2nd Machine Learning in Heliophysics
Boulder, 21 – 25 March 2022

Invited Orals

Gary Doran
Responsive Onboard Science for Europa Clipper

Europa Clipper will carry an instrument suite capable of collecting a wide range of observations that will inform our understanding of Europa, including a visible imager (EIS), a thermal imager (E-THEMIS), an imaging spectrometer (MISE), and a Faraday Cup based plasma instrument (PIMS). The combination of extreme distance, limited lifetime due to high radiation, and limited data downlink creates an opportunity for reliable autonomous operations to increase the science yield of the mission. By analyzing data onboard the spacecraft, observations with positive detections of phenomena of interest (plumes, thermal anomalies, compositional anomalies, etc.) can be marked for high-priority downlink to Earth to plan future flybys. Onboard analysis can also be used to decide when to change instrument observing modes, such as when passing through magnetospheric boundaries. This talk discusses data analysis and machine learning methods that can operate onboard and increase the rate of exploration and discovery, including our work to evaluate these methods to address specific use cases of interest to the Europa Clipper mission. Our ongoing evaluation includes an investigation of practical considerations, such as each algorithm’s ability to operate using limited computational resources and robustness to the effects of Jupiter’s high radiation environment.

Maria Elena Innocenti

A versatile technique for unsupervised classification and preliminary analysis of simulation results

Classification of data, either from simulations or from observations, is often a fundamental first step towards further analysis of space physics data. A classification procedure that delivers information on the physical processes occurring in the different clusters can therefore be an asset.
In this talk we present an unsupervised classification procedure based on Self-Organizing Maps, SOMs. We apply it to very different simulations, a global simulation of the terrestrial magnetosphere done with the MHD code OpenGGCM and a fully kinetic simulation of plasmoid instability done with the Particle In Cell, semi-implicit, energy conserving code ECsim. In both cases, we obtain classification results that match well our a priori knowledge of the simulated environment. We then investigate different aspects of the trained SOMs, e.g. feature maps, unified distance matrixes, distribution of node weights, looking for signatures of the physical processes at work in each cluster.

Innocenti, M. E., Amaya, J., Raeder, J., Dupuis, R., Ferdousi, B., & Lapenta, G. (2021). Unsupervised classification of simulated magnetospheric regions. Annales Geophysicae Discussions, 1-28.
https://angeo.copernicus.org/articles/39/861/2021/angeo-39-861-2021.html

Jay Johnson
Information Horizon of Flares and Magnetic Active Regions

The evolution of solar active regions and flares is closely related to the underlying dynamics of the solar dynamo and magnetic activity cycle. This study explores the hierarchy of timescales on which information is retained throughout time in active solar regions and flares. Recent analysis [Snelling et al., 2020, Ashwanden and Johnson, 2021] shows that solar flares exhibit memory on different timescales. Information theory shows that the time ordering of flare events is not random, but rather there is dependence between successive flares. Increased mutual information results from the clustering of flares, which we demonstrate by comparing the distribution function of successive flares with that of surrogate sequences of flares obtained by random permutation of flares within rate-variable Bayesian blocks. Differences between the distribution functions is substantial on a timescale around 3 hours, suggesting that flare recurrence on that timescale is more likely than would be expected from a nonstationary Poisson process. Similar behavior is seen in the activity cycle of sun-like stars. For solar active regions, we consider the sequence of Carrington rotation magnetogram synoptic map images over four solar cycles. Mutual information is used to identify active regions and determine their coherence over time. The mutual information of structures drops off drastically within the first 20 Carrington rotations, suggesting a short-term memory of about 0.14 solar cycles. Mutual information peaks in multiples of 140 Carrington rotations, showing that images separated by multiples of the solar cycle are similar. Long-term memory across multiple solar cycles was explored using conditional mutual information showing residual memory across solar cycles.

Alan Kaptanoglu
Machine Learning for discovering sparse models of fluids, plasmas, and much more

Many tasks in fluid and plasma physics, such as design optimization and control, are challenging because of nonlinearity and a large range of scales in both space and time. This range of scales necessitates exceedingly high-dimensional measurements and computational discretization to resolve all relevant features, resulting in vast data sets and time-intensive computations. Indeed, fluid dynamics is one of the original big data fields, and many high-performance computing architectures, experimental measurement techniques, and advanced data processing and visualization algorithms were driven by decades of research in fluid mechanics. The analysis of plasmas, especially space plasmas, suffers from an additional setback; it is exceedingly difficult and costly to make high-quality measurements of extra-terrestrial plasmas. Machine learning constitutes a growing set of powerful techniques to extract patterns and build models from both sparse and dense nonlinear systems data, complementing existing theoretical, numerical, and experimental efforts. The sparse identification of nonlinear dynamics (SINDy) algorithm is one such method that identifies a minimal dynamical system model while balancing model complexity with accuracy, avoiding overfitting. This approach tends to promote models that are interpretable and generalizable, capturing the essential physics of the system. We discuss recent advances with the SINDy method, including the identification of PDE systems, the incorporation of physical constraints from global conservation laws, promoting global stability, solving for weak-formulation differential equations, and more. These advances have been consolidated into the open-source PySINDy code, enabling anyone with access to measurement data to engage in scientific model discovery. We conclude with possible bridges and applications to the heliophysics and space physics fields.

Maria J. Molina
Machine Learning for the Geosciences

Supervised and unsupervised machine learning methods can be used to detect features, extend predictions, and uncover patterns within large datasets of the physical world. Several pressing geoscience problems have similarities to heliophysics questions and therefore, the application of machine learning tools across different physical science domains can be leveraged to make needed advances. This talk will highlight the following three applications of machine learning for the geosciences: (i) detecting organized convection with a U-Net, (ii) extending precipitation prediction to timescales that exceed two weeks with neural networks, and (iii) unsupervised learning of dominant atmospheric flow patterns over North America with self-organizing maps. The focus will be on methodology and conclude with a discussion of the transferability of these applications to heliophysics.

Katariina Nykyri
Information Theory and Machine Learning Applications to Solar Wind Magnetosphere Interactions

Understanding the plasma transport, heating and acceleration processes in geospace system is important for improved forecasting of space weather events. However, limited amount of in-situ spacecraft measurements in vast volume of space makes it challenging to track the pathways of the plasma and energy transport in this complex system. Information theory is a powerful method to analyze the dynamics of complex systems and is particularly useful in characterizing responses that are nonlinear and for determining causal relationships and the underlying dynamics. In this talk I review some results of our group’s recent work on information theory applications on ARTEMIS and MMS spacecraft data to study the propagation of plasma and magnetic field structures in solar wind -magnetosphere system. I will also briefly discuss our artificial neural network developed for Kp-prediction and physical motivation for some of the parameters used in neural network training.

Eunsu Park
Application of image translation methods based on deep learning to solar data

We have applied image translation methods based on deep learning to various solar and space weather data. Major results from our studies are as follows. First, we successfully generate solar farside magnetograms from STEREO/EUVI EUV images. For this we traine an image translation model from SDO/AIA EUV images to SDO/HMI magnetograms, then apply the model to STEREO/EUVI images. Second, we denoise SDO/HMI magnetograms by translating the original magnetograms to the 21-frame-stacked ones. Further, we denoise solar magnetograms without target images by using an autoencoder method. Third, we generate modern satellite images from Galileo sunspot drawings in 1612. For this we train an image translation model from Mt. Wilson sunspot drawings to the corresponding SDO/AIA EUV images and SDO/HMI magnetograms.

Maziar Raissi
Data-Efficient Deep Learning using Physics-Informed Neural Networks

A grand challenge with great opportunities is to develop a coherent framework that enables blending conservation laws, physical principles, and/or phenomenological behaviors expressed by differential equations with the vast data sets available in many fields of engineering, science, and technology. At the intersection of probabilistic machine learning, deep learning, and scientific computations, this work is pursuing the overall vision to establish promising new directions for harnessing the long-standing developments of classical methods in applied mathematics and mathematical physics to design learning machines with the ability to operate in complex domains without requiring large quantities of data. To materialize this vision, this work is exploring two complementary directions: (1) designing data-efficient learning machines capable of leveraging the underlying laws of physics, expressed by time dependent and non-linear differential equations, to extract patterns from high-dimensional data generated from experiments, and (2) designing novel numerical algorithms that can seamlessly blend equations and noisy multi-fidelity data, infer latent quantities of interest (e.g., the solution to a differential equation), and naturally quantify uncertainty in computations.

Contributed Orals

Sigiava Aminalragia-Giamini

Radiation belt model including semi-annual variation and Solar driving (SENTINEL)

The Earth’s outer radiation belt response to geospace disturbances is extremely variable spanning from a few hours to several months. In addition, the numerous physical mechanisms, which control this response, depend on the electron energy, the time-scale and the types of geospace disturbances. As a consequence, the various models that currently exist are either specialized, orbit-specific data-driven models, or sophisticated physics-based ones. In this paper we present a new approach for radiation belt modelling using Machine Learning methods driven solely by solar wind speed and pressure, Solar flux at 10.7 cm and the Russell-McPherron angle. We use Van Allen Probes data to train our model and show that it can successfully reproduce and predict the electron fluxes of the outer radiation belt in a broad energy (0.033–4.062 MeV) and L-shell (2.5–5.9) range and, moreover, it can capture the long-term modulation of the semi-annual variation. We also present validation studies of the model’s performance using data from other missions which are outside the spatio-temporal training regime such as the E>0.8 MeV electron flux measurements from GOES-15/EPEAD at geostationary orbit.

Jhassmin A Aricoché

Modeling ionograms with deep neural networks: Contrasting models

The state parameters of the ionosphere are of fundamental importance not only for space weather studies but also for technological applications such as satellite radio communications. As with many geophysical phenomena, the ionosphere dynamics are governed by nonlinear processes that make ionospheric forecasting a challenging endeavor. However, we have available enormous datasets and ubiquitous experimental sources that can help us find the complex regularities in these phenomena.We forecasted ionograms for different solar activity times and database sizes using deep neural networks. Due to the neural network's extrapolation of virtual heights for all frequencies given to the model, we estimated foF2 using two different models to identify the last frequency of each ionogram. The predictions were compared to measurements collected with the Digisonde system at the Jicamarca Radio Observatory, a persistence model, International Reference Ionosphere model estimations, and the SAMI2 model estimations. Finally, we will present preliminary results on another virtual heights model that predicts the difference between consecutive ionograms using geophysical parameters and current virtual heights.

Georgios Balasis

Machine Learning Techniques for Automated ULF Wave Recognition in Swarm Time Series

Machine learning (ML) techniques have been successfully introduced in the fields of Space Physics and Space Weather, yielding highly promising results in modeling and predicting many disparate aspects of geospace. Magnetospheric ultra-low frequency (ULF) waves play a key role in the dynamics of the near-Earth electromagnetic environment and, therefore, their importance in Space Weather studies is indisputable. Magnetic field measurements from recent multi-satellite missions are currently advancing our knowledge on the physics of ULF waves. In particular, Swarm satellites have contributed to the expansion of data availability in the topside ionosphere, stimulating much recent progress in this area. Coupled with the new successful developments in artificial intelligence, we are now able to use more robust approaches for automated ULF wave identification and classification. Here, we present results employing various neural networks (NNs) methods (e.g. Fuzzy Artificial Neural Networks, Convolutional Neural Networks) in order to detect ULF waves in the time series of low-Earth orbit (LEO) satellites. The outputs of the methods are compared against other ML classifiers (e.g. k-Nearest Neighbors (kNN), Support Vector Machines (SVM)), showing a clear dominance of the NNs in successfully classifying wave events.

Shanshan Bao

A gray-box approach in modeling atmospheric precipitation in global geospace models

Atmospheric precipitation plays an important role in the magnetosphere-ionosphere-thermosphere (M-I-T) coupling. The magnetospheric electrons resonate with various types of plasma waves, such as the whistler mode chorus waves, the hiss waves and the electron cyclotron harmonic (ECH) waves. Their pitch angles are altered by the wave-particle resonance which leads to variations in particle lifetime as they are scattered into the loss cone. The electron precipitation alters the thermospheric ionization rate, affects the ionospheric conductivities and causes multiscale responses in the M-I-T system. In this study, we implement a gray-box approach to model the atmospheric precipitation in a fully coupled global geospace model, Multiscale Atmosphere-Geospace Environment (MAGE). This approach combines statistics-based wave-induced electron loss models and the physics-based particle precipitation module inside the ring current model of MAGE, the Rice Convection Model (RCM). The electron loss models are parameterized by the geomagnetic activity levels, the magnetospheric equatorial locations and the particle energies. The RCM tracks the equatorial trajectory and energy of the inner magnetospheric drifting particles and constantly refer to the electron loss model for electron lifetime. In unit time, the differential number flux of electron precipitation at different energies is decided jointly by the electron spatial distribution and the statistical occurrence and amplitude of the related waves. We derive the precipitation energy spectrum and conduct cross-model comparisons among different statistical models and model-data comparisons with the DMSP observations. We also explore the geospatial consequences caused by the wave-driven precipitation using the fully coupled M-I-T model.

Elena G Broock

Farnet-II: application of Convolutional LSTM and attention mechanisms to solar far-side activity detection

Far-side helioseismology is the branch of astrophysics dedicated to inferring the activity on the far hemisphere of the Sun using the wave-field from the near-side surface. Recently, the neural network FarNet, with a U-net architecture widely used for semantic segmentation, has been proven to improve the activity predictions of phase-sensitive holography, the standard method for applying far-side helioseismology. This was achieved using as inputs temporal sequences of nearside phase-shift maps. The network returned far-side activity probability maps for the central date of each input.We have developed FarNet-II, a new network that expands the capacities of FarNet by adding Convolutional LSTM modules and attention mechanisms to the model. This new tool uses the same phase-shift maps as inputs but returns one activity probability map for each image date on the input sequence. We found that the prediction capabilities are greatly improved with respect to FarNet. Also, the outputs of this network keep better temporal coherence among them than those obtained with FarNet. Improved predictions from FarNet-II can contribute to a great number of applications on space weather, such as spectral irradiance and solar wind forecasting.

Dattaraj B Dhuri

Deep learning reconstruction of sunspot vector magnetic fields for forecasting solar storms

Solar magnetic activity produces extreme solar flares and coronal mass ejections, which pose grave threats to electronic infrastructure and can significantly disrupt economic activity. It is therefore important to appreciate the triggers of explosive solar activity and develop reliable space-weather forecasting. Photospheric vector-magnetic-field data capture sunspot magnetic-field complexity and can therefore improve the quality of space-weather prediction. However, state-of-the-art vector-field observations are consistently only available from Solar Dynamics Observatory/Helioseismic and Magnetic Imager (SDO/HMI) since 2010, with most other current and past missions such as Global Oscillations Network Group (GONG) only recording line-of-sight (LOS) fields. Here, using an inception-based convolutional neural network, we reconstruct HMI sunspot vector-field features from LOS magnetograms of HMI as well as GONG with high fidelity 90% correlation and sustained flare-forecasting accuracy. We rebuild vector-field features during the 2003 Halloween storms, for which only LOS-field observations are available, and the CNN-estimated electric-current-helicity accurately captures the observed rotation of the associated sunspot prior to the extreme flares, showing a striking increase. Our study thus paves the way for reconstructing three solar cycles worth of vector-field data from past LOS measurements, which are of great utility in improving space-weather forecasting models and gaining new insights about solar activity.

Jonathan Donzallaz

SolarNet: Solar Flares Prediction with Self-Supervised Learning

Solar flares release a huge amount of energy. In the worst case, they can affect the Earth. Predicting these events is therefore of major importance.A significant effort in the community strives to address this problem by applying machine learning algorithms. This work focuses on a new deep learning method called self-supervised learning (SSL). The method has two steps. First, networks are pre-trained on auxiliary synthetic tasks, exploiting large sets of unlabeled images to learn patterns and structures. Second, the networks are fine-tuned on the targeted “downstream” task using labeled data. We show here that SSL applies well to solar data and to solar flares forecasting that benefits from the pre-training phase of this method.For this work, a curated dataset is processed and refined for SSL and solar flares prediction. Another dataset called SDO-Benchmark is used for benchmarking.Our findings are summarized as follows: (1) SSL is applied to solar images following a contrastive approach taken from the SimCLR framework and proves to learn a good representation of the data. (2) A dataset is prepared and is now available for many tasks, including SSL pre-training and flares classification. (3) A library resulting from this work shows exemplary reproducibility ability and permits the use of the pre-trained models.By combining these findings, a classifier fine-tuned using the SSL model on the SDO-Benchmark dataset achieves a True-Skill-Score (TSS) of 0.646 on binary classification (detecting ≥C-class flares in a 24 h period), while operational forecasting reaches TSS of 0.446 on the same task. The encoder trained using the SSL method provides a good and valuable representation of the input. It could be used as a feature extractor for many downstream tasks with low constraints on the amount of data, time, and processing power.

Marius Giger

Unsupervised event detection in heliophysics

Deep learning has seen a lot of success in so many fields because of its ability to learn strong feature representations without the need for hand-crafted features, generating models with a high representational power. However, many of these models are based on supervised learning and therefore depend on the availability of large annotated datasets, which are often difficult to obtain because they require human input. A general challenge for researchers in the heliophysics domain is the sparsity of annotations in a lot of the datasets that are available which are either unlabelled or the labels are inconclusive (missing or incomplete labels, unclear quality of labels, labels reported by different data sources). In order to alleviate the data bottleneck of unannotated datasets, unsupervised deep learning has become an important strategy, with anomaly detection as one of its most prominent applications. Unsupervised models have been successfully applied in various domains, such as medial imaging or video surveillance, to distinguish normal from abnormal data. In our work, we investigate how a purely unsupervised approach can be used to detect and track solar phenomena in SDO AIA images. We have successfully applied a Variational Autoencoder (VAE) to detect out-of-distribution samples and localize interesting regions in order to detect solar activity. Our current work brings in a Self-Supervised Learning (SSL) approach, including the application of the "Cutpaste" method that first learns a self-supervised representation of the data, then builds a one-class classifier on learned representations to distinguish data with anomalous patterns from normal ones. By using an unsupervised approach, we hope to contribute to the tools for space weather monitoring and to a better understanding of the drivers of space weather.

Andong Hu

Innovative Dst predictions using neural networks

We present two innovative prediction models for the Disturbance storm time (Dst) geomagnetic index: 1) a long lead-time model (between 1 and 3 days) that estimates what is the probability that the Dst index will exceed a value of -100 nT; and 2) a short lead-time model (between 1 and 6 hours) that predicts the value of Dst, with associated uncertainty.The Dst probability model is developed using an ensemble of Convolutional Neural Networks (CNNs) that are trained using SoHO images (MDI, EIT and LASCO). This work also presents a novel methodology to train the individual models and to learn the optimal ensemble weights iteratively, by using a customized class-balanced mean square error (CB-MSE) loss function. The proposed model can predict the probability that Dst<-100nT 24 hours ahead with a True Skill Statistic (TSS) of 0.62 and Matthews Correlation Coefficient (MCC) of 0.37. The alternative weighted TSS and MCC (see Guastavino et al., 2021) are 0.68 and 0.47, respectively.The Dst index model takes advantage of a combination of Gated Recurrent Unit (GRU) recurrent neural networks and Kalman fiter assimilative models, by exploiting the novel ACCRUE method for predicting uncertainties (Camporeale, 2021). The developed model can predict the Dst 6 hours ahead with a RMSE of 15 nT and Matthews Correlation Coefficient (MCC) of 0.60 with a threshold of -100nT. The Shapley Additive Explanation (SHAP) method is also used to interpret the importance of each variable.

Cedric Huwyler

Using Multiple Instance Learning for Explainable Flare Prediction

In this work we leverage a weakly-labeled dataset of spectral data from NASA's IRIS satellite for the prediction of solar flares using the Multiple Instance Learning (MIL) paradigm. While standard supervised learning models expect a label for every instance, MIL relaxes this and only considers bags of instances to be labeled. This is ideally suited for flare prediction with IRIS data that consists of time series of bags of UV spectra measured along the instrument slit. In particular, we consider the readout window around the Mg II k/h lines that encodes information on the dynamics of the solar chromosphere. Given labels at the bag-level, our MIL models are not only able to predict whether flares occur within the next 25 minutes but are also able to explain which spectral profiles from a bag were particularly important for their bag-level prediction. This information can be used to highlight regions of interest in ongoing IRIS observations in real-time and to identify candidates for typical flare precursor spectral profiles. We use k-means clustering to extract groups of spectral profiles that appear relevant for flare prediction and identify similar groups as previous works, albeit using a very different approach. We advocate MIL as an easy way to add explainability to machine learning models and suggest to apply it also to solar data in the image domain.

