Learning From Data:

Evolution and Revolution

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MLC

Outline

- Buzzwords/Terminology
- Historical Perspective
- The Essence
- The Revolution
- Challenges

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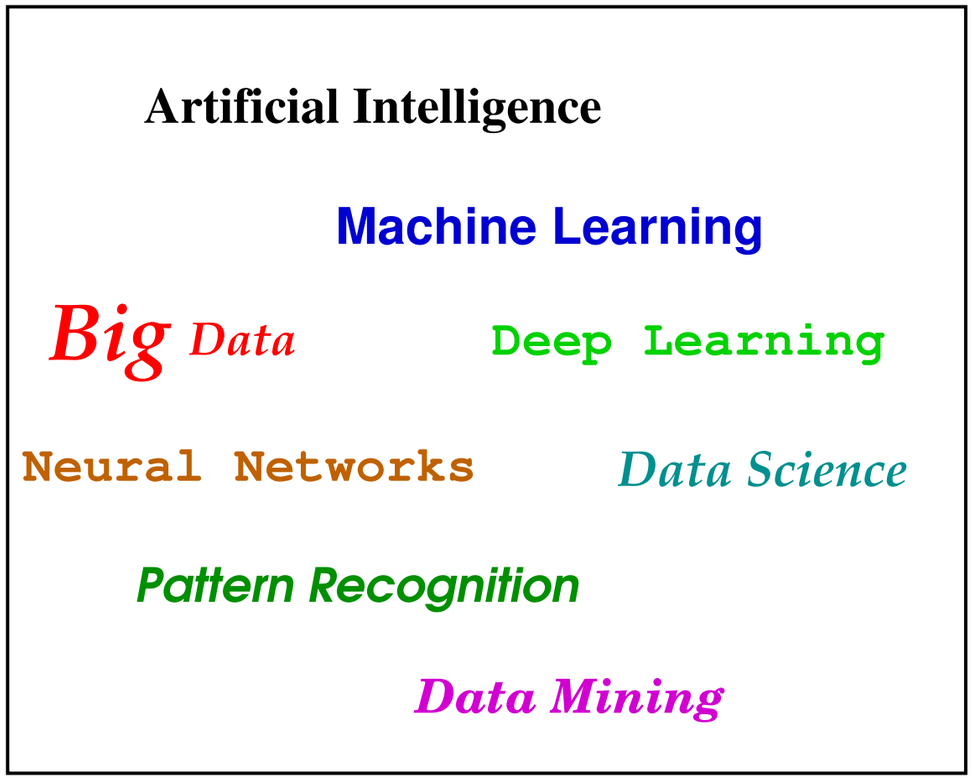
What are all these buzzwords?



Here is the dictionary!

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Deep Learning $=$ Neural Networks

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$$\text{Deep Learning} = \text{Neural Networks}$$

$$\text{Neural Networks} \subset \text{Machine Learning}$$

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$$\text{All other buzzwords} \approx \text{Machine Learning}$$

Machine Learning $\Longrightarrow$ Artificial Intelligence

Different levels that capture our notion of intelligence:

-
-
-
-

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Evolution

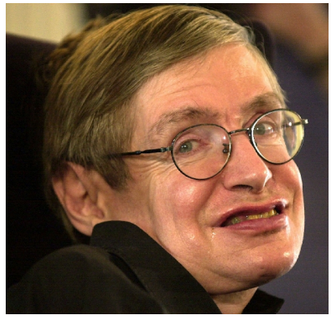
$\downarrow$

Revolution

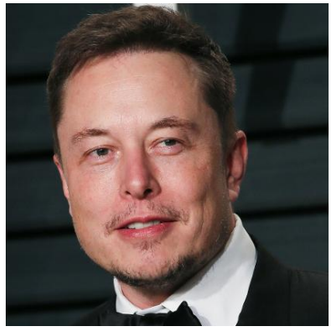
$\downarrow$

Hype?

Maybe it's not hype! 🙂



Stephen Hawking: "the development of full artificial intelligence could spell **the end of the human race**."



Elon Musk: "I think we should be very careful about artificial intelligence. If I were to guess at what **our biggest existential threat** is, it's probably that."

Learning is the key buzzword

Jeopardy's Watson (IBM) is a one-task machine. Big task, but one task.

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From Evolution to Revolution

Over the past 7 years, ML models and applications have moved

- From -

- To -

- **Low Hanging Fruit:**

  Almost any application can use ML for immediate benefit from the data.

- **Very Ambitious Goals:**

  Advanced ML creates super-human performance in intelligent tasks.

It was a long, bumpy road that led to this achievement.

Timeline of Ups and Downs

ML: Machine Learning **AI**: Artificial Intelligence

- **1950's:** **ML**/**AI** is the great future.

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- **2010's:** Neural networks are great after all.
- **Now:** **ML**/**AI** is the great future.

