Attention and transformers

E. Decencière

Mines Paris
PSL Research University
Center for Mathematical Morphology

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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
- 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 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].

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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

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- The same arguments apply to artificial visual systems

+ Some degree of invariance
+ Interpretability

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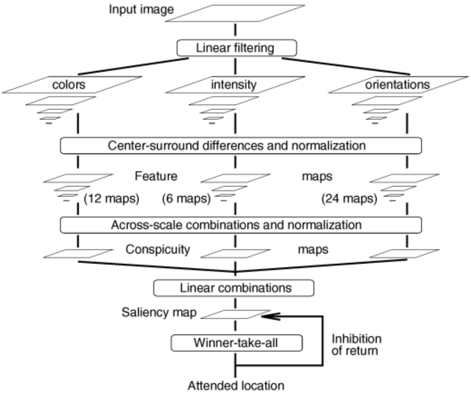
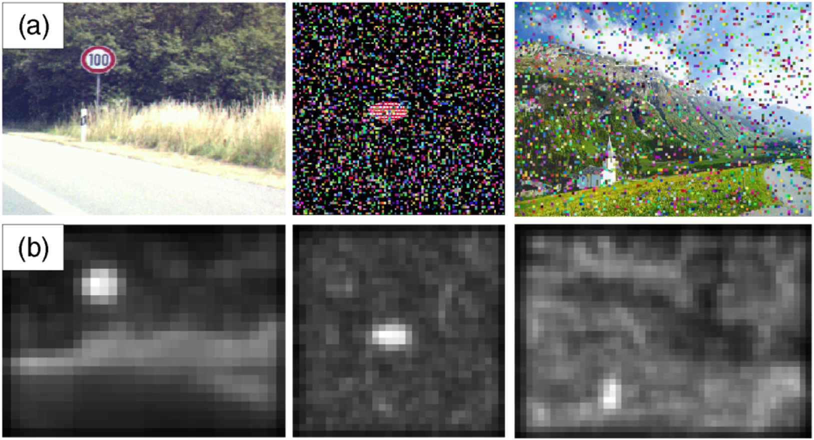
A classical bottom-up model

- 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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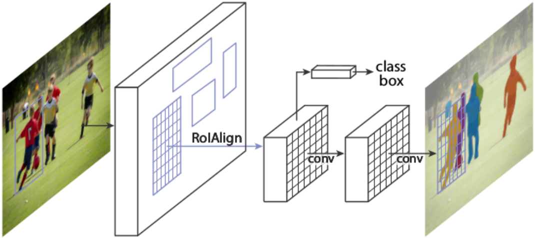
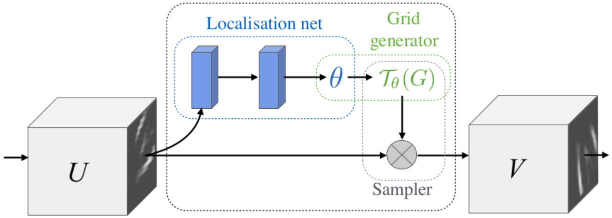
Region proposal networks [Ren et al., 2015]

- 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.

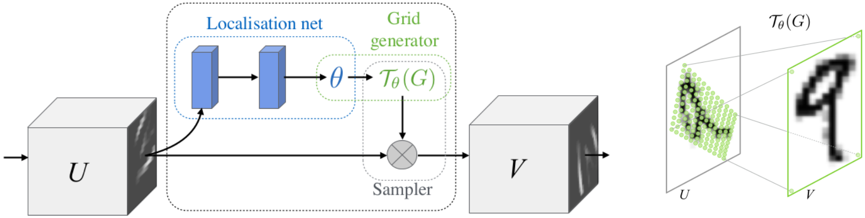


A region proposal module is used by mask R-CNN [He et al., 2017]

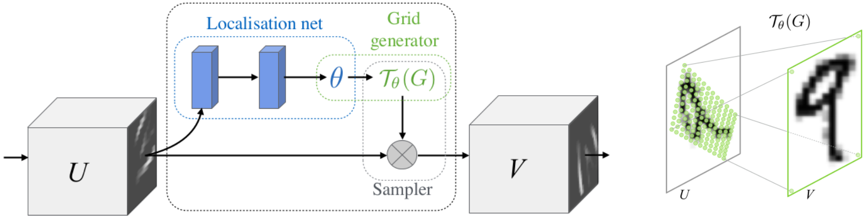
Spatial transformers [Jaderberg et al., 2016]



Spatial transformers [Jaderberg et al., 2016]

