Machine Learning in Heliophysics Amsterdam,
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Abstract book

Invited talks

Daniel Baker (LASP, University of Colorado Boulder, CO, USA)
Heliophysics Data Science: Past Experience and Future Prospects

Acquisition of relatively large data sets based on measurements in the interplanetary medium, throughout Earth's magnetosphere, and from ground-based platforms has been a hallmark of the heliophysics discipline for several decades. Early methods of time series analysis with such data sets revealed key causal physical relationships and led to successful forecast models of magnetospheric substorms and geomagnetic storms. Applying neural network methods and linear prediction filtering approaches provided tremendous insights into how solar wind-magnetosphere-ionosphere coupling worked under various forcing conditions. Some applications of neural net and related methods were viewed askance in earlier times because it was not obvious how to extract or infer the underlying physics of input-output relationships. Today, there are powerful new methods being developed in the data sciences that harken back to earlier successful prediction and forecasting methods. This talk will review earlier work and look at new prospects for heliophysics prediction methods.

Joe Borovsky (Center for Space Plasma Physic, Space Science Institute, Boulder, CO, USA)
Vector-Vector Correlations: The Solar Wind and the Magnetosphere

For analysis of the solar-wind-driven magnetosphere-ionosphere-thermosphere system, we have developed a methodology to reduce a state-vector description of a time-dependent driven system to a composite scalar picture of the activity in the system. The technique uses canonical correlation analysis to reduce the two multidimensional time series of the system and driver state vectors to time-dependent system and driver scalars, with the scalars describing the response in the system that is most-closely related to the driver. This description that is a reduction from the state vectors has advantages: low noise, high prediction efficiency, linearity in the described system response to the driver, and compactness. The scalar description of the magnetosphere also has versatility with respect to (a) storm-versus-quiet intervals, (b) solar maximum versus solar minimum, and (c) the various types of solar-wind plasma. The methodology has been used to identify independent modes of reaction of the magnetospheric system to its solar-wind driver.

Cyril Furtlenher (INRIA, Paris, France)

A machine learning approach to solar wind speed forecasting from solar images

Forecasting the solar wind speed close to the earth is an important aspect in the domain of space weather in order to anticipate damaging solar eruptions.
Considering the quantity of daily observations of the sun provided by the various observation satellites and the complexity of the phenomena involved in the solar wind propagation from the sun to the earth magnetosphere, it is tempting to look for a purely data driven approaches to address this problem. Following this way, the problem naturally breaks up into two parts from the machine learning point of view.
The first one consists to extract features from various sources of solar images; the second one uses those features as input variables to the prediction of time lagged solar wind speed near the earth. The first stage is tackled by means of various auto-encoders leading to reduce the input signal to a few hundreds of real valued features. The second stage involve a non-standard time series forecasting problem where the output signal and the time lag have to be jointly predicted from a rather large dimensional input, without any explicit observation of the time lag. We tackle this second problem by learning a latent probabilistic model encoding the time lag with latent binary states, considered as a function of the input. Building blocks of the model consists of neural network based regression functions, which are eventually assembled into a single integrated architecture with the encoder obtained from the first stage problem. Proofs of concept will be presented on artificial data and results on real data experiments will then be discussed to conclude.

George Em Karniadakis (Division of Applied Mathematics, Brown University, USA)

Physics-Informed Neural Networks (PINNs)

We will present a new approach to develop a data-driven, learning-based framework for predicting outcomes of physical and biological systems and for discovering hidden physics from noisy data. We will introduce a deep learning approach based on neural networks (NNs) and generative adversarial networks (GANs). Unlike other approaches that rely on big data, here we “learn” from small data by exploiting the information provided by the physical conservation laws, which are used to obtain informative priors or regularize the neural networks. We will also make connections between Gauss Process Regression and NNs and discuss the new powerful concept of meta-learning. We will demonstrate the power of PINNs for several inverse problems in fluid mechanics, solid mechanics and biomedicine including wake flows, shock tube problems, material characterization, brain aneurysms, etc, where traditional methods fail due to lack of boundary and initial conditions or material properties. We will address the issue of total uncertainty quantification, namely the uncertainty associated with the network separately from the uncertainty in the parameters, data and models.

Adam Lesnikowski (NVIDIA, USA)

Data-Driven Datasets: Deep Active Learning and Beyond

How can we optimally employ data-intensive ML methods when we have a limited labeling budget? Today we are able to collect much more data than we can typically label, and so are faced with the challenge of either carefully choosing what to label or bear with suboptimal performance. I will introduce a few techniques that my team and I at Nvidia have worked on to address this challenge, with a particular example application area on autonomous vehicle technology. These techniques have included active learning and Bayesian uncertainty estimation, in addition to familiar techniques like pre-training and fine-tuning. I will propose a couple of promising applications to heliophysics using these techniques, with a focus on how we can reduce the dependence on large labelled datasets with costly labeling budgets. Time permitting, I will cover some of the most recent trends and promises of using simulators, generative models and other synthetic data generation methods to address limited labeling budgets.

Robert L. McPherron (UCLA)

Early Studies in Space Physic Using Machine Learning

Machine learning is defined as the study of algorithms to allow computers to solve specific tasks without explicit instructions. One example in space science is called supervised learning. In this process a set of data containing inputs and outputs is used to construct a function that transforms the input to the output. Linear and local linear prediction filters are examples of this process that have a long history in space physics. A generalization of this process is the neural network (NN). These algorithms use historical data to train a network of nodes connected through numerical weights to fulfill a certain task such as classification or prediction. Discrepancies between the known result and a prediction are used to alter the weights to improve the predictions. Detailed understanding of the underlying processes is not required. In a practical sense this is a virtue but the ultimate goal of science is understanding and there is no obvious procedure for using the weights to achieve this goal. Genetic algorithms are another form of machine learning. The weights within an NN may be thought of as its genotype. Alteration of these weights by mutation and crossover can produce a new set of weights whose performance is either better or worse than the initial set. Elimination of bad sets and further evolution of good sets is expected to produce improved performance of the network. Another example of machine learning includes probabilistic forecasting. In many cases the inputs to a system can only be determined as probability distributions dependent on slowly changing but observable conditions. A history of actual observations of the relation between input and output can be used to establish the probability of a given outcome given observable conditions. Yet another form of machine learning is the expert system where human expertise experience is encoded in a set of rules that allows a computer program to convert a sequence of known facts into the most probable conclusion. The author of this paper has participated in numerous studies that apply some of these techniques to space physics. He will review some of the early work and relate it to current developments.

Naoto Nishizuka (NICT, Japan)

Solar Flares and Eruptions Predicted by Deep Neural Networks: Deep Flare Net (DeFN)

Solar flare prediction is one of our important tasks for space weather forecasting, because flares can affect the earth by X-ray emissions as well as eruptions and energetic particles in the Heliosphere. People have tried to reveal fundamental mechanisms of flares/eruptions and developed prediction methods, such as (i) empirical, (ii) statistical, (iii) numerical and (iv) machine-learning (ML) methods. Now it is a hot topic to apply ML techniques to flare predictions, and some models have succeeded in improving skill scores. The deep neural network (DNN) is a newly developed algorithm which shows the highest accuracy of prediction in general. In DNN models, Convolutional Neural Network (CNN) can automatically extract features from images and accelerated DNN applications, but it has a disadvantage of unexplainability.

Here, we introduce our solar flare prediction model using DNNs named Deep Flare Net (DeFN; Nishizuka et al. 2018). This model can calculate the probability of flares occurring in the following 24 hr in each active region, which is used to determine the most likely maximum classes of flares via a two-class classification (≧M vs. <M class, or ≧C vs. <C class). From 3x10^5 observation images taken by SDO during 2010–2015, we detected active regions and calculated 79 features for each region, to which we annotated labels of X-, M-, and C-class flares. We adopted the features used in Nishizuka et al. (2017) and added some features for operational prediction: coronal hot brightening at 131 Å (T≧10^7 K) and the X-ray and 131 Å intensity data 1 and 2 hr before an image. For operational evaluation, we divided the database into two for training and testing in a chronological way: the data set in 2010–2014 for training, and the one in 2015 for testing. The DeFN model consists of deep multilayer neural networks formed by adapting skip connections and batch normalizations.

The DeFN model was optimized to maximize the skill score, i.e., the true skill statistic (TSS). As a result, we succeeded in predicting flares with TSS=0.80 for ≧M class flares and TSS=0.63 for ≧C class flares. Note that in usual DNN models, the feature extraction process is a black box. However, the features used in the DeFN model are manually designed by experts, and it is possible to analyze which features are effective for prediction after evaluation. Furthermore, this model can be applied to predict eruptions like CMEs. In this talk, we would like to discuss the feature ranking revealed by DNN model and also the dependence of the optimization methods by TSS and other skill scores.

Barbara Thompson (NASA Goddard, USA)

Frontiers in Data Science and Machine Learning in Heliophysics

Great progress has been made by researchers using cutting-edge tools and technologies from the field of data science, including machine learning, to impact many areas of heliophysics. The clearest examples are in the field of space weather – the “prediction” ethos of machine learning naturally lends itself to the growing need to improve forecasts.

However, the arena of high potential is broad, including:

1) Computational Acceleration and Model Emulation: tasks that are computationally burdensome can be "learned" and then emulated, resulting in a dramatic increase in speed and flexibility;

2) Downscaling and Resampling: models can be trained to predict small-scale structures more accurately than interpolations or even physical models, thereby increasing resolution; and
3) Explainability/Interpretability: advances in our ability to interpret the way an algorithm arrives at a particular result leads to improved understanding of the system as a whole. By driving towards explainability, we challenge ourselves to understand not only _what_ result was achieved, but also _why_. The explainability/interpretability approach can be leveraged to derive knowledge about the relationships between variables, leading to a greater physical understanding of the system itself.

Peter Wintoft (Swedish Institute of Space Physics, Sweden)

Space weather - Dynamical systems modeled by neural networks

Machine learning (ML) is the overarching term for many different algorithms designed to extract knowledge and mappings from data. Examples of algorithms are neural networks, support vector machines, and gaussian processes. The focus of this work will be on neural networks and their application to space weather modelling and forecasting, a history that goes back to the early 1990's. Neural networks offer great capabilities of modelling non-linear systems that may also be chaotic. Over the recent decade a lot of progress have been made on new network architectures and new training algorithms. At the same time the availability of free software and the ongoing increase in computing power have led to an tremendous increase in their application. The difficult task for a space weather modeller is to decide if and what ML approach to adopt considering that there is little theoretical guidance in which models are appropriate for a specific problem and that the search in the hyper-parameter space is time consuming due to the large number of combinations. In this work different networks, such as time-delay and recurrent networks with different activation functions, will be compared to simple mathematical dynamical models (i.e. differential equations) in an attempt to generalise to real systems. Having a simple mathematical model that captures some aspects of the real system has the advantage that artificial data can be generated from which experience can be gained for the network modelling. The simple model can also be used as a baseline model to evaluate the network trained on real data. Another aspect is that the validation and testing on data independent from the training data are extremely important as that is the only way to get an estimate of the true performance. To learn about limits in prediction accuracy and potential future improvements it is useful to study the distribution of errors in addition to summary metrics such as mean-square-error or coefficient-of-determination. The above points will be discussed in the context of the connection between the solar wind and geomagnetic activity and solar activity.

Contributed talks

Jorge Amaya (KU Leuve, Belgium)

Automatic unsupervised classification of the solar wind using Self-Organizing Maps

Multiple authors have proposed different classification methods of the solar wind observed at 1 AU. These include simple models that use the solar wind speed to separate “fast” from “slow” flows (Arya and Freeman, 1991, Yordanova et al., 2009, among others), complex empirical methods binning the solar wind properties in four possible categories associated with the plasma source in the solar atmosphere (Xu et Borovsky, 2015), and more recently automatic unsupervised machine learning models using Gaussian processes (Camporeale et al., 2017).
Classifying the solar wind serves four main objectives: 1) to perform statistical analysis of different wind types, 2) to interpret in-situ observations of the magnetosphere, 3) to diagnose physical processes ongoing at the Sun, and 3) to study the effects of solar cycle variations on the Earth plasma environment.
In this work we use the machine learning technique known as Self-Organizing Maps (SOM) to classify the solar wind at 1AU using in-situ properties of the plasma and remote measurements of solar properties. At any given point in time all the properties measured can be viewed as a single point in a multi-dimensional (ND) space. SOM transform this ND space into a 2D space with a small number of L x L nodes. These nodes are the 2D representation of the ND space and group together, around a single node, points with similar properties. The nodes in the 2D map are also inter-related, thus maintaining a structural topology that is used to better interpret the final results.
Using SOM we can reclassify the solar wind into L x L classes. We compare the results obtained using SOM with the methods introduced above.
This contribution has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No 776262 (AIDA, www.aida-space.eu)

Sigiava Aminalragia-Giamini (SPARC, Greece)

High quality particle fluxes from space radiation monitor data using Artificial Intelligence and Machine Learning methods

Space radiation monitors are instruments that monitor the particle radiation environment and provide alerts regarding elevated radiation levels to the host spacecraft. They are designed to detect particles in energy ranges that can harm instruments, corrupt measurements, cause various types of malfunction from simpler data losses to catastrophic failures, and can be harmful or detrimental to human health. Monitors are typically sensitive to protons with energies of a few MeVs up to hundreds of MeVs and to electrons with energies of a few hundred keVs up to a few MeVs. These monitors can record particles from some of the most intense space weather phenomena, such as Solar Proton Events, and the Van Allen Radiation Belts, the harshest regions of space near Earth. In this sense, they can provide a trove of particle measurements in wide energy ranges and from multiple regions of space, which can be very valuable for scientists, engineers, spacecraft operators, and mission planning. However, the calculation of particle fluxes from monitor measurements, i.e. unfolding of count-rates to fluxes, is not straight-forward and has often hampered or prohibited the wider exploitation of such data. Unfolding is an inverse ill-posed problem and can often provide results which, while mathematically correct, may be physically non-meaningful, for example negative fluxes. We present an unfolding method using Artificially Intelligence, which manages to calculate fluxes that reproduce very accurately the monitor count-rate measurements and provide physically meaningful differential spectra with high energy resolution. Our approach employs two different methods used in tandem: Case Based Reasoning and a Genetic Algorithm. The first provides a rough spectral estimation and the latter fine-tunes the spectra to match measurements more precisely - creating a tool that can successfully unfold fluxes from instruments with very different response functions and for different types of particles. Results are presented for data from two different radiation monitors: ESA's Standard Radiation Environment Monitor (SREM) on board the INTEGRAL mission; and the Environmental Monitoring Unit (EMU) on the EU Galileo satellite Galileosat-15 (Antonianna). The results are validated with data from the SEPEM Reference Dataset v2.0 for proton fluxes and data from the Van Allen Probes instruments Magnetic Electron Ion Spectrometer (MagEIS) and Relativistic Electron Proton Telescope (REPT) for electron fluxes.

John A. Armstrong (University of Glasgow, UK)

RADYNVERSION: Learning to invert a solar flare atmosphere using invertible neural networks

During a solar flare, it is believed that reconnection takes place in the corona followed by fast energy transport to the chromosphere. The resulting intense heating strongly disturbs the chromospheric structure, and induces complex radiation hydrodynamic effects. Interpreting the physics of the flaring solar atmosphere is one of the most challenging tasks in solar physics. I will present a novel deep learning approach, an invertible neural network, to understanding the chromospheric physics of a flaring solar atmosphere via the inversion of observed solar line profiles in Hα and Ca II λ8542. Our network is trained using flare simulations from the 1D radiation hydrodynamics code RADYN and then applied to an observation of an M1.1 solar flare taken with SST/CRISP instrument. The inverted atmospheres obtained from observations provide physical information on the electron number density, temperature and bulk velocity flow of the plasma throughout the solar atmosphere ranging from 0-10 Mm in height. The density and temperature profiles appear consistent with the expected atmospheric response, and the bulk plasma velocity provides the gradients needed to produce the broad spectral lines whilst also predicting the expected chromospheric evaporation from flare heating. We conclude that we have taught our novel algorithm the physics of a solar flare according to RADYN and that this can be confidently used for the analysis of flare data taken in these two wavelengths. This algorithm can also be adapted for many inverse problems whilst providing extremely fast results. The network is open source and freely available.

A. R. Azari (Unversity of Michigan, USA)

Multivariate Supervised Classification for Instabilities at Saturn: A Comparison of Methods for Automated Event Detection in Magnetospheres

In 2004 the Cassini mission arrived at Saturn. For the next 13 years the mission collected large amounts of data, resulting in a highly sampled magnetosphere of Saturn. Due to Cassini, Saturn is now the second most observed magnetosphere after that of Earth now allowing opportune applications of large scale statistical methods. Much of our previous expectations about the Saturn environment have been overturned, including the primary source of mass in the system. Enceladus, located at 4 Saturn radii outgasses ~ 250 kg/s of H20 into the magnetosphere, forming a dense disk of material spreading well into the middle magnetosphere. Saturn differs from Earth due to this extensive mass source, but also due to its rapid rotation, leading to a co-rotating plasma environment in < 11 hours per rotation. These two differences in the environment set up a Rayleigh-Taylor like instability wherein the dense plasma is forced into the less dense plasma. The dense plasmas created from the Enceladus H20, interchange with less dense energetic H+, resulting in the observed transport of H+ towards the planet, termed as interchange injections.

In this work we will first present a previous effort to both identify and characterize interchange injections from high-energy (3 – 220 keV) ion intensities using the methods commonly employed in supervised classification tasks merged with required physical assumptions of the Saturnian environment. This work created a unique and reproducible list of events by combining predictive data analytics with background plasma environment characterization, uniquely allowing for subsequent statistical analysis on these events. These events are both identified and characterized by severity against the background plasma environment through our automated method. This effort represented the first automated event detection algorithm implemented to detect such events.

We then discuss issues in automated data analysis within dynamic planetary systems, such as Saturn by comparing our previous method to additional multivariate supervised classification models including random forest as an illustrative example. These issues include non-equal sampling, extreme temporal and spatial variability, and missing or invalid values. We focus on solutions to allow for the applications of classification tasks and automated event detection methods to benefit from the new surge of planetary space physics data now available to characterize the outer planets.

Hazel Bain (CIRES, University of Colorado, Boulder & NOAA SWPC, USA)

Solar Energetic Particle Forecasting Using Machine Learning Classification Techniques

Radiation storms consisting of solar energetic particles (SEPs) are a major component of space weather. SEPs events have the capacity to damage electrical hardware on spacecraft leading to malfunctions; disrupt long distance high frequency (HF) radio communication causing possible long-term blackouts at high Earth latitudes; and pose a radiation hazard to passengers and crew on aircraft flying over the poles. Furthermore, for human spaceflight and deep space exploration, to the Moon and Mars, astronauts will be exposed to the full extent of these storms. Therefore, an essential aspect of space weather forecasting is to predict the occurrence of SEPs before they hit.

Physics-based numerical models are not yet at the level where they can provide real-time forecasts required in an operational setting. As such, we apply machine learning classification algorithms (Logistic Regression, Support Vector Machines, Adaboost etc) to a historical dataset of SEP events to assess the applicability of this approach for SEP forecasting. Performance of the model is measured against the PROTONS prediction model currently used in operations at NOAA Space Weather Prediction Center and other empirical models capable of operating in real-time.

Mayur Bakrania (Mullard Space Science Laboratory, University College London, UK)

Using Big Data Techniques to Classify Solar Wind Electron Populations

Solar wind electron velocity distributions at 1 au consist of three main populations: the thermal (<50 eV) population called the core and two suprathermal (∼50–1000 eV) populations called halo and strahl. The core and halo are quasi-isotropic populations, whereas the strahl travels along the interplanetary magnetic field (IMF) and can be observed in either the parallel or antiparallel magnetic field direction.

Using spin averaged electron data from the Cluster PEACE instruments, we analyse differential energy flux vs. both energy and pitch angle to classify these electron populations. Initially, we train supervised learning algorithms on these three classifications in order to categorise the entire dataset. Subsequently, we use unsupervised algorithms to independently classify these distributions, enabling us to perform comparisons between the two methods.