- Then and Now -

CNN

1989 by Bell Labs

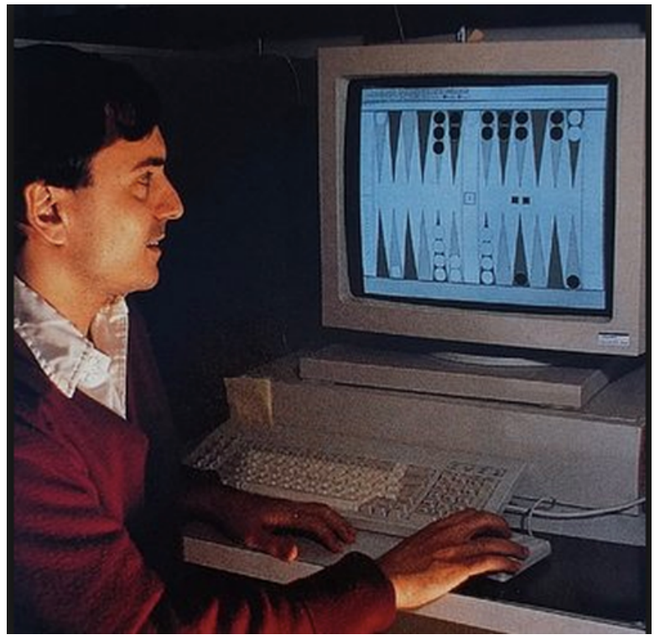
AlexNet

2012 by Alex Krizhevsky

- Then and Now -

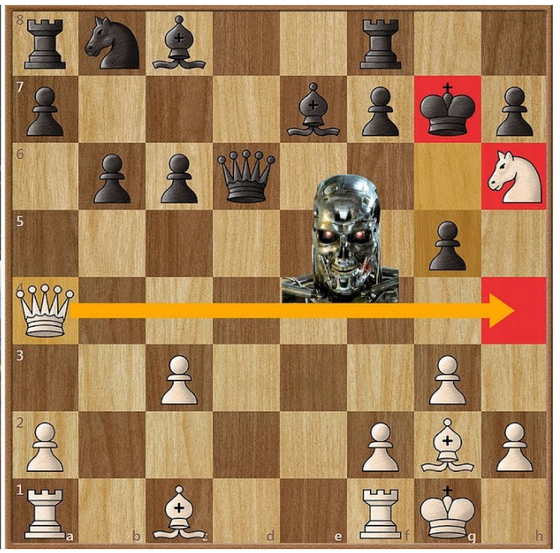
TD Gammon

1992 by G. Tesauro (IBM)



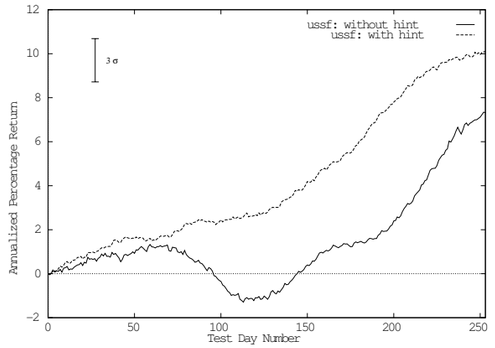
AlphaZero

2017 by DeepMind

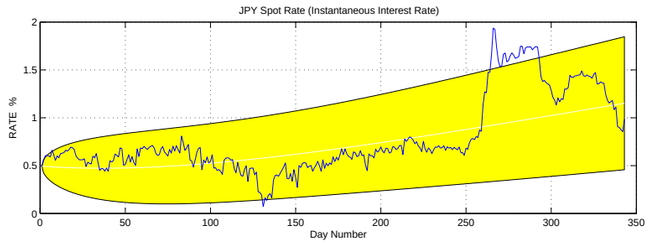


1st Wave of Success: Financial Applications

- Market forecasting



- Financial model calibration



- Consumer and corporate credit assessment.

Biggest Early Success of Neural Networks

Detection of credit-card fraud - huge commercial success:

NEURAL NETWORKS: HECHT-NIELSON NEUROCOMPUTERS WINS FUNDS

CBR STAFF WRITER
13TH AUGUST 1987

The radically new computing technology of neural networking, which mimics in simple form the operation of the central nervous system of vertebrates, has taken a significant step forward with four venture capital firms coming forward to finance one of the first start-up companies in the field. The company is Hecht-Nielsen Neurocomputer Corp, San Diego, which [...]

2nd Wave of Success: E-commerce

- Recommender systems (Amazon, fashion, ...)

- Profiling

Famous ML e-commerce problem

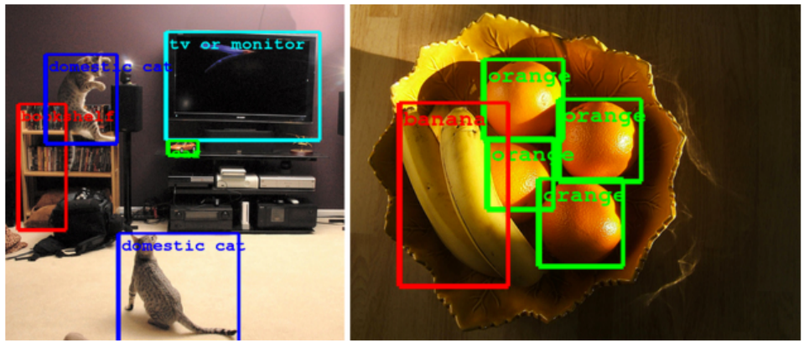
2006 - 2009

US$1,000,000 Prize for the first 10% improvement

3rd Wave of Success: Perception Tasks

The last 7 years witnessed a huge ML surge in computer vision and other perception tasks

speech recognition



object detection

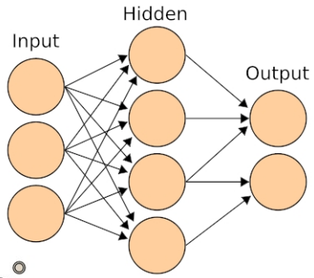
machine translation

The revival of neural networks, with more layers this time.

