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)
M. Cash, H. Singer, C. Balch (NOAA/SWPC)
Z. Huang, G. Toth (U. Michigan), D. Del Moro (U. Tor Vergata, Rome)
G. Wilkie (PPPL), J. Bortnik (UCLA)
R. McGranaghan (ASTRA), Y. Shprits (GFZ)

University of Colorado Boulder

CIRES

Centrum Wiskunde & Informatica

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 776262 (AIDA)

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**

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 hÉigeartaigh[a]

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

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

How We're Predicting AI – or Failing to*

Stuart Armstrong[1] and Kaj Sotala[2]

© 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

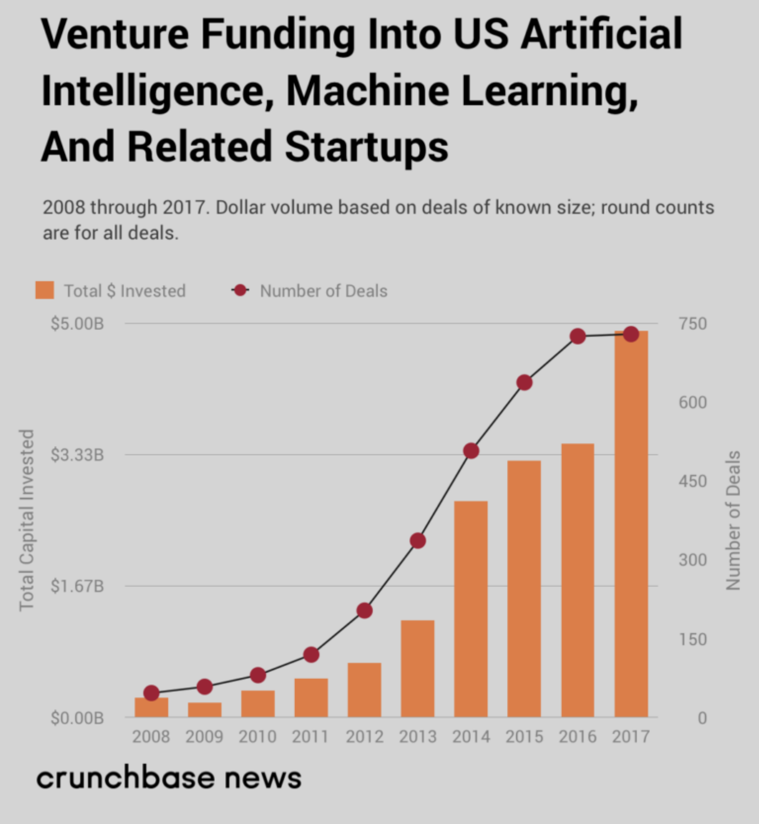
Mariya Yao
@thinkmariya

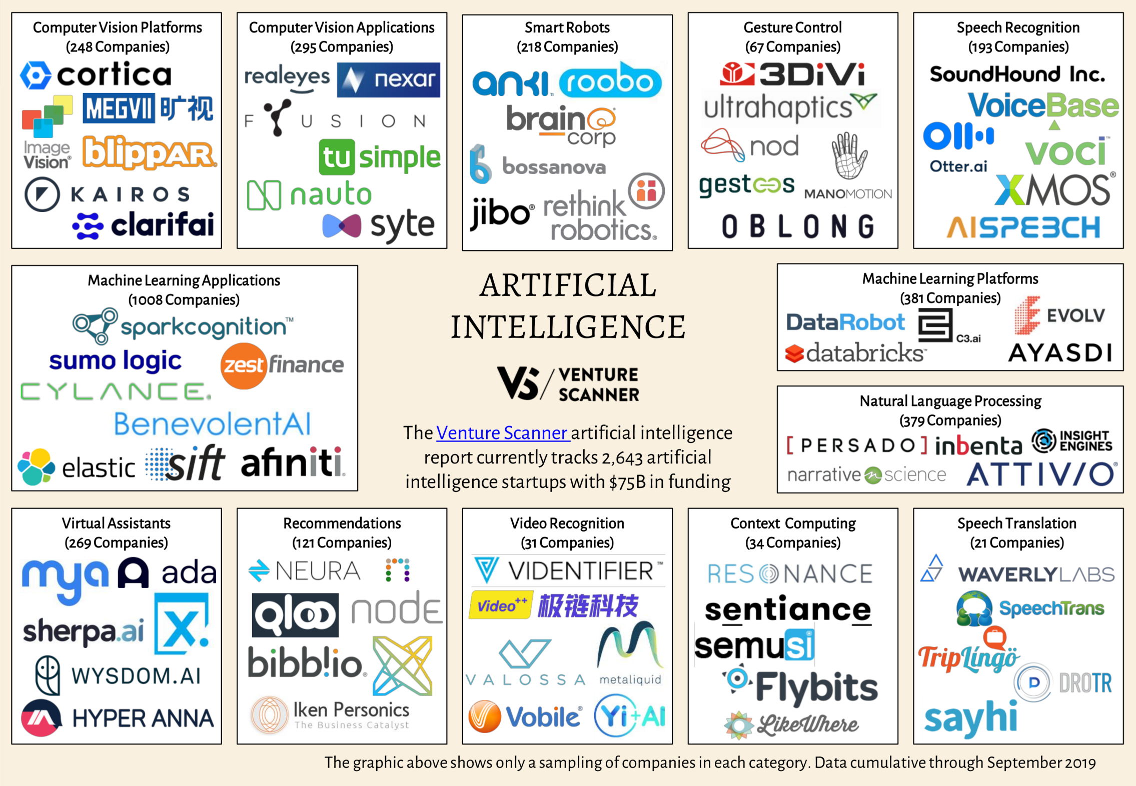
AI is like teenage sex: everyone talks about it, nobody knows how to do it, everyone thinks everyone else is doing it & so claims to do it

