Copyright Notice

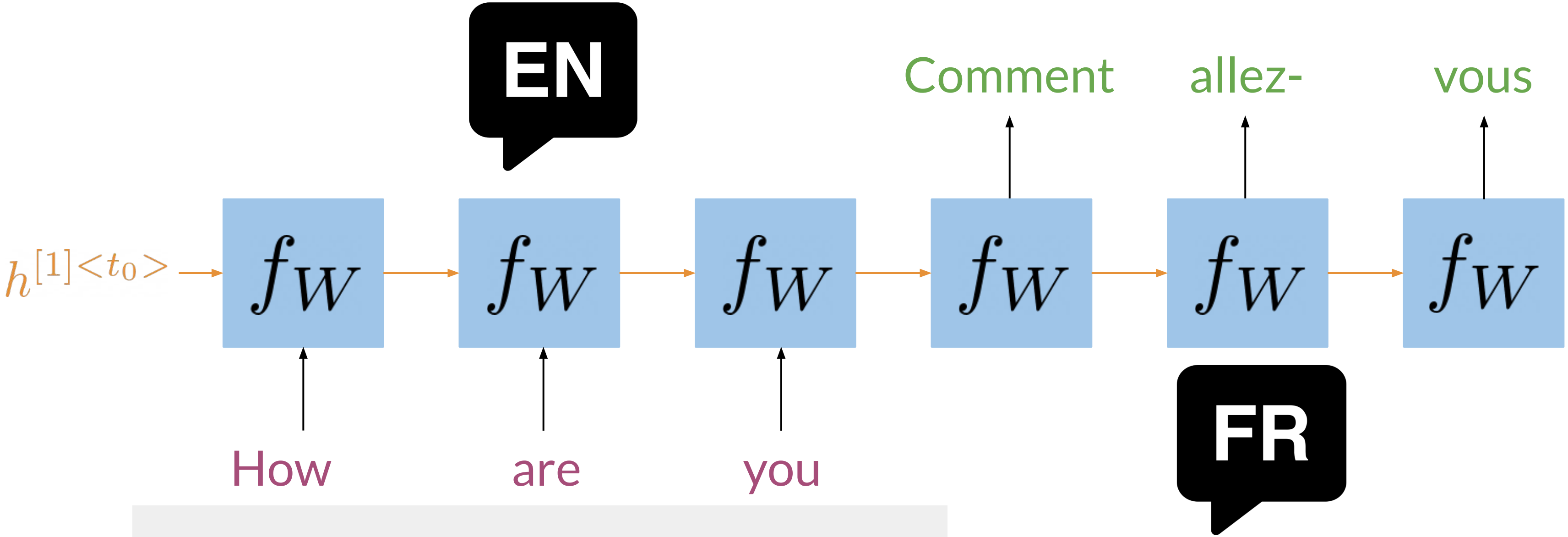
Transformers vs RNNs

deeplearning.ai

Outline

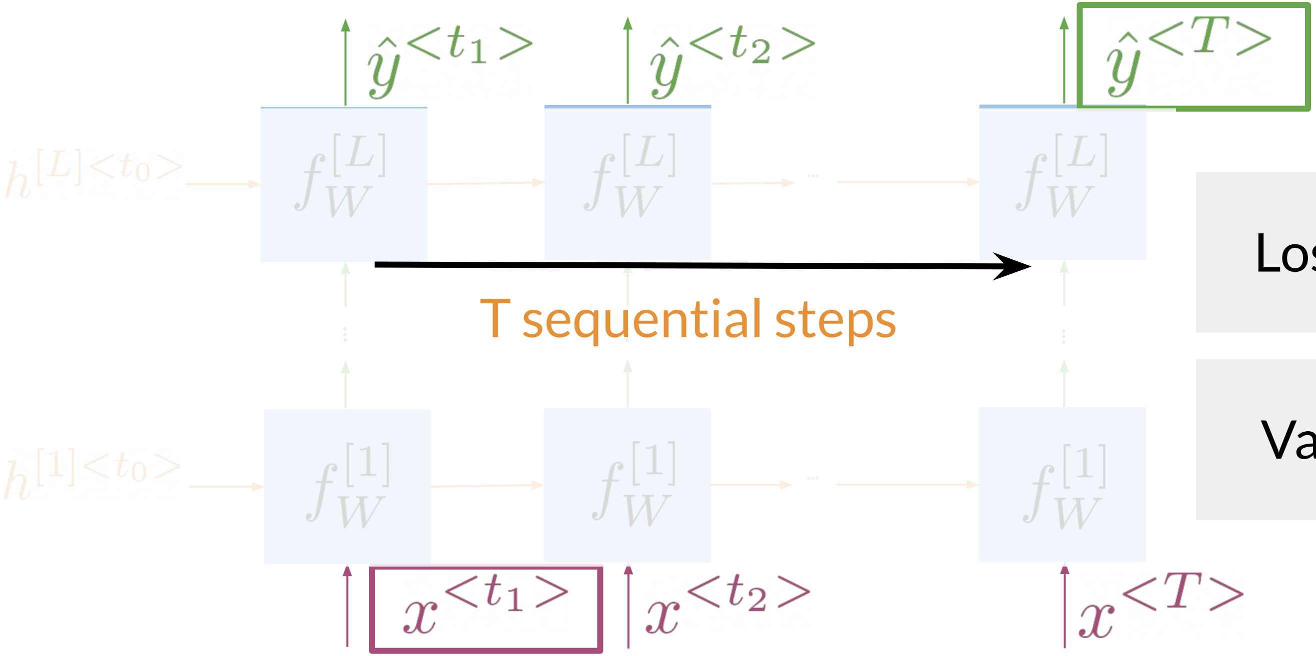
- Issues with RNNs
- Comparison with Transformers

Neural Machine Translation



No parallel computing!

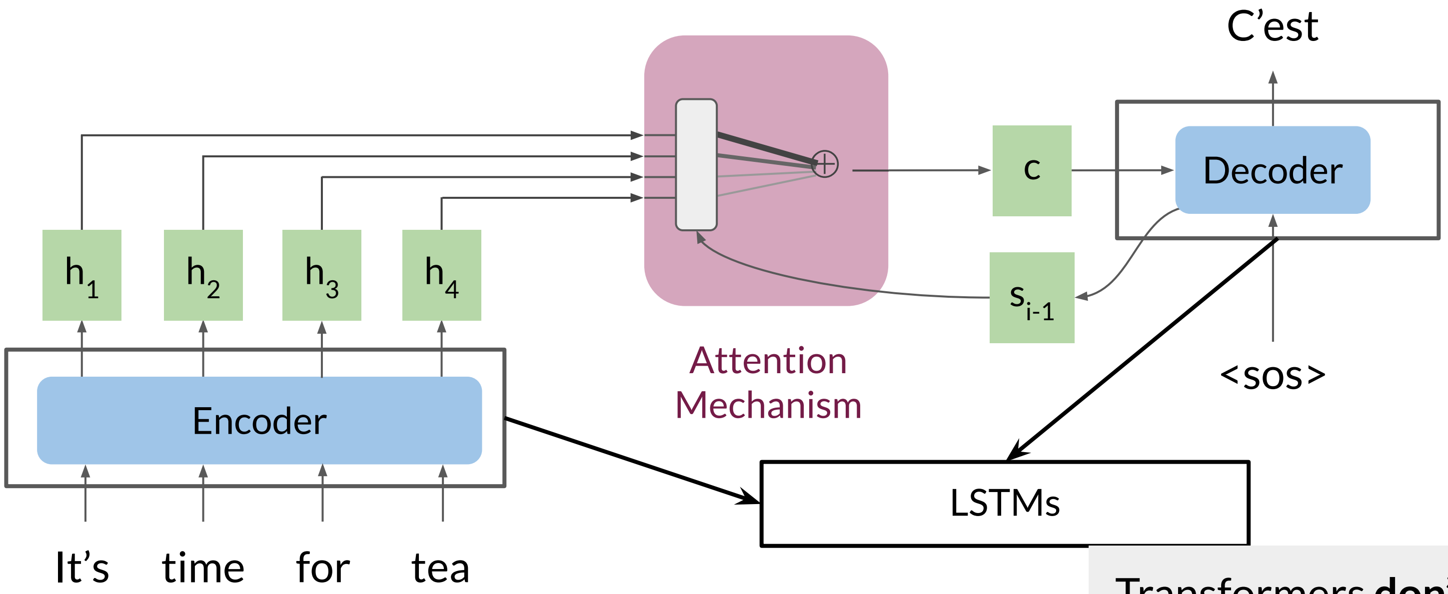
Seq2Seq Architectures



Loss of information

Vanishing gradient

RNNs vs Transformer: Encoder-Decoder



Transformers **don't** use RNNs, such as LSTMs or GRUs

deeplearning.ai

Transformers Overview

The Transformer Model

Attention Is All You Need

Ashish Vaswani[*]
Google Brain
avaswani@google.com

Noam Shazeer[*]
Google Brain
noam@google.com

Niki Parmar[*]
Google Research
nikip@google.com

Jakob Uszkoreit[*]
Google Research
usz@google.com

Llion Jones[*]
Google Research
llion@google.com

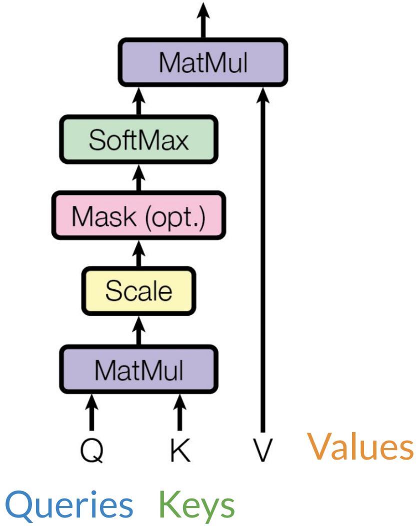
Aidan N. Gomez[*, †]
University of Toronto
aidan@cs.toronto.edu

