

MATLAB EXPO

2021

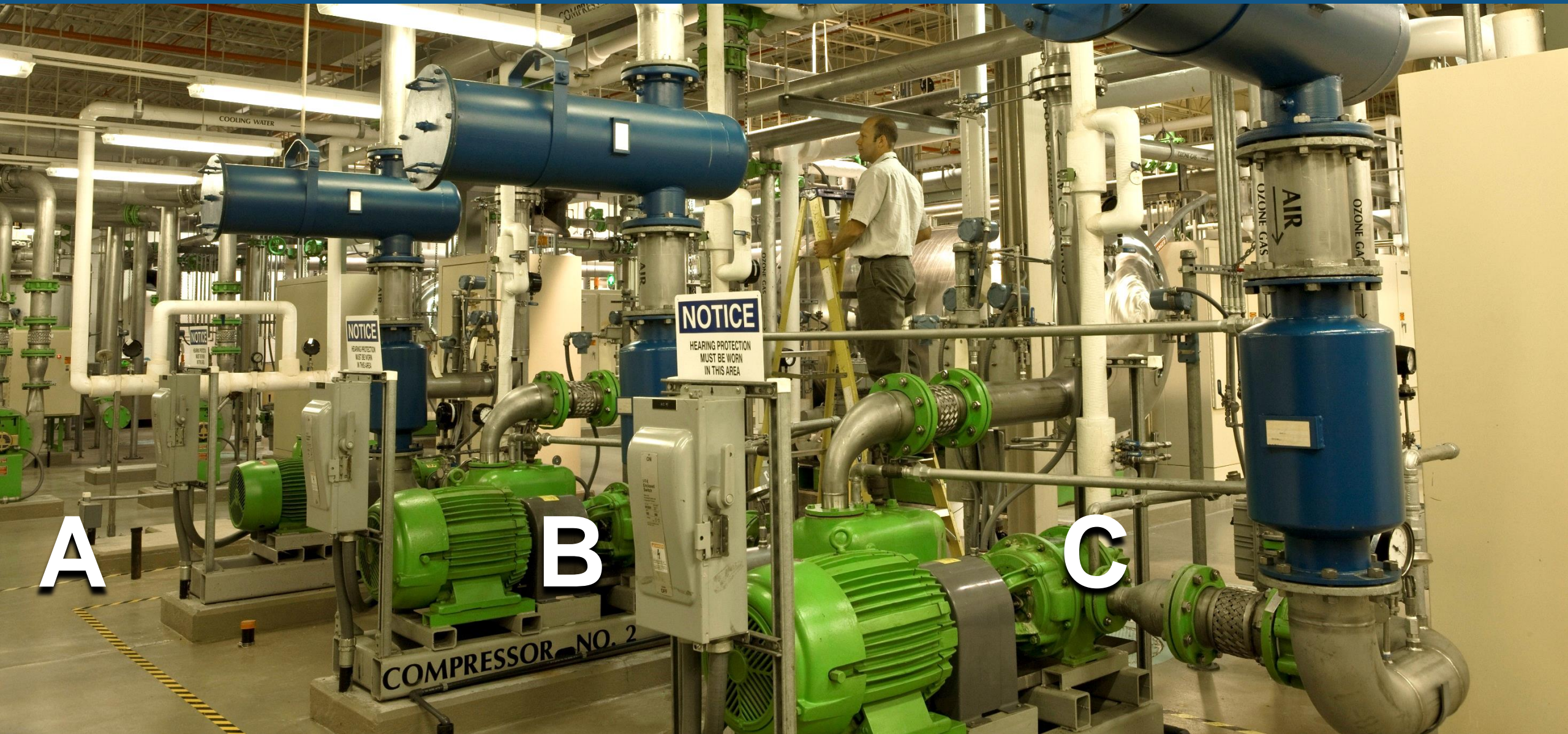
Predictive Maintenance Using Deep Learning

Sudheer Nuggehalli

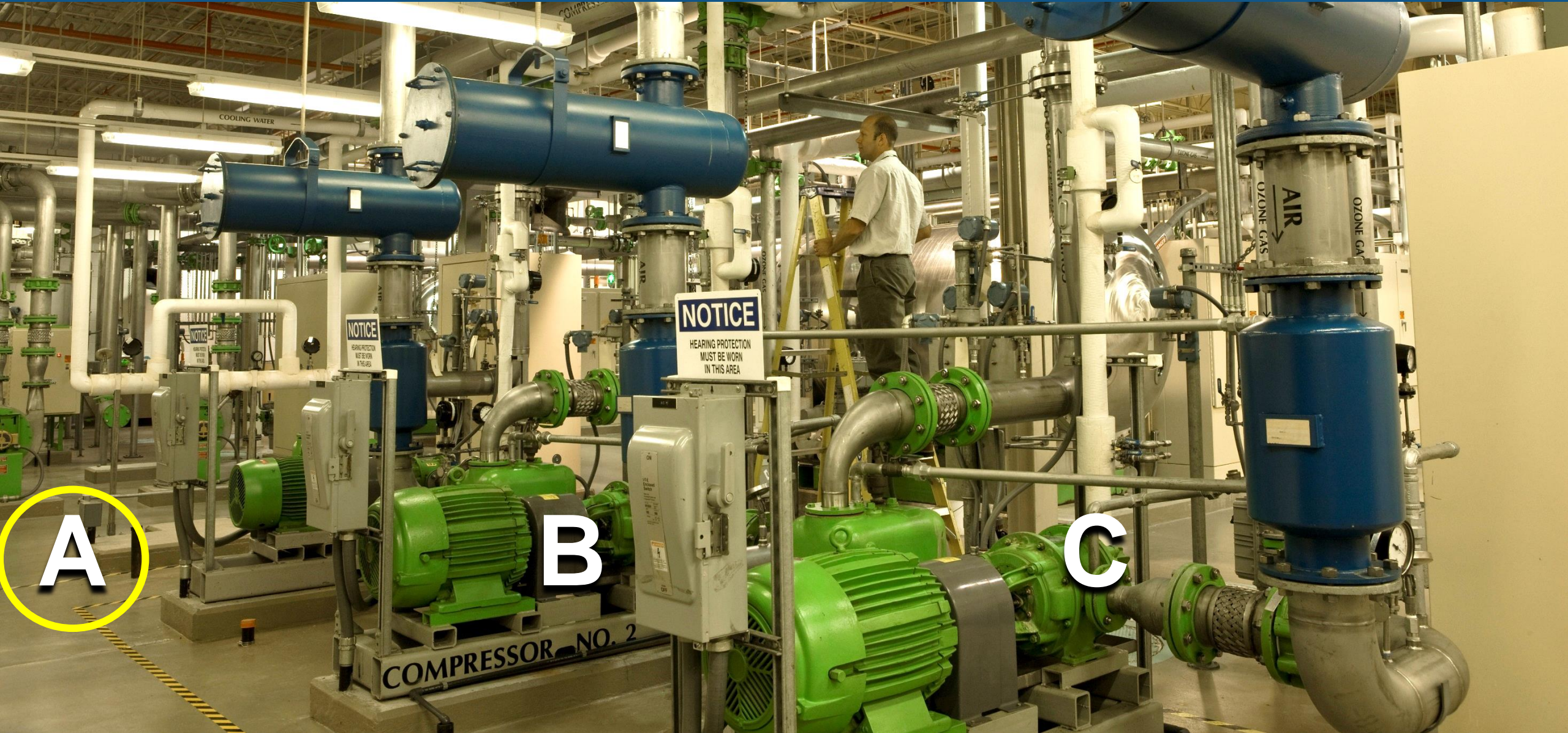
Rachel Johnson



Listen carefully. Which compressor has a faulty bearing?



