



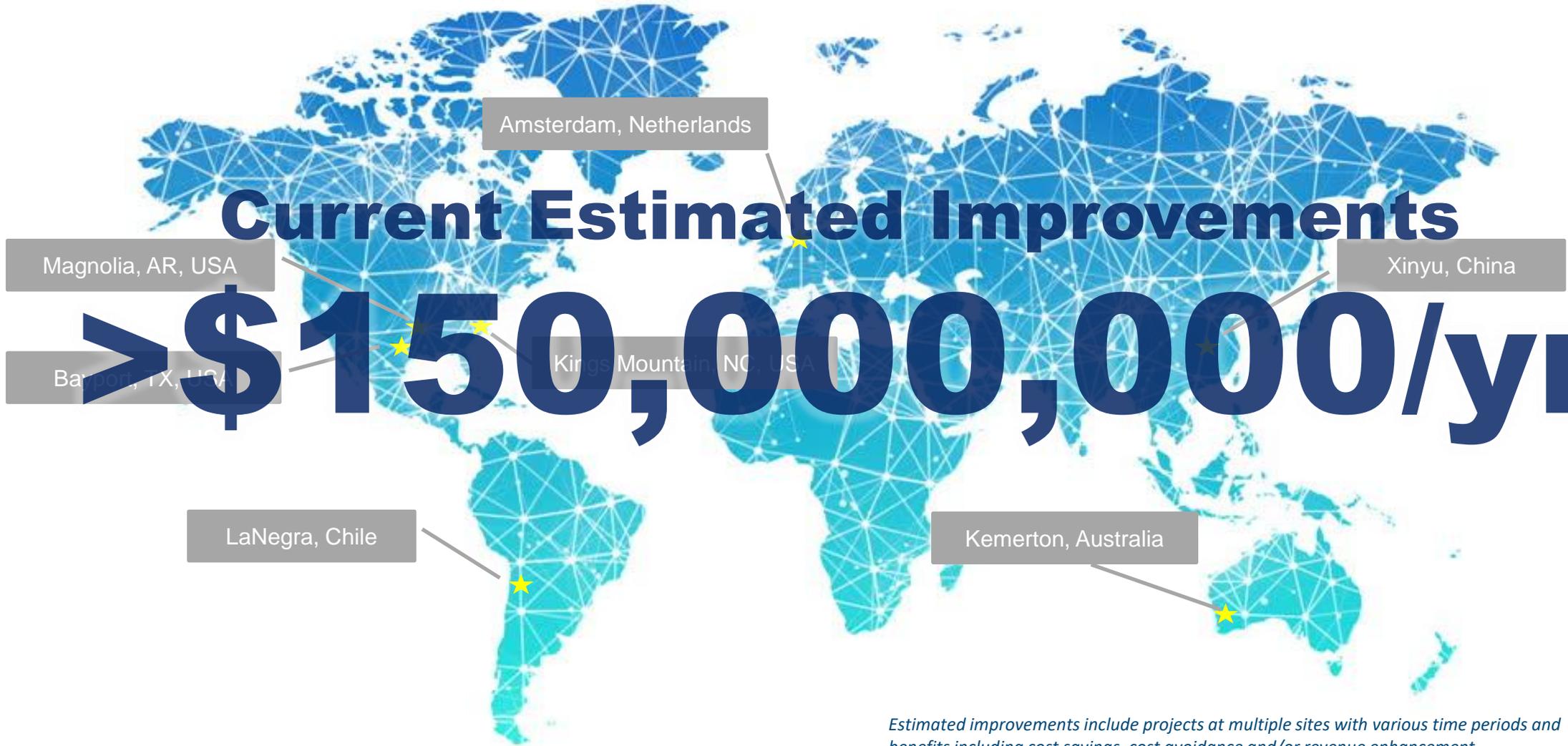
AVEVA WORLD

Albemarle Intelligence

**Top 10 Reasons Why You are Stuck in Pilot Purgatory:
*Preventing ROAI & Realizing Economies of Scale***

Presented by: Jonathan Alexander



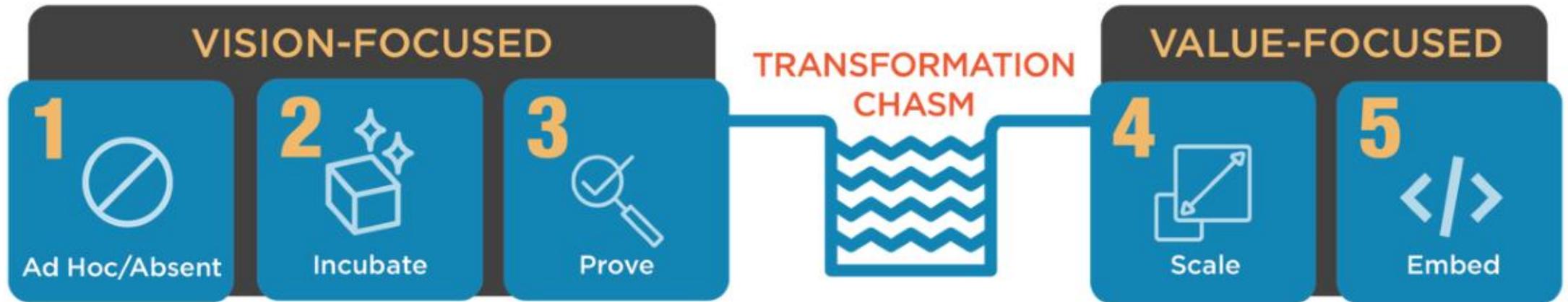


Current Estimated Improvements

> \$150,000,000/yr

Estimated improvements include projects at multiple sites with various time periods and benefits including cost savings, cost avoidance and/or revenue enhancement.

Five Stages of Transformation Maturity



Source:  LNS Research



**Top 10 Reasons
you're stuck in
Pilot Purgatory**

Reason #1



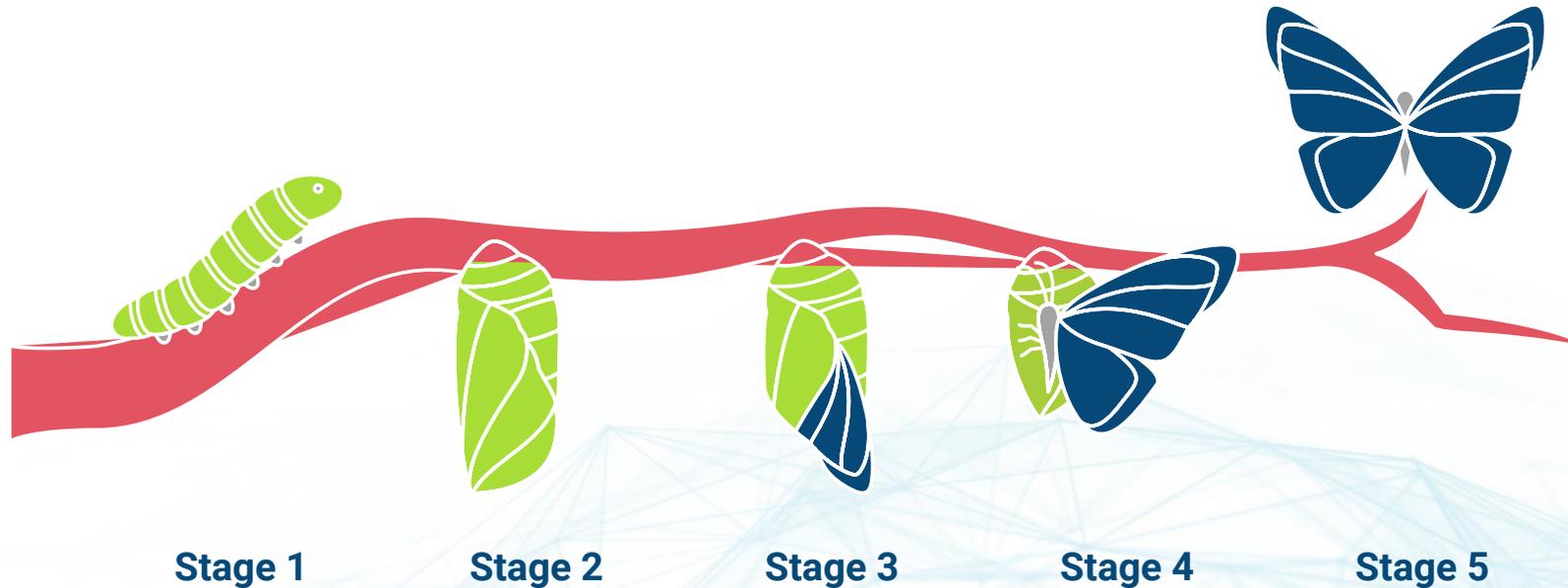
**Rome wasn't
built in a day**

The Journey to Realizing Economies of Scale



Competing on Analytics - Five Stages of Analytical Maturity

AI Maturity Transformation



Stage 1 Analytically Impaired

The company has some data and management interest in analytics.

Stage 2 Localized Analytics

Functional management builds analytics momentum and executives' interest through applications of basic analytics.

Stage 3 Analytical Aspirations

Executives commit to analytics by aligning resources and setting a timetable to build a broad analytical capability.

Stage 4 Analytical Company

Enterprise-wide analytics capability under development; top executives view analytic capability as a corporate priority.

Stage 5 Analytical Competitor

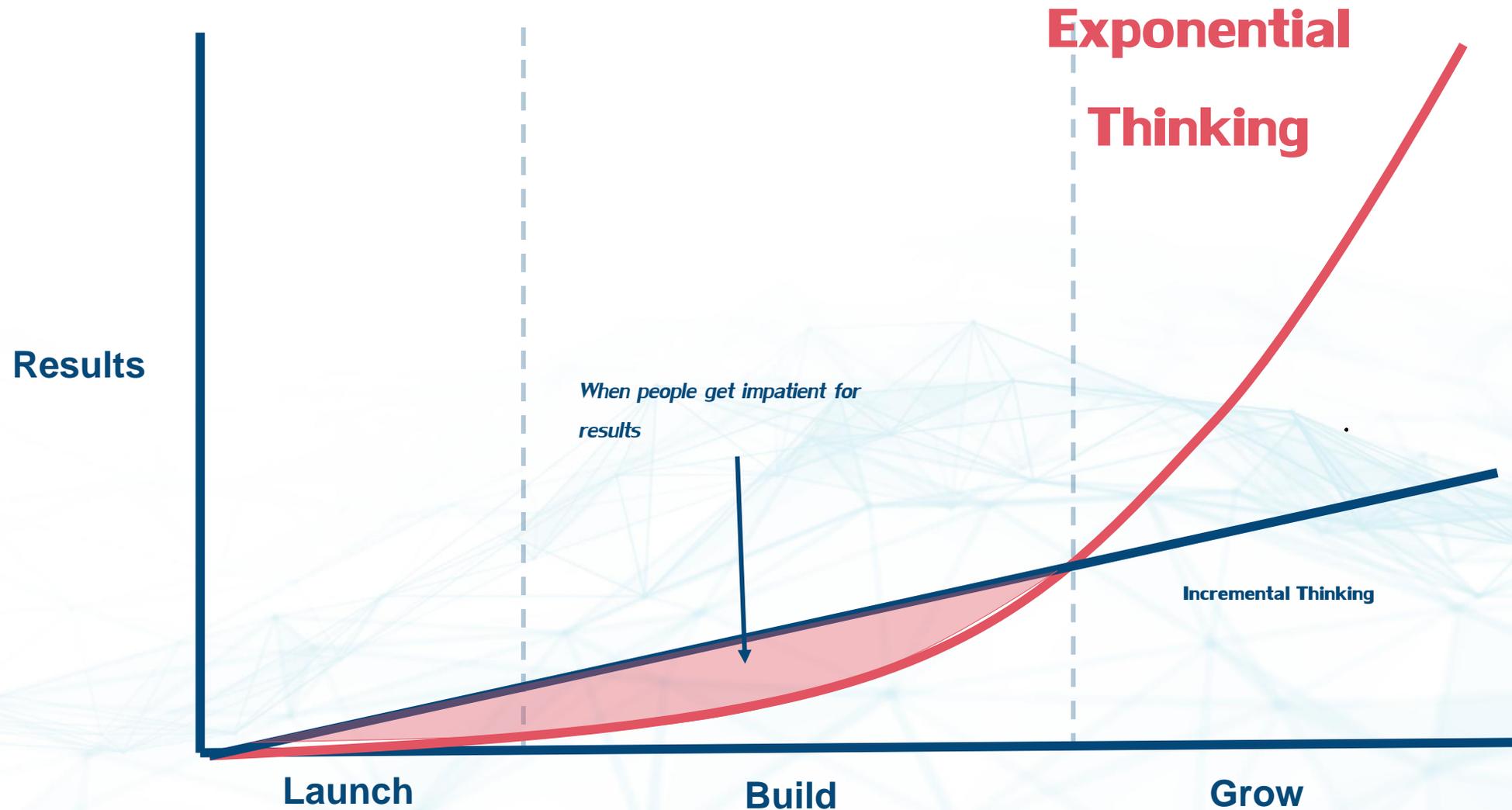
The company routinely reaps benefits of its enterprise-wide analytics capability and focuses on continuous analytics review.

AI Maturity Index



	 Beginner	 Foundational	 Advanced	 World Class
Data Governance	Minimal data governance; siloed and unstructured data.	Basic data management policies in place; some centralized storage.	Enterprise-wide data governance framework; standardized data practices.	Fully integrated, automated data governance with real-time compliance.
Statistical Process Control	No formal SPC; reactive quality control.	Basic SPC tools implemented; manual monitoring.	Automated SPC with real-time alerts and analytics.	AI-driven SPC with predictive quality insights and autonomous adjustments.
Machine Learning	Limited awareness; isolated experiments.	Early adoption; ML models used for specific tasks.	Scalable ML models integrated into workflows.	AI-powered decision-making with continuous learning and optimization.
Predictive Analytics	Basic dashboards with historical data analysis.	Simple trend analysis and forecasting.	Predictive models guiding business decisions.	AI-driven prescriptive analytics optimizing operations in real-time.
Generative AI	No generative AI implementation.	Experimentation with text/image generation in isolated use cases.	Generative AI integrated into product design and optimization.	Fully autonomous generative AI creating insights, reports, and designs with minimal human input.

Phases of Digital Transformation – Incremental vs. Exponential



Reason #2



Garbage In, Garbage Out

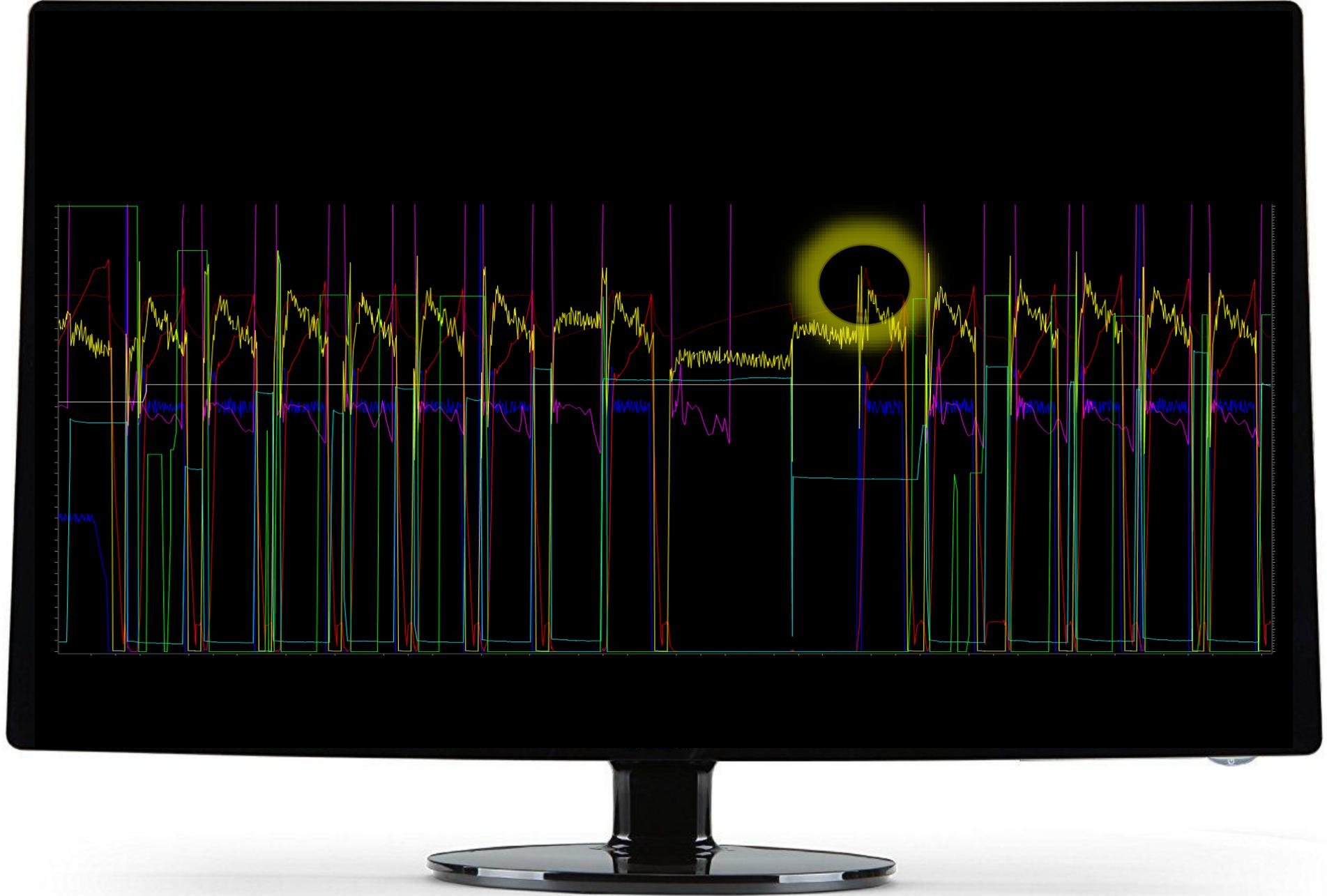


What can I help with?

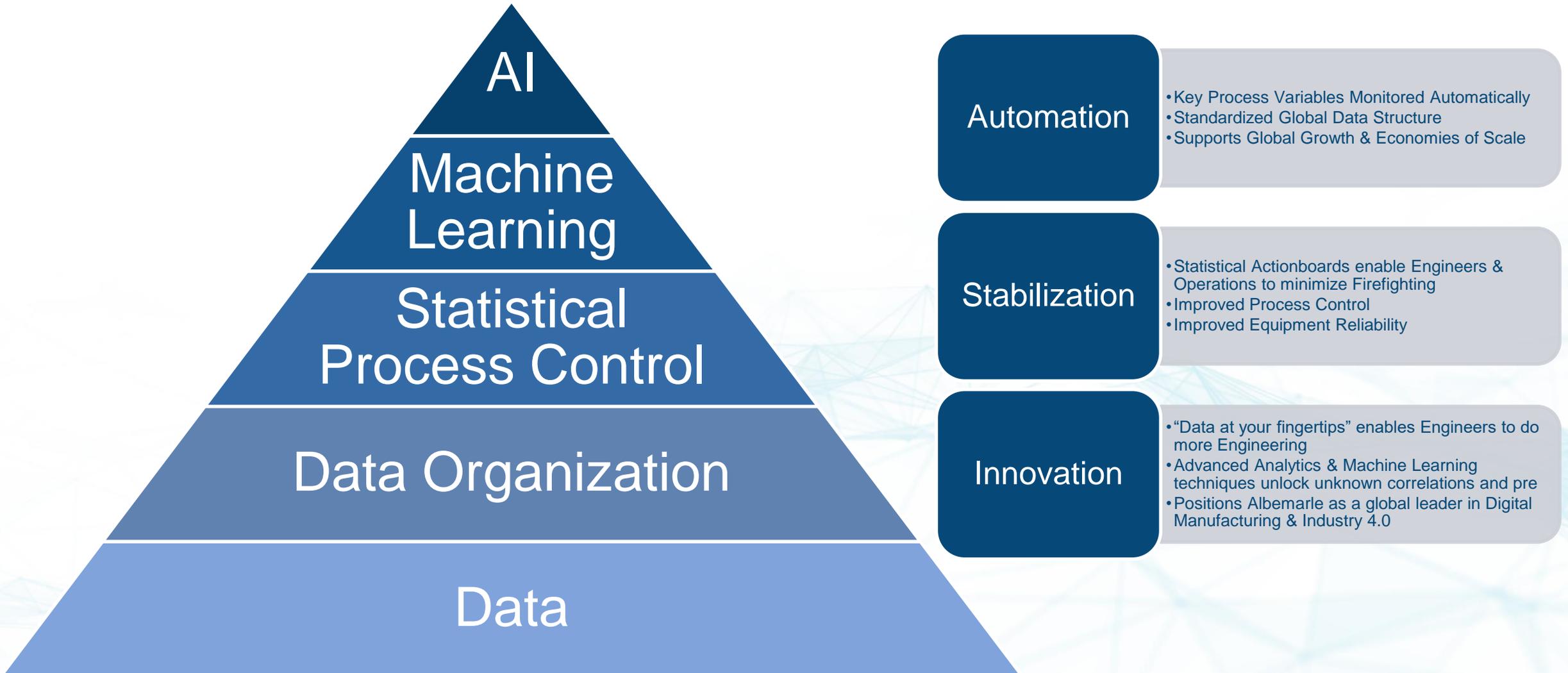
Ask anything 

  Search  Deep research  

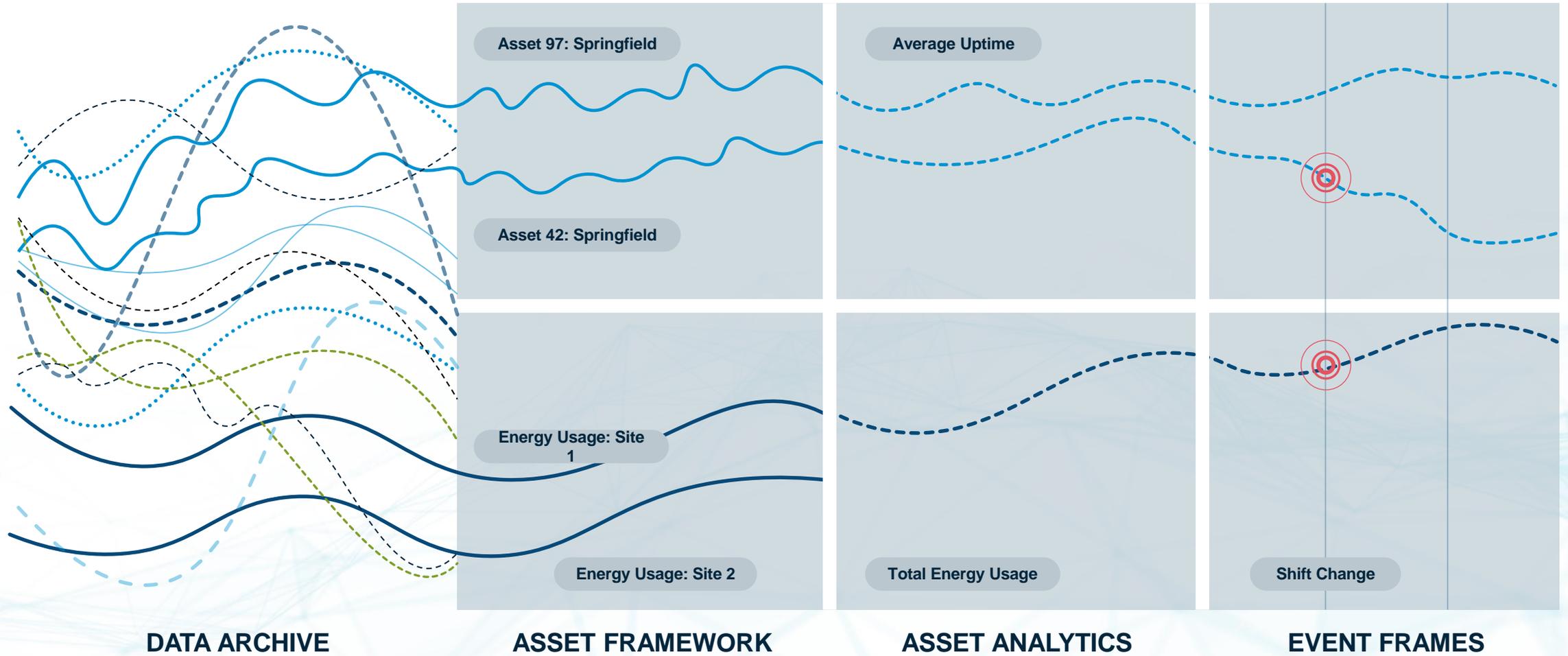
-  Create image
-  Help me write
-  Summarize text
-  Code
-  Brainstorm
- More



AI Strategy



Scaling Event Frames as an Analytical Engine

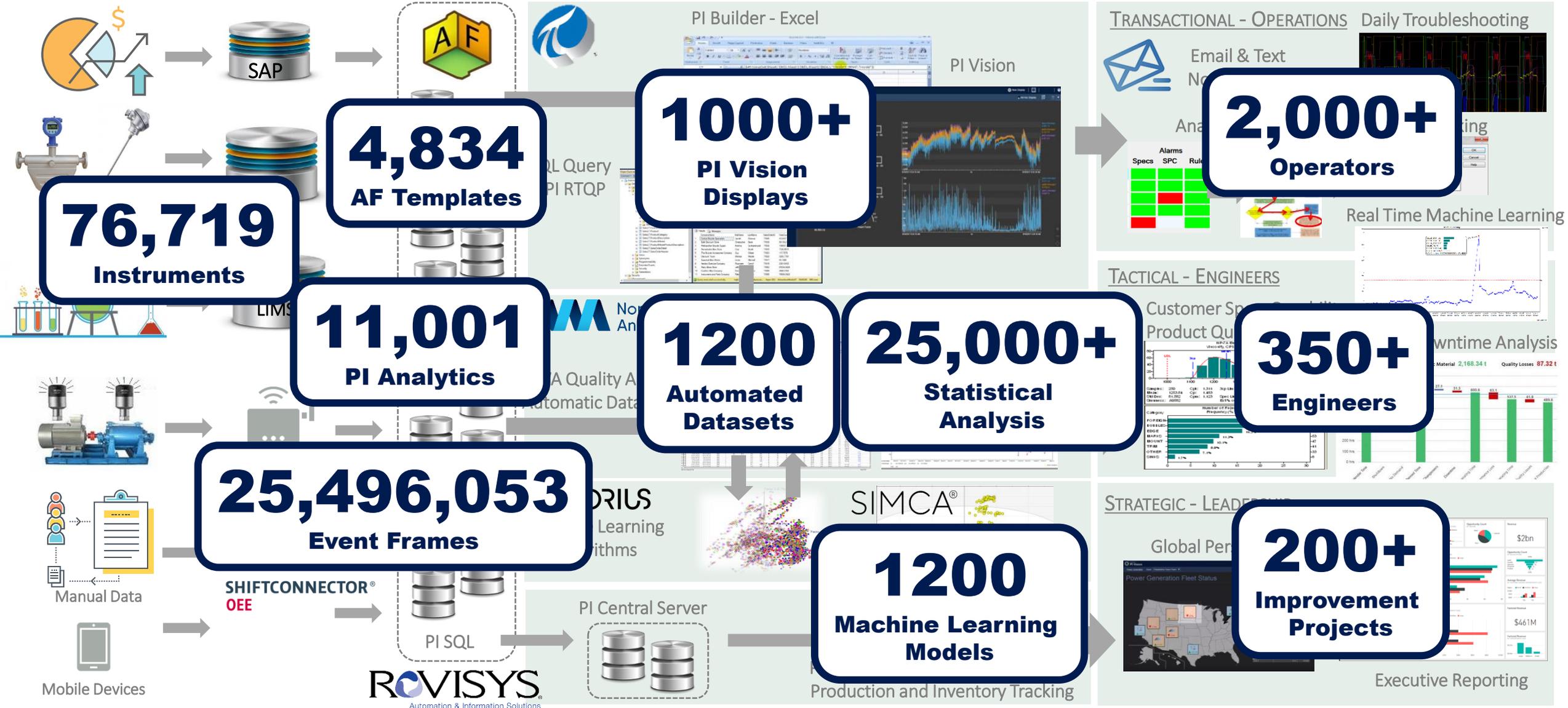


DATA SOURCES

AVEVA PI SYSTEM ASSET FRAMEWORK

DATA ANALYTICS SUITE

USER ROLES



Reason #3

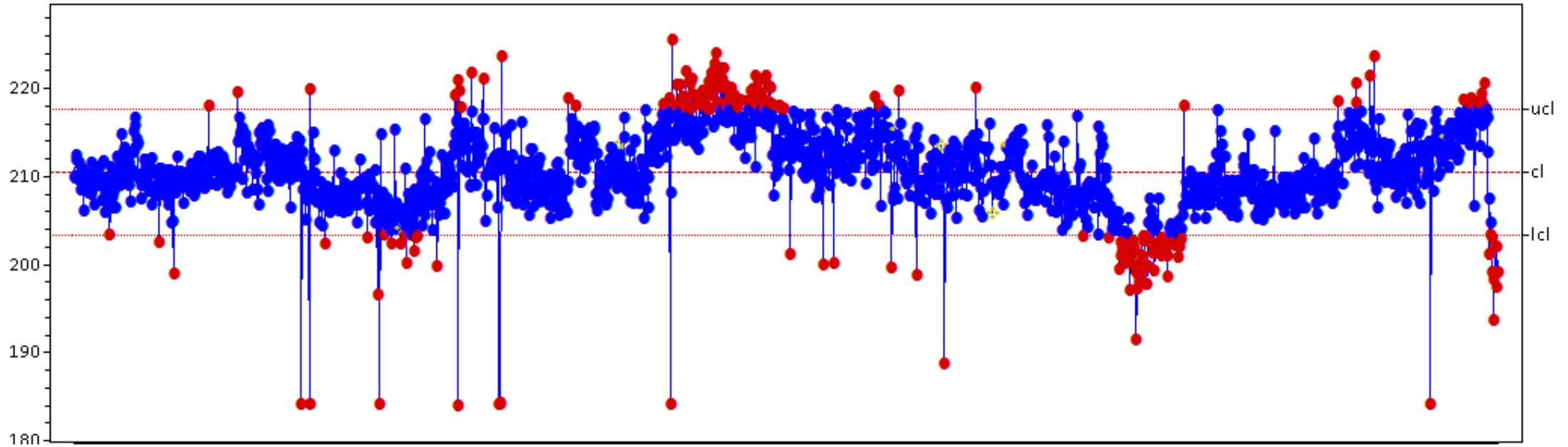
An aerial photograph of a vast forest during sunrise. The sun is low on the horizon, casting a golden glow over the landscape. The forest is a mix of dark green coniferous trees and lighter green deciduous trees. In the background, a range of mountains is visible under a sky with soft, golden light and some clouds. The overall scene is peaceful and scenic.

**You miss the
forest from
the trees**

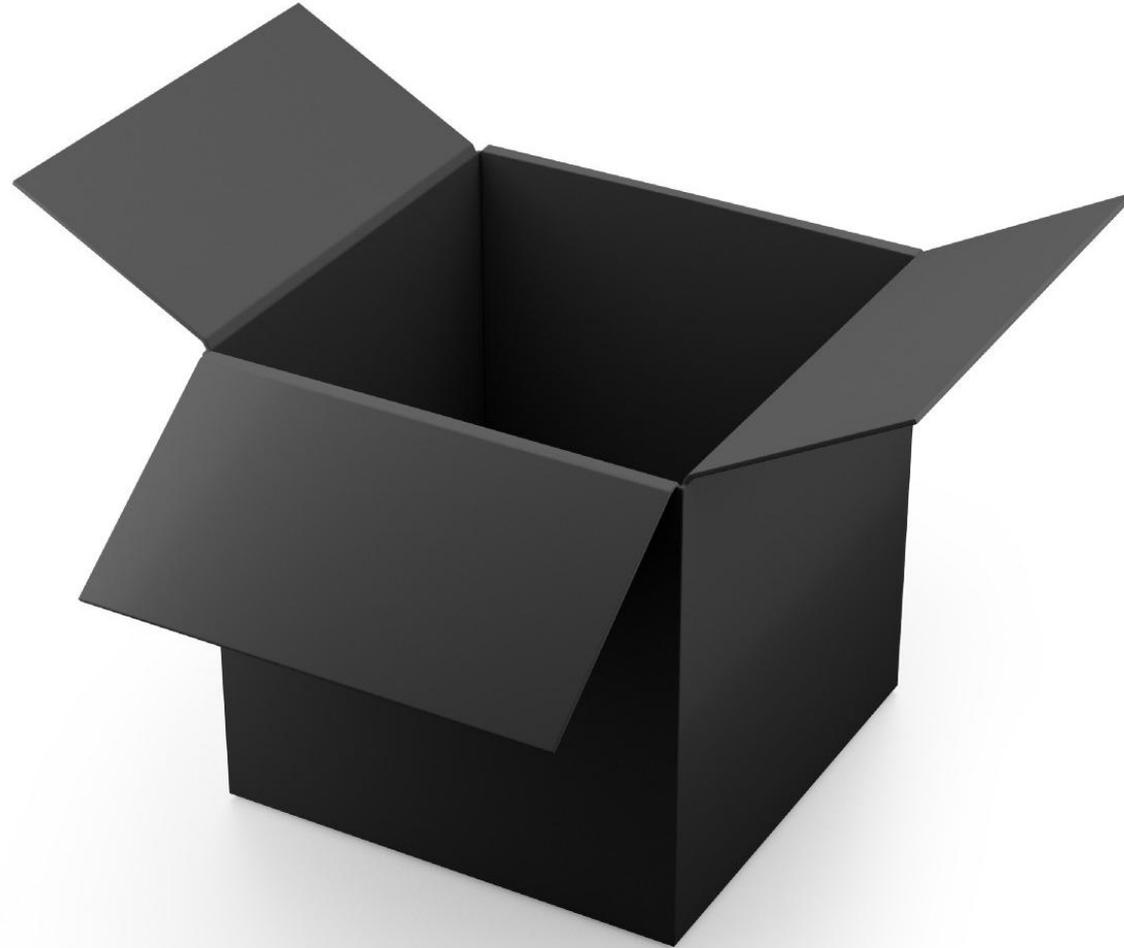


A-Shift vs C-Shift

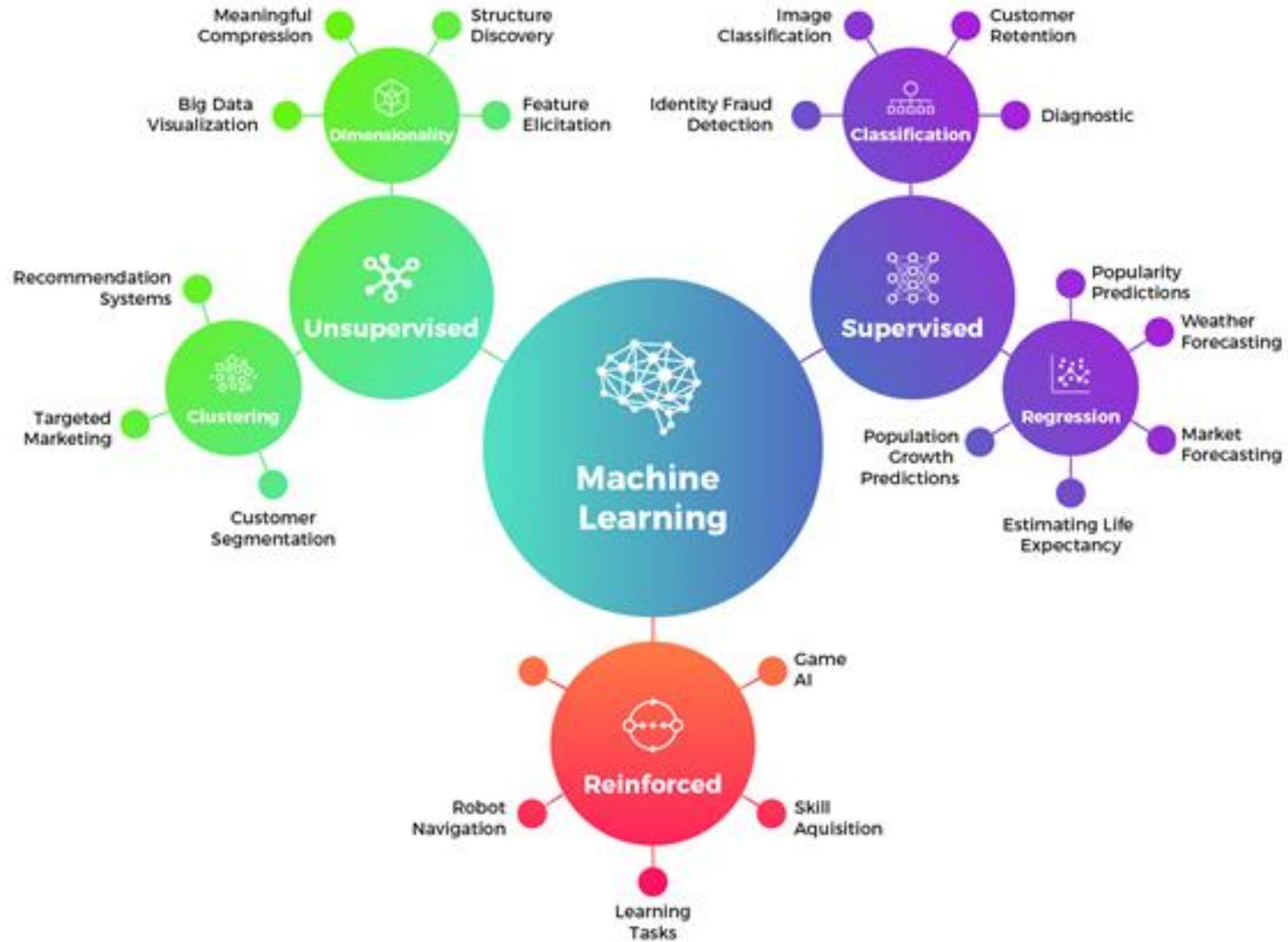
3 Month Statistical Analysis – w/ Event Frames



