Attention and transformers

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Contents

Contents

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

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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].

Contents

Contents

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

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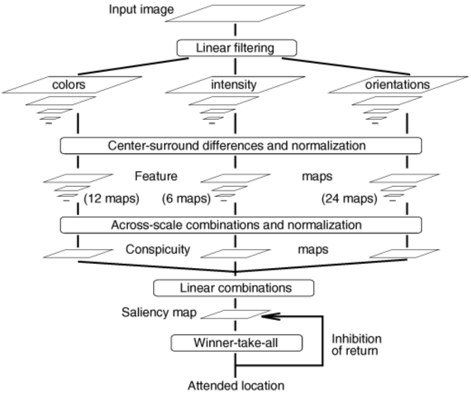
- The same arguments apply to artificial visual systems

+ Some degree of invariance
+ Interpretability

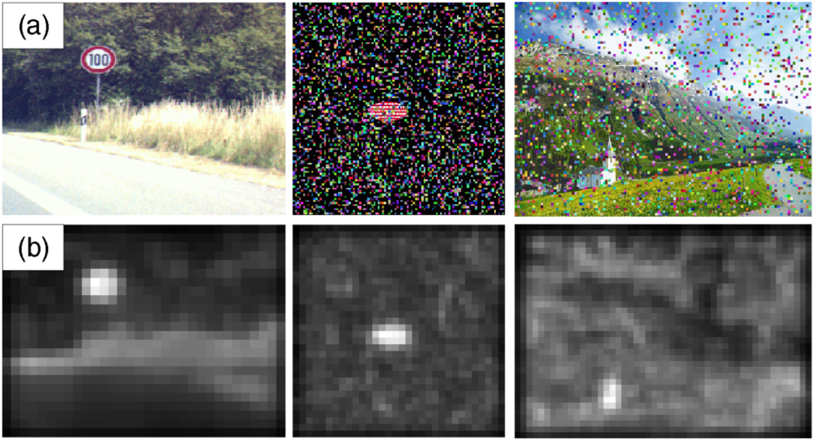
Contents

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.



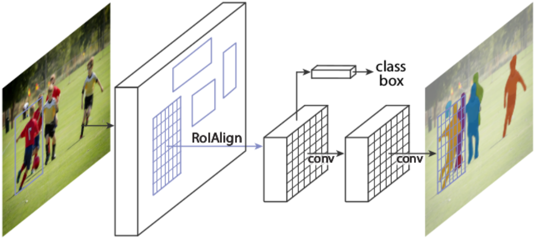
Examples [Itti et al., 1998]



Contents

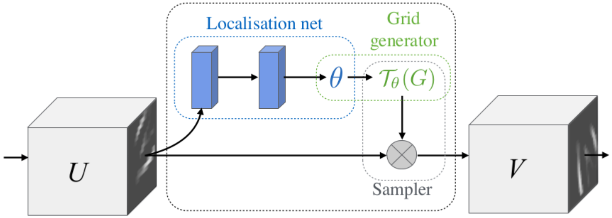
Region proposal networks [Ren et al., 2015]

- 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.

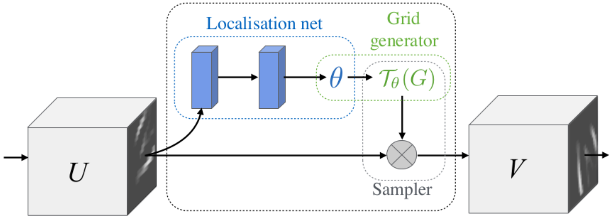


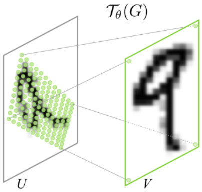
A region proposal module is used by mask R-CNN [He et al., 2017]

Spatial transformers [Jaderberg et al., 2016]

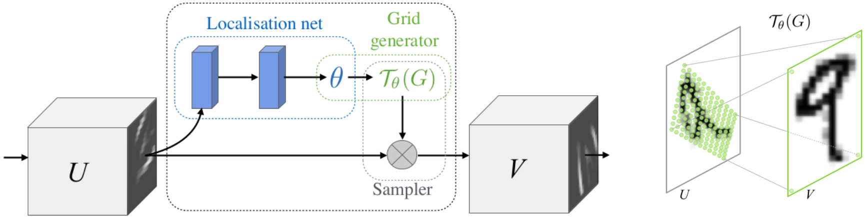


Spatial transformers [Jaderberg et al., 2016]