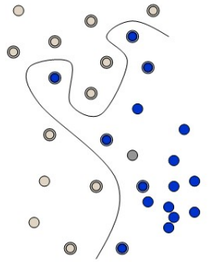
The comeback of Neural Networks

The dominant ML models over the past 40 years:

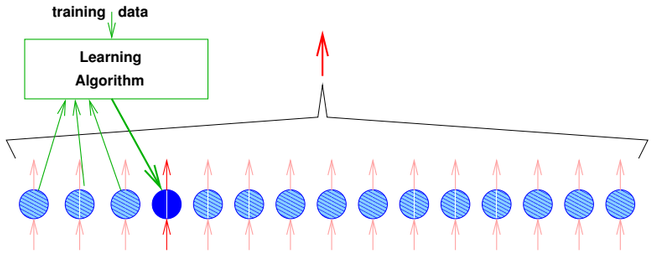
- **1980's**: Neural Networks



- **1990's**: Support Vector Machines



- **2000's**: Boosting Algorithms



- **2010's**: New, improved neural networks. 

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1. What Machine Learning Does

The technical core of all these fields:

- *Machine Learning*
- *Artificial Intelligence*
- *Data Mining*
- *Pattern Recognition*

"Automated detection of a pattern based on the data"

Example: Credit Approval

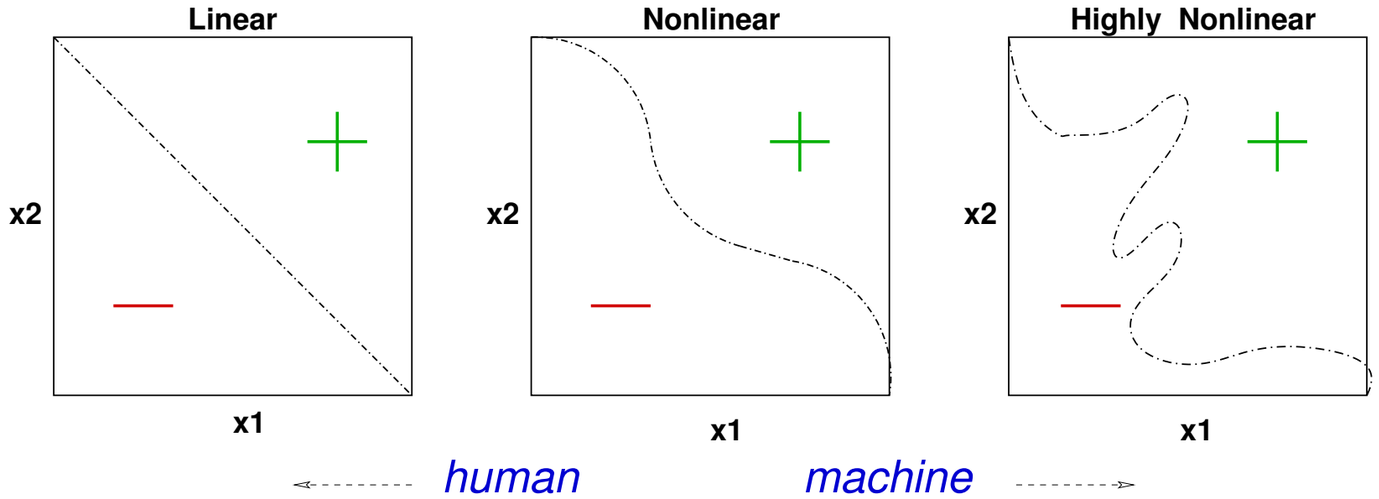
Given the data of an applicant:

age	23 years
gender	male
annual salary	$30,000
years in residence	1 year
years in job	1 year
current debt	$15,000

should we extend credit?

Human Solution versus Machine Learning

Historical records of good and bad customers used to decide the boundary between credit approval and denial.



The learning algorithm constructs the boundary based on the data.

2. When should ML be used?

ML is the technology of choice when:

- A pattern exists.
- We cannot pin it down mathematically.
- We have a representative data set.