We find high accuracies in determining whether there exists a dominant population in any given distribution, with both supervised learning and unsupervised learning methods showing very similar results. We also assign probabilities to distributions with multiple populations. By characterising the three electron populations dependent on solar wind parameters, with the verification of machine learning techniques, we can show a difference in breakpoint energies between core/halo and core/strahl populations. Furthermore, combining clustering methods and Gaussian fitting algorithms enables the percentage contribution of each electron population to be calculated for a given timeframe.

We discuss our results in the context of potential scattering mechanisms for solar wind electrons.

Will Barnes (Lockheed Martin Solar and Astrophysics Laboratory, USA)

Seeing the Trees through a Random Forest: Details of Active Region Heating Revealed through Forward Modeling and Classification

Understanding how loops in active regions are heated is a critical step in solving the coronal heating problem. In particular, constraining the frequency at which individual strands are reenergized can shed light on what mechanism releases energy from the highly-stressed magnetic field into the coronal plasma. To address this problem, we forward model time-dependent AIA intensity maps of active region NOAA 1158 for low-, intermediate-, and high-frequency nanoflares using a combination of loop hydrodynamics, potential field extrapolations, and detailed atomic physics. We then compute emission measure slopes and time lags for all possible channel pairs (15 in total) in every pixel of our synthesized active region. We apply this same analysis to twelve hours of AIA observations of NOAA 1158. To make quantitatively meaningful comparisons between our synthetic and observed data, we train a random forest classifier on the synthetic emission measure slopes and time lags and apply it to our observed slopes and time lags in order to classify the heating frequency in each pixel of the active region. This approach allows us to easily and efficiently incorporate multiple observables in deciding with which heating model the observations are most consistent. We find that high-frequency heating dominates in the center of active region and is coincident with the areas of large magnetic field strength while intermediate-frequency heating is more likely in longer loops surrounding the center of the active region. Low-frequency heating is not needed to explain most of the observed diagnostics. Additionally, we find that the emission measure slope is the strongest predictor of the heating frequency.

Monica Bobra (Stanford University, USA)

An Overview of Solar Flare Prediction Using Machine Learning Techniques

Solar flare forecasting has come a long way in the last few years. Many previous studies forecasted flares by identifying a physically meaningful feature of the magnetic field on the solar surface -- for example, the polarity inversion line, which is a relatively thin band on photosphere where oppositely signed magnetic fields collide -- and studying the relationship between this feature and flaring activity using standard statistical techniques. These studies laid the groundwork for the modern approach to solar flare forecasting, which uses many features of both the solar photosphere and corona in conjunction with machine learning models to produce results that almost universally outperform traditional methods. In this talk, we will discuss progress in flare forecasting over the last decade, assess its current state, and identify ways to improve the future of the discipline.

Enrico Camporeale (University of Colorado, Boulder, USA)

On the generation of probabilistic forecasts from deterministic models

Most of the methods that produce space weather forecasts are based on deterministic models. In order to generate a probabilistic forecast, a model needs to be run several times sampling the input parameter space, in order to generate an ensemble from which the distribution of outputs can be inferred.

However, ensemble simulations are costly and often preclude the possibility of real-time forecasting. We introduce a simple and robust method to generate uncertainties from deterministic models, that does not require ensemble simulations. The method is based on the simple consideration that a probabilistic forecast needs to be both accurate and well calibrated (reliable). We argue that these two requirements are equally important, and we introduce the Accuracy-Reliability cost function that quantitatively measures the trade-off between accuracy and reliability. We then define the optimal uncertainties as the standard deviation of the Gaussian distribution that minimizes the cost function. We demonstrate that this simple strategy, implemented here by means of a deep neural network, produces accurate and well-calibrated forecasts, showing examples both on synthetic and real-world space weather data.

Eoin Carley (Trinity College Dublin, Ireland)
Using supervised machine learning to automatically detect type II and III solar radio bursts

Solar flares are often associated with high-intensity radio emission known as `solar radio bursts' (SRBs). SRBs are generally observed in dynamic spectra and have five major spectral classes, labelled type I to type V depending on their shape and extent in frequency and time. Due to their morphological complexity, a challenge in solar radio physics is the automatic detection and classification of such radio bursts. Classification of SRBs has become necessary in recent years due to large data rates (3 Gb/s) generated by advanced radio telescopes such as the Low Frequency Array (LOFAR). Here we test the ability of several supervised machine learning algorithms to automatically classify type II and type III solar radio bursts. We test the detection accuracy of support vector machines (SVM), random forest (RF), as well as an implementation of transfer learning of the Inception and YOLO convolutional neural networks (CNNs). The training data was assembled from type II and III bursts observed by the Radio Solar Telescope Network (RSTN) from 1996 to 2018, supplemented by type II and III radio burst simulations. The CNNs were the best performers, often exceeding >90% accuracy on the validation set, with YOLO having the ability to perform radio burst burst localisation in dynamic spectra. This shows that machine learning algorithms (in particular CNNs) are capable of SRB classification, and we conclude by discussing future plans for the implementation of a CNN in the LOFAR for Space Weather (LOFAR4SW) data-stream pipelines.

Ruizhu Chen (Stanford University, USA)
Estimating the Sun's Far-Side Magnetic Flux from EUV flux by deep learning

The Sun's far-side magnetic field is crucial to space weather forecasting and solar wind modeling, but it cannot be directly observed. For about four years, the extreme ultraviolet (EUV) 304Å flux of the far side was observed by the STEREO/EUVI, providing a chance for us to map the far-side magnetic flux using a deep-learning method. We take about 6000 pairs of near-side SDO/HMI magnetic-field maps and SDO/AIA 304Å flux images, observed simultaneously and covering a period of about 8 years, and train a neural-network that is able to convert the EUV flux images into magnetic-flux maps. The trained network is evaluated on a test set of data, and satisfactory agreements are found between computer-generated magnetic flux maps and the observations. The trained deep-learning code is then applied on the STEREO far-side 304Å observations to generate the far-side magnetic flux maps. These data can be used to calibrate far-side acoustic maps generated by helioseismic far-side imaging method to magnetic flux maps (see presentation by S. Hess Webber). These data are also useful to assess the validity of the far-side magnetic field produced by flux-transport models, and to examine the solar wind models with and without including the far-side magnetic field.

Gonzalo, Cucho-Padin (University of Illinois at Urbana-Champaign, USA)
Dynamic Tomographic Estimation of Global Exospheric Hydrogen Density and its Response to Geomagnetic Storms

Charge exchange collisions between ring current ions and hydrogen (H) atoms in the terrestrial exosphere serve to dissipate magnetospheric energy, particularly during the slow recovery phase of geomagnetic storms, through the generation of energetic neutral atoms (ENAs) which escape Earth’s gravity on ballistic trajectories. Imaging of the resulting ENA flux is a well-known technique to infer the ring current ion distribution, but its accuracy depends critically on the specification of the exospheric H density distribution. Although measurements of H airglow emission exhibit storm-time variations, the H density distributions used in ENA image inversion are typically assumed to be static, and the current lack of knowledge regarding global exospheric evolution during storms represents an important source of error in investigations of ring current dynamics. In this work, we present a method for reconstructing the dynamic 3-D exospheric Hydrogen density from observations of its optically thin emission at 121.6 nm acquired from the Lyman-alpha detectors onboard the NASA TWINS satellites. The technique is based on our recent development of a robust tomographic inversion algorithm, which is modified to incorporate the temporal dimension via Kalman filtering.

Varad Deshmukh (Swx TREC, CO, USA)

Leveraging Topological Data Analysis and Deep Learning for Solar Flare Prediction

In this work, we propose a novel computational technique for forecasting solar flares based on a combination of topological data analysis (TDA) and machine learning applied to sunspot magnetogram data. On a magnetogram, sunspots manifest as large-scale, high-magnitude dipolar structures, whose shapes and their evolution provide important clues that may help predict flares erupting from these regions. We primarily propose the use of TDA and computational geometry to characterize the evolving structure of solar magnetogram data from the Helioseismic and Magnetic Imager (HMI) instrument on the NASA Solar Dynamics Observatory satellite. To compute the topology of a data set requires an interpolation scheme; the theory of persistent homology leverages this to describe shape as a function of scale, as encoded in a persistence diagram. We present a feature engineering approach to use variants of these persistent diagrams along with geometrical characteristics of magnetogram data as input features for a neural network flare-prediction model. In parallel, we pursue a deep learning approach by developing a convolutional neural network (CNN) to predict flares using HMI magnetogram images. Instead of a single magnetogram image, we use stacks of sequential magnetogram images as CNN inputs to extract the temporal changes in the sunspot structure for improving flare prediction. For both models, we also experiment with the use of improved labeling schemes for input magnetograms to generate a more precise forecast. Finally, we provide a performance comparison to determine if the feature engineering approach provides any advantage over the deep learning approach used by the CNN model.

Dattaraj Dhuri (Tata Institute, Mumbai, India)

Deep learning applied to detect pre-emergence photospheric magnetic field patterns

Magnetic flux generated within solar convection zone rises to the surface forming active regions (ARs) and sunspots. Early detection of ARs will be useful for gaining warning time against a variety explosive events - such as flares and coronal mass ejections - that lead to severe space weather consequences. Evidence of any pre-emergence signatures will also shed light on subsurface processes responsible for emergence. Here we use deep convolutional neural networks (CNN) to analyse SDO/HMI line-of-sight magnetograms of pre-emerging ARs. The CNN classifies pre-emerging ARs (PEs) from a control set of non-emerging ARs (NEs) with a True Skill Statistic score (TSS) of ~ 90%, 3 hrs prior to emergence and ~ 40%, 24 hrs prior to emergence. We also develop techniques to "open up" the trained CNN and highlight detected pre-emergence magnetic field patterns.

Carlos José Díaz Baso (Institute for Solar Physics, Stockholm University, Sweden)

Solar image denoising with convolutional neural networks

The topology and dynamics of the solar chromosphere are dominated by magnetic fields. The latter can be inferred by analyzing polarimetric observations of spectral lines. However, polarimetric signals induced by chromospheric magnetic fields are particularly weak, and in most cases very close to the detection limit of current instrumentation. Therefore there are few observational studies that have successfully reconstructed the three components of the magnetic field vector in the chromosphere. Traditionally, the signal-to-noise ratio of observations has been improved by performing time-averages or spatial averages, but in both cases some information is lost. More advanced techniques, like Principal-component-analysis, have also been employed to take advantage of the sparsity of the observations in the spectral direction. In the present study, we propose to use the spatial coherence of the observations to reduce the noise using deep-learning techniques. We have designed a neural network that is capable of recovering weak signals under a complex noise corruption (including instrumental artifacts and non-linear post-processing). The training of the network is carried out without a priori knowledge of the clean signals, or an explicit statistical characterization of the noise or other corruption, only using the same observations as our generative model. Synthetic experiments are used to demonstrate the performance of this method. After that, we show examples of the improvement in typical signals obtained in current telescopes such as the Swedish 1-meter Solar Telescope.

Romain Dupuis (KU Leuven, Belgium)

Identifying specific features for the study of magnetic reconnection from PIC simulations using unsupervised learning at the particle scale.

Unsupervised learning methods aim at searching and identifying hidden structures or features within the input space. Such methods can be advantageously used to study physical processes which vary over a wide range of temporal and spatial scales, for instance magnetic reconnection. Targeting specific underlying physics with these methods can help to improve physical understanding.

Magnetic reconnection is characterized by various different regions, such as the diffusion region, the inflow regions, or the outflow regions. In particular, the MMS mission highlighted crescent-

shaped features in the velocity distributions explained by the acceleration of electrons [1]. Thus, unsupervised learning appears as well suited to study such processes at the particle scale as they can identify complex distribution shapes.
We propose to apply unsupervised learning on outputs from particle-in-cell (PIC) simulations, in particular density estimation methods. Determining automatically electron and ion velocity distributions provide a fine identification of structures with various shapes. The analysis of these structures can relate them to specific regions.
After presenting the main density estimation methods, in particular kernel density estimation and Gaussian mixture model [2], the talk will present several approaches to alleviate the general problem of determining a suitable number of components for the distributions. These solutions are derived primarily from information theory and variational Bayesian methods with the obvious goal to try to include physical meaning in the parameters of the models.
This contribution has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No 776262 (AIDA, www.aida-space.eu).

Madhulika Guhathakurta (NASA, USA)
NASA Frontier Development Lab: Applied AI for Science & Exploration

The recent advances in Artificial Intelligence (AI) capabilities are particularly relevant to NASA Heliophysics because there is growing evidence that AI techniques can improve our ability to model, understand and predict solar activity using the petabytes of space weather data already within NASA archives. This represents a strategic opportunity, since the need to improve our understanding of space weather is not only mandated by directives such as the National Space Weather Action Plan and the Presidential Executive Order for Coordinating Efforts to Prepare the Nation for Space Weather Events, but also because space weather is a critical consideration for astronaut safety as NASA moves forward with the Space Policy Directive to leave LEO and return to the Moon.
The Frontier Development Lab (FDL) is an AI research accelerator that was established in 2016 to apply emerging AI technologies to space science challenges which are central to NASA's mission priorities. FDL is a partnership between NASA Ames Research Center and the SETI Institute, with corporate sponsors that include IBM, Intel, NVidia, Google, Lockheed, Autodesk, Xprize, Space Resources Luxembourg, as well as USC and other organizations. The goal of FDL is to apply leading edge Artificial Intelligence and Machine Learning (AI/ML) tools to space challenges that impact space exploration and development, and even humanity.

Laura A. Hayes (NASA GSFC, USA)
Predicting Global Navigation Satellite System (GNSS)

Signal Disruptions Using Machine Learning Techniques Space weather-driven fluctuations in the Earth's ionosphere produce rapid variations in radio signals that propagate through it. These ‘scintillation’ events significantly compromise the receptivity of Global Navigation Satellite System (GNSS) signals at ground calibration stations and billions of devices enabled with global positioning capabilities. Many aspects of modern day society relies on seamless access to GNSS, and the ability to accurately predict service disruptions is thus vital to mitigate the effects of space weather. However, our understanding of space-weather driven effects in the ionosphere, particularly at high-latitudes, remain incomplete. To date no reliable predictive model of ionospheric disturbances of GNSS signals at high latitudes exists. To tackle this challenge as part of the NASA Frontier Development lab project we employ a data-driven approach, and build machine learning models to take advantage of the vast amount of historical data to produce a predictive model of GNSS disturbances. Using a Sun-to-Earth system approach, the machine learning pipeline utilizes data from both space- and ground- based observations of solar activity, geomagnetic variations, and ionospheric conditions derived from GNSS signal data. Here, we will present the results of this approach for predicting ionospheric scintillation and discuss future directions that will build upon this research.

Egor Illarionov (Moscow State University, Russia)

Segmentation of solar disk images with a convolutional neural network

Interpretation of solar disk observations is a challenging task. For example, there is a long-running discussion about a proper way of sunspot counting. Other solar features are a matter of similar discussions. As a result, neither type of solar features has a well-formalized definition. On the other hand, segmentation of solar features is essential in many tasks, e.g. in space weather forecasting. We analysed several catalogues with automatically isolated coronal holes (CHs) and observed a dramatic difference between them. In our opinion, this is a manifestation of the fact, that typical image analysis algorithms based on formal rules are rather inefficient in fuzzy problems. In contrast, machine learning algorithms are possible to approximate complex relations. In our work we implemented a U-Net neural network model and trained it on a dataset of SDO/AIA 193A images and corresponding catalogue of CHs provided by the Kislovodsk Mountain Astronomical Station. We provide various tests that demonstrate stability and quality of the model segmentation. We also open-source the code in a repository https://github.com/observethesun/coronal_holes to make the work reproducible. The repository contains a link to online model demo that allows SDO image uploading and segmentation. We believe that this approach has enough capabilities to approximate an expert-level interpretation of solar disk observations.

Michael Kirk (NASA, GSFC, USA)

Using Deep Learning to Segment Features in Solar EUV Images

We present first results of applying a deep learning architecture to the problem of segmenting solar images. Since 2010, the SDO satellite has taken about 150 Million images of the sun in 9 different wavelengths of light as well as magnetic field measurements to monitor changes on the sun. A complete set of these images are recorded about once every 12 seconds. Along with this flow of data, the Heliophysics Events Knowledge-base (HEK) runs a collection of computer vision routines to detect, segment, and archive various dynamic events and quasi-static features on the sun. By combining the HEK with the stream of SDO images, we have a labeled dataset of almost 30,000 images. Using this dataset, we are able to train, validate, and test a convolutional neural network (CNN) to segment sunspots, active regions, and coronal holes. We will present the results of this effort and estimates of its accuracy and applicability to other solar features.

Timo Laitinen (University of Central Lancashire, UK)

Bayesian analysis of solar wind turbulence for solar energetic particle transport

Solar energetic particle (SEP) propagation in the heliosphere is controlled by the turbulent solar wind magnetic fields. To model the SEP propagation, we need information on the turbulence power and composition. Typically turbulence is modelled to have a slab and a 2D component, which contribute to propagation along and across the mean field direction, respectively. Bieber et al (1996) used spectra obtained from Helios spacecraft to analyse the turbulence composition by deriving a relation between the observed frequency spectra of the magnetic turbulence, and the ratio of the turbulence power in slab and 2D components. They fitted the model to 454 individual spectra and found that on average the slab-2D power ratio is 20%:80%.

In this work, we use the Bieber et al model to investigate the evolution of the turbulence composition in time, instead of obtaining a long-time average. This is necessary if we want to have a better understanding of individual SEP events. In order to quantify the uncertainties of the turbulence composition, we use Bayesian inference to analyse the likelihood of the slab/2D ratio. The analysis is built using Python package PyMC3, which provides Markov chain Monte Carlo method to fit and analyse Bayesian models. Our results are in general in line with the other workers finding dominance of the 2D component, however we demonstrate the importance of understanding the significance of uncertainties. We discuss the results and the issues affecting the analysis and uncertainties of the turbulence composition.

Derek Lamb (Southwest Research Institute, USA)

Comparing Statistical and Neural Network Approaches to Flux Emergence Identification

Despite its obvious and striking visual appearance, magnetic flux emergence can be surprisingly difficult process to identify with high specificity and sensitivity. The broad range of spatial and temporal scales across which emergence occurs, the variety of emergence morphologies, measurement, projection and geometrical effects, the evolution of magnetic flux due to surface flows, and more subtle interactions between and signal and noise all make accurate detection difficult to implement. In this presentation, we compare two approaches to flux emergence identification: a statistical approach and a neural network approach. Both of them use full disk magnetograms as input data, broken into regions of equal angular size and encoding their time evolution into user-defined quantities such as signed and unsigned magnetic flux in a region. In the statistical approach we develop a logistic regression model based on thresholds of our user-defined quantities. A backward stepwise approach is used to find the best predictors of magnetic flux emergence, and the score cutoff chosen to maximize the paired sensitivity and specificity. The final model is evaluated using the area under the Receiver-Operator-Characteristic (ROC) curve. In the neural network approach, we deploy a convolutional neural network (CNN) operating on the time curves of our user-defined quantities for adjacent regions. CNNs are neural networks whose architecture is optimized to identify the most important morphological features of the input data to perform classification of the input data (or regression between the input and output data). In our case our goal is to ingest the time evolution of our features to identify emergence. We compare and contrast the results obtained with the two different approaches and discuss their strengths, weaknesses, and how to pull the best of both to automatically detect flux emergence events across the largest range of time and spatial scales possible.

Ryan M. McGranaghan (ASTRA, USA)

What is the social engineering challenge of data science for Heliophysics and how do we solve it?

Antidisciplinary is "about working in spaces that simply do not fit into any existing academic discipline—a specific field of study with its own particular words, frameworks, and methods" [Ito, 2014], and it indicates profound new opportunities to transform research across all fields of science and engineering.

