Deep Learning for Space (T708-609OS)

ESA/ESOC – 16/06/2023

Agenda

- Welcome and Study Presentation

- Activities Summary
  - OPS/AIT Use Cases Selection & Technology Mapping
  - Use Cases Implementation & Results:
    - Fluctuation on Malargüe Ka-band signal amplitude
    - Mars Express Thermal Power Consumption
    - Device-Under-Test Events Investigation
    - Device-Under-Test Anomaly Detection

- Assessment, Lessons Learned & Recommendations

Study Overview

Study Overview

- The objective of the activity
  - to assess the applicability and impact of deep learning in space applications
  - to identify which space applications will benefit the most from deep learning
  - to map which deep learning methods (e.g. architectures) work best for each identified application

- Examples of deep learning applications to be considered includes: early anomaly detection, contextual anomaly detection, diagnosis, prediction, knowledge discovery and more

- Assess the impact of using deep learning in each application (e.g. cost reduction, risk mitigation, enabling functionality, increased science return)
  - For Space Operations (OPS)
  - For Assembly, Integration, and Test (AIT)

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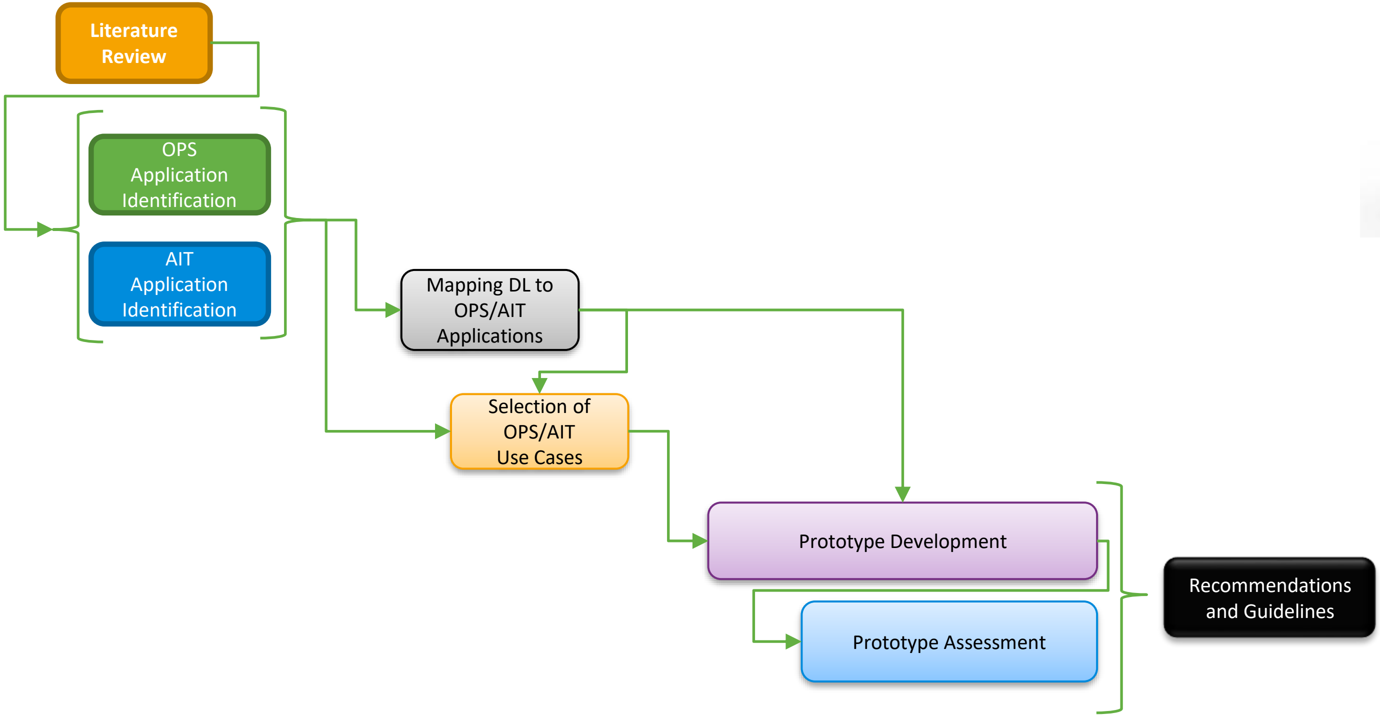
Study Logic


Literature Review
OPS Application Identification
AIT Application Identification
Mapping DL to OPS/AIT Applications
Selection of OPS/AIT Use Cases
Prototype Development
Prototype Assessment
Recommendations and Guidelines