Bazzalisk @bazzalisk · Apr 5, 2017
Replying to @thinkmariya and @cstross
And when it does happen it usually leads to unintended consequences.

1

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





… 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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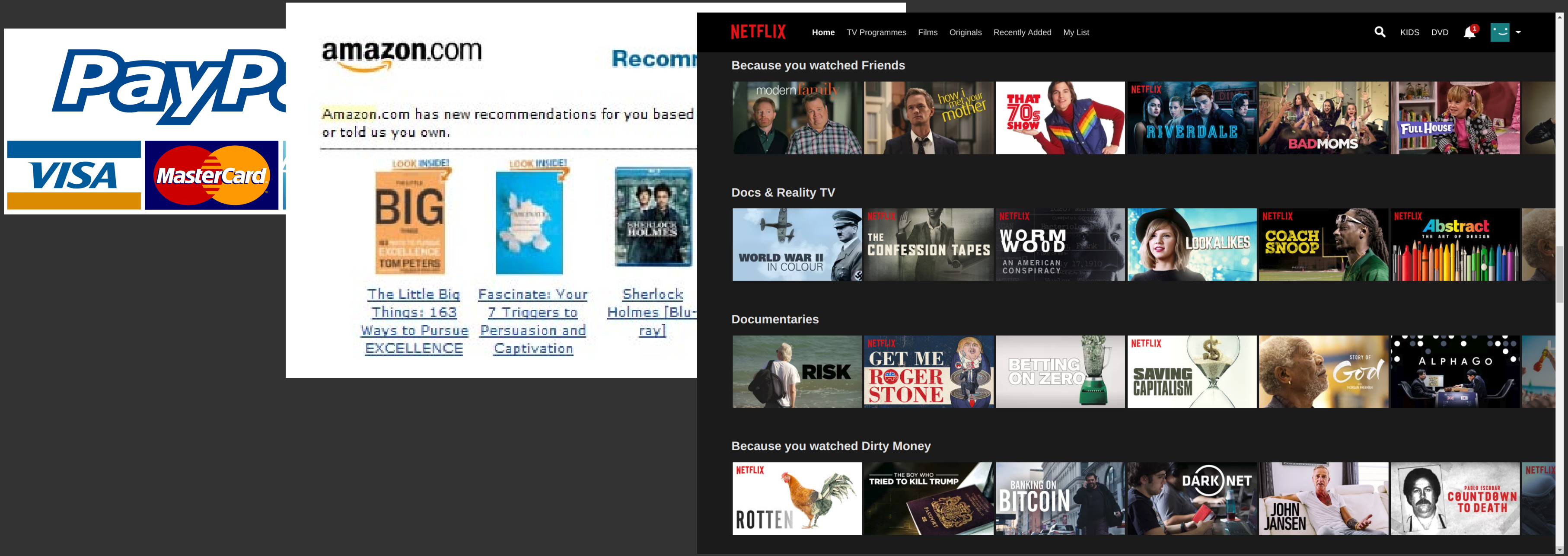

