

Detecting Spacecraft Anomalies Using LSTMs and Nonparametric Dynamic Thresholding

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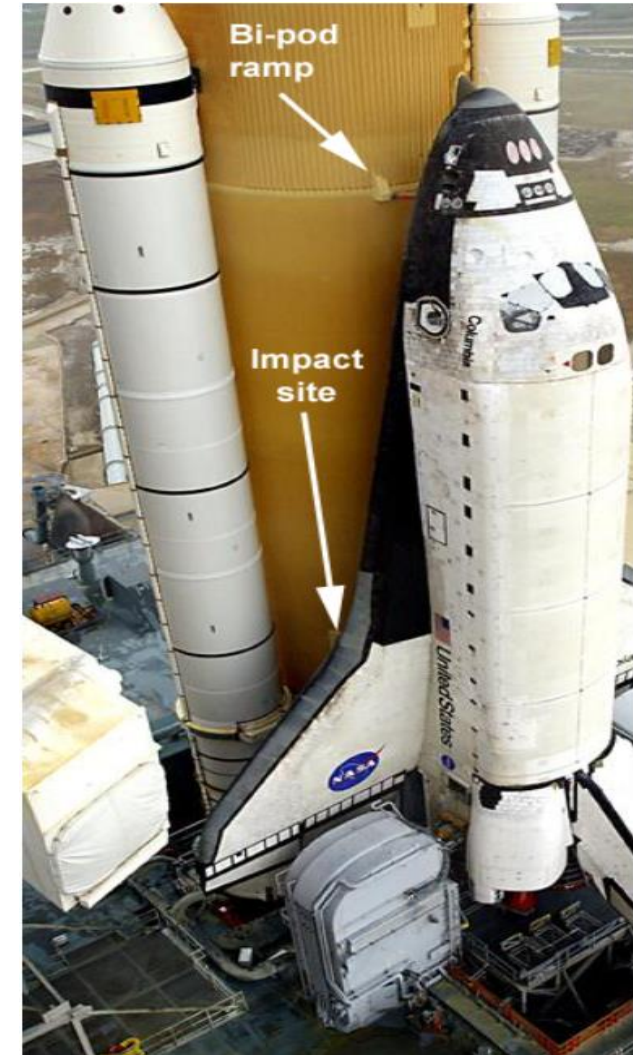
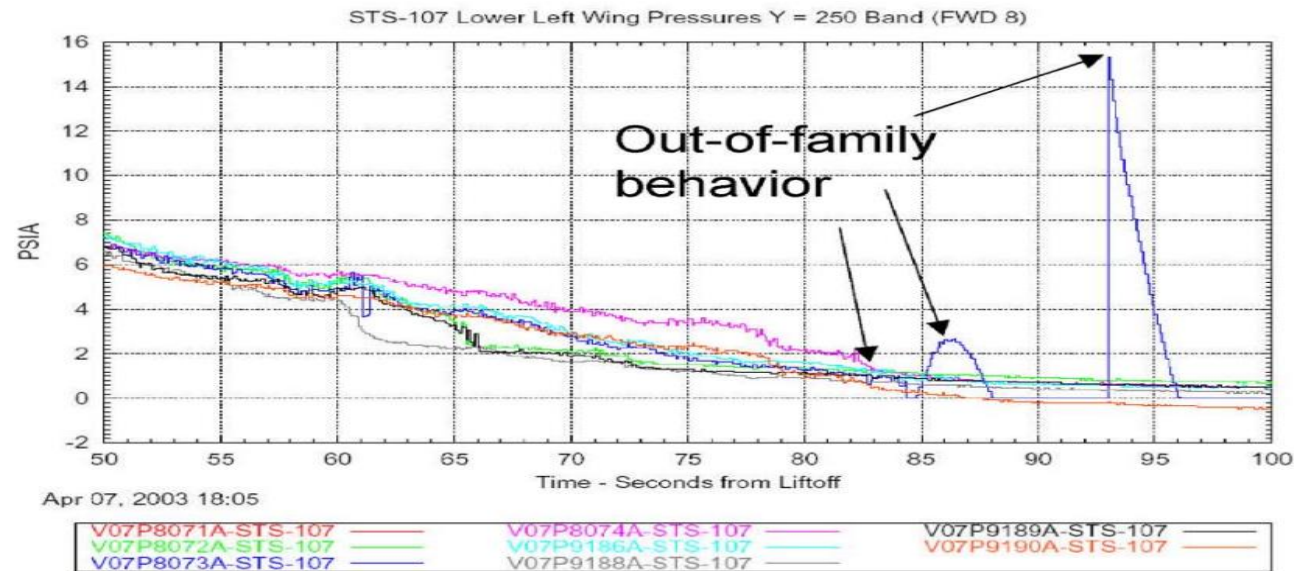
Presenter: Avisha Bhiryani

