Microsoft

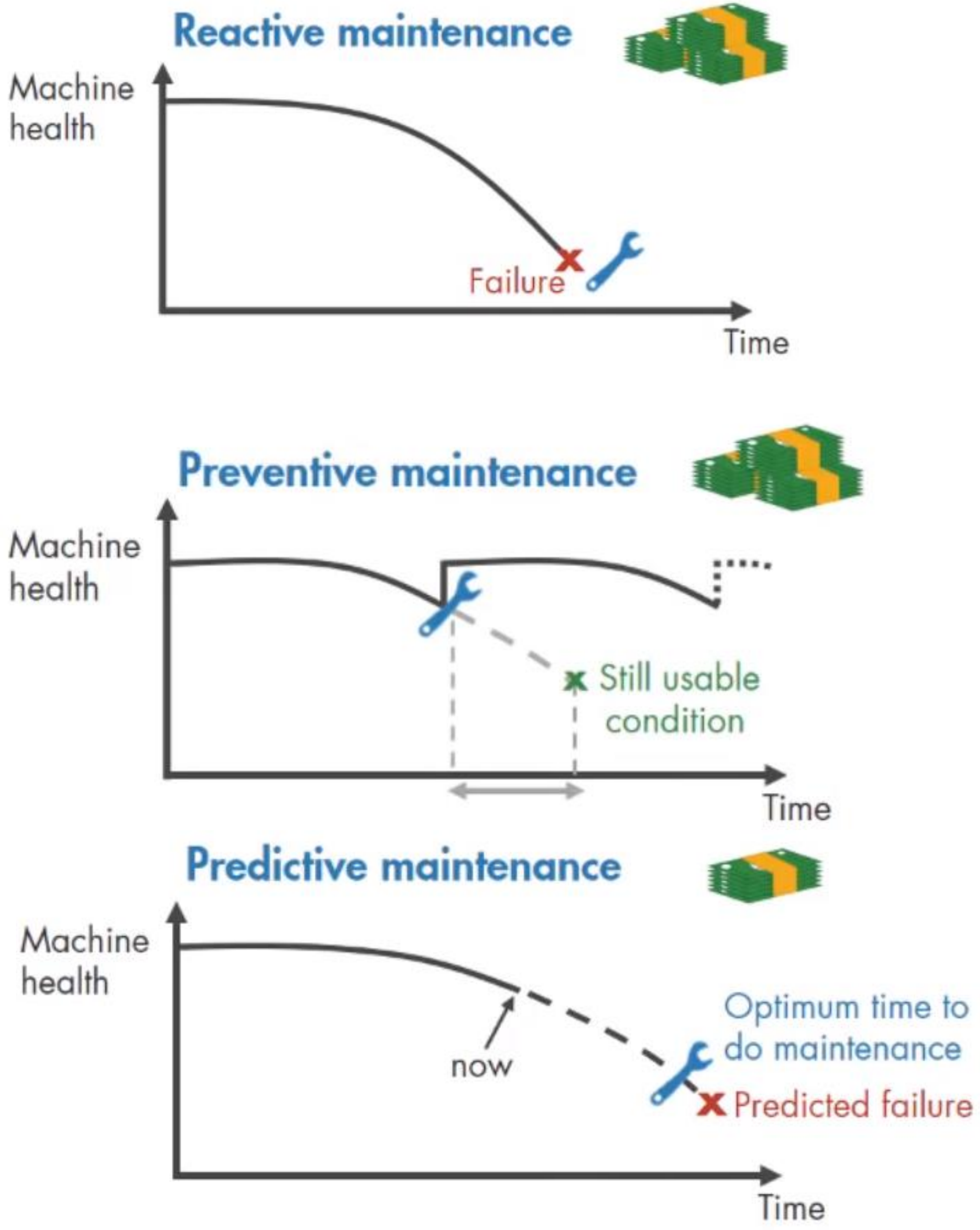
Predictive Maintenance

Fix Your Equipment Before it Breaks Down

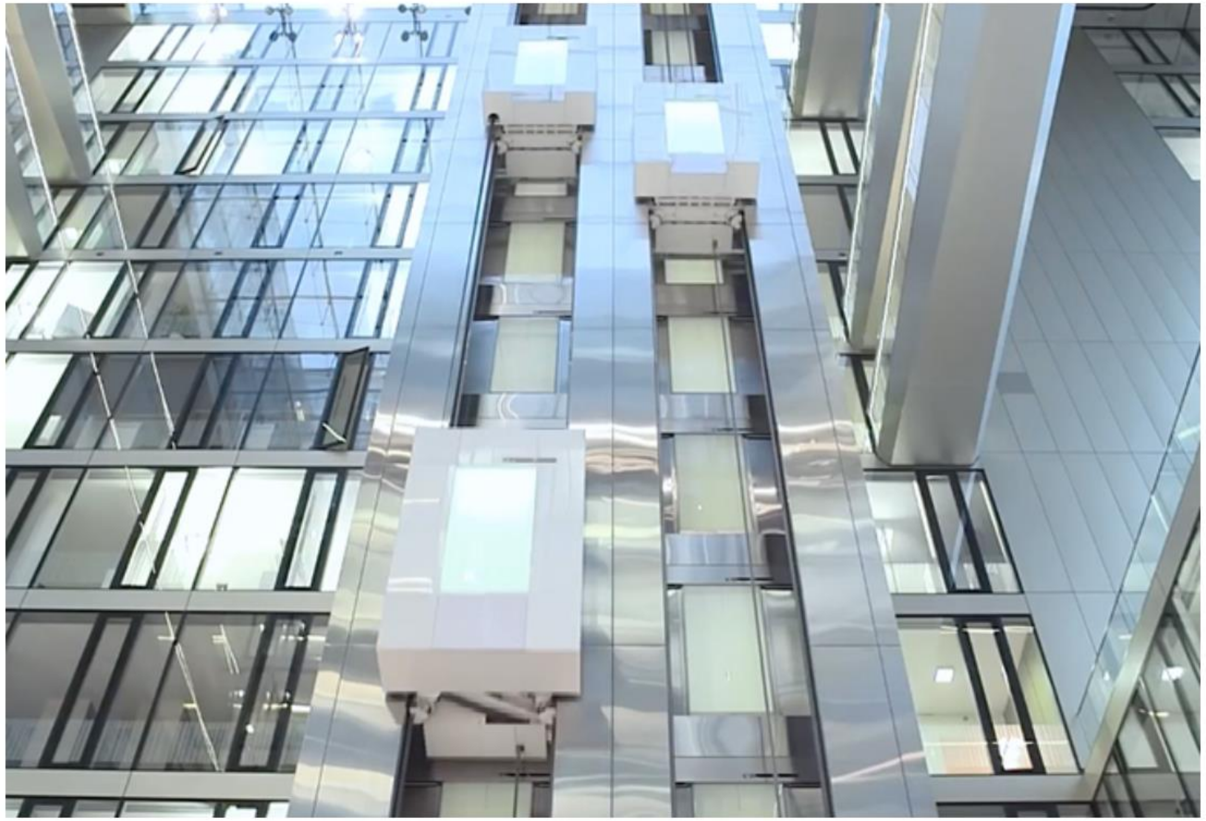
Sorin Peste
Technology Solutions Professional
Microsoft

source: xkcd.com

Predictive Maintenance | Types of Maintenance



thyssenkrupp



thyssenkrupp brings a new vision to elevator maintenance

Already using the predictive maintenance capabilities of Azure IoT Suite to reduce downtime and costs, thyssenkrupp is taking their IoT solution even further by enhancing their connected field service with HoloLens. Now their field technicians can access remote assistance to better identify problems and make time-saving interventions at the 1.1 million elevators the company maintains worldwide.

