Predictive Asset Management and Applications to Manufacturing

NIST STANDARDS REQUIREMENTS WORKSHOP

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Rotary & Mission System (RMS)
Analytics, Prognostics & Health Management, and Artificial Intelligence (APAI) Innovations

LM produces some of the most sophisticated equipment on the planet…

- Planes
- Helicopters
- Satellites
- UAVs
- Rockets
- Ships
- Radars
- Lasers
- Fusion reactors
- and more..

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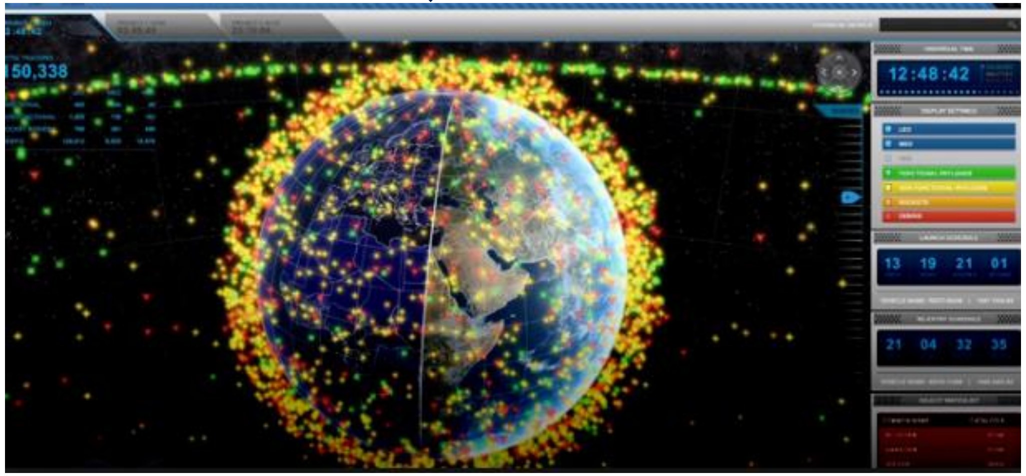
…with some very important and complex missions

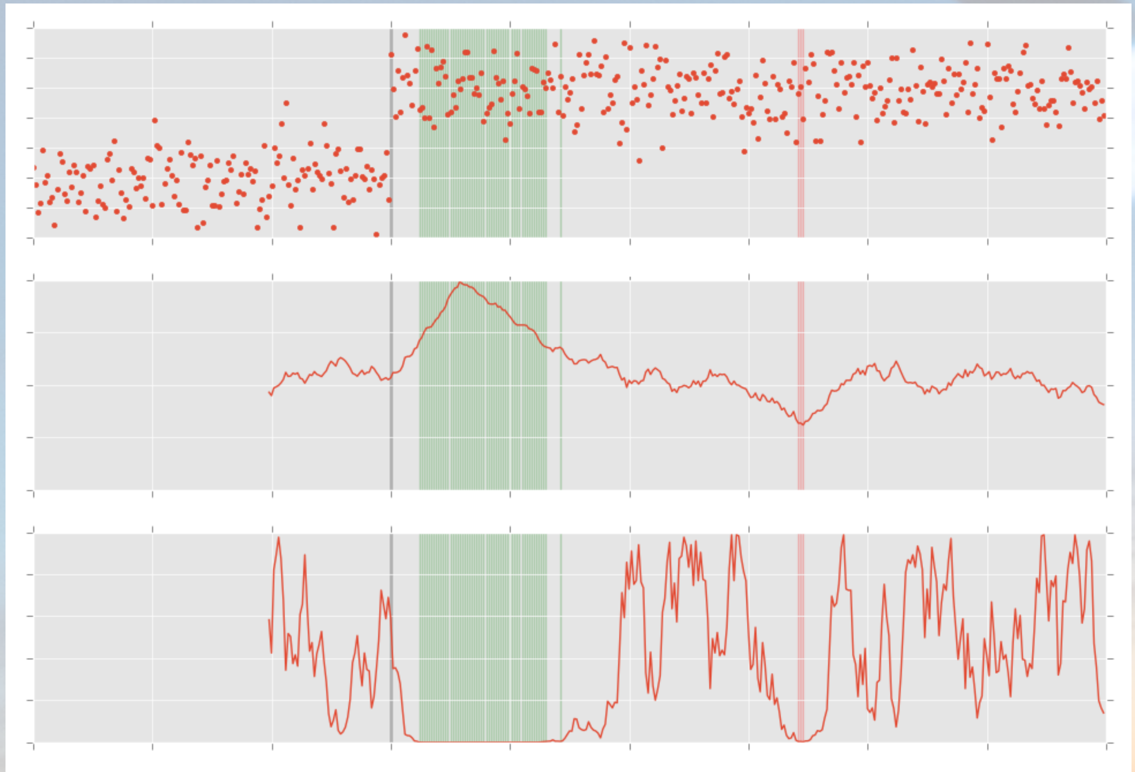
- **Humanitarian Assistance & Disaster Relief**
- **Global materiel transport**
- **Human Mission to Mars**
- **Even tracking space junk!**

