Space Weather: a Multidisciplinary Approach
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Scientific Organizers: E. Camporeale, S. Wing, J. Johnson, P. Grunwald

Talks (alphabetical order)

Disentangling the geospace magnetic storm-magnetospheric substorm relationship through a multivariate information-theoretic method

George Balasis
National Observatory of Athens

The storm-substorm relationship is one of the most controversial aspects of geospace magnetic storm dynamics and one of the unresolved topics of solar-terrestrial coupling. Here we investigate the statistical dependencies between storm and substorm indices in conjunction with multiple relevant solar wind variables with an information-theoretic causal inference approach. We find that the vertical component of the interplanetary magnetic field (IMF) is the strongest driver of both storms and substorms. Importantly, this common driver explains the transfer of entropy between substorms and storms found by a previous bivariate analysis. These results hold during two years close to solar maximum (2001) and minimum (2008), respectively, and suggest that, at least based on the analyzed indices, there is no statistical evidence for a direct or indirect dependency between substorms and storms. A physical mechanism by which substorms drive storms or vice versa is, therefore, unlikely.

Machine-Learning in Practice: Solar Flare Prediction

Monica Bobra
Stanford University

In this talk, we will present a machine-learning model to predict solar flares (Bobra & Couvidat, 2015; Bobra & Ilonidis, 2016; Jonas et al., 2017). We develop our predictive model in four steps: [1] We automatically detect active regions in image data taken by the Solar Dynamics Observatory, [2] We characterize both the physical and spatial properties of these active regions, [3] We train and test a machine-learning algorithm on these characteristics, and [4] We estimate our performance using forecast verification metrics, with an emphasis on the True Skill Score (Bloomfield, 2012). We will explain our method, discuss our results, and address general challenges in using machine learning for space science applications.

Introduction to Deep Learning

Sander Bohte
Centrum Wiskunde & Informatica, Amsterdam

Deep Learning is driving current advances in AI, beating humans in tasks as diverse as computer vision and Go.
In this talk, I will give a brief introduction into deep learning, from simple neural networks to modern Generative Adversarial Networks. I will then try to place this within the framework of space weather requirements, and discuss possible advances and implementations.

The Magnetosphere and Its Problems

Joe Borovsky
Space Science Institute

This tutorial will consist of four parts. The first part will be an overview of the Earth's magnetosphere, driven by the highly variable solar wind and connected to the dynamic ionosphere. This will include a discussion about the geography of the various trapped plasmas in the magnetosphere and their coupling via plasma waves. The second part of the tutorial will focus on how the magnetosphere-ionosphere system is measured. The third part of the talk will discuss outstanding scientific questions about how the system operates. The fourth part will discuss aspects of the magnetosphere-ionosphere system that are considered to be "space weather", and will discuss outstanding issues concerning space weather.

A Bayesian Approach to Space Weather Predictions

Enrico Camporeale[1], Mandar Chandorkar[1], Algo Care[1], Joe Borovsky[2]
[1] Centrum Wiskunde & Informatica, Amsterdam
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Give a look at the forecasts provided by the Space Weather Prediction Center (NOAA), or the ESA Space Weather Portal. Most of them share a common feature: they are *not* probabilistic forecasts, i.e. they provide a single-value prediction, or maybe an interval of values, and not a probability distribution over possible values. Forecasts that are not probabilistic have several deficiencies: they are hard to verify and validate, they are of little use in a decision-making scenario, they inform us very little on the validity of the model and assumptions used to derive them. Perhaps, it is even arguable that a forecast is not really a forecast, if it is not probabilistic (not surprisingly, we are so used to probabilistic meteorological forecasts, that we take them for granted).

In this talk, we present a Bayesian approach to Space Weather forecasting, based on the use of Gaussian Processes (GP). Although Bayesian statistics and GP are routinely used in many fields of physics, this is not the case in Space Physics and Space Weather. After a short introduction to the basic concepts, we discuss three very diverse applications: the one-hour-ahead forecasting of the geomagnetic DST index, the problem of (probabilistic) classification of solar wind type, and the problem of estimating the electron loss timescale in quasi-linear radiation belt simulations. Finally, we make a connection to the problem of Uncertainty Quantification of physics-based ensemble simulations.

Dynamical Networks characterization of geomagnetic activity

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The plasma and magnetic field of earths near-space environment is highly dynamic, with its own space weather. Space weather observations are increasingly becoming a data analytics challenge. Constellations of satellites observe the solar corona, the upstream solar wind and throughout earth's magnetosphere. Space weather effects on the ground are monitored by 100+ magnetometer stations in the auroral region. Ionospheric currents can be detected by magnetometers on (for example the 60+ Iridium) polar orbiting satellites in low earth orbit. These data are multipoint in space and extended in time, so in principle are ideal for study using dynamical networks. There are several challenges however. The spatial sampling points are not uniformly spatially distributed and are moving w.r.t. the plasma-current system under observation, and the plasma-current system itself is non-linear and highly dynamic. Whilst networks are in widespread use in the data analytics of societal and commercial data, there are also additional challenges in their application to physical timeseries. Determining whether two nodes (here, ground based magnetometer stations) are connected in a network (seeing the same dynamics) requires normalization w.r.t. the detailed sensitivities and dynamical responses of specific observing stations which also have seasonal variations. We perform a dynamical network study of the auroral current system which is observed by the SuperMAG set of over a hundred ground based magnetometers. The dynamics of this current system reflect the dynamical response of the earth's magnetosphere to solar wind driving where energy is stored and then released in a bursty manner (substorms). Spatio-temporal patterns of correlation between the magnetometer time series can be used to form a dynamical network [1], the properties of the network can then be captured by (time dependent) network parameters. This offers the possibility of characterizing detailed spatio-temporal pattern by a few parameters, so that many events can then be compared [2] with each other and with theoretical predictions.

