An Image is Worth 16 x 16 Words: Transformers for Image Recognition at Scale

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Course: Advanced topic in Machine Learning for Image Analysis.

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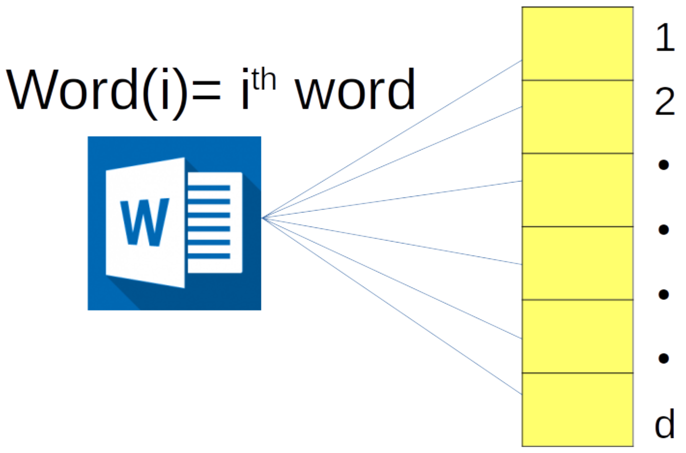
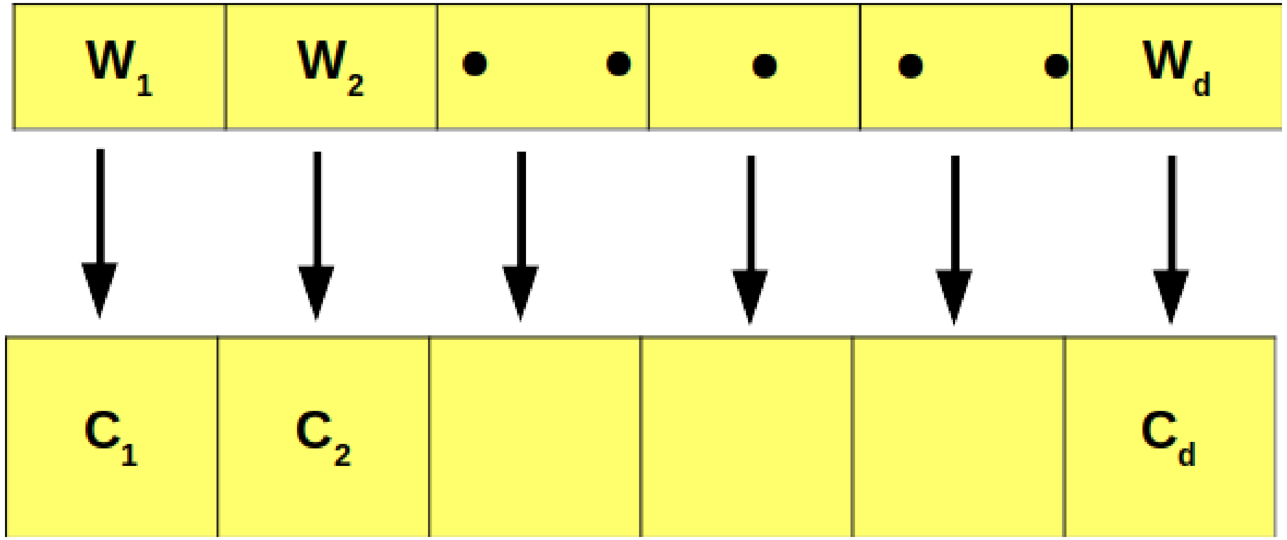
Introduction to Transformer

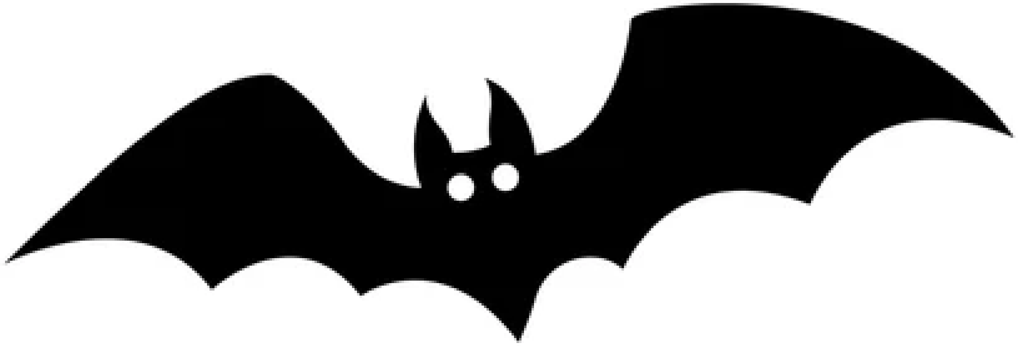




Word mapping

Transformer

Bat ?!



