Natural Language Processing

CS 3216/UG, AI 5203/PG

Week-9

Multi-head attention, Transformers

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Recap

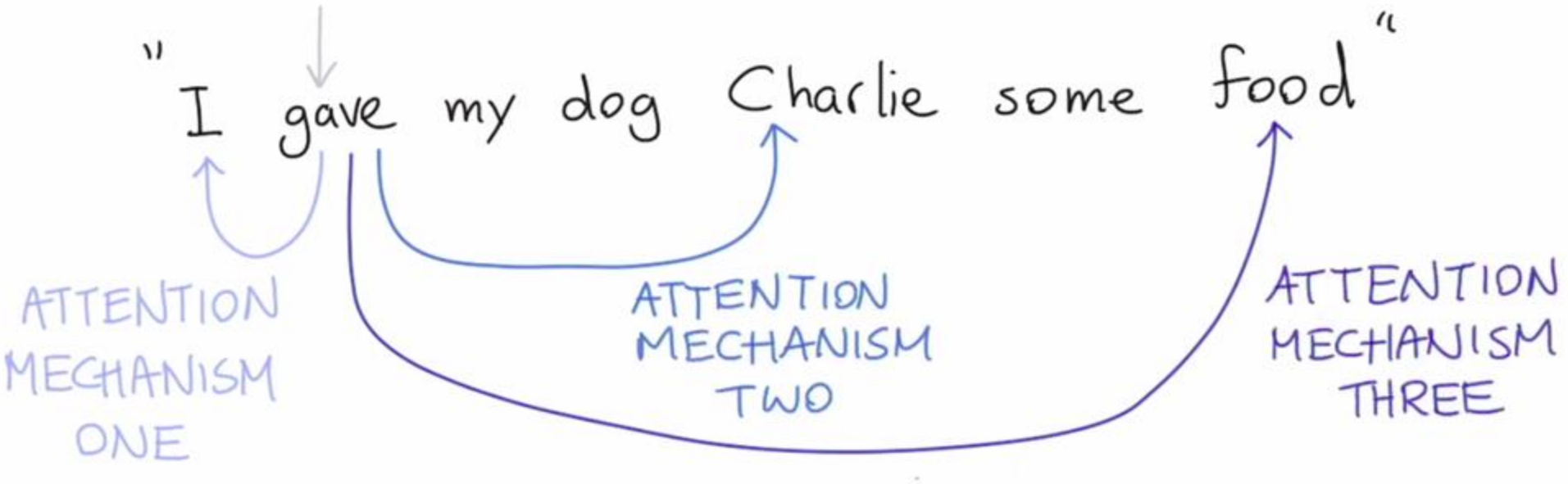
- Language modeling
- Recurrent Neural Network and Implementation
- Applications of Recurrent Neural Network
- Language modeling using Long Short-term Memory
- Sequence to Sequence learning
- Attention

So Far covered.....Intuition behind Attention

- The weighted sum is a selective summary of the information contained in the values, where the query determines which values to focus on.
- Attention is a way to obtain a fixed-size representation of an arbitrary set of representations (the values), dependent on some other representation (the query)

https://web.stanford.edu/class/archive/cs/cs224n/cs224n.1244/slides/cs224n-2024-lecture08-transformers.pdf

Do we have enough attention?



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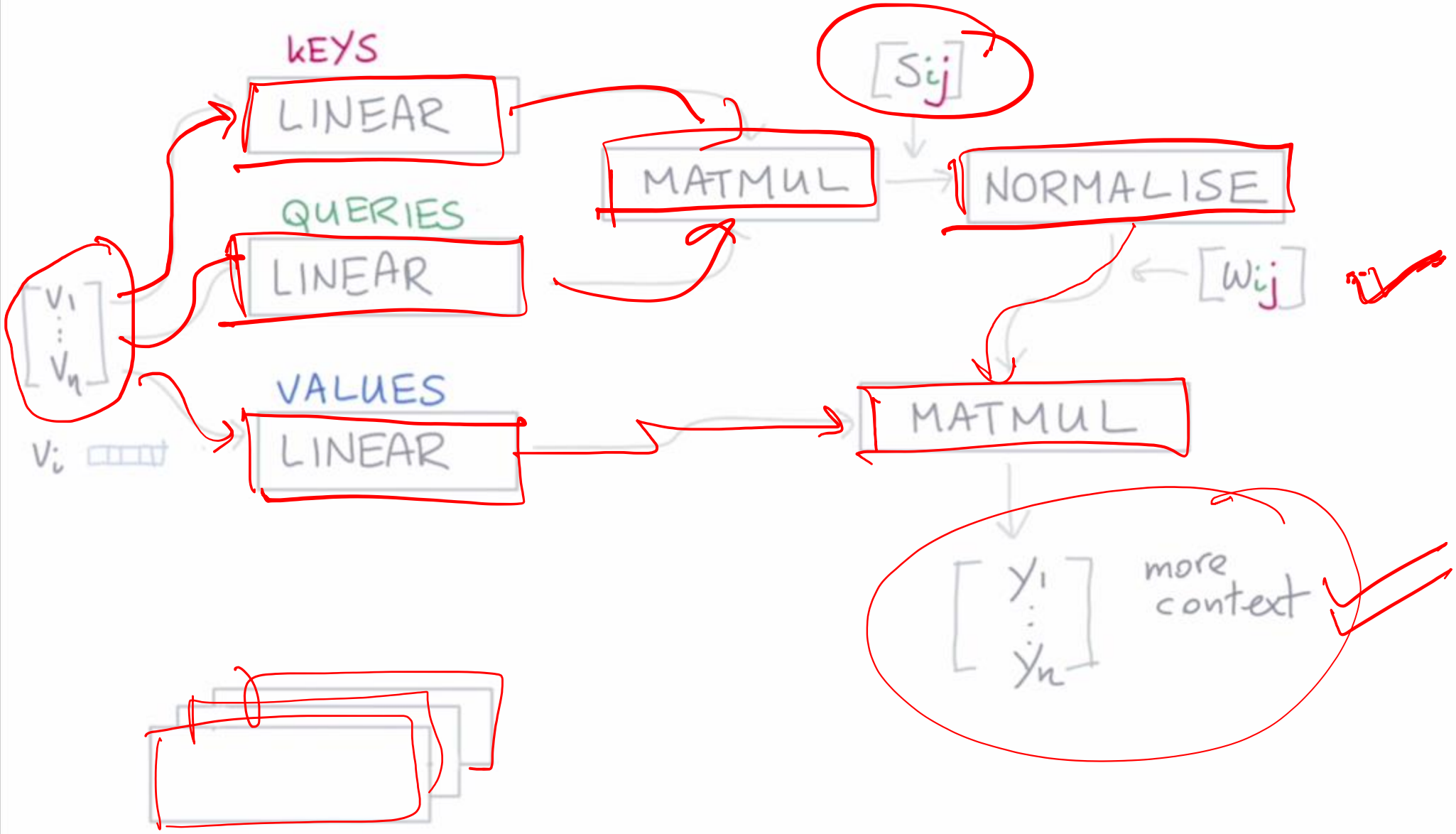

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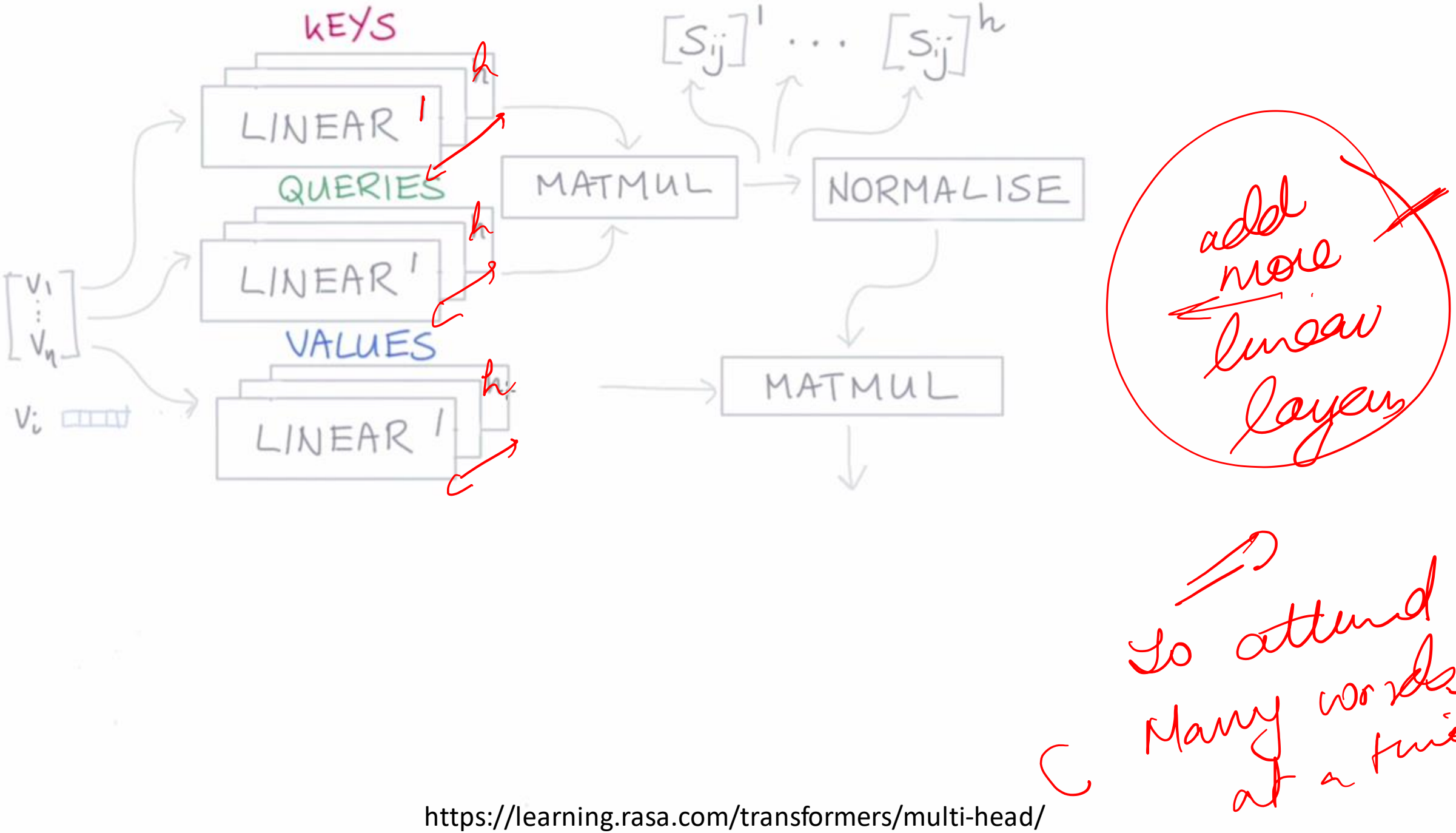

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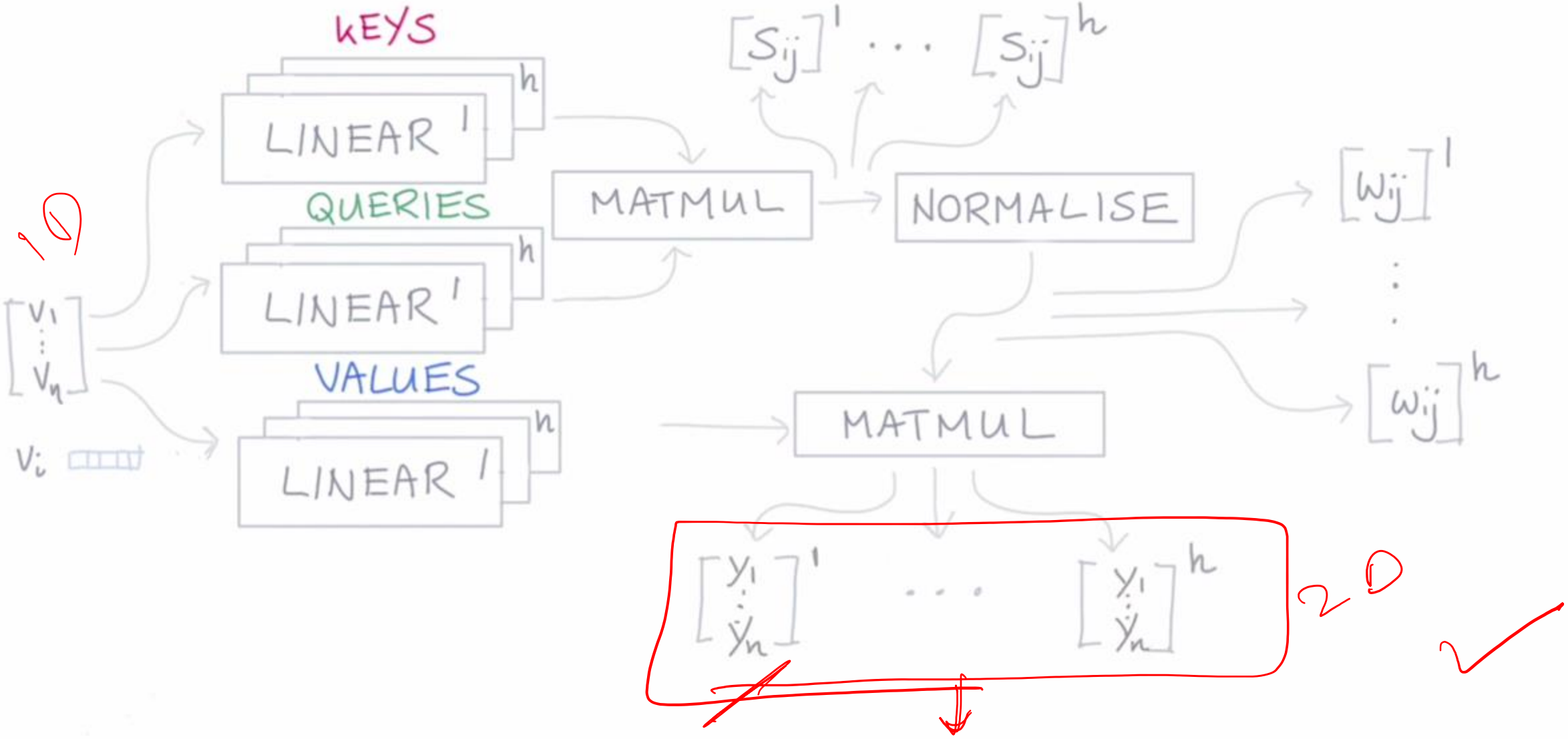

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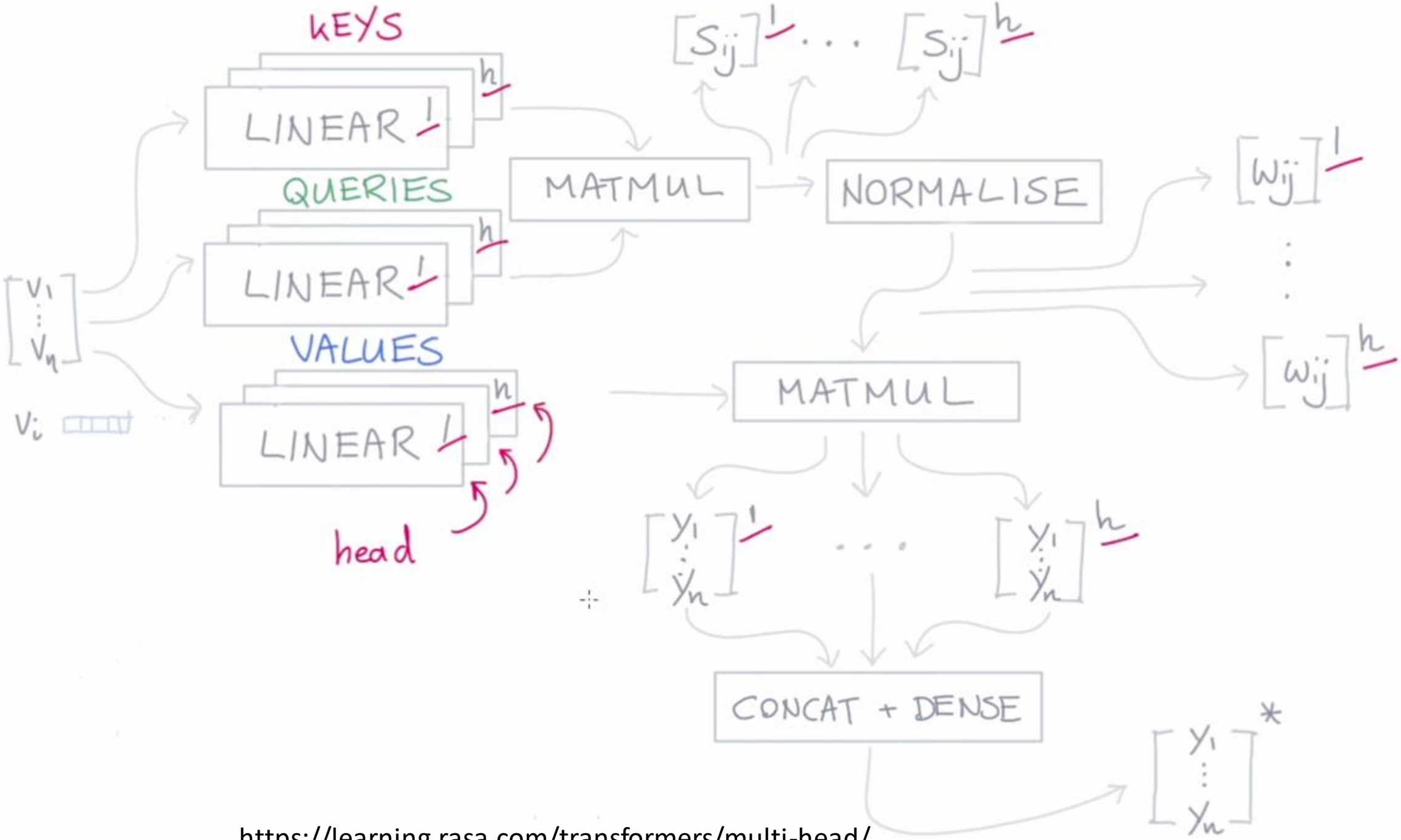

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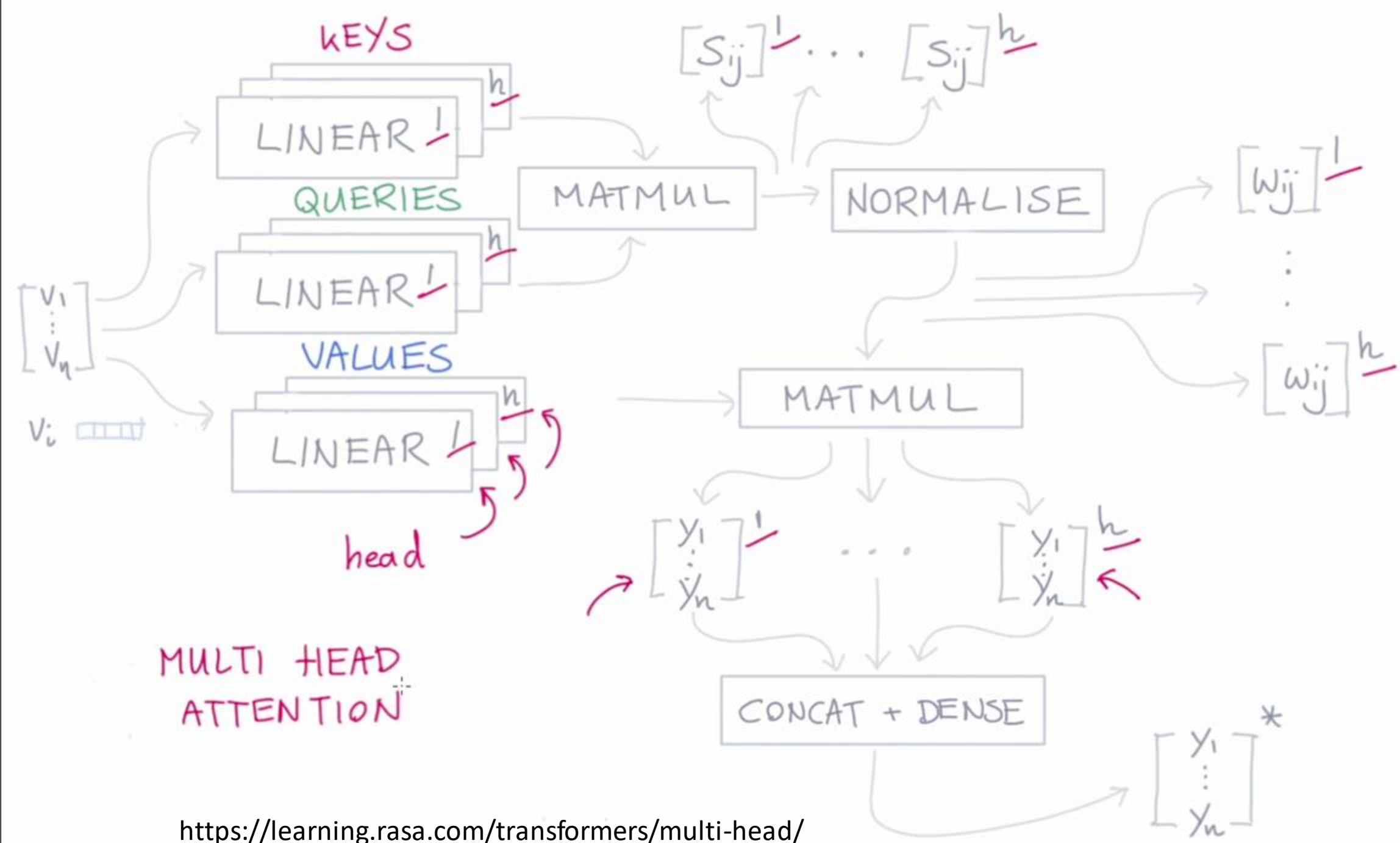

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Multi-head attention

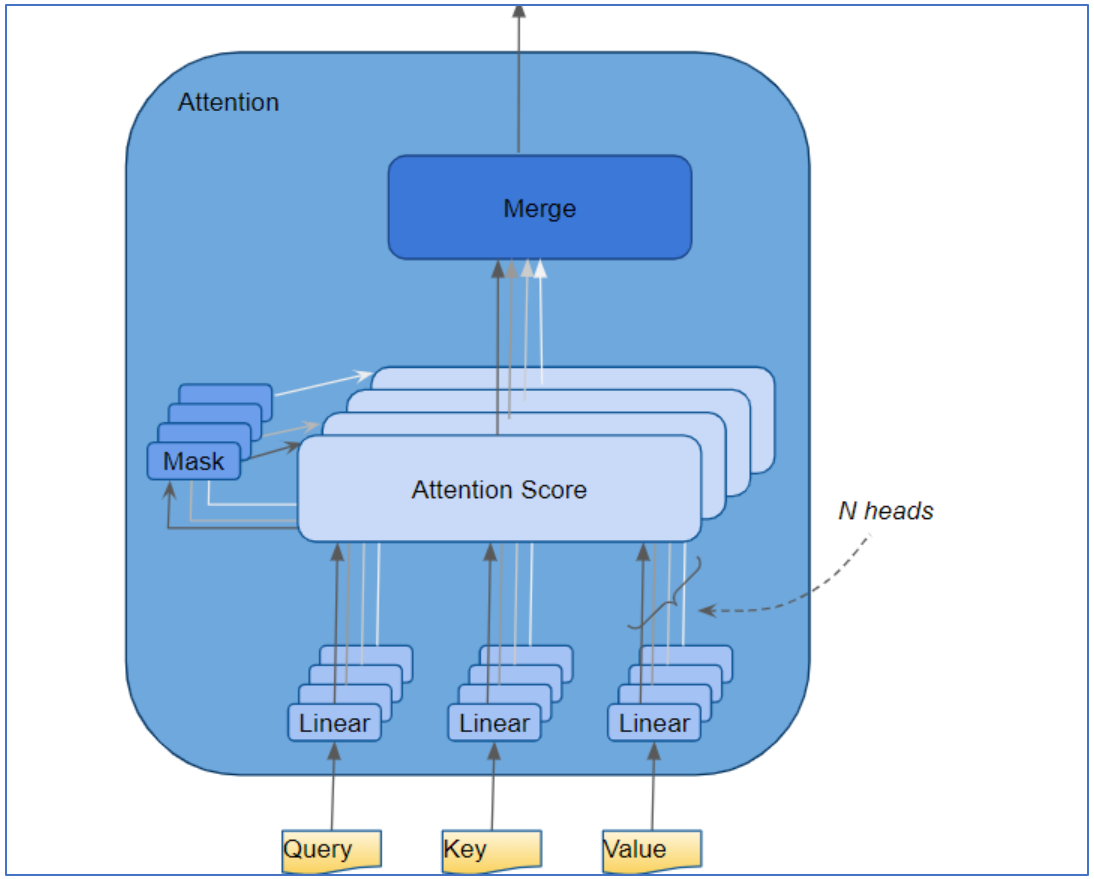
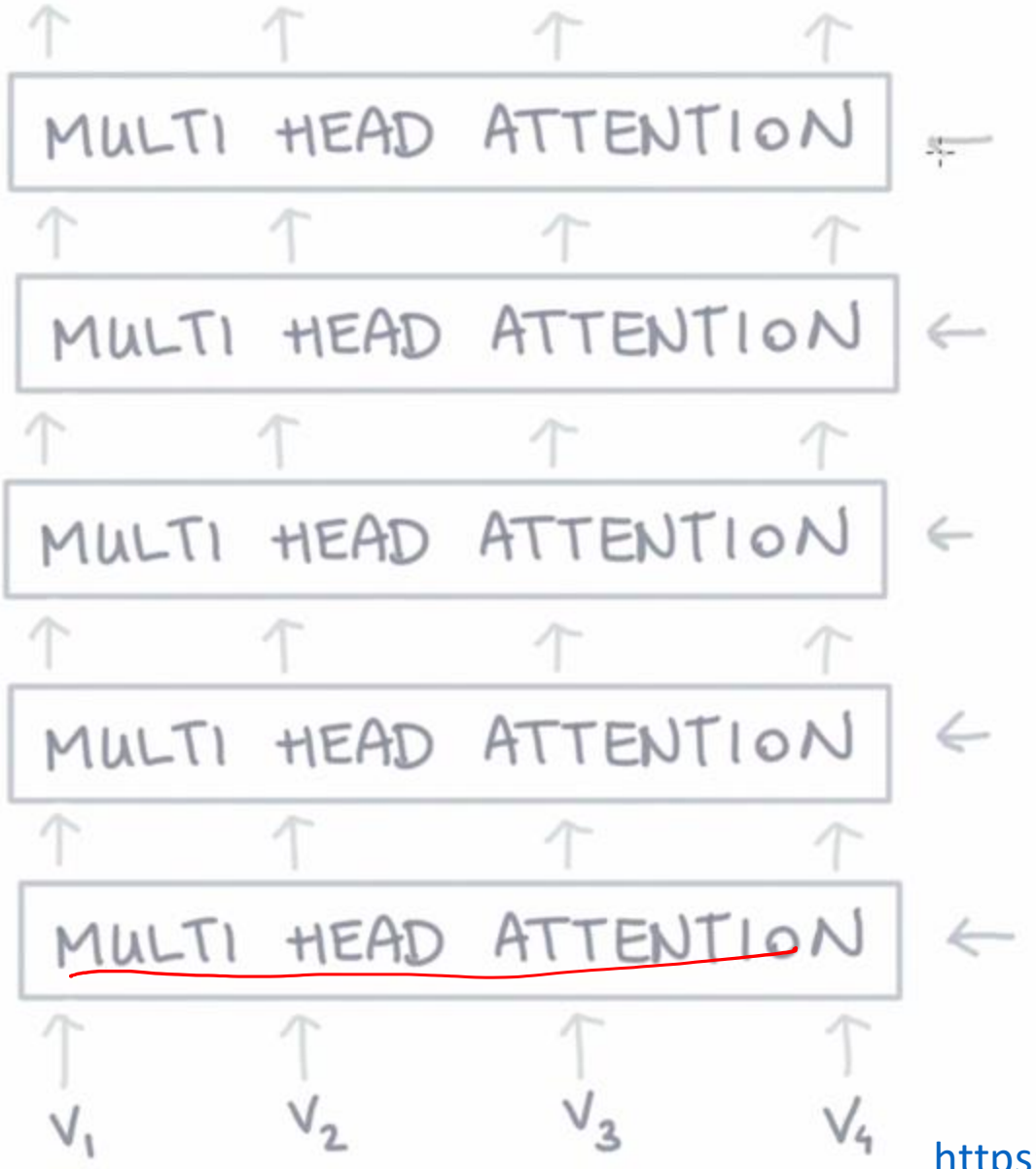
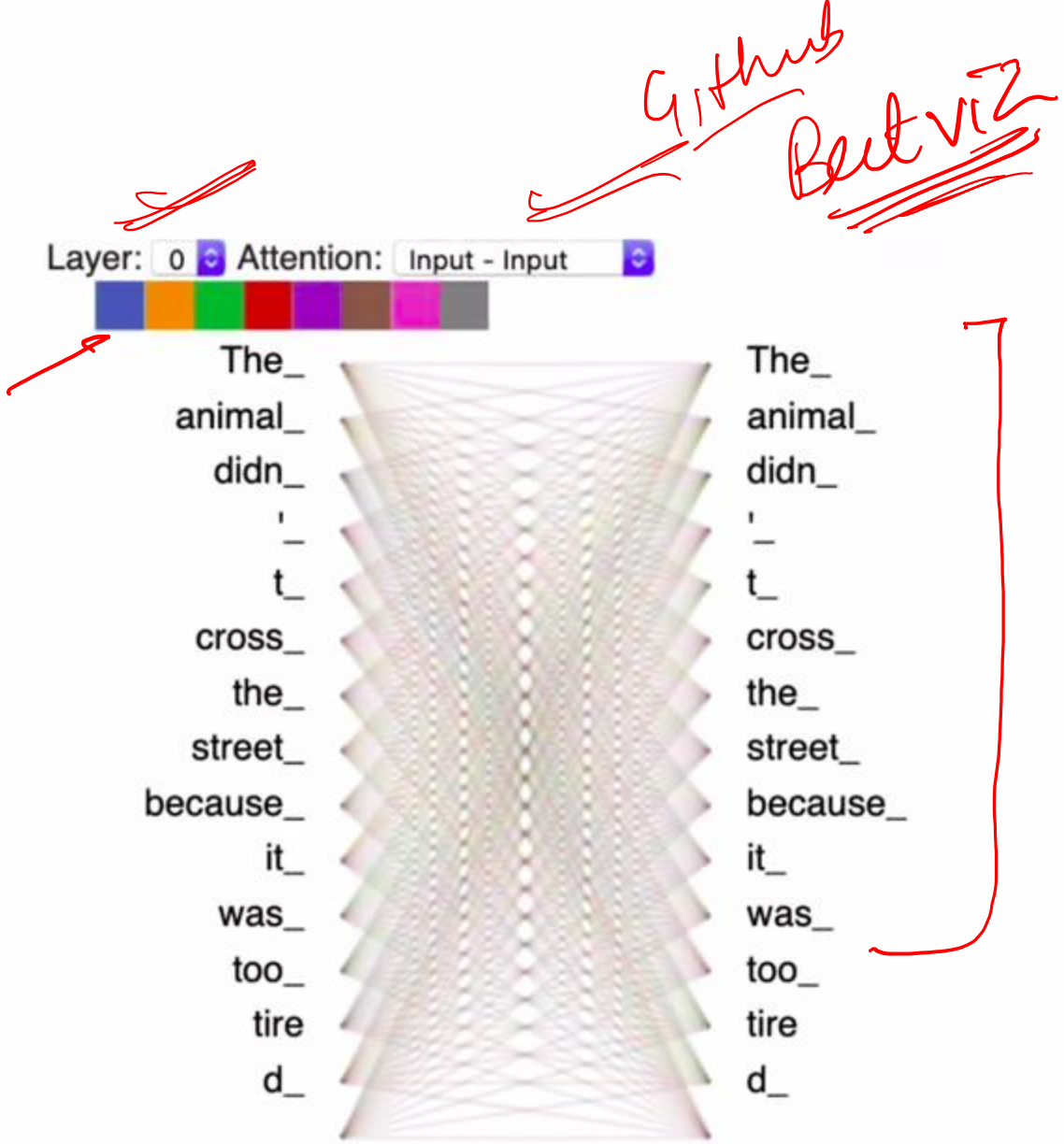


