

Attention and transformers

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Transformers: a new revolution in deep learning?

- Transformers [Vaswani et al., 2017] have brought a break-through in natural language processing
 - Bidirectional Encoder Representations from Transformers (BERT, by Google [Brown et al., 2020])
 - Generative Pre-trained Transformer 3 (GPT-3, by OpenAI [Devlin et al., 2019]): 175 billion parameters.
- They contribute to the development of new natural language processing applications (translation, voice assistants, etc.)
- Will they do the same in image analysis?

NB: Our aim through this lesson is to (hopefully!) review the main ideas on attention and transformers, through selected examples. However, this overview is not exhaustive.

What are transformers?

Definition

A transformer is a neural network architecture module that allows the network to **adaptively focus its attention** on certain regions of the data.

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A transformer is a neural network architecture module that allows the network to **adaptively focus its attention** on certain regions of the data.

Transformers today

Nowadays, when people refer to the transformer, they generally mean the architecture proposed by Vaswani et al. in 2017 [Vaswani et al., 2017].

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- Attention in image analysis
- Attention with deep learning

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How do we look at an image?



Credits: Ilya Repin, An Unexpected Visitor, 1884.

How do we look at an image?



Tasks:

- Age of the characters?
- How long has the visitor been away?
- Memorize the objects in the scene.

Credits: Experiments on visual attention
[Yarbus, 1967]

Information used by human visual attention

- Bottom-up:
 - local features (orientation, intensity, junctions, colour, motion, etc.)
 - local features contrast
 - context
- Top-bottom: task related
- Construction of a single *saliency map*

Exploring the image



- Winner-takes all! We focus on the maximum of the saliency map.
- Inhibition of return: We explore the following maxima, at first avoiding those that have already been inspected

Why has visual attention evolved?

- Photoreceptor cells are expensive
- Processing power is limited
- Solution: concentrate the cells in a given region and use the gaze to optimize their use

Why has visual attention evolved?

- Photoreceptor cells are expensive
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 - Solution: concentrate the cells in a given region and use the gaze to optimize their use
-
- The same arguments apply to artificial visual systems
 - + Some degree of invariance
 - + Interpretability

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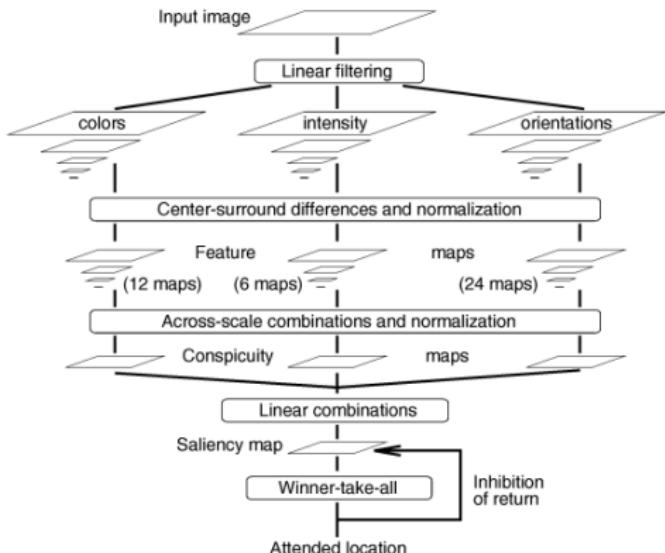
- Attention in human vision
- **Attention in image analysis**
- Attention with deep learning

