Neural Networks and Deep Learning

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Q: **Why "Deep"?**

A:
- because it exploits Deep Neural Networks, composed by many nested layers of neurons
- because it exploits deep features of data, that is features extracted from other features

ML recap

What is Machine Learning about?

There are problems that are difficult to address with traditional programming techniques:

- classify a document according to some criteria (e.g. spam, sentiment analysis, ...)
- compute the probability that a credit card transaction is fraudulent
- recognize an object in some image (possibly from an inusual viewpoint, in new lighting conditions, in a cluttered scene)
- ...

Typically the result is a weighted combination of a large number of parameters, each one contributing to the solution in a small degree.

The Machine Learning approach

Suppose to have a set of input-output pairs (training set)

$$\{\langle x_i, y_i \rangle\}$$

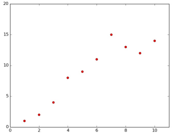
the problem consists in guessing the map $x_i \mapsto y_i$

The M.L. approach:

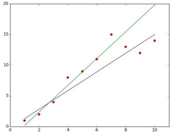
- describe the problem with a **model** depending on some parameters Θ (i.e. choose a parametric class of functions)
- define a **loss function** to compare the results of the model with the expected (experimental) values
- **optimize** (fit) the parameters Θ to reduce the loss to a minimum

Example: a regression problem

You have some points on the plane and you want to fit a line through them

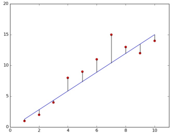


Step 1 Fix a parametric class of models.
For intance linear functions $y = ax + b$;
a and b are the parameters of the model



Step 2 Fix a way to decide when a line is better than another (loss function)
For instance, mean square error (mse)

Step 3 Try to tune the parameters in order to reduce the loss (training).



Why Learning?

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So, we use **iterative** techniques (typically, gradient descent) to progressively approximate the result.

This form of iteration over data can be understood as a way of progressive learning of the objective function based on the experience of past observations.

Using gradients

Goal: minimize a loss function E over (fixed) training samples:

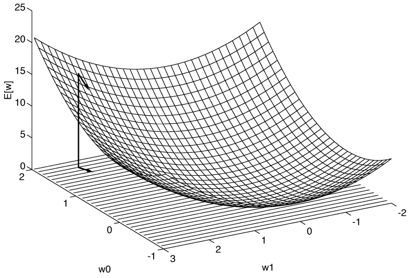
$$\Theta(w) = \sum_i E(o(w, x_i), y_i)$$

See how it changes according to small perturbations $\Delta(w)$ of the parameters w: this is the gradient

$$\nabla_w[\theta] = [\frac{\partial \Theta}{\partial w_1}, \ldots, \frac{\partial \Theta}{\partial w_n}]$$

of Θ w.r.t. w.

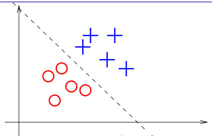
The gradient is a vector pointing in the direction of steepest ascent.



A bit of taxonomy

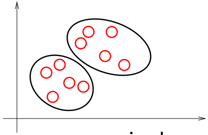
Different types of Learning Tasks

- **supervised learning**:
  inputs + outputs (labels)
  - classification
  - regression



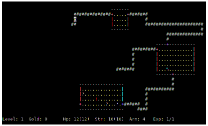
supervised

- **unsupervised learning**:
  just inputs
  - clustering
  - component analysis
  - anomaly detection
  - generative techniques



unsupervised

- **reinforcement learning**
  actions and rewards
  - learning long-term gains
  - planning



reinforcement

Discriminative vs. Generative AI

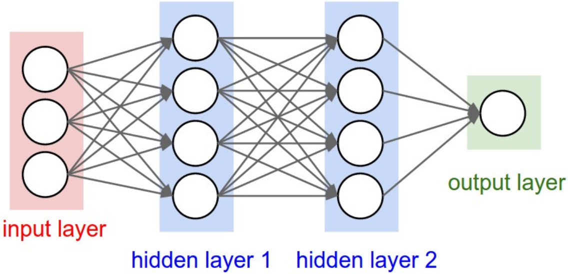
A different dichotomy:

- **Discriminative models** learn decision boundaries over data.
- **Generative models** learn the data distribution.

