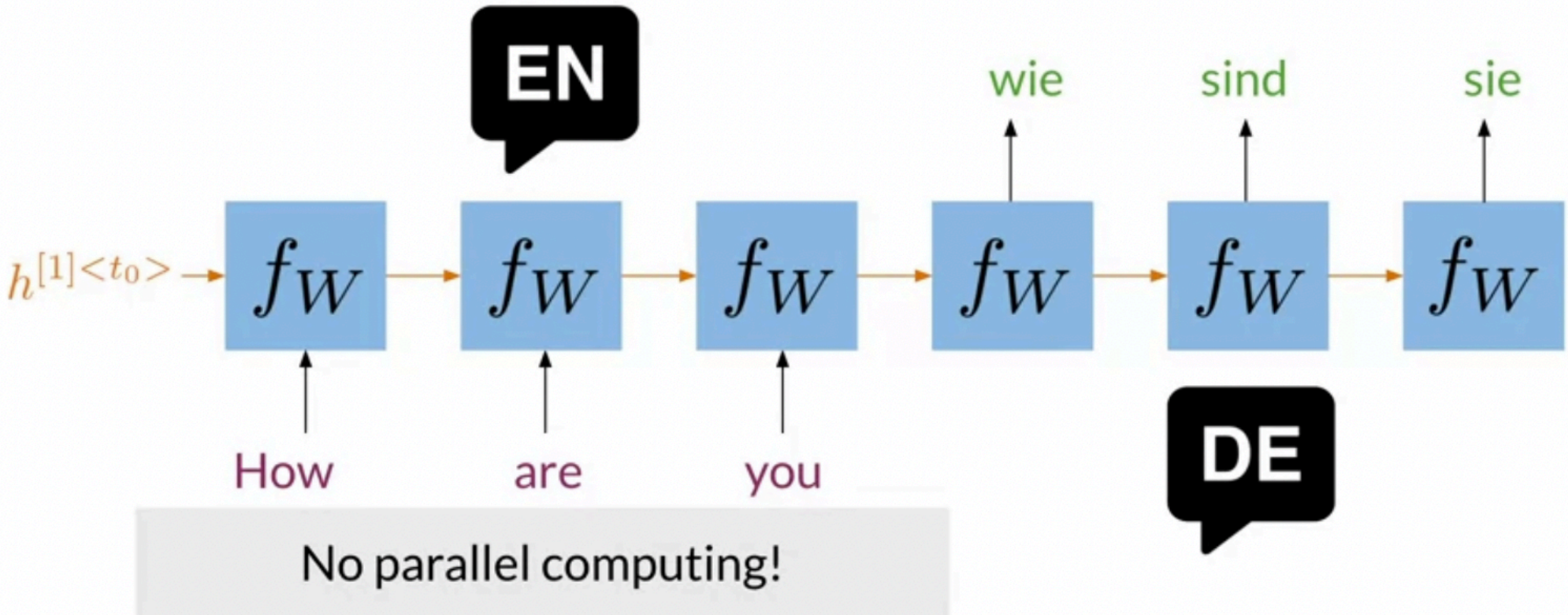
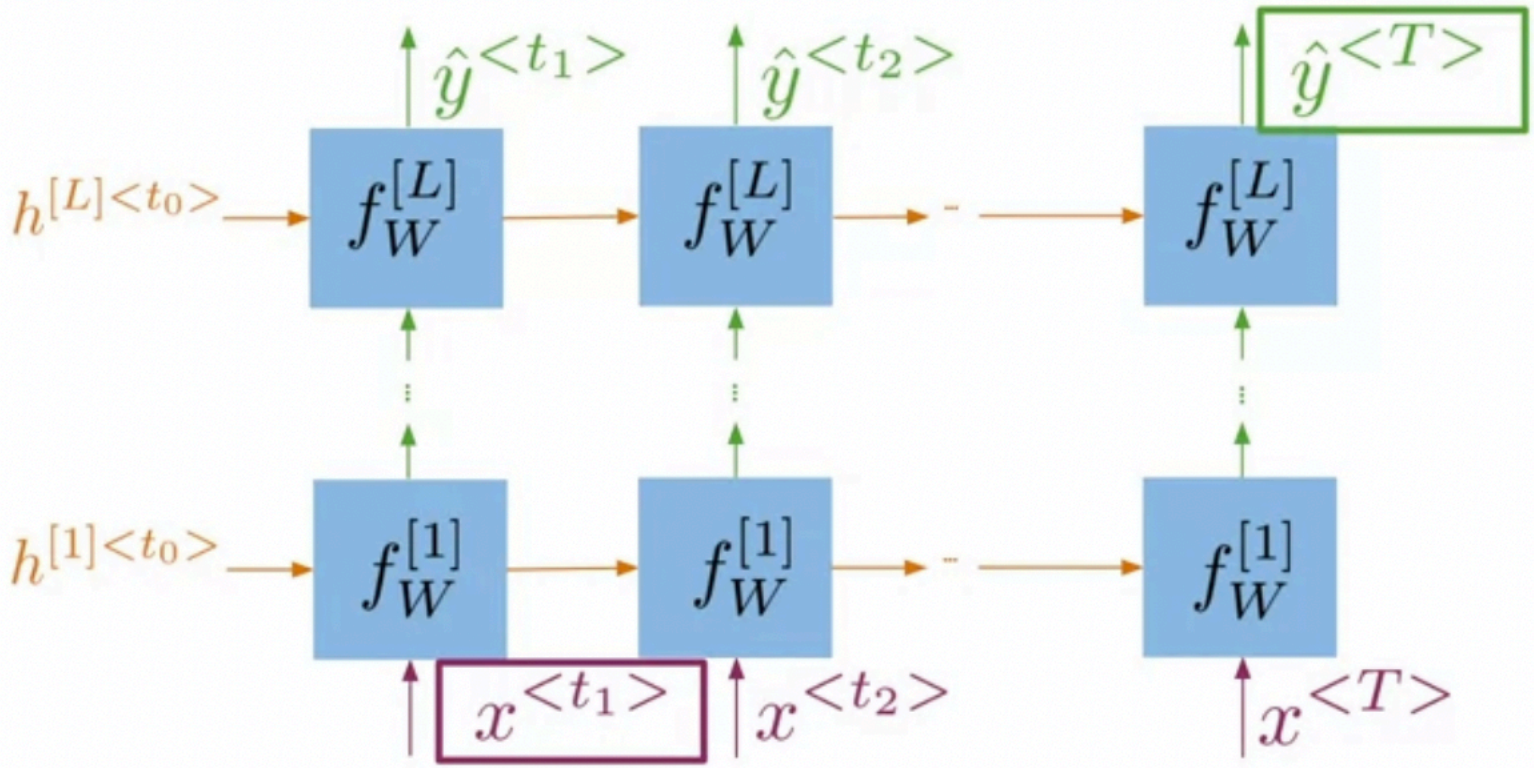
Outline

