PREDICT PROCESS AND EQUIPMENT PROBLEMS WITH UNIFORMANCE ASSET SENTINEL
Digital Transformation Example… Where is my bike rack?

Travel History

<table>
<thead>
<tr>
<th>Date/Time</th>
<th>Activity</th>
<th>Location</th>
</tr>
</thead>
<tbody>
<tr>
<td>6/12/2017</td>
<td>?</td>
<td>SANTA ROSA, NM</td>
</tr>
<tr>
<td>6/14/2017</td>
<td>Wednesday</td>
<td>SANTA ROSA, NM</td>
</tr>
<tr>
<td>8:02 am</td>
<td>In transit</td>
<td>SANTA ROSA, NM</td>
</tr>
<tr>
<td>6/13/2017</td>
<td>Tuesday</td>
<td>TULSA, OK</td>
</tr>
<tr>
<td>8:53 pm</td>
<td>In transit</td>
<td>TULSA, OK</td>
</tr>
<tr>
<td>8:36 am</td>
<td>Departed FedEx location</td>
<td>CHICAGO, IL</td>
</tr>
<tr>
<td>6/12/2017</td>
<td>Monday</td>
<td>CHICAGO, IL</td>
</tr>
<tr>
<td>11:13 pm</td>
<td>Arrived at FedEx location</td>
<td>CHICAGO, IL</td>
</tr>
<tr>
<td>6:21 pm</td>
<td>Left FedEx origin facility</td>
<td>DUBUQUE, IA</td>
</tr>
<tr>
<td>5:15 pm</td>
<td>Arrived at FedEx location</td>
<td>DUBUQUE, IA</td>
</tr>
<tr>
<td>3:06 pm</td>
<td>Picked up</td>
<td>DUBUQUE, IA</td>
</tr>
<tr>
<td>10:00 am</td>
<td>Shipment information sent to FedEx</td>
<td>DUBUQUE, IA</td>
</tr>
</tbody>
</table>

Ship date: Mon 6/12/2017
Scheduled delivery: Thu 6/15/2017 by end of day

Where its been?

When will it get there?
What is ‘Prediction’?

To Tell in Advance of Foretell
Why Prediction?

• To drive proactive response:
  - … to prepare for, intervene in, or control an *expected occurrence* or situation, especially a negative or difficult one; anticipatory
Elements of Predictive / Proactive Solutions

• Continuous monitoring “Digitization” / Digital Twin
• Run-time analytics
  - Data pre-processing / cleansing
  - Basic calculations
  - First Principles Models
  - Data driven / parameter estimation
• Fault Detection
  - Simple limit violations
  - Complex logic
• Fault Management (workflow)
  - Detect
  - Decide
  - Act
How These Decisions are Made Today

Find / Import Data

<table>
<thead>
<tr>
<th>Tag Name</th>
<th>Tag Desc</th>
</tr>
</thead>
<tbody>
<tr>
<td>XUTT901.PV</td>
<td>HE91 Shell In Temp</td>
</tr>
<tr>
<td>XUTT902.PV</td>
<td>HE91 Shell Out Temp</td>
</tr>
</tbody>
</table>

Analyze Data (Excel & Other Tools)

Reports

Time Consuming

- Missed Opportunities
- Difficult to Sustain

Blind Spots

- Varied Approaches & Results
- Difficult to Share Information

What is your process and equipment analytics platform?
Uniformance® Suite Creating the Digital Twin

**Connect**
Connect and store relevant real-time process and event data both on-site & in the cloud

**Analyze**
Calculate, analyze, and detect risks and opportunities with asset-centric advanced analytics

**Visualize**
Interactive visualization of trends, charts, and graphics across variety of data sources for process & manufacturing intelligence

**Act**
Notifications and workflow for accelerated decision-making to maximize business performance
Uniformance Suite – Along with PHD… the following

**Calculations (Actual & Predicted)**
- Pre-Processing / Cleansing
  - \( \text{Head} = 3960 \times \text{HP} \)
  - Flow
- User Defined Calculations
- UniSim® - Estimate/ Predicted
- Data Driven

**Even Detection (Compare Actual to Predicted)**
- Fault Models
- Fault Prioritization (Fault Severity \* Asset Criticality)

**Event Management**
- Event Management
- Notifications

**Investigations**
- Performance Curves

**Business Dashboards**

**Insight**
- Process Graphics & Trends

**Executive**
Example Equipment Models

Pump

Required instrumentation:
- Pump Flow
- Pump Suction & Discharge Pressure
- Driver Power

