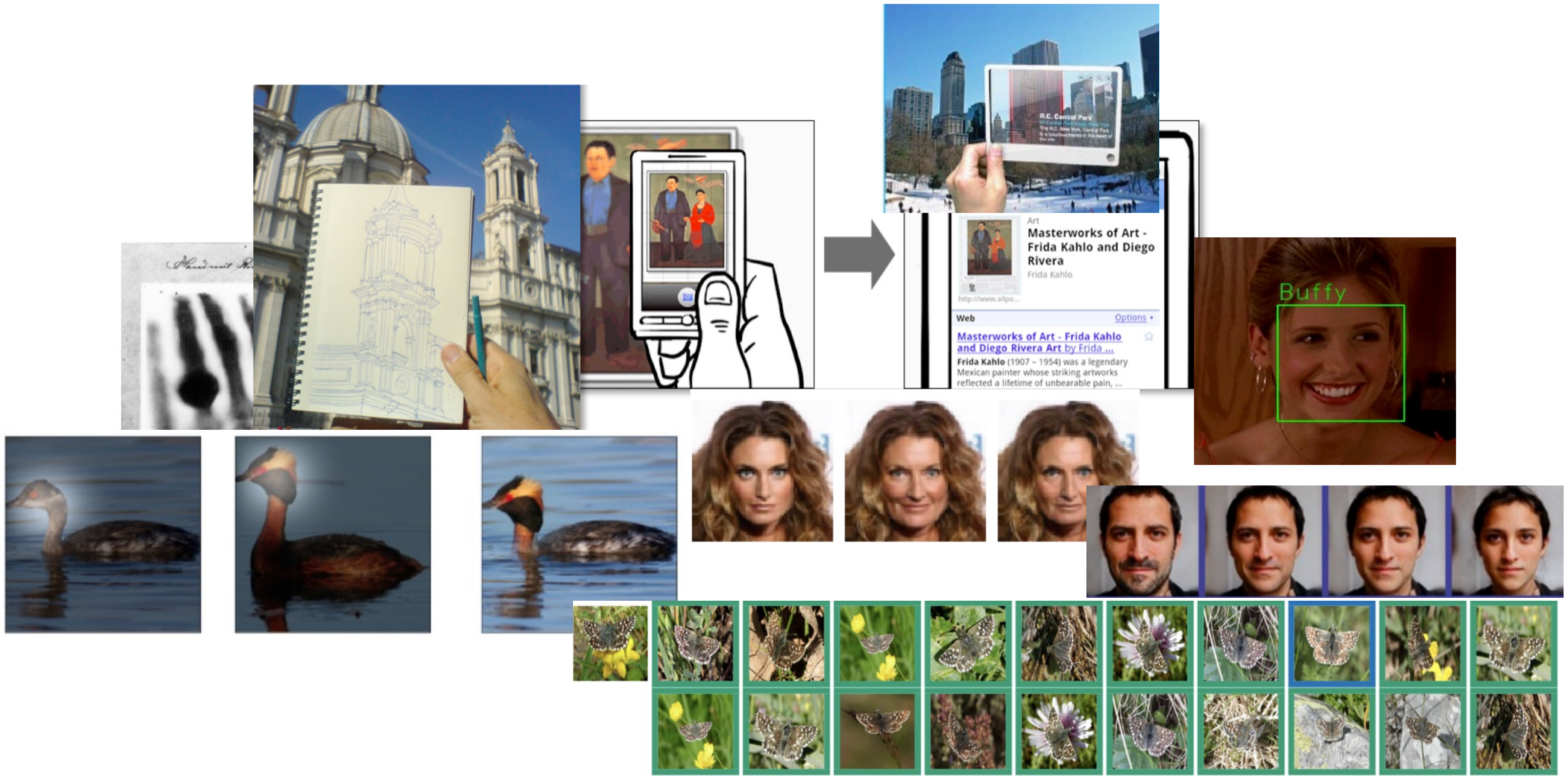
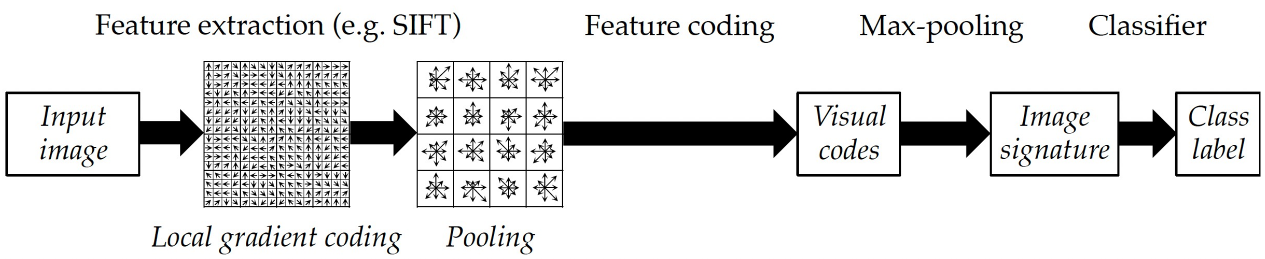


COURS RDFIA deep Image

Matthieu Cord
Sorbonne University

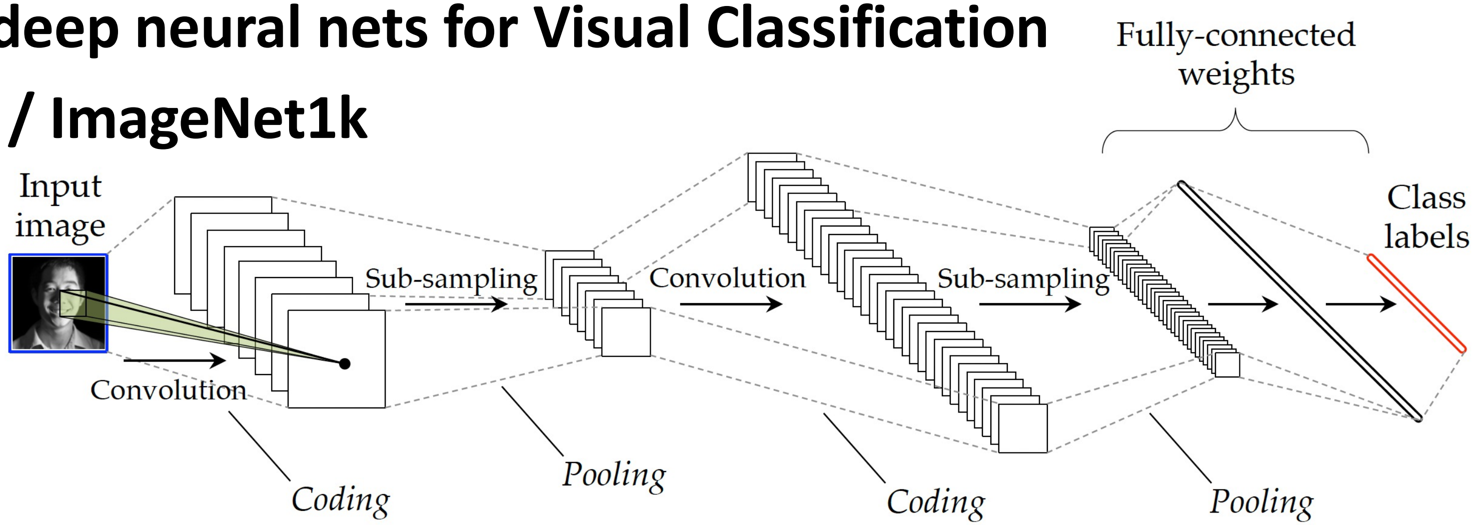
Context: Image classification **Before/After** ImageNet (2009)

