



Exploration & **SPACE**
Communications

More than you ever imagined...

Utilization of Machine Learning Techniques for Managing the Tracking and Data Relay Satellite Constellation

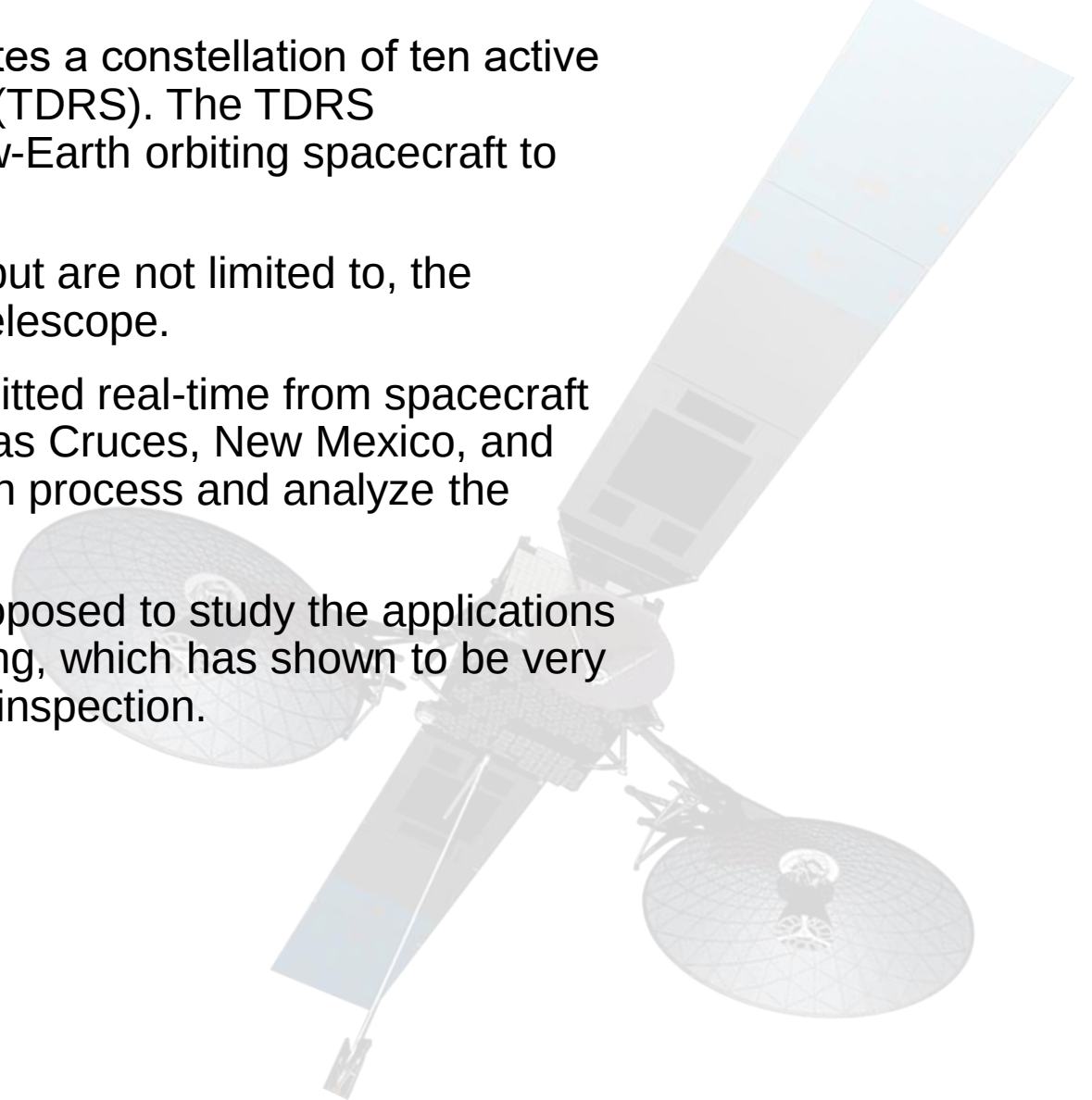
Presenter: Kenneth Y. Ma



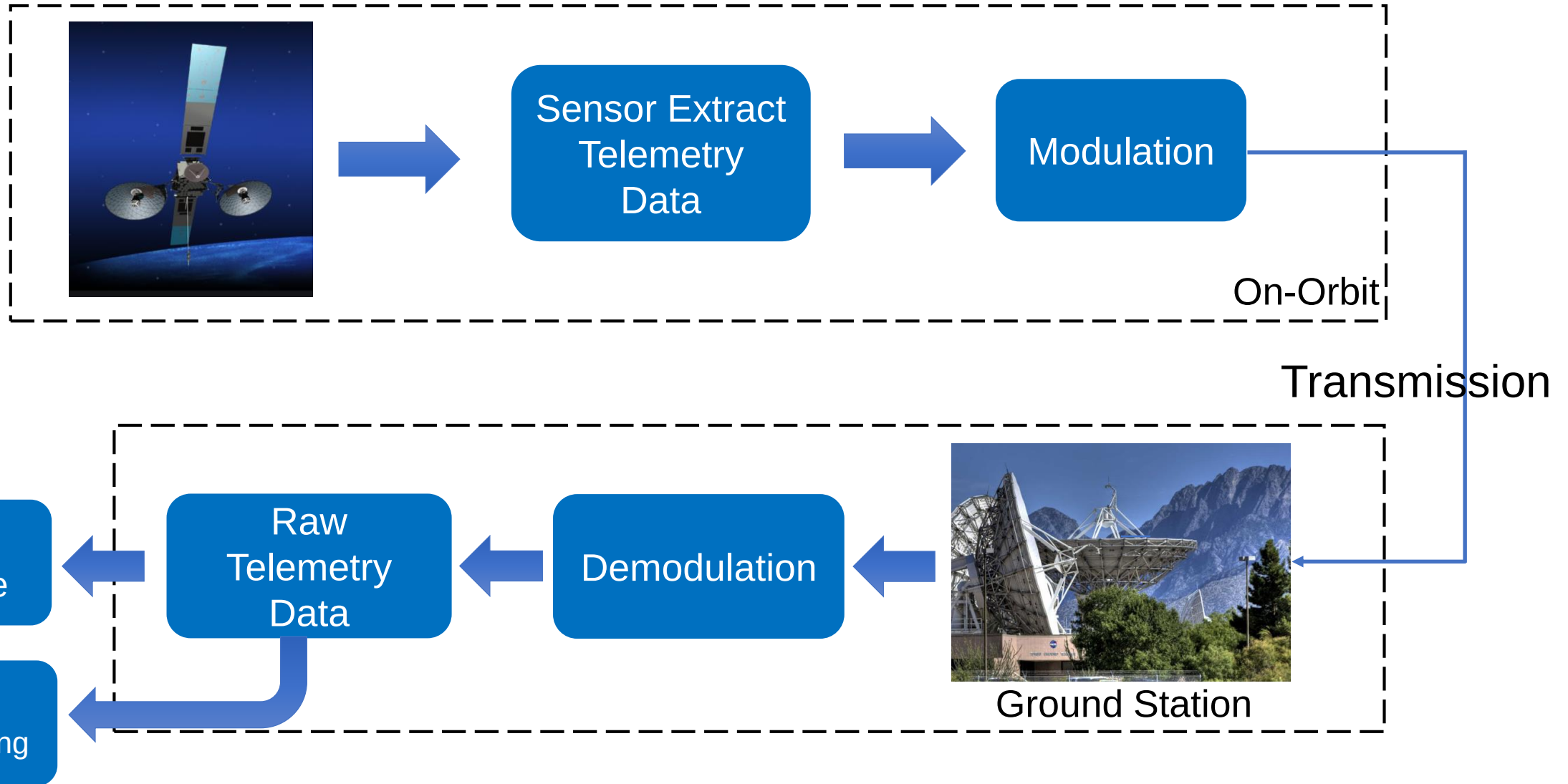
Introduction



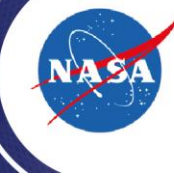
- NASA's Goddard Space Flight Center (GSFC) operates a constellation of ten active geosynchronous Tracking and Data Relay Satellites (TDRS). The TDRS constellation provides relay communications from low-Earth orbiting spacecraft to the primary ground stations.
- Major customers of the TDRS constellation include, but are not limited to, the International Space Station and the Hubble Space Telescope.
- Thousands of gigabytes of telemetry data are transmitted real-time from spacecraft to a ground station at the White Sands Complex in Las Cruces, New Mexico, and recorded as a historical dataset so that engineers can process and analyze the events occurring on-orbit.
- During the past several years, many papers were proposed to study the applications of machine learning (ML) on telemetry data processing, which has shown to be very useful to improve the efficiency of traditional manual inspection.



