Deep Learning

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About me

- 2006 Laurea Degree of Computer Engineering University of Florence
- 2006 Visiting Scholar Carnegie Mellon University (CMU), Pittsburgh (U.S.A.)
- 2010 Ph.D. in Computer Engineering, Multimedia and Telec. (University of Florence)
- 2011 Visiting Scholar TELECOM ParisTech, Paris, France
- 2011-2014: Postdoctoral Fellow (University of Florence and Modena and Reggio Emilia)
- 2014 2016 Assistant Professor of Computer Engineering (University of Modena and Reggio Emilia)
- 2017 Assistant Professor of Computer Science with tenure track (University of Udine)
- 2019 Associate Professor of Computer Science (University of Udine)

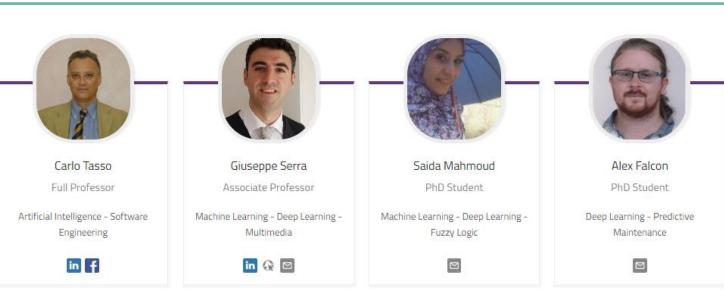




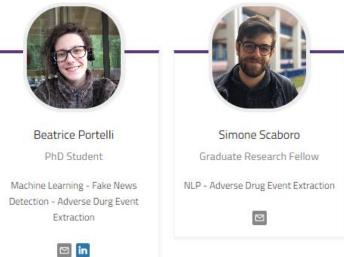
Artificial Intelligence LAB (AILAB-UDINE)

See our website:

http://ailab.uniud.it/



AILAB on Linkedin





Office Hours and Materials

Office Hours:

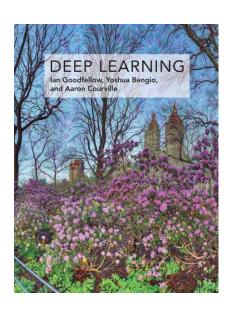
• Tuesday 11:00-12:00 (please send me an email to book a slot)

Contents:

Videos and slides are on Teams

References:

- <u>CS230 Deep Learning (Stanford University)</u>
- <u>UVA Deep Learning (University of Amsterdam)</u>
- Deep Learning Book, by I. Goodfellow, Y. Bengio and A. Courville
- Other links I will provide you



Terminology



Artificial Intelligence

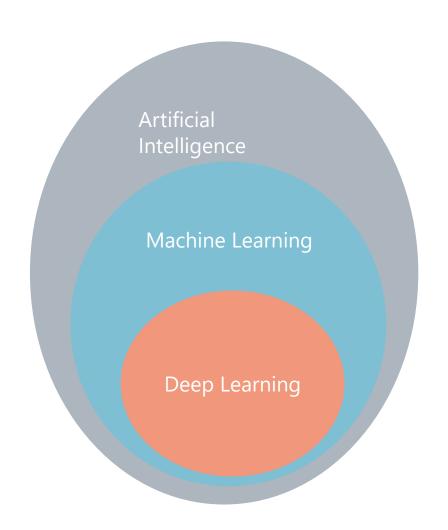
Any technique which enables computers to mimic human behavior.

Machine Learning

Subset of AI techniques which use statistical methods to enable machines to improve with experiences without explicitly being programmed

Deep Learning

Extract patterns from data (or raw data) using neural networks





Machine and Deep Learning

Machine learning algorithms can roughly divided in:

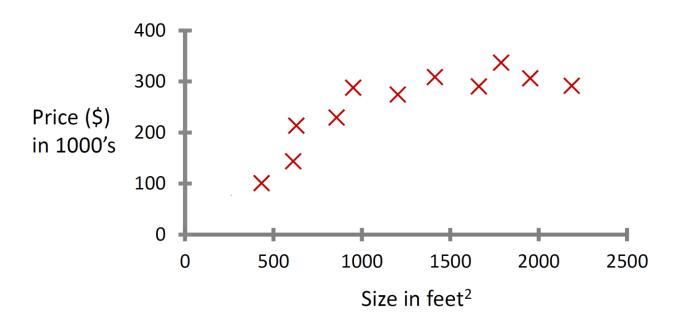
- Supervised learning
- Unsupervised learning
- Reinforcement learning
- Generative Learning

Deep Learning (DL) is cross-sectorial technique based on Neural Network.