Fields primed to benefit from the antidisciplinary ideal are those grappling with the timely co-evolution of: 1) drastic data growth; 2) increased sophistication of data-intensive computing capabilities; and 3) sophisticated data science technologies. Given the prevalence of all three components in the space sciences, Heliophysics and space weather represent a fantastic use case, and, indeed, exciting efforts across the community are already navigating this New Frontier [McGranaghan et al., 2017].

This talk will introduce the antidisciplinary ethos in the context of ML for space weather and feature recent efforts to deploy it through teams of space scientists, ML practitioners, and applied mathematicians. Through [three] specific examples we will emphasize the new practices and approaches that are being applied, and pragmatically examine lessons learned. The goal of this talk will be three-fold:

1. Capture knowledge about best practices for antidisciplinary research;
2. Spark new research vistas and collaboration; and
3. Initiate a new white paper to that serves as a reference for cutting-edge approaches to space weather research.

This talk will attempt to be an actionable piece to complement the inherently interdisciplinary emphasis of the Machine Learning in Heliophysics Conference.

Adeline Paiement (Université de Toulon, France)

Detection and parameter estimation for type II solar radio bursts

Solar radio bursts of type II are the signature of shock propagation in heliosphere related to electron acceleration. Their occurrence gives information on the way solar events, such as flares and CMEs propagate in the heliosphere, thus constraining velocity and density of particle propagation, which are fundamental for the study of its impact on Earth magnetosphere and ionosphere.

It is desirable to automate the detection and analysis of solar radio bursts, to assist with cataloguing the events, as well as facilitating the forecasting of space-weather. Previous works have addressed these tasks using classical image processing techniques, and as such have mainly focused on type III bursts [2,3,4] due to their more simplistic characteristics. An attempt at detecting type II bursts [1], based on a line fitting algorithm, achieved a detection rate of 78% of a selection of 46 events. However, these methods suffer from a high number of false positives at a rate of one false event every 100 hours. Furthermore, they require the design of new image pre-processing steps for all newly considered sensing instruments.

To address these issues, we propose the use of machine-learning methods to detect and extract the parameters of type II solar radio bursts in dynamic spectra. First, we implement and compare different classical computer vision and state-of-the-art deep learning paradigms for burst detection. Second, detection and parameter estimation for the bursts being interdependent problems, we demonstrate a joint solving solution that optimises both tasks simultaneously in a deep learning framework. We also introduce a hybrid data-driven and physics-based model, where learning from previously catalogued events is complemented by physics-based constraints to improve the robustness and trust for the algorithm. This novel hybrid approach also helps tackle the well-known machine learning issue of learning from a too small dataset.

We experiment on ~300 events from the years 1997–2016 of archived data from Wind/WAVES. The different machine learning approaches are compared and the usefulness of the joint solving and of the integration of physics-based constraints are assessed. We also evaluate the performance of the methods under various scenarios, such as different solar activity periods, or the presence of overlapping bursts of other types.

This work was supported by the Centre National d'Etudes Spatiales (CNES). It is based on observations with the radio WAVES instrument embarked on the WIND mission.

Constantinos Papadimitriou (National Observatory of Athens, Greece)

Investigating dynamical complexity in the topside ionosphere using information-theoretic measures

Recently, many novel concepts originated in dynamical systems or information theory have been developed, partly motivated by specific research questions linked to geosciences, and found a variety of different applications. This continuously extending toolbox of nonlinear time series analysis highlights the importance of the dynamical

complexity to understand the behavior of the complex Earth's system and its components. Here, we propose to apply such new approaches, mainly a series of entropy methods to the time series of the Earth's magnetic field measured by the Swarm constellation. Swarm is an ESA mission launched on

November 22, 2013, comprising three satellites at low Earth polar orbits. The mission delivers data that provide new insight into the Earth's system by improving our understanding of the Earth's interior as well as the near-Earth electromagnetic environment. We show successful applications of methods originated in information theory to quantitatively studying complexity in the dynamical response of the topside ionosphere, at Swarm altitudes, associated with the intense magnetic storms occurred in 2015.

Savvas Raptis (KTH, Royal Institute of Technology, Sweden)

Classification of Magnetosheath Jets using Neural Networks and High Resolution OMNI (HRO) data.

The Magnetosheath is a highly disturbed region between the Bowshock and the Magnetopause. In this region, several phenomena occur, including "Magnetosheath Jets". These jets are enhancements of dynamic pressure above the general fluctuation level, indicating a locally increased plasma flow. Such jets are believed to be a key element in the coupling of Solar Wind and Magnetosphere while also being possibly associated with other physical phenomena such as magnetic reconnection and the population of the Radiations Belts.

In this work, we use a dataset with thousands of Magnetosheath Jets that has been created based on the concept that there are two main types of jets. The jets found in the Quasi Parallel Magnetosheath ($\theta\_Bn<45°$) and those found in the Quasi-perpendicular ($\theta\_Bn>45°$), where θ_Bn is the angle between the Interplanetary Magnetic Field (IMF) and the bow shock's normal vector. This initial dataset has been derived by using in-situ measurements of various plasma moment quantities and magnetosheath magnetic field as measured by the Magnetospheric Multiscale (MMS) mission during 11/2015 – 03/2019.

We use one-minute High Resolution OMNI (HRO) data that were measured outside of the Magnetosheath and have been time-shifted to the Earth's bowshock in order to predict the class (Quasi-Perpendicular / Quasi-Parallel) of the Jets that were later observed inside the Magnetosheath region by MMS. The predictive classification is done with Neural Networks (NNs) and multiple inputs including several solar wind particle moments, electric field, and IMF values.

Using this data and a deep NN with optimized hyper-parameters, we achieve predictive classification of the Jet type with accuracies up to 92%.

These results support the initial classification scheme of the Magnetosheath Jets. More importantly, they show that even in the absence of crucial information, such as the angle of the IMF, the use of machine learning methods allow a direct connection between the solar wind particle population before and after its complex interaction with Earth's bow shock as measured by different missions.

Pete Riley (Predictive Science, Inc., USA)

A Metric-Based Assessment of New Solar Wind Forecast Models incorporating Data Assimilation

Accurate modeling of the ambient solar wind is a crucial component in forecasting the arrival time at Earth of: (1) coronal mass ejections (CMESs); and (2) fast solar wind streams. It also plays an important role in the evolution of interplanetary CME structure. In this presentation, we describe a study to improve the accuracy of solar wind solutions through the use of data assimilation, ensemble modeling techniques, time-dependent modeling, and the application of rigorous metrics and skill score, using PSI's CORona-HELiosphere (CORHEL) framework. The pipeline begins with the processing of magnetograms from a variety of sources (e.g., AFRL/ADAPT, HMI, NSO/GONG and NSO/SOLIS), with the focus being on ADAPT maps, which provide time-dependent ensembles, and which, we anticipate, will lead to quantifiable improvements in forecast accuracy. These boundary conditions drive a model of the solar corona and inner heliosphere, the results of which are tested directly against NOAA and CCMC's currently implemented frameworks. We employ basic ensemble modeling methodologies in several ways, including the generation of multiple coronal solutions using a set of ADAPT realizations for each time period (as well as other observatories) and compare them with a range of observed outputs (e.g., coronal hole boundaries and in situ measurements). We also describe several refinements currently underway. For example, we are incorporating "data assimilation" techniques by computing modeled-coronal hole boundaries and comparing them with automatically-determined boundaries from SDO observations, which will allow us to select the realizations with the highest likelihood of matching 1 AU measurements. Additionally, we are developing time-dependent solutions, driven by evolving ADAPT maps. This study, we believe, will help demonstrate the crucial role that an accurate specification of the background solar wind plays, and identify some of the key attributes that a successful operational forecasting model must possess.

Tarik Mohammad Salman (University of New Hampshire, USA)

Forecasting Periods of Strong Southward Magnetic Field Following Interplanetary

Shocks Long-duration and strong southward magnetic field periods are known to be the primary cause of intense geomagnetic storms. Most of such periods are caused by the passage over Earth of a magnetic ejecta. Irrespective of the interplanetary cause, fast-forward shocks often precede such periods. We first investigate the correlation between long-duration and strong southward magnetic field periods and fast-forward shocks measured by the Wind spacecraft in a 22.4-year span. We find that 76% of such periods are preceded within 48 hr by at least a fast-forward shock, but only about 23% of all shocks are followed within 48 hr by such periods. Then, we devise a threshold-based probabilistic forecasting method based on the shock properties and the pre-shock near-Earth solar wind plasma and IMF characteristics through a superposed epoch analysis-like approach. Our analysis shows that solar wind conditions in the 30-min interval around the arrival of fast-forward shocks have a significant contribution to the prediction of long-duration and strong southward Bz periods. This model may provide on average a 14-hr warning time for an upcoming Bz period. Evaluating the forecast capability of the model through a statistical and skill score-based approach reveals that it outperforms a coin-flipping forecast. We verify the logicality of the best prediction method with inclusion and prediction of Bz periods outside the time span of this study. We also test the model for long-duration and strong southward Bz periods preceded by shock-like discontinuities to expand the event selection criterion.

Rakesh Sarma (CWI, Amsterdam, The Netherlands)

On improvement of Phase Space Density estimation with Bayesian Inference and Deep Learning

The determination of the phase space density of energetic particles trapped in the Earth's radiation belts is a crucial component of Space Weather modelling. The one-dimensional Fokker Planck equation is commonly used in the community to model the particle dynamics. This approach captures the motion due to violation of the third invariant L or the radial diffusion of particles due to interaction with ULF waves. The wave-particle interactions are parameterised through a diffusion coefficient, while all other un-modelled physical processes are accounted through a loss term, and variable boundary conditions. Obviously, the choice of the form of the parameterisation and the coefficient values are important to improve accuracy.

In this work, we derive a data-driven probabilistic description of the diffusion coefficient and the electron loss timescale, based on two approaches. First, we develop a Bayesian model based on a standard Markov chain Monte Carlo to identify the coefficients of the 1-D radial diffusion model. The identification data is based on the measurements of the Van Allen probes. The other approach is based on a Physics-Informed Deep Learning network, which is based on a data-driven discovery of the underlying partial differential equation. Finally we compare our predictions to the estimations provided in the literature.

Meetu Verma (Leibniz Institute for Astrophysics Potsdam, Germany)

Classification of High-resolution Solar Hα Spectra using t-SNE

The Hα spectral line is a well-studied absorption line, revealing properties of the highly structured and dynamic solar chromosphere. Typical features with distinct spectral signatures in Hα include filaments/prominences, bright active region plages,

superpenumbrae around sunspots, surges, flares, Ellerman bombs, filigree, and mottles/rosettes, among others. This study is based on high-spectral resolution Hα spectra obtained with the Echelle spectrograph of the Vacuum Tower Telescope (VTT) located at Observatorio del Teide, Tenerife, Spain. The t-distributed Stochastic Neighbor Embedding

(t-SNE) is a machine learning algorithm, which is used for nonlinear dimensionality reduction. In this application, it projects the Ha spectra onto a two-dimensional map where it is easy to classify them according to results of Cloud Model (CM) inversions, i.e., optical depth, Doppler width, line-of-sight velocity, and source function of the cloud material. Initial results of t-SNE indicate its strong discriminatory power to separate quiet-Sun and plage profiles from those that are suitable for CM inversion. In addition, the identified classes are

linked to chromospheric features, the impact of seeing conditions on the classification is assessed, the projection of new Hα spectral data (different observing time and target) onto the 2D t-SNE maps is inspected to optimize CM inversions, and representative Hα spectra are determined as input for deep neural networks speeding up the CM inversion.

Gregal Vissers (Institute for Solar Physics, Stockholm University, Sweden)

Classification and tracking of ultraviolet reconnection bursts as tracers of lower-atmosphere field evolution

Characterising the magnetic field reconfiguration during flux emergence and active region evolution provides essential information to evaluate the conditions that may lead to solar flares and eruptions. While the Solar Dynamics Observatory (SDO) obtains photospheric fields near-continuously for the full Earth-facing side of the Sun, following the field evolution throughout the lower solar atmosphere is severely hampered by the lack of chromospheric magnetic field measurements with corresponding field-of-view coverage. At the same time, compact transient brightenings like microflares, ultraviolet bursts and Hα-observed Ellerman bombs are tell-tale heating signatures of magnetic reconnection at different atmospheric heights during field reconfiguration. As these reconnection brightenings are ubiquitously observed in developing active and emerging flux regions, often producing corresponding signatures in the ultraviolet continua at 1600Å and/or 1700Å that are routinely observed by SDO's Atmospheric Imaging Assembly (AIA), they may serve as valuable proxies of lower-atmospheric field evolution. Here we employ co-ordinated observations in Hα from the Swedish 1-m Solar Telescope, in Si IV from the Interface Region Imaging Spectrograph and SDO/AIA UV continuum imaging to train a convolutional neural network to differentiate between the UV continuum brightenings that correspond to UV bursts, microflares and/or Ellerman bombs, as proxy of the height to which field reconfiguration proceeds. We also evaluate performance when including magnetogram information from SDO's Helioseismic and Magnetic Imager, as well as upper-atmosphere diagnostics from AIA in the training process. We present the statistical properties of our identification results and discuss them in light of known properties of these event classes, as well as the relation between them (including timing, occurrence locations, proper motion, lifetimes, peak brightness, etc.). Finally, we address their potential use as additional flare-predictive parameters.

Paul Wright (Stanford University, USA)

DeepEM: A Deep Learning Approach for DEM Inversion

The differential emission measure (DEM) is a critical component for understanding the physics of the solar corona. However, inferring DEM maps from observations is an ill-posed inverse problem that requires the expensive optimisation of basis functions on a pixel-by-pixel basis, using multiple image channels (e.g. Cheung et al 2015). In the case of data obtained from the Atmospheric Imaging Assembly (AIA) onboard the Solar Dynamics Observatory (SDO), this involves six EUV channels at a resolution of 4096 x 4096 pixels. As a means to reduce the cost of calculating these DEMs we propose the use of neural networks. Neural networks can be seen as a technique that enables complex transformations of the input data that takes advantage of the informational content contained in those data. This makes it possible for them to “learn” physically meaningful relationships. This approach for DEM inversion is able to perform tens-of-millions of DEM calculations per second, with similar fidelity to basis pursuit (Cheung et al 2015).

Irina Zhelavskaya (GFZ Potsdam, Germany)

A combined neural network- and physics-based approach for modeling the plasmasphere dynamics during extreme geomagnetic storms

Plasmasphere is a torus of cold plasma surrounding the Earth and is very dynamic. Its dynamics is driven by space weather, and having an accurate model of the plasmasphere is very important for radiation belt modeling and wave-particle interactions. In the recent years, feedforward neural networks have been successfully applied to reconstruct the global plasmasphere dynamics in the equatorial plane [Bortnik et al., 2016, Zhelavskaya et al., 2017, Chu et al., 2017]. These neural network-based models have been able to capture the large-scale dynamics of the plasmasphere, such as plume formation and the erosion of the plasmasphere on the night side. However, neural networks (NNs) have one limitation. NNs perform well when data is abundant, but when data is limited, which typically happens during extreme geomagnetic storms, they do not, since they cannot learn from a limited number of examples. This limitation can be overcome by employing physics-based modeling during the periods of high geomagnetic activity. Physics-based models perform stably during high geomagnetic activity intervals, if initialized and configured correctly. In this work, we present the combined approach to model the global plasmasphere dynamics that utilizes advantages of both neural network- and physics-based modeling and produces accurate global plasma density reconstruction during extreme events. The approach is based on data assimilation and allows blending the models in an efficient way. We validate the global density reconstructions by comparing them to the IMAGE EUV images of the He+ particles distribution in the Earth’s plasmasphere for the same time periods. We present the examples of the obtained global plasma density reconstruction for a number of extreme geomagnetic storms that have occurred in the past, including Halloween storm in 2003.

Posters

Tanja Amerstorfer (Space Research Institute, Austrian Academy of Sciences, Austria)
Automated CME tracking within heliospheric images

Heliospheric imagers (HI) provide observations of the propagation of coronal mass ejections (CMEs) throughout the inner heliosphere. These observations are predestined for predicting the arrival times of CMEs at Earth or other targets, especially when the data are available in real time in sufficient quality as planned for a space weather mission at the Lagrangian point 5. Usually the CME leading edge is manually tracked within HI images. The difference of CME arrival time predictions based on such tracks measured by different persons can reach up to 30 hours. A solution for this problem is an automated extraction of the CME track from HI observations. We present work in progress of a first approach to reach this goal by applying image processing and computer vision methods to HI observations and assess the outcome by performing CME arrival predictions based on these tracks.

Ute Amerstorfer (Space Research Institute, Austrian Academy of Sciences, Austria)
Forecasting of magnetic flux rope fields at the Sun-Earth L1 point

Forecasting of coronal mass ejection magnetic flux rope fields at L1 is a long-standing challenge and one of the major problems in space weather forecasting. We attempt to make progress by the application of several new approaches, and show first results. We derive synthetic magnetic field and plasma data from empirical flux rope modeling with our own 3DCORE simulation, and combine the results with pattern recognition algorithms accessing the long-term OMNI solar wind data sets. An analysis is shown how well the CME flux rope fields can be anticipated when 10-50% of the flux rope have already been observed at L1. For the real time application, the usage of DSCOVR L1 data as an ongoing constraint is considered.

Matthew R. Argall (University of New Hampshire, USA)
Automated magnetopause detection to facilitate diffusion region studies with MMS

Global-scale energy flow throughout Earth's magnetosphere is catalyzed by processes that occur at Earth's magnetopause (MP) in the electron diffusion region (EDR) of magnetic reconnection. Until the launch of the Magnetospheric Multiscale (MMS) mission only rare, fortuitous circumstances permitted a glimpse of the electron dynamics that break magnetic field lines and energize plasma. MMS employs automated burst triggers onboard the spacecraft and a Scientist-in-the-Loop (SITL) on the ground to select intervals likely to contain diffusion regions. Only low-resolution survey data is available to the SITL, which is insufficient to resolve electron dynamics. A strategy for the SITL, then, is to select all MP crossings. This has resulted in >35 potential MP EDR encounters but is labor- and resource-intensive; after manual classification, just ~0.7% of MP crossings, or ~0.0001% of the mission lifetime, during MMS's first two years contained an EDR. We introduce two machine learning models to detect MP crossings and automate the SITL classification process: 1) a hierarchical Bayesian mixture model (HBM) with linear and auto regressive components, and 2) a limited short term memory (LSTM) recurrent neural network. The HBM selects twice as many magnetopause regions as a boosted regression tree model without significant over selection, achieving a 31% true positive rate and 93% true negative rate. The LSTM has been implemented in the MMS data stream to provide automated predictions to the SITL. Both methods facilitate EDR studies by consolidating manual classification processes into automated routines.

Kirsten Arnason (University of Calgary, Canada)

Relationship between Precipitation of High Energy Electrons and Solar Wind and Ring Current

Beginning with the results from a study by Reeves et al 2011[1] (herein "R2011"), and the data used therein, as a foundation, we build connections to parameters recorded on a daily basis by ground based riometers. R2011 explores the connection between solar wind velocity and radiation belt electron flux in the 1.8-3.5 MeV range. The data presents itself in a distinct triangle distribution as the solar wind velocity relates to the lower bound of electron flux while there appears to be no upper limit, leaving it unbounded. We have recreated the results of the triangle distribution and are applying machine learning techniques to investigate the amount of information shared between parameters to rank the degree of coupling between them [2]. We will explore the connections between the data set used in R2011 and the measurements recorded by riometers. The data from R2011 are comprised of parameters recorded from geosynchronous orbit whereas the riometer dataset comes from a network of ground-based instruments deployed across Canada. Riometers measurements provide information about electromagnetic wave absorption in the ionosphere, which is an indicator of the precipitation of high energy electrons (>30keV). By leveraging the riometer data recorded over a range of latitudes we can infer information about the radial distribution of high energy electron precipitation (and hence about high energy electron populations in the magnetosphere). We will provide results pertaining to the latitude profile of daily electron precipitation based on solar wind and ring current parameters as well as ranking of the information transfer between parameters.

