Deep Learning for Space

Executive Summary Report

Based on the recent success obtained by Deep Learning (DL) techniques in many different areas, the "Deep Learning for Space" activity at ESA/ESOC assessed the readiness and measured the possible impact of Deep Learning applied to space applications and, in particular, to Space Operations (OPS) and Assembly, Integration, and Test (AIT).

This activity evaluated the potential, benefits and limitations of different DL algorithms for their application in space operations and AIT. Objectives of the project were:

- 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
- to demonstrate the benefits of DL over 4 prototypes, 2 in OPS and 2 in AIT
- to provide lessons learned, recommendations and guidelines for using DL in space

Suitable Space Operations applications to investigate the benefits and limitations of DL have be collected by involving ESA experts, asking them to propose suitable use cases from their domains where they would have liked to investigate possibilities of Deep Learning and asking them to take part in two workshops, one for OPS and one for AIT. The following prototypes have been implemented:

- Fluctuation on Malargüe Ka-band signal amplitude. To understand what influences the occurrence of high fluctuations in the Malargüe's Ka-band carrier.
- Mars Express Thermal Power Consumption. To predict the values of 33 Mars Express power lines.
- Device-Under-Test Events Investigation. To find the root cause for higher severity spacecraft events during AIT.
- Complex Systems Anomaly Detection. To classify an event raised in an AIT session as a real anomaly or a false alarm due to the integration status.

The conclusions of this study include recommendations for future work and improvements, highlighting the role that Deep Learning can have in space applications. Among the most important Lessons Learned we can report:

- It is not conclusive if Deep Learning is always the right choice for any problem, indeed classical Machine Learning (ML) and DL should be considered as complementary tools of a toolbox

- Deep Learning gives much more possibilities than classical ML, but need a lot of independent data while classical ML works better with smaller datasets
- For Anomaly Detection, Deep Learning is not always superior to classical ML and it requires more computational resources

Among the most general Recommendations we can synthesize:

- It is advisable to foster **cross-functional collaboration between subject matter experts and industry** during all the phases of the mission, in order to reduce costs and increase efficiency of the AI application process.
- Data preparation remains the most time-consuming task in ML projects. **Investments should focus on feature engineering and data preparation and labeling** to improve the data quality and usability.
- About Deep Learning for Explanation, create good features if the explainability is the main focus and use features engineered need not only to carry predictive power but also to be intuitive to domain experts

In conclusion it has been assessed that **ML/DL approaches can be a great advantage and most probably a game changer both for OPS and AIT applications**. But the recommendations is "**do not to put all your eggs in one basket**" and consider the wide spectrum of alternatives that a combination of AI/ML/DL can provide.