Transformer

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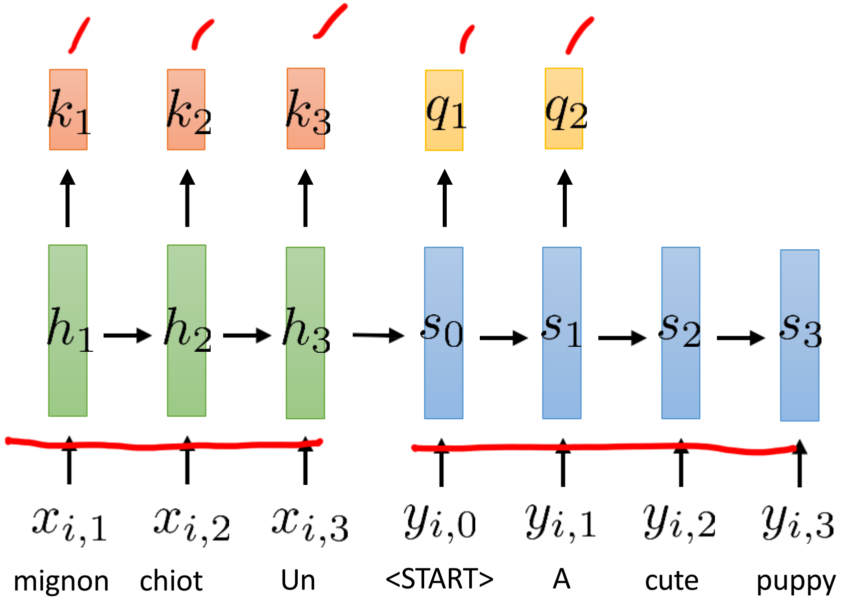
https://tanmoychak.com/

Slides are adopted from Sergey Levine

Is Attention All We Need?

Slides by Sergey Levine

Recap: Attention



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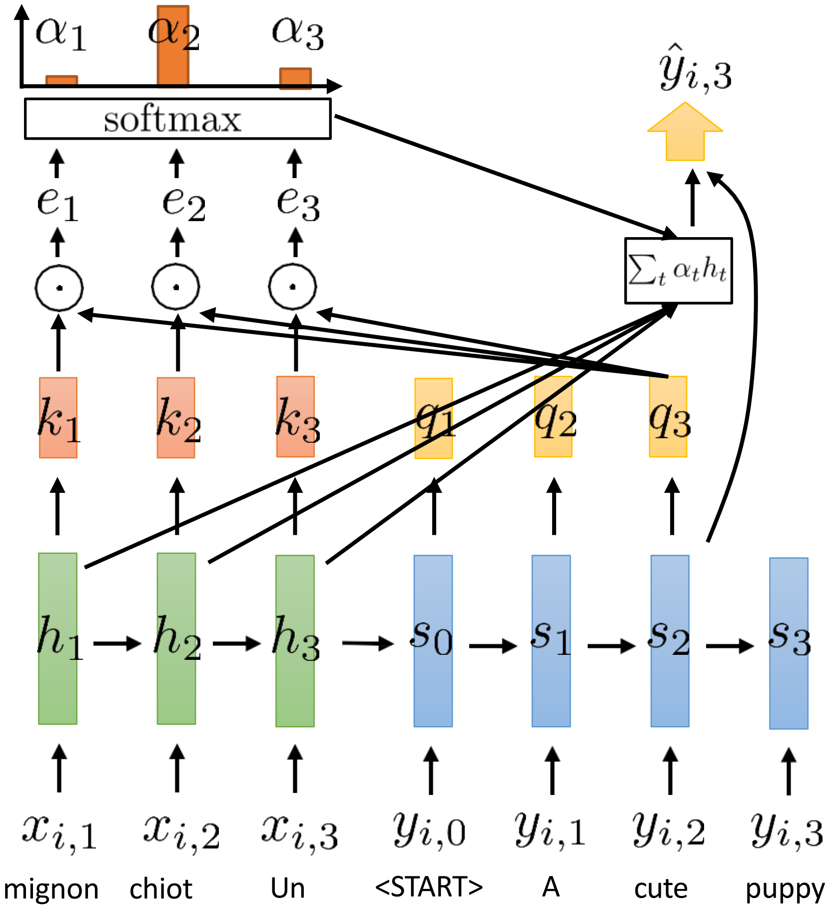

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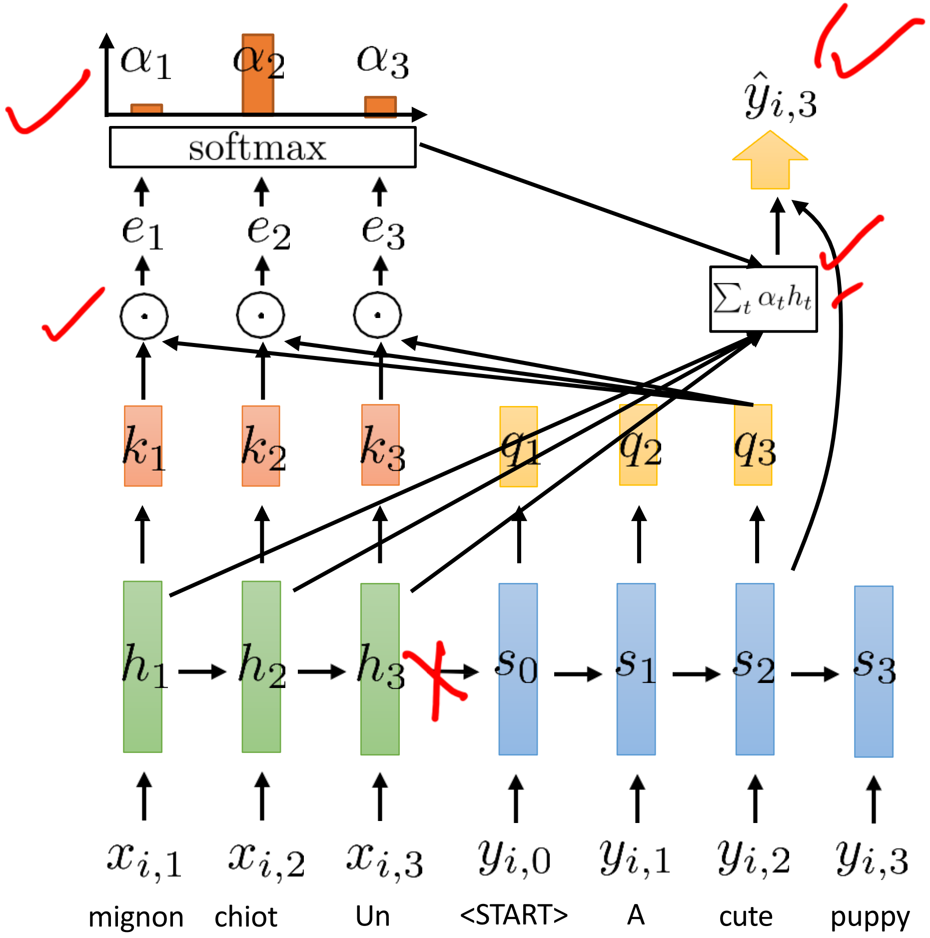
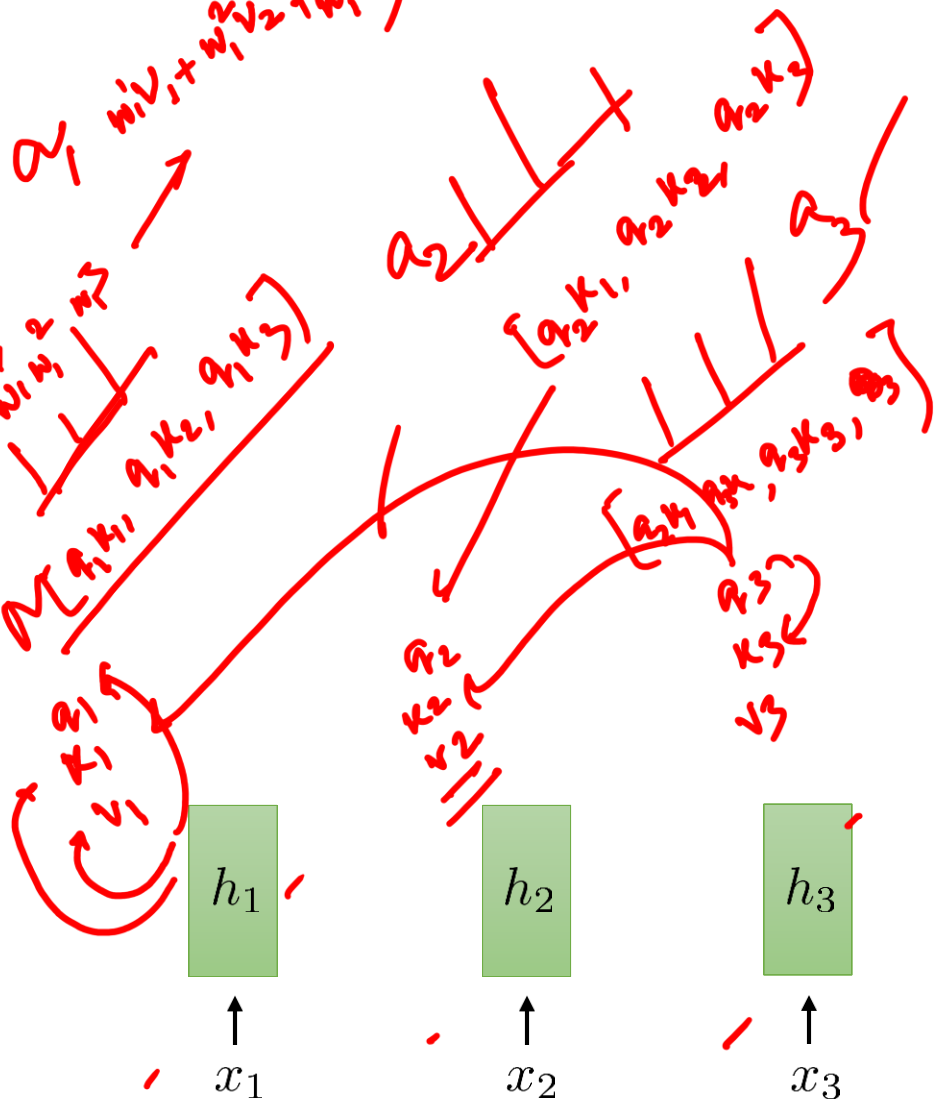


- If we have **attention**, do we even need recurrent connections?
- Can we transform our RNN into a **purely attention-based model**?
- Attention can access all time steps simultaneously, potentially doing everything that recurrence can, and even more. However, this approach presents some challenges:

The encoder lacks temporal dependencies at all!

Self-Attention



this is *not* a recurrent model!

but still weight sharing:

$$h_t = \sigma(W x_t + b)$$

shared weights at all time steps

(or any other nonlinear function)

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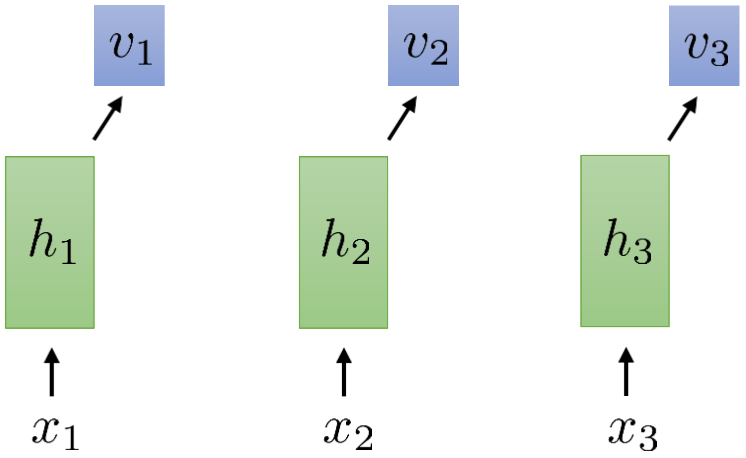

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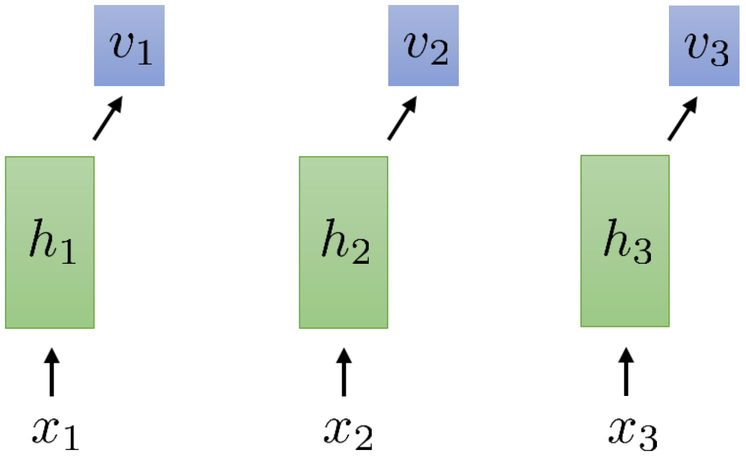

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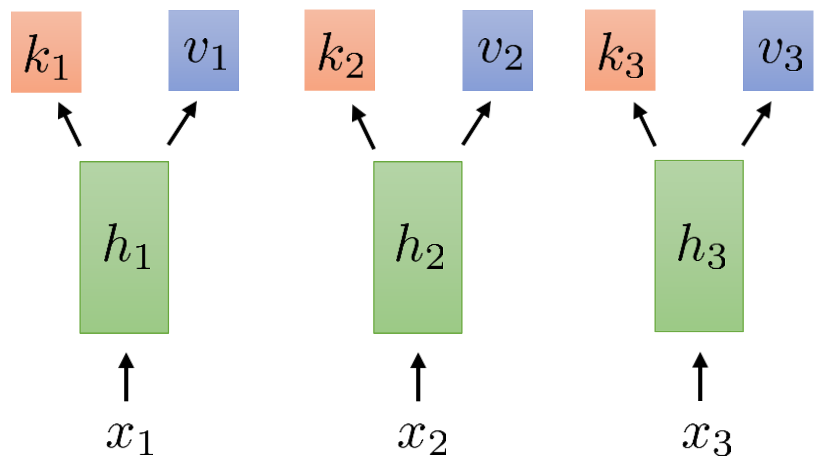

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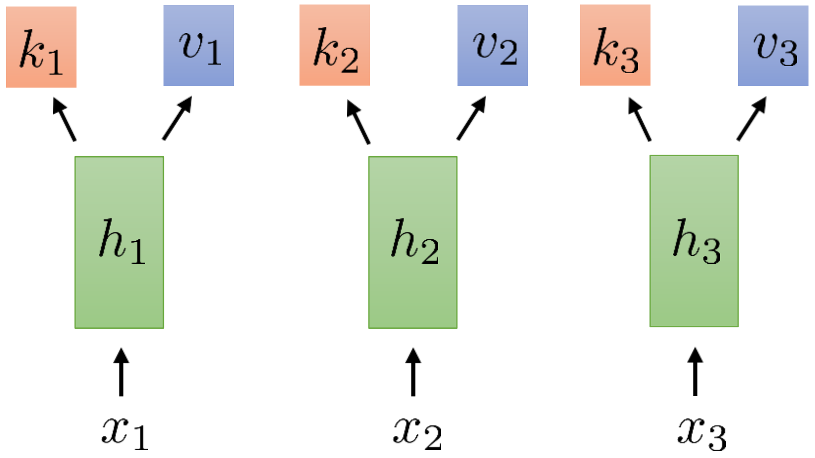

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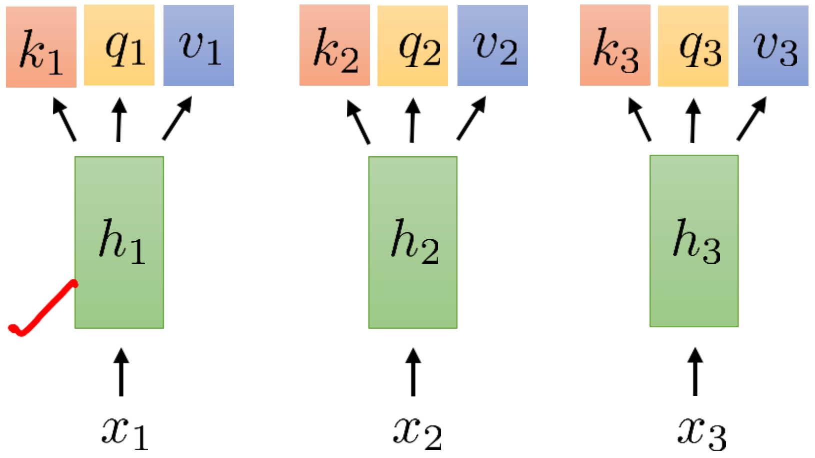

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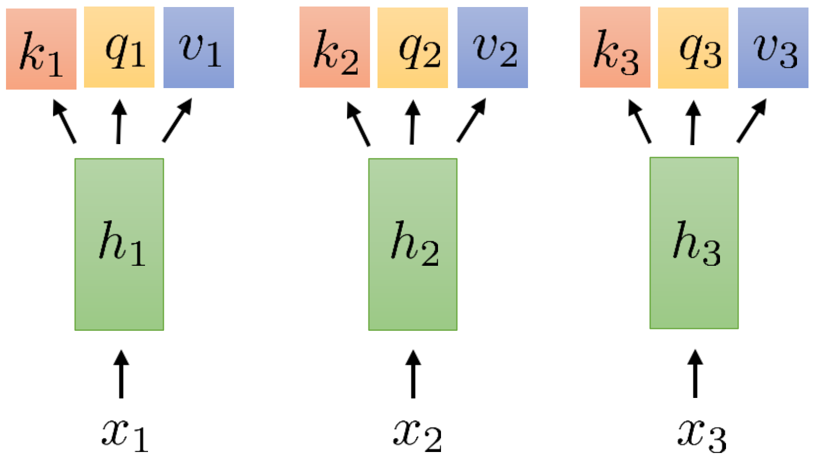

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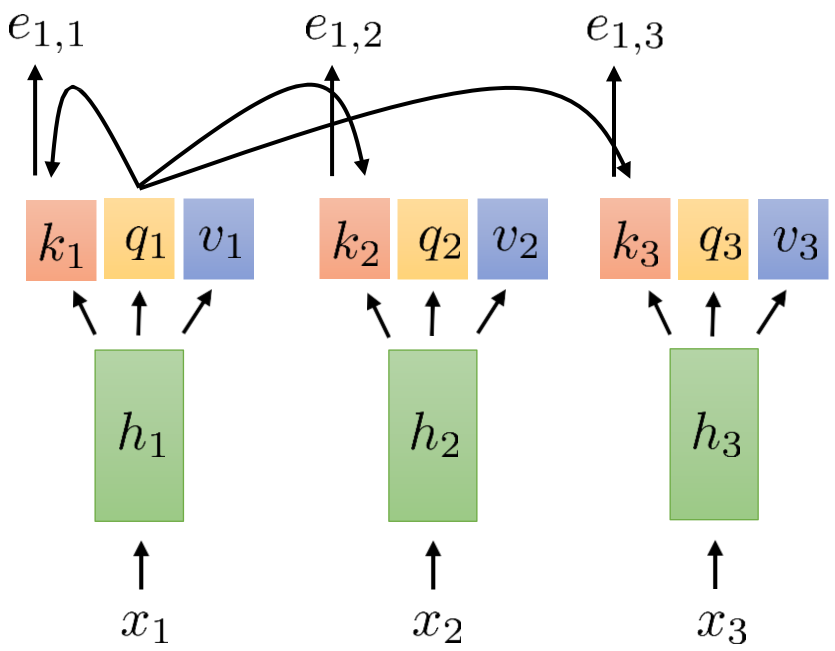