The 2000s: *BoWs image modeling + SVMs* for Visual Classification



The 2010s: *Large* deep neural nets for Visual Classification

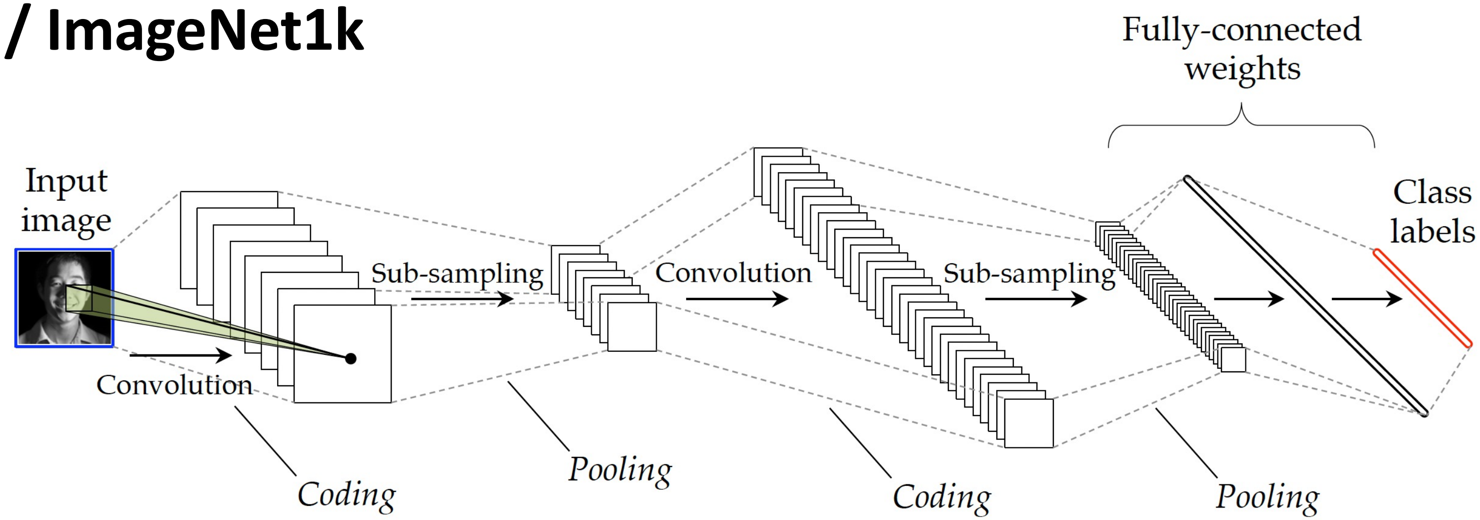
The star: **ConvNet / ImageNet1k**



Context: Image classification **After** ImageNet (2009)

The 2010s: *Large* deep neural nets for Visual Classification

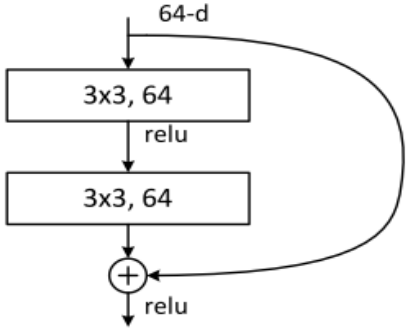
The star: **ConvNet / ImageNet1k**



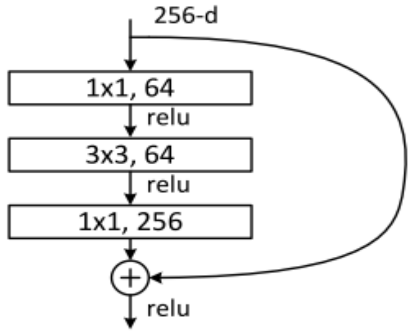
AlexNet 2012

- Same model as LeCun'98 but:
  - Bigger model (8 layers)
  - More data (10^6 vs 10^3 images)
  - GPU implementation (50x speedup over CPU)
  - Better regularization (DropOut)

Post-2012 revolution: ResNet Architecture

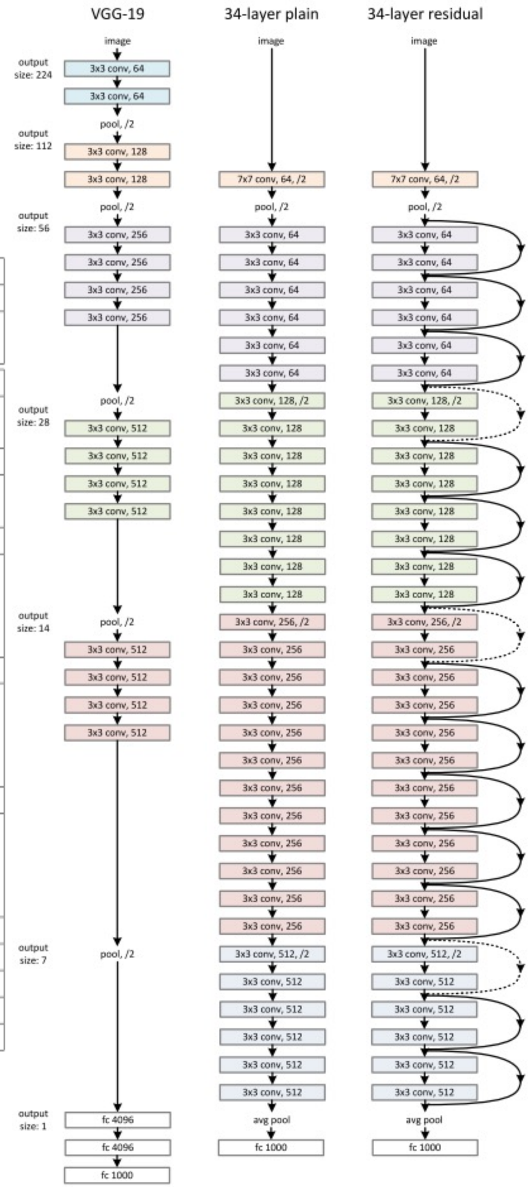


A naïve residual block



“bottleneck” residual block
(for ResNet-50/101/152)

ConvNet Configuration			
B	C	D	E
13 weight layers	16 weight layers	16 weight layers	19 weight layers
put (224 × 224 RGB image)			
conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool			
conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool			
conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool			
conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool			
conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool			
FC-4096			
FC-4096			
FC-1000			
soft-max			



Context: Beyond ImageNet?

The 2000s: *BoWs image modeling + SVMs* for Visual Classification

The 2010s: *Large* deep neural nets for Visual Classification

What is expected for the 2020s?

"Attention is all you need": **Transformers** for Vision !?

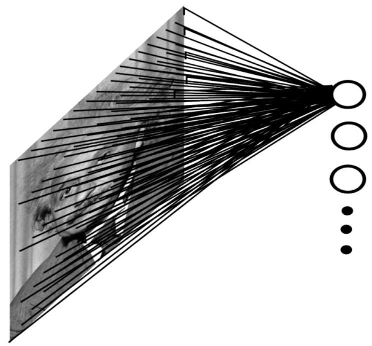
And **datasets? Internet…**

[Vaswani et al., Attention is all you need, NeurIPS 2017]

Outline

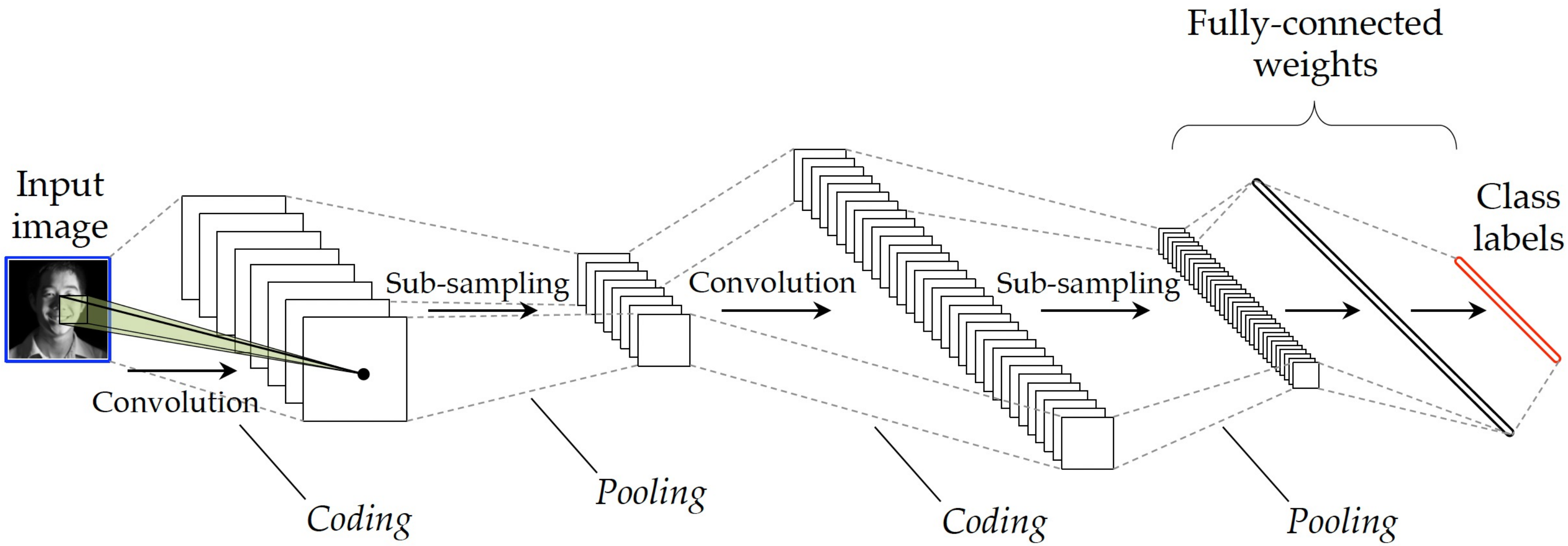
1. Attention and Vision Transformers
   - NLP: Attention is all you need

