Examples of Heliophysics Applications in Machine Learning

Enrico Camporeale

Queen Mary University of London (UK)
University of Colorado (USA)

Thanks to: Andong Hu, Thomas Berger, Greg Lucas, Jacob Bortnik, George Wilkie, Alexander Drozdov, Raffaello Foldes, Raffaele Marino (et al...)

Acknowledgment: NASA grants 80NSSC20K1580, 80NSSC21K1555, 80NSSC20K1275, 80NSSC23M0192

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Machine Learning

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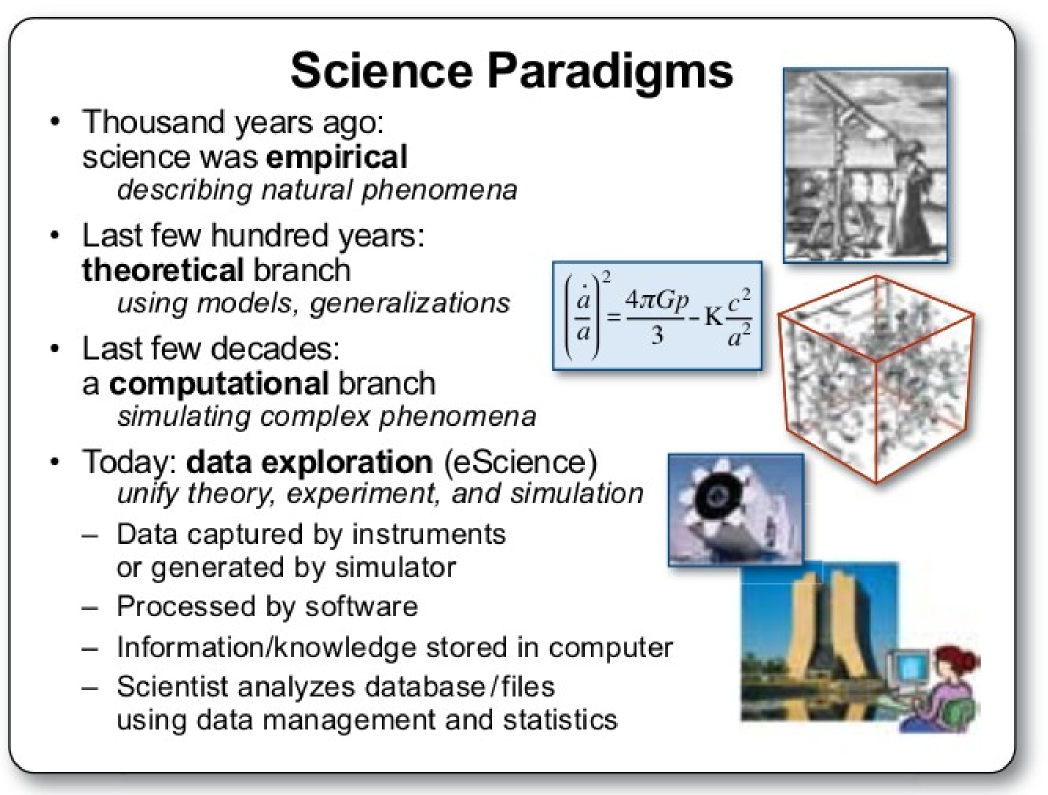
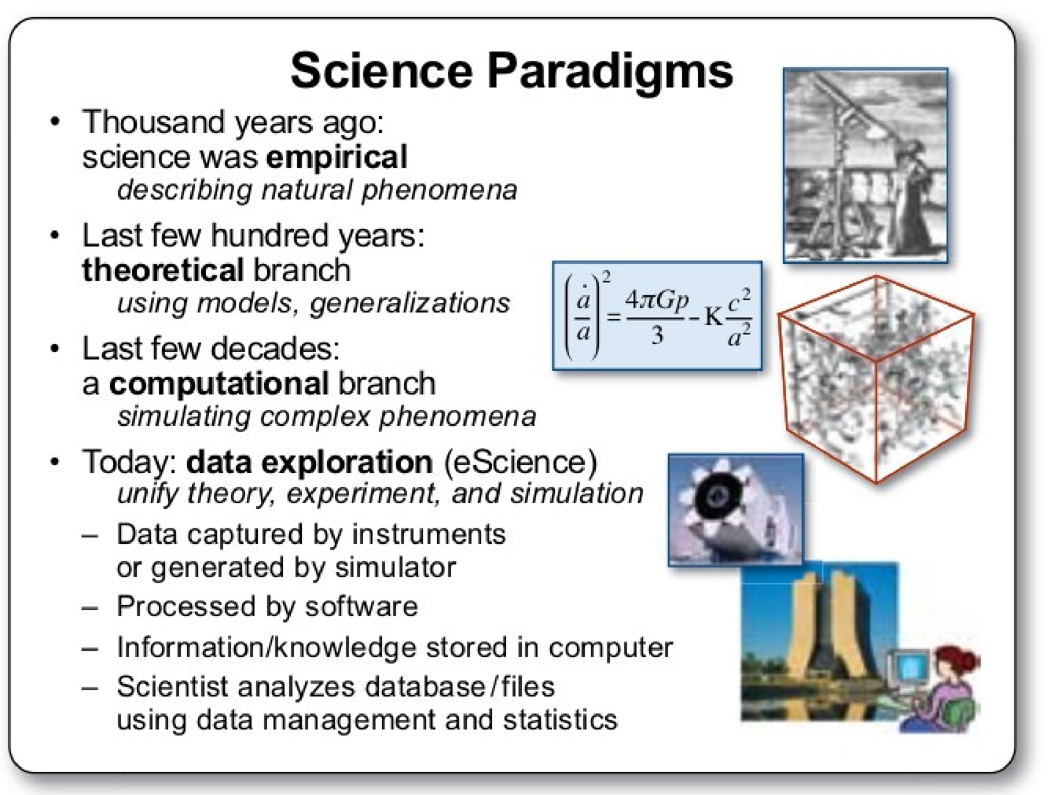
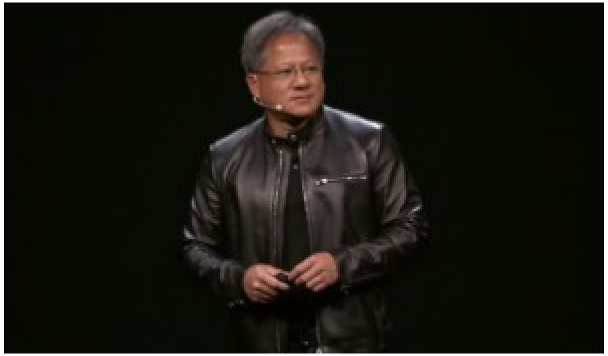
Data Science as the fourth pillar of the scientific method



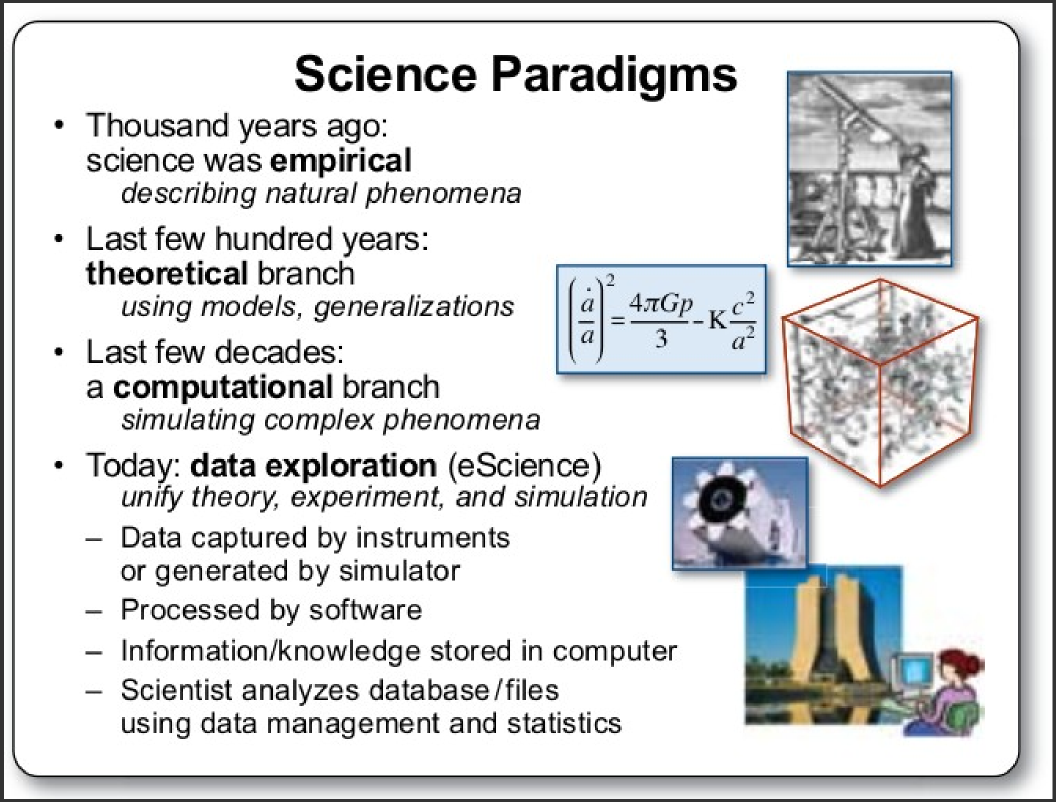
Data Science as the fourth pillar of the scientific method

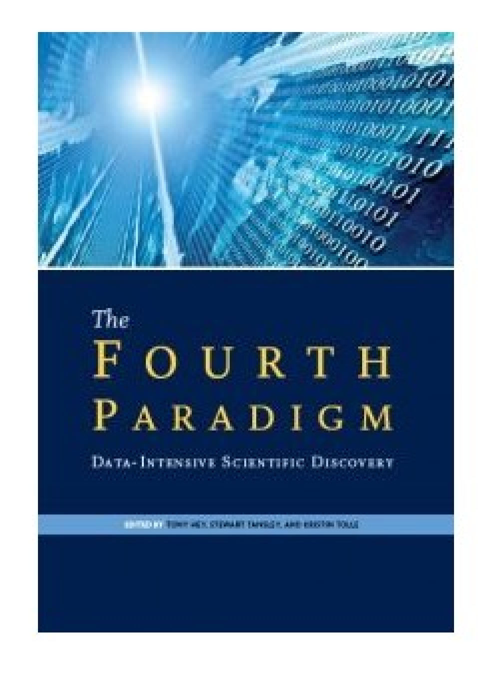




Data science is the fourth pillar of the scientific method, says NVidia Jensen Huang

Data Science as the fourth pillar of the scientific method





The Fourth Paradigm: Data-Intensive Scientific Discovery

Tony Hey, Stewart Tansley, Kristin Tolle, Jim Gray
Published by Microsoft Research | October 2009
ISBN: 978-0-9825442-0-4

JGR Machine Learning and Computation

EDITORIAL
10.1029/2024JH000184

Key Points:

- This editorial introduces *JGR: Machine Learning & Computation* to the community

Our Vision for JGR: Machine Learning and Computation

E. Camporeale[1,2], R. Marino[3], and the Editorial Board[4]

[1]Queen Mary University of London, London, UK, [2]Space Weather Technology, Research and Education (SWx TREC), University of Colorado, Boulder, CO, USA, [3]Laboratoire de Mécanique des Fluides et d'Acoustique, UMR 5509, CNRS, École Centrale de Lyon, INSA Lyon, Université Claude Bernard Lyon 1, Ecully, France, [4]See Appendix A

Here, we posit that a novel foundational component is being incorporated into the process of scientific discovery: data-driven methods are emerging as the fourth pillar. This proposition has sparked considerable debate and controversy, with one prevalent argument asserting that the scientific community should avoid the inclination

to some, and it fundamentally asserts the supremacy of data. A prime example of this new paradigm is seen in the prediction of complex nonlinear systems, for example, global weather forecasting, where "black-box" neural network models have demonstrated comparable performance to large-scale physics-based numerical prediction models while executing a few orders of magnitude times faster. The new paradigm is obviously not restricted to geoscience; AlphaFold has shown the ability to predict the structure of proteins with atomic precision at a large scale and within minutes, essentially solving a 50-year grand challenge and showcasing AI's potential to greatly expedite scientific breakthroughs, thereby propelling human advancement (Jumper et al., 2021).

A loose taxonomy

- Inference/prediction/forecast:
  - Surrogate models
  - ROM models

  Goals:
  - devise a model that runs faster than a baseline (trade-off accuracy vs speed)
  - Forecast output of interest in the future (space weather: “understanding is neither necessary nor sufficient for prediction”)
- Data-driven discovery of models / algorithms

  Goals:
  - Discover new physics from data (in intelligible way)
  - Find new parameterizations of missing physics in models

The literature is exploding!

Solar flares

Forecasting **solar flares** using magnetogram-based predictors and **machine learning**
K Florios, I Kontogiannis, SH Park, JA Guerra… - Solar Physics, 2018 - Springer
… We propose a forecasting approach for **solar flares** based on data from Solar Cycle 24, taken … We exploit several **machine learning** (ML) and conventional statistics techniques to predict …
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Predicting **solar flares** with **machine learning**: Investigating solar cycle dependence
X Wang, Y Chen, G Toth, WB Manchester… - The Astrophysical …, 2020 - iopscience.iop.org
A deep **learning** network, long short-term memory (LSTM), is used to predict whether an active region (AR) will produce a flare of class Γ in the next 24 hr. We consider Γ to be≥ M (…
☆ Save 99 Cite Cited by 66 Related articles All 7 versions Web of Science: 43 Import into B

[HTML] **Machine learning** techniques applied to **solar flares** forecasting
F Ribeiro, ALS Gradvohl - Astronomy and Computing, 2021 - Elsevier
… , we present the **machine learning** techniques used to predict the occurrence of **solar flares**. Next, … We also discuss the data splitting process for building a **machine learning** model, the …
☆ Save 99 Cite Cited by 20 Related articles All 4 versions Web of Science: 15 Import into B

Using **machine learning** methods to forecast if **solar flares** will be associated with CMEs and SEPs
F Inceoglu, JH Jeppesen, P Kongstad… - The Astrophysical …, 2018 - iopscience.iop.org
… event, we investigate the performances of two **machine learning** algorithms. To achieve this objective, we employ support vector **machines** (SVMs) and multilayer perceptrons (MLPs) …
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Predicting solar flares using a long short-term memory network
H Liu, C Liu, JTL Wang, H Wang - The Astrophysical Journal, 2019 - iopscience.iop.org
… data together with **flaring** history to **predict solar flares** that … **solar-flare prediction** task, the observations in each AR form time-series data, and hence LSTMs are suitable for this **prediction** …
☆ Save 99 Cite Cited by 127 Related articles All 5 versions Web of Science: 83 Import into

Predicting solar flares using a novel deep convolutional neural network
X Li, Y Zheng, X Wang, L Wang - The Astrophysical Journal, 2020 - iopscience.iop.org
… important, and the **prediction** of space weather, especially for **solar flares**, has … **prediction** for both ≥C-class and ≥M-class **flares** within 24 hr. We collect magnetogram samples of **solar** …
☆ Save 99 Cite Cited by 75 Related articles All 5 versions Web of Science: 50 Import into B

Predicting solar flares using CNN and LSTM on two **solar** cycles of active region data
Z Sun, MG Bobra, X Wang, Y Wang, H Sun… - The Astrophysical …, 2022 - iopscience.iop.org
… **flare prediction** problem that distinguishes **flare**-imminent active regions that produce an M- or X-class **flare** … quiet active regions that do not produce any **flares** within ±24 hr. Using line-of…
☆ Save 99 Cite Cited by 40 Related articles All 15 versions Web of Science: 24 Import into

Predicting solar flares with machine learning: Investigating **solar** cycle dependence
X Wang, Y Chen, G Toth, WB Manchester… - The Astrophysical …, 2020 - iopscience.iop.org
… Based on the results presented in this paper, the LSTM is a valid method for the **solar flare prediction** task. The skill scores from this paper are very close to those generated by other, …
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Solar flares

THE ASTROPHYSICAL JOURNAL, 798:135 (11pp), 2015 January 10 doi:10.1088/0004-637X/798/2/135

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

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

Earth, Planets and Space

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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]

