

All models are wrong, but some *Machine-Learned* models are useful

Enrico Camporeale

CIRES / CU Boulder & NOAA Space Weather Prediction Center
Center for Mathematics and Computer Science (CWI), Amsterdam, Netherlands

Thanks to:

R. Sarma, C. Shneider, A. Hu, J. Teunissen (CWI)
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G. Wilkie (PPPL), J. Bortnik (UCLA)
R. McGranaghan (ASTRA), Y. Shprits (GFZ)



University of Colorado
Boulder



Centrum Wiskunde & Informatica



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**Enjoy the talk...
Don't worry about references!
Slides available on**

ecamporeale.github/talks

AI winters and springs

Fears of an AI pioneer

Stuart Russell argues that AI is as dangerous as nuclear weapons *By John Bohannon*

252 17 JULY 2015 • VOL 349 ISSUE 6245

sciencemag.org SCIENCE

Future of
Humanity
Institute

University
of Oxford

Centre for
the Study of
Existential
Risk

University of
Cambridge

Center for a
New American
Security

Electronic
Frontier

The Malicious Use
of Artificial Intelligence:
Forecasting, Prevention,
and Mitigation
arXiv:1802.07228

How We're Predicting AI – or Failing to*

Stuart Armstrong¹ and Kaj Sotala²

© Springer International Publishing Switzerland 2015
J. Romportl et al. (eds.), *Beyond Artificial Intelligence*,
Topics in Intelligent Engineering and Informatics 9, DOI: 10.1007/978-3-319-09668-1_2

Journal of Experimental & Theoretical Artificial Intelligence, 2014
Vol. 26, No. 3, 317–342, <http://dx.doi.org/10.1080/0952813X.2014.895105>



Taylor & Francis
Taylor & Francis Group

The errors, insights and lessons of famous AI predictions – and what they
mean for the future

Stuart Armstrong^{a*}, Kaj Sotala^b and Seán S. Ó hÉigearaigh^a

The AI spring of 2018

As nations race for dominance in the field of artificial intelligence,
Sofia Olhede and **Patrick Wolfe** consider the implications for statistics and statisticians



Mariya Yao @thinkmariya

AI is like teenage sex: everyone talks about it, nobody
knows how to do it, everyone thinks everyone else is
doing it & so claims to do it



Bazzalisk @bazzalisk · Apr 5, 2017
Replying to @thinkmariya and @cstross

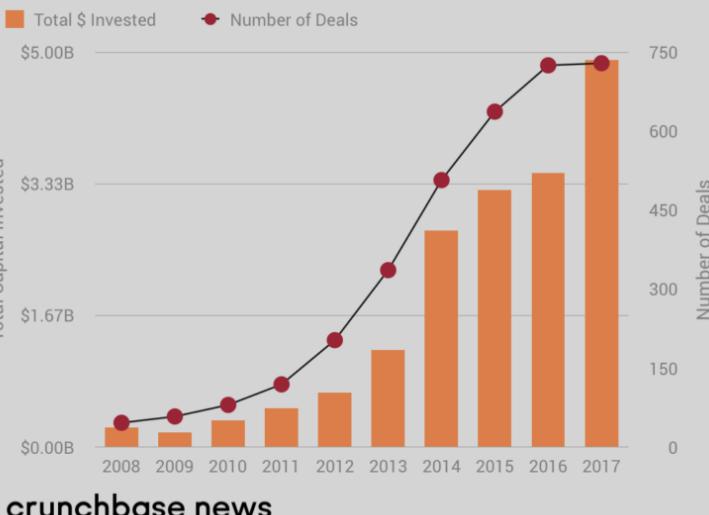
And when it does happen it usually leads to unintended consequences.



... but this time is for real (because it's profitable...)

Venture Funding Into US Artificial Intelligence, Machine Learning, And Related Startups

2008 through 2017. Dollar volume based on deals of known size; round counts are for all deals.



ARTIFICIAL INTELLIGENCE

VS / VENTURE SCANNER

The Venture Scanner artificial intelligence report currently tracks 2,643 artificial intelligence startups with \$75B in funding

Computer Vision Platforms (248 Companies)

Computer Vision Applications (295 Companies)

Smart Robots (218 Companies)

Gesture Control (67 Companies)

Speech Recognition (193 Companies)

Machine Learning Applications (1008 Companies)

Machine Learning Platforms (381 Companies)

Natural Language Processing (379 Companies)

Virtual Assistants (269 Companies)

Recommendations (121 Companies)

Video Recognition (31 Companies)

Context Computing (34 Companies)

Speech Translation (21 Companies)

The graphic above shows only a sampling of companies in each category. Data cumulative through September 2019

**... but this time is for real
(because it's profitable...)**

- AI has entered industrial production
- It is used for everyday activities

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... but this time is for real (because it's profitable...)

- AI has entered industrial production
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The image is a composite of two screenshots. On the left, there is a white rectangular box containing payment method logos: the PayPal logo at the top, followed by VISA and MasterCard logos below it. On the right, there is a screenshot of an Amazon.com page. At the top, it says "amazon.com" with the Amazon smile logo. Below that, it says "Recommended for You". A subtext message reads: "Amazon.com has new recommendations for you based on items you purchased or told us you own." Below this, there are four product recommendations with their titles and small images:

- The Little Big Things: 163 Ways to Pursue EXCELLENCE
- Fascinate: Your 7 Triggers to Persuasion and Captivation
- Sherlock Holmes [Blu-ray]
- Alice in Wonderland [Blu-ray]

... but this time is for real (because it's profitable...)

