State of the art and open challenges of Machine Learning in Space weather

Enrico Camporeale

(enrico.camporeale@noaa.gov)

CIRES / CU Boulder & NOAA Space Weather Prediction Center

Thanks to:
A. Hu, H. Singer, M. Cash, C. Balch, E. Adamson, G. Toth, Z. Huang, J. Bortnik, G. Wilkie, A. Drozdov, M. Gruet, M. Chandorkar, A. Care', J. Borovsky, G. Lapenta, X. Chu, R. McGranaghan, …, and probably others…

This project is supported by NASA under grant 80NSSC20K1580

University of Colorado Boulder

CIRES

NOAA
NATIONAL OCEANIC AND ATMOSPHERIC ADMINISTRATION
U.S. DEPARTMENT OF COMMERCE

Outline

- What can Machine Learning do for Space Weather?
- Why does it work so well? (a short digression)
- Path forward: challenges and opportunities

What can ML do for Space Weather?
(a non-comprehensive list)

- Regression problems, i.e. predict:
  - The value of a geomagnetic index (Dst, Kp, etc.);
  - The arrival time of a Coronal Mass Ejection;
  - Global Total Electron Content (TEC) maps;
  - Solar wind speed;
  - Relativistic electrons at GEO;
  - Ground magnetic field (dB/dt)
  - Electron precipitation

What can ML do for Space Weather?
(a non-comprehensive list)

- Classification problems, i.e. what is the probability that:
  - An active region will flare in the next 24 hours?
  - dB/dt will exceed a given value?
  - The solar wind is originated by coronal holes/ejecta, etc.
  - A region of the Sun belongs to a coronal hole

Geomagnetic indices

- ML works better than physics-based simulations to forecast global/average indexes such as Dst
  - Why? Because in a physics-based approach of a complex system you need to get 'every single piece right'

The Dst (Disturbance storm time) index is an index of magnetic activity derived from a network of near-equatorial geomagnetic observatories

Space Weather

RESEARCH ARTICLE
10.1029/2018SW001898

Multiple-Hour-Ahead Forecast of the Dst Index Using a Combination of Long Short-Term Memory Neural Network and Gaussian Process

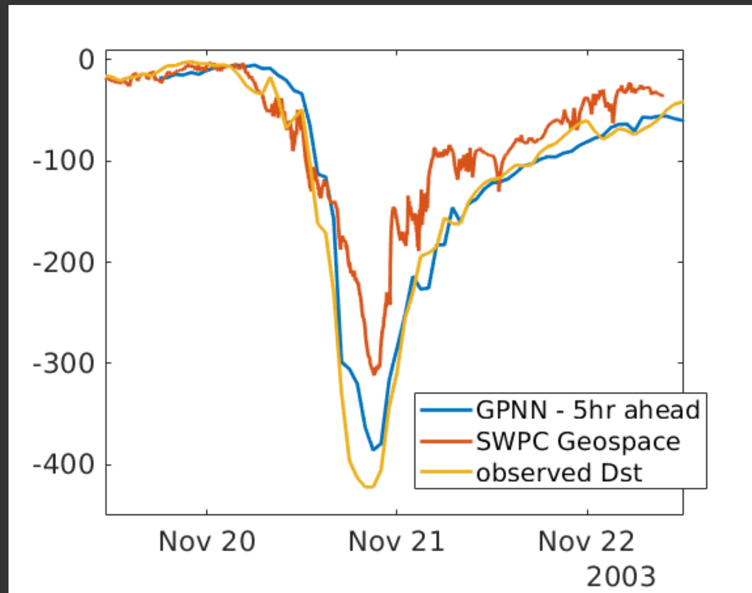
M. A. Gruet[1], M. Chandorkar[2], A. Sicard[1], and E. Camporeale[2]

[1]ONERA, The French Aerospace Lab, Toulouse, France, [2]Center for Mathematics and Computer Science (CWI), Amsterdam, Netherlands

Key Points:
- First use of a Long Short-Term Memory network to provide single-point prediction of the Dst index, up to 6 hr ahead
- Development of a method that combines neural network and

Multi-Hour Ahead Dst Index Prediction Using Multi-Fidelity Boosted Neural Networks

A. Hu[1], E. Camporeale[1,2], B. Swiger[1,2]



Geomagnetic indices

- ML works better than physics-based simulations to forecast global/average indexes such as Dst
  - Why? Because in a physics-based approach of a complex system you need to get 'every single piece right'

The Dst (Disturbance storm time) index is an index of magnetic activity derived from a network of near-equatorial geomagnetic observatories

