CS 584 Natural Language Processing

Introduction to Transformer and BERT

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Transformer

- Vaswani, Ashish, et al. "Attention is all you need." NeurIPS 2017.

Attention Is All You Need

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Attention is all you need

A Vaswani, N Shazeer, N Parmar… - Advances in neural …, 2017 - proceedings.neurips.cc

… to attend to **all** positions in the decoder up to and including that position. **We need** to prevent … **We** implement this inside of scaled dot-product **attention** by masking out (setting to $-\infty$) …

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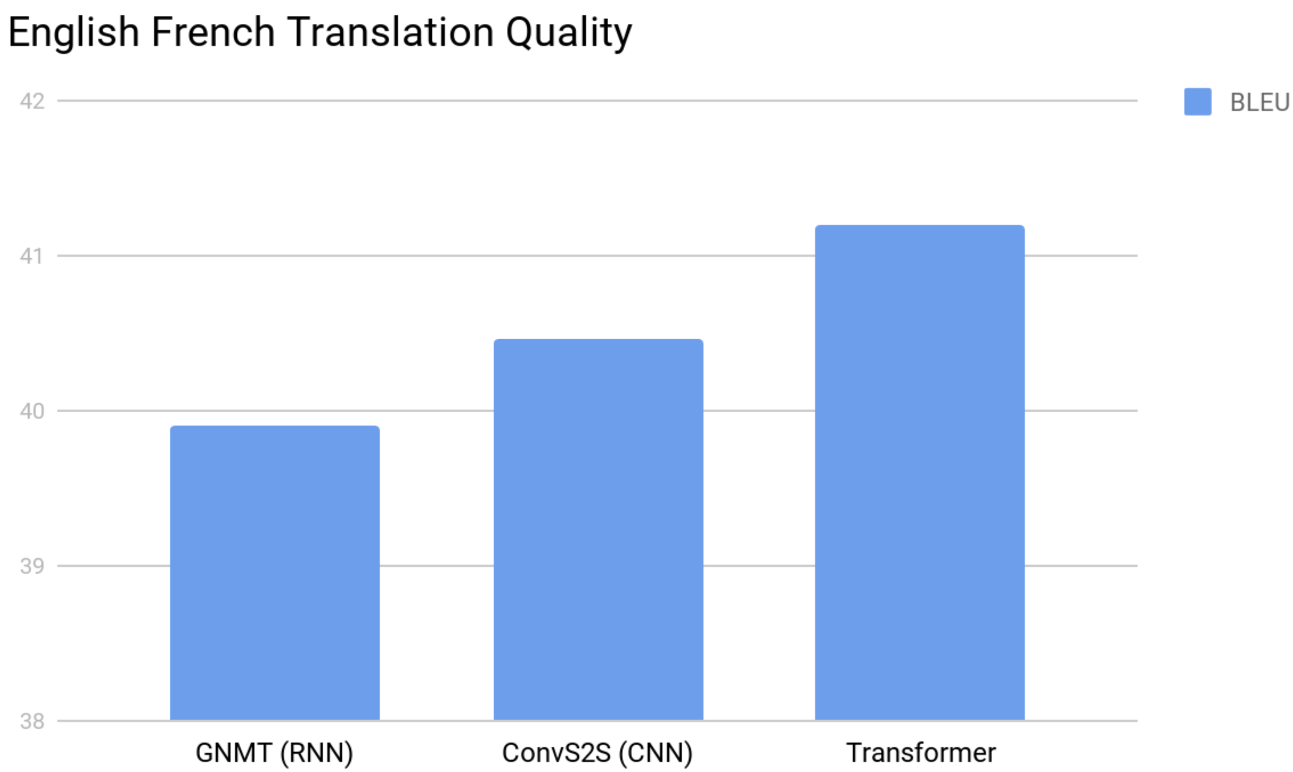
Transformer: Overview

- BLEU score: EN-FR



https://ai.googleblog.com/2017/08/transformer-novel-neural-network.html

Transformer: Overview

- ❖ Seq2seq: Encoder + Decoder
- ❖ Encoder: Self-attention
- ❖ Decoder: Self-attention + Cross-attention

