Deep Learning for Computer Vision

Self-Attention and Transformers

Vineeth N Balasubramanian

Department of Computer Science and Engineering
Indian Institute of Technology, Hyderabad

भारतीय प्रौद्योगिकी संस्थान हैदराबाद
Indian Institute of Technology Hyderabad

Review: Question

Other ways to evaluate Visual Dialog systems?

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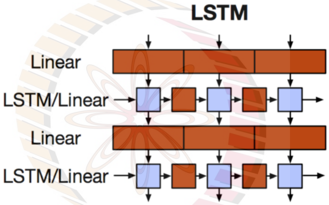
Look to NLP for consensus metrics that measure consensus between answers generated by model and a set of relevant answers; see Masciceti et al, A Revised Generative Evaluation of Visual Dialogue, arXiv 2020

Acknowledgements

- Most of this lecture's slides are based on Jay Alammar's article on "The Illustrated Transformer"
- Unless explicitly specified, assume that content and figures are either directly taken or adapted from above source

Motivation for Transformers

- Sequential computation prevents parallelization



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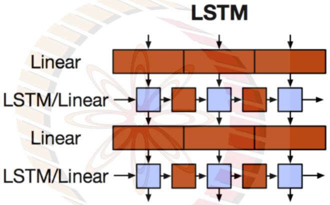

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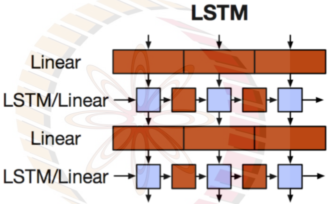
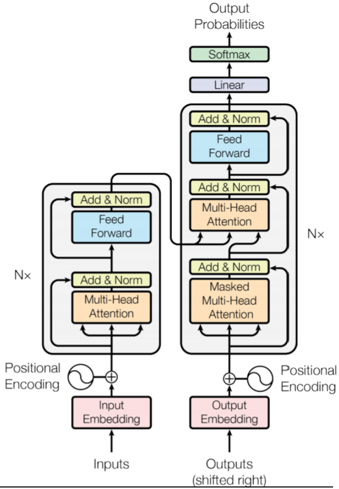


- Despite GRUs and LSTMs, RNNs still need attention mechanism to deal with long-range dependencies – path length for co-dependent computation between states grows with sequence length
- But if attention gives us access to any state, maybe we don't need the RNN?!

Credits: Richard Socher (Stanford CS224n)

Transformers[1]



- The work "Attention is All you Need" (Vaswani et al, NeurIPS 2017) first made it possible to do Seq2Seq modeling without RNNs

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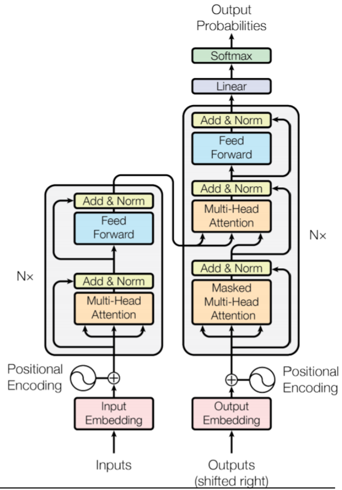

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- Proposed **transformer model**, entirely built on **self-attention mechanism** without using sequence-aligned recurrent architectures

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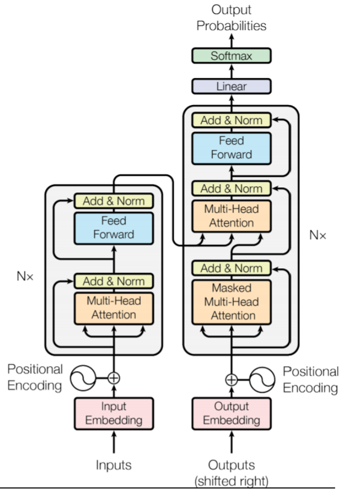

- The work "Attention is All you Need" (Vaswani et al, NeurIPS 2017) first made it possible to do Seq2Seq modeling without RNNs
- Proposed **transformer model**, entirely built on **self-attention mechanism** without using sequence-aligned recurrent architectures
- Key components:
  - Self-Attention
  - Multi-Head Attention
  - Positional Encoding
  - Encoder-Decoder Architecture

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Transformers in a Nutshell

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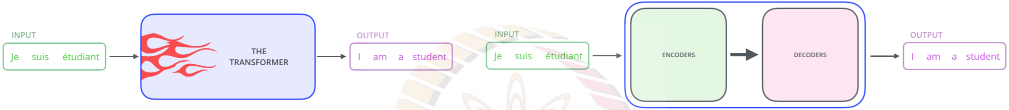

