RÉALTRA
SPACE SYSTEMS ENGINEERING

UCD DUBLIN

Developing Machine Learning Models for Space Based Edge AI Platforms

James Murphy

Space Software & AI Engineer, PhD Student

jmurphy@realtra.space

www.realtra.space

IRISH RESEARCH COUNCIL
An Chomhairle um Thaighde in Éirinn

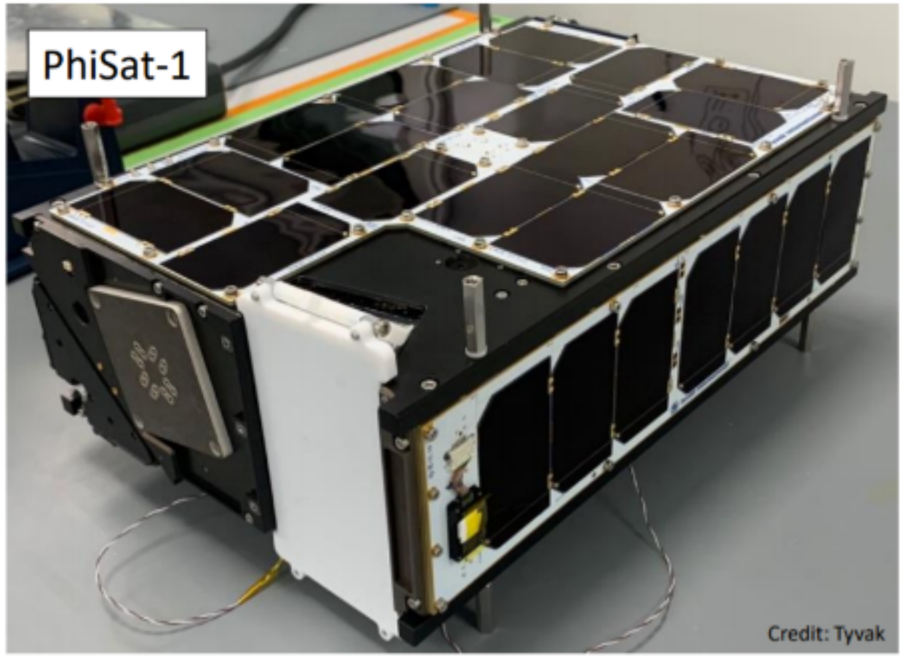
New Space Environment

- Increasing number of satellites
  - Small satellites in large numbers
  - New low cost missions
  - Large constellations
- Increased need for automation
  - Satellite operator workload
  - Large amounts of data generated
  - Mission sustainability & costs
- How can we account for this new space environment?

Credit: ESA Phi-Lab

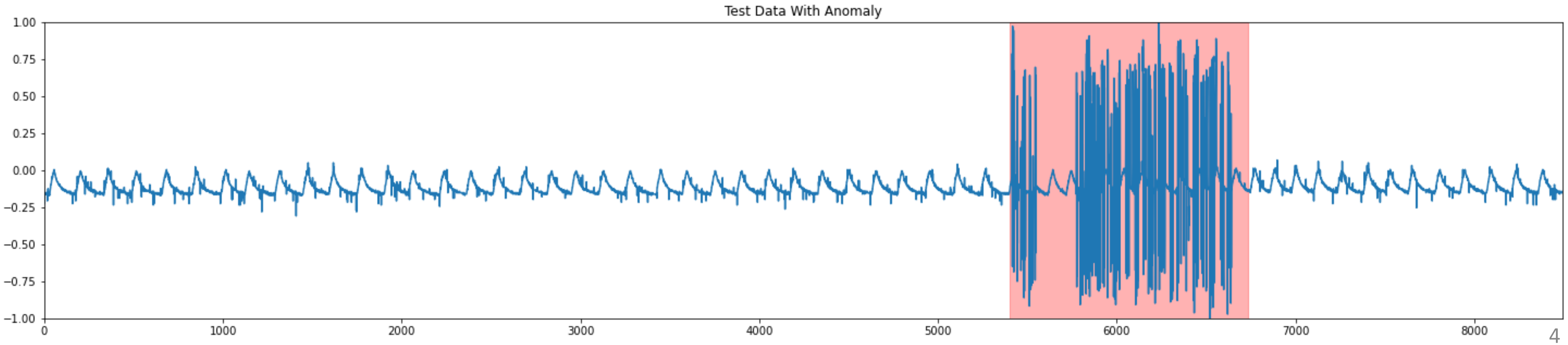
AI in Space

- Artificial Intelligence/Machine Learning
- Use cases:
    - Earth Observation
    - Collision Avoidance
    - Communications Monitoring
    - Satellite Health Monitoring
- Onboard data processing vs ground based
    - Real-time reactions
    - Reduction in image data sizes
    - Limited hardware