Łukasz Kaiser[*]
Google Brain
lukaszkaiser@google.com

Illia Polosukhin[*, ‡]
illia.polosukhin@gmail.com

https://arxiv.org/abs/1706.03762

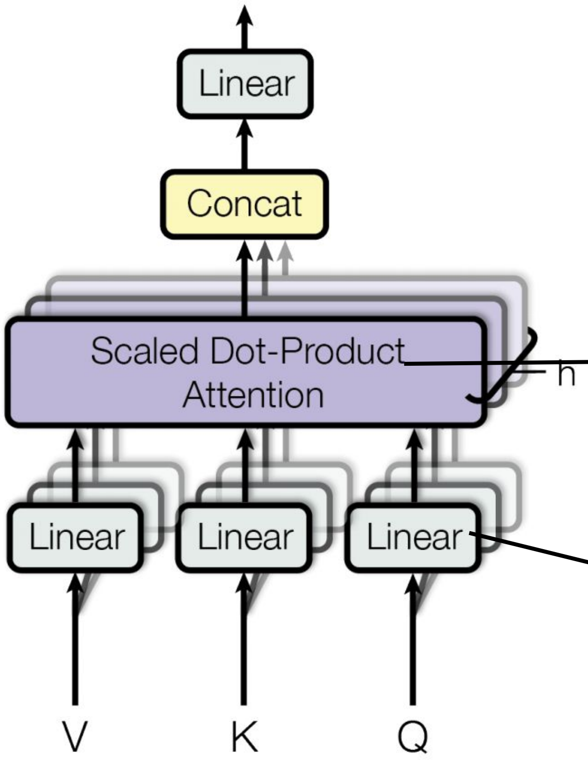
Scaled Dot-Product Attention



(Vaswani et al., 2017)

$$\mathrm{softmax}\left(\frac{QK^\top}{\sqrt{d_k}}\right)V$$

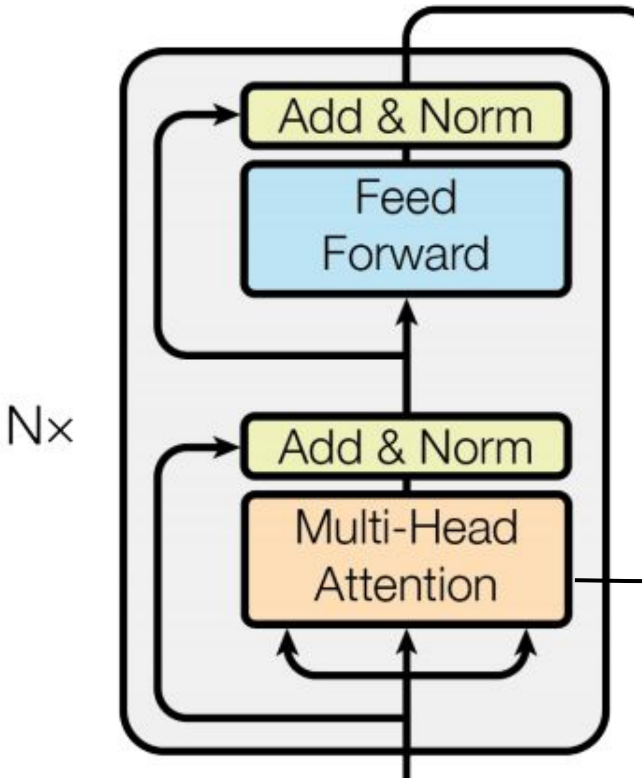
Multi-Head Attention



Scaled **dot-product attention multiple times** in parallel

Linear transformations of the input queries, keys and values

The Encoder

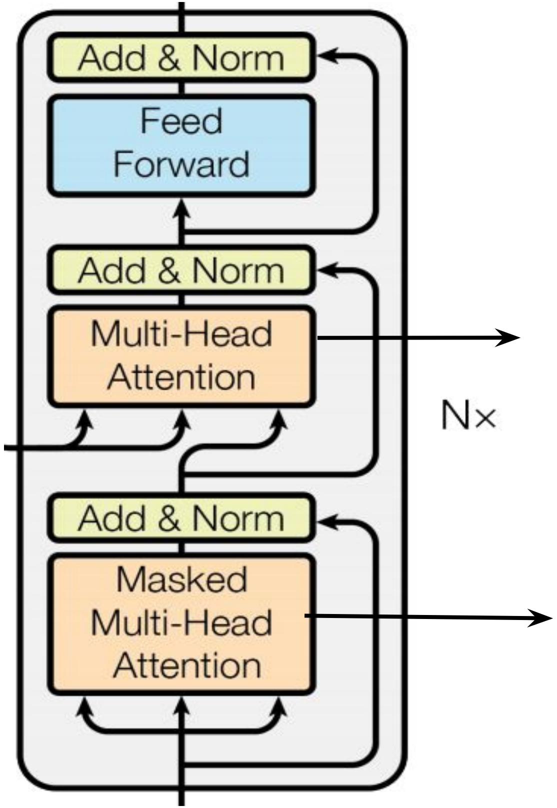


Provides contextual representation of each item in the input sequence

Self-Attention

Every item in the input attends to every other item in the sequence

The Decoder



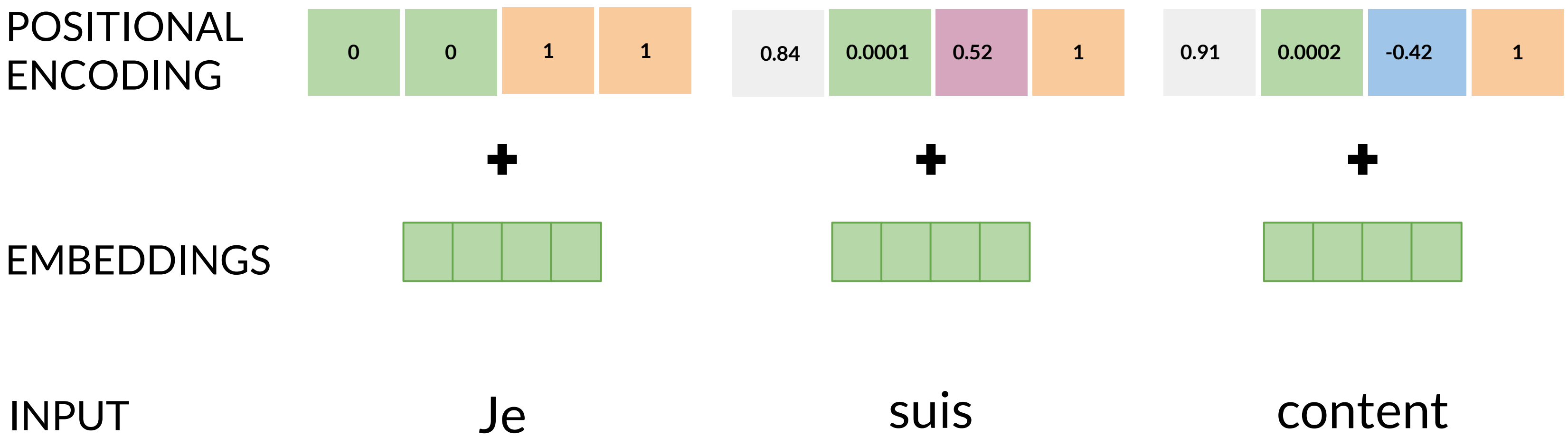
Encoder-Decoder Attention

Every position from the decoder attents to the outputs from the encoder

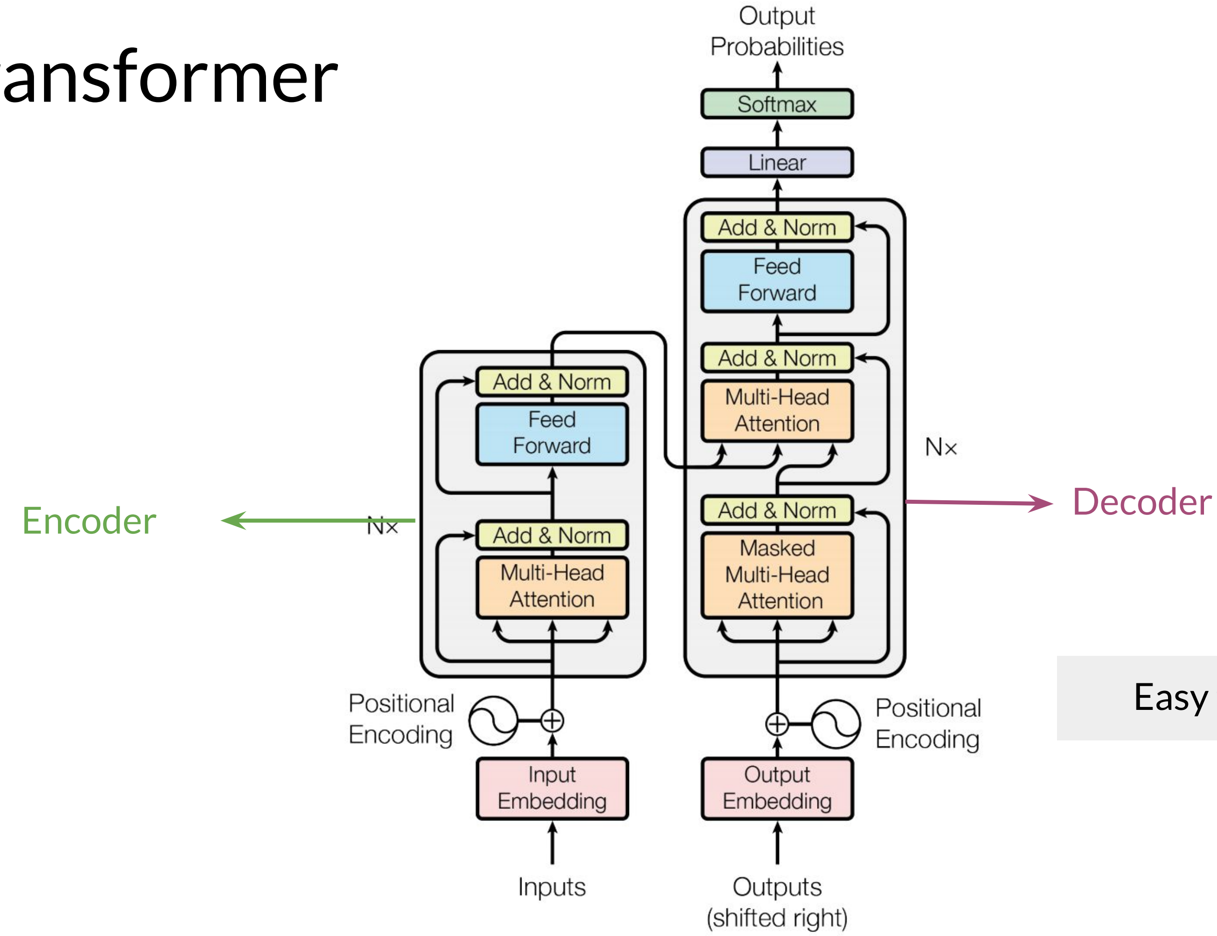
Masked Self-Attention

Every position attends to **previous** positions

RNNs vs Transformer: Positional Encoding



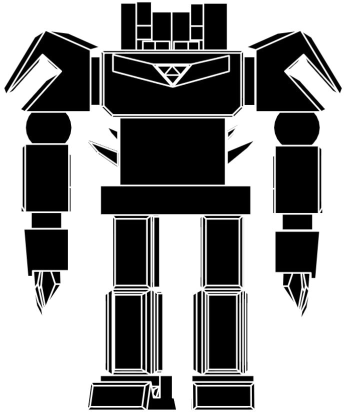
The Transformer



Easy to parallelize!