- AI has entered industrial production
- It is used for everyday activities

The collage consists of three side-by-side screenshots:

- PayPal:** A screenshot of the PayPal logo with payment method icons for VISA and MasterCard.
- Amazon.com:** A screenshot of the Amazon website showing personalized recommendations based on the user's viewing history, specifically for the TV show "Friends". Recommendations include "modern family", "how i met your mother", "THAT '70s SHOW", "RIVERDALE", "BAD MOMS", and "Full House". Below this, there are sections for "Docs & Reality TV" and "Documentaries".
- Netflix:** A screenshot of the Netflix homepage showing personalized recommendations based on the user's viewing history, specifically for the documentary "Dirty Money". Recommendations include "ROTTEN", "THE BOY WHO TRIED TO KILL TRUMP", "BANKING ON BITCOIN", "DARK NET", "JOHN JANSEN", and "COUNTDOWN TO DEATH".

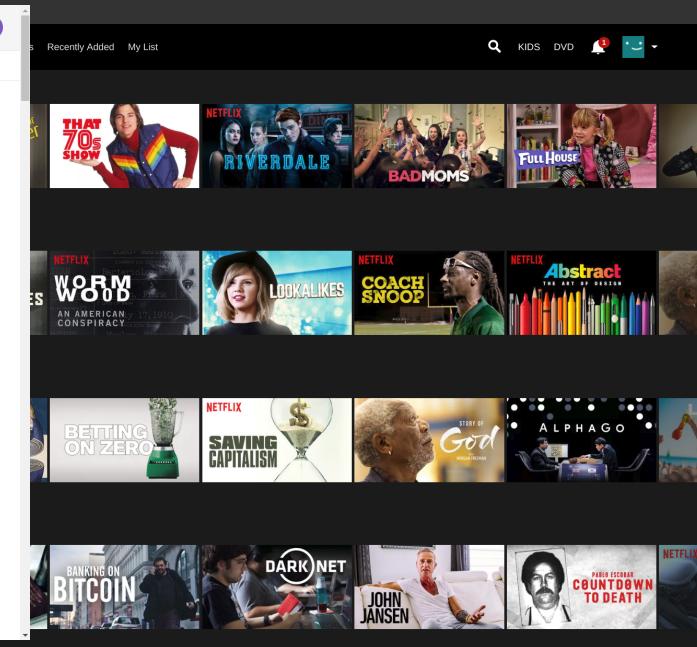
... but this time is for real (because it's profitable...)

- AI has entered industrial production
- It is used for everyday activities

Google Scholar search results:

- Applications of Information Theory in Solar and Space Physics**
J. Lopez, S. W. M. ... - arXiv preprint arXiv ..., 2019 - arxiv.org
6 days ago - Characterizing and modeling processes at the sun and space plasma in our solar system are difficult because the underlying physics is often complex, nonlinear, and not well understood. The drivers of a system are often nonlinearly correlated with one ...
☆ 99 Cites Transfer entropy and cumulant-based cost as measures of nonlinear ... 80
- Characterizing magnetic reconnection regions using Gaussian mixture models on particle velocity distributions**
R. Dupuis, MV Goldman, DL Newns, J. Amaya, ... - arXiv preprint arXiv ..., 2019 - arxiv.org
5 days ago - We present a method based on Gaussian mixture models to identify regions of interest in particle velocity distributions as a signature pattern. An automatic density estimation technique is applied to particle distributions provided by PIC simulations ...
☆ 98 Cites Multiple-hour-ahead forecast of the Dst index using a combination of ... 80
- Achieving Robustness to Aleatoric Uncertainty with Heteroscedastic Bayesian Optimisation**
RF Griffiths, M Garcia-Ortega, AA Aldrich, ... - arXiv preprint arXiv ..., 2019 - arxiv.org
10 days ago - Bayesian optimisation is an important decision-making tool for high-stakes applications in drug discovery and materials design. An oft-overlooked modelling consideration however is the representation of input-dependent or heteroscedastic aleatoric ...
☆ 99 All 3 versions 80
- Weighted Monte Carlo with least squares and randomized extended Kaczmarz for option pricing**
D Filippov, K Glau, Y Nakatsukasa, ... - Swiss Finance Institute ..., 2019 - papers.ssm.com
11 days ago - We propose a methodology for computing single and multi-asset European option prices, and more generally expectations of scalar functions of (multivariate) random variables. This new approach combines the ability of Monte Carlo simulation to handle high ...
☆ 99 All 6 versions 80
- Rapid adjustment and post-processing of temperature forecast trajectories**
N. Sorooshian, T. Tuncunoglu, A. Lenhart, arXiv preprint arXiv ..., 2019 - arxiv.org
14 days ago - Modern weather forecasts are commonly issued as consistent multi-day forecast trajectories with a time resolution of 1-3 hours. Prior to issuing, statistical post-processing is routinely used to correct systematic errors and misrepresentations of the ...
☆ 99 All 2 versions 80
- NGBoost: Natural Gradient Boosting for Probabilistic Prediction**
T. Duan, A. Awati, DY. Ding, S. Basu, AY. Ng, ... - arXiv preprint arXiv ..., 2019 - arxiv.org

