Report from Dagstuhl Seminar 23461

Space and Artificial Intelligence

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Abstract

This report documents the program and the outcomes of the Dagstuhl Seminar 23461 "Space and Artificial Intelligence". The seminar was interdisciplinary, situated at the intersection of research on AI / computer science and space research. Since each of these is a very wide field on its own, we focussed on a selection of topics from each of the two and their intersections.

On the artificial intelligence side, we focused on data-driven AI, which makes use of data in order to produce intelligent behaviour and notably includes machine learning approaches. We also considered knowledge-based AI, which is focussed on the explicit formalisation of human knowledge and its use for tasks such as reasoning, planning, and scheduling. On the space research side, we considered the two major branches of space operations (SO) and Earth observation (EO).

The seminar brought together a diverse set of players, including researchers from academia, on one hand, and practitioners from space agencies (ESA, NASA) and industry, on the other hand. The seminar included plenary talks and parallel group discussions. Through the plenary talks, we obtained insight into the state-of-the-art in the different areas of AI research and space research, and especially in their intersections. Through the parallel group discussions, we identified obstacles and challenges to further progress and charted directions for further work.

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2012 ACM Subject Classification Computing methodologies → Computer vision; Computing methodologies → Knowledge representation and reasoning; Computing methodologies → Planning and scheduling; Computing methodologies → Learning paradigms; Computing methodologies → Learning settings; Computing methodologies → Machine learning approaches; Computing methodologies → Modeling and simulation; Applied computing → Aerospace; Applied computing → Astronomy; Applied computing → Engineering; Applied computing → Earth and atmospheric sciences

Keywords and phrases Artificial Intelligence, Machine Learning, Data-based AI, Knowledge-based AI, Deep Learning, Foundation Models, Explainable Artificial Intelligence, Space Research, Space Operations, Earth Observation

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1 Executive Summary

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Scope of the Seminar

Our interdisciplinary seminar on *Space and Artificial Intelligence* was situated at the intersection of research on AI / computer science and space research. Since each of these is a very wide field on its own, below we give a broad outline of each of the two. We focus on the aspects that were topics of discussion at our Seminar.

Artificial intelligence studies computer systems that behave similarly to humans, in a way that the resulting behaviour would be considered intelligent if exhibited by humans. The field of AI thus focusses on the design and analysis of algorithms and systems that can replicate, support or surpass human perceptual, linguistic, and reasoning processes; learn, draw conclusions, and make predictions based on large or small quantities of data; replicate or enhance human perception; support humans in diagnosis, planning, scheduling, resource allocation, and decision making; and cooperate physically and intellectually with humans and other AI systems (`https://claire-ai.org/what-is-ai/`). All these topics are relevant for space research.

At a high level, AI can be categorised into three (non-exclusive) categories:

Data-driven AI makes use of data in order to produce intelligent behaviour; it prominently encompasses machine learning, data mining, and pattern recognition approaches and is often referred to simply as machine learning. In this area, methods based on neural networks have been particularly successful and, as a result, become a major focus of attention for the last decade, but many other approaches exist and continue to be used with considerable impact, including support vector machines and random forest models for supervised learning, and various types of clustering methods for unsupervised learning.

Knowledge-based AI is focussed on the explicit formalisation of human knowledge and its use for tasks such as reasoning, planning, and scheduling. Although knowledge-based AI is currently somewhat less prominent than data-driven AI, it has important and impactful uses, e.g., in ensuring the correctness of computer hard- and software, and in solving a broad range of real-world industrial optimisation problems. Many AI experts now believe that combinations of data-driven and knowledge-based methods are likely to provide the basis for next-generation trustworthy AI systems. In this context, explainable AI (XAI), where the results of AI solutions can be understood by humans, is gaining importance.

Embodied AI concerns the design and study of AI systems that interact directly with the physical world. This area is also known as robotics and has very important applications in an increasingly broad range of application sectors, including manufacturing, medicine, and agriculture. Interaction with the physical environment (including other robots and humans) poses unique challenges, e.g., in terms of safety, robustness, and real-time requirements. Most experts in the field of robotics make use of knowledge-based and data-driven approaches, in addition to specialised methods for dealing with the previously mentioned challenges.

Legal and ethical aspects of AI have also started to attract attention recently. The legal part includes laws that regulate the use and development of artificial intelligence. The ethical part is concerned with the moral behavior of humans as they design, make, use, and handle artificially intelligent systems, but also with the moral behavior of machines (machine ethics).

The different forms of AI can be applied to a variety of problems in space-related research, of which here we highlight two major branches:

Space Operations (SO) are concerned with all aspects of operating spacecraft, including the planning, implementing, and operating of all (also ground segment) systems required for reliable and efficient spaceflight missions. This includes all relevant mission operations, ground infrastructure, flight dynamics, mission planning, communications, and data acquisition functions. Large amounts of data about space operations are collected and can be utilized by ML / data-driven AI to address challenges that include autonomous spacecraft route planning, spacecraft anomaly detection, and optimal spacecraft operations.

Earth Observation (EO) is a major instrument for monitoring our planet, its land and ocean processes, and their dynamics. A large number of spacecraft carrying a broad range of instruments generate a wide variety of sensor data (active / passive) of many resolutions: With these data now accessible to researchers and agencies, as well as the general public, a final barrier remains the need to convert the enormous quantities of raw EO data (generated on a daily basis) into valuable information for making decisions and taking concrete actions, e.g., towards achieving the Sustainable Development Goals. Needless to say, the potential for applying AI and ML in this context is almost unlimited.

Many other space-related AI applications can be conceived, typically related to the use of ML for the analysis of data collected during specific space missions. These include, e.g., modeling and forecasting space weather, mapping planet surfaces, galaxy profiling, identifying exoplanets and their environment, as well as analyzing astro-biology data. Several of these belong to astronomy and concern data collected via astronomical observatories in orbit.

Seminar topics

The seminar covered many different aspects of Artificial Intelligence for space and touched upon a wide variety of topics. However, it focussed specifically on the following four topics – all of which are currently actively researched – structured along two dimensions (AI approaches and Space applications):

Data-driven AI, e.g., machine learning, for space. The first topic of the seminar addressed machine learning methods for the analysis of the ever larger quantities of data resulting from space related research and exploration, their current state-of-the-art, and directions for further development.

Knowledge-driven AI, e.g., explainable AI, for space. The second topic of the seminar was concerned with methods and techniques from knowledge representation and reasoning, and explainable AI, their current state-of-the-art, and directions for further development.

Space Operations applications of AI. The third topic of the seminar concerned various aspects of operating spacecraft and managing missions, the potential applications of AI in this area, and the challenges they pose for Artificial Intelligence methods.