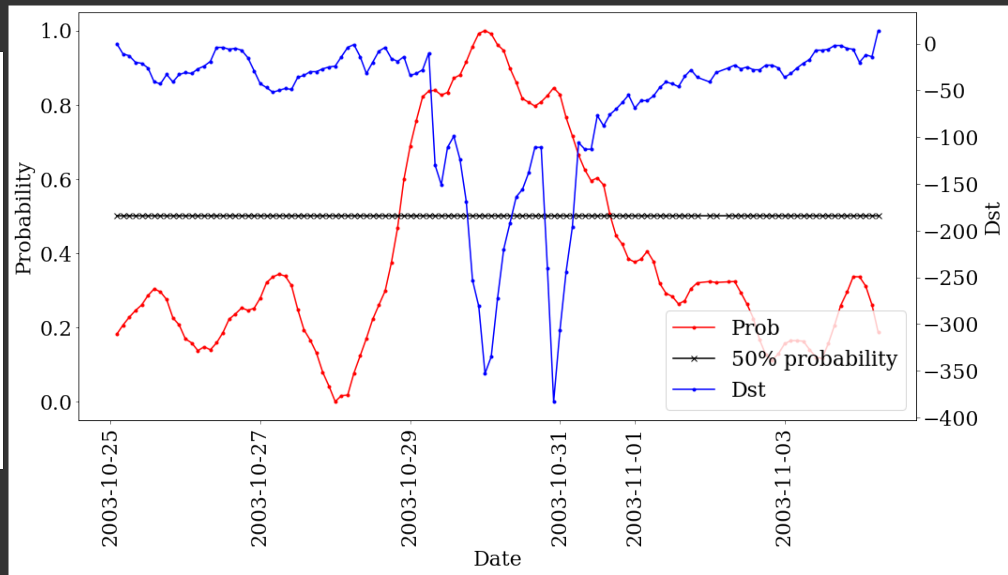

Space Weather®

Research Article | Open Access

Probabilistic Prediction of *Dst* Storms One-Day-Ahead Using Full-Disk SoHO Images

A. Hu, C. Shneider, A. Tiwari, E. Camporeale

First published: 23 May 2022 | https://doi.org/10.1029/2022SW003064

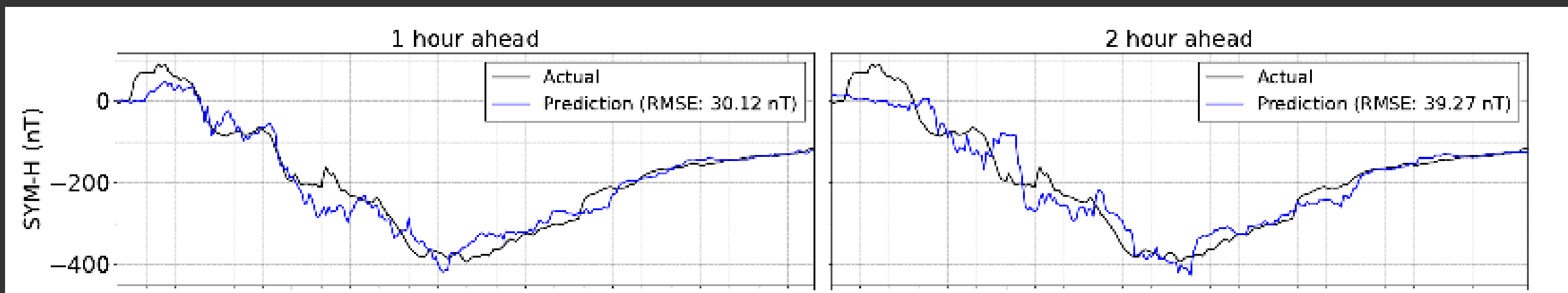


Geomagnetic indices

manuscript submitted to *Space Weather*

New Findings from Explainable SYM-H Forecasting using Gradient Boosting Machines

Daniel Iong[1], Yang Chen[1], Gabor Toth[2], Shasha Zou[2], Tuija Pulkkinen[2], Jiaen Ren[2], Enrico Camporeale[3,4], Tamas Gombosi[2]

