

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?

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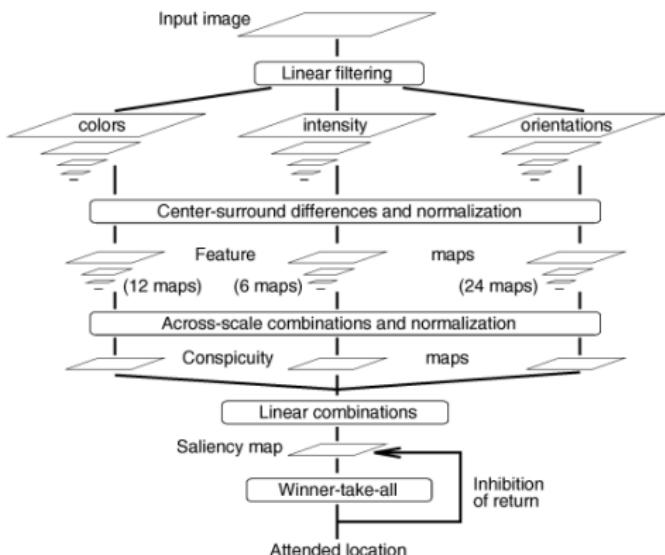
- Attention in human vision
- **Attention in image analysis**
- Attention with deep learning

3 The transformer architecture and its applications in computer vision

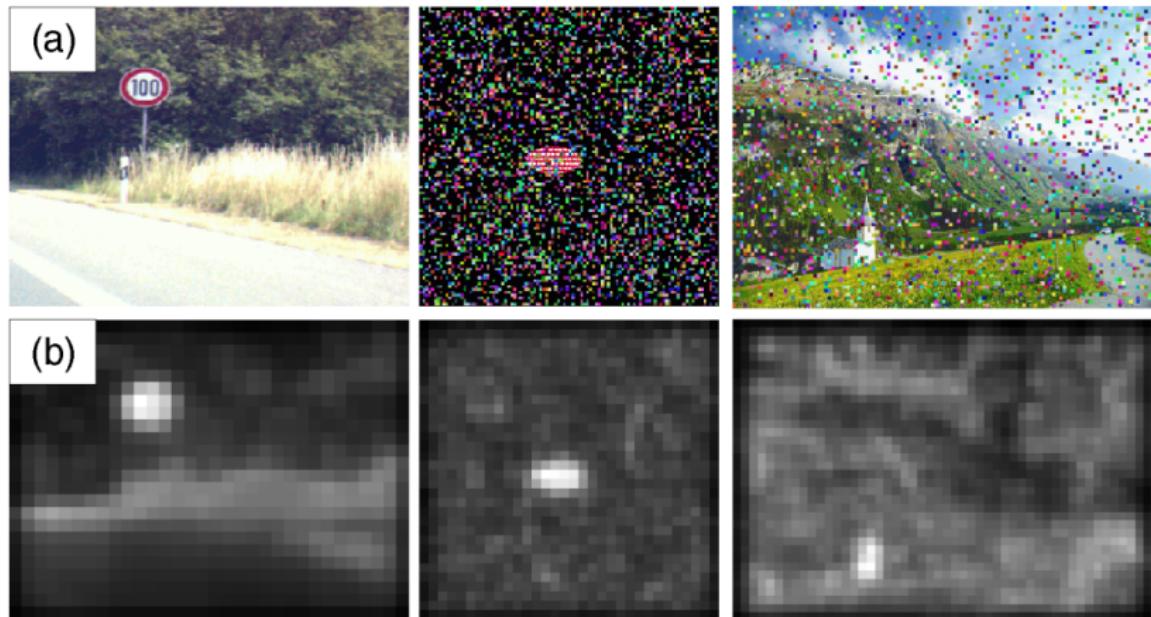
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A classical bottom-up model

- 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]



Top-down attention models

- These are task-dependant.
- Note that all detection methods can be considered as task-oriented attention methods

Example: Face detection with the Viola-Jones method [Viola and Jones, 2001]

