

### **User Group**

# Machine Learning and Al for Industrial Applications

April 14, 2021

#### **Our Guest Panelists**

#### Niraj Kachadia

Rockwell Automation Architecture & Software Business Lead

#### Mike Masterson Wayne Welk Brian Mikeska

The Reynolds Company Automation Specialists

### 2021 Online Events Register to receive a calendar invite



#### **TechTalks**

 WIN911 Alarm Notifications for Industry and IIoT

Wed, Apr 21, 2021 @ 10am

CIP Safety over Ethernet/IP

Wed, May 12, 2021 @ 10am

PowerFlex Drives Integration with Fisher ROC

Wed, May 26, 2021 @ 10am

#### **User Groups**

Machine Safety vs Process Safety - SIL vs PLe
 Wed, May 19, 2021 @ 10am

### 2021 PTC LiveWorx Online





**Episode One: Work Methods Changing the Workplace** 

Thurs, March 25 – Now on Demand

**Episode Two: The New Frontier of Product Development** 

Thurs, Apr 22, 2021 @ 9 am CST

**Episode Three: Digital Transforms Physical** 

Thurs, June 24, 2021 @ 9 am CST

**PTC Global Partner Summit** 

Tues, June 15, 2021

#### ANALYTICS

The *discovery*, *interpretation*, and *communication* of meaningful patterns in data. Analytics relies on the application of statistics, computer programming and operations research to quantify performance.

"I want someone delivering Analytics who was in a plant last week, last month and last year and not someone who was making video games recently."

— A Rockwell Automation Customer

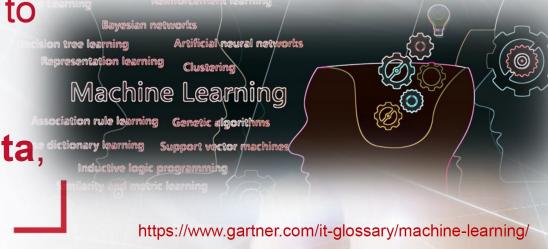




### Machine Learning 101

Machine learning is a field of computer science that uses statistical techniques to give computer systems the ability to "learn" (i.e., progressively improve performance on a specific task) with data, without being explicitly programmed.

https://en.wikipedia.org/wiki/Machine\_learning



Advanced machine learning algorithms are composed of many technologies (such as deep learning, neural networks ... unsupervised and supervised learning ... guided by lessons from existing information [data].



#### Similarities...

#### Similarities in Neural Networks and State-Based Control

#### State-Based Representation...

The most general state-space representation of a linear system with p inputs, q outputs and n state variables is written in the following form: [6]

$$\dot{\mathbf{x}}(t) = A(t)\mathbf{x}(t) + B(t)\mathbf{u}(t)$$

$$\mathbf{y}(t) = C(t)\mathbf{x}(t) + D(t)\mathbf{u}(t)$$

#### where:

 $\mathbf{x}(\cdot)$  is called the "state vector",  $\mathbf{x}(t) \in \mathbb{R}^n$ ;

 $\mathbf{y}(\cdot)$  is called the "output vector",  $\mathbf{y}(t) \in \mathbb{R}^q$ ;

 $\mathbf{u}(\cdot)$  is called the "input (or control) vector",  $\mathbf{u}(t) \in \mathbb{R}^p$ ;

 $A(\cdot)$  is the "state (or system) matrix",  $\dim[A(\cdot)] = n \times n$ ,

 $B(\cdot)$  is the "input matrix",  $\dim[B(\cdot)] = n \times p$ ,

 $C(\cdot)$  is the "output matrix",  $\dim[C(\cdot)] = q \times n$ ,

 $D(\cdot)$  is the "feedthrough (or feedforward) matrix" (in cases where the system model does not have a direct feedthrough,  $D(\cdot)$  is the zero matrix),  $\dim[D(\cdot)] = q \times p$ ,

$$\dot{\mathbf{x}}(t) := \frac{\mathrm{d}}{\mathrm{d}\,t}\mathbf{x}(t).$$

# Block Diagram... B A \* wikipedia

#### **Neural Networks**

Advanced ML / Al Technique

#### Neural Network Concept (Similar To) Control Concept

(NN) Back Propagation

→ Feedback Loop, A(t)X(t)

(NN) Gates "Memory"/"State"

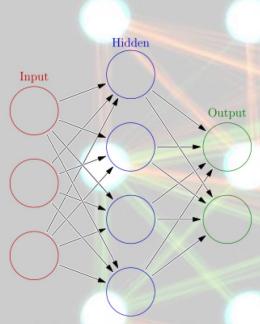
→ Feedforward Loop, D(t)U(t)

Think... ML / Al is a Black Box Model... Leveraging Advanced Statistics and Mathematics



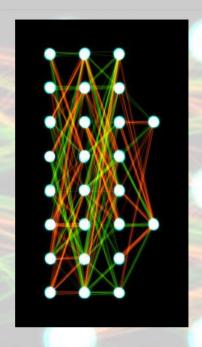
#### Differences...

