

# MATLAB EXPO

## 2021

### Predictive Maintenance Using Deep Learning

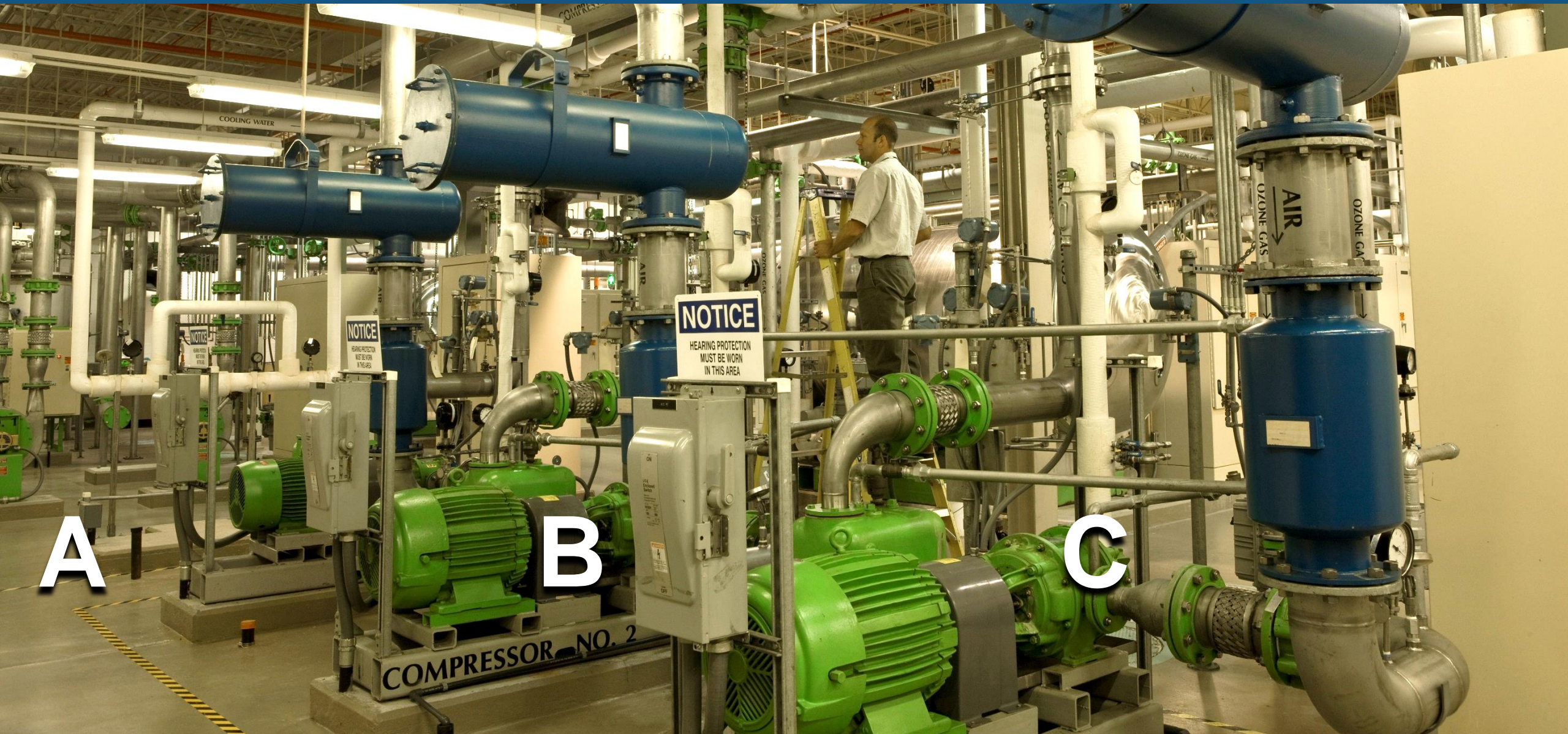
*Sudheer Nuggehalli*

*Rachel Johnson*





Listen carefully. Which compressor has a faulty bearing?



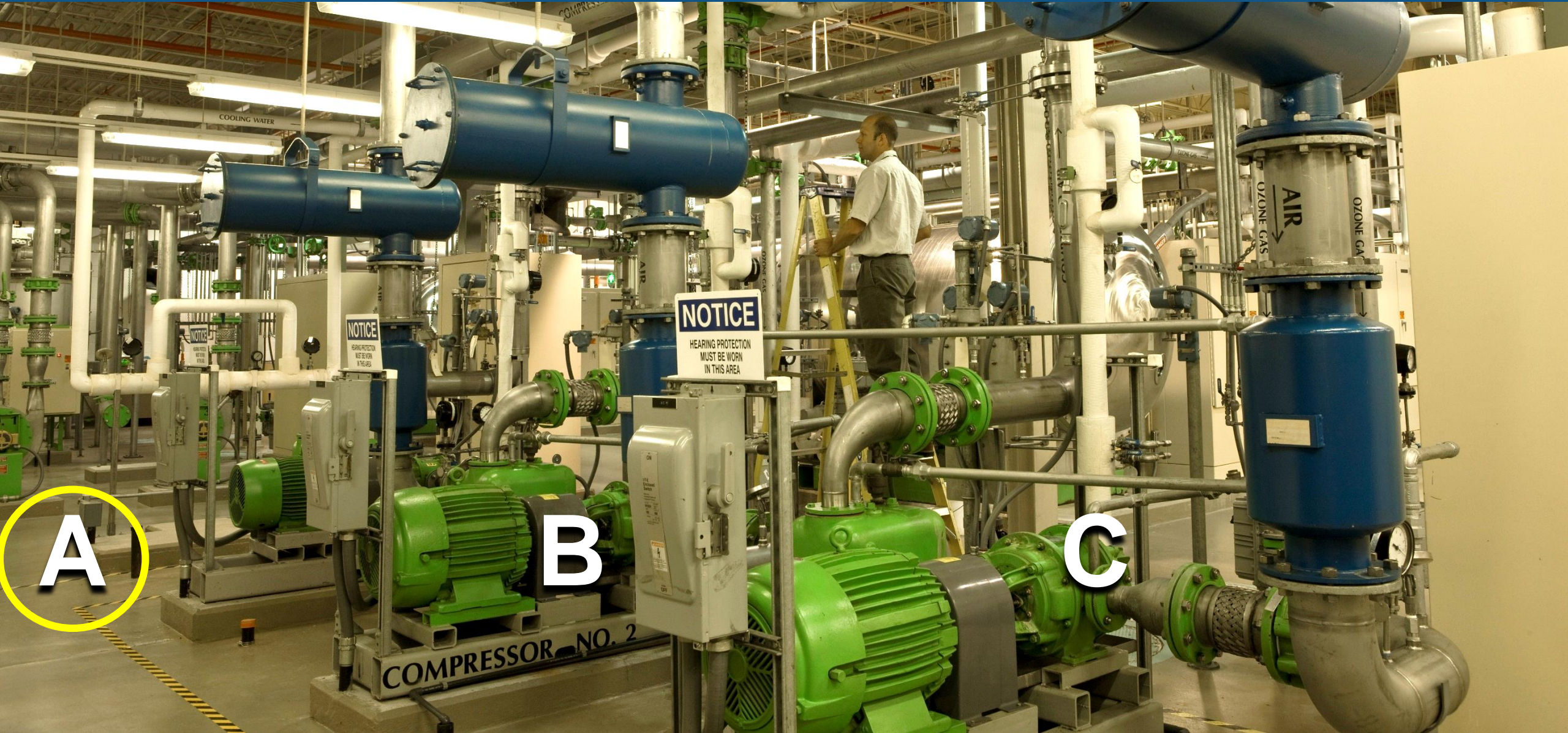
A

B

C



Listen carefully. Which compressor has a faulty bearing?



A

B

C



# MATLAB EXPO

## 2021

### Predictive Maintenance Using Deep Learning

*Sudheer Nuggehalli*

*Rachel Johnson*



## Key Takeaways for Predictive Maintenance



Small gains can yield big rewards.  
Try different approaches, including deep learning.