PLAN

Project Activities

AI, Machine Learning & Deep Learning Overview

- Artificial Intelligence is the general concept of intelligent programs
- Machine Learning (ML) is the usage of algorithms to create programs that can learn from data relationships
- Deep Learning is a subset of ML relying on deep Artificial Neural Networks and vast amounts of data to learn more complex relationships

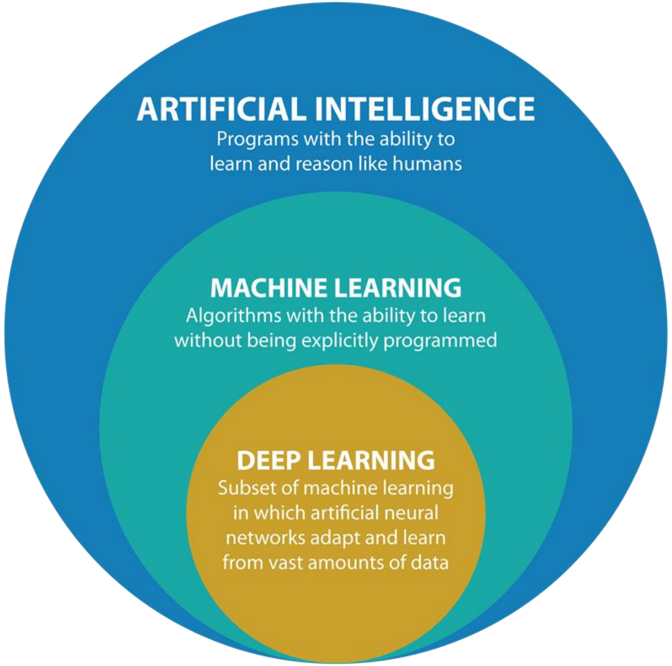
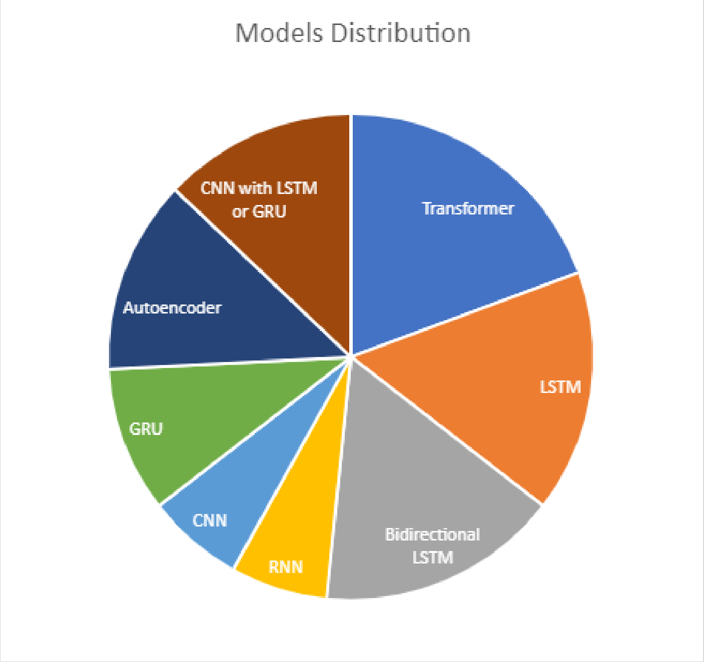


Image from: https://www.argility.com/argility-ecosystem-solutions/industry-4-0/machine-learning-deep-learning/

Literature Review

Latest Deep Learning technologies

- Usually studied conjointly with classical ML
- Advanced architectures are sometimes mix of ML and DL
- 711 publications were identified in the latest 5 years
- 20 use-cases were identified across those articles



OPS & AIT Application Identification

- 2 Workshops organized with ESA (ESOC/ESTEC)
- Viable Use Cases Identified :
  - 9 for OPS
    - **Mars Express Thermal Power Consumption**
    - Integral Radiation Belt Entry & Exit Prediction
    - Predicting the Impact of the Wind in Deep Space Antenna Pointing
    - Surrogate Models for High Computation Demanding Tasks (e.g. SIMULUS Simulators)
    - Find Optimal Policies with Reinforcement Learning
    - Anomaly Detection, Contextual Anomaly Detection, Anomaly Investigation
    - **Fluctuation of signal in Ka-bands links**
  - 7 for AIT
    - **Device-Under-Test Events Investigation**
    - Device-Under-Test Anomaly Detection
    - **Complex Systems Anomaly Detection**
    - EGSE Environment Event Investigator
    - EGSE Environment Anomaly Early Detection
    - Complex Systems Dynamics analyzer
    - Facilities maintenance and health monitoring

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Selection of OPS & AIT Use Cases

- Data Availability – Do we have access to the data?
- Data Richness – Volume big enough?
- Data Quality – How many data errors ?
- Feasibility – Is the problem solveable by DL?
- Automatic Solution Evaluation – Can we check a solution without human interactions?
- New Paradigm – Novel approach or just DL applied?
- Scalability – Can it be adapted to other use cases?
- Relevance – What would be the impact?
- Timeliness – How urgent is a solution required?