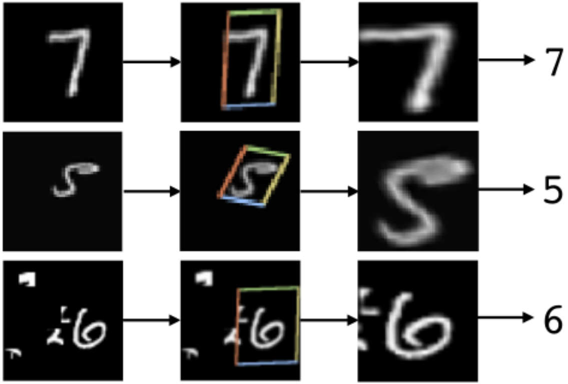


Spatial transformers [Jaderberg et al., 2016]

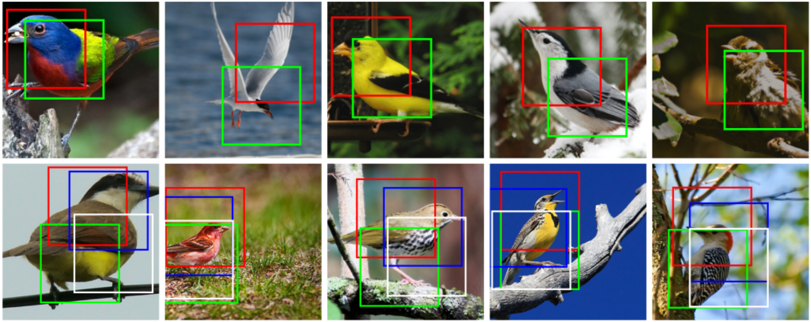


- This module can be added to any convolutional network
- End-to-end learning

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

Contents

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.