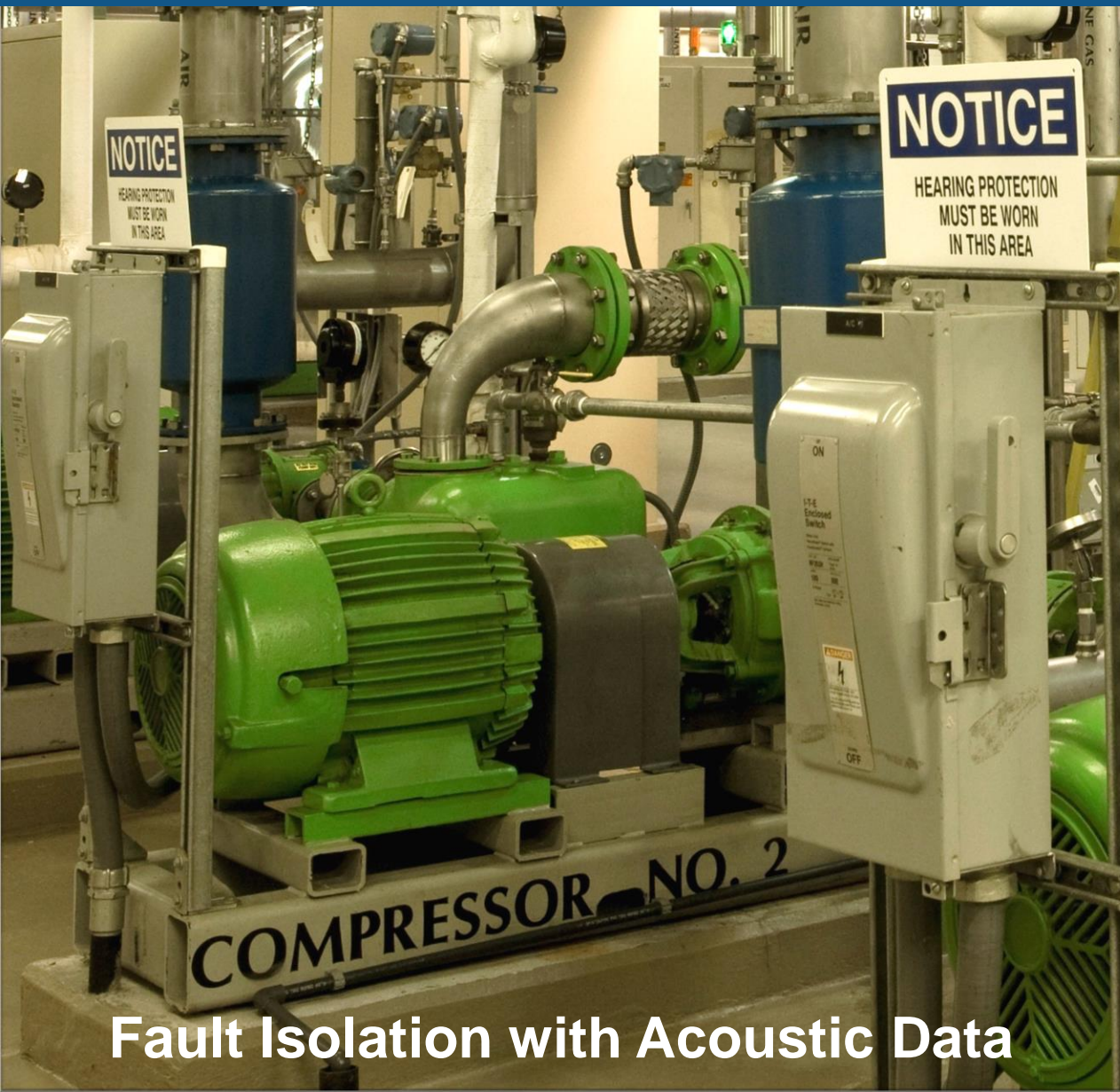
You need AI *and* domain expertise.  
MATLAB helps you do both.



MATLAB can automate your entire workflow



**Journey 1:**  
*Do you speak air compressor?*



**Fault Isolation with Acoustic Data**

**Journey 2:**  
*Data, data, everywhere*

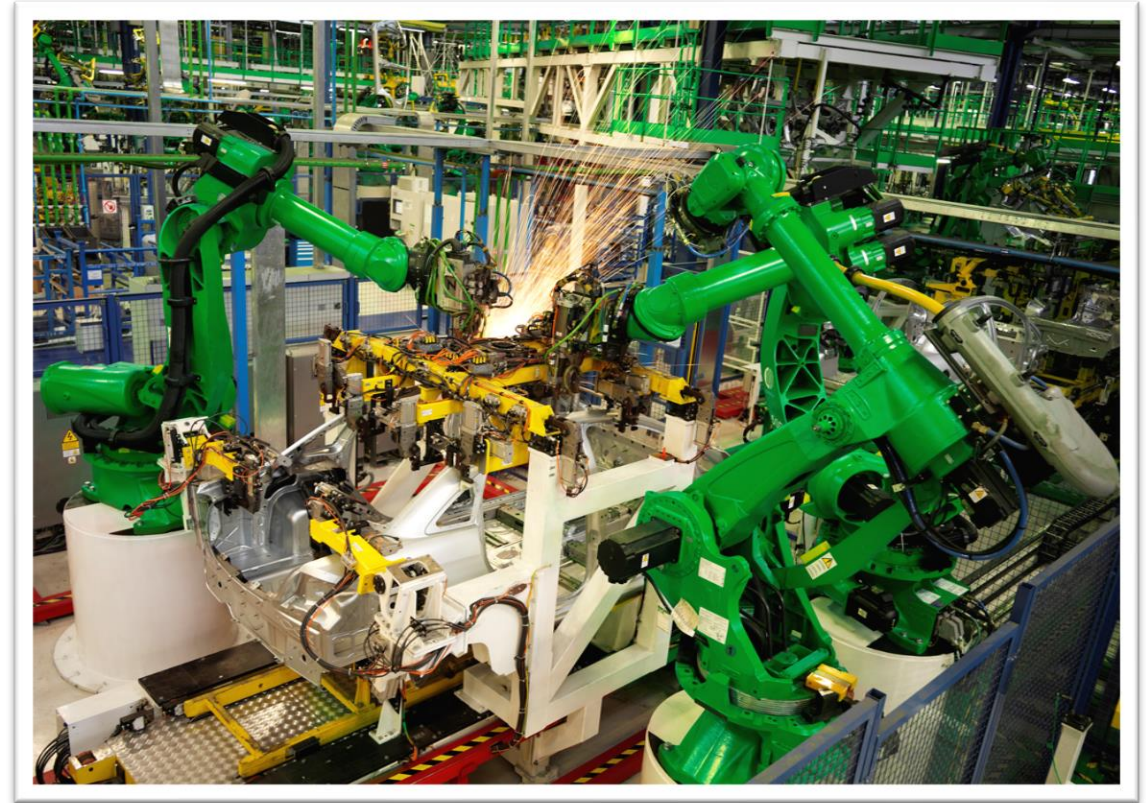


**Anomaly Detection with Vibration Data**



## Meet Rachel\*

- Mechanical Engineer at Membrane Manufacturing\*\*
- Responsible for a fleet of industrial machines
- New company AI initiative
- No deep learning experience