Dissecting the “Black Box” with Machine Learning



DIFFERENT TYPES OF MACHINE LEARNING



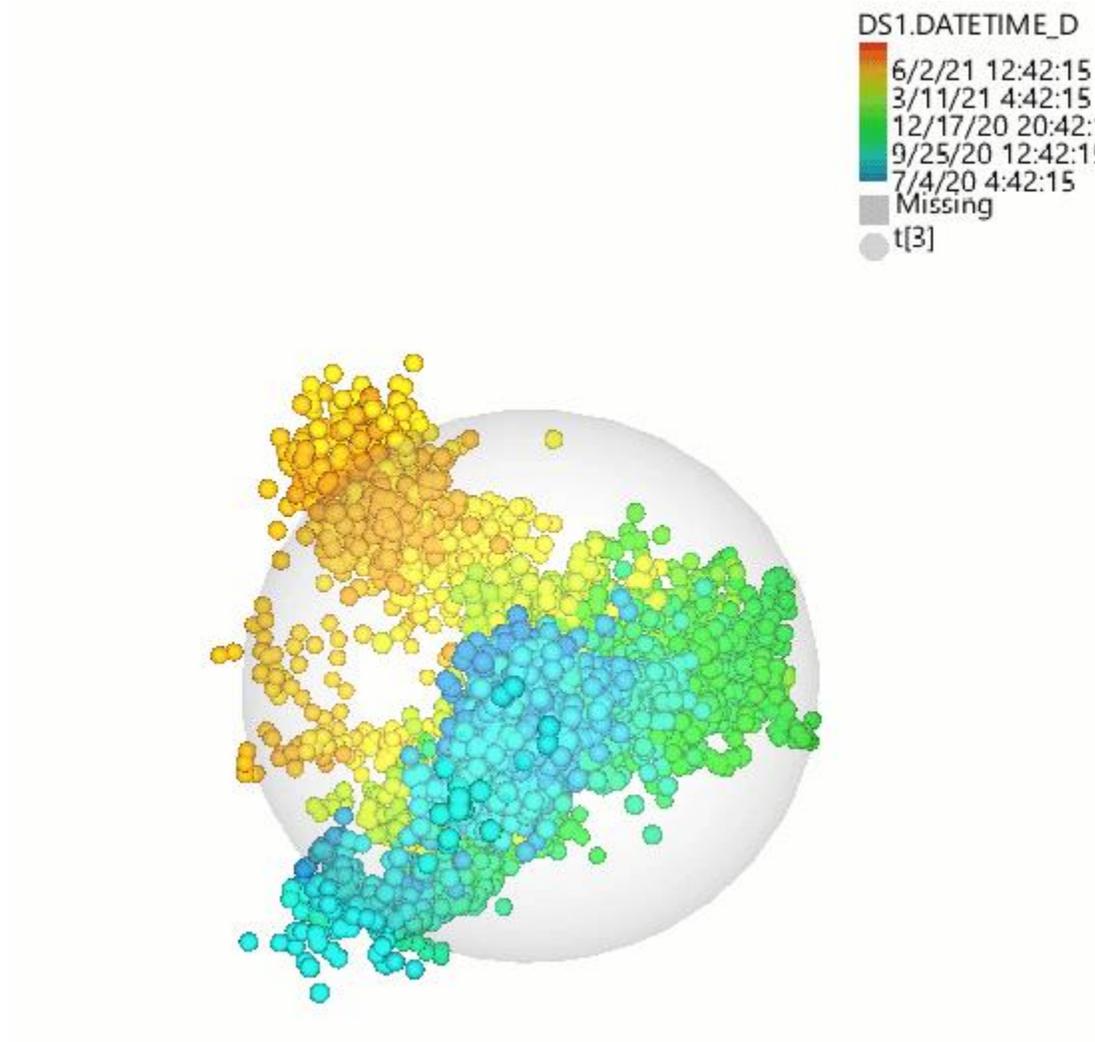
Principle Component Analysis



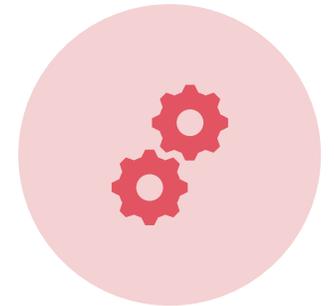
DATA EXPLORATION



FINDING HIDDEN PATTERNS / STRUCTURE

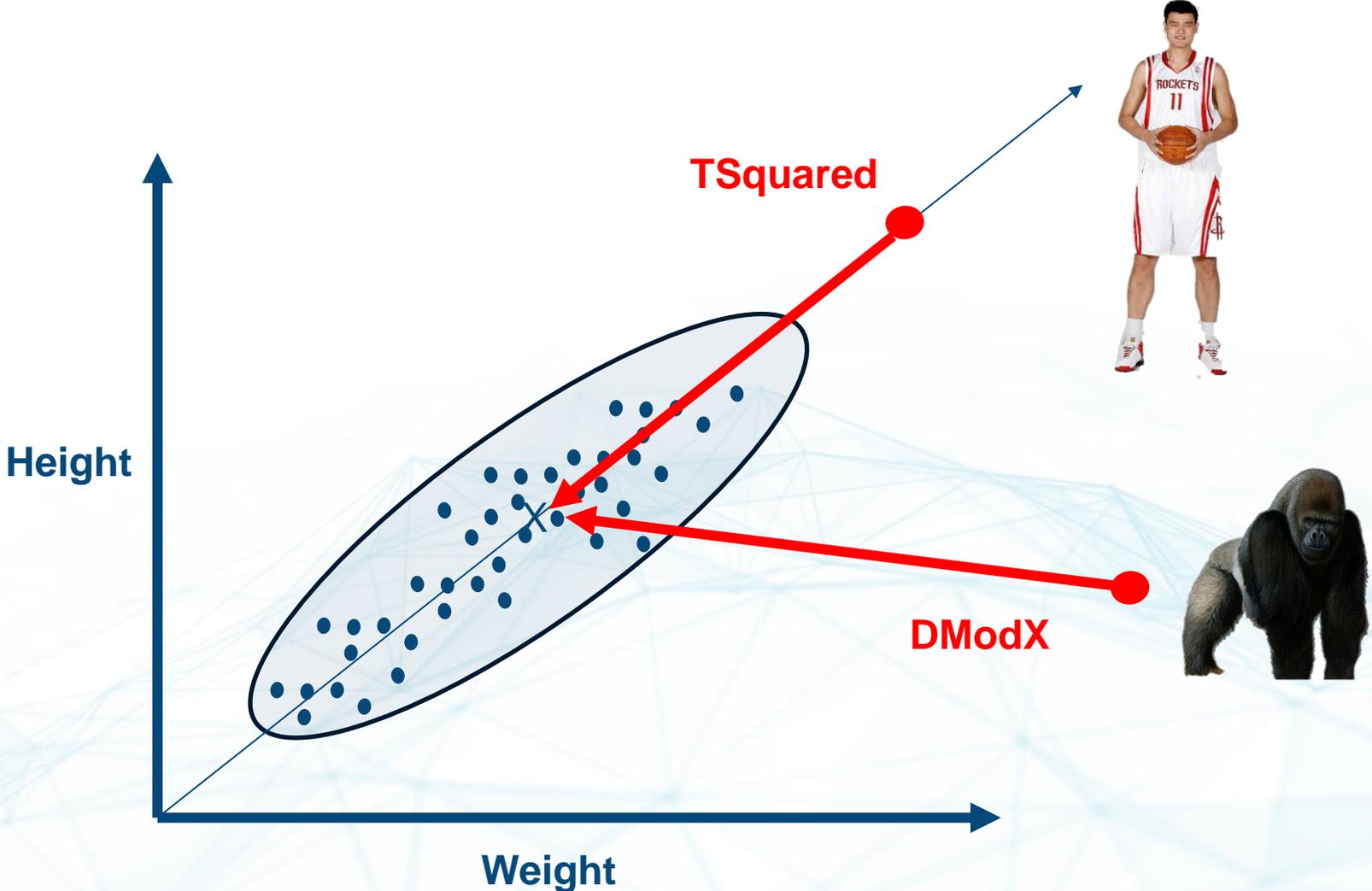


ANOMALY & OUTLIER DETECTION



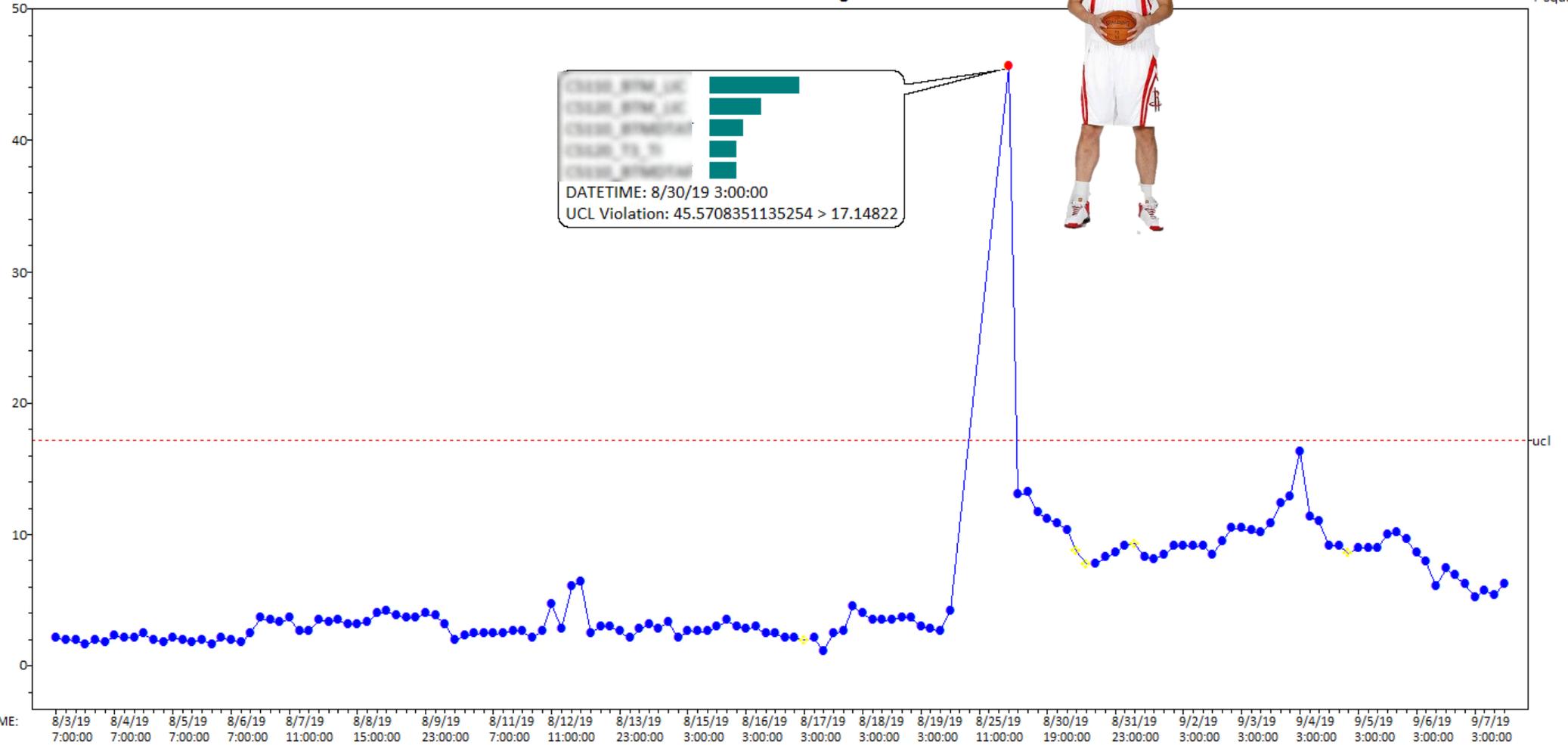
CHANGE IN OPERATING CONDITIONS

Machine Learning – Outlier & Anomaly Detection



Machine Learning

T-Squared



CLASS_BPM_LIC	45.5708351135254
CLASS_BPM_LIC	42.5
CLASS_BPM_LIC	38.5
CLASS_TL_10	35.5
CLASS_BPM_LIC	32.5

DATETIME: 8/30/19 3:00:00
UCL Violation: 45.5708351135254 > 17.14822

DATETIME: 8/3/19 7:00:00 8/4/19 7:00:00 8/5/19 7:00:00 8/6/19 7:00:00 8/7/19 11:00:00 8/8/19 15:00:00 8/9/19 23:00:00 8/11/19 7:00:00 8/12/19 11:00:00 8/13/19 23:00:00 8/15/19 3:00:00 8/16/19 3:00:00 8/17/19 3:00:00 8/18/19 3:00:00 8/19/19 3:00:00 8/25/19 11:00:00 8/30/19 19:00:00 8/31/19 23:00:00 9/2/19 3:00:00 9/3/19 3:00:00 9/4/19 3:00:00 9/5/19 3:00:00 9/6/19 3:00:00 9/7/19 3:00:00

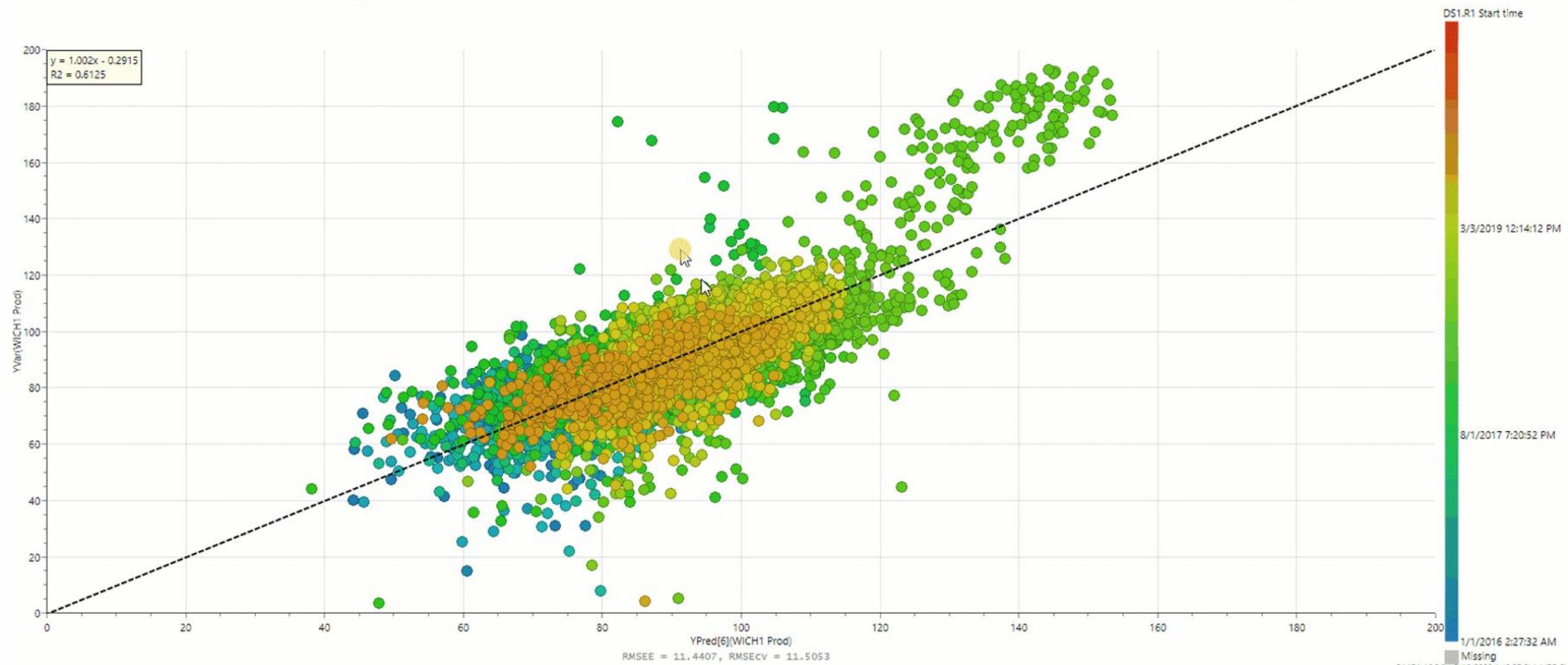
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◆ Rule Violation

Project Window - M20 (PLS) - Up to Dec '19

Number	Model	Type	A	N	R2X(cum)	R2Y(cum)	Q2(cum)	Date	Title	Hierarchical
17	M17	PLS	5	641	0.294	0.302	0.254	4/30/2020		
18	M18	PLS	10	641	0.526	0.299	0.241	4/30/2020		
19	M19	PLS	10	639	0.537	0.306	0.251	4/30/2020		
20	M20	PLS	6	7230	0.337	0.389	0.385	6/16/2020	Up to Dec '19	

Observed vs. Predicted [M19] | Loading Scatter Plot [M19] | Score Scatter Plot [M19] | Contribution Plot [M20] | **Observed vs. Predicted [M20]** | Contribution Plot [M20] | XVar Plot [M20] | Contribution Plot [M20] | XVar Plot [M20]



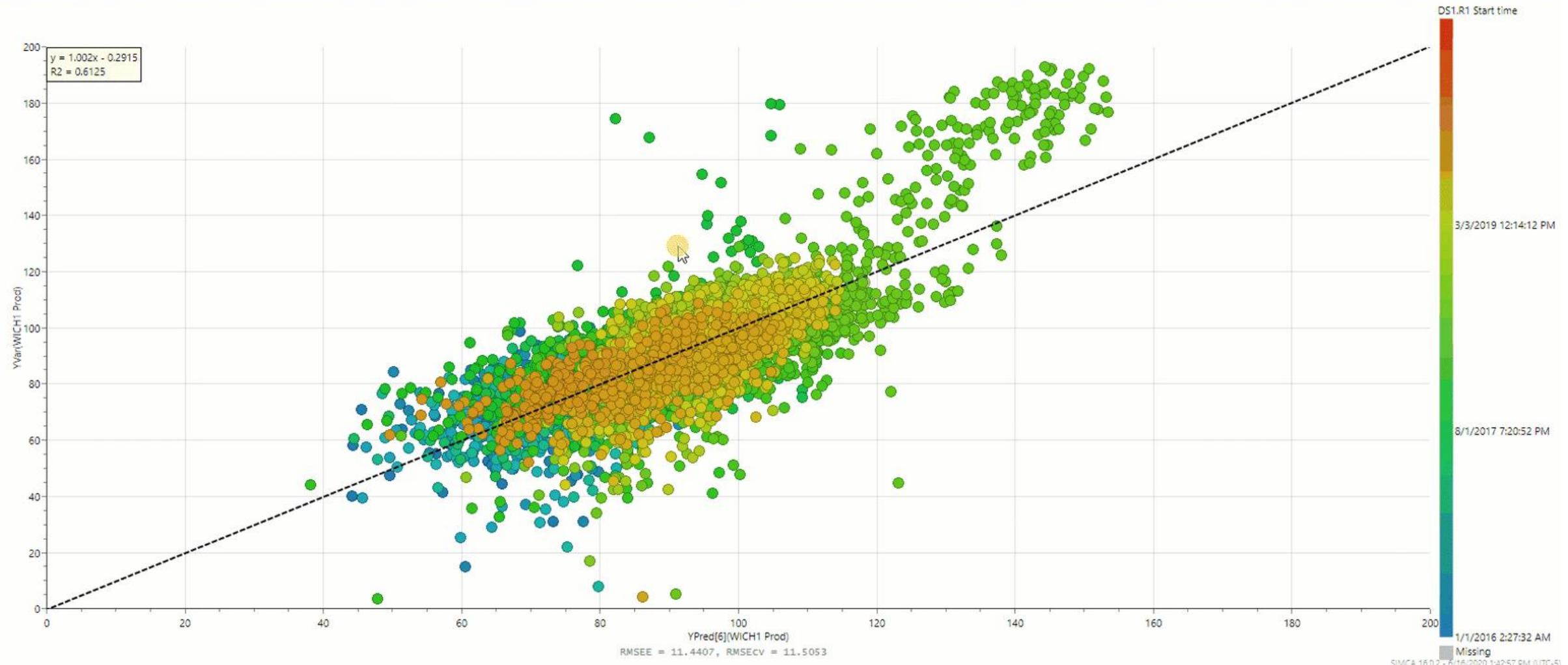
File Home Data Analyze Predict View Tools Marked items

Dataset New as Edit Delete Statistics Model type Autofit Remove Summary of fit Overview Scores Loadings Hotelling's T2 DMod VIP Obs. vs. pred. Coefficients Create Plot/list

Project Window - M20 (PLS) - Up to Dec '19

Number	Model	Type	A	N	R2X(cum)	R2Y(cum)	Q2(cum)	Date	Title	Hierarchical
17	M17	PLS	5	641	0.294	0.302	0.254	4/30/2020		
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Observed vs. Predicted [M19] Loading Scatter Plot [M19] Score Scatter Plot [M19] Contribution Plot [M20] Observed vs. Predicted [M20] Contribution Plot [M20] XVar Plot [M20] Contribution Plot [M20] XVar Plot [M20]



File Home Data Analyze Predict View Tools Marked items

List Scatter Line Column Plot XObs Plot YObs Exclude Include Class Labels Hide Show all Unlock column Layout

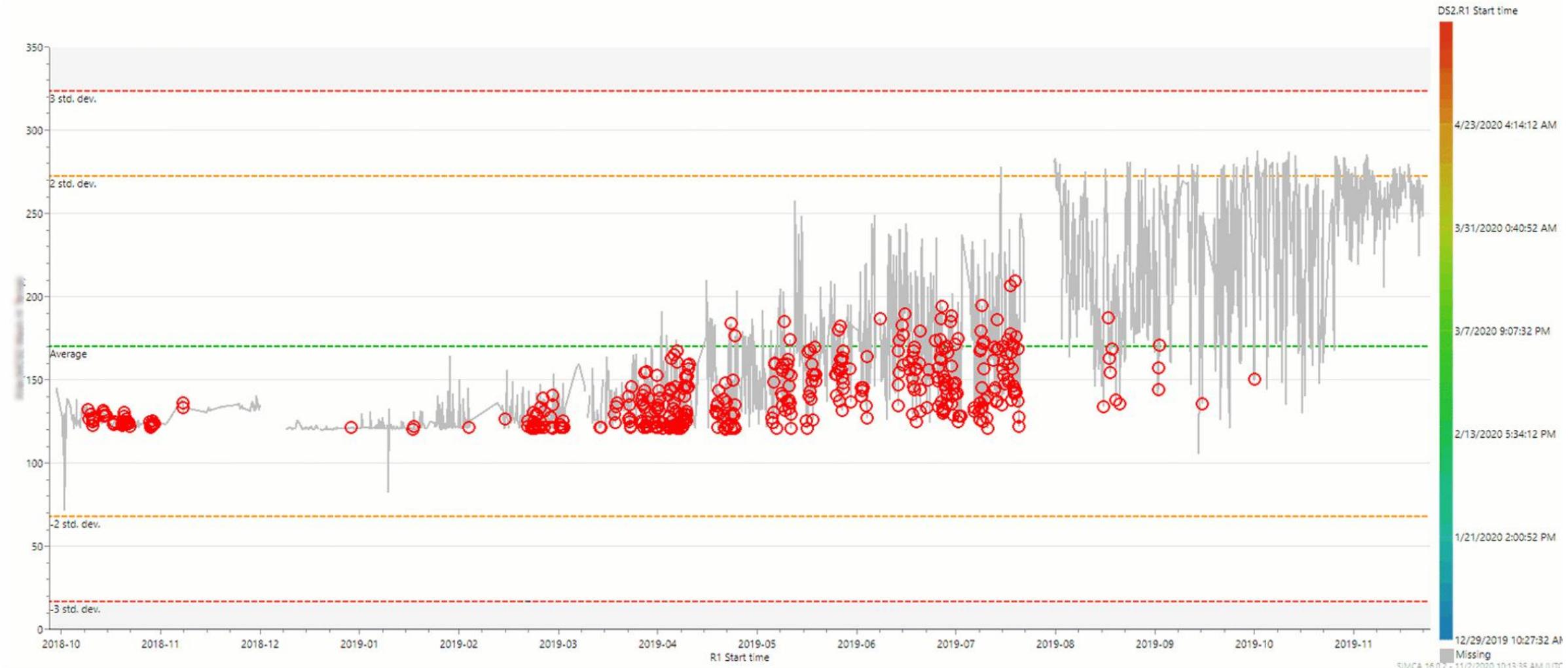
Create from marked items Drill down Modify model

Format symbol Format label

Project Window - M20 (PLS) - Up to Dec '19

Number	Model	Type	A	N	R2X(cum)	R2Y(cum)	Q2(cum)	Date	Title	Hierarchical
17	M17	PLS	5	641	0.294	0.302	0.254	4/30/2020		
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19	M19	PLS	10	639	0.537	0.306	0.251	4/30/2020		
20	M20	PLS	6	7230	0.337	0.389	0.385	6/16/2020	Up to Dec '19	

Scatter Plot [M19] Score Scatter Plot [M19] Contribution Plot [M20] Observed vs. Predicted [M20] Contribution Plot [M20] XVar Plot [M20] Contribution Plot [M20] XVar Plot [M20] Contribution Plot [M20] XVar Plot [M20] x



Reason #4



**Your Insights
never convert
to Action**

Data

Insights

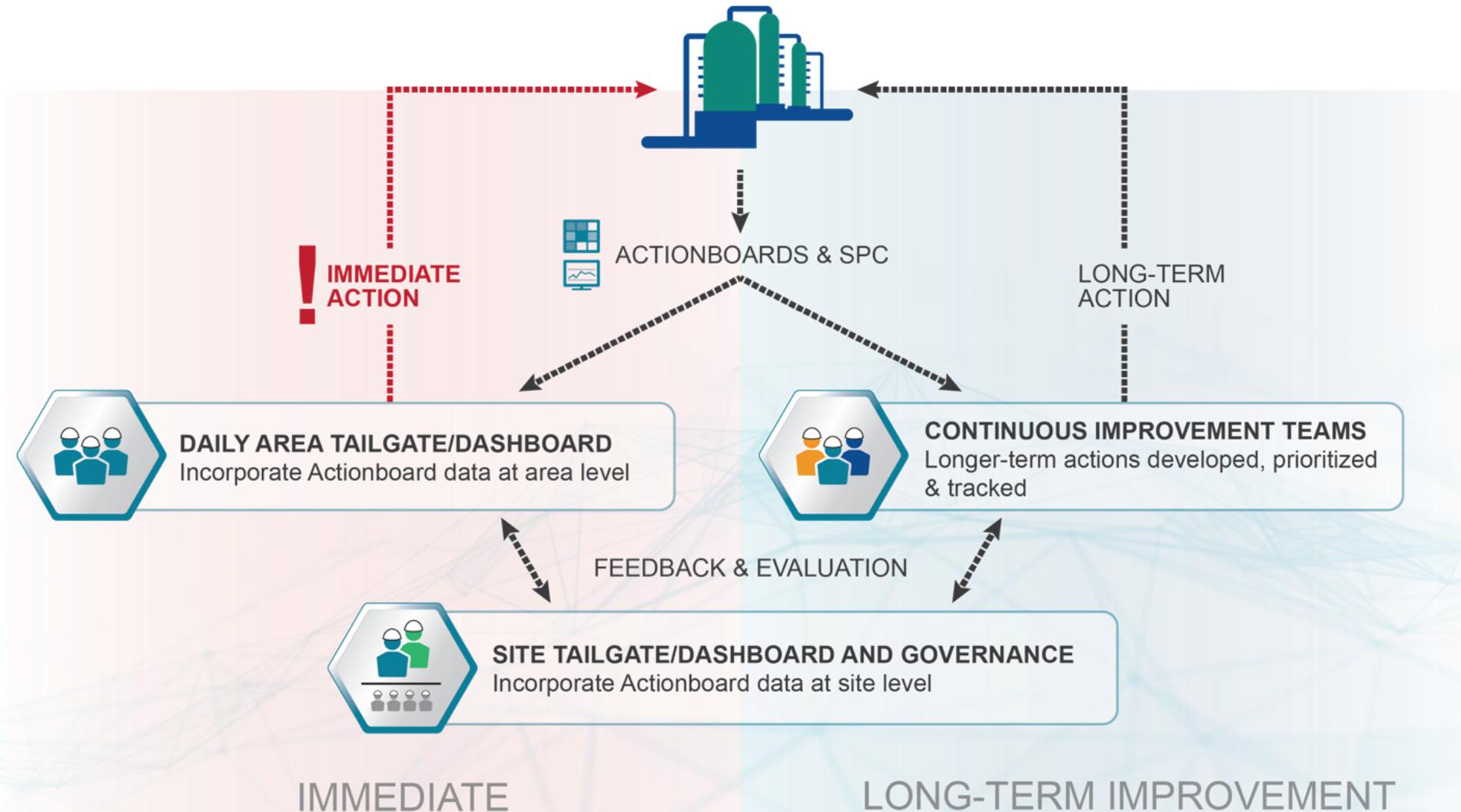


**I GOT A FEVER, AND THE ONLY
PRESCRIPTION IS**

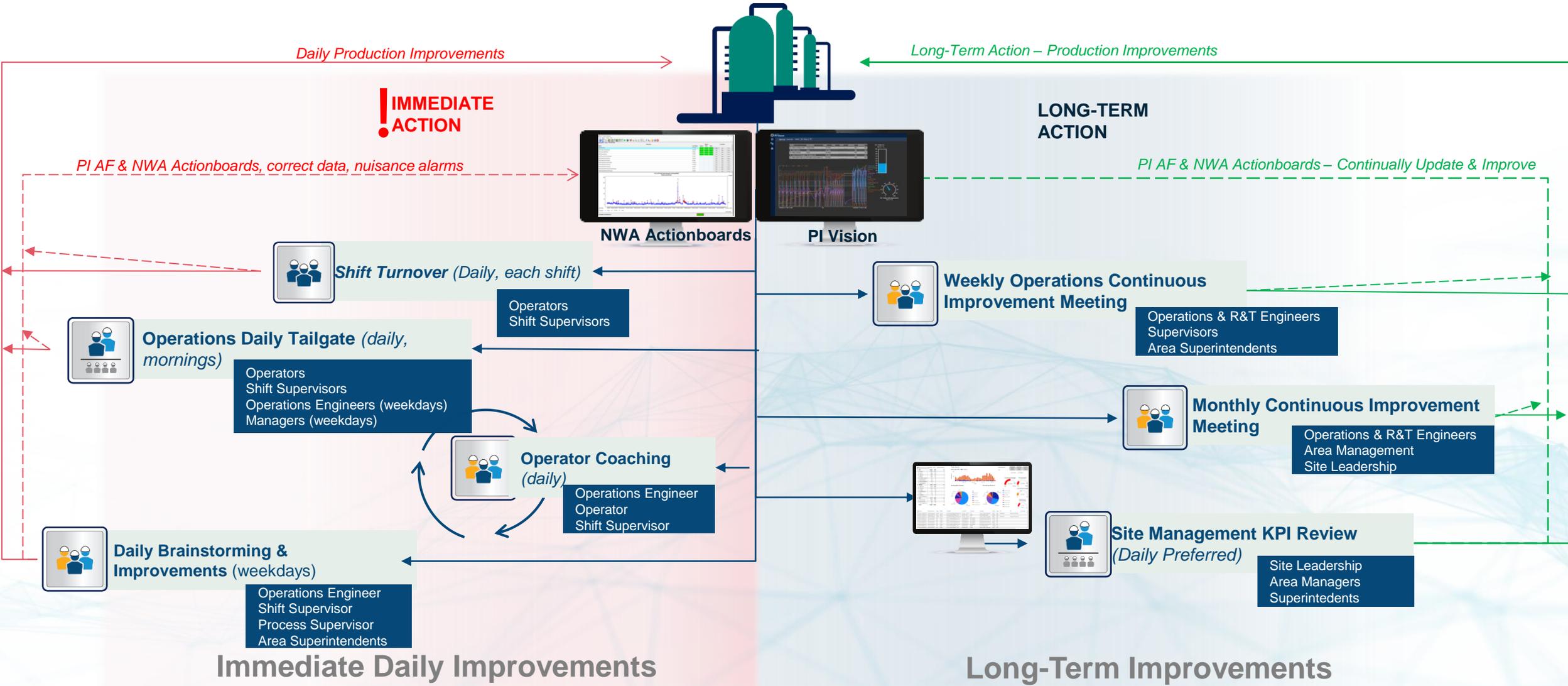


MORE DASHBOARD!

AI-Powered Continuous Improvement



Actionboard Standard Work – Continuous Improvement

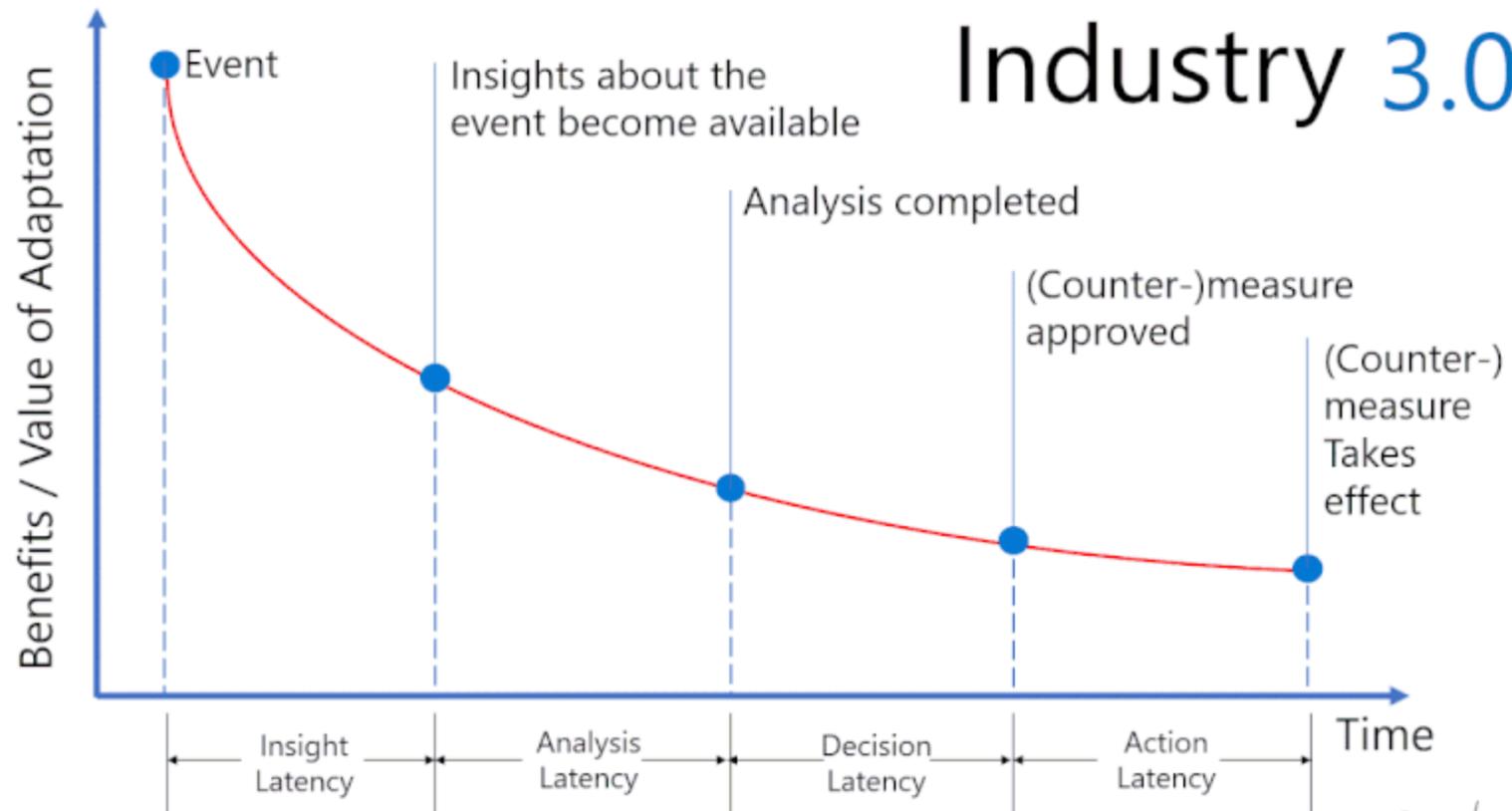


Reason #5

A man in a dark suit and red tie stands in a museum-like setting, looking at a large, glowing orange diamond on a pedestal. The diamond is the largest and brightest, with rays of light emanating from it. Several other smaller, glowing orange diamonds are on pedestals in the background. The scene is lit with dramatic, warm light, and the floor is highly reflective. The text "Shiny Object Syndrome" is overlaid in large, bold, dark blue letters.