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

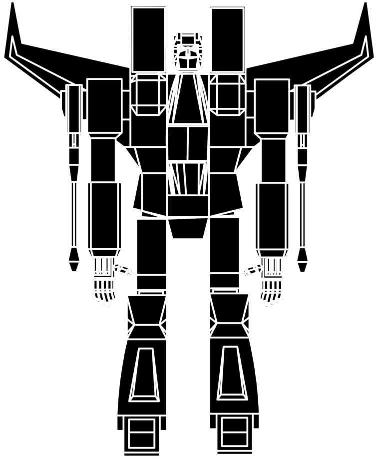


Transformer Applications

deeplearning.ai

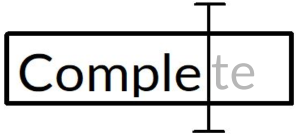
Outline

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



Transformer NLP applications

Text summarization



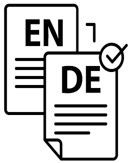
Auto-Complete

The	wind	blows	hard
Article	Noun	Verb	Adiective

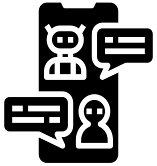
Named entity recognition (NER)

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

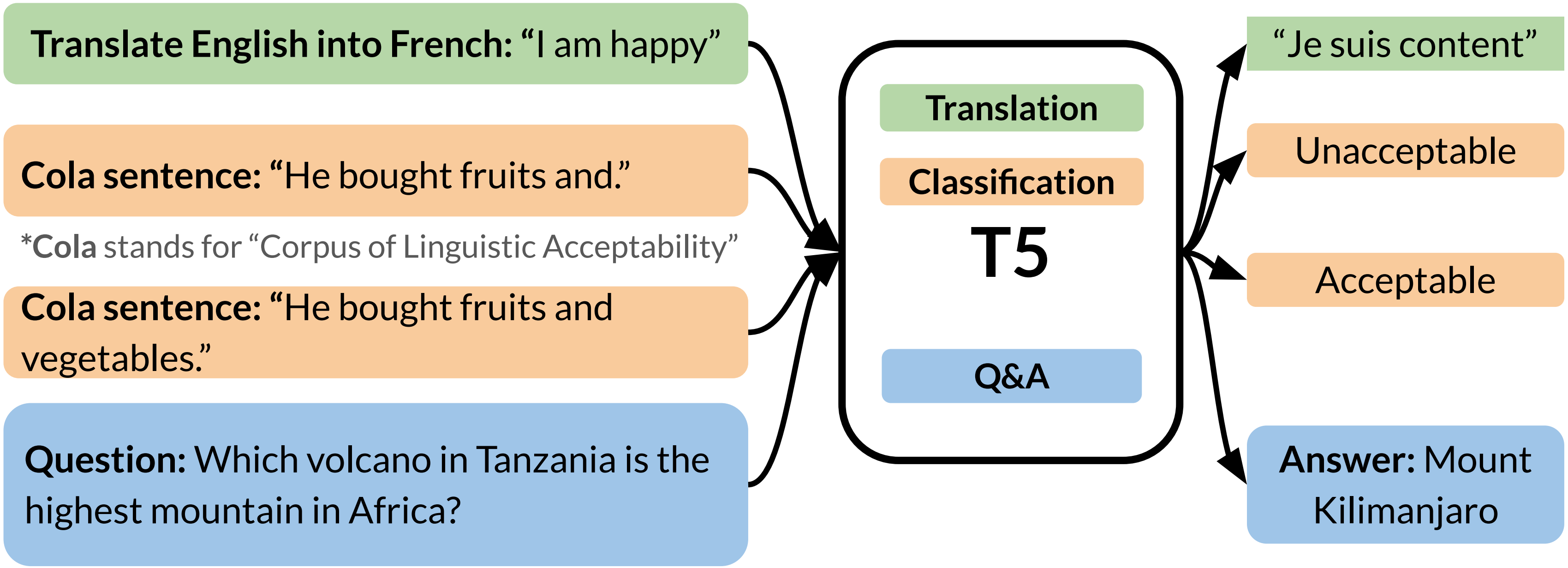
Devlin, J., et al. (2018)
Google AI Language

