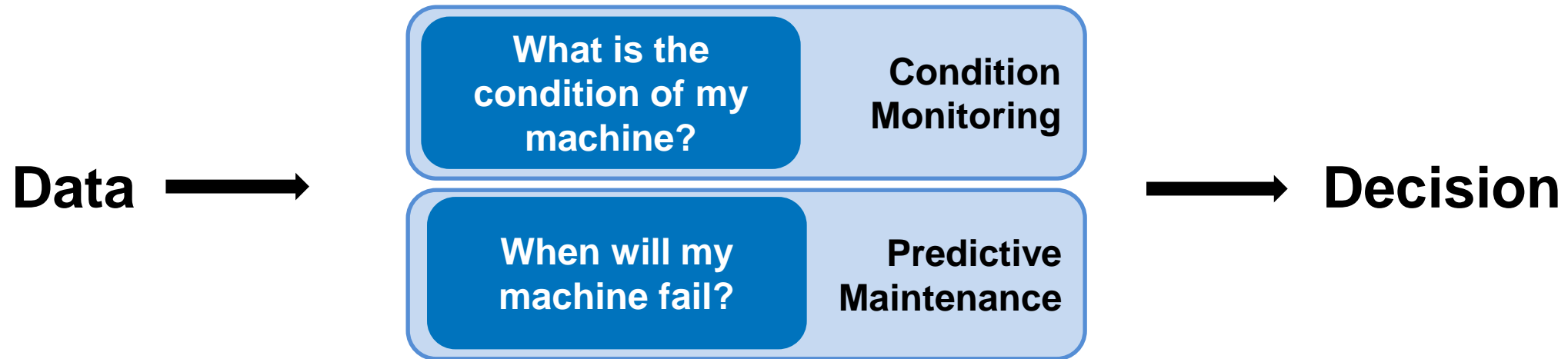
# Types of Maintenance

- Reactive – Do maintenance once there's a problem
  - Example: replace car battery when it fails
  - Problem: unexpected failures can be expensive and potentially dangerous
- Scheduled – Do maintenance at a regular rate
  - Example: change car's oil every 5,000 miles
  - Problem: unnecessary maintenance can be wasteful; may not eliminate all failures
- Predictive – Forecast when problems will arise
  - Example: certain GM car models forecast problems with the battery, fuel pump, and starter motor
  - Problem: difficult to make accurate forecasts for complex equipment



# What does a Predictive Maintenance algorithm do?

*Helps make maintenance decisions based on large volumes of complex data*

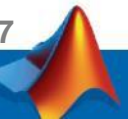


## Condition Monitoring

Process of monitoring sensor data from machines (vibration, temperature etc.) in order to identify significant changes which can indicate developing faults

## Predictive Maintenance

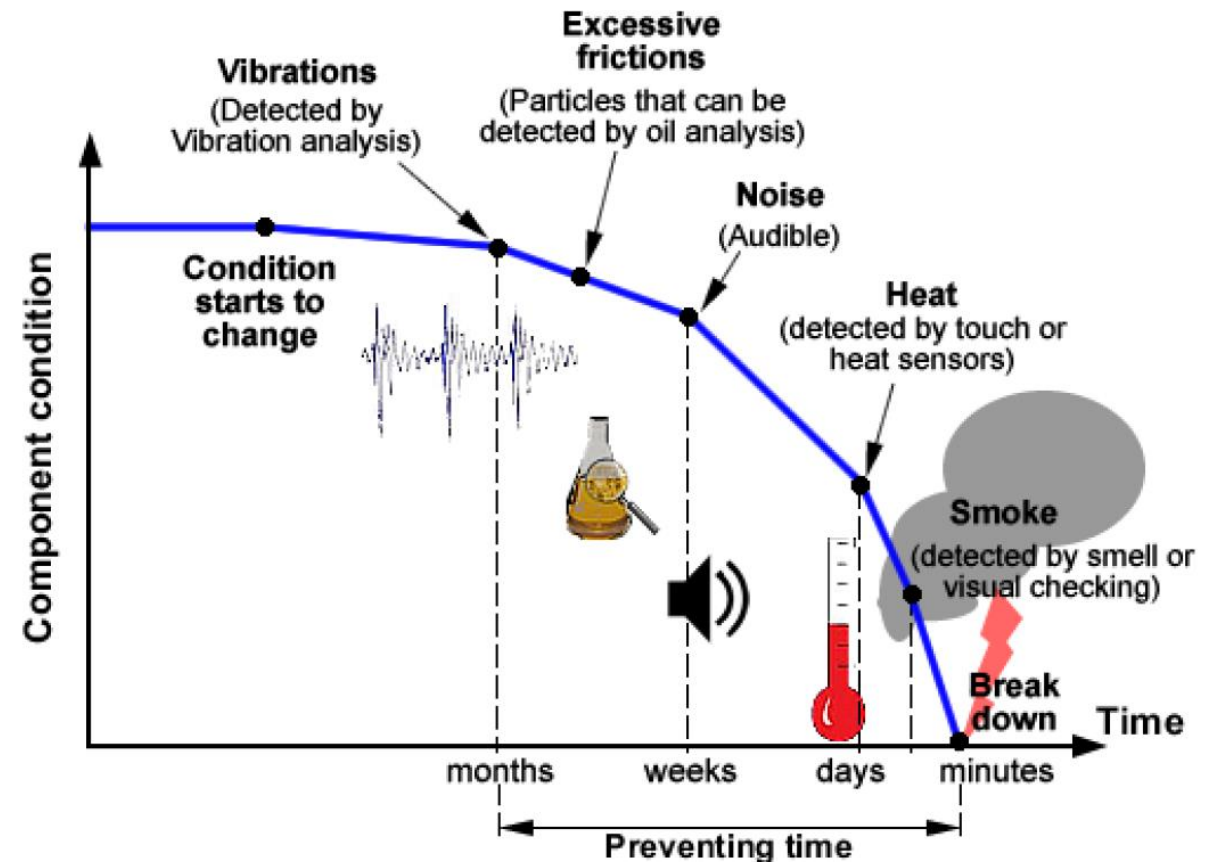
Technique that determines **time-to-failure/remaining useful life (RUL)** from sensor data & historical data in order to predict when maintenance should be performed





# Before getting started on data...

- What do you want to detect?
- How long before do you need to detect it?
- What are the accessible data?
- How much risk can you take?
- Apps on PC or deploy to the devices?

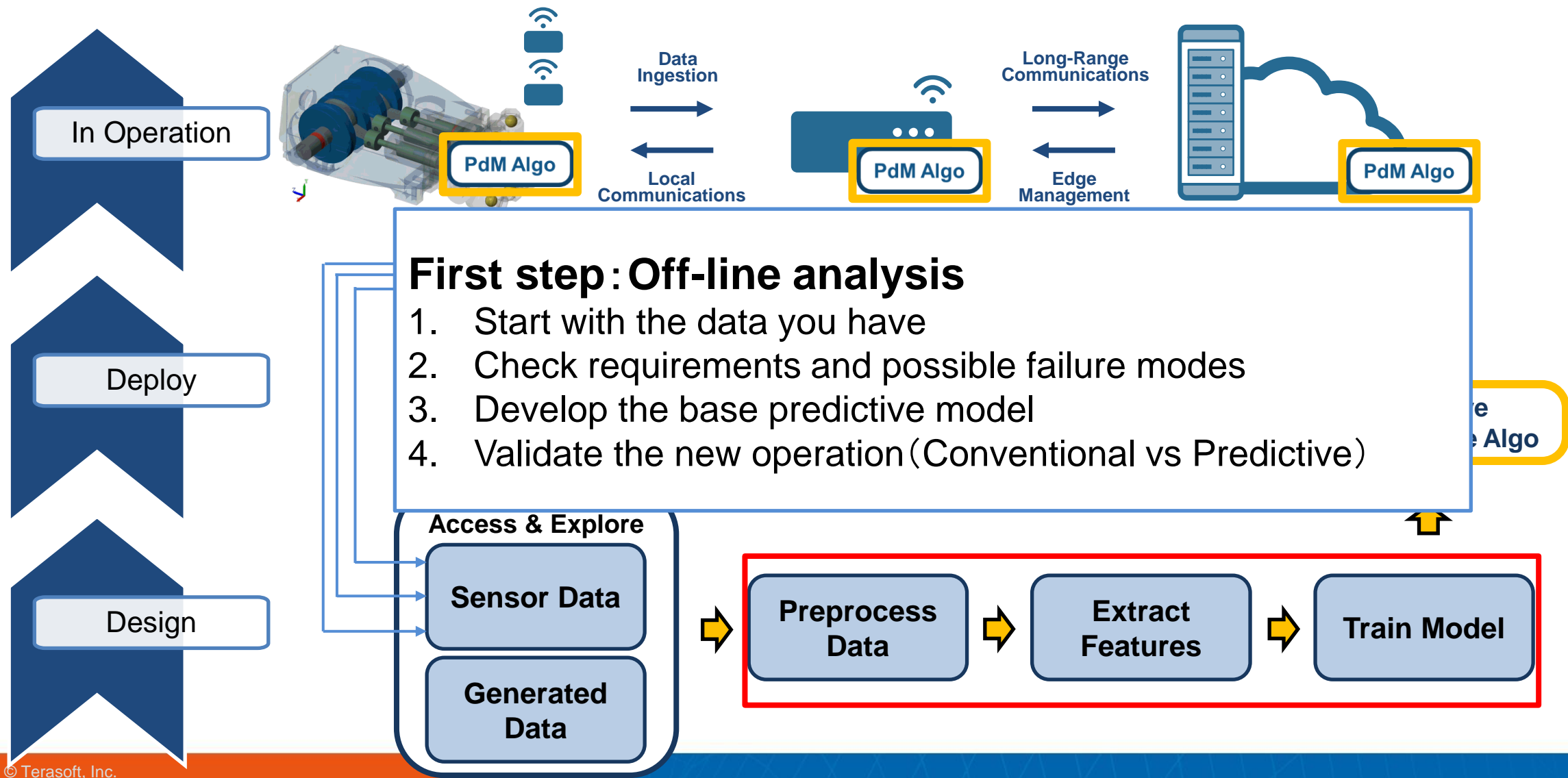


Typical development of a machine failure (Ex. Wind Turbine)