[I] Dods et al, J. Geophys. Res 120, doi:10.1002/2015JA02 (2015).
[2] Dods et al, J. Geophys. Res. 122, doi:10.1002/2016JA02 (2017).

On the Earth's Magnetospheric Dynamical Complexity and Space Weather

Giuseppe Consolini
INAF-Istituto di Astrofisica e Planetologia Spaziali, Roma, Italy

In the last two decades it has been widely shown how the Earth's magnetosphere displays dynamical complexity in response to changes of interplanetary plasma and magnetic field conditions. The Earth's dynamical complexity manifests in scale-invariant features of geomagnetic disturbances and high-latitude energy relaxation events, and is the consequence of internal magnetospheric processes involving plasma loading-unloading in the Earth's magnetospheric tail regions. Recently, it has been shown that there is a clear separation of timescales between internal and external magnetospheric dynamics, and that at timescales below 200 min the Earth's magnetospheric dynamics is essentially determined by internal processes [Alberti et al., 2017]. Here, we present a review of the scale-invariant features of the Earth's magnetospheric dynamics discussing its relevance and impact on the Space Weather forecasts with a special emphasis on the role of timescale separation between internal and externally driven processes.

Supervised and non-supervised classification in solar physics using advanced techniques

Véronique Delouille
STCE/Royal Observatory of Belgium
Joint work with: Kevin Moon, Alfred O. Hero, Stefan Hofmeister, Martin Reiss, Manuela Temmer, Astrid Veronig.

Advances in statistical signal processing allow us to gaze at solar data from a new perspective, and to make better predictions. For example, the problem of clustering active regions and sunspots from magnetogram and continuum data can be looked at with image patch analysis and matrix factorization lenses. Such method provides a characterization of fine scale structures encoded e.g. by localized gradients, or locally smooth areas. The resulting clusterings are related to large scale descriptors of an active region such as its size, local magnetic field distribution, and complexity as measured by Mount Wilson classification.

Supervised classification in the presence of an imbalanced dataset is another example where recent advances bring added accuracy. I will illustrate this on the problem of separating filaments (FL) from coronal holes (CH) using a labelled dataset of features, where the FL/CH proportion in the observed sample is 6/94. Various strategies for dealing with imbalance will be discussed. This is a generic problem, that may also appear e.g. when one want to distinguish flare-productive from more quiet active regions.

Blind source separation applications in space weather

Thierry Dudok de Wit
LPC2E, University of Orléans, France

Blind source separation (BSS) aims at separating a set of source signals from their mixture, using the least possible information on these source signals or their mixing process. This highly underdetermined problem has often been addressed by means of principal component analysis. However, in the last decade, more advanced numerical schemes have turned this into a very active field of research, with powerful techniques that incorporate physically relevant constraints.

BSS is particularly appropriate for exploratory analysis or for cases wherein multiple (and partly redundant) noisy observations can be described by the combination a small number of elementary contributions (or sources). In the context of space weather, this typically arises with synoptic observations (e.g. solar images taken at several wavelengths, sunspot observations from multiple observers, etc.) or with measurements from arrays of instruments (e.g. geomagnetic networks, neutron monitor networks, etc.).

I shall illustrate BSS with a some examples from solar-terrestrial science wherein this approach (or variants thereof) either gives us deeper unstanding of the underlying physics or allows to overcome some common problems, such filling in data gaps in multivariate data. Of course, this approach has its limitations too, which will also be addressed.

Geomagnetic storms during the last decade: Cluster and Double Star observations

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The launch of the Cluster spacecraft almost coincided with one of the largest geomagnetic storm of the last decade, well known as the "Bastille Day" storm, on 14-15 July 2000. Planned on 15 July, the launch was aborted a few minutes before due to a thunderstorm that had hit the Baikonour cosmodrome and made a disruption in the communication lines with the rocket. The launch took place the day after, on 16 July 2000. Our US colleagues had warned us about the storm and recommended not to launch on 15 July. Given the facts that (1) Cluster was built to study the effects of space weather and geomagnetic storms and (2) that the Russian launch authorities were not concerned for the Soyuz rocket, it was decided to go ahead with the launch. The launch was fine and, after a second launch less than a month later, the four Cluster spacecraft were put successfully in their 4x19 RE polar orbit. Since then, Cluster has observed many geomagnetic storms and could observe, for the first time with a constellation of four spacecraft, the dynamics induced in the magnetosphere by coronal mass ejections or interplanetary shocks coming from the Sun. In this talk we will use storms observed by Cluster and Double Star in the last decade to illustrate how the magnetosphere was affected. We have observed large compressions of the magnetosphere, distortions of the polar cusp, acceleration of particles associated with chorus and ULF waves, intensification of the ring current imaged by energetic neutral atom imagers, oxygen outflow from polar regions, and tail current sheet motions.

