ARTIFICIAL INTELLIGENCE IN SPACE WEATHER PREDICTION: EMERGING TRENDS

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Space Science Institute, Boulder, CO

22 February 2018

ARTIFICIAL INTELLIGENCE IN SPACE WEATHER PREDICTION: EMERGING TRENDS

- Background
- Methods of AI
- Scope in Space Weather
- Predictions of Kp & Bz
- Summary & Concluding Remarks

BACKGROUND

How Does Intelligence Work?

AI originated from the scientific question above.

- How does our brain give rise to our cognitive abilities?
- Could this ever be implemented in a machine?

AI and ML

pattern recognition

face perception, image identification, …

AI and ML

ML is a requirement for AI because:

for a system to be called intelligent, it must have the capability to learn from its changing environment and adapt to it.

Machine Learning

— Alan Turing — the Turing Machine — 1936

A programming language that is Turing complete is theoretically capable of expressing all tasks accomplishable by computers.

— John McCarthy — coined the term Artificial Intelligence

— Marvin Minsky

— Allen Newell

— Herbert A. Simon

Machine Learning

- Regression - decision trees
- Convolution Neural Networks
- Recurrent Neural Networks
- Bayesian Networks
- Reinforcement learning
- Perceptron
- Support Vector machines (SVM)
- Kalman Filtering

Machine Learning

Random Forest
<u>Gradient Boosting</u>
AdaptiveBoost
Extra Trees

Ensemble

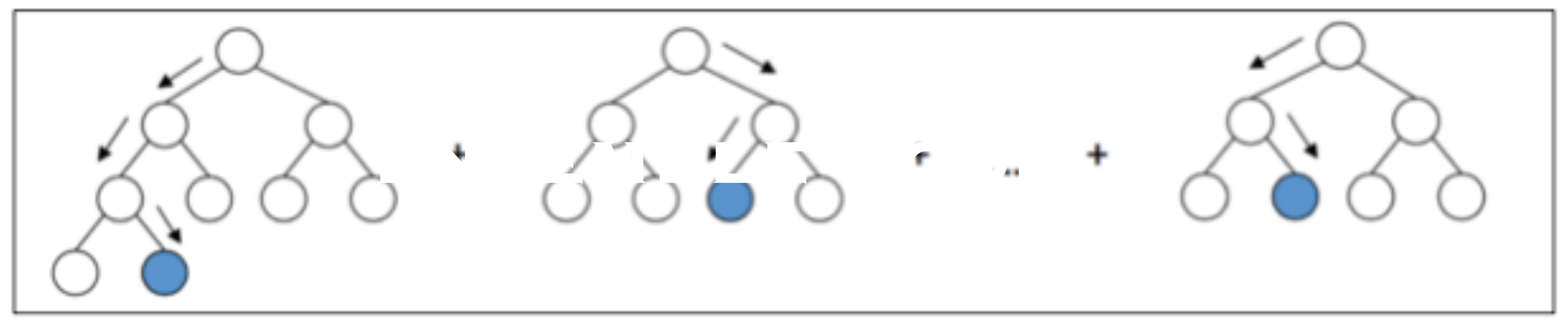
Long Short Term Memory (LSTM)

Recurrent Neural Network

ENSEMBLE MODELS

Ensemble Models

Decision Trees



Ensemble Models

Decision Trees

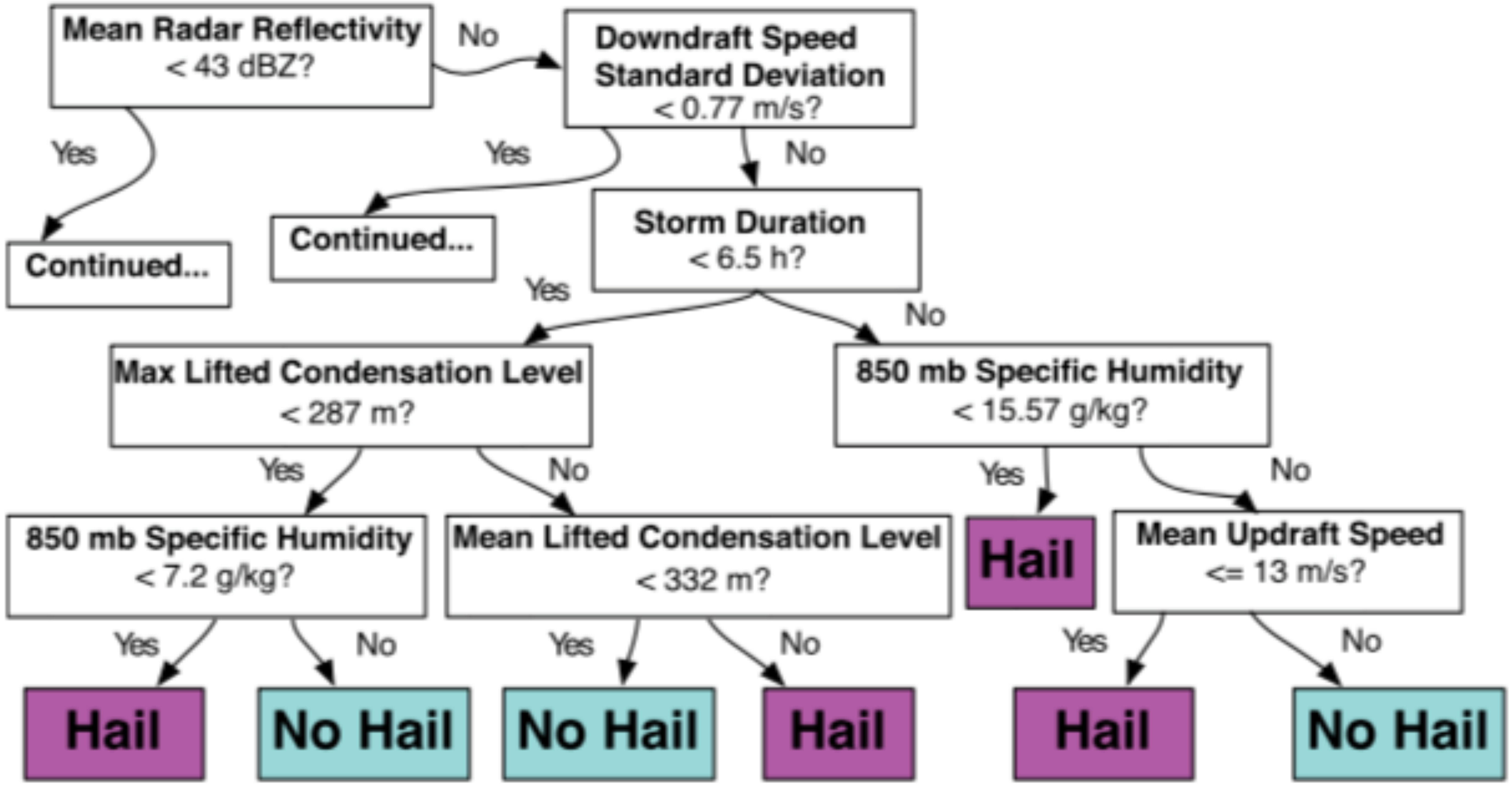
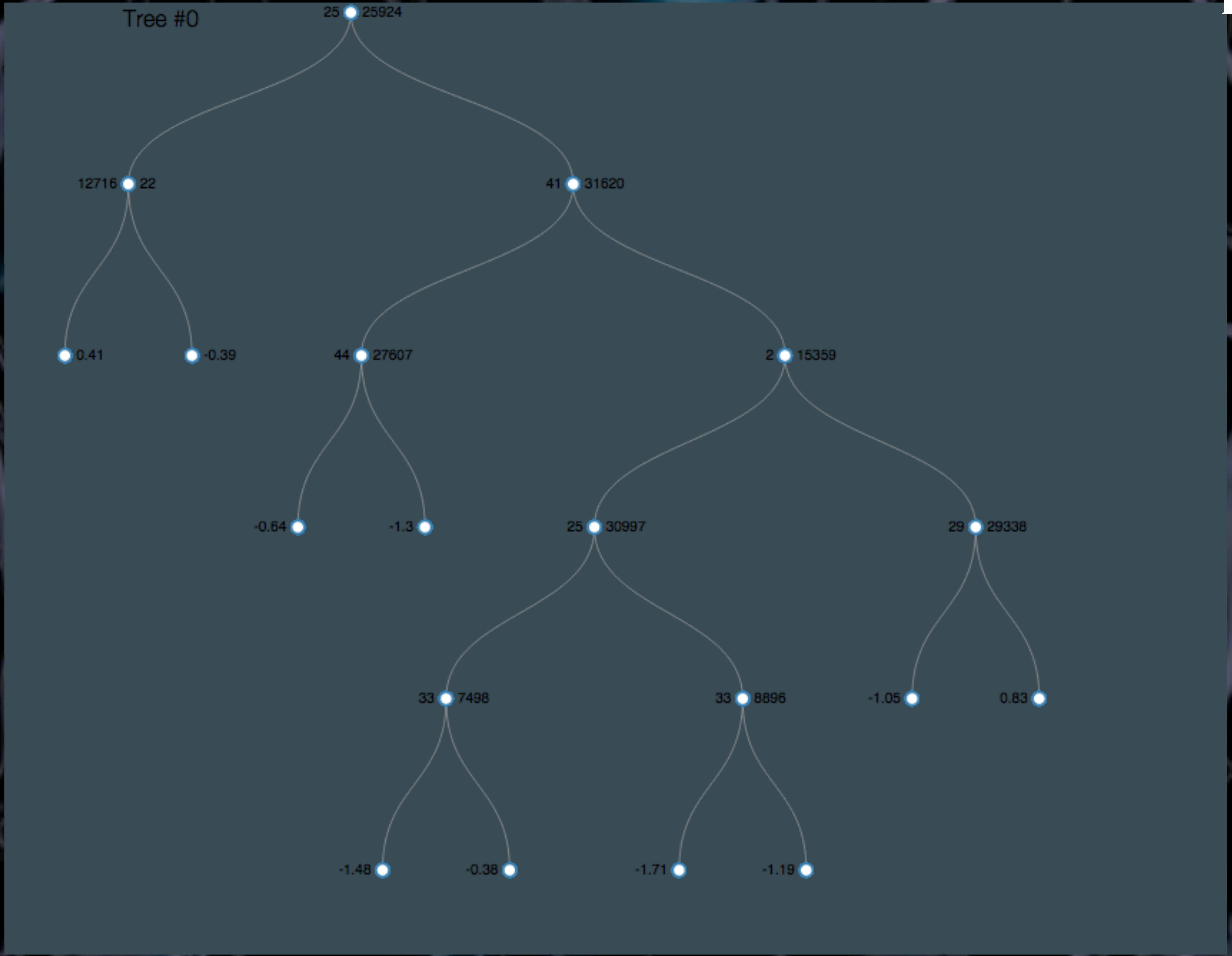