- Issues with RNNs
- Comparison with Transformers

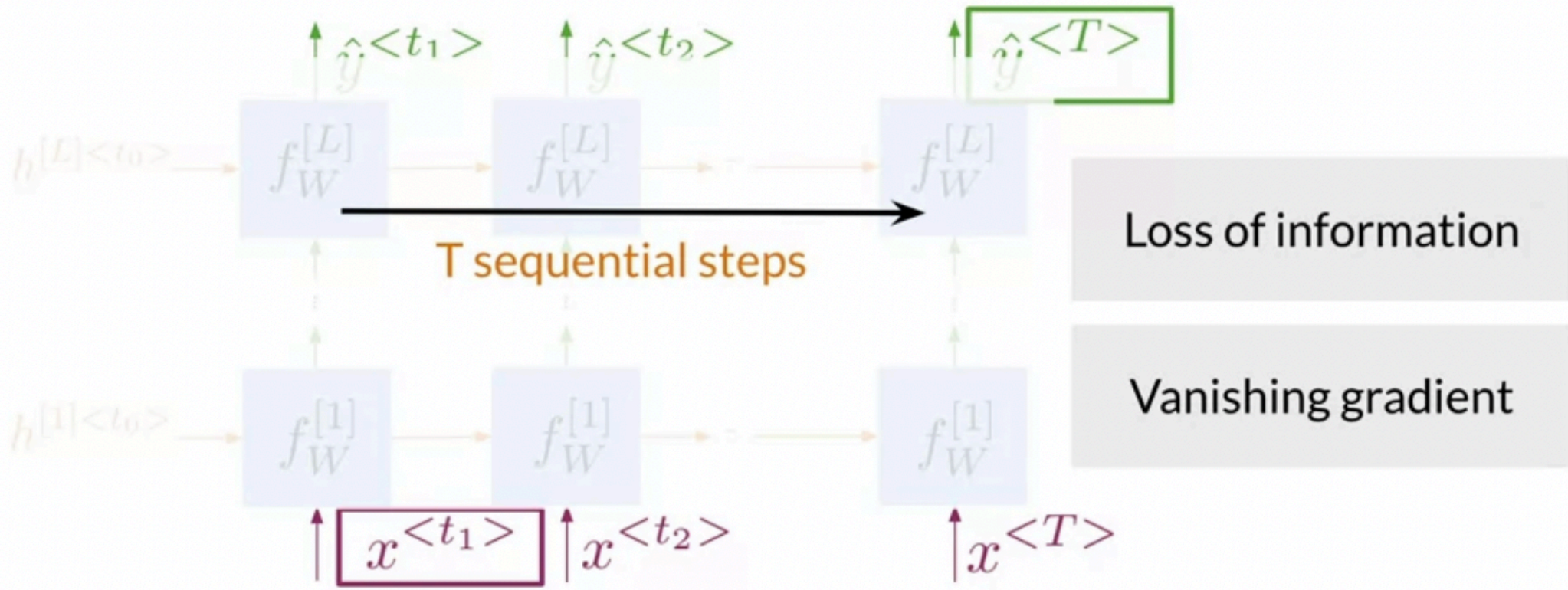
Neural Machine Translation



Seq2Seq Architectures



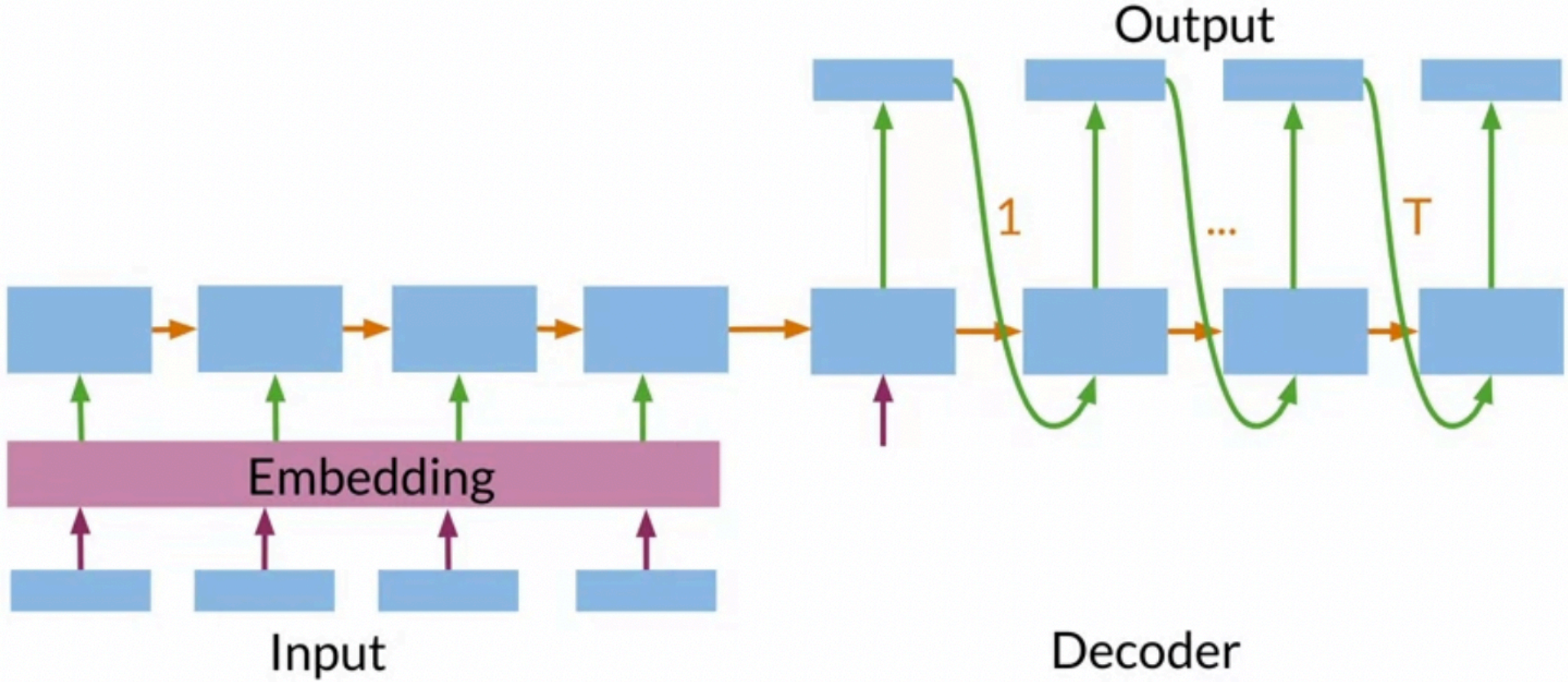
Seq2Seq Architectures



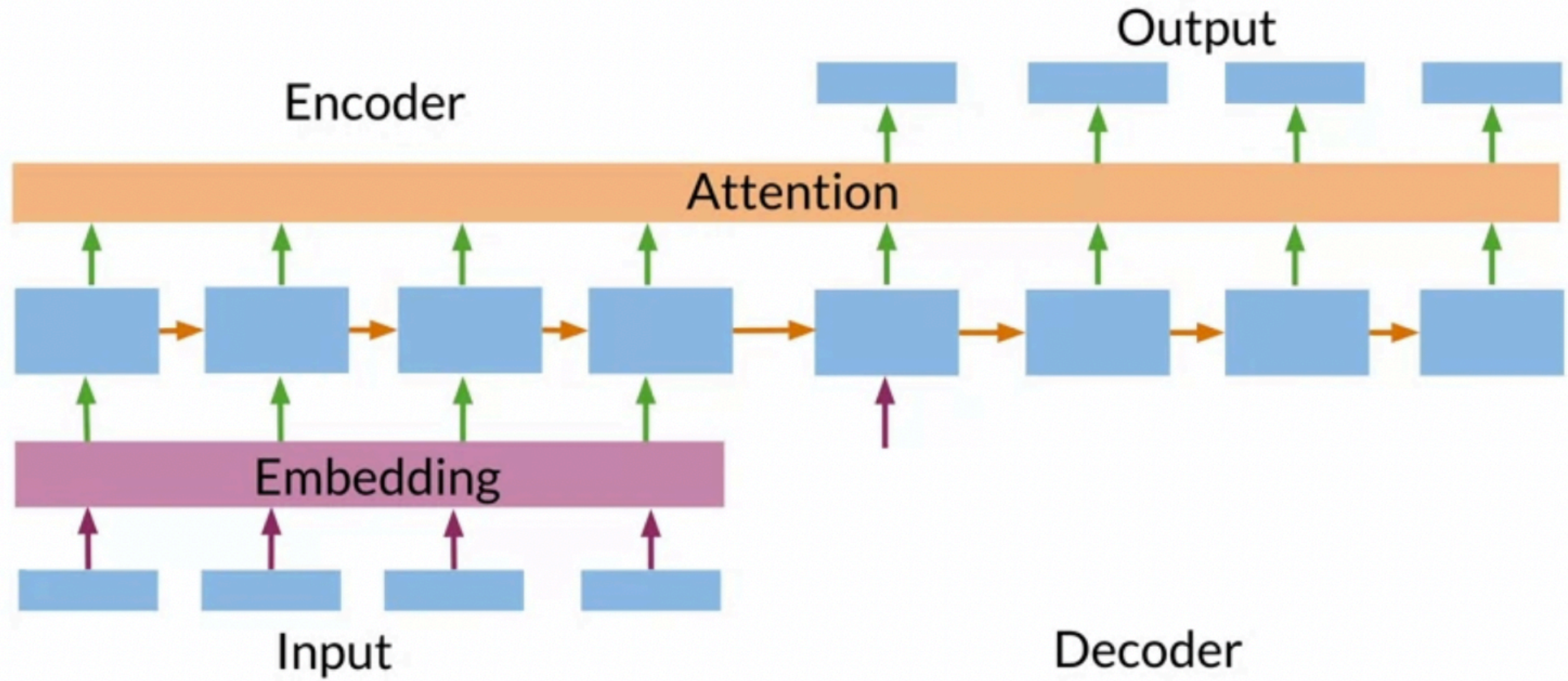
Loss of information

Vanishing gradient

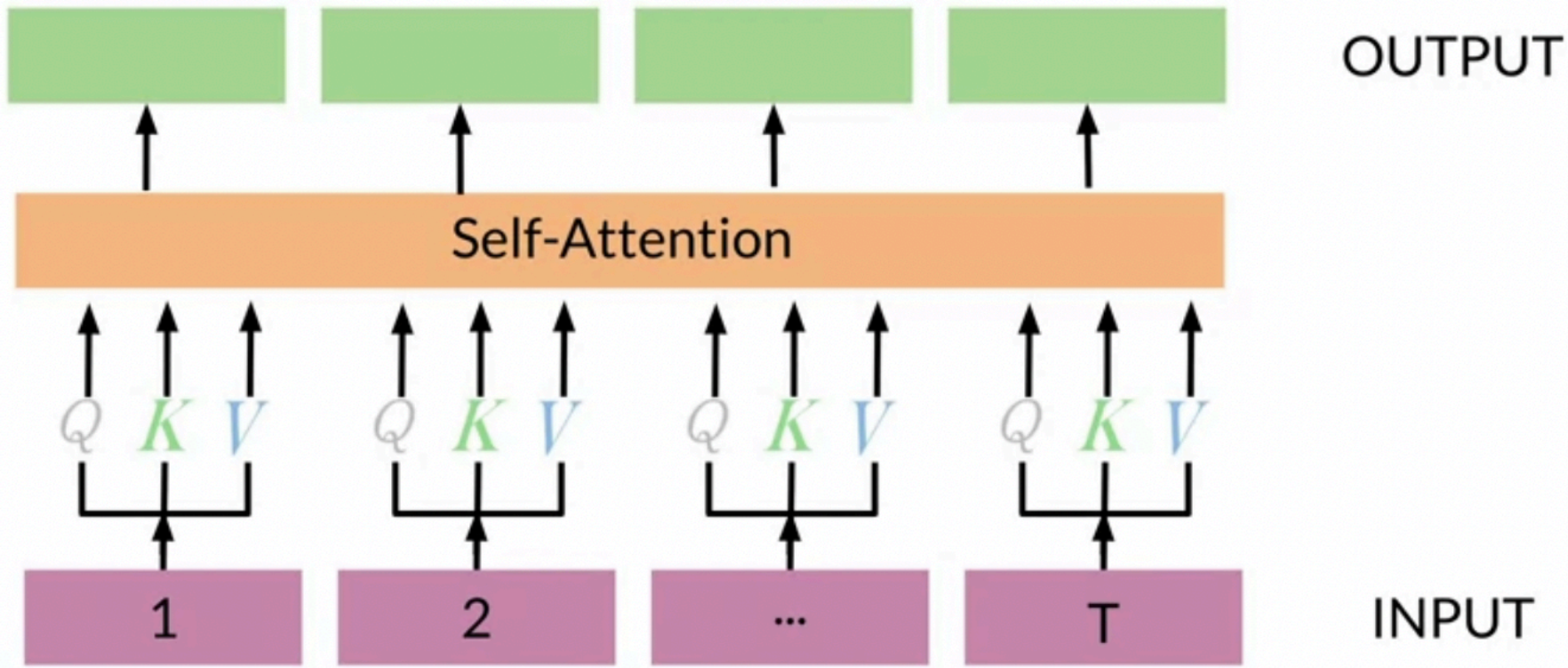
RNNs vs Transformer: Encoder-Decoder



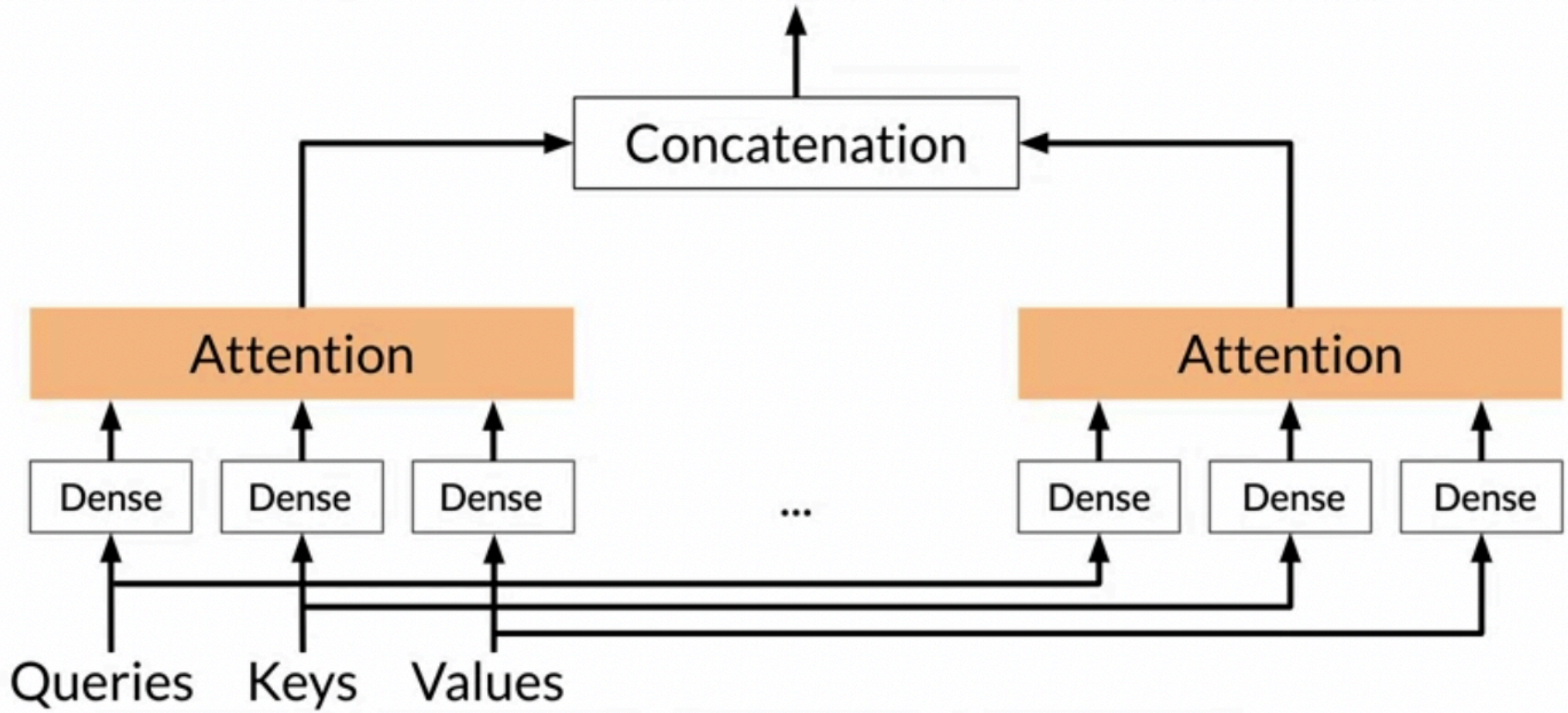
RNNs vs Transformer: Encoder-Decoder



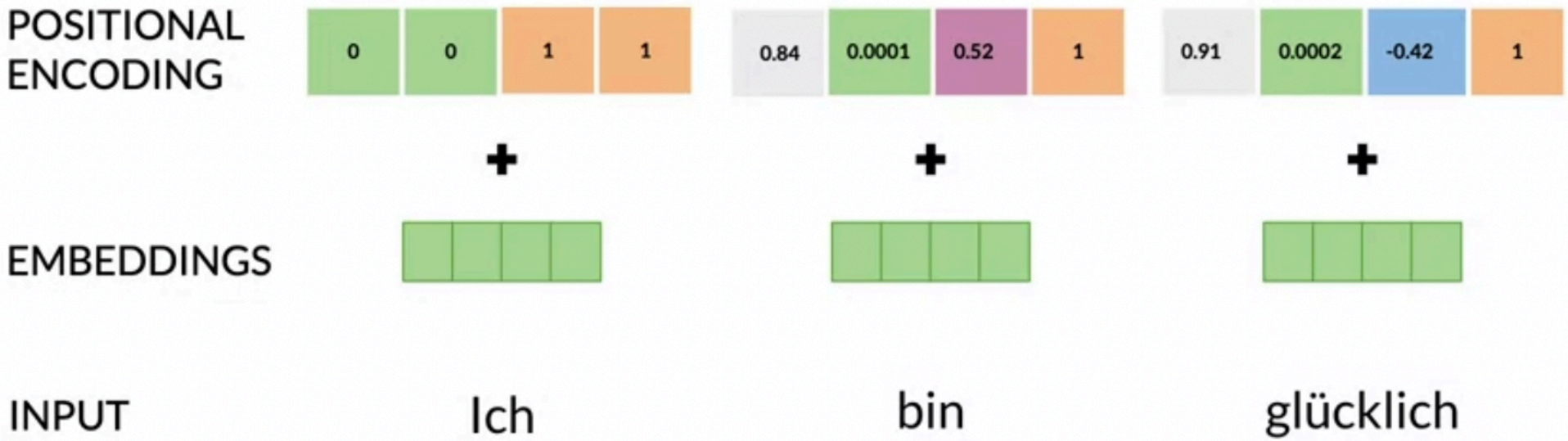
RNNs vs Transformer: Multi-headed attention



RNNs vs Transformer: Multi-headed attention

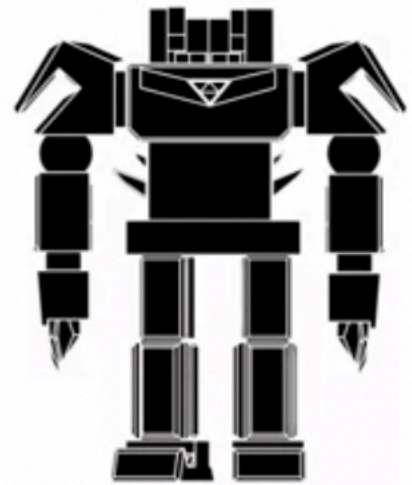


RNNs vs Transformer: Positional Encoding



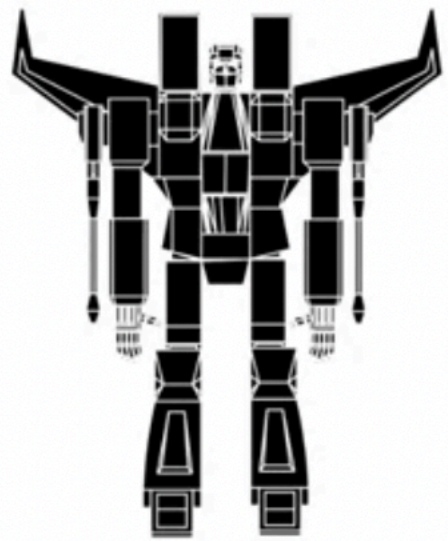
Summary

- In RNNs parallel computing is difficult to implement
- For long sequences in RNNs there is loss of information
- In RNNs there is the problem of vanishing gradient
- Transformers help with all of the above



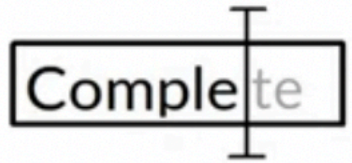
Outline

- Transformers applications in NLP
- Some Transformers
- Introduction to T5

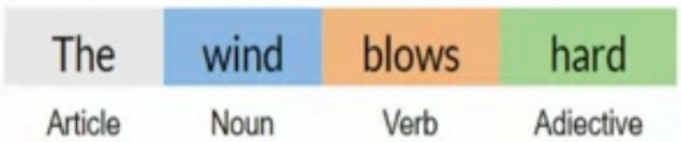


Transformer NLP applications

Text summarization



Auto-Complete



Named entity recognition (NER)