Image source:
https://towardsdatascience.com/transformers-explained-visually-part-3-multi-head-attention-deep-dive-1c1ff1024853





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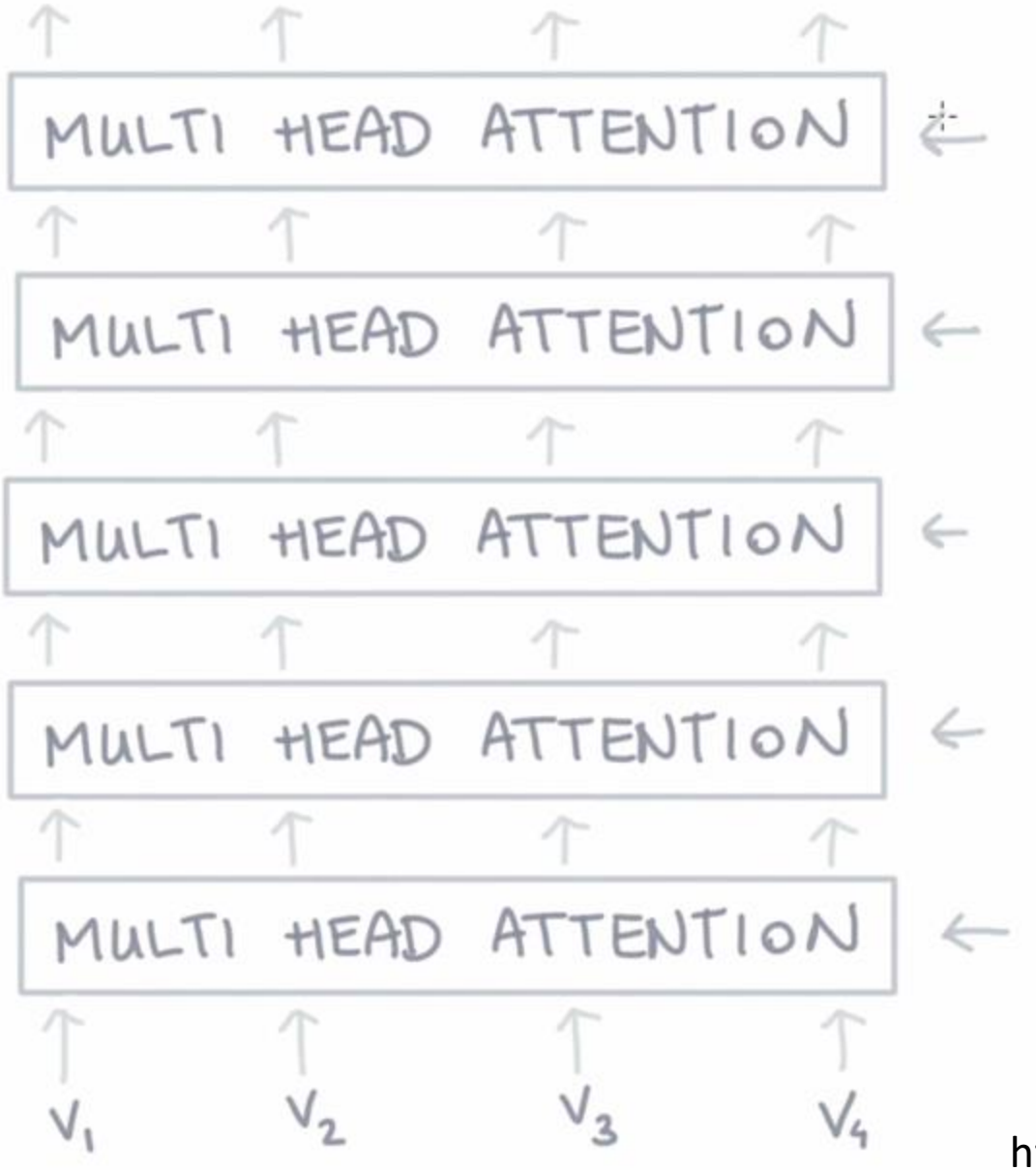

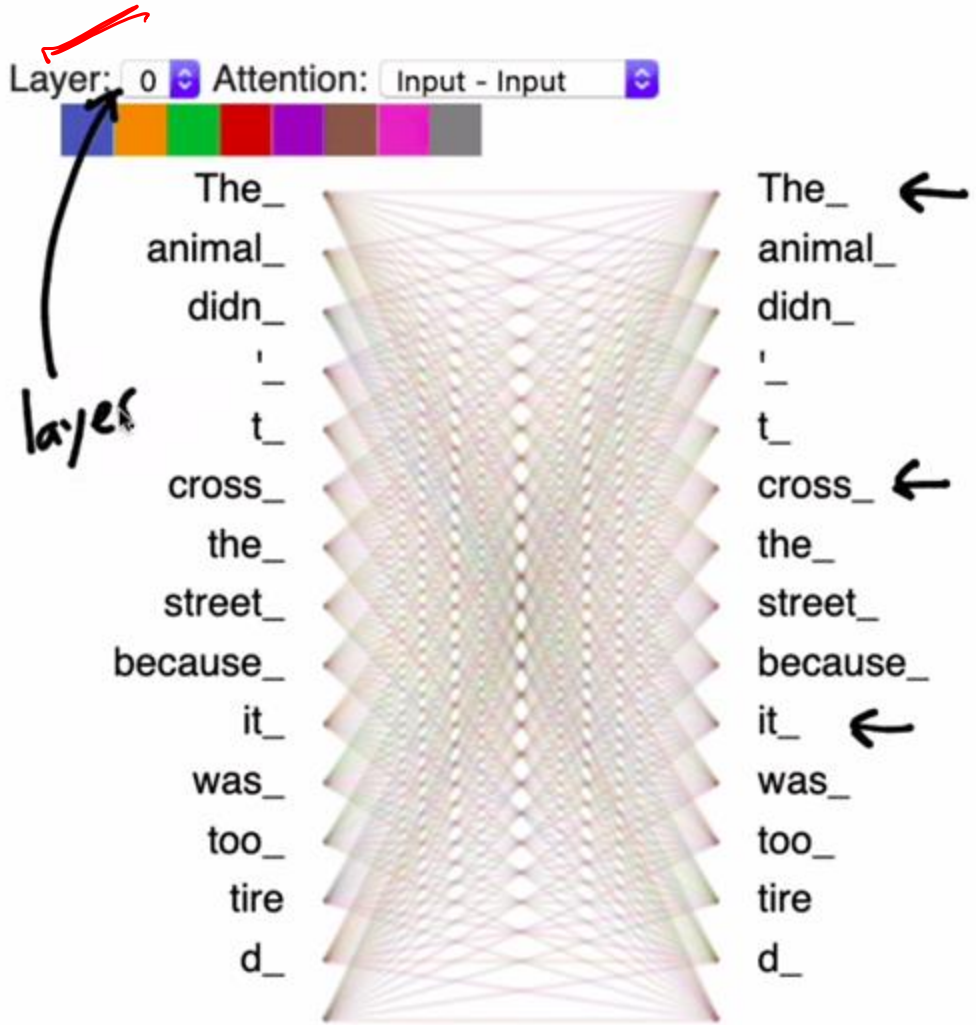

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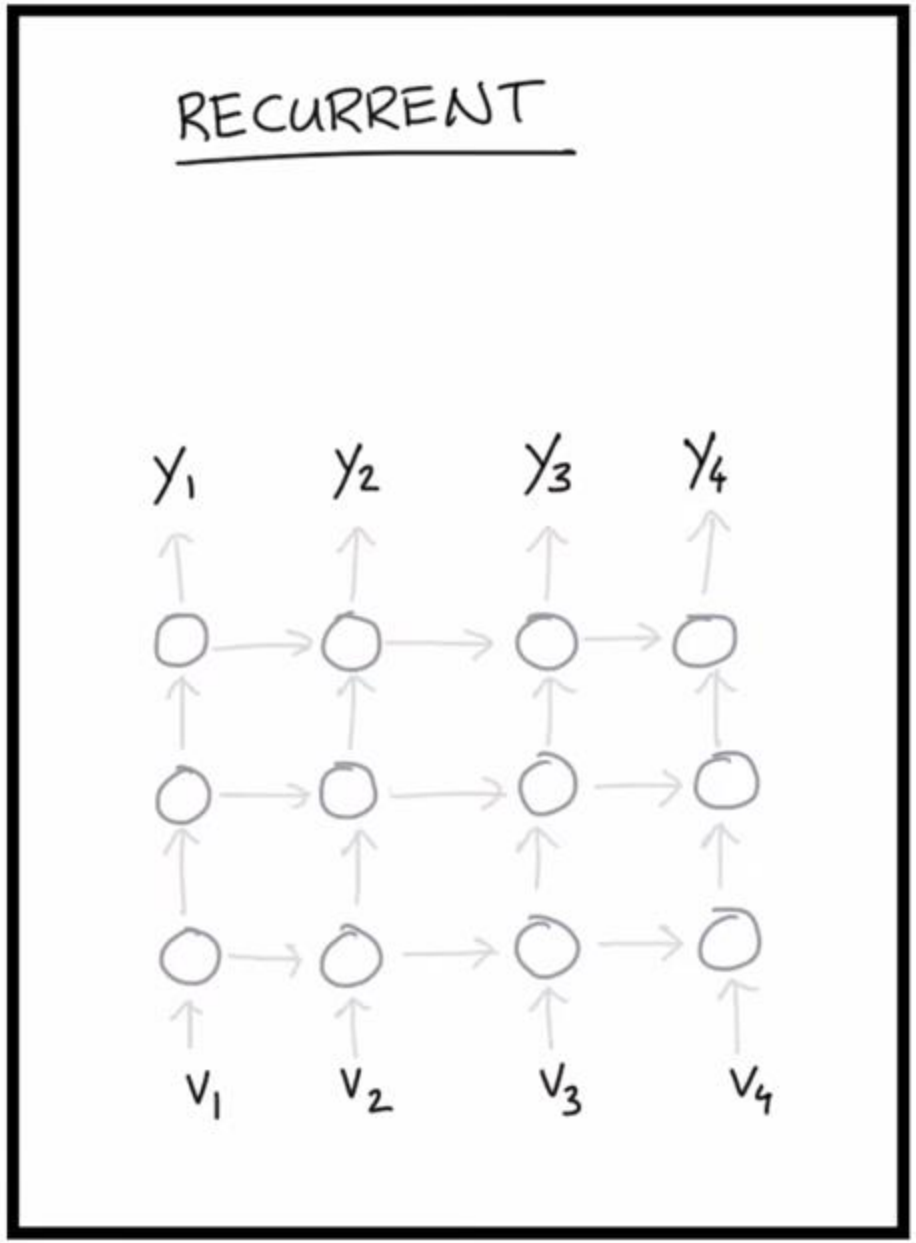

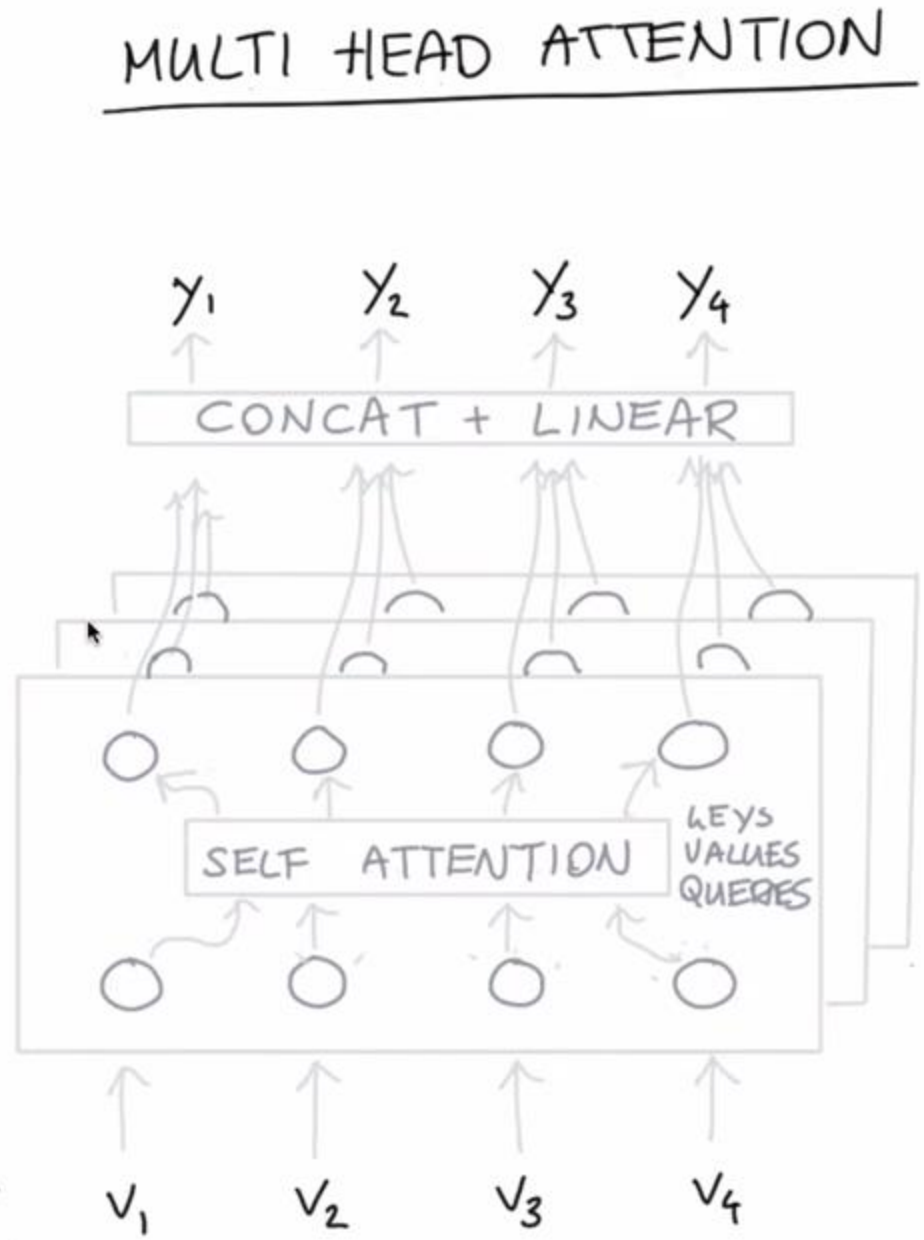

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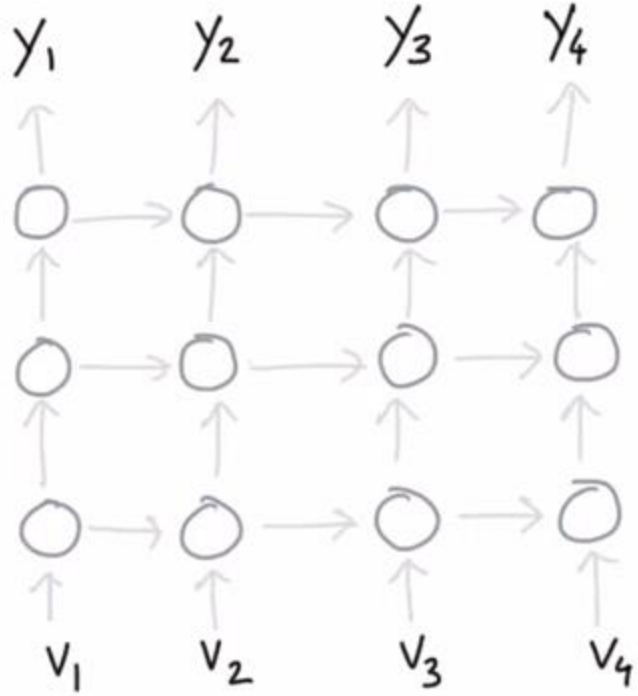
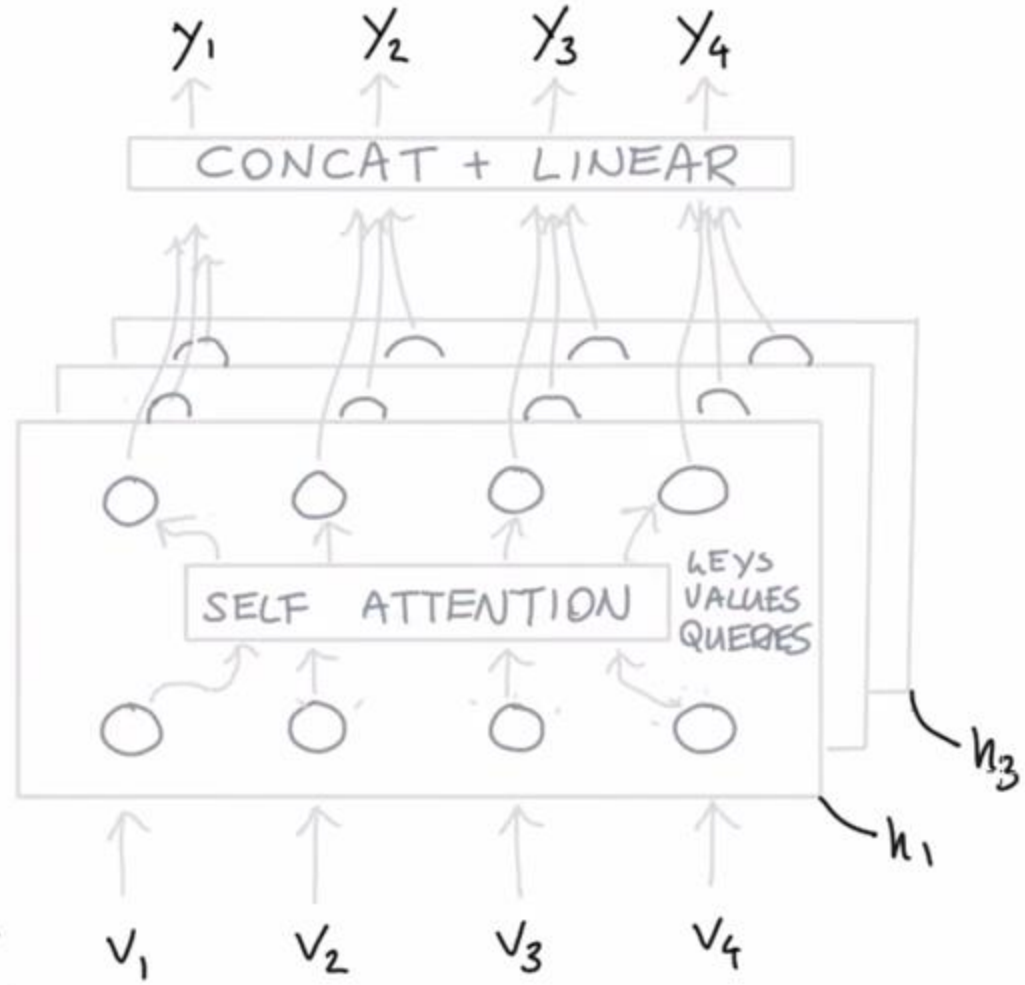
RECURRENT



MULTI HEAD ATTENTION



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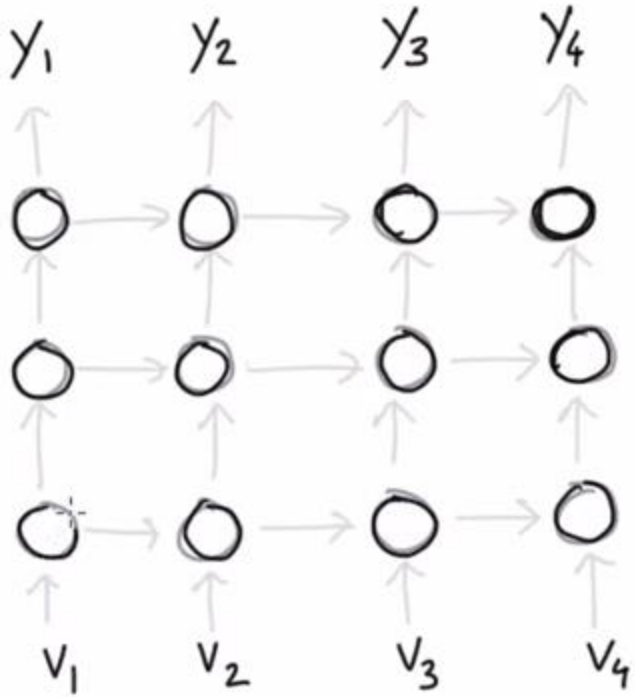
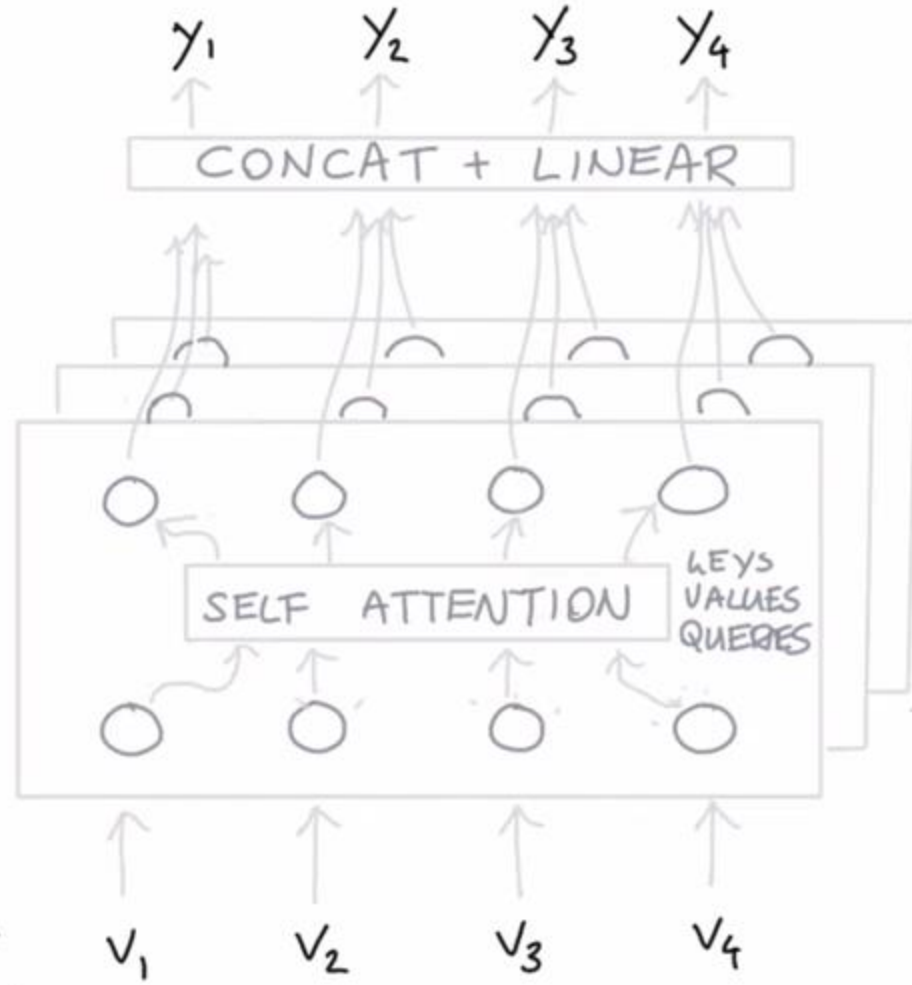


MULTI HEAD ATTENTION



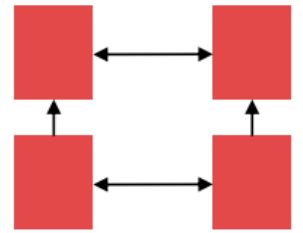
https://learning.rasa.com/transformers/multi-head/

Issues with Recurrent models: Linear interaction distance

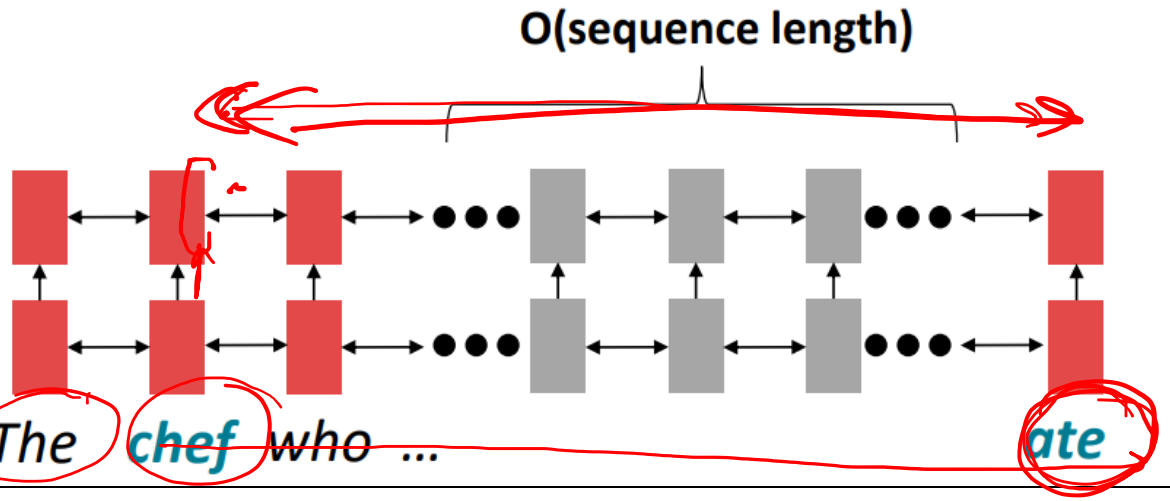
RNNs are unrolled "left-to-right".

It encodes linear locality: a useful heuristic!

- Nearby words often affect each other's meanings



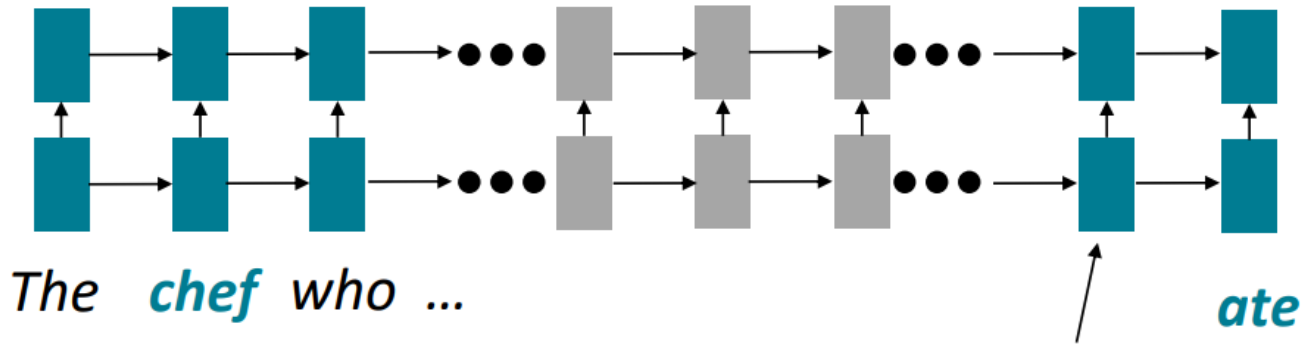
Problem: RNNs take **O(sequence length)** steps for distant word pairs to interact.



Issues with Recurrent models: Linear interaction distance

O(sequence length) steps for distant word pairs to interact means:

- Hard to learn long-distance dependencies (because gradient problems!)
- Linear order of words is "baked in"; we already know sequential structure doesn't tell the whole story...

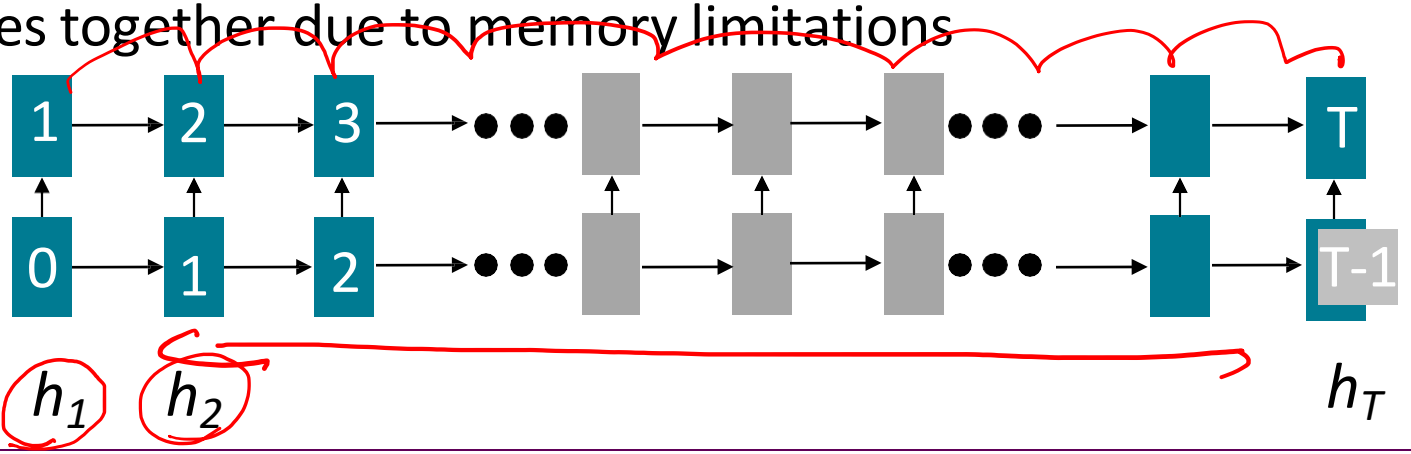


Info of ***chef*** has gone through O(sequence length) many layers!