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*

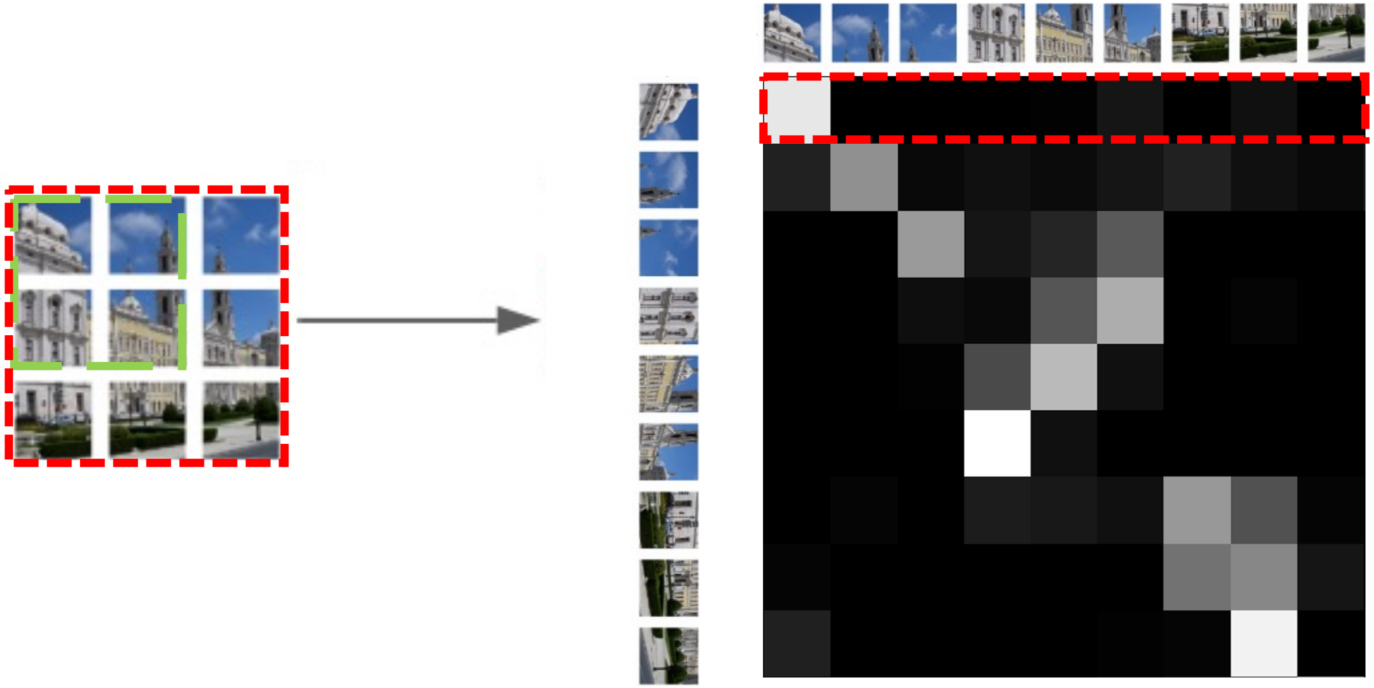
Rq: less local after many layers



Global (Self) attention

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

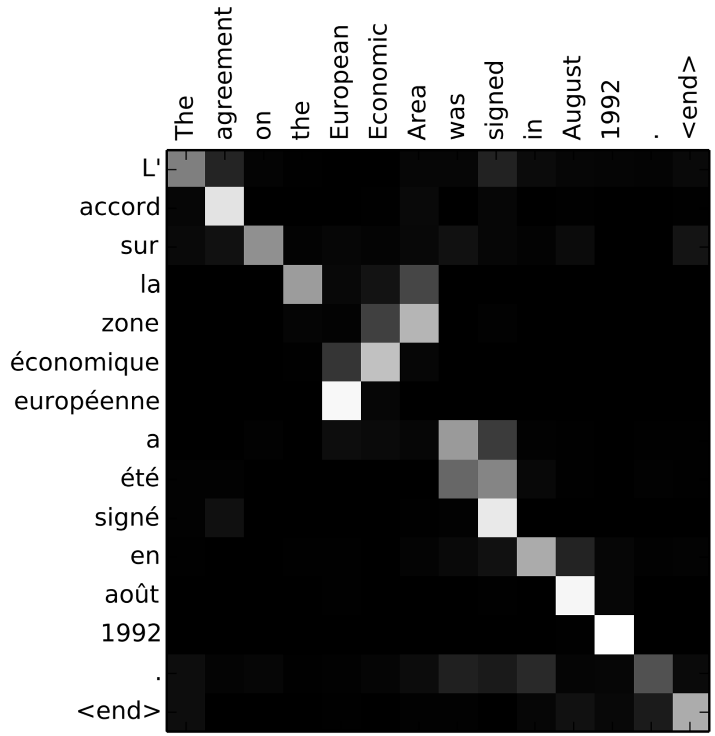
=> Different than convNet!



