IBM Watson IoT

IOT Predictive Maintenance:
Building Predictive Vibration Analysis Models

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Building Predictive Vibration Analysis Models

The purpose of this presentation is to outline a proposed method for building predictive vibration models that could be used in an edge/cloud/on-prem environment to detect bearing failures and prevent more costly downtime using predictive and IoT technologies

IoT is driving Digital Disruption of the Physical World

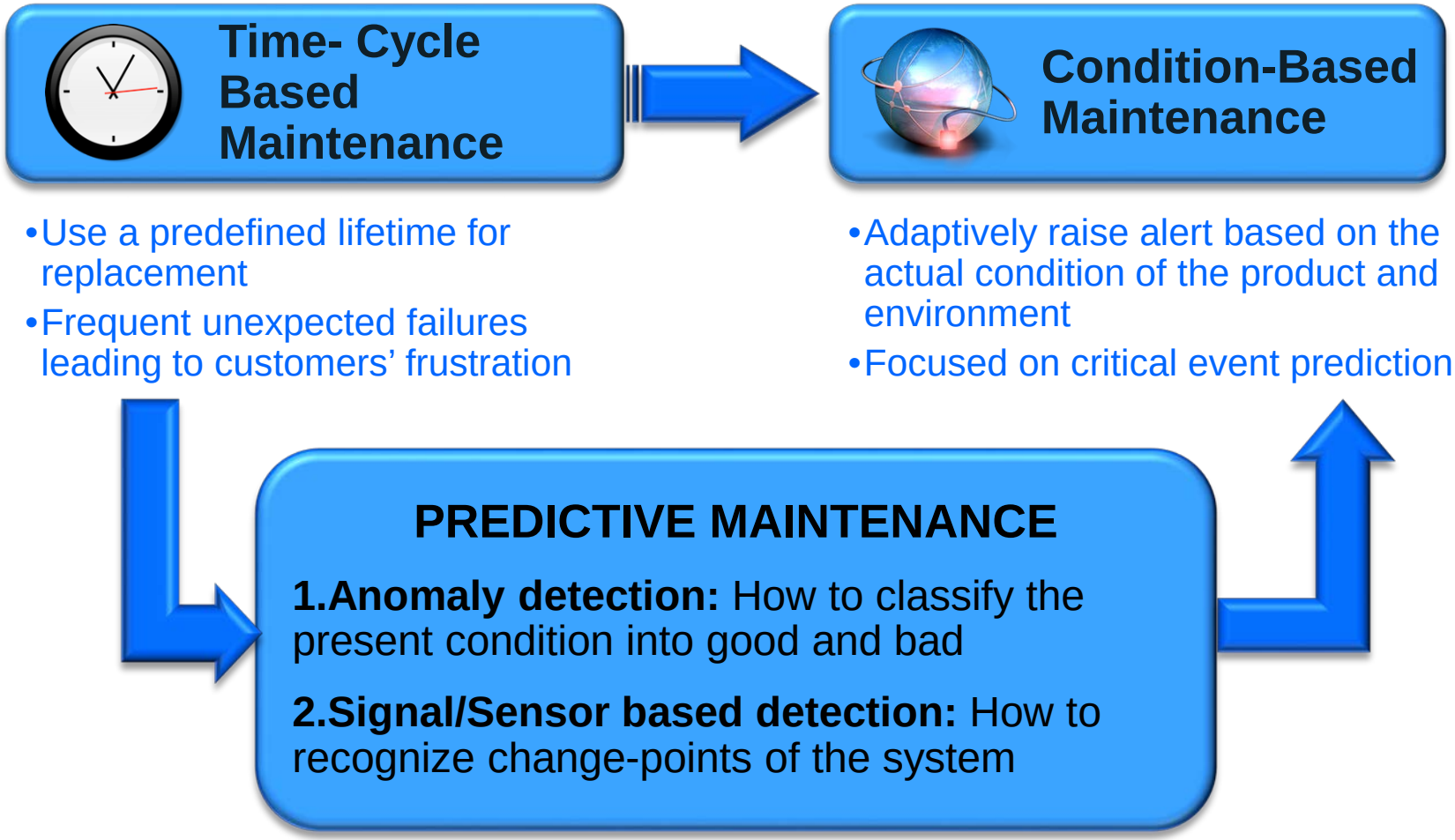
Accelerating advances in technology

- Cognitive analytics
- Cloud computing
- Pervasive connectivity
- Product Lifecycle Management
- Embedded sensors

And transforming every part of business

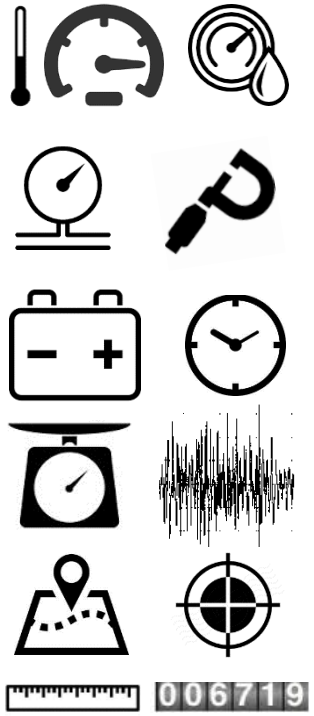
- Improving operations and lowering costs
- Creating new products and business models
- Driving engagement and customer experience