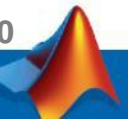
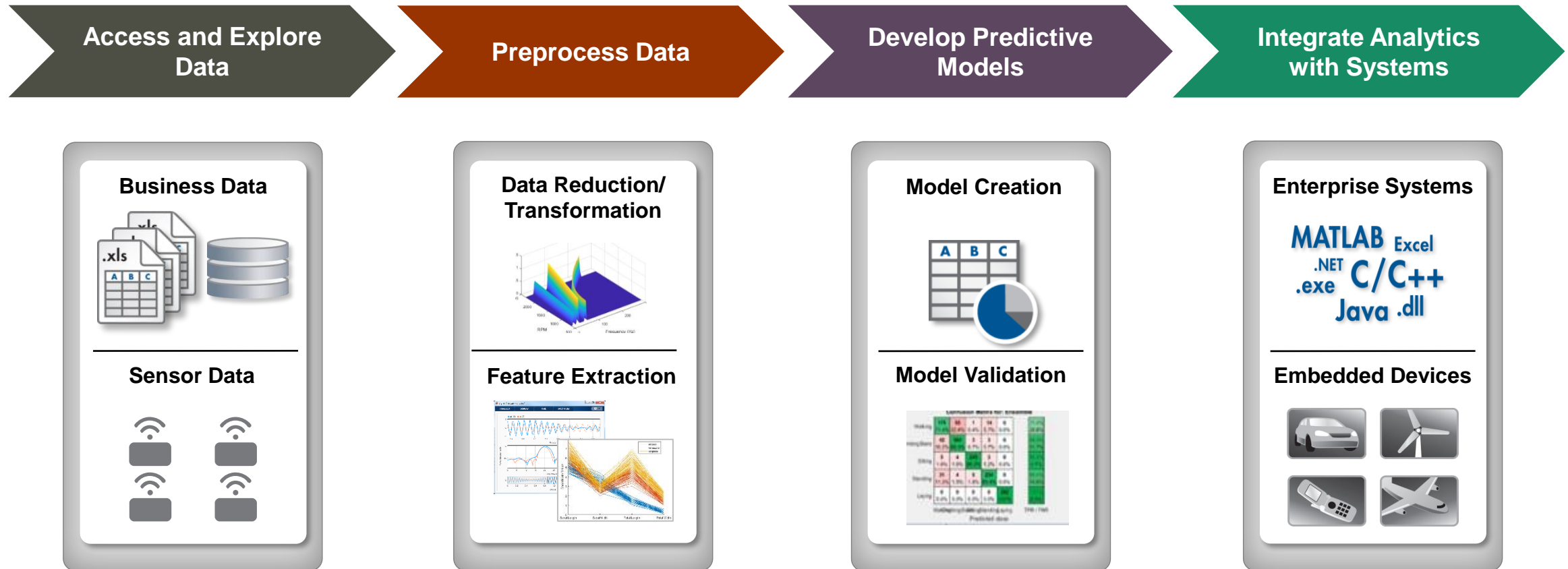
Tchakoua, Pierre, et al. "Wind turbine condition monitoring: State-of-the-art review, new trends, and future challenges." *Energies* 7.4 (2014): 2595-2630.



# Predictive Maintenance Solution – Common Workflow

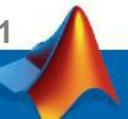
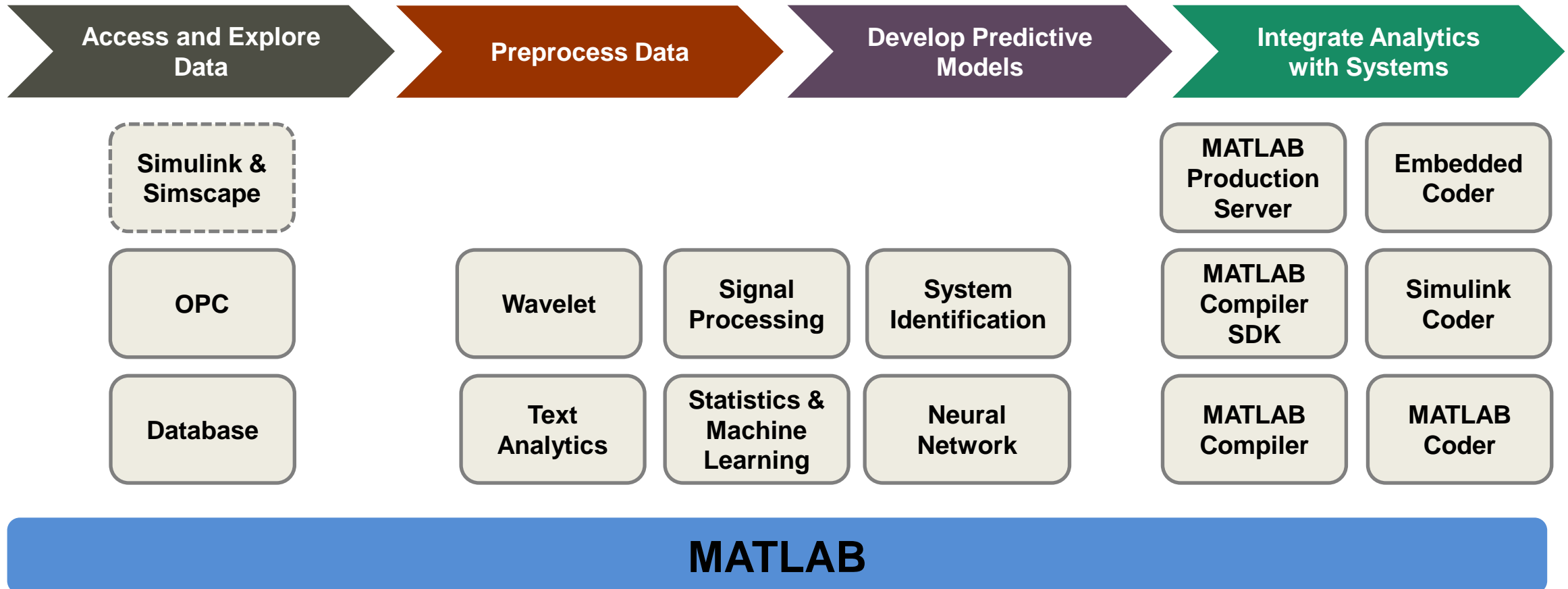


# Predictive Maintenance Workflow : Four steps



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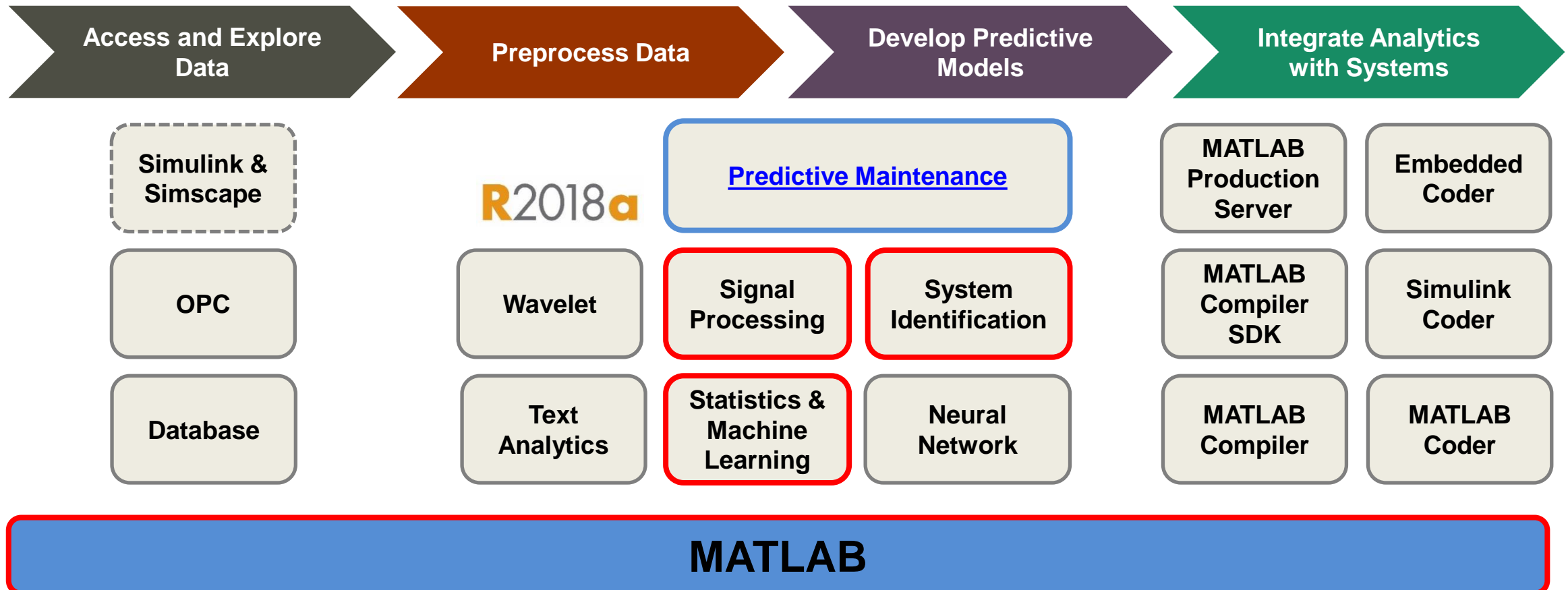
## Product examples



# Predictive Maintenance Workflow : Four steps

## Product examples

Prerequisites



# Common Challenges

- How do I get started with developing algorithms?
  - Reference examples
  - Workflow-based documentation
- How do I manage data and what if I don't have any data?
  - Command line functions to organize data
  - Examples showing Simulink models generating failure data
- How do I choose condition indicators and estimate the RUL?
  - Functions for computing condition indicators
  - Functions provided for estimating RUL

The screenshot shows a 'Documentation' window with a search bar and a 'CONTENTS' menu. The main content area displays the title 'Nonlinear State Estimation of a Degrading Battery System' with a version tag 'R2017b'. Below the title, there is a section of MATLAB code for running simulations and creating an ensemble. The code includes comments and function calls like 'createSimulationEnsemble'. Below the code, there is a log of simulation progress, showing the start of a parallel pool, loading of Simulink models, and the completion of 10 out of 208 simulation runs. At the bottom, there are three sections: 'Detect and Predict Faults', 'Deploy Predictive Maintenance Algorithms', and 'Applications', each with a brief description.

```
% Run the simulations and create an ensemble to manage the simulation results
mkdir('.\Data') % Create directory to store results
runAll = true;
if runAll
    ens = createSimulationEnsemble([gridSimulationInput, randomSimulationInput], ...
    [pwd '\Data'], 'UseParallel', true);
else
    ens = createSimulationEnsemble(gridSimulationInput(1:10), [pwd '\Data']);
end
```