Earth Observation applications of AI. The fourth topic of the seminar concerned various aspects of applying AI to Earth observation data, the vast variety of potential applications of AI in this area, and the challenges they pose for Artificial Intelligence methods.

Note that the topics along the space applications dimension interact strongly with the AI approaches dimension. For example, space operations applications, such as estimating the current and predicting the future states of spacecraft, have a strong temporal dimension requiring the use of data stream mining approaches from AI. On one hand, this poses challenges to address in the development of novel AI methods. On the other hand, this can provide excellent benchmarking opportunities for the evaluation of AI methods.

The above four topics were the focus of the seminar. Given the interests of the participants of the seminar, we also considered a few additional topics (to a lesser extent). These included, for example, legal, ethical, and social aspects of Space AI.

Structure of the seminar

The structure of our seminar was standard for Dagstuhl. We started with an introduction round on Monday morning. The majority of the time was taken by plenary talks and parallel discussions in working groups: There were two of the latter, one on Tuesday morning and one on Friday morning. The social event on Tursday afternoon included a visit to the Völklingen Ironworks UNESCO industrial heritage site and a dinner.

Plenary talks. Given the highly interdisciplinary nature of the seminar, participants from one discipline needed to be brought up to speed with the state of the art in the other relevant disciplines. Some of the talks were thus of an overview or tutorial nature. Examples of such talks are "Introduction to Space Operations" and "Introduction to Explainable Artificial Intelligence". Other talks were more specific, addressing particular AI methods or classes thereof or particular (areas of) AI applications in space research.

The plenary talks can be clustered into four different groups

- Plenary talks on machine learning,
- Plenary talks on explainable AI,
- Plenary talks on earth observation, and
- Plenary talks on space operations.

Parallel discussion in working groups. A substantial part of the seminar time was split into structured small-group work sessions. The aim of the structured work sessions was to address the focal topics of the seminar that were most interesting for the participants. The participants could more effectively share knowledge and experiences from their own areas of expertise in the smaller working groups. The highlights of these structured small-group sessions were presented to the seminar as a whole.

The parallel discussions in working groups on Tuesday morning addressed the following topics:

- Sustainable development goals and AI for good,
- AutoML and benchmarks,
- On-board and frugal AI, and
- Responsible AI.

The parallel discussions in working groups on Friday morning all addressed the same topic of challenges in AI & space and future research directions.

Outcomes of the seminar

The seminar brought together a diverse set of players. These included researchers from academia, on one hand, and practitioners from space agencies (ESA, NASA) and industry, on the other hand. It covered a broad range of aspects relevant for the further development of the field.

The major outcomes of the seminar are as follows:

1. It gave researchers from the different contributing disciplines an integrated overview of current research in the area of artificial intelligence for space.
2. It reinforced the communication channels for researchers tackling challenges in space applications using AI, including both data driven and knowledge-driven approaches to AI, such as machine learning and explainable AI, thereby bridging the divide between computer science and space research.
3. It defined the landscape of potential applications of artificial intelligence in space, in particular in the areas of Space Operations and Earth Observation.
4. It identified the central research questions and challenges for artificial intelligence approaches that need to be resolved for successful use of AI in space applications.
5. It put forward some strategies for designing artificial intelligence tools for space applications and for developing benchmarking suites for evaluating such approaches.

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3 Plenary talks: Machine Learning

3.1 Semi-supervised and multi-label classification of remotely sensed images

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Joint work of Marjan Stoimchev, Jurica Levatić, Dragi Kocev, Michelangelo Ceci, Sašo Džeroski
Main reference Marjan Stoimchev, Dragi Kocev, Sašo Džeroski: "Deep Network Architectures as Feature Extractors for Multi-Label Classification of Remote Sensing Images", Remote. Sens., Vol. 15(2), p. 538, 2023.
URL https://doi.org//10.3390/RS15020538

The talk will discuss recent work on semi-supervised (SS) [4] and multi-label classification (MLC) of remotely sensed images (RSI) [1]. For MLC, we employ deep neural networks (DNNs), either as feature extractors for predictive clustering trees (PCTs) and ensembles thereof, or in an end-to-end manner. In the former case, we leverage the existing capabilities of semi-supervised PCTs and ensembles: explainability of single tree models and state-of-the-art predictive performance of random forest ensembles [3, 2]. Furthermore, the parametrization of the amount of supervision in PCTs allows us to build supervised, semi-supervised, or unsupervised models, depending on the demands of the dataset at hand. This provides a safety mechanism enabling the semi-supervised models to consistently perform better or as good as their supervised counterparts.

We also develop end-to-end semi-supervised DNNs for multi-label and multi-class classification of remotely sensed images. This method mimics the mechanism of semi-supervised PCTs that have been proven to work well. We introduce a novel loss function that combines classification loss (computed on labeled data) and reconstruction loss (computed on both labeled and unlabeled data) with a weight parameter that enables the same aforementioned "safety mechanism".

The capabilities of PCTs and ensembles of PCTs (e.g. Random Forests) enable us to perform hierarchical MLC of remotely sensed images – a novel formulation of the classification task in this field. To this end, we exploit the intrinsic label hierarchies of the BigEarthNet dataset and explore the effects different label hierarchies and their different handling have on predictive performance.

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3.2 Self-supervised Learning, Foundation Models, and ModelZoos

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Joint work of Damian Borth, Diyar Taskiran, Konstantin Schürholt, Boris Knyazev, Xavier Giró-i-Nieto
Main reference Konstantin Schürholt, Boris Knyazev, Xavier Giró-i-Nieto, Damian Borth: "Hyper-Representations as Generative Models: Sampling Unseen Neural Network Weights", in Proc. of the Advances in Neural Information Processing Systems, 2022.
URL https://openreview.net/forum?id=uyEYNg2HHFQ

Self-supervised learning allowed us to train large task agnostic backbones, which can be successfully finetuned for specialized downstream tasks with only little supervision. This opened the path towards the training of so-called foundation models, a family of task-agnostic representations potentially able to consume multiple modalities of inputs and able to not only encapsulate a wide range of known tasks but are also able to extend this range to new task with only few shots of example. One popular family of such foundation models are large-scale language models.

This talk will provide an overview of self-supervised learning, its pretext tasks, and proposed learning methods from the last years. It further introduces the idea of learning from populations of neural networks, so called model zoos and shows how task-agnostic representation from these model zoos – so called hyper-representations – can be learned. Finally, it demonstrates how these representations can be exploited for multiple discriminative and generative downstream tasks linking them to model diagnostic, inspection and model sampling, finetuning.