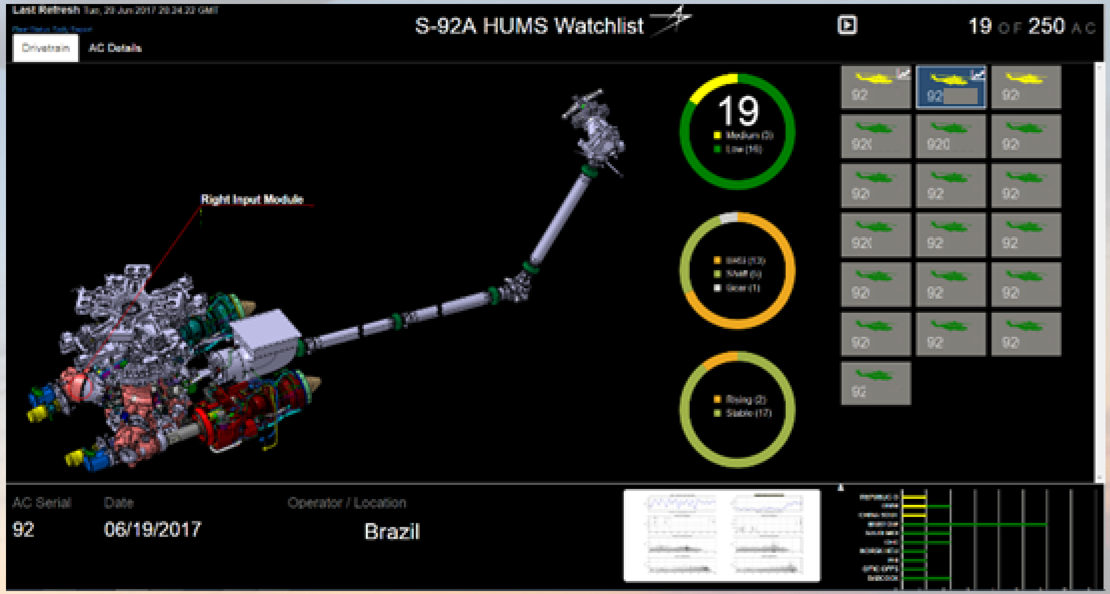


…so we collect lots of data (variety & volume) to help us sustain these fleets.

- Platform Operational data (e.g. Health & Usage Monitoring Systems (HUMS)
- Flight Tests
- Supply chain & logistics
- Maintenance
- Safety
- Operator meta-data
- Engineering

Equipment Prognostics & Health Management (PHM)

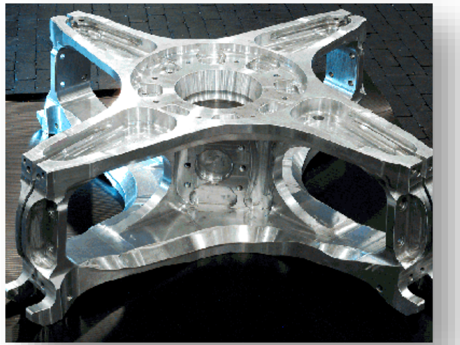




Reducing Costs and Improving Reliability

Level-of-Repair Optimization
Opportunity to reduce removals

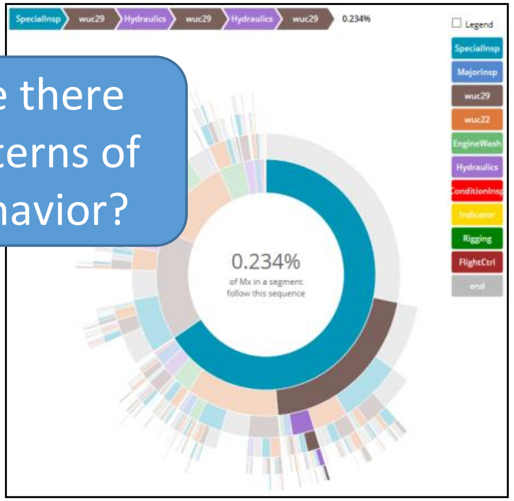
Extending Time-on-Wing
Leveraged HUMS and maintenance data to identify candidates for TBO extension



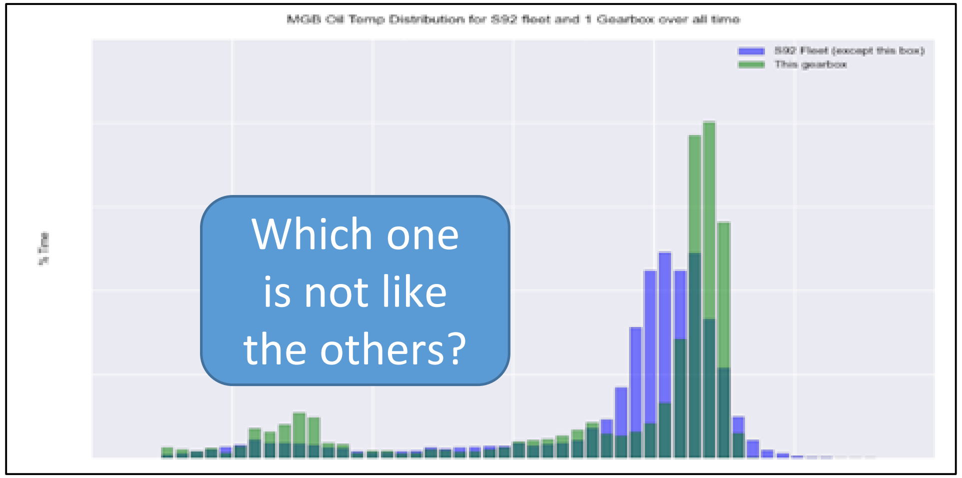
Repairability
Developed repairs to reduce scrap rates

Downtime Avoidance
HUMS trend monitoring

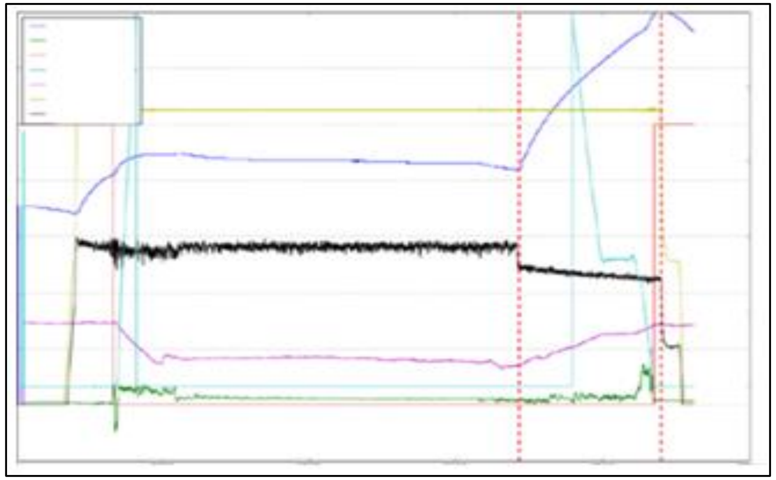
Ad Hoc Analyses

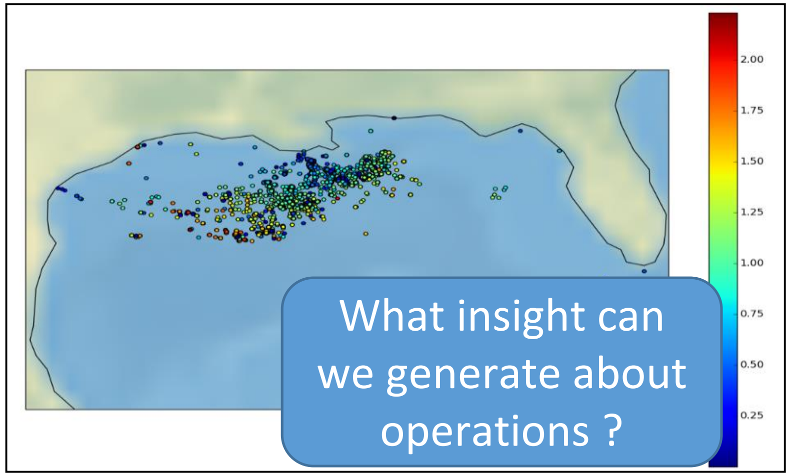


Are there patterns of behavior?