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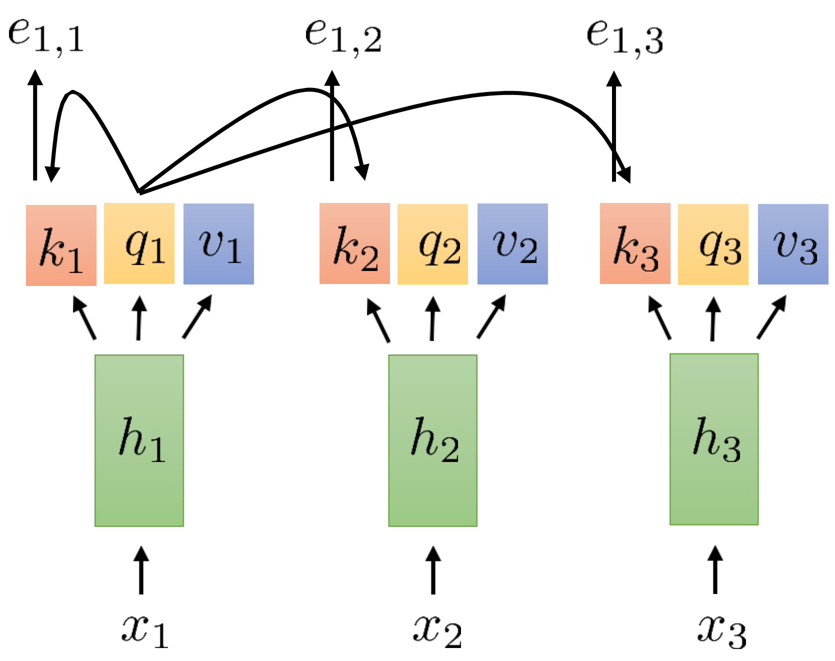

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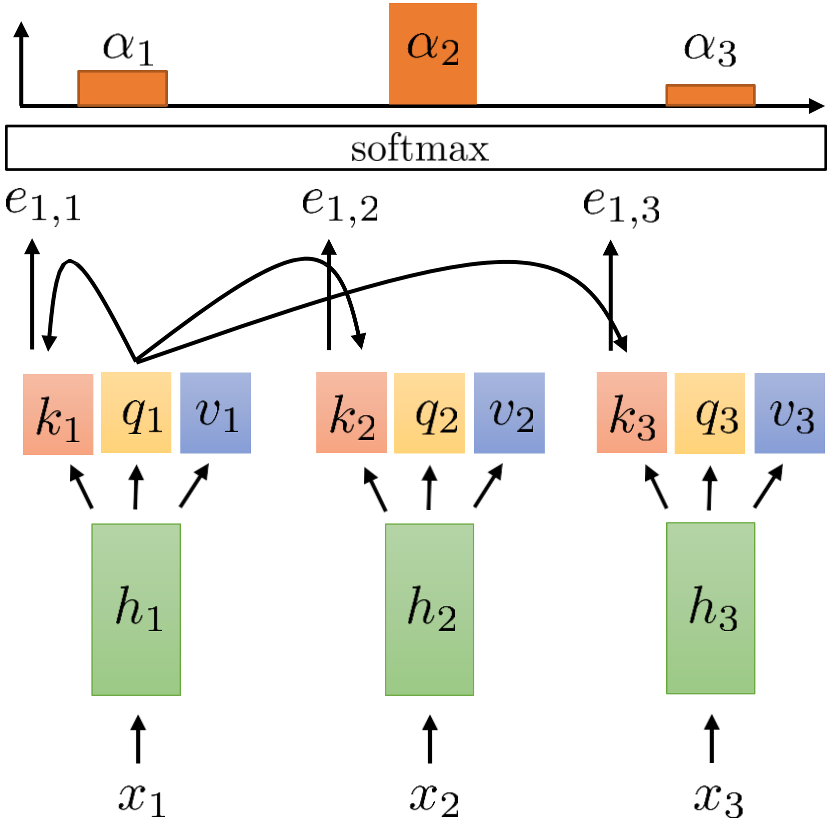

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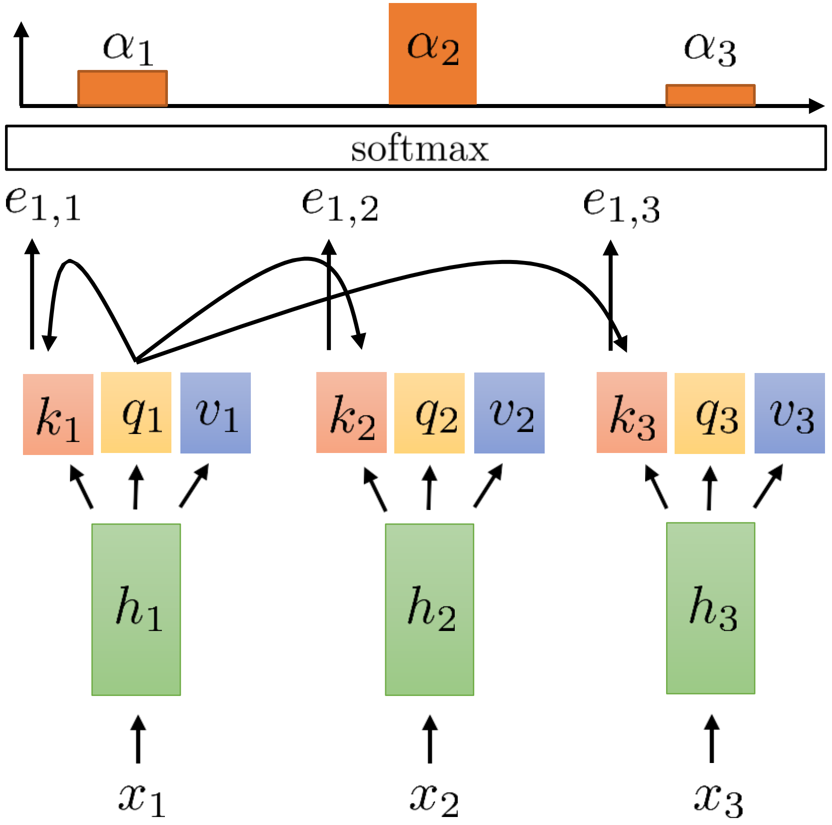

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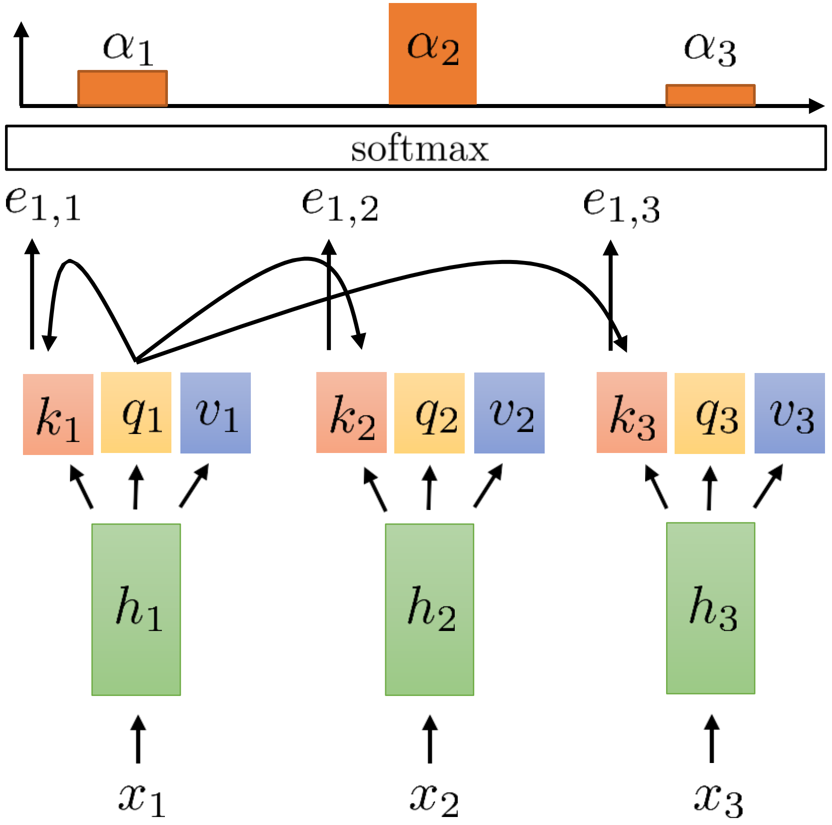

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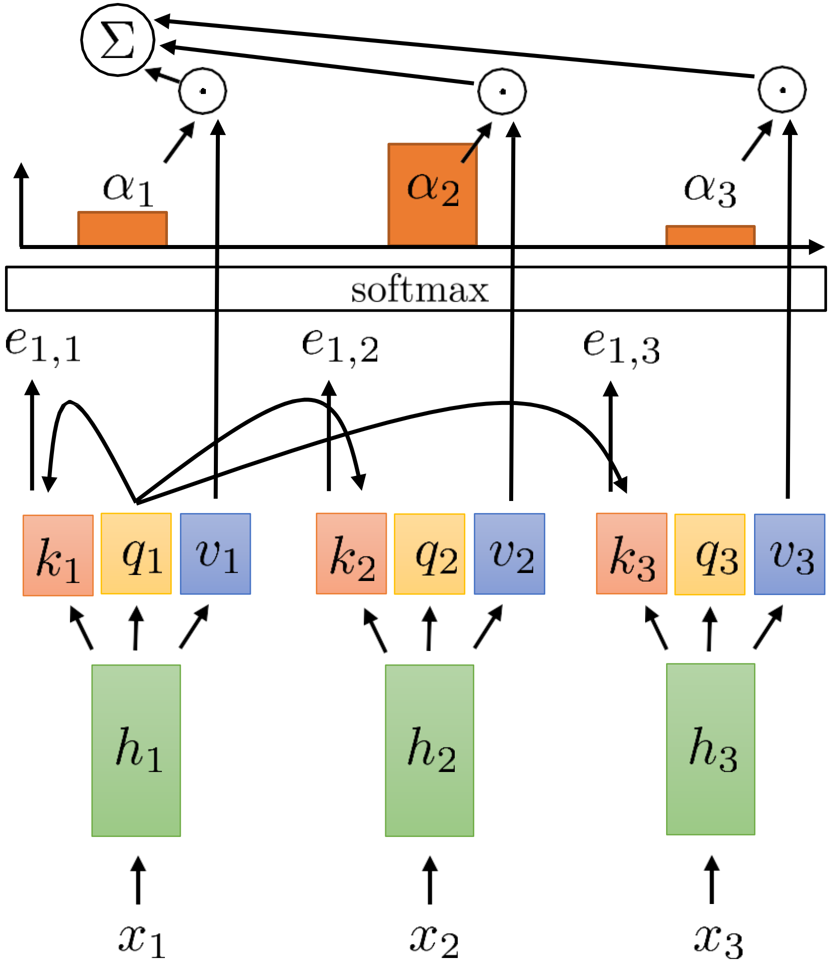

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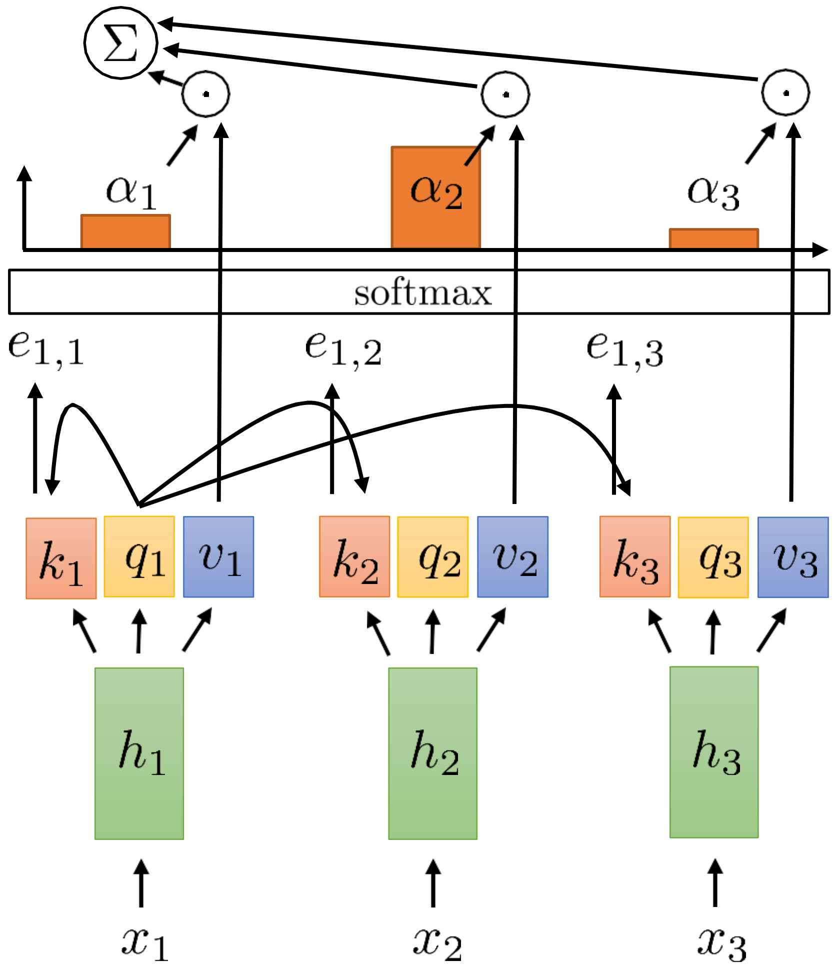

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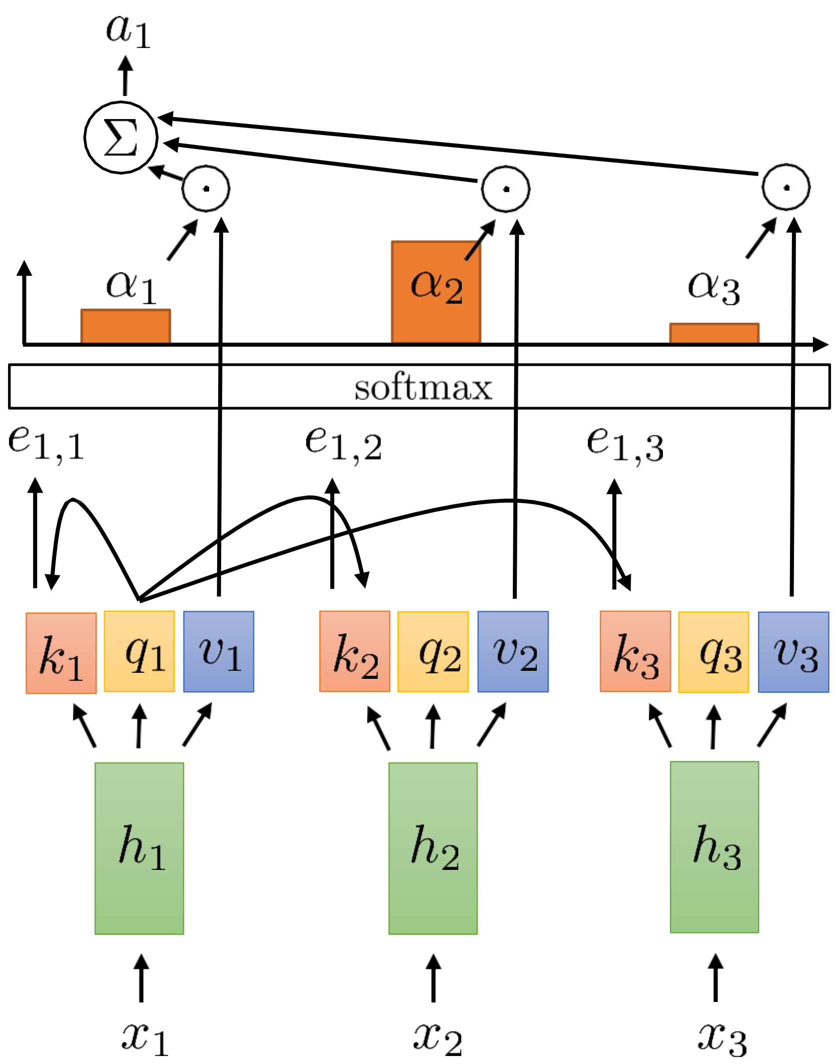

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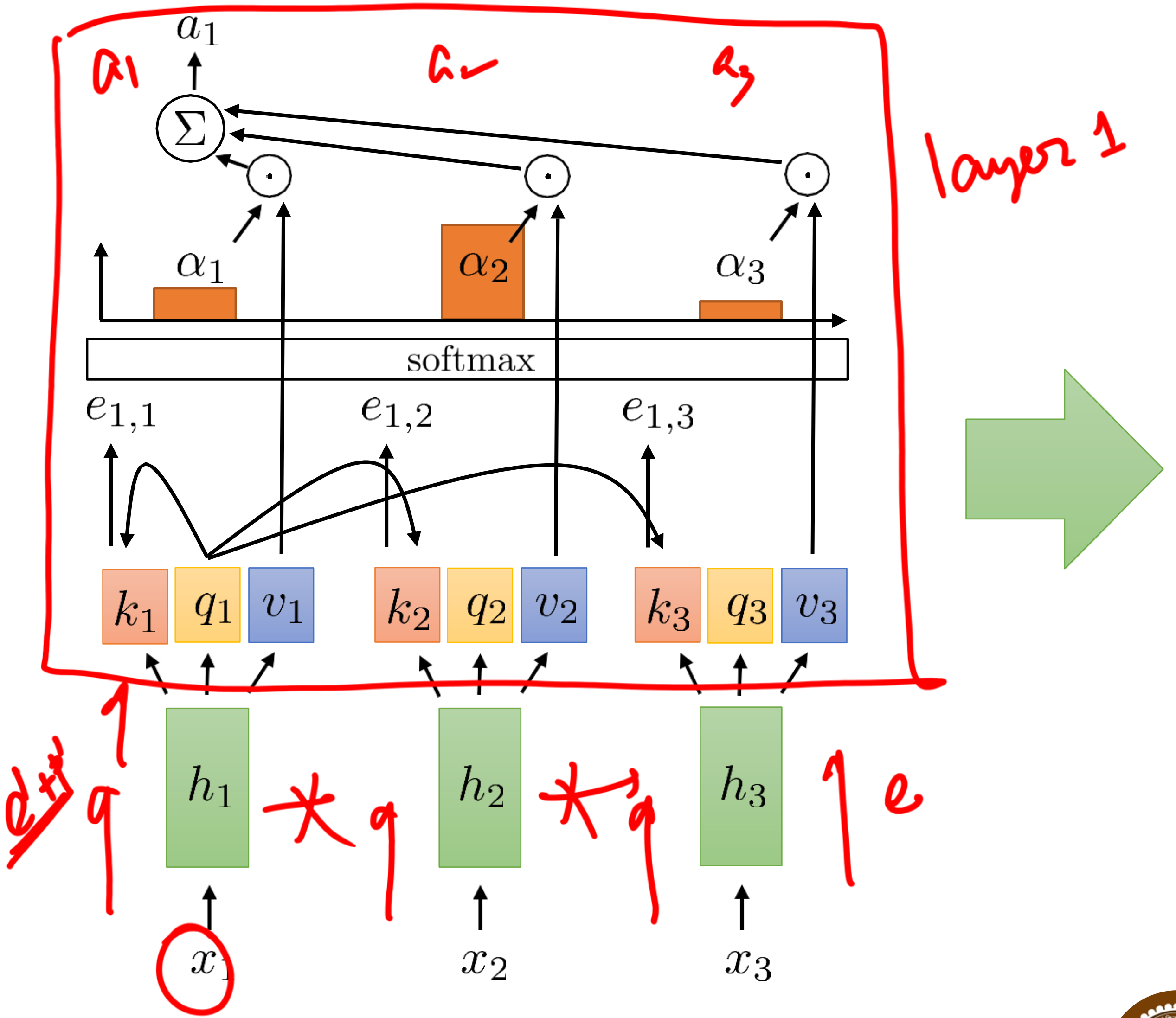

