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Poster
Satellite mission have long been vulnerable to high radiation events caused by solar storms, necessitating the monitoring and forecasting of solar weather. While early methods relied on empirical data, recent advancements now harness vast datasets, complex algorithms, and AI to achieve unprecedented accuracy. Despite these improvements, current models still face challenges, such as high computational demands and difficulties in predicting rare events. At Booz Allen, we are developing an MLOps framework called Sun2OD, which employs cutting-edge deep learning, efficient model architectures, and high-fidelity Space Domain Awareness (SDA) data. This framework enhances our AI-enabled Space Battle Management (SBM) capability through continuous learning feedback loops on SDA/SBM data streams, leading to improved reliability and precision in predictions crucial for satellite safety and operational functionality.

The most immediate information affecting the space environment is light from the sun. Therefore, the first component of Sun2OD we present is a deep learning-based solar weather forecasting system based on solar imagery. Solar flares and coronal mass ejections (CMEs) can adversely impact satellite electronics, while solar radiation heats the atmosphere, affecting satellite trajectories. Indirect measurements of extreme ultraviolet (EUV) radiation often fail to capture the full spectrum of solar dynamics impacting the atmosphere. These methods typically rely on empirical models and approximations, resulting in forecasts that may not fully account for the complex interactions between solar activity and atmospheric density. Our approach leverages direct observation of high-fidelity EUV imagery from NASA's Solar Dynamics Observatory (SDO), offering a comprehensive and accurate representation of these solar events. This leads to more precise predictions and a deeper understanding of how solar dynamics influence atmospheric conditions.

Inspired by recent successes in deep learning, our approach aims to enhance solar weather forecasting by using SDO data to train a foundational deep learning model of solar activity. By extending the computationally efficient Hierarchical Vision Transformer (HiViT) to ingest 12-channel SDO imagery, which we call SDOViT, we extract an information-dense solar feature space from masked image modeling (MIM) pretraining. This image feature space is combined with atmospheric model drivers, such as F10.7, F30, Dst, F15, Kp, and Ap, augmenting historical model driver data to train a space weather forecast model called SWFCast. Preliminary results show that SWFCast averages a 30% improvement in 27-day forecast accuracy compared to the NOAA 27-day persistence model baseline over a solar cycle.

Additionally, we are developing a foundation model using coronagraphs and geomagnetic indices to predict CMEs and solar flares. This model will integrate data from coronagraphs and geomagnetic indices, such as Dst, F15, Kp, and Ap, to provide early warnings and enhance the accuracy of solar weather predictions. By incorporating these additional datasets, we aim to enrich our models and expand the coverage of learned solar dynamics.

The future direction of Sun2OD includes several key advancements. First, we will integrate additional datasets, such as Dst, F15, Kp, Ap, and coronographs, to enrich our models and expand coverage of learned solar dynamics. We will develop solar flare and CME prediction capabilities to provide early warnings to satellite operations. Finally, we will create deep learning models to improve anomaly detection and maneuver planning based on high-fidelity satellite ephemerides, ensuring robust and adaptive space operations. Together, these advancements form a comprehensive AI-enabled Space Battle Management solution for solar weather forecasting.

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