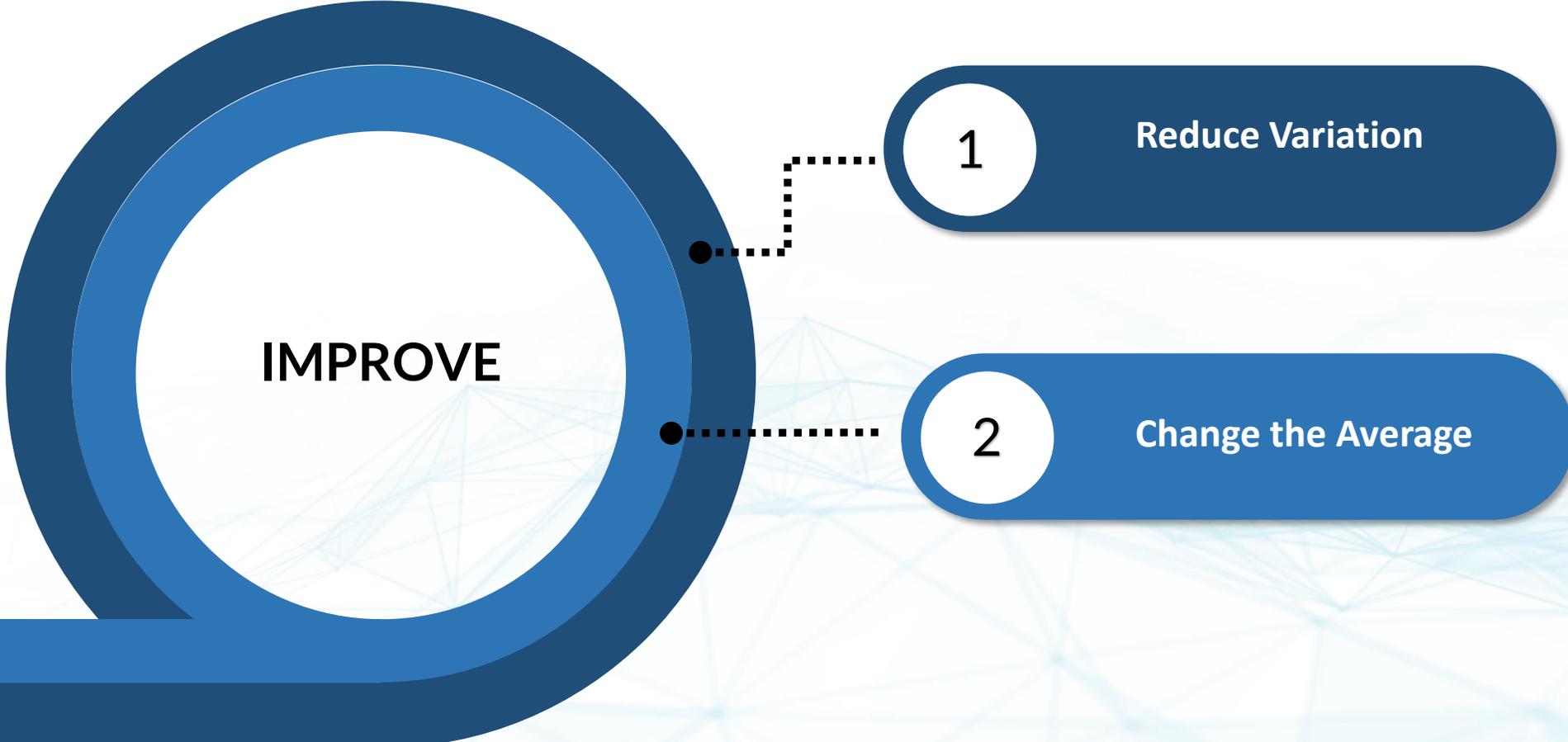
Shiny Object Syndrome

Industry 3.0



Source: Acatech's Industrie 4.0 Maturity Index

Jeff Winter



IMPROVE

1

Reduce Variation

2

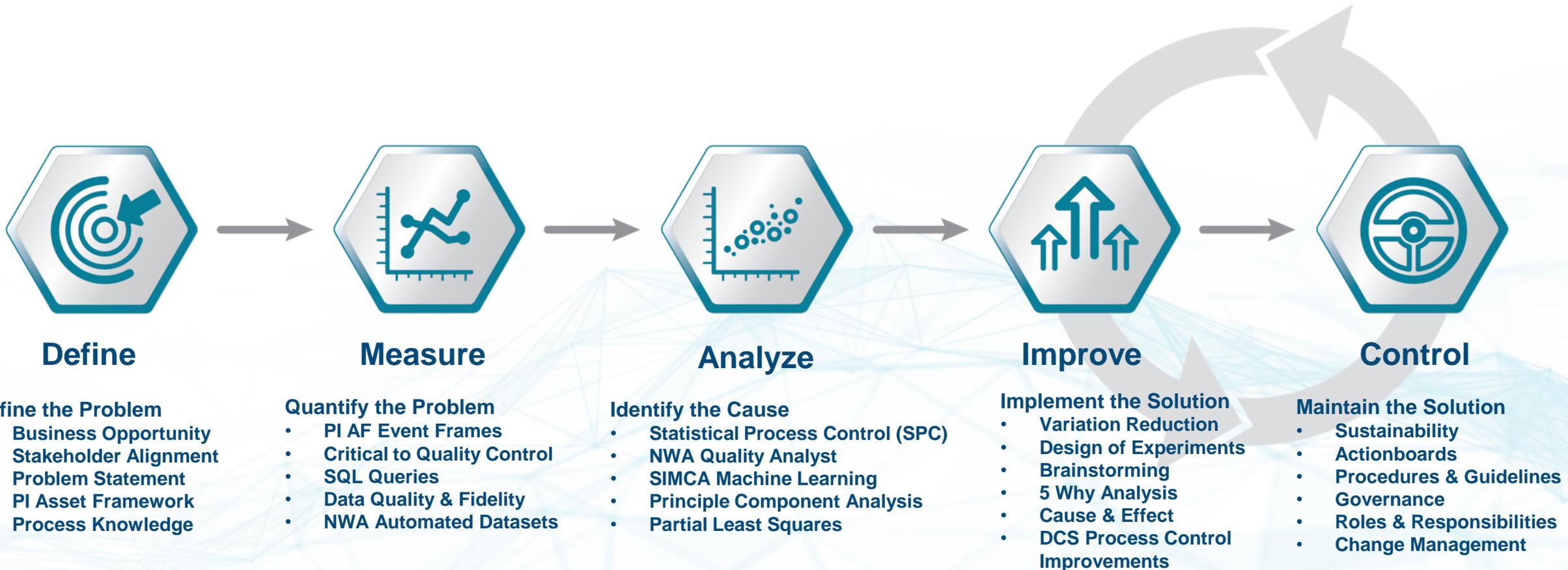
Change the Average

Agile Continuous Improvement

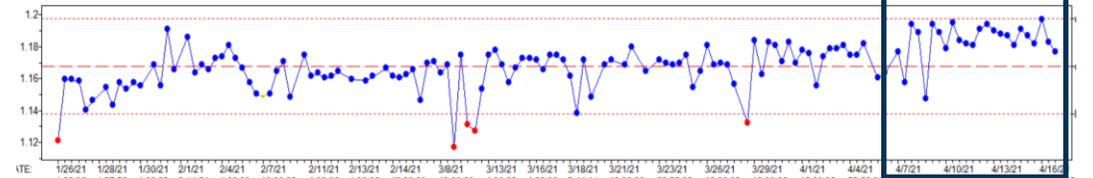
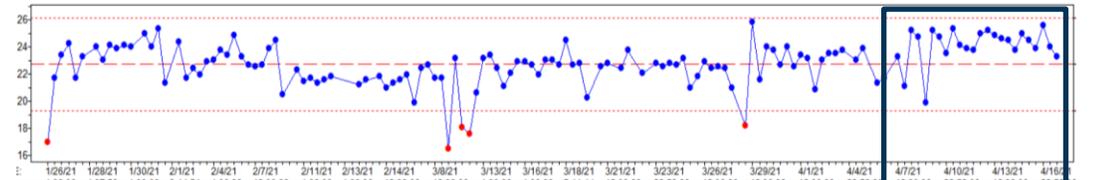
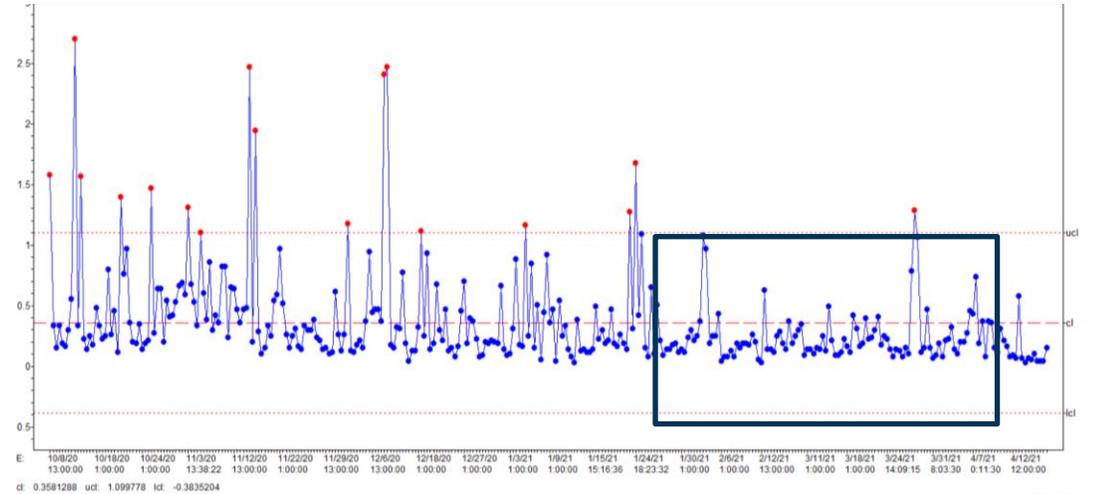
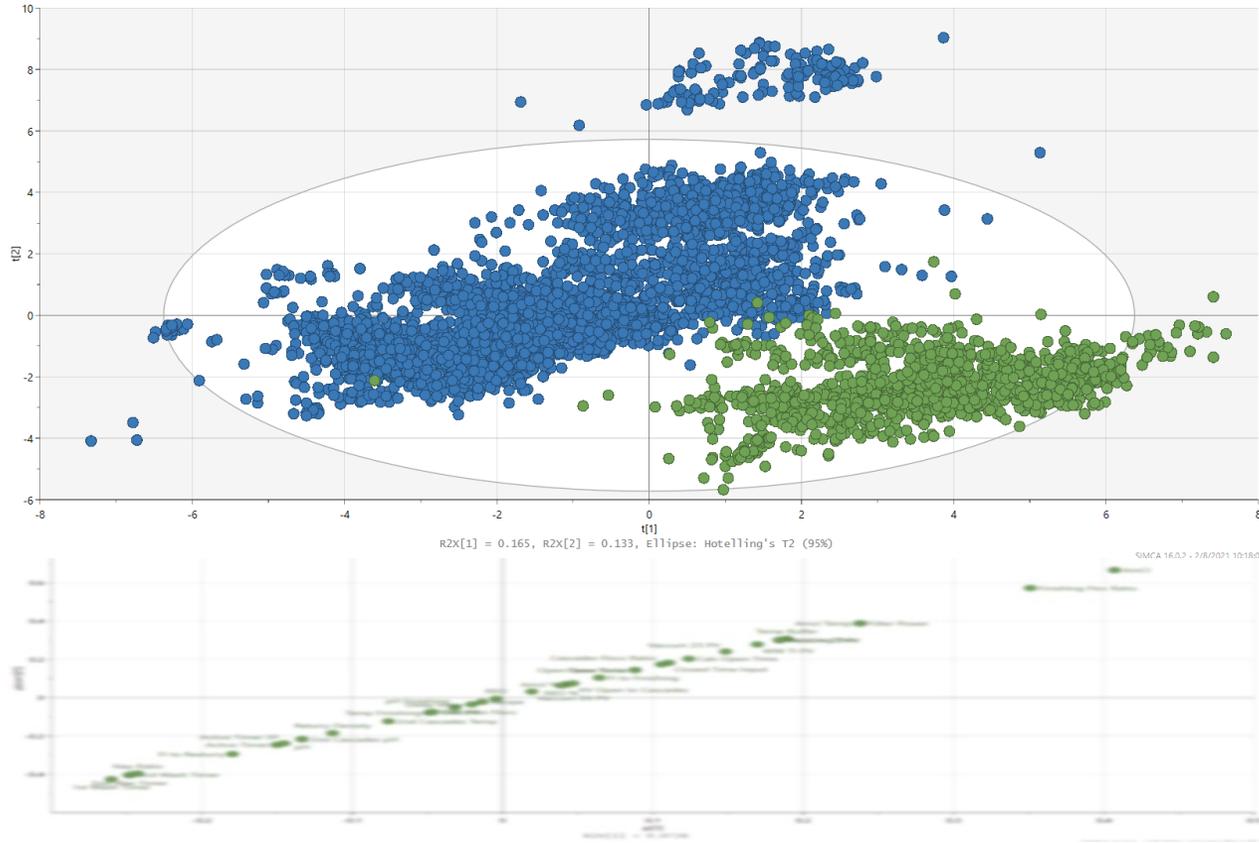




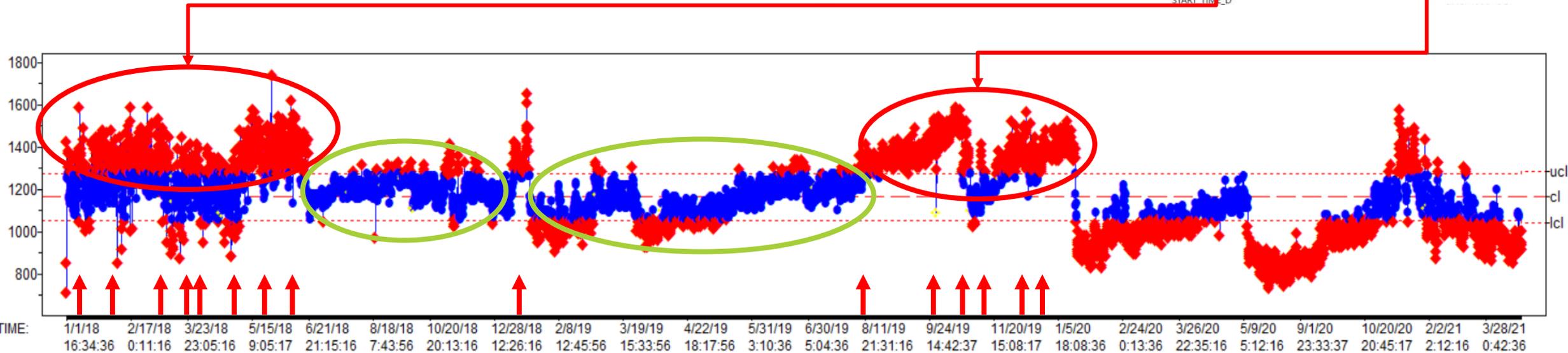
AI ALBEMARLE INTELLIGENCE



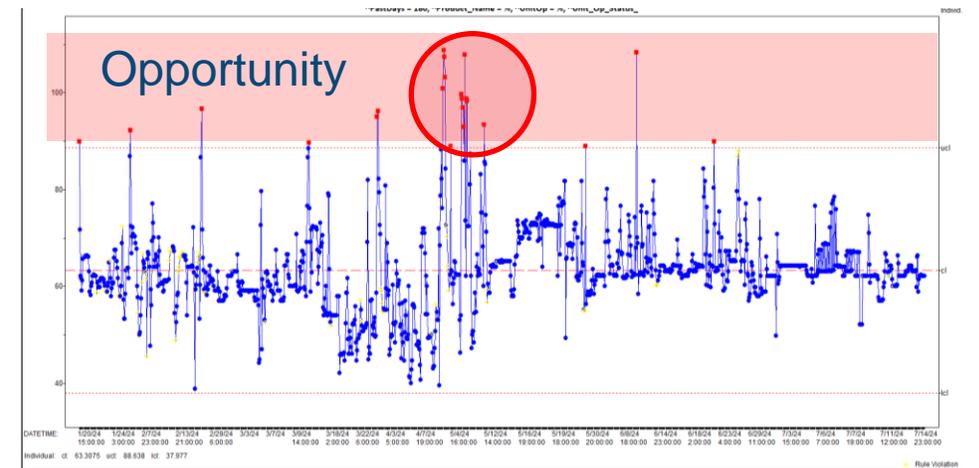
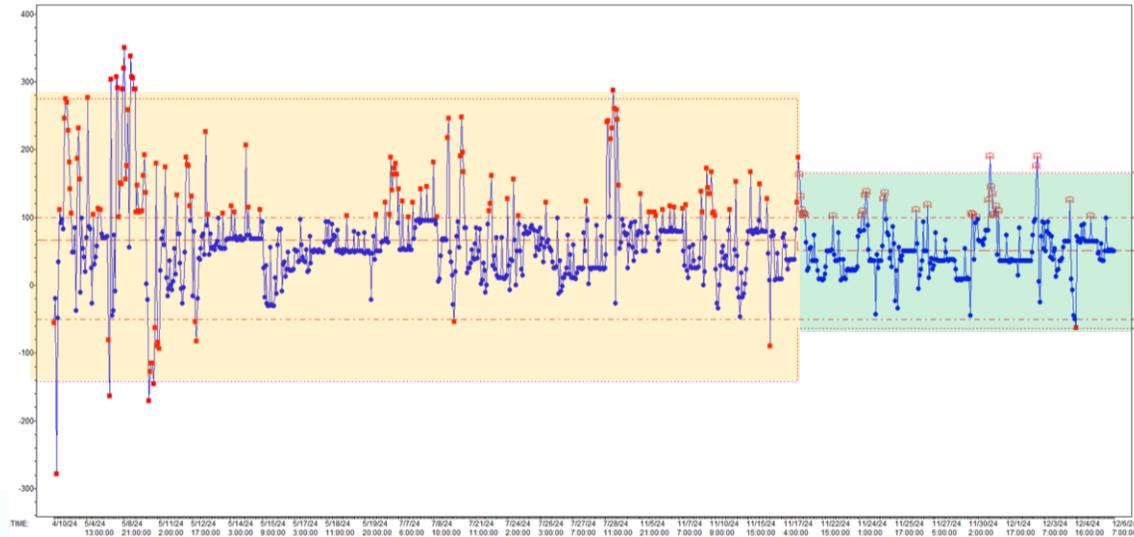
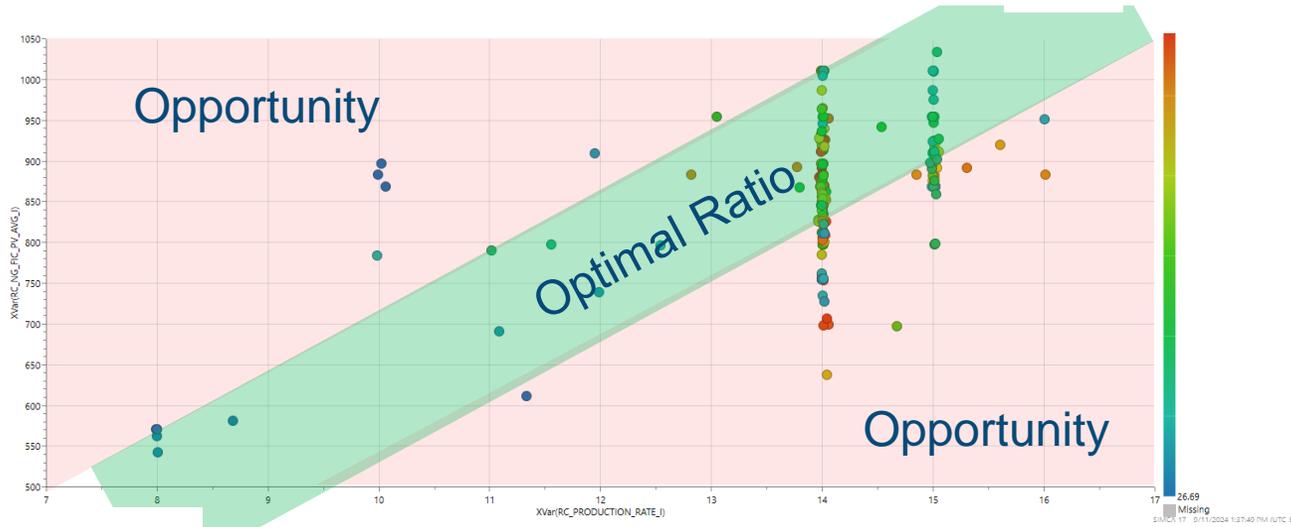
Albemarle Intelligence – Engineer Improvement Project



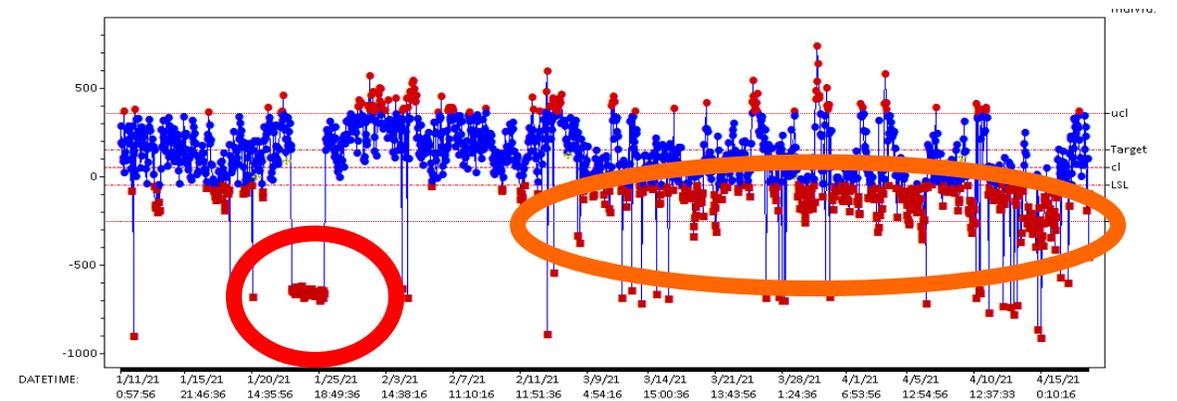
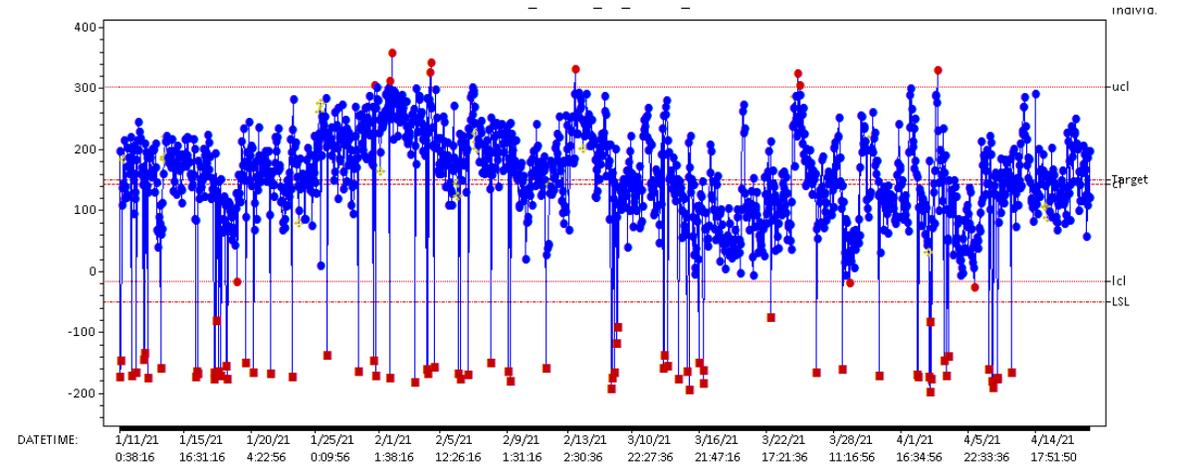
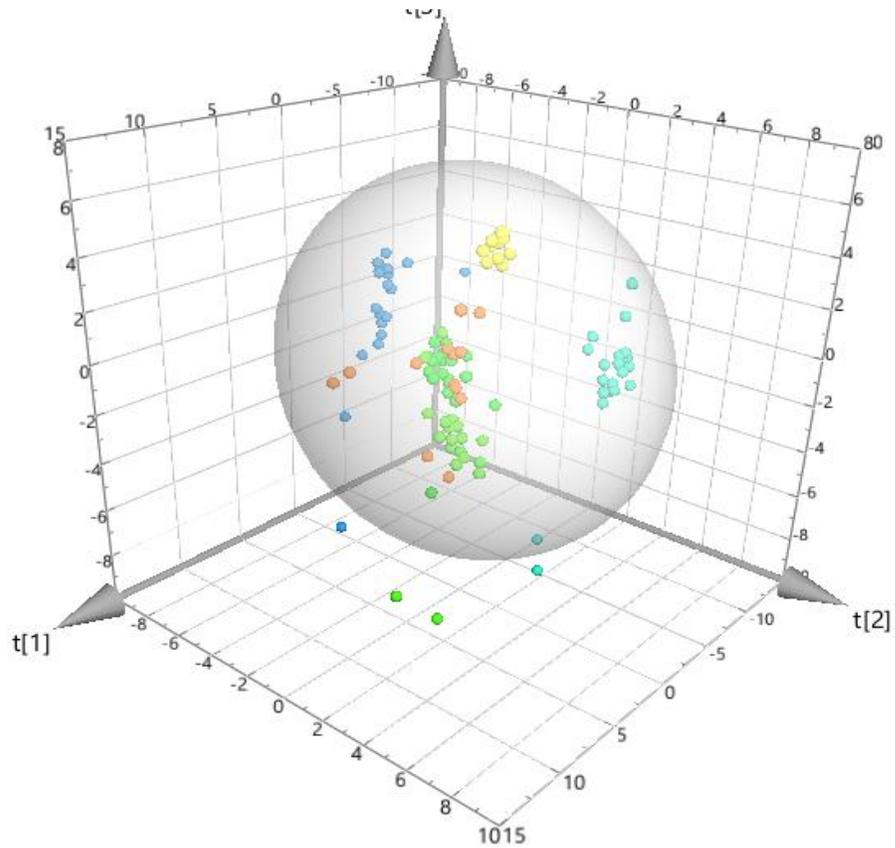
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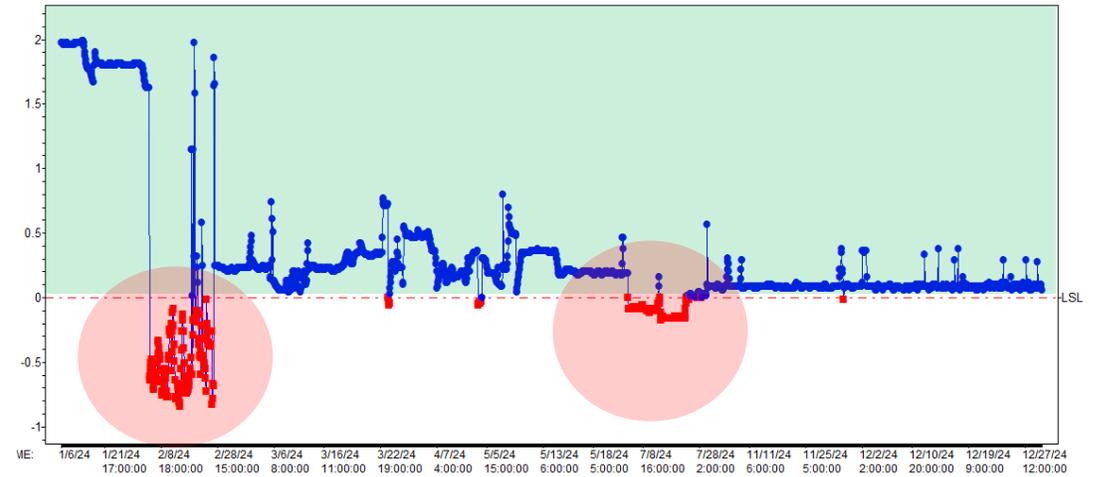
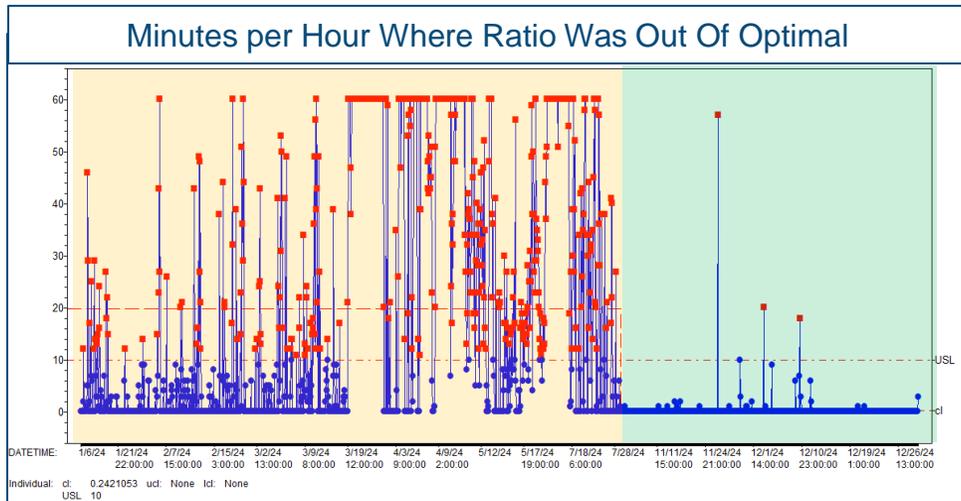
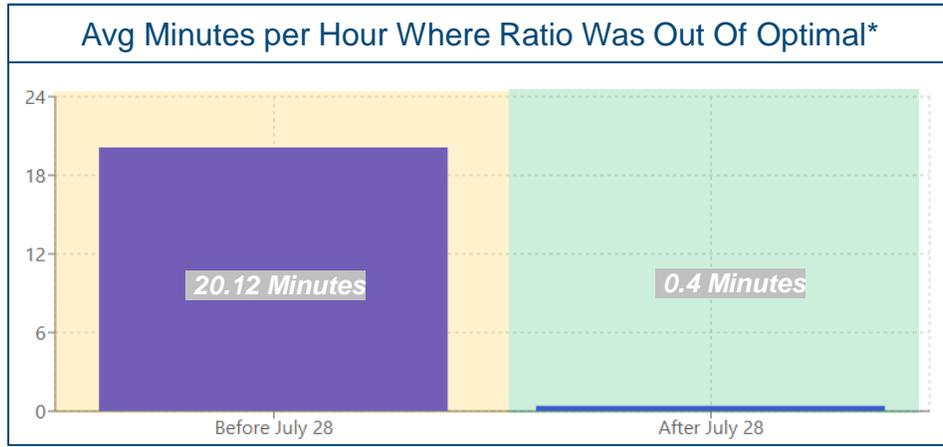
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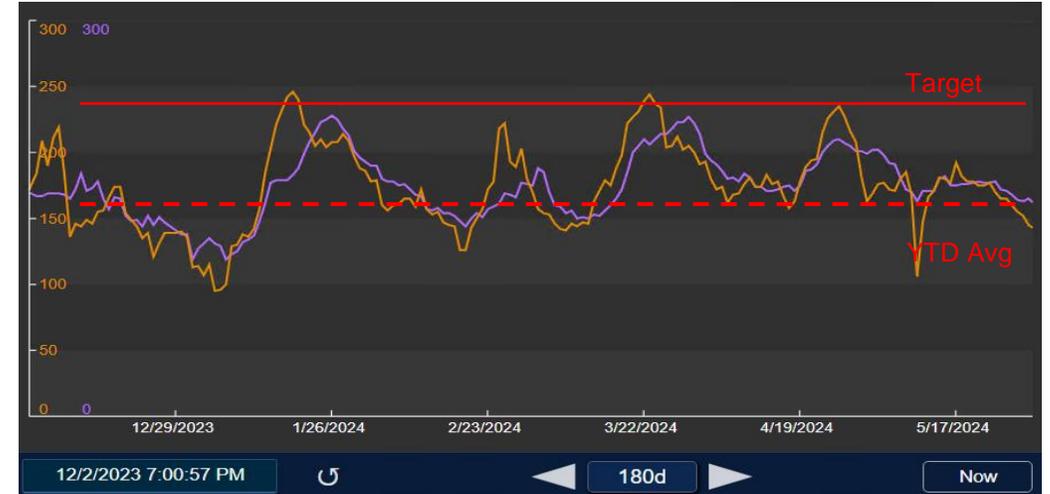
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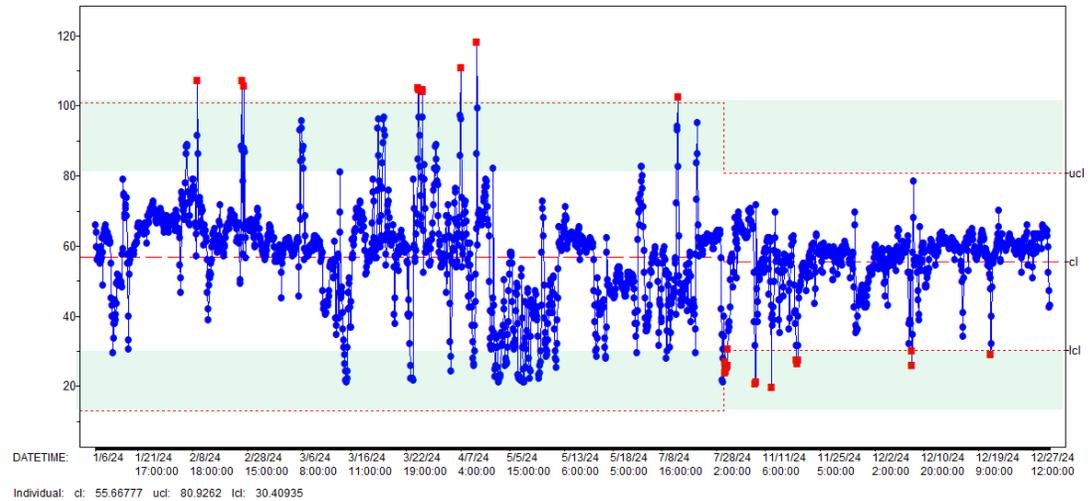
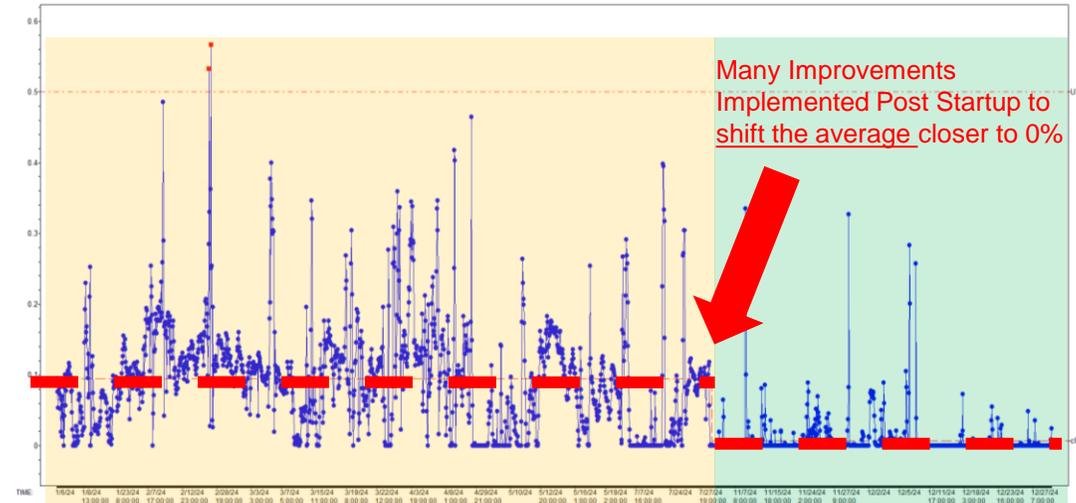
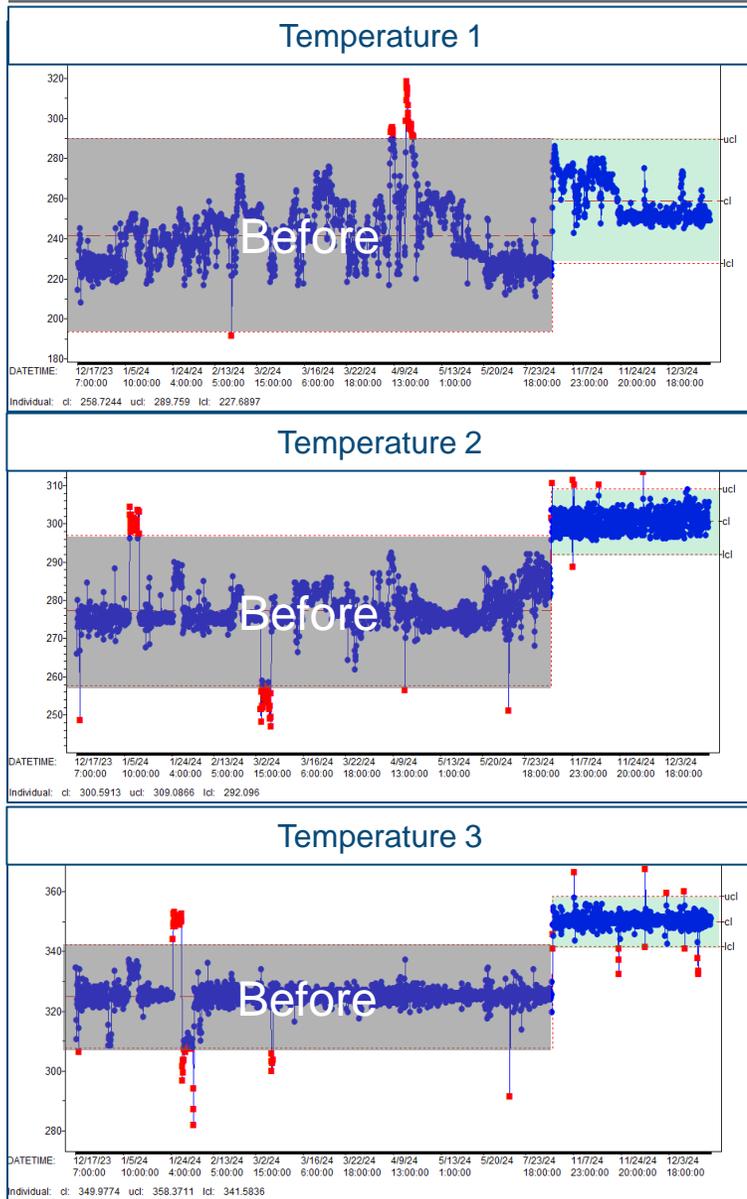
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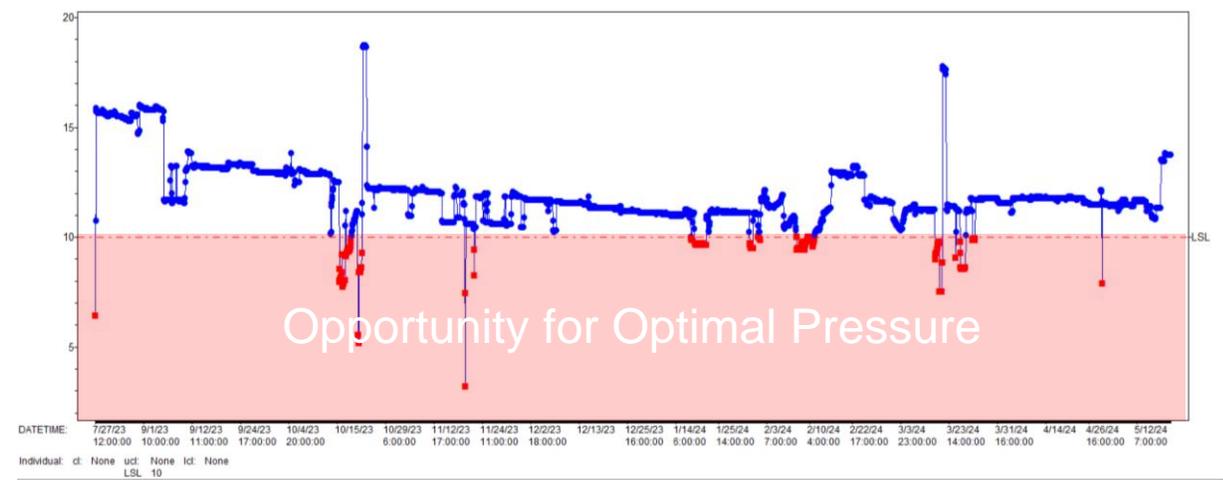
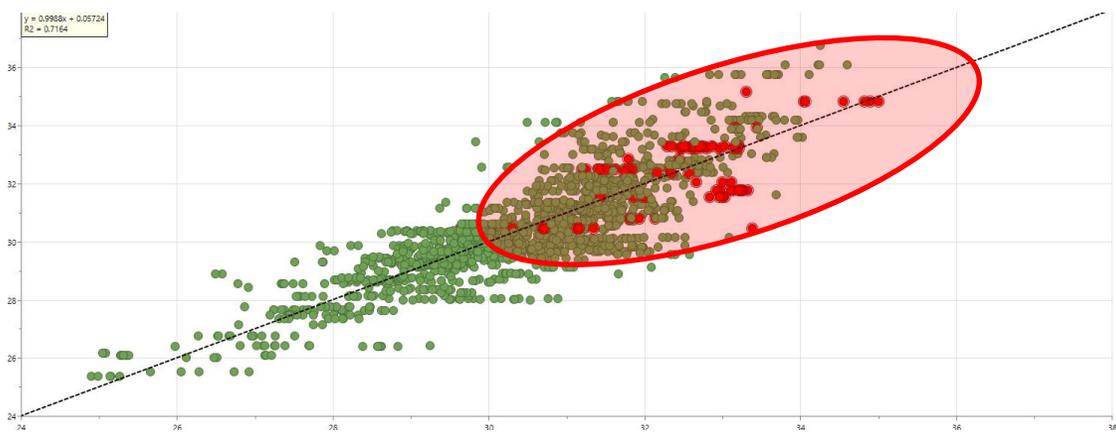
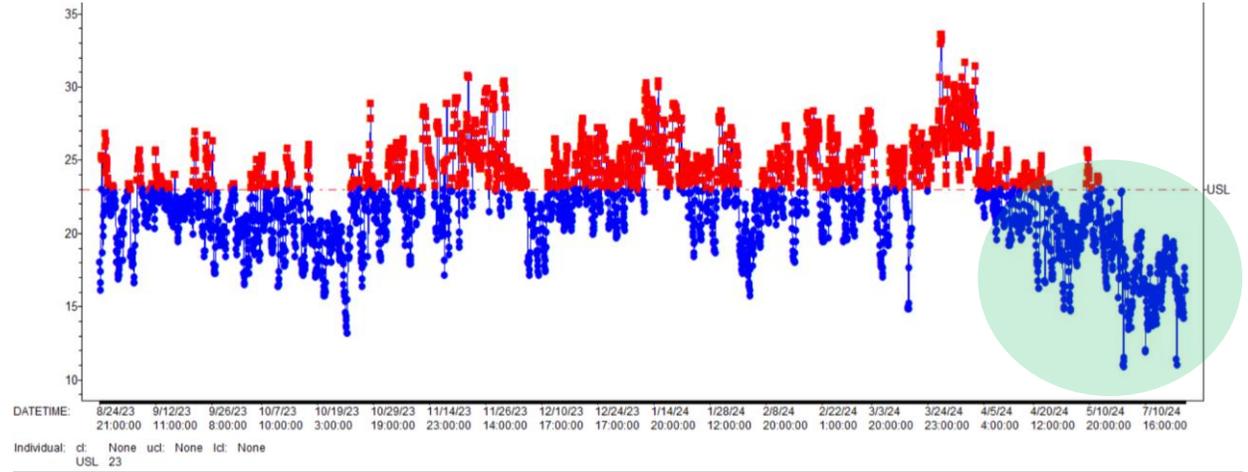
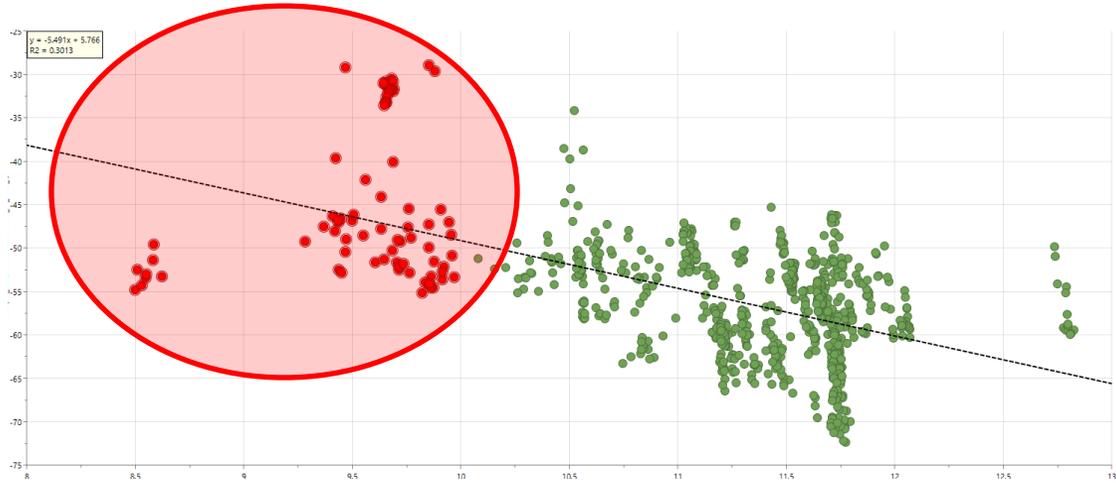
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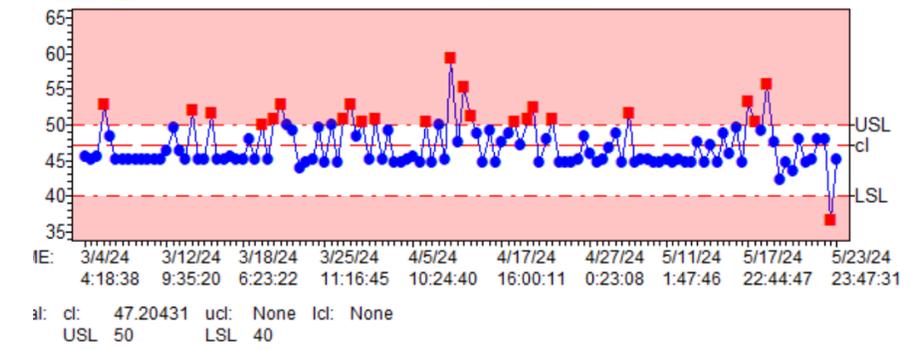
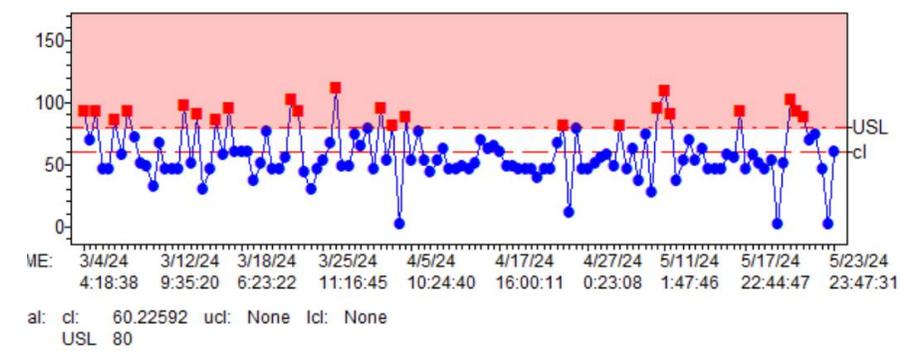
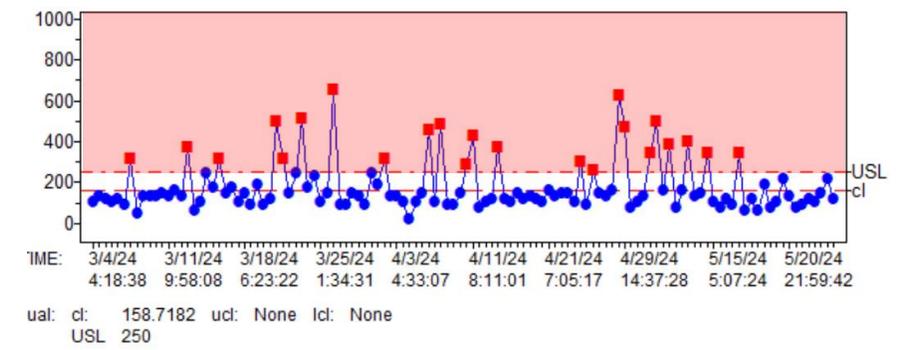
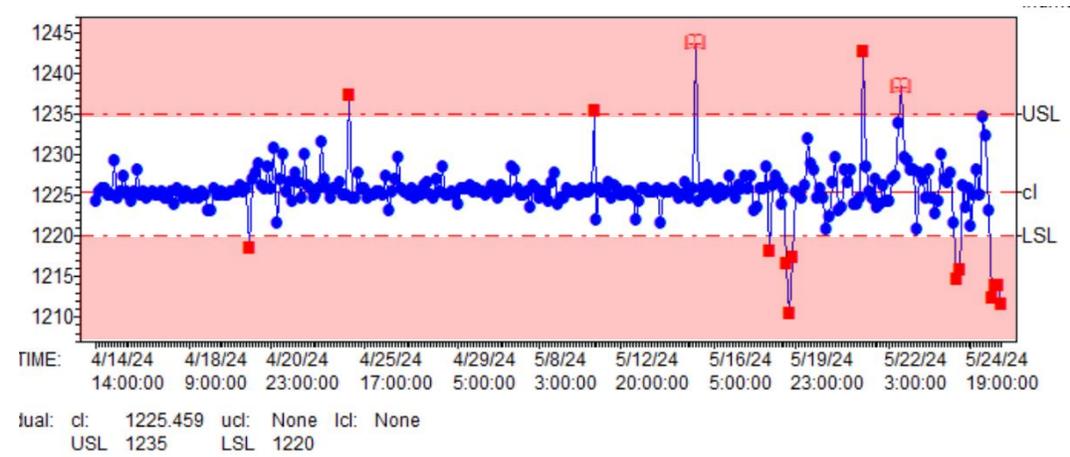
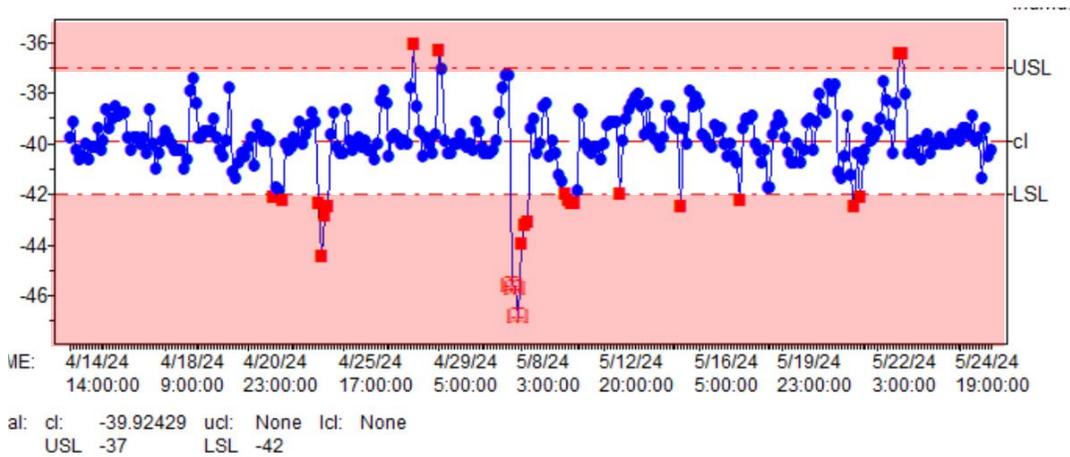
Albemarle Intelligence – Engineer Improvement Project