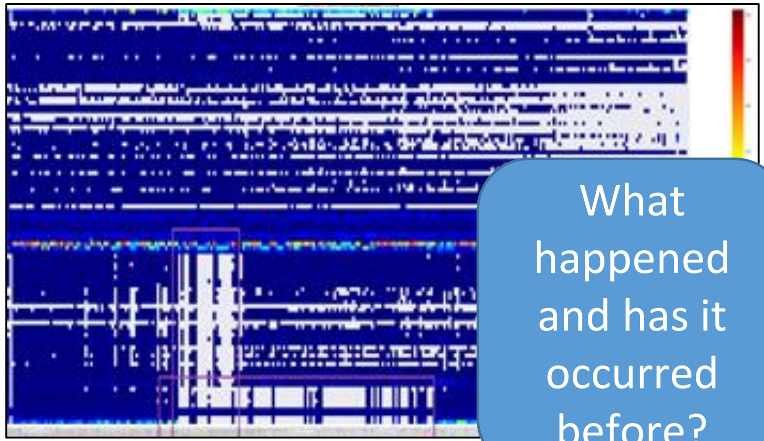


Which one is not like the others?

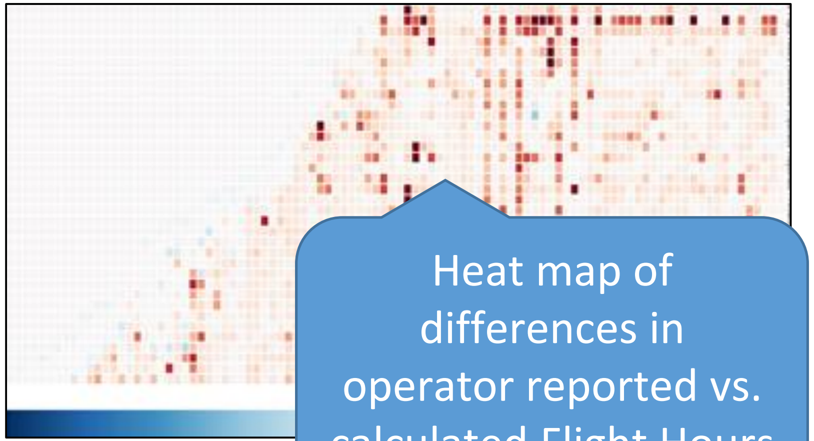




What insight can we generate about operations ?



What happened and has it occurred before?



Heat map of differences in operator reported vs. calculated Flight Hours

Total System Health Management

Engine
Auto Power Assurance
LRU Fault Diagnostics
Propulsion System Diagnostic Reasoner
Engine Prognostics

Drive System
Loads Monitoring
Adv. Dynamic Load-Based Diagnostics
Drive System Diagnostic Reasoner
Oil condition & debris monitoring

Rotor & Propulsion System
Rotor State - Load & Motion Sensors
Virtual Monitoring Loads
Rotor Component Health Monitoring
Rotor System Diagnostic Reasoner
Blade Impact Detection & Characterization
Automated Rotor Track & Balance

Airframe
GW/CG monitoring
Global/Local Loads & Impact Monitoring
Environment Monitoring & Risk Assessment
Fatigue, Corrosion, Impact/Battle Damage Detection
Structural Integrity Reasoner

Adaptive Controls
Load limiting controls
Damage adaptive controls

Flight Controls & Hydraulics
Hydraulic Leak Detection
Hydraulic Pump Diagnostics
Servo Diagnostics

Electric Power & Wiring
Smart solid state power
Distribution components
Wire fault detection & isolation
LRU diagnostic reasoner

Fleet Management
Usage-Based Maintenance
Condition-Based Maintenance
Damage Tolerance
Maintenance-Free Operation Period

