Deep Learning
MSDS 631

Attention and the Transformer

Michael Ruddy

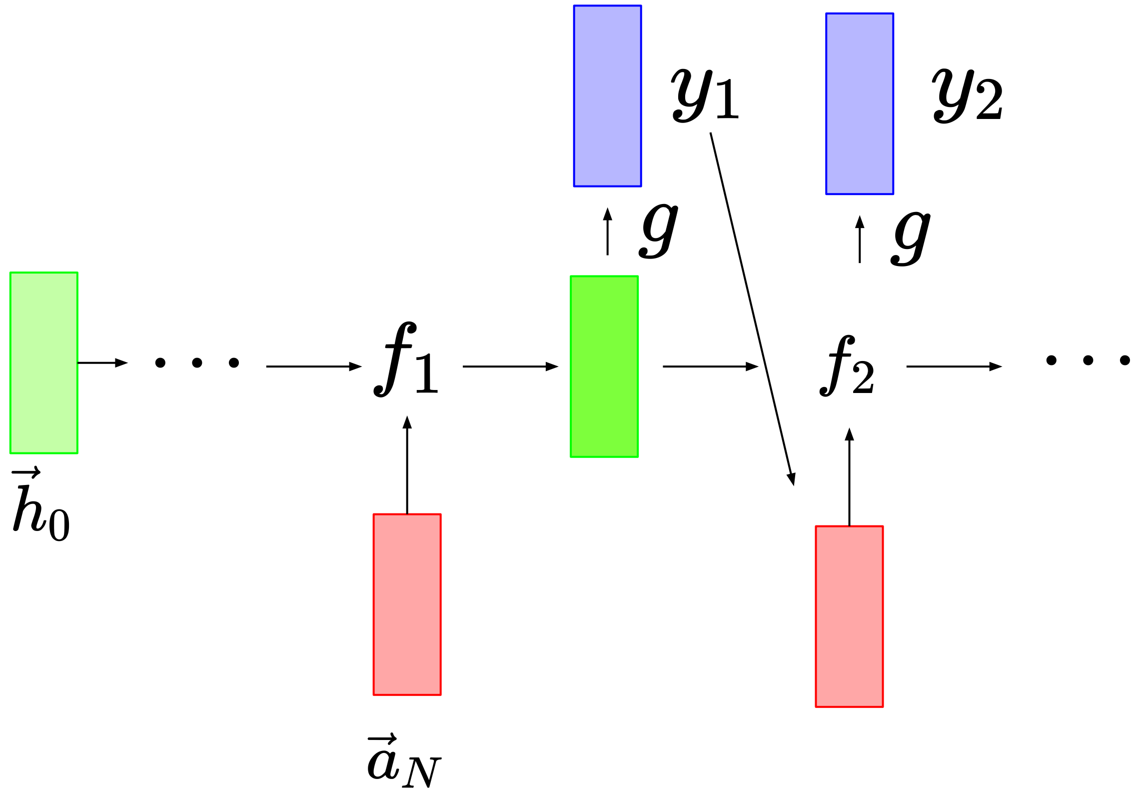
Questions?

- From last lecture?
- From the homework?

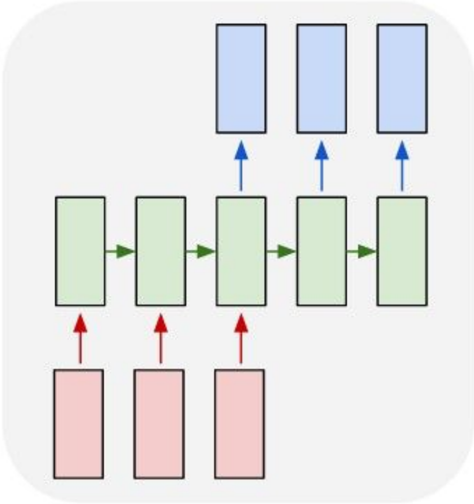
Overview

- Attention
- The Transformer
- BERT

Seq2Seq Models

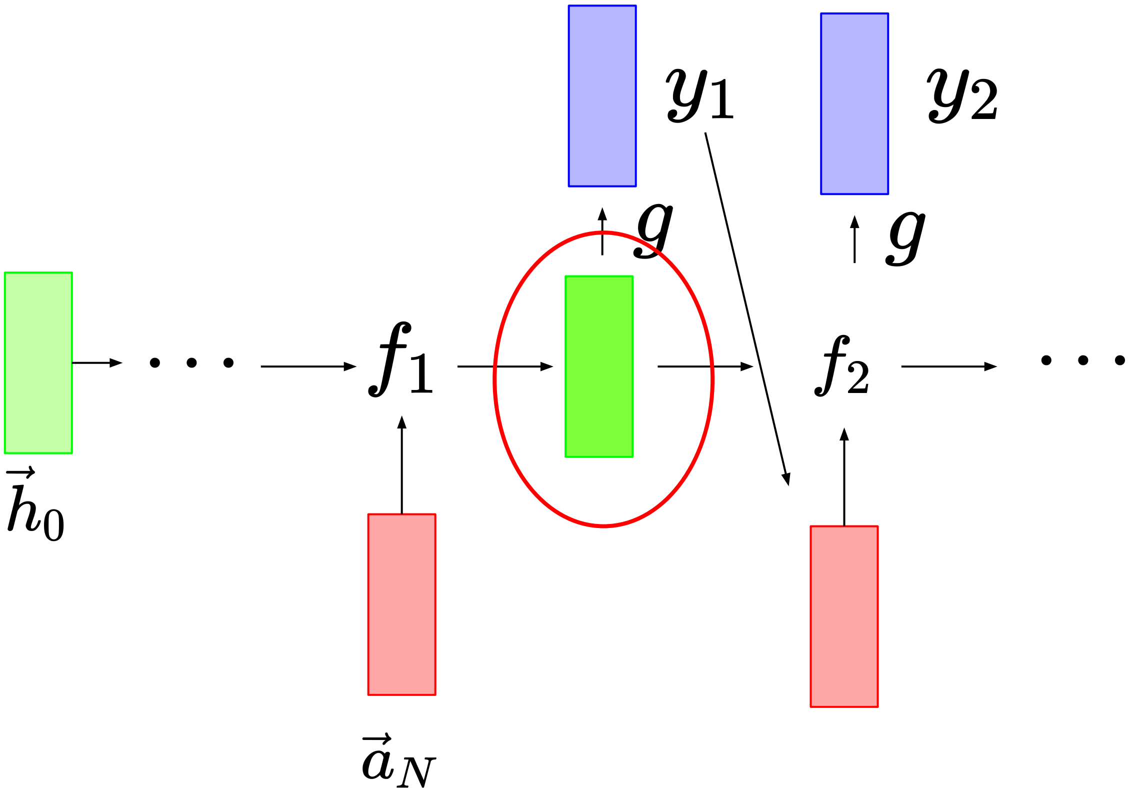


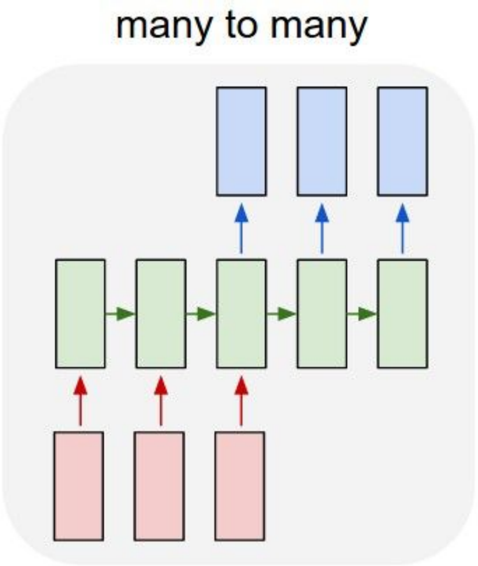
many to many



Seq2Seq Models

- Information Bottleneck!

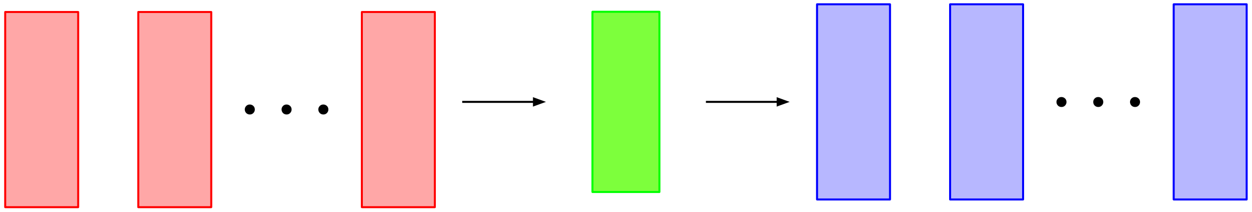




Problems with translation

- Have to encode a full sentence into one vector

Ich muss auf den Markt gehen. → I must go to the Market.



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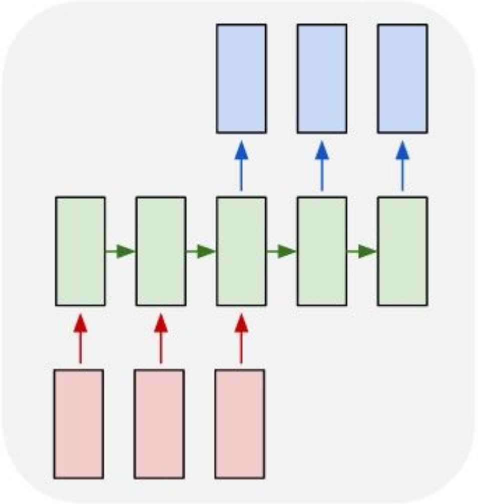

Attention

- Use the hidden states generated by the encoder RNN.
- In each decoding step, weight the hidden states (attention mechanism) and use the weighted sum to predict the next element.

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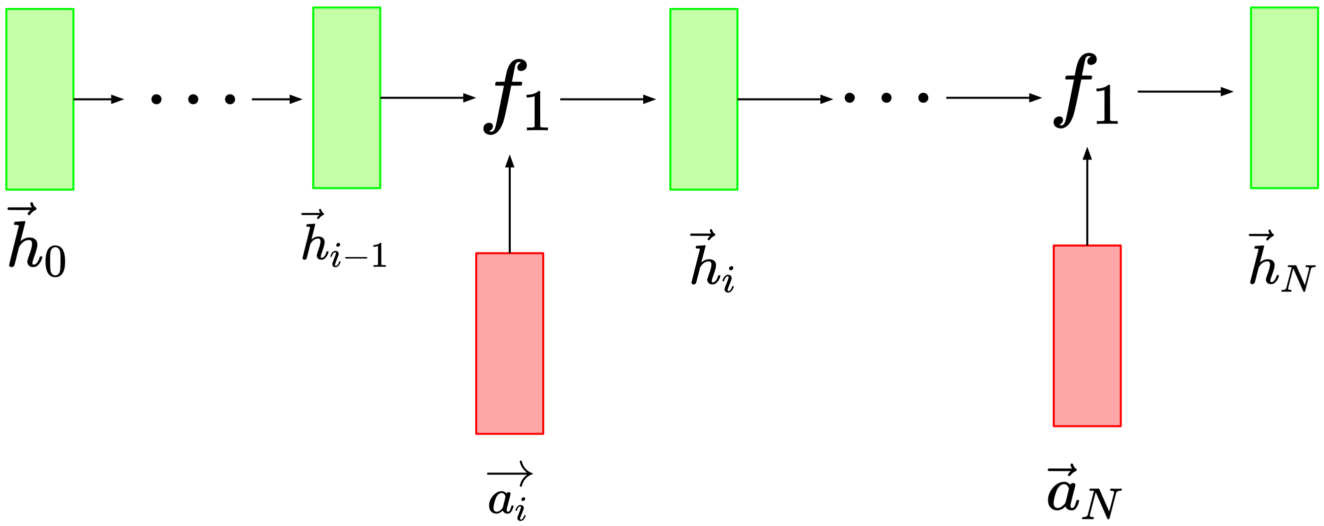

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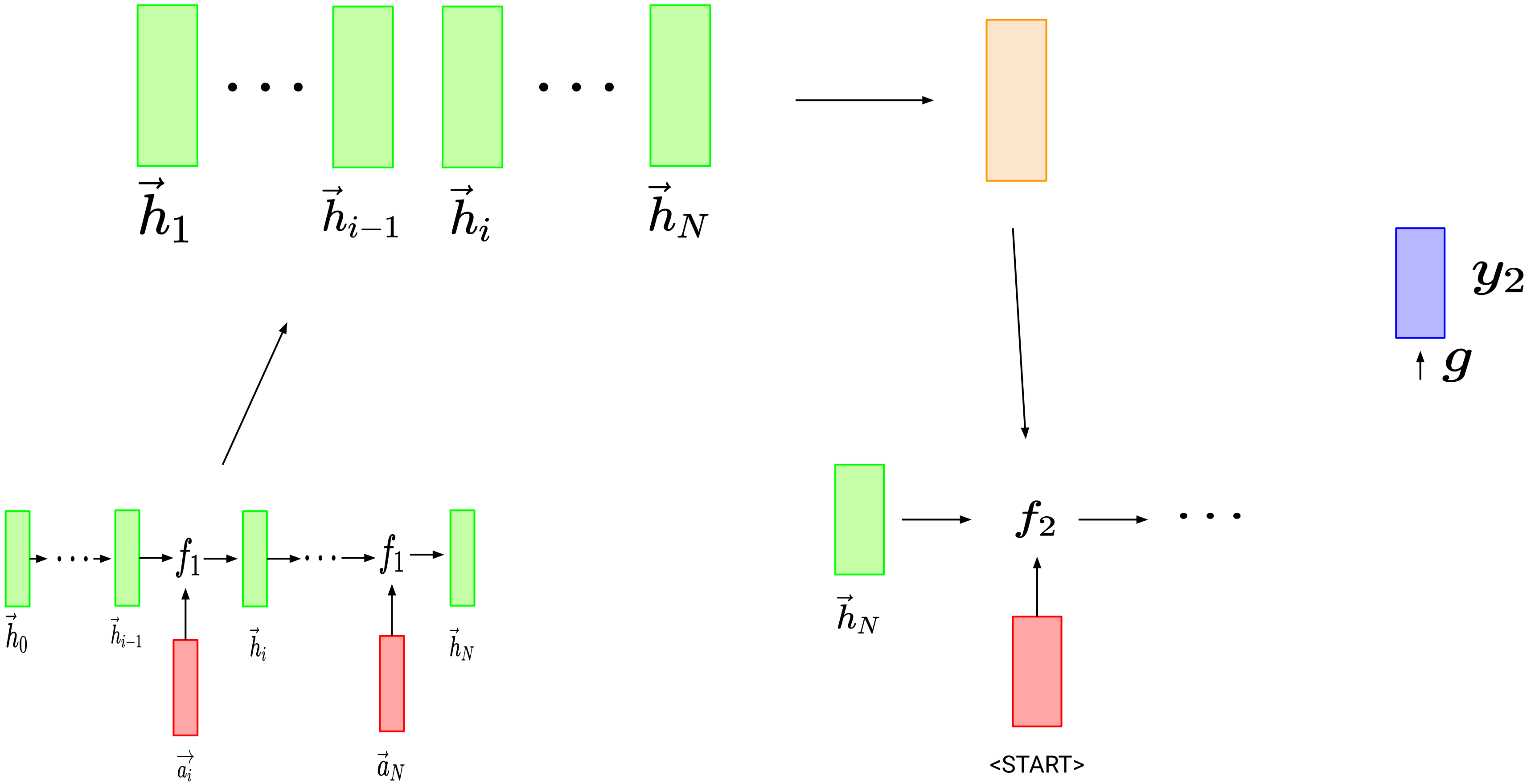
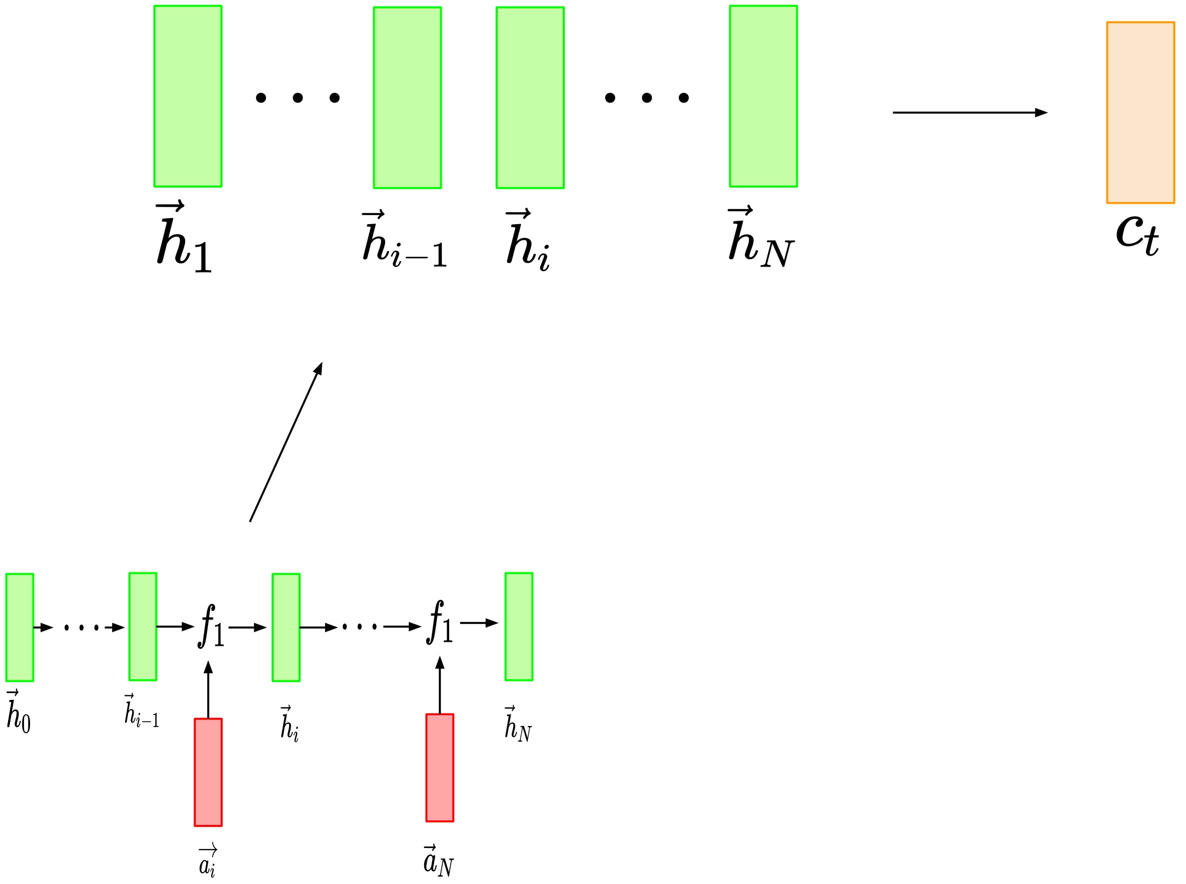