Supervised Learning - Regression



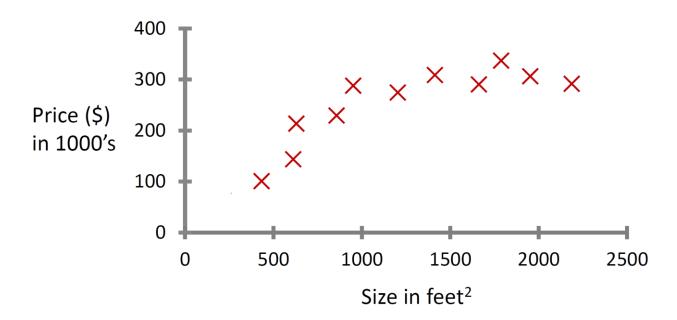






Housing price prediction

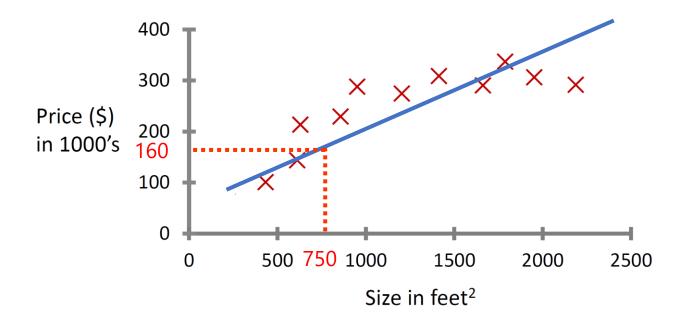
Suppose you have a friend with a house of 750 feet². How can a learning algorithm help you?





Housing price prediction

Suppose you have a friend with a house of 750 feet². How can a learning algorithm help you?



A learning algorithm can fit a straight line to the data. Based on that, it looks like maybe the house can be sold for about \$ 150,000.



Supervised Learning

The **supervised learning** refers to the fact that we use a dataset in which "the right answer" are given.

Dataset:

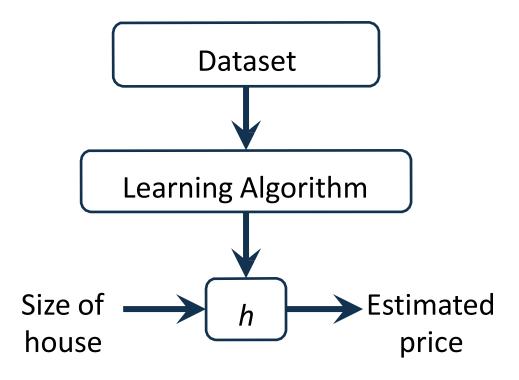
| Size in feet ² (x) | Price (\$) in 1000's (y) |
|-------------------------------|--------------------------|
| 2104 | 460 |
| 1416 | 232 |
| 1534 | 315 |
| 852 | 178 |
| ••• | ••• |

x's = input variable /features

y's = «output» variable / «target» variable



Supervised Learning - Regression



H = hypothesis (historical name). Today we can call it «model»

In regression the output of the model is a real and continuos value.



Regression with Multiple Features

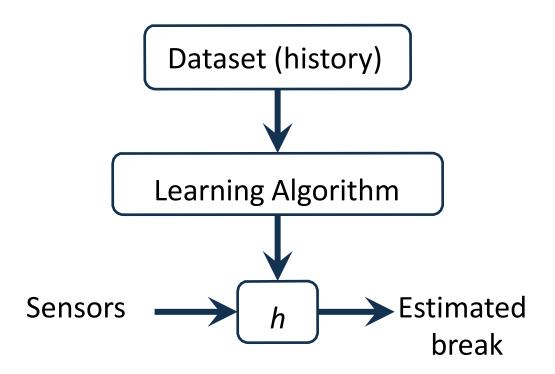
| Size (feet²) | Number of bedrooms | Number of floors | Age of home (years) | Price (\$1000) |
|--------------|--------------------|------------------|---------------------|----------------|
| | | | | |
| 2104 | 5 | 1 | 45 | 460 |
| 1416 | 3 | 2 | 40 | 232 |
| 1534 | 3 | 2 | 30 | 315 |
| 852 | 2 | 1 | 36 | 178 |
| | | | | |

