



Capstone Project for Data Science

1

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Course Information

- ▶ Course web:
 - ▶ <https://yao-lab.github.io/capstone/2021.fall/>
- ▶ Time and Venure:
 - ▶ **Lecture: TuTh, 3:00-4:20pm**
 - ▶ *Rm 5510, Lift 25-26, Zoom* Meetings from CANVAS
 - ▶ *Tutorial: Mon 1:30-2:20pm?* -> Thurs. 18-18:50pm
 - ▶ to-be-changed
- ▶ Instructor:
 - ▶ Yuan Yao <yuany@ust.hk> (<https://yao-lab.github.io/>)
- ▶ Teaching Assistant:
 - ▶ **LIANG, Zhicong** <zliangak@connect.ust.hk>



Course Requirement



- ▶ **Prerequisite:** (Statistical) Machine Learning, e.g. working knowledge about linear regression, classification, logistic regression, decision trees (CART), boosting, random forests, support vector machines, neural networks
- ▶ With these, you can pursue basic projects in this class
- ▶ Advanced project needs **convolutional Neural Networks**



➤ **Projects:**

➤ Basic level:

➤ Kaggle Contest: Home Credit Default Risk

➤ <https://www.kaggle.com/c/home-credit-default-risk/overview>

➤ Advanced level:

➤ Kaggle contest: Nexperia Image Classification

➤ <https://www.kaggle.com/c/semi-conductor-image-classification-first>

➤ Team works are encouraged!

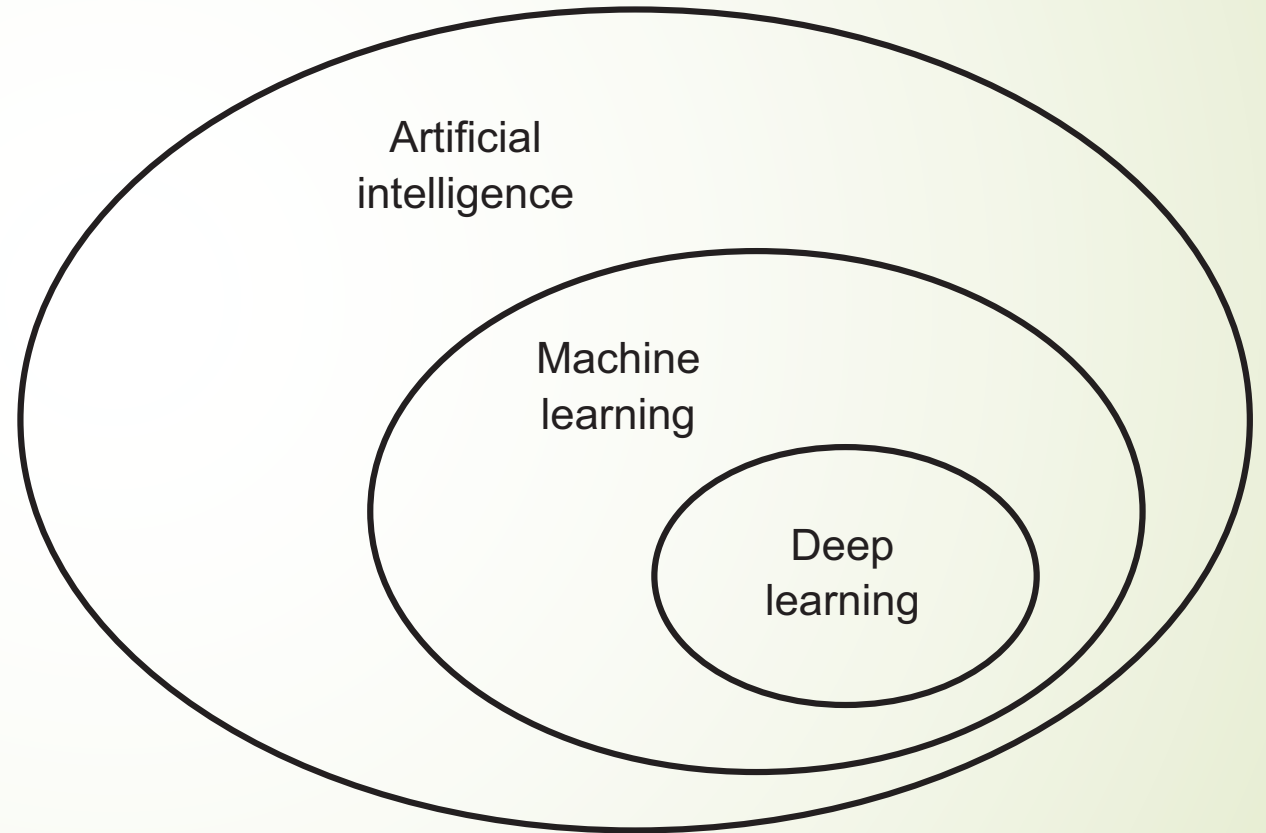
➤ Let's introduce each other...



A Brief History of AI, Machine Learning, and Deep Learning

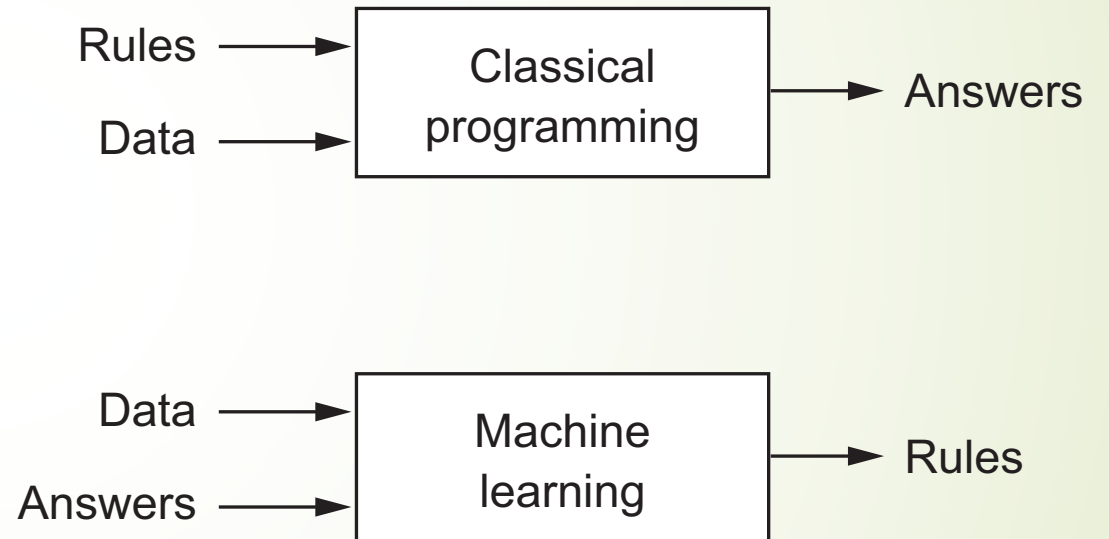
Artificial Intelligence, Machine Learning, and Deep Learning

- ▶ AI is born in 1950s, when a handful of pioneers from the nascent field of computer science started asking **whether computers could be made to “think”**—a question whose ramifications we’re still exploring today.



Machine Learning is a new paradigm of computer programming

- ▶ During 1950s-1980s, two competitive ideas of realizing AI exist
 - ▶ Rule based inference, or called **Expert System**
 - ▶ Statistics based inference, or called **Machine Learning**
- ▶ 1990s- Machine Learning becomes dominant

