Maximizing Operator Impact:
Leveraging Machine Learning to Improve Trending Analysis for the Magnetospheric Multiscale (MMS) Mission

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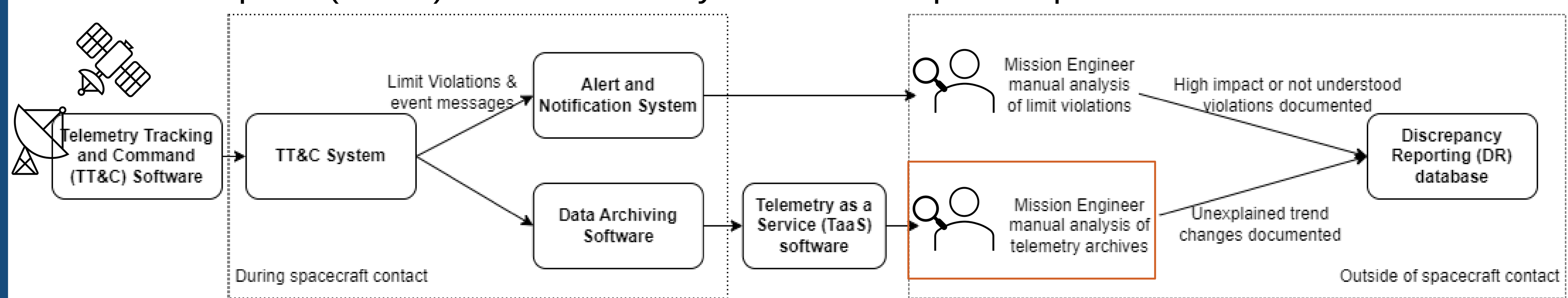
Background

Launched in 2015, MMS is a constellation of 4 NASA GSFC-built satellites in a Highly Elliptical Orbit (HEO) exploring magnetic reconnection, a fundamental process essential to better understanding solar flares and other space weather events impacting Earth.

While the four satellites were designed to be "identical," changes and degradation over time require constant evolution of Health and Safety (H&S) monitoring techniques:

- Telemetry analysis is crucial to detect mission anomalies
- Current techniques rely on pre-defined thresholds (limits) developed by subsystem Subject Matter Experts (SMEs) to autonomously detect and report on possible anomalies

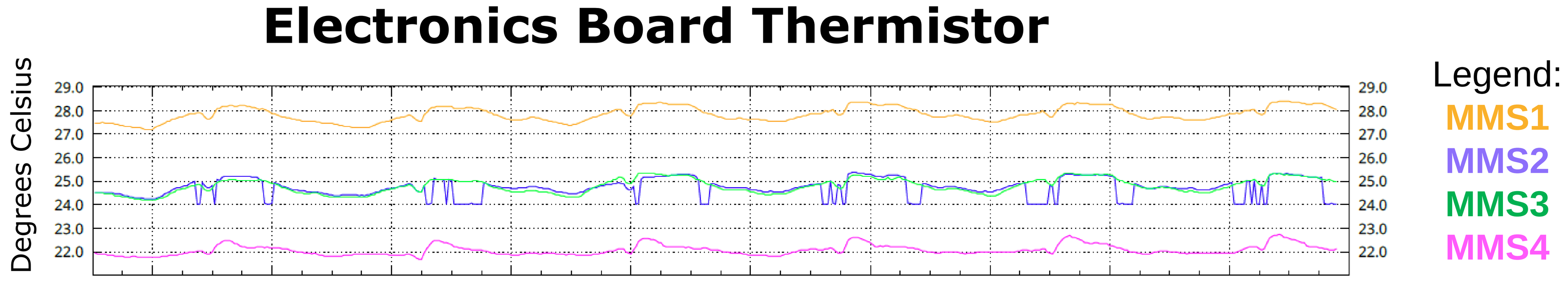


Our effort applies ML techniques on collected MMS mission telemetry data to develop a suite of algorithms capable of both predicting and detecting mission anomalies.

Data

We leverage packetized H&S telemetry from the mission Telemetry as a Service (TaaS) archive to train our ML models. Sample historical anomalies are used to evaluate model performance.

