

COURS Reconnaissance Visuelle par deep learning https://cord.isir.upmc.fr/teaching-multimedia/

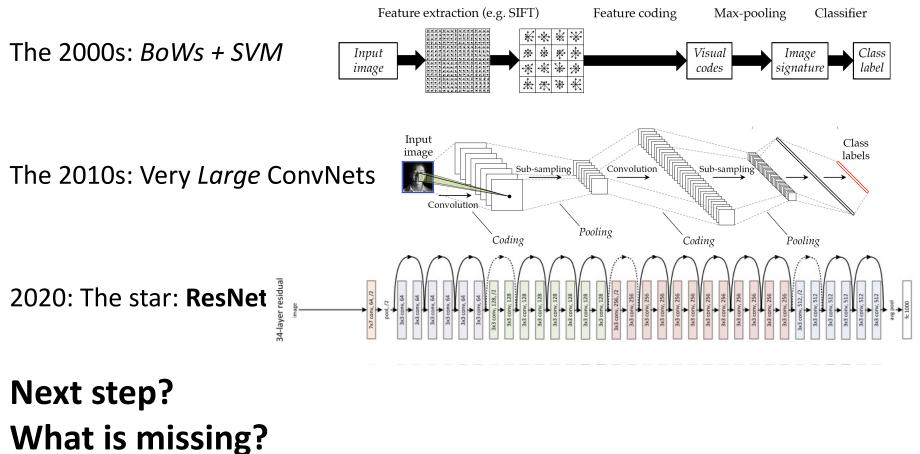
Course Outline

- 1. Intro to Computer Vision and Machine Learning
- 2. Intro to Neural Networks
- 3. Machine Learning complements
- 4. Neural Nets for Image Classification
 - 1. Recap MLP
 - 2. Convolutional Neural Networks
 - 3. Examples: LeNet5, AlexNet, GoogLeNet, VGG, ResNet

5. Vision Transformers

- 1. NLP: Attention is all you need
- 2. Transformer for Image Classification

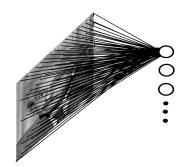
Image classification: where we are and what is missing?

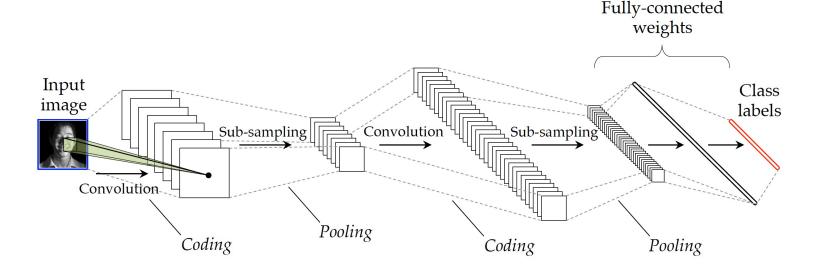


Attention process in ConvNets

In ConvNets, what information is shared between pixels (or features) in one block? => 2D spatial locality (typically 3x3) => attention is done locally

Rq: less local after many layers

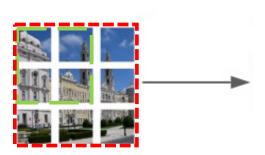


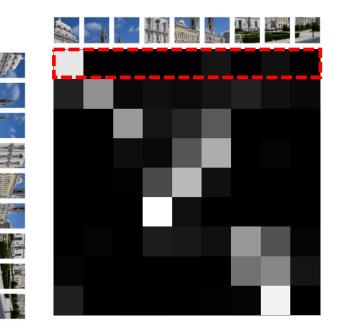


Global (Self) attention

How to build a deep architecture with local global attention inside? Meaning that one patch may interact with all others!

=> Different than convNet!

