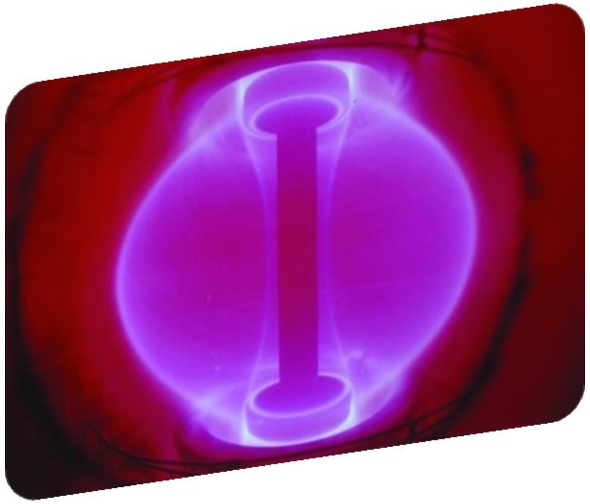
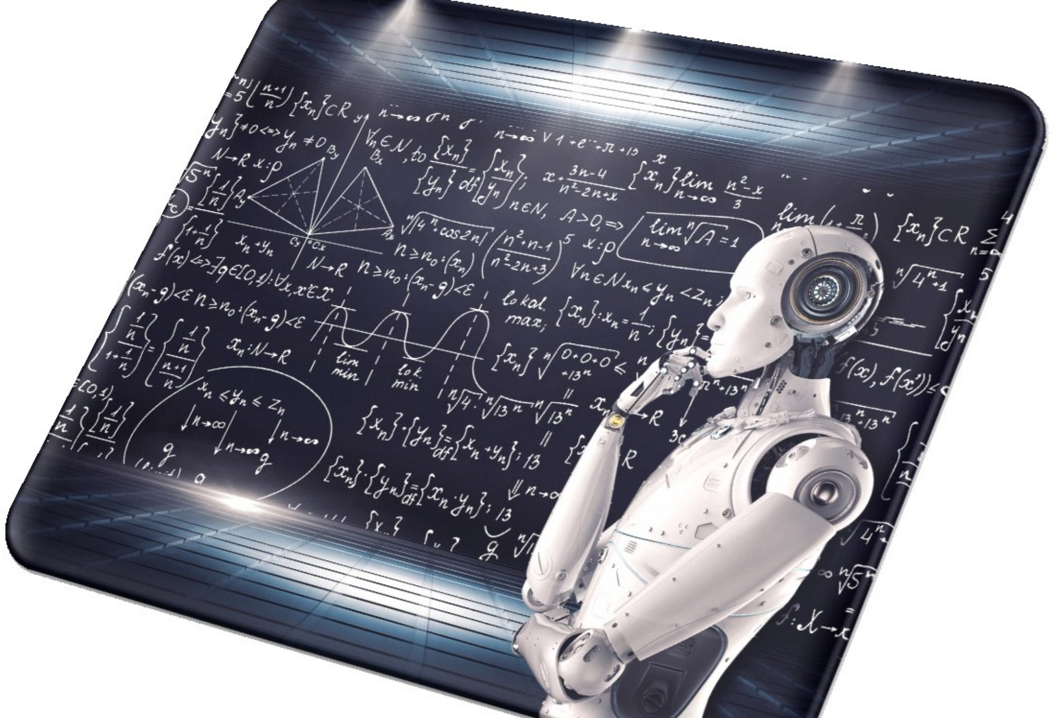




Recent Advancements in Computational Plasma Physics : Intelligence and Data Science

Yavar Taheri Yeganeh

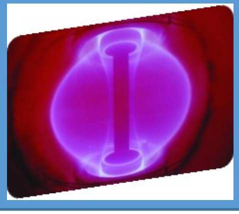
Department of Physics

Shahid Beheshti University (SBU)

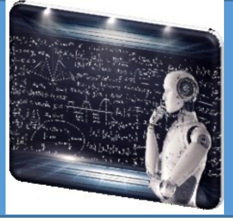
Plasma Physics Seminar @ SBU Physics

October 8, 2019

Please Note: References are not listed in the slides



Introduction & Content



- Who am I ?
- My Current Research
- Today Topic : Stimulating

Quick Introduction and Review : Next Talk > Details

- AI Revolution and Plasma
- Brief Introduction on AI and DS
- AI and DS in Research
- Computational Advancements in Plasma Physics
- Conclusion > Discussion

YAVAR TAHERI YEGANEH

y.taheriyeganeh@mail.sbu.ac.ir
yavaryeganeh@gmail.com
(+98)9380493329
LinkedIn

Department of Physics
Shahid Beheshti Univerity
Evin, Tehran 19839, Iran

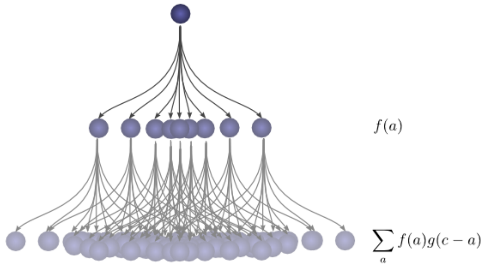
Education

MSc in Physics, Department of Physics, Shahid Beheshti University, Iran
Thesis title: 'Study on absorption of electromagnetic waves near UH resonance in high-beta plasma'
Supervisor: Prof. Mohammad Ghorbanalilu

BSc in Robotics Engineering (Machine Intelligence & Robotics),
Department of Electrical and Robotics Engineering, Shahrood University of Technology, Iran
Thesis title: 'Design, study and construction of magnetic robot'
Supervisor: Dr. Masoud Mahdizadeh

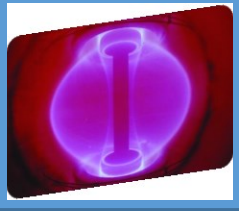
Areas of Interest

Plasma Physics • Artificial Intelligence • Machine Learning and Data Science • Computational Physics
Numerical Simulation • Control Theory • Plasma Diagnostics • High Performance Computing
Many-Body Physics • Experimental Particle Physics • Quantum Electrodynamics



Resources are practically unlimited

Deuterium in a bath tub full of water and **Lithium** in a used laptop battery suffice for a family over 50 years



AI Revolution and Plasma : Fusion

Fusion research: Towards burning plasmas

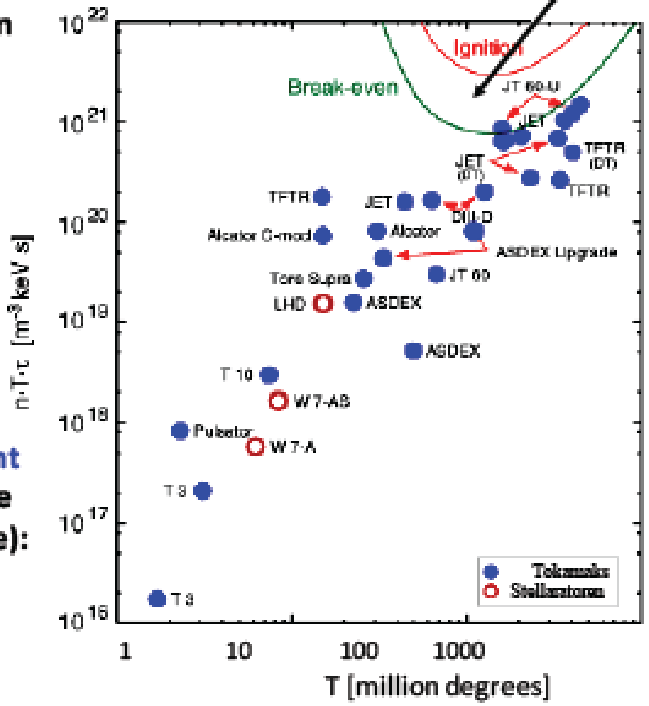
Self-heating must compensate energy losses:

- Electromagnetic radiation
- Turbulent transport

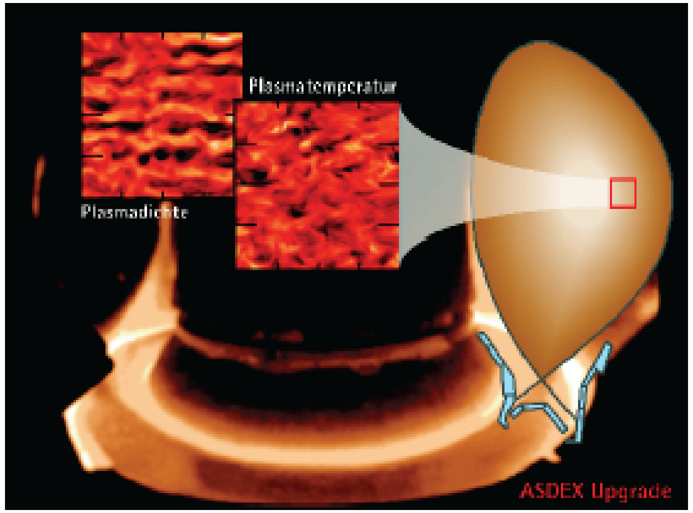
Key requirements:

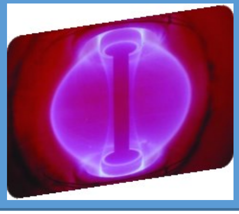
- Large central pressure (limited by onset of large-scale instabilities)
- Large energy confinement time (limited by small-scale instabilities, i.e. turbulence):

$\tau_E = E_{plasma} / P_{loss}$

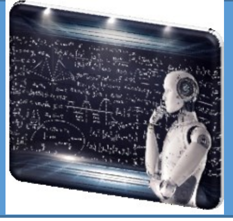


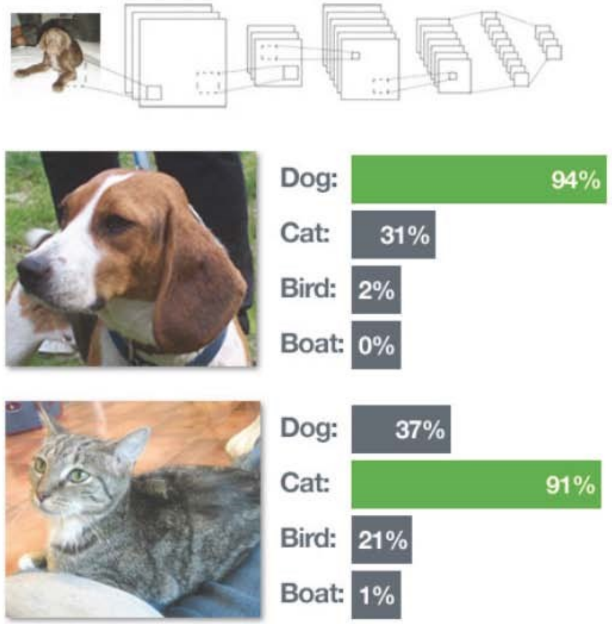
Radial heat transport due to small-scale turbulence controls energy confinement time



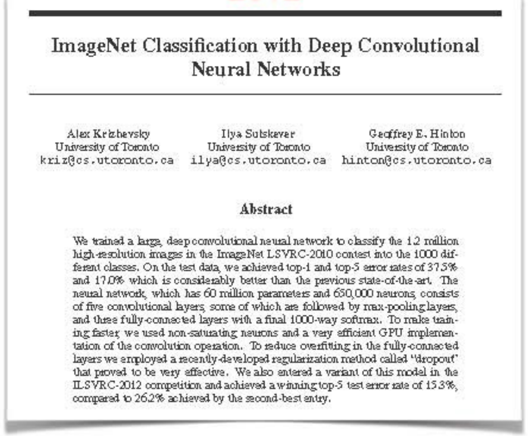


AI Revolution and Plasma : AI





2012



ImageNet Classification with Deep Convolutional Neural Networks

Alex Krizhevsky
University of Toronto
kriz@cs.utoronto.ca

Ilya Sutskever
University of Toronto
ilya@cs.utoronto.ca

Geoffrey E. Hinton
University of Toronto
hinton@cs.utoronto.ca

Abstract

We trained a large, deep convolutional neural network to classify the 1.2 million high-resolution images in the ImageNet LSVRC-2010 contest into the 1000 different classes. On the test data, we achieved top-1 and top-5 error rates of 37.5% and 17.0% which is considerably better than the previous state-of-the-art. The neural network, which has 60 million parameters and 650,000 neurons, consists of five convolutional layers, some of which are followed by max-pooling layers, and three fully-connected layers with a final 1000-way softmax. To make training faster, we used non-saturating neurons and a very efficient GPU implementation of the convolution operation. To reduce overfitting in the fully-connected layers we employed a recently-developed regularization method called "dropout" that proved to be very effective. We also entered a variant of this model in the ILSVRC-2012 competition and achieved a winning top-5 test error rate of 15.3%, compared to 26.2% achieved by the second-best entry.

