ASRC FEDERAL

Ground System Architectures Workshop

GSAW 2020 Intelligent Systems Working Group

Lightning Round Panel

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Customer-Focused. Operationally Excellent.

ASRC Federal is *the* AI/ML thought leader for Aerospace

with real world experience

Decades of mission specific knowledge/expertise

Advanced AI/ML research

Applications of ML deployed for NOAA & NASA

Operational	**Pre-Operational**	**Working Prototype**
• Data monitoring & anomaly management for NOAA/GOES-R instrument data and S/C housekeeping data - GEO missions • Predictive financial analytics for NOAA/NESDIS OCFO	• Anomaly management for spacecraft health and safety on LEO missions (NPP-Suomi spacecraft) –Under consideration for NOAA Joint Polar Satellite Sys (4 S/C, 2020-24) • Enterprise situational awareness across missions	• Mission event log analytics (unstructured text) • ML model and algorithm development/training tools (GSAW ’20 Topic) • Event driven actions/ commands

U.S. AIR FORCE

Machine Learning capabilities fundamentally change the approach for flight mission implementation and operations

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Our View of Current / Future Aerospace Challenges

Near Term Drivers (based on our experience)

New Missions

- **Increasing data volumes/products, increasing complexity**
  - CubeSats, MicroSats, Hyperspectral Imagers, Laser, Radar, Drones, Constellations, etc.
  - Increasing number of sensors on missions requiring characterization, calibration and management (e.g. (NOAA GOES-R ABI – 7000 sensors, NASA WFIRST 18x4Kx4K cryo imager)
  - Built-in autonomy for “safeing” instruments and spacecraft; rover operations (Mars)
- **Single string vs. dual string**
  - Some use of non-radiation hardened flight processors (e.g. SpaceCube)
- **Data Volume/complexity**
  - Expanding beyond a human’s cognitive ability to make assessments/ analyses in near real-time (without intelligent tools)
- **Push to lower cost with more capability**

Quality Improvements & Risk Reduction Drive

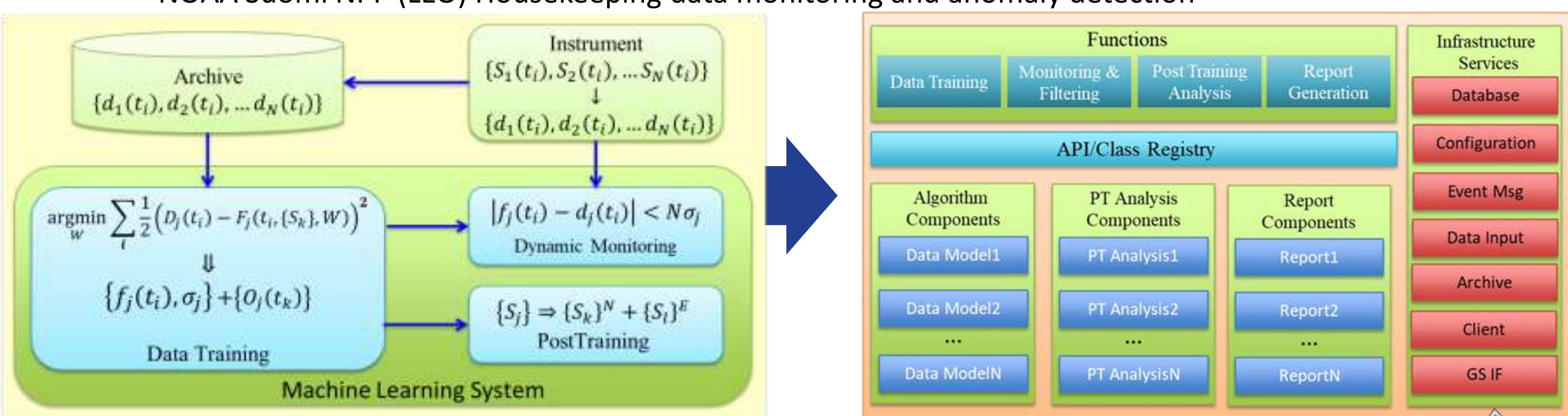
- Increased quality/availability with fewer data anomalies
- Reduce/eliminate human errors, or remove humans-in-the-loop
- Early detection of problems/anomalies – to prevent catastrophic failure
- Enterprise level visibility - Improved communication/understanding/awareness