- Define weak learners based on integrals on rectangles
- Select learners using AdaBoost
- Apply them in a hierarchical way

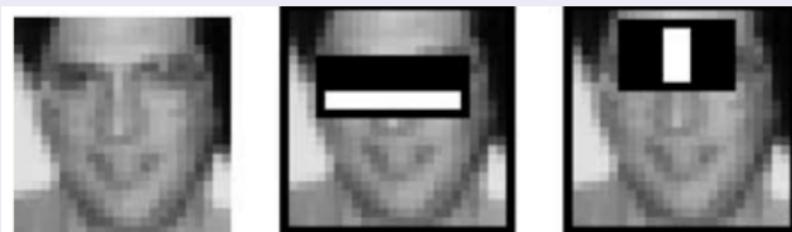
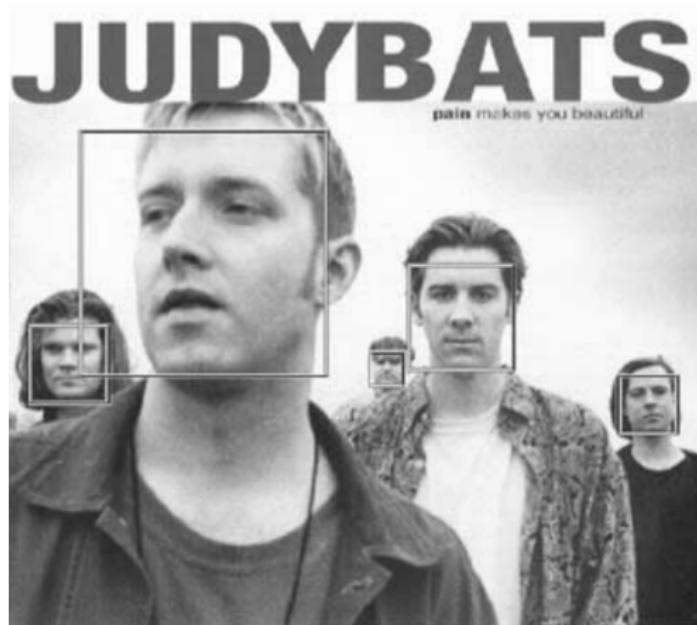


Image size: 24 × 24 pixels

Illustration [Viola and Jones, 2001]



Once attention is focused, the corresponding regions can be further analysed. Here, for identification purposes, for example.

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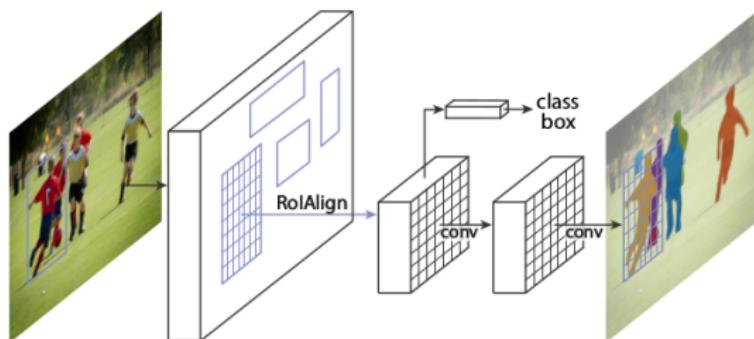
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3 The transformer architecture and its applications in computer vision

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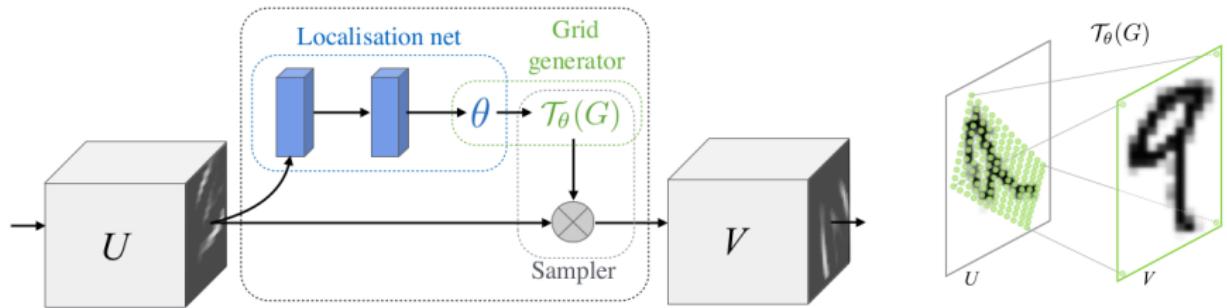
Region proposal networks [Ren et al., 2015]

- 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.