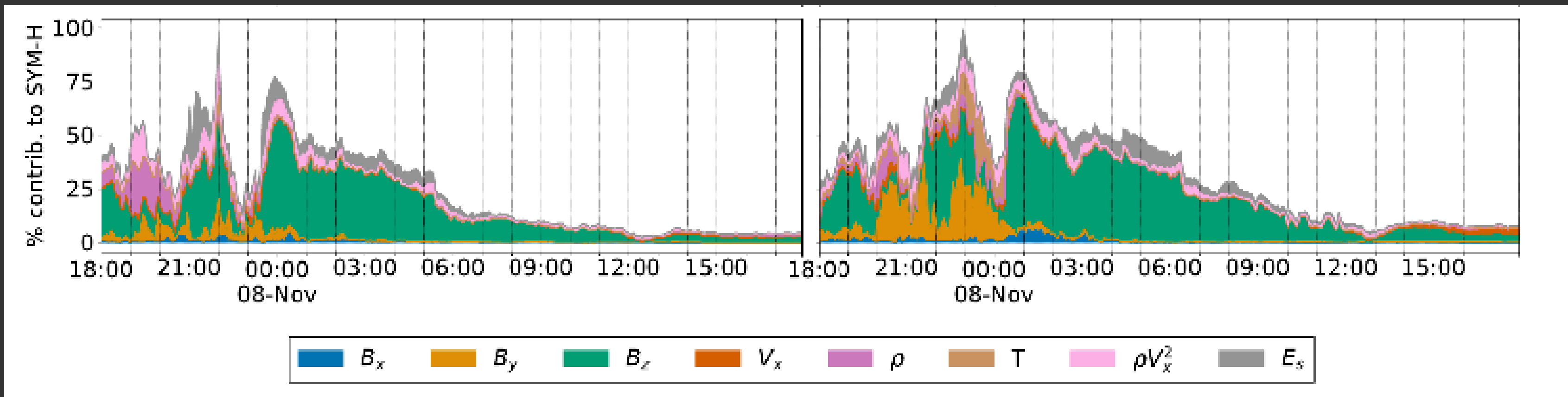


Geomagnetic indices

manuscript submitted to *Space Weather*

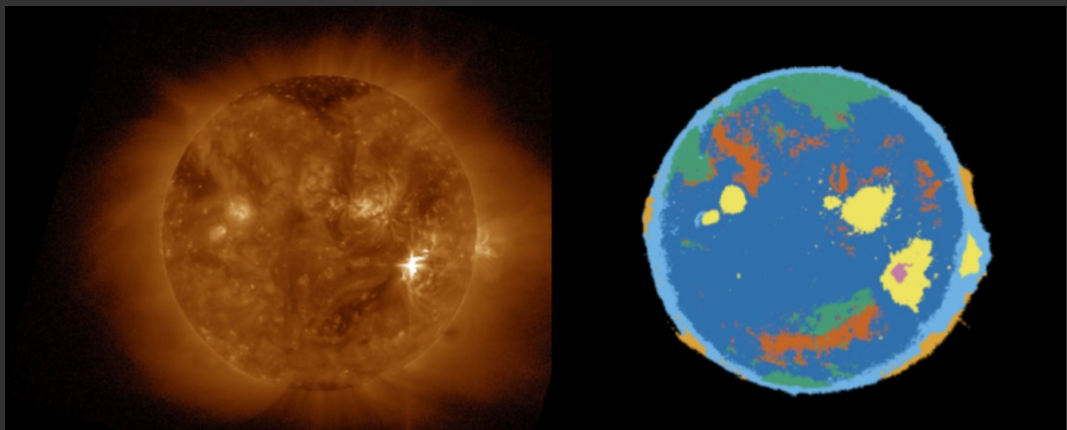
New Findings from Explainable SYM-H Forecasting using Gradient Boosting Machines

Daniel Iong[1], Yang Chen[1], Gabor Toth[2], Shasha Zou[2], Tuija Pulkkinen[2], Jiaen Ren[2], Enrico Camporeale[3,4], Tamas Gombosi[2]



Segmentation of coronal holes in solar disk images

- Segmentation of solar disk images (supervised or unsupervised):
  - Automatically extract different solar regions (that are associated with different solar wind/geoeffectiveness)



Monthly Notices of the ROYAL ASTRONOMICAL SOCIETY
MNRAS **481,** 5014–5021 (2018)
Advance Access publication 2018 October 1
doi:10.1093/mnras/sty2628

Segmentation of coronal holes in solar disc images with a convolutional neural network

Egor A. Illarionov[1,2★] and Andrey G. Tlatov[2,3]

Solar Phys (2019) 294:117
https://doi.org/10.1007/s11207-019-1517-4

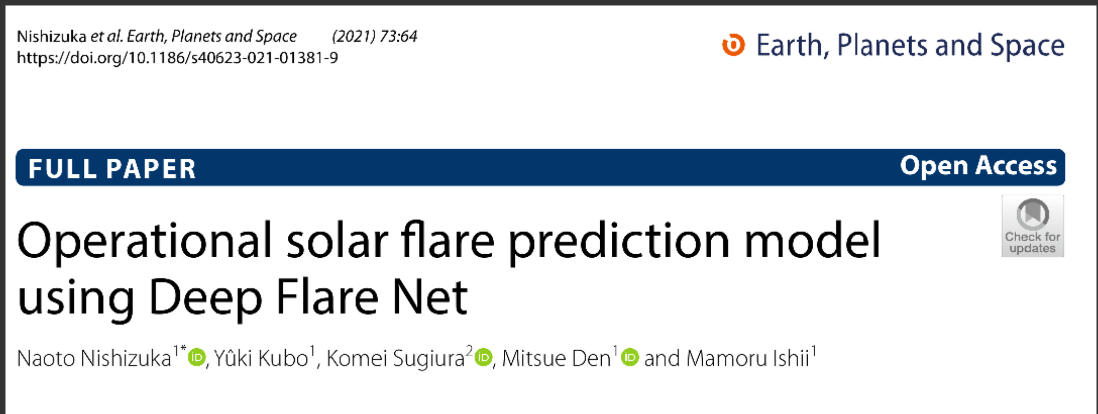
Solar Filament Recognition Based on Deep Learning

Gaofei Zhu[1,2,3] · Ganghua Lin[1,3] · Dongguang Wang[1,3] · Suo Liu[1,3,4] · Xiao Yang[1,3]

Courtesy of Dan Seaton and J. Marcus Hughes, NCEI, CIRES, and University of Colorado Boulder

Solar flare prediction

- Possibly the most active research area in ML for space weather!