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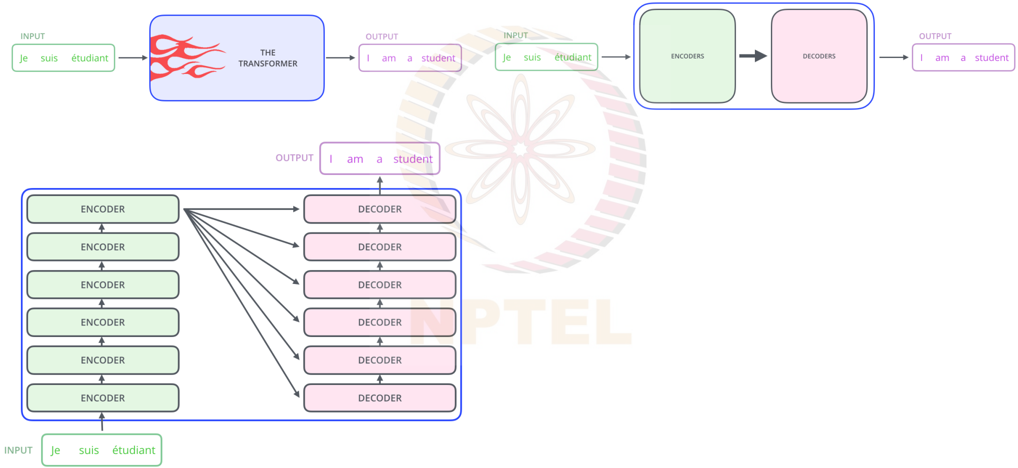

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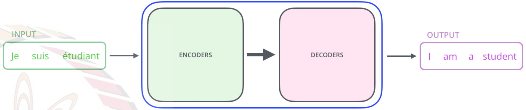
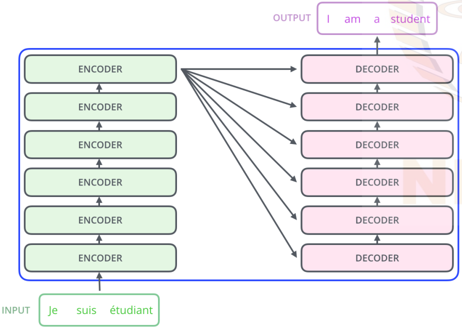
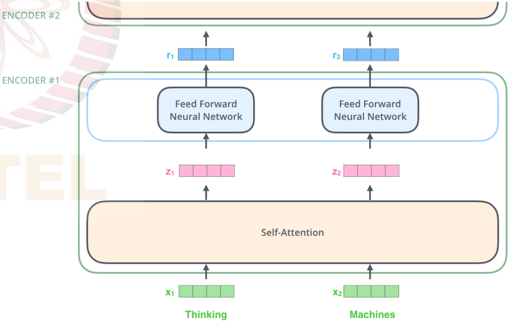
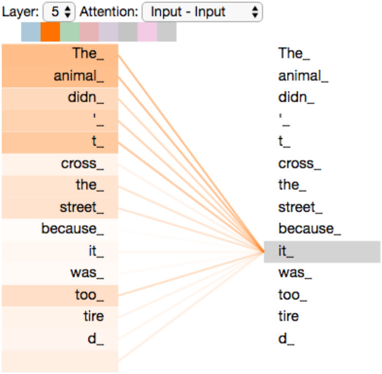






Self-Attention



- Consider two input sentences we want to translate:

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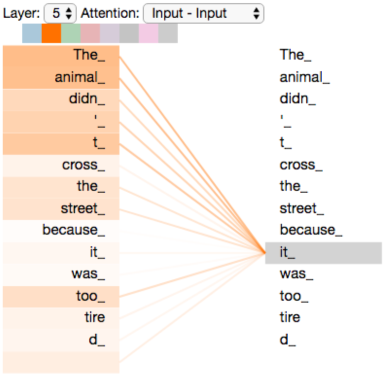

- Consider two input sentences we want to translate:
  - *The animal didn't cross the street because it was too tired*

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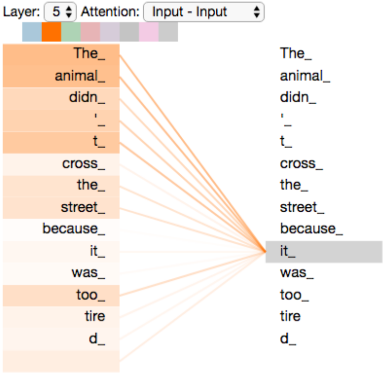