3 The transformer architecture and its applications in computer vision

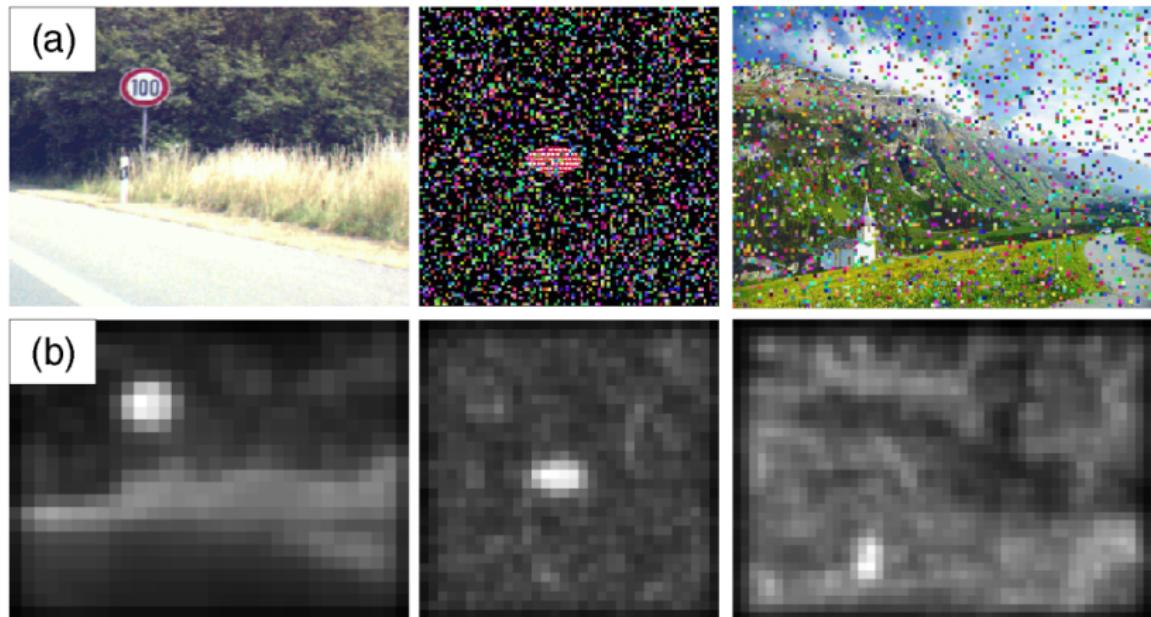
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A classical bottom-up model

- Itti et al. [Itti et al., 1998] proposed a model inspired by the primate visual system.
- It only uses low-level information.



Examples [Itti et al., 1998]



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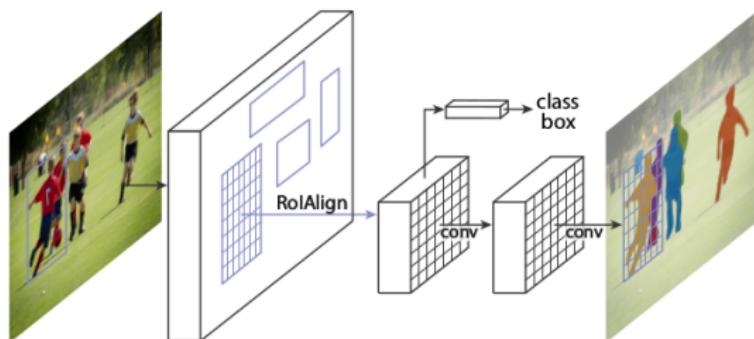
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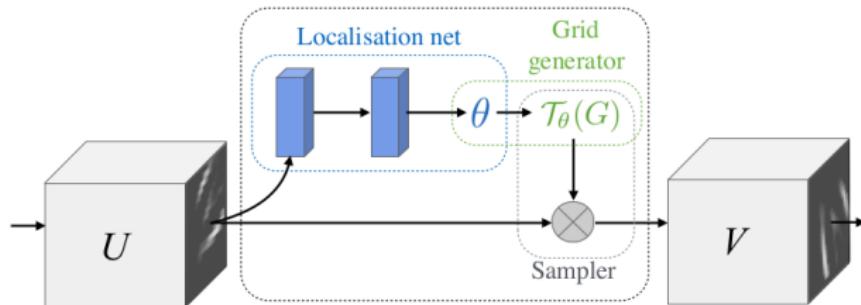
Region proposal networks [Ren et al., 2015]

- Detection and instance segmentation methods use region proposal networks, that can be interpreted as an attention mechanism.
- The region proposal network gives the coordinates of the rectangle and a probability that it contains an object.