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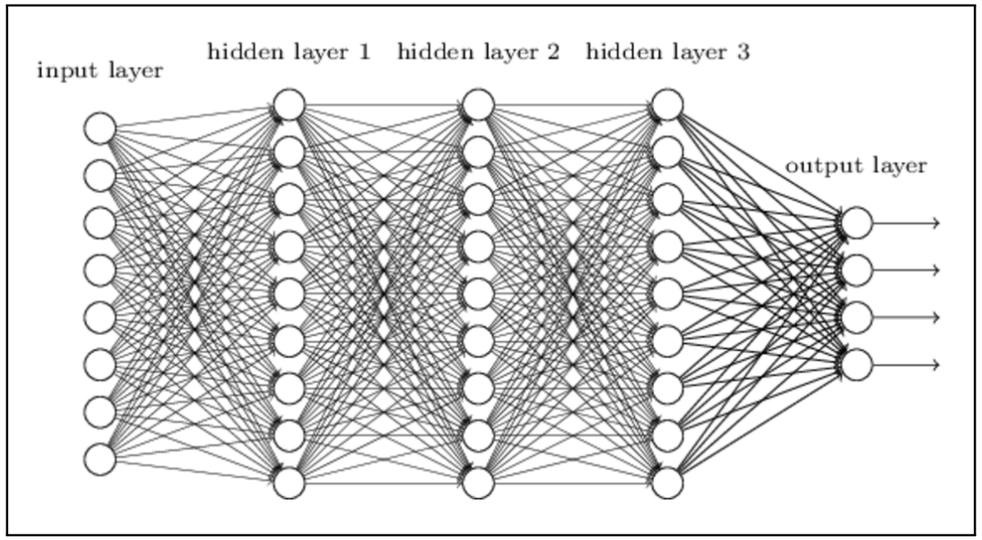
3. The building block

The Deep Neural Network - most successful ML model to date:



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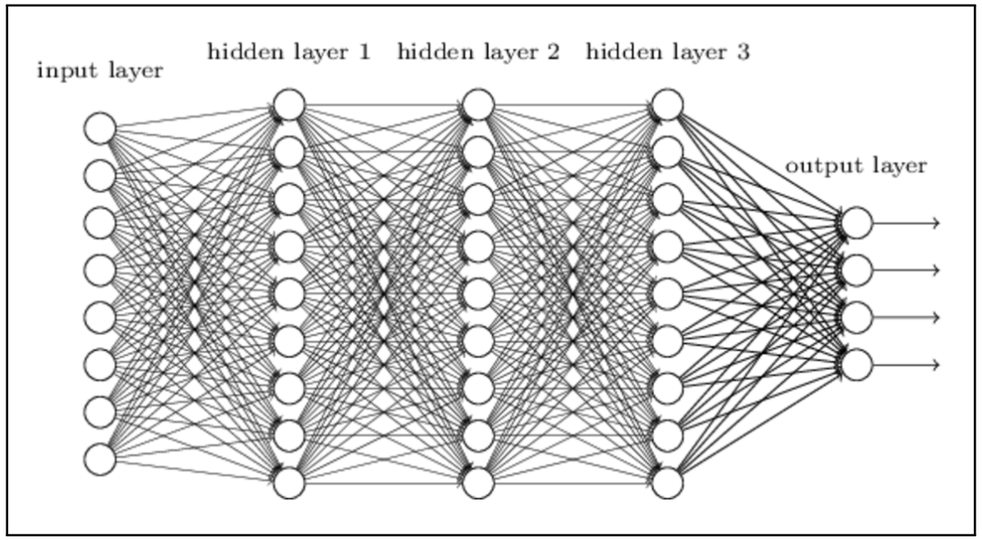

(a) Expressive: Higher and higher level representations capture complex patterns.

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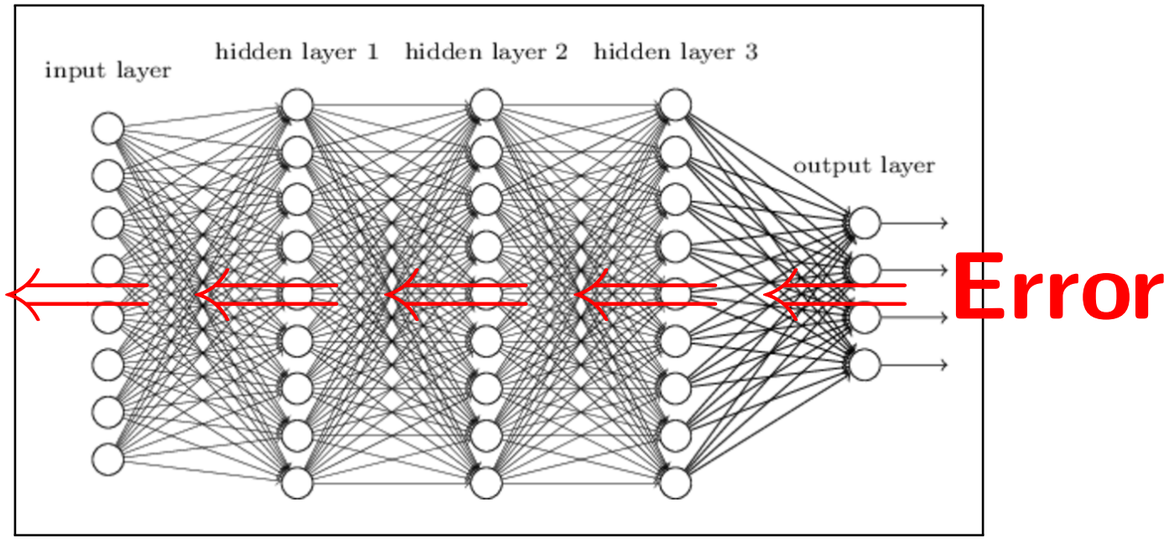

(b) Composable: Chain rule (backpropagation) allows for various compositions.

