Machine Learning in Space Weather

Enrico Camporeale

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Thanks to NASA grant 80NSSC20K1580 (Ensemble Learning for Accurate and Reliable Uncertainty Quantification)







Space Weather Workshop 20 – 22 April 2021

Current trend in ML (stating the obvious...)

We are experiencing a general exponential growth of ML research!



Search "Machine Learning" on https://ui.adsabs.harvard.edu/

Search "Space Weather" AND "Machine Learning" on https://ui.adsabs.harvard.edu/

(a non-comprehensive list...)

- Regression problems, i.e. predict:
 - The value of a geomagnetic index (Dst, Kp, etc.);

Space Weather

RESEARCH ARTICLE

10.1029/2018SW001898

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

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

M. A. Gruet¹ (D), M. Chandorkar² (D), A. Sicard¹, and E. Camporeale² (D)

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

(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;

THE ASTROPHYSICAL JOURNAL, 855:109 (10pp), 2018 March 10 © 2018. The American Astronomical Society. All rights reserved.

https://doi.org/10.3847/1538-4357/aaae69



A New Tool for CME Arrival Time Prediction using Machine Learning Algorithms: CAT-PUMA

Jiajia Liu¹,⁽¹⁾, Yudong Ye^{2,3}, Chenglong Shen^{4,5}, Yuming Wang^{4,5}, and Robert Erdélyi^{1,6}

(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;

Space Weather

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RESEARCH ARTICLE 10.1029/2020SW002501

Special Section:

Scientific Challenges of Space Weather Forecasting Including Extremes

Forecasting Global Ionospheric TEC Using Deep Learning Approach

Lei Liu^{1,2,3} (D), Shasha Zou² (D), Yibin Yao¹ (D), and Zihan Wang² (D)

¹School of Geodesy and Geomatics, Wuhan University, Wuhan, China, ²Department of Climate and Space Sciences and Engineering, University of Michigan, Ann Arbor, MI, USA, ³College of Engineering, Space Weather Technology, Research and Education Center, University of Colorado Boulder, Boulder, CO, USA

(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;

Space Weather

RESEARCH ARTICLE

10.1029/2020SW002478

Machine learning models are

Key Points:

Solar Wind Prediction Using Deep Learning

Vishal Upendran^{1,2}, Mark C. M. Cheung^{3,4}, Shravan Hanasoge⁵, and Ganapathy Krishnamurthi²

(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;



Machine Learning Techniques for Space Weather 2018, Pages 279-300



Chapter 11 - Artificial Neural Networks for Determining Magnetospheric Conditions

Jacob Bortnik *, Xiangning Chu *, Qianli Ma *, [†], Wen Li [†], Xiaojia Zhang *, Richard M. Thorne *, Vassilis Angelopoulos [‡], Richard E. Denton [§], Craig A. Kletzing [¶], George B. Hospodarsky [¶], Harlan E. Spence [|], Geoffrey D. Reeves **, Shrikanth G. Kanekal ^{††}, Daniel N. Baker ^{‡‡}

(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)

Comparison of Deep Learning Techniques to Model Connections Between Solar Wind and Ground Magnetic Perturbations

Amy M. Keesee^{1*}, Victor Pinto¹, Michael Coughlan¹, Connor Lennox², Md Shaad Mahmud² and Hyunju K. Connor³

(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

Space Weather

Research Article 🛛 🔂 Open Access 🛛 😨 🚺

Toward a next generation particle precipitation model: Mesoscale prediction through machine learning (a case study and framework for progress)

Ryan M. McGranaghan 🕱, Jack Ziegler, Téo Bloch, Spencer Hatch, Enrico Camporeale, Kristina Lynch, Mathew Owens, Jesper Gjerloev, Binzheng Zhang, Susan Skone

First published: 16 April 2021 | https://doi.org/10.1029/2020SW002684

(a non-comprehensive list...)

- Classification problems, i.e. what is the probability that:
 - An active region will flare in the next 24 hours?

The Astrophysical Journal, 798:135 (11pp), 2015 January 10

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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

(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?

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. Cash³, H. J. Singer³, C. C. Balch³, Z. Huang⁴, and G. Toth⁴

(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.

Journal of Geophysical Research: Space Physics

RESEARCH ARTICLE

10.1002/2017JA024383

Classification of Solar Wind With Machine Learning

Key Points:

• Gaussian Process classification yields excellent accuracy in classifying the solar wind according to the Xu and Enrico Camporeale¹, Algo Carè¹, and Joseph E. Borovsky²

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

(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



Egor A. Illarionov^{1,2 \star} and Andrey G. Tlatov^{2,3}

(a non-comprehensive list...)

- Less standard methods (unsupervised, self-supervised, physicsinformed):
 - What is the uncertainty associated to a prediction?

Space Weather

RESEARCH ARTICLE

10.1029/2018SW002026

Key Points:

• We introduce a new method to estimate the uncertainties associated

On the Generation of Probabilistic Forecasts From Deterministic Models

E. Camporeale^{1,2}, X. Chu³, O. V. Agapitov⁴, and J. Bortnik⁵

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

ACCRUE: ACCURATE AND RELIABLE UNCERTAINTY ESTIMATE IN DETERMINISTIC MODELS

Enrico Camporeale^{1,*} & Algo Carè²

(a non-comprehensive list...)

- Less standard methods (unsupervised, self-supervised, physicsinformed):
 - What is the uncertainty associated to a prediction?
 - Inverse problems: what are the optimal coefficients to use in a physicsbased or empirical model?

Data-driven discovery of Fokker-Planck equation for radiation belt electrons using physics-informed neural networks	
Authors	Enrico Camporeale, George John Wilkie, Rakesh Sarma, Alexander Drozdov, Jacob Bortnik
Publication date	2020/12/10
Journal	AGU Fall Meeting 2020
Publisher	AGU
Scholar articles	Data-driven discovery of Fokker-Planck equation for radiation belt electrons using physics-informed neural networks E Camporeale, GJ Wilkie, R Sarma, A Drozdov AGU Fall Meeting 2020, 2020 All 2 versions

Why does it work (so well) ?

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}

^aComputational Neurobiology Laboratory, Salk Institute for Biological Studies, La Jolla, CA 92037; and ^bDivision 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!**



The infamous R2O gap

• None of the examples mentioned in this presentation are OPERATIONAL



- All of them outperform current operational models (or claim to do so)
- How expensive is ML?
 - Fairly expensive to train (human resources / hardware)
 - SWx TREC Deep Learning Laboratory (CU Boulder) is in the process of purchasing a ~\$350k machine (110k+ CUDA cores)*
 - Extremely cheap to deploy
 - ML runs on your smartphone

* Thanks to NASA/NSF SWQU and AFOSR/DURIP grants

Final remarks (of course, all personal opinions...)

- The operational products are lagging behind what the research community has shown to be possible;
- There is a wrong perception that black-box ML is not trustworthy because not interpretable:
 - The 'gray-box' approach builds on our long-standing physics understanding, and it will become more and more interpretable
 - It will improve existing models pushing 'good predictions' to become 'actionable predictions'
- The majority of SWx products will be based on ML in the foreseeable future
 - Will this happen in 5, 10, or 20 years? As usual (sigh) it depends on money!
- Funding instruments <u>exclusively focused on ML</u> are needed to fill the O2R2O gap

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