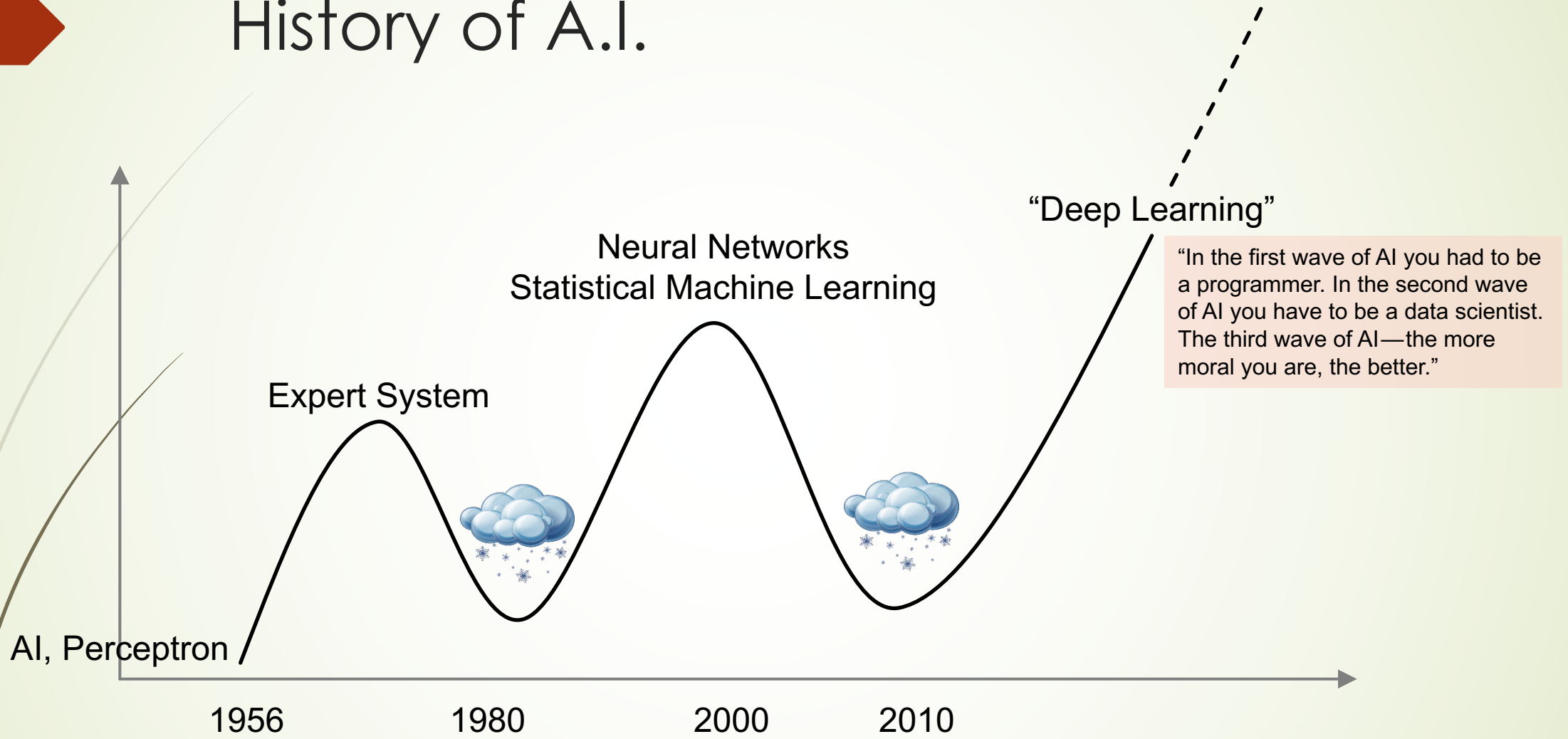


A brief history of AI



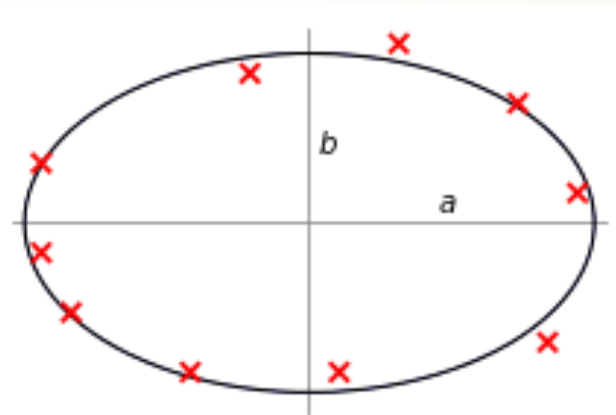
- **1943:** McCulloch & Pits proposed a boolean circuit model of neurons
- **1949:** Donald Hebb proposed **Hebbian learning rule**.
- **1950:** Alan Turing published "**Computing Machinery and Intelligence**" with **Turing test**.
- **1956:** John McCarthy at the Dartmouth Conference coined terminology "**Artificial Intelligence**"
- **1957:** Rosenblatt invented **Perceptron**
- **1960s:** golden years till **1969 Minsky-Papert's** critical book **Perceptron**
- **1970s:** the first AI winter
- **1980s:** boom of AI with **Expert System**
- **1990s:** the second AI winter, rise of **statistical machine learning**
- **1997: IBM Deep Blue** beats world chess champion Kasparov
- **2012:** return of neural networks as **deep learning** (speech, ImageNet in computer vision, NLP, ...)
- **2016-2017: Google AlphaGo "Lee" and Zero**
- **2020: Google AlphaFold**
- ...

History of A.I.



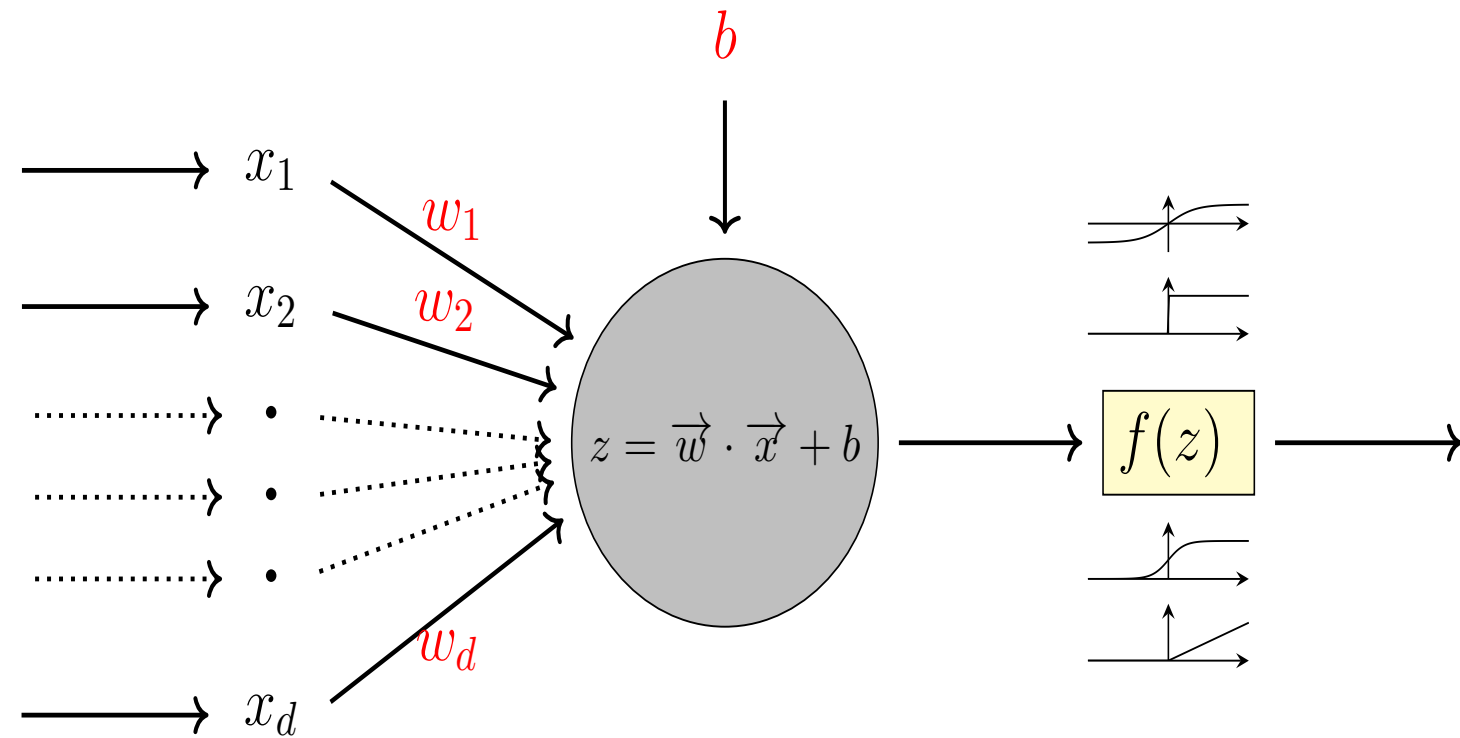
The 1st machine learning method: Least Squares

- Invention:
 - **Carl Friedrich Gauss** (~1795/1809/1810),
 - Adrien-Marie Legendre (1805)
 - Robert Adrain (1808)
- Application:
 - Prediction of the location of asteroid Ceres after it emerged from behind the sun (Franz Xaver von Zach 1801)
 - Orbits of planets, Newton Laws
 - Statistics,
 - ...



The 1st neural network: Perceptron

- Invented by Frank Rosenblatt (1957)



The Perceptron Algorithm for classification

$$\ell(w) = - \sum_{i \in \mathcal{M}_w} y_i \langle w, \mathbf{x}_i \rangle, \quad \mathcal{M}_w = \{i : y_i \langle \mathbf{x}_i, w \rangle < 0, y_i \in \{-1, 1\}\}.$$

The Perceptron Algorithm is a *Stochastic Gradient Descent* method
(**Robbins-Monro 1951**):

$$\begin{aligned} w_{t+1} &= w_t - \eta_t \nabla_i \ell(w) \\ &= \begin{cases} w_t - \eta_t y_i \mathbf{x}_i, & \text{if } y_i w_t^T \mathbf{x}_i < 0, \\ w_t, & \text{otherwise.} \end{cases} \end{aligned}$$

Finiteness of Stopping Time and Margin

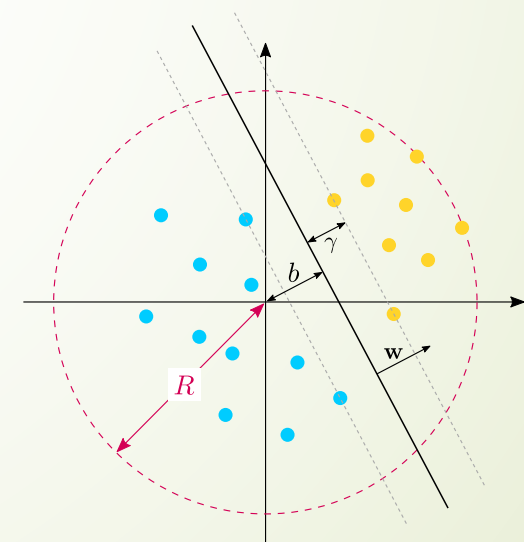
The perceptron convergence theorem was proved by Block (1962) and Novikoff (1962). The following version is based on that in Cristianini and Shawe-Taylor (2000).

