Some Applications of Machine Learning to Astronomy

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20/fev/2018

Overview

- Introduction
  - Definition
  - Neural Nets
- Applications do Astronomy
- Ads: Machine Learning Course

Introduction

Machine Learning (to play Checkers)

Coined the term Machine Learning ("Field of study that gives computers the ability to learn without being explicitly programmed.")

"it will learn to play a better game of checkers than can be played by the person who wrote the program."

search tree
alpha-beta pruning
scoring functions

1959

Arthur Samuel

Machine Learning - definition

- "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."

1998

Tom Mitchell

Machine Learning – definition (cont.)

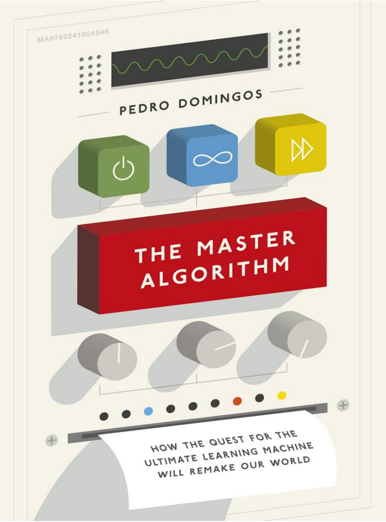
Suppose some computer program watches which objects you mark as galaxy/star, and based on that learns how to tell these two object apart.

- In such context:
  - T → star/galaxy separation
  - E → several labeled examples (images or catalog)
  - P → purity/completeness

ML Tribes

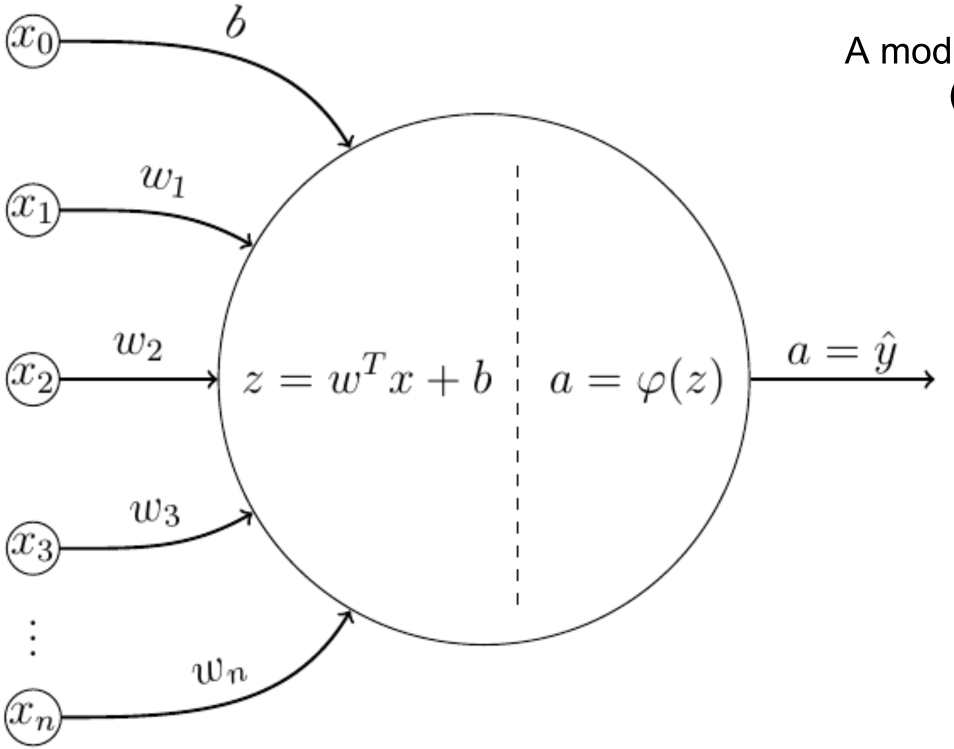
- There are several ML tribes!
  - Symbolists (rule-based systems)
  - Evolutionists (evolutionary computation, GAs)
  - Analogists (SVMs, k-NN, …)
  - Bayesians (Bayes update rule)
  - **Connectionists (ANNs)**

Pedro Domingos



Artificial Neural Nets (ANNs)