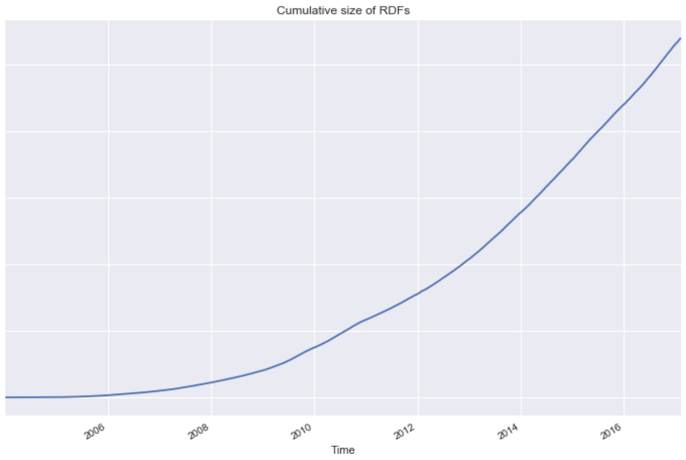
Fleet Management

Dealing With The Data

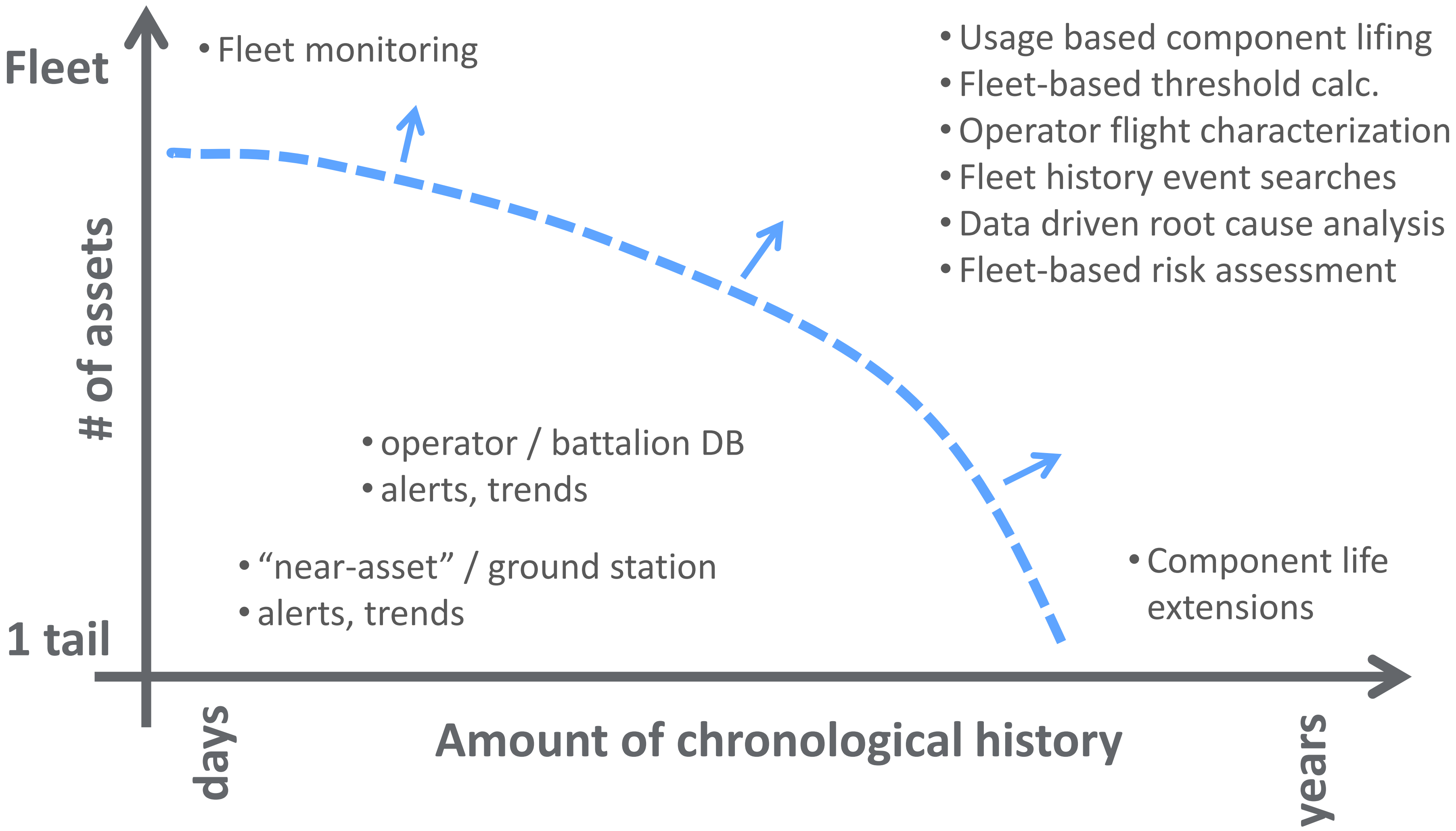
Platform Operational Data

e.g. Health & Usage Monitoring Systems (HUMS)

- Hundreds to thousands of raw parameters sampled continuously throughout operation
- Thousands of discrete event types
- Thousands of indicators calculated from raw data
- Thousands of usage metrics
- and more…