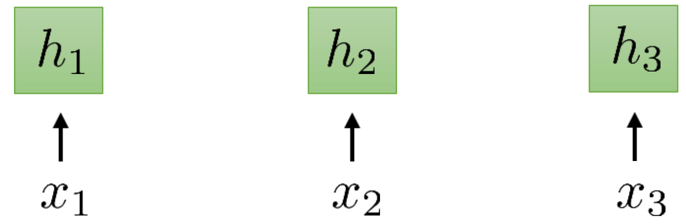

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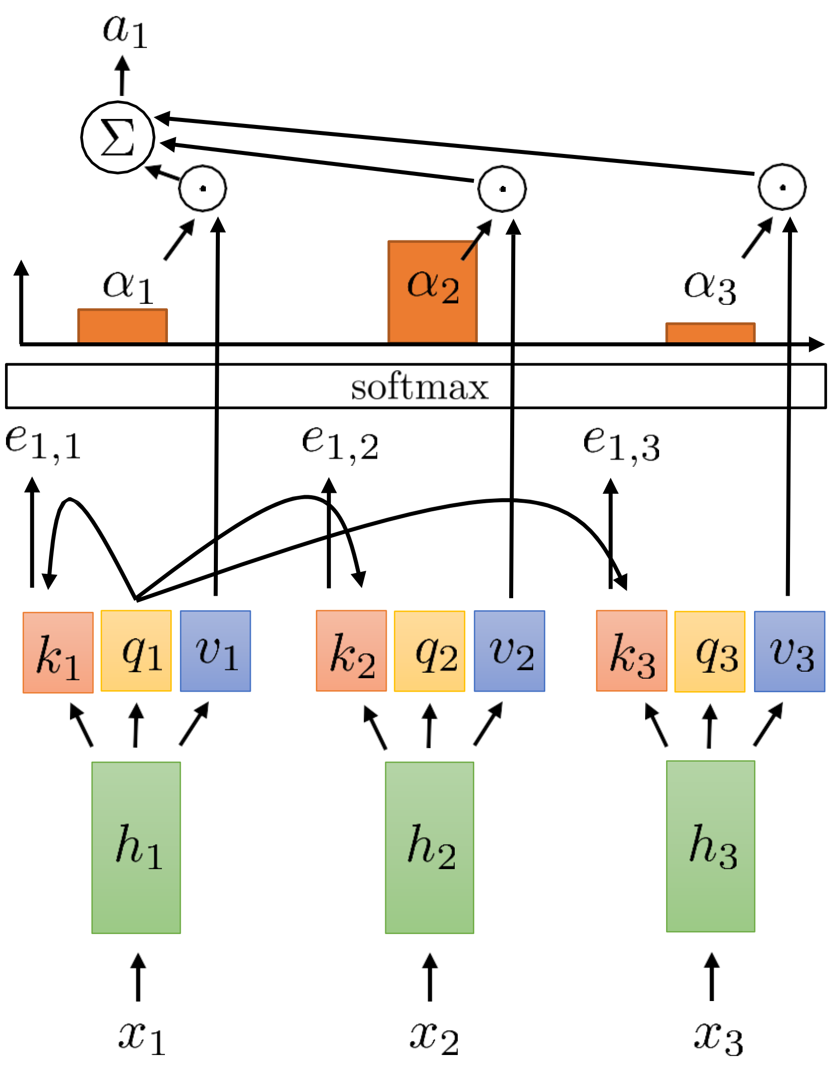

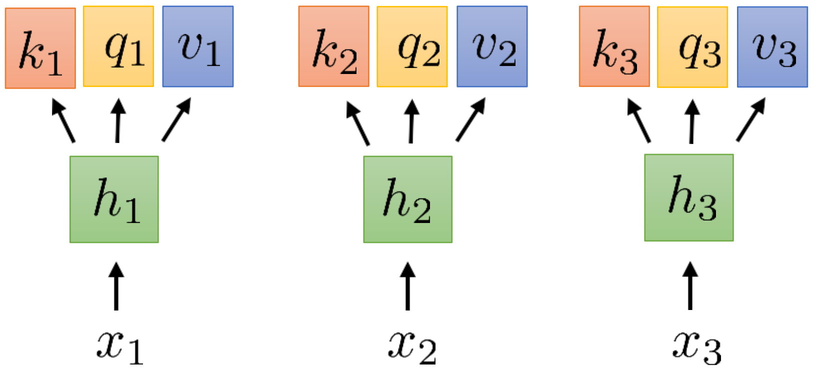

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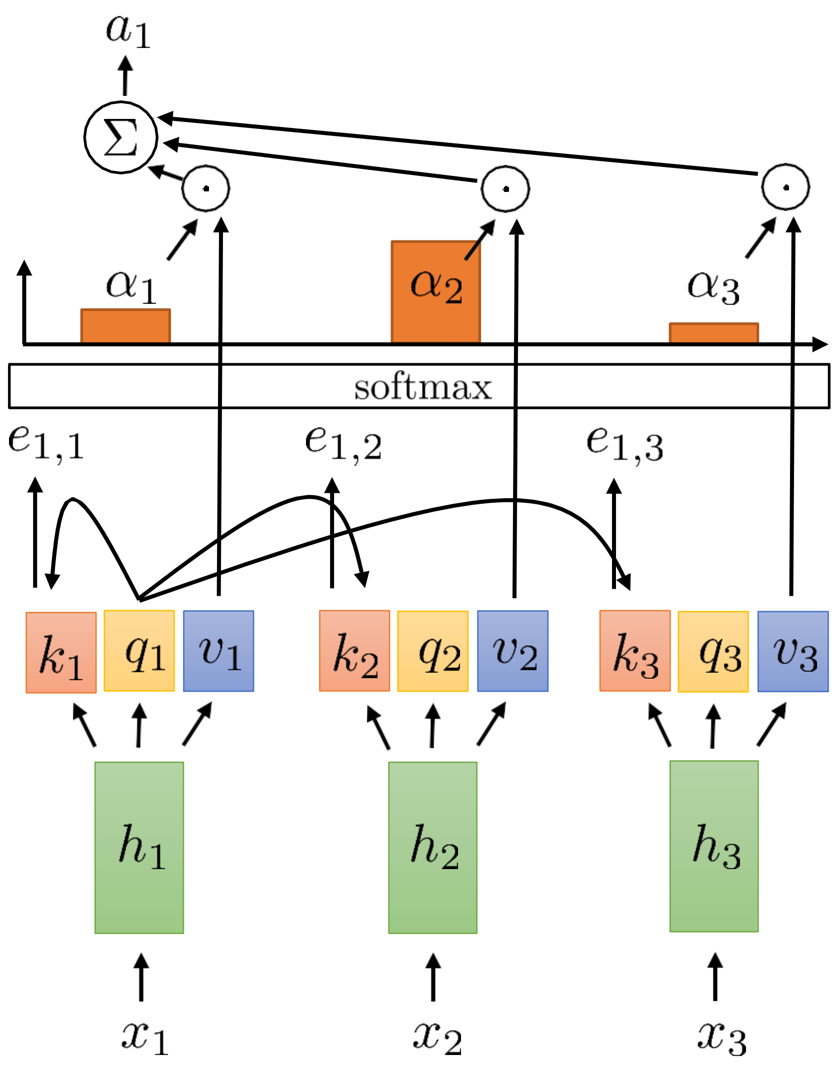

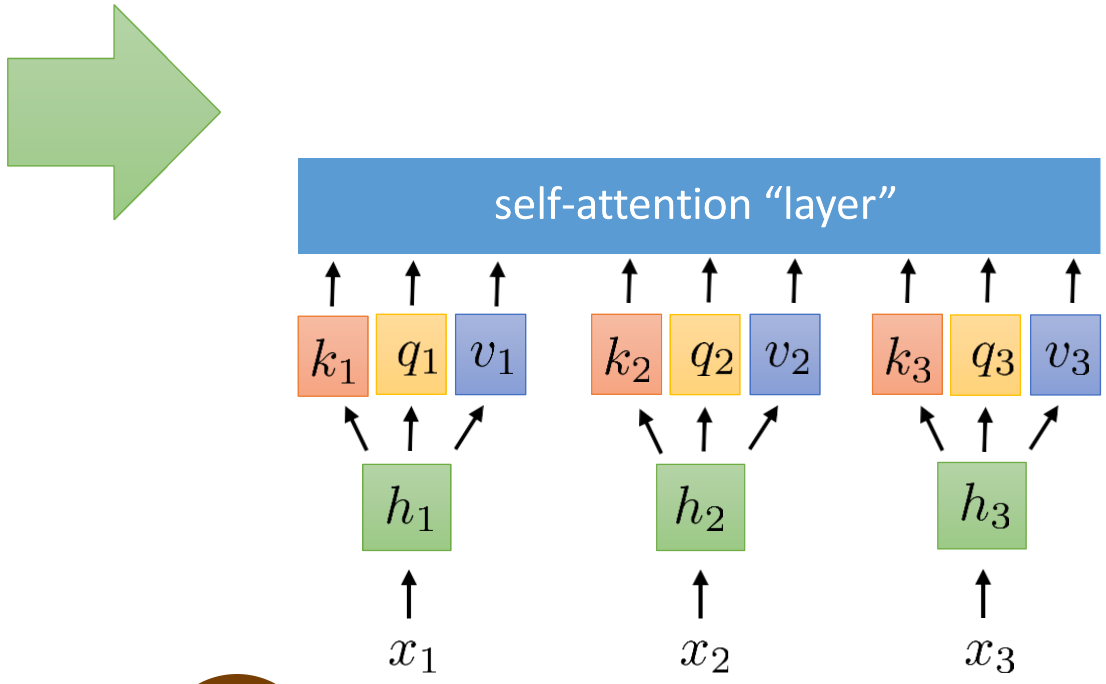

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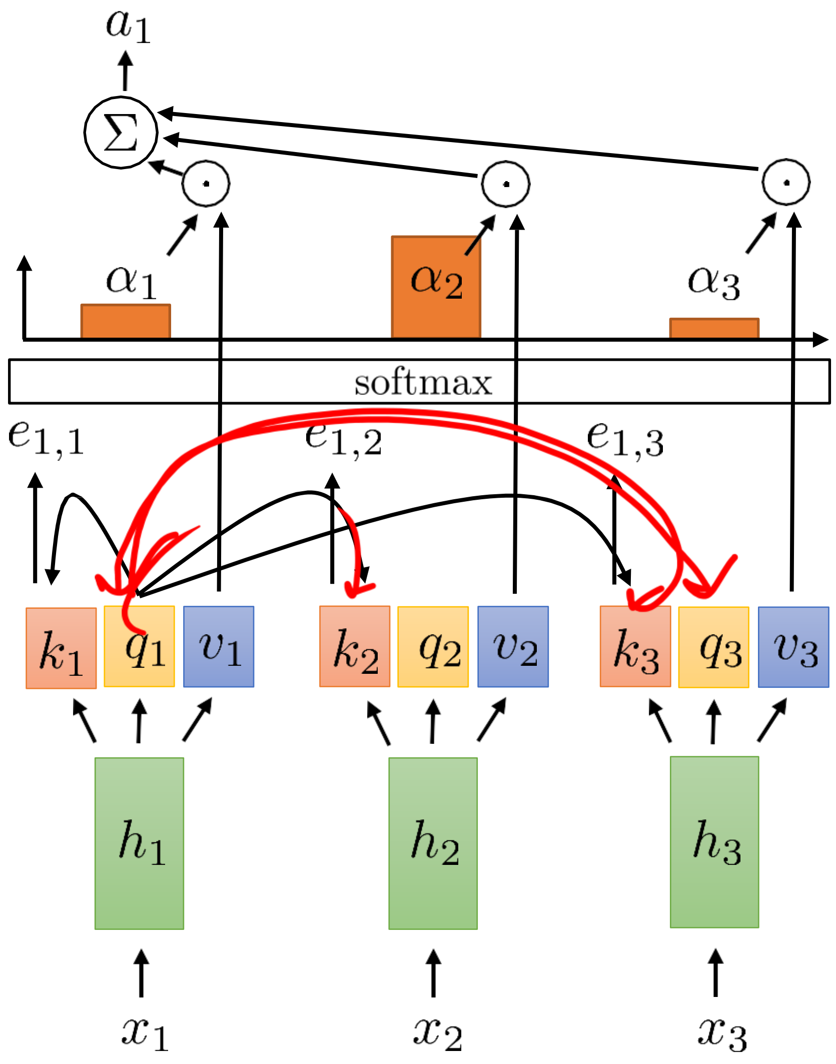

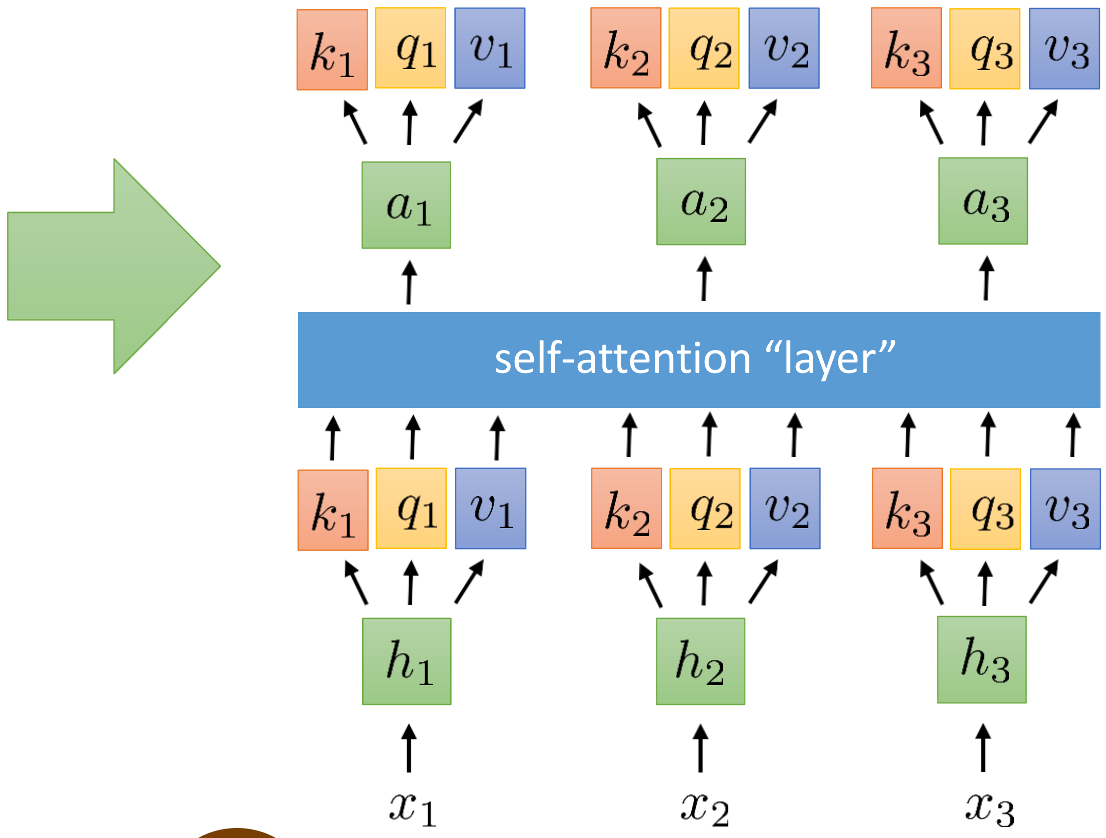

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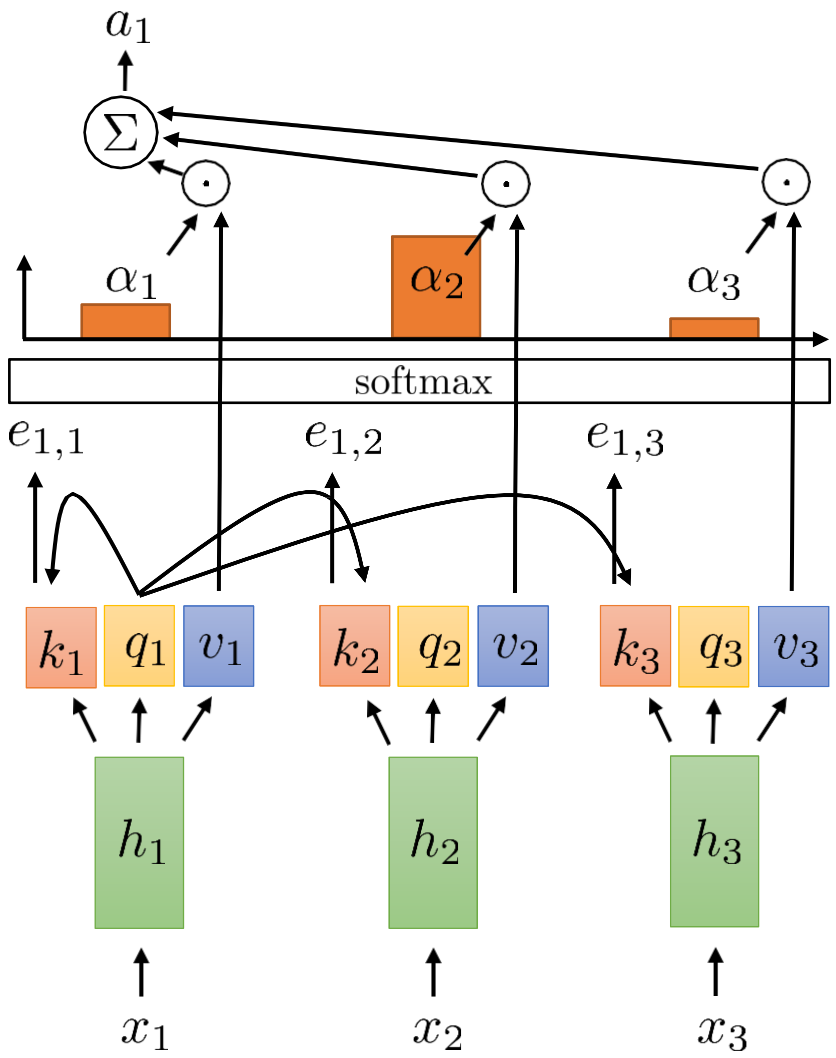

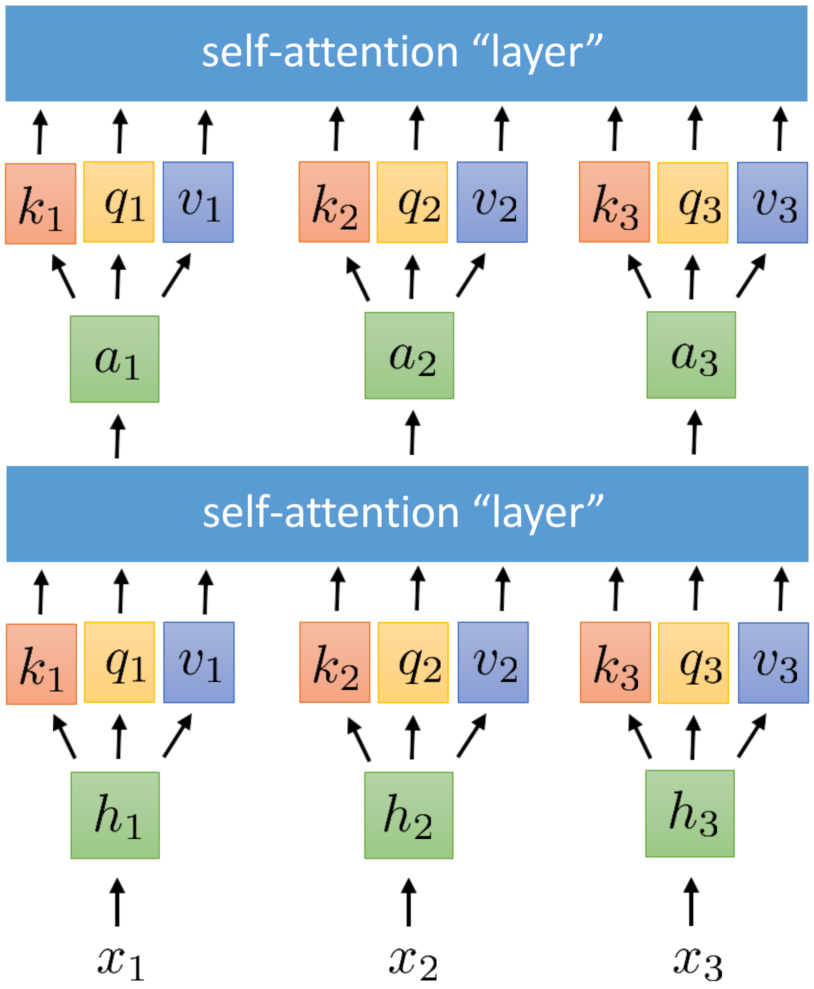

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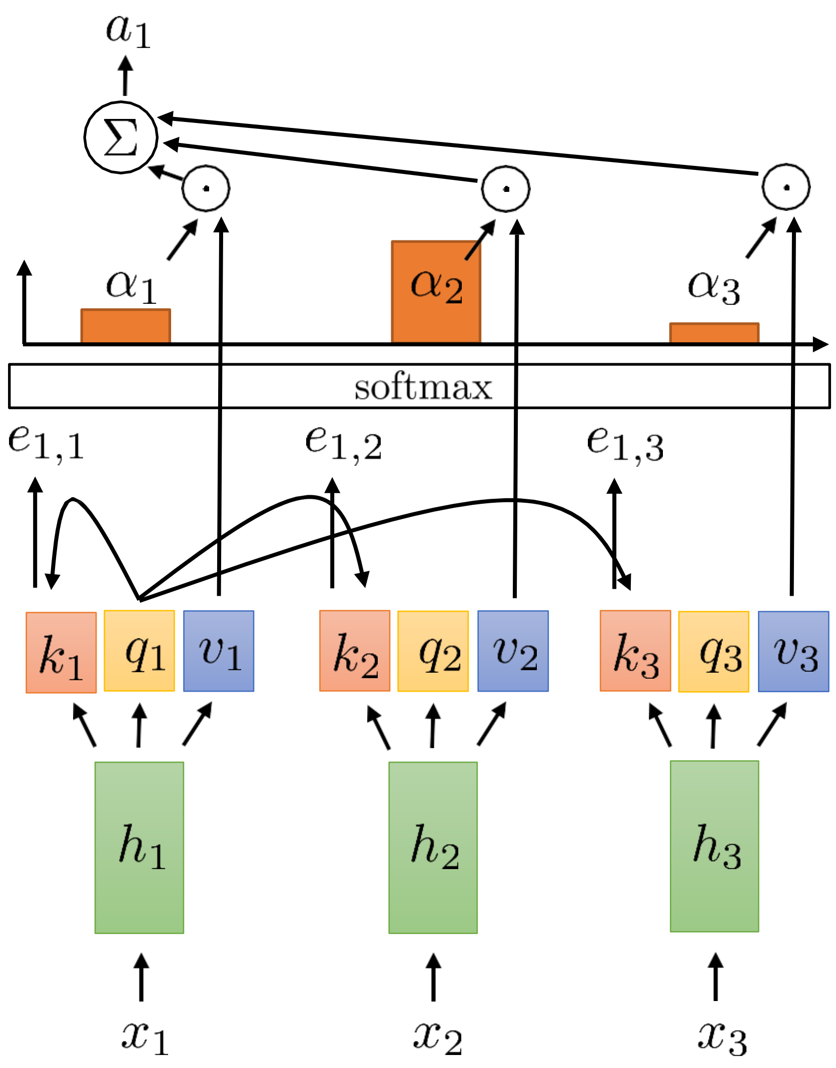