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

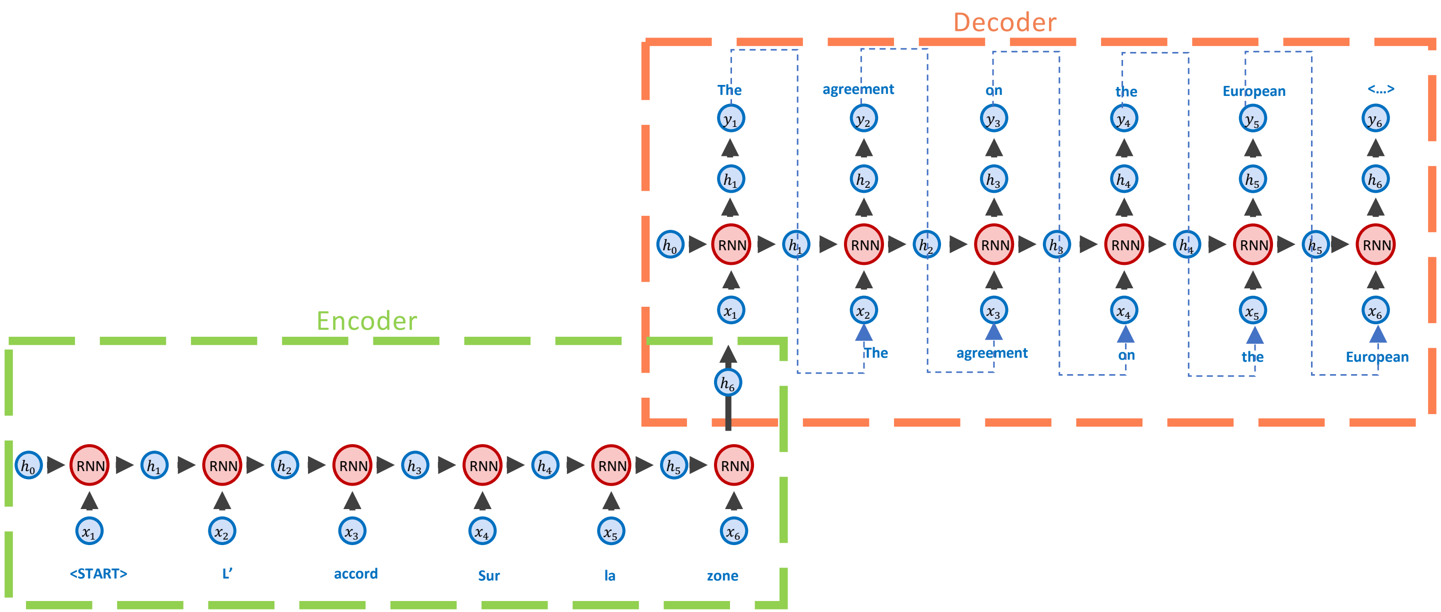


Attention process in NLP

Basic language translation models: Encoder/Decoder

Ex.: Seq2Seq -- RNNs2RNNs

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

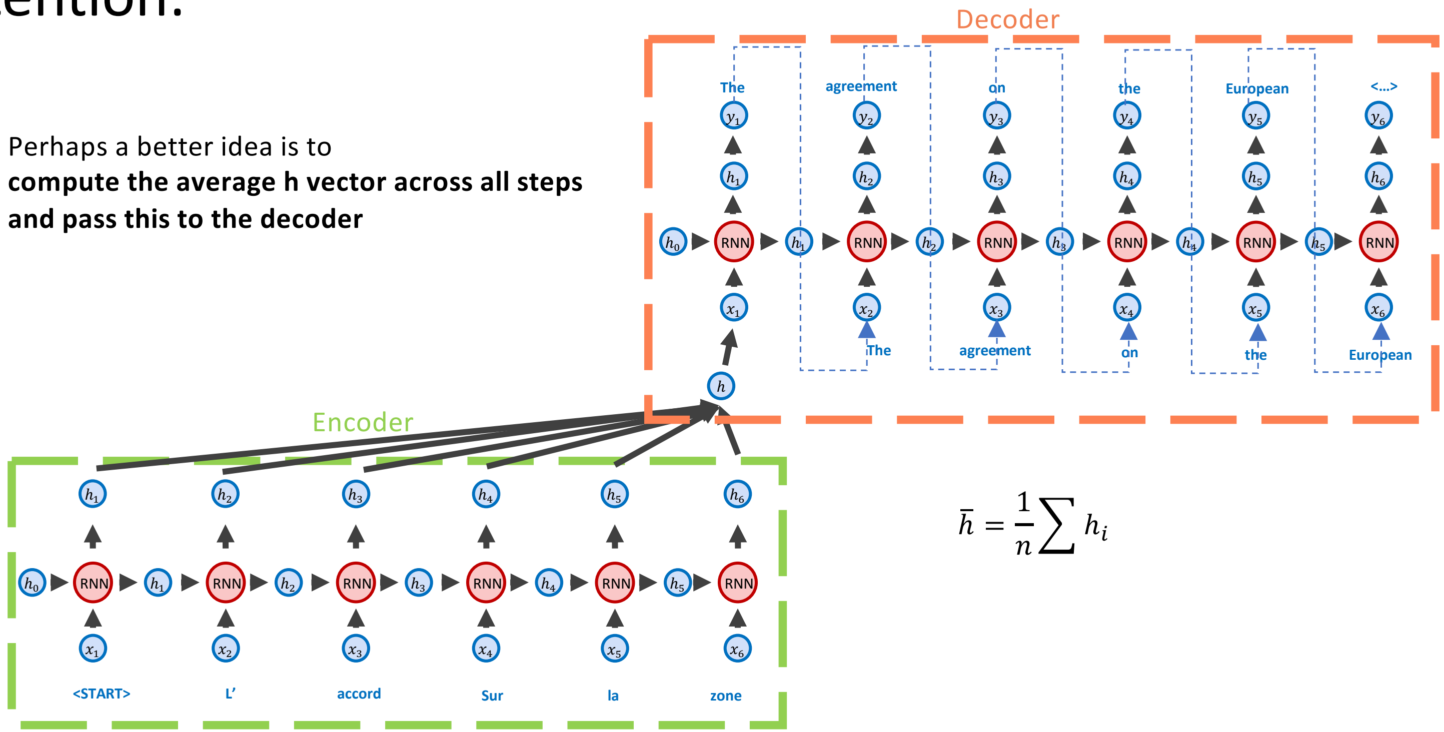


Attention process in NLP

Basic language translation models: Encoder/Decoder

Cross-attention:

Perhaps a better idea is to
compute the average h vector across all steps and pass this to the decoder



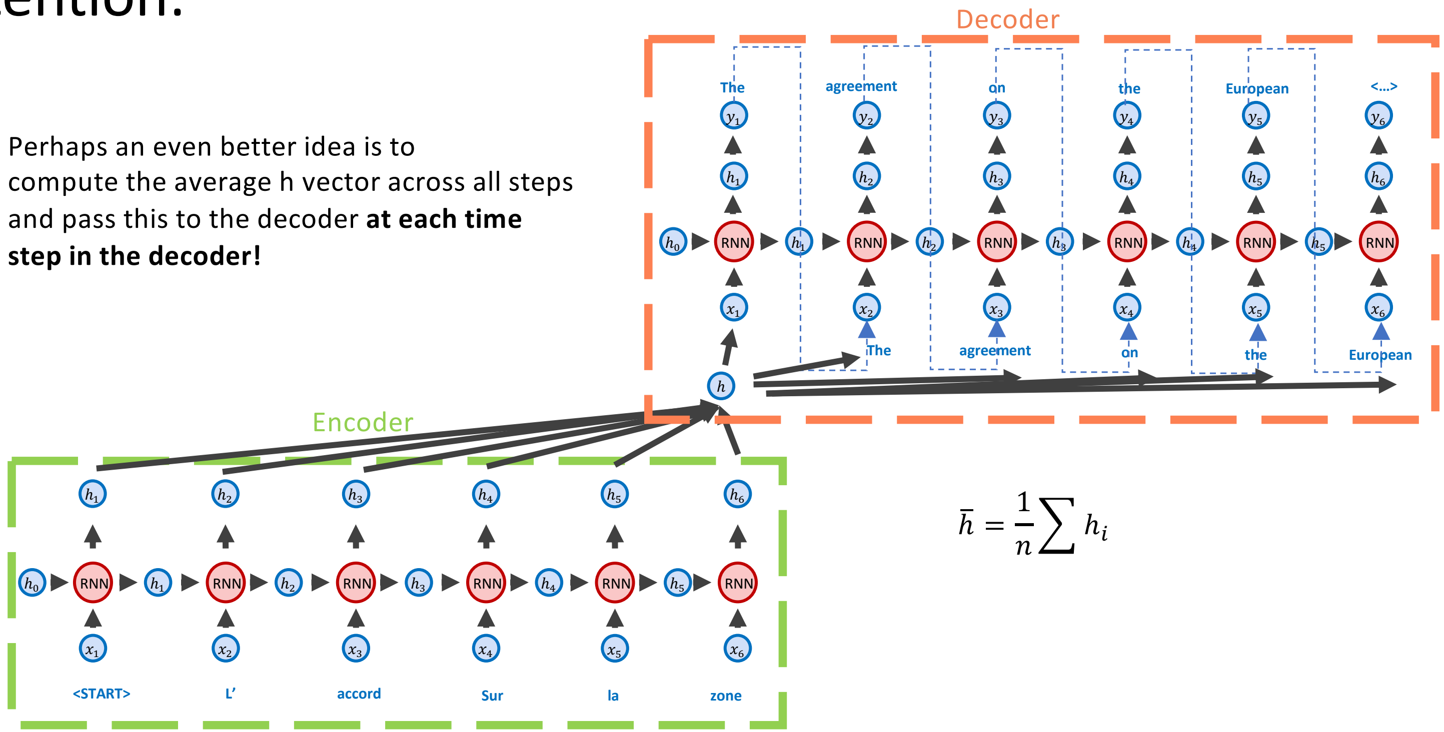
$$\bar{h} = \frac{1}{n}\sum h_i$$

Attention process in NLP

Basic language translation models: Encoder/Decoder

Cross-attention:

Perhaps an even better idea is to compute the average h vector across all steps and pass this to the decoder **at each time step in the decoder!**