Lekshmi B (Center of Excellence in Space Sciences India, IISER Kolkata)

Predicting Solar Active Region Emergence Using Machine Learning

Solar active regions which are areas of intense magnetic field on the solar surface, initiate eruption of mass and energy in the form of flares and Coronal Mass Ejections (CMEs), and can severely disrupt space-reliant technologies. Predicting the emergence of active regions on the solar surface becomes important in this context. The emerging magnetic field may have its signature on the surface velocities which can be inferred by local helioseismology [1]. We track solar surface dopplergram and magnetogram patches, three to five days prior to the active region formation. The power spectra calculated by tracking the active region and quiet sun patches, along with the parameters obtained by power spectra fitting [2], are used for training our machine learning algorithm. Doppler velocity and magnetic field observations from Helioseismic and Magnetic Imager (HMI) onboard the Solar Dynamics Observatory (SDO) are used in this work. With this technique we expect to develop a machine learning algorithm to predict the emergence of active regions on the solar surface and further estimate the emerging magnetic flux using specialized deep learning [3][4]. Here we outline our strategy for achieving this goal.

Rachel Bailey (Space Research Institute, IWF)

PREDSTORM and SOLARWIND2GIC: Forecasting of space weather effects and geomagnetically induced currents with Python

The PREDSTORM Python package aims to predict the solar wind properties at the Sun-Earth L1 point from a variety of different input sources. This output can be coupled to models to predict the Dst index at Earth as well as the consequences of space weather such as geomagnetically induced currents (GICs) in power transmission lines. Here we will present first results on Dst forecasting from PREDSTORM L1 predictions using STEREO-A data, as well as the coupling of the PREDSTORM model output to a recurrent neural network model (SOLARWIND2GIC) trained to predict the root-mean-square GICs at power grid substations on Earth, specifically in Austria.
Téo Bloch Solar Wind Classification using Unsupervised Machine Learning Unsupervised machine learning provides an under-utilised set of tools for increasing the objectivity associated with scientific investigation and discovery. We present two new solar wind origin classification schemes developed using a variety of the techniques available. The schemes aim to classify solar wind into three types: coronal hole wind, streamer belt wind, and ‘unclassified' which does not fit into either of the previous two categories. The classification schemes are created using non-evolving solar wind parameters, such as ion charge states and composition, measured during Ulysses' three fast-pass latitude-scans. The schemes are subsequently applied to the whole of the Ulysses and ACE datasets. Given the choice of parameter type, the scheme is grounded in the physical properties of the solar source regions. Furthermore, the techniques used are selected specifically to reduce the introduction of subjective biases. We demonstrate significant ‘best case’ disparities (7% - 18%) with the traditional "fast" and "slow" solar wind determined using speed thresholds.

Vincent Barra (Université Clermont Auvergne, CNRS, France)

Image-to-image translation model to generate magnetogram out of EUV images

Magnetograms are used as boundary condition of physical models to reconstruct the global solar magnetic field, but we have a direct access to magnetogram from a limited number of sources, and up now, only one vantage point. EUV images on the other hand offers vantage points from the far side of the Sun thanks to the STEREO mission. It is thus of interest to generate magnetogram out of EUV images, and to assess the errors made when using the generated models into PFSS models, and later on, models of the solar wind such as EUHFORIA.
In this preliminary work, we use paired and unpaired image-to-image translation models to generate magnetograms from 171, 193 and 304 EUV images. The models also allows to reverse the process in order to generate EUV images from HMI. We evaluate the confidence these generated images using a test set, and we shed lights on some potential improvements and generalization processes.

Sabrina Bechet (Royal Observatory of Belgium, Belgium)

Data homogenization for a network of ground-based synoptic imaging telescopes

Ground-based synoptic imaging telescopes are used nowadays for continuous whole-disk monitoring of solar activity as a lightweight patrol for space weather forecasts. However, one single station has limited time coverage due to the night-day cycle and variable observing conditions. This can be mitigated by considering a network of stations at different geographical locations.

However, before such multi-station data can be merged, we need to homogenize images from different instruments (different optical set-up, bandpasses, CCD), or from identical instruments at different sites (different observing conditions, slightly different spectral bandpass, ..) such as the planned SOLARNET-SPRING network. This is a first mandatory step towards more advanced products such as synoptic maps and solar feature or event detection.

We present the ongoing development of such homogenization algorithms for full disk images at three different wavelengths (white-light, Ca II K and H-alpha). In particular we illustrate the correction of geometrical differences (disk re-centering, intensity normalization) as well as radial and non-radial photometric inhomogeneities (limb darkening, atmospheric transparency, stray-light) on synoptic images taken at the Royal Observatory of Belgium (ROB) and at the Kanzelhöhe Observatory (KSO).

Bernard Benson (The University of Alabama in Huntsville, USA)

Determining the parameter for the linear force-free magnetic field model with multi-dipolar configurations using deep neural networks

Recent advances in the field of neural networks have made convolutional neural networks (CNNs) a conventional algorithm for many computer vision tasks including image recognition and object detection. Because modeling the coronal magnetic field of the Sun is an important objective in heliophysics, this study extends the use of CNNs to the application of coronal magnetic field modeling. We employ a simple one-parameter model of linear force-free magnetic fields (LFFFs) to model active regions of multiple dipolar configurations including the Active Region (AR) 11117. We use state-of-the-art architectures such as ResNet and Inception networks, and develop our customized network ‘‘SolarNet" to determine the associated LFFF parameter alpha from a set of pseudo-coronal loop images, which are generated using the modeled active regions. Our results show very high accuracy of determining the LFFF parameter alpha, thereby demonstrating the effectiveness of the generic and customized deep CNN architectures to understand the coronal magnetic field. The usefulness of the LFFF parameter alpha and its response to observed images is also studied.

Monica Bobra (Stanford University, USA)

HelioML: Machine Learning, Statistics, and Data Mining for Heliophysics

We present HelioML, a book about machine learning, statistics, and data mining for heliophysics. This online and open source book includes a collection of interactive Jupyter notebooks, written in Python, that explicitly shows the reader how to use machine learning, statistics, and data mining techniques on various kinds of heliophysics data sets to reproduce published results. We consider this book to be a living document with frequent updates. Please contact us if you'd like to submit a chapter!

Jacob Bortnik (UCLA, USA)

Neural network based reconstruction of inner magnetospheric density, waves, and energetic electron fluxes

The volume of space physics data continues to rise exponentially, and promises to accelerate its growth in the near future to the point that individual projects return on the order of a petabyte of data. At the same time, our analysis techniques have not kept pace with the rapid growth of data, and often do not exploit the capabilities of the data to their fullest potential. Here, we present a novel method based on machine learning technology, that aims to convert a sequence of point measurements of some given quantity Q made over a long period of time (for example observations made on a satellite), into a 3-dimensional dynamic spatiotemporal model of that quantity. As an example, we show a three-dimensional dynamic electron density (DEN3D) model in the inner magnetosphere, that can provide full coverage of the inner magnetosphere and in fact is sufficiently accurate that it points the way to new physical discoveries. We also show reconstructions of whistler-mode chorus and plasmaspheric hiss waves, and show how these models can be used as inputs to downstream models, that can subsequently predict the dynamics of 'data starved' quantities, such as ultra-relativistic electron fluxes.

Pedro Brea (Significant Opportunities in Atmospheric Research and Science (SOARS), USA)

Using Machine Learning Techniques to Forecast Solar Energetic Particles

Solar energetic particles (SEPs) pose a threat to satellites, air traffic, and communications on Earth, among other effects. The ability to forecast these events in advance is essential to prevent the loss of assets in the atmosphere and in space, as well as the lives of space faring passengers. Considering that the method of acceleration and transport of these particles is still an area of active research and that physics-based models are, currently, computationally slower than empirical models, forecasters at NOAA's Space Weather Prediction Center (SWPC) make use of the latter to make real-time decisions. This project attempts to improve upon the results of the current statistical model in use at SWPC. Machine learning models learn and make decisions based on empirical data and are currently much quicker than numerical models for issuing a forecast. Classic machine learning techniques are used to make a binary classification, i.e. whether or not there will be an SEP event based on the physical parameters associated with solar flares and coronal mass ejections. Preliminary results seem to show that the boosted decision trees outperform the current SWPC Proton Prediction Model.

Wendy Carande (Laboratory for Atmospheric and Space Physics, University of Colorado, USA)
Challenges of Using Machine Learning for Solar Flare Prediction and Prospective Solutions

The question of how to use machine learning to predict solar flares has been explored extensively in recent years. Although the field has advanced dramatically, there are many challenges we still face in using machine learning for solar flare prediction. We will discuss some of these challenges, from data imbalance, to appropriate training set selection, to finding ways to explain the physical mechanisms underlying our machine learning results, from a multidisciplinary perspective. Using examples and results from our convolutional neural network and multilayer perceptron models, we'll display how we approached these challenges and sought to fix them and what methods we propose as we further develop our models. We'll also discuss the importance of feature engineering as it relates to solar flare prediction, and the obstacles and rewards of creating our own in-house features.

Angelica M. Castillo (GFZ German Research Centre for Geosciences, Potsdam, Germany)
Data assimilation of LEO satellite data into VERB-3D simulations

Understanding the dynamics of energetic electrons in the radiation belts is key to protect space borne equipment and astronauts on-board spacecraft missions. Therefore, global reconstruction of the near-Earth radiation environment should be available at all times, radial distances and geomagnetic latitudes. In order to accomplish such a challenging task, we can combine sparse data from a number of satellite missions at various orbits with physics-based models of the radiation belts and blend them together using data assimilation techniques. Additionally, data assimilation can help us to identify unknown physical processes, reanalyze the past state of the radiation belts, study model errors and offers the most advanced forecasting tool of the radiation belts available at the moment. Low Earth Orbit (LEO) satellites are of special interest to us, because they provide a large data set of rapid observations of the radiation belt region over a wide range of magnetic local times (MLT). However, rather fewer studies on data assimilation have used this data set due to possible proton contamination of electron fluxes and the observation of electron precipitation, leading to high variability of electron measurements, considerable instrumental errors and the need for background correction. In this study, we use a split-operator Kalman filter technique to assimilate data from the POES and MetOp fleet into the 3-D Versatile Electron Radiation Belt (VERB-3D) code. Background correction is performed through estimation and extraction of particles in the bounce and drift loss cones. We study the effect of varying the instrumental errors, i.e. error variation in dependence of the radial distance. Using these techniques we perform a one-year re-analysis of the state of the radiation belt electrons and compare it to electron flux data from Van Allen probes and GOES.

Mandar Chandorkar (CWI Amsterdam & INRIA Paris-Saclay)
Predicting Time Lagged Effects of Solar Activity: A Deep Learning Approach

It is often the case with natural and man-made phenomena, that cause and effect are temporally separated i.e. there is a time lag between occurrence of an event and the observation of its consequences. In complex systems, this time lag between cause and effect can be uncertain and dynamic. Mathematically this can be expressed as y{t + g(xt}) = f(xt), where xt is a time series representing the causes, yt represents the effects and functions f and g represent the input-output and input-time lag relationships. In the context of space weather, one can see this when active regions on the Sun, give rise to high speed solar wind streams which cause disturbances in the Earth's geomagnetic state, several hours, or even days later. To increase the prediction window of space weather forecasting systems, it is important to model the temporal relationship between space weather drivers and geomagnetic quantities in the vicinity of the Earth. We present ongoing work in learning dynamic causal time lags from noisy time series. Our methodology is based on a neural network which learns the input-output and input-time lag relationships simultaneously. We evaluate our models performance on a set of toy problems as well as on the problem of solar wind propagation using Solar and OMNI data sets.

Alemayehu Cherkos (Addis Ababa University, Ethiopia)
Effect of viscosity on propagation of MHD waves in astrophysical plasma

We determine the general dispersion relation for the propagation of magnetohydrodynamic (MHD) waves in an astrophysical plasma by considering the effect of viscosity with an anisotropic pressure tensor. Basic MHD equations have been derived and linearized by the method of perturbation to develop the general form of the dispersion relation equation. Our result indicates that an astrophysical plasma with an anisotropic pressure tensor is stable in the presence of viscosity and a strong magnetic field at considerable wavelength.

Eurico Covas (Universidade de Coimbra, Portugal)
Spatial-temporal forecast of the sunspot butterfly diagram

Neural networks, and in general machine learning techniques, have been widely employed in forecasting time series. In particular, there is a wide range of literature in forecasting solar related time series, such as the sunspot number and sunspot area data sets (one of the longest continuously recorded daily measurements made in science - (Owens, 2013)), and the solar flares, solar irradiance, solar wind, solar magnetic fields and other series. From all of this research, only a small part attempts to forecast in both space and in time, i.e., to predict the entire spatially extended series. Recently this field has become more active, with the application of empirical relationships to forecast the butterfly diagram (Jiang et al., 2011; Santos et al., 2015; Cameron, Jiang, and Schüssler, 2016) or those using solar surface magnetic field datasets (McIntosh et al., 2014b,a; Jiang and Cao, 2018). Here, long established theoretical results from the field of non-linear dynamical systems (Takens 1981) have been applied to perform spatial-temporal embeddings of the sunspot area butterfly data (Covas 2017) and more recently these results have been connected with neural networks in another spatial-temporal forecast of the butterfly diagram (Covas, Peixinho and Fernandes, 2019). This method of forecasting can be used for any sufficiently long spatial-temporal series. Furthermore, a new technique using transfer learning (Pan and Yang 2010) allows to use the knowledge learned from one dataset (such as the sunspot data above) to jump start the learning of another related data set (such as the magnetic field intensity). These techniques can easily be applied using new open source technology from Google such as the TensorFlow library (Abadi et al. 2016) for the python computer language. Interestingly, these results, which draw widely from the theoretical foundations presented in Takens (1981), also point the way for a possible non-linear dynamical systems theory conjecture on how to construct the optimal neural network feature selection for spatial-temporal forecasting (Covas and Benetos, 2019, submitted).

Daniel da Silva (Johns Hopkins University, USA)

Case Study of Applying Neural Network to Remove Non-Linear Instrument Noise

Scientific instruments are no doubt indispensable tools for studying the heliopsphere, but no measurement comes without noise and its own set of nuances. The cookbook of remedies to instrument imperfections has been written for the ones that can be solved with a simple equation. There is no question how to subtract background, adjust for lost sensitivity, or calibrate to a known environment. What machine learning uniquely has to offer are data-driven solutions to highly non-linear problems for which there is no simple equation. In this presentation, we will present a case study of utilizing feed-forward neural networks to filter out a hard-to-solve class of measurement artifacts in the Fast Plasma Instrument (FPI) on the Magnetospheric MultiScale Mission (MMS). Lossy compression on-board the spacecraft early on in the mission added a level of distortion to the measurements, similar in respect to image processing with what happens when a JPEG or GIF image is over-compressed on a desktop computer. In this talk we will explore framing of the task to be performed, design and preparation of the training data, selection of method, validation, and communication of the method to those without a bridge into the world of machine learning.

Silvia Dalla (University of Central Lancashire, USA)

SPARX: a propagation based modelling system for Solar Energetic Particle Space Weather forecasting

We present SPARX (Solar PArticle Radiation Space Weather [SWx]) a modelling system simulating the propagation of Solar Energetic Particles for space weather purposes. SPARX incorporates a fully 3D model, using a full-orbit test particle approach, to simulate the propagation of solar energetic particles (SEPs) from the Sun to any given location in the heliosphere. The model is able to describe particle transport across the magnetic field and includes the effect of drifts. The SPARX system can forecast the time dependent particle flux within various energy ranges and output parameters of interest to space weather such as maximum flux, onset time, peak time and duration of the SEP event.

SPARX is integrated within the SEPForecast tool of the EU FP7 COMESEP project and can also be used independently. SPARX forecasts the near-Earth integral proton flux profiles in the E>10 MeV and E>60 MeV ranges, comparable to those supplied by the GOES spacecraft.

We describe the methodology behind the modelling and forecasting system, as well as applications of the test particle approach to heliospheric configurations obtained from ENLIL.

Curt A de Koning (University of Colorado, Boulder, USA)

Noise Analysis and Noise Reduction of Differenced STEREO/COR2 Images

We plan to analyse running and fixed difference images from the STEREO/COR2 catalog. Since STEREO/COR2 observes the SUn every 15 minutes, running difference images during time periods without any transient activity - 'quiet' time periods - should have close to zero signal; therefore, analysis of such images can be used to quantify the noise in STEREO/COR2 images. Based on the type of noise that is present, we plan to use the appropriate non-local means algorithm for image denoising. Denoised coronagraph images can be used for improved CME reconstruction, which has applications in space weather forecasting.

Dattaraj Dhuri (Tata Institute, Mumbai, India)

Deep learning applied to detect pre-emergence photospheric magnetic field patterns

Magnetic flux generated within solar convection zone rises to the surface forming active regions (ARs) and sunspots. Early detection of ARs will be useful for gaining warning time against a variety explosive events - such as flares and coronal mass ejections - that lead to severe space weather consequences. Evidence of any pre-emergence signatures will also shed light on subsurface processes responsible for emergence. Here we use deep convolutional neural networks (CNN) to analyse SDO/HMI line-of-sight magnetograms of pre-emerging ARs. The CNN classifies pre-emerging ARs (PEs) from a control set of non-emerging ARs (NEs) with a True Skill Statistic score (TSS) of ~ 90%, 3 hrs prior to emergence and ~ 40%, 24 hrs prior to emergence. We also develop techniques to "open up" the trained CNN and highlight detected pre-emergence magnetic field patterns.

Andrea Diercke (Leibniz Institute for Astrophsics Potsdam, Germany)

Automatic extraction of Polar Crown Filaments using machine learning techniques

Polar Crown Filaments are prominent features on the Sun, which show a cyclic behavior similar to the sunspot cycle. The cyclic behavior can be monitored by regular full-disk H-alpha observations. The Chromospheric Telescope (ChroTel, Tenerife, Spain) provides such regular observations of the Sun in three chromospheric wavelengths: H-alpha, Ca II K, and He I 1083 nm. Since 2012, ChroTel observed on 965 days the Sun and is providing every three minutes full-disk observations in all observed wavelengths. To analyze the cyclic behavior and the statistical properties of the polar crown filaments, we have to extract the filaments from the images. A manual extraction is tedious, and extraction with morphological image processing tools, produces a large number of false positive detection and takes up too much time. Automatic feature detection and extraction in a reliable manner allows to process more data in a shorter time. We will present an overview of the ChroTel database and a prototype of a machine learning pipeline, which allows a unified extraction of, for example, filaments from the ChroTel data.

Grigol Dididze (Ilia State University Abastumani Astrophysical Observatory, Georgia)

Comparative analysis of solar radio bursts before and during CME propagation

As is well known, CME propagation often results in the fragmentation of the solar atmosphere on smaller regions of density (magnetic field) enhancement (depletion). It is expected that this type of fragmentation may have radio signatures. The general aim of the present paper is to perform a comparative analysis of type III solar and narrow-band type-III-like radio burst properties before and during CME events, respectively. The main goal is to analyze radio observational signatures of the dynamical processes in solar
corona. In particular, we aim to perform a comparison of local plasma parameters without and with CME propagation, based on the analysis of decameter radio emission data.
In order to examine this intuitive expectation, we performed a comparison of usual type III bursts before the CME with narrow-band type-III-like bursts, which are observationally detectable on top of the background type IV radio bursts associated with CME propagation. We focused on the analysis of in total 429 type III and 129 narrow-band type-III-like bursts. We studied
their main characteristic parameters such as frequency drift rate, duration, and instantaneous frequency bandwidth using standard statistical methods. Furthermore, we inferred local plasma parameters (e.g., density scale height, emission source radial sizes) using known definitions of
frequency drift, duration, and instantaneous frequency bandwidth.
The analysis reveals that the physical parameters of coronal plasma before CMEs considerably differ from those during the propagation of CMEs (the observational periods 2 and 4 with type IV radio bursts associated with CMEs). Local density radial profiles and the characteristic spatial scales of radio emission sources vary with radial distance more drastically during
the CME propagation compared to the cases of quasistatic solar atmosphere without CME(s) (observational periods 1 and 3).
The results of the work enable us to distinguish different regimes of plasma state in the solar corona. Our results create a solid perspective from which to develop novel tools for coronal plasma studies using radio dynamic spectra.