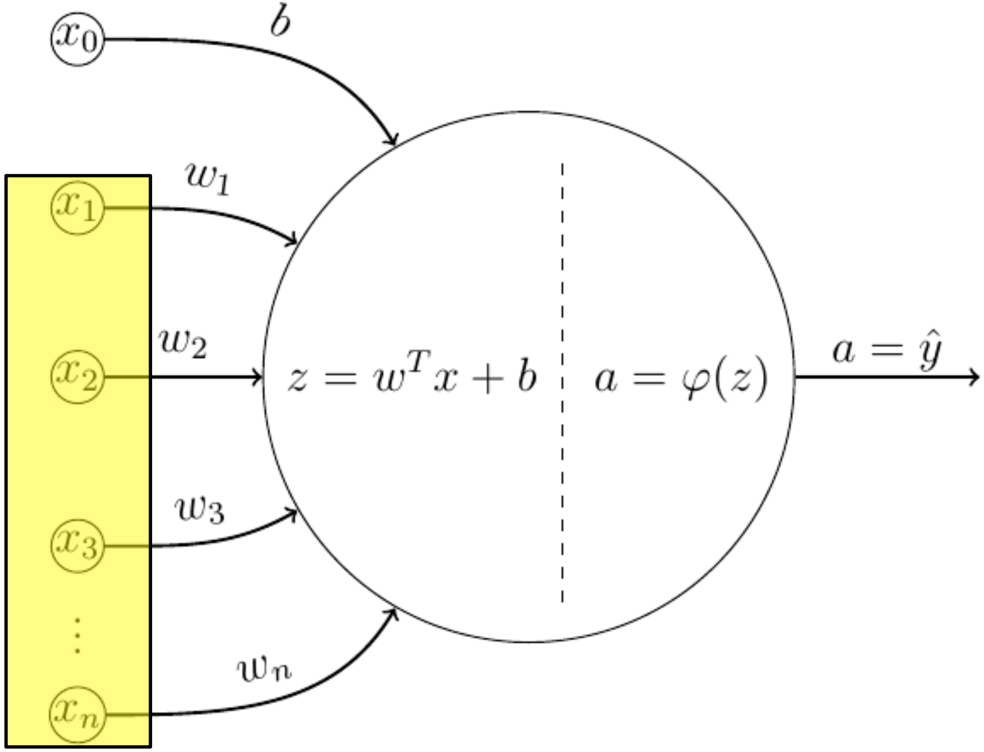
Artificial Neuron



A model inspired in the real one (biological neuron).

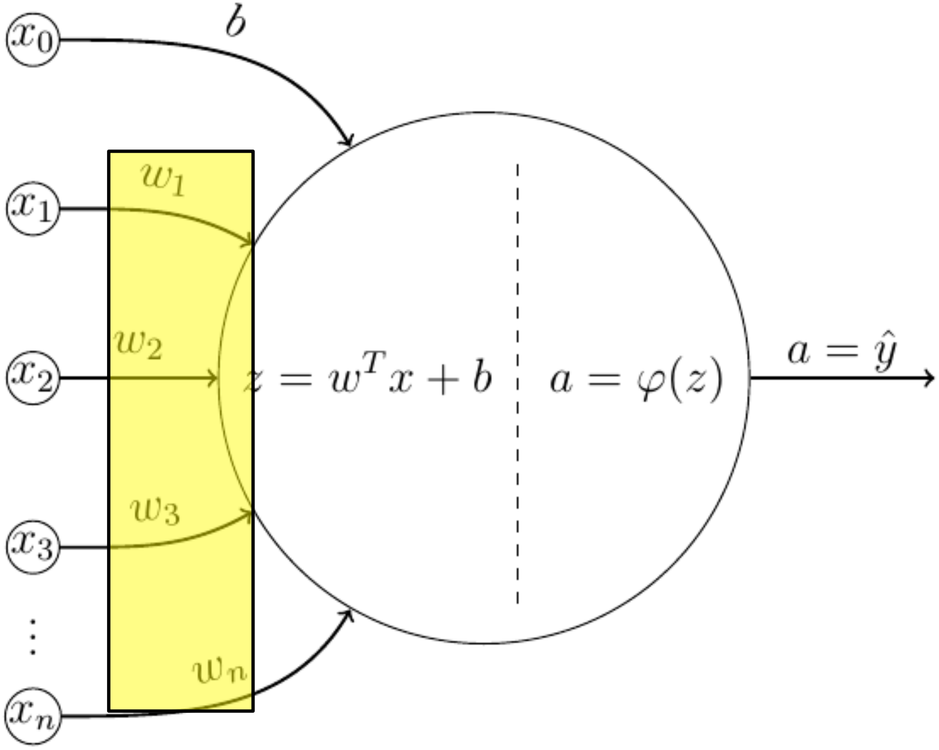
Artificial Neuron - input

$$x = \begin{bmatrix} x_1 \\ x_2 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$$