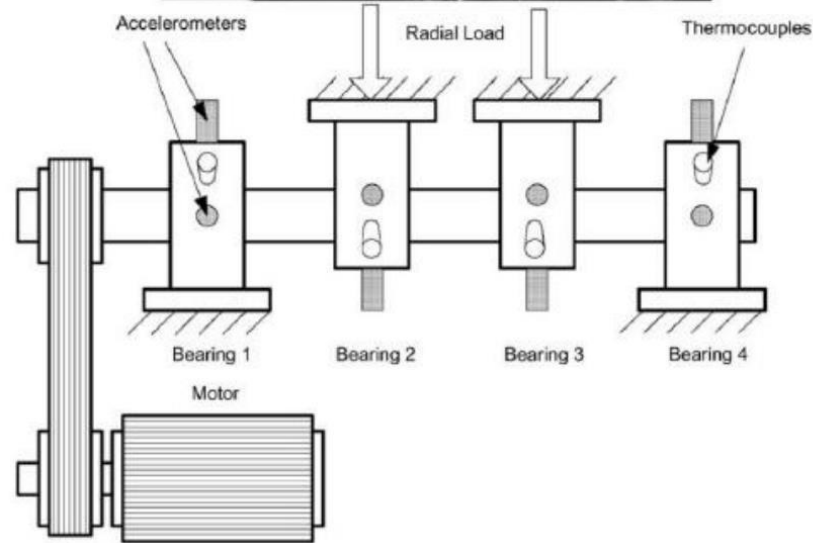
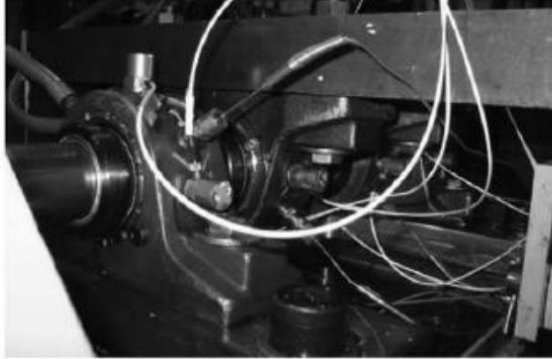
[21-Nov-2017 09:06:31] Checking for availability of parallel pool...  
Starting parallel pool (parpool) using the 'local' profile ...  
connected to 6 workers.  
[21-Nov-2017 09:06:56] Loading Simulink on parallel workers...  
[21-Nov-2017 09:07:12] Configuring simulation cache folder on parallel workers...  
[21-Nov-2017 09:07:12] Loading model on parallel workers...  
[21-Nov-2017 09:07:18] Running simulations...  
Analyzing and transferring files to the workers ...done.  
[21-Nov-2017 09:07:37] Completed 1 of 208 simulation runs  
[21-Nov-2017 09:07:38] Completed 2 of 208 simulation runs  
[21-Nov-2017 09:07:38] Completed 3 of 208 simulation runs  
[21-Nov-2017 09:07:39] Completed 4 of 208 simulation runs  
[21-Nov-2017 09:07:39] Completed 5 of 208 simulation runs  
[21-Nov-2017 09:07:39] Completed 6 of 208 simulation runs  
[21-Nov-2017 09:07:46] Completed 7 of 208 simulation runs  
[21-Nov-2017 09:07:46] Completed 8 of 208 simulation runs  
[21-Nov-2017 09:07:47] Completed 9 of 208 simulation runs  
[21-Nov-2017 09:07:47] Completed 10 of 208 simulation runs

**Detect and Predict Faults**  
Train decision models for condition monitoring and fault detection; predict remaining useful life (RUL)

**Deploy Predictive Maintenance Algorithms**  
Implement and deploy condition-monitoring and predictive-maintenance algorithms

**Applications**  
Examples of predictive-maintenance algorithm development

# Example: Features from Bearing Data

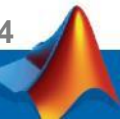


- 4 bearings installed on a shaft.
- Recorded over 7 days with 10 mins interval at 2000 RPM with load on shaft
- Each segment covers 1sec at 20kHz
- At the end of the experiment, failure occurred.

Data provided by NASA PCoE

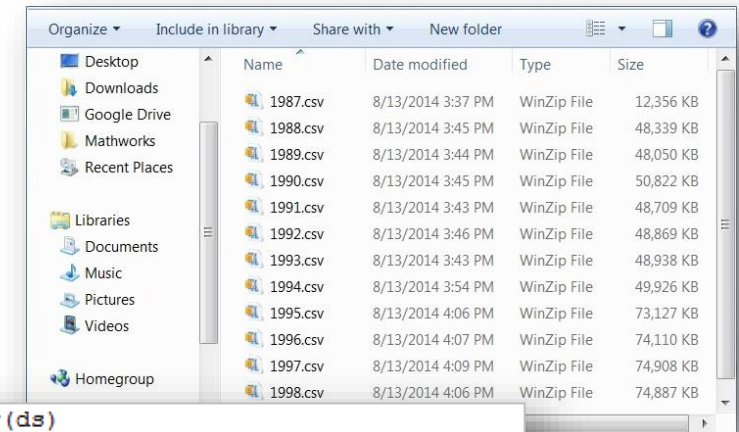
J. Lee, et.al. "Bearing Data Set", NASA Ames Prognostics Data Repository

(<http://ti.arc.nasa.gov/project/prognostic-data-repository>), NASA Ames Research Center, Moffett Field, CA



# Access Big Data datastore

- Easily specify data set
  - Single text file (or collection of text files)
  - Database (using Database Toolbox)
- Preview data structure and format
- Select data to import using column names
- Incrementally read subsets of the data



A screenshot of a Windows File Explorer window. The left sidebar shows the 'Libraries' section with 'Documents' selected. The main pane displays a list of files named '1987.csv' through '1998.csv'. The columns are 'Name', 'Date modified', 'Type', and 'Size'. All files are 'WinZip File' type. The dates are all from 8/13/2014. The sizes range from 12,356 KB to 74,887 KB.

Name	Date modified	Type	Size
1987.csv	8/13/2014 3:37 PM	WinZip File	12,356 KB
1988.csv	8/13/2014 3:45 PM	WinZip File	48,339 KB
1989.csv	8/13/2014 3:44 PM	WinZip File	48,050 KB
1990.csv	8/13/2014 3:45 PM	WinZip File	50,822 KB
1991.csv	8/13/2014 3:43 PM	WinZip File	48,709 KB
1992.csv	8/13/2014 3:46 PM	WinZip File	48,869 KB
1993.csv	8/13/2014 3:43 PM	WinZip File	48,938 KB
1994.csv	8/13/2014 3:54 PM	WinZip File	49,926 KB
1995.csv	8/13/2014 4:06 PM	WinZip File	73,127 KB
1996.csv	8/13/2014 4:07 PM	WinZip File	74,110 KB
1997.csv	8/13/2014 4:09 PM	WinZip File	74,908 KB
1998.csv	8/13/2014 4:06 PM	WinZip File	74,887 KB

```
>> preview(ds)
ans =
```

Year	Month	DayofMonth	DayOfWeek
1987	10	21	3
1987	10	26	1
1987	10	23	5
1987	10	23	5

```
airdata = datastore('*.csv');
airdata.SelectedVariables = {'Distance', 'ArrDelay'};

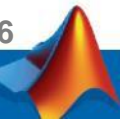
data = read(airdata);
```



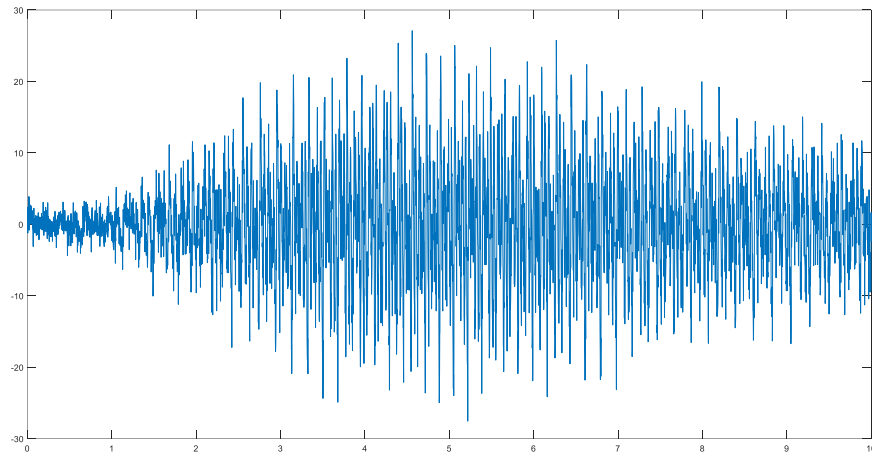
# How to use “DATASTORE” function

## Demo 1.1 : reading files with ‘datastore’

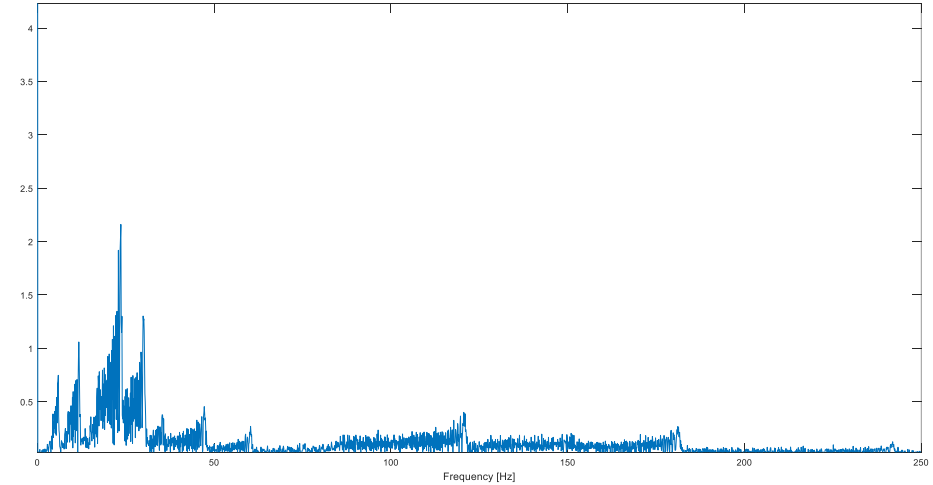
- `ds = datastore(location, Name, Value)`
  - Location:
    - file direction ( ‘C:\dir\data\file.csv’ )
    - Read from HDFS ( ‘hdfs://myserver:7867/data/file1.txt’ )
  - Name-Value Pair
    - TextscanFormats
    - SelectedVariableNames, SelectedFormat
    - Delimiter
    - ReadSize
- Methods of DATASTORE object
  - preview, read, readall