Fig. 1. An example of a decision tree for predicting if hail will occur. A version of this decision tree first appeared in Gagne (2016).

Ensemble Models

Decision Trees



Decision Trees

ENSEMBLE MODELS

These models rank the input features (parameters) according to their relative importance in making the decision for the output (prediction).

<u>Gradient Boosting</u>
AdaBoost
Extra Trees
Random Forest

ENSEMBLE MODELS

main drawback

of decision trees

they tend to overfit the training data

this can be overcome

by combining several trees

each tree different from others

each tree does a good prediction by overfitting on part of the data but different from other trees

the overfitting can be reduced

by combining several of such trees & averaging their results

the reduction in overfitting while retaining the predictive power of trees can be proved using rigorous mathematics

ENSEMBLE MODELS

Ensemble models consider additive models of the form:

$$F(x) = \sum_{m=1}^{M} \gamma_m h_m(x)$$

describing in a forward stage wise fashion:

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x)$$

ENSEMBLE MODELS

$$y1 = F(x)[\text{minimizing (y1 - y)2}]$$

$$F_1(x) = F(x) - h(x)$$

$$= y$$

$$\text{Therefore,} \quad h(x) = y - F(x)[\text{the residual}]$$

ENSEMBLE MODELS

we made use of the industry--standard, open source ML software packages:

- scikit-learn
- Keras
- Tensorflow

Machine Learning

KERAS

an open source neural network (NN) library written in Python

Scikit-Learn

a free ML library for Python

contains various classification, regression & clustering algorithms

support vector machines (SVMs)
random forests (RF)
gradient boosting

designed to operate with Python numerical & scientific libraries NumPy & SciPy

TensorFlow

an open source software library designed for building & training neural networks to detect and decipher patterns & correlations

ENSEMBLE MODELS

HyperParameters

- n_estimator
- max_features/ max_depth
- n_features
- learning_rate

- the number of trees to be built
- the tree-depth
- the number of input features
- controls over-fitting

default values of max_features

- for classification

max_features = sqrt(n_features)

- for regression

max_features = n_features

ENSEMBLE MODELS

HyperParameters

Random Forest (RF)

trees are determined randomly

- n_estimator = 10
- max_features = default
- n_features = over 50

default values of max_features

- for classification

  max_features = sqrt(n_features)

- for regression

  max_features = n_features

RF can be parallelized across multiple CPU cores, especially on large data sets
we haven't implemented it in our present study

ENSEMBLE MODELS

HyperParameters

Adaptive Boosting

- n_estimator = 50
- learning_rate = 1
- n_features = over 50

Extra Tree

- n_estimator = 10
- max_features = default
- n_features = over 50

default values of max_features

- for classification — max_features = sqrt(n_features)
- for regression — max_features = n_features

ENSEMBLE MODELS

HyperParameters

Gradient Boosting

- n_estimator = 100
- max_depth = 3
- learning_rate = 0.1
- n_features = over 50

trees are built serially & are shallow

tuning the parameters of GB accurately (the challenge and, therefore, the drawback), it can provide great accuracy — the most widely used supervised machine learning method

Gradient Boosting Regressor

ML method	1h ahead	3h ahead	6h ahead
Persist	0.007	0.020	0.025
Mean	0.046	0.046	0.046
Median	0.048	0.048	0.048
Gradient Boosting	0.007	0.015	0.021
Adaptive Boost	0.012	0.018	0.032
Extra Trees	0.009	0.021	0.027
Random Forest	0.015	0.015	0.026