Differences in Neural Networks and State-Based Control



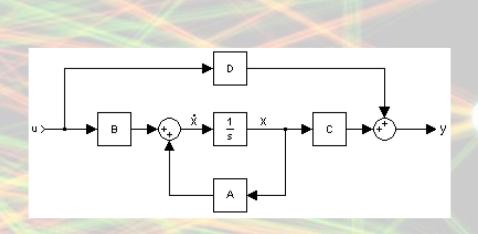
1-Layer "Shallow" Neural Network

- 3 Inputs
- 1x4 Hidden Nodes
- 2 Outputs



Multi-Layer (2+) "Deep" Neural Network

- 8 Inputs
- 2x8 Hidden Nodes
- 2 Outputs



Conceptualize "Control Loop" @ Nodes in the Neural Network

Note – "Glossing" over some / a lot of the details for simplicity of concepts

\* wikipedia

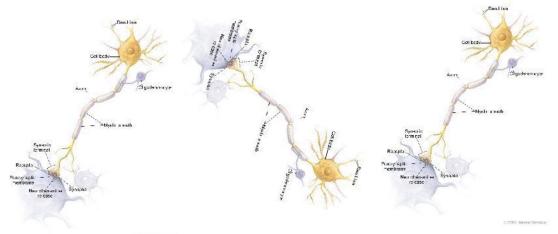
Think... Control and ML / Al Both Leverage Statistics and Mathematics (and Inputs / Outputs)



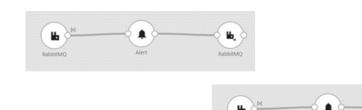
#### An aside... Related to Neural Networks... HI / Al...

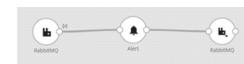
Synapses / Neurons, and Queues / Big Data Pipelines...

#### **Human Intelligence (HI)**



#### **Artificial Intelligence (AI)**





#### **Neurons**

- Basic Working
  Unit of the
  Nervous System
  100B Neurons in
- 100B Neurons in the Brain

#### Synapses

- "Connectors" between Neurons
- Nerve Impulses (Data) transfer between Neurons...

#### Nervous System / Brain (Similar To) Big Data Pipelines

Synapses

→ Queues

Neurons

→ Individual Big Data Pipeline

Brain

→ Massive Set of Big Data Pipelines

Note – "Glossing" over some / a lot of the details for simplicity of concepts

\* wikipedia

Think... HI / AI – Human Intelligence / Artificial Intelligence



### Another aside... Related to Learning... HL / AL...

Learning...

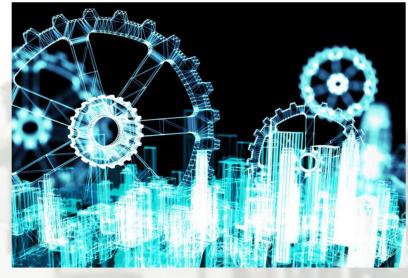
#### **Human Learning (HL)**



Think... HL / AL – Human Learning / Artificial Learning (aka Machine Learning, ML)



#### **Artificial Learning (AL)**



"ET Moment"...
Augmented Learning and Augmented Intelligence...



### **Analytics Spectrum**

**BASIC ANALYTICS** 

#### **ADVANCED ANALYTICS**

AUTONOMOUS FACTORIES

#### ACTION

Human Intelligence

Artificial Intelligence

**DESCRIPTIVE** 

Historical data

WHAT HAPPENED?

Motor fault

**DIAGNOSTICS** 

Historical

WHY DID IT HAPPEN?

Motor fault – high current

**PREDICTIVE** 

**Future** 

WHAT IS ABOUT TO HAPPEN?

Motor will fault

PRESCRIPTIVE

Future action

WHAT CAN I DO TO AVOID IT?