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3.3 Hybrid modelling: examples and challenges

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Joint work of Nuno Carvalhais, Shanning Bao, Rackhun Son, Christian Requena, Lazaro Alonso, Markus Reichstein
Main reference Rackhun Son, Tobias Stacke, Veronika Gayler, Julia E. M. S. Nabel, Reiner Schnur, Lazaro Alonso, Christian Requena-Mesa, Alexander J. Winkler, Stijn Hantson, Sönke Zaehle, Ulrich Weber, Nuno Carvalhais: "Integration of a Deep-Learning-Based Fire Model Into a Global Land Surface Model", Journal of Advances in Modeling Earth Systems, Vol. 16(1), p. e2023MS003710, 2024.
URL https://doi.org//10.1029/2023MS003710

Challenges in representing the spatial and temporal dynamics of carbon and water cycles in land ecosystems arise both from parametric and or epistemic uncertainties. Understanding and quantifying ecosystem responses to changes in climate and environmental conditions underpins the quantification of coupled climate-carbon cycle feedbacks, key for addressing today's Earth system challenges. The growing volume in Earth observation data delivers an unprecedented perspective for improving understanding as well as unprecedented challenges in traditional Earth system model development. Here, we propose two hybrid modelling approaches for maximizing the information content uptake in improving carbon cycle modelling leveraging EO and machine learning approaches.

On the one hand, we propose an end-to-end approach that learns the spatial variation in parameters controlling the daily to seasonal response of photosynthesis to climate and atmospheric CO2 as described by a light use efficiency (LUE) model. The LUE model parameters emerge from the outputs of a multi-layer perceptron fed by a set of features representing vegetation, soils and bioclimatic properties. The MLP learns from the minimization of mismatch between modelled and observed fluxes of carbon and water in eddy covariance sites. The cross-validation results show a robust comparison to observations, being close to calibration results, and the only parameter generalization approach robust to represent spatial and temporal patterns.

On the other hand, we explore the potential of infusing traditional process-based models with machine learning components to describe largely uncertain processes. We develop an MLP architecture standing on parallel long short-term memory components to represent the role of the atmosphere, land surface properties and anthropogenic features to predict burned area dynamics at global scales as observed from EO. Upon integrating the trained MLP within the process-based model we observe a stark contrast in model performance in comparison to the benchmark fire model. Reductions in performance in some regions of the globe in comparison to the EO-driven MLP are related to internal biases in process-based modelled state variables, reflecting the need to develop online training approaches.

Overall, while the predictive performance in hybrid modelling improves significantly from current baselines in process-based modelling approaches, we are challenged by features collinearity for attributing variability in parameters and global patterns in burned area dynamics. In a context of climate change, being able to appropriately attribute statistical and causal dependence in parameterizations and processes is key for advancing our understanding and quantification of Earth system dynamics.

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3.4 Automated Machine Learning for SeaICE Charting

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Joint work of Jan N. van Rijn, Sven van Collenburg, Holger Hoos, Andreas Stokholm
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URL https://doi.org//10.1109/TGRS.2022.3149323

In this presentation, I will discuss the work that we have carried out under the ESA-visiting professor program towards automated machine learning for sea ice charting. Sea ice charting is an important task for ships sailing across the North Pole, as the best sailing route depends on the location and type of sea ice. Where the charting process was originally carried out by professional charters who have access to SAR satellite data, artificial intelligence can now play an important role in supporting the charting expert.

In earlier work, Stokholm et al. [1] successfully trained a U-NET neural network on the SAR satellite images to predict the various classes of sea ice. Neural networks are highly sensitive to their hyperparameter settings, and properly tuning the hyperparameters can make the difference between mediocre performance and state-of-the-art performance. In this work, we set out to use automated machine learning (AutoML) to automate the hyperparameter tuning for this specific problem domain.

As this is an interdisciplinary audience, I will briefly cover the basics of AutoML, such as: why would we use AutoML, what is AutoML and what are basic algorithms in AutoML. Additionally, I will talk about how AutoML was used for this specific domain, and how it automated this crucial part of the data science loop.

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3.5 Automated Machine Learning for Spatio-temporal Datasets

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Joint work of Laurens Arp, Julia Wasals, Peter van Bodgem, Alistair Fracis, Suzanne Marselis, Michael Marszalek, Nuno Sa, Victor Neuteboom, Nguyen Dang, James Wheeler, Nicolas Longepe, Holger Hoos, Mitra Baratchi
Main reference Laurens Arp, Mitra Baratchi, Holger H. Hoos: "VPint: value propagation-based spatial interpolation", Data Min. Knowl. Discov., Vol. 36(5), pp. 1647–1678, 2022.
URL https://doi.org//10.1007/S10618-022-00843-2

Automated machine learning (AutoML) is a young research area aiming at making high-performance machine-learning techniques accessible to a broad set of domain users by identifying all design choices in creating a machine-learning model and addressing them automatically. In this talk, I provided a number of examples that show different opportunities provided by taking an Automated Machine Learning approach to address various AI problems based on Earth observations.

The first opportunity lies in making use of all existing solutions to create a search space composed of available algorithms for specific task. Taking an efficient search strategy to find models in this search space allows the configuration of customised models for each dataset automatically. I provided an example demonstrating this approach by showing how available deep learning algorithms for super-resolution can be used to create an AutoML system that configures deep learning models for super-resolution. The second opportunity demonstrates that adding new algorithmic solutions to the search space of AutoML systems can provide an opportunity to generate much stronger AutoML systems. As an example, I presented VPint [2], an interpolation algorithm and how it can be used to complement AuotML systems when used for cloud removal purposes.

Next, I presented an approach that allows to use the knowledge in a specific class of physical models called radiative transfer models to generate physics-aware machine learning pipelines. The first example [4] extends an existing AutoML system to create an ensemble of physics-driven and data-driven models. The second example [5] provides a framework to address the fundamental problem of ill-posedness of a class of physical models known as radiative transfer models.

This talk inspired a lively discussion on AutoML systems for Earth observation. Notably, the audience discussed the challenges of using different classes of physical models, for instance, radiative transfer models and dynamical system models. It also sparked discussions on different opportunities for performing cross-validation considering the spatial and temporal correlations.