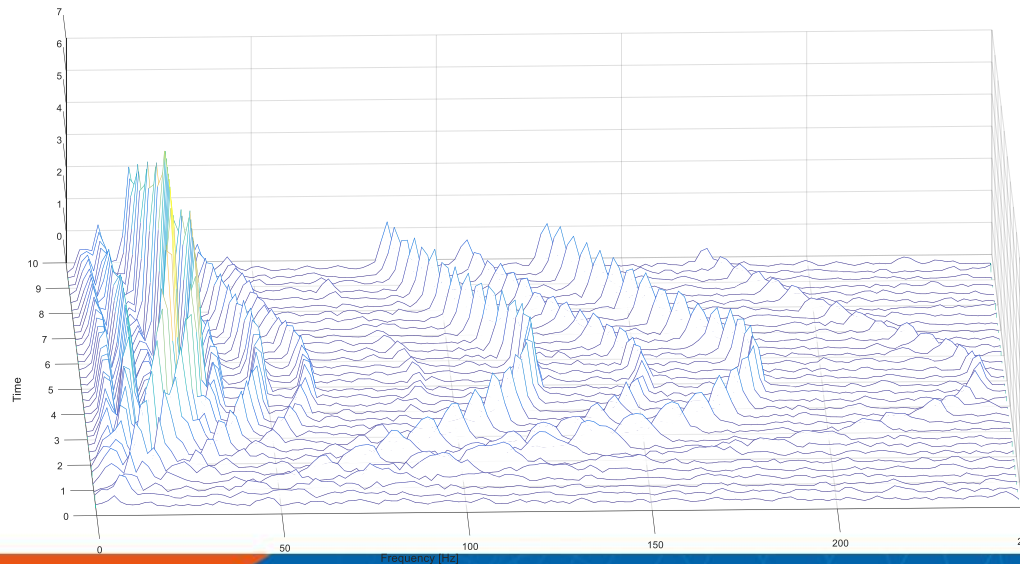
# Feature Extraction : Signal Processing Techniques



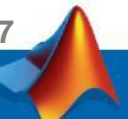
Time domain



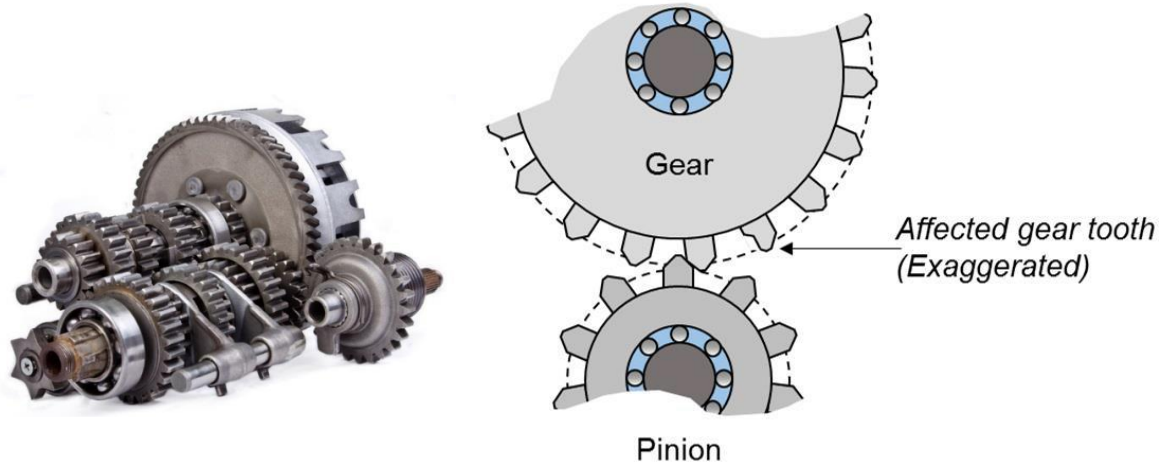
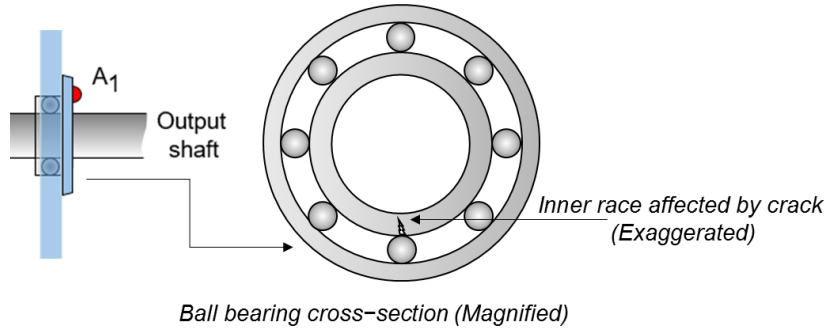
Frequency domain



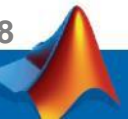
Frequency-RPM map waterfall



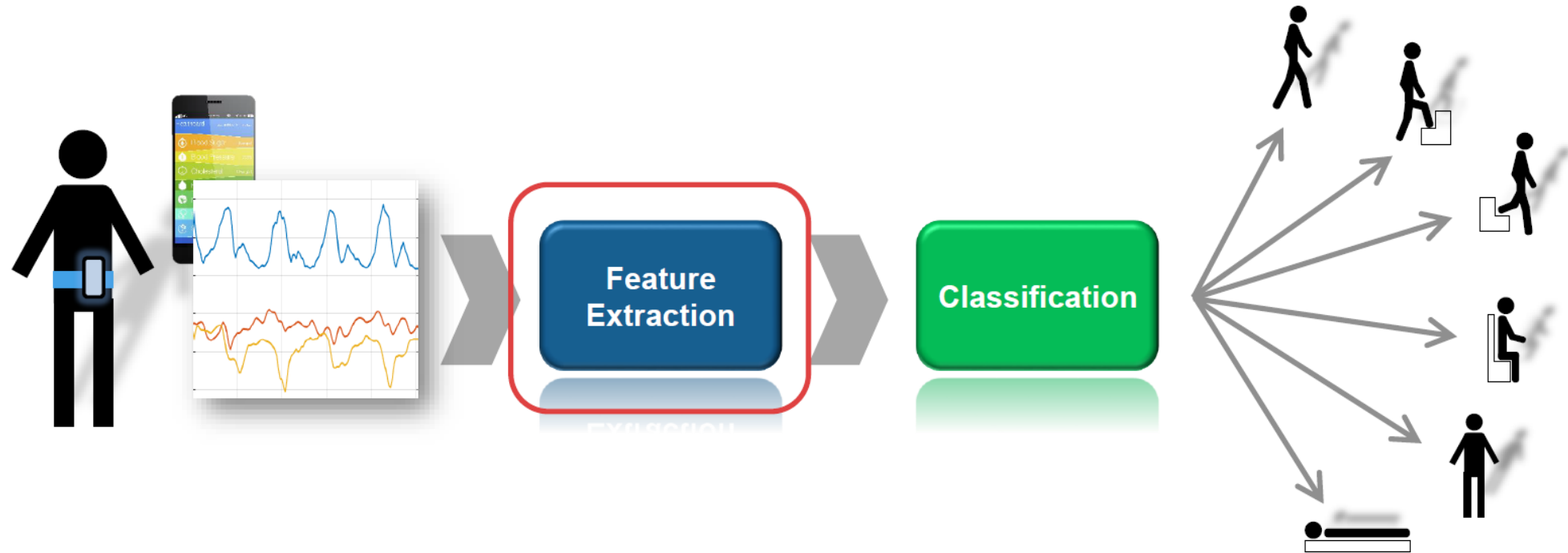
# Common Feature for Vibration Analysis



- 常見旋轉機械故障類型
  - 軸不平衡
  - 軸彎曲
  - 不對中 (平行、角度)
  - 鬆動
  - 油膜旋振
  - 油膜晃蕩
  - 內環損傷
  - 外環損傷
  - 氣隙不均
  - 轉子條斷裂
  - 齒輪偏心
  - 齒輪磨耗
  - 齒輪不對中
- 常見的振動訊號特徵
  - Root mean square
  - Peak frequency
  - Harmonics components
  - Crest factor
  - Entropy, Energy, Kurtosis
  - Largest Lyapunov exponent
  - Envelope spectrum
  - Mean frequency
  - Variance of frequency
  - Standard Deviation
  - Kurtosis
  - Skewness
  - etc...

