

COURS Reconnaissance Visuelle par deep learning

https://cord.isir.upmc.fr/teaching-multimedia/

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Outline

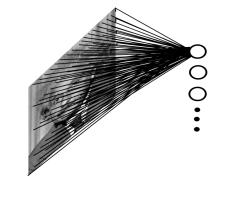
1. Attention and Vision Transformers

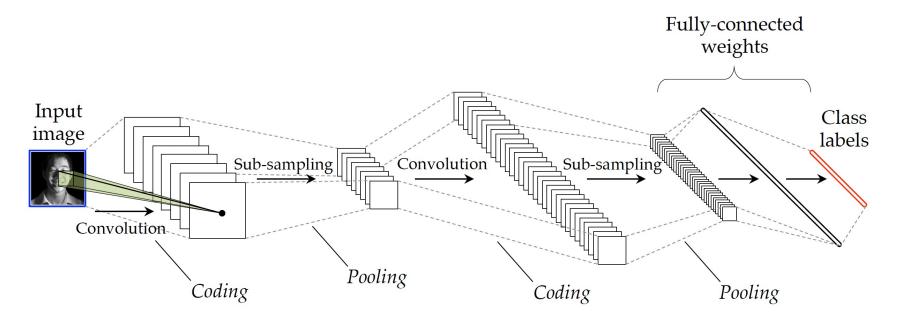
• NLP: Attention is all you need

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

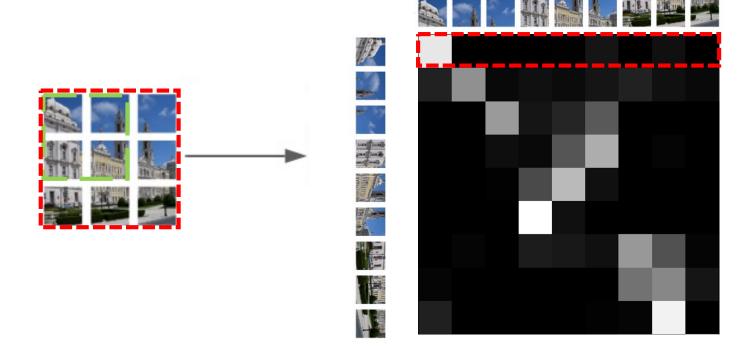




Global (Self) attention

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

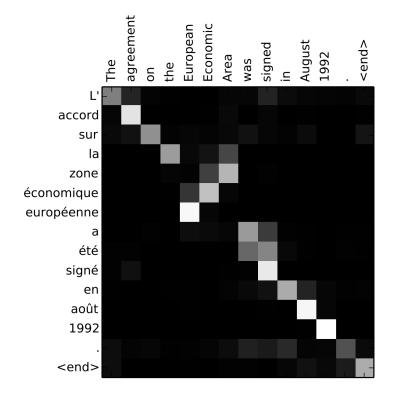
=> Different than convNet!



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

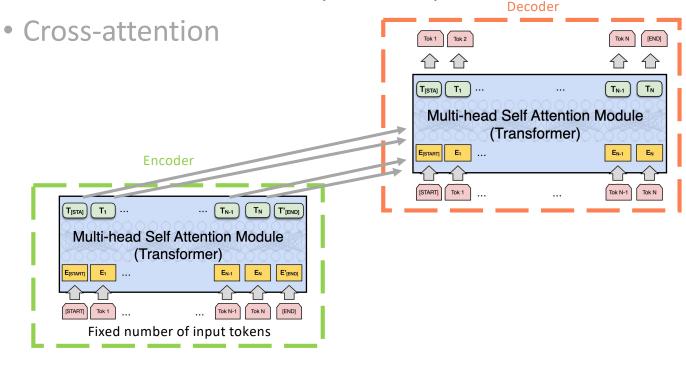
Attention between words in Machine translation process:

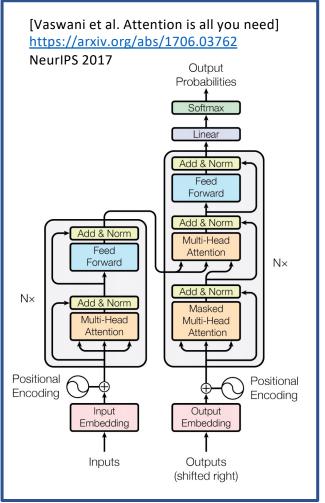
- 1. Computing of weights
- 2. Use them to compute new features