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Columbia STS-107 Tragedy

- Picture on the right is the very reason for the loss of Columbia STS-107 space-shuttle along with the 7 member crew on board.
- Purpose of the Modular Auxiliary Data System(MADS) on board the Columbia Orbiter was to support annunciation of vehicle system failures and out-of-tolerance system conditions.



[Left]:<https://history.nasa.gov/columbia/Troxell/Columbia%20Web%20Site/CAIB/CAIB%20Website/CAIB%20Report/Volume%204/part03.pdf>

[Right]:<https://www.cbsnews.com/network/news/space/home/memorial/107.html>

Data at Hand

- Thousands of telemetry channels detailing aspects such as: Temperature, Radiation, Power, Instrumentation and computational activities.
- Data at hand is multivariate time series data.
- Challenges:
 - Lack of labelled anomalies
 - Noisy and high dimensional data
 - Context dependent

Introduction to Anomalies in Time Series

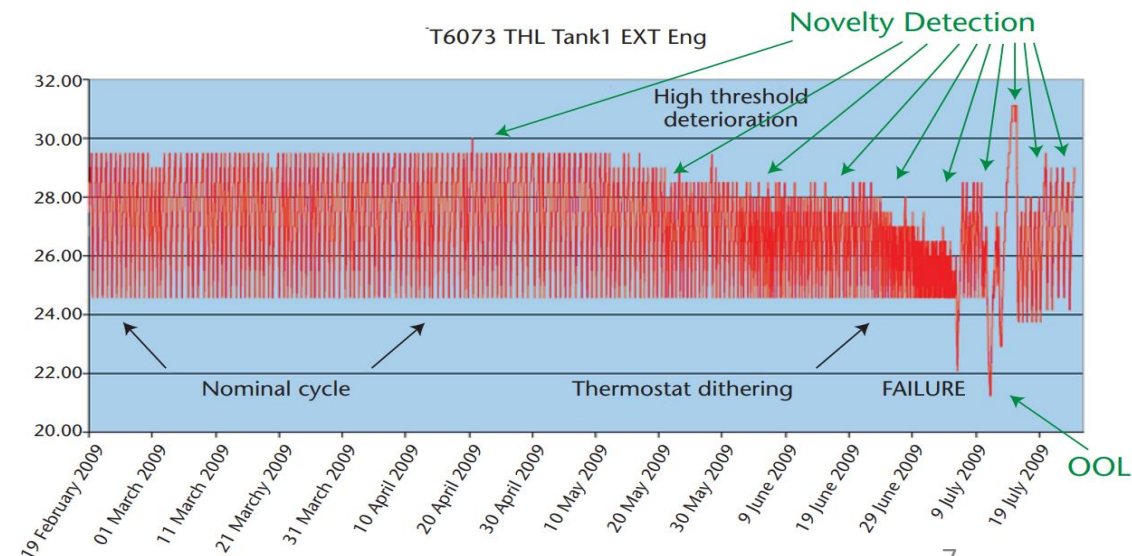
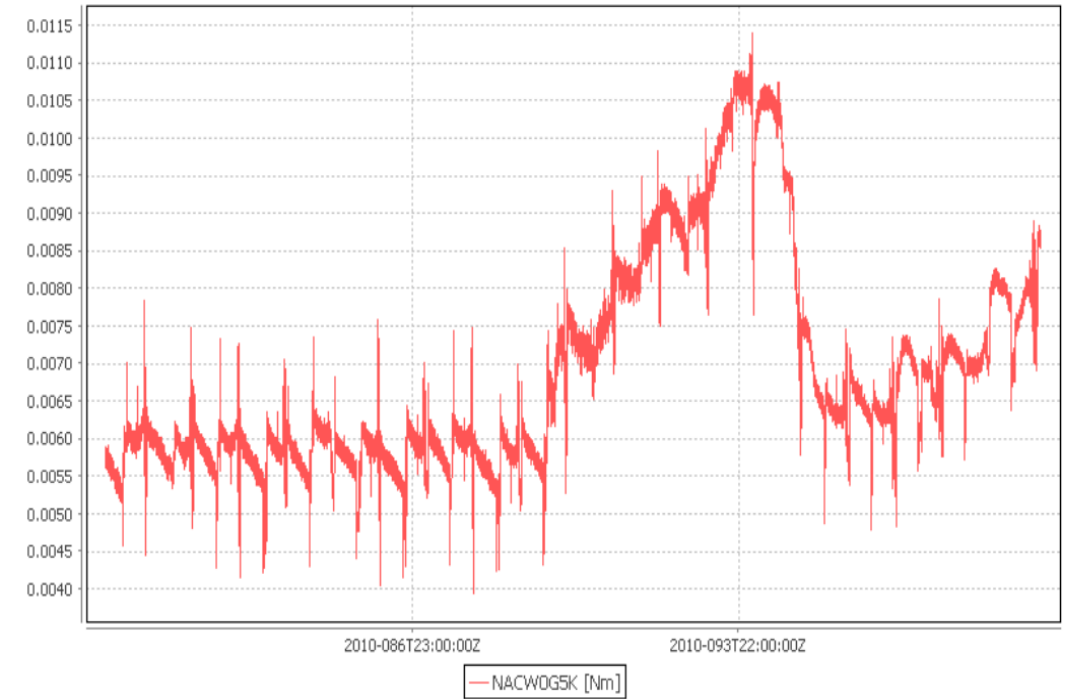
- Anomalies in time series data are the patterns that do not conform to the past behavior of the data.
- There are 3 categories of anomalies
 - Point: Single values that fall within low density region of values.
 - Collective: Sequence of anomalies rather than a single one.
 - Contextual: They do not fall in regions of low density values but are anomalous w.r.t the local values



Anomaly detection in Aerospace

- Different Approaches to detect anomalies in spacecraft telemetry data are as follows, but not limited to:
 - OOL(Out of limits)
 - Clustering
 - Nearest Neighbor
 - Expert systems
 - Deep Learning

- Out of Limits(OOL):
 - Alarm is triggered when a measurement goes beyond the set lower or upper threshold.
 - Lot of manual intervention needed:
 - Engineers will inspect the parameter that is out of limits and determine whether it is an anomaly or not and decide which action to take.
 - OOL bounds are not defined for every parameter.
 - Most popular approach:
 - Low computational expense, broad and straight-forward applicability, and ease of understanding.