Alina Donea (Monash University, Australia)

Training data sets for machine learning algorithms to detect magnetic polarities of far side solar regions

The training data set in machine learning is gaining mainstream presence for data and solar scientists nowdays via its implementation of a series of algorithms for the autonomous detection and tracking of solar features. It supports the mathematical technical foundation necessary for developing algorithms, to map the Sun's far hemisphere. Using the far-side seismic monitor, large active regions in the far hemisphere can be detected. This is well established. But what is the magnetic polarity of this region? What is its magnetic complexity? So, the aim is to build an accurate machine learning-based predictive model to estimate the solar magnetic polarity and its complexity. Before doing this, we have to understand the type of available data, the training data. In this paper, I will present the training data set and ask incipient questions about what is the best algorithm to train the machine to recognise magnetic polarities of near site solar regions.

Khaled Ali Elden (Helwan University, Cairo, Egypt)
Predicting the Stream Interaction Regions at Earth: A Machine Learning Approach

Solar wind is the outward, supersonic expansion of the solar corona, extending all the way to the heliopause and merging with the interstellar space. The solar wind flows out radially and is structured with two distinct components - the fast stream, with a speed above 450 km/s, and the slow stream, with speed below 450 km/s. The fast and slow solar wind originate from different locations on the Sun and their physical properties are characteristically different. A fast wind often runs into a slow wind moving ahead, creating a region of compression at the leading edge while a region of rarefaction is formed at the trailing edge. This structure is known as the stream interaction region (SIR). Occasionally, these structures recur as the Sun rotates, giving rise to what is known as corotating interaction regions (CIRs). These structures can be clearly identified in the spacecraft measurements of solar wind properties and a list of SIRs (including CIRs, marked distinctly) based on the STEREO observations is publicly available. Using this catalog, we adopted machine learning techniques to predict the arrival times of SIRs at Earth. We present our method and the results obtained.

Frederic Effenberger (GFZ Potsdam, Germany)
Deep Learning with Solar Images

The Solar Dynamics Observatory (SDO) offers an uprecedented, very large dataset of solar images in different optical and EUV wavelength bands, capturing solar atmospheric structures in high resolution and with excellent coverage since 2010. This dataset is thus well suited to study the application of advanced machine learning techniques that require large amounts of data for training, such as deep learning approaches. Here, we present our initial results of deep learning as applied to solar images and discuss issues and pathways for future research. In particular, we address the scope for generative adversarial training and convolutional neural networks in application to resolution enhancement, feature tracking and synthetic feature engineering. The need for a community-driven, physics-based basis to establish evaluation criteria for generative models will be emphasized.

Laurel Farris (New Mexico State University, USA)
Enhanced chromospheric 3-minute oscillatory power associated with the 2011-February-15 X2.2 flare

Flare-induced 3-minute oscillations in the chromosphere have been attributed to both slow magnetoacoustic waves %with frequencies higher than the acoustic cutoff propagating from the photosphere, and to oscillations generated within the chromosphere itself at its natural frequency as a response to a disturbance. Here we present an investigation of the spatial and temporal behavior of the chromospheric 3-minute oscillations before, during, and after the SOL2011-02-15T01:56 X2.2 flare. Observations in ultraviolet emission centered on 1600 and 1700 Angstroms obtained at 24-second cadence from the Atmospheric Imaging Assembly on board the Solar Dynamics Observatory are used to create power maps as functions of both space and time. We detect an increase in the 3-

minute power during the X-class flare, as well as during other smaller events before and after the flare. The enhancement is not global, instead it is concentrated in small areas around the active region, which is attributed to the localized injection of energy by nonthermal particles.

Bea Gallardo-Lacourt (NASA Goddard Space Flight Center, USA)
Automatic Polar Cap Boundary Identification Using Redline Imaging Data

The location of the polar cap boundary is typically determined using low-orbit satellite measurements in which the boundary is identified by its unique signature of a sharp decrease in energy and particle flux poleward of the auroral oval. A previous study based in optical data by Blanchard et al. [1995] suggested that a dramatic gradient in redline aurora may also be an indicator of the polar cap boundary. While this study has been heavily cited, it was only based on few events and its findings have largely gone uncontested. In recent years, satellite instrumentation and available auroral data have improved significantly. Auroral imaging has moved well beyond the capabilities of the instrumentation in the previous study in terms of sensitivity and both spatial and temporal resolution. We now have access to decades of optical data from arrays spanning a huge spatial range; none of which was available previously.
In the first part of this study we have used data from the Defense Meteorological Satellite program (DMSP) satellites in conjunction with the University of Calgary's REdline Geospace Observatory (REGO) data to assess the viability of automated detection of the polar cap boundary. In our analysis we used redline (630nm) auroral signatures from the ground based imagers around the location of the polar cap boundary observed in satellite data. This analysis allows us to characterize the polar cap boundary luminosity and location using auroral data during different geomagnetic conditions. Our results enable a new tool to identify the polar cap boundary and provides a suitable training set to automatically identify the polar cap boundary. This work will enable us to reach a deeper understanding of the connection between polar cap location and auroral activity.

Philippe Garnier (IRAP, CNRS, France)
Automatic detection of magnetopause reconnection diffusion regions

Our Sun is continuously expelling plasma (the so-called Solar Wind) from its corona, which fills the whole Solar system and interacts with all its planets and bodies. Among the various plasma processes that occur in the interaction between the solar wind and the Earth’s magnetosphere, magnetic reconnection is the main driver of energy and mass transfer.
The NASA Magnetospheric Multiscale mission (MMS, mms.gsfc.nasa.gov), launched in March 2015, consists of four spacecraft flying in tetrahedron formation on a highly elliptical orbit designed to study the solar wind - magnetosphere interaction and magnetic reconnection in particular. MMS is the first of its class, equipped with a full suite of state-of-the-art instrumentation that makes possible to study plasma processes down to electron scales. This is achieved with 3D electron distribution function measures at a cadence of 30ms, 100 times higher than any previous space mission.

MMS has already been producing a very large dataset with invaluable information about how the solar wind and the Earth's magnetosphere interact. However, it remains challenging to process all these new data and convert it into scientific knowledge, the ultimate goal of the mission. Data science and machine learning are nowadays a very powerful and successful technology that is employed to many applied and research fields such as speech recognition, artificial vision, or automatic driving, to name a few. In this paper, we will discuss the tentative use of neural networks-based machine learning techniques to the automatic detection and classification of magnetic reconnection in the MMS data set, with a focus on the critical but poorly understood electron diffusion region at the Earth's dayside magnetopause.

Forrest Gasdia (University of Colorado, Boulder, CO, USA)

VLF Mapping of the D-region Ionosphere Using an LETKF

The D-region of the ionosphere is influenced by many phenomena from both above and below. Solar conditions, atmospheric gravity waves, energetic particle precipitation, galactic cosmic rays, and lightning-induced heating are all believed to affect the electron density profile in the D-region, yet little is known about this region compared to the higher ionospheric layers. The height of the D-region (varying from about 70 to 90 km) and low electron densities (1 to 1000 e-/cm^3) means the usual ionospheric measurement techniques are ineffective. Sounding rockets measure in situ electron density profiles, but these are sparse in space and time. Most D-region investigations are performed by measuring very low frequency (VLF) radio signals. At VLF radio frequencies, electromagnetic waves propagate efficiently down a waveguide formed by Earth and the D-region. Lightning sferics and the signal from high power submarine communication transmitters can be received from thousands of kilometers away. Conditions along the waveguide boundaries, including the effective height and slope of electron density in the D-region, affect the amplitude and phase of the transmitted signal as measured by a fixed receiver in the guide.

By inverting VLF receiver measurements, we can infer the D-region conditions along the propagation path. This is an ill-posed and under-determined problem to which we have applied the update step of the local ensemble transform Kalman filter (LETKF). By assimilating measurements from a network of VLF transmitters and receivers into the prior best model estimate of the D-region, we are able to produce a spatial map of the D-region over a large geographic area. The EnKF technique both enables a formal inversion of amplitude and phase measurements into electron density parameters and provides support around likely values for an otherwise indeterminate problem. This technique is particularly useful for improving knowledge of the ``typical" undisturbed D-region. Simulated observation experiments have been conducted for several ionospheric conditions using the LETKF, including day, night, and terminator ionospheres, as well as energetic particle precipitation events.

Vincent Génot (IRAP/CNRS/UPS, France)

Automated detection and dynamics of Martian plasma boundaries

The planetary environments (Venus, Mars, ... and of course the Earth) have been or are being visited by numerous probes whose measurements make it possible to understand the dynamics of these environments and their evolution (e.g. the escape of Martian water and the role of the solar wind). The instruments collect information on the magnetic field and / or particle distributions around these bodies with a temporal resolution of the order of a second or a minute over time scales of several months to several years. Part of the researcher's job is therefore to go through these long time series to detect 'events' that are characterized by variations of one or more parameters at a time. Automatically detecting these events, however, is a long time search which, once achieved, allows the researcher to correlate these occurrences with various parameters, including solar activity, in order to refine the understanding of their dynamics. We shall present our recent approach of this challenge that consists in training a neural network to recognize plasma boundaries such as the shock in the Martian case (weak dynamic dependence on the solar wind). Data from Mars Express and MAVEN missions have been used together with published lists of events (Hall et al., 2016; Fang et al., 2017; Gruesbeck et al., 2018). The importance of physical insight in the post-processing phase will be highlighted. Finally a prototype which generates updated catalogues of events by running on data from the French plasma physics data centre (AMDA on http://www.cdpp.eu/) will be presented.

Andriy Gorobets (Leibniz-Institut fuer Sonnenphysik, KIS)

Small-scale magnetism of the quite Sun: quantifying temporal dynamics.

Line-of-sight magnetic fields in the solar photosphere exhibit a very complex spatial and temporal behavior. Characterizing their dynamics in response to the surface turbulence seen as magnetic features is a challenging subject in solar physics. Motivated by critics of solar feature-tracking algorithms, we have developed an approach allowing us to analyze evolution of magnetic fields as a continuous media being sampled at pixels of magnetograms. By discarding the notion of magnetic features and subjective assumptions about their identification and interaction, we treat evolving magnetic fields as time ordered fluctuations. These observed non-equilibrium fluctuations obey Markov properties. Furthermore, employing concepts from ensemble thermodynamics and information theory, we quantify the quiet Sun magnetism evolution by a theoretical rate of long-time limit convergence towards a unique equilibrium state with a maximum entropy. We obtained remarkably different rates of convergence for data with different spatial resolution and in the presence of mixing-polarity fluctuations. Our analysis has been applied to observations of magnetic fields of relatively quiet areas around an active region, obtained with the SUNRISE-II/IMAX balloon telescope, and quiet Sun areas at the disk center recorded by the SDO/HMI space mission.

Luiz Fernando Guedes dos Santos (Catholic University of America/NASA-GSFC, USA)
Using Image Recognition and Supervised Learning to Identify Flux Ropes

The magnetic field configurations associated with interplanetary coronal mass ejections (ICMEs) are the in-situ manifestations of the entrained magnetic structure associated with the coronal mass ejections (CMEs). The prediction of such configurations is essential to Space Weather in order to forecast any resulting geomagnetic disturbances. The main hypothesis in such predictions is to assume that such structure is a flux rope. However, the in-situ imprints in the magnetic field observations sometimes reveals deviations from the expected magnetic field direction rotation associated with flux ropes. It is a fact that our information about the internal magnetic structure of ICME is limited to the 1D observations of a single spacecraft crossing the large structure, leaving a considerable amount of uncertainty. Thus, this might result from changes during interplanetary (IP) evolution (see Manchester et al., 2017, and reference therein), from spacecraft crossing far from the ICME core, or possibly from the topological complexity of the magnetic structure during CME initiation in the solar corona.
In this work, we carry out a sophisticated analysis of flux rope magnetic field configurations using image recognition in order to better understand the internal magnetic structure of the ICMEs. To accomplish our goal, we combine the analytical flux rope model, extracted from the physical principles, with the more advanced machine learning techniques.

Verena Heidrich-Meisner (Kiel University, Germany)
How similar are time series of elemental abundances of different low first ionization potential elements?

It is well known that the elemental abundance is determined in the solar atmosphere and is in particular different in different types of solar wind. The abundance of heavy elments in the solar wind is specific for the respective source region and solar wind type. Therefore, the upcoming Solar Oribter mission aims to identify the source regions of the slow solar wind with coordinated observations of low first ionization potential elements with in-situ and remote sensing instruments. However, this relies on the assumption that time series of these elements, typically Fe, Mg, and Si, are indeed well correlated on all relevant time scales. Here, we scrutinize this assumption and investigate the Spearman ranking correlation between time series of elemental abundances measured by the Solar Wind Ion Composition Spectrometer (SWICS) onboard the Advanced Composition Explorer (ACE) and compare these to the contained mutual information. We repeat this analysis for time scales corresponding to the size of individual solar wind flux tubes, the typical length of solar wind streams, and longer times scales up to a few Carrington rotations.

Shea Hess Webber (Stanford University, USA)
Using Deep-Learning to Map the Solar Far-Side Magnetic Flux from Helioseismic Measurements

The solar far-side magnetic flux is a crucial physical quantity for space weather forecasting and solar wind modeling, but it is not currently directly observed. For about 4 years, the extreme ultraviolet (EUV) 304 Angstrom flux of the far side was observed by STEREO/EUVI, which is used to produce proxy far-side magnetic flux maps (see presentation by R. Chen). Helioseismic far-side imaging methods are also used to produce far-side acoustic maps from near-side observations, which indirectly detect large active regions on the far side; however, these acoustic maps are not calibrated to magnetic flux. In this work, we use a deep-learning approach to produce far-side magnetic flux maps in near-real-time using near-side observations alone. Our neural network is trained on ~2500 pairs (3.5 years, two pairs of maps per day) of far-side acoustic maps and magnetic flux proxy maps, and then test on the remaining half year of data. The final product can then be further calibrated to magnetic flux-transport maps for additional validation. This neural network will be applied to future far-side acoustic maps to produce near-real-time far-side magnetic flux maps, without the need for direct far-side observations.

Jürgen Hinterreiter (Space Research Institute, Austrian Academy of Sciences, Graz, Austria)

Statistical study on CME arrival prediction using ELEvoHI ensemble modeling

We present the results of a statistical study on post-event prediction of CME arrivals using ELEvoHI (ELlipse Evolution model based on Heliospheric Imager observations) ensemble modeling. The model uses time-elongation profiles provided by HI (Heliospheric Imager) onboard STEREO (Solar TErrestrial RElations Observatory) to predict the arrival time and arrival speed of CMEs. ELEvoHI assumes an elliptical shape of the CME front and that the drag force exerted by the ambient solar wind is the dominant force influencing the CME propagation in the IP-space. We select CMEs occurring between June 2009 to June 2010, corresponding to a location of STEREO-B close to Lagrange point 5 (60° trailing Earth) making the model results valuable for future studies (STEREO-A near L5 in mid-2020) and for a planned space weather mission at L5. We calculate well-established skill scores based on a contingency table (hit/false alarm/miss/true rejection) and compare the times and speeds for the predicted and observed events arriving at Earth. The statistical results will be used as a benchmark for future enhanced ELEvoHI versions in which we attempt to include machine learning techniques.

Andong Hu (CWI, Amsterdam)

Using Gaussian Process-aided Deep Neural Network Method for Ionospheric NmF2 Modelling Based on GNSS Radio Occultation Measurements

An advanced machine learning method—Gaussian process (GP)—is used to assist deep neural network (DNN) for F2 layer peak electron density (NmF2) modelling based on GNSS radio occultation (GNSS-RO) measurements from satellite missions, including Constellation Observing System for Meteorol- ogy, Ionosphere, and Climate (COSMIC), Gravity Recovery and Climate Experiment (GRACE) and CHAllenging Mini-satellite Payload (CHAMP) in this study. Different from the classic neural network, i.e. with one hidden layer (hereinafter called 'ANN model'), the DNN contains three hidden layers with different activation functions, and the L2 regularised factor and the initialisation method developed by He et al. are also used in this network (the configuration is the same as Hu et al., hereinafter called 'DNN model'). A GP is then used to estimate the uncertainty/covariance of the DNN model for further improving the performance of the DNN model (hereinafter called ‘GP-DNN model’ or ‘GP model’). The performance of the new model is assessed using out-of-sample GNSS-RO data as the reference. The spatial and temporal variation in NmF2 generated by the GP-DNN model is also investigated. In order to verify the feasibility and reliability of the new model during extreme space weather events, the new model outputs are tested during a geomagnetic storm period (the St. Patrick’s storm, March 17, 2013). The data used for developing the GP-DNN model are total 3,268,803 GNSS-RO profiles from the three satellite missions during 2001-2017. The new model results are also compared with the outputs from the International Union of Radio Science (URSI) model [3] which is the default model inside the latest International Reference Ionosphere (IRI) model (IRI-2016), and with the ANN and DNN models. Results showed that: (1) The Root-Mean-Squares Deviations (RMSDs) of the differences of the results of the GP-DNN, DNN, ANN and URSI models from the reference were 1.37, 1.46, 1.92 and 3.24 ×105el/cm3 respectively, which suggested the new model outperforms the other three; (2) The new model significantly outperformed the DNN model mostly in the low and high latitude regions; and (3) The new model could well capture the features of NmF2 during the St. Patrick’s storm occurred in 2013.

Raluca Ilie (University of Illinois at Urbana-Champaign)

Forecasting the magnetospheric plasma conditions using Machine Learning Techniques and Cluster RAPID data

There are generally two types of the model suited for space weather prediction: physics-based and statistics-based models. While the first type of model is built on physical assumptions and mathematical expressions, a statistical model primarily makes predictions based on past data.

We present here a newly developed decision tree-based machine learning model that has the capability to make predictions of various plasma parameters of the Earth’s magnetosphere. The training data set is provided by the 15 years of Cluster RAPID data. We will present the prediction outcomes, error analysis and performance assessments. By stepping through the structure and the algorithms of this model, we show that it can be modified to be applicable to any large dataset with one or more parameters, depending on other parameters which are available without spacecraft operations. Based on the model’s relatively fast speed, we can estimate the plasma conditions at any given position in a short amount of time, and therefore provide significant insight to forecasting space weather. This model could also be used to provide plasma boundary conditions, when unavailable from observations, to first principle models. In addition, we demonstrate a new, 3-D visualization tool for plasma observations from Cluster spacecraft, that further aids the understanding of the magnetospheric processes that dictate the dynamics in the region.

Jack Ireland (NASA Goddard Spaceflight Center, USA)

Detecting and tracking large scale EUV waves in the solar atmosphere

Extreme ultraviolet (EUV) waves are large-scale propagating disturbances observed in the solar corona, frequently associated with coronal mass ejections and flares. They appear as faint, extended structures propagating from a source region across the structured solar corona. To measure these waves, we have constructed the Automated Wave Analysis and REduction (AWARE) algorithm.

AWARE analyzes time series of Solar Dynamics Observatory Atmospheric Imaging Assembly (AIA) image data. AWARE is implemented in two stages. In the first stage, we use image processing techniques to isolate the propagating, brightening wavefronts as they move across the corona. In the second stage, AWARE measures the distance traveled by the wave, its velocity, and its acceleration. We explore the use of the Huygens principle, dynamic time warping and a simple parametric representation of the wavefront as potential methods for detecting and tracking non-radial EUV wave propagation.