Discriminative models typically require supervised data, but generative models can be trained in both supervised and unsupervised settings (e.g. for conditional generation).

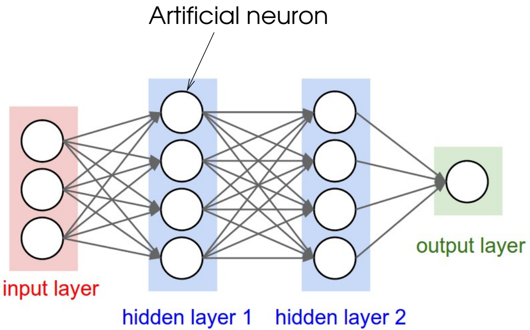
Next argument

Neural Networks



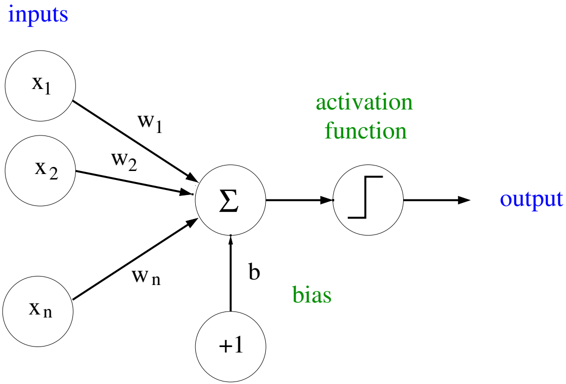
Neural Network

A network of (artificial) neurons



Each neuron takes multiple inputs and produces a single output (that can be passed as input to many other neurons).

The artificial neuron

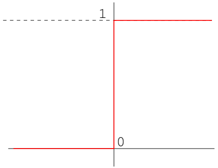


Each neuron (!) implements a logistic regressor

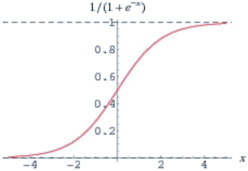
$$\sigma(wx + b)$$

Different activation functions

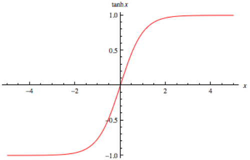
The activation function is responsible for threshold triggering.



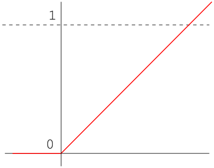
threshold: if $x > 0$ then 1 else 0



logistic function: $\frac{1}{1+e^{-x}}$

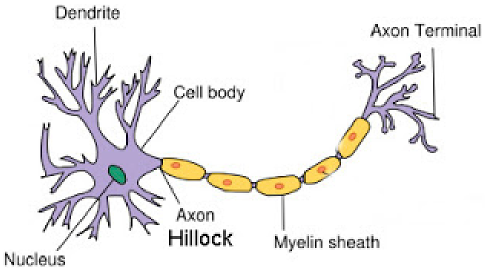


hyperbolic tangent: $\frac{e^x - e^{-x}}{e^x + e^{-x}}$



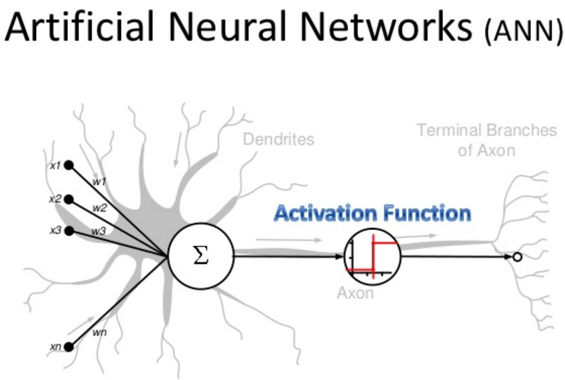
rectified linear (RELU): if $x > 0$ then x else 0

The cortical neuron



- the dendritic tree of the cell collects inputs from other neurons, that get summed together
- when a triggering threshold is exceeded, the Axon Hillock generate an impulse that get transmitted through the axon to other neurons.