\*Rachel is an actor who works at MathWorks

\*\*Not a real company

# Predictive Maintenance Workflow

## DATA PREPARATION



Data access and preprocessing



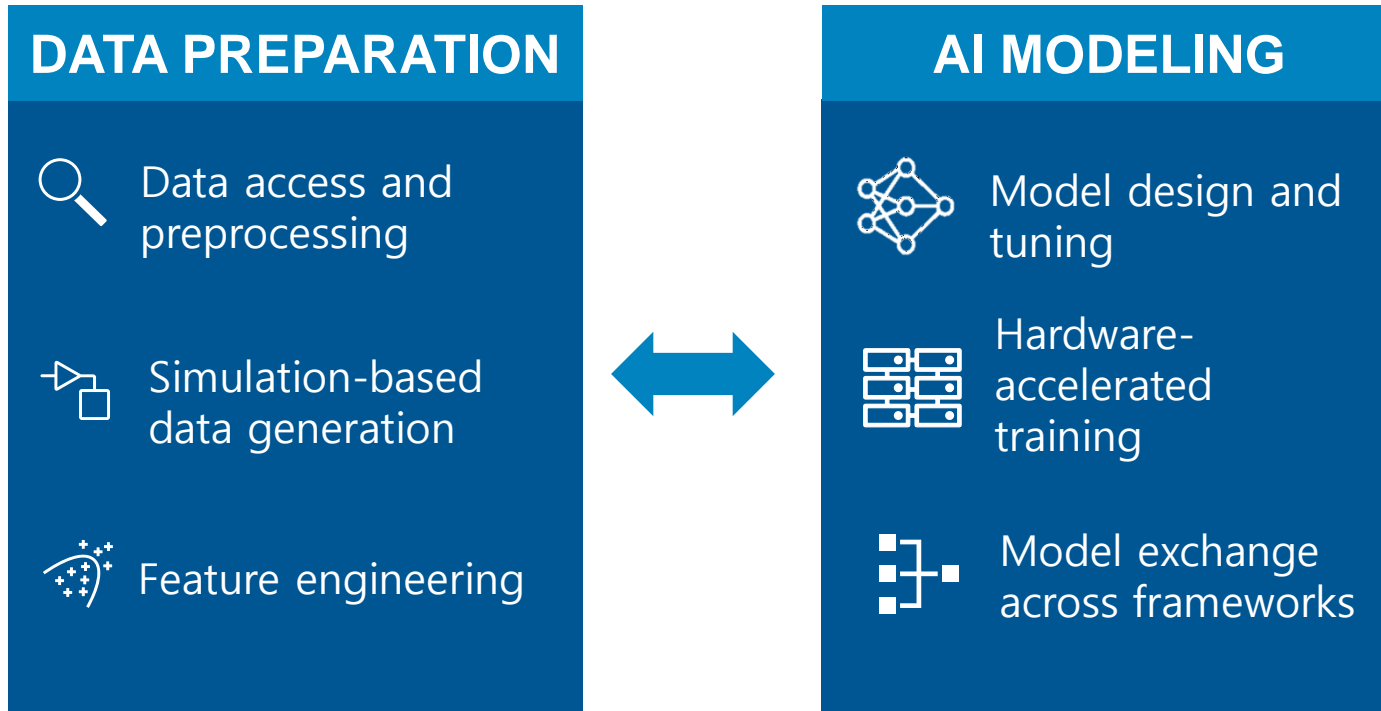
Simulation-based data generation



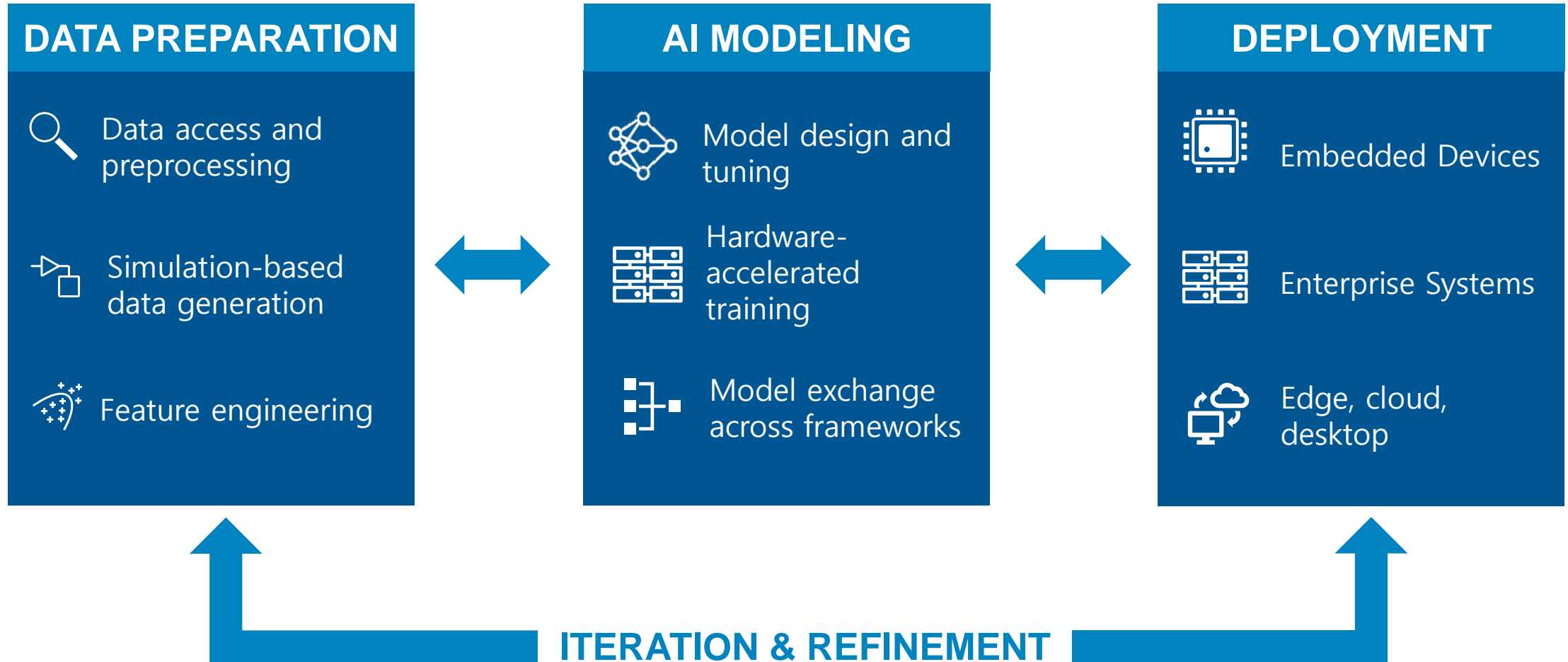
Feature engineering



# Predictive Maintenance Workflow



# Predictive Maintenance Workflow





# Journey 1: Do you speak air compressor?





# Journey 1: Do you speak air compressor?



Goal



Data

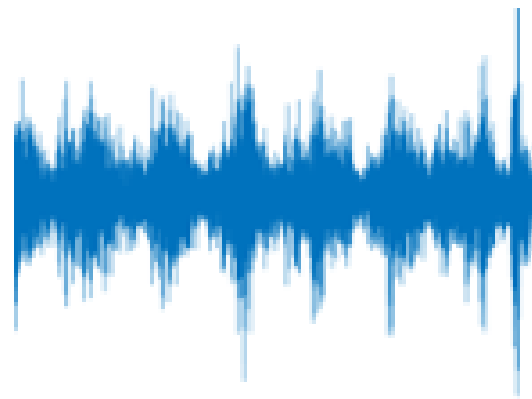


Approach



Result

- **Fault detection:** Identify specific faults to enable maintenance staff to respond more quickly





# Journey 1: Do you speak air compressor?



Goal



Data

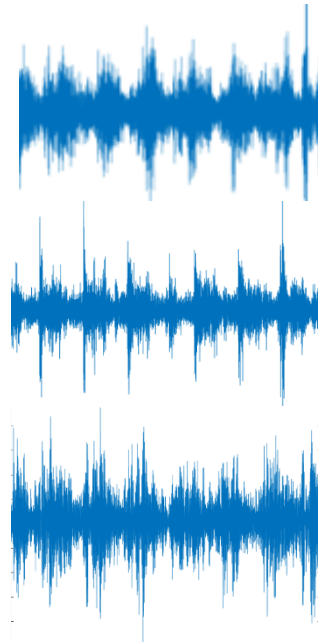


Approach



Result

- Acoustic time series data from sensors
- Labeled faults from maintenance logs



1. Healthy
2. Leakage Inlet Valve fault
3. Leakage Outlet Valve fault
4. Non-Return Valve fault
5. Piston Ring fault
6. Flywheel fault
7. Rider Belt fault
8. Bearing fault

# Journey 1: Do you speak air compressor?

**Goal****Data****Approach****Result**

Method	Validation Accuracy
Ensemble Bagged Trees	88%
Deep Neural Network	?