THE ASTROPHYSIC

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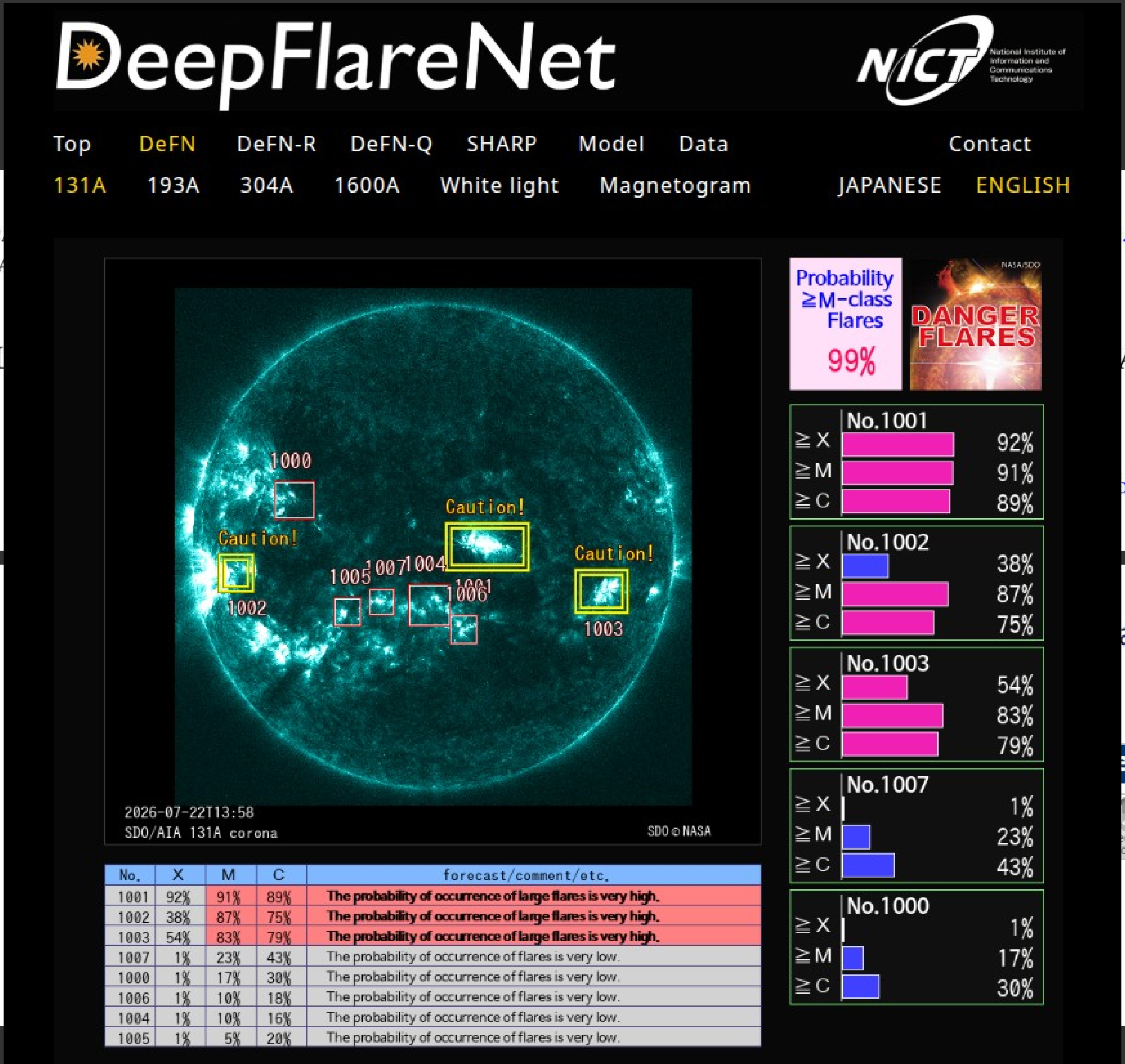

No.	X	M	C	forecast/comment/etc.
1001	92%	91%	89%	The probability of occurrence of large flares is very high.
1002	38%	87%	75%	The probability of occurrence of large flares is very high.
1003	54%	83%	79%	The probability of occurrence of large flares is very high.
1007	1%	23%	43%	The probability of occurrence of flares is very low.
1000	1%	17%	30%	The probability of occurrence of flares is very low.
1006	1%	10%	18%	The probability of occurrence of flares is very low.
1004	1%	10%	16%	The probability of occurrence of flares is very low.
1005	1%	5%	20%	The probability of occurrence of flares is very low.

.1088/0004-637X/798/2/135

A WITH A

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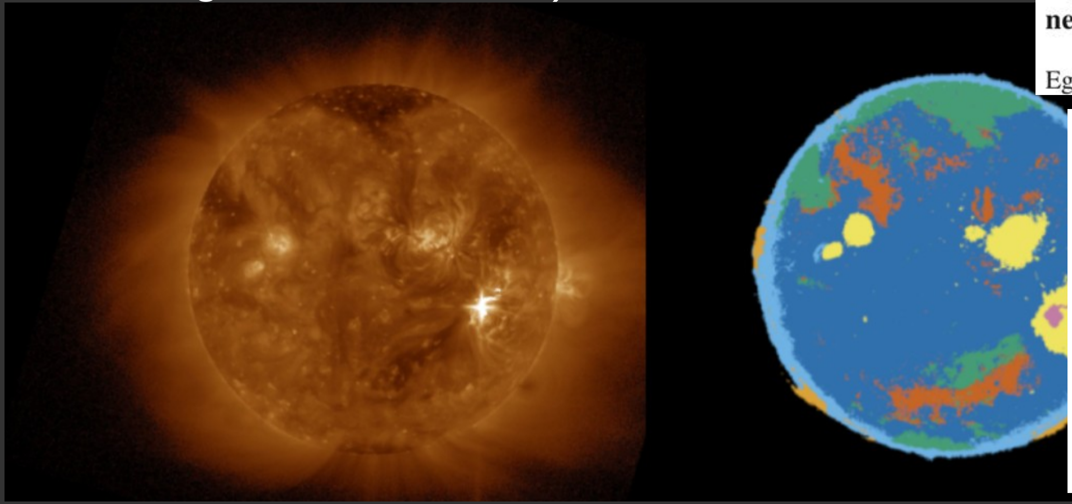
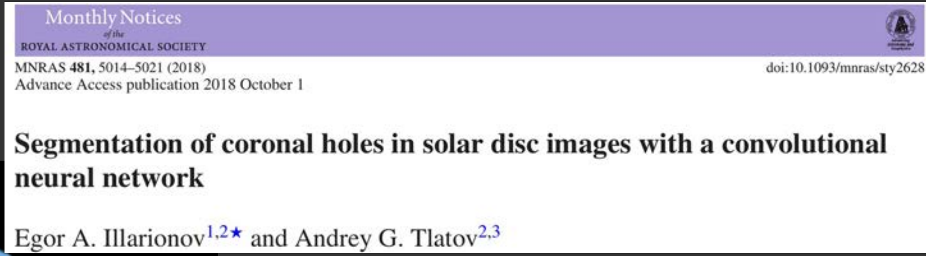
ace

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) doi:10.1093/mnras/sty2628
Advance Access publication 2018 October 1

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

Radiation belt flux

Modeling the dynamic variability of sub-relativistic outer radiation belt electron fluxes using machine learning
D Ma, X Chu, J Bortnik, SG Claudepierre… - Space …, 2022 - Wiley Online Library
… energy (~<100 keV) electron **fluxes** during storms. The models have reliable prediction …
not limited to **radiation belt fluxes** and could be used to build **machine learning** models for a …
Save Cite Cited by 26 Related articles All 7 versions Web of Science: 17 Import into BibTeX

Medium energy electron flux in earth's outer radiation belt (MERLIN): A machine learning model
AG Smirnov, M Berrendorf, YY Shprits… - Space …, 2020 - Wiley Online Library
… **flux** in the outer **radiation belt** based on **machine learning**. We use … We set up a 3D model
for **flux** prediction in terms of L-values, … **radiation belt** and has wide space weather applications. …
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Opening the black box of the radiation belt machine learning model
D Ma, J Bortnik, X Chu, SG Claudepierre, Q Ma… - Space …, 2023 - Wiley Online Library
… A set of neural network models named Outer **RadIation belt** Electron … **flux** of the outer **radiation belt**. In this work, we demonstrate the general flow of explaining the **machine learning** (ML) …
Save Cite Cited by 15 Related articles All 9 versions Web of Science: 3 Import into BibTeX

[HTML] **Reconstruction of electron radiation belts using data assimilation and machine learning**
AY Drozdov, D Kondrashov, K Strounine… - Frontiers in Astronomy …, 2023 - frontiersin.org
… We present a reconstruction of **radiation belt** electron **fluxes** using data … **machine learning**
methods: multivariate linear regression (MLR) and neural network (NN). The reconstructed **flux** …
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Relativistic electron model in the outer radiation belt using a neural network approach
X Chu, D Ma, J Bortnik, WK Tobiska, A Cruz… - Space …, 2021 - Wiley Online Library
We present a machine-learning-based model of relativistic electron fluxes> 1.8 MeV using a
neural network approach in the Earth's outer radiation belt. The Outer RadIation belt …
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Machine-learning based discovery of missing physical processes in radiation belt modeling
E Camporeale, GJ Wilkie, A Drozdov… - arXiv preprint arXiv …, 2021 - arxiv.org
… where f is the particles' Phase Space Density (PSD), Φ is the third adiabatic invariant (magnetic
flux enclosed by a drift shell), t is time, and Eq.(1) is understood to be valid for constant …
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Machine learning interpretability of outer radiation belt enhancement and depletion events
D Ma, J Bortnik, Q Ma, M Hua… - Geophysical Research …, 2024 - Wiley Online Library
… of outer **radiation belt** electron **fluxes** to different solar wind and geomagnetic indices using
an interpretable **machine learning** method. We reconstruct the electron **flux** variation during …
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Forecasting megaelectron-volt electrons inside Earth's outer radiation belt: PreMevE 2.0 based on supervised machine learning algorithms
R Pires de Lima, Y Chen, Y Lin - Space Weather, 2020 - Wiley Online Library
… supervised **machine learning** algorithms with optimized selection of input parameters. …
learning problem as a **flux** forecasting task, consider predicting the 1 MeV electron **fluxes** at time t …
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Predicting geostationary 40–150 keV electron flux using ARMAX (an autoregressive moving average transfer function), RNN (a recurrent neural network), and logistic …
LE Simms, NY Ganushkina, M Van der Kamp… - Space …, 2023 - Wiley Online Library
We screen several algorithms for their ability to produce good predictive models of hourly 40–
150 keV electron flux at geostationary orbit (data from GOES-13) using solar wind …
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Solar wind

Solar wind prediction using **deep learning**
V Upendran, MCM Cheung, S Hanasoge… - Space …, 2020 - Wiley Online Library
… In this work, we explore the use of **machine learning** models to predict the solar wind speed as measured at the Lagrangian Point 1 (L1) between the Sun and Earth. The best …
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CNN-based **deep learning** model for solar wind forecasting
H Raju, S Das - Solar Physics, 2021 - Springer
… The main motive behind this work is to analyse and improve the application of CNN in **solar-wind prediction** with adaptive time delay employed during training. The advantage of using …
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Combining Empirical and Physics-Based Models for **Solar Wind Prediction**
R Johnson, S Filali Boubrahimi, O Bahri, SM Hamdi - Universe, 2024 - mdpi.com
… loss to guide **deep learning** models for the task of **solar wind prediction**. We demonstrate the variability of the proposed physics-informed loss across five **deep learning** baseline models. …
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Solar Wind Speed Prediction With Two-Dimensional Attention Mechanism
Y Sun, Z Xie, Y Chen, X Huang, Q Hu - Space Weather, 2021 - Wiley Online Library
… of the solar wind using a **machine learning** model. Solar images in … A **deep learning** model based on the two-dimensional … Therefore, the establishment of a reliable **solar wind prediction** …
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Using gradient boosting regression to improve ambient solar wind model predictions
RL Bailey, MA Reiss, CN Arge, C Möstl… - Space …, 2021 - Wiley Online Library
… Here, we present a **machine learning** approach in which solutions from magnetic models of … Table of ambient **solar wind prediction** error metrics in terms of arithmetic mean (AM), …
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Prediction of solar wind speed at 1 AU using an artificial neural network
Y Yang, F Shen, Z Yang, X Feng - Space Weather, 2018 - Wiley Online Library
… provide unique useful constraining information on **solar wind prediction**, we discuss the effect of … the **solar wind prediction** will be greatly improved with more advanced **machine learning** …
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Physics-Informed Neural Networks For **Solar Wind Prediction**
R Johnson, SF Boubrahimi, O Bahri… - … Conference on Pattern …, 2022 - Springer
… guide **deep learning** models for the task of solar wind forecasting. To our best knowledge, this is the first effort to build a hybrid physics and **deep learning** model for **solar wind prediction**…
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Three-day Forecasting of Solar Wind Speed Using SDO/AIA Extreme-ultraviolet Images by a **Deep-learning** Model
J Son, SK Sung, YJ Moon, H Lee… - The Astrophysical …, 2023 - iopscience.iop.org
… Table 1 shows comparison of the results of the 24 hr prediction by our model with those of other **solar wind prediction** models. Even though they cannot be compared directly to the …
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Dynamic time lag regression: Predicting what and when
M **Chandorkar**, C Furtlehner, B Poduval… - … on **Learning** …, 2020 - inria.hal.science
… Would the lag be constant, the **solar wind prediction** problem would boil down to a mainstream regression problem. The challenge here is to predict, from the solar image x(t) at time t …
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Attention-based **machine** vision models and techniques for **solar wind** speed forecasting using solar EUV images
EJE **Brown**, F Svoboda, NP Meredith, N Lane… - Space …, 2022 - Wiley Online Library
… In this study, we build a **machine learning** model to use solar images to forecast the **solar wind** … The field of **machine learning** has built a lot of momentum over the last 10 years. This has …
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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

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

Key Points:

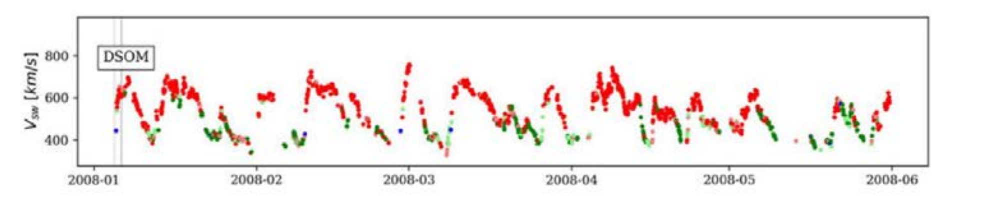
- Gaussian Process classification yields excellent accuracy in classifying the solar wind according to the Xu and

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

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]

Solar Wind Speed Prediction via Graph Attention Network

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

[1]College of Intelligence and Computing, Tianjin University, Tianjin, China, [2]National Astron
Academy of Sciences

Published as a conference paper at ICLR 2020

Dynamic Time Lag Regression: Predicting What & When

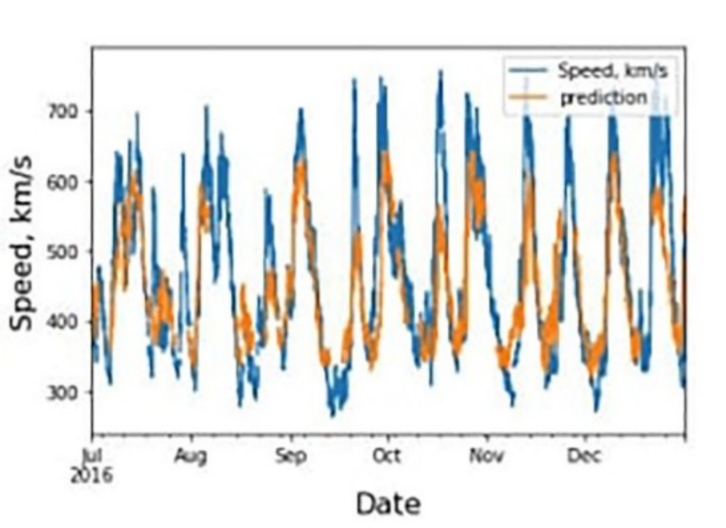
Mandar Chandorkar
Centrum Wiskunde en Informatica
Amsterdam 1098XG