Available Outputs:
- Power, Load
- Actual Head, Efficiency
- Expected Head, Efficiency
- Head & Efficiency Deviation

Faults
- Compressor Load High / Low Limit
- Performance Warnings High & Critical
- Surge Warning
- Bearing Vibration & Temp Faults

Heat Exchanger

Required instrumentation:
- Inlet and Outlet Temp for shell and tube streams
- Inlet and Outlet Pressures for shell and tube streams
- Shell & Tube Stream Flow

Available Outputs:
- Heat Exchanger Duty
- Actual Heat Transfer Coefficient
- Expected Heat Transfer Coefficient
- Fouling Factor
- Heat Transfer Efficiency

Faults
- Heat Transfer Efficiency Warning / Critical
- Coolant Temperature High
- Fouling Warning / High
  - Fouling Factor
  - Tube Pressure Difference Warning/High
  - Shell Pressure Difference Warning / High
Process Model - CDU

Process Operations:
- Column head temperature & pressure
- Feed temperature
- Condenser duty
- Bottom stripping steam
- Reflux ratio
- Sidestream tray temperature
- Pumparounds duty
- Tower flooding proactive detection with impact on fractionation yields and fractionation capacity
- Monitoring of unit yields and fractionation by correlating operating condition such as total pump around heat recovery, condenser capacity, reflux ratio, steam/hydrocarbon ratio.

Quality:
- LPG C5+ content
- Naptha RVP
- Naptha PT95%
- Jet / Kero Flash point
- Jet Freezing point
- Gasoil PT95%

Corrosion / Reliability
- monitoring thickness and acid crude properties
Event Management – Orientation
Event Detection - Decide

Fault

Symptoms

Column T100

T100 Reflux Pump

Column is Unstable

6/14/2017 4:00 PM

Column is stable

6/14/2017 2:48 PM

Column DP is high

Column is not steady

Column is Unstable due to Feed Rate Change

High ROC in Btm Temperature
Event Management - Decide

Help Tab

Recommendations

Links to supporting documentation

ASSETS

Equipment Monitoring

Refinery

Alky Unit

Crude Distillation

Debutanizer

Column T100

T100 Reflux Pump

K101

K102

Logical

LOPA

Process Sensors

Process Streams

Utilities

Event Monitor | Column T100

Status: Running

ASSET NAME | START TIME | NAME | D. | STATUS | CONDITION | PRIORITY | TYPE

Column T100 | 6/14/2017 3:56 PM | Column is not Steady | Active | New | Symptom | 4

Fault Details for: Column T100, D. 4

Recommendation:

Cause: Low reflux rate, high reboiler duty, loss of cooling duty of any of the overhead exchangers, too much light component in feed

Consequence: Inefficient operation, Overpressure of the column leading to potential flaring

Corrective Action: Reduce bottoms temperature, increase reflux rate, trend reflux temperature and check overhead exchangers for fouling/loss of cooling if temperature increased.

Associated Links

| NAME | CATEGORY | LINK |

FurnaceGraphic | Reliability | /MES/HMIWeb/UI/DisplayService1.0/view/Displays/Furnace.htm |

ProcessTrends | Process | /MES/ILM/UI/UAS/view/a1a84157-fa0s-4054-5213-7e200e3854d0?assetId=T100 |
### Performance Monitoring – Column Attribute Overview

