Day 6 Lecture 4

The Transformer

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Acknowledgments

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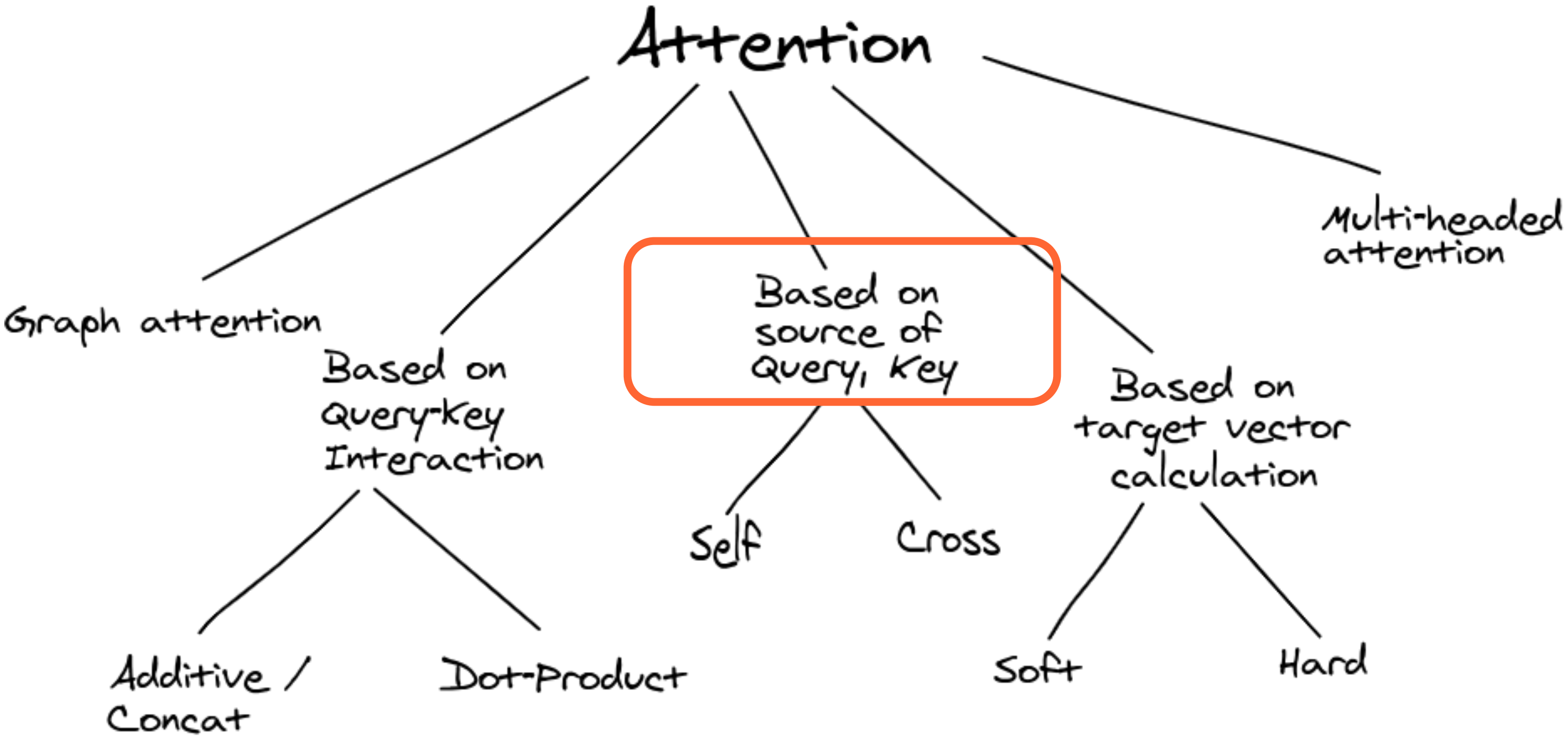
Outline

1. **Reminders**

Reminder



Nikhil Sha, [“Attention ? An other Perspective!”](). 2020.

Reminder

Attention is a mechanism to compute a context vector (c) for a **query (Q)** as a weighted sum of **values (V).**

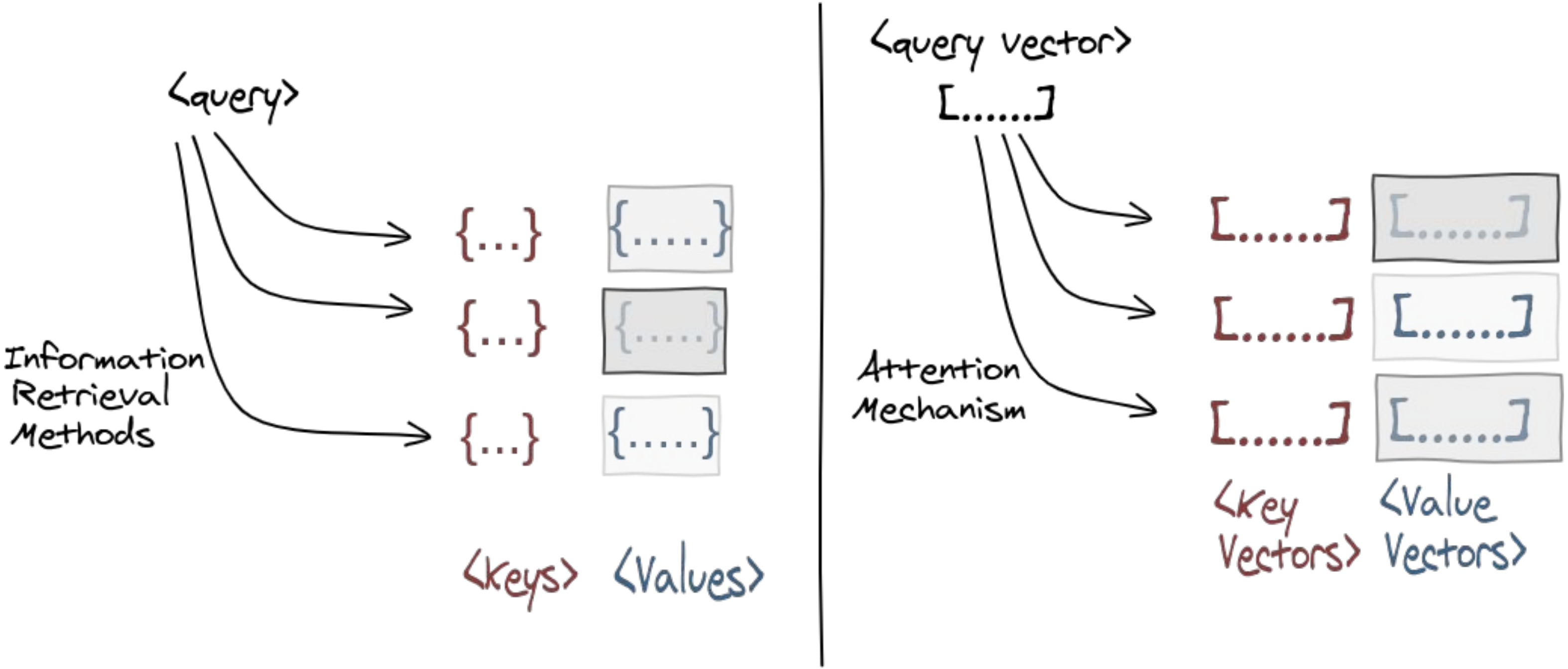
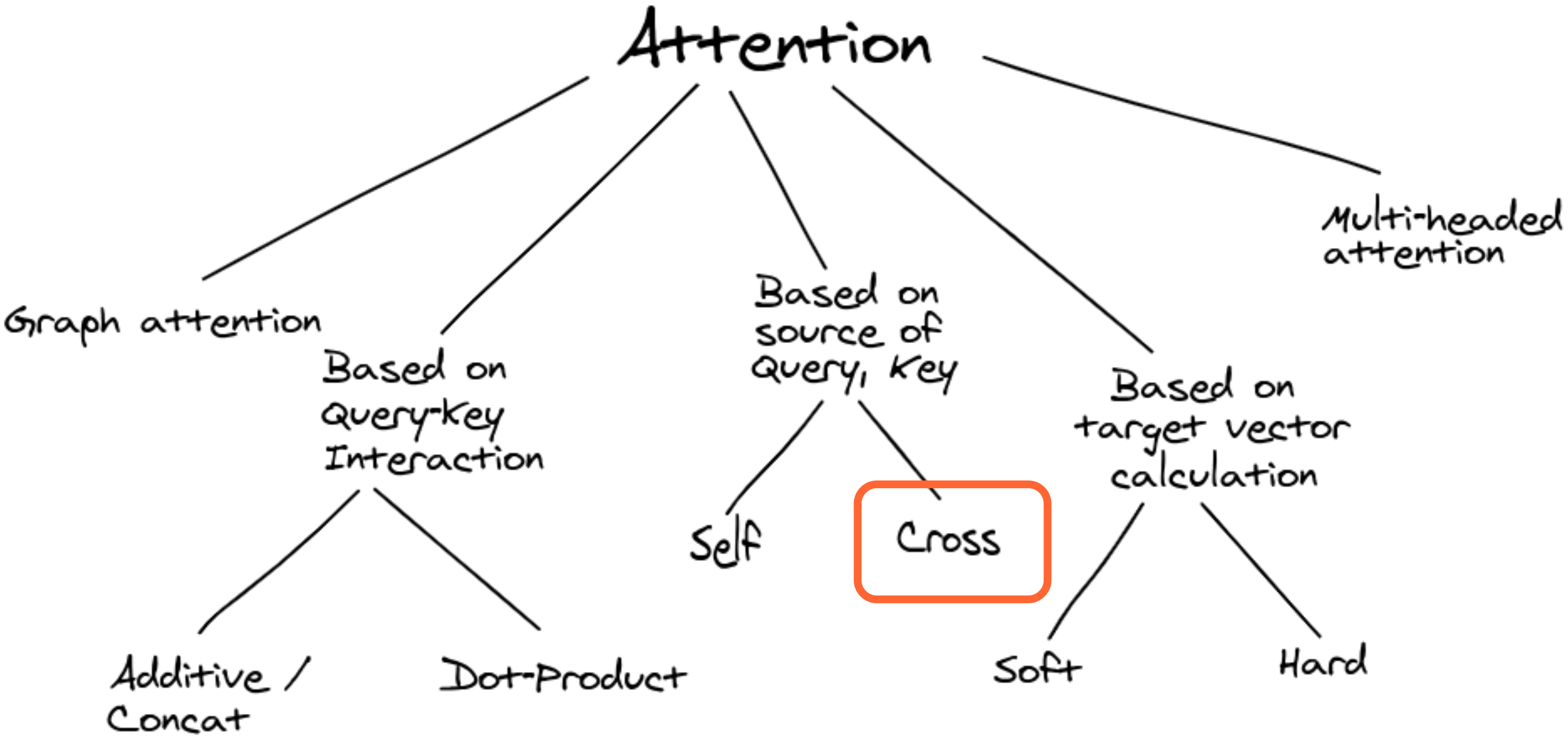


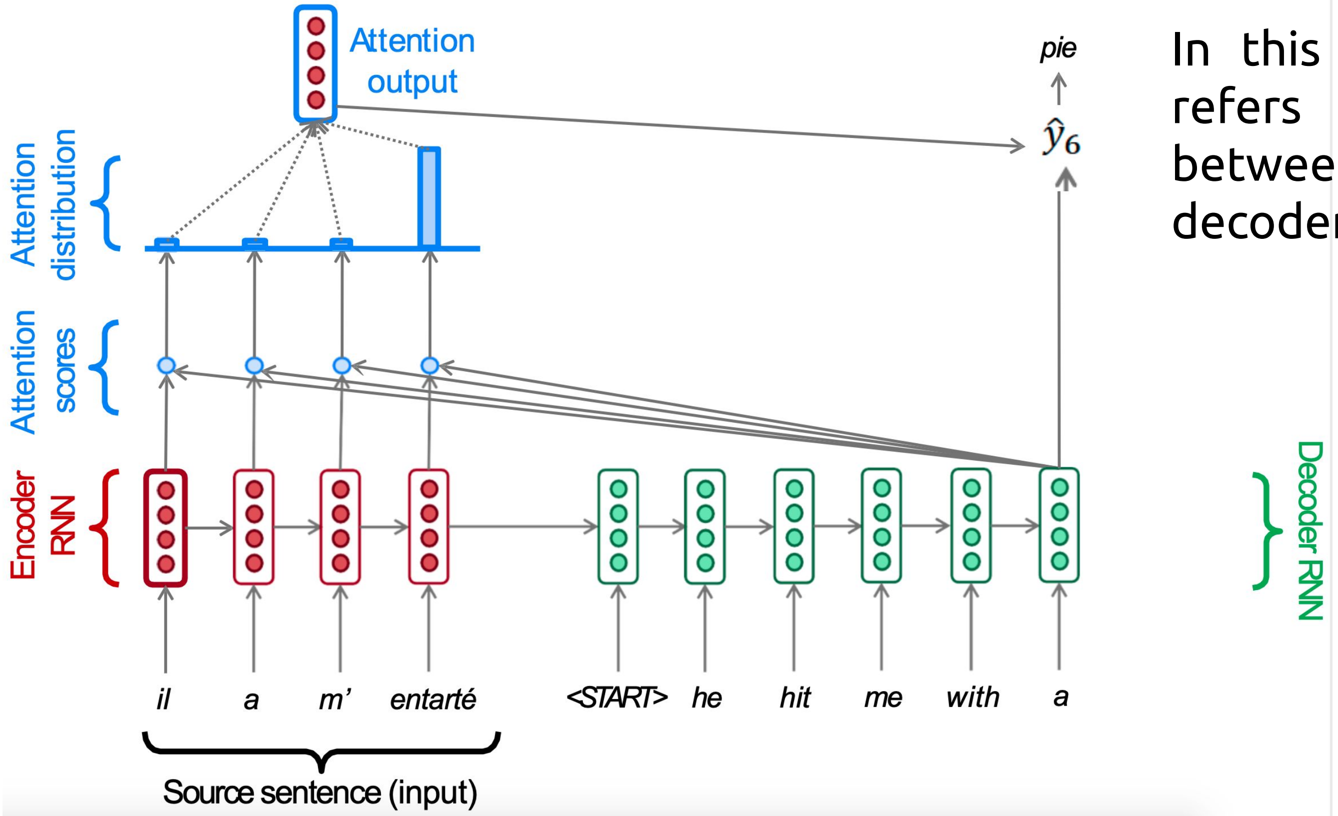
Figure: Nikhil Shah, [“Attention? An Other Perspective! [Part 1]”](#) (2020)

Reminder



Nikhil Sha, "Attention ? An other Perspective!". 2020.

