



ASRC FEDERAL

Monitoring Satellite Health & Safety of GEO Satellite with a Machine Learning Application

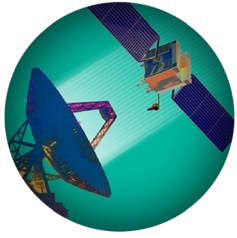
Dr. Zhenping Li

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Agenda

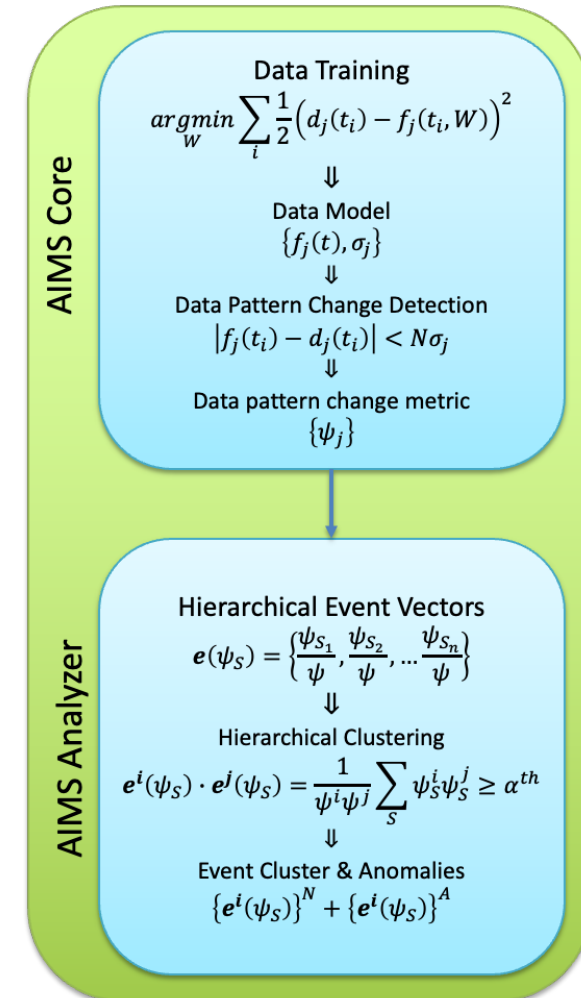
A person is standing on a snow-covered mountain peak. The background shows a vast, forested valley with a layer of mist or low clouds. The scene is captured in a cool, blue-toned light, suggesting a high-altitude or winter environment.

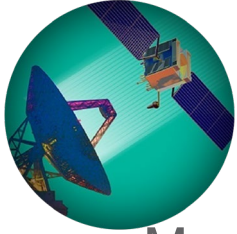
- 1** A ML Application for GEO Satellite
- 2** GEO satellite data and operations
- 3** Data Training Approaches
- 4** Event-Based Engineering Analysis
- 5** Long-Term data trend
- 6** Summary



A ML Solution for Monitoring Satellite Health & Safety

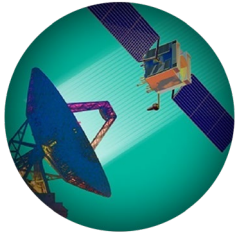
- The ML solution involves
 - Data Training and detection of data pattern changes.
 - The event-based engineering analysis to profile operational events and detect anomalies.
- The solution is not specific to GEO satellites and can also be applied to LEO satellites.
- It is currently deployed in the GOES-R ground system to monitor the health and safety of the GOES constellation.
 - Performs ML data processing for around 1800 telemetry datasets per satellite in operational environments.
 - The iterative data training technology provides data training efficiency, accuracy, and robustness for telemetry datasets with outliers.





GEO Satellite Data and Operations

- More diverse data types and patterns.
 - Some datasets have no clear orbital pattern at all.
- Seasonal effects have more impact on data patterns.
 - Two factors determine data patterns for telemetry datasets:
 - GEO satellites moving around Earth determine the orbital patterns.
 - Earth moving around the Sun determines the seasonal patterns.
 - The datasets for power systems and thermal profiles show different patterns during the eclipse season.
 - Orbital patterns are slowly changing along seasonal patterns.
- New approaches are needed to reduce data training complexity and enhance data pattern changes
- More operations for GEO satellite
 - Momentum dumps
 - Station-keeping maneuvers.
 - This leads to data pattern changes in the Power, GNC, Propulsion, and Thermal subsystems.
 - Event-based engineering analysis is critical.
 - Establish data pattern change profiles for operational events and connect these profiles to satellite directives.
 - Separate data pattern changes caused by anomalies from those caused by operational events.