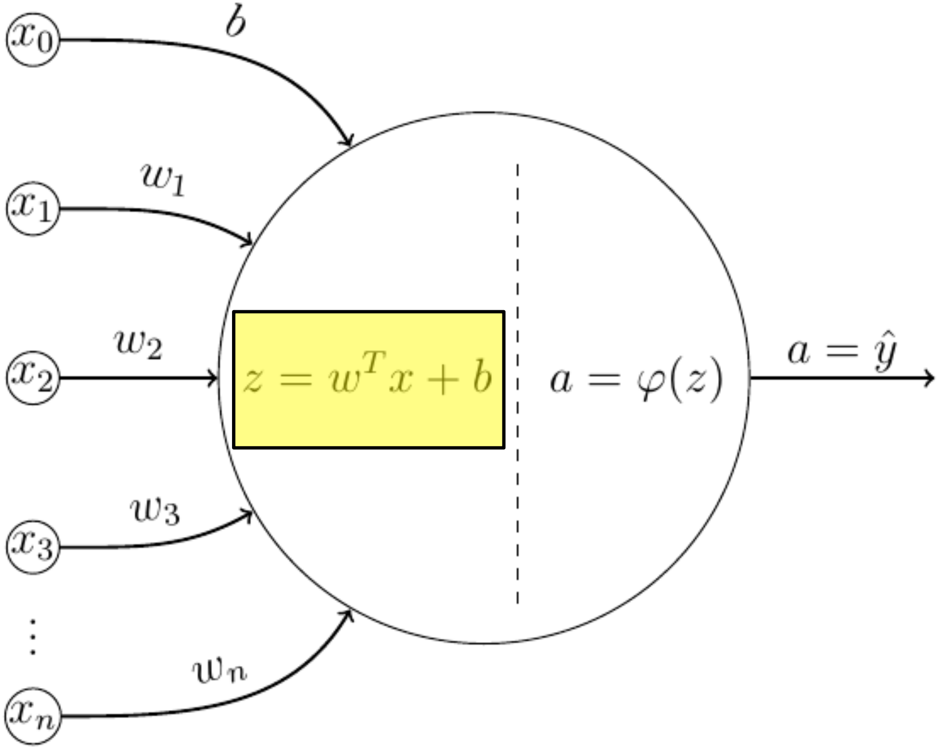


Artificial Neuron – parameters

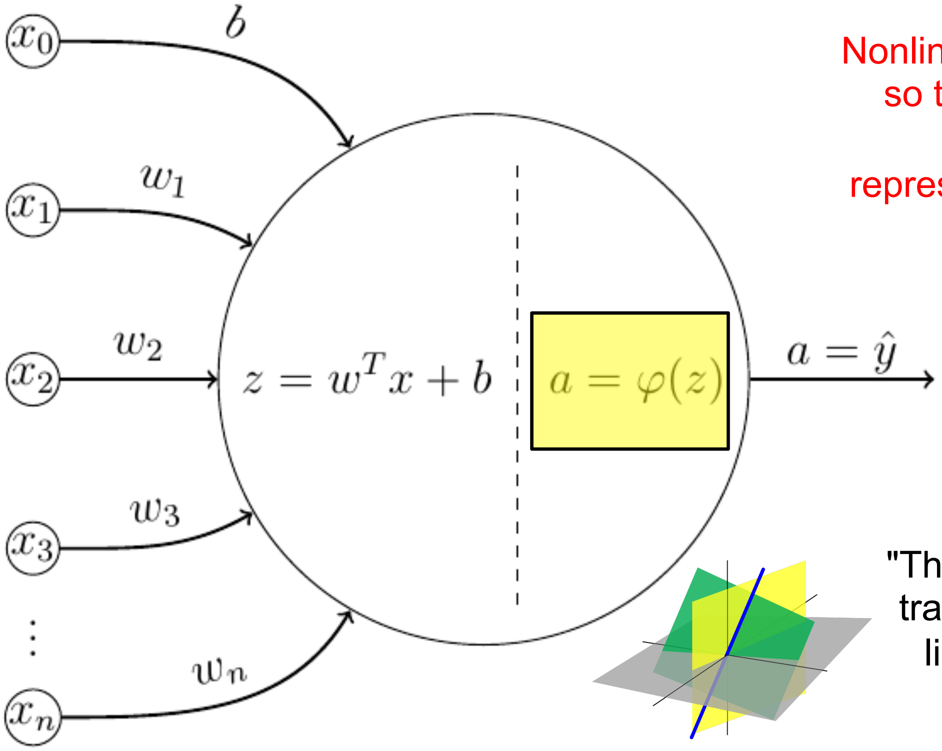
$$w = \begin{bmatrix} w_1 \\ w_2 \\ w_2 \\ \vdots \\ w_n \end{bmatrix}$$