Question answering (Q&A)

Translation

Chat-bots

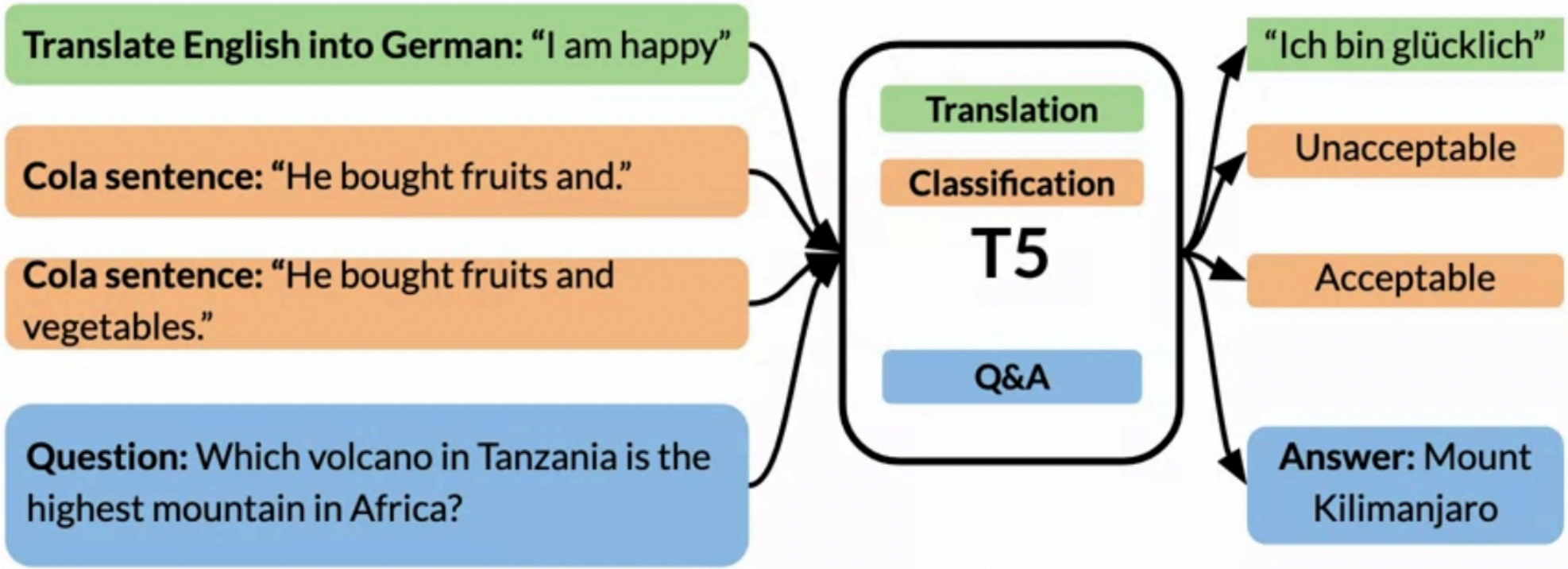
Other NLP tasks

- Sentiment Analysis
- Market Intelligence
- Text Classification
- Character Recognition
- Spell Checking

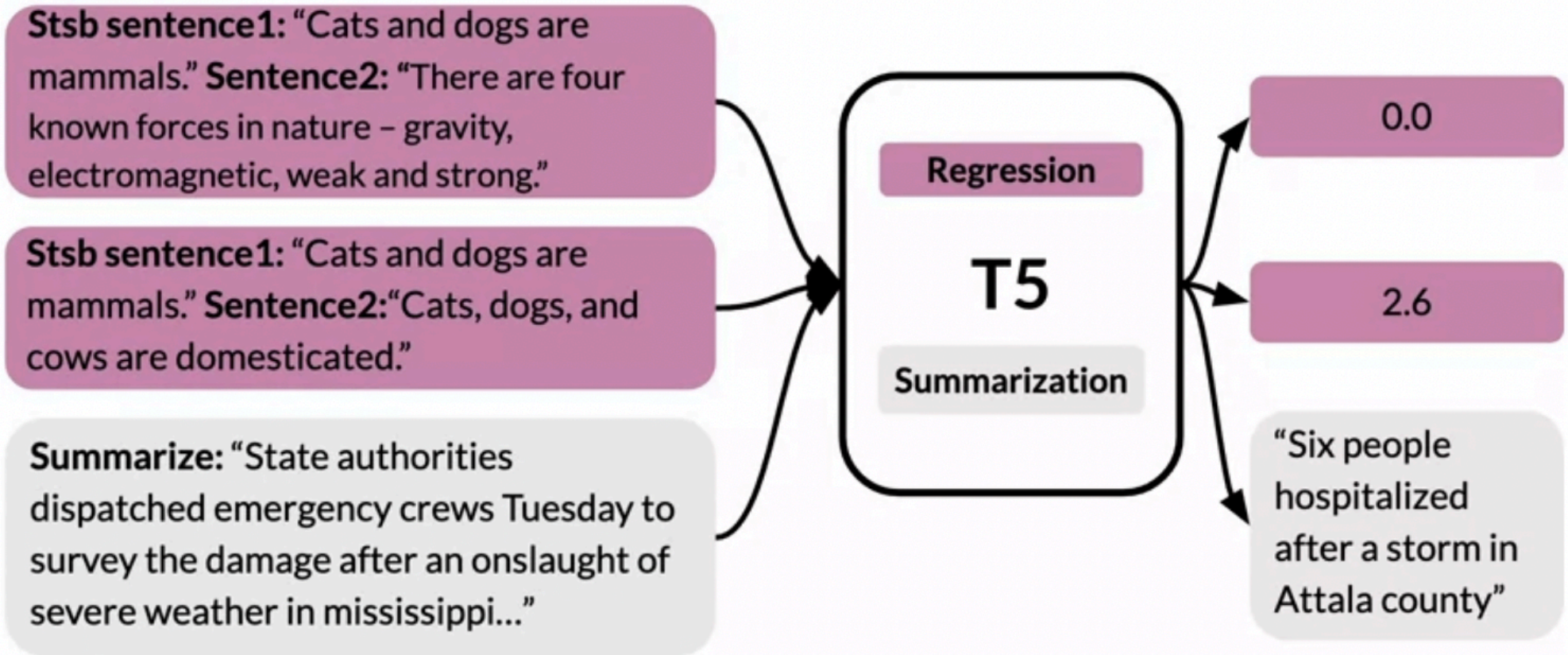
State of the Art Transformers

Radford, A., et al. (2018) Open AI	GPT-2: Generative Pre-training for Transformer
Devlin, J., et al. (2018) Google AI Language	BERT:Bidirectional Encoder Representations from Transformers
Colin, R., et al. (2019) Google	T5: Text-to-text transfer transformer

T5: Text-To-Text Transfer Transformer

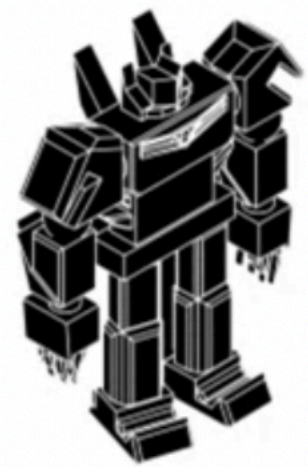


T5: Text-To-Text Transfer Transformer



Summary

- Transformers are suitable for a wide range of NLP applications
- GPT-2, BERT and T5 are the cutting-edge Transformers
- T5 is a powerful multi-task transformer

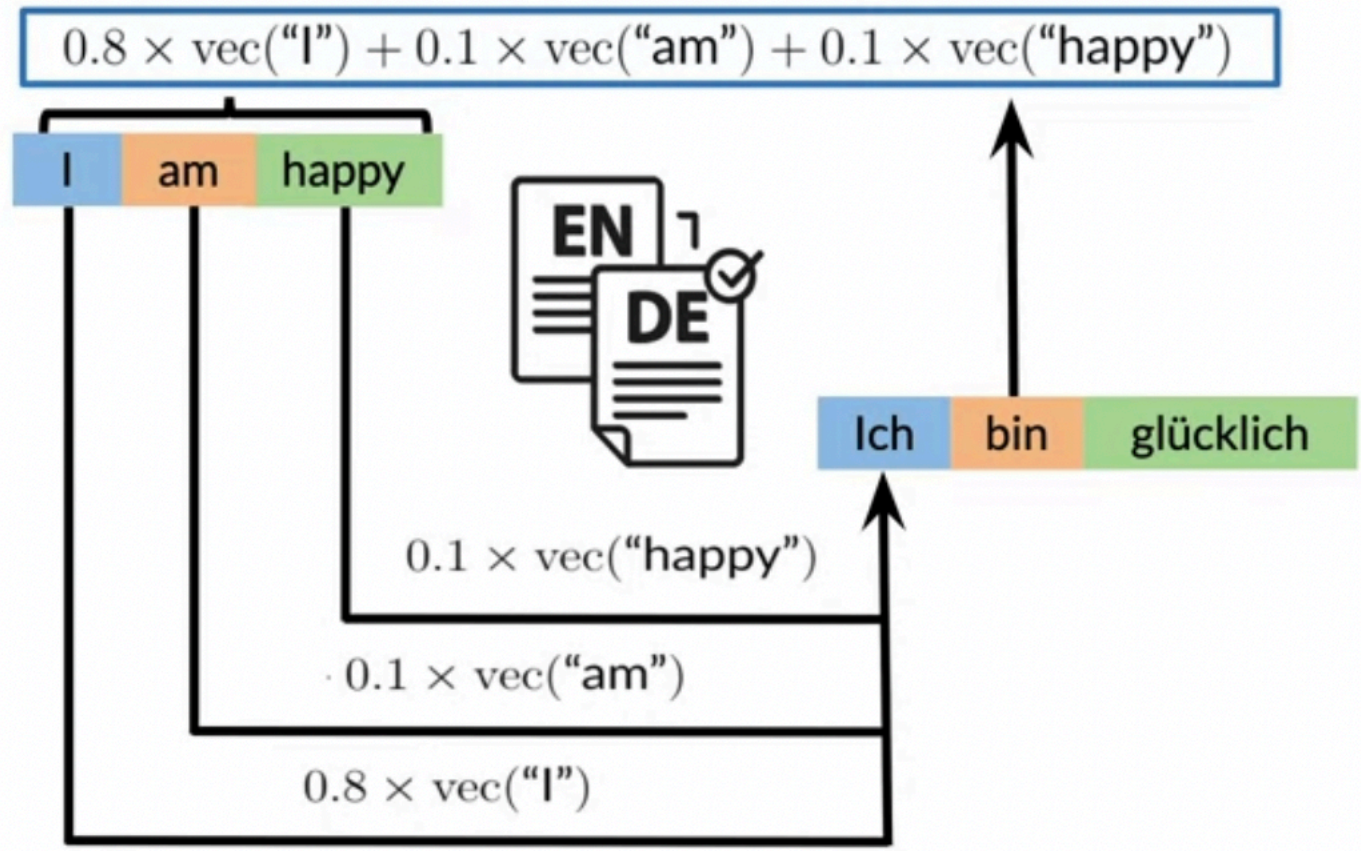


Outline

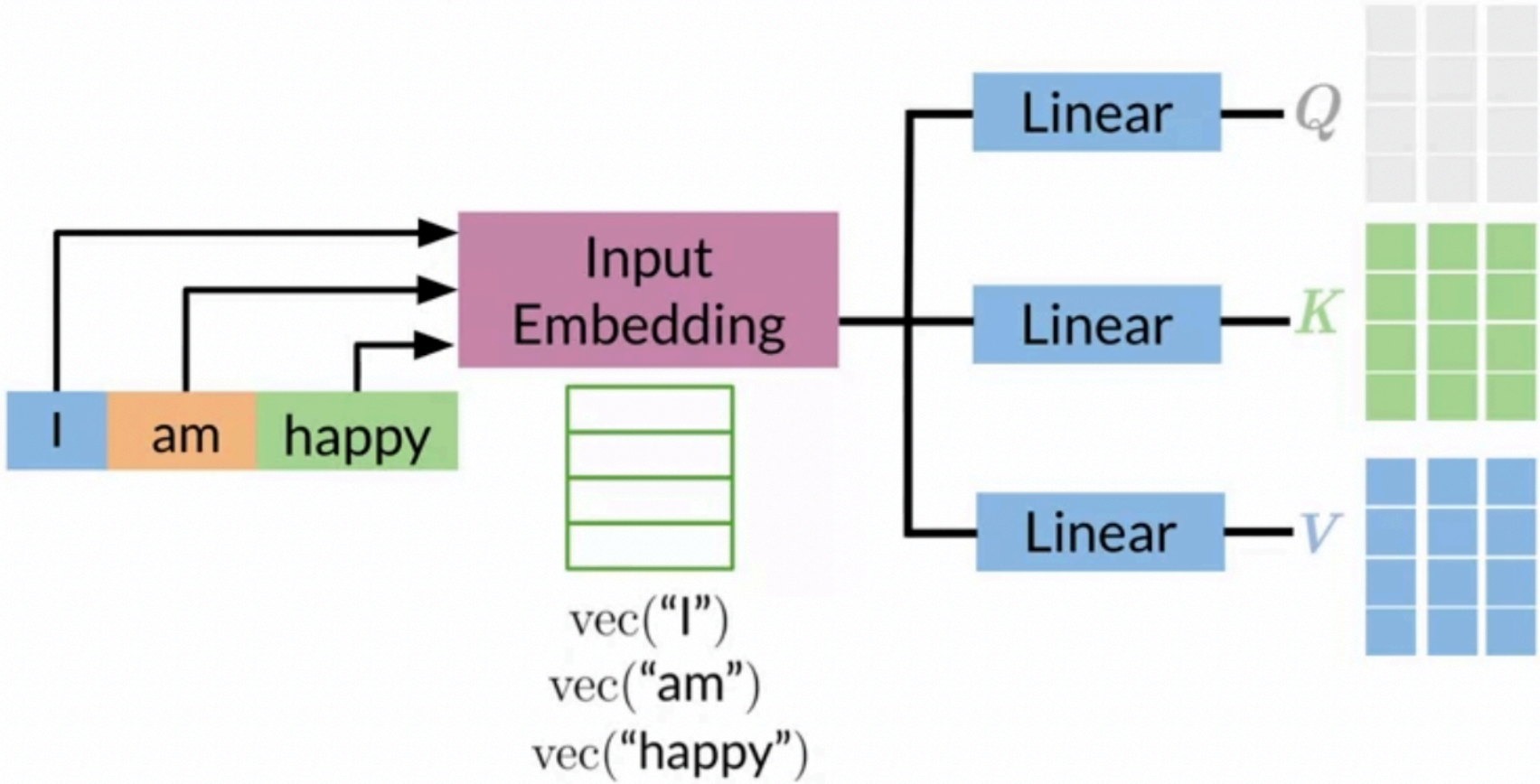
- Introducing attention (Translation example)
- Mathematics behind Attention