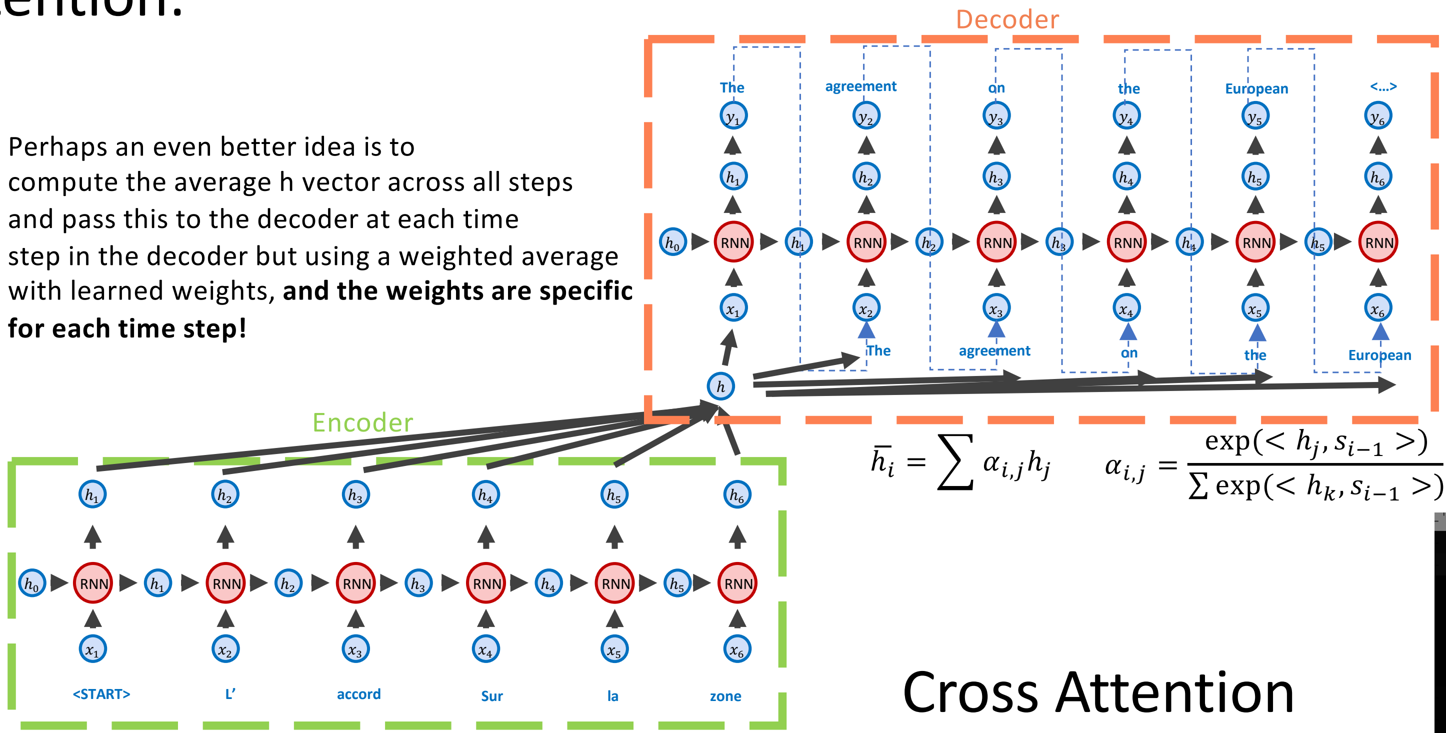
$$\bar{h} = \frac{1}{n}\sum h_i$$

Attention process in NLP

Basic language translation models: Encoder/Decoder

Cross-attention:

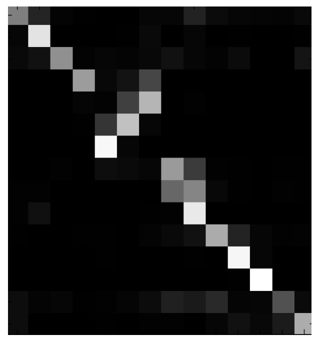
Perhaps an even better idea is to compute the average h vector across all steps and pass this to the decoder at each time step in the decoder but using a weighted average with learned weights, **and the weights are specific for each time step!**



$$\bar{h}_i = \sum \alpha_{i,j} h_j \qquad \alpha_{i,j} = \frac{\exp(< h_j, s_{i-1} >)}{\sum \exp(< h_k, s_{i-1} >)}$$

Cross Attention

Encoder/ Decoder

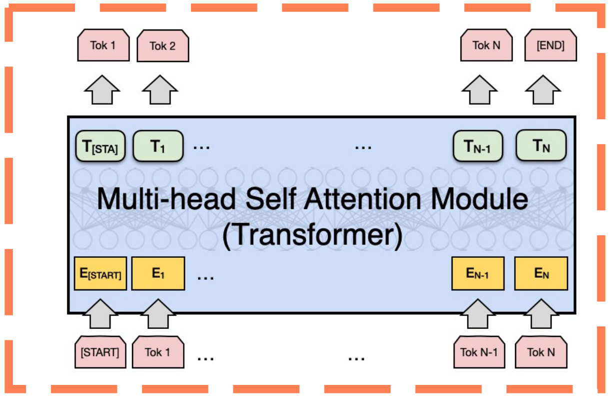


Attention process in NLP

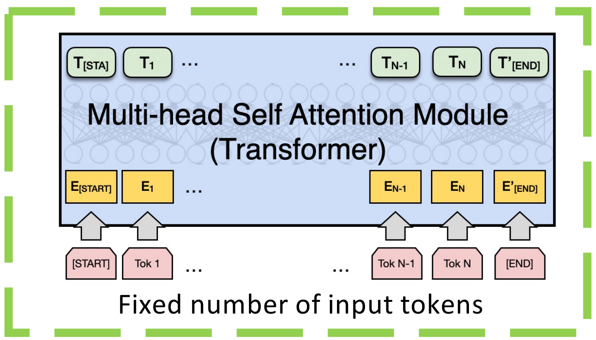
Basic language translation models: Encoder/Decoder

Transformer architecture (no RNNs)

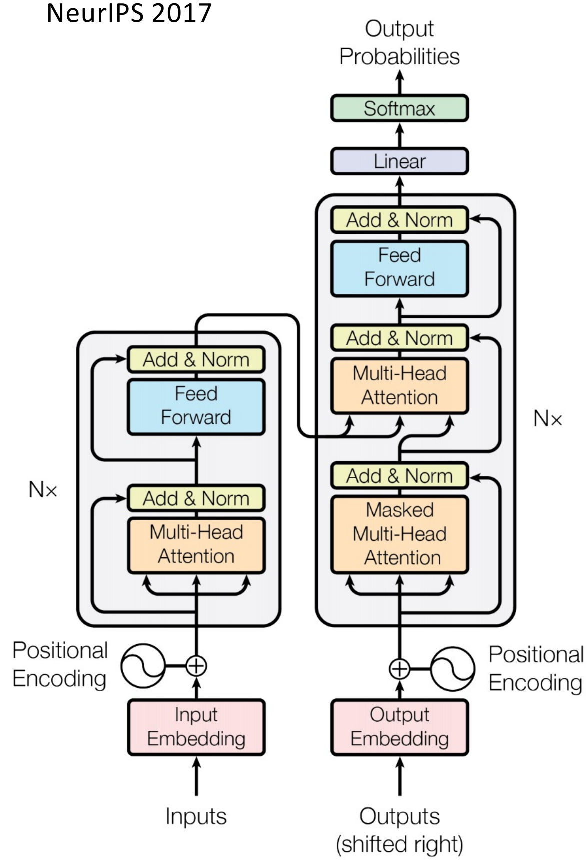
Decoder



Encoder



[Vaswani et al. Attention is all you need]
https://arxiv.org/abs/1706.03762
NeurIPS 2017

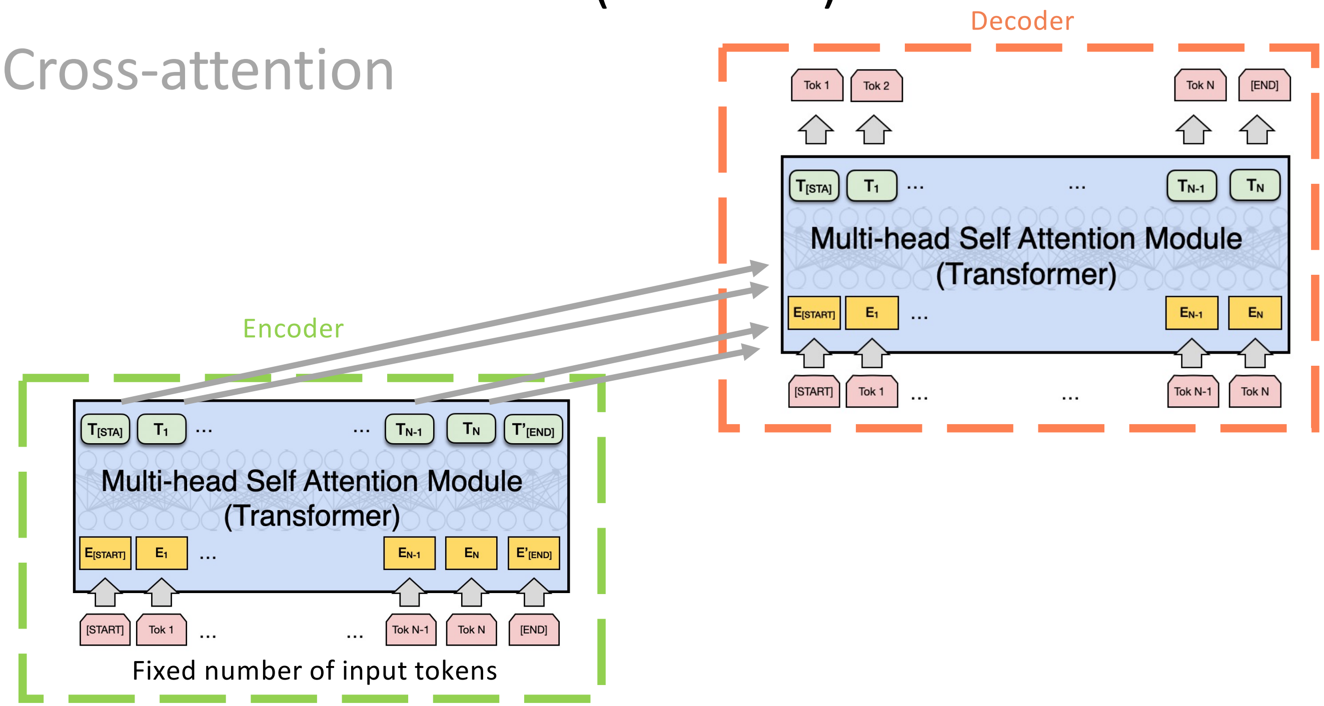


Attention process in NLP

Basic language translation models: Encoder/Decoder

Transformer architecture (no RNNs)