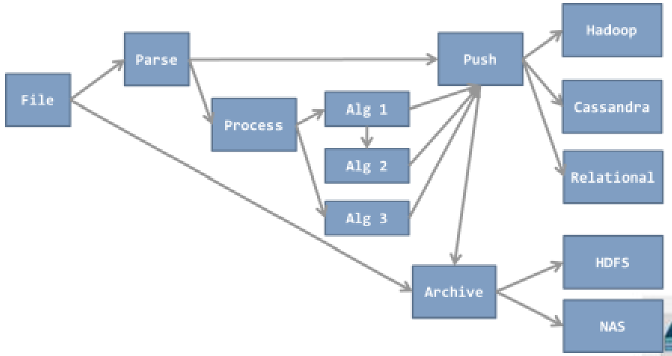


Using all of the data…

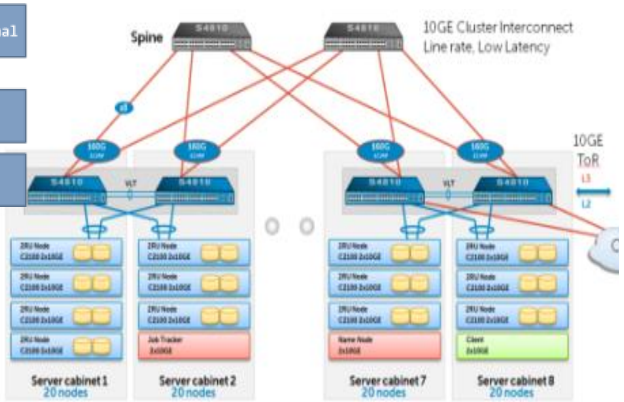


Data Problems

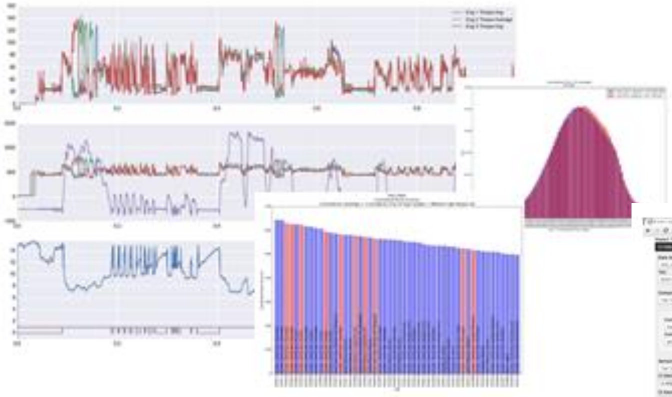
Ingest



Store



Process



Retrieve

Applications Leveraging GPUs

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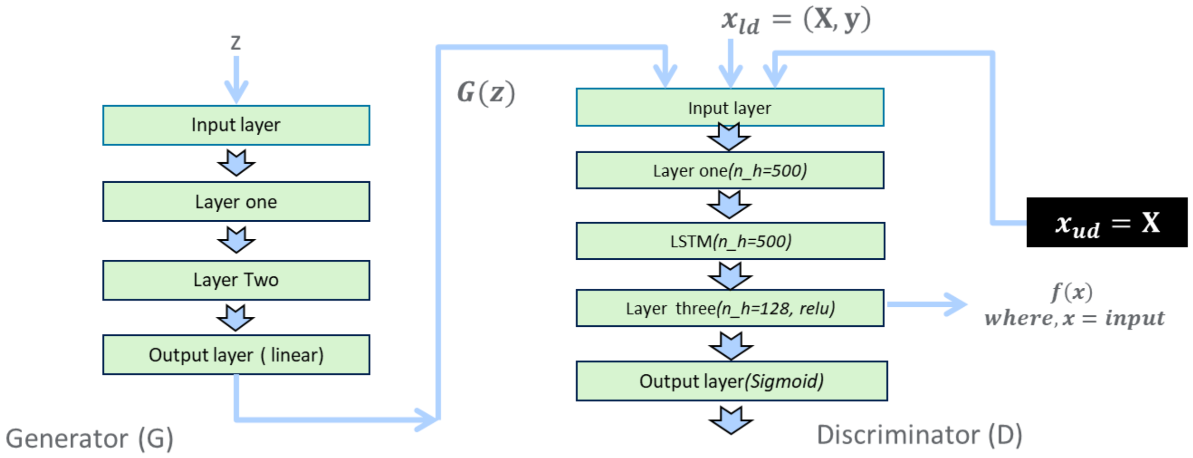
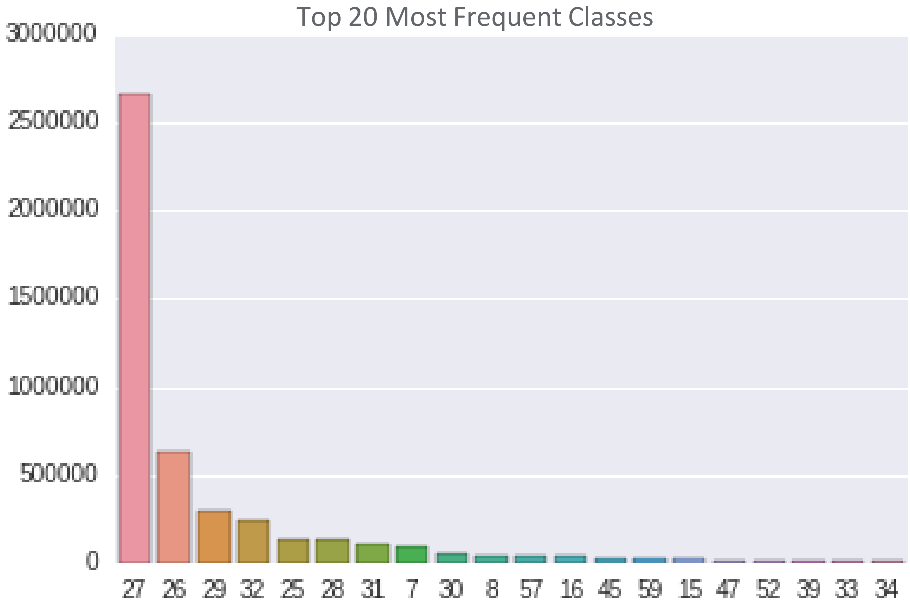
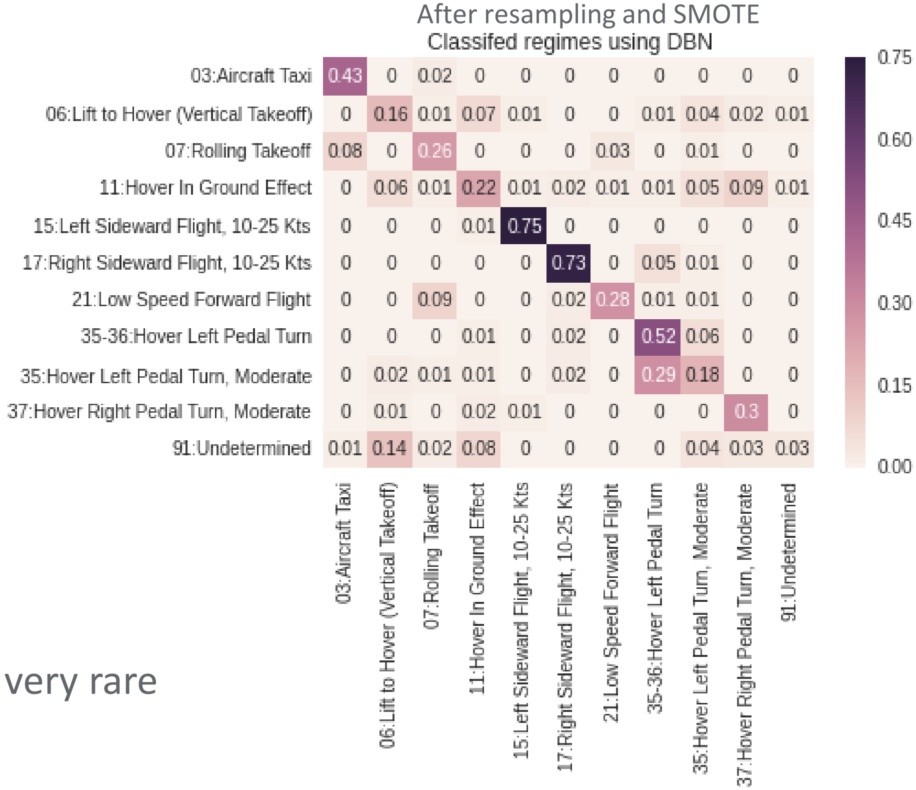
Multivariate Timeseries Data

- Classification
- Anomaly Detection
- Signal reconstruction
- Virtual monitoring