BERT:Bidirectional Encoder Representations from Transformers

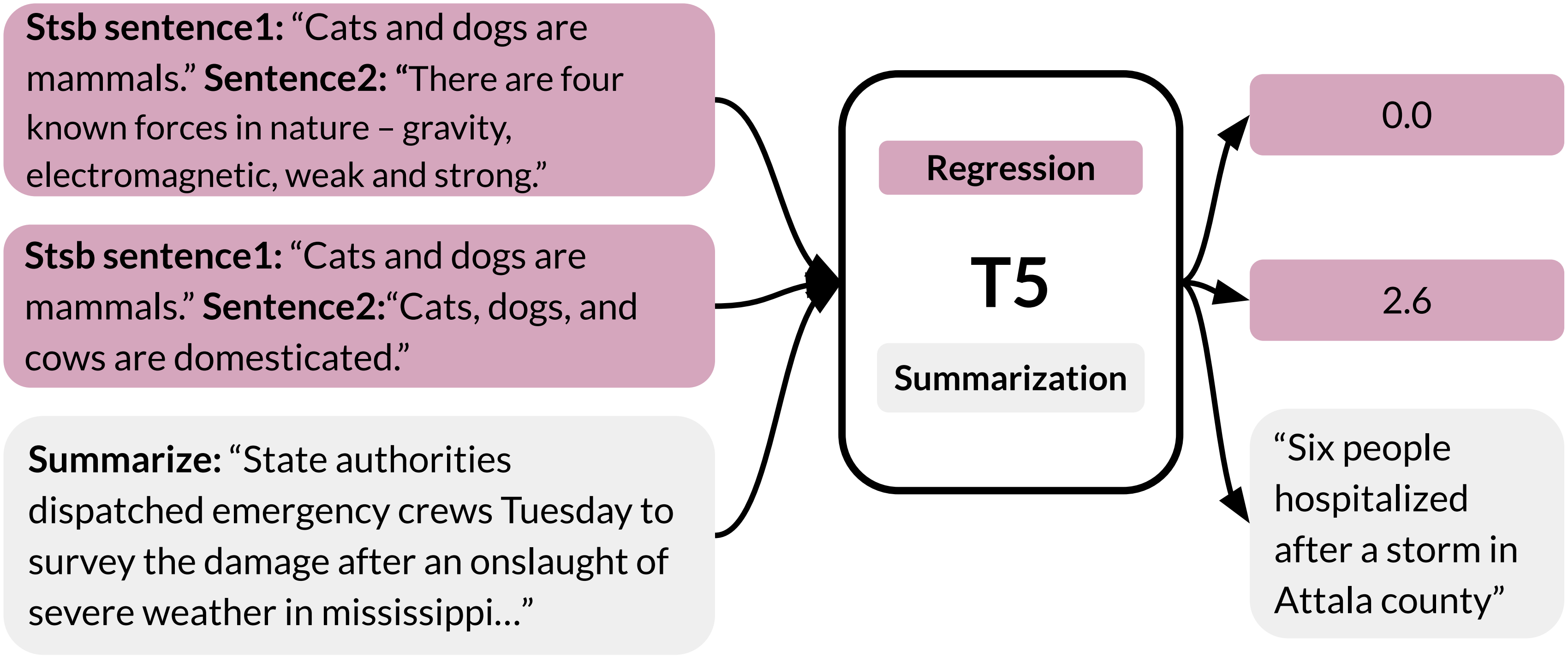
Colin, R., et al. (2019)
Google

T5: Text-to-text transfer transformer

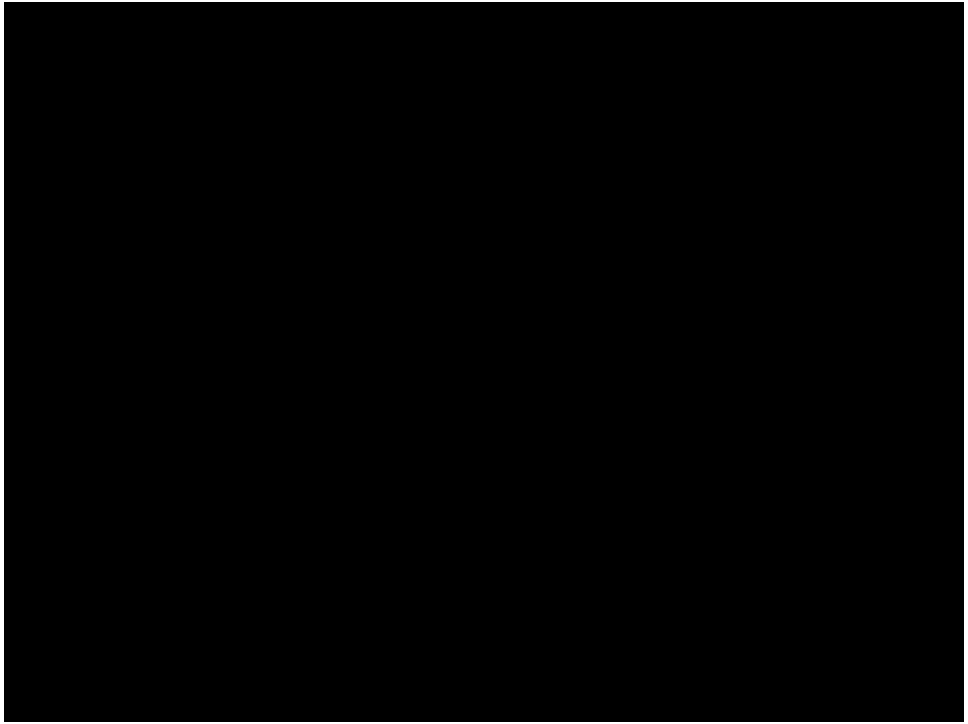
T5: Text-To-Text Transfer Transformer



T5: Text-To-Text Transfer Transformer

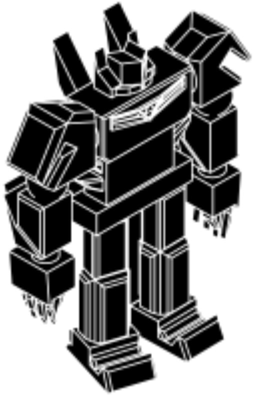


T5: Demo



Summary

- Transformers are suitable for a wide range of NLP applications
- Some transformers include GPT, BERT and T5
- T5 is a powerful multi-task transformer

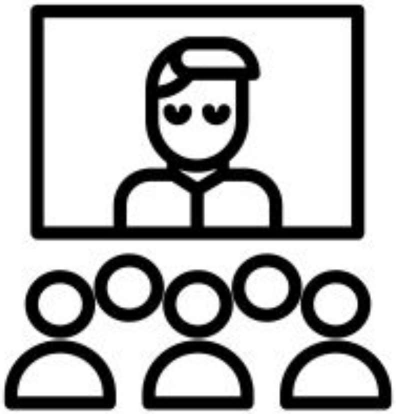


deeplearning.ai

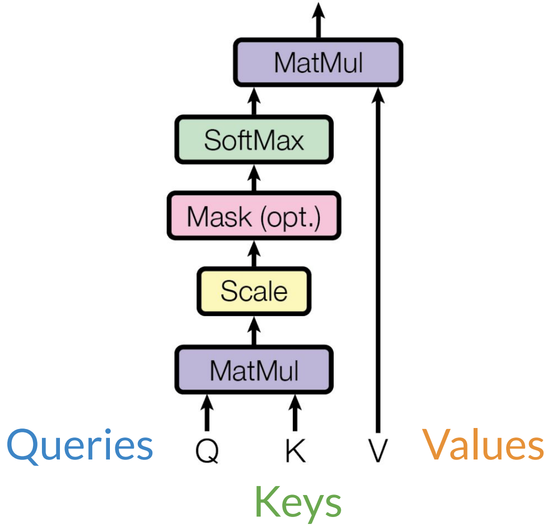
Scaled Dot-Product Attention

Outline

- Revisit scaled dot product attention
- Mathematics behind Attention



Scaled dot-product attention



(Vaswani et al., 2017)

Improves performance

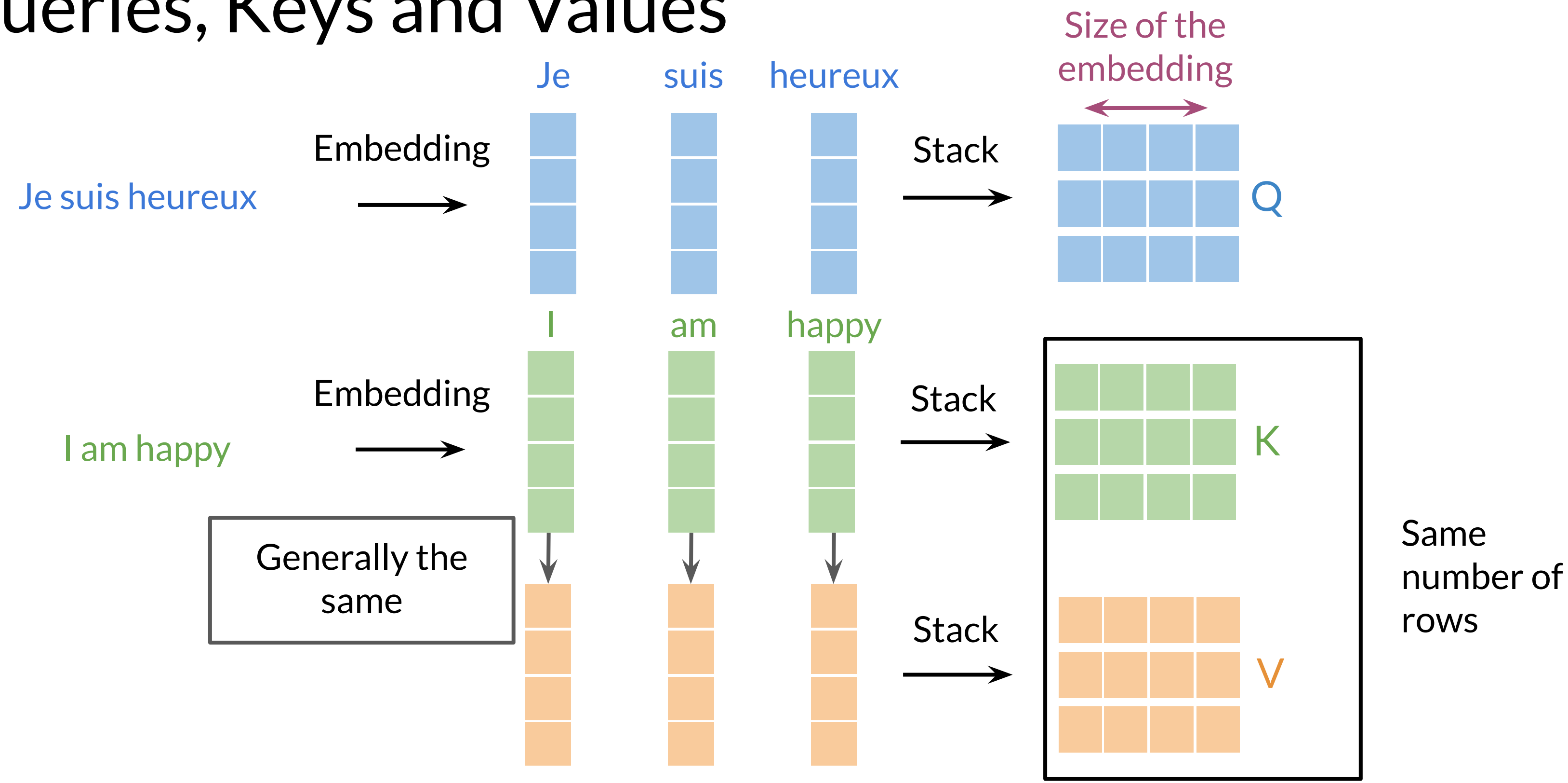
Weights add up to 1

$$\text{softmax}\left(\frac{QK^\top}{\sqrt{d_k}}\right)V$$

Weighted sum of values V

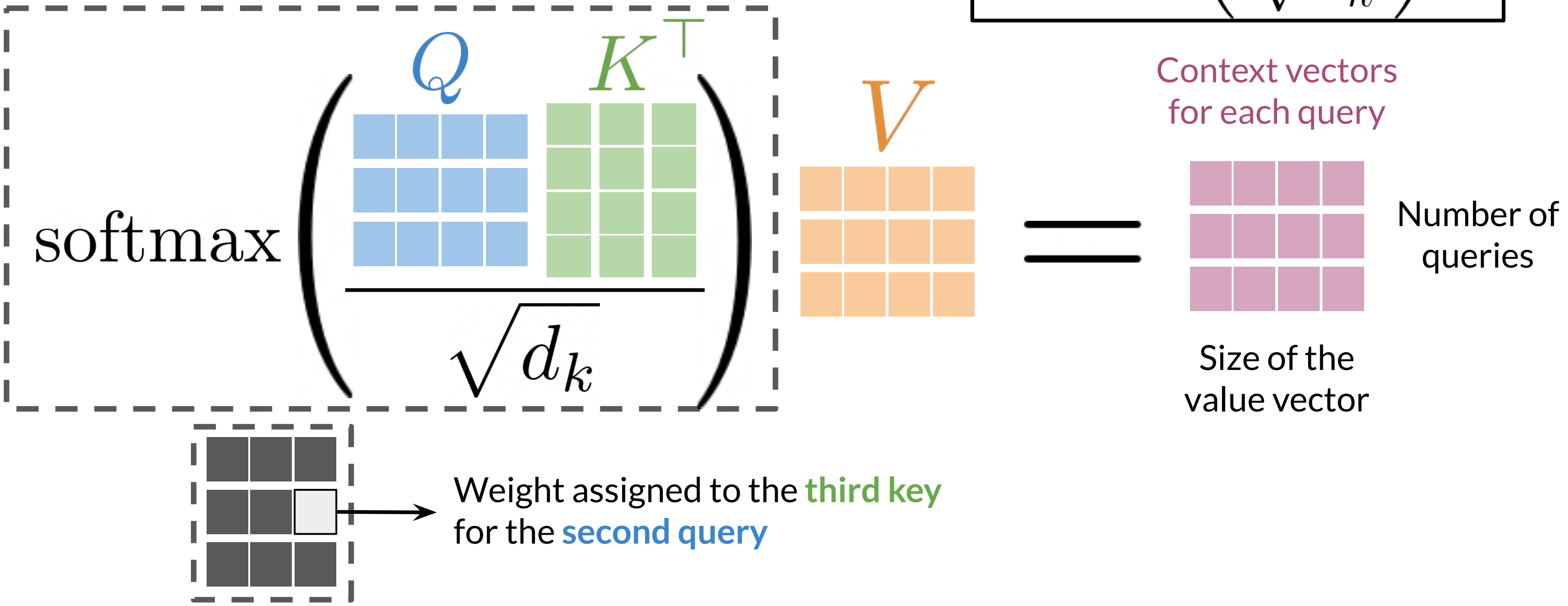
Just two matrix multiplications and a Softmax!