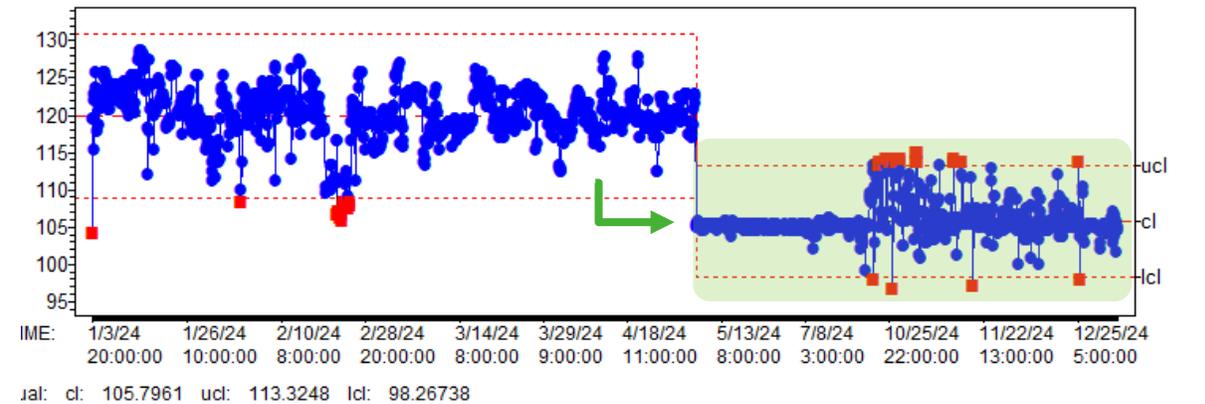
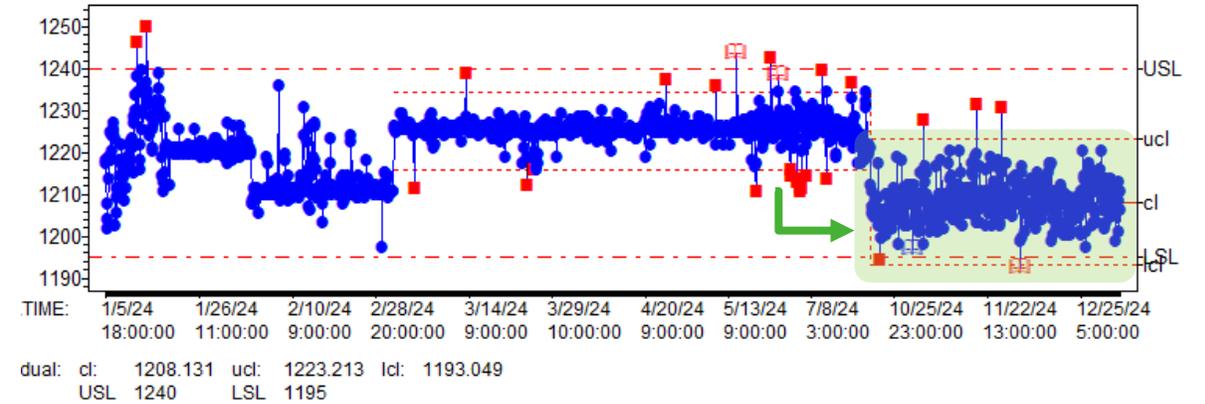
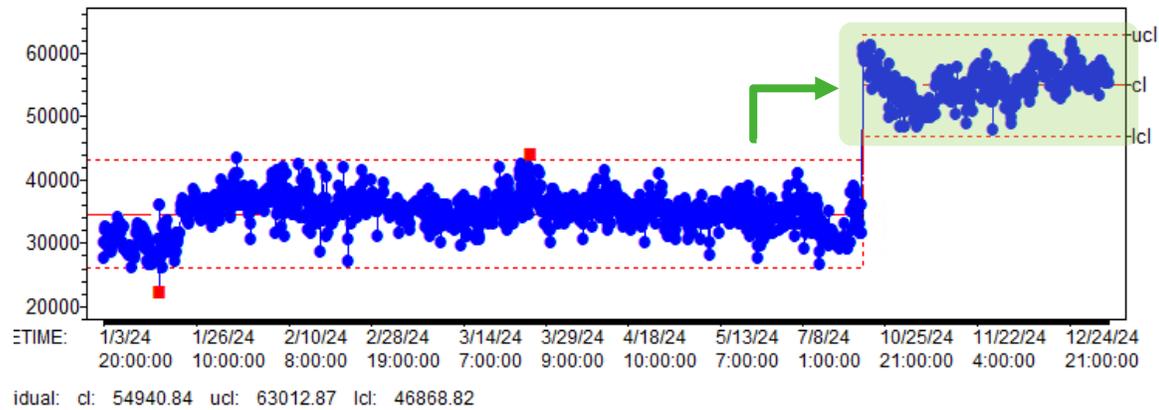
Albemarle Intelligence – Engineer Improvement Project



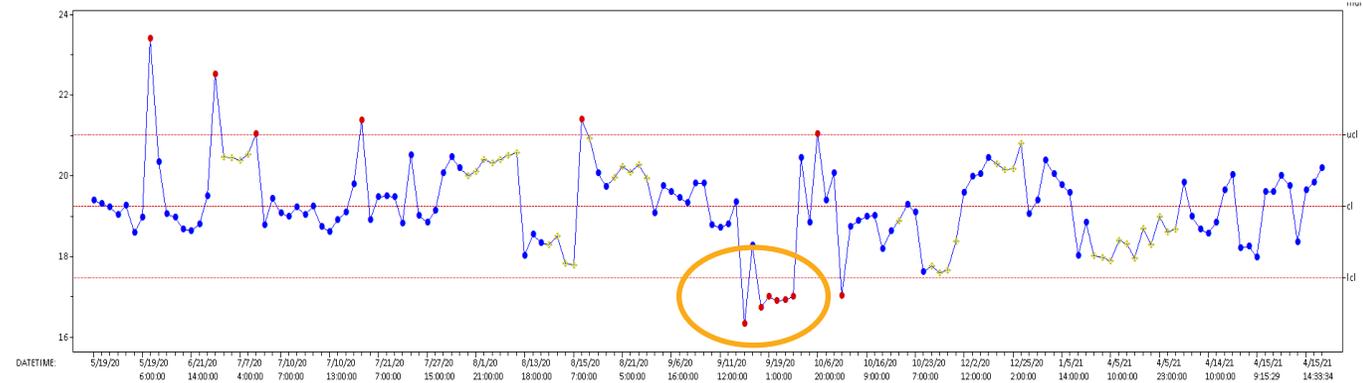
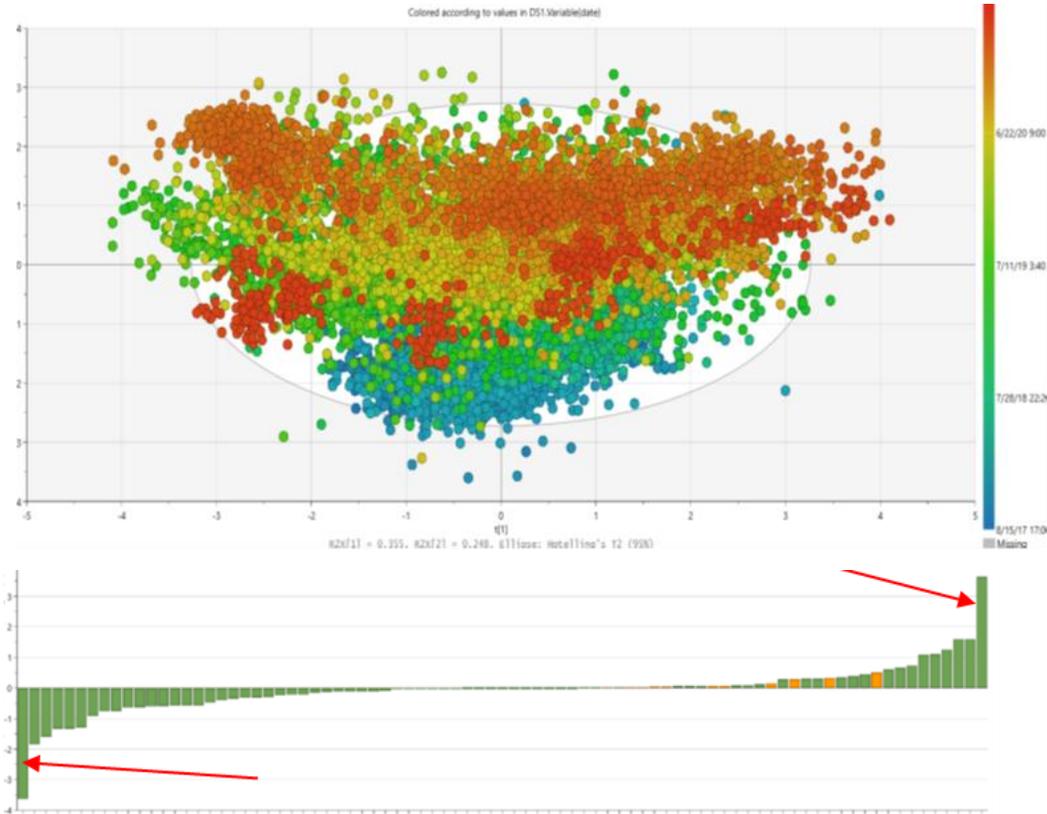
Albemarle Intelligence – Engineer Improvement Project



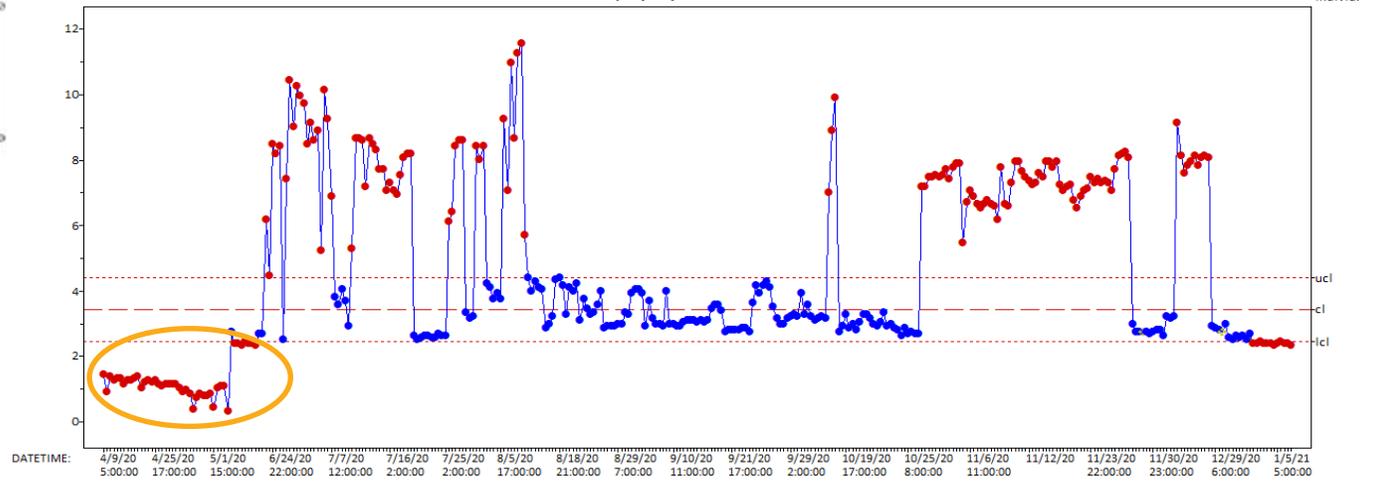
Albemarle Intelligence – Engineer Improvement Project



Albemarle Intelligence – Engineer Improvement Project



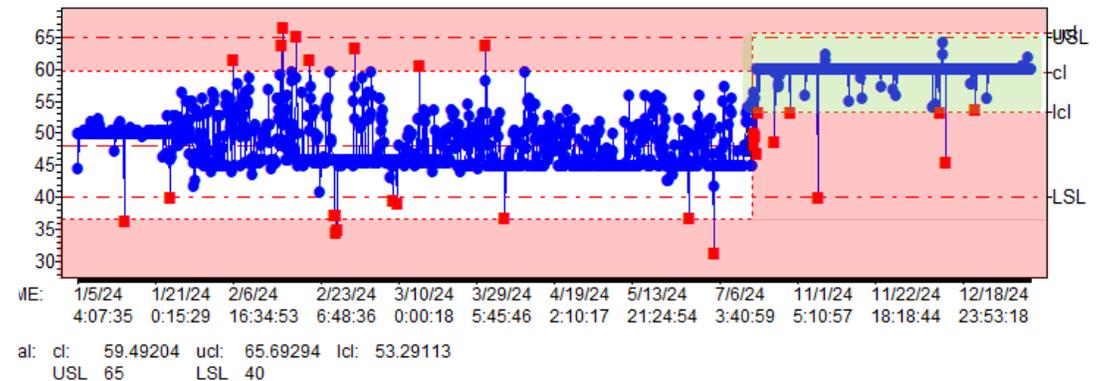
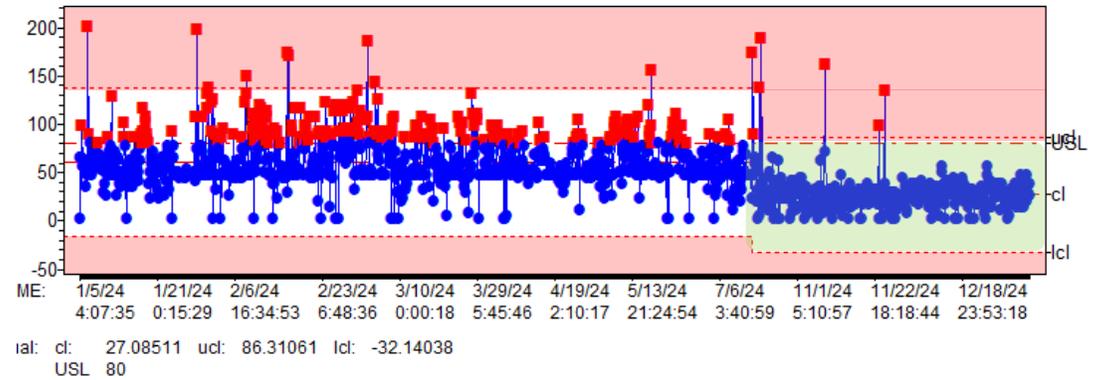
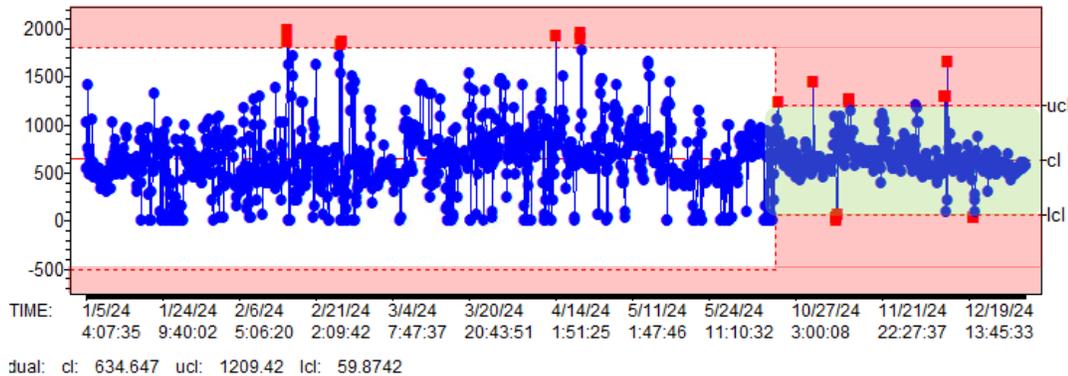
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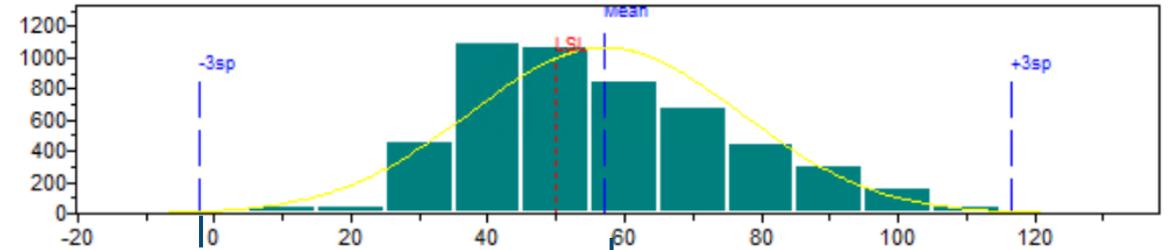
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◆ Rule Violation

Albemarle Intelligence – Engineer Improvement Project



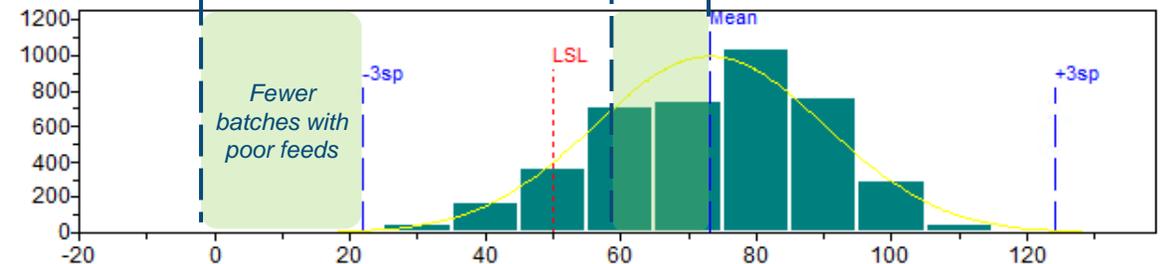
Albemarle Intelligence – Engineer Improvement Project



Samples: 5283 Cpk: 0.1196 3sp Lim: (-2.2475, 116.44)
 Mean: 57.09592
 Std Dev: 19.78115 Spec Lim: (50,)
 Skewness: 0.48873 Est % out: (35.9902,)

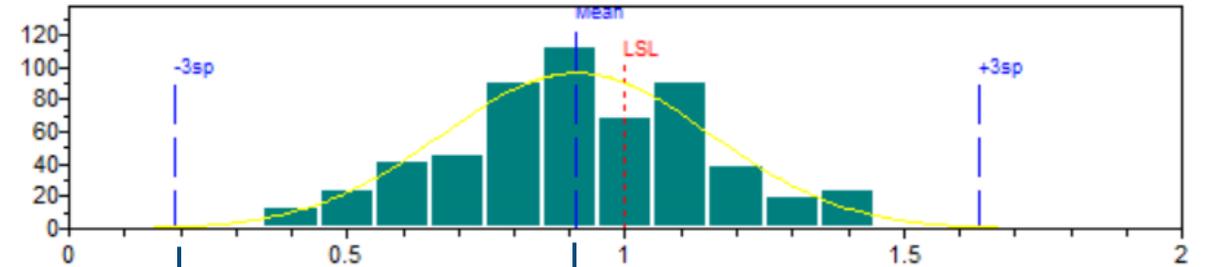
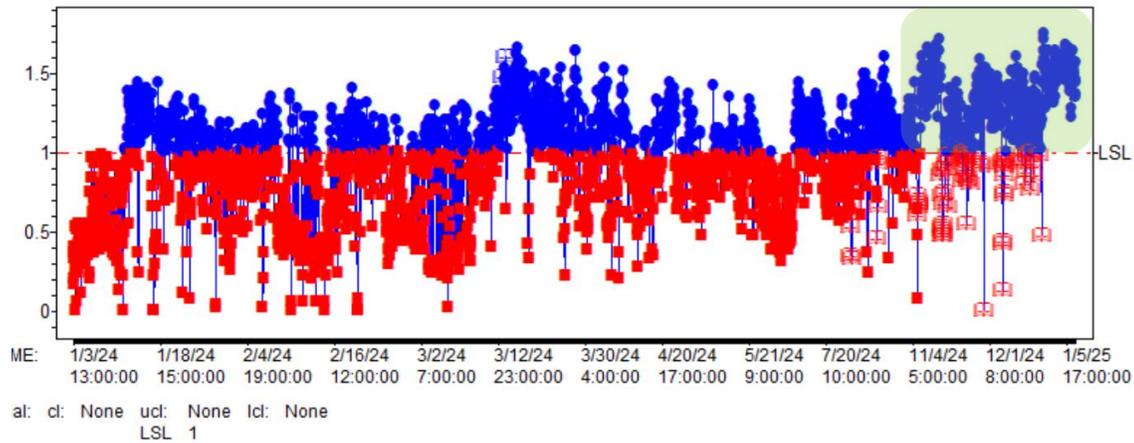
Reduced variation

Mean Shift



Samples: 4254 Cpk: 0.4525 3sp Lim: (22.022, 124.23)
 Mean: 73.12503
 Std Dev: 17.03418 Spec Lim: (50,)
 Skewness: -0.46521 Est % out: (8.7301,)

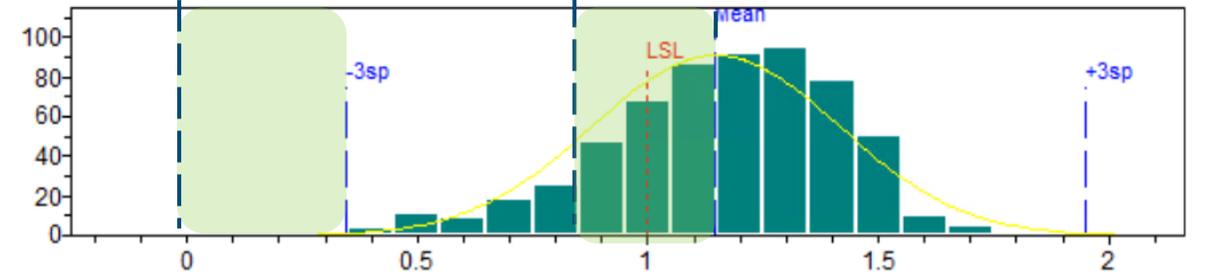
Albemarle Intelligence – Engineer Improvement Project



Samples: 504 Cpk: -0.1213 3sp Lim: (0.18877, 1.6357)
 Mean: 0.9122364 Spec Lim: (1,)
 Std Dev: 0.2411541 Est % out: (64.2045,)
 Skewness: -0.11896

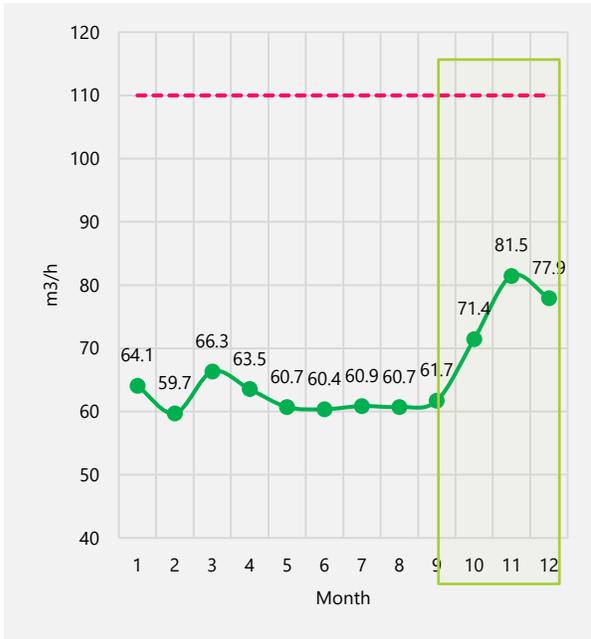
Reduced
 variation

Mean
 shift

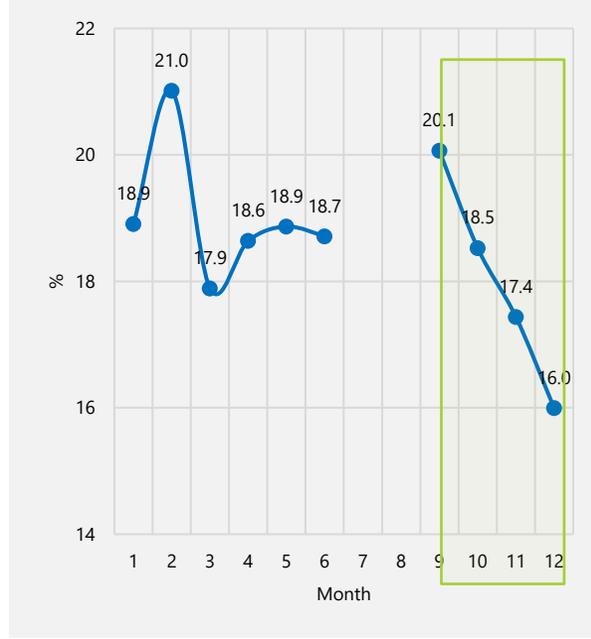


Samples: 610 Cpk: 0.1831 3sp Lim: (0.34445, 1.9494)
 Mean: 1.146945 Spec Lim: (1,)
 Std Dev: 0.2674977 Est % out: (29.1388,)
 Skewness: -0.85271

