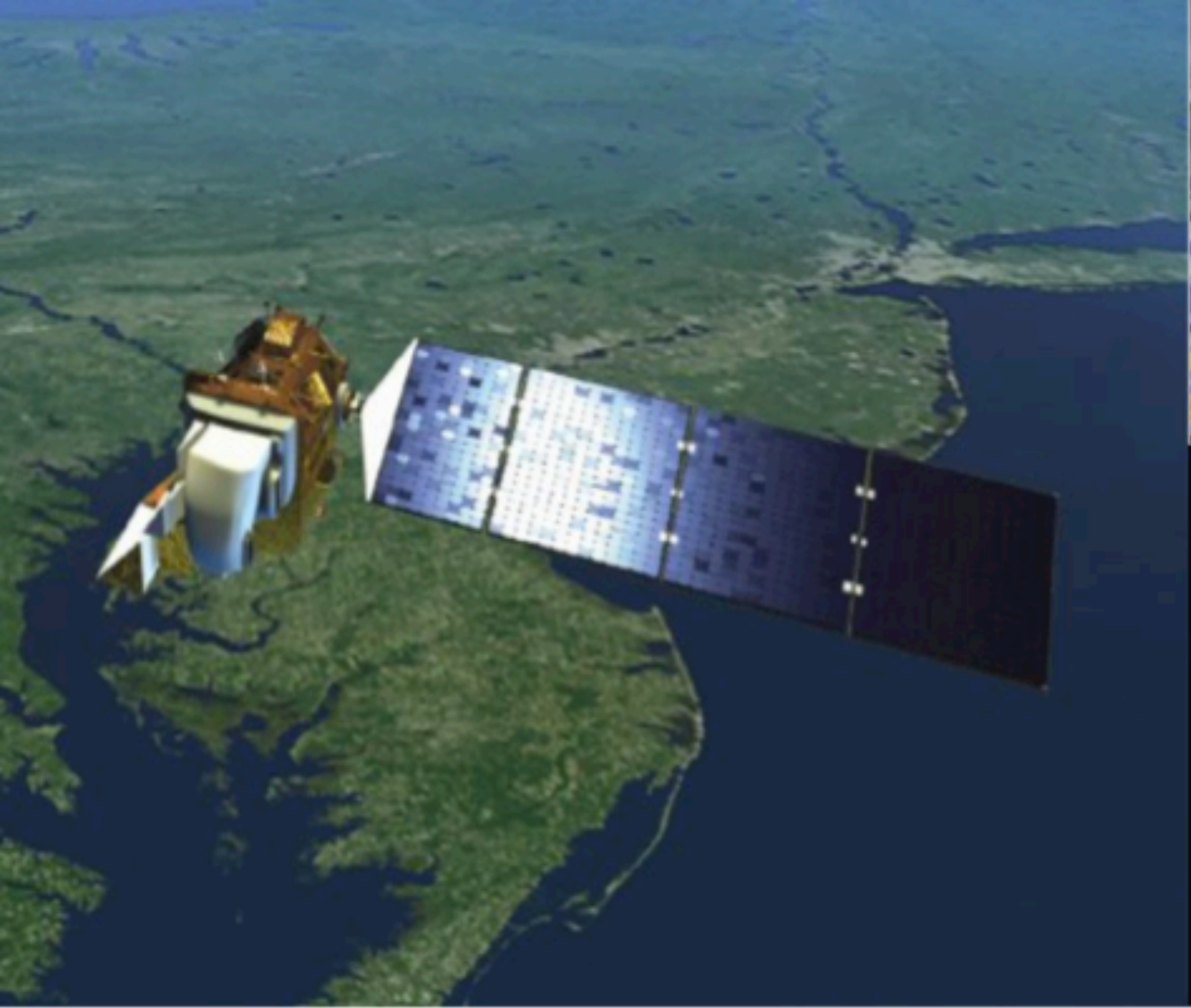

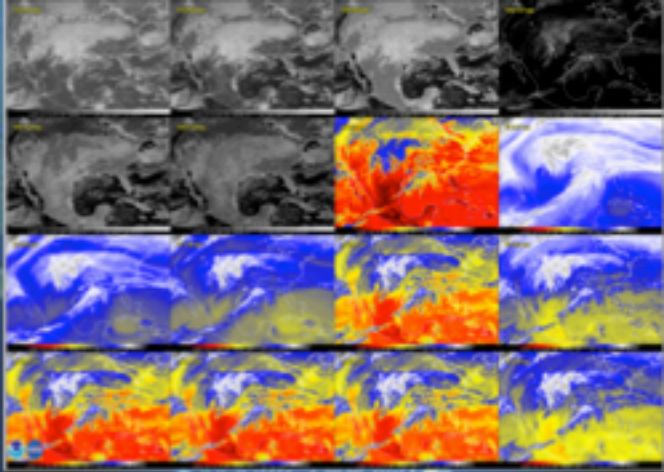

Develop Machine Learning Solutions for Space Missions