Case Study: Anomaly Detection

- What is an anomaly?
    - Unexpected variance in telemetry data
- What does an anomaly look like?
    - Point/Contextual
- What causes anomalies?
    - The Space Environment

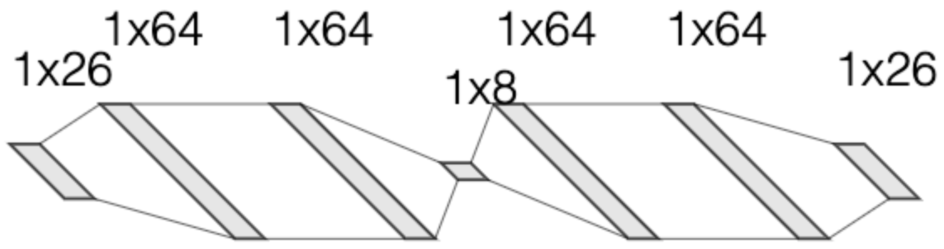


Anomaly Detection Paradigm

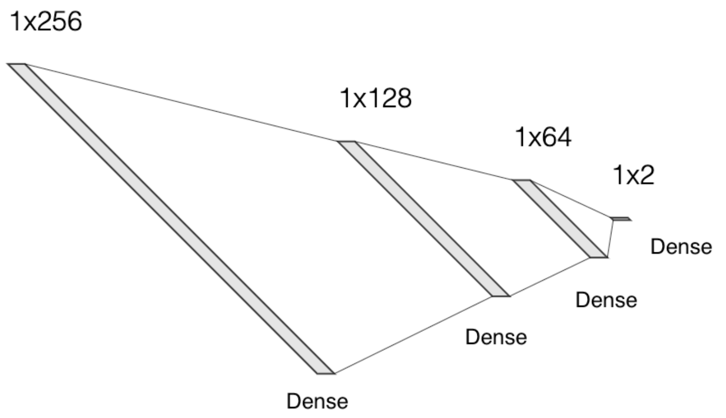
- Current Industry Standards
  - FDIR: Failure Detection, Isolation and Recovery
  - Thresholding on data streams
  - Statistical methods
- How Machine Learning can enhance current methods
  - Better at detecting contextual anomalies
  - Multivariate analysis on multiple channels
  - Online learning to update model throughout mission
  - Real-time reactions to potential catastrophic events

Models Used

- Basic Dense Autoencoder
- Compress and Decompress Data
- Compares reconstructed data to original
- Trains only on nominal data
- Learns to recognise nominal



- Multi-Layer Perceptron
- Basic feed forward network
- Trains on both nominal and abnormal data with labels
- Learns to distinguish between nominal and abnormal



Approach to ML Anomaly Detection

- What is a Feature?
- What is a Hyperparameter?
- Moving window approach
- Window size becomes a Hyperparameter
- Autotuning software written to search for best parameters
  - Grid Search of hyperparameters
  - 512 models trained per telemetry channel
  - 2 hours total training time per channel