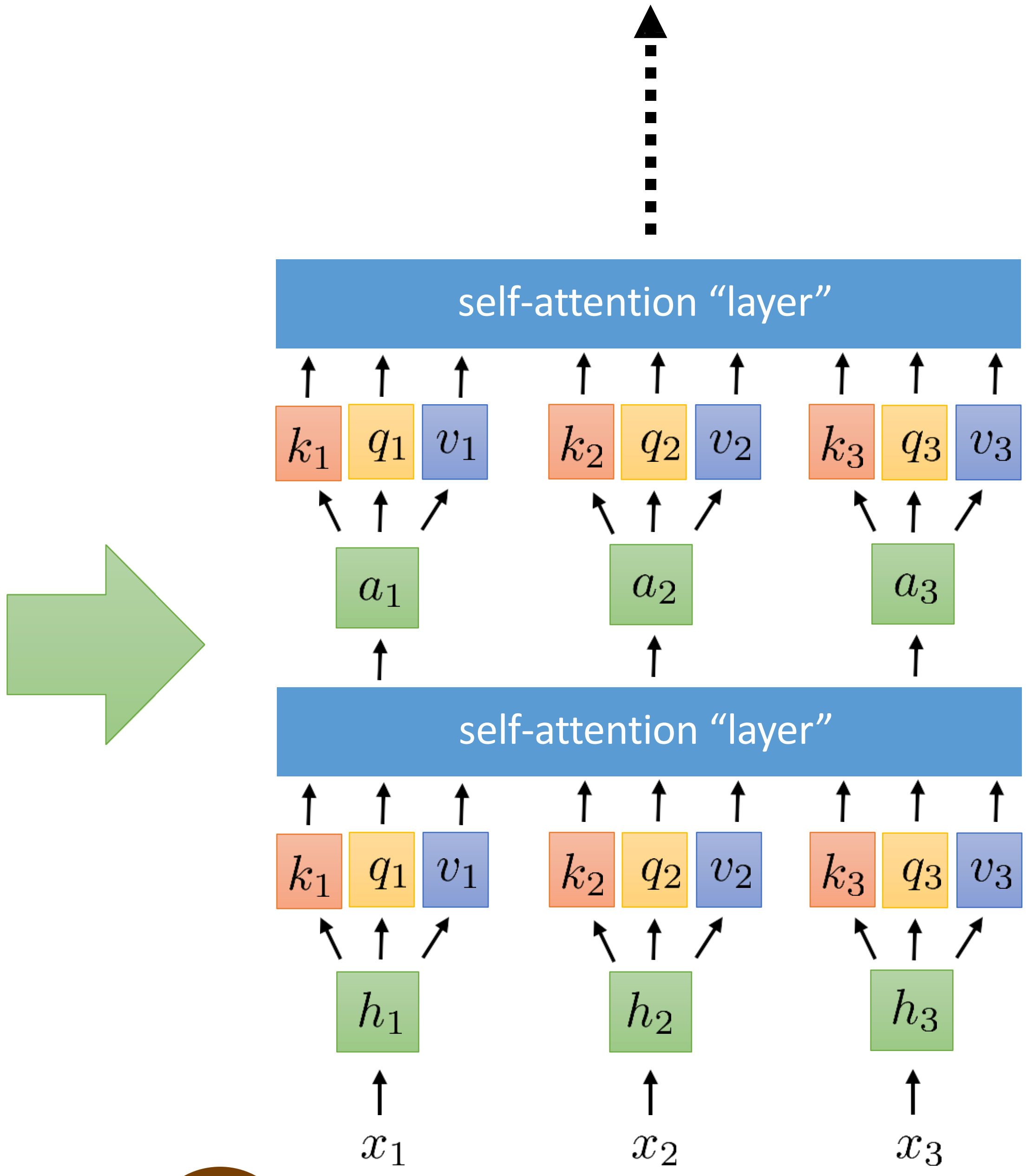

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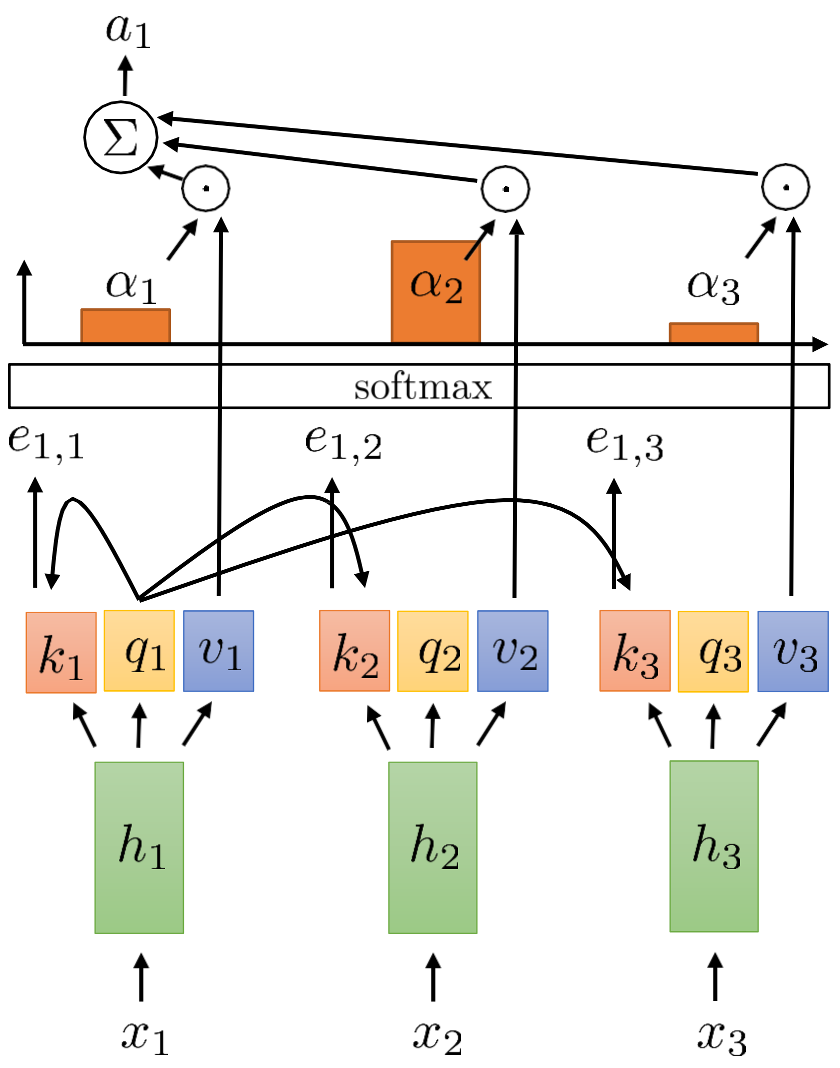

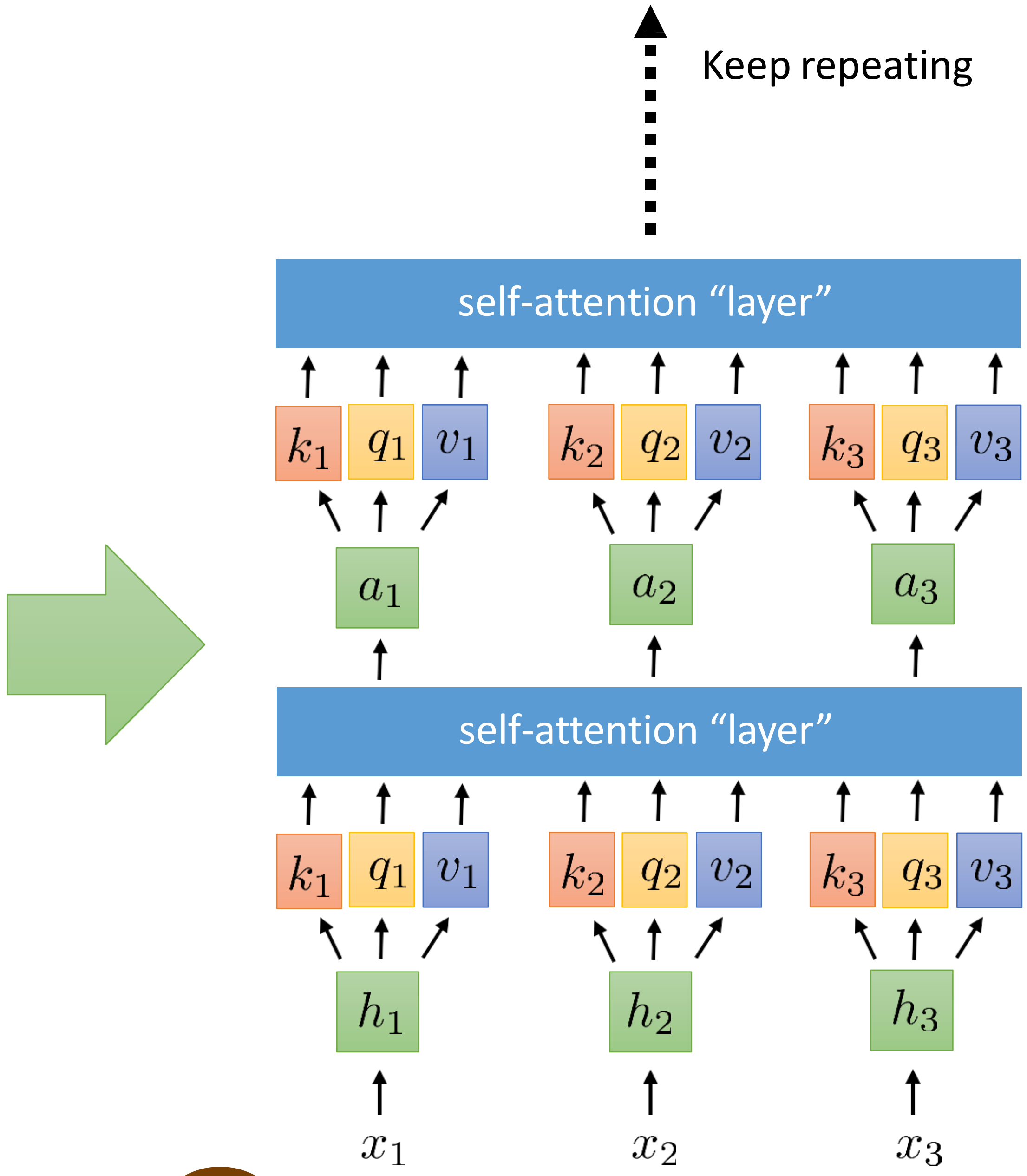

From Self-Attention to Transformers

- We will talk about a class of models for processing sequences that does not use recurrent connections but instead relies entirely on attention and will build up towards a class of models called **Transformers**.
- To address a few key limitations, we need to add certain elements:

1. Positional encoding	addresses lack of sequence information
2. Multi-headed attention	allows querying multiple positions at each layer
3. Adding nonlinearities	so far, each successive layer is *linear* in the previous one
4. Masked decoding	how to prevent attention lookups into the future?

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Positional Encoding - Motivation

- **Problem :** Self-attention processes all the elements of a sequence in parallel without any regard for their order.
  - Example : the sun rises in the east
  - Permuted version : rises in the sun the east

    the east rises in the sun
  - Self-attention is permutation invariant.
  - In natural language, it is important to take into account the order of words in a sentence.
- **Solution :** Explicitly add positional information to indicate where a word appears in a sequence

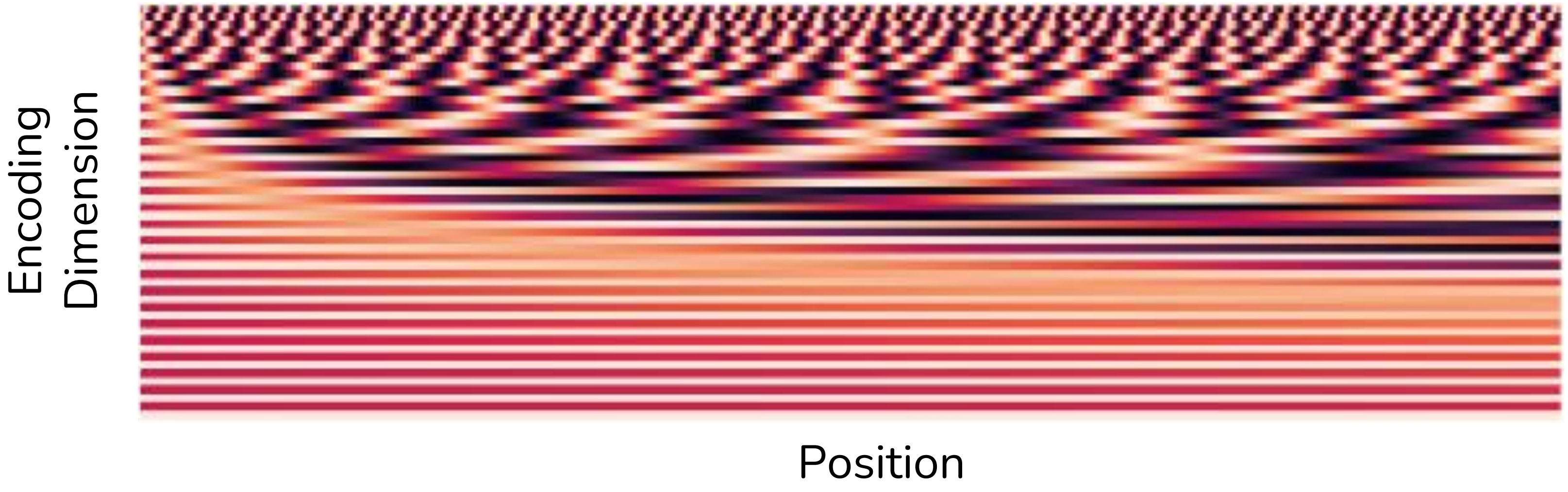
Bag of Words

in , the , rises , east , sun

Sinusoidal Positional Encoding

- Helps it determine the position of each word (absolute positional information), or the distance between different words in the sequence(relative positional information)
- The frequency decreases along the encoding dimension.

$$PE_{(pos,2i)} = sin(pos/10000^{2i/d_{\text{model}}})$$
$$PE_{(pos,2i+1)} = cos(pos/10000^{2i/d_{\text{model}}})$$



Will be discussed in the next module!

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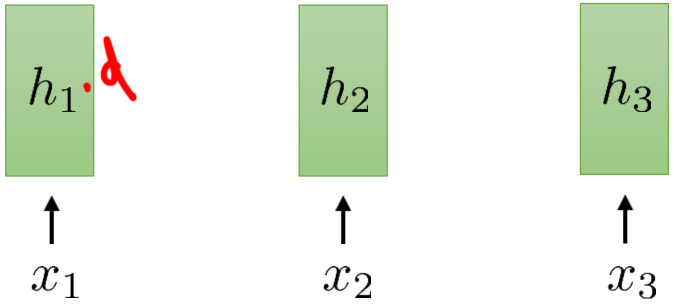
Multi-Head Attention

Given that we're fully depending on attention now, it could be beneficial to include more than one time step.



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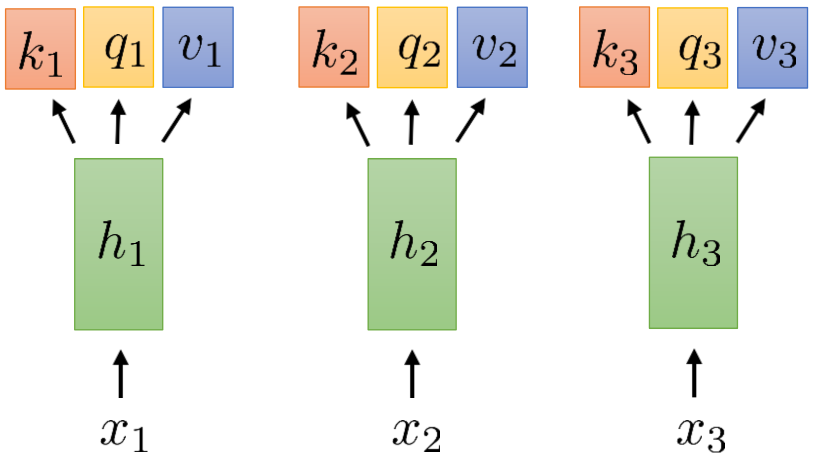

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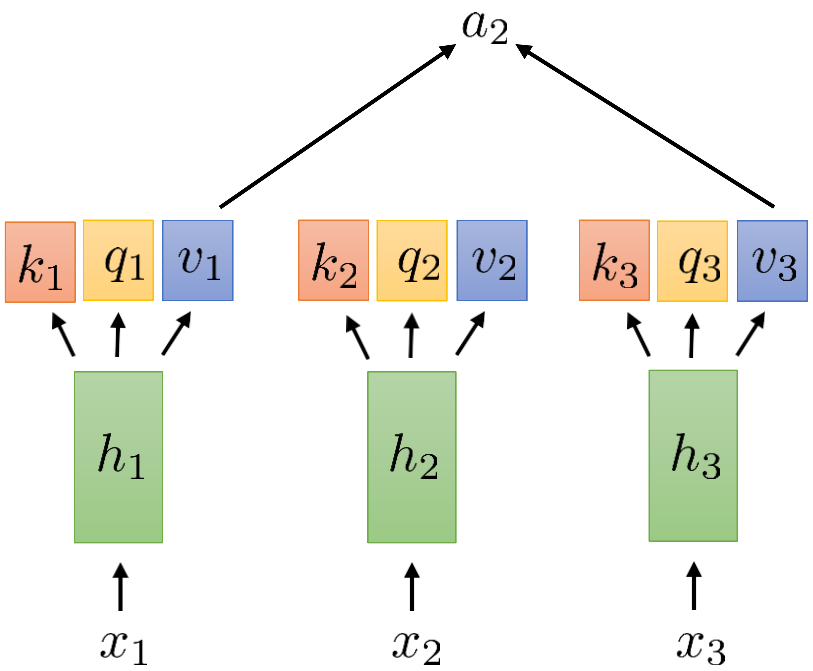

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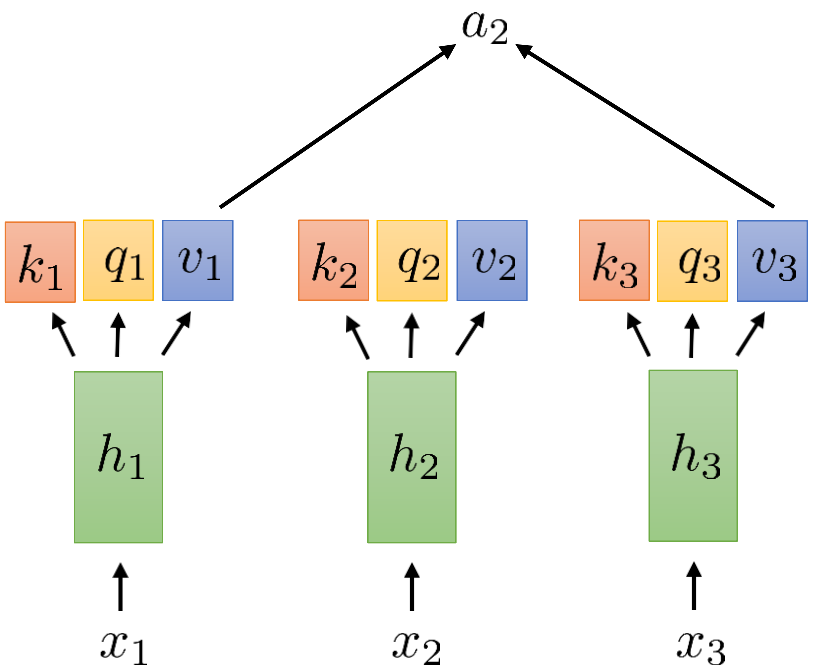

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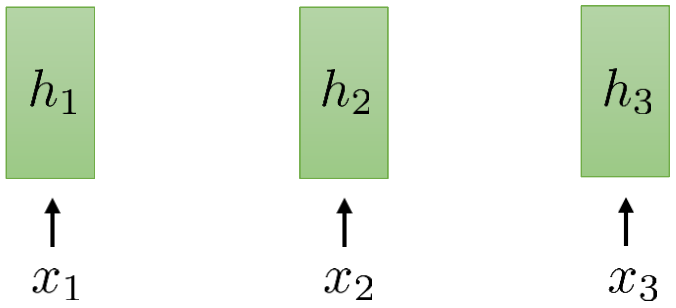
Due to the softmax function, this will be heavily influenced by a single value.

$$e_{l,t} = q_l \cdot k_t$$

It's challenging to clearly specify that you want two distinct elements, like the subject and object in a sentence.