Bayesian learning - successes and problems

Peter Grünwald
Centrum Wiskunde & Informatica, Amsterdam

Some claim that Bayesian inference is the only fully coherent way of learning from data, and indeed, it is often very successful practice. On the other hand, Bayesian approaches are sometimes outperformed as well - we provide an example where the Bayesian Lasso for regression is significantly outperformed by the standard Lasso. We highlight the roots of this discrepancy: Bayesian inference is not 'targeted' towards the loss function of interest, which can hurt if models are only partly specified or misspecified. We present 'safe Bayesian inference' as a modification of Bayesian inference addressing this issue. Time permitting, we will also briefly discuss the connection between Bayes factor model selection and information-theoretic approaches to model choice such as MDL.

Choosing the right method for optimization with COCO

Verena Heidrich-Meisner
Kiel University

Machine learning research has produced - and continues to do produce - a multitude of specialised algorithms for typical machine learning scenarios. This leaves a practitioner with the difficult task to identify which of these many algorithms is the optimal choice for her particular problem. From the no-free-lunch theorems one can conclude that no algorithm exists that is always the best choice. Therefore, the choice of algorithm needs to depend on the properties of the problem to be solved. So, in order to select an appropriate algorithm two pieces of information are needed: (1) some knowledge about the properties of the problem and (2) results of the considered candidate algorithms for known benchmark problems.

Here, we illustrate for the simple example of black box optimisation how (well crafted) benchmark suites can guide the choice of an appropriate algorithm given some knowledge about the objective function. The COCO (comparing continuous optimizers) benchmark suite includes functions that are single-and multi-objective (with and without global structure), separable, noise-free and noisy, and can have low, moderate or high conditioning. Recurring benchmark workshops have produced results for a large variety of optimisation algorithms. Since all results are available online, these represent an effective tool to choose an appropriate optimisation algorithm.

Automated event identification techniques for magnetic and plasma signatures of reconnection

Caitriona Jackman
University of Southampton

With the wealth of data now available from spacecraft throughout our solar system, there is a need within the Space Physics community for analysis tools to deal with the amount and complexity of data. Traditional data analysis has relied on by-eye identification of events which is time-consuming, biased and not easily reproducible.

My research has focussed on the giant planet magnetospheres, with particular emphasis on the study of magnetic reconnection at Saturn. The Cassini spacecraft has been in orbit at Saturn since 2004, with quasi-continuous magnetometer, plasma and radio data spanning a full solar cycle. I have been searching for in situ evidence of magnetic reconnection in the form of plasmoids, evidenced by bipolar changes in the magnetic field, with accompanied heating of plasma and change in plasma flow direction. Early papers on this topic involved a small number of case studies selected by eye [e.g. Jackman et al., GRL, 2007, DOI: 10.1029/2007GL029764]. As the field has developed, event searches have become more sophisticated, with simple automation, searching for changes in magnetic field above background [e.g. Jackman et al., JGR, 2014, doi:10.1002/2013JA019388]. In recent years we have extended the automated searches to include wavelet and minimum variance analysis [e.g. Smith et al., JGR, 2017, doi:10.1002/2016JA022994] and to employ quantile-quantile plotting [e.g. Tindale and Chapman, GRL, 2016, doi:10.1002/2016GL068920; Smith et al., in preparation, 2017] to search for changes in plasma spectrograms associated with magnetotail dipolarizations.

My goal for this workshop is to bring my domain knowledge of the solar wind and planetary magnetotails, to show my group's recent efforts in automated event detection, and to explain how these techniques can be adapted from planetary tails to magnetospheric boundaries or to the solar wind. I look forward to interacting with other data analysts and with experts on machine learning to make the most of our large datasets to understand these fascinating environments.

Coupling Fluid and Kinetic Scales for Space Weather Applications

Giovanni Lapenta
KU Leuven

First the bad news. The solar system is big and electrons are small. Modelling the whole Sun-Earth connection at the kinetic level is impossible for now. But we can include some limited kinetic aspects to improve global fluid models. The procedure can take two paths: from big to small or from small to big.

Macro going towards micro: we can make more advanced fluid models that go beyond single fluid MHD and include more physics. But no fluid model is going to give particle acceleration. However, test particles can be added to get the additional physics. A more advanced approach is to interlink kinetic models to fluid models so that some portion of the system can be described kinetically at scales where kinetic models can be used.

Micro going towards macro: we can make kinetic models that are robust to scale variations. There is no violation of any laws of physics by solving the Vlasov equations on large scales if the method can efficiently avoid resolving the smallest scales. The Vlasov (or Boltzmann in presence of collisions) equation is valid at all scales and it gives higher fidelity results than fluid models at all scales. The only reason for using fluid models is that they cost less. But if a kinetic model could be run at reasonable costs at macro scales there is no reason for not doing so.