- **Nearest Neighbor Approach:**

- Orca(currently being used on International Space Station) uses a nearest-neighbour approach to search for anomalies by calculating the distance of each data point from neighbouring points.
- The program outputs a score for each point representing the average distance to the nearest k-neighbours. Points that have a larger average distance to their nearest neighbours than most other points in are considered outlier.
- Issues:
 - Amount of past data to consider needs to be decided.
 - High computational complexity and memory consumption
 - Can only find global outliers

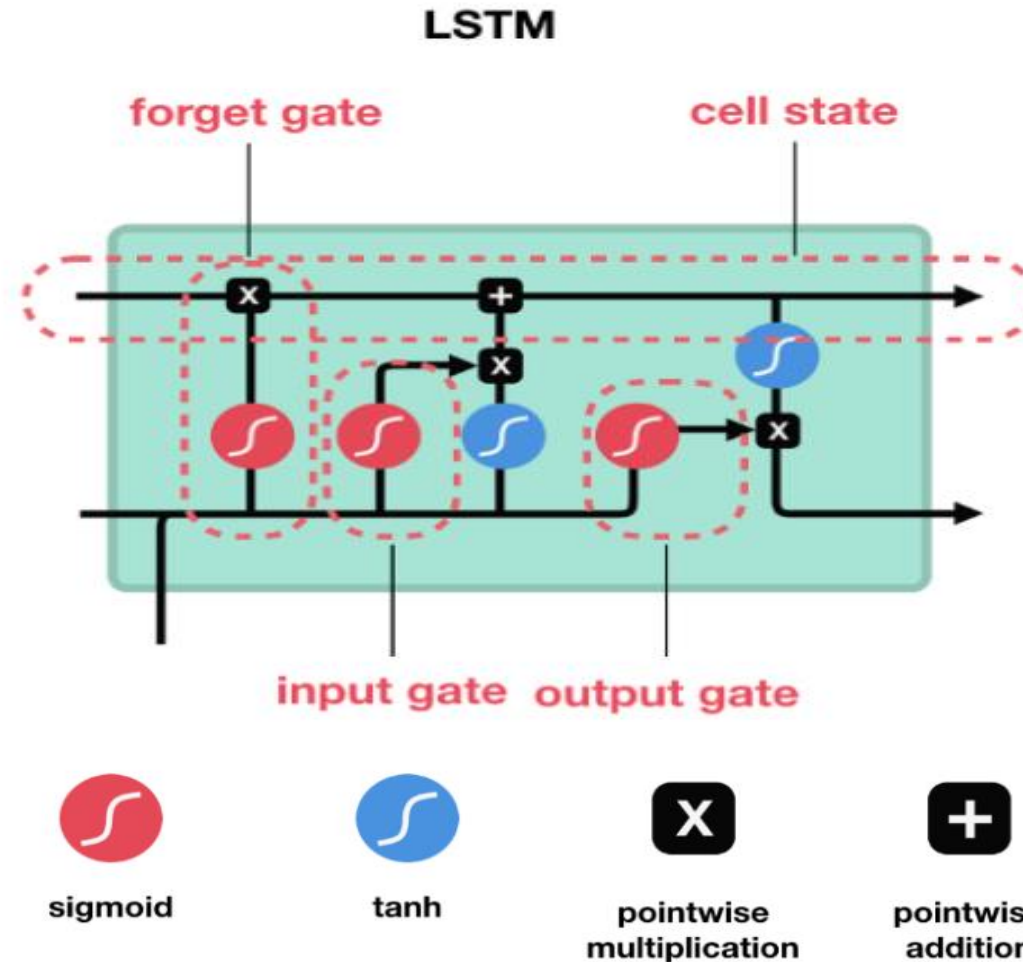
- **Clustering based Approach:**

- The Inductive Monitoring System(IMS)(currently being used on ISS) tool uses clustering to analyze archived spacecraft data and characterize nominal interactions between selected parameters. This model, is compared with real time or archived system data to detect off nominal behaviour.
- IMS returns the distance that vector falls from the nearest nominal operating region.

Deep Learning Approach: Long Short Term Memory

- Core Concept:
 - Cell State: Memory of the network
 - Gates: Information get's added or removed to the cell state through gates.
- Forget Gate:
 - It decides what is relevant to keep from prior steps.
- Input Gate:
 - It decides what information is relevant to add from the current step.
- Output Gate:
 - The output gate determines what the next hidden state should be
- Advantages of using LSTM:
 - Overcomes the Vanishing Gradient problem, so can learn long term correlations in a sequence.
 - LSTM networks obviate the need for a pre-specified time window.