Cyril Furtlehner
INRIA-Saclay

Bala Poduval
University of New Hampshire
Durham, NH 03824

Enrico Camporeale
CIRES, University of Colorado
Boulder, CO

Michèle Sebag
CNRS – Univ. Paris-Saclay



https://fdl.ai/benchlab-solar-wind-prediction-2026

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Coronal Mass Ejection (CME)

Predicting **coronal mass ejections** using **machine learning** methods
MG Bobra, S Ilonidis - The Astrophysical Journal, 2016 - iopscience.iop.org
… In Section 2, we describe the **solar** data and the event catalog; in Section 3, we describe the application of the **machine-learning** algorithms to these data; and in Section 4 we present …
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Automatic detection of interplanetary **coronal mass ejections** from in situ dat
A **deep learning** approach
G Nguyen, N Aunai, D Fontaine… - The astrophysical …, 2019 - iopscience.iop.org
Decades of studies have suggested several criteria to detect interplanetary **coronal mass ejections** (ICME) in time series from in situ spacecraft measurements. Among them, the most …
☆ Save 99 Cite Cited by 27 Related articles All 11 versions Web of Science: 15 Import into

A **machine learning** approach to predicting SEP events using properties of **coronal mass ejections**
J Torres, L Zhao, PK Chan, M Zhang - Space Weather, 2022 - Wiley Online Library
… We use the properties of **coronal mass ejections** (CMEs) … **machine learning** algorithms to forecast SEP events. … these instances are analyzed by a **machine learning** algorithm and can be …
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Prediction of the Transit Time of **Coronal Mass Ejections** with an Ensemble **Machine-learning** Method
Y Yang, JJ Liu, XS Feng, PF Chen… - The Astrophysical …, 2023 - iopscience.iop.org
Coronal mass ejections (CMEs), a kind of violent **solar** eruptive activity, can exert a significant impact on space weather. When arriving at the Earth, they interact with the geomagnetic …
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… the **Arrival Time** Estimates of **Coronal Mass Ejections** by Using Magnetohydrodynamic Ensemble Modeling, Heliospheric Imager Data, and **Machine Learning**
T Singh, B Benson, SAZ Raza, TK Kim… - The Astrophysical …, 2023 - iopscience.iop.org
… in a data-driven **solar** wind background. We found that for six CMEs studied in this work the MAE in **arrival time** was ~8 hr. We further improved our **arrival time** predictions by using …
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Physics-driven **machine learning** for the prediction of **coronal mass ejection** travel **times**
S Guastavino, V Candiani, A Bemporad… - The Astrophysical …, 2023 - iopscience.iop.org
… CME that has been detected in the **corona** by a remote-sensing telescope will hit the Earth; and, if so, at which **time** (**time** of **arrival**, ToA) and speed (speed of **arrival**, SoA) the impact will …
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A new tool for CME **arrival time** prediction using **machine learning** algorithm
CAT-PUMA
J Liu, Y Ye, C Shen, Y Wang… - The Astrophysical …, 2018 - iopscience.iop.org
… **Coronal mass ejections** (CMEs) are arguably the most violent eruptions in the **solar** system. CMEs … Fast and accurate prediction of CME **arrival time** is vital to minimize the disruption that …

CME **arrival time** prediction using convolutional neural network
Y Wang, J Liu, Y Jiang, R Erdélyi - The Astrophysical Journal, 2019 - iopscience.iop.org
… **arrival time** of **coronal mass ejections** (… **machine-learning** techniques to **solar**-flare predictions, not much effort has been devoted to applying **machine learning** to CME **arrival**/transit-ti
☆ Save 99 Cite Cited by 36 Related articles All 4 versions Web of Science: 22 Import into B

CME **Arrival** Modeling with **Machine Learning**
S Chierichini, J Liu, MB Korsós… - The Astrophysical …, 2024 - iopscience.iop.org
… **Coronal mass ejections** (CMEs) are among the main drivers … to provide information on their **arrival** at Earth's nearby space … of a **machine-learning** approach to study the **arrival** of CMEs …
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Geomagnetic indices

Multi-hour-ahead Dst index prediction using multi-fidelity boosted neural networks

A Hu, E Camporeale, B Swiger - Space Weather, 2023 - Wiley Online Library

… The Disturbance storm time (Dst) is a **geomagnetic index** … In this study, we first train a model using a **machine learning** (… by using the ACCRUE method (**Camporeale** & Carè, 2021), also …

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Forecasting *SYM-H* Index: A Comparison Between Long Short-Term Memory and Convolutional Neural Networks

F Siciliano, G Consolini, R Tozzi, M Gentili… - Space …, 2021 - Wiley Online Library

… **deep learning** Application Programming Interface (API) written in Python, running on top of the **machine learning** … the first attempt to forecast a **geomagnetic index** using a CNN. We have …

Save Cite Cited by 45 Related articles All 8 versions Web of Science: 30 Import into Bi

Disturbance storm time index prediction using long short-term memory **machine learning**

HD Purnomo, S Trihandaru - 2021 4th International …, 2021 - ieeexplore.ieee.org

… the **Dst geomagnetic index** time-series prediction using the ANN-**machine learning** method: … The research in this paper aims to model the **Dst**-index prediction using the LSTM model. …

Save Cite Cited by 3 Related articles Import into BibTeX

Forecasting the ***Dst*** index using a swarm-optimized neural network

JA Lazzús, P Vega, P Rojas, I Salfate - Space Weather, 2017 - Wiley Online Library

… These results show that the hybrid algorithm is a powerful technique for forecasting the **Dst** … to forecast the **Dst** index with appropriate precision and that **Dst** past behavior significantly …

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Comparison of the Efficiency of **Machine Learning** Methods in Studying the Importance of Input Features in the Problem of Forecasting the ***Dst*** **Geomagnetic Index**

RD Vladimirov, VR Shirokiy, IN Myagkova… - Geomagnetism and …, 2023 - Springer

… the most efficient **machine learning** model for predicting the **Dst geomagnetic index** by sequential removal of input features based on the following **machine learning** methods: linear …

Save Cite Cited by 3 Related articles All 4 versions Import into BibTeX

[HTML] **Machine Learning** Models for Predicting Geomagnetic Storms Across Five Solar Cycles Using **Dst** Index and Heliospheric Variables

D Sierra-Porta, JD Petro-Ramos… - Advances in Space …, 2024 - Elsevier

… the **Dst geomagnetic index**, which measures the Earth's ring current and is expressed in nanoteslas (nT). The **Dst** … Negative values of the **Dst** index indicate a greater disturbance in the …

Save Cite Related articles Import into BibTeX

Prediction of the **Dst** index with bagging ensemble-**learning** algorithm

SB Xu, SY Huang, ZG Yuan, XH Deng… - The Astrophysical …, 2020 - iopscience.iop.org

… **Dst** index is a commonly **geomagnetic index** used to measure the strength of geomagnetic activity. The accurate prediction of the **Dst** … of **machine learning** and **deep learning**, various …

Save Cite Cited by 27 Related articles All 3 versions Web of Science: 17 Import into BibTeX

[HTML] Fast **Dst** computation by applying **deep learning** to Swarm satellite magnetic data

G Cianchini, A Piscini, A De Santis… - Advances in Space …, 2022 - Elsevier

… A **geomagnetic index** describes the intensity of the geomagnetic disturbance for a certain period of time, all over the globe or regionally. There are sets of indices used to describe such …

Save Cite Cited by 6 Related articles All 5 versions Web of Science: 4 Import into BibTeX

LiveDst
Geomagnetic storm prediction

SWx TREC

Dst model | Model description | Data API

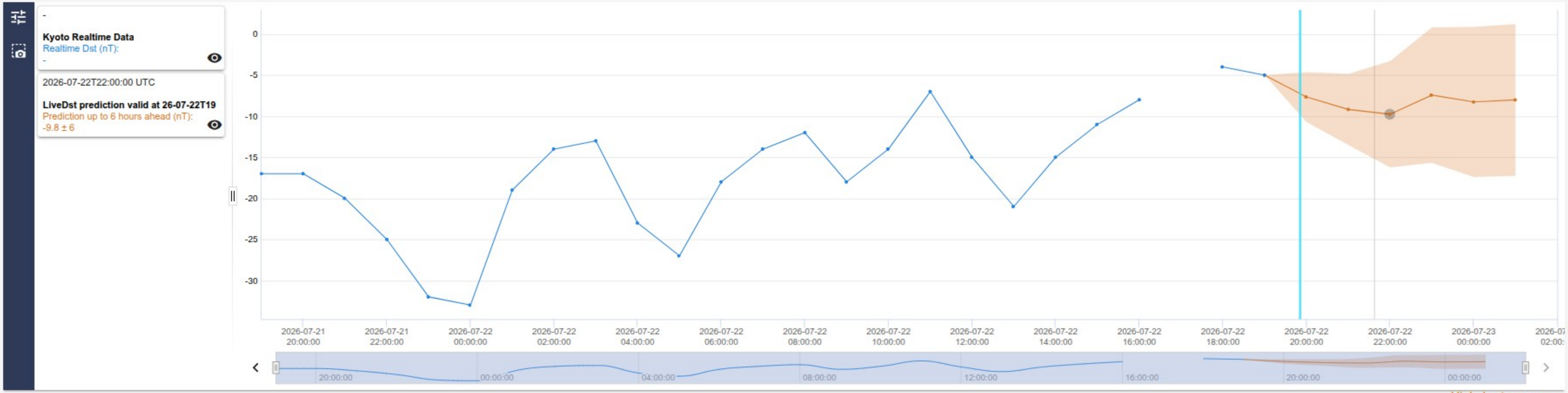
Current time (UTC): 2026-07-22 19:51

Selected Date Range **2026-07-21 19:00 to 2026-07-23 02:00**

SET DATE RANGE

DATASET SELECT AND DOWNLOAD

Show LiveDst Verification Plot



Model Run Hour	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●				
Realtime Dst	-17	-17	-20	-25	-32	-33	-19	-14	-13	-23	-27	-18	-14	-12	-18	-14	-7	-15	-21	-15	-11	-8	X	-4	-5				
+1 hr		2	0	-1	9	5	-16	-8	-4	7	2	-7	-2	-9	3	-9	-14	1	2	-2	-2	-2	-6		-2	-8			
+2 hr		13	6	0	5	11	-3	-18	-11	6	7	-5	-4	-2	-10	-3	-17	-11	3	-2	-1	-5	-10	-6		-4	-9		
+3 hr		3	10	3	5	5	-4	-9	-18	-1	7	-4	-10	-8	1	-17	-11	-12	-8	-8	-6	-7	-18	-9	-10		-9	-10	

...vs realtime

Predicted Dst

Neutral density estimate

Machine learning based modeling of thermospheric mass density
Q Pan, C Xiong, H Lühr, A Smirnov, Y Huang… - … **Weather**, 2024 - Wiley Online Library
… see the observations (blue line) show larger values around dawn and dusk hours, which is biased by the orbital coverage but not the real diurnal variation of the **neutral density** at …
Save Cite Cited by 2 Related articles All 3 versions Import into BibTeX

[HTML] Orbit-centered atmospheric density prediction using artificial neural networks
D Pérez, B Wohlberg, TA Lovell, M Shoemaker… - Acta Astronautica, 2014 - Elsevier
… We address the problem of predicting drag/**neutral density** on a given orbit. … very interesting from the point of view of **space weather** and therefore were selected for testing. During 2003 (…
Save Cite Cited by 58 Related articles All 13 versions Import into BibTeX

[PDF] The **machine learning** enabled thermosphere advanced by the high accuracy satellite drag model
K Tobiska, B Bowman, MD Pilinski, P Mehta… - … optical and **space** …, 2021 - amostech.com
… **space weather** forecasting technologies and techniques by providing: i) information for scientific and operational use via new **machine learning** (… The effect of **neutral density** estimation …
Save Cite Cited by 1 Related articles All 3 versions Import into BibTeX

Improved **neutral density** predictions through **machine learning** enabled exospheric temperature model
RJ Licata, PM Mehta, DR Weimer… - **Space Weather**, 2021 - Wiley Online Library
… of locations and **space weather** conditions. Researchers have … as a function of different **space weather** conditions over time. The … **Machine learning** (ML) models tend to be ambiguous in …
Save Cite Cited by 10 Related articles All 13 versions Import into BibTeX

Uncertainty quantification techniques for **space weather** modeling: Thermospheric density application
RJ Licata, PM Mehta - arXiv preprint arXiv:2201.02067, 2022 - arxiv.org
… **Machine learning** (ML) has been applied to **space weather** … **Space weather** originates from solar perturbations and is … The most prominent integration of real-time data for **neutral density** …
Save Cite Cited by 3 Related articles Import into BibTeX

Machine learning-based thermospheric density modelling and estimation for **space** operations
V Nateghi - 2020 - politesi.polimi.it
… **space weather**. These perplexities make such force a primary source of uncertainty in orbit prediction. However, existing atmospheric density models, both empirical and semiempirical, …
Save Cite Cited by 2 Related articles All 2 versions Import into BibTeX

Improving Thermospheric Density Predictions in Low-Earth Orbit With **Machine Learning**
G Acciarini, E Brown, T Berger, M Guhathakurta… - … **Weather**, 2024 - Wiley Online Library
… **Machine learning** (ML) models can significantly outperform existing physics-based thermospheric **neutral density** … due to miscalculations in the predicted **space weather** indices, and the …
Save Cite Related articles All 8 versions Import into BibTeX

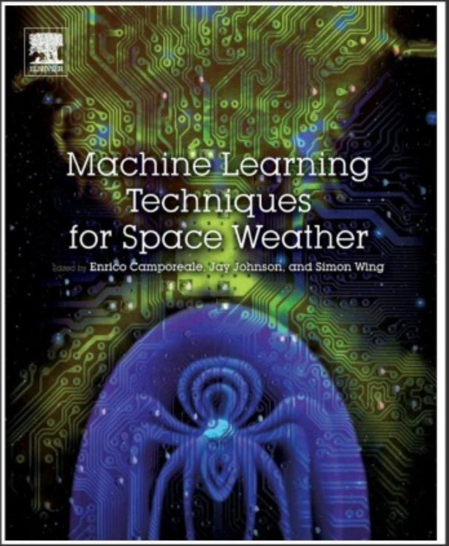
Understanding and Modeling the Dynamics of Storm-time Atmospheric **Neutral Density** using Random Forests
KR Murphy, AJ Halford, V Liu, J Klenzing… - arXiv preprint arXiv …, 2024 - arxiv.org
… In this paper we investigate the dynamics of **neutral density** … Random Forest **machine learning** models of **neutral density**. … storms, periods of extreme **space weather**. Overall this work …
Save Cite Related articles All 4 versions Import into BibTeX

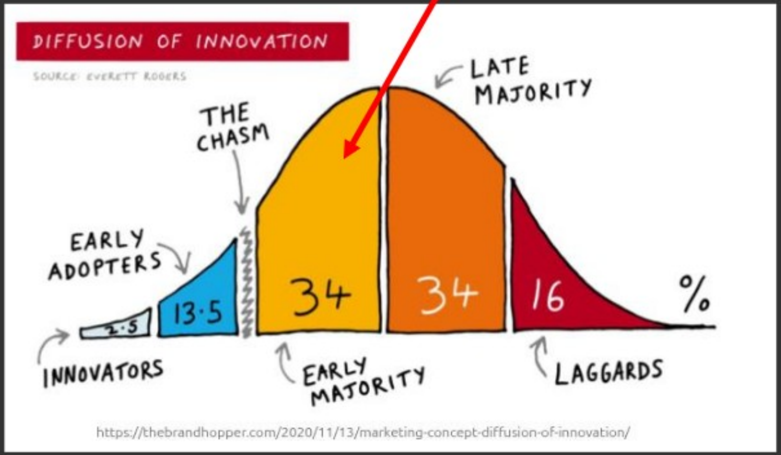
ML in Heliophysics

In the last 10 years or so, Machine Learning has been applied to ANY task in space weather forecasting.