Telemetry Data Classification





	03:Aircraft Taxi	06:Lift to Hover (Vertical Takeoff)	07:Rolling Takeoff	11:Hover In Ground Effect	15:Left Sideward Flight, 10-25 Kts	17:Right Sideward Flight, 10-25 Kts	21:Low Speed Forward Flight	35-36:Hover Left Pedal Turn	35:Hover Left Pedal Turn, Moderate	37:Hover Right Pedal Turn, Moderate	91:Undetermined
03:Aircraft Taxi	0.43	0	0.02	0	0	0	0	0	0	0	0
06:Lift to Hover (Vertical Takeoff)	0	0.16	0.01	0.07	0.01	0	0	0.01	0.04	0.02	0.01
07:Rolling Takeoff	0.08	0	0.26	0	0	0	0.03	0	0.01	0	0
11:Hover In Ground Effect	0	0.06	0.01	0.22	0.01	0.02	0.01	0.01	0.05	0.09	0.01
15:Left Sideward Flight, 10-25 Kts	0	0	0	0.01	0.75	0	0	0	0	0	0
17:Right Sideward Flight, 10-25 Kts	0	0	0	0	0	0.73	0	0.05	0.01	0	0
21:Low Speed Forward Flight	0	0	0.09	0	0	0.02	0.28	0.01	0.01	0	0
35-36:Hover Left Pedal Turn	0	0	0	0.01	0	0.02	0	0.52	0.06	0	0
35:Hover Left Pedal Turn, Moderate	0	0.02	0.01	0.01	0	0.02	0	0.29	0.18	0	0
37:Hover Right Pedal Turn, Moderate	0	0.01	0	0.02	0.01	0	0	0	0	0.3	0
91:Undetermined	0.01	0.14	0.02	0.08	0	0	0	0	0.04	0.03	0.03

- Top 5 regimes encompass 90% of data, others are very rare
- Rare classes are difficult to learn

Parameter Inference and Virtual Monitoring

- Using deep networks to generate missing signals

Autoencoder Approach

0	input0	1x32x32
1	conv2d	16x30x30
2	conv2d	16x28x28
3	maxpool2d	16x14x14
4	conv2d	32x12x12
5	maxpool2d	32x6x6
6	reshape	1152
7	dense	256
8	encode	40
9	dense	256
10	dense	2048
11	reshape	32x8x8
12	upscale2d	32x16x16
13	conv2d	16x18x18
14	upscale2d	16x36x36
15	conv2d	16x34x34
16	conv2d	1x32x32
17	dense 256	
18	dense 32 (linear)	

Sequence Modeling (RNN-LSTM) Approach

Input layer (10 x 36)
10 sec Time sequence
36 features

↓

LSTM layer
(n_h=500)

↓

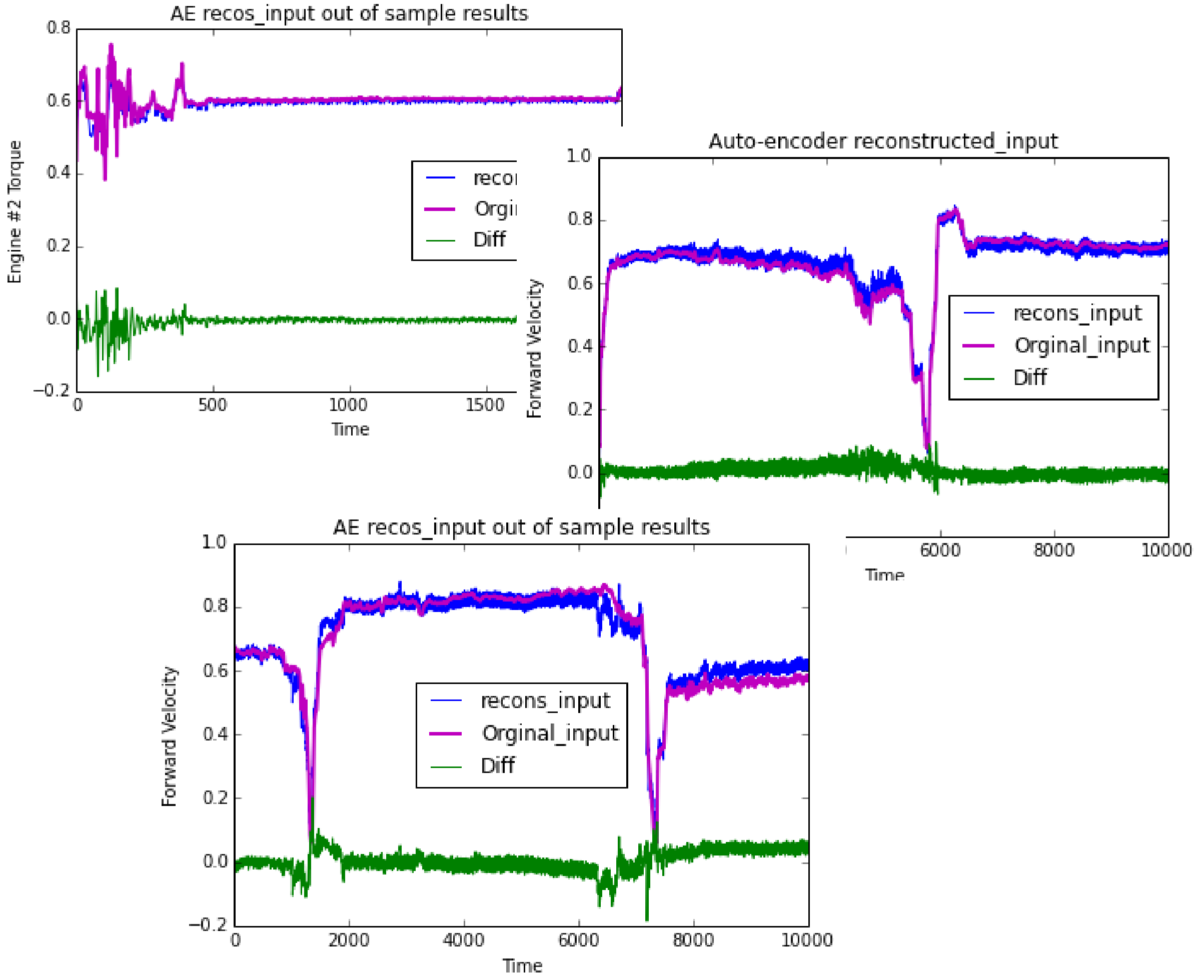
LSTM layer
(n_h=500)