Listen carefully. Which compressor has a faulty bearing?



A

B

C

COMPRESSOR NO. 2

NOTICE

HEARING PROTECTION
MUST BE WORN
IN THIS AREA

COOLING WATER

AIR
OZONE GAS

OZONE GAS

COMPRESSED AIR

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

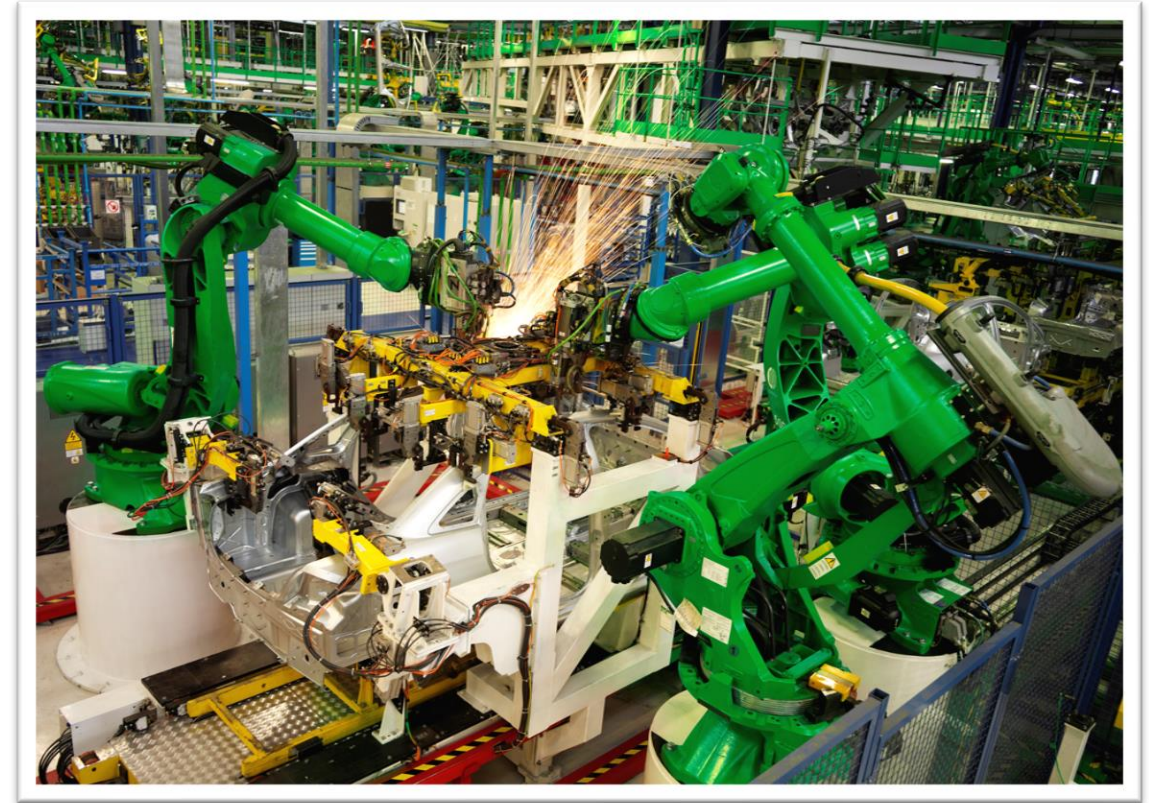
Journey 2:
Data, data, everywhere



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

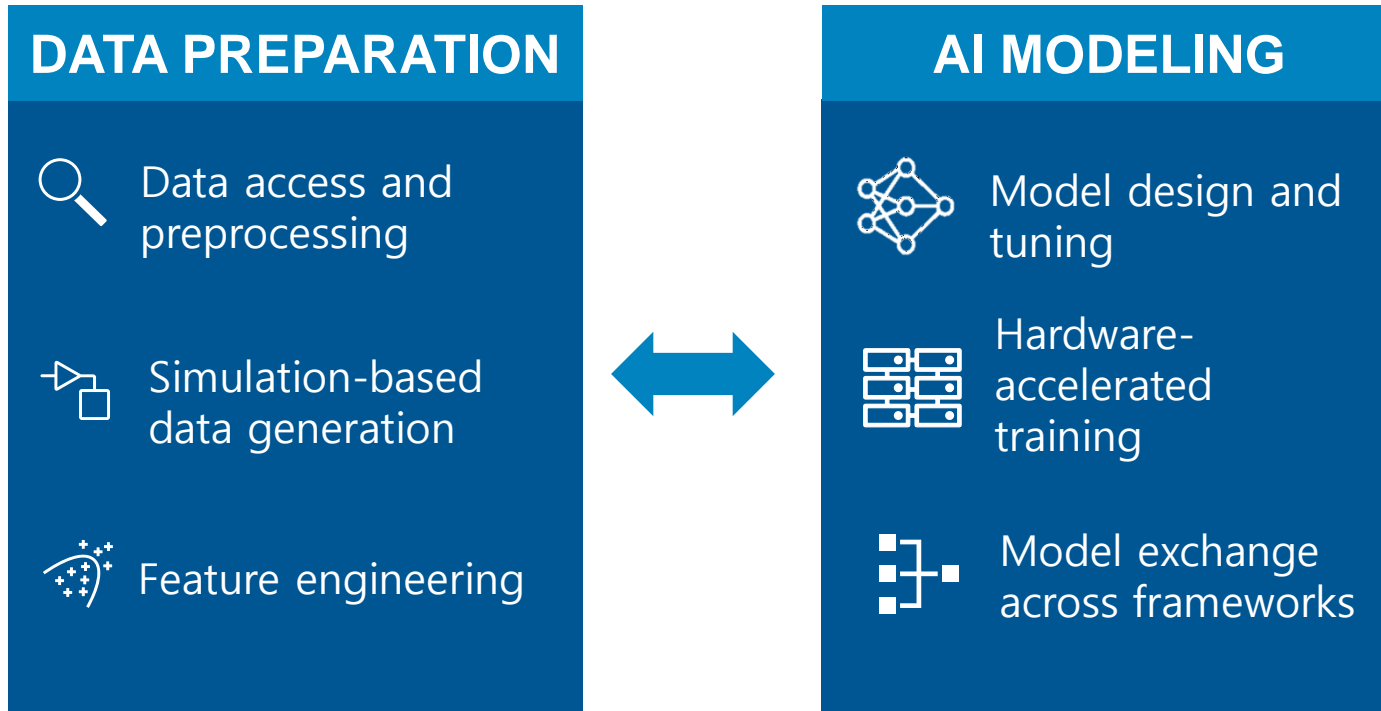


Simulation-based data generation

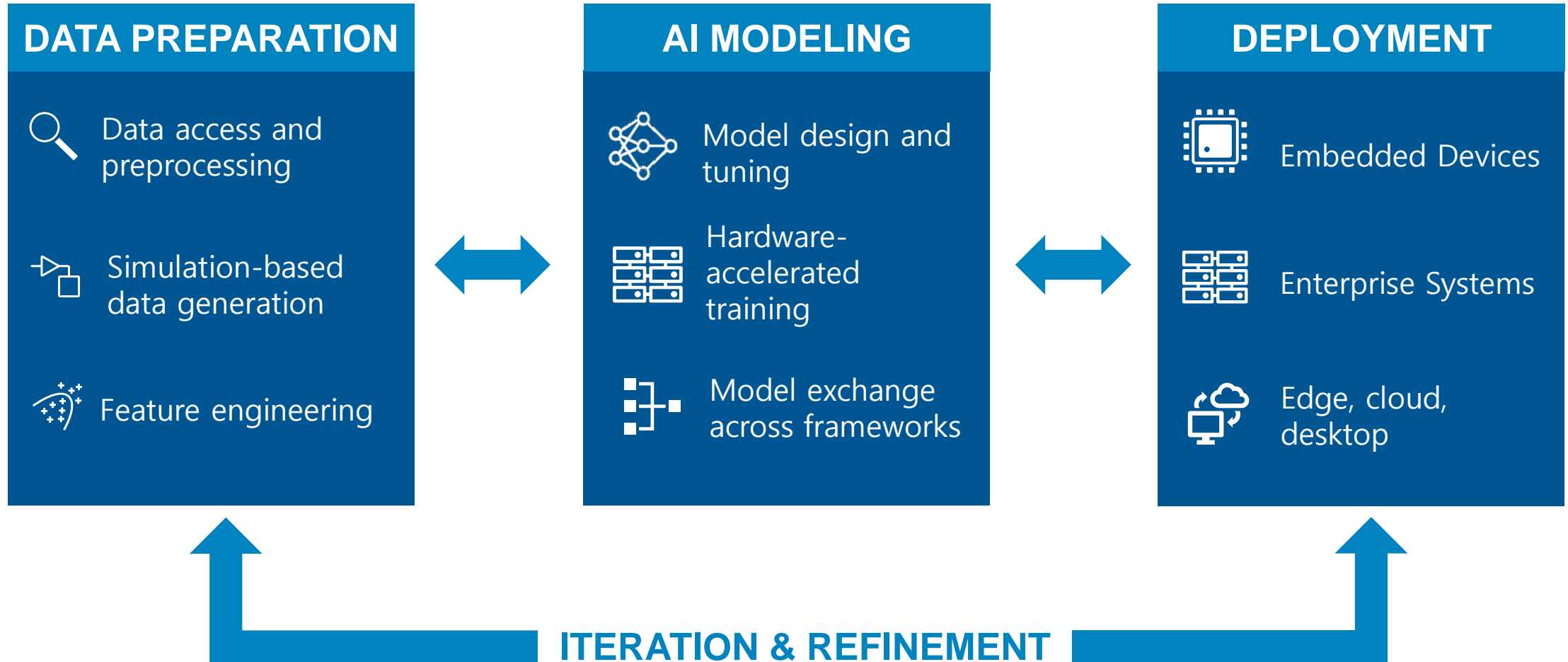


Feature engineering

Predictive Maintenance Workflow



Predictive Maintenance Workflow



Journey 1: Do you speak air compressor?



Journey 1: Do you speak air compressor?



Goal



Data

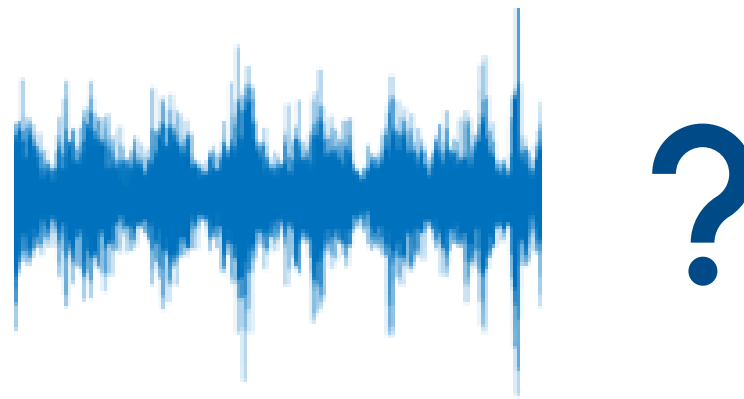


Approach



Result

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



