As scientific instruments collect increasing amounts of data, improved systems are needed to analyze, condense, and present this data to engineers and scientists.

Automated anomaly detection for spacecraft telemetry is an area where modern data science and machine learning methods could provide substantial value.

We use Recurrent Neural Networks (LSTMs) to predict incoming telemetry values using recent telemetry, commands, and event records (EVRs) as inputs.

Where predictions are substantially different from actual telemetry values, these are identified as potentially anomalous events. We use a novel nonparametric method for determining “substantially different”.

Increasing data rates for missions necessitate automated anomaly detection methods. For example, NASA/JPL’s upcoming SWOT, NISAR missions will be generating 3-4 terabytes (TB) of data daily.

Current spacecraft monitoring systems only target a subset of anomaly types and often require costly expert knowledge to develop and maintain.

Thresholding systems, for example, are unable to detect “contextual” anomalies (anomalies which stay within the limits of their channel’s values, yet exhibit abnormal behavior in the context of their surrounding “normal” telemetry values).

Our nonparametric dynamic thresholding method outperformed gaussian tail method for thresholding.

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Experiment to evaluate system looked at historical telemetry values for SMAP and MSL missions, and tried to detect ~115 expert-labeled anomalies (ISAs).

This pilot was a key step in establishing that a large-scale telemetry monitoring system is feasible. Future work will focus on extending this system to other missions, and improving the telemetry predictions primarily through improved feature engineering.

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