Queries, Keys and Values



Attention Math

$$\text{softmax}\left(\frac{QK^\top}{\sqrt{d_k}}\right)V$$



Summary

- Scaled Dot-product Attention is essential for Transformer
- The input to Attention are queries, keys, and values
- GPUs and TPUs

deeplearning.ai

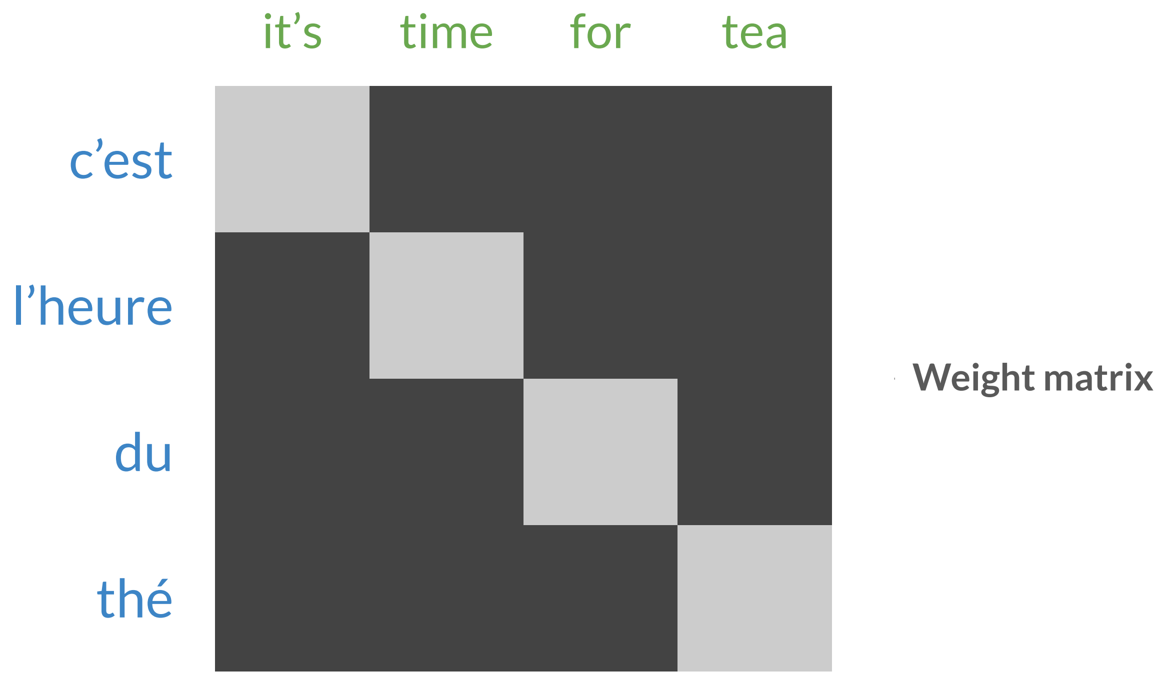
Masked Self-Attention

Outline

- Ways of Attention
- Overview of masked Self-Attention

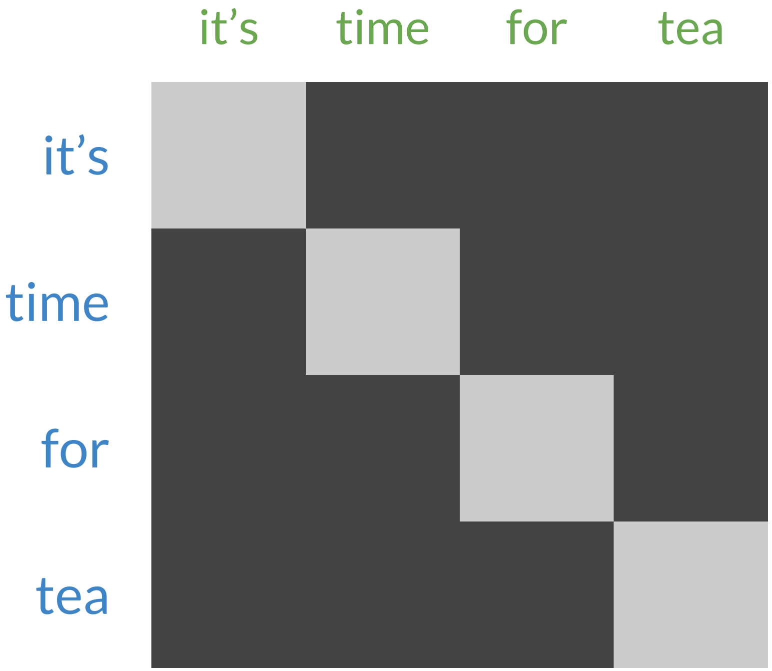
Encoder-Decoder Attention

Queries from one sentence, keys and values from another



Self-Attention

Queries, keys and values come from the **same sentence**



Weight matrix

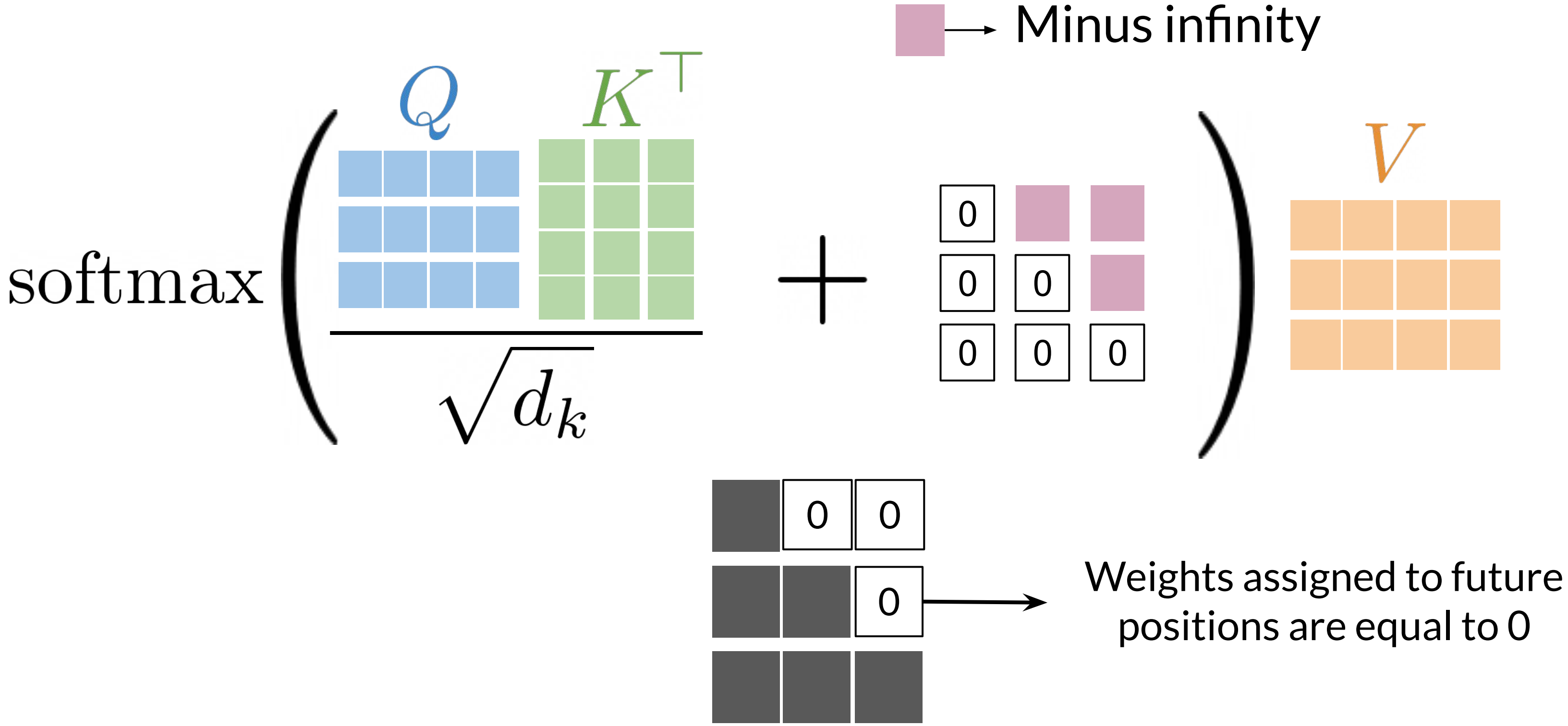
Meaning of each word **within** the sentence

Masked Self-Attention

Queries, keys and values come from the **same sentence**. Queries don't attend to future positions.