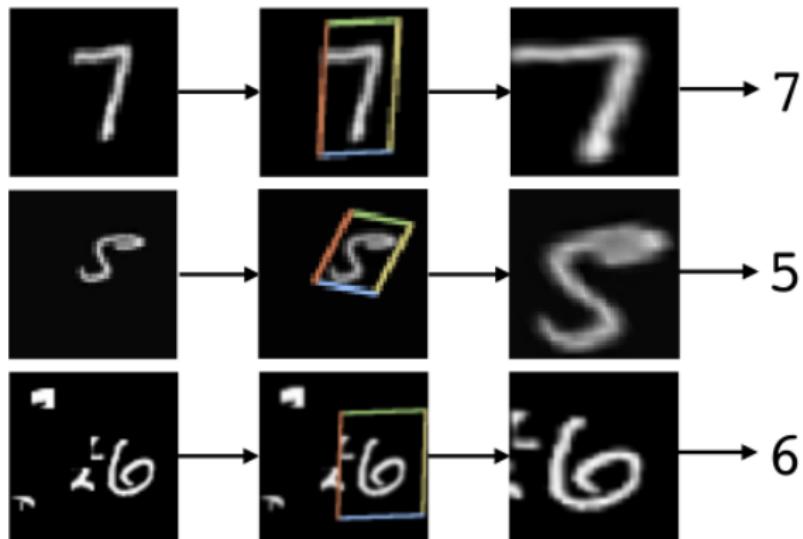
A region proposal module is used by mask R-CNN [He et al., 2017]

Spatial transformers [Jaderberg et al., 2016]