# Journey 1: Do you speak air compressor?



Goal



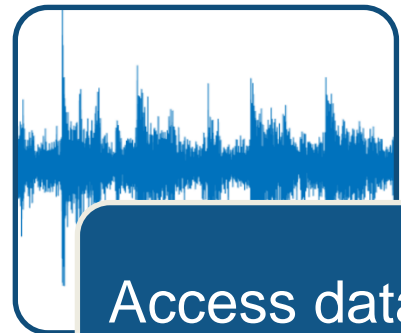
Data



Approach



Result

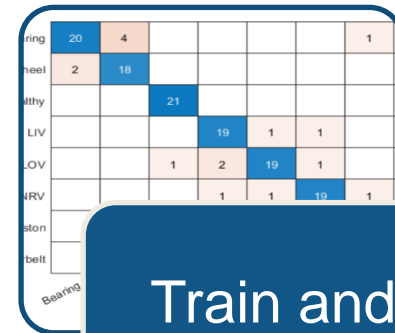


Access data with datastore



```
audioFeatureExtractor('SampleRate', 16000, 'Window', hamming(windowLength, 'periodic'), 'OverlapLength', overlapLength, ...
    'spectralCentroid', true, ...
    'spectralCrest', true, ...
    'spectralDecrease', true, ...
    'spectralEntropy', true, ...
    'spectralFlatness', true, ...
    'spectralFlux', false);
```

Extract features with Audio Toolbox



Train and validate LSTM



```
d extractFeatures_init
config.linearSpectrum.No
for (int i = 0; i < 257
config.OneSidedSpectr
+ 1U);
config.linearSpectrum
rt>(
co
tic
```

Generate C code for edge deployment

HOME PLOTS APPS LIVE EDITOR INSERT VIEW

Search Documentation

FILE NAVIGATE TEXT CODE SECTION RUN

C:\Work\Local Demos\AirCompressorClassificationDemo\Part01\_DataPreparation.mlx

Part01\_DataPreparation.mlx

# Air Compressor Data Classification

## Part 1: Data Preparation

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[Human Insight](#)

[Generate Training Features](#)

[Normalize Training Features](#)

[Generate and Normalize Validation Features](#)

[Generate MATLAB function compatible with C/C++ Code Generation](#)



# Journey 1: Do you speak air compressor?



Goal



Data



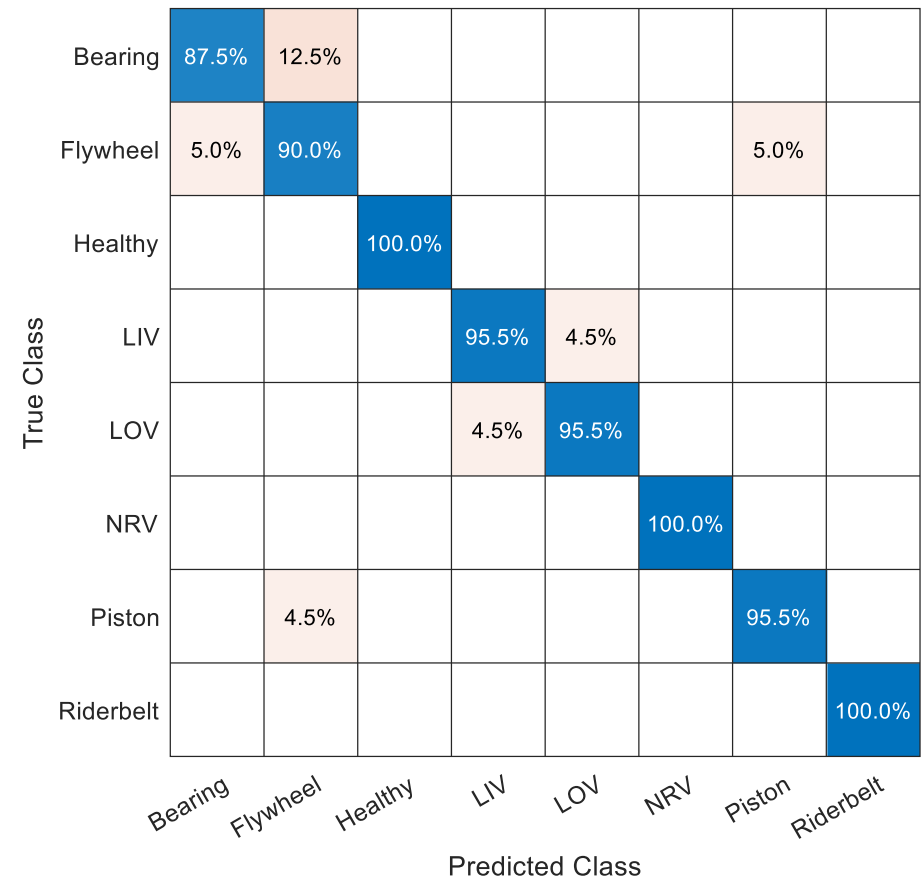
Approach



Result

- Successfully identified faults with 95% validation accuracy

Method	Validation Accuracy
Ensemble Bagged Trees	88%
Deep Neural Network	95%



# Journey 1: Do you speak air compressor?



Goal



Data



Approach



Result

- Successfully identified faults with 95% validation accuracy

Bearing	87.5%	12.5%
Flywheel	5.0%	90.0%

True Class	Bearing	87.5%	12.5%						
	Flywheel	5.0%	90.0%				5.0%		
	Healthy			100.0%					
	LIV				95.5%	4.5%			
	LOV				4.5%	95.5%			
	NRV						100.0%		
	Piston		4.5%					95.5%	
	Riderbelt								100.0%
		Bearing	Flywheel	Healthy	LIV	LOV	NRV	Piston	Riderbelt
		Predicted Class							



# Journey 1: Do you speak air compressor?



Goal



Data



Approach



Result

## Poll: How could we improve the results?

- Collect more data
- Tune network hyperparameters
- Try a different feature set
- Try a different algorithm
- Buy more GPUs