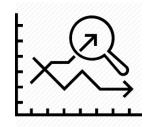












Supervised Learning - Classification



The classification problem is like the regression problem, except that the values we want to predict take on only a small number of discrete values.

Some examples:

Spam/ Not Spam

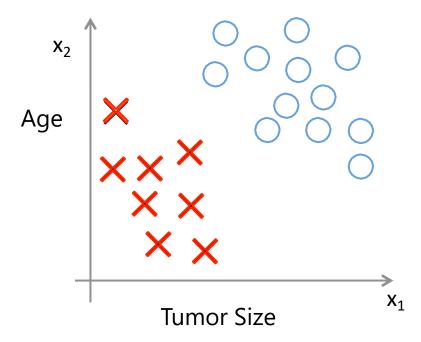
Image with a face / image without a face

Malignant tumor / Benign tumor

Binary classification problem: predictions can take on only two values, 0 (usually called "Negative Class") or 1 (usually called "Positive Class").



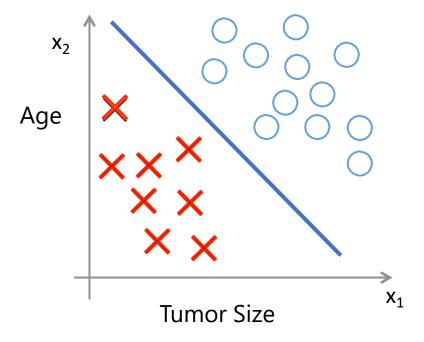
Suppose we have a tumor classification problem and we have as features both the age of the patients and the tumour sizes. The dataset could look like this:







A Classification algorithm tries to estimate the decision boundary (i.e. the line that separates the data)

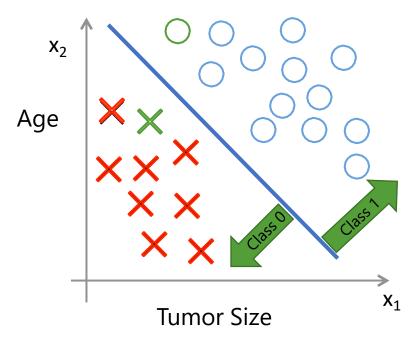






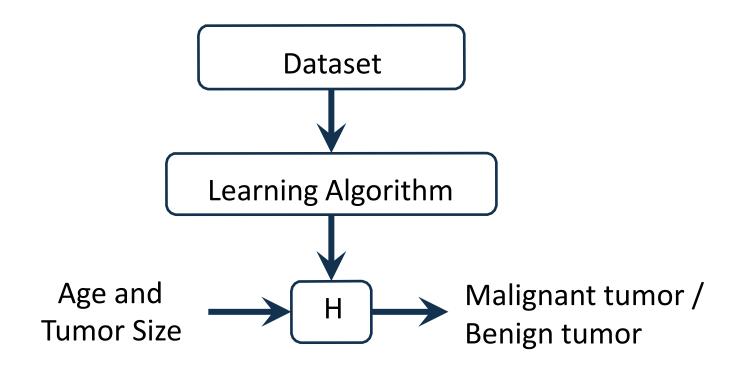


Once you have a classifier you can use it for prediction of new samples.