Artificial Neuron – pre-activation



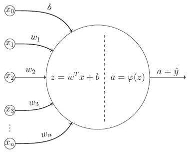
Artificial Neuron – activation function

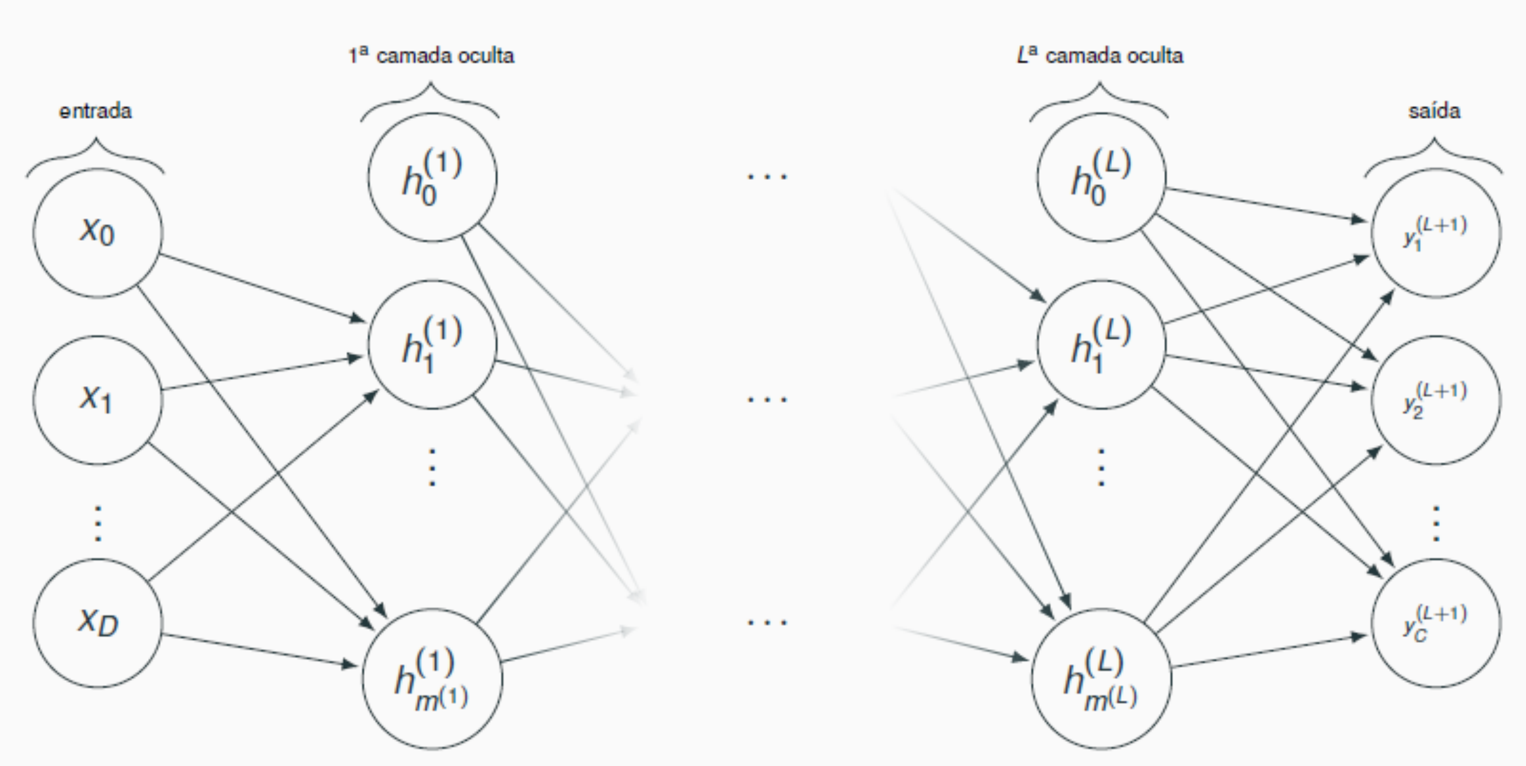


Nonlinearities are necessary so that the network can learn complex representations of the data.

"The composition of linear transformations is also a linear transformation"

Artificial Neural Net

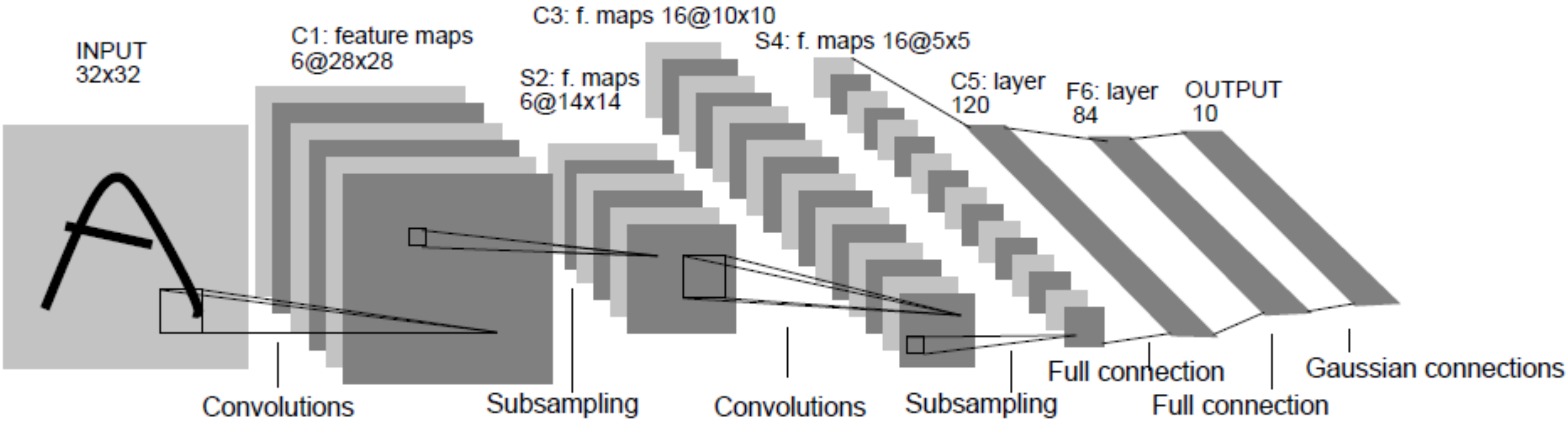




Feedforward Neural Network

LeNet

Yan Lecun



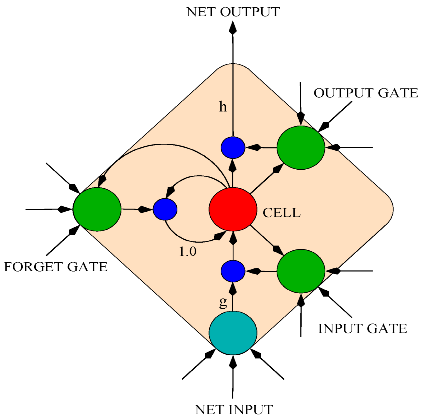
1998

Gradient-Based Learning Applied to Document Recognition

Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner

LSTM Neural Nets

“if you can understand the paper, you are better than many people in ML. It took 10 years until people understand what they were talking about”.
– Jeff Hinton



