Course 4: Deep Learning

IMT Atlantique
Bretagne-Pays de la Loire
École Mines-Télécom

2024-10-24

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Summary

Last session

1. Unsupervised learning - discover structure from unlabeled data
2. Clustering
3. Decomposition - sparse dictionary learning
4. Practical ethics

Today's session

- Multi-Layer Perceptron
- Convolutional Neural Networks
- Transformers

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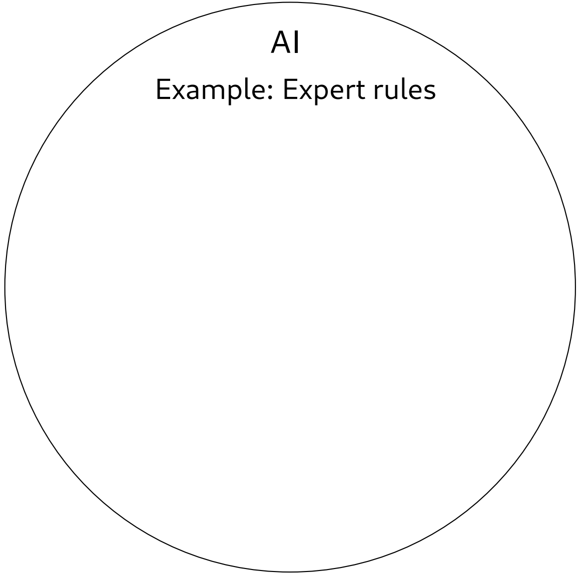
1 Unsupervised learning - discover structure from unlabeled data
2 Clustering
3 Decomposition - sparse dictionary learning
4 Practical ethics
Today's session
Multi-Layer Perceptron
Convolutional Neural Networks
Transformers

Global overview…



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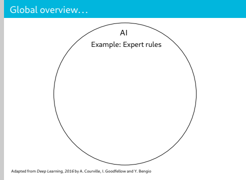
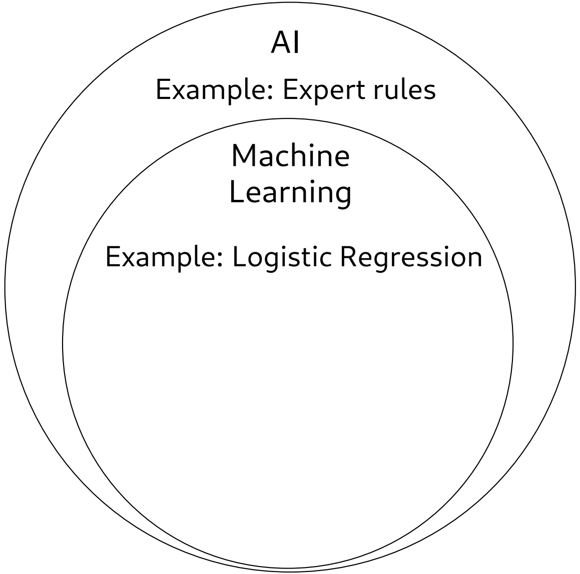
└Global overview…



Deep Learning is a particular case of Machine Learning.



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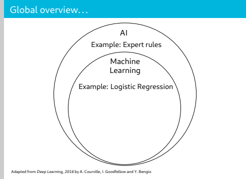

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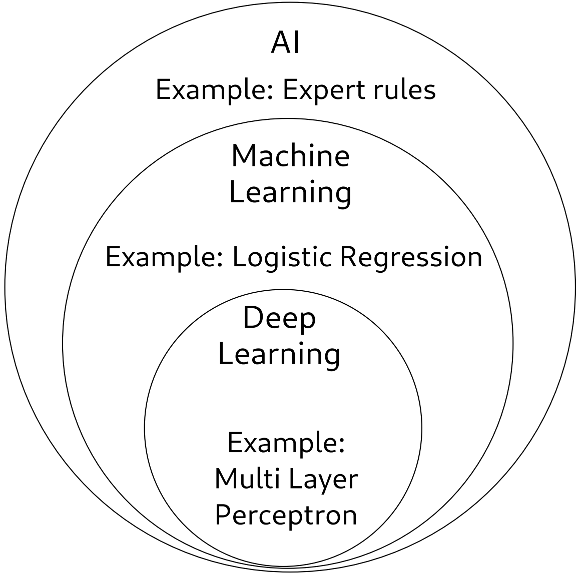

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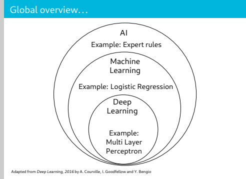

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Deep Learning in a nutshell (1/3)

Definition

Using *deep* Artificial Neural Networks.