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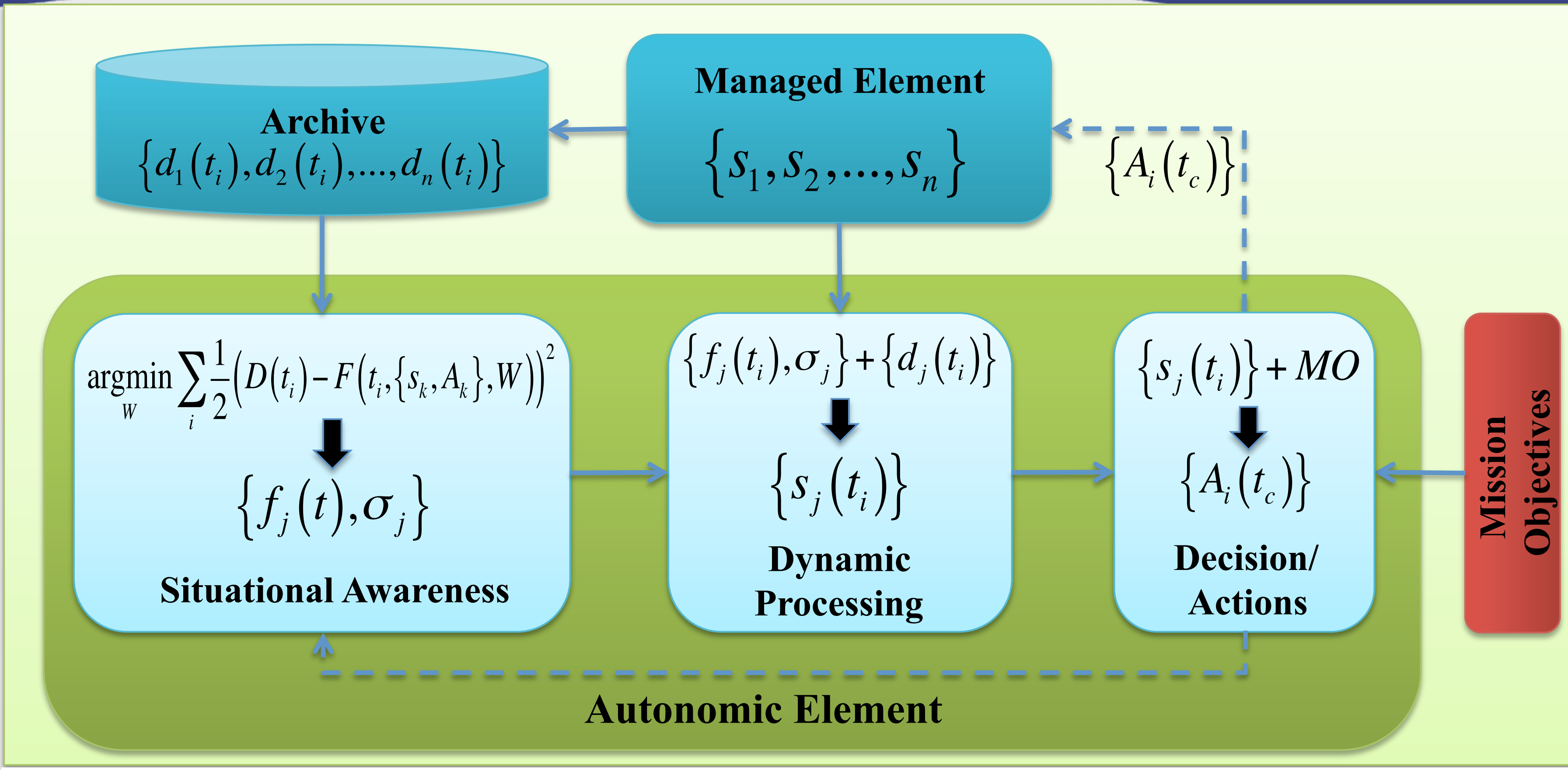
Objectives and challenges