Watch the video ▷

Read the full case study >

https://www.microsoft.com/en-us/internet-of-things/customer-stories#manufacturing&thyssenkruppelevator

Rolls-Royce

Predictive analytics help optimize Rolls-Royce airplane engine performance

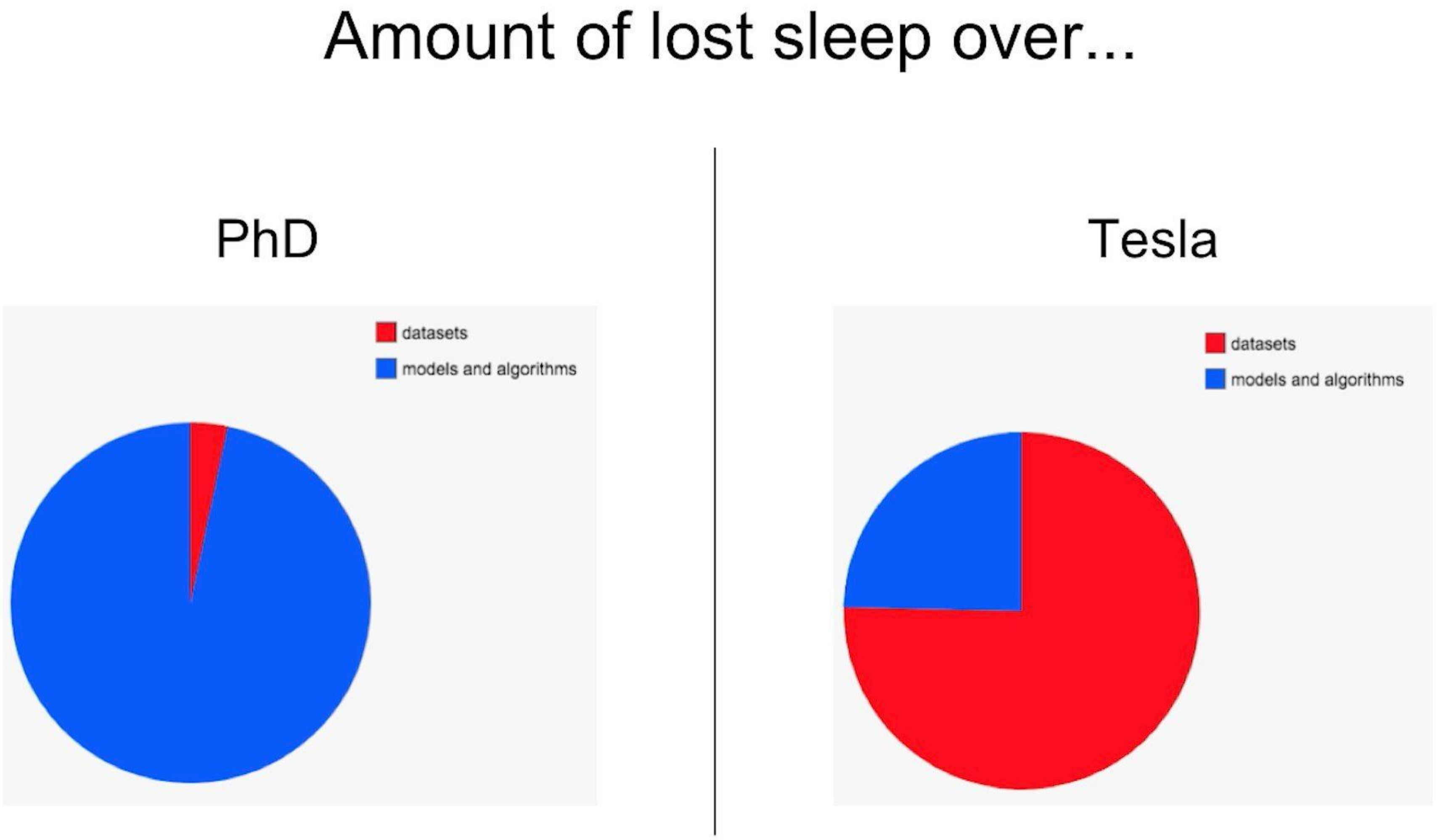
To better serve its customers and maintain its more than 13,000 commercial aircraft engines around the world, Rolls-Royce applied the predictive analytics capabilities of Azure IoT Suite to access data that helped them reduce fuel consumption, minimize maintenance costs, and improve the customer experience.

Watch the video ▷

Read the full case study >

https://www.microsoft.com/en-us/internet-of-things/customer-stories#manufacturing&rollsroyce

Predictive Maintenance | It's a Data Problem



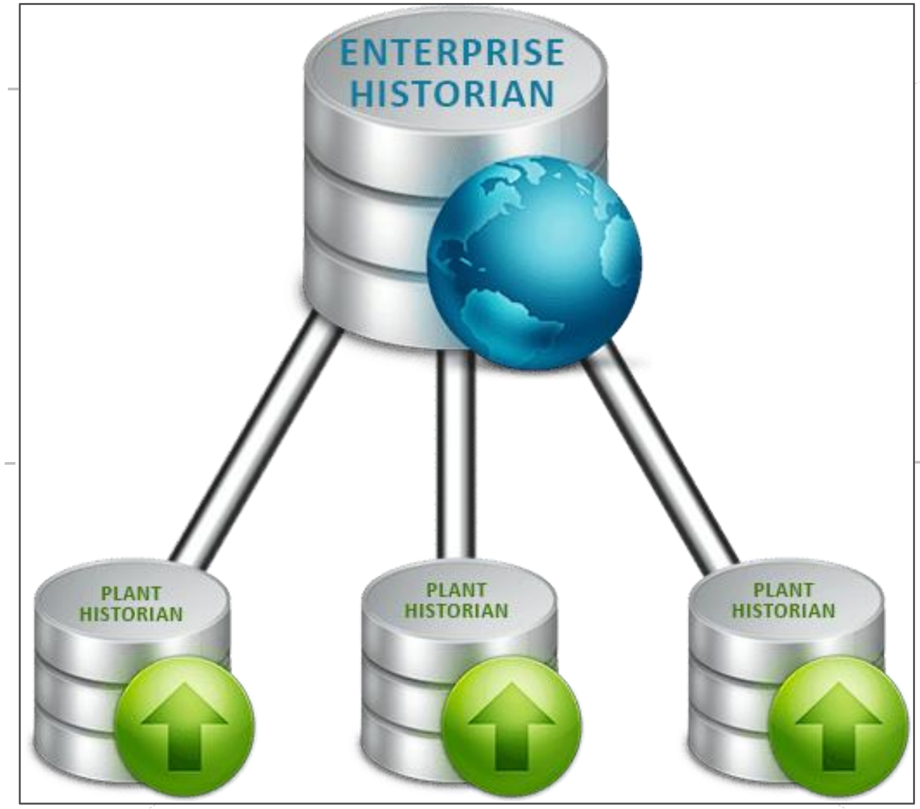
https://www.figure-eight.com/wp-content/uploads/2018/06/TRAIN_AI_2018_Andrej_Karpathy_Tesla.pdf

Predictive Maintenance | Data Sources

FAILURE HISTORY
The failure history of a machine or component within the machine

OPERATOR ATTRIBUTES
The attributes of the operator who uses the machine, e.g. driver

OPERATING CONDITIONS
Environmental features, e.g. location, outside temperature, etc



MAINTENANCE HISTORY
The repair history of a machine, e.g. components replaced, maintenance activities performed.

MACHINE CONDITIONS
The operation conditions of a machine, e.g. data collected from sensors

MACHINE FEATURES
The features of machine or components, e.g. model, age, technical specifications

Predictive Maintenance | The Five Rules

The better the raw materials, the better the product.

Question is sharp
E.g. Predict whether component X will fail in the next Y days

Data measures what you care about
E.g. Identifiers at the level you are predicting

Data is accurate
E.g. Failures are really failures, human labels on root causes

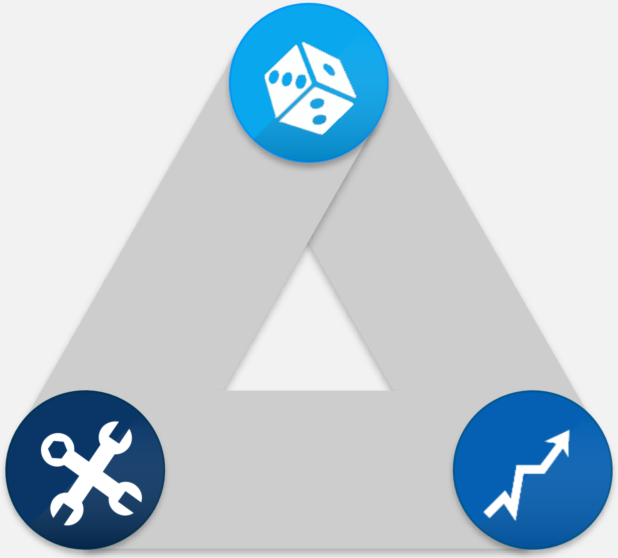
Data is connected
E.g. Machine information linkable to usage information

10010
01010

A lot of data
E.g. Will be difficult to predict failure accurately with few examples

Predictive Maintenance | A Good Question

What is the probability that an equipment will fail in the next T time periods?