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OPS Prototypes

Fluctuation on Malargüe Ka-band signal amplitude

Summary of the use case

- Malargüe Ka-band signal link suffers from amplitude fluctuations
- Goal: understand what causes fluctuations (e.g., troposphere, wind, antenna position, etc.)

Fluctuation on Malargüe Ka-band signal amplitude

- Framed as a **nowcast** problem

TDCS (radiometer in tracking mode)
- IWV
- LWP
- ATT32000
- BTM31400

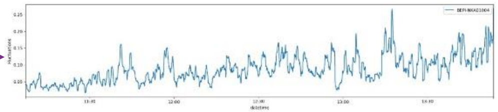
Weather Station
- Rain Intensity
- Wind Speed
- Wind Direction

Antenna Unit Control
- Azimuth + Elevation pos, average pos error, peak pos error

Feature Engineering

Deep Learning (Machine Learning)

Current Fluctuations



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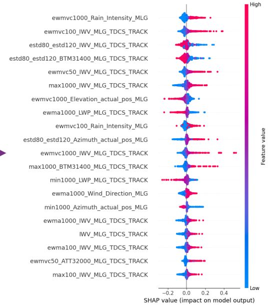
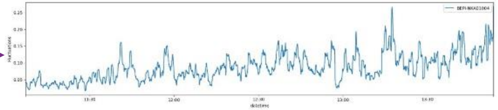
Feature Engineering

Deep Learning (Machine Learning)

Explainable AI



Current Fluctuations

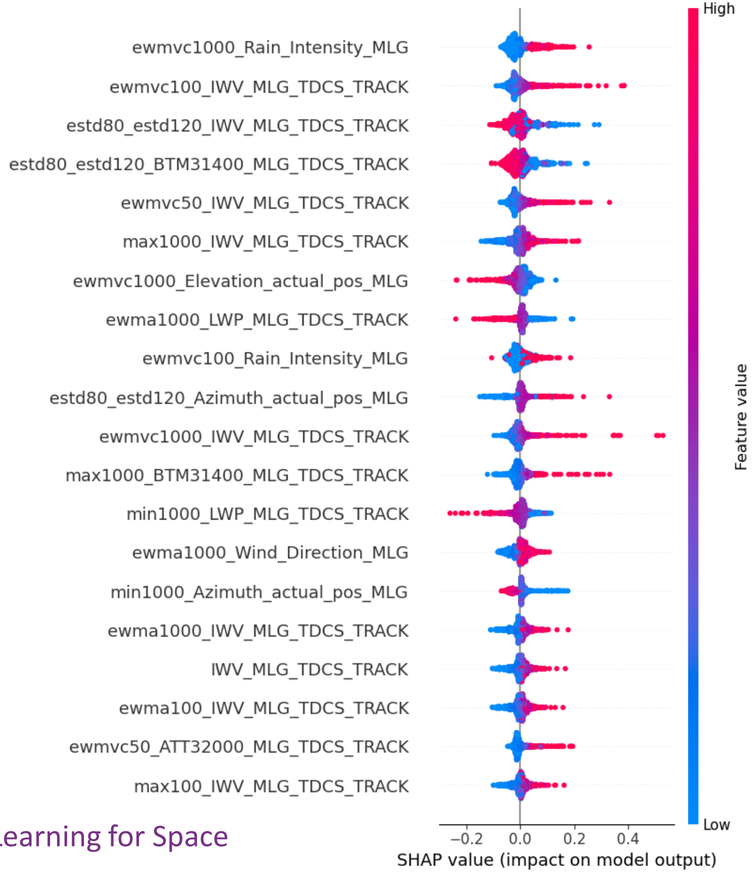


Fluctuation on Malargüe Ka-band signal amplitude

- Scenarios:
  - Uplink (KaT)
  - Downlink
  - Radio Science downlink

- Technologies
  - Classical ML (Gradient Boosting Trees) + Deep Learning
  - Deep Learning: Dense, 1D Convolutional, Recurrent
  - Explainable AI