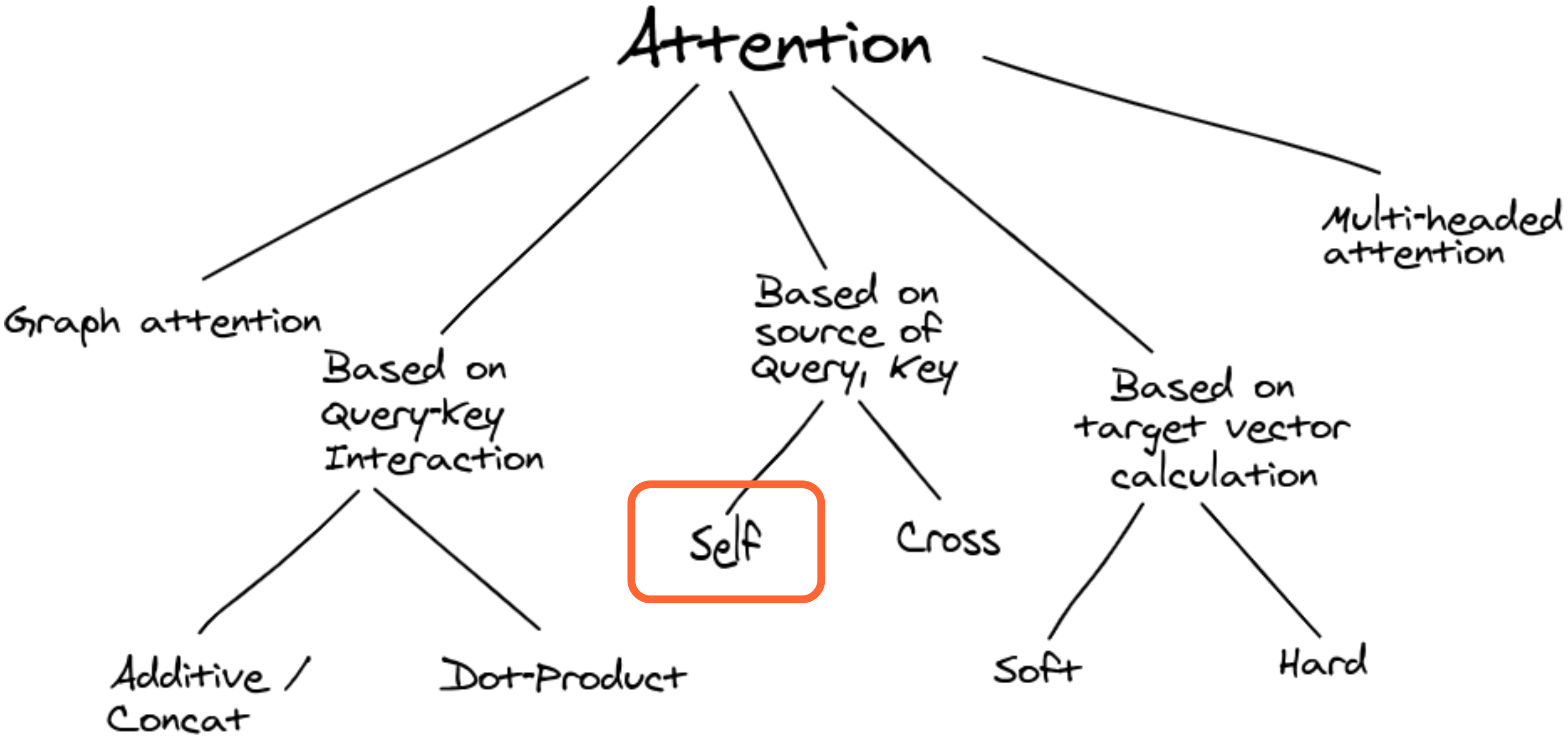
Reminder: Seq2Seq with Cross-Attention



In this case, **cross-attention** refers to the attention between the encoder and decoder states.

Slide concept: Abigail See, Matthew Lamm (Stanford CS224N), 2020

What may the term “self” refer to, as a contrast of “cross”-attention ?



Nikhil Sha, [“Attention ? An other Perspective!”](). 2020.

Outline

1. Motivation
2. **Self-attention**

Self-Attention (or intra-Attention)

Self-attention refers to attending to other elements from the SAME sequence.

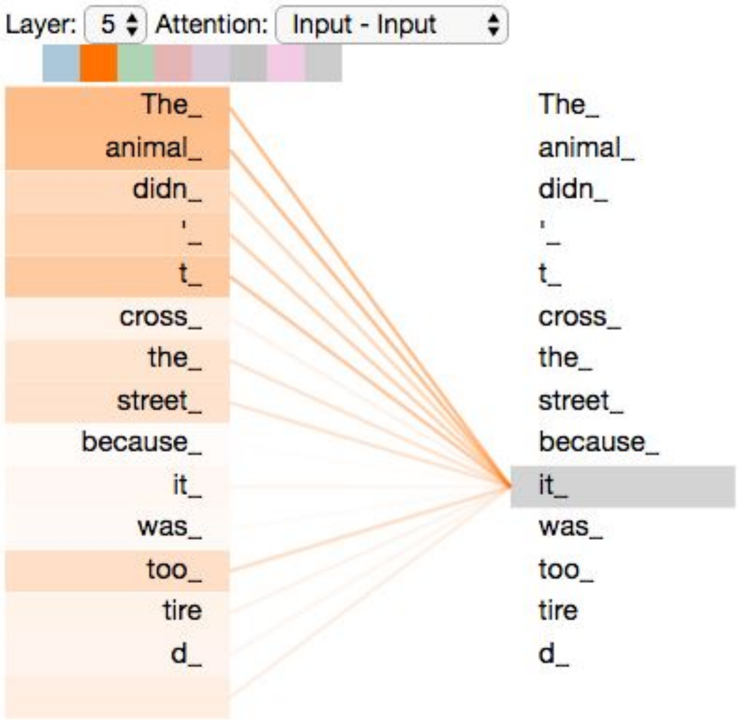
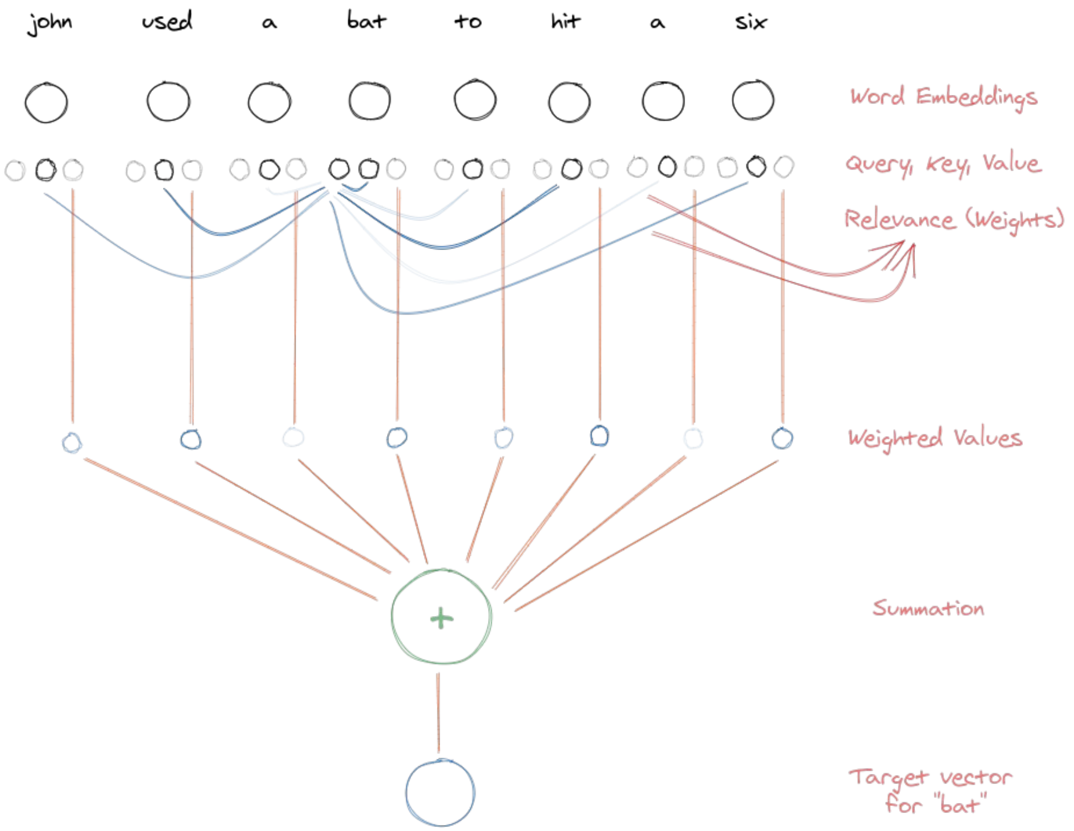


Figure:
Jay Alammar,
["The Illustrated Transformer"]

Lin, Z., Feng, M., Santos, C. N. D., Yu, M., Xiang, B., Zhou, B., & Bengio, Y. A structured self-attentive sentence embedding. ICLR 2017.

Self-Attention (or intra-Attention)



Query (Q)
$g(x) = W^Q x$

Key (K)
$f(x) = W^K x$

Value (V)
$h(x) = W^V x$

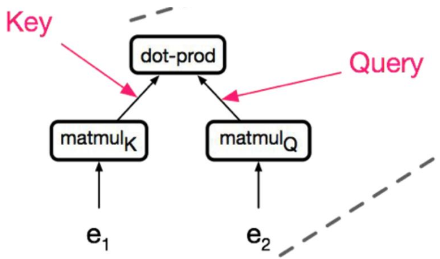
W^Q, W^K and W^V are **projection layers** shared across all words.

Nikhil Sha, "Attention ? An other Perspective!". 2020.

Self-Attention (or intra-Attention)

Which steps are necessary to compute the contextual representation of a word embedding e_2 in a sequences of four words embeddings (e_1, e_2, e_3, e_4) ?

A (scaled) dot-product is computed between each pair of word embeddings (eg. e_1 and e_2)...

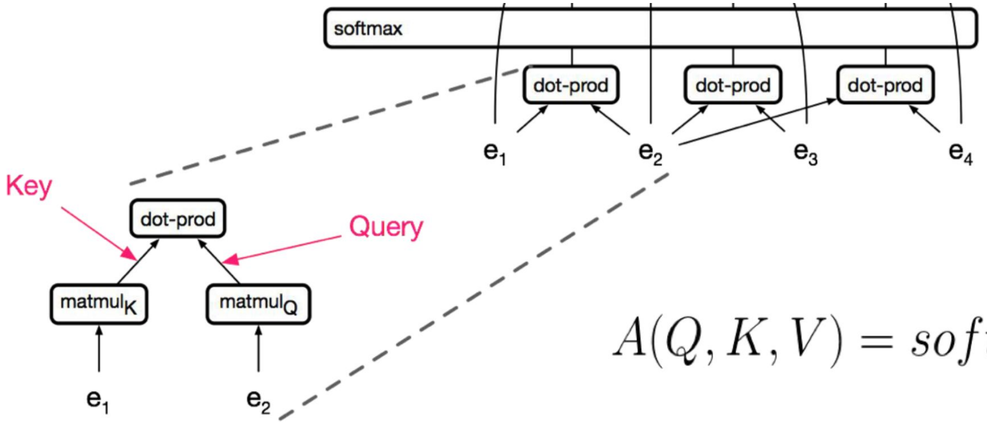


#Transformer Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I.. [Attention is all you need](). NeurIPS 2017.

Self-Attention (or intra-Attention)

Which steps are necessary to compute the contextual representation of a word embedding e_2 in a sequences of four words embeddings (e_1, e_2, e_3, e_4) ?

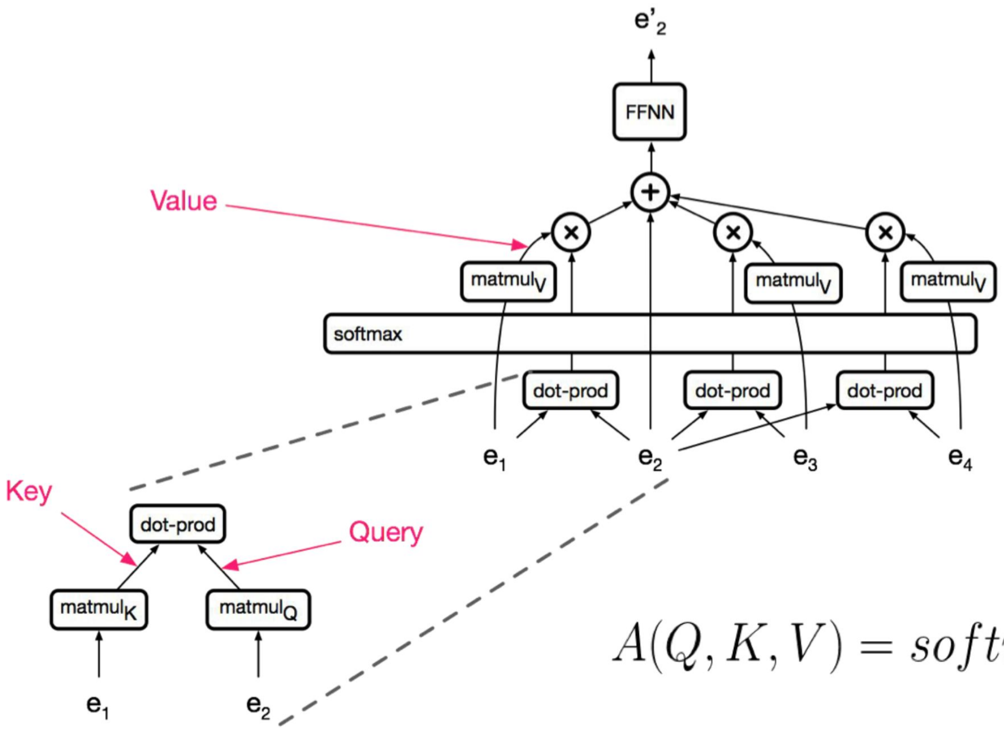
… a softmax layer normalizes the attention scores to obtain the attention distribution…



$$A(Q,K,V) = softmax(\frac{QK^T}{\sqrt{d_k}})V$$

Self-Attention (or intra-Attention)

Which steps are necessary to compute the contextual representation of a word embedding e_2 in a sequences of four words embeddings (e_1, e_2, e_3, e_4) ?