Introducing attention - Translation example

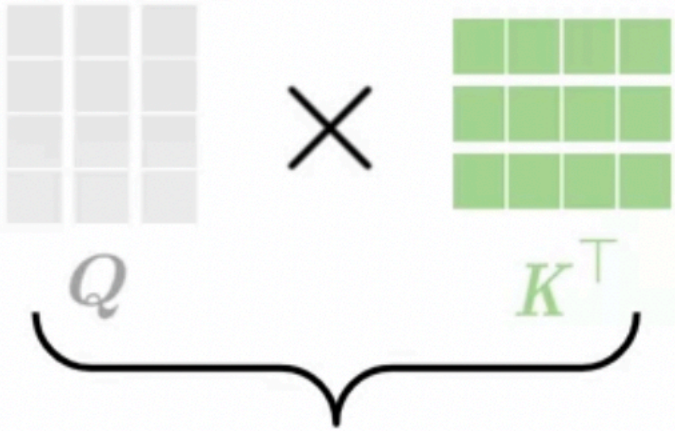
- A query (German word) looks for similar keys (English words).
- Each key has a probability of being a match for the query.
- Return sum of the keys weighted by their probabilities.



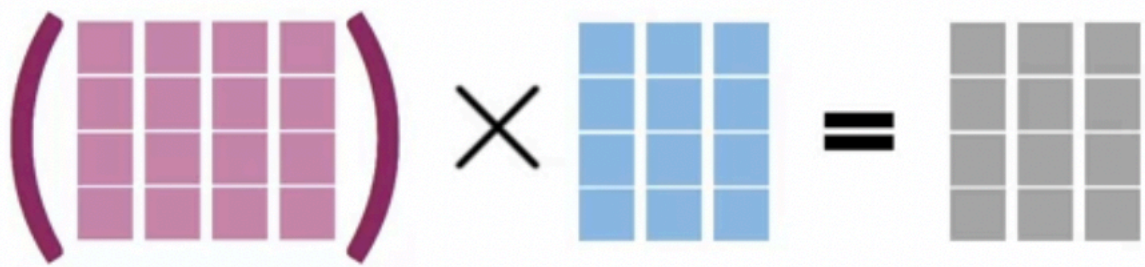
Queries, Keys and Values



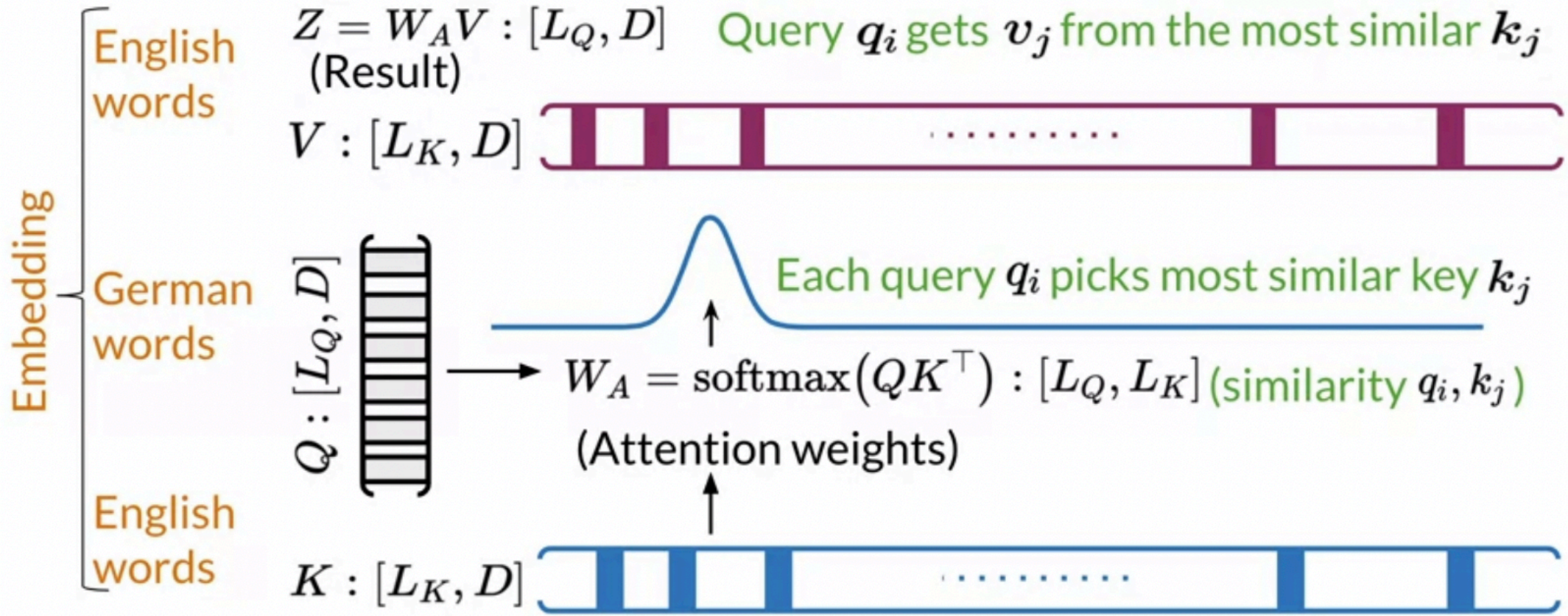
Concept of attention



$$\text{softmax}(QK^\top)V = Z$$



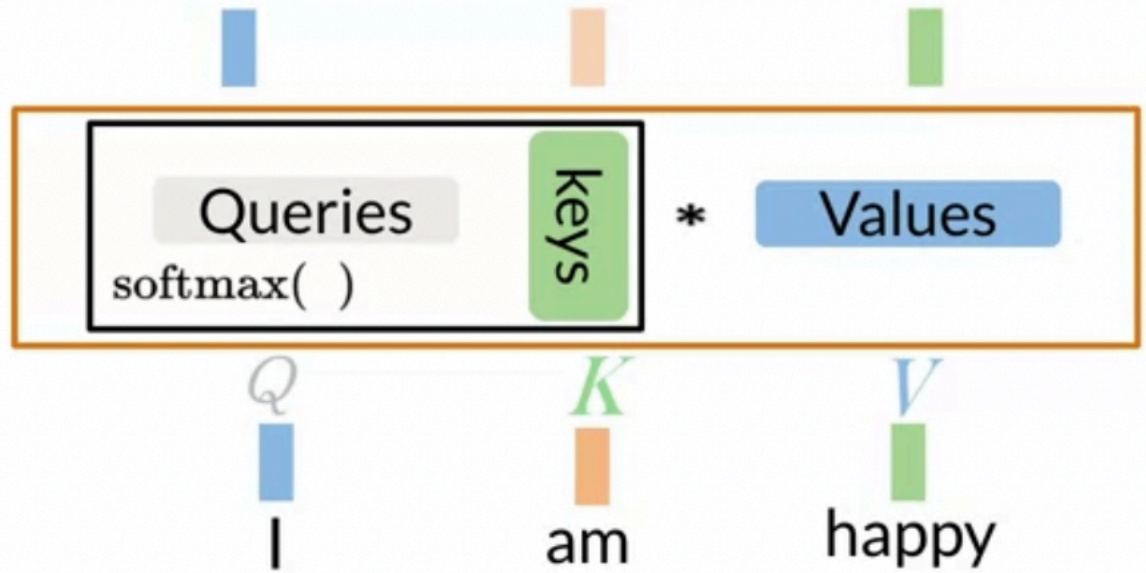
Attention math



Attention formula

$$Z = \text{attention}(Q, K, V) = \text{softmax}(QK^\top)V = W_A V$$

(Result)



Summary

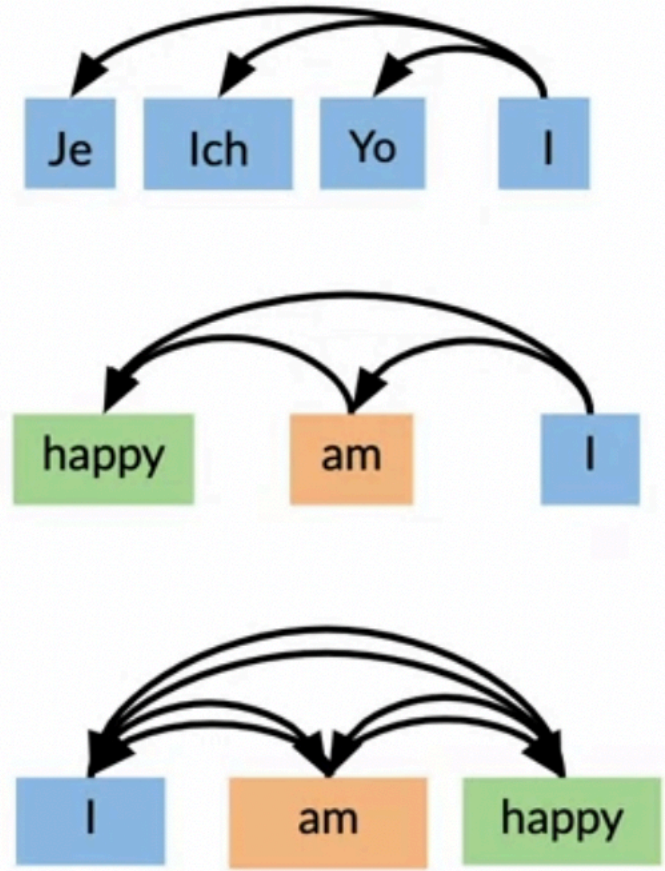
- Dot-product Attention is essential for Transformer
- The input to Attention are queries, keys, and values
- A softmax function makes attention more focused on best keys
- GPUs and TPUs is advisable for matrix multiplications

Outline

- Ways of Attention
- Overview of Causal Attention
- Math behind causal attention

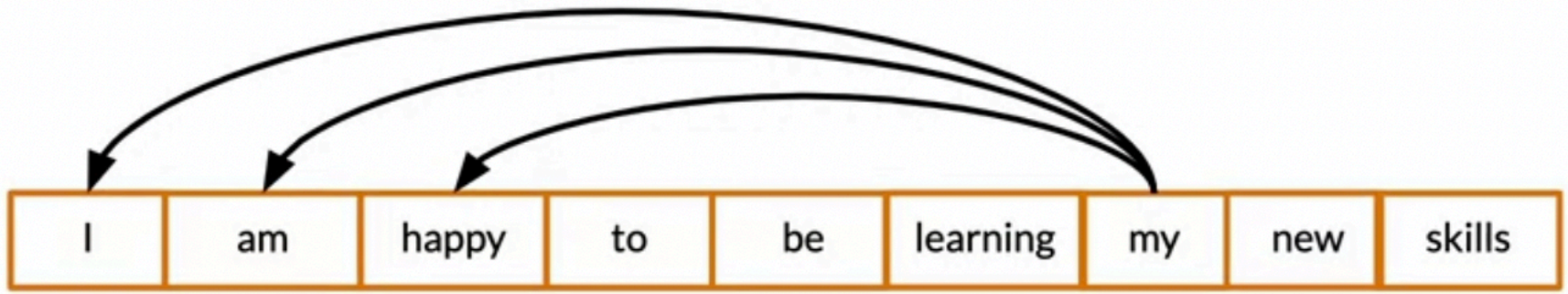
Three ways of attention

- **Encoder/decoder attention**: One sentence (decoder) looks at another one (encoder)
- **Causal (self) attention**: In one sentence, words look at previous words (used for generation)
- **Bi-directional self attention**: In one sentence, words look at both previous and future words