# Journey 1: Do you speak air compressor?



Goal



Data



Approach

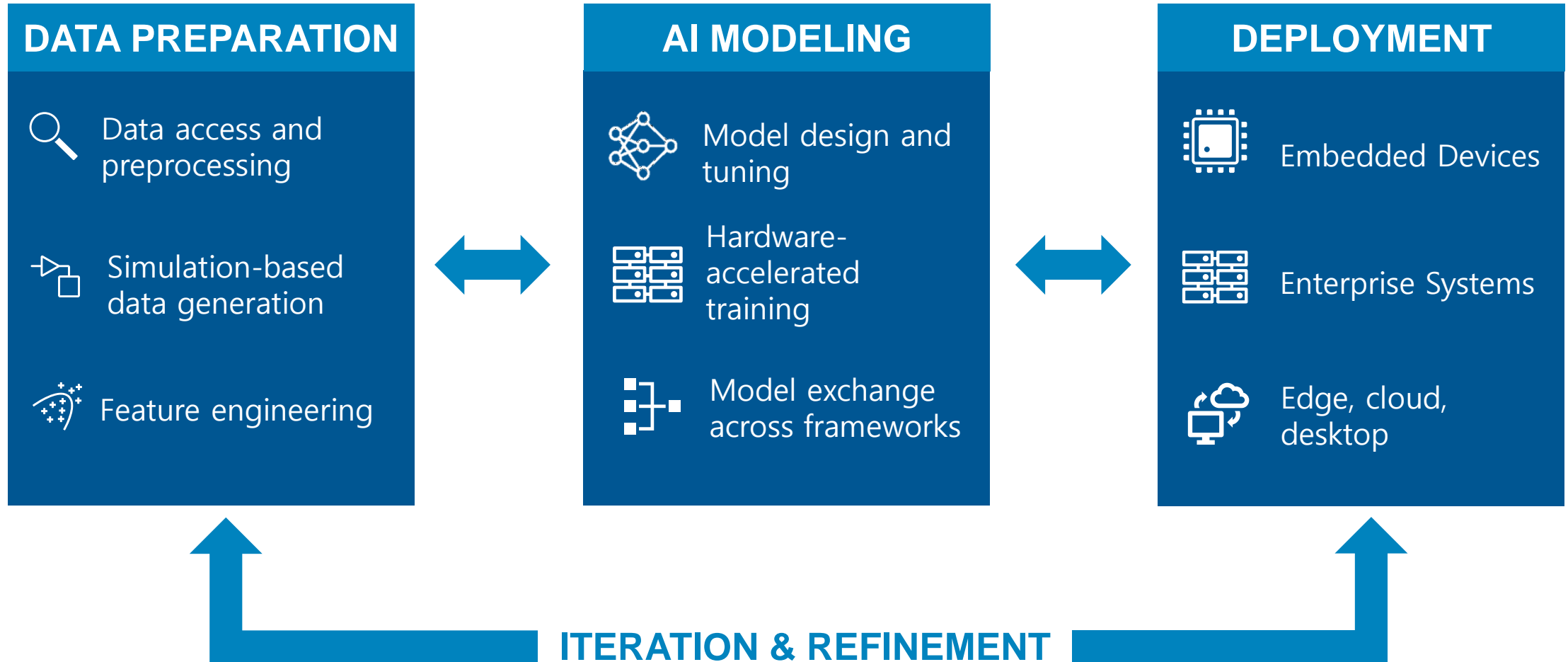


Result

## Poll: How could we improve the results?

- Collect more data
- Tune network hyperparameters
- Try a different feature set
- Try a different algorithm
- Buy more GPUs

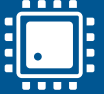


# Journey 1: Do you speak air compressor?

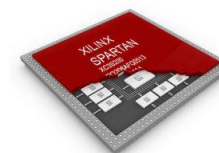
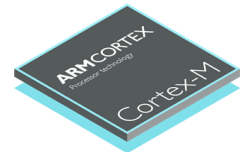
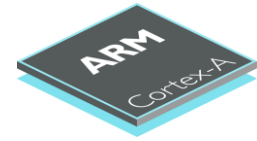
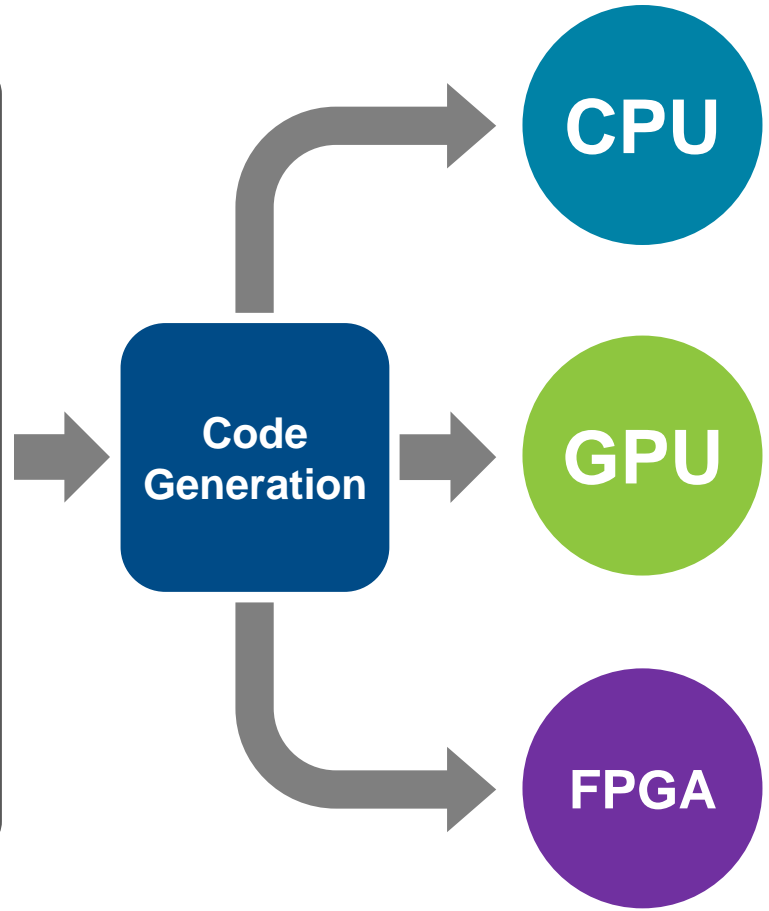
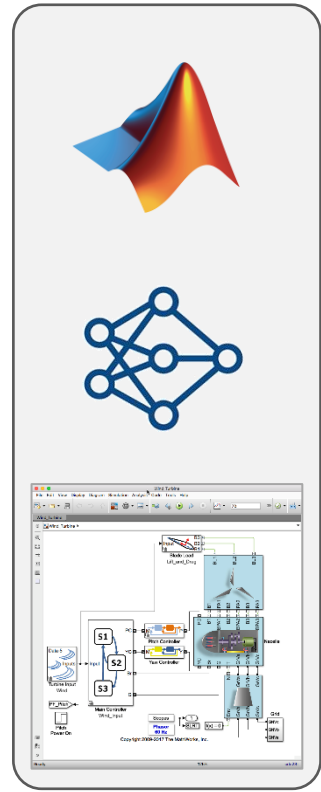




# Journey 1: Do you speak air compressor?

**DEPLOYMENT**

-  Embedded Devices
-  Enterprise Systems
-  Edge, cloud, desktop



# Journey 1: Do you speak air compressor?



Goal



Data



Approach

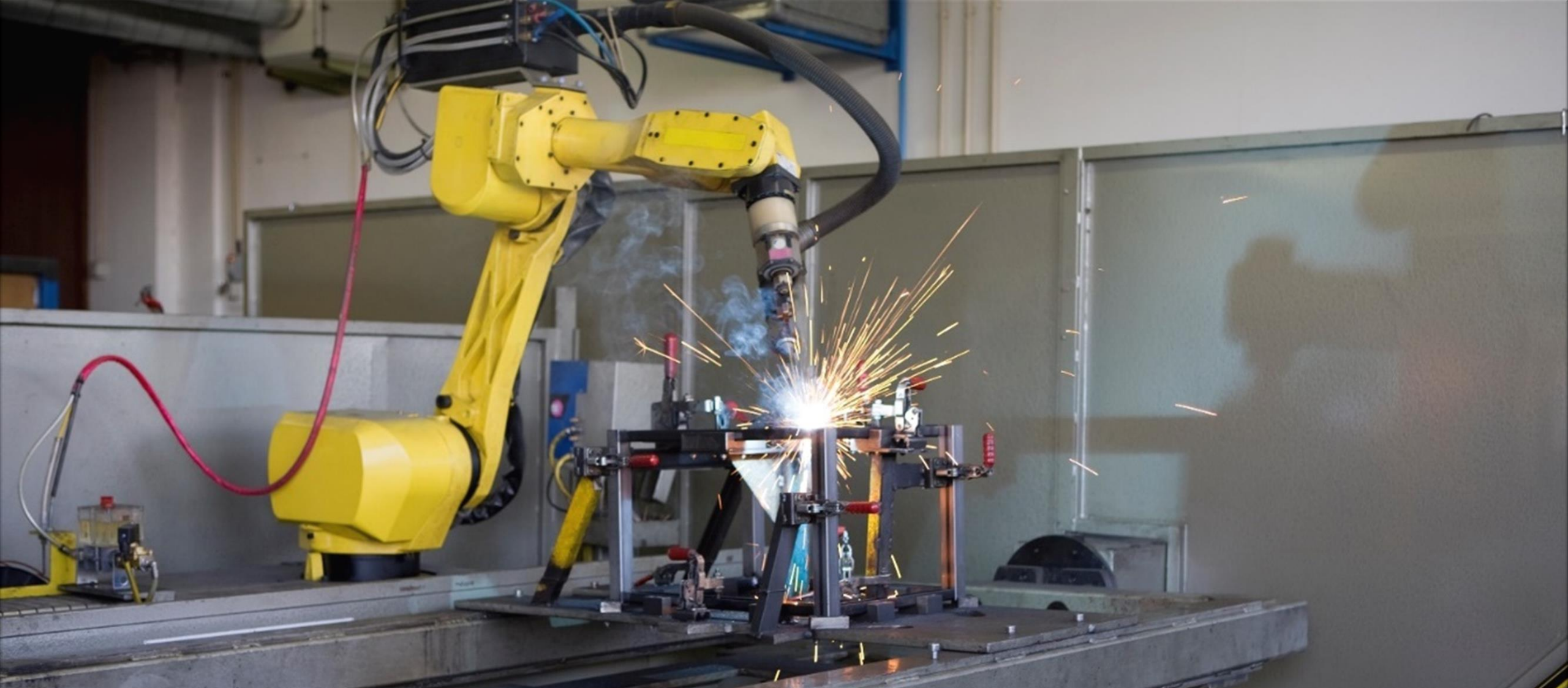


Result

- What's Next?