Theorem 1 (Block, Novikoff). *Let the training set $S = \{(\mathbf{x}_1, t_1), \dots, (\mathbf{x}_n, t_n)\}$ be contained in a sphere of radius R about the origin. Assume the dataset to be linearly separable, and let \mathbf{w}_{opt} , $\|\mathbf{w}_{\text{opt}}\| = 1$, define the hyperplane separating the samples, having functional margin $\gamma > 0$. We initialise the normal vector as $\mathbf{w}_0 = \mathbf{0}$. The number of updates, k , of the perceptron algorithms is then bounded by*

$$k \leq \left(\frac{2R}{\gamma}\right)^2. \quad (10)$$

Input ball: $R = \max_i \|\mathbf{x}_i\|.$

Margin: $\gamma := \min_i y_i f(x_i)$



Hilbert's 13th Problem

Algebraic equations (under a suitable transformation) of degree up to 6 can be solved by functions of two variables. What about

$$x^7 + ax^3 + bx^2 + cx + 1 = 0?$$

Hilbert's conjecture: $x(a, b, c)$ cannot be expressed by a superposition (sums and compositions) of bivariate functions.

Question: can every continuous (analytic, C^∞ , etc) function of n variables be represented as a superposition of continuous (analytic, C^∞ , etc) functions of $n - 1$ variables?

Theorem (D. Hilbert)

There is an analytic function of three variables that cannot be expressed as a superposition of bivariate ones.



Kolmogorov's Superposition Theorem

Theorem (A. Kolmogorov, 1956; V. Arnold, 1957)

Given $n \in \mathbb{Z}^+$, every $f_0 \in C([0, 1]^n)$ can be represented as

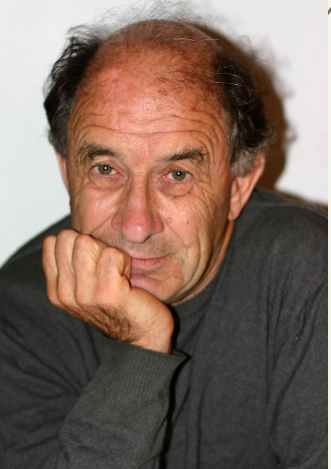
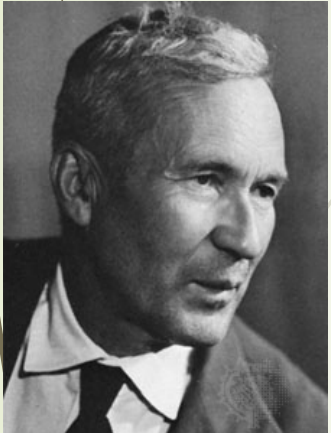
$$f_0(x_1, x_2, \dots, x_n) = \sum_{q=1}^{2n+1} g_q \left(\sum_{p=1}^n \phi_{pq}(x_p) \right),$$

where $\phi_{pq} \in C[0, 1]$ are increasing functions independent of f_0 and $g_q \in C[0, 1]$ depend on f_0 .

- Can choose g_q to be all the same $g_q \equiv g$ (Lorentz, 1966).
- Can choose ϕ_{pq} to be Hölder or Lipschitz continuous, but not C^1 (Fridman, 1967).
- Can choose $\phi_{pq} = \lambda_p \phi_q$ where $\lambda_1, \dots, \lambda_n > 0$ and $\sum_p \lambda_p = 1$ (Sprecher, 1972).

If f is a multivariate continuous function, then f can be written as a superposition of composite functions of mixtures of continuous functions of single variables:

finite **composition** of continuous functions of a **single variable** and the **addition**.



Kolmogorov's Exact Representation is not stable or smooth

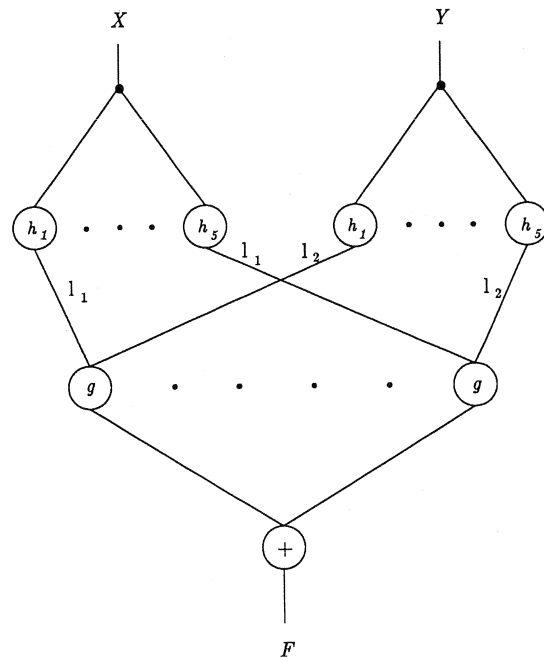


Figure 1: The network representation of an improved version of Kolmogorov's theorem, due to Kahane (1975). The figure shows the case of a bivariate function. The Kahane's representation formula is $f(x_1, \dots, x_n) = \sum_{q=1}^{2n+1} g[\sum_{p=1}^n l_p h_q(x_p)]$ where h_q are strictly monotonic functions and l_p are strictly positive constants smaller than 1.



- [Girosi-Poggio' 1989] Representation Properties of Networks: Kolmogorov's Theorem Is Irrelevant, <https://www.mitpressjournals.org/doi/pdf/10.1162/neco.1989.1.4.465>
- Lacking smoothness in h and g [Vitushkin' 1964] fails to guarantee the **generalization ability (stability)** against noise and perturbations
- The representation is **not universal** in the sense that g and h both depend on the function F to be represented.

A Simplified illustration by David McAllester

A Simpler, Similar Theorem

For (possibly discontinuous) $f : [0, 1]^N \rightarrow \mathbb{R}$ there exists (possibly discontinuous) $g, h_i : \mathbb{R} \rightarrow \mathbb{R}$.

$$f(x_1, \dots, x_N) = g \left(\sum_i h_i(x_i) \right)$$

Proof: Select h_i to spread out the digits of its argument so that $\sum_i h_i(x_i)$ contains all the digits of all the x_i .

Universal Approximate Representation

[Cybenko' 1989, Hornik et al. 1989, Poggio-Girosi' 1989, ...]

For continuous $f : [0, 1]^N \rightarrow \mathbb{R}$ and $\varepsilon > 0$ there exists

$$\begin{aligned} F(x) &= \alpha^\top \sigma(Wx + \beta) \\ &= \sum_i \alpha_i \sigma \left(\sum_j W_{i,j} x_j + \beta_i \right) \end{aligned}$$

such that for all x in $[0, 1]^N$ we have $|F(x) - f(x)| < \varepsilon$.

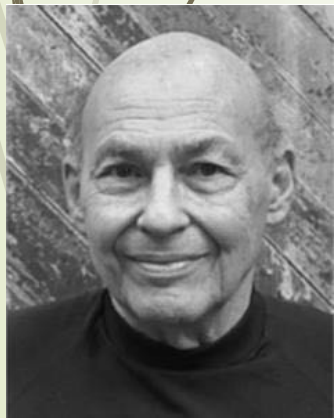
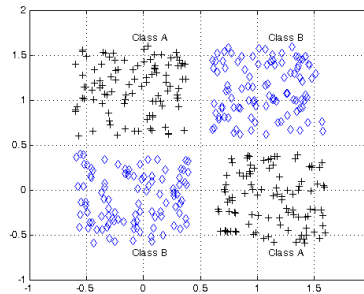
Complexity (regularity, smoothness) thereafter becomes the central pursuit in Approximation Theory.

Locality or Sparsity of Computation

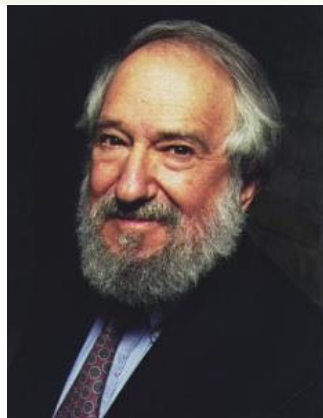
Minsky and Papert, 1969

Perceptron can't do **XOR** classification

Perceptron needs infinite global information to compute **connectivity**



Marvin Minsky

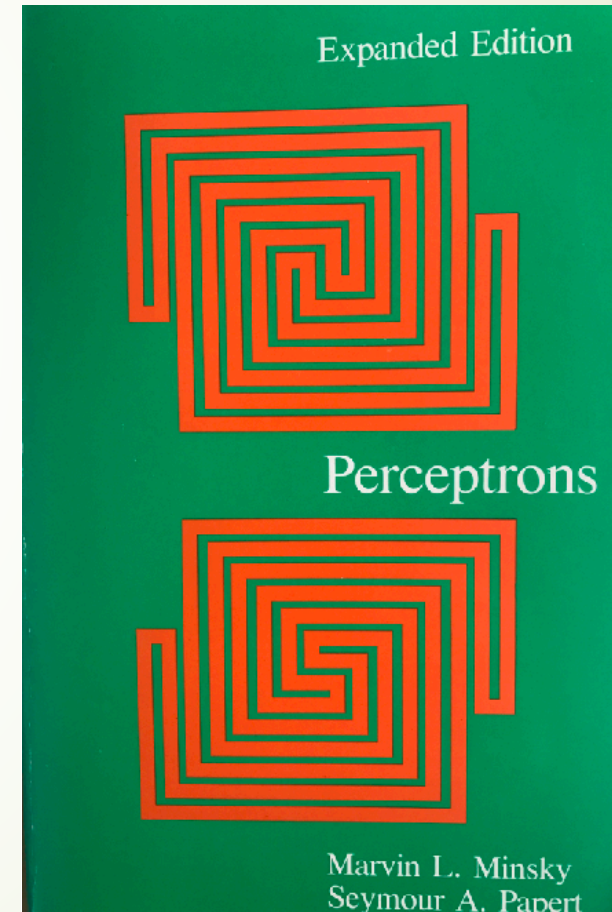


Seymour Papert

Locality or **Sparsity** is important:

Locality in time?