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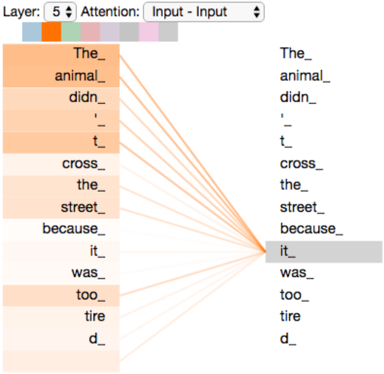

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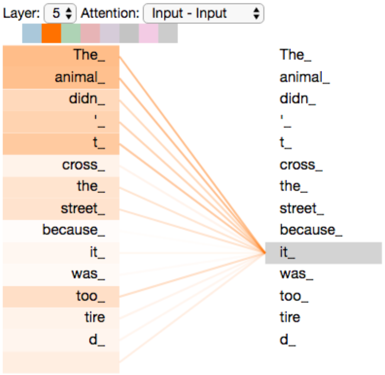

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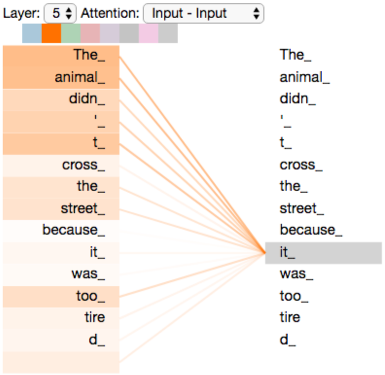

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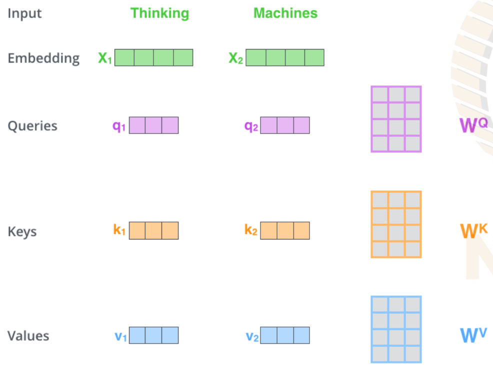
- Recall RNNs: we now no longer need to maintain a hidden state to incorporate representation of previous words/vectors!

Self-Attention



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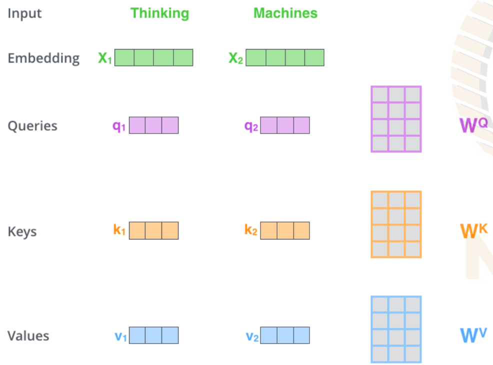

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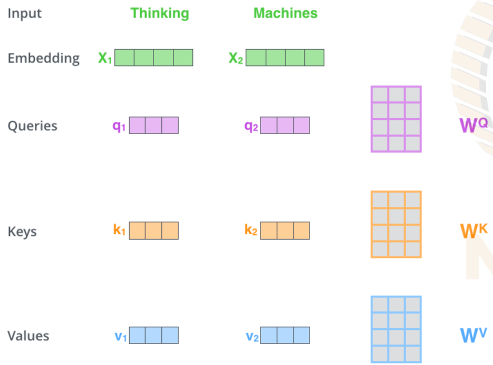

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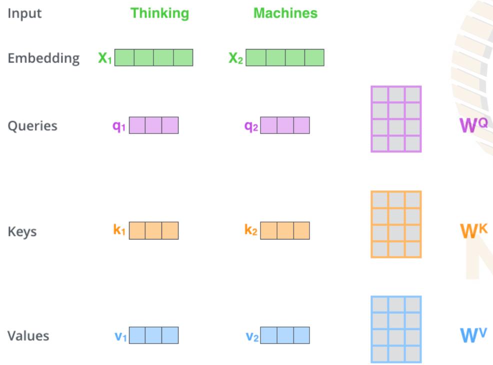

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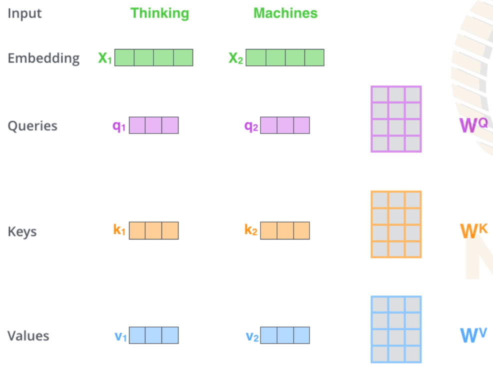

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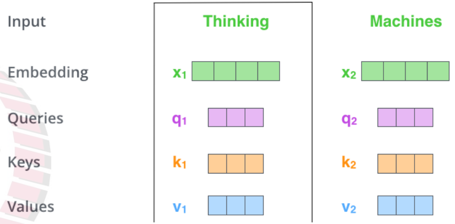
- In the paper, $q, k, v \in \mathbb{R}^{64}$ and $x \in \mathbb{R}^{512}$
- Do q, k, v always have to be smaller than x? No, this was done perhaps to make computation of multi-headed attention constant
- What are the dimensions of W^Q, W^K, W^V?