...the same word embeddings are combined to obtain the contextual representation e_2'.

$$A(Q, K, V) = softmax(\frac{QK^T}{\sqrt{d_k}})V$$

Self-Attention (or intra-Attention)

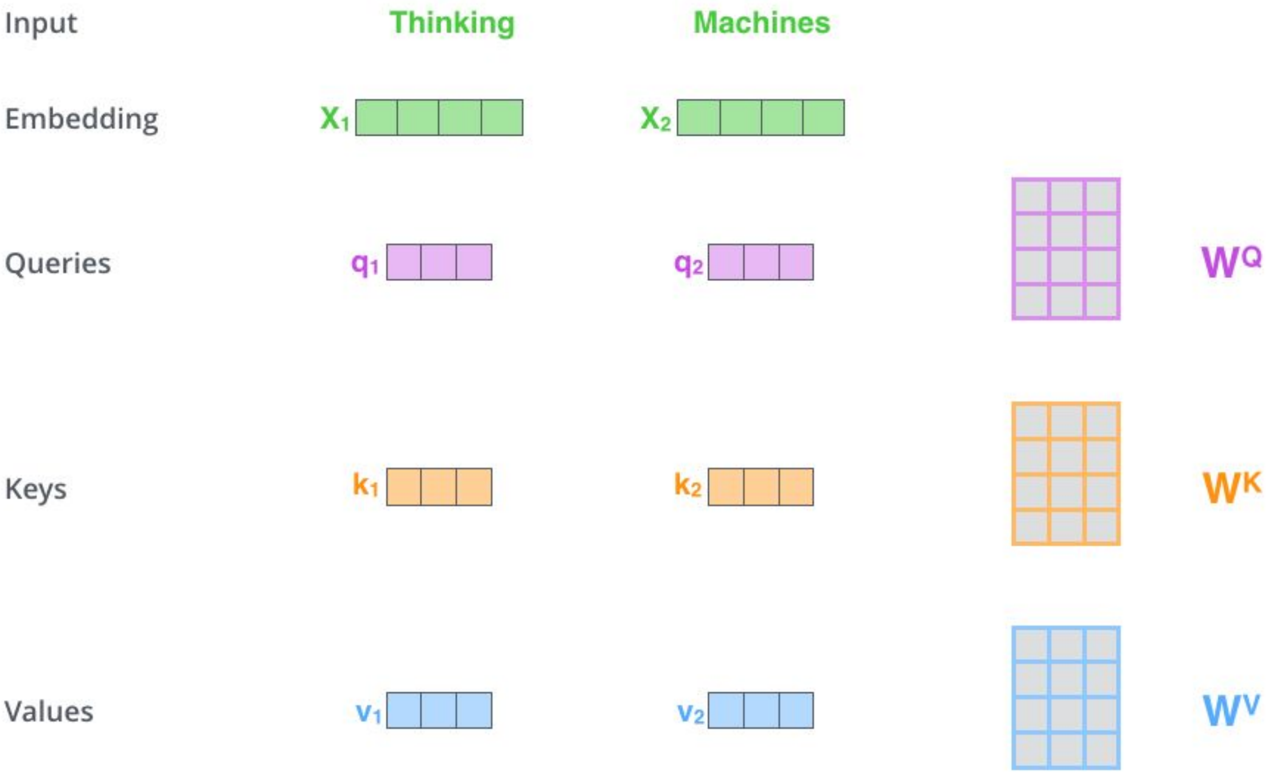


Figure: Jay Alammar, "The illustrated Transformer" (2018)

Self-Attention (or intra-Attention)

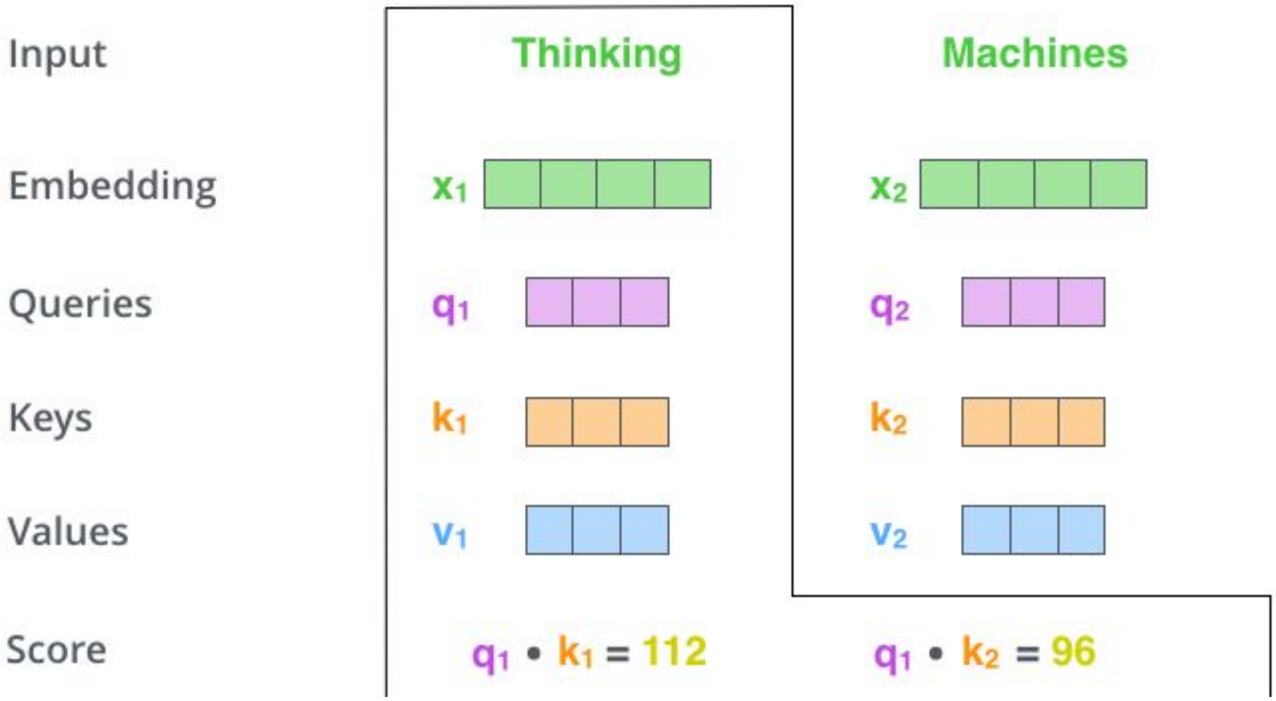


Figure: Jay Alammar, [“The illustrated Transformer”]() (2018)

Self-Attention (or intra-Attention)

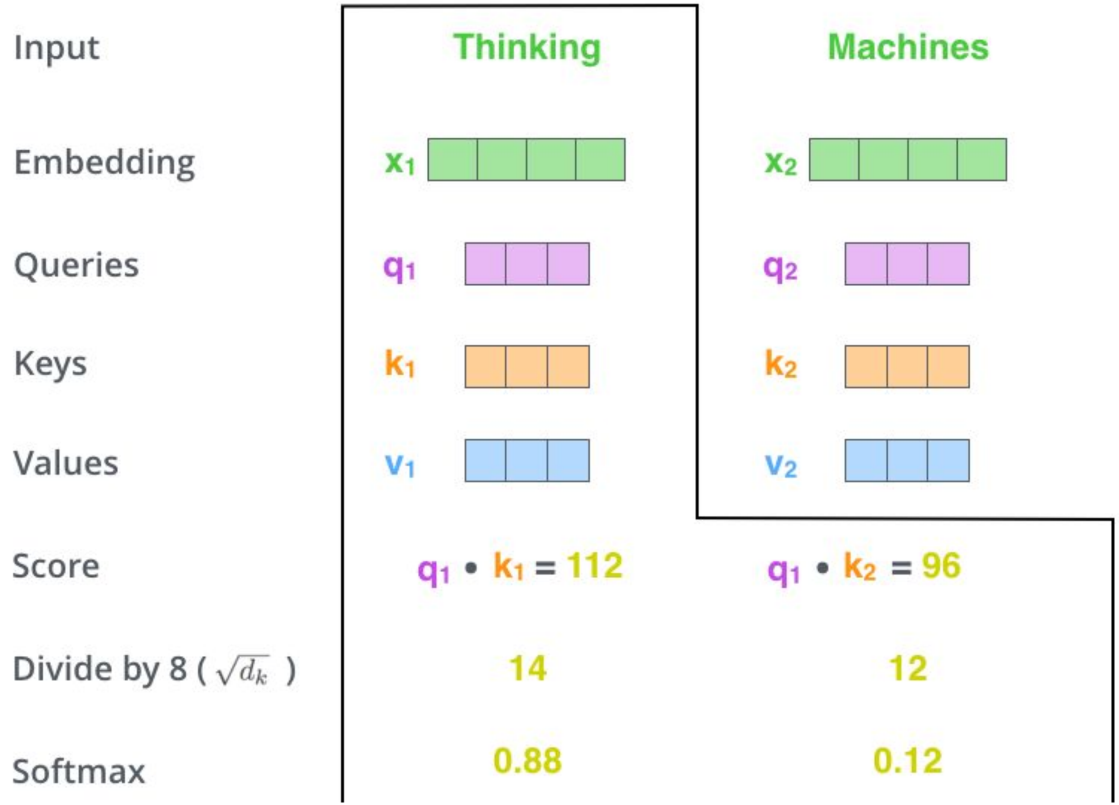


Figure: Jay Alammar, [“The illustrated Transformer”]() (2018)

Self-Attention (or intra-Attention)

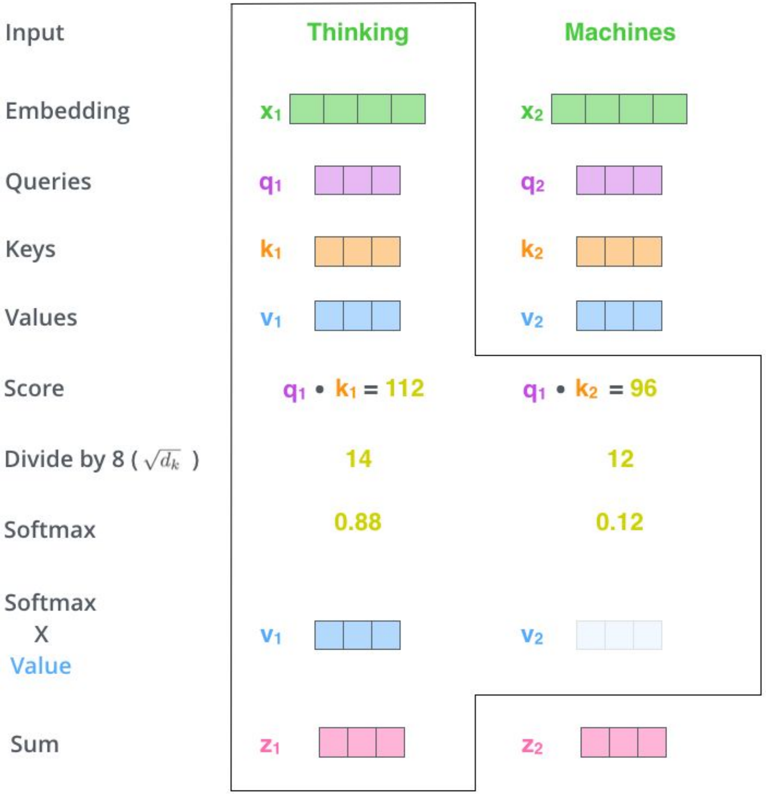


Figure: Jay Alammar, [“The illustrated Transformer”](#) (2018)

Self-Attention (or intra-Attention)

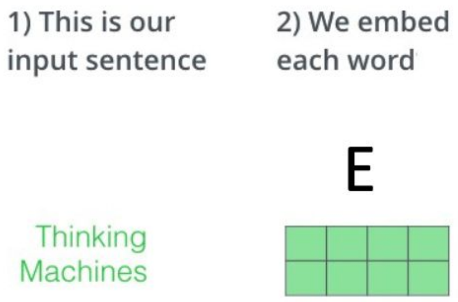


Figure: Jay Alammar, "The illustrated Transformer" (2018)

Self-Attention (or intra-Attention)