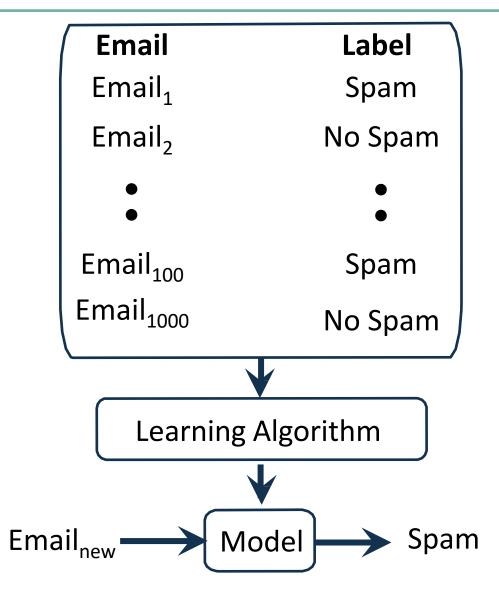








Examples – Spam Detection



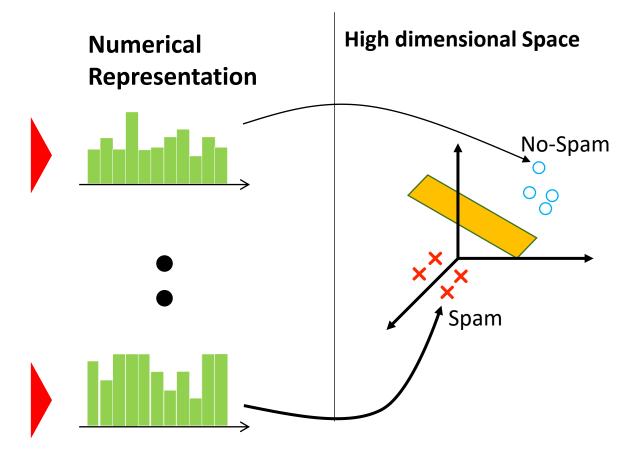




Email

Our photograph was forwarded to us as part of an article we are publishing for your approval or any changes you would like.

we have logged your IP-address on more than 40 illegal Websites. Important: Please answer our questions!







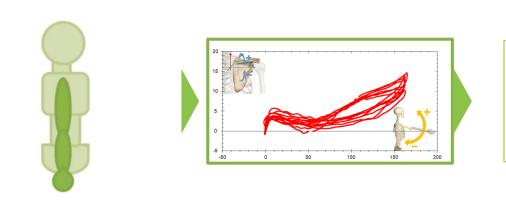


Examples - Arm Pathology Analysis





Examples - Arm Pathology Analysis



Artificial Intelligence Algorithm "Pathology"

Prediction

"No Pathology"





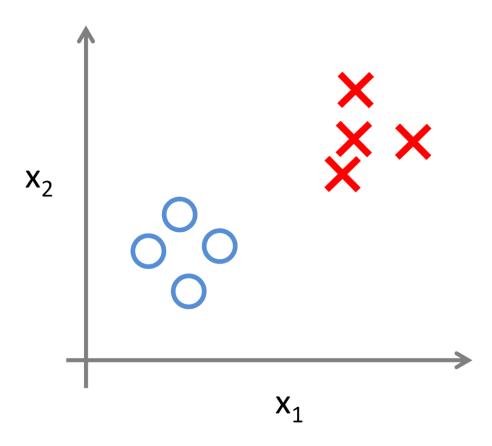
| Input(x) | Output (y) | Application |
|-------------------|------------------------|---------------------|
| Home features | Price | Real Estate |
| Ad, user info | Click on ad? (0/1) | Online Advertising |
| Image | Object (1,,1000) | Photo tagging |
| Audio | Text transcript | Speech recognition |
| English | Chinese | Machine translation |
| Image, Radar info | Position of other cars | Autonomous driving |

Unsupervised Learning





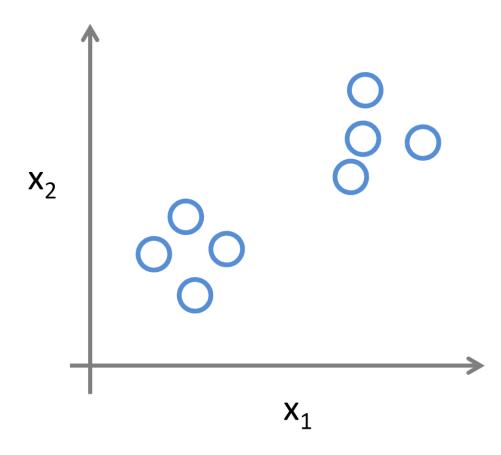
Recall, in supervised problem each example is labelled either as a positive or as negative





Unsupervised Problem

In unsupervised problem each example is NOT labelled either as a positive or as negative