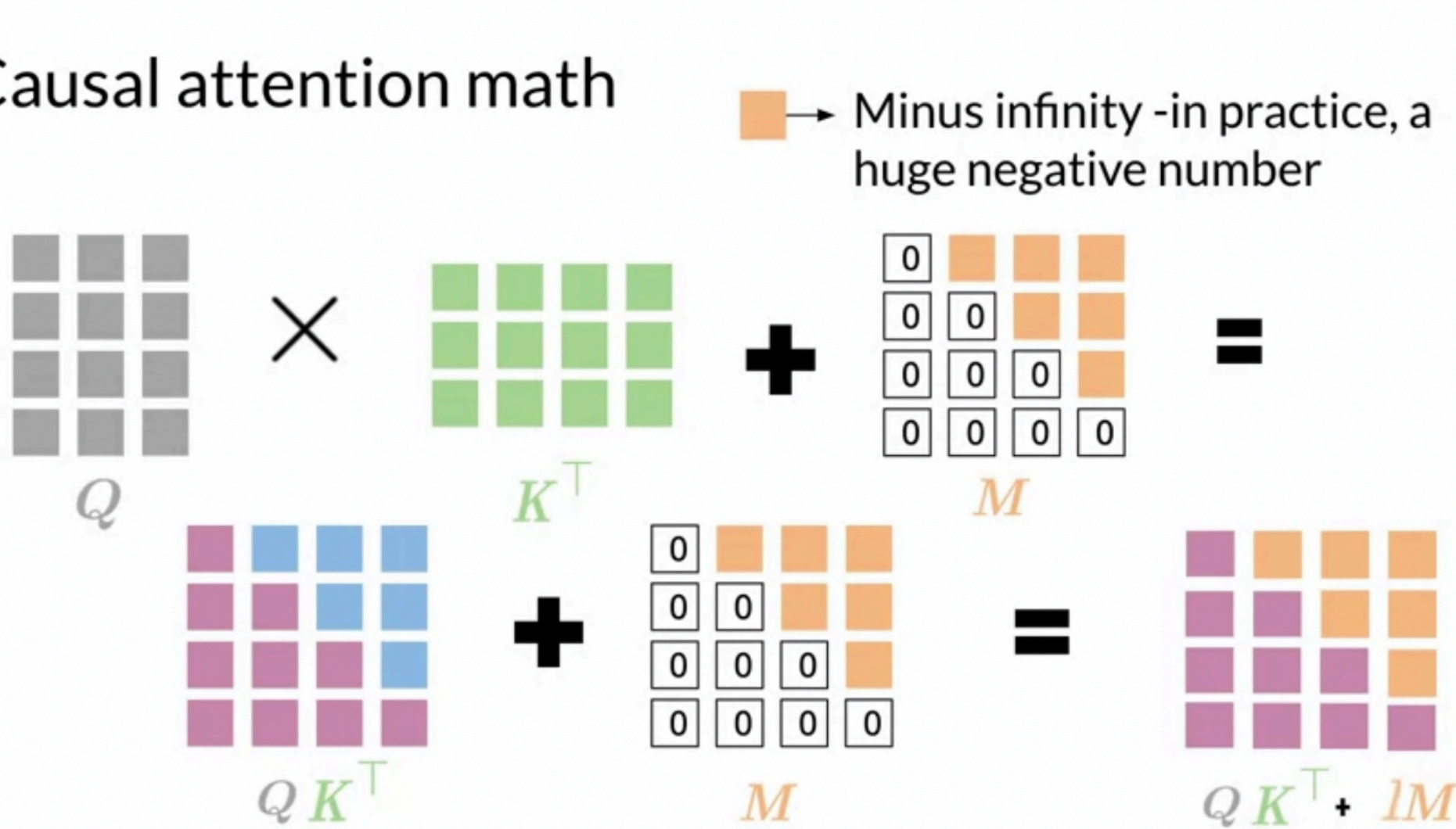


Causal attention

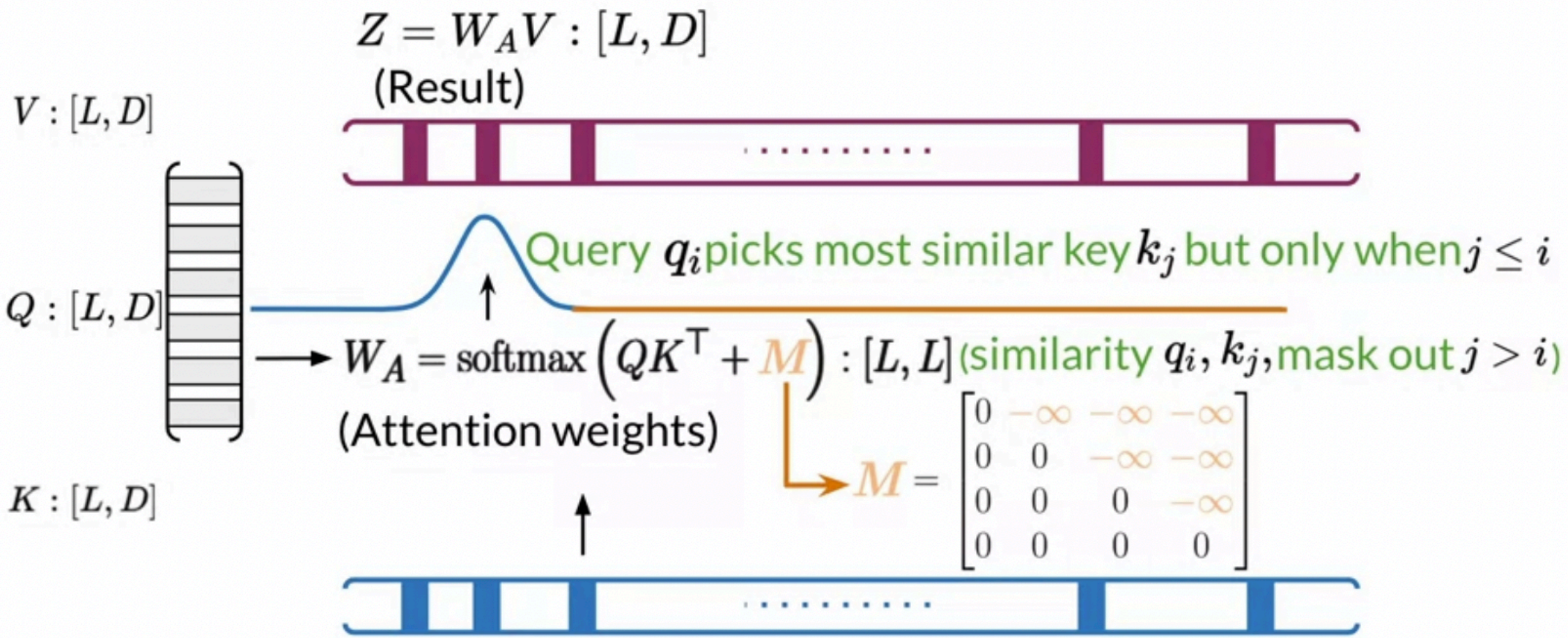
- Queries and keys are words from the same sentence
- Queries should only be allowed to look at words before



Causal attention math



Causal attention math



Summary

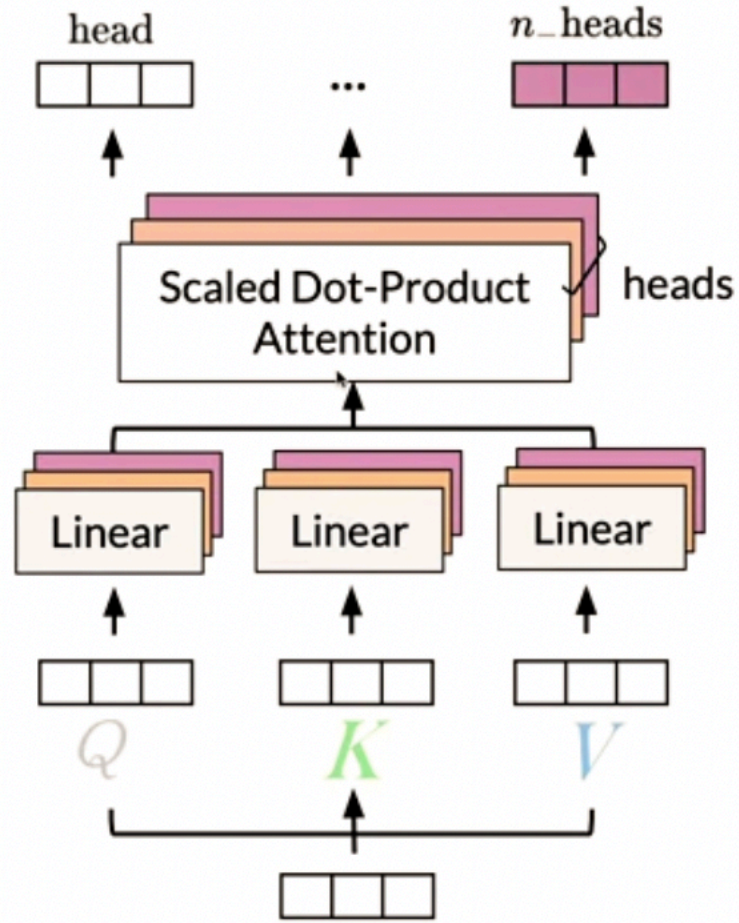
- There are three main ways of Attention: Encoder/Decoder, Causal and Bi-directional type
- In causal attention, queries and keys come from the same sentence and queries search among words before only

Outline

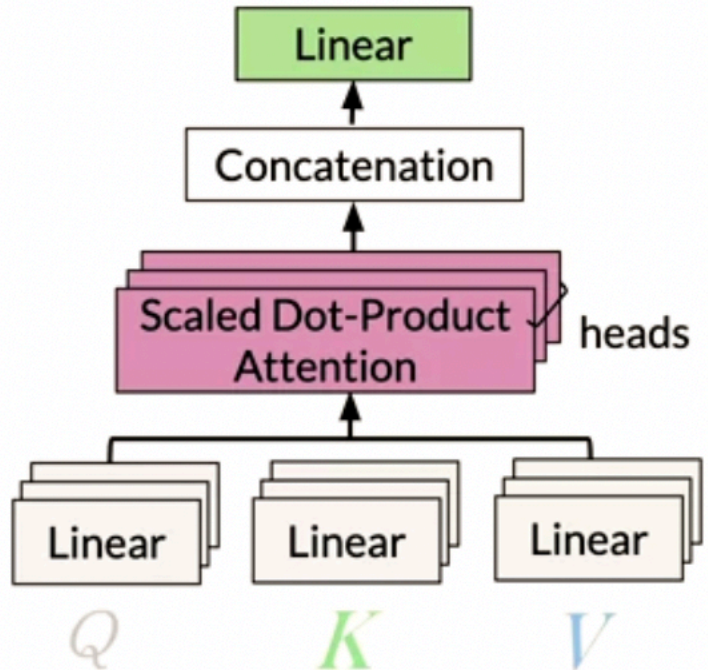
- Intuition of Multi-Head Attention
- Scaled dot-product and concatenation
- Multi-Head Attention formula

Multi-Head Attention

- Each head uses different linear transformations to represent words
- Different heads can learn different relationships between words



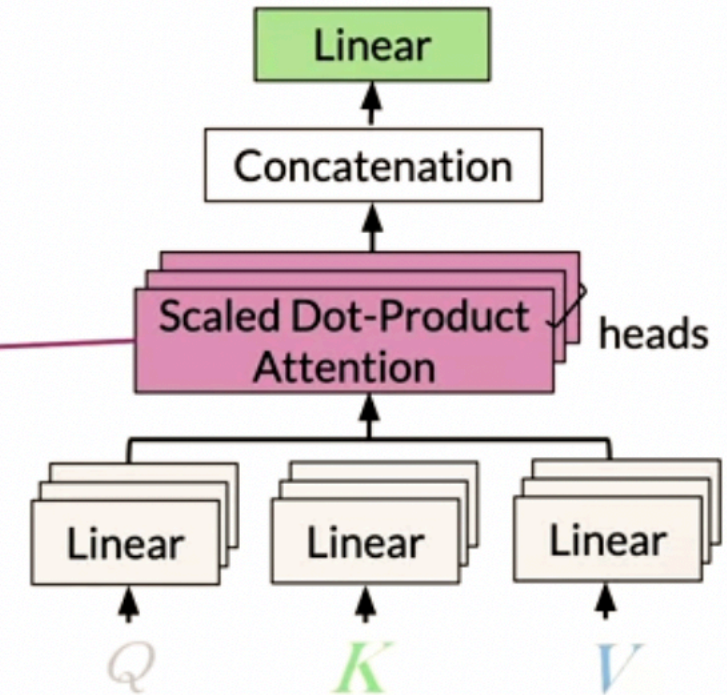
Multi-Head Attention - Overview



Multi-Head Attention - Scaled dot product

$$\text{Attention}(Q, K, V) = \text{Softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

Query and key dimension



Multi-Head Attention - Concatenation

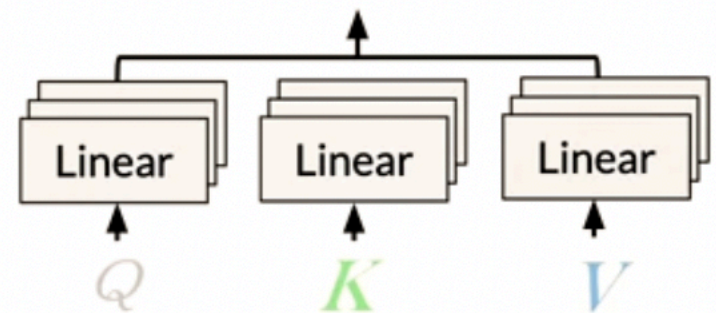
- Input(Q, K, V): `[batch, length, d_model]`

512, 1024

Multi-Head Attention - Concatenation

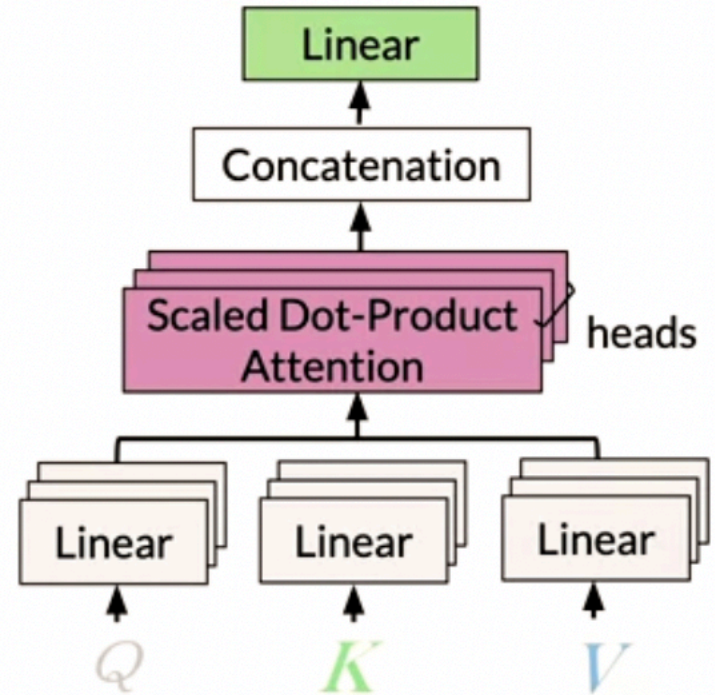
- Input(Q, K, V): `[batch, length, d_model]`
- Linear layer: `[batch, length, n_heads * d_head]`