$\vec{h}_1$ ... $\vec{h}_{i-1}$ $\vec{h}_i$ ... $\vec{h}_N$
y_2
g
$\vec{h}_0$ ... $\vec{h}_{i-1}$ f_1 $\vec{h}_i$ ... f_1 $\vec{h}_N$
$\vec{a}_i$
$\vec{a}_N$
$\vec{h}_N$ f_2 ...
<START>

Attention

Context Vector

$$\sum_{i=1}^{N} \alpha_i^t h_i = c_t$$

$$\sum_{i=1}^{N} \alpha_i^t = 1$$



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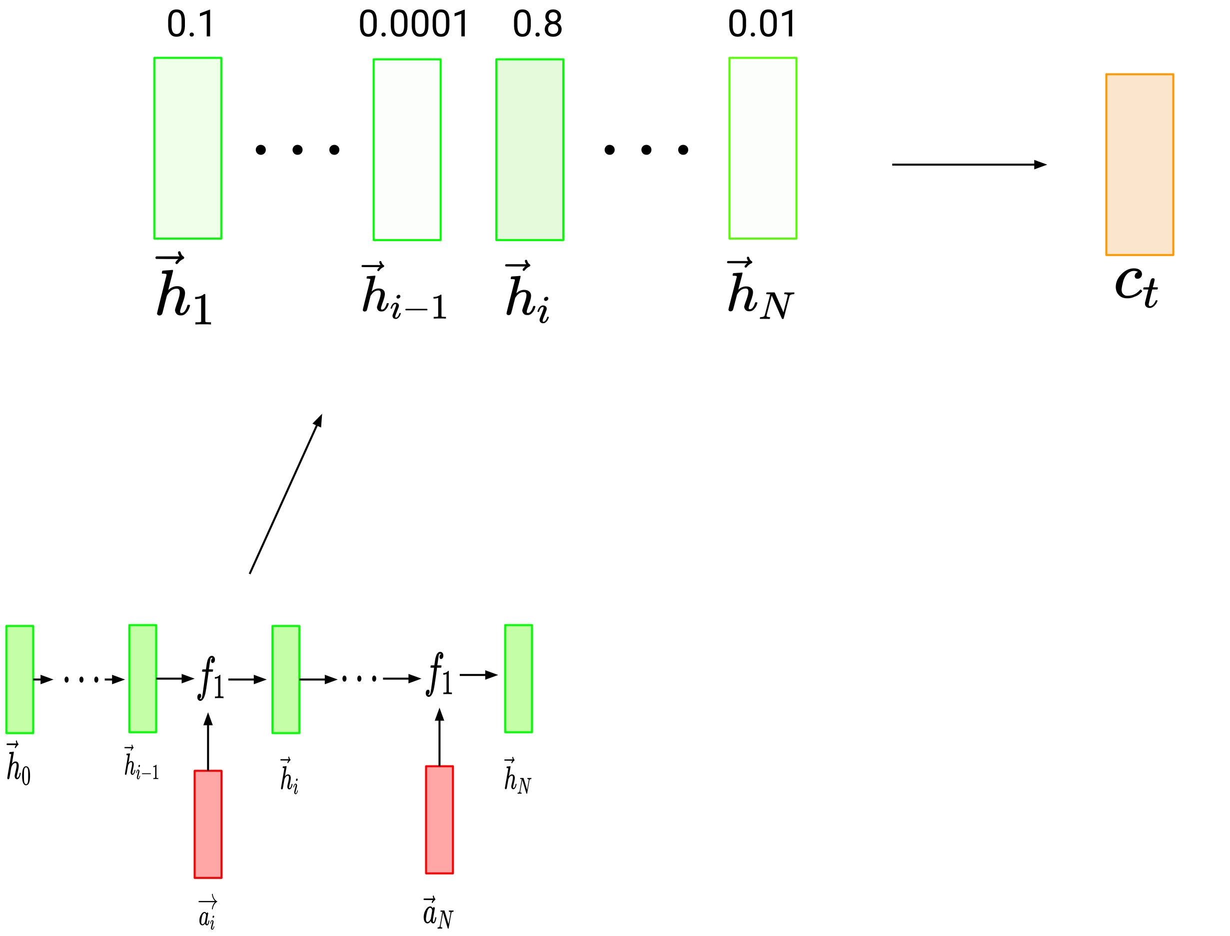

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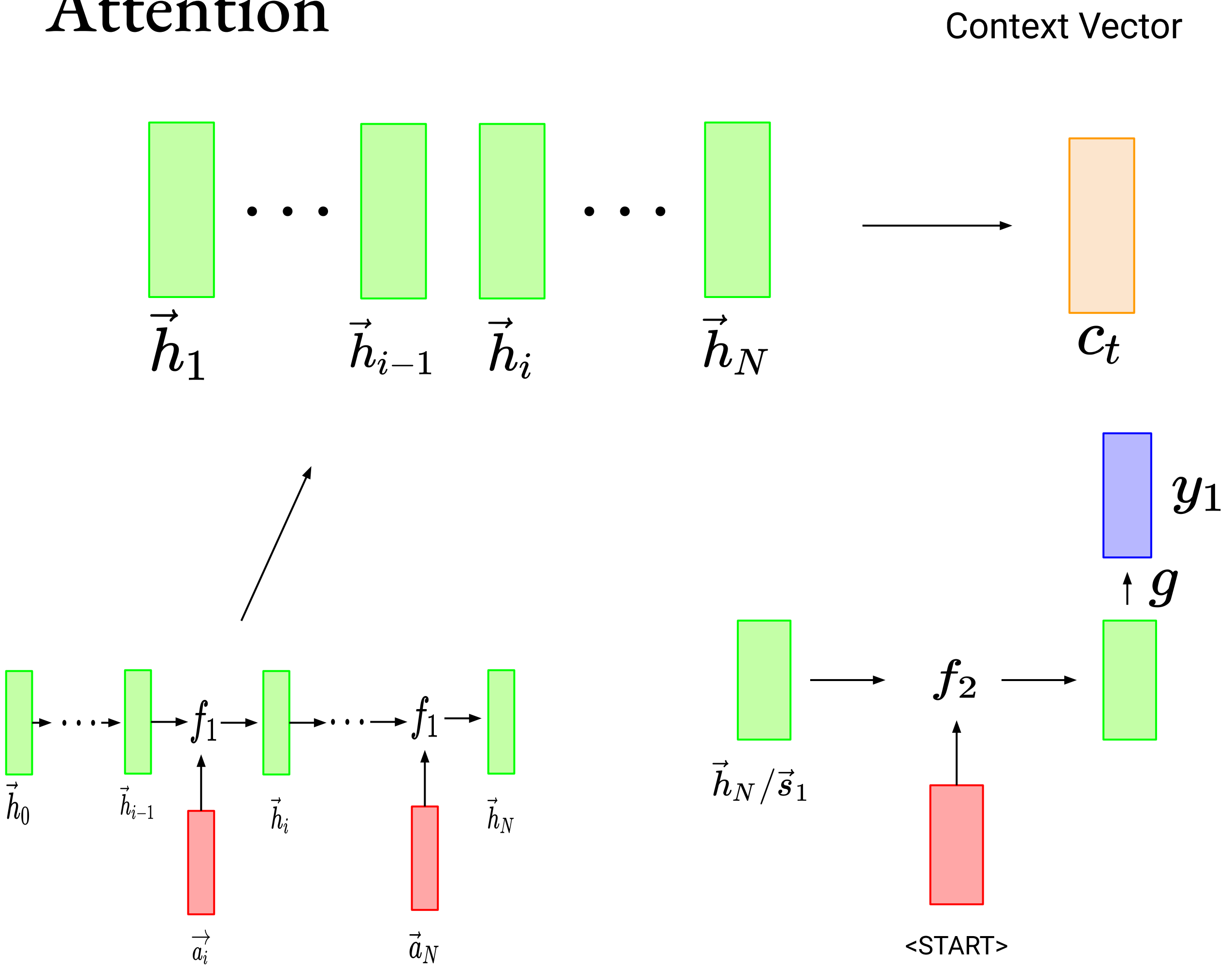

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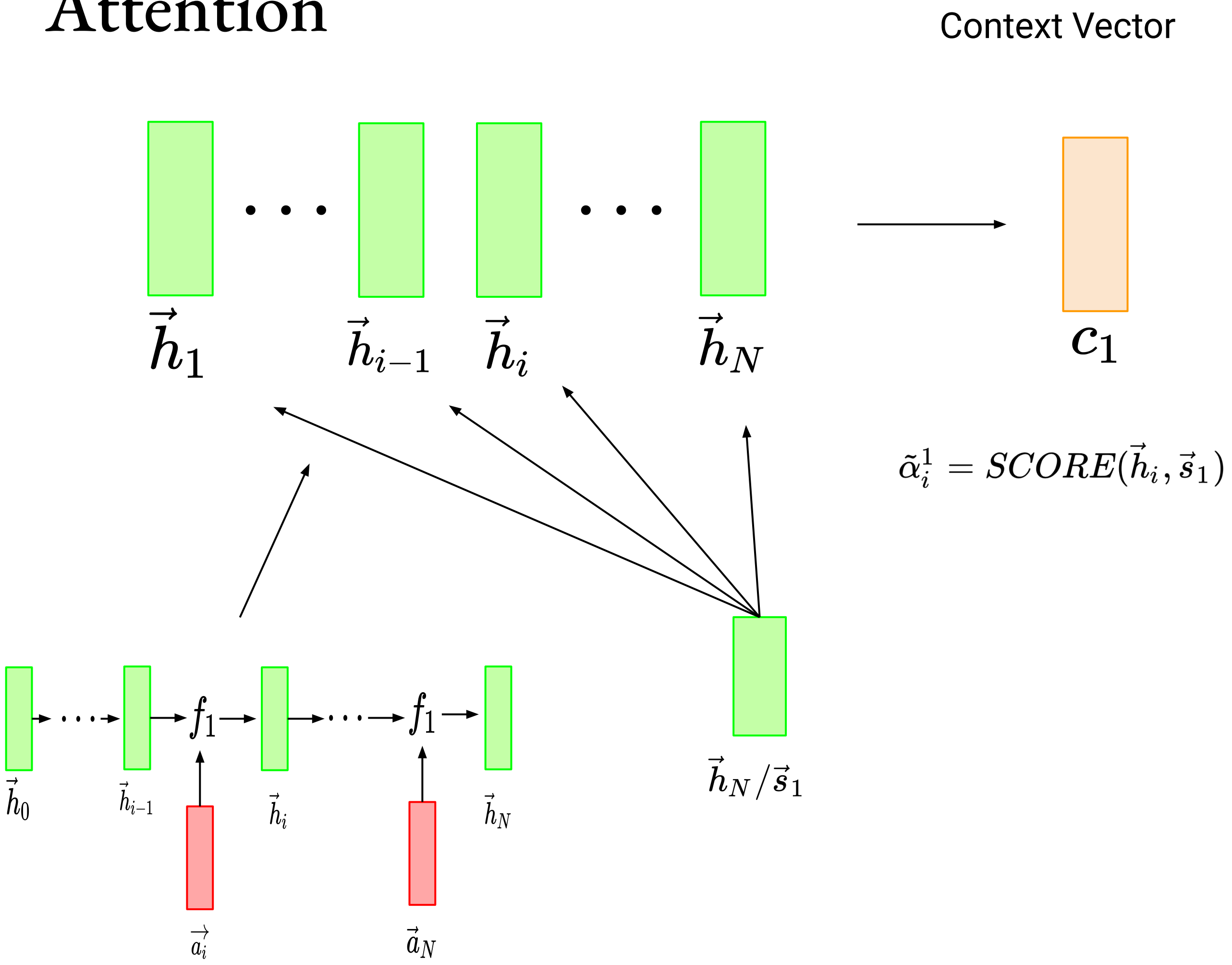