Accounting for the Word Context

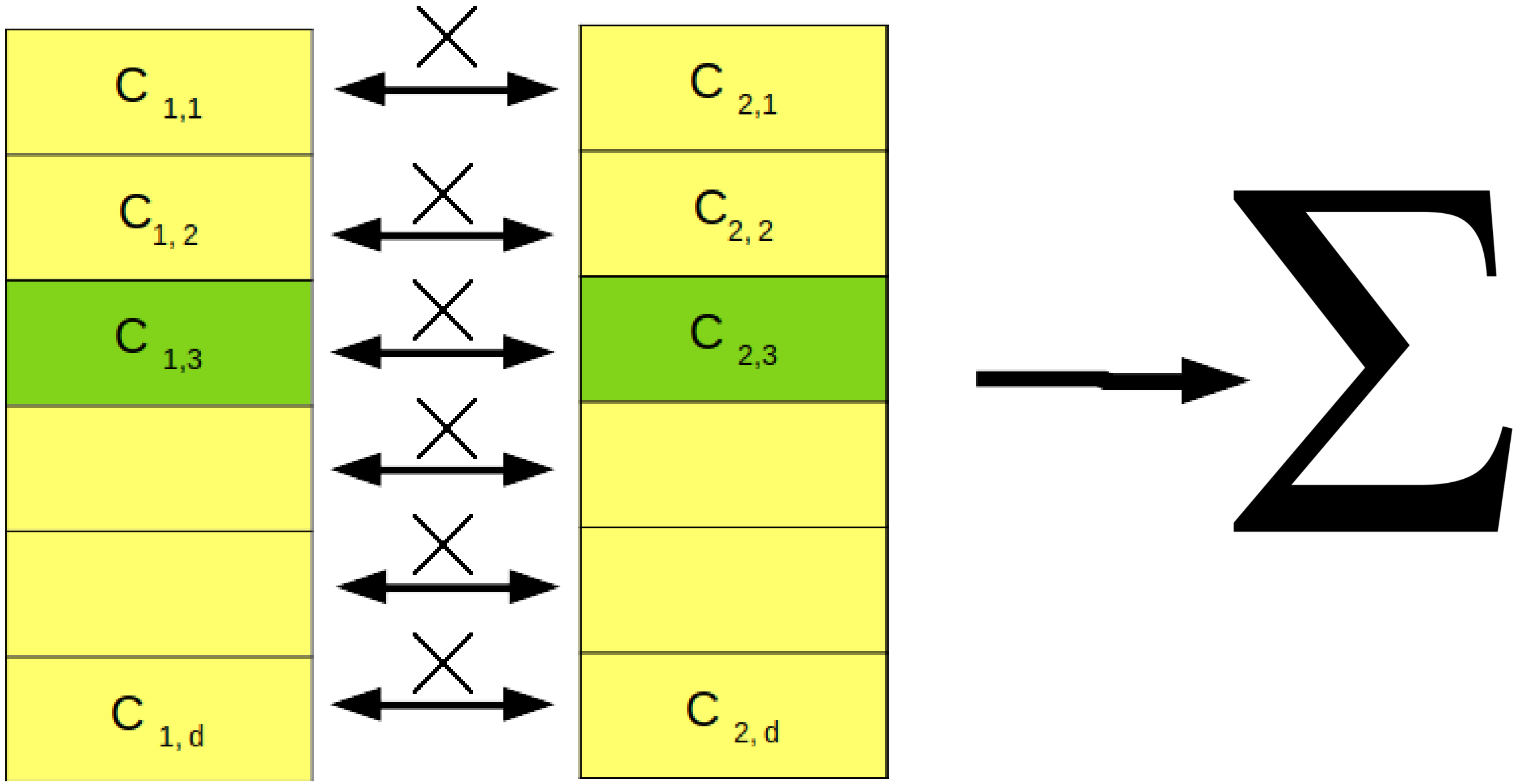
- Mapping each word to a single vector is restrictive!
- Words often have different meanings!