4, 6, 16, ... 64, 128

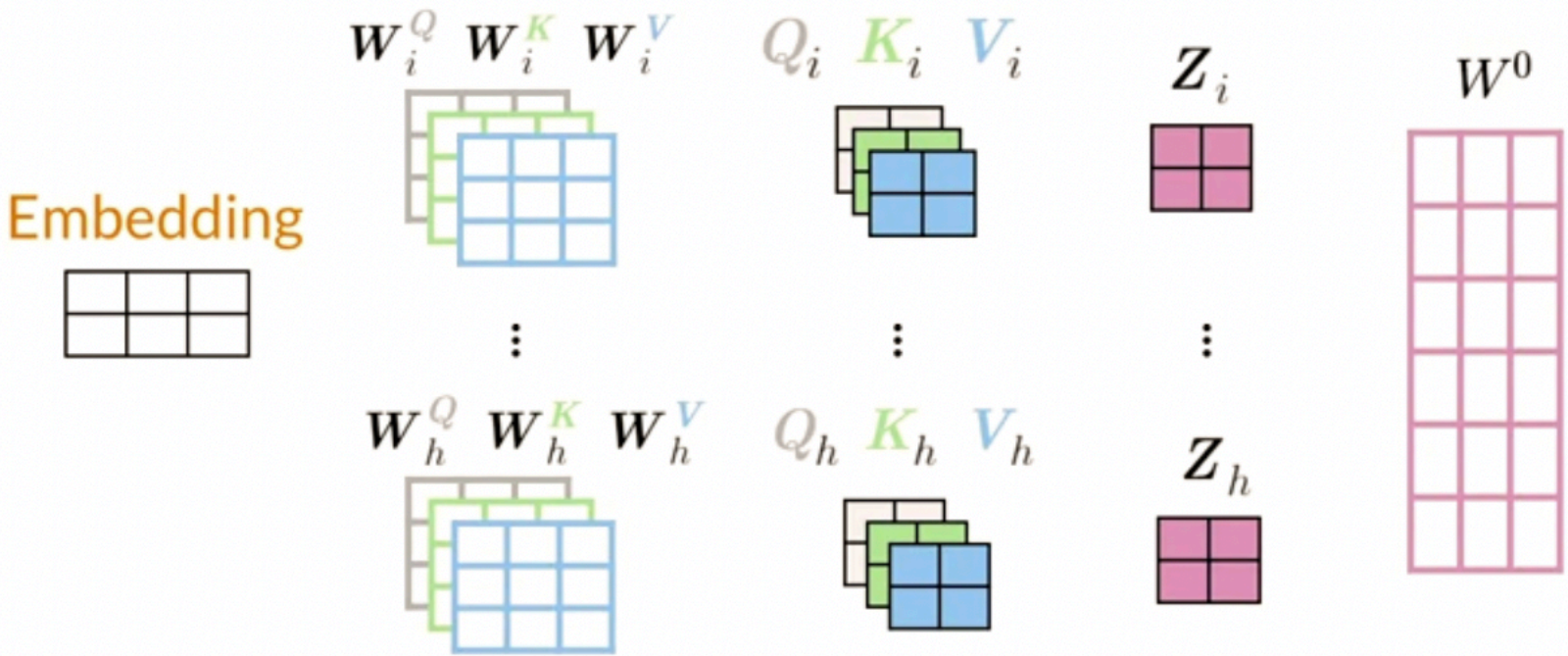


Multi-Head Attention - Concatenation

- Input(Q, K, V): `[batch, length, d_model]`
- Linear layer: `[batch, length, n_heads * d_head]`
- Transpose: `[batch, n_heads, length, d_head]`
- Apply attention treating `n_heads` like batch
- Result shape: `[batch, n_heads, length, d_head]`
- Transpose: `[batch, length, n_heads * d_head]`
- Linear layer into: `[batch size, length, d_model]`



Multi-Head Attention math

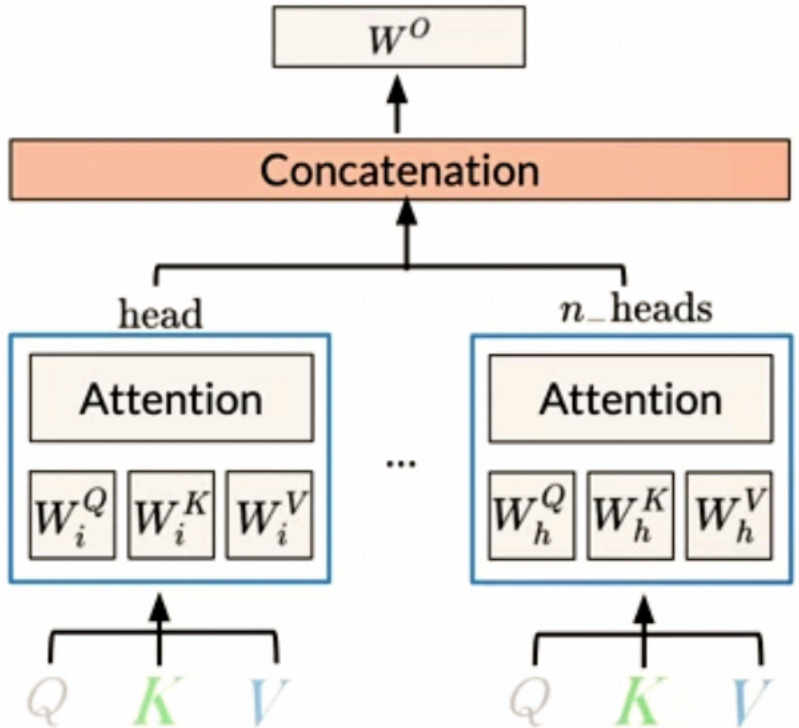


Multi-Head Attention Formula

$$\text{MultiHead}(Q, K, V) = \text{Concat}(h_1, \ldots, h_h)W^0$$

where $h_i = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V)$

Each head h_i is the attention function of **Query, Key and Value** with trainable parameters (W_i^Q, W_i^K, W_i^V)



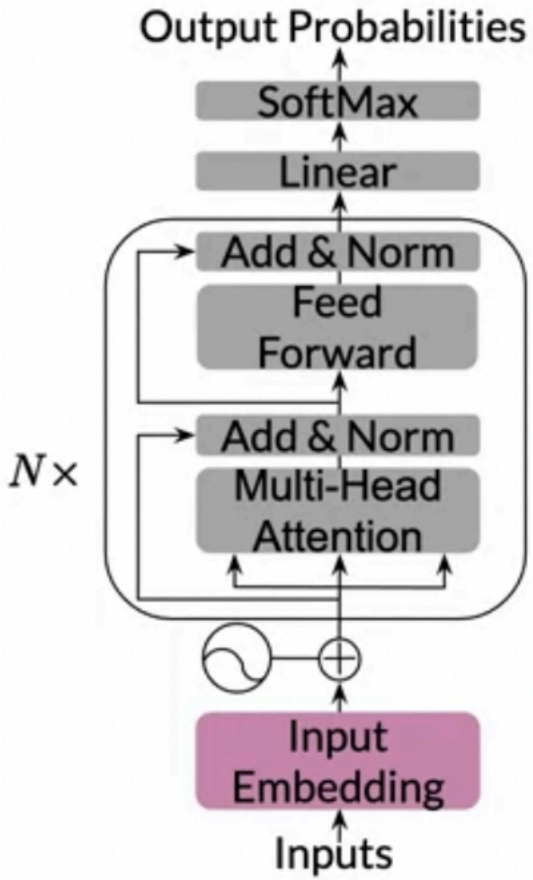
Summary

- Different heads can learn different relationship between words
- Scaled dot-product is adequate for Multi-Head Attention
- Multi-Headed models attend to information from different representations at different positions

Outline

- Overview of Transformer decoder
- Implementation (decoder and feed-forward block)

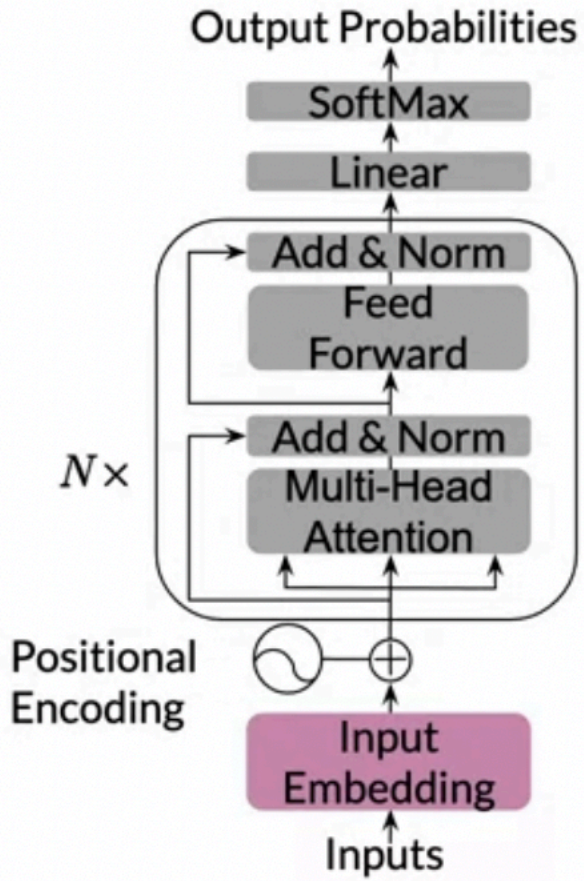
Transformer decoder



Overview

- input: sentence or paragraph
  - we predict the next word

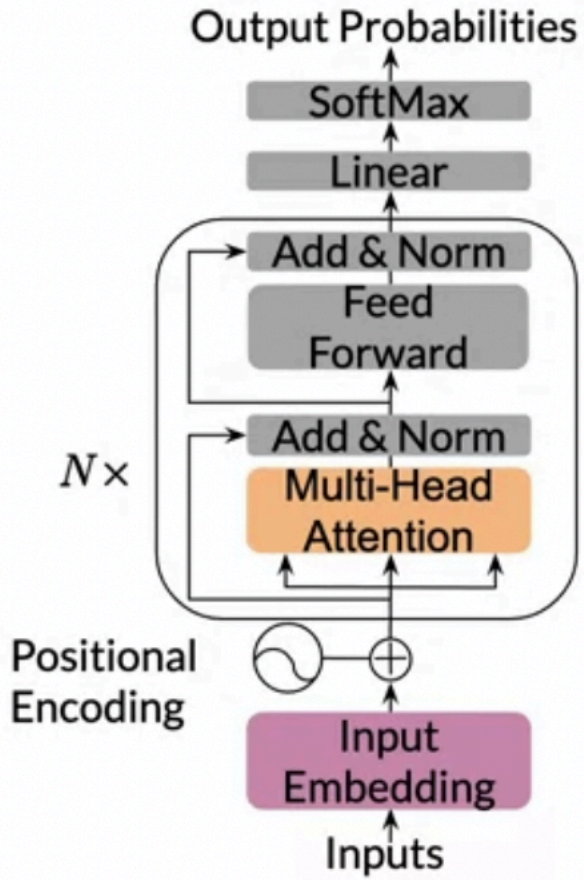
Transformer decoder



Overview

- input: sentence or paragraph
  - we predict the next word
- sentence gets embedded, add positional encoding
  - (vectors representing $\{0, 1, 2, \ldots, K\}$)

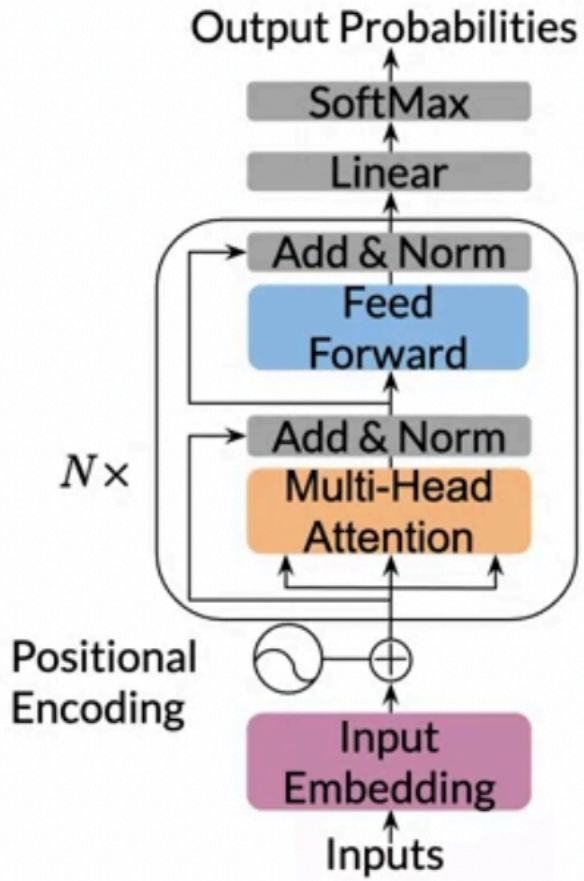
Transformer decoder



Overview

- input: sentence or paragraph
  - we predict the next word
- sentence gets embedded, add positional encoding
  - (vectors representing $\{0, 1, 2, \ldots, K\}$)
- multi-head attention looks at previous words

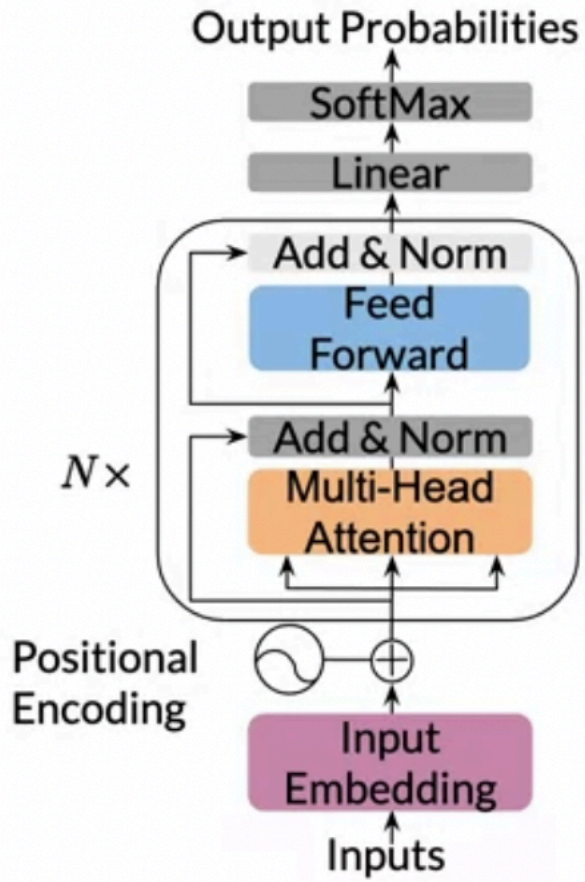
Transformer decoder



Overview

- input: sentence or paragraph
  - we predict the next word
- sentence gets embedded, add positional encoding
  - (vectors representing $\{0, 1, 2, \ldots, K\}$)
- multi-head attention looks at previous words
- feed-forward layer with ReLU
  - that's where most parameters are!