In this scenario we present three new methods. First, we describe the multi-level multi-domain [1] method to couple different grid acting at different levels. Second, we describe how one level can be kinetic while the other can be MHD [2, 3]. Finally, we describe how a new implicit particle in cell method (called ECSim) can be run at macroscopic scales resolving only the desired range of scales [4], effectively replacing the need for fluid models.

[1] Innocenti, M. E., Lapenta, G., Markidis, S., Beck, A., & Vapirev, A. (2013). A multi level multi domain method for particle in cell plasma simulations. *Journal of Computational Physics*, *238*, 115-140.

[2] Ashour-Abdalla, M., Lapenta, G., Walker, R. J., El-Alaoui, M., & Liang, H. (2015). Multiscale study of electron energization during unsteady reconnection events. *Journal of Geophysical Research: Space Physics*, *120*(6), 4784-4799.
[3] Daldorff, L. K., Tóth, G., Gombosi, T. I., Lapenta, G., Amaya, J., Markidis, S., & Brackbill, J. U. (2014). Two-way coupling of a global Hall magnetohydrodynamics model with a local implicit particle-in-cell model. *Journal of Computational Physics*, *268*, 236-254.
[4] Lapenta, G. (2017). Exactly energy conserving semi-implicit particle in cell formulation. *Journal of Computational Physics*, *334*, 349-366.

From empirical models to causal models: a generative neural network approach

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Models learned from empirical data usually are predictive models. An exuberant hope about Big Data is to learn models that could support educated interventions (e.g., in medicine, in social sciences, in politics, in numerical engineering). However, most predictive models are based on correlations, and these do /not/ support interventions. Typically, although one can rightfully conclude from the presence of umbrellas in the street that it rains, one should not expect that taking his umbrella will make it rain.

The models supporting interventions are causal models, defined as: i) they fit the real data; ii) under simulated, relevant, modifications of the data distribution, the data generated from the causal model fit the real data distribution under the same modifications. Causal models classically rely on (often expensive, unethical or impossible) controlled experiments. An alternative is based on using pure empirical data, and defining new machine learning criteria, amenable to learn causal models.

After discussing the state of the art, the talk will present a new approach to causal modeling from observational data. This approach, called Causal Generative Neural Networks (CGNN), leverages the power of Deep Learning to learn a generative model of the joint distribution of the domain variables, minimizing the Maximum Mean Discrepancy of the generated data with respect to the observed data. An approximate learning criterion is proposed to alleviate the computational cost of the approach, with linear complexity in the dataset size.

Extensive experiments on artificial and real-world benchmarks show that CGNN compares favorably to the state of the art: i) regarding the bivariate cause-effect problem; ii) regarding the full multivariate functional causal model, based on the variable dependencies; iii) in presence of confounders (unobserved common causes).

Joint work with Olivier Goudet, Diviyan Kalainathan, Aris Tritas, Philippe Caillou, Isabelle Guyon, Paola Tubaro.

The forecast of the Magnetosphere as a Complex System

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The magnetosphere is a complex self-similar nonlinear systems, which displays dynamics that is turbulent and self-organized and as such is a subject at the forefront of astrophysics and space research. It is clear that the understanding of these processes must have relevance for the forecasting of Space weather. In this presentation we will try to reconcile these two seemingly contradicting concepts by looking at some of the techniques that can be used to forecast some magnetospheric indexes such as Dst, AE, and spatial patters of magnetic fluctuations.

Empirical modeling of the plasmasphere dynamics using neural networks

Irina Zhelavskaya
GFZ Potsdam

Empirical modeling of the plasmasphere dynamics using neural networks The electron number density is a critical parameter for radiation belt modeling and wave-particle interactions. Despite its importance, the distribution of cold plasma and its dynamic dependence on solar and geomagnetic conditions remain poorly quantified. Existing empirical models tend to be oversimplified presenting statistical averages based on static geomagnetic parameters [e.g., Carpenter and Anderson, 1992; Sheeley et al., 2001]. These models do not include solar and geomagnetic activity parameters and, therefore, cannot reproduce the dynamics of the quickly varying plasmasphere environment, especially during periods of high geomagnetic activity. Global imaging provides qualitative insights on the plasmasphere dynamics but quantitative inversion to electron number density has been lacking. In this work, we present an alternative, data-driven approach, to modeling the plasmasphere dynamics. We employ feedforward neural networks to build an empirical model of electron number density that takes solar wind and geomagnetic activity parameters as an input. The neural networks are trained on the large database of electron density obtained with the NURD (Neural-network-based Upper hybrid Resonance Determination) algorithm [Zhelavskaya et al., 2016] for the period of October 1, 2012 - July 1, 2016. We determine the activity parameters that best quantify the plasmasphere dynamics by training multiple neural networks with different combinations of input parameters (geomagnetic indices, solar wind data, and different durations of their time history) and comparing their cross validation errors and also by comparing the predicted global density reconstructions to the global images of He+ distribution in the Earth's plasmasphere from NASA's IMAGE mission. We show results of both local and global plasma density reconstruction. This study illustrates how the global dynamics of the plasmasphere can be reconstructed from sparse local in-situ density measurements by using machine learning techniques.