Sepp Hochreiter

https://scholar.google.de

1997

Citações: 2012: 75; out/2016: 1027; nov/2017: 2846

Juergen Schmidhuber

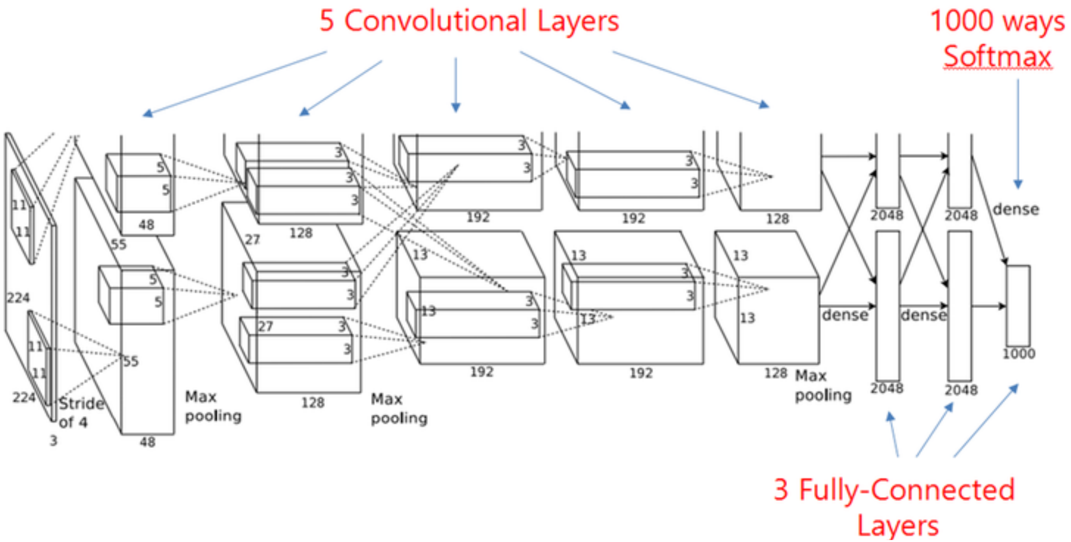
Deep Learning explosion

2012-now

Also known as: ***Revenge of the ~~Sith~~ Neural Nets!***

Example: AlexNet

8 layers



2012

ImageNet Classification with Deep Convolutional Neural Networks

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

Geoffrey E. Hinton
University of Toronto
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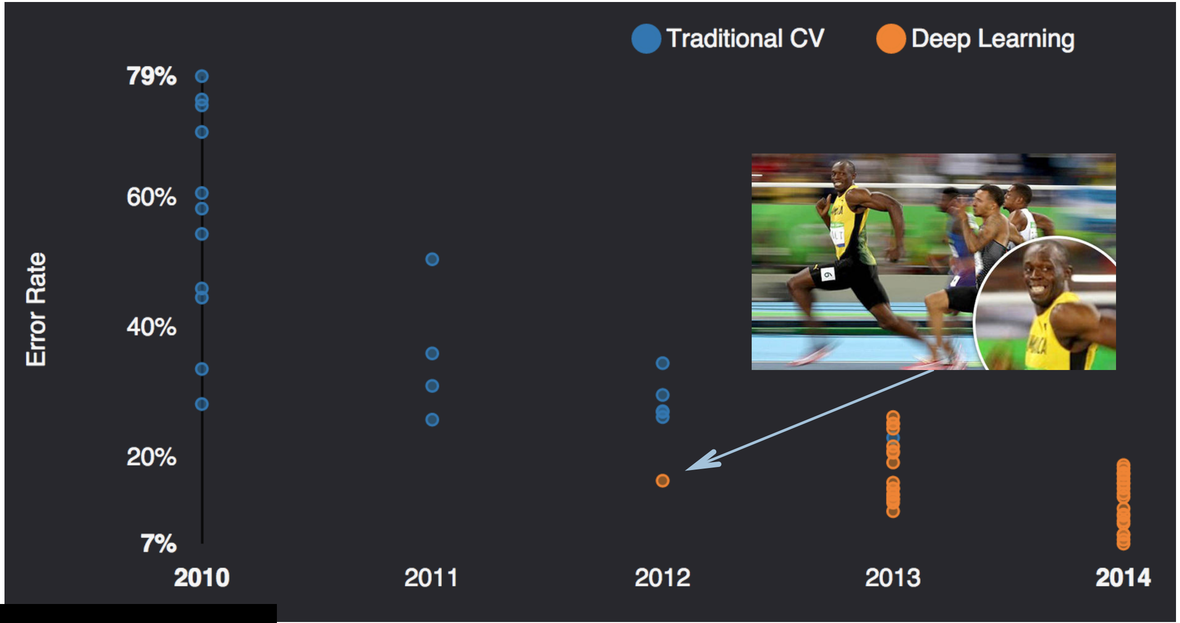
Example: AlexNet