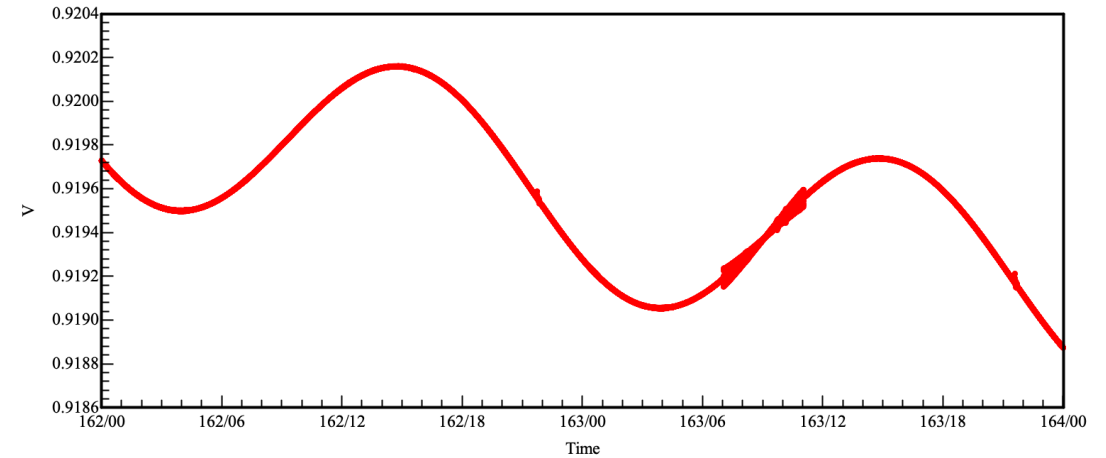


The Data Training of Derivatives

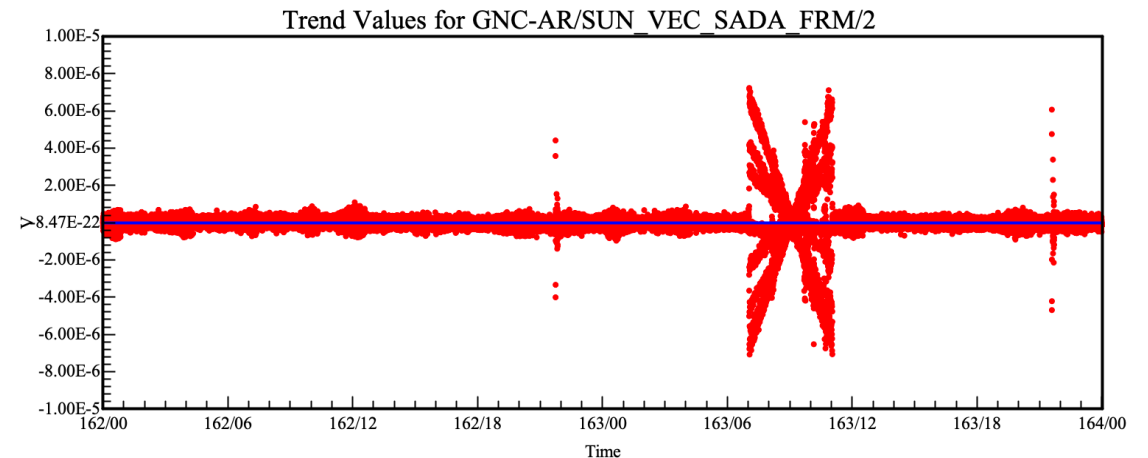
- Some telemetry datasets can not be easily modeled with ML algorithms.
- Perform trending on the Derivatives of datasets

$$\delta(t_i) = \frac{d(t_i) - d(t_{i-1})}{t_i - t_{i-1}}$$

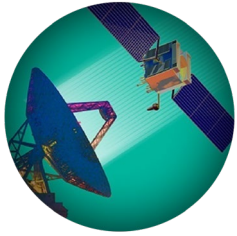
- The derivative datasets $\{\delta(t_i)\}$ are constant and noisy
 - The data model is a statistical collection during the data period.
- The derivatives are more sensitive to data pattern changes for this dataset.
 - Data pattern changes are generally enhanced.
- It is very important part of the data training of telemetry data.
- Used mainly for telemetry datasets in the GNC subsystems.