Adapted from cs224n-2024-lecture08-transformers.pdf (stanford.edu)

Lack of Parallelizability in RNN

- Forward and backward passes have **O(seq length)** unparallelizable operations
  - GPUs (and TPUs) can perform many independent computations at once!
  - But future RNN hidden states can't be computed in full before past RNN hidden states have been computed
  - Inhibits training on very large datasets!
  - Particularly problematic as sequence length increases, as we can no longer batch many examples together due to memory limitations



Numbers indicate min # of steps before a state can be computed

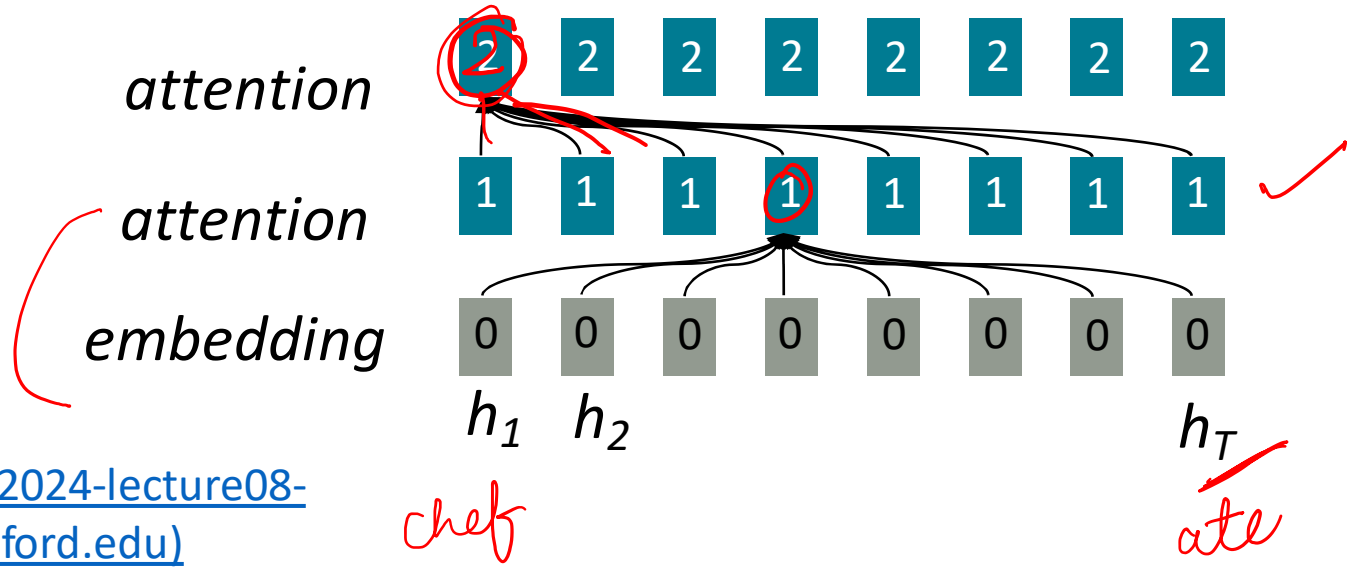
Adapted from cs224n-2024-lecture08-transformers.pdf (stanford.edu)

High-Level Architecture: Transformer is all about

(Self) Attention

To recap, **attention** treats each word's representation as a **query** to access and incorporate information from **a set of values.**

- Last lecture, we saw attention from the **decoder** to the **encoder** in a recurrent sequence-to-sequence model
- **Self-attention** is **encoder-encoder** (or **decoder-decoder**) attention where each word attends to each other word **within the input (or output)**.



All words attend to all words in previous layer; most arrows here are omitted

[Adapted from cs224n-2024-lecture08-transformers.pdf (stanford.edu)]

Transformer architecture

The Transformers authors had 3 desirata when designing this architecture:

1.Minimize (or at least not increase) computational complexity per layer.
2. Minimize path length between any pair of words to facilitate learning of long-range dependencies.
3. Maximize the amount of computation that can be parallelized.

Adapted from cs224n-2024-lecture08-transformers.pdf (stanford.edu)

Computational Complexity per layer

When sequence length (n) << representation dimension (d), complexity per layer is lower for a Transformer compared to the recurrent models we've learned about so far.

Table 1: Maximum path lengths, per-layer complexity and minimum number of sequential operations for different layer types. n is the sequence length, d is the representation dimension, k is the kernel size of convolutions and r the size of the neighborhood in restricted self-attention.

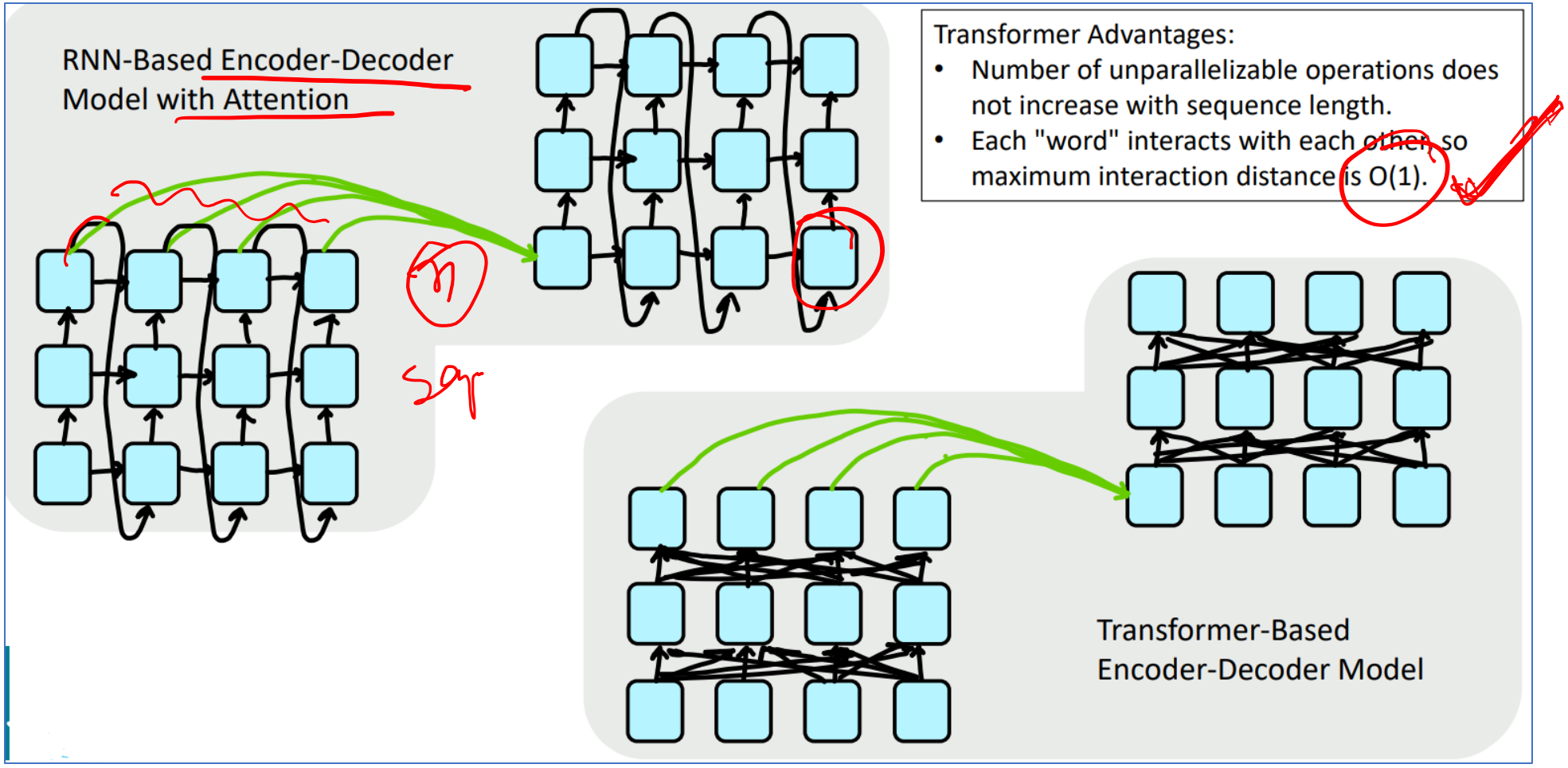
Layer Type	Complexity per Layer	Sequential Operations	Maximum Path Length
Self-Attention	$O(n^2 \cdot d)$	$O(1)$	$O(1)$
Recurrent	$O(n \cdot d^2)$	$O(n)$	$O(n)$
Convolutional	$O(k \cdot n \cdot d^2)$	$O(1)$	$O(log_k(n))$
Self-Attention (restricted)	$O(r \cdot n \cdot d)$	$O(1)$	$O(n/r)$

Table 1 of the Transformer paper.

d = vector representation dimension
n = sequence length

https://arxiv.org/abs/1706.03762

Path Length minimization and Parallelization



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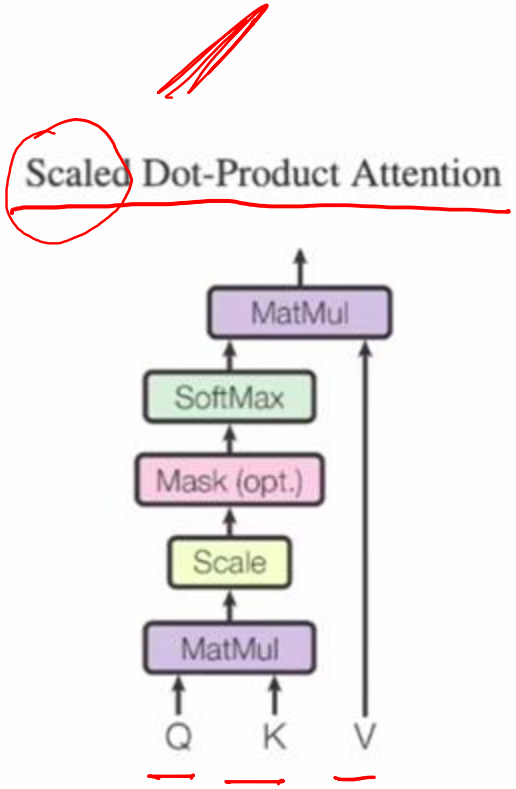
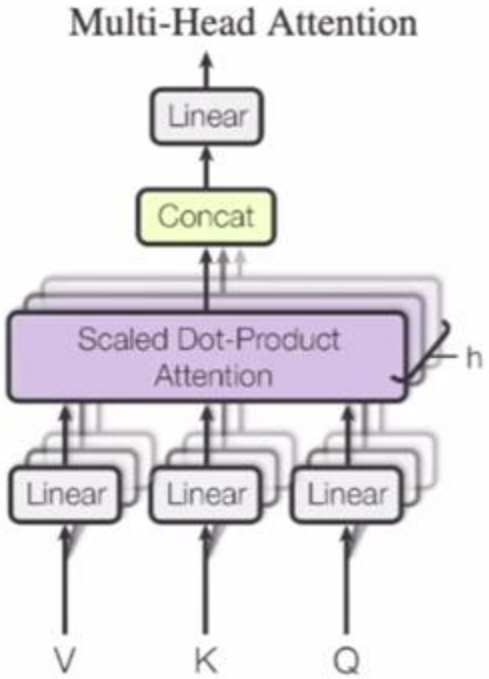
Transformer





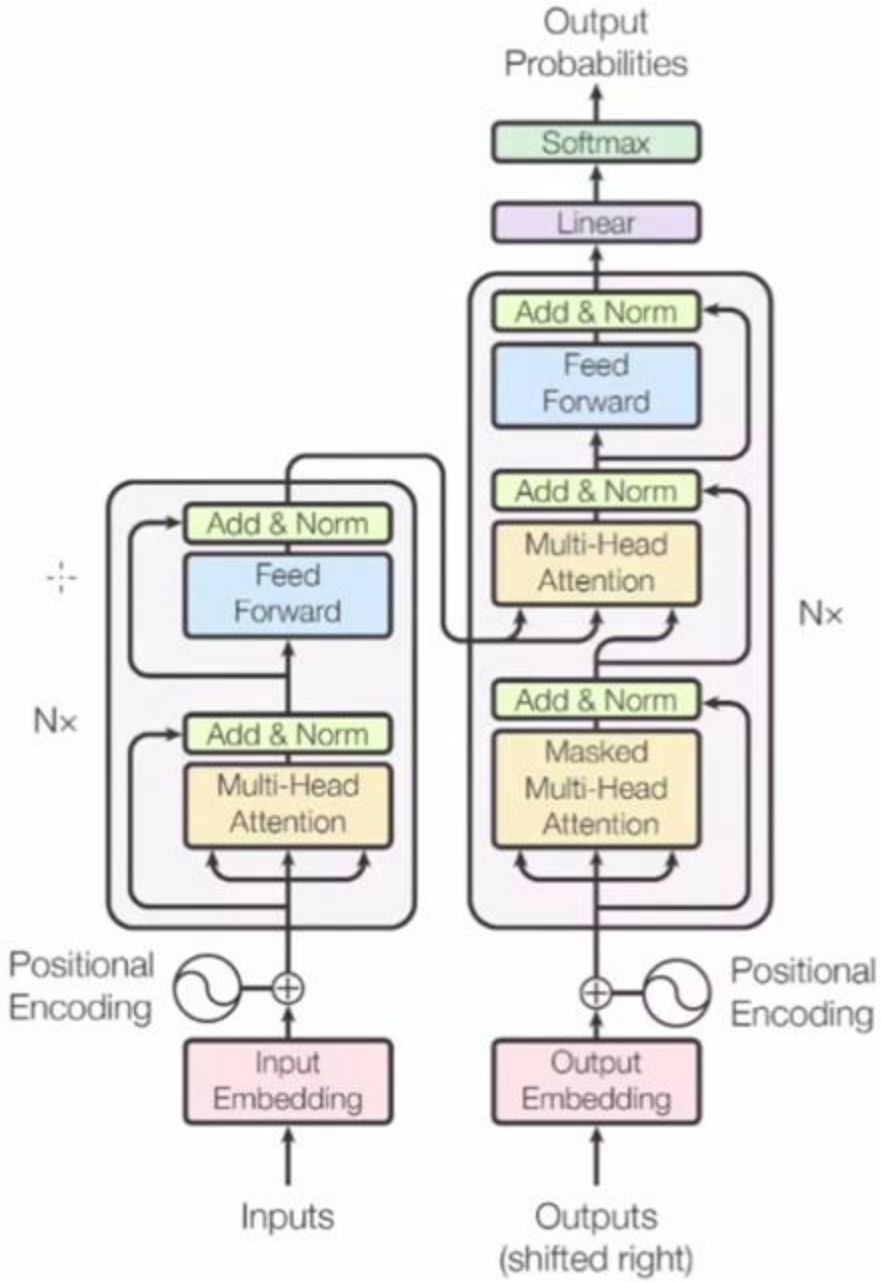
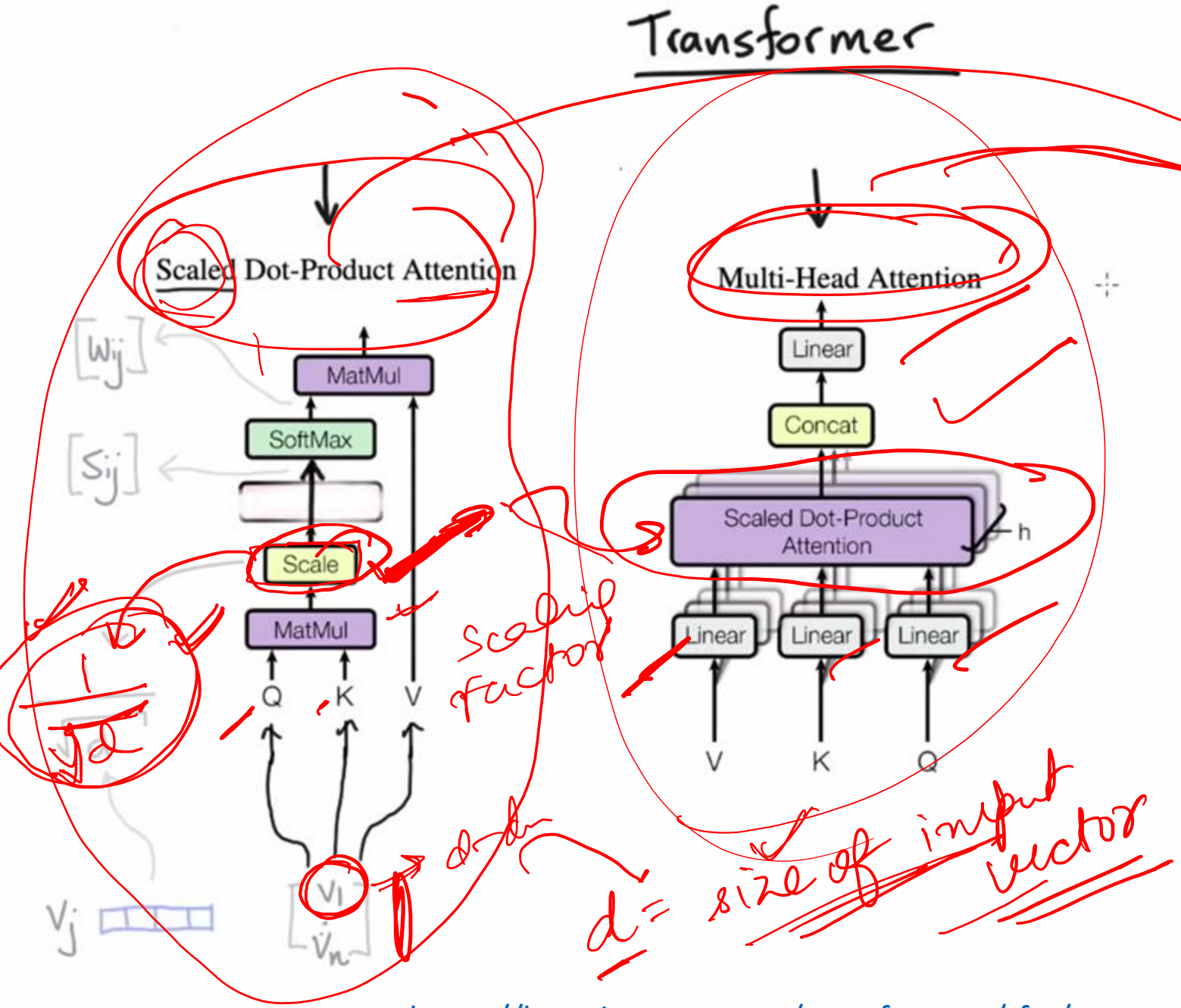
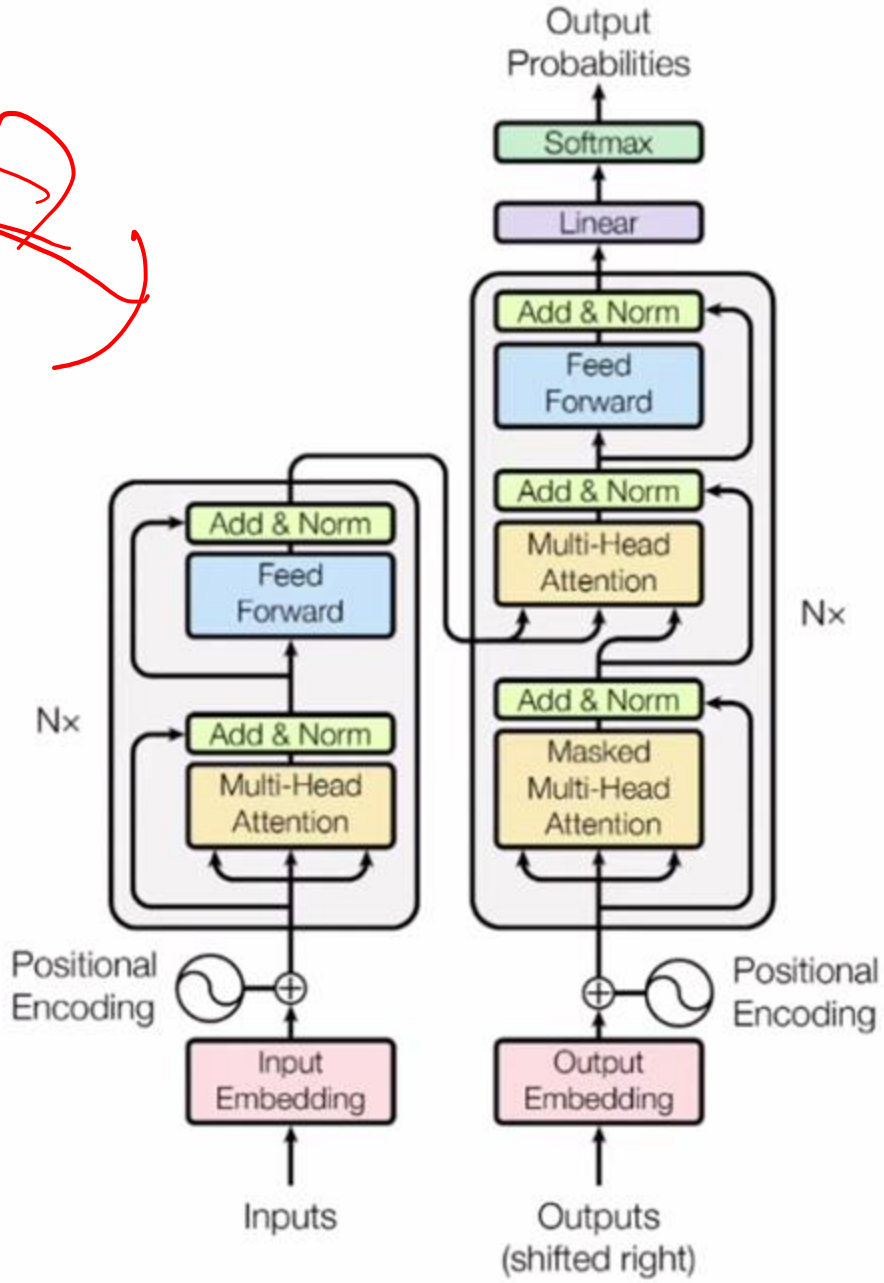


Figure 1: The Transformer - model architecture.

https://learning.rasa.com/transformers/tfm/

Transformer





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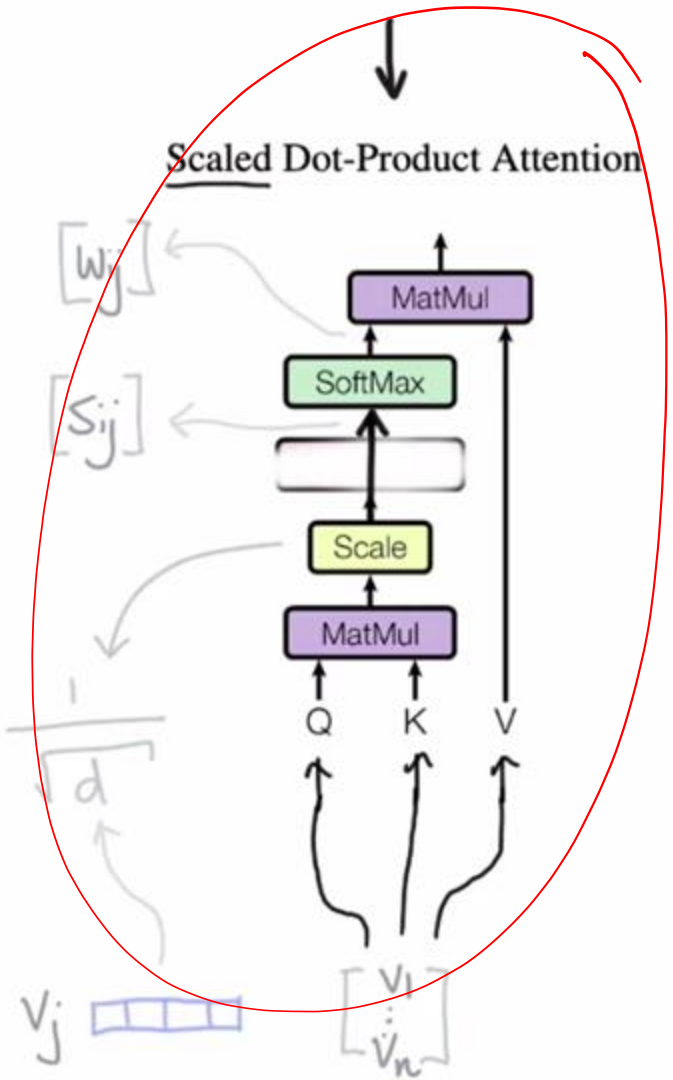
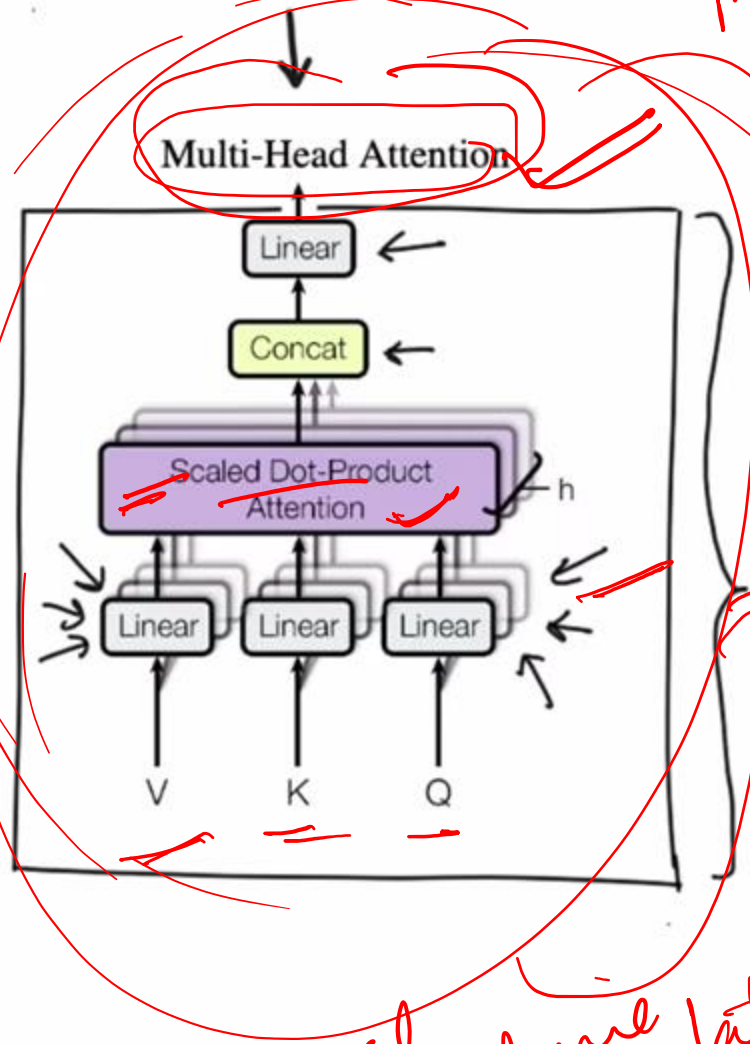
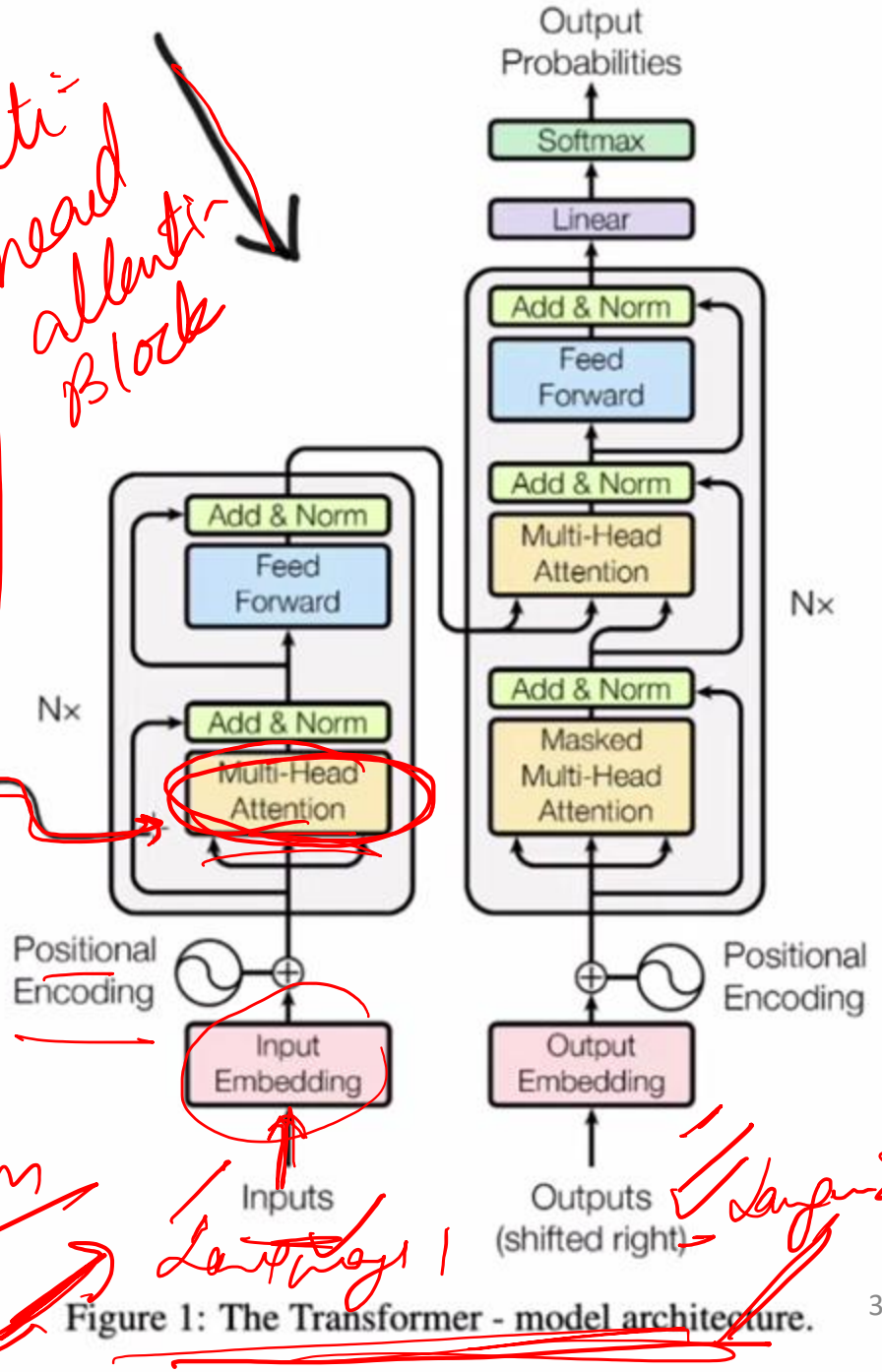
Transformer