Weight matrix

Masked self-attention math



Summary

- There are three main ways of Attention: Encoder/Decoder, self-attention and masked self-attention.
- In self-attention, queries and keys come from the same sentence
- In masked self-attention queries cannot attend to the future

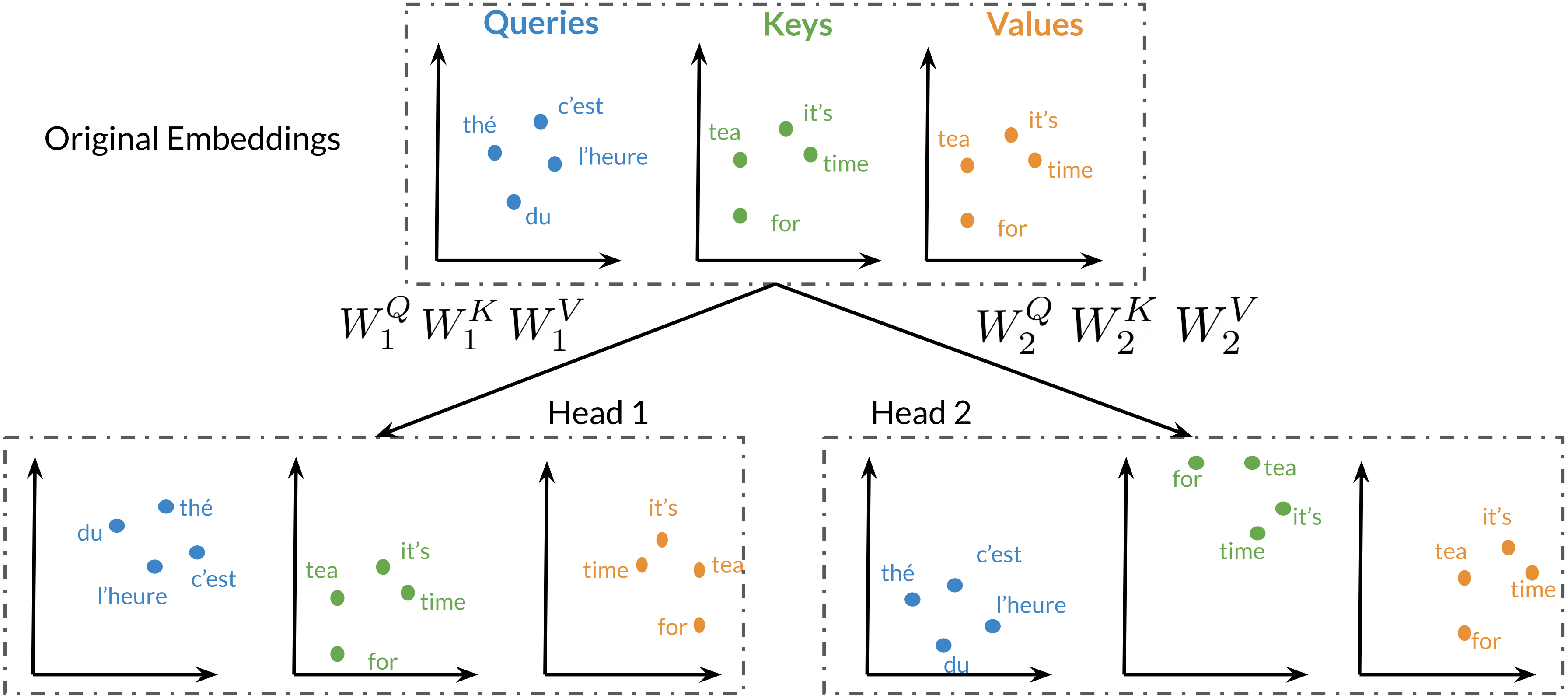
deeplearning.ai

Multi-head Attention

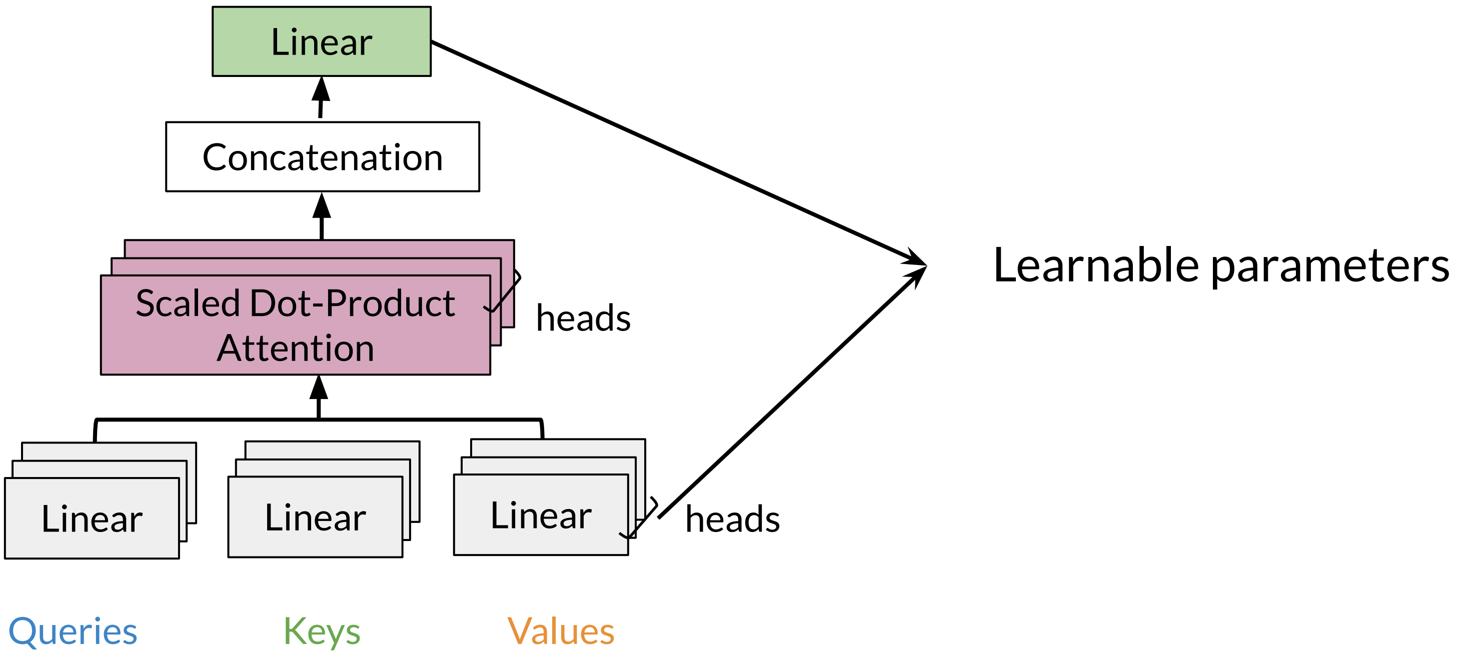
Outline

- Intuition Multi-Head Attention
- Math of Multi-Head Attention

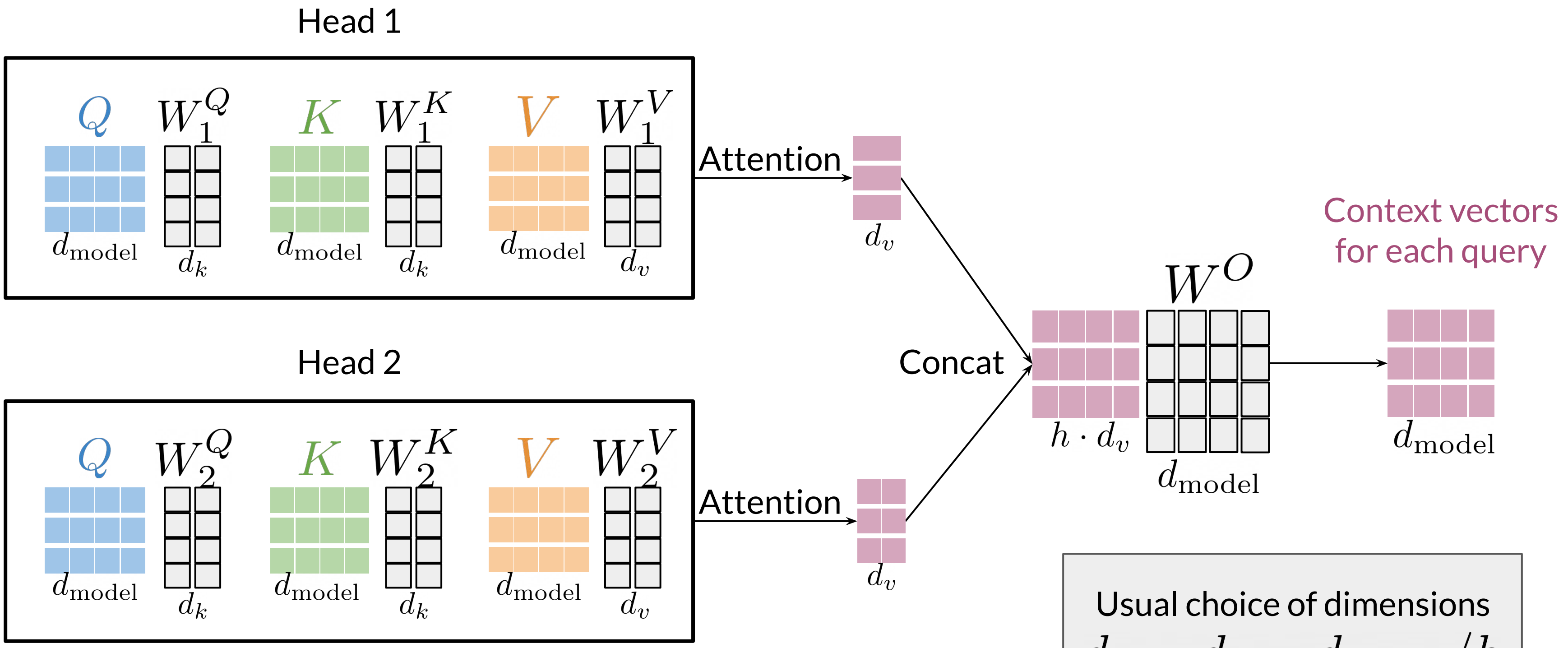
Multi-Head Attention - Overview



Multi-Head Attention - Overview



Multi-Head Attention



d_{model} : Embedding size

Usual choice of dimensions

$$d_k = d_v = d_{\text{model}}/h$$

Summary

- Multi-Headed models attend to information from different representations
- Parallel computations
- Similar computational cost to single-head attention