We generally talk about "Neural Networks instead of "Artificial Neural Networks" (but this is the most correct terminology!)

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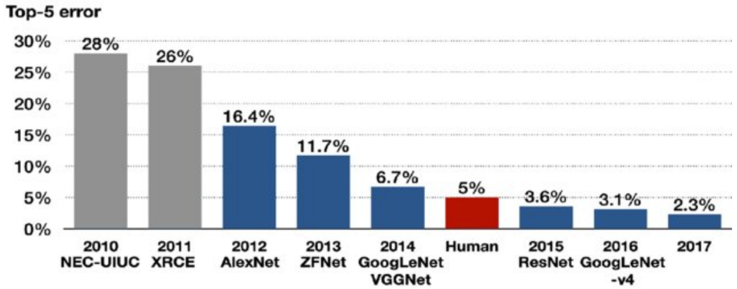
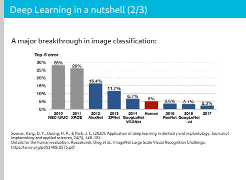
A major breakthrough in image classification:

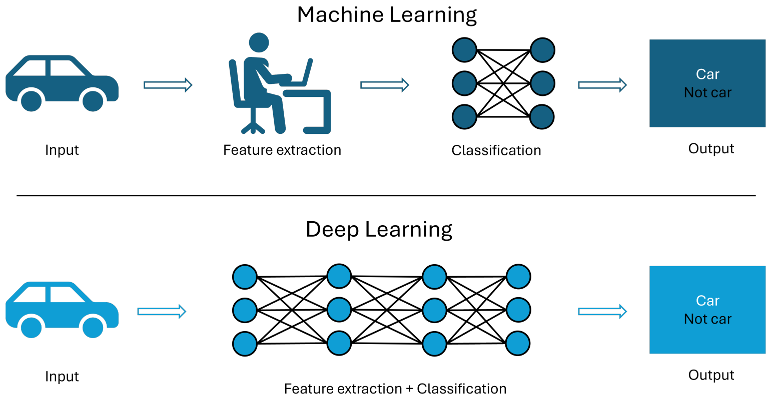


Source: Kang, D. Y., Duong, H. P., & Park, J. C. (2020). Application of deep learning in dentistry and implantology. Journal of implantology and applied sciences, 24(3), 148-181.
Details for the human evaluation: Russakovsk, Dieg *et al.*. ImageNet Large Scale Visual Recognition Challenge, https://arxiv.org/pdf/1409.0575.pdf

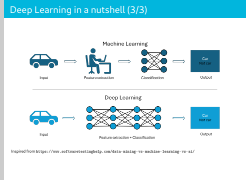


The landscape of Machine Learning changed in 2012: Deep Neural Networks, a technique used in a minority of cases until then, suddenly won the Image Classification contest on ImageNet, a standard image classification dataset. From this point, Deep Neural Networks became mainstream, and the performance of Deep Neural Network models skyrocketed.

Deep Learning in a nutshell (3/3)



Inspired from `https://www.softwaretestinghelp.com/data-mining-vs-machine-learning-vs-ai/`



Outline

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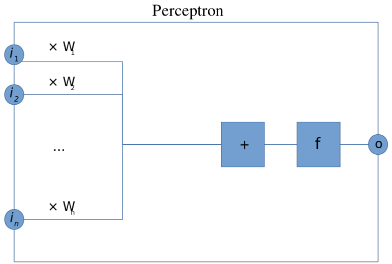
1 Multi-layer Perceptron
2 Convolutional Neural Networks (CNN)
3 Transformers

Perceptron

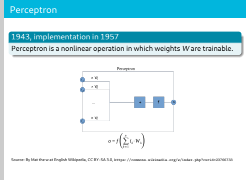
1943, implementation in 1957

Perceptron is a nonlinear operation in which weights W are trainable.



$$o = f\left(\sum_{k=1}^{n} i_k \cdot W_k\right)$$

Source: By Mat the w at English Wikipedia, CC BY-SA 3.0, `https://commons.wikimedia.org/w/index.php?curid=23766733`



The Perceptron is a matrix multiplication, followed by a nonlinear function $f()$. It is important to say that the Perceptron is old!! Hence, AI is not a brand new thing, but an old research domain.