Typically, a ML algorithm claims to be outperforming its physics-based equivalent (in terms of accuracy, computational cost, etc)

We are somewhere here





NG011 - Ten Years of Machine Learning in Heliophysics

Submit an Abstract to this Session

Since its inception, this session has been a focal point for machine learning (ML) in Heliophysics and Space Weather. Now marking its tenth edition, we reflect on progress from early exploration to scientifically grounded applications that enhance physical understanding and predictive capability. We invite contributions spanning deep learning, generative AI, inverse problems, Bayesian methods, uncertainty quantification, and physics-informed ML. Priority will be given to studies that move beyond proof-of-concept and clearly demonstrate how ML advances domain science. We particularly encourage submissions at the intersection of AI and scientific computing, including foundation and generative models in research workflows, agentic AI for autonomous or semi-autonomous discovery, and new integrations of data-driven and physics-based approaches. Contributions on reproducibility, interpretability, and the evolving role of AI are also welcome. This session celebrates a decade of progress while defining the path forward for impactful, scientifically meaningful AI in Heliophysics and Space Weather.

Primary Convener

Enrico Camporeale

University of Colorado, Queen Mary University of London

Conveners

Ryan McGranaghan

Jet Propulsion Laboratory, California Institute of Technology

Jacob Bortnik

University of California Los Angeles

Tomoko Matsuo

University of Colorado Boulder

Why does it work (so well) ?

A short digression

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!**

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%.

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]

Extra resources

- On the myth of analogy with meteorology:

  https://www.youtube.com/watch?v=rHBeM2JPRT0

- 10 ways of using ML:

  https://eos.org/opinions/ten-ways-to-apply-machine-learning-in-earth-and-space-sciences

  - Coming up: 10 ways of using LLMs...

- Timeline of Machine Learning for Space Weather: Past, Present, and Future

  https://prezi.com/view/Ww8VeVqttGqZDRGVrI3n/

(six) Open challenges

Space Weather

FEATURE ARTICLE
10.1029/2018SW002061

GRAND CHALLENGES
CENTENNIAL COLLECTION

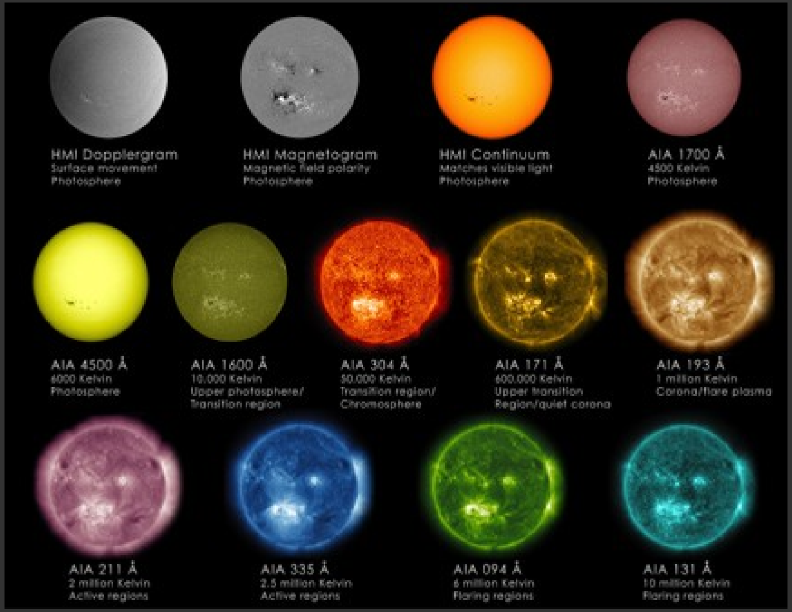
The Challenge of Machine Learning in Space Weather: Nowcasting and Forecasting

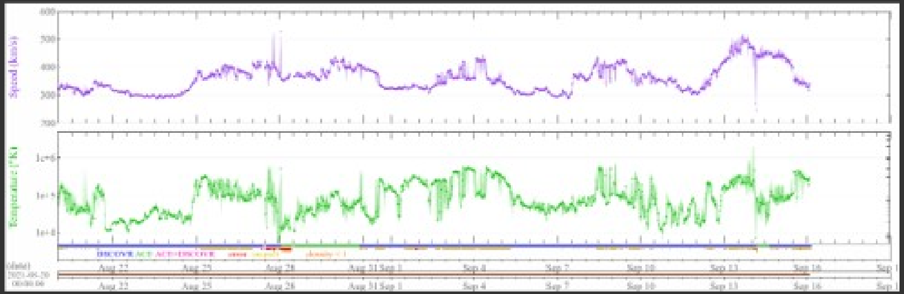
E. Camporeale[1,2]

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

First published: 04 July 2019 | https://doi.org/10.1029/2018SW002061

1) The information problem (aka feature extraction)



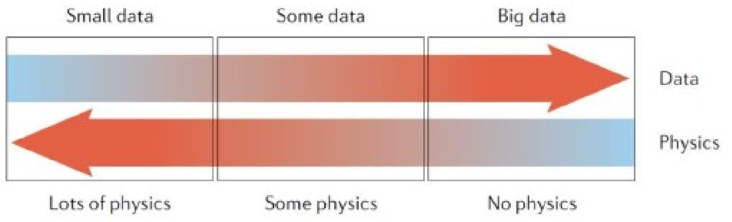


200 M pixels → a few scalar outputs

Paper	Year	Method	Reported performance
Bobra & Couvidat	2015	Support Vector Machine (SVM)	TSS ≈0.75–0.80; FAR ≈30–40%
Liu et al.	2017	Random Forest	TSS ≈0.7–0.8; FAR ≈30–40%
Deep Flare Net (Nishizuka et al.)	2018	Deep Neural Network	TSS ≈0.8; FAR ≈30–40%
Modern deep-learning approaches	2020–2025	CNNs, Transformers, hybrid ML	Typically TSS ≈0.7–0.85; FAR ≈30–50%

200 M pixels → a few scalar outputs

2) The gray-box problem (physics vs data)



Karniadakis, G.E., Kevrekidis, I.G., Lu, L. *et al.* Physics-informed machine learning. *Nat Rev Phys* **3,** 422–440 (2021). https://doi.org/10.1038/s42254-021-00314-5

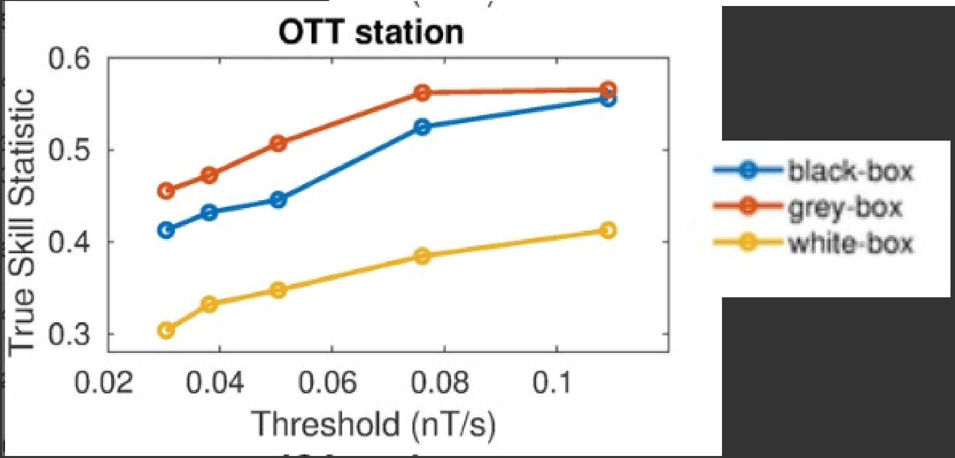
JGR Space Physics

Research Article | Free Access

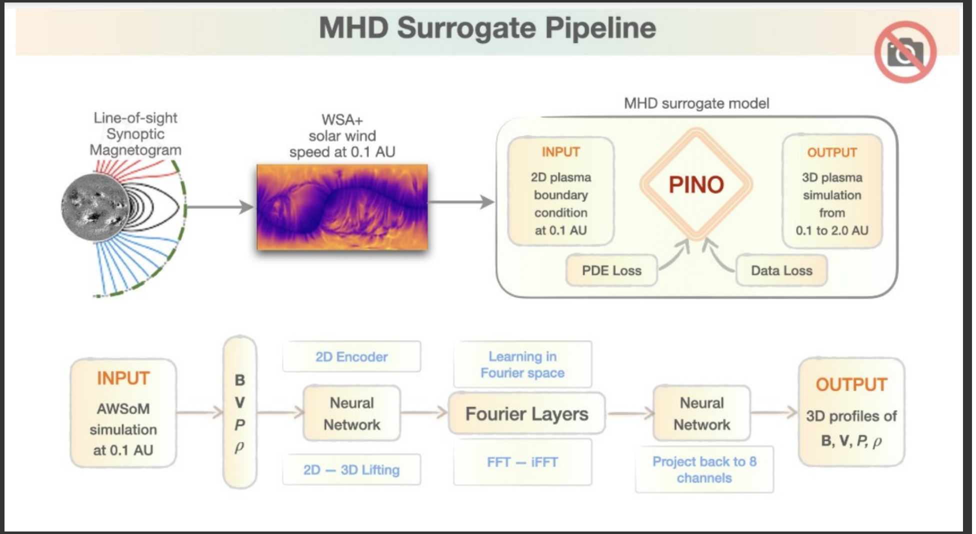
A Gray-Box Model for a Probabilistic Estimate of Regional Ground Magnetic Perturbations: Enhancing the NOAA Operational Geospace Model With Machine Learning

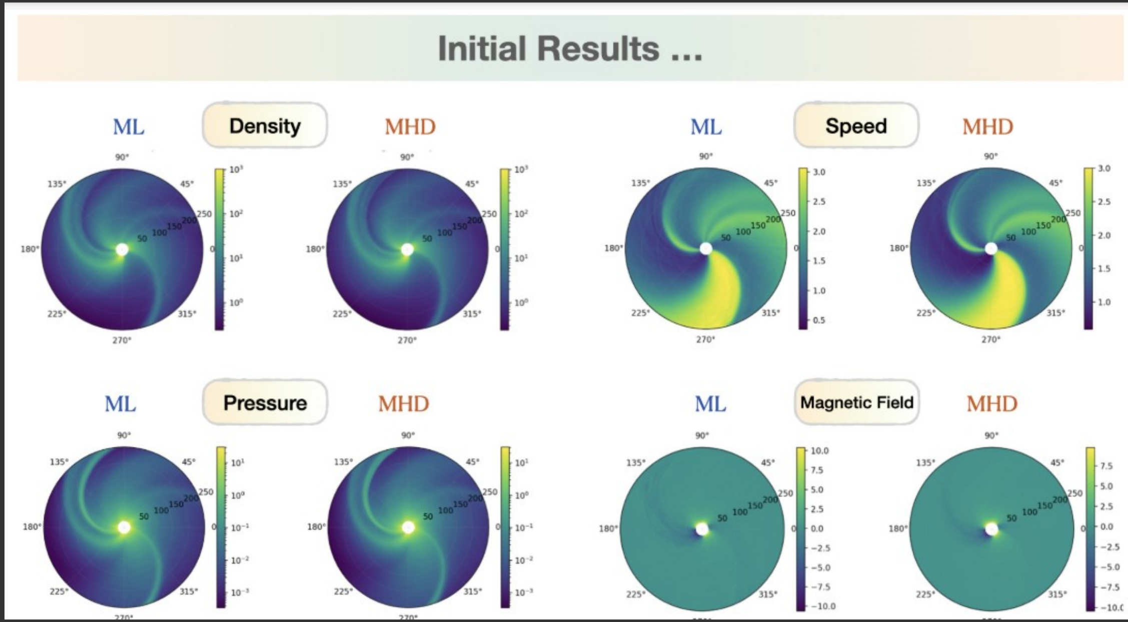
E. Camporeale, M. D. Cash, H. J. Singer, C. C. Balch, Z. Huang, G. Toth

First published: 17 October 2020 | https://doi.org/10.1029/2019JA027684 | VIEW METRICS



3) The surrogate problem





Work by Prateek Mayank (CU Boulder)

4) The knowledge discovery 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?

JGR Space Physics

RESEARCH ARTICLE
10.1029/2022JA030377

Special Section:
Machine Learning in Heliophysics

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

Key Points:

- We analyze the relative importance between drift and diffusion, with

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

Standard model + missing physics

5) The uncertainty problem

(a forecast is not a forecast if it is not probabilistic)

Most Space Weather services provide forecast in terms of single-point predictions. There is a clear need of understanding and assessing the uncertainty associated to these predictions.

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]*

[1]University of Colorado, Boulder, Colorado, USA

[2]University of Brescia, Brescia, Italy

Space Weather

Research Article | Free Access

On the Generation of Probabilistic Forecasts From Deterministic Models

E. Camporeale, X. Chu, O. V. Agapitov, J. Bortnik

First published: 20 February 2019 | https://doi.org/10.1029/2018SW002026 | VIEW METRICS

6) The too often too quiet problem

(aka imbalanced regression:
interesting events < 1% of dataset)

arXiv > stat > arXiv:2512.06950

Statistics > Machine Learning

[Submitted on 7 Dec 2025]

PARIS: Pruning Algorithm via the Representer theorem for Imbalanced Scenarios

Enrico Camporeale

The too often too quiet problem

- Dataset imbalance is rapidly becoming the number one challenge in using data-driven methods (machine learning) in space weather.
  - Examples:

  Solar flare prediction: ratio of days without over with an X flare ~ 40

  Geomagnetic index:

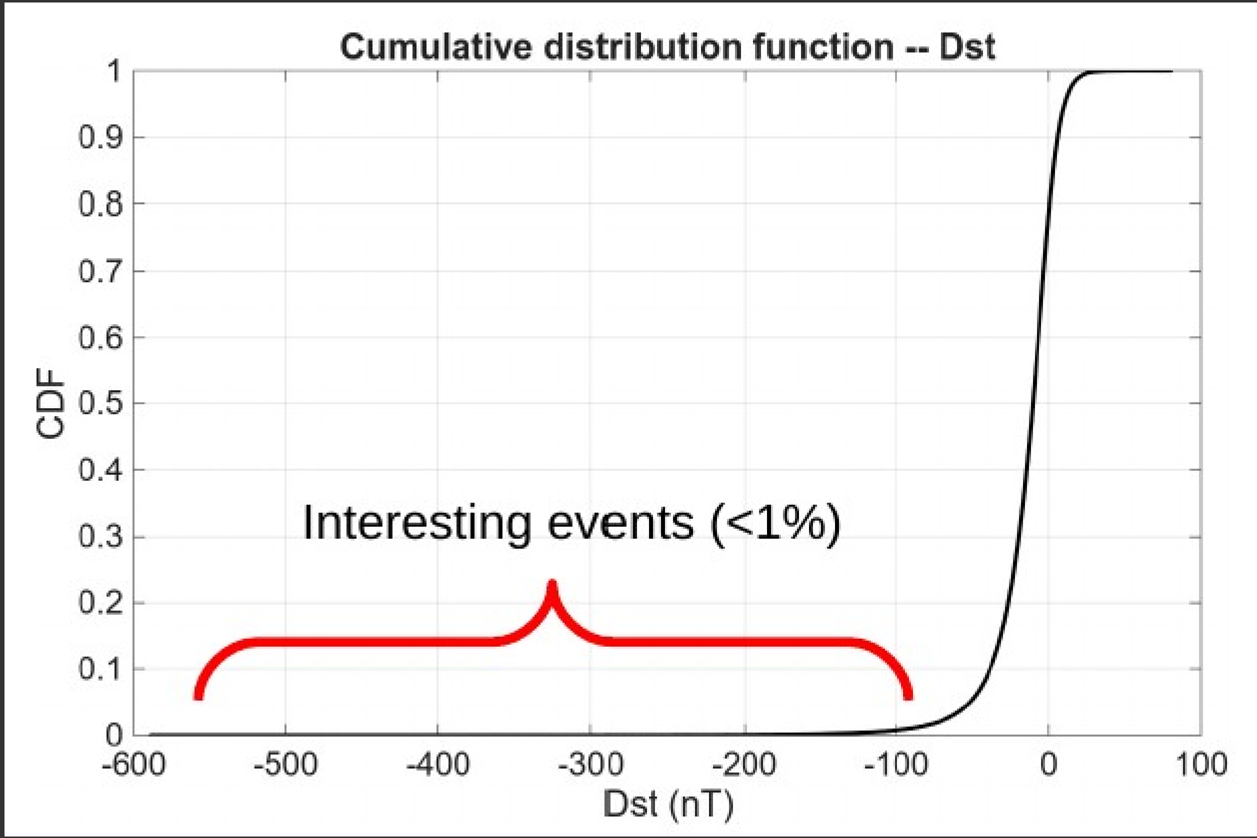
  Dst < -100 nT (0.7%)

  Dst < -200 nT (0.07%)

  Dst < -300 nT (0.01%)

- ALL Regression targets in space weather are skewed
- This imbalance makes standard ML methods under-performing!