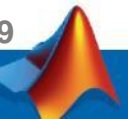


# Signal Processing on Human Activity Data



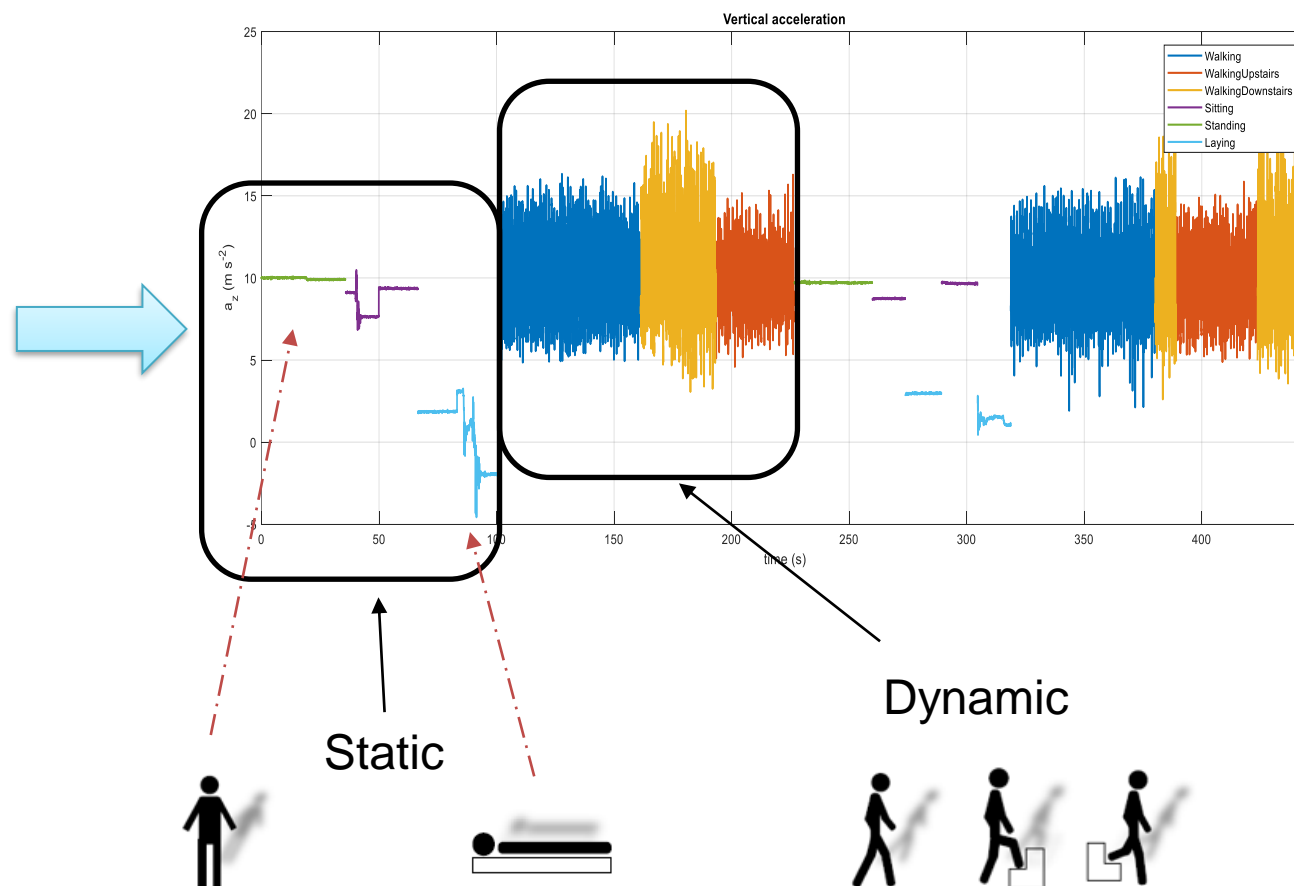
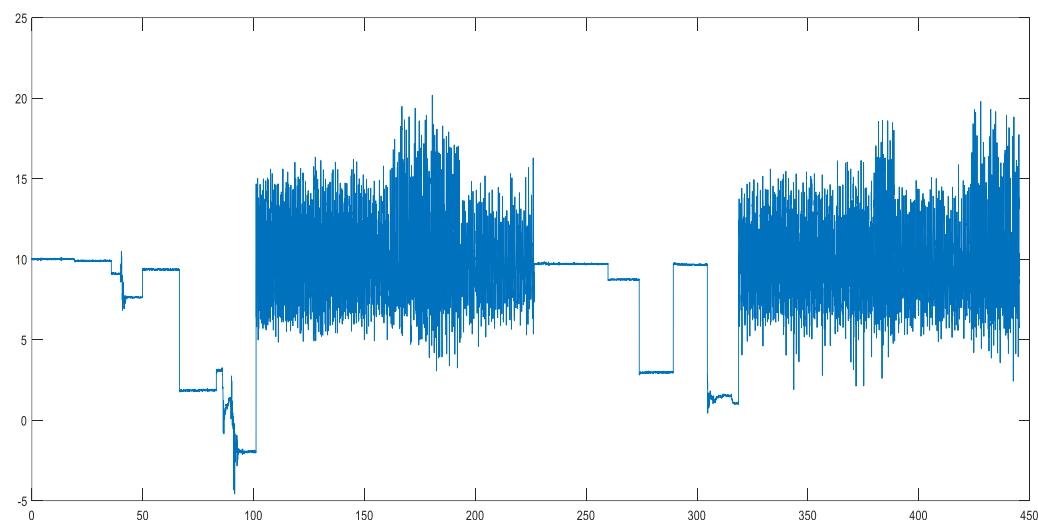
**Dataset courtesy of:**

DavideAnguita, Alessandro Ghio, Luca Oneto, Xavier Parra and Jorge L. Reyes-Ortiz. *Human Activity Recognition on Smartphones using a Multiclass Hardware-Friendly Support Vector Machine*. International Workshop of Ambient Assisted Living (IWAAL 2012). Vitoria-Gasteiz, Spain. Dec 2012  
<http://archive.ics.uci.edu/ml/datasets/Human+Activity+Recognition+Using+Smartphones>



# Insight from Visualization by Activity

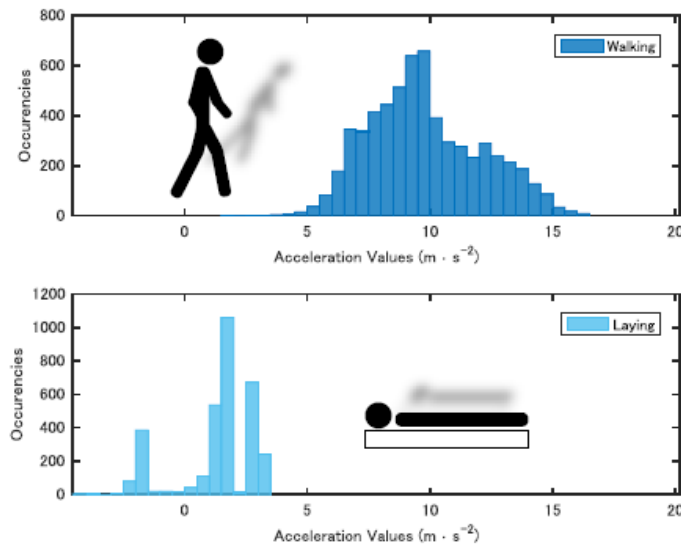
## Human Activity Analysis and Classification



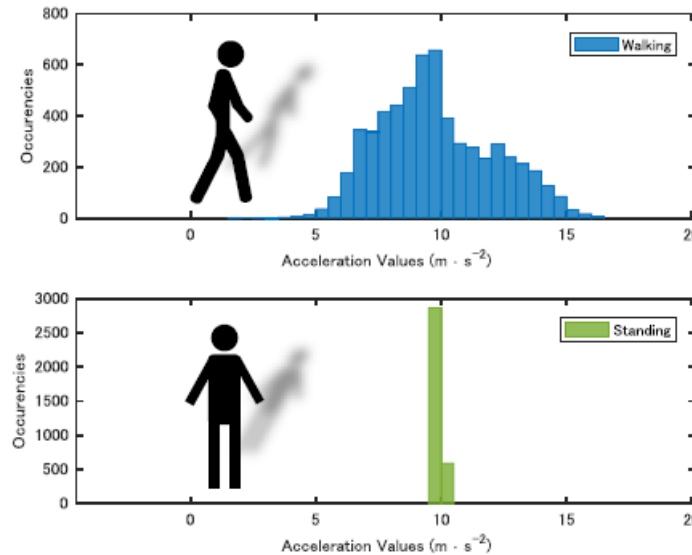
# Features from Histogram Visualization

## Demo 1.2 : Extracting standard deviations from sensor signal

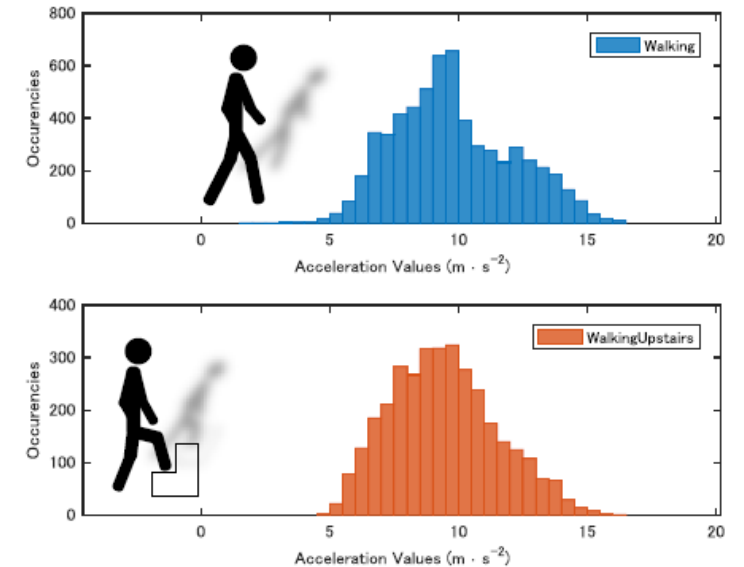
What are the differentiators?



**Mean value!**



**RMS!**



**Ummm..**

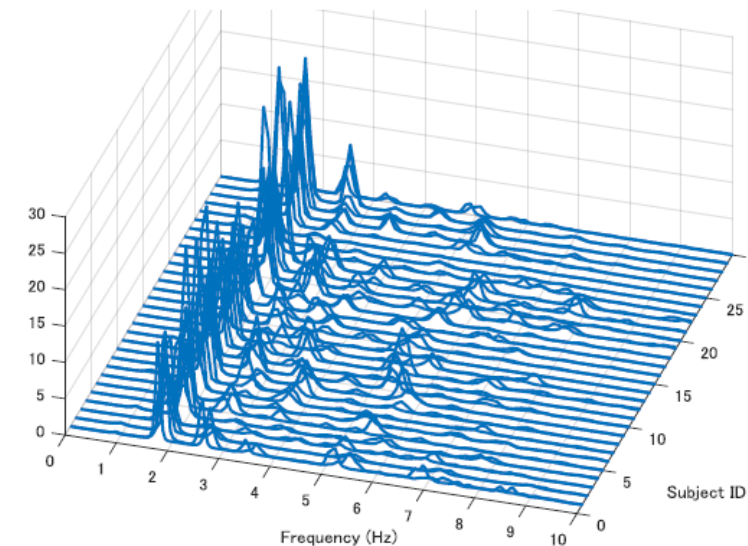
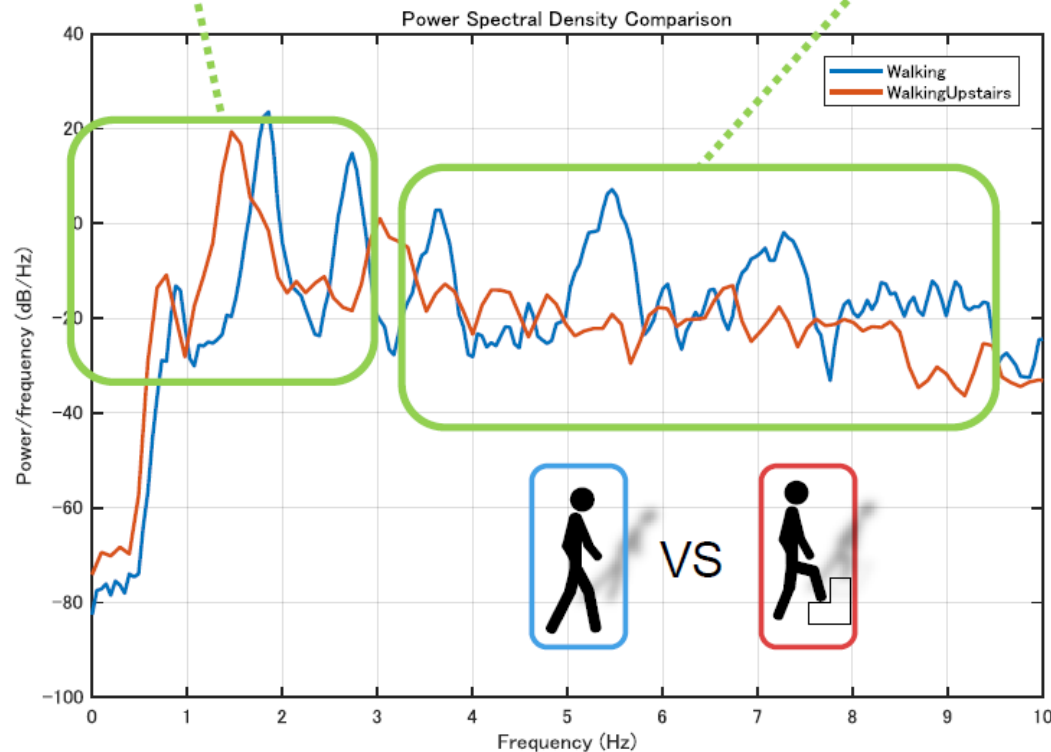
# Features from Spectral Visualization