Predictive Maintenance and Quality enables the transition from static maintenance models to dynamic and condition-based maintenance models to predictive models



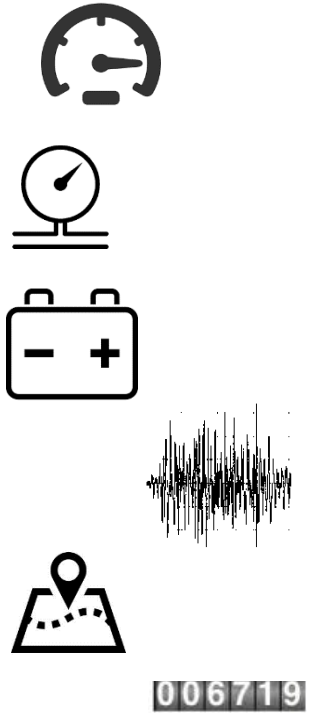
Analyze data and develop predictive models

data sources → apply modeling algorithms → identify relevant data sources → develop optimum model(s)

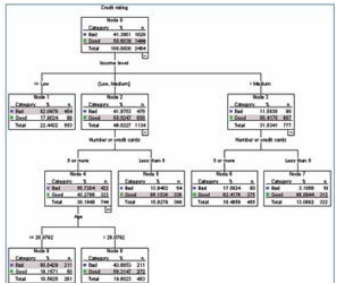


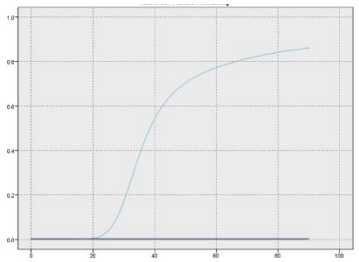
- maintenance logs
- inspection reports
- repair invoices
- customer complaints
- warranty claims
- operator profiles
- test results

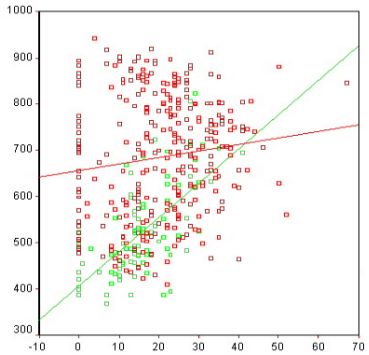
maintenance
sensor health
top failure reasons
integrated health
feature based
custom
ensemble
industry-specific assets



- maintenance logs
- warranty claims







Bearing Vibration Modeling

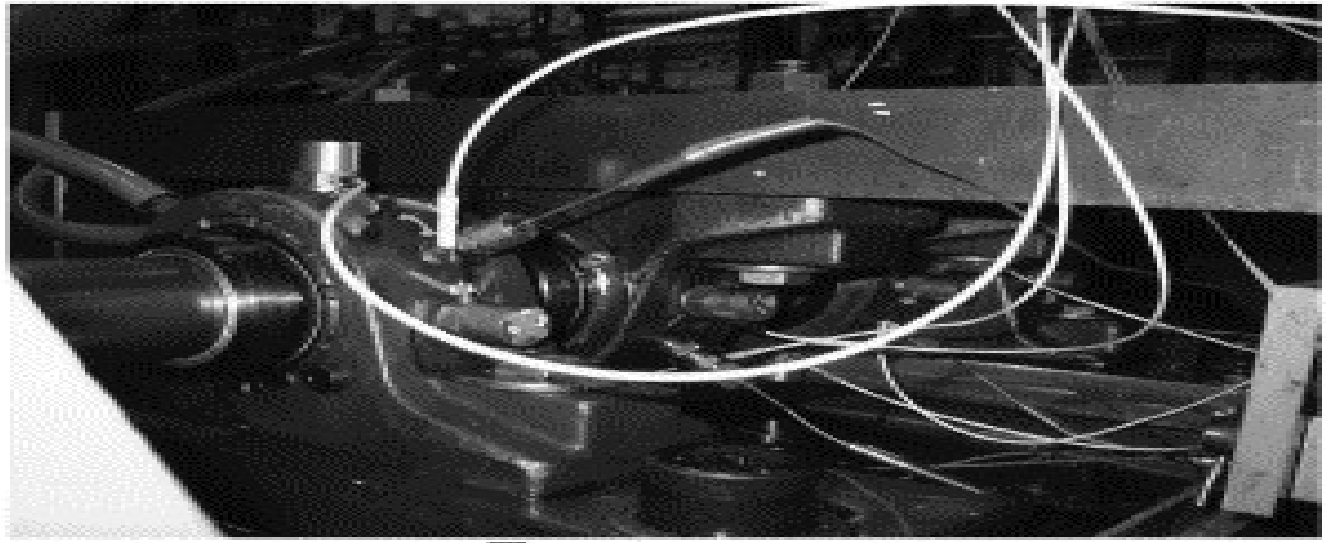
Building Predictive Vibration Analysis Models (Background)