Posters (alphabetical order)

Innovative techniques and technology for the study of space weather

Jorge Amaya, Giovanni Lapenta
KU Leuven

Fluid methods have been historically used to model the interaction of the solar wind with the planets of the solar system. MHD codes are expected to perform forecasting, in the same way as CFD codes predict the weather on Earth. However, these approach has two pitfalls: 1) kinetic effects are very important for the physics of the magnetosphere of the planets; these effects are not self-consistently present in MHD models; 2) There are no accurate in-situ measurements of the solar wind between the Sun and the L1 point. Data assimilation is the key for CFD predictions of weather on Earth, and until we fill the gaps between the Sunand the Earth with satellites, we will not be able to make accurate predictions of space weather.
We propose to use innovate techniques and new technology to fill the missing gap of space weather forecasting. This approach is based on the use of two key technologies: a) the use of Deep Learning systems to connect the Sun with solar wind conditions at 1 AU, and b) modern, fully kinetic, particle-in-cell codes that make use of the next generation of exascale supercomputers.

Three ideas for adaptive sampling of points in uncertainty quantification

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We are interested in how uncertainties on some simulation parameters propagate through a computationally expensive simulation. By taking a probabilistic approach, the uncertainty on the parameters are described by a probability distribution and the goal is computing the probability distribution of the simulation output. For example, this approach was used in 2D radiation belt simulations, and it revealed that reducing the uncertainty on the average electron density in the radiation belts is of uttermost importance for boosting the prediction of the output electron flux.

However, in computationally expensive simulations, choosing the sample points, i.e., the parameters values at which the simulations are run, is always a critical issue. Monte-Carlo sampling methods are a viable solution, but it is a fact that their convergence as the number of sampled points increases can be strongly improved if prior information is available. In particular, prior information can be used to interpolate the function that maps the values of the uncertain parameters into the simulation output.

Our research is guided by three ideas.
1) Since we are interested in the output probability, the interpolant that we build should be evaluated only by its effect on the output probability.
2) The information that we can get from a small amount of data is limited, especially in the presence of many parameters. Therefore, a confidence value

has to be attached to the interpolator, and new sampling points should be decided adaptively based on the interpolator *and* the confidence we have in it. 3) Prior knowledge, or ansatz, is encoded in the class of the possible interpolators that we use. In spite of all our best efforts, sometimes our ansatz will be wrong. In this case, the sampling method should not perform worse than a standard Monte Carlo method.

Probabilistic forecasting of the disturbance storm time index: An autoregressive Gaussian process approach

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We present a methodology for generating probabilistic predictions for the *Disturbance Storm Time*(*Dst*) geomagnetic activity index. We focus on the *One Step Ahead* prediction task and use the OMNI hourly resolution data to build our models. Our proposed methodology is based on the technique of *Gaussian Process Regression*. Within this framework we develop two models; *Gaussian Process Autoregressive* (GP-AR) and *Gaussian Process Autoregressive with eXogenous inputs* (GP-ARX). We also propose a criterion to aid model selection with respect to the order of autoregressive inputs. Finally, we test the performance of the GP-AR and GP-ARX models on a set of 63 geomagnetic storms between 1998 and 2006 and illustrate sample predictions with error bars for some of these events.

Real-time automated detection of coronal mass ejections using ground-based coronagraph instruments

M. D. Galloy [1], W. T. Thompson [2], O. C. St. Cyr [3], J. T. Burkepile [1], A. Posner [4], G. de Toma [1]
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Coronal mass ejections (CMEs) are dynamic events that eject magnetized plasma from the Sun's corona into interplanetary space. CMEs are a major driver of solar energetic particle (SEP) events and geomagnetic storms. SEP events and geomagnetic storms pose hazards to astronauts, satellites, communication systems, and power grids. Understanding CME formation and predicting their impacts at Earth are primary goals of the National Space Weather program. St. Cyr et al. (2017) reported on the use of near real-time white light observations of the low corona from the COSMO K-Coronagraph (K-Cor) to provide an early warning of possible SEP events driven by fast CMEs. Following that work, one of us (Thompson) created a new CME detection algorithm adapted from the Solar Eruptive Event Detection System (SEEDS) code for use with K-Cor observations from the Mauna Loa Solar Observatory (MLSO) in Hawaii. We develop performance metrics and report on the success of the algorithm to detect CMEs in the 2017 K-Cor observations. Measures of success include the ability of the algorithm to detect an event and the amount of time between the event onset and its detection. The algorithm successfully detected 21 of the 38 CMEs

identified between Jan 1 and Sept 10, 2017 in the K-Cor data. There were 11 false positive events possibly due to instrument noise and adverse sky conditions (e.g. aerosols). The threshold for CME detection is discussed as a function of CME visibility, instrument background, and sky noise. The code has been modified to run in an automated mode and is in the process of being integrated into the real-time data processing pipeline at Mauna Loa. We report on current status, real-time alerts, and future upgrades.