Journey 1: Do you speak air compressor?



Goal



Data

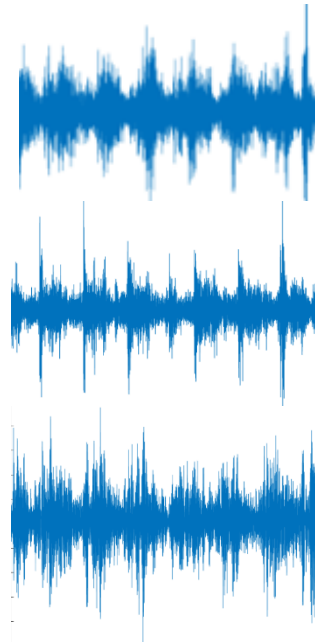
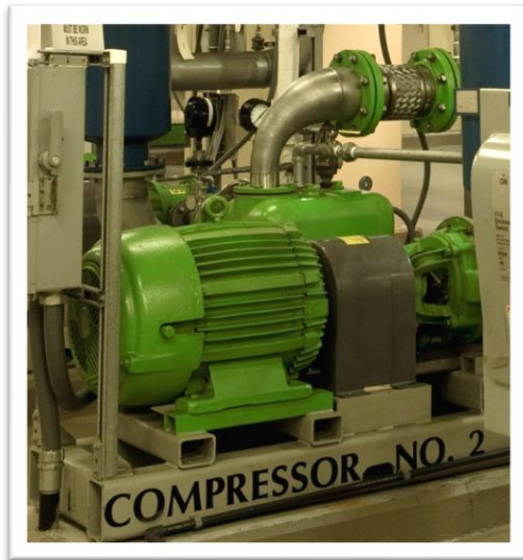


Approach



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



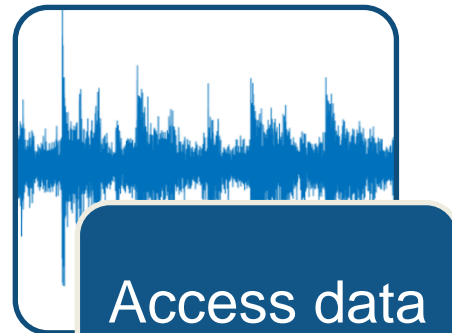
Data



Approach



Result

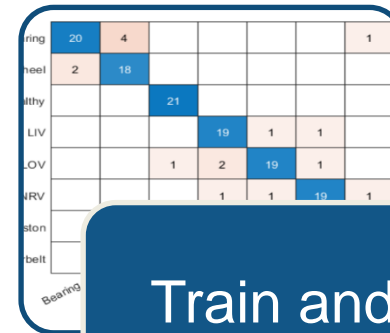


Access data with datastore



```
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



```
function extractFeatures_init
    % Initialize the configuration for the linear spectrum
    config.linearSpectrum.NoOfBins = 257;
    for (int i = 0; i < 257; i++)
        config.OneSidedSpectrum(i) = 1;
    end
    config.linearSpectrum.NoOfBins = 257;
    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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[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