**MATLAB EXPO**

**Deploying AI to Embedded and Production Systems**



**Journey 2: Data, data, everywhere...**



## Journey 2: Data, data, everywhere...



Goal



Data

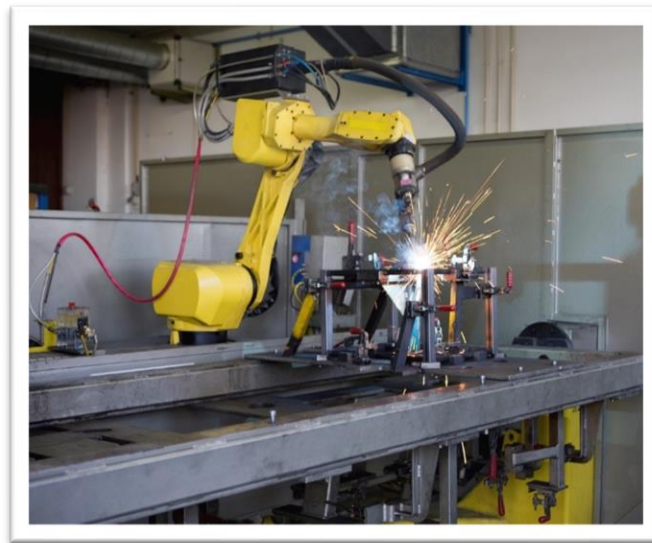


Approach



Result

- **Anomaly Detection:** Detect when the machine deviates from normal operation.
- Avoid surprises. Address anomalies before catastrophic failure occurs.



### Currently

- Routine monthly maintenance
- Not many failures
- But when failures do happen...

## Journey 2: Data, data, everywhere...



Goal



Data

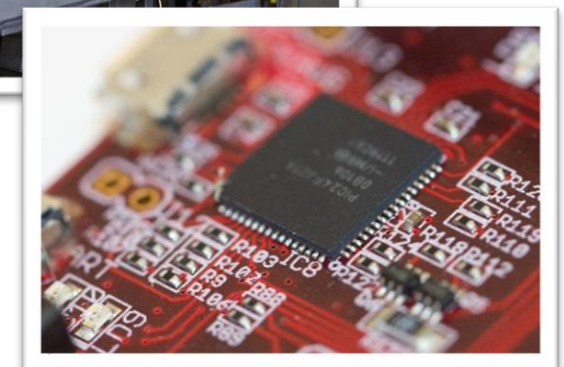
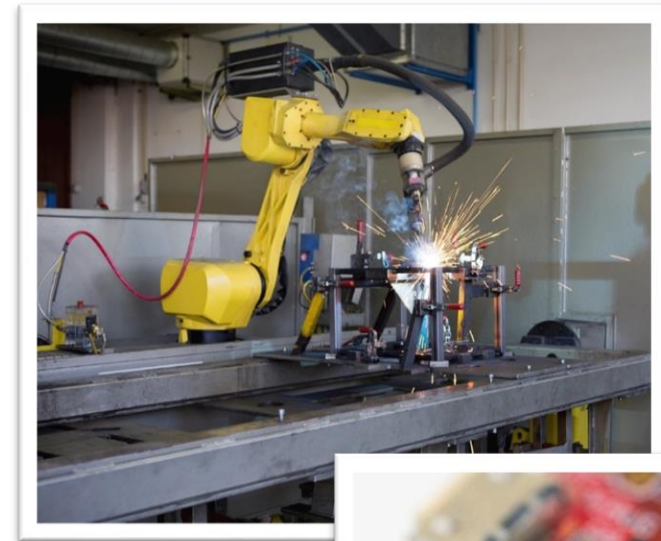


Approach



Result

- Vibration data from 3-axis accelerometers
- Labeled “before” and “after” maintenance
  - “After” data = Normal ✓
  - “Before” data = Not sure ?
- Some data tagged as “abnormal” by maintenance crews



## Journey 2: Data, data, everywhere...



Goal



Data



Approach



Result

Method	Validation Accuracy
K-Means Clustering	85%
Autoencoder	?