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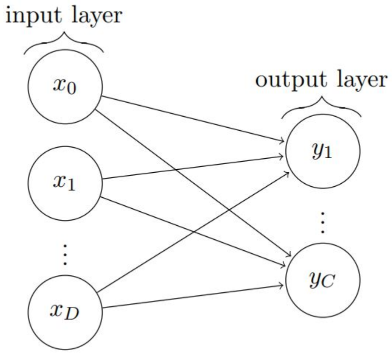
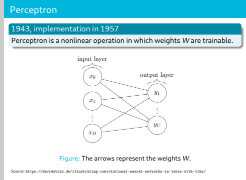


Figure: The arrows represent the weights W.

Source: `https://davidstutz.de/illustrating-convolutional-neural-networks-in-latex-with-tikz/`



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Optimizing the weights

Loss

- Prediction: $y = f\left(\sum_{d=0}^{D} x_d W_d\right)$
- Ground truth: $\hat{y}$
- Loss (one example:) $\mathcal{L}(x, W, \hat{y}) = d(y, \hat{y})$
  (ex: $d(y, \hat{y}) = \|y - \hat{y}\|_2^2$)
- Loss (i examples): $J(W) = \sum_i \mathcal{L}(x^{(i)}, W, \hat{y}^{(i)})$

Gradient descent

- Compute the gradient: $\frac{\partial J(W)}{\partial W}$ (high dimensional derivative)
- Update weights: $W \leftarrow W - \eta \frac{\partial J(W)}{\partial W}$

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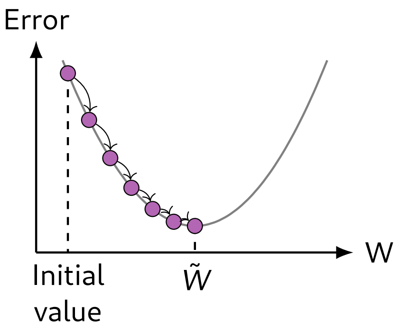
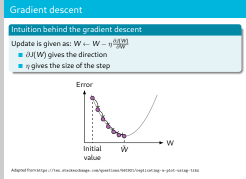
Intuition behind the gradient descent

Update is given as: $W \leftarrow W - \eta \frac{\partial J(W)}{\partial W}$

- $\partial J(W)$ gives the direction
- η gives the size of the step



Adapted from `https://tex.stackexchange.com/questions/561921/replicating-a-plot-using-tikz`



The gradient follows the increase of the error function, hence the inverse of the gradient follows its decrease. Parameter η, the learning rate, gives the size of the step to take at each iteration. If too small, the model will slowly converge. If too large, the model can be unstable and never reach the optimal solution. In practice, setting the learning rate is not easy.

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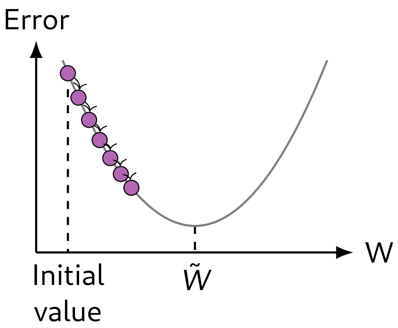
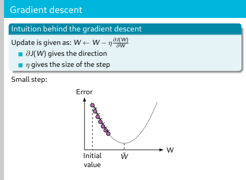
Small step:





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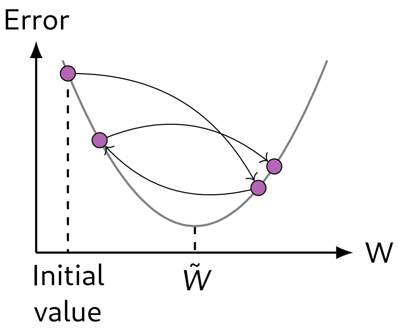
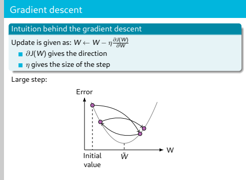
Large step:





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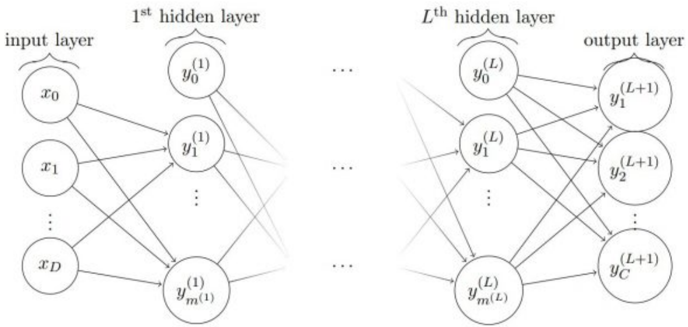
Multi-Layer Perceptron

Multi-Layer Perceptron (= *fully-connected* network)

- Stacking Perceptrons.
- The ***deep*** term comes form this stacking
- Prediction: $y = f\left(W^{(L)} \cdots f\left(W^{(2)} f(W^{(1)} x)\right)\right)$



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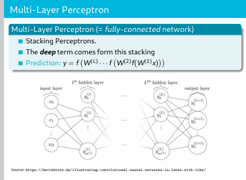

The bias are removed from the equations for simplicity, but say that they exist orally.