## Human Activity Analysis and Classification



Peaks at (relatively) the lower frequency  
→ **Slower** movement

Less activity at higher frequency  
→ **Smoother** movement



Same trend observed from 3D plot

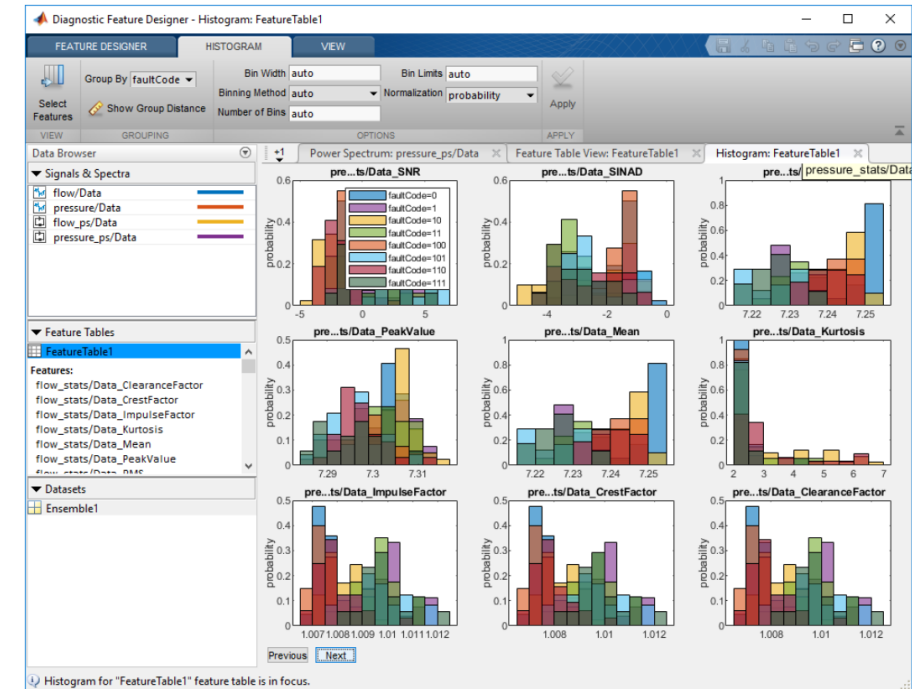


# The Diagnostic Feature Designer App

>> diagnosticFeatureDesigner

Using this app, you can:

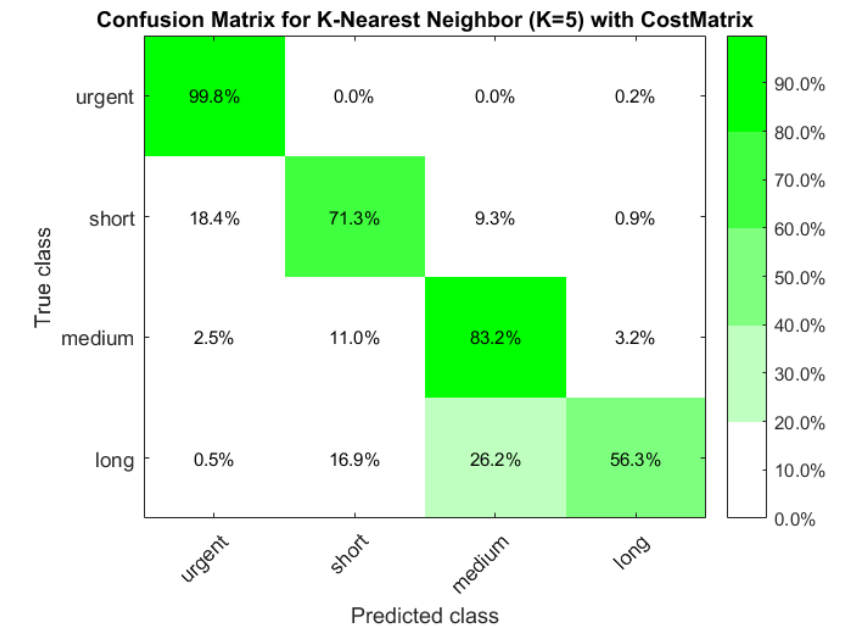
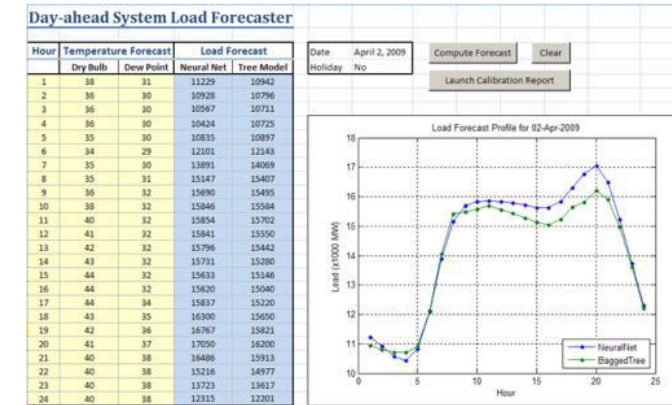
- ✓ Import measured or simulated data from individual files, an ensemble file, or an ensemble datastore that references files external to the app.
- ✓ Interactively visualize data to plot the ensemble variables you import or that you compute within the app.
- ✓ Generate features from your variables, and visualize their effectiveness using histograms. Features include signal statistics, nonlinear metrics, rotating machinery metrics, and spectral metrics.
- ✓ Use conditional ranking with labeled features
- ✓ Use prognostic ranking with features extracted from run-to-failure data



# Overview -Machine Learning

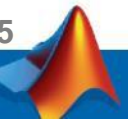
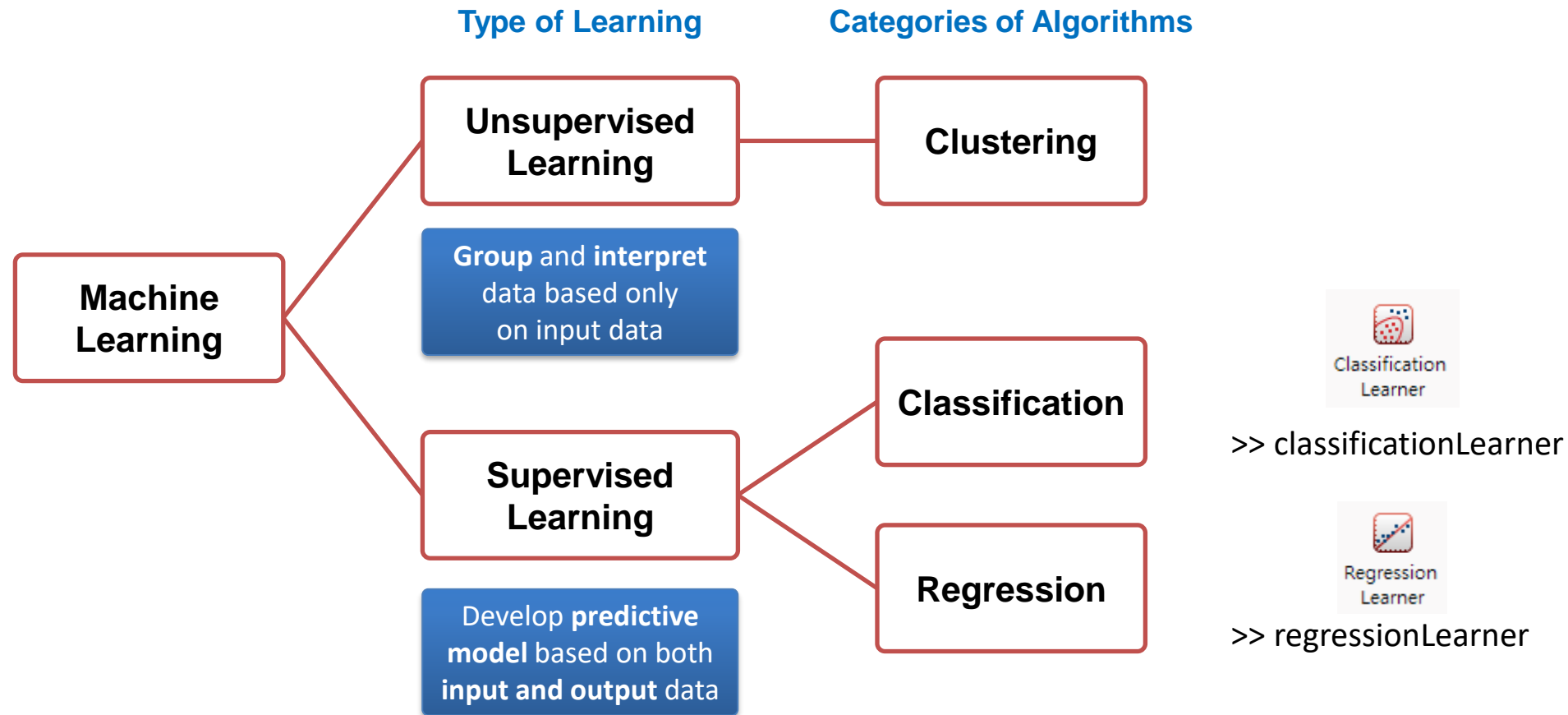
## Characteristics and Examples

- Characteristics
  - Too many variables
  - System too complex to know the governing equation(*e.g., black-box modeling*)
- Examples
  - Pattern recognition (*speech, images*)
  - Financial algorithms (*credit scoring, algo trading*)
  - Energy forecasting (*load, price*)
  - Biology (*tumor detection, drug discovery*)
  - Engineering (*fleet analytics, predictive maintenance*)