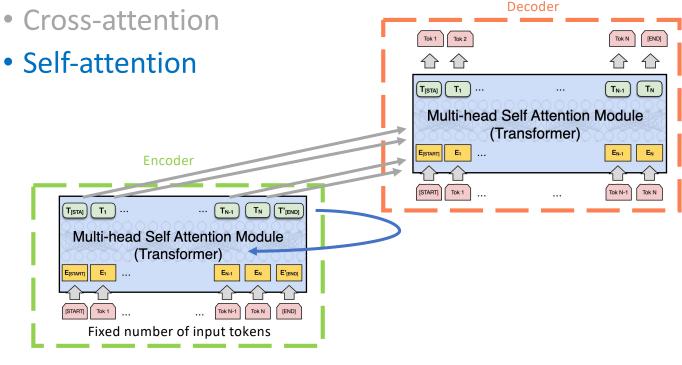
Basic language translation models: Encoder/Decoder

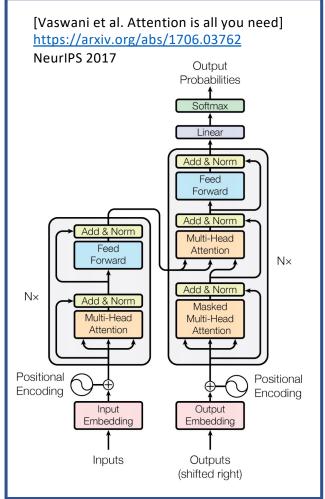
Transformer architecture (no RNNs)

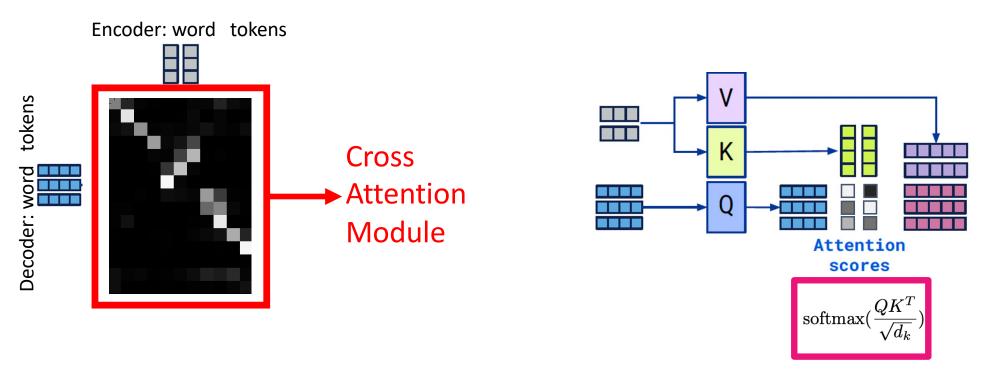




Basic language translation models: Encoder/Decoder Transformer architecture (no RNNs)



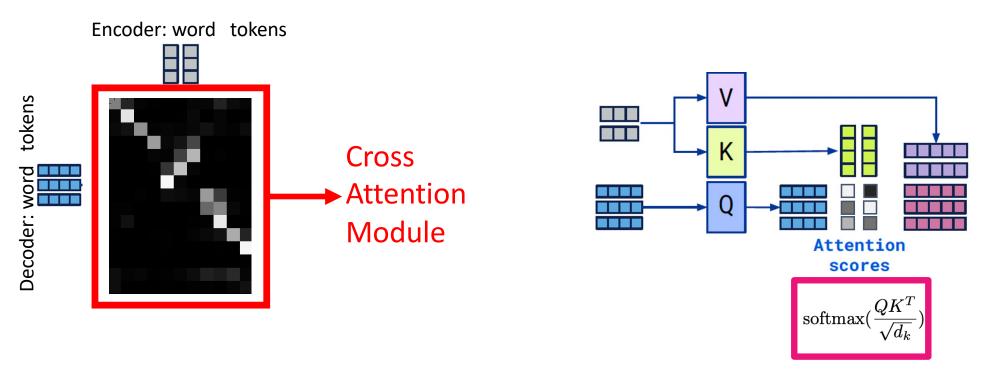




$$\operatorname{Attention}(Q, K, V) = \operatorname{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$