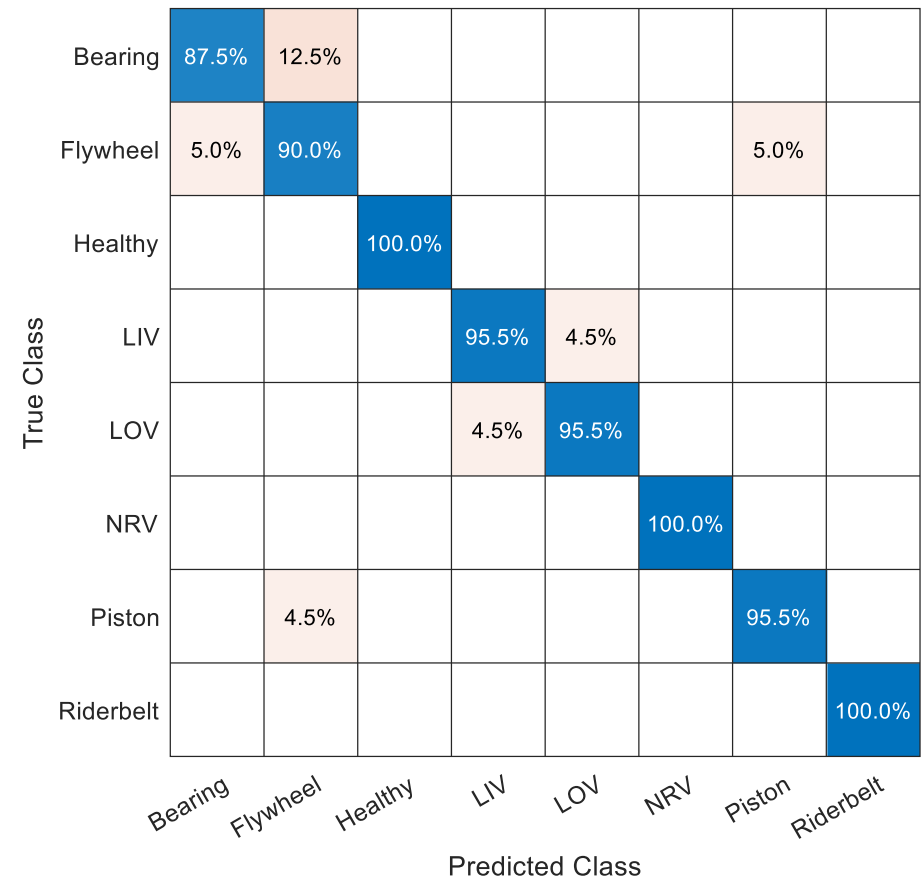
Approach



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

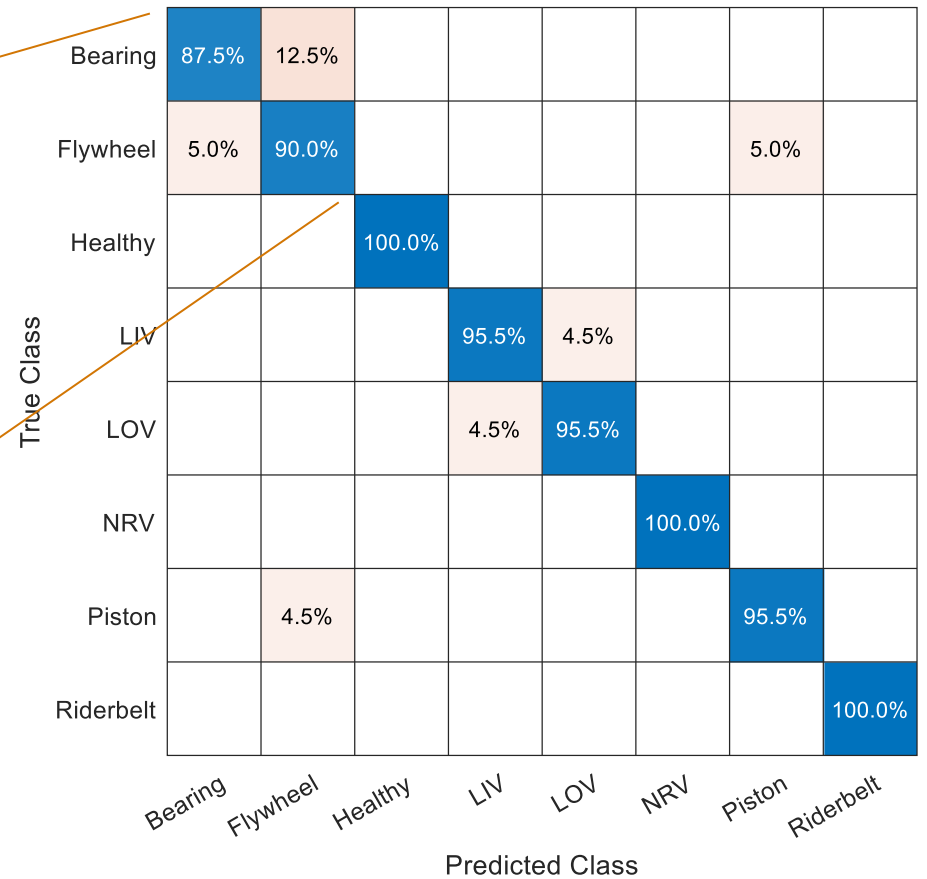
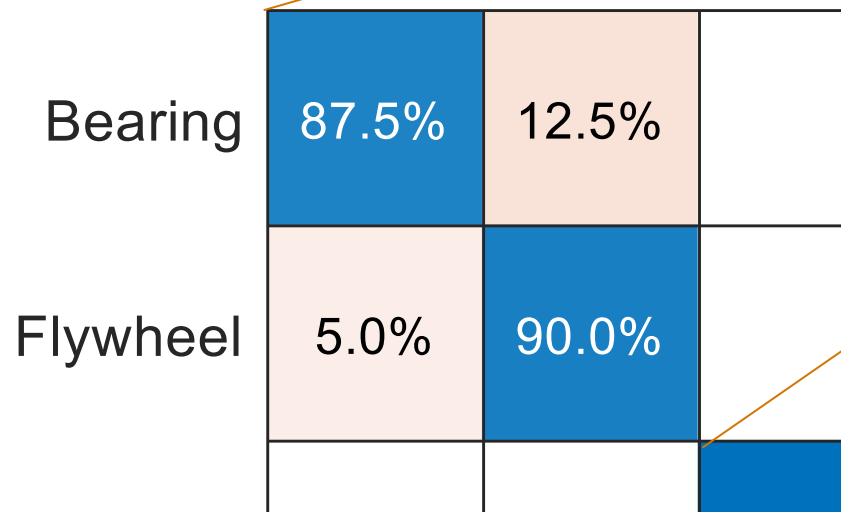