2015

News & Analysis

Microsoft, Google Beat Humans at Image Recognition

Deep learning algorithms compete at ImageNet challenge

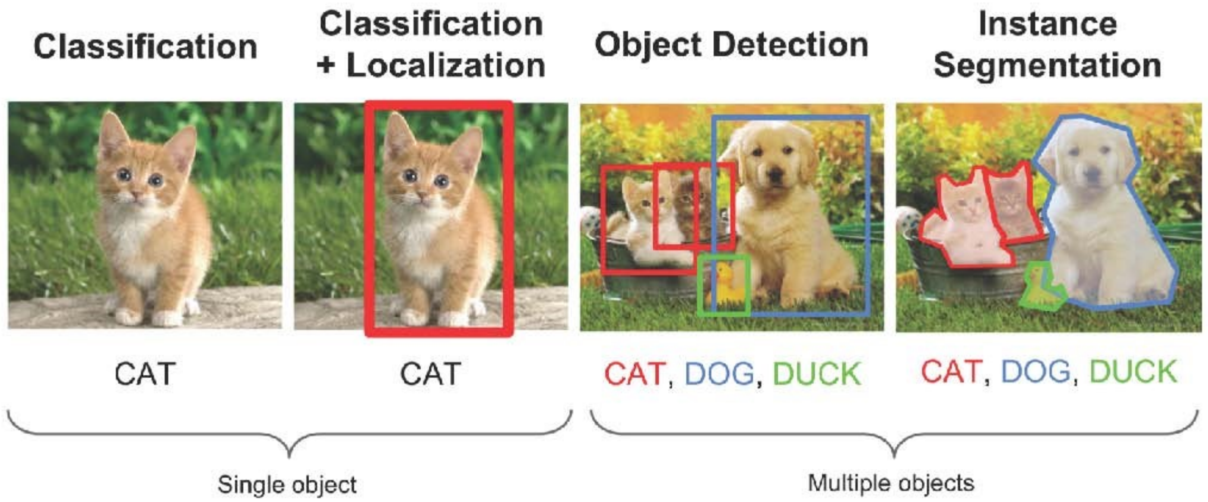
R. Colin Johnson
2/18/2015 03:15 AM EST
14 comments

1 saves
LOGIN TO RATE

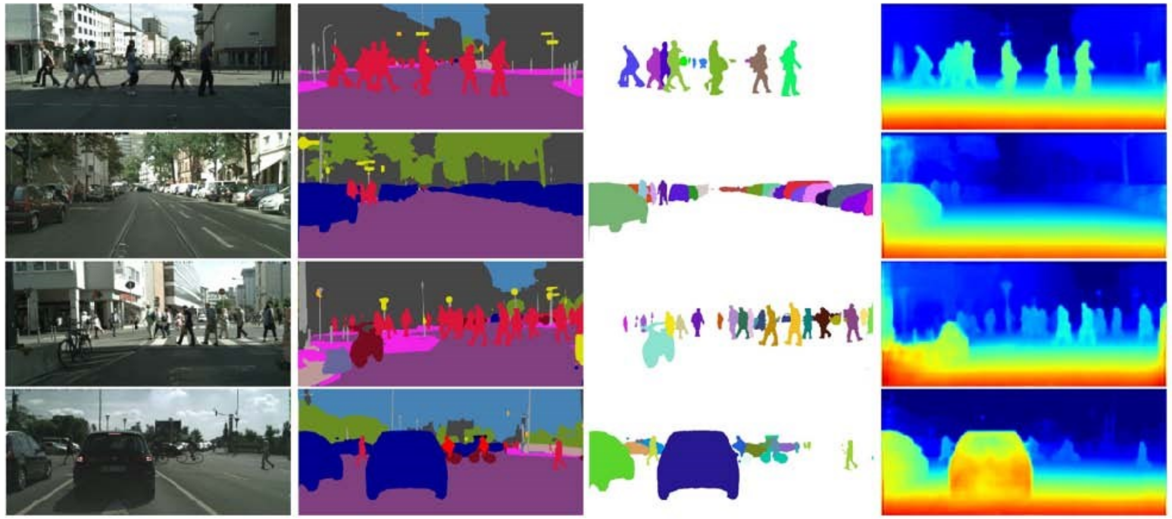
3

AI Revolution and Plasma : AI

CLASSIFICATION → SEGMENTATION



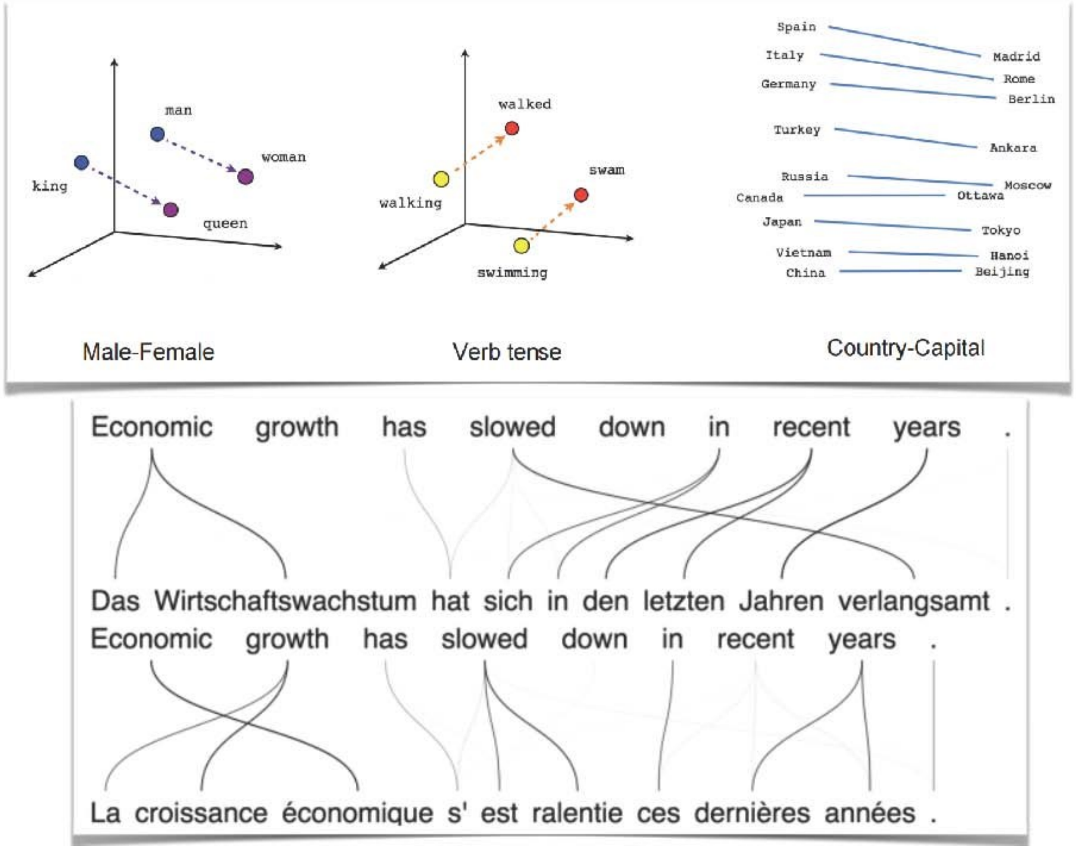
COMPUTER VISION



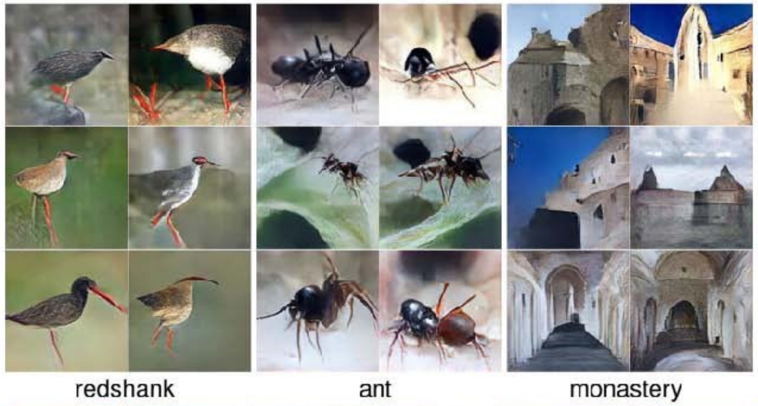
(a) Input image (b) Segmentation output (c) Instance output (d) Depth output

https://alexgkendall.com/computer_vision/bayesian_deep_learning_for_safe_ai/ 5

WORD EMBEDDINGS & TRANSLATION



GENERATIVE MODEL FOR IMAGES



7

GENERATIVE MODEL FOR IMAGES

How an A.I. 'Cat-and-Mouse Game' Generates Believable Fake Photos

By CADE METZ and KEITH COLLINS JAN. 2, 2018

This one is computer-generated

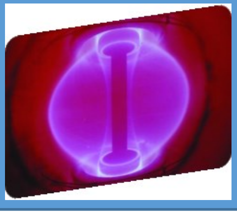
This one is also computer-generated

8

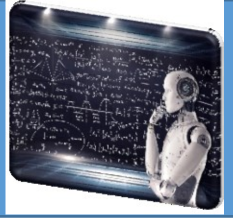
None of these faces is real. The faces in the top row (A) and left-hand column (B) were constructed by a generative adversarial network (GAN) using building-block elements of real faces. The GAN then combined basic features of the faces in A, including their gender, age and face shape, with finer features of faces in B, such as hair color and eye color, to create all the faces in the rest of the grid.

—

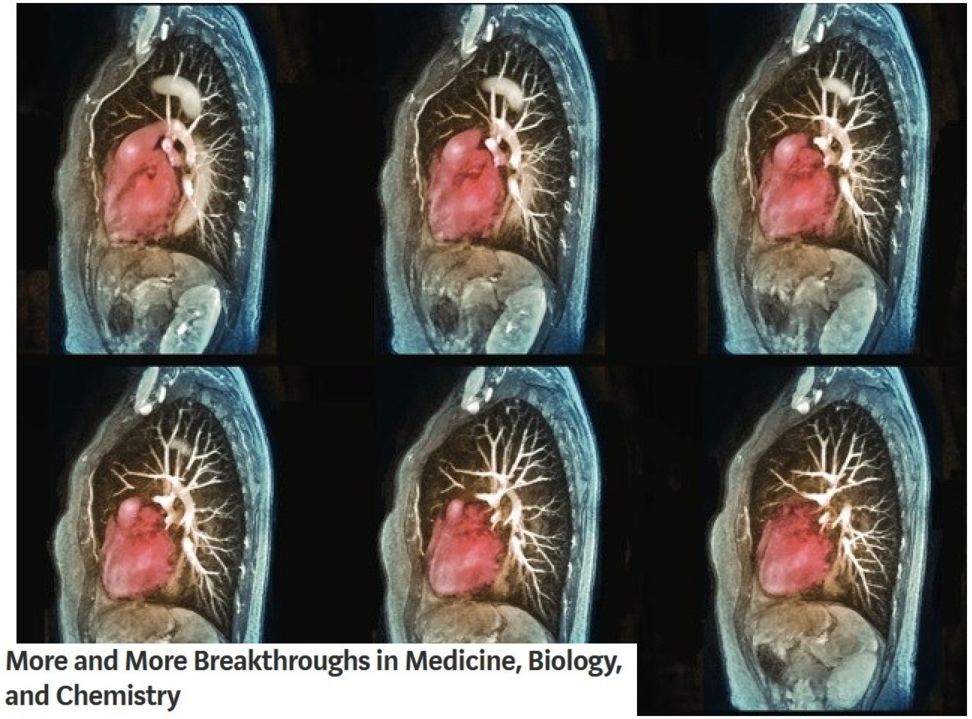
Adapted from NVIDIA



AI Revolution and Plasma : AI



- AI is Transforming almost everything including Science and Research



More and More Breakthroughs in Medicine, Biology, and Chemistry

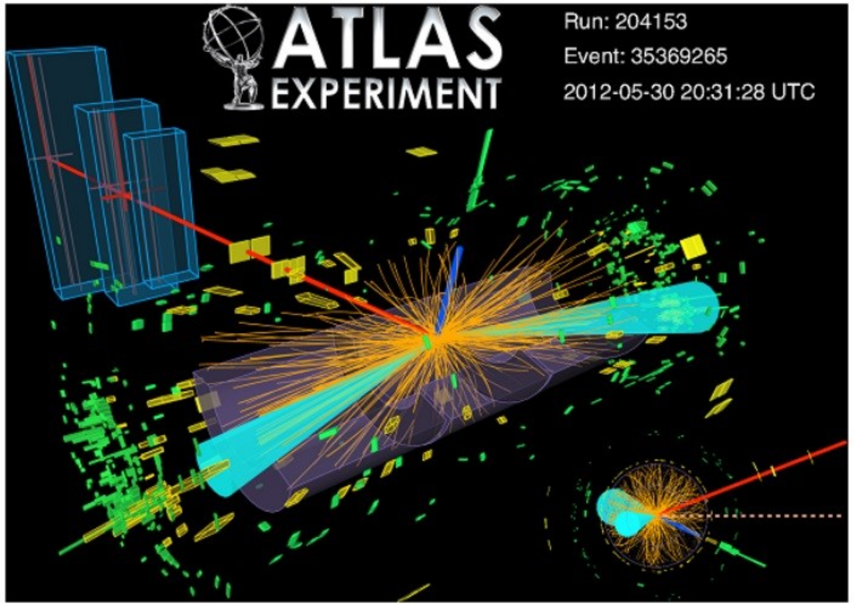
When less is more: Taking MRI scans quickly avoids capturing unwanted movements of the internal organs, but it can result in compromised images. Machine learning, however, could reconstruct improved images based on incomplete data. (Courtesy: Zephyr/Science Photo Library)

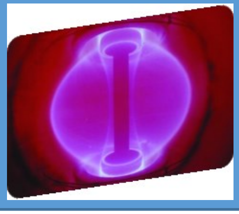
Higgs challenge

Higgs Boson Machine Learning Challenge

Use the ATLAS experiment to identify the Higgs boson

$13,000 · 1,785 teams · 5 years ago





AI Revolution and Plasma : AI

Deep Learning Classifies the Protein Universe

Max Bileschi, David Belanger, Drew Bryant, Theo Sanderson, Brandon Carter, D. Sculley, Mark DePristo, Lucy Colwell

initial Submission to BioArxiv (2019)

Characterizing Quantum Supremacy in Near-Term Devices

Sergio Boixo, Sergei Isakov, Vadim Smelyanskiy, Ryan Babbush, Nan Ding, Zhang Jiang, Michael J. Bremner, John

Nature Physics, vol. 14 (2018), 595–600

Optimization of Molecules via Deep Reinforcement Learning

Zhenpeng Zhou, Steven Kearnes, Li Li, Richard Zare, Patrick Riley

Scientific Reports, vol. 9 (2019), pp. 10752

Commercialize Quantum Technologies in Five Years

Masoud Mohseni, Peter Read, Hartmut Neven, Sergio Boixo, Vasil Denchev, Ryan Babbush, Austin Fowler, Vadim...

Nature, vol. 543 (2017), 171–174

Neural Message Passing for Quantum Chemistry

Justin Gilmer, Samuel S. Schoenholz, Patrick F. Riley, Oriol Vinyals, George E. Dahl

ICML (2017)

Scalable Quantum Simulation of Molecular Energies

Peter O'Malley, Ryan Babbush, Ian Kivlichan, Jonathan Romero, Jarrod McClean, Rami Barends, Julian Kelly,...