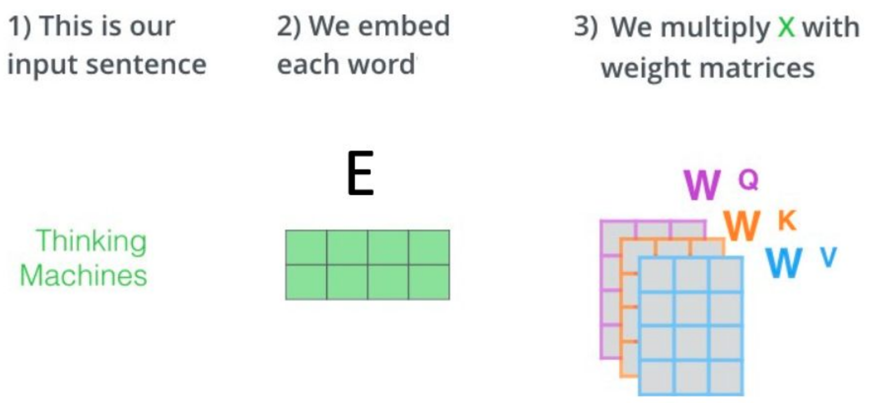
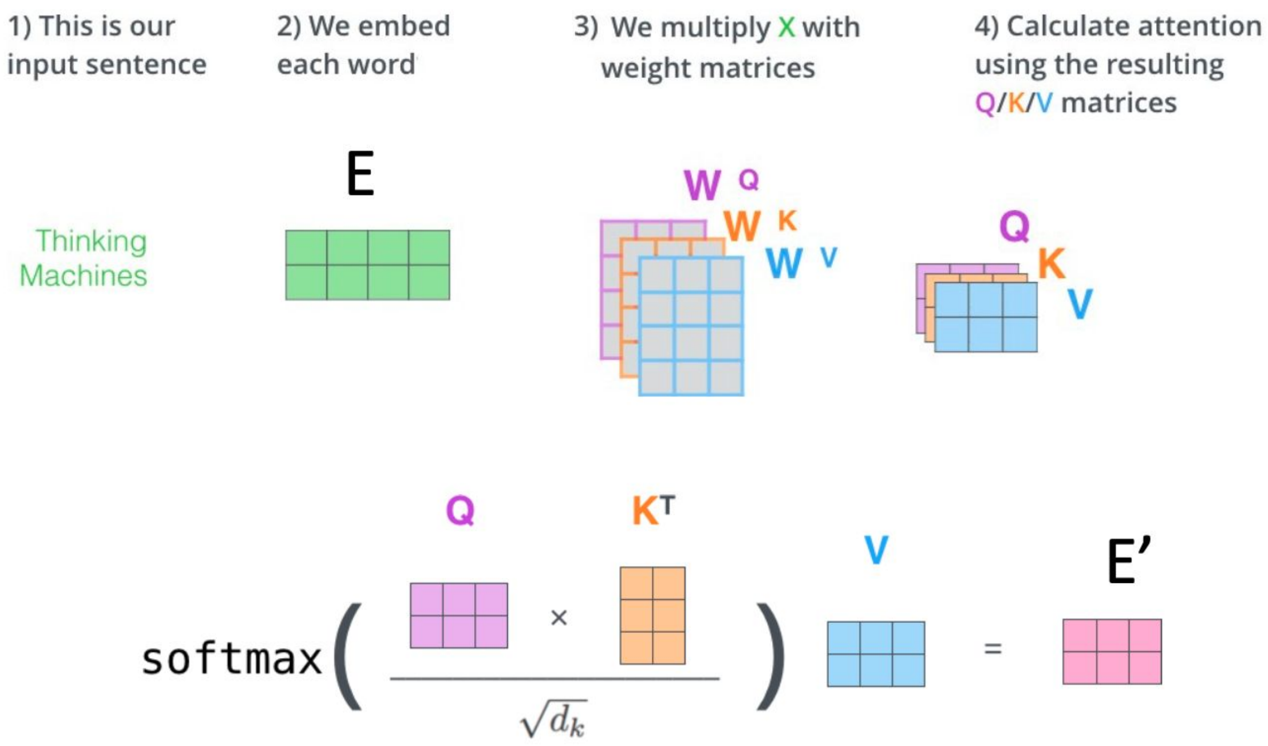


Figure: Jay Alammar, [“The illustrated Transformer”]() (2018)

Self-Attention (or intra-Attention)



$$\text{softmax}\left(\frac{Q \times K^T}{\sqrt{d_k}}\right) V = E'$$

Figure: Jay Alammar, "The illustrated Transformer" (2018)

Self-Attention (or intra-Attention)

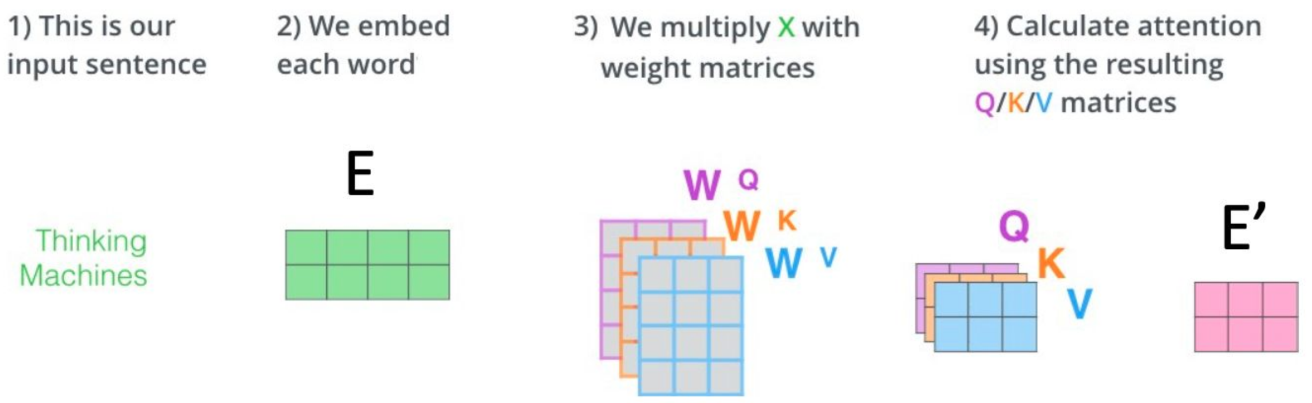
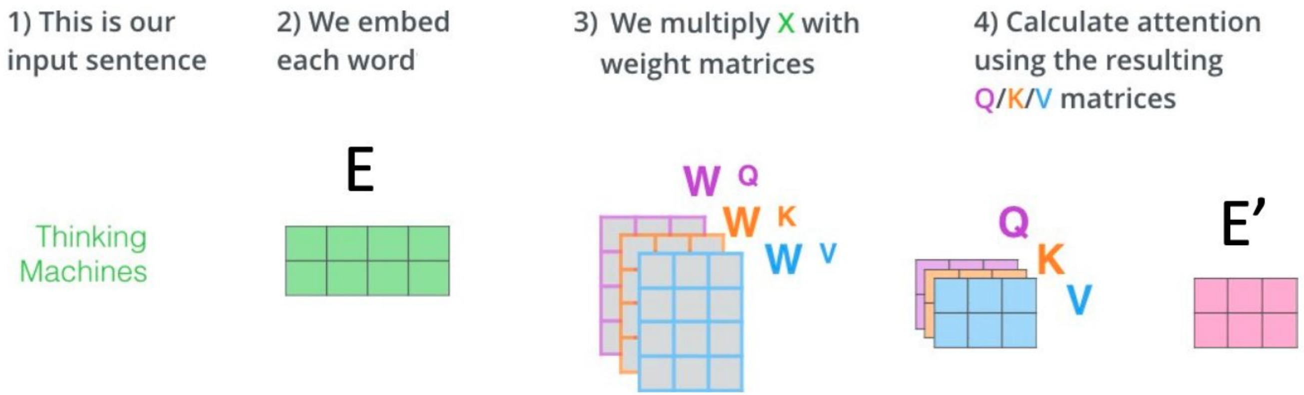


Figure: Jay Alammar, “The illustrated Transformer” (2018)

Self-Attention (or intra-Attention)



Scaled dot-product attention

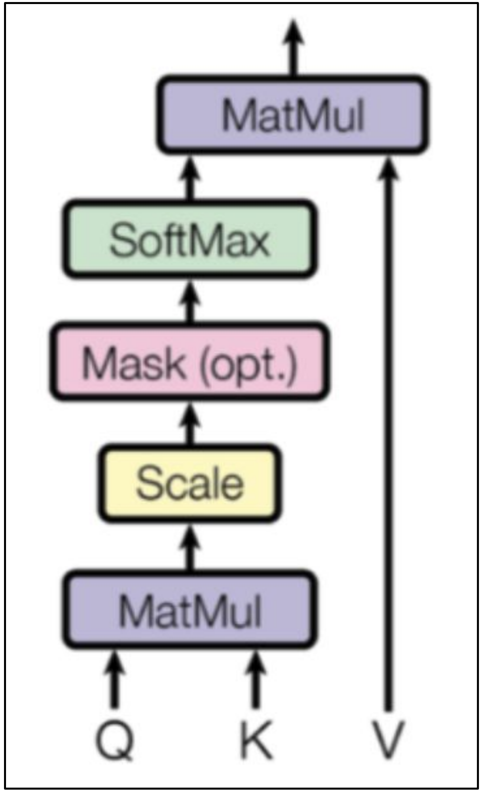


Figure: Jay Alammar, "The illustrated Transformer" (2018)

Study case: Self-Attention in images

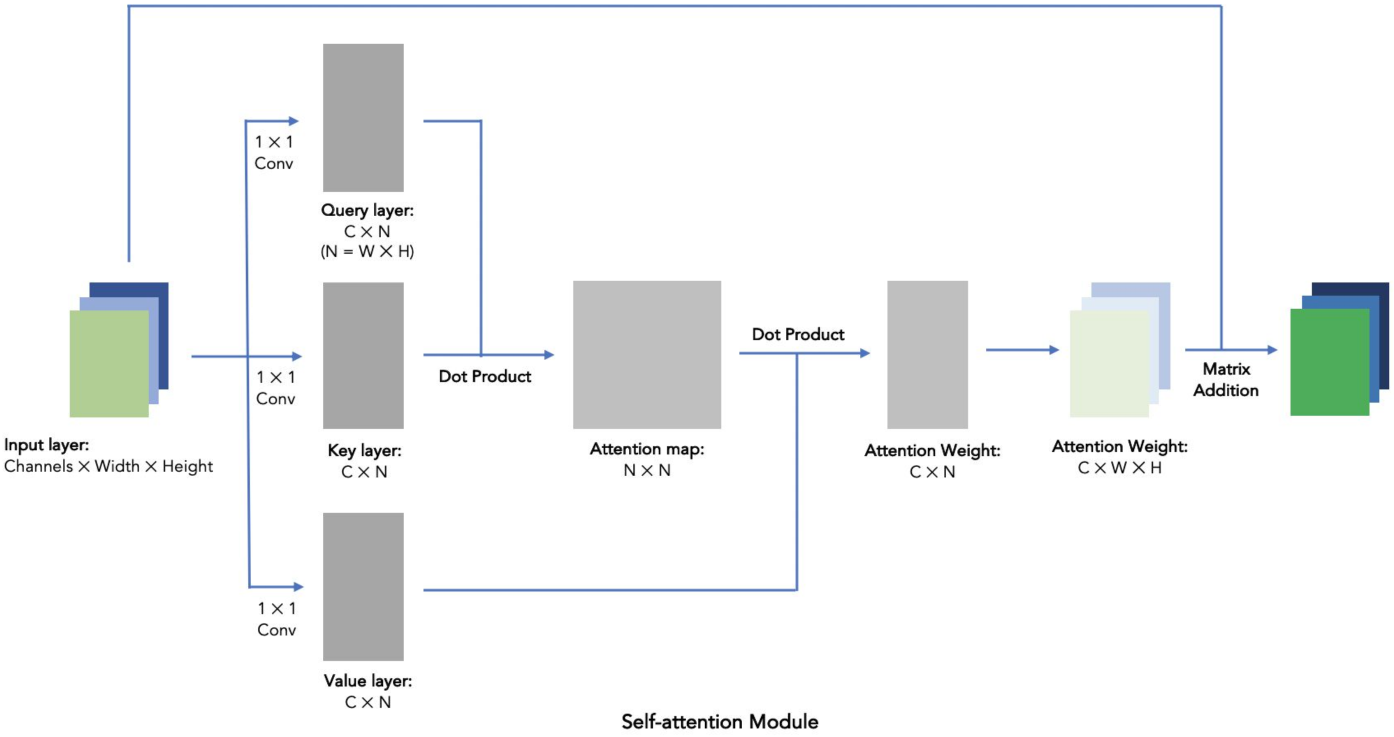


Figure:
[Frank Xu]

#SAGAN Zhang, Han, Ian Goodfellow, Dimitris Metaxas, and Augustus Odena. ["Self-attention generative adversarial networks."] ICML 2019. [[video]]

Outline

1. Motivation
2. Self-attention
3. **Multi-head Self-Attention (MHSA)**

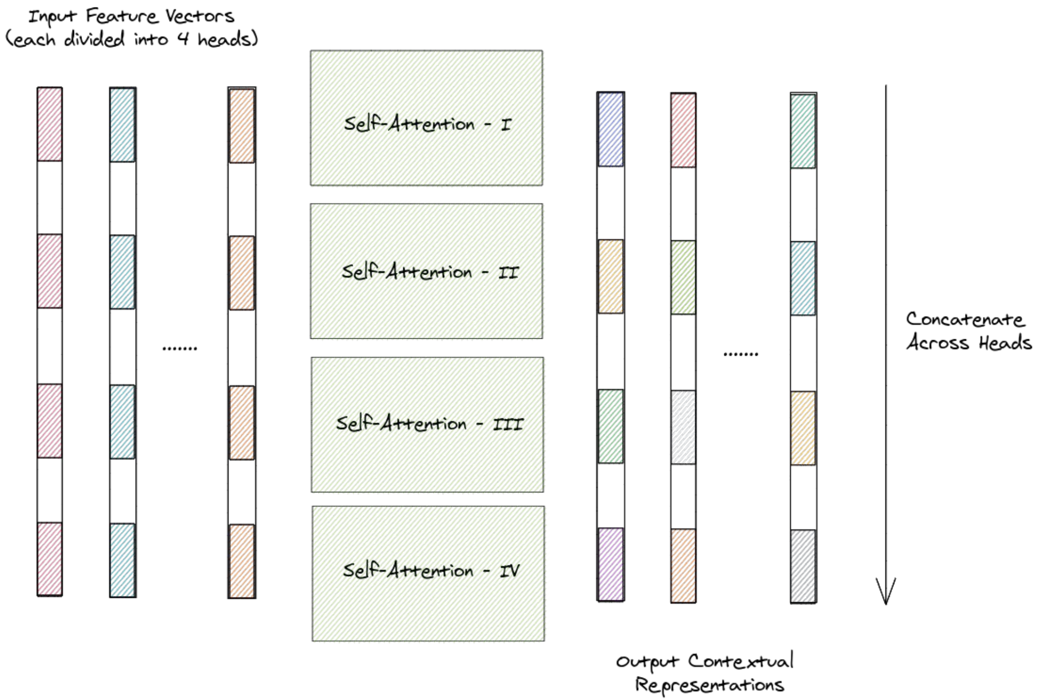
Multi-Head Self-Attention (MHSA)

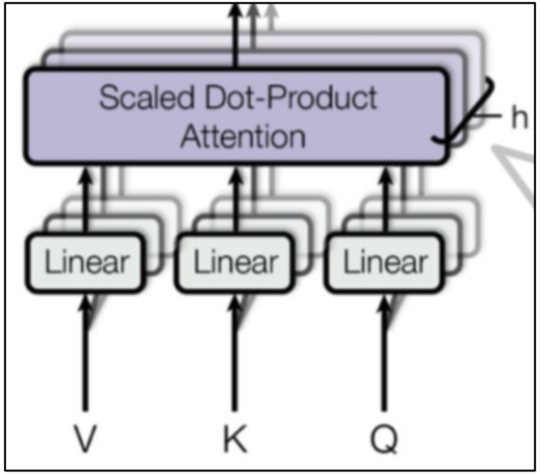
In vanilla self-attention, a single set of projection matrices W^Q, W^K, W^V is used.