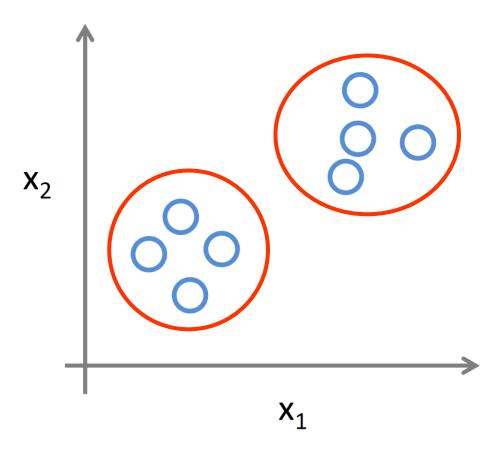




Unsupervised Problem

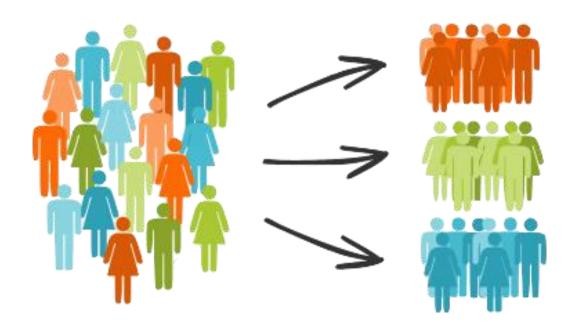
How can we find a structure of these data?

An unsupervised learning algorithm might decide that these data live in two different clusters (clustering algorithm)