How to read SHAP summary plots



KaT Deep Learning Regression

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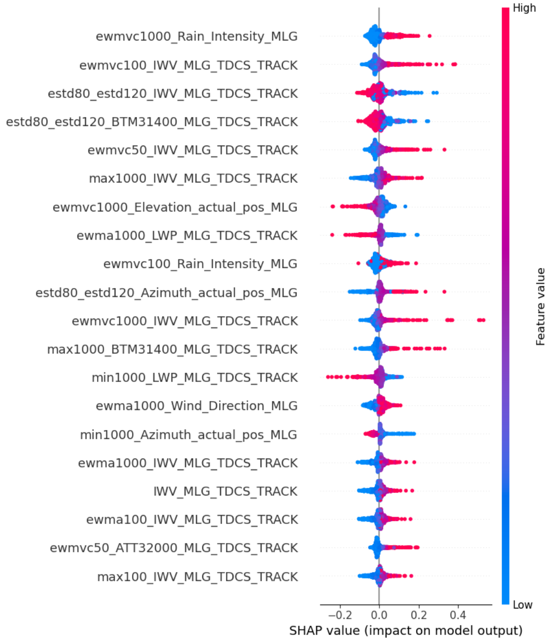
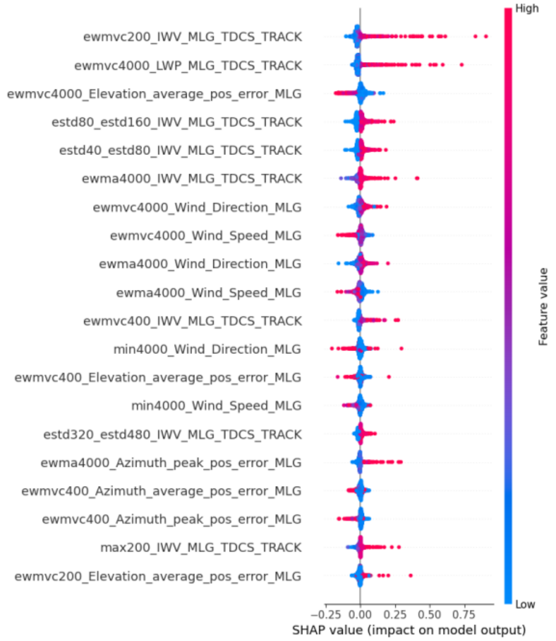
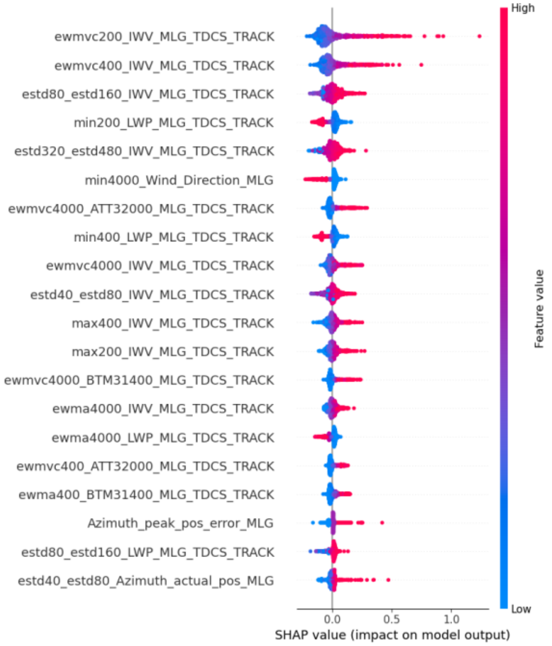
Fluctuation on Malargüe Ka-band signal amplitude



KaT Deep Learning Regression



Downlink Deep Learning Regression



Radio Science Deep Learning Regression

Malargüe Fluctuations use case - Conclusions

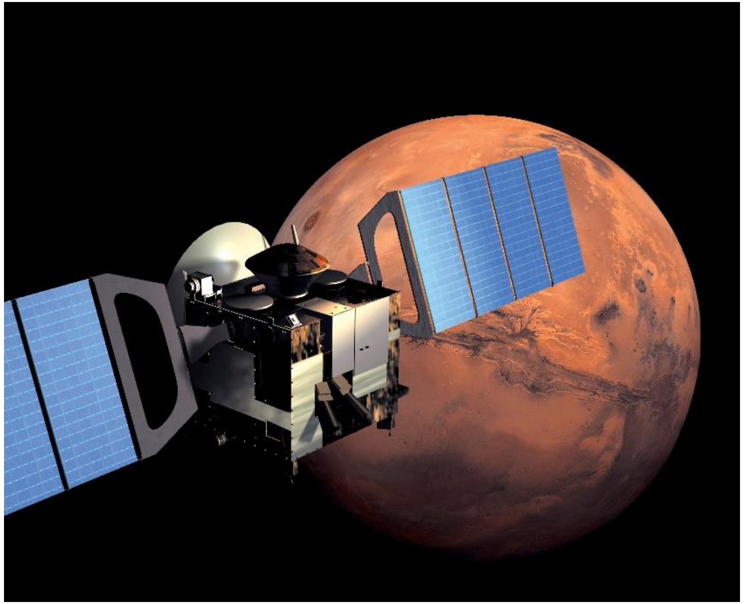
- Usually, DL and ML are used to predict the future
  - In this use case we used Deep Learning to nowcast
  - Explainability was the goal