Prediction of the magnetic index am based on development and performance comparisons of static and dynamic neural networks

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Space weather forecast aims to predict solar events and its impact on human activities. It is based on the knowledge gathered from years of research and on statistical models. Here we focus on the development of particular statistical models called neural networks. They have the ability to estimate an output using various inputs, after a phase of learning and optimisation using large training databases.
Databases consist of solar wind data and magnetic index values. Solar wind parameters are propagated data from OMNI databases and magnetic parameters are provided by INTERMAGNET network. We aim to develop neural networks to predict magnetic index using solar wind parameters collected by the satellite ACE, located at the Lagragian Point L1.
To characterise the intensity of geomagnetic activity on a planetary scale, existing models predict the magnetic index Kp. So far, there is no model predicting am, which just as Kp, has a time resolution of 3h but is based on a network better distributed and better located in latitude and longitude. It also has the advantage of being defined in terms of amplitude, and is not based on a logarithmic scale between 0 and 9.
The terrestrial magnetosphere is a very complex and dynamic system, so the main challenge is to find the neural network that will be the most adapted to represent this system.
Most of the time, networks such as Multilayer Feedforward neural networks are considered to predict Kp (Boberg et al., 1999, Bala et al., 2005). Those are by definition quite simple model that are limited as they do not account for dynamics. We consider dynamic models such as time delay neural networks and recurrent networks that already proved their efficiency to predict the Dst index (Wu et al.,1996) and the AE index (Gleisner et al., 2001).
We also decided to developp a new model which has not been tested yet to model the behaviour of the magnetosphere, it is the Long Short Term Memory recurrent network. It is of interest because it has the ability to be insensitive to important gap length. This could be helpful when there is an important solar activity which impact detectors onboard satellites and generate missing datas.
With this poster, we would like to show ongoing developments and performance comparisons of various neural networks, using Matlab and Python techniques, to find the network the most adapted for the prediction of the magnetic index am from solar wind data.

Modeling Ensemble Forecasts of Solar Flares

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In the past decade several new methods for forecasting solar flares have been developed. Different methods often produce different forecasts for the same event because they are based on different empirical relations or models, use different input data, and/or they are trained with different datasets. In addition, some of these methods might depend partially or entirely on human decisions and expertise. Therefore, direct comparison between the performances of different methods has proven to be a difficult task thus far.
In this work we investigate the use of numerical weather prediction methods as an alternative to historical flare forecasting techniques. Ensemble forecasting has been used in terrestrial weather forecasting for many years as a way to combine different predictions in order to obtain a more accurate result. Here we construct ensemble forecasts for major solar flares (M and X classes) by linearly combining the full-disk probabilistic forecasts from a group of operational forecasting methods (ASSA, ASAP, NOAA, MAG4, MOSWOC, and SolarMonitor). Forecasts from each method are weighted by a factor that accounts for the method's ability to predict previous events.
These combination weights are then calculated in several ways: 1) by metric optimization using probabilistic forecasts, 2) by metric optimization using categorical forecasts, and 3) by estimation of the cumulative partial quadratic errors. Several performance metrics (probabilistic and categorical) were considered in this analysis.
We demonstrate the existence of several linear combinations that perform better than the average ensemble. The results provide a guideline for space weather forecasters on how to construct ensemble forecasts based on the methods of their preference, choosing different metrics in order to fit different end-users needs.

Toward improved morphological characterization of solar eruptive features using fully convolutional networks and semantic segmentation

Kamen A. Kozarev
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Imaging observations of solar activity at high energies (EUV, X-ray) have increased significantly in size and temporal resolution in the last decade. The SDO overwhelms solar physicists with a data rate of 1.5 Terabytes per day â€“ one image (4K Ã— 4K pixels) every second. Data from planned instruments, such as the Daniel K. Inouye Solar Telescope (DKIST) and future space-based missions will undoubtedly surpass these rates. Such amounts of observing data clearly require new approaches to their analysis, which involve machine learning and artificial intelligence. We present the outline of a study in progress, which aims to leverage the power of fully convolutional neural networks and semantic segmentation algorithms for the direct recognition and tracking of large-scale compressive waves and shocks, associated with coronal mass ejections and flares. Apart from exploring the capabilities of deep learning algorithms for solar

activity analysis, our ultimate goal is to improve and automate the morphological and kinematic characterization of solar eruptive phenomena.

What Stochastic Dynamics can do for Space Weather

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Heliospheric and near-Earth plasmas, the evolution and interaction of which determine what we refer to as Space Weather, are open dynamical systems undergoing the action of irregular forcers, well representable as stochastic tems in equations. Stochastic terms may enter equations of space plasmas in two ways: on the one hand, any space plasma system interacts with spatially external forcers of unknown precise configuration (for instance, near-Earth plasma are forced by the solar wind fluctuations, triggered in turn by impulsive, unpredictable events on the Sun, well described probabilistically); on the other hand, any level of description of the plasma, e.g. MHD, multi-fluid, kinetic or other, use dynamical variables interacting with “microscopic modes” evolving on smaller time scales, that can be encoded in noise terms. In this contribution, some examples are given of space plasma dynamics, relevant to Space Weather, cast into the form of Langevin equations, i.e. ODEs or PDEs, with stochastic terms of known statistics, making dynamical variables evolve probabilistically. Once Langevin equations are written for a plasma system, the statistical dynamics of the latter can be formulated through a functional formalism, based on path integrals, in which it is possible to calculate the probability of a particular evolution of the system. Finally, a roadmap, for the extensive use of these tools for Space Weather applications, is traced.