Robert Jarolim (Institute of Physics, University of Graz, Austria)

Image Quality Assessment and Reconstruction of Solar H-alpha Images with Deep Learning

Local atmospheric and seeing conditions are a major challenge of ground-based solar observations. To maintain a high image quality either an appropriate selection procedure or image corrections need to be applied. In preparation for the Solar Physics Research Integrated Network Group (SPRING), which anticipates a global observation network for full-disk solar images in multiple channels, we are developing techniques for the image quality assessment of single-site full-disk solar observations. The aim is to establish image quality and selection criteria for multi-site observations. Additionally, we are investigating reconstruction methods to compensate for local seeing conditions. Recent approaches with neural networks have proven to perform well on image quality assessment. As a baseline we use the currently operating quality estimation of the Kanzelhöhe Observatory for Solar and Environmental Research (KSO), which is based on a combination of parameters that describe local and global properties extracted from each image (Pötzi et al. 2015). Our dataset consists of manually annotated H-alpha images between 2008 and 2019, covering a wide range of solar activity conditions. In this work we use a neural network to translate between high- and low-quality images. This is achieved by an architecture based on generative adversarial networks (GANs) with cycle-consistency loss (Zhu et al. 2017). We use high-quality images as conditional input for a generating neural network to create realistic low-quality images, in parallel a second generator is trained to reproduce the original image. With this approach a dataset of paired ground-truth and degraded images is created. To enforce the generation of low-quality images a discriminating network is used to identify the differences between low-and high-quality images. With further training on the full augmented dataset this network serves as an image quality classifier. We expect that the reconstructed images serve as homogenized input for detection systems, maintaining the overall reliability.

Robert Jarolim (Institute of Physics, University of Graz, Austria)

Multi-Channel Coronal Hole Detection with a Convolutional Neural Network

Coronal holes are the source region of the high velocity solar wind stream, which may cause recurrent geomagnetic storms. The correct identification of coronal holes is therefore of critical importance for space weather predictions. To account for a reliable automatic detection system the full information of area, shape and position is required. Existing extraction algorithms are generally based on intensity thresholds or clustering algorithms to obtain a pixel wise classification of coronal hole regions. Due to the similar appearance of filament channels, current algorithms tend to misclassifications. In addition, nearby bright coronal loops can outshine the dark coronal hole regions, which leads to incomplete segmentations. A strong indicator to distinguish between coronal holes and filaments is the distinct flux imbalance of coronal hole regions. In this work we introduce a fully-convolutional neural network which uses as input EUV imagery from multiple filters (94Å, 131Å, 171 Å, 193 Å, 211 Å, 304 Å, 335 Å) of the Atmospheric Imaging Assembly (AIA) onboard the Solar Dynamics Observatory (SDO) combined with magnetograms from SDO's Helioseismic and Magnetic Imager (HMI). This drastically increases the available information for the identification of coronal holes. The availability of large data sets makes this approach especially appealing, nevertheless is the manual creation of a pixel-wise labeled data set a costly task. We utilize the dataset by Delouille et al. (2018) which was generated with a modified SPoCA version and revised for misclassifications. This dataset still lacks from some incomplete segmentations, therefore we tune the network on a smaller manually classified dataset to its best performance.

Seong-gyeong Jeon (Kyung Hee University)

Generation of future solar magnetograms from previous SDO/HMI data using conditional Generative Adversarial Networks (cGAN)

In this study, we generate future full disk magnetograms in 12, 24, 36 and 48 hours advance from SDO/HMI images using deep learning. To perform this generation, we apply the conditional generative adversarial network (cGAN) algorithm to a series of SDO/HMI magnetograms. We use SDO/HMI data from 2011 to 2016 for training four models. The models make AI-generated images for 2017 HMI data and compare them with the actual HMI magnetograms for evaluation. The AI-generated images by each model are similar to the actual images. In the case of 12 hour forecast, the average correlation coefficients between the two images with 2 by 2 binning are 0.76 for full-disk images and 0.77 for active regions. In the future we will use pix2pix HD and video2video translation networks for image prediction.
This work was supported by Institute for Information & communications Technology Promotion(IITP) grant funded by the Korea government(MSIP) (2018-0-01422, Study on analysis and prediction technique of solar flares).

Anjali J. Kaithakkal (Leibniz Institute for Solar Physics, Germany)

Identification and tracking of small-scale magnetic features on the solar photosphere

Small-scale, short-lived magnetic features that carry significant amount of magnetic flux are ubiquitous on the solar surface. Studying their formation, evolution and eventual disappearance is essential to understand the flux budget of the photosphere, and multitude of dynamic events like bombs, jets, bursts etc. and their contribution to upper atmospheric heating. We use an automatic code based on multi-level magnetic field thresholds to identify these magnetic features. Then we track them over time using spatial coincidence. This identification and tracking method do return reasonable results. However, this method is limited by our choice of thresholds and criteria we employ for tracking, and also the code needs tweaking for different datasets. We plan to use machine learning code in the future to identify and track the small-scale magnetic elements and thereby to study their dynamic evolution. We are also interested in learning how machine learning code can be used to derive horizontal plasma velocity on the solar surface.

Maria Kazachenko (CU Boulder / NSO / LASP, USA)

A Database of Flare Ribbon Properties From Solar Dynamics Observatory

We present a database of >3000 of solar flare ribbon events corresponding to every flare of GOES class C1.0 and greater within 45 degrees from the disk center, from April 2010 until April 2019, observed by the Solar Dynamics Observatory (SDO). For every event in the database, we compare GOES X-ray flare properties with corresponding active-region and flare-ribbon properties. We present the results and discuss other flare quantities one could derive from the SDO to deepen our understanding of solar flare physics.

Kim Kimoon (Kyung Hee University)

Generation of COMS VIS images from COMS IR images at night by Deep Learning

Communication, Ocean and Meteorological Satellite (COMS) has continuously monitored weather through InfraRed (IR) and visible channels. At night time, only IR images are avaliable. In this study, we apply a deep learning method for image-to-image translation, which is based on conditional Generative Adversarial Networks (cGAN), to COMS IR and visible images. We train our model using data sets from 2012 to 2017. We evaluate our model using data sets in 2018. Our model successfully produce AI-generated visible images from IR ones, which gives a very good mean correlation (r=0.90) between actual visible images and AI-generated ones for 361 test samples. Using our model, we can monitor weather at night by IR images as well as AI-generated visible images.

Michael Kirk (NASA GSFC / CUA, USA)

Extracting Science from the AIA Trash Pile with Machine Learning

The Solar Dynamics Observatory's Atmospheric Imaging Assembly (SDO AIA) has revolutionized solar imaging with its high temporal and spatial resolution, unprecedented spatial and temporal coverage, and seven EUV channels. Automated algorithms routinely clean these images to remove cosmic ray intensity spikes as a part of its preprocessing algorithm. We take a novel approach to survey the entire set of AIA "spike" data to identify and group compact bright points across the entire SDO mission. The AIA team applies a de-spiking algorithm to remove magnetospheric particle impacts on the CCD cameras, but it has been found that compact, intense solar bright points are often removed as well. We use the spike database and unsupervised machine learning techniques to mine the data and form statistics on these discarded features. There are approximately 3 trillion "spiked pixels" removed from images over the mission to date. We estimate that 0.001% of those are of solar origin and removed by mistake, giving us a scientifically interesting dataset of 30 million events. We explore the implications of these statistics and the physical qualities of the “spikes” of solar origin.

Othniel Konan (University of Cape Town, South Africa)

Investigation of Modern Machine Learning Techniques to Detect and Characterize Whistler Waves

Lightning strokes create powerful electromagnetic pulses that routinely cause very low frequency (VLF) waves to propagate across hemispheres along geomagnetic field lines.
VLF antenna receivers can be used to detect these whistler waves generated by these lightning strokes.
The particular time/frequency dependence of the received whistler wave enables the estimation of electron density in the plasmasphere region of the magnetosphere.
Therefore the identification and characterisation of whistlers are important tasks to monitor the plasmasphere in real time and to build large databases of events to be used for statistical studies.
The current state of the art in detecting whistler is the Automatic Whistler Detection (AWD) method developed by Lichtenberger (2009) [1].
This method is based on image correlation in 2 dimensions and requires significant computing hardware situated at the VLF receiver antennas (e.g. in Antarctica).
The aim of this work is to develop a machine learning based model capable of automatically detecting whistlers in the data provided by the VLF receivers.
The approach is to use a combination of image classification and localization on the spectrogram data generated by the VLF receivers to identify and localize each whistler. The data at hand has around 2300 events identified by AWD at SANAE and Marion and will be used as training, validation, and testing data.
In the final version of the paper, we shall present an algorithm based on machine learning techniques that identify starting and ending point of any whistlers given a spectrogram of the data collected alongside performance metrics of the identification.

Alexandros Koukras (KU Leuven, Royal Observatory of Belgium)

Flare Prediction using Deep Learning with multiple wavelength SDO data

Our goal is to utilize the state of the art of Deep Learning (DL) in image recognition algorithms to predict the flaring activity of the Sun.
In combination with the prediction we aim to identify and examine the most prominent physical features that are indications of a possible flare.
There have been many attempts to predict flaring activity of the Sun with different methods and data. But almost all of them use as input the calculated features extracted from line-of-sight magnetograms. But recently there is a growing interest in the automatic detection of features and the use of a Machine Learning subfield, called Deep Learning.

We attempt to make a probabilistic prediction of a specific flare class, using a Convolutional Neural Network (CNN). The basic role of the CNN is to automatically detect features from the images, instead of hand-picking different features for input. Using observations (magnetograms + EUV images) from the whole life span of SDO we create a training dataset of flaring and non-flaring active regions, which is used to train the CNN. The performance of the prediction is estimated using multiple forecast verification metrics (Sensitivity, Accuracy, False-Alarm ratio, Heidke skill score and True Skill Statistics).

The “novelty” of this work is the additional use of EUV images in multiple channels for the training of the CNN instead of magnetogram data only. This is useful because a number of studies have shown that there is valuable information, for the prediction of flares, in the higher layers of the Sun’s atmosphere.

In this work we approach the use of the CNN as a source of information and not as a black box. To accomplish that we look back at the detected features that are activated when there is a classification of a certain type of flare. This is possible through the visualization of the feature map of the CNN, which is a common technique in image recognition algorithms and give us the ability to examine which features draw the attention of the CNN and derive information about the physical processes that trigger a flare.

Elena Kronberg (Max Planck Institute for Solar System Research)

Prediction of soft protons in the near-Earth space using machine learning

Energetic particles in the Earth's plasma environment can potentially be dangerous for space instrumentation. It is highly required to have a tool to predict the intensities of soft protons depending on the solar wind and geomagnetic activity. Using Cluster/RAPID observations and machine learning technique we develop a model that predicts the proton intensity level in the terrestrial magnetosphere. With this model we can predict the proton fluxes along e.g. XMM–Newton trajectories. This helps us to identify the sources of the contamination of X-ray observations from this mission.

Christoph Kuckein (Leibniz Institute for Astrophysics Potsdam, Germany)

Automatic identification of solar phenomena using high-resolution GREGOR images

The 1.5-meter GREGOR telescope, Europe’s largest solar telescope located on the island of Tenerife (Spain), produces a huge amount of data with its three main instruments. In particular, the High-Resolution Fast Imager (HiFI) can acquire up to 4 TB of images per day. The instrument is in operation since 2016 and comprises two synchronized cameras with 2560 x 2160 pixels each. The achieved frame rates are up to 50 Hz. Only the reduced data are archived at the Leibniz Institute for Astrophysics Potsdam (AIP) and are publicly available after one year (or two years for PhDs). In the past three years, data were recorded on 82 days, producing a total amount of about 30,000 files and 6 million images. The images were acquired with different filters, meaning that different structures such as granulation, sunspots, pores, and small bright points can be identified on the Sun.

This wealth of data is well suited for automatic classification and image identification algorithms. As part of the Horizon 2020 project “SOLARNET”, we will explore this data archive for identification of solar phenomena using convolutional neural networks (CNNs) or other deep learning algorithms. The aim is to create a toolkit for object identification, which can be applied to any type of high-resolution solar images.

Brecht Laperre (KU Leuven, Belgium)

Pitfalls in the prediction of the Dst index using ANN

We use Artificial Neural Networks (ANN) to forecast the Dst index several hours in advance, using as input solar wind observations at 1AU. Inspired by state-of-the-art models used in automatic translation and image captioning, we use Long-Short Term Memory (LSTM) ANNs to treat the prediction of the Dst as a sequence-to-sequence analysis. Using as input values during the window of time of the previous hours, the goal of the LSTM model is to ""translate"" this time series into the Dst series of the upcoming 6 hours.
We used 4 different models and compared them against results published in the literature. The models were evaluated using 3 different metrics and by close comparison against a test dataset. Our results rise an important issue not mentioned in the space physics literature: complex ANN models barely outperform simple persistence models.
Machine Learning is a relatively new tool used in space weather forecasting, we find that it is important to highlight the possible pitfalls of applying these techniques as a black box. ANNs have many adjustable parameters, from the input features to the number of neurons in the hidden layers. It is important that the output of ANN models is observed not only using performance metrics, but also by close comparisons between the model and the test data.
In addition, we will focus on aspects not covered in previous literature relative to the specific architecture, software and dataset used for the analysis of the ANNs. This to ensure reproducability of the results.
We will give an introduction to the AIDApy python package and the AIDAdb database that contain the ANN models that we studied. These models can be use in conjunction with OMNI datasets to reproduce our results.
This contribution has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No 776262 (AIDA, www.aida-space.eu).

Daye Lim (School of Space Research, Kyung Hee University)

Prediction of Major Flares Based on Short, Mid, and Long-term Active Region Properties

We investigate the prediction of major flares based on short, mid, and long-term active region properties and their relative contribution. For this, we consider magnetic parameters, which are characterized by field distribution and non-potentiality, from Solar Dynamics Observatory/Helioseimic and Magnetic Imager and flare list from Geostationary Operational Environmental Satellites. In this study, we use flare occurrence rates during short (1 day), mid (several days), and long-term (several years) together. In our model, the predicted rate is given by

the combination of weighted three rate terms satisfying that their sum of the weights is 1. We calculate Brier skill scores (BSSs) for investigating weights of three terms giving the best prediction performance using ARs from 2015 April to 2018 April. The BSS (0.22) of the model with only long-term is higher than that with only short-term (0.07) or mid-term (0.08). When short/mid-term is additionally considered, the BSS is improved to 0.28/0.24. Our model has the best performance (BSS = 0.29) when all three terms are considered, and their relative contribution of short, mid, and long-term rates are about 20%, 20%, and 60% on average, respectively. In addition, this model with three terms seems to be more effective when predicting major flares in strong solar ARs.
This work was supported by Institute for Information & communications Technology Promotion (IITP) grant funded by the Korea government (MSIP) (2018-0-01422, Study on analysis and prediction technique of solar flares).

Chia-Hsien Lin
Examining the EUV intensity in the open magnetic field regions associated with coronal holes
Coronal holes can be identified as the regions with lowest EUV and soft X-ray intensities, or the regions with an open magnetic-field structure, which means that the magnetic field lines inside the coronal holes
extend far away from the Sun. An open magnetic-field configuration allows large amount of plasma flow into interplanetary space, resulting in lower plasma density, which can reduce EUV emission in the source region. Coronal holes with lowest EUV intensity (LIR) and coronal holes with open magnetic field (OMF) structure are often
considered to be the same regions, statistically speaking. However, our study reveals that only 12% of OMF regions are coincident with LIRs. The aim of this study is to investigate the conditions that affect the EUV intensity of an OMF region. Our results indicate that the EUV intensity and the magnetic field expansion factor of the OMF regions are weakly positively correlated when plotted in logarithmic scale, and that the bright OMF regions are likely to locate inside or next to the regions with closed field lines."

Chia-Hsien Lin (National Central University)
Helioseismic investigation of the solar-cycle variation of the meridional flows in the solar convection zone

Solar meridional flows are axisymmetric flows on meridional planes. Here we study their solar-cycle variations in the convective zone using SOHO/MDI helioseismic data from 1996 to 2010, which includes two solar minima and one maximum. The travel-time difference between northward and southward waves is measured with the time-distance method as a function of travel distance, latitude, and time. An inversion method is applied to invert the travel-time difference to obtain meridional flows at the minimum and the maximum. Our results indicate that the flow has a three-layer pattern during the minimum, and changes to a more complicated pattern at the maximum. The flow change extends all the way down to 0.68R. The change above 0.9R shows that the flow speed is reduced at the maximum and that a convergent flow centered at the active latitudes is generated at the maximum.

These two phenomena are consistent with the surface meridional flows measured with surface tracers in previous studies. The results indicate that the active latitudes play a role in the flow change. This suggests that magnetic fields are
responsible for the flow change, which could be used to probe the solar cycle variations of magnetic fields in the deep convection zone.

Stefan Lotz (SANSA, South Africa)

A neural network based method for input parameter selection

Artificial neural networks (NNs) provide a convenient method for predicting an output parameter that is driven by a known set of input parameters. In space physics this type of regression problem has been studied extensively for various combinations of solar wind-based inputs and a terrestrial disturbance index as output / predicted parameter. Surely the most often attempted problem of this type is the prediction of the disturbance storm time index (Dst) using solar wind parameters as input.

In this work we tackle a version of this famous problem, with the 1-minute SYM-H index (acting as high-resolution Dst proxy) as output parameter and solar wind parameters from the 1-minute OMNI data set as inputs. The data set utilised consists of about 90 intense geomagnetic storms (minimum SYM-H index < -100 nT) occurring between 2000-2015. The entire duration of each storm, from sudden commencement until recovery (SYM-H > -20 nT), is identified and the corresponding OMNI solar wind data is selected.

The focus of this work is not only on achieving accurate predictions, but also to enable an examination of the relative contribution of each input parameter. We show how the NN training procedure could be used to (i) identify the most influential set of input parameters from a larger set of candidate inputs, and (ii) show the relative contribution of each input parameter at different stages of a geomagnetic storm.

We demonstrate this on the relatively well studied case of solar wind -- SYM-H interaction in the hope that this will be found useful for more difficult problems where the exact set of drivers of a certain phenomena are not known.

Simon Mackovjak (Slovak Academy of Sciences)

Comparison of airglow intensities prediction by ML models and physical model

The Earth’s upper atmosphere is a dynamic environment that is continuously affected by the space weather from above and the troposphere weather from below. An effective way for observation of these processes is monitoring of the airglow intensities. The airglow is produced in different altitudes by influence of the solar radiation with the short wavelengths during the day. During the night, its emission can be effectively detected by photometers in specific wavelength bands. The data from 20 years long time series of airglow photometric measurements from Georgia in wavelengths 557.7 nm, 630 nm and 900 - 1055 nm were used for demonstration if machine learning

(ML) methods can be successfully used for prediction of airglow intensities from space weather and atmospheric weather data. The ML models were compared with the generally used physical GLobal airglOW model model GLOW (Solomon, 2017). In the contribution, the general overview of airglow phenomenon will be introduced, the source of the data and their reduction will be described, the process of ML approach will be presented in detail and the consequences of comparison with the physical model GLOW will be discussed.

Shane Maloney

X-ray Image Deconvolution using Neural Networks

X-ray image deconvolution is a difficult problem and has been the subject of numerous studies over the last three decades. Traditional deconvolution algorithms typically use iterative approaches which can be difficult to develop, computationally expensive, and may fail to converge. We propose a convolution neural network (CNN) based approach which is significantly faster while at least matching the accuracy of the current methods.

Recently it has been observed that a step from an iterative deconvolution algorithm consists of filtering followed by the application of a point-wise non-linearity, the same form as a layer in a CNN [a]. Based on this we have developed and applied a CNN approach to the deconvolution of x-ray images. The network a modified U-Net is trained on synthetic data, pairs of model and dirty maps. The CNN learns to remove the artefacts from the dirty map due to the sparse sampling of the u-v plane [b]. The layers of the CNN act as numerous iterations in a traditional scheme with the benefit of the inherent multi-scale nature of the CNN architecture.