Self-Attention

- **STEP 2:** Calculate self-attention scores - score all words of input sentence against themselves; how?



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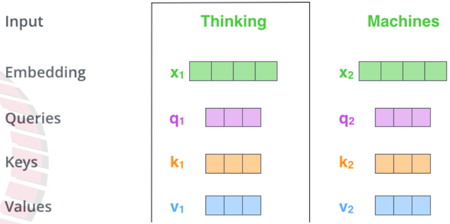

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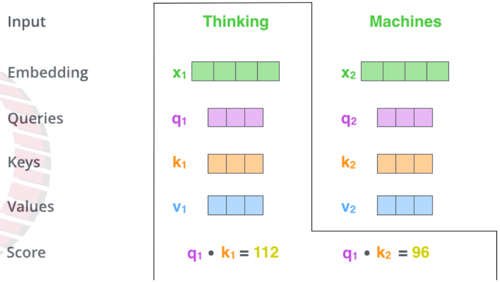

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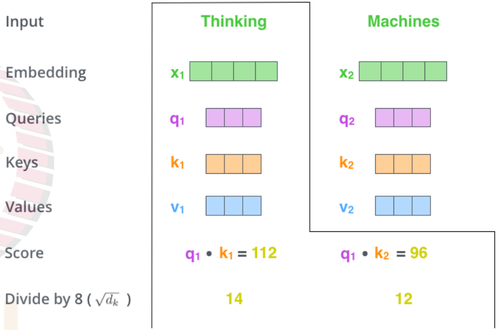

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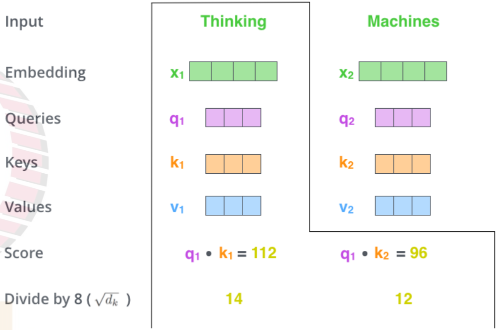
- This is **Scaled Dot-Product Attention**, recall from W9P1; this design choice leads to more stable gradients



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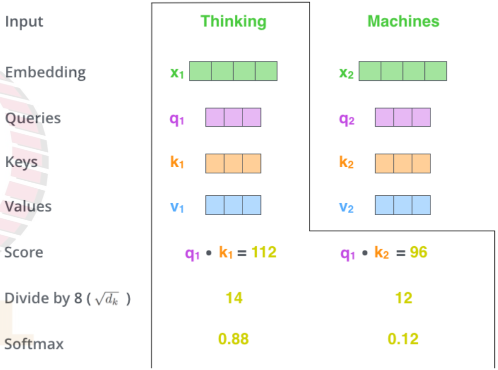

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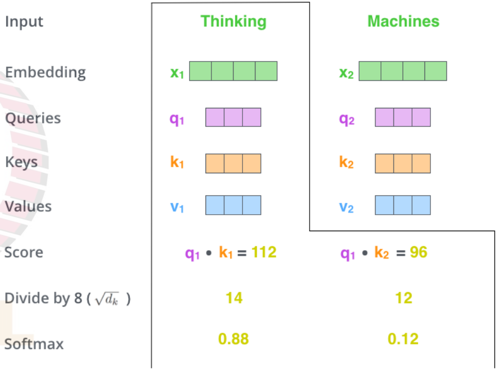

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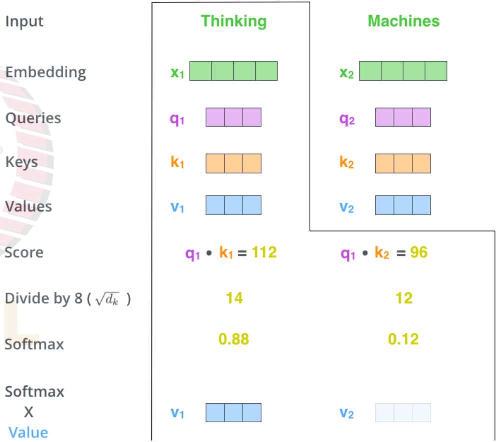