Robert Jarolim

Probing the coronal magnetic field with physics informed neural networks

While the photospheric magnetic field of our Sun is routinely measured, its extent into the upper solar atmosphere (the corona) remains elusive. Extrapolation and simulation methods are therefore used to provide an estimation of the three-dimensional distribution of the coronal magnetic field, which is essential to understand the genesis and initiation of solar eruptions, and to finally successfully predict the occurrence of high-energy events from our Sun.In this study, we present a novel approach for coronal magnetic field extrapolation using physics informed neural networks. We train our neural network to predict the magnetic field vector for a given input coordinate, such that our model acts as representation of the simulation volume. The neural network is optimized to match SDO/HMI data of the photospheric magnetic field vector at the bottom boundary, and to simultaneously satisfy the force-free and divergence-free equations in the entire simulation volume. We demonstrate that our method can be directly applied to noisy input data, can account for error uncertainties and is able to find a suitable trade-off between the boundary-condition and the force-free magnetic field assumption.We utilize meta-learning concepts to simulate the evolution of an active region magnetic field during 5 days of observations at full cadence (720 s), requiring less than 10 hours computation time. A systematic comparison with a state-of-the-art coronal field extrapolation method, the derived evolution of the free magnetic energy and helicity in the active region, as well as comparison to EUV observations demonstrates the validity of our approach. Our method excels over existing methods as estimated by standard metrics and largely improves the computation time, allowing for close to real-time magnetic field simulations. The flexibility in terms of data and the possibility of extending the underlying physical model, offers great potential for the field of magnetic field simulations.

Sahib Julka

An active learning approach for automatic detection of bow shock and magnetopause crossing signatures in Mercury's magnetosphere using MESSENGER magnetometer observations.

Accurate and timely detection of bow shock and magnetopause crossings has significant utility for instrument parameter adjustment and understanding the dynamics of these events. However due to the variable nature of Mercury’s magnetosphere owing to a weak internal magnetic field, and close proximity to the sun, it is a rather challenging task. Existing approaches based on geometric equations are hard to generalise to changing environments. On the other hand, data-driven methods require large amounts of annotated data to account for variations, which can get costly quite fast. We introduce an approach based on active learning that includes only the most informative orbits from the MESSENGER dataset measured by a criterion from information theory. This greatly reduces the need for manual labelling. We report our best model- a CRNN with 1D Convolutions followed by LSTM cells- can account for most uncertainty by only training on just two Hermean years worth of data, which is less than 10% of the total dataset. The model achieves a macro F1 score of 0.81 and 78% and 87% accuracy on the bow shock and magnetopause crossings respectively. Further, in this work we discuss a set of general approaches for the task and highlight the merits and demerits of each. This work may be relevant to future research during the BepiColombo mission which is expected to enter orbit around Mercury in December 2025.

Michael S. Kirk

The Center for HelioAnalytics

HelioAnalytics is the cross-disciplinary convergence of communities of physicists, statisticians, and computer scientists. It is intended to foster research into advanced methodologies for heliophysical research, and to promulgate such methods into the broader community. NASA Goddard's Center for HelioAnalytics establishes an “expert group” to focus on topics such as machine learning, neural networks, AI, and data analytics to expand the discovery potential for key heliophysics research topics and missions. This goes far beyond simple data analysis; by harnessing data science capabilities and applying them to our core mission, we can design future missions and projects that exceed traditional limits.

Delores J Knipp

Geophysical interpretations from machine learning superstorm signature identification in satellite precipitating particle data

Presently space weather forecasters convey information about geomagnetic storm strength to the public via geomagnetic indices, such as the Kp index. Many space weather enthusiasts have leaned toward descriptions of storm strength in terms of auroral visibility and auroral boundaries. Researchers have developed an affinity for the Disturbance storm time (Dst Index) and/or the Equatorward Auroral Boundary Index. Our project is looking for the physical changes in flux and energy in auroral particle precipitation that can help us to understand how these indices and boundaries are linked, and further to understand whether extreme storms drive the ‘system dynamics’ into a different state during superstorms. In this presentation we will show and interpret the Defense Meteorological Satellite Program auroral particle variations extracted from a machine-learning-ready data set and unsupervised machine learning anomaly detection methods (Marlowe et al. this conference). Of particular interest is the source and influence of a population of low-energy ions that are rarely monitored. We will present examples from the extreme storms of October and November 2003 and the severe event of December 2006 and compare them to times of ‘fair’ space weather and geomagnetic indices.

Xiaoyue Li

Transfer-Solar-GAN: Generation of Input Sources for Solar Wind Models with Deep Learning

The state-of-the-art heliospheric model EUHFORIA (European Heliospheric Forecasting Information Asset, Pomoell and Poedts 2018), which models the solar wind conditions in the inner heliosphere and the propagation of solar eruptions, is initialized exclusively with magnetogram synoptic maps. However, magnetograms are complex observations available from only a limited number of sources. In this study, we use conditional Generative Adversarial Networks (cGAN) and propose a method called ‘Transfer-Solar-GAN’, where the cGAN algorithm is used together with transfer learning theory to provide magnetograms from the EUV images. The aim of the study is to use such AI-magnetograms as input sources for EUHFORIA. For data preparation, we generate series of AIA synoptic maps with 27-consecutive-day AIA full-sun images and synchronize them with GONG synoptic maps.To assess the quality of these AI-generated magnetograms for further scientific studies, we use both AI-generated and GONG synoptic magnetogram as input to EUHFORIA and compare the output results in terms of solar wind parameter values.Pomoell, J.; Poedts, S. EUHFORIA: European heliospheric forecasting information asset. J. Space Weather. Space Clim. 2018, 8, A35.doi:10.1051/swsc/2018020

Allison Liu

Data Augmentation of Magnetograms for Solar Flare Prediction using GANs

Space weather forecasting remains a national priority in the United States due to the impacts of events like solar flares to life on Earth. High energy bursts of radiation originating from solar flares have the potential to disrupt critical infrastructure systems, including the power grid and GPS and radio communications. The rise of machine learning and the development of more advanced instruments has greatly improved solar flare prediction models over the past decade. However, the magnetogram data used for solar flare forecasting—taken by the Solar and Heliospheric Observatory/Michelson Doppler Interferometer (SOHO/MDI) and the NASA Solar Dynamic Observatory/Helioseismic and Magnetic Imager (SDO/HMI) instruments—are incompatible due to differences in the cadence, resolution, and size of the data. Furthermore, many studies only focus on data from a single instrument which disregards decades worth of potential training data that is necessary to understand solar cycles. In this work, we show Generative Adversarial Networks (GANs) can be used to super-resolve the historic lower-quality SOHO/MDI data set to match SDO/HMI quality to create a standardized magnetogram data set. The implementation of a Pix2Pix GAN produced some undesirable artifacts due to mode collapse, while image translation methods CycleGAN and CUT preserved solar features present in the data more accurately in the absence of paired data. The resulting combined, higher-quality data set will be used to improve the predictive power of current solar flare forecasting models.

Simon Mackovjak

Towards explanation of airglow variation by ML techniques

The Earth's upper atmosphere acts as an interface between processes in space and on Earth. It is a very dynamic environment continuously influenced by solar radiation and space weather from above and by atmospheric weather and electrical discharges from below. To describe processes in this interface environment is a very challenging task that requires consideration of a very wide range of phenomena. To overcome this challenge, we have developed a data-driven approach based on state-of-the-art machine learning techniques to model important thermosphere-ionosphere characteristic - airglow radiation (Mackovjak et al., 2021a). We realized that this data-driven approach might be even more precise if we involve additional information that are not commonly available. For this reason, we have developed SCSS-net - one of the most precise model for solar corona structures segmentation based on deep neural networks (Mackovjak et al., 2021b) that allow automatic characterization of solar activity with high temporal and spatial resolution. We have also developed a deep learning approach for automatic detection of tweek atmospherics (Maslej-Krešňáková et al., 2021) and a system for autonomous detection of TLE's (Amrich et al., 2021), generated by lightning strikes, that provide additional information about the state of the lower ionosphere. The main points of all these results will be presented and new ongoing challenges will be discussed.- Mackovjak et al.: 2021a, JGR Space Phys., 126, 3, https://doi.org/10.1029/2020JA028991- Mackovjak et al.: 2021b, Mon. Not. R. Astron. Soc., 508, 3, https://doi.org/10.1093/mnras/stab2536- Maslej-Krešňáková et al.: 2021, Earth Space Sci., 8, 11, https://doi.org/10.1029/2021EA002007- Amrich et al.: 2021, J. Instrum, 16, T12016, https://doi.org/10.1088/1748-0221/16/12/T12016

Hannah R Marlowe

An unsupervised learning approach to superstorm signature identification in precipitating particle data

The Defense Meteorological Satellite Program (DMSP) SSJ precipitating particle instrument measures in-situ total flux and energy distribution of low-to-medium energy electrons and ions at low earth orbit. These precipitating particles produce aurora during normal and very strong geomagnetic storms. Recently under NASA sponsorship, several years of DMSP particle data were reprocessed to remove radiation belt contamination and then re-archived at NASA CDAWeb. We present an investigation of the drivers and emergent signals of solar-geomagnetic superstorm events using unsupervised machine learning (ML) approaches to identify both anomalous detector performance and extreme geophysical events in the data. We additionally describe a data processing workflow leveraging publicly available data, open-source Python libraries, and cloud computing resources to prepare SSJ data for use in ML model training. We discuss preparation of a an ML-ready data set, modeling considerations, results, and interpretations related to superstorm categorization.

Mohamed Nedal

Forecasting the Solar Energetic Protons Integral Flux using the Bi-Directional Long Short-Term Memory Neural Network

Estimating the Solar Energetic Protons (SEP) flux is crucial to anticipate the behavior of the near-Earth space environment, in order to protect assets in space. Recently, Artificial Neural Networks (ANN) have become very widely used in several scientific fields, including space weather nowcasting and forecasting, due to the availability of big data and the emergence of faster computational machines. In this work, we take advantage of utilizing deep learning methods and develop a Bi-Directional Long-Short Term Memory (BiLSTM) model in order to make long-term and short-term forecasting of the SEP integral flux at 1 AU, in 3 energy channels (>10 MeV, >30 MeV, and >60 MeV). For long-term forecasting, we use daily-averaged data to make a 3-day, 5-day, and 7-day forecasting. For short-term forecasting, we use hourly-averaged data to make 6-hour, 12-hour, and 24-hour forecasting for the SEP fluxes.The input features are the sunspot number and the F10.7 index obtained from the OMNI database; the soft and hard X-ray fluxes obtained from the GOES database, all for the past four solar cycles (from 1976 to 2019). We found that the Mean-Squared Errors (MSE) of the SEP integral fluxes are ranging between 0.009 - 0.382 for the daily-averaged data, and between 0.001 - 0.618 for the hourly-averaged data. The error values might get lower after performing more tuning for the model hyperparameters. The input horizon is fixed to 2 years for long-term forecasting, 1 month for short-term forecasting. We found that the prediction uncertainty for the SEP integral flux at >10 MeV increases as the output horizon increases, as is expected. However, the opposite is reported for the SEP fluxes at >30 MeV and >60 MeV, which is interesting. We will extend the model to forecast the SEP spectra in the long and short terms and compare them with previous works.

Daniel I Okoh

Results from a 3-D electron density model developed from COSMIC radio occultation data using artificial neural networks

A 3-D electron density model is developed from COSMIC radio occultation electron density profiles. Motivation for this work is based on the fact that the COSMIC radio occultation electron density profiles usually smear over wide range latitudes/longitudes, and so they are not precise representations of vertical electron density profiles for particular locations as often approximated in many research. Artificial neural networks are trained to learn 3-D ionospheric electron density distribution from numerous COSMIC radio occultation profiles. From the developed model, vertical electron density profiles that compare well with ionosonde vertical profiles are derived. Additional advantages for the developed model are that the COSMIC profiles used for the model development include topside measurements that reach about 800 km, and they also have good spatial coverage. Results from the developed model also enhance our understanding of phenomena like the equatorial ionization anomaly in 3-D space.

Vivian Otugo

Estimation of ionospheric critical plasma frequencies from GNSS-TEC measurements using artificial neural networks

The study describes a new neural network-based approach to estimate ionospheric critical plasma frequencies (f0F2) from GNSS-VTEC (Global Navigation Satellite System – Vertical Total Electron Content) measurements. The motivation for this work is to provide a method that is realistic and accurate for using GNSS receivers (which are far more commonly available than ionosondes) to acquire f0F2 data. Neural networks were employed to train VTEC and corresponding f0F2observations respectively obtained from closely located GNSS receivers and ionosondes in various parts of the globe. Available data from 52 pair of ionosonde-GNSS receiver stations for the 17-year period from 2000 to 2016 were used. Results from this work indicate that the relationship between f0F2 and TEC is mostly affected by the seasons, followed by the level of solar activity, and then the local time. Geomagnetic activity was the least significant of the factors investigated. The relationship betweenf0F2 and TEC was also shown to exhibit spatial variation; the variation is less conspicuous for closely located stations. The results also show that there is a good correlation between the f0F2 and TEC parameters. The analysis of errors show that the model developed in this work (known as the NNT2F2 model) can be used to estimate the f0F2 from GNSS TEC measurements with accuracies of less than 1 MHz. The new approach described in this paper to obtain f0F2 based on GNSS TEC data represents an important contribution in space weather prediction.

Ramiz A. Qudsi

Algorithm Development for Magnetic Field topology Reconstruction in a 3-D Simulation Box Using Machine Learning

At present we cannot image full structure of the interplanetary magnetic field using a few spacecraft. However, constellations with larger and larger number of spacecraft are becoming increasingly common with several possible missions to be launched in near future. Thus with a view towards the future, we carried out a study to reconstruct the 3-D topology and morphology of the interplanetary magnetic field from observations made by such a constellation with finite number of spacecraft. Using Gaussian Processes in machine learning for different configurations of number and arrangement of spacecraft, we showed that we need a baseline of 24 spacecraft to successfully carry out such a process. A complete 3-D image of the magnetic field will significantly advance our understanding of turbulence in space plasmas and shed light on the exact process of turbulence cascade. We also report on the change of quality of reconstructed images for different number of spacecraft and configuration.

Mikhail Sitnov

Resolving the geomagnetic tail current sheet structure with data mining

Earth’s magnetotail is the main reservoir where the energy of the solar wind-magnetosphere interaction is accumulated in the form of the stretched magnetic field and then suddenly released by its dipolarization during substorms. Substorms together with steady magnetospheric convection power magnetic storms in the inner magnetosphere and thus directly affect key space weather phenomena. The sharply stretched magnetic field configuration is provided by the tail current sheet whose structure and stability determine storm and substorm energetics. Deriving its properties from data is very challenging because its in-situ observations at any moment of time are available only in a few points. However, the recurring nature of storms and substorms allows one to mine data from similar phases of other storms and substorms to form large swarms of synthetic data. Here we mine data in a quarter century-long archive of spaceborne magnetometer observations from many missions to resolve the tail current sheet structure. Specifically, we determine if the thick current sheet has a substructure on the scale of the ion gyroradius and how that thin current sheet looks in space and evolves in time. Resolving this multiscale current structure is important because it determines the stability of the tail with respect to dipolarizations, the location of the latter and the underlying magnetic reconnection in the tail. It is also important to build the plasma models of the tail current sheets and in particular to distinguish between isotropic, anisotropic and agyrotropic plasma models.

Andrew Smith

Producing ML-driven Real-Time Forecasts of the Probability of Large Rates of Change of the Surface Magnetic Field in the UK

Rapid changes in the surface geomagnetic field can induce potentially damaging currents in conductors on the ground; this is a critical consideration for the operation of power networks and pipelines. Forecasting intervals when there may be a risk of large induced currents would enable mitigating action to be taken. Several physical drivers of such field variability exist, including solar wind pressure pulses, geomagnetic storms and substorms. These phenomena are complex but are ultimately driven by the coupling and interaction of the magnetosphere with the solar wind. In the context of space weather, this coupling may be typically forecast via observations of the upstream solar wind conditions measured at the L1 point. However, this data, particularly that available in near-real-time, can include critical data gaps or erroneous values.We test the ability of several distinct machine learning model architectures (including convolutional and recurrent neural networks) to skilfully process the time history of the solar wind and provide a probabilistic forecast as to whether the rate of change of the ground magnetic field will exceed specific, high thresholds in the UK. We assess the volume of historical values that the models require to produce skilful forecasts, as well as the time horizon with which the forecasts can be made. Further, we test the validity and continuity of the data that are available in near-real-time from the solar wind monitors at L1, and examine how the use of the science or real-time data sets impacts model performance.

Oleg V Stepanyuk

Advanced Image Preprocessing and Feature Tracking for Remote CME Characterization with Deep Learning

Coronal Mass Ejections (CMEs) influence the interplanetary environment over vast distances in the solar system by injecting huge clouds of fast solar plasma and energetic particles (SEPs). A number of fundamental questions remain about how SEPs are produced, but current understanding points to CME-driven shocks and compressions in the solar corona. At the same time, unprecedented remote (AIA, LOFAR, MWA) and in situ (Parker Solar Probe, Solar Orbiter) solar observations are becoming available to constrain existing theories.One of the goals of MOSAIICS project under the VIHREN programme is to develop a suite of Python tools to reliably analyze radio and EUV remote imaging observations of CMEs and shock waves. Technically, these problems mainly involve application of image segmentation and feature tracking methods. The data-driven approach with pre-trained convolutional neural network (CNN) models is a widely used approach for such class of tasks; nevertheless, reliable training sets for classification, segmentation and tracking of CME-related phenomena with CNN models are missing.Recently (Stepanyuk et.al, "Multi-scale Image Preprocessing and Feature Tracking for Remote CME Characterization", Journal of Space Weather and Space Climate, submitted), we have demonstrated the method and the software (https://gitlab.com/iahelio/mosaiics/wavetrack) for smart characterization and tracking of solar eruptive features, based on the a-trous wavelet decomposition technique, intensity rankings and a set of filtering techniques. Here we present the natural extension of that work by using feature masks produced by Wavetrack software for training of CNN models. We demonstrate data-driven characterization and tracking of solar eruptive features on a set of CME-event related datasets obtained from SDO/AIA telescope.

Sophie Teichmann

Influence of solar wind parameters on unsupervised solar wind classification

The properties of the solar wind depend on the conditions in therespective solar source region. In addition,some properties of the solar wind are changed by transporteffects. While the charge distributions are reasonably assumed to befrozen-in already in the solar corona, other parameters change due tothe expansion of the solar wind and due to interaction at solar windstream boundaries. Other transport effects, i.e. wave-particleinteractions and collisions, are relevant for some but not all typesof solar wind. Thus, solar wind parameters measured at 1 AU withinstruments on the Advanced Composition Explorer (ACE) alwaysrepresent a varying mixture of signatures of the solar source regionand transport effects. Consequently, if in situ solar windobservations are presented to an unsupervised learning method, thismethod would not disentangle the respective solar origins anddifferent transport histories but detect solar wind types that are amixture of both. Therefore, the emerging number of solar wind types isexpected to be larger than the number of solar wind types withdifferent solar origin.However, the ability of a machine learning method to differentiatebetween solar wind types crucially depends on the selection of inputfeatures. Here, we study the influence of different solar windparameters on the results of a clustering obtained by k-means forvarying values of k. To this end, the similarity of the resultingclustering is compared for all combinations of proton speed, protondensity, proton temperature, proton-proton collisional age, magneticfield strength, mean Fe charge state, and O7+/O6+ charge stateratio. We found that the most important parameters are proton densityand proton temperature. The relevance of charge state information(O7+/O6+ charge state ratio or mean Fe charge state) dependssensitively on the choice of k for the k-means clustering.