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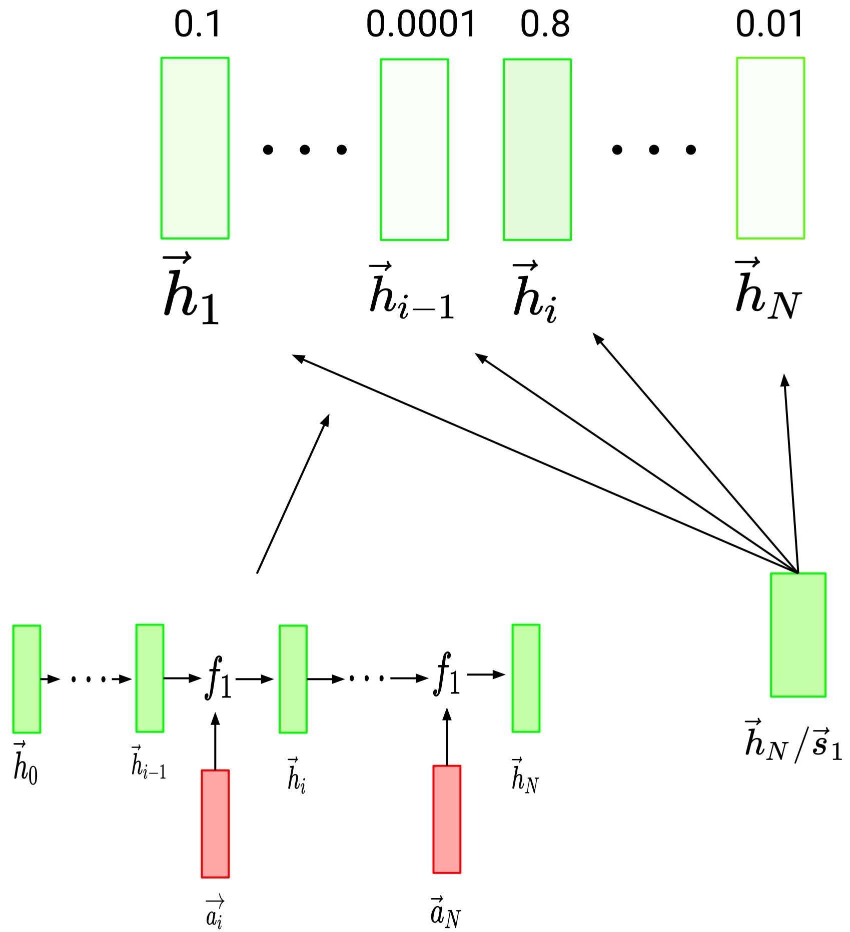

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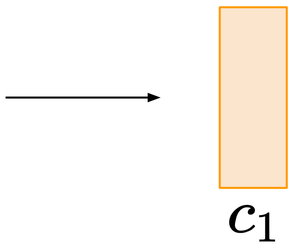

$$\tilde{\alpha}_i^1 = SCORE(\vec{h}_i, \vec{s}_1)$$

Softmax

$$\alpha_i^1 = \frac{\exp(\tilde{\alpha}_i^1)}{\sum_{j=1}^{N} \exp(\tilde{\alpha}_j^1)}$$

Attention

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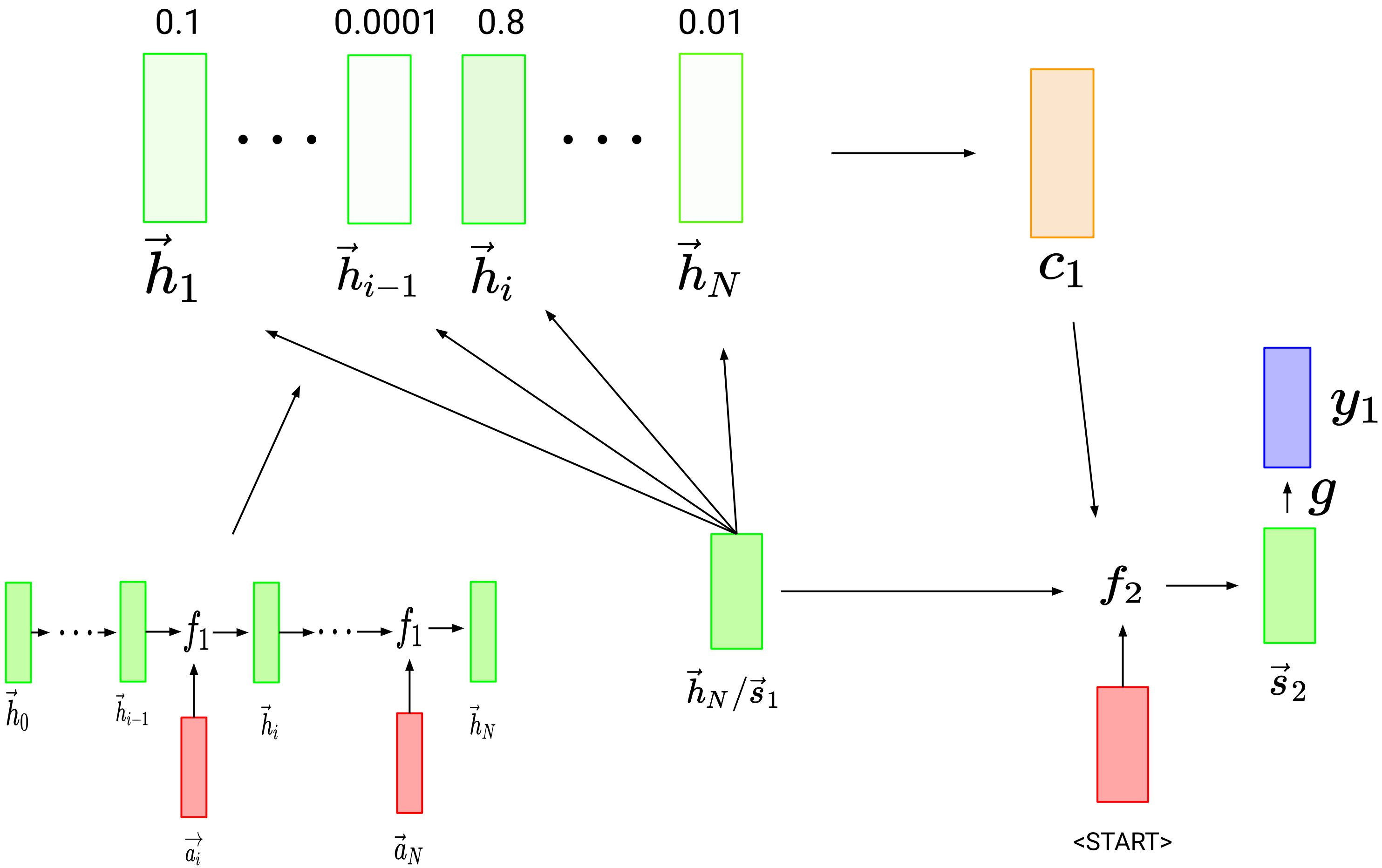

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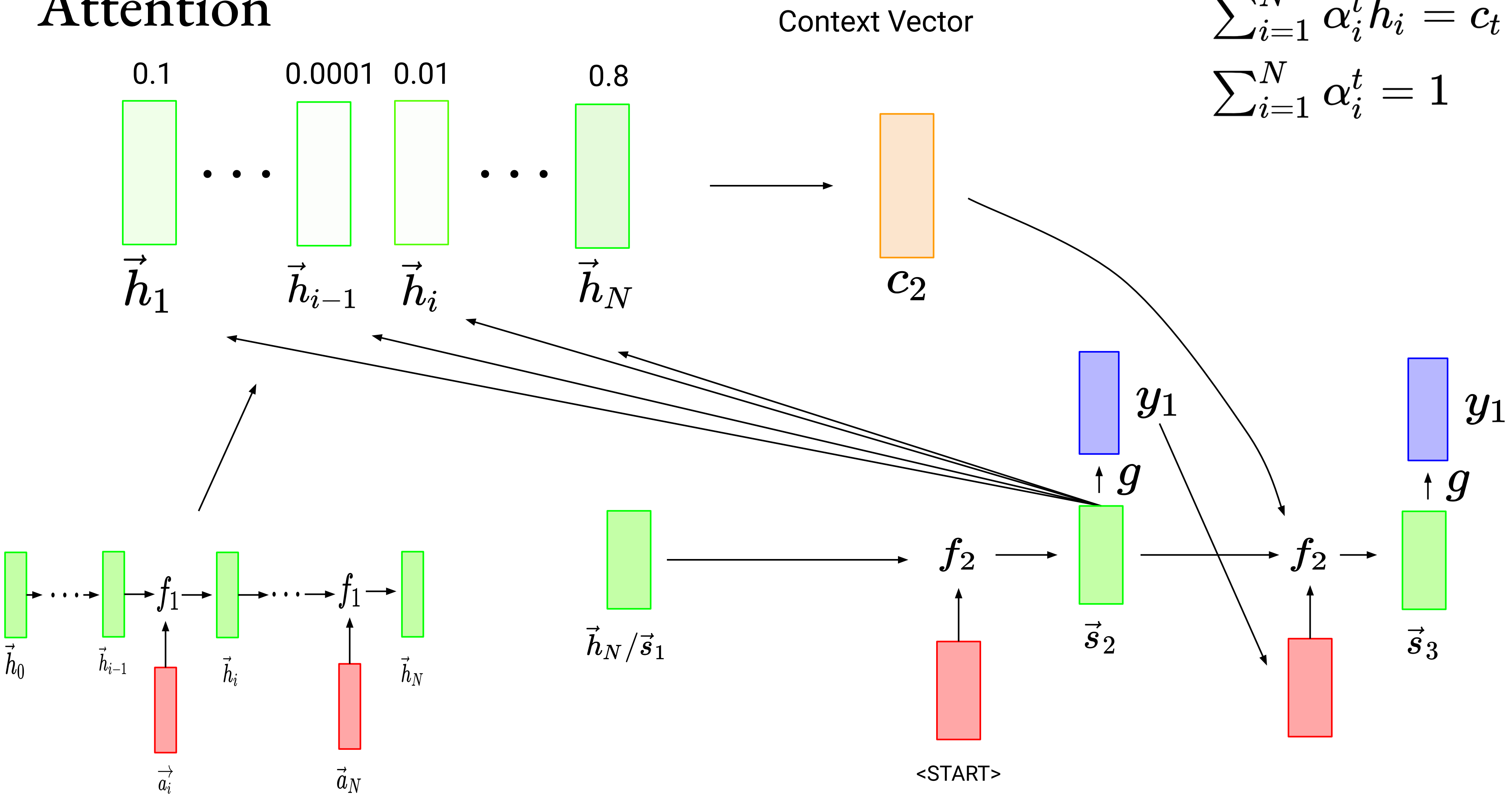

Attention

- The Attention Score function can be as simple as: $\vec{s}_t \cdot \vec{h}_i$
- Or a weight matrix can be introduced: $\vec{s}_t \cdot W_a \vec{h}_i$
    - (More can be found here)

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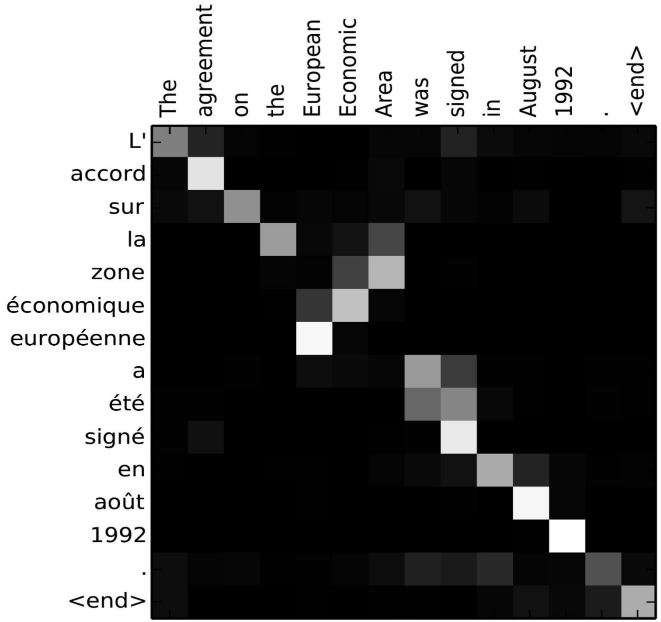

Bahdanau et al., 2015

- Attention Matrix
- Introduces some *Explainability*.

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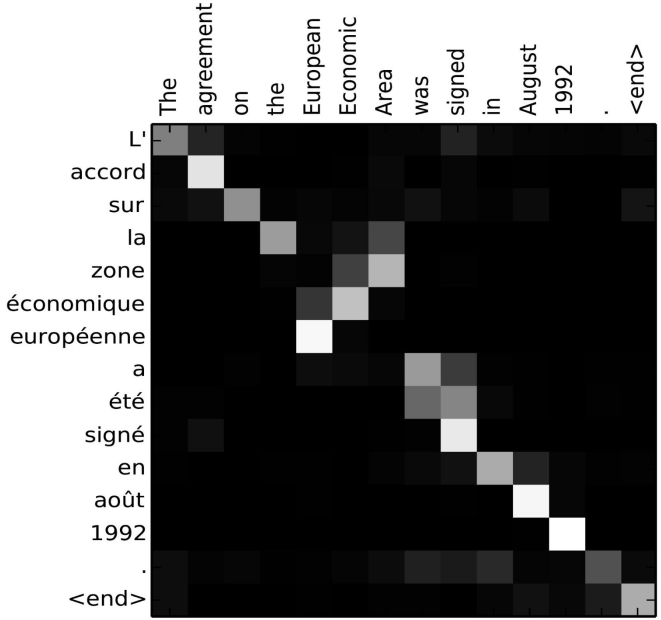
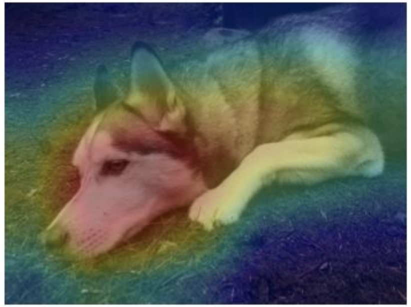


Bahdanau et al., 2015

- Attention Matrix
- Introduces some *Explainability*.

Just because you pay attention to the right thing doesn't mean you are paying attention for the right *reason*.

	Test Image	Evidence for Animal Being a Siberian Husky	Evidence for Animal Being a Transverse Flute
Explanations Using Attention Maps			

Stop Explaining Black Box Machine Learning Models for High Stakes Decisions and Use Interpretable Models Instead
By Cynthia Rudin 2018
link

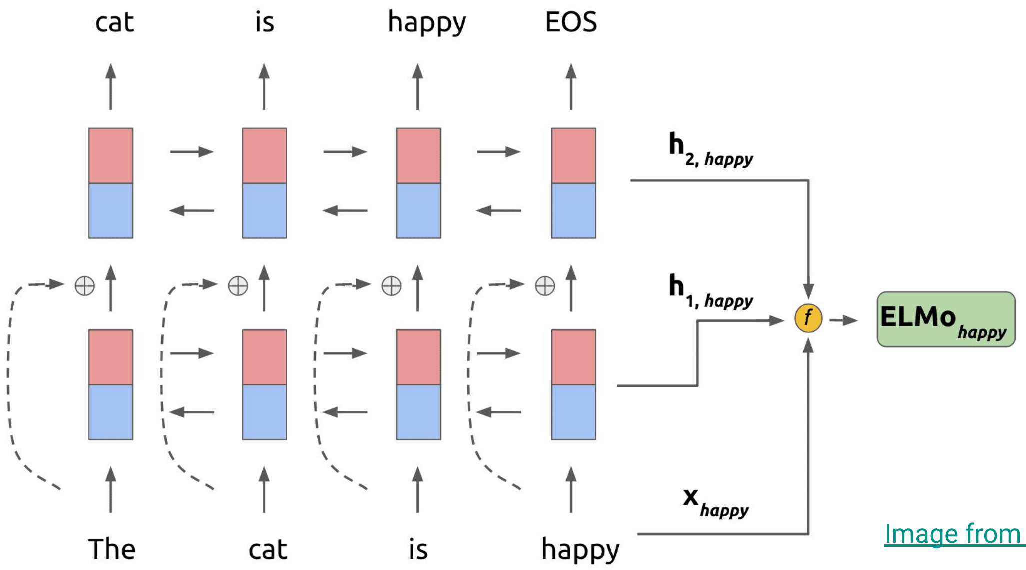
Just because you pay attention to the right thing doesn't mean you are paying attention for the right *reason*.