- Objectives:
  - Increasing automation and autonomy
    - The operations for space missions become predictive and analytics based.
    - Situational awareness with machine learning automates the engineering analysis operations
  - Leveraging the enterprise architecture
    - Developing machine learning solutions as software components in an enterprise architecture.
    - Low cost and low risk solution that works with both legacy and new systems.
- Challenges:
  - Define the data representation on machine learning platform.
  - Large volume of datasets with different data patterns and arbitrary scales.
    - The training algorithms in operation environment must be both efficient and accurate.
  - Retrieve actionable information from the data training output.
    - Data training outputs provide information on the operational status of space missions.

Architecture Model for Machine Learning Solutions



- Machine learning solutions establish the data models of optimal states in a dynamic system, and detect the deviations from them.
- Anomalies in space missions are rare events and should not be modeled by machine learning. Anomalies are characterized by data pattern changes.

Time Dependent Trend

- A continuous dataset $\{d_j\{t_i\}\}$ in a dynamic system is characterized by
  - The time dependent function:

$$s_j = f\left(t, \{s_k\}\right)$$

  - Noise level σ:

$$\sigma_j = \sqrt{\frac{1}{N}\sum_i \left(f\left(t_i, \{s_k\}\right) - d(t_i)\right)^2}$$

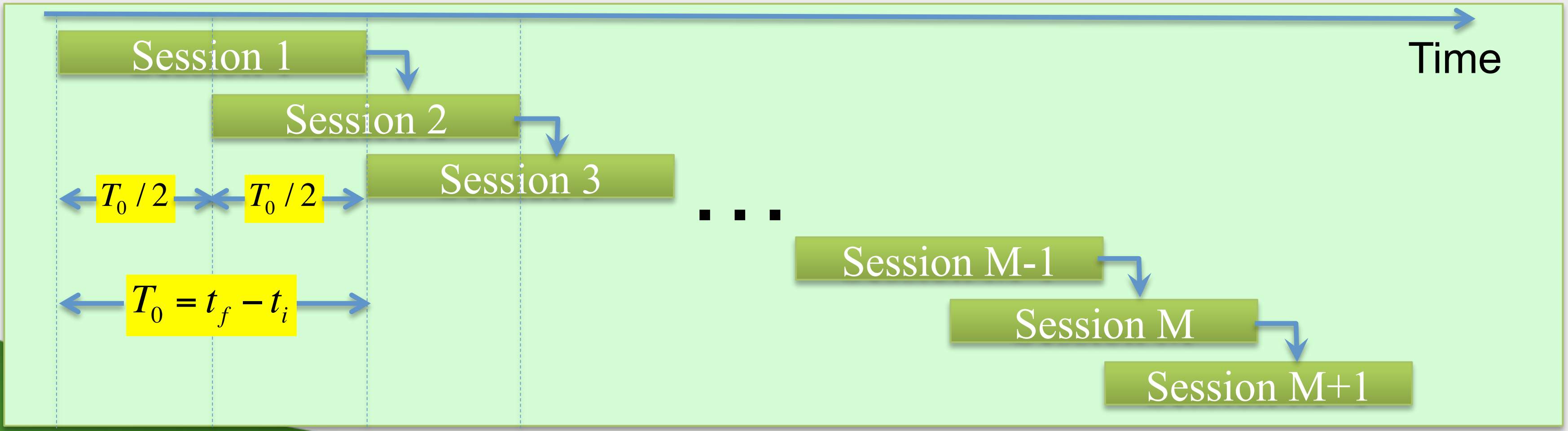
- The combination $\{f\left(t, \{s_k\}\right), \sigma\}$ is defined as the time dependent trend.
- The time dependent trend is another representation of the Gaussian probability distribution.