Challenges for ML Applications in Satellite Telemetry

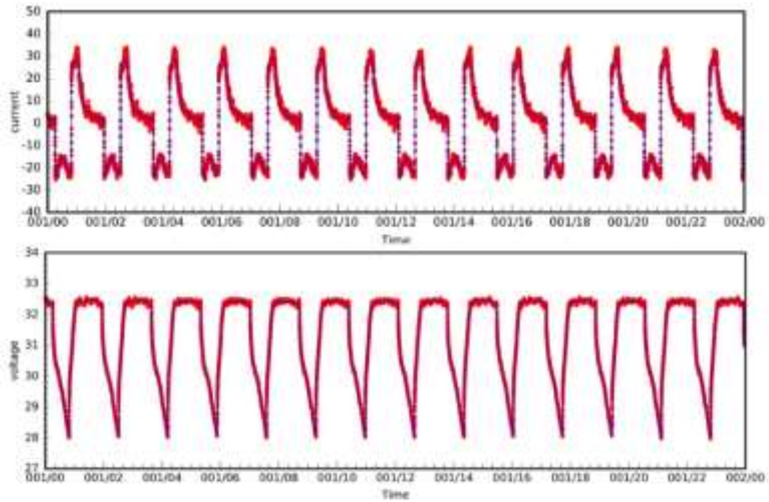
- **A satellite is highly complex dynamical system - many subsystems that interact with each other (some are dependent)**
- **Data Training Challenges**
  - More diverse data types (linear, non-linear, continuous, discontinuous)
  - Highly complex data patterns (especially LEO missions)
  - Relationships among datasets – simple and complex correlation
- **Anomaly Detection Challenges**
  - Difficult to isolate anomalies in general WRT satellite health and safety telemetry from data pattern changes in a single dataset
    - Interactions among subsystems in a satellite lead to strong correlations in telemetry datasets
    - Correlation among multiple telemetry datasets in multiple subsystems must be taken into account for anomaly management
  - Both event-triggered operations and anomalies can result in deviations within data pattern changes
    - Event triggered operations refers to operations by an external command to change system behavior, such as an orbit maneuver
    - Separating anomalies from event triggered operations is a considerable challenge (we have addressed this challenge for LEO spacecraft)

Common Machine Learning Architecture for Space Missions

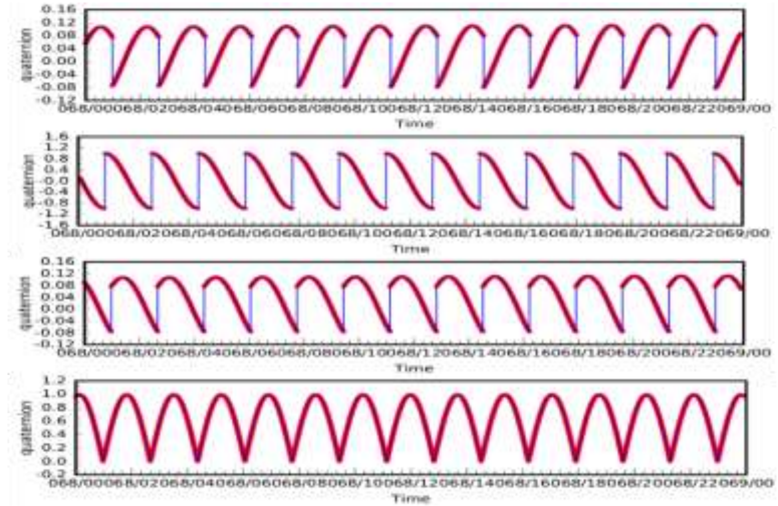
- **ML systems for satellite operations should have a common architecture model**
  - Involving data training and post training analysis processes
- **A software architecture must support rapid development and an Enterprise approach**
  - Separate the common services and infrastructure from the mission specific components
  - ML algorithms for data training and post training are integrated as plug-and-play components using standard API
  - Provides flexibility to select algorithms for datasets with specific patterns without understanding the space mission operations infrastructure (ground and flight system, networks, communications, etc.)
  - Scalable and extensible
- **The same architecture has been deployed in the Advanced Intelligent Monitoring System (AIMS) for the following missions**
  - NOAA GOES-R ABI Instrument Calibration monitoring
  - NOAA GOES-R Housekeeping data monitoring and anomaly detection
  - NOAA Suomi NPP (LEO) Housekeeping data monitoring and anomaly detection



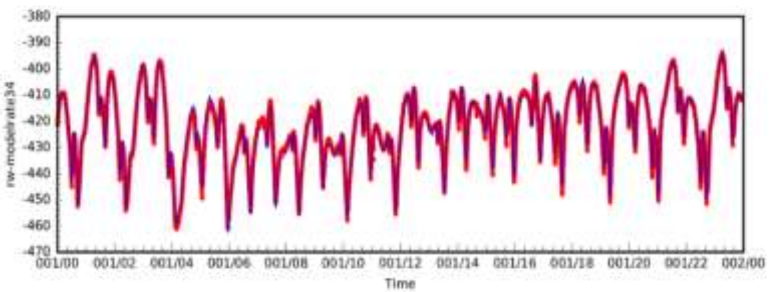
Data Training Outputs for NPP House Keeping Data (Generated by AIMS)