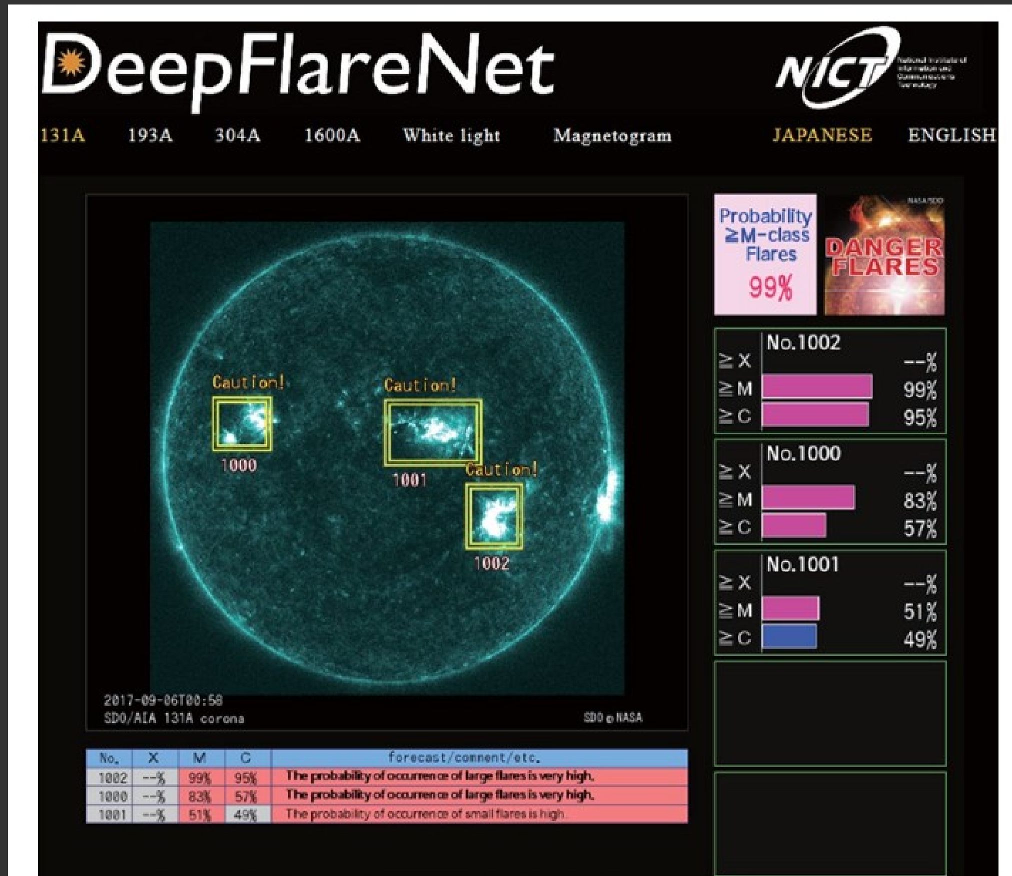
Nishizuka *et al. Earth, Planets and Space* (2021) 73:64
https://doi.org/10.1186/s40623-021-01381-9

Earth, Planets and Space

FULL PAPER Open Access

Operational solar flare prediction model using Deep Flare Net

Naoto Nishizuka[1*], Yûki Kubo[1], Komei Sugiura[2], Mitsue Den[1] and Mamoru Ishii[1]



Solar flare predictions

SOLAR FLARE PREDICTION USING *SDO*/HMI VECTOR MAGNETIC FIELD DATA WITH A MACHINE-LEARNING ALGORITHM

M. G. Bobra and S. Couvidat
W. W. Hansen Experimental Physics Laboratory, Stanford University, Stanford, CA 94305, USA; couvidat@stanford.edu
Received 2014 August 1; accepted 2014 November 1; published 2015 January 8

CrossMark

Predicting Solar Flares with Machine Learning: Investigating Solar Cycle Dependence

Xiantong Wang[1], Yang Chen[2], Gabor Toth[1], Ward B. Manchester[1], Tamas I. Gombosi[1], Alfred O. Hero[3], Zhenbang Jiao[2], Hu Sun[2], Meng Jin[4,5], and Yang Liu[6]
[1] Department of Climate and Space Sciences and Engineering, University of Michigan, Ann Arbor, MI, USA; xtwang@umich.edu
[2] Department of Statistics, University of Michigan, Ann Arbor, MI, USA
[3] Department of Electrical Engineering and Computer Science, University of Michigan, Ann Arbor, MI, USA
[4] Lockheed Martin Solar and Astrophysics Laboratory, Palo Alto, CA, USA
[5] SETI Institute, Mountain View, CA 94043, USA
[6] Hansen Experimental Physics Laboratory, Stanford University, Stanford, CA 94305, USA
Received 2020 January 22; revised 2020 April 13; accepted 2020 April 14; published 2020 May 19

Solar Phys (2018) 293:28
https://doi.org/10.1007/s11207-018-1250-4

Forecasting Solar Flares Using Magnetogram-based Predictors and Machine Learning

Kostas Florios[1,2] · Ioannis Kontogiannis[1] · Sung-Hong Park[3] · Jordan A. Guerra[3] · Federico Benvenuto[4] · D. Shaun Bloomfield[5] · Manolis K. Georgoulis[1]

CrossMa

Decreasing False-alarm Rates in CNN-based Solar Flare Prediction Using SDO/HMI Data

Varad Deshmukh[1], Natasha Flyer[2], Kiera van der Sande[3], and Thomas Berger[4]

Solar wind classification

- The geoeffectiveness of solar wind is related to its source region
- Xu & Borovsky (2015) introduced a 4-category solar wind: ejecta, coronal holes, sector reversal, streamer belts
- 40 years of OMNI data have been automatically categorized (based on a training set of ~9,000 hours covering 1995-2008)

Journal of Geophysical Research: Space Physics

RESEARCH ARTICLE

10.1002/2017JA024383

Key Points:

- Gaussian Process classification yields excellent accuracy in classifying the solar wind according to the Xu and

Classification of Solar Wind With Machine Learning

Enrico Camporeale[1], Algo Carè[1], and Joseph E. Borovsky[2]