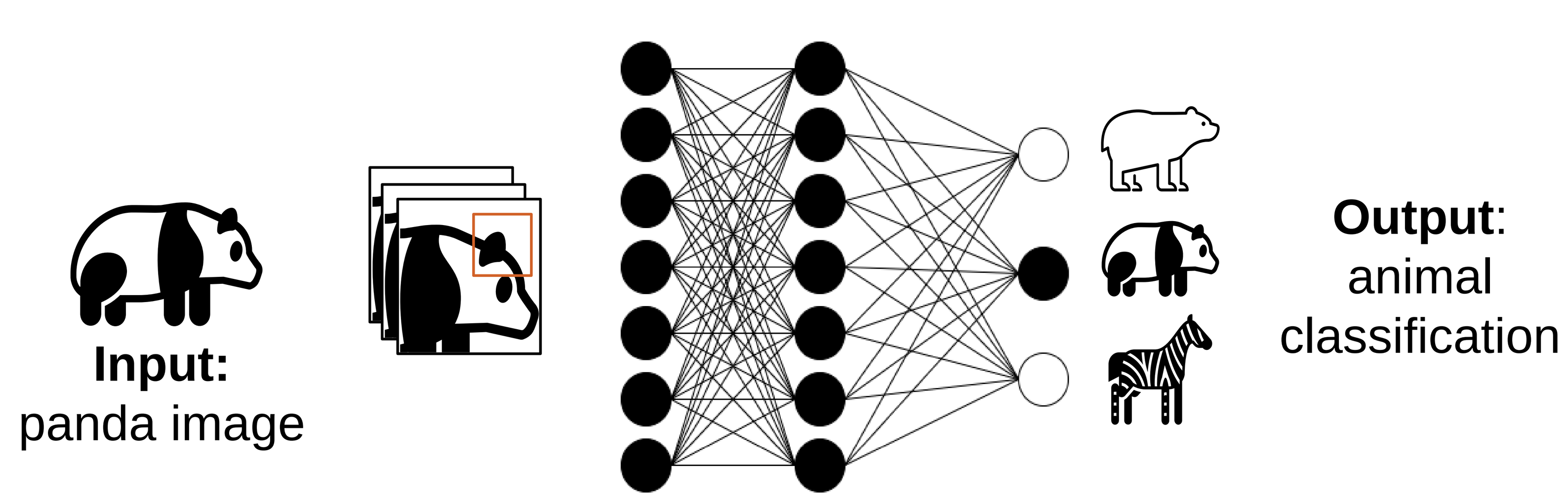
Electronics Board Thermistor



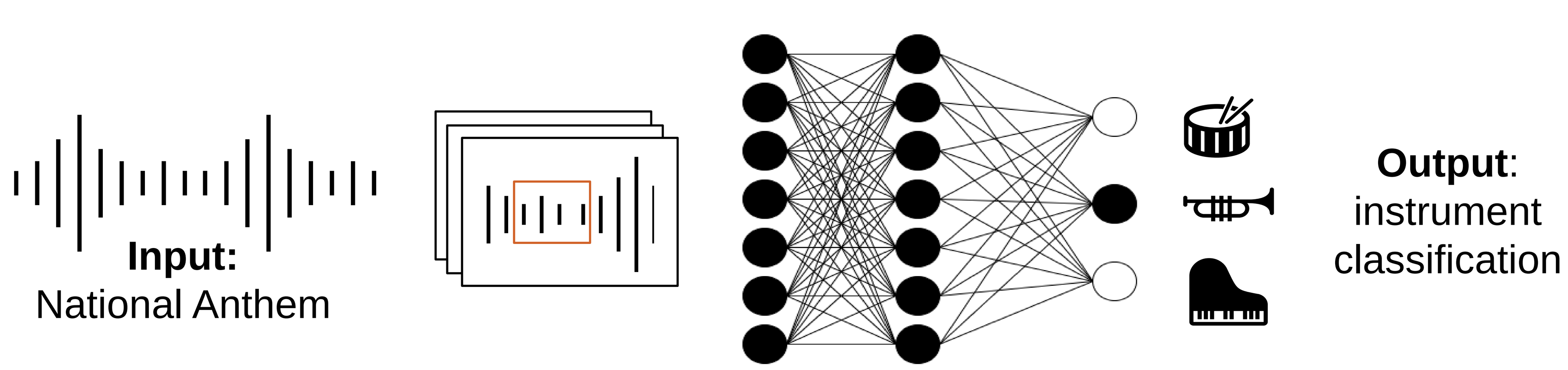
The anomalous trend detected on MMS2 (above) did not trigger an automatic limit violation. We will use this anomaly to test our trained models!

Classic Convolutional Neural Networks (CNN)

Classic CNNs use filters to extract features. The combination of these features can help in classification problems. Due to their architecture, these CNNs are robust to modified inputs.