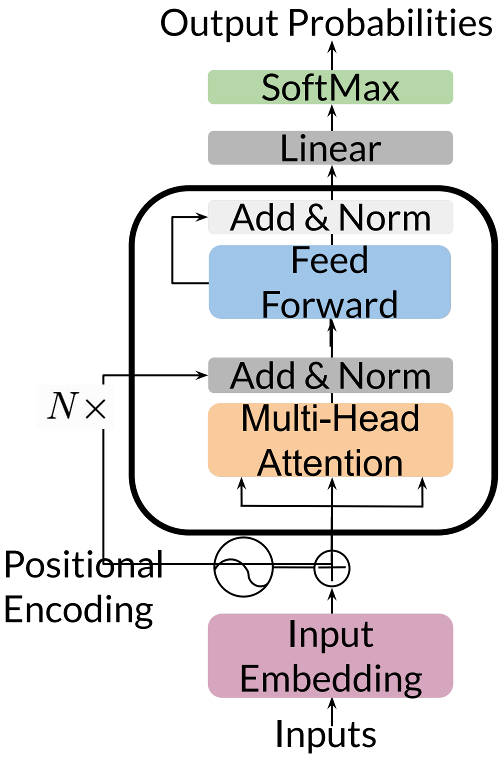
deeplearning.ai

Transformer decoder

Outline

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

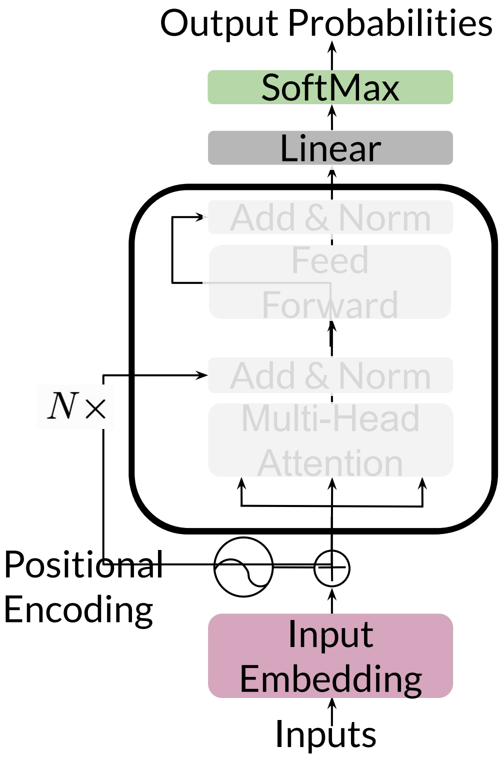
Transformer decoder



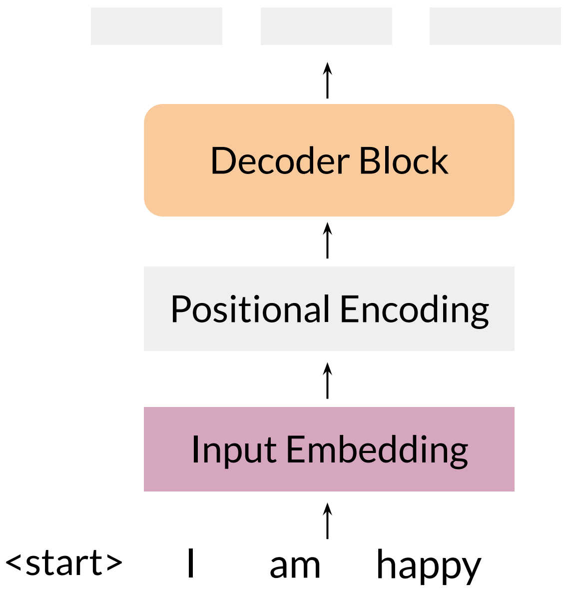
Overview

- 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
- dense layer and softmax for output