Locality in space?



Multilayer Perceptrons (MLP) and Back-Propagation (BP) Algorithms

D.E. Rumelhart, G. Hinton, R.J. Williams (1986)

Learning representations by back-propagating errors, *Nature*, 323(9): 533-536

BP algorithms as **stochastic gradient descent** algorithms (**Robbins–Monro 1950; Kiefer-Wolfowitz 1951**) with Chain rules of Gradient maps

Deep network may classify **XOR**. Yet **topology**?

We address complexity and geometric invariant properties first.



NATURE VOL. 323 9 OCTOBER 1986 LETTERS TO NATURE 533

Learning representations by back-propagating errors

David E. Rumelhart*, Geoffrey E. Hinton† & Ronald J. Williams*

* Institute for Cognitive Science, C-015, University of California, San Diego, La Jolla, California 92093, USA
 † Department of Computer Science, Carnegie-Mellon University, Pittsburgh, Philadelphia 15213, USA

We describe a new learning procedure, back-propagation, for networks of neuron-like units. The procedure repeatedly adjusts the weights of the connections in the network so as to minimize a measure of the difference between the actual output vector of the net and the desired output vector. As a result of the weight adjustments, internal 'hidden' units which are not part of the input or output come to represent important features of the task domain, and the regularities in the task are captured by the interactions of these units. The ability to create useful new features distinguishes back-propagation from earlier, simpler methods such as the perceptron-convergence procedure¹.

There have been many attempts to design self-organizing neural networks. The aim is to find a powerful synaptic modification rule that will allow an arbitrarily connected neural network to develop an internal structure that is appropriate for a particular task domain. The task is specified by giving the desired state vector of the output units for each state vector of the input units. If the input units are directly connected to the output units it is relatively easy to find learning rules that iteratively adjust the relative strengths of the connections so as to progressively reduce the difference between the actual and desired output vectors². Learning becomes more interesting but more difficult when we introduce hidden units whose actual or desired states are not specified by the task. (In perceptrons, there are 'feature analysers' between the input and output that are not true hidden units because their input connections are fixed by hand, so their states are completely determined by the input vector; they do not learn representations.) The learning procedure must decide under what circumstances the hidden units should be active in order to help achieve the desired input-output behaviour. This amounts to deciding what these units should represent. We demonstrate that a general purpose and relatively simple procedure is powerful enough to construct appropriate internal representations.

The simplest form of the learning procedure is for layered networks which have a layer of input units at the bottom; any number of intermediate layers; and a layer of output units at the top. Connections within a layer or from higher to lower layers are forbidden, but connections can skip intermediate layers. An input vector is presented to the network by setting the states of the input units. Then the states of the units in each layer are determined by applying equations (1) and (2) to the connections coming from lower layers. All units within a layer have their states set in parallel, but different layers have their states set sequentially, starting at the bottom and working upwards until the states of the output units are determined.

The total input, x_j , to unit j is a linear function of the outputs, y_i , of the units that are connected to j and of the weights, w_{ji} , on these connections

$$x_j = \sum_i y_i w_{ji} \quad (1)$$

Units can be given biases by introducing an extra input to each unit which always has a value of 1. The weight on this extra input is called the bias and is equivalent to a threshold of the opposite sign. It can be treated just like the other weights.

A unit has a real-valued output, y_j , which is a non-linear function of its total input

$$y_j = \frac{1}{1 + e^{-x_j}} \quad (2)$$

¹ To whom correspondence should be addressed

Parallel Distributed Processing

by Rumelhart and McClelland, 1986

Minsky and Papert set out to show which functions can and cannot be computed by this class of machines. They demonstrated, in particular, that such perceptrons are unable to calculate such mathematical functions as parity (whether an odd or even number of points are on in the retina) or the topological function of connectedness (whether all points that are on are connected to all other points that are on either directly or via other points that are also on) without making use of absurdly large numbers of predicates. The analysis is extremely elegant and demonstrates the importance of a mathematical approach to analyz-

of multilayer networks that compute parity). Similarly, it is not difficult to develop networks capable of solving the connectedness or inside/outside problem. Hinton and Sejnowski have analyzed a version of such a network (see Chapter 7).

Essentially, then, although Minsky and Papert were exactly correct in their analysis of the *one-layer perceptron*, the theorems don't apply to systems which are even a little more complex. In particular, it doesn't apply to multilayer systems nor to systems that allow feedback loops.



BP algorithm = Gradient Descent Method

- Training examples $\{x_0^i\}_{i=1}^n$ and labels $\{y^i\}_{i=1}^n$
- Output of the network $\{x_L^i\}_{i=1}^m$
- Objective Square loss, cross-entropy loss, etc.

$$J(\{W_l\}, \{b_l\}) = \frac{1}{n} \sum_{i=1}^n \frac{1}{2} \|y^i - x_L^i\|_2^2 \quad (1)$$

- Gradient descent

$$W_l = W_l - \eta \frac{\partial J}{\partial W_l}$$

$$b_l = b_l - \eta \frac{\partial J}{\partial b_l}$$

In practice: use Stochastic Gradient Descent (SGD)

Derivation of BP: Lagrangian Multiplier

LeCun et al. 1988

Given n training examples $(I_i, y_i) \equiv (\text{input}, \text{target})$ and L layers

- Constrained optimization

$$\begin{aligned} \min_{W, x} \quad & \sum_{i=1}^n \|x_i(L) - y_i\|_2 \\ \text{subject to} \quad & x_i(\ell) = f_\ell[W_\ell x_i(\ell - 1)], \\ & i = 1, \dots, n, \quad \ell = 1, \dots, L, \quad x_i(0) = I_i \end{aligned}$$

- Lagrangian formulation (Unconstrained)

$$\begin{aligned} \min_{W, x, B} \quad & \mathcal{L}(W, x, B) \\ \mathcal{L}(W, x, B) = \sum_{i=1}^n \quad & \left\{ \|x_i(L) - y_i\|_2^2 + \right. \\ & \left. \sum_{\ell=1}^L B_i(\ell)^T \left(x_i(\ell) - f_\ell[W_\ell x_i(\ell - 1)] \right) \right\} \end{aligned}$$

BP Algorithm: Forward Pass

- Cascade of repeated [linear operation followed by coordinatewise nonlinearity]'s
- Nonlinearities: sigmoid, hyperbolic tangent, (recently) ReLU.

Algorithm 1 Forward pass

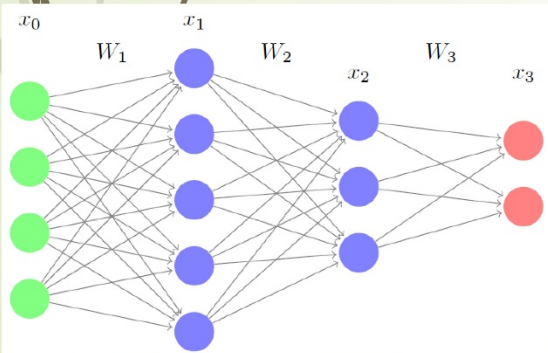
Input: x_0

Output: x_L

1: **for** $\ell = 1$ to L **do**

2: $x_\ell = f_\ell(W_\ell x_{\ell-1} + b_\ell)$

3: **end for**



back-propagation – derivation

25

- $\frac{\partial \mathcal{L}}{\partial B}$

Forward pass

$$x_i(\ell) = f_\ell \left[\underbrace{W_\ell x_i(\ell-1)}_{A_i(\ell)} \right] \quad \ell = 1, \dots, L, \quad i = 1, \dots, n$$

- $\frac{\partial \mathcal{L}}{\partial x}, z_\ell = [\nabla f_\ell] B(\ell)$

Backward (adjoint) pass

$$z(L) = 2 \nabla f_L [A_i(L)] (y_i - x_i(L))$$

$$z_i(\ell) = \nabla f_\ell [A_i(\ell)] W_{\ell+1}^T z_i(\ell+1) \quad \ell = 0, \dots, L-1$$