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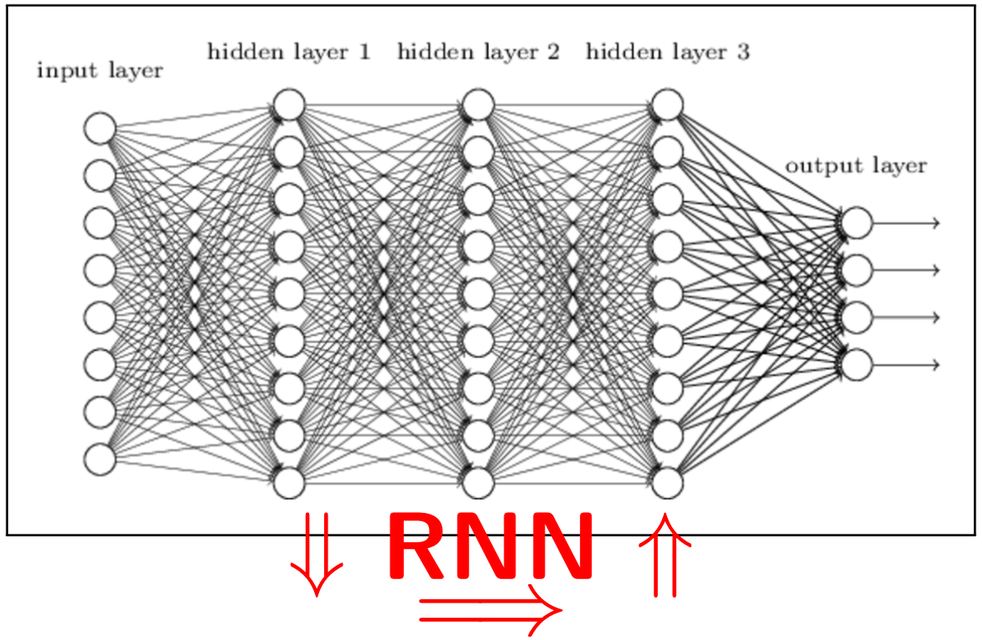

(c) Flexible: Architecture easily modified to incorporate different functionalities.

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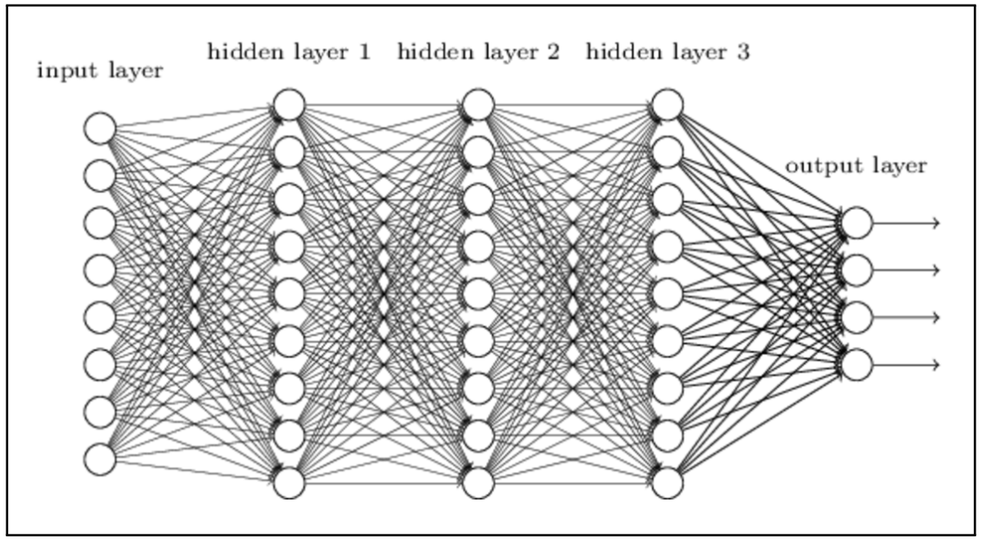

(d) Specialization: CNN (vision), LSTM (NLP), GAN (generative), Embedding.