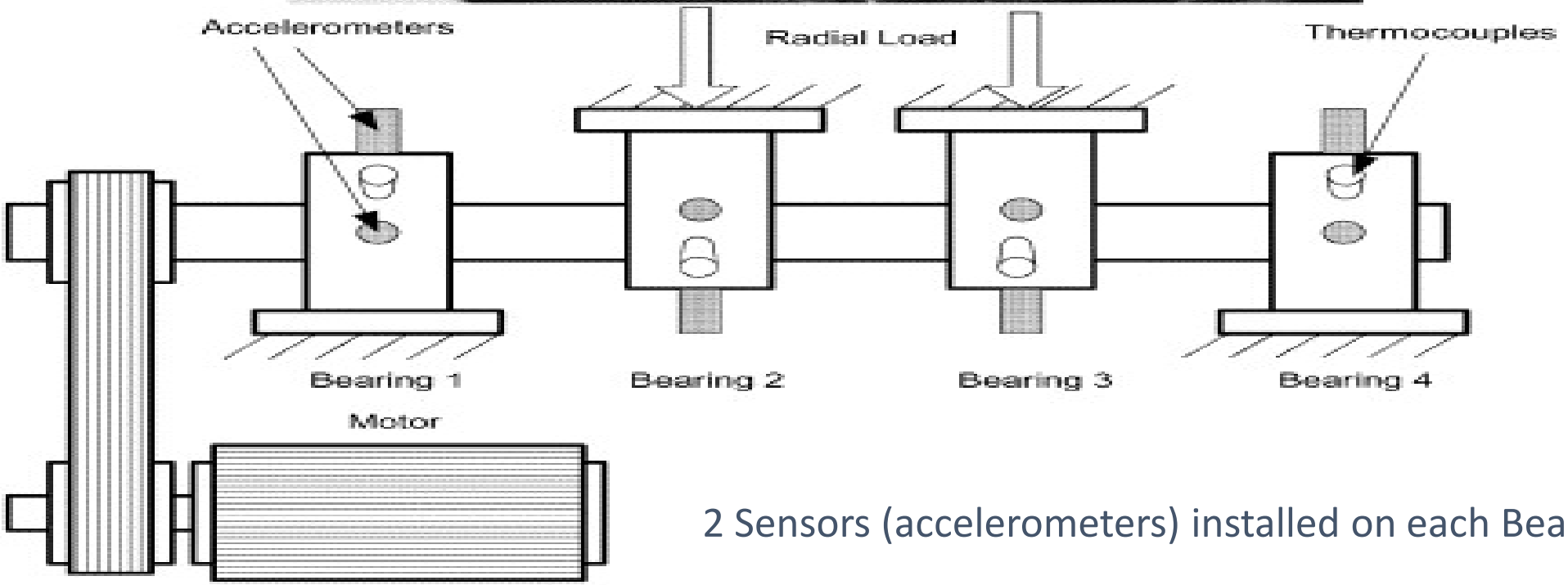
- Data provided from the Prognostics Data Repository hosted by NASA specifically, the bearing dataset
- Data gather from experiment studying four bearings installed on a loaded rotating shaft with a constant speed of 2000 rpms

Building Predictive Vibration Analysis Models (Background)

- **Data Details**:
  - The analysis period range (10/22/2003 12:06 - 11/25/2003 23:39)
  - Two sensors for each bearing (x, y axis)
  - Data recorded for a 1 second window every 5 or 10 minutes
  - Sampling Rate 20 khz
  - Data was recorded in 2,156 files
  - No engineering specifications for the bearing assemblies or the experimental setup was provided -therefore we could not calculate the expected FFT components i.e.
    - Fundamental Train Frequency
    - Ball-Spin Frequency
    - Ball-Pass Outer-Race
    - Ball-Pass Inner-Race

Building Predictive Vibration Analysis Models (Background)