Contextual Word Embeddings

- What about homonyms?
    - He took a *train*.
    - He likes to *train* in the mornings.

Contextual Word Embeddings

- ELMo: Embeddings from Language Models
    - Trained on self-supervised task such as predict the next word or Part of Speech tagging
    - Creates contextual word embeddings



Idea: Stack bi-directional LSTMs to produce multiple embeddings of words that use the context.

- (Can get more complicated, but that's the core)

Image from here

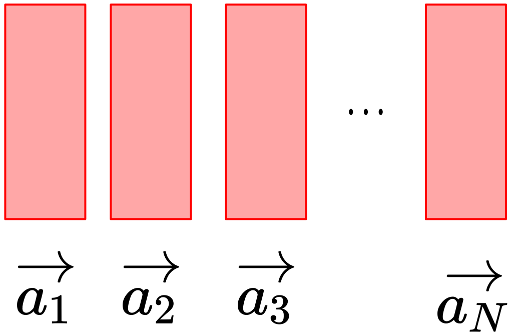
Self-Attention

- Goal: Only use Attention mechanism to encode a sequence of tokens.
  - Generate contextual embeddings of the tokens without RNNs!

Self-Attention

$$W_Q, W_K, W_V$$

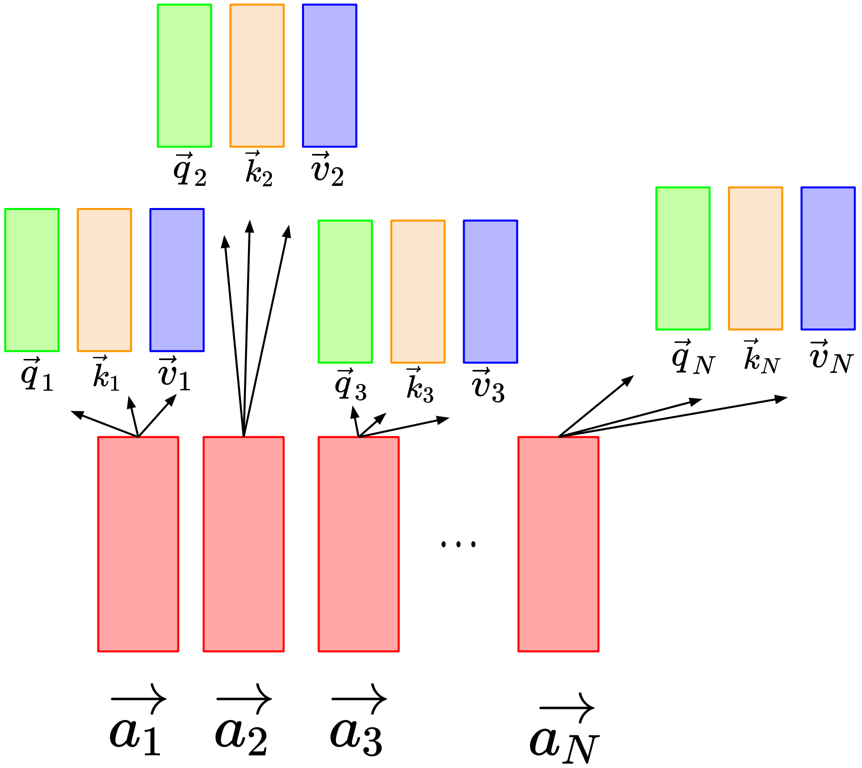
- Initial Embeddings
- 3 weight matrices: Query, Key Value



Self-Attention

W_Q, W_K, W_V

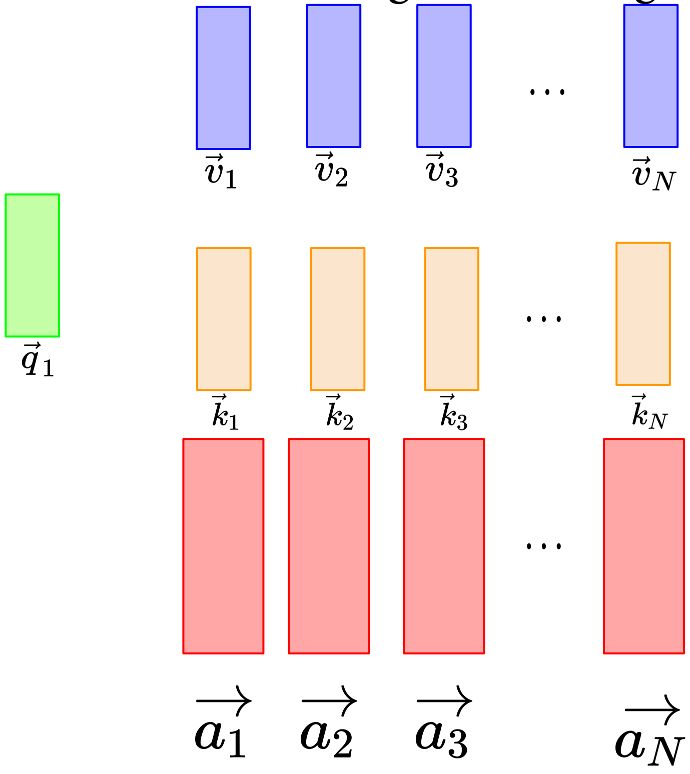
- Each token gets a Query, Key, and Value vector.



Self-Attention

$$W_Q, W_K, W_V$$

- For each vector we use *its query* to explore *all the keys* which generate weights.
- The resulting embedding is the weighted sum of all the value vectors.



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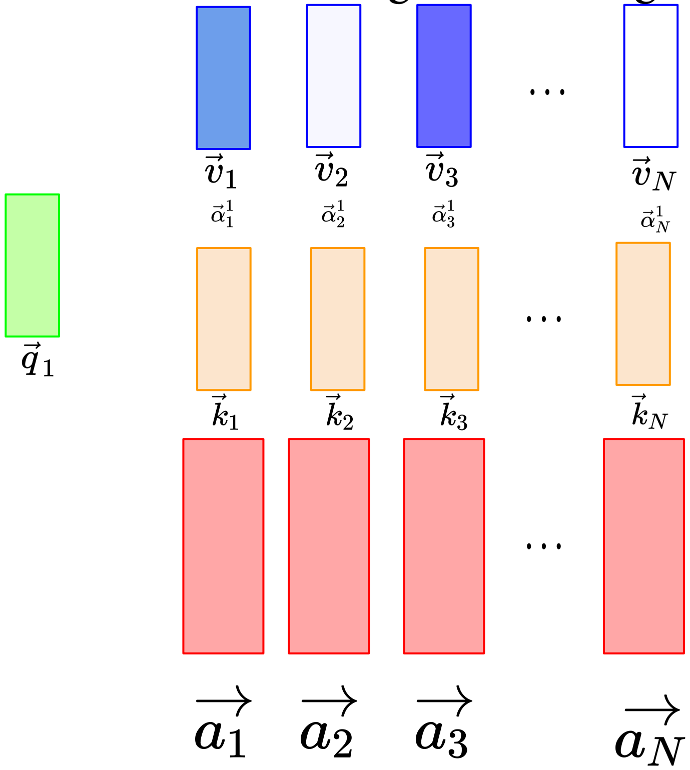

- We first take the dot product of q1 with every key vector.
- We get the weights by using a softmax layer.
- Sometimes there is a constant multiplier in there as well (for stability purposes)

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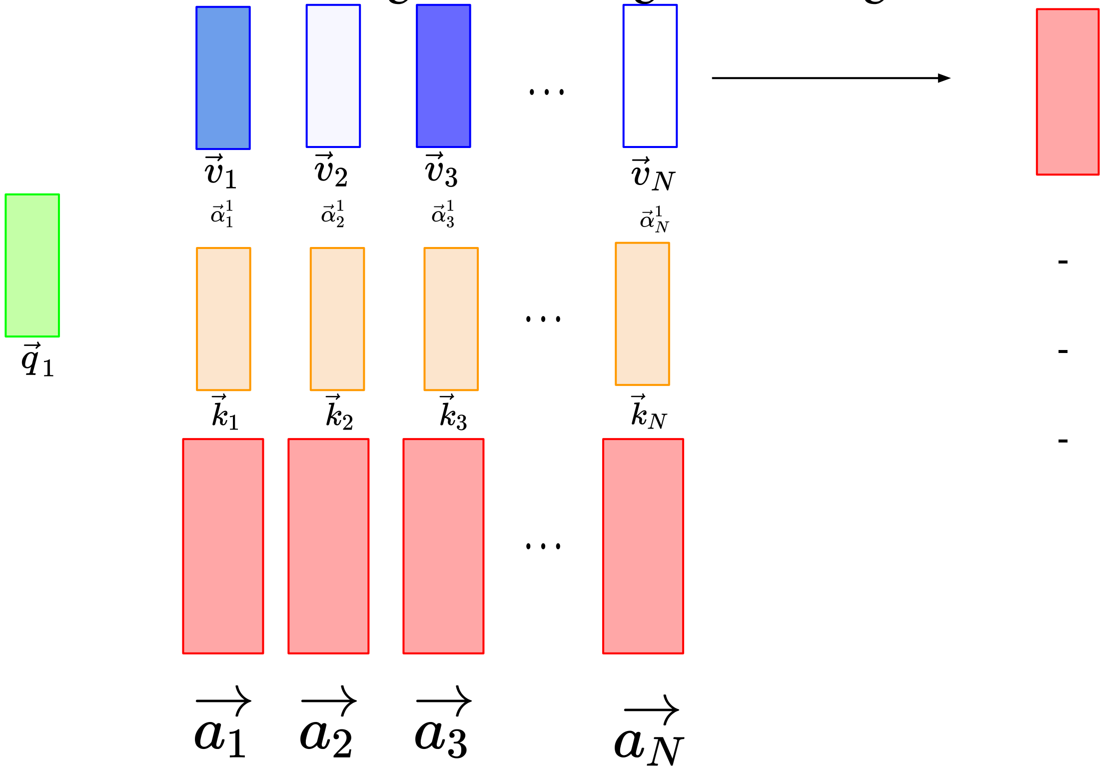

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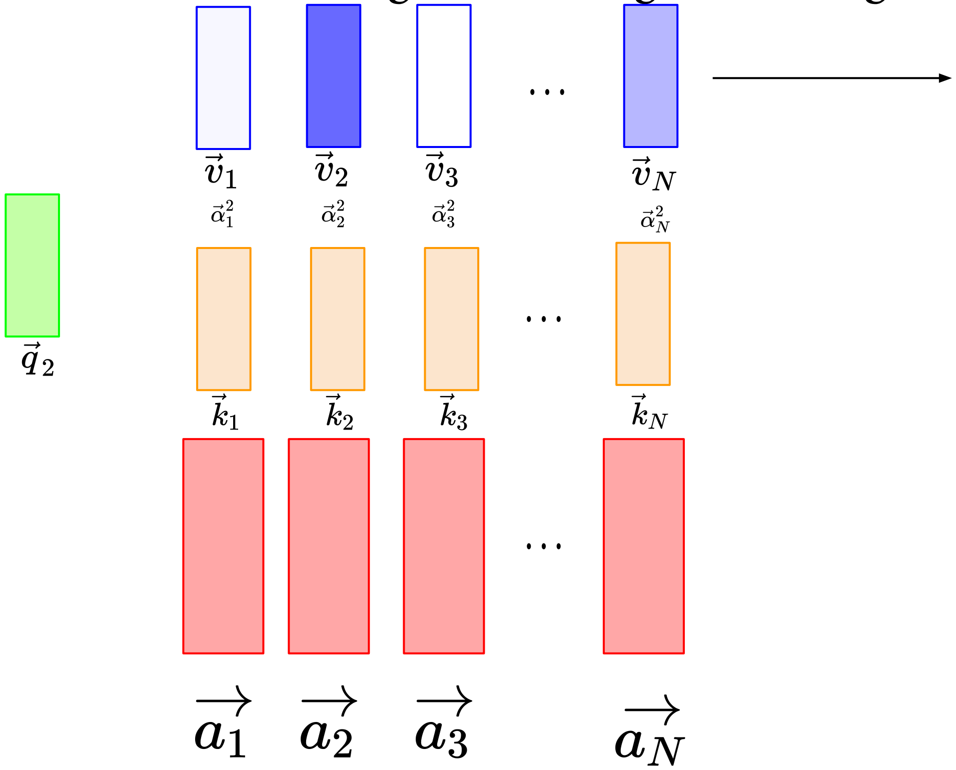

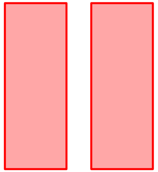

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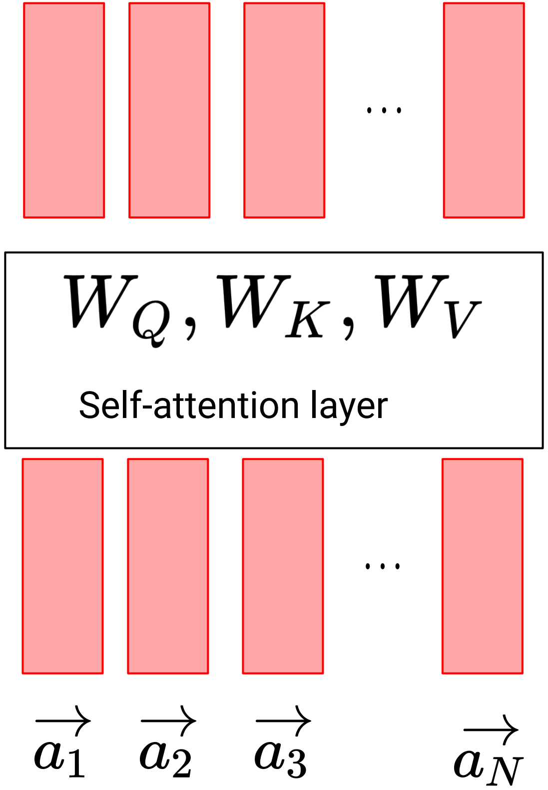
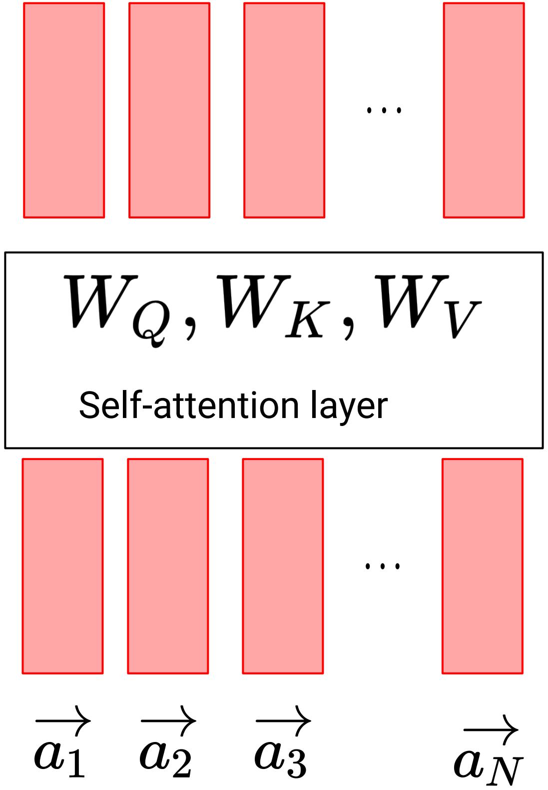
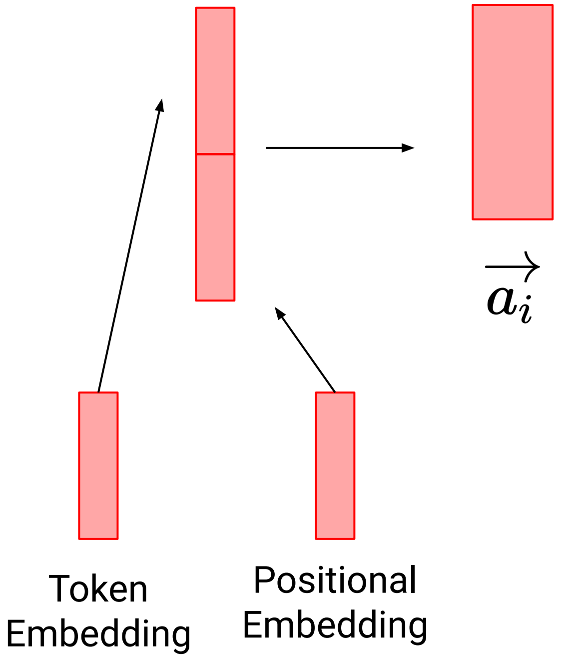
- Contextual Embeddings!