$$P\left(d_i; s_i, \sigma\right) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{\left(d_i\left(t\right) - s_i\right)^2}{2\sigma^2}\right)$$

- An extension of the statistical trend used in the current operations.

Time Dependent Trending

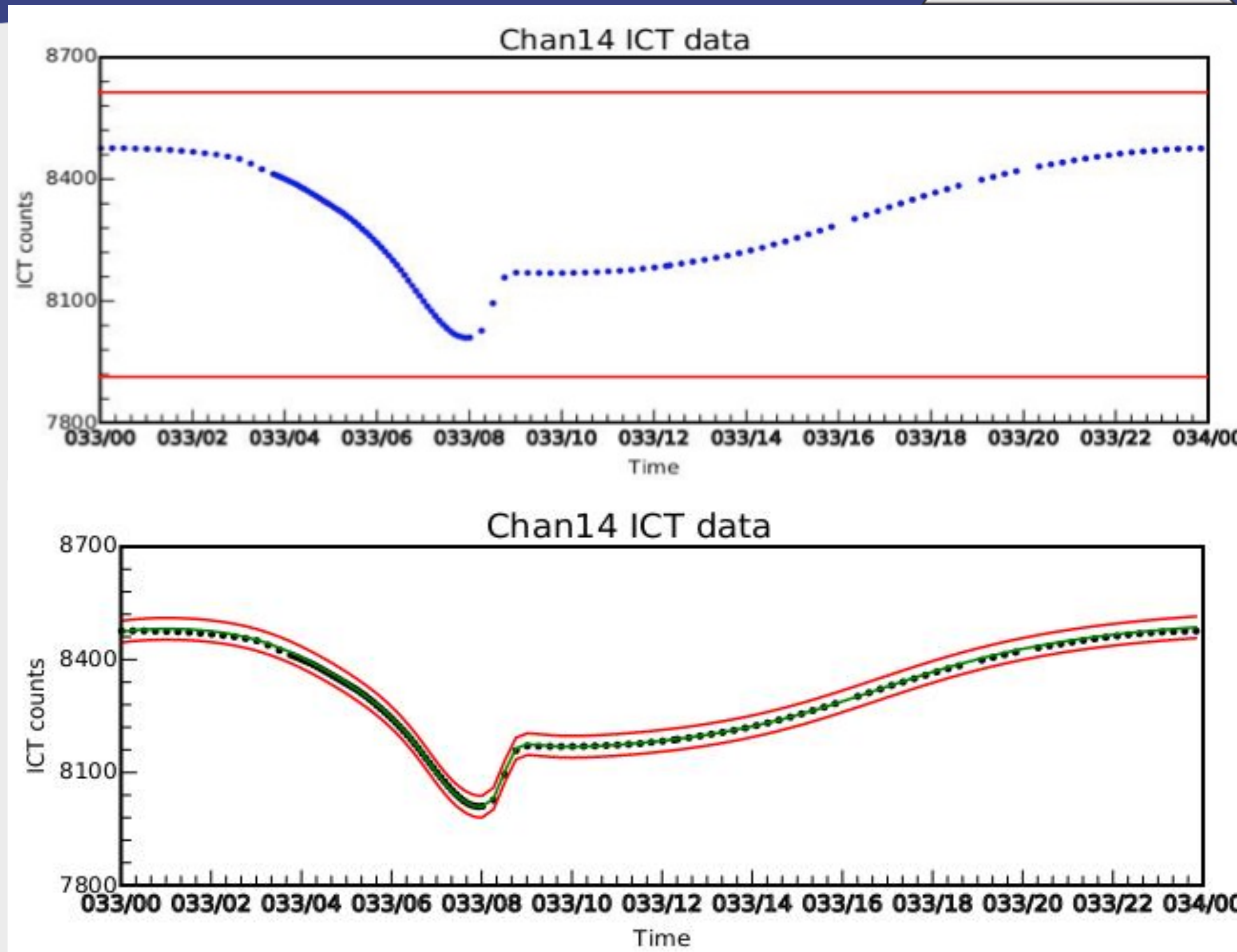
- Find $\{f_j(t,\{s_k\}),\sigma_j\}$ for dataset $\{d_j\{t_i\}\}$ in a given period $\{t_i,t_f\}$ using the machine learning approach.
- Operation Concept in operational environments:
  - Time dependent trending is performed periodically in sessions.
  - Two neighboring trending sessions overlap to ensure the continuity and the stability of the data training outcomes.
  - The output of the trending session M is used as the input of the trending session M+1 to improve the trending efficiency.