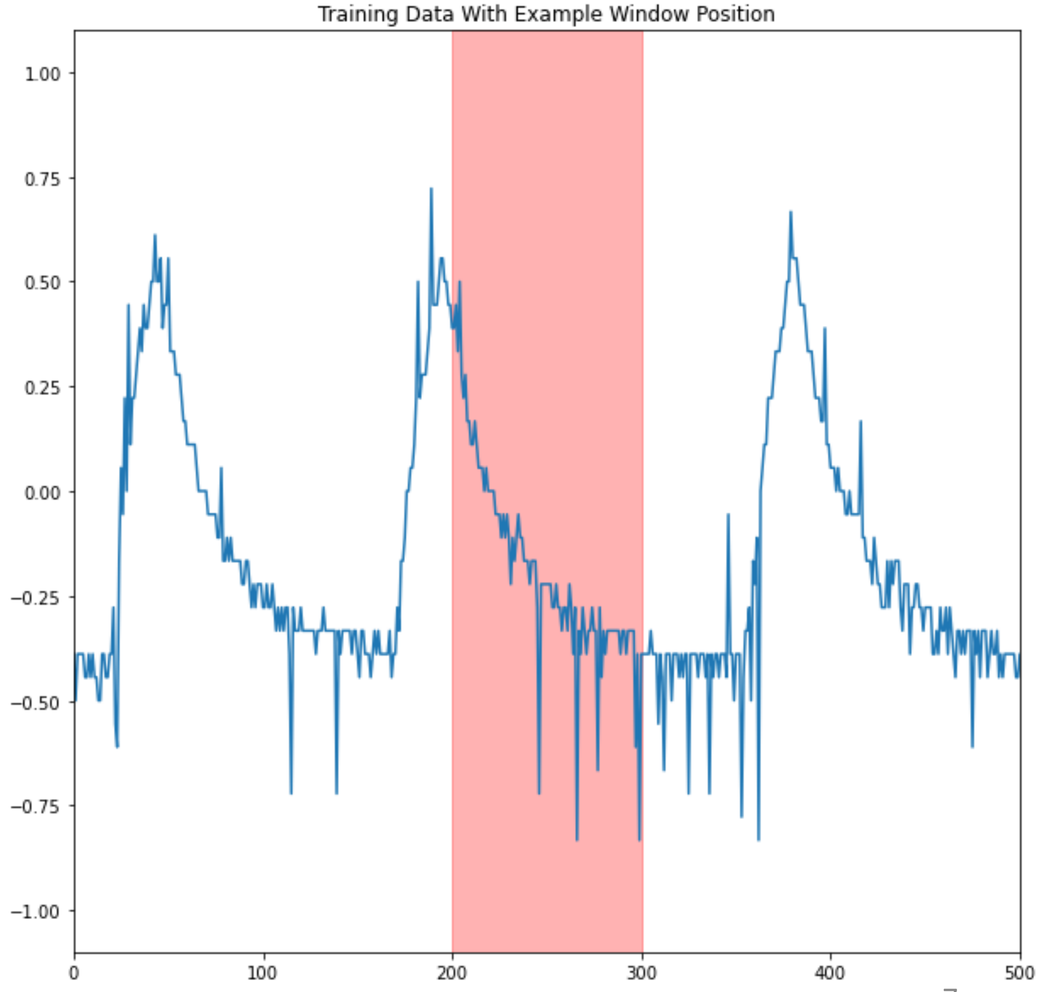
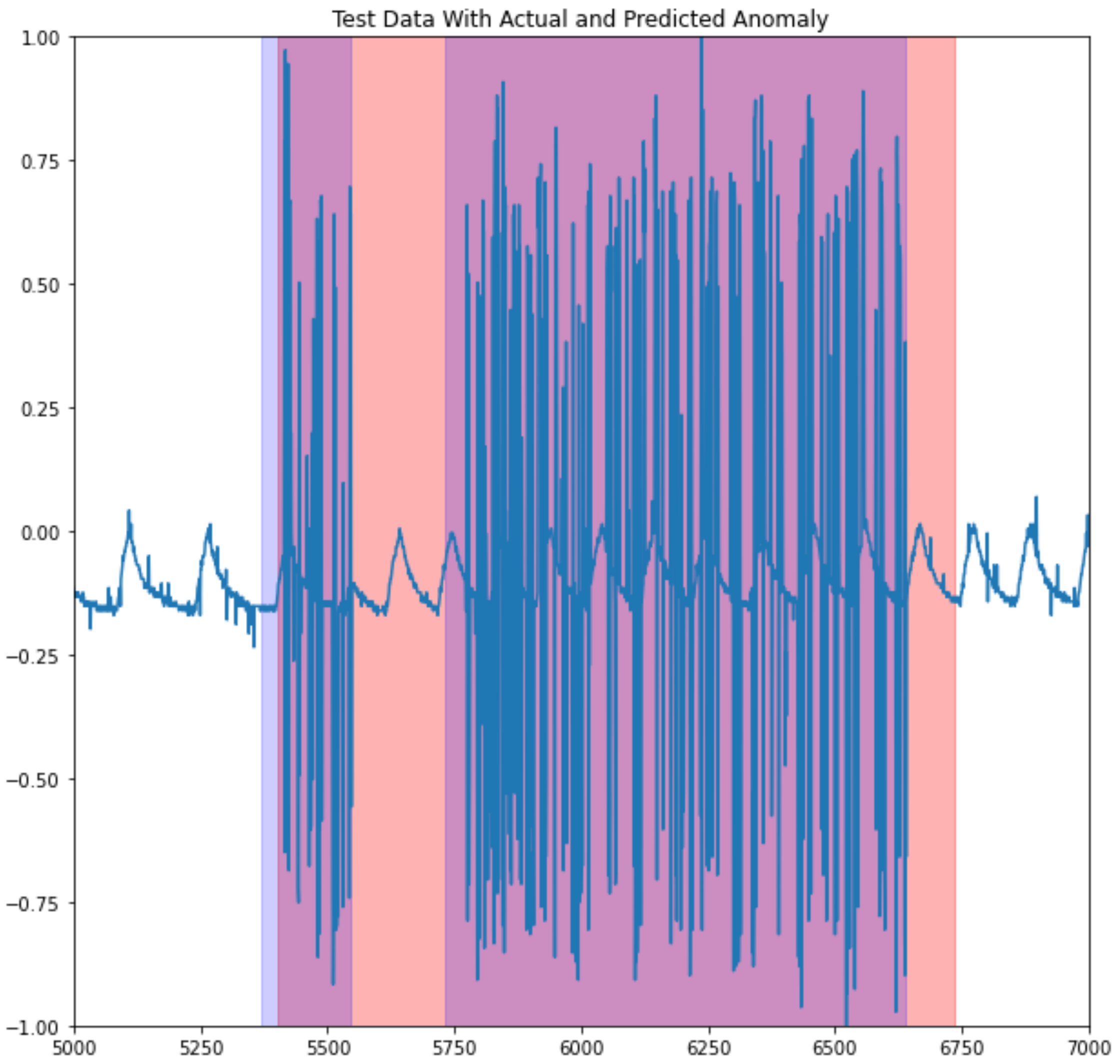