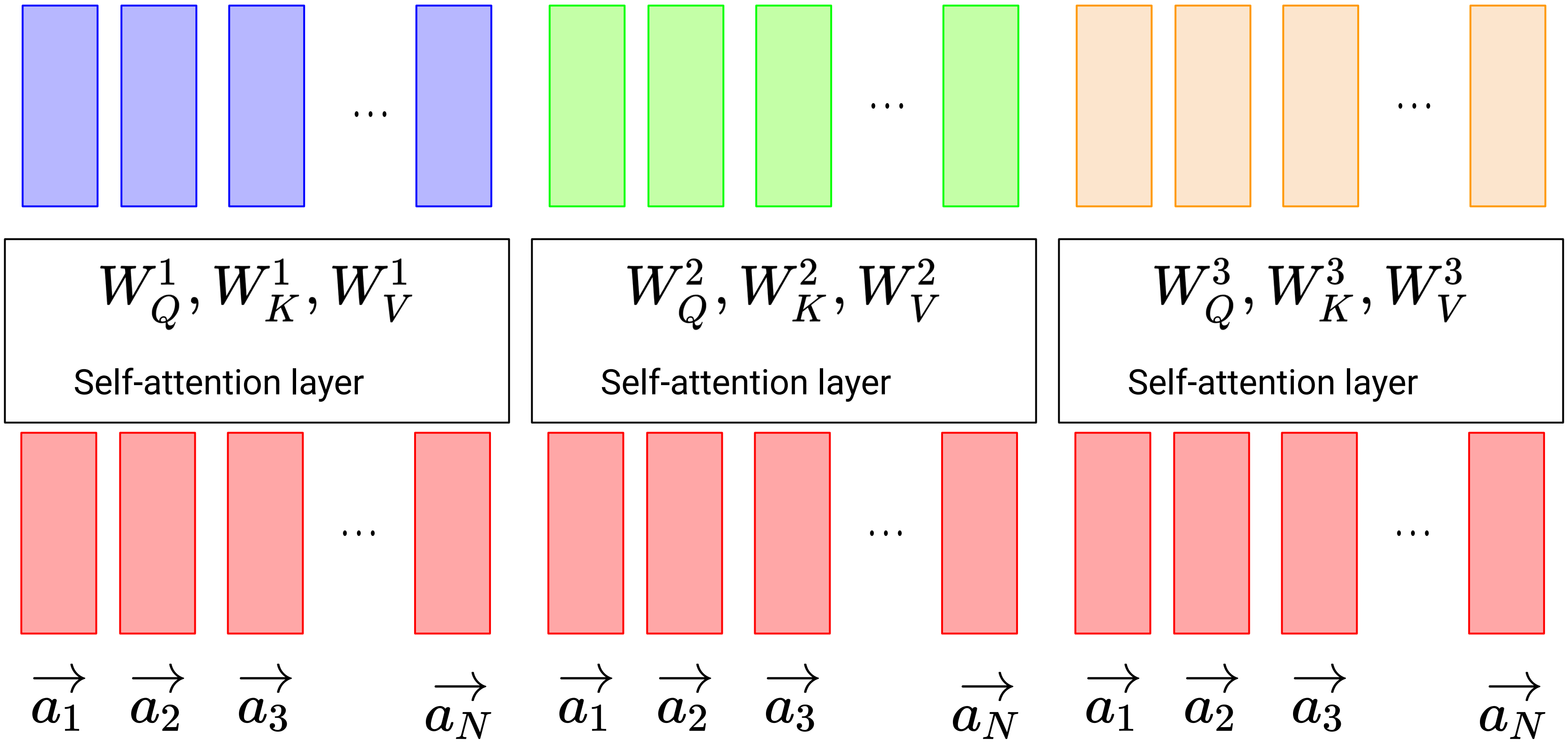
Self-Attention

- Sequence Agnostic! Often Positional Embeddings are added here as well.





Multi-Head Attention



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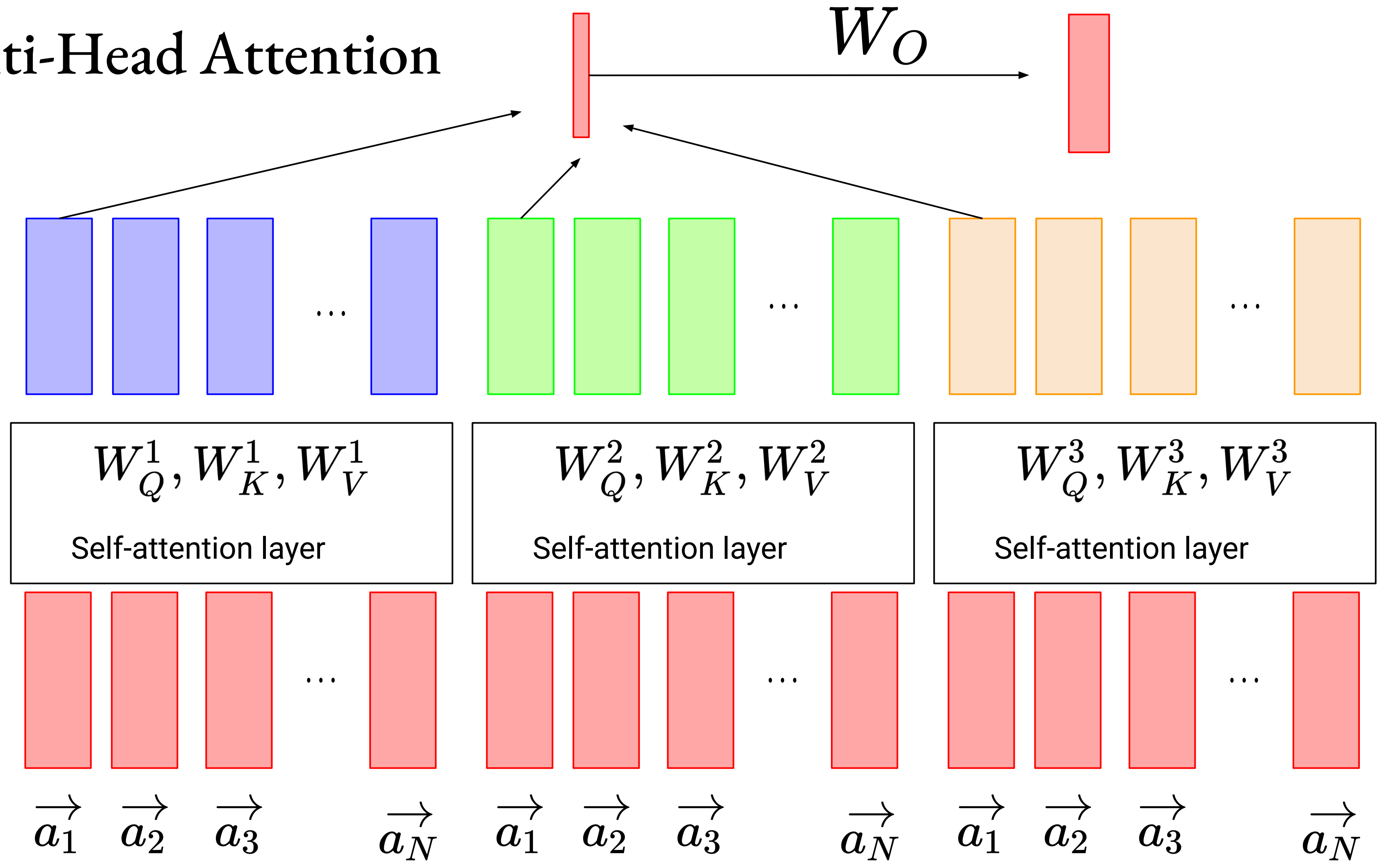

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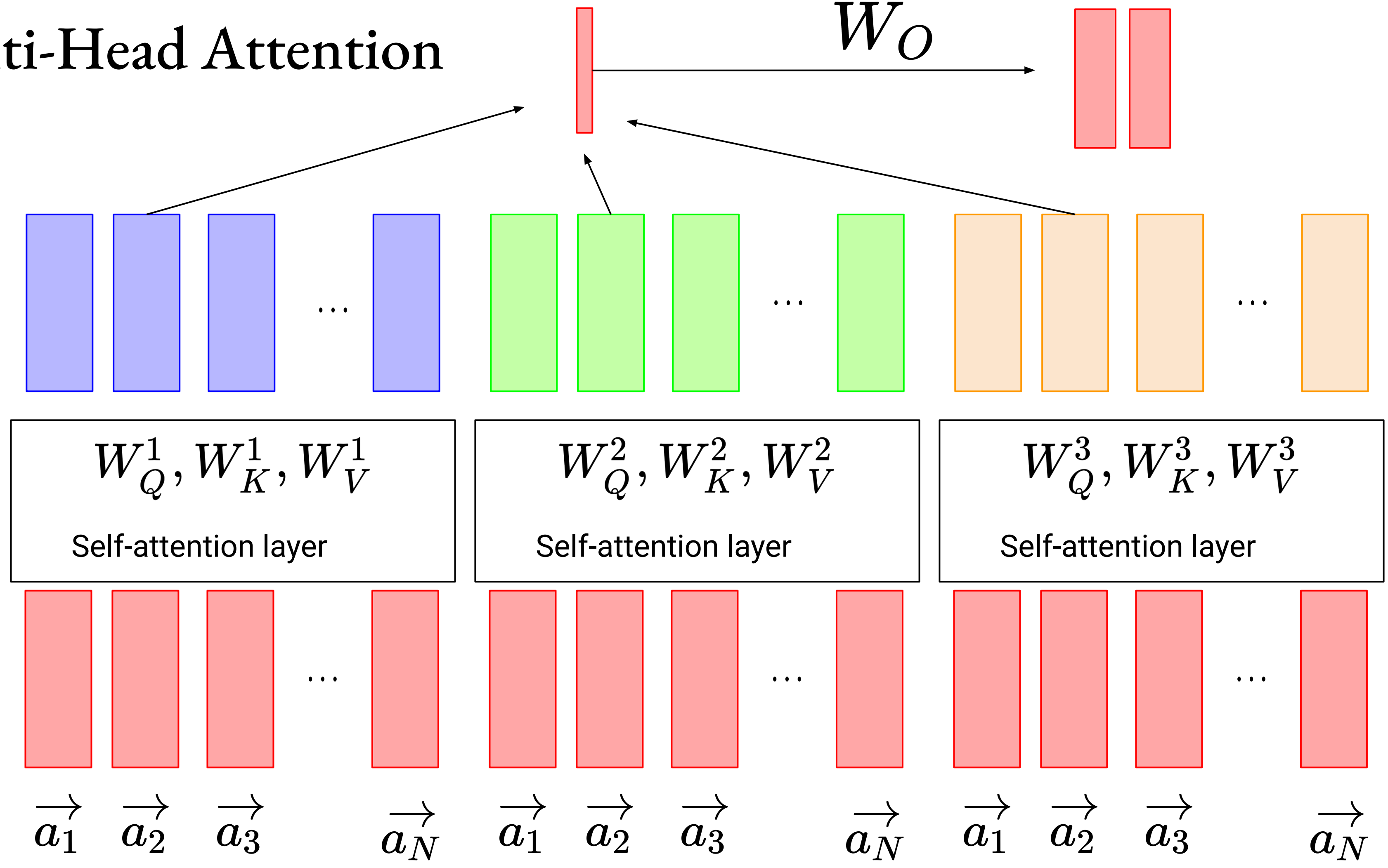