Long Short Term Memory:



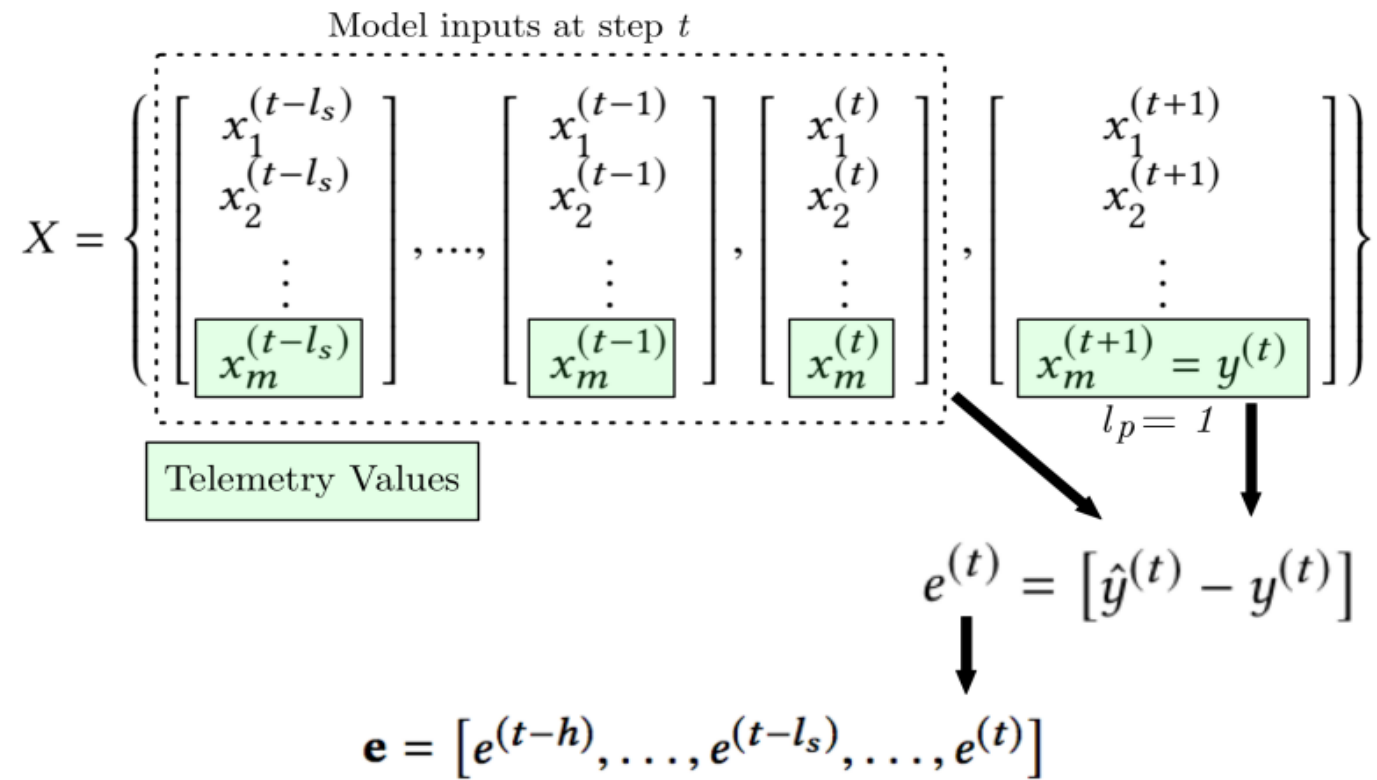
Source: <https://towardsdatascience.com/illustrated-guide-to-lstms-and-gru-s-a-step-by-step-explanation-44e9eb85bf21>

Core Components:

- LSTMs are used to predict telemetry data by learning from normal command and telemetry data
- An unsupervised thresholding method is then used to automatically assess hundreds of diverse streams of telemetry data and determine whether resulting prediction errors represent spacecraft anomalies.
- In order to mitigate false positive errors, certain strategies are employed.