8 layers



2012

Credits: Mathew Zeiler (Clarifai)

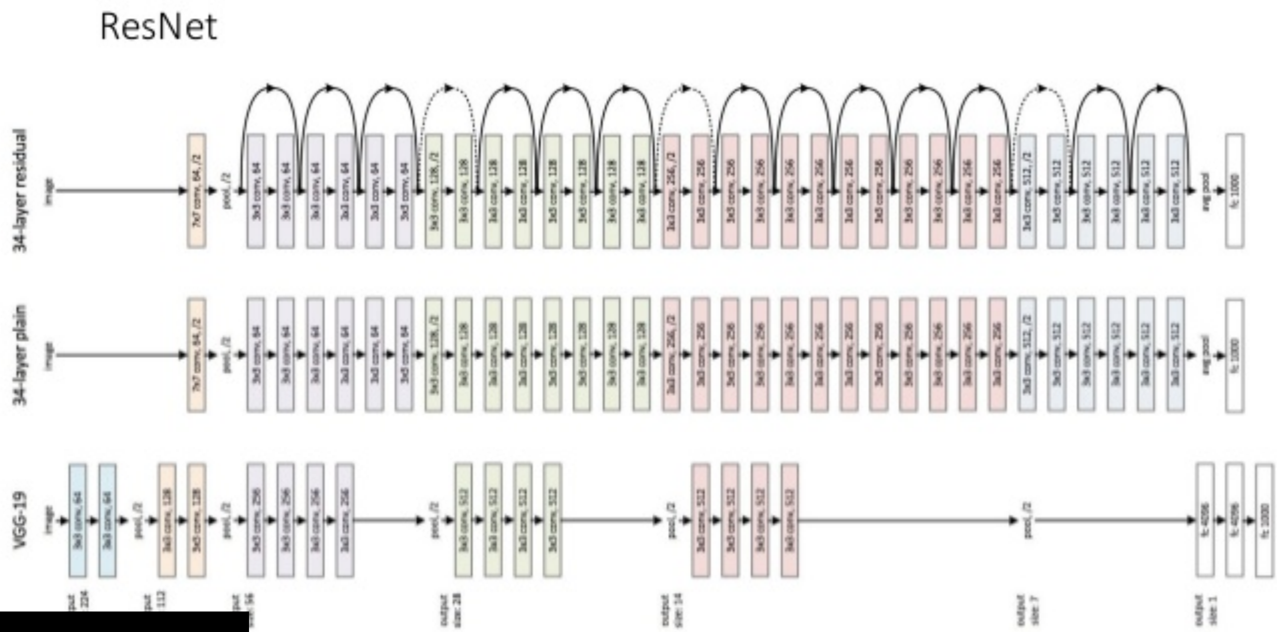
Example: GoogleNet

22 layers

2014

Example: ResNet

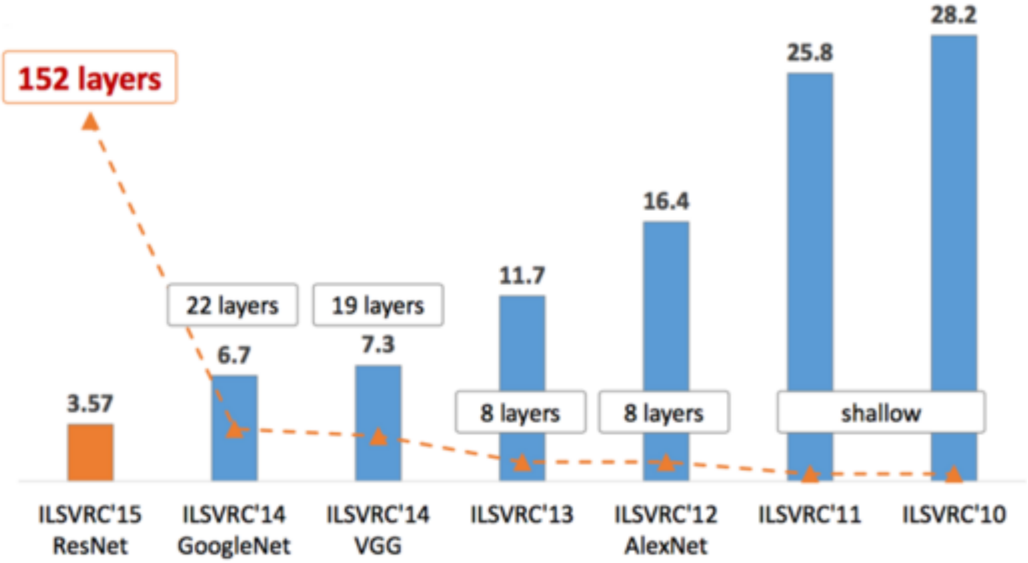
152 layers



2015

Deep Nets

Well said Leo, well said



Neural Nets

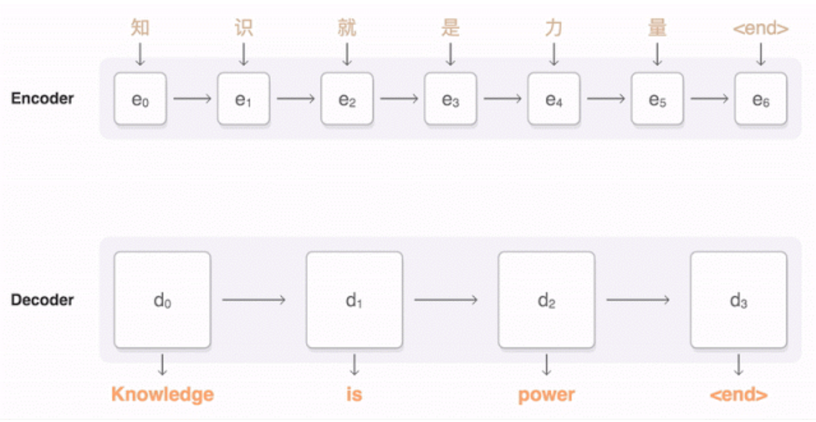
Deep Neural Networks for Acoustic Modeling in Speech Recognition

Geoffrey Hinton, Li Deng, Dong Yu, George Dahl, Abdel-rahman Mohamed, Navdeep Jaitly, Andrew Senior, Vincent Vanhoucke, Patrick Nguyen, Tara Sainath, and Brian Kingsbury

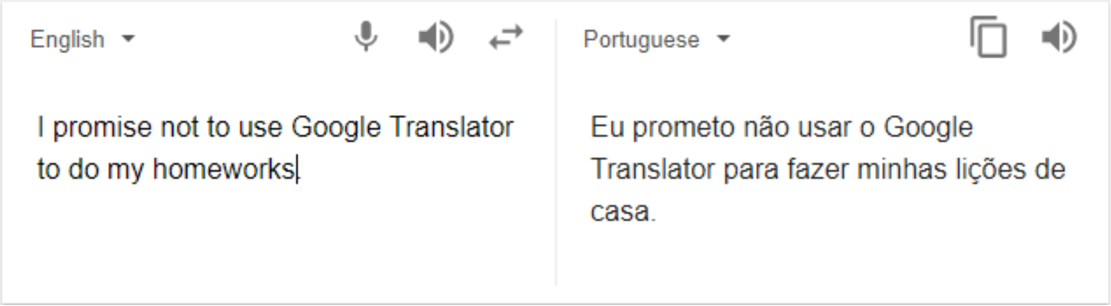
2012

Neural Nets

Language Translation



2014



Neural Nets

Computer Vision + Text Processing

A close up of a hot dog on a bun.

A bath room with a toilet and a bath tub.

A vase filled with flower sitting on a table.

2016

Long-term Recurrent Convolutional Networks for Visual Recognition and Description, 2016.

Deep Learning: success factors

- Big Data (e.g, MNIST ~ 70k; ImageNet ~ 10^6)
- Hardware improvements
- Crowdsourcing