Panagiotis Tigas

Global geomagnetic perturbation forecasting using deep learning

Geomagnetically induced currents (GICs), which result due to the interaction of the solar wind with Earth's magnetosphere, can result in devastating consequences for our technology-driven society. Due to a lack of openly available GIC data, the time variation of the horizontal component of the ground magnetic field perturbations is used as a proxy. Forecasting these perturbations at high spatial resolution, temporal cadence, and large forecast horizon across the whole Earth is necessary for effective mitigation against the effects of GICs. In this work, we develop a grid-free global perturbation forecasting model using deep learning. The model considers 120 minutes of solar wind measurements and generates forecasts of perturbations across the whole Earth 30 minutes after the latest input. The model is made grid-free by a spherical harmonic formulation, while the mapping from solar wind to perturbations is performed using Gated Recurrent Units (GRU). On a held-out test set, the model clearly outperforms the state-of-practice low cadence global model of Weimer (2013), and shows consistent performance with a perturbation persistence of 30 minutes. Furthermore, the model outperforms the model of Weimer (2013) for both 2011 and 2015 benchmark storm data, while it outperforms the persistence scheme for the 2011 storm dataset alone. We also find that our model clearly outperforms or shows consistent performance for the Ottawa station when compared with the deep learning-based high time cadence local model of Keese+ (2020). Thus, our model combines the best of both the worlds of global high spatial resolution forecasts with high time cadence models. Such quick inferences hence may ultimately enable accurate forewarning of GICs for any place on Earth, enabling precautionary measures to be taken in an informed manner.

Benoit Tremblay

Emulation of MHD simulations to Infer Flows in Granulation, Sunspots, and Active Regions

Knowledge of flows in the solar photosphere is important for understanding aspects of solar physics, such as the transport of magnetic energy from the solar surface to the solar atmosphere where it can be released in the form of space weather events. Flows are also needed to derive realistic boundary conditions for data-driven simulations of the atmosphere necessary for studying these events. Finally, it's been suggested that flow patterns are signatures of the pre-emergence of active regions (ARs). While line-of-sight velocities are routinely derived from observational data, it is far less common for transverse velocities. Methods to infer transverse flows from surface observations include physics-based methods, which rely on magnetograms and Dopplergrams and solve the induction equation for velocities in ARs, and tracking methods, which measure optical flows from magnetograms in ARs and intensitygrams in the Quiet Sun. We trained convolutional neural networks using data from MHD models of the Sun’s photosphere to create a mapping function between observables of the surface (intensitygrams, magnetograms, Dopplergrams) and the depth-dependent transverse velocity vector which is known in this case. Through supervised learning, the neural network tries to emulate the transverse flows from the training simulation. In application, it approximates what would be the flows in the training simulation if the input data were generated by the training simulation. We discuss examples including application to Quiet Sun data, the generalization to sunspots and active regions, and the challenges associated with the application to observational data.

Sergio Vidal-Luengo

Whistler-mode Waves and Relativistic Precipitation Event Detection by Employing Self-Organizing-Maps

The Earth’s outer Van Allen Belt is mainly composed of trapped relativistic electrons (>1 MeV) with gyrofrequency between [1-5] kHz. This frequency range is similar to the whistler-mode chorus waves commonly observed also in the outer Van Allen Belt. The similarity in their frequency suggests an interaction and transfer of energy between the electrons and the waves. This wave-particle interaction can result in the change of the pitch angle of the relativistic electrons and is likely to be responsible for the Relativistic Electron Precipitation (REP) events observed by low orbit spacecraft at similar L-shell values, but the conditions required to trigger REP events are still unknown. REP events are especially important as they can rapidly deplete the electron content of the outer radiation belt towards the upper atmosphere. Currently there are several years of spacecraft data available for the study of the relation between whistler-mode waves on the radiation belts and REP at low orbit. However, the detection of events of interest is overly complex and cannot be automatically performed using codes that search for specific characteristics in the data as they arbitrarily discard observations that may not fit under pre-established conditions. Limiting the benefit of having a large number of observations available. In this study, we use an unsupervised machine learning technique called Self-Organizing-Maps (SOM) that has already been tested for the purpose of unsupervised classification of waves in the magnetosphere. This technique is used to reduce the dimensionality of a data set while preserving their topological structure. The resulting product will be a 2D map that allows an easier classification of the observations for both whistler-mode waves, and REP events. The classified events can then be compared to help with the determination of which conditions give rise to REP events.

Kiera van der Sande

Comparing Solar Flare Irradiance in GOES X-ray and SDO/AIA EUV Data via Machine Learning Regression

There is growing interest in using ultraviolet and extreme ultraviolet images from instruments such as SDO/AIA for solar flare prediction as these images may reveal more features associated with flaring than the photospheric magnetic field data that has been primarily used to date. Along the way to developing a probabilistic solar flare forecast using these data, we seek to understand how to define flaring activity given only AIA data, and how well this correlates to the GOES full-disk X-ray measurements. Currently, solar flare magnitudes are based on the peak full-disk X-ray intensity over the flaring event, as measured by the GOES satellite. This is a single-pixel spectral irradiance measurement, which means that there is no spatial data. Instead, human forecasters are tasked with labeling the active region on the sun associated with the flare, adding potential for errors since at least two separate observational systems are required. We have encountered mismatches between GOES peak and AIA peak timing, issues with active region cutouts and flare catalog errors. Furthermore, how to define the peak flaring time in AIA data is nontrivial as it does not necessarily align with the GOES X-ray data. We show correlation between X-ray intensity and AIA image cutouts of solar active regions for large M and X class flares by using scalar features extracted from the images and an extremely randomized trees regression model. This could be useful for verifying flare active region labels. We further study the correspondence between flare start and end times obtained from GOES flare catalogs and flare timing in various AIA wavelengths. We hope that this investigation will lay the groundwork for improved usage of AIA data for machine learning based flare prediction.

Talwinder Singh
Improving the Arrival Time Prediction of Coronal Mass Ejections using Magnetohydrodynamic Ensemble Modeling, Heliospheric Imager data and Machine Learning
Coronal mass ejections (CMEs) are responsible for extreme space weather which has many undesirable consequences to our several space-based activities. The arrival time prediction of CMEs is an area of active research. Many methods with varying levels of complexity have been developed to predict CME arrival. However, the mean absolute error in the predictions have remained above 12 hours even with the best methods. In this work, we develop a method for CME arrival time prediction that uses magnetohydrodynamic simulations of a data constrained flux rope-based CME model which is introduced in a data driven solar wind background. We found that for 6 CMEs studied in this work, the mean absolute error in arrival time was 8 hours. We further improved the arrival time predictions by using ensemble modeling and comparing the ensembles with STEREO A and B heliospheric imager data by creating synthetic J-maps from our simulations. A machine learning method called lasso regression was used for this comparison. Our mean absolute error was reduced to 4.1 hours after using this method. This is a significant improvement in the CME arrival time prediction. Thus, our work highlights the importance of using machine learning techniques in combination of other models for improving space weather predictions.

Sai Gowtam Valluri
An Artificial Neural Network-based global three-dimensional ionospheric electron density model: present state, challenges, and future directions
The vertical electron density (Ne) information is crucial for the ever-increasing satellite-based communication and navigation applications. During extreme space weather events, the ionospheric Ne show dramatic changes, causing large errors in communication and navigation. For accurately predicting the vertical Ne profiles, a new global three-dimensional ionospheric electron density model is developed by using artificial neural networks (ANNIM-3D) with nearly two decades of ionospheric observations from the ground-based Digisonde (GIRO-Digisonde network), the satellite-based topside sounders (TOPIST), and the global positioning system radio occultation (CHAMP, GRACE and COSMIC-1) measurements. The vertical Ne profiles derived from the ANNIM-3D are found to be consistent with the ground-based incoherent scatter radar observations at Jicamarca and Millstone Hill. The model results have been thoroughly validated and showed good agreement with the ground-based Digisonde and satellite in situ observations at different altitudes. This model successfully reproduces the large-scale ionospheric phenomena like diurnal and seasonal variations of equatorial ionization anomaly and its hemispheric asymmetries, annual anomaly, and the main ionospheric trough. Further, the ANNIM-3D is also tested under severe space weather

conditions (Kp>6). The model could qualitatively predict the ionospheric disturbances due to disturbed geomagnetic conditions that are consistent with the Joule heating and meridional wind circulation. In the presentation, the merits and the limitations of this model will be thoroughly discussed. Finally, under the Machine-learning Algorithms for Geomagnetic Induced Currents in Alaska and New Hampshire (MAGICIAN) project, ANNIM-3D will be further improved towards the real-time prediction, now-cast, and the forecast of the vertical Ne profiles by combining the deep learning and the data assimilation techniques will also be discussed.

Simon Wing

Modeling radiation belt electrons with information theory informed neural networks

An empirical model of radiation belt electrons is developed. The model inputs the solar wind and magnetospheric parameters and outputs radiation belt electron phase space density (PSD). The empirical model consists of two parts: information theory module at the front end and neural networks at the backend. The process of selecting input parameters is complex. Many solar wind and magnetospheric parameters are correlated or anticorrelated with one another, making it difficult to determine which parameters would carry relevant and which would carry redundant information. Information theory is used to determine the relevant input parameters and their response lag times. For example, the solar wind density (nsw) negatively correlates with electron phase space density (PSD) (averaged energy ~ 1.5 MeV) with time lag (🔀) = 15 hr, but when the effect of solar wind velocity (Vsw) is removed, 🔀 shifts to 7–11 hr, which is a more accurate time scale for the radiation belt electron loss process. The peak correlation between Vsw and PSD shifts from 🔀 = 38 hr to 46 hr, when the effect of nsw is removed. This suggests that the time scale for electron acceleration to 1–2 MeV is about 46 hr following Vsw enhancements. The effect of nsw is significant only at L* = 4.5–6 (L* > 6 is highly variable) whereas the effect of Vsw is significant only at L* = 3.5–6.5. The peak response of PSD to Vsw is the shortest and most significant at L* = 4.5–5.5. As time progresses, the peak response broadens and shifts to higher t at higher and lower L*, consistent with local acceleration at L* = 4.5–5.5 followed by outward and inward diffusion. The outward radial diffusion time scale at L* = 5–6 is ~40 hr per RE. The input parameters are ranked based on their information transfer to the radiation belt electrons. Using this ranking as a guide for selecting input parameters, the radiation belt electron model based on neural networks is developed.

Kiley Yeakel

Automated algorithm for the detection of dispersionless electron injection events in Earth's magnetotail

We present an algorithm for the detection of dispersionless electron injection events utilizing MMS data from the tail seasons of 2017 through 2021. Using a Savitzky-Golay filter over cumulative relativistic electron count rates from the Fly's Eye Energetic Particle Spectrometer (FEEPS) over a tuned, limited energy range (80 – 150 keV), we find approximately 40,000 events over 5 seasons of data, greatly expanding the statistical significance and spatial and temporal coverage (extending up to 30 RE in Earth's magnetotail) of known injection events from previous datasets and statistical studies. A portion of the 2018 tail season was compared with a manual, subject-matter-expert generated, list of events, and we find that the algorithm is able to correctly identify 96% of the labeled dispersionless injections in addition to finding an additional ~3k events on a finer temporal scale. Spatial patterns in the distribution of algorithm-identified events were binned according to driving solar wind conditions and geomagnetic indices to uncover potential physical drivers. We find the spatial distribution of identified events correlates well with previously identified injection mechanisms such as central plasma sheet crossings, bursty bulk flows (BBFs), and magnetotail reconnection, while perhaps finding a new driving mechanism near the magnetopause flanks.

List of posters (v=virtual; p=in person)

Session A (Tuesday 22)

1) Amy Keesee (p)

Methods to improve magnitude accuracy for machine learning predictions of ground magnetic field perturbations

The perturbations in Earth's magnetic field measured at the surface that occur during geomagnetically active intervals are used to understand storm dynamics and as a proxy for determining likelihood of geomagnetically induced currents that can disrupt power grids. Machine learning models have been developed to predict such perturbations. While timing of perturbations in these models tends to be good, the modeled amplitudes are consistently lower than those measured. We present several methods used to improve the predicted amplitude, including training on storm-time-only data, varying loss functions, and varying the train-test split to include extreme events.

2) Jasmine R Kobayashi (v) *Machine Learning Models as an Alternative to Standard Interpolation Techniques for Estimating Gaps in OMNI Data*

NASA's OMNI data provide information about the solar wind plasma parameters and interplanetary magnetic field in the near-Earth environment. OMNI data is widely used to drive numerical and machine learning models. However, especially during geomagnetic storms, there can be significant data gaps in the OMNI data, which could significantly affect the model performance and results. In this study, we have tested traditionally used interpolation techniques and different machine learning models to predict data gaps in plasma parameters. We have created artificial data gaps in the OMNI data to evaluate the performance of different methods. We found that among different interpolation methods linear interpolation resulted in the lowest root mean square error for data gaps between 30 to 60 minutes. In addition, we found that the Random Forest regression model outperformed all other methods in predicting plasma parameters, especially for data gaps over 2 hours. The results suggest that machine learning models can serve as a better alternative to standard interpolation methods in filling data gaps in plasma parameters.

3) Dattaraj B Dhuri (v) *A deep learning model of proton auroras on Mars*

We present a deep learning model of proton aurora observations at Mars made using the Imaging UltraViolet Spectrograph (IUVS) onboard NASA's Mars Atmosphere and Volatile EvolutioN (MAVEN) spacecraft. Proton auroras on Mars are identified as a significant intensity enhancement in the hydrogen Lyman-alpha (121.6 nm) emission between ~110 and 150 km altitudes. Proton auroras on Mars are believed to be triggered by electron stripping and charge exchange between solar wind protons and the neutral hydrogen in the corona which form the energetic neutral hydrogen atoms penetrating down to the thermosphere. We create a database of Lyman-alpha profiles from IUVS limb scan observations between October 2014 - December 2017. We design a multi-input deep neural network to reproduce these Lyman-alpha profiles using in-situ measurements of density, speed, temperature and magnetic field as well as energy spectra of penetrating protons. We demonstrate that the individual Lyman alpha intensities are reproduced with a Pearson correlation 90% along with a faithful reconstruction of the measured ly alpha profile. We analyse the dependence of the reconstructions on inputs to show that stronger induced magnetic fields facilitate proton auroras at lower solar zenith angles.

4) Charles Topliff (p) *A domain transfer approach to forecasting the Solar Wind at L1*

5) Talha Siddique (v) *A Bayesian Ensemble Machine Learning Approach For Prediction of Geomagnetically Induced Currents (GICs) With Uncertainty Quantification*

Machine Learning (ML) has emerged as a promising methodology for space science prediction. The literature consists of studies where ML techniques like Deep Learning (DL), have been used to predict space weather data like Geomagnetically Induced Currents (GIC). While ML or DL holds great promise, such models' results could become unreliable due to uncertainty. Uncertainty refers to situations involving imperfect knowledge and is inherent in a stochastic environment. For example, GIC data are time series in nature and the data distribution is subject to change over time due to environmental variability. An ML model generates an optimal solution based on the training data. If uncertainty is not considered, such optimal solutions have a high risk of real-world deployment failure. To this end, a Bayesian Ensemble Learning technique has been developed to predict GIC values with 95% confidence interval for reliability. The Ensemble model determines the optimal "next time-step" window for ground horizontal magnetic component prediction. The Bayesian nature of the model quantifies model parameter and output uncertainty, which ensures reliability.

6) Adam T Michael (v) *Radiation Belt Variability due to Wave-Particle Interactions: A Multiscale Modeling Approach*

Many of our spacecraft are vulnerable to damage caused by enhanced levels of relativistic electron intensities in Earth's radiation belts that can occur during geomagnetic storms. Understanding the variability of radiation belt intensities has remained a major challenge due, in part, to local acceleration and loss mechanisms often occurring simultaneously with large-scale convection and discrete, mesoscale (~1 Re) plasma sheet injections. Global magnetosphere and test particle simulations are capable of capturing evolution through realistic global electromagnetic fields, including crucial mesoscale magnetotail dynamics necessary for radial transport and buildup of the radiation belts; however, until recently, they have lacked microscale energization and scattering processes due to wave-particle interactions. In this work, we incorporate local resonant interactions of radiation belt electrons with parallel propagating whistler modes into our radiation belt model. This is done through a grey box model that concurrently evolves test particles through an empirical wave model of lower band chorus waves superimposed onto the electromagnetic fields from the global MHD model (GAMERA) coupled with the RCM. Pitch-angle scattering and energization of electrons are computed using a stochastic differential equation based on analytical expressions for the quasi-linear diffusion coefficients. The plasma solution is used to dynamically evolve the location of the waves in the magnetosphere as well as the magnitude of the diffusion coefficients to more consistently include the impact of the interactions with the dynamic state of the magnetosphere. The model has a modular framework to enable determination of the relative contribution of each acceleration mechanism. We quantify the impact of wave-particle interactions on the radiation belts during the 17 March 2013 geomagnetic storm through direct comparisons when resonant interactions are not included.

7) Spiridon Kasapis (p) *Machine Learning-Based Forecasting of SEP Events Using the Recently Published MDI Data*

We use machine learning methods to predict whether an active region (AR) which produces flares will lead to a solar energetic particle (SEP) event using Space-Weather Michelson Doppler Imager (MDI) Active Region Patches (SMARPs). This new data product is derived from maps of the solar surface magnetic field taken by the Michelson Doppler Imager (MDI) aboard the Solar and

Heliospheric Observatory (SOHO). We survey the SMARP active regions associated with flares that appear on the solar disk between June 5, 1996 and August 14, 2010, label those that produced SEPs as positive and the rest as negative. The AR SMARP features that correspond to each flare are used to train two different types of machine learning methods, the support vector machines (SVMs) and the regression models. The results show that the SMARP data can predict whether a flare will lead to an SEP with accuracy (ACC) < 0.72 +- 0.12 while allowing for a competitive leading time of 55.3 + 28.6 minutes for forecasting the SEP events.

8) Pete Riley (v) *What Machine Learning Algorithms Teach us about Which Explanatory Variables Matter Most in Predicting Bz within Coronal Mass Ejections*

Accurately predicting the z-component of the interplanetary magnetic field, particularly during the passage of an interplanetary coronal mass ejection (ICME) is a crucial objective for space weather predictions. Currently, only a handful of techniques have been proposed and they remain limited in scope and accuracy. Recently, a robust machine learning (ML) technique was developed for predicting the minimum value of Bz within ICMEs based on a set of 42 'features', that is, variables calculated from measured quantities upstream of the ICME and within its sheath region. In this study, we investigate these so-called explanatory variables in more detail, focusing on those that were (1) statistically significant; and (2) most important. We find that number density and magnetic field strength, as well as the minimum value of IMF By accounted for a large proportion of the variability. Taken together, these features capture the degree to which the ICME compresses the ambient solar wind ahead. Intuitively, this makes sense: Energy made available to CMEs as they erupt is partitioned into magnetic energy density and kinetic energy. Thus, more powerful CMEs are launched with larger flux-rope fields (larger Bz), at greater speeds, resulting in more sheath compression (increased number density, By, and total field strength).

9) Rainer Arlt (v) *Machine learning for digitization of historical records of solar activity*

The possibility of involving historical data in the study of solar activity is often limited by the labor intensity of the digitization process. A spectacular example are the scanned catalogs of the Zurich Observatory covering the end of the late 19th and early 20th centuries (1883–1936). These 12 books, ranging from 1 to 2 thousand pages each, consist entirely of handwritten tables with the coordinates of sunspots, prominences, and faculae observed on the solar disk. Although these data complement the popular and widely used Greenwich data, they remain inaccessible for systematic analysis due to the lack of a proper digitization method. We present a machine-learning model based on a combination of convolutional and recurrent neural networks (CRNN) trained to recognize sequential textual data (decimal numbers). The model produces a ranked list of possible interpretations of each handwritten number, along with an estimate of the confidence of each interpretation. Using internal correlations between table data, we obtain a reliable dataset of historical sunspot positions. In the presentation, we will focus on the model architecture and details of the training process, which may be useful for other applications, as well as demonstrate the first results of the analysis of the digitized dataset.

