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Event-Trained Anomaly Detection for Satellite Telemetry

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Agenda

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Introduction

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Introduction

- **A novel ML technique for anomaly detection in satellite telemetry has been developed**
- **Unique and important features of this technique include:**
  - Suitable for irregularly occurring, event-based time series
  - Intrinsically multivariate
  - Makes no assumptions of periodicity or trending in data
  - Based on powerful machine learning architecture
  - Unsupervised
  - Provides easy-to-interpret results
- **Prototyped and validated with GOES-16 telemetry from North-South and East-West station keeping maneuvers**
- **Universally applicable to many other domains with minimal fine-tuning**

Motivation

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Why is automated anomaly detection in satellite telemetry needed?

- **Modern Satellites operational methodologies, coupled with expediential growth in sensors technology, generates extensive amounts of telemetry data, consequently:**
  - Timely interpretation of such data is needed
  - But direct monitoring by domain experts requires too much manpower
  - If required, it would be costly and impractical
- **Software tools for automated anomaly detection are needed to:**
  - Constantly monitor the satellite telemetry
  - Notify engineers for unusual behavior
  - Mere claiming of anomaly is not enough
  - Report specific time series with anomalies
  - Report specific periods of time with anomalies

What are the traditional techniques?

- **Telemetry time series may stay constant or show periodic patterns**
- **Patterns are learned by a ML model trained over past periods**
- **Model's prediction over the next period is a baseline against which new observations are compared**
- **Strong deviations from the baseline are flagged as anomalies**
- **Deviation limits can be**
  - set threshold values
  - learned threshold values
  - dynamically changing functions learned from training data
- **Periodicity assumption is essential**

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Why event-trained techniques are needed?

- **Traditional approaches work great in most cases.**
- **However, they fail when periodicity is violated.**
- **When special events are spaced irregularly in time, they**
  - disrupt periodic patterns in data
  - hinder convergence in training
  - trigger false positive alarms in inference
- **For example, during station keeping maneuvers thruster's firing raises temperature of nearby components well above normal.**
- **Anomaly alarm is triggered because observed and predicted temperatures differ significantly.**
- **Large number of false positives is distracting for operation engineers and needs to be avoided.**
- **Ignoring all positive alarms during special event eliminates false positives but creates false negatives.**

Why event-trained techniques are needed?

- **We designed an event-trained anomaly detector to address the periodicity weakness of traditional approaches.**
  - trained on data collected during special events
  - inference is applied only on data from special events
  - detects only anomalies relevant to special events
  - does not model individual time series
  - analyzes all relevant time series simultaneously
- **Its utility goes beyond simply declaring the presence of anomaly**
  - it reports the specific telemetry time series with most abnormal behavior
  - it reports the exact time interval in which that behavior is observed
- **Last functionality is of great benefit for operation engineers as it takes them directly to the "time and place" where anomaly is.**

Our approach – event-trained unsupervised ML

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Training our event-trained ML model with NSSK events

- **Applied the technique to GOES-16's station keeping maneuver data from the last three years.**
- **For North-South Station Keeping (NSSK) maneuvers we had**
  - 82 relevant telemetry time series identified by domain-experts
  - time intervals for 200 nominal NSSK maneuvers
  - time intervals for 50 non-nominal NSSK maneuvers
- **Nominal maneuvers were randomly partitioned into training, validation, and test sets in 8:1:1 split.**
- **Experimental search over hyperparameter space led to a particular neural net architecture which learned the training data well.**
- **Training was guided by loss evaluation on validation data at the end of each training epoch.**

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Testing our event-trained ML model on NSSK events