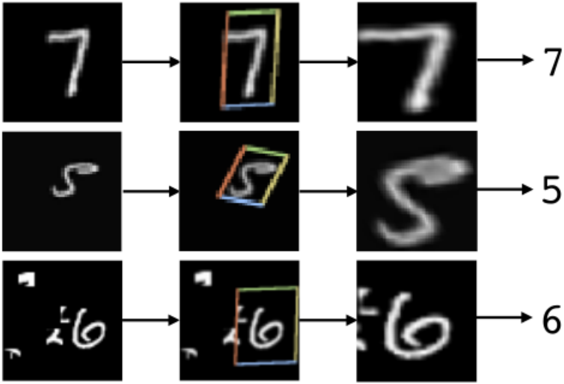


Spatial transformers [Jaderberg et al., 2016]

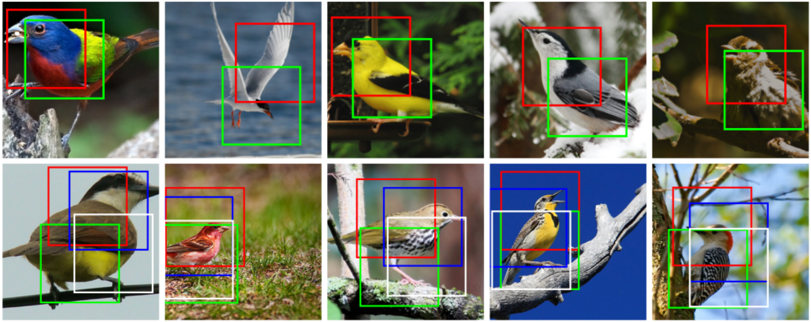


- This module can be added to any convolutional network
- End-to-end learning

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

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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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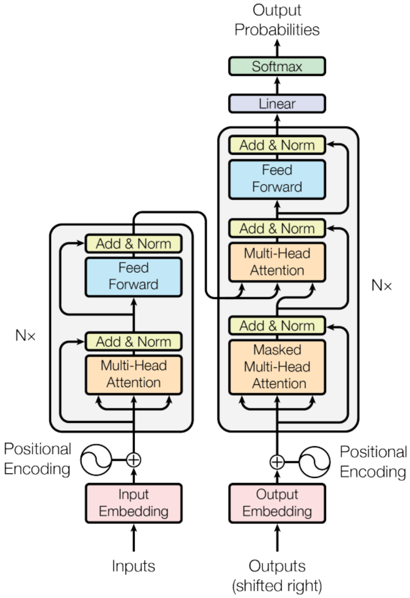
The rise of transformers

The paper that started it all

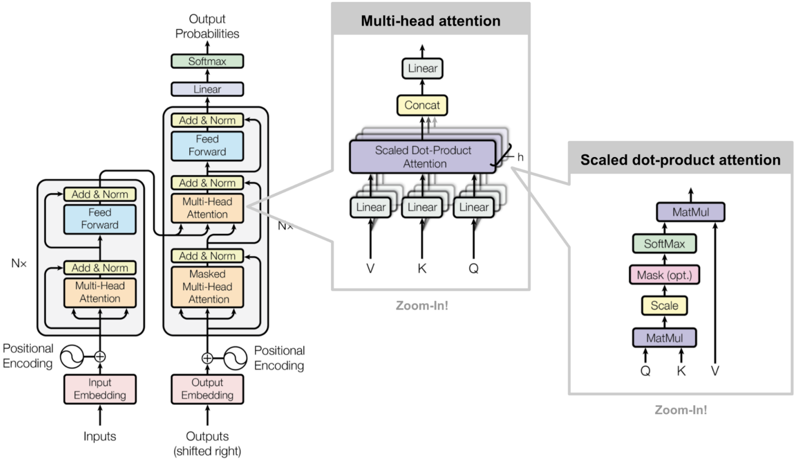
Vaswani et al., Attention is all you need, Neurips 2017.

This architecture was developed for text processing.

NB: the first general differentiable attention mechanism was published in 2015 [Bahdanau et al., 2015].



Architecture [Vaswani et al., 2017]



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

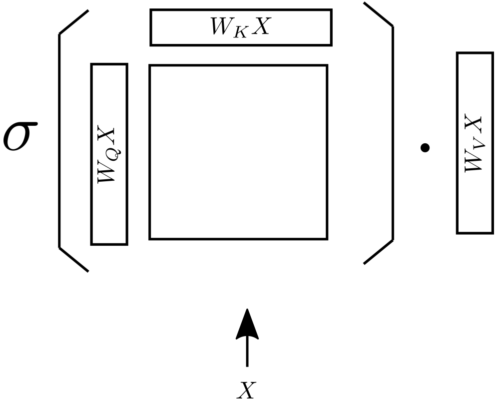
Scaled dot-product attention

Definition

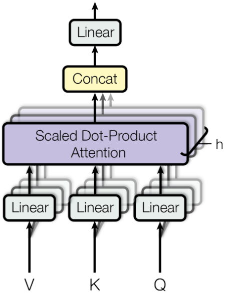
$$Att(Q, K, V) = \sigma\left(\frac{QK^t}{\sqrt{d_K}}\right)V$$

- 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.