What is the likely cause of a failure?

What is the remaining useful life (RUL) of an equipment?

Predictive Maintenance | A Pragmatic Approach

1

Remote Monitoring

Near real-time monitoring
of asset performance
using man-made alert rules

2

Anomaly Detection

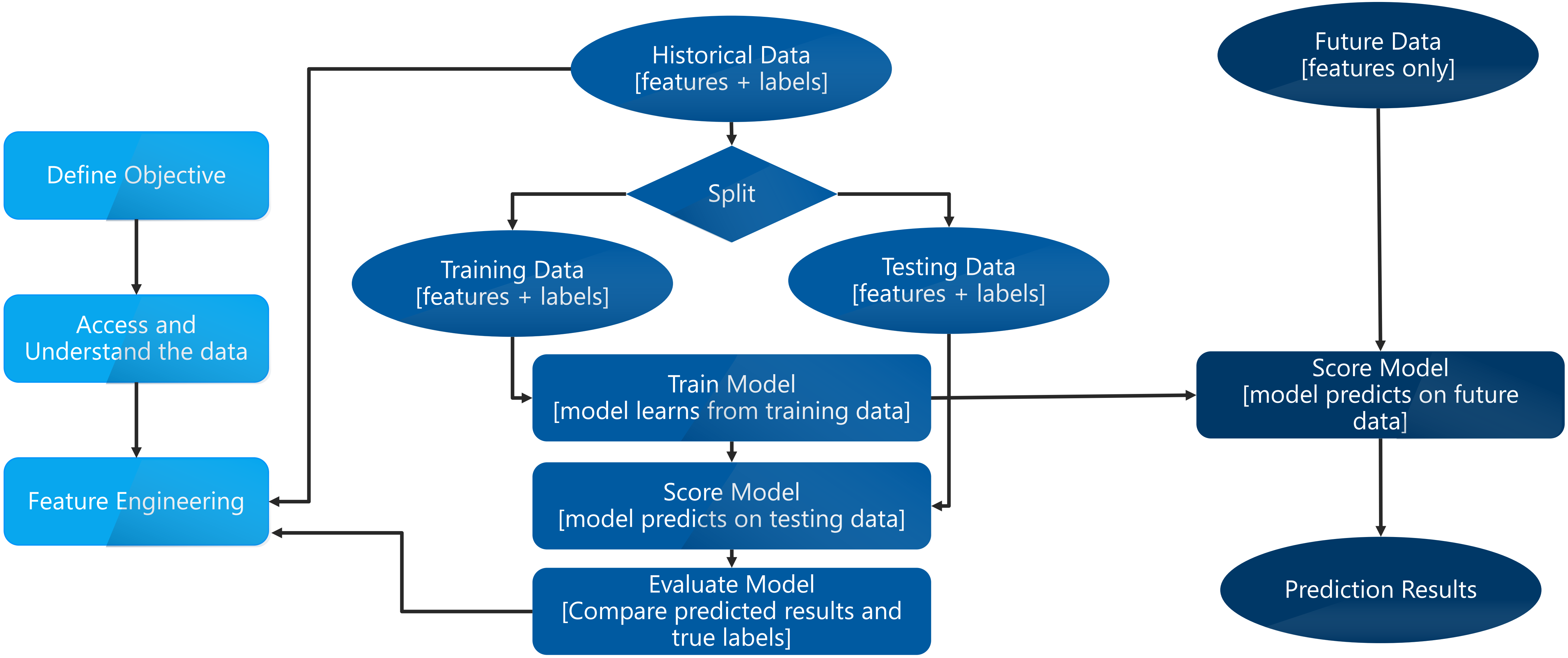
Unsupervised learning
used to detect
unusual operation regimes

3

Failure Prediction

Supervised learning
used to predict failures

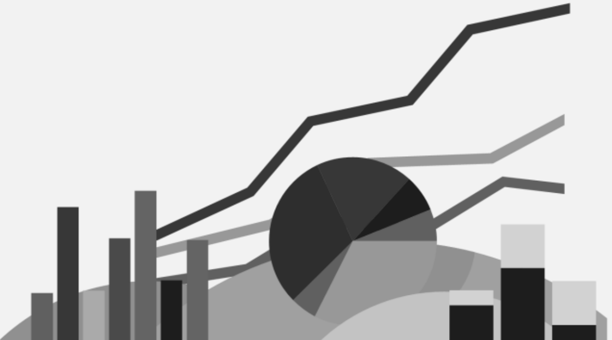
Predictive Maintenance | Process Flow



Predictive Maintenance | Feature Engineering

- **Feature Engineering** is the process of using domain knowledge to create features that provide additional predictive power to the learning algorithm

- We attempt to conceptually describe and abstract a machine’s health condition at a given time using historical data that was collected up to that point in time

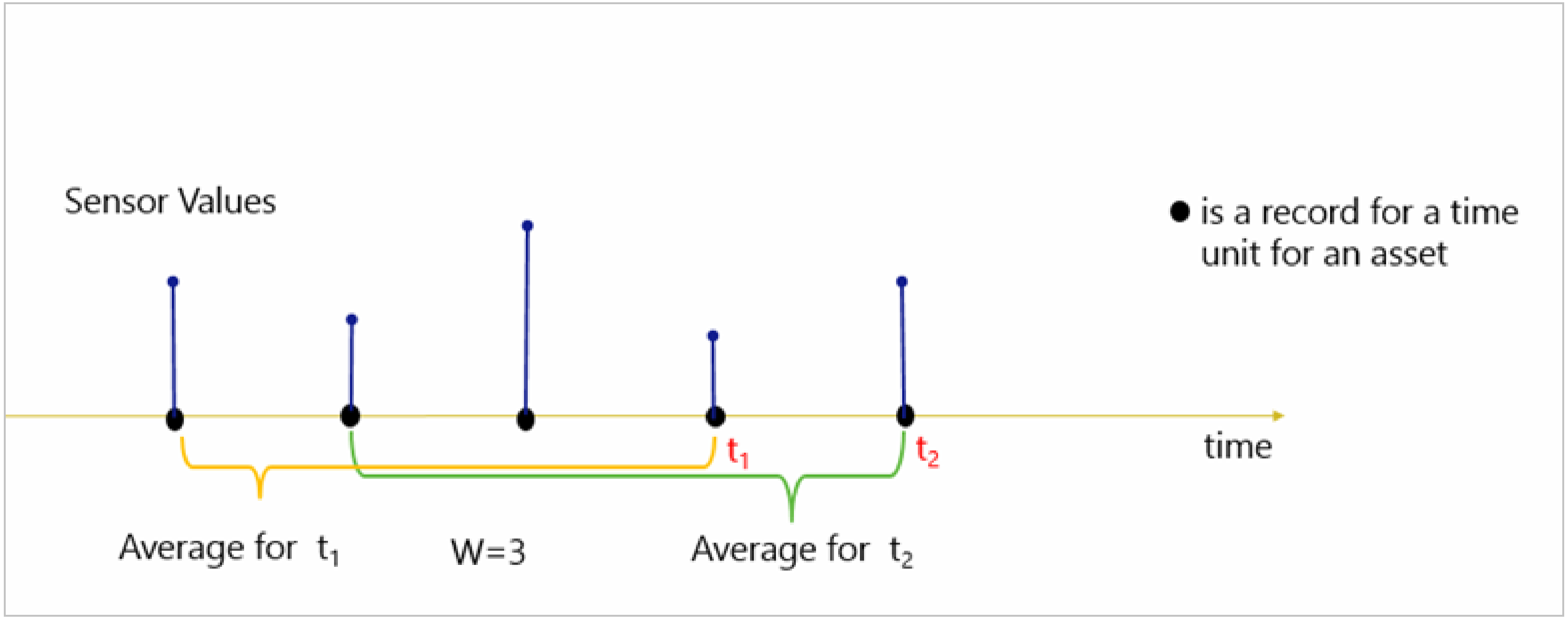


Potential approaches for Feature Engineering

Change from initial value	Velocity of change	Frequency count over a predefined threshold