Motor will fault, decrease load

Al Control

Action

WRITEBACK TO CONTROLLER

Load decreased









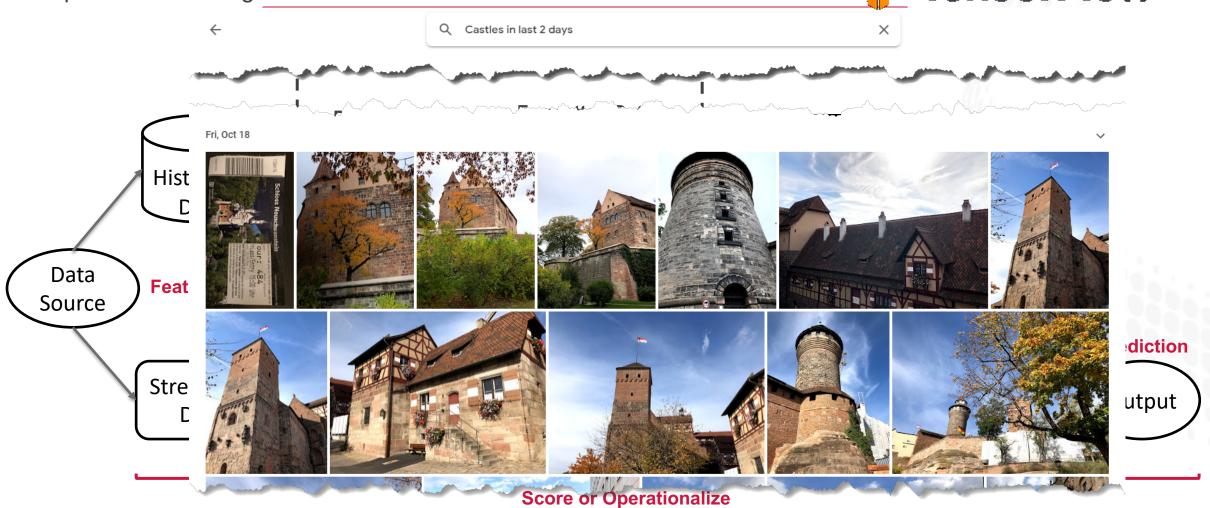




#### **Basic Machine Learning**

Supervised Learning Model Training



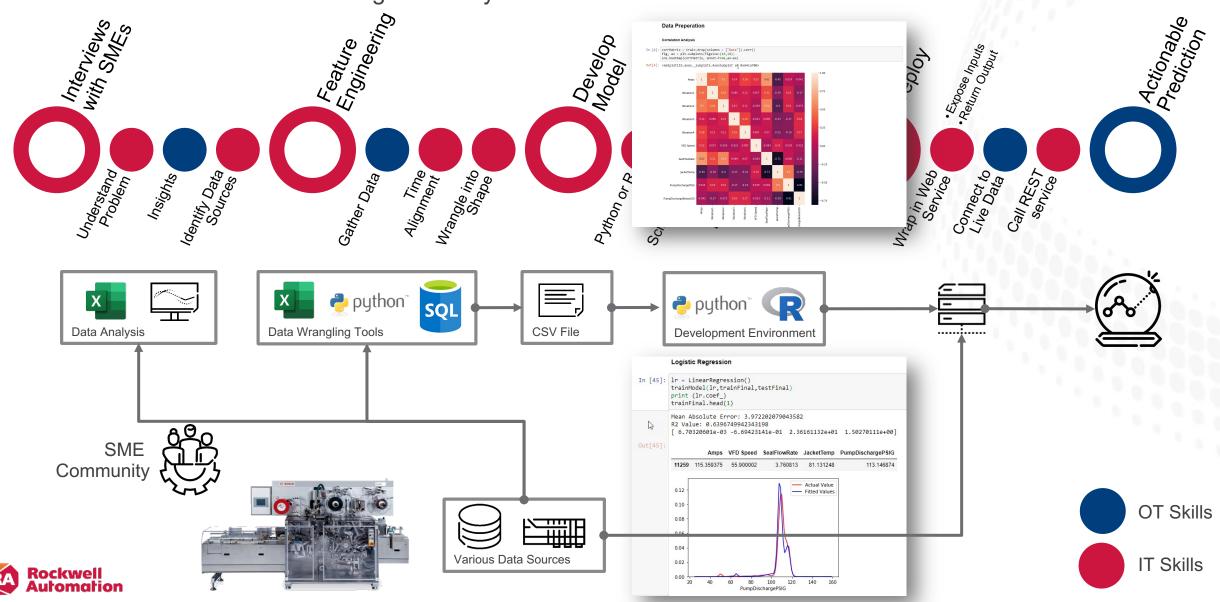




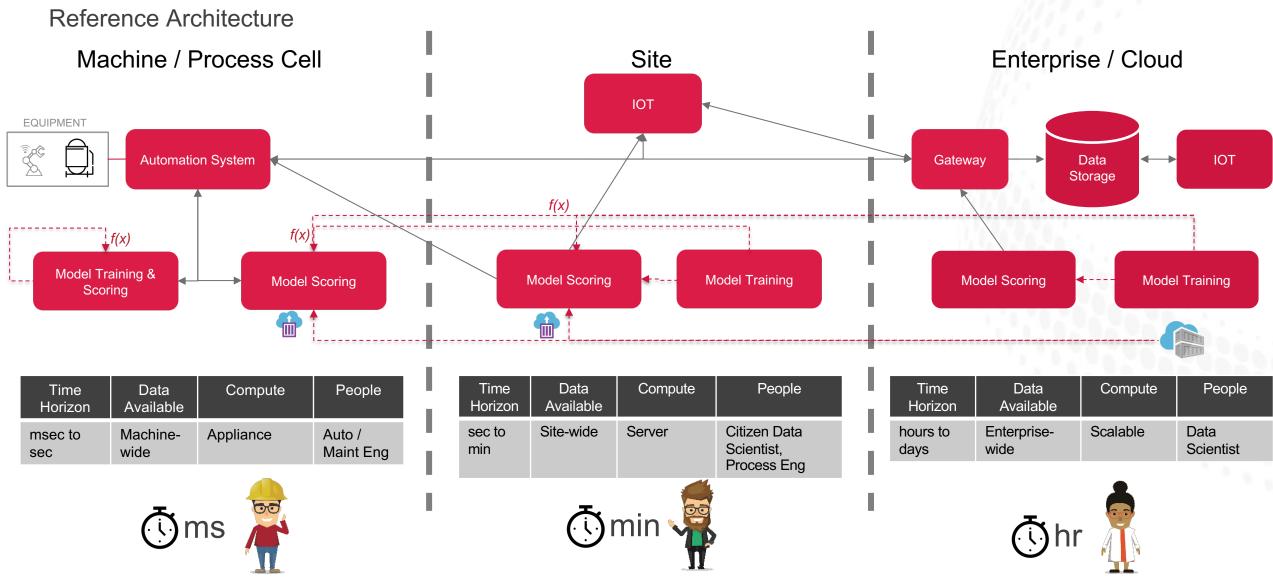
#### **Predictive Analytics Process** Clearly defined business Experiment with multiple models problem Choose the most optimal model Set success criteria Create a feedback loop Define clear data Put your models to work for you in science objectives production Data transforms need to be applied Understand data points and constraints Maximum value realized Formulate data analytics strategy