- Explainability comes in terms of the provided features
  - Features need to carry predictive power
  - Features need to be easy to understand by domain experts

- Explanations from Deep Learning models found to be more useful than those provided by classical Machine Learning

Mars Express

- Mars Express orbiter
- Launched in 2003
  - Data available from 2008 to 2016
- Competition launched in 2016
  - To predict the power used by the thermal subsystem



Mars Express - Data

- 6 data types are available:

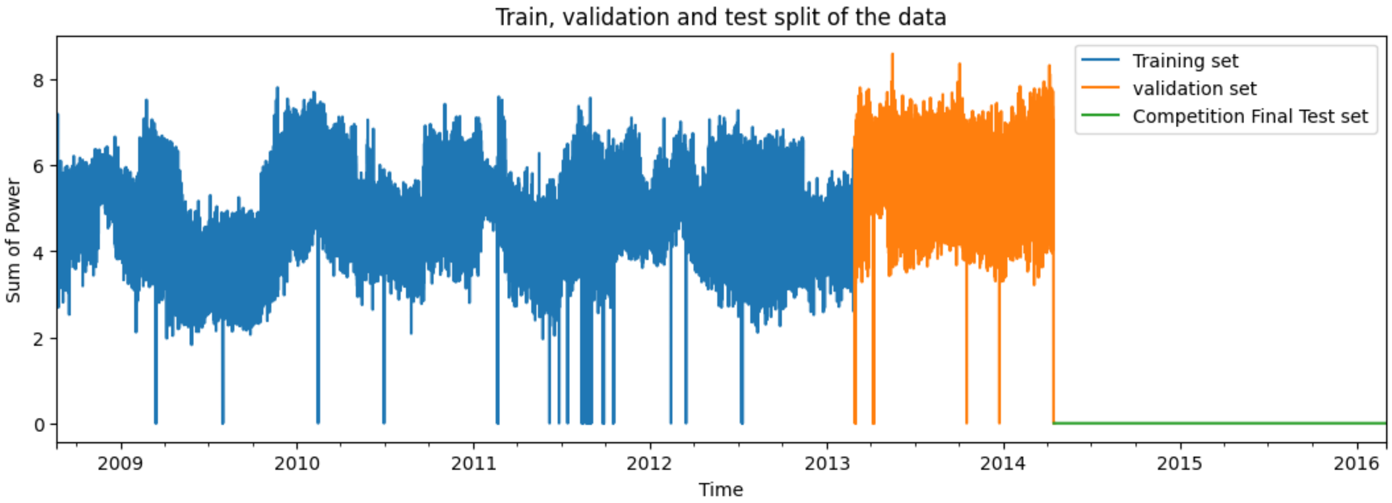
Input
1. **SAAF**: Solar Aspect Angles.
2. **LTDATA**: Long term data such as the sun-mars distance.
3. **DMOP**: Detailed Mission Operations Plan.
4. **FTL**: Flight dynamics TimeLine
5. **EVTF**: Other events (including eclipses).

Output
6. **POWER**: Electric current of 33 thermal power lines.

- Data is Downloaded from the competition website: https://kelvins.esa.int/mars-express-power-challenge/

Mars Express - Data

- Data splitting
- Operation changed in 2013
    - Validation set match Competition test set



