# Course 4: Deep Learning

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# Summary

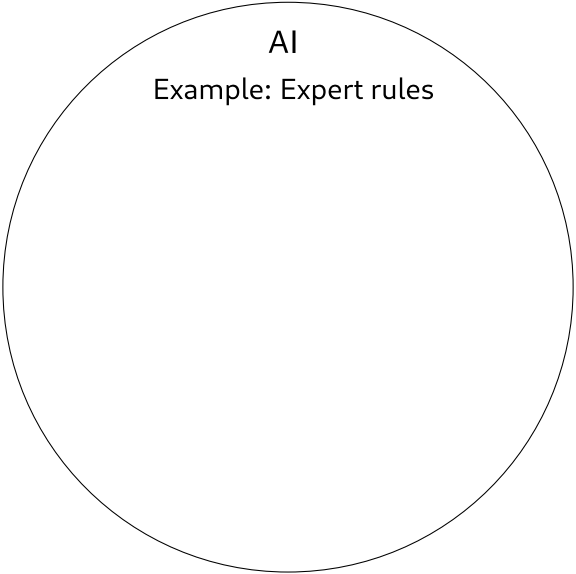
**Last session**

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

**Today's session**

- Deep Learning

# Global overview…




Adapted from *Deep Learning, 2016* by A. Courville, I. Goodfellow and Y. Bengio

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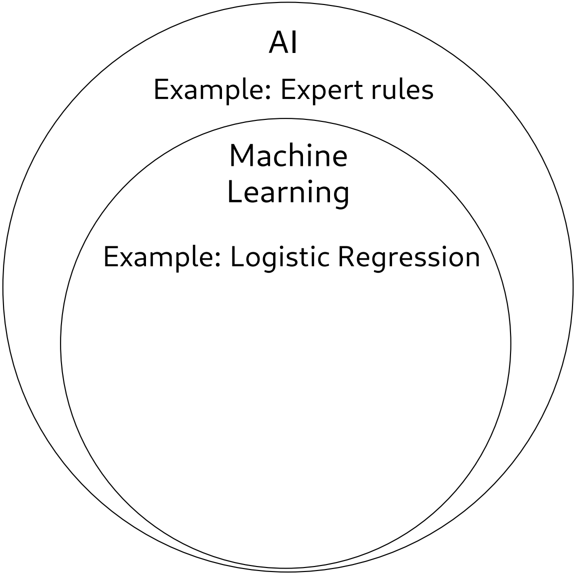


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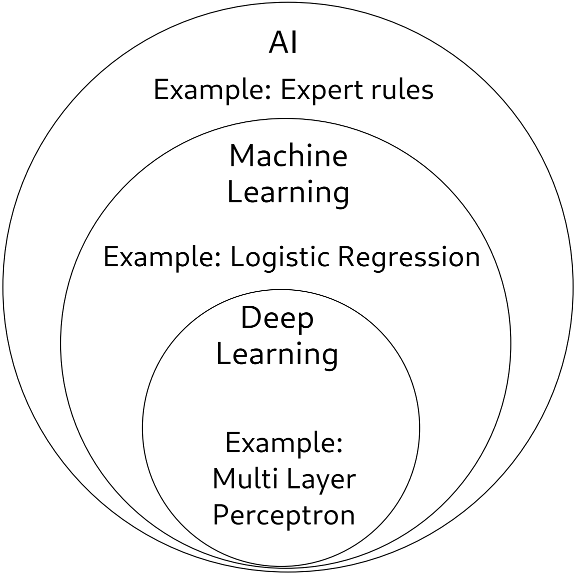


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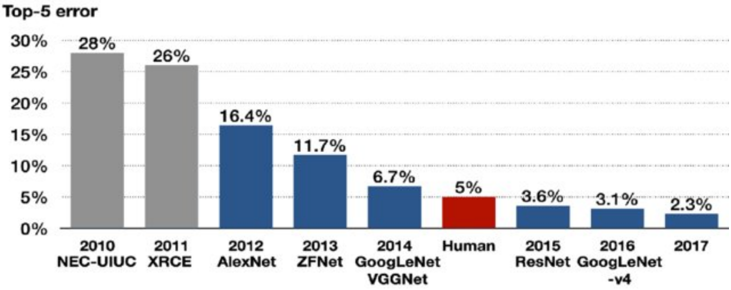
# Deep Learning in a nutshell (1/2)