Perform required transformation **Model Training Model Scoring** Map to Machine Define Business Data **Exploratory Data** Learning Modeling Evaluation Operationalize Problem Preparation **Analysis** Problem Perform statistical and visual analysis Break business problems to Discover and handle outliers/errors data science problems Shortlist predictive modeling techniques Identify Machine Learning Problem categories Understanding Data Preparation Deployment **DATA CRISP-DM**

#### Traditional approach to creating Predictions

How are Data Scientists achieving this today...



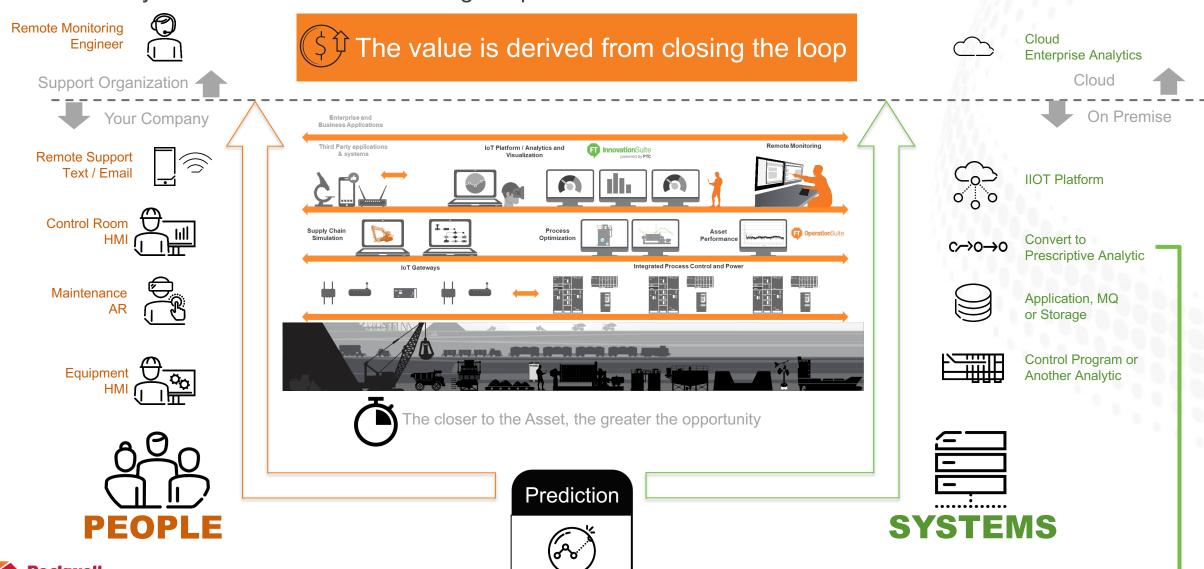
#### **Analytics & Machine Learning Deployment Strategies**