Transformer

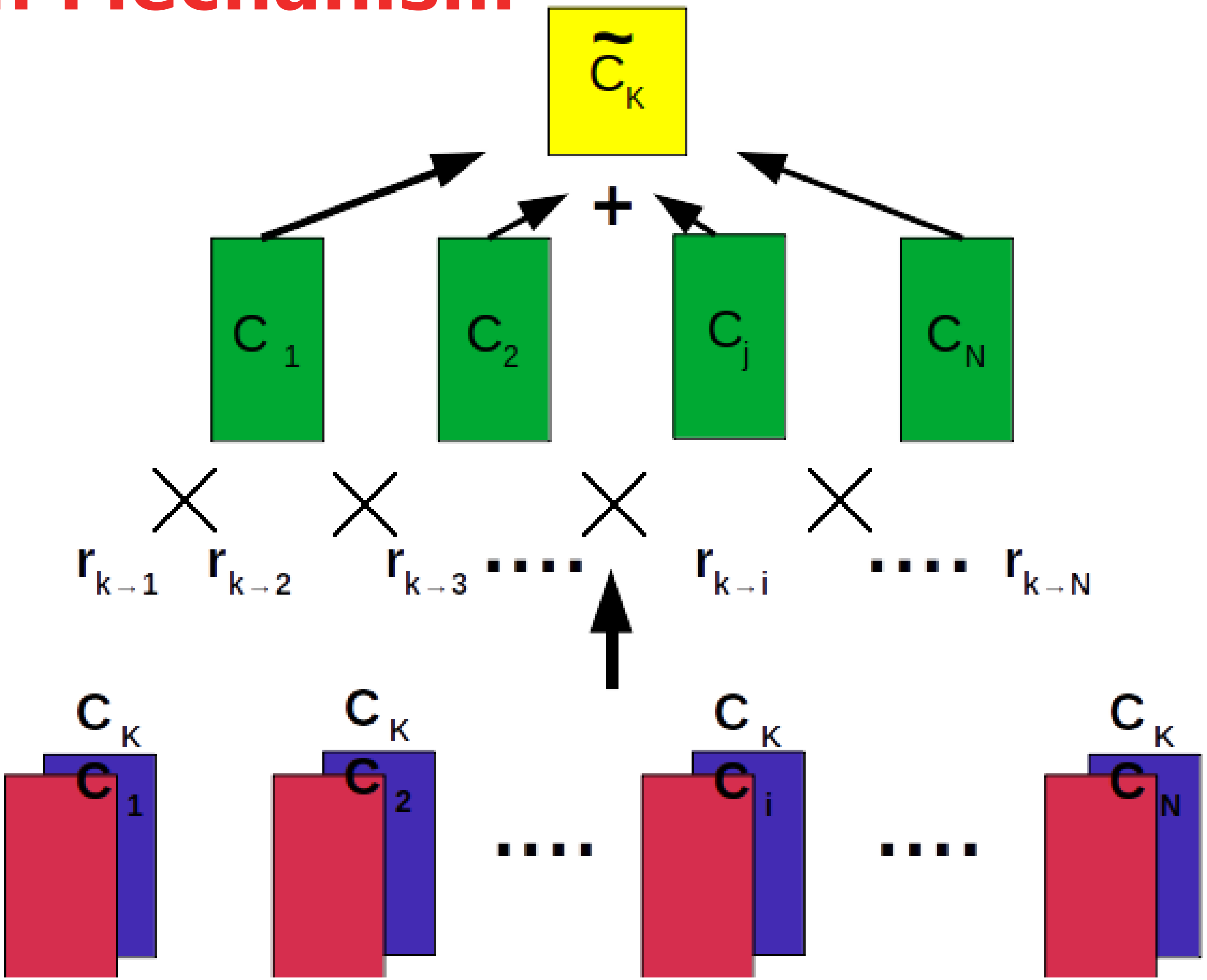
Inner Product between two vectors!

Goal!
Quantify how similar kth word is to the sequence!