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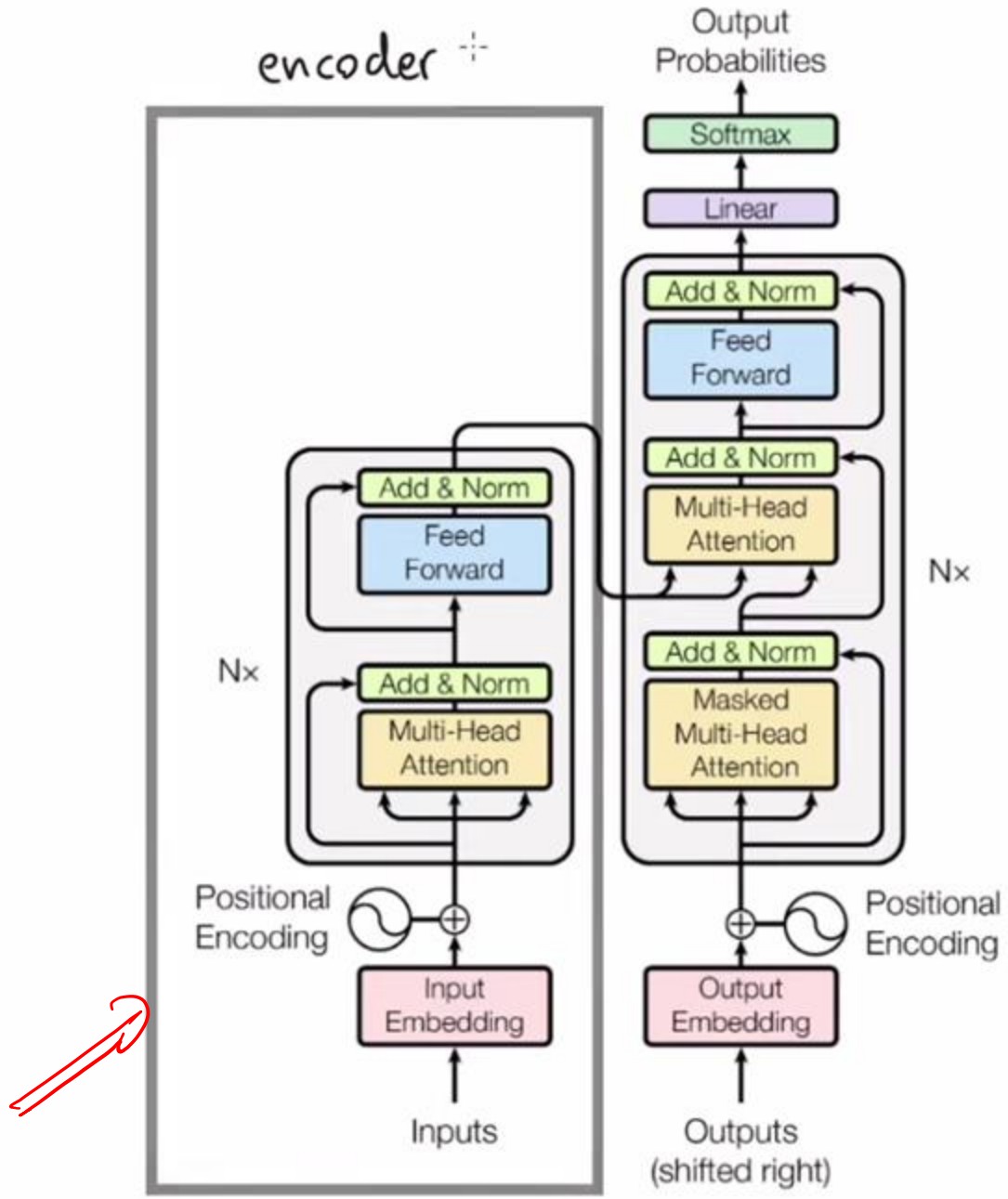
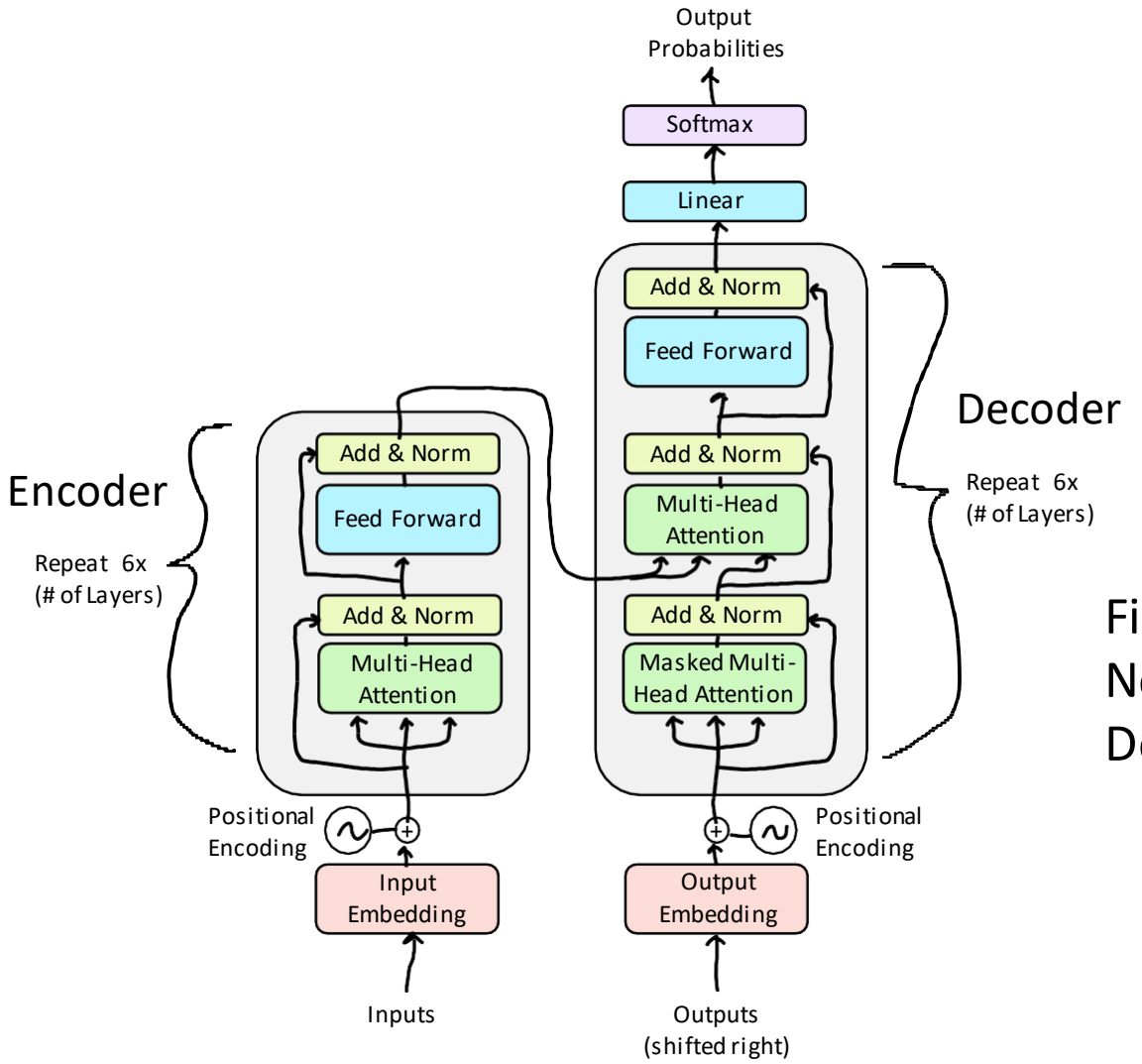


Figure 1: The Transformer - model architecture.

Translation

The Transformer Encoder-Decoder [Vaswani et al., 2017]

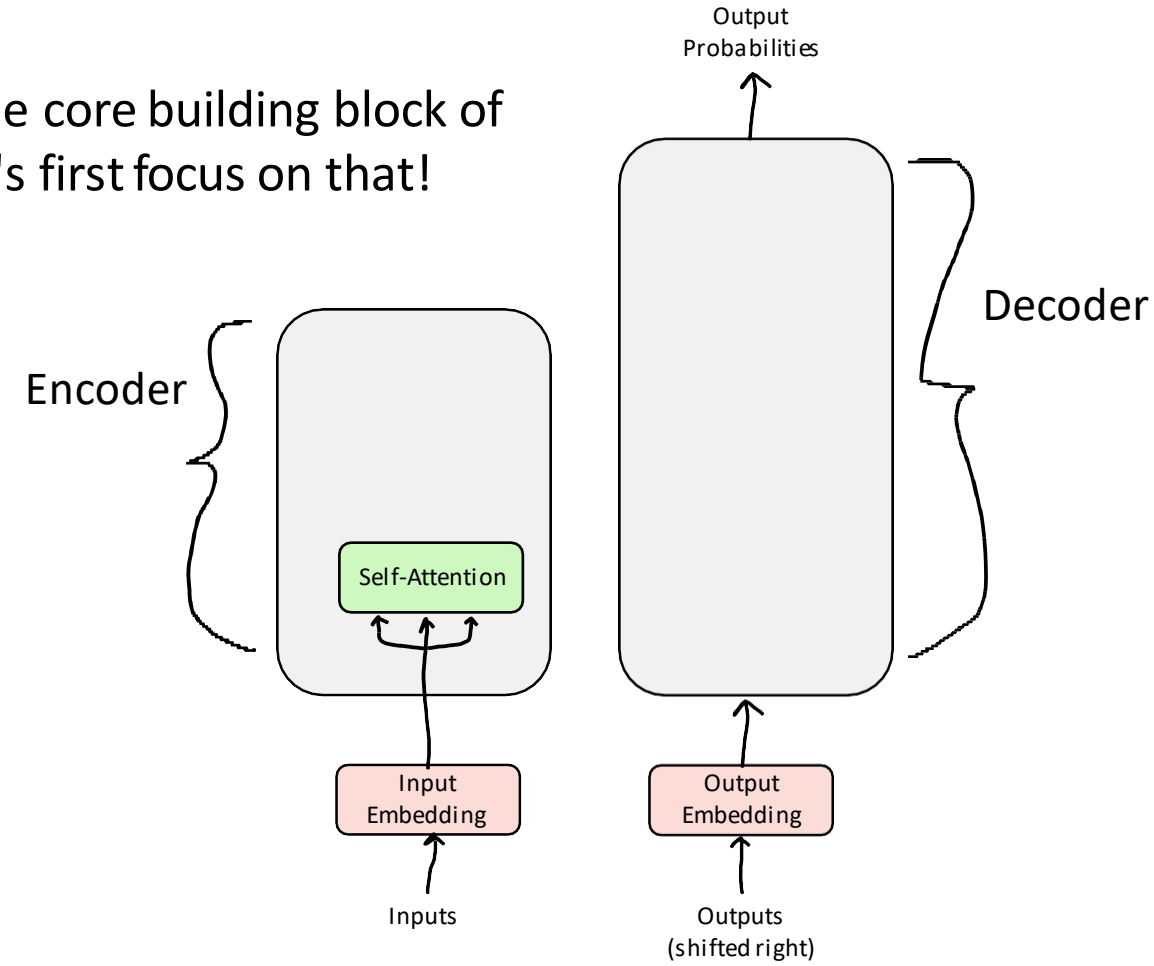


First, we will talk about the Encoder!
Next, we will go through the Decoder (which is quite similar)!

Adapted from cs224n-2024-lecture-slides

Encoder: Self-Attention

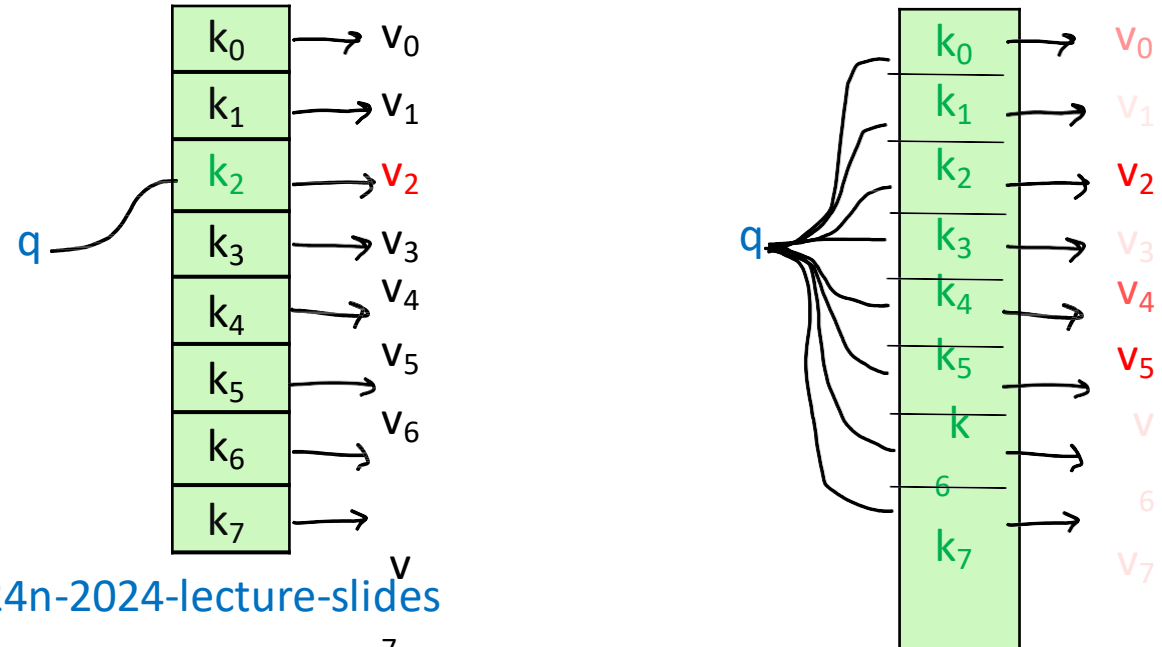
Self-Attention is the core building block of Transformer, so let's first focus on that!



Adapted from cs224n-2024-lecture-slides

Intuition for Attention Mechanism

- Let's think of attention as a "fuzzy" or approximate hashtable:
  - To look up a **value**, we compare a **query** against **keys** in a table.
  - In a hashtable (shown on the bottom left):
    - Each **query** (hash) maps to exactly one **key**-**value** pair.
  - In (self-)attention (shown on the bottom right):
    - Each **query** matches each **key** to varying degrees.
    - We return a sum of **values** weighted by the **query**-**key** match.



Adapted from cs224n-2024-lecture-slides

Recipe for Self-Attention in the Transformer Encoder

- Step 1: For each word x_i, calculate its **query**, **key**, and **value**.

$$q_i = W^Q x_i \quad k_i = W^K x_i \quad v_i = W^V x_i$$

- Step 2: Calculate attention score between **query** and **keys**.

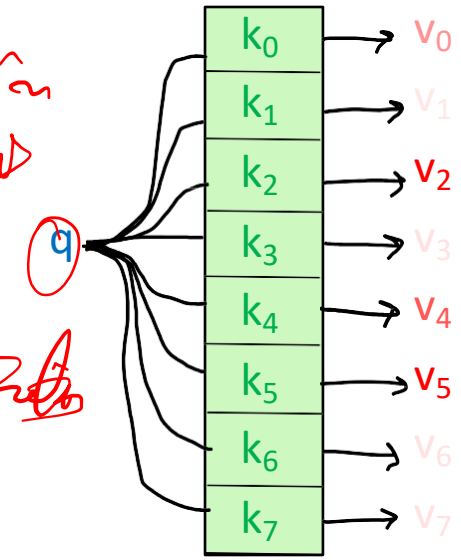
$$e_{ij} = q_i \cdot k_j$$

- Step 3: Take the softmax to normalize attention scores.

$$\alpha_{ij} = softmax(e_{ij}) = \frac{exp(e_{ij})}{\sum_k exp(e_{ik})}$$

- Step 4: Take a weighted sum of **values**.

$$Output_i = \sum_j \alpha_{ij} v_j$$



Adapted from cs224n-2024-lecture-slides

Recipe for (Vectorized) Self-Attention in the Transformer Encoder

- Step 1: With embeddings stacked in X, calculate **queries**, **keys**, and **values**.

$$Q = XW^Q \quad K = XW^K \quad V = XW^V$$

- Step 2: Calculate attention scores between **query** **and** **keys.**

$$E = QK^T$$

- Step 3: Take the softmax to normalize attention scores.

$$A = softmax(E)$$

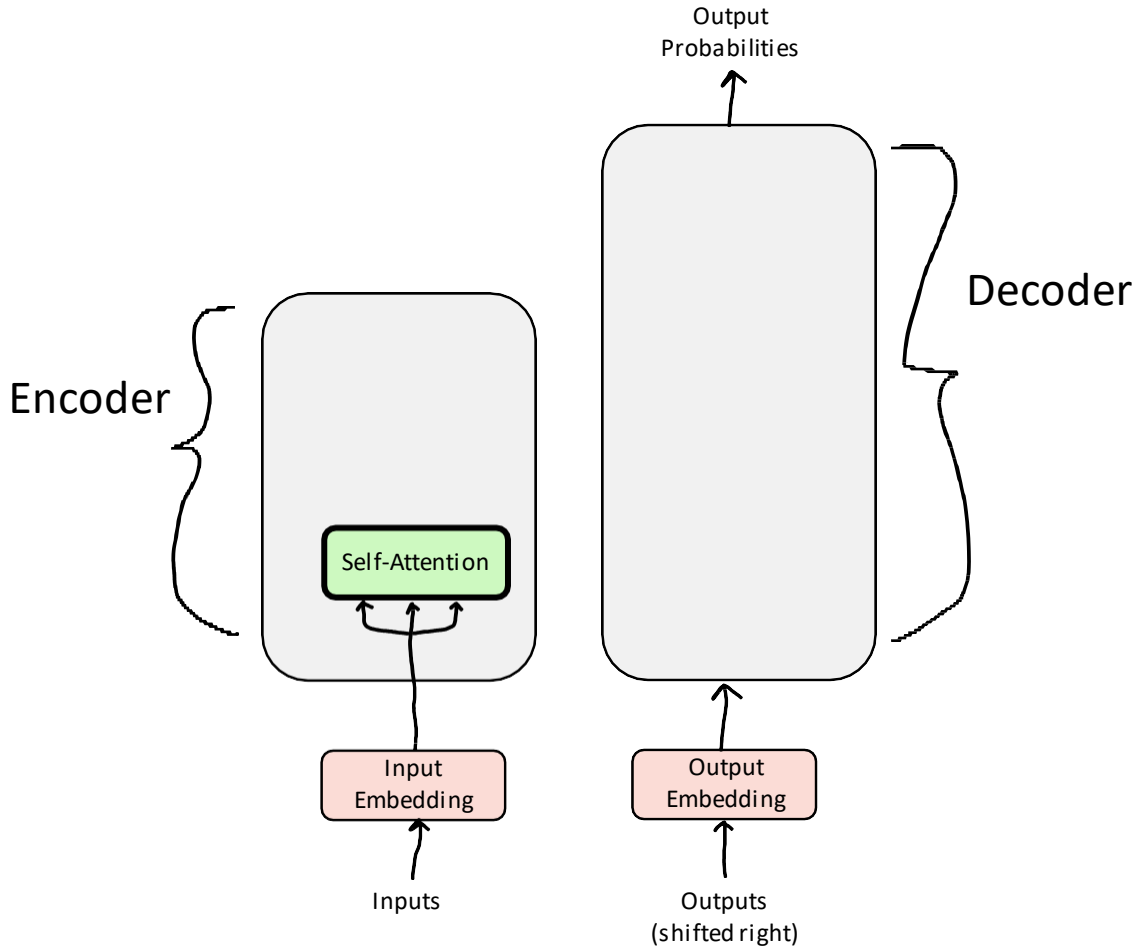
- Step 4: Take a weighted sum of **values**.

$$Output = AV$$

$$Output = softmax\left(QK^T\right)V$$

Adapted from cs224n-2024-lecture-slides

What We Have So Far: (Encoder) Self-Attention!



Adapted from cs224n-2024-lecture-slides

Attention is All you need!!

Attention Is All You Need

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https://arxiv.org/pdf/1706.03762

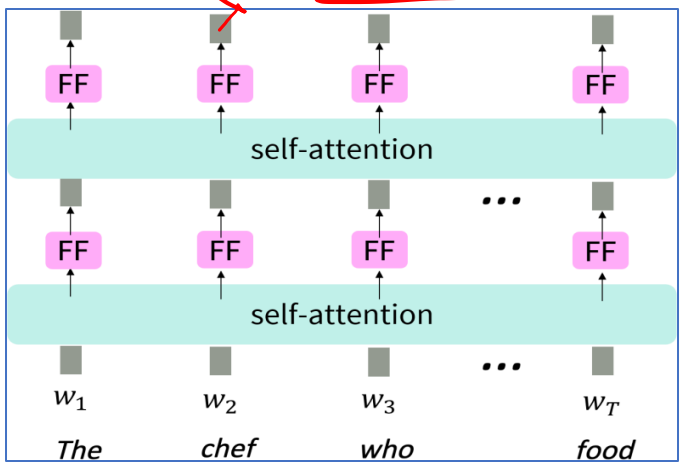
But attention isn't quite all you need!

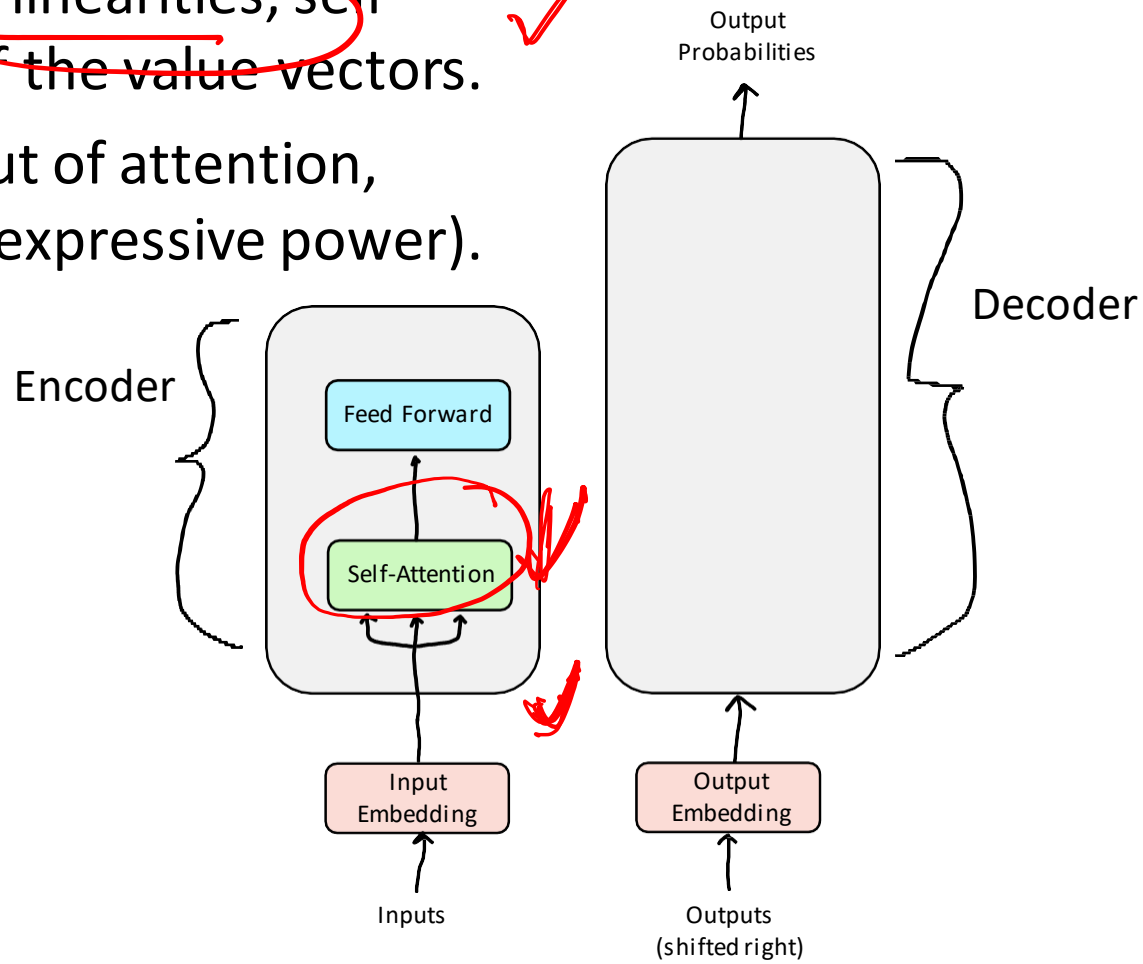
Problem: Since there are no element-wise non-linearities, self-attention is simply performing a re-averaging of the value vectors.

Easy fix: Apply a feedforward layer to the output of attention, providing non-linear activation (and additional expressive power).

Equation for Feed Forward Layer

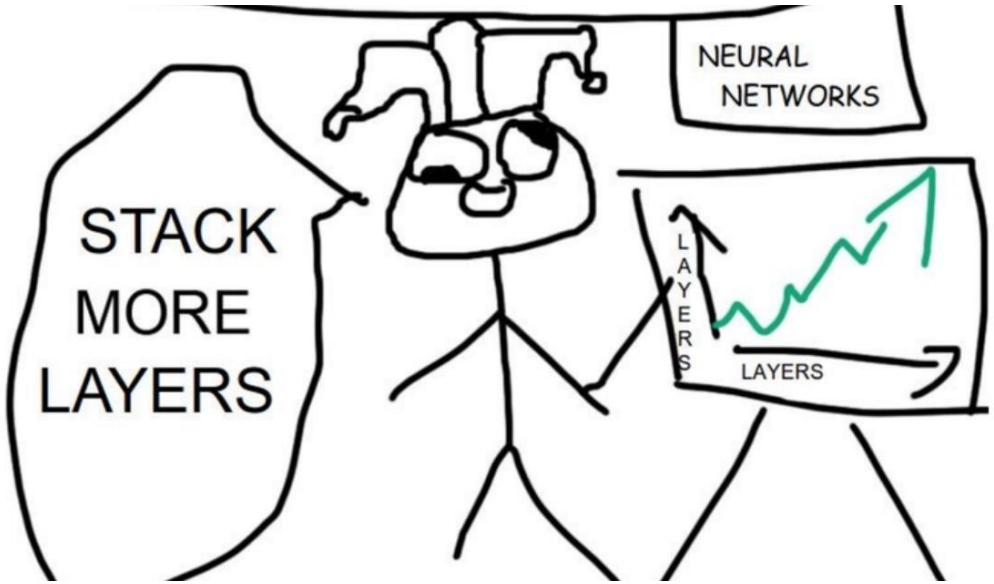
$$m_i = MLP(\text{output}_i)$$
$$= W_2 * \text{ReLU}(W_1 \times \text{output}_i + b_1) + b_2$$

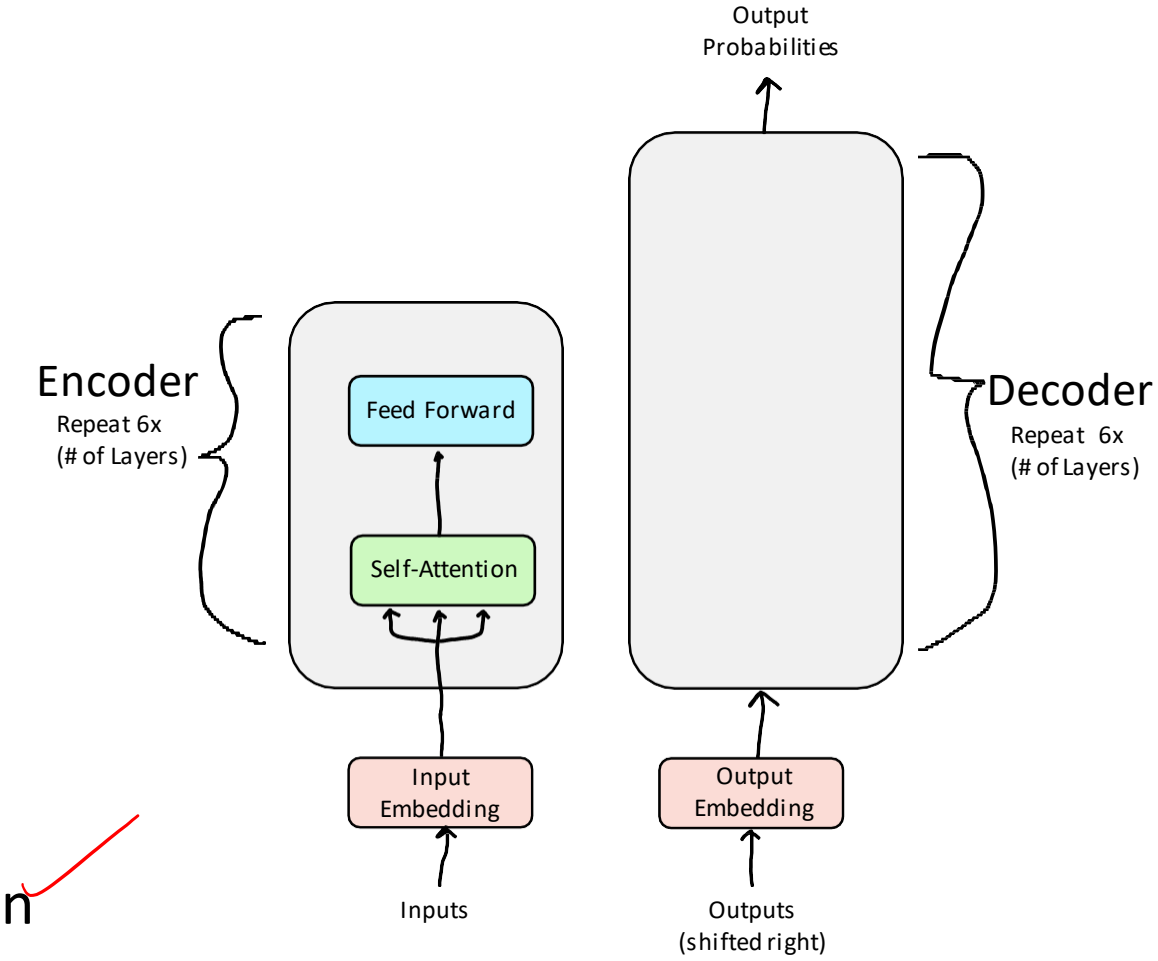




Adapted from cs224n-2024-lecture-slides

But how do we make this work for deep networks?