Original data

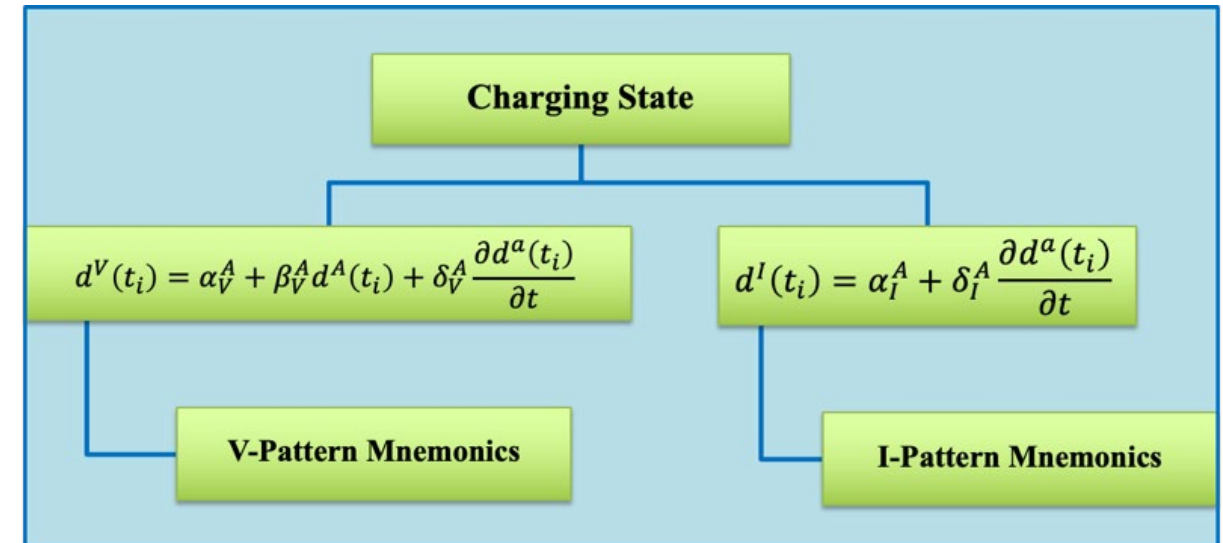


Derivative data

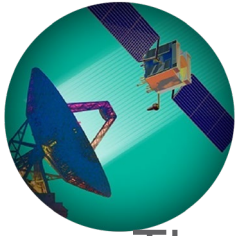


Relationships in Telemetry Datasets

- ML algorithms model relationships among telemetry datasets in addition to time dependence.
 - It is an important part of the ML solution for satellite telemetry.
- Relationships between two telemetry datasets are generally determined by the physics or underlined dynamics or from the analysis of datasets.
 - A relationship map could be created for telemetry datasets.
- The relationships exist among telemetry datasets in the power system.
 - The voltage and current have explicit dependence on the charge state.
 - There are two groups of mnemonics, which depend on the current or the voltage.
- Relationship modeling reduces the data training complexity for the telemetry datasets in the power systems with strong seasonal effects.



An example of relationships in battery systems. The relationship map among mnemonics in GOES-R battery systems is obtained from analyzing data patterns in battery telemetry datasets. The datasets in the left box have the V pattern, while those in the right box belong to I patterns.