- Cross-attention



[Vaswani et al. Attention is all you need]
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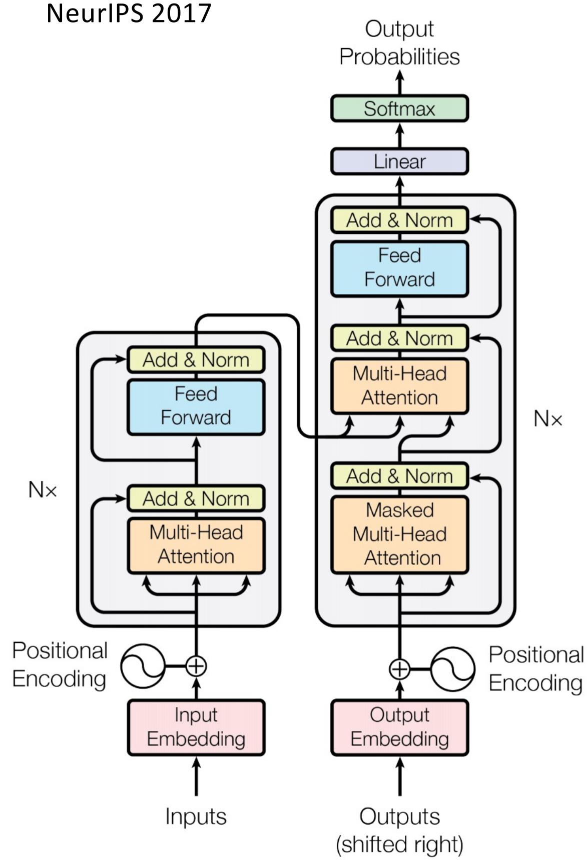
NeurIPS 2017

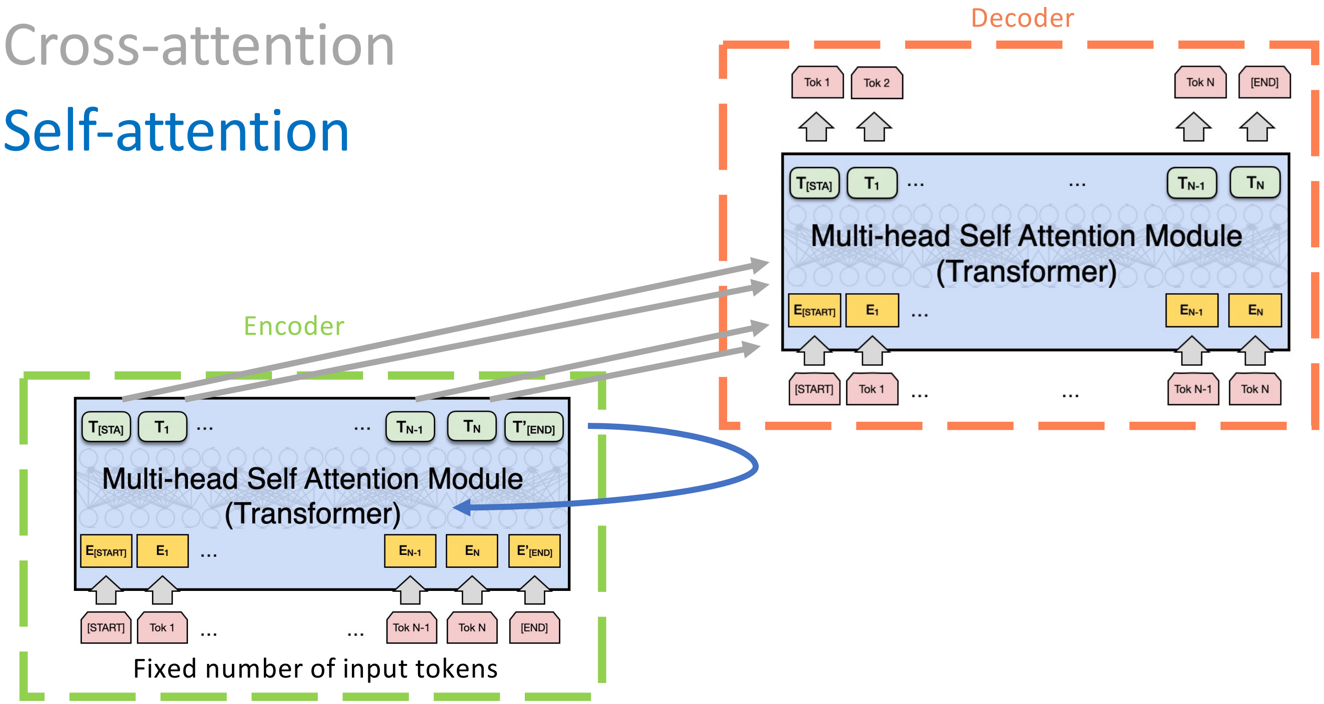


Attention process in NLP

Basic language translation models: Encoder/Decoder

Transformer architecture (no RNNs)

- Cross-attention
- Self-attention



[Vaswani et al. Attention is all you need]
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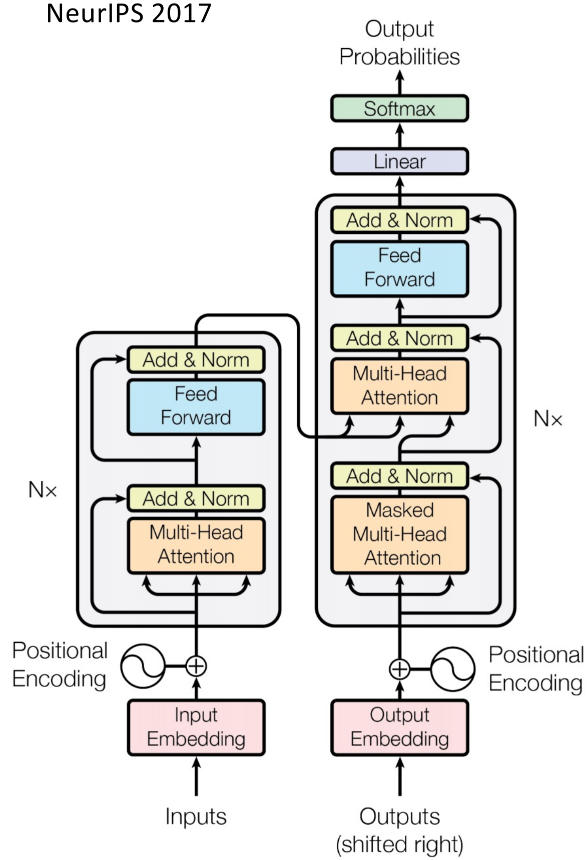
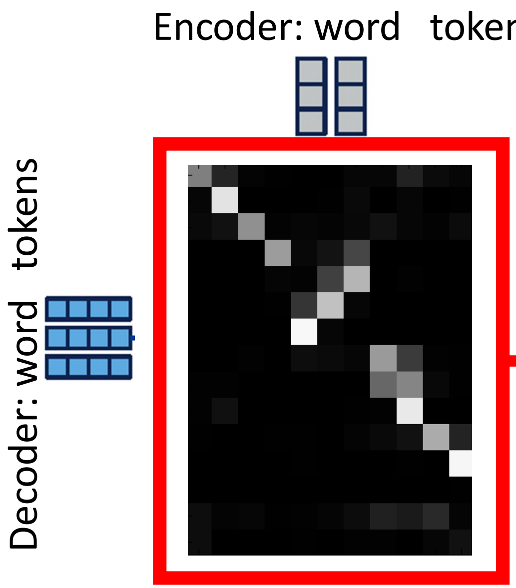
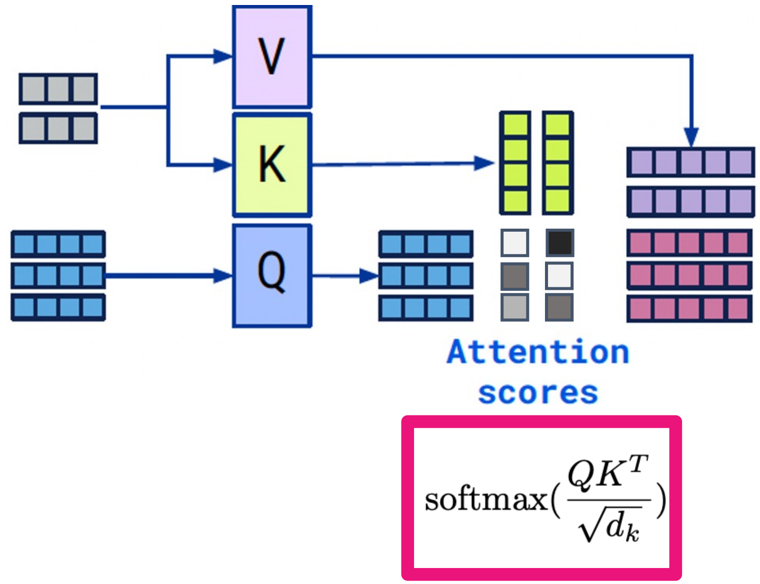
NeurIPS 2017