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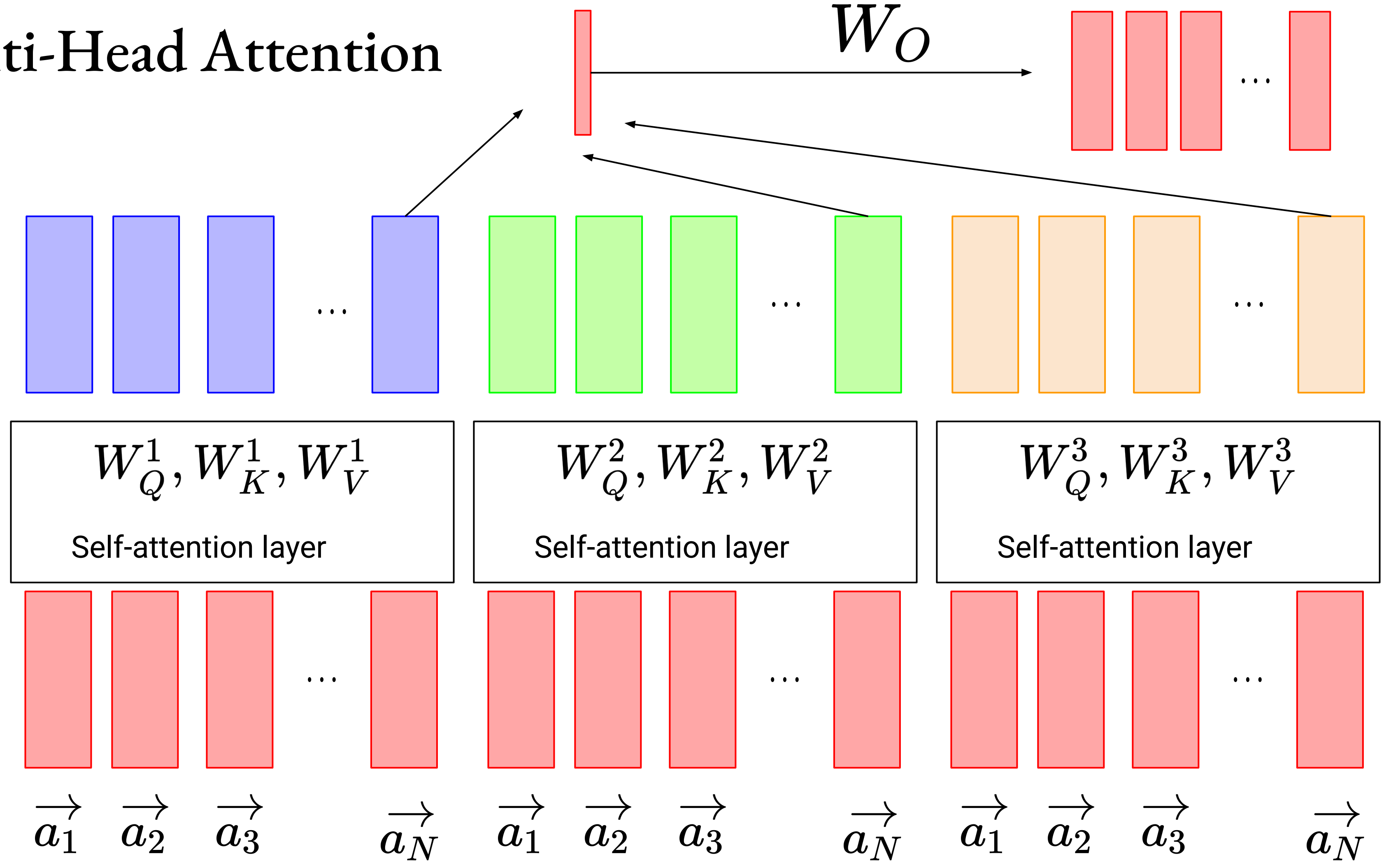
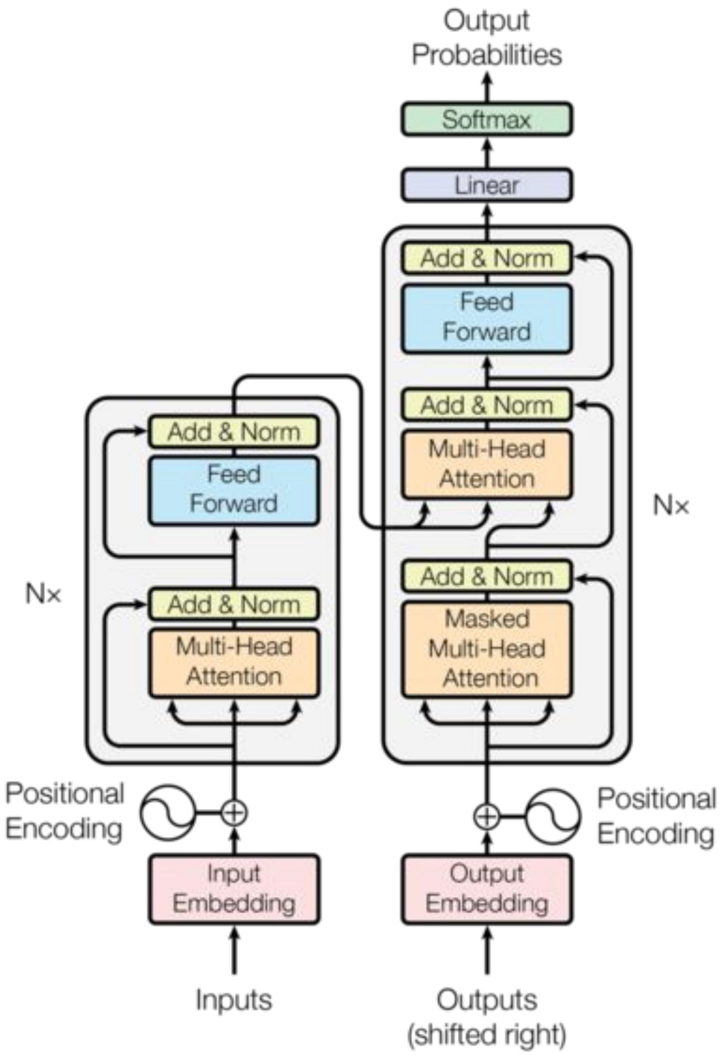


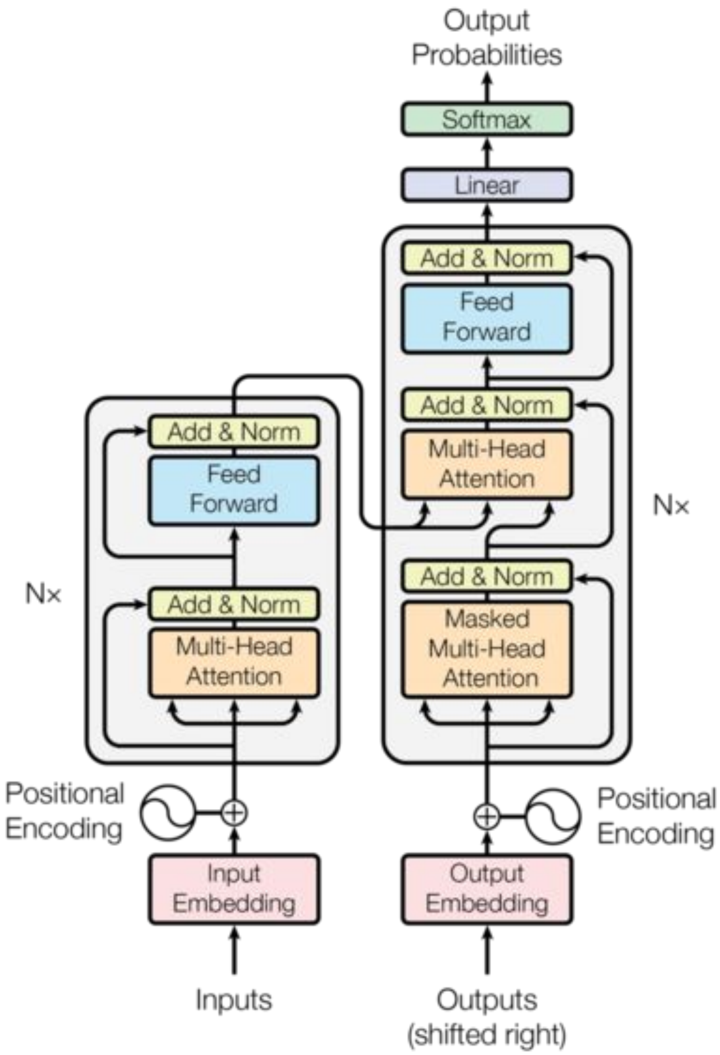
Transformer

- You can now understand everything in this famous diagram from the “Attention is All You Need” paper.



Transformer

- You can now understand everything in this famous diagram from the "Attention is All You Need" paper.
  - "Add & Norm" is like a residual connection
  1. Add the initial sequence embedding to the output of the MHA layer.
  2. Pass it through a Layer Normalization.



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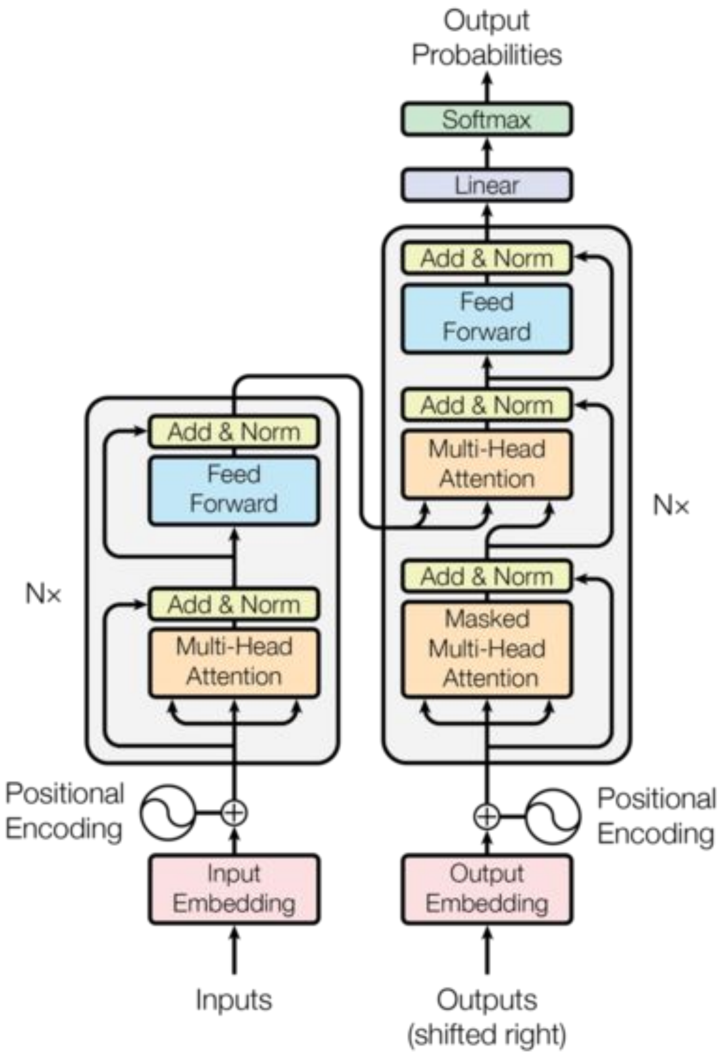
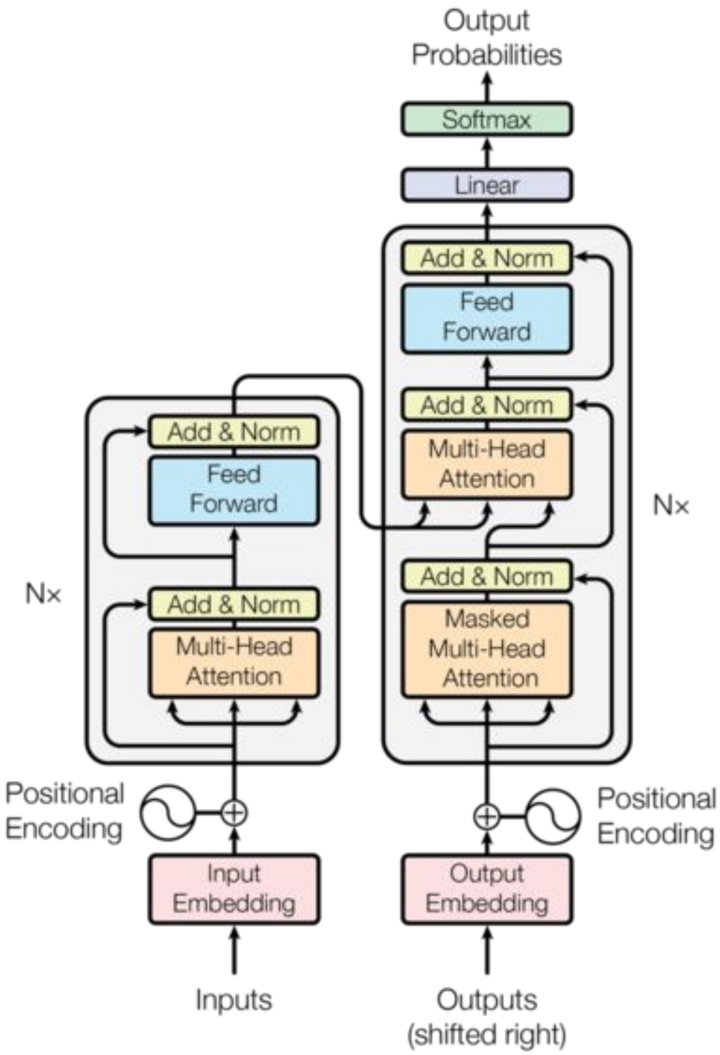
    - That output gets put into a feed forward layer (and then another residual connection)



Transformer

- You can now understand everything in this famous diagram from the "Attention is All You Need" paper.
  - "Add & Norm" is like a residual connection
  - That output gets put into a feed forward layer (and then another residual connection)
  - Original model has 6 Transformer encoder layers stacked on one another.



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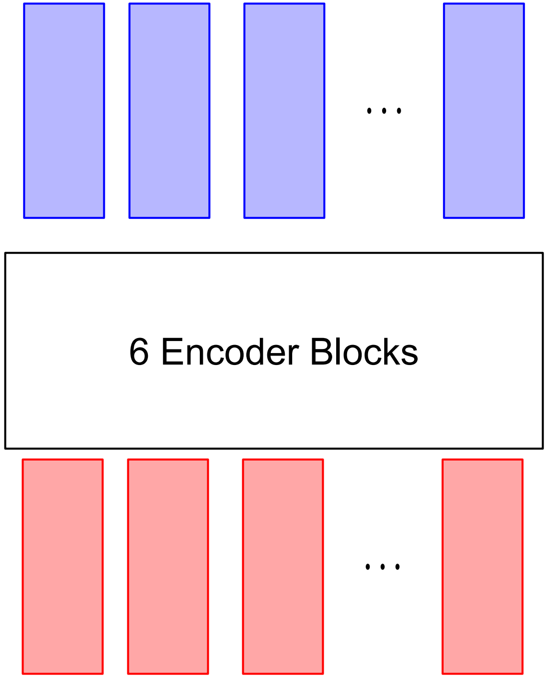