Multi-Head Attention

Solution: Use multiple keys, queries, and values for each time step



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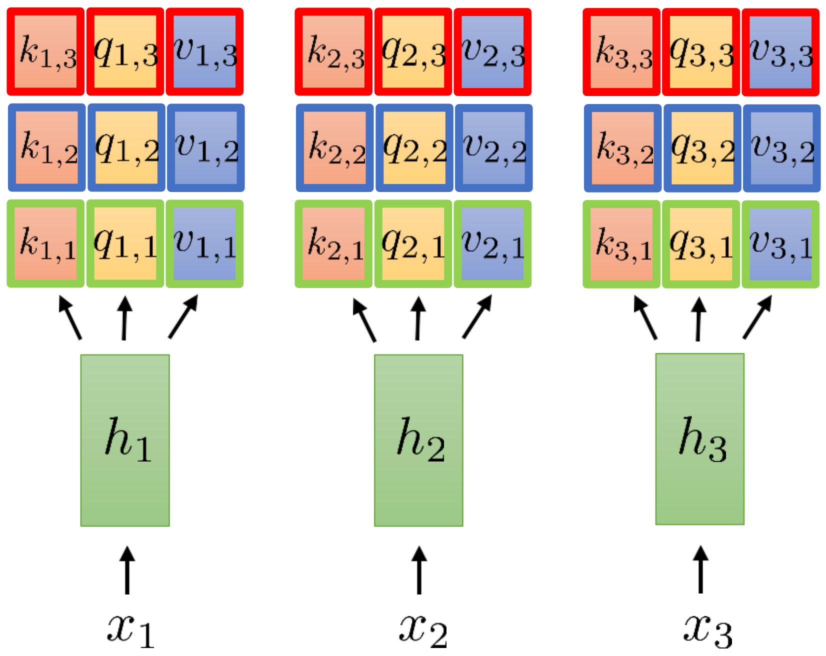

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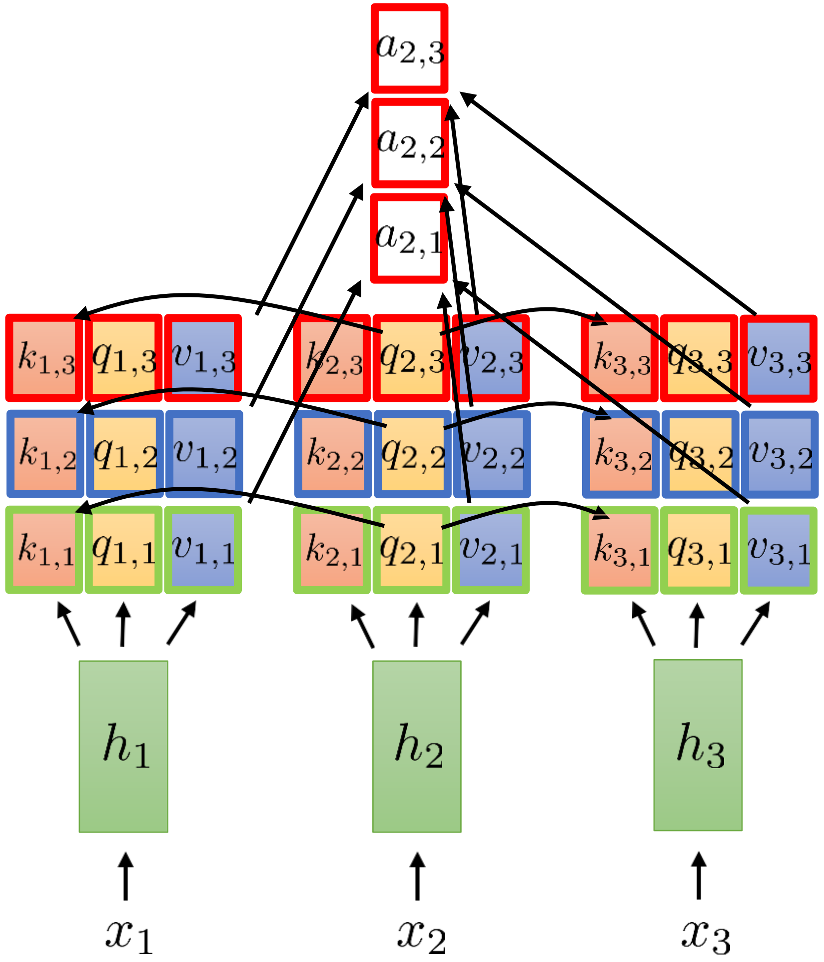

full attention vector formed by concatenation:

$$a_2 = \begin{bmatrix} a_{2,1} \\ a_{2,2} \\ a_{2,3} \end{bmatrix}$$

compute weights **independently** for each head

$$e_{l,t,i} = q_{l,i} \cdot k_{l,i}$$

$$\alpha_{l,t,i} = \exp(e_{l,t,i}) / \sum_{t'} \exp(e_{l,t',i})$$

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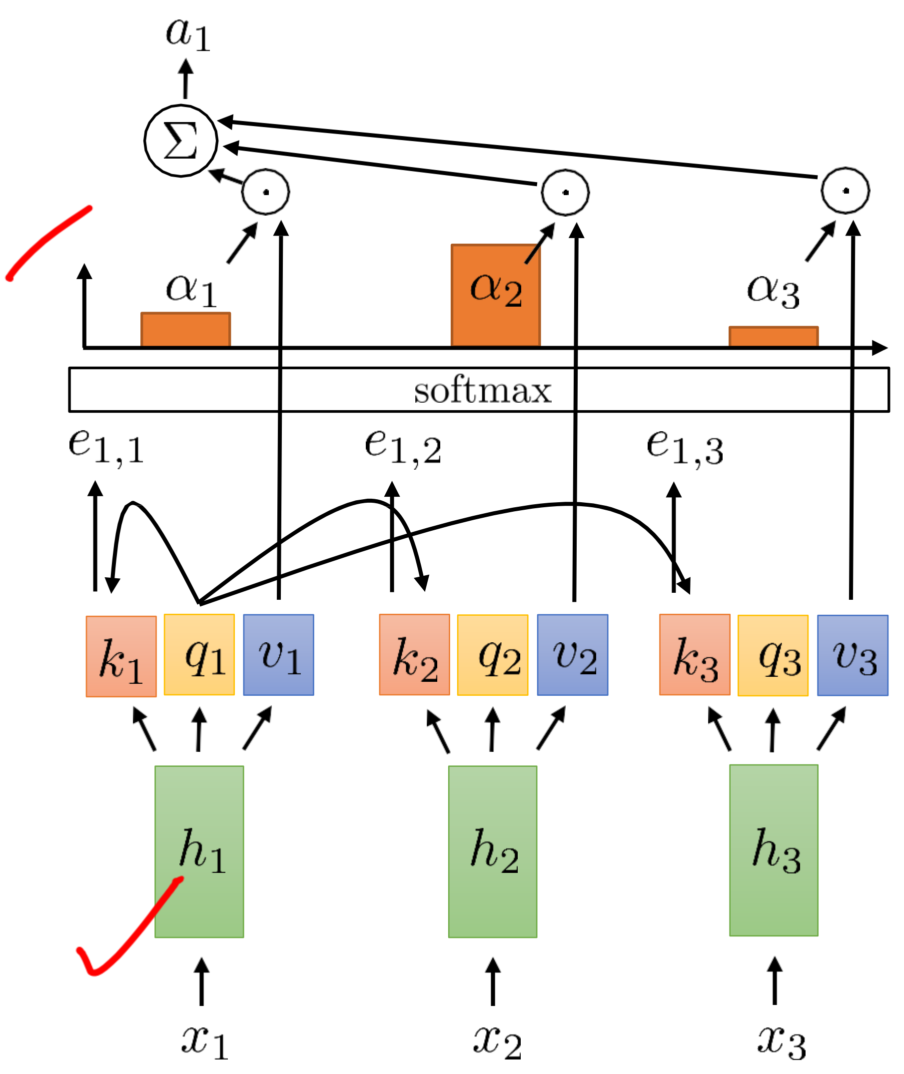
Self-Attention Is "Linear"



$k_t = W_k h_t \qquad q_t = W_q h_t \qquad v_t = W_v h_t$

$\alpha_{l,t} = \exp(e_{l,t}) / \sum_{t'} \exp(e_{l,t'})$

$e_{l,t} = q_l \cdot k_t$

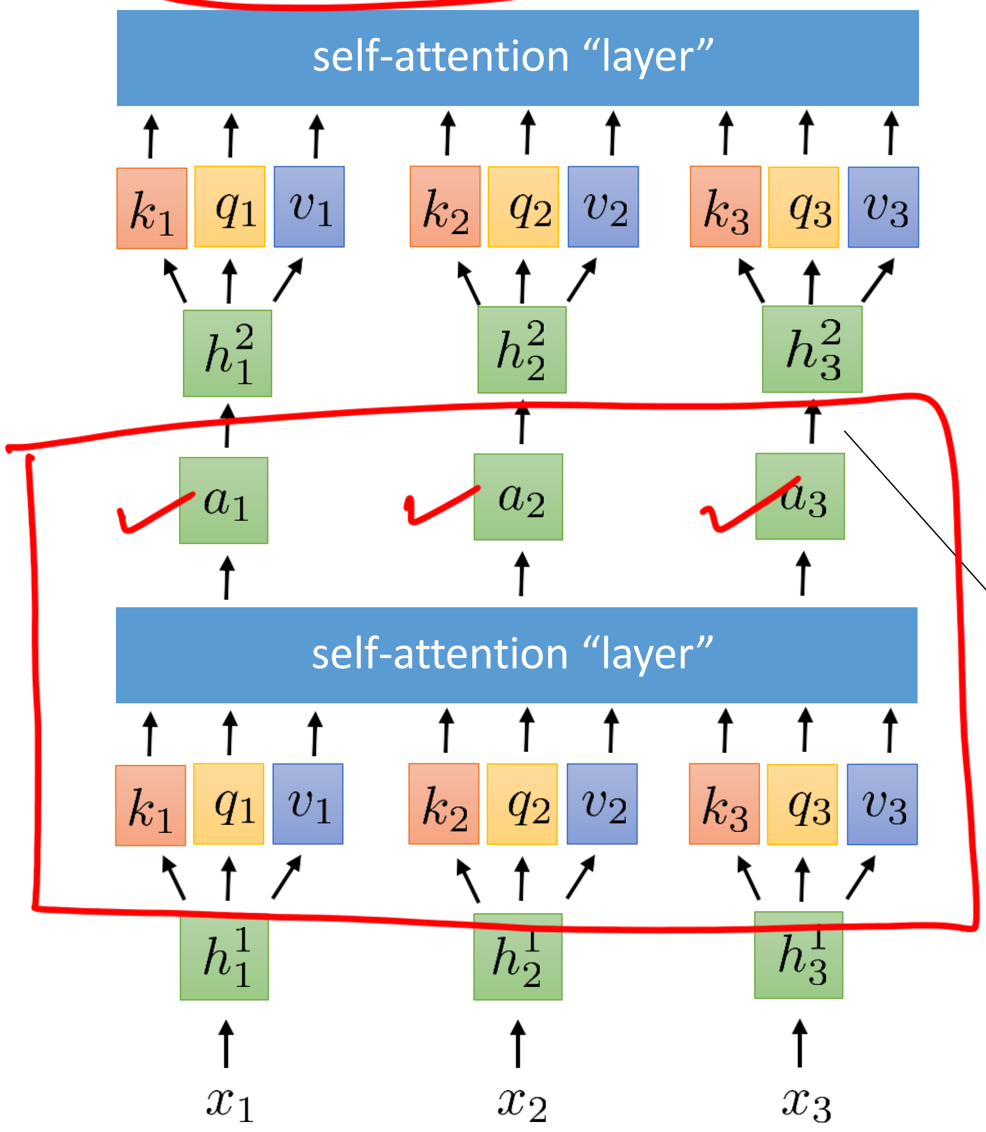
$a_l = \sum_t \alpha_{l,t} v_t = \sum_t \alpha_{l,t} W_v h_t = W_v \sum_t \alpha_{l,t} h_t$

linear transformation

non-linear weights

Problem: Every self-attention layer is a linear transformation of the previous layer with non-linear weights.

Position-wise Feed-Forward Networks



- **Solution :** Make the model more expressive is by alternating use of self-attention and non-linearity.
- Non-linearity is incorporated by means of a feed-forward network which consists of two linear transformations with a ReLU activation in between.

$$\mathrm{FFN}(x) = \max(0, xW_1 + b_1)W_2 + b_2$$

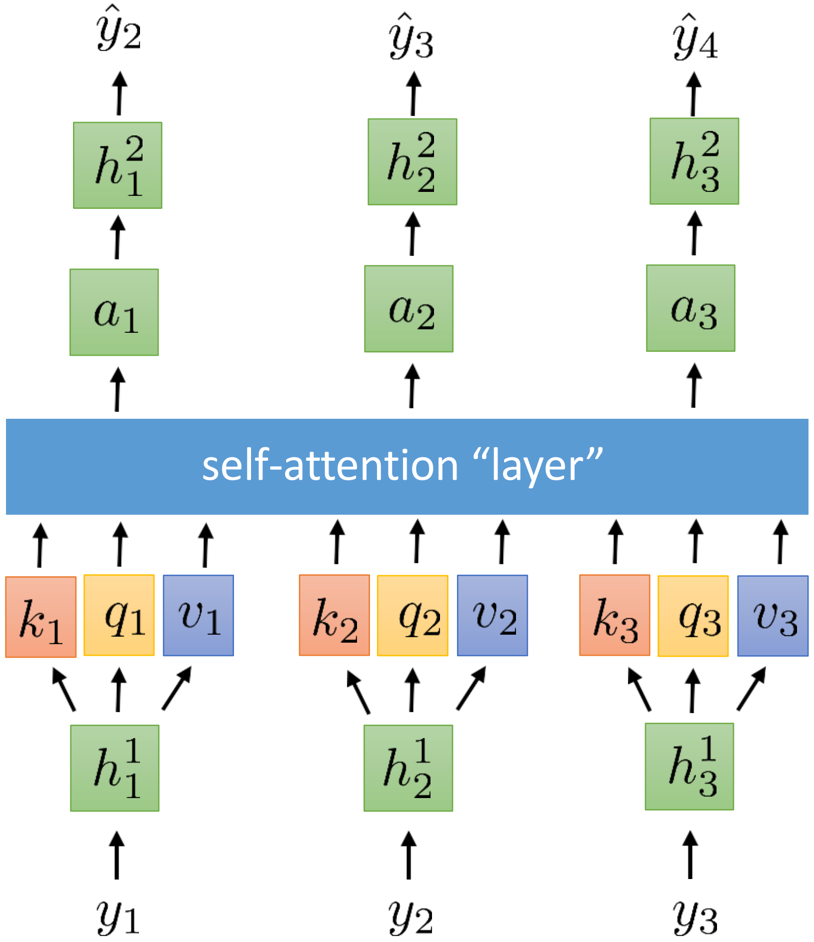
- The same non-linearity is utilized across various positions but they differ from layer to layer.

From Self-Attention to Transformers

- We will talk about a class of models for processing sequences that does not use recurrent connections but instead relies entirely on attention and will build up towards a class of models called transformers.
- To address a few key limitations, we need to add certain elements:

1. Positional encoding	addresses lack of sequence information
2. Multi-headed attention	allows querying multiple positions at each layer
3. Adding nonlinearities	so far, each successive layer is *linear* in the previous one
4. Masked decoding	how to prevent attention lookups into the future?

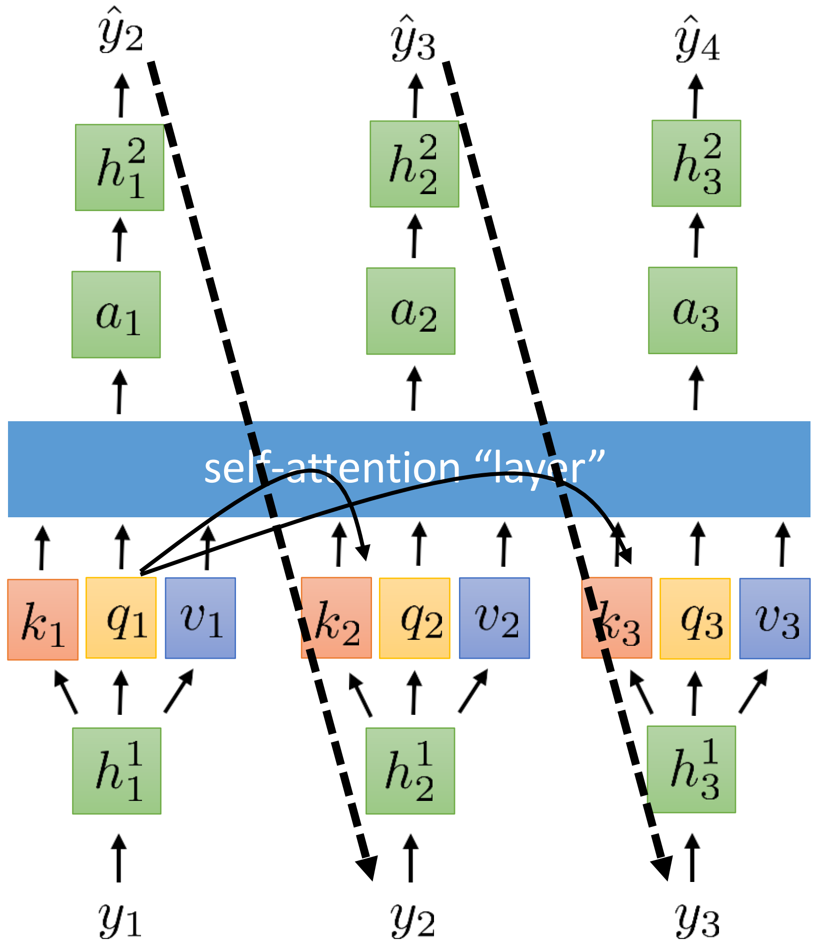
Self-attention can see the future!



A **crude** self-attention "language model":

In practice, there would be several alternating self-attention layers and position-wise feedforward networks

Self-attention can see the future!