Mars Express - Metric

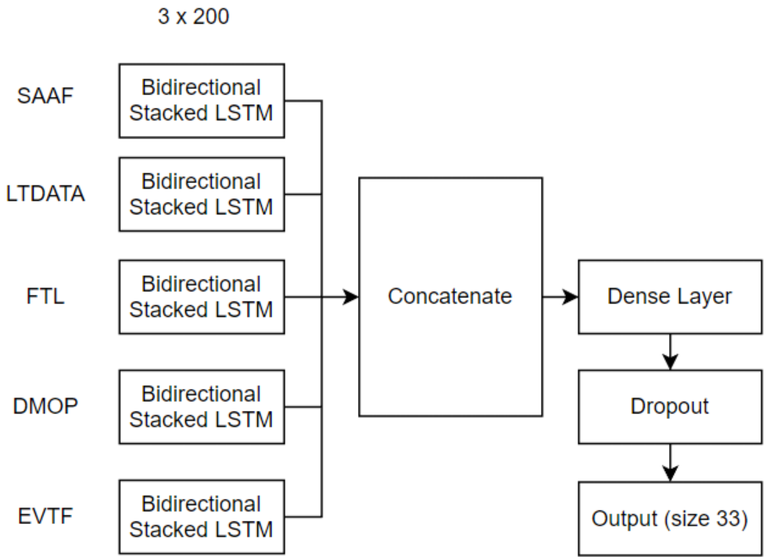
- Metric used: RMSE
  - Lower is better

$$\epsilon = \sqrt{\frac{1}{NM} \sum (c_{ij} - r_{ij})^2}$$

- Baseline score
  - Using mean values for each of the 33 power lines
  - Achieve RMSE of **0.138** on test set
- Best score of the competition is a RMSE of **0.08**

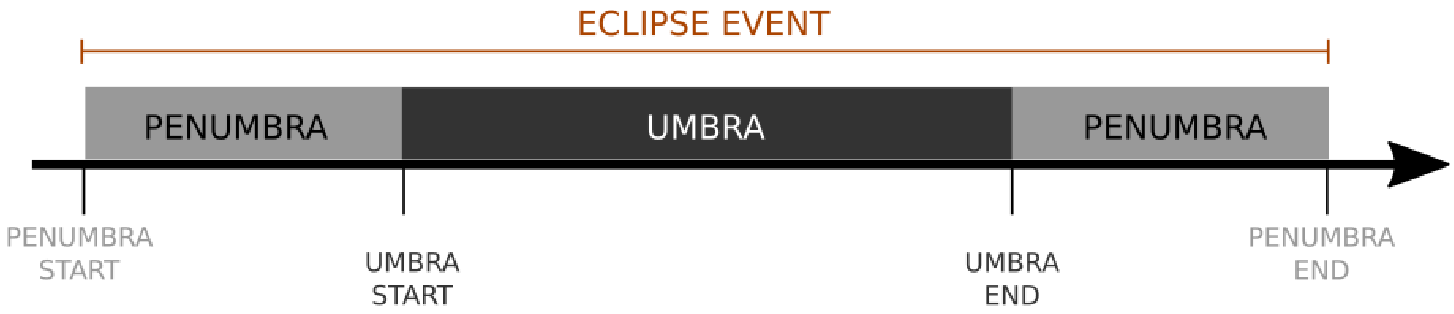
Mars Express - Models

- Data of different sampling rates
- Deep learning Models
  - Dense (Fully connected)
  - CNN
  - LSTM
  - Transformers (TST)
- 10 different models tested
  - With hyperparameter tuning



Mars Express - Models

- Adding CNN help the models
- Extracting Eclipses from EVTF file improve score



Mars Express - Results

- DL models are better than Baseline
  - CNN is the best architecture
- Not able to beat best of competition
  - Feature engineering helps a lot
- Scores are still in top 30 of competition

Model Version	Baseline (mean value)	V7 (CNN-LSTM)	V8 (DENSE only)	V9 (CNN only)	V10 (TST)
RMSE (best 0.08)	0.138	0.113	0.118	0.111	0.124
Training time	-	82 minutes	81 minutes	84 minutes	87 minutes

AIT Prototypes

AIT Overview

- AIT consists in a systematic step by step verification via testing from component level to fully integrated system
  - Focus of this project in electrical functional testing
  - Large amounts of data are systematically archived
- The spacecraft correct integration is checked
- The spacecraft software is verified based on housekeeping
  - Applications valid for AIT should be transferable to OPS

AIT Data for the Use Cases

- Complete E-AIT phases of the Meteosat Third Generation (MTG) project
  - Electrical functional test in every step of the integration
  - Full spacecraft tests
  - From 5 satellites
- Focus on housekeeping telemetries from the spacecraft software

AIT: Device-Under-Test Events Investigation

- Objective:
  - Go back to the root causes of an anomaly when an event happens.
- Type of Data:
  - Time Series:
    - Satellite Telemetry
    - Events of 4 different severities
  - The events can be used as labels for classification.

AIT: Device-Under-Test Events Investigation

- Methodology:
  - Supervised classification of events.
  - TSAI has been used to try multiple timeseries models
  - Use XAI (LIME) to find the importance of each input.
  - The model use a window of time before an event.
  - In simulated real time, when an event occurs the DL model prediction is compared with the real event. If identical, XAI can show the root cause.

