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Artificial Intelligence in Planetary Science and Astronomy: Applications and Research Potential

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Introduction

Artificial Intelligence (AI) is one of the most influential fields of the 21st century (Zhang et al., 2021). Rich, E (2019) candidly described it as "the study of how to make computers do things which, at the moment, people do better", today AI often surpasses human ability in tasks like large-scale data mining and pattern recognition - its true strength. AI's subfields - Machine Learning (ML) and deep learning (DL), play a critical role in expanding the usage to a vast variety of fields like planetary science, astronomy, earth observations, and remote sensing, just to name a few. There is an expected inclination towards incorporating AI more frequently in the studies of planetary science given the vast and complex nature of planetary data. In fact, AI has already been instrumental in extracting meaningful insights and advancing research in both interplanetary and astronomical studies.

In planetary sciences, several AI techniques have been employed in order to bridge gaps in our understanding of the varied patterns and occurrences for studying the natural features observable from the data returned by scientific payloads. For example, PCA and cluster analysis can help in detecting patterns of compositional variation from multi and hyper-spectral imagery (Moussaoui et al., 2008; D'Amore & Padovan, 2022). Furthermore, to study specific features and patterns in their occurrences, correlations with neighbouring features; unsupervised algorithms and more complex -supervised techniques can be helpful depending on the scale of the task.

From simple methods of unsupervised learning like clustering used to study the spectral signatures of Jezero crater on Mars (Pletl et al., 2023) to applying large language models to track asteroids affected by gravitational effects which alter the asteroid's orbit (Carruba et al., 2025), such applications highlight the prospects of AI in the field of planetary science. Henceforth, to develop a deeper understanding of the potential and applications of ML, below is a typical AI workflow.

Typical AI workflow

A typical workflow for an AI model involves an initial step of selecting a model suitable for your goals (Figure 2). Data format, quality of the data, static or dynamic features of interest, etc can influence the choice of AI model or techniques. Data preparation steps, like normalizing the data i.e. scaling the data from [-1,1] values, prevents dominance of any one feature in the data and stabilizes the model training process.

Furthermore, parameters or hyperparameters are selected depending on the complexity of the model. While more complex models; deep neural networks or Vision Transformers will need hyperparameter adjustment to maximize performance, simpler models mainly rely on predefined weights or fixed rules. Likewise, a model architecture shall be established as per the data and targets. One example is the usage of the Faster-R-CNN - a robust and high accuracy yielding model which can be employed to train on high-resolution labelled images to perform object-detection tasks like identifying craters.

In scientific use cases, the workflow often encompasses actual data that must be separated into a training set, validation set (to optimize the hyper-parameters) and a test set, completely independent from the training. To evaluate "how well" the model has learnt from the training dataset, accuracy, precision, recall, F1-score, and intersection-over-union (IoU) are the most popular statistics. Subsequently, model predictions can help in developing an understanding of the potential areas for fine-tuning and refining the model for the use case. Henceforth, fine-tuning the model is another crucial step.

Figure 2: A typical AI workflow

Potential of AI

A successful application of ML in planetary science can be driven by a collaboration of scientists and ML experts. Scientists (astronomers, geologists, planetary scientists etc.) are arguably more equipped to answer science-based questions like what can be called a crater and conversely, ML experts may be more adept at assessing data preparation techniques to eradicate noise. The field of planetary sciences encompasses themes like anomaly detection, simulation and surface modeling, atmospheric studies, gravitational behavior and its effects on planets and smaller bodies, instrumentation and spacecraft design etc. which necessitates such collaborations for the optimum result. In recent years, Large Language Models (LLMs) have had a significant paradigm shift in AI applications due to their understanding of patterns acquired through their vast pre-training phase. For time series analysis, image classification, and pattern identification tasks common in planetary sciences, LLMs can significantly streamline workflows by reducing the need for specialized preprocessing steps.

Given the enormous data from missions and observational surveys, and the numerous applications of planetary sciences, it is the need of the hour to produce workflows that not only automates but helps in an objective/standard decision making for problem statements of planetary sciences. The Europlanet Machine Learning Working Group does exactly this by sharing the latest techniques, tools, and applications and opens doors for people who want to apply these robust techniques.

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