Approach



Result

- Successfully identified faults with 95% validation accuracy



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

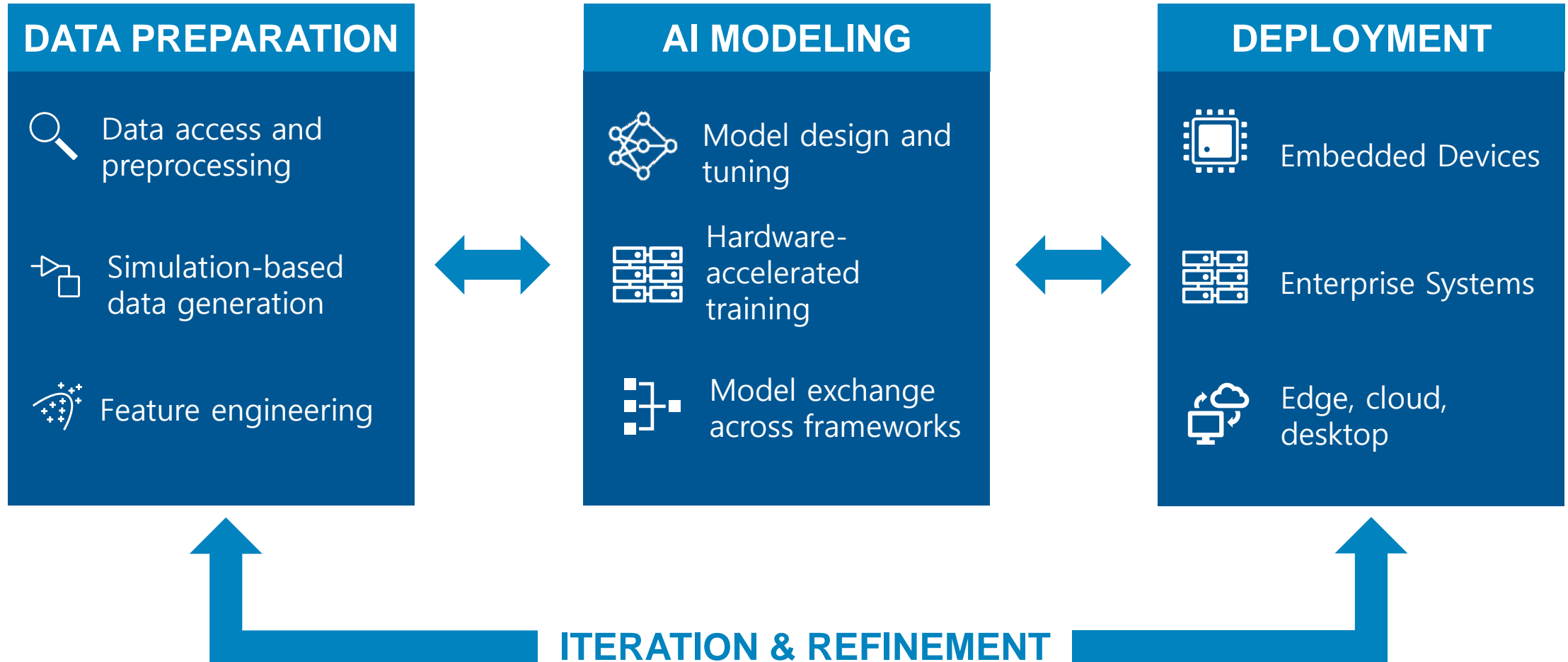


Result

Poll: How could we improve the results?

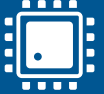


- Collect more data
- Tune network hyperparameters
- Try a different feature set
- Try a different algorithm
- Buy more GPUs

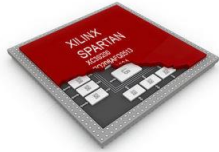
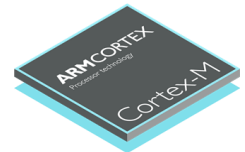
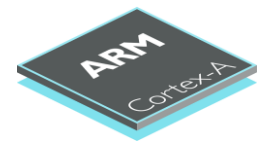
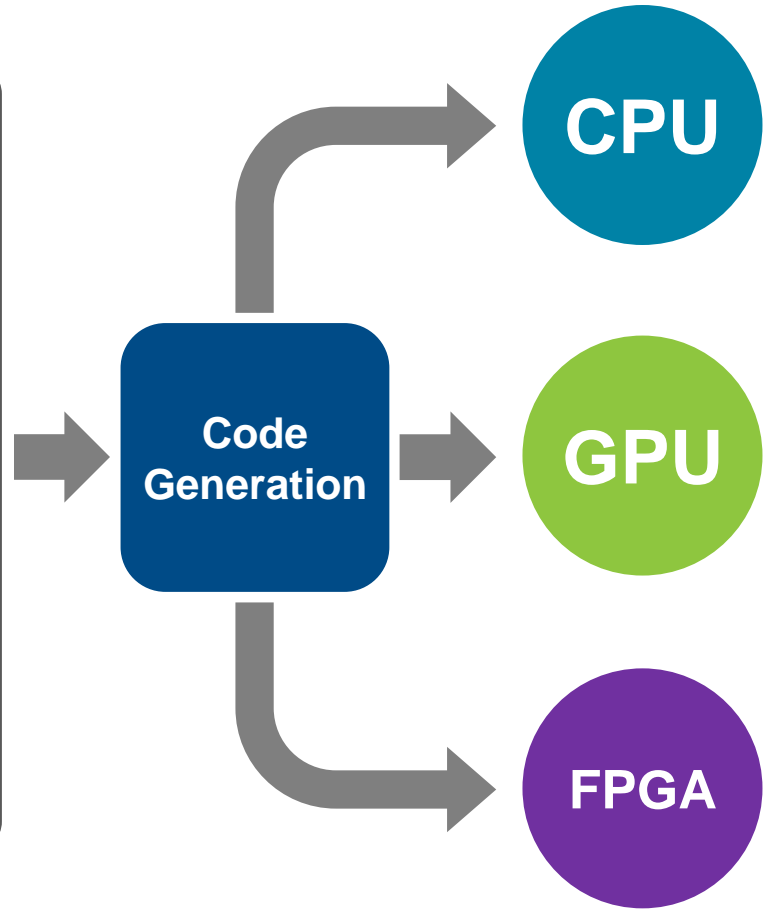
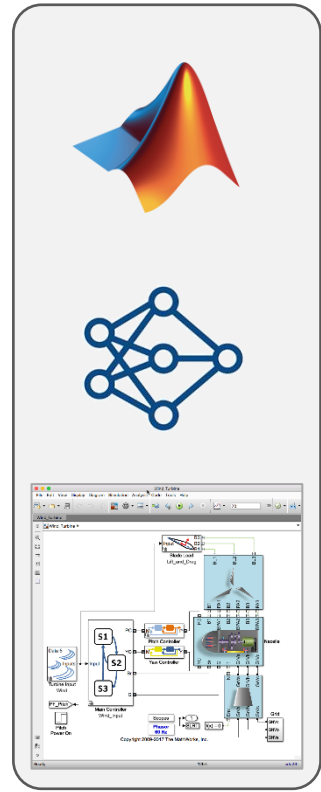
Journey 1: Do you speak air compressor?