AIT: Device-Under-Test Events Investigation

Severity 3

Classical ML (Random Forest)

	precision	recall	f1-score	support
0	0.98	0.99	0.99	139
1	0.00	0.00	0.00	2
2	0.00	0.00	0.00	1
3	0.94	0.85	0.89	40
4	0.00	0.00	0.00	1
5	0.98	1.00	0.99	81
6	0.00	0.00	0.00	1
micro avg	0.97	0.95	0.96	265
macro avg	0.41	0.41	0.41	265
weighted avg	0.95	0.95	$\boxed{0.95}$	265
samples avg	0.97	0.96	0.96	265

DL (Minirocket)

	precision	recall	f1-score	support
0	0.98	0.94	0.96	139
1	0.00	0.00	0.00	2
2	0.00	0.00	0.00	1
3	0.86	0.93	0.89	40
4	0.33	1.00	0.50	1
5	0.91	1.00	0.95	81
6	0.00	0.00	0.00	1
micro avg	0.88	0.94	0.91	265
macro avg	0.44	0.55	0.47	265
weighted avg	0.92	0.94	$\boxed{0.93}$	265
samples avg	0.91	0.94	0.92	265

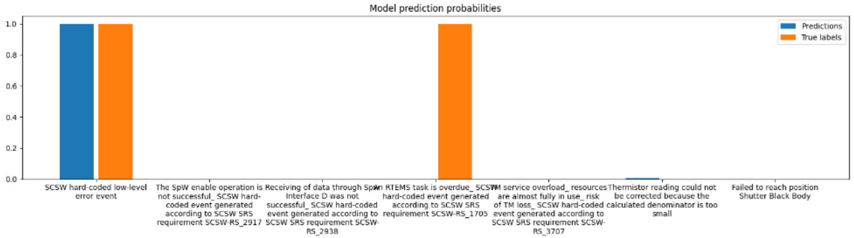
AIT: Device-Under-Test Events Investigation

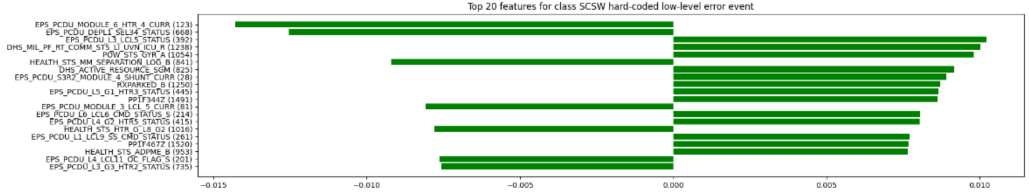
- Data for severity 3 events is quite small (~265 different events for the test set -> ~1060 for training, 7 classes of events).
- Performance for DL and ML methods is comparable
- DL however is able to find some classes that only have a few samples in the test set.
- For severity 4, DL seems promising,
  more data/ better filtering might improve the classifier.

	Baseline	ML (RF)	DL (MiniRocket)
Severity 4	0.01	0.04	0.21
Severity 3	0.56	0.95	0.93

AIT: Device-Under-Test Events Investigation

- Example of explainability graphs





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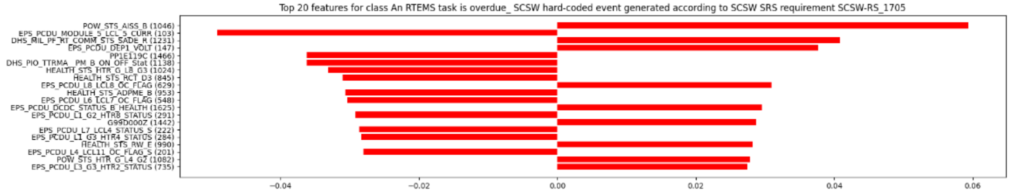

AIT: Device-Under-Test Events Investigation

- Multiple explainability graphs have been given to AIT experts
  - Physically meaningful relationships between inputs and events identified
  - Indirect dependencies found, compensating the lack of directly related signals in the inputs given
  - Only SCSW engineers with hands on experience on the mission could exploit fully the report → Need to involve the right personnel
- Explainability provides a good starting point to know which HK signals to focus on.

AIT: Complex Systems Anomaly Detection

- Objective:
  - Filter false alarms raised by the FDIR system by using a DL model to detect real anomalies.
- Type of Data:
  - Satellite Parameter Telemetry (Time Series)
  - High severity events
- Methodology:
  - Unsupervised Anomaly Detection
  - Events are used for fuzzy evaluation based on Precision@N, …
  - Evaluation of flagged events is done manually by AIT experts

AIT: Complex Systems Anomaly Detection

- Data Preparation (without final TM parameter selection)

[AIT SQL files]
260GB

[TM Data Sheet]
Sample Rate: 10s
Rows: 322k
Parameters 2.6k
Sessions: 279

AIT: CSAD – Benchmark Options

- Benchmark options:
  1. Algorithm: Isolation Forest *(baseline, classic ML)*, AutoEncoder, DeepSVDD, ~~Variational Autoencoder~~, ~~AnoGAN~~
  2. Contamination rate: (0.0, 1.0)
  3. Aggregated windows or sliding windows (with *n*-windows)
  4. Train on last session or on all previous sessions