Training Trick #1: Residual Connections

Training Trick #2: LayerNorm

Training Trick #3: Scaled Dot Product Attention

Adapted from cs224n-2024-lecture-slides

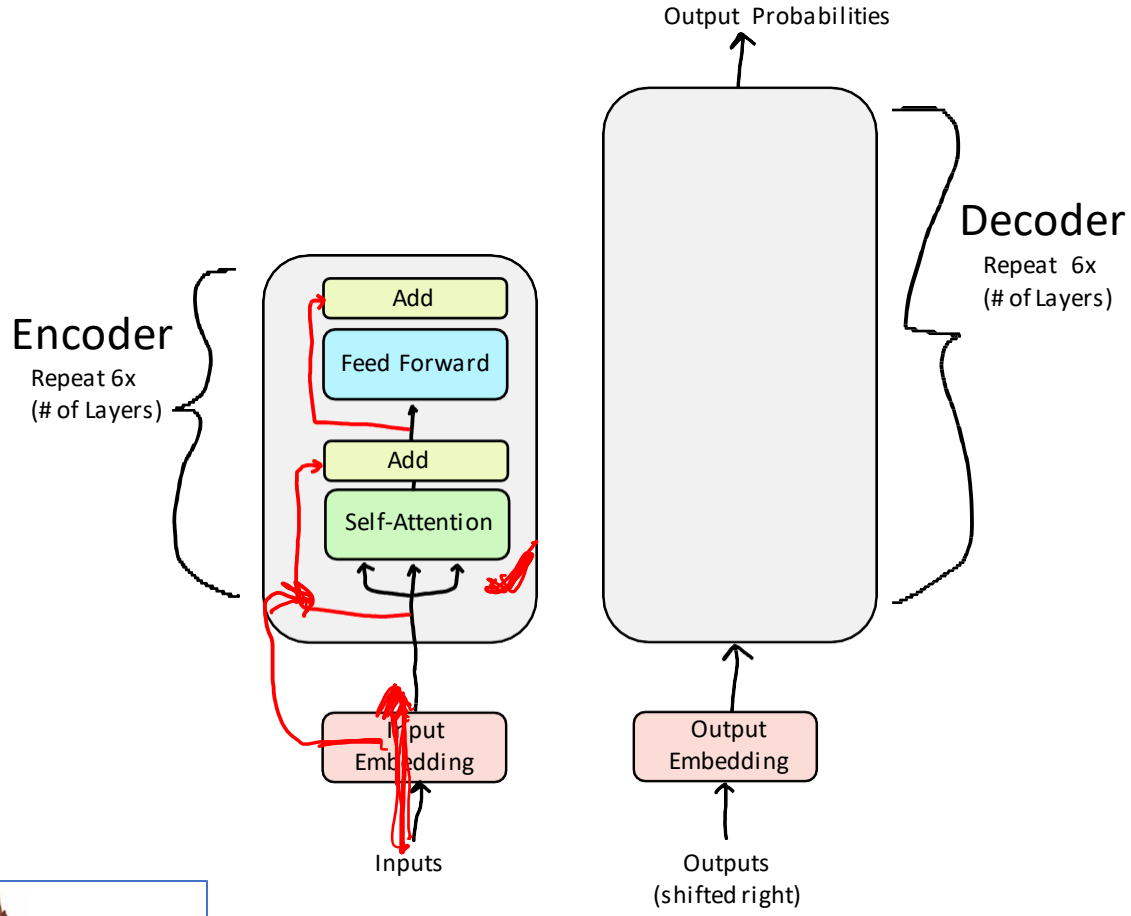
Training Trick #1: Residual Connections [He et al., 2016]

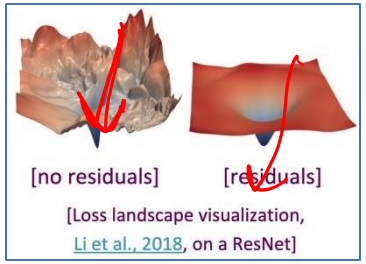
- Residual connections are a simple but powerful technique from computer vision.
- Deep networks are surprisingly bad at learning the identity function!
- Therefore, directly passing "raw" embeddings to the next layer can actually be very helpful!

$$x_\ell = F(x_{\ell-1}) + x_{\ell-1}$$

- **This prevents the network from "forgetting" or distorting important information as it is processed by many layers.**

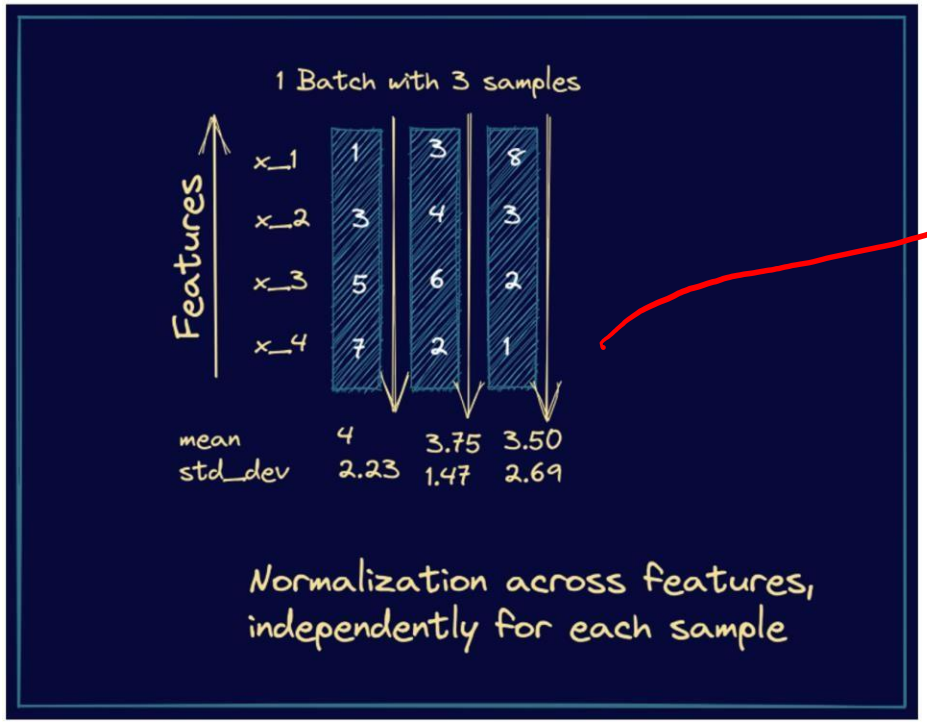
Residual connections are also thought to smooth the loss landscape and make training easier!





Adapted from cs224n-2024-lecture-slides

Training Trick #2: Layer Normalization [Ba et al., 2016]

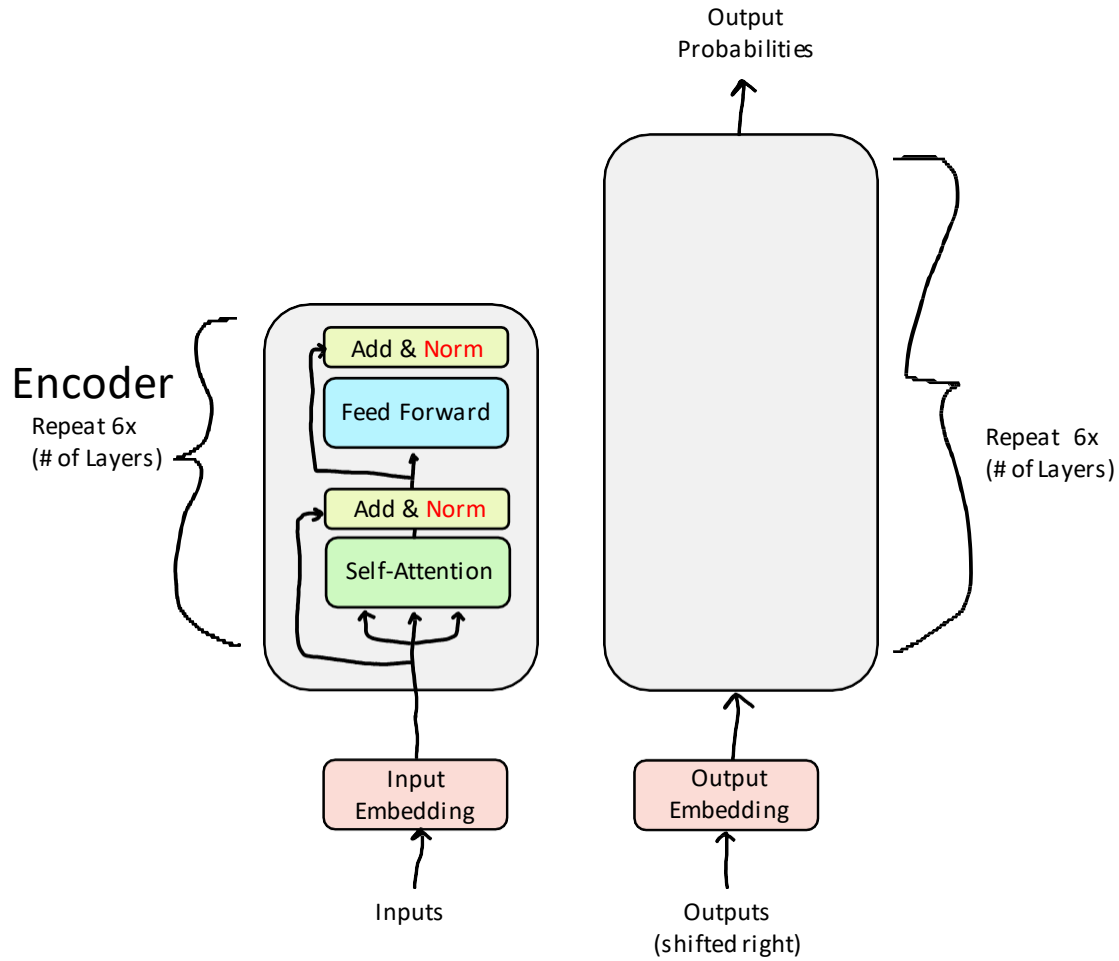


An Example of How LayerNorm Works (Image by Bala Priya C, Pinecone)

Mean: $\mu^l = \frac{1}{H}\sum_{i=1}^{H} a_i^l$ Standard Deviation: $\sigma^l = \sqrt{\frac{1}{H}\sum_{i=1}^{H}(a_i^l - \mu^l)^2}$

$$x^{\ell\prime} = \frac{x^\ell - \mu^\ell}{\sigma^\ell + \epsilon}$$

Hidden layers



Adapted from cs224n-2024-lecture-slides

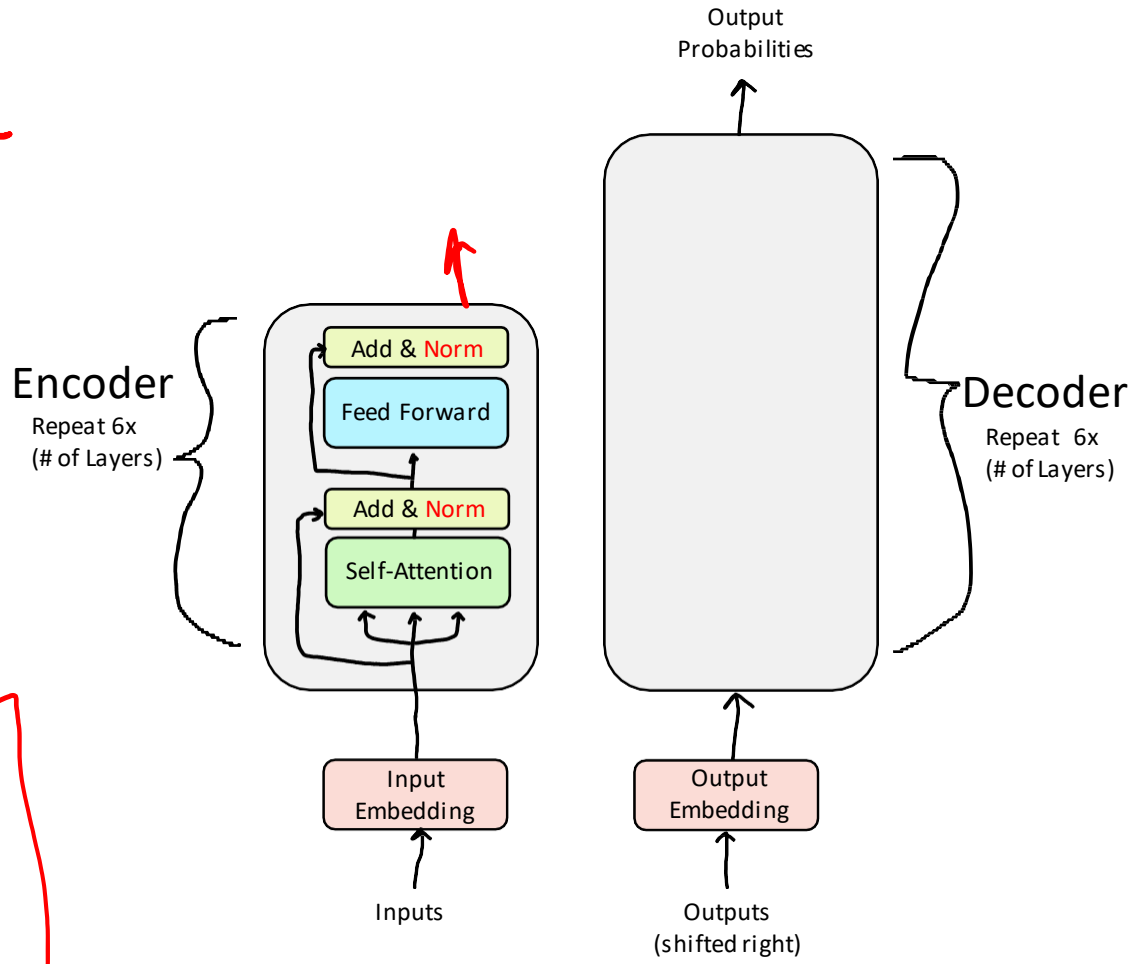
Training Trick #2: Layer Normalization [Ba et al., 2016]

- **Problem:** Difficult to train the parameters of a given layer because its input from the layer beneath keeps shifting.
- **Solution:** Reduce variation by **normalizing** to zero mean and standard deviation of one within each **layer**.

Mean: $\mu^l = \frac{1}{H}\sum_{i=1}^{H} a_i^l$ Standard Deviation: $\sigma^l = \sqrt{\frac{1}{H}\sum_{i=1}^{H}(a_i^l - \mu^l)^2}$

$$x^{\ell\prime} = \frac{x^\ell - \mu^\ell}{\sigma^\ell + \epsilon}$$

Mean ✓ Variance ✓ SD



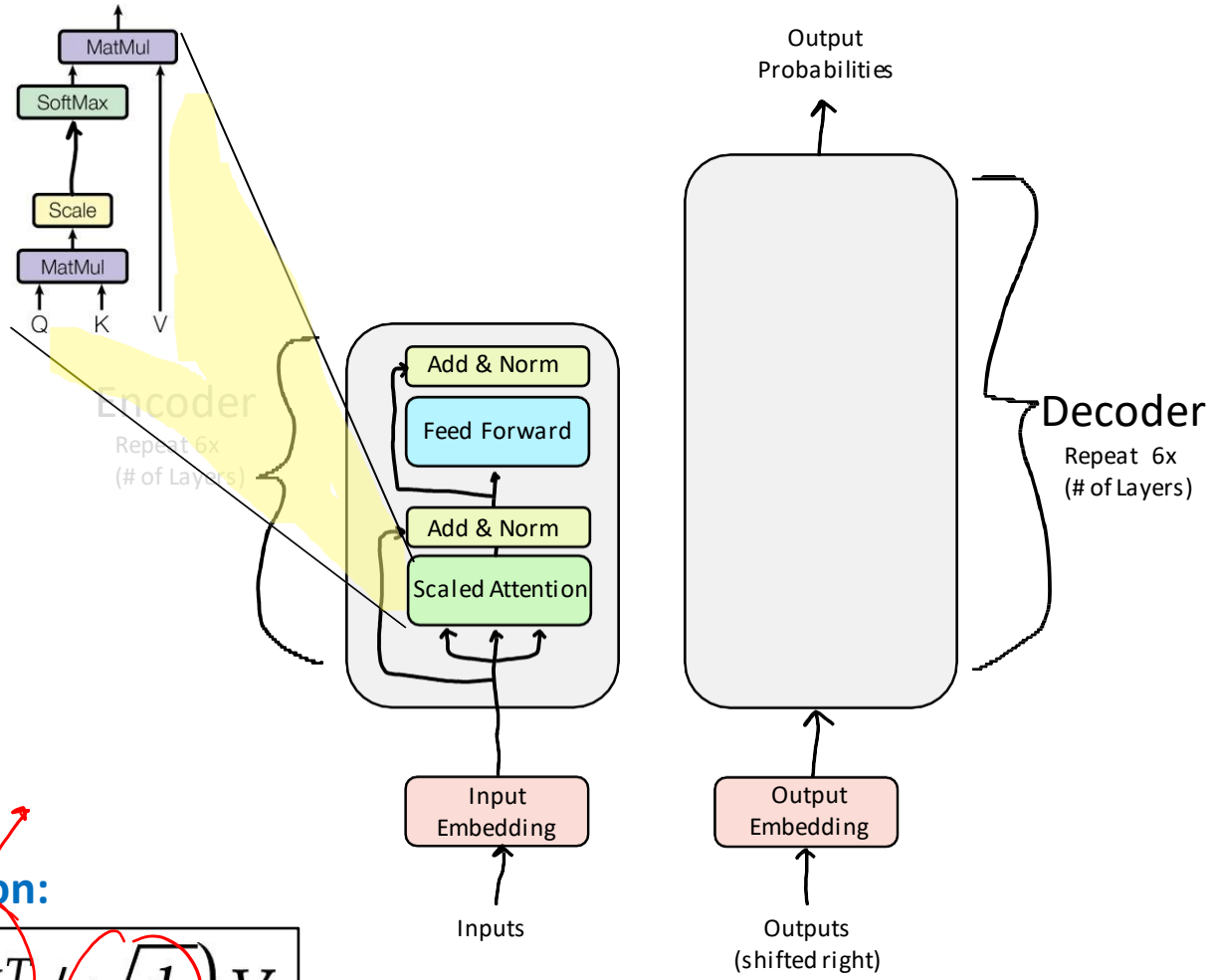
Adapted from cs224n-2024-lecture-slides

Training Trick #3: Scaled Dot Product Attention

- After LayerNorm, the mean and variance of vector elements is 0 and 1, respectively. (Yay!)
- However, the dot product still tends to take on extreme values, as its variance scales with dimensionality d_k

Quick Statistics Review:

- Mean of sum = sum of means = $d_k * 0 = 0$
- Variance of sum = sum of variances = $d_k * 1 = d_k$
- To set the variance to 1, simply divide by $\sqrt{d_k}$!



Updated Self-Attention Equation:

$$Output = softmax\left(QK^T / \sqrt{d_k}\right)V$$

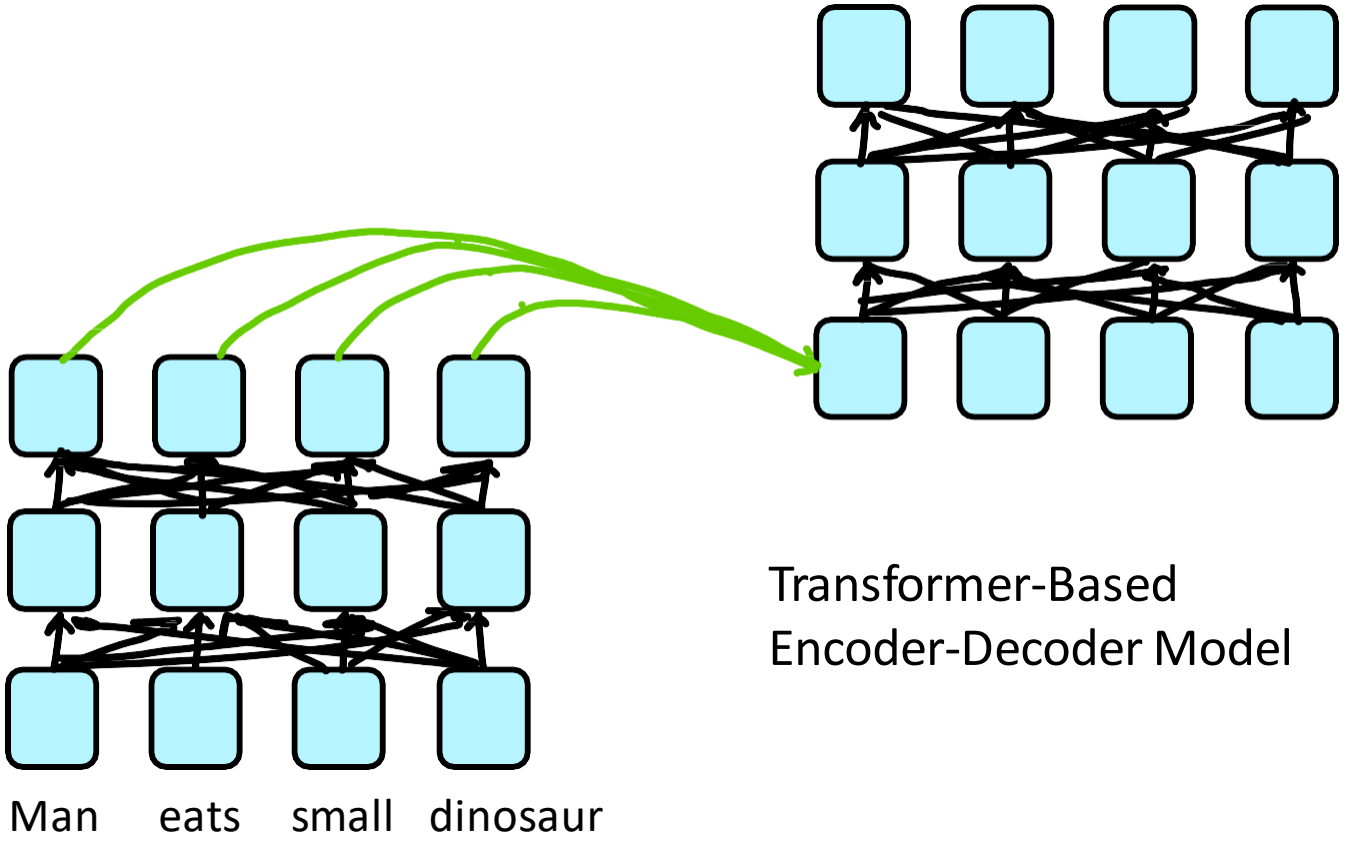
Adapted from cs224n-2024-lecture-slides

Almost done with Encoder?
What is the Major Problem here?
Can you spot it?

$$Output = softmax\left(QK^T / \sqrt{d_k}\right)V$$

Consider this sentence:

- **"Man eats small dinosaur."**



Transformer-Based
Encoder-Decoder Model

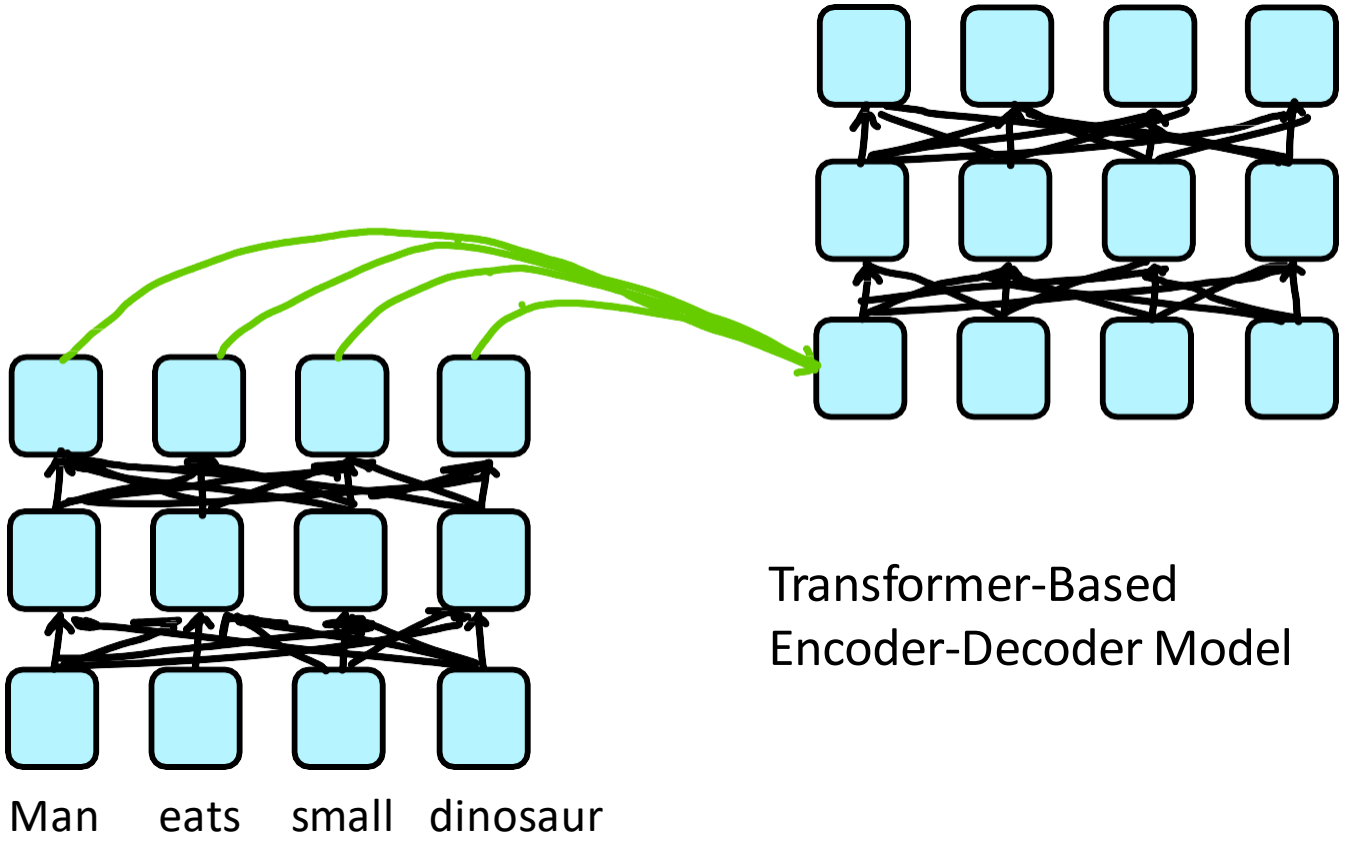
Adapted from cs224n-2024-lecture-slides

Major issue!

- We're almost done with the Encoder, but we have a major problem! Has anyone spotted it?
- Consider this sentence:

  "Man eats small dinosaur."
- Wait a minute, order doesn't impact the network at all!
- **This seems wrong given that word order does have meaning in many languages, including English!**

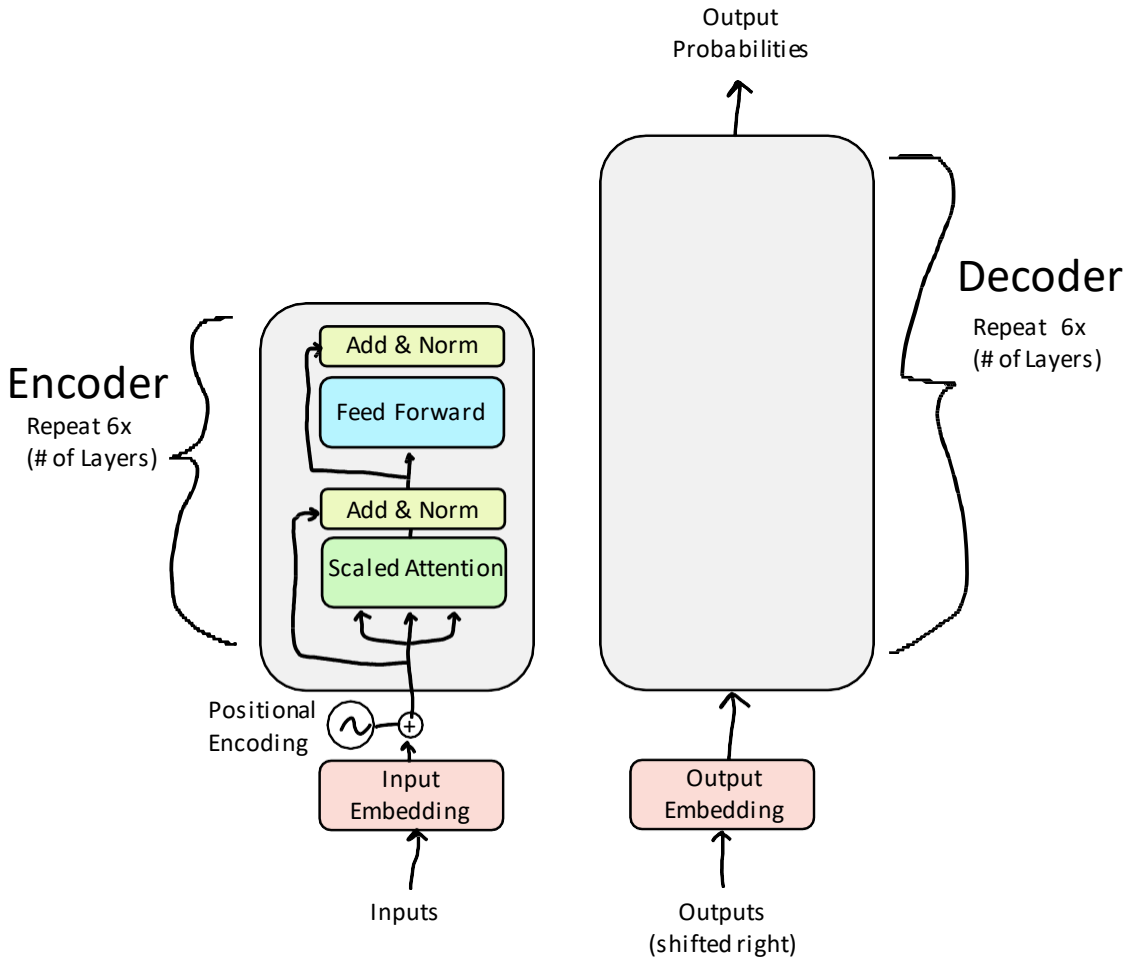
$$Output = softmax\left(QK^T / \sqrt{d_k}\right)V$$



Transformer-Based Encoder-Decoder Model

Adapted from cs224n-2024-lecture-slides

Solution: Inject Order Information through Positional Encodings!