Definitions

$$\mathbf{y}^{(l+1)} = f(\mathbf{W}^{(l)}\mathbf{y}^{(l)} + \mathbf{b}^{(l)}) = \phi^{(l)}(\mathbf{y}^{(l)})$$

- Each building block $\mathbf{y}^{(l+1)}$ is called a **layer**.
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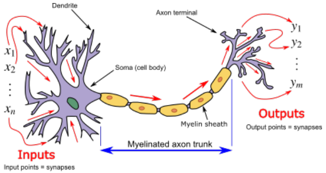
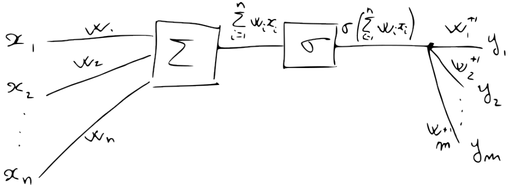
Why is it called Neural Network?

"Neurons" may be seen as **loosely** inspired from the human brain.



Attribution: Egm4313.s12 at English Wikipedia,

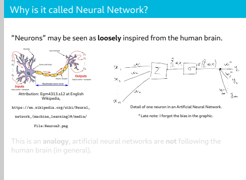
`https://en.wikipedia.org/wiki/Neural_network_(machine_learning)#/media/File:Neuron3.png`



Detail of one neuron in an Artificial Neural Network.

* Late note: I forgot the bias in the graphic.

This is an **analogy**, artificial neural networks are **not** following the human brain (in general).



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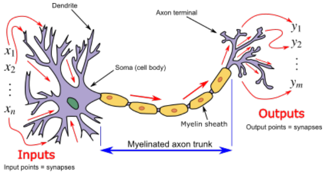

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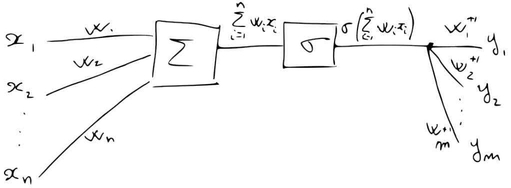

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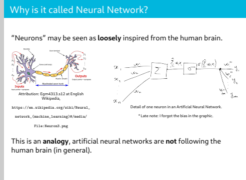
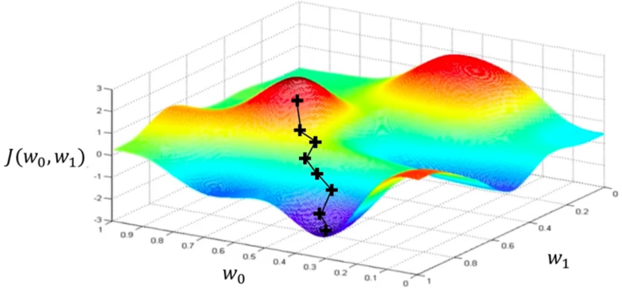
Course 4: Deep Learning
└Multi-layer Perceptron
└Why is it called Neural Network?



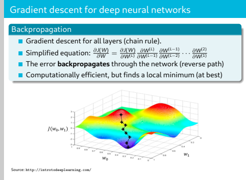
Gradient descent for deep neural networks

Backpropagation

- Gradient descent for all layers (chain rule).
- Simplified equation: $\frac{\partial J(W)}{\partial W} = \frac{\partial J(W)}{\partial W^{(L)}} \frac{\partial W^{(L)}}{\partial W^{(L-1)}} \frac{\partial W^{(L-1)}}{\partial W^{(L-2)}} \cdots \frac{\partial W^{(2)}}{\partial W^{(1)}}$
- The error **backpropagates** through the network (reverse path)
- Computationally efficient, but finds a local minimum (at best)



Source: `http://introtodeeplearning.com/`



Careful: the given equation is not correct, just conveniently simplified. For better details, refer to `https://en.wikipedia.org/wiki/Backpropagation`.