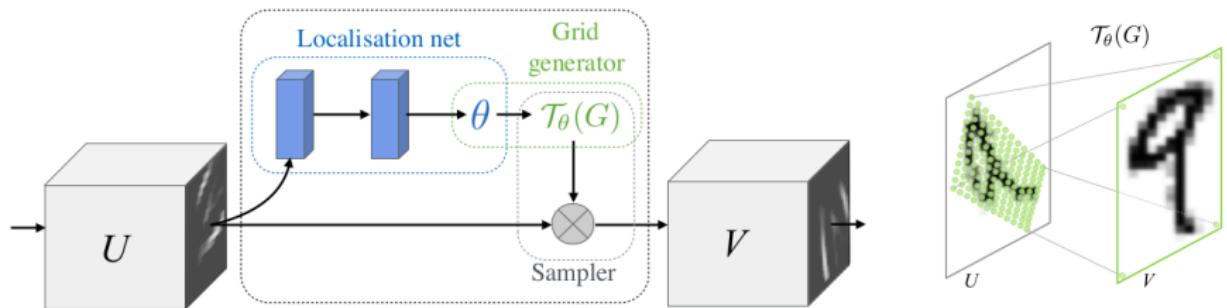


A region proposal module is used by mask R-CNN [He et al., 2017]

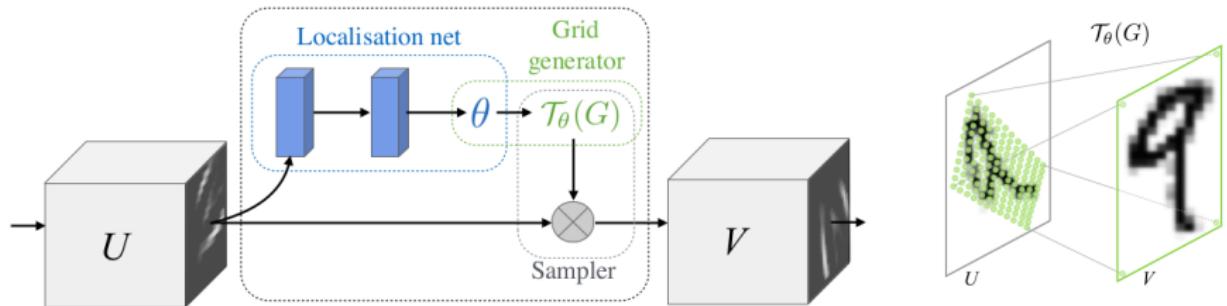
Spatial transformers [Jaderberg et al., 2016]



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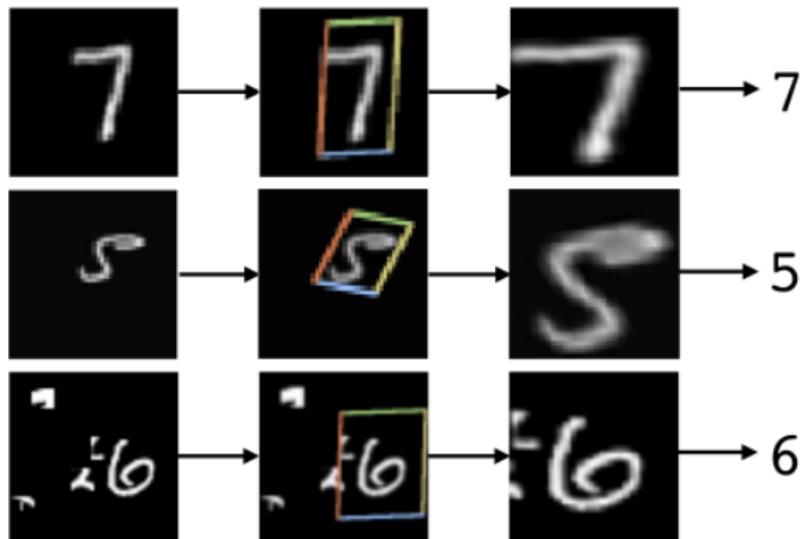


Spatial transformers [Jaderberg et al., 2016]