Adapted from cs224n-2024-lecture-slides

Fixing the first self-attention problem: **sequence order**

- Since self-attention doesn't build in order information, we need to encode the order of the sentence in our keys, queries, and values.
- Consider representing each **sequence index** as a **vector**

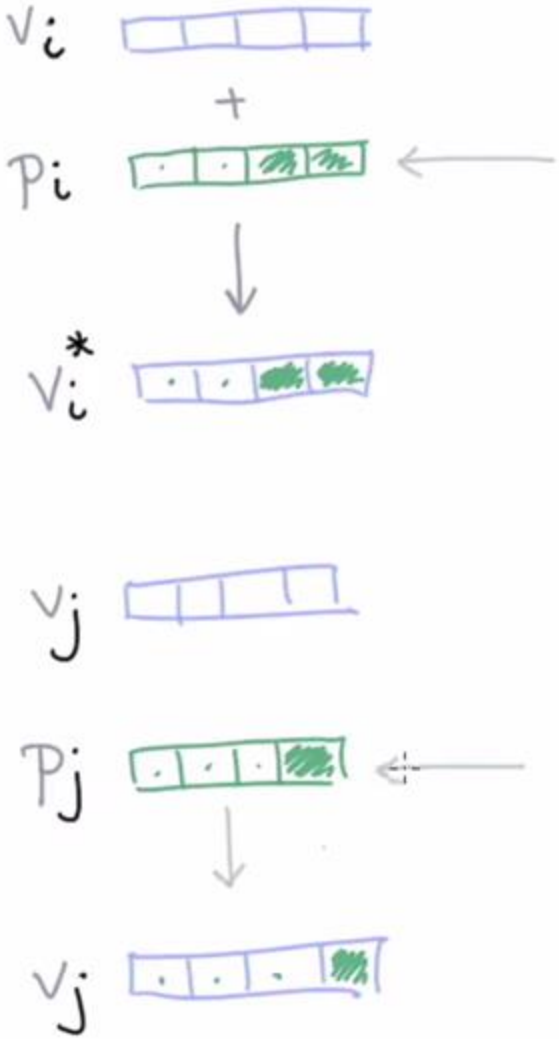
$$p_i \in \mathbb{R}^d \text{, for } i \in \{1,2, \dots, T\} \text{ are position vectors}$$

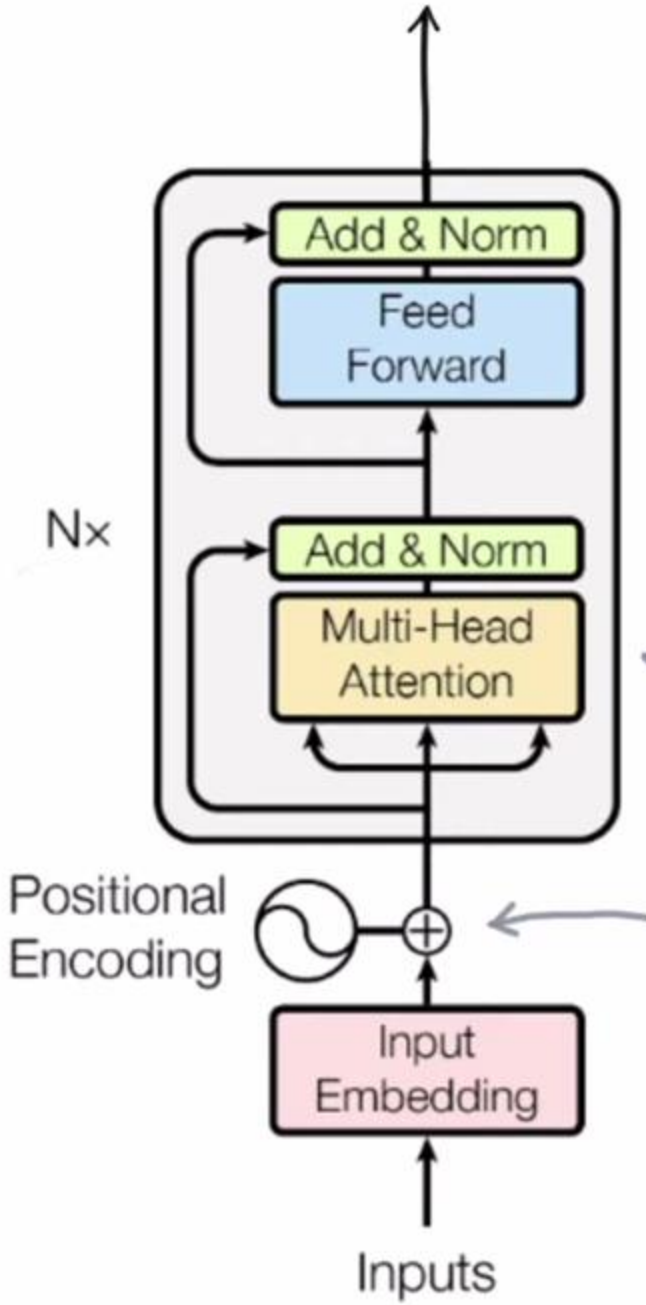
- Don't worry about what the p_i are made of yet!
- Easy to incorporate this info into our self-attention block: just add the p_i to our inputs!

In deep self-attention networks, we do this at the first layer! You could concatenate them as well, but people mostly just add…

Adapted from cs224n-2024-lecture-slides

Transformer Encoder

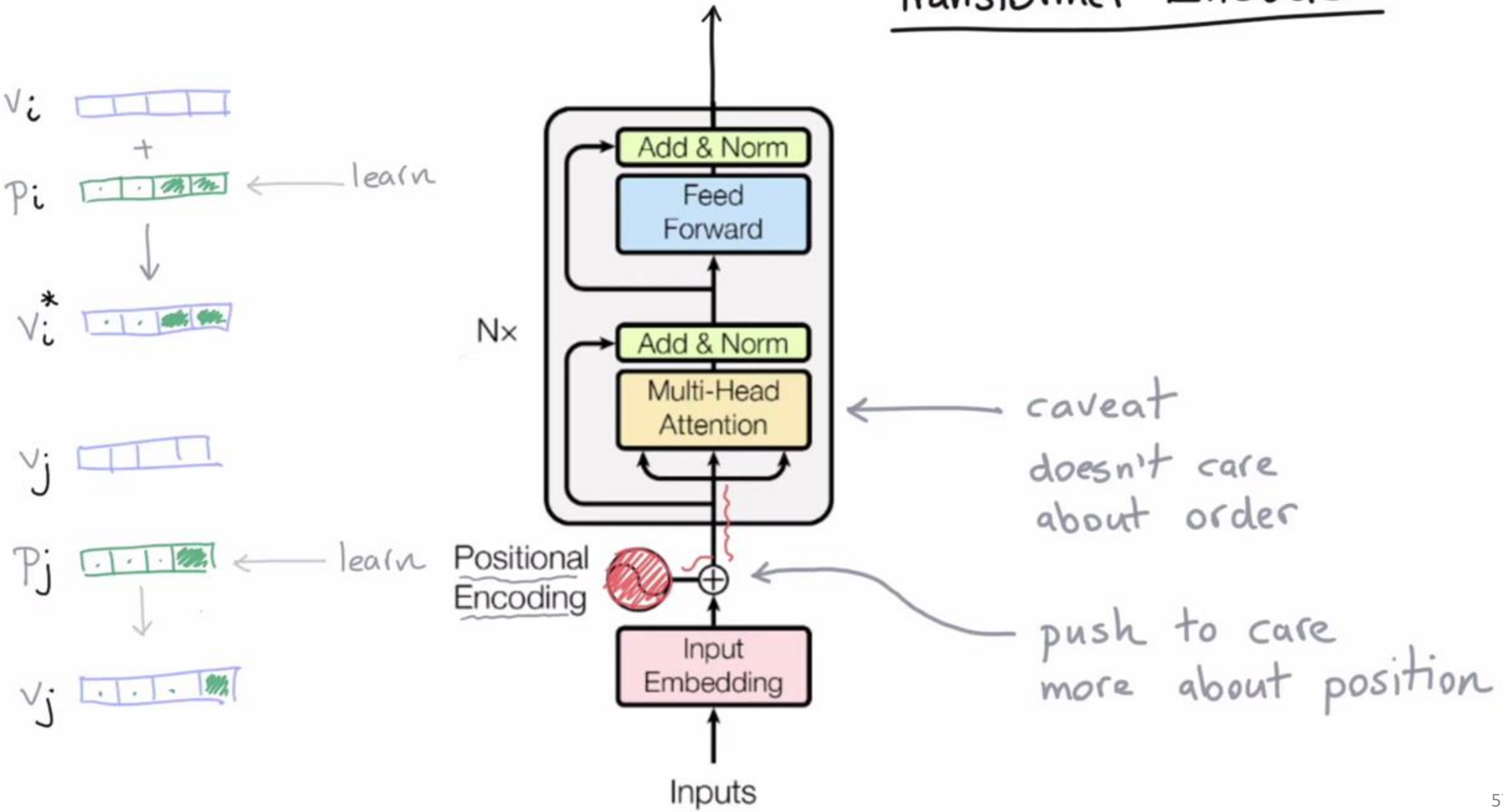




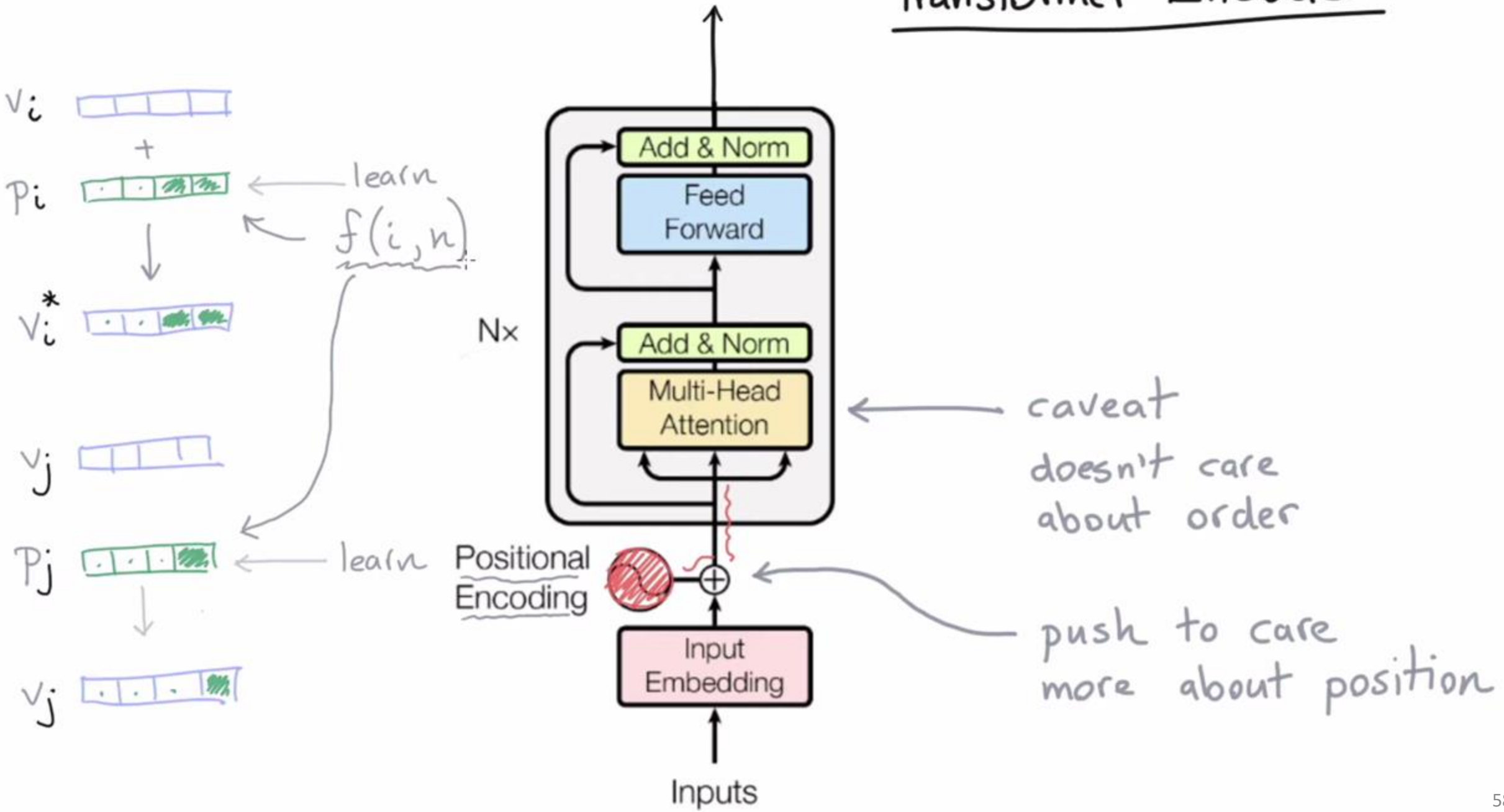
caveat
doesn't care
about order

push to care
more about position

Transformer Encoder



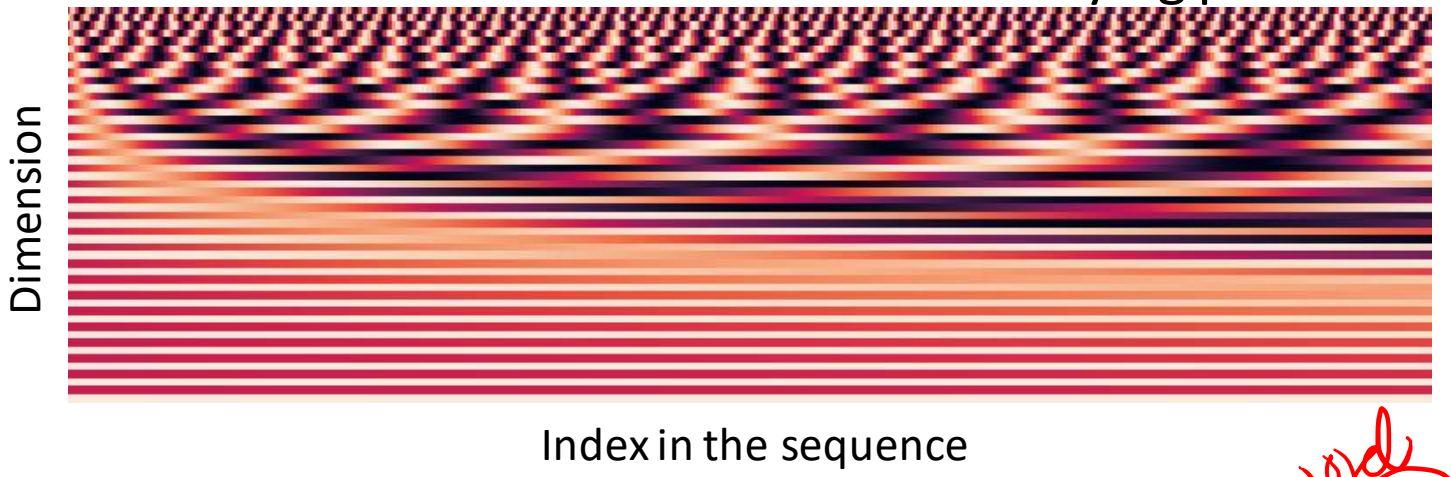
Transformer Encoder



Position representation vectors through sinusoids (original)

- **Sinusoidal position representations:** concatenate sinusoidal functions of varying periods:

$$p_i = \begin{pmatrix} \sin(i/10000^{2*1/d}) \\ \cos(i/10000^{2*1/d}) \\ \vdots \\ \sin(i/10000^{2*2/d}) \\ \cos(i/10000^{2*2/d}) \end{pmatrix} \quad \frac{d}{2}$$



- Pros:
  - Periodicity indicates that maybe "absolute position" isn't as important
  - Maybe can extrapolate to longer sequences as periods restart
- Cons:
  - Not learnable; also the extrapolation doesn't really work

Adapted from cs224n-2024-lecture-slides Image: https://timodenk.com/blog/linear-relationships-in-the-transformers-positional-encoding/

Extension: Self-Attention w/ Relative Position Encodings

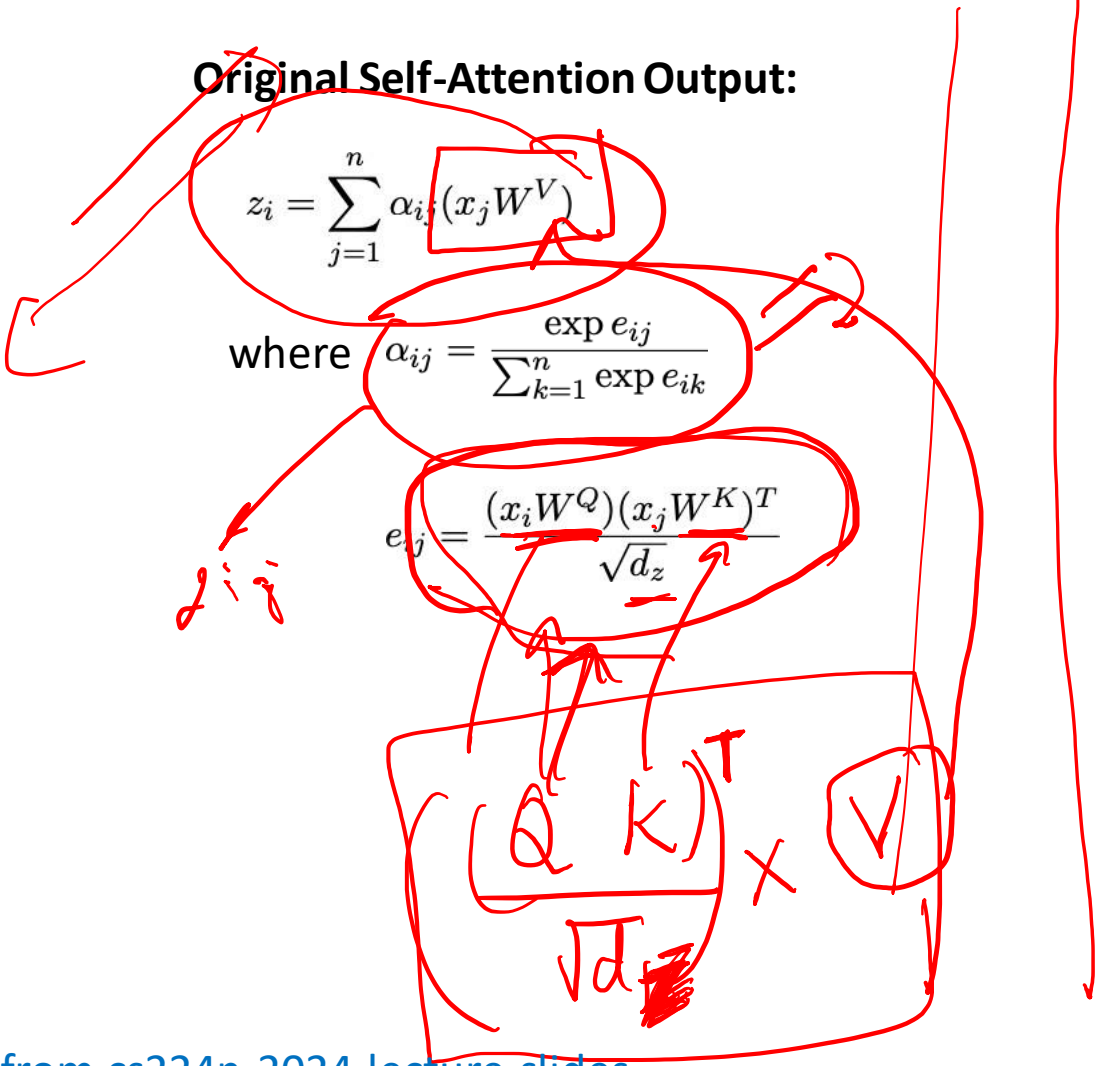
Key Insight: The most salient position information is the relationship (e.g. "cat" is the word before "eat") between words, rather than their absolute position (e.g. "cat" is word 2).

Original Self-Attention Output:

$$z_i = \sum_{j=1}^{n} \alpha_{ij}(x_j W^V)$$

where $\alpha_{ij} = \frac{\exp e_{ij}}{\sum_{k=1}^{n} \exp e_{ik}}$

$$e_{ij} = \frac{(x_i W^Q)(x_j W^K)^T}{\sqrt{d_z}}$$



Relation-Aware Self-Attention Output:

$$z_i = \sum_{j=1}^{n} \alpha_{ij}(x_j W^V + a_{ij}^V)$$

where $\alpha_{ij} = \frac{\exp e_{ij}}{\sum_{k=1}^{n} \exp e_{ik}}$

$$e_{ij} = \frac{x_i W^Q (x_j W^K + a_{ij}^K)^T}{\sqrt{d_z}}$$

$$a_{ij}^K = w_{\text{clip}(j-i,k)}^K$$

$$a_{ij}^V = w_{\text{clip}(j-i,k)}^V$$

$$\text{clip}(x, k) = \max(-k, \min(k, x))$$

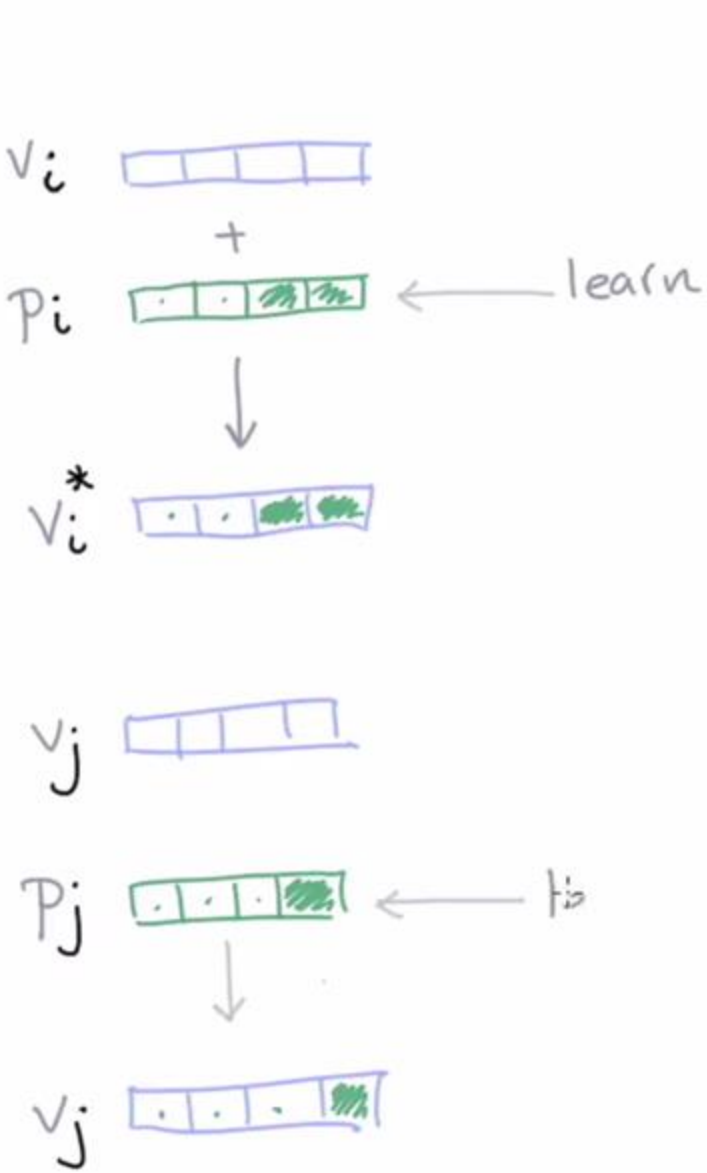
We then learn relative position representations $w^K = (w_{-k}^K, \ldots, w_k^K)$ and $w^V = (w_{-k}^V, \ldots, w_k^V)$

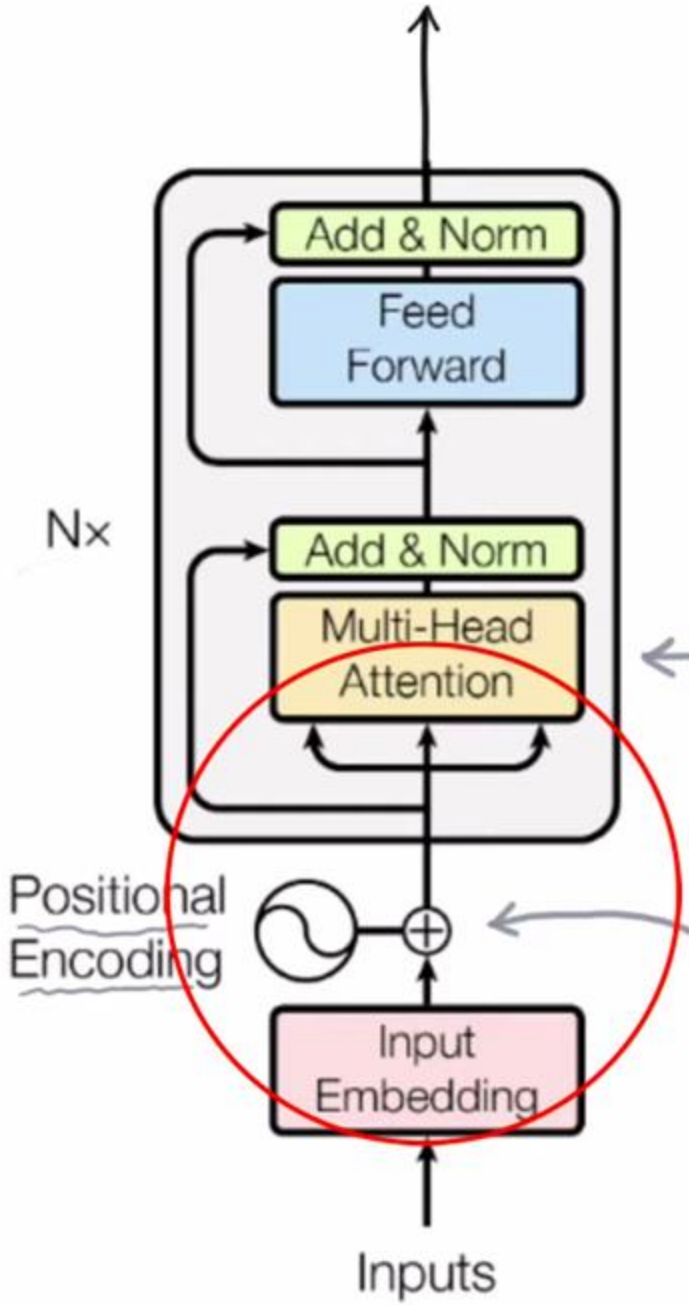
k	EN-DE BLEU
0	12.5
1	25.5
2	25.8
4	25.9
16	25.8
64	25.9
256	25.8

Table and Equations From [Shaw et al., 2018]

Adapted from cs224n-2024-lecture-slides

Transformer Encoder

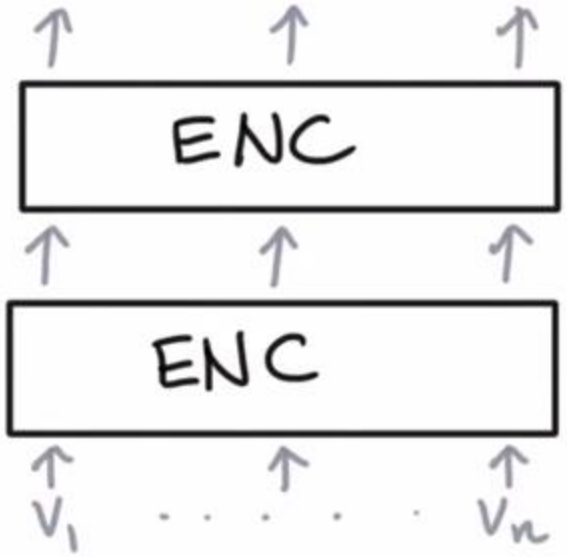




caveat
doesn't care about order

push to care more about position

Transformer Encoder

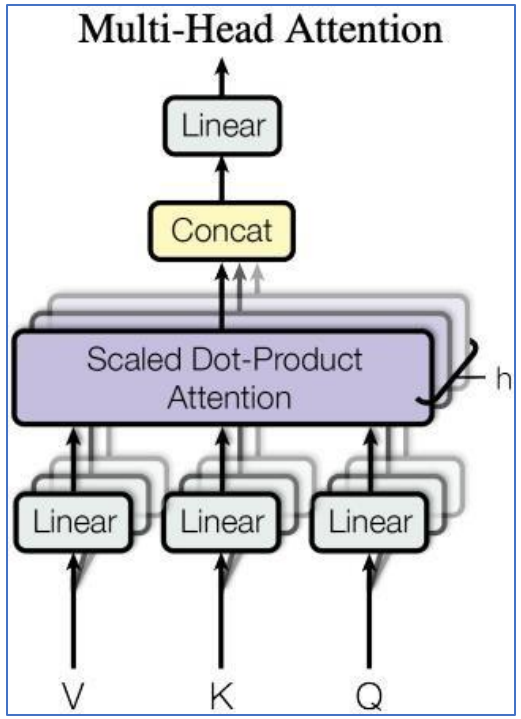


hyper param

number of heads
hyper param

Multi-Headed Self-Attention: k heads are better than 1!

- **High-Level Idea:** Let's perform self-attention multiple times in parallel and combine the results.