<table>
<thead>
<tr>
<th>ASSET</th>
<th>ATTRIBUTE</th>
<th>DESCRIPTION</th>
<th>CURRENT</th>
<th>TIMESTAMP</th>
<th>LOW LIMIT</th>
<th>HIGH LIMIT</th>
<th>HISTORICAL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Column T100</td>
<td>Btm_Pressure</td>
<td>Btm_Pressure</td>
<td>13.530</td>
<td>6/14/2017 4:00:49 PM</td>
<td>882.77</td>
<td>1513.3</td>
<td></td>
</tr>
<tr>
<td>Column T100</td>
<td>Btm_Product_Flow</td>
<td>Btm_Product_Flow</td>
<td>161.80</td>
<td>6/14/2017 4:00:49 PM</td>
<td>17.500</td>
<td>30.000</td>
<td></td>
</tr>
<tr>
<td>Column T100</td>
<td>Btm_Product_Recover</td>
<td>Btm_Product_Recover</td>
<td>64.350</td>
<td>1/1/2001 12:00:00 AM</td>
<td>118.80</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Column T100</td>
<td>Btm_Product_Temp</td>
<td>Btm_Product_Temp</td>
<td>205.01</td>
<td>6/14/2017 4:00:49 PM</td>
<td>129.35</td>
<td>238.80</td>
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</tr>
<tr>
<td>Column T100</td>
<td>Btm_Temperature</td>
<td>Btm_Temperature</td>
<td>220.12</td>
<td>6/14/2017 4:00:49 PM</td>
<td>139.30</td>
<td>238.80</td>
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</tr>
<tr>
<td>Column T100</td>
<td>DeltaP</td>
<td>DeltaP</td>
<td>-0.87129</td>
<td>6/14/2017 4:00:51 PM</td>
<td>13.650</td>
<td>25.200</td>
<td></td>
</tr>
<tr>
<td>Column T100</td>
<td>DeltaP_Btm</td>
<td>DeltaP_Btm</td>
<td>-0.020056</td>
<td>6/14/2017 4:00:51 PM</td>
<td>641.55</td>
<td>1099.8</td>
<td></td>
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<tr>
<td>Column T100</td>
<td>DeltaP_Top</td>
<td>DeltaP_Top</td>
<td>0.85124</td>
<td>6/14/2017 4:00:51 PM</td>
<td>595.73</td>
<td>1099.8</td>
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</tr>
<tr>
<td>Column T100</td>
<td>Feed_Flow</td>
<td>Feed_Flow</td>
<td>432.83</td>
<td>6/14/2017 4:00:49 PM</td>
<td>304.15</td>
<td>521.40</td>
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<tr>
<td>Column T100</td>
<td>Feed_Pressure</td>
<td>Feed_Pressure</td>
<td>13.510</td>
<td>6/12/2017 12:21:08 PM</td>
<td>30.000</td>
<td>150.00</td>
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</tr>
<tr>
<td>Column T100</td>
<td>Feed_Temp</td>
<td>Feed_Temp</td>
<td>40.167</td>
<td>6/14/2017 4:00:51 PM</td>
<td>70.050</td>
<td>145.20</td>
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</tr>
</tbody>
</table>
# Process Monitoring – Performance Attributes

![Performance Overview](Image)

### Performance Overview | Column T100

<table>
<thead>
<tr>
<th>ASSET</th>
<th>ATTRIBUTE</th>
<th>DESCRIPTION</th>
<th>CURRENT</th>
<th>TIMESTAMP</th>
<th>LOW LIMIT</th>
<th>HIGH LIMIT</th>
<th>HISTORICAL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Column T100</td>
<td>DeltaP</td>
<td>DeltaP</td>
<td>-0.39086</td>
<td>6/14/2017 4:01:51 PM</td>
<td>13.850</td>
<td>25.200</td>
<td></td>
</tr>
<tr>
<td>Column T100</td>
<td>Feed Pressure</td>
<td>Feed Pressure</td>
<td>13.510</td>
<td>6/12/2017 12:21:00 PM</td>
<td>30.000</td>
<td>150.00</td>
<td></td>
</tr>
<tr>
<td>Column T100</td>
<td>Feed Temp</td>
<td>Feed Temp</td>
<td>6/14/2017 4:01:51 PM</td>
<td>30.000</td>
<td>150.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Column T100</td>
<td>Reflux Feed Rate</td>
<td>Reflux Feed Rate</td>
<td>0.40660</td>
<td>6/14/2017 4:00:51 PM</td>
<td>35.750</td>
<td>66.000</td>
<td></td>
</tr>
<tr>
<td>Column T100</td>
<td>Top Pressure</td>
<td>Top Pressure</td>
<td>12.847</td>
<td>6/14/2017 4:01:49 PM</td>
<td>36.500</td>
<td>66.000</td>
<td></td>
</tr>
</tbody>
</table>
Performance Monitoring – Integrated Trending
Event Management – Act (Close-out)

Reason Code, Cause, Action

Impact
- Cost – negative
- Savings - positive
Machine Learning & Big Data - Marketing vs Reality

There is no magic weight loss pill – it is HARD WORK
**Asset Sentinel**  
(Complex Event Processing)

- **Event Management**  
  - Notification  
  - Investigation  
  - Close-out

- **Event Detection**  
  - Deviation Detection  
    - Heuristic  
    - Trained