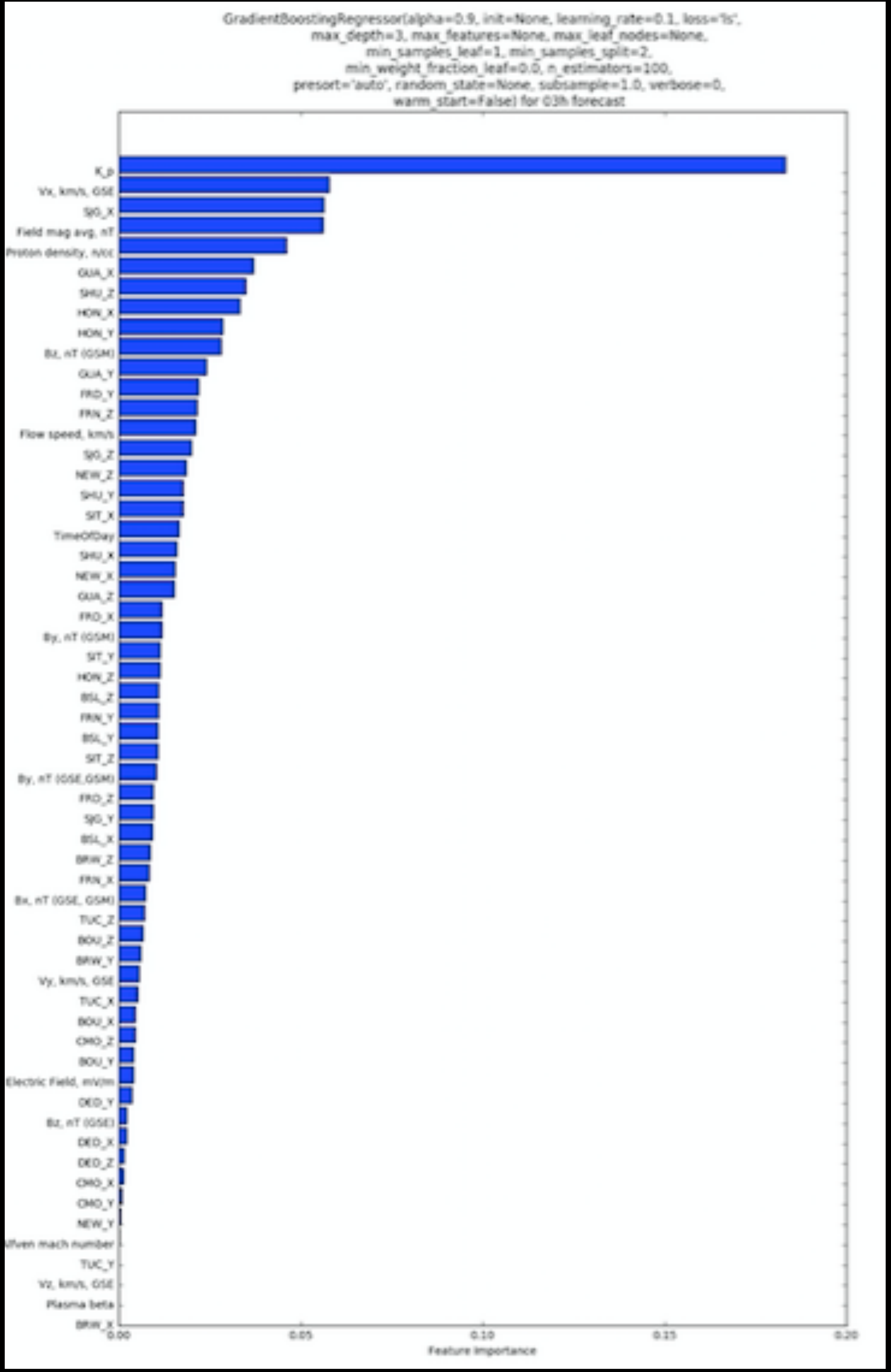
> 95% confidence level

Gradient Boosting Regressor

2016

— OMNI Solar wind data
— Geomagnetic data (14 USGS stations)
— Kp index

Prediction lead time: 3 hr



Gradient Boosting Regressor

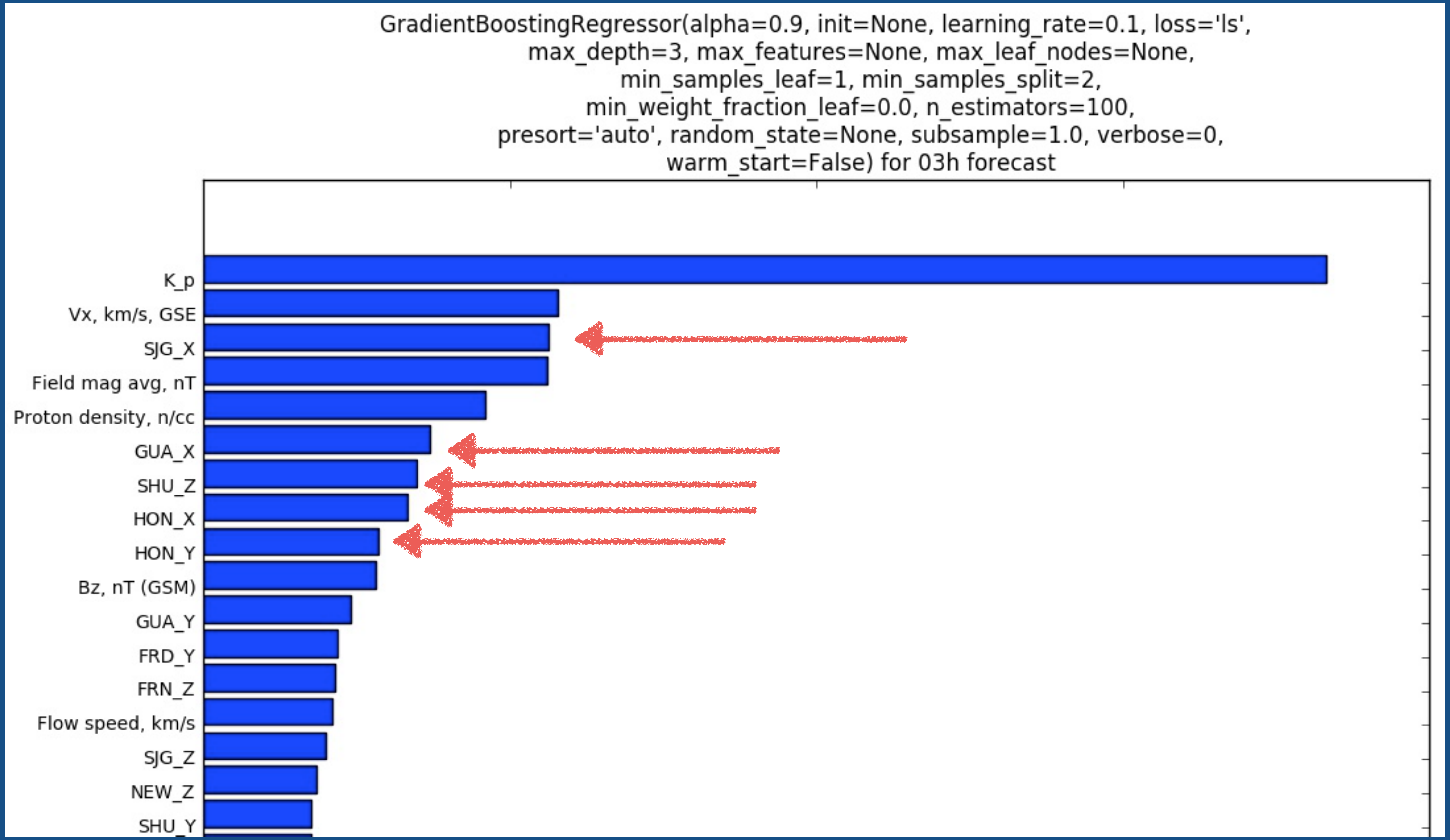
2016

— OMNI Solar wind data

— Geomagnetic data (14 USGS stations)