A **crude** self-attention "language model":

In practice, there would be several alternating self-attention layers and position-wise feedforward networks

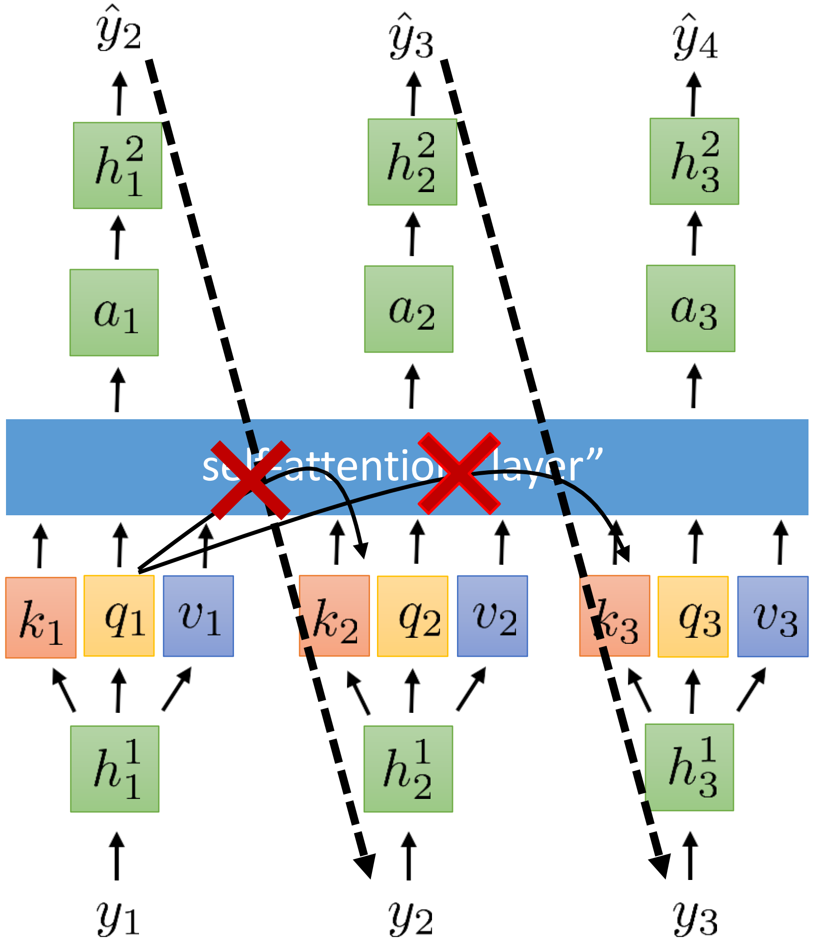
Big problem: self-attention at step 1 can look at the value at steps 2 & 3, which is based on the **inputs** at steps 2 & 3

At test time (when decoding), the **inputs** at steps 2 & 3 will be based on the output at step 1…

…which requires knowing the **input** at steps 2 & 3

Masked Attention

A **crude** self-attention "language model":



At test time (when decoding), the **inputs** at steps 2 & 3 will be based on the output at step 1…

…which requires knowing the **input** at steps 2 & 3

Must allow self-attention into the **past**…

…but not into the **future**

Easy solution:

$$e_{l,t} = q_l \cdot k_t$$

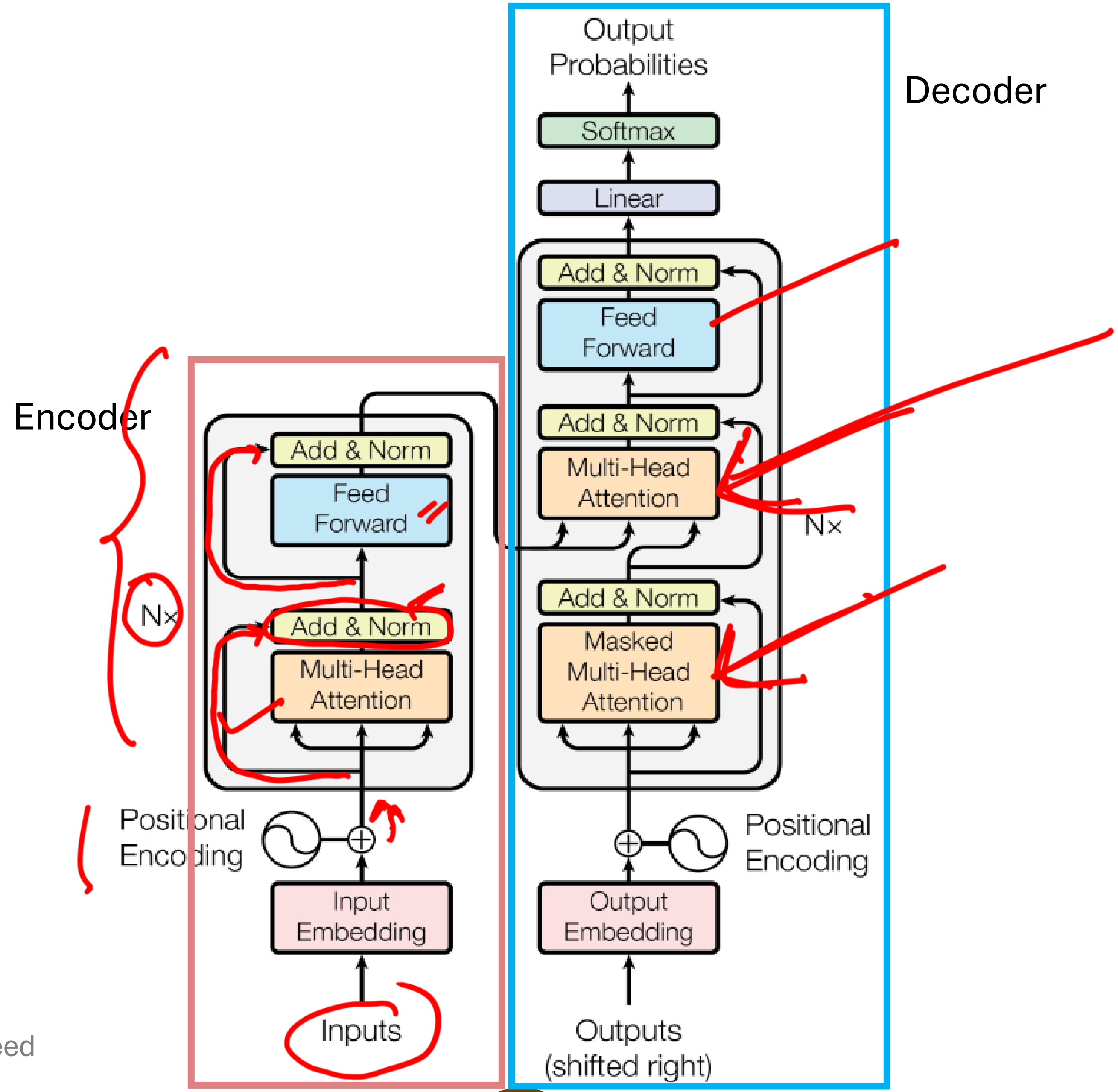
$$e_{l,t} = \begin{cases} q_l \cdot k_t & \text{if } l \geq t \\ -\infty & \text{otherwise} \end{cases}$$

in practice:

just replace $\exp(e_{l,t})$ with 0 if $l < t$

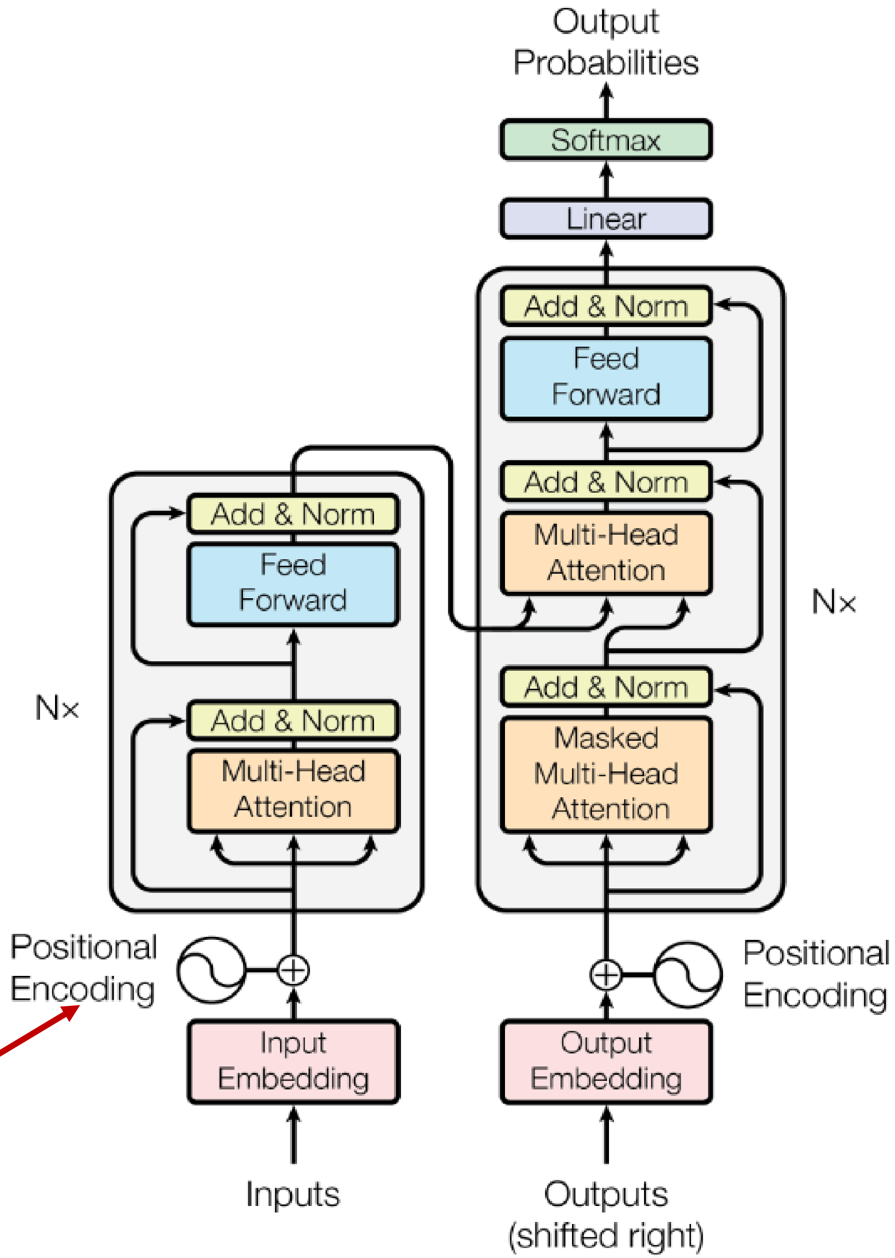
inside the softmax

Transformer Architecture



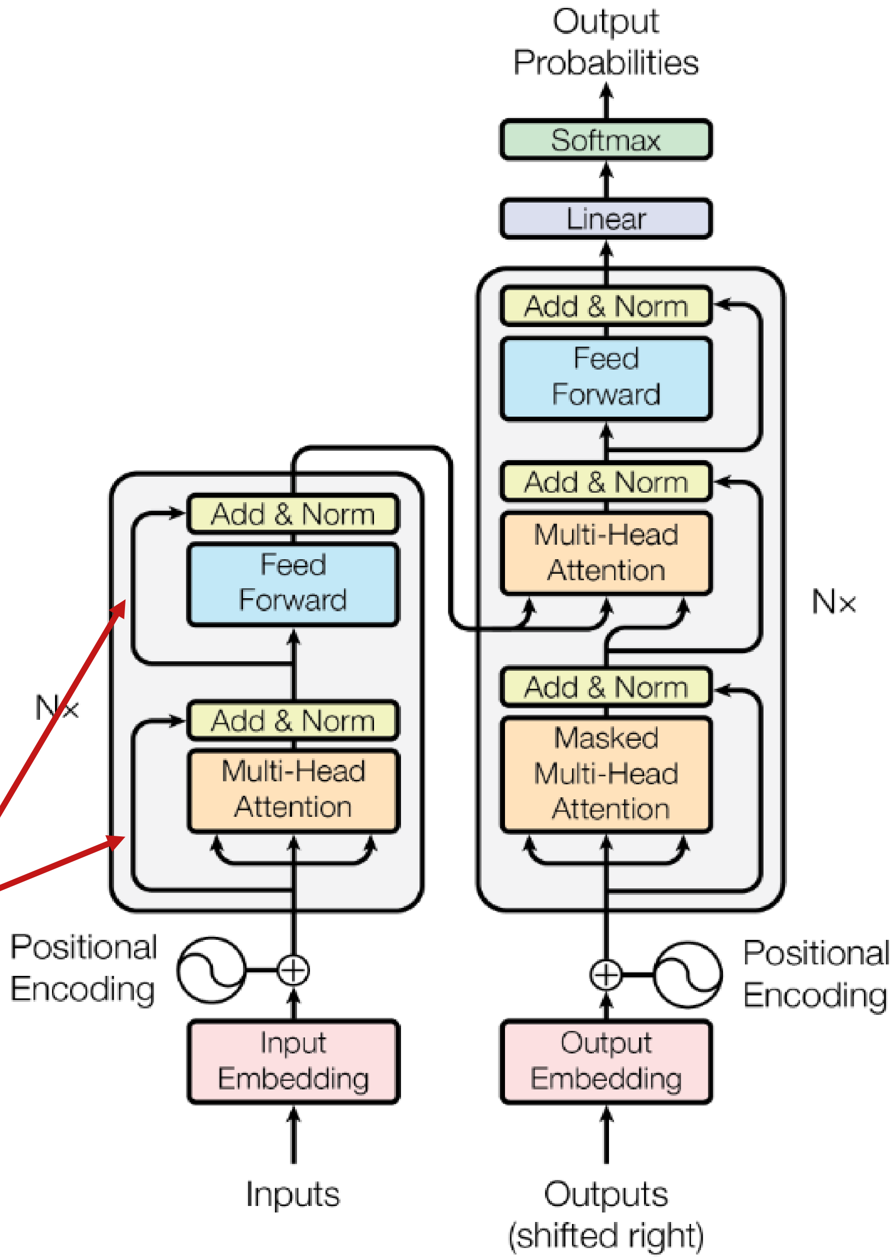
Source of Image : Attention is all you need (Vaswani t al., 2017)

Transformer Architecture



Position embeddings are *added* to each word embedding. Otherwise, since we have no recurrence, our model is unaware of the position of a word in the sequence!

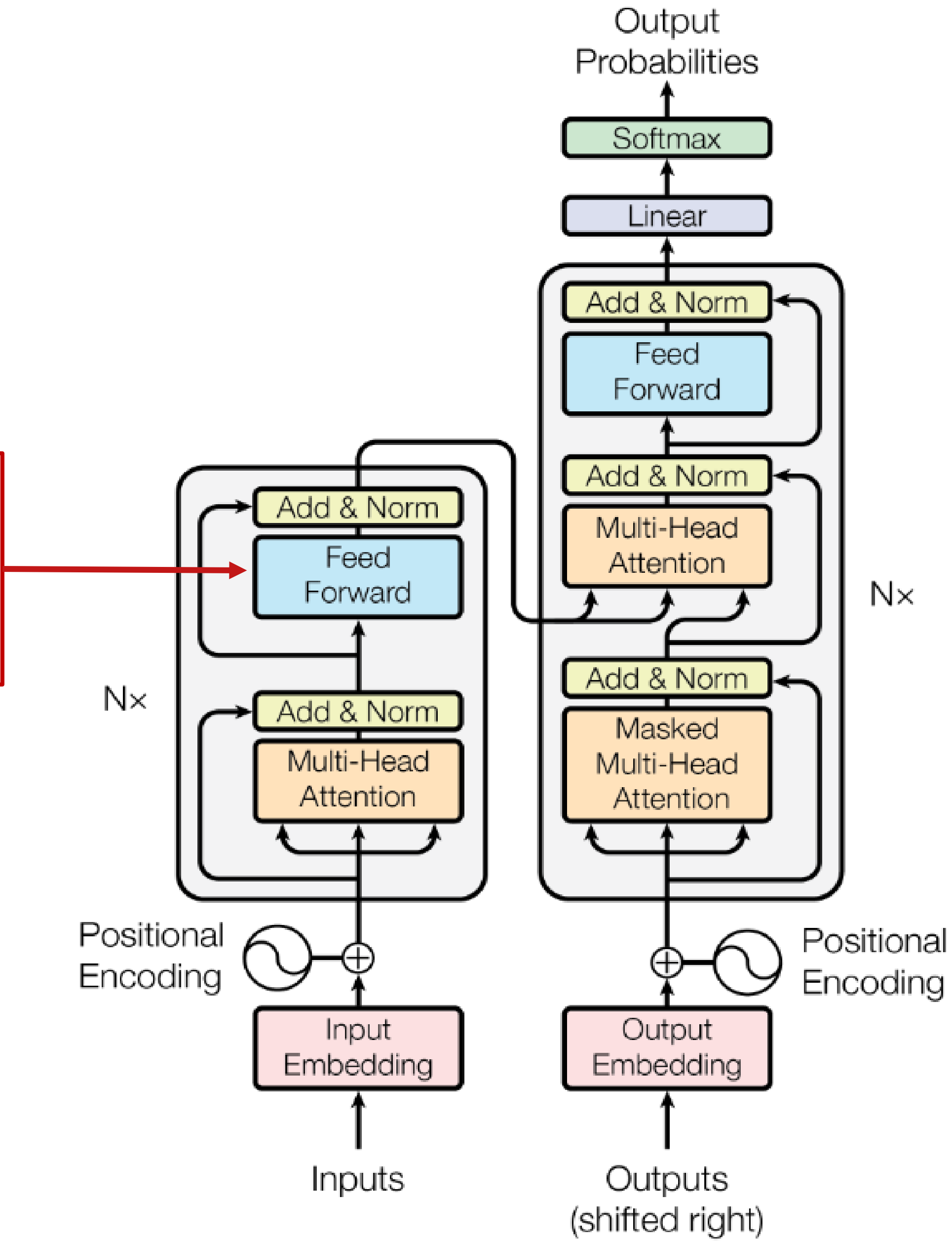
Transformer Architecture



Residual connections, which mean that we add the input to a particular block to its output, help improve gradient flow

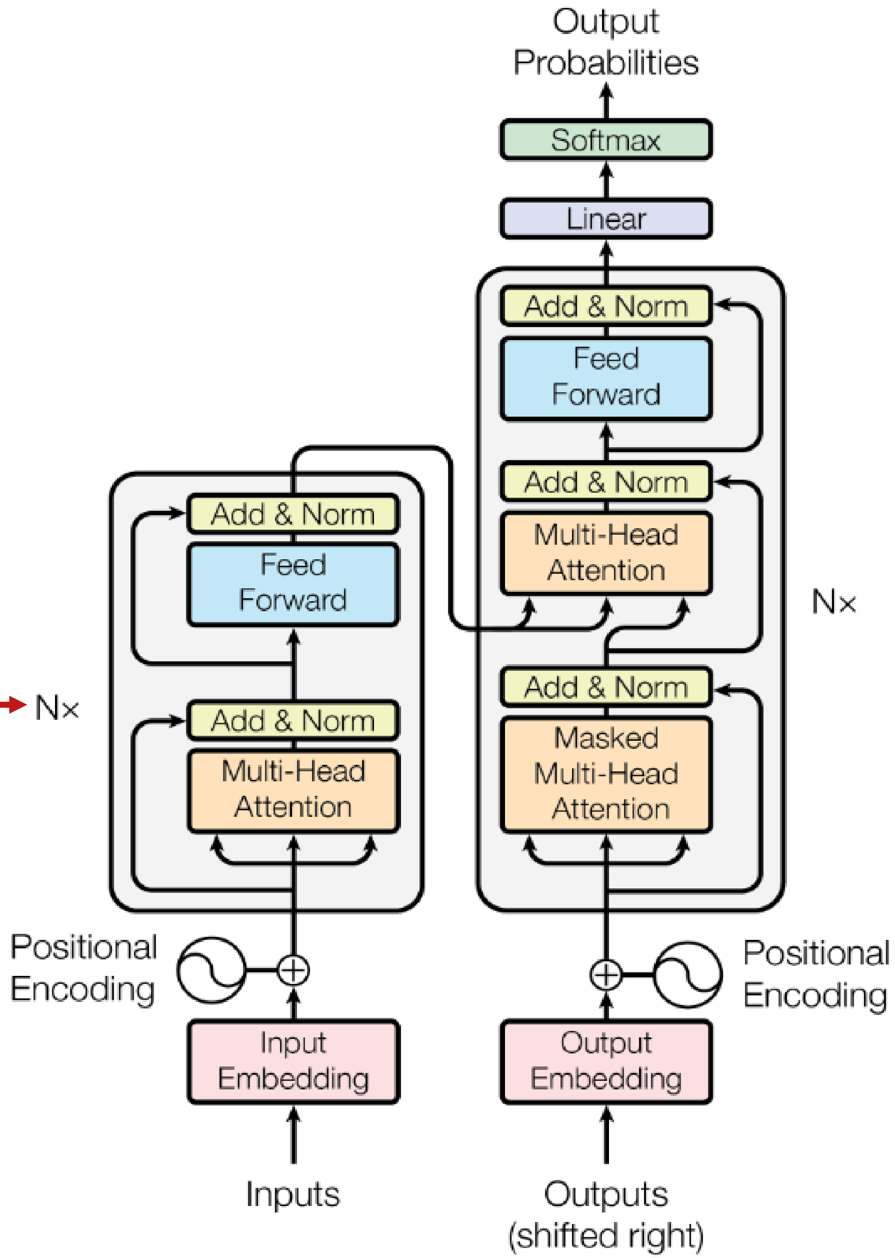
Transformer Architecture

A **feed-forward layer** on top of the attention- weighted averaged value vectors allows us to add more parameters / nonlinearity