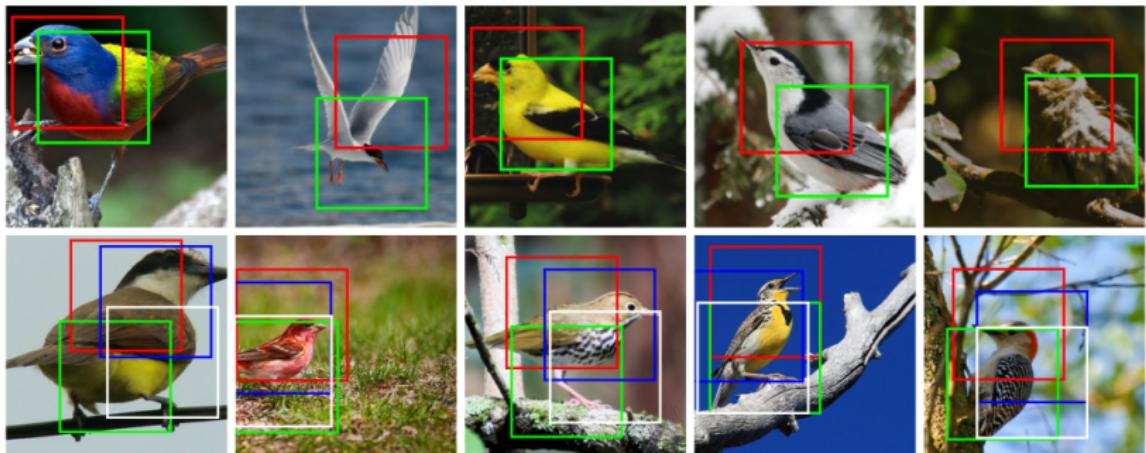


- This module can be added to any convolutional network
- End-to-end learning

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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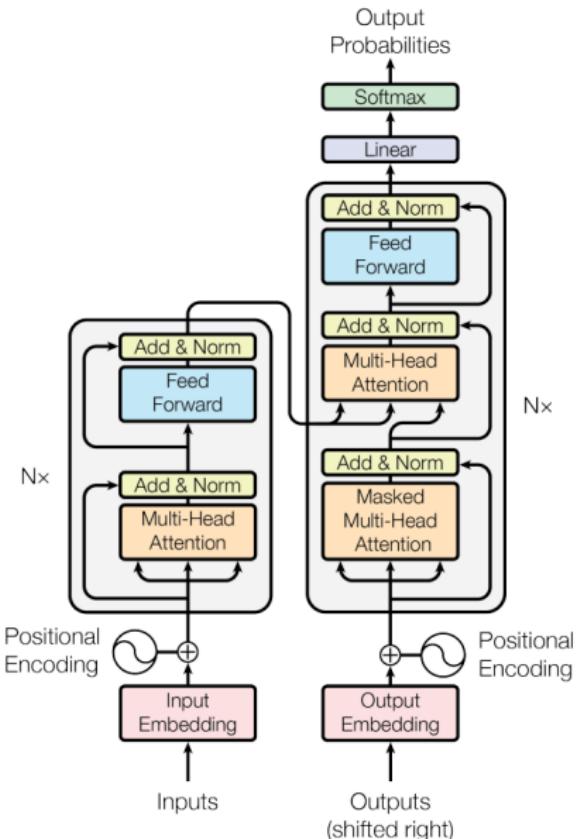
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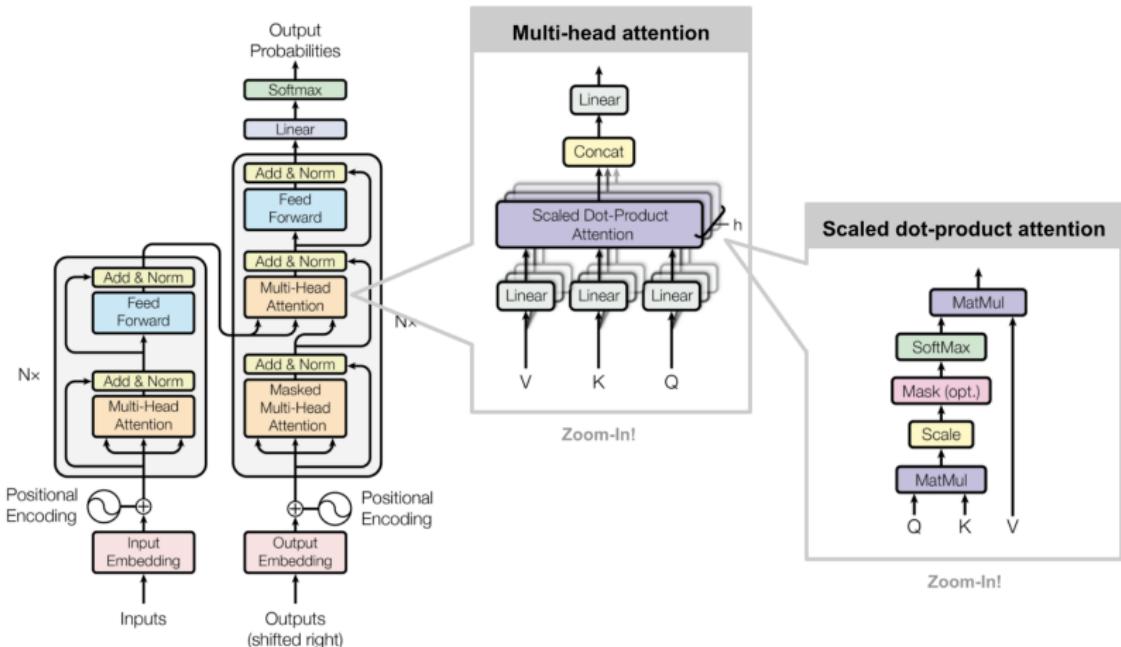
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The rise of transformers

The paper that started it all
Vaswani et al., Attention is all you need, Neurips 2017.