- **Model**  
  - Normal & Abnormal  
    - First Principles  
    - Statistical  
    - State estimation

**Process Data**  
Real-time & Historical  
(Small Data)

---

**Rule Definition and Creation Process**

- **Process / Equipment Engineer**

  - Manual Rule Creation
    - T_Diff = L_EGT - R_EGT
    - If T_Diff > T_Diff_Hi_Limit
    - T_Diff_Hi_Alarm = TRUE
    - Calculations
    - If-then-else rules logic

- **Visual Analytics**  
  (Process Data)
    - Pattern search
    - Value Search
    - Combinations
    - Cleanse / Filter

- **Statistical Analytics**  
  (Process Data)
    - Multivariate statistical (PCA, PLS, Kernel Regression…)
    - Black-box (Neural Nets…)

- **Big Data Analytics**
  - Data vol. & variety (unstructured / text)
  - Feature Selection / Extraction
  - ML (Random Forest, SVM, Naïve Bayes…)

---

**Analytics Algorithms**

---

**Analytics Data Infrastructure & Management**

- **Storage** - (Cloud Historian)
- **Data Prep**
- **Connectivity** (Time-series, Event, Transactional)

---

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# Proactive Detection Approaches – Start at the top and work down

<table>
<thead>
<tr>
<th>Approach</th>
<th>Technique</th>
<th>Examples</th>
<th>Complexity</th>
<th>Risk</th>
</tr>
</thead>
</table>
| 1. Physical & Heuristic          | Basic perf mon for broad set of assets & detection deviation from predicted vs actual | • UOP – Connected Perf. Services  
• Middle East Gas co.– 1200 assets                                         | Low        | Low |
| 2. Univariate Prediction         | Predicting single variable time to reach a value Regression e.g. (H_TimeFit) or Soft Sensor | • Heat Exchanger Fouling prediction  
• Transmitter Inferential Model*                                              |            |      |
| 3. Adaptive Filtering/Thresholding | Data cleansing and moving window of historical window & compare current short term to historical | • Extensively used on offshore O&G compressor vibration                                    |            |      |
| 4. Basic Pattern Recognition     | Detect behavior of single or group of sensors according to know heuristic relationships | • O&G – Spike with amplitude of Xpsi occurring Y times over Z minutes                       |            |      |
| 5. Data Driven - Multivariate Early Event Detection | Statistical pattern detection and recognition including OLS, PLS, PCA, Neural Nets, etc. | • Choke Valve Leak Detection*  
• Multiple projects*  
• Furnace Flooding POC*                                                      |            |      |
| 6. Big Data                      | Big Data using variety of data sources including maintenance and reliability data | • Haul Truck Engine Prediction Example*  
• Honeywell Aero APU Example*                                                   | High       | High |

*see slides for more details

**Hybrid Approaches Needed**
**Offshore Oil & Gas Surveillance (Analytics Platform)**

*Example of steps 1-4 on previous slide without using data driven ML models*

<table>
<thead>
<tr>
<th>Background</th>
<th>Problem / Need</th>
<th>Solution</th>
<th>Results / Lessons</th>
</tr>
</thead>
</table>
| Exception Based Surveillance (EBS) Shell Deep Water Assets in Gulf of Mexico & Brazil  
- Fully operational for 4-5 yrs  
- Doubled in capacity in last 2-3 yrs  
- Integrated with Remote Ops | Production surveillance & diagnostic system to provide predictive notifications to reduce 'deferment'  
Pure data-driven models not actionable and too many false positives. | Workprocess for event detection, triage (investigation) and close-out  
Developed over 220+ 'algorithms' using 1st principles models, adaptive thresholding, univariate prediction & pattern recognition | Report $30M/year reduction in deferment & costs  
Application of heuristic / engineering rules reduces # of false positives and increases actionability.  
Evaluated 'data driven' models with limited results.  
POC on 'visual' analytics to accelerate 'algorithm development |

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## Sample of Bridge Surveillance Groups - Summary