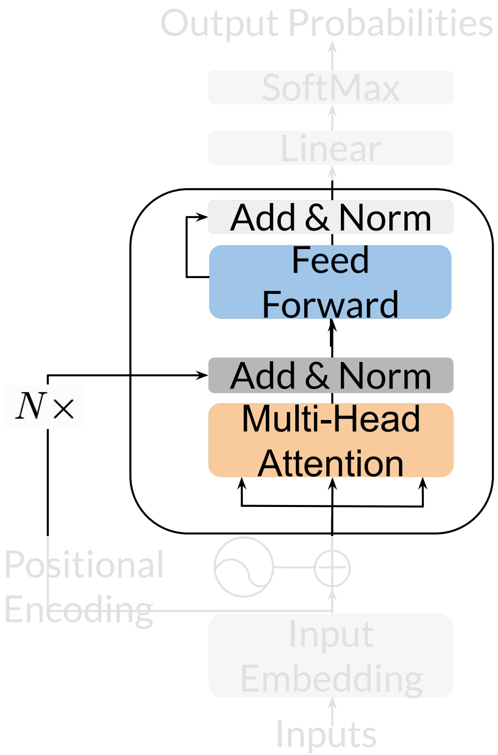
Transformer decoder

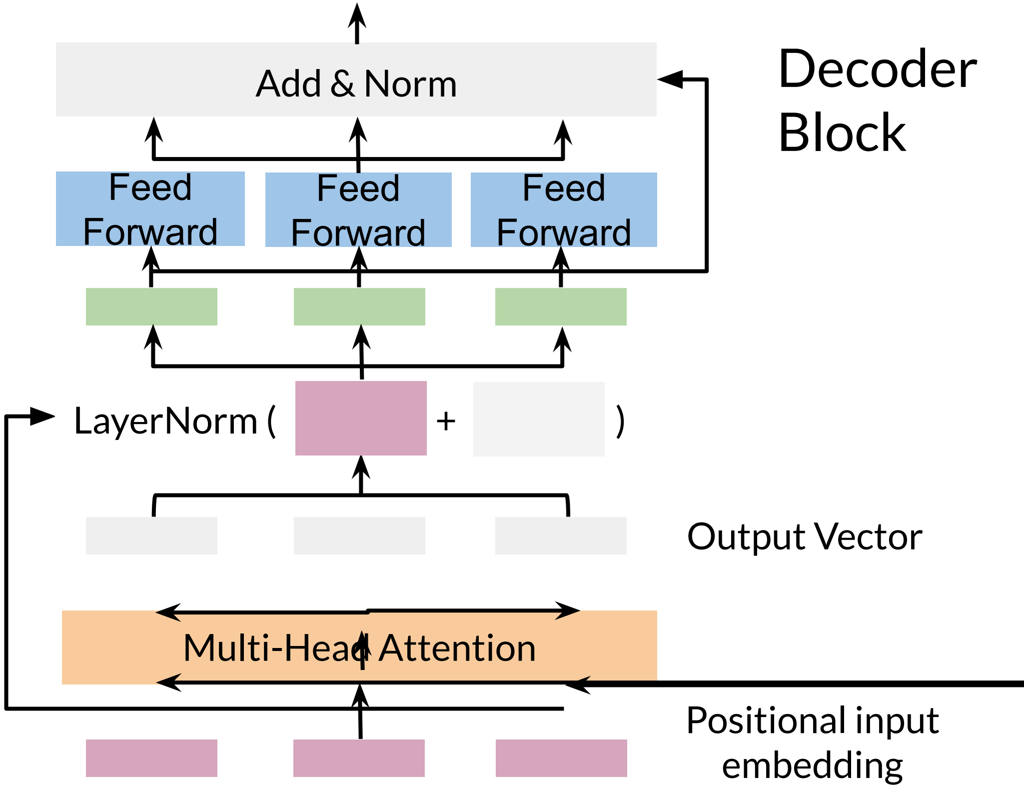


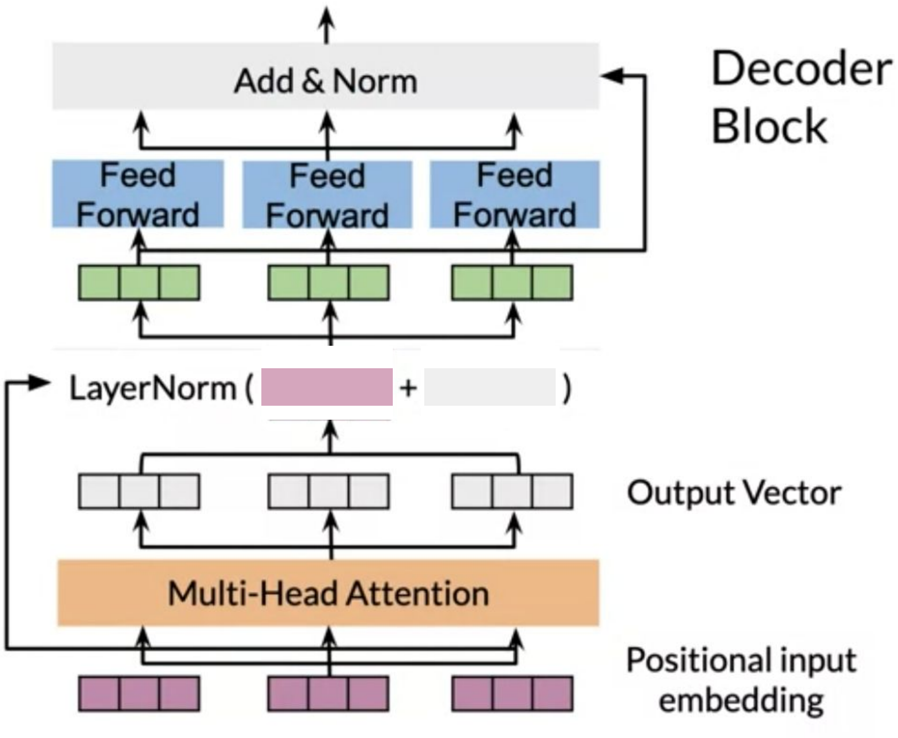
Explanation



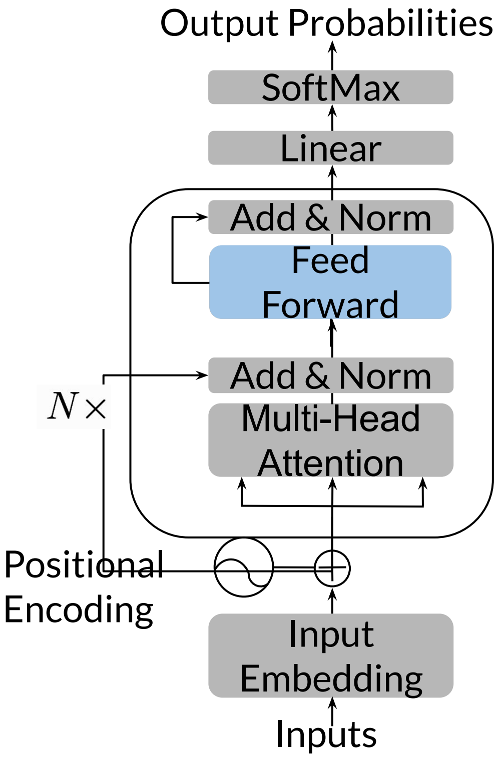
The Transformer decoder



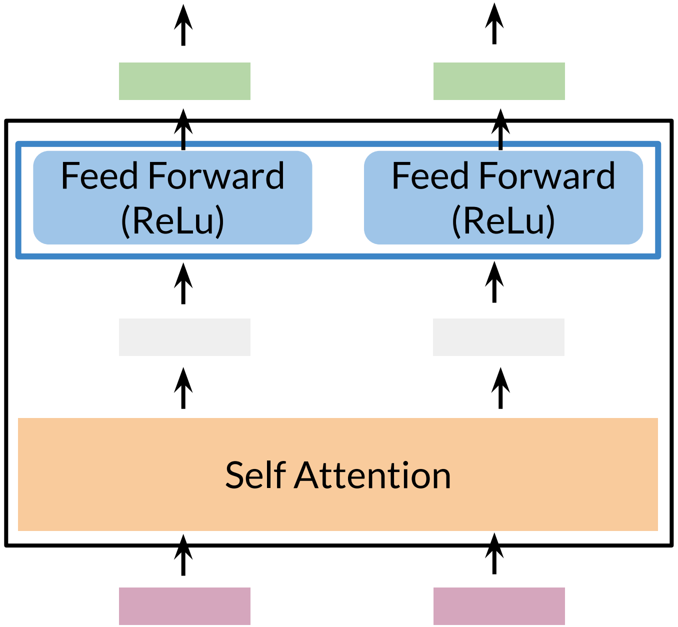



Add & Norm
Decoder Block
Feed Forward
Feed Forward
Feed Forward
LayerNorm (+)
Output Vector
Multi-Head Attention
Positional input embedding

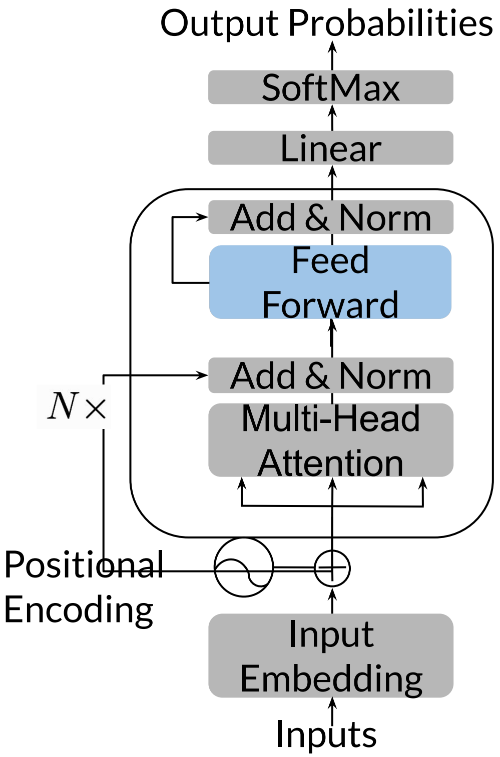
The Transformer decoder

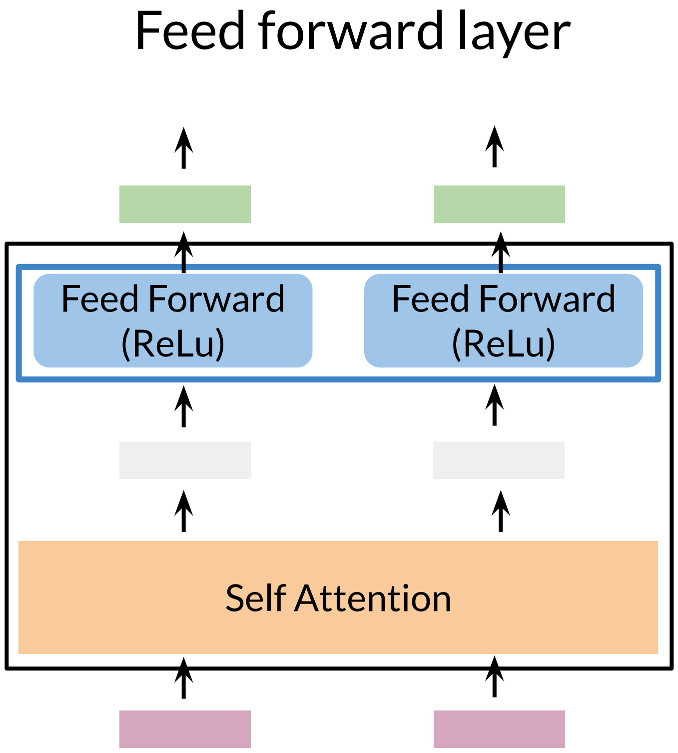


Feed forward layer



The Transformer decoder





Summary

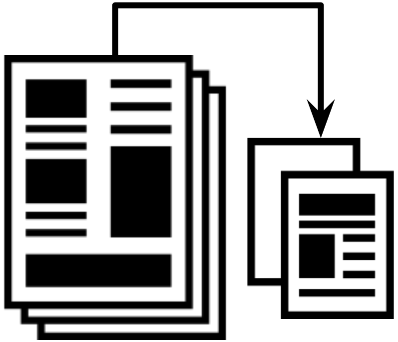
- Transformer decoder mainly consists of three layers
- Decoder and feed-forward blocks are the core of this model code
- It also includes a module to calculate the cross-entropy loss

deeplearning.ai

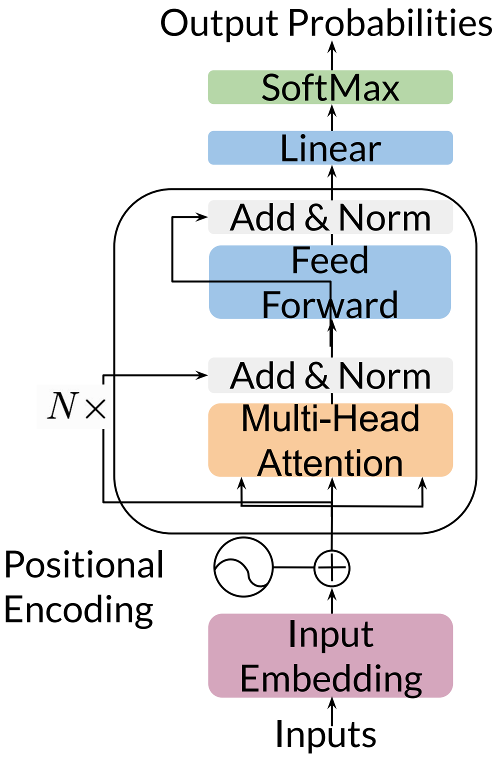
Transformer summarizer

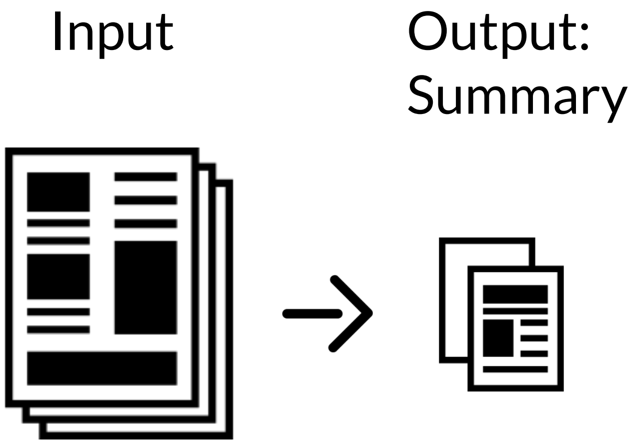
Outline

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

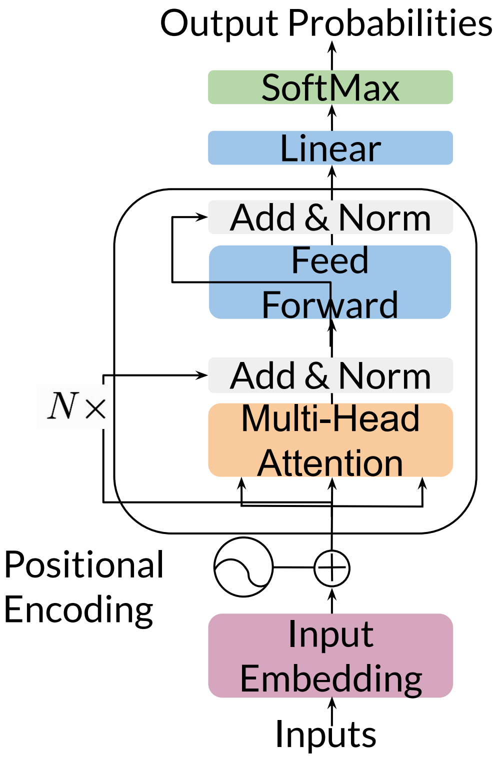


Transformer for summarization





Technical details for data processing



Model Input:

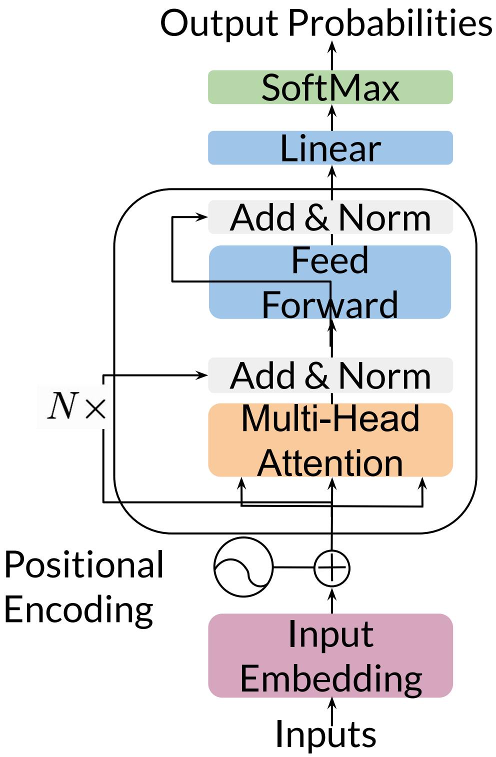
```
ARTICLE TEXT <EOS> SUMMARY <EOS> <pad> ...
```

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

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

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