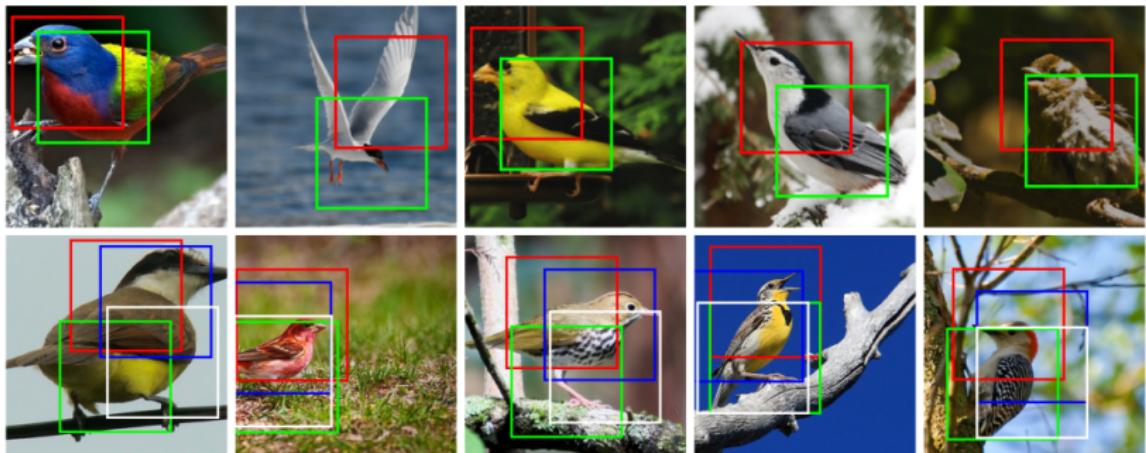


- This module can be added to any convolutional network
- End-to-end learning

Spatial transformers illustration



Spatial transformers with multiple heads



Remarks

- Note that in the first row one transformer tends to focus on the bird's head, while the second is centered on the body
- In the second row, the specialization is less apparent

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Transformer avatars

Some examples

- Graph transformers [Lecun et al., 1998]
- Transforming auto-encoders [Hinton et al., 2011]
- Spatial transformers [Jaderberg et al., 2016]

The transformer [Vaswani et al., 2017].

Today, when people refer to the transformer, they generally mean the architecture proposed by Vaswani et al. in 2017.

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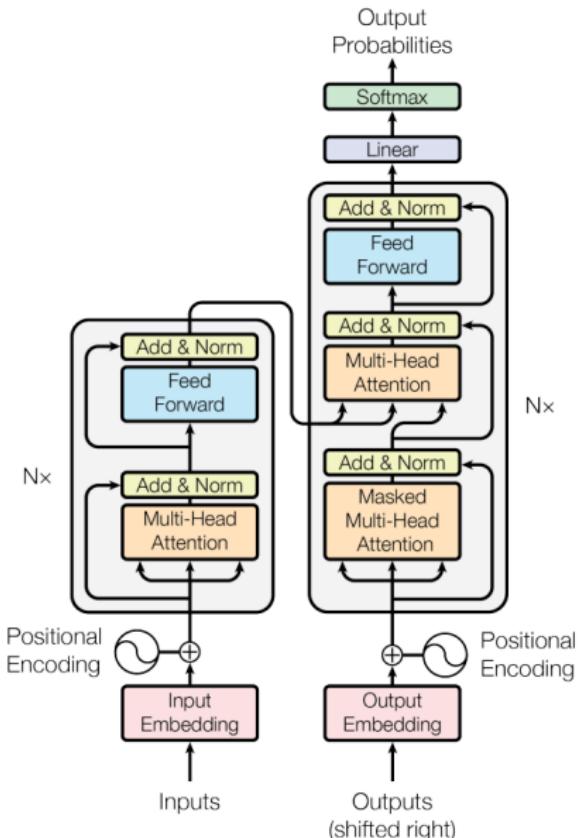
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The rise of transformers