Attention process in NLP



Cross Attention Module

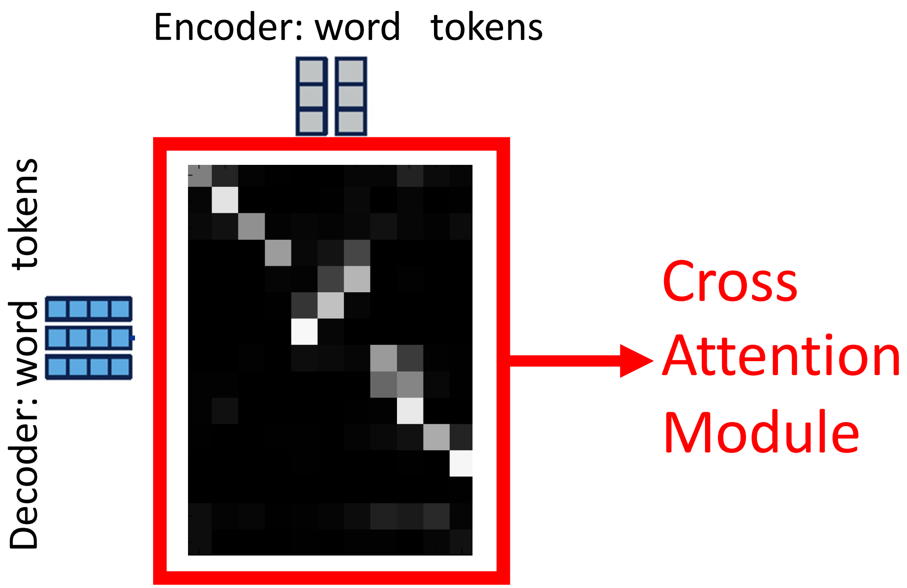


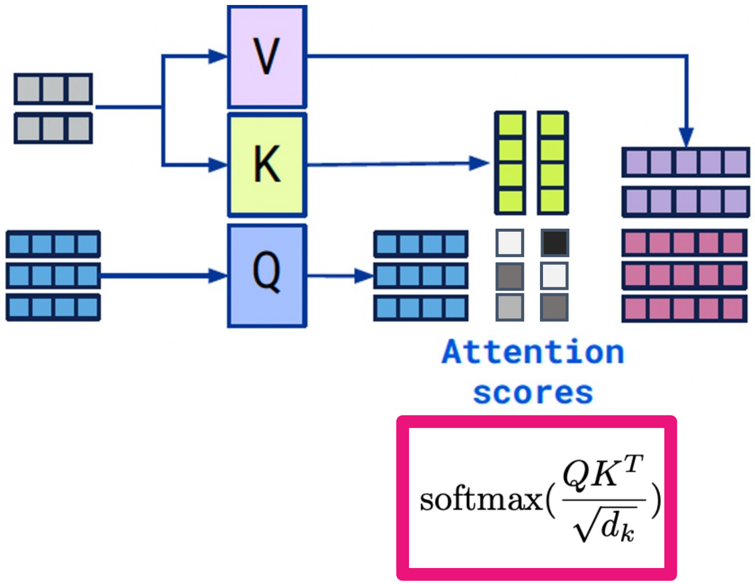
$$\mathrm{Attention}(Q, K, V) = \mathrm{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$

Outline

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

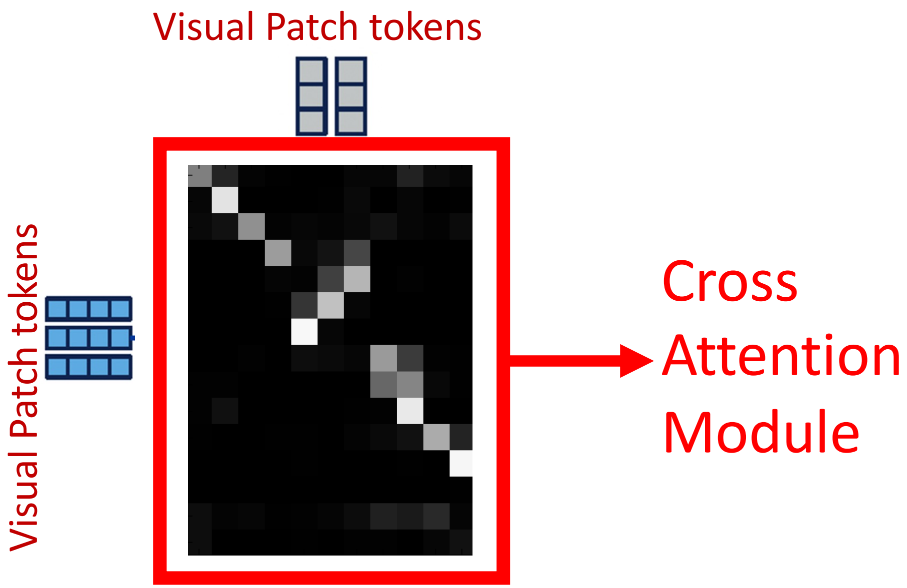
Attention process in NLP

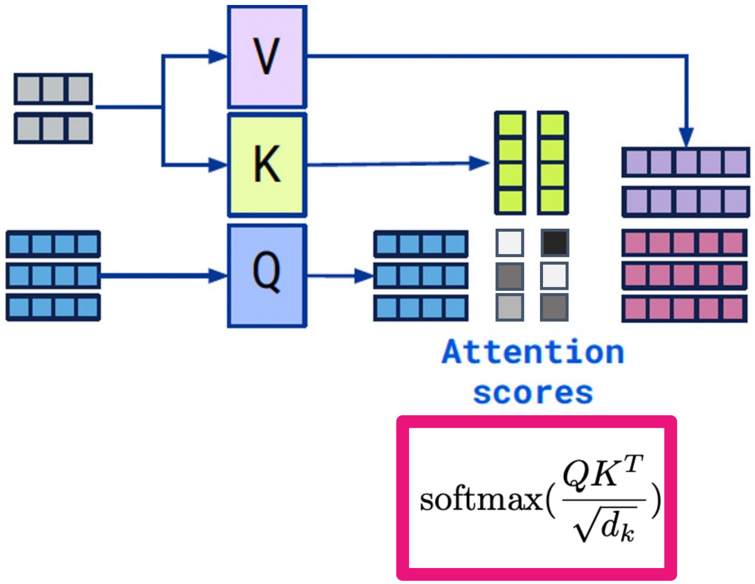




$$\mathrm{Attention}(Q, K, V) = \mathrm{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$

Attention process in Vision





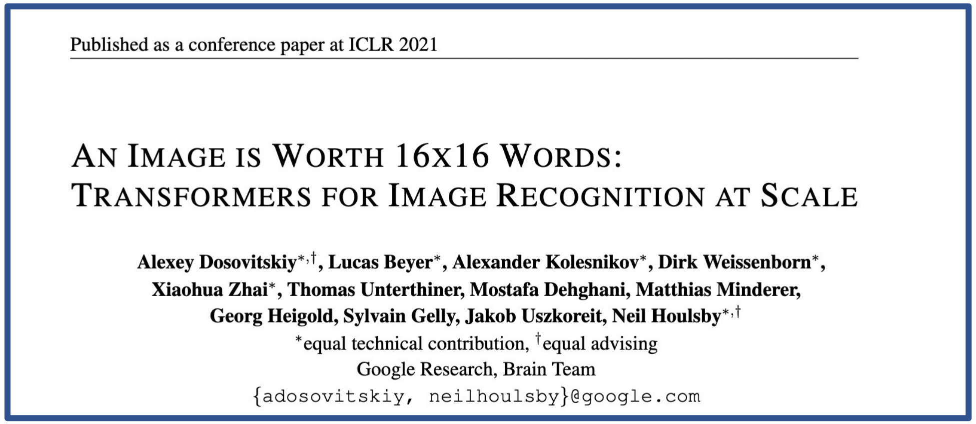
$$\mathrm{Attention}(Q, K, V) = \mathrm{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$

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

Attention process in Vision

Is it possible to mimic this attention-based 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