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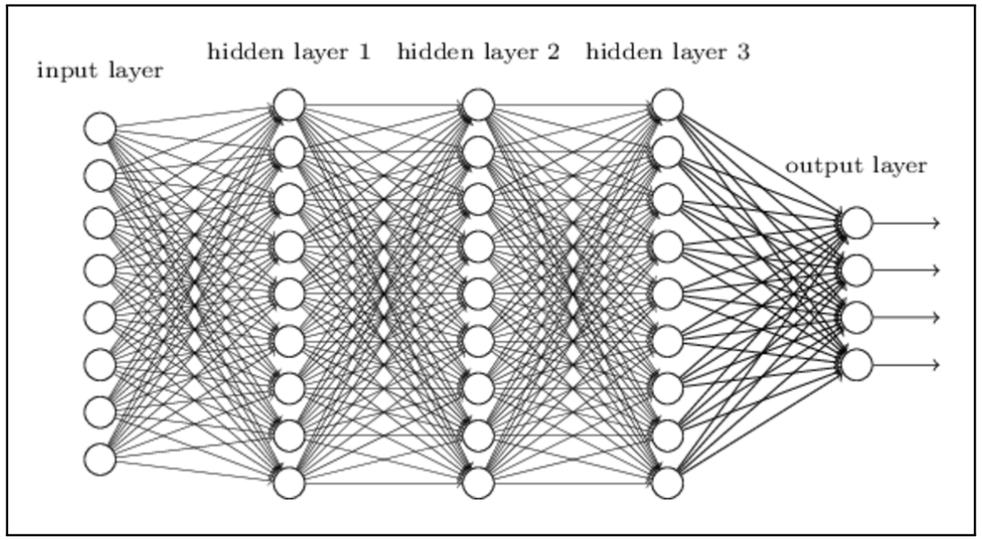
Learning
versus
Evolution



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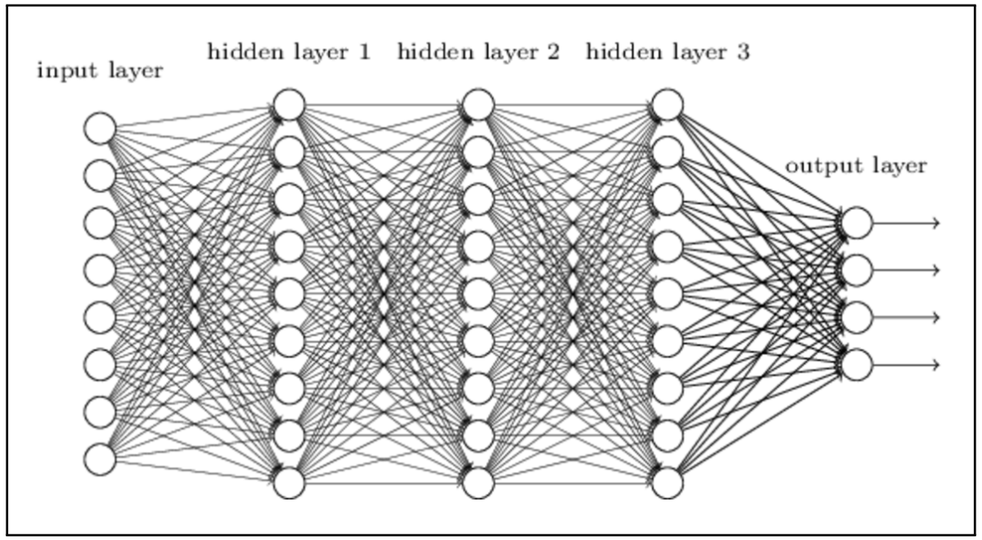

Target

Error

(e) Soft Objective: Reinforcement learning and related paradigms.

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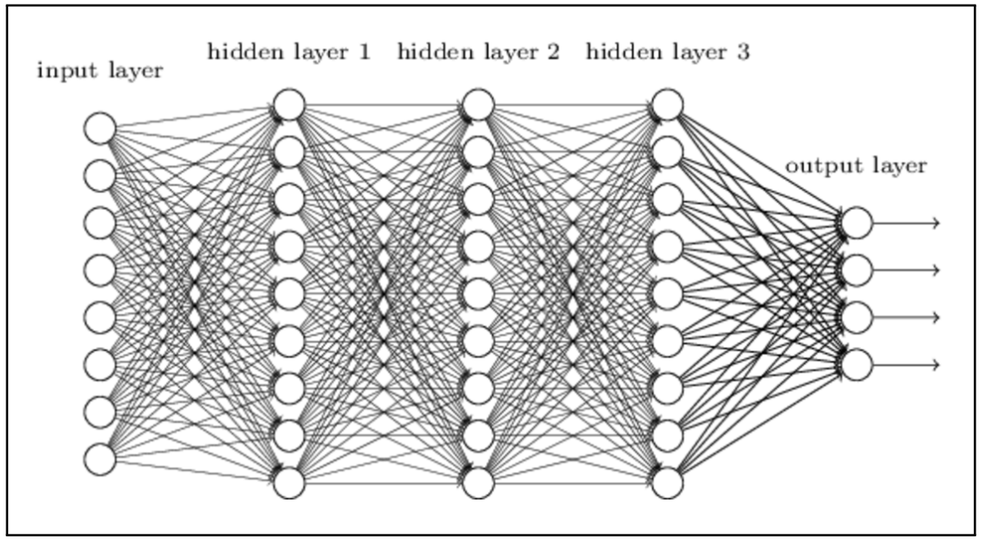

(f) Generalizes well: Not susceptible to overparameterization!!!