Physical Review X, vol. 6 (2016), pp. 031007

In Silico Labeling: Predicting Fluorescent Labels in Unlabeled Images

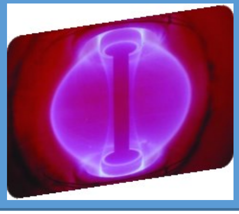
Eric Christiansen, Samuel Yang, Mike Ando, Ashkan Javaherian, Gaia Skibinski, Scott Lipnick, Elliot Mount, Alison O'Neil,

Cell (2018)

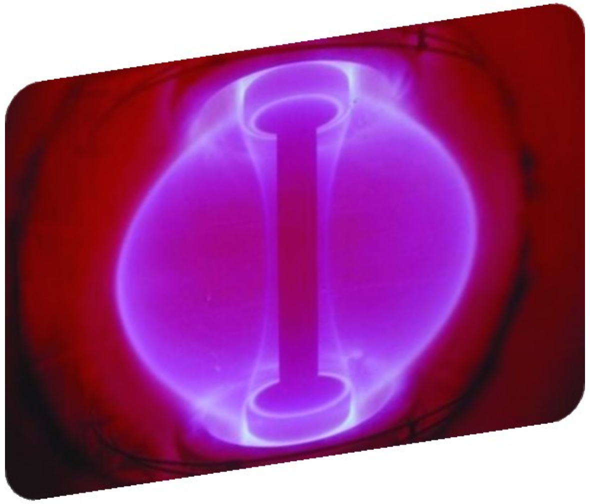
Achievement of Sustained Net Plasma Heating in a Fusion Experiment with the Optometrist Algorithm

E.A. Baltz, E. Trask, M. Binderbauer, M. Dikovsky, H. Gota, R. Mendoza, J.C. Platt, P.F. Riley

Scientific Reports, vol. 7 (2017), pp. 6425



AI Revolution and Plasma : Intelligent Computations



WHAT IS ARTIFICIAL INTELLIGENCE?

Artificial intelligence encompasses technologies and processes that augment human knowledge and capabilities. Demis Hassabis, co-founder and CEO of Google DeepMind, defines AI as the "science of making machines smart."

AI concepts include:

- Machine learning
- Deep learning
- Image recognition
- Natural-language generation
- Computer vision
- Cognitive computing

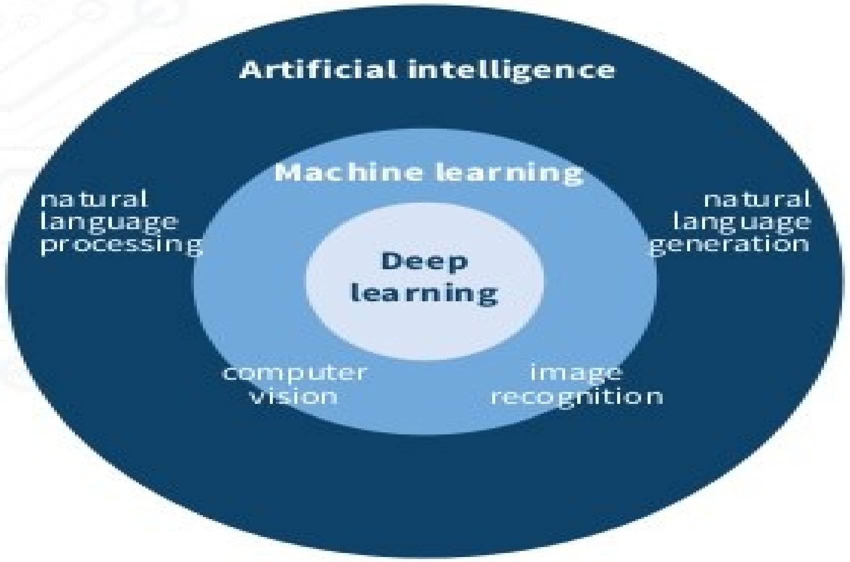
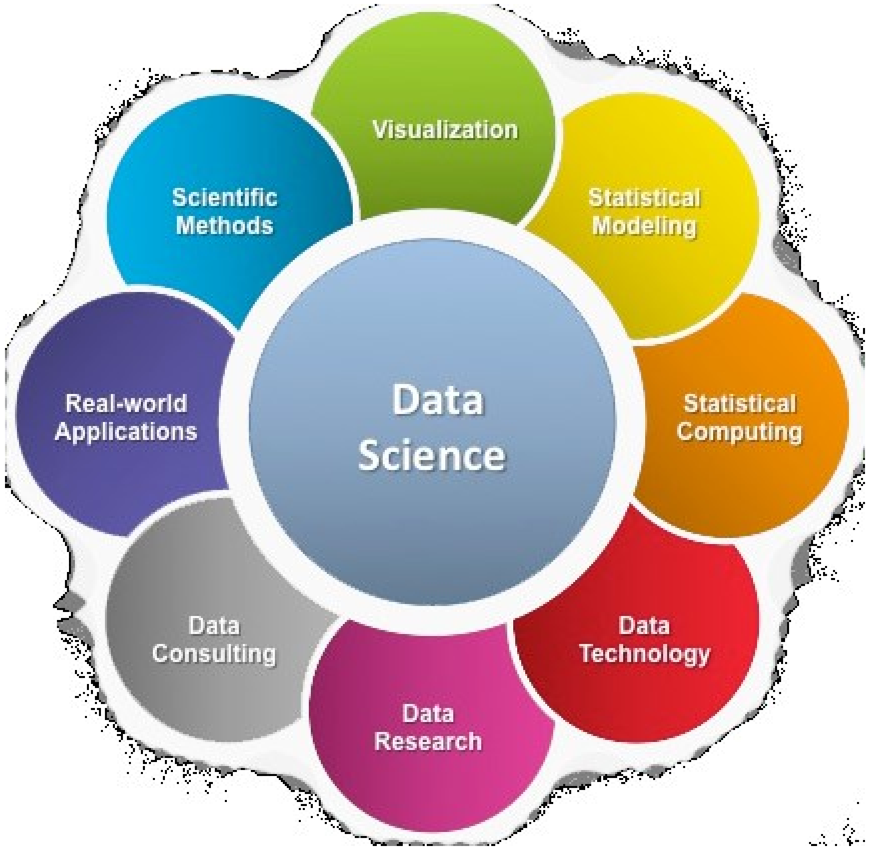
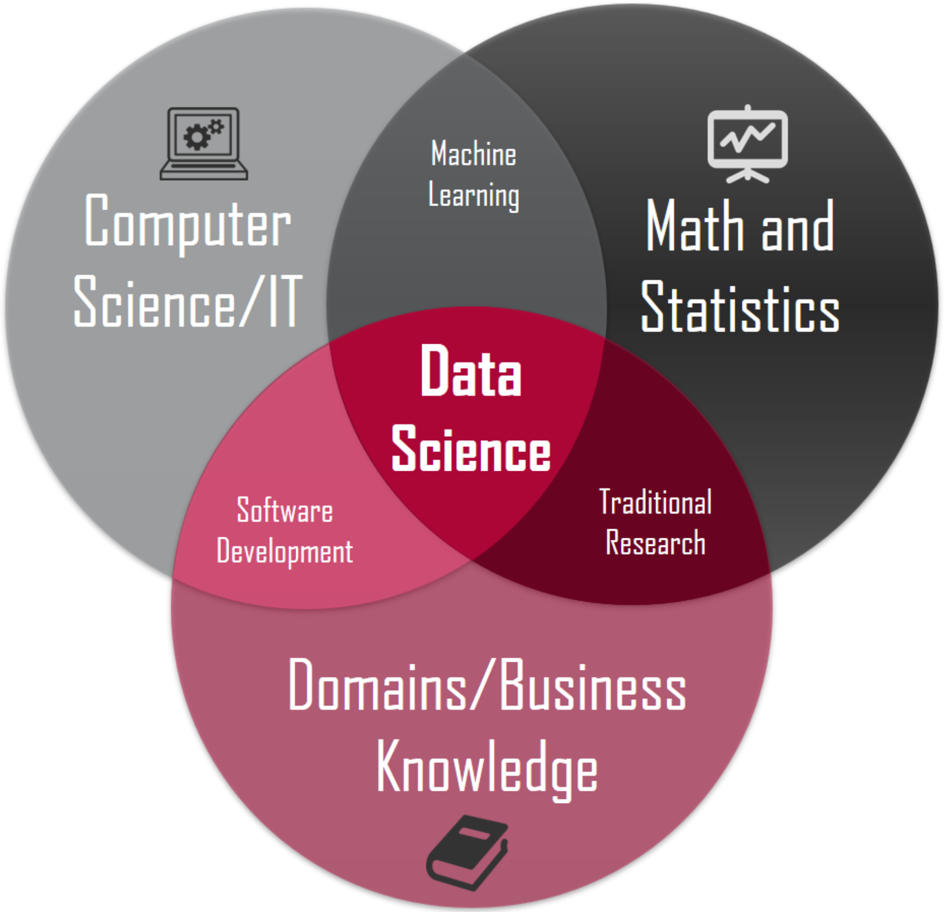


*Image source

Brief Introduction on AI and DS : Data Science





Brief Introduction on AI and DS : AI

- Models of intelligence
  - Cognitive Psychology: Psychological basis, the process of human learning.
  - Neurobiology: Physiological basis, the brain, the neuron.
- Knowledge/concepts
  - Cognitive Psychology: What is a concept? Why we use the concepts we use? How do we represent them internally? How do we organize them?
  - Mathematical Logic: Learning of symbolic models/Use of prior knowledge
  - Statistics: Learning of probabilistic models/Data Uncertainty
  - Optimization: Learning as function approximation

Brief Introduction on AI and DS : AI > ML

What Is Machine Learning?

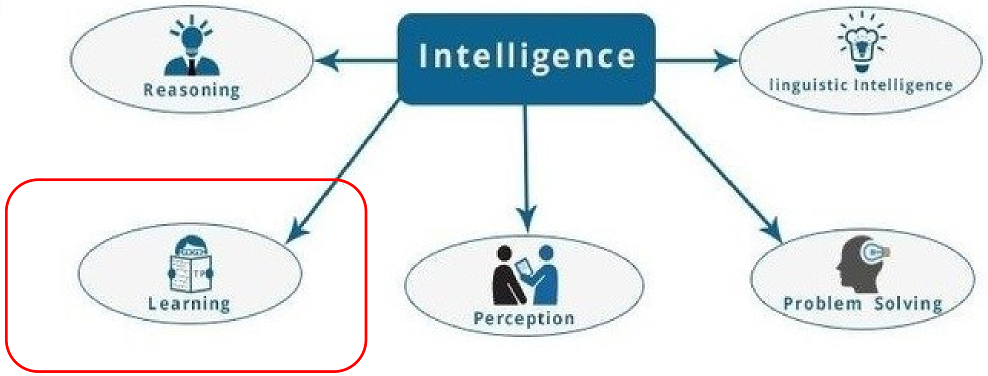
Machine Learning is the science (and art) of programming computers so they can *learn from data*.

Here is a slightly more general definition:

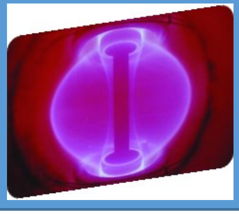
> [Machine Learning is the] field of study that gives computers the ability to learn without being explicitly programmed.
>
> —Arthur Samuel, *1959*

And a more engineering-oriented one:

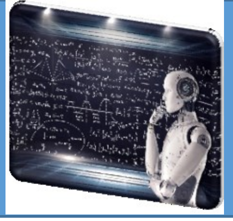
> A computer program is said to learn from experience E with respect to some task T and some performance measure P, if its performance on T, as measured by P, improves with experience E.
>
> —Tom Mitchell, *1997*



AI > Learning (Machine)

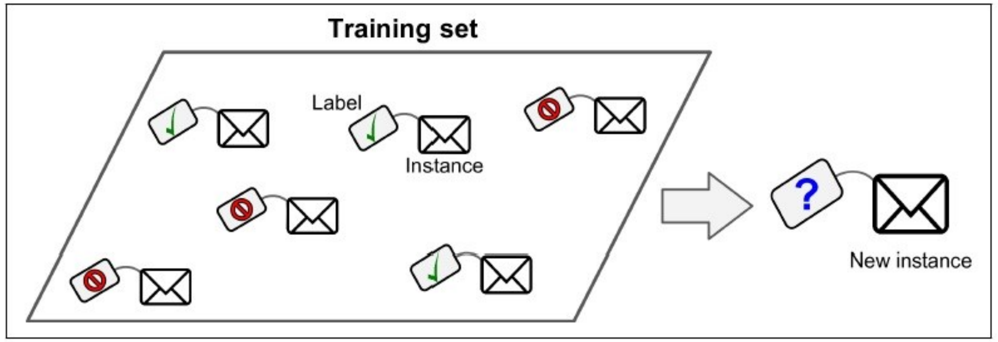


Brief Introduction on AI and DS : ML > ANN



Supervised learning

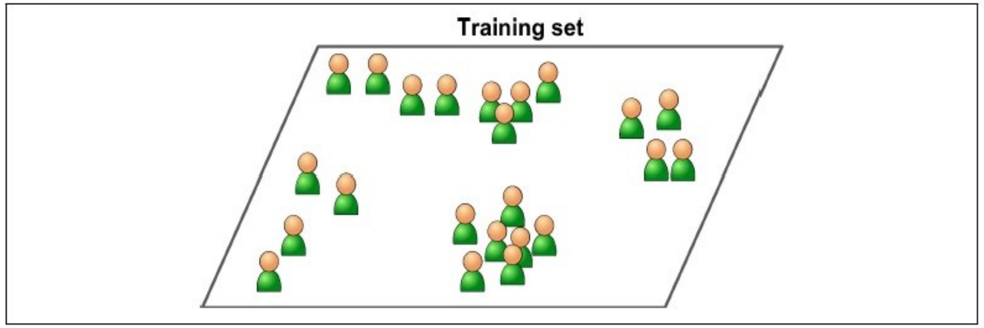
In *supervised learning*, the training data you feed to the algorithm includes the desired solutions, called *labels* (Figure 1-5).