Introduction: Telemetry Data Transmission Model



Machine Learning for Telemetry

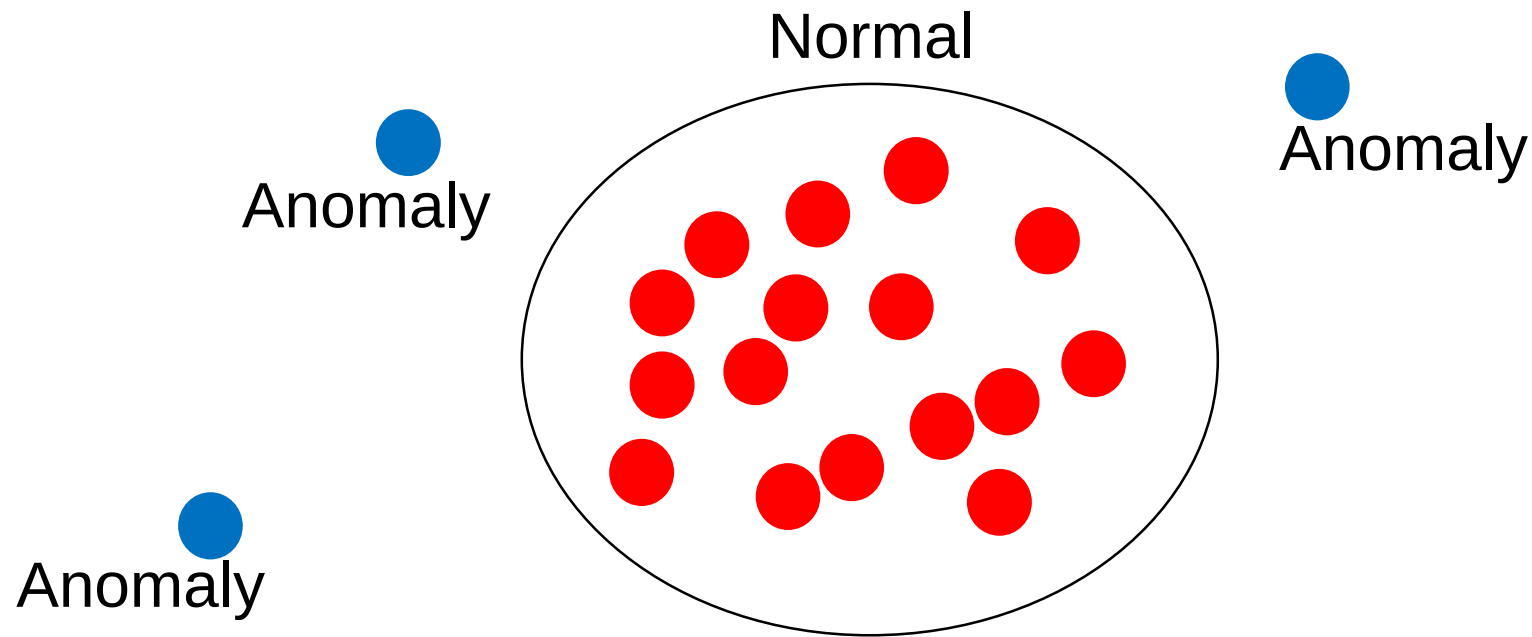


- Improve operations and extend the life of the TDRS fleet
- Develop an “Automatic Anomaly Detection System” that will analyze telemetry and inform ground station of an anomaly in near-real time.