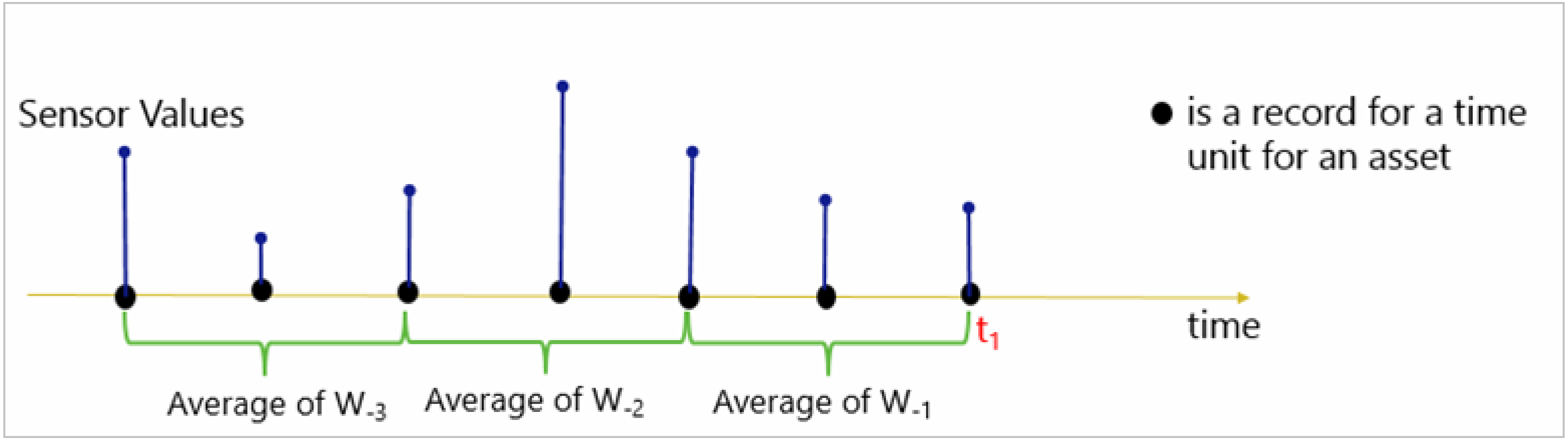
Predictive Maintenance | Feature Engineering

Telemetry – Rolling Aggregates



Predictive Maintenance | Feature Engineering

Telemetry – Tumbling Aggregates



Predictive Maintenance | Feature Engineering

Telemetry

datetime	machine ID	volt	pressure	vibration
2015-01-01 06:00:00	1	176.2179	113.0779	45.08769
2015-01-01 07:00:00	1	162.8792	95.46053	43.41397
2015-01-01 08:00:00	1	170.9899	75.2379	34.17885
2015-01-01 09:00:00	1	162.4628	109.2486	41.12214
2015-01-01 10:00:00	1	157.61	111.8866	25.99051
2015-01-01 11:00:00	1	172.5048	95.92704	35.65502

Rolling Aggregates (Mean)

datetime	machine ID	voltmean_24hrs	pressuremean_24hrs	vibrationmean_24hrs
2015-01-02 05:00:00	1	169.7338	96.79711	40.38516
2015-01-02 08:00:00	1	170.5257	97.66725	39.78667
2015-01-02 11:00:00	1	170.0497	96.90616	40.01651
2015-01-02 14:00:00	1	170.342	96.22952	39.92196
2015-01-02 17:00:00	1	170.0606	96.35744	39.99047
2015-01-02 20:00:00	1	169.3693	98.04201	39.53167

Predictive Maintenance | Feature Engineering

Telemetry

datetime	machine ID	volt	pressure	vibration
2015-01-01 06:00:00	1	176.2179	113.0779	45.08769
2015-01-01 07:00:00	1	162.8792	95.46053	43.41397
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2015-01-01 10:00:00	1	157.61	111.8866	25.99051
2015-01-01 11:00:00	1	172.5048	95.92704	35.65502

Rolling Aggregates (Standard Deviation)

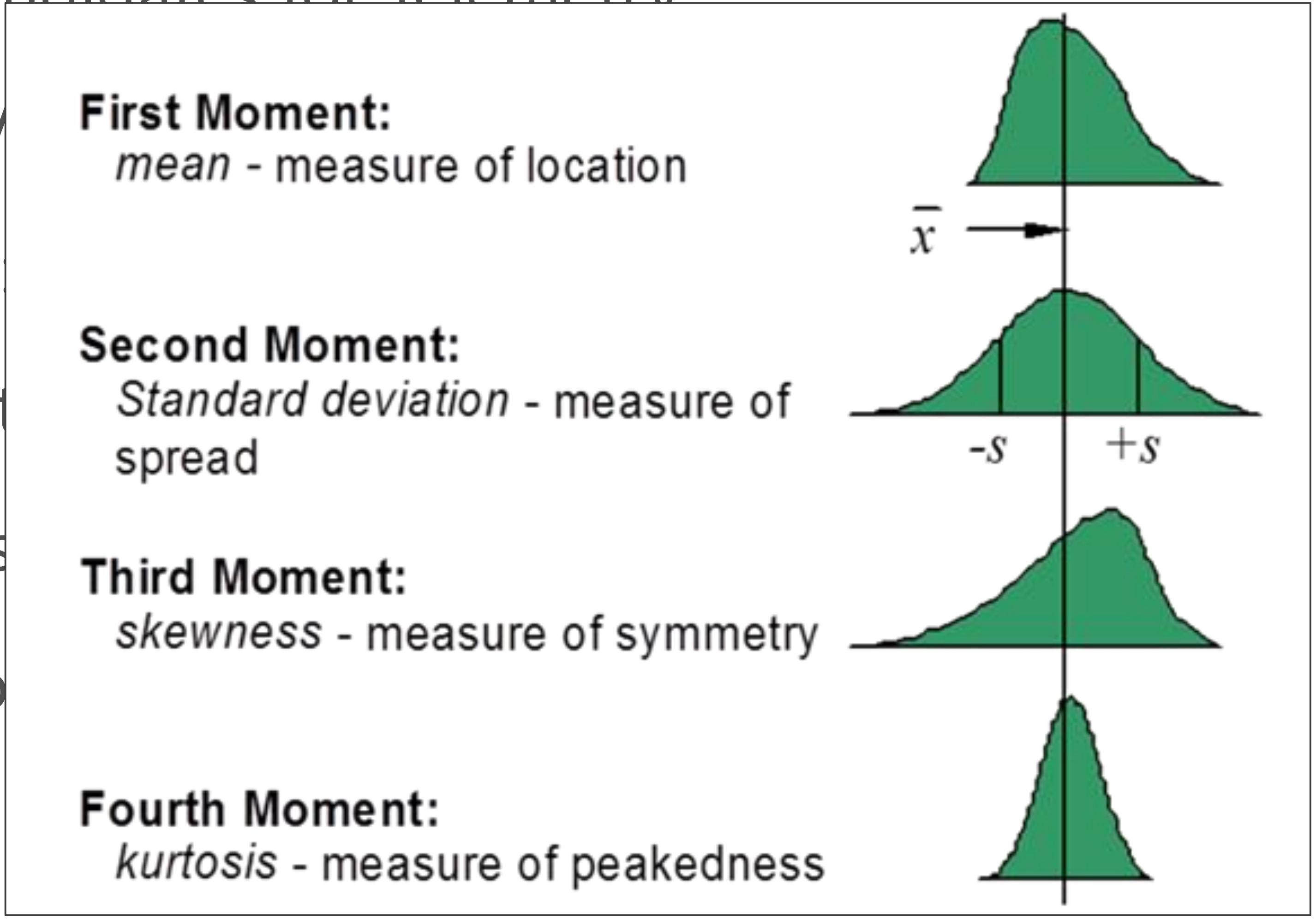
datetime	machine ID	voltsd_24hrs	pressuresd_24hrs	vibrationsd_24hrs
2015-01-02 05:00:00	1	11.23312	10.07988	5.853209
2015-01-02 08:00:00	1	12.59195	9.406795	6.098173
2015-01-02 11:00:00	1	13.27734	9.071472	5.481724
2015-01-02 14:00:00	1	13.81716	8.256794	5.862312
2015-01-02 17:00:00	1	14.79287	8.669605	5.907157
2015-01-02 20:00:00	1	15.67479	10.60795	6.205887