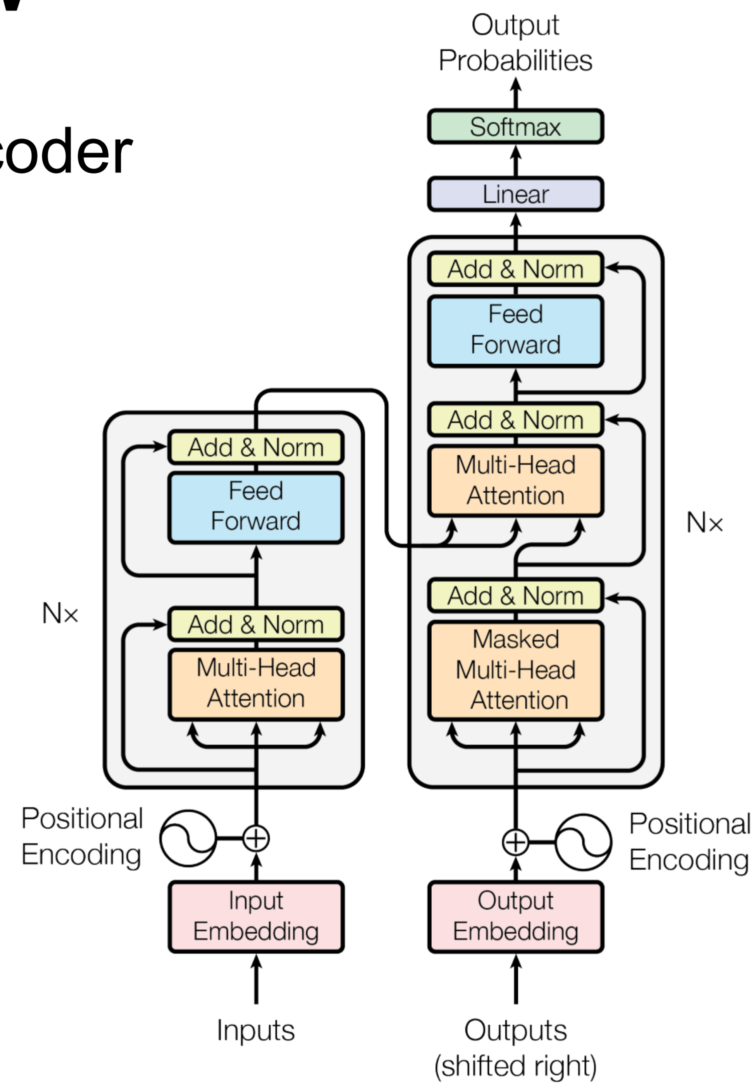
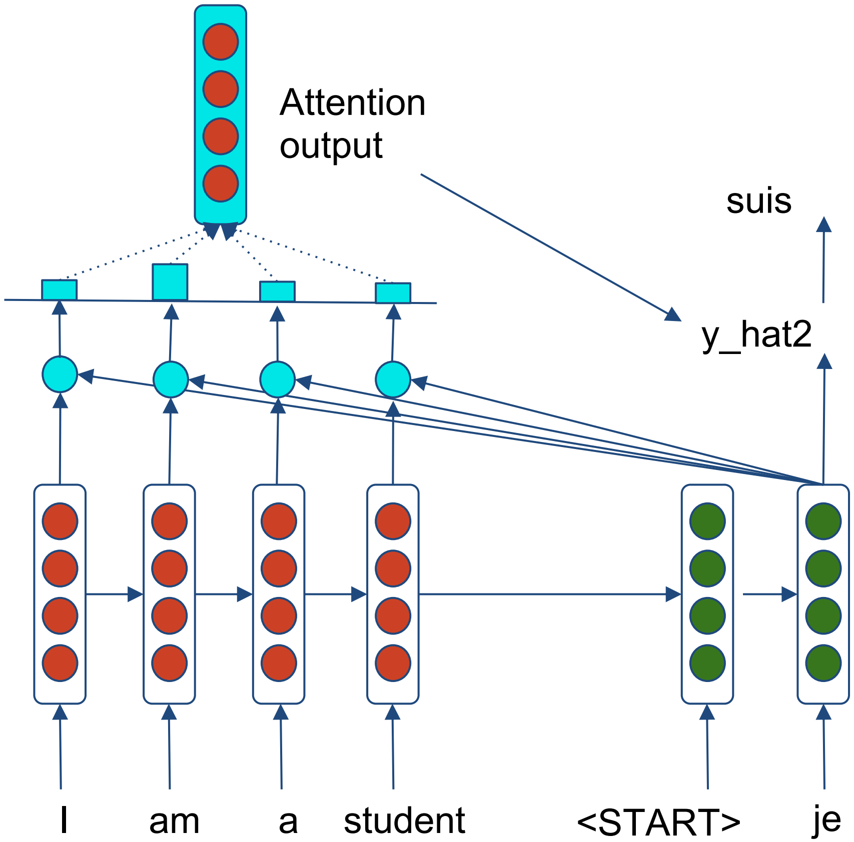