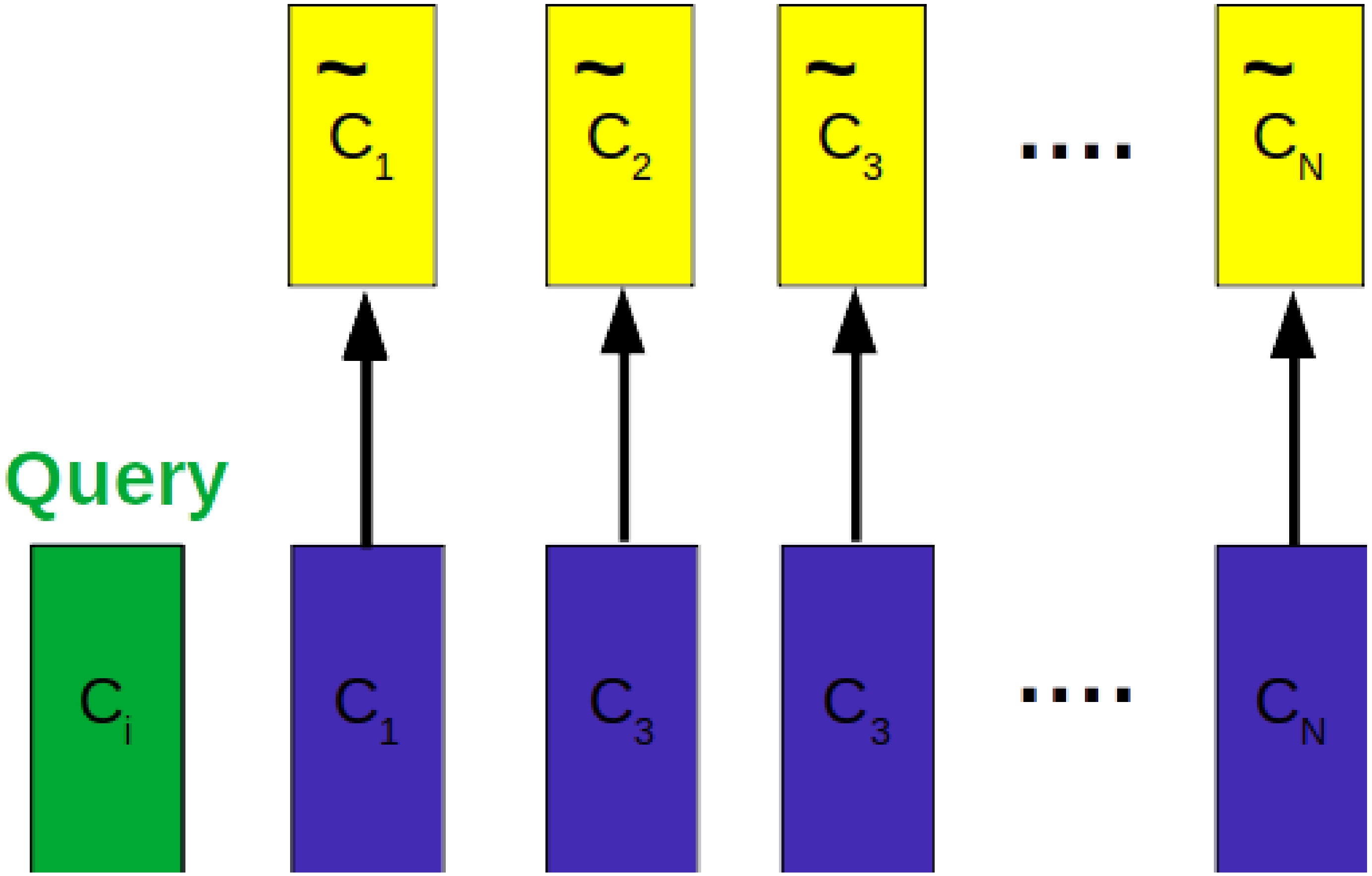
- **If inner product is positive, then words are similar**
- **If inner product is negative, then words are dissimilar**