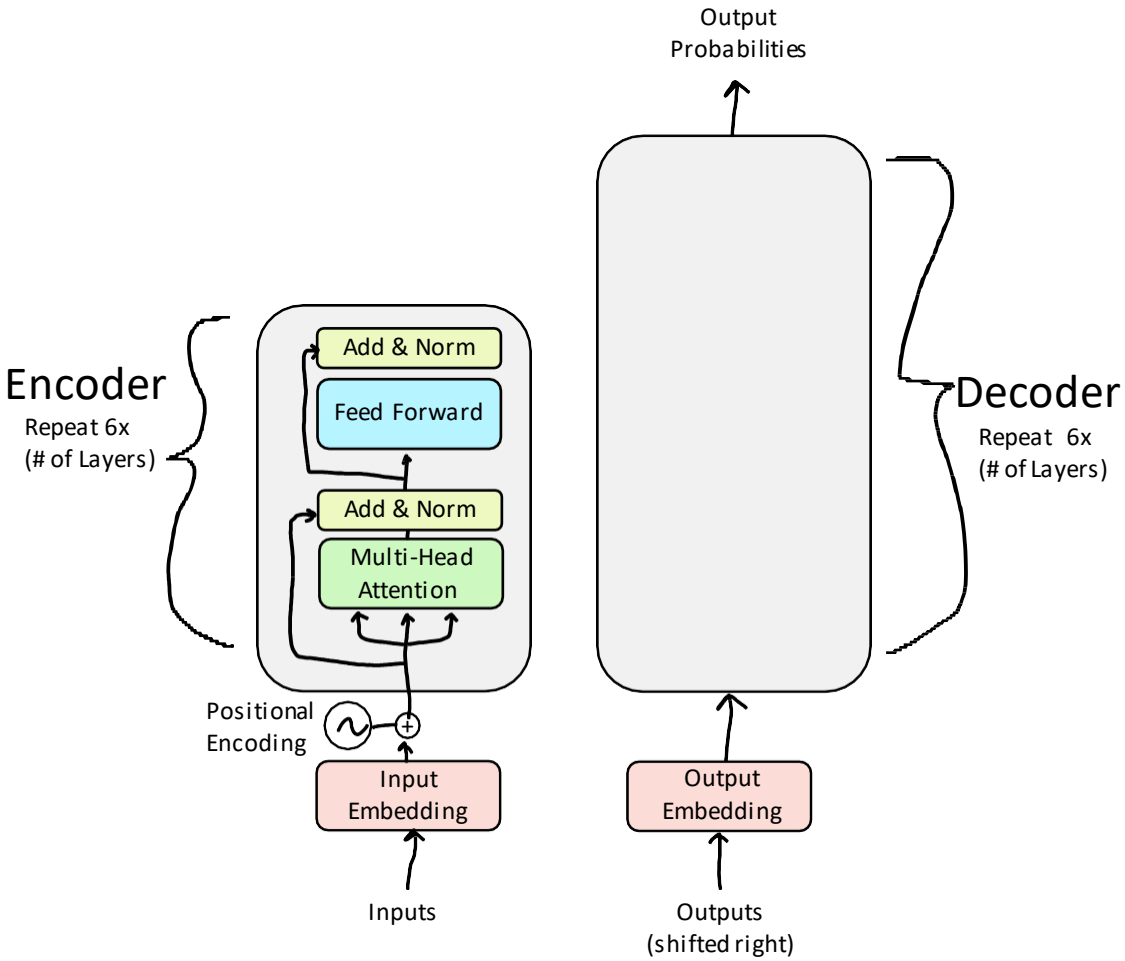


[Vaswani et al. 2017]

Wizards of the Coast, Artist: Todd Lockwood

Adapted from cs224n-2024-lecture-slides

Yay, we've completed the Encoder! Time for the Decoder...



Adapted from cs224n-2024-lecture-slides

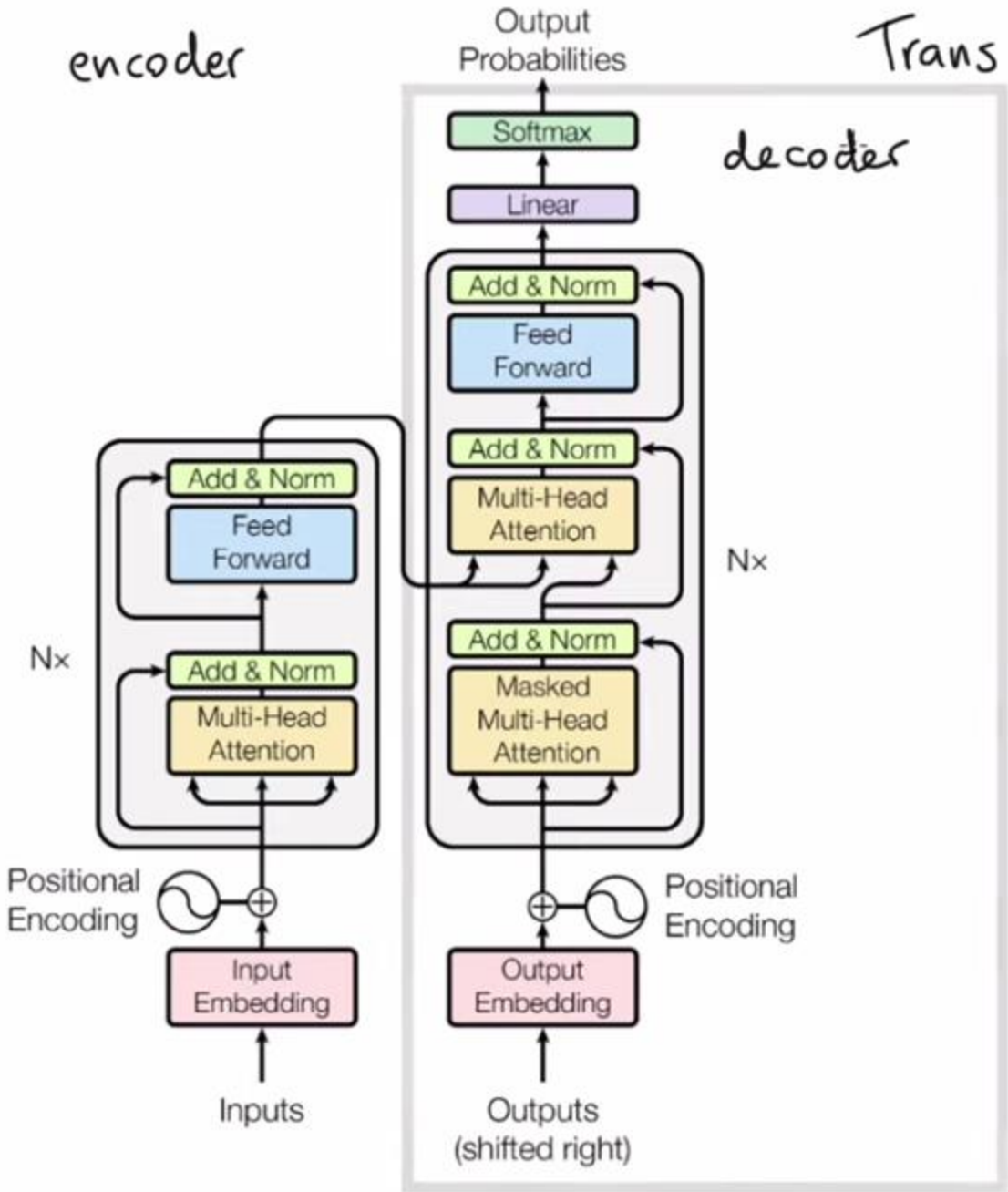


Figure 1: The Transformer - model architecture.

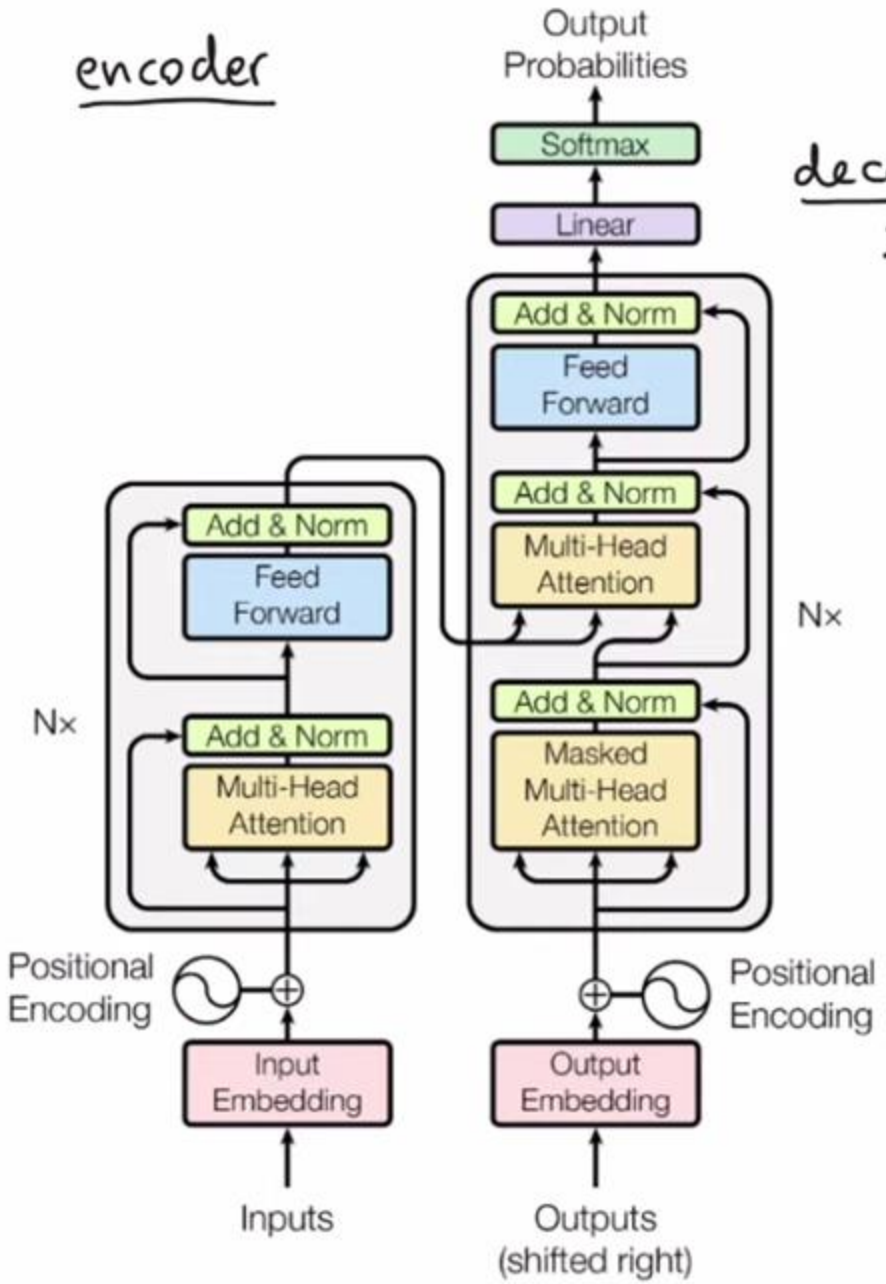
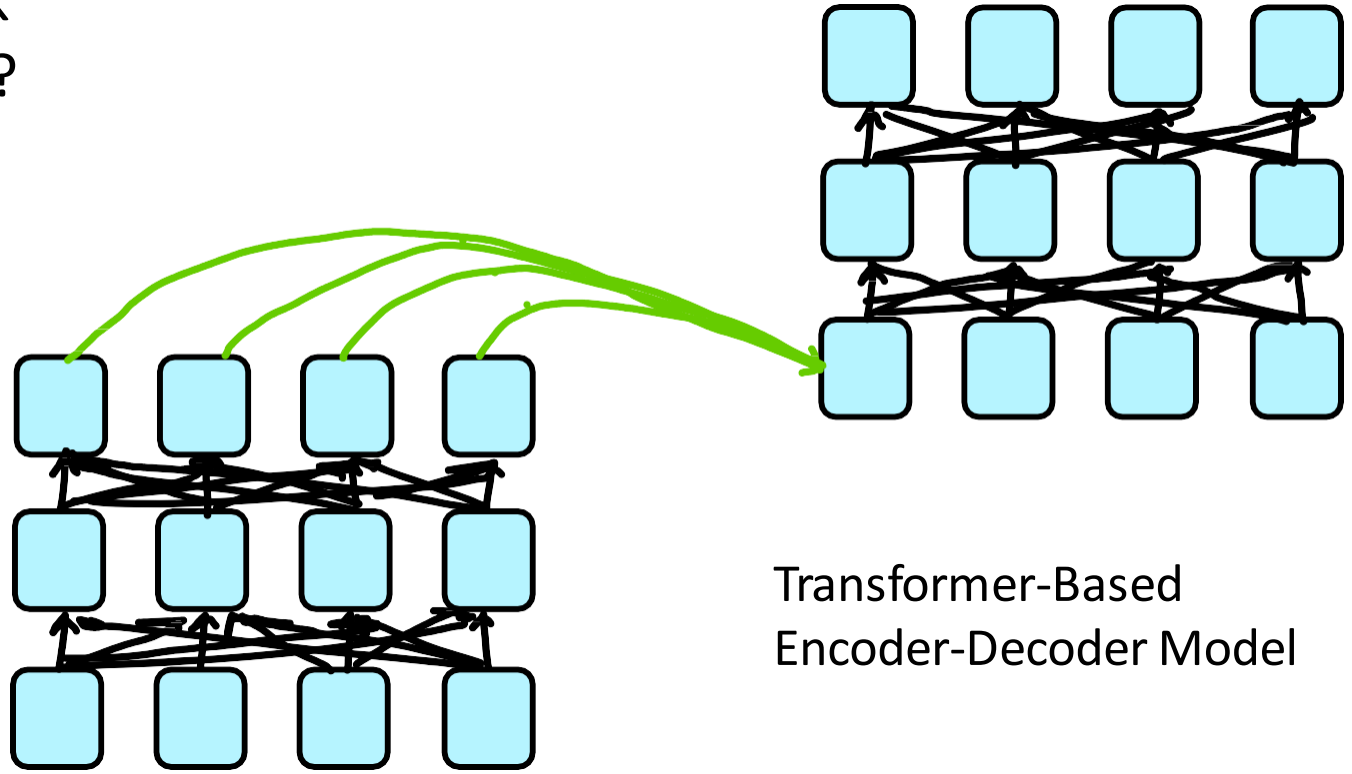


Figure 1: The Transformer - model architecture.

Decoder: Masked Multi-Head Self-Attention

- **Problem:** How do we keep the decoder from “cheating”? If we have a language modeling objective, can't the network just look ahead and "see" the answer?

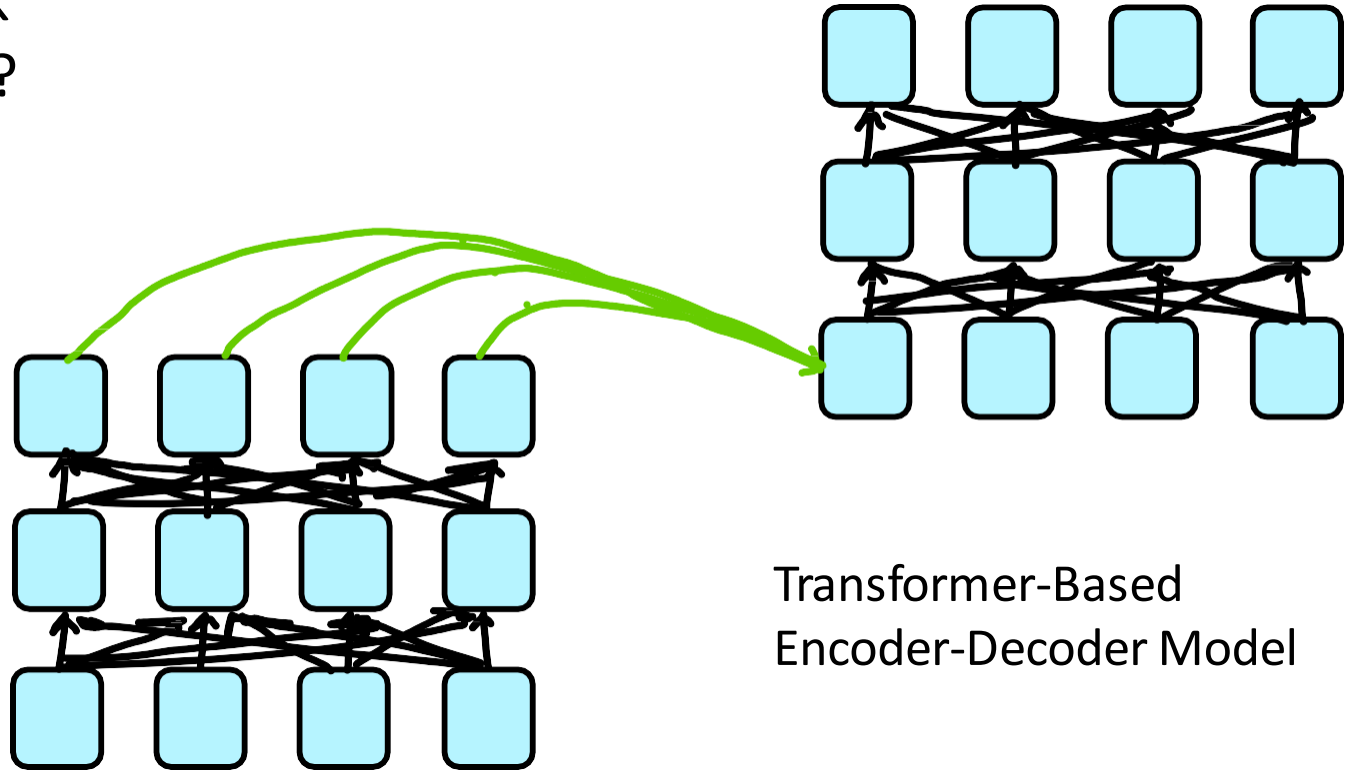


Transformer-Based Encoder-Decoder Model

Adapted from cs224n-2024-lecture-slides

Decoder: Masked Multi-Head Self-Attention

- **Problem:** How do we keep the decoder from "cheating"? If we have a language modeling objective, can't the network just look ahead and "see" the answer?
- **Solution:** Masked Multi-Head Attention. At a high-level, we hide (mask) information about future tokens from the model.



Transformer-Based Encoder-Decoder Model

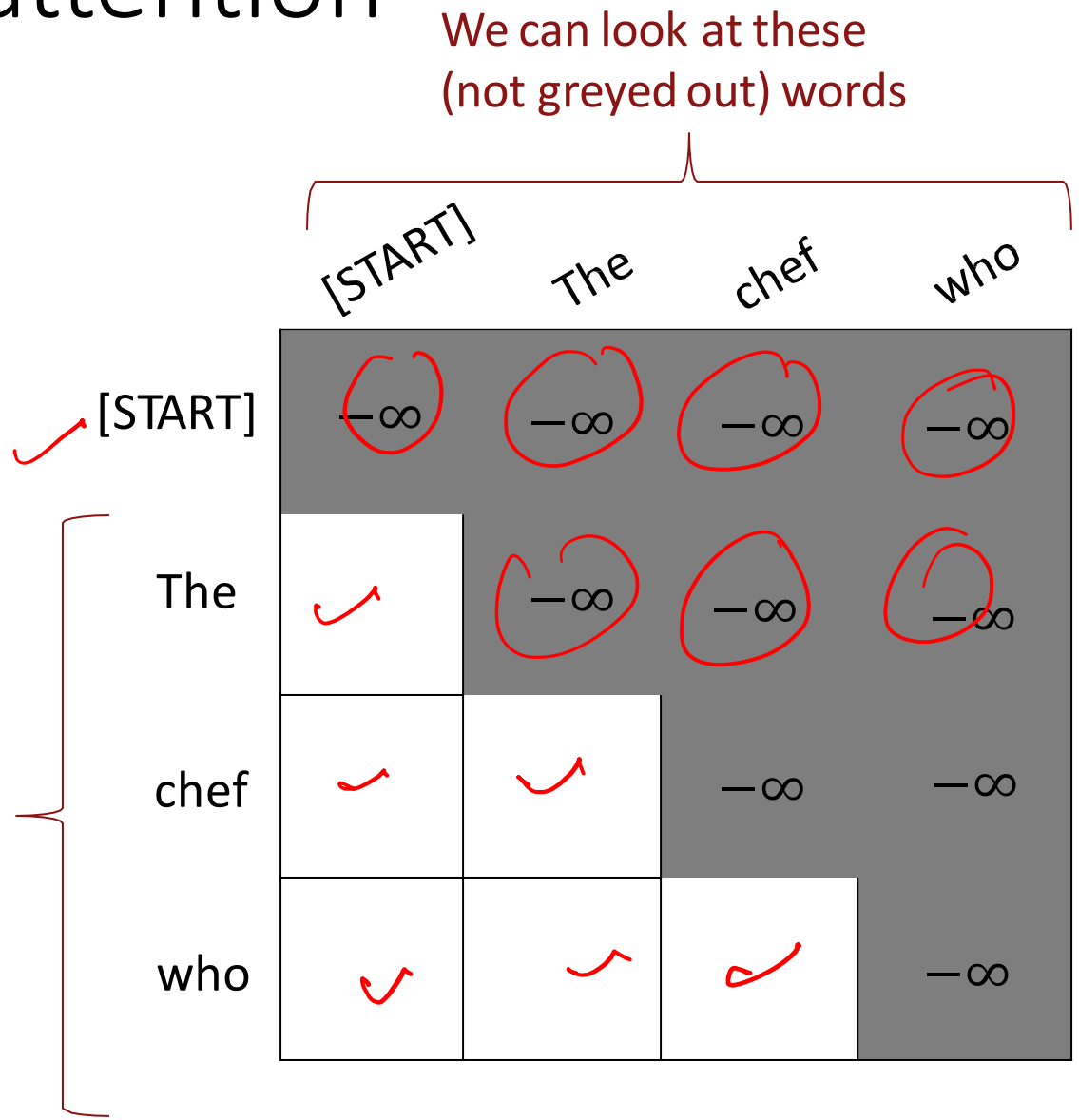
Adapted from cs224n-2024-lecture-slides

Masking the future in self-attention

- To use self-attention in **decoders**, we need to ensure we can't peek at the future.

- At every timestep, we could change the set of **keys and queries** to include only past words. (Inefficient!)

- To enable parallelization, we **mask out attention** to future words by setting attention scores to $-\infty$.



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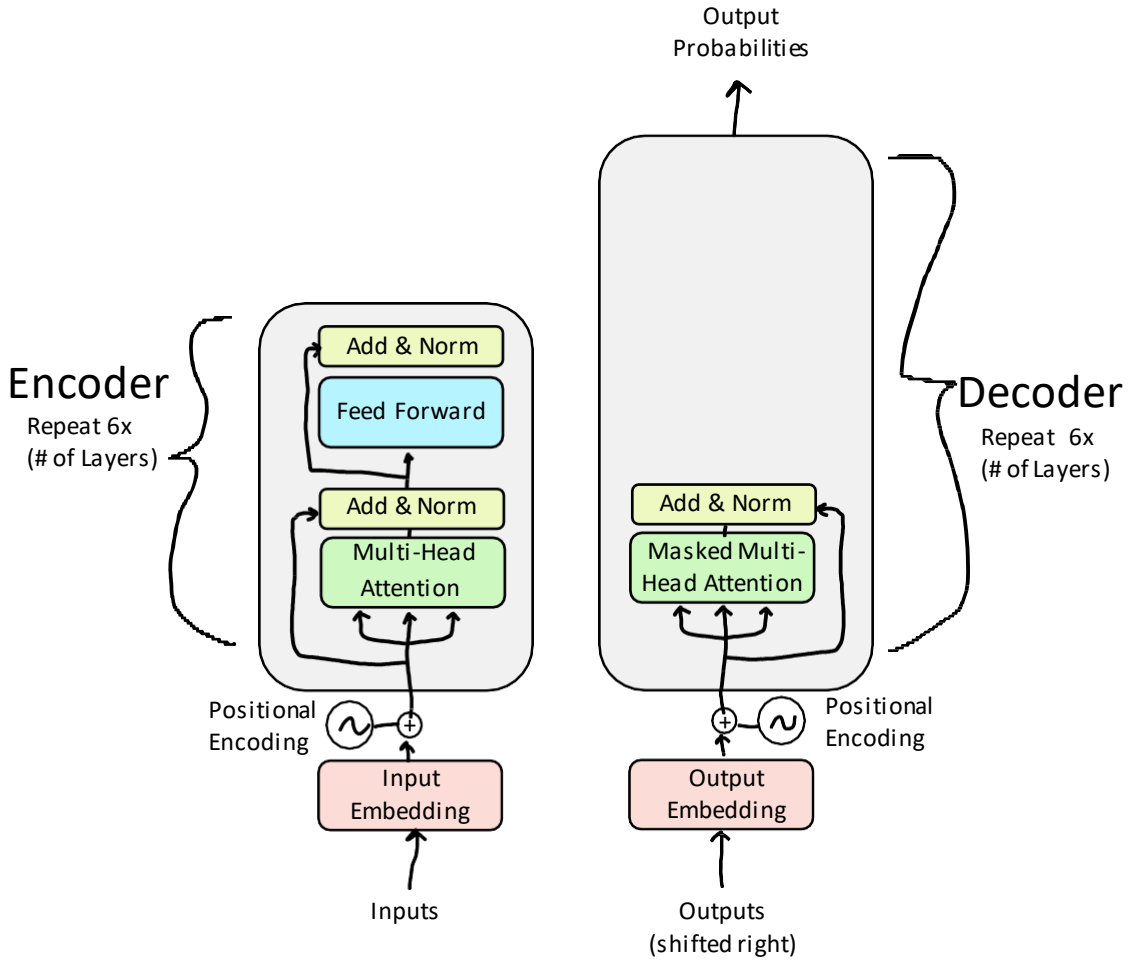
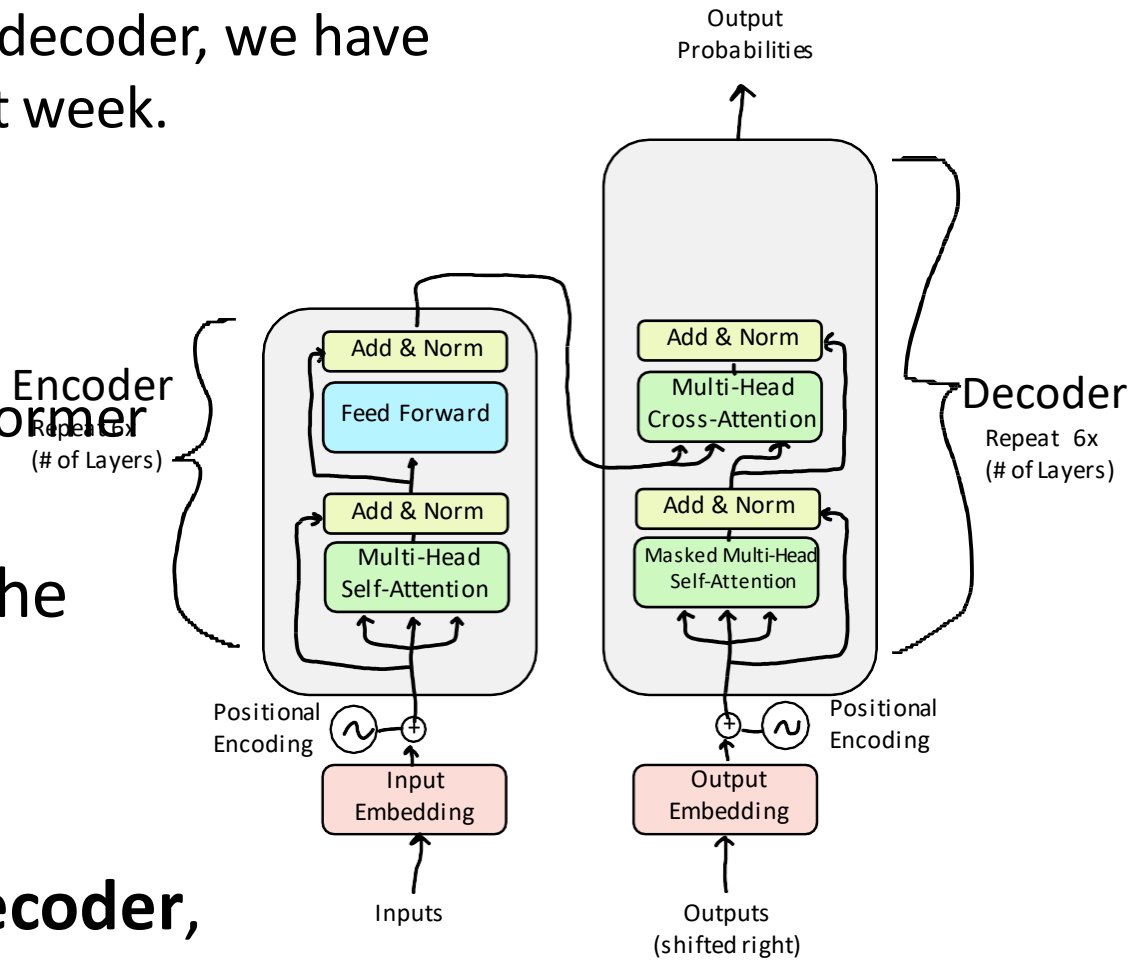
Decoder: Masked Multi-Headed Self-Attention



Adapted from cs224n-2024-lecture-slides

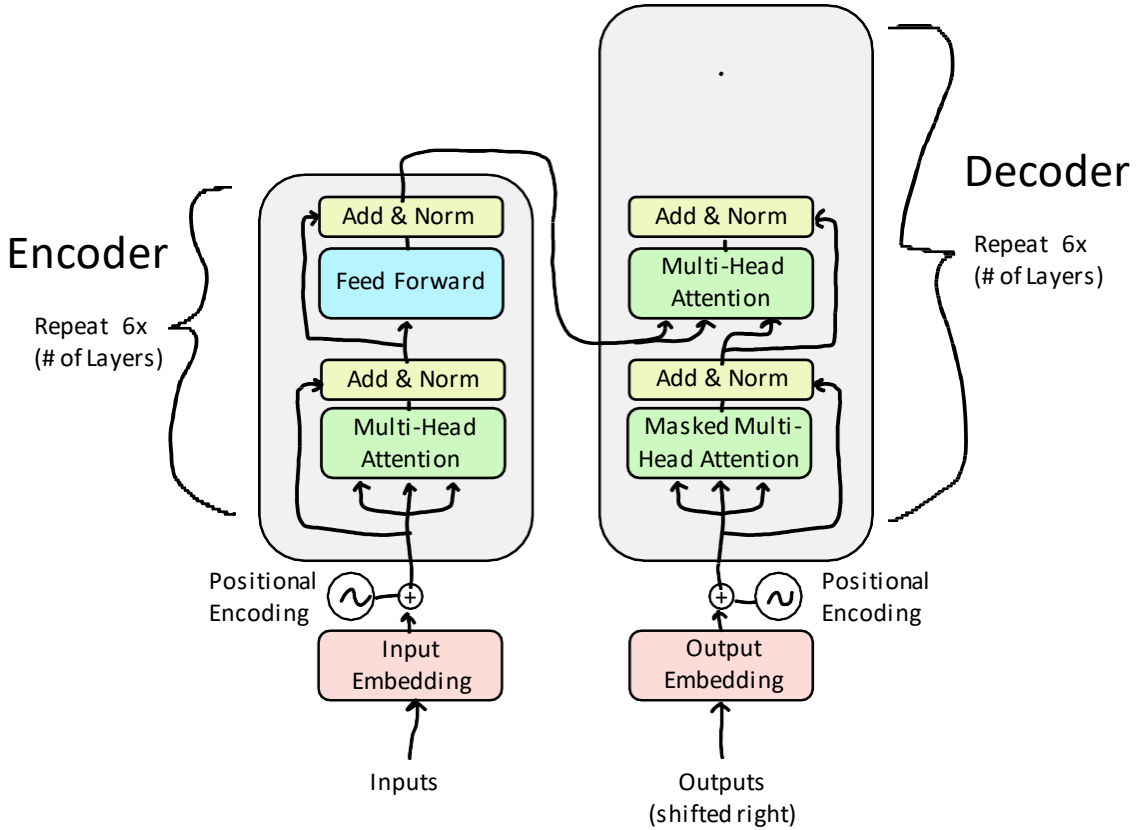
Encoder-Decoder Attention

- We saw that self-attention is when keys, queries, and values come from the same source. In the decoder, we have attention that looks more like what we saw last week.
- Let $h_1, \ldots, h_T$ be **output** vectors **from** the Transformer **encoder**; $x_i \in \mathbb{R}^d$
- Let $z_1, \ldots, z_T$ be input vectors from the Transformer **decoder**, $z_i \in \mathbb{R}^d$
- Then keys and values are drawn from the **encoder** (like a memory):
  - $k_i = Kh_i, v_i = Vh_i.$
- And the queries are drawn from the **decoder**, $q_i = Qz$.