Nikhil Sha, [“Attention ? An other Perspective!”](). 2020.

Multi-Head Self-Attention (MHSA)

In multi-head self-attention, multiple sets of projection matrices are used, and can provide <u>different</u> contextual representations for the same input token.

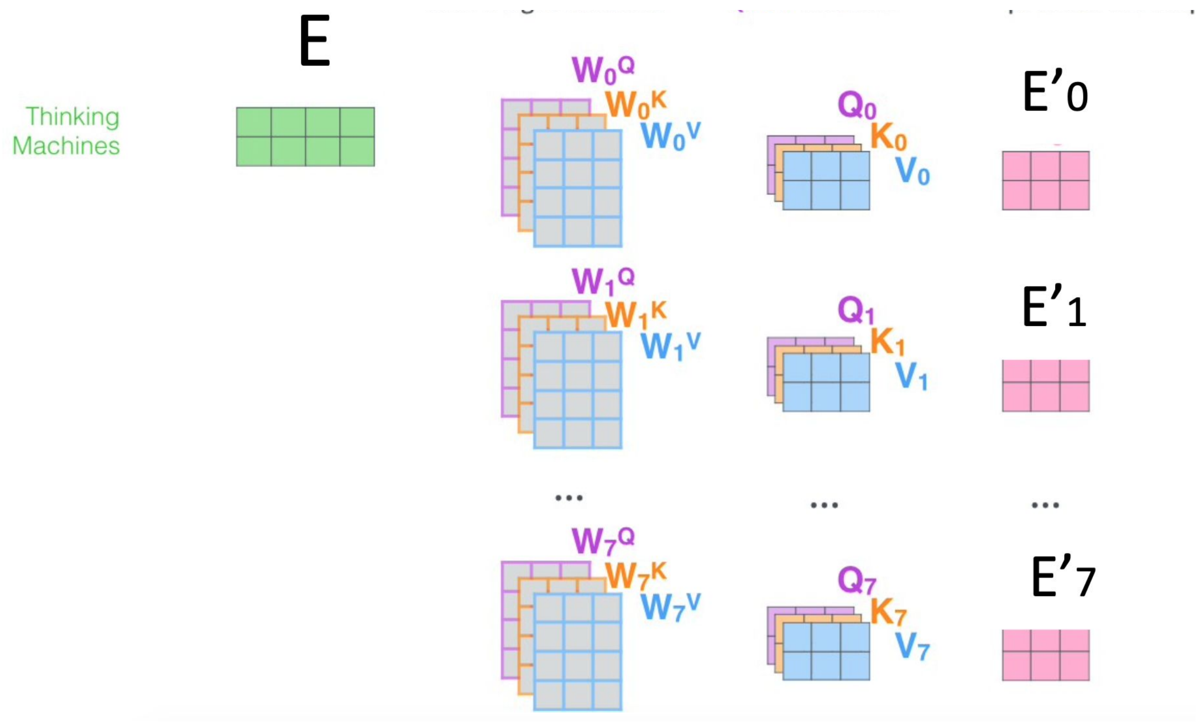




Nikhil Sha, "Attention ? An other Perspective!". 2020.

Multi-Head Self-Attention (MHSA)

The multi-head self-attended E'_i matrixes are concatenated:



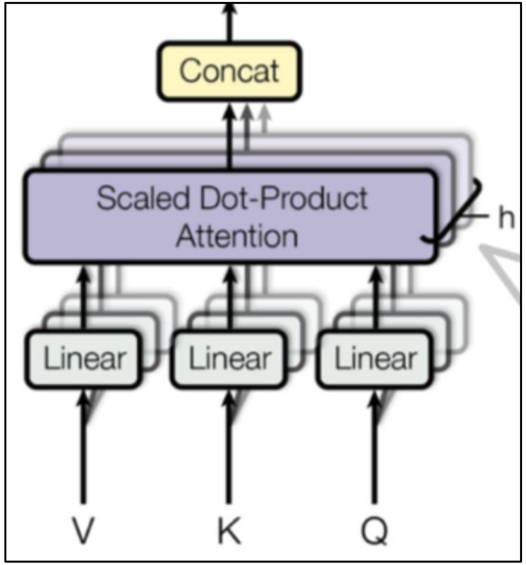
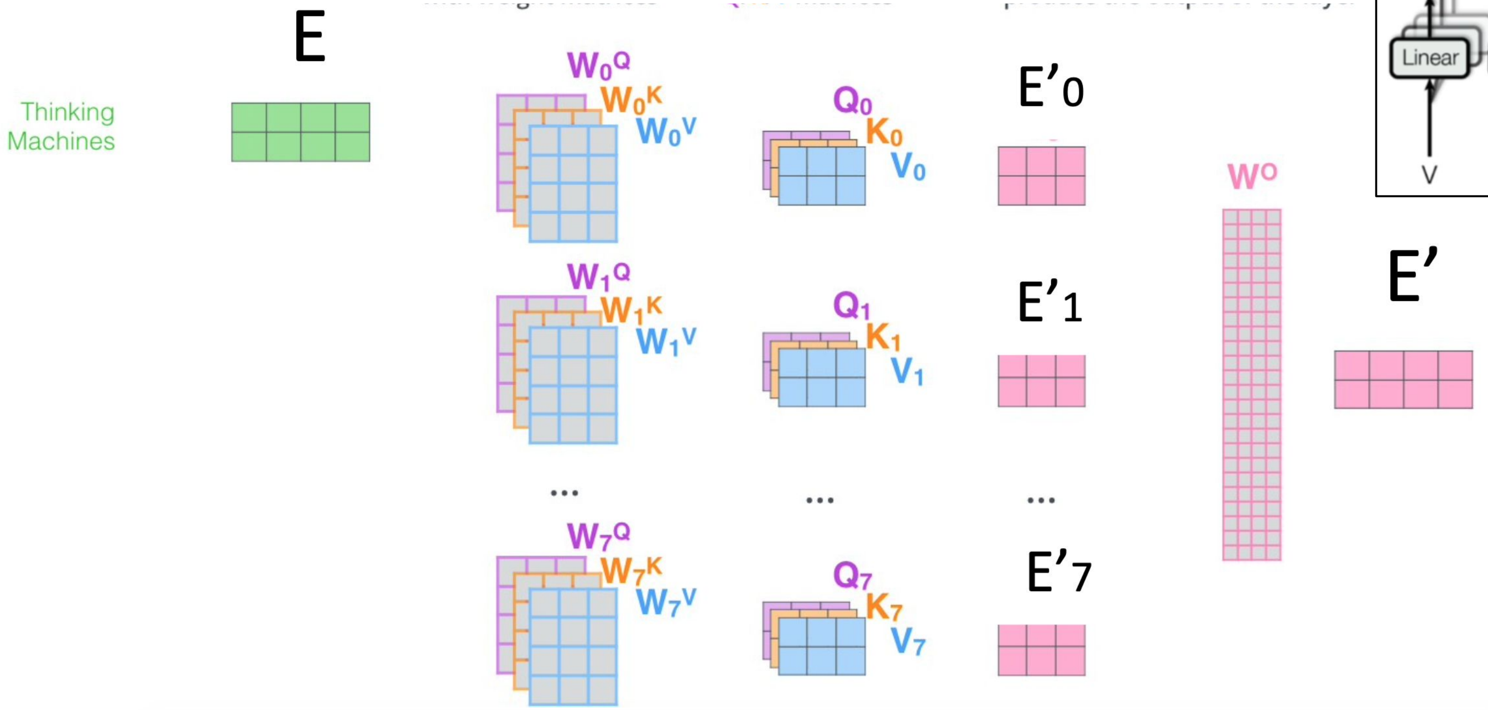


Figure: Jay Alammar, "The illustrated Transformer" (2018)

Multi-Head Self-Attention (MHSA)

A fully connected layer on top combines everything in a new E’.



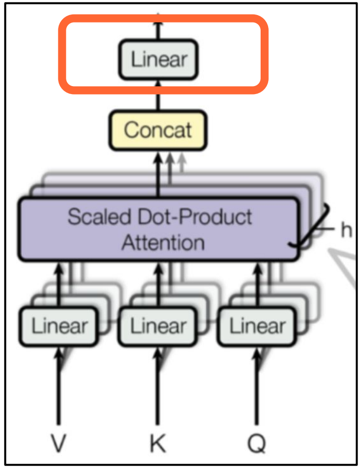
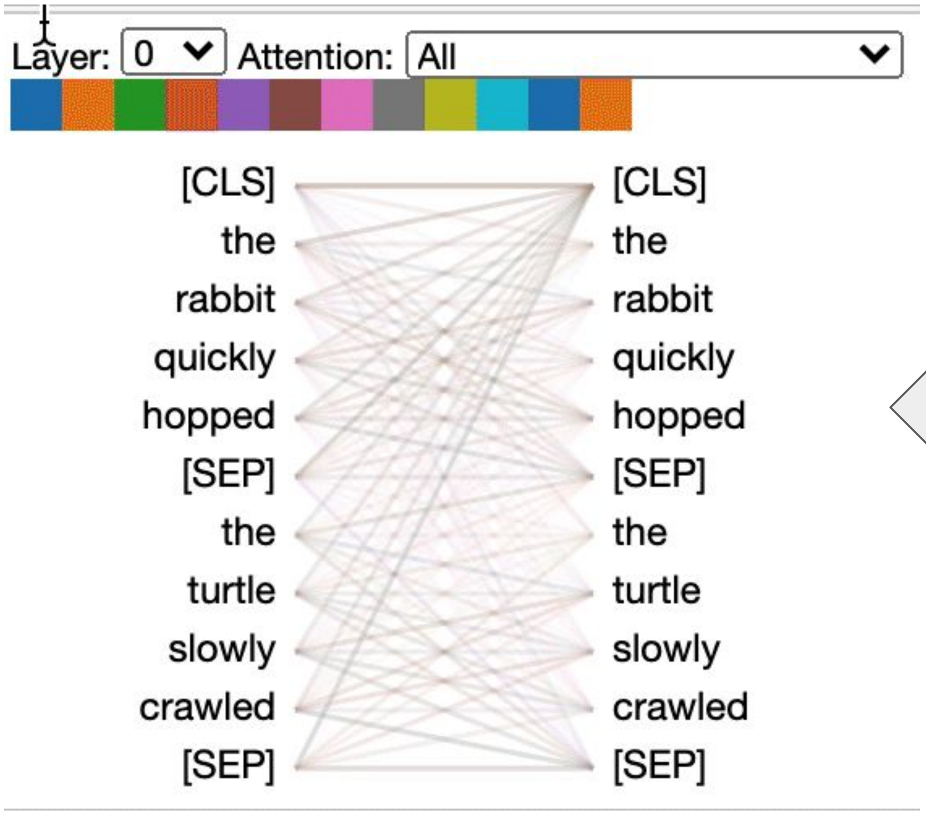


Figure: Jay Alammar, [“The illustrated Transformer”](#) (2018)

Multi-head Self-Attention: Visualization

Each colour corresponds to a head.



Blue: First head only.

Multi-color: Multiple heads.

#BertViz Vig, Jesse. ["A multiscale visualization of attention in the transformer model."]() ACL 2019. [[code]()] [[tweet]()]

Self-Attention and Convolutional Layers

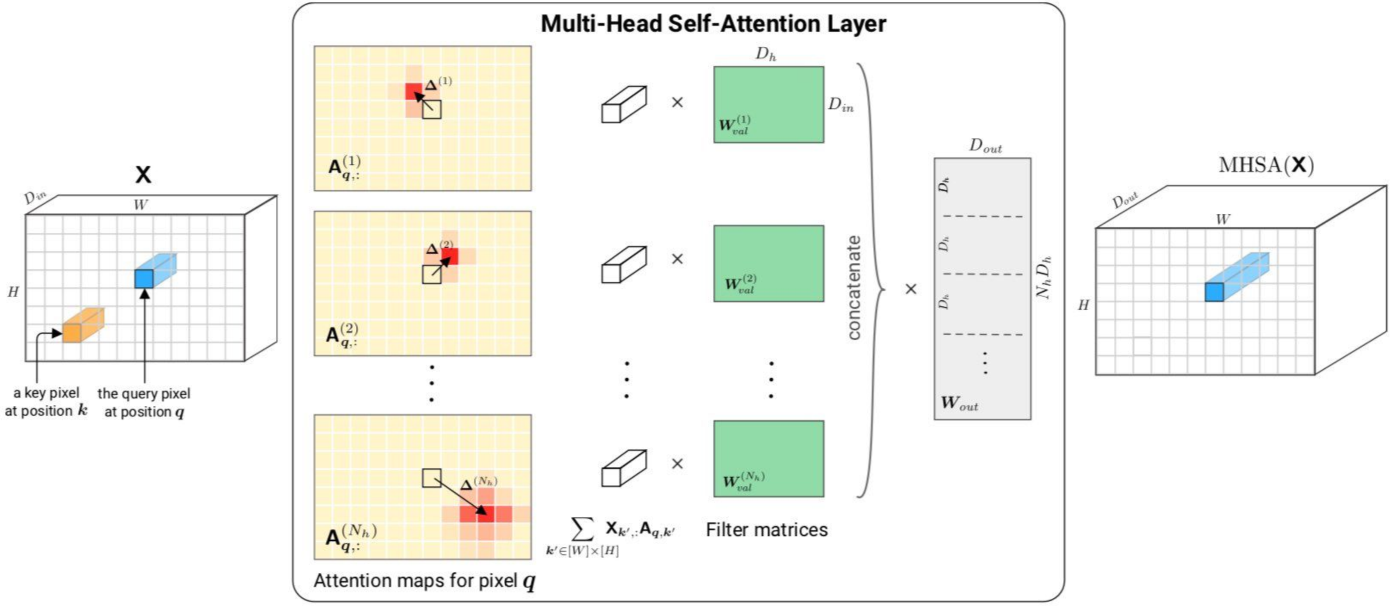


Figure 1: Illustration of a Multi-Head Self-Attention layer applied to a tensor image $\mathbf{X}$. Each head h attends pixel values around shift $\mathbf{\Delta}^{(h)}$ and learn a filter matrix $\boldsymbol{W}_{val}^{(h)}$. We show attention maps computed for a query pixel at position $\boldsymbol{q}$.