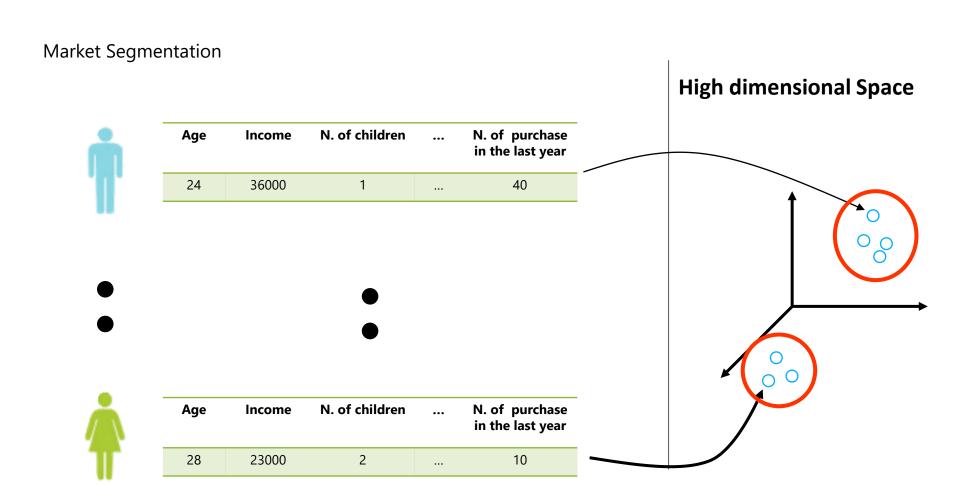








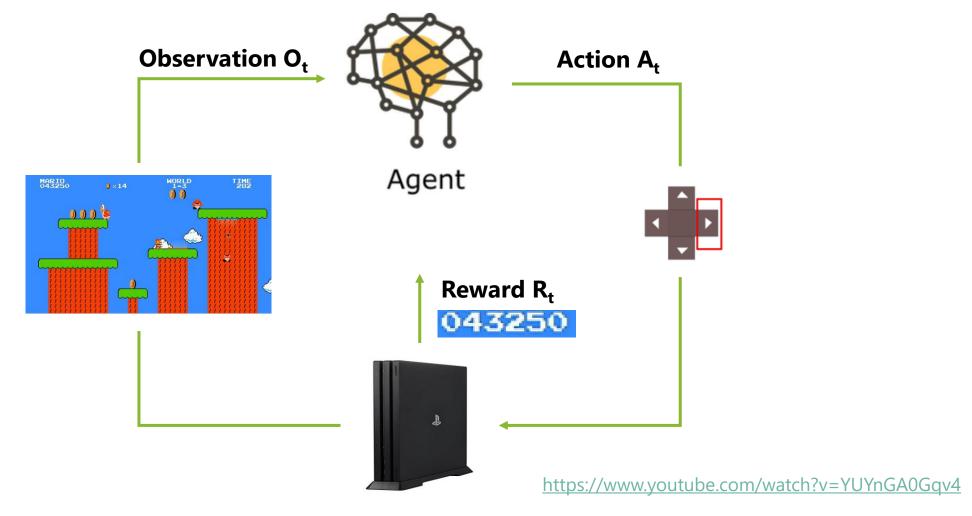
Example – Market Segmentation



Reinforcement Learning



Reinforcement Learning







Learning Hand-Eye Coordination for Robotic Grasping with Deep Learning and Large-Scale Data Collection

Sergey Levine Peter Pastor Alex Krizhevsky Deirdre Quillen Google

Generative Learning



Generative Adversarial Networks

Generative Adversarial Networks (GANs) are an exciting recent innovation in Machine Learning.

GANs are *generative* models: they create new data instances that resemble your training data.

For example, GANs can create images that look like photographs of human faces, even though the faces don't belong to any real person. These images were created by a GAN:









Original image



Artistic images

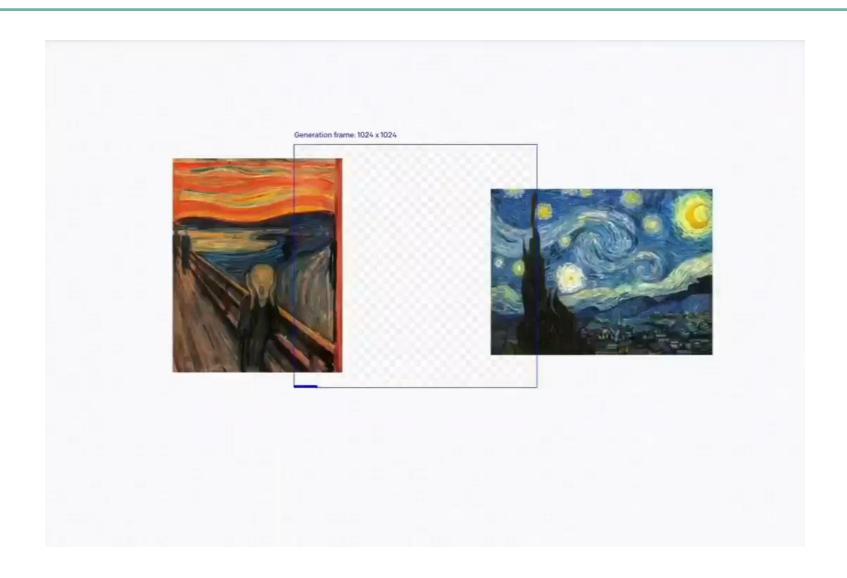




Outputs



Example – DALLE 2



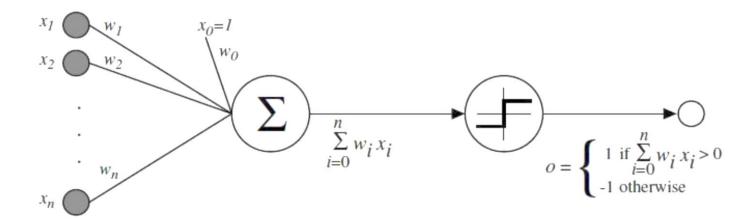
A brief history of Neural Networks & Deep Learning





Perceptron

- The perceptron algorithm was invented in 1958 at the <u>Cornell Aeronautical Laboratory</u> by <u>Frank Rosenblatt</u>
- The perceptron became the first model for binary classification.
 - One weight w_i per input x_i ;
 - If the result is larger than a threshold it returns 1, otherwise 0 (Non-Linearity)