- $W \leftarrow W + \lambda \frac{\partial \mathcal{L}}{\partial W}$

Weight update

$$W_\ell \leftarrow W_\ell + \lambda \sum_{i=1}^n z_i(\ell) x_i^T(\ell-1)$$

Convolutional Neural Networks: shift invariances and locality

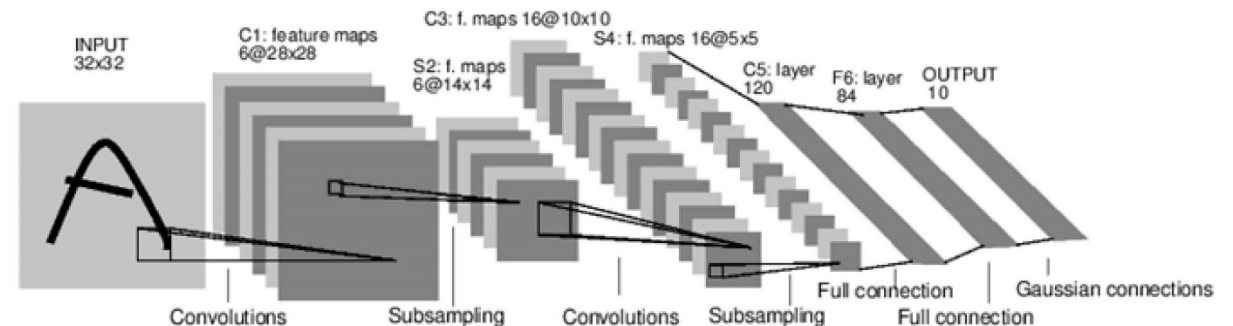
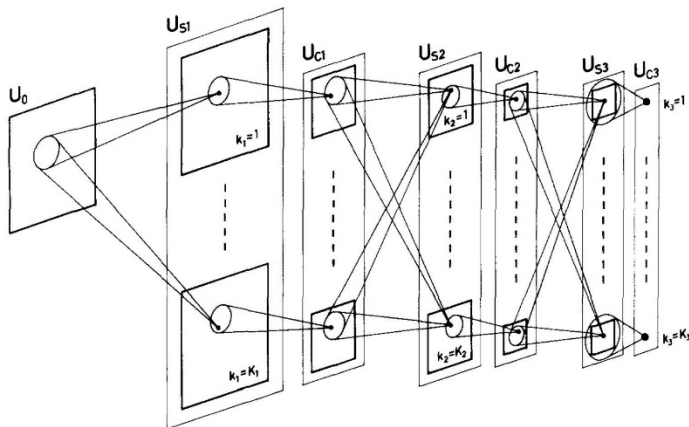
- Can be traced to *Neocognitron* of Kunihiko Fukushima (1979)
- Yann LeCun combined convolutional neural networks with back propagation (1989)
- Imposes **shift invariance** and **locality** on the weights
- Forward pass remains similar
- Backpropagation slightly changes – need to sum over the gradients from all spatial positions

Biol. Cybernetics 36, 193–202 (1980)

Neocognitron: A Self-organizing Neural Network Model for a Mechanism of Pattern Recognition Unaffected by Shift in Position

Kunihiko Fukushima

NHK Broadcasting Science Research Laboratories, Kinuta, Setagaya, Tokyo, Japan

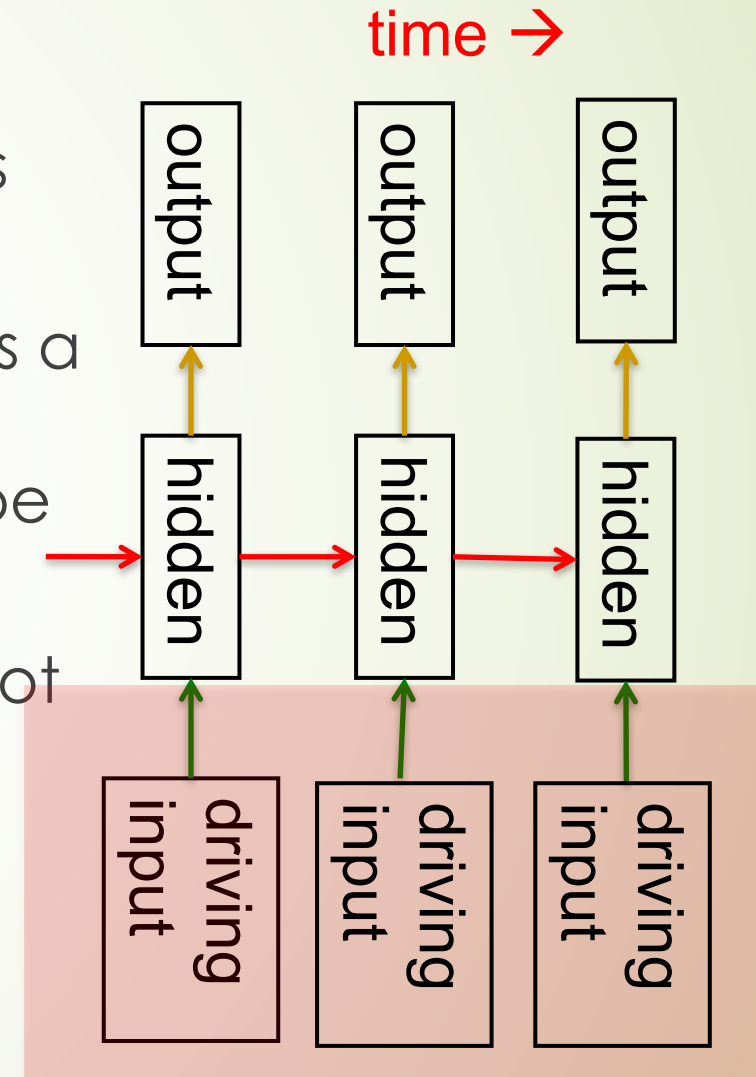


Linear Dynamical Systems (1940s-)

- ▶ The hidden state has linear dynamics with Gaussian noise and produces the observations using a linear model with Gaussian noise.
- ▶ Kalman Filter: A linearly transformed Gaussian is a Gaussian. So the distribution over the hidden state given the data so far is Gaussian. It can be computed using “Kalman filtering”.
- ▶ To predict the next output (so that we can shoot down the missile) we need to infer the hidden state.

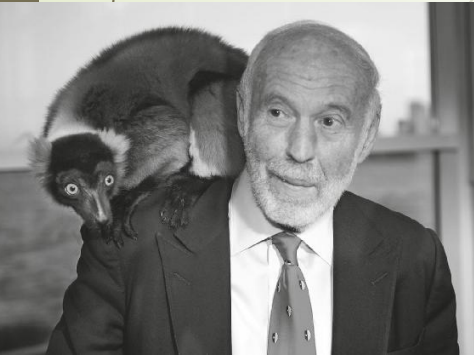
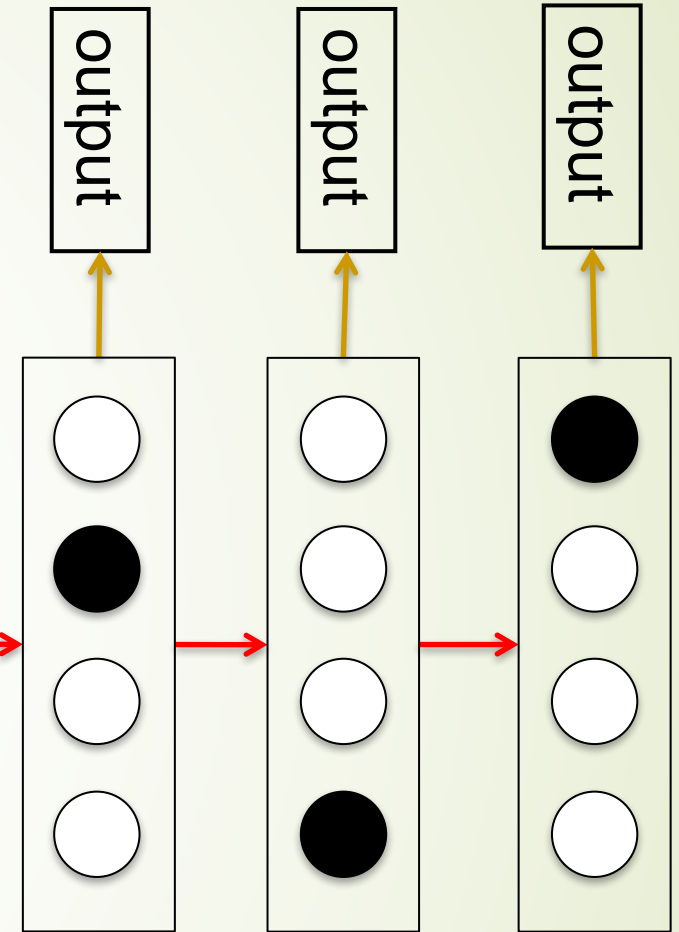
$$h_t = W_{hh}h_{t-1} + W_{hx}x_t + \epsilon_t^h$$

$$y_t = W_{yh}h_t + W_{yx}x_t + \epsilon_t^y$$



Hidden Markov Models (1970s-)

- Hidden Markov Models have a discrete one-of-N hidden state. Transitions between states are stochastic and controlled by a transition matrix. The outputs produced by a state are stochastic.
- We cannot be sure which state produced a given output. So the state is “hidden”.
- It is easy to represent a probability distribution across N states with N numbers.
- To predict the next output we need to infer the probability distribution over hidden states.
 - HMMs have efficient algorithms (**Baum-Welch or EM Algorithm**) for inference and learning.
 - **Jim Simons** hires Lenny Baum as the founding member of Renaissance Technologies in 1979



Lenny Baum became a devoted Go player despite his deteriorating eyesight.

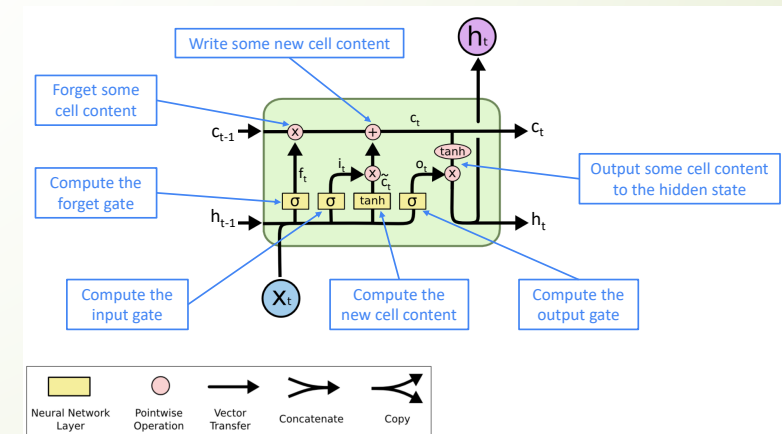


Recurrent Neural Networks (1986-)

- ▶ **The issue of a hidden Markov model (HMM):**
 - ▶ At each time step it must select one of its hidden states. So with N hidden states it can only remember $\log(N)$ bits about what it generated so far.
- ▶ RNNs are very powerful, because they combine two properties:
 - ▶ Distributed hidden state that allows them to store a lot of information about the past efficiently.
 - ▶ Non-linear dynamics that allows them to update their hidden state in complicated ways.
- ▶ Rumelhart et al. enables training by **BP** algorithm
 - ▶ With enough neurons and time, RNNs can compute anything that can be computed by your computer.