Dynamic vs. Static Monitoring

Static Monitoring in current operations: Compare the value of a data point with the static red/yellow limits pre-defined in the telemetry database.

Dynamic Monitoring in the machine learning framework: Compare the value of a data point with the prediction of its time dependent trend. The data bound is determined by its noise level



$$f\left(t_i,\{s_k\}\right) - N^O\sigma_j < d_j\left(t_i\right) < f\left(t_i,\{s_k\}\right) + N^O\sigma_j$$

Outliers, Anomaly and Data Pattern Changes

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- An Outlier $O(d_j(t_i))$ is defined as

$$O(d_j(t_i)) = N^O\left(\frac{|f_j(t_i) - d_j(t_i)|}{\sigma_j} > N^O\right)$$

- An anomaly means unexpected data pattern changes in datasets
- Define outlier cluster for consecutive outliers

$$C_j(t_f - t_i) = \left\{O(d_j(t_i)), O(d_j(t_{i+1})), \ldots, O(d_j(t_f))\right\}$$

  - $t_f - t_i$: the cluster period.
- One can define time limit T for the outlier cluster period as the threshold for data pattern change.
- The data pattern change can be detected in both real-time monitoring and trending sessions
  - Can be quantitatively characterized through the metrics that measures the pattern changes.

Anomaly Characterization

- The data pattern changes lead to
  - **Outlier Clusters** in both real-time monitoring and trending sessions.

$$\chi_j^O = N^O \frac{(t_f - t_i)}{T}$$

  - **Temporal Changes** in trending outcomes from trending sessions.

$$\chi_j^T = \frac{\sigma_j^M - \sigma_j^{M-1}}{\sigma_j^M}$$

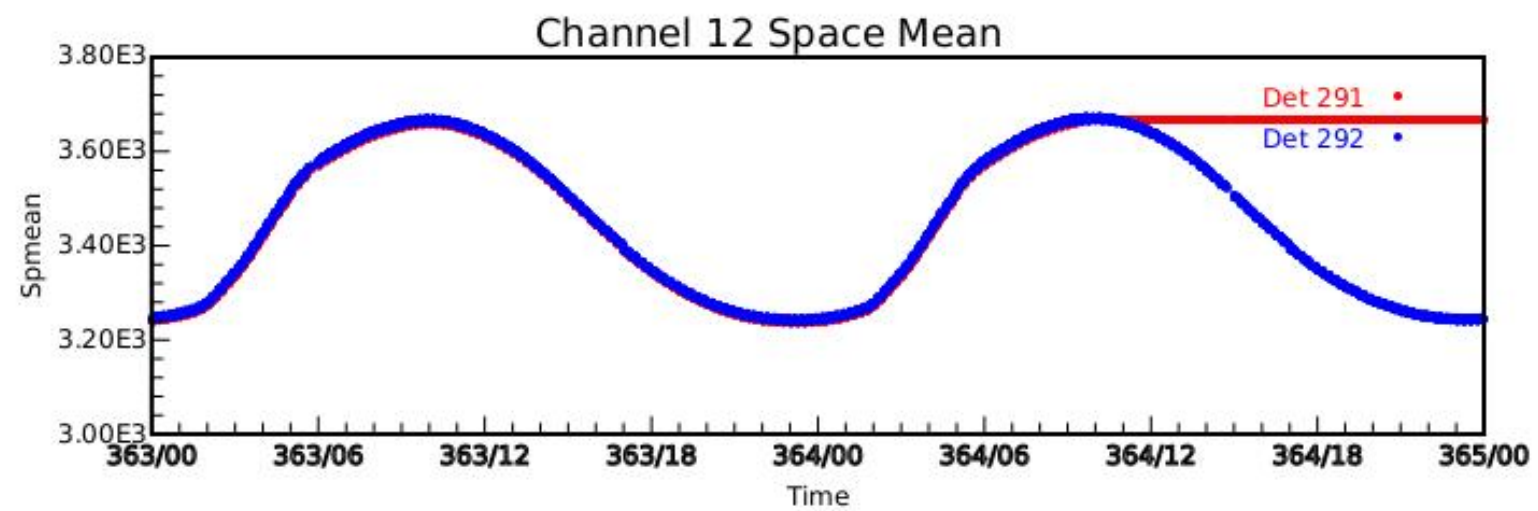
  - **'Spatial' changes** in trending outcomes from trending sessions.