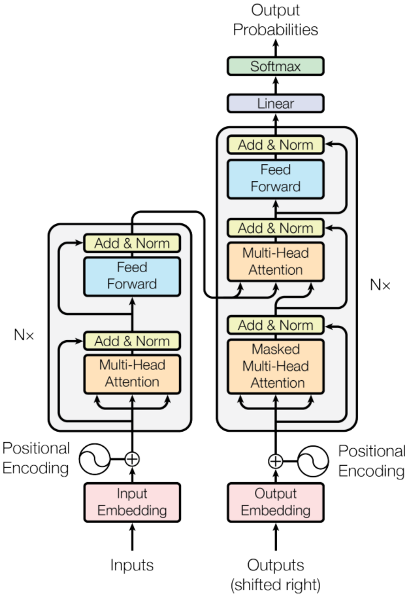
Contents

The rise of transformers

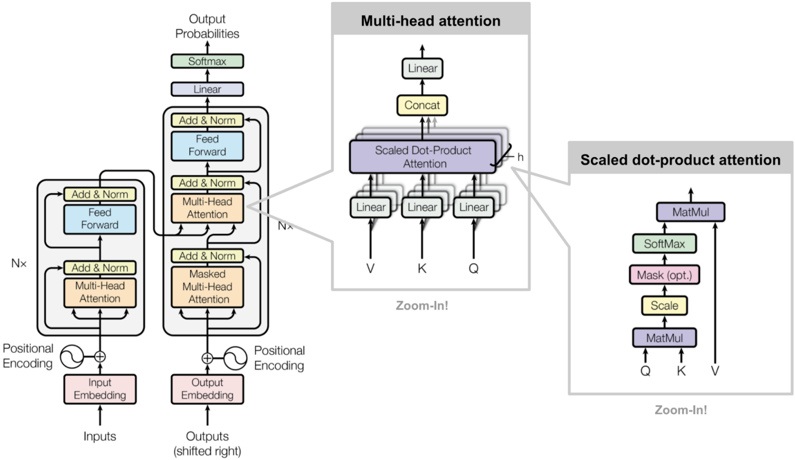
The paper that started it all

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

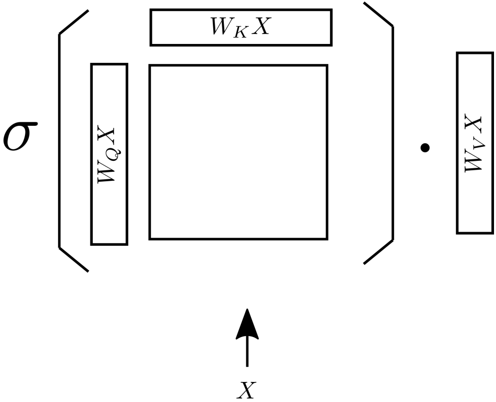
Scaled dot-product attention

Definition

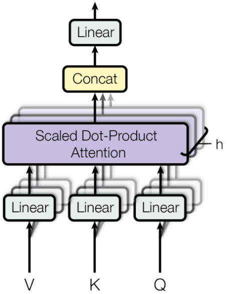
$$Att(Q, K, V) = \sigma\left(\frac{QK^t}{\sqrt{d_K}}\right)V$$

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

Self-attention

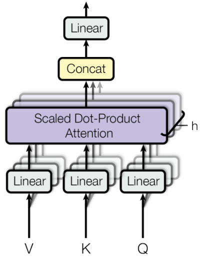


Multi-head attention



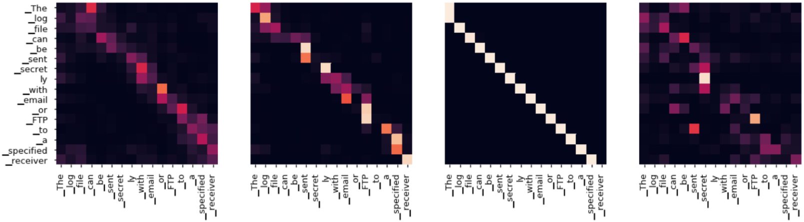
- Matrices W_Q, W_V and W_V are learnable.
- h heads work in parallel.

Dot-product self-attention illustration



In the case of self-attention:

- $V = K = Q = X$



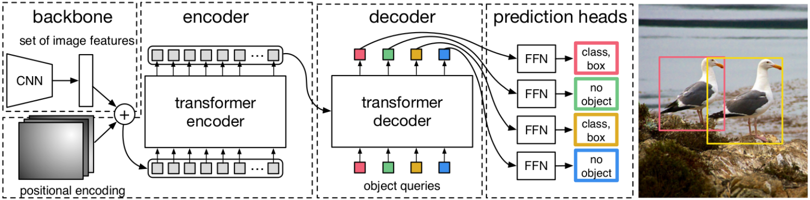
Credits:
https://nlp.seas.harvard.edu/2018/04/03/a

Success of transformers 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.

Contents

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

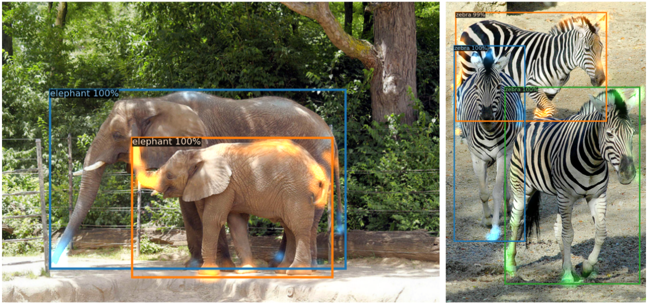


Remarks

- 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 $\emptyset$).

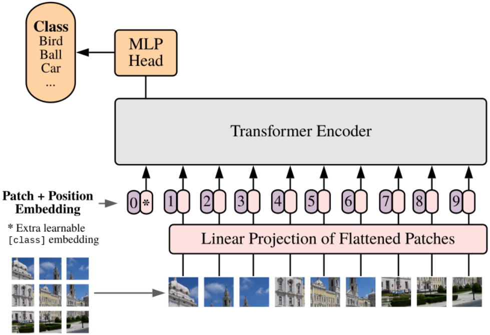
Results and comments

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



Contents

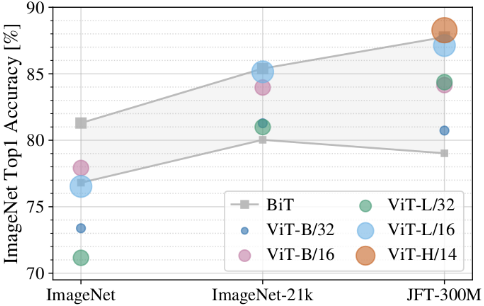
ViT: the vision transformer [Dosovitskiy et al., 2021]