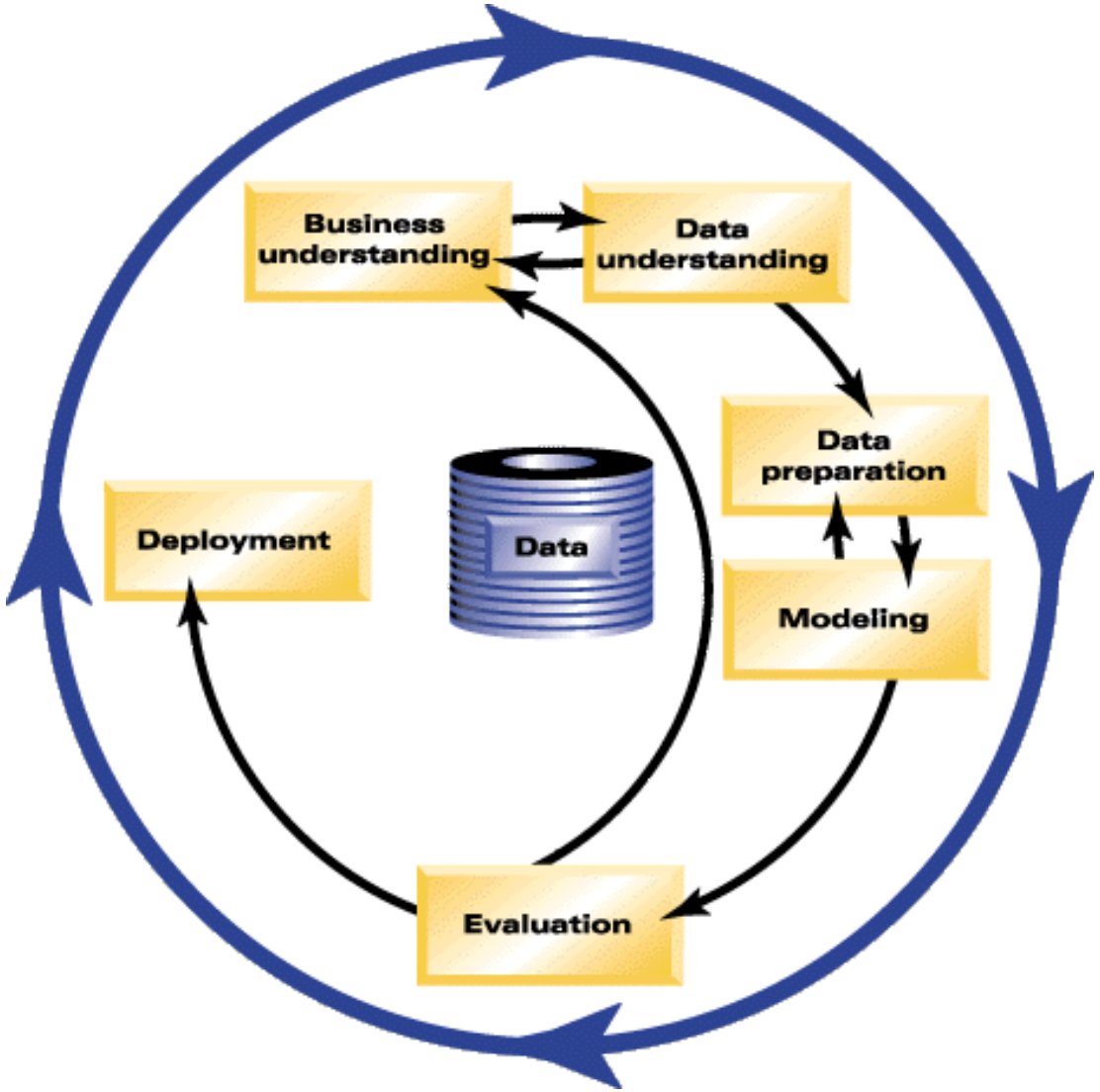




2 Sensors (accelerometers) installed on each Bearing (x and y axis)

CRISP-DM Modeling Methodology

- 6 Phases
  - Business Understanding
  - Data Understanding
  - Data Preparation
  - Modeling
  - Evaluation
  - Deployment



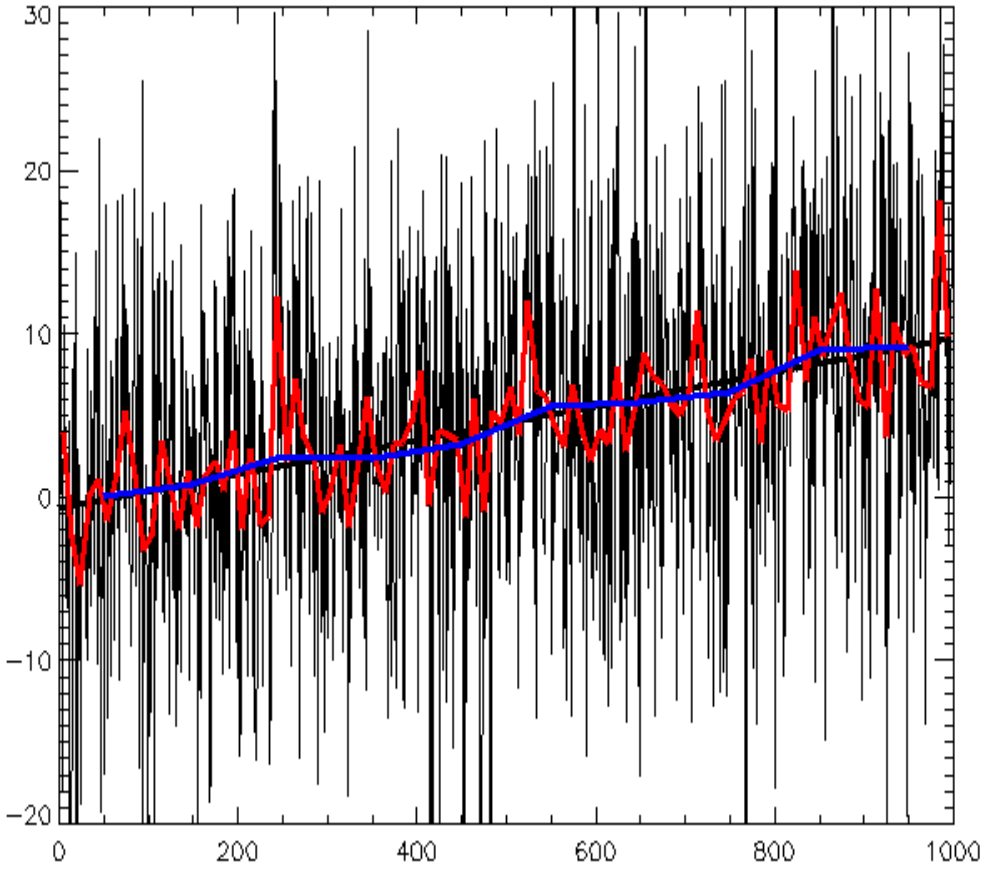
Building Predictive Vibration Analysis Models
Modeling WorkFlow:

- Business use case:
  - Build a model to predict when a bearing is likely to fail based upon data gather from sensors (accelerometers) mounted on the bearing supports. This model could be used at the Edge level or in an IoT cloud based configuration

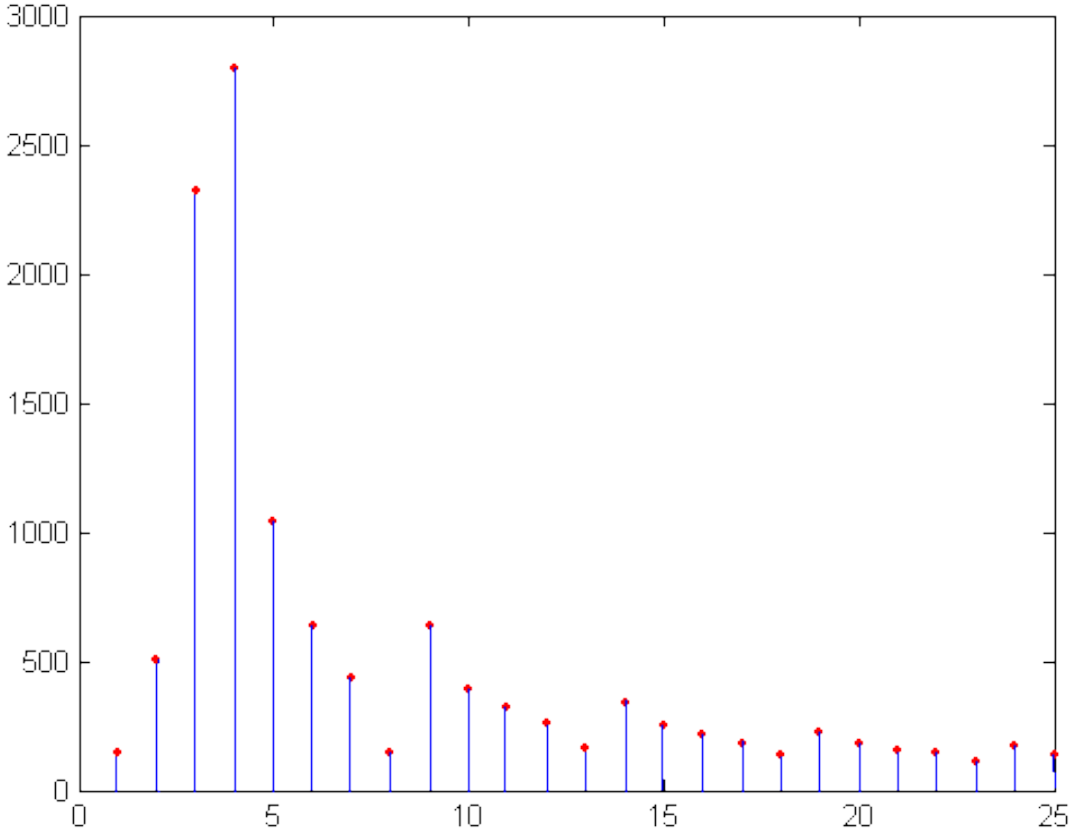
- Data Preparation-Data Visualization:
  - Analyze the input Time Series data - Exploratory Data Analysis (EDA)
  - Iterate through each time series file containing accelerometer measurements and calculate the top 5 highest “frequency spikes” for each file (1 second intervals). Store these new FFT representative features along with their respective time stamp in a new file for each bearing assembly. File in Excel *.csv format
  - This creates a file for each bearing with 2156 records (four files total) for the interval
  - Create visualizations to determine when failure events occur

