A Transformer-Based Deep Learning Approach to Anomaly Detection of High-Bandwidth Multivariate Time-Series Satellite Communications

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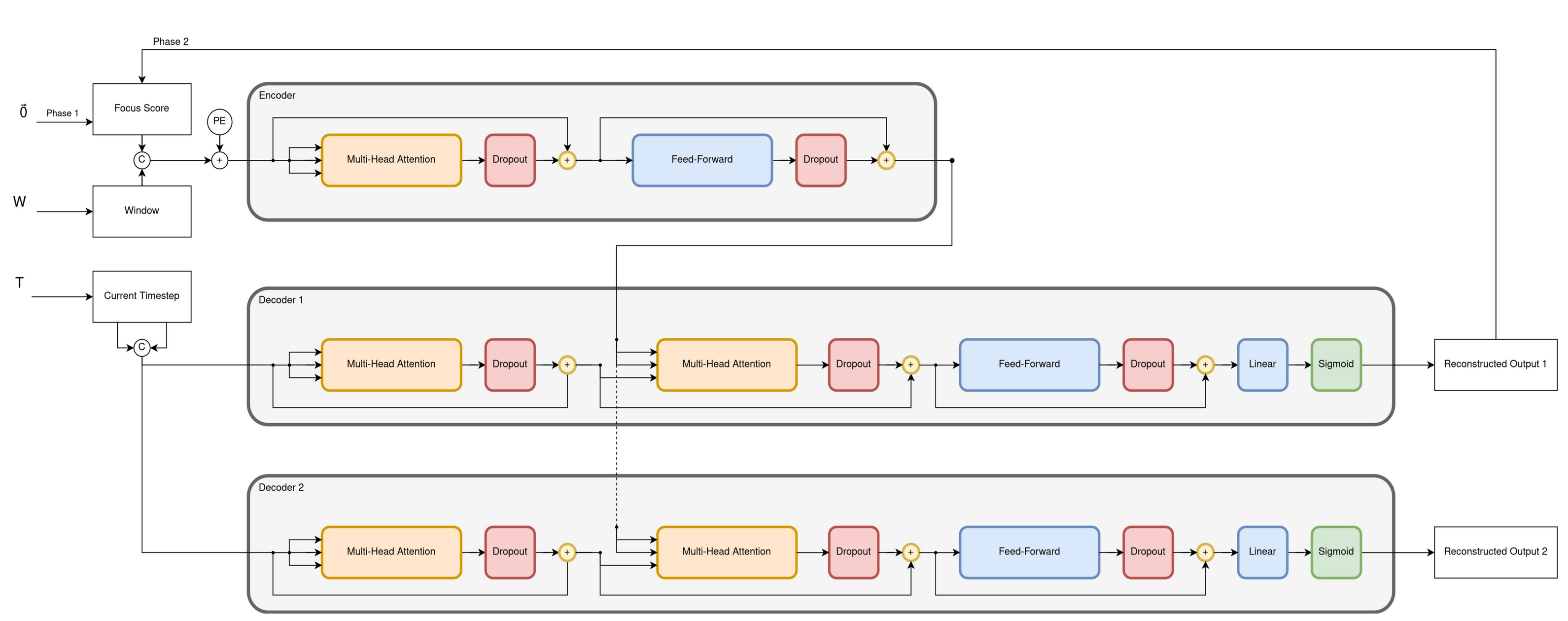
Introduction

- NASA's JPL has a problem: we keep launching satellites but there *isn't enough funding* to hire Spacecraft Operations Engineers to monitor the data in the Deep Space Network (DSN) [1].
- Previous research has studied using deep learning models on time-series data to detect anomalies [2,3,4,5].
- We build upon existing literature to improve the State of the Art (SotA) model on a novel dataset from JPL.

Method

- Transformer-based autoencoder architecture (TranAD+).
- Self-supervised 2-phased adversarial training.
- Base model is built from previous work (TranAD) [2].



Public Contributions

- DSN dataset will be publicly released.
- Source code and unit-tests will be made public.
- Trained model weights for TranAD+ will be released publicly.