- Develop a system by which engineer can query the AI/ML knowledge vault during anomaly recovery
- Build out machine learning model (neural networks) for classes of problems or anomalies to assist engineer operation

Anomaly (Outlier) detection

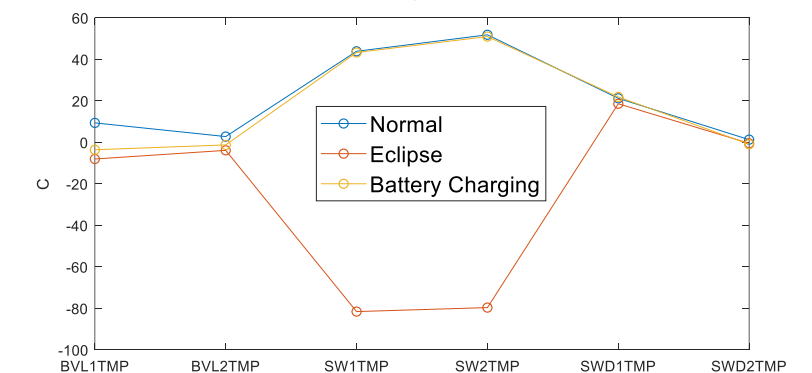
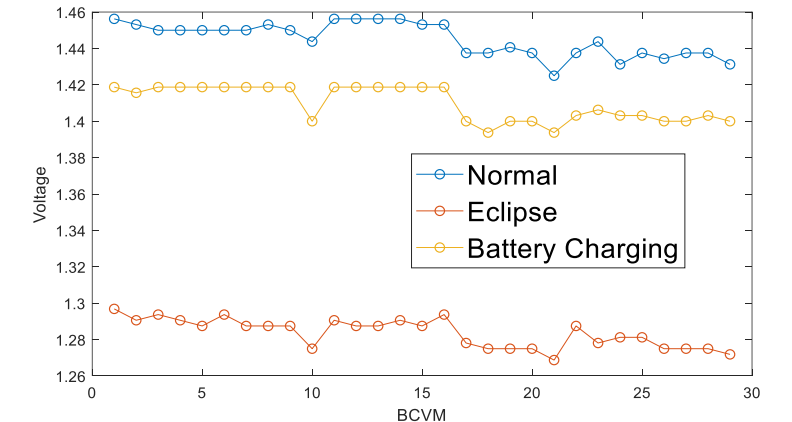
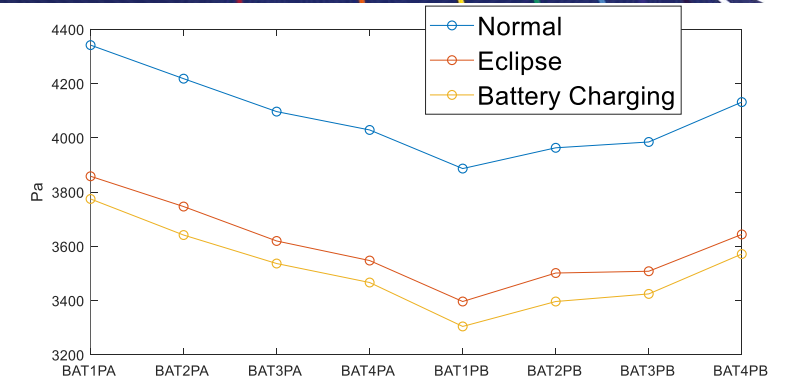
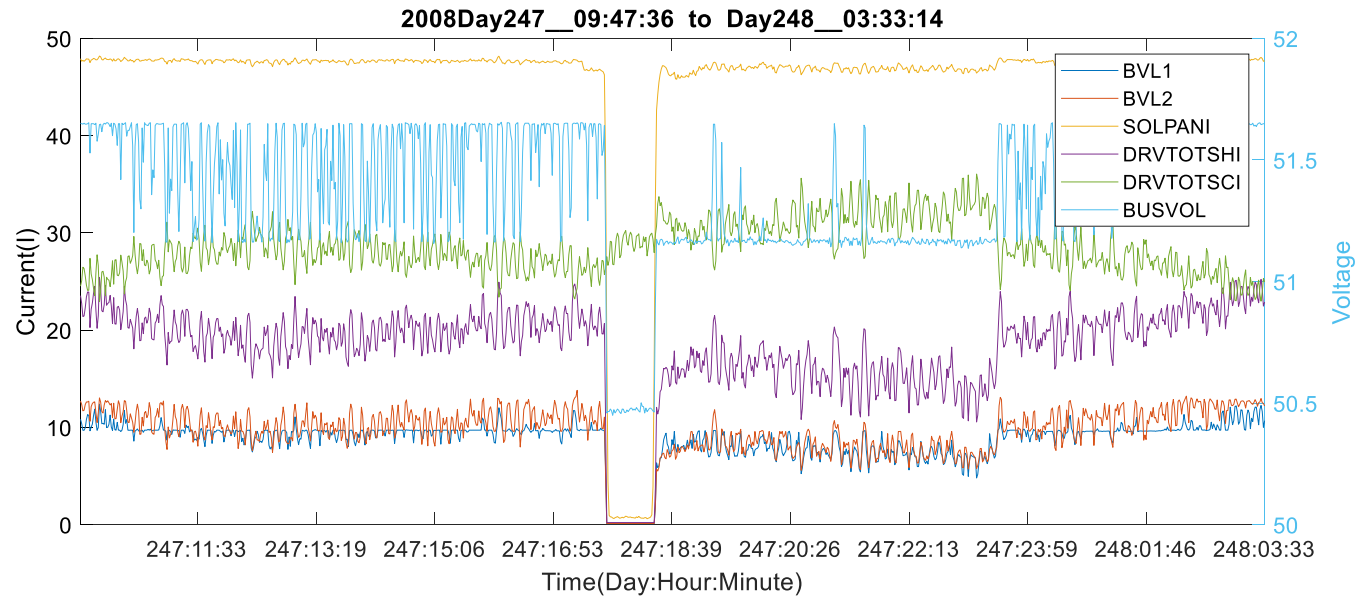