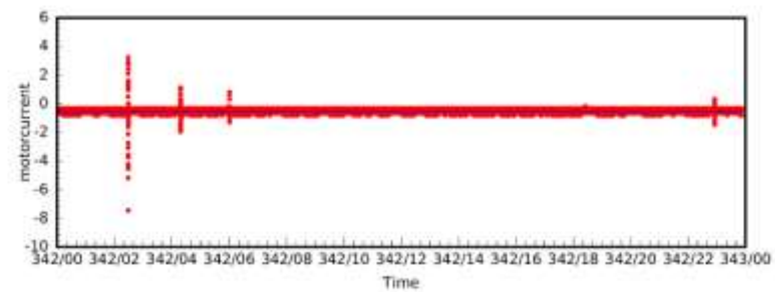
Power System



Quaternions



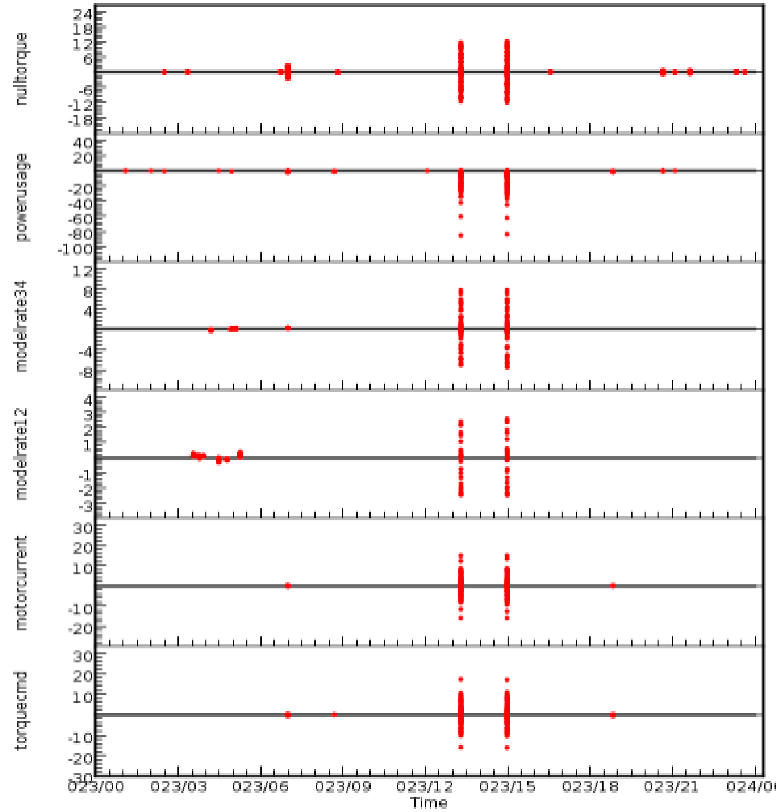
Reaction Wheel Momentum Profile



Reaction Wheel Motor Current Profile

Keys to Address these Challenges

- We developed highly accurate ML algorithms
  - To model satellite health and safety telemetry data (LEO)
  - Enables accurate detection of data pattern changes in telemetry datasets
- Developed graphical and mathematical representations LEO spacecraft
  - Called hierarchical event vectors to characterize correlations among outliers in different telemetry datasets (from multiple subsystems)
  - Based on data training outputs
- Developed clustering algorithms for event classification and anomaly detection
  - Provides key signatures on different types of event triggered operations
  - Characterizes anomalies: the root-cause



Correlation among different datasets: vertical lines are outliers in telemetry datasets, and aligned at the same time period, forms an event vector.

In Summary

- ASRC Federal successfully developed an approach to characterize the correlation of subsystem events on spaceflight systems - key for anomaly detection, especially for LEO missions
  - Clustering of correlation patterns is critical
  - Our approach for anomaly detection has been very successful on the NPP-Suomi mission (polar orbit)
- Data volume and system complexity are expanding beyond a human's cognitive ability to make assessments/analyses in near real-time - Intelligent tools (AI) are necessity
- A common/standard machine learning architecture for space missions is needed
  - To reduce implementation/integration cost (similar to the GMSEC approach)
  - To enable data scientists/engineers to rapidly develop AI solutions without deep knowledge of the ground and flight system
  - ASRC Federal's ML PaaS is one approach using an API and a plug-and-play interface for ML models and algorithms