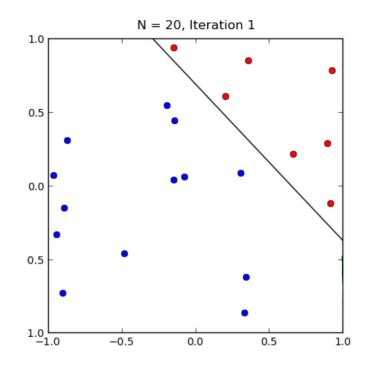




Training a Perceptron

- Rosenblatt's innovation was mainly the learning algorithm for a perceptron
- Learning algorithm:
 - Initialize weights randomly
 - Take one sample x_i and predict y_i
 - For erroneous predictions update weights
 - If prediction $\hat{y} = 0$ and ground truth $y_i = 1$, increase weights
 - If prediction $\hat{y} = 1$ and ground truth $y_i = 0$, decrease weights
 - Repeat until no errors are made

Demo: https://lecture-demo.ira.uka.de/neural-network-demo/?preset=Rosenblatt%20Perceptron



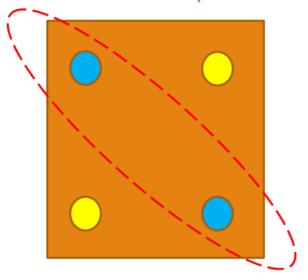


XOR & Single-layer Perceptron

However, the exclusive or (XOR) cannot be solved by a perceptron [Minsky and Papert, "Perceptrons", 1969]

| Α | В | Q | | |
|------|---|---|--|--|
| 0 | 0 | 1 | | |
| 0 | 1 | 0 | | |
| 1 | 0 | 0 | | |
| 1 | 1 | 1 | | |
| XNOR | | | | |

The classification boundary to solve XOR is not a line!!



- Multi-layer perceptrons can solve XOR
- Problem: how to train a multi-layer perceptron? Rosenblatt's algorithm not applicable (it expects to know the ground truth for each perceptron)



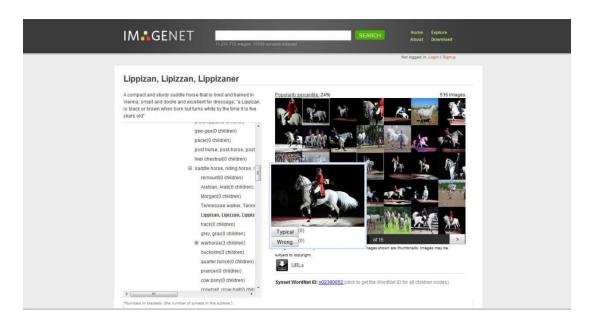


- What everybody thought: "If a perceptron cannot even solve XOR, why bother?
- Results not as promised (too much hype!) -> no further funding -> Al Winter
- Still, significant discoveries were made in this period:
 - **Backpropagation** (Learning algorithm for MLPs) (see next classes)
 - Recurrent Neural Networks (see next classes)
- Neural Network problems a decade ago
 - Lack of processing power
 - Lack of data



ImageNet Challenge

- In 2009 the ImageNet dataset was published [Deng et al., 2009]
 - Collected images for each of the 100K terms in Wordnet (16M images in total)
 - Terms organized hierarchically: "Vehicle"->"Ambulance"
- ImageNet Large Scale Visual Recognition Challenge (ILSVRC)
 - 1 million images
 - 1,000 classes
 - Top-5 and top-1 error measured





Step 1:

Collect candidate images via the Internet



Step 2: up the candida

Clean up the candidate Images by humans









Deep learning at ImageNet classification challenge

CNN based, non-CNN based

| 2012 Teams | %error |
|-----------------------|--------|
| Supervision (Toronto) | 15.3 |
| ISI (Tokyo) | 26.1 |
| VGG (Oxford) | 26.9 |
| XRCE/INRIA | 27.0 |
| UvA (Amsterdam) | 29.6 |
| INRIA/LEAR | 33.4 |
| | |
| | |
| | |

| ı | 2013 Teams | %error |
|---|------------------------|--------|
| C | Clarifai (NYU spinoff) | 11.7 |
| ٨ | IUS (singapore) | 12.9 |
| Z | eiler-Fergus (NYU) | 13.5 |
| A | . Howard | 13.5 |
| C | OverFeat (NYU) | 14.1 |
| L | JvA (Amsterdam) | 14.2 |
| A | dobe | 15.2 |
| V | 'GG (Oxford) | 15.2 |
| ٧ | 'GG (Oxford) | 23.0 |

| 2014 Teams | %error |
|--------------|--------|
| GoogLeNet | 6.6 |
| VGG (Oxford) | 7.3 |
| MSRA | 8.0 |
| A. Howard | 8.1 |
| DeeperVision | 9.5 |
| NUS-BST | 9.7 |
| TTIC-ECP | 10.2 |
| XYZ | 11.2 |
| UvA | 12.1 |