Long-Short-Term-Memory (LSTM)

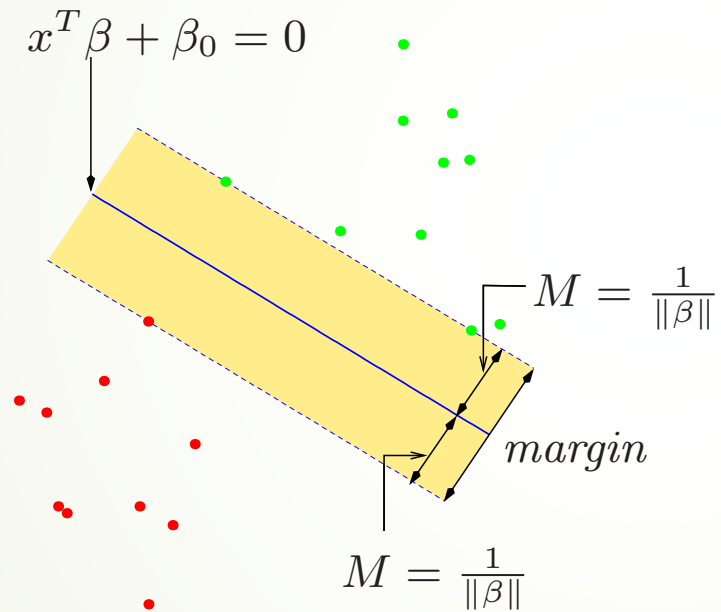
- [Sepp Hochreiter; Jürgen Schmidhuber \(1997\). "Long short-term memory". *Neural Computation*. 9 \(8\): 1735–1780. \(https://www.bioinf.jku.at/publications/older/2604.pdf\)](https://www.bioinf.jku.at/publications/older/2604.pdf)
- Introduction of short path to learn deep networks without vanishing gradient problem.



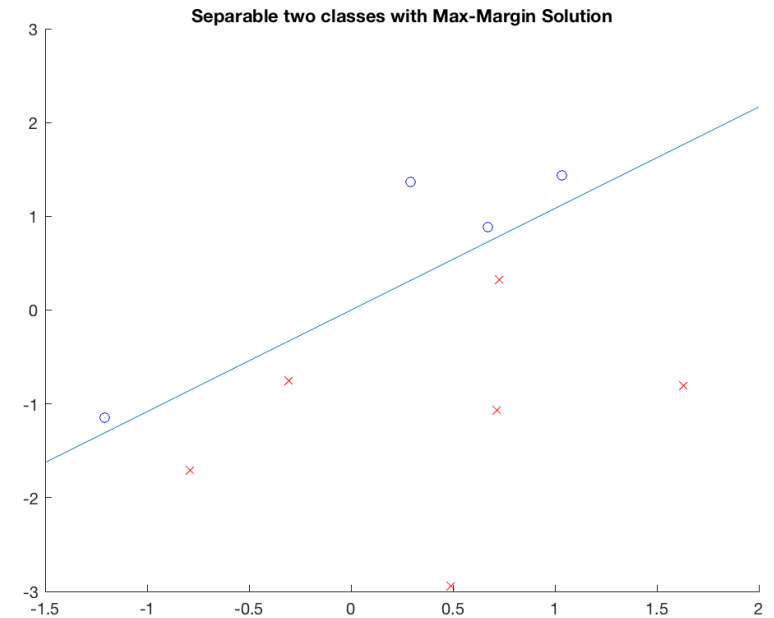
Max-Margin Classifier (SVM)

$$\text{minimize}_{\beta_0, \beta_1, \dots, \beta_p} \|\beta\|^2 := \sum_j \beta_j^2$$

subject to $y_i(\beta_0 + \beta_1 x_{i1} + \dots + \beta_p x_{ip}) \geq 1$ for all i



Vladimir Vapnik, 1994



MNIST Dataset Test Error

LeCun et al. 1998



Simple SVM performs
as well as Multilayer
Convolutional Neural
Networks which need
careful tuning (LeNets)

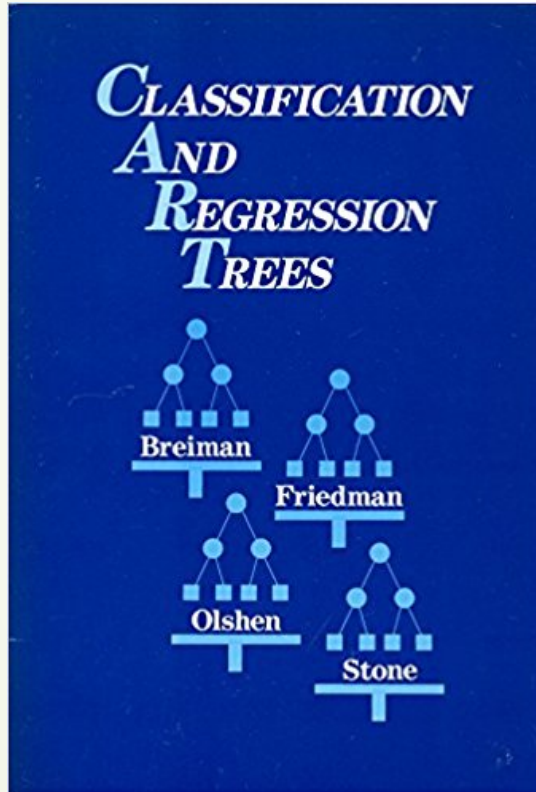
Dark era for NN: 1998-2012



2000-2010: The Era of SVM, Boosting, ... as nights of Neural Networks



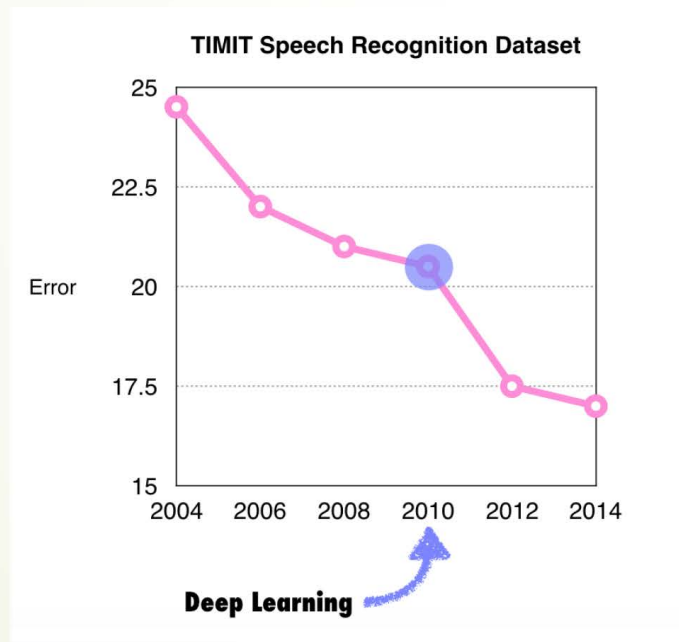
Decision Trees and Boosting



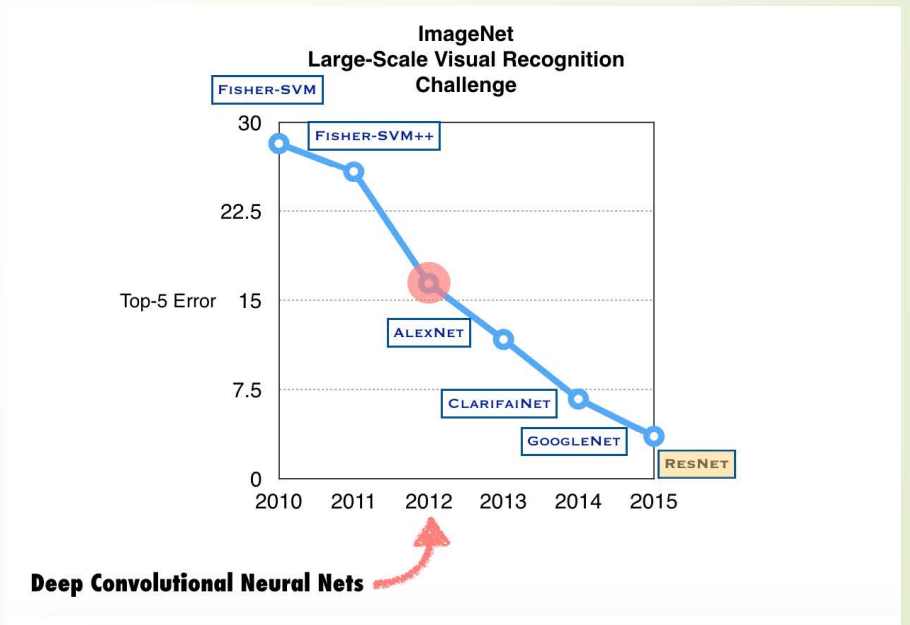
- Breiman, Friedman, Olshen, Stone, (1983): CART
- “The Boosting problem” (M. Kearns & L. Valiant): **Can a set of weak learners create a single strong learner?** (三个臭皮匠顶个诸葛亮?)
- Breiman (1996): Bagging
- Freund, Schapire (1997): **AdaBoost** (“the best off-the-shelf algorithm” by Breiman)
- Breiman (2001): **Random Forests**