10) Gonzalo A Cucho-Padin (p) *A machine learning framework for the reconstruction of the 3-D ion density distributions and energetic fluxes in the Earth's cusp*

The possibility of involving historical data in the study of solar activity is often limited by the labor intensity of the digitization process. A spectacular example are the scanned catalogs of the Zurich Observatory covering the end of the late 19th and early 20th centuries (1883–1936). These 12 books, ranging from 1 to 2 thousand pages each, consist entirely of handwritten tables with the coordinates of sunspots, prominences, and faculae observed on the solar disk. Although these data complement the popular and widely used Greenwich data, they remain inaccessible for systematic

analysis due to the lack of a proper digitization method. We present a machine-learning model based on a combination of convolutional and recurrent neural networks (CRNN) trained to recognize sequential textual data (decimal numbers). The model produces a ranked list of possible interpretations of each handwritten number, along with an estimate of the confidence of each interpretation. Using internal correlations between table data, we obtain a reliable dataset of historical sunspot positions. In the presentation, we will focus on the model architecture and details of the training process, which may be useful for other applications, as well as demonstrate the first results of the analysis of the digitized dataset.

11) Shan Jiahui (v) *Transfer learning for the three-dimensional reconstruction of CMEs*

The SECCHI-COR1 coronagraphs onboard the STEREO have provided extensive polarization observations. Based on the polarization ratio (PR) technique, the three-dimensional coronal mass ejections (CMEs) can be reconstructed. We proposed a method that can automatically derive CME sequences of the mask of the CME region to reconstruct 3-d CME. The system can be described in four main steps: classification, segmentation, tracking, 3-d reconstruction.Considering the high similarity of running difference of the SECCHI-COR1 and the SOHO-LASCO C2 coronagraphs, the classification VGG model and the segmentation PSPnet model trained on the data set of LASCO C2 running difference both are successfully applied to another data set. On the other hand, the method Gradient-weighted Class Activation Mapping (Grad-CAM) interprets that the trained classification model can still focus on the CME region in the SECCHI-COR1 running difference image. The CME mask part can be obtained by applying a combination of convex hull algorithm and circular filter to the segmented image. For the tracking CME procedure, we adjusted the parameters suitable for COR1, and improved the merging CME regions and velocity fitting. After tracking, the first image of the CME sequence can be used to generate the base polarized brightness (PB) and total brightness (TB). Compared with other PR methods, the mask of the CME region is automatically generated and the results of calculated parameters, such as longitude, latitude, are relatively accurate. A five-year 3D CME catalog of COR1-A is in development. We calculated that the difference in the average start time between the COR1 manual catalog and our catalog is within twenty minutes. In the future, our method can also be adapted to reconstruct the 3-d CMEs from the observations of the Lyman-alpha Solar Telescope (LST) coronagraph onboard the Advanced Space-based Solar Observatory (ASO-S).

12) Xiukuan Zhao (v) *Ionospheric scintillation prediction using gradient boosting algorithm*

Ionospheric scintillation is the rapid fluctuation of radio signals traversing through ionospheric irregularities. Severe scintillation can cause loss of lock for the systems using Global Navigation Satellite System (GNSS) signals. The dependences of scintillation on seasonal, solar and geomagnetic activities have been widely studied, but its day-to-day variability and prediction still remain a challenge. The relationship between scintillation occurrences and a variety of factors is complex. The machine learning algorithm could handle nonlinear problems and thus uncover the implicit correlations between multiple factors. Using the long-term ground-based GNSS receiver and ionosonde data collected in the Brazilian longitude sector during 2012-2020, an ionospheric strong scintillation prediction model based on the gradient boosting algorithms XGBoost, LightGBM and CatBoost is created and tested. The relative importance of different parameters affecting EPB/scintillation occurrence for building the prediction model is examined. A comparison of daily scintillation occurrence from the modeled and observed results during 2014 (solar maximum) and 2020 (solar minimum) shows that the gradient boosting algorithms are effective for predicting strong scintillations over low latitude, with a prediction accuracy of ~85%. The results suggest that the trained model with input of total electron content, equatorial F layer peak height and critical frequency before sunset could be well employed to predict the occurrence/nonoccurrence of intense scintillations over low latitude after sunset on a daily basis.

13) Kimberly D Moreland (p) *A machine-learning oriented remote and in-situ database for forecasting SEP occurrence and properties*

A new parameter-rich database using over 17,000 flares from the NOAA/SWPC flare event list extending from 1998 to 2013 is described. Each event in this database includes remote solar images, along with spacecraft measured x-ray, radio, proton, electron, upstream interplanetary (IP) plasma and magnetic field properties; in addition to associated IP coronal mass ejections and IP shock parameters. In-situ data comes from multiple instruments onboard the GOES and ACE spacecraft. The remote sensing data, also from various instruments, comprises of full-disc magnetograms, EUV, and coronagraph images. Selection criteria for flare classification are described, methods for calculating important SEP properties such as peak flux and fluence are explained, and the methods and time windows for calculating solar wind plasma and the magnetic field properties are detailed.We aim at providing a validated dataset with parameters specifically tailored for forecasting the occurrence and the subsequent properties of SEP events near 1 AU. Special consideration is given to data that is currently obtained in operational real-time or will be available in real-time on upcoming missions.

14) Anna L Morozova (v) *Comparison of the performance of PCA-NN models for daily mean TEC over the Iberian Peninsula: performance of different neural networks configuration*

The total electron content (TEC) over the Iberian Peninsula was modeled using a PCA-NN models based on the decomposition of the observed TEC series using the principal component analysis (PCA) and reconstruction of the daily mean TEC and daily PCA modes' amplitudes by different types of neural networks (NN) using several types of space weather parameters as predictors. Lags of 1 and 2 days between the TEC and space weather parameters are used.Two main goals are set:1.To find a NN configuration(s) that produces forecasts of reasonable quality with minimal amount of input data2.To find a best set of space weather parameters that work as predictors for PCA-NN modelsHere we present preliminary results related to the first goal: PCA-NN models with different NN configuration are compared. Only adaptation of ready-to-use packages are used.

15) Daniel T S Wrench (v) *Exploring the potential of neural networks to predict statistics of solar wind turbulence*

Time series data sets usually have corrupted entries, which need to be ignored in data analysis, creating gaps. For example, in the context of space physics, calibration issues, satellite telemetry issues, and unexpected events can make parts of the time series unusable. Various approaches exist to tackle this problem such as mean/median imputation, linear interpolation, and autoregressive modeling to name a few. Here we study the utility of artificial neural networks (ANNs) to predict statistics, particularly second order structure functions, of turbulent time-series in the solar wind. A neural network is trained and validated on a data-set to predict second order structure functions. This model is then tested on an unseen dataset to quantify its performance. It is shown that, in a limited way, ANNs work better than mean imputation or linear interpolation when the percentage of missing data is high. Caveats regarding their utility and potential future improvements are discussed as well.

16) Raman Mukundan (p) *Optimizing a Neural Network for Regional Forecasting of Ground Magnetic Perturbations Using Spherical Elementary Current Systems*

Machine learning models used to forecast geomagnetically induced currents (GICs) often predict the horizontal component of deflections in the ground-level magnetic field as a proxy variable due to a greater availability of magnetic field data. Since intense geomagnetic fluctuations are often highly localized compared to the sparse distribution of science-grade magnetometers (such as the SuperMAG network), existing machine learning models may be operationally inadequate. In this work, a fully-connected feed-forward neural network is trained on data generated by the spherical elementary current system (SECS) method. This physics-informed method spatially interpolates magnetic field data between magnetometer stations, providing the ability to forecast magnetic field perturbations as a continuous function of location on the Earth's surface. This work explores the optimization of some parameters of the SECS method and investigates how forecasting might be improved by choosing a neural network architecture suited to the training data.

17) Rukundo Wellen (v) *Forecasting of ionospheric electron content (TEC) using a time series neural network*

Forecasting of ionospheric TEC is an important consideration for GNSS applications in positioning, timing, and navigation. However, its variability in the low latitude regions is characterized by high spatial and temporal variations which become extreme during solar maxima. We propose a nonlinear autoregressive TEC model (NARX TEC) with fourteen external inputs that accurately and consistently forecasted ionospheric TEC variation during the high solar activity year (2014) of the solar cycle 24. The key factor to the development of this model is the addition of estimated parameters representing the equatorial electrojet (EJJ) and ExB drift to network inputs. These parameters effectively represent the low latitude ionospheric features resulting from the equatorial ionization anomaly and the equatorial plasma fountain effects. The TEC model forecasted diurnal TEC variation in 2014 with a root mean squared error of 2.11 and a correlation coefficient of 0.99 between modeled and actual TEC. The model also forecasted the summer solstice of June and the winter anomaly better than the equinox. This is in reverse with the IRI-2016 model which predicted the winter anomaly and equinox asymmetry better than the summer solstice. In comparison, the NARX TEC model predicted the ionospheric TEC variation during high solar activity better than the IRI-2016 model at all cases for diurnal, monthly, and seasonal variation. An important recommendation from comparison with the IRI-2016 model is the need to specify the IRI-model parameters according to geographical location and specific ionospheric conditions for more accurate modeled TEC values.

18) Xiangning Chu (v) *Relativistic Electron Model in the Outer Radiation Belt Using a Neural Network Approach*

We present a machine-learning-based model of relativistic electron fluxes >1.8 MeV using a neural network approach in the Earth's outer radiation belt. The Outer RadIation belt Electron Neural net model for Relativistic electrons (ORIENT-R) uses only solar wind conditions and geomagnetic indices as input. For the first time, we show that the state of the outer radiation belt can be determined using only solar wind conditions and geomagnetic indices, without any initial and boundary conditions. The most important features for determining outer radiation belt dynamics are found to be AL, solar wind flow speed and density, and SYM-H indices. ORIENT-R reproduces out-of-sample relativistic electron fluxes with a correlation coefficient of 0.95 and an uncertainty factor of ∼2. ORIENT-R reproduces radiation belt dynamics during an out-of-sample geomagnetic storm with good agreement to the observations. In addition, ORIENT-R was run for a completely out-of-sample period between March 2018 and October 2019 when the AL index ended and was replaced with the predicted AL index (lasp.colorado.edu/home/personnel/xinlin.li). It reproduces electron fluxes with a correlation coefficient of 0.92 and an out-of-sample uncertainty factor of ∼3. Furthermore, ORIENT-R captured the trend in the electron fluxes from low-earth-orbit (LEO) SAMPEX, which is a completely out-of-sample data set both temporally and spatially. In sum, the ORIENT-R model can reproduce transport, acceleration, decay, and dropouts of the outer radiation belt anywhere from short timescales (i.e., geomagnetic storms) and very long timescales (i.e., solar cycle) variations.

19) Luiz F Guedes dos Santos(p) *Exploring the ability of Convolutional Neural Networks to predict Solar wind quantities at 1 AU*

The solar wind is a continuous stream of charged particles that pervades everything in the solar system, including Earth and other planets. It is made up of two types of the solar wind: fast and slow, with the primary differences being their velocity and origin. When it reaches the Earth, each form of the solar wind has a different effect. The solar magnetic field is included in the solar wind since it is a charged flow. As a result, solar wind has a significant impact on Earth's space weather forecasting and prediction. One of today's issues in space weather forecasting is understanding solar wind dynamics and estimating its velocity hours and days in advance.To comprehend and forecast the solar wind speed in a defined interval, this research integrates solar pictures from the Solar Dynamics Observatory's Atmospheric Imagery Assembly and solar wind time-series measurements from the OMNI dataset. We use AIA photos to match solar wind speed data at 1AU with potential solar wind sources using powerful machine learning algorithms. Deep learning is used to discover and classify the characteristics of solar features that cause a shift in solar wind speed, as well as to generate an accurate prediction of its speed at 1AU.

20) Hannah T Rüdisser (v) *Automatic Detection of Interplanetary Coronal Mass Ejections*

Interplanetary coronal mass ejections (ICMEs) are one of the main drivers for space weather disturbances. In the past, different machine learning approaches have been used to automatically detect events in existing time series resulting from solar wind in situ data. However, classification, early detection and ultimately forecasting still remain challenges when facing the large amount of data from different instruments. We propose a pipeline using a Network similar to the ResUNet++ (Jha et al. (2019)), for the automatic detection of ICMEs. Comparing it to an existing method, we find that while achieving similar results, our model outperforms the baseline regarding GPU usage, training time and robustness to missing features, thus making it more usable for other datasets. The method has been tested on in situ data from WIND. Additionally, it produced reasonable results on STEREO A and STEREO B datasets with less input parameters. The relatively fast training allows straightforward tuning of hyperparameters and could therefore easily be used to detect other structures and phenomena in solar wind data, such as corotating interaction regions.Europlanet 2024 RI has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No 871149.

21) Luisa Capannolo (v) *Investigating the Relativistic Electron Precipitation using Deep Learning Techniques*

Electron precipitation is a known process that depletes radiation belts of energetic electrons. Magnetospheric plasma waves can interact with energetic electrons and cause them to precipitate into the Earth’s atmosphere. Here, precipitation is a source of energy input that can drive several effects often related to atmospheric and ionospheric physics (e.g., conductance and chemistry variability). Electron precipitation can also result from a significant variation of the configuration of magnetic field lines. If a field line is stretched away from Earth, its curvature radius decreases and when it becomes comparable to the gyroradius of the electrons, the field line is no longer able to trap electrons and force their gyro-motion. This phenomenon often occurs on the nightside where the magnetic field lines are stretched the most. In this work, we focus on electron precipitation at energies >700 keV, which has been associated either with waves or with field line scattering. We adopt deep learning techniques to identify the precipitation events and also classify them between events due to wave-particle interactions and those caused by stretched field lines. Rather than using magnetospheric data to find waves or stretched field lines, we rely on the electron precipitation flux observed at low-Earth-orbit by the POES/MetOp satellites. The profile of precipitation is characteristic of the associated driver. Our LSTM-based model is able to both identify precipitation events and categorize them between the two classes. The model output is useful to understand the distribution of wave-driven precipitation compared to that due to field line scattering, as well as their relative contribution to the total electron precipitation. Furthermore, the model output can be used together with geomagnetic activity variables (e.g., solar images, solar wind parameters, geomagnetic indices, etc.) to build a model that predicts the occurrence in time and location of a precipitation event.

22) Alexander Boyd (v) *SHELLS Model: Specifying High-altitude Electrons using Low-altitude LEO Systems*

Specifying the internal charging hazard for non-GEO orbits (LEO, MEO and HEO) remains a challenging problem. To address this, we've developed the SHELLS model, a deep learning artificial neural network model of the near-Earth space environment. The model uses inputs of geomagnetic indices and LEO electron flux measurements from the NOAA POES spacecraft to output the energetic electron flux as observed by the MagEIS instrument on NASA's Van Allen Probes. We have recently completed improvements to the model architecture including integration of L-shell and B-mirror dependences into a single neural network. These improvements allow for better spatial and temporal coverage. Here, we will discuss the model architecture, present out-of-sample validation results, and demonstrate where the model can be accessed and run.

23) Kamen Kozarev (p) T*owards Lucky Imaging for Quiet-Time Low-Frequency Radio Solar Observations*

Low-frequency interferometric radio imaging observations (20-250 MHz) of the quiet Sun may hold important information about the state of the large-scale corona and the young solar wind, as well as non-burst activity too dim to be observed in spectral data. Yet such observations are still rarely reported in the literature, both because of the relative scarcity of observations, but also because of the difficulty to obtain high quality processed images. The daytime ionosphere severely impacts imaging observations and reduces their quality, especially when long integrations are needed for imaging the dimmer outer corona. To mitigate the effects of the ionosphere on low-frequency solar radio images, we are exploring machine learning (ML) techniques that enable automated snapshot lucky imaging with the LOFAR telescope. Here, we outline our approach for using ML to select images of sufficient quality, and present initial results.

24) Michael K Coughlan (v) *Using a Convolutional Neural Network with Uncertainty to Forecast GIC Risk of Occurrence at Mid-Latitudes.*

Geomagnetically induced currents (GICs) can cause massive disruptions to electrical systems and other vital infrastructure. GIC events are more likely to occur during periods of geomagnetic disturbance and their magnitude is correlated to the intensity of the disturbance. In-situ GIC measurements are rarely available, so fluctuations in the horizontal component of the ground magnetic field are often used as a proxy for determining the risk of GIC occurrence. Machine Learning methods can offer us a computationally inexpensive way to both predict these GIC events and help us understand the underlying processes behind them. In this work, a Shuffle Split is performed over training/validation data inputs to a Convolutional Neural Network (CNN) to determine the risk of GIC occurrence. A confidence interval is produced to establish a level of uncertainty in the results, as well as a method of analyzing input features.

25) Victor A Pinto (v) *Developing near real-time ground magnetic field perturbations predictions with machine learning models*

Ground magnetic field perturbations (dB/dt) forecast has been an important topic of research for the space weather community, as it is commonly used as a proxy to assess the risk of occurrence and severity of geomagnetically induced currents (GIC). In the past years, machine learning models have shown promise by achieving reasonable performance in prediction capabilities when comparing against established models, but at a fraction of the computational time once trained. These advancements allow for the implementation of near real-time forecasting of dB/dt with minimal computational requirements. In this work, we present our recent efforts to develop, test, evaluate and deploy ground magnetic fluctuations (dB/dt) prediction models using machine learning algorithms to predict in near real-time. We use historical data from the L1 monitor ACE spacecraft and Supermag data to train an artificial neural network, and then the trained models are used with near real-time data provided by NOAA and compared against the available data from ground magnetometer stations located at high and mid-latitudes.

26) Xudong Sun (v) *SpIn4D: Spectropolarimetric Inversion in Four Dimensions with Deep Learning*

he National Science Foundation's Daniel K. Inouye Solar Telescope (DKIST) will provide high-cadence, high-resolution, and multi-line measurements of the solar photosphere. New algorithms are required to meet the demand of the large data volume and to exploit the spatiotemporal information encoded in the polarized spectra. Here, we describe an NSF-funded project that aims to perform spectropolarimetric inversion in four dimensions with Deep Learning (SpIn4D). We first perform realistic magnetohydrodynamic (MHD) simulations of the solar photosphere, and forward synthesize a large library of DKIST-like spectra. Using these spectra as the input and the known MHD ground-truth as the target, we then train, validate, and benchmark a set of convolutional neural networks that can rapidly infer the physical variables of interest. Finally, as DKIST data become available, we will apply adversarial domain adaptation techniques to reduce the systematic differences between simulated and real data.

27) Kendra Bergstedt (p) *Machine Learning Algorithms for the Detection of Plasmoids in Multiple-X-Line Collisionless Reconnection Regions*

Correctly identifying structures in multiple-X-line reconnection regions is crucial for understanding the physics of the coupling of the microscale to the macroscale, such as the potential role that the plasmoid instability plays in reconnection dynamics and energy transfer. One specific area of research where this is important is the study of naturally occurring reconnection regions in Earth's magnetotail via analysis of in-situ data from spacecraft. A limitation of this data is that spacecraft can only sample a single point in space for each timestep, and trace a 1D path through the plasma. This limitation makes detection and identification of dynamic plasma structures difficult, especially if the plasma is sampled by only a single spacecraft. Techniques such as identifying structures by eye and by fitting to mathematical models are commonly and effectively used, but neither is well suited for the detection of large numbers of structures which are stretched or warped from their idealized shape. A previous work that tackled this methodological problem used a simple hand-tuned algorithm for detection and classification (Bergstedt et al. 2020). This work develops a more nuanced and robust detection algorithm which utilizes a set of simulated 'spacecraft' trajectories through 2D PIC simulations of reconnection to train a machine learning model to identify regions of data corresponding to plasmoids. The results from a simple binary classifier based on a 1D Convolutional Neural Network (CNN) architecture are presented and evaluated. Potential applications of the classifier are discussed.

28) Rong Lin (v) *Predicting Ambient Solar Wind Speed at L1-point based on Convolutional Neural Network and PFSS Magnetogram*

An accurate model for ambient solar wind speed is important for space weather predictions, catastrophic event warning and other issues concerning solar wind – magnetosphere interaction. In this work, we construct a model based on Convolutional Neural Network (CNN), considering a solar wind source surface of $r_{SS} = 2.5*R_{sun}$, aiming to predict the ambient solar wind speed at L1-point. The input of our model consists of four Potential Field Source Surface (PFSS) Magnetograms at r_{SS}, which are 7, 6, 5 and 4 days before the target epoch. The model provides predictions with an averaged correlation coefficient (CC) of 0.50 and a root mean square error (RMSE) of 94km/s.