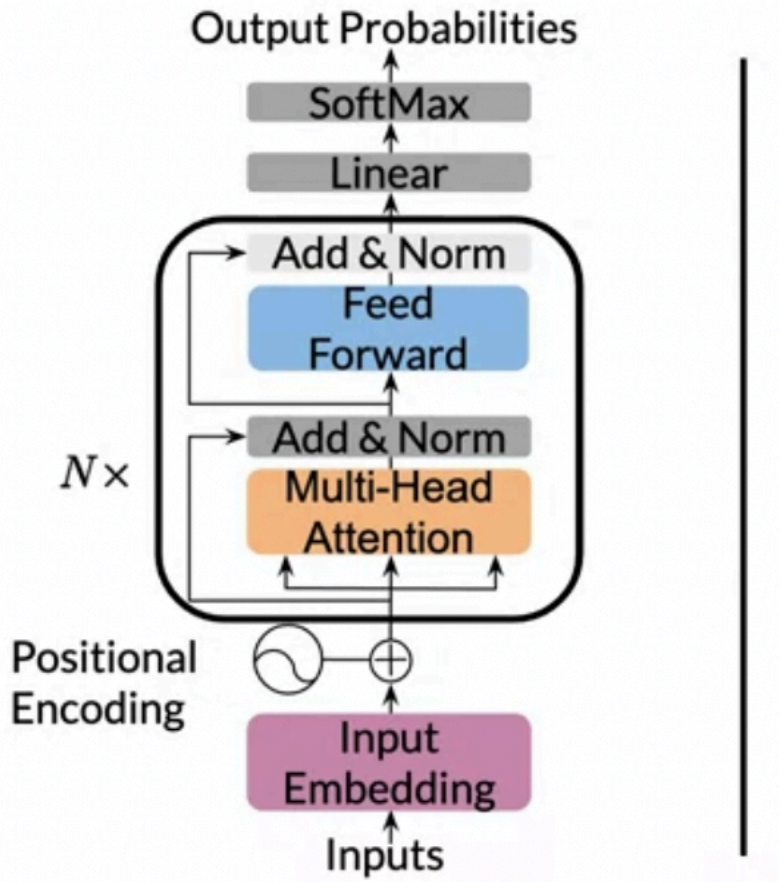
Transformer decoder



Overview

- input: sentence or paragraph
  - we predict the next word
- sentence gets embedded, add positional encoding
  - (vectors representing $\{0, 1, 2, \ldots, K\}$)
- multi-head attention looks at previous words
- feed-forward layer with ReLU
  - that's where most parameters are!
- residual connection with layer normalization

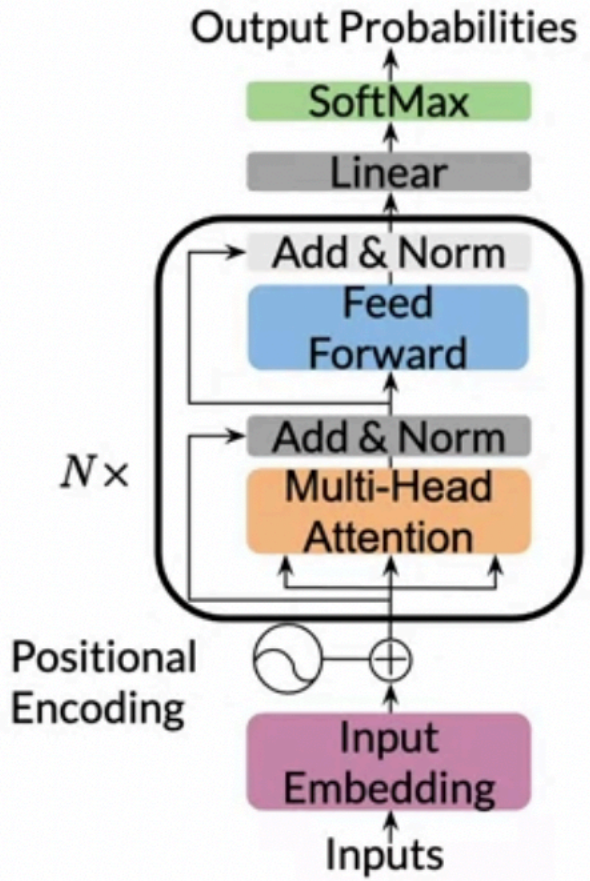
Transformer decoder



Overview

- input: sentence or paragraph
  - we predict the next word
- sentence gets embedded, add positional encoding
  - (vectors representing $\{0, 1, 2, \ldots, K\}$)
- multi-head attention looks at previous words
- feed-forward layer with ReLU
  - that's where most parameters are!
- residual connection with layer normalization
- repeat N times

Transformer decoder



Overview

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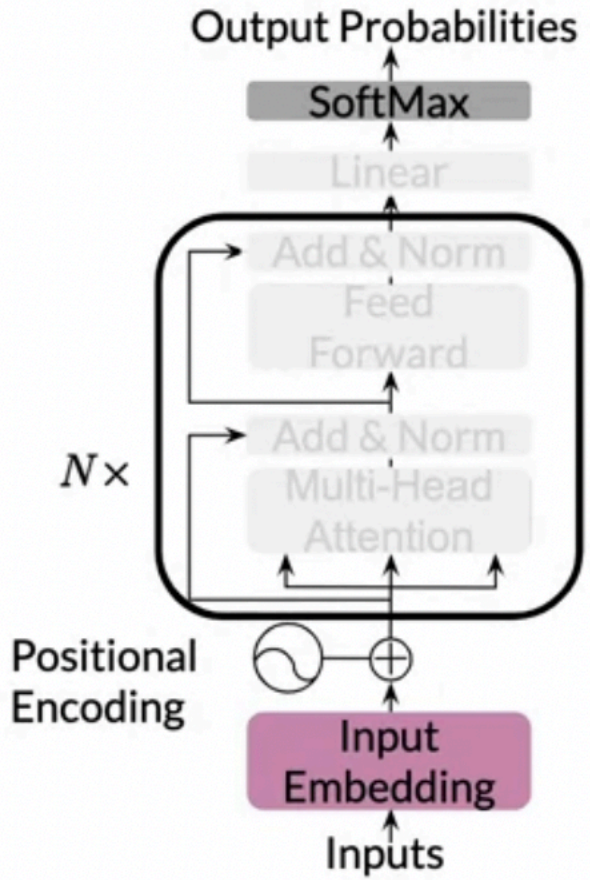
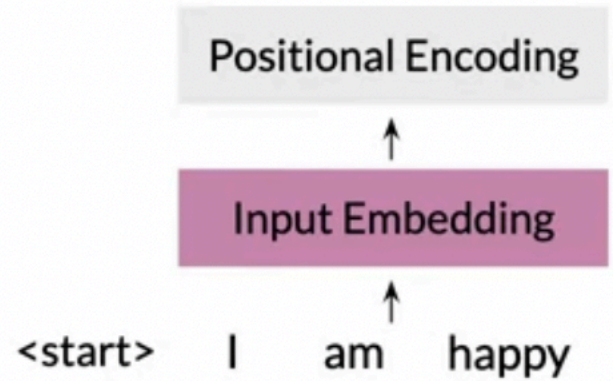
  - we predict the next word
- sentence gets embedded, add positional encoding
  - (vectors representing $\{0, 1, 2, \ldots, K\}$)
- multi-head attention looks at previous words
- feed-forward layer with ReLU
  - that's where most parameters are!
- residual connection with layer normalization
- repeat N times
- dense layer and softmax for output