Around the year of 2012: return of NN as 'deep learning'

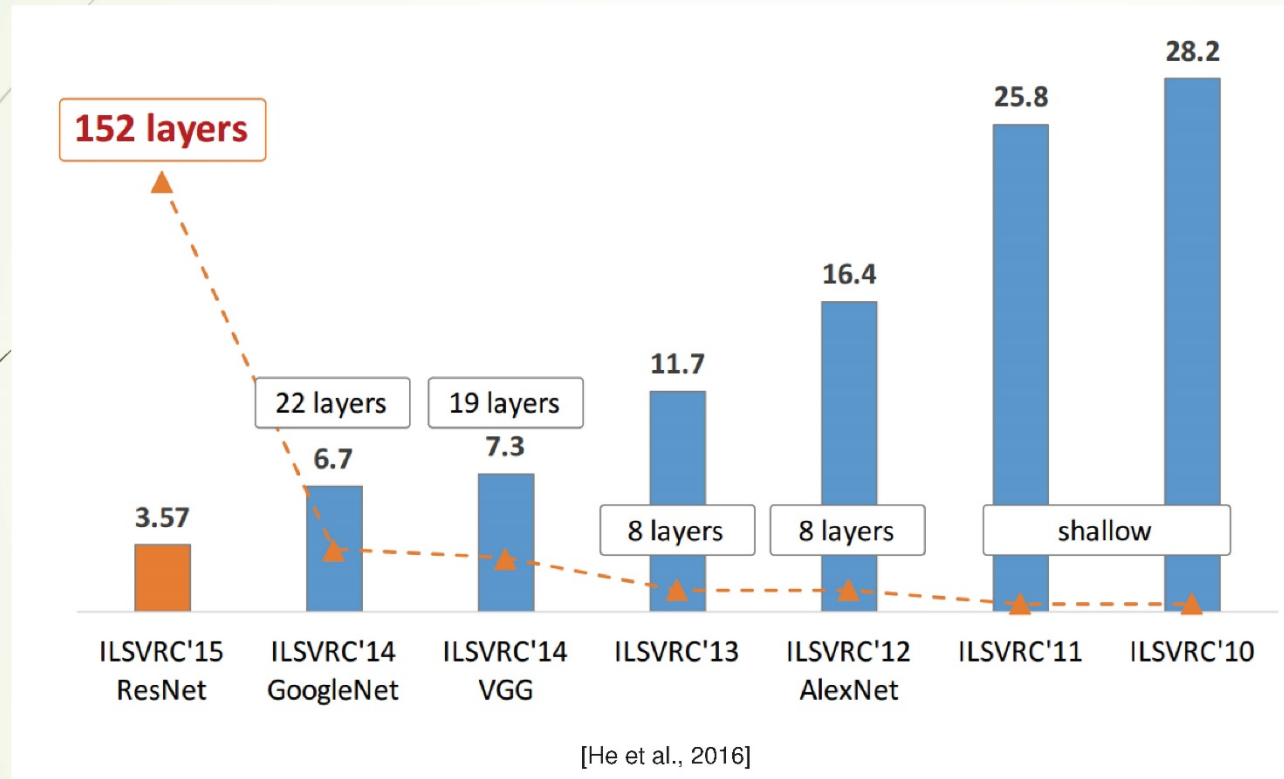
Speech Recognition: TIMIT



Computer Vision: ImageNet

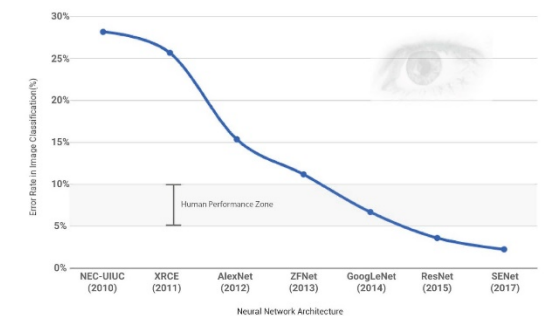


Depth as function of year



ILSVRC ImageNet Top 5 errors

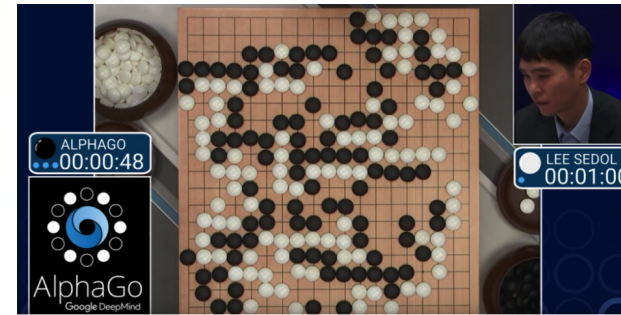
- ImageNet (subset):
 - 1.2 million training images
 - 100,000 test images
 - 1000 classes
- ImageNet large-scale visual recognition Challenge



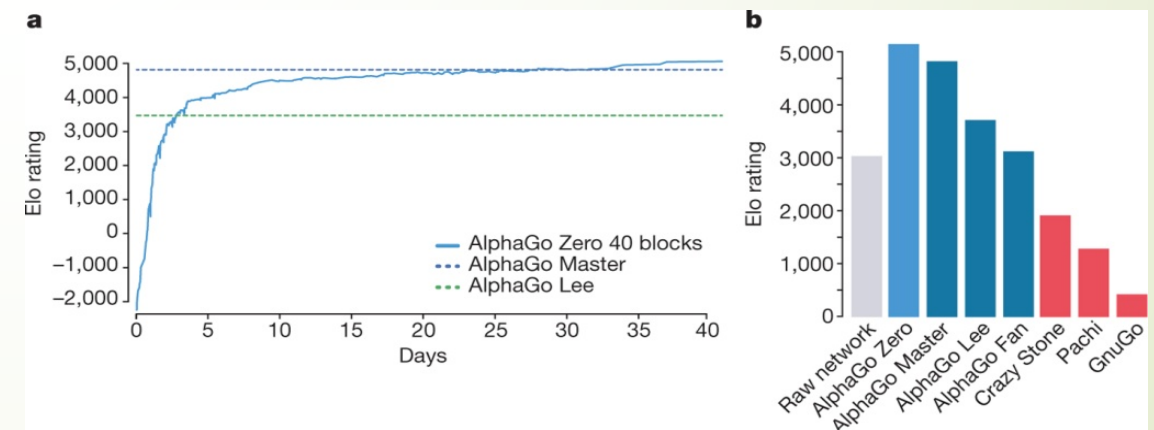
Reaching Human Performance Level in Games



Deep Blue in 1997



AlphaGo "LEE" 2016



NLP and Machine Translation

- In **2013-2015**, **LSTMs** started achieving state-of-the-art results
 - Successful tasks include: handwriting recognition, speech recognition, machine translation, parsing, image captioning
 - LSTM became the dominant approach
- In **2019**, other approaches (e.g. **Transformers**) have become more dominant for certain tasks.
 - For example in **WMT** (a MT conference + competition):
 - In WMT 2016, the summary report contains "RNN" 44 times
 - In WMT 2018, the report contains "RNN" 9 times and "Transformer" 63 times
 - **Source:** "Findings of the 2016 Conference on Machine Translation (WMT16)", Bojar et al. 2016, <http://www.statmt.org/wmt16/pdf/W16-2301.pdf>
 - **Source:** "Findings of the 2018 Conference on Machine Translation (WMT18)", Bojar et al. 2018, <http://www.statmt.org/wmt18/pdf/WMT028.pdf>