— Kp index

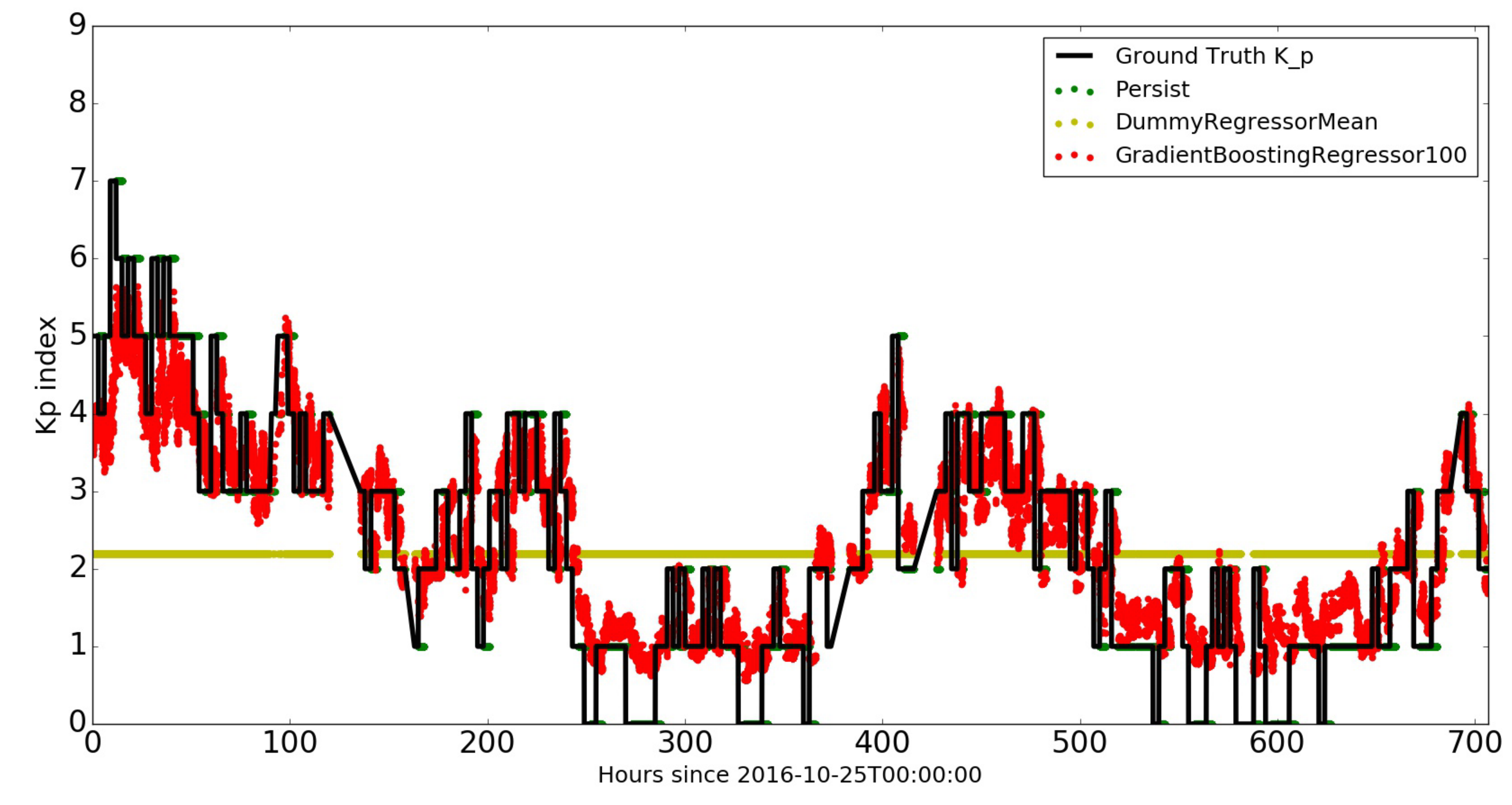
Prediction lead time: 3 hr



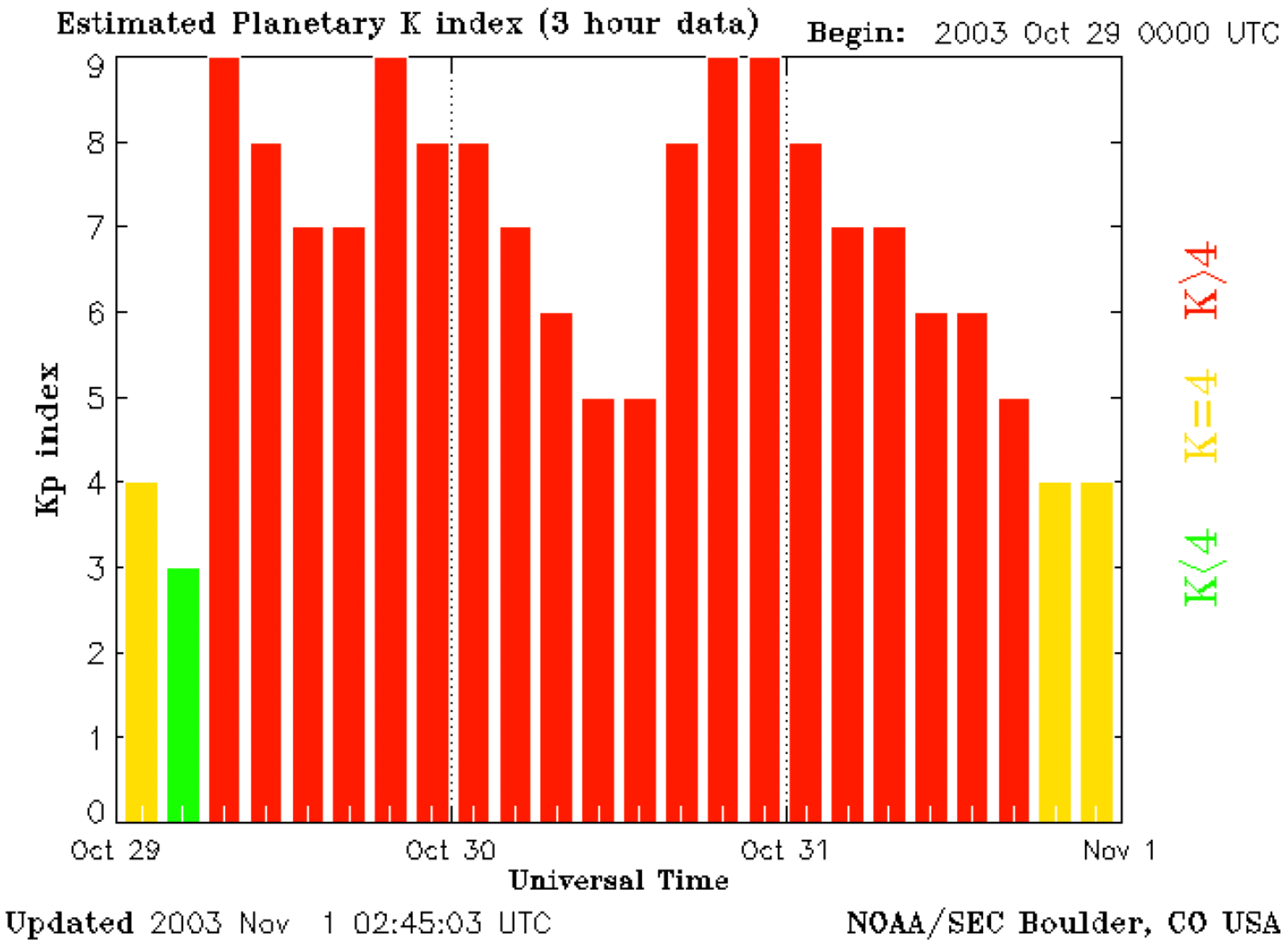
Ensemble

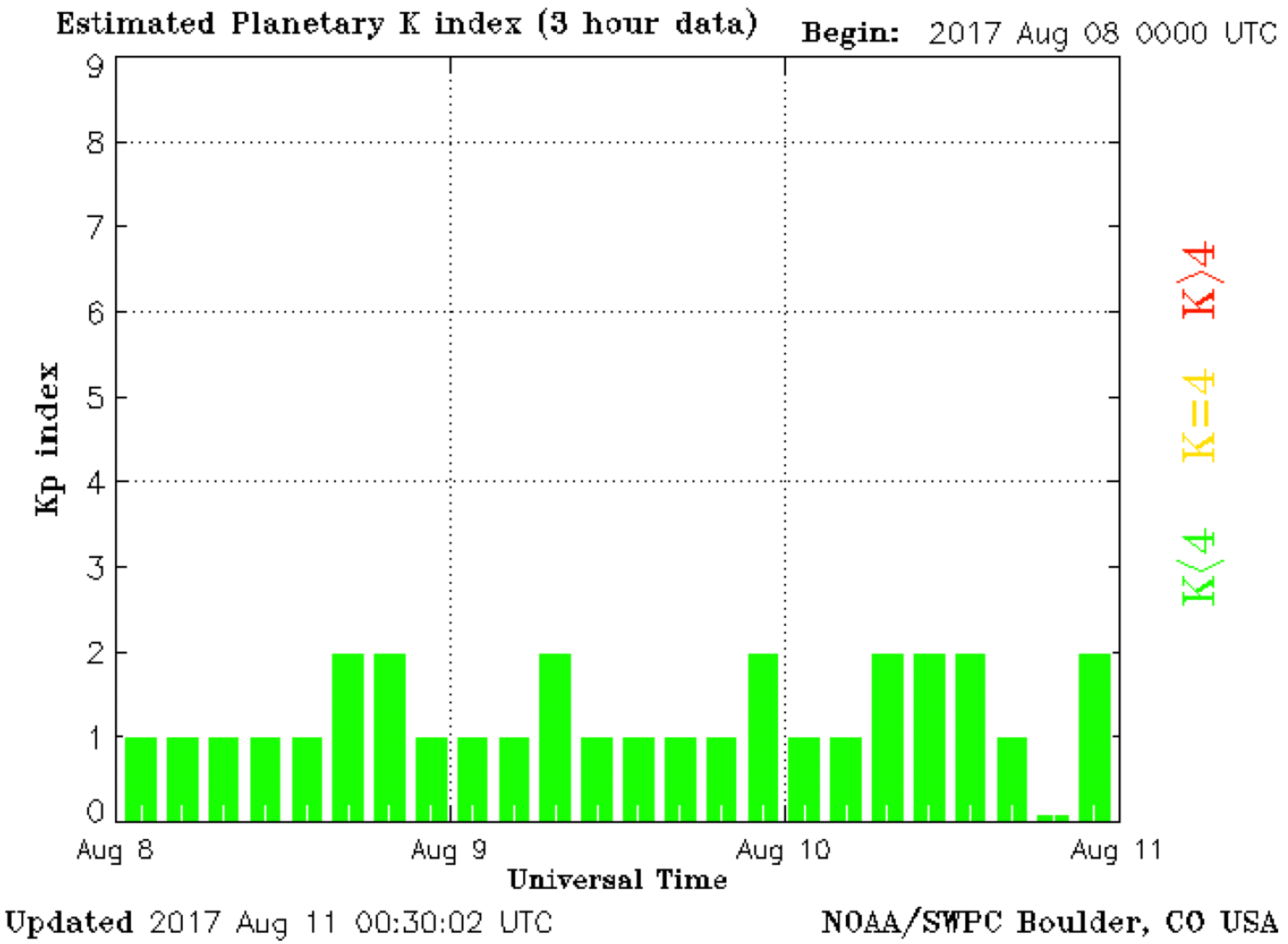

RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None,
max_features='auto', max_leaf_nodes=None,
min_impurity_decrease=0.0, min_impurity_split=None,
min_samples_leaf=1, min_samples_split=2,
min_weight_fraction_leaf=0.0, n_estimators=10, n_jobs=1,
oob_score=False, random_state=None, verbose=0, warm_start=False) for 03h forecast
K_p
SJG_X
Field mag avg, nT
SJG_Z
FRN_Z
HON_X
GUA_X
GUA_Z
Vx, km/s, GSE
HON_Y
GUA_Y
SHU_Z
HON_Z
TUC_Z
NEW_Z
SHU_Y
FRD_Z
BOU_Z
SJG_Y
Proton density, n/cc
ExtraTreesRegressor(bootstrap=False, criterion='mse', max_depth=None,
max_features='auto', max_leaf_nodes=None,
min_impurity_decrease=0.0, min_impurity_split=None,
min_samples_leaf=1, min_samples_split=2,
min_weight_fraction_leaf=0.0, n_estimators=10, n_jobs=1,