Attention Mechanism



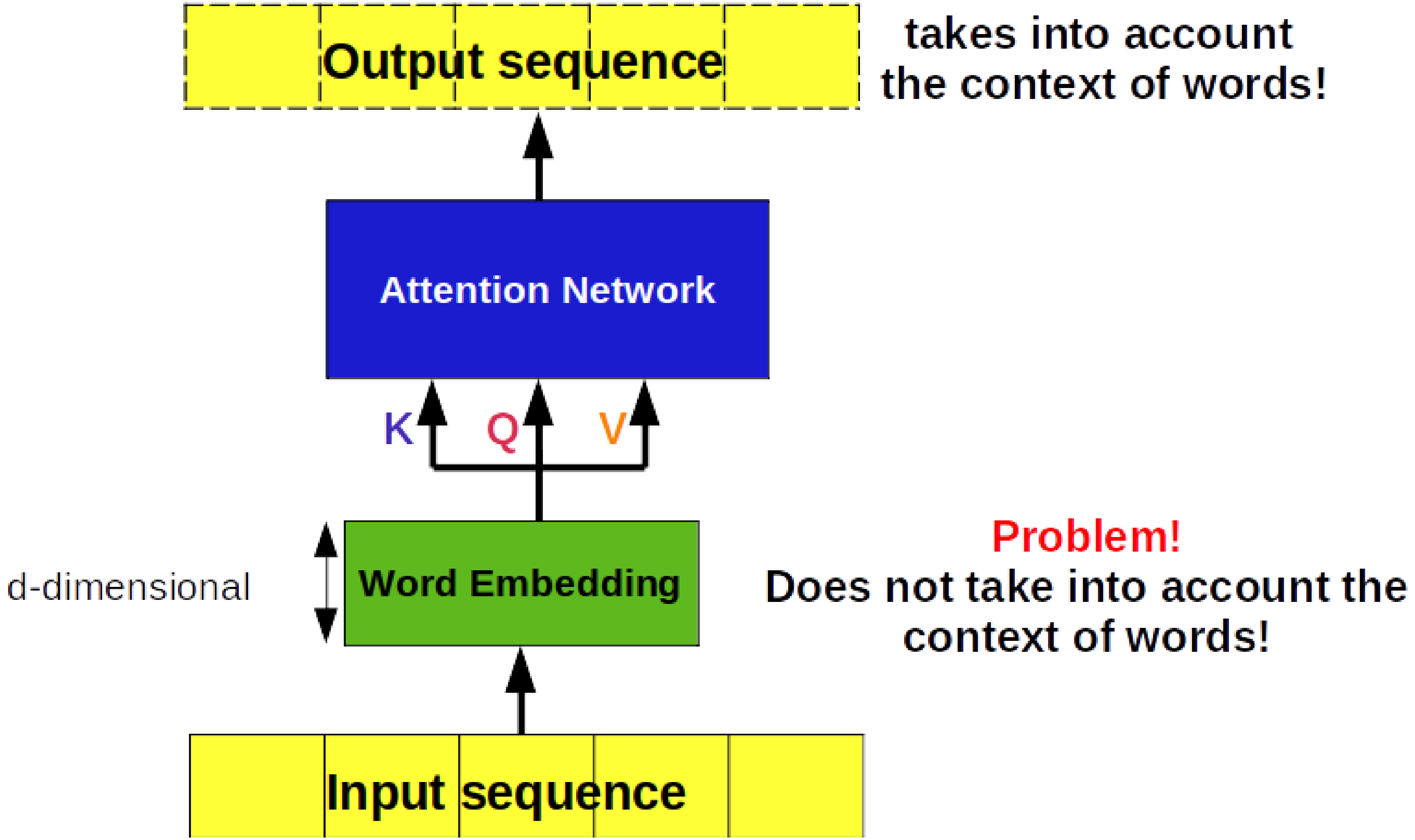
Transformer



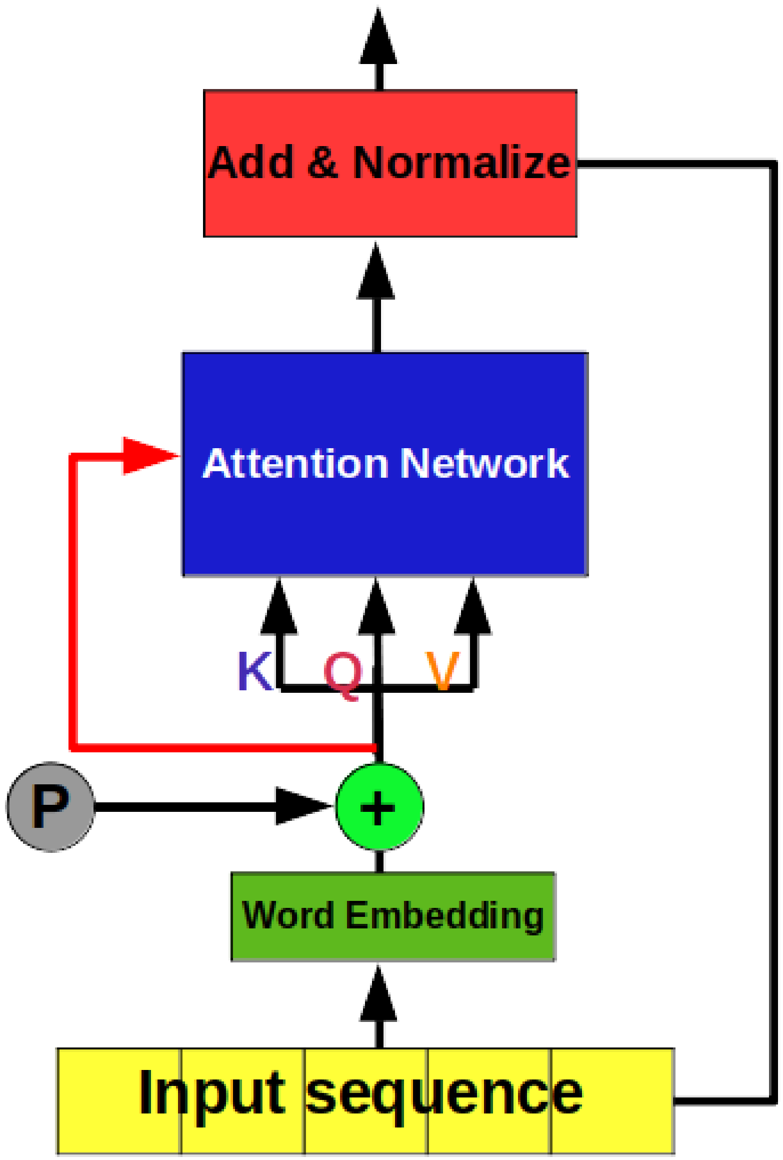
Attention

- Original sequence of words
- Map to corresponding code(Problem: original code independent of surrounding words!)
- Updated codes take into account the context of surrounding words!