The relationship example in the battery system

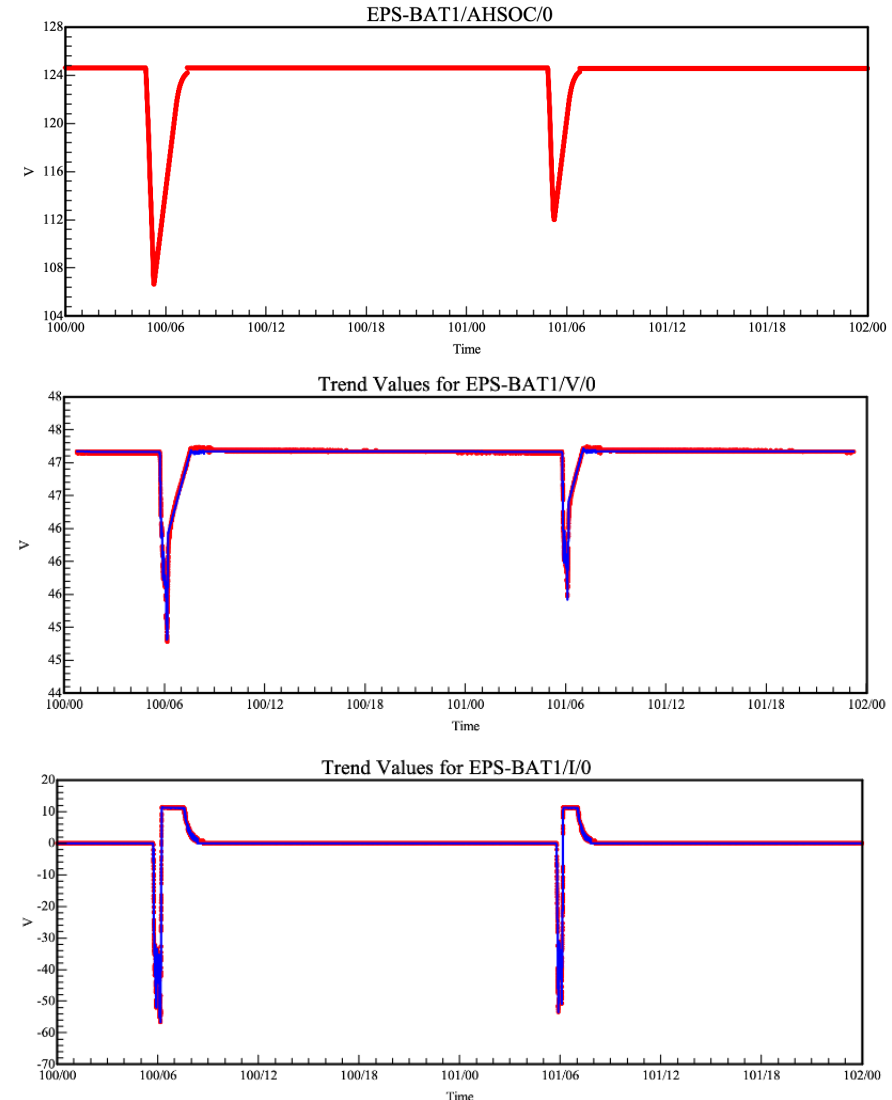
- The voltage (middle) and current (bottom) in the battery system are dependent on the battery charging state (top) with the relationships:

$$d^V(t_i) = \alpha_V^C + \beta_V^C d^C(t_i) + \delta_V^A \frac{\partial d^C(t_i)}{\partial t}$$

$$d^I(t_i) = \alpha_I^C + \delta_I^C \frac{\partial d^C(t_i)}{\partial t}$$

- $\{\alpha_V^C, \beta_V^C, \delta_V^C\}$ and $\{\alpha_I^C, \delta_I^C\}$ are parameter set to be determined in data trainings for the voltage and the current in the battery system.
- Blue lines are the data training output.
- The datasets with $d^v(t_i)$ and $d^i(t_i)$ patterns have the linear dependence on the voltage $d^V(t_i)$ or the current $d^I(t_i)$.