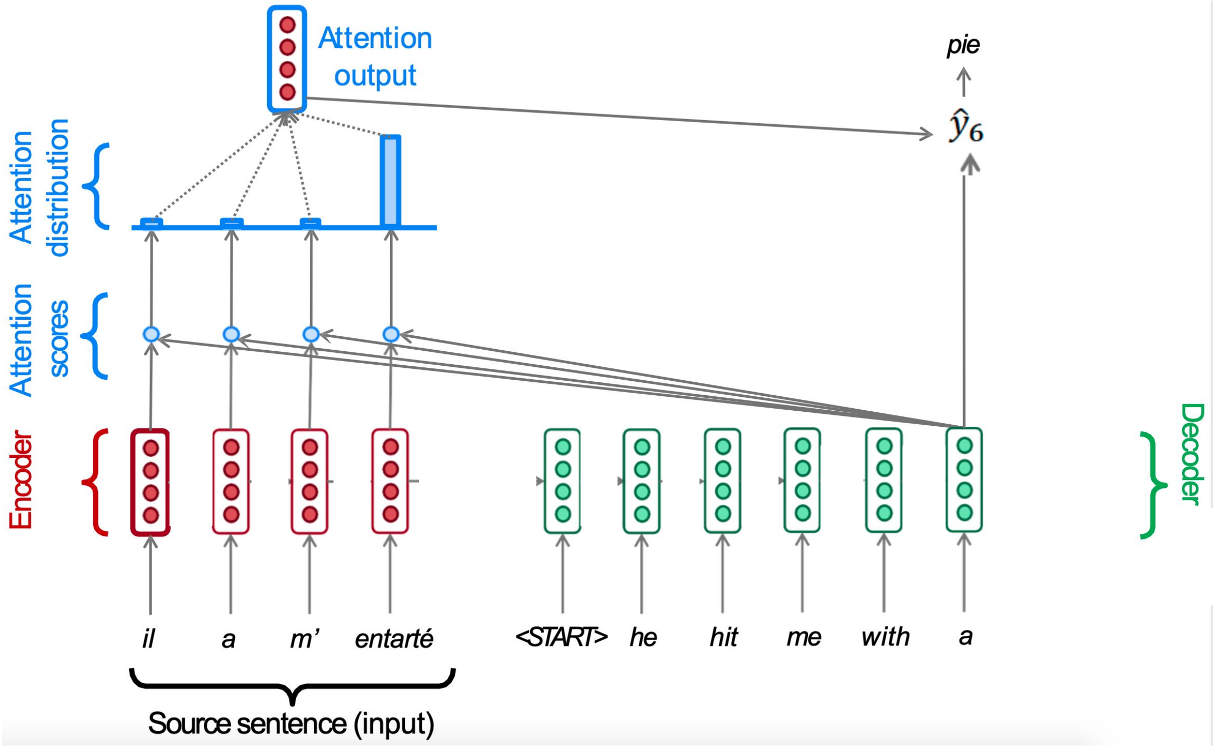
Cordonnier, J. B., Loukas, A., & Jaggi, M. [On the relationship between self-attention and convolutional layers](). ICLR 2020.
[tweet] [code]

Outline

1. Motivation
2. Self-attention
3. Multi-head Attention
4. **Positional Encoding**

Positional Encoding

Given that the attention mechanism allows accessing all input (and output) tokens, we no longer need a memory through recurrent layers.



Positional Encoding

Where is the relative relation in the sequence encoded ?

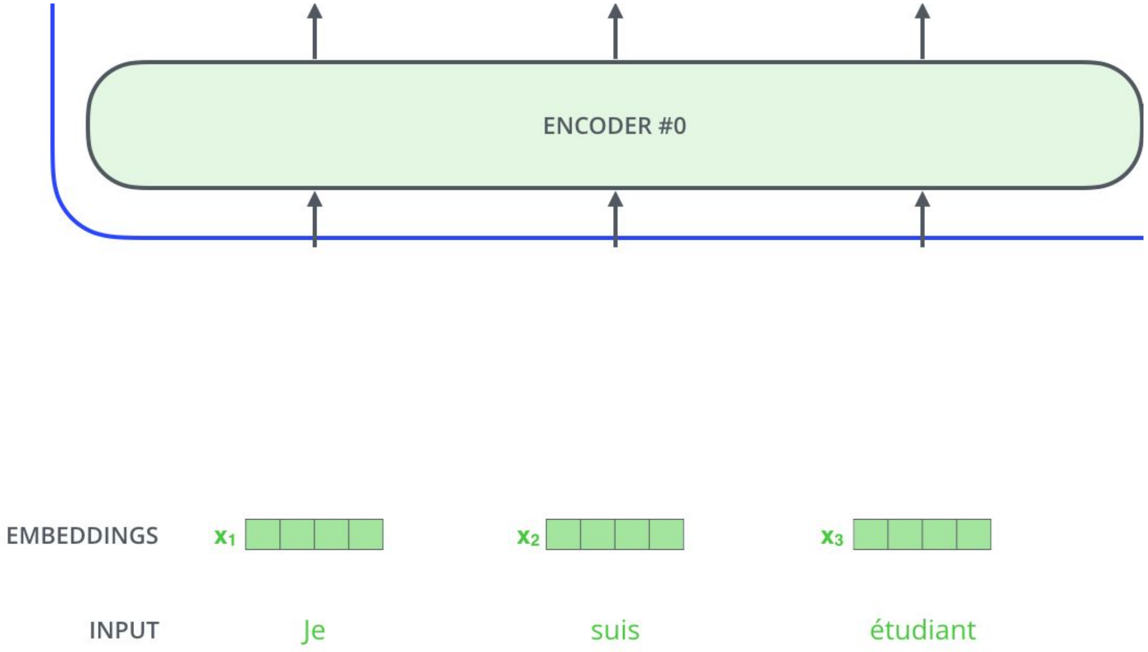


Figure: Jay Alammar, [“The illustrated Transformer”](#) (2018)

Positional Encoding

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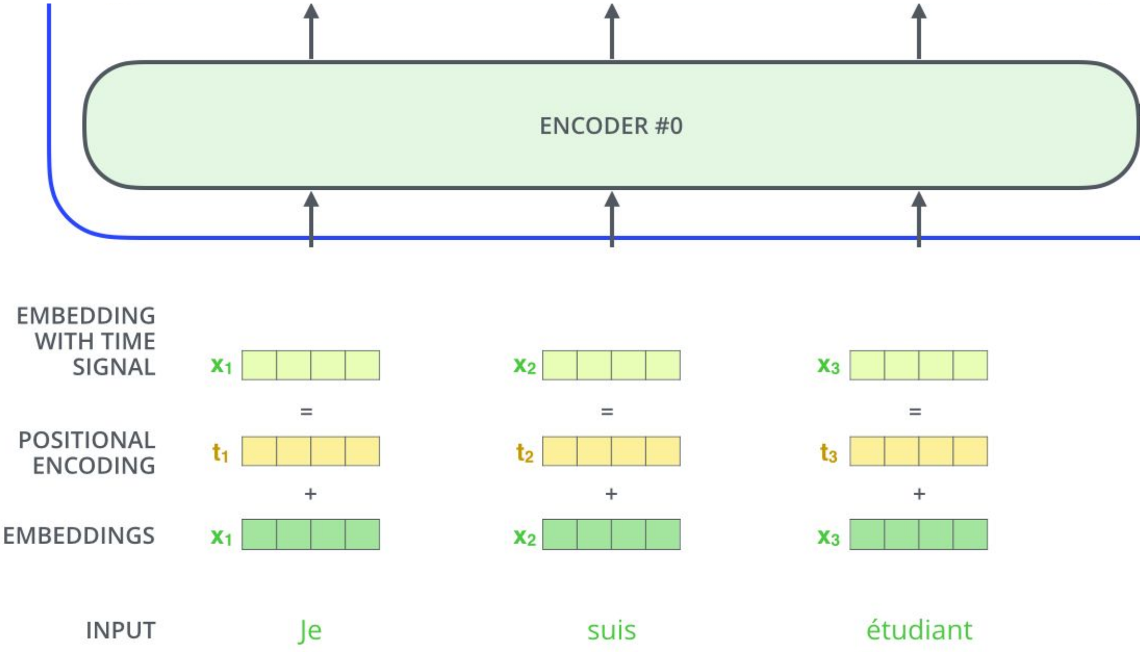
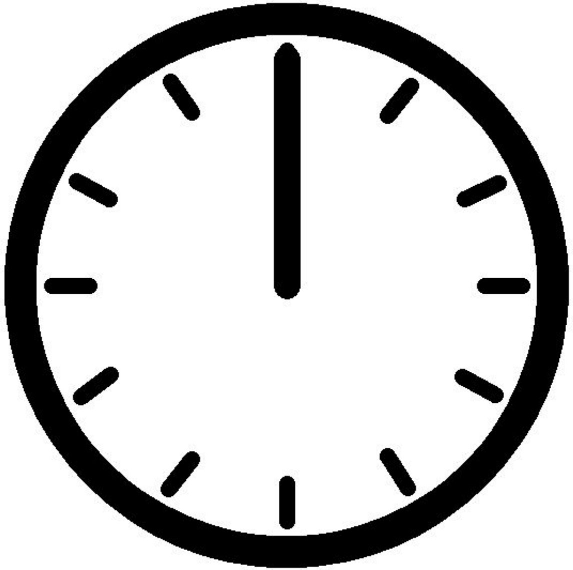
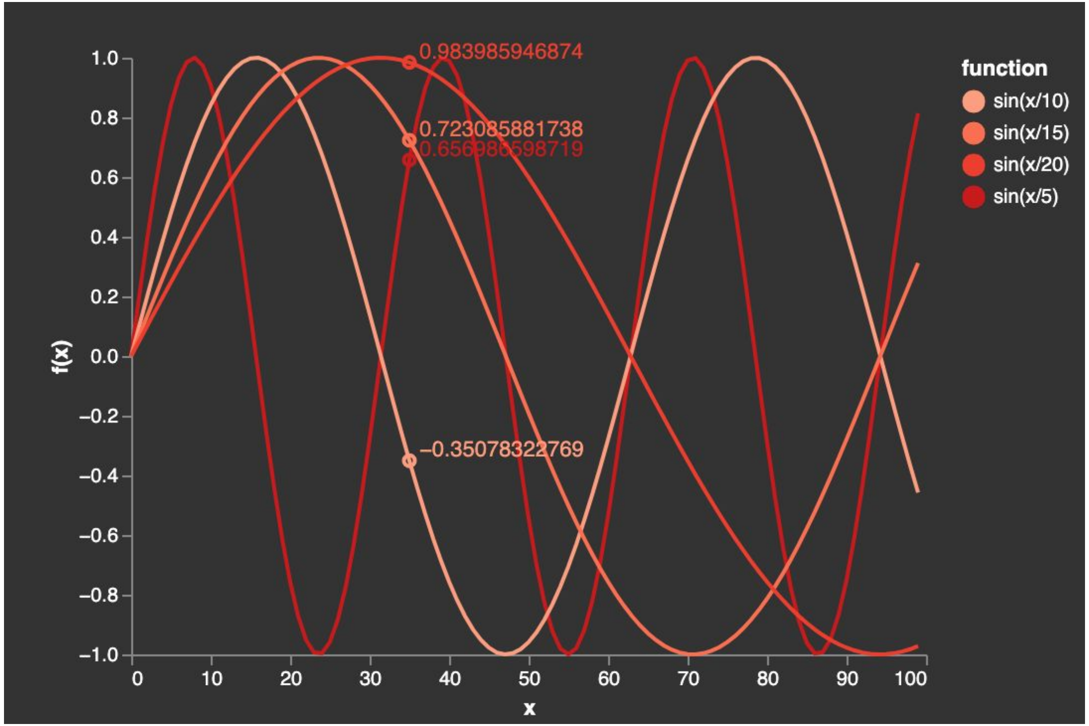


Figure: Jay Alammar, [“The illustrated Transformer”](#) (2018)

Positional Encoding

Sinusoidal functions are typically used to provide positional encodings.





Maria Ribalta, Pere-Pau Vàzquez, [“Visualization is all you need”](). UPC GCED 2020.