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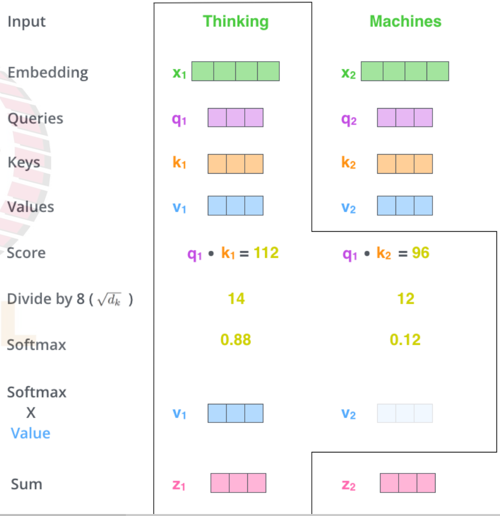
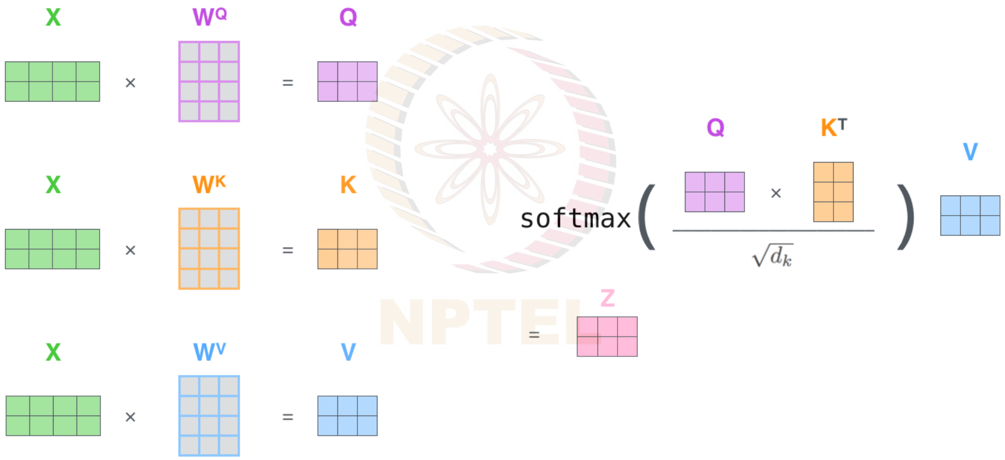
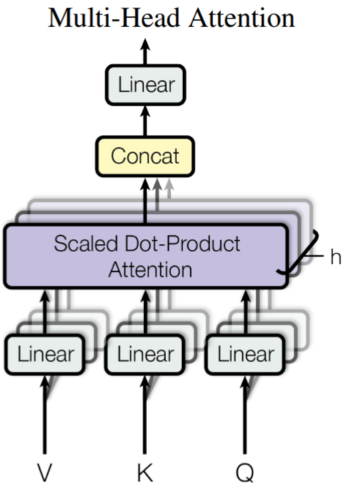
- **STEP 5:** Sum up weighted value vectors $\rightarrow$ produces output of self-attention layer at this position (for first word)



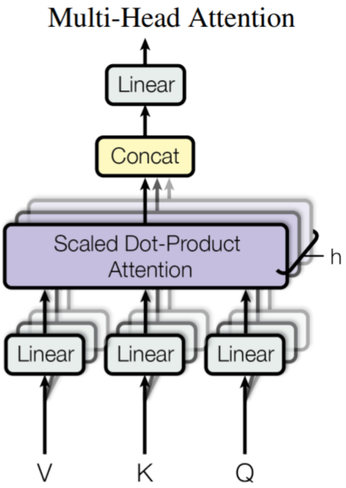
Self-Attention: Illustration





- Improves performance of the attention layer in two ways:

Multi-Head Attention



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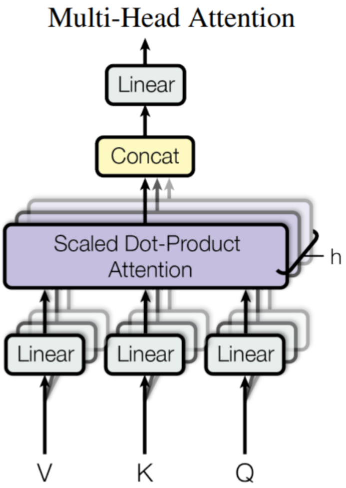
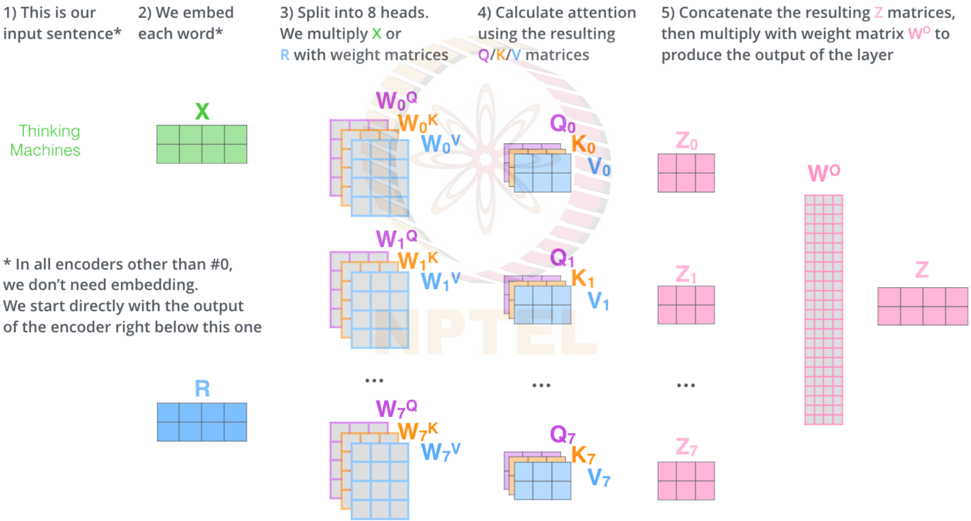


- Improves performance of the attention layer in two ways:
  - Expands model's ability to focus on different positions. In example above, z_1 contains a bit of every other encoding, but dominated by actual word itself
  - Gives attention layer multiple "*representation subspaces*"; we have not one, but multiple sets of Query/Key/Value weight matrices; after training, each set is used to project input embeddings into different representation subspaces

Credit: Vaswani et al, Attention is All You Need, NeurIPS 2017

Multi-Head Attention: Illustration



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- Final input embeddings are concatenation of learnable embedding and positional encoding

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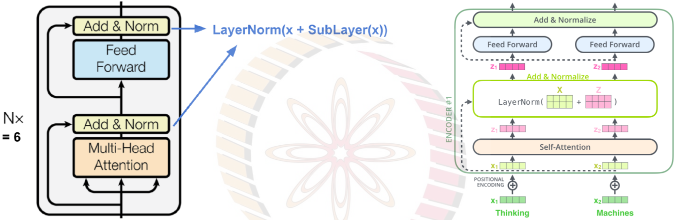

- Stack of N=6 identical layers

Credit: "Attention? Attention!" by Lilian Weng

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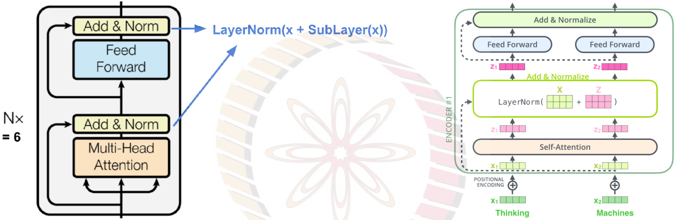

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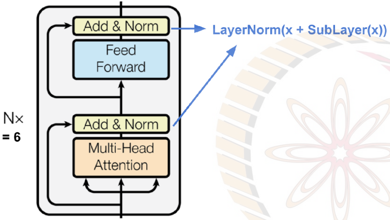

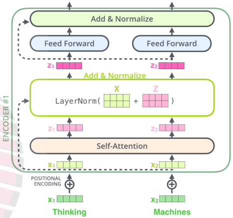

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- Each layer has a **multi-head self-attention layer** and a simple position-wise fully connected **feedforward network**
- Each sub-layer has a **residual** connection and **layer-normalization**; all sub-layers output data of same dimension $d_{model} = 512$

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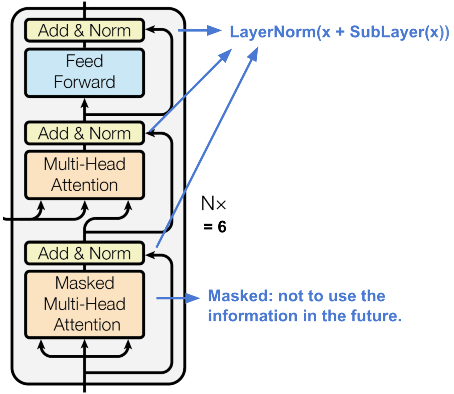
Decoder