These two indicators are better than that of the Wang-Sheeley-Arge (WSA) model. This model is independent of input other than the magnetogram (e.g., solar wind speed several 27 days before) so that it has the potential to generate a solar wind speed map that covers a large range of solar latitude (from ~45N° to ~45S°) and the whole solar longitude.

29) Mario Cobos Maestre (v) *Stability of loss functions for solar wind forecasting using Deep Learning*

Loss functions play an essential role in Machine Learning. They guide the fitting process and ultimately define, along with the training data andtechnique, the weights of connections in the resulting model. The most used loss functions, Mean Squared Error (MSE) and Mean Absolute Error (MAE), assume data to present a normal distribution.Solar wind data, however, presents a bi-normal distribution due to the existence of a fast and a slow solar wind component. As a result, these functions consider outliers to be prevalent in most possible solar wind datasets. We present a brief comparison of the robustness of both loss functions, both theoretically and empirically, in the context of solar wind forecasting. Furthermore, we attempt to determine the best choice for the specific conditions encountered in our ongoing research into this problem.

30) Armando Collado-Villaverde(v) *Deep Neural Networks With Convolutional and LSTM Layers for SYM-H and ASY-H Forecasting.*

Geomagnetic indices quantify the disturbance caused by the solar activity in particular regions of the Earth. Several works are undergoing to develop geomagnetic indices forecasting, both from the physics perspective and employing ML techniques by exploiting Sun data gathered from different space probes during the last decades. The physics approach enables a comprehensive understanding of the different components involved in a geomagnetic storm; however, the problem is extremely complex, involving magnetic entanglements, plasma physics, orbital dynamics and so on. Thus, forecasting models based on a pure physics approach is almost unfeasible nowadays. However, as there are large datasets of Sun observations, it is possible to use ML techniques, specifically, the usage of Deep Learning (DL) and Deep Neural Networks (DNN) is being established as the most promising approach to forecast the indices. Among them, the SYM-H and ASY-H indices, which represent the geomagnetic disturbance of the horizontal component of the magnetic field at mid-latitude with a 1-minute resolution, are commonly used. Their resolution, along with their relation to the solar wind parameters, makes them a great candidate as forecasting targets for DNNs. In this work, we present two DNNs developed to forecast the SYM-H and ASY-H indices. Both networks have been trained using the Interplanetary Magnetic Field (IMF) measured by ACE's MAG experiment and the related index for the geomagnetic storms of considerable intensity that occurred in the last two solar cycles. As a result, the networks are able to accurately forecast the indices two hours in advance, considering the IMF and indices values for the previous 200 minutes. The evaluation of both networks reveals a great forecasting precision, including good predictions for large storms that occurred during the solar cycle 23 and comparing with the persistence model for the period 2013-2020, when there were almost no intense storms.

31) Andong Hu (p) *A Multi-Hour-Ahead global geospace model using Gated Recurrent Unit (GRU) networks and SuperMAG data*

We present a new global geospace model for predicting the horizontal component of ground-based geomagnetic fields 1-6 hours ahead from solar wind drivers, using SuperMAG data and Gated Recurrent Unit (GRU) recurrent neural networks. A geomagnetic fields forecast model is first trained for each SuperMAG station, i.e., 573 overall. A simple curve fit method is then used to interpolated the geomagnetic fields globally. Finally, data from several SuperMAG stations is used to assess the accuracy of the predictions. For example, the overall RMSE of north component of the geomagnetic field during low, middle and high latitudes are 9.0, 7.0 and 13.6 nT respectively. The NOAA Operational Geospace Model (SWMF) is then used for comparison.

32) Suvadip Sinha (v) *A comparative study of supervised machine learning algorithms to forecast solar flares*

Solar flares are sudden bursts of high-energy electromagnetic radiation that occur in the solar corona. Because of high radiation exposure, flares can pose serious threats to modern technologies such as satellite communications, global positioning systems, power grids, and many more. Therefore, forecasting solar flare is a challenging as well as demanding aspect of space weather studies to mitigate economic losses. Recent advancements in machine learning allow us to handle high-dimensional data and have shown its usefulness in the domain of space weather forecasting. From early studies, we know that the triggering of a flare has an internal connection with the active region's magnetic field properties. Here we demonstrate a comparative analysis with four robust machine learning algorithms to predict active region's flare potential using Spaceweather HMI Active Region Patch (SHARP) data as inputs. The training dataset consists of 10 years of active region data covering almost the entire solar cycle 24. We have achieved an excellent True skill score with logistic regression and support vector machine algorithms. Furthermore, We have identified key magnetic parameters which play a vital role in predicting solar flares. Our study will be helpful in constructing a highly accurate operational flare forecasting system.

33) Tommaso Alberti (v) *Chaos and spontaneous stochasticity: two sides of (un)predictability*

In 1963 Lorenz discovered what is usually known as “chaos”, that is the sensitive dependence of deterministic chaotic systems upon initial conditions. Since then, this concept has been strictly related to the notion of unpredictability pioneered by Lorenz. However, one of the most interesting and unknown facets of Lorenz ideas is that multiscale fluid flows could spontaneously lose their deterministic nature and become intrinsically random. This effect is radically different from chaos. The near-Earth electromagnetic environment is one of the large set of natural systems when Lorenz ideas can be touched by the hand. It presents rich dynamics originating from non-trivial processes in scale space, non-stationary forcing, emerging behaviors, and geometrical constraints. This complexity appears via non-hyperbolic chaos, randomness, state-dependent persistence and predictability. All these features have prevented a full characterization of the underlying turbulent (stochastic) attractor, which will be the key object to unpin this complexity. Here we discuss the theoretical framework behind the two concepts of chaos and spontaneous stochasticity strictly related to the intrinsic randomness and predictability of multiscale deterministic systems. We present a novel formalism to map unstable fixed points to extremes and to trace the evolution of their structural characteristics when moving from small to large scales and vice versa, providing a full characterization of the attractor. We provide evidence of non-hyperbolic chaos and state-dependent predictability of short-term processes as the result of a complex interplay between processes and phenomena of internal origin activated by the triggering of external-source processes. Our observations support the idea that the near-Earth electromagnetic environment is a far-from-equilibrium complex system.

34) Juliana Vievering (p) *Real-Time Solar Flare Predictions using Machine Learning*

Understanding when and where solar flares and eruptive events will occur continues to be an important goal for the heliophysics community, from both fundamental science and space weather perspectives. Currently available flare forecasts typically fall into two main categories: (1) long-term probabilistic forecasts (e.g., probability that a flare of a certain magnitude is going to occur over the next 24 hours), and (2) flare alerts (e.g., notification when the GOES X-ray flux reaches a high threshold). For a wide variety of operations and research purposes, there is an additional need for flare predictions that are more actionable than long-term forecasts and provide earlier notice of extreme events than current flare alerts. To address this need, we seek to develop a tool using machine learning that rapidly aggregates near-real-time signatures of flare onset, including X-ray and EUV irradiance measurements, to provide early prediction of the magnitude and duration of ensuing solar eruptive events. This tool will provide crucial notice (~minutes) prior to the arrival of harmful radiation in near-Earth space to mitigate effects on astronauts and radio communications and will enable triggered observations of scientifically interesting events. Here we present our approach and the early stages of this work.

35) Verena Heidrich-Meisner (v) *Neural network reconstruction of in-situ solar wind parameters*

The properties of the solar wind change with different solar sourceregions. In addition most solar wind properties are affected bytransport effects. Relevant transport effects are expansion,collisions, stream interaction regions and wave particleinteraction. On the one hand, the charge state composition of thesolar wind is particularly well suited to identify the solar sourceregion, since in good approximation the charge state compositionremains unchanged after the solar wind leaves the hot corona. On theother hand, proton plasma properties and the magnetic field strengthare better suited to identify solar wind plasma that is affected bytransport effects, for instance stream interactionregions. Nevertheless, proton plasma properties also change with thesolar source region. In this study, we evaluate this redundancy withthe help of neural networks. Five solar wind parameters areconsidered, proton speed, proton density, proton temperature, magneticfield strength and the O7+/O6+ charge state ratio. Four of them aretaken as input to a feed-forward neural network which is trained toreconstruct the remaining parameter. The results show that it iseasier to predict the proton speed and proton temperature from theother transport-affected proton plasma properties than predicting theproton density, the magnetic field strength or the purelysource-dependent O7+/O6+ ratio from the proton plasmaproperties. Nevertheless, the neural network prediction also succeededto recover the O7+/O6+ from solar wind parameters that are alltransport-affected, however less accurate than in the case of thesolar wind speed. It is also notable that the prediction is morereliable during the solar activity minimum.

36) Ute V Amerstorfer (v) *Machine Learning Solutions for Data Analysis and Exploitation in Planetary Science - A Work Package in Europlanet 2024 Research Infrastructure*

Funded through the European Commission’s Horizon 2020 programme, Europlanet 2024 Research Infrastructure (RI) provides free access to planetary simulation and analysis facilities, data services and tools, a ground-based observational network and programme of community support activities. The University of Kent, UK, leads the Europlanet 2024 RI consortium, which has 57 beneficiary institutions from 25 countries in Europe and around the world, with a further 44 affiliated partners.The work package „Machine Learning Solutions for Data Analysis and Exploitation in Planetary Science“ develops ML powered data analysis and exploitation tools optimized for planetary science and integrates expert knowledge on ML into the planetary community. We give an overview of our work package and ML activities within Europlanet 2024 RI.Europlanet 2024 RI has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No 871149.

37) Ajay Kumar Tiwari (v) *CME-learn: An interactive playground to benchmark CME databases for the time of arrival (ToA) prediction for using machine learning methods*

Coronal mass ejections are one of the most significant drivers of space weather. The ToA predictions along with the Arrival speed of the CMEs are one of the crucial pieces of information for preparing for the possible geomagnetic storms. Geomagnetic storms can have adverse effects on several key components of modern society e.g. communications and electrical grids. The development of many machine learning methods provides us with the opportunity to use these tools in space weather applications. There have been several studies using machine learning methods for ToA predictions. In this study, we present an interactive dashboard to apply several machine learning methods (regression models) to test on the several CME databases used in the community. We also use this opportunity to benchmark various CME databases for TOA and CME arrival speed predictions. We also welcome the community to use this interactive dashboard as a tool to learn about machine learning.

38) Subhamoy Chatterjee (p) *Forecasting the Occurrence Probability and Properties of Solar Energetic Particle Events using a Multivariate Ensemble of Convolutional Neural Networks*

"The Sun continuously affects the interplanetary (IP) environment by a host of interconnected and dynamic physical processes. Solar flares, Coronal Mass Ejections (CMEs), and Solar Energetic Particles (SEPs) are among the key drivers of space weather in the near-Earth environment and beyond. While some CMEs and flares are associated with intense SEPs, some show no or little SEP association. Furthermore, there is no clear and consistent connection between the properties of SEPs observed at 1 au and their progenitors at or near the Sun. The latter is due to the very complex environment that dominates SEP origin, acceleration, and transport in the IP space. To date, robust long-term (hours-days) forecasting of SEP properties (e.g., onset, peak intensities, heavy ion composition) does not effectively exist and the search for such a development continues.

In this work, we present an ensemble of convolutional neural networks that ingests remote and in-situ data from different sources. The outcome of the forecasting model is two fold: (i) the true probability of SEP occurrence and (ii) SEP properties (peak, fluence, duration) weighted by the occurrence probabilities determined in (i). This provides flexibility for the users of our forecast to determine their own acceptable level of risk, rather than imposing a threshold of detection that optimizes an arbitrary binary classification metric. Furthermore, the ensemble of models, trained utilizing the large class-imbalance between positive and negative events, provides a clear measure of uncertainty in our forecast."

39) Donglai Ma (v) *Machine learning based reconstruction and prediction of radiation belt flux*

The outer radiation belt of the Earth consists primarily of energetic electrons ranging in energy from tens of keV to several MeV and is known to be a significant threat to a variety of satellite systems. Thus, developing a useful model to describe the trapped electron flux has long been a challenging task. In this work, we present a trapped electron radiation belt model developed using a neural network with electron flux measurements obtained from NASA's Van Allen Probes. The model is driven by a set of geomagnetic indices (and their time histories), supplemented by solar wind parameters. It can accurately reconstruct the observed electron flux for different energy channels from Van Allen Probes: MagEIS and REPT, anywhere in the outer radiation belt between L~3-6 for any time in the past. Its predictive ability is tested on the out-of-sample time range, which shows excellent agreement. This trapped electron radiation model has wide space weather applications. It can help us understand dropouts and refilling events in the radiation belts as well as provide real-time or hours ahead predictive information about radiation belt dynamics.

40) Enrico Camporeale (p) *Space Weather with Quantified Uncertainty: Optimizing Ensembles for Probabilistic Predictions*

In this paper we focus on the problem of assigning uncertainties to single-point predictions generated by a deterministic model that outputs a continuous variable. This problem applies to any state-of-the-art physics or engineering models that have a computational cost that does not readily allow running ensembles and estimating the uncertainty associated to single-point predictions. Essentially, we devise a method to easily transform a deterministic prediction into a probabilistic one. We show that for doing so, one has to compromise between the accuracy and the reliability

(calibration) of such a probabilistic model. Hence, we introduce a cost function that encodes their trade-off, and we call this new method ACCRUE (ACCurate and Reliable Uncertainty Estimate). We use the continuous rank probability score to measure accuracy and we derive an analytic formula for the reliability, in the case of forecasts of continuous scalar variables expressed in terms of Gaussian distributions. The new ACCRUE cost function is then used to estimate the input-dependent variance, given a black-box “oracle” mean function, by solving a two-objective optimization problem. The simple philosophy behind this strategy is that predictions based on the estimated variances should not only be accurate, but also reliable (i.e., statistically consistent with observations). Conversely, early works based on the minimization of classical cost functions, such as the negative log probability density, cannot simultaneously enforce both accuracy and reliability. We show several examples both with synthetic data, where the underlying hidden noise can accurately be recovered, and with large real-world datasets.

41) Liam Smith (v) *Machine Learning for Ionospheric Extrapolation and Forecasting in a Data-Model Fusion Approach*

Ionospheric properties are key in space weather monitoring. Of particular note is the electron density as a function of altitude, which helps infer the impacts of space weather. There exist different ionospheric prediction approaches, such as physics-based modelling like SAMI3, as well as empirically supported models. The physics-based models require a lot of computational power and often cannot be expanded with arbitrary additional parameters. Despite this, the quality of results from physics-based models is still desirable. We have trained neural networks using the outputs of SAMI3 in addition to other inputs to demonstrate forecasting ability without the need for a heavy computational model. Additionally, the machine learning approach is tending towards extension with the integration of external observational data sets, which leads to data-model fusion.

Various neural networks approaches have been designed to forecast electron density using interplanetary magnetic field (IMF) parameters alongside SAMI3 outputs. Most recently, the networks have been adjusted to perform spatial extrapolation in addition to the forecasting to allow for input of observed ionospheric conditions and expected spatial and temporal propagation of those conditions.

42) Kyle Domico (v) *A Machine Learning and Computer Vision Approach to Geomagnetic Storm Forecasting*

Geomagnetic storms, disturbances of Earth's magnetosphere caused by masses of charged particles being emitted from the Sun, are an uncontrollable threat to modern technology. Notably, they have the potential to damage satellites and cause instability in power grids on Earth, among other disasters. They result from high sun activity, which are induced from cool areas on the Sun known as sunspots. Forecasting the storms to prevent disasters requires an understanding of how and when they will occur. However, current prediction methods at the National Oceanic and Atmospheric Administration (NOAA) are limited in that they depend on expensive solar wind spacecraft and a global-scale magnetometer sensor network. In this paper, we introduce a novel machine learning and computer vision approach to accurately forecast geomagnetic storms without the need of such costly physical measurements. Our approach extracts features from images of the Sun to establish correlations between sunspots and geomagnetic storm classification and is competitive with NOAA's predictions. Indeed, our prediction achieves a 76% storm classification accuracy. This paper serves as an existence proof that machine learning and computer vision techniques provide an effective means for augmenting and improving existing geomagnetic storm forecasting methods.

43) Dominique L Stumbaugh (p) *Predicting Equatorial Electron Flux Measurements from Low Earth Orbit*

"The outer radiation belt is very dynamic, both spatially and temporally. One of the keys to understanding this dynamic variability is to understand the loss processes for radiation belt electrons. Local precipitation loss due to pitch angle (PA) scattering by magnetospheric waves is the focus of our analysis. Plasma waves can alter the course of a charged particle and influence a previously trapped electron from the magnetosphere to penetrate the Earth’s upper atmosphere. Once in the upper atmosphere, a charge particle can ionize air molecules leading to the destruction of ozone and interfere with technological systems. It is critical that particle measurements from different platforms are inter-calibrated as these data are needed to validate increasingly important radiation belt models.

The proposed project aims to understand when and how electrons precipitate into the atmosphere based on different enabling local conditions and to establish a predictable relationship between low-Earth-orbit and high altitude orbit data. To do so, we use coordinated electron measurements from the Van Allen Probes, or Radiation Belt Storm Probes (RBSP), and the Polar Operational Environmental Satellites (POES) as inputs for a neural network. The two spacecraft should be measuring the same particle population when connected on the same magnetic field line.

Low earth orbit (LEO) missions, like POES, continue to provide continuous and more accessible monitoring of the radiation belts. It is becoming more essential to ensure that LEO data is a good proxy for high latitude data."

44) Yong Ji (v) *Composite model for predicting sym-H index*

Predicting the sym-H index is of significance in space weather because it quantifies the disturbance of geomagnetic field during the magnetic activities caused by the solar wind disturbances. This study presents a composite model to predict sym-H index based on solar wind parameters by combing the empirical magnetospheric dynamical equation and the neural network. The formula of sym-H equation learns from the well-known empirical relationship between interplanetary conditions and Dst put forward by Burton et al. [J. Geophys. Res., 80, 4204-4214(1975)]. In particular, the coefficients in the empirical equation are determined by using neural network which is good at approaching the function between the coefficients and the solar wind paprameters. The composite model is trained using the solar wind density, velocity, the Interplanetary Magnetic Field (IMF) and the related storm index for both the storm periods and the quiet time in the last two solar cycles. It turns out that the forecast of sym-H in 1h and 2h ahead during storm time is reliable and the precision is even better than the latest models solely based on deep neural networks. It is meaningful for understanding the relation between the solar wind conditions, the ring current particle injection and motions, as well as the ring current particle loss processes.

45) Matthew G Lennard (v) *Machine Learning in Heliophysics*

Solar Active regions (ARs) have been of particular interest to solar scientists since their first observations more than a hundred years ago. As their name suggests, they are regions of dynamic magnetic activity on the solar surface and can generate solar flares (SF) and Coronal Mass Ejections (CMEs). When the magnetic flux is large, this may bring about ruinous events such as the massive release of high-energy particles and strong electromagnetic radiation in SFs and CMEs where, combined, these can damage electronics from onboard spacecrafts to transformers on the ground as well as disrupting communication and navigation technologies which much of the modern world depends upon.Forecasting these events presents many challenges – we do not have a complete understanding of the Sun’s dynamo nor can we directly observe many of the features in the solar atmosphere due to a number of technical limitations. In the present study we used Machine Learning (ML) technique, in particular DeepVel (Ramos et al. A&A, 2017), for recovering velocity fields to detect topological changes in photospheric plasma flow fields. Predicted flows (prior AR to emergence and during its lifecycle) was used for the further analysis of ARs plasma flow topology by applying methods from the dynamical systems theory e.g. the Finite-Time Lyapunov Exponent (FTLE) and Lagrangian coherent structures (LCS). The obtained results gain insight to the behaviour of the velocity and magnetic fields of ARs over a day in advance.We have also shown that through the application of high resolution magnetoconvection simulations, such as those produced from the R2D2 code, to the DeepVel network, it is possible to recover the velocity field of the solar surface and forecast the formation of a pore or sunspot in an AR long before significant magnetic flux emerges.