A comparison with the cortical neuron



Slide credit : Andrew L. Nelson

Some figures for human brains

- number of neurons: $\sim 2 \cdot 10^{10}$
- switching time for neuron: $1 - 5$ ms. (slow!)
- synapses (connections) per neuron: $\sim 10^{4-5}$
- time to process an image: 100 ms.

not too deep (< 100)

very high parallelism

Motivations behind neural computation

- to understand, via simulation, how the brain works
- to investigate a different paradigm of computation

  very far from traditional programming languages
- **to solve practical problems difficult to address with algorithmic techniques**

  useful even if the brain works in a different way

Next argument

A closer look at Networks

Feed-forward and recurrent networks

If the network is acyclic, it is called a feed-forward network.

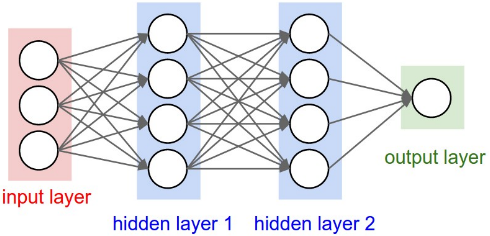
If it has cycles it is called recurrent.

The large majority of modern NNs are feed-forward.

The main class of recurrent networks are the so called Long Short-Term Memory models (LSTM) and variants.

Layers

In a feed-forward network, neurons are usually organized in layers.



If there is more than one hidden layer the network is deep, otherwise it is called a shallow network.

Layers and Tensors

Each Layer takes in input a Tensor and returns a new Tensor.

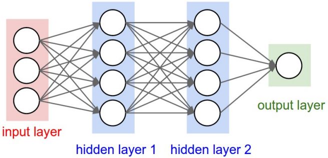
A Tensor is simply a multi-dimensional array.
A Layer computes an algebraic mainupaltion of the inpout tensor.

There are many different kind of layers, serving different purposes:

- **Processing layers**: dense (linear), convolutional, attention, ...
- **Shaping layers**: Upsampling, Dowsampling, Pooling, Reshape, ...
- **Structural layers**: concatenation (shortcuts), sum (residuality), ...
- **Normalization and regularization layers**: BatchNormalization, Dropout, ...

An example: the dense layer

Dense layer: each neuron at layer $k-1$ is connected to **each each** neuron at layer k.



A single neuron:

$$I^n \cdot W^n + B^1 = O^1$$

the operation can be vectorized to pruduce m outputs in parallel:

$$I^n \cdot W^{n \times m} + B^m = O^m$$

- dense layers usually work on flat (unstructured) inputs
- the order of elements in input is irrelevant

Parameters and hyper-parameters

The weights W_k are the parameters of the model: they are **learned** during the training phase.

The number of neurons and the way they are connected together are hyper-parameters: they are chosen by the user and **fixed** before training may start.

Other important hyper-parameters govern training such as learning rate, batch-size, number of ephocs an many others.

A first example

[demo]

Understanding Deep Learning

- understand the **different layers**, and their purpose
- understand how layers can be organized in **relevant architectures**
- understand the different possible **applications** of DL, and their specific solutions
- understand the main **issues, problems** and **costs**

Frameworks for DL

- PyTorch, Meta, OpenAI
- TensorFlow/Keras, Google Brain
- JAX, Google Research
- MindSpore, Huawey

We shall mostly make examples in Keras, for its simplicitly.

Historical remarks - Legacy

Legacy

1958	perceptron
1975	backpropagation
1980	convolutional layers
1992	Max-pooling
1997	LSTM
...	...