- k-Nearest Neighbors
- Linear Regression
- Logistic Regression
- Support Vector Machines (SVMs)
- Decision Trees and Random Forests
- Neural networks[2]

Unsupervised learning

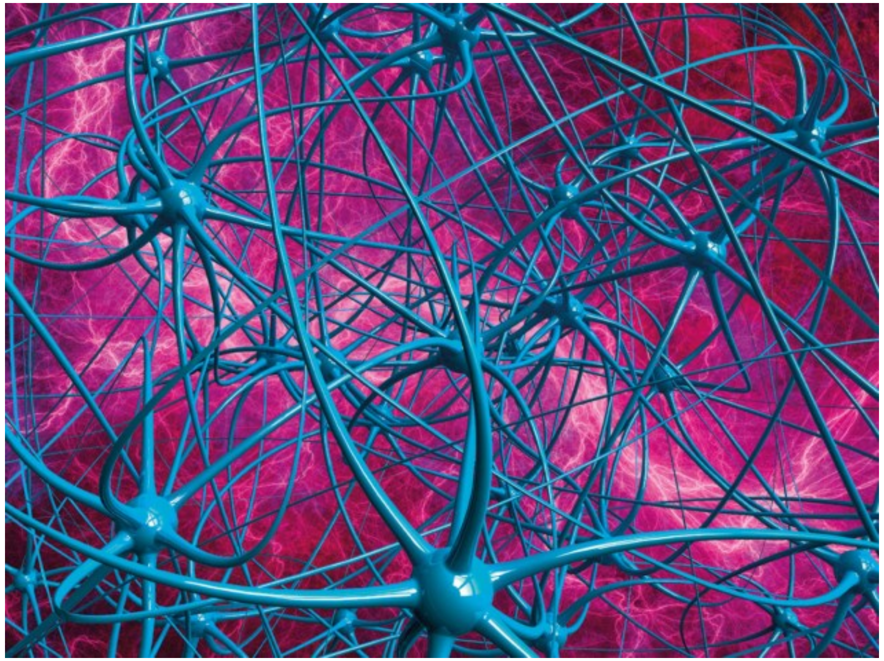
In *unsupervised learning*, as you might guess, the training data is unlabeled (Figure 1-7). The system tries to learn without a teacher.

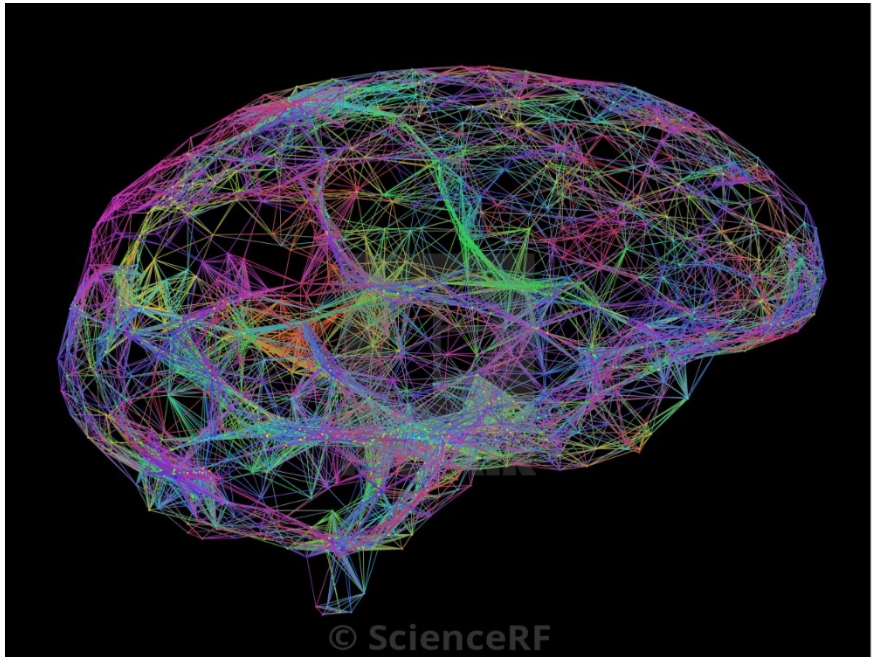


- Clustering
  - — K-Means
  - — DBSCAN
  - — Hierarchical Cluster Analysis (HCA)
- Anomaly detection and novelty detection
  - — One-class SVM
  - — Isolation Forest

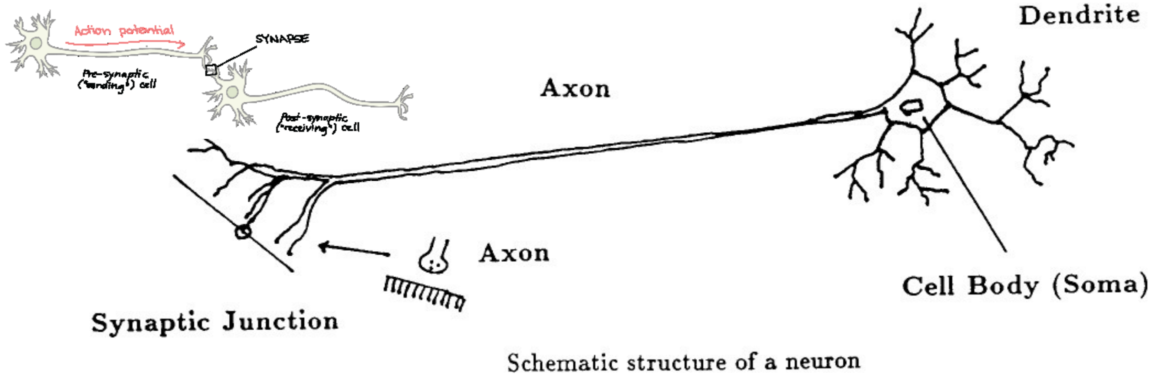
ANN

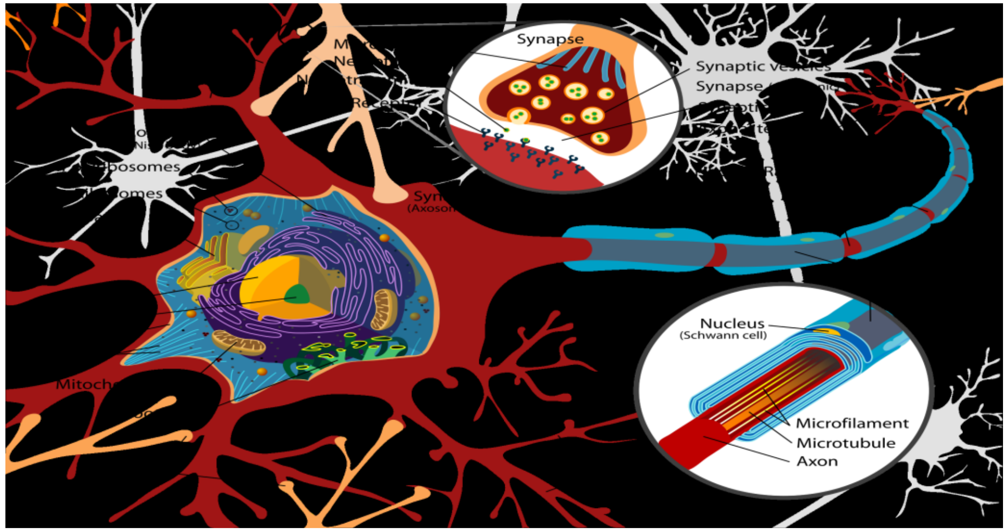
- Artificial Neural Networks : **Simulation of Biological Intelligence**

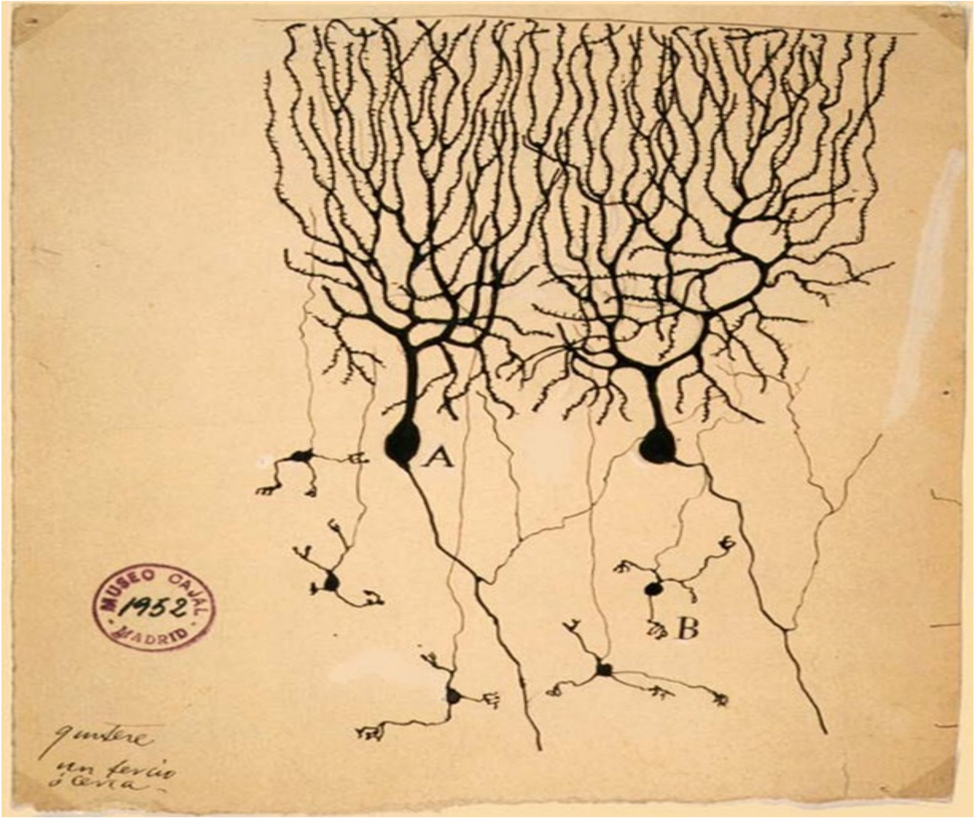




Brief Introduction on AI and DS : ANN



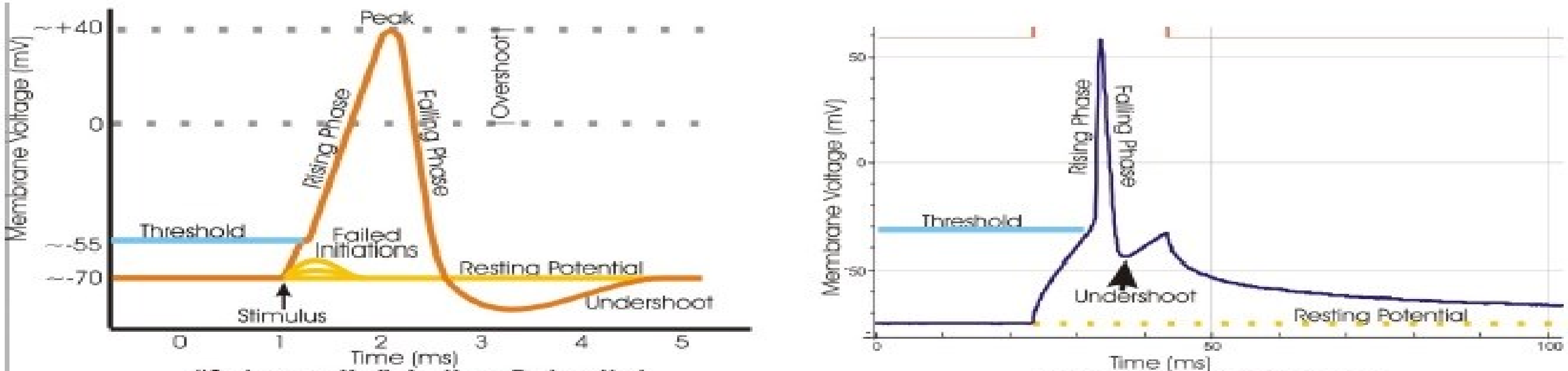




1906 Nobel Prize in Physiology or Medicine. Drawing by Ramon y Cajal.

Brief Introduction on AI and DS : ANN

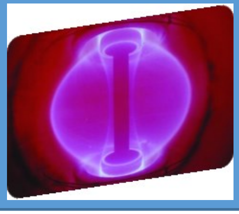
Action Potential of an Excited Neuron



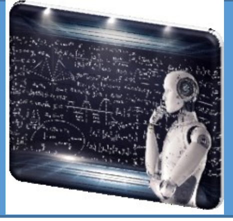
"Schematic" Action Potential
"Real" Action Potential

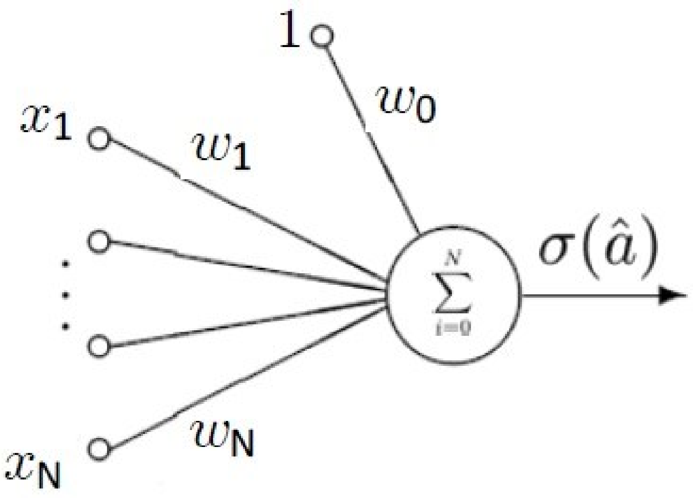
Neuron Networks in the Brain

- The human brain contains about 10^{11} neurons connected in tree-like networks.
- The cell body of a neuron has as many as 10^5 dedrites or tree-like fibers on its surface
- The neuron integrates electrochemical signals received by its dendrites from other neurons
- If the integrated signal exceeds a threshold the neurons generates a spike-train of soliton-like signals that propagate along its axon



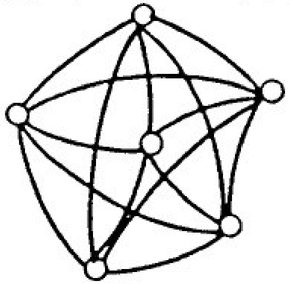
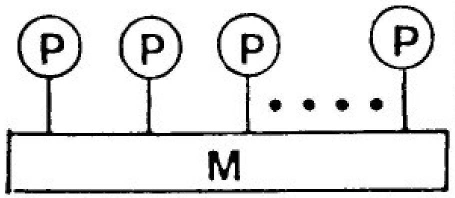
Brief Introduction on AI and DS : ANN



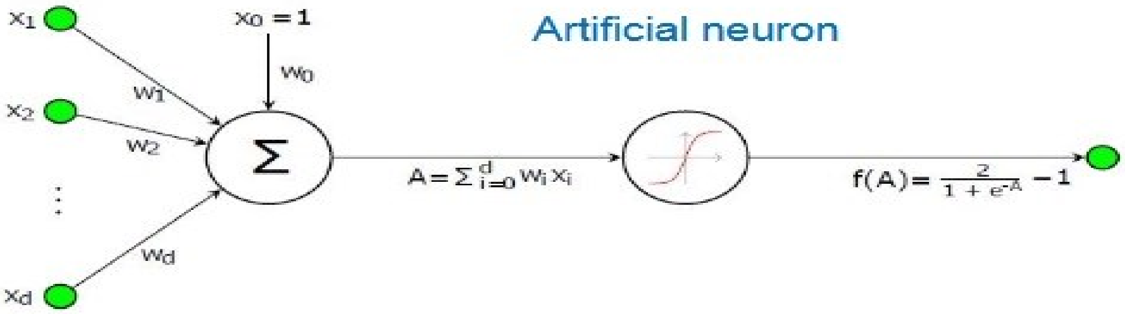


$$\sigma(\hat{a}(\mathbf{x})) \equiv p(signal|\mathbf{x})$$

Visualization of a neuron: Weighted summation of the inputs and nonlinear (sigmoid) transformation at the output. (Figure adopted from [1], modified.)