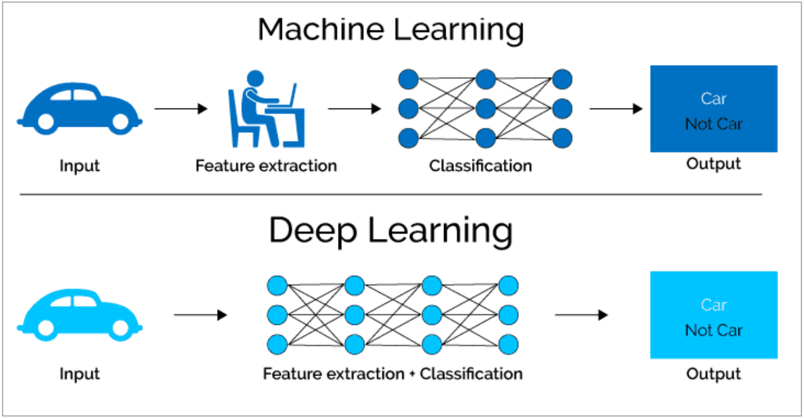
## Definition of Deep Learning

- Using *deep* neural networks
- 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

# Deep Learning in a nutshell (2/2)

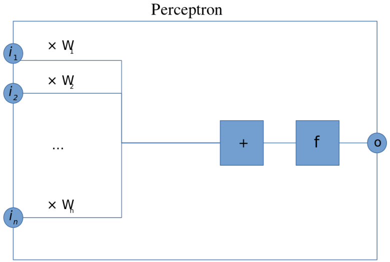



Source: `https://www.softwaretestinghelp.com/data-mining-vs-machine-learning-vs-ai/`

# Deep Neural Networks (1/7)

## 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`

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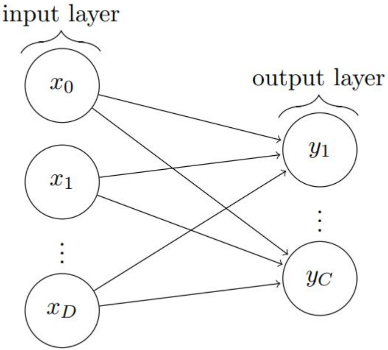



Figure: The arrows represent the weights $W$.

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

# Deep Neural Networks (2/7)

## 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): $J(W) = \sum_i \mathcal{L}(x^{(i)}, W, \hat{y}^{(i)})$

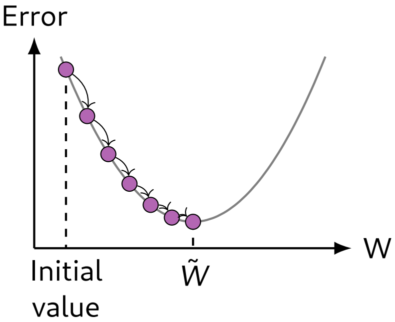
## Gradient descent

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

## 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
- $\eta$ gives the size of the step




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

# Deep Neural Networks (3/7)

## Intuition behind the gradient descent

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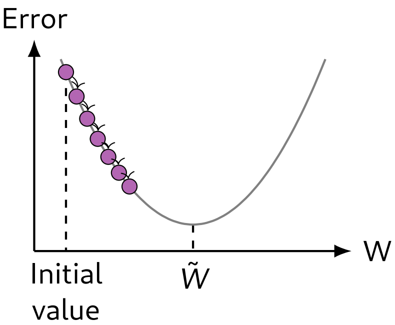
Small step:



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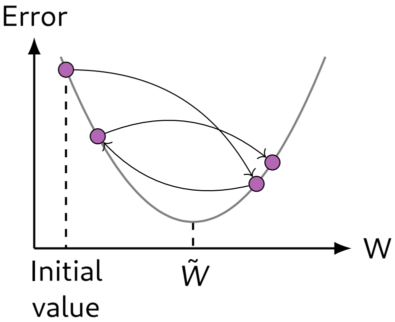
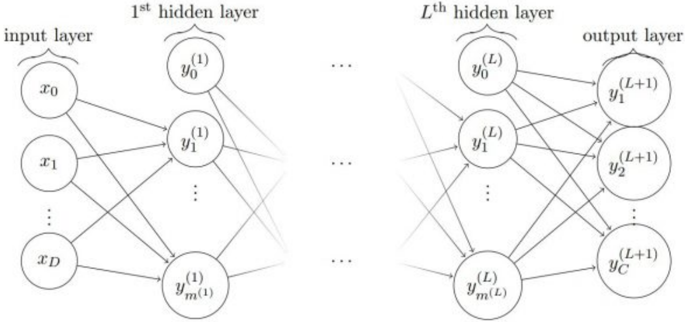
Large step:



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

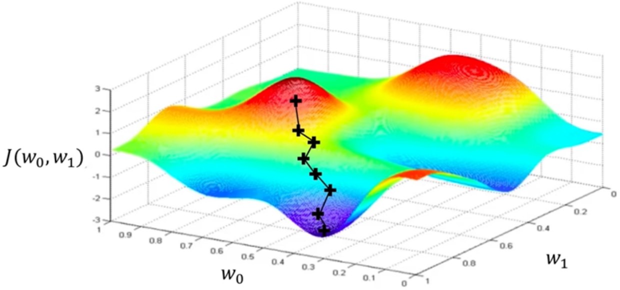
- Stacking perceptions. Each perceptron is a **layer**.
- The ***deep*** term comes form this stacking
- Prediction: $y = f\left(W^{(L)} \cdots f\left(W^{(2)} f(W^{(1)} x)\right)\right)$




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

## 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/`

# Deep Neural Networks (6/7)

## Batch

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

# Deep Neural Networks (7/7)

## Limits of Multi-Layer Perceptrons

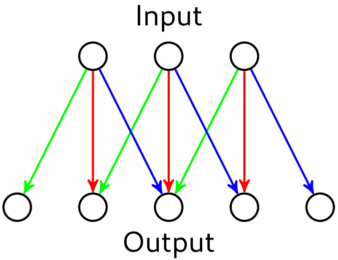
- Computationally heavy for large inputs
- Large number of parameters: prone to overfitting
- No notion of structure in the input: everything is a vector

# 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**




$$\begin{pmatrix} w_1 & w_2 & w_3 & 0 & 0 \\ 0 & w_1 & w_2 & w_3 & 0 \\ 0 & 0 & w_1 & w_2 & w_3 \end{pmatrix}$$

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`

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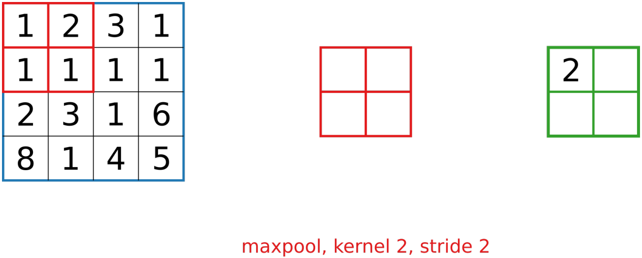
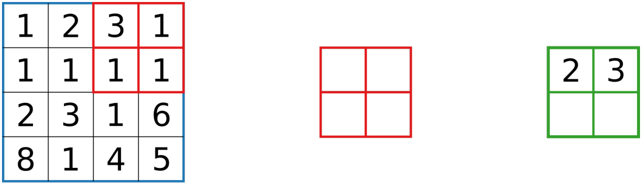


# Convolutional Neural Network (3/5)

Example of 2D pooling:




maxpool, kernel 2, stride 2

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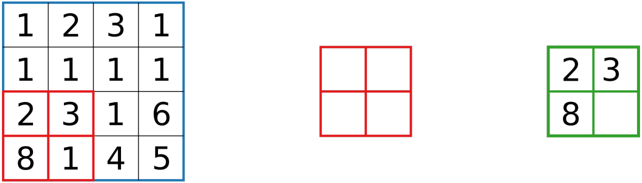