- Anomaly detector examines the majority of the data to identify the large population of data samples that defines “normal” while marking the remainder small population defines “anomalies”



Telemetry Feature Vector

- Different parameters are connected as a vector to represent the characteristic of spacecraft in each time. The correlation between different parameters then can be included in data analysis.



Reed-Xiaoli Detector (RXD)



- Anomaly detector (AD) is based on the assumption that the occurrence of anomalous data is very **rare** compared to normal data.
- K-RXD (δ^{k-AD}), which takes advantage of removing Second order statistic **K** from original data set and calculates the anomaly score based on Mahalanobis Distance (MD):

$$\delta^{k-AD} = (\mathbf{r} - \boldsymbol{\mu})^T \mathbf{K}^{-1} (\mathbf{r} - \boldsymbol{\mu}), \quad \mathbf{K} = \frac{1}{N} \sum_{i=1}^N (\mathbf{r}_i - \boldsymbol{\mu})(\mathbf{r}_i - \boldsymbol{\mu})^T$$

- R-RXD (δ^{r-AD}), where the covariance matrix **K** is replaced by correlation matrix **R**:

$$\delta^{R-AD} = \mathbf{r}^T \mathbf{R}^{-1} \mathbf{r}, \quad \mathbf{R} = \frac{1}{N} \sum_{i=1}^N \mathbf{r}_i \mathbf{r}_i^T$$

- In real time application, the detected anomaly data should not be counted into correlation matrix:

$$\tilde{\mathbf{R}} = \mathbf{R} - \sum_{\mathbf{r}_i \in \Delta} \mathbf{r}_i \mathbf{r}_i^T$$

Signature Discriminability Measurement (SDM)



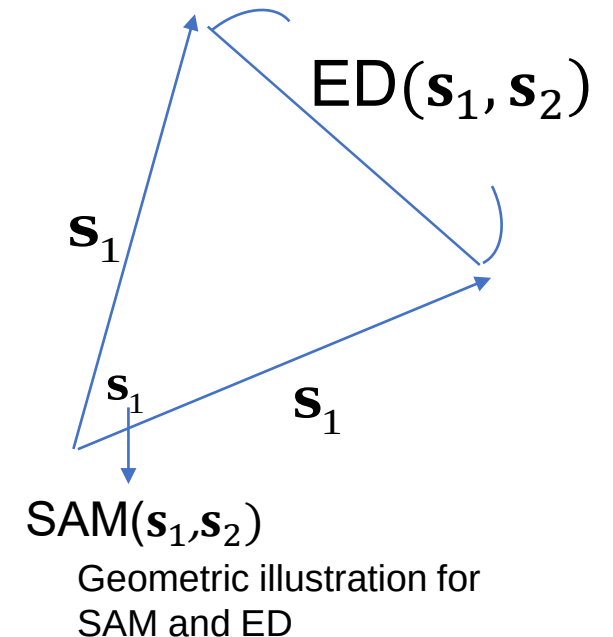
- SDM is primarily based on measuring the divergence between two input signals. This can be significantly useful to compute discriminability between health subsystem signal and failed substance signal.
- Euclidean Distance (ED):

$$\mathbf{s}_1 = (s_{11}, s_{12}, \dots, s_{1L})^T \quad \mathbf{s}_2 = (s_{21}, s_{22}, \dots, s_{2L})^T$$

$$ED(\mathbf{s}_1, \mathbf{s}_2) = \|\mathbf{s}_1 - \mathbf{s}_2\|_2 = \sqrt{\sum_{l=1}^L (s_{1l} - s_{2l})^2}$$

- Signature Angle Mapper (SAM):

$$SAM(\mathbf{s}_1, \mathbf{s}_2) = \cos^{-1} \left(\frac{\langle \mathbf{s}_1, \mathbf{s}_2 \rangle}{\|\mathbf{s}_1\| \|\mathbf{s}_2\|} \right)$$



Signature Discriminability Measurement (SDM)



- Signature Information Divergence (SID) method using relative entropy in information theory to compute discriminability between two signals.