The Dst sandbox



ML as an accelerator

- Computing L* in radiation belt simulations

Geosci. Model Dev., 4, 669–675, 2011
www.geosci-model-dev.net/4/669/2011/
doi:10.5194/gmd-4-669-2011

Geoscientific Model Development

LANL* V2.0: global modeling and validation

J. Koller and S. Zaharia

Space Science and Applications, ISR-1, Los Alamos National Lab, Los Alamos, USA

drift path is closed and Φ is adiabatically conserved. A more convenient quantity is L^* (L-star) which is defined as

$$L^* = -\frac{2\,\pi\,k_0}{\Phi\,R_\mathrm{E}}, \tag{1}$$

where k_0 is the Earth's dipole moment, R_E is the radius of the Earth (6370 km) and Φ is defined as

$$\Phi = \int_\mathrm{S} \boldsymbol{B} \cdot \mathrm{d}\,\boldsymbol{S}. \tag{2}$$

In a dipole magnetic field, L^* is the distance from the center of the Earth to the equatorial point of a given field line,

ML as an accelerator

- Accelerate computational tasks within PIC simulations

arXiv > physics > arXiv:2110.12444

Physics > Plasma Physics

[Submitted on 24 Oct 2021]

Machine learning accelerated particle-in-cell plasma simulations

R. Kube, R.M. Churchill, B. Sturdevant

Precondition GMRES solver

J. Plasma Phys. (2022), *vol.* 88, 895880602 © The Author(s), 2022.
Published by Cambridge University Press
doi:10.1017/S0022377822001180

Machine-learning-based models in particle-in-cell codes for advanced physics extensions

Chiara Badiali[1,†,‡], Pablo J. Bilbao[1,‡], Fábio Cruz[1,2] and Luís O. Silva[1,†]

Estimate Compton scattering

2021 IEEE International Conference on Cluster Computing (CLUSTER)

A Deep Learning-Based Particle-in-Cell Method for Plasma Simulations

Xavier Aguilar, Stefano Markidis
Electrical Engineering and Computer Science School
KTH Royal Institute of Technology
Stockholm, Sweden

Calculate electric field from particle phase space

ML as an accelerator

- High-order statistics-informed NN (H-SiNN) for dimensionality reduction

Physics of Fluids ARTICLE pubs.aip.org/aip/pof

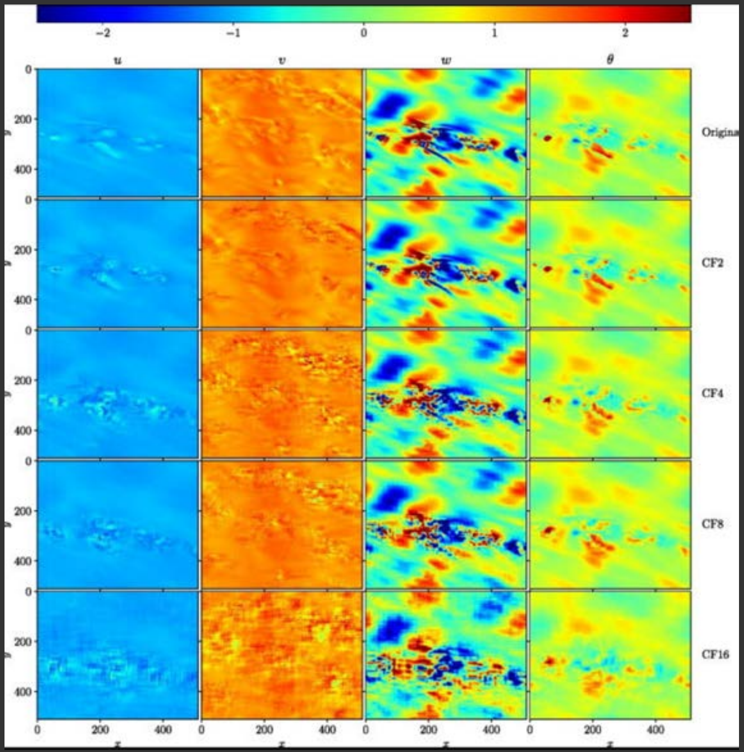
Low-dimensional representation of intermittent geophysical turbulence with high-order statistics-informed neural networks (H-SiNN)

Cite as: Phys. Fluids 36, 026607 (2024); doi: 10.1063/5.0179132
Submitted: 29 September 2023 · Accepted: 13 January 2024 ·
Published Online: 8 February 2024

View Online Export Citation CrossMark

R. Foldes,[1,2,a)] E. Camporeale,[3,4] and R. Marino[1]

$$
\begin{aligned}
\mathcal{L}(y,\tilde{y}) = \frac{1}{D}\Bigg(& W_1 \sum_{y}^{[u,v,w,\theta]} \sum_{i=1}^{M} \frac{(y_i-\tilde{y}_i)^2}{M} + W_2 \sum_{i=1}^{M} \frac{(\sigma_{w_i}-\sigma_{\tilde{w}_i})^2}{M} \\
& + W_3 \sum_{i=1}^{M} \frac{(Sk_{w_i}-Sk_{\tilde{w}_i})^2}{M} + W_4 \sum_{i=1}^{M} \frac{(K_{w_i}-K_{\tilde{w}_i})^2}{M} \Bigg) \\
= \frac{1}{D} & \sum_{j=1}^{4} W_j R_j
\end{aligned}
$$



A recent (2021) breakthrough: from function approximation to functionAL approximation

ARTICLES

https://doi.org/10.1038/s42256-021-00302-5

nature machine intelligence

Check for updates

Learning nonlinear operators via DeepONet based on the universal approximation theorem of operators

Lu Lu[1], Pengzhan Jin[2,3], Guofei Pang[2], Zhongqiang Zhang[4] and George Em Karniadakis[2] ✉

~1800 citations

Computer Science > Machine Learning

[Submitted on 18 Oct 2020 (v1), last revised 17 May 2021 (this version, v3)]

Fourier Neural Operator for Parametric Partial Differential Equations

Zongyi Li, Nikola Kovachki, Kamyar Azizzadenesheli, Burigede Liu, Kaushik Bhattacharya, Andrew Stuart, Anima Anandkumar

The classical development of neural networks has primarily focused on learning mappings between finite-dimensional Euclidean spaces. Recently, this has been generalized to neural operators that learn mappings between function spaces. For partial differential equations (PDEs), neural operators directly learn the mapping from any functional parametric dependence to the solution. Thus, they learn an entire family of PDEs, in contrast to classical methods which solve one instance of the equation. In this work, we formulate a new neural operator by parameterizing the integral kernel directly in Fourier space, allowing for an expressive and efficient architecture. We perform experiments on Burgers' equation, Darcy flow, and Navier-Stokes equation. The Fourier neural operator is the first ML-based method to successfully model turbulent flows with zero-shot super-resolution. It is up to three orders of magnitude faster compared to traditional PDE solvers. Additionally, it achieves superior accuracy compared to previous learning-based solvers under fixed resolution.

2200+ citations

A recent (2021) breakthrough: from function approximation to functionAL approximation

5.4 ZERO-SHOT SUPER-RESOLUTION.

The neural operator is mesh-invariant, so it can be trained on a lower resolution and evaluated at a higher resolution, without seeing any higher resolution data (zero-shot super-resolution). Figure 1 shows an example where we train the FNO-3D model on $64 \times 64 \times 20$ resolution data in the setting above with ($\nu = 1\mathrm{e}{-4}, N = 10000$) and transfer to $256 \times 256 \times 80$ resolution, demonstrating super-resolution in space-time. Fourier neural operator is the only model among the benchmarks (FNO-2D, U-Net, TF-Net, and ResNet) that can do zero-shot super-resolution. And surprisingly, it can do super-resolution not only in the spatial domain but also in the temporal domain.

Computer Science > Machine Learning

[Submitted on 18 Oct 2020 (v1), last revised 17 May 2021 (this version, v3)]

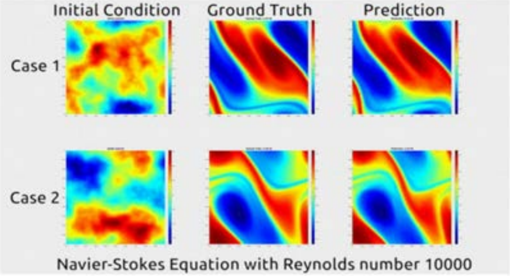
Fourier Neural Operator for Parametric Partial Differential Equations

Zongyi Li, Nikola Kovachki, Kamyar Azizzadenesheli, Burigede Liu, Kaushik Bhattacharya, Andrew Stuart, Anima Anandkumar

The classical development of neural networks has primarily focused on learning mappings between finite-dimensional Euclidean spaces. Recently, this has been generalized to neural operators that
between function spaces. For partial differential equations (PDEs), neural operators directly learn the mapping from any functional parametric dependence to the solution. Thus, they learn an entire
contrast to classical methods which solve one instance of the equation. In this work, we formulate a new neural operator by parameterizing the integral kernel directly in Fourier space, allowing for a
efficient architecture. We perform experiments on Burgers' equation, Darcy flow, and Navier-Stokes equation. The Fourier neural operator is the first ML-based method to successfully model turbule
shot super-resolution. It is up to three orders of magnitude faster compared to traditional PDE solvers. Additionally, it achieves superior accuracy compared to previous learning-based solvers under

MIT Technology Review

Featured Topics Newsletters



The paper has gotten a lot of buzz on Twitter, and even a shout-out from rapper MC Hammer. Yes, really.

MHD solar wind surrogate

AGU25 WHERE SCIENCE CONNECTS US

NG11A-02
Next-Generation MHD Modeling Of Solar Wind Plasma Using Neural Operators

Prateek Mayank, *SWx TREC, University of Colorado, Boulder, Boulder, United States, Enrico Camporeale, University of Colorado, Queen Mary University of London, Boulder, United States, Zhenguang Huang, Climate and Space Science and Engineering, Ann Arbor, United States and Gabor Toth, University of Michigan, Climate and Space Sciences and Engineering, Ann Arbor, United States*

Abstract

Monday, 15 December 2025

08:45 - 09:00

298-299 (MCCNO)

WSA+ Neural Optimizer

THE ASTROPHYSICAL JOURNAL LETTERS, 994:L5 (8pp), 2025 November 20 https://doi.org/10.3847/2041-8213/ae1735

Neural Enhancement of the Traditional Wang–Sheeley–Arge Solar Wind Relation

Prateek Mayank[1,2], Enrico Camporeale[1,3], Arpit K. Shrivastav[4], Thomas E. Berger[1,5], and Charles N. Arge[6]
[1] Space Weather TREC, University of Colorado, Boulder, CO 80303, USA; pmayank@ucar.edu
[2] University Corporation for Atmospheric Research, CPAESS, Boulder, CO 80301, USA
[3] School of Physical and Chemical Sciences, Queen Mary University of London, London E1 4NS, UK
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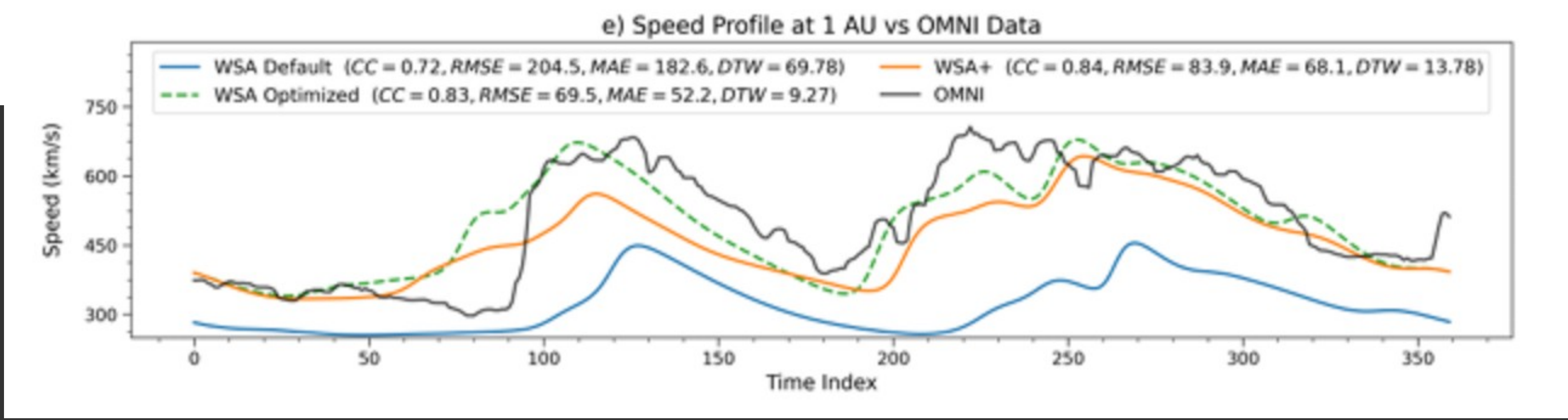


MHD (turbulence) surrogate

MACHINE LEARNING
Science and Technology

PAPER • OPEN ACCESS

Magnetohydrodynamics with physics informed neural operators

Shawn G Rosofsky[1,2,3] and E A Huerta[5,1,2,4]

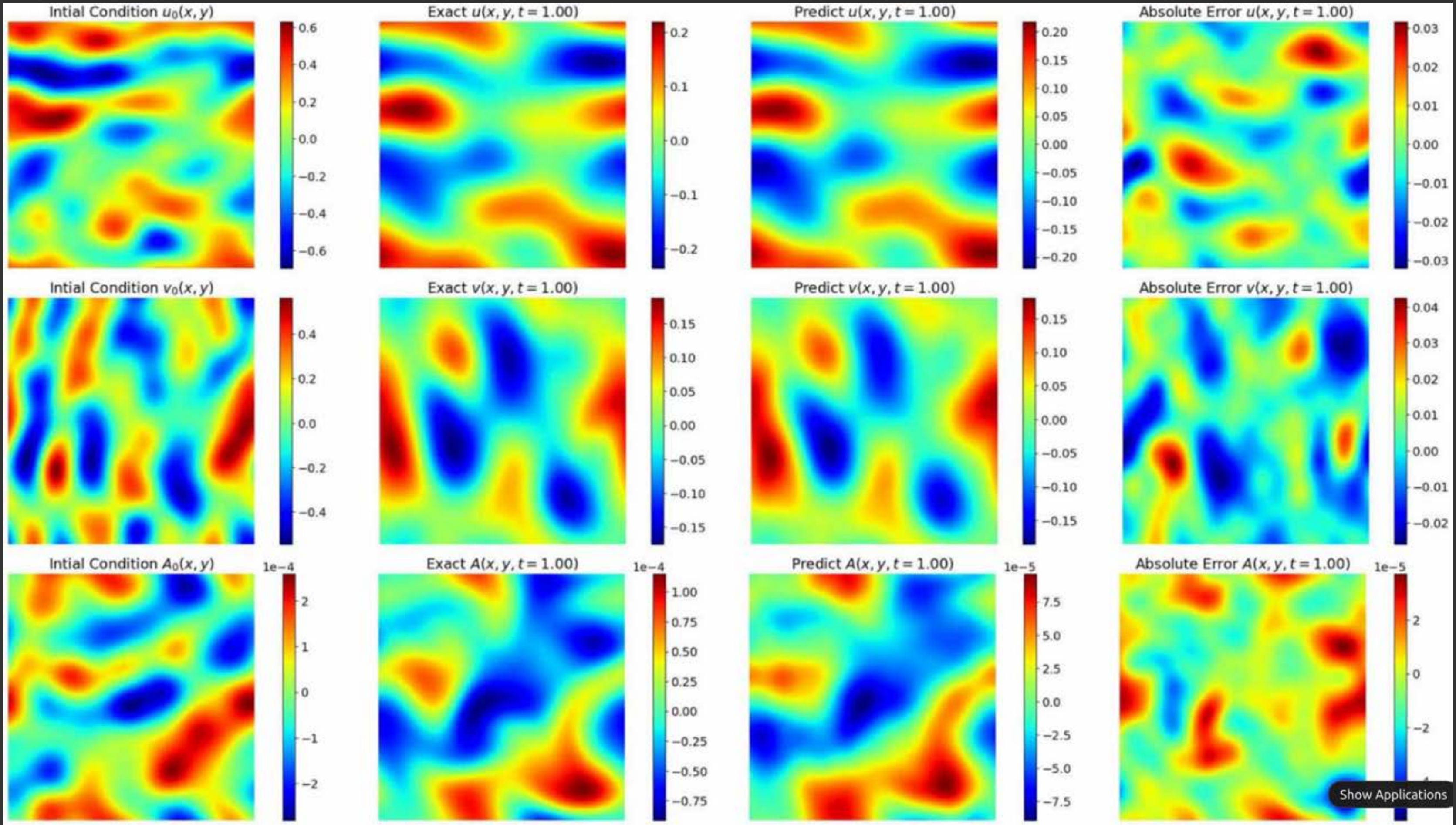
Published 6 July 2023 •

Machine Learning: Science and Technology, Volume 4, Number 3

Citation Shawn G Rosofsky and E A Huerta 2023 *Mach. Learn.: Sci. Technol.* **4** 035002