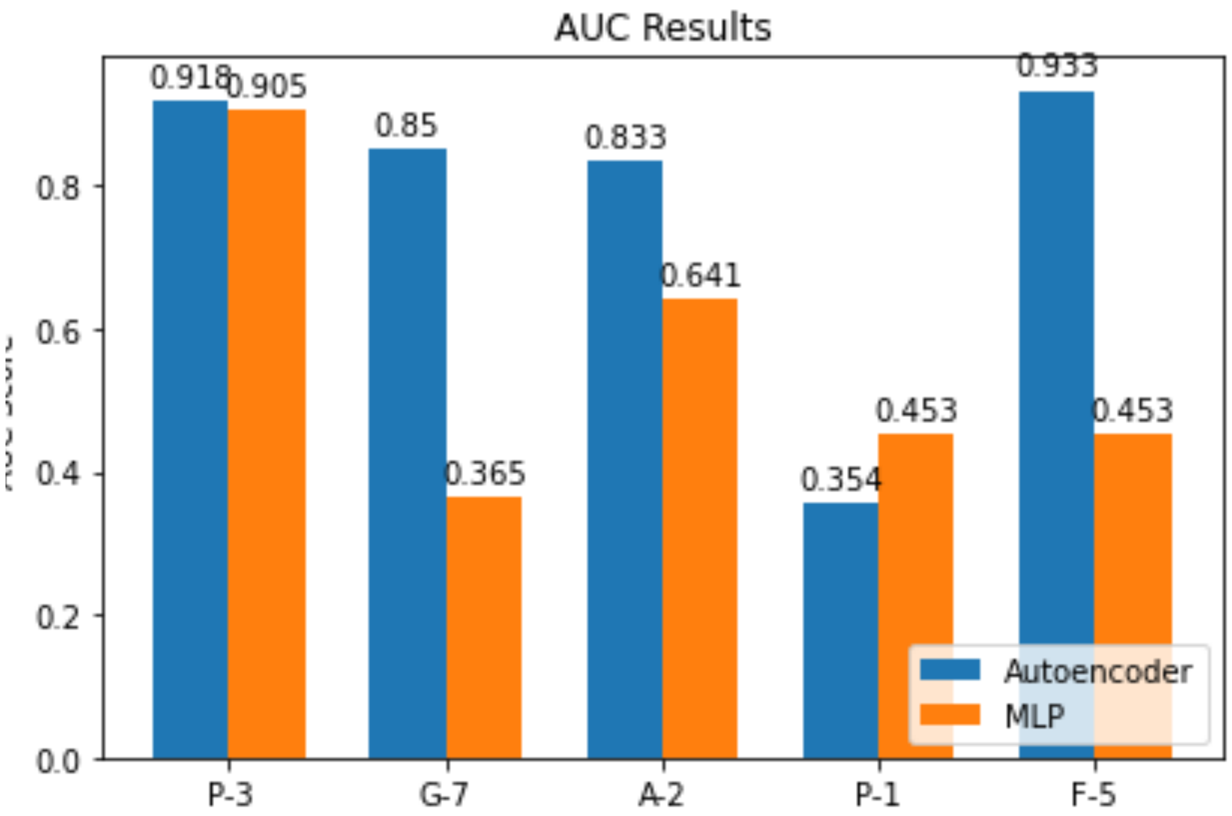