Architecture [Vaswani et al., 2017]



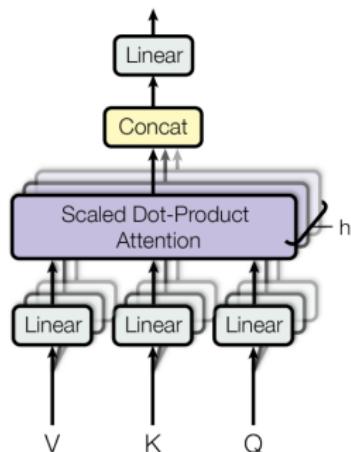
Credits: <https://lilianweng.github.io/lil-log/2018/06/24/attention-attention.html>

Multi-head attention

Dot-product attention

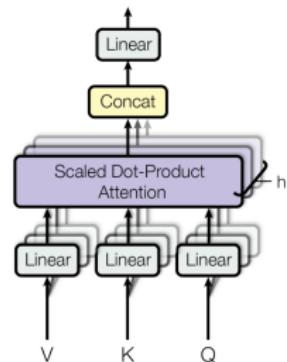
$$Att(Q, K, V) = \text{softmax} \left(\frac{QW_Q(KW_V)^t}{\sqrt{d_{K'}}} \right) VW_V$$

$$Att(Q, K, V) = \text{softmax} \left(\frac{Q'(K')^t}{\sqrt{d_{K'}}} \right) V'$$



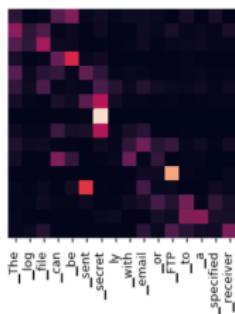
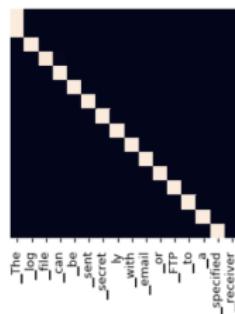
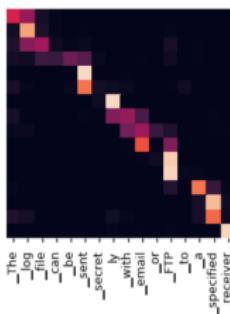
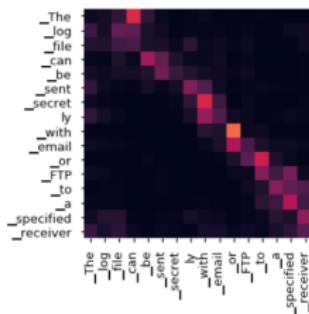
- V : values; K : keys; Q : queries.
- Matrices W_Q , W_K and W_V are learnable.
- $d_{K'}$ is the length of K' .

Dot-product self-attention illustration



In the case of self-attention:

- $V = K = Q = X$



Credits:

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

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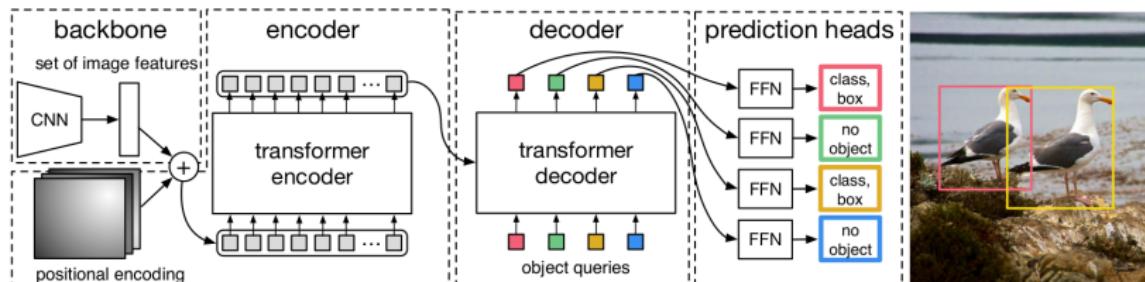
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DETR: detection transformer [Carion et al., 2020]