Building Predictive Vibration Analysis Models Data Preparation

Time Series



Frequency Domain

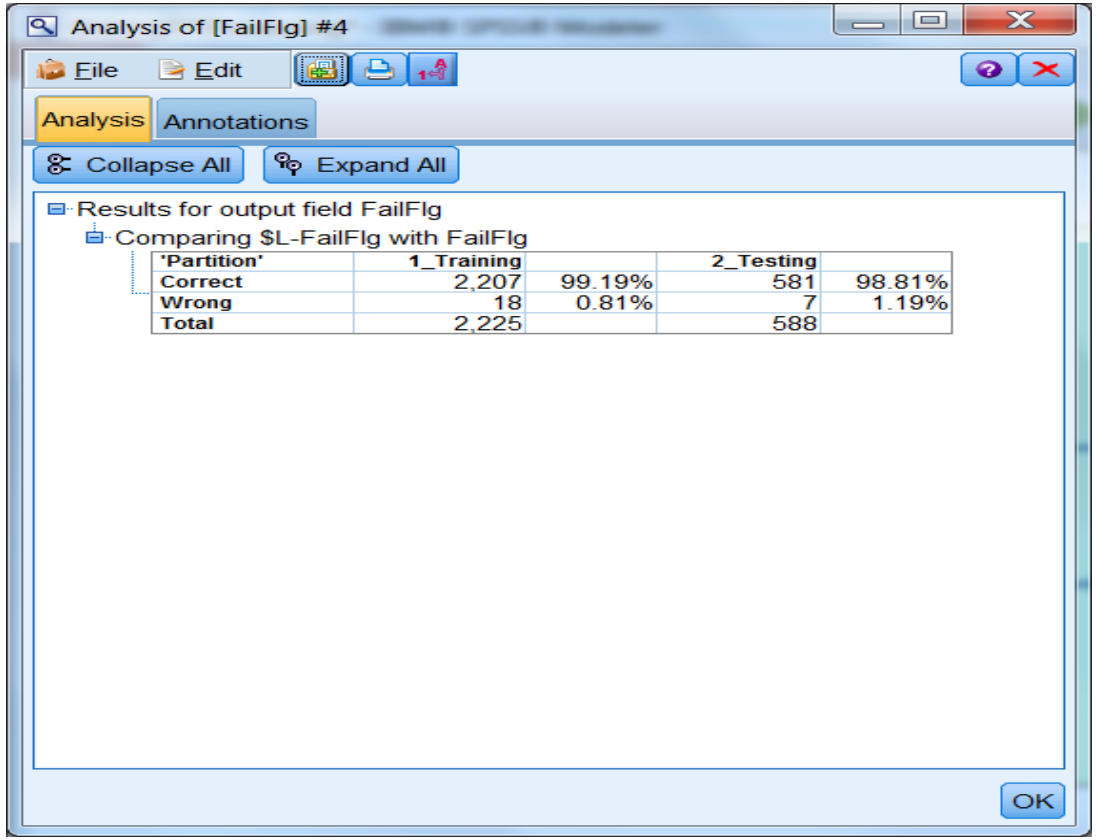


Building Predictive Vibration Analysis Models: Predictive Modeling WorkFlow

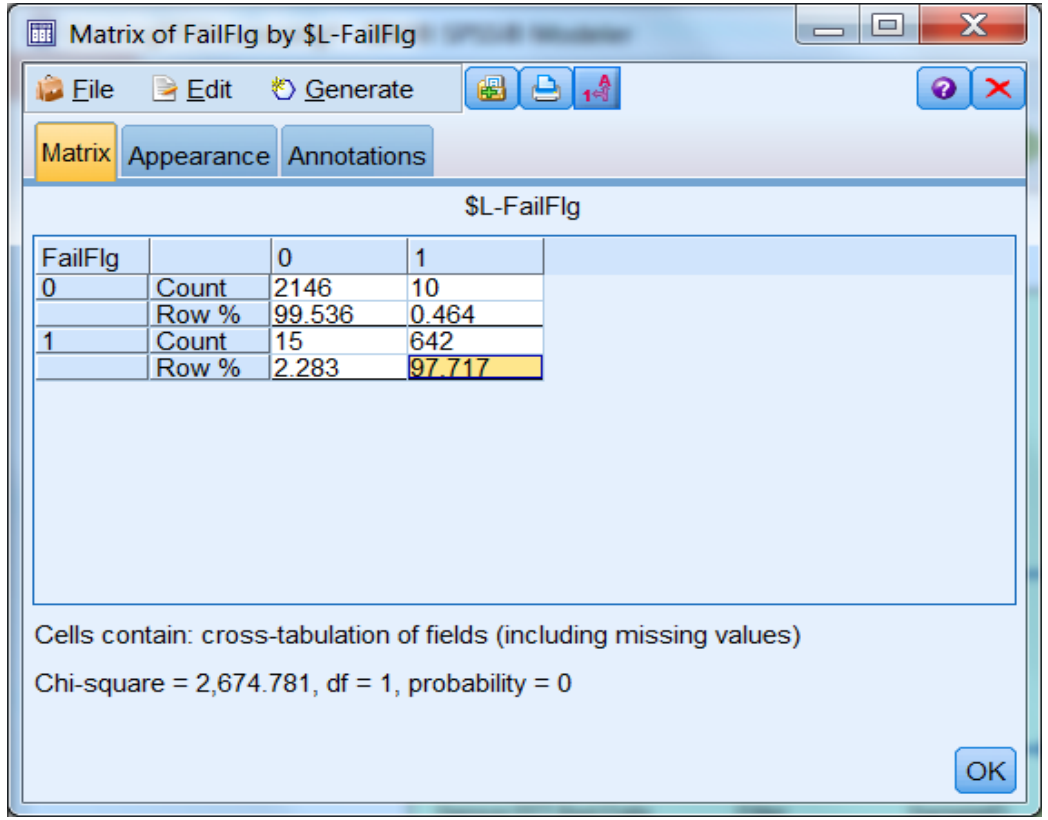
- Modeling:
  - Dataset built combined data from Sensor 1 (good data) and Sensor 4 (data with fault occurring) * *Assumption is that these bearings are the same with the same engineering specifications and exhibiting the same levels of vibration at key frequencies*
  - The dataset contains 76.64 % of records with no fault and 23.36% with bearing failure pattern occurring
  - The dataset was portioned into training/test sets with a 80/20 split
  - A Logistic Regression model was fitted to the data

Building Predictive Vibration Analysis Models
Predictive Modeling WorkFlow: (Evaluation)

The model was evaluated on training and test set with the following results. It should be notes this was against a very small dataset .Result likely to vary with more data.