Telemetry Value Prediction using LSTM:

- A single model is created for each telemetry channel and each model is used to predict values for that channel.
- This is because:
 - LSTMs struggle to accurately predict high dimensional data.
 - Modeling each channel independently also allows traceability of the issue down to the channel level.
 - If the system were to be trained to detect anomalies at the subsystem level without this traceability, operations engineers would still need to review a multitude of channels and alarms across the entire subsystem to find the source of the issue
 - Early stopping can be used to limit training to models and channels that show decreases in validation error.



Dynamic Error Thresholding

- Only abnormally high or low smoothed prediction errors should be considered as spacecraft anomalies.
- Set of errors are then smoothed to dampen spikes in errors that frequently occur with LSTM-based predictions.
- To determine the threshold:
 - Values evaluated for ϵ are determined using z , where z is an ordered set of positive values representing the number of standard deviations above the mean of smoothed error vector.
 - A threshold is found that, if all values above are removed, would cause the greatest percent decrease in the mean and standard deviation of the smoothed errors
 - Then the highest smoothed error in each sequence of anomalous errors is given a normalized score based on its distance from the chosen threshold.

$$\mathbf{e}_s = [e_s^{(t-h)}, \dots, e_s^{(t-l_s)}, \dots, e_s^{(t-1)}, e_s^{(t)}]$$

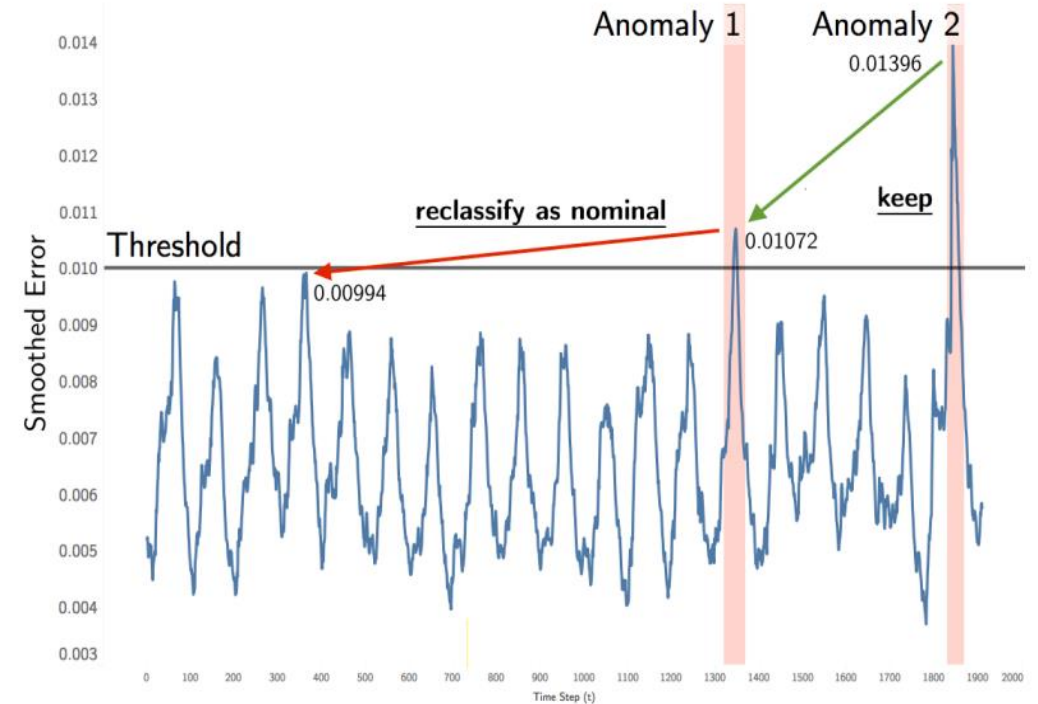
$$\epsilon = \mu(\mathbf{e}_s) + z\sigma(\mathbf{e}_s)$$