46) Simon Bouriat (p) *Forecasting low-energy particle flux in LEO using DMSP satellites: data analysis and first results*

"The new space industry has brought fresh challenges to the space weather community as new satellites often appear to be more vulnerable to the natural environment than they used to. The recent incident involving Space X’s Starlink satellites loss caused by a geomagnetic storm is one of the many pieces of evidence. In this context, there is a growing need for a better understanding of space weather related hazards, especially in LEO where several constellations are about to be brought in the upcoming years. The exponential growth in the use of AI techniques has shown tremendous results and is very promising to answer this need.

One of the dangers from Space Weather is spacecraft charging, the accumulation of charged particles on (surface charging) and in (internal charging) the satellite, triggering electrostatic discharge. Only few satellites (e.g., DMSP) measure them, and there still is a lack of models to characterise them. The transport of particles from the Sun to the Earth is a very complex phenomenon, and while a lot of different simulations exists to model the environment (e.g., Vlasiator - University of Helsinki), it still is difficult to forecast with a moderate computational complexity. The purpose of this poster is to present the first steps of an AI, physics-oriented algorithm, that aims at forecasting low-energy particle flux in Low-Earth Orbit (LEO).

The preliminary results here focus on a simple neural network applied to propagated ACE solar wind (SWEPAM) and interplanetary magnetic field (MAG) data. The work consists of (1) a preliminary analysis of ACE data and, (2) first results of applying several deep learning supervised algorithms to forecast pre-processed DMSP particle flux data."

47) Emmanuel De Leon *Automatic detection of the electron density from the WHISPER instrument onboard CLUSTER*

The Waves of HIgh frequency and Sounder for Probing Electron density by Relaxation (WHISPER) instrument, is part of the Wave Experiment Consortium of the CLUSTER mission. The instrument consists of a receiver, a transmitter, and a wave spectrum analyzer. It delivers active (sounding) and natural electric field spectra. The characteristic signature of waves indicates the nature of the ambient plasma regime and, combined with the spacecraft position, reveals the different magnetospheric boundaries and regions. The thermal electron density can be deduced from the characteristics of natural waves in natural mode and from the resonance triggered in the sounding mode. This mesearument is a key parameter of scientific interestand major driver for the calibration of particles instrument.Until recently, the electron density required a manual intervention consisting in visualizing input parameters from the experiments, such as the WHISPER active/passive spectrograms combined with the dataset from the other instruments onboard CLUSTER. To automate this process, knowledge of the region (plasma regime) is highly desirable. In order to try to determinate the different plasma regions , a Multi-Layer Perceptron model has been implemented. For each detected region, a GRU, recurrent network model combined with an ad-hoc algorithm are used to determine the plasma frequency. The models are trained using the plasma frequency values manually found on active and natural measurements. The accuracy can reach until 98% in some plasma regions. A production pipeline using these models has been implemented to deliver electron density, reducing human intervention up to 10 times. Work is currently ongoing to create some models to process natural measurements where the data volume is much higher and the validation process more complex. These models of electron density automated determination will be useful for other space missions.

For more information read our article on this topic

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Session B (Thursday 24)

48) Luiz F Guedes dos Santos(p) *Forecasting flux rope's orientation using CNNs*

The identification and reconstruction of monotonic and coherent magnetic configuration of internal magnetic configuration observed within Interplanetary Coronal Mass Ejections (ICMEs), often associated with a spacecraft crossing a large flux rope with a helical magnetic field lines topology, is essential to predict the geomatic effect of these structures arriving at Earth. Inspired by Nieves-Chinchilla et al. (2018b) and Nieves-Chinchilla et al. (2019), we take advantage of ML techniques to interpret the ICME in situ magnetic field observations and understand in depth what in situ magnetic field observations should be expected when a spacecraft crosses flux ropes with different trajectories. The identification of a flux rope's orientation and critical characteristics (e.g. latitude, longitude, chirality, and spacecraft impact parameter) is currently a lengthy and manual operation. We investigate the capacity of a CNN to identify flux rope signatures based on the combined hodograms and therefore predict the direction of the predicted flux rope. This project develops CNNs that have been trained using magnetic field vectors derived from analytical flux rope data. The flux ropes simulated cover a wide range of spacecraft trajectories and flux rope orientations.

The CNNs are trained using full-duration flux ropes first, then partial-duration flux ropes. The first establishes a baseline for how well CNNs can identify and predict flux rope orientation, while the second investigates real-time forecasting by showing how accuracy is impacted by the fraction of flux rope viewed. The method for converting physics issues into machine learning challenges is also addressed. We examine the effects of experimenting with different neural network topologies on prediction accuracy. Finally, early findings from testing the trained network against WIND's observed ICMEs from 1995 to 2015 are reported.

49) Henrik Eklund (v) *Image refinement and estimation of intensity contrast degradation at small scales events of Solar observations.*

The point spread function generally constitutes the resolution element in astronomical observations, which degrades the contrast in intensities and leaving structures at smaller angular resolution unresolved. For targets that are highly dynamic at short time-scales, such as the Sun, the evolution of and interference between dynamic features can be used to extract further information below the full width half maximum of the point spread function. An artificial neural network is trained to recognise dynamic patterns at both the spatial and temporal domains and perform estimations of the intensity contrast degradation. The Neural network is trained using radiative transfer calculations from state-of-the-art three dimensional numerical simulations of the solar atmosphere.The artificial neural network is able to recognise the dynamic patterns and perform accurate estimations on the intensities across the field of view at a spatial resolution higher than the observations, corresponding to that of the numerical model.The neural network can to large accuracy distinguish if an event or feature is well resolved or not.We apply the neural network to give an estimate on the actual intensities of brightening events at millimeter wavelength observations, which can be used to derive the heating of different layers of the solar atmosphere in connection to the specific events.There is a great potential to use this method as a diagnostics tool for small-scale dynamics in solar observations with low angular resolution but a high cadence, such as for continuum millimeter wavelength observations with the Atacama Millimeter sub-millimeter Array, where the intensities also are closely related to the plasma temperature, which enable to study the chromospheric heating at small scales.

50) Adeline T M Paiement (v) *Cloud removal from ground-based images of the Sun*

We present a new method for cleaning ground-based images of the Sun from their cloud contamination. Previous works, e.g. (Feng 2014), have addressed this problem with low-pass filtering approaches, and achieved good results with clouds of low to medium opacity and isotropic texture. However, low-pass filtering fails in cases of long and filamentary clouds which results in a trade-off between keeping some cloud signal and loosing some solar structures. We propose a deep learning based method that addresses this issue. A convolutional neural network is modified to render it more sensitive to the oriented textures that are typical of elongated and filamentary clouds. Since these clouds tend cross the entire image, an attention mechanism is introduced to capture long-range orientation dependencies and better capture their large scale structures. Our method is trained and tested on CaII and Halpha images from Paris-Meudon Observatory. It may be easily re-trained with images from different observatories, including with different image sizes and resolutions.

51) Elizabeth P O'Dwyer (v) *Machine Learning for the Classification of Low Frequency Extensions of Saturn Kilometric Radiation*

Saturn Kilometric Radiation is an auroral emission that occurs between a few kHz to 1.2MHz, and peaks in the frequency range 100-400 kHz. It was detected quasi-continuously by Cassini from its arrival at Saturn in 2004 until mission end in 2017 and its properties have been extensively studied. SKR bursts which are global intensifications of SKR as well as extensions of the main SKR band down to lower frequencies, known as Low Frequency Extensions (LFEs), result from internally-driven tail reconnection and from solar wind compressions of the magnetosphere, which also trigger tail reconnection. LFEs have been selected by eye and also using a numerical criterion based on an intensity threshold [Reed et al., 2018]. In our work we propose to develop a supervised machine learning algorithm to select SKR bursts with an associated LFE from the entire Cassini dataset. The algorithm will be built using data from the Cassini radio instrument (RPWS), with LFEs selected by eye using a polygon selector tool by Empey et al., 2021 [zenodo.5636922] and will include examples of LFEs detected from a broad range of spacecraft locations. We plan to explore different types of algorithms that may be based on images, or on time series data e.g RNN, CNN, U-Net.

52) Carlos J Diaz Baso (p) *Bayesian Stokes inversion with Normalizing flows*

Stokes inversion techniques are very powerful methods for obtaining information on the thermodynamic and magnetic properties of solar and stellar atmospheres. Most of the existing inversion codes are designed for finding the optimum solution to the nonlinear inverse problem. However, to obtain the location of potentially multimodal solutions, degeneracies, and uncertainties, algorithms such as Markov chain Monte Carlo require to evaluate the model thousand of times. Recently, standard artificial neural networks have been shown to be much faster in learning the average mapping between spectra and physical quantities, but they do not perform properly if there are degeneracies, and they do not provide uncertainty estimates. In this study, we explore a technique known as normalizing flows that combines both methods and allows us to perform fast Bayesian inference. The performance of this method is demonstrated on two experiments with different complexity: a simple Milne-Eddington model and a complex non-LTE inversion. The training procedure need only be performed once for a given prior parameter space and the resulting network can then generate samples describing the posterior distribution several orders of magnitude faster than existing techniques. Given the generality of the technique, it can be applied to any inference process and physical quantity.

53) Harry Arnold (v) *Using Effective Resistivity Maps Derived From Data Mining for Global MHD Simulations of the Magnetosphere*

Magnetic reconnection in the magnetotail is an important driver of many aspects of space weather during magnetospheric substorms. However, reproducing the timing and location of x-lines during specific substorms is difficult with current global magnetohydrodynamic (MHD) simulations as they are incapable of including crucial kinetic scale physics that feedback on the larger scale dynamics. Recently, the location of x-lines in the magnetotail have been successfully reproduced using k-nearest neighbors data mining techniques. By looking at only the most relevant in situ measurements from spacecrafts, the global magnetic field can be recreated. This includes the correct location of nearly all iondiffusion regions identified by the Magnetospheric Multiscale Mission in 2017-2020. These new results give us the location of ion diffusion regions throughout the substorms which is a drastic improvement on the handful of data points from in situ measurements. By using these regions as maps for introducing explicit resistivity, we can force magnetic reconnection to occur in global magnetosphere MHD simulations that will accurately reproduce the state of the magnetosphere for specific storms. We present the first results of these explicit resistivity maps in MHD simulations and compare them to in situ observations.

54) Ajay Kumar Tiwari (v) *Predicting Arrival Time and Arrival Speed for CMEs: Machine Learning and Ensemble Methods*

Coronal mass ejections (CMEs) are arguably one of the most violent explosions in our solar system. CMEs are also one of the most important drivers for space weather. CMEs can have direct adverse effects on several human activities. Reliable and fast prediction of the CMEs arrival time is crucial to minimize such damage from a CME. We present a new pipeline combining machine learning (ML) with a physical drag-based model of CME propagation to predict the arrival time of the CME. We evaluate both standard ML approaches and a combination of ML + probabilistic drag based models (PDBM, Napoletano et al. 2018,2021). More than 200 previously observed geo-effective partial-/full-halo CMEs make up the database for this study (with information extracted from the Richardson & Cane 2010 catalogue, the CDAW data centre CME list, the LASCO coronagraphic images, and the HEK database - Hurlburt et al. 2010). The P-DBM provides us with a reduced computation time, which is promising for space weather forecasts. We analyzed and compared various machine learning algorithms to identify the best performing algorithm for this database of the CMEs. We also examine the relative importance of various features such as mass, CME propagation speed, and height above the solar limb of the observed CMEs in the prediction of the arrival time. The model is able to accurately predict the arrival times of the CMEs with a mean square error of about 9 hours. We also explore the differences in prediction from ML models and ensemble prediction methods namely P-DBM model. We also present an interactive dashboard for the community to explore the database and use the said database to make predictions using the models that were used in this study.

55) Laura Simms (v) *A comparison of ARMAX (autoregressive moving average transfer function) and RNN (recurrent neural network) models to predict geostationary keV electrons*

An ARMAX (autoregressive moving average transfer function) model can effectively predict future behavior of hourly geostationary electron flux (40-150 keV) measured by GOES-13 MAGED instrument with a validation correlation of 0.73 – 0.75. These models incorporate AR and MA terms to model flux behavior over time, as well as solar wind velocity, number density, and pressure, AE, IMF B and Bz, Ey, Kp, and Sym-H as exogenous predictors. The predictive ability can be improved by generating a separate model for each MLT (validation r = 0.77 - 0.81) or by including previous hour's flux (r = 0.86 – 0.91). However, including previous flux in the ARMAX models results in predictions that lag behind observations. Recurrent neural network (RNN) models using the same exogenous predictors produce validation correlations similar to the ARMAX models (r = 0.71 - 0.75). Generating a separate model for each MLT also modestly improves the RNN predictions (r = 0.75 – 0.76). The addition of previous flux to the RNN models results in somewhat more improvement (r = 0.74 – 0.83), but without the problem of predictions lagging behind observations. Although ARMAX and RNN models appear to be accessing similar patterns in the data, the RNN models are somewhat more successful at turning these into useful predictions.

56) Yigit Aytac (p) *A Computer Vision Approach for Real-time Solar Event Detection*

We present a solar event object detector for automated detection and alerting in real time, and automated event labeling for historic solar flare observations. We used the open-source python library SunPy interfaces for the Heliophysics Event Knowledgebase (HEK) and the Federated Interned Data Obtainer (FIDO) to obtain and prepare the training and validation datasets based on SDO's AIA detector. The model was trained using full-disk solar images with train and validation sets split by event date. We conducted experiments to evaluate across C, M and X solar flare brightness categories separately and together to compare model performances. The real-time model runs with a 90 FPS inference rate for 1024X1024 pixel full disk images when tested on a single NVIDIA Tesla V100 GPU. The results demonstrate the potential of computer vision object detection and classification approaches for solar event detection to be used independently or in conjunction with more traditional approaches.

57) Dogacan S Ozturk (v) *A predictive model for the high-latitude ionospheric convection*

The Super Dual Auroral Radar Network (SuperDARN) provides thorough coverage of the ionospheric convection patterns in the Northern Hemisphere. These convection patterns are parameterized by the solar wind velocity, Interplanetary Magnetic Field (IMF) vector, and dipole tilt angle to provide climatological patterns for the use of the scientific community. As the role of meso-scale structures in ionospheric convection is better understood for the coupling of the magnetosphere with high-latitude ionosphere-thermosphere systems, the prediction of convection at these scales gains more importance. In this study, we leverage the high-resolution measurements provided by SuperDARN radars to resolve meso-scale ionospheric convection patterns. In this study, we specifically utilize the nine-year grid datafrom the Prince George Radar which is operated by the University of Saskatchewan to predict latitudinal and longitudinal ionospheric convection velocities. The input data set consists of OMNI data of solar wind velocity, density, IMF vector, geomagnetic indices, and radar specific spatiotemporal information. Among various machine learning models, we found that the best prediction performance was obtained by using a multi-layer perceptron model. This presentation will include a discussion of the developed model and evaluation of its performance, as well as lessons learnt towards building a global multi-scale prediction model of ionospheric convection.

58) Aliaa A. M. Afify (v) *Development of a forecasting technique for ionospheric plasma irregularities by applying a supervised machine learning regression technique to spaceborne GPS measurements*

Ionospheric Total Electron Content (TEC) measurements can help researchers better understand the characteristics of ionospheric irregularities produced by solar and geomagnetic space weather. The Global Positioning System (GPS) Attitude, Position, and Profiling (GAP) experiment onboard the Swarm-E satellite includes four GPS receivers, three for topside (above spacecraft) ionospheric observations and the fourth for radio occultation observations of the ionosphere. GAP provides high-resolution (up to 100Hz) measurements of ionospheric total electron content (TEC), allowing for observation of sub-km scale ionospheric structures. The elliptical polar orbit of Swarm-E also provides observations from low to polar latitudes, at from a range of altitudes. Here we study irregular variations in the GAP TEC using wavelet analysis techniques, in order to obtain the characteristic features of small-medium scale ionospheric plasma irregularities (roughly 100s of meters up to 100 kms). By comparing the GAP TEC and associated continuous wavelet transforms (CWTs) with various solar wind parameters and geomagnetic indices (e.g. PC, AE, DST), we will evaluate the dependency of observed plasma irregularity characteristics (e.g. occurrence probability, intensity) on these solar wind and geomagnetic parameters. We are currently exploring supervised machine learning techniques such as regression analysis to determine these dependencies, which will be used to develop forecasting capabilities for plasma irregularity characteristics. In this presentation, we will discuss the GAP dataset, the determination of plasma irregularity characteristics observed by GAP, and ongoing development of machine learning techniques applied to the GAP dataset.

59) Matthew Blandin (v) *Predicting Geomagnetically Induced Currents across Alaska utilizing Multi-Variate LSTM models*

During periods of rapidly changing geomagnetic conditions electric fields form within the Earth's surface and induce currents known as geomagnetically induced currents (GICs), which interact with unprotected electrical systems our society relies on. In this study, we train multi-variate Long-Short Term Memory neural networks to predict geomagnetic field strength at multiple ground magnetometer stations across Alaska provided by the SuperMAG database with an uptime goal of predicting geomagnetic field disturbances. Each neural network is driven by solar wind and interplanetary magnetic field inputs from the NASA OMNI database spanning from 2000-2015 and is fine tuned for each station to maximize the effectiveness in predicting the magnitude of the northsouth component (|B_N|). The neural networks are then compared against multivariate linear regression models driven with the same inputs at each station using Heidke skill scores with thresholds at the 50, 75, 85, and 99 percentiles for |B_N|. Linear regression models show consistent low values (<0.5) for these thresholds while the neural networks indicate significant performance increases with average skill score values exceeding 0.5. To retain the full form of the geomagnetic field, a secondary so-called polarity model is utilized to predict the direction. The polarity model is run in tandem with the neural networks predicting geomagnetic field in an ensemble approach and results in a high correlation between predicted and observed values at the College, Alaska magnetometer station (CMO). We find this model a promising starting point for a machine learned geomagnetic field model to be expanded upon through increased output time history and fast turnaround times.

60) Robert Jarolim (p) *ITI for the Sun: Improved intercalibration of multi-instrument heliophysics data series with Instrument-To-Instrument translation*

In solar physics, the study of long-term evolution typically exceeds the lifetime of single instruments. Data-driven approaches are limited in terms of homogeneous historical data samples. We demonstrate how machine learning enabled Instrument-To-Instrument translation (ITI; Jarolim et al. 2022) can leverage recent instrumental improvements and provide a so far unused resource to foster novel research and accelerate data-driven solar research.In this study, we aim at providing a uniform data series of EUV observations from SDO/AIA, STEREO/EUVI and SOHO/EIT. The application of unpaired image-to-image translation methods to standard reduced SDO/AIA data shows a sensitivity for insufficiently corrected device degradation, leading to differences between the calibrated series. Here, we apply the auto-calibration from Dos Santos et al. (2021), to obtain a more consistent calibration for the SDO/AIA series and use the ITI framework to translate observations from STEREO/EUVI and SOHO/EIT to the same domain. We demonstrate that with this adjustment we can achieve a better calibration between the three instruments. Comparisons of aligned observations demonstrate high perceptual quality and a strong similarity to reference observations.The resulting data series covers uniform observations dating back to 1996, including simultaneous observations from multiple vantage points. This method paves the way towards a new generation of solar cycle studies of the solar EUV corona, contributes additional samples for data-driven methods and enables the application of automated methods that were developed specifically for SDO/AIA data to the full EUV data series without further adjustments.

61) Reynaldo O Rojas Zelaya (v)*Forecasting Spread F at Jicamarca*

Ionospheric dynamics are governed by the interaction of non-linear mechanisms. Equatorial Spread F (ESF) is one of the phenomena that occurs in this region and it may have a negative impact on radiowave propagation related to satellite communications and radio navigation systems. Thus, it is crucial to develop a predictive tool that leverages the vast data captured by different radar systems in order to give estimates of when Spread F events will occur. Even though some tools exist for this task, most of them are based on statistical models that capture the climatological behavior of ESF occurrence but may be incapable of capturing day-to-day variability.We have implemented a neural network that predicts ESF occurrence above Jicamarca as defined by the echoes obtained with the JULIA radar. In addition, we have compared the performance our model to FIRST (Forecasting Ionospheric Real-time Scintillation Tool). Moreover, we have analyzed the sensitivity of our predictions to various model inputs and performed a hyperparameter tuning for better results. In this presentation, we will show some preliminary results obtained with a nowcasting model for echoes observed by JULIA.