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4 Plenary talks: Explainable Artificial Intelligence

4.1 Introduction to Explainable Artificial Intelligence

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Joint work of Yazan Mualla, Amro Najjar
Main reference Yazan Mualla, Igor Tchappi, Timotheus Kampik, Amro Najjar, Davide Calvaresi, Abdeljalil Abbas-Turki, Stéphane Galland, Christophe Nicolle: "The quest of parsimonious XAI: A human-agent architecture for explanation formulation", Artif. Intell., Vol. 302, p. 103573, 2022.
URL https://doi.org//10.1016/J.ARTINT.2021.103573

Recently, eXplainable AI (XAI) gained momentum both in academia and industry to explain the results of black-box machine learning algorithms. A landscape of XAI branches along with strategies for developing explainable models are provided. Latest empirical studies have confirmed that explaining a system's behavior to human users fosters the latter's acceptance of the system. However, providing overwhelming or unnecessary information may also confuse the users and cause failure. For these reasons, parsimony has been outlined as one of the key features of XAI with parsimonious explanation defined as the simplest explanation that describes the situation adequately. Our work proposes HAExA, a human-agent explainability architecture to formulate parsimonious explanations for remote robots. This is particularly applicable to space since the communication with Earth has limited bandwidth and significant delay. Finally, some challenges, opportunities, and applications of XAI directed to different space stakeholders are presented.

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4.2 Causal inference for data-driven science

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Joint work of Jakob Runge, Andreas Gerhardus, Veronika Eyring, Gustau Camps-Valls
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Machine learning excels in learning associations and patterns from data and is increasingly adopted in natural-, life- and social sciences, as well as engineering[6]. However, many relevant research questions about such complex systems are inherently causal and machine learning alone is not designed to answer them [2]. At the same time there often exists ample theoretical and empirical knowledge in the application domains.

Causal inference provides the theoretical foundations to use data and qualitative domain knowledge to quantitatively answer these questions, complementing statistics and machine learning techniques [5, 3, 4]. Given the strong causal implications, the application of causal inference methods requires a thorough reasoning about the the appropriateness of the assumptions that can give rise to causal conclusions. Furthermore, causal methods still share the same challenges that affect the statistical and machine learning techniques that they employ, from finite sample issues to the problem of hyperparameter tuning and computational complexities.

A problem that is especially relevant in applications of causal inference concerns the broad language gap between the methodological and domain science communities. In this contribution [7], we explain the use of causal inference frameworks with a focus on the challenges of time series data and particular application scenarios, from process understanding to the evaluation and comparison of physical simulation models via causal methods. Integrating causal thinking into data-driven science will facilitate process understanding and more robust machine learning and statistical models for spatio-temporal problems in Earth sciences, allowing to tackle many open problems with relevant environmental, economic, and societal implications.

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4.3 Causality is all you need

Gustau Camps-Valls (University of Valencia, ES, gustau.camps@uv.es)

This talk encapsulates a foundational exploration into causal inference, discovery, and effect estimation, offering a comprehensive 101 guide to the methods and techniques essential for understanding cause-and-effect relationships. This presentation navigated through theoretical and applied challenges, providing a holistic view of the complexities inherent in unravelling causation, especially for Earth and climate sciences. Some case studies served the purpose: from deciphering the drivers of migration to assessing the impact of humanitarian aid on food insecurity, as well as employing causal feature representation learning to unveil the influence of the El Niño-Southern Oscillation (ENSO) on vegetation greenness in Africa.

I also introduce the innovative causeme.net platform, a powerful tool for web-based causality analyses. This platform facilitates the exploration of causal relationships and is a practical resource for researchers and practitioners. The presentation concluded by teasing the integration possibilities between Large Language Models (LLMs) and causality studies. This forward-looking perspective hinted at the exciting potential for synergy between advanced language models and the nuanced understanding of causation, paving the way for future breakthroughs at the intersection of language processing and causal inference.

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5 Plenary talks: Space Operations

5.1 Introduction to Space Operations

Alessandro Donati (former AI and Operations Innovation Manager at ESA, retired, DE, alessandro.donati@lilium.de)

The talk introduces space operations fundamental concepts in brief. First, the phases in time. The operations preparation phase, includes the setting up and customization of the ground segment elements, made of hardware, software, procedures, the specialists training and the simulation campaign. Then the operations execution, split in LEOP, Commissioning phase, Routine phase and decommissioning. The second part addresses the two parallel chains of health caring of the spacecraft and the productive chain, made of planning, execution, payload data acquisition and dissemination. Both parallel chains incorporate a variety of tasks that can embed AI algorithms. The identified tasks are preparation, planning, execution, monitoring, forecasting, diagnostic, optimization.

5.2 Exploring Challenges and Innovations in the Space Domain: Curated Datasets, Optimization Problems, and Machine Learning Applications

Dario Izzo (European Space Agency's Advanced Concepts Team – Noordwijk, NL, dario.izzo@esa.int)

Joint work of Dario Izzo, Marcus Maertens, Gabriele Meoni, Thomas Uriot, Luis F. Simoes, Pablo Gomez, Dominik Dold, Simone D'Amico

Main reference Dario Izzo, Gabriele Meoni, Pablo Gomez, Domink Dold, Alexander Zoechbauer: "Selected Trends in Artificial Intelligence for Space Applications" in Artificial Intelligence for Space: AI4SPACE: Trends, Applications, and Perspectives (1st ed.). CRC Press, 2023

URL https://doi.org/10.1201/9781003366386

This presentation addresses several challenges in the space domain that have prompted the creation and dissemination of meticulously curated datasets and optimization problems, contributing to the broader academic community. An overview of significant challenges, including the Proba-V super resolution challenge [1], the data-driven "The OPS-SAT case"challenge [3], the collision avoidance challenge [4], and the pose estimation challenge [2], is provided. The talk delves into each challenge, offering brief insights into their objectives and methodologies, while also sharing select results achieved in these endeavors. Additionally, the application of Machine Learning (ML) inversion techniques within the domain of Geodesy for irregular solar system bodies is presented highlighting the utilization of ML methods to address challenges specific to Geodesy, showcasing results obtained through this innovative approach. The incorporation of ML in geodetic processes not only introduces a novel dimension to a traditional problem but also demonstrates its potential to yield meaningful insights on the internal structure of irregular bodies.

The talk aims to shed light on the interdisciplinary applications of ML techniques in the space domain, emphasizing the collaborative and innovative efforts that drive advancements in space-related research.