#### **Consumers of Analytics & ML Results**

User and Systems benefit from consuming the prediction



#### **Types of Machine Learning**

Use Cases vs Techniques

### PREDICTIVE MAINTENANCE

Reduced maintenance costs
Less unplanned downtime
Less production failures
Less process downtime
Reduced maintenance costs

#### **PREDICTIVE**

#### **KPIs**

Safety / Quality Less off-spec Less give-away

Reduced incidents

### **OPERATIONS**IMPROVEMENTS

More throughput

Less energy/product

Reduced energy spend

Reduced under-delivered utilities

#### BASIC ML SUPERVISED LEARNING

MODEL
PREDICTIVE CONTROL

### **ANOMALY**DETECTION



**Anomaly Detection** 

- System unusual behavior alert
  - Incorrect set-up
  - Wrong/bad feedstock
  - Equipment failure
- Know as soon as something is wrong!
- Provide causal indicators (why).

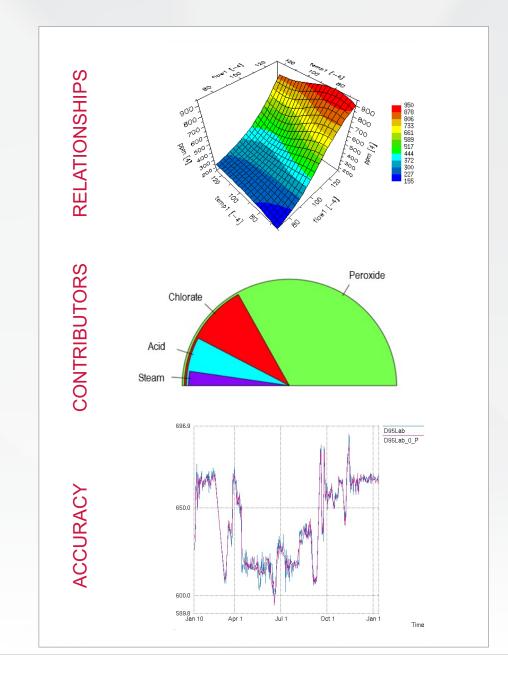




#### **Predictive KPI**

#### SOFT SENSOR® VIRTUAL ONLINE ANALYZERS

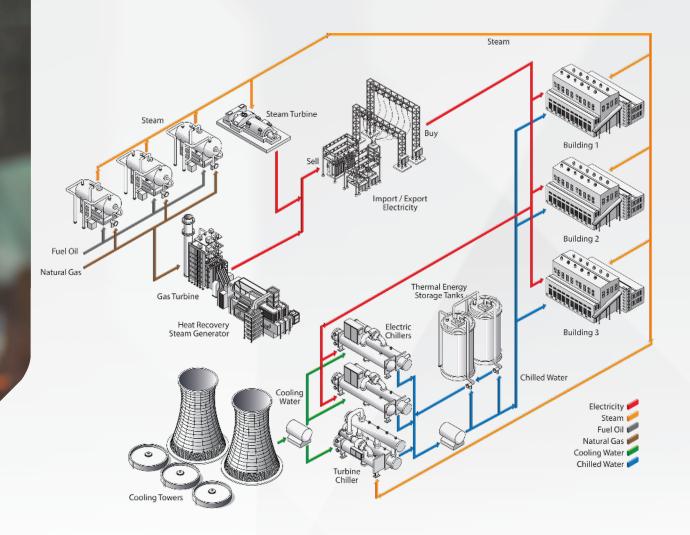
- Lab results in real-time.
- What will production be today?
- What causes poor performance?
- Know now. Reduce knowledge delays.
- Reduce expensive sampling.