"What was wrong in the 80's is that **we didn't have enough data and we didn't have enough computer power**"

Geoffrey Hinton

Applications to Astronomy

Application: Star-Galaxy Separation

- SGSP: telling apart stars and galaxies in photometric catalogs.
- The huge number of galaxies and stars in typical surveys requires that such separation be automated.
- This is an instance of a classification task in ML.

Application: Star-Galaxy Separation

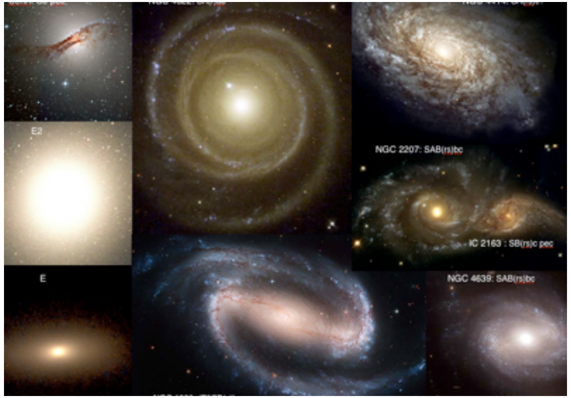
- "…we present a comparative analysis of several ML methods targeted at solving the SGSP at faint magnitudes."
- COSMOS survey was used.
- ML methods: ANNs, k-NN, SVM, Random Forests and Naive Bayes

Exploring Machine Learning Methods for the Star/Galaxy Separation Problem

Eduardo Machado[1], Marcello Serqueira[1], Eduardo Ogasawar[1], Ricardo Ogando[2], Marcio A. G. Maia[2], Luiz Nicolaci da Costa[2], Riccardo Campisano[1], Gustavo Paiva Guedes[1] and Eduardo Bezerra[1]
[1]CEFET/RJ; [2]Observatório Nacional, LIneA., Brazil