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

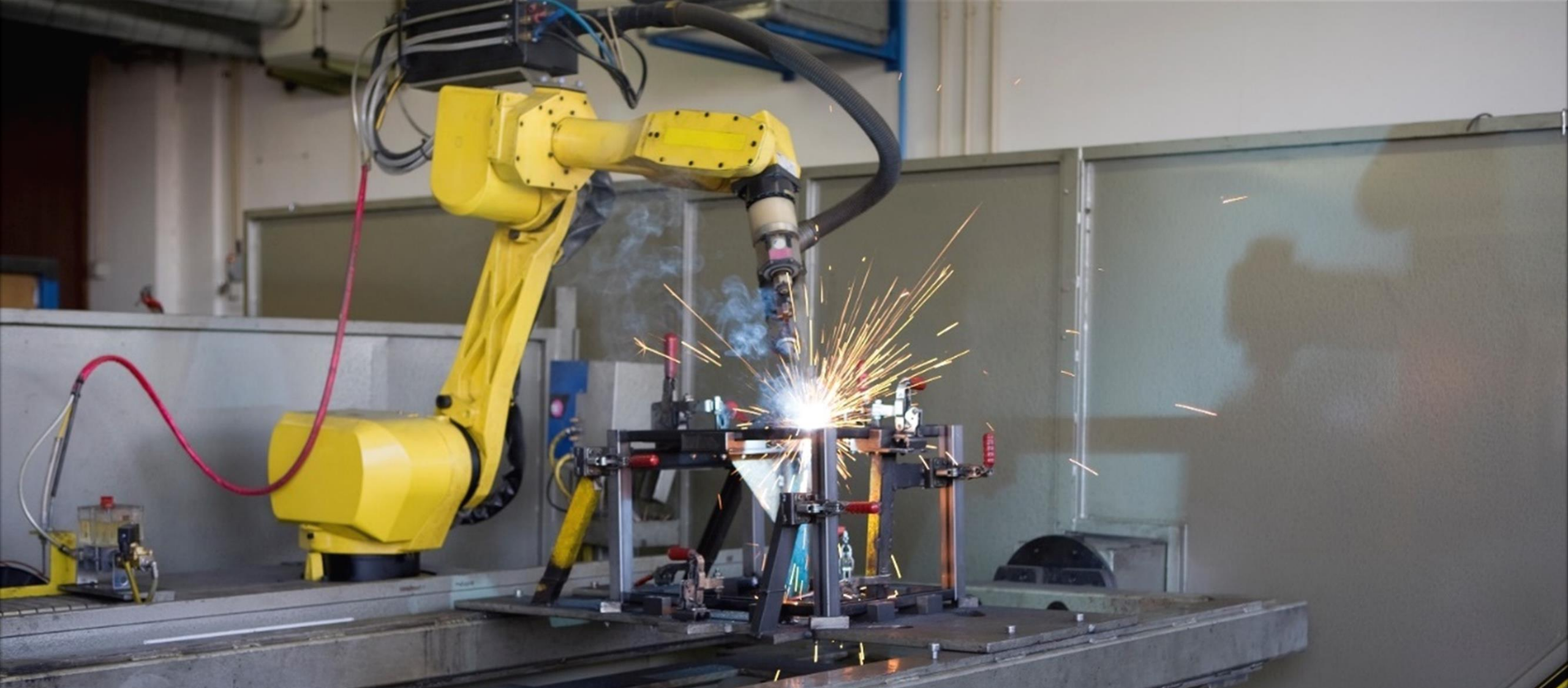


Result

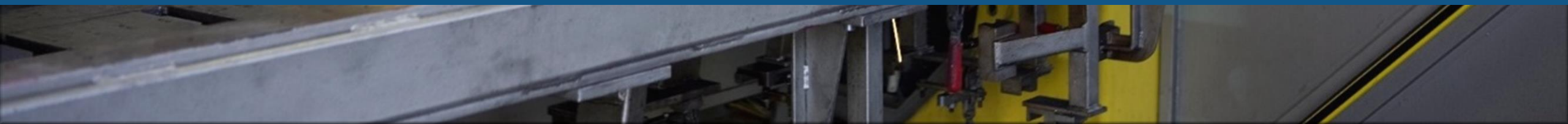
- What's Next?

MATLAB EXPO

Deploying AI to Embedded and Production Systems



Journey 2: Data, data, everywhere...



Journey 2: Data, data, everywhere...



Goal



Data

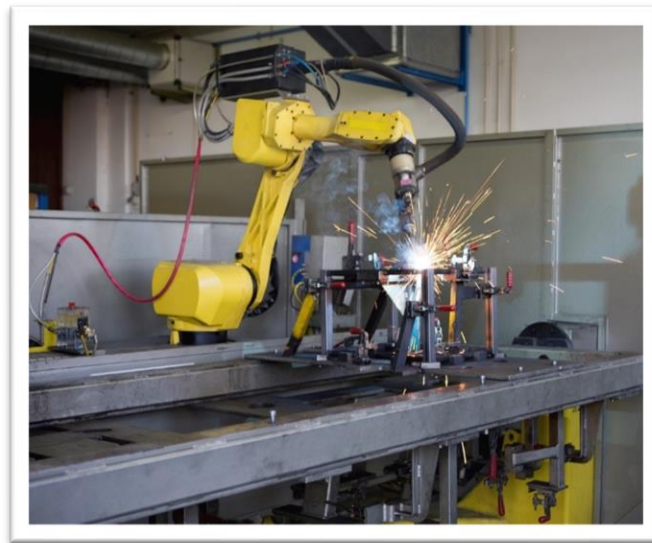


Approach



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

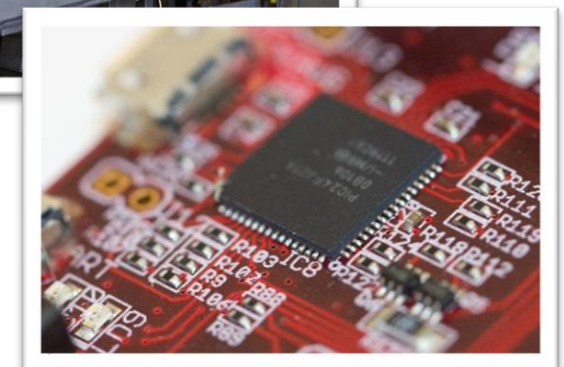
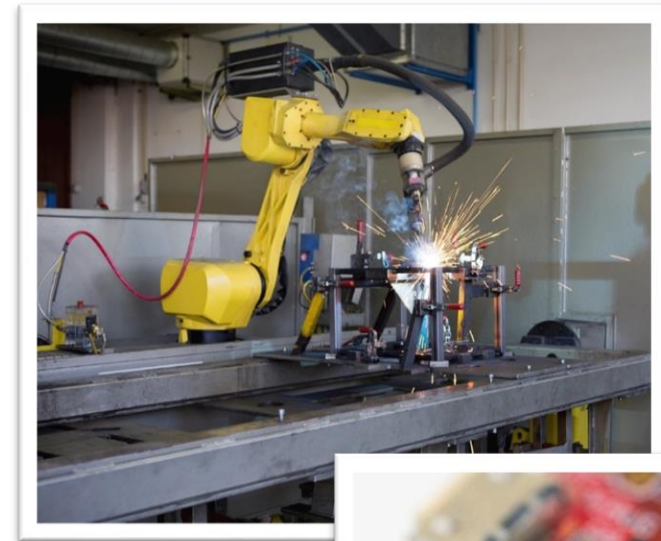