Notional meaning of Transformer



Transformer Encoder



Positional Embedding

Accounts for the Order

1. Vaswani et al., 2017

Vision Transformer (ViT)

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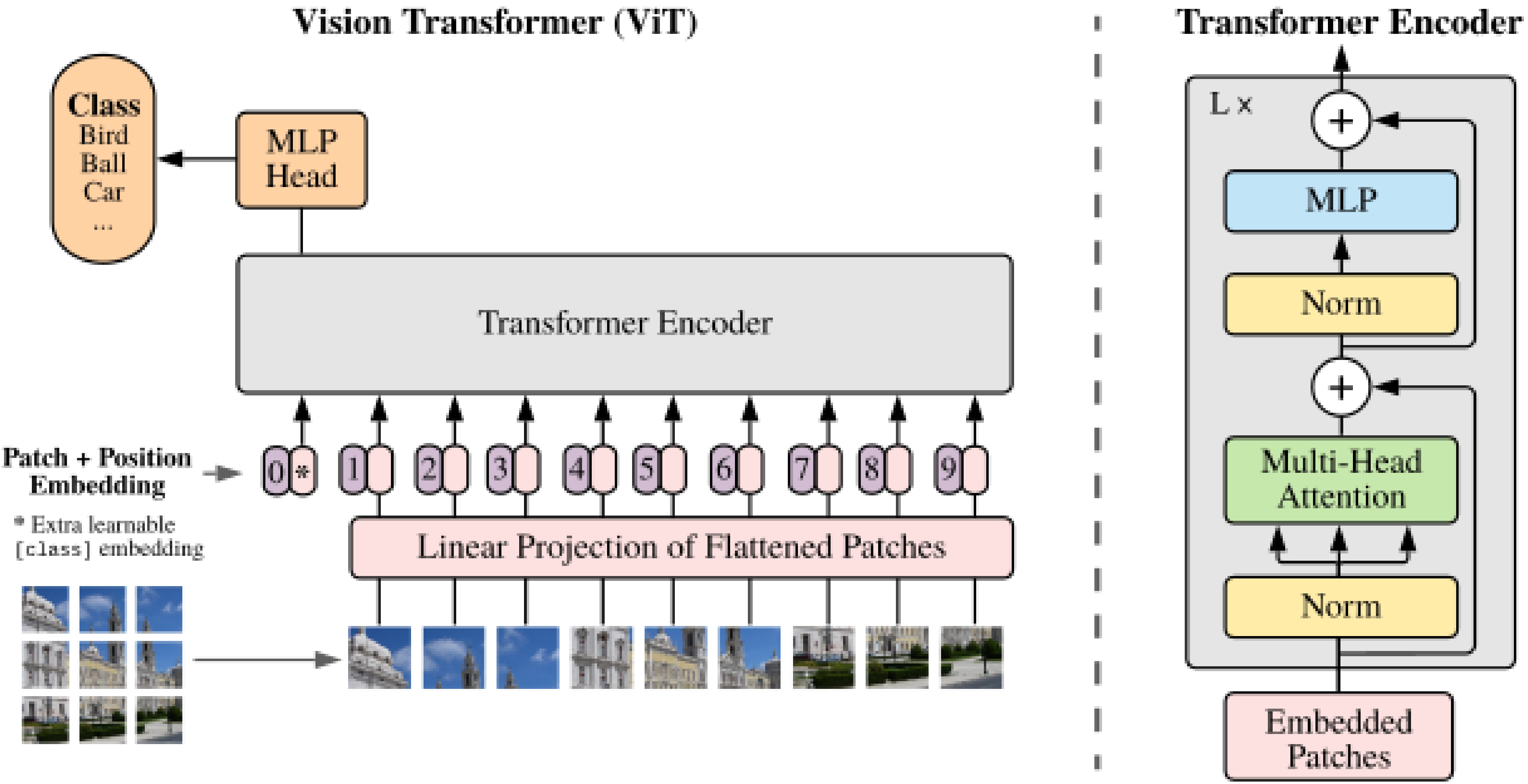


Vision Transformer (ViT) Method:
1) ViT Components

- Close to original Transformer (Vaswani et al., 2017).
- Transformer receives as input 2D images.
- Reshape the image into 2 sequence of flattened 2D patches with same resolution of the original image.
- ViT uses constant latent vector size D through all of its layers.
- Position embeddings are added to the patch embeddings to retain positional information.