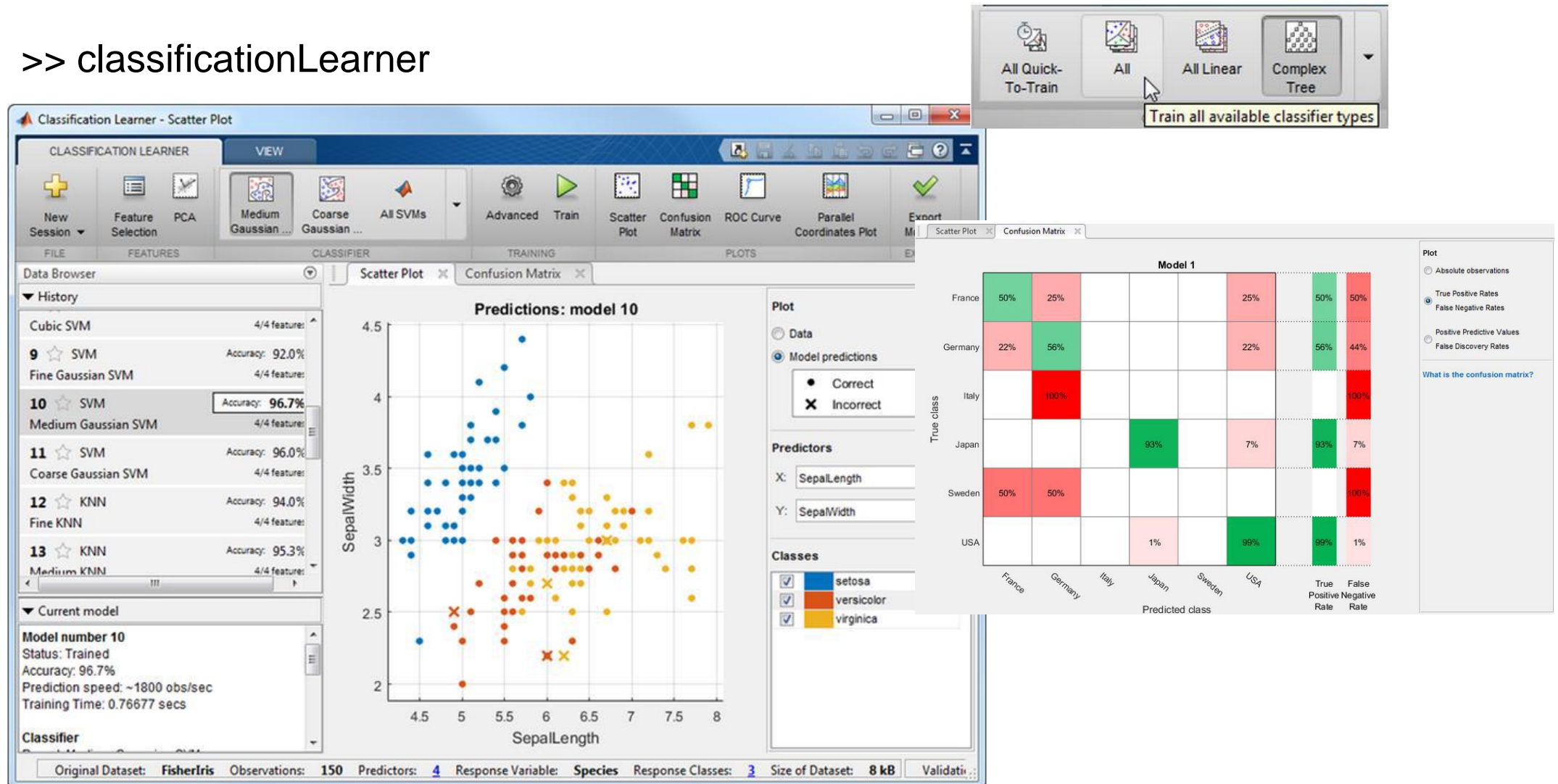
# Overview – Machine Learning

## Algorithm types



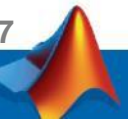
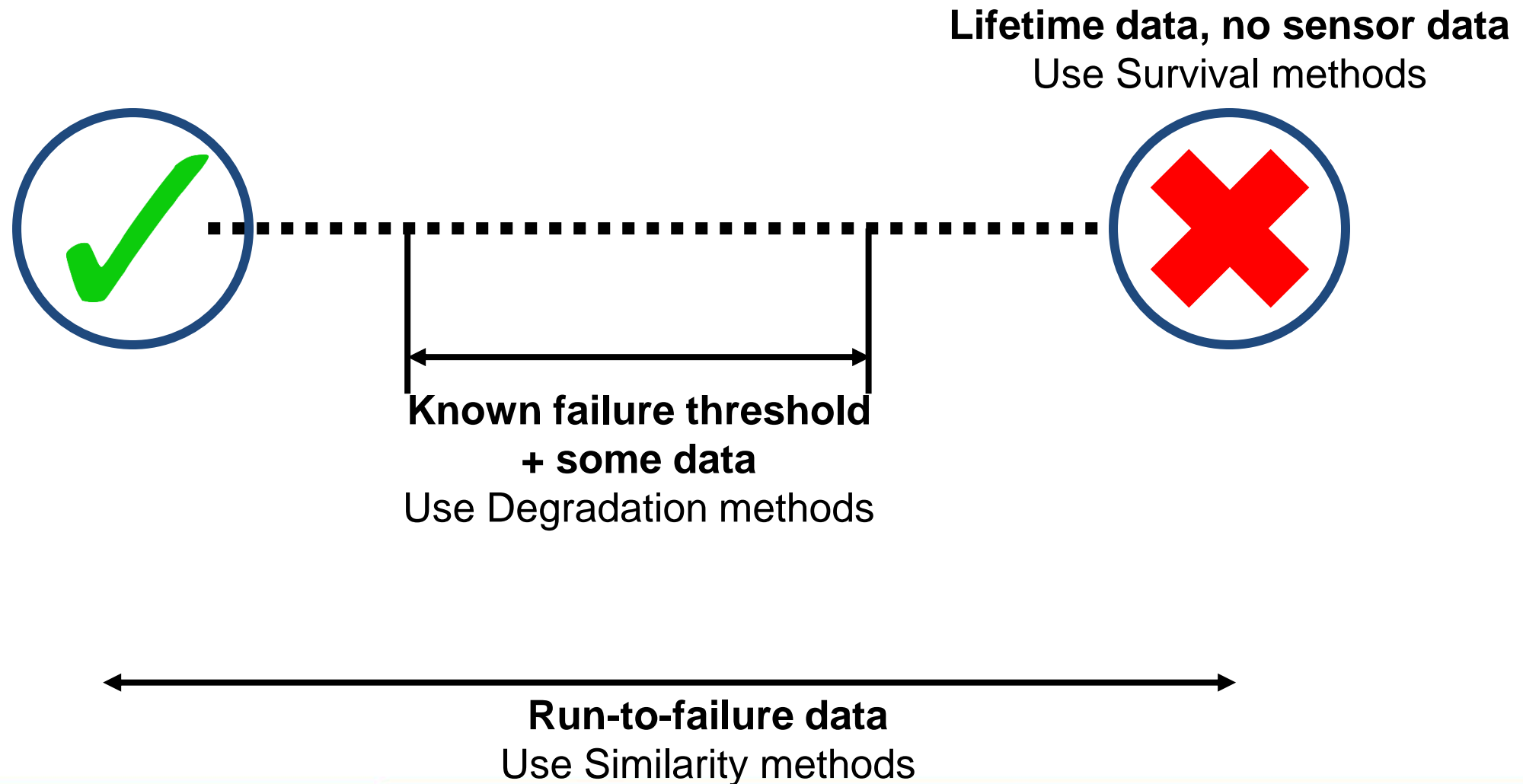
# The Classification Learner APP

>> classificationLearner



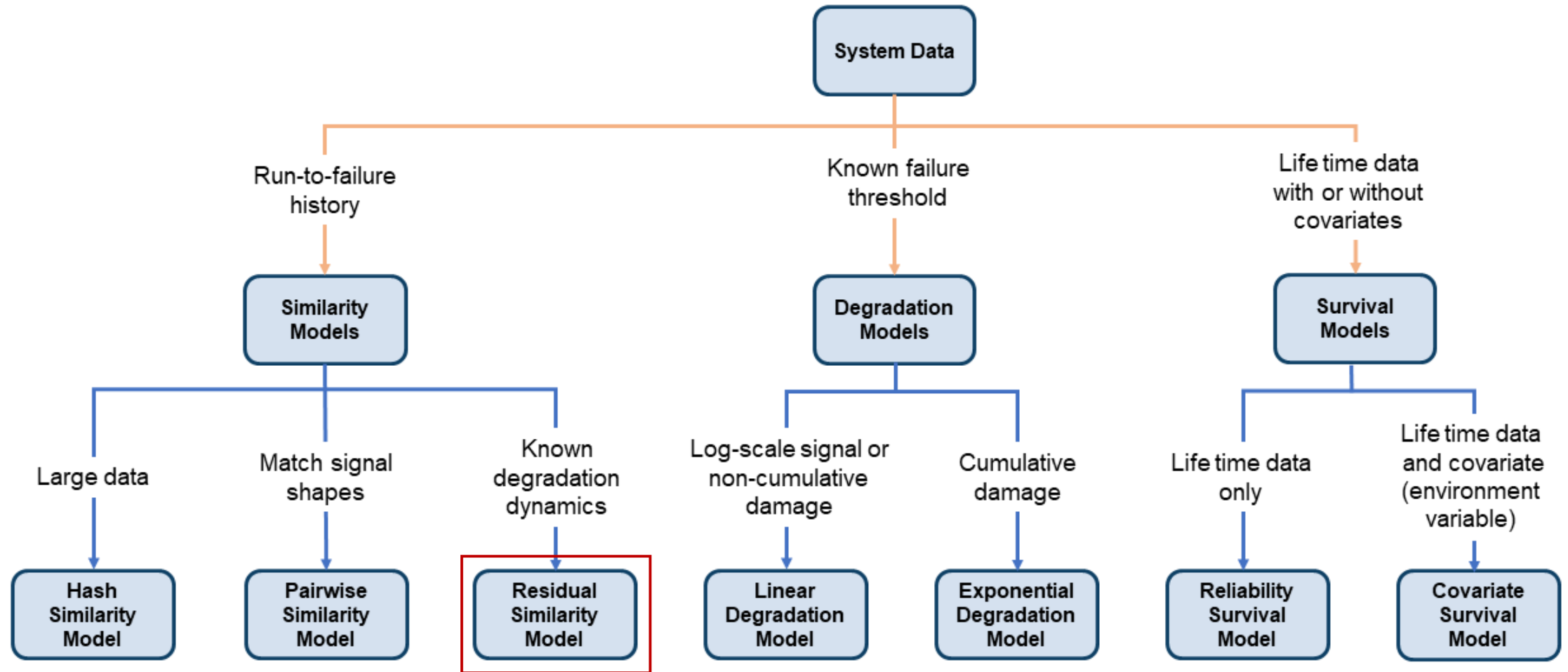
# Remaining Useful Life (RUL) Estimation Methods