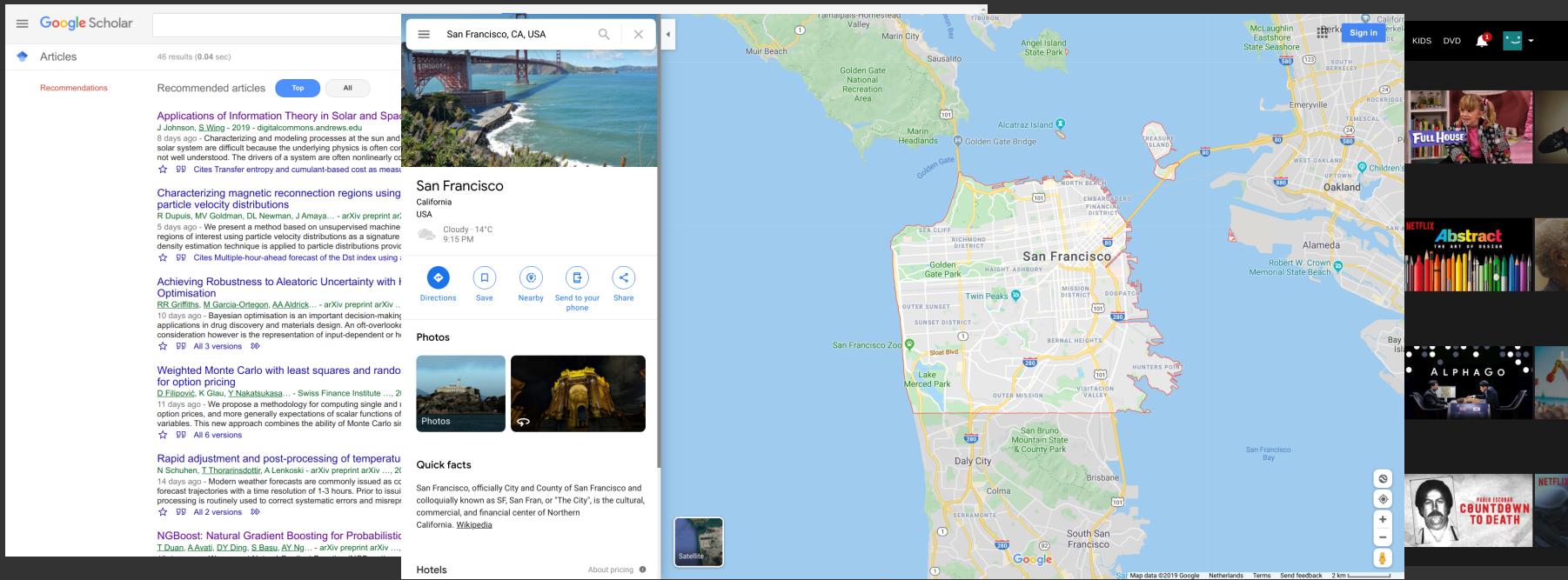
Recently Added My List



The image shows a grid of movie and TV show thumbnails from a streaming service interface. The titles visible include "THAT 70s SHOW", "NETFLIX", "RIVERDALE", "BAD MOMS", "Full House", "WORM WOOD", "LOOKALIKES", "COACH SNOOP", "Abstract: The Art of Design", "BETTING ON ZERO", "SAVING CAPITALISM", "STORY OF GOD", "ALPHAGO", "BANKING ON BITCOIN", "DARK NET", "JOHN JANSEN", and "COUNTDOWN TO DEATH". The interface includes navigation buttons for KIDS, DVD, and other categories.