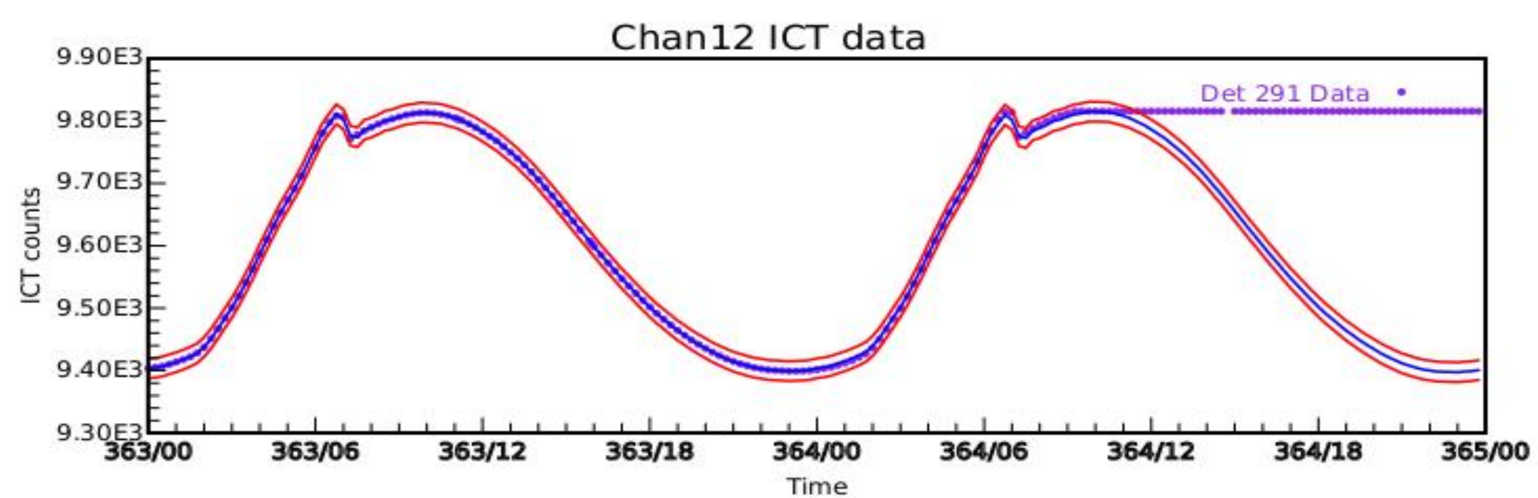
$$\chi_j^S = \frac{\sigma_j}{\frac{1}{N}\sum_{k \subset \{j\}} \sigma_k}$$

- The metrics $\{\chi_j^O, \chi_j^T, \chi_j^S\}$ are dimensionless, which can be used in clustering analysis to isolate anomalous datasets from the normal ones.
  - The main cluster is located around $\{\chi_j^O \approx 0, \chi_j^T \approx 0, \chi_j^S \approx 1\}$

An Example of Data Pattern Change

Both spacelook and ICT values became saturated around 364/10Z. Machine learning approach detected this immediately. The pattern changes leads to very high values in both metrics. $\{\chi_j^N, \chi_j^S\}$ The pattern change can also be detected in the real-time data monitoring.