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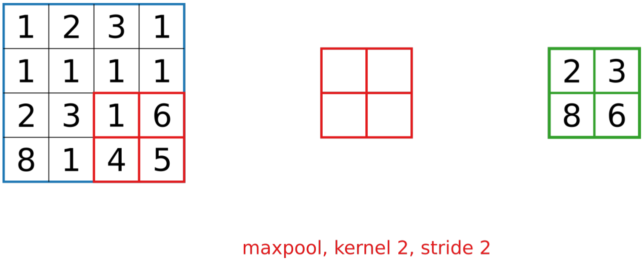
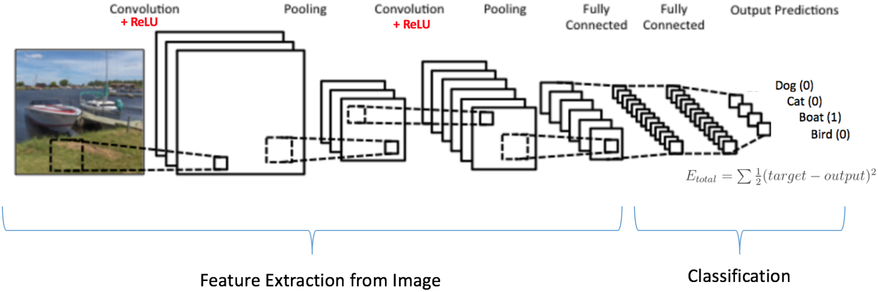


# Convolutional Neural Network (4/5)

## And repeat...

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

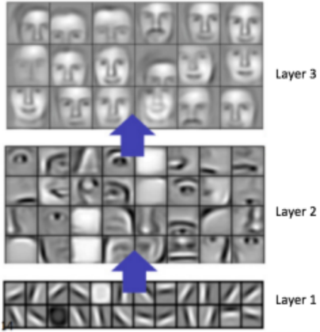



Source: `https://ujjwalkarn.me/2016/08/11/intuitive-explanation-convnets/`

# Convolutional Neural Network (5/5)

## 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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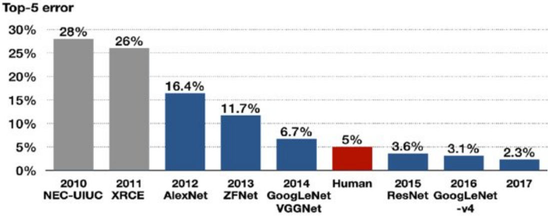
# What happened in 2012?




## 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

# 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?* $\rightarrow$ *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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# Large Language Models are greedy

## Model sizes

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

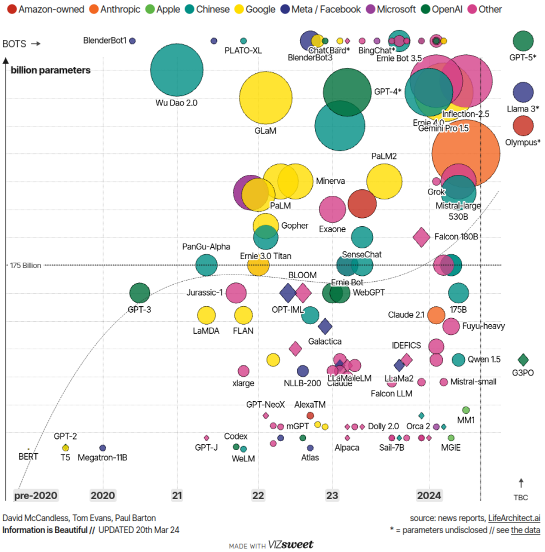


Image source:
`https://informationisbeautiful.net/visualizations/the-rise-of-generative-ai-large-langua`

# Transformers

## Standard architecture nowadays

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

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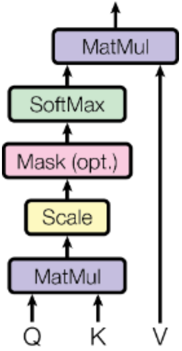
## Transformer block

Based on 3 elements:

- Key
- Query
- Value

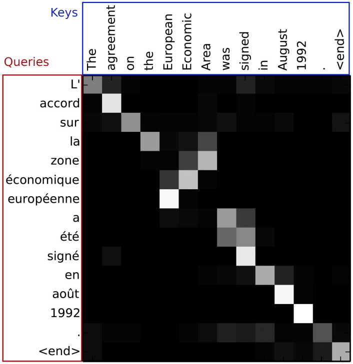
Image source: Vaswani, A. *et al.* (2017). Attention is all you need. Advances in neural information processing systems, 30.