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5.3 Architecting a data-driven future in space

Dan Crichton (Jet Propulsion Laboratory, California Institute of Technology – Pasadena, CA, USA, daniel.j.crichton@jpl.nasa.gov)

Joint work of Dan Crichton, Steve Chien, Richard Doyle, Riley Duren, Thomas Huang, Lukas Mandrake, Ben Smith, Hui Su
Main reference Daniel J. Crichton, Chris A. Mattmann, John S. Hughes, Sean C. Kelly, Andrew F. Hart: "A Multidisciplinary, Model-Driven, Distributed Science Data System Architecture", pp. 117–143, Springer, 2011.
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JPL and NASA have achieved unprecedented scientific understanding using remote sensing to explore of our solar system, the mysteries of the universe, and our home planet, Earth. Significant technical progress in mission capabilities and remote sensing instruments has dramatically changed over JPL's history. Missions today generate immense volumes of data, challenging conventional methods for capturing, managing, analyzing, and deriving insights from this wealth of information. Further, computational constraints onboard, coupled with bandwidth limitations in being able to transfer data the ground, require new innovative approaches to optimizing science yield and mission. Areas such as mission planning, onboard and ground-based data and science processing, data management, and science analysis can all benefit from new approaches in data science, artificial intelligence, autonomy, and computing.

JPL has already made substantial progress in these domains. Examples include onboard planning to facilitate more autonomous operations, real-time detection of transient events on Mars' surface, machine learning algorithms capable of identifying and classifying features in imaging, and the development of massively scalable data repositories to enable data mining. Much of these advances have been built on pioneering work JPL performed in areas such as machine learning applied to optical astronomy in the 1990s for analyzing images captured in nightly sky surveys. These breakthroughs have allowed JPL to continue to respond to opportunities to bring new computing capabilities to support both space mission operations and science.

This presentation will discuss the progress, challenges, and opportunities in applying data science, AI, software, and computing to space observing systems. It will present use cases and examples of successful operational deployments. Finally, it will explore the integration of these capabilities and their criticality for advancing next generation data-driven space observing architectures, highlighting areas for future research to scale computing capabilities in space and on the ground.

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5.4 Challenges in fielding AI in Space Operations

Simone Fratini, Jose Martinez Heras (Solenix Engineering GmbH – Darmstadt, DE, simone.fratini@solenix.ch, jose.martinez@solenix.ch)

AI is a game-changer that is gathering momentum in space activities, as a prominent building block of enabling technology for future missions. But as much has been done so far, still many challenges remain.

In our talk we discussed some open challenges that, from our experience, when tackled, can bring substantial benefits for AI in space operations.

First, we acknowledge that even if operators need anomaly detection, we are only able to offer novelty detection. In most cases, novelty detection is close enough to anomaly detection to be useful. From our experience in Space Operations we highlight the problem of false alarms which drive the counter intuitive preference for precision (in detriment of recall), as having false alarms will cause operators to stop looking at any novelty detection system. We also stress the importance of being able to detect first time anomalies (i.e., anomalies that nobody thought this could happen) as they have the biggest impact in space operations.

Regarding diagnostics, we discuss several attempts and their limitations. Smart filtering can reduce the number of telemetry parameters operators need to consider but it cannot tell cause from effect, and it often produces many results. With Dependency Finder we can learn the relationship between different parameters from data; however, while it is useful to gain understanding, it cannot be used for deriving causes for a particular anomaly as it is based on large amounts of data. With Explainable AI (i.e., SHAP) we can tell which features are more relevant to get predictions in a Machine Learning model; however, it is not a causal relationship but a predictive relationship.

In terms of fielding AI for space operations, 4 levels of support have been discussed: augmentation, assistance, decision automation and autonomy. The variety and heterogeneity of knowledge to be engineered to implement AI-based support in operation, as well as the diversity of tasks to be considered, suggest that an hybrid approach would probably be the best option, combining various AI approaches as learning, modeling, reasoning and interaction.

In terms of autonomy, it has been discussed how many autonomous capabilities we will need in the near future, where and to do what. 4 scenarios of increasing autonomous levels where discussed: Augmentation and Support (the AI suggest and enhance the human being), Reactivity and Adaptiveness (the AI can perceive and respond to changes), Proactiveness (the AI can initiate action to meet its objectives) and Autonomy (the AI collaborates with the human being, "peer-to-peer").

It was finally pointed out as XAI and AI qualification more in general will be driving factors and essential enabling factors for a successful fielding of AI technologies in operations.

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6 Plenary talks: Earth Observation

6.1 Foundational Models for Earth Observation

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Over the past decade, Earth Observation (EO) has undergone a significant transformation thanks to the deep learning revolution and the increasing use of Artificial Intelligence (AI) to address various EO challenges. Although a standard framework for developing AI solutions to EO problems has been established, it still faces several challenges such as lack of labeled data, generative modeling, and integration of physics.

Foundational models offer a new perspective by integrating unsupervisedly learned knowledge in large models that can be adapted to various use-cases. The Phileo foundational model is presented as an example of desirable features, including global-scale training and the combination of pillar models with various pretext tasks. The European Space Agency has commissioned future European Foundational Models for EO and Society, as well as Climate, which will further advance this field.

6.2 How can the EO "revolution" benefit NWP and climate prediction?

Jonathan Bamber, (University of Bristol, GB, J.Bamber@bristol.ac.uk)

In the last decade there has been an exponential rise in New Space missions, many with an EO focus. There is limited coordination between national space agencies and commercial actors in the space sector while at the same time there is an urgent need to improve forecast skill, range and robustness in numerical weather prediction but also for longer term climate projections.

Conventional modelling approaches are reaching the limit of computational capability as well as hard limits in power consumption. How can ML methods be best used to improve forecast skill, computational efficiency and data fusion in a highly distributed data centre structure? Should the focus be on Open Source foundation models that can be a community tool or hybrid model approaches or DTE types of approach? And what are the risks of one or two Big Tech companies developing a monopoly in the field and pushing not for profit organisations such as ECMWF out of the market?

6.3 Planning satellite observations for global monitoring of physical parameters: Some research questions

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Joint work of Jean-Loup Farges, Gauthier Picard, Cédric Pralet

Operating Earth observation satellite constellation raises many challenges for AI and Agent-based Approaches [1]. Here, we identify questions about planning observation tasks as to monitor physical parameters using taskable agile EO satellites. Notably,

1- For monitoring physical phenomena, each acquisition carried out by a satellite provides not only instantaneous information on the observed area, but also (a) information on neighboring areas due to spatial correlations and (b) information on the value of physical parameters in the future, due to temporal dependencies. Therefore, a difficulty lies in assessing the value of each observation, knowing that due to limited capacity, planning systems for satellite constellations must select observations from a set of candidate observations [2, 3]. 2- The satellites considered can be equipped with different sensors, and some satellites are even capable of carrying out observations in several modes (for example, "wide field observation" mode versus "targeted observation" mode). Managing this heterogeneity is also a challenge for evaluating the reward associated with each observation. For example, it is necessary to find a compromise between, on the one hand, continuously maintaining global knowledge on the value of physical parameters, and on the other hand, carrying out targeted observations on areas where phenomena have been detected. 3- The choice of a good observation strategy depends on the dynamics of the physical process being monitored. For example, monitoring deforestation does not require the same frequency of observation as monitoring illicit degassing from ships. Ideally, the automated planning system should be able to learn a good observation strategy from a global request to monitor a parameter, rather than waiting for basic observation requests formulated by users.