Approach



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

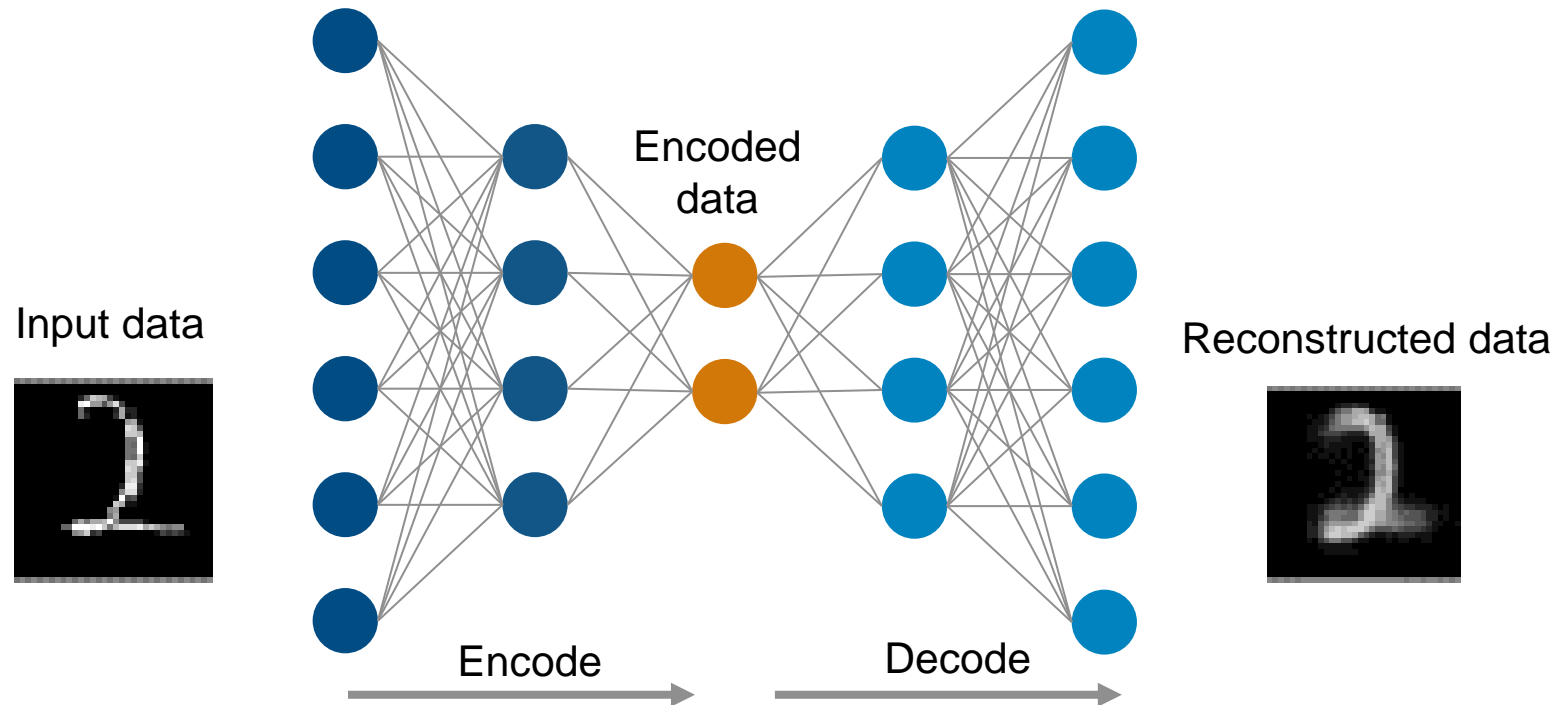


Approach



Result

Autoencoder



Journey 2: Data, data, everywhere...