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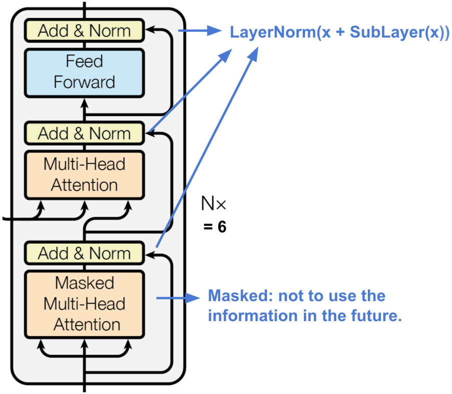

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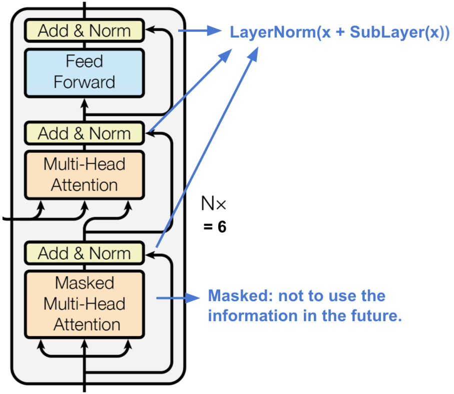

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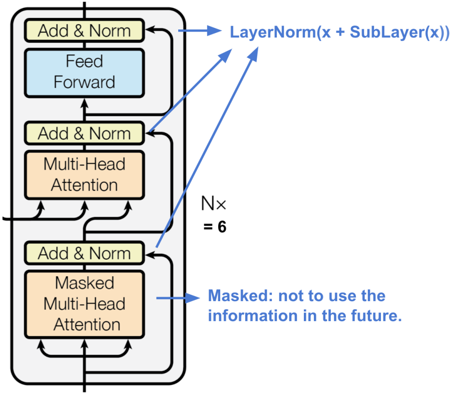

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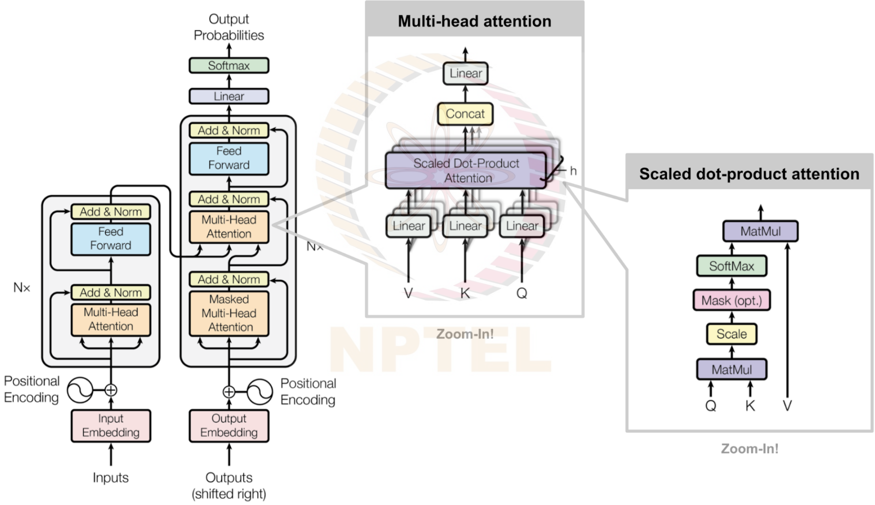
- Each layer has two sub-layers of **multi-head attention** mechanisms and one sub-layer of fully-connected **feedforward network**
- Similar to encoder, each sub-layer adopts a **residual connection** and a **layer-normalization**
- First multi-head attention sub-layer is modified to prevent positions from attending to subsequent positions, as we don't want to look into future of target sequence when predicting current position

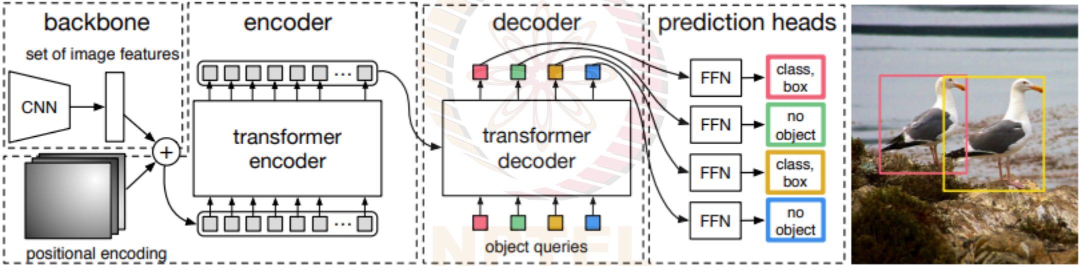
Credit: "Attention? Attention!" by Lilian Weng