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6.4 Artificial Intelligence and Earth Observation for The Sustainable Development Goals

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Main reference C. Persello, Jan Dirk Wegner, Ronny Hansch, Devis Tuia, Pedram Ghamisi, M. Koeva, Gustau Camps-Valls: "Deep learning and earth observation to support the sustainable development goals: Current approaches, open challenges, and future opportunities", pp. 172–200, IEEE, 2022.
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The combination of Artificial Intelligence (AI) and Earth observation (EO) promises significant advances to support the United Nations' Sustainable Development Goals (SDGs). New developments and applications are already changing how humanity will face our planet's challenges. This talk provides an overview of the areas where AI and EO can contribute the most towards achieving the SDGs, discussing opportunities and open challenges. Research activities on AI methods for EO data are presented along with their applications toward monitoring the progress and achieving the SDGs. Case studies are presented to achieve zero hunger (SDG 2), create sustainable cities (SDG 11), deliver tenure security (multiple SDGs), and mitigate and adapt to climate change (SDG 13). Important societal, economic, and environmental implications are covered.

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6.5 In-Domain Self-Supervised Learning Improves Remote Sensing Image Scene Classification

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Joint work of Ivica Dimitrovski, Ivan Kitanovski, Nikola Simidjievski, Dragi Kocev
Main reference Ivica Dimitrovski, Ivan Kitanovski, Nikola Simidjievski, Dragi Kocev: "In-Domain Self-Supervised Learning Improves Remote Sensing Image Scene Classification", IEEE Geoscience and Remote Sensing Letters, Vol. 21, p. 1–5, Institute of Electrical and Electronics Engineers (IEEE), 2024.
URL https://doi.org//10.1109/lgrs.2024.3352926

We investigate the utility of in-domain self-supervised pre-training of vision models in the analysis of remote sensing imagery. Self-supervised learning (SSL) has emerged as a promising approach for remote sensing image classification due to its ability to exploit large amounts of unlabeled data. Unlike traditional supervised learning, SSL aims to learn representations of data without the need for explicit labels. This is achieved by formulating auxiliary tasks that can be used for pre-training models before fine-tuning them on a given downstream task. A common approach in practice to SSL pre-training is utilizing standard pre-training datasets, such as ImageNet. While relevant, such a general approach can have a sub-optimal influence on the downstream performance of models, especially on tasks from challenging domains such as remote sensing. In this paper, we analyze the effectiveness of SSL pre-training by employing the iBOT framework coupled with Vision transformers trained on Million-AID, a large and unlabeled remote sensing dataset. We present a comprehensive study of different self-supervised pre-training strategies and evaluate their effect across 14 downstream datasets with diverse properties. Our results demonstrate that leveraging large in-domain datasets for self-supervised pre-training consistently leads to improved predictive downstream performance, compared to the standard approaches found in practice.

7 Parallel working group discussions on different topics

7.1 Working Group on SDG and AI4Good

Jonathan Bamber (University of Bristol, Technical University of Munich, DE)
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Gustau Camps-Valls (University of Valencia, ES)
Žiga Kokalj (Research Centre of Slovenian Academy of Sciences and Arts – Ljubljana, SI)
Jose Martinez-Heras (Solenix, DE)
Claudio Persello (University of Twente – Enschede, NL)
Michelangelo Ceci (University of Bari, IT)
Dino Ienco (INRAE – MOntpellier, FR)
Sašo Džeroski (Jožef Stefan Institute – Ljubljana, SI)
Alessandro Donati (European Space Agency, DE)
Sylvain Lobry (Université Paris Cité, FR)
Nuno Carvalhais (Max Planck Institute for Biogeochemistry – Jena, DE)

7.1.1 Discussed Problems

The group discussed several topics related to the promises and the challenges of using Artificial Intelligence (AI) and Earth Observation (EO) to support the Sustainable Development Goals (SDGs). First, the group discussed the possible tasks in SDG using AI and EO. These include the i) identification of the deprivation areas (for example, identify slums, informal settlements and inadequate houses, ii) identification of the best areas for installing renewable energy plants, iii) delineation of smallholder farms and semi-automated extraction of cadastral boundaries, iv) study of the local impacts of changes in climate and extreme events. The group then identified challenges in SDG using AI and EO. These include i) data quality, uncertainty quantification and difficulty in identifying the classes, ii) transferability of the models from one place to another vs. locality of the models, iii) ethical and privacy issues that apply to EO data, especially for high-resolution images. The last main topic discussed by the group concerns the exploitation of the models. Specifically, the problems that emerged are: i) policy makers need to make decisions, but also track the impact of the implementation of such decisions; ii) the implementation of these decisions largely depends on different governments and it's outside the scope of the influence of the EO and AI experts.

7.1.2 Conclusions

The contribution of AI and EO for SDG was considered very relevant by the group in order to solve many relevant tasks discussed during the meeting. However, several issues arise, which require the consideration of additional technologies, data and techniques (for example, integrating additional data to compensate the low-quality data available or the absence of some data). Transferability is also not easy and requires taking into account the peculiarities of the specific places. In terms of the exploitation of findings and results, it is necessary to call for outreach activities to present scientific results in a convincing way to compel politicians to act. An important point is to shift from model-centric towards data and user-centric AI.

7.2 Working Group on AutoML and Benchmarks

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Mitra Baratchi (Leiden University, NL)
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Joaquin Vanschoren (Eindhoven University of Technology, NL)

This working group concentrated on the use of AutoML methods in Space Operations and Earth Observation, as well as the presence of benchmarks.

7.2.1 Discussed Problems

During the breakout session, a variety of challenges and potential strategies surrounding the evaluation and development of Space Operations (SpaceOps) and Earth Observation (EO) foundational models were discussed. The conversation opened with questions about the current methods used to evaluate these models and whether foundational models truly offer superior performance. This led to a broader discussion on the necessity of creating new benchmarks specifically designed for EO data, highlighting the potential to develop something akin to a meta-album for Earth observation. Such benchmarks could cover a wide range of tasks, including image segmentation, pixel-level classification, and the use of multi-spectral data, underscoring the value of both labeled and unlabeled data for training purposes.

The session also tackled the difficulties AI researchers face in accessing EO data, emphasizing the need for better data availability to advance the field. The discussion acknowledged the complexity of integrating data from diverse sources, including different satellites, resolutions, and types (visual vs. radar), and the challenges of domain transfer, class-incremental learning, and cross-sentinel data integration. These issues highlight the need for benchmarks that can accommodate a variety of data characteristics and learning tasks.