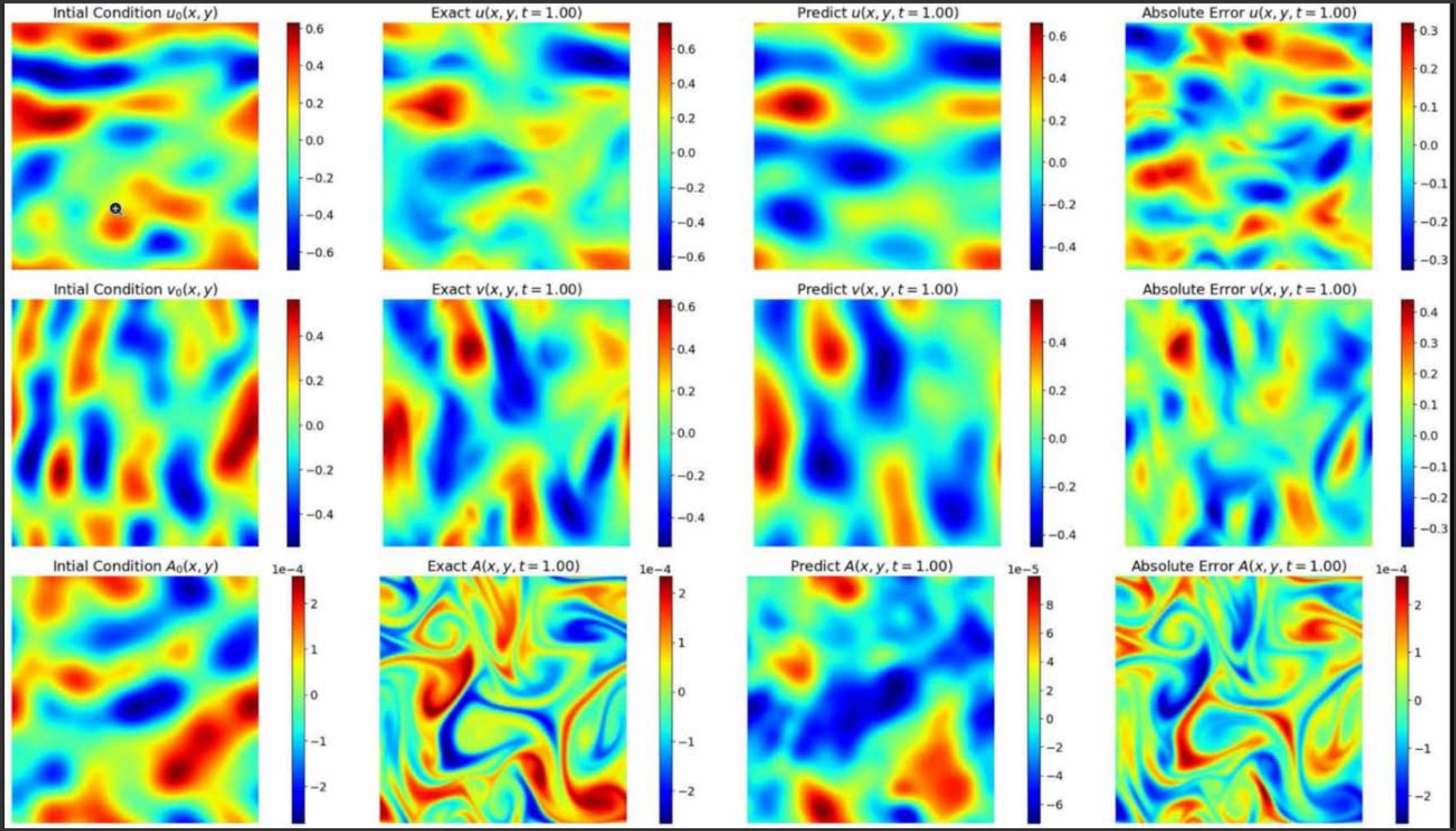
DOI 10.1088/2632-2153/ace30a

MHD (turbulence) surrogate



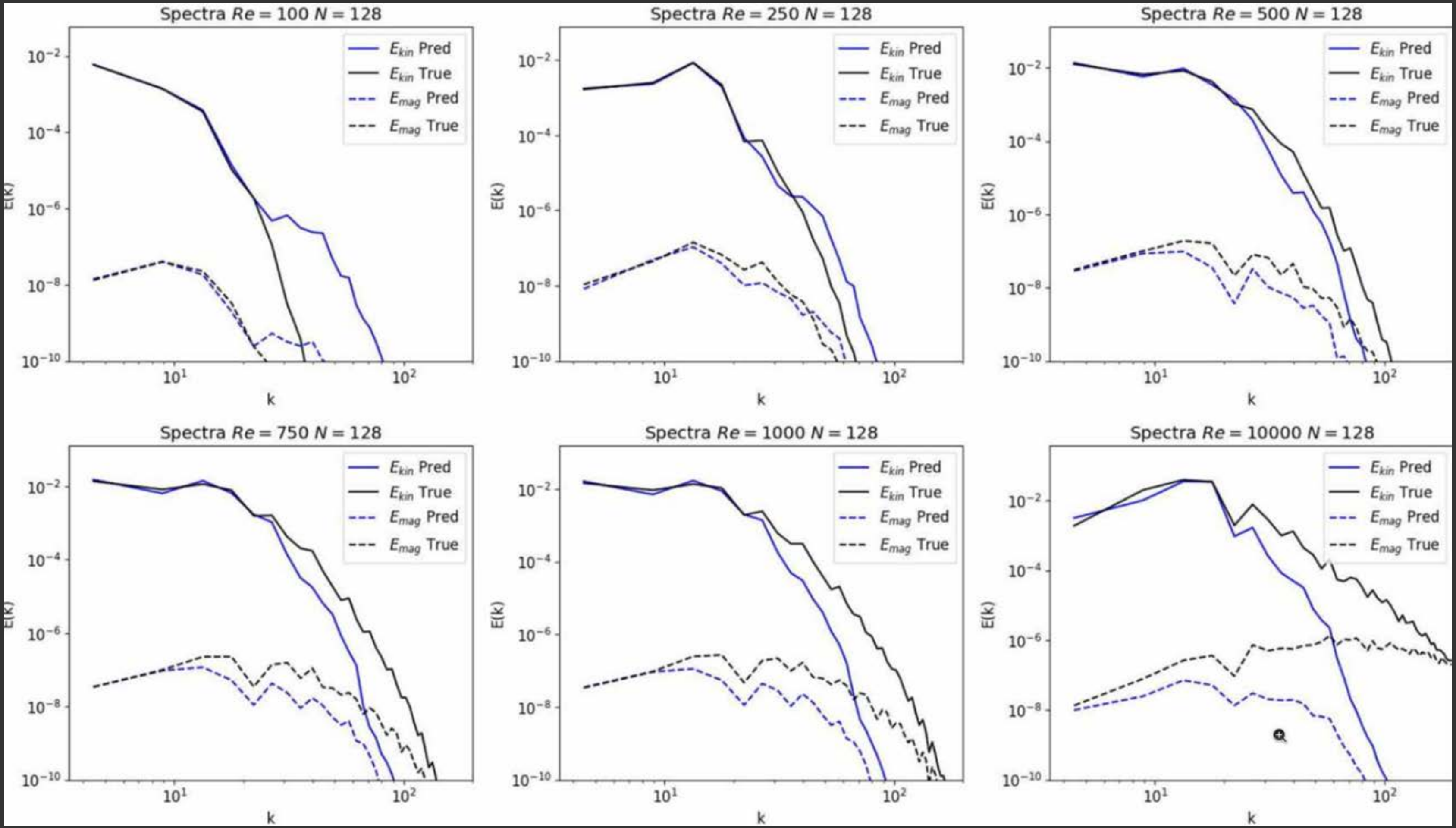
Low Re

MHD (turbulence) surrogate



High Re

MHD (turbulence) surrogate



Discovering new physics

- Symbolic regression (SINDy, Weak SINDy, etc.)
- Physics-informed Neural Networks

Discovering new physics: closure problem

RESEARCH ARTICLE | JULY 22 2020

Neural network representability of fully ionized plasma fluid model closures FREE

Romit Maulik; Nathan A. Garland; Joshua W. Burby; Xian-Zhu Tang; Prasanna Balaprakash

Check for updates

+ Author & Article Information

Phys. Plasmas 27, 072106 (2020)

RESEARCH ARTICLE | APRIL 01 2020

Machine learning surrogate models for Landau fluid closure FREE

Chenhao Ma; Ben Zhu; Xue-Qiao Xu; Weixing Wang

Check for updates

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Phys. Plasmas 27, 042502 (2020)

Discovering new physics: closure problem

RESEARCH ARTICLE | JULY 22 2020

Neural network representability of fully ionized plasma fluid model closures FREE

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Check for updates

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Phys. Plasmas 27, 0

RESEARCH ARTICLE | APRIL 01 2020

ure

Journal of Plasma Physics

The machine learning approach to moment closure relations for plasma: a review

Published online by Cambridge University Press: 21 July 2026

Samuel Burles and Enrico Camporeale

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Discovering new physics:
Electron transport in Radiation Belts

JGR Space Physics

Research Article | Free Access

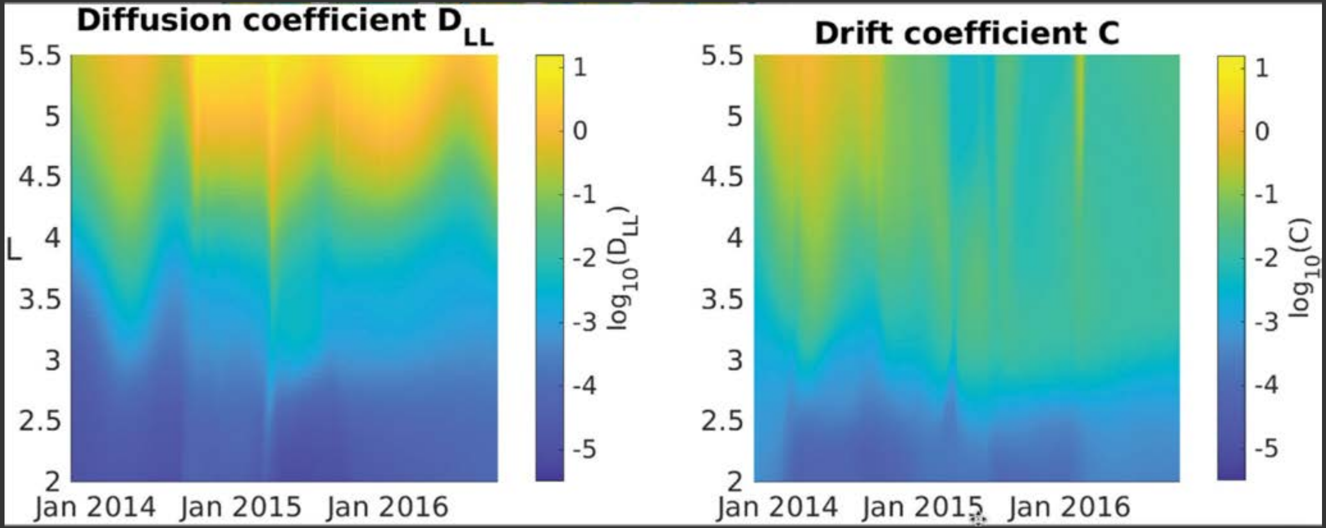
Data-Driven Discovery of Fokker-Planck Equation for the Earth's Radiation Belts Electrons Using Physics-Informed Neural Networks

E. Camporeale, George J. Wilkie, Alexander Y. Drozdov, Jacob Bortnik

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

Discovering new physics: Electron transport in Radiation Belts

- After solving the inverse problem



PINN is the only method that can solve a general inverse problem (no a-priori paramerization for unknown coefficients...)

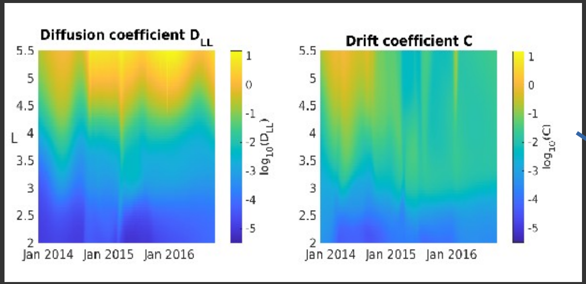
Parameter estimation pipeline

Assumption:
The physics obeys FP equation

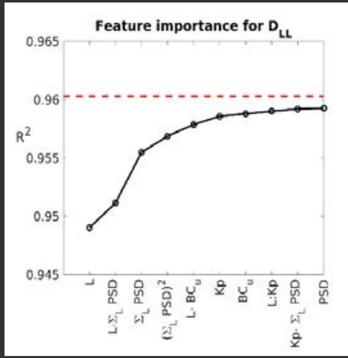
$$\frac{\partial f(L,t)}{\partial t} = L^2 \frac{\partial}{\partial L}\left(\frac{D_{LL}}{L^2}\frac{\partial f(L,t)}{\partial L}\right) - \frac{\partial C f(L,t)}{\partial L},$$

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!