'Partition'	1_Training		2_Testing	
Correct	2,207	99.19%	581	98.81%
Wrong	18	0.81%	7	1.19%
Total	2,225		588	



FailFlg		0	1
0	Count	2146	10
	Row %	99.536	0.464
1	Count	15	642
	Row %	2.283	97.717

PMQ Demo - Bearing Vibration Predictive Modeling WorkFlow:

- Deployment:
  - A scoring stream was created to score as set of bearing records against the logistic model that was created in the modeling phase. **Note**: *The dataset records for this scoring stream were previously converted from time series to FFT format this is a fairly trivial undertaking.* In a production setting this processing would be added to the scoring stream.
  - This scoring model *could* be used in a variety of deployment environments including:
    - Edge Devices
    - Cloud Based SaaS application
    - On Prem operational systems

PMQ Demo - Bearing Vibration

Demo

PMQ Demo - Bearing Vibration

Q/A


predictive maintenance modeling?

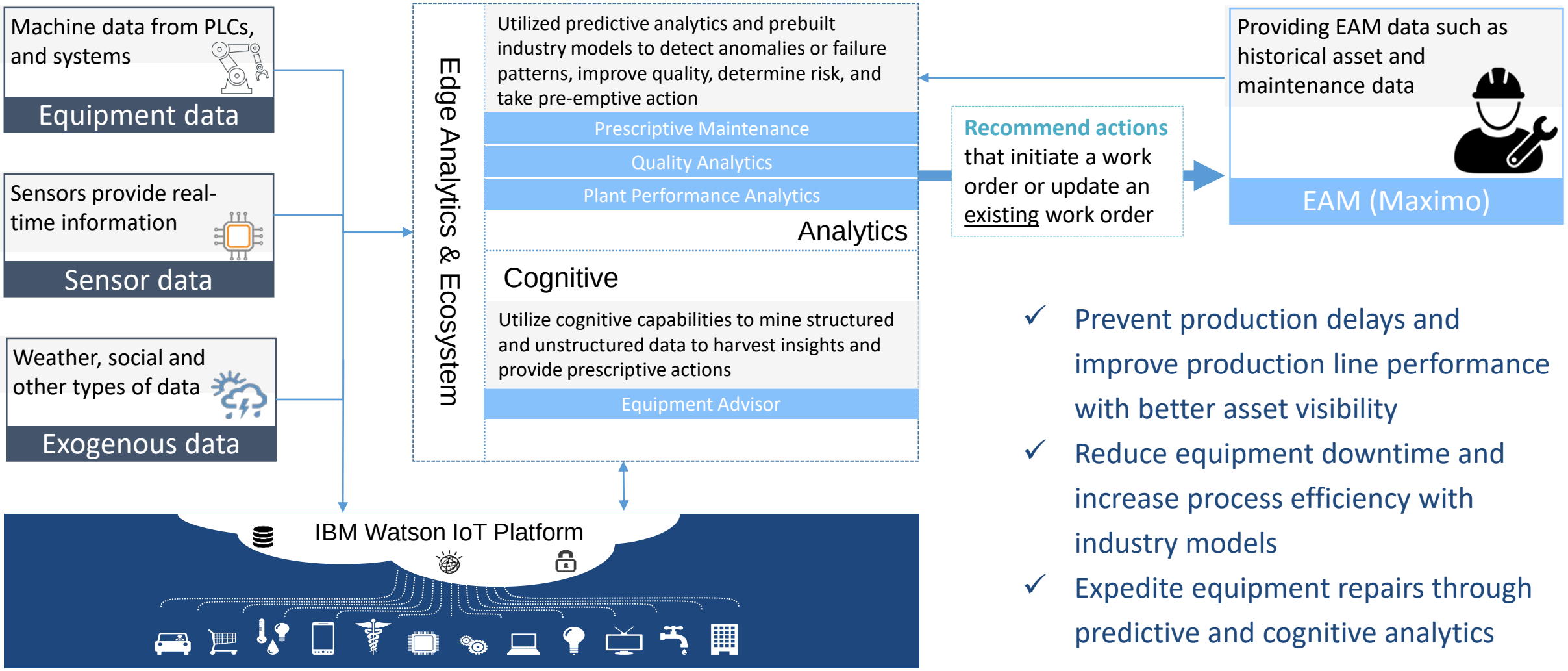
Thank You

Important links:

Detecting bearing tones with vibration analysis	https://www.youtube.com/watch?v=5MNyLM0N6l0
Vibration Analysis - Diagnosing a Bearing Defect (Real World)	https://www.youtube.com/watch?v=g8h2aFAVGH0
Very special Thanks to Dr. Victoria Catterson who provided much of the bulk data prep code in r for this presentation	http://cowlet.org/2013/09/15/understanding-data-science-feature-extraction-with-r.html

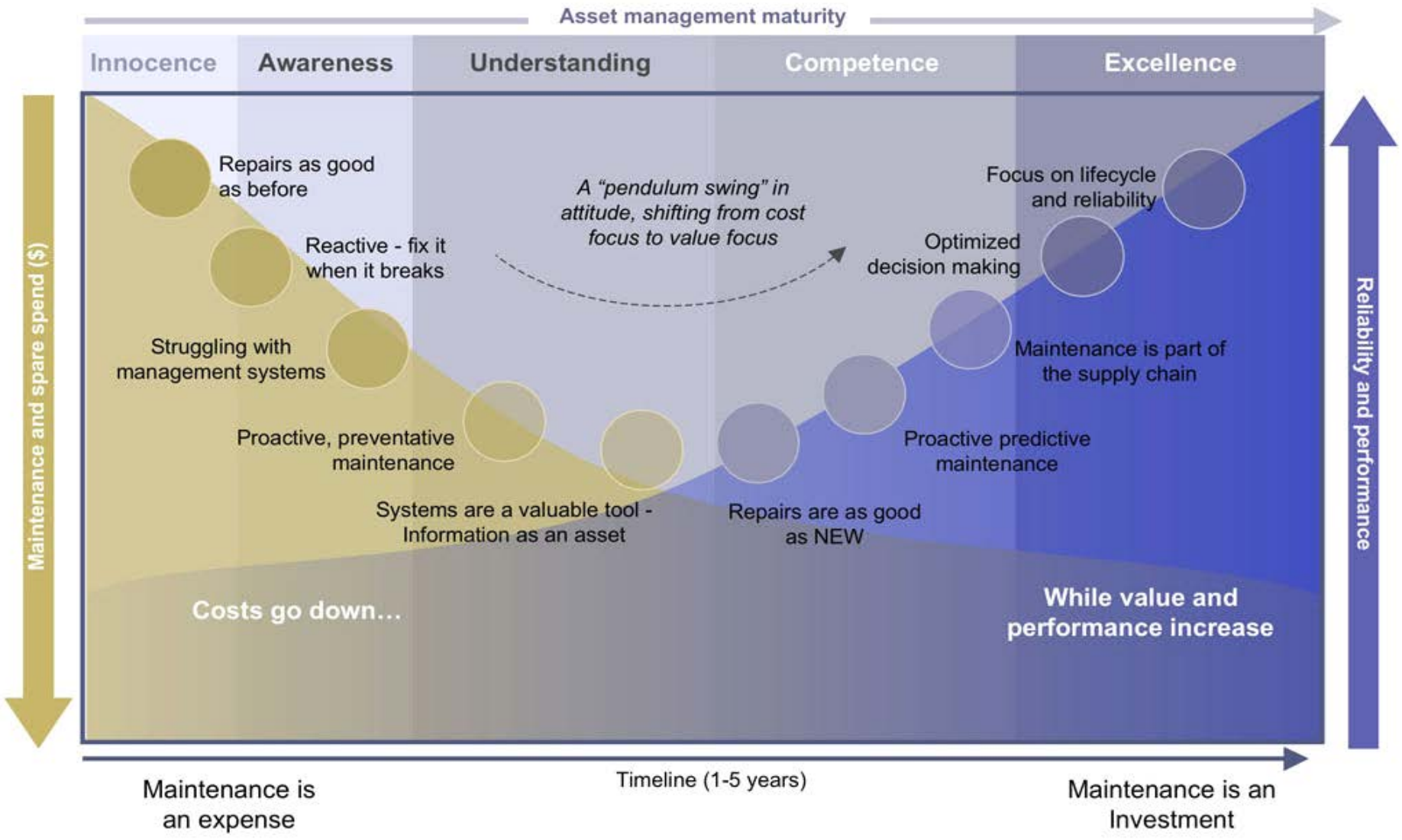
Intelligent Assets and Equipment:

Improve reliability and performance of your equipment and assets through better visibility, predictability, and operation



- ✓ Prevent production delays and improve production line performance with better asset visibility
- ✓ Reduce equipment downtime and increase process efficiency with industry models
- ✓ Expedite equipment repairs through predictive and cognitive analytics

The Journey


Asset management maturity
Innocence
Awareness
Understanding
Competence
Excellence
Maintenance and spare spend ($)
Reliability and performance
Repairs as good as before
Reactive - fix it when it breaks
Struggling with management systems
Proactive, preventative maintenance
Systems are a valuable tool - Information as an asset
A "pendulum swing" in attitude, shifting from cost focus to value focus
Repairs are as good as NEW
Proactive predictive maintenance
Maintenance is part of the supply chain
Optimized decision making
Focus on lifecycle and reliability
Costs go down…
While value and performance increase
Maintenance is an expense
Timeline (1-5 years)
Maintenance is an Investment