oob_score=False, random_state=None, verbose=0, warm_start=False) for 03h forecast
K_p
SJG_X
HON_X
SJG_Z
HON_Y
GUA_X
GUA_Z
SHU_Z
FRD_Z
FRN_Z
GUA_Y
TUC_Z
HON_Z
BOU_Z
NEW_Z
BSL_X
SJG_Y
BSL_Z
TUC_X
SHU_Y
FRN_Y
FRD_X
AdaBoostRegressor(base_estimator=None, learning_rate=1.0, loss='linear',
n_estimators=50, random_state=None) for 03h forecast
K_p
SJG_X
Field mag avg, nT
SHU_Z
HON_Y
Vx, km/s, GSE
TimeOfDay
FRD_X
NEW_Z
SJG_Z
HON_Z
NEW_Y
Proton density, n/cc
FRN_Z
NEW_X
By, nT (GSE,GSM)
HON_X
By, nT (GSM)
GradientBoostingRegressor(alpha=0.9, init=None, learning_rate=0.1, loss='ls',
max_depth=3, max_features=None, max_leaf_nodes=None,
min_samples_leaf=1, min_samples_split=2,
min_weight_fraction_leaf=0.0, n_estimators=100,
presort='auto', random_state=None, subsample=1.0, verbose=0,
warm_start=False) for 03h forecast
K_p
Vx, km/s, GSE
SJG_X
Field mag avg, nT
Proton density, n/cc
GUA_X
SHU_Z
HON_X
HON_Y
Bz, nT (GSM)
GUA_Y
FRD_Y
FRN_Z
Flow speed, km/s
SJG_Z
NEW_Z
SHU_Y