## Journey 2: Data, data, everywhere...



Goal



Data

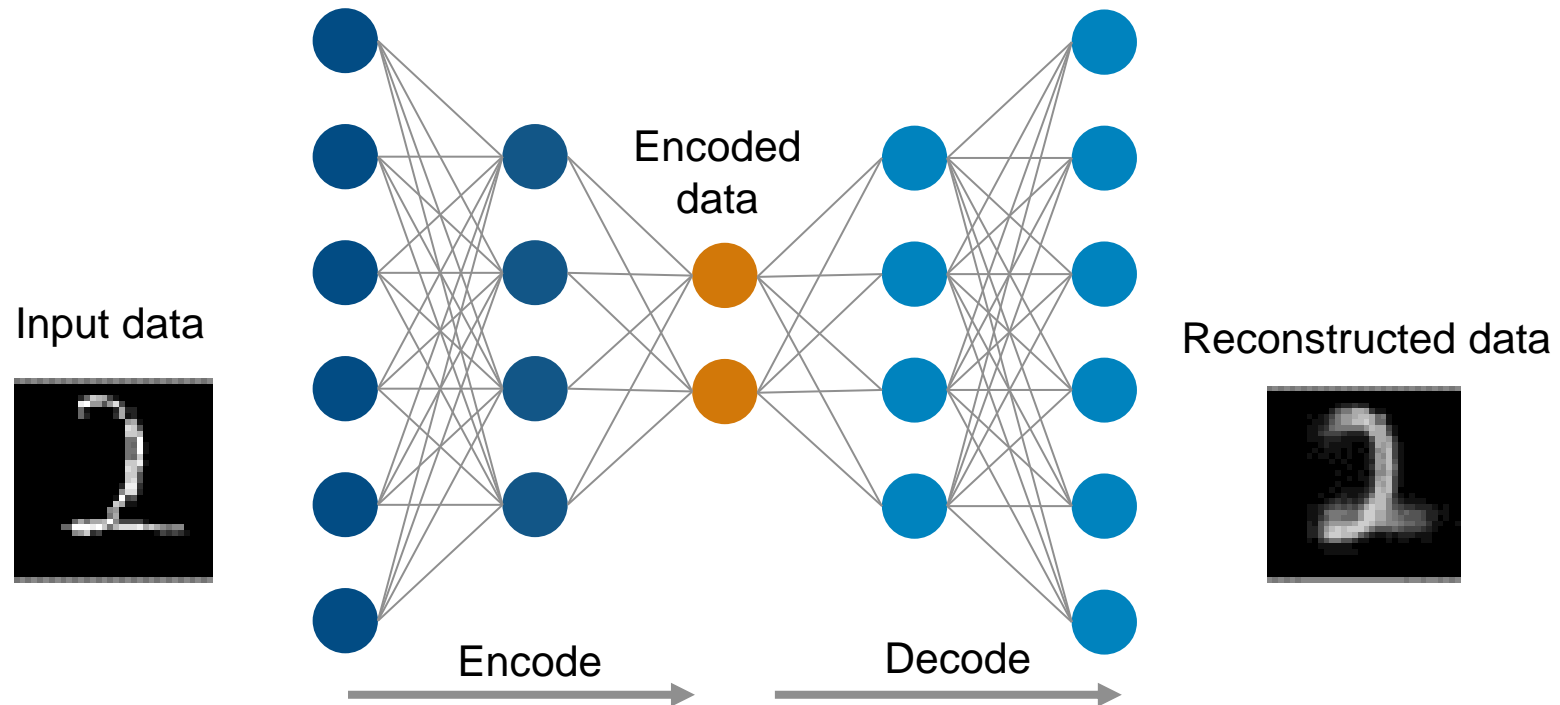


Approach



Result

### Autoencoder



# Journey 2: Data, data, everywhere...



Goal



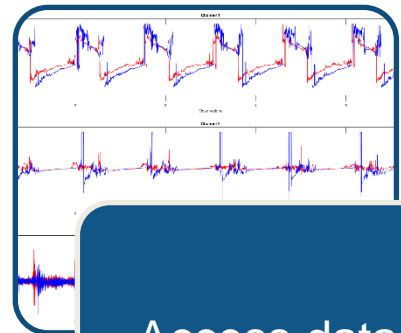
Data



Approach



Result



Access data from files



Extract and rank features with Diagnostic Feature Designer App



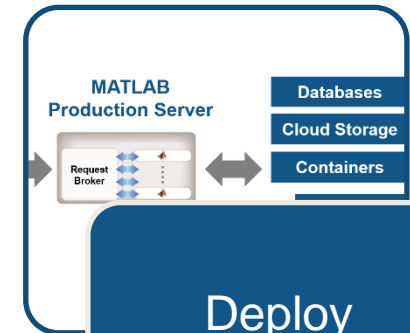
```

the biLSTM network layers
s = [ sequenceInputLayer(featureDimension, 'Name',
biLstmLayer(16, 'Name', 'biLstm1')
eluLayer('Name', 'relu1')
biLstmLayer(32, 'Name', 'biLstm2')
eluLayer('Name', 'relu2')
biLstmLayer(16, 'Name', 'biLstm3')]
eluLayer('Name', 'relu3')
ullyConnectedLayer(featureDimension, 'Name', 'fc')
egressionLayer('Name', 'out') ];

Training
ns = tra
Plots',
MiniBatc
MaxEpoch

trainNe
    
```

Train autoencoder on normal data



Deploy algorithms to the cloud

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New Open Save Compare Print Export FILE

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Title B I U M TEXT

Code Control Task CODE

Refactor

Run Section Run and Advance Run to End SECTION

Run Step Stop RUN

C:\Work\Local Demos\anomaly-detection-using-autoencoders

Live Editor - C:\Work\Local Demos\anomaly-detection-using-autoencoders\Part01\_DataPrepFeatureExtraction.mlx

Part01\_DataPrepFeatureExtraction.mlx

# Part 1: Data Preparation and Feature Extraction

## *Industrial Machinery Anomaly Detection*

### Table of Contents

[Load Data](#)

[Visualize Data Before and After Maintenance](#)

[Extract Features with Diagnostic Feature Designer App](#)

## Load Data

```
1 load("IndustrialMachineData.mat")
```

## Visualize Data Before and After Maintenance

Visualize data before and after maintenance across channels for one member of the ensemble



# Journey 2: Data, data, everywhere...



Goal



Data



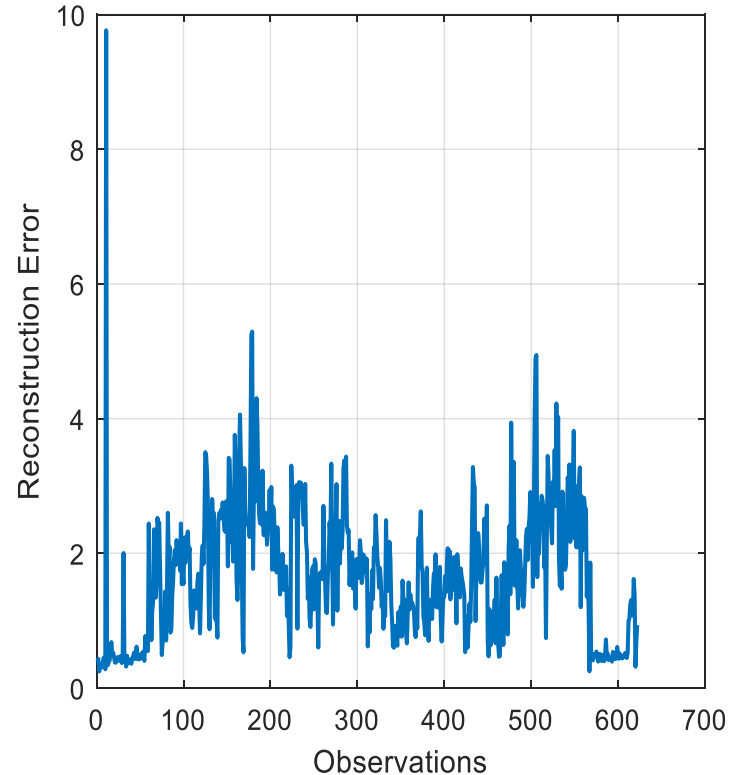
Approach



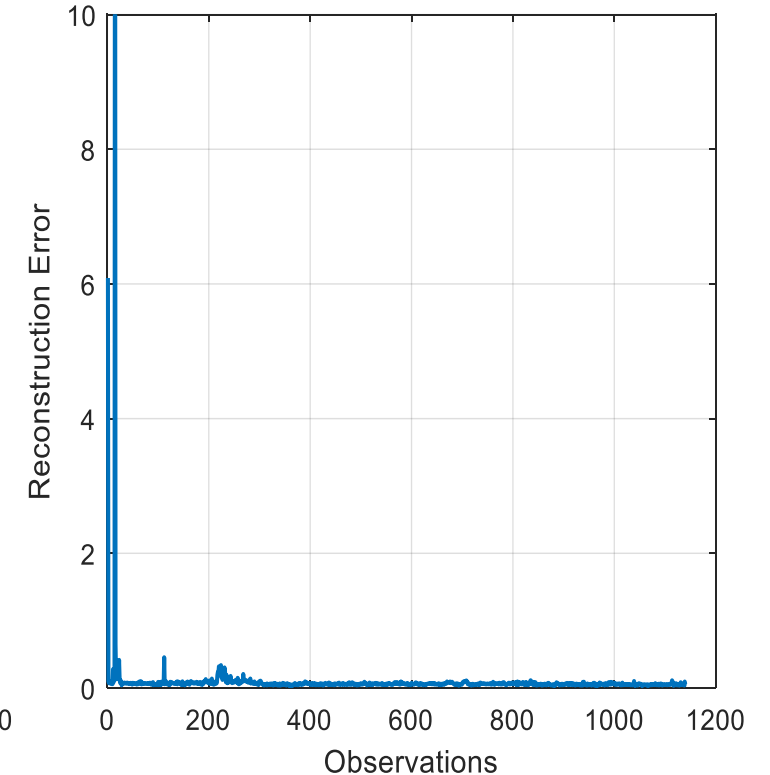
Result

Method	Validation Accuracy
K-Means Clustering	85%
Autoencoder	99%

Reconstruction Error on Abnormal Validation Data  
Mean Error: 1.68



Reconstruction Error on Normal Validation Data  
Mean Error: 0.09



## Journey 2: Data, data, everywhere...



Goal



Data



Approach



Result

- What's Next?