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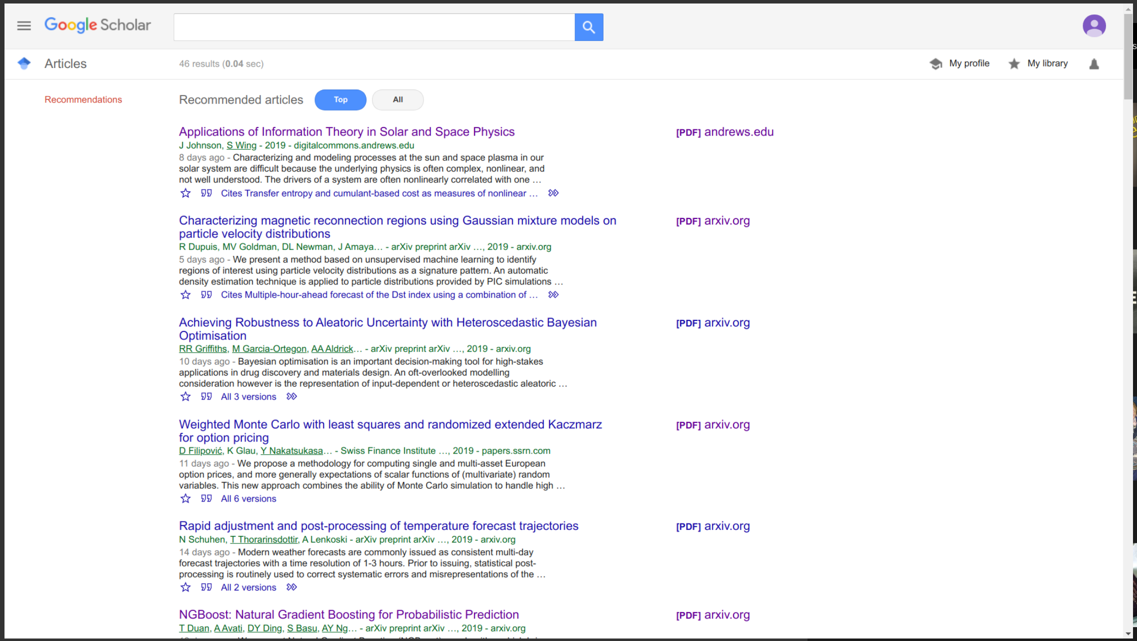