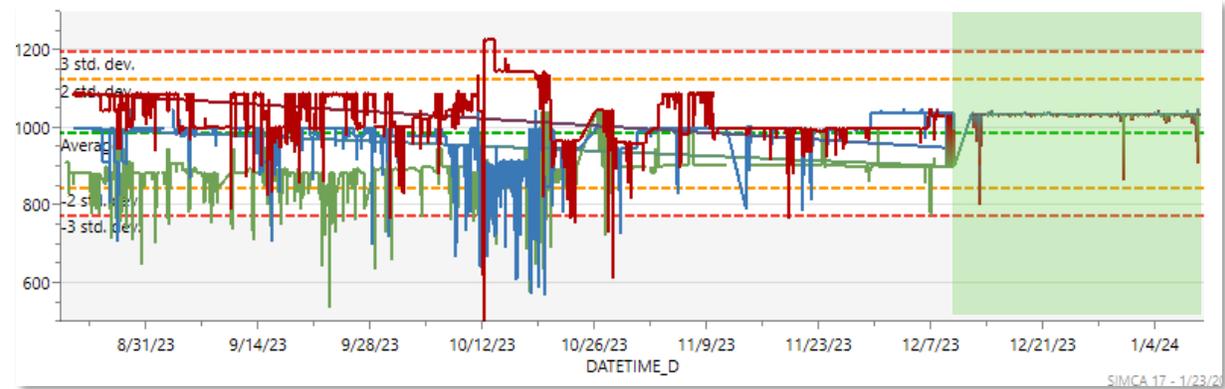
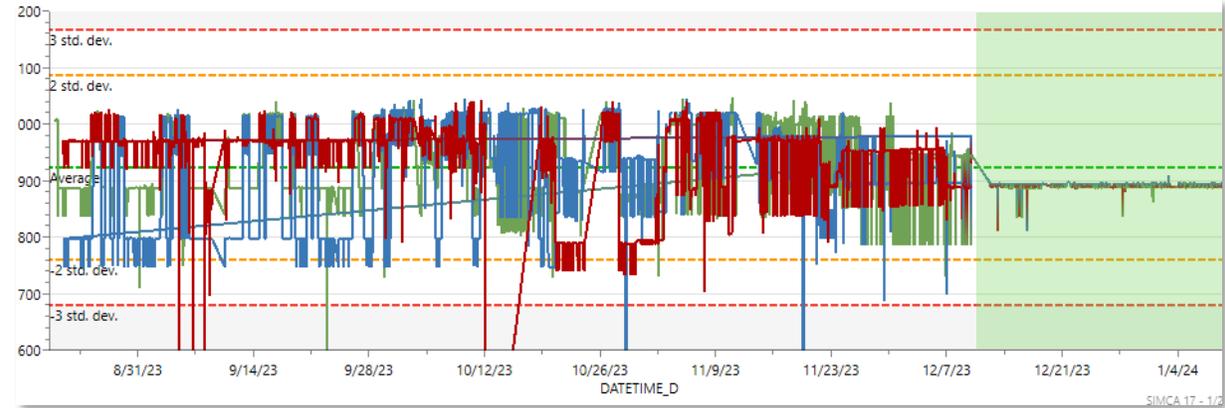
Albemarle Intelligence – Engineer Improvement Project



Increase in production rate



Quality Improvement



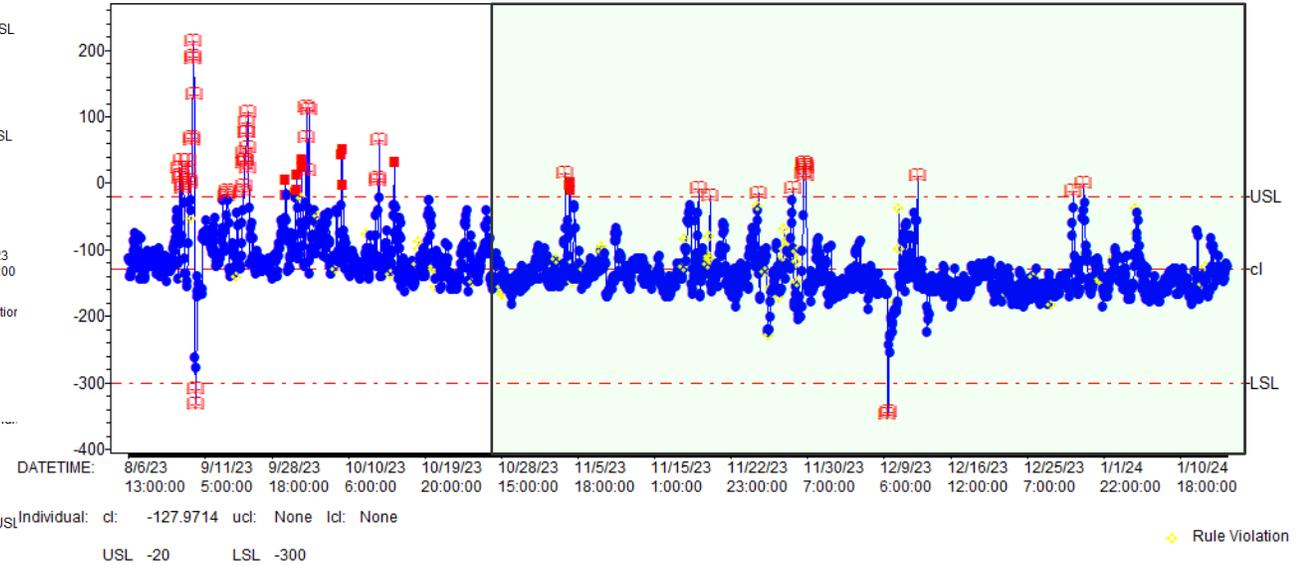
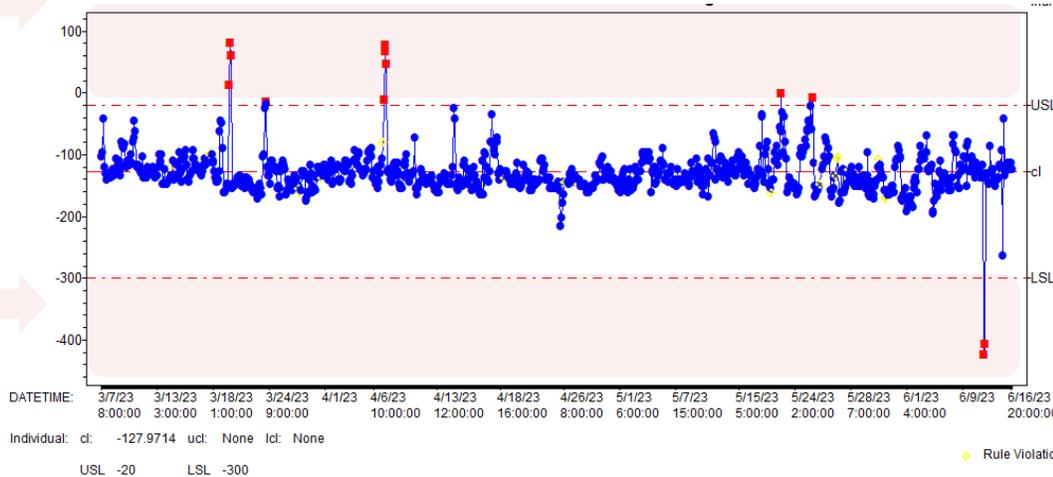
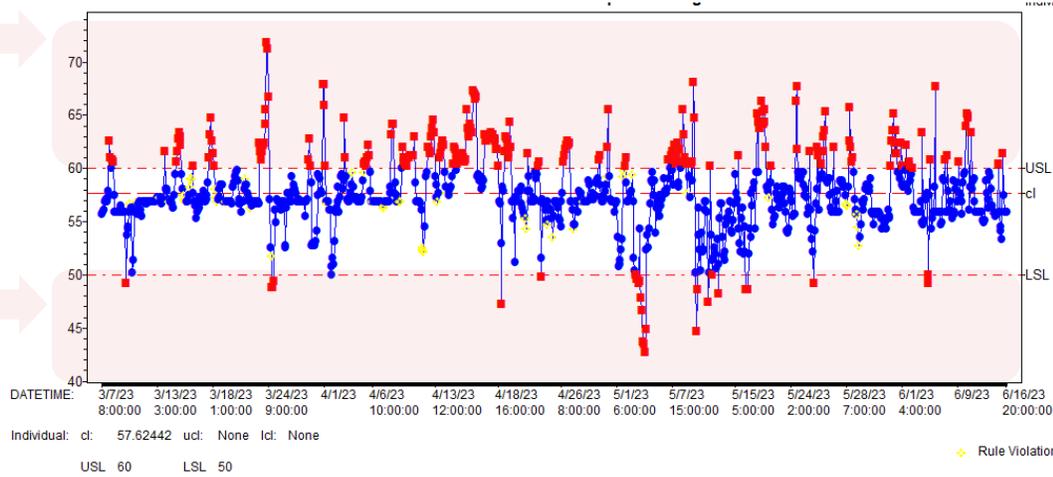
Albemarle Intelligence – Engineer Improvement Project



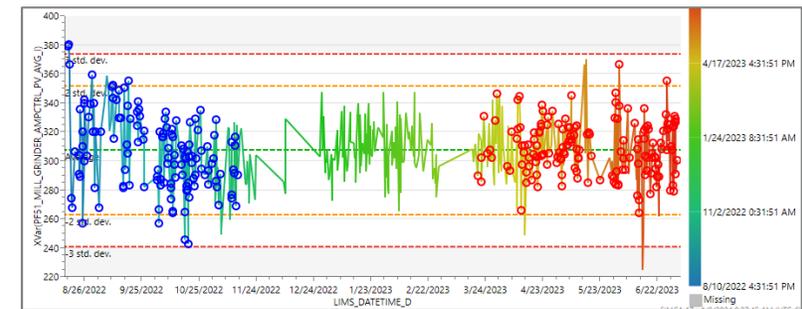
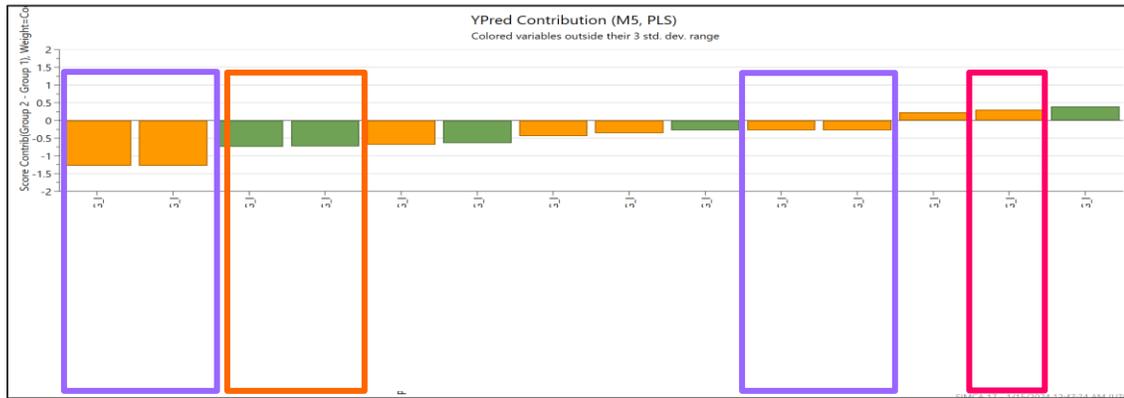
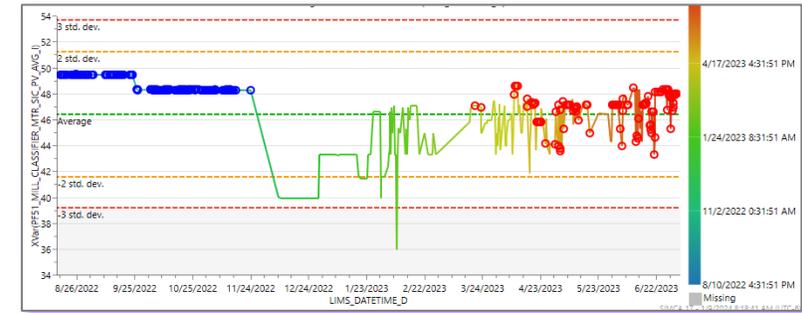
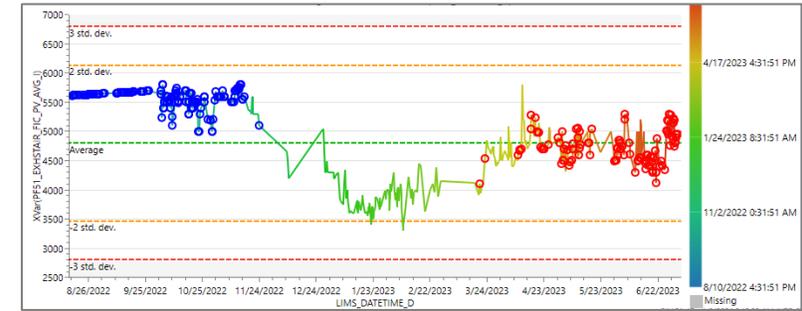
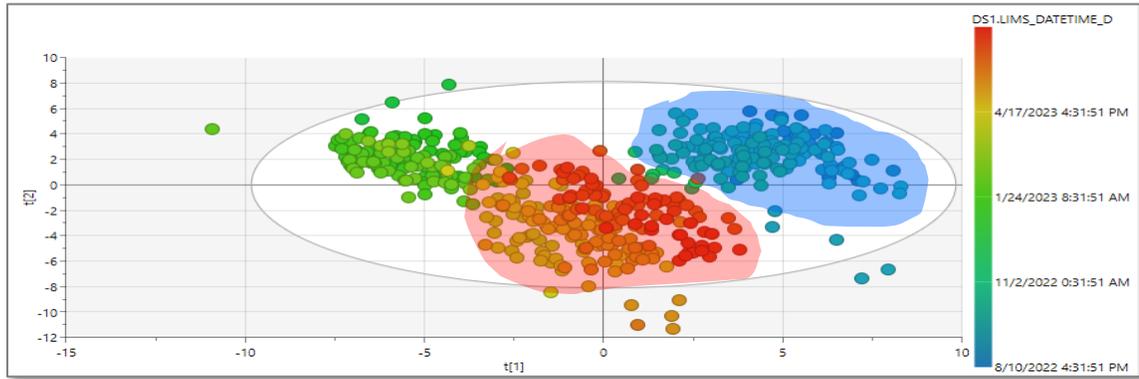
✓ Increase in the monthly production

Albemarle Intelligence – Engineer Improvement Project

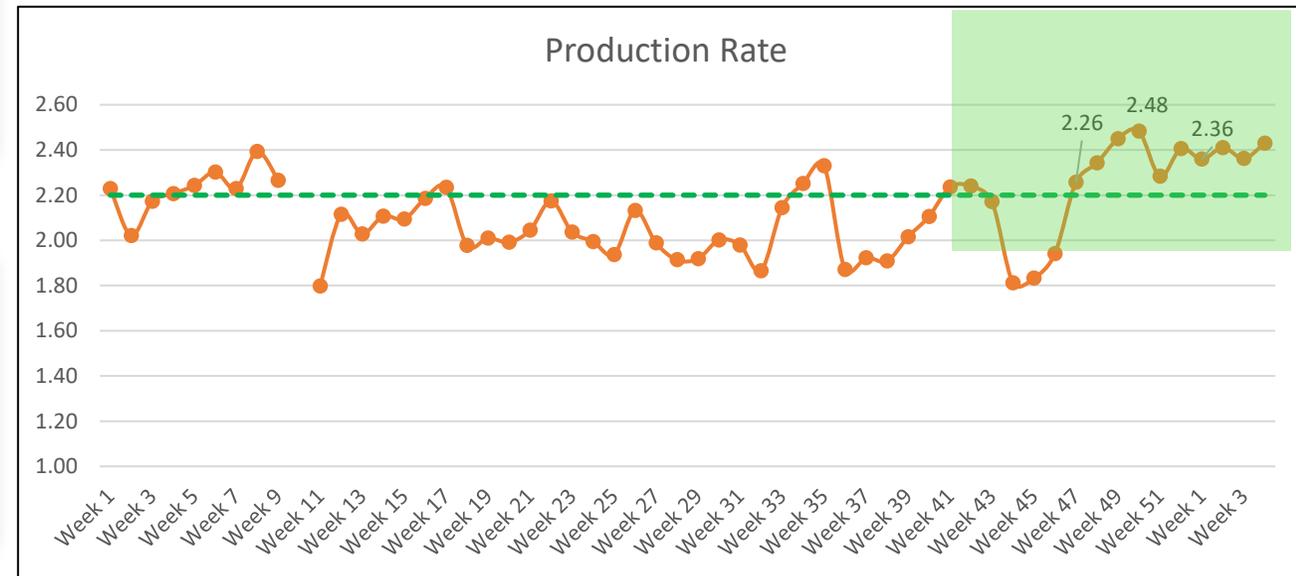
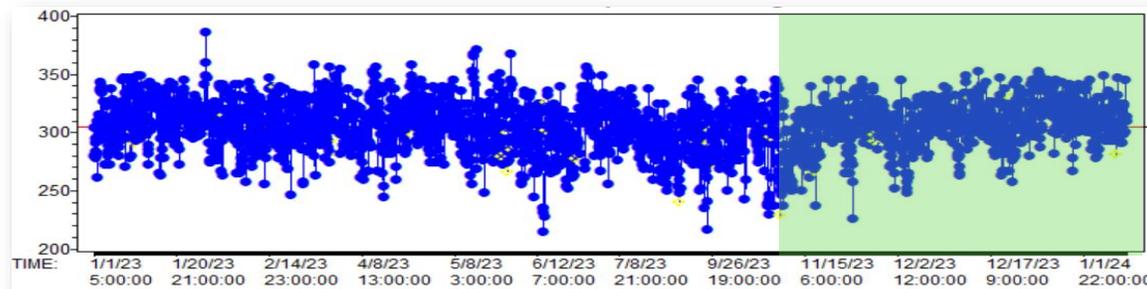
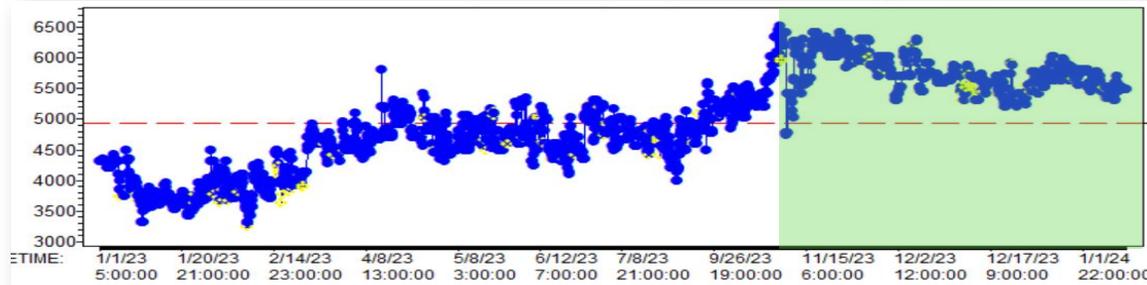
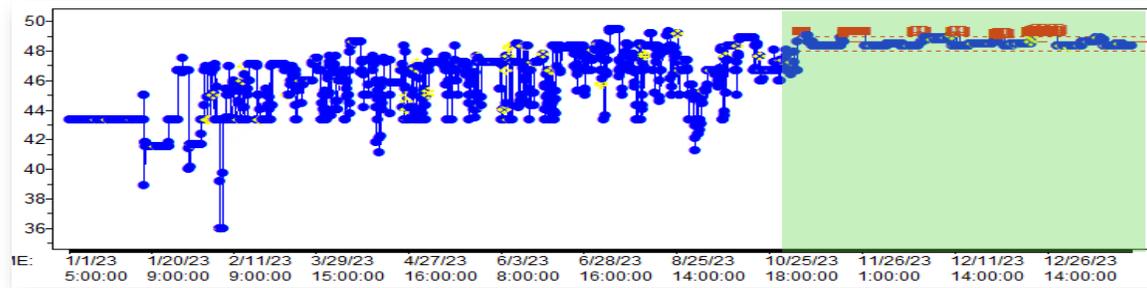
Opportunities



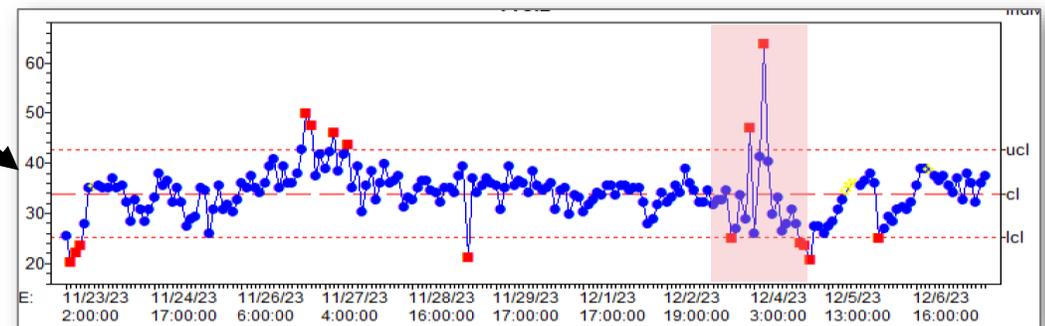
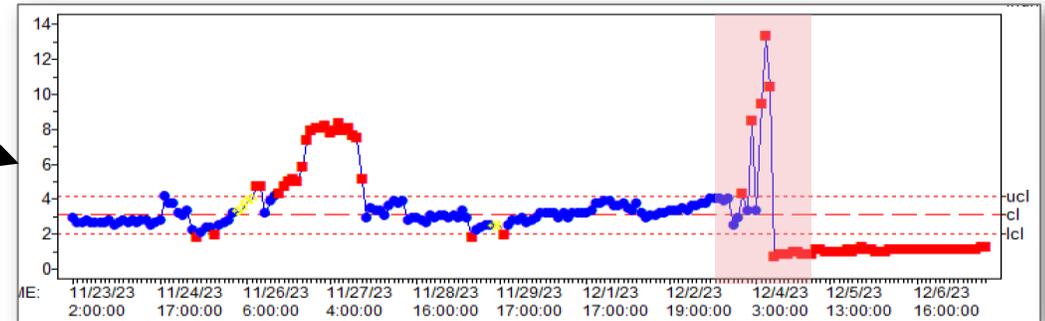
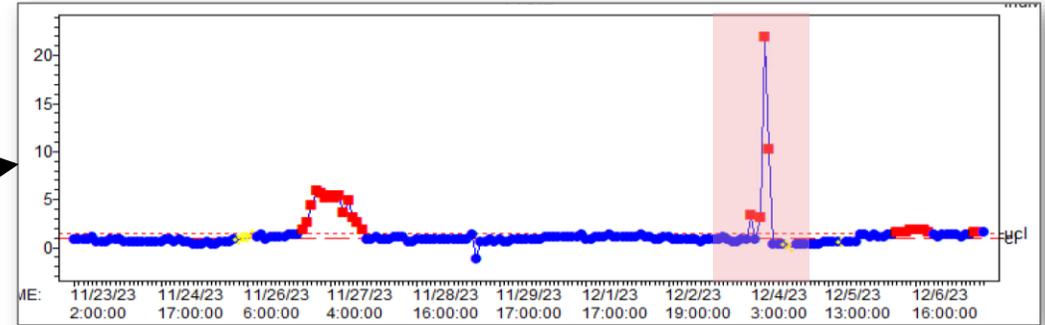
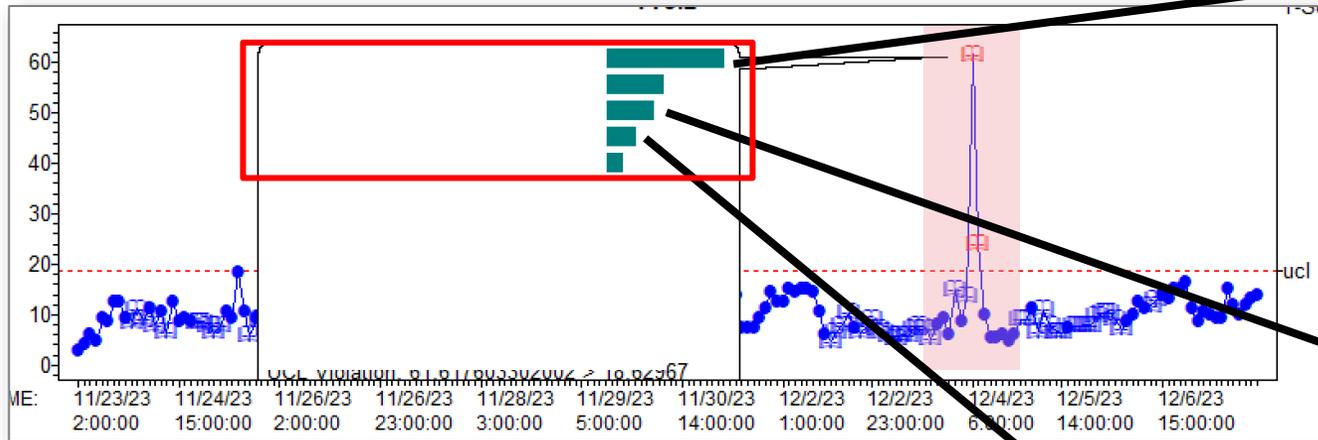
Albemarle Intelligence – Engineer Improvement Project



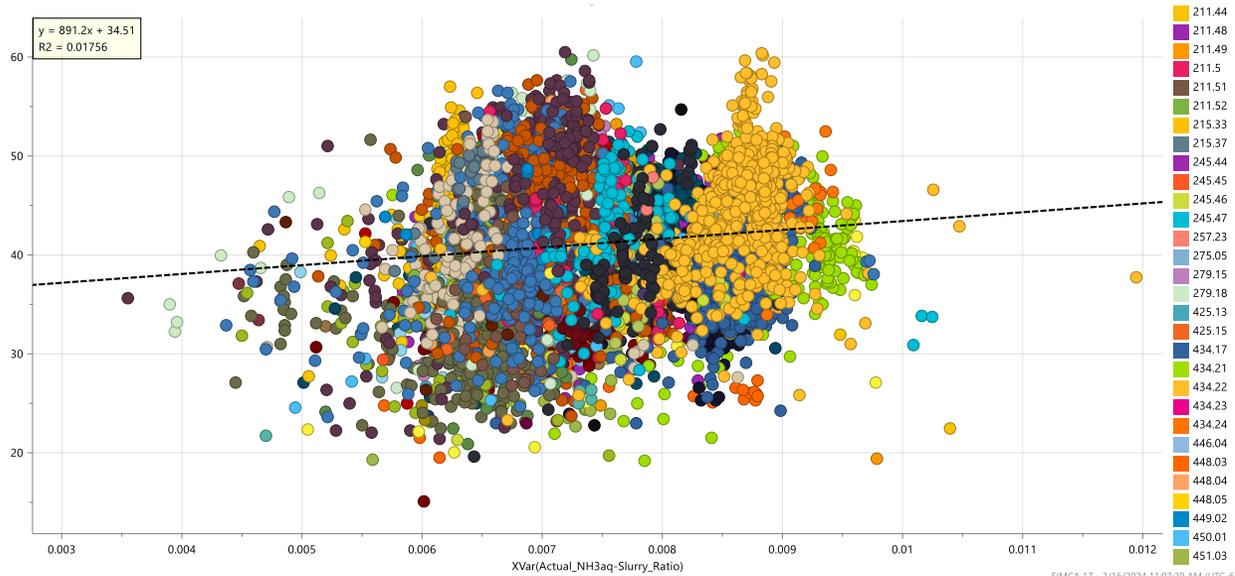
Albemarle Intelligence – Engineer Improvement Project



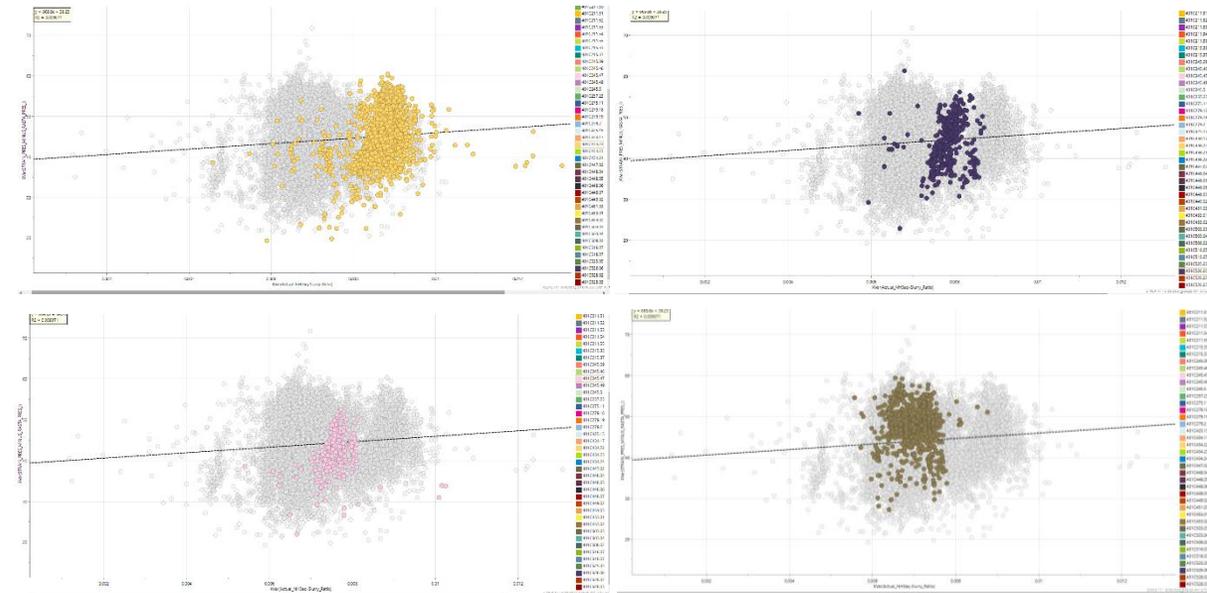
Albemarle Intelligence – Engineer Improvement Project



Albemarle Intelligence – Engineer Improvement Project



SIMCA 17 - 2/16/2024 11:07:20 AM (UTC-6)



Reason #6



**Fragmented
Technology,
Fragmented
Results**





PI System Asset Framework

EXCAVATION



PI System Event Frames & Analytics

PROCESSING



NWA Statistical Process Control & SIMCA Machine Learning

REFINING



Actionboards

SHIPMENT NT







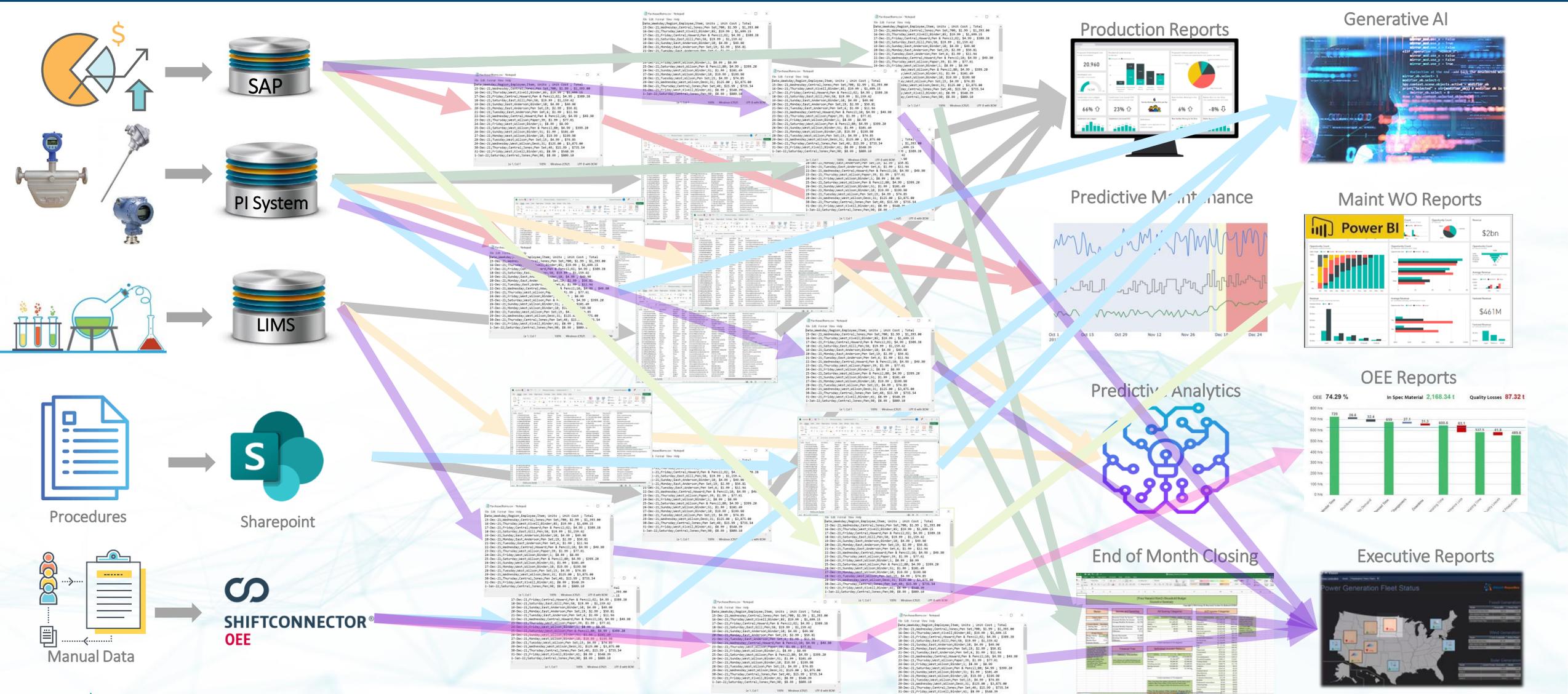
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2	12/18/18 10:31:45	13052	1	000	303.0	80.2	2048	44.5	23	101	106	154.01	7148	0400.0	2.3	8409.153	
3	12/20/18 1:06:45	13053	1	007	303.7	81.4	2226	44.5	24	101	105	154.13	7148	0306.1	2.3	8479.928	
4	12/20/18 7:45:45	13054	1	010	303.7	81.8	2316	44.5	25	98	102	154.01	7151	0327.4	2.3	8499.394	
5	12/20/18 14:29:45	13055	1	010	303.7	80.8	2080	44.5	26	98	100	152.23	7150	0338.3	2.3	8611.963	
6	12/21/18 7:50:45	13056	1	008	304.6	81.4	1227	45	27	108	140	162.42	7148	0447.9	2.3	8883.088	
7	12/21/18 14:09:45	13057	1	000	304.9	82.7	2054	45	28	98	140	162.27	7151	0362.0	2.3	8832.448	
8	12/21/18 20:24:45	13058	1	010	303.9	83.4	2001	45	29	97	144	162.09	7150	0405.9	2.2	7750.021	
9	12/22/18 2:37:45	13059	1	010	303.2	81.2	-	45	30	97	87	162.21	7150	0440.3	2.2	8021.211	
10	12/22/18 8:33:45	13060	1	011	303.7	80.9	2013	45	31	117	97	162.12	7180	0329.9	2.3	8285.421	
11	12/23/18 3:43:45	13061	1	009	308.9	79.9	2140	45	32	107	87	162.38	7148	0326.2	2.3	7762.582	
12	12/23/18 10:00:45	13062	1	006	303.7	80.9	2176	45	33	98	137	162.26	7148	0387.6	2.2	8291.748	
13	12/23/18 16:50:45	13063	1	011	300.2	85.1	2004	45	34	90	137	162.29	7151	0414.4	2.2	7906.285	
14	12/23/18 22:54:45	13064	1	-	311.6	81.9	2048	45	35	102	126	162.70	7152	0328.4	2.3	10099.071	
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20	12/25/18 17:28:45	13070	1	002	312.4	85.1	2056	45	41	96	167	162.22	7154	0183.3	2.8	10347.81	
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22	12/26/18 6:03:45	13072	1	009	309.7	83.9	2148	45	43	94	139	162	158.67	7158	0812.0	2.8	11300.13
23	12/26/18 12:05:45	13073	1	003	312.7	83.8	2022	45	44	99	173	162.26	7153	0170.2	2.8	9911.619	
24	12/26/18 19:22:45	13074	1	005	307.8	85.4	2051	45	45	98	137	162.18	7150	0102.3	2.8	7096.47	
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26	12/27/18 8:48:45	13076	1	006	308.8	83.8	2168	45	47	101	109	162.03	7148	0233.1	2.9	8123.846	
27	12/27/18 12:44:45	13077	1	009	313.8	84.4	2019	45	48	108	112	161.68	7147	0333.8	2.9	8789.883	
28	12/27/18 18:53:45	13078	1	003	307.8	84.7	1897	45	49	104	130	161.39	7149	0387.0	2.8	8932.923	
29	12/28/18 0:09:45	13079	1	002	307.6	85.2	2097	45	50	104	128	161.63	7150	0237.0	2.9	9011.07	
30	12/28/18 7:06:45	13080	1	002	309.8	85.0	2012	45	51	103	130	161.62	7151	0163.3	2.7	8939.528	
31	12/28/18 16:17:45	13081	1	008	308.8	85.6	1937	45	52	118	288	161.21	7151	0004.4	2.7	8986.875	
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33	12/28/18 5:20:45	13083	1	000	307.0	85.0	1852	45	54	117	130	161.17	7151	0358.3	2.7	9537.63	
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36	1/12/19 8:16:45	13086	1	077	305.3	85.4	1908	45	58	117	109	160.97	7151	0336.5	2.8	10049.31	
37	1/12/19 8:52:45	13087	1	002	303.1	83.7	1944	45	59	117	162	160.99	7148	0377.2	2.8	8881.688	
38	1/12/19 12:23:45	13088	1	002	306.0	84.0	1797	45	60	118	126	161.85	7148	0423.7	2.8	9841.389	
39	1/13/19 4:11:45	13089	1	006	302.9	82.0	1735	45	61	119	156	160.85	7144	0283.0	2.9	8940.879	
40	1/13/19 10:39:45	13090	1	002	303.4	83.7	2006	45	62	118	132	161.87	7147	0332.8	2.7	9604.894	
41	1/13/19 17:18:45	13091	1	003	302.9	82.5	1940	45	63	110	124	160.97	7147	0046.4	2.9	9181.318	
42	1/13/19 23:48:45	13092	1	002	304.9	83.1	2076	45	64	119	122	161.89	7148	0238.0	2.9	9786.119	
43	1/14/19 0:23:45	13093	1	002	303.3	83.5	2041	45	65	117	140	160.90	7147	0148.1	2.9	9389.789	
44	1/14/19 12:00:45	13094	1	002	303.7	83.9	2026	45	66	117	136	161.01	7147	0171.1	2.9	9540.422	
45	1/14/19 19:23:45	13095	1	002	304.3	83.9	2013	45	67	118	135	161.83	7147	0187.4	3.0	9524.005	
46	1/15/19 1:47:45	13096	1	002	300.9	83.5	2004	45	68	120	120	161.73	7146	0279.3	2.9	9932.090	
47	1/15/19 8:09:45	13097	1	003	309.9	83.7	1977	45	69	121	121	161.88	7148	0387.2	2.9	9844.638	
48	1/15/19 14:28:45	13098	1	002	312.1	83.6	1990	45	70	119	124	161.81	7147	0395.9	2.4	10440.04	