Batch

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- The *i* examples are divided in *batches* (small excerpt)
- Allows one to train without loading the whole dataset in memory
- Accelerate the learning phase

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- Computationally heavy for large inputs
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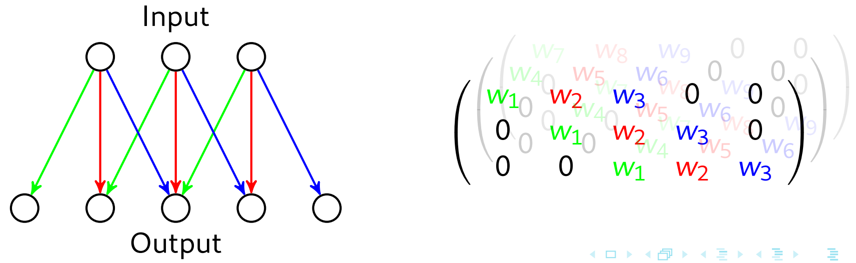
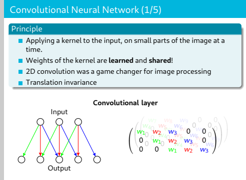
Convolutional Neural Network (1/5)

Principle

- Applying a kernel to the input, on small parts of the image at a time.
- Weights of the kernel are **learned** and **shared**!
- 2D convolution was a game changer for image processing
- Translation invariance

Convolutional layer





Convolution neural networks are the most common architecture for neural networks nowadays. They are particularly successful for image processing, were not challenged until very recently, with Vision Transformers (see Transformers in the last slides). The translation invariance is really important for image processing, as objects can be anywhere on the image. It contributed to the success of Convolutional Neural Networks.

Convolutional Neural Network (2/5)

Example of 2D convolution:

$$\underbrace{\begin{pmatrix} 0 & 1 & 1 & 1_{\times 1} & 0_{\times 0} & 0_{\times 1} & 0 \\ 0 & 0 & 1 & 1_{\times 0} & 1_{\times 1} & 0_{\times 0} & 0 \\ 0 & 0 & 0 & 1_{\times 1} & 1_{\times 0} & 1_{\times 1} & 0 \\ 0 & 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}}_{I} * \underbrace{\begin{pmatrix} 1 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 1 \end{pmatrix}}_{K} = \underbrace{\begin{pmatrix} 1 & 4 & 3 & \boxed{4} & 1 \\ 1 & 2 & 4 & 3 & 3 \\ 1 & 2 & 3 & 4 & 1 \\ 1 & 3 & 3 & 1 & 1 \\ 3 & 3 & 1 & 1 & 0 \end{pmatrix}}_{I * K}$$

Source: `https://tex.stackexchange.com/questions/437007/drawing-a-convolution-with-tikz`

Convolutional Neural Network (2/5)
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Source: https://tex.stackexchange.com/questions/437007/drawing-a-convolution-with-tikz

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$$\underset{I}{\begin{pmatrix} 0 & 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 & 0 \\ \underset{\times 1}{0} & \underset{\times 0}{0} & \underset{\times 1}{0} & 1 & 1 & 0 & 0 \\ \underset{\times 0}{0} & \underset{\times 1}{0} & \underset{\times 0}{1} & 1 & 0 & 0 & 0 \\ \underset{\times 1}{0} & \underset{\times 0}{1} & \underset{\times 1}{1} & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}} * \underset{K}{\begin{pmatrix} 1 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 1 \end{pmatrix}} = \underset{I * K}{\begin{pmatrix} 1 & 4 & 3 & 4 & 1 \\ 1 & 2 & 4 & 3 & 3 \\ 1 & 2 & 3 & 4 & 1 \\ \boxed{1} & 3 & 3 & 1 & 1 \\ 3 & 3 & 1 & 1 & 0 \end{pmatrix}}$$

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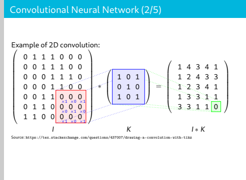
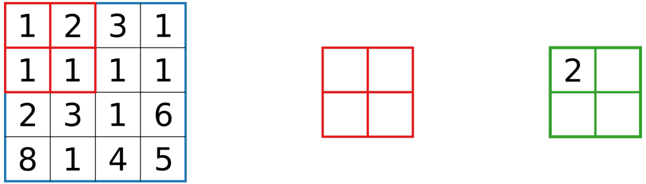
Course 4: Deep Learning
└Convolutional Neural Networks (CNN)
└Convolutional Neural Network (2/5)



Example of 2D pooling:

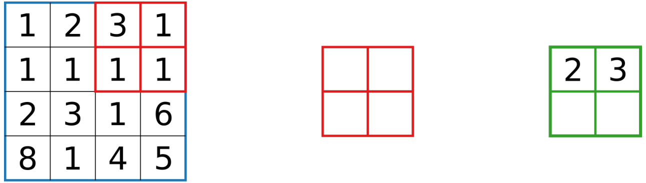


maxpool, kernel 2, stride 2

Convolutional Neural Network (3/5)
Example of 2D pooling:
maxpool, kernel 2, stride 2

Convolutional Neural Network (3/5)

Example of 2D pooling:



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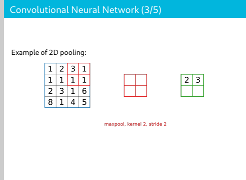

Convolutional Neural Network (3/5)

Example of 2D pooling:

1	2	3	1
1	1	1	1
2	3	1	6
8	1	4	5

2	3
8	

maxpool, kernel 2, stride 2

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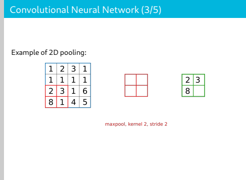
Course 4: Deep Learning
└Convolutional Neural Networks (CNN)
└Convolutional Neural Network (3/5)



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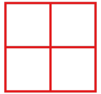


2	3
8	6

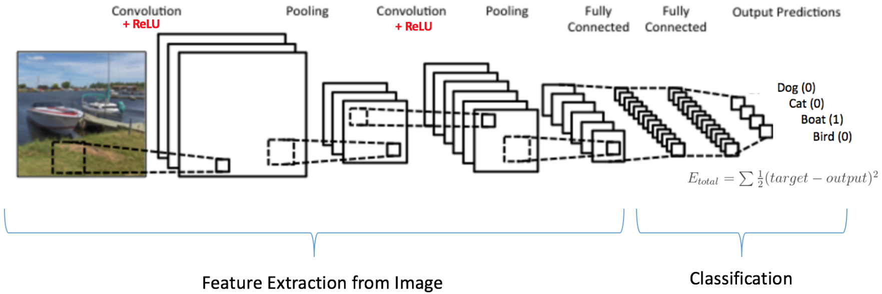
maxpool, kernel 2, stride 2

Convolutional Neural Network (3/5)
Example of 2D pooling:
1 2 3 1
1 1 1 1
2 3 1 6
8 1 4 5
2 3
8 6
maxpool, kernel 2, stride 2

Convolutional Neural Network (4/5)

And repeat...

- Convolutional neural network: mainly *Convolution* + *Pooling*.
- ...But many other components may be added! (batch norm, dropout, skip connections, concatenation, ...)



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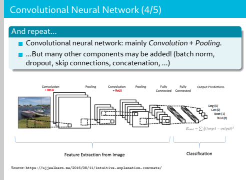
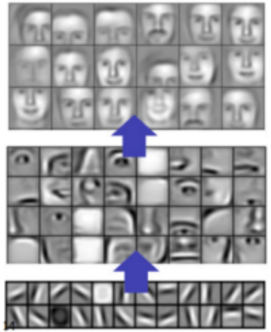


Why convolutions?

- Kernels capture important information in images
- The kernels become more and more complex with the depth of the network



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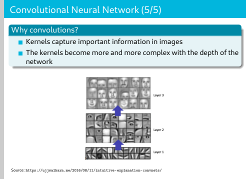
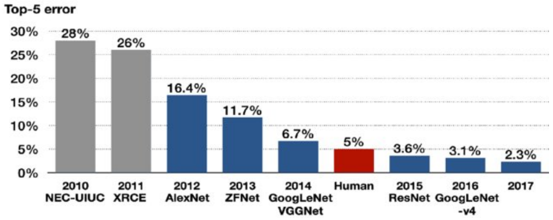


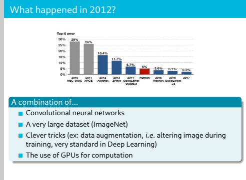
Convolution are able to catch simple shapes (lines, edges) which turn into complex shapes in the subsequent layers.

What happened in 2012?



A combination of...

- Convolutional neural networks
- A very large dataset (ImageNet)
- Clever tricks (ex: data augmentation, *i.e.* altering image during training, very standard in Deep Learning)
- The use of GPUs for computation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Outline

Outline

1 Multi-layer Perceptron
2 Convolutional Neural Networks (CNN)
3 Transformers

What about now?