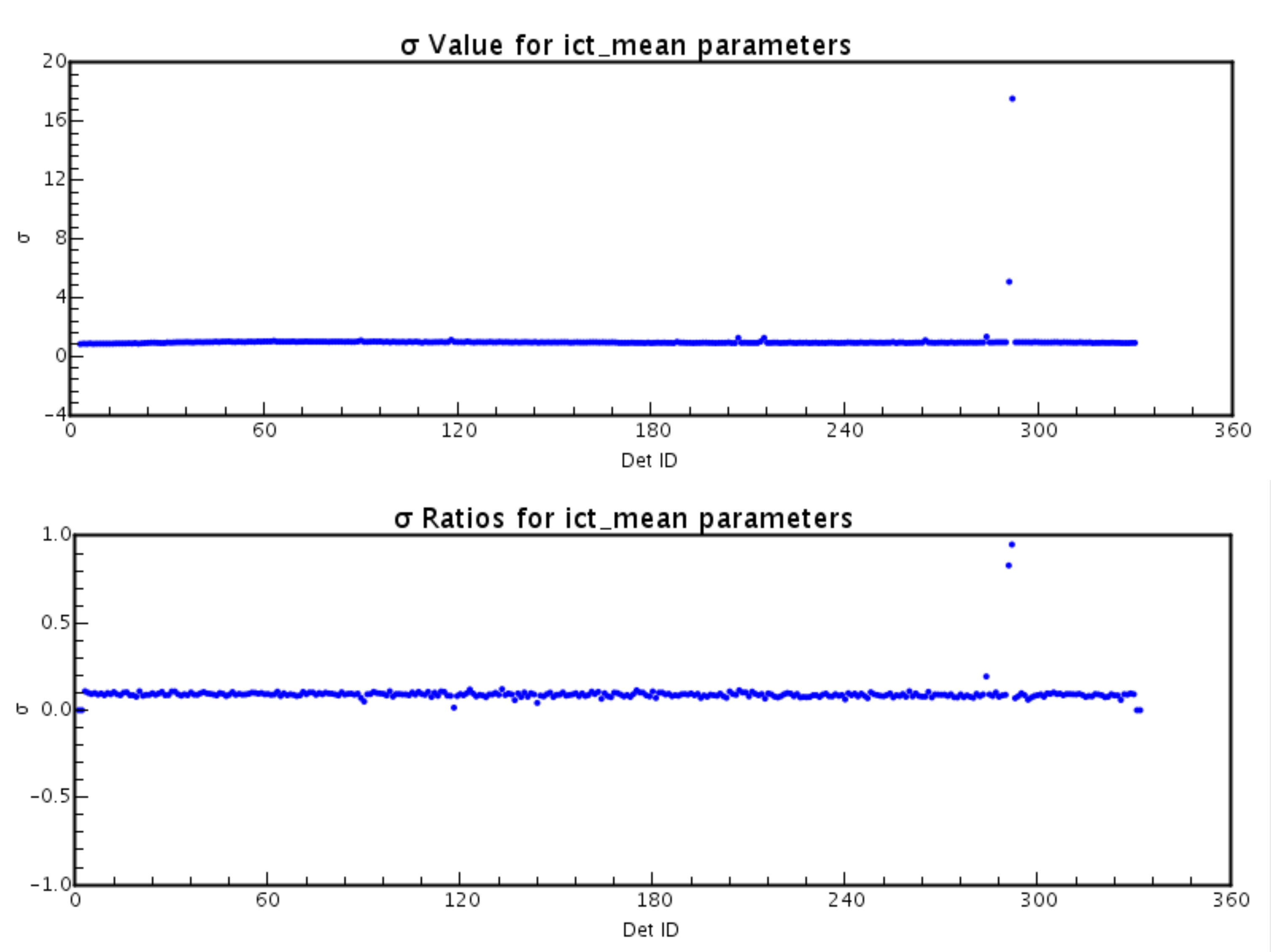
The pattern change can not be detected with the static red/yellow limits