ALBEMARLE INTELLIGENCE

DATA SOURCES

DATA PIPELINES

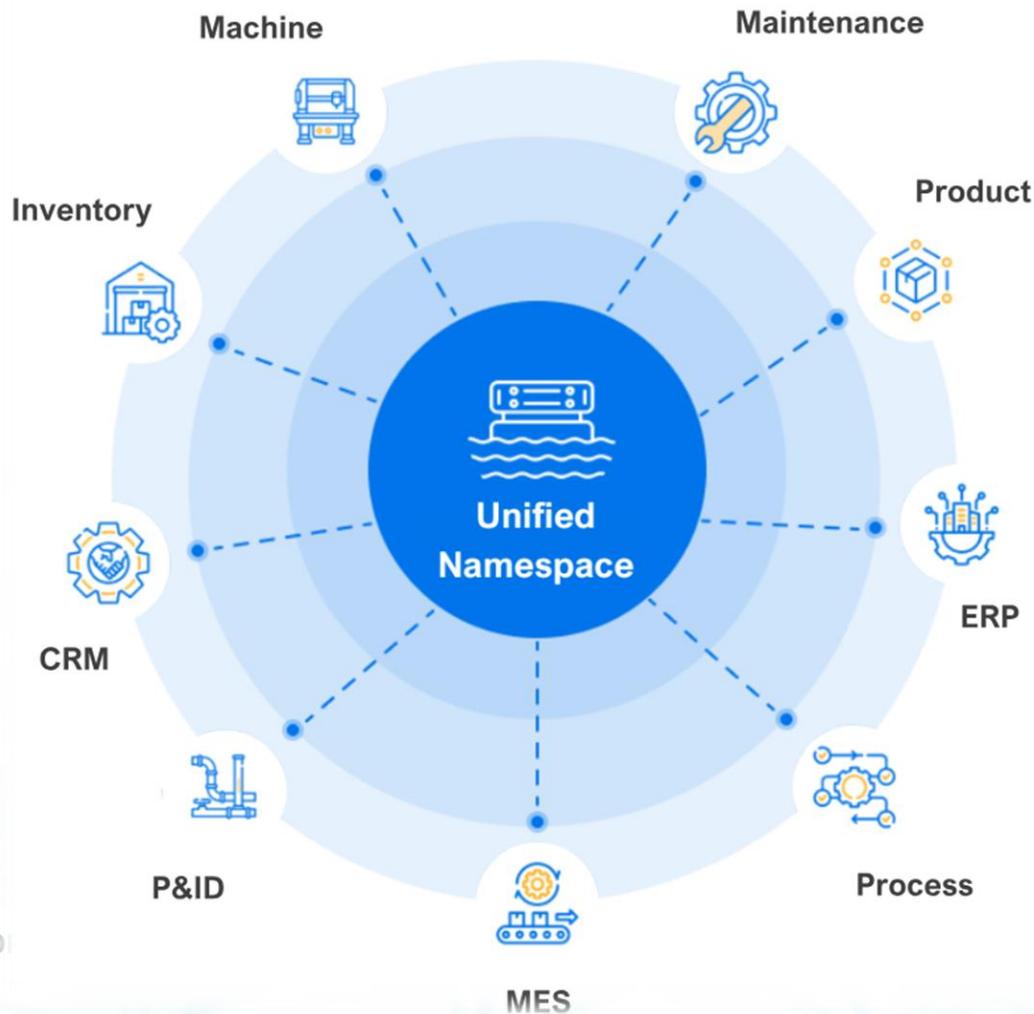
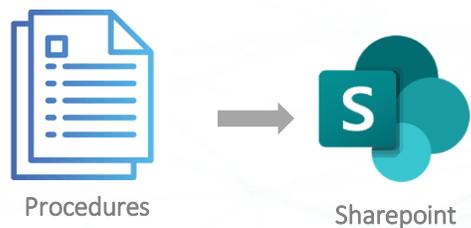
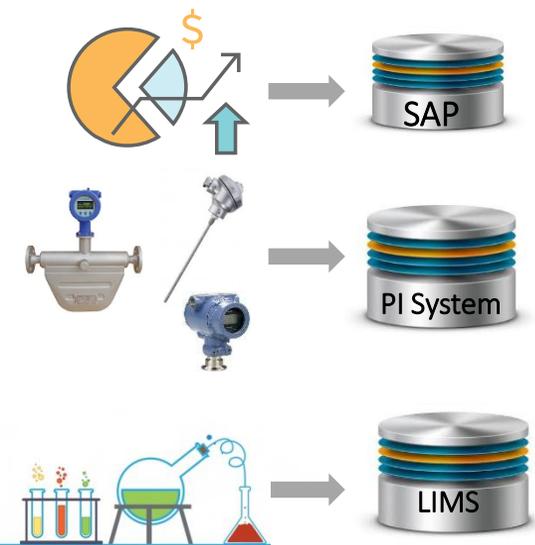
END USERS



DATA SOURCES

DATA PIPELINES

END USERS



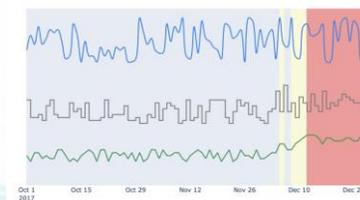
Production Reports



Generative AI



Predictive Maintenance



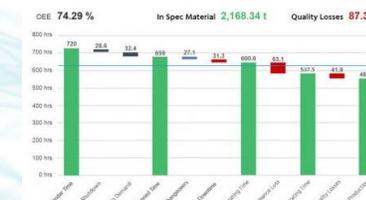
Maint WO Reports



Predictive Analytics



OEE Reports

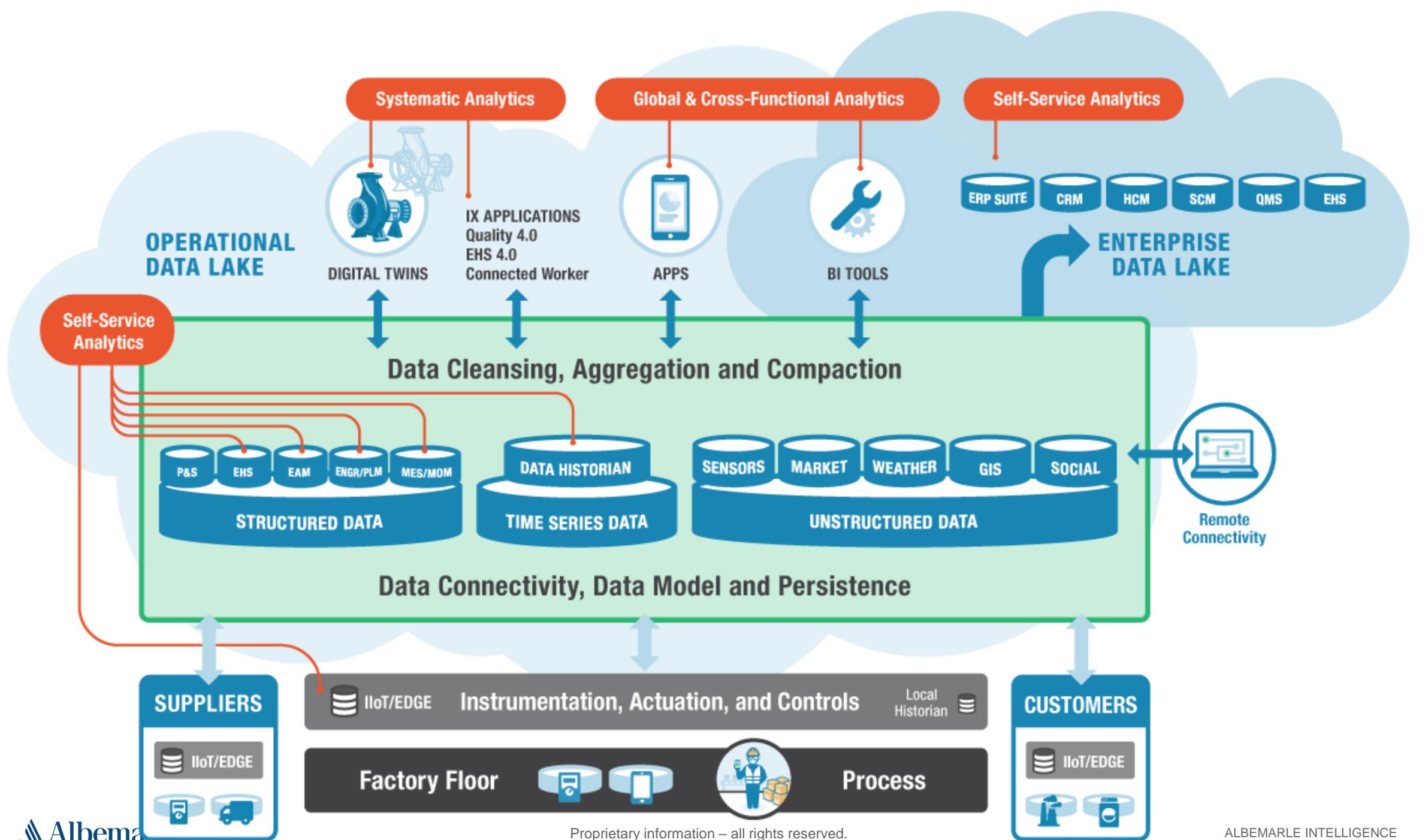


End of Month Closing

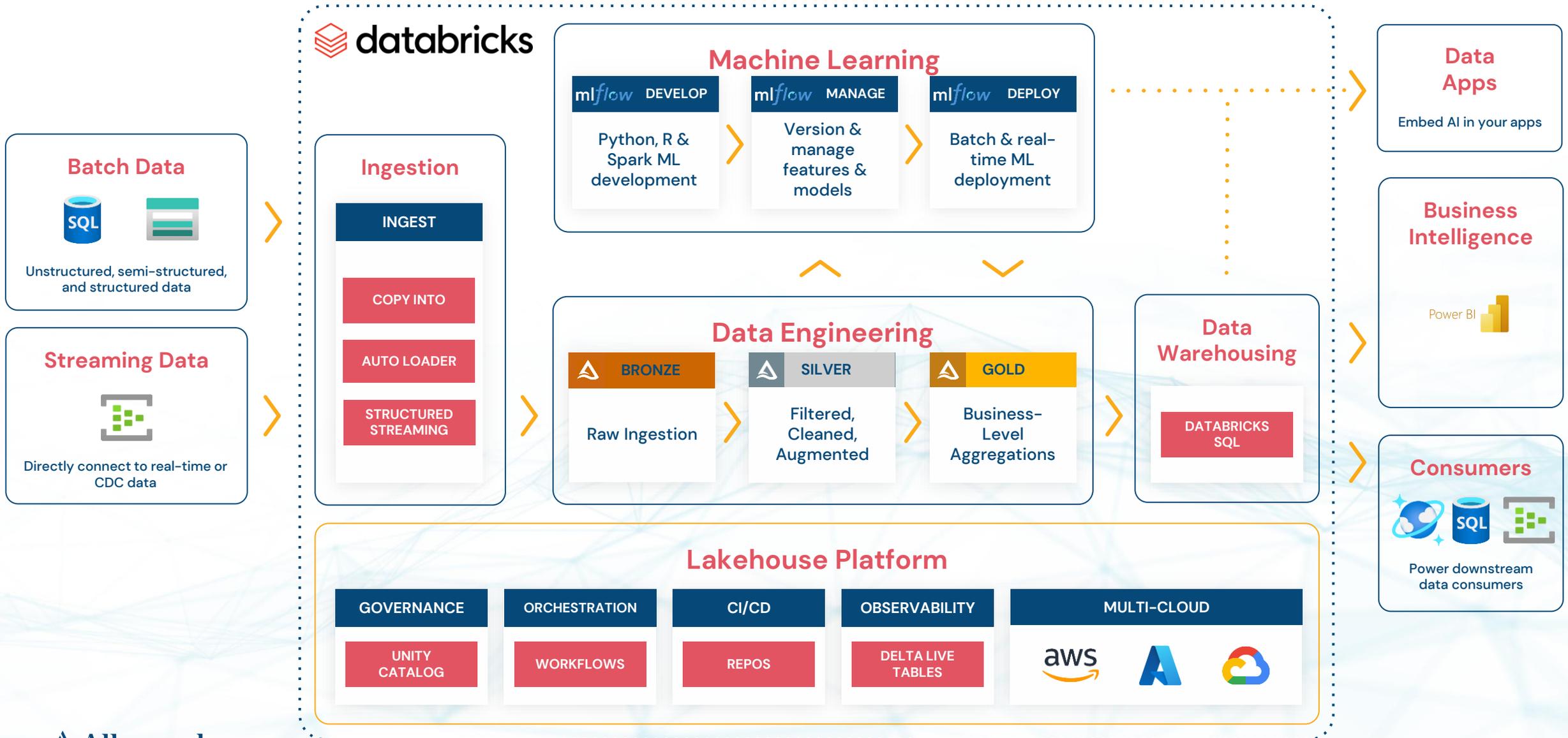
A screenshot of a spreadsheet used for end-of-month closing, showing various financial and operational data points in a grid format.

Executive Reports



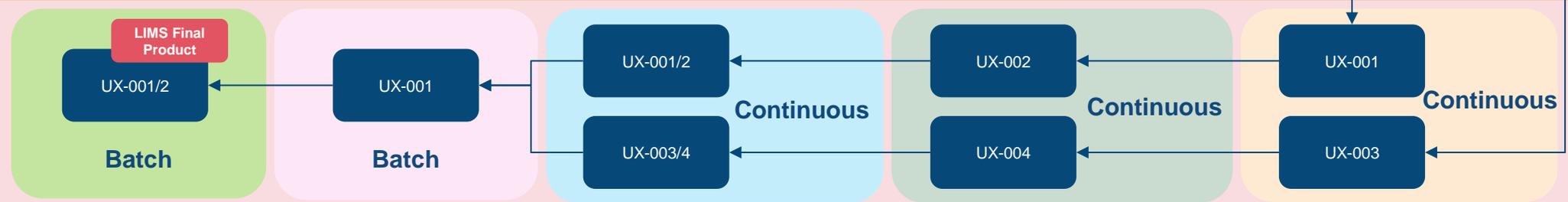
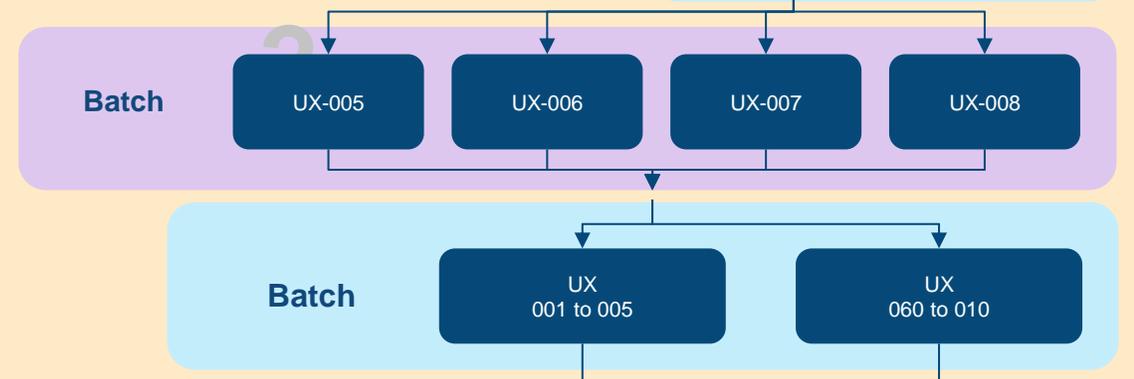
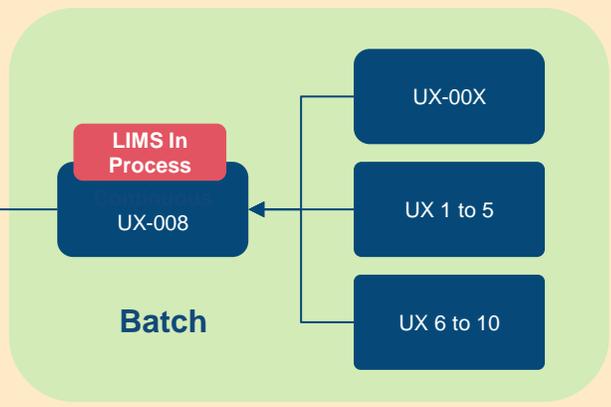
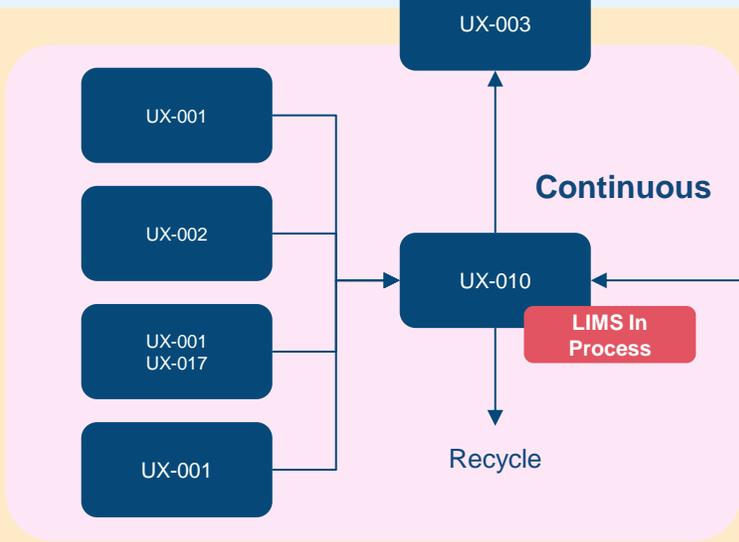
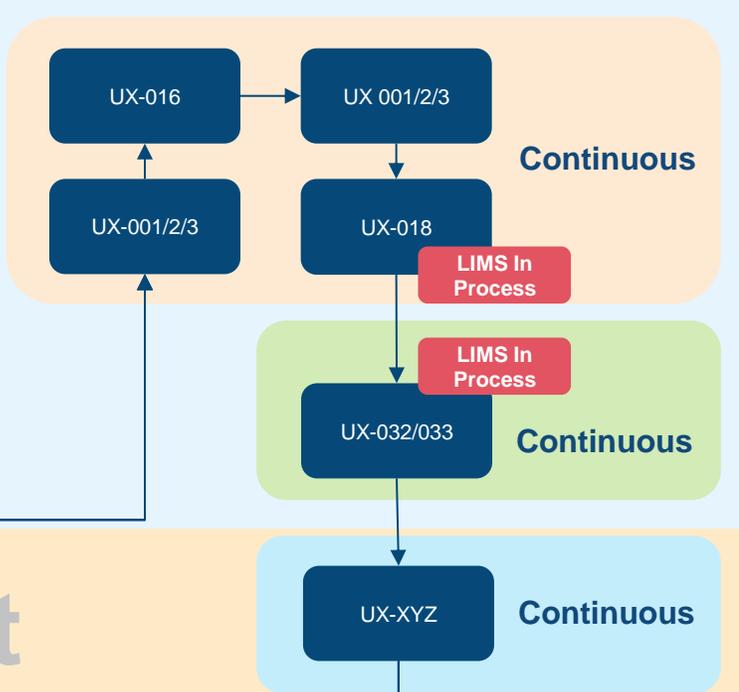
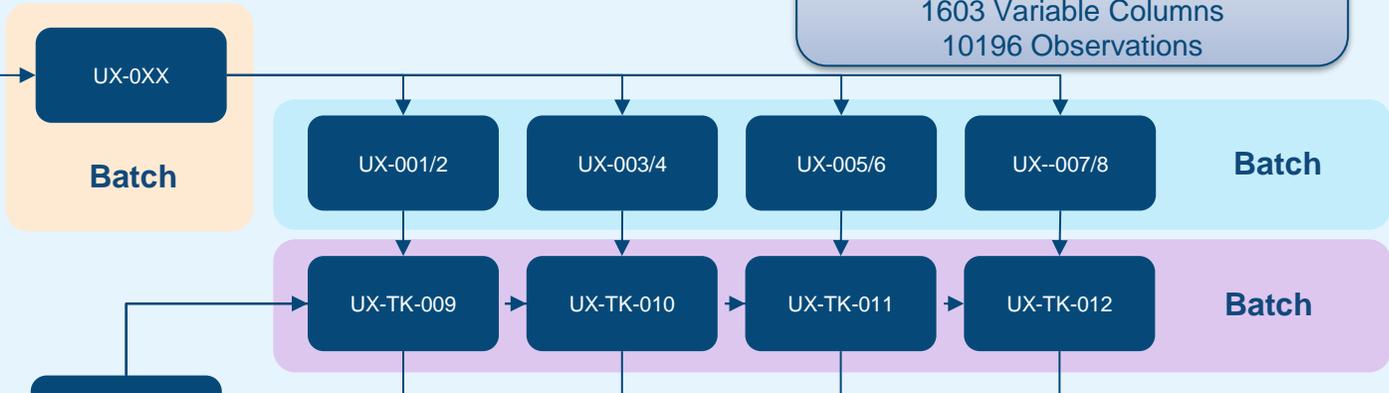
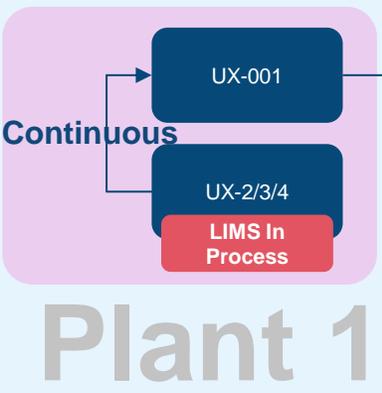


Azure Databricks Lakehouse Architecture



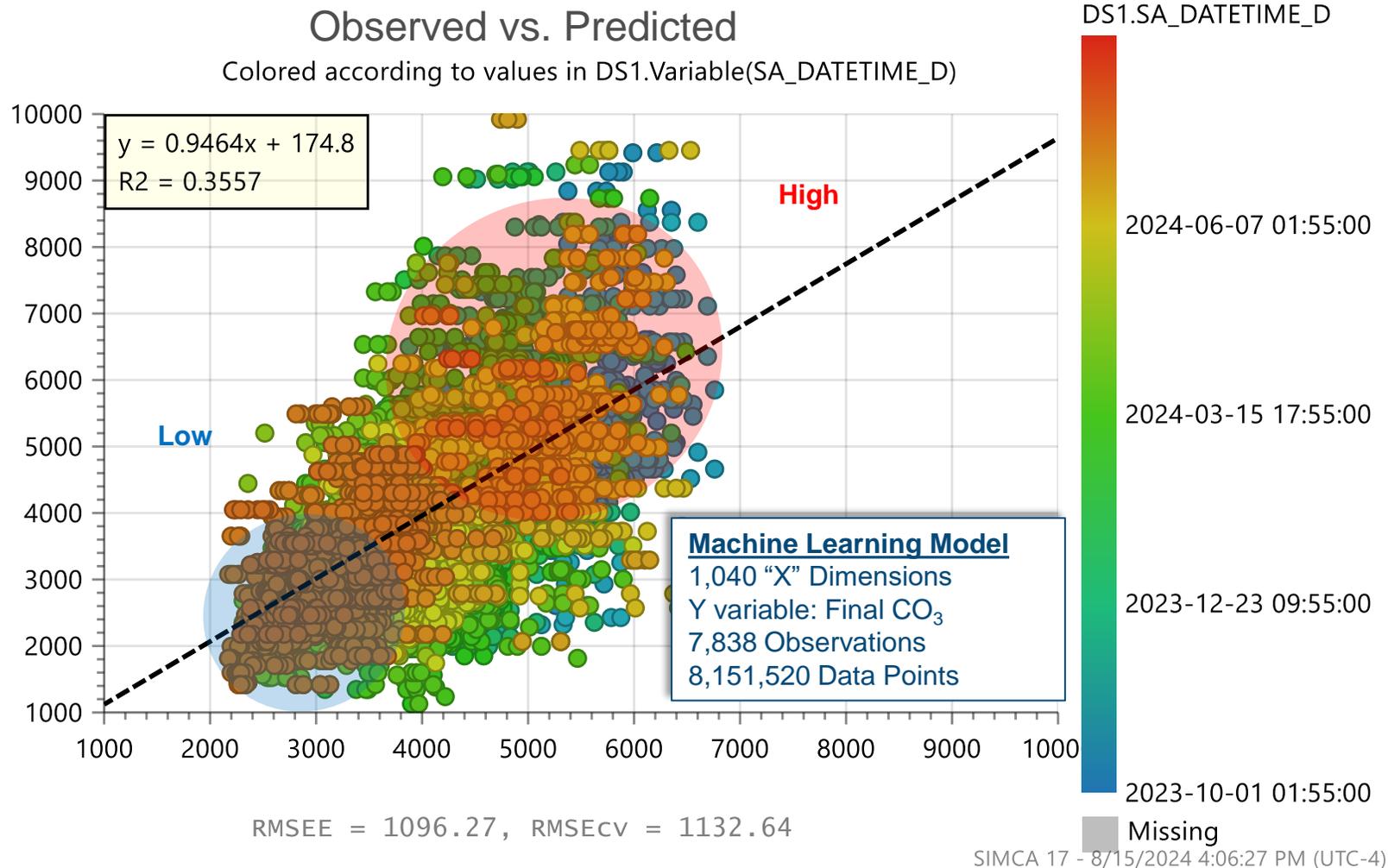
Data Merging Map

Sitewide Dataset Statistics
 45 Unit Ops
 8 LIMS sample points
 1603 Variable Columns
 10196 Observations



Plant 3

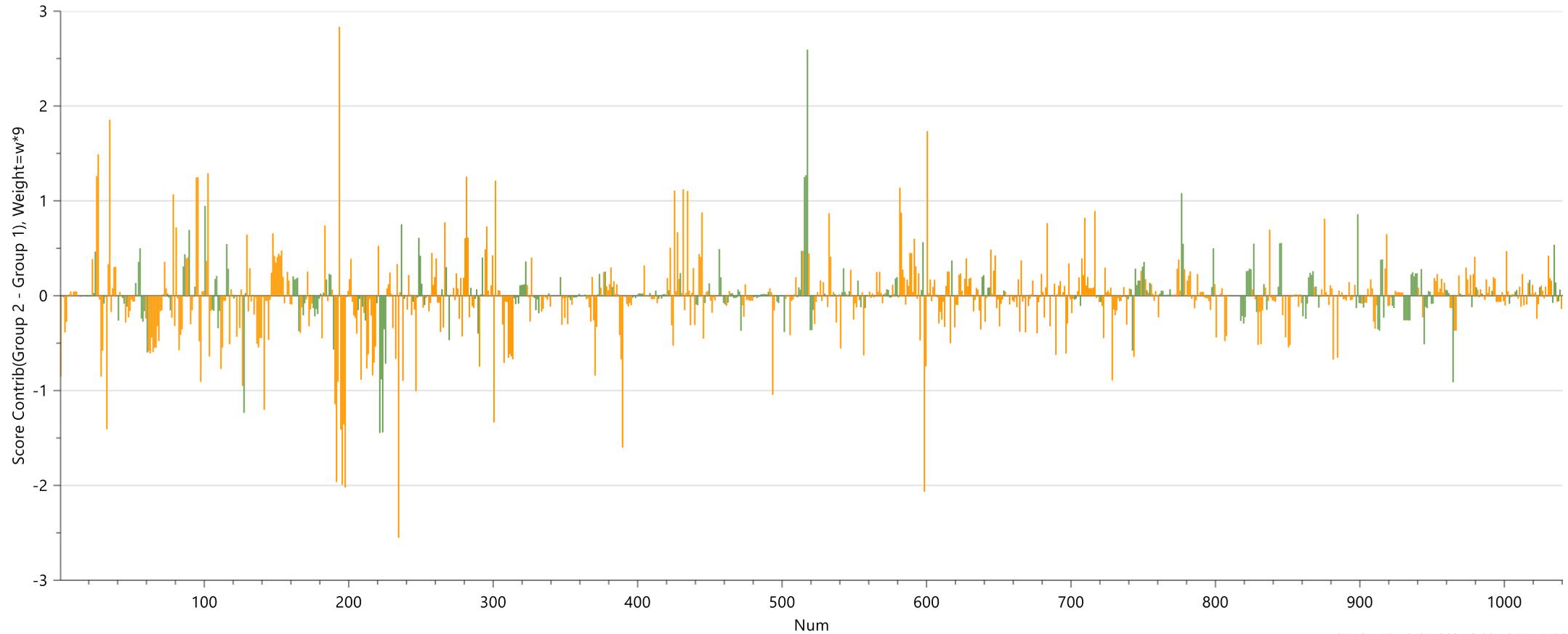
Machine Learning Predictive Modeling – Quality Parameter 1



Machine Learning Predictive Modeling – Quality Parameter 1

YPred contribution Group 2 vs. Group 1

Colored variables outside their 3 std. dev. range



SIMCA 17 - 8/21/2024 3:08:46 PM (UTC-4)

Sitewide Data Merging Map

Sitewide Dataset Statistics

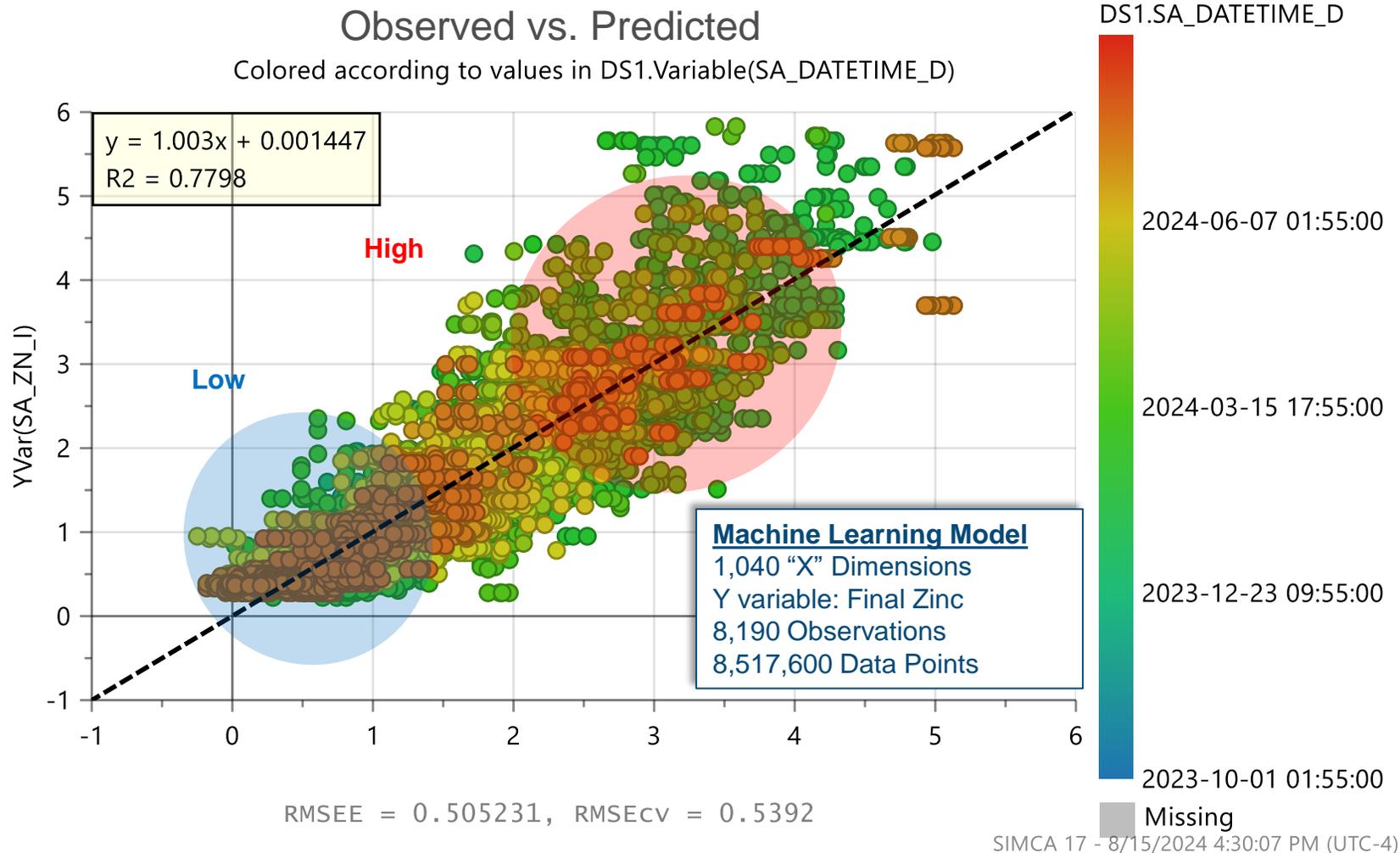
45 Unit Ops
8 LIMS sample points
1603 Variable Columns
10196 Observations

PIAF Dataset
LIMS Dataset

Each row represents the same material passing through the plant as it travels through each unit and sample point.