$$\epsilon = \operatorname{argmax}(\epsilon) = \frac{\Delta\mu(\mathbf{e}_s)/\mu(\mathbf{e}_s) + (\Delta\sigma(\mathbf{e}_s)/\sigma(\mathbf{e}_s))}{|\mathbf{e}_a| + |\mathbf{E}_{seq}|^2}$$

$$s^{(i)} = \frac{\max(\mathbf{e}_{seq}^{(i)}) - \operatorname{argmax}(\epsilon)}{\mu(\mathbf{e}_s) + \sigma(\mathbf{e}_s)}$$

Mitigating False Positives

- The precision of prediction-based anomaly detection approaches heavily depends on the amount of historical data (h) used to set thresholds and make judgments about current prediction errors.
- At large scales it becomes expensive to process historical data in real-time scenarios and a lack of history can lead to false positives that are only deemed anomalous because of the narrow context in which they are evaluated
- To mitigate false positives and limit memory and compute cost, a pruning procedure has been introduced



$$\mathbf{e}_{max} = [0.01396, 0.01072, 0.00994]$$

$$p = 0.1.$$

$$d^{(1)} = 0.23 > p \quad , \quad d^{(2)} = .07 < p$$

Experiment Setup

- Spacecraft data used: SMAP, MSL
- Incident Surprise, Anomaly Reports (ISA) were used to obtain labeled anomalies
- A 5-day span around anomalies is selected to get deeper insight into precision and also reasonable computational cost.
- Sequence Length and the amount of prior values that are used to evaluate a batch of values are selected through experiment result.

Model Parameters	
hidden layers	2
units in hidden layers	80
sequence length (l_s)	250
training iterations	35
dropout	0.3
batch size	64
optimizer	Adam
input dimensions	25 (SMAP), 55 (MSL)

Metrics

- True Positive: Only one true positive is recorded even if portions of multiple predicted sequences fall within a labeled sequence.
- False Positive: For all predicted sequences that do not overlap a labeled anomalous region.