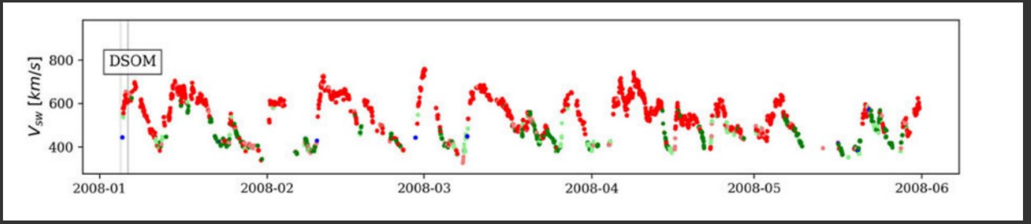
[1]Center for Mathematics and Computer Science (CWI), Amsterdam, Netherlands, [2]Center for Space Plasma Physics, Space Science Institute, Boulder, CO, USA

Unsupervised classification

Visualizing and Interpreting Unsupervised Solar Wind Classifications

Jorge Amaya, Romain Dupuis, Maria Elena Innocenti and Giovanni Lapenta*

Mathematics Department, Centre for Mathematical Plasma-Astrophysics, KU Leuven, Leuven, Belgium



Data-Driven Classification of Coronal Hole and Streamer Belt Solar Wind

Téo Bloch[1] · Clare Watt[1] · Mathew Owens[1] · Leland McInnes[2] · Allan R. Macneil[1]

Objectively Determining States of the Solar Wind Using Machine Learning

D. Aaron Roberts[1], Homa Karimabadi[2], Tamara Sipes[3], Yuan-Kuen Ko[4], and Susan Lepri[5]

Solar wind speed

Space Weather

RESEARCH ARTICLE
10.1029/2021SW002976

Special Section:
Heliophysics and Space Weather Studies from the Sun-Earth Lagrange Points

Attention-Based Machine Vision Models and Techniques for Solar Wind Speed Forecasting Using Solar EUV Images

Edward J. E. Brown[1,2,3], Filip Svoboda[1], Nigel P. Meredith[2], Nicholas Lane[1,4], and Richard B. Horne[2]

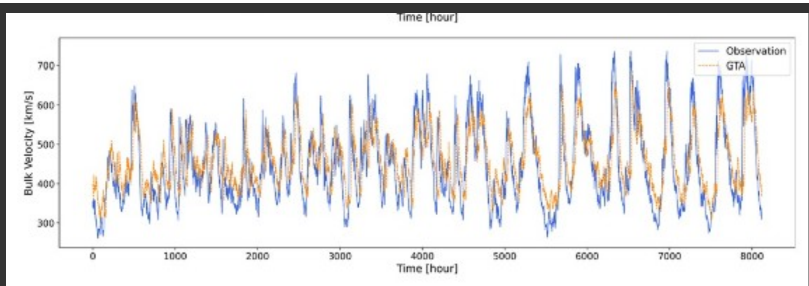
[1]Department of Computer Science and Technology, University of Cambridge, Cambridge, UK, [2]Space Weather and Atmosphere Team, British Antarctic Survey, NERC, Cambridge, UK, [3]BAS AI Lab, British Antarctic Survey, NERC, Cambridge, UK, [4]Samsung AI Center, Cambridge, UK

Edward J. E. Brown and Filip Svoboda contributed equally to this work.

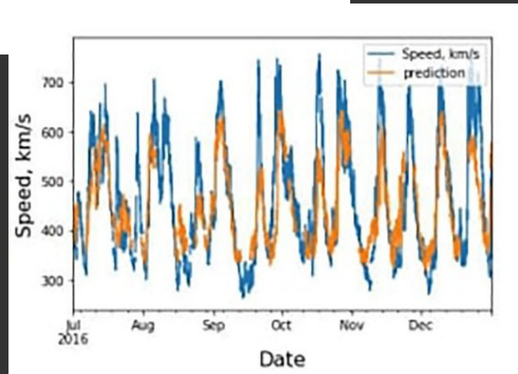
Solar Wind Speed Prediction via Graph Attention Network

Yanru Sun[1], Zongxia Xie[1], Haocheng Wang[1], Xin Huang[2], and Qinghua Hu[1]

[1]College of Intelligence and Computing, Tianjin University, Tianjin, China, [2]National Astronomical Observatories, Chinese Academy of Sciences, Beijing, China



(a) Horizon = 24h



Radiation belts' electron flux

Space Weather

RESEARCH ARTICLE
10.1029/2021SW002808

Relativistic Electron Model in the Outer Radiation Belt Using a Neural Network Approach

Xiangning Chu[1], Donglai Ma[2], Jacob Bortnik[2], W. Kent Tobiska[3], Alfredo Cruz[3], S. Dave Bouwer[3], Hong Zhao[4], Qianli Ma[2,5], Kun Zhang[6], Daniel N. Baker[1], Xinlin Li[1], Harlan Spence[7], and Geoff Reeves[8]

Key Points:

- A neural network model was developed to forecast relativistic electron fluxes with energies

JGR Space Physics

RESEARCH ARTICLE
10.1029/2022JA030377

Data-Driven Discovery of Fokker-Planck Equation for the Earth's Radiation Belts Electrons Using Physics-Informed Neural Networks

E. Camporeale[1,2], George J. Wilkie[3], Alexander Y. Drozdov[4], and Jacob Bortnik[4]

[1]CIRES, University of Colorado, Boulder, CO, USA, [2]NOAA, Space Weather Prediction Center, Boulder, CO, USA, [3]Princeton Plasma Physics Laboratory, Princeton, NJ, USA, [4]University of California Los Angeles, Los Angeles, CA, USA

Special Section:
Machine Learning in Heliophysics

Key Points:

- We analyze the relative importance

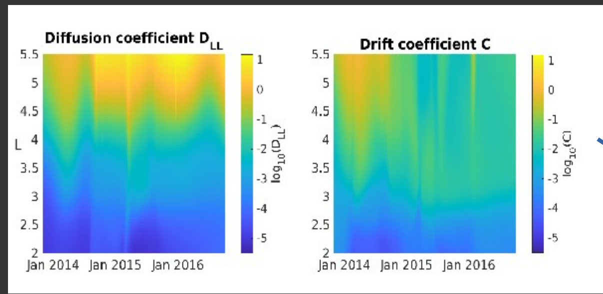
The final frontier: Interpretable AI

Assumption:
The physics obeys FP equation

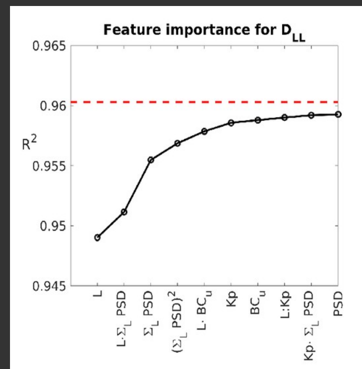
$$\frac{\partial f(L,t)}{\partial t} = L^2 \frac{\partial}{\partial L}\left(\frac{D_{LL}}{L^2}\frac{\partial f(L,t)}{\partial L}\right) - \frac{\partial C f(L,t)}{\partial L},$$

PINN

Optimal coefficients



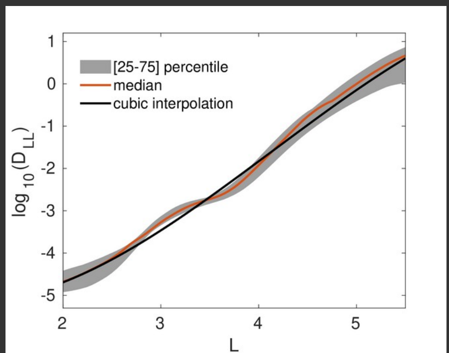
Feature selection

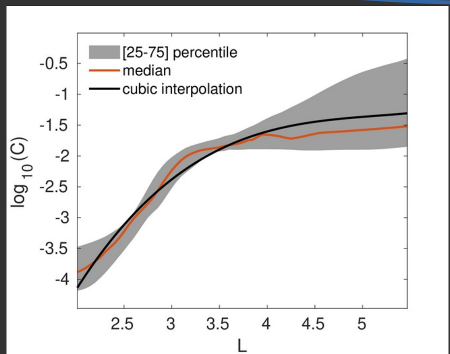


~~Train a ML model that predicts D_{LL} and C at a given time~~

Solve the equation with PINN-discovered and ML-learned coefficients!

Instead: approximate D_{LL} and C with cubic interpolation





$$\log_{10} D_{LL} = -0.0593L^3 + 0.7368L^2 - 1.33L - 4.505$$

$$\log_{10} C = 0.0777L^3 - 1.2022L^2 + 6.3177L - 12.6115$$

Why does it work (so well) ?

A short digression

The Unreasonable Effectiveness of Mathematics in the Natural Sciences

Richard Courant Lecture in Mathematical Sciences delivered at New York University, May 11, 1959

EUGENE P. WIGNER

Princeton University

“The miracle of the appropriateness of the language of mathematics for the formulation of the laws of physics is a wonderful gift which we neither understand nor deserve.”

Why does it work (so well) ?

The Unreasonable Effectiveness of Data

Alon Halevy, Peter Norvig, and Fernando Pereira, *Google*

The unreasonable effectiveness of deep learning in artificial intelligence

Terrence J. Sejnowski[a,b,1]

[a]Computational Neurobiology Laboratory, Salk Institute for Biological Studies, La Jolla, CA 92037; and [b]Division of Biological Sciences, University of California San Diego, La Jolla, CA 92093

We are not in the same boat with image and text recognition, self-driving, or recommendation systems!

Why does it work (so well) ?

Physics to the rescue!

- Physical properties such as invariance, symmetry, conservation laws, etc. reduce drastically the ‘search space’ of parameters
- Any system that follows ‘laws of physics’ should be learnable by Machine Learning
- Any simulation can be emulated by ML
- The major hurdle is **Data Quality & Quantity!**

J Stat Phys (2017) 168:1223–1247
DOI 10.1007/s10955-017-1836-5
CrossMark

Why Does Deep and Cheap Learning Work So Well?

Henry W. Lin[1] · Max Tegmark[2] · David Rolnick[3]

Why does it work (so well) ?

Physics to the rescue!

SCIENCE ADVANCES | RESEARCH ARTICLE

COMPUTER SCIENCE

AI Feynman: A physics-inspired method for symbolic regression

Silviu-Marian Udrescu[1] and Max Tegmark[1,2]*

A core challenge for both physics and artificial intelligence (AI) is symbolic regression: finding a symbolic expression that matches data from an unknown function. Although this problem is likely to be NP-hard in principle, functions of practical interest often exhibit symmetries, separability, compositionality, and other simplifying properties. In this spirit, we develop a recursive multidimensional symbolic regression algorithm that combines neural network fitting with a suite of physics-inspired techniques. We apply it to 100 equations from the *Feynman Lectures on Physics*, and it discovers all of them, while previous publicly available software cracks only 71; for a more difficult physics-based test set, we improve the state-of-the-art success rate from 15 to 90%.