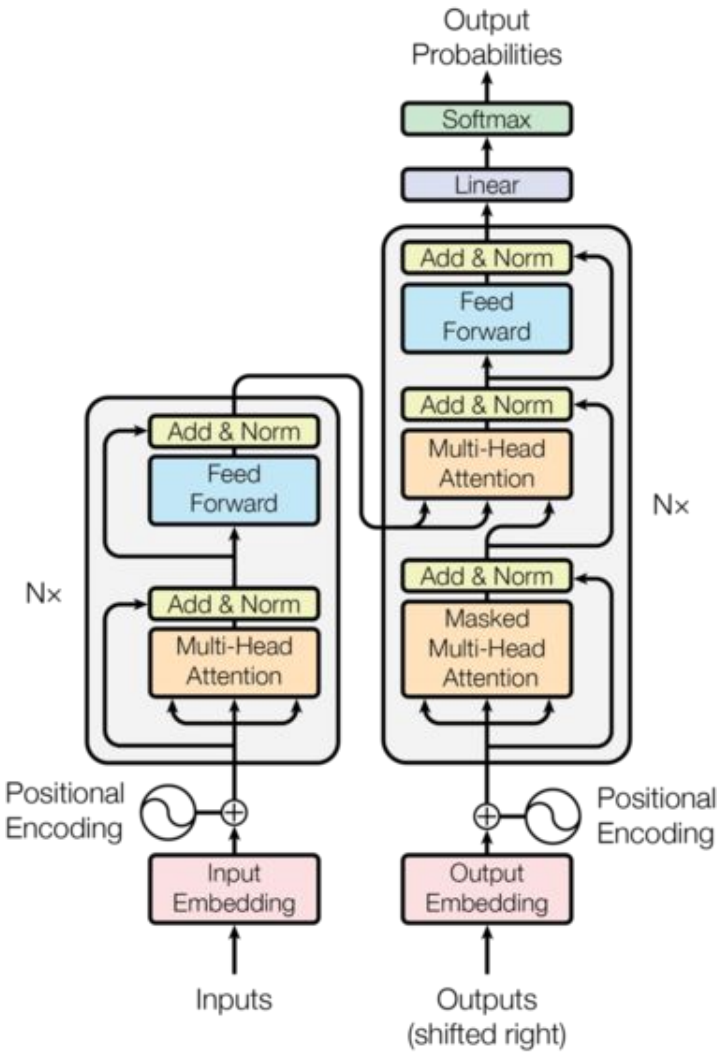

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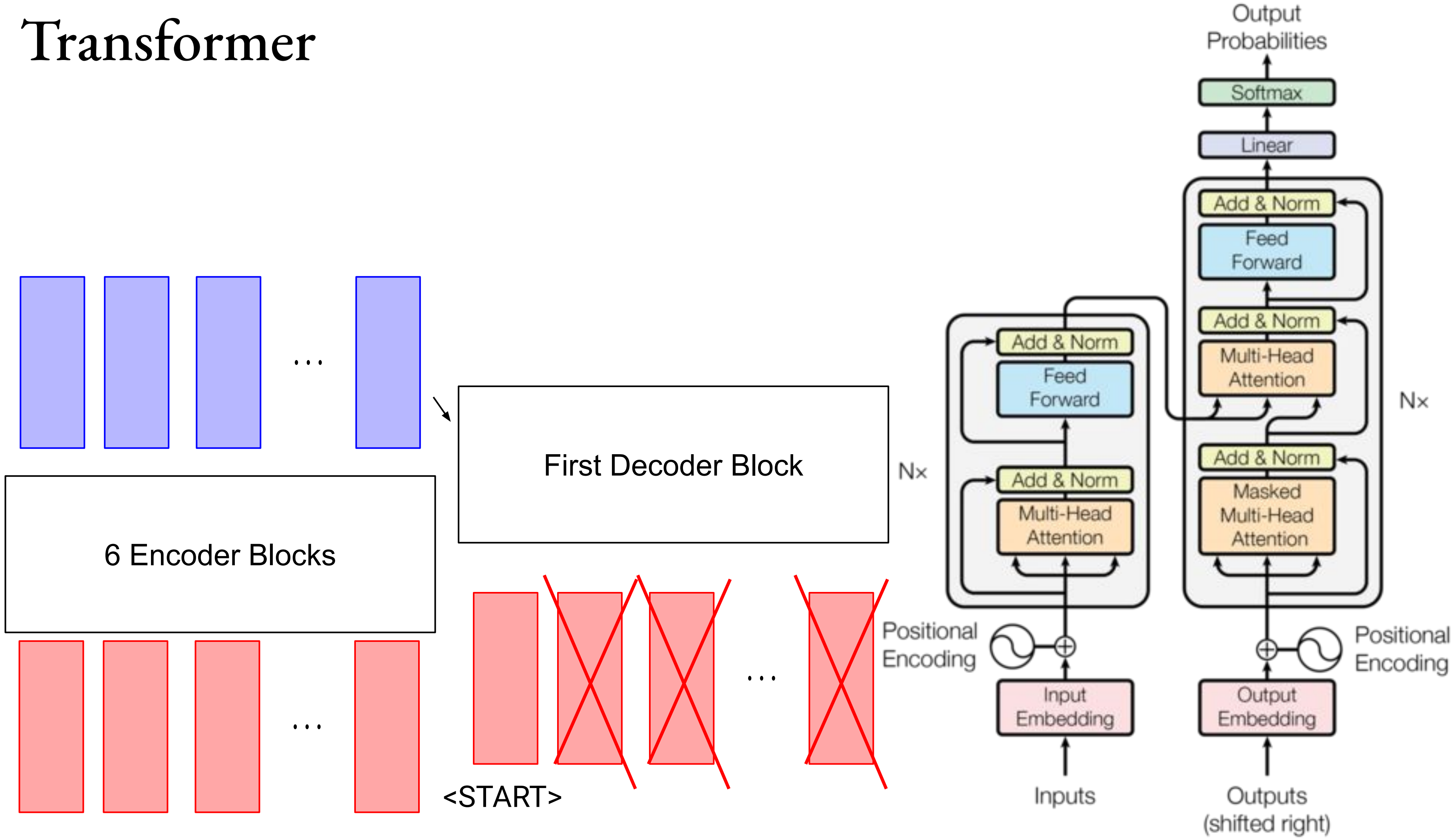
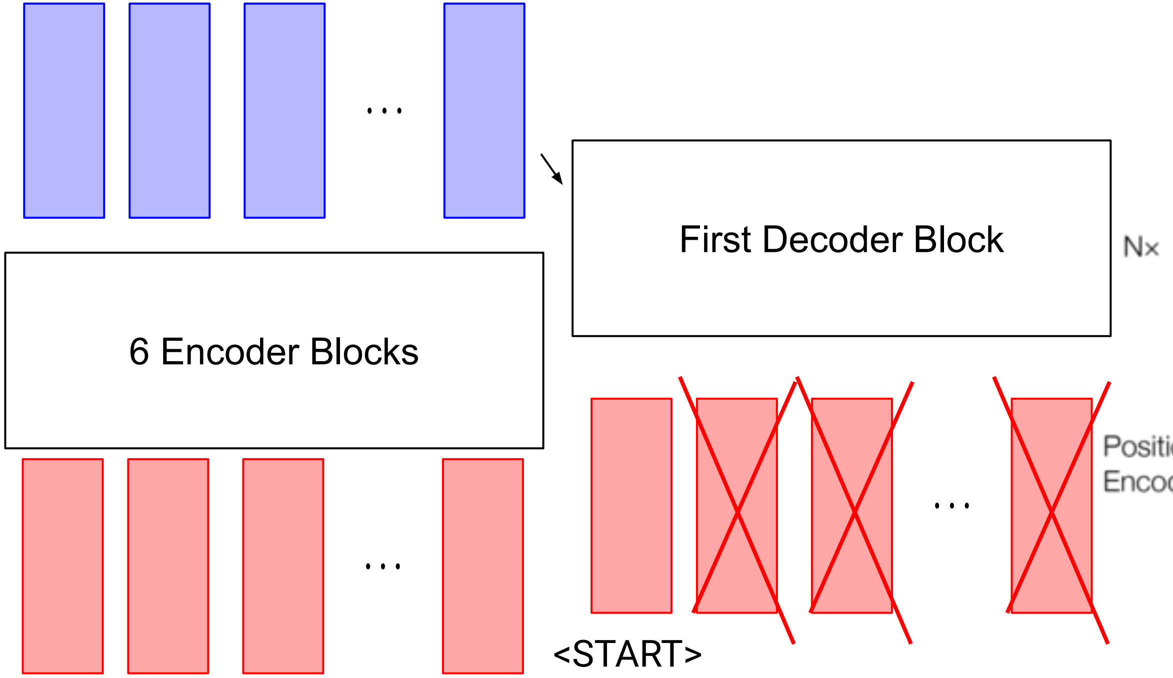
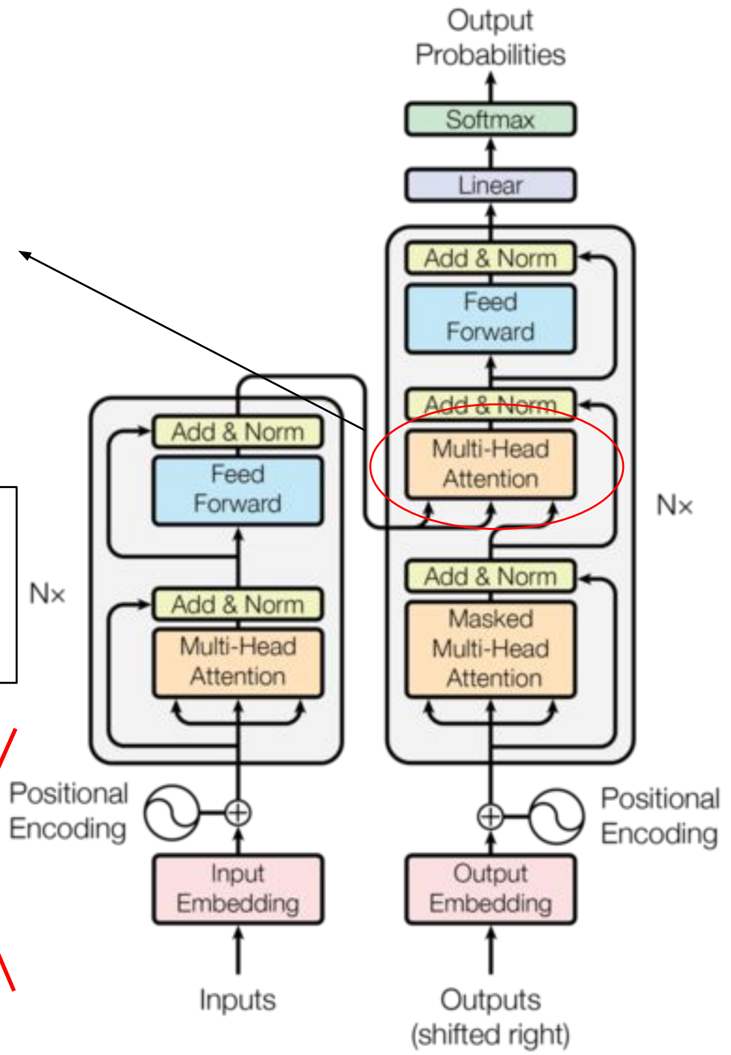


Transformer

Keys and values come from encoder stack output

Queries come from decoder





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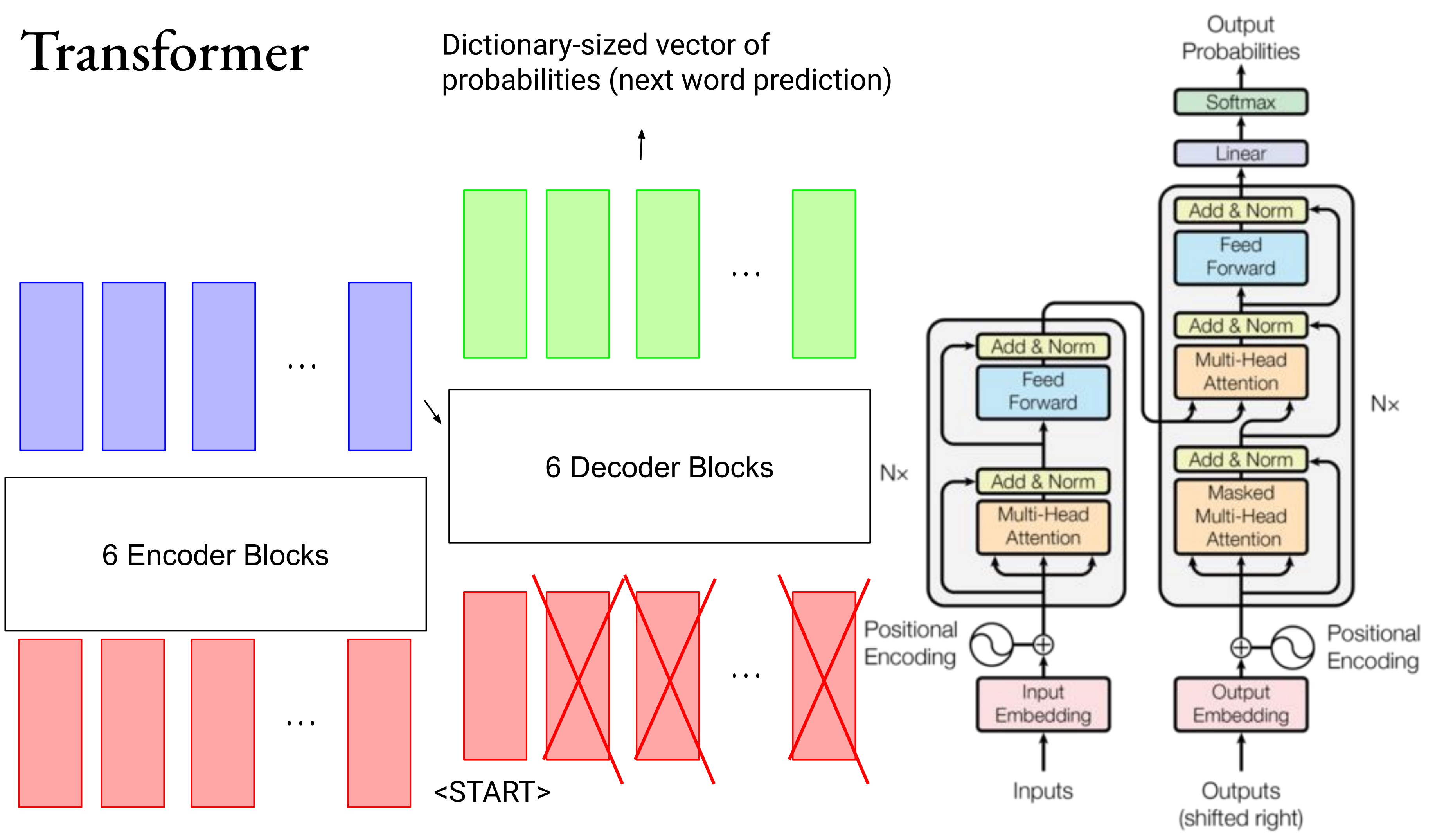