Image classification

- Image classification for a single dataset is (almost) solved
- Challenges of adapting models to unseen datasets
- Challenges when data is scarce
- Specific domains with few variability or complex classification are still challenging (ex: medical imaging)

Large Language Models

- Large Language Models caught everyone's attention (ChatGPT)
- Challenges of reducing their resources (data/power)
- May hallucinate: lack of robustness

Many other domains

Multimodal models (DALL-E, ...), Audio, Games, Video, ...

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Focus on Large Language Models

Many models

- GPT (Open-AI)
- LLaMA (Meta)
- Gemini (Google)
- Mistral 8x7B (MistralAI)
- Many others... And more to come!

Masked Language Modeling

*How are **you** doing today?* → *How are ... doing today?*

- The network learns to reconstruct masked words
- No supervision!
- Allows to leverage immense datasets (ex: GPT-3 was learned on an **Internet scale** dataset)

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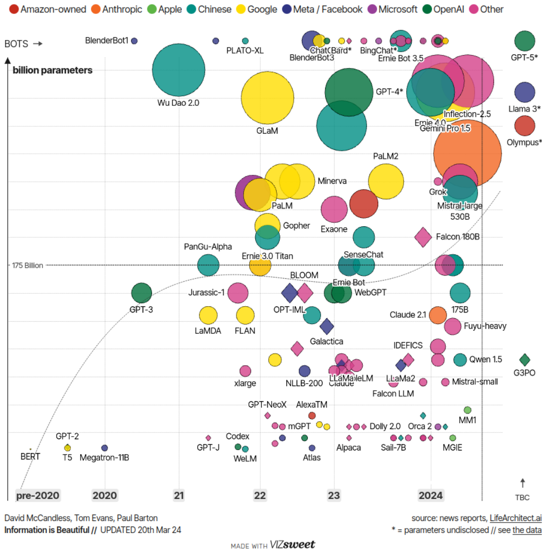
Model sizes

- AlexNet (2012): 62 Million parameters
- GPT-3 (2020): 175 Billion parameters

Image source:
`https://informationisbeautiful.net/visualizations/the-rise-of-generative-ai-large-langua`



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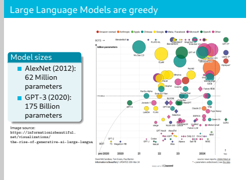
Course 4: Deep Learning
└Transformers
└Large Language Models are greedy



Standard architecture nowadays

- No convolution
- Based on *attention*: what should be important for context?
- Used for text, image, audio, ...

Transformers

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Transformer block

Based on 3 elements:

- Key
- Query
- Value

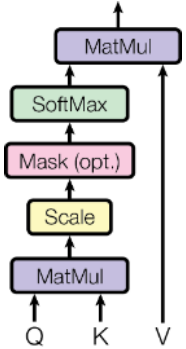

Image source: Vaswani, A. *et al.* (2017). Attention is all you need. Advances in neural information processing systems, 30.

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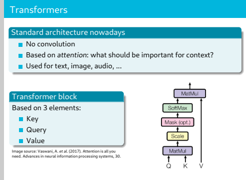
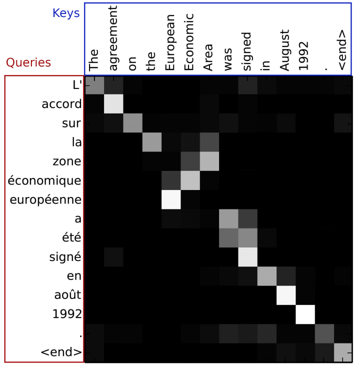
└Transformers

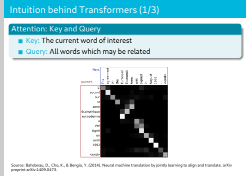


Attention: Key and Query

- Key: The current word of interest
- Query: All words which may be related



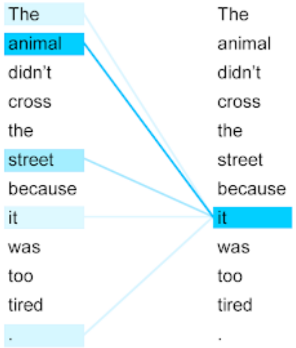
Source: Bahdanau, D., Cho, K., & Bengio, Y. (2014). Neural machine translation by jointly learning to align and translate. arXiv preprint arXiv:1409.0473.



Attention consists in asking: which word is important to explain my current word?

From Attention to Self-Attention

In self-attention, Keys and Queries come from the same text: **context**.