Figure 1: The Transformer - model architecture.

Recall: RNN + Attention

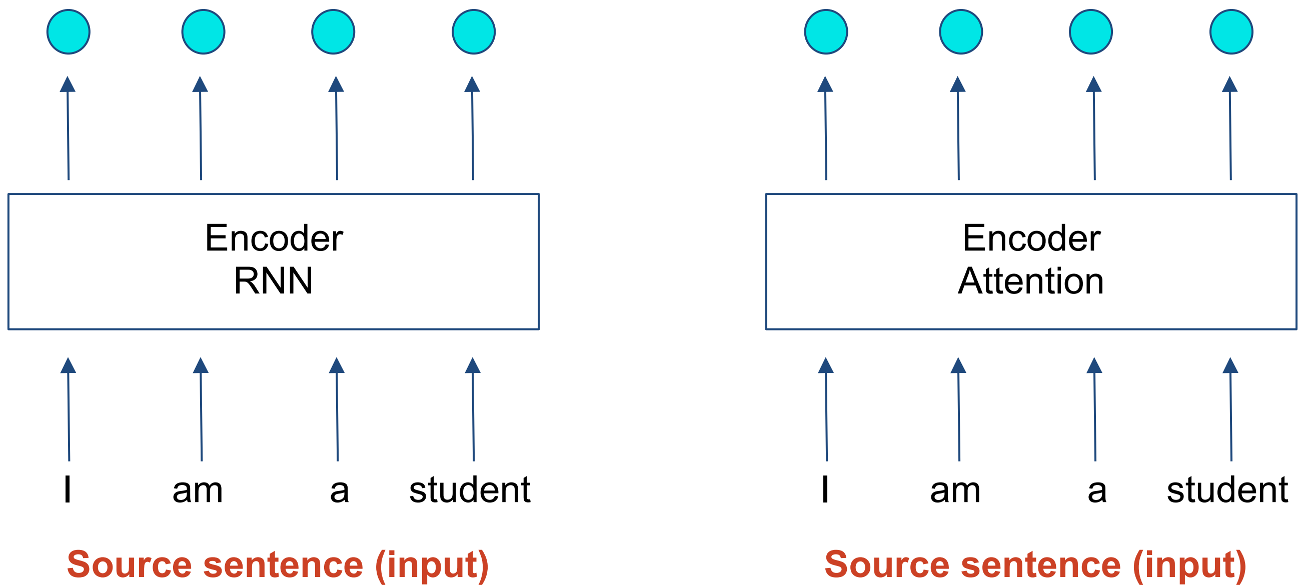
- ❖ Encoder: RNN
- ❖ Decoder: RNN + Attention
- ❖ Problem:
  - Gradient vanishing / exploding, i.e., forget on long inputs
  - RNN is slow