Datasets

- **Deep Space Network 1k (DSN):** is a new *large* dataset presented in this work obtained from the Deep Space Network. Contains *numerical*, *categorical*, and *missing* information.

Dataset:	SMAP	MSL	SWaT
Number of tracks	54	27	1
Total Training Length	138,004 (24.05%)	58,317 (44.16%)	495,000 (52.39%)
Total Testing Length	435,826 (75.95%)	73,729 (55.84%)	449,919 (47.61%)
Total Length	573,830	132,046	944,919
Number of Anomalies	55,922 (12.83%)	7,766 (10.53%)	54,621 (12.14%)
Number of Parameters	25	55	51
Types of Parameters	Float	Float	Float
Number of NANs	0 (0%)	0 (0%)	0 (0%)

Dataset:	WADI	SMD	DSN_1k
Number of tracks	1	28	999
Total Training Length	784,571 (81.95%)	708,405 (50%)	3,367,256 (77.76%)
Total Testing Length	172,801 (18.05%)	708,420 (50%)	962,832 (22.24%)
Total Length	957,372	1,416,825	4,330,088
Number of Anomalies	9,977 (5.77%)	29,444 (4.16%)	247,247 (25.68%)
Number of Parameters	128	38	129 (98 float, 31 byte)
Types of Parameters	Float	Float	Float, Byte
Number of NANs	3,829,522 (3.13%)	0 (0%)	43,956,130 (7.87%)

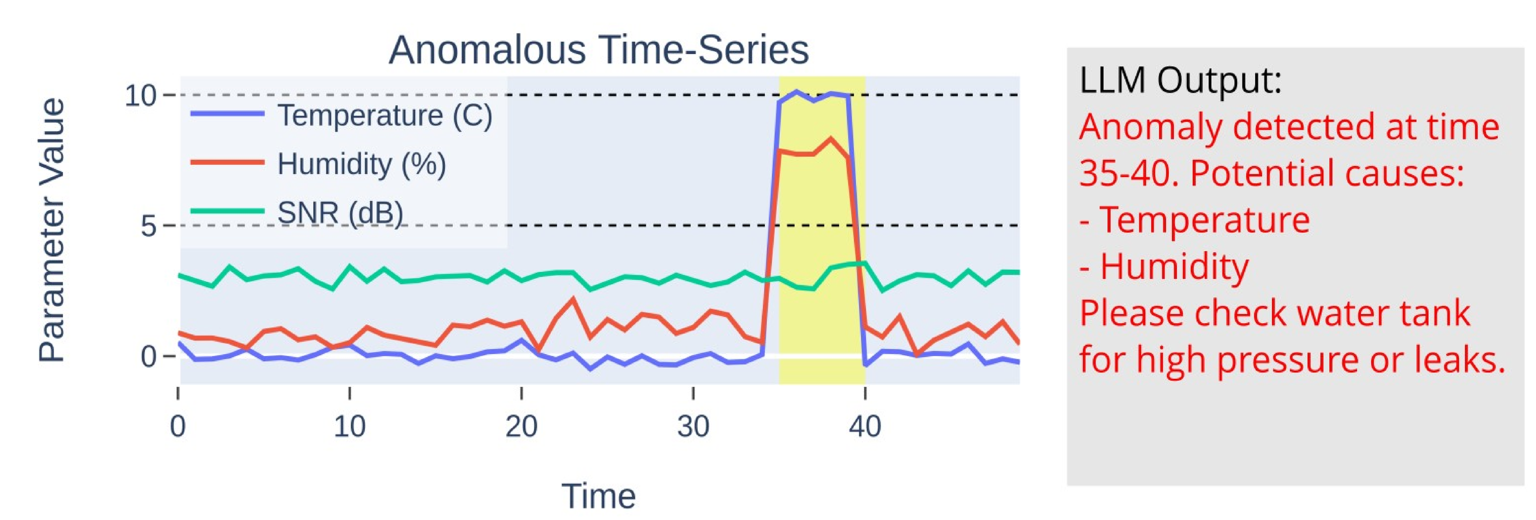
Results

- TranAD+ *outperforms* previous SotA Anomaly Detection models on the new DSN dataset in F1 and AUC.
- Outperforms F1 on SMAP, SWaT, and SMD.
- Outperforms AUC on WADI and MSL.