Cont	Batch	Batch		Batch		Continuous		Cont	Cont	Batch		Batch		Cont	Cont	Cont	Batch	Final																								
00.00.0	Belt Filter 06	Belt Filter 2181	FI A	A	Night	Night	15.3132	26.33236	3.563491	449.9914	0.02738	12.3883	0.019759	30	0	0	0	0	380.1828	19.60374	16.5572	0.204708	0	84.16695	33.95994	20	80	0.86548	3.10511	0.629352	05.06917	944.0433	56.97776	55.00237	55	-60.626	8.154482	A	1.370769	15.31322	20.96089	36.33
00.00.0	Belt Filter 06	Belt Filter 2181	FI A	A	Night	Night	15.35757	26.3331	3.563491	449.9972	0.028246	13.22519	0.021579	30	0	0	0	0	389.8162	19.63025	16.5507	0.148008	0	84.16695	33.95994	20	80	0.87839	3.10511	0.629352	05.06917	944.0433	56.97776	55.00237	55	-60.626	8.154482	A	1.36687	15.35757	20.96089	36.33
00.00.0	Belt Filter 06	Belt Filter 2181	FI A	A	Night	Night	15.34756	26.3919	3.563491	449.9975	0.02914	12.96495	0.020582	30	0	0	0	0	389.9618	19.57608	16.54757	0.14876	0	84.16695	33.95994	20	80	0.8823	3.10511	0.629352	05.06917	944.0433	56.97776	55.00237	55	-61.2631	8.146521	A	1.366297	15.34756	20.96089	36.33
00.00.0	Belt Filter 06	Belt Filter 2181	FI A	A	Night	Night	15.3747	26.27371	3.563491	449.9919	0.030034	12.7997	0.017235	30	0	0	0	0	389.8867	19.20369	16.57133	0.161918	0	84.16695	33.95994	20	80	0.8907	3.10511	0.629352	05.06917	944.0433	56.97776	55.00237	55	-60.3322	7.918858	A	1.372884	15.3747	21.10768	36.47
00.00.0	Belt Filter 06	Belt Filter 2181	FI A	A	Night	Night	15.66816	26.2398	3.563491	449.9972	0.030928	13.0206	0.013887	30	0	0	0	0	389.8108	19.06469	16.60032	0.175076	0	84.16695	33.95994	20	80	0.89911	3.10511	0.629352	05.06917	944.0433	56.97776	55.00237	55	-59.9491	8.08086	A	1.371103	15.66816	21.48266	36.2
00.00.0	Belt Filter 06	Belt Filter 2181	FI A	A	Night	Day	15.68155	26.1049	3.537752	449.9972	0.031822	12.59099	0.010539	30	0	0	0	0	390.1464	19.27256	16.56965	0.188235	0	84.16695	33.95994	20	80	0.90752	3.10511	0.629352	05.06917	944.0433	56.97776	55.00237	55	-59.1368	8.002915	A	1.369533	15.68155	21.4764	36.22
00.00.0	Belt Filter 06	Belt Filter 2181	FI A	A	Night	Day	15.68055	26.09939	3.563491	450.0028	0.032716	12.26393	0.007191	30	0	0	0	0	390.3155	19.49032	16.56333	0.200745	0	84.16695	33.95994	20	80	0.91593	3.10511	0.629352	05.06917	944.0433	56.97776	55.00237	55	-59.1681	8.434136	A	1.371398	15.68055	21.50427	36.22
00.00.0	Belt Filter 06	Belt Filter 2181	FI A	A	Night	Day	15.58494	26.21661	3.481916	449.9972	0.03361	11.90992	0.003843	30	0	0	0	0	390.2192	19.46033	16.5588	0.192588	0	84.16695	33.95994	20	80	0.87788	3.10511	0.629352	05.06917	944.0433	56.97776	55.00237	55	-59.4941	8.143876	A	1.378705	15.58494	21.48703	37.00
00.00.0	Belt Filter 06	Belt Filter 2181	FI A	A	Night	Day	15.58182	26.11684	3.486673	450.0028	0.032258	13.1869	4.96E-04	30	0	0	0	0	390.7449	19.86496	16.55046	0.194077	0	84.16695	33.95994	20	80	0.89249	3.10511	0.629352	05.06917	944.0433	56.97776	55.00237	55	-58.9551	8.005714	A	1.378577	15.58182	21.48074	37.00
00.00.0	Belt Filter 06	Belt Filter 2181	FI A	A	Night	Day	15.6061	26.03729	3.36754	449.9917	0.024186	12.38759	-0.00273	30	0	0	0	0	391.4444	20.06633	16.53811	0.177747	0	84.16695	33.95994	20	80	0.96595	3.10511	0.629352	05.06917	944.0433	56.97776	55.00237	55	-58.2597	8.003524	A	1.375838	15.6061	21.47147	36.82
00.00.0	Belt Filter 06	Belt Filter 2181	FI A	A	Night	Day	15.63345	25.94886	3.36754	449.9972	0.015664	11.62605	-0.00233	30	0	0	0	0	390.7449	19.86496	16.55046	0.194077	0	84.16695	33.95994	20	80	0.89746	3.10511	0.629352	05.06917	944.0433	56.97776	55.00237	55	-57.5304	8.263752	A	1.374522	15.63345	21.48852	36.55
00.00.0	Belt Filter 06	Belt Filter 2181	FI A	A	Night	Day	15.63528	25.85064	3.36754	450	0.007142	10.0948	-2.41E-04	30	0	0	0	0	390.7159	20.45195	16.52978	0.192187	0	84.16695	33.95994	20	80	0.7346	3.10511	0.629352	05.06917	944.0433	56.97776	55.00237	55	-56.7535	8.106703	A	1.375917	15.63528	21.52185	36.76
00.00.0	Belt Filter 06	Belt Filter 2181	FI A	A	Night	Day	15.66636	25.55799	3.36754	450	0.00138	10.0478	0.001846	30	0	0	0	0	391.4399	20.45703	16.55571	0.199407	0	84.16695	33.95994	20	80	0.75402	3.10511	0.629352	05.06917	944.0433	56.97776	55.00237	55	-55.4599	7.997003	A	1.371663	15.66636	21.48897	36.35
00.00.0	Belt Filter 06	Belt Filter 2181	FI A	A	Night	Day	15.67754	25.59921	3.36754	450	-0.0099	9.945353	0.003932	30	0	0	0	0	390.9588	20.07588	16.57905	0.199979	0	84.16695	33.95994	20	80	0.60649	3.10511	0.629352	05.06917	944.0433	56.97776	55.00237	55	-56.0954	8.071118	A	1.371733	15.67754	21.49976	36.35
00.00.0	Belt Filter 06	Belt Filter 2181	FI A	A	Night	Day	15.65481	25.52224	3.316684	449.9969	0.01842	9.869372	0.006018	30	0	0	0	0	391.4576	19.27983	16.60222	0.174968	0	84.16695	33.95994	20	80	0.71367	3.10511	0.629352	05.06917	944.0433	56.97776	55.00237	55	-56.0443	8.033635	A	1.372383	15.65481	21.4844	36.41
00.00.0	Belt Filter 06	Belt Filter 2181	FI A	A	Night	Day	15.60858	25.49652	3.374679	450	0.02694	10.30001	0.008104	30	0	0	0	0	390.9542	19.29473	16.58413	0.170059	0	84.16695	33.95994	20	80	0.873888	3.10511	0.629352	05.06917	944.0433	56.97776	55.00237	55	-56.2452	8.034025	A	1.377717	15.60858	21.50421	36.92
00.00.0	Belt Filter 06	Belt Filter 2181	FI A	A	Night	Day	15.58672	25.66354	3.374679	449.9972	0.023711	13.31716	0.01019	30	0	0	0	0	390.1195	19.29389	16.54871	0.169701	0	84.16695	33.95994	20	80	0.99769	3.10511	0.629352	05.06917	944.0433	56.97776	55.00237	55	-57.0066	8.055152	A	1.379817	15.58672	21.56272	37.11
00.00.0	Belt Filter 06	Belt Filter 2181	FI A	A	Night	Night	15.57915	25.8094	3.374679	450.0028	0.02272	14.22026	0.012243	30	0	0	0	0	390.0054	18.91033	16.50263	0.169344	0	84.16695	33.95994	20	80	0.87678	3.10511	0.629352	05.06917	944.0433	56.97776	55.00237	55	-57.9649	8.113949	A	1.379326	15.57915	21.48873	37.11
00.00.0	Belt Filter 06	Belt Filter 2181	FI A	A	Night	Night	15.58137	25.82887	3.374679	450	0.01557	14.42076	0.01331	30	0	0	0	0	389.967	18.34214	16.51355	0.176602	0	84.16695	33.95994	20	80	0.75402	3.10511	0.629352	05.06917	944.0433	56.97776	55.00237	55	-57.8932	8.334682	A	1.380761	15.58137	21.51275	37.15
00.00.0	Belt Filter 06	Belt Filter 2181	FI A	A	Night	Night	15.49747	25.82562	3.374679	450	0.00841	11.52661	0.013918	30	0	0	0	0	390.0137	20.00163	16.56567	0.157164	0	84.16695	33.95994	20	80	0.69791	3.10511	0.629352	05.06917	944.0433	56.97776	55.00237	55	-57.6192	8.621061	A	1.387322	15.49747	21.49998	37.2
00.00.0	Belt Filter 06	Belt Filter 2181	FI A	A	Night	Night	15.43973	25.82022	3.374679	449.9972	0.00126	10.56877	0.014527	30	0	0	0	0	390.1097	21.14643	16.57526	0.157384	0	84.16695	33.95994	20	80	0.72566	3.10511	0.629352	05.06917	944.0433	56.97776	55.00237	55	-57.6879	8.356791	A	1.393285	15.43973	21.51234	38.3
00.00.0	Belt Filter 06	Belt Filter 2181	FI A	A	Night	Night	15.44213	25.78129	3.374679	450	0.005892	10.32316	0.015136	30	0	0	0	0	390.2532	21.03401	16.60927	0.182402	0	84.16695	33.95994	20	80	0.71333	3.10511	0.629352	05.06917	944.0433	56.97776	55.00237	55	-57.2437	8.345386	A	1.391427	15.44213	21.4886	38.30
00.00.0	Belt Filter 06	Belt Filter 2181	FI A	A	Night	Night	15.40347	25.69442	3.320555	450	0.013045	11.33952	0.015744	30	0	0	0	0	390.3263	21.01473	16.56485	0.186165	0	84.16695	33.95994	20	80	0.72774	3.10511	0.629352	05.06917	944.0433	56.97776	55.00237	55	-56.7894	8.417252	A	1.394228	15.40347	21.47595	38.4
00.00.0	Belt Filter 06	Belt Filter 2181	FI A	A	Night	Night	15.45533	25.7242	3.461726	449.9972	0.024724	12.6101	0.016962	30	0	0	0	0	391.6885	21.14982	16.54024	0.218465	0	84.16695	33.95994	20	80	0.83623	3.10511	0.629352	05.06917	944.0433	56.97776	55.00237	55	-56.6942	8.182807	A	1.390933	15.45533	21.49733	37.

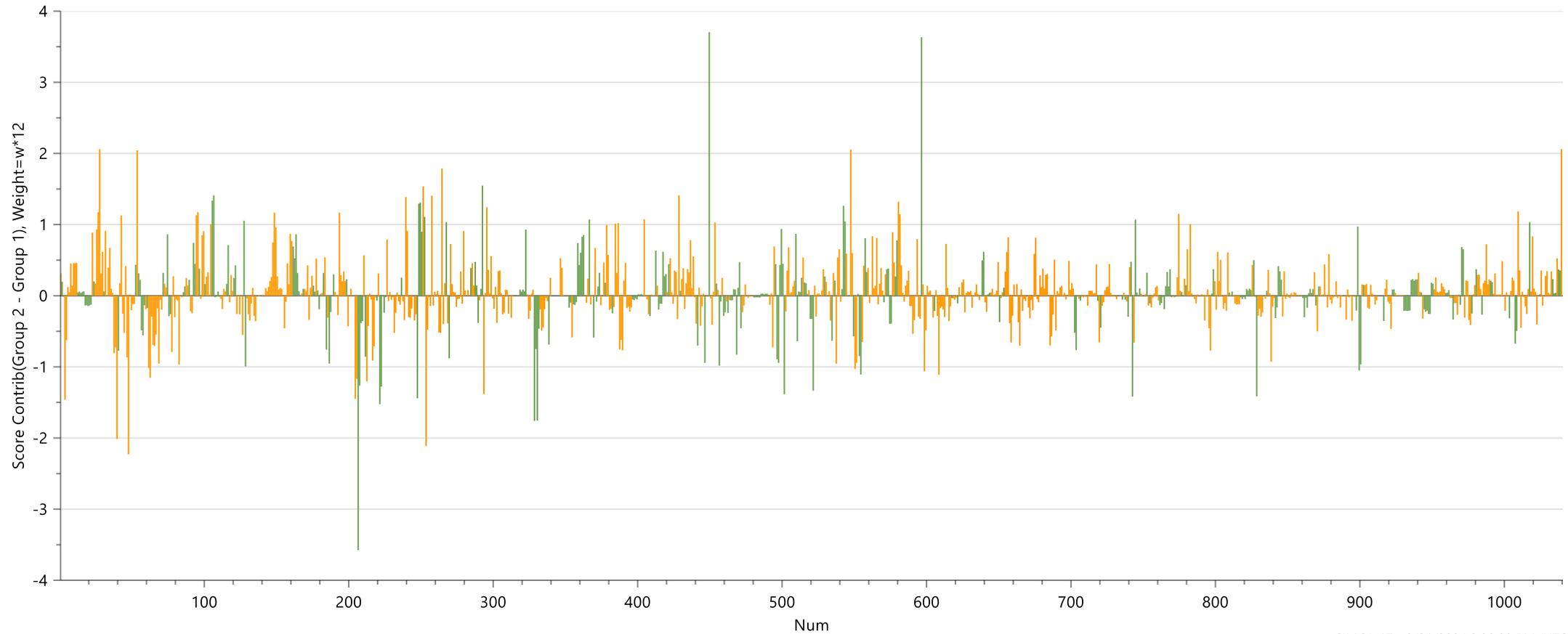
Machine Learning Predictive Modeling – Quality Parameter 2



Machine Learning Predictive Modeling – Final Prod Zinc

YPred contribution Group 2 vs. Group 1

Colored variables outside their 3 std. dev. range



SIMCA 17 - 8/21/2024 3:29:09 PM (UTC-4)

Modern Machine Learning for Time Series – XGBoost



Feature Importance (Python)

Import Notebook

1

```
from pyspark.sql import SparkSession
from pyspark.sql.functions import col
from pyspark.sql.types import NumericType
import pandas as pd
import numpy as np
!pip install networkx
import networkx as nx
import warnings
warnings.filterwarnings("ignore")
%pip install xgboost
from sklearn.ensemble import IsolationForest
from sklearn.impute import SimpleImputer
import xgboost as xgb
from sklearn.model_selection import train_test_split, cross_val_score, KFold
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import make_scorer, mean_squared_error
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import RobustScaler

# Drop rows with NaN values in the target column from the original dataframe before splitting
df_filtered_zn_clean = df_filtered_zn.dropna(subset=[target_column])

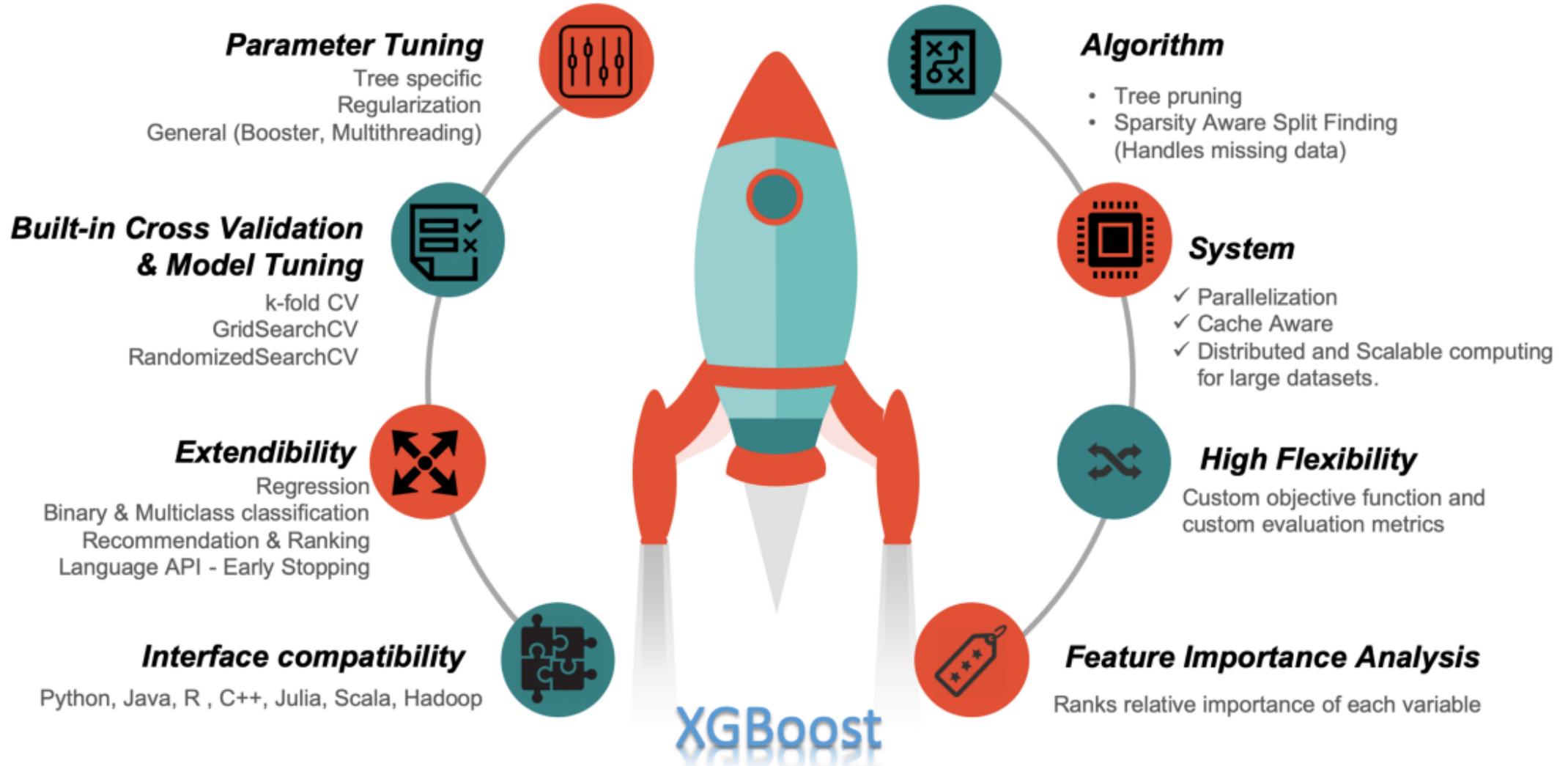
X = df_filtered_zn_clean.drop(target_column, axis=1)
y = df_filtered_zn_clean[target_column]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

xgb_model = xgb.XGBRegressor(missing=None, random_state=42)
kf = KFold(n_splits=5, shuffle=True, random_state=42)
mse_scorer = make_scorer(mean_squared_error, greater_is_better=False)
cv_scores = cross_val_score(xgb_model, X_train, y_train, cv=kf, scoring=mse_scorer)

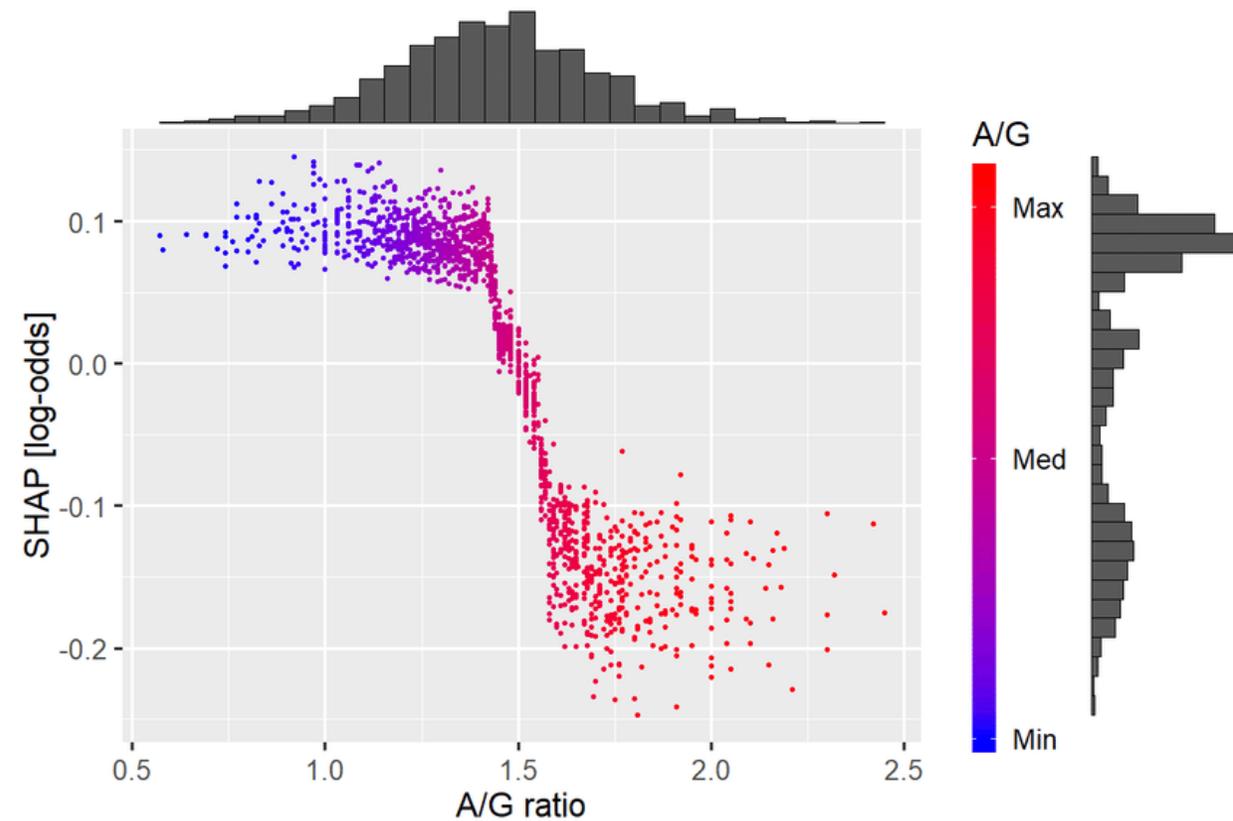
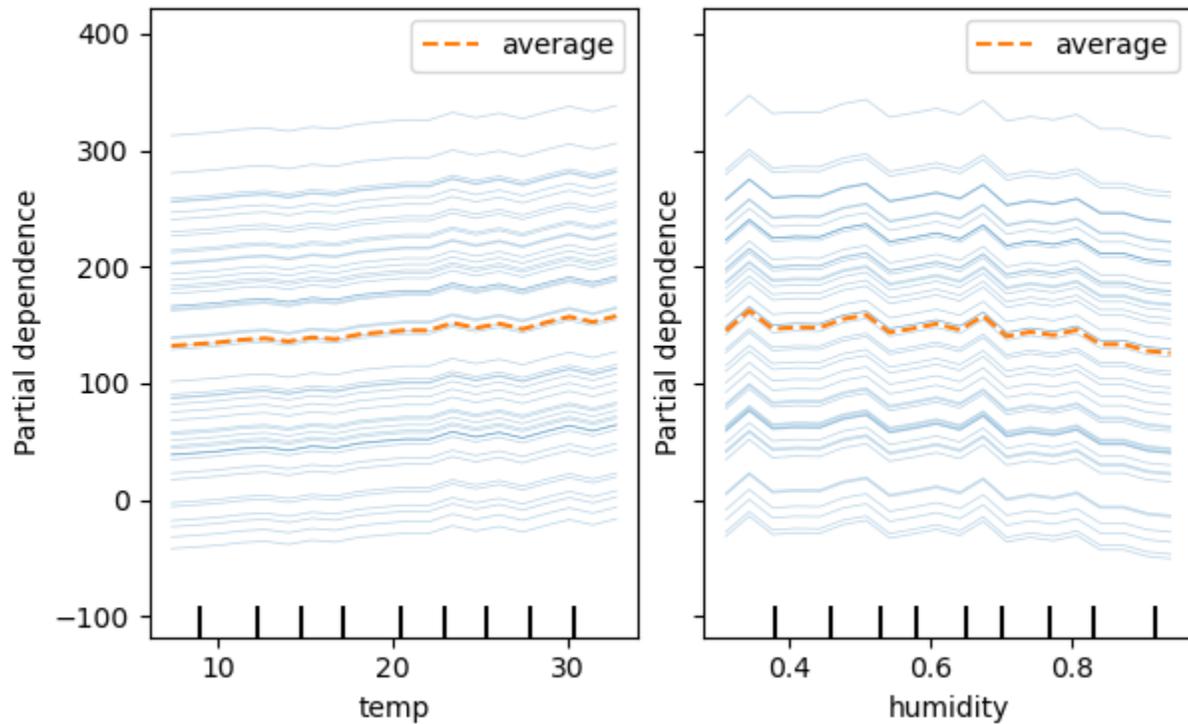
xgb_model.fit(X_train, y_train)
```

Modern Machine Learning for Time Series – XGBoost

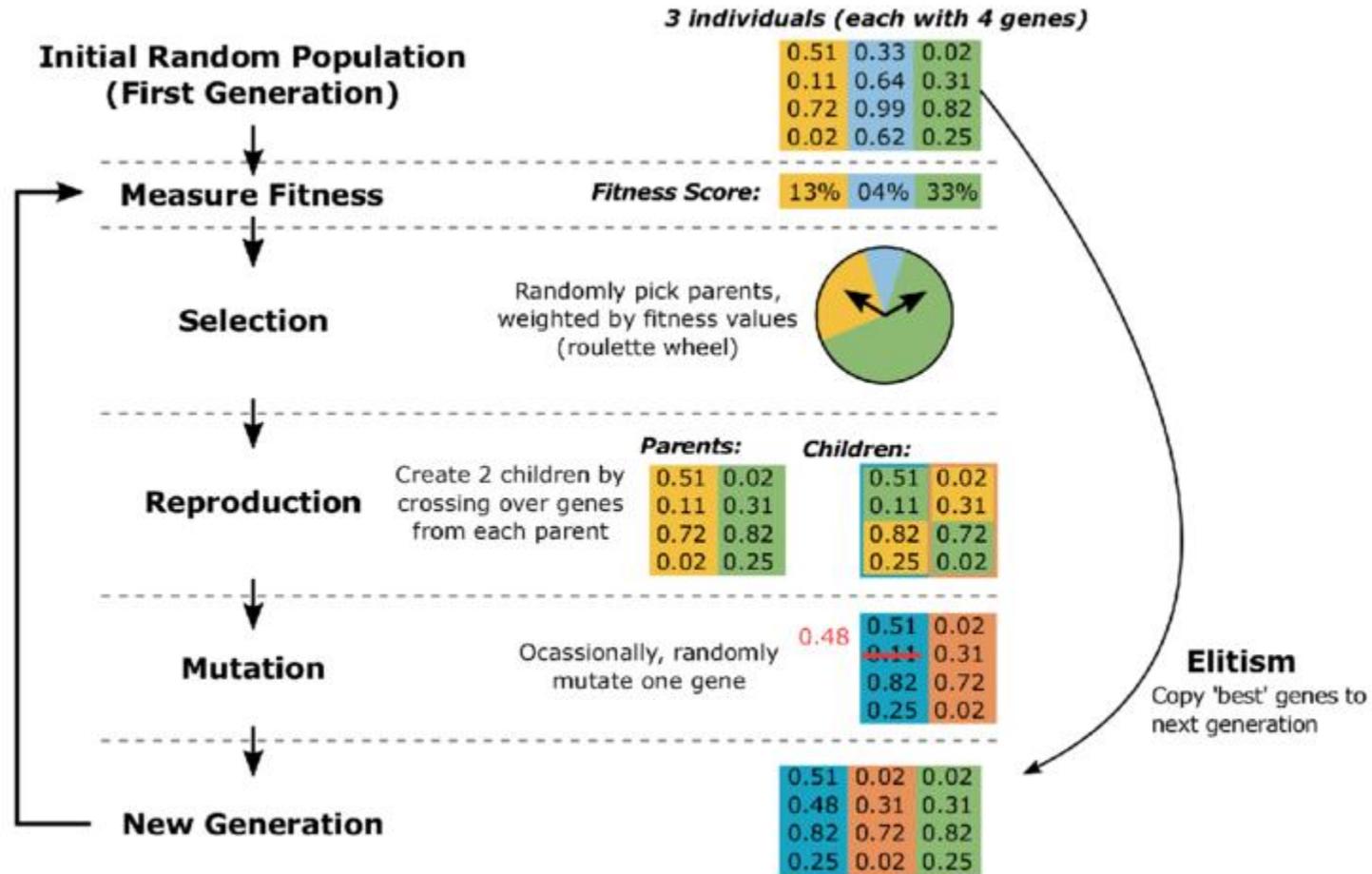


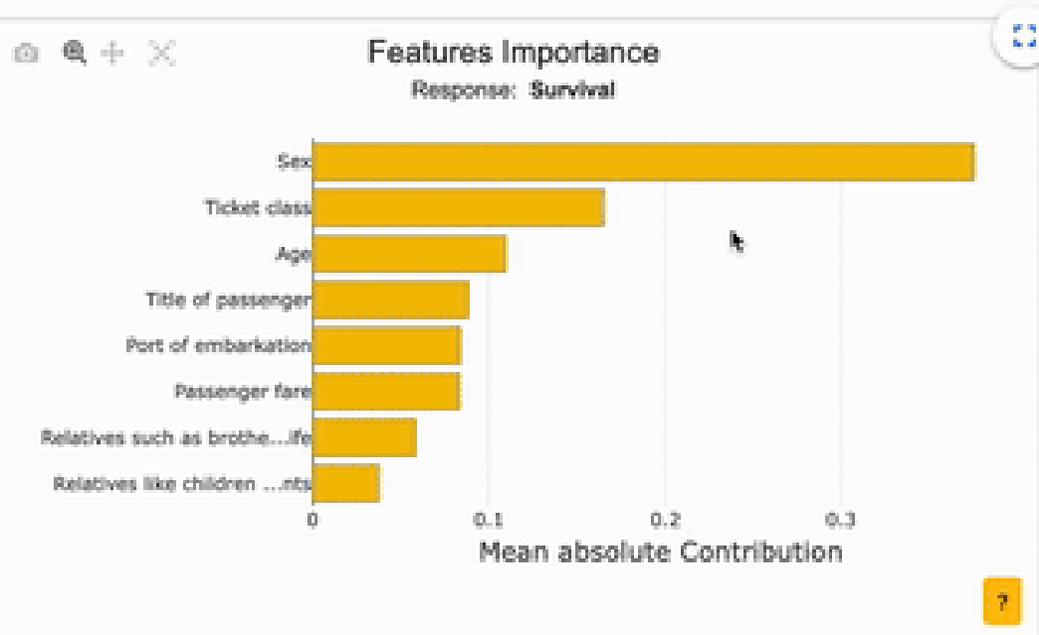
XGBoost Optimization – SHAP & Partial Dependency

ICE and PDP representations



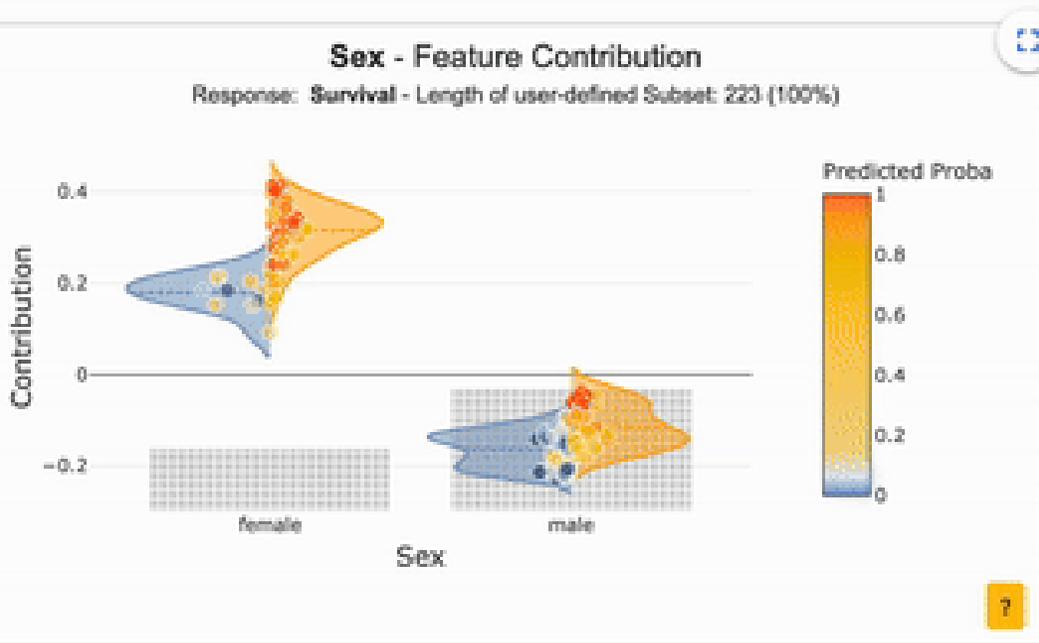
Optimization – NSGA II Genetic Algorithms





Dataset | Dataset Filters | True Values Vs Predicted Values

index	_predict_	_target_	Age	Embarked	Fare	Parch	Pclass	Sex
10	1	1	14	Cherbourg	30.1	0	Second class	female
14	0	0	39	Southampton	31.3	5	Third class	male
16	1	1	55	Southampton	16	0	Second class	female
21	0	0	35	Southampton	26	0	Second class	male
23	1	1	15	Queenstown	8	0	Third class	female
27	0	0	29.5	Cherbourg	7.2	0	Third class	male
35	1	0	28	Cherbourg	82.2	0	First class	male
47	0	0	29.5	Queenstown	15.5	0	Third class	male
49	1	0	29.5	Cherbourg	21.7	0	Third class	male
51	0	0	7	Southampton	39.7	1	Third class	male
54	1	1	29	Southampton	26	0	Second class	female



Select a valid single sample to display Local Explanation plot.

Threshold: 0

Features to display: 8

Contributions to display:

Positive Negative

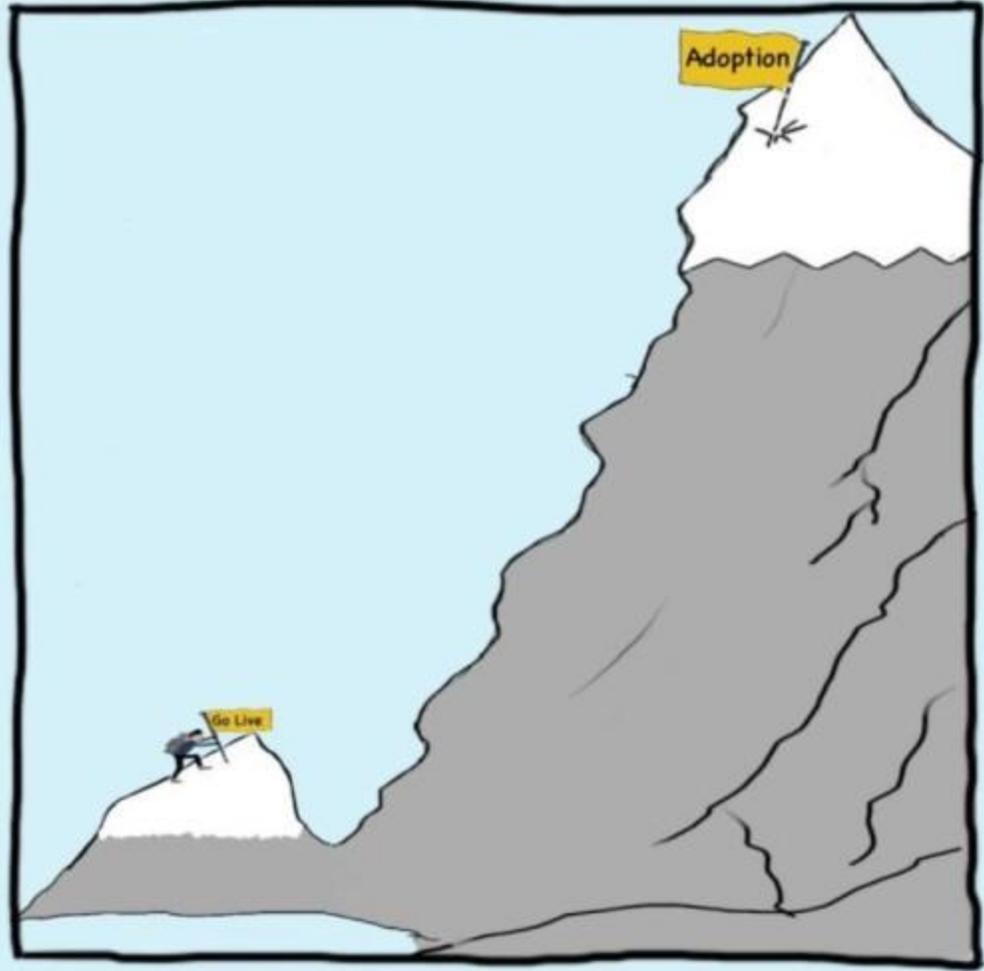
Feature(s) to mask:

Reason #7

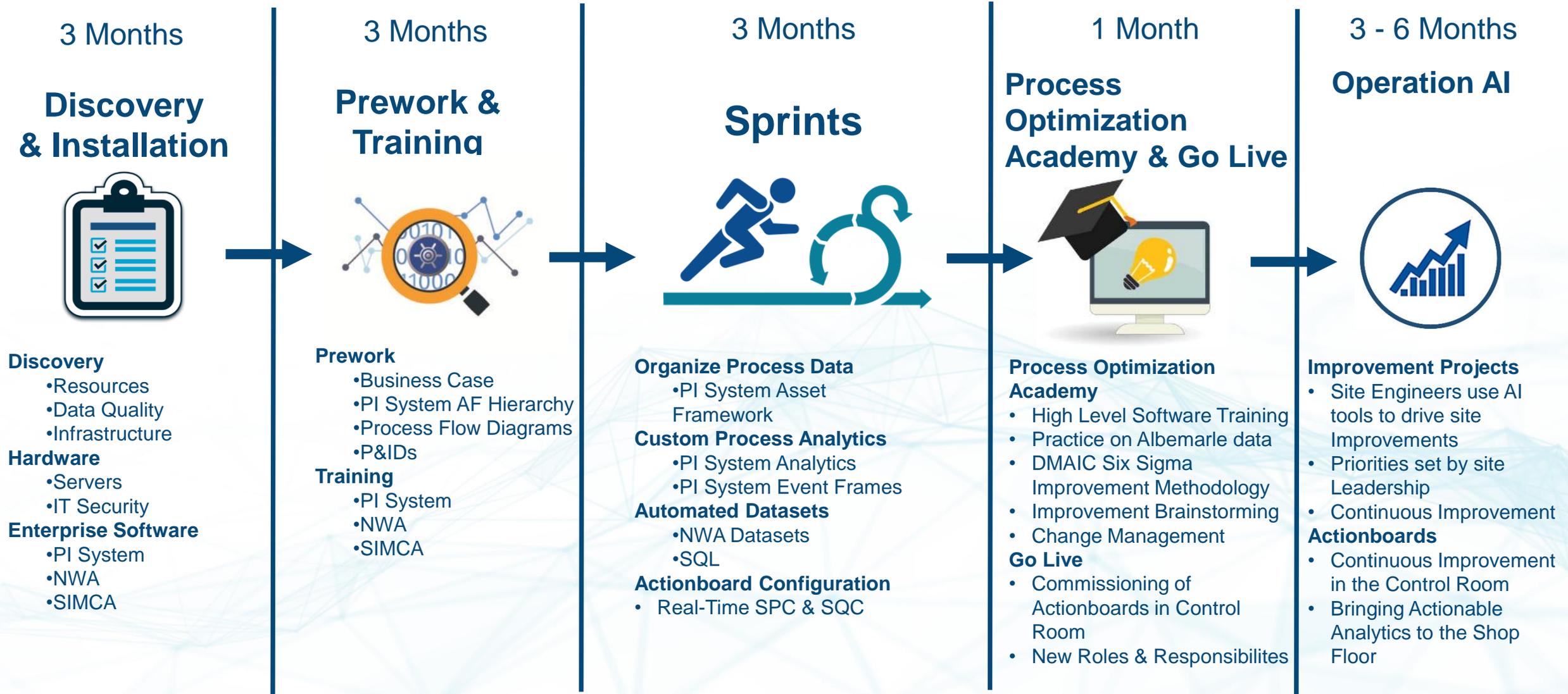


**Success
Doesn't End at
Launch**





Implementation Roadmap



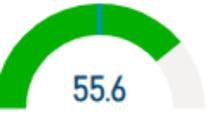
% Usage



Percent of alarms that were acknowledged on the Actionboard | Target > 90%



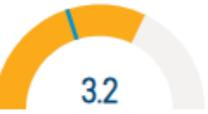
Response Quality



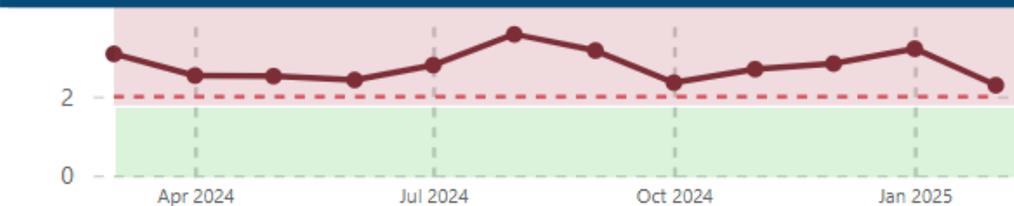
Avg # of characters in comments. Longer comments have more details and are more valuable | Target > 50



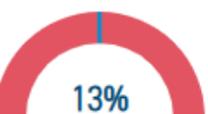
Response Hours



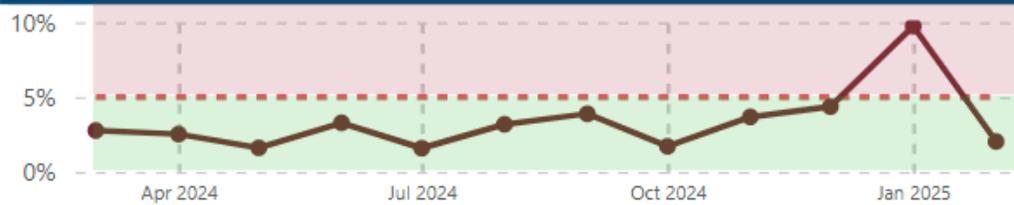
Average time from when the alarm appears on the actionboard until it has been responded to | Target < 2



% Nuisances



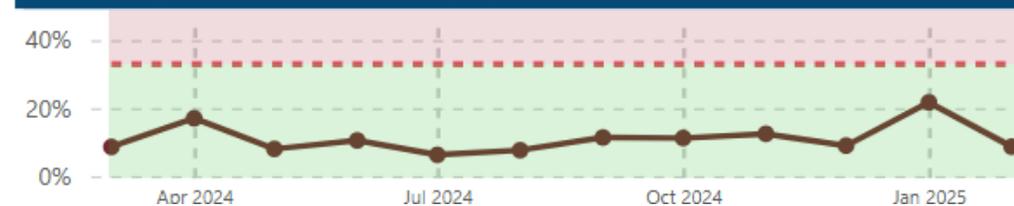
Percent of Nuisance alarms, as selected by operator | Target < 5%



% No Action



Percent of insights with no Corrective Action | Target < 33%



Month Selection for Gauges

Jan 2025

Range Selection for Charts

Last 12 Months

Actionboard

All

Phase

All

Increased Coverage Over Time



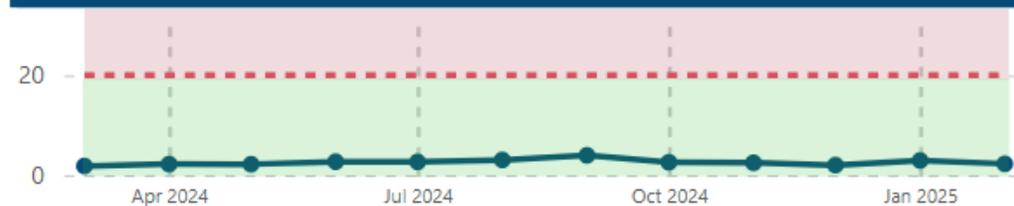
Count of charts with alarm over past month | Target > 5 additional charts per month



Insights per Hour



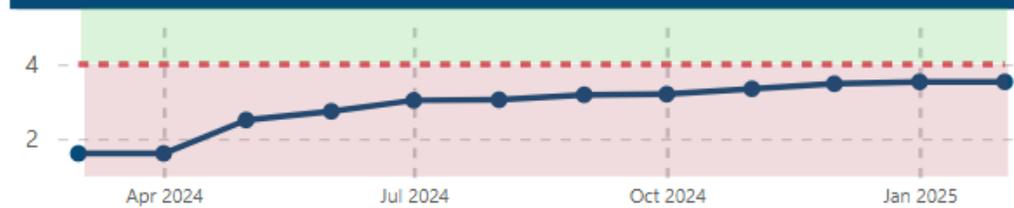
Average number of insights generated per hour | Target < 20



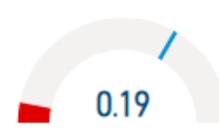
Unit Op Coverage



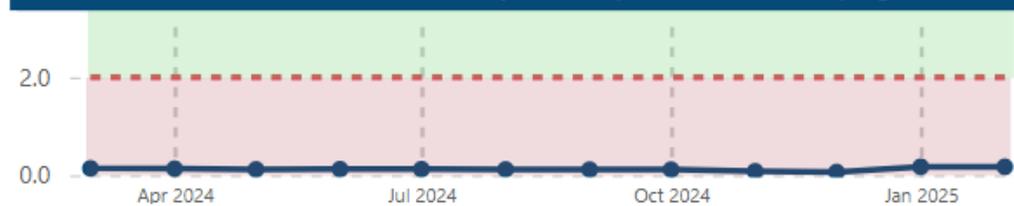
Total # of charts with alarms enabled divided by # of unit ops on the actionboards | Target > 4



SPC Alarms per UnitOp



Total # of charts with SPC alarms enabled divided by # of unit ops on the actionboards | Target > 2



Reason #8

A composite image showing a baseball field in the center, surrounded by rows of corn. The scene is set at sunset or sunrise, with a warm orange and yellow glow on the horizon. In the background, there are utility poles, a small house with a blue roof, and a larger barn with lit windows. The sky is filled with soft, wispy clouds.