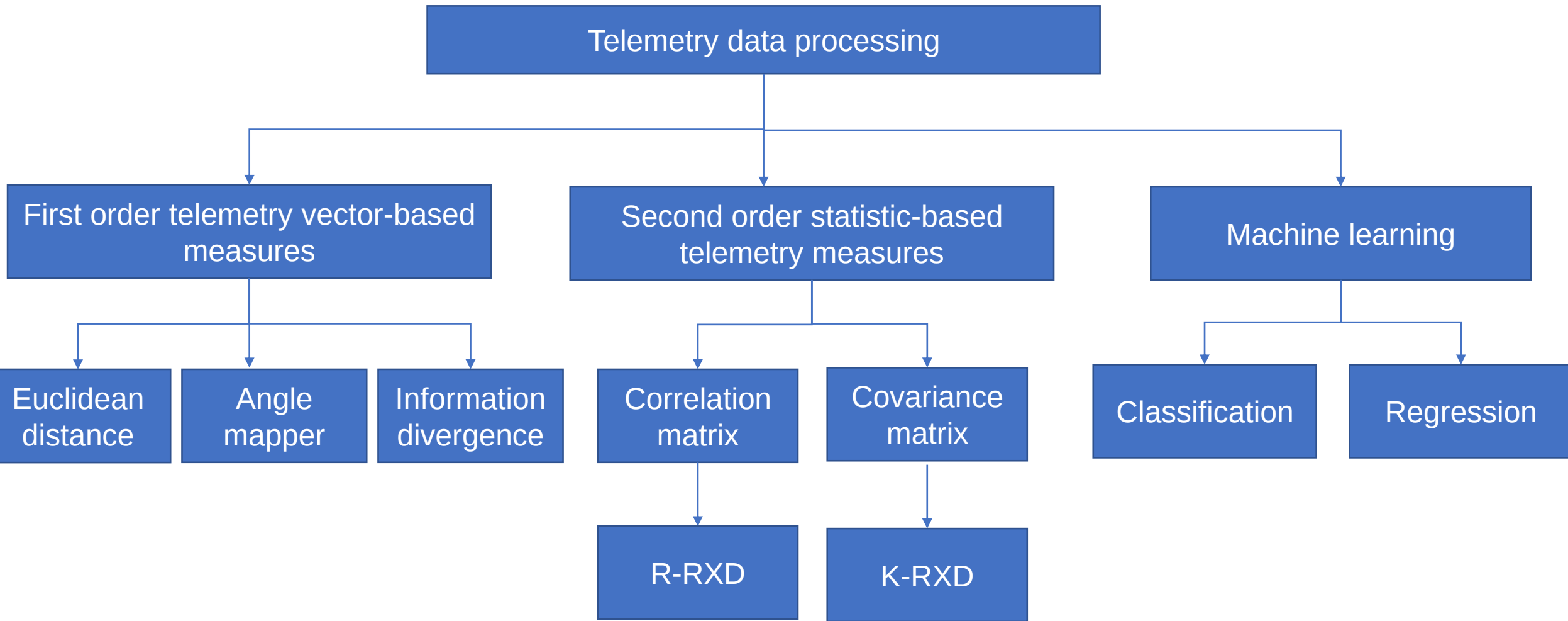
$$p_{1l} = s_{1l} / \sum_{l=1}^L s_{1l} \quad p_{2l} = s_{2l} / \sum_{l=1}^L s_{2l}$$

$$D(\mathbf{s}_1 \parallel \mathbf{s}_2) = \sum_{l=1}^L p_{1l} \log(p_{1l} / p_{2l})$$

$$D(\mathbf{s}_2 \parallel \mathbf{s}_1) = \sum_{l=1}^L p_{2l} \log(p_{2l} / p_{1l})$$

$$\text{SID}(\mathbf{s}_1, \mathbf{s}_2) = D(\mathbf{s}_1 \parallel \mathbf{s}_2) + D(\mathbf{s}_2 \parallel \mathbf{s}_1)$$