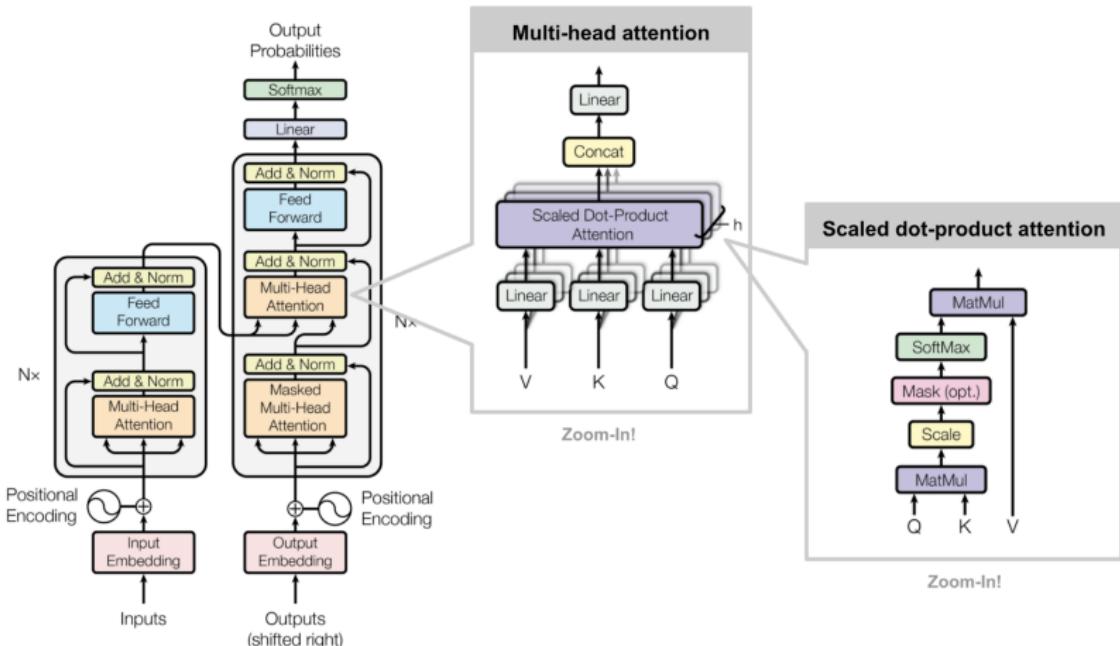
The paper that started it all

Vaswani et al., Attention is all you need, Neurips 2017.

This architecture was developed for text processing.



Architecture [Vaswani et al., 2017]



Credits: <https://lilianweng.github.io/lil-log/2018/06/24/attention-attention.html>

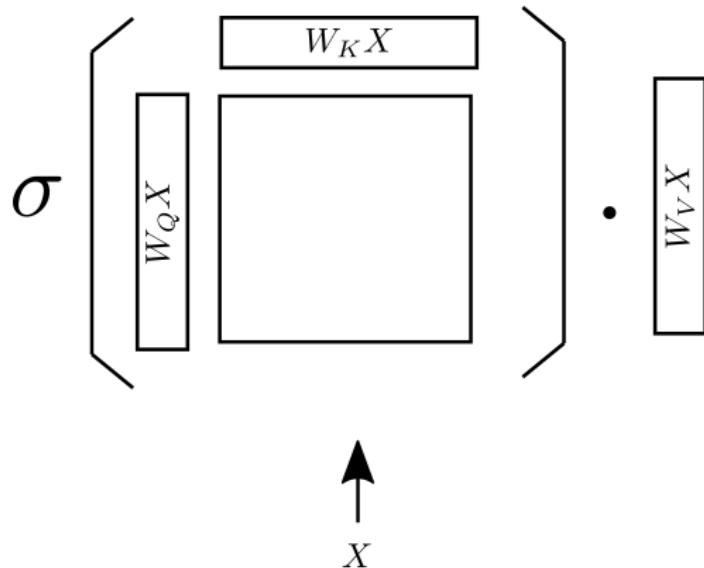
Scaled dot-product attention

Definition

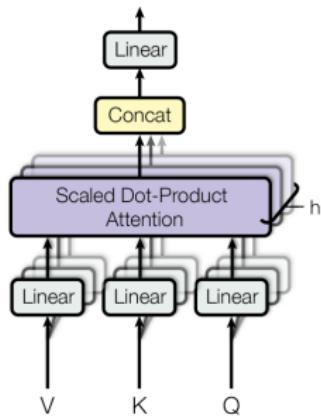
$$Att(Q, K, V) = \sigma \left(\frac{QK^t}{\sqrt{d_K}} \right) V$$

- V : values; K : keys; Q : queries.
- d_K is the length of K .
- σ : row-wise soft-max.