Next Generation Methodologies to Advance Space Weather Monitoring and Predictability: A New Perspective through Network Analysis

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Disruption of the near Earth space environment caused by the solar-terrestrial connection, or space weather, has emerged as an area of critical importance to humankind’s economic and social well-being. Our ability to predict space weather phenomena relies on an accurate understanding and specification of the complex, highly coupled magnetosphere-ionosphere-thermosphere (MIT) system (altitudes from ~100 km–several Earth radii).
Fundamental to improved specification of the MIT system is the ability to describe coupling phenomena, especially in the polar regions where the effects are most direct. This coupling is controlled by space weather phenomena connecting the magnetosphere and ionosphere. In order to create new understanding of these phenomena at finer spatial and temporal scales, understand their cross-scale

effects, and quantify the impact on the polar region new data analysis approaches are required.
We perform the first complex network analysis of ionospheric total electron content from Global Navigation Satellite System (GNSS) signals to investigate magnetosphere-ionosphere connections and their effects in the polar region. Our cutting-edge approach complements existing approaches, addressing critical gaps, thereby enhancing the utility of GNSS data for space weather research. We complement these findings with preliminary results from machine learning methods applied to GNSS signals, further extending their utility for space weather discovery.
This work illustrates the importance of data-driven discovery for the increasingly critical need to understand and predict space weather.

3D Visualisation of petabyte-scale solar and heliospheric data

Daniel Mueller

The next generation of ESA/NASA heliophysics missions, Solar Orbiter and Solar Probe Plus, 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 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.

Within a few years, the scientific community will have access to large volumes of complex remote-sensing and 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 science community has the necessary tools at hand to visualize these data and assimilate them into sophisticated models.

A key piece needed to bridge the gap between observables, derived quantities like magnetic field extrapolations and model output is a tool to routinely and intuitively visualize large heterogeneous, multidimensional, time-dependent data sets. The open-source JHelioviewer software, which is part of the ESA/NASA Helioviewer Project, is addressing this need. This contribution will highlight recent extensions of JHelioviewer’s functionality.

Investigating the Coronal Magnetic Field from the Type-II radio burst event on 2 May 2013

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We studied the characteristics of the Type-II solar radio burst event which occurred on 2 May 2013 through combined space observations from the Solar and Heliospheric Observatory (SOHO) and the Solar Terrestrial Relations Observatory (STEREO), in parallel with the ground-based observation from the DARO-CALLISTO station in Germany. The type-II burst frequency range was 25 –

180 MHz and it was preceded by a group of Type-III radio bursts related to a solar flare event (M1.1) from the same active region (AR 1731). We calculated the density jump and the Alfven Mach number by applying the Rankin – Hugoniot relations on the clear band-splitting. By using the four-fold Newkirk electron density model we could convert the plasma frequency of the type-II burst into height [R] in terms of solar radii. Then we calculated the shock speed [Vs], the Alfven speed [Va], and the coronal magnetic field strength [B] at heights ranging from 1.961 – 1.988 Rs. The accompanied partial-halo (Angular width = 344° from SOHO) CME event was detected by STEREO Ahead, with a linear speed 518 km s^{-1}, by STEREO Behind, with a linear speed 429 km s^{-1}, and by SOHO, with a linear speed 671 km s^{-1}, and we traced the evolution of the event using the height-time profile. We found a common behavior in the shock speed, Alfven speed, and the coronal magnetic field strength dependencies with height, in which these features are decreasing steeply with height until reaching the height (~ 1.975 Rs) then they continue decreasing slightly.

The COMESEP Space Weather Alert System

Luciano Rodriguez

COMESEP stands for COronal Mass Ejections and Solar Energetic Particles: forecasting the space weather impact. It consists of several interconnected tools that work together to analyse data and automatically provide alerts for geomagnetic storms and SEP radiation storms. The system is triggered by different solar phenomena, such as CMEs and solar flares. After the automatic detection in solar data of any of these transients, the different modules of the system communicate in order to exchange information and produce a series of coherent space weather alerts that are then displayed online and sent by email to subscribed users.

Forecasting the AE indices using neural networks

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The AU and AL indices, and the joint AE index, is a measure of the auroral electrojet activity in the Northern Hemisphere and indicate the intensity of geomagnetic substorms. These indices are often used in studies related to space weather effects, such as e.g. geomagnetically induced currents (GIC), or in radiation belt models.

We predict the AE indices, using neural networks, driven by solar wind data B, By, Bz, plasma density and velocity. Additional inputs are the UT and DOY. In this study we used measured data from ACE. Due to the high time resolution of the AE index, which is not realistic to be captured by any model, the AE indices and solar wind data were resampled to 5 and 30 minutes.