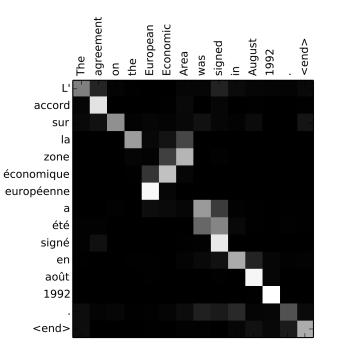




Let's see what they do in Natural Language Processing (NLP):

Attention between words in Machine translation process:

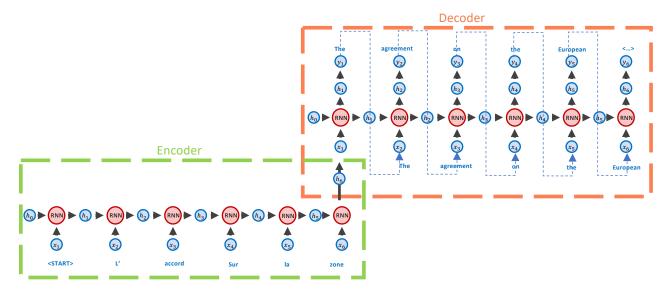
- 1. Computing of weights
- 2. Use them to compute new features



Basic language translation models: Encoder/Decoder

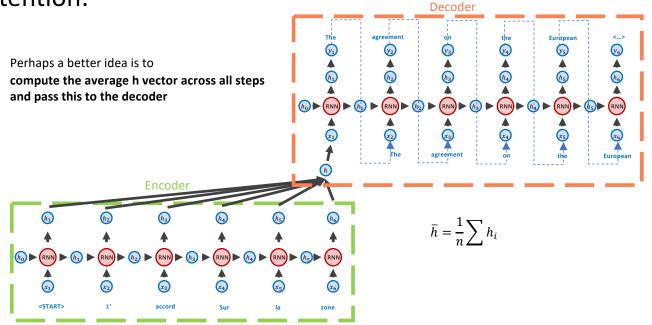
Ex.: Seq2Seq -- RNNs2RNNs

Cross-attention for language translation in at the end of Encoder



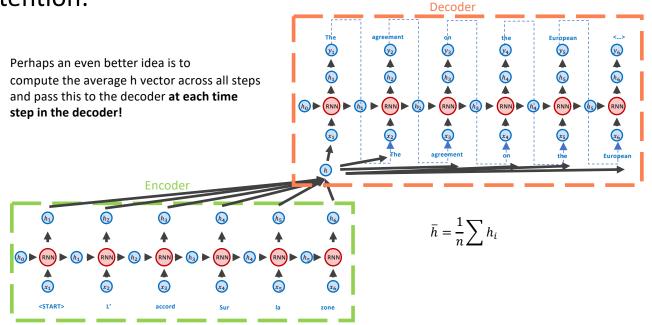
Basic language translation models: Encoder/Decoder

Cross-attention:



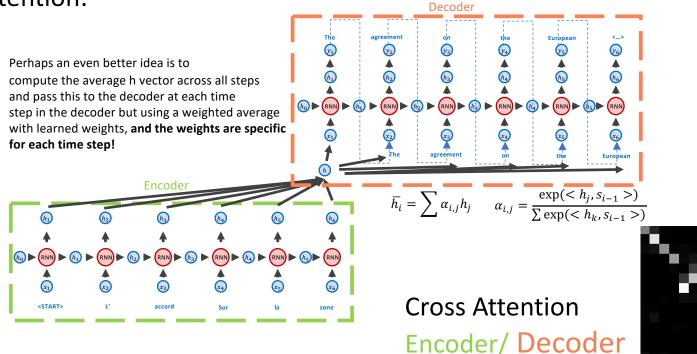
Basic language translation models: Encoder/Decoder