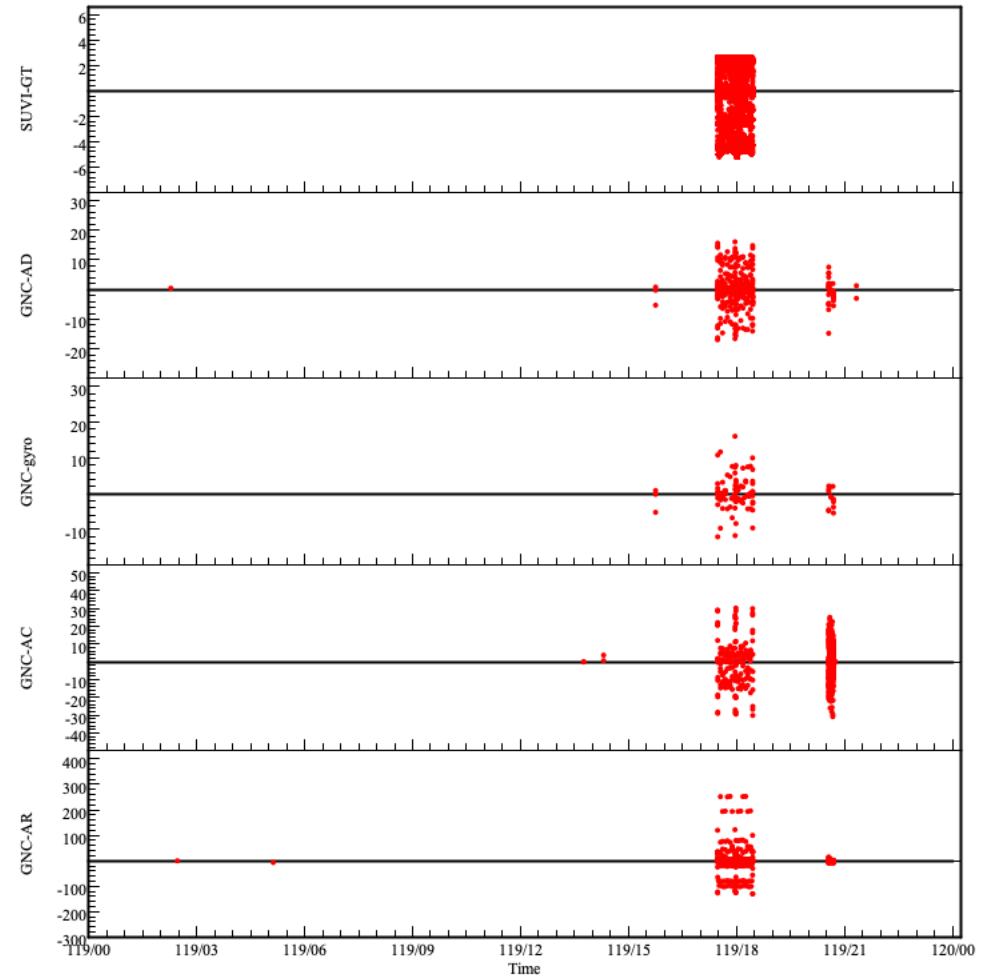
$$d^{v,i}(t_i) = \alpha_{v,i} + \beta_{v,i} d^{V,I}(t_i)$$

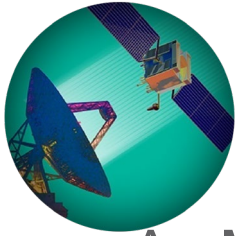




Outlier Distribution Plots (ODP)

- Outliers are detected in the data training process:
 - *An outlier is defined by its magnitude (severity) and time (when it happened).*
- ODP is a hierarchical scattering plot of outliers
 - *Highlights correlations among mnemonics or subsystems in data pattern changes*
- Outliers in different subsystems generally appear in the same period.
 - *It may correspond to an operational event or a potential anomaly.*
- Enable engineers to connect events in ODP with those in operations
- Provides an overview of system operation status
 - *Potential anomalies can be easily identified*





Event-Based ML Engineering Analysis

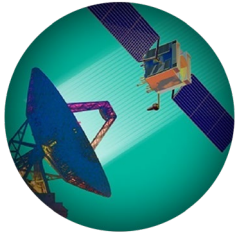
- An ML representation characterizes data pattern changes in telemetry data generated by operation events or anomalies

$$e(\psi_S) = \left\{ \frac{\psi_{S_1}}{\psi}, \frac{\psi_{S_2}}{\psi}, \dots, \frac{\psi_{S_n}}{\psi} \right\} \quad \text{and} \quad e(\psi_S) \cdot e(\psi_S) = \frac{1}{\psi^2} \sum_{S_k} \psi_{S_k}^2 = 1$$

- A unit event vector characterized by the composition of datasets and their relative strength.
- Both operation events and anomalies cause data pattern changes in multiple datasets in multiple subsystems.
- Captures correlations among different datasets in multiple subsystems.
- Implementing a clustering algorithm to separate normal operation events from anomalies