Goal



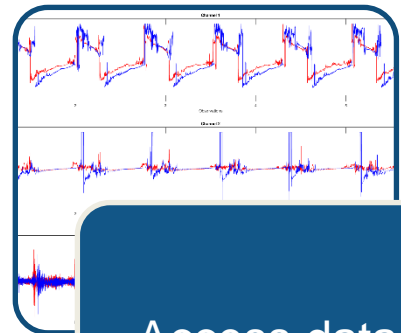
Data



Approach



Result



Access data from files



Extract and rank features with Diagnostic Feature Designer App



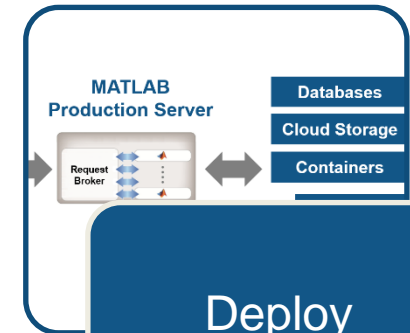
```

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

HOME PLOTS APPS LIVE EDITOR INSERT VIEW

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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

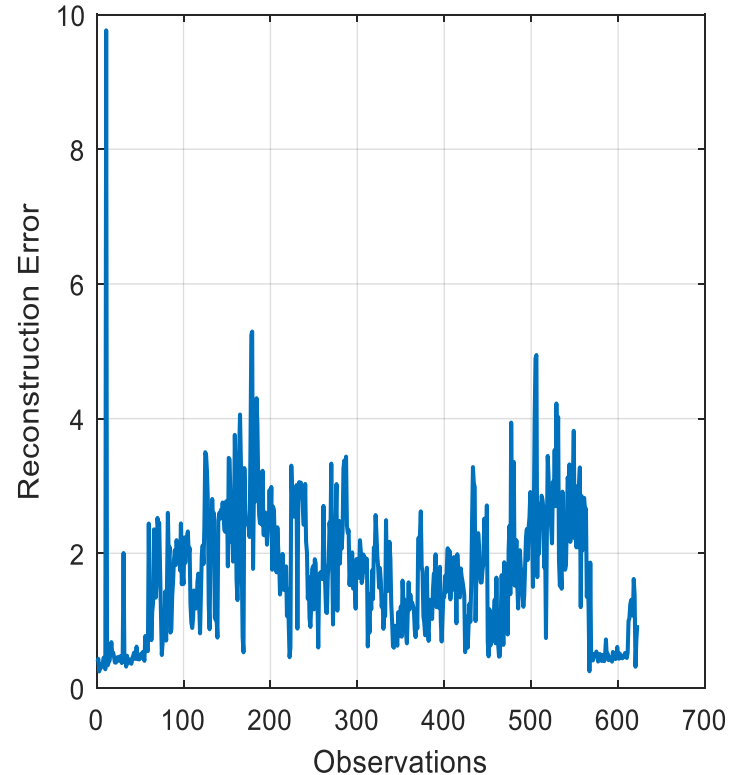
Visualize data before and after maintenance across channels for one member of the ensemble

Journey 2: Data, data, everywhere...

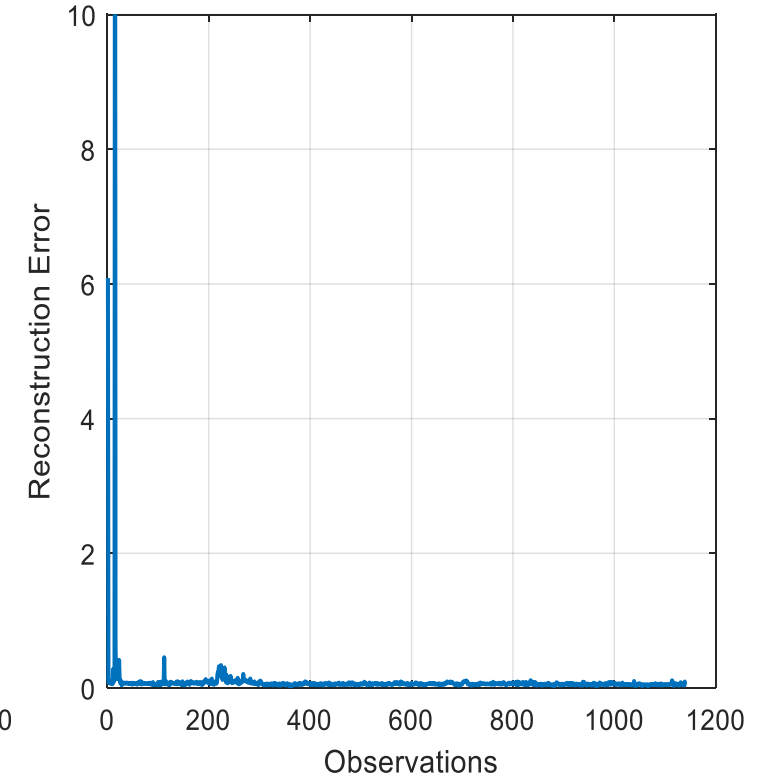
**Goal****Data****Approach****Result**

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?

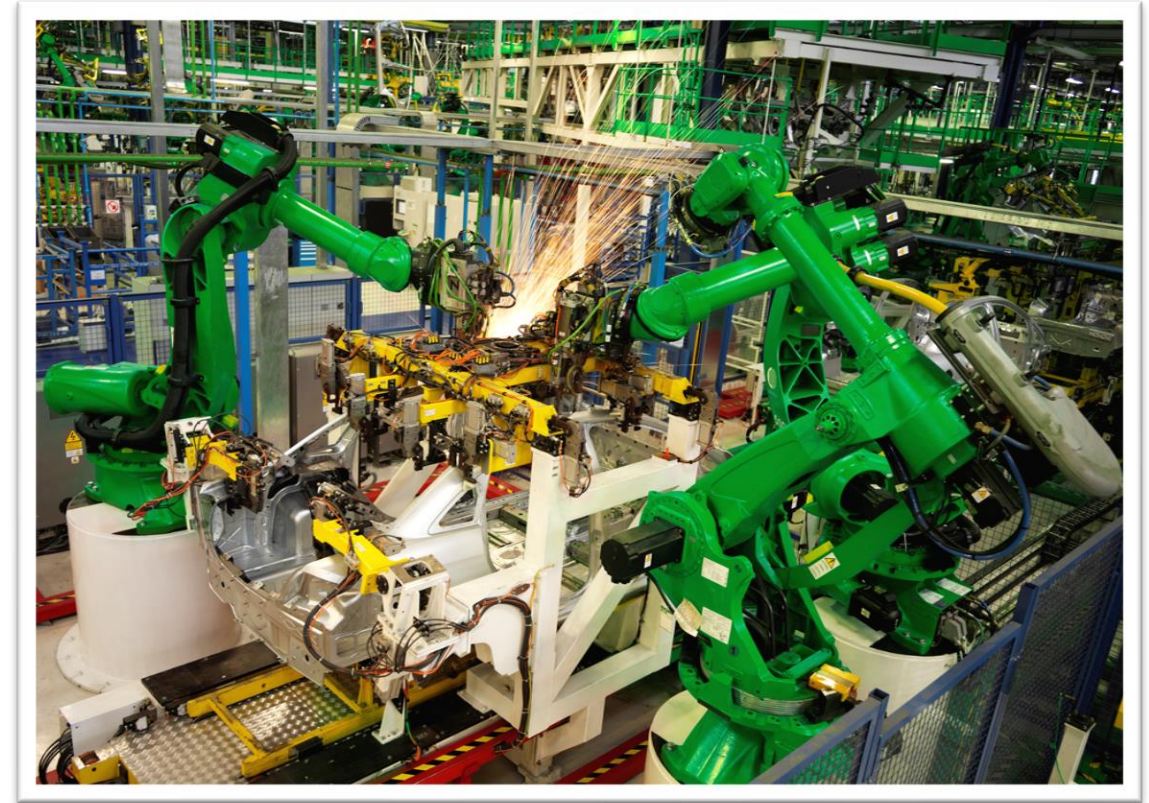
MATLAB EXPO

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

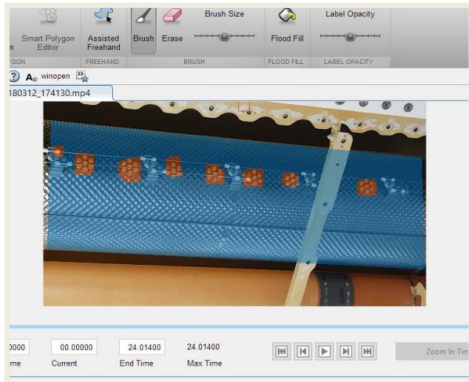
Six months later...

Six Months Later

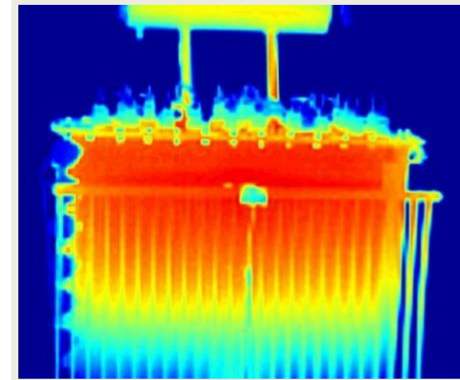
- Increased uptime by 10%
- Want to expand to entire fleet, multiple locations
- Next project: Predict Remaining Useful Life (RUL)
- Got a promotion! 😊



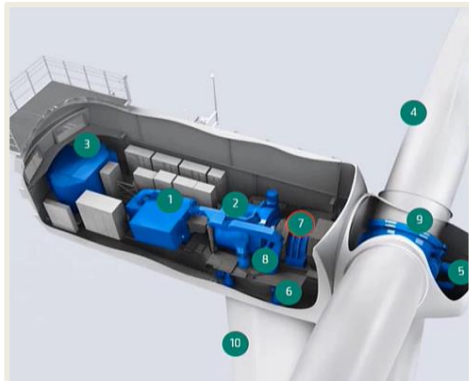
Companies are succeeding with MATLAB for Predictive Maintenance



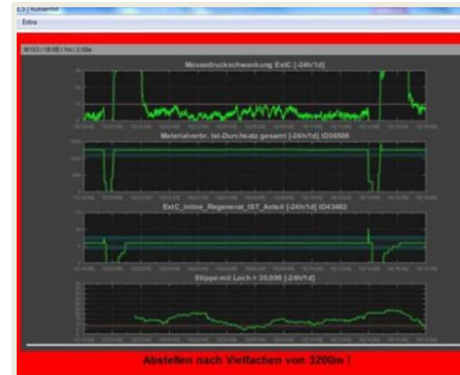
[Airbus](#) detects defects in aircraft pipes with semantic segmentation



[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

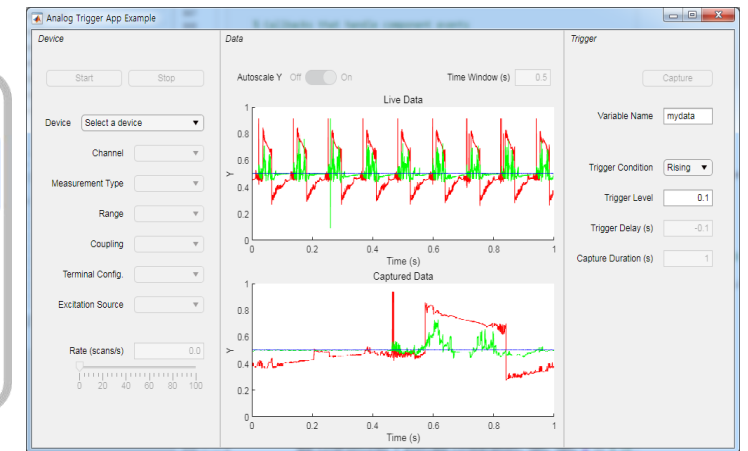
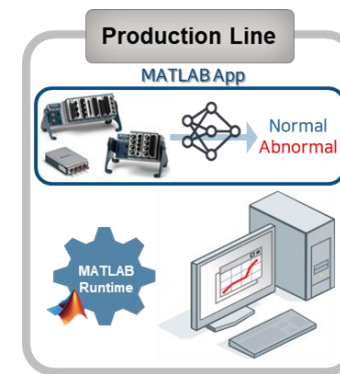
Maintenance of equipment in the factory also depends on the site engineer's opinion, and sometimes those are a bit conservative

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