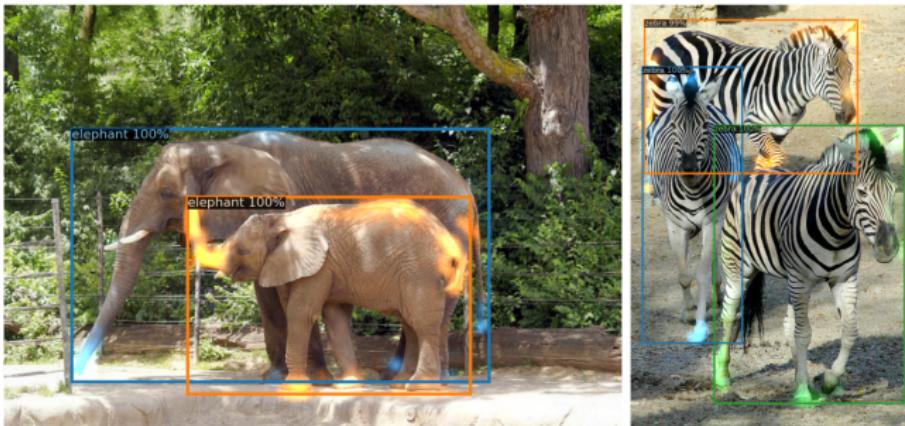


Remarks

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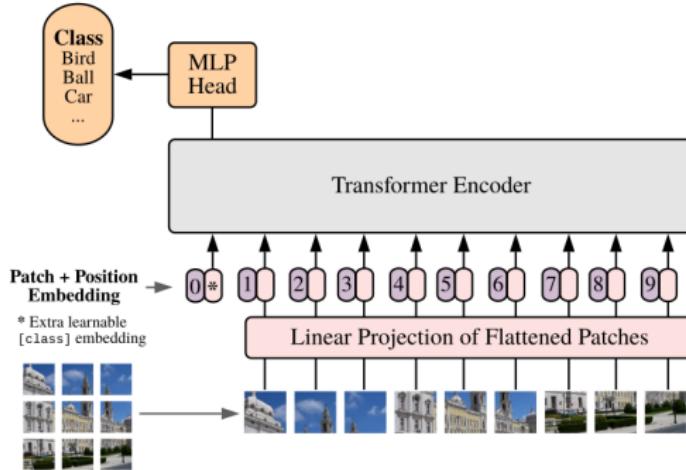
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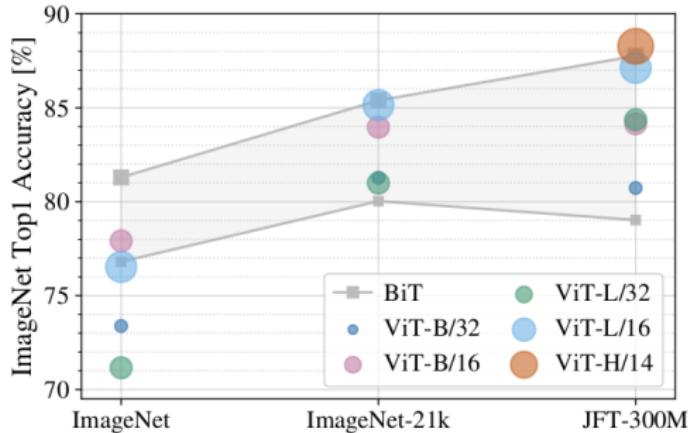
ViT: the vision transformer [Dosovitskiy et al., 2021]



Remarks

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

ViT results



- ViT-H/14 requires 2500 TPUv3-core-days for pre-training
- BiT: Big transfer [Kolesnikov et al., 2020]

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Convolutional neural networks

- Convolutional networks are based on two inductive biases:

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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?