Vertebrate Brain (Parallel Distributed Proc.)	Conventional Computer (von Neumann machine)
	
Power dissipation: $\approx$ 100W	Power dissipation: $\approx 10^5$W
Good at: - recognition - adaption - optimization (rough)	Good at: - a+b, a $\cdot$ b,... - if (....) else - state space exploration
$\tau = \mathcal{O}(ms)$	$\tau = \mathcal{O}(ns)$
Parallel Robust Fault Tolerant	Serial/parallel Fragile

Brief Introduction on AI and DS : ANN

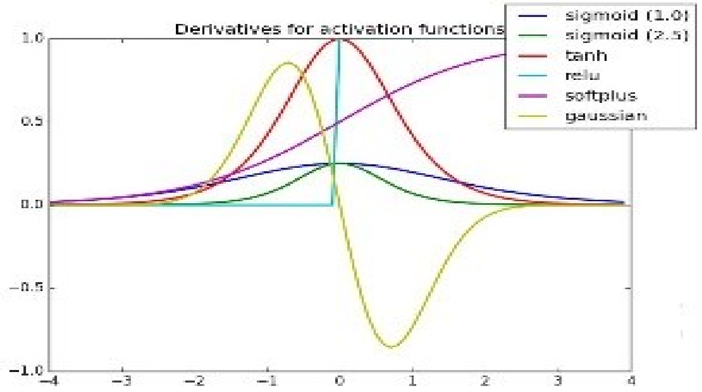


An ANN mimics the behaviour of the biological neuronal networks and consists of an interconnected group of processing elements (referred to as neurons or nodes) arranged in layers.

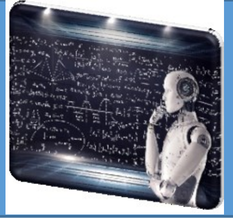
The first layer, known as the input layer, receives the input variables (x1; x2; …xd). Each connection to the neuron is characterised by a weight (w1; w2; … wd) which can be excitatory (positive weight) or inhibitory (negative weight). Moreover, each layer may have a bias (x0 = 1), which can provide a constant shift to the total neuronal input net activation (A), in this case a sigmoid function:

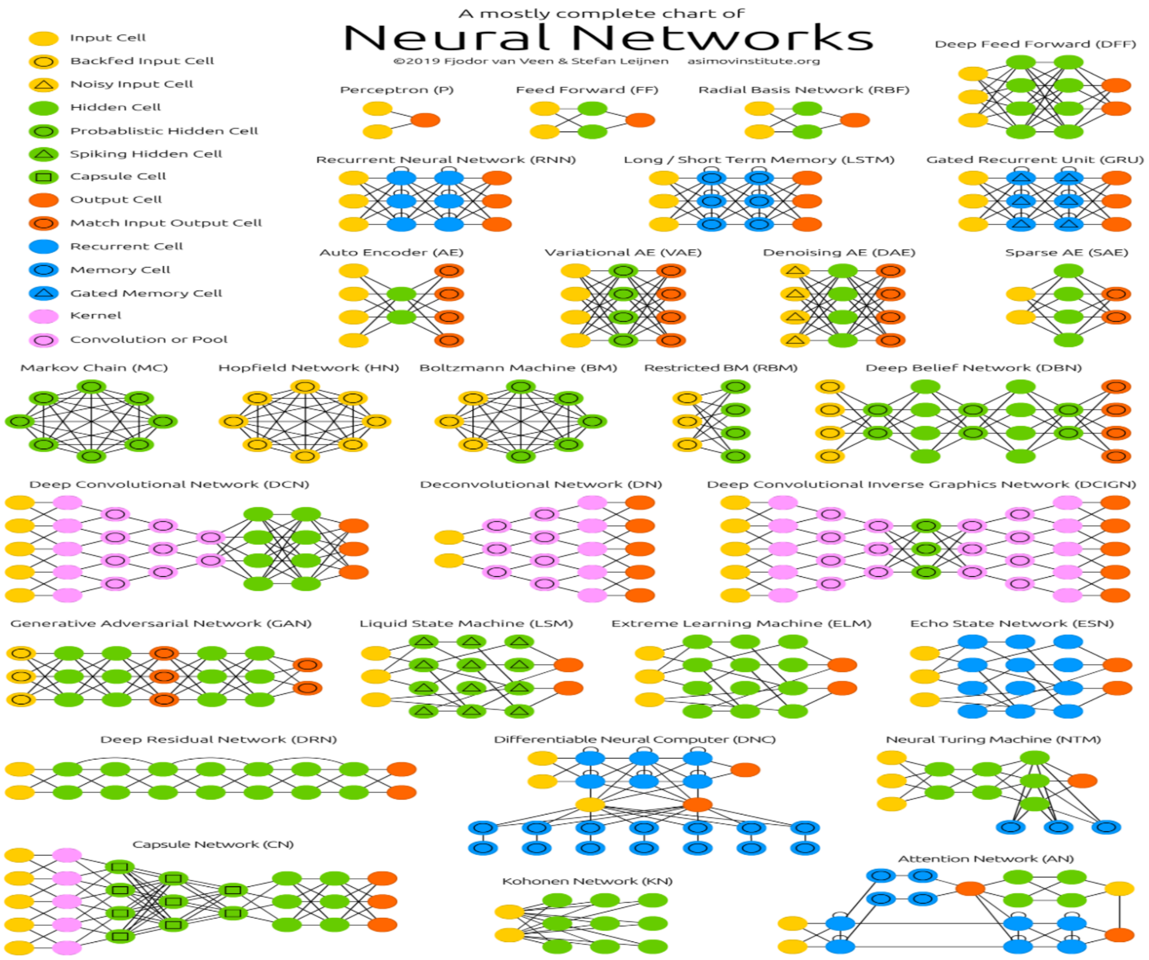
$$f(A) = \frac{2}{1 + e^{-A}} - 1,$$

$$A = \sum_{i=1}^{d} w_i x_i + w_0 = \sum_{i=0}^{d} w_i x_i.$$



Brief Introduction on AI and DS : ANN



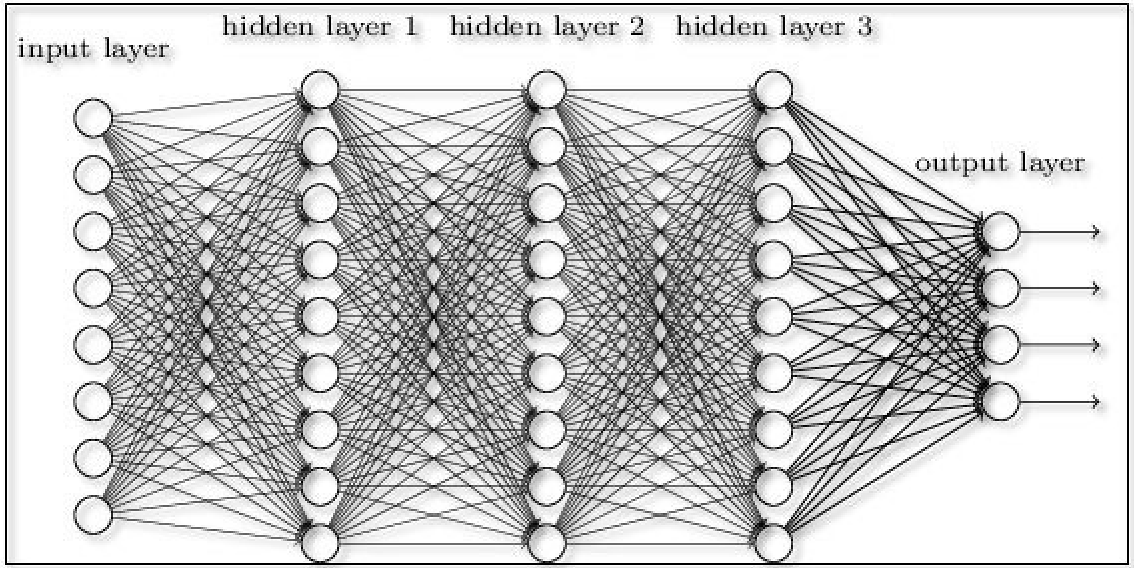


NN architecture: Structure of the networks, and the node connectivity can be adapted for problem at hand

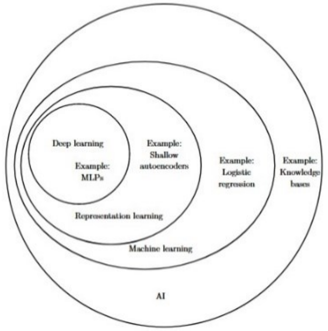
Convolutions: shared weights of neurons, but each neuron only takes subset of inputs

Difficult to train, only recently possible with large datasets, fast computing (GPU) and new training procedures / network structures

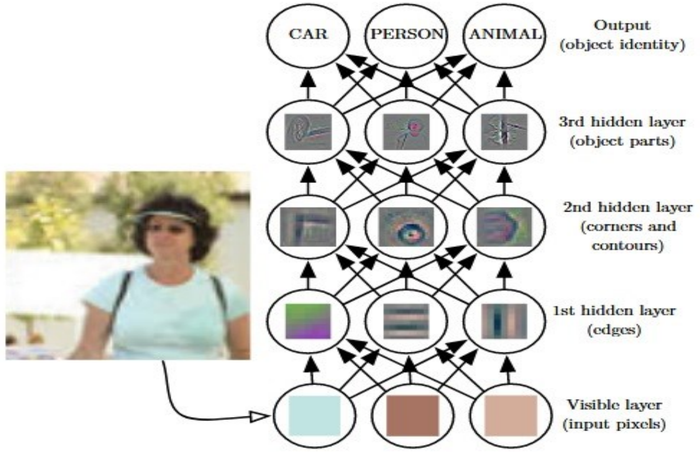
Brief Introduction on AI and DS : DNN

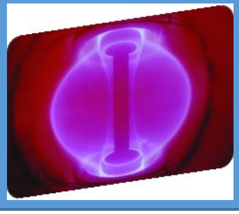


Machine Learning and AI

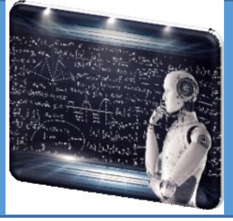


Depth: Repeated Composition





AI and DS in Research : HEP



Machine learning usage at the LHC

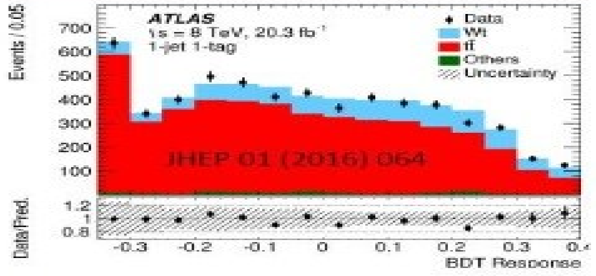
Search

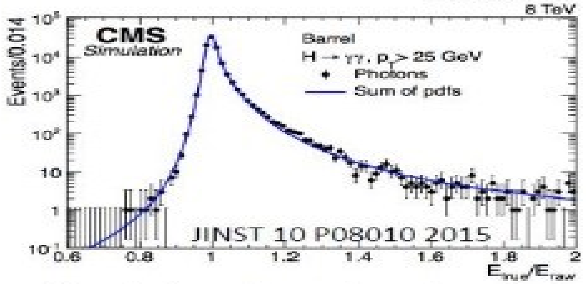
- **In analysis:**
  – Classifying signal from background, especially in complex final states
  – Reconstructing heavy particles and improving the energy / mass resolution

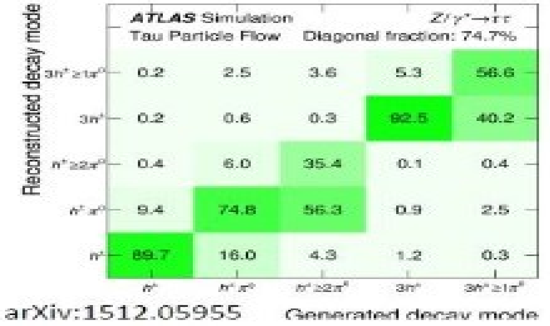
- **In reconstruction:**
  – Improving detector level inputs to reconstruction
  – Particle identification tasks
  – Energy / direction calibration

- **In the trigger:**
  – Quickly identifying complex final states

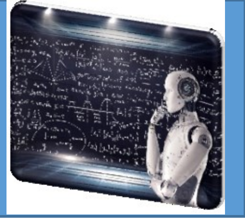
- **In computing:**
  – Estimating dataset popularity, and determining needed number and best location of dataset replicas





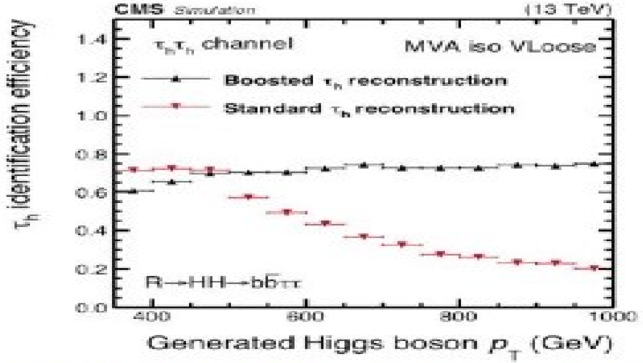


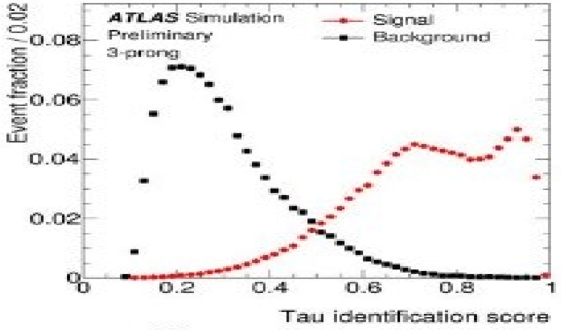
AI and DS in Research : HEP

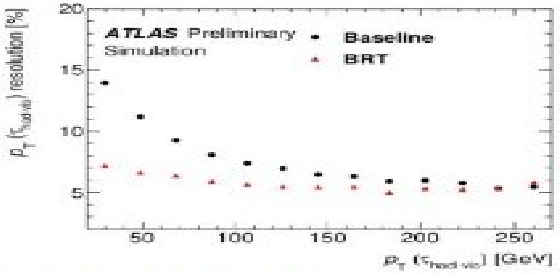


ML@LHC: object identification

BDT for hadronic tau at CMS for ID (classification), at ATLAS for ID & energy calibration (regression).