Table of Results

Channel	Source	Anomaly Type	AUC Autoencoder	AUC MLP
P-3	SMAP	Point	0.918	0.905
G-7	SMAP	Point & Contextual	0.850	0.365
A-2	SMAP	Contextual	0.833	0.641
P-1	SMAP	Contextual	0.354	0.453
F-5	MSL	Point	0.933	0.453

Results Contd.





Deployment

Channel	Source	Anomaly Type	CPU Time AE (s)	NCS Time AE (s)	CPU Time MLP (s)	NCS Time MLP (s)
P-3	SMAP	Point	0.00018	0.00181	0.000129	0.0017
G-7	SMAP	Point & Contextual	0.000175	0.00198	0.000135	0.00179
A-2	SMAP	Contextual	0.000183	0.00192	0.000152	0.00174
P-1	SMAP	Contextual	0.000176	0.00185	0.000151	0.00176
F-5	MSL	Point	0.00044	0.00193	0.000138	0.00178

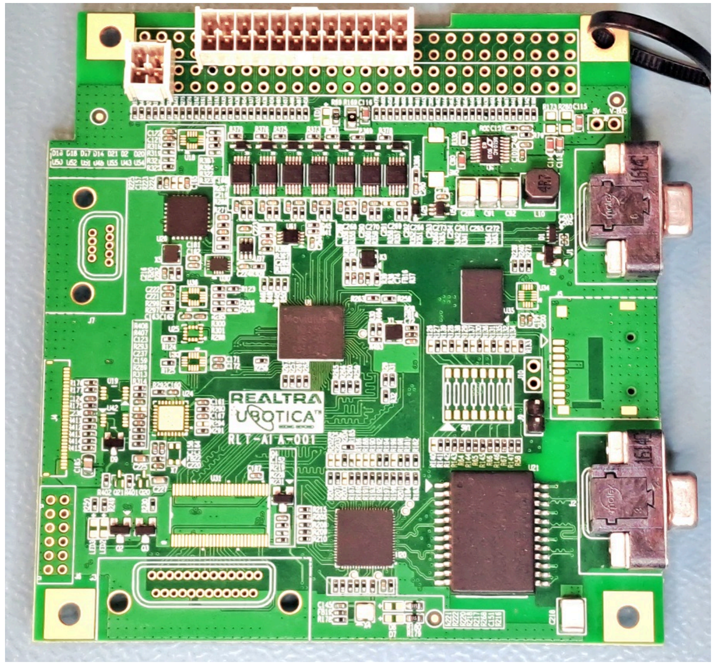
Credit: Intel Movidius Neural Compute Stick

Conclusion

- Anomalies within spacecraft telemetry can be detected using basic model architectures
- These models can detect anomalies with a modest to high amount of classification accuracy
- The autocoder used in this study had superior results on this dataset
- Sufficient hardware exists to deploy these models on “the edge”

Future Work

- Phase 2 study with more complex models with features such as convolutional neural networks CNN and long to short-term memory cells is feasible and will be conducted
- Space ready hardware using Myriad 2 available in a Cubesat form factor
- Already flown on previous missions (Phi-Sat-1)



Credit: Réaltra Space Systems Engineering

Thank You!

James Murphy

jmurphy@realtra.space

This work was supported by Réaltra Space Systems Engineering. This work was also supported by the Irish Research Council under the Employment-based postgraduate Scheme (IRC-EBPPG/2020/11).