62) Laura Simms (v) *The use of differencing to remove spurious correlations in models of geostationary 2 MeV electron flux*

Both geosynchronous and ground-based measurements may depend on magnetic local time. Such simultaneous diurnal variations can result in high, spurious correlations even when there is no physical relationship between factors. This has implications for accurate modelling using regression and for feature selection. A difference transformation (y(t) – y(t-24)) successfully removes diurnal and longer cycles (e.g., the 27 d solar cycle) and trends. Other methods of diurnal cycle removal (daily averaging, moving averages, and simple spectral subtraction using regression) are less successful at removing cycles that contribute to inflated correlations. Differenced electron flux and ULF index show lower correlations than previously reported (maximum of 0.1). Correlations of electron flux and the ULF index with solar wind velocity (differenced at y(t) – y(t-1)) are also low (≤ 0.1). An autoregressive, moving average transfer function model (ARIMAX) shows that there are significant cumulative effects of solar wind velocity on ULF activity over long periods, but significant correlations of velocity and ULF waves with flux are only seen over shorter time spans of more homogeneous geomagnetic activity levels.

63) Naoto Nishizuka (v) *Reliable Probability Forecast of Solar Flares using Deep Neural Networks*

We developed two types of solar flare prediction models using deep neural networks (DNNs), Deep Flare Net (DeFN) and Deep Flare Net-Reliable (DeFN-R). These two models are deterministic and probabilistic forecasting models and have been used in operational daily forecast (https://defn.nict.go.jp). The models can predict the maximum classes of flares that occur in the following 24 hr after observing images, along with the event occurrence probability. We detected active regions from 3×10^5 solar images taken during 2010–2015 by Solar Dynamic Observatory and extracted 79 features for each region, which we annotated with flare occurrence labels of X-, M-, and C-classes. We adopted a chronological split of the database into two for training and testing in an operational setting: the data set in 2010–2014 for training and the one in 2015 for testing. DeFN and DeFN-R are composed of multilayer perceptrons formed by batch normalizations and skip connections. By tuning optimization methods, DeFN and DeFN-R were trained to optimize the True skill statistic (TSS) and the Brier skill score (BSS), respectively. DeFN achieved TSS=0.80 for >=M-class flares, but it tends to overforecast flares. On the other hand, DeFN-R succeeded in improving the reliability. It achieved BSS=0.41 for >=C-class flares and 0.30 for >=M-class flares by improving the reliability diagram while keeping the relative operating characteristic curve almost the same. Note that DeFN is optimized for deterministic prediction, which is determined with a normalized threshold of 50%. On the other hand, DeFN-R is optimized for a probability forecast based on the observation event rate, whose probability threshold can be selected according to users' purposes. In this presentation, we will compare our two models and discuss how to develop the reliable probabilistic forecasting model using DNNs.

64) Paul J Wright (p) *SDOVIS: A Vision Transformer Model for Solar Dynamics* Observatory (SDO) Data

SDOML v2.0: Introducing an updated machine learning dataset for SDO data.

SDO Overview

* Since its launch in 2010, NASA's Solar Dynamics Observatory (SDO; (Pesnell et al. 2012) has continuously monitored Sun's activity, delivering a wealth of valuable scientific data for heliophysics researchers with the use of three instruments:

* The Atmospheric Imaging Assembly (AIA; Lemen et al. 2012), which captures 4096 x 4096 resolution images (with 0.6 arcsecond pixel size) of the full Sun in two ultraviolet (centered at 1600, and 1700 Å), seven extreme ultraviolet (EUV; centered at 94, 131, 171, 193, 211, 304, and 335 Å), and one visible (centered at 4500 Å) wavelength band.

* The Helioseismic and Magnetic Imager (HMI; Schou et al. 2012) captures visible wavelength filtergrams of the full Sun at 4096 x 4096 resolution (a pixel size of 0.5 arcsecond), which are then processed into a number of data products, including photospheric Dopplergrams, line-of-sight magnetograms, and vector magnetograms (Hoeksema et al. 2014).

* The EUV Variability Experiment (EVE; Woods et al. 2012) monitors the solar EUV spectral irradiance from 1 to 1050 Å. This is done by utilizing multiple EUV Grating Spectrographs (MEGS) that disperse EUV light from the full disk of the Sun and its corona onto a 1024 x 2048 charge coupled device (CCD).

The SDO ML Dataset (covering 2010 - 2018) was originally published as Galvez et al (2019), and is hosted on the Stanford Digital Repository in Numpy's compressed array format (.npz).

In version 2.0, we present an update to the work outlined in Galvez et al (2019), in which the full dataset has been converted to cloud friendly Zarr (.zarr) format. In addition, SDO/AIA data has been updated to account for a change in calibration after 2019. In addition to the change in calibration, this updated format includes:

> FITS header/keyword information (such as observation time, and exposure time).

> & Processes for continually updating the data until the present day.

Who is the SDO ML Dataset for?

* The sheer volume of structured scientific data recorded by SDO (over 18 PB, and counting) is ideal for a range machine learning tasks (from time-series, to computer vision), as well as more traditional approaches.

* While the level 1 data are easily accessible, pre-processing these data for scientific analysis often requires specialized heliophysics (and instrument-specific) knowledge. This may act as an unnecessary hurdle for non-heliophysics machine learning researchers who may wish to experiment with datasets from the physical sciences, but are unaware of domain-specific nuances (e.g., that images must be spatially and temporally adjusted).

* This talk demonstrates the process for interacting with a subset of the curated SDO (AIA, HMI, EVE) dataset, that is mission-ready for machine-learning applications. Our aim is to supply this standardized dataset for heliophysicists who wish to use machine learning in their own research, as well as machine-learning researchers who wish to develop models specialized for the physical sciences.

65) Constantinos Papadimitriou (v) *Application of information theoretical measures for improved machine learning modelling of the electron radiation belt*

In the past ten years Artificial Neural Networks (ANN) and other machine learning methods have been used in a wide range of models and predictive systems, to capture and even predict the onset and evolution of various types of phenomena. These applications typically require large datasets, composed of many variables and parameters, the number of which can often make the analysis cumbersome and prohibitively time consuming, especially when the interplay of all these parameters is taken into consideration. Thankfully, Information-Theoretical measures can be used to not only reduce the dimensionality of the input space of such a system, but also improve its efficiency. In this work, we present such a case, where differential electron fluxes from the Magnetic Electron Ion Spectrometer (MagEIS) on board the Van Allen Probes satellites are modelled by a simple ANN, using solar wind parameters and geomagnetic activity indices as inputs, and illustrate how the proper use of Information Theory measures can improve the efficiency of the model by minimizing the number of input parameters and shifting them with respect to time, to their proper time-lagged versions.

66) Hemapriya Raju (v) *Deep learning analysis on CMEs assosciated with flares and filaments*

Solar eruptions such as CMEs, flares, and filaments disrupt geomagnetic and communication systems on Earth. While flares are abrupt, bright events that occur in the solar atmosphere and emit massive amounts of energy in the 10^28 to 10^32 erg range, CMEs are intense eruptions that hurl plasma into interplanetary space. CMEs can be found in conjunction with flares, filaments, or independent. Although both flares and CMEs are understood as triggered by a common physical process magnetic reconnection, yet, the degree of association is unknown.We attempted to use this association of CMEs with flares and filaments through extensive Machine Learning and Deep Learning techniques to study the occurrence of CMEs.Further, since there is significant imbalance between the classes, we had explored approaches such as undersampling majority class, SMOTE and generation ofsamples using GAN. We achieved accuracy of around 90% for prediction of CMEs associated with flares and around 96% for those associated with filaments.

67) Ryan McGranaghan (v) *A Next Generation Space Weather Particle Precipitation Model: Mature machine learning approaches, multiscale mesoscale prediction, and an open science framework for machine learning*

Space weather is the impact of solar energy on society and a key to understanding it is the way that regions of space between the Sun and the Earth's surface are connected. It represents a grand challenge for trans-disciplinary collaboration, requiring knowledge and communication from a wide range of communities.One of the most important and most challenging components of space weather to model are the way that energy is carried into the upper atmosphere (100–1,000 km altitude). Particles moving along magnetic field lines “precipitate” into this region, carrying energy and momentum which drive space weather. We have produced a new model, using machine learning (ML), that better captures the dynamics of this precipitation from a large volume of data. Machine learning models, carefully evaluated, are capable of better representing nonlinear relationships than simpler approaches. We reveal our approach to using ML for space weather and provide a new framework to understand these models.Open science refers to a new sensibility for scientific discovery towards transparency, inclusivity, accessibility, and community. This work will models the open science ethos and we will speak to those components.

68) Andrea Diercke (p) *Automatic Extraction of Solar Filaments Using Machine Learning Techniques*

Filaments are omnipresent features in the solar chromosphere. Regular full-disk H-alpha observations allow us to analyze statistical properties of filaments. Therefore, filaments have to be extracted from the images. Manual extraction is tedious and takes too much time; extraction with morphological image processing tools produces a large number of false-positive detection. Automatic object detection and extraction in a reliable manner allows us to process more data in a shorter time. The Chromospheric Telescope (ChroTel), Tenerife, Spain, the Kanzelhöhe Solar Observatory (KSO), Austria, and the Global Oscillation Network Group (GONG), provide regular full-disk observations of the Sun in the core of the chromospheric H-alpha absorption line. We will present a machine learning application allowing us to reliably extract solar filaments from H-alpha filtergrams. First, we train the object detection algorithm YOLOv5 with labeled filament data of ChroTel H-alpha filtergrams. The accuracy of the object detection is very high and it is possible to apply the algorithm to other H-alpha filtergrams to create a larger training data set for the further steps. In a second step, we apply a semi-supervised training approach, where we use the bounding boxes of filaments, that were created with YOLOv5, to learn a pixel-wise classification of solar filaments. Therefore, we utilize a standard deep learning model for semantic segmentation, i.e., DeepLabv3. With the resulting segmentation masks, physical parameters such as the area or tilt angle of filaments can be easily determined and studied. In a last step, we apply the filament detection and the segmentation of filaments on a different H-alpha data set belonging to ChroTel, KSO and GONG, to estimate the general applicability of our method.

69) Sumanth A.T. Rotti (v) *Machine Learning Dataset of SEP Events from Solar Cycles 22, 23 and 24.*

Machine Learning (ML) is a fascinating area that has found its place in the solar and space weather community. The motivation to use ML is that the models can learn and make decisions based on observational data and issue quicker forecasts to improve upon the results of the existing statistical models. Nonetheless, it is crucial to establish basic needs such as reliable data collection & analysis, feature engineering, and infrastructure. In this view, the work developed here highlights the ML-ready dataset for solar energetic particle (SEP) events.SEP events determine the dosage exposure on astronauts and spacecraft equipment outside the Earth's magnetosphere, while proton events >100MeV can penetrate until the Earth's upper atmosphere. Hence, accurate and efficient forecasting of SEPs is essential to protect our astronauts and their equipment.Between 1984 and 2020, we have identified a comprehensive 346 SEP events using existing catalogs. We have generated multivariate time series (MVTS) slices of the SEP events for studies with ML models. We classify this derived list of SEPs into weak (>0.1pfu to <10pfu) and strong (>10pfu) events based on the flux enhancements in the >10 MeV proton channels. Our classification here is restricted to support our ML experiments.Considering the X-ray, proton, and electron fluxes from the Geostationary Operational Environmental Satellites (GOES), we examine the correlations of these fluxes and the correlations that happen across the proton (P2 to P7) and electron (E2 & E3) channels. This strategy offers a new perspective in establishing criteria for geo-effective SEP events arising from a large flare.The work here aims to support the community in implementing the MVTS dataset with their favorite ML model(s) while adhering to near-real-time (NRT) data analysis and operations with optimized methods.

70) Yana Shtyk (v) *Solar flare prediction using a multi-channel model*

In recent years, deep learning approaches have become very popular thanks to the achieved performance in many domains. In our work, we apply the well-known residual neural network (ResNet) to learn patterns and structures in solar images to predict flares. As a dataset, we use the series called SDOBenchmark that consists of images of active regions cropped from SDO data. Dataset labels correspond to the 24-hour prediction horizon. As the dataset includes 10 different SDO channels, we investigate the prediction capabilities of all of them. The best true skill score (TSS) of 0.64 was obtained for the HMI Magnetogram channel. Furthermore, other channels such as AIA 211, AIA 193, AIA 94 show good prediction capabilities for this specific dataset, with a TSS of 0.6. Using the multi-channel nature of the SDOBenchmark dataset, we investigate the performance of multi-channel models where the different channels are first trained independently and then aggregated using two techniques of aggregation: the majority voting, and the summation. The majority voting technique predicts the same output as the majority of the individual channels, while the summation technique makes a decision based on the sum of the soft outputs of the individual channels. Additionally, we investigate a third type of aggregation called deep aggregation that is implemented as a model where the different channels are jointly used for the training. Both majority voting and deep aggregation have shown only a slight improvement of the performance with regard to the individual-channel models. Nevertheless, the aggregation via summation of the soft outputs of the individual channels substantially improves the prediction capabilities. Using this technique we achieve a TSS of 0.7. As a future work, we aim to deeply investigate multi-channel training with more complex aggregation techniques and to apply the proposed multi-channel approach to bigger datasets like SDO.

71) Pavithra G Srinivas (v) *Development Of An Onboard Space Weather Module For Satellite Operations*

We propose a space weather hardware module, which would be onboard satellites, that will provide 24/7 live updates, information, prediction, and alerts on space weather. The objectives of the system are to produce predictions of geomagnetic storms and substorms, spacecraft charging (overall and differential), other radiation predictions, alerts, updates to astronauts, and provide data for research. The capabilities of the system are to effectively communicate with other spacecraft systems and ground systems for inputs, to produce accurate results, it must run 24/7 with live feed, provide data from machine learning, manage existing and incoming data. A specialized ground-based module, consisting of a suite of instruments, a local software prediction model, run other supporting models, and software such as machine learning, data processing, CTMC, and dissemination. Using local plasma and particle measurements, together with orbit, attitude, and schedule information, and a low dimensional model of the earth's magnetosphere called WINDMI, the system will output local indices to alert the satellite's main control system of space weather events. Additionally, the spacecraft module will monitor the spacecraft power system for noise, spacecraft charging values, and other indicators in real-time to provide situational awareness status to the satellite control system. The main focus here is the machine learning software which is a key component of the module. It is used to improve the accuracy rates of the predictions. The output data each time would be fed into the machine learning software which would have an external input (at first) from an astronaut or researcher confirming the predictions and their levels. This would be done based on observing the values of various parameters during a geomagnetic event. The first parameter to be tested would be spacecraft charging, by studying a particular satellite, like RBSP probes.

72) Denny Oliveira (p) *Perspectives on the use of data assimilation for improving thermospheric empirical models: Focus on extreme magnetic storms*

Orbits of human assets such as satellites, crewed spacecraft, and stations in low-Earth orbit (LEO) are very sensitive to the highly dynamic environment in which they fly. Atmospheric drag caused by the interaction between the orbiting object and the local thermospheric neutral mass density affects the satellite's lifetime and orbital tracking, which becomes increasingly inaccurate or uncertain with storm intensity. Given the planned increase of government and private satellite presence in LEO, the need for accurate density predictions for collision avoidance and lifetime optimization, particularly during extreme events, has become an urgent matter and requires comprehensive international collaboration. Additionally, long-term solar activity models and historical data suggest that the solar activity will significantly increase in the following years and decades. In this presentation, we briefly summarize the main achievements in the research of thermospheric density response to magnetic storms occurring particularly after the launching of many satellites with state-of-the-art accelerometers for density determination (CHAMP, GRACE, GOCE, Swarm). We argue that specification models (e.g., HASDM) perform reasonably well during storm main and recovery phases of extreme storms, but forecasting models (e.g., JB2008) do not perform well throughout the storm cycle. We will discuss how forecasting models can be improved by looking into two directions: first, to the past, by adapting historical extreme storm datasets for density predictions, and second, to the future, by facilitating the assimilation of large-scale data sets that will be collected in future events. We invite the community to the discussion on the possible use of several hundreds of satellites with lower resolution density measurements along with data assimilation schemes or the use of ~100 high precision tracked satellites as a more effective approach for future density determinations.

73) Grant K Stephens (v) *Global structure of magnetotail reconnection unveiled by mining spaceborne magnetometer data*

X-lines, where magnetic field lines reconnect and detach from plasma, are microscopic in their cross section, comparable to plasma particle gyroradii. In 2015 the Magnetospheric MultiScale (MMS) mission was launched to fly through these regions to understand the microscale processes which govern magnetic reconnection. During the 2017–2020 seasons, 26 magnetotail reconnection sites were found in the form of Ion Diffusion Regions. Despite these advancements, their global structure and evolution, critical for the total energy conversion and understanding their formation mechanisms, remained unknown because of the data paucity. Here we show that mining spaceborne magnetometer data from 20+ spacecraft covering more than a quarter century, combined with a basis-function expansion of magnetospheric currents, resolves the global structure of these X-lines. This technique confidently reconstructs 23 of the 26 MMS encounter points, many within ~1 RE (RE: Earth radius, or 6374 kilometers) in a magnetospheric volume of > 10^4 RE3.

74) Vanessa M Mercea (v) *Detection of sunquakes in Egression Power Maps using Deep Autoencoders*

Sunquakes have been studied in detail for cause and signatures. Yet, an automatic tool for detecting these signatures has not been established. In this work we attempt to detect sunquakes using Egression power maps based on their observational signatures. We apply Deep Autoencoders for feature extraction and Multilayer Perceptron for classification to a dataset consisting of timeseries of 35 sunquakes over solar cycle 23. Our work proposes a model that can detect the presence of a sunquake by learning relevant information from the data. This model consists of both an unsupervised and a supervised component. To extract relevant information, we use an Autoencoder constructed from Residual Blocks with Convolutional Layers, and for classification, we use a Multilayer perceptron. In our experiments, the model's performance is compared against class imbalance specific loss functions and regularizers. We take the first steps towards demonstrating that by using an Autoencoder for feature extraction, the frames can be encoded into a small latent space that preserves the quake information and other relevant features. We then use this latent space for classification. Initial reconstructions resulting from the Autoencoder have shown good correlation with known sunquake sources when using medium sized latent space representation. The proposed feature extraction model not only facilitates the detection of a sunquake in a frame, but also opens doors for other downstream tasks such as temporal and spatial features extraction. We hope that our approach will show that Machine Learning methods are promising for Heliophysics applications.

75) Anthony Sciola (v) *Ring current plasma pressure reconstructed from empirical magnetic field distributions embedded within a global MHD model*

The storm-time ring current is dominated by suprathermal ions and their non-MHD, energy-dependent drift motions. The ring current energy density dominates in the inner magnetosphere, and influences the magnetospheric dynamics on global MHD scales. A self-consistent description of both thermal and suprathermal particle populations is difficult because kinetic ring current models lack inertial and MHD wave effects, while global MHD models do not include the energy-dependent drifts. In this study we derive a representation of the total plasma pressure, including thermal and suprathermal populations, from an empirical reconstruction of the geomagnetic field. The empirical pressure is derived from the quasistatic force balance of its gradient and the Lorentz force jxB, which in turn is derived from archives of spaceborne magnetometers via the TS07D algorithm which combines elements of machine learning and data mining. We then ingest the empirical ring current pressure in the global MHD GAMERA model. To reconcile the isotropic plasma approximation in the MHD description with the empirical magnetic field, which cannot guarantee pressure isotropy, the force balance equation is reduced to a Poisson-type equation for pressure with an isotropy constraint. We demonstrate that directly ingesting the empirical pressure into the MHD solution leads to an unstable and eruptive inner magnetosphere, whereas ingesting pressure such that flux tube entropy is conserved results in a much more stable solution. The resulting evolution of the storm-time magnetosphere is described, including the buildup and decay of the ring current and its feedback on the global magnetosphere.