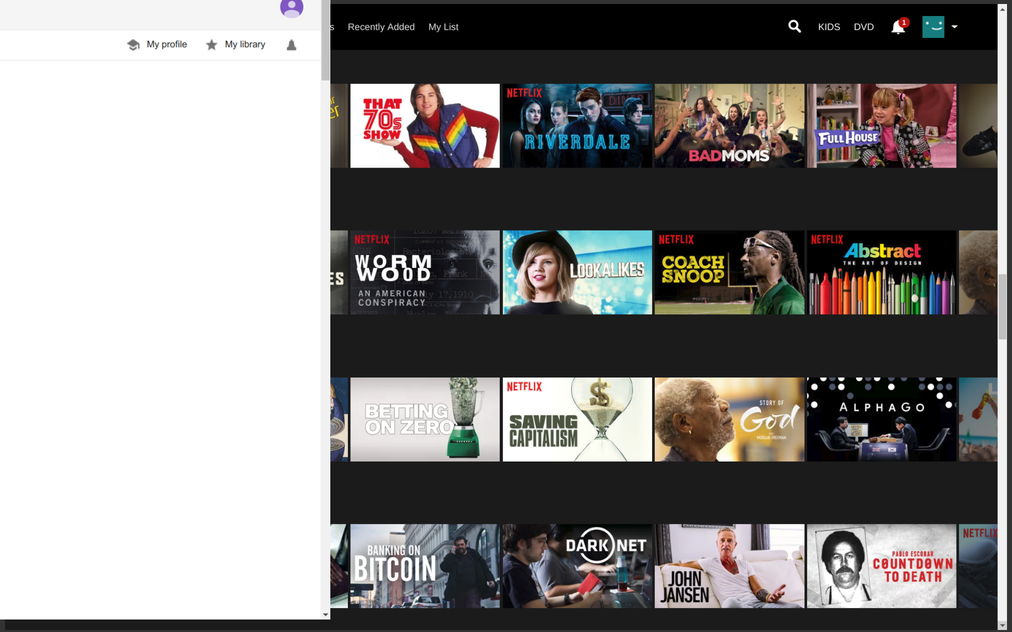

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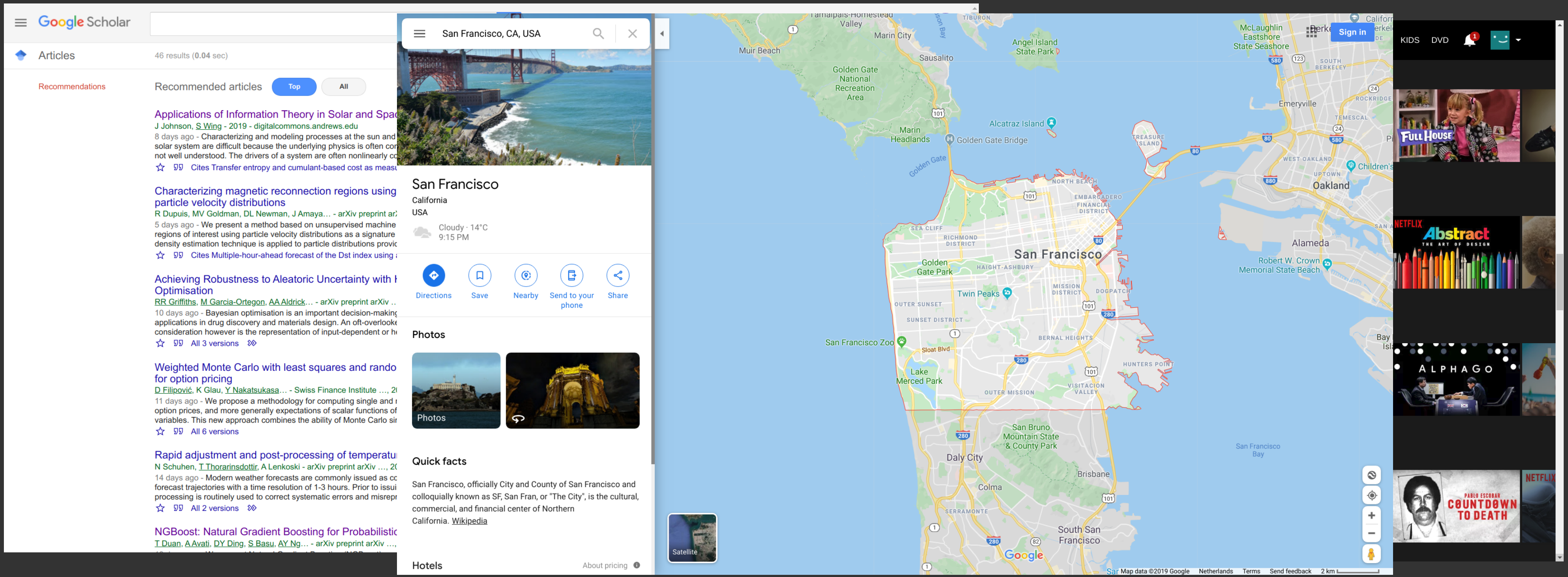

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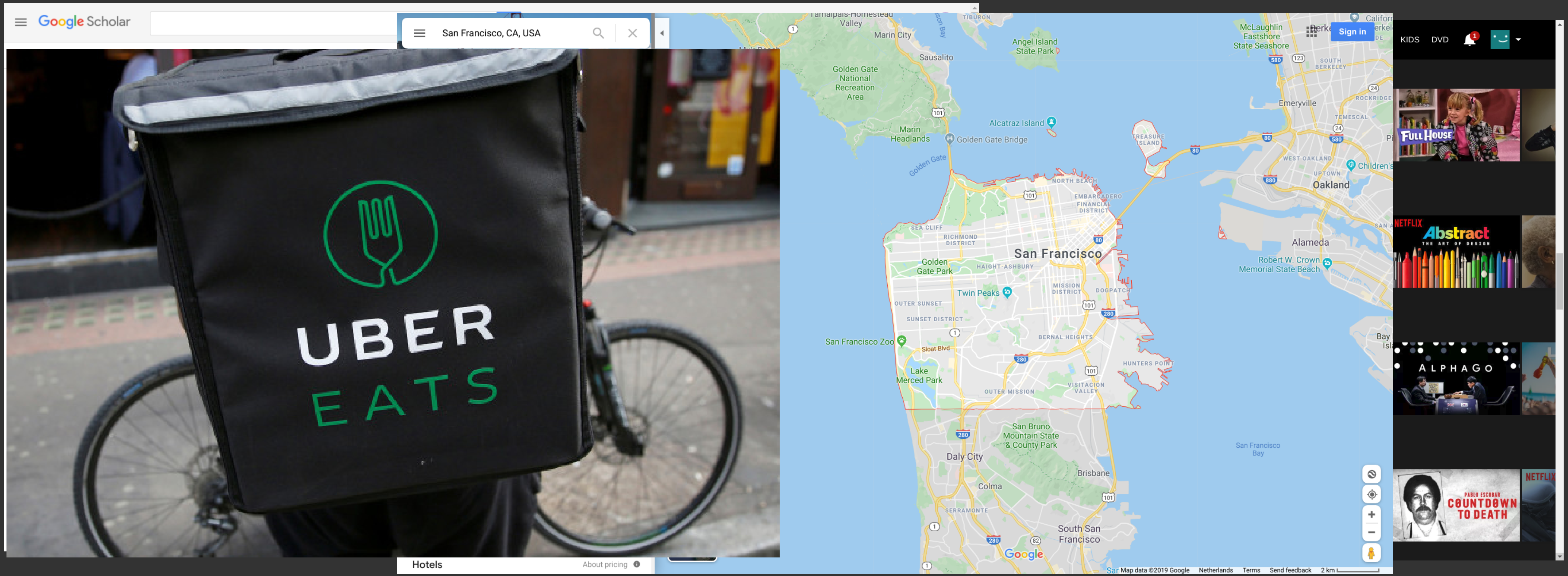