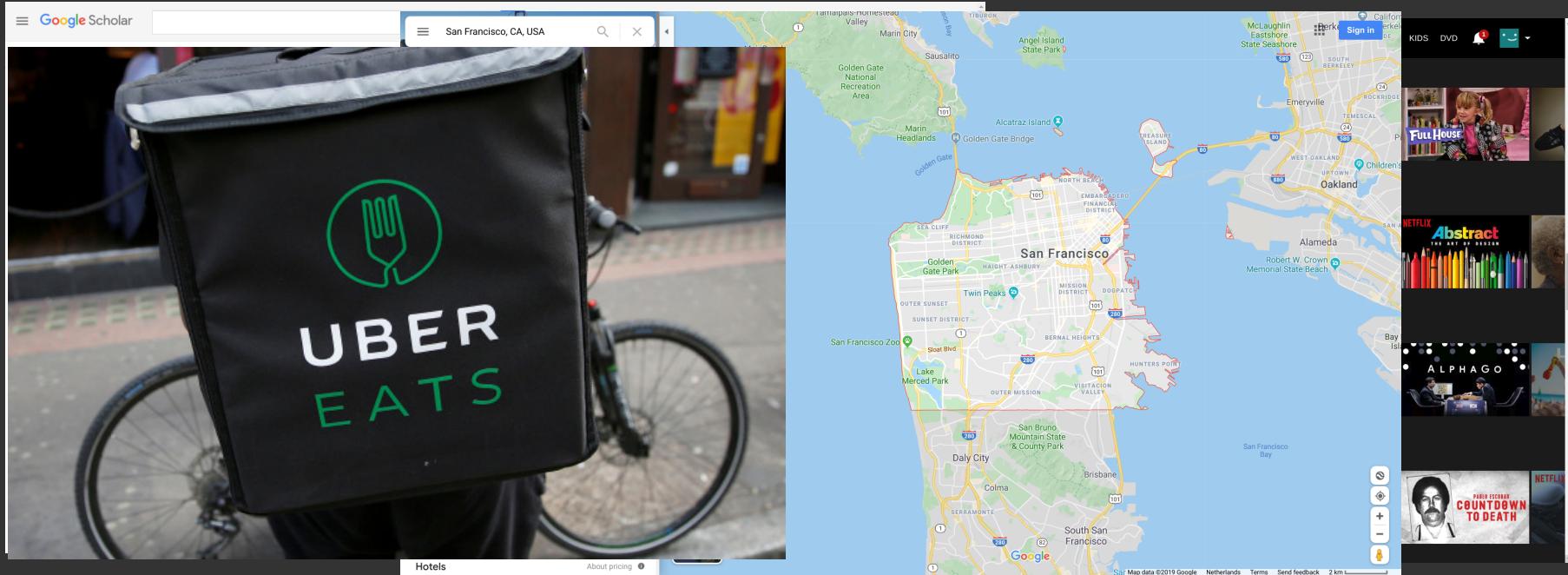
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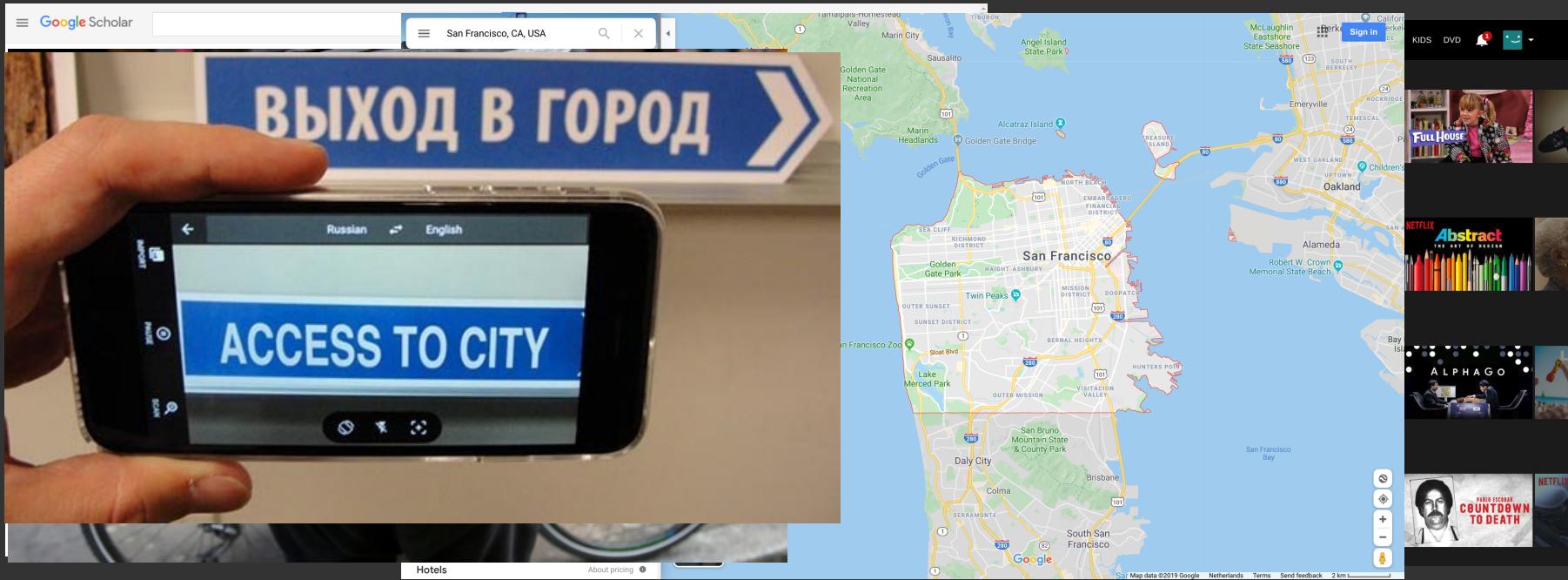
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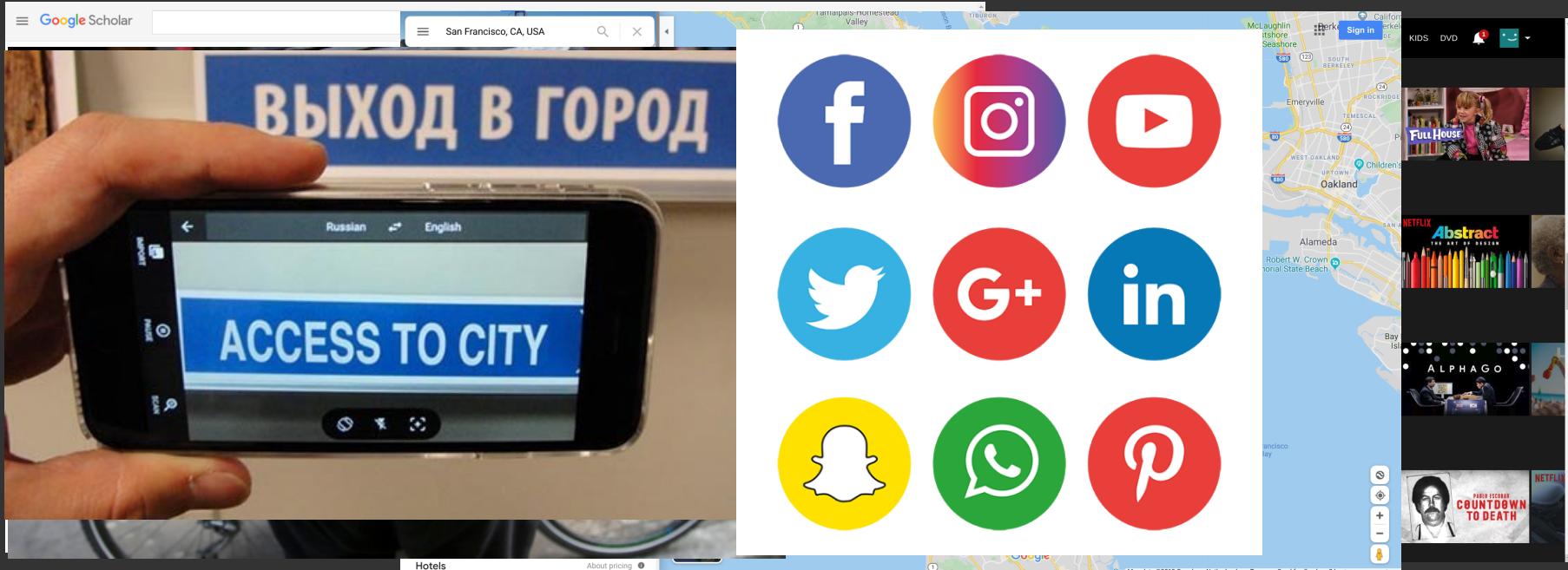
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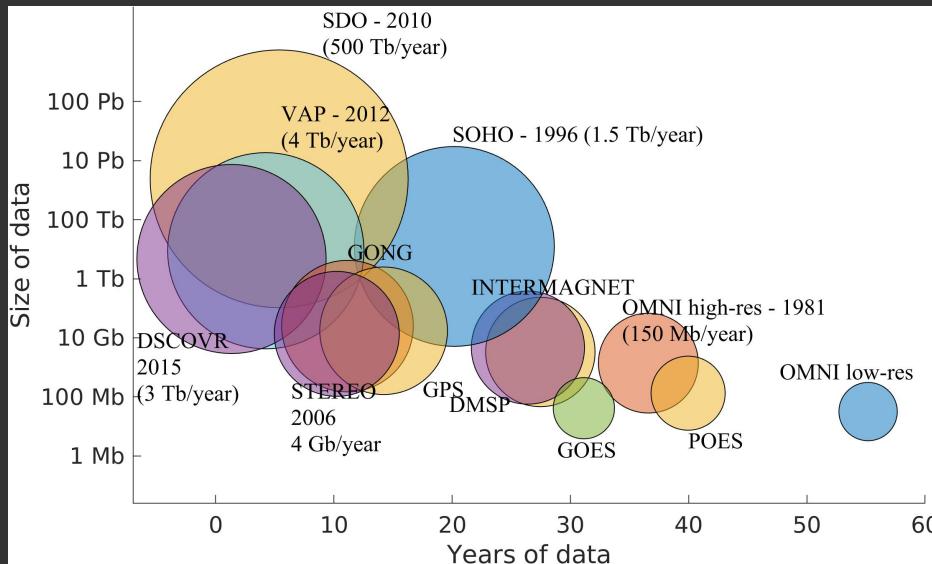
... but this time is for real (because it's profitable...)