Extremely slow progress

Until 2010 Neural Networks played a completely marginal role in AI and Computer Science

The Deep Learning revolution

2011	Google Brain foundation	2017	PPO
2012	ReLU and Dropout	2018	JAX release
2012	ImageNet Competition	2018	Transformers
2013	DQN	2018	BERT/GPT
2014	GANs	2018	Soft Actor Critic
2014	Attention	2019	AlphaStar
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Just to mention a few milestones ...

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The Deep Learning revolution

Notable technical improvements

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The Deep Learning revolution

Important Architectures

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The Deep Learning revolution

Deep Reinforcement Learning

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The New Revolution

Generative AI and Large Language Models

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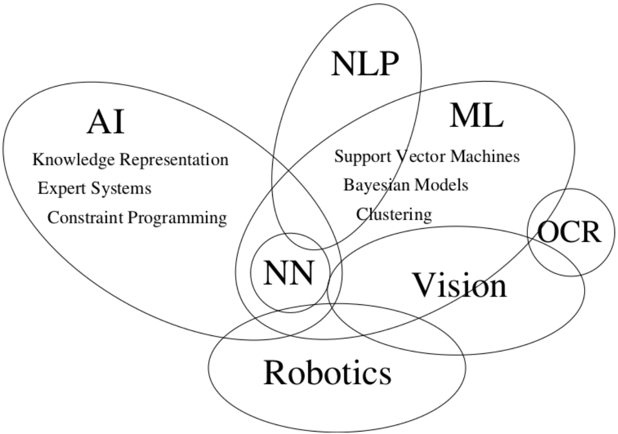
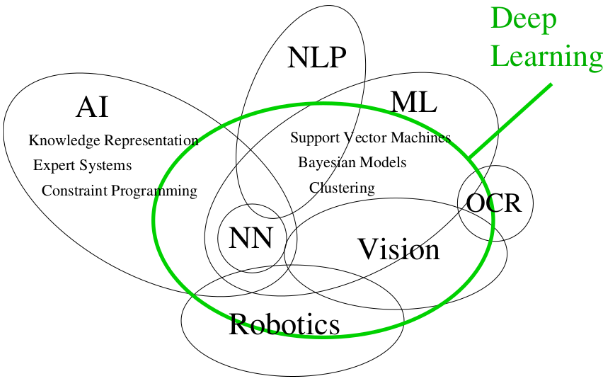
The situation at the beginning of the century



The deep learnig era



See my blog for a short historical perspective.

Didactic Information

- structure of the course
- books, tutorials and blogs
- software
- exam
- office hours

Structure of the course

Frontal lessons intermixed with demos + labs

- Domains of application of Deep Learning
- Expressiveness
- Backpropagation
- Computational Layers
- Other layers
- Major Architectures
- Interpretability
- Object Detection and Segmentation
- Generative Models for imaging
- Recurrent Networks and LSTM
- Introduction to LLMs
- Reinforcement Learning (if time permits)

Text Books

Suggested reading:

- Dive into deep learning (D2L)

Very good online material (fast updating):

- Tensorflow tutorials
- Towards data science
- Keras blog. By F.Chollet.
- Machine learning tutorial with Python
- Deep Learning Tutorial. LISA lab. University of Montreal.
- a lot of interesting lessons and seminars on youtube
- a lot of material on github
- . . .

Code and Datasets

Important code repositories:

- Hugging Face
- The State of the Art site! (papers with code)

Data sets and more...

- Tensor flow dataset
- Kaggle Datasets
- Coco, . . .
- CelebA, Labeled Faces in the Wild, . . .
- Biomedical challenges
- Amazon Datasets
- ...

Exam modalities:

At each exam session you will receive a project assignement that you are supposed to complete in **7 days**.

You are supposed to deliver:

- the code source (Keras/TensorFlow) in the form of a **single**, **commented** pyhton notebook

The work will be evaluated according to

1. 80% : comparative evaluation of results (measured in an objective way according to given metrics);
2. 20% : descriptive quality of the notebook

You may possibly integrate the grade with an oral examination.

Office hours

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Via Zanolini 41 (ex-stazione Veneta)

If you need to talk to me, just send me an email and we shall fix a meeting, either in presence or on line, as you prefer.