We performed several model studies: deep and wide networks, varying input parameters, lead time, and time delays. The results are compared against final AE data.

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Untangling the drivers of nonlinear systems with information theory

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Many systems found in nature are nonlinear. The drivers of the system are often nonlinearly correlated with one another, which makes it a challenge to understand the effects of an individual driver. For example, solar wind velocity (Vsw) and density (nsw) are both found to correlate well with radiation belt fluxes and are thought to be drivers of the magnetospheric dynamics; however, the Vsw is anti-correlated with nsw, which can potentially confuse interpretation of these relationships as causal or coincidental. Information theory can untangle the drivers of these systems, describe the underlying dynamics, and offer constraints to modelers and theorists, leading to better understanding of the systems. Two examples are presented. In the first example, the solar wind drivers of geosynchronous electrons with energy range of 1.8–3.5 MeV are investigated using mutual information (MI), conditional mutual information (CMI), and transfer entropy (TE). The information transfer from Vsw to geosynchronous MeV electron flux (Je) peaks with a lag time (τ) of 2 days. As previously reported, Je is anticorrelated with 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 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. nsw transfers about 36% as much information as Vsw (the primary driver) to Je. Nonstationarity in the system dynamics are investigated using windowed TE. When the data is ordered according to high or low transfer entropy it is possible to understand details of the triangle distribution that has been identified between Je(t + 2 days) vs. Vsw(t). In the second example, the previously identified causal parameters of the solar cycle such as the solar polar field, meridional flow, polar faculae (proxy for polar field), dipole axis strength, are investigated. We discuss the response lag times of the sunspot numbers and information transferred to the sunspot numbers from the dynamic time series of these parameters.

Predicting Kp from solar wind data using ensemble of neural networks

Peter Wintoft and Magnus Wik

We present here our latest development of Kp prediction models driven by solar wind data. Three-hour filtering of one-minute solar wind total magnetic field B, Bz component, plasma density and velocity are applied to match the 3-hour Kp. As Kp is a global representation of the maximum range of geomagnetic variation over 3-hour intervals we conclude that sudden changes in the solar wind can have a big effect on Kp. Therefore, the 3-hour filter includes in addition to averages also minimum and maximum values to capture sudden changes in the solar wind. The minima/maxima on the inputs have a large effect on the prediction accuracy. During model development we noticed that different optimal neural networks with the same number of processing units and inputs show very similar predictions for Kp<6, while predictions for larger Kp have a tendency to show a larger variability. We interpret this is an effect of the lower sampling density in the input space for the stronger events, thereby leading to a higher uncertainty in the function estimation. The prediction accuracy can be much improved by taking the median prediction from an ensemble of models. We present various measures of prediction accuracy over time and range of Kp, and also show the latest predictions for the event from Sep. 7 2017.

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Applications of machine learning technique at the inner magnetosphere: a 2D plasmasheet pressure model and a 3D plasma density model

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The plasma sheet pressure and its spatial structure during the substorm growth phase are crucial to understanding the development and initiation of substorms. Here, we constructed a 2-D equatorial empirical pressure model and an error model within r ≤ 20 RE using the Support Vector Regression Machine with solar wind dynamic pressure (PSW), energy loading, and sunspot number, which are the three primary factors controlling the growth phase pressure change, as input. The model predicts the plasma sheet pressure accurately with a correlation coefficient of 0.97 and median errors of 5%, and the predicted pressure gradients agree reasonably well with observed gradients obtained from THEMIS two-probe measurements. The model shows that pressure increases linearly as PSW increases, and the PSW effect is stronger under lower energy loading. However, the pressure responses to energy loading and sunspot number are nonlinear. The pressure model can also be applied to understand the pressure changes observed during a substorm event by providing evaluations of the effects of energy loading and PSW, as well as the temporal and spatial effects along the spacecraft trajectory.
Another application of the machine learning technique at the inner magnetosphere is the 3D plasmas density model (DEN3D) development, which

used a feedforward neural network with electron densities obtained from four satellite missions. The DEN3D model takes spacecraft location and time series of solar and geomagnetic indices (F10.7, SYM-H, and AL) as inputs. It can reproduce the observed density with a correlation coefficient of 0.95 and predict test dataset with error less than a factor of 2. Its predictive ability on out-of-sample data is tested on field-aligned density profiles from the IMAGE satellite. DEN3D's predictive ability provides unprecedented opportunities to gain insight into the 3D behavior of the inner magnetospheric plasma density at any time and location. As an example, we apply DEN3D to a storm that occurred on 01 June 2013. It successfully reproduces various well-known dynamic features in three dimensions, such as plasmaspheric erosion and recovery, as well as plume formation. Storm-time long-term density variations are consistent with expectations; short-term variations appear to be modulated by substorm activity or enhanced convection, an effect that requires further study together with multi-spacecraft in-situ or imaging measurements. Investigating plasmaspheric refilling with the model we find that it is not monotonic in time, and is more complex than expected from previous studies, deserving further attention.