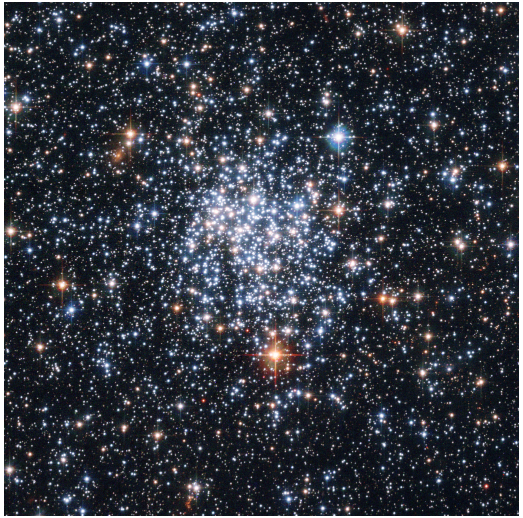
Application: Galaxy Morphology

- Studies exist that train some classification algorithm to assign T types to images for which measured parameters are available. Such parameters can be purely morphological, or include other information such (e.g., color).



Application: Stellar Clusters Detection

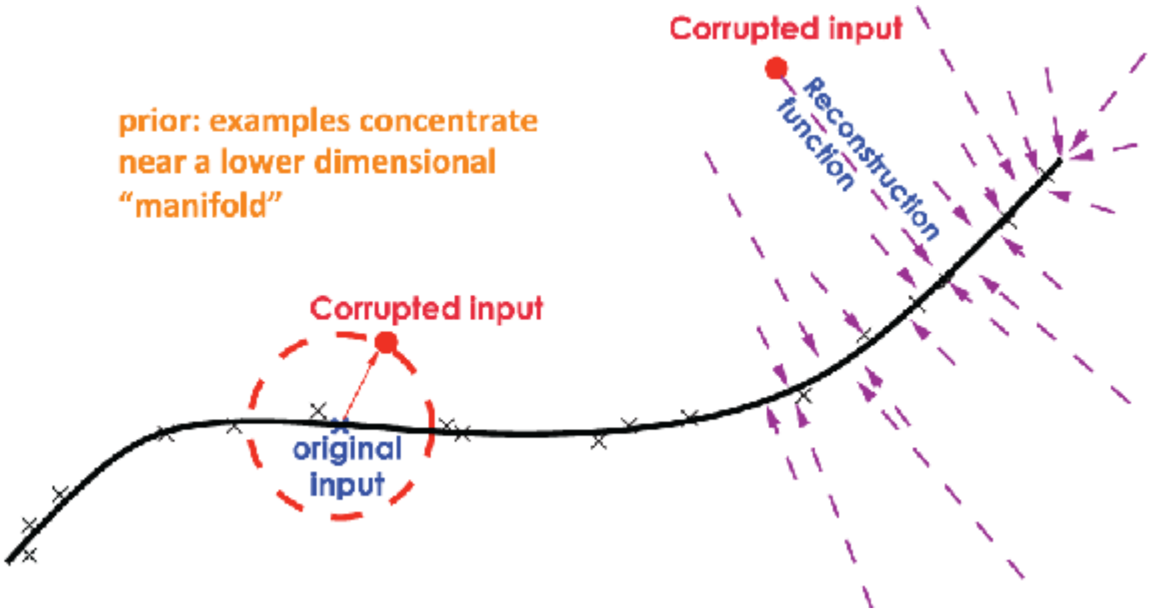
- Problem: In a given field, segregate the field and cluster stars.



Bezerra, E.; Lima, L.; Krone-Martins, **A.,** ***A formulation of stellar cluster membership assignment as a distance*** *geometry problem, Proceedings of the Workshop on Distance Geometry and Applications, 2013*.

Application: Image Denoising

- Denoising autoencoders



Credits: Hugo Larochelle

Aplication: Event Detection

- LSST is expected to see millions of transients per night that need to be detected in real time to allow for follow-up observations.
  - The time dimensional is paramount here!
- Recurrent Neural Nets (e.g., LSTMs) should be appropriate in this case.

Aplication: Event Detection (cont.)

- Timestamped datasets are expected to become increasingly important with the advent of LSST.
- For example, LSST is expected to produce a list of 1000 new supernovae each night for 10 years (LSST FAQ).
- There are several challenges, though:
  - handling multiple observations of the same object
  - handling heteroskedasticity (i.e., variability itself can change),
  - robust classification of large streams of data in real time, the volume and storage of time domain information.
- In all of these, give ML methods a try!

References

Big Universe, Big Data: Machine Learning and Image Analysis for Astronomy

Jan Kremer, Kristoffer Stensbo-Smidt, Fabian Gieseke,
Kim Steenstrup Pedersen, and Christian Igel, *University of Copenhagen*

2017

SCIENTIFIC DATA MINING IN ASTRONOMY

Kirk D. Borne

Department of Computational and Data Sciences, George Mason University,
Fairfax, VA 22030, USA
kborne@gmu.edu

2010

Ads: Machine Learning Course

- An introductory course, comprising two parts
  - 1st part: basic ML concepts and methods
  - 2nd part: Artificial Neural Nets (aka Deep Learning, if you will!)
- 12 lectures, starting in may/2018
- Available to members to the INCT e-Universe.
- For more details, see the LIneA news.

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THANKS!

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