Operational and technical challenges, such as data storage, licensing, and the infrastructure needed to host and share data and models, were also identified as significant hurdles. In this context, the potential role of AutoML in enhancing EO model development was explored. AutoML could simplify the search for optimal model configurations, leverage pretrained models for better efficiency and transferability, and help in defining effective search spaces.

7.2.2 Conclusions

The session concluded with a strong consensus on the need for new benchmarks and datasets that accurately reflect the complexities of Earth observation tasks. Engaging with the space community, utilizing resources like the upcoming Anomaly Detection dataset from ESA, and leveraging platforms such as kelvins.esa.int were identified as crucial steps forward. Moreover, operational considerations such as addressing data licensing and storage, and creating an infrastructure for model sharing, were acknowledged as essential for the progress of the field. The development of a benchmark, encompassing the selection of data, tasks, and metrics, was highlighted as a key action point, alongside the formation of a project team dedicated to building this benchmark. This collaborative approach, including research into the application of AutoML for foundational models, aims to overcome the challenges discussed and advance the field of Earth observation.

7.3 Working Group on On-board and Frugal AI

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Dan Crichton (Jet Propulsion Laboratory, California Institute of Technology – Pasadena, US)
Simone Fratini (Solenix Engineering GmbH – Darmstadt, DE)
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Jakub Nalepa (Silesian University of Technology – Gliwice, PL)

7.3.1 Discussed Problems

The discussions revolved around the necessity for frugality in AI application within space systems, particularly emphasizing the efficient use of training data, computational efforts, and the size/efficiency of the trained models. This approach, aimed at optimizing performance with minimal resource expenditure, is critical in scenarios where AI models are trained on Earth and deployed for inference on board spacecraft or satellites. The debate extended to whether the focus should solely be on machine learning (ML) techniques or include other AI approaches such as planning and scheduling, which are vital for autonomous decision-making in space.

A significant issue identified was the current state of onboard AI compared to ground operations, which is considered unsatisfactory. Despite planned developments for AI accelerators and dedicated software, there is a pressing need for broader community support to enhance these technologies' capabilities. Onboard autonomy in space requires a blend of model-based decision-making for task allocation and resource optimization, and learning for various functions including science inference and image analytics. AutoML and AutoAI emerge as potential solutions to reduce computational demands by automating algorithm selection and configuration, as well as performance prediction.

Another discussed problem was the need for multi-objective AutoML to balance performance with resource usage effectively, considering computation, memory, bandwidth, and response time. Furthermore, robustness against adversarial attacks and security concerns for open-source systems were highlighted, alongside the need for technology controlled by trusted entities to mitigate reliance on commercial enterprises.

7.3.2 Conclusions

The challenges in implementing frugal AI and autonomy in space are manifold. First, developing AI that can efficiently operate with limited resources on board, closing the sense-plan-act loop, remains a daunting task. This includes the integration of model-based planning, scheduling, and learning mechanisms that are capable of adapting to the dynamic space environment.

Second, the adoption of AutoML and other automated AI approaches requires advancements in multi-objective optimization to navigate the trade-offs between performance and resource consumption. This is particularly relevant for tasks like Earth Observation (EO), where satellites need to make autonomous decisions based on real-time data, such as cloud coverage.

Third, ensuring the robustness of onboard AI systems against adversarial attacks and addressing security vulnerabilities in open-source software are critical for maintaining the integrity and reliability of space missions. This is compounded by the challenge of developing and deploying AI technologies that remain under the control of trusted entities, avoiding over-reliance on commercial solutions.

Lastly, the computational complexity of combining data-driven and other AI methodologies for effective problem-solving in space poses a significant challenge. This includes optimizing task allocations and resource management in agile EO satellites, which require sophisticated planning and machine learning strategies to adapt to changing conditions and priorities.

Addressing these challenges necessitates a collaborative effort from the global research community, focusing on the development of advanced AI technologies that are efficient, secure, and capable of autonomous operation in the demanding conditions of space.

7.4 Working Group on Responsible AI

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7.4.1 Discussed Problems

The discussions addressed several critical issues regarding the regulation and application of artificial intelligence (AI) from a legal perspective. A key point was the unique nature of AI as a commodity, which necessitates a different regulatory approach than that applied to other powerful technologies, such as nuclear power. This distinction raises questions about how to appropriately regulate AI to ensure safety and accountability without stifling innovation.

Another significant issue was the differentiation between humans and AI-enhanced humans, particularly in legal contexts. Traditional punitive measures, like imprisonment, are not applicable to AI systems, highlighting the need for a responsible human principal behind AI operations. This situation parallels the legal treatment of companies but introduces complexities due to the varied intelligence levels of AI systems, ranging from highly intelligent to rudimentary.

The application of AI in space presents unique challenges, distinct from those on Earth. Privacy concerns, prevalent on Earth, are less relevant in space, where issues such as sovereignty, resource utilization, and the ethical implications of AI in scenarios without human intervention come to the forefront. These challenges underscore the need for international legal harmonization and collaboration in space activities.

7.4.2 Conclusions

The discussion highlights the critical need for a refined and tailored approach to the regulation of AI. The concept of "trustworthy AI," encompassing ethics, responsibility, and explainability, is identified as crucial for guiding future regulatory frameworks. However, implementing these principles faces significant challenges, both on Earth and in space.

On Earth, the focus is on creating unbiased datasets and ensuring fairness within the bounds of domestic laws. In space, the challenges are amplified, with concerns about resource management, ethical decision-making in critical scenarios, and the need for AI to operate with limited human intervention. The EU act "7 key requirements that AI systems should meet in order to be deemed trustworthy" highlight the importance of human oversight, safety, privacy, transparency, and accountability, which are particularly pertinent in the context of space.

Challenges arise in achieving a global consensus on AI regulation, especially for space activities. Despite these challenges, there is a shared commitment to developing AI that benefits humanity, with an emphasis on responsible innovation and the pursuit of harmonized standards on a global scale.

8 Parallel working group discussions on challenges in AI & space and future research directions

On Friday morning, the participants split into four discussion groups. All groups discussed the same general topic of challenges for AI and space, as well as future research directions. Summaries of the discussions, per working group, are given below.