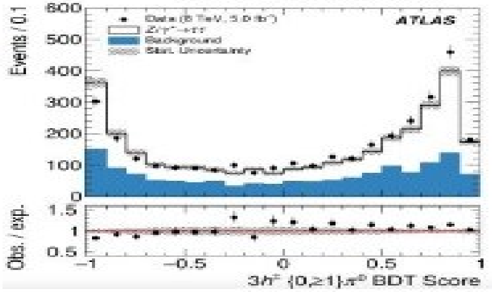




ATLAS BDT (BRT) regression improves resolution.

CMS & ATLAS each two BDTs for ID:

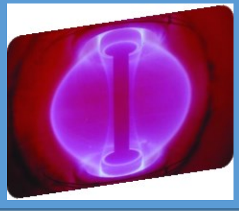
- tau (had) vs jet (q, gluon)
- tau (electron) vs electron
- Also boosted di-tau reco.
- CMS-TAU-16-003;
- ATL-PHYS-PUB-2015-045



Inputs from baseline method, plus tau particle flow (using tracks for low pT), plus other calorimeter and tracking variables. ATLAS-CONF-2017-029

- ATLAS differentiate different decay modes of already identified tau by counting pi^0 PERF-2014-06.

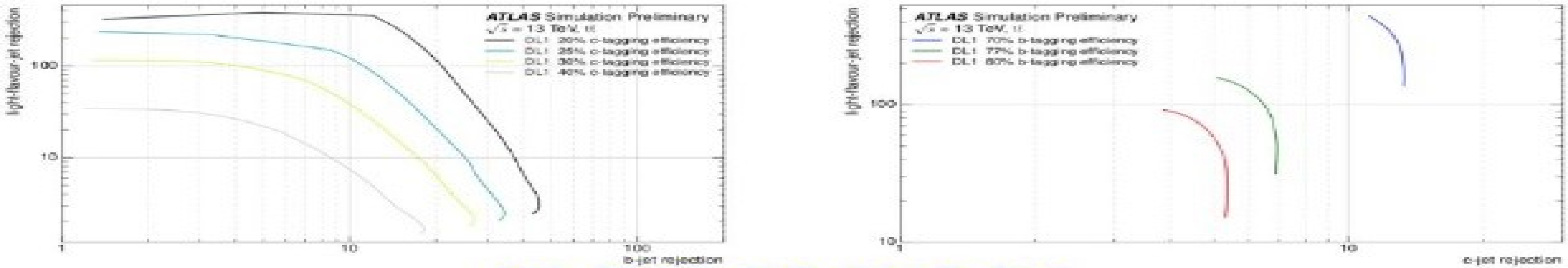
Tau group was first in ATLAS to introduce a BDT ID at trigger level.



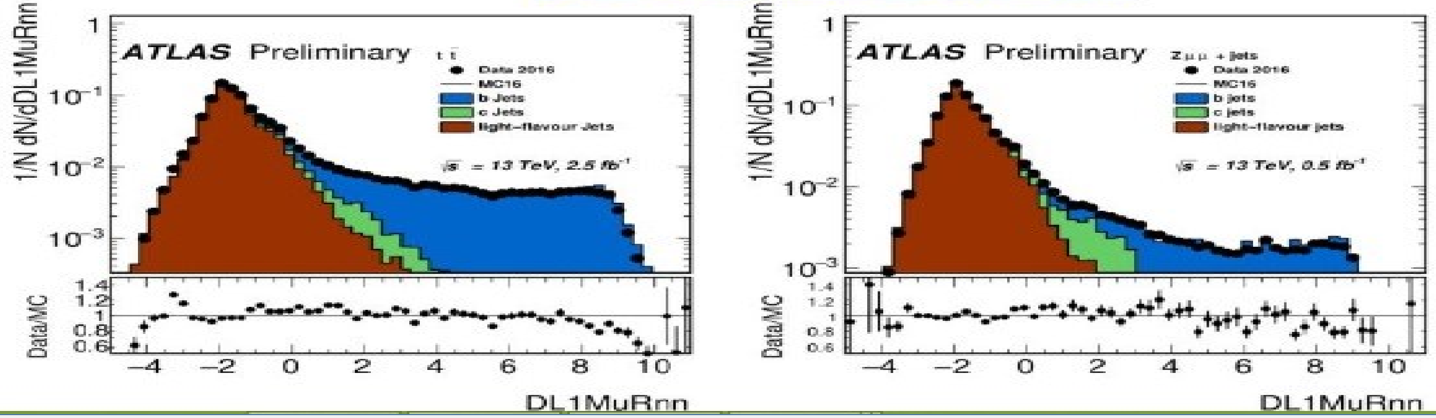
AI and DS in Research : HEP

ML@LHC: b-jet identification

Deep neural network (DNN) vs BDT for b-tagging.
For b-tagging similar performance, opens R&D.



ATL_PHYS_PUB_2017_013



Same inputs, but at lower level.

Three outputs as probabilities of b, c, l (no tau).

Can be used for c-tagging too.

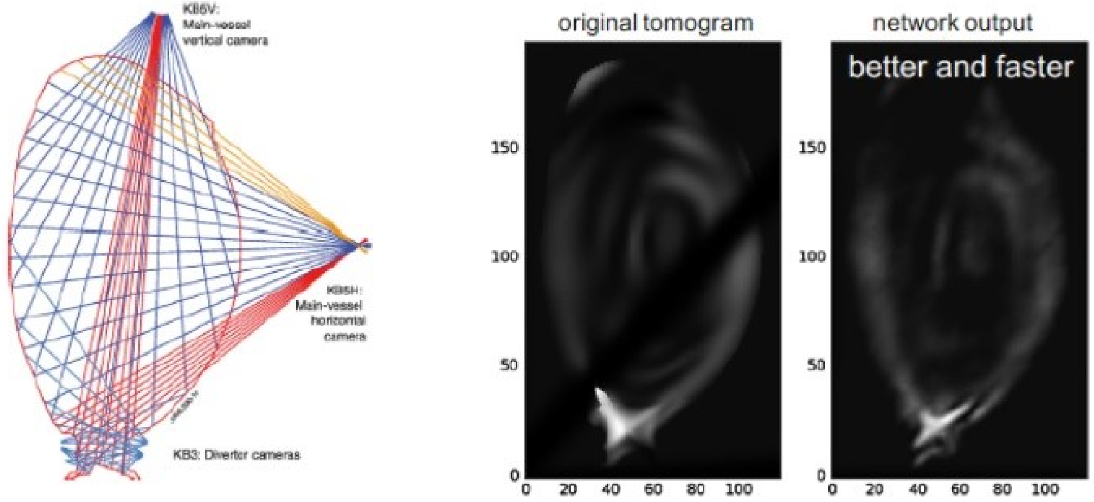
FESAC Report (2018)

Transformative Enabling Capabilities for fusion

Advanced Algorithms – Advanced algorithms will transform our vision of feedback control for a power-producing fusion reactor. The vision will change from one of basic feasibility to the creation of intelligent systems, and perhaps even enabling operation at optimized operating points whose achievement and sustainment are impossible without high-performance feedback control. The area of advanced algorithms includes the related fields of mathematical control, machine learning, artificial intelligence, integrated data analysis, and other algorithm-based R&D. Given the pace of advances, control solutions that establish fusion reactor operation will become within reach, as will the discovery and refinement of physics principles embedded within the data from present experiments. This TEC offers tools and methods to support and accelerate the pace of physics understanding, leveraging both experimental and theoretical efforts. These tools are synergistic with advances in exascale and other high-performance computing capabilities that will enable improved physics understanding. Machine learning and mathematical control can also help to bridge gaps in knowledge when these exist, for example to enable effective control of fusion plasmas with imperfect understanding of the plasma state.

Deep Learning for real-time plasma control

Plasma tomography: Use CNNs to reconstruct cross-section from projections



Traditional inversion schemes:

- Varying runtime
- Dependence on additional data (magnetic equilibrium)
- Not real-time capable

Deep learning for plasma tomography using the bolometer system at JET

PhD student at IPP

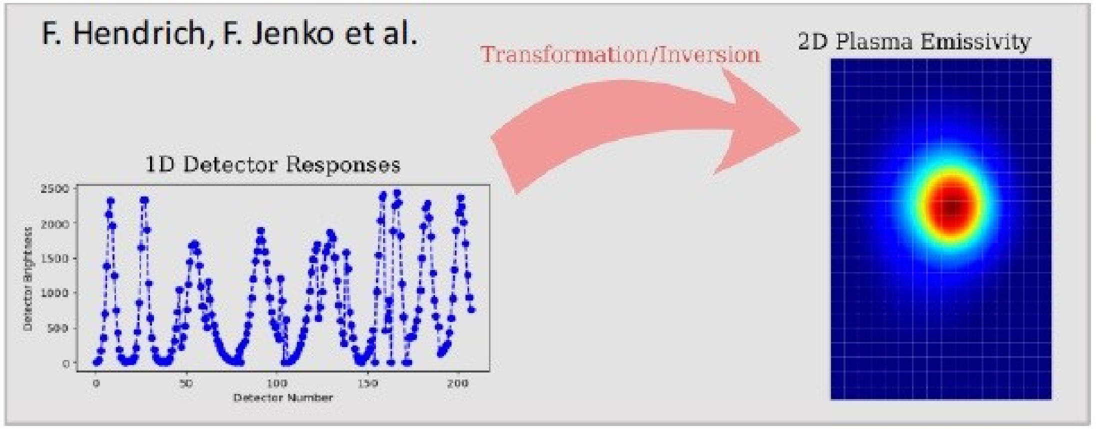
Francisco A. Matos[a], Diogo R. Ferreira[a,*], Pedro J. Carvalho[b], JET Contributors[1]

- In plasma diagnostics, **tomography** aims at reconstructing the cross-section of the plasma from radiation measurements. This reconstruction can be computed with neural networks.

Highlights

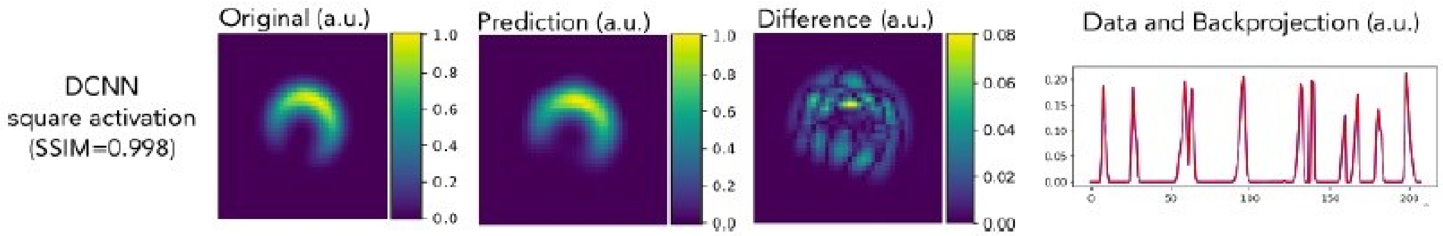
- Plasma tomography is able to reconstruct the plasma profile from radiation measurements along several lines of sight.
- The reconstruction can be performed with neural networks, but previous work focused on learning a parametric model.
- Deep learning can be used to reconstruct the full 2D plasma profile with the same resolution as existing tomograms.
- We introduce a deep neural network to generate an image from 1D projection data based on a series of up-convolutions.
- After training on JET data, the network provides accurate reconstructions with an average pixel error as low as 2%.