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.
- Generative Pre-trained Transformer 4 (2023) : undisclosed number of parameters.

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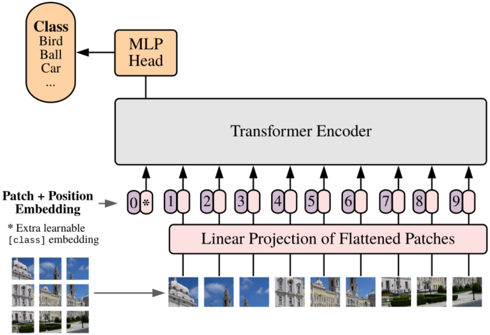
ViT: the vision transformer [Dosovitskiy et al., 2021]



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)

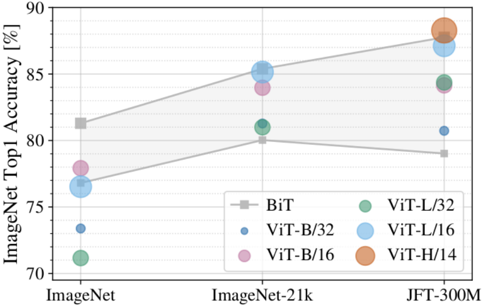
ViT results

	Ours-JFT (ViT-H/14)	Ours-JFT (ViT-L/16)	Ours-I21K (ViT-L/16)	BiT-L (ResNet152x4)	Noisy Student (EfficientNet-L2)
ImageNet	**88.55** ± 0.04	87.76 ± 0.03	85.30 ± 0.02	87.54 ± 0.02	88.4/88.5*
ImageNet ReaL	**90.72** ± 0.05	90.54 ± 0.03	88.62 ± 0.05	90.54	90.55
CIFAR-10	**99.50** ± 0.06	99.42 ± 0.03	99.15 ± 0.03	99.37 ± 0.06	–
CIFAR-100	**94.55** ± 0.04	93.90 ± 0.05	93.25 ± 0.05	93.51 ± 0.08	–
Oxford-IIIT Pets	**97.56** ± 0.03	97.32 ± 0.11	94.67 ± 0.15	96.62 ± 0.23	–
Oxford Flowers-102	99.68 ± 0.02	**99.74** ± 0.00	99.61 ± 0.02	99.63 ± 0.03	–
VTAB (19 tasks)	**77.63** ± 0.23	76.28 ± 0.46	72.72 ± 0.21	76.29 ± 1.70	–
TPUv3-core-days	2.5k	0.68k	0.23k	9.9k	12.3k

Remarks

- Models pre-trained on JFT-300M
- Note the required processing power

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]

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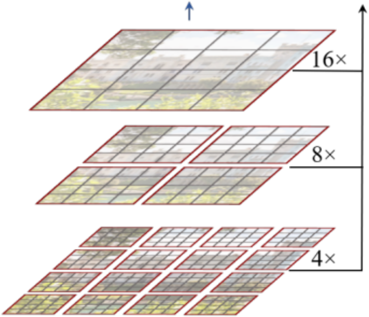
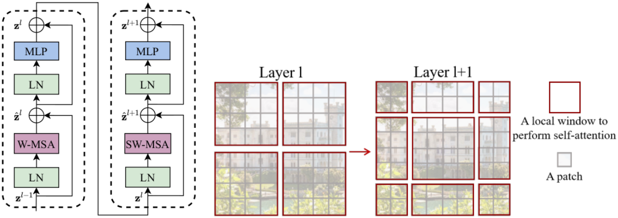
Shifted window (SWIN) transformer [Liu et al., 2021]



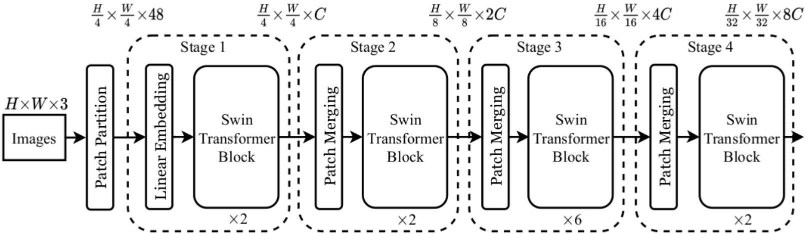
- The transformer modules are applied within each window
- Hierarchical approach: patches are merged at some levels
- The model uses **shifted windows**