Gradient Boosting Regressor



Kp Index





EXTREME
Halloween Event

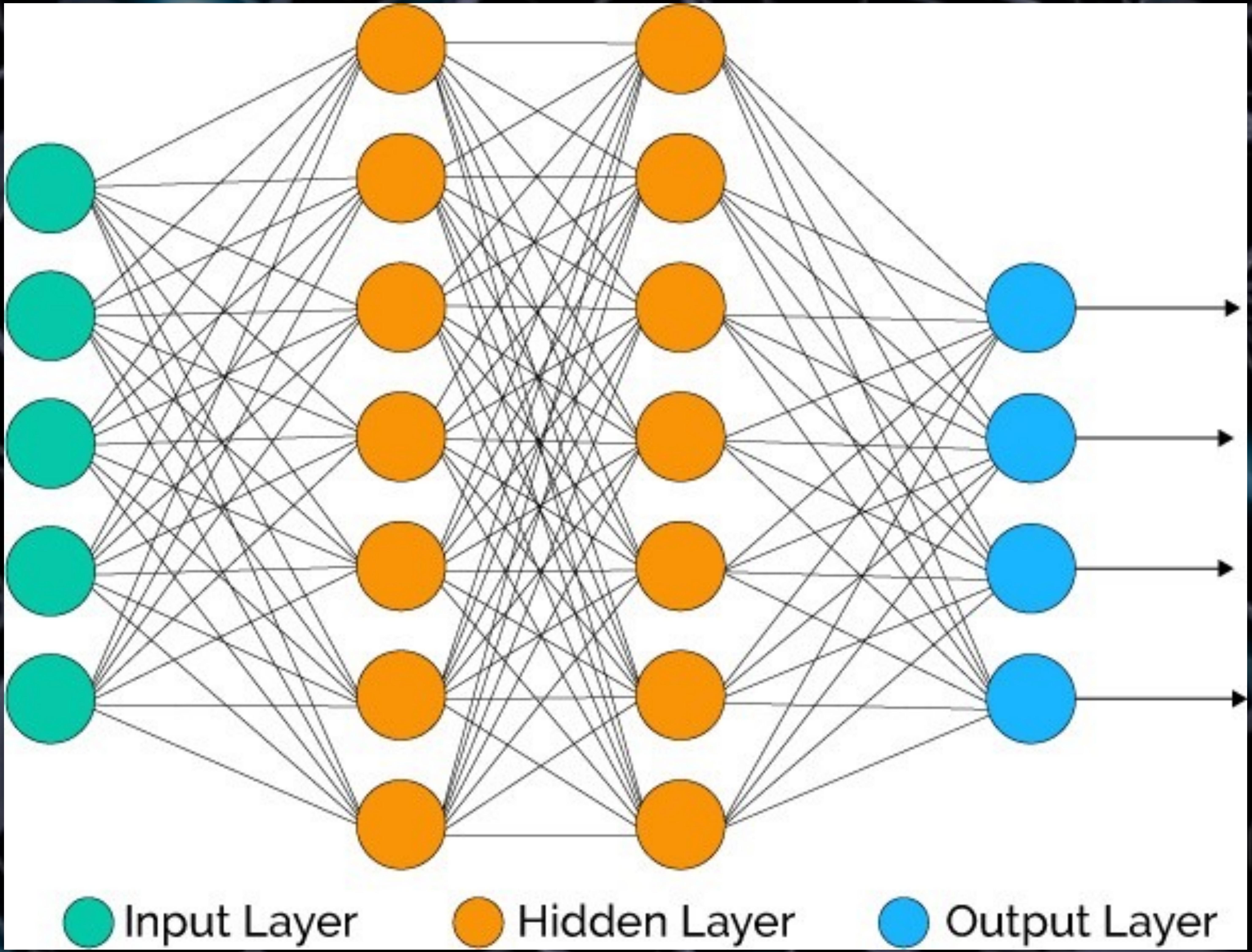
QUIET

Summary

input features, according to their order of importance, as raked by GB model:

1. *current Kp index*
2. *solar wind speed,*
3. *X-comp. geomagnetic field - SJG (San Juan, Puerto Rico, 18°N),*
4. *HMF total strength,*
5. *solar wind proton density,*
6. *X-comp. geomagnetic field - GUA (Guam, 13° N),*
7. *Z-comp. geomagnetic field - SHU (Shumagin, Alaska, 53° N),*
8. *X-comp. of geomagnetic field - HON (Honolulu, Hawaii, 21° N),*
9. *Y-comp. of geomagnetic field - HON,*
10. *HMF z-component, Bz (GSM).*

NEURAL NETWORKS


Input Layer
Hidden Layer
Output Layer

Long Short-Term Memory (LSTM)

A type of recurrent neural network (RNN), developed in 1997 by Hochreiter & Schmidhuber

— Time series prediction
— Robotics
— Grammar learning

—Natural language processing
—Handwriting recognition
— Rhythm learning
— Music composition

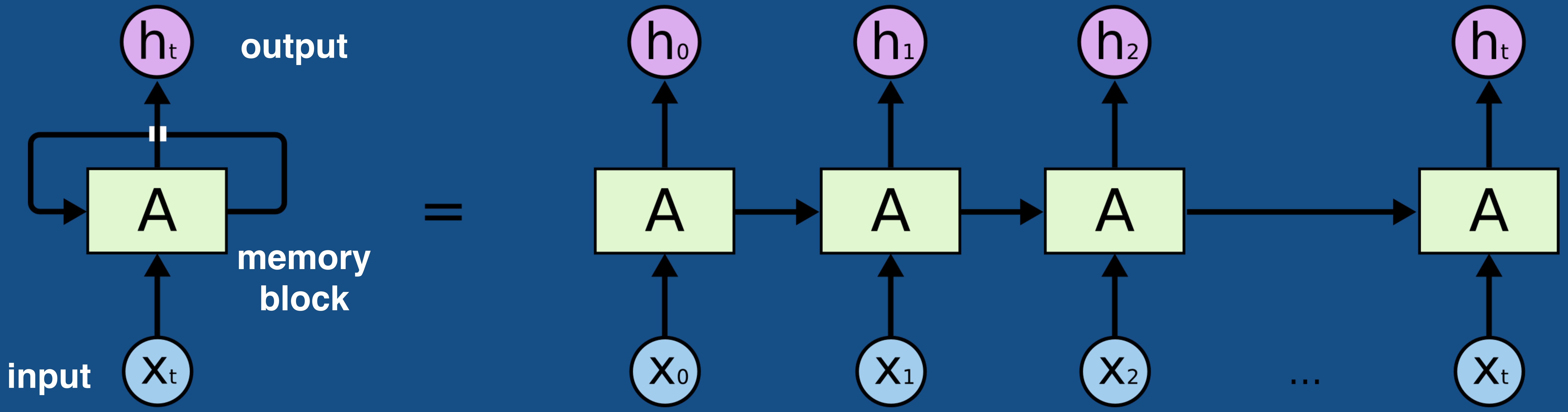
Google

- Speech recognition on Smart Phones
- Google translate

Apple

- Quicktype functions on iPhone & Siri
- Amazon Alexa

Long Short-Term Memory (LSTM)



Recurrent Neural Networks have loops

Chain-like nature of RNNs make them suitable for time series data

Long Short-Term Memory (LSTM)

— a deep learning system

— can learn tasks requiring memories of events happened thousands or even millions of discrete time steps earlier

— works even when long gaps exist between significant events

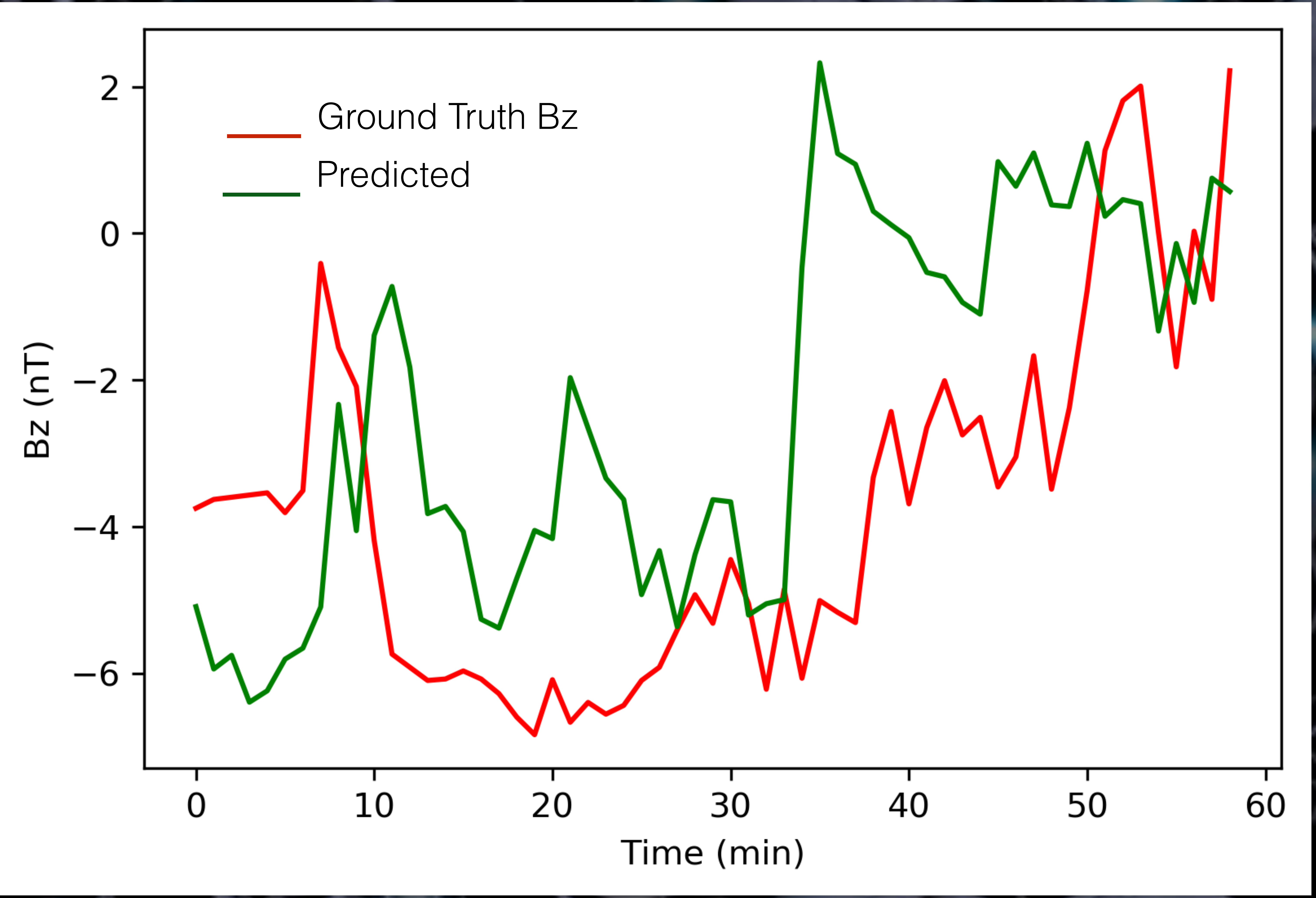
— can handle signals with mixed low & high frequencies