#### **Energy Optimization**

DISPATCH CHILLERS, PUMPS, BOILERS, TURBINES AND COMPRESSORS INTELLIGENTLY AND ECONOMICALLY

- Reduce utility center energy costs
- Maximally use free/low-cost energy
- Operate equipment within limits
- Forecast future demand
  - Graphically layout equipment
  - Automatic model updates
  - Reconcile data for accurate results





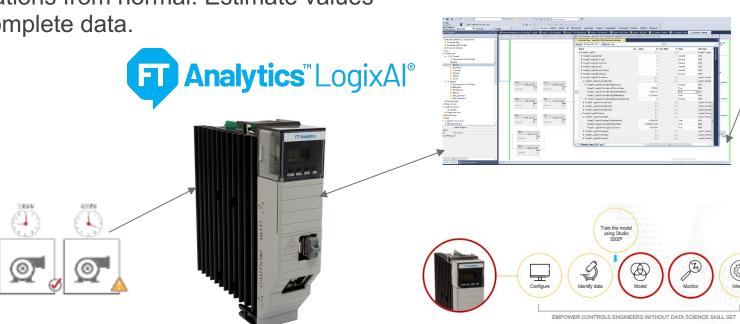
### Predictive Maintenance Solutions

#### Machine/Process Cell Predictive Analytics

I want automatic ML, as easy as possible.

I need something connected to my controller.

Automated Machine Learning Modeling for ControlLogix® Tags. Learn what's normal, find deviations from normal. Estimate values from incomplete data.







#### Edge Support High level data flow

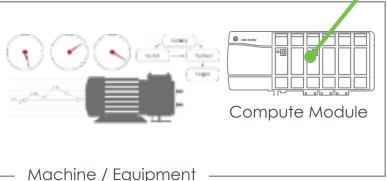


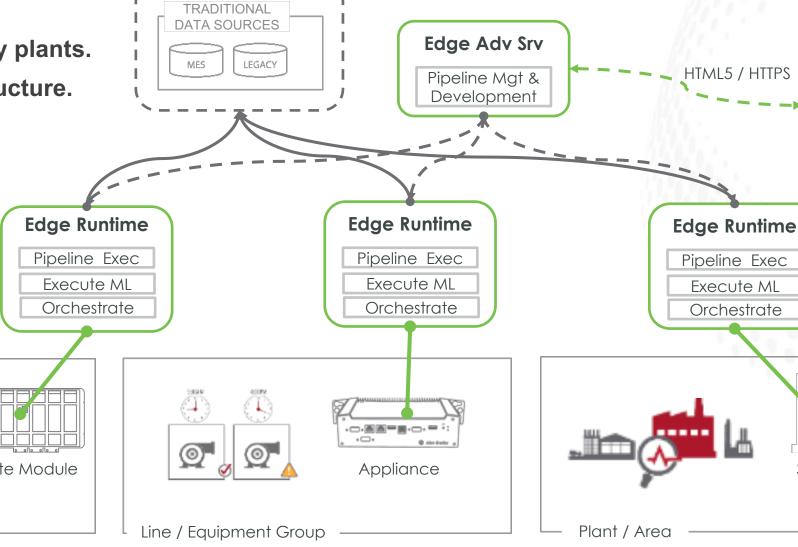
Desktop/Laptop

Server

I need ML support in my plants. Must be a local infrastructure.

- Construct model offline, externally.
- Deploy locally.
- Send results to your control system.







#### System/Site

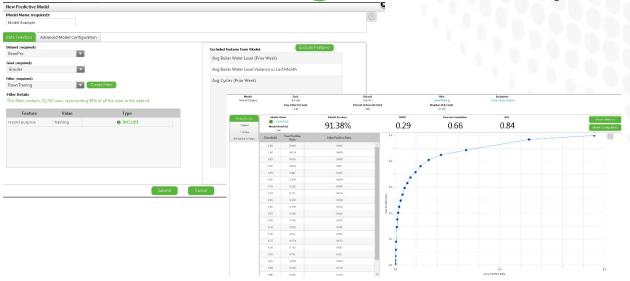
I need a simpler way to construct a broad variety of applications. I want to easily deploy & run on an Analytic platform.

- Data Science Citizen supported, open machine learning toolset.
- Supported model deployment in Edge, On-Prem or Cloud with FactoryTalk® Analytics™.
- AutoML toolset for machine learning.