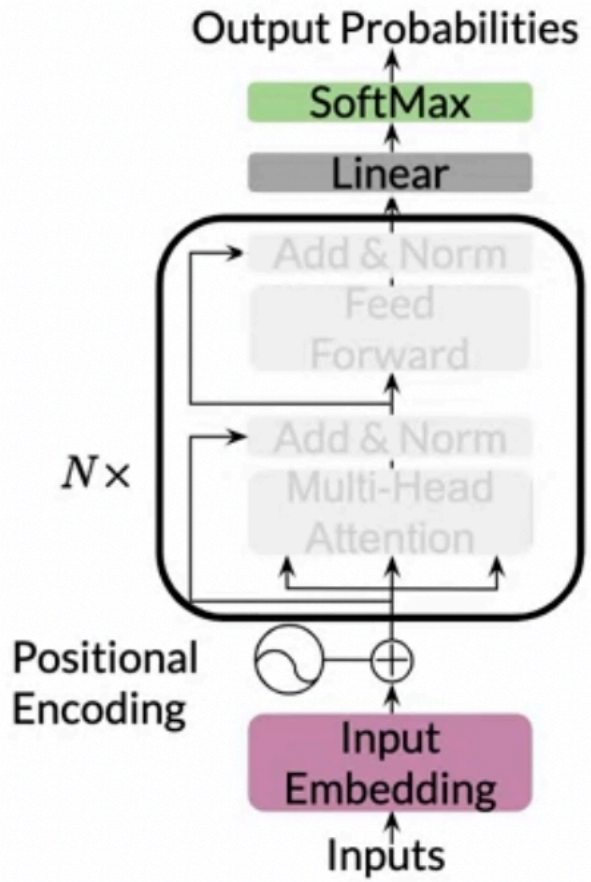
Transformer decoder



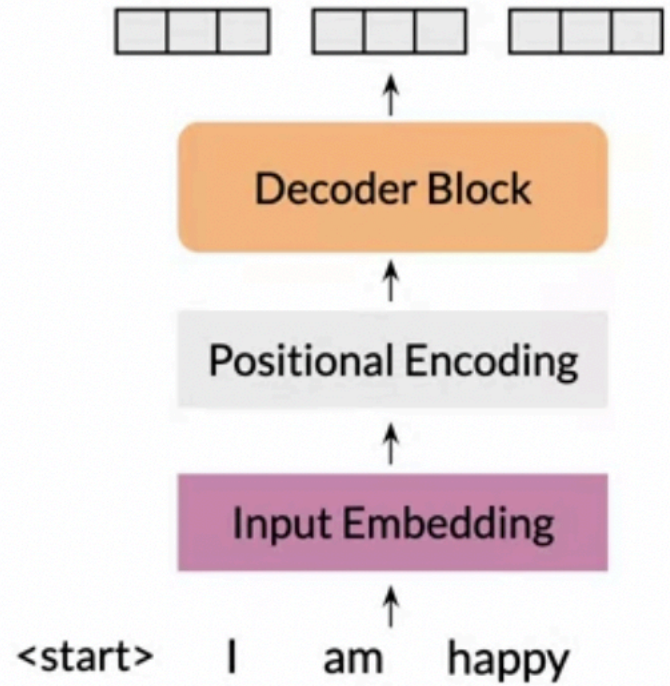
Explanation



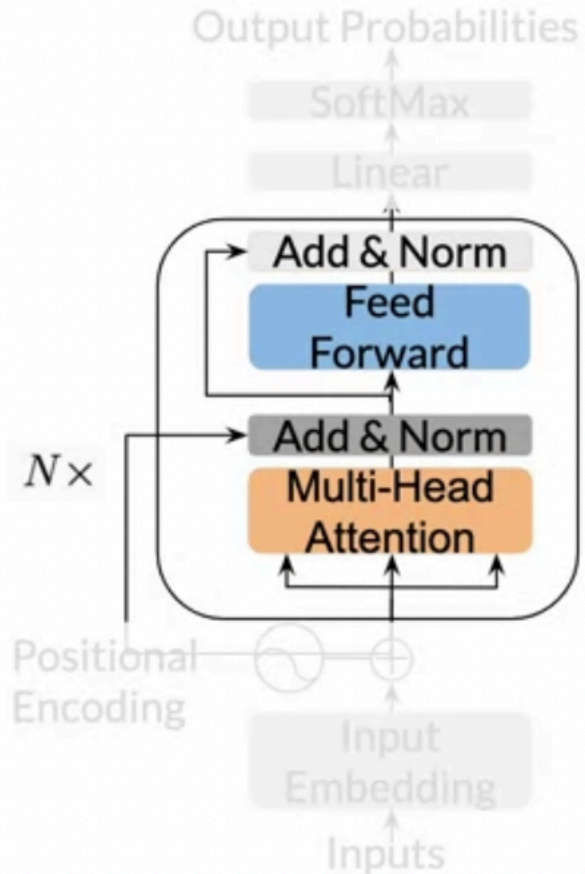
Transformer decoder

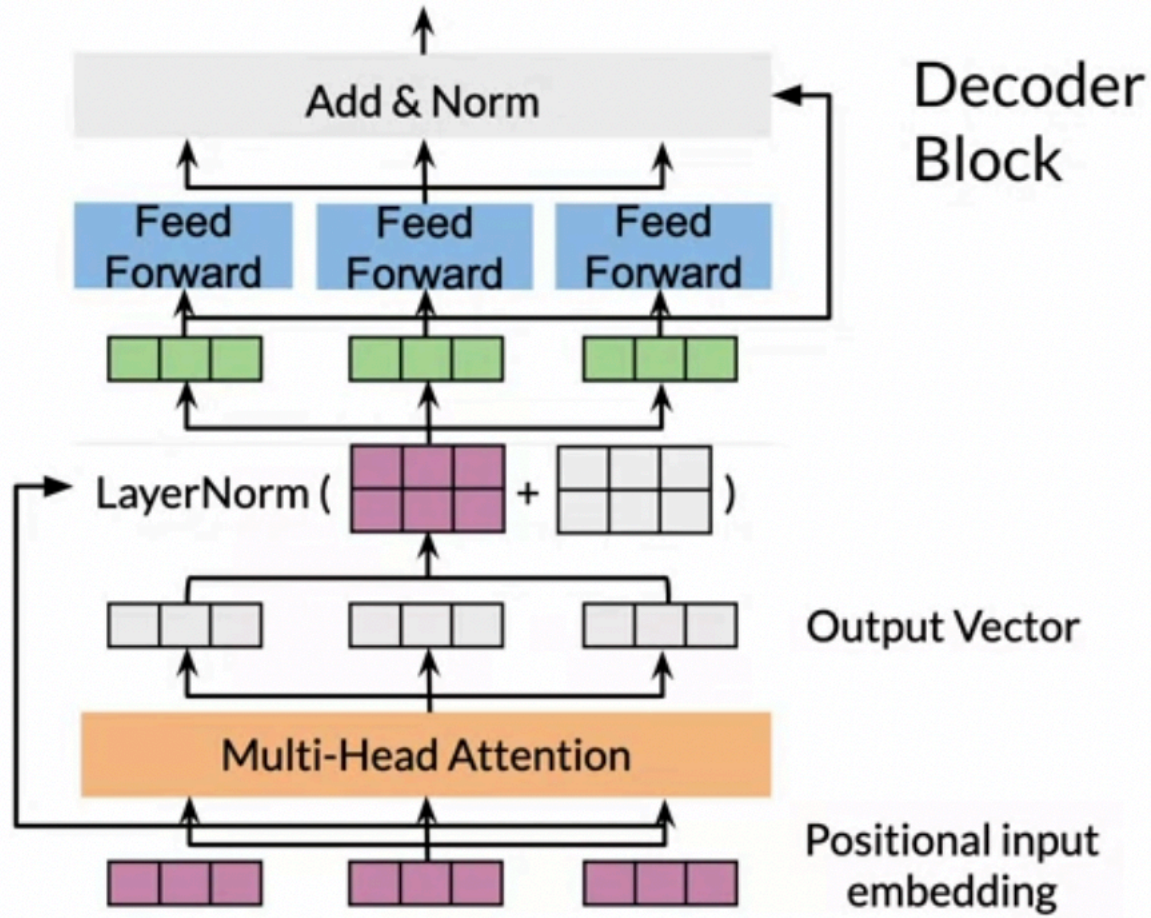


Explanation

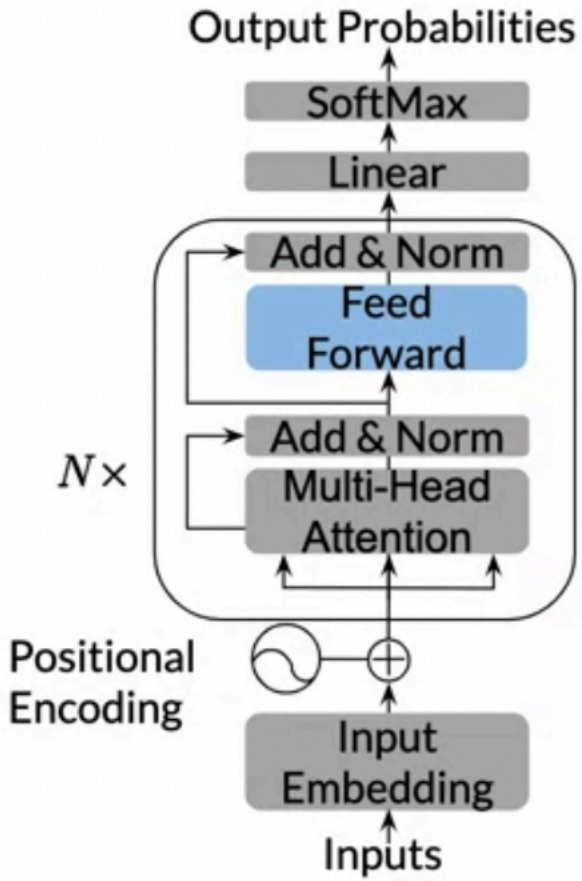


The Transformer decoder

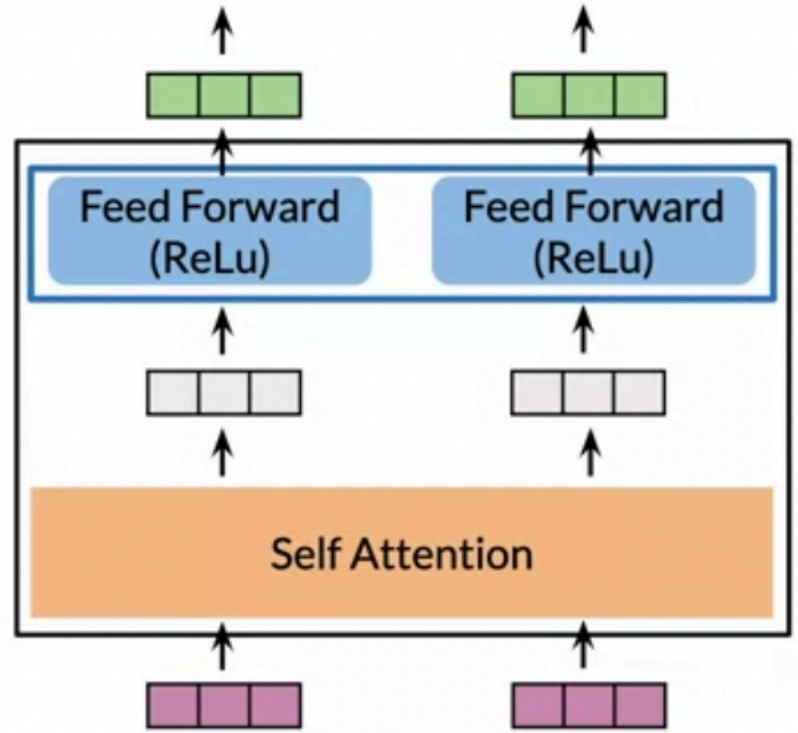




The Transformer decoder



Feed forward layer

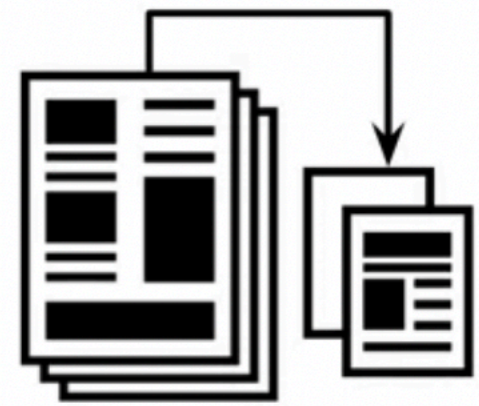


Summary

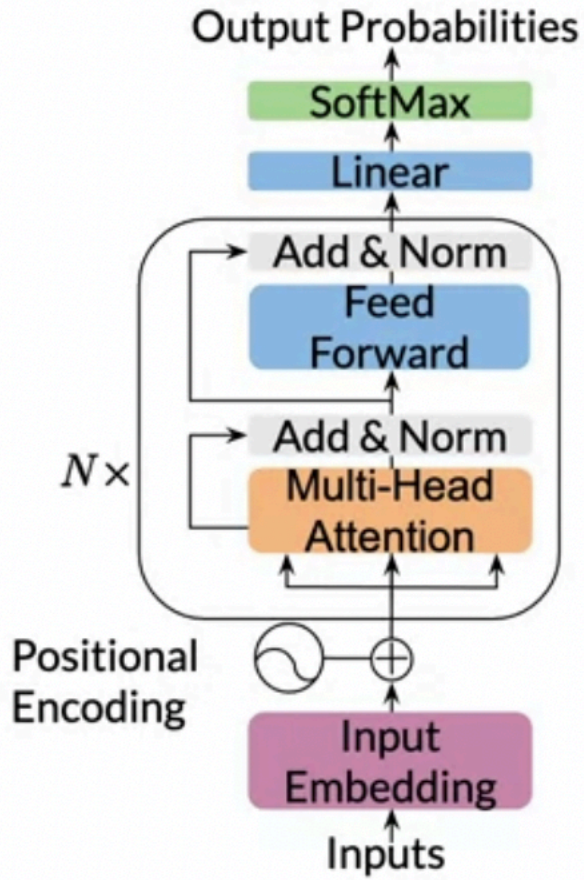
- Transformer decoder mainly consists of three layers
- Decoder and feed-forward blocks are the core of this model code
- It also includes a module to calculate the cross-entropy loss

Outline

- Overview of Transformer summarizer
- Technical details for data processing
- Inference with a Language Model

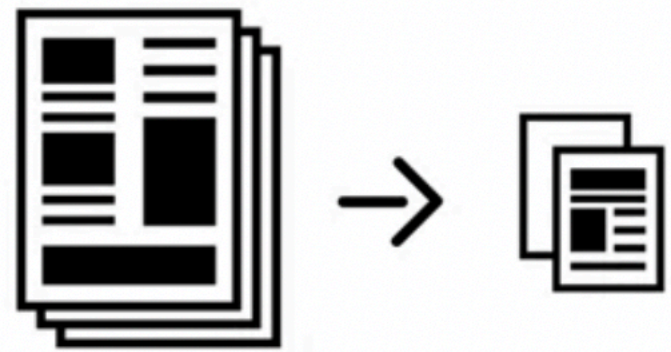


Transformer for summarization

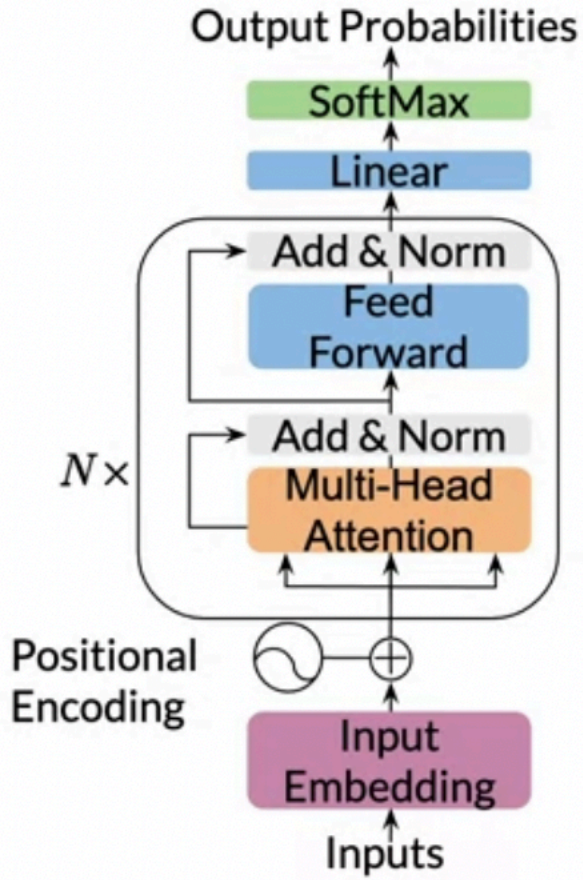


Input

Output: Summary



Technical details for data processing



Model Input:

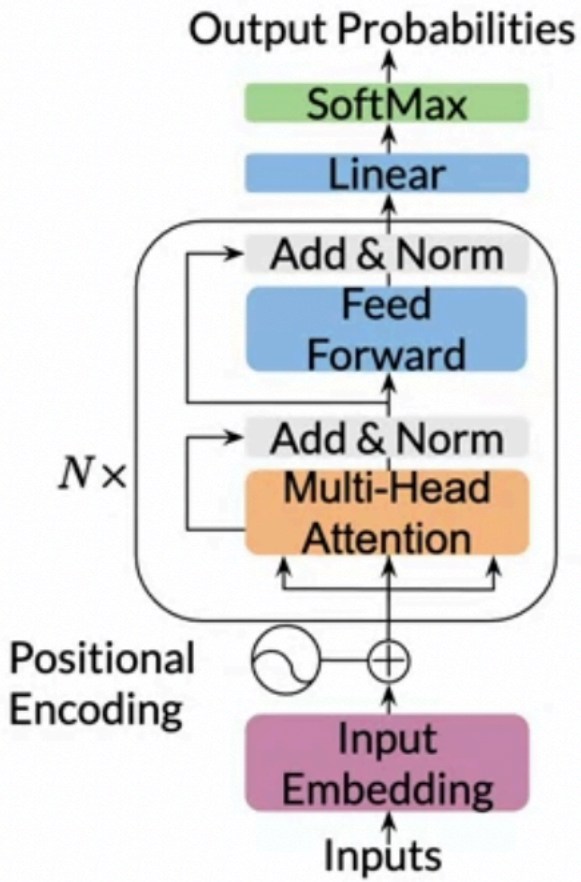
```
ARTICLE TEXT <EOS> SUMMARY <EOS> <pad> ...
```

Tokenized version:

```
[2,3,5,2,1,3,4,7,8,2,5,1,2,3,6,2,1,0,0]
```

Loss weights: 0s until the first `<EOS>` and then 1 on the start of the summary.

Cost function



Cross entropy loss

$$J = -\frac{1}{m}\sum_{j}^{m}\sum_{i}^{K} y_j^i \log \hat{y}_j^i$$

j : over summary

i : bach elements

Inference with a Language Model

Model input:

`[Article] <EOS>  [Summary] <EOS>`

Inference:

- Provide: [Article] <EOS>

- Generate summary word-by-word
  - until the final <EOS>

- Pick the next word by random sampling
  - each time you get a different summary!

Summary

- For summarization, a weighted loss function is optimized
- Transformer Decoder summarizes predicting the next word using
- The transformer uses tokenized versions of the input