Long Short-Term Memory (LSTM)

2016 OMNI Solar wind data

Hyperparameters
batch size = 1
epochs = 100
neurons = 4

Training data: 20000
Testing: 2000
Prediction lead time: 1 min



IN THE LITERATURE

Available online at www.sciencedirect.com
ScienceDirect
Advances in Space Research 38 (2006) 862–867
ADVANCES IN SPACE RESEARCH (a COSPAR publication)
www.elsevier.com/locate/asr

Solar activity modelled and forecasted: A new approach

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Received 6 September 2004; received in revised form 30 March 2006; accepted 30 March 2006

Abstract

A new approach of exploring, predicting and explaining solar activity is introduced. The Lund Solar Activity Model (LSAM) is based on new wavelet methods and a hybrid physics-based neural network. The model uses as input different kinds of indicators of solar activity. Different time scales of solar activity are selected with scalograms and ampligrams. The processes behind the variability are revealed with wavelet time scale spectra. How new solar laws could be discovered with neural networks and how solar theory could be coded into neural networks are then discussed. Finally, forecasts and explanations are described with LSAM.

Pergamon

Journal of Atmospheric and Terrestrial Physics, Vol. 58, No. 7, pp. 821–830, 1996

0021–9169/96 $15.00+0.00
0021–9169(95)00105–0

Solar origin of geomagnetic storms and predictions

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(*Received in final form* 20 *April* 1995; *accepted* 21 *April* 1995)

Abstract—Changes of the large-scale solar magnetic fields are described and related to the occurrence of solar coronal phenomena which are associated with geomagnetic storms. Only for the very largest geomagnetic storms is there agreement on the coronal origin. However, when and where coronal mass ejections occur are still very difficult questions to answer. Artificial neural networks have been used to forecast geomagnetic storms either from daily solar input data or from hourly solar wind data. With solar data as input, predictions one–three days or even a month in advance are possible, while using solar wind data as input predictions about an hour in advance are possible. The latter predictions have been very successful. Finally, the effects of geomagnetic storms on power and satellite systems are reviewed.

AI Techniques in Geomagnetic Storm Forecasting

Henrik Lundstedt

Swedish Institute of Space Physics, Solar-Terrestrial Physics Division, Box 43, S-221 00 Lund, Sweden

This review deals with how geomagnetic storms can be predicted with the use of Artificial Intelligence (AI) techniques. Today many different AI techniques have been developed, such as symbolic systems (expert and fuzzy systems) and connectionism systems (neural networks). Even integrations of AI techniques exist, so called Intelligent Hybrid Systems (IHS). These systems are
mathematical functions underlying the operation of non-l
and also to explain the knowledge they have learned. V
systems exist at present. Two such examples are the Magne
Forecast Model of Rice University and the Lund Space W
University. Various attempts to predict geomagnetic storm

SOLAR ORIGIN OF GEOMAGNETIC STORMS AND PREDICTION OF STORMS WITH THE USE OF NEURAL NETWORKS

H. LUNDSTEDT
Lund Observatory, Box 43, S-221 00 Lund, Sweden

Abstract. This review deals with how the changes of the large-scale solar magnetic fields are related to the occurrence of solar phenomena, which are associated with geomagnetic storms. The review also describes how artificial neural networks have been used to forecast geomagnetic storms either from daily solar input data or from hourly solar wind data. With solar data as input predictions 1-3 days or a month in advance are possible, while using solar wind data as input predictions about an hour in advance are possible. The predictions one hour ahead of the geomagnetic storm index D_{st}

GEOPHYSICAL RESEARCH LETTERS, VOL. 29, NO. 24, 2181, doi:10.1029/2002GL016151, 2002

Operational forecasts of the geomagnetic *Dst* index

H. Lundstedt
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H. Gleisner
Danish Meteorological Institute, Copenhagen, Denmark

P. Wintoft
Swedish Institute of Space Physics, Lund, Sweden

Received 22 August 2002; revised 4 October 2002; accepted 29 October 2002; published 24 December 2002.

[1] We here present a model for real time forecasting of the geomagnetic index *Dst*. The model consists of a recurrent neural network that has been optimized to be as small as possible without degrading the accuracy. It is driven solely by hourly averages of the solar wind magnetic

[4] ESA initiated the Space Weather Programme Study in 1999. We participated in the consortium led by Alcatel Space, where we developed a prototype forecast service of space weather and effects, using real-time knowledge-based neurocomputing [*Lundstedt*, 2002]. The Lund operational

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

ABSTRACT

We attempt to forecast M- and X-class solar flares using a machine-learning algorithm, called support vector machine (SVM), and four years of data from the *Solar Dynamics Observatory*'s Helioseismic and Magnetic Imager, the first instrument to continuously map the full-disk photospheric vector magnetic field from space. Most flare forecasting efforts described in the literature use either line-of-sight magnetograms or a relatively small number of ground-based vector magnetograms. This is the first time a large data set of vector magnetograms has been used to forecast solar

JOURNAL OF GEOPHYSICAL RESEARCH, VOL. ???, XXXX, DOI:10.1002/,

Classification of Solar Wind with Machine Learning

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

Automated Prediction of Solar Flares Using Neural Networks and Sunspots Associations

T. Colak and R. Qahwaji

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Abstract. An automated neural network-based system for predicting solar flares from their associated sunspots and simulated solar cycle is introduced. A sunspot is the cooler region of the Sun's photosphere which, thus, appears dark on the Sun's disc, and a solar flare is sudden, short lived, burst of energy on the

Scientific Research Publishing

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ISSN Print: 2169-9623

Geomagnetic Kp Index and Earthquakes

Nobuo Urata[1], Gerald Duma[2*], Friedemann Freund[1]

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[2]Central Institute for Meteorology and Geodynamics, Vienna, Austria
Email: nobuo.urata@geocosmo.org

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ionosphere, the solar winds generate electrical currents. On
, these currents cause magnetic field fluctuations. These fl

OPEN ACCESS
IOP Publishing
Environmental Research Letters
Environ. Res. Lett. 9 (2014) 115009 (6pp)
doi:10.1088/1748-9326/9/11/115009

Modulation of UK lightning by heliospheric magnetic field polarity

M J Owens[1], C J Scott[1], M Lockwood[1], L Barnard[1], R G Harrison[1], K Nicoll[1], C Watt[1] and A J Bennett[2]

[1] Department of Meteorology, University of Reading, UK
[2] Bristol Industrial and Research Associates Limited, Bristol, UK