We find compared to CLEAN the CNN approach is superior in terms of accuracy and speed. The substantial speed increase opens new analysis avenues - outlier visibility detection, image confidence maps, source size errors - even if the CNN method only matches the accuracy of more complex iterative algorithms (MEM, PIXON, etc.)

Sophie Mathieu (UCL, London, UK)

Modelling of sunspot time series for improved quality control

Observing sunspots and counting them constitutes the longest-running scientific experiment with first observations by Galileo dating some 400 years ago. Today the sunspot number time series acts as a benchmark of solar activity in a large variety of physical models.

This time series lacks however a proper statistical processing tailored to its complex nature.

In this work, we detail the first comprehensive noise model of sunspot counts using a multiplicative framework. We estimate the distribution of errors in various regimes of solar activity and for each component of the sunspot number: the number of spots (Ns), the number of groups (Ng), and the composite (Nc=Ns+10Ng). We distinguish errors occurring at short-term, long-term, and during minima of solar activity for each observing station.

We also present a robust estimator for Ns, Ng, and Nc respectively, as well as a model for their density that takes into account intrinsic characteristics such as over-dispersion, excess of zeros, and multiple modes.
Finally, we developed a statistics-based simulation for the sunspot number in order to better understand the nature of the data, and to study the effect of the noise on the estimation and quality control procedures. The goal of this monitoring is to alert the observers when they start deviating from the network and therefore prevent large drifts in the sunspot counts time series.

Ryan McGranaghan (ASTRA, USA)

New capabilities in geospace prediction: Machine learning advances for the complex, multiscale ionosphere

The Heliophysics system, extending from the near Earth space environment, through the magnetosphere and interplanetary space, to the Sun, is characterized by variability and complexity. To unravel the critical variabilities and complexities and to evolve beyond current approaches to understand the solar-terrestrial connection, new data-driven approaches and data analysis technologies are required. These data-driven methods are taking on new importance in light of the shifting Heliophysics data landscape. Our community faces both an exciting opportunity and an important imperative to create a new frontier built at the intersection of traditional approaches and state-of-the-art data-driven sciences and technologies.

This talk will first discuss the meaning of data science in the context of Heliophysics, highlighting data science as the actionable exploration of the full data lifecycle, covering collection, through storage, to analysis and decision-based communication of the analysis. We will then reveal two efforts to apply data science to Heliophysics:

1. A Jet Propulsion Laboratory Data Science Working Group pilot project to leverage data science innovation to utilize a powerful data set to study the geospace environment – Global Navigation Satellite Systems (GNSS) signals.

2. New machine learning models of particle transfer in geospace — for both particle precipitation from the magnetosphere to the ionosphere and ion outflow in the opposite direction. These results are the outcomes of an International Space Sciences Institute (ISSI) project ""Novel approaches to multiscale geospace particle transfer" (http://www.issibern.ch/teams/multigeopartransfer/).

These investigations will be used to illustrate broader lessons for data science innovation in Heliophysics.

Karen Meyer (Abertay, Scotland)

Determining Properties of Solar Active Regions using Machine Learning

Advances in Machine Learning techniques mean that we now have the ability to analyse and derive statistics from large datasets of complex features. This project aims to train an artificial intelligence (including a deep neural network) to extract a consistent dataset of desired properties of solar Active Regions (ARs) from three decades of observed synoptic magnetograms. The methodology is initially developed using simulation data from a well-established flux transport model. This will then be adapted for application to observed synoptic maps, a subset of which have the desired AR properties catalogued, for verification of the technique.

Momchil Molnar (University of Colorado, Boulder, CO, USA)

Recovering spectral line profiles multiplexed with Fabry-Perot etalon with Machine Learning approach

Advances in the emerging field of compressive sensing have shown that the Nyquist-sampling theorem does not necessarily apply for signals with a priori known classes of shapes. These signals can be represented in a coordinate basis as a sparse vector, potentially allowing us to almost fully recover the signal with a significantly smaller number of measurements performed in the sparse basis. Solar spectral lines are examples of such types of sparse signals. Fabry-Perot interferometers (FPI) are increasingly used in solar spectroscopy, with the advantage that they can observe many spatial points simultaneously. However, experiment design considerations lead to limits on the spectral resolution and the number of sampled points, reducing the amount of directly observed spectral information.

The goal of this project is to test the possibility of recovering the underlying spectral line profiles measured with an FPI-based instrument with a finite spectral transmission profile. We utilize a convolutional neural network (CNN) for deconcovolution of the spectral line profiles. The CNN training is performed on a data set obtained with both a FPI system and a spectrograph with high spectral resolution as the reference. The results and fidelity of the method will be relevant for the numerically efficient deconvolution of spectra obtained with instruments with a broad spectral transmission profiles, such as the VTF on the upcoming DKI Solar Telescope.

Another multiplexing approach would be to sample a solar spectral region with an instrument having a periodic transmission profile (i.e. using the multiple peaks of a single FPI etalon). This observational technique could retrieve the full spectral profile with fewer sampling steps, and a resulting increase in overall sampling cadence. We test the idea with data taken using a single FPI etalon with the Interferometric Bidimensional Spectrometer (IBIS).

Christian Möstl (Space Research Institute (IWF), Austrian Academy of Sciences)

PREDSTORM - a new L1 solar wind and magnetic storm prediction system

We will show first results from PREDSTORM, our open source modeling package in python, which can produce real-time predictions of the L1 solar wind. It also couples to models to predict geomagnetic effects such as Dst, the aurora location, and geomagnetically induced currents. The package is driven by real-time heliospheric data (currently STEREO-A, DSCOVR) in connection with empirical modeling (3DCORE), and includes classical machine learning (Analogue Ensembles) as well as deep learning (LSTM) parts. The main focus is to enhance the prediction accuracy and lead time for geomagnetic storms. As this project is under development we will show first results and focus on the open challenges in real time solar wind prediction.

Daniel Mueller (ESA)

3D Visualization of Solar Data: Preparing for Solar Orbiter and Parker Solar Probe

Solar Orbiter and Parker Solar Probe will focus on exploring the linkage between the Sun and the heliosphere. These new missions will collect unique data that will allow us to study, e.g., the coupling between macroscopic physical processes to those on kinetic scales, the generation of solar energetic particles and their propagation into the heliosphere and the origin and acceleration of solar wind plasma. Combined with the several petabytes of data from NASA's Solar Dynamics Observatory, the scientific community will soon have access to multidimensional remote-sensing and complex in-situ observations from different vantage points, complemented by petabytes of simulation data.
Answering overarching science questions like “How do solar transients drive heliospheric variability and space weather?” will only be possible if the community has the necessary tools at hand. In this contribution, we will present recent progress in visualizing the Sun and its magnetic field in 3D using the open-source JHelioviewer framework, which is part of the ESA/NASA Helioviewer Project.

Andrés Muñoz-Jaramillo (Southwest Research Institute, Colorado, USA)

Homogenization of 50 Years of Magnetograms Using Convolutional Neural Networks

Here we present the results of a project performed in the context of 2019 NASA’s Frontier Development Laboratory (FDL) that aims to use convolutional neural networks (CNNs) to assemble a homogeneous set of magnetograms spanning four decades of observations.
Currently space weather forecast largely involves the use of empirical tables and expertise by professional forecasters, with minimal contribution from forecasting algorithms or computational aids. This means that deep learning applications have the potential of revolutionizing space weather forecasting.
Given that deep learning applications require a large amount of training data, it is natural to consider the array of imagers on board the Solar Dynamics Observatory (SDO) as an obvious data source. SDO has been continuously taking nine 4k x 4k images of the ultra-violet solar corona, as well as maps of the solar magnetic and velocity fields every 10 seconds since May-2010. Unfortunately, the SDO era coincides with the weakest cycle (24) of the last century, significantly limiting the amount of space weather events available for ML training (for example, there are only 688 M-class and 46 X-class flares in cycle 24). In reality, there is no single observational survey with sufficient time coverage to enable an effective deep-learning space weather forecasting application. Only a multi-instrument composite, spanning decades of observations, would contain a sufficient number of events. To give perspective to the importance of such a multi-instrument composite, the last four decades contain 6,336 M-class and 491 X-class flares – around 10 times the number of strong events observed by the SDO era alone (8 years).
We expect to have results homogenizing data from the Michelson Doppler Imager (MDI) on board the Solar and Heliospheric Observatory (SOHO), the Helioseismic and Magnetic Imager (HMI) on board of SDO, and the Solar Optical Telescope on board Hinode. In this presentation, we will

discuss the optimal approaches and CNN architectures for magnetograph calibration, their limitations, and the lessons learned of relevance to future ML instrumental cross-calibration.

Sophie Murray (Trinity College Dublin, Ireland)

Forecasting Solar Wind Velocities from Coronal Hole Properties using Machine Learning Techniques

Solar coronal holes (CH) are regions of open magnetic fields that appear as dark areas on the solar disk in extreme ultraviolet passbands. These regions are associated with high speed solar wind streams. We predict the solar wind speed at L1 with correlation coefficient of ~0.7 between measured and forecast solar wind, and define the main variables and areas of interest on the solar disk for solar wind forecasting. Solar wind data was measured by the Advance Composition Explorer, CH data is extracted by the CHIMERA algorithm from Solar Dynamics Observatory images, and the forecast was performed using machine learning techniques, such as random forest regression, support vector regression, and neural networks. Inputs to the machine learning algorithm include CH area, CH magnetic field properties, and CH disk locations. This improvement to solar wind speed prediction shows the value of machine learning for space weather forecasting.

Yasuhiro Nariyuki (Faculty of Human Development, University of Toyama)

Stochastic modeling of charged particle scattering by transverse electromagnetic waves in space plasmas

Scattering of charged particles is a fundamental process in particle diffusion in space plasmas such as plasmas in radiation belt, solar wind, and so on. Nonlinearity of waves and inhomogeneity of background field/plasmas often affect the particle diffusion in space plasmas. For instance, it is suggested phase-bunching/trapping by whistler chorus waves affects increase of electron flux in the radiation belt [e.g., Saito et al, JGR, 2016]. In this presentation, we discuss stochastic modeling of such a particle scattering process by transverse electromagnetic waves. Stochastic models to describe physical processes are compared with direct numerical simulations of test particles. Derivation of stochastic models from governing equations is also discussed. To clarify relationship between characteristics of particle diffusion and parameters of waves/background variables, results of classification/regression via machine learning such as random forest will also be shown.

Mohamed Nedal (Space Weather Monitoring Center (SWMC), Helwan University)

Predicting the transit time of Halo-Coronal Mass Ejections using Machine Learning Techniques

Machine learning techniques have been widely used in several applications and recently they proved their validity and reliability in the field of space weather. In this work, the regression and classification techniques have been applied and the Artificial Neural Networks (ANN) have been employed to estimate the transit time of the Halo-Coronal Mass Ejections (HCME) during the period 2009 - 2015. The list of events from (Gopalswamy et al., 2010) with 176 CME-ICME pairs have been used as a training set, and the models have been tested on an independent testing set of

48 events obtained from (Michałek et al., 2004). Then, the models have been applied on 256 HCMEs obtained from SOHO/LASCO catalog. For the regression approach, the best result had RMSE = 17.63 hours. For the classification approach, the best result had a mean error of 4.5%. Using the ANN approach, the mean error was 13.14%.

Adeline Paiement (LIS - Université de Toulo, France)

Solar RCNN: detection and segmentation of solar active regions from 3-dimensional multispectral images

Solar active regions (AR) are major actors of solar activity. Understanding their evolutions plays an important role in space weather studies. The availability of multi-spectral images provides 3-dimensional information about ARs over multiple layers of the heliosphere. Their analysis is traditionally done in single image bands independently from each-others, which ignores the valuable 3D information provided by the combination of these bands [1,2].

Previous works for detecting and/or segmenting ARs on single band images (e.g. [1,2,3]) used traditional image processing approaches, sometimes complemented by some classical machine learning algorithms such as C-means and its variants [1]. These approaches are very pre- and post-processing dependant, and they don't adapt well to new image sources and quality.

Deep learning currently achieves state-of-the-art results for the detection and segmentation problems. Its data-driven models may adapt naturally to new image data. In addition, it was recently demonstrated on multispectral images, e.g. for detection tasks on aerial terrestrial observation [4] or medical images [5]. In such applications, multiple bands reveal different aspects of a 2D object. However, in the case of solar ARs, they also span a volumetric scene.

Therefore, in this work, we further develop the multispectral deep learning paradigm to handle the special case of multi-band imaging of the heliosphere, with the aim to solve the AR detection and segmentation problems. Our proposed method is based on a multi-task deep neural network (DNN) inspired by [6,7] takes into account the 3D nature of the data through the introduction of parallel and semi-(in)dependent image processing branches. Our DNN fuses information from the available image bands to perform detection and segmentation simultaneously in all images. Thus, although each image band gets its own detection/segmentation results, these results are guided by data from all bands, hence maximising accuracy and consistency. Our new architecture may be scaled to any number of available imaging bands straightforwardly through the addition of the required number of parallel image processing branches. We additionally propose the pre-training of a generic image processing branch to speed up this scaling process. Our new architecture may be scaled to any number of available imaging bands straightforwardly through the addition of the required number of parallel image processing branches. We additionally propose the pre-training of a generic image processing branch to speed up this scaling process.

We evaluate our proposed approach on both space-based (SOHO) and ground based (Paris-Meudon) images. The accuracy and consistency of results are compared against those of baseline methods and previous works, and the effectiveness of exploiting the 3-dimensional information is assessed against individual analysis of single images. We also evaluate the performance of the method under various scenarios, such as different solar activity levels and imaging band availabilities.

Shaktivel Pillai (Astronomical Institute of Charles University, Czech Republic)

Automated Detection and Tracking of Active Regions(Machine Learning over Traditional approach)

The current paradigm is that solar magnetic fields are generated by dynamo action deep in the convection zone. When the magnetic field becomes sufficiently strong it becomes buoyant and emerges in a form of toroidal flux ropes oriented in the east–west direction, forming bipolar active regions (ARs thereafter) on the surface. The question of the possible detection of signatures of the emerging magnetic field prior to its actual emergence is a “hot” and controversial topic. The dynamics in the solar active regions occurs on various spatial and temporal scales. Reliable information about the structure of active regions beneath the surface does not exist (Moradi et al. 2010). Although there were attempts to use local helioseismology to infer the deep structure of sunspots.Thus all of our useful knowledge about the 3-D structure of e.g. sunspots comes from theoretical models (e.g. Rempel et al. 2009) or topological studies (e.g. Chintzoglou & Zhang 2013). Machine Learning (ML) algorithms incorporate the most sophisticated way to analyze and classify tons of data received every day from the ground and space-borne solar telescopes. ML uses feature selection as its main advantages is its high speed and efficiency over traditional methods. It is expected to have better accuracy over spatial and temporal resolution revealing more quality information of the images of the source.

Bala Poduval (University of New Hampshire, USA)

Determination of a Solar Wind Index for Space Weather Prediction using Machine Learning

Solar wind interaction with the magnetosphere gives rise to phenomena that pose potential threats to our technological infrastructure, manned space exploration and instruments on board various spacecraft. There are more than 50 physical parameters that characterize the solar wind and their influence on the Earth's magnetosphere and atmosphere that are measured by spacecraft or various ground-based instruments. Of these, only a few are used in most geospace models built from first-principles and a thorough knowledge of the relative contribution of each of these parameters to the various solar-terrestrial effects would be greatly useful in the advance predictions of these phenomena known as space weather.

Using machine learning (ML) techniques, we developed a method to determine a subset of the solar wind properties that can be used to reconstruct the solar wind pattern (solar wind index, SWI). This has been done for solar wind of different origin (such as ejecta, coronal holes, streamers and sector reversal: Camporeale et al., JGR 122, 2017) separately to infer the dependence, if any, of the source region on SWI. We present the ML method we adopted and the results.

This project has received funding from the European Union's Horizon 2020 research and innovation program under grant agreement 776262 (AIDA).

Sumiaya Rahman (Kyung Hee University, Korea)

SDO/HMI image Super Resolution using Deep Learning Method

Super resolution (SR) is a technique that enhances the resolution of a low resolution image. In this study, we use a method for enhancing the solar image resolution using a Deep-learning model which generates a high resolution HMI image from a low resolution HMI image (4 by 4 binning). The Helioseismic and Magnetic Imager (HMI) is the instrument of Solar Dynamics Observatory (SDO) to study the magnetic field and oscillation at the solar surface. The HMI image is not enough to analyze very small magnetic features on solar surface since it has a spatial resolution of one arcsec. Deep learning networks try to find the hidden equation between low resolution image and high resolution image from given input and the corresponding output image. In this study, we trained a model based on a very deep residual channel attention networks (RCAN) with HMI images in 2014 and test it with HMI images in 2015. We find that RCAN model achieves high quality results in view of both visual and measures: 31.40 peak signal-to-noise ratio(PSNR), Correlation Coefficient (0.96), Root mean square error (RMSE) is 0.004. This result is much better than the conventional bi-cubic interpolation. We will apply this model to full-resolution SDO/HMI, GST and hinode magnetograms.

This work was supported by Institute for Information & communications Technology Promotion(IITP) grant funded by the Korea government(MSIP) (2018-0-01422, Study on analysis and prediction technique of solar flares).

Yeimy Rivera (University of Michigan, USA)

Investigating a prominence eruption using a non equilibrium ionization code constrained to heliospheric measurements of composition

Coronal mass ejections are often observed to be rapidly heated as they travel through the corona. This is evident as cool prominence material quickly transitions from absorption to emission lines in EUV images as it undergoes ionization. However, to date, there are still uncertainties behind the source of this heating. To gain insight to the heating, we empirically determined the thermodynamic evolution of an erupting CME by simulating ion distributions of the plasma between its release and ion freeze-in distances using the Michigan Ionization Code. Through an extensive iterative search, we varied the density, temperature and velocity of the propagating plasma until agreement between simulated ion populations and in-situ ion observations of the Interplanetary CME was reached. We find that a combination of ions generated within four plasma structures undergoing distinct thermodynamic evolution effectively reproduced the observed charge state distributions. The plasma properties at the Sun suggest the ions originated within prominence and the prominence-corona transition region (PCTR) structures and partly from the surrounding corona. Furthermore, the relative abundances computed for each plasma reveal compositional variation between the filament and adjacent CME structures. Lastly, using the derived plasma evolution, we've computed energetics for the event to provide constraints to the heating mechanism. In future work, we plan to investigate the feasibility of proposed mechanisms using these results.

Han-Wen Shen (Institute of Space Science, National Central University, Taiwan)

Geomagnetic effects in precipitating particles of the high-latitude ionosphere

As plasma and magnetic fields carried by the solar wind vary, the interactions between the solar wind and magnetosphere can create magnetic disturbances, such as storms or substorms, in the environment of the magnetosphere. Particles precipitating into the high-latitude ionosphere resulted from the disturbances can then be affected. Here we attempt to investigate the effects in the variations in fluxes of these particles by variable geomagnetic conditions. To achieve the goal, we first divided the region of the high-latitude ionosphere into several areas according to magnetic latitudes and local time sectors. We then applied the Empirical Orthogonal Function (EOF) method to particle fluxes obtained from the NOAA satellites and the Kp geomagnetic index. In the process of the EOF analysis, the time evolution was replaced by monotonically increasing Kp values. We then derived a model of particle fluxes in the high-latitude ionosphere as functions of Kp for space weather operations. The physical meaning of each component decomposed in EOF will be discussed in the presentation.

Carl Shneider (CWI, Amsterdam, The Netherlands)

A Deep Learning Approach to Forecast Tomorrow's Solar Wind Parameters

Deep learning has proven extremely successful both in classification and regression problems, especially when it is trained on very large datasets. In the Space Weather context, despite the unarguably large amount of data at our disposal, it remains an open question whether historical datasets contain enough information to build a predictive deep learning system. In this work, we use multi-wavelength solar images from SOHO (Solar and Heliospheric Observatory) as inputs to a deep convolutional neural network, to predict solar wind parameters observed at L1, 3 - 5 days ahead.