Transformers: Full Architecture



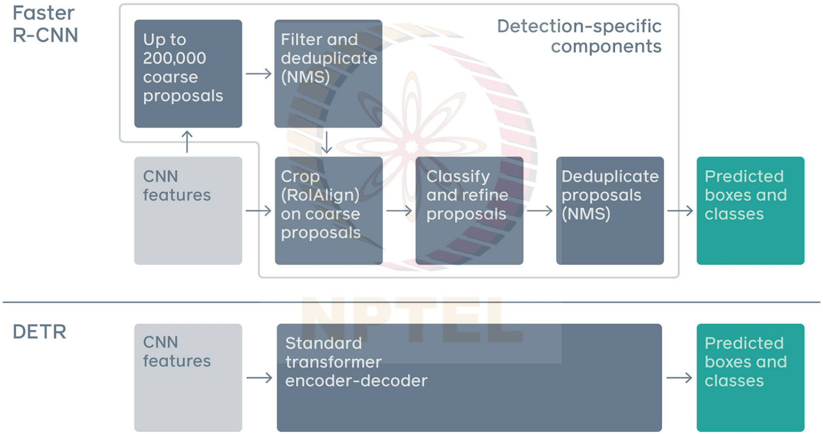
Credit: "Attention? Attention!" by Lilian Weng

Transformers in Computer Vision: Object Detection[2]



[2]Carion et al, End-to-End Object Detection with Transformers, ECCV 2020

Transformers in Computer Vision: Object Detection



Credit: *Ram Sagar, Analytics India Mag*

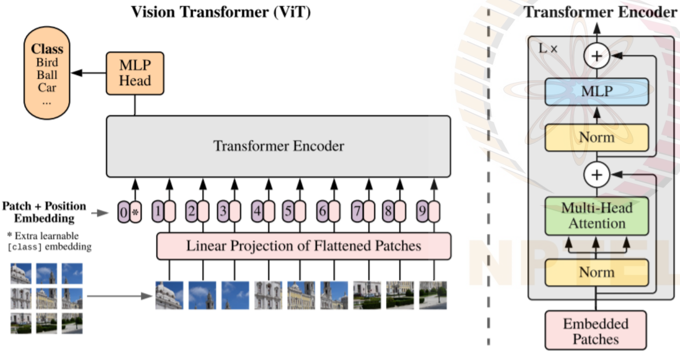
Transformers in Computer Vision: Object Detection[3]

Results on MS COCO validation set

Model	GFLOPS/FPS	#params	AP	AP_{50}	AP_{75}	AP_S	AP_M	AP_L
Faster RCNN-DC5	320/16	166M	39.0	60.5	42.3	21.4	43.5	52.5
Faster RCNN-FPN	180/26	42M	40.2	61.0	43.8	24.2	43.5	52.0
Faster RCNN-R101-FPN	246/20	60M	42.0	62.5	45.9	25.2	45.6	54.6
Faster RCNN-DC5+	320/16	166M	41.1	61.4	44.3	22.9	45.9	55.0
Faster RCNN-FPN+	180/26	42M	42.0	62.1	45.5	26.6	45.4	53.4
Faster RCNN-R101-FPN+	246/20	60M	44.0	63.9	**47.8**	**27.2**	48.1	56.0
DETR	86/28	41M	42.0	62.4	44.2	20.5	45.8	61.1
DETR-DC5	187/12	41M	43.3	63.1	45.9	22.5	47.3	61.1
DETR-R101	152/20	60M	43.5	63.8	46.4	21.9	48.0	61.8
DETR-DC5-R101	253/10	60M	**44.9**	**64.7**	47.7	23.7	**49.5**	**62.3**

[3] Carion et al, End-to-End Object Detection with Transformers, ECCV 2020

Transformers in Computer Vision: Image Recognition[4]



Credit: *Nabil Madali, Gitconnected*

- Image split into fixed-size patches
- Each of them linearly embedded
- Position embeddings added to resulting sequence of vectors
- Patches fed to standard Transformer encoder
- In order to perform classification, standard approach of adding an extra learnable "classification token" added to sequence

[4]Dosovitskiy et al, An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale, arXiv 2020

Homework

Readings

- Watch the Transformers in Action video provided in the week's lecture materials
- The Illustrated Transformer article by Jay Alammar
- A detailed explanation of positional encoding by Amirhossein Kazemnejad
- For more information: Attention is All You Need paper by Vaswani, et al. (NeurIPS 2017)

Questions

- Are transformers faster or slower than LSTMs? What is the reason for your opinion?