Predictive Maintenance | Feature Engineering

Some Synthetic Feature Candidates for Telemetry

- **Basic Statistics**: Mean, V
- **Higher-Order Statistics**
- **Impulsive Metrics**: Crest
- **Others**: Count of outliers

  Count of observations o



Predictive Maintenance | Feature Engineering

Maintenance Data

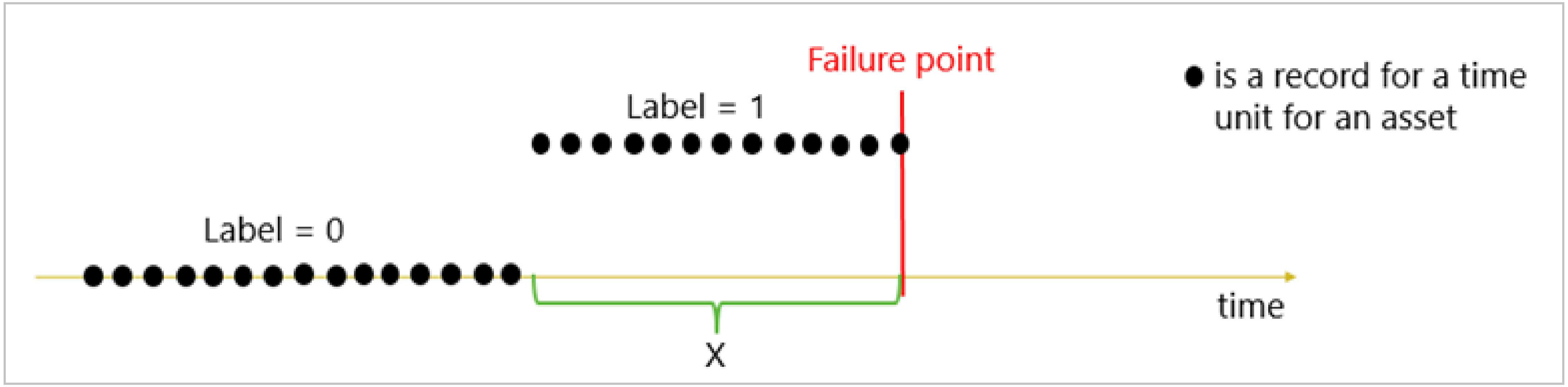
datetime	machineID	comp1	comp2	comp3
2014-06-01 06:00:00	1	0	1	0
2014-07-16 06:00:00	1	0	0	0
2014-07-31 06:00:00	1	0	0	1
2014-12-13 06:00:00	1	1	0	0
2015-01-05 06:00:00	1	0	0	0
2015-01-05 06:00:00	1	1	0	0

Time Since Last Service

datetime	machineID	sincelastcomp1	sincelastcomp2	sincelastcomp3
2015-01-02 05:00:00	1	19.95833	214.9583	154.9583
2015-01-02 08:00:00	1	20.08333	215.0833	155.0833
2015-01-02 11:00:00	1	20.20833	215.2083	155.2083
2015-01-02 14:00:00	1	20.33333	215.3333	155.3333
2015-01-02 17:00:00	1	20.45833	215.4583	155.4583
2015-01-02 20:00:00	1	20.58333	215.5833	155.5833

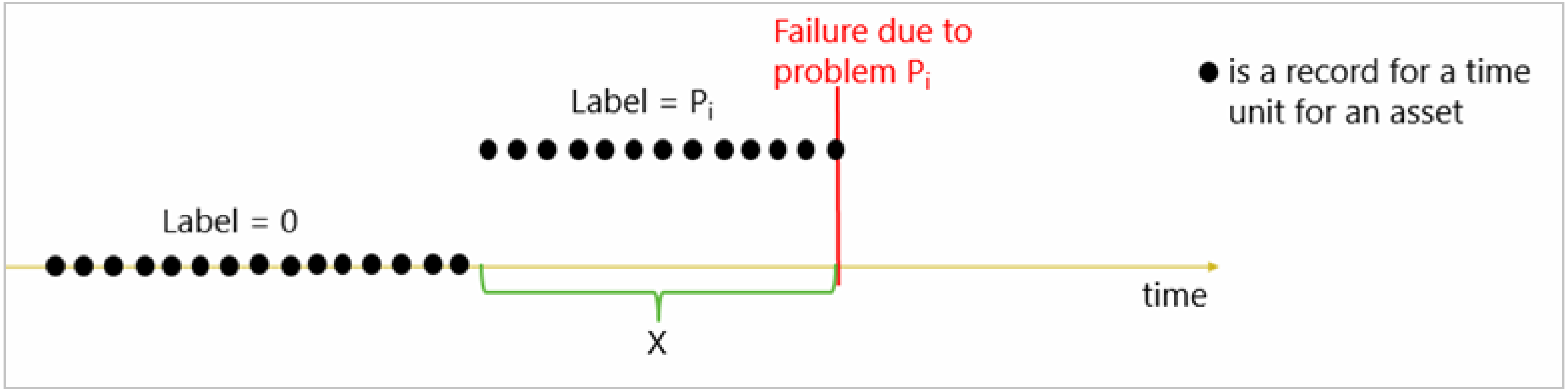
Predictive Maintenance | Label Construction

"Will the component fail within X time units?" – Binary Classification



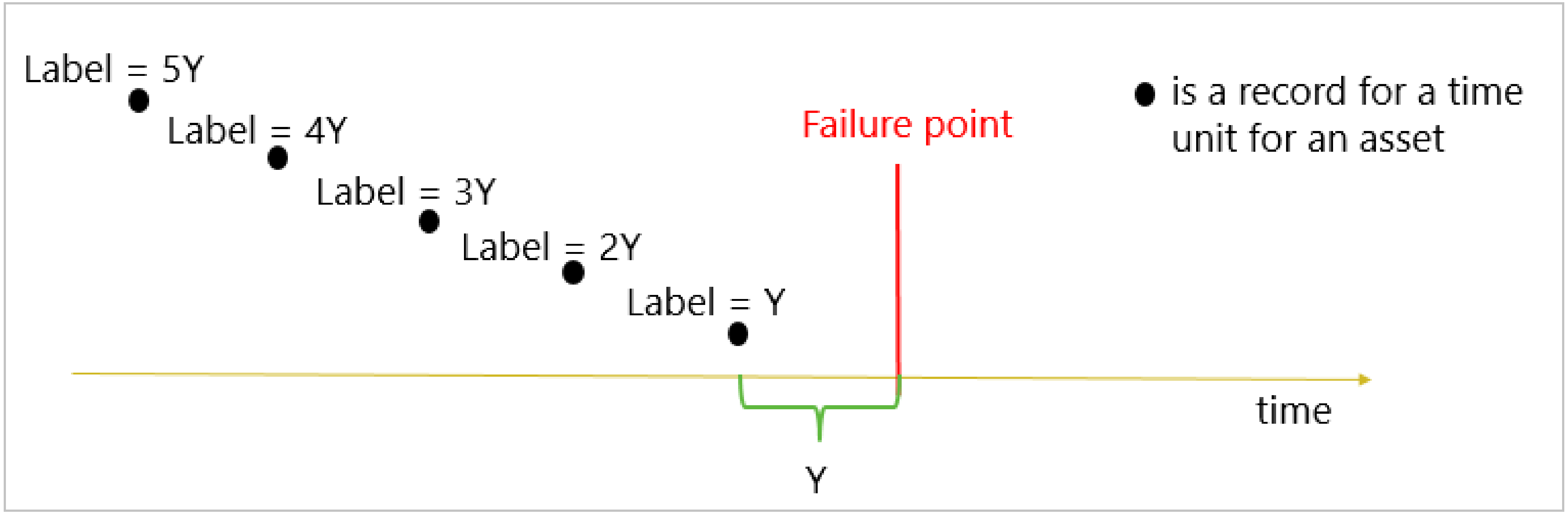
Predictive Maintenance | Label Construction