Unsupervised inversion with Deep Learning



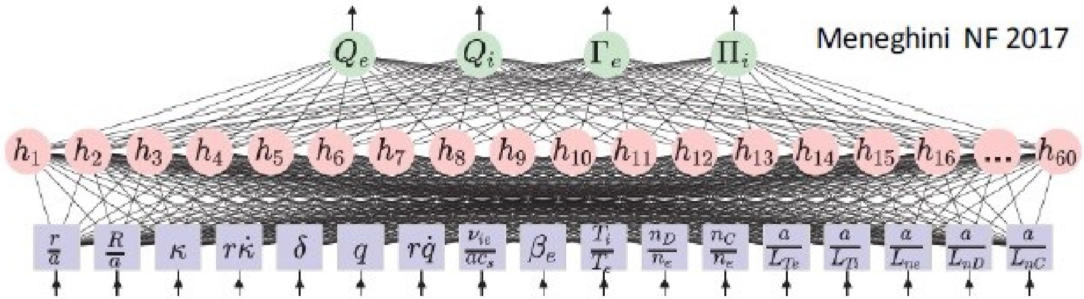
Encode (weak) prior knowledge directly in the NN architecture (in lieu of minimizing an additional regularization term):

- Positivity
- Locality (smoothness)

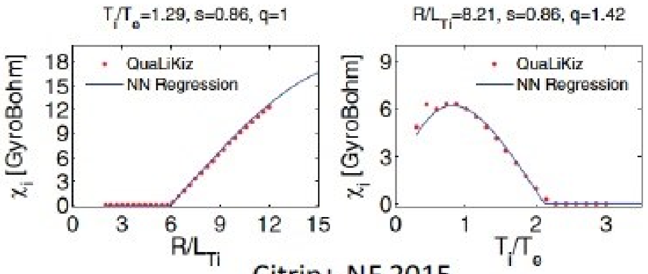


Real-time plasma profile prediction

From *nonlinear* gyrokinetics to *quasilinear* gyrokinetics/gyrofluids to NNs:
Calls for **deep understanding of turbulence** in plasmas



Meneghini NF 2017



Citrin+ NF 2015

NL gyrokinetics: ~10^5 core-h

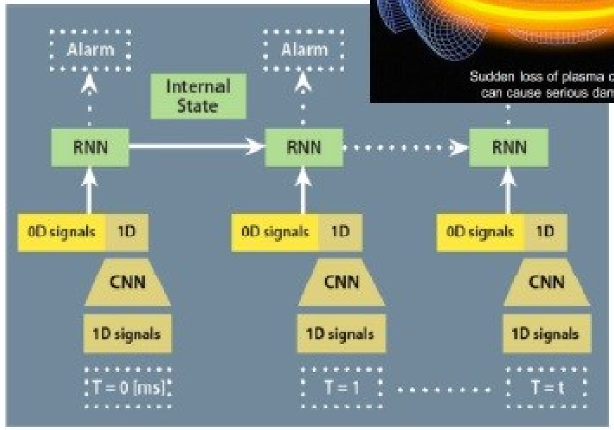
QL gyrokinetics: ~10^{-3} core-h

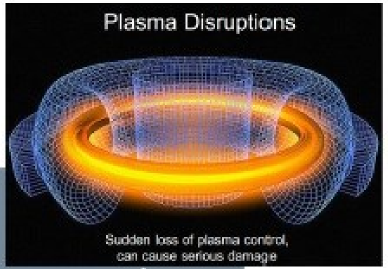
NNs: real-time capability

Similarity to financial data analysis, earthquake prediction etc.

DL for real-time disruption prediction

Recurrent NNs



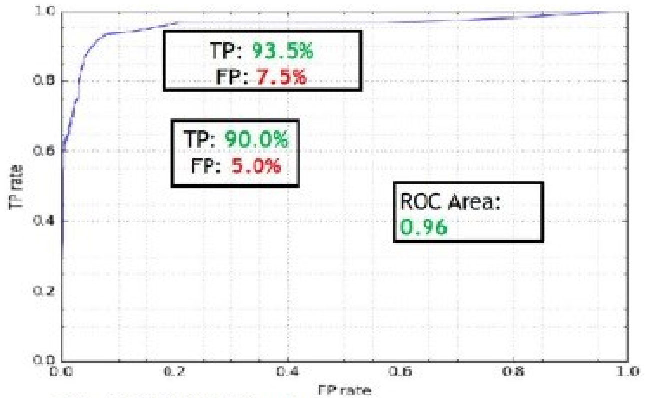


This campaign won the NVIDIA Global Impact Award at the 2018 GPU Technology Conference

FRNN Code PERFORMANCE: ROC CURVES

JET ITER-like Wall Cases @30ms before Disruption

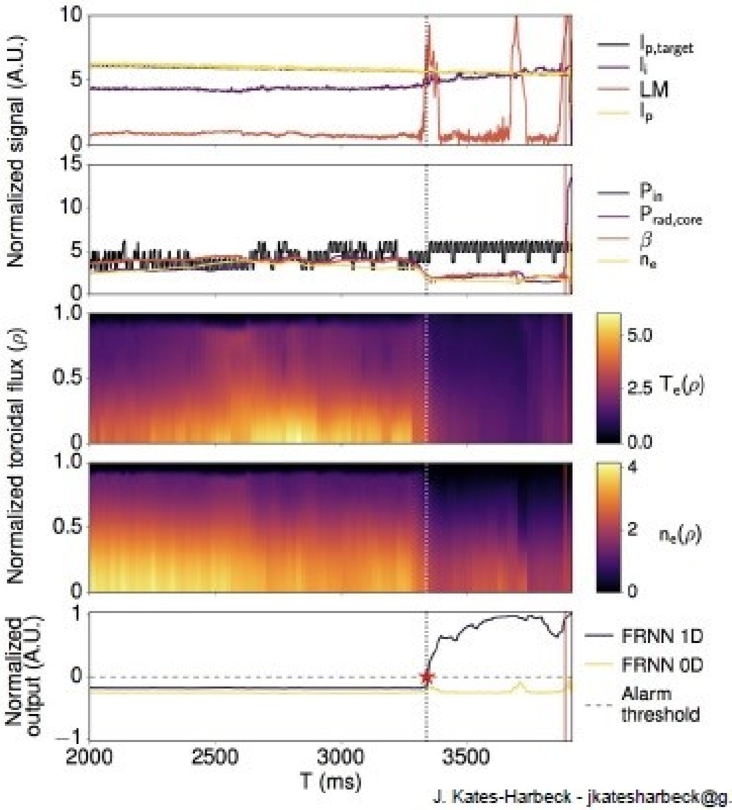
Performance Tradeoff: Tune True Positives (good: correctly caught disruption) vs. False Positives (bad: safe shot incorrectly labeled disruptive).



Data (~50 GB), 0D signals:
- Training: on **4100 shots** from JET C-Wall campaigns
- Testing **1200 shots** from Jet ILW campaigns
- **All shots used**, no signal filtering or removal of shots

W. Tang et al. (talk by D. Keyes @ WS1)

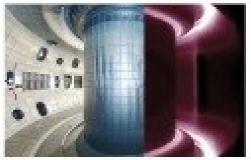
Deep RNN can generalize better



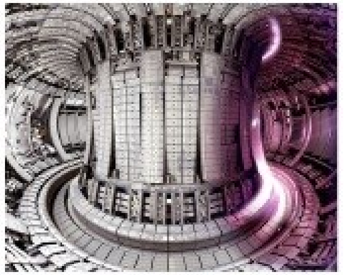
J. Kates-Harbeck - jkatesharbeck@g.harvard.edu / SciDAC PPPL / June 2018

Deep RNN can learn invariant representation of input features and generalize better:

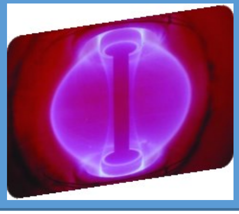
- Make full use of **high dimensional** data (e.g. profiles) and **time-varying** features
- **Transfer learning:** accuracy increase when a small number (~5) of JET disruptions are added to the test set.
- Accuracy of cross-device prediction and **comparable to shallow learning on single device**



Train (DIII-D)



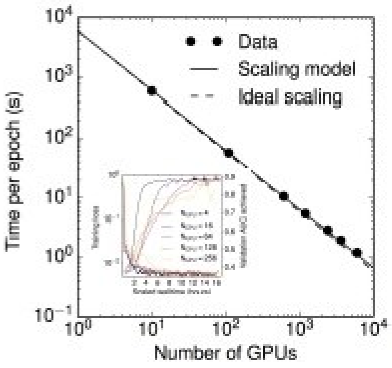
Test (JET)

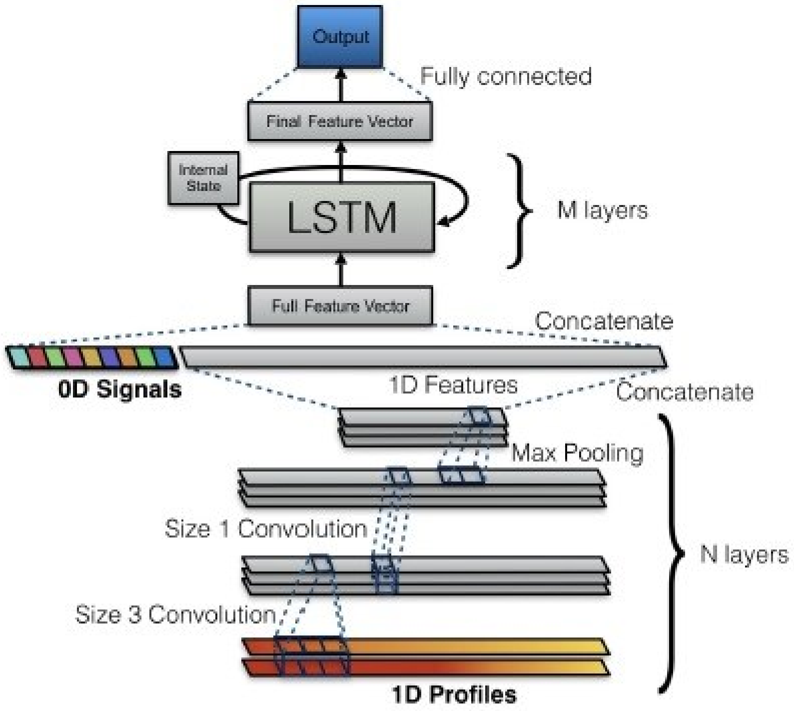


Computational Advancements in Plasma Physics

Disruption Prediction via deep Recurrent Neural Network - FRNN

- FRNN model:
  - **Convolutional layers** to learn features from 1D data (profiles)
  - **LSTM** to learn temporal patterns
- Plug other **ML models**
  - (SVM, MLP, RF, GBT, etc.)
- **HPC** to accelerate training and hyperparameter tuning





J. Kates-Harbeck - jkatesharbeck@g.harvard.edu / SciDAC PPPL / June 2018

JET Disruption Data

# Shots	Disruptive	Nondisruptive	Totals
Carbon Wall	324	4029	4353
Beryllium Wall (ILW)	185	1036	1221
Totals	509	5065	5574

JET produces ~ Terabyte (TB) of data per day

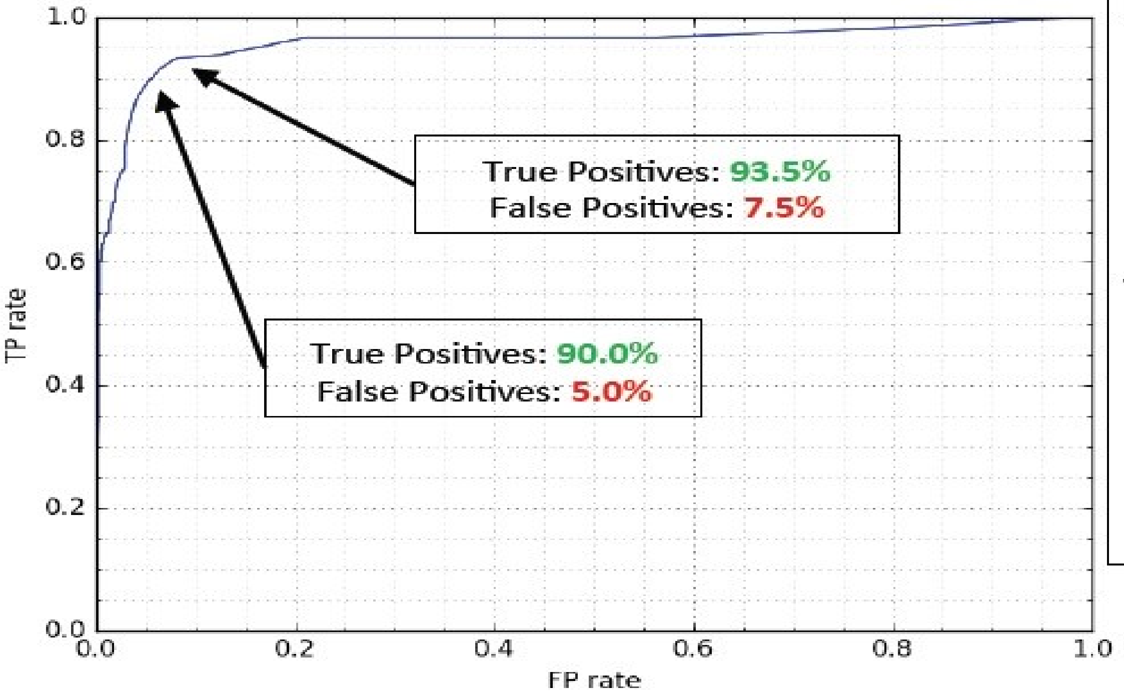
Sample 7 Signals of zero-D time traces (07)	Data Size (GB)
Plasma Current	1.8
Mode Lock Amplitude	1.8
Plasma Density	7.8
Radiated Power	30.0
Total Input Power	3.0
d/dt Stored Diamagnetic Energy	2.9
Plasma Internal Inductance	3.0

~55 GB data collected from each JET shot

→***Well over 350 TB total amount with multi-dimensional data yet to be analyzed***

FRNN ("Fusion Recurrent Neural Net") Code Performance (ROC Plot)

Performance Tradeoff: Tune True Positives (good: correctly caught disruption) **vs.** False Positives (bad: safe shot incorrectly labeled disruptive).