76) Ravindra T Desai (p) *Using a neural network to model ultra-relativistic charged particles and exploit sparse datasets*

While often seen as an alternative to physics-based approaches, physics-informed machine learning has the potential to significantly enhance the manner in which physics is conducted. In this study we train a neural network (NN) for two distinct, yet related, applications. We first train the network to simulate the motion of a relativistic charged particle in electromagnetic fields. This has direct application to planetary radiation belts where the long-term self-consistent evolution is intensive to compute. The NN results agree well with theoretical predictions, accurately predicting a range of particle drifts. After demonstrating this underlying concept, we discuss how this approach might be applied to long-term modelling and extreme regimes where deep learning isn't typically utilised. We then train our NN on a sparse dataset collected by Cassini across the Titan's atmosphere, to derive underlying physical and seasonal trends. The NN is able to reproduce latitude, longitude and altitude trends after exposure to a small training dataset and, after exposure to the full dataset, provides a prediction at locations across the moon not sampled by Cassini. We discuss how deep learning informed by underlying physical laws can further probe the multi-faceted dynamics controlling Titan's hazy atmosphere.

77) Sachin A Reddy (v) *Predicting Equatorial Plasma Bubbles with Machine Learning and CubeSats*

Equatorial Plasma Bubbles (EPBs) are plumes of low density plasma that form in bottom side of the nightside F region. EPBs are a known cause of disruptive radio wave scintillations which can cause outages for GNSS, ground-to-satellite, and satellite-to-satellite communications.

SWARM is an Earth observing constellation mission which launched into a near-polar orbit in 2013. We use ion moments and spacecraft potential to classify and predict EPBs.

Our Random Forest classifier has an accuracy of 99%, recall of 94%, precision of 82% and an f1 score of 88%. Longitude is the most important feature, which aligns with previous non-ML work. We also find that spacecraft potential is a key feature in classifying an EPB and we have not seen this reported before.

78) Edward J E Brown (v) *Attention-based machine vision models and techniques for solar wind speed forecasting using solar EUV images*

Extreme ultraviolet images taken by the Atmospheric Imaging Assembly on board the Solar Dynamics Observatory make it possible to use deep vision techniques to forecast solar wind speed - a difficult, high-impact, and unsolved problem. At a four day time horizon, this study uses attention-based models and a set of methodological improvements to deliver an 11.1% lower RMSE and a 17.4% higher prediction correlation compared to the previous work testing on the period from 2010 to 2018. Our analysis shows that attention-based models combined with our pipeline consistently outperform convolutional alternatives. Our study shows a large performance improvement by using a 30 minute as opposed to a daily sampling frequency. Our model has learned relationships between coronal holes' characteristics and the speed of their associated high speed streams, agreeing with empirical results. Our study finds a strong dependence of our best model on the phase of the solar cycle, with the best performance occurring in the declining phase.

79) Stefano Bianco (v) *A neural network model of the plasmasphere dynamics*

We will present a version of the PINE model designed for real-time plasmaspheric forecasts. It consists of a neural-network model of the plasma density having the time history of the solar wind features and of the Kp index as inputs. We will highlight the good features and limitations of the model, during moderate and extreme geomagnetic storms. This model runs in real-time in the PAGER project, producing one-day-ahead plasma-density forecasts and its output is available at https://www.spacepager.eu/data-products/forecast-of-plasma-density.

80) Thomas Berger (p) *Decreasing False Alarm Rates in ML-based Solar Flare Prediction using SDO/HMI Data*

We propose a hybrid two-stage machine learning architecture that addresses the problem of excessive false positives (false alarms) in solar flare prediction systems. The first stage is a convolutional neural network (CNN) model based on the VGG-16 architecture that trains on a temporal stack of consecutive Solar Dynamics Observatory (SDO) Helioseismic and Magnetic Imager (HMI) magnetograms to produce a flaring probability. This probability, along with a feature vector derived from the magnetograms, is then used to train an extremely randomized trees (ERT) model in the second stage to produce a binary deterministic prediction (flare/no flare) in a 12-hour forecast window. For tuning the architectural hyperparameters a new evaluation metric is introduced, the ``scaled True Skill Statistic (TSS)''. This metric addresses the large discrepancy between the true positive rate (TPR) and the false positive rate (FPR) in the highly imbalanced solar flare event training datasets. Through hyperparameter tuning to maximize the scaled TSS, our two-stage architecture drastically reduces false positives by $\approx$ 48% without significantly affecting the true positives (reduction by $\approx$ 12%), when compared with predictions from the first stage VGG-16 alone. This, in turn, improves various traditional binary classification metrics sensitive to false positives such as the precision, F1 and the Heidke Skill Score (HSS). This results in a more robust 12-hour flare prediction system that could be combined with existing operational flare forecasting methods to develop a higher-confidence short-term flare warning. Additionally, using the ERT-based feature ranking mechanism, we show that the output probability from the CNN model is highly ranked in terms of flare prediction relevance.

81) Shah Mohammad Bahauddin(v) *Unboxing the Black Box: Learning to identify acoustic wave sources on the Sun from Deep Learning*

The Sun and many stars are pulsationally stable but display acoustic oscillations none-the-less. These stars are likely stochastically excited by small-scale convective dynamics, but the detailed properties of the acoustic sources are unknown. Although global acoustic modes are readily resolvable, it remains extremely difficult to resolve local source sites which contribute to the power-spectrum of the modes. The difficulties stem from the inherent challenges in separating the faint (several orders of magnitudes weaker than the background) local wave field induced by the acoustic events from the background superposition of convective flow and global resonant p-modes. Even in numerical simulations the unambiguous separation of the convective motions from the contributions of individual compressive sources to the total flow remains problematic. Here we show a robust method for the unambiguous identification of individual acoustic sources that can be readily applied to observations. The method was developed by, first training a deep learning algorithm to reliably identify the signature of local acoustic sources in Radiative MHD simulation of the upper solar convection zone, and then deciphering what underlies the algorithms success. Once diagnosed, we reconstructed the filter that the learning algorithm was applying and applied it directly to the simulated photospheric time series, bypassing the dependence on deep-learning and allowing direct visualization of the local wave pulses that propagate outward from acoustic source sites. We have also successfully identified their signatures in simulated spectrum using a separate deep learning algorithm, and learned clues from it regarding what may be the physical reason behind its success in spectrum space.

82) Donglai Ma (v) *Automatic discovery of the equations governing radiation belt dynamics*

The Earth's radiation belts consist of high energy electrons and protons that are trapped in the geomagnetic field, and constitute a hazard for spacecraft and astronauts. The dynamic variability of the radiation belts has typically been studied using the Fokker-Planck diffusion equation, which assumes that the particles are scattered diffusively, and requires a large number of parameterized diffusion coefficients and boundary conditions representing various physical effects. Typically, various parameterizations are attempted and the Fokker-Planck simulation is run over some long period of time, and when the simulation look fairly close to the observations, it is assumed that the correct physical processes have been identified. However, this traditional mode of analysis is fairly heuristic and there is no guarantee that the diffusion coefficients and their parameterizations are unique, there is no assurance that it is optimal, or indeed that the form of the Fokker-Planck equation is sufficient to capture all the various physical mechanisms that affect radiation belt dynamics. In order to address some of these shortcomings, here we present a completely different approach which relies on the machine learning-based discovery of the underlying Partial Differential Equations (PDEs) that optimally describe the observational data set. This approach does not impose any assumptions on the basic physics, it is general, flexible and can be applied to various physical parameters (as well as energetic electron fluxes) with only minor modifications. We show its application on a long, multi-spacecraft intercalibrated phase space density dataset, and discuss strategies to address typical issues such as noise and spare satellite trajectories.

83) Saida Milena Diaz Castillo (v)*Dense segmentation of solar granulation structures using deep learning*

Solar granulation is the visible signature of convective cells emerging from the inner layers of the solar atmosphere towards the solar surface. High-resolution images of the solar surface have revealed the high complexity of the granulation, evidencing new dynamic phenomena e.g. exploding granules or granular lanes. Such unprecedented data promote new statistical studies focused on understanding solar small-scale phenomena on the solar surface, advocating the development of new automatic tools for the effective identification and localization of the different resolved structures. In this contribution, we present the current advances of our classification algorithm of solar granulation morphologies based on neural semantic segmentation. From a supervised approach, we investigate the ability of the U-net architecture, a convolutional neural network initially proposed for biomedical image segmentation, to the dense segmentation of solar granulation. We use continuum intensity maps of the IMaX instrument onboard the Sunrise balloon-borne solar observatory and their corresponding segmented maps as the training set initially labelled using the multiple-level technique (MLT) and also labelled by hand. We study the performance and precision of this approach to assess the versatility of the U-Net architecture for this task. We found an interesting potential of the U-Net architecture to identify cellular patterns in solar granulation images reaching matching in pixels greater than 80% on the training process. With the proposed procedure, our model achieves high levels of accuracy in the identification of the intergranular network allowing the effective separation of granular cells. We also identify that the network architecture is sensitive in identifying characteristic patterns, such as dots and lanes inside granules.

84) Harim Lee (p) *Generation of Modern Satellite Data from Galileo Sunspot Drawings by Deep Learning*

Historical sunspot drawings are very important resources for understanding past solar activity. We generate solar magnetograms and EUV images from Galileo sunspot drawings using a deep learning model based on conditional generative adversarial networks. We train the model using pairs of sunspot drawings from the Mount Wilson Observatory and their corresponding magnetograms (or UV/EUV images) from 2011 to 2015 except for every June and December by the Solar Dynamic Observatory satellite. We evaluate the model by comparing pairs of actual magnetograms (or UV/EUV images) and the corresponding AI-generated ones in June and December. Our results show that bipolar structures of the AI-generated magnetograms are consistent with those of the original ones and their unsigned magnetic fluxes (or intensities) are consistent with those of the original ones. Applying this model to the Galileo sunspot drawings in 1612, we generate Helioseismic and Magnetic Imager-like magnetograms and Atmospheric Imaging Assembly-like EUV images of the sunspots. We hope that the EUV intensities can be used for estimating solar EUV irradiance at long-term historical times.

85) James Lende (v) *Statistical Investigation of the Erosion and Refilling of the Plasmasphere - Neural Network Model Approach*

The density and composition of Earth’s Plasmasphere strongly influences wave growth and propagation, as well as energetic particle scattering. This affects Earth-to-space communication and killer electron behavior. The plasmaspheric dynamics are both time-dependent and history-dependent. Previous empirical plasma density models have been based on statistical averages and are limited in their capability to make accurate predictions of the dynamic state of Earth’s plasmasphere. With recent advances in machine learning techniques, we are able to more accurately quantify complex global processes and nonlinear responses to driving conditions, especially during geomagnetic storms. This project presents a three-dimensional dynamic electron density model based on an artificial neural network. This model uses a feedforward neural network which was generated using electron densities from the satellite missions of CRRES, ISEE, IMAGE, and POLAR. The three-dimensional electron density model takes spacecraft location as well as time series of solar wind and geomagnetic indices (AE and F10.7) obtained from NASA's OMNI database as inputs. The model can predict out-of-sample data with a correlation coefficient of 0.94, meaning over 90% of the variations are captured. The three-dimensional model was applied to a number of magnetic storms, and it successfully reconstructed the expected plasmaspheric dynamics. We carried out a statistical analysis of the plasmaspheric erosion rates and refilling processes during these geomagnetic storms using the ML-based reconstruction, which show the plasmaspheric dynamics that cannot be obtained using spacecraft observations. The statistical results are consistent with previous studies. This model demonstrates the potential for machine learning techniques to be utilized in understanding the physics and insight discovery, as well as advance the state-of-the-art space weather prediction.

86) John C Dorelli (v) *Vlasov Informed Super Resolution (VISR): A Deep Learning Approach for De-Aliasing Particle Data*

NASA science missions must solve the challenging problem of understanding the structure and dynamics of severely under-sampled systems. Missions are designed with a suite of instruments on one or more spacecraft, each instrument making observations along spacecraft world lines sampling a very small volume of space and time. In the case of particle instruments, the sample space is the full seven-dimensional single-particle phase space, and the fi nite energy sweep limits the temporal resolution. Solving this "aliasing" problem would enable an order of magnitude increase in the temporal resolution of particle instruments. Deep learning approaches have shown great promise in addressing the problem of recovering structure from sparse observations. Specifically, PhysicsInformed Neural Networks (PINN) build in partial differential equation (PDE) constraints into the loss function, greatly reducing the number of observations required to build an accurate and predictively powerful model. We apply a newly developed PINN technique -- Vlasov Informed Super Resolution(VISR) -- to "de-alias" particle data and recover dynamics on time scales faster than the energy sweep. We demonstrate the feasibility of the VISR approach using data from NASA's Magnetospheric Multiscale (MMS) mission.

87) Xin Cao (v) *Investigation of the response of equivalent ionospheric current to upstream solar wind and magnetospheric activity: a neural network approach*

"It is well known that geomagnetic field disturbances can be generated at high latitudes due to strong ionospheric electrojet currents during substorms and geomagnetic storms. These large magnetic disturbances, usually accompanied by a large rate-of-change in the magnetic field dB/dt, will also produce geoelectric fields and geomagnetically induced currents (GIC).

In order to study the variations of ionospheric currents (i.e., the Equivalent Ionospheric Currents (EICs) and the Spherical Elementary Current (SEC) amplitudes) and its response to upstream solar wind and the magnetospheric activities, we developed an ANN-SEC model based on the feedforward neural network to reproduce the ionospheric current obtained from the SEC technique. The conventional statistical analysis is incapable of providing a quantitative prediction and reproduction of the EICs and SEC amplitudes with relatively high accuracy due to the high nonlinearity of this system. Understanding how the upstream solar wind, the magnetospheric dynamics, and the Earth's ionosphere coupled with each other is essential. The data utilized are measured by multiple spacecraft and ground-based observations, and the target values of the ANN-SEC model are the ionospheric currents obtained from the SEC technique, including both components of the EICs and the SEC amplitudes. The input parameters include the locations of the measurements (longitude and latitude), solar wind parameters (e.g., solar wind velocity, magnetic field, dynamic pressure), and geomagnetic indices (e.g., AL, AU, AE, SYM-H, ASY-H). Based on the result of our ANN-SEC model, we found that our model is promising in predicting the Earth’s ionospheric currents using the driving mechanism of the solar wind and the magnetosphere. Our model can provide spatial and temporal reconstruction of the ionospheric currents whenever and wherever they are not directly available from the SEC current system."

88) Subhamoy Chatterjee (p) *Utilizing a Convolutional Neural Network to Efficiently Label a Solar Flux Emergence Video Dataset*

Supervised Machine learning is becoming a vital tool for interrogation of large complex data. However, labeling large datasets requires human effort and is thus time consuming. Here we show that convolutional neural networks (CNNs), trained on crudely labeled astronomical videos, can be leveraged to improve the quality of data labeling and reduce the need for human intervention. We use videos of the solar photospheric magnetic field measured by SoHO/MDI, crudely labeled into two classes: emergence or non-emergence of large bipolar magnetic regions (BMRs). We train the CNN using crude labeling, manually verify, correct labeling vs. CNN disagreements, and repeat this process until convergence. This results in a high-quality labeled dataset requiring the manual verification of only ~50% of all videos. On a manually verified test set we achieve 83% classification accuracy and find no dependence of the same on solar cycle phase. Furthermore, by gradually masking the videos and looking for maximum change in CNN inference, we locate BMR emergence time without retraining the CNN. Additionally using saliency analysis on representative examples we find that the CNN model is able to give importance to the right spatial information to reach at an expected video label. This demonstrates the versatility of CNNs for simplifying the challenging task of labeling complex dynamic events.

89) Zeyu Sun(v) *Predicting Solar Flares Using CNN and LSTM on Two Solar Cycles of Active Region Data*

We consider the flare prediction problem that distinguishes flare-imminent active regions that produce an M- or X-class flare in the future 24 hours, from quiet active regions that do not produce any flare within ± 24 hours. Using line-of-sight magnetograms and parameters of active regions in two data products covering Solar Cycle 23 and 24, we train and evaluate two deep learning algorithms---CNN and LSTM---and their stacking ensembles. The decisions of CNN are explained using visual attribution methods. We have the following three main findings.(1) LSTM trained on data from two solar cycles achieves significantly higher True Skill Scores (TSS) than that trained on data from a single solar cycle with a confidence level of at least 0.95.(2) On data from Solar Cycle 23, a stacking ensemble that combines predictions from LSTM and CNN using the TSS criterion achieves significantly higher TSS than the ``select-best'' strategy with a confidence level of at least 0.95.(3) A visual attribution method called Integrated Gradients is able to attribute the CNN's predictions of flares to the emerging magnetic flux in the active region. It also reveals a limitation of CNN as a flare prediction method using line-of-sight magnetograms: it treats the polarity artifact of line-of-sight magnetograms as positive evidence of flares.

90) Linnea Wolniewicz (v) *SEARCH: SEgmentation of Active Regions and Coronal Holes*

Coronal Holes (CHs) and Active Regions (ARs) are features of the Sun that are associated with solar magnetic activity and space weather. This has consequently led to the development of various segmentation methods for their automatic detection and characterization from satellite images, most notably in the context of forecasts. For example, neural networks have been trained to emulate existing databases of CH detections and then make predictions of CH boundaries when presented with a EUV image (i.e., supervised machine learning). We introduce the SEgmentation of Active Regions and Coronal Holes (SEARCH) project in which we apply unsupervised machine learning methods (e.g., clustering and a W-net convolutional neural network) to identify features consistent with CHs and ARs without the biases that supervised learning methods may encompass. We present work in progress regarding the application of said methods to synchronic maps generated by Predictive Science Inc. (PSI) that combines EUV data from three vantage points (STEREO-A, STEREO-B, and SDO) during the 2010-2014 epoch. Derived segmentation maps are used, for example, to study the relationship between polar CH area and magnetic activity. Finally, the characterization of CHs and ARs in solar images through the proposed unsupervised learning approaches may help assess the contributions of these features to solar wind parameters.

91) Enrico Camporeale (p) *The PRAISE Initiative: Promoting Research in Artificial Intelligence for the Space Economy*

A wake-up call for the ML-Helio community!

92) Kevin Smith *Machine Learning Classification of Mercury Magnetospheric Boundary Crossings*

We present work to classify magnetic regions near the planet Mercury (magnetosphere, magnetosheath, and solar wind) using magnetometer data from the NASA MESSENGER spacecraft and a manually classified catalogue of bow shock and magnetopause crossings from Sun et al. [2020]. These crossing times allow us to unambiguously define different regions with distinctive magnetic characteristics. From this we take a supervised learning approach and train various machine learning architectures, including a Recurrent Neural Network (RNN) to accurately and rapidly classify regions in MESSENGER data across its 4 years of near Mercury observations.

93) Daniel E da Silva (p) *Semi-Empirical Data Compression for Heliophysics Space Mission Data*

The ability for Heliophysics sensors to measure higher and higher resolution data has outpaced the ability to transmit the data. A mission’s limited telemetry budget has become a bottleneck, with high-resolution measurements now being discarded simply because there is not enough bandwidth to transmit them. We present a new algorithm, SEPC (Semi-Empirical Plasma Compression) which implements data compression for ion velocity distribution functions in units of counts, validated through preservation of the derived plasma moments. The algorithm utilizes a block-oriented transform method via a neural network auto-encoder to associate to-be-compressed measurements with previous measurements to reduce the dimensionality. The dimensionality reduction from the auto-encoder is followed by quantization of the floating-point coefficients and lossless entropy coding to produce a final compressed result. Applications for other type of Heliophysics space mission data such as solar imagery are expected to follow. The algorithm designed and discussed here are made to be simple and fast enough to be suitable for spaceflight through on-board flight software.

Sponsors

Time difference calculator

(Note: on this week USA is on Daylight Saving time, while Europe and Australia are still on winter time)

Boulder	Rome	New Delhi	Tokyo	Sydney
MDT (UTC -6)	CE T (UTC+1)	IST (UTC +5:30)	JST (UTC +9)	AEDT (UTC +11)
8:00 am	3:00 pm	7:30 pm	11:00 pm	1:00 am
12:00 pm	7:00 pm	11:30 pm	3:00 am	5:00 am
3:00 pm	10:00 pm	2:30 am	6:00 am	8:00 am
5:00 pm	12:00 am	4:30 am	8:00 am	10:00 am