thingworx analytics



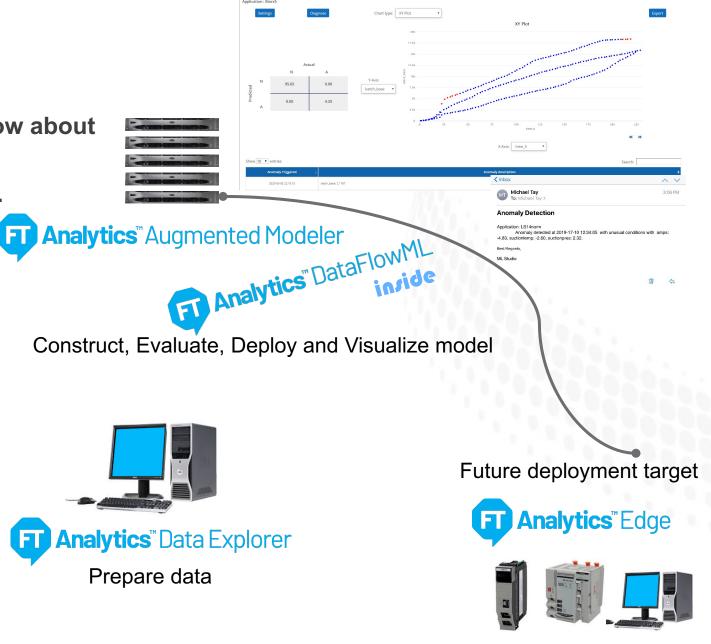


#### On Prem and Cloud

I want my engineers to leverage what we know about our equipment and data.

I have concerns that ML will be difficult here.

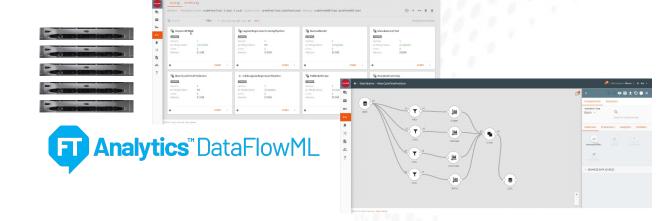
- Visual interactive support.
- Prepare data; data wrangling (explore, clean, enrich, filter).
- Visualize and evaluate model representation.
- Visualize and interact with your online model.
- ML Solution augmentation for ease-of-use.
- Send email alerts or use fit-for-purpose dashboards.





#### On Prem and Cloud

We need a powerful, enterprise platform for ML. We want to leverage data science tools we know.

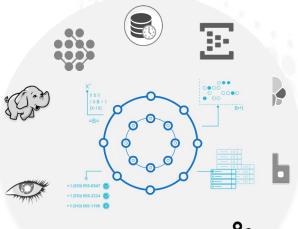


- Open connectivity
- Data preparation, transformation and processing
- Open, extensible platform with machine learning tool integration
- Model building, training and evaluation
- Extremely scalable up to Big Data















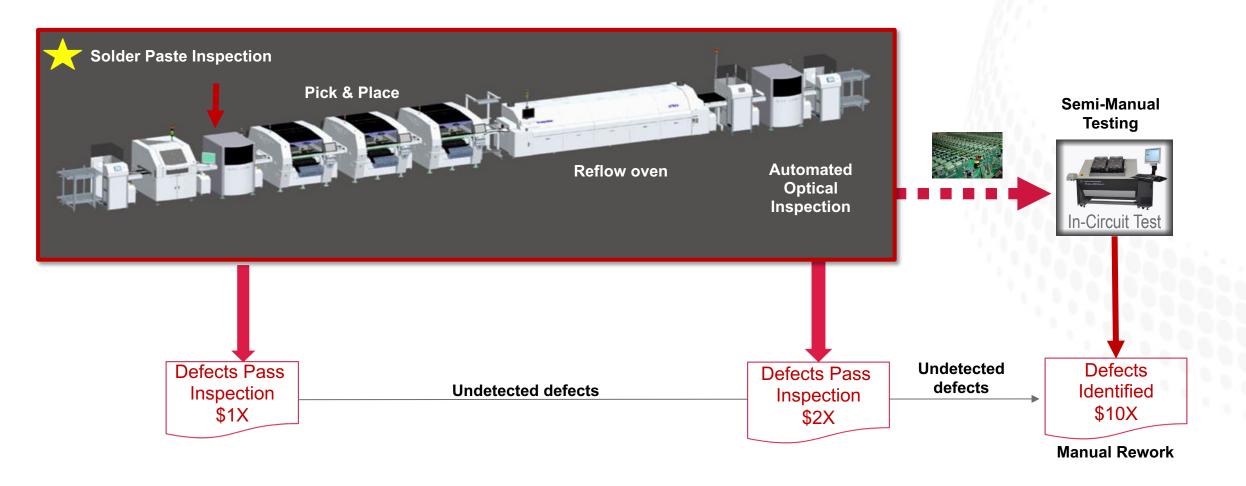




# Real-World Predictive Example

#### **SPI Use Case Baseline State**

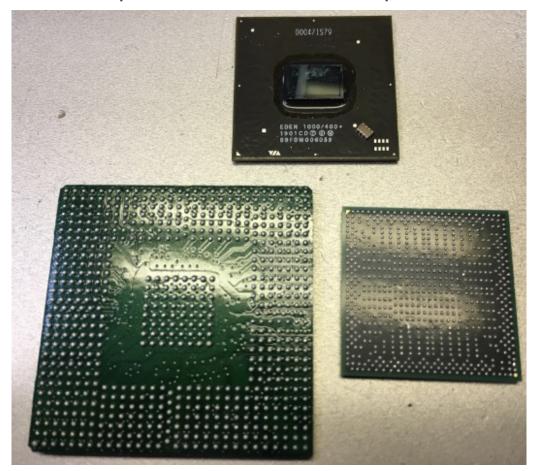
Reducing Defects in Electronic Assembly Manufacturing of Allen-Bradley® Products