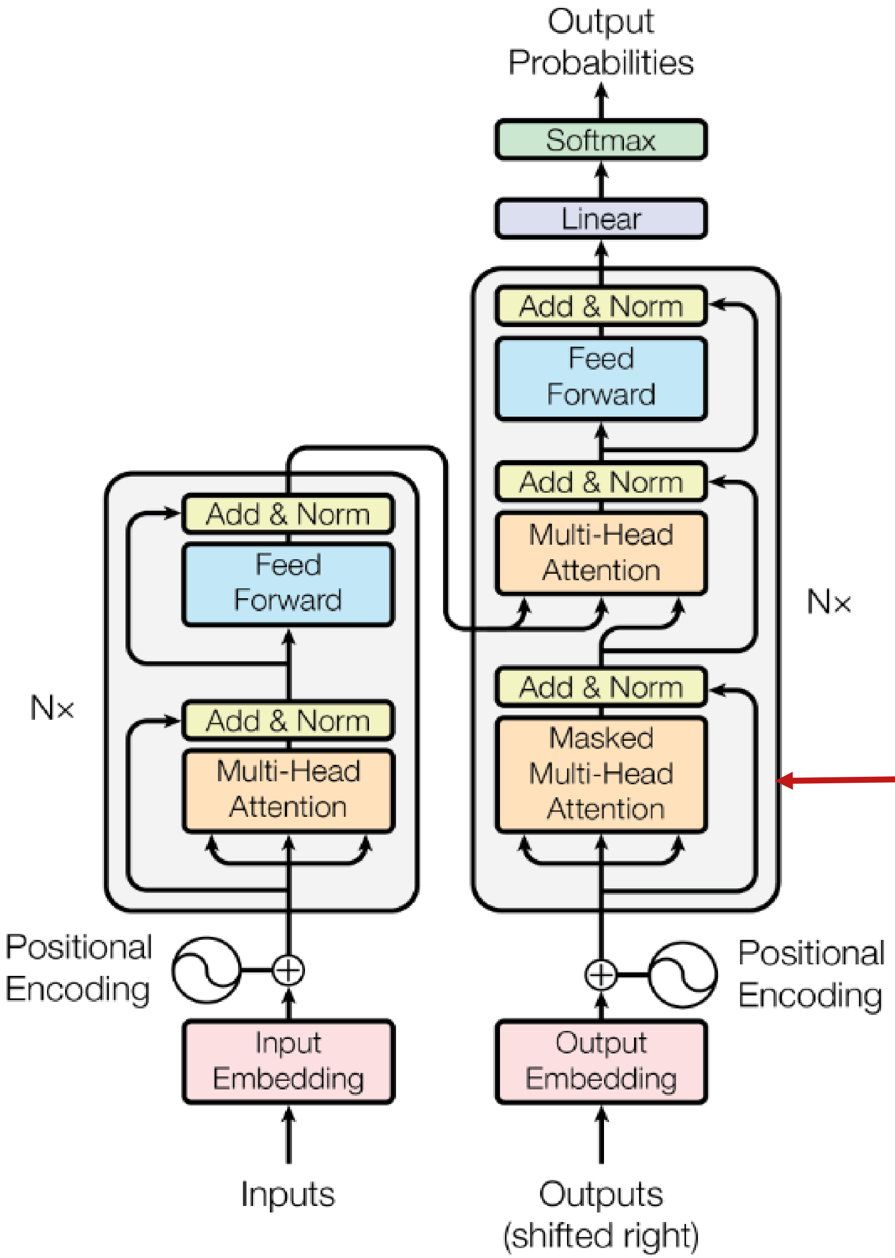


Transformer Architecture

We stack as many of these ***Transformer* blocks** on top of each other as we can (bigger models are generally better given enough data!)

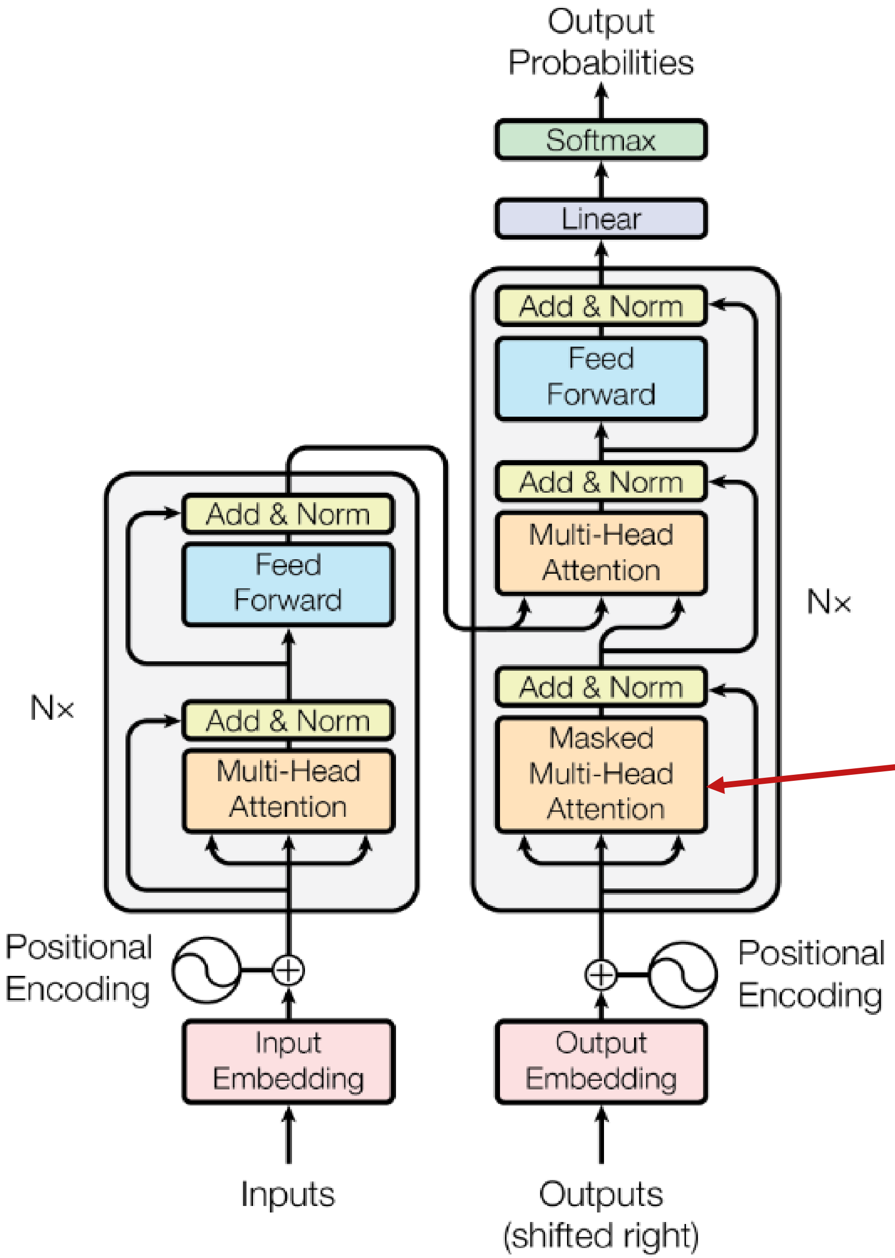


Transformer Architecture



Moving onto the decoder, which takes in English sequences that have been shifted to the right (e.g., *<START> schools opened their*)

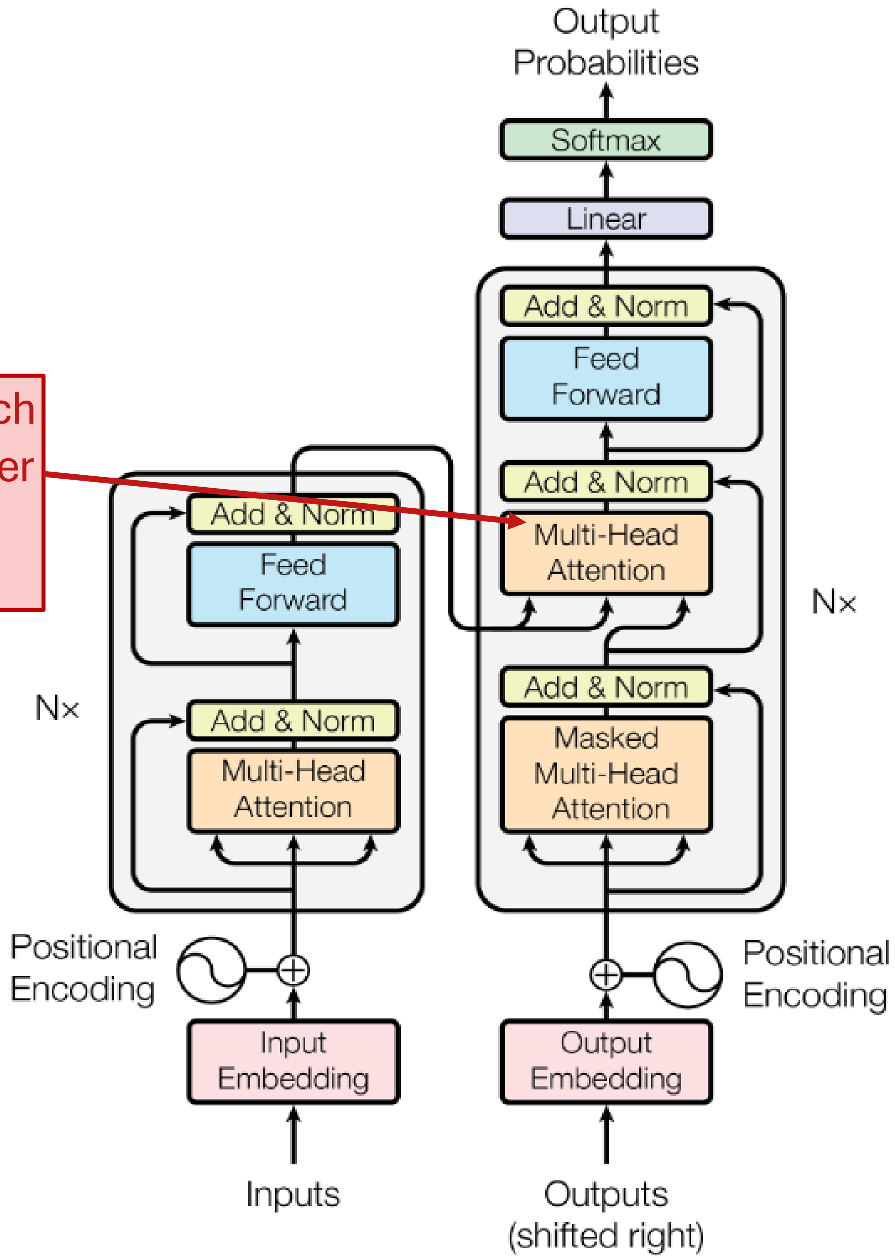
Transformer Architecture



We first have an instance of **masked self attention**. Since the decoder is responsible for predicting the English words, we need to apply masking as we saw before.

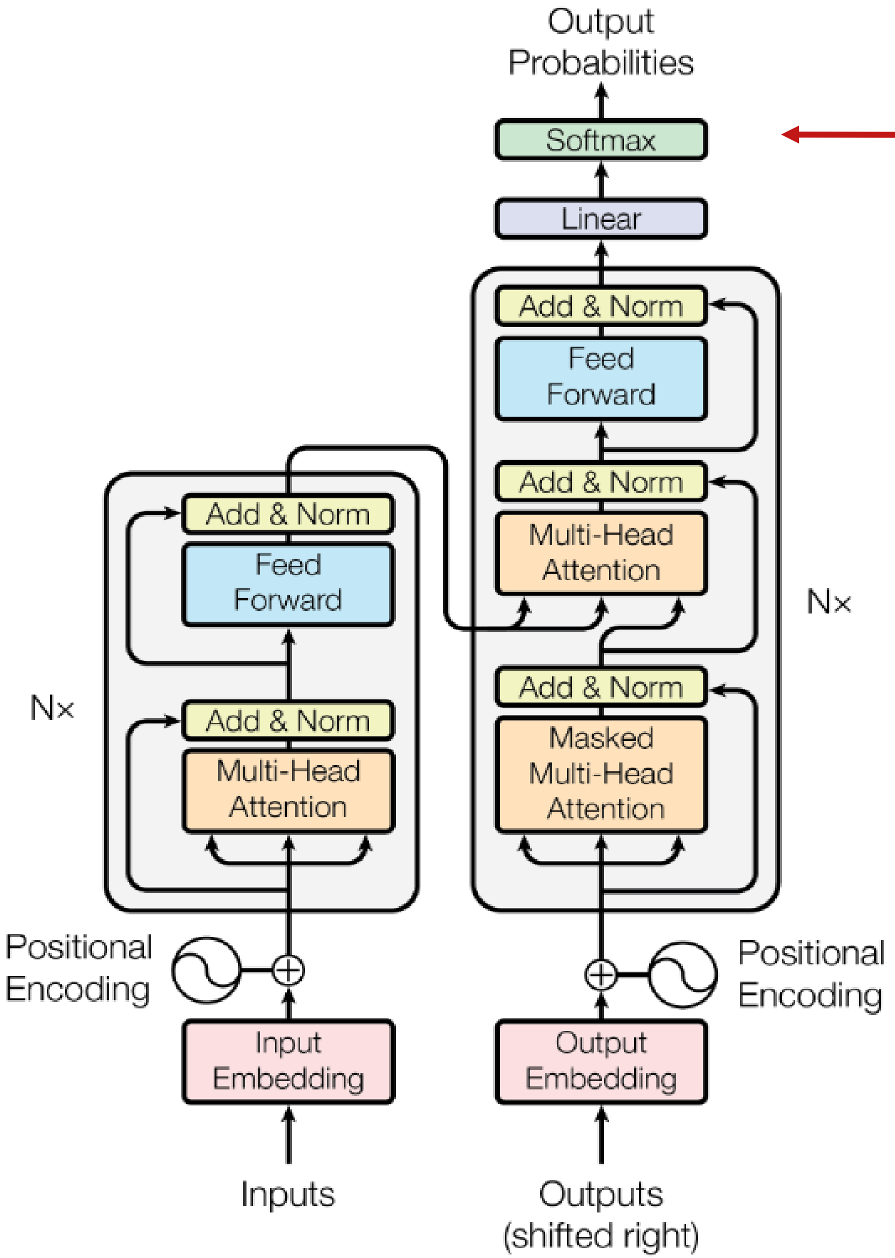
Transformer Architecture

Now, we have ***cross attention***, which connects the decoder to the encoder by enabling it to attend over the encoder's final hidden states.



Source of Image : Attention is all you need (Vaswani et al., 2017)

Transformer Architecture



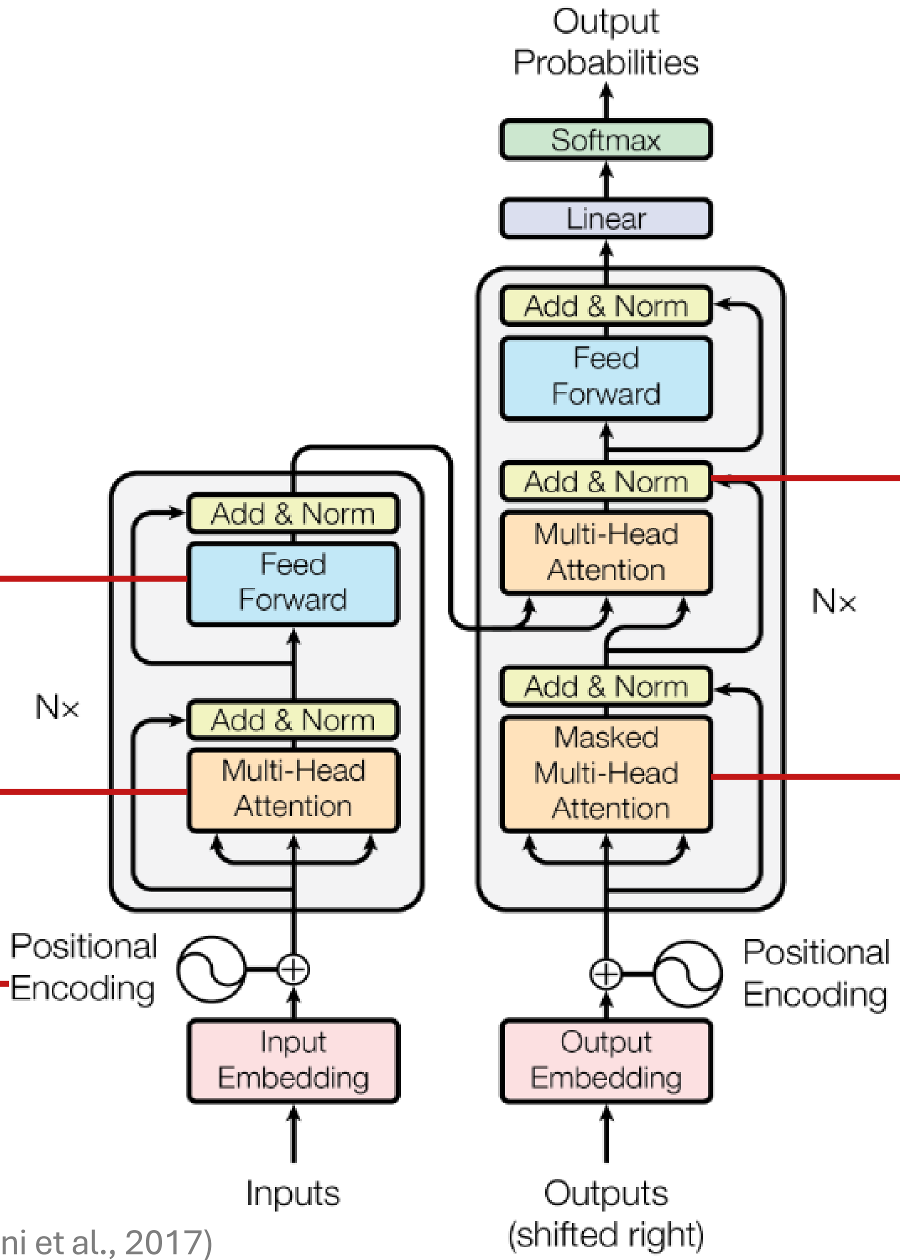
After stacking a bunch of these decoder blocks, we finally have our familiar **softmax** layer to predict the next English word.

Transformer Architecture

Adding non-linearities

Allows querying multiple positions at each layer

Adds positional information



Reduces covariance shift and makes the system stable

Prevents attention lookups into the future while decoding

Source of Image : Attention is all you need (Vaswani et al., 2017)

Layer normalization

- **Main idea:** Batch normalization is quite beneficial, but it's challenging to apply with sequence models. The varying lengths of sequences make it difficult to normalize across a batch. Sequences can be very long, which often results in smaller batch sizes.
- **Solution:** Layer normalization

$a_1, a_2, \ldots, a_B$ ← d-dimensional vectors for each sample in batch

d-dim → μ

$$\mu = \frac{1}{B}\sum_{i=1}^{B} a_i \quad \sigma = \sqrt{\frac{1}{B}\sum_{i=1}^{B}(a_i - \mu)^2}$$

$$\bar{a}_i = \frac{a_i - \mu}{\sigma}\gamma + \beta$$

Batch Norm

different *dimensions* of a → a_j

1-dim → μ

$$\mu = \frac{1}{d}\sum_{i=1}^{d} a_j \quad \sigma = \sqrt{\frac{1}{d}\sum_{i=1}^{d}(a_j - \mu)^2}$$

$$\bar{a} = \frac{a - \mu}{\sigma}\gamma + \beta$$

Layer Norm

From Self-Attention to Transformers

- We will talk about a class of models for processing sequences that does not use recurrent connections but instead relies entirely on attention and will build up towards a class of models called transformers.
- To address a few key limitations, we need to add certain elements:

1. Positional encoding	addresses lack of sequence information
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4. Masked decoding	how to prevent attention lookups into the future?