*Requirement: Need to know what constitutes failure data*

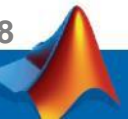


# RUL Methods and when to use them

*Requirement: Need to know what constitutes failure data*



[Details on model selection in the documentation](#)



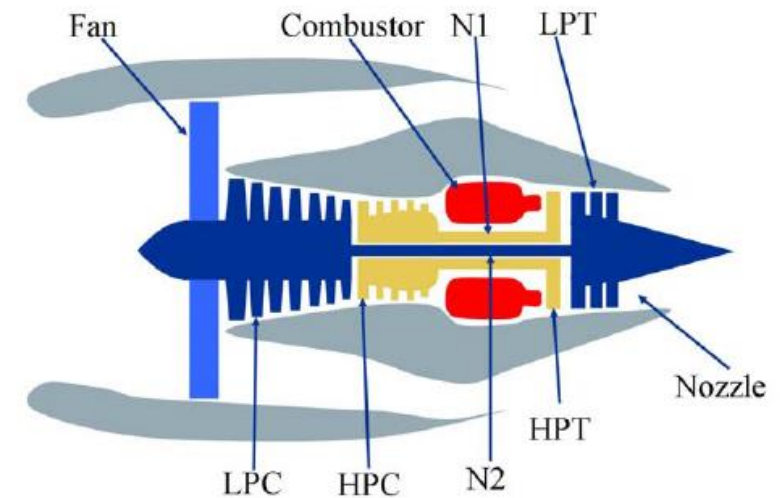


# Predictive Maintenance of Turbofan Engine

Sensor data from 200 engines of the same model

## Forecast Remaining Useful Life

- Have some combination of:
  - Sensor data from the equipment
  - Known failure thresholds
  - Runtime to failure of similar equipment
- Use condition monitoring to determine when system starts degrading
- Can we predict how much longer we can use our equipment once degradation begins?



Data provided by NASA PCoE

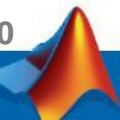
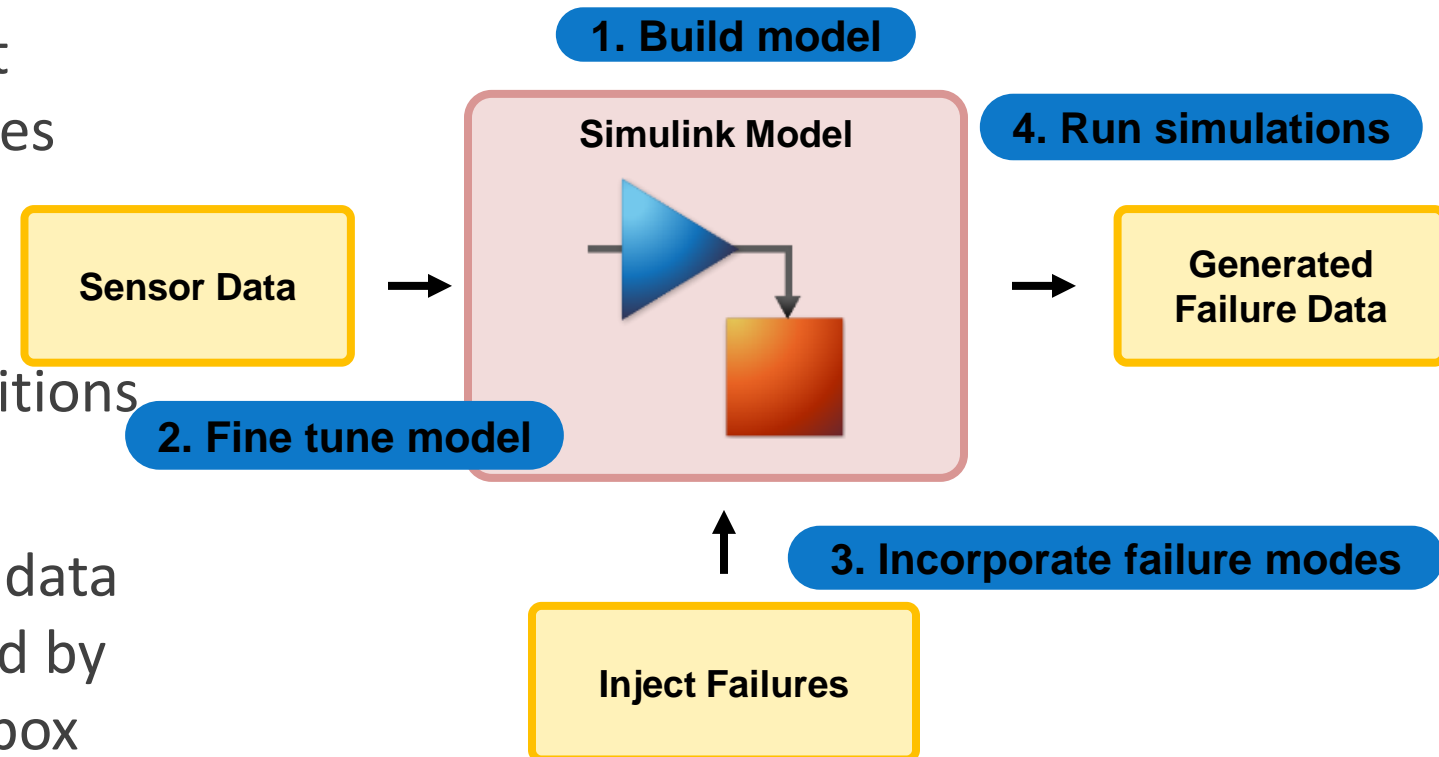
<https://ti.arc.nasa.gov/tech/dash/groups/pcoe/prognostic-data-repository>



# Failure Data Generation from Simulink

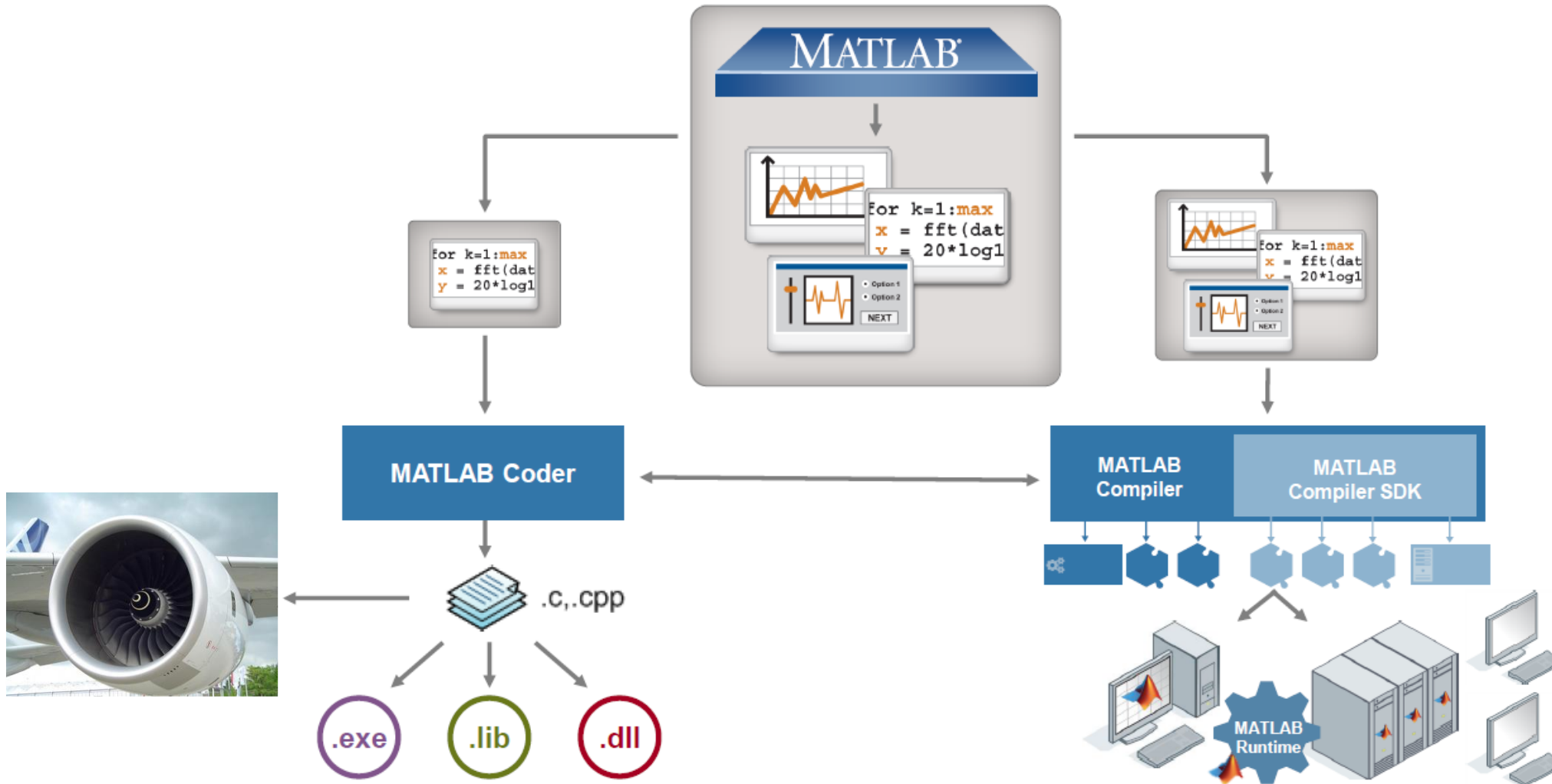
*Use simulation data that is representative of actual machine failures to train your algorithm*

- Construct a model of your machine using Simulink and Simscape that captures its different failure modes
- Run multiple simulations of your model under different fault conditions
- Manage and label this simulated data using ensemble objects provided by the Predictive Maintenance Toolbox



# Integrate analytics with your enterprise systems *MATLAB*

## Compiler and MATLAB Coder



# Predictive Maintenance

## Customer Examples



### Pump Health Monitoring System

- Spectral analysis and filtering on binary sensor data and neural network model prediction
- More than \$10 million projected savings



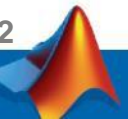
### Online engine health monitoring

- Real-time analytics integrated with enterprise service systems
- Predict sub-system performance (oil, fuel, liftoff, mechanical health, controls)



### Production machinery failure warning

- Reduce waste and machine downtime
- MATLAB based HMI warns operators of potential failures
- > 200,000 € savings per year



# Key Takeaways

- Frequent maintenance and unexpected failures are a large cost in many industries
- MATLAB enables engineers and data scientists to quickly create, test and implement predictive maintenance programs
- Predictive maintenance
  - Saves money for equipment operators
  - Increases reliability and safety of equipment
  - Creates opportunities for new services that equipment manufacturers can provide