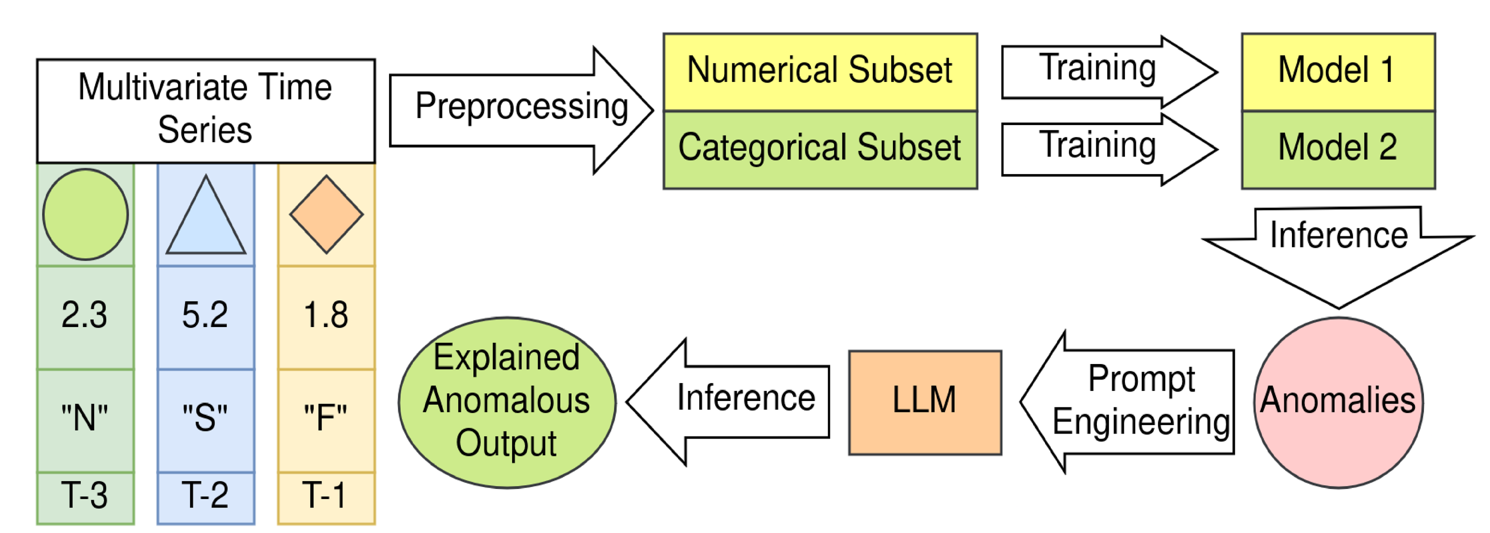
	Dataset	DSN_1k			
Model		F1	Precision	Recall	AUC
MTAD-GAT	POT	0.7033	**0.9399**	0.5619	0.7747
	Best F1	0.8445	0.7434	0.9774	0.9304
OmniAnomaly	POT	0.4087	0.2568	**1.0000**	0.5000
	Best F1	0.7434	0.7116	0.7783	0.8346
USAD	POT	0.8185	0.7484	0.9031	0.8991
	Best F1	0.8138	0.7246	0.9279	0.9030
TranAD	POT	0.8785	0.8092	0.9607	**0.9413**
	Best F1	**0.8805**	0.8951	0.8663	0.9157
TranAD+	POT	**0.9247**	0.8653	0.9929	**0.9698**
	Best F1	0.8044	**0.9662**	0.6890	0.8403

Future Directions

- Parse anomaly data and generate reports using LLMs.
- Allows critical failures to be addressed quicker by providing workers with a generated report of what potentially caused an anomaly to occur.
- Can lead to increases in company auditing speed.



- Adjust model architecture for categorical information by separating underlying data to specialized models.



References / Acknowledgement

[1] NASA Office of Inspector General. *Audit of NASA's Deep Space Network.* June 2023. url: https://www.nasa.gov/wp-content/uploads/2023/08/ig-23-016.pdf.

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