Transformer Positional Encoding

$$PE_{(pos,2i)} = \sin\left(\frac{pos}{10000^{2i/d_{model}}}\right)$$

$$PE_{(pos,2i+1)} = \cos\left(\frac{pos}{10000^{2i/d_{model}}}\right)$$

For $\mathbf{d_{model}} = \mathbf{512}$,

Positional encoding is a 512-dimensional vector

(Note: **Dimension of positional encoding is same as dimension of the word embeddings**)

i = a particular dimension of this vector

pos = position of the word in the sequence

Example

ROPE

For example, for word w at position $pos \in [0, L-1]$ in the input sequence $\boldsymbol{w} = (w_0, \cdots, w_{L-1})$, with 4-dimensional embedding e_w, and $d_{model} = 4$, the operation would be

$$e'_w = e_w + \left[sin\left(\frac{pos}{10000^0}\right), cos\left(\frac{pos}{10000^0}\right), sin\left(\frac{pos}{10000^{2/4}}\right), cos\left(\frac{pos}{10000^{2/4}}\right) \right]$$
$$= e_w + \left[sin\,(pos)\,, cos\,(pos)\,, sin\left(\frac{pos}{100}\right), cos\left(\frac{pos}{100}\right) \right]$$

where the formula for positional encoding is as follows

$$\text{PE}(pos, 2i) = sin\left(\frac{pos}{10000^{2i/d_{model}}}\right),$$

$$\text{PE}(pos, 2i+1) = cos\left(\frac{pos}{10000^{2i/d_{model}}}\right).$$

https://datascience.stackexchange.com/questions/51065/what-is-the-positional-encoding-in-the-transformer-model

Pre-training Strategies

Tanmoy Chakraborty
Associate Professor, IIT Delhi
https://tanmoychak.com/

LABORATORY FOR COMPUTATIONAL SOCIAL SYSTEMS

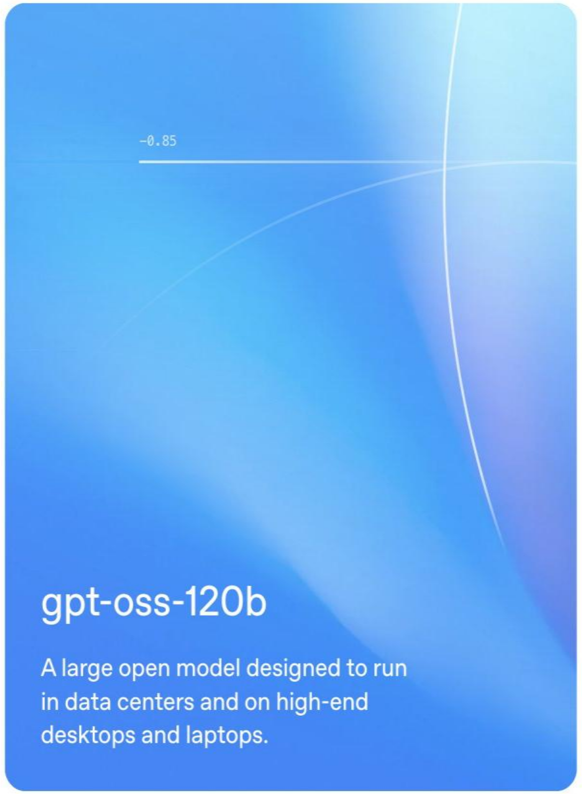
OpenAI introduces GPT-OSS

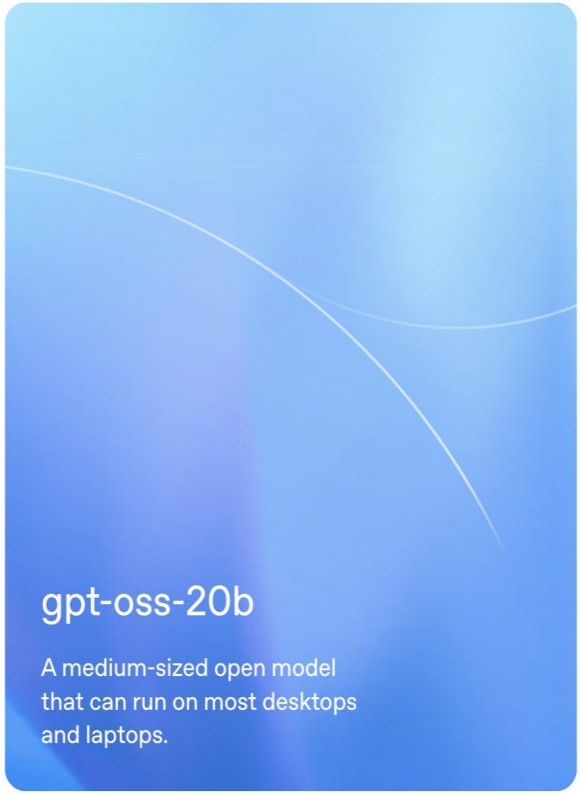
An open weights model with strong reasoning performance

Announced on August 5, 2025

OpenAI Blog

The **120B** model is on par with o4-mini on reasoning benchmarks , while running efficiently on a single 80 GB GPU





They also released a **20b** model, which shows similar performance to that of o3-mini. It only requires 16 GB of memory and can easily run on edge devices, making it ideal for local inference.

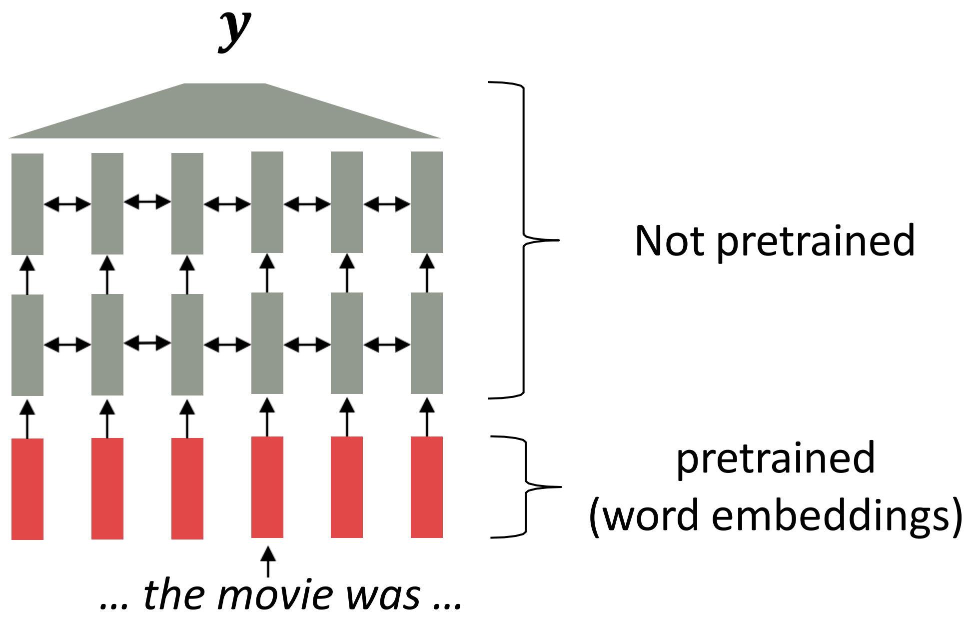
This is a huge deal, allowing people to run state-of-the-art gpt models locally on their devices

Where We Were: Pre-trained Word Vectors

Context-independent / Static

ELMO

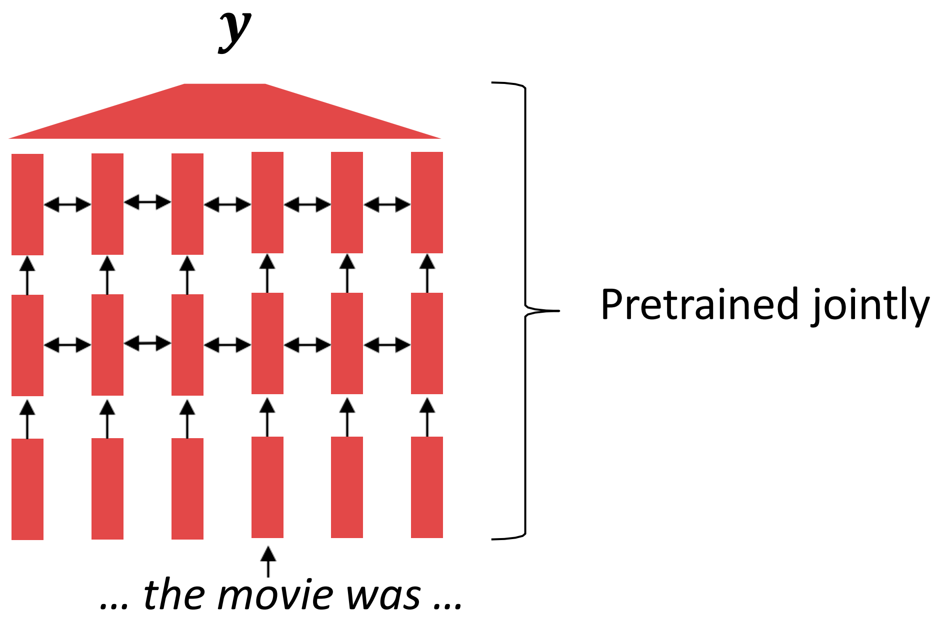
- Start with pretrained word embeddings (no context!)
- Learn how to incorporate context in an LSTM or Transformer while training on the task.
- The training data we have for our **downstream task** (like question answering) must be sufficient to teach all contextual aspects of language.
- Most of the parameters in our network **are randomly initialized**!



Pre-trained Word Vectors -> Pre-trained Models

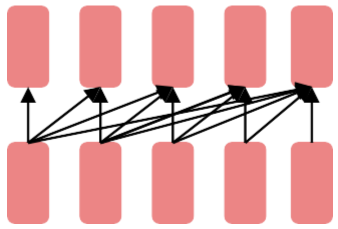
- All (or almost all) parameters in NLP networks are initialized via **pretraining**.
- Pretraining methods hide parts of the input from the model, and train the model to reconstruct those parts.

- This has been exceptionally effective at building strong:
  - **representations of language**
  - **parameter initializations** for strong NLP models.
  - **Probability distributions** over language that we can sample from



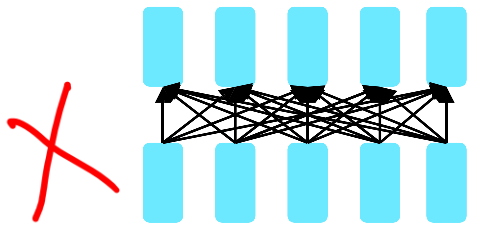
Pretraining for Three Types of Architectures

The neural architecture influences the type of pretraining, and natural use cases.



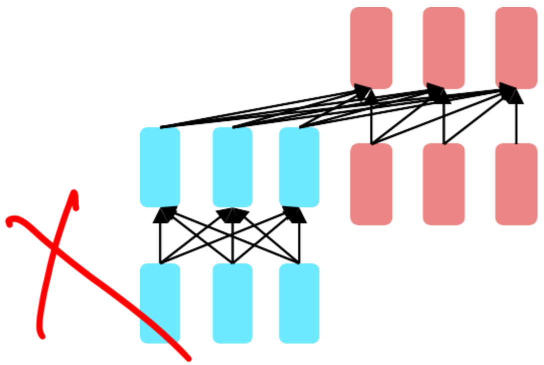
Decoders

- Language models! What we've seen so far.
- Nice to generate from; can't condition on future words



Encoders

- Gets bidirectional context – can condition on future!
- How do we pretrain them?



Encoder-Decoders

- Good parts of decoders and encoders?
- What's the best way to pretrain them?

BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

Jacob Devlin **Ming-Wei Chang** **Kenton Lee** **Kristina Toutanova**
Google AI Language
{jacobdevlin,mingweichang,kentonl,kristout}@google.com

Slides are adopted from Jacob Devlin

Self-Supervised learning

Background - Bidirectional Context

- Bidirectional context, unlike unidirectional context, takes into account both the left and right contexts.

Target Word (fruit)

Apple is my favourite fruit and I eat it all the time.

Left Context: "Apple is my favourite" | Right Context: "and I eat it all the time."

Target Word (brand)

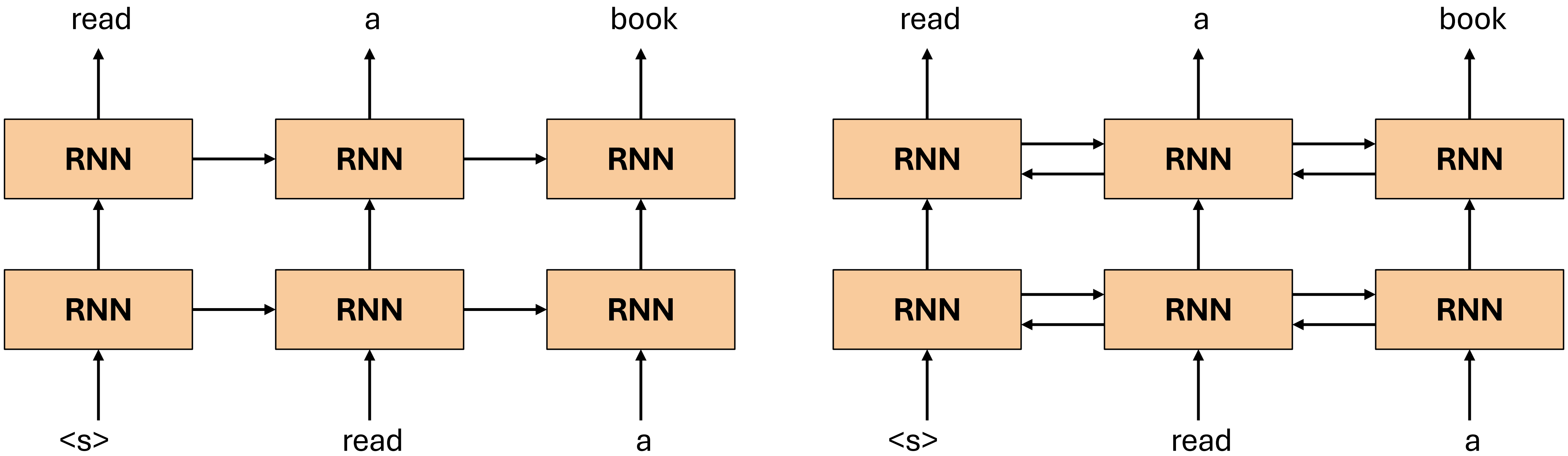
Apple is my favourite brand for buying laptop and other gadgets.

Left Context: "Apple is my favourite" | Right Context: "for buying laptop and other gadgets."

Motivation

- **Problem with previous methods:**
  - Language models only use left context or right context.
  - But language understanding is **bidirectional**.
- **Possible Issue:**
  - Directionality is needed to generate a well-formed probability distribution.
  - Words can see themselves in a bidirectional model.

Unidirectional vs. Bidirectional Models



Unidirectional **Bidirectional**

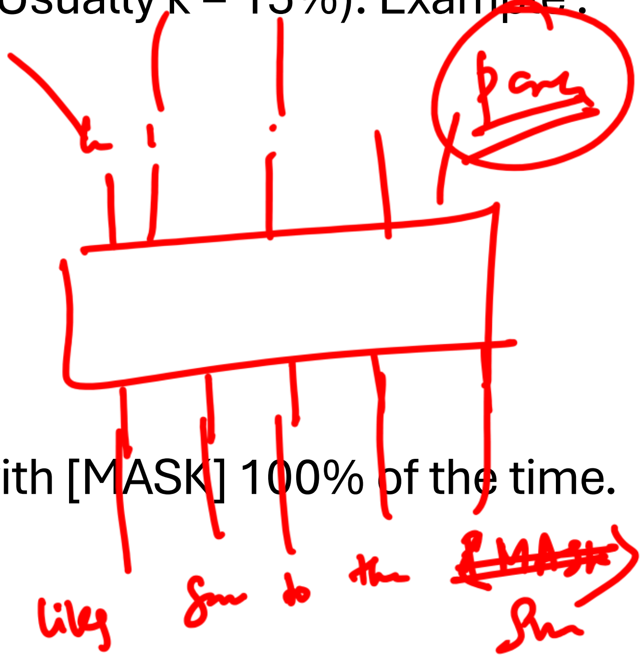
Masked Language Modelling

- Mask out k% of the input words, and then predict the masked words (Usually k = 15%). Example :

I like going to the [MASK] in the evening

↓

park



  - Too little masking: Too expensive to train
  - Too much masking: Not enough context
- The model needs to predict 15% of the words, but we don't replace with [MASK] 100% of the time. Instead:
  - 80% of the time, **replace with [MASK]**
    - Example : like going to the park → like going to the [MASK]
  - 10% of the time, **replace random word**
    - Example : like going to the park → like going to the store
  - 10% of the time, **keep same**
    - Example : like going to the park → like going to the park

Next Sentence Prediction

- To learn relationships between sentences, predict whether Sentence B is actual sentence that proceeds Sentence A, or a random sentence.

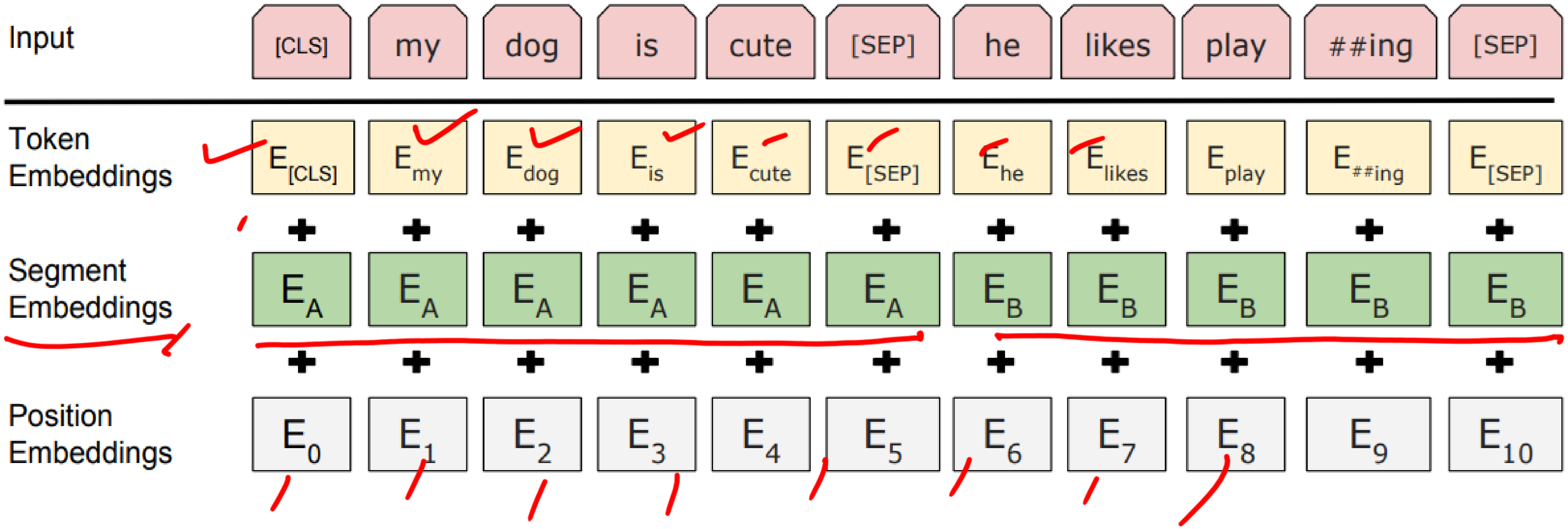
Input = [CLS] I enjoy read [MASK] book ##s [SEP]
I finish ##ed a [MASK] novel [SEP]
Label = IsNext

Input = [CLS] I enjoy read ##ing book [MASK] [SEP]
The dog ran [MASK] the street [SEP]
Label = NotNext

- Important for many important downstream tasks such as Question Answering (QA) and Natural Language Inference (NLI)
- How to choose sentences A and B for pretraining?
  - 50% of the time B is the actual next sentence that follows A (labeled as IsNext)
  - 50% of the time it is a random sentence from the corpus (labeled as NotNext)

Input Representation

- Use 30,000 WordPiece vocabulary on input.
- For a given token, its input representation is constructed by summing the token embeddings, the segmentation embeddings and the position embeddings.



Source of Image : BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding (Devlin et al., NAACL 2019)

Training Details

- Data: Wikipedia (2.5B words) + BookCorpus (800M words)
- Batch Size: 131,072 words (1024 sequences * 128 length or 256 sequences * 512 length)
- Training Time: 1M steps (~40 epochs)
- Optimizer: AdamW, 1e-4 learning rate, linear decay
- BERT-Base: 12-layer, 768-hidden, 12-head
- BERT-Large: 24-layer, 1024-hidden, 16-head
- Trained on 4x4 or 8x8 TPU slice for 4 days

Fine-Tuning Procedure