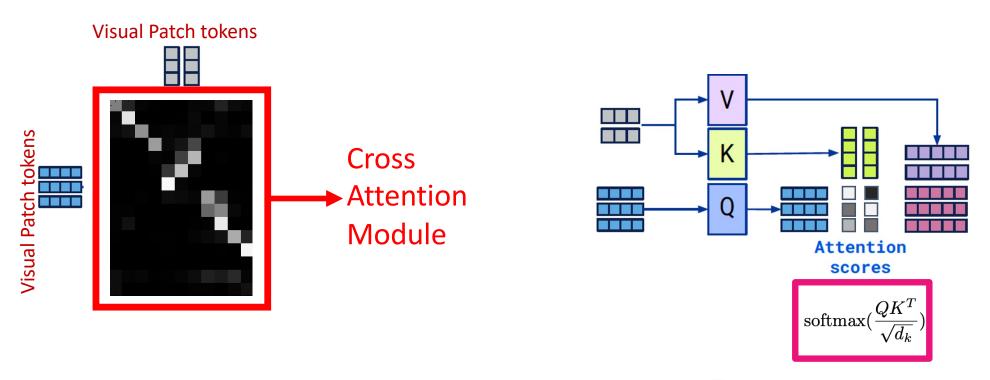
Outline

- 1. Attention and Vision Transformers (ViT)
 - NLP: Attention is all you need
 - Transformer for image classification



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

Attention process in Vision



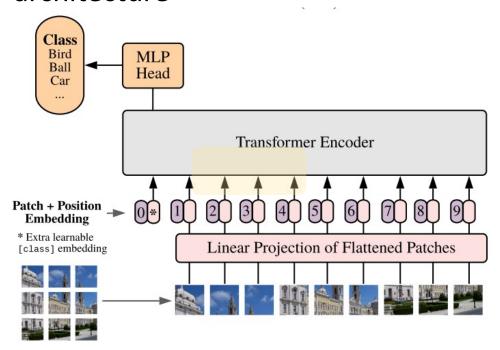
$$Attention(Q, K, V) = softmax(\frac{QK^T}{\sqrt{d_k}})V$$

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



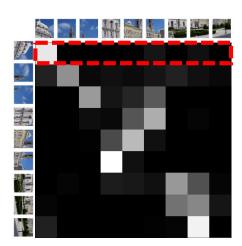
Published as a conference paper at ICLR 2021

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

Alexey Dosovitskiy*,†, Lucas Beyer*, Alexander Kolesnikov*, Dirk Weissenborn*, Xiaohua Zhai*, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, Jakob Uszkoreit, Neil Houlsby*,†

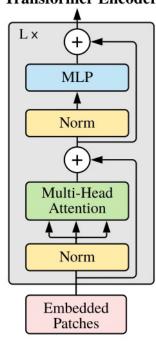
> *equal technical contribution, †equal advising Google Research, Brain Team

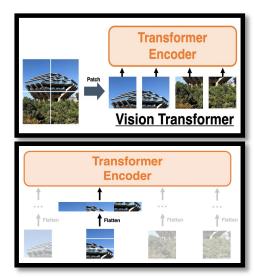
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Attention process in Vision

Transformer Encoder





$$egin{aligned} \mathbf{z}_0 &= [\mathbf{x}_{ ext{class}}; \ \mathbf{x}_p^1 \mathbf{E}; \ \mathbf{x}_p^2 \mathbf{E}; \cdots; \ \mathbf{x}_p^N \mathbf{E}] + \mathbf{E}_{pos}, \ \mathbf{z'}_\ell &= \operatorname{MSA}(\operatorname{LN}(\mathbf{z}_{\ell-1})) + \mathbf{z}_{\ell-1}, \ \mathbf{z}_\ell &= \operatorname{MLP}(\operatorname{LN}(\mathbf{z'}_\ell)) + \mathbf{z'}_\ell, \ \mathbf{y} &= \operatorname{LN}(\mathbf{z}_L^0) \end{aligned}$$

[class=CLS] token: a learnable embedding to the sequence of embedded patches

Layernorm (LN) before every block, and residual connections after every block

MSA: Multi Head Self Attention

MLP: two layers with a GELU non-linearity

Hybrid Architecture: Raw image patches --> Feature map of a CNN

$$x \in \mathbb{R}^{H \times W \times C}$$

$$x_p \in \mathbb{R}^{N \times (P^2 \cdot C)}$$

$$N = HW/P^2$$

$$\mathbf{E} \in \mathbb{R}^{(P^2 \cdot C) \times D}, \ \mathbf{E}_{pos} \in \mathbb{R}^{(N+1) \times D}$$

$$\ell = 1 \dots L$$

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