**MATLAB EXPO**

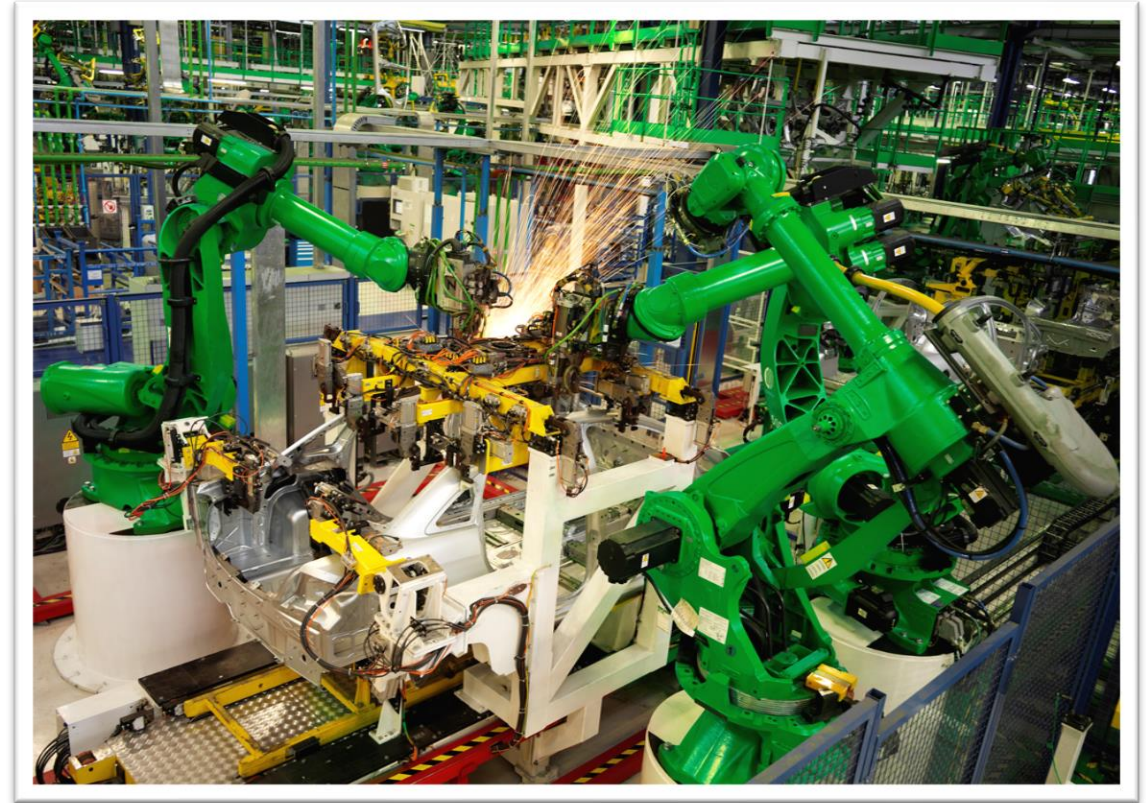
**DevOps for Software and Systems:  
Putting Algorithms and Models in Operation**

Six months later...

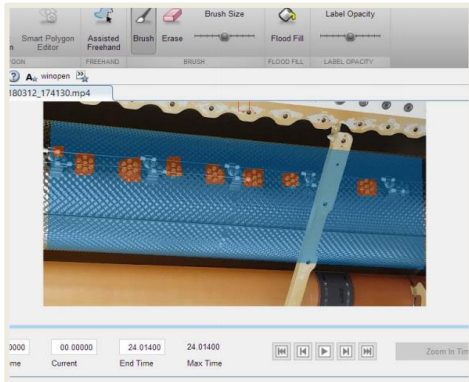


## Six Months Later

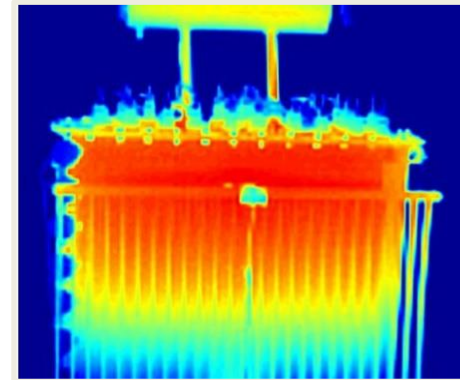
- Increased uptime by 10%
- Want to expand to entire fleet, multiple locations
- Next project: Predict Remaining Useful Life (RUL)
- Got a promotion! 😊



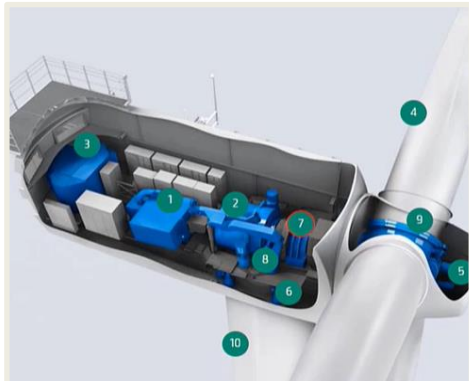
# Companies are succeeding with MATLAB for Predictive Maintenance



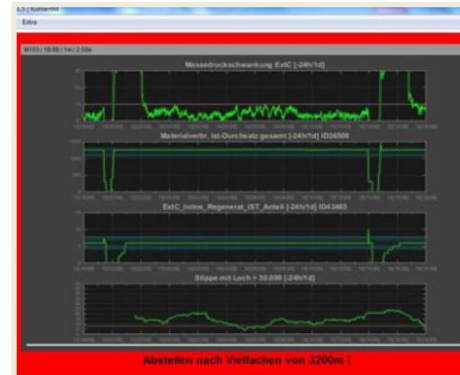
[Airbus](#) detects defects in aircraft pipes with semantic segmentation



[Siemens](#) develops health monitoring system for distribution transformers



[RWE Renewables](#) detects anomalies in wind turbine bearings using neural networks



[Mondi](#) develops and deploys algorithms to predict plastic production machine failures

# LG Energy Solution used Deep Learning for Predictive Maintenance on industrial cutter

## Challenge

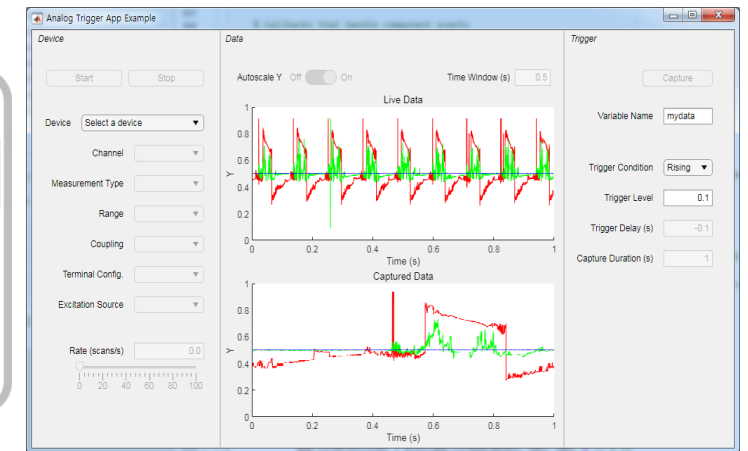
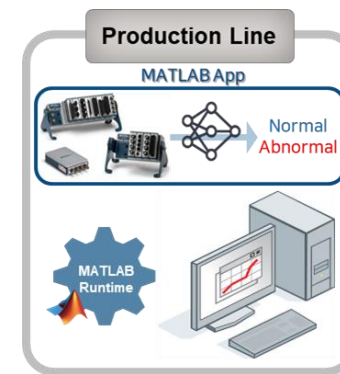
Maintenance of equipment in the factory also depends on the site engineer's opinion, and sometimes those are a bit conservative

## Solution

Developed a condition monitoring system and deployed standalone executable which can acquire raw data from NI device directly, make a prediction and display the result in GUI

## Advantages of using MATLAB and Simulink

- Interactive Apps for generating features and training various AI models
- Capabilities of entire workflow from data acquisition to deployment
- Leveraged MathWorks engineer's support for fast prototyping



## Condition monitoring system using Deep Learning

*“3 advantages of MATLAB that lead our project to success: App-based AI development workflow, compatibility with 3rd party hardware and short test cycle with rapid prototyping.”*

*Junghoon Lee, LG Energy Solution*



## Key Takeaways for Predictive Maintenance



Small gains can yield big rewards.  
Try different approaches, including deep learning.



You need AI *and* domain expertise.  
MATLAB helps you do both.



MATLAB can automate your entire  
Predictive Maintenance workflow

# MATLAB EXPO 2021

Thank you