Self-attention



Multi-head attention

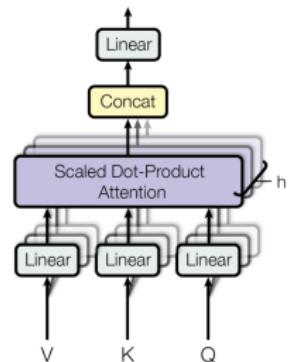


- Matrices W_Q , W_V and W_V are learnable.
- h heads work in parallel.

Application of scaled dot-product attention

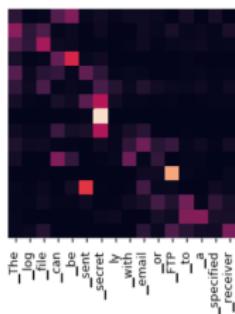
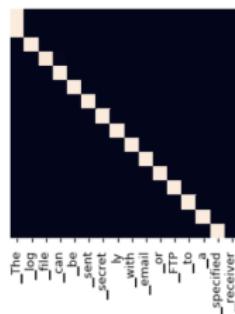
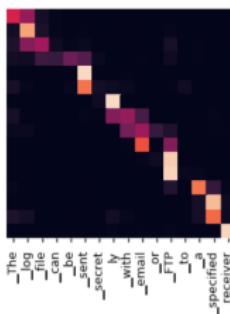
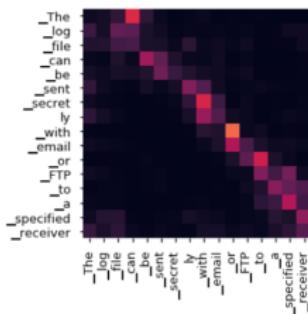
$$\begin{aligned} \text{Att}(W_Q Q, W_K K, W_V V) &= \sigma \left(\frac{W_Q Q (W_K K)^t}{\sqrt{d_{K'}}} \right) V W_V \\ &= \sigma \left(\frac{Q' (K')^t}{\sqrt{d_{K'}}} \right) V' \end{aligned}$$

Dot-product self-attention illustration



In the case of self-attention:

- $V = K = Q = X$



Credits:

<https://nlp.seas.harvard.edu/2018/04/03/attention>

Success of transformers in natural language processing

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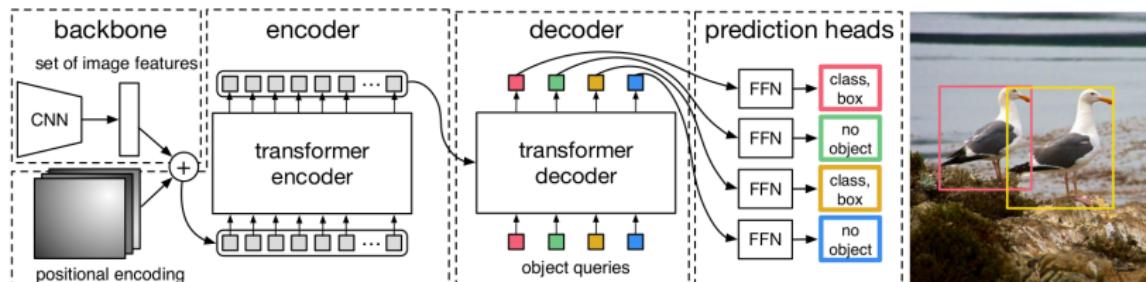
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- **Detection transformer**
- Vision transformer

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DETR: detection transformer [Carion et al., 2020]