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

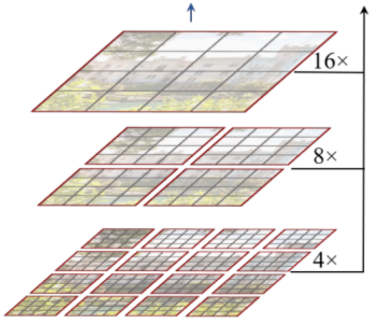


[1]

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

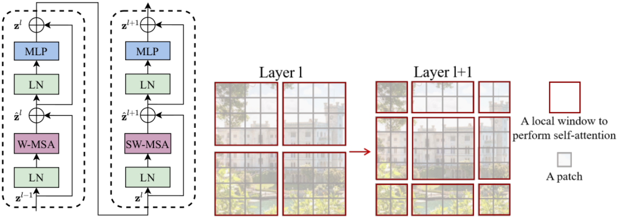
[1] BiT: Big transfer [Kolesnikov et al., 2020]

Shifted window (SWIN) transformer [Liu et al., 2021]



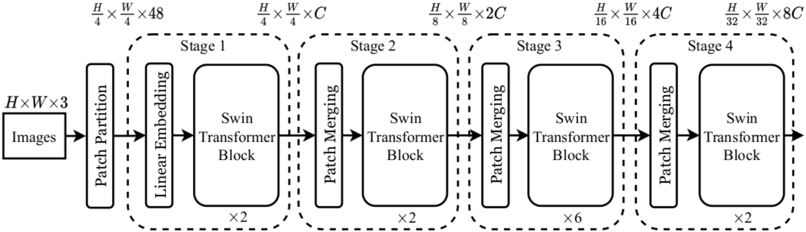
- The transformer modules are applied within each window
- Hierarchical approach: patches are merged at some levels
- The model uses **shifted windows**

SWIN blocks



- Multi-headed self-attention with regular (W-MSA) and shifted (SW-MSA) windowing configurations are applied alternatively

SWIN architecture



Results

The Swin transformer obtains better results than previous methods on:

- ImageNet 1k and 22k classification
- COCO object detection and image segmentation
- ADE20k semantic segmentation

Contents

Discussion

Convolutional neural networks

- Convolutional networks are based on two inductive biases:

Transformers

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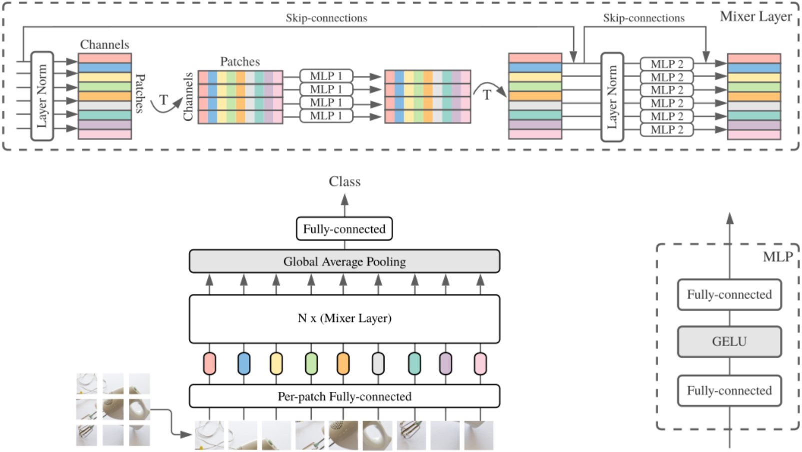
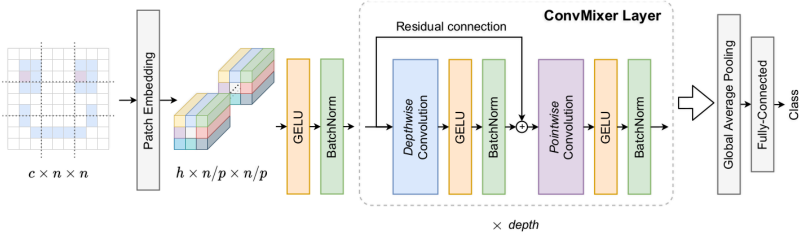
Transformers

- Transformers, like fully connected layers, do not make any assumptions on the data structure
  - Localization is brought by a positional encoding
- 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? [Trockman and Kolter, 2022]



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