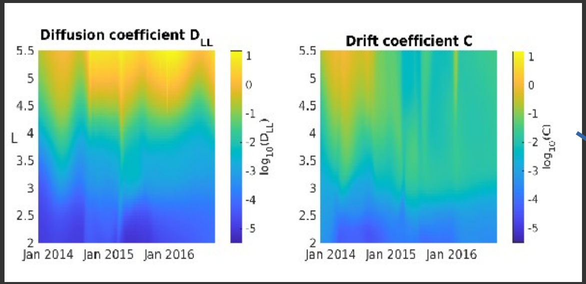
The final frontier: Interpretable AI

Assumption:
The physics obeys FP equation

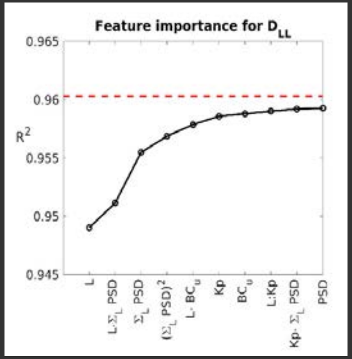
$$\frac{\partial f(L,t)}{\partial t} = L^2 \frac{\partial}{\partial L}\left(\frac{D_{LL}}{L^2}\frac{\partial f(L,t)}{\partial L}\right) - \frac{\partial C f(L,t)}{\partial L},$$

PINN

Optimal coefficients

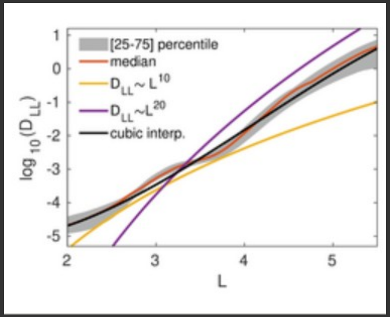


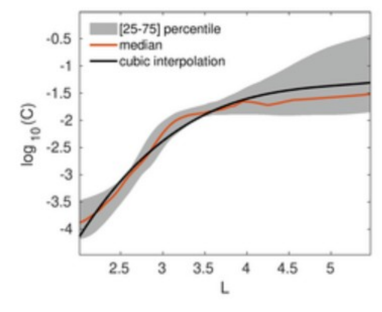
Feature selection



~~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

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

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

Automatic Event Identification

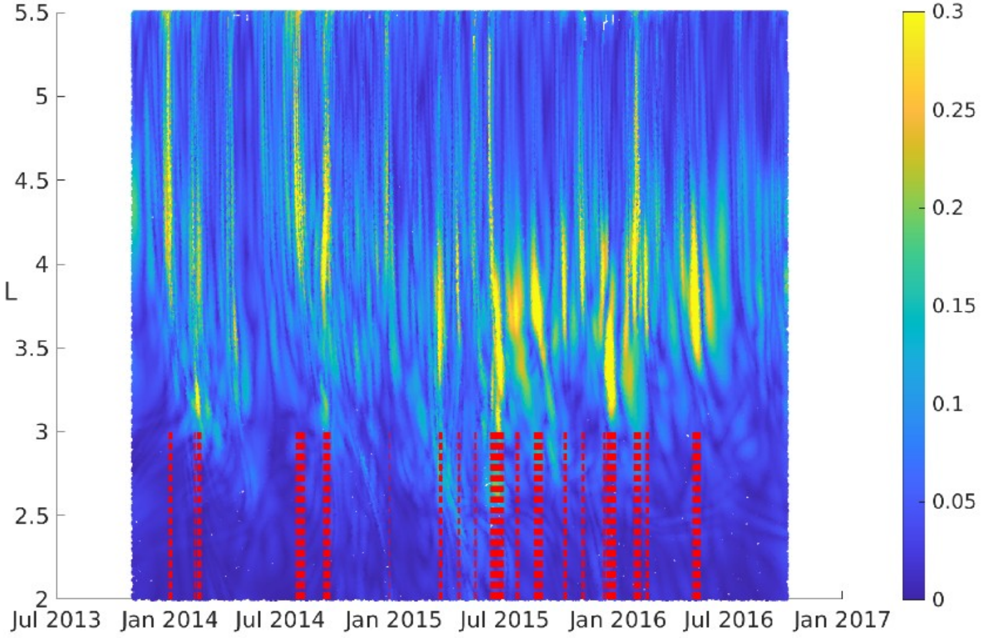


Figure 16. Heat map of the residual of Eq.(4), normalized on its maximum value, over the training set. The red dashed lines denotes time at which the value of the residual is in the 99 percentile of its distribution.

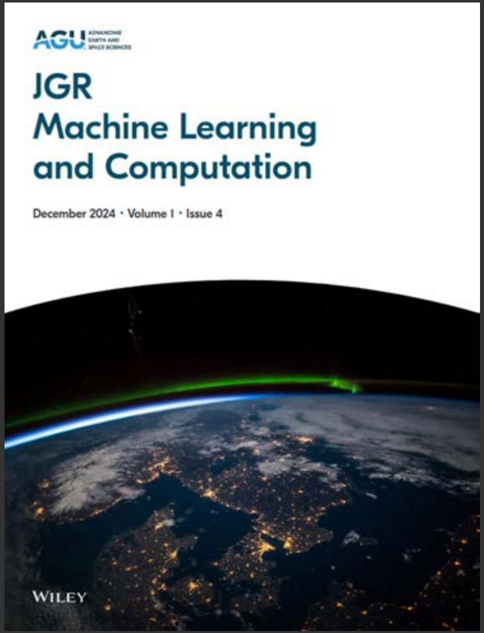
Start time	End time	Previously studied in the literature?
30-Dec-2013	04-Jan-2014	CIR-associated storm (Shen et al., 2017)
10-Feb-2014	10-Feb-2014	
14-Feb-2014	20-Feb-2014	Geomagnetic storm due to multiple interacting ICMEs
		(Kilpua et al., 2019; Vlasova et al., 2020)
25-Jul-2014	7-Aug-2014	
08-Sep-2014	18-Sep-2014	Dropout event
		(Ozeke et al., 2017; Alves et al., 2016; Jaynes et al., 2015b; Ma et al., 2020)
24-Dec-2014	24-Dec-2014	
15-Mar-2015	20-Mar-2015	CME-associated storm
		(Shen et al., 2017; Baker et al., 2016)
15-Apr-2015	17-Apr-2015	
12-May-2015	14-May-2015	CIR-associated storm (Shen et al., 2017)
07-Jun-2015	28-Jun-2015	CIR and CME-associated storms(Shen et al., 2017; Baker et al., 2016);
		Moderate event(Reeves et al., 2020);
		Sudden Particle Enhancements at Low L Shells(Turner et al., 2017)
19-Jul-2015	23-Jul-2015	Sudden Particle Enhancements at Low L Shells (Turner et al., 2017)
17-Aug-2015	31-Aug-2015	Moderate event(Reeves et al., 2020)
05-Oct-2015	09-Oct-2015	Moderate event(Reeves et al., 2020)
03-Nov-2015	06-Nov-2015	
08-Dec-2015	11-Dec-2015	
14-Dec-2015	28-Dec-2015	Moderate and strong storms
		(Boyd et al., 2018b; L.-F. Li et al., 2020; Sotnikov et al., 2019)
27-Jan-2016	07-Feb-2016	Dropout event (Wu et al., 2020)
15-Feb-2016	19-Feb-2016	Moderate event(Reeves et al., 2020); Fast magnetosonic waves(Yu et al., 2021)
01-May-2016	14-May-2016	Moderate event(Reeves et al., 2020; Moya et al., 2017)

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*



Enrico.camporeale@qmul.ac.uk

Extra slides

The engines under the hood at U. Colorado (SWx-TREC)

- ACCRUE (ACCurate and Reliable Uncertainty Estimate)
  - A forecast is not a forecast if it is not probabilistic!
  - Ref: Camporeale, E., & Carè, A. (2021). ACCRUE: Accurate and reliable uncertainty estimate in deterministic models. *International Journal for Uncertainty Quantification*, 11(4).

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

ACCRUE: ACCURATE AND RELIABLE UNCERTAINTY ESTIMATE IN DETERMINISTIC MODELS

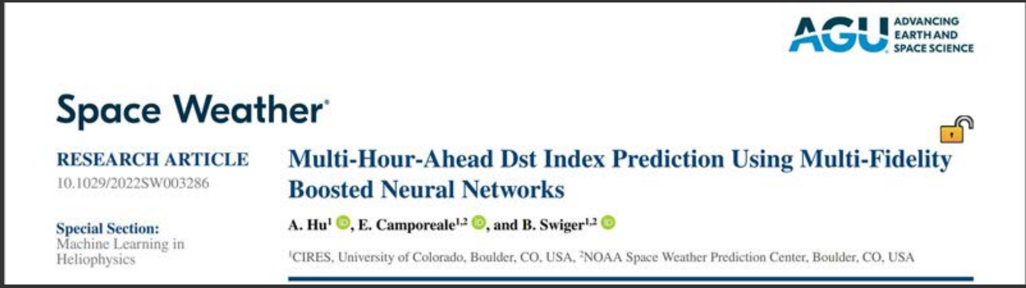
Enrico Camporeale[1,] & Algo Carè[2]*

[1]*University of Colorado, Boulder, Colorado, USA*

[2]*University of Brescia, Brescia, Italy*

*Address all correspondence to: Enrico Camporeale, University of Colorado, Boulder, Colorado, USA, E-mail: enrico.camporeale@colorado.gov

- ProBoost (Probabilistic Boosting)
  - Ref: in preparation!



AGU ADVANCING EARTH AND SPACE SCIENCE

Space Weather

RESEARCH ARTICLE

10.1029/2022SW003286

Special Section:
Machine Learning in Heliophysics

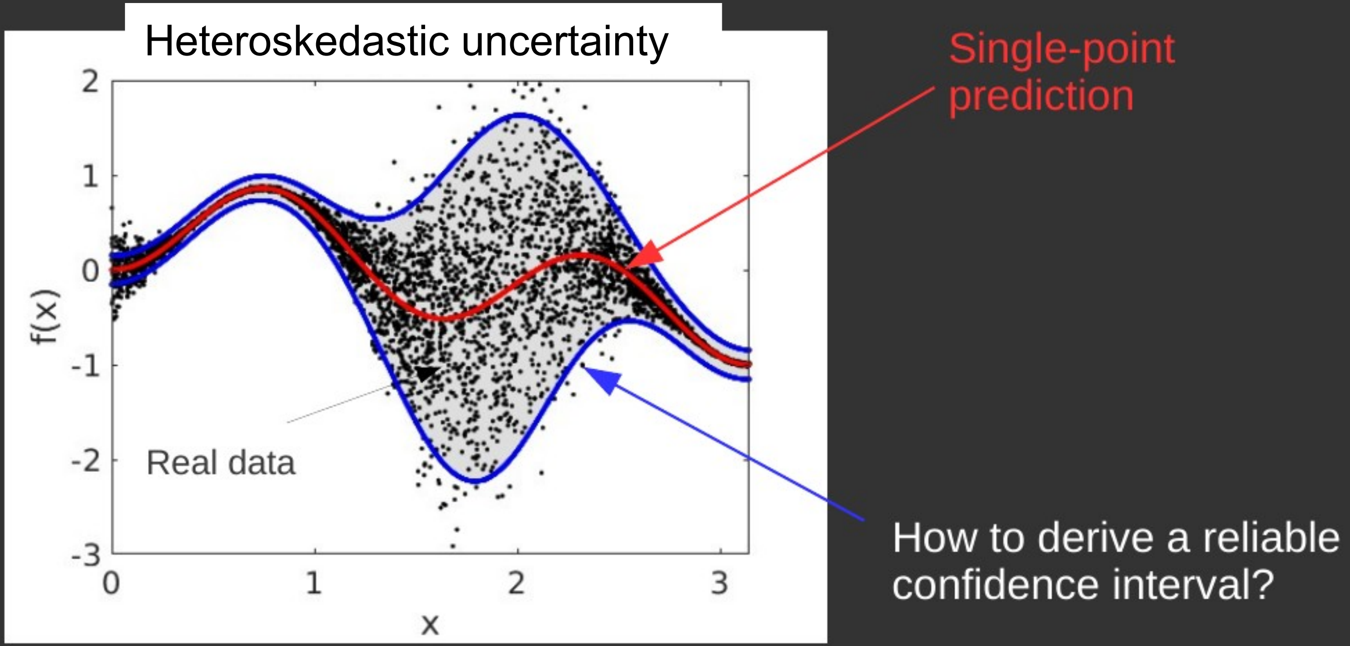
Multi-Hour-Ahead Dst Index Prediction Using Multi-Fidelity Boosted Neural Networks

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

[1]CIRES, University of Colorado, Boulder, CO, USA, [2]NOAA Space Weather Prediction Center, Boulder, CO, USA

ACCRUE: Accurate and Reliable Uncertainty Estimate

How to estimate the uncertainty of a deterministic model?



ACCRUE:
Accurate and Reliable Uncertainty Estimate

How to estimate the uncertainty of a deterministic model?

Given a deterministic model that produces a scalar output μ for a given input

Given the true values (noiseless observations)

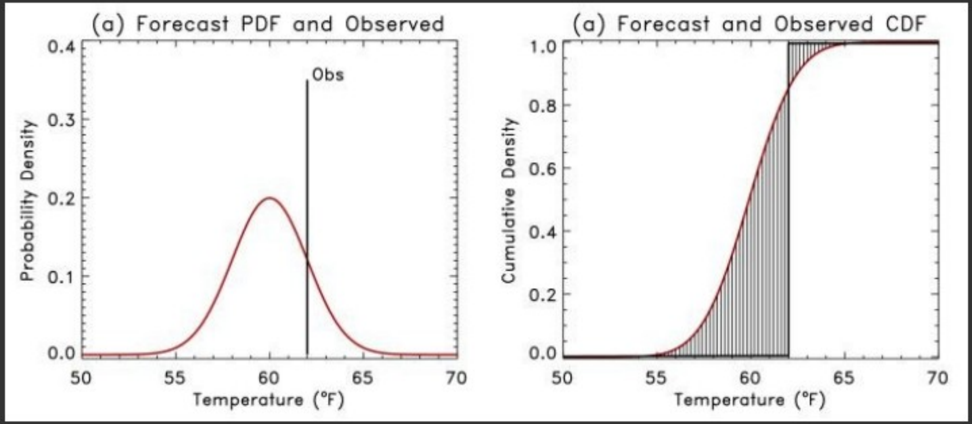
We want to produce a probabilistic forecast in terms of **Gaussian** probability density with mean μ and unknown variance.

How do we define the "optimal" variance?
We want it to be accurate and reliable

Continuous Rank Probability Score (probabilistic forecast of continuous variables)

$$\mathrm{CRPS} = \int_{-\infty}^{\infty} \left[P(y) - H(y - y^o)\right]^2 dy \qquad (1)$$

where $P(y)$ is the cumulative distribution (cdf) of the fore-cast, $H(y)$ is the Heaviside function, and y^o is the true (observed) value of the forecasted variable. CRPS is a



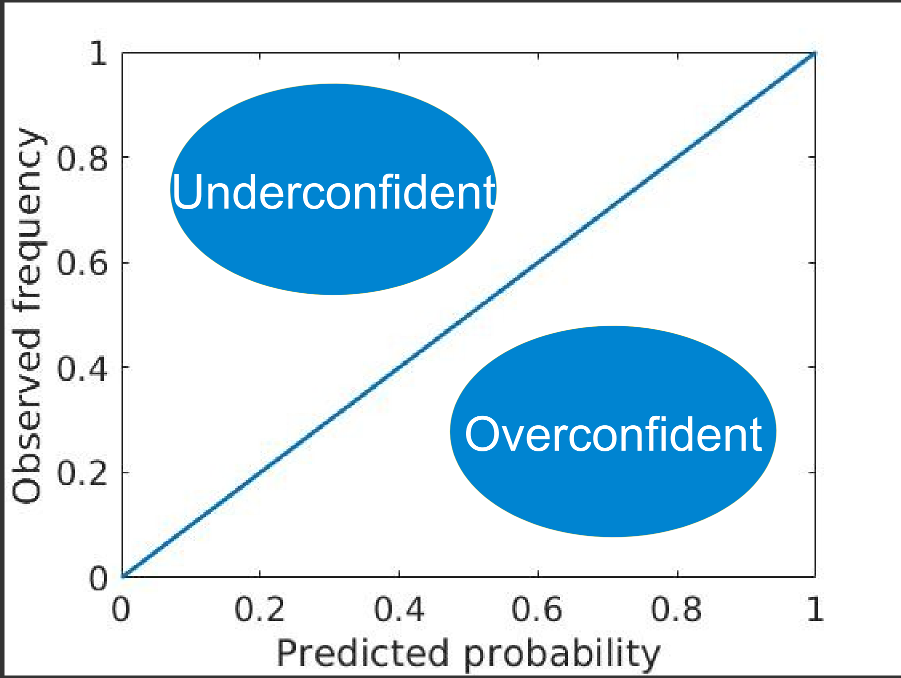
Closed form for Gaussians

Becomes the Mean Absolute Error for sigma -> 0

Reliability diagram

Reliability is the property of a probabilistic model that measures its **statistical consistency with observations.**

For example, for forecasts of discrete events, the reliability measures if an event occurs on average with frequency *p*, when it has been predicted to occur with probability *p*.



Two-objective optimization problem

Accuracy and reliability are competing objectives!