"Will the component fail within X time units
due to problem P(i)?" – Multiclass Classification



Predictive Maintenance | Label Construction

"What is the Remaining Useful Life (RUL) of component?" - Regression

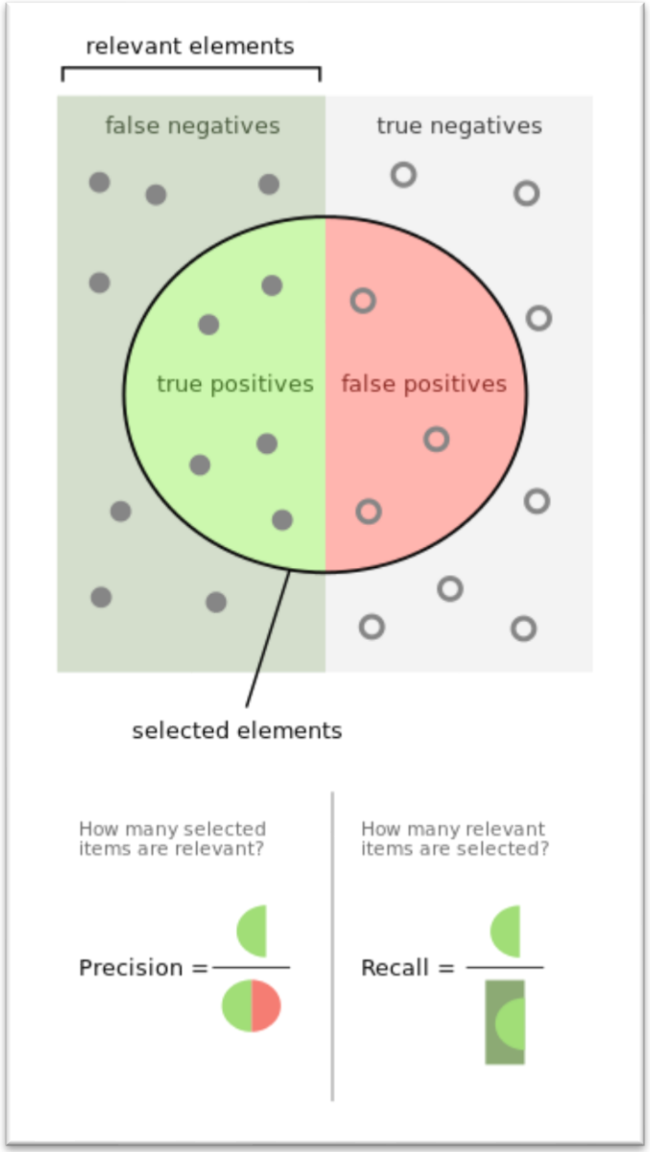


Predictive Maintenance | Performance Criteria

Question: Will Component X fail during the next Y days?

Precision = What percentage of predicted failures were really failures?

Recall = What percentage of actual failures were predicted by the model?



Predictive Maintenance | Performance Criteria

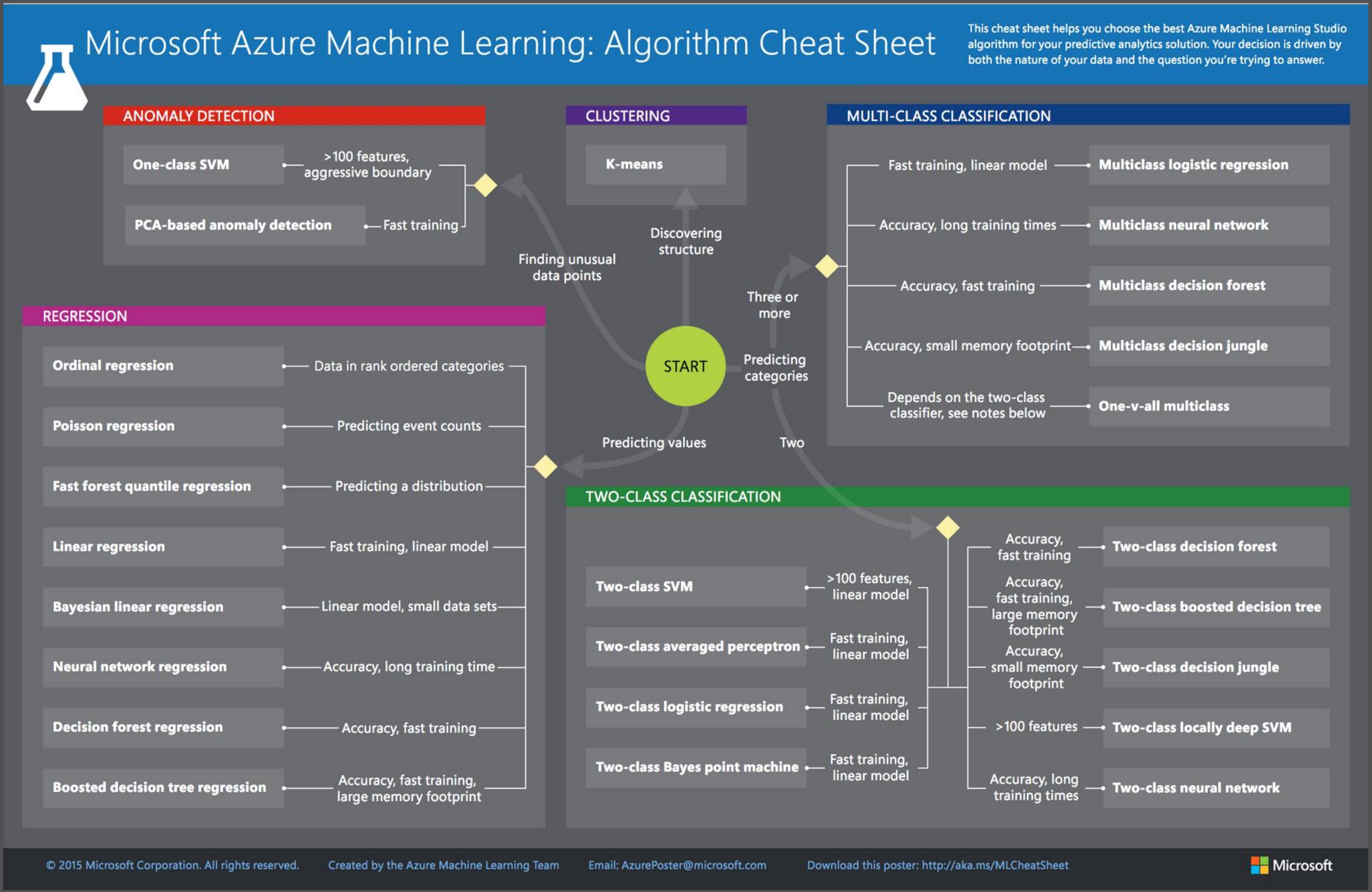
Example

In one year the system experienced 8 failures.
The model correctly predicted 4 of them.
The model also incorrectly predicted 1 additional failure.