<table>
<thead>
<tr>
<th>Surveillance Category</th>
<th>Surveillance Group</th>
<th>Surveillance Types</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Surface Engineering</strong></td>
<td>Chemical Performance Surveillance</td>
<td>8</td>
</tr>
<tr>
<td></td>
<td>Compressor Optimization Surveillance</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>Compressor Reliability Surveillance</td>
<td>16</td>
</tr>
<tr>
<td></td>
<td>Instrumentation System Surveillance</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>Process System Surveillance</td>
<td>16</td>
</tr>
<tr>
<td></td>
<td>Pump and Generator Surveillance</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td>Water Injection Surveillance</td>
<td>13</td>
</tr>
<tr>
<td></td>
<td>Water Separation Surveillance</td>
<td>8</td>
</tr>
<tr>
<td><strong>Subsea Engineering</strong></td>
<td>Chemical Performance Surveillance</td>
<td>8</td>
</tr>
<tr>
<td></td>
<td>Choke Performance Surveillance</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>Christmas Tree Surveillance</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Electric Submersible Pump Surveillance</td>
<td>26</td>
</tr>
<tr>
<td></td>
<td>Flowline Surveillance</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>HPU Surveillance</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>Multiphase Flow Meter Surveillance</td>
<td>37</td>
</tr>
<tr>
<td></td>
<td>EPU Surveillance</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>POD Electrical and Hydraulic Surveillance</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>Valve Surveillance</td>
<td>2</td>
</tr>
<tr>
<td><strong>Subsurface Engineering</strong></td>
<td>Annulus Pressure Surveillance</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Choke Performance Surveillance</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Gas Lift Surveillance</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Operating Guidelines Surveillance</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Rate and Phase Surveillance</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Sand Management Surveillance</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Shut In Well Surveillance</td>
<td>5</td>
</tr>
</tbody>
</table>

- **30M data elements processed per day**
- **230K daily executed anomaly detections**
Visual Analytics – Accelerating Surveillance Model Development

1. Step#1: Period of Interest +30min and -30min of lab sample – Propane data

2. Step#2: Calculate Analyzer Average Value in the period of interest and mark timestamp as middle i.e. 7:00 AM

3. Step#3: Calculate the deviation between average analyzer value and Raw Lab data

4. Step#4: Identify period where the deviation are higher than 30%

5. Step#5: Tune threshold to desired level of sensitivity
Asset Sentinel / Seeq Integration

Asset Sentinel

Calculations
- Pre-Processing / Cleansing
  - Head = 3960 * HP
  - Flow
- User Defined Calculations

Event Mgt.
- Fault Models
- Event Investigations

Asset Model

Trends & Graphics

Seeq (Visual Analytics)

Asset Model
- Cleansed / Enriched Data
- Conditions, Series, Patterns

Visual Rule Discovery

OPC-HDA & DAS

OPC-DA

PHD

Other
ESP Standing Valve Leak Detection

Example of Data Driven Model for more complex problem

Background
- Offshore Oil & Gas with large population of aging electrical submersible pumps and choke valves

Problem / Need
Challenge to accurately detect choke valve seal leakage when ESP stops with minimum # of false positives. When is flow & riser pressure change considered to be a leak?

Solution
Dynamic PCA trained with leak and no leak data. Dynamic PCA determines lag in data and shifts matrix accordingly. T2 (representing variance from mean) & SPE (indicating residual variance) indices on moving time window used to detect leakage when pump stops

Results / Lessons
DPCA markedly better than PCA in this use case confirmed leaking conditions. DPCA model detected 3 leak conditions detected in training data set

<table>
<thead>
<tr>
<th></th>
<th>DPCA</th>
<th>PCA</th>
</tr>
</thead>
<tbody>
<tr>
<td>True Positive</td>
<td>31</td>
<td>22</td>
</tr>
<tr>
<td>False Positive</td>
<td>1</td>
<td>9</td>
</tr>
<tr>
<td>False Negative</td>
<td>1</td>
<td>2</td>
</tr>
</tbody>
</table>
Combination of $T^2$ and SPE indicate Fault
# Mining Haul Truck Engine Failure Prediction

Example of Big Data Analytics – more complex problem

<table>
<thead>
<tr>
<th>Background</th>
<th>Problem / Need</th>
<th>Solution</th>
<th>Results / Lessons</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Corporate mobile equipment monitoring program (500+ assets) with suite of rule-based predictors</td>
<td>Desire to augment prediction capability on engine failure</td>
<td>Merged alarm data (OEM and rule based alerts), oil analysis &amp; engine failure data. Created correlation model (oil dilution, soot, engine de-rate, after cooler, oil filter…)</td>
<td>Combination of approaches (oil analysis, heuristic rules, &amp; machine learning) increased fleet availability by 6% and reduced /hr operating cost by 13%</td>
</tr>
</tbody>
</table>