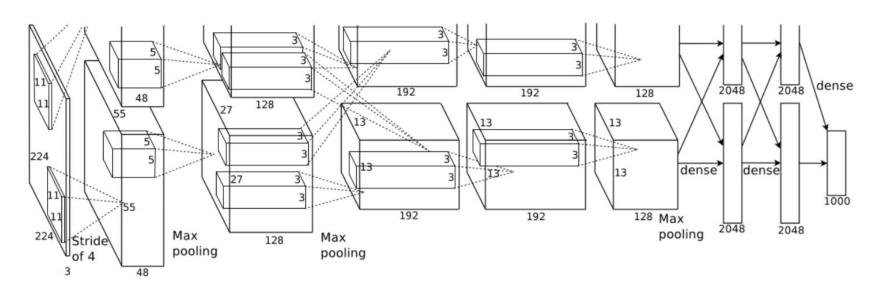


Figure 2: An illustration of the architecture of our CNN, explicitly showing the delineation of responsibilities between the two GPUs. One GPU runs the layer-parts at the top of the figure while the other runs the layer-parts at the bottom. The GPUs communicate only at certain layers. The network's input is 150,528-dimensional, and the number of neurons in the network's remaining layers is given by 253,440–186,624–64,896–64,896–43,264–4096–4096–1000.

Krizhevsky, Sutskever & Hinton, NIPS 2012



The Game of Go

In 2016 AlphaGo (Deep Mind) won Lee Sedol, the world's top Go player.



See more info:

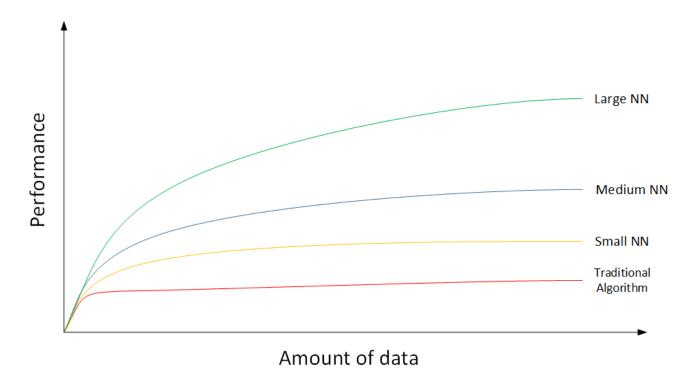
http://airesearch.com/tag/go/

<u>AlphaGo – The Movie (Full Documentary)</u>



Scale drives Deep Learning progress

- When a small amount of data when the performance of traditional learning model (Logistic Regression, SVM, Decision Tree etc) is better.
- **Deep learning** is the **first class of learning algorithms that is scalable**: performance just keeps getting **better** as you feed them **more data** (see the NLP Model GPT-3 with 175 billion machine learning parameters).

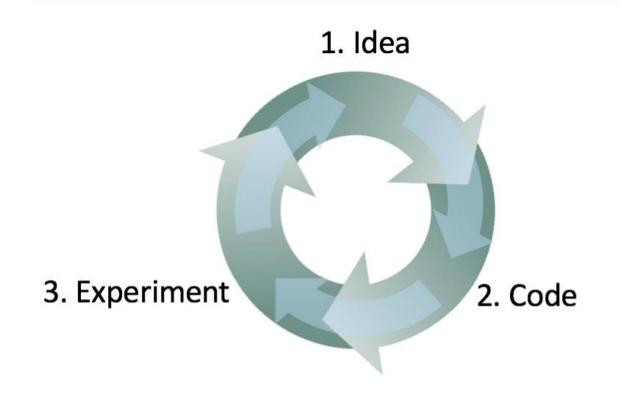




Scale drives Deep Learning progress

Three key factors:

- Data
- Computation/Hardware
- Algorithms



If faster computing, for each step, the less time-consuming, so the more the circulation can be efficiently performed.