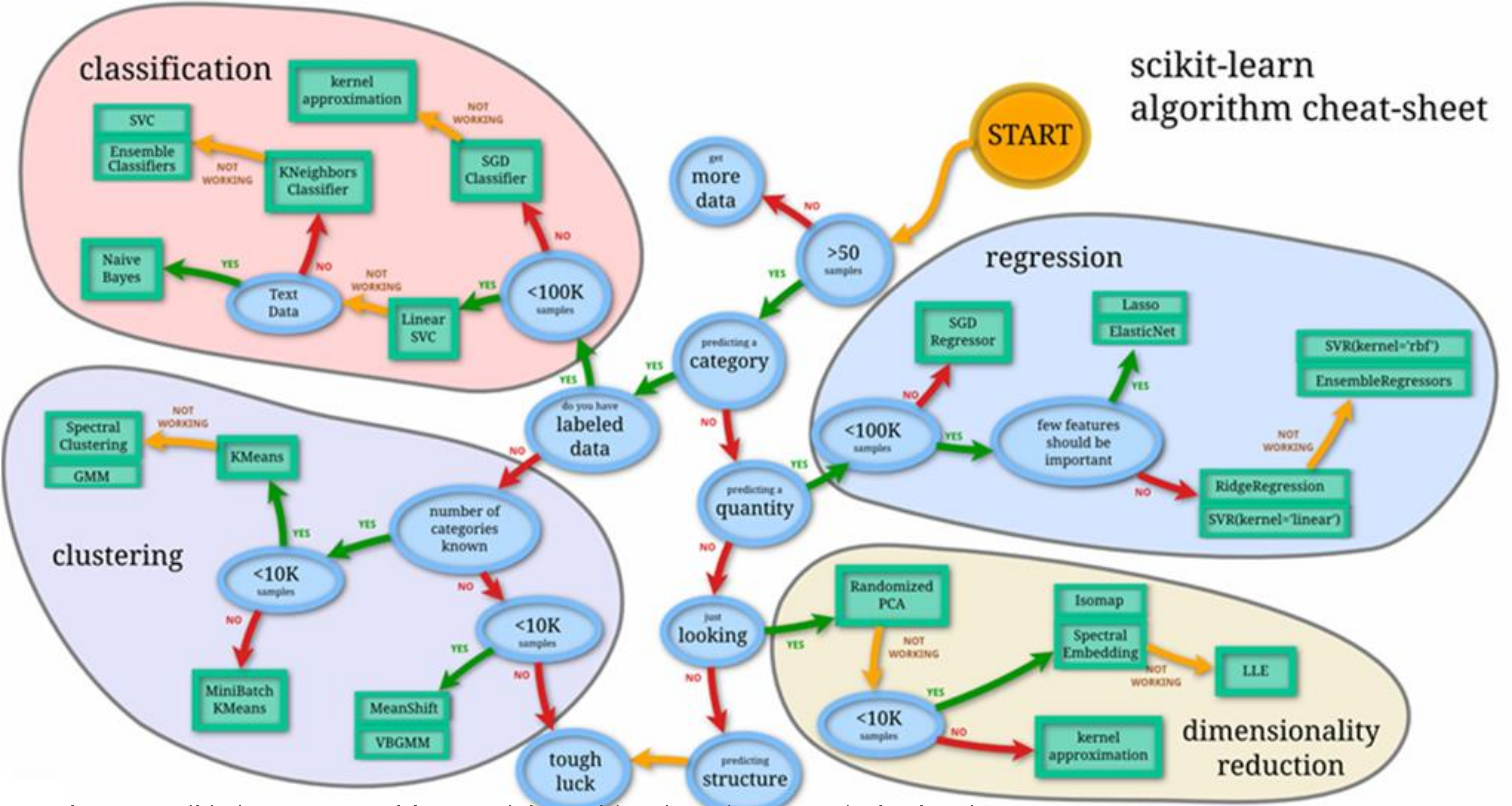
Precision = 4 / (4 + 1) = 80%

Recall = 4 / 8 = 50%

Calculate monetary value of incorrect predictions
and optimize model to minimize that



http://aka.ms/mlcheatsheet



https://scikit-learn.org/stable/tutorial/machine_learning_map/index.html

Predictive Maintenance | Learning Algorithms

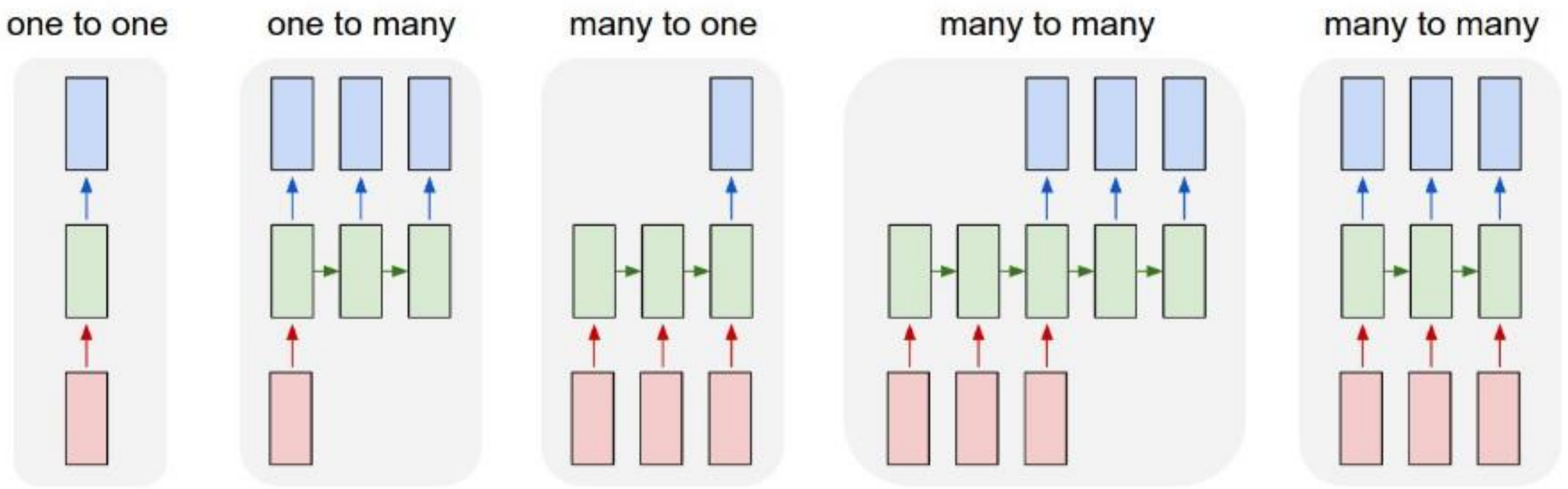
- **Classification**: Random Forest, Gradient Boosted Trees, SVM
- **Regression**: Random Forest Regression, SVR
- **Anomaly Detection**: One-Class SVM, PCA-based Anomaly Detection

Predictive Maintenance | Learning Algorithms

Wait, what about Deep Learning?