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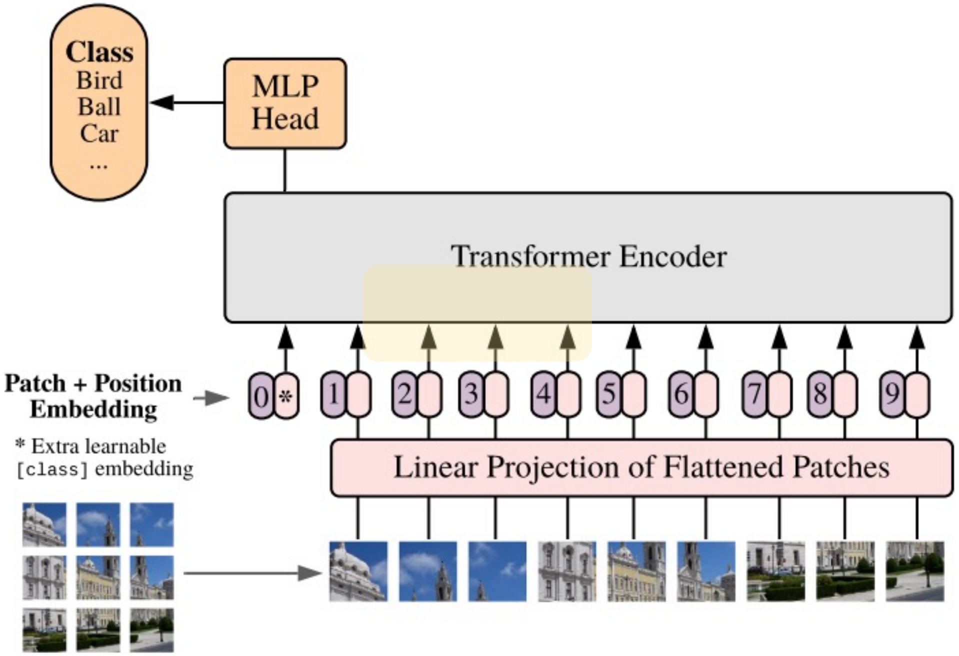
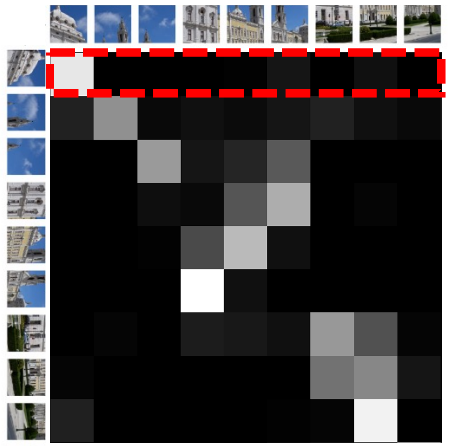
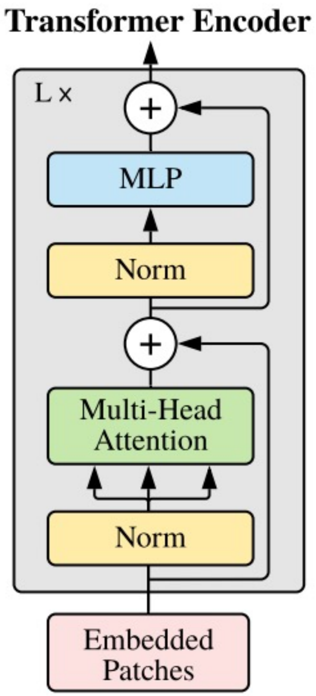
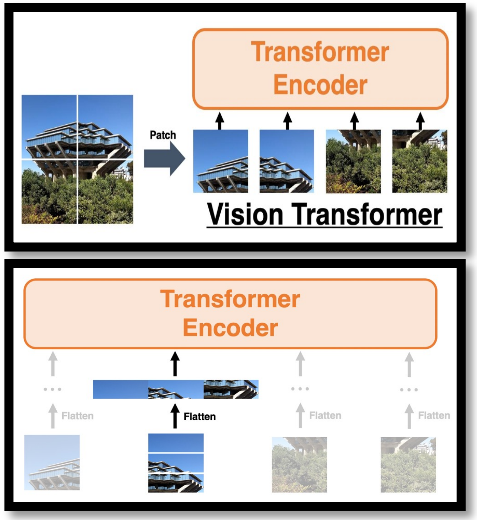




Attention process in Vision





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

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

$N = HW/P^2$

CLS token

$$\mathbf{z}_0 = [\mathbf{x}_{\text{class}};\, \mathbf{x}_p^1\mathbf{E};\, \mathbf{x}_p^2\mathbf{E};\, \cdots;\, \mathbf{x}_p^N\mathbf{E}] + \mathbf{E}_{pos}, \qquad \mathbf{E} \in \mathbb{R}^{(P^2 \cdot C) \times D},\ \mathbf{E}_{pos} \in \mathbb{R}^{(N\boxed{+1}) \times D}$$

$$\mathbf{z'}_\ell = \text{MSA}(\text{LN}(\mathbf{z}_{\ell-1})) + \mathbf{z}_{\ell-1}, \qquad \ell = 1 \ldots L$$

$$\mathbf{z}_\ell = \text{MLP}(\text{LN}(\mathbf{z'}_\ell)) + \mathbf{z'}_\ell, \qquad \ell = 1 \ldots L$$

$$\mathbf{y} = \text{LN}(\mathbf{z}_L^0)$$

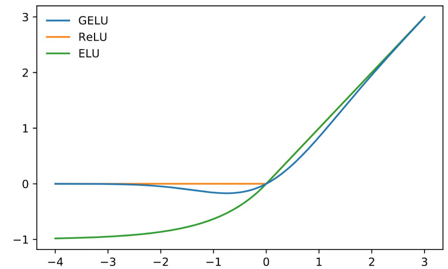
[class=CLS] token: a learnable embedding to the sequence of embedded patches

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

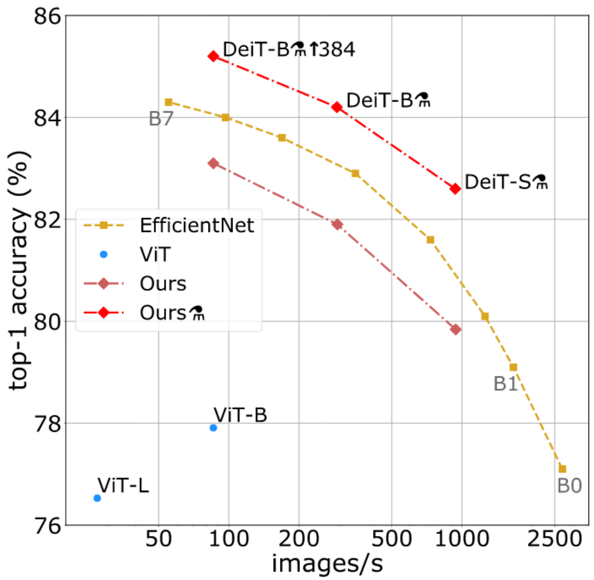


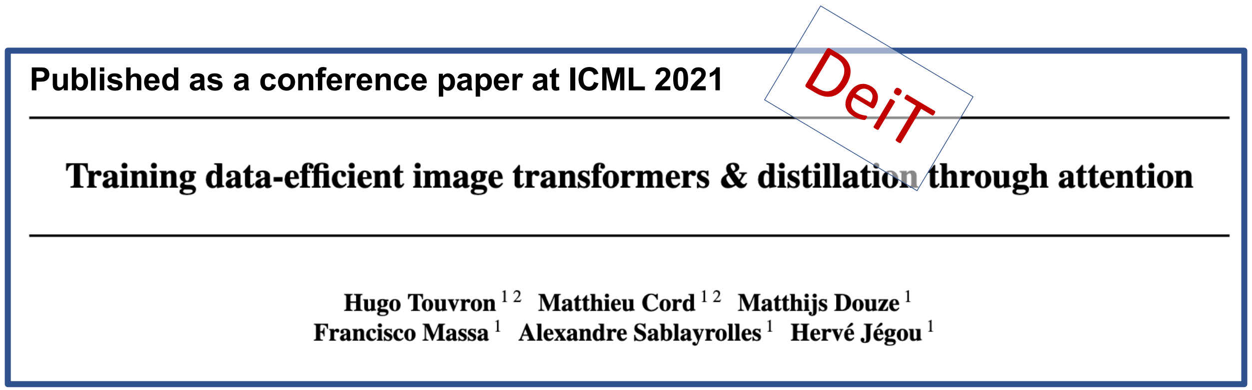
Attention process in Vision

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, …





Published as a conference paper at ICML 2021

Training data-efficient image transformers & distillation through attention

Hugo Touvron [1 2] Matthieu Cord [1 2] Matthijs Douze [1]
Francisco Massa [1] Alexandre Sablayrolles [1] Hervé Jégou [1]