'Spatial' and Temporal Changes in Training Output

χ_j^S Example

Both examples show elevated values for detectors 290 and 291

χ_j^T Example



OPS Concept for Machine Learning in Ground Systems

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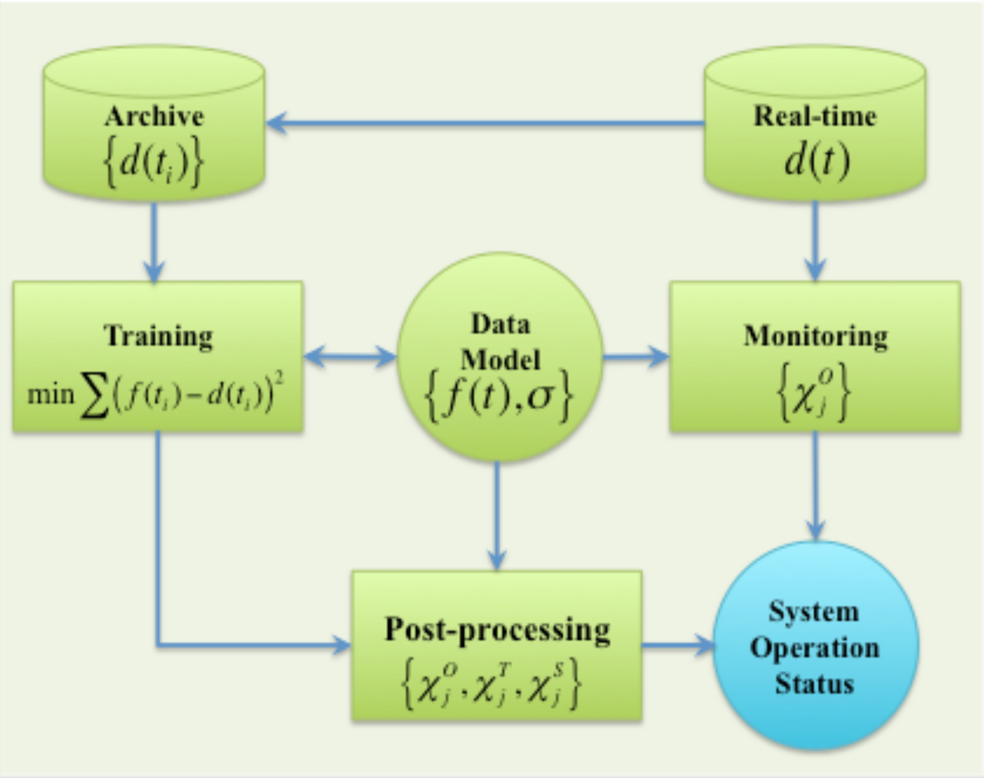
- The OPS CON is only for system monitoring
- The manual data training is performed in the software deployment phase to create the initial data patterns in the trending archive used as the input for the data training in operations
- Periodic data retraining using the existing data patterns in the archive as inputs during normal operation



- The system operation status is generated during the post-training process by clustering the trending output with three metrics
- The real-time or near real-time monitoring is performed to determine the operation status by evaluating the outlier cluster metric, $\{\chi_j^O\}$

Ground System Implementations

- Machine learning software should be implemented as a platform for data models and training algorithms.
  - Implemented as container/pluggable component architecture.
  - Able to handle more than 20k datasets for daily operations
- The manual training interface to adjust the model structure parameters and hyper-parameters.
- Post Training process to evaluate the operational status.
  - Clustering techniques.
- Real-time/near real-time monitoring.
- Automated training for the daily operations.
- Archive for time dependent trending operations.
- The integration of machine learning software in an enterprise architecture leads more capabilities and operational scenarios.