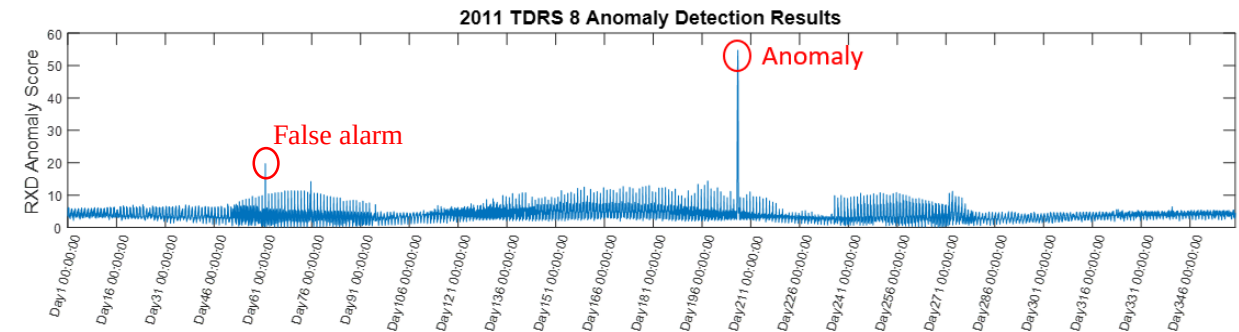
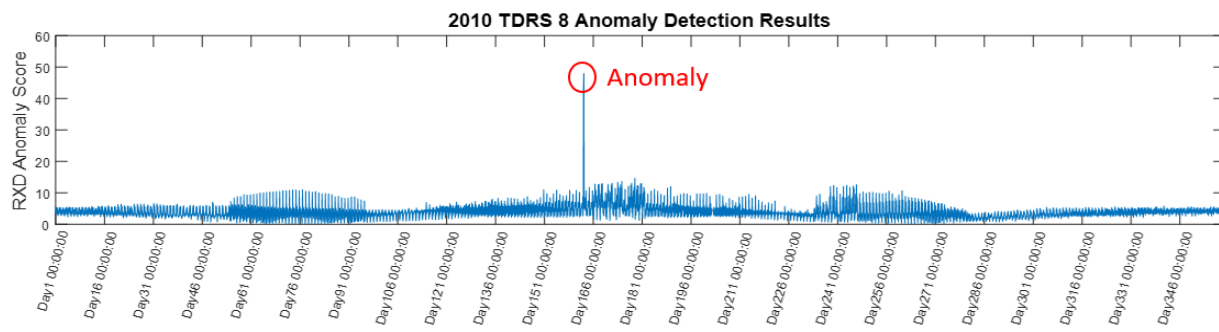
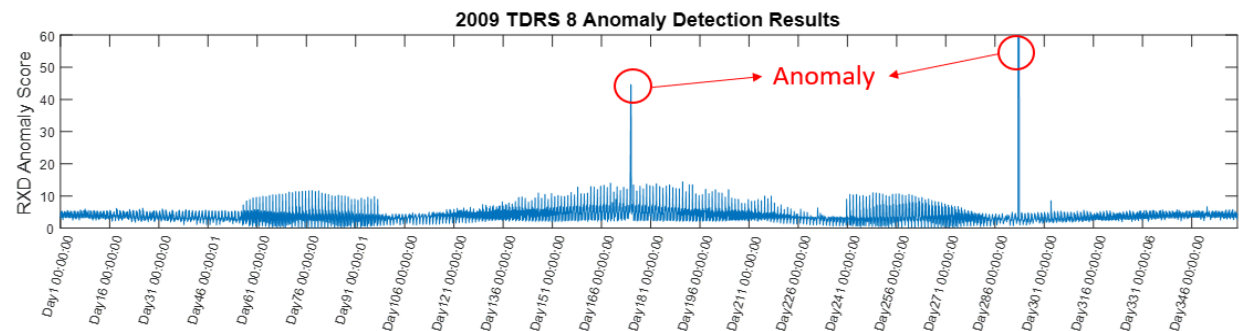
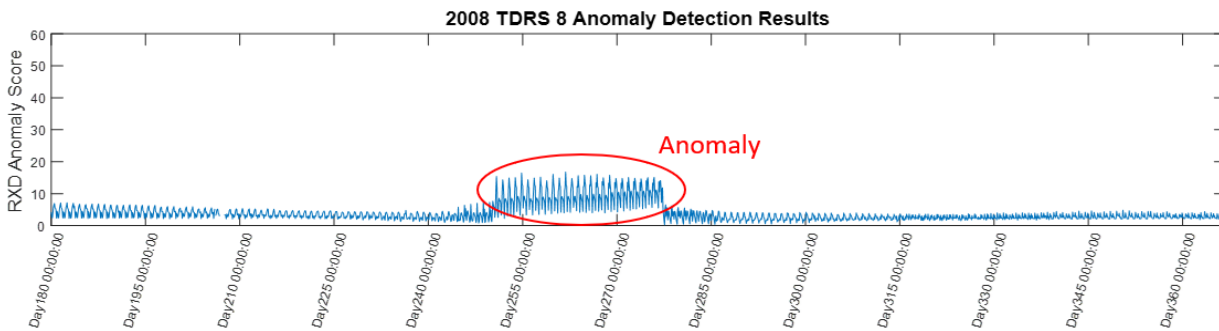
Block Diagram of Various Telemetry Measures