↓

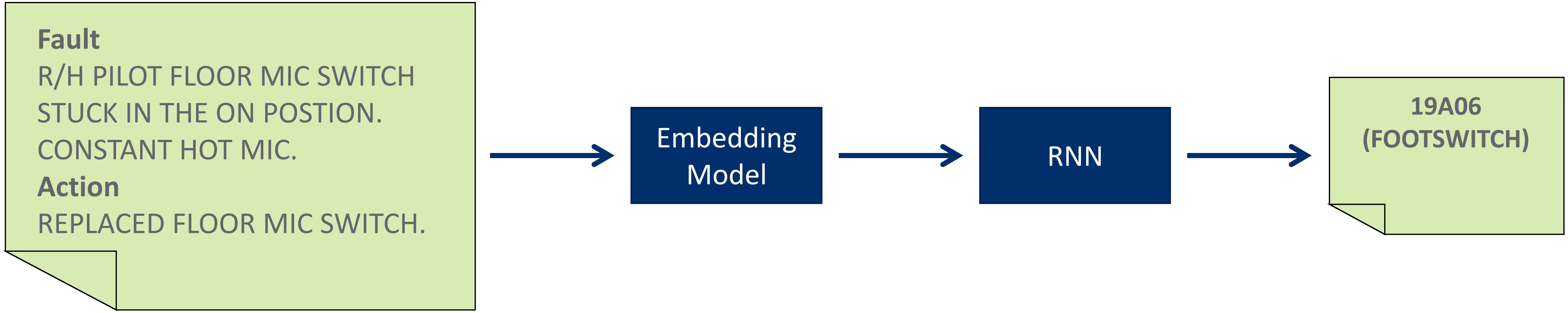
Dense layer
(linear)

↓

Output layer



NLP For Text Classification



Fault & Action text → Maintenance code
Free form text → Malfunction code
Maintenance data → Machine summary
etc

FRACAS Code Scoring

FRACAS: Failure Reporting, Analysis, and Corrective Action System
WUC: Work Unit Code

Fault	Action
R/H PILOT FLOOR MIC SWITCH STUCK IN THE ON POSTION. CONSTANT HOT MIC.	REPLACED FLOOR MIC SWITCH.

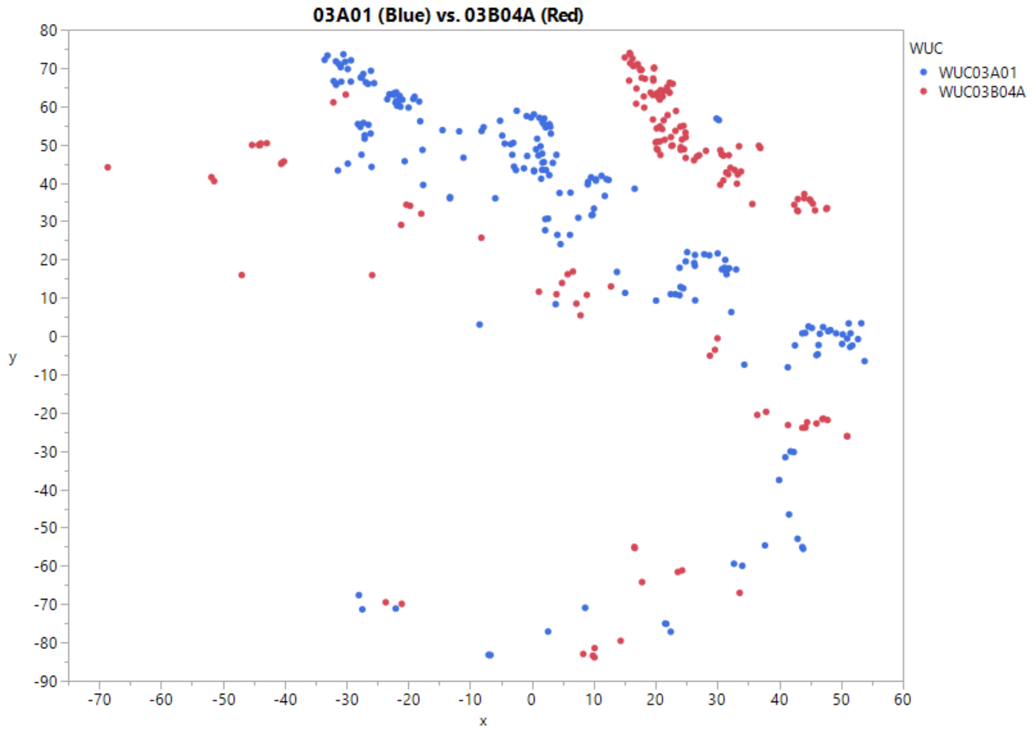
→

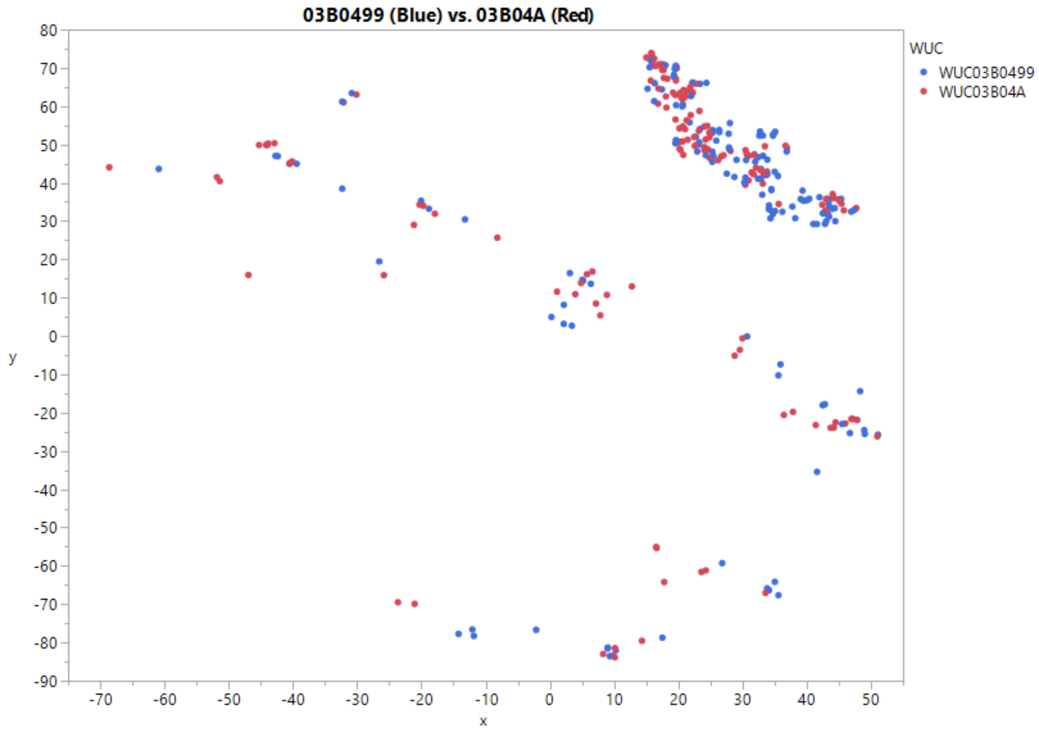
WUC	Model Confidence	Most Indicative Words
19A06 (FOOTSWITCH)	96.2%	• ‘MIC’ • ‘FLOOR’ • ‘HOT’ • ‘SWITCH’ • ‘STUCK’