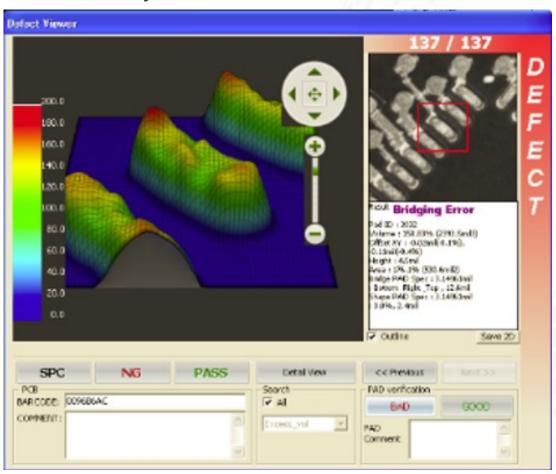


#### **Business Issue: BGA Defects – Costly/Risky/Difficult to Detect**

Resolution: Operationalize Closed-Loop Real-Time Defect Prediction System



Typical BGA components (solder joints are hidden beneath)



Out of the Box SPI inspection only focuses on individual deposits



#### Business Issue: BGA Defects – Costly/Risky/Difficult to Detect cont.

Resolution: Operationalize Closed-Loop Real-Time Defect Prediction System

SPI Output



Edge Prediction (ETL+Scoring)



MES/Line



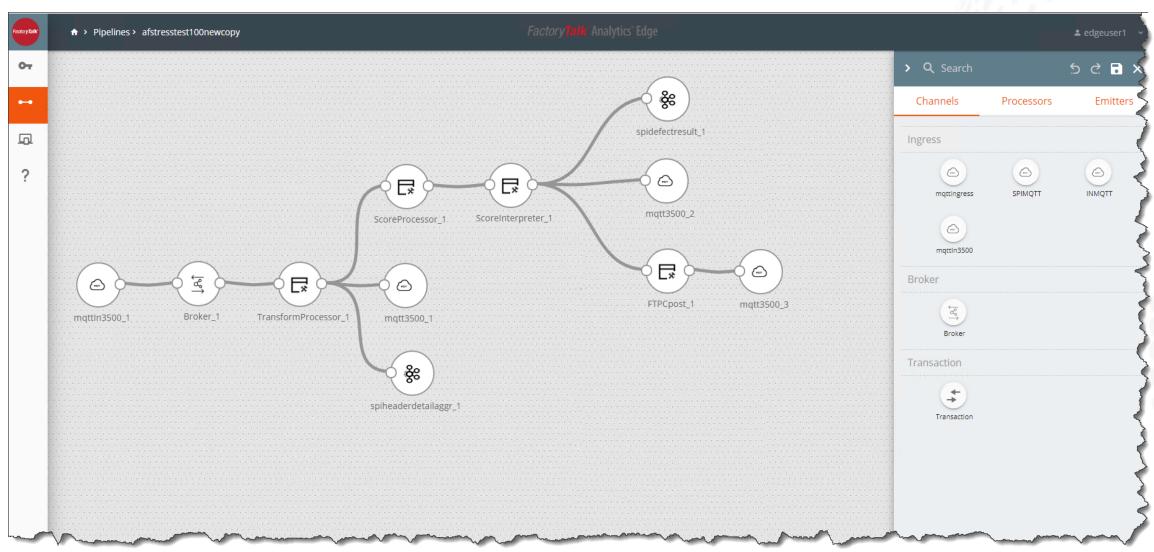
Enable/Disable
Processing to Line





#### FactoryTalk® Edge Data Pipeline added

Contents of Orange Highlighting from above slide







### Wrap Up and Takeaways

#### Wrap Up and Takeaways

Predictive Maintenance and other advanced analytic solutions deliver performance and intelligent equipment oversight.

- Real world advanced analytics like predictive maintenance are not as easy as frequently wished for or advertised.
- FactoryTalk® InnovationSuite offers a range of the right answers to fit different manufacturing needs.
- You can improve
  - Intelligent Asset Optimization
  - Digital Workforce Productivity
  - Enterprise Operational Intelligence
  - Scalable Production Management
- Today on your Edge, Site or Cloud platforms







expanding **human possibility**™

### Thank you



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