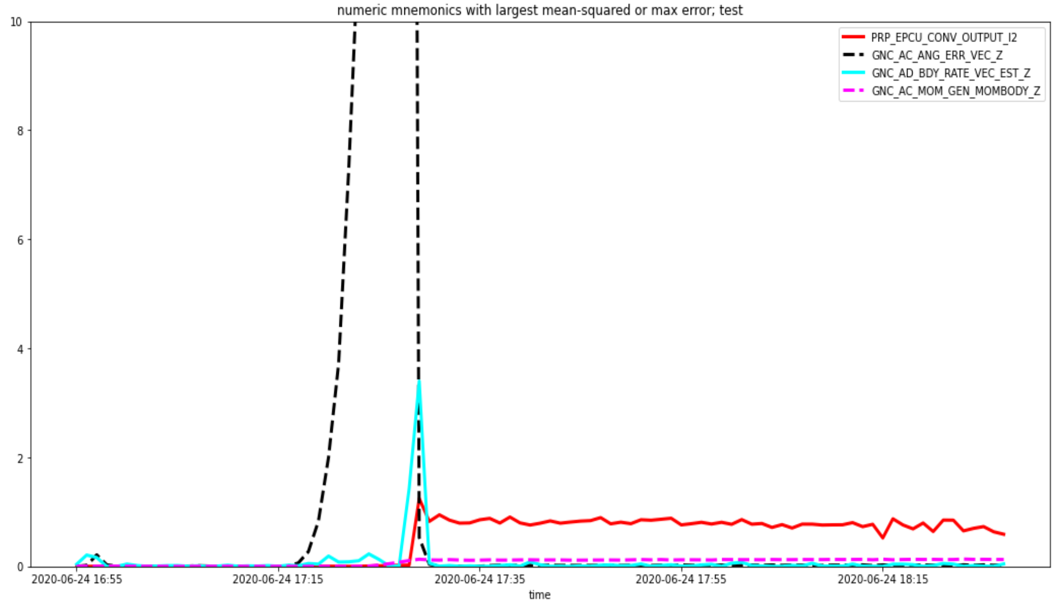
- **Tested on 20 nominal NSSK maneuvers set aside for that purpose.**
  - Only one was flagged as anomalous.
  - Expert review confirmed presence of unusual benign behavior in that NSSK maneuver.
- **Tested on 50 NSSK maneuvers labeled by domain-experts as aborted, degraded, or otherwise non-nominal.**
  - All but two were flagged as anomalous.
  - The two false negatives were originally expert-labeled as degraded.
  - When examined by a different domain expert they were found nominal.
- **In summary, the one false positive was justified by rare behavior, while the two false negatives were due to incorrect ground truth.**

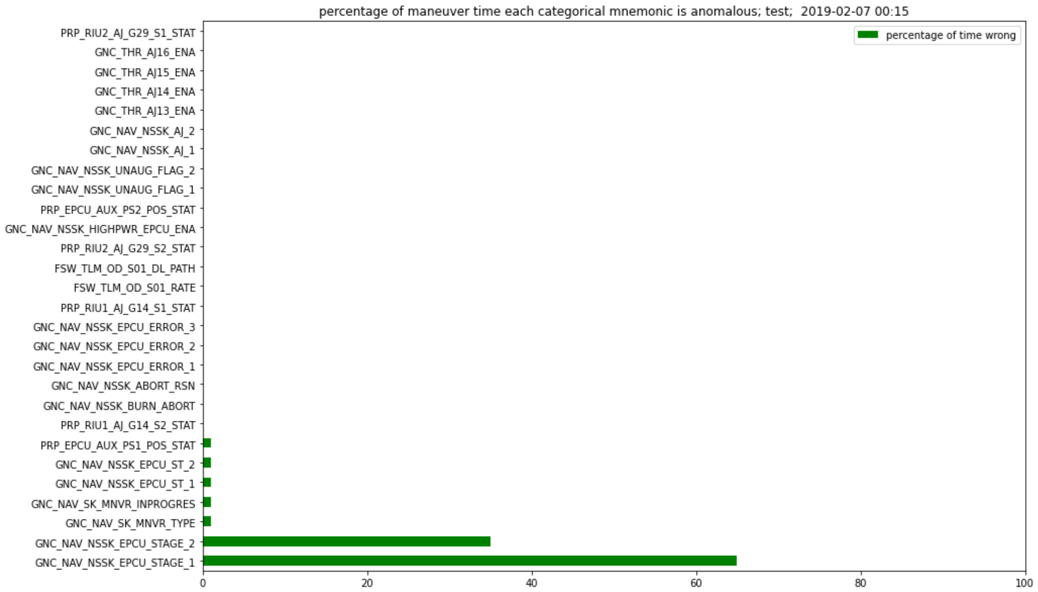
Applying our event-trained ML technique to EWSK events

- **For East-West Station Keeping (EWSK) maneuvers the method worked equally well.**
- **EWSK maneuvers on GOES-16 are performed with one of two thruster configurations.**
- **Trained a separate model for each of the two configuration.**
- **5 of the EWSK maneuvers were flagged as anomalous.**
  - A domain-expert explained all 5 alarms with a known "bubble" effect.
  - The effect is benign and occasionally is strongly expressed.
- **In summary, our models did not generate any unreasonable false positives.**
- **All false positives were due to insufficient representation in training data.**

Interpretability of detected anomalies

- **Anomaly detections are easy to interpret because the algorithm:**
  - uncovers the individual univariate components responsible for the non-nominal behavior.
  - pinpoints the time periods of non-nominal behavior.
- **Operation engineers can jump directly to the core of a problem.**