Algorithm helps prioritize overhaul planning via probability of failure
Aerospace Auxiliary Power Unit (gas turbine) Failure Prediction

Example of Big Data Analytics – more complex problem

**Background**
- 2000+ Gas Turbine global fleet monitoring program (1st principles model w fuzzy logic)

**Problem / Need**
- Need to improve prediction for 2 failure modes
  - Auto-shutdown (service interruption / unplanned maint)
  - Severe wear (high overhaul costs)

**Solution**
- Merged operational data and maint (text data mining)
  - Classifier for features/failures correlation:
    - Random Forest – contributors
    - SVM – separation of variables
    - Naïve Bayes - probabilities

**Results / Lessons**
- 17% improvement in predictability of severe wear
- 43% improvement in predicting auto-shutdown
Sample Algorithms Used on Projects

• Principal Component Analysis (PCA) - Unsupervised
  - Reveals the inner linear structure of the data and explains the variance by transforming the data into a new, lower-dimensional subspace
  - Q statistic measures the lack of model fit for each sample based on the distance a data point falls from the PC model

• Support Vector Machine (SVM) – Supervised/Semi
  - Learns a decision function for novelty detection to classify new data as similar or different to the training set

• AutoEncoder (deep learning) - Unsupervised
  - DeepLearning methodology also known as Replicator Neural Network
  - Aims at reducing feature space in order to distill the essential aspects of the data
  - Autoencoding is the non-linear alternative to PCA
Data Drive Modeling – Lessons & Recommendations

• Start with clear objective of what problem you are trying to solve
  - Trained fault detector
    ▪ High “failure to feature” ratio to **reliably predict** particular failure model
    ▪ Lower false positive rate
    ▪ Only detects what you have experienced in the past
    ▪ Tend to be more ‘actionable’ to diagnose the problem
  - Generic Anomaly Detector
    ▪ Trained on normal data – **detects all anomalous** behavior
    ▪ High false positive rate
    ▪ Difficult to attribute specific action associated with model anomalies
    ▪ 50% - 80% of problems found are sensor problems

• Set realistic expectations –
  - Model should match operating situation at scale
  - Machine learning and statistical methods are not flawless
  - Define work process and event management infrastructure to deliver results (i.e. Bridge)

• Signal to perform the task is not always in data (no volume will help)
• Sufficient volume of quality data required to perform the task
• Selection of correct machine learning technique critical to success
  - Packaged product vs. programming environment like R
Honeywell Connected Plant Solutions
IIoT by Honeywell Ecosystem

- Smart and Secure Collaboration
- Advanced Analytics
- Self Serve Analytics
- Data Management and Onsite Control
- Smart & Connected Assets & Devices

Honeywell IIoT Open & Secure Framework

- Honeywell App Store
- External App Developers
- Knowledge Vendors
  - EPCs
  - OEMs
  - SIs
  - Process Licensors
- Data Scientists

Unifomance Suite

- Time Series Data
- Context Model
- Big Data Storage

Cloud Historian

- Equip. Vendors
  ex. Flow Serve, MHI, etc.
- DCS Process Data
- Ancillary System Data
  ex. SAP, ERP, LIMS, etc.

Ecosystem Critical to Add Domain Knowledge to Solve Challenging Problems
Digital Transformation Benefits

Formalize Work Processes & Standard Work

Single Version of the Truth
Enabling Process Intelligence

Apply High Skill Resources to High Skill Tasks

Reduce Missed Opportunities & Accelerate Response

Alerts!

T1

T2

T3

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Value – Reduce Unplanned Capacity Loss / Lost Profit Opps

- Reduced Capacity Loss
- Mitigation Strategies
- Original Capacity Loss
- Leading Cause

- Rare
- Frequent

- Low
- High

- Process Deviations
- Non-Critical Eq. Failure
- Critical Eq. Failure
- Unit Shutdown

- Degraded Efficiency
- Performance Mon.
- Health Mon.
Check it out!

• Visit Uniformance Asset Sentinel Website
• Visit UOP Connected Performance Services for examples of Asset Sentinel at work
• Brochure, Case Studies, and More
• See it at Honeywell Users Group Americas and EMEA
• Watch product demo videos on the Uniformance YouTube playlist at www.hwll.co/UniformanceVideos
• Watch the Lundin Edvard Grieg Video Case Study
• Visit Uniformance.com for quick access to more information or to request a product demonstration