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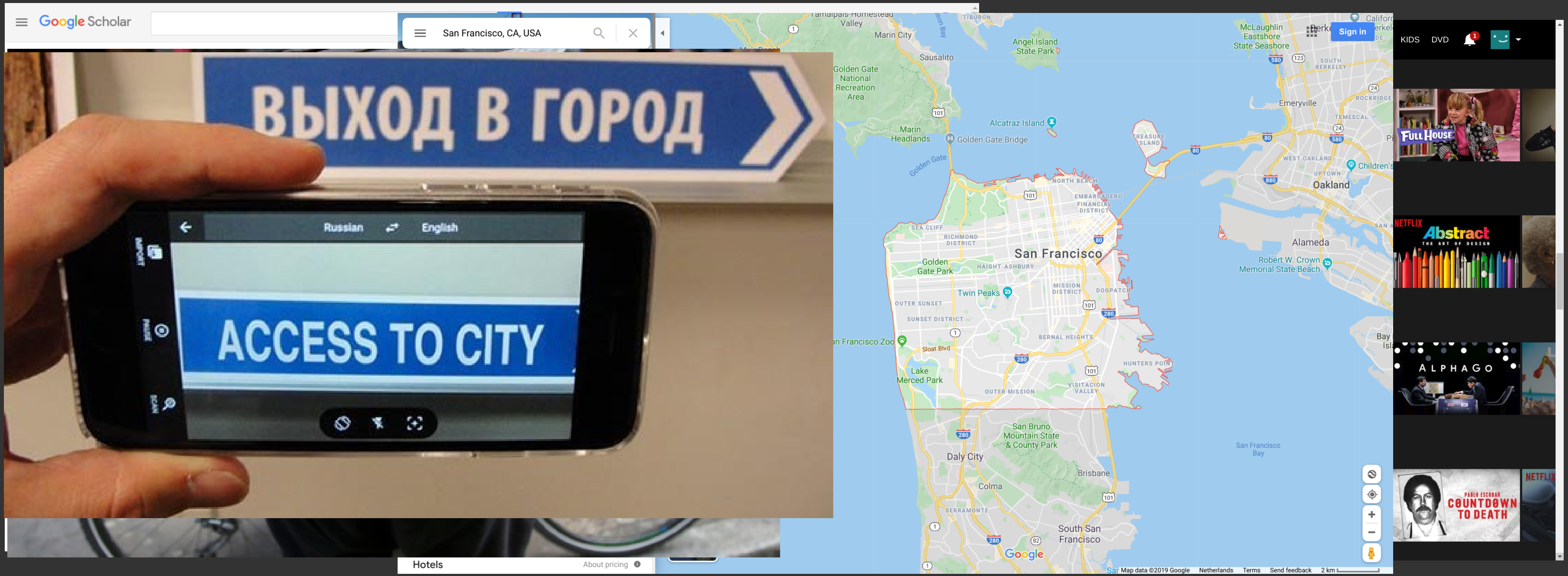