E-mail: m.j.owens@reading.ac.uk

OPEN ACCESS
IOP Publishing
Environmental Research Letters
Environ. Res. Lett. 9 (2014) 055004 (12pp)
doi:10.1088/1748-9326/9/5/055004

Evidence for solar wind modulation of lightning

C J Scott, R G Harrison, M J Owens, M Lockwood and L Barnard

Department of Meteorology, University of Reading, Reading, Berkshire, UK

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(IJACSA) International Journal of Advanced Computer Science and Applications, Vol. 9, No. 1, 2018

Deep Learning Technology for Predicting Solar Flares from (Geostationary Operational Environmental Satellite) Data

Tarek A M Hamad Nagem, Rami Qahwaji, Stan Ipson
School of Electrical Engineering and Computer Science
University of Bradford
Bradford, United Kingdom

Zhiguang Wang
GE Global Research
San Ramon, CA, United States of America

Alaa S. Al-Waisy
School of Electrical Engineering and Computer Science
University of Bradford
Bradford, United Kingdom

Abstract—Solar activity, particularly solar flares can have significant detrimental effects on both space-borne and grounds

flare prediction system would be much cheaper than the cost of repairing damage caused by such

AGU PUBLICATIONS

Space Weather

RESEARCH ARTICLE
10.1002/2017SW001752

Special Section:
Low Earth Orbit Satellite Drag: Science and Operational Impact

An Ensemble Kalman Filter for the Thermosphere-Ionosphere

S. M. Codrescu[1], M. V. Codrescu[2], and M. Fedrizzi[1,2]

[1]Cooperativ
Weather Pre

FORECASTING IONOSPHERIC TOTAL ELECTRON CONTENT MAPS WITH DEEP NEURAL NETWORKS

Noëlie Cherrier, Thibaut Castaings, Alexandre Boulch

ONERA, The French Aerospace Lab,
Chemin de la Hunière, 91123 Palaiseau, France

ABSTRACT

cations and Global Navigation Satellite
ld benefit from an early prediction of
y. The Total Electron Content (TEC)
e are already locally predicted by mod-
ies, but no model exists to our knowl-
edge for worldwide prediction. A large amount of data for

Europe, the ESA Ionospheric Weather Expert Service Center combines products from different national services to provide global and regional 1-hour TEC forecasts. However, the records of the input data and forecasts are not published.

A global analytical TEC model has been proposed in [5], using open source TEC data from the Center for Orbit Determination in Europe (CODE). This model is intended to apply

ANNALI DI GEOFISICA, VOL. 5-6, November-December 1998

Artificial neural network applications in ionospheric studies

Ljiljana R. Cander
CLRC Rutherford Appleton Laboratory, Chilton, Didcot, Oxon, U.K.

SPACE WEATHER, VOL. ???, XXXX, DOI:10.1029/,

A Deep-Learning Approach for Operation of an Automated Realtime Flare Forecast

Yuko Hada-Muranushi,[1] Takayuki Muranushi,[2] Ayumi Asai,[1] Daisuke Okanohara,[3] Rudy Raymond,[3] Gentaro Watanabe,[3] Shigeru Nemoto,[4,5] and Kazunari Shibata[1]

Abstract. Automated forecasts serve important role in space weather science, by providing statistical insights to flare-trigger mechanisms, and by enabling tailor-made forecasts and high-frequency forecasts. We have been operating unmanned flare forecast service since August, 2015 that provides 24-hour-ahead forecast of solar flares, every 12 minutes. We report the method and prediction results of the system.

Astronomy & Astrophysics manuscript no. deepvel
April 25, 2017

DeepVel: deep learning for the estimation of horizontal velocities at the solar surface

A. Asensio Ramos[1,2], I. S. Requerey[1,2], N. Vitas[1,2]

[1] Instituto de Astrofísica de Canarias, 38205, La Laguna, Tenerife, Spain; e-mail: aasensio@iac.es
[2] Departamento de Astrofísica, Universidad de La Laguna, E-38205 La Laguna, Tenerife, Spain

Received September 15, 1996; accepted March 16, 1997

ABSTRACT

Many phenomena taking place in the solar photosphere are controlled by plasma motions. Although the line-of-sight component of the velocity can be estimated using the Doppler effect, we do not have direct spectroscopic access to the components that are

USING ARTIFICIAL INTELLIGENCE TO IMPROVE REAL-TIME DECISION-MAKING FOR HIGH-IMPACT WEATHER

Amy McGovern, Kimberly L. Elmore, David John Gagne II, Sue Ellen Haupt, Christopher D. Karstens, Ryan Lagerquist, Travis Smith, and John K. Williams

AGU PUBLICATIONS JGR

Journal of Geophysical Research: Space Physics

RESEARCH ARTICLE
10.1002/2017JA024464

A neural network model of three-dimensional dynamic electron density in the inner magnetosphere

X. Chu[1], J. Bortnik[1], W. Li[1,2], Q. Ma[1,2], R. Denton[3], C. Yue[1,4], V. Angelopoulos[5], R. M. Thorne[1], F. Darrouzet[6], P. Ozhogin[7,8], C. A. Kletzing[9], Y. Wang[10], and J. Menietti[9]

[1]Department of Atmospheric and Oceanic Sciences, University of California, Los Angeles, California, USA, [2]Center for Space Physics, Boston University, Boston, Massachusetts, USA, [3]Department of Physics and Astronomy, Dartmouth College, Hanover, ...rtment of Earth, ...e for Space Aeronomy ...well, Massachusetts, ...f Iowa, Iowa City, Iowa, ...aryland, USA

Key Points:
- A neural-network-based 3-D dynamic electron density model is developed in the inner magnetosphere
- The DEN3D model successfully

Int'l Conf. on Advances in Big Data Analytics | ABDA'16 |

Application of Deep Convolutional Neural Networks for Detec... Extreme Weather in Climate Datasets

Yunjie Liu[1],Evan Racah[1],Prabhat[1],Joaquin Correa[1],Amir Khosrowshahi[2], David Lavers[3],Kenneth Kunkel[4],Michael Wehner[1],William Collins[1]
[1]Lawrence Berkeley Lab, Berkeley, CA, US
[2]Nervana Systems, San Diego, CA, US
[3]Scripps Institution of Oceanography, San Diego, CA, US
[4]National Oceanic and Atmospheric Administration, Asheville, NC, US

Abstract—*Detecting extreme events in large datasets is a major challenge in climate science research. Current* ... extreme climate events in terabytes of data pr... unprecedented challenge for climate science.

AGU PUBLICATIONS

Space Weather

RESEARCH ARTICLE
10.1002/2017SW001627

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

M. Chandorkar[1], E. Camporeale[1], and S. Wing[2]

[1]Multiscale Dynamics, Centrum Wiskunde Informatica (CWI), Amsterdam, Netherlands, [2]The Johns Hopkins University Applied Physics Laboratory, Laurel, Maryland, USA

Key Points:
- Gaussian process models offer a tractable and flexible methodology for probabilistic forecasting
- In one step ahead prediction of *Dst* index, the persistence model plays an important role in model building
- The key design decisions in building Gaussian process predictors are choosing the covariance structure and model selection algorithms

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Abstract We present a methodology for generating probabilistic predictions for the *Disturbance Storm Time* (*Dst*) geomagnetic activity index. We focus on the *One Step Ahead* prediction task and use the OMNI hourly resolution data to build our models. Our proposed methodology is based on the technique of *Gaussian Process Regression*. Within this framework we develop two models; *Gaussian Process Autoregressive* (GP-AR) and *Gaussian Process Autoregressive with eXogenous inputs* (GP-ARX). We also propose a criterion to

Key Messages

- AI is more than robotics.
- The world may be taken over or controlled by robots is a myth.
- While heavily dependent on statistical techniques, there is still room of science exploration and understanding.
- Space weather is an area that benefits from AI.


Boston Dynamics