Path forward for ML in SWx

Freely adapted from:

Space Weather

FEATURE ARTICLE
10.1029/2018SW002061

GRAND CHALLENGES
CENTENNIAL COLLECTION

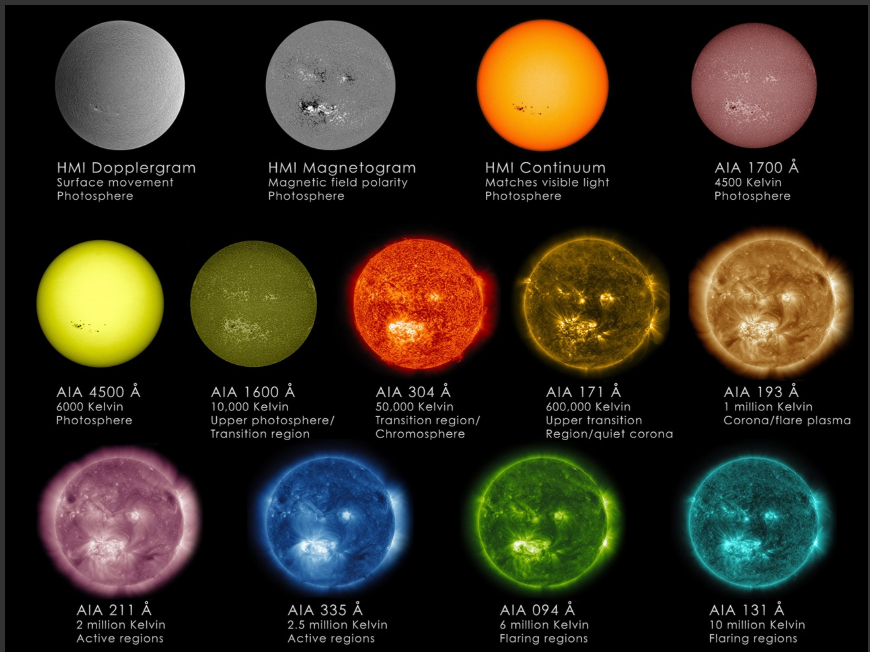
The Challenge of Machine Learning in Space Weather: Nowcasting and Forecasting

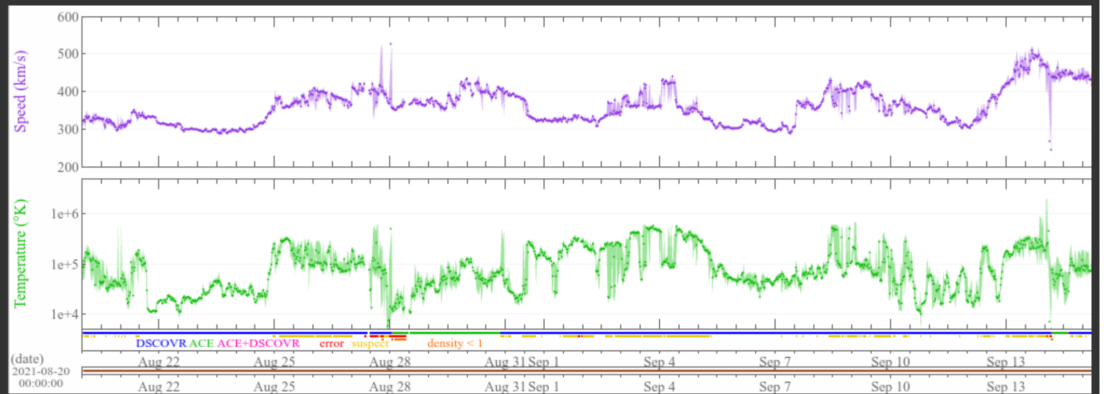
E. Camporeale[1,2]

[1]CIRES, University of Colorado Boulder, Boulder, CO, USA, [2]Centrum Wiskunde & Informatica, Amsterdam, The Netherlands

Path forward for ML in SWx

- *The information problem*: What is the minimal physical information required to make a forecast?





200M pixels → 1 scalar value

Path forward for ML in SWx

- *The gray-box problem:* What is the best way to make an optimal use of both our physical understanding and our large amount of data in the Sun-Earth system?

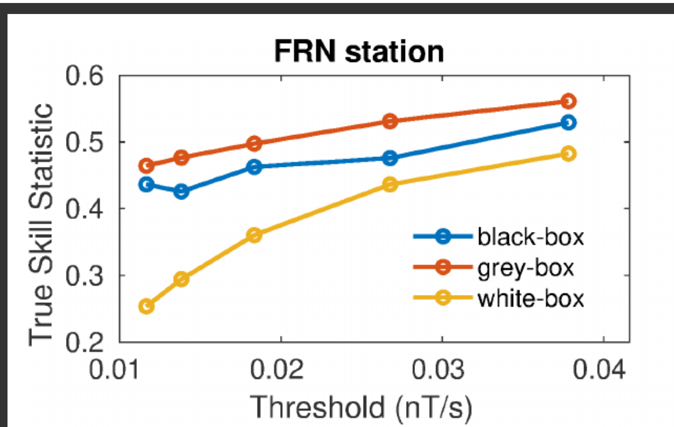
JGR Space Physics

RESEARCH ARTICLE
10.1029/2019JA027684

Key Points:
- We present a new model to forecast the maximum value of *dB*/*dt* over 20-min intervals at specific locations

A Gray-Box Model for a Probabilistic Estimate of Regional Ground Magnetic Perturbations: Enhancing the NOAA Operational Geospace Model With Machine Learning

E. Camporeale[1,2], M. D. Cash[3], H. J. Singer[3], C. C. Balch[3], Z. Huang[4], and G. Toth[4]



Path forward for ML in SWx

- *The surrogate problem:* What components in the Space Weather chain can be replaced by an approximated black-box surrogate model? What is an acceptable trade-off between lost of accuracy and speed-up?

arXiv > physics > arXiv:2203.13372

Physics > Computational Physics

[Submitted on 24 Mar 2022]

Predicting Solar Wind Streams from the Inner-Heliosphere to Earth via Shifted Operator Inference

Opal Issan, Boris Kramer

Path forward for ML in SWx

- *The uncertainty problem:* Most Space Weather services provide forecast in terms of single-point predictions. There is a clear need for understanding and assessing the uncertainty associated to these predictions and how uncertainty propagates.