Positional Encoding

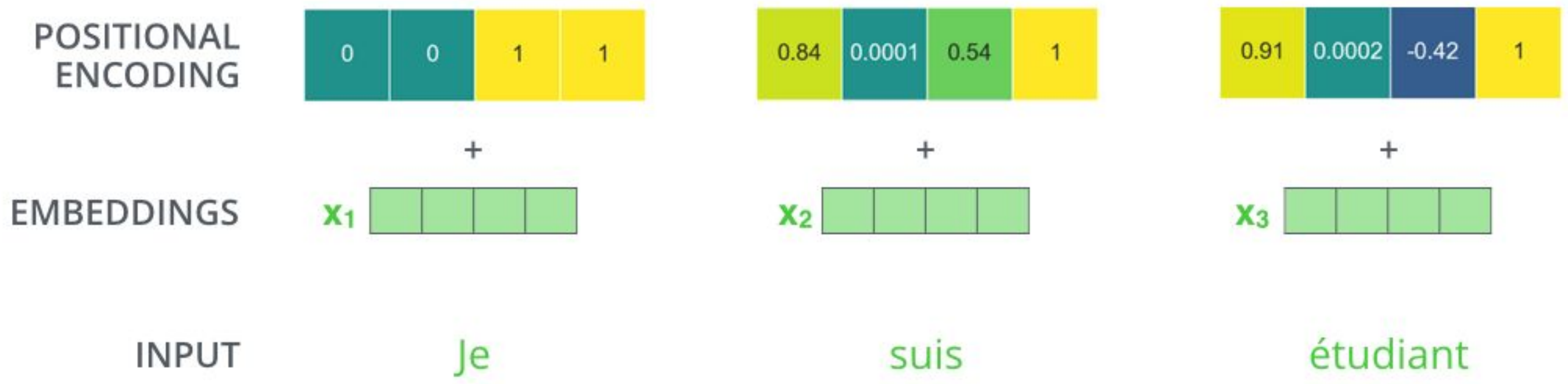


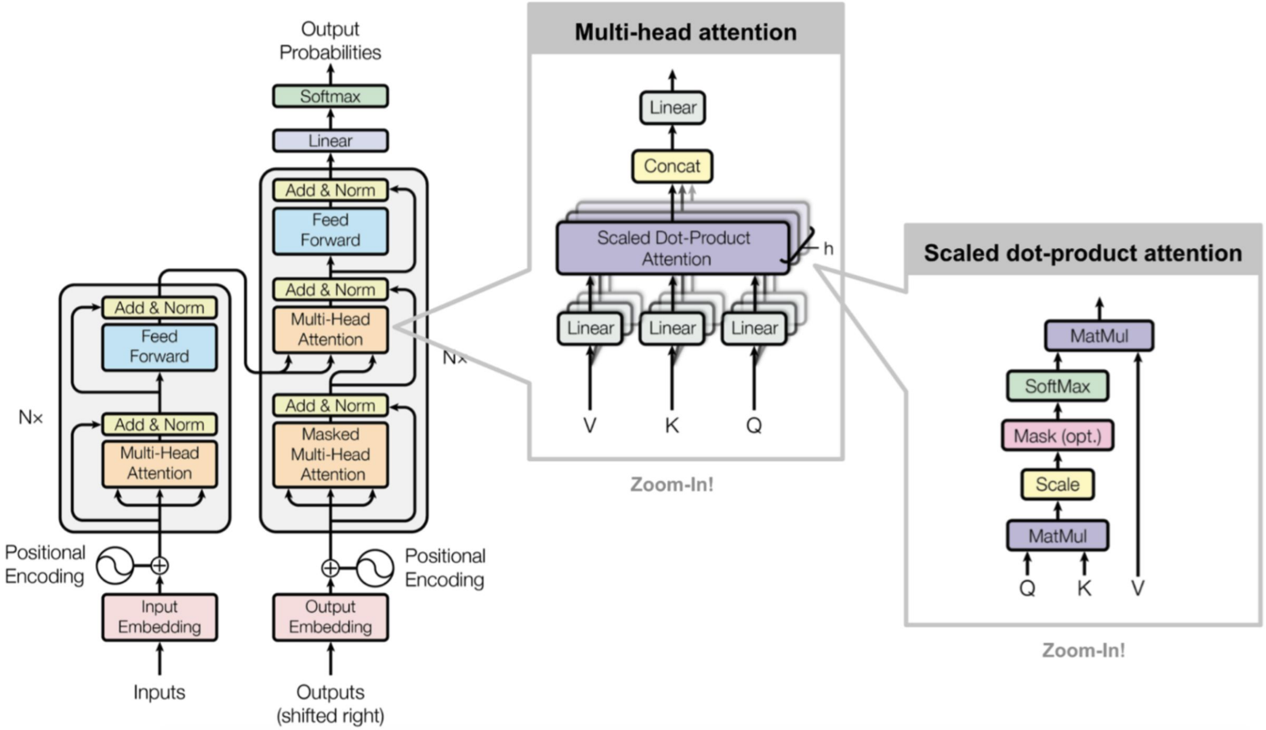
Figure: Jay Alammar, “The illustrated Transformer” (2018)

Outline

1. Motivation
2. Self-attention
3. Multi-head Attention
4. Positional Encoding
5. **The Transformer**

The Transformer

The Transformer was a revolutionary architecture in machine translation.

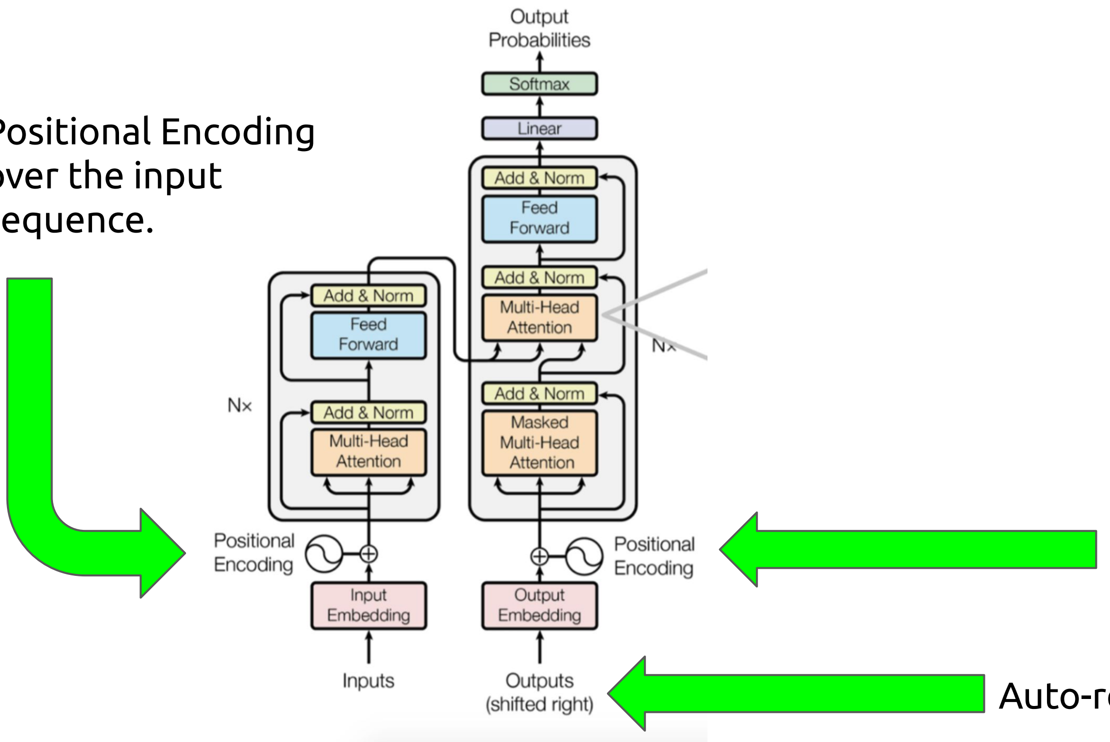


#Transformer Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I.. Attention is all you need. NeurIPS 2017.

The Transformer

The Transformer removed the recurrent layer and adopted an auto-regressive approach (at test).

Positional Encoding over the input sequence.



Positional Encoding over the output sequence.

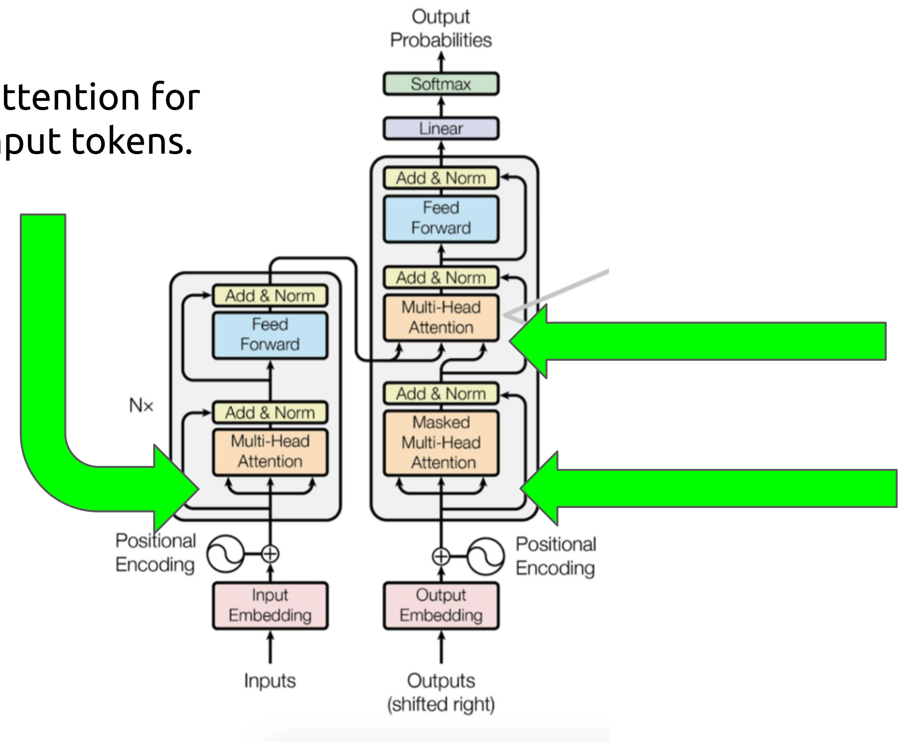
Auto-regressive.

#Transformer Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I.. [Attention is all you need](). NeurIPS 2017.

The Transformer

The Transformer was a revolutionary architecture that removed the recurrent layers to process sequences.

Self-attention for
the input tokens.



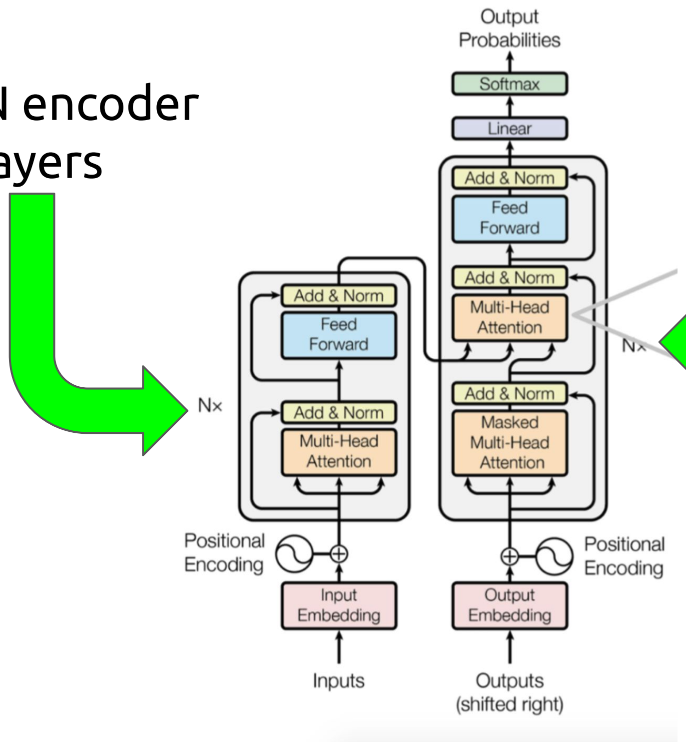
Cross-Attention (or inter-attention)
between input and output tokens

Self-attention for the output tokens.

#Transformer Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I.. [Attention is all you need](). NeurIPS 2017.

The Transformer: Layers

N encoder layers

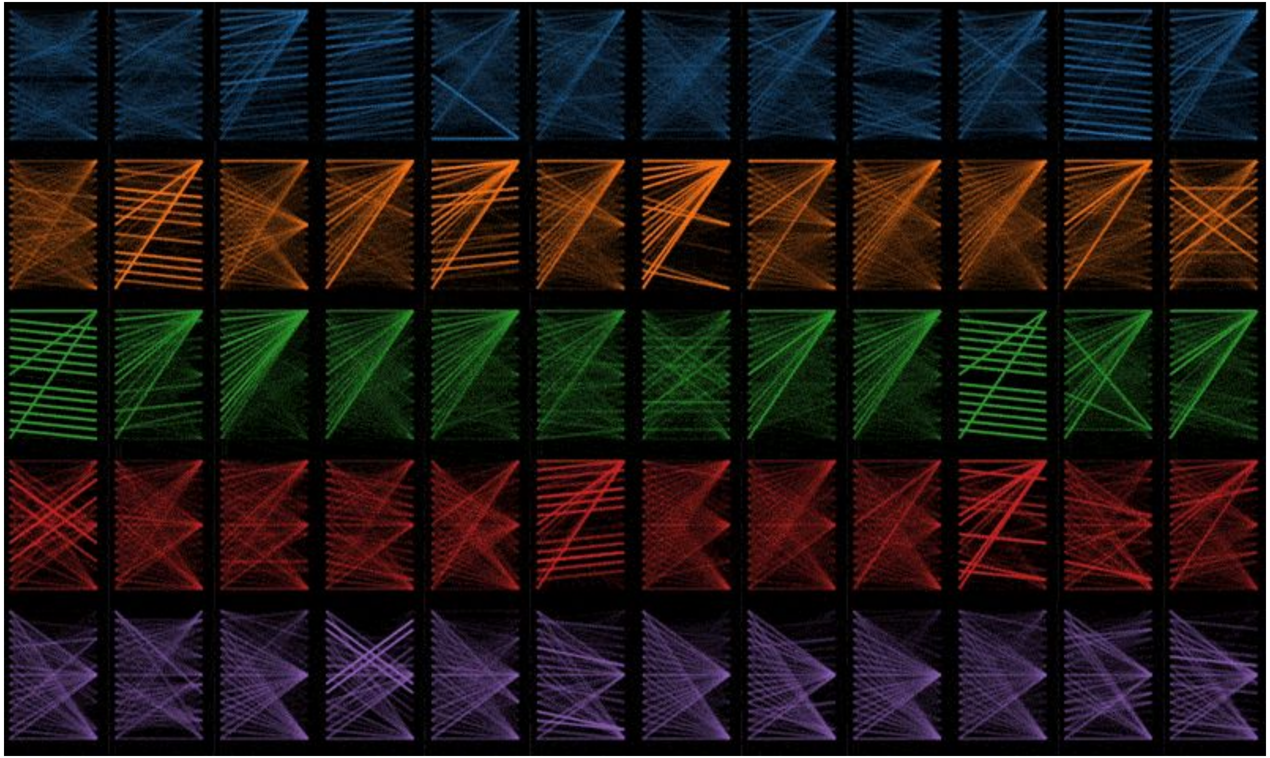


N decoder layers

#Transformer Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I.. [Attention is all you need](). NeurIPS 2017.