Anomaly Detection



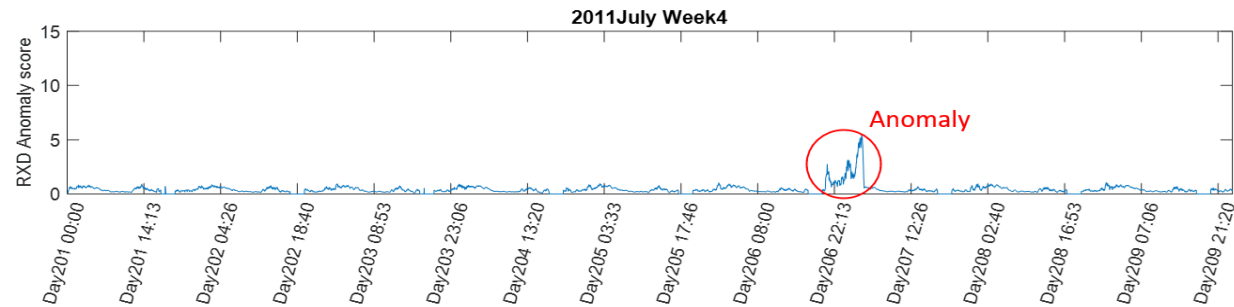
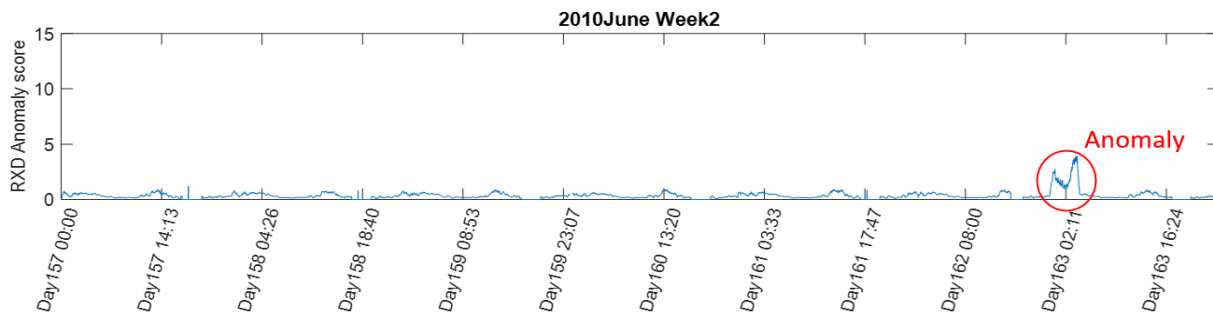
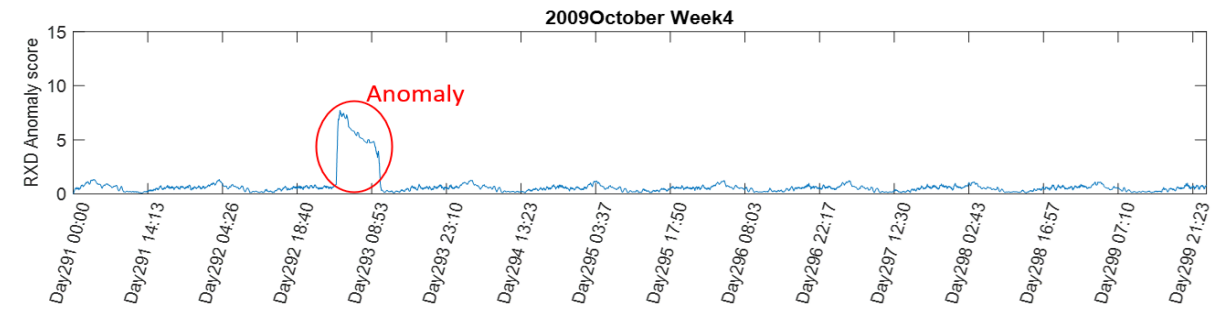
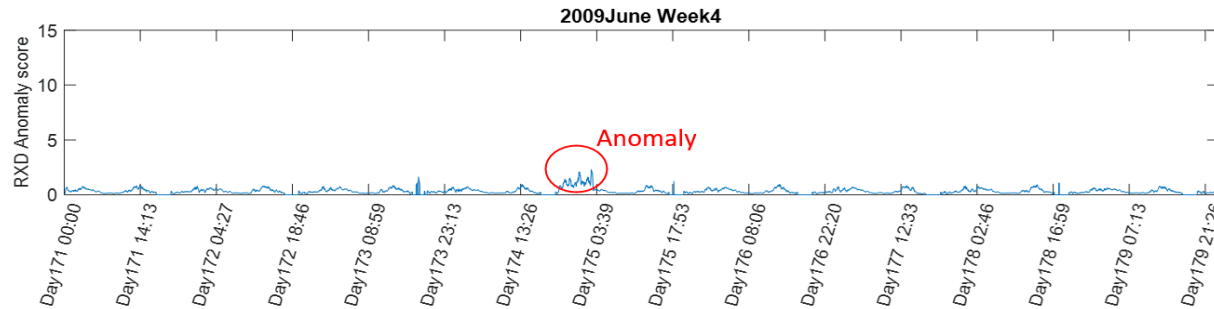
- In this analysis, we implement RXD using a sample mean generated from 2-hour telemetry window.
 - Used parameters: Bus voltage limiter current, Bus voltage limiter temperature and bus voltage



Anomaly Detection



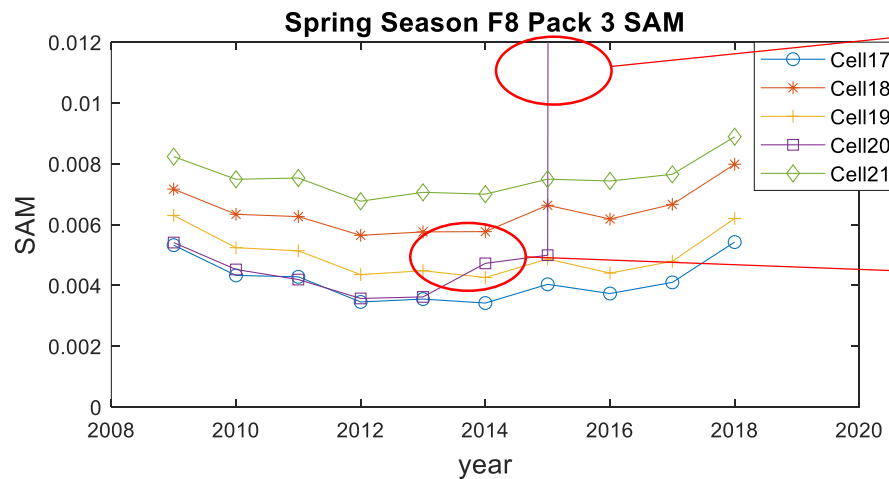
- In this analysis, we implement RXD using a sample mean generated from 1-minute telemetry window.
 - Used parameters: Bus voltage limiter current, Bus voltage limiter temperature and voltage of bus