Space Weather

RESEARCH ARTICLE

10.1029/2018SW002026

On the Generation of Probabilistic Forecasts From Deterministic Models

E. Camporeale[1,2], X. Chu[3], O. V. Agapitov[4], and J. Bortnik[5]

Key Points:

- We introduce a new method to estimate the uncertainties associated

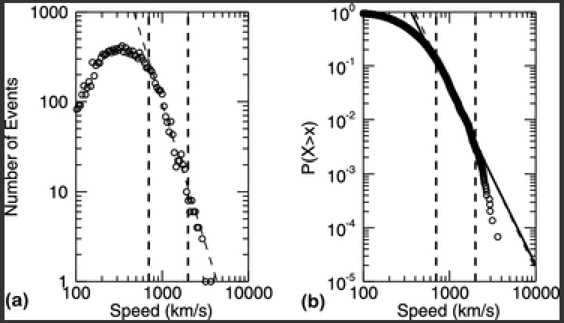
International Journal for Uncertainty Quantification, 11(4):81–94 (2021)

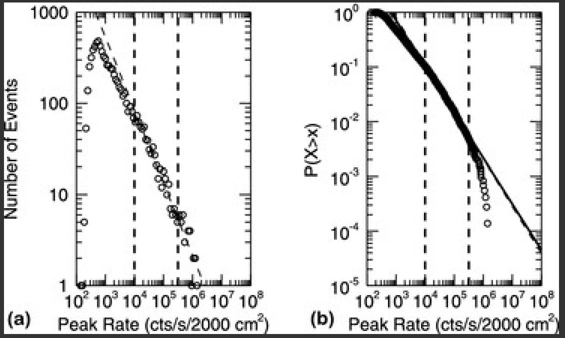
ACCRUE: ACCURATE AND RELIABLE UNCERTAINTY ESTIMATE IN DETERMINISTIC MODELS

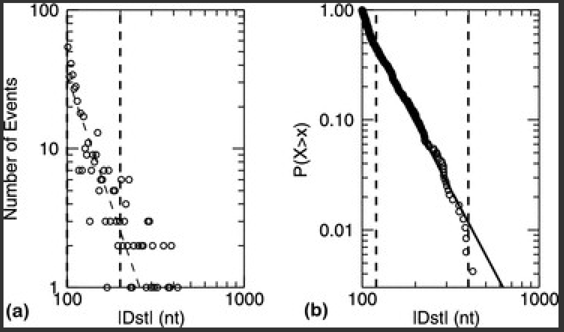
Enrico Camporeale[1,] & Algo Carè[2]*

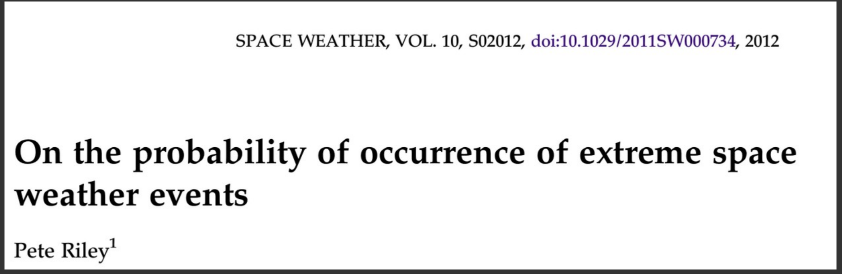
Path forward for ML in SWx

- *The too often too quiet problem:* Space weather data sets are typically imbalanced: many days of quiet conditions and a few hours of storms. This poses a serious problem for any machine learning algorithm. It is also problematic for defining meaningful metrics that actually assess the ability of a model to predict interesting but rare events.








SPACE WEATHER, VOL. 10, S02012, doi:10.1029/2011SW000734, 2012

On the probability of occurrence of extreme space weather events

Pete Riley[1]

Path forward for ML in SWx

- *The knowledge discovery and explainability problem:* How do we distill some knowledge from a machine learning model and improve our understanding of a given system? How do we open the black-box and reverse-engineer a machine learning algorithm?

arXiv.org > physics > arXiv:2107.14322

Physics > Space Physics

[Submitted on 29 Jul 2021]

Machine-learning based discovery of missing physical processes in radiation belt modeling

Enrico Camporeale, George J. Wilkie, Alexander Drozdov, Jacob Bortnik

Summary

ML 4 SWx is the quintessential interdisciplinary field.

These 6 problems not only hinder progress in Space Weather, but pose fundamental challenges in the fields of AI and UQ.

- *The information problem*
- *The gray-box problem*
- *The surrogate problem*
- *The uncertainty problem*
- *The too often too quiet (rare events) problem*
- *The knowledge discovery and explainability problem*

Contact: **enrico.camporeale@noaa.gov**