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The Machine Learning renaissance

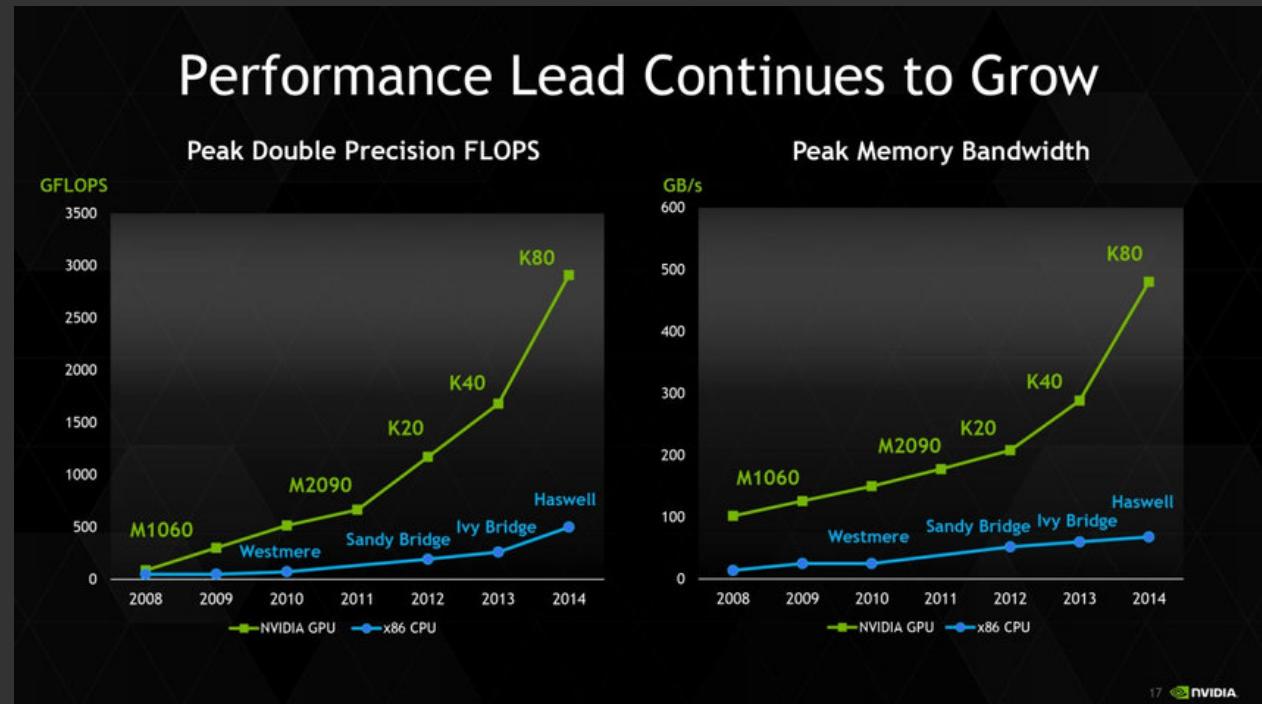
- Three enabling factors:
 - Big data



**90% of data created
in the last 2 years**

The Machine Learning renaissance

- Three enabling factors:
 - Big data
 - GPU computing

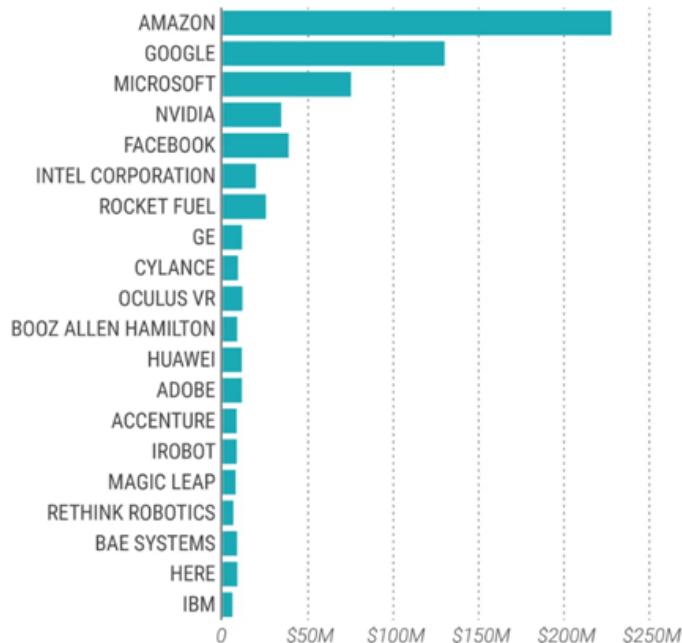


The Machine Learning renaissance

- Three enabling factors:
 - Big data
 - GPU computing
 - Massive investments

Top 20 Companies Investing in AI Talent

No other company comes close to matching the \$227.8 million that hiring and salary firm Pysa estimates Amazon will spend hiring artificial intelligence talent.