8.1 Working Group 1

Damian Borth (University of St. Gallen, CH)
Dan Crichton (Jet Propulsion Laboratory, California Institute of Technology – Pasadena, US)
Alessandro Donati (European Space Agency, DE)
George Anthony Long (Legal Parallax – Fountain Hills, US)
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Žiga Kokalj (Research Centre of Slovenian Academy of Sciences and Arts – Ljubljana, SI)

From the discussion of this group, a number of short term and long-term opportunities were identified. Short-term opportunities include:
- Continuous engagement with users
- Increased collaboration between agencies and research facilities
- Make agencies (ESA, NASA, etc) visible to the research community
- Connect ESA and NASA to agree on some agreements to be competitive world-wide

Long-term opportunities include:
- International agreements on common approaches, standardization, and shared capabilities in AI/ML
- Space-based Autonomy for longer-term flights, system level control and onboard decisions
- Use of AI for space mining

8.2 Working Group 2

Michelangelo Ceci (University of Bari, IT)
Michai Datcu (University Politehnica of Bucharest, RO)
Simone Fratini (Solenix Engineering GmbH – Darmstadt, DE)
Dario Izzo (European Space Agency's Advanced Concepts Team – Noordwijk, NL)
Marjan Stoimchev (Jožef Stefan Institute – Ljubljana, SI)

The working group 2 discussed the following points:
- Verification and Validation (for software and products of ML pipelines)
- Open Source Pipelines and Benchmarks (especially in Operations)
- Smaller is better (produce smaller models, trade off between model accuracy and size)
- Edge computing for ground/space segments.

A summary of the discussion for each point follows below.

Verification and Validation (software).
- The ECSS handbook is widely used in ESA/space. A section thereof for ML models is underway.
- Qualitative validation beyond accuracy or other measures is neede. There are some techniques already in place for this that create some constraints for the model output, also looking at variables not seen by the model.
- Undecidability of the presence of bugs from the achieved accuracy of models. ML corrects for that and helps hide them. Certification procedures should account for these effects.
- We need ontologies of image labels.

Verification and Validation (products).
- New products are derived from ML pipelines (synthetic data). These need to be certified and /or traced back to the originating pipeline/images.
- Detection of fakes might become important to guarantee product value. Might be related to anomaly detection.
- Revise TRL definitions are based on experience from 20 years ago. ML changed all this and they should be reassessed.
- Revise technology trees to account for the change in philosophy coming from ML advances and technological innovations.

Open Source.
- Many projects need to be extended to account for space constraints (Normalization for example needs to happen in a very specific way, often not provided in the OS toolboxes)

- One needs to be careful in general because some data (EO) have a geopolitical value that may drive (wrongly or rightly) political decisions. (example forecast of crop productions). A solution might come on the availability of reference data, or anonymization of data (difficult to do, needs some compromise).
- Complete lack of benchmarks for operation scenarios. A fact. EO is very well ahead w.r.t. other fields in space.
- Culture change needed .... Many agree on the importance of opening up data, but nobody wants to sign documents allowing it.

Edge Computing.

- Importance of having computational constraints accounted for in the development of ML models from early stages.
- Hardware available on board is moving slowly towards higher capabilities but will never close the gap with Earth counterparts. Awareness on application requirements must drive the development of models that fit on foreseeable on board architectures.
- Pruning,distilling, teacher-student models are actively researched areas in ML that should be assessed for space applications.

8.3 Working Group 3

Jurica Levatic (Jožef Stefan Institute – Ljublana, SI)
Sylvain Lobry (Université Paris Cité, FR)
Luke Lucas (LSE Space – Darmstadt, DE)
Jose Martinez-Heras (Solenix – Darmstadt, DE)
Gauthier Picard (ONERA/DTIS, Université de Toulouse, FR)

The working group 3 discussed the following points:

- The loop between planning, execution and monitoring should be closed.
- Anonymization (i.e. adding noise so parameters cannot be reversed-engineered) is something to be investigated.
- In foundation models, standardization and data availability are main issues.
- Existing foundation models could be used for on-board lossless compression or compression with loss (select relevant data to downlink).
- In anomaly detection, the end-user should be involved in the designing of the tool. The use of of AI should be planned from the early stages of mission development.
- In diagnostics, smart filtering, dependency analysis, and XAI are used, but not yet causality. Causal Inference remains a challenge in space operations. It will be very useful for diagnosing anomalies and increasing understanding.

8.4 Working Group 4

Jonathan Bamber (University of Bristol, GB & Technical University of Munich, DE)
Sašo Džeroski (Jožef Stefan Institute – Ljubljana, SI)
Dino Ienco (INRAE – Montpellier, FR)
Ana Kostovska (Jožef Stefan Institute – Ljubljana, SI)
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The discussion of the working group 4 can be summarized as follows. Descriptions of the different types of data collected by different EO missions are needed. This would facilitate their use, reuse and combination. This is especially important for applying ML methods to these data and combinations thereof.

- **Ground-truth data is sorely needed.** The same holds for meta-data describing the ground-truth data, which is even more important, because in some cases the data might not be available. Meta-data are essential for finding data relevant to a problem at hand. In addition, it would be very important for transfer learning and learning foundation models. The decision on which foundation model is most relevant for a particular downstream task can be also taken much more competently if we have a description of the data at hand (geographical region, type of urban system/ ecosystem, type of data).
- **Reuse of historical heterogeneous data** (sensors and calibration data) in order to make value of that information for nowcasting/ forecasting is of primary importance and AI can provide methodologies and techniques for such "transfer".
- **Hindcasting is an interesting avenue for further work.** If we have, e.g., both Landsat and LIDAR, for a recent period, we could learn to map forest cover (height and density) from Landsat. We could then get estimates of forest cover for the entire historical period (60 years), where we have Landsat data.
- **Incrementally/Continually updating machine learning models with new EO and calibration data** in order to avoid retraining the system from scratch is also a possible challenge. This is especially important in the context of EO missions that are acquiring systematically new information on the different areas of the Earth surface.
- **Federated learning holds significant potential for EO applications.** The decentralized training methodology would enable us to learn from massive amounts of data without the need of centralizing it. This aspect is particularly advantageous in EO, where data can be voluminous, diverse, and often sensitive w.r.t. privacy and security. Initial work on EO federated learning can be found in `https://arxiv.org/pdf/2311.06141.pdf`. Federated and transfer learning can be used to avoid issues with sharing data. When data cannot be shared, but models can, models can be sequentially (pre)trained and (fine)tuned. The data can stay in place, but models can move around and evolve.
- **Semantic resources for EO need to be developed**, e.g. controlled vocabularies/ ontologies for describing EO-related data, as well as EO-related machine learning tasks, to match to methods.
- **Open publicly funded centre for AI.** There is a high risk that one of the big tech companies creates a monopoly in the field of AI4EO and particularly by the development of very large foundation models. To avoid the risks associated with commercial imperatives that might drive such an approach, publicly funded foundation models are needed.

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