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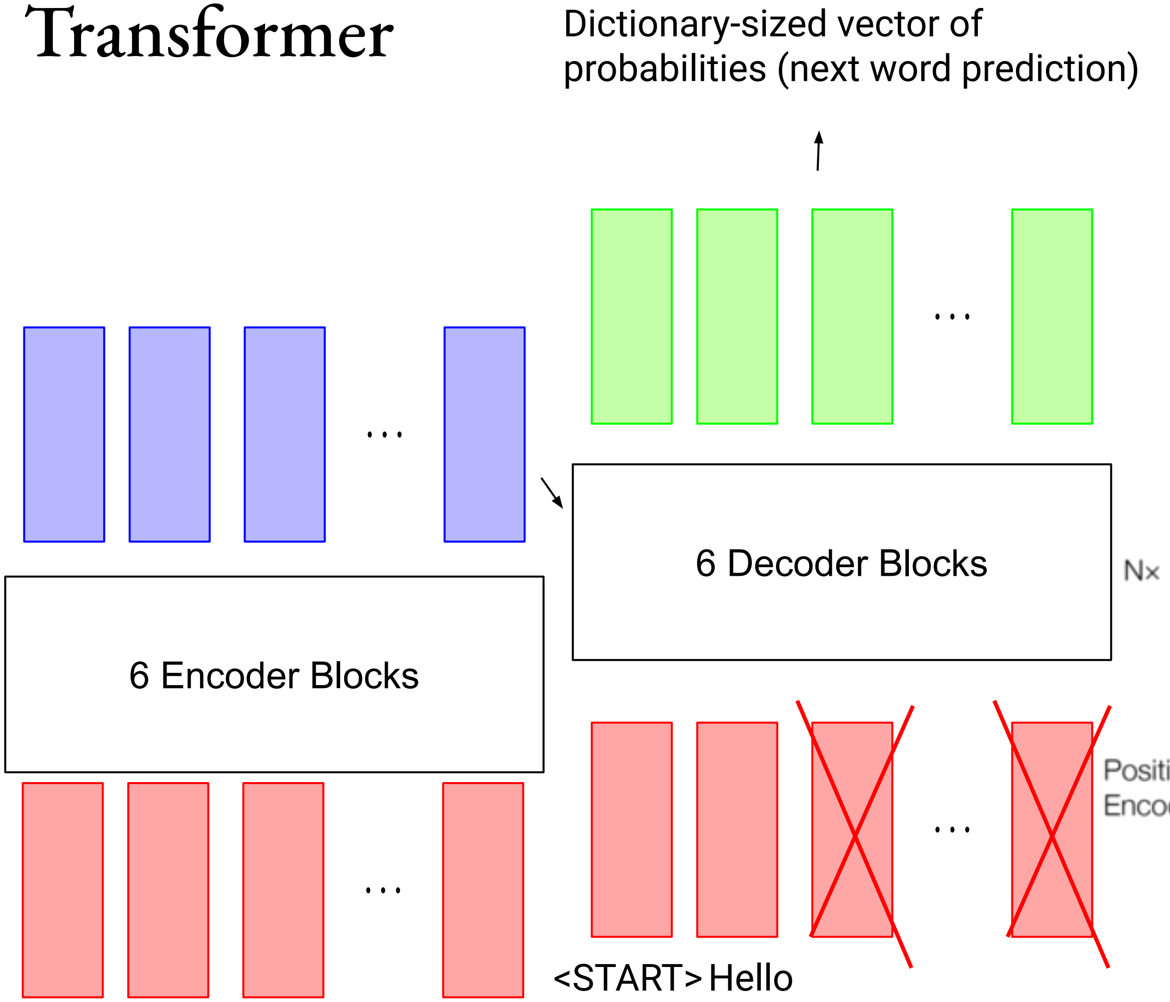
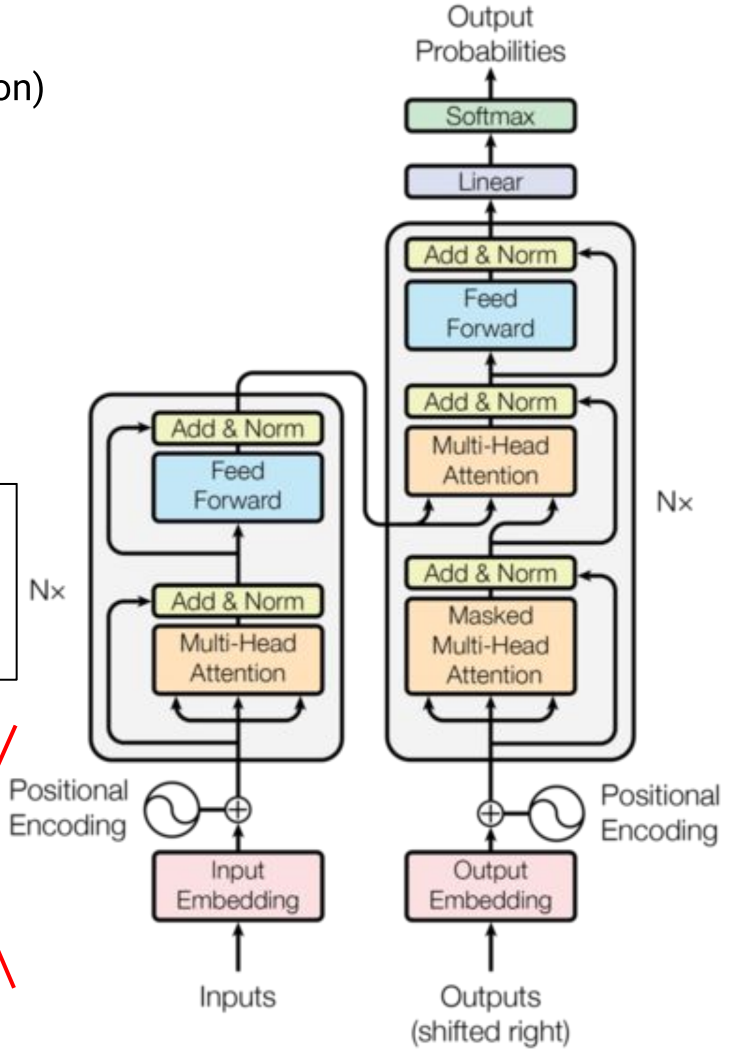
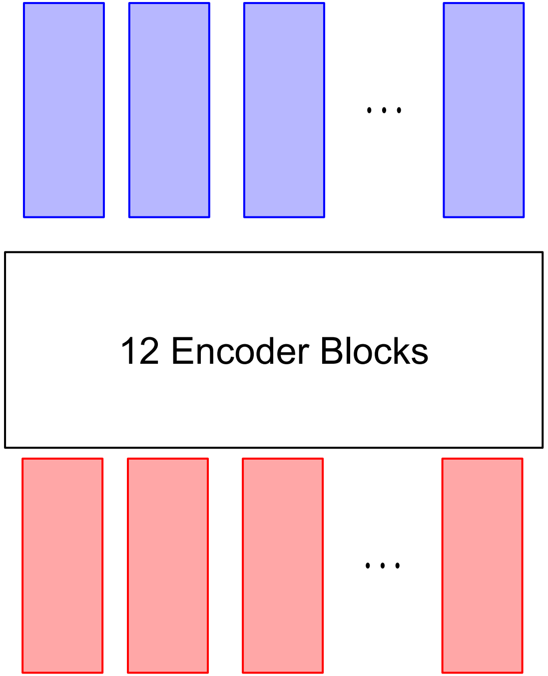




Self-Supervised Learning

- BERT: Bidirectional Encoder Representations from Transformers
  - Encoder-only model
  - 12 Encoders



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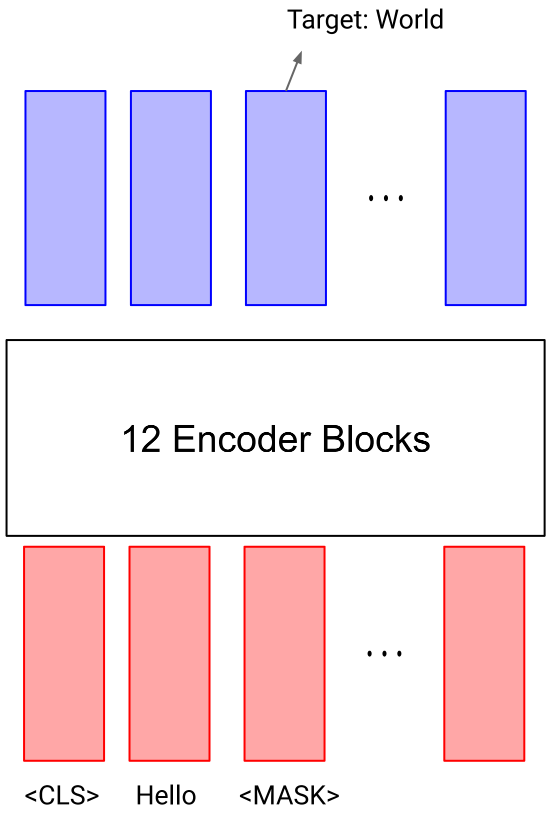
- Self-supervised Task #1

1. Take a mountain of text.
2. Mask ~15% of the words
3. Try to predict the masked words.



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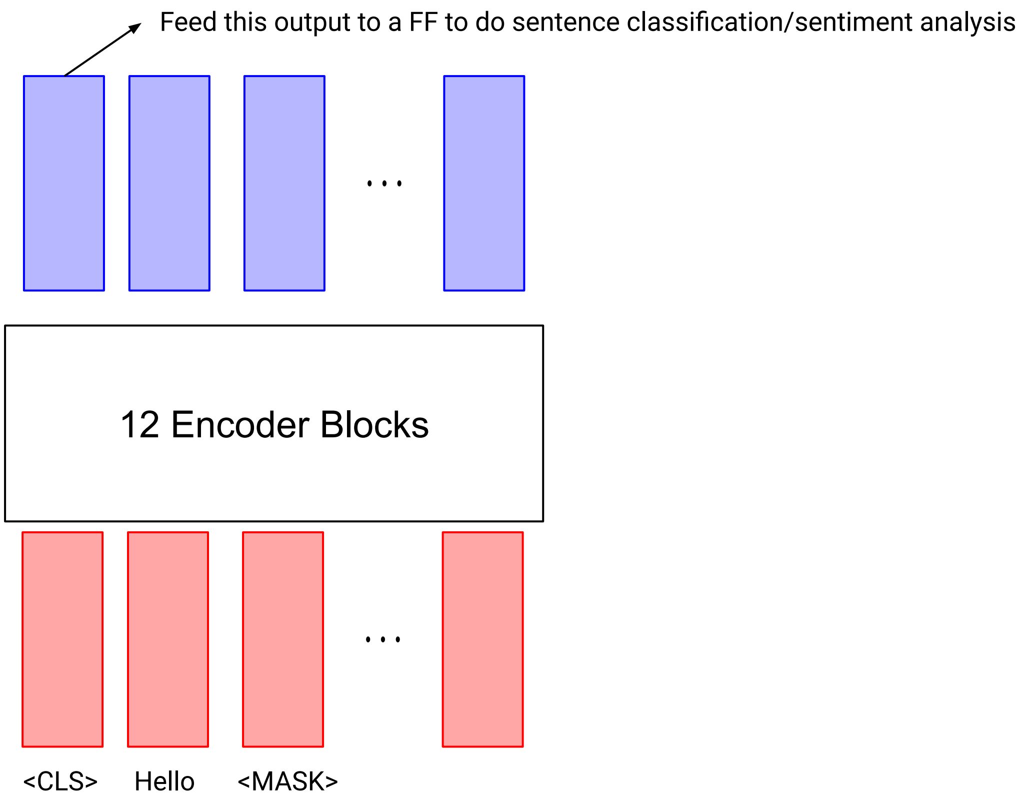
- <CLS> is a special token



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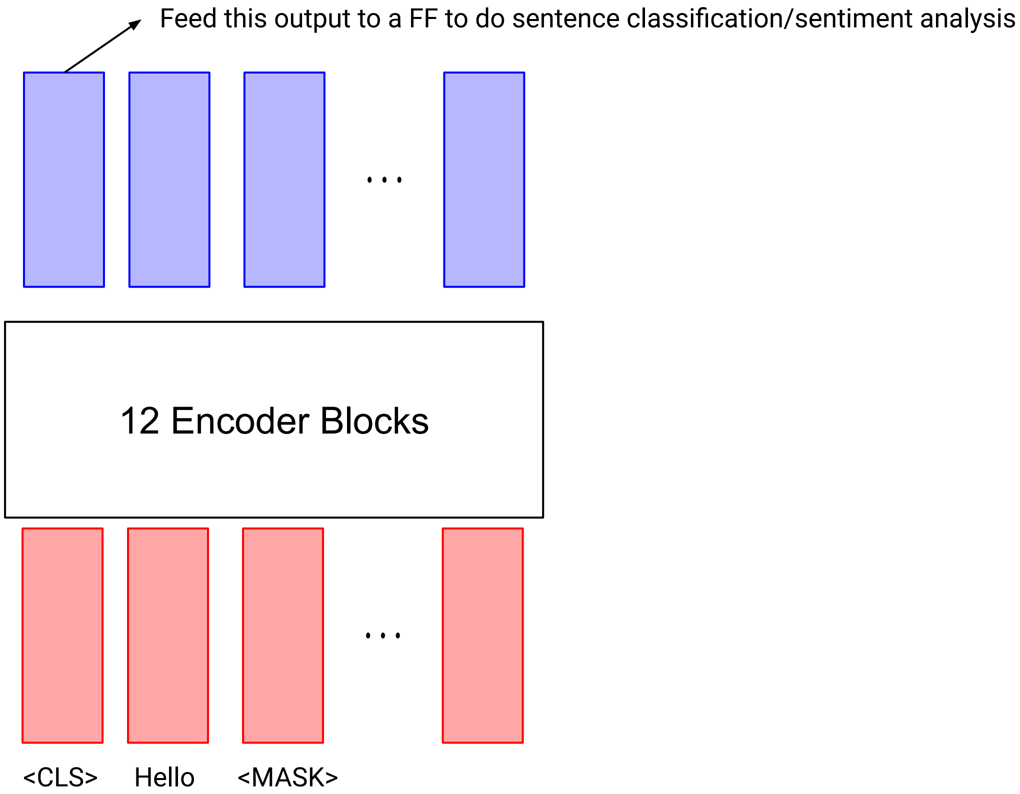
- <CLS> is a special token
- <SEP> is a token that separates sentences (Q/A tasks)

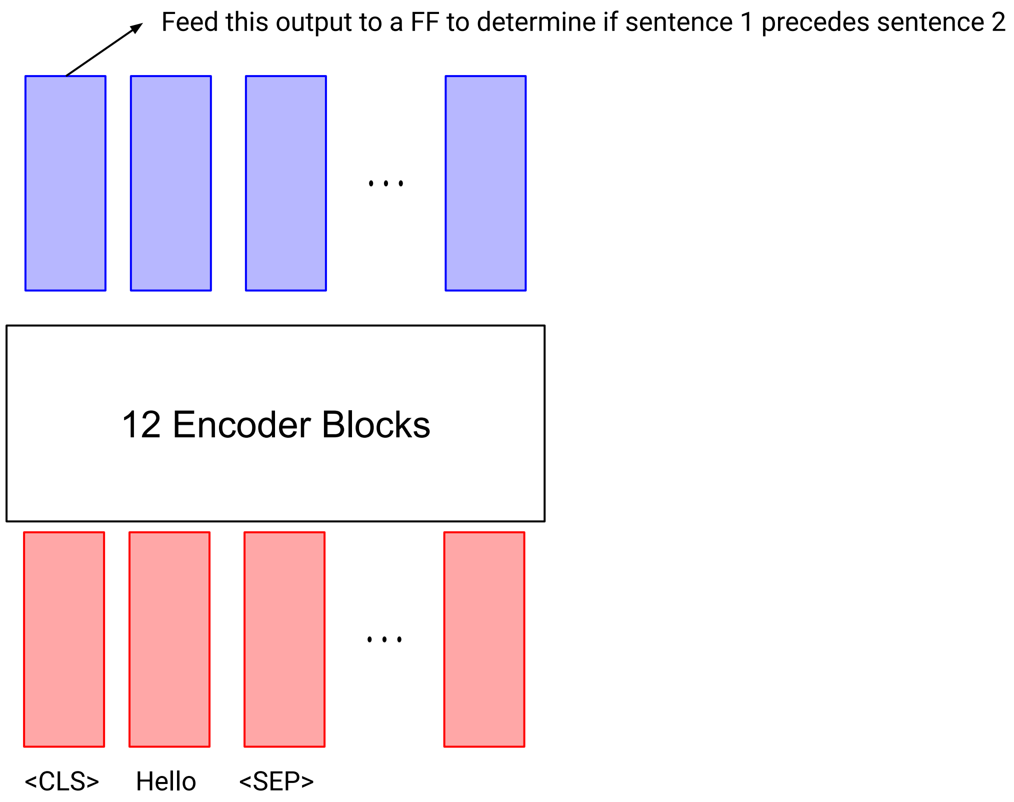


Self-Supervised Learning

- BERT: Bidirectional Encoder Representations from Transformers
  - Encoder-only model
  - 12 Encoders
- Self-supervised Task #2

1. Take a mountain of text.
2. Take Two Sentences
3. Predict whether the first sentence follows the second

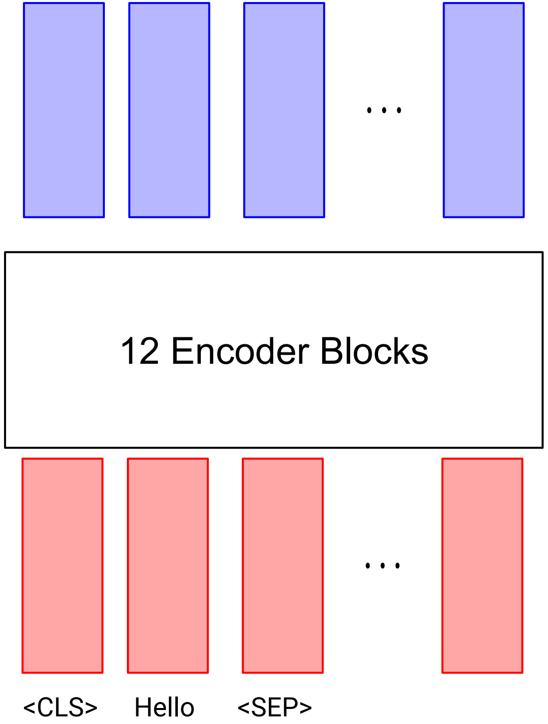
- <CLS> is a special token
- <SEP> is a token that separates sentences (Q/A tasks)



Self-Supervised Learning

- BERT: Bidirectional Encoder Representations from Transformers
  - Encoder-only model
  - 12 Encoders
- Fine-tune the pre-trained BERT for your task of choice!

- Can use frozen embeddings from any layer of BERT! (feature extraction)



Nice Blog Posts

- Illustrated Transformer
- Illustrated BERT