SDM Battery Cell Performance Analysis

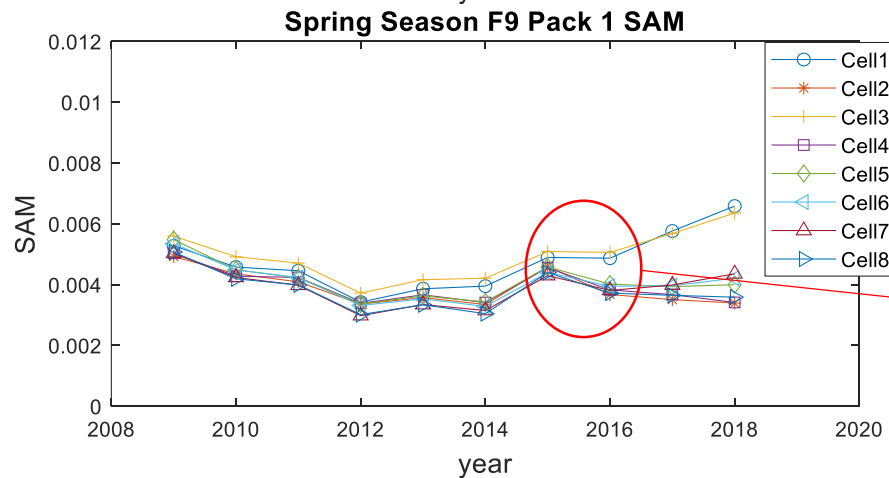
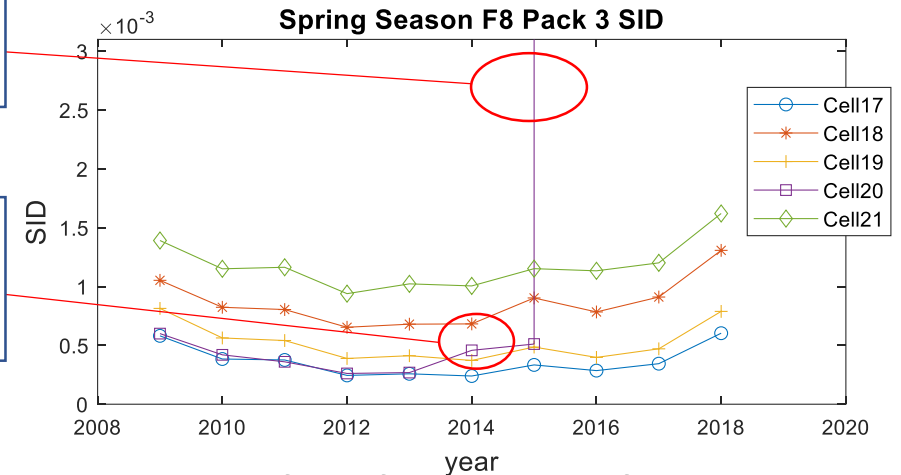


- SDM applied to quantify current performance of battery cell. The cell with abnormal discriminability when compared to the rest of the cells in same pack indicates the anomalous event. These anomalies could be the failure of a scanner, the leaking of chemical substance or other unknown events.

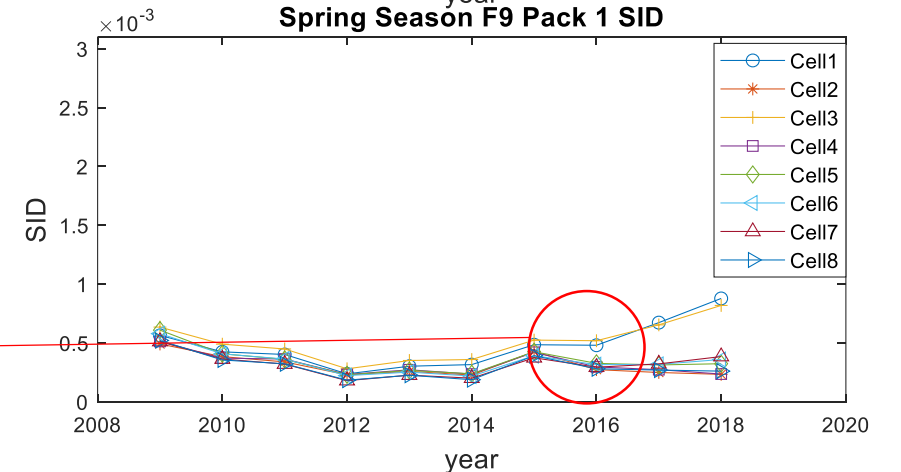


F8 cell 20 failed at fall 2015

SDM results showing that we can observe some signs of failure since spring 2014



F9 Cell 1 and cell 3 started to diverge from rest cells since 2016. We can say these two cells have potential failure.



Conclusion



- For the sensor that collects telemetry data in real time, the best tool to evaluate data is an unsupervised algorithm.
- In the event that telemetry data is not collected, sample statistics are generally available. In that case, more a powerful machine learning algorithm can be applied to classified anomaly data in each subsystems.
- Reduce the storage requirement of historical telemetry data.
- Continue develop algorithms for analyzing each subsystems to improve the efficiency in monitoring spacecraft quality.
- Future Work:
 - Reaction wheel anomaly detection and analysis
 - Bus voltage limiter (BVL) anomaly detection and analysis.
 - Thruster anomaly and failure prediction