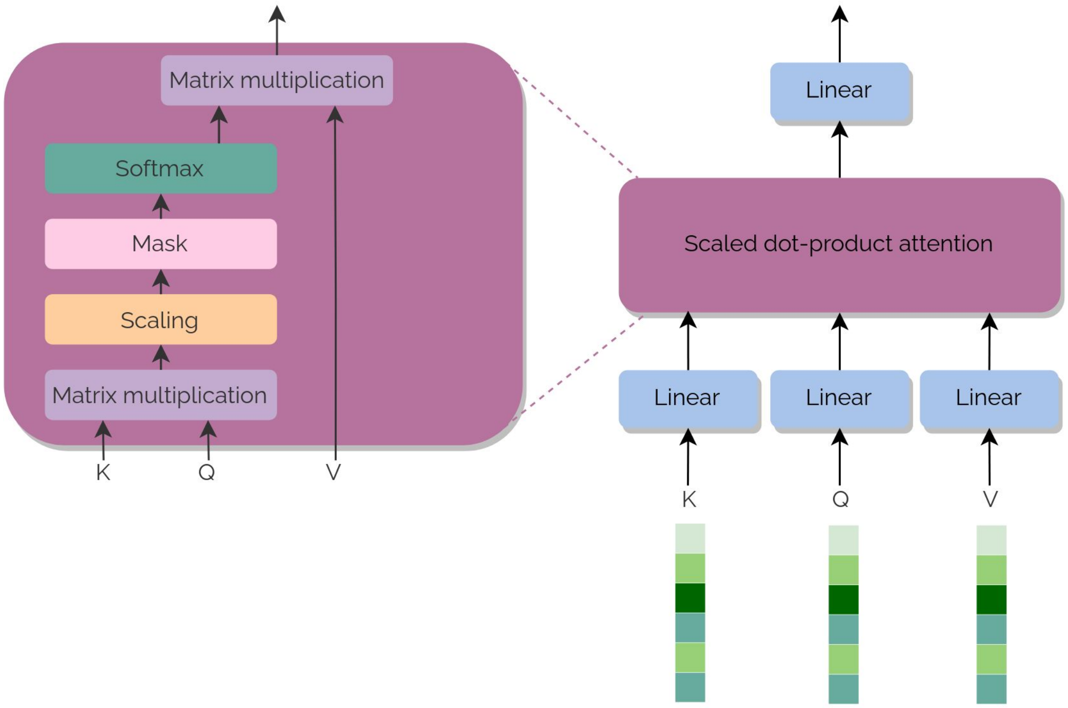
The Transformer: Layers

A birds-eye view of attention across all of the model's layers and heads



#BertViz Vig, Jesse. ["A multiscale visualization of attention in the transformer model."]() ACL 2019. [[code]()] [[tweet]()]

The Transformer: Visualization



Maria Ribalta, Pere-Pau Vàzquez, [“Visualization is all you need”](). UPC GCED 2020.

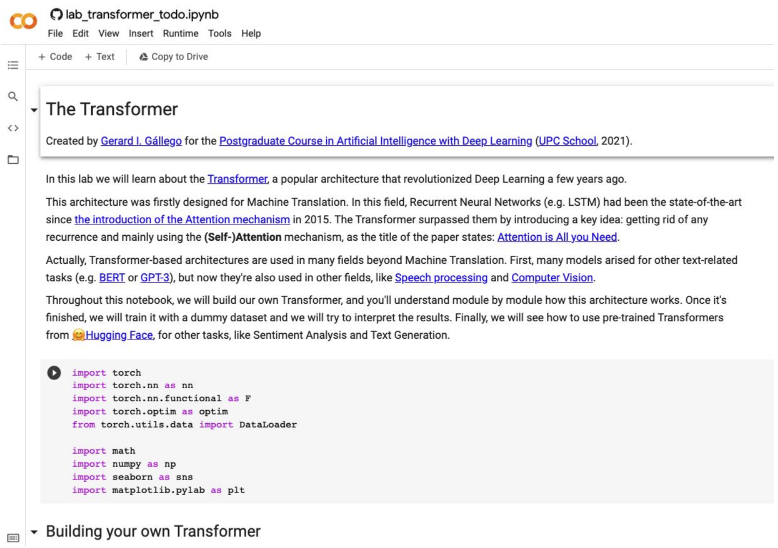
Are Transformers for Language only ? NO !!

#ViT Dosovitskiy, Alexey, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani et al. "An image is worth 16x16 words: Transformers for image recognition at scale." ICLR 2021. [blog] [code]

Outline

1. Motivation
2. Self-attention
3. Multi-head Attention
4. Positional Encoding
5. The Transformer

(extra) PyTorch Lab on Google Colab



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Student PhD
Universitat Politecnica de Catalunya
Technical University of Catalonia

DL resources from UPC Telecos:

- Lectures (with Slides & Videos)
- Labs

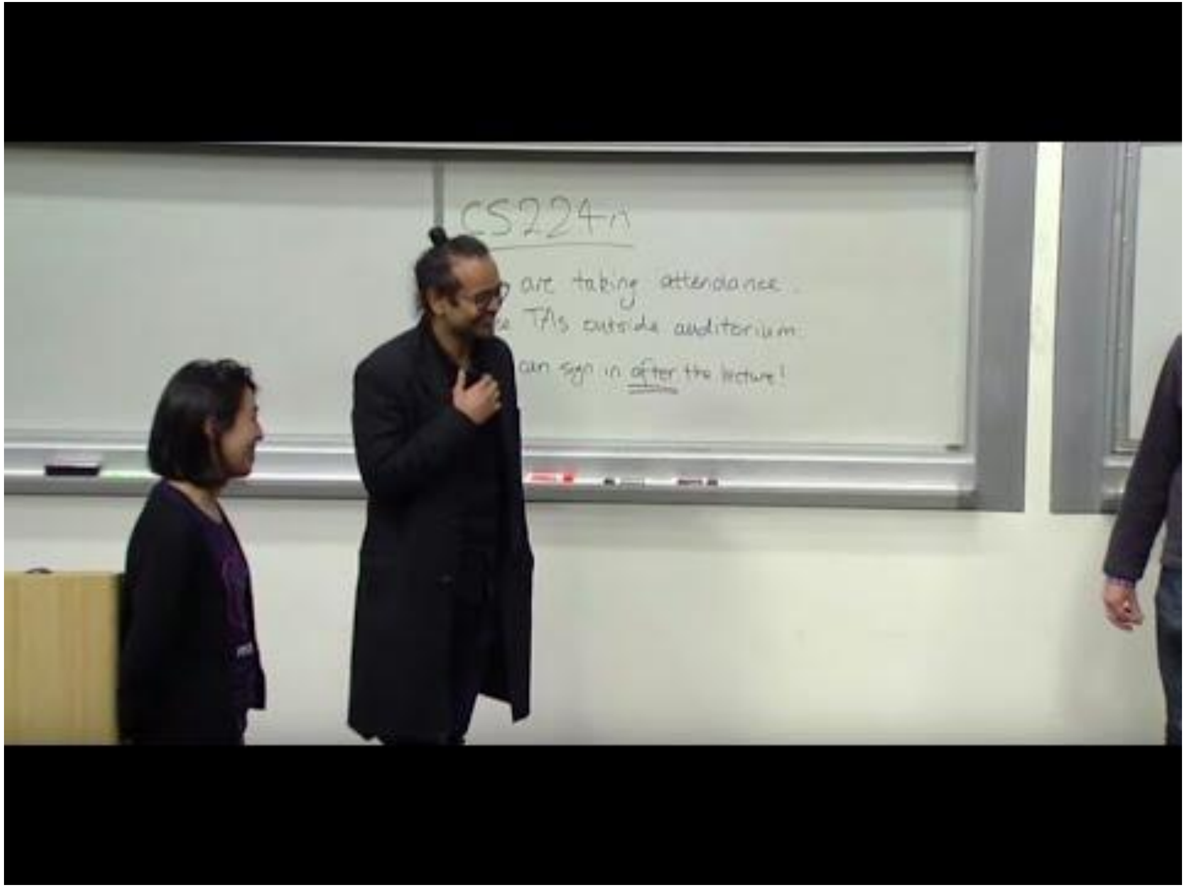
Software

- Transformers in HuggingFace.
- GPT-Neo by EleutherAI
    - Similar results to GPT-3, but smaller and open source.
- Andrej Karpathy, minGPT (2020).

available GPT implementations

minGPT

Learn more

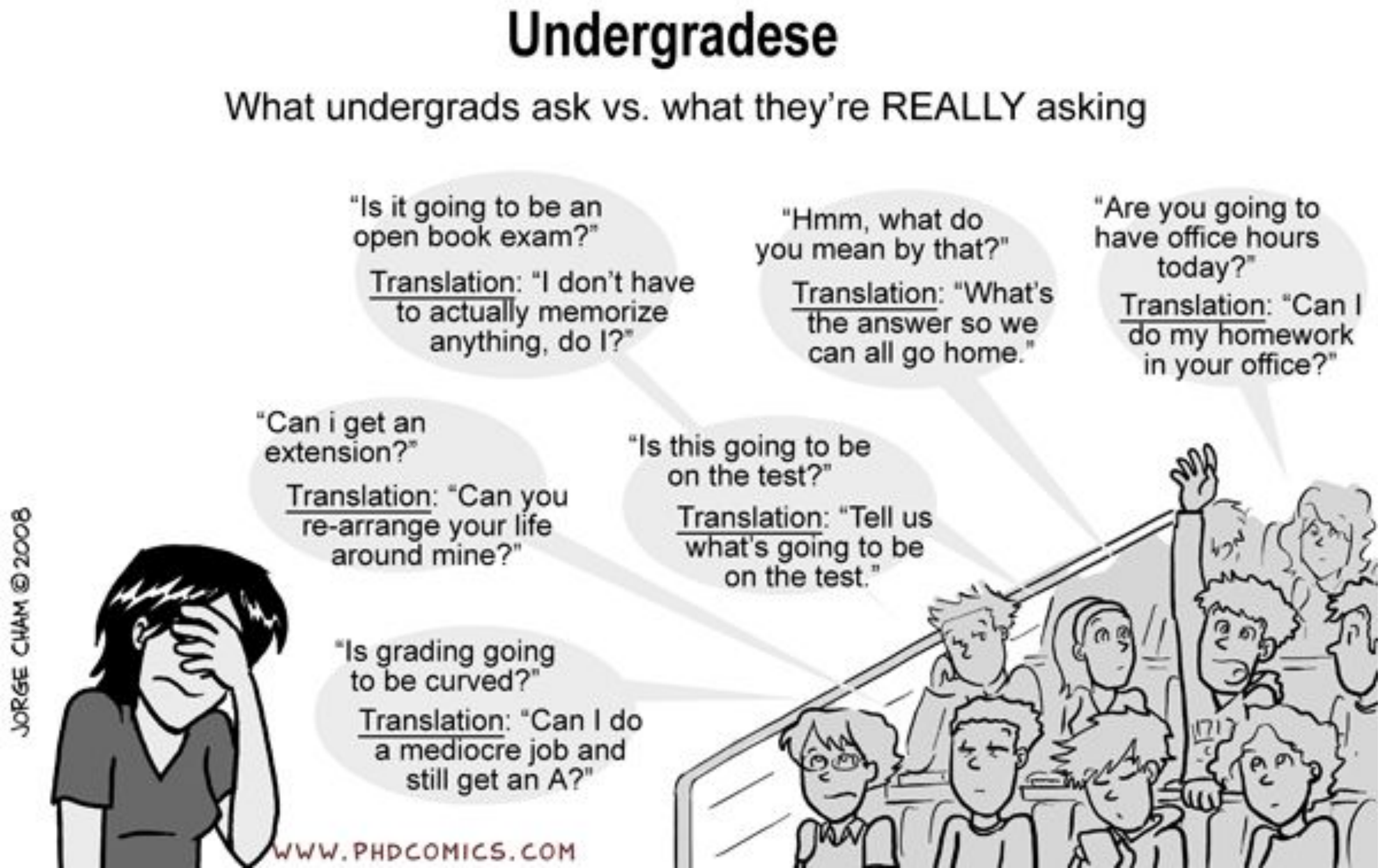


Ashihs Vaswani, Stanford CS224N 2019.

Learn more

- Tutorials
  - Sebastian Ruder, Deep Learning for NLP Best Practices # Attention (2017).
  - Chris Olah, Shan Carter, “Attention and Augmented Recurrent Neural Networks”. distill.pub 2016.
- Demos
  - François Fleuret (EPFL)
- Twitter threads
  - Christian Wolf (INSA Lyon)
- Scientific publications
  - Katharopoulos, A., Vyas, A., Pappas, N., & Fleuret, F. (2020). Transformers are rnns: Fast autoregressive transformers with linear attention. ICML 2020.
  - Siddhant M. Jayakumar, Wojciech M. Czarnecki, Jacob Menick, Jonathan Schwarz, Jack Rae, Simon Osindero, Yee Whye Teh, Tim Harley, Razvan Pascanu, “Multiplicative Interactions and Where to Find Them”. ICLR 2020. [tweet]
  - Self-attention in language
    - Cheng, J., Dong, L., & Lapata, M. (2016). Long short-term memory-networks for machine reading. arXiv preprint arXiv:1601.06733.
  - Self-attention in images
    - Parmar, N., Vaswani, A., Uszkoreit, J., Kaiser, Ł., Shazeer, N., Ku, A., & Tran, D. (2018). Image transformer. ICML 2018.
    - Wang, Xiaolong, Ross Girshick, Abhinav Gupta, and Kaiming He. "Non-local neural networks." In CVPR 2018.
    - **#SAGAN** Zhang, Han, Ian Goodfellow, Dimitris Metaxas, and Augustus Odena. "Self-attention generative adversarial networks." ICML 2019. [video]

Questions ?


Undergradese
What undergrads ask vs. what they're REALLY asking
"Is it going to be an open book exam?" Translation: "I don't have to actually memorize anything, do I?"
"Hmm, what do you mean by that?" Translation: "What's the answer so we can all go home."
"Are you going to have office hours today?" Translation: "Can I do my homework in your office?"
"Can i get an extension?" Translation: "Can you re-arrange your life around mine?"
"Is this going to be on the test?" Translation: "Tell us what's going to be on the test."
"Is grading going to be curved?" Translation: "Can I do a mediocre job and still get an A?"
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WWW.PHDCOMICS.COM