Source: Pysa
STACY JONES/FORTUNE

The Machine Learning renaissance

- Three enabling factors:
 - Big data
 - GPU computing
 - Massive investments → open source software

}

A virtuous circle



A double-edged sword ?

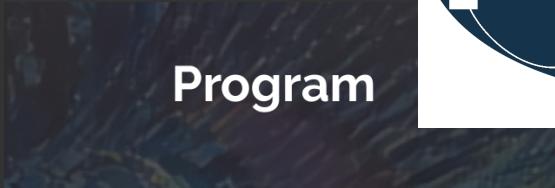
```
model = keras.Sequential([
    keras.layers.Flatten(input_shape=(28, 28)),
    keras.layers.Dense(128, activation='relu'),
    keras.layers.Dense(10, activation='softmax')
])

model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])

model.fit(train_images, train_labels, epochs=10)
```

Machine Learning in Heliophysics

<https://ml-helio.github.io/>



Program

INVITED SPEAKERS

Daniel Baker, University of Colorado
Joe Borovsky, Space Science Institute
Cyril Furtlehner, INRIA Paris
George Kariadakis, Brown University
Adam Lesnikowski, NVIDIA
Robert McPherron, UCLA
Naoto Nishizuka, NICT (Japan)
Barbara Thompson, NASA Goddard
Peter Wintoft, Swedish Institute of Space Physics

PROGRAM

[Download the poster presentations](#)
[Download the oral presentations](#)
Final Program ([download here](#))
Book of abstract available [here](#)

[Back to the top](#)

Classification: What class does an event belong to?

Using supervised machine learning to automatically detect type II and III solar radio bursts

Eoin P. Carley^{1,2}, Peter Gallagher^{2,1}, Joe McCauley¹, Pearse Murphy^{1,2}

¹ Trinity College Dublin, Ireland

² Dublin Institute for Advanced Studies, Ireland

Segmentation of solar disk images with a convolutional neural network

Egor ILLARIONOV (Moscow State University)

Andrey TLATOV (Kislovodsk Mountain Solar Station)

RESEARCH ARTICLE

10.1002/2017JA024383

Key Points:

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

Classification of Solar Wind With Machine Learning

Enrico 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

Classification: What class does an event belong to?

Classification of Magnetosheath
Jets using Neural Networks and
High Resolution OMNI (HRO)
data

Savvas Raptis¹, S. Aminalragia-Giamini², Tomas Karlsson¹
& Per-Arne Lindqvist¹

¹Space and Plasma Physics, School of Electrical Engineering and
Computer Science, KTH Royal Institute of Technology, Sweden

²Space Applications & Research Consultancy (SPARC), Greece

THE ASTROPHYSICAL JOURNAL

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

M. G. Bobra and S. Couvidat

Published 2015 January 8 • © 2015. The American Astronomical Society. All rights reserved.
[The Astrophysical Journal, Volume 798, Number 2](#)

SOLAR ACTIVE REGIONS LOCALIZATION OVER MULTI-SPECTRAL OBSERVATIONS



Swansea
University
Prifysgol
Abertawe



LIS
LABORATOIRE
D'INFORMATIQUE
& SYSTEMES
LIS/IS

Majedaldein Almahasneh¹, Adeline Paiement²,
Xianghua Xie¹, Jean Aboudarham³, and Jingjing Deng¹

¹Swansea University, UK ²Laboratoire d'Informatique et Systèmes, Université de Toulon, France

³LESIA, Observatoire de Paris, PSL University, France



Laboratoire d'Etudes Spatiales et d'Instrumentation en Astrophysique

Regression: what is the relation between inputs and outputs?

Predicting GNSS Disruptions using Machine Learning

ML in Heliophysics 2019

Laura A. Hayes

Kibrom Ebub Abraha, Daniel Kumar, Karthik Venkataramani

Asti Bhatt, Red Boumghar, Sylvester Kaczmarek, Ryan McGranaghan, Sean McGregor



Neural network based reconstruction of inner magnetospheric density, waves, and energetic electron fluxes

J. Bortnik¹; X. Chu²; Q. Ma^{1,3}, C. Yue¹; W. Li³; R. Denton⁴; R. M. Thorne¹; V. Angelopoulos¹; ¹UCLA, ²CU-Boulder/LASP, ³Boston U., ⁴Dartmouth College

JGR Space Physics

Technical Reports: Methods | Free Access

Automated determination of electron density from electric field measurements on the Van Allen Probes spacecraft

I. S. Zhelavskaya , M. Spasojevic, Y. Y. Shprits, W. S. Kurth

First published: 13 May 2016 | <https://doi.org/10.1002/2015JA022132> | Citations: 21

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 , M. Chandorkar² , A. Sicard¹, and E. Camporeale²

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



Solar wind prediction using Deep learning

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

¹Inter-University Centre for Astronomy and Astrophysics, Post Bag-4, Ganeshkhind, Pune, India; ²Department of Engineering Design, Indian Institute of Technology – Madras, Chennai, India; ³Lockheed Martin Solar and Astrophysics Laboratory, Palo Alto, CA, USA;

⁴Hansen Experimental Physics Laboratory, Stanford University, Stanford, CA, USA; ⁵Department of Astronomy and Astrophysics, Tata Institute of Fundamental Research, Mumbai, India

Regression: what is the relation between inputs and outputs?