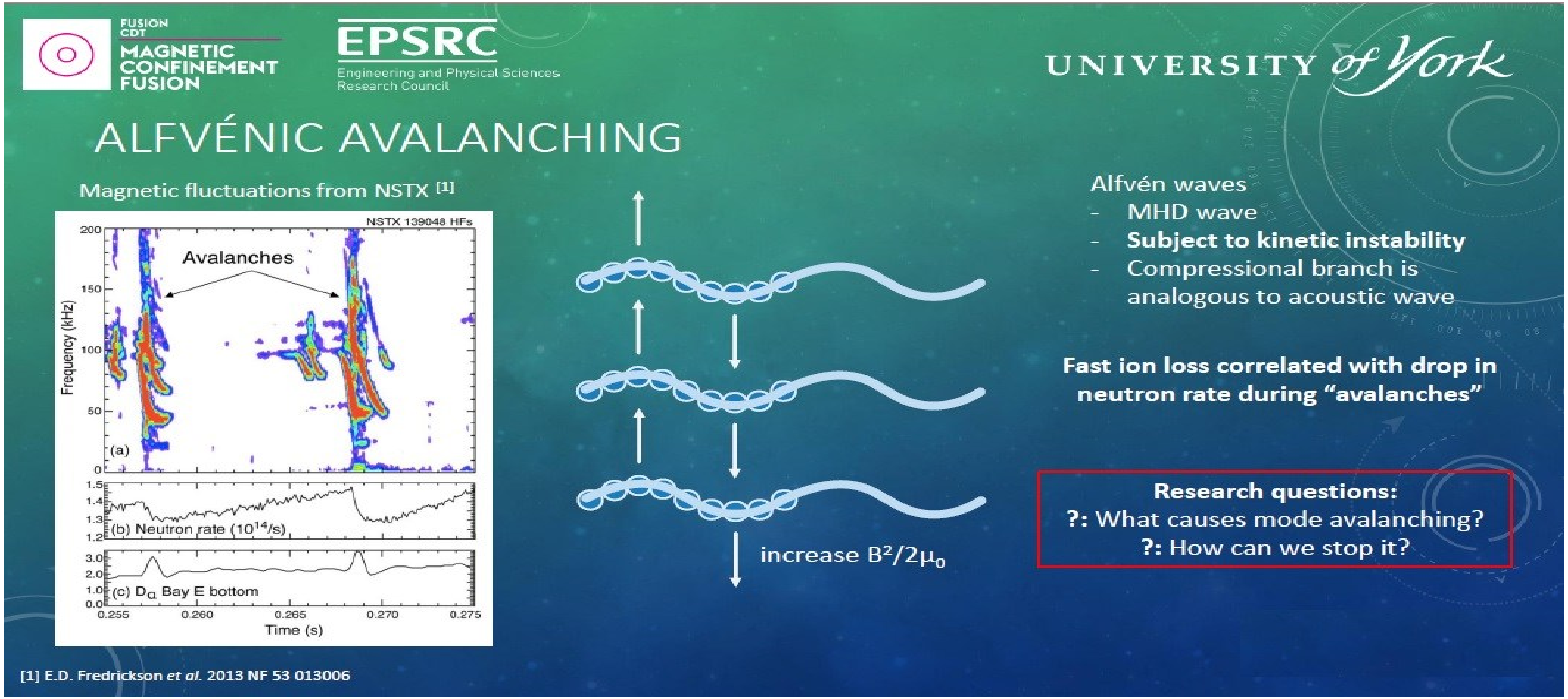
RNN Data:

- Testing **1200 shots** from Jet ILW campaigns (C28-C30)
- **All shots used**, no signal filtering or removal of shots

Jet SVM* work:

- **990 shots** from same campaigns
- **Filtering** of signals, **ad hoc removal of shots** with abnormal signals
- **TP** 80 to 90%, **FP** 5%

*Vega, Jesús, et al. "Results of the JET real-time disruption predictor in the ITER-like wall campaigns." *Fusion Engineering and Design* 88.6 (2013): 1228-1231.



FUSION CDT
MAGNETIC CONFINEMENT FUSION
EPSRC
Engineering and Physical Sciences Research Council
UNIVERSITY of York
ALFVÉNIC AVALANCHING
Magnetic fluctuations from NSTX [1]
NSTX 139048 HFs
Avalanches
Frequency (kHz)
200
150
100
50
0
(a)
1.5
1.4
1.3
1.2
(b) Neutron rate (10^14/s)
3.0
2.0
1.0
0.0
(c) Dα Bay E bottom
0.255
0.260
0.265
0.270
0.275
Time (s)
increase B²/2μ0
Alfvén waves
- MHD wave
- Subject to kinetic instability
- Compressional branch is analogous to acoustic wave
Fast ion loss correlated with drop in neutron rate during "avalanches"
Research questions:
?: What causes mode avalanching?
?: How can we stop it?
[1] E.D. Fredrickson et al. 2013 NF 53 013006

FUSION CDT MAGNETIC CONFINEMENT FUSION

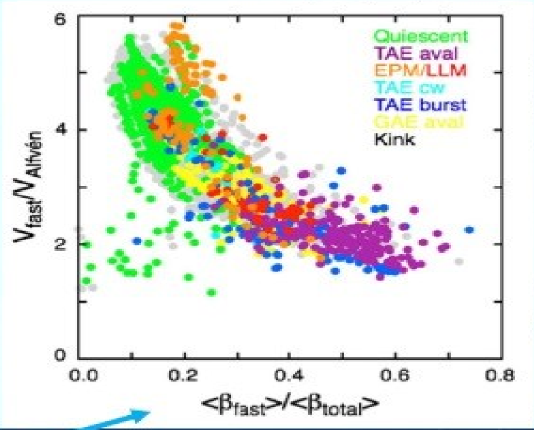
EPSRC Engineering and Physical Sciences Research Council

UNIVERSITY of York

MACHINE LEARNING FOR FUSION APPLICATIONS

- Vast increase in speed for certain tasks
  - Data analysis can be done faster
  - Computational predictions can be extracted faster
  - May prove **vital** for operational performance of a tokamak
- Can we train an AI to recognise and characterise chirping?
  - Potentially feed into overall control system
- Knowledge of correlations between plasma parameters and mode character is **key**
  - i.e. turbulent suppression of mode chirping [3,4]

[2]



very time consuming to produce

only 2 parameters

[2] E. D. Fredrickson *et al.* 2014 NF 54, 093007
[3] V. N. Duarte *et al.* 2017 NF 57, 054001
[4] B. J. Q. Woods *et al.* 2018 NF 58, 082015

Surrogate modelling using feed forward neural networks for turbulent transport in fusion plasmas

[1*]van de Plassche, K.L., [1]Citrin, J., [2]Bourdelle, C., [3]Camenen, Y., [4]Casson, F.J., [1]Dagnelie, V.I., [5]Felici, F., [1]Ho, A & [†]JET Contributors

* lead presenter

[1] *DIFFER, PO Box 6336, 5600 HH Eindhoven, The Netherlands*

[2] *CEA, IRFM, F-13108 Saint-Paul-lez-Durance, France*

[3] *CNRS, Aix-Marseille Univ., PIIM UMR7345, Marseille, France*

[4] *CCFE, Culham Science Centre, Abingdon, UK*

[5] *EPFL-SPC, CH-1015, Lausanne, Switzerland*

[†] *See the author list of* X. Litaudon et al 2017 Nucl. Fusion 57 102001

* k.l.vandeplassche@differ.nl

Surrogate models approximate more complex, computationally expensive models while being faster to run. They can be used for tasks where using the slow original model is infeasible, for example in optimization and control. In this work we apply this methodology within a fusion energy context, using feed-forward neural networks (FFNNs) as a surrogate model five orders of magnitude faster than the underlying model: the quasilinear turbulent transport code QuaLiKiz[1, 2]. QuaLiKiz is used to describe heat, particle, and momentum transport in tokamaks, and was used to create a large database of 3.10^8 flux calculations using 1.3 MCPUh on HPC resources (Edison@NERSC). Embedding known physical constraints in the training of the networks is essential for the surrogate model to perform well in transport predictions. As such, we show the importance of choosing the right cost function and more fundamentally, choosing which target variables the networks have to be trained on. Custom figures of merit and visualisation tools were developed to aid with neural network accuracy verification.

The neural network surrogate turbulent transport model is applied within the RApid Plasma Transport Simulator RAPTOR[3, 4] and the integrated modelling suite JINTRAC [5] to predict the temperature and density evolution of JET fusion plasmas, in excellent agreement with the original QuaLiKiz model, yet orders of magnitude faster. This allows us to simulate one second of plasma evolution in 10 seconds, a speed that is unprecedented for first-principle based transport simulations, opening up new avenues for tokamak scenario optimization and realtime control applications.

Machine Learning Control for fusion devices

E. Kolemen
Princeton University, PPPL, USA
ekolemen@princeton.edu

Commercial fusion reactors will need to achieve high performance and stable operations at the same time. This requires control of the plasma for multiple objectives which gets complicated as the number of objectives grow. Physics physics based simulations that are currently available only give only good qualitative predictions are not good enough to optimize or control the plasmas. An alternative approach where experimental data is used to come up with plasma model. Then these machine learning models can be used to control the fusion reactor. A step further is to design the control directly from the experimental data. I will talk about the current state of the machine learning control development and application to fusion reactors, and possible paths forward to data-driven controls for ITER and future commercial reactors.

Learning-based predictive models: a new approach to integrating large-scale simulations and experiments

[1]*Brian K. Spears, [1]Luc Peterson, [1]Timo Bremer, [1]Gemma Anderson, [1]Rushil Anirudh, [1]Benjamin Bay, [1]Scott Brandon, [1]Victor Castillo, [1]Jim Gaffney, [1]John Field, [1]Kelli Humbird, [1]David Hysom, [1]Sam Ade Jacobs, [1]Joe Koning, [1]Michael Kruse, [1]Bogdan Kustowski, [1]Steve Langer, [1]Shusen Liu, [1]Peter Robinson, [1]Jessica Semler, [1]Jay Thiagarajan, [1]Brian Van Essen, [1]Jae-Sung Yeom

*lead presenter

[1]*Lawrence Livermore National Laboratory, USA*

* spears9@llnl.gov

Accelerated predictive models for scenario optimization and control of tokamaks

[1*]Boyer, M.D., [1]Erickson, K.G., [1]Kaye, S., [2]Gajaraj, V., [3]Kunimune, J., & [1]Zarnstorff, M.

*lead presenter

[1] *Princeton Plasma Physics Laboratory, USA*

[2] *New York University, USA*

[3] *Olin College, USA*

* mboyer@pppl.gov

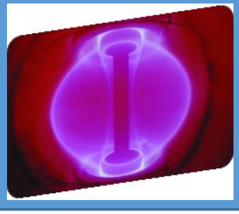
Employing machine learning for theory validation and identification of experimental conditions in laser-plasma physics

A. Gonoskov[1,2,3,*], E. Wallin[4], A. Polovinkin[5], and I. Meyerov[3]

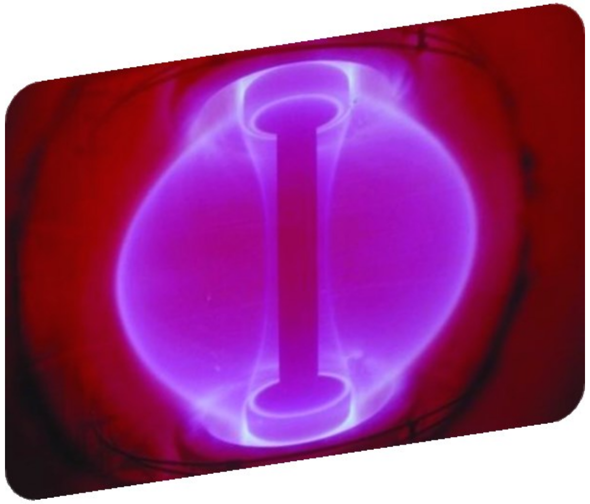
[1]Chalmers University of Technology, SE-41296 Gothenburg, Sweden
[2]Institute of Applied Physics, RAS, Nizhny Novgorod 603950, Russia
[3]Lobachevsky State University of Nizhni Novgorod, Nizhny Novgorod 603950, Russia
[4]Department of Physics, Umeå University, SE-90187 Umeå, Sweden
[5]Adv Stat & Machine Learning, LTD, Intel, USA
*arkady.gonoskov@chalmers.se

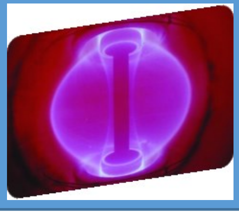
ABSTRACT

The validation of a theory is commonly based on appealing to clearly distinguishable and describable features in properly reduced experimental data, while the use of ab-initio simulation for interpreting experimental data typically requires complete knowledge about initial conditions and parameters. We here apply the methodology of using machine learning for overcoming these natural limitations. We outline some basic universal ideas and show how we can use them to resolve long-standing theoretical and experimental difficulties in the problem of high-intensity laser-plasma interactions. In particular we show how an artificial neural network can "read" features imprinted in laser-plasma harmonic spectra that are currently analysed with spectral interferometry.

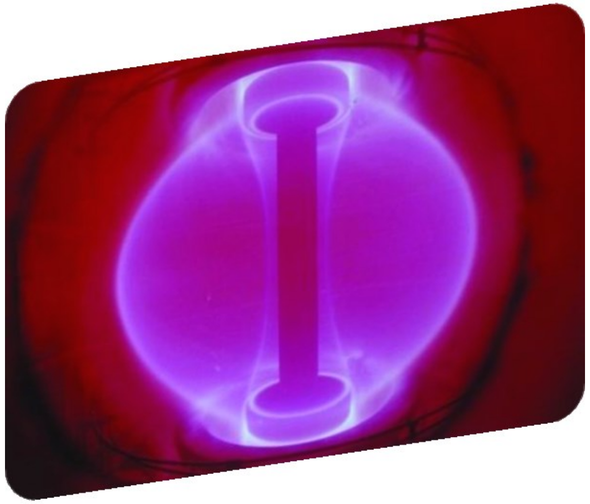


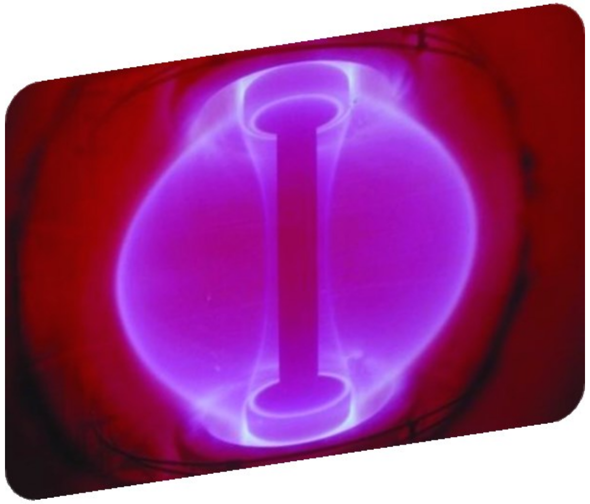
Conclusion : Intelligent Computations





Questions & Answers : Discussion





Thank you