AIT: CSAD - Key insights of the fuzzy evaluation

- Note: **Test set was too small** to provide secure results –
  only 111 high-severity events in total due filtering of specific subsystems
- **Isolation Forest seems to perform better if high precision is required** but
  only by sacrificing the recall
  (Prec. 0.18%, Recall 0.98%)
- The **deep learning models seem to have an advantage in a ranking scenario**, they lead the table ordered by Precision@N
  (DeepSVDD 0.55% vs 0.45% IForest)
- **DeepSVDD was our fastest algorithm**
  (DeepSVDD 40sec vs 140sec IForest)

AIT: CSAD – Manual Evaluation by AIT Experts

Anomaly data: TM Parameter, value and importance (based on LIME) which lead to the classification

AIT event data: TM Parameter and value which triggered the event

1.1.1 Finding #0 for timestamp 2021-07-27 10:49:30

Table with top most influencing parameters for the finding.

	importance	value
PP1E010K__0	0.025677	33.384617
PP1F742Z_OFF__0	0.024498	1.000000
PP1E129C__-3	0.022606	-0.000161
PP1E208V__-2	0.021499	0.019531
PP1E065C__0	0.017381	0.017425
PP1E080C__-1	0.016648	0.002070
PP1E124C__-3	0.016302	0.018332
PP1E022C__0	0.016034	0.015436

Table with information about the event

spid	name	rawValue	engValue
188880736	P88F50ZX	269942483	FCISTC_RP2L
	P88F554X	153	*NO VAL*
	P88F555X	656408980	PP1E252X
	P88F556X	1	EXPECTVALUE
	P88F557X	128	*NO VAL*
	P88F668X	0	*NO VAL*
	P88F669X	128	*NO VAL*
	P88F560X	0	EV_WL
	P88F561X	4	UV_BL
	P88F562X	9853035634518	1970-01-01T02:44:13.035
	P88F606X	9853	*NO VAL*
	P88F614X	597848	*NO VAL*

- Results:
  - Algorithm identified a valid high severity event in the dataset
  - Related signals provided to the tester had physical relationship with event.

Assessment, Lessons Learned & Recommendations

Lessons Learned - OPS

- Malargüe Use Case:
  - DL explanations better compared to explanations coming from classical ML
  - The XAI explanations come in terms of features. Craft features that are:
    - Predictive
    - Easy to understand by domain experts
- Mars Express Use Case:
  - Deep Learning algorithms could not catch some dependencies already known by experts, but still ranking good compared to other approaches
  - The absence of features engineering work to be considered in the balance

Lessons Learned - AIT

- The biggest challenge was related with data selection, preparing and processing

- Data structure, standard and practices of AIT are not defined with the purpose of being integrated in a ML/DL loop

- Once the data is available and processed, DL and classical ML algorithms don't show major differences

- AIT data availability for OPS shows great potential for DL/ML application

Lessons Learned – DL vs Classical ML

- It is not conclusive if Deep Learning is always the right choice for any problem
- Classical ML methods and newer DL should be considered as complementary tools of a toolbox
- Deep Learning vs Classical Machine Learning
  - Deep Learning gives much more possibilities than Classical ML
  - Need a lot of independent data for Deep Learning
  - Classical ML works better with smaller datasets
  - The community is working more on Deep Learning now
- Anomaly Detection
  - Deep Learning is not always superior to Classical ML
  - Deep Learning require more resources
- Conclusion: **Do not put all your eggs in one basket**

Recommendations

- Data Quality & Labeling
  - Investment should focus on data preparation and labeling to improve the data quality and usability
  - the cleaner and better documented the data is, the easier and more efficient it becomes for data-driven projects

- Explanation
  - Create good features if the explainability is the main focus
  - Features engineered need not only to carry predictive power but also to be intuitive to domain experts

- A New Mindset
  - Instore a DL/ML mindset earlier in the process
  - Foster cross-functional synergy between experts and industry during all the phases of the mission

Conclusions

- A review of Deep Learning literature oriented to Space Applications
- An analysis of possible applications in OPS and AIT that could benefit from DL
- An analysis of most promising DL technologies for space applications
- Evaluation of the impact of Explainable AI (XAI) to understand how DL technologies are taking decisions
- 4 prototypes to show and study applicability of Deep Learning in Operations and in Assembly, Integration & Tests
- Assessment, Lessons Learned and Recommendations for the applicability and benefits of DL for space applications

Thank You

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Discussion