THE ASTROPHYSICAL JOURNAL, 855:109 (10pp), 2018 March 10

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<https://doi.org/10.3847/1538-4357/aaaе69>



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

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

Space Weather

RESEARCH ARTICLE

10.1029/2018SW001955

Prediction of Solar Wind Speed at 1 AU Using an Artificial Neural Network

Yi Yang^{1,2}, Fang Shen^{1,2,3} , Zicai Yang^{1,2}, and Xueshang Feng^{1,3}

Key Points:

- The prediction of solar wind speed

arXiv.org > physics > arXiv:1912.01038

Search...

Help | About

Physics > Space Physics

A gray-box model for a probabilistic estimate of regional ground magnetic perturbations: Enhancing the NOAA operational Geospace model with machine learning

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

(Submitted on 2 Dec 2019)

**Whatever your field is...
You can enhance your model with
Machine Learning!**

The gray-box approach



First-principles
model

Table 2
Comparison Between White- and Black-Box Approaches

	White (physics-based)	Black (data-driven)
Computational cost	Generally expensive. Often not possible to run in real-time.	Training might be expensive (depending on the datasize) but execution is typically very fast.
Robustness	Robust to unseen data and rare events.	Not able to extrapolate outside the range of the training set.
Assumptions	Based on physics approximations.	Minimal set of assumptions.
Consistency with observations	Verified a posteriori.	Enforced a priori.
Uncertainty quantification	Usually not built-in. It requires Monte Carlo ensemble.	It can be built-in.

From E. Camporeale (2019), *Space Weather*, 17, 8

Empirical model

Machine
Learning

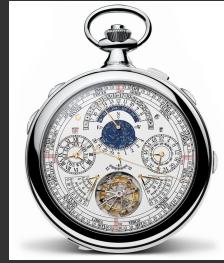
The gray-box approach



First-principles
model

assumptions &
approximations

(reduced)
physics-based model



Empirical model

Machine
Learning

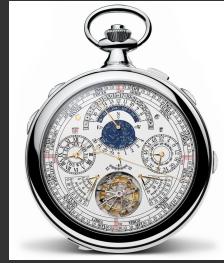
The gray-box approach



First-principles
model

assumptions &
approximations

(reduced)
physics-based model



Empirical model

Machine
Learning

The gray-box approach



First-principles
model

assumptions &
approximations

ML Enhanced
(reduced)
physics-based model



Empirical model

inform the free parameters

Machine
Learning

The gray-box approach

NG21A-06 - Physics-informed machine learning for estimating the electron flux in the Earth's radiation belts



Tuesday, 10 December 2019



09:15 - 09:30



Moscone West - 2012, L2

Authors

Rakesh Sarma

Centrum Wiskunde & Informatica

George John Wilkie

Centrum Wiskunde & Informatica

Princeton Plasma Physics Laboratory

Enrico Camporeale

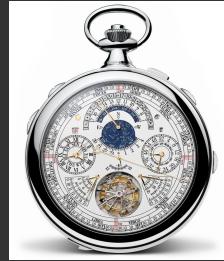
Centrum Wiskunde & Informatica

University of Colorado

Alexander Drozdov

University of California Los Angeles

The gray-box approach



assumptions &
approximations

“business as usual”

ML Enhanced
(reduced)
physics-based model

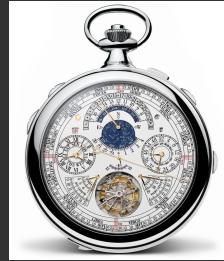
Ensemble of ML and
physics-based models

inform the free parameters

Machine
Learning

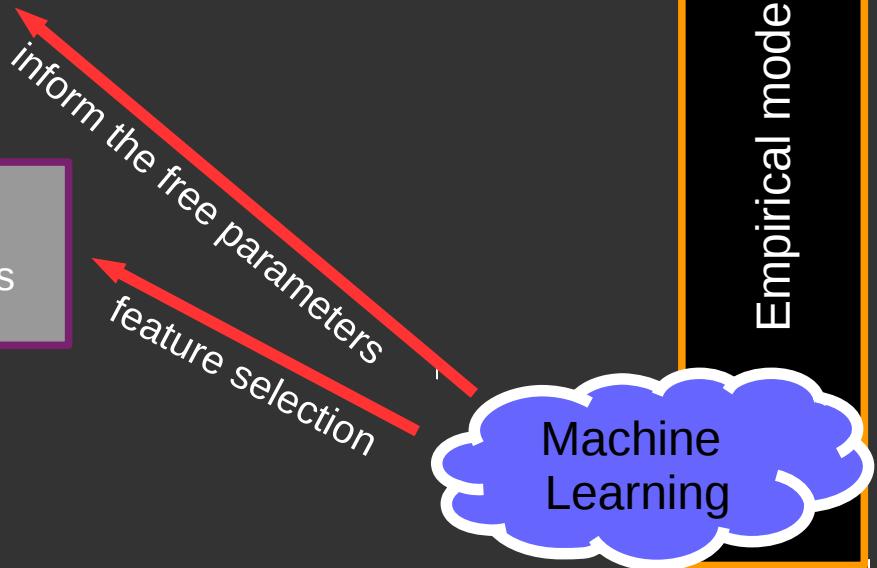
Empirical model

The gray-box approach



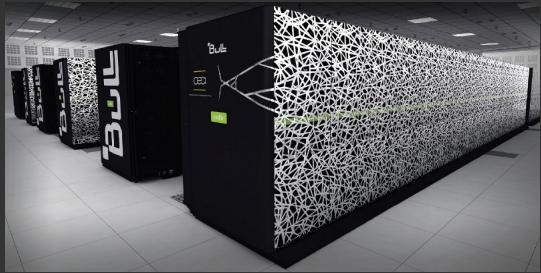
ML Enhanced
(reduced)
physics-based model