Scope, applicability, and implementation

Scope and applicability

- **The approach can be easily adapted to other special events.**
- **Uniquely suitable for events that occur irregularly, with varying start time and duration.**
- **Most other approaches are not applicable under such conditions.**
- **Only assumptions on the special events are the following:**
  - telemetry time series affected by the events are a priori identified
  - events occur often enough to provide sufficient training data
  - most of the events are nominal, that is, they occurred as planned

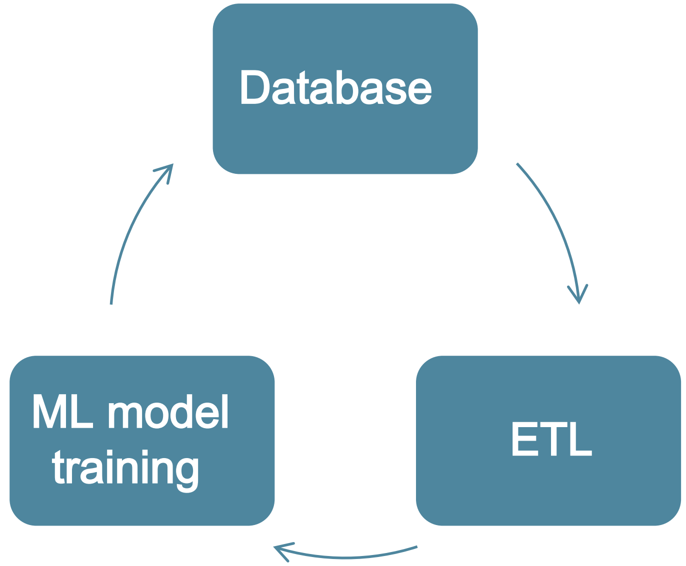
Scope and applicability

- **First assumption is to have a relevant and complete set of telemetry time series.**
  - If some time series are not relevant, we will waste model resources to learn patterns that do not matter
  - If relevant time series are missing, we may fail to detect an anomalous event as such.
- **Second assumption is that the ML model needs training data to learn from.**
- **Last assumption is that one should not train with too many bad examples.**
  - Quantitatively, our unsupervised model will learn perfectly well if anomalous events in training data are less than 0.1%.
  - If they are more, a domain expert would be required to bring their percentage to below 1%.

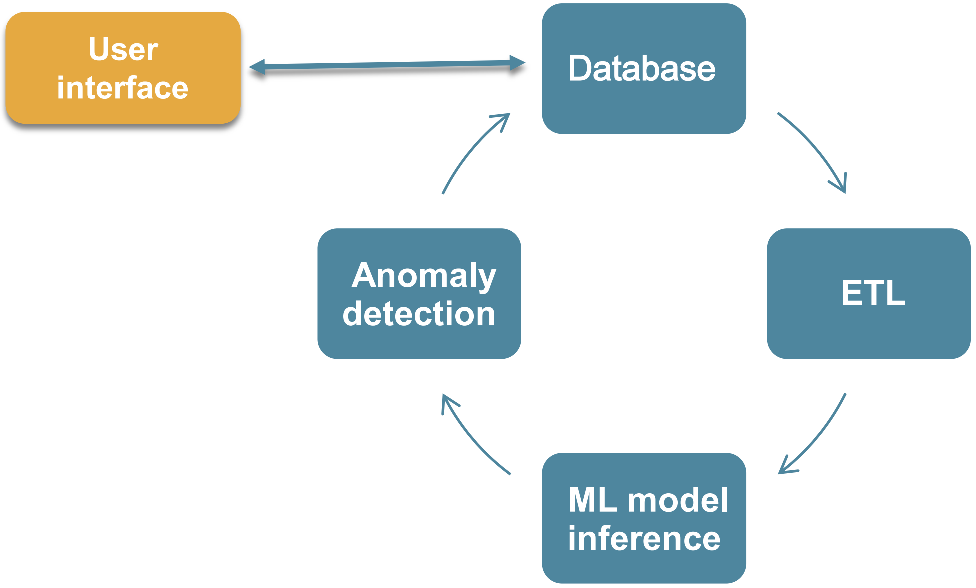
Implementation

- 90% of our source code can be reused for other special events as is.
- Implemented in Python, Tensorflow/Keras.

Training



Interference



Conclusion

In conclusion

- A novel ML technique for anomaly detection in satellite telemetry is developed.
- Intrinsically multivariate.
- Suitable for event-training.
- Unsupervised ML model learns all correlations in the entire data set simultaneously.
- Anomaly detection is based on the deviations from the learned correlations.
- Algorithm uncovers individual time series and timestamps with anomalous behavior.
- Prototyped and validated with GOES-16 telemetry from North-South and East-West station keeping maneuvers.
- Soon to be ready for deployment on the ground system.

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Quyanaq !

Thank you!

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