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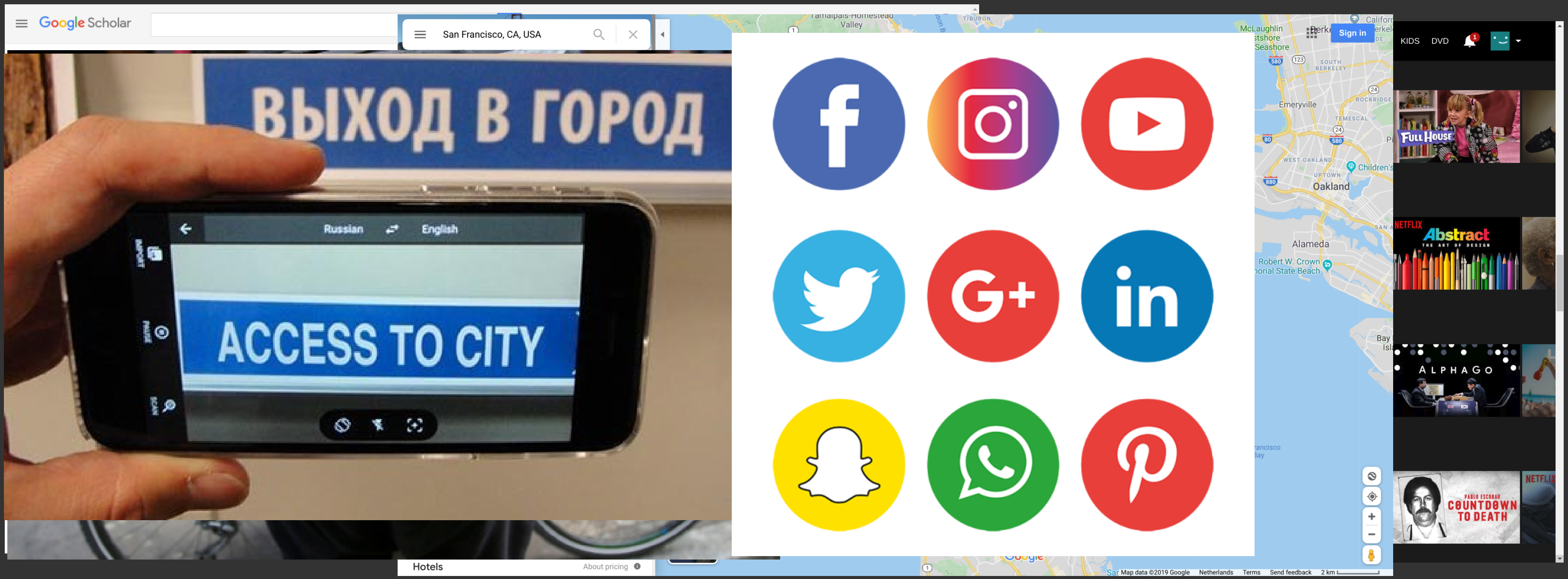
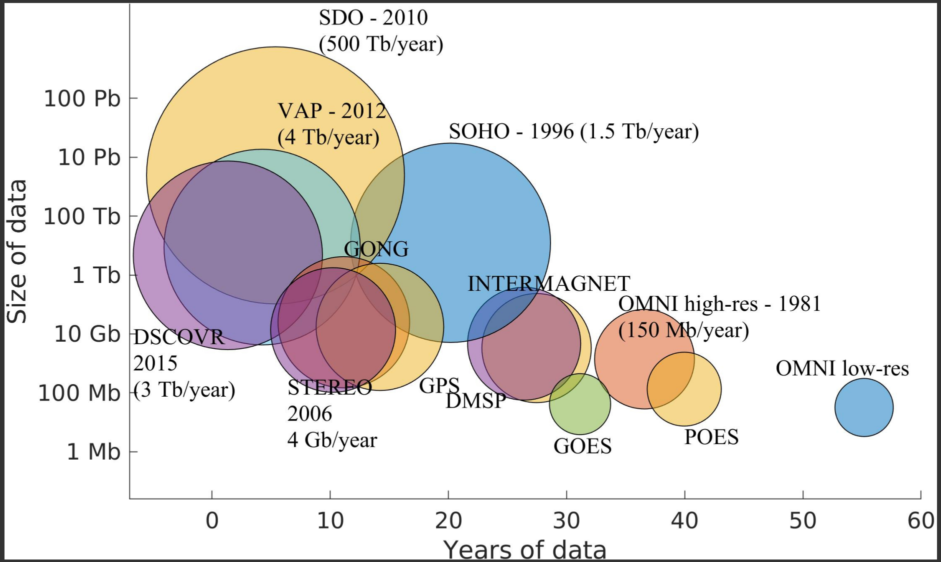