Number of AI papers on arXiv, 2010-2019

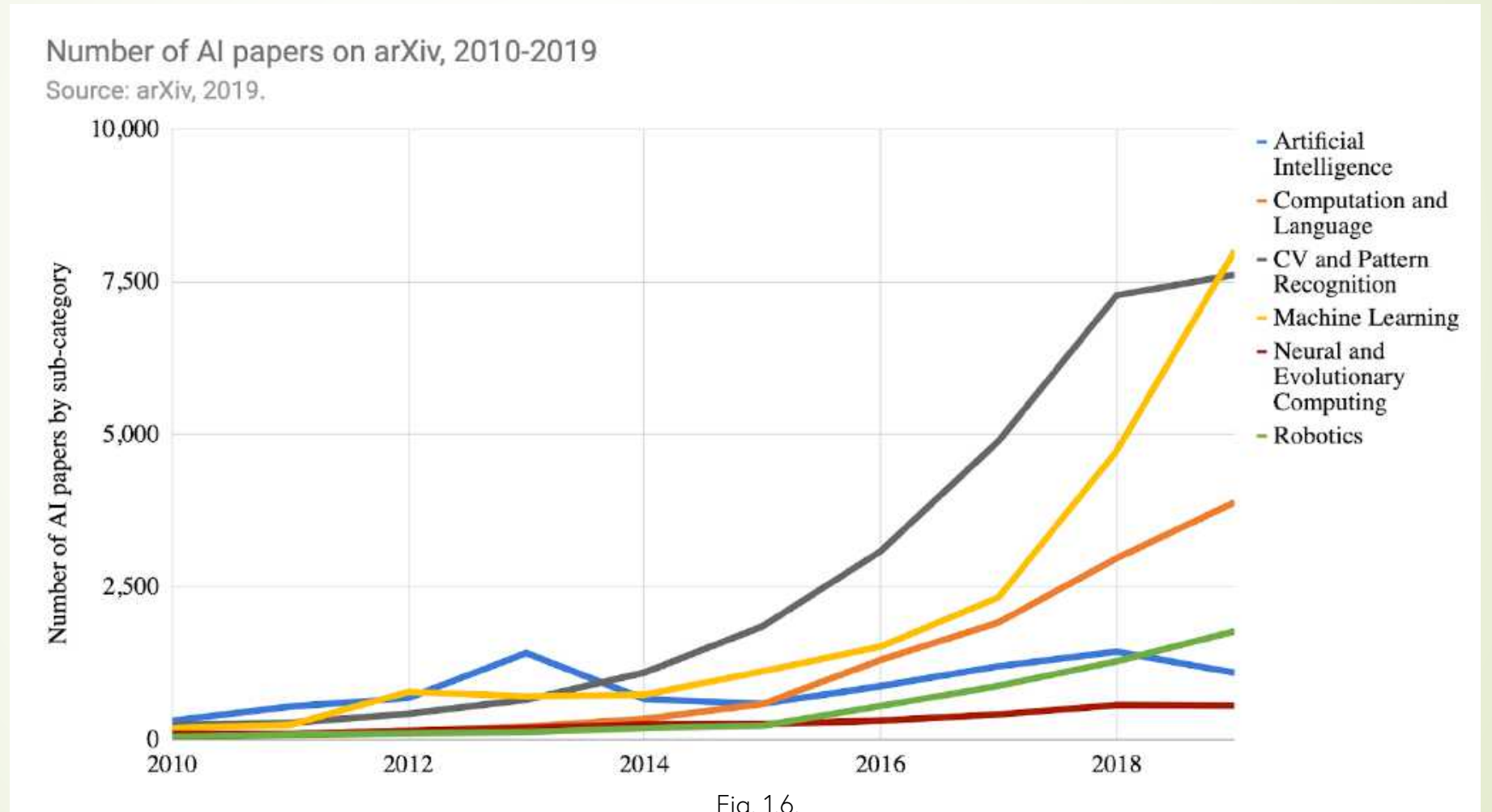
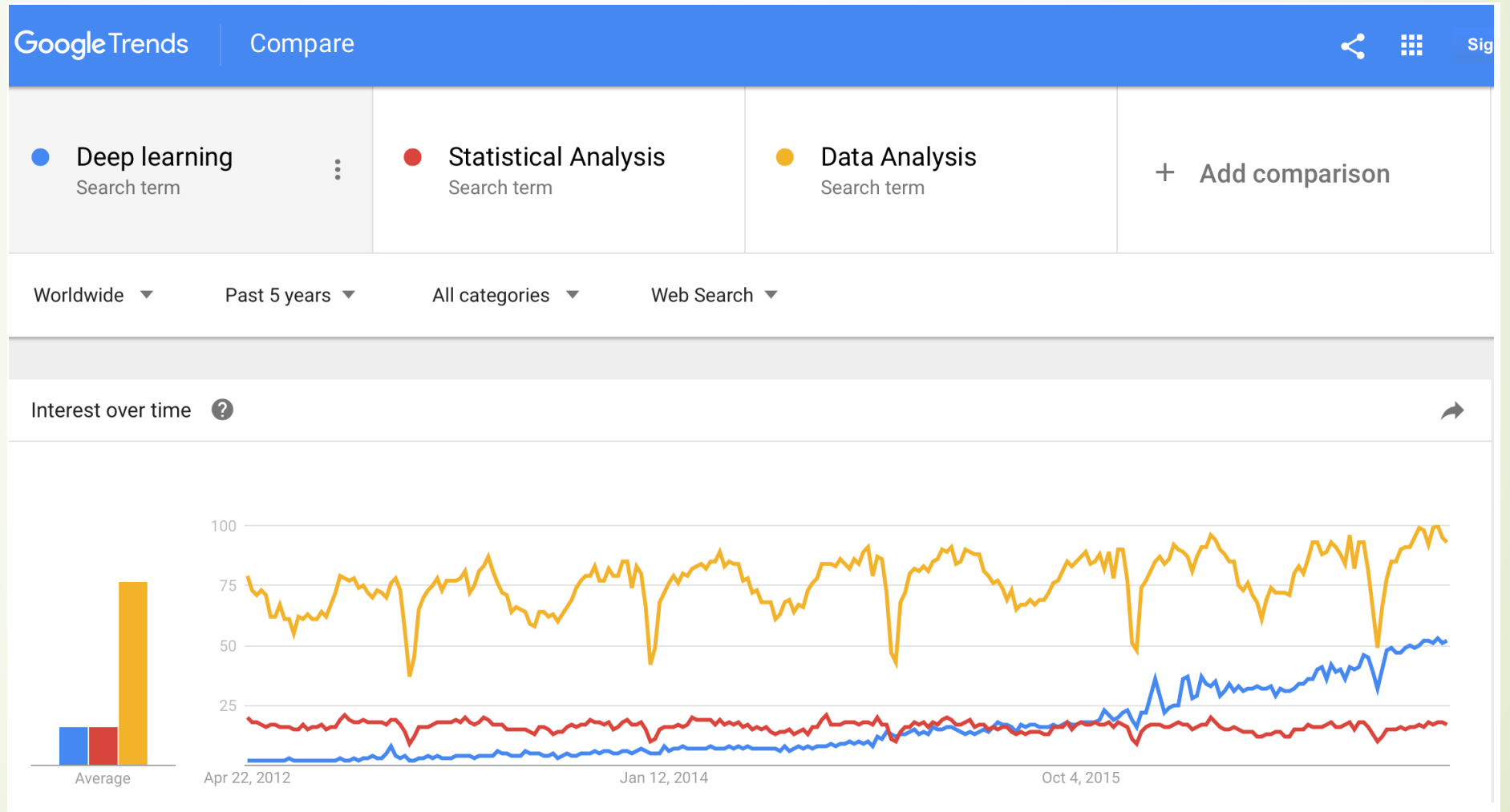


Fig. 1.6.

Growth of Deep Learning

'Deep Learning' is coined by Hinton et al. in their Restricted Boltzman Machine paper, *Science* 2006, not yet popular until championing ImageNet competitions.



Some Cold Water: Tesla Autopilot Misclassifies Truck as Billboard



Problem: Why? How can you trust a blackbox?

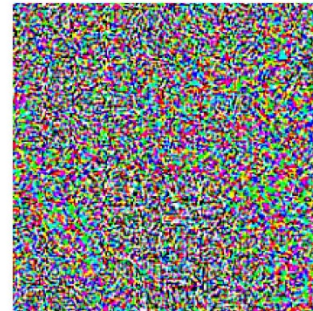
Deep Learning may be fragile in generalization against noise!

 x

"panda"

57.7% confidence

+ .007 ×

 $\text{sign}(\nabla_x J(\theta, x, y))$

"nematode"

8.2% confidence

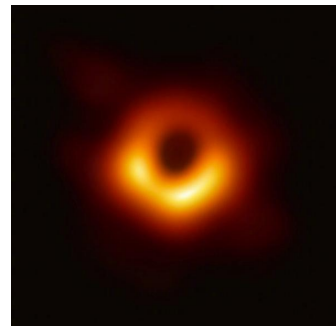
=

 $x +$ $\epsilon \text{sign}(\nabla_x J(\theta, x, y))$

"gibbon"

99.3% confidence

[Goodfellow et al., 2014]



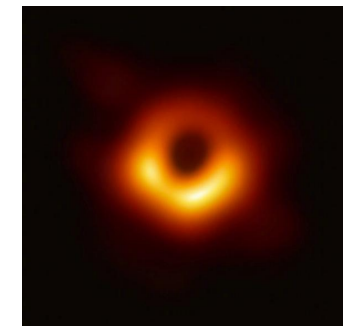
"black hole"

87.7% confidence

+ .007 ×



=



"donut"

99.3% confidence



CNN learns **texture** features, not **shapes**



(a) Texture image
81.4% **Indian elephant**
10.3% indri
8.2% black swan



(b) Content image
71.1% **tabby cat**
17.3% grey fox
3.3% Siamese cat



(c) Texture-shape cue conflict
63.9% **Indian elephant**
26.4% indri
9.6% black swan

Geirhos et al. ICLR 2019

<https://videoken.com/embed/W2HvLBMhCJQ?tocitem=46>

Overfitting causes **privacy leakage**

- ▶ Model inversion attack leaks privacy



Figure: Recovered (Left), Original (Right)

What's wrong with deep learning?

Ali Rahimi NIPS'17: Machine (deep) Learning has become **alchemy**.


<https://www.youtube.com/watch?v=ORHFOndEzPc>

Yann LeCun CVPR'15, invited talk: **What's wrong with deep learning?**
One important piece: **missing some theory (clarity in understanding)!**

<http://techtalks.tv/talks/whats-wrong-with-deep-learning/61639/>



Being alchemy is certainly not a shame, not wanting to work on advancing to chemistry is a shame! -- **by Eric Xing**




“ Shall we see soon an
emergence
from Alchemy to Science
in deep leaning? ”

How can we teach our students in the next generation science rather than alchemy?



In this class

- ▶ Understand its principles: statistics, optimization
 - ▶ Analyze the real world data with the methods
 - ▶ Team-work (no more than 3 persons per team)!
- 

Thank you!