# Intuition behind Transformers (1/3)

## Attention: Key and Query

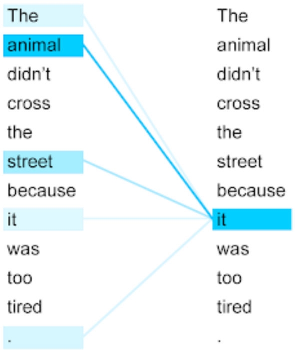
- Key: The current word of interest
- Query: All words which may be related




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

## From Attention to Self-Attention

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




Source:
https://research.google/blog/transformer-a-novel-neural-network-architecture-for-language-understanding/

# Intuition behind Transformers (2/3)

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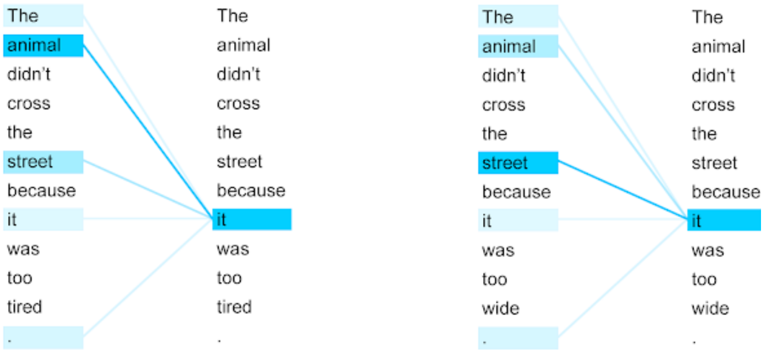


Source:
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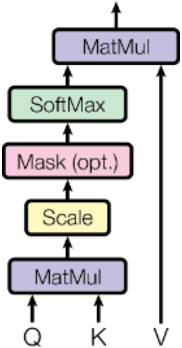
## Transformer block

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

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# Intuition behind Transformers (3/3)

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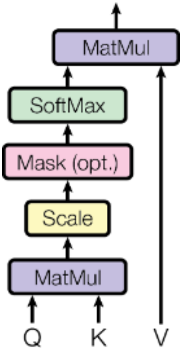


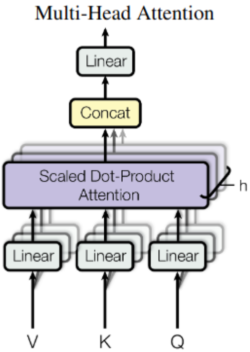


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## Repeat Transformer blocks: **Deep** model

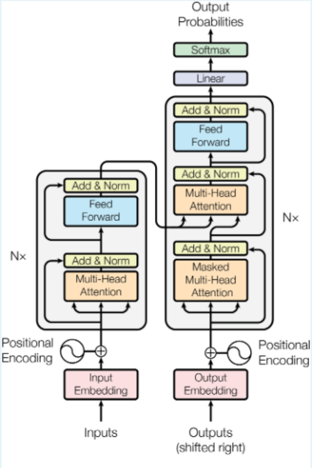


Figure 1: The Transformer - model architecture.

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

## 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?si=yOVkwOsOvDHVZbQj
- Ethics and reflexions (french): Science4all & M.Phi

https://youtu.be/sAjm3-IaRtI?si=j41k66_FYX77L_HT | https://youtu.be/_XJsAQsT0Bo?si=OFJdmqR7YvF5wJA-

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# Practical session

## Lab

- Lab Pytorch: manipulating the basics of PyTorch
- Lab PyRat: learning a player for PyRat