Source:
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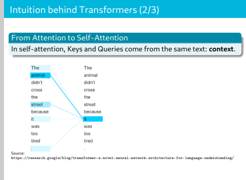

Notice how the model is able to understand the context of the “it” in the examples: “it” refers to the animal in the first example, and to the street in the second. The model has caught this behavior.

Intuition behind Transformers (2/3)

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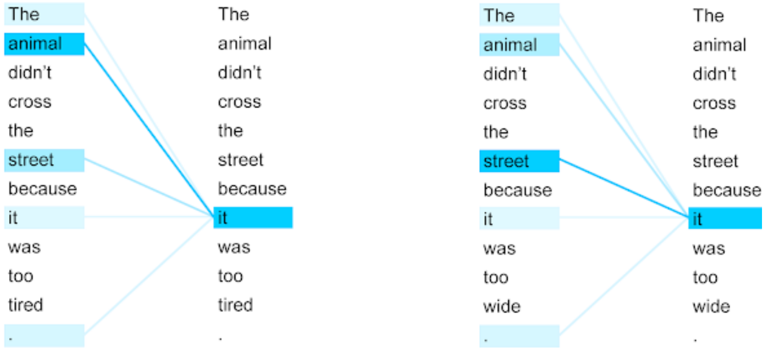

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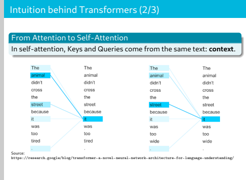

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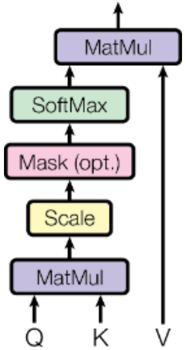
Transformer block

- Key and Query: Context
- Value: Modify the current work, to integrate context



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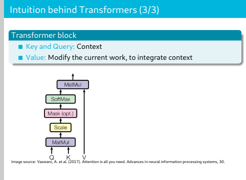

Finally, a Transformer block will modify each word for it to integrate the context learned with Keys and Queries. In the end, the whole sentence is encoded through the embeddings of each word.

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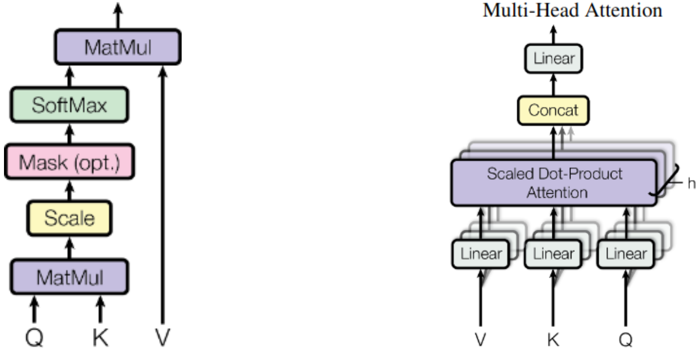

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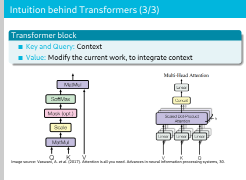

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Repeat Transformer blocks: **Deep** model

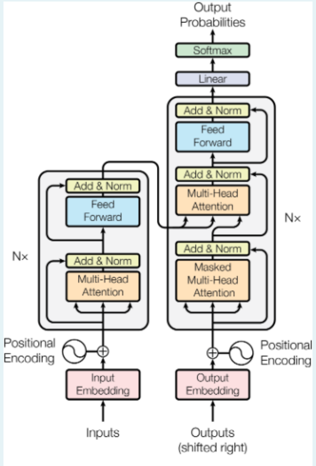
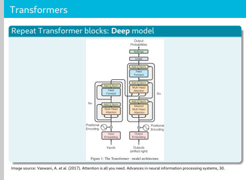


Figure 1: The Transformer - model architecture.

Image source: Vaswani, A. *et al.* (2017). Attention is all you need. Advances in neural information processing systems, 30.



doesn't need to go in details, just present the fact that blocks are repeated.

Conclusion

- Deep Learning algorithms: **powerful** without feature extraction
- They require **a lot** of data to be trained
- The architecture plays an important role

Common criticisms

- Hard to interpret
- Reproduce biases from data
- May require massive amounts of energetic consumption

Going further

- Details and maths behind IA: https://youtu.be/aircAruvnKk
- Ethics and reflexions (french): Science4all & M.Phi

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- Lab Pytorch: manipulating the basics of PyTorch
- Lab Modality: try a first baseline on your modality

Practical session
Lab
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