2-Dimensional filters (above) may look at a body part and capture the shape or color of a particular body part. 1-Dimensional filters (below) may qualify the pitch or brightness of a sound

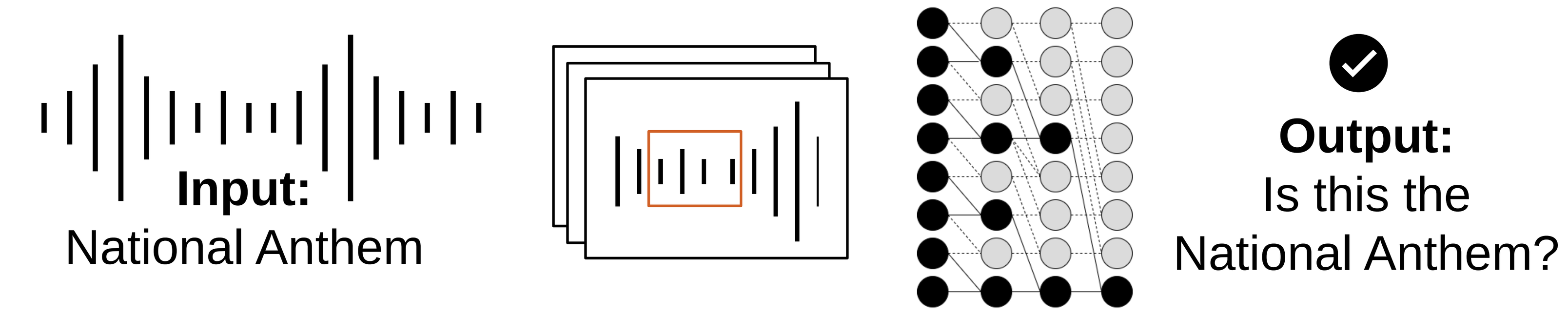


Our Approach: Temporal Convolutional Network (TCN)

We use a specialized version of a Convolutional Neural Network (CNN) called a Temporal Convolutional Network (TCN).

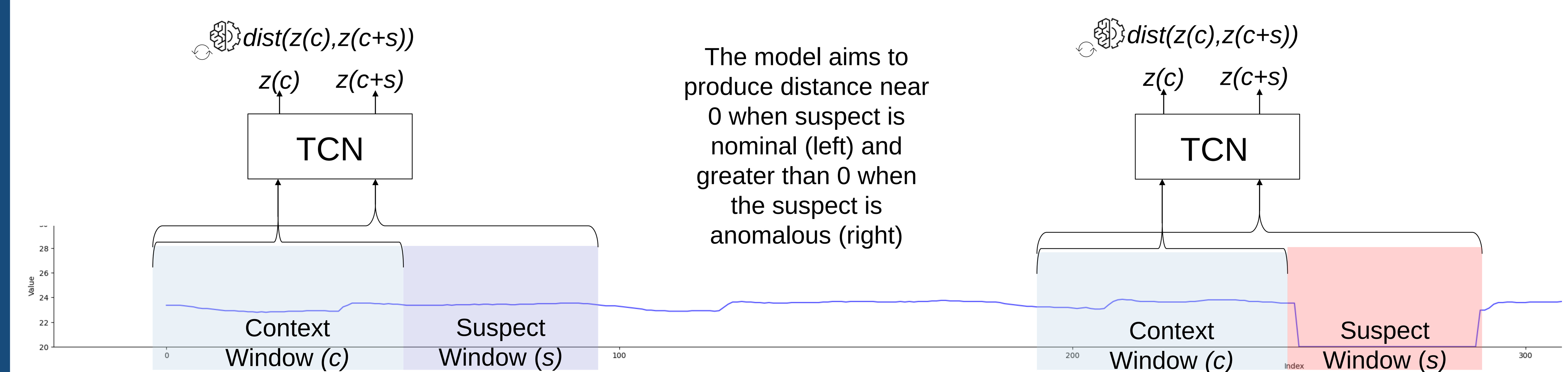
A TCN is used with sequential data:

- Causal convolutions preserve order
- Dilated convolutions capture long-term dependencies



Inspired by Carmona et. al's publication "Neural Contextual Anomaly Detection (NCAD) for Time Series" we use a TCN to detect anomalous trends in telemetry data. We illustrate the training process below:

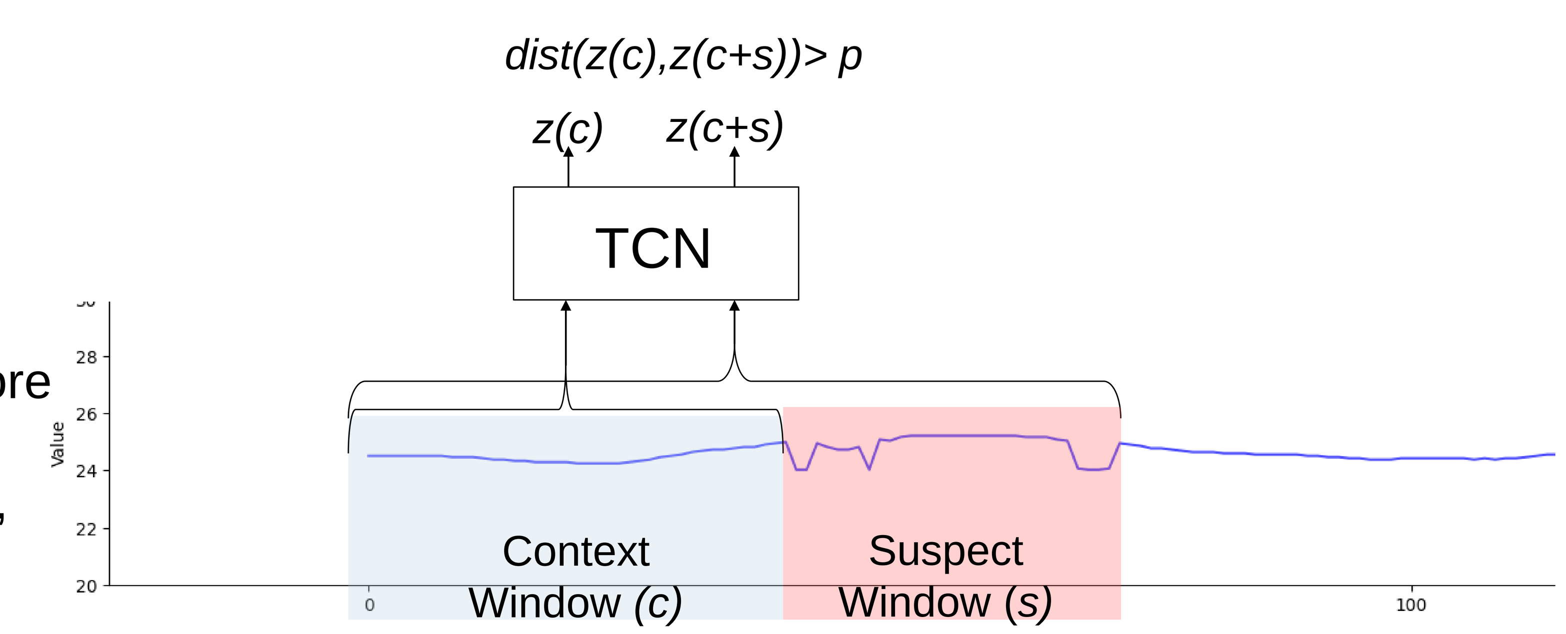
- Look at one section of data at a time, splitting it into context (*c*) and suspect (*s*) windows
- Pass the context window and full window (*c+s*) through our TCN to produce new vector representations of the input
- Compute the distance between these vectors



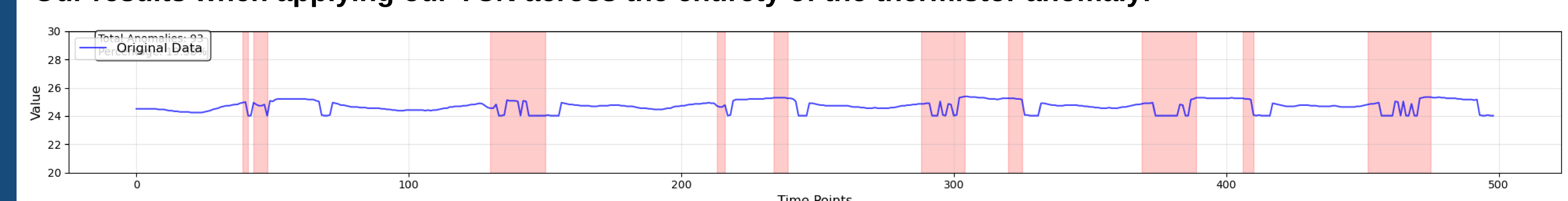
Results to Date

We use the trained TCN model on new test data:

- Slide the context and suspect windows across test data
- Use the computed distance as an anomaly score
- Threshold with median absolute deviation
- If the distance is greater than the threshold (*p*), flag the suspect window as an anomaly.



Our results when applying our TCN across the entirety of the thermistor anomaly:



The red bars indicate flagged anomalies. Our results are encouraging—further tuning of the model will improve accuracy!

Future Work

- Experiment with variations of model architecture
- Apply model to new datasets
- Fine tune models with domain experts
  - Address false positives
  - Account for known events that impact trends
- Integrate models with existing GSFC telemetry post-processing tools
- Apply a 'library of models' technique giving operators more control

Acknowledgements

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Carmona C., Aubet F., Flunkert V., Gasthaus J. Neural Contextual Anomaly Detection for Time Series, URL https://arxiv.org/abs/2107.07702