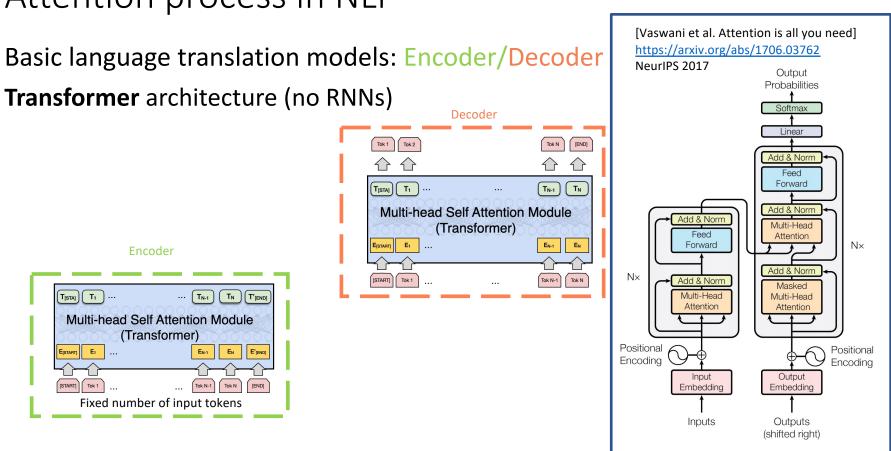
Cross-attention:

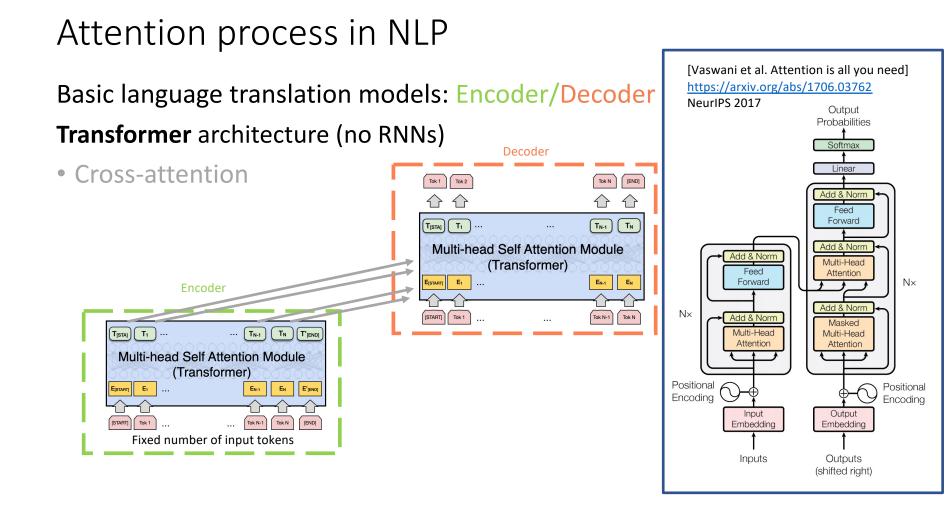


Basic language translation models: Encoder/Decoder

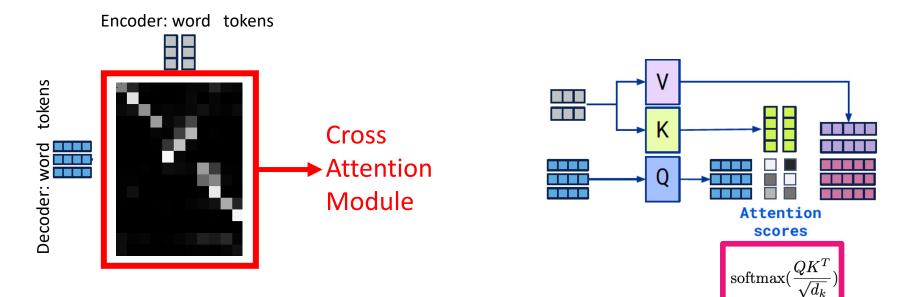
Cross-attention:







Attention process in NLP [Vaswani et al. Attention is all you need] Basic language translation models: Encoder/Decoder https://arxiv.org/abs/1706.03762 NeurIPS 2017 Output Probabilities **Transformer** architecture (no RNNs) Softmax Decoder Cross-attention Linear Tok 2 [END] Tok 1 Tok N Add & Norm Self-attention Feed Forward T_[STA] T₁ ... TN T_{N-1} Multi-head Self Attention Module Add & Norm Add & Norm Multi-Head (Transformer) Feed Attention N× Forward E[START] E1 E_{N-1} Encoder Add & Norm N× [START] Tok 1 Tok N-1 Add & Norm Tok N Masked TN T'[END] Multi-Head (T_{N-1} Multi-Head Attention Attention Multi-head Self Attention Module (Transformer) Positional Positional EN E'IENDI Encoding Encoding Input Output Tok N [END] Embedding Embedding Fixed number of input tokens Inputs Outputs (shifted right)



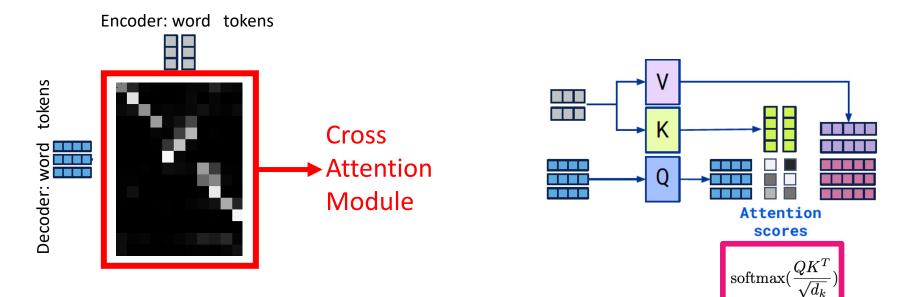
$$\operatorname{Attention}(Q, K, V) = \operatorname{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$

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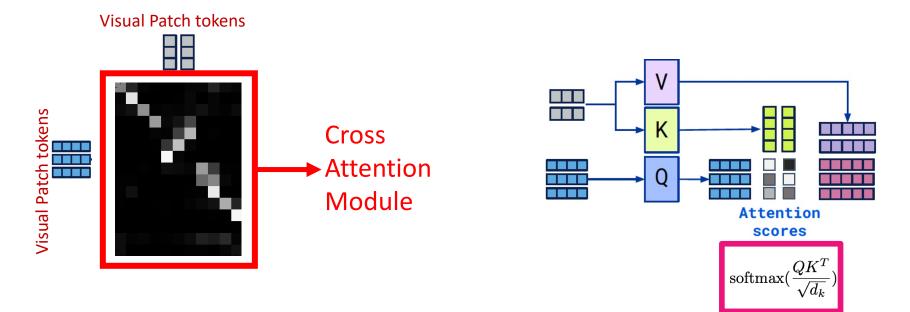
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Attention process in Vision



$$\operatorname{Attention}(Q, K, V) = \operatorname{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$

Very similar except that Visual token is definitively less natural than word for NLP

Attention process in Vision

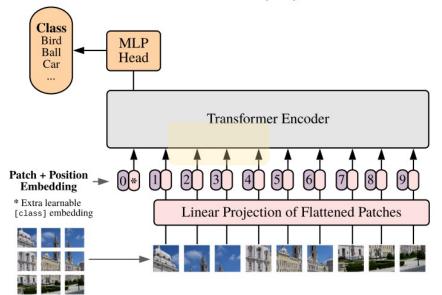
Is it possible to mimic this attentionbased architecture for vision processing?

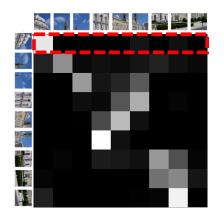
Yes! **ViT** (Vision image Transformers) architecture



AN IMAGE IS WORTH 16x16 WORDS: TRANSFORMERS FOR IMAGE RECOGNITION AT SCALE

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Attention process in Vision

Experiments with ViT (and variants DeiT, CaiT) transformers for image classification

State-of-the-art performance on ImageNet1k classification!

From ViT paper, **many tricks/discussions to simplify learning** in DeiT, CaiT, ...