Vision Transformer (ViT)
Method:
2) Fine-tuning and higher resolution

- Typically, pre-train ViT on large datasets, and fine-tune to (smaller) downstream tasks.
  - Remove the pre-trained prediction head and attach a zero-initialized $D \times K$ feedforward layer, where K is the number of downstream classes.
  - Fine-tune at a higher resolution than pre-training -> keep the patch size the same, which results in a larger effective sequence length.

2. Dosovitskiy, Alexey, et al. 2021

Vision Transformer (ViT)
Experiment:

Model	Layers	Hidden size D	MLP size	Heads	Params
ViT-Base	12	768	3072	12	86M
ViT-Large	24	1024	4096	16	307M
ViT-Huge	32	1280	5120	16	632M

Details of Vision Transformer model variants

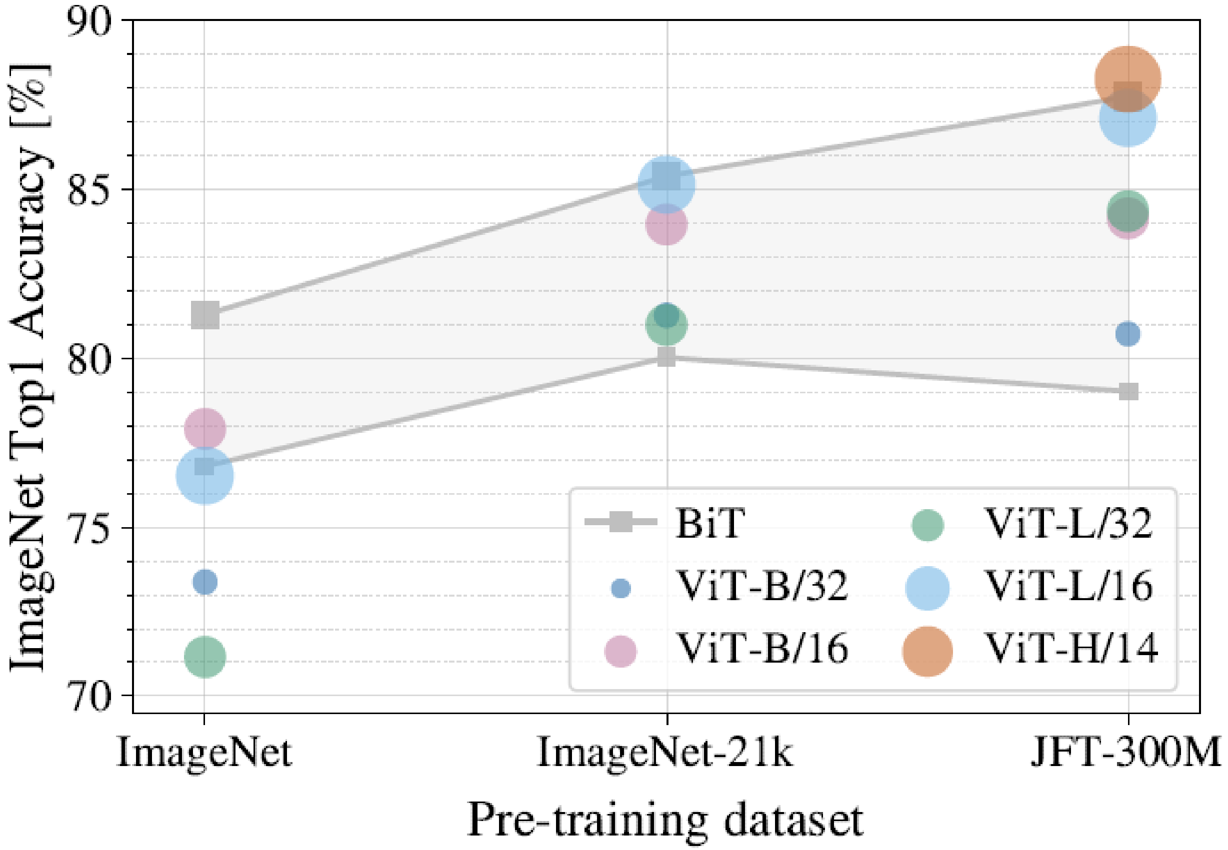
2. Dosovitskiy, Alexey, et al. 2021

Vision Transformer (ViT)
Experiment:

	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

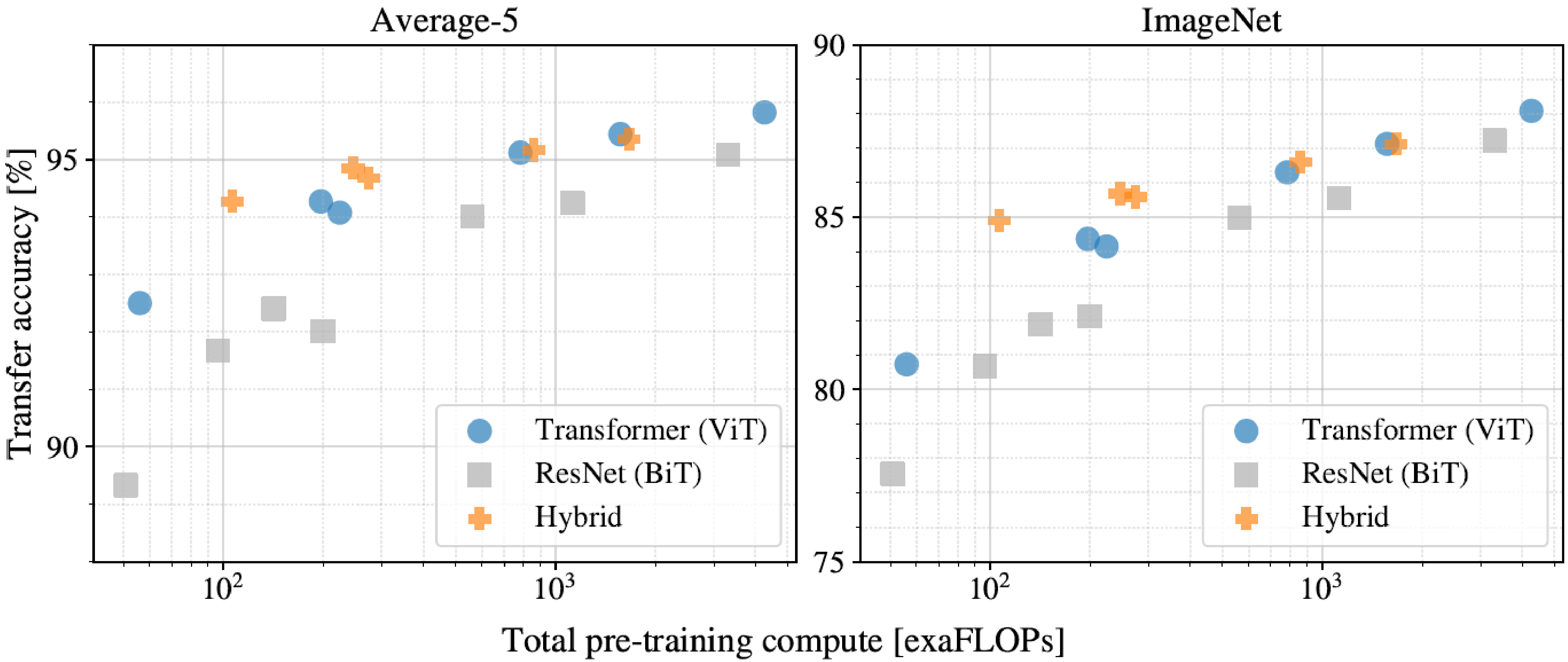
Comparison with state of the art on popular image classification benchmarks

Vision Transformer (ViT)
Experiment:



Transfer to ImageNet

Vision Transformer (ViT)
Experiment:



Performance vs pre-training compute for different architectures

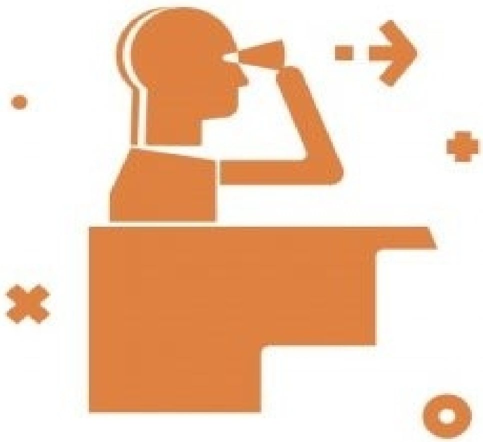
Vision Transformer (ViT) Conclusion

- ViT interprets an image as a sequence of patches and process it by a standard Transformer encoder as used in NLP.

- cheap to pre-train.

Vision Transformer (ViT)
Future work

- Apply ViT to other computer vision tasks.
- Exploring self-supervised pre-training methods.
- Scaling of ViT



2. Dosovitskiy, Alexey, et al. 2021

References

1. Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. In NIPS, 2017.
2. Dosovitskiy, Alexey, et al. “An Image Is Worth 16x16 Words: Transformers for Image Recognition at Scale.” *ArXiv:2010.11929 [Cs]*, June 2021.