Ensemble of ML and
physics-based models



Empirical model

The gray-box approach



assumptions &
approximations

ML Enhanced
(reduced)
physics-based model



inform the frame

cal model

S

IN41B-15 - A gray-box model for a probabilistic estimate of regional ground magnetic perturbations: Enhancing the NOAA operational Geospace model with machine learning

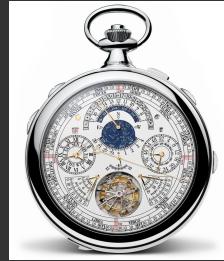


Thursday, 12 December 2019



Moscone South - eLightning Theater III

The gray-box approach



assumptions &
approximations

“business as usual”

provide training data

ML Enhanced
(reduced)
physics-based model

Ensemble of ML and
physics-based models

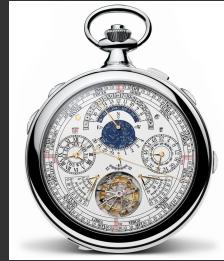
Surrogate model with
physics constraints
(trade-off accuracy vs speed)

inform the free parameters
feature selection

Machine Learning

Empirical model

The gray-box approach



assumptions &
approximations

“business as usual”

provide training data

ML Enhanced
(reduced)
physics-based model

Ensemble of ML and
physics-based models

Surrogate model with
physics constraints
(trade-off accuracy vs speed)

Empirical model

Machine
Learning



The gray-box approach



ML Enhanced
(reduced)
physics-based model



NG31A-0833 - Using Deep Learning for Spectropolarimetric Inversions



Wednesday, 11 December 2019



08:00 - 12:20



Moscone South - Poster Hall

Authors

Serena Flint

University of Rochester

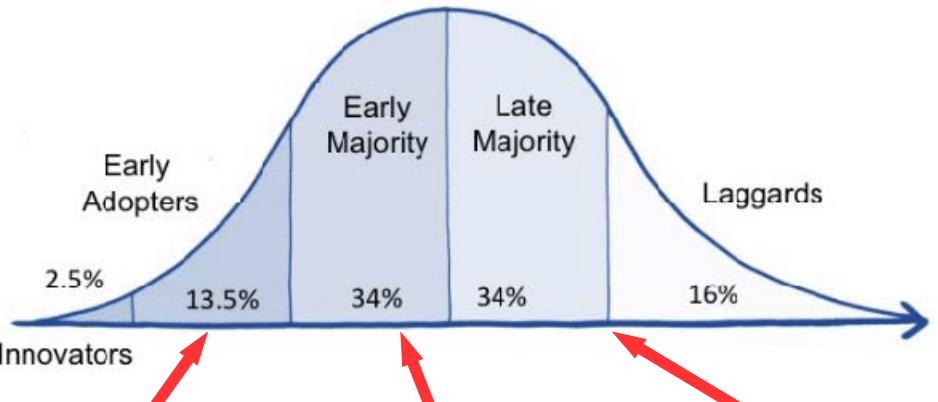
Ivan Milic

University of Colorado at Boulder

National Solar Observatory

My vision: ML as the fourth pillar. An analogy with scientific computing

Rogers' *Diffusion of Innovations*



1994:
the 1st parallel
workstation
(Beowulf)

2001:
Scientific Discovery
through Advanced
Computing
(SCIDAC)

2013:
Nobel Prize in
Chemistry for
“simulation stuff”

Digital technologies: Computation

physicsworld.com

The third pillar

Computing has quickly evolved to become the third “pillar” of science. But to reap its true rewards, researchers need software code that is flexible and can be easily adapted to meet new needs, as **Benjamin Skuse** finds out

OCTOBER 21, 2019

New supercomputer simulations explore magnetic reconnection and make a surprising discovery

by American Physical Society

The fourth pillar: an analogy with scientific computing

No free lunch!



Introducing Ludwig, a Code-Free Deep Learning Toolbox

Piero Molino, Yaroslav Dudin, and Sai Sumanth Miryala

www.youtube.com

**Tensorflow and
deep learning -
without a PhD by
Martin Görner -
YouTube**

February 11, 2019

References

NG21A - Machine Learning in Space Weather I

★ 📅 ✎ Tuesday, 10 December 2019
🕒 08:00 - 10:00 ⏰ 10:20 - 12:20
📍 Moscone West - 2012, L2

SH34B - Machine Learning and Data Assimilation as Emerging Tools for Characterization and Forecasting of Solar Variability and Space Weather Events I

★ 📅 ✎ Wednesday, 11 December 2019
🕒 16:00 - 18:00
📍 Moscone South - 208, L2

SH34A - Innovative Approaches in Solar Flare Forecasting I

★ + ✎ Wednesday, 11 December 2019
🕒 16:00 - 18:00
📍 Moscone South - 211-212, L2

Machine Learning, Statistics, and Data Mining for Heliophysics

By [Monica Bobra](#) and [James Mason](#)



Space Weather

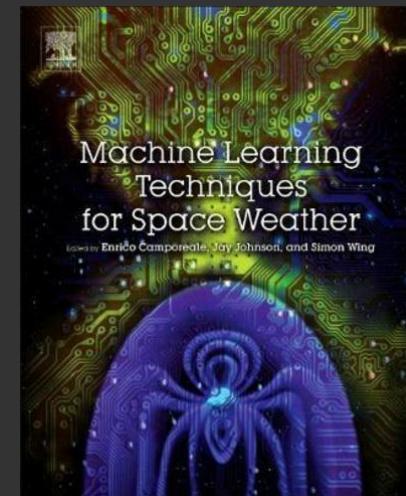
FEATURE ARTICLE
10.1029/2018SW002061



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

E. Camporeale^{1,2} ⓘ

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



Slides available on: ecamporeale.github/talks

Contact: enrico.camporeale@noaa.gov