Jieh-Hong Shue (National Central University)

Automatic identification on elements of whistler-mode chorus waves

Discrete elements are best known as the most striking feature of whistler-mode chorus waves. In past studies, researchers usually used human eyes to identify discrete elements from the spectra. This visual method possibly lacks of a consistent standard by individual identifiers. Here we utilize a standardized procedure in high-resolution magnetic fields obtained from the Time History of Events and Macroscale Interaction during Substorms (THEMIS) mission. The whole procedure includes a short-time Fourier transform, an area segmentation, a threshold calculation, an edge search, a trend deduction, and an endpoint determination. We then create a computer program to implement the procedure, which can automatically output the start and end times, and the start and end frequencies of all elements. With the derived timing and frequency information, we can perform a statistical analysis on the lasting time and frequency shift, for example, the average lasting time of dawn side chorus is 0.26 s, which is in the same order of magnitude as the past values. With such an automatic analysis, we can complete a job that took a month in just a few hours. Most importantly, a standardized procedure is performed through on all chorus elements under various conditions of background noise. The chorus parameters derived from this study are important to some follow-up studies on chorus generation in the equatorial plane of the magnetosphere and acceleration of particles in the radiation belts by particle-wave interactions.

Jih-Hong Shue (National Central University)

An Application of Random Forest Method in Retrieving Importance of Parameters that Quantify Characteristics of Chorus Elements

Chorus emissions are usually generated outside the plasmapause in the equatorial region of the magnetosphere. In terms of frequency shift and time separation, the characteristics of chorus elements can be quantified by three parameters: sweep rate, lasting time, and repetition period. The random forest method, an ensemble algorithm in machine learning, can not only make a prediction, but also infer the importance of parameters that control the system. The larger importance value is a parameter, the more important is the parameter. Here we use the burst-mode waveform data from the Time History of Events and Macroscale Interaction during Substorms (THEMIS) probes to estimate the chorus parameters and systematically investigate their relationships with the background plasma and magnetic field parameters, such as electron density, temperature, anisotropic level, and the ratio of plasma frequency to gyrofrequency, using the random forest method. With its importance analysis, we find that the magnetic field possesses the largest importance value for the sweep rate among all the background parameters, indicating that the magnetic field is the most important parameter that controls the sweep rate. For the lasting time and repetition, the most important parameter is the temperature.

Andy Smith (MSSL/UCL, UK)

The Rate of Change of the Surface Magnetic Field in the UK: Sources and Forecasting

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. Several physical drivers of such field variability exist, including solar wind pressure pulses, geomagnetic storms and substorms. In this work we investigate the physical sources of the largest rates of change of the horizontal magnetic field (R) recorded by three UK based ground stations. We then investigate possible methods of forecasting intervals of large R using prior observations of the solar wind and geomagnetic indices.

Firstly, we classify the physical causes of the largest rates of change measured by the UK magnetometers using multivariate classification/clustering techniques. The process of classification further enables the robust selection of relevant parameter inputs for the purposes of forecasting. The forecasting problem is then considered as a multivariate timeseries prediction: given the preceding solar wind and geomagnetic conditions, what are the expected future values of R? Models including LSTM (Long Short-Term Memory) neural networks are evaluated and compared to persistence and ARIMA (AutoRegressive Integrated Moving Average) models. Finally, it is useful to predict whether a threshold value of R will be exceeded during a future interval, given the observed solar wind and geomagnetic conditions. To this end ensemble models such as decision trees are evaluated and compared to climatological predictions.

Barbara J. Thompson (NASA, GSFC, USA)

AI "Fails": How unsuccessful experiments help us learn faster

One of the standard sayings about data science is that we are able to "Fail Faster," meaning that with accelerated computing capabilities we can try multiple approaches and determine which are most promising. However, this only works if the "fails" are correctly identified as such. There are many examples of machine-learning-based results that did not work as expected. In the worst cases, it can cause the user to come to an incorrect conclusion or take an inadvisable action.

There are several ways this can happen. Sometimes, the data sample collected does not adequately represent the system being modeled. Or, it may be that the training and testing sets are not compatible to support performance evaluation. Another common problem is the improper establishment of performance metrics or loss function; the model's solution may be optimized for criteria that do not reproduce the user's desired product.

Each type of mistake can be made even by experienced users. The presentation will give several examples of "failures" in different categories, and outline how the lessons learned by these fails can help us improve our results in the future."

Benoit Tremblay (Université de Montréal, Canada)

Emulating Numerical Simulations of the Sun to Infer Synthetic Plasma Motions at the Photosphere and in the Upper Convection Zone

Eruptive events of the Sun, which often occur in the context of flares, convert large amounts of magnetic energy into emission and particle acceleration that can have significant impacts on Earth's environment. Satellites and ground-based observatories probe the Sun's photosphere and atmosphere and are key in studying solar activity. The wealth of data available has been instrumental in investigating physical features relevant to the onset of flares through statistical analyses and machine-learning algorithms. Meanwhile, numerical models have attempted to bridge the gap between the physics of the solar interior and such observations. However, there are relevant physical quantities that can be modelled but that cannot be directly measured and must be inferred. For example, direct measurements of plasma motions at the photosphere are limited to the line-of-sight component. Recently, neural network computing has been used in conjunction with numerical models of the Sun to be able to recover the full velocity vector in photospheric plasma of the Quiet Sun (i.e. in the absence of significant magnetic activity). We used satellite observations as input in a fully convolutional neural network to generate instantaneous synthetic plasma motions, i.e. plasma motions that reflect the physics of a model but are made to look as if they were observed by a specific instrument. We recently attempted to use a similar approach to reconstruct plasma motions below the Sun's surface from photospheric continuum images. A parallel technique could then be invoked to eventually be able to derive the plasma velocity vector maps of solar active regions and, by extension, other physical quantities of interest that can not yet be measured directly at the photosphere or anywhere else in the solar atmosphere.

Vishal Upendran (Inter University Center for Astronomy and Astrophysics)
Solar wind prediction using Deep learning

Emanating from the base of the Sun's corona, the solar wind fills the interplanetary medium with a magnetized stream of charged particles. The interaction of the solar wind with the Earth's magnetosphere results in space weather effects like geomagnetic storms and aurorae. Accurate predictions of the solar wind driven by changing conditions at the Sun remains one of the unsolved problems in heliophysics.

In this work, we use deep learning for the prediction of solar wind properties. Specifically, we use 193 Å and 211 Å Extreme Ultraviolet (EUV) full disk images of the solar corona from the Atmospheric Imaging Assembly (AIA) on board NASA's Solar Dynamics Observatory (SDO) to predict the solar wind velocity as available in the NASA OMNIWEB dataset, measured at Lagrangian point 1 of Sun-Earth system. We build a set of models containing different lengths of time series of AIA images as inputs, with different delays between the latest image and our day of prediction. Model performance is evaluated by 5-fold cross-validation (CV). We evaluate our CV models against auto-regressive, persistence and naive baseline models, and find our CV models outperform the benchmark models for all delays more than 1 day. Our best fit CV model gives a correlation with observation of 0.557+/-0.028, which is obtained on using the 193 Å channel.

We further use Grad-Cam maps to visualize and investigate how the model uses data to make predictions, and find our proposed model has higher activation at the coronal holes (CHs) approximately 3-4 days prior to prediction, and the other regions give higher activations further away from the day of prediction- especially for a fast solar wind and a slow solar wind respectively. Since the active regions (ARs) seem to be long lived features, the machine tends to look at the AR closer to the prediction day. This trend of activation for CHs is consistent with the prevalent view in the literature that the fast wind emanates from CHs. We further quantify these activations by performing automated segmentation of CHs and ARs, and obtain a mean activation value for comparison across days. The CV results show the trend seen in the Grad-Cam images, but the spread in these activation values is large, thus indicating the results are not very robust to CV.

These results suggest the deep neural network is able to learn some of the salient associations between coronal and solar wind structure without a priori, built-in physics knowledge. While our results here represent a starting point of prediction, visualization and validation of such fully data-driven models, such an approach may help us discover hitherto unknown relationships in heliophysics data sets.

Ruggero Vasile (Helmholtz Zentrum Potsdam – GFZ, Germany)
Understanding geomagnetic activity through supervised learning

The geomagnetic Kp index is one of the most widely used measures of geomagnetic activity. It captures short-term magnetic field variations within the Earth's magnetosphere driven by space weather. Forecasting of the Kp index is of crucial importance since the Kp index is used operationally as an input for various thermosphere and radiation belt models as well as in satellite drag calculations.

Current algorithms for the real-time forecast of the Kp index are based on models driven by solar wind and IMF measurements at the L1 Lagrange point as well as historical values of the index. In this study, we present a systematic investigation of the short time Kp forecast systems by comparing performance of different machine learning algorithms for different forecast lead times. In order to simplify the models and at the same time preserving the quality of the forecast, we employ and compare several feature dimensionality reduction schemes. Some of these schemes allow to select and rank the most important features contributing to the accuracy of the models. Finally, we present the preliminary results on the topic of error uncertainty quantification applied to the Kp index forecast problem.

Matthias Waidele (Leibniz-Institut für Sonnenphysik)
Helioseismology of Sunspots: Surface effects of simple fluxtubes

Sunspots play an important role in understanding the dynamical nature of the solar magnetic field. Although their surface appearance has been observed for over four centuries, little is known about the subsurface structure. Sunspots are known to strongly influence solar acoustic modes and there is a variety of possible interactions of the magnetic field with the waves.
In this work we will expand on the theoretical studies and investigate surface wave signals caused by simple fluxtubes. We use the SPARC code for MHD simulations with fluxtubes of varying subsurface topology. Thereon, methods to probe magnetic field configurations of sunspots will be developed, with which we can ultimately learn more about the whole structure of a sunpot.

Harry Warren (NRL)
Event Detection in Observations and Simulations of Solar Active Regions

It is widely believed that the solar atmosphere is heated by numerous, small-scale impulsive heating events. Large data volumes, however, make gathering information on such heating events from both observations and numerical simulations very challenging. In this poster we present the application of simple classification and clustering algorithms to observations taken by the Extreme Ultraviolet Imaging Spectrometer (EIS) on the Hinode spacecraft and 3D magnetohydrodynamic simulations of braided active region loops. Initial tests indicate that even simple machine learning algorithms can accurately identify and track events in these large data volumes. We discuss initial results on the properties of event distributions derived from both the observations and simulations.
Andreas Jeffrey Weiss Inferring initial conditions of coronal mass ejections using a fast data generative model and approximate bayesian computation Currently initial CME parameters, such as the direction and inclination, are usually manually estimated using coronagraph images and various fitting models. The accuracy of these methods are strongly dependent on the quality of the coronagraph images and their relative locations with respect to the CME. We attempt to gain the same type of information using only the in situ observations of the magnetic field of the CME's as they are measured by various spacecraft. Using a data generative model (3DCORE) which can simulate the time series of the magnetic field, as measured by any solar wind monitor, we aim to recover the intractable likelihood of model parameters (longitude, latitude, inclination) from actual

in situ measurements using approximate bayesian computation. Comparing our results to those from coronagraph images we can further assess the accuracy and validity of our model.

Magnus Wik (Swedish Institute of Space Physics, Sweden)

Forecasting the AU and AL indices using recurrent networks

The auroral electrojet indices were created as a measure of global electrojet activity in the auroral zone. The AU and AL indices, represent the strongest current intensity of the eastward and westward electrojets, respectively. The difference between these, the AE index, represents the overall electrojet activity, substorm activity and the energy flow from the magnetosphere into the ionosphere.

These indices are often used in studies related to space weather effects, such as e.g. geomagnetically induced currents (GIC), input to radiation belt models and forecasting the aurora.

We predict the AU and AL indices, from LSTM recurrent networks, using cross-validation and ensemble techniques. We use solar wind data B, By, Bz, plasma density and velocity from the ACE spacecraft. Additional inputs are the UT and DOY. The models are verified using standard verification techniques.

George Wilkie (Princeton Plasma Physics Laboratory, USA)

Neural-network informed parameterization of diffusion in the radiation belts

Quasilinear theory demands that energetic electrons in the outer radiation belt obey a diffusion equation over sufficiently long timescales. The diffusion coefficient and a loss term can be parametrized in phase space from physical arguments and empirical observation. The magnitude of these terms remains an unknown function of the geomagnetic indices. Using a neural network trained against data from the Van Allen Probes, we determine the magnitude of these coefficients that best reproduce observations. These estimates are compared with those obtained from other techniques.

Simon Wing (The Johns Hopkins University, USA)

Information theoretic approach to discovering causalities in the solar cycle

The causal parameters and response lag times of the solar cycle dynamics are investigated with transfer entropy, which can determine the amount of information transfer from one variable to another. The causal dependency of the solar cycle parameters is bidirectional. The transfer of information from the solar polar field to the sunspot number (SSN) peaks at lag time (ㄹ) ~ 30–40 months, but thereafter it remains at a persistent low level for at least 400 months (~ 3 solar cycles) for the period 1906–2014. The latter may indicate the persistency of the polar fields from cycle to cycle. It may lend support to the idea that the polar fields from the last 3 or more solar cycles can affect the production of SSN of the subsequent cycle. There is also a similarly long term information transfer from the SSN to the polar field. Both the meridional flow speed and flux emergence (proxied by the SSN) transfer information to the polar field, but one transfers more information than the other, depending on the lag times. The meridional flow speed transfers more information to the polar field than SSN at ㄹ ~28–30 months and at ㄹ ~90–110 months, which may be consistent with some flux transfer dynamo models and some surface flux transport models. However, the flux emergence transfers more information to the polar field than the meridional flow at ㄹ ~60–80 months, which may be consistent with a recently developed surface flux transport model. The transfer of information from the meridional flow to SSN peaks at ㄹ ~110–120 months (~1 solar cycle), suggesting that the meridional flow can be used to predict SSN about one cycle ahead.

Simon Wing (The Johns Hopkins University, USA)

Untangling the solar wind drivers of the radiation belt electrons

Characterizing and modeling processes at the sun and space plasma in our solar system are difficult because the underlying physics is often complex, nonlinear, and not well understood. The drivers of a system are often nonlinearly correlated with one another, which makes it a challenge to understand the relative effects caused by each driver. However, entropy based information theory can be a valuable tool that can be used to determine the information flow among various parameters, causalities, untangle the drivers, and provide observational constraints that can help guide the development of the theories and physics-based models. The solar wind drivers of radiation belt electrons are investigated using mutual information (MI), conditional mutual information (CMI), and transfer entropy (TE). As previously reported, radiation belt electron flux (Je) is anticorrelated with solar wind density (nsw) with a lag of 1 day. However, this lag time and anticorrelation can be attributed mainly to the Je(t + 2 days) correlation with solar wind velocity (Vsw)(t) and nsw(t + 1 day) anticorrelation with Vsw(t). Analyses of solar wind driving of the magnetosphere need to consider the large lag times, up to 3 days, in the (Vsw, nsw) anticorrelation. Using CMI to remove the effects of Vsw, the response of Je to nsw is 30% smaller and has a lag time < 24 hr, suggesting that the loss mechanism due to nsw or solar wind dynamic pressure has to start operating in < 24 hr. Nonstationarity in the system dynamics is investigated using windowed TE. The triangle distribution in Je(t + 2 days) vs. Vsw(t) can be better understood with TE.

Paul Wright (Stanford University, USA)

A Machine Learning Dataset From the NASA Solar Dynamics Observatory

We present a curated dataset from the NASA Solar Dynamics Observatory (SDO) mission in a format suitable for machine learning research. Beginning from level 1 scientific products we have processed various instrumental corrections, downsampled to manageable spatial and temporal resolutions, and synchronized observations spatially and temporally. We illustrate the use of this dataset with two example applications: forecasting future EVE irradiance from present EVE irradiance and translating HMI observations into AIA observations. For each application we provide metrics and baselines for future model comparison. We anticipate this curated dataset will facilitate machine learning research in heliophysics and the physical sciences generally, increasing the scientific return of the SDO mission.

The NASA SDO Machine Learning data set totals 6.5TB and is available from the Stanford Digital Repository: e.g. https://purl.stanford.edu/vk217bh4910 for the 2010 data set.

Taras Yakobchuk (Leibniz-Institut für Sonnenphysik, KIS)

Scattering linear polarization of late-type active stars

It is known from spectroscopic and photometric observations that many active stars are covered in spots, much more so than the Sun. Breaking the visible stellar disk symmetry, such star spots should induce non-zero intrinsic linear polarization.

Using models for a center-to-limb variation of the intensity and polarization in presence of continuum scattering and adopting a simplified two-temperature photosphere model, we aim to estimate the intrinsic linear polarization for late-type stars of different gravity, effective temperature, and spottedness.

We developed a code that simulates various spot configurations or uses ready surface maps, performs numerical disk integration, and builds Stokes parameter phase curves for a star over a rotation period for a selected wavelength. It allows estimating minimum and maximum polarization values for a given set of stellar parameters and spot coverages.

Based on assumptions about photosphere-to-spot temperature contrasts and spot size distributions, we calculate the linear polarization for late-type stars with Teff = 3500 K-6000 K, log g = 1.0-5.0, using the plane-parallel and spherical atmosphere models. Employing random spot surface distribution, we analyze the relation between spot coverage and polarization and determine the influence of different input parameters on results. Furthermore, we consider spot configurations with polar spots and active latitudes and longitudes.

Although small, considered effect might be useful for star spot studies, and, particularly, for a future polarimetric atmosphere characterization of exoplanets orbiting active host stars."

Kiley Yeakel (Johns Hopkins University Applied Physics Lab, USA)

Automatic Determination of In-Situ Magnetospheric Regions Around Saturn

Any spacecraft orbiting a planet with a magnetosphere will pass through various plasma regimes. Time-based classification of the different plasma regimes encountered in a spacecraft’s orbit is useful for data down-selection, queuing of science instruments, etc. Typically, scientists manually examine data from one or more instruments to create a catalog of crossings between the various regions. Two such catalogs are available for the time period 2004 to 2016 when the Cassini-Huygens spacecraft was orbiting Saturn. These were made by examining data from the Cassini Plasma Spectrometer (CAPS, which measures in-situ low energy ions and electrons) and magnetometer (MAG) data sets. Each catalog indicates when Cassini was in the magnetosphere proper, the magnetosheath, or the solar wind.

We present a machine learning algorithm for determining the current magnetospheric region of Cassini using only the MAG data and orbit location relative to Saturn. We trained a deep recurrent neural network (DRNN) to predict the region the spacecraft would encounter at the next time step (~37 seconds in the future) given the spacecraft’s position and MAG observations from the previous twenty measurements (spanning approximately 12.5 minutes) utilizing the plasma region catalogs as our training set. A prediction accuracy of 96.3% was obtained on unseen test data, demonstrating the viability of this technique for potential use in on-board determination of plasma regimes for future missions.

Ambelu Yirdaw (Bahir Dar University)

Feedforward neural network based ionospheric model for the East African region

In this paper, a neural network based regional ionospheric model is developed using GPS-TEC data from 01 January 2012 to 31 December 2015. For this purpose, nine GPS station TEC data in the time intervals 2012 to 2014 were used to determine model parameters. TEC data obtained in various years and geographical locations which are excluded in the training time are used to validate the performance of the model. For the first case, TEC data from each station in the year 2015 is used to validate the performance of the model. In the second case, GPS observations at Metu, Robe, and Serb stations are used to investigate the model's performance in the year 2012, 2014 and 2013-2014, respectively. In both cases, to validate the accuracy and quality of the model, GPS-TEC values were compared with the predicted TEC. The results indicate that the proposed model can capture most of the spatiotemporal variations of the regional TEC. The present model reproduces the observed hourly TEC with RMS values that lie around 3 to 6.05 TECU at different geographical locations for both one hour and one day ahead prediction. For one day ahead prediction, a comparison of the NN method using NeQuick 2 model outputs with GPS derived measurements have also been conducted. The results indicate that the NN TEC model proposed has a good performance in representing TEC variations compared to climate NeQuick 2 model.