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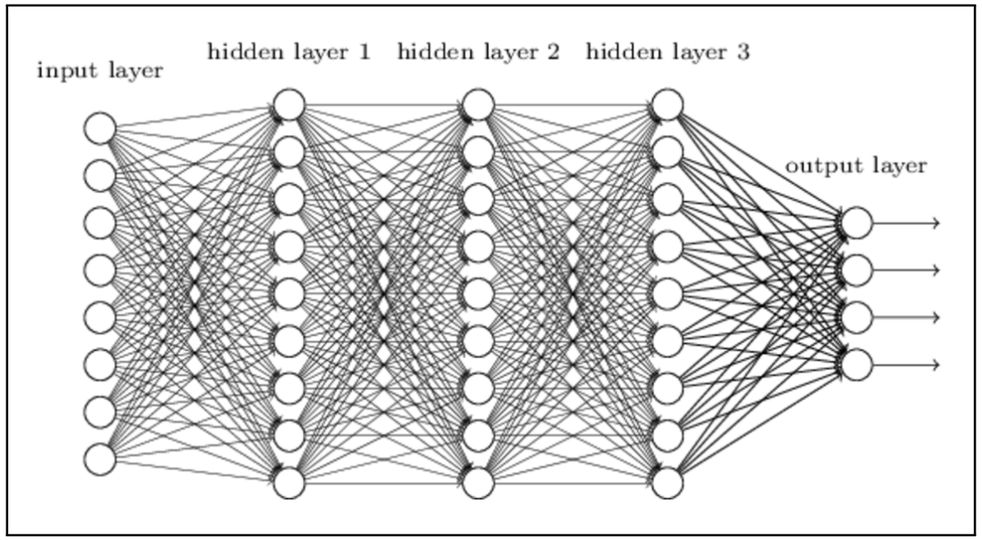
The Deep Neural Network - most successful ML model to date:

Is it the Depth?



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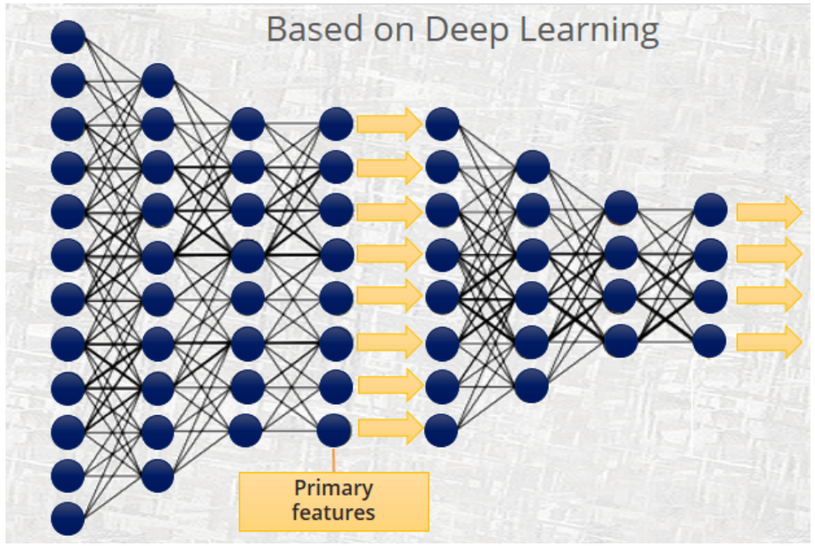
1st Factor: Learned Features

Automated Feature Extraction:



- Getting our 'wisdom' out of the way!
- We still sneak in by designing the architecture.

2nd Factor: Jump in computation speed

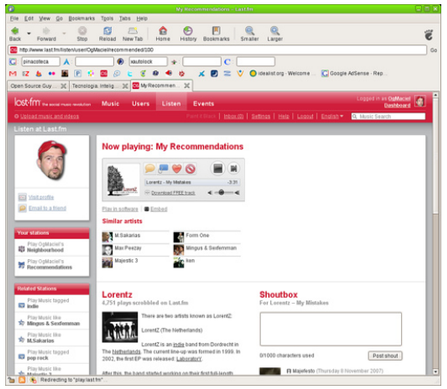
Commercially available specialized hardware

Gain in ML speed can be more than **2 orders of magnitude**

3rd Factor: Elaborate data resources

Using multiple data sources:

For example, using movie preferences, Facebook posts, Amazon purchases, etc.



to profile a person.

4th Factor: Crowdsourcing

Public and Free Software/Hardware Resources:

- TensorFlow

- GitHub

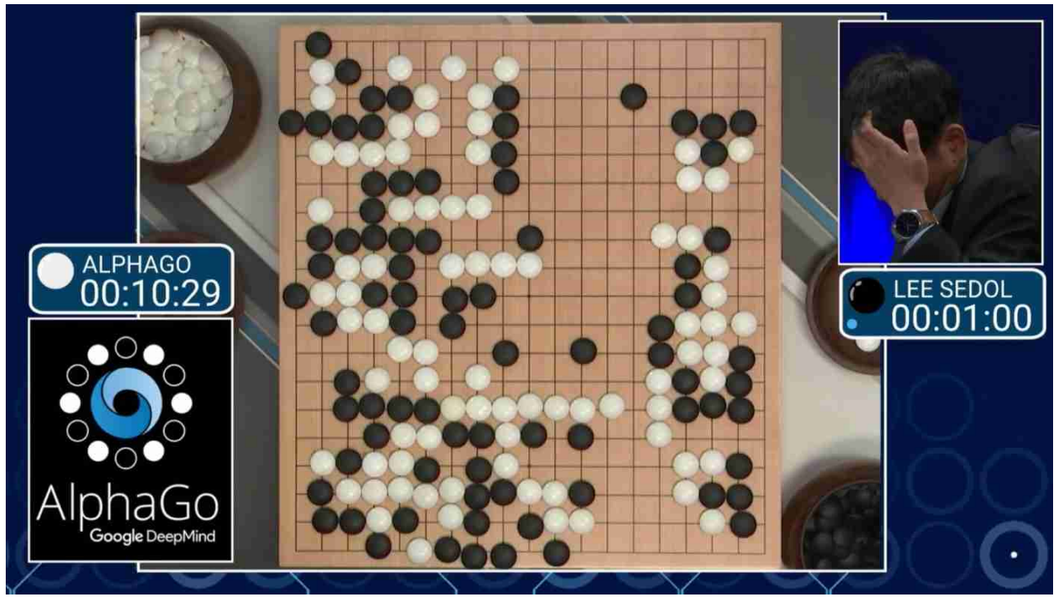
- Google Colab

- AWS

No barrier to entry; a great opportunity for researchers in the developing world.

Main Achievement: Superior "Intelligence"

From: Replicating human skills **To:** Beating human intelligence



ML system can discover novel patterns and strategies beyond human capacity.

Upcoming Breakthrough

Self-driving cars will have a huge economic and social impact.

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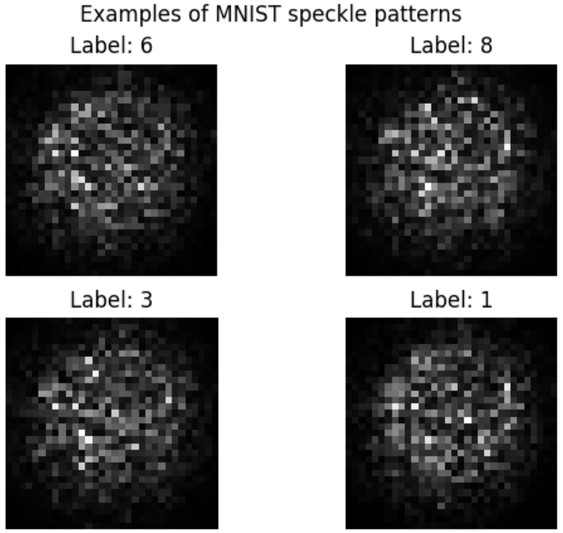
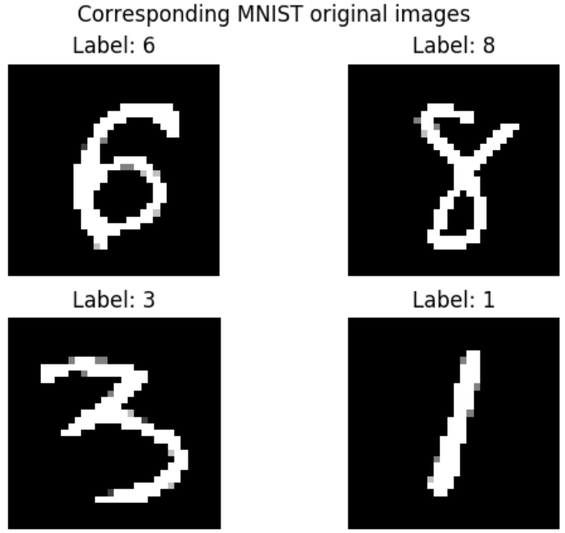
1. Technical Challenge

How does the neural network avoid overfitting?

There are some partial answers (optimization method, special minima). The dilemma:





For some problems, the network overfits. In some cases, it overfits terribly.

2. Practical Challenges

Two interrelated challenges:

- **Bias:** Inadvertently allowing gender and other biases.

- **Interpretability:** Digging into the 'black box' of a neural network

Understanding what the network is doing & Avoiding irrelevant traps

Latest Google effort: **TCAV** (Testing with Concept Activation Vectors)

3. Human Challenges

1. **Security Risks:**

   Hacking on steroids - Super Intelligence

2. **Social Risks:**

   Replacing human workers - Human interaction

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- If you ignore AI, you will become **medieval** (technologically).

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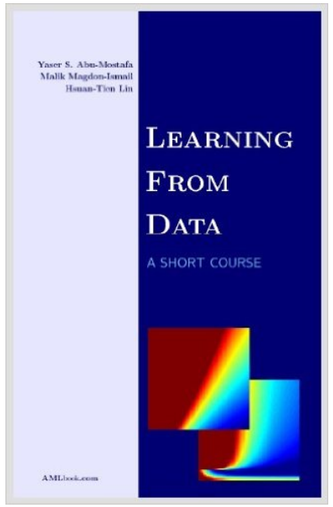
- Profound impact on the economy and on security.
- The fast change will have serious social ramifications.
- If you ignore AI, you will become **medieval** (technologically).
- AI is not Big Brother!

Further Reading

- **Online Lectures:** http://work.caltech.edu/telecourse
- **Book:** *Learning From Data*



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