References |

- [Brown et al., 2020] Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., Agarwal, S., Herbert-Voss, A., Krueger, G., Henighan, T., Child, R., Ramesh, A., Ziegler, D. M., Wu, J., Winter, C., Hesse, C., Chen, M., Sigler, E., Litwin, M., Gray, S., Chess, B., Clark, J., Berner, C., McCandlish, S., Radford, A., Sutskever, I., and Amodei, D. (2020). Language Models are Few-Shot Learners. [arXiv:2005.14165 \[cs\]](https://arxiv.org/abs/2005.14165). arXiv: 2005.14165.
- [Carion et al., 2020] Carion, N., Massa, F., Synnaeve, G., Usunier, N., Kirillov, A., and Zagoruyko, S. (2020). End-to-End Object Detection with Transformers. In Vedaldi, A., Bischof, H., Brox, T., and Frahm, J.-M., editors, *Computer Vision – ECCV 2020*, Lecture Notes in Computer Science, pages 213–229, Cham. Springer International Publishing.
- [Devlin et al., 2019] Devlin, J., Chang, M.-W., Lee, K., and Toutanova, K. (2019). BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. [arXiv:1810.04805 \[cs\]](https://arxiv.org/abs/1810.04805). arXiv: 1810.04805.
- [Dosovitskiy et al., 2021] Dosovitskiy, A., Beyer, L., Kolesnikov, A., Weissenborn, D., Zhai, X., Unterthiner, T., Dehghani, M., Minderer, M., Heigold, G., Gelly, S., Uszkoreit, J., and Houlsby, N. (2021). An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale. In [arXiv:2010.11929 \[cs\]](https://arxiv.org/abs/2010.11929). arXiv: 2010.11929.

References II

- [He et al., 2017] He, K., Gkioxari, G., Dollár, P., and Girshick, R. (2017). Mask R-CNN. *arXiv:1703.06870 [cs]*. arXiv: 1703.06870.
- [Hinton et al., 2011] Hinton, G. E., Krizhevsky, A., and Wang, S. D. (2011). Transforming Auto-Encoders. In Honkela, T., Duch, W., Girolami, M., and Kaski, S., editors, *Artificial Neural Networks and Machine Learning – ICANN 2011*, Lecture Notes in Computer Science, pages 44–51, Berlin, Heidelberg. Springer.
- [Itti and Koch, 2001] Itti, L. and Koch, C. (2001). Computational modelling of visual attention. *Nature Reviews Neuroscience*, 2(3):194–203. Number: 3 Publisher: Nature Publishing Group.
- [Itti et al., 1998] Itti, L., Koch, C., and Niebur, E. (1998). A model of saliency-based visual attention for rapid scene analysis. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 20(11):1254–1259. Conference Name: IEEE Transactions on Pattern Analysis and Machine Intelligence.
- [Jaderberg et al., 2016] Jaderberg, M., Simonyan, K., Zisserman, A., and Kavukcuoglu, K. (2016). Spatial Transformer Networks. *arXiv:1506.02025 [cs]*. arXiv: 1506.02025.
- [Kolesnikov et al., 2020] Kolesnikov, A., Beyer, L., Zhai, X., Puigcerver, J., Yung, J., Gelly, S., and Houlsby, N. (2020). Big Transfer (BiT): General Visual Representation Learning. In *European Conference on Computer Vision*.

References III

- [Lecun et al., 1998] Lecun, Y., Bottou, L., Bengio, Y., and Haffner, P. (1998). Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11):2278–2324.
- [Ren et al., 2015] Ren, S., He, K., Girshick, R., and Sun, J. (2015). Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. *Advances in Neural Information Processing Systems*, 28:91–99.
- [Vaswani et al., 2017] Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L., and Polosukhin, I. (2017). Attention is All you Need. *Advances in Neural Information Processing Systems*, 30.
- [Viola and Jones, 2001] Viola, P. and Jones, M. (2001). Rapid object detection using a boosted cascade of simple features. In *Proceedings of the 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition. CVPR 2001*, volume 1, pages I–I. ISSN: 1063-6919.
- [Yarbus, 1967] Yarbus, A. L. (1967). Eye Movements During Perception of Complex Objects. In Yarbus, A. L., editor, *Eye Movements and Vision*, pages 171–211. Springer US, Boston, MA.