SWIN blocks



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

SWIN architecture

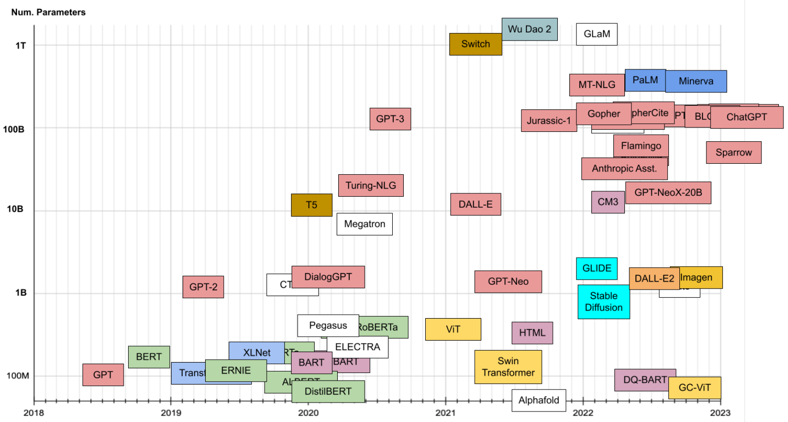


Results

The Swin transformer obtains better results than previous methods on:

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

Transformers chronology [Amatriain, 2023]



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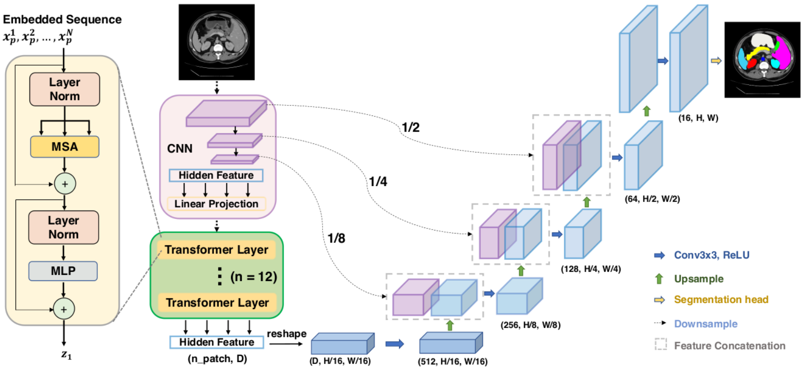
TransUNet [Chen et al., 2021]



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Task: segment the rabbits that are in danger

Credits: Images generated by DALL.E 2

Discussion

Convolutional neural networks

- Convolutional networks are based on two inductive biases:

Transformers

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Transformers

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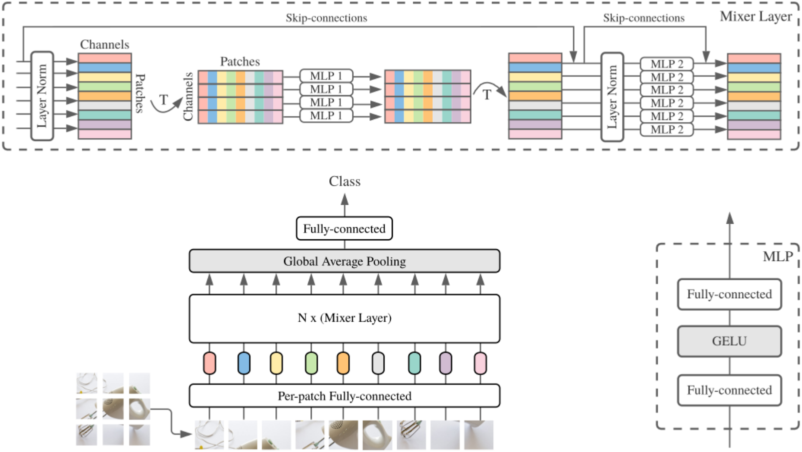
Transformers

- 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]



And the winner is ...

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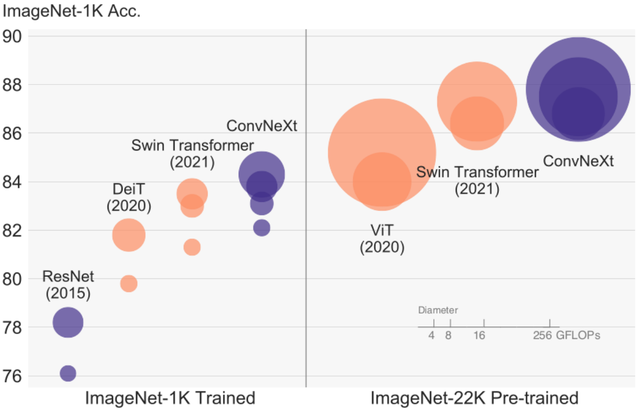

Competition is still ongoing [Liu et al., 2022]...

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