Adapted from cs224n-2024-lecture-slides

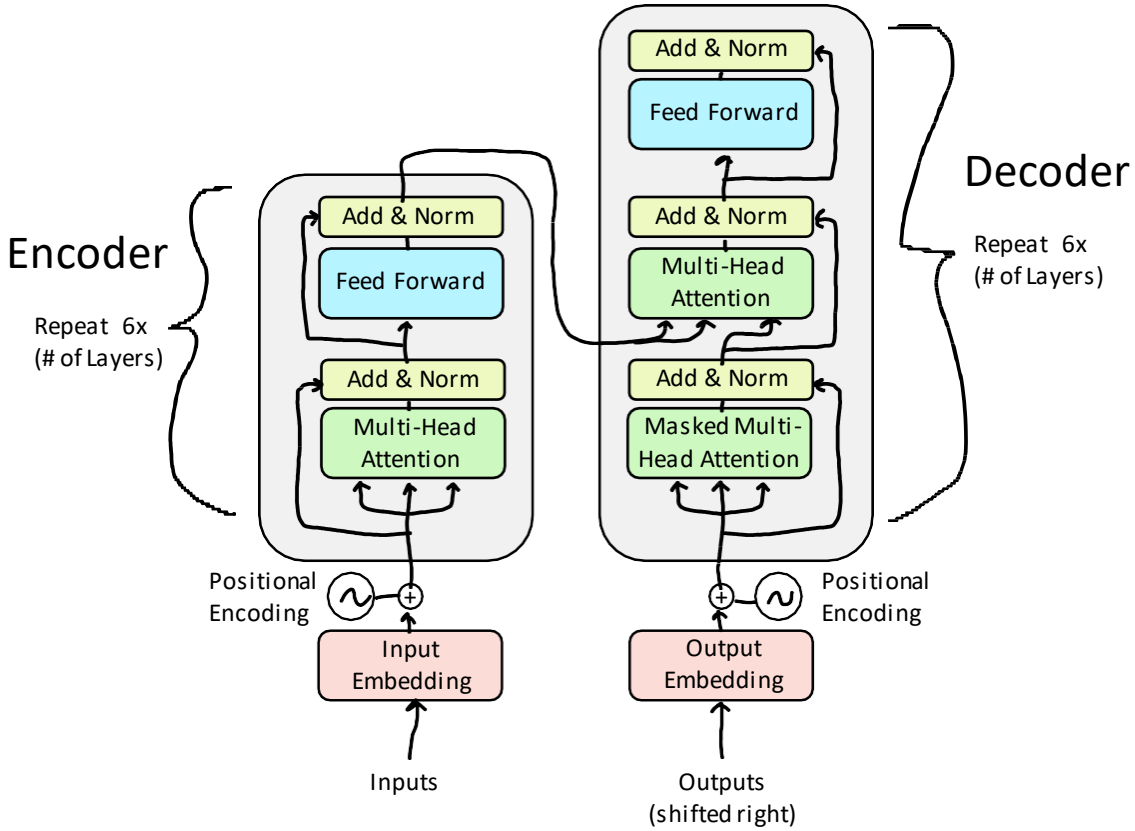
Decoder: Finishing touches!



Adapted from cs224n-2024-lecture-slides

Decoder: Finishing touches!

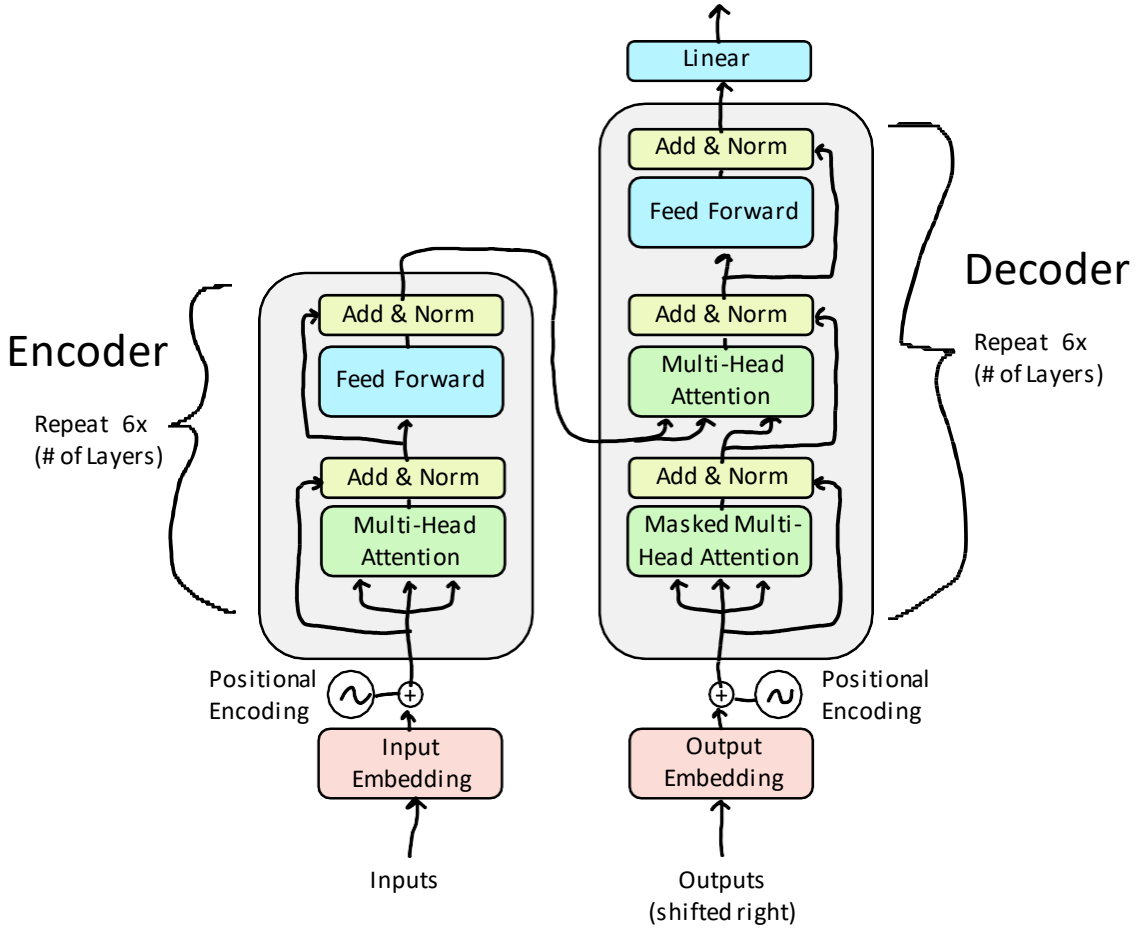
- Add a feed forward layer (with residual connections and layer norm)



Adapted from cs224n-2024-lecture-slides

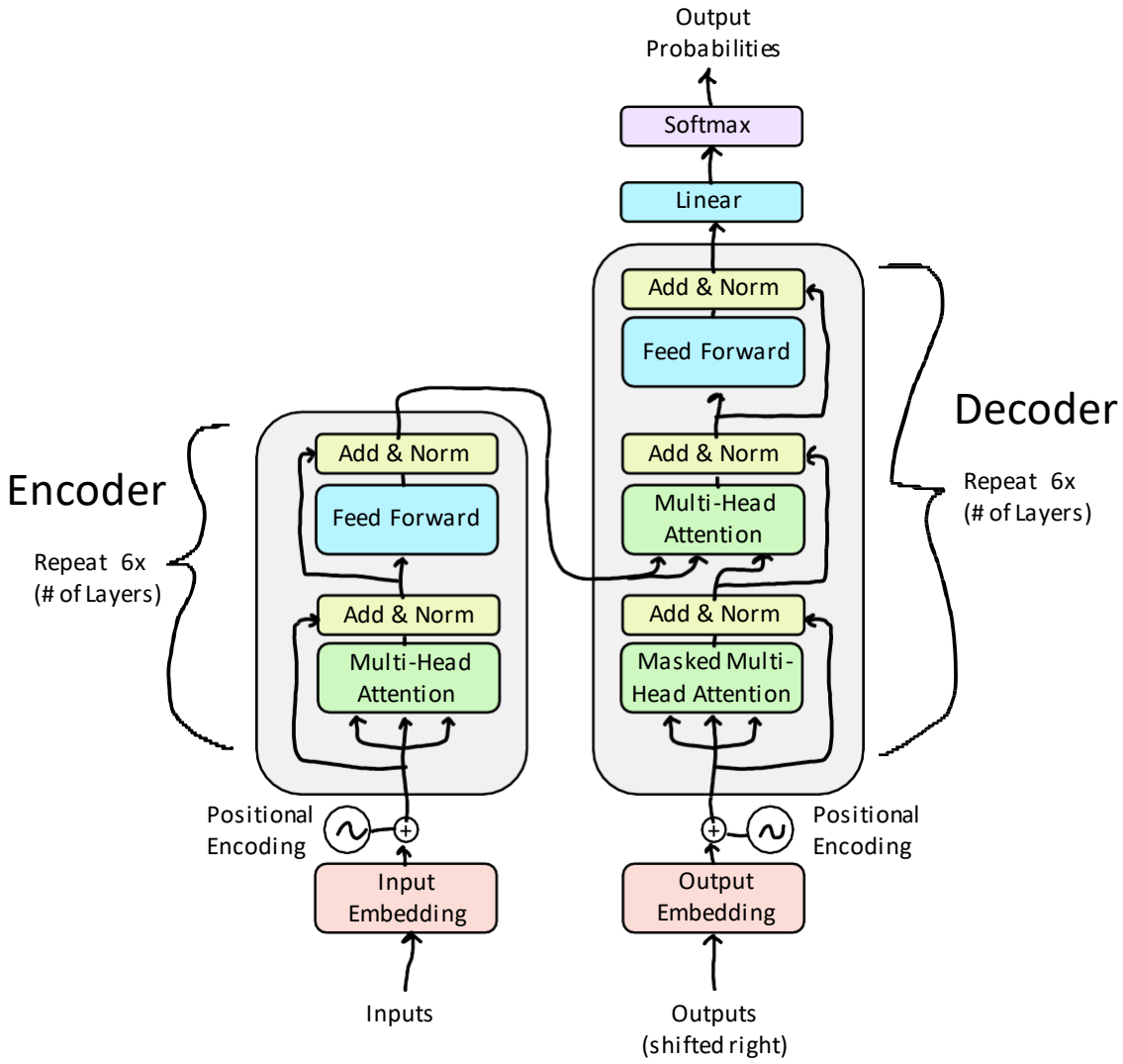
Decoder: Finishing touches!

- Add a feed forward layer (with residual connections and layer norm)
- Add a final linear layer to project the embeddings into a much longer vector of length vocab size (logits)

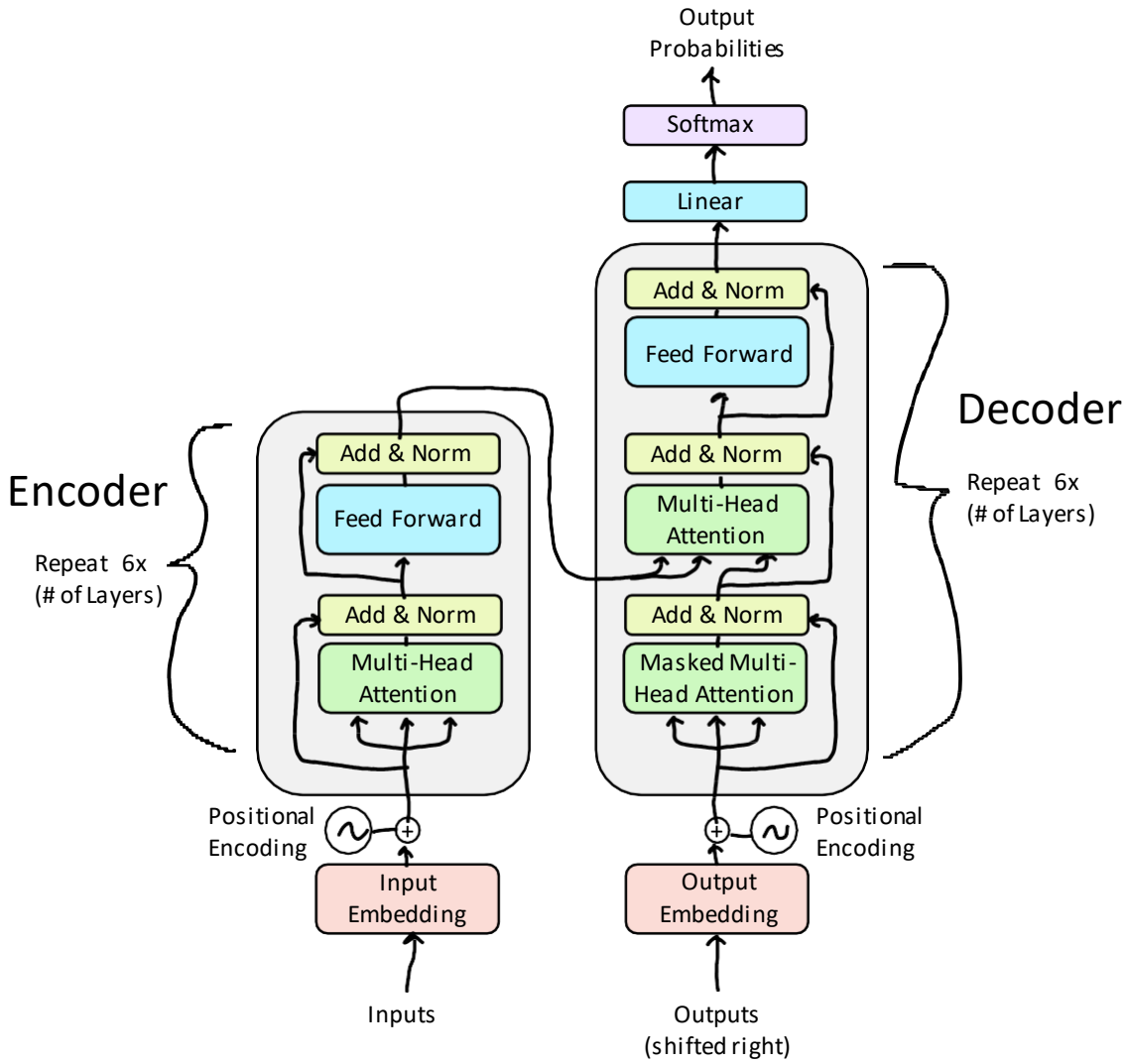


Decoder: Finishing touches!

- Add a feed forward layer (with residual connections and layer norm)
- Add a final linear layer to project the embeddings into a much longer vector of length vocab size (logits)
- Add a final softmax to generate a probability distribution of possible next words!



Recap of Transformer Architecture



Adapted from cs224n-2024-lecture-slides

What would we like to fix about the Transformer?

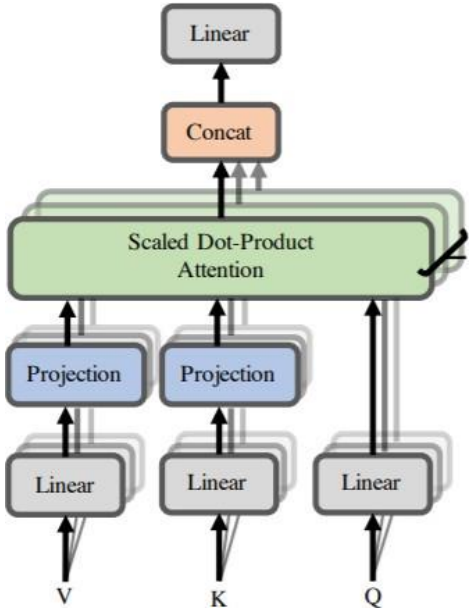
- **Quadratic compute in self-attention (today)**:
  - Computing all pairs of interactions means our computation grows **quadratically** with the sequence length!
  - For recurrent models, it only grew linearly!
- **Position representations**:
  - Are simple absolute indices the best we can do to represent position?
  - As we learned: Relative linear position attention [Shaw et al., 2018]
  - Dependency syntax-based position [Wang et al., 2019]
  - Rotary Embeddings [Su et al., 2021]

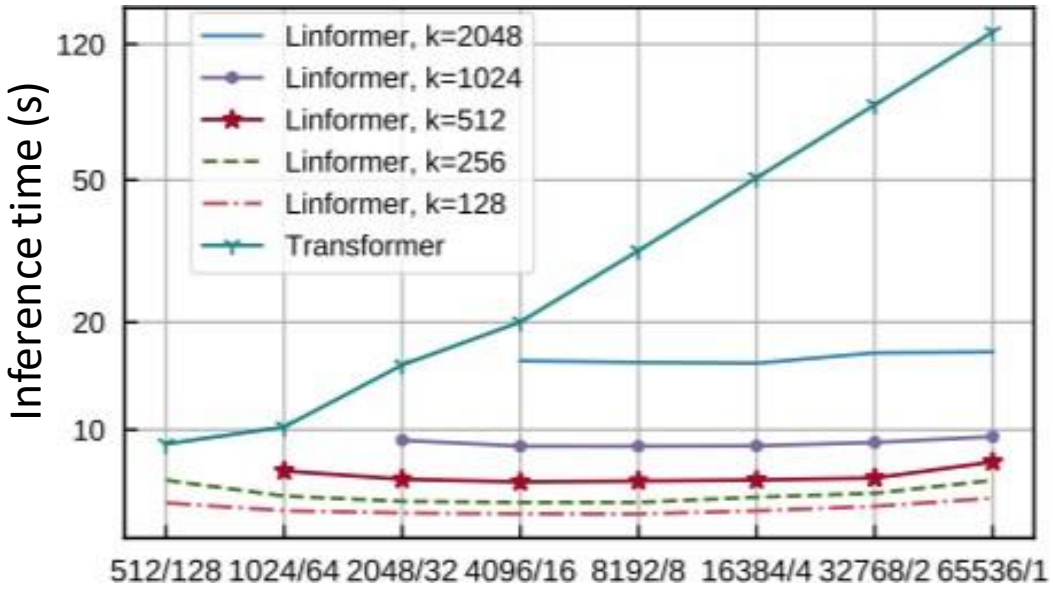
Adapted from cs224n-2024-lecture-slides

Recent work on improving on quadratic self-attention cost

- Considerable recent work has gone into the question, *Can we build models like Transformers without paying the $O(T^2)$ all-pairs self-attention cost?*
  - For example, **Linformer** [Wang et al., 2020]

Key idea: map the sequence length dimension to a lower-dimensional space for values, keys



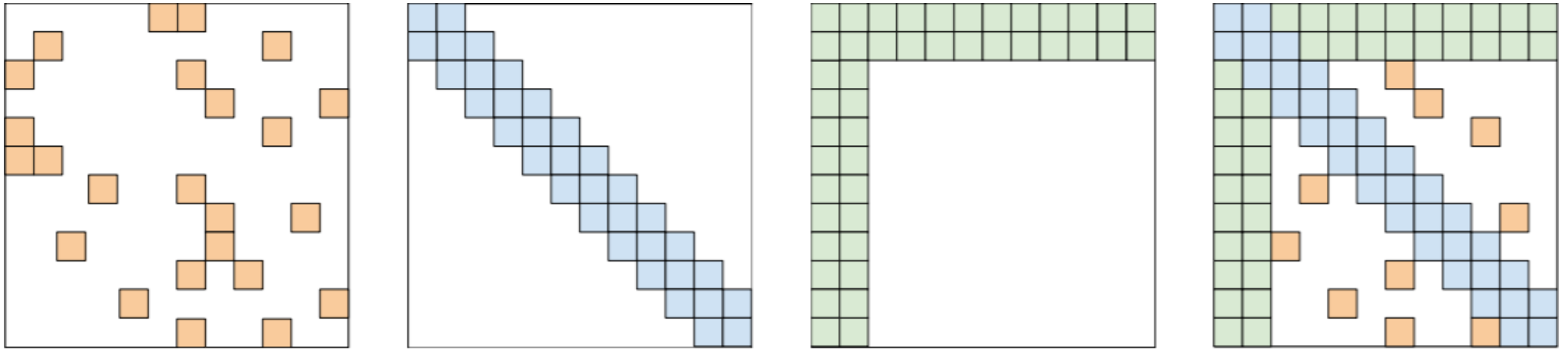


Adapted from cs224n-2024-lecture-slides

Recent work on improving on quadratic self-attention cost

- Considerable recent work has gone into the question, *Can we build models like Transformers without paying the $O(T^2)$ all-pairs self-attention cost?*
- For example, **BigBird** [Zaheer et al., 2021]

Key idea: replace all-pairs interactions with a family of other interactions, **like local windows**, **looking at everything**, and **random interactions**.



(a) Random attention (b) Window attention (c) Global Attention (d) BIGBIRD

Adapted from cs224n-2024-lecture-slides

Do Transformer Modifications Transfer?

- "Surprisingly, we find that most modifications do not meaningfully improve performance."

Model	Params	Ops	Step/s	Early loss	Final loss	SGLUE	XSum	WebQ	WMT EnDe
Vanilla Transformer	223M	11.1T	3.50	2.182 ± 0.005	1.838	71.66	17.78	23.02	26.62
GeLU	223M	11.1T	3.58	2.179 ± 0.003	1.838	**75.79**	**17.86**	**25.13**	26.47
Swish	223M	11.1T	3.62	2.186 ± 0.003	1.847	**73.77**	17.74	**24.34**	**26.75**
ELU	223M	11.1T	3.56	2.270 ± 0.007	1.932	67.83	16.73	23.02	26.08
GLU	223M	11.1T	3.59	2.174 ± 0.003	**1.814**	**74.20**	**17.42**	24.34	**27.12**
GeGLU	223M	11.1T	3.55	2.130 ± 0.006	**1.792**	**75.96**	**18.27**	**24.87**	**26.87**
ReGLU	223M	11.1T	3.57	2.145 ± 0.004	**1.803**	**76.17**	**18.36**	**24.87**	**27.02**
SeLU	223M	11.1T	3.55	2.315 ± 0.004	1.948	68.76	16.76	22.75	25.99
SwiGLU	223M	11.1T	3.53	2.127 ± 0.003	**1.789**	**76.00**	**18.20**	**24.34**	**27.02**
LiGLU	223M	11.1T	3.59	2.149 ± 0.005	**1.798**	**75.34**	**17.97**	**24.34**	26.53
Sigmoid	223M	11.1T	3.63	2.291 ± 0.019	1.867	**74.31**	17.51	23.02	26.30
Softplus	223M	11.1T	3.47	2.207 ± 0.011	1.850	**72.45**	17.65	**24.34**	**26.89**
RMS Norm	223M	11.1T	3.68	2.167 ± 0.008	**1.821**	**75.45**	**17.94**	**24.07**	**27.14**
Rezero	223M	11.1T	3.51	2.262 ± 0.003	1.939	61.69	15.64	20.90	26.37
Rezero + LayerNorm	223M	11.1T	3.26	2.223 ± 0.006	1.858	70.42	17.58	23.02	26.29
Rezero + RMS Norm	223M	11.1T	3.34	2.221 ± 0.009	1.875	70.33	17.32	23.02	26.19
Fixup	223M	11.1T	2.95	2.382 ± 0.012	2.067	58.56	14.42	23.02	26.31
24 layers, $d_{ff} = 1536$, $H = 6$	224M	11.1T	3.33	2.200 ± 0.007	1.843	**74.89**	17.75	**25.13**	**26.89**
18 layers, $d_{ff} = 2048$, $H = 8$	223M	11.1T	3.38	2.185 ± 0.005	**1.831**	**76.45**	16.83	**24.34**	**27.10**
8 layers, $d_{ff} = 4608$, $H = 18$	223M	11.1T	3.69	2.190 ± 0.005	1.847	**74.58**	17.69	**23.28**	**26.85**
6 layers, $d_{ff} = 6144$, $H = 24$	223M	11.1T	3.70	2.201 ± 0.010	1.857	**73.55**	17.59	**24.60**	**26.66**
Block sharing	65M	11.1T	3.91	2.497 ± 0.037	2.164	64.50	14.53	21.96	25.48
+ Factorized embeddings	45M	9.4T	4.21	2.631 ± 0.305	2.183	60.84	14.00	19.84	25.27
+ Factorized & shared embeddings	20M	9.1T	4.37	2.907 ± 0.313	2.385	53.95	11.37	19.84	25.19
Encoder only block sharing	170M	11.1T	3.68	2.298 ± 0.023	1.929	69.60	16.23	23.02	26.23
Decoder only block sharing	144M	11.1T	3.70	2.352 ± 0.029	2.082	67.93	16.13	**23.81**	26.08
Factorized Embedding	227M	9.4T	3.80	2.208 ± 0.006	1.855	70.41	15.92	22.75	26.50
Factorized & shared embeddings	202M	9.1T	3.92	2.320 ± 0.010	1.952	68.69	16.33	22.22	26.44
Tied encoder/decoder input embeddings	248M	11.1T	3.55	2.192 ± 0.002	1.840	**71.70**	17.72	**24.34**	26.49
Tied decoder input and output embeddings	248M	11.1T	3.57	2.187 ± 0.007	**1.827**	**74.86**	17.74	**24.87**	**26.67**
Untied embeddings	273M	11.1T	3.53	2.195 ± 0.005	**1.834**	**72.99**	17.58	**23.28**	26.48
Adaptive input embeddings	204M	9.2T	3.55	2.250 ± 0.002	1.899	66.57	16.21	**24.07**	**26.66**
Adaptive softmax	204M	9.2T	3.60	2.364 ± 0.005	1.982	**72.91**	16.67	21.16	25.56
Adaptive softmax without projection	223M	10.8T	3.43	2.229 ± 0.009	1.914	**71.82**	17.10	23.02	25.72
Mixture of softmaxes	232M	16.3T	2.24	2.227 ± 0.017	**1.821**	**76.77**	17.62	22.75	**26.82**
Transparent attention	223M	11.1T	3.33	2.181 ± 0.014	1.874	54.31	10.40	21.16	**26.80**
Dynamic convolution	257M	11.8T	2.65	2.403 ± 0.009	2.047	58.30	12.67	21.16	17.03
Lightweight convolution	224M	10.4T	4.07	2.370 ± 0.010	1.989	63.07	14.86	23.02	24.73
Evolved Transformer	217M	9.9T	3.09	2.220 ± 0.003	1.863	**73.67**	10.76	**24.07**	26.58
Synthesizer (dense)	224M	11.4T	3.47	2.334 ± 0.021	1.962	61.03	14.27	16.14	**26.63**
Synthesizer (dense plus)	243M	12.6T	3.22	2.191 ± 0.010	1.840	**73.98**	16.96	**23.81**	**26.71**
Synthesizer (dense plus alpha)	243M	12.6T	3.01	2.180 ± 0.007	**1.828**	**74.25**	17.02	**23.28**	26.61
Synthesizer (factorized)	207M	10.1T	3.94	2.341 ± 0.017	1.968	62.78	15.39	**23.55**	26.42
Synthesizer (random)	254M	10.1T	4.08	2.326 ± 0.012	2.009	54.27	10.35	19.56	26.44
Synthesizer (random plus)	292M	12.0T	3.63	2.189 ± 0.004	1.842	**73.32**	17.04	**24.87**	26.43
Synthesizer (random plus alpha)	292M	12.0T	3.42	2.186 ± 0.007	**1.828**	**75.24**	17.08	**24.08**	26.39
Universal Transformer	84M	40.0T	0.88	2.406 ± 0.036	2.053	70.13	14.09	19.05	23.91
Mixture of experts	648M	11.7T	3.20	2.148 ± 0.006	**1.785**	**74.55**	**18.13**	**24.08**	**26.94**
Switch Transformer	1100M	11.7T	3.18	2.135 ± 0.007	**1.758**	**75.38**	**18.02**	**26.19**	**26.81**
Funnel Transformer	223M	1.9T	4.30	2.288 ± 0.008	1.918	67.34	16.26	22.75	23.20
Weighted Transformer	280M	71.0T	0.59	2.378 ± 0.021	1.989	69.04	16.98	23.02	26.30
Product key memory	421M	386.6T	0.25	2.155 ± 0.003	**1.798**	**75.16**	17.04	**23.55**	**26.73**

Do Transformer Modifications Transfer Across Implementations and Applications?

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Summary

- Yay, you now understand Transformers!
- Good luck on Class activity!
- Remember to work on your project presentatic

Acknowledgments

- These slides were adapted from the book SPEECH and LANGUAGE PROCESSING: An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition
- Some modifications from CS224N presentations and resources found in the WEB by several scholars.

Reference materials

- https://vlanc-lab.github.io/mu-nlp-course/

- Lecture notes

- (A) Speech and Language Processing by Daniel Jurafsky and James H. Martin
- (B) Natural Language Processing with Python. (updated edition based on Python 3 and NLTK 3) Steven Bird et al. O'Reilly Media