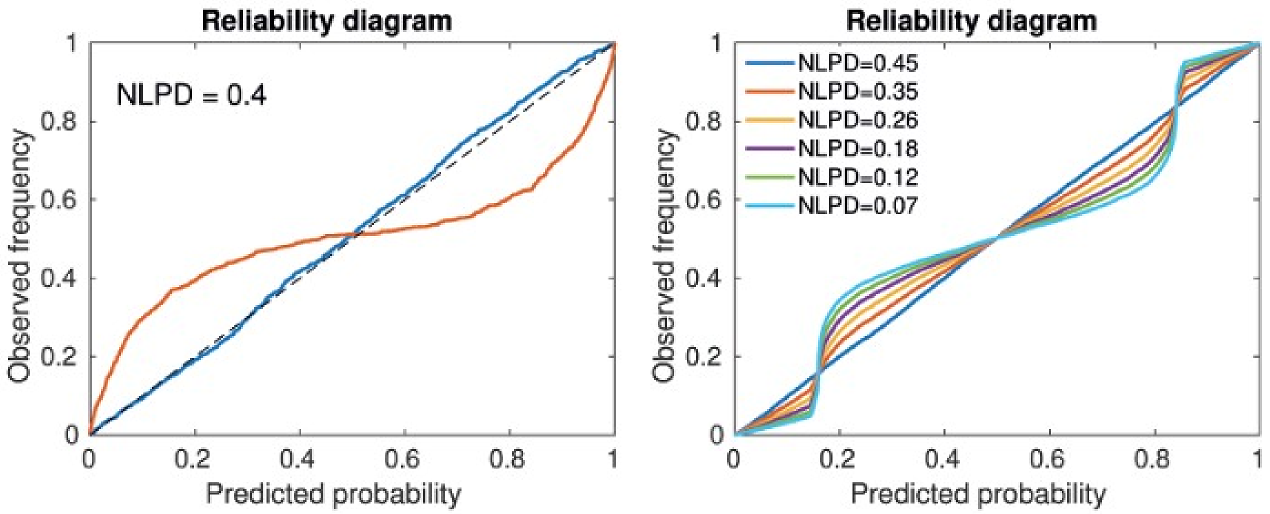


FIG. 2: Left: example of two models with identical value of NLPD = 0.4, and different reliability diagram. Right: Example of several models for which the NLPD decreases (from NLPD = 0.45 for the blue line to NLPD = 0.07 for the cyan line), at the expense of reliability. See text for details of how the synthetic data has been generated. Figures published online in color.

ACCRUE algorithm

- The optimal Gaussian width (sdt) is the one that optimizes both accuracy and reliability.
- This is a two-objective optimization problem, because reliability and accuracy are competing objectives.
- We define the Accuracy-Reliability (AR) cost function:

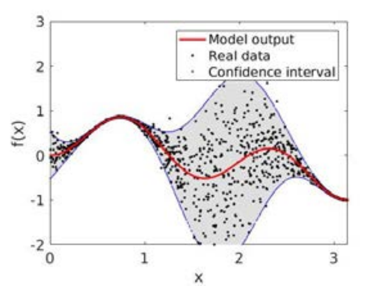
$$AR = CRPS + RS$$

- Accuracy and Reliability cannot both be minimized simultaneously and we have to find the best trade-off
- The minimization problem can be solved in a number of ways

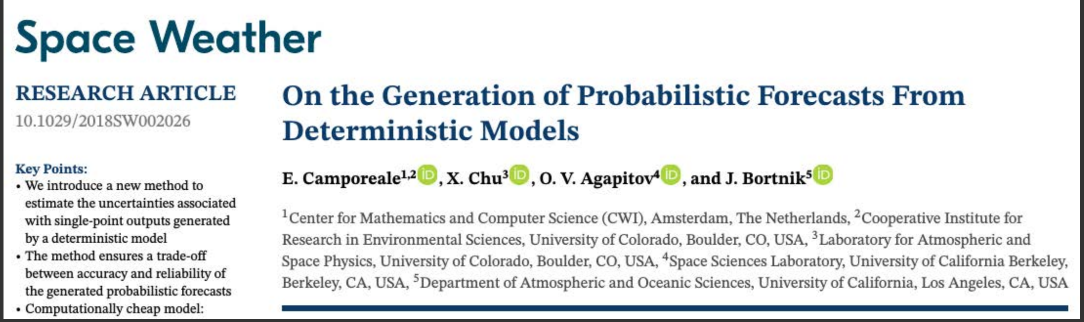
In multiple dimensions, a deep neural network works well to minimize the cost function

ACCRUE model

Deterministic model → **ACCRUE** → Probabilistic model



A-posteriori UQ estimate of a deterministic model (enforcing accuracy and reliability)


Space Weather

RESEARCH ARTICLE

10.1029/2018SW002026

Key Points:
- We introduce a new method to estimate the uncertainties associated with single-point outputs generated by a deterministic model
- The method ensures a trade-off between accuracy and reliability of the generated probabilistic forecasts
- Computationally cheap model:

On the Generation of Probabilistic Forecasts From Deterministic Models

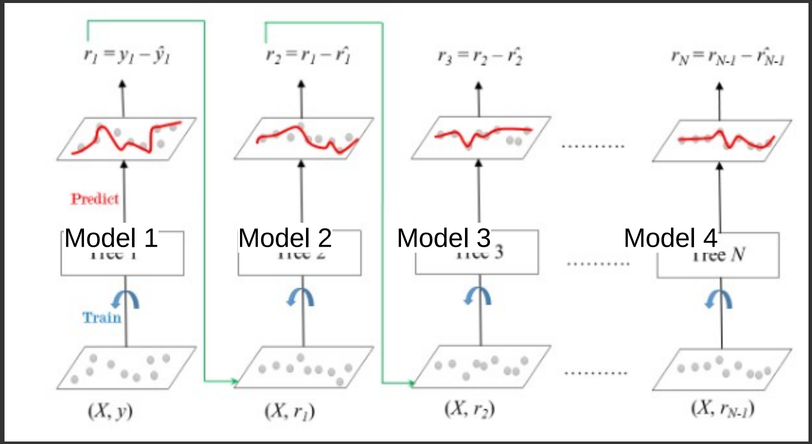
E. Camporeale[1,2], X. Chu[3], O. V. Agapitov[4], and J. Bortnik[5]

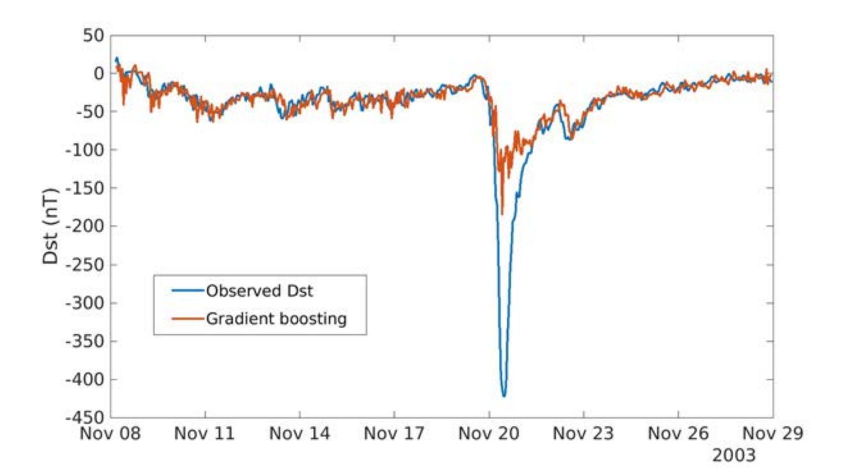
[1]Center for Mathematics and Computer Science (CWI), Amsterdam, The Netherlands, [2]Cooperative Institute for Research in Environmental Sciences, University of Colorado, Boulder, CO, USA, [3]Laboratory for Atmospheric and Space Physics, University of Colorado, Boulder, CO, USA, [4]Space Sciences Laboratory, University of California Berkeley, Berkeley, CA, USA, [5]Department of Atmospheric and Oceanic Sciences, University of California, Los Angeles, CA, USA

- No need to run ensembles
- Plug-and-play
- Code available on https://zenodo.org/record/1485608

Gradient Boosting in one slide

- A hierarchy of models is built
- Each model is trained on the errors of the previous one
- The final model is an additive combination of all sub-models
- One of the strongest algorithm
  - But it under-performs on imbalanced datasets





ProBoost in one slide

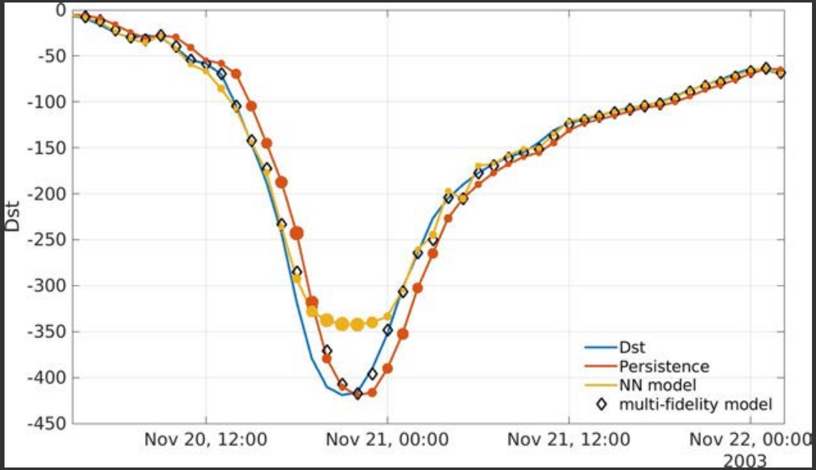
- We can use the power of ACCRUE to identify regions (in feature space) where a predictor works well and where it doesn't

ProBoost in one slide

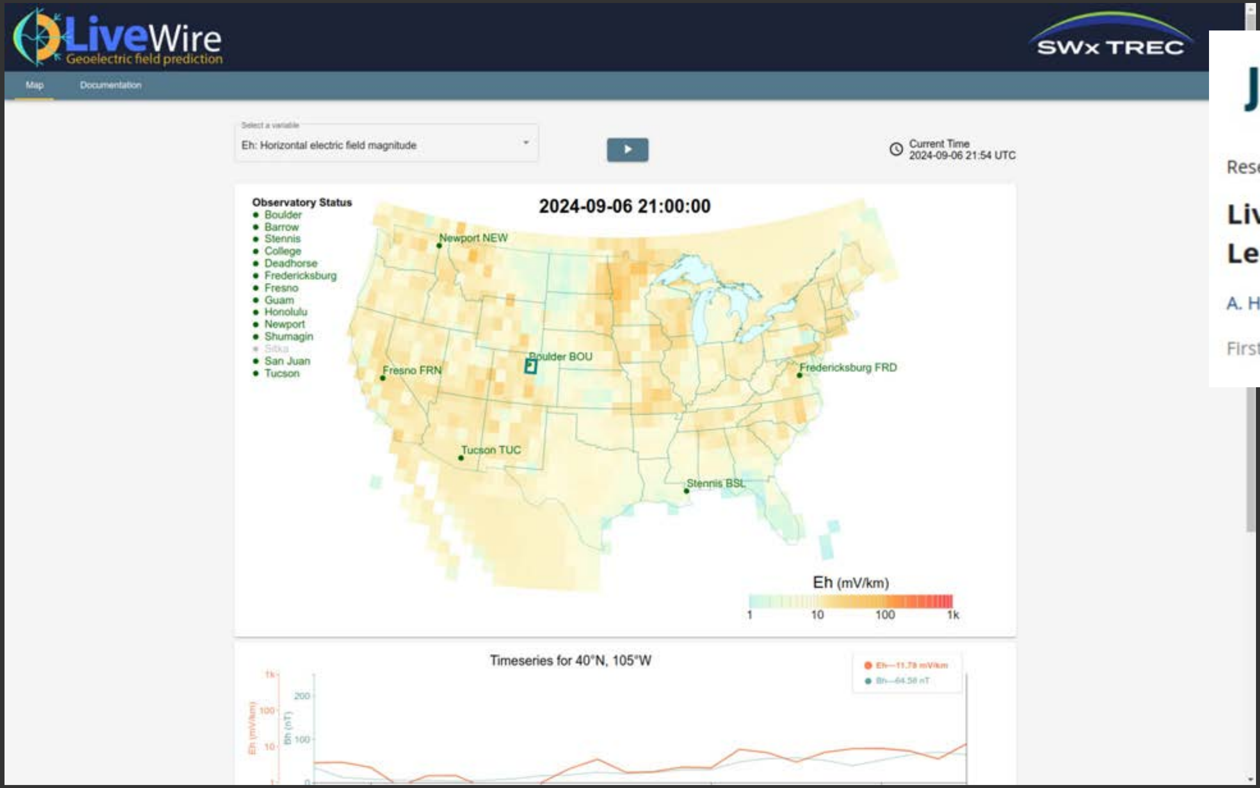
- We can use the power of ACCRUE to identify regions (in feature space) where a predictor works well and where it doesn’t
- An ensemble of models is built by sub-sampling the training set
  - The sub-sampling criterion is based on the ACCRUE uncertainty

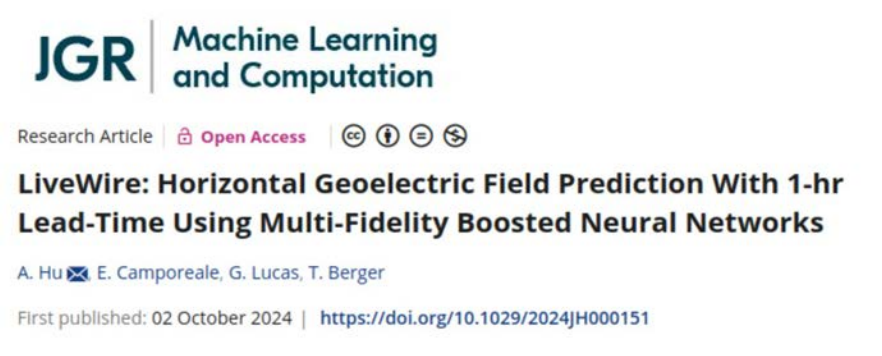
ProBoost in one slide

- We can use the power of ACCRUE to identify regions (in feature space) where a predictor works well and where it doesn't
- An ensemble of models is built by sub-sampling the training set
  - The sub-sampling criterion is based on the ACCRUE uncertainty
- Sub-models are combined weighted by their precision = $1/\sigma^2$



LiveWire: Regional GeoElectric field forecast




JGR | Machine Learning and Computation

Research Article | Open Access

LiveWire: Horizontal Geoelectric Field Prediction With 1-hr Lead-Time Using Multi-Fidelity Boosted Neural Networks

A. Hu, E. Camporeale, G. Lucas, T. Berger

First published: 02 October 2024 | https://doi.org/10.1029/2024JH000151

1-hr ahead forecast of the horizontal Electric field (Eh)

Interactive map:
the time series of
magnetic and electric fields are
shown everywhere on the map

Typical approaches to imbalance regression

- Resampling strategies
  - Oversample rare events or undersample frequent ones
  - Synthetic data generation (SMOTE, ADASYN)

$$\mathcal{L} = \frac{1}{N}\sum_i w(y_i)(y_i - \hat{y}_i)^2$$

- Re-weighted Loss Function
  - Use weighting schemes such as inverse frequency or dynamic scaling.

PARIS: results with 75% pruning!

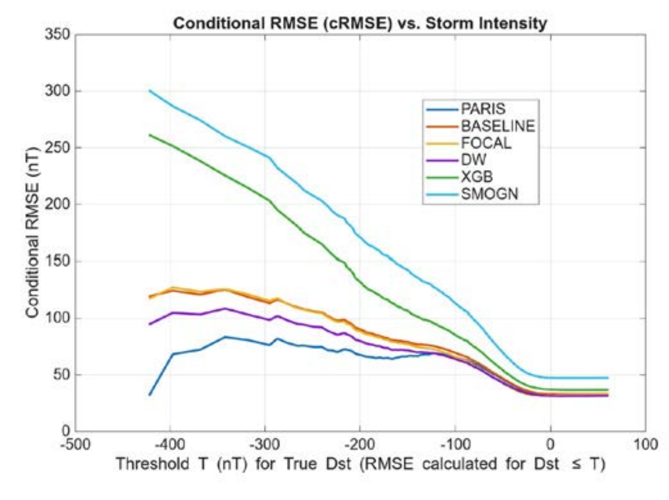
arXiv > stat > arXiv:2512.06950

Statistics > Machine Learning

[Submitted on 7 Dec 2025]

PARIS: Pruning Algorithm via the Representer theorem for Imbalanced Scenarios

Enrico Camporeale



Model	RMSE on Lowest Percentiles of Dst (nT)					
	1%	2%	5%	10%	20%	50%
PARIS	**75.02**	**73.46**	**65.39**	**68.17**	59.47	42.51
BASELINE	112.56	105.36	86.06	76.15	61.80	43.26
focal	114.56	104.57	84.50	73.38	57.97	**39.22**
DW	97.46	91.53	76.44	69.59	**56.84**	39.93
XGB	204.71	170.12	123.55	97.79	74.43	49.52
SMOGN	242.44	208.30	162.51	130.78	97.98	63.47