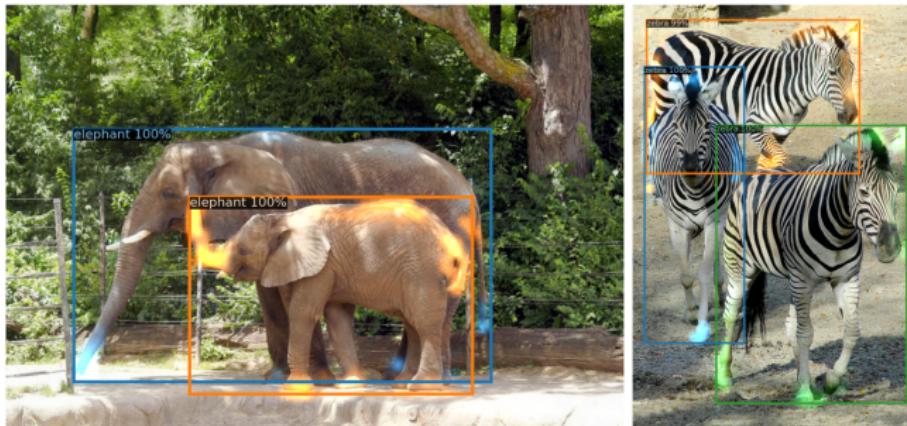


Remarks

- Convolutional layers are used to encode the image
- After a 1×1 convolutional layers, each feature map is flattened and considered as an input for the transformer encoder
- Decoder outputs are processed by a feed-forward network (FFN) to generate the box coordinates and label (possibly \emptyset).

Results and comments

- Similar accuracy and run-time performance to Faster R-CNN on the COCO object detection dataset
- Optimization was apparently difficult (extra losses, for instance)



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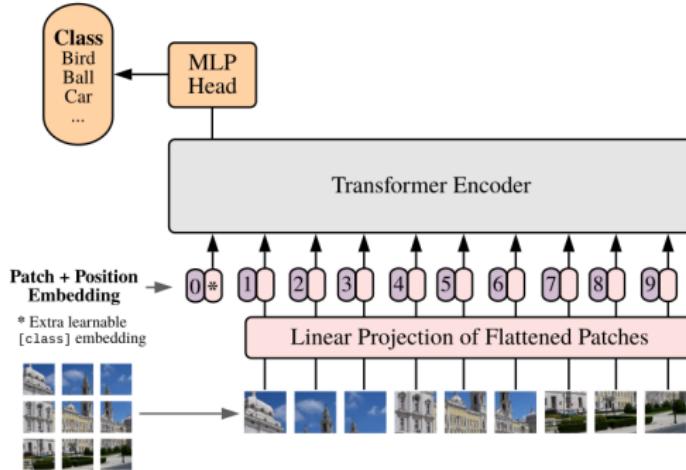
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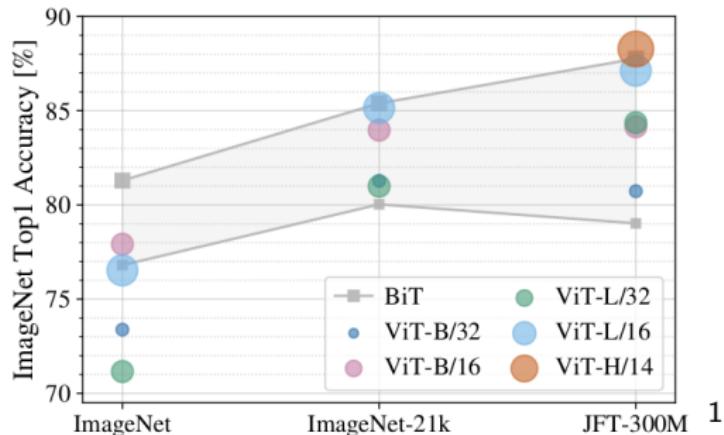
ViT: the vision transformer [Dosovitskiy et al., 2021]



Remarks

- Only uses the transformer encoder
- Directly takes as inputs image patches
- Achieves state-of-the-art results when pre-trained on very large databases (Google's JFT-300M dataset)

ViT results



- ViT-H/14 requires 2500 TPUv3-core-days for pre-training
- But: “Training data-efficient image transformers & distillation through attention” [Touvron et al., 2021].