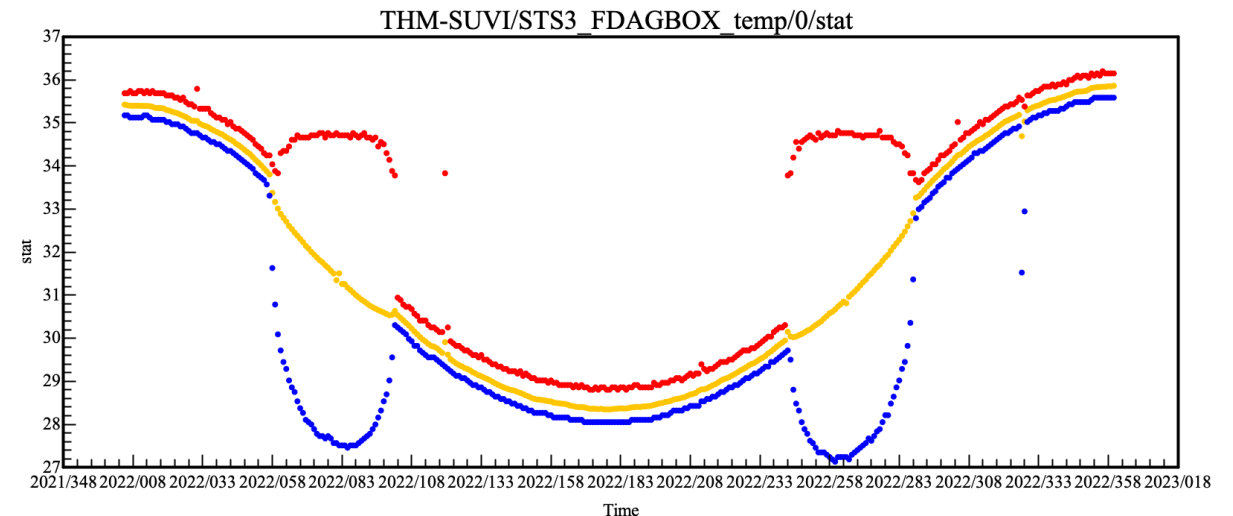
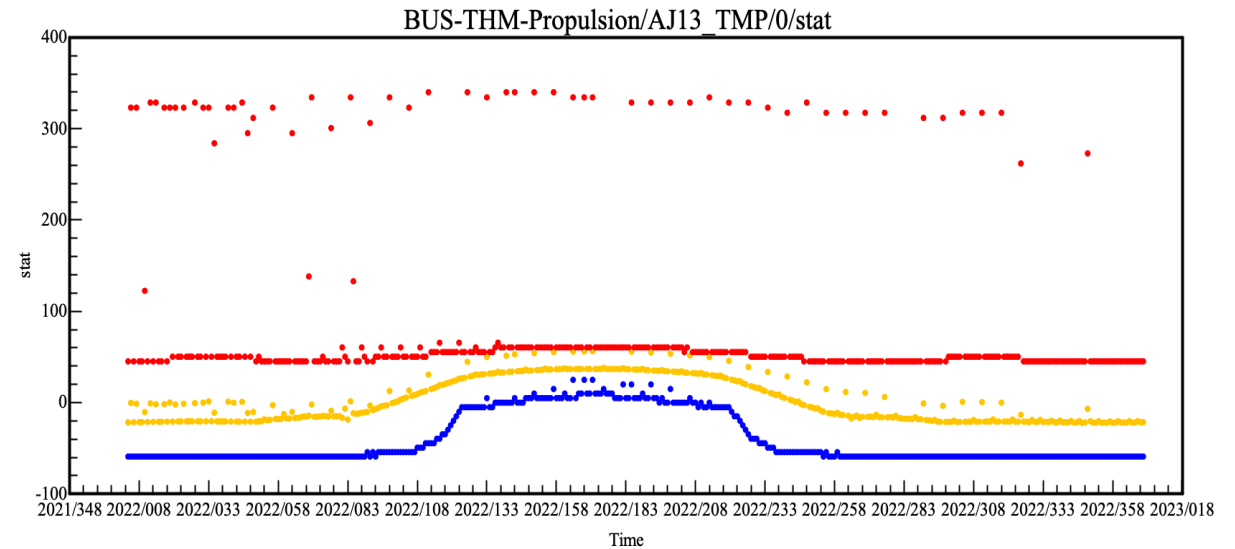
$$\alpha_S^{i,j} = e^i(\psi_S) \cdot e^j(\psi_S) = \frac{1}{\psi^i \psi^j} \sum_{S_k} \psi_{S_k}^i \psi_{S_k}^j \geq \alpha$$