The Machine Learning renaissance

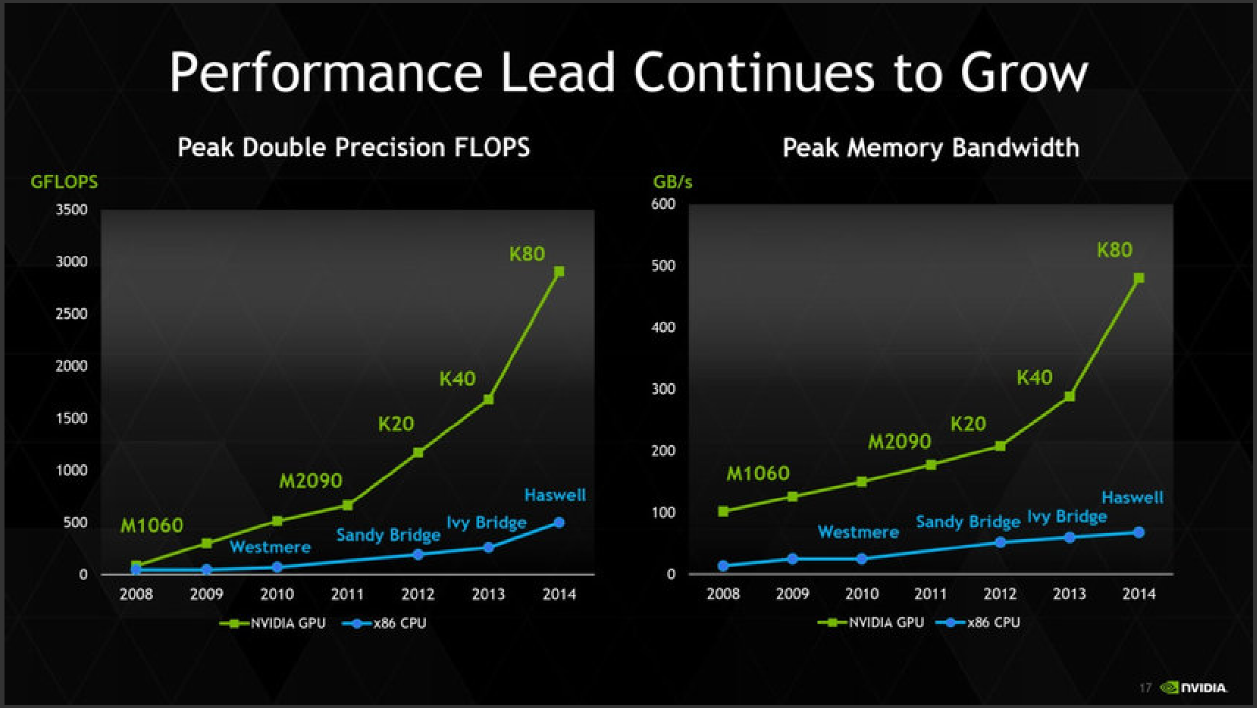
- Three enabling factors:
  - Big data



90% of data created in the last 2 years

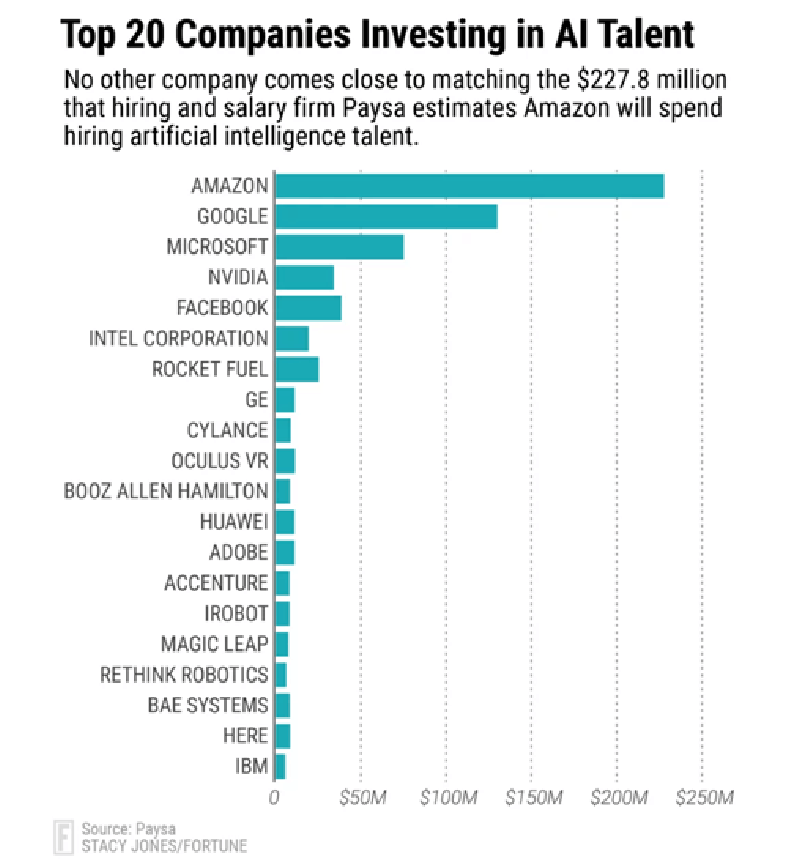
The Machine Learning renaissance

- Three enabling factors:
  - Big data
  - GPU computing



The Machine Learning renaissance

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



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 Karniadakis, 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 McCauley[1], 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 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

Classification:
What class does an event belong to?

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

Savvas Raptis[1], S. Aminalragia-Giamini[2], Tomas Karlsson[1] & Per-Arne Lindqvist[1]

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

[2]Space 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 •
The Astrophysical Journal, Volume 798, Number 2

SOLAR ACTIVE REGIONS LOCALIZATION OVER MULTI-SPECTRAL OBSERVATIONS

Majedaldein Almahasneh[1], Adeline Paiement[2], Xianghua Xie[1], Jean Aboudarham[3], and Jingjing Deng[1]

[1]Swansea University, UK [2]Laboratoire d'Informatique et Systèmes, Université de Toulon, France
[3]LESIA, Observatoire de Paris, PSL University, France

Regression: what is the relation between inputs and outputs?