¹BiT: Big transfer [Kolesnikov et al., 2020]

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Discussion

Convolutional neural networks

- Convolutional networks are based on two inductive biases:

Transformers

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Transformers

- Transformers, like fully connected layers, do not make any assumptions on the data structure
 - Localization is brought by a positional encoding

Discussion

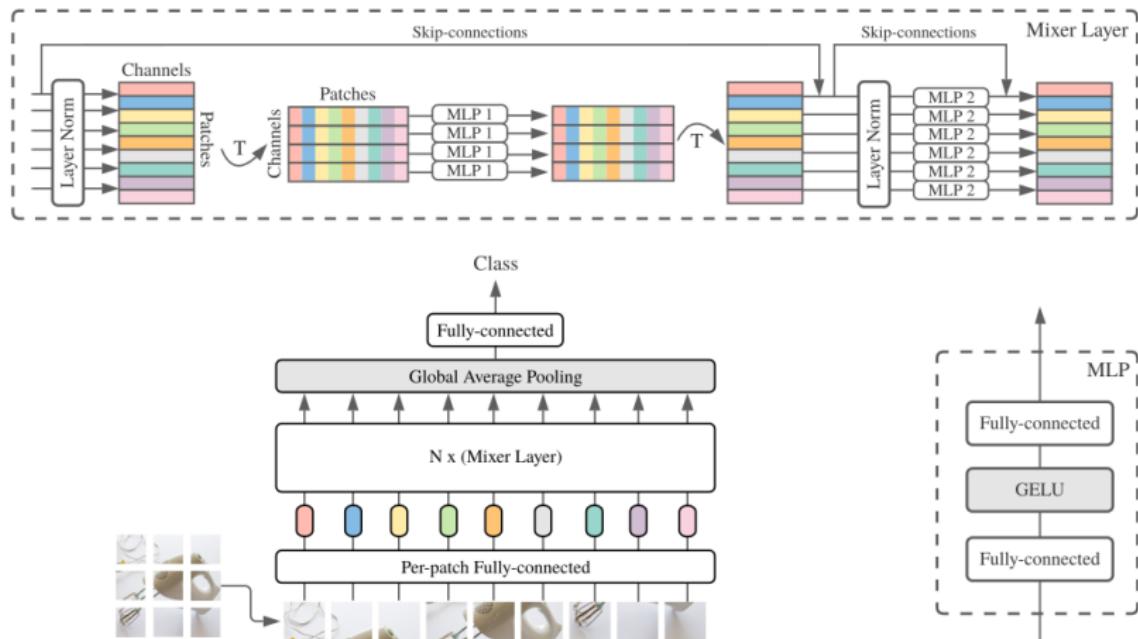
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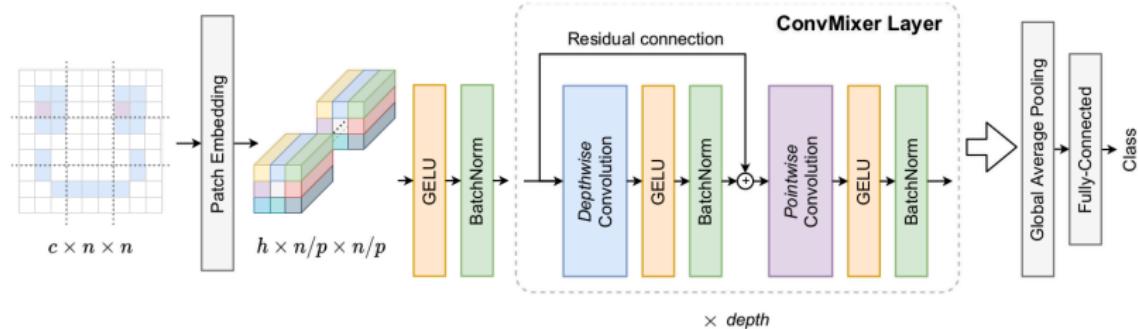
Transformers

- Transformers, like fully connected layers, do not make any assumptions on the data structure
 - Localization is brought by a positional encoding
- Are transformers a smart way of analysing images with fully connected layers?

MLPs is all you need [Tolstikhin et al., 2021]



Patches are all you need? [submitted to ICLR 2022]



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