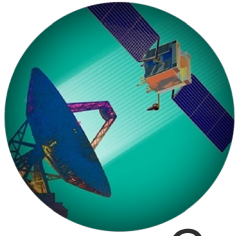
- $\alpha_S^{i,j}$ is the 'distance' metric between two events in clustering algorithm with the range from 0 to 1.
 - 1.0 means two events are the same type events, 0 means two events are totally unrelated.



Long-Term Data Trends

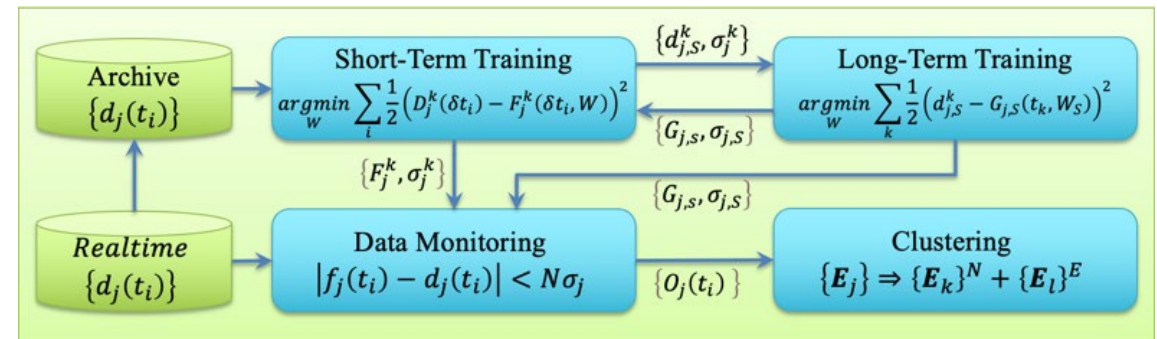
- Inputs to long-term data trends of a dataset are aggregated values over an orbital period:
 - Statistical data: maximum, minimum, and mean values per orbit for datasets with orbital patterns
 - The standard deviation of data training output
- It is an essential part of engineering analysis:
 - Enable more accurate predictions of near-future behaviors on max/min/mean based on seasonal patterns
 - The long-term trend of σ values provides insights into component degradations



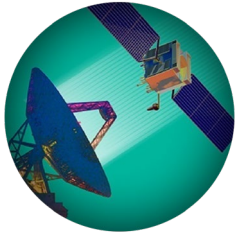


The Data Training of Long-Term Trends

- Complement the short-term Models to provide a complete solution for satellite data patterns
- Validate data inputs for short-term data training
- Neural networks require data scaling based on datasets' max/min/mean values. If max or min values are outliers, the training outputs are distorted.
- More accurate predictions of near-future behaviors
 - Long-term models can predict max/min/mean based on seasonal patterns, which are used to scale incoming datasets
 - Critical for real-time or near real-time monitoring.
- The long-term trend of σ values provides insights into component degradations
 - Predictive maintenance. (condition-based maintenance)



- The outputs of short-term training are the inputs of long-term data training.
- The ML models for the long-term training are used to validate the max/min/mean values in the short-term training.
- ML models are used to predict coefficients $\{\alpha_k, \beta_k\}$ in data monitoring, which is important for neural network models.



Summary

- The derivative and relationship data training reduces the data training complexities and provides new insights into the dynamics of a satellite.
- Event-based ML engineering analysis generates profiles of operational events and detects potential anomalies.
 - Profiles of operational events can be linked to command telemetry and schedules.
 - Reduce false positives.
 - More automated engineering analysis that leads to improved operation efficiency.
- The ML analysis of long-term data trends is essential for GEO satellite data.
 - Complement short-term data trends and improve the accuracy of predictions of short-term behaviors.
 - Enables predictive maintenance that optimizes satellite operations.
 - More use cases are needed for ML analysis of long-term data trends.



Quyanaq!

Thank you!

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Expert Software Engineer