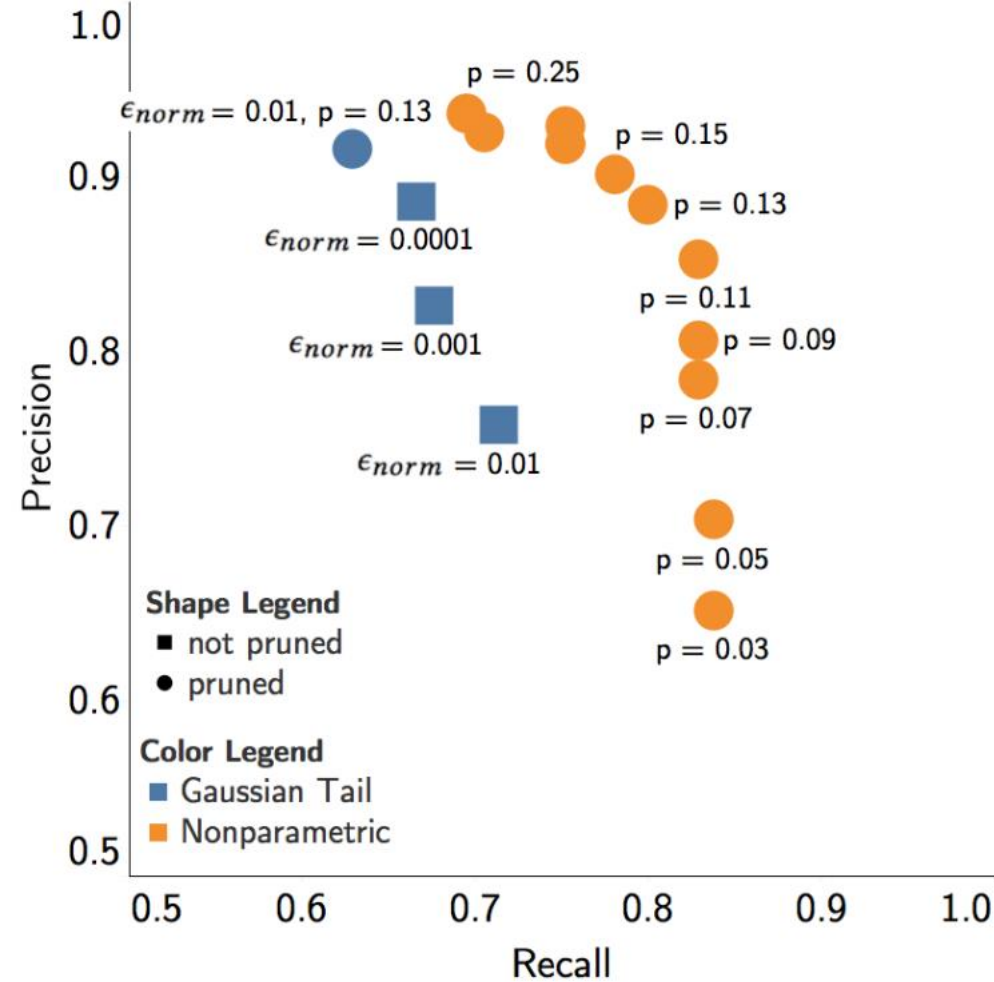
		Predicted	
		Negative	Positive
Actual	Negative	True Negative	False Positive
	Positive	False Negative	True Positive

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

$$\text{F1} = 2 \times \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

Experiment Result:



Thresholding Approach	Precision	Recall	$F_{0.5}$ score
Non-Parametric w/ Pruning ($p = 0.13$)			
MSL	92.6%	69.4%	0.69
SMAP	85.5%	85.5%	0.71
Total	87.5%	80.0%	0.71
Non-Parametric w/out Pruning ($p = 0$)			
MSL	75.8%	69.4%	0.61
SMAP	43.0%	92.8%	0.44
Total	48.9%	84.8%	0.47
Gaussian Tail ($\epsilon_{norm} = 0.0001$)			
MSL	84.2%	44.4%	0.54
SMAP	88.5%	78.3%	0.71
Total	87.5%	66.7%	0.66
Gaussian Tail ($\epsilon_{norm} = 0.01$)			
MSL	61.3%	52.8%	0.48
SMAP	82.4%	81.2%	0.68
Total	75.8%	71.4%	0.62
Gaussian Tail w/ Pruning ($\epsilon_{norm} = 0.01, p = 0.13$)			
MSL	88.2%	41.7%	0.54
SMAP	92.7%	73.9%	0.71
Total	91.7%	62.9%	0.66

Criticism

- Does not generalize well.
- Along with the telemetry data, channel specific command information is also an input to the model that needs to be refined.
- The dependencies between different channels is not taken into account here.

Dataset	MSL			SMAP			SMD		
	Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1
LSTM-NDT	0.5944	0.5374	0.5640	0.8965	0.8846	0.8905	0.5684	0.6438	0.6037
LSTM-VAE	0.5257	0.9546	0.6780	0.8551	0.6366	0.7298	0.7922	0.7075	0.7842
DAGMM	0.5412	0.9934	0.7007	0.5845	0.9058	0.7105	0.5835	0.9042	0.7093
OmniAnomaly	0.8867	0.9117	0.8989	0.7416	0.9776	0.8434	0.8334	0.9449	0.8857
MTAD-TF	0.9043	0.8988	0.9015	0.9779	0.8192	0.8916	0.9045	0.9048	0.8940

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