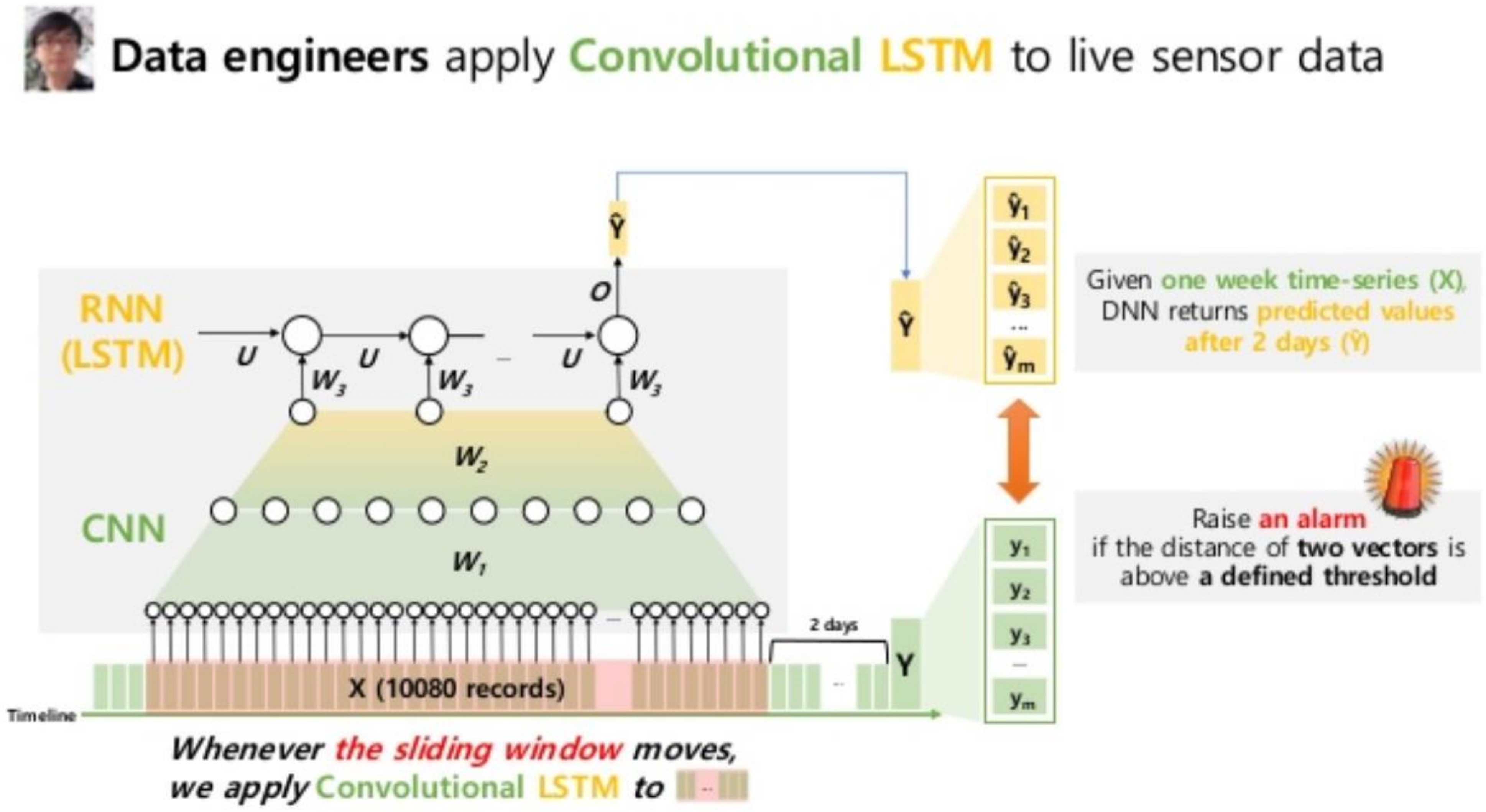
Predictive Maintenance | Learning Algorithms

Recurrent Neural Networks (RNN) can learn from sequences



http://karpathy.github.io/2015/05/21/rnn-effectiveness/

Predictive Maintenance | Learning Algorithms



https://www.slideshare.net/FlinkForward/flink-forward-berlin-2017-dongwon-kim-predictive-maintenance-with-apache-flink

Predictive Maintenance | A How-to Guide

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COLLECTION

Predictive Maintenance Modelling Guide

FU Fidan Boylu Uz • March 25, 2016

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Summary

This collection provides the steps to implement a predictive maintenance model through feature engineering, label creation, training and evaluation. Created by a Microsoft Employee.

Description

A major problem faced by businesses in asset-heavy industries such as manufacturing is the significant costs associated with delays in the production process due to mechanical problems. Most of these businesses are interested in predicting these problems in advance so that they can proactively fix these issues before they occur which will reduce the costly impact caused by downtime.

This collection is a supplement to the Playbook for Predictive Maintenance which covers the common use

https://gallery.azure.ai/Collection/Predictive-Maintenance-Modelling-Guide-1

Predictive Maintenance | Learning

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Build a Predictive Maintenance Solution using Decision Trees and Random Forests

8 MODULES | 29 HR | BEGINNER > INTERMEDIATE

This intermediate level AI Learning Path provides instructions on how to build a predictive maintenance solution using classic ML algorithms like Decision Trees and Random forest.

Modules

Basic Statistics
1 STEP | 2 HR | BEGINNER
Save Module

Hypothesis Testing and Handling Data
1 STEP | 5 HR | BEGINNER
Save Module

Data and Feature Management
1 STEP | 2 HR | INTERMEDIATE
Save Module

Machine Learning basics
1 STEP | 4 HR | INTERMEDIATE
Save Module

Introduction to PySpark
1 STEP | 4 HR | INTERMEDIATE
Save Module

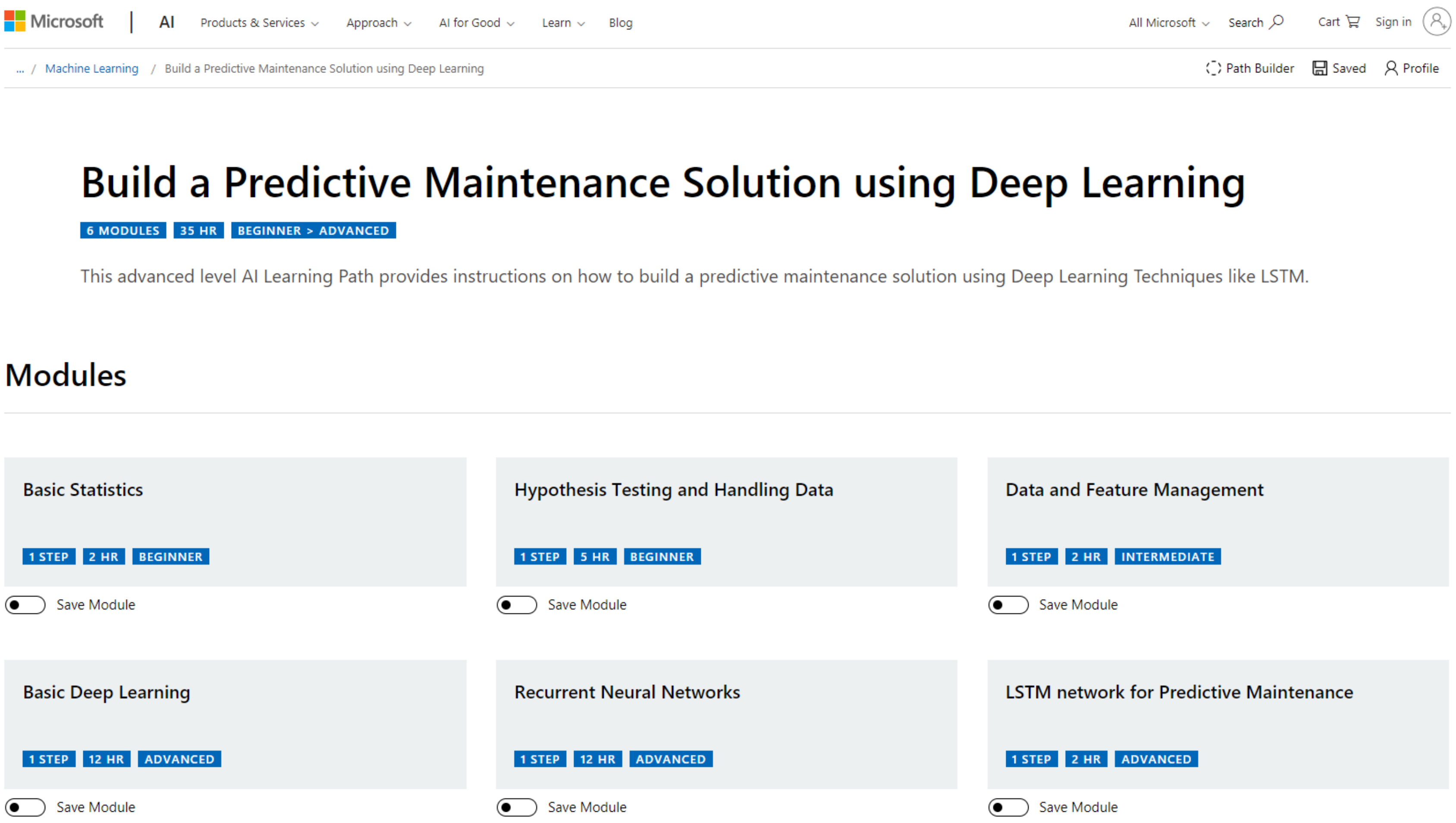
Basic Decision Trees
1 STEP | 1 HR | INTERMEDIATE
Save Module

Implementing Decision Trees
1 STEP | 8 HR 30 MIN | INTERMEDIATE

Building and Deploying a Decision Tree/Random Forest model using PySpark
1 STEP | 2 HR | INTERMEDIATE

https://aischool.microsoft.com/en-us/machine-learning/learning-paths/1H5vH5wAYcAy88CoQWQcA8

Predictive Maintenance | Learning



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Thank You