Predicting GNSS Disruptions using Machine Learning

ML in Heliophysics 2019

Laura A. Hayes

Kibrom Ebuy 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. Bortnik[1]; X. Chu[2]; Q. Ma[1,3], C. Yue[1]; W. Li[3]; R. Denton[4]; R. M. Thorne[1]; V. Angelopoulos[1];
[1]UCLA, [2]CU-Boulder/LASP, [3]Boston U., [4]Dartmouth 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

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

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

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

Key Points:

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

Solar wind prediction using Deep learning

Vishal Upendran[1,2], Mark C.M. Cheung[3,4], Shravan Hanasoge[5], Ganapathy Krishnamurthi[2]

[1]Inter-University Centre for Astronomy and Astrophysics, Post Bag-4, Ganeshkhind, Pune, India; [2]Department of Engineering Design, Indian Institute of Technology – Madras, Chennai, India; [3]Lockheed Martin Solar and Astrophysics Laboratory, Palo Alto, CA, USA; [4]Hansen Experimental Physics Laboratory, Stanford University, Stanford, CA, USA; [5]Department 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
https://doi.org/10.3847/1538-4357/aaae69

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

Jiajia Liu[1], 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 | Ac

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

(reduced)
physics-based model

assumptions &
approximations

First-principles
model

Empirical model

Machine
Learning

The gray-box approach

(reduced)
physics-based model

assumptions &
approximations

First-principles
model

Empirical model

Machine
Learning

The gray-box approach

ML Enhanced
(reduced)
physics-based model

assumptions &
approximations

First-principles
model

inform the free parameters

Empirical model

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

First-principles model

assumptions & approximations

ML Enhanced (reduced) physics-based model

"business as usual"

Ensemble of ML and physics-based models

inform the free parameters

Empirical model

Machine Learning

The gray-box approach

ML Enhanced
(reduced)
physics-based model

assumptions &
approximations

First-principles
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Ensemble of ML and
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inform the free parameters

feature selection

Empirical model

Machine
Learning

The gray-box approach

ML Enhanced
(reduced)
physics-based model

assumptions &
approximations

inform the fr

es

cal model

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

First-principles model

assumptions & approximations

ML Enhanced
(reduced)
physics-based model

“business as usual”

Ensemble of ML and
physics-based models

provide training data

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

inform the free parameters

feature selection

Machine Learning

Empirical model

The gray-box approach

First-principles model

assumptions & approximations

ML Enhanced
(reduced)
physics-based model

"business as usual"

Ensemble of ML and physics-based models

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

Empirical model

Machine Learning

inform the free parameters

feature selection

training

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

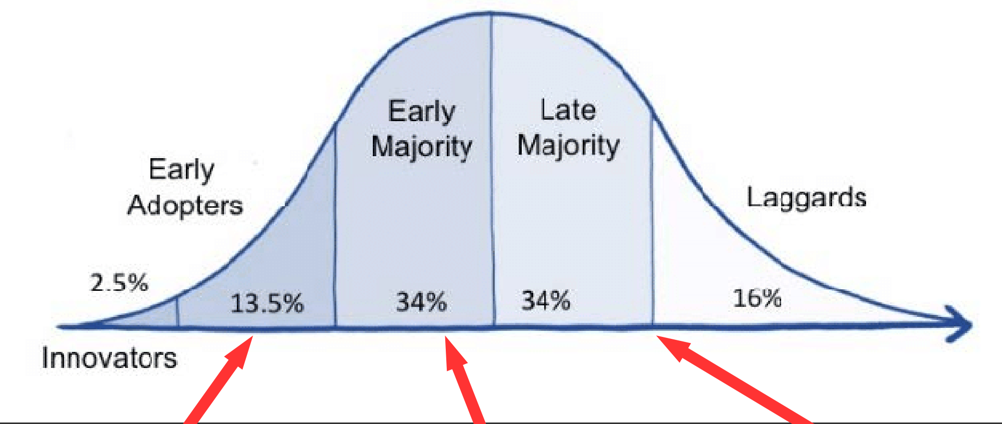
Authors

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!

www.youtube.com

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

Introducing Ludwig, a Code-Free Deep Learning Toolbox

Piero Molino, Yaroslav Dudin, and Sai Sumanth Miryala

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

HelioML

Space Weather

FEATURE ARTICLE

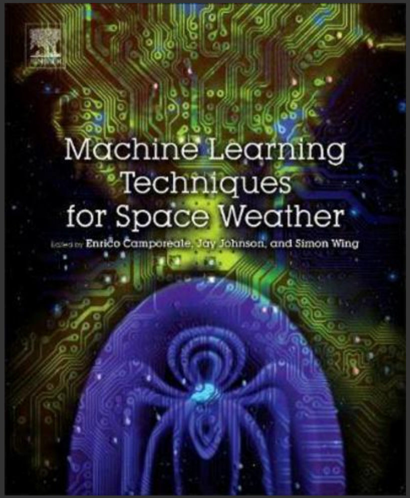
10.1029/2018SW002061

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



Slides available on: ecamporeale.github/talks

Contact: enrico.camporeale@noaa.gov