**If You Build it,
They Won't
Come**

Digital Transformation Framework

The key elements to modernize your business

Leadership & Vision

Having a clear vision for the digital transformation journey and effectively communicating it to all employees

Digital Skills & Training

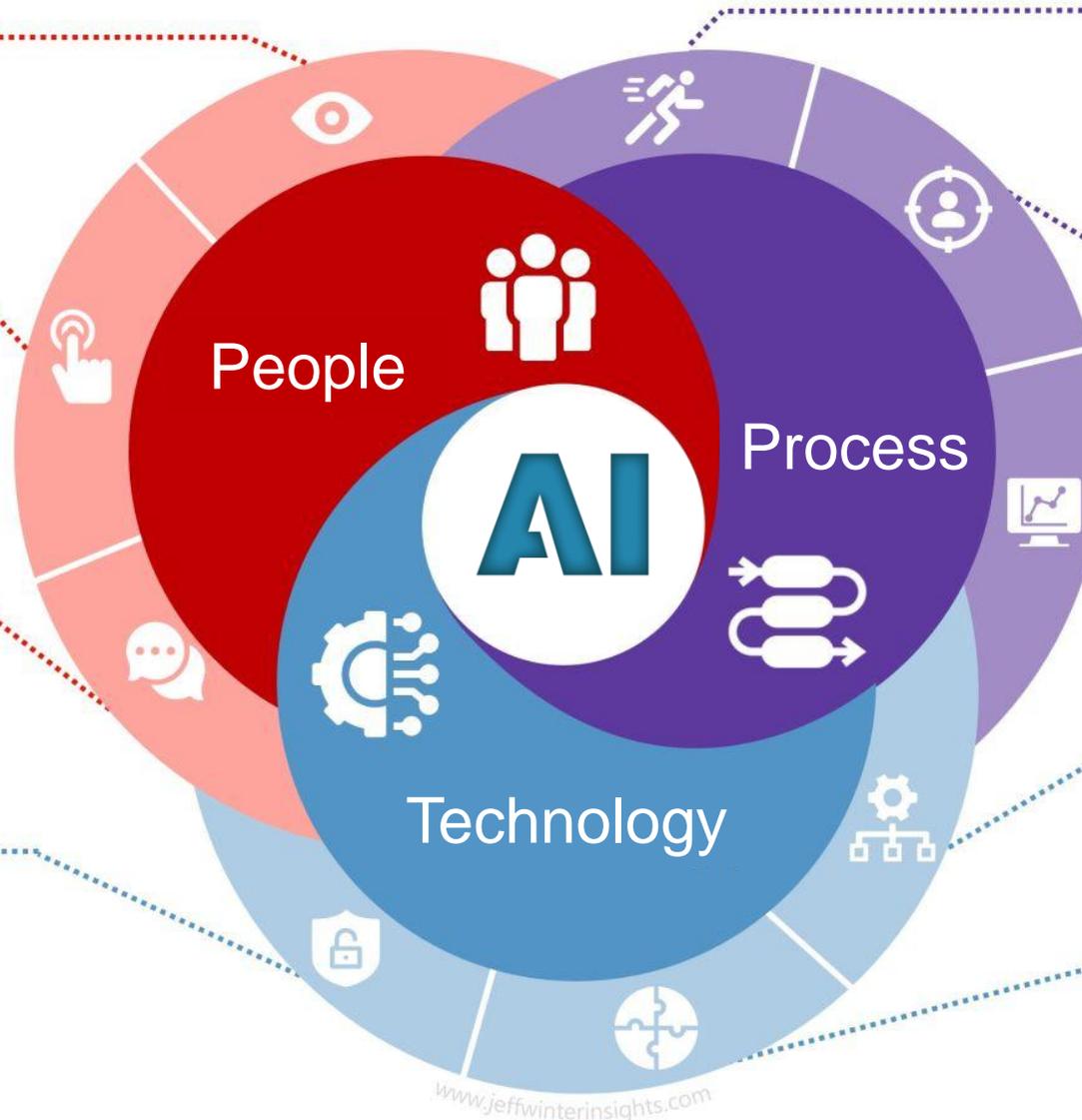
Equipping the employees with the necessary digital skills to navigate new technologies and tools

Collaboration & Communication

Fostering the right culture by breaking down silos, encouraging cross-functional teams, and facilitating knowledge sharing across the organization

Cybersecurity

Implementing strong cybersecurity measures to protect data, systems, and networks from potential attacks



Agile Methodologies

Implementing iterative and incremental approaches to project management and product development to be nimbler and more responsive to change

Customer-Centricity

Adopting a design thinking approach and continuously seeking feedback from customers

Data-Driven Decision-Making

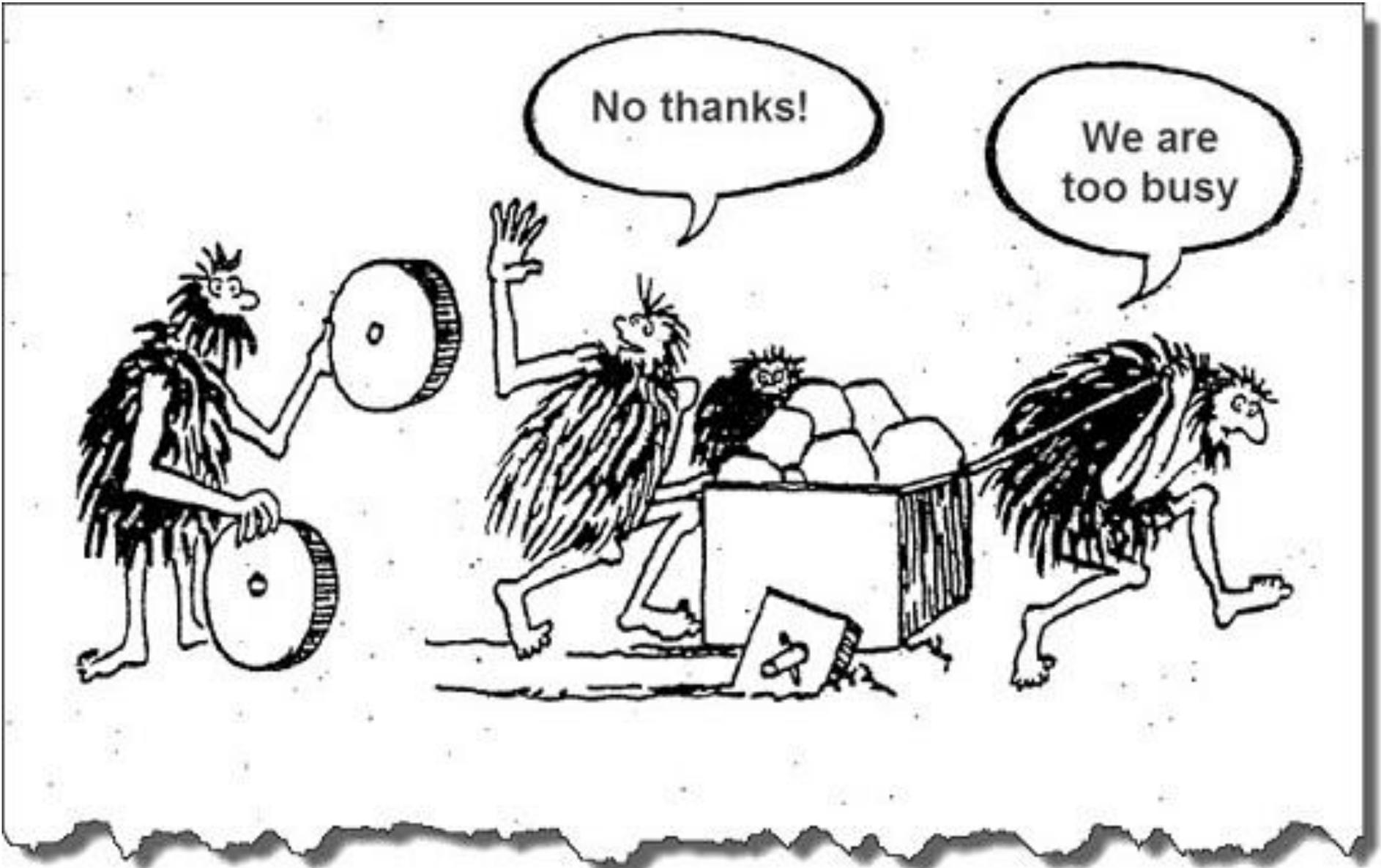
Leveraging data and analytics as an integral part of decision-making processes

Infrastructure

Investing in a robust and scalable digital infrastructure that can support the organization's needs

Integration

Ensuring seamless integration of different systems and platforms across business functions

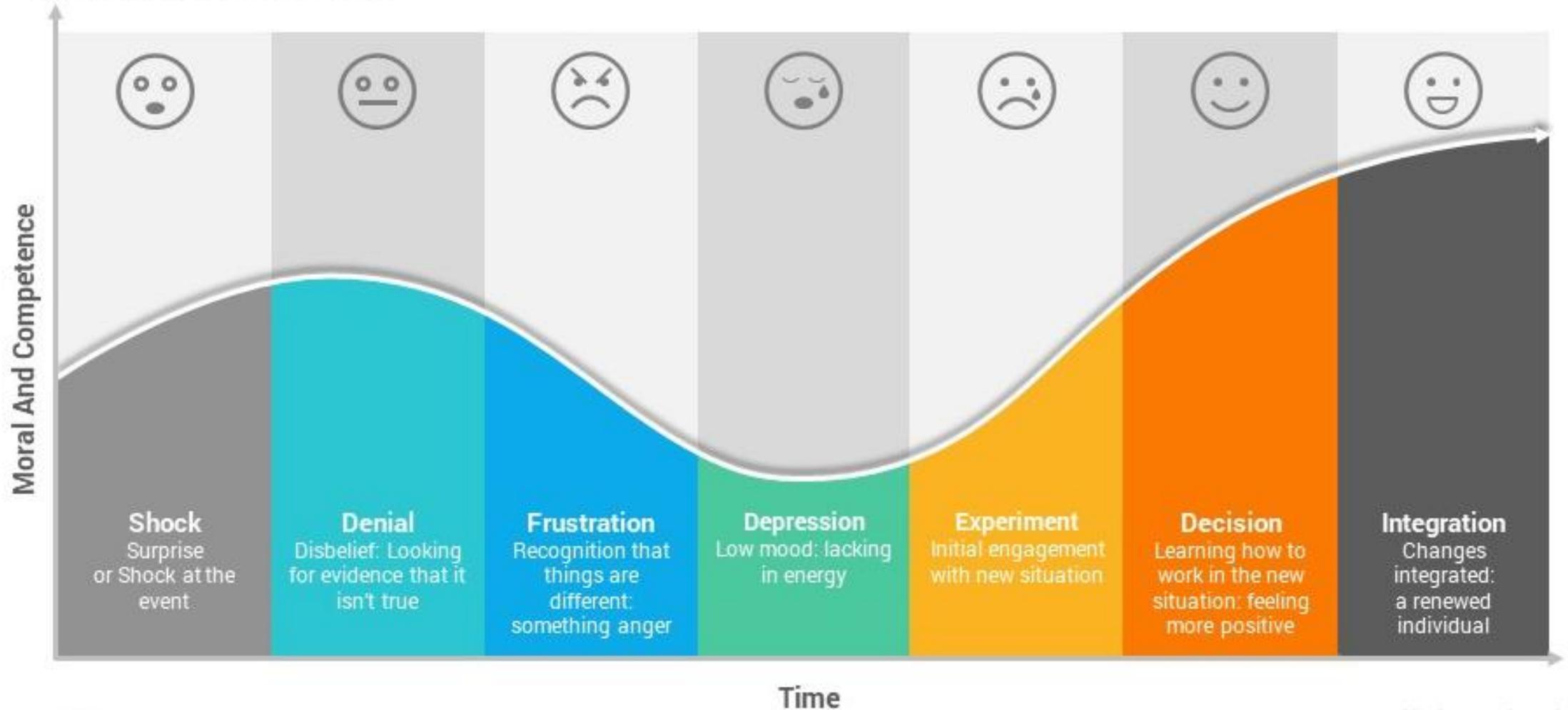


ADKAR Change Management



Kübler-Ross Change Model Curve Template

Emotional Response to Change

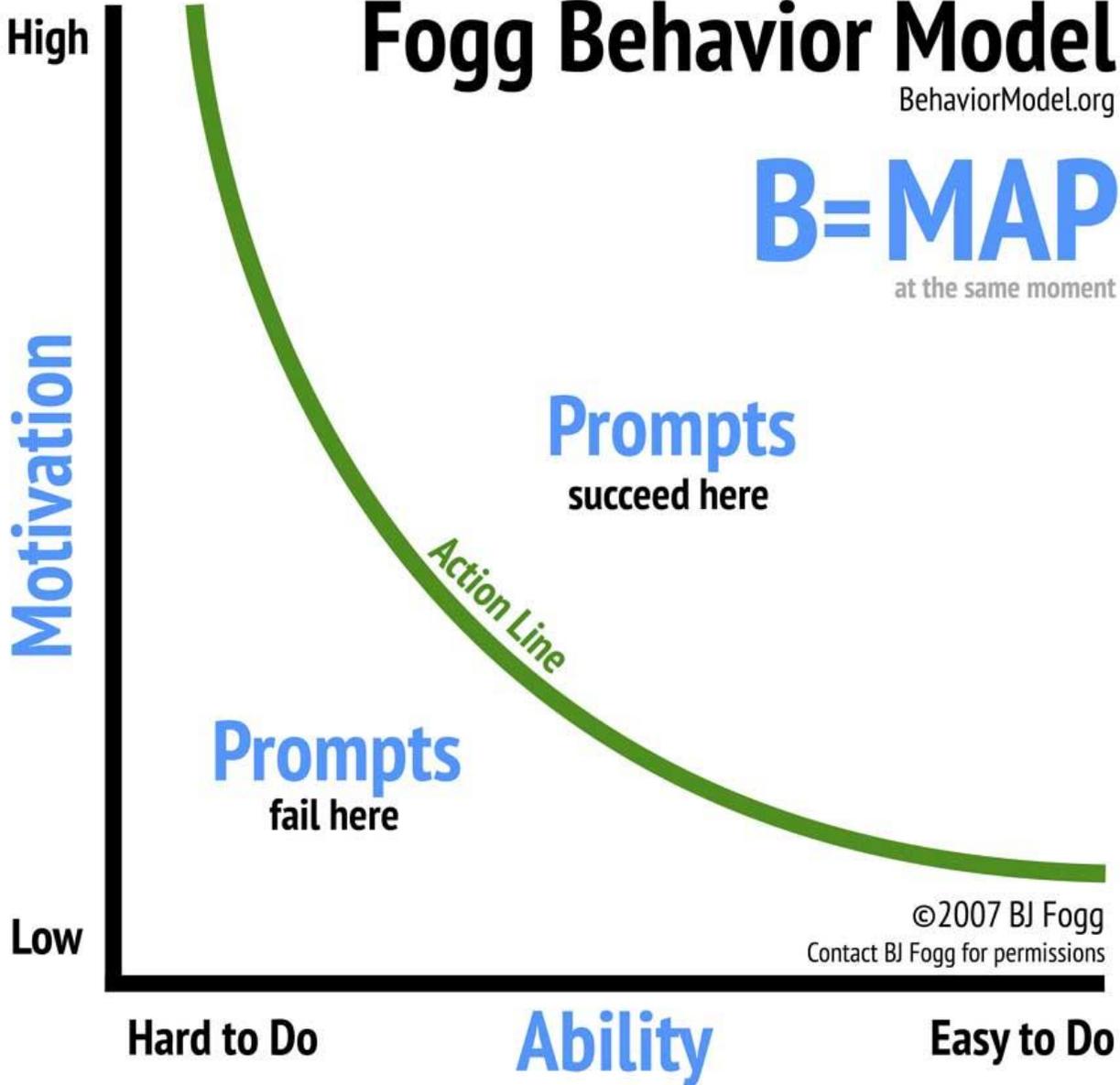


Fogg Behavior Model

BehaviorModel.org

$$B = MAP$$

at the same moment



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Reason #9



Culture Eats Strategy for Breakfast





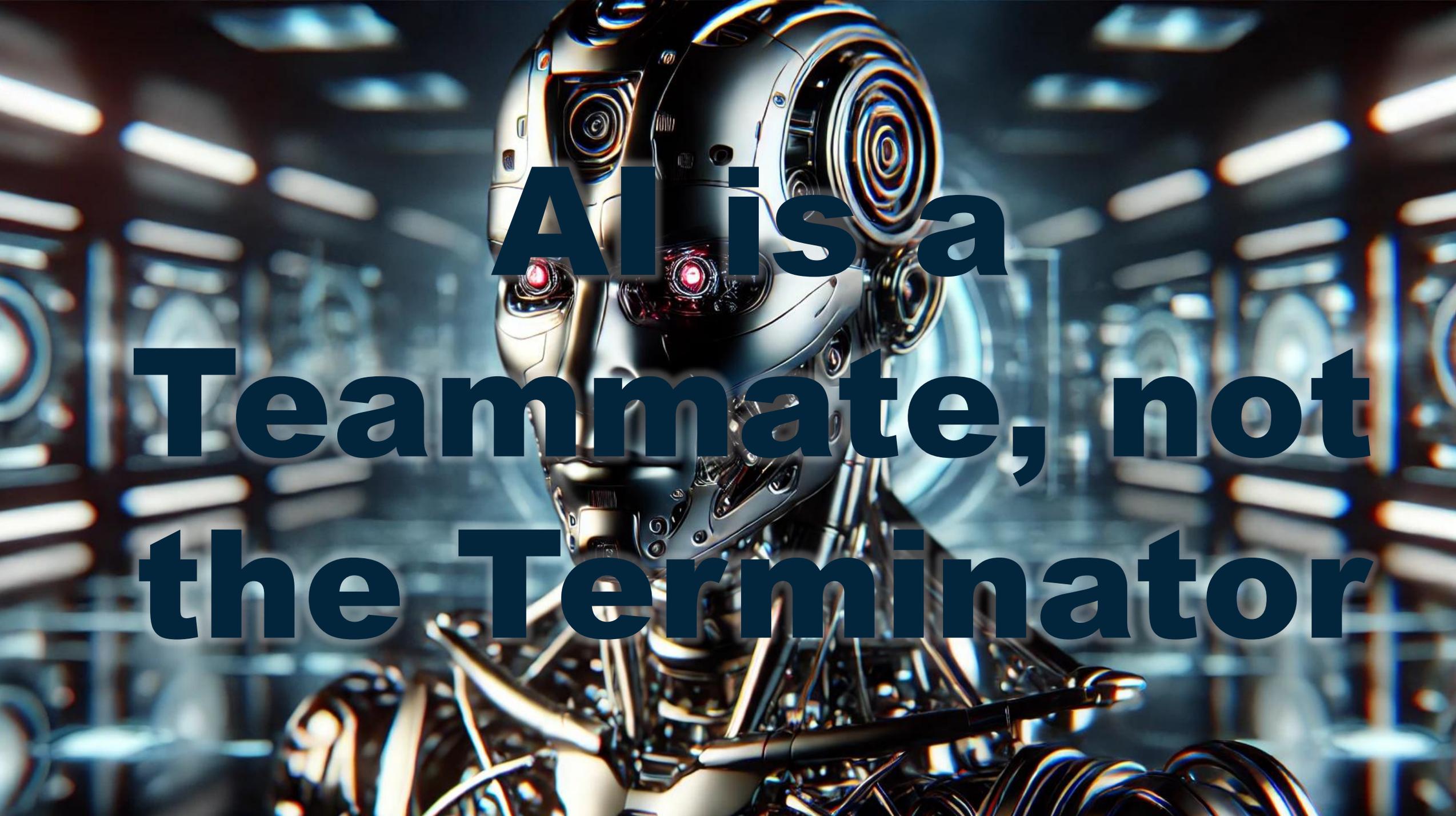




ALBEMARLE INTELLIGENCE



Reason #10



**AI is a
Teammate, not
the Terminator**



0101

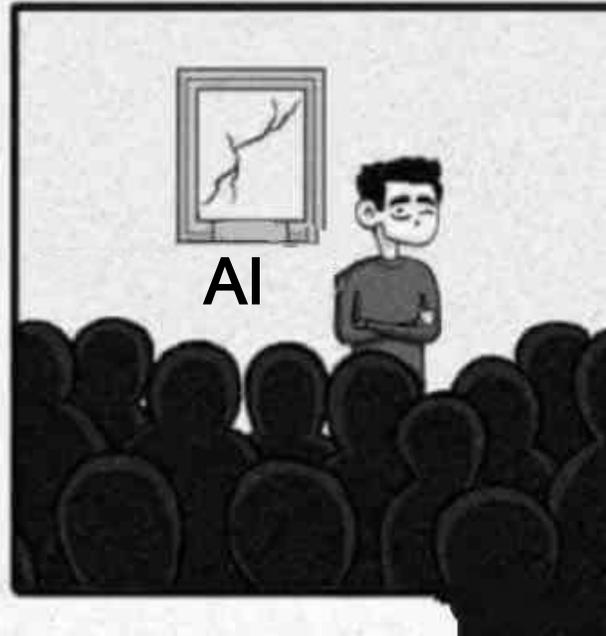
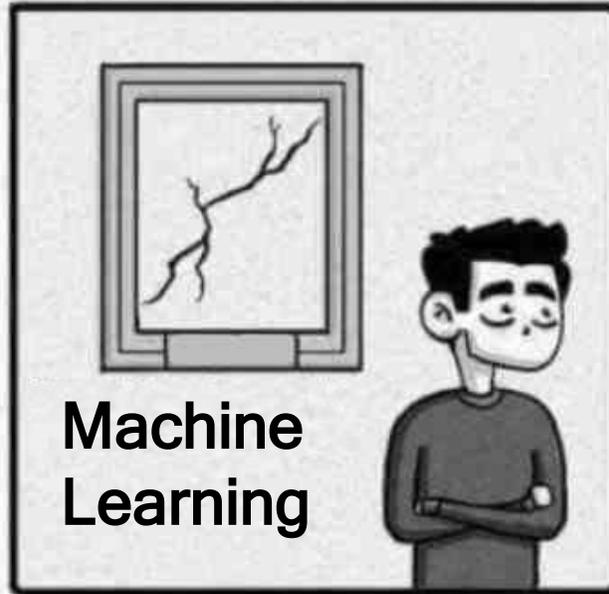
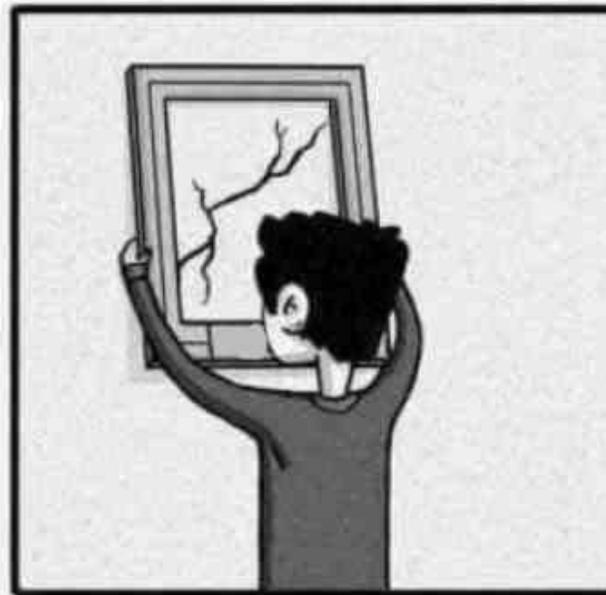
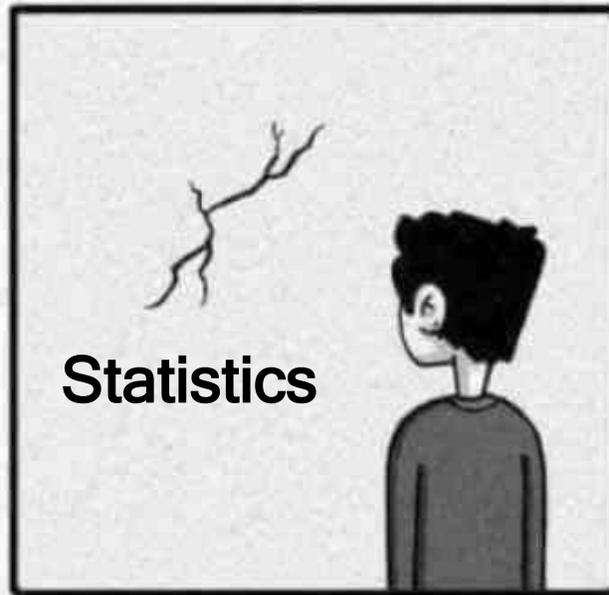
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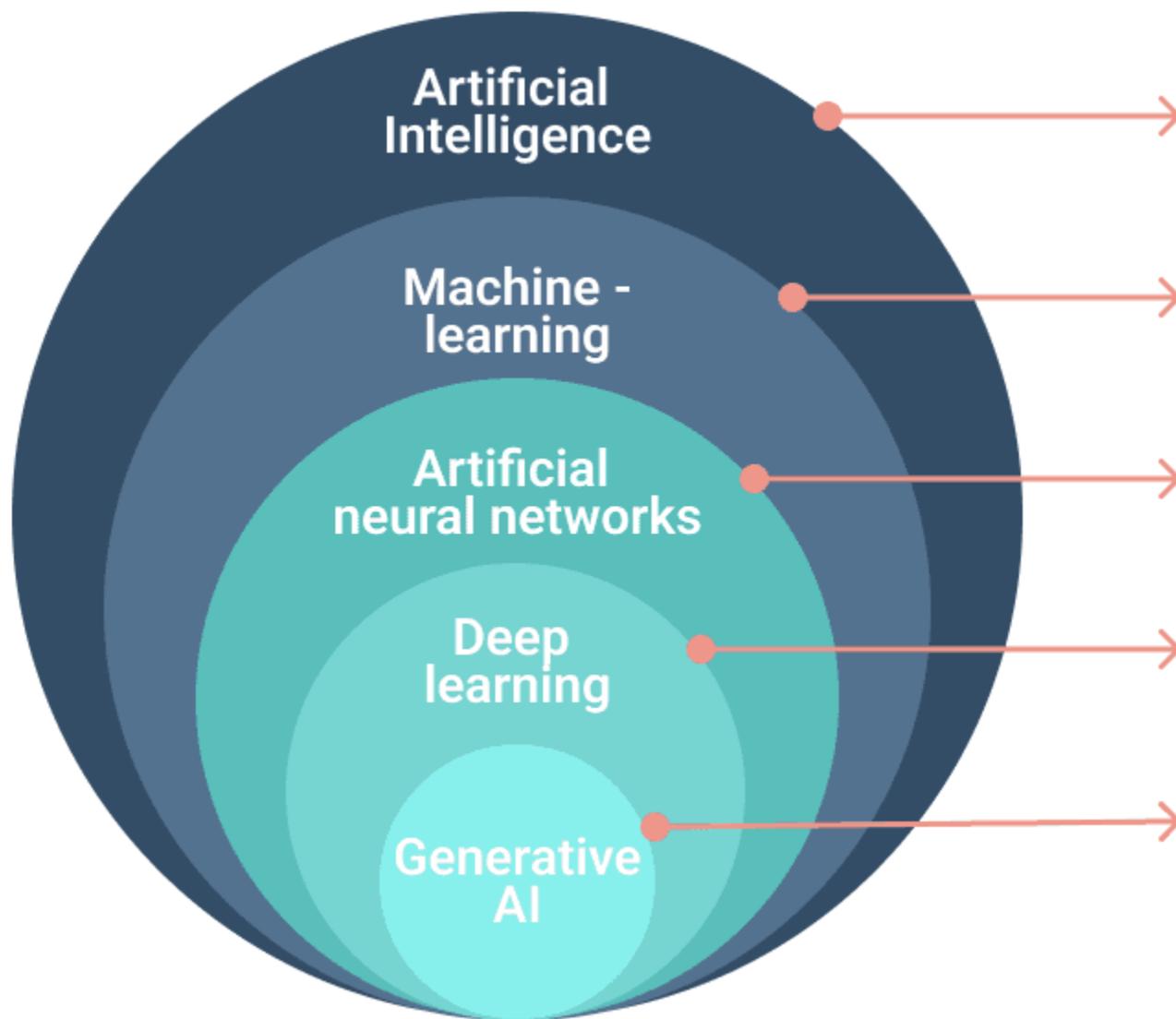
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Artificial Intelligence (AI)

Development of machines that can perform tasks requiring human-like intelligence.

Machine-learning (ML)

Training of computers to learn and make predictions or decisions without being explicitly programmed.

Artificial neural networks (ANN)

Human brain-inspired machine-learning models.

Deep learning (DL)

Neural networks with multiple layers to extract complex patterns and make accurate predictions or decisions.

Generative AI (GenAI)

Creating models and systems that can generate new and original content.

Image 2. AI subsets



Ensure that artificial general intelligence (AGI) benefits humanity.

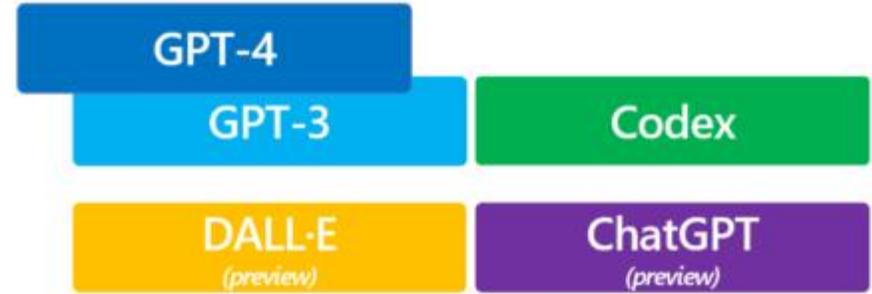
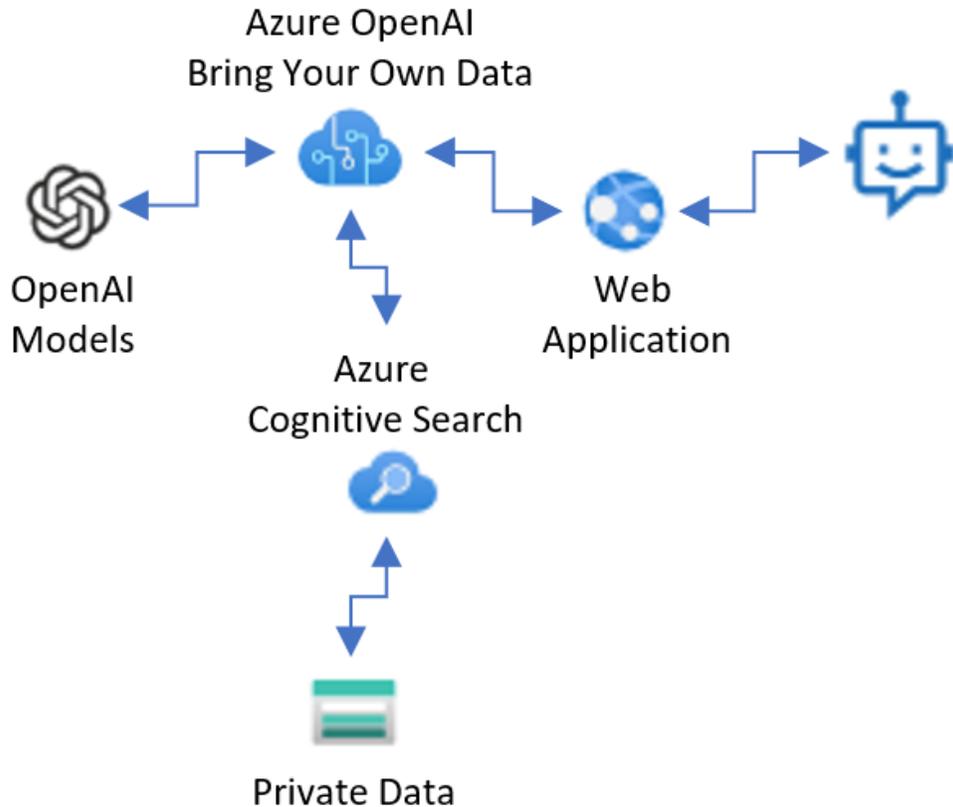


Microsoft

Empower every person and organization on the planet to achieve more



Azure OpenAI Service



Enterprise-grade, scalable infrastructure



Custom AI models fine-tuned with your data and hyperparameters



Enterprise-grade security with role-based access control and private networks



Built-in responsible AI to detect and mitigate harmful use



Chat with your data

Ask anything or try an example

Where does my raw water pump get its water from?

What modes does my BMS have on my calciner?

How does my fuel/air ratio control work for my calciner burner?



Type a new question (e.g. does Functional Control Description include Software standards?)



■ Hey Chat GPT,
finish this building...

■ Hey Chat GPT,
finish this building...

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ALBEMARLE
INTELLIGENCE

Automated Information

Analytics Innovation

Actionable Insight



Albemarle People
Empowered by Technology
Unlocking the value of information



AUTOMATIZACIÓN DE LA INFORMACIÓN

ANALÍTICA CON INNOVACIÓN

ACCIONES INFORMADAS

**INTELIGENCIA
ALBEMARLE**



Personal de Albemarle,
Empoderados por la Tecnología,
Liberando el Valor de la Información



自动信息

分析创新

切实可行的洞察

雅保智能



雅保人，
技术赋能，
释放信息的价值

Albemarle creates 25 Million Event Frames, with estimated improvements >\$150 million annually

Challenge

- Hundreds of thousands of data points
- Manual data sharing and reporting processes led to information bottlenecks
- Massive manufacturing growth and demand – fueling the need for more efficient manufacturing processes

Solution

- Deployed a massive, standardized implementation of the full AVEVA™ PI System™
- Created Albemarle Intelligence Program, merging the experience and skillset from all of our manufacturing employees, with world-class technology

Results

- >\$150 million in estimated annual improvements



Albemarle
PEOPLE 1: A2
Empowered by
TECHNOLOGY
To unlock the
VALUE
of information

AVEVA



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