Proportion >90% confident: 53%

FRACAS Code Scoring

tSNE showing semantic separability between two WUCs in the maintenance records





Applications to the Factory

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Factory Sustainment

Drive System
Loads Monitoring
Adv. Dynamic Load-Based Diagnostics
Drive System Diagnostic Reasoner
Oil condition & debris monitoring

Fleet Management
Usage-Based Maintenance
Condition-Based Maintenance
Maintenance-Free Operation Period

Electric Power & Wiring
Smart solid state power
Distribution components
Wire fault detection & isolation

Fleet Sustainment to Factory Sustainment

Takeaways

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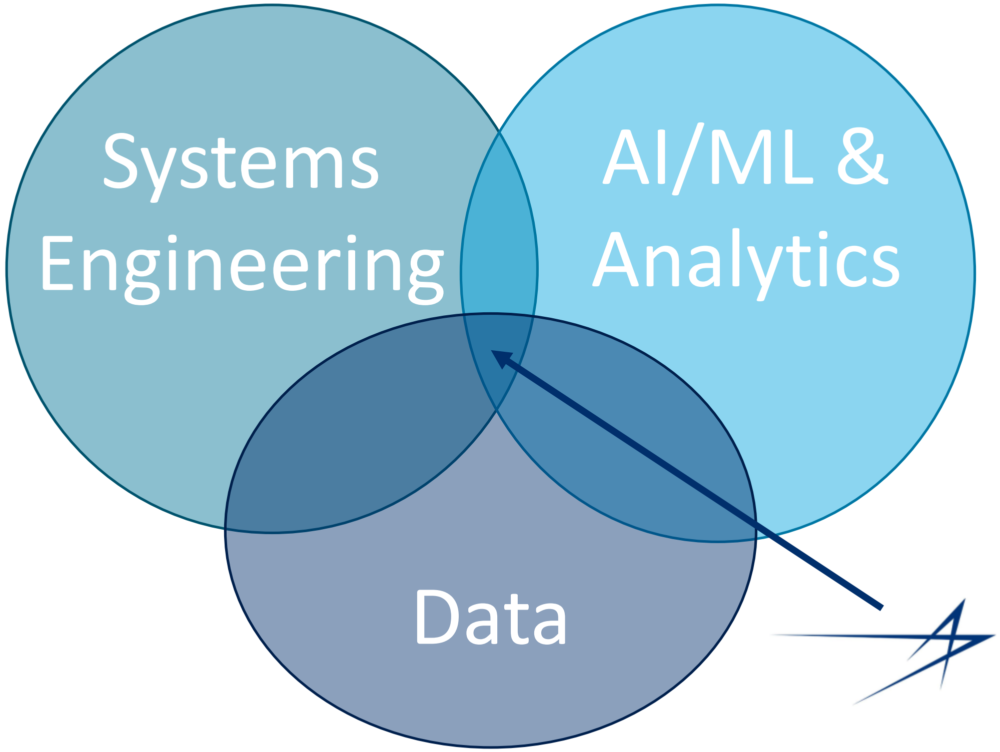
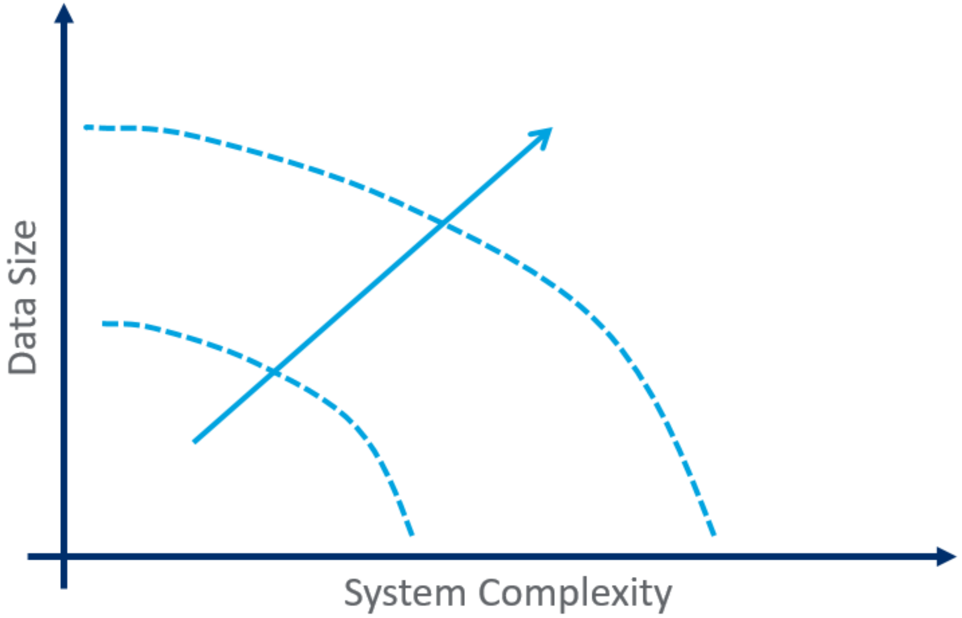
Takeaways



Sustainment analytics requires relevant data, informed application of analytics tools and engineering expertise.



Frontiers must be pushed and GPUs are a critical enabling technology that has allowed us to pioneer.

Takeaways

Data is Data. The challenges of maintaining Fleets of Aerospace vehicles are the same as the challenges of maintain "Fleets" of Factory Machines

Designing in high-quality contextualized data is an enabler for providing high value Predictive Asset Management Solutions.

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