Idea of Transformer

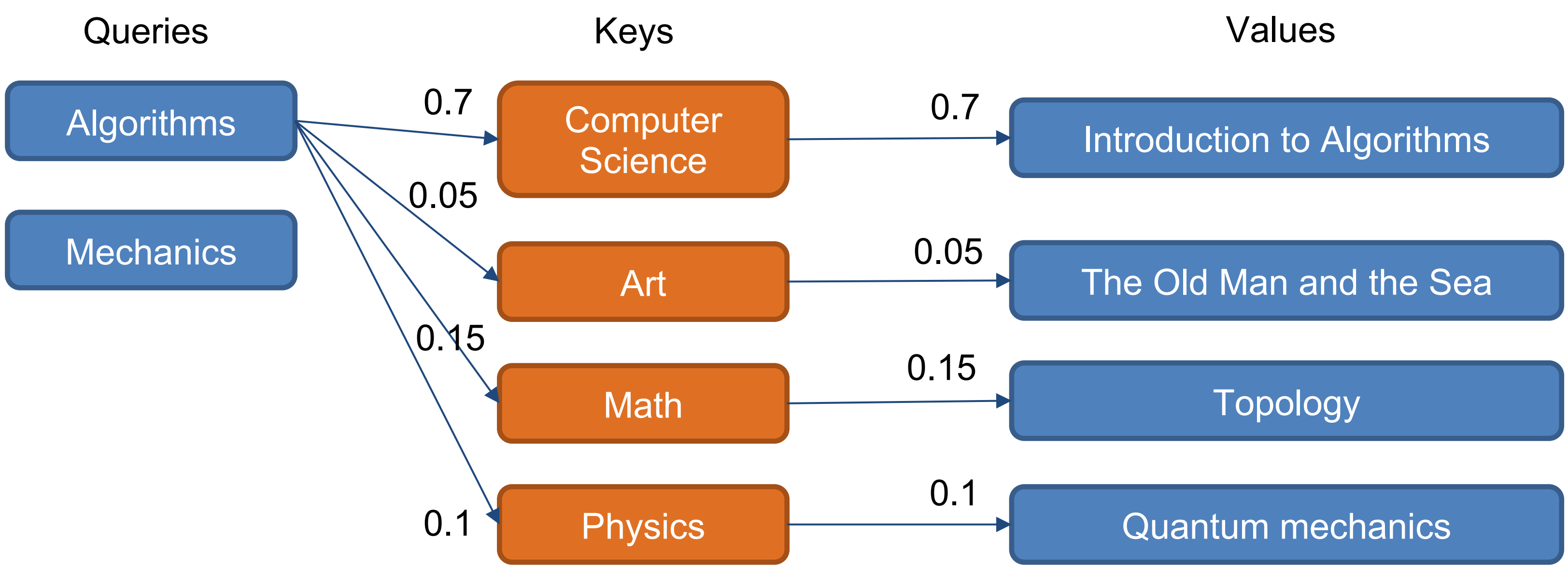
❖ **Use Attention to replace RNN**

- Every token can see all other/previous tokens



Self-attention

- Scaled dot-product attention: query, key, value
- Example: book search



Self-attention

- **Scaled dot-product attention: query, key, value**

$$\mathrm{Attention}(Q, K, V) = \mathrm{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$

  - $Q, K, V: R^{n \times T \times d}$, (batch_size x seq_len x embedding_size)
  - d_k: scaling factor, embedding size

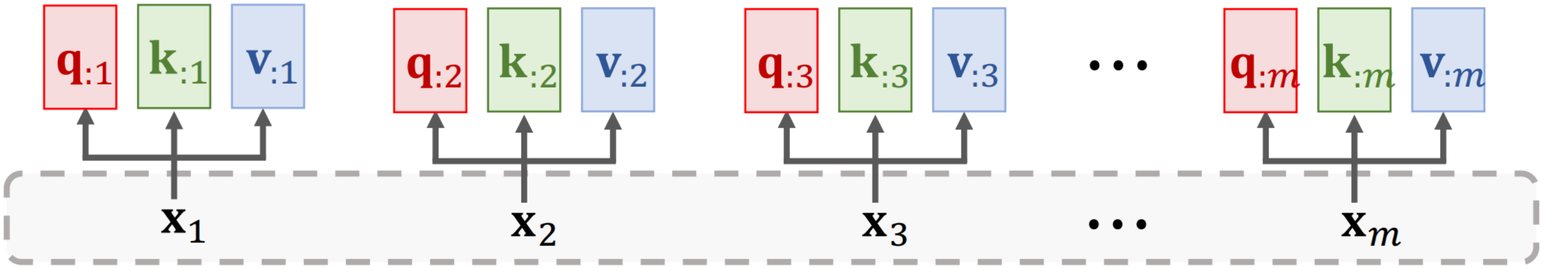
- **Explanation:**
  - $QK^\top: R^{n \times T \times T}$, dot product between query and key
  - Softmax: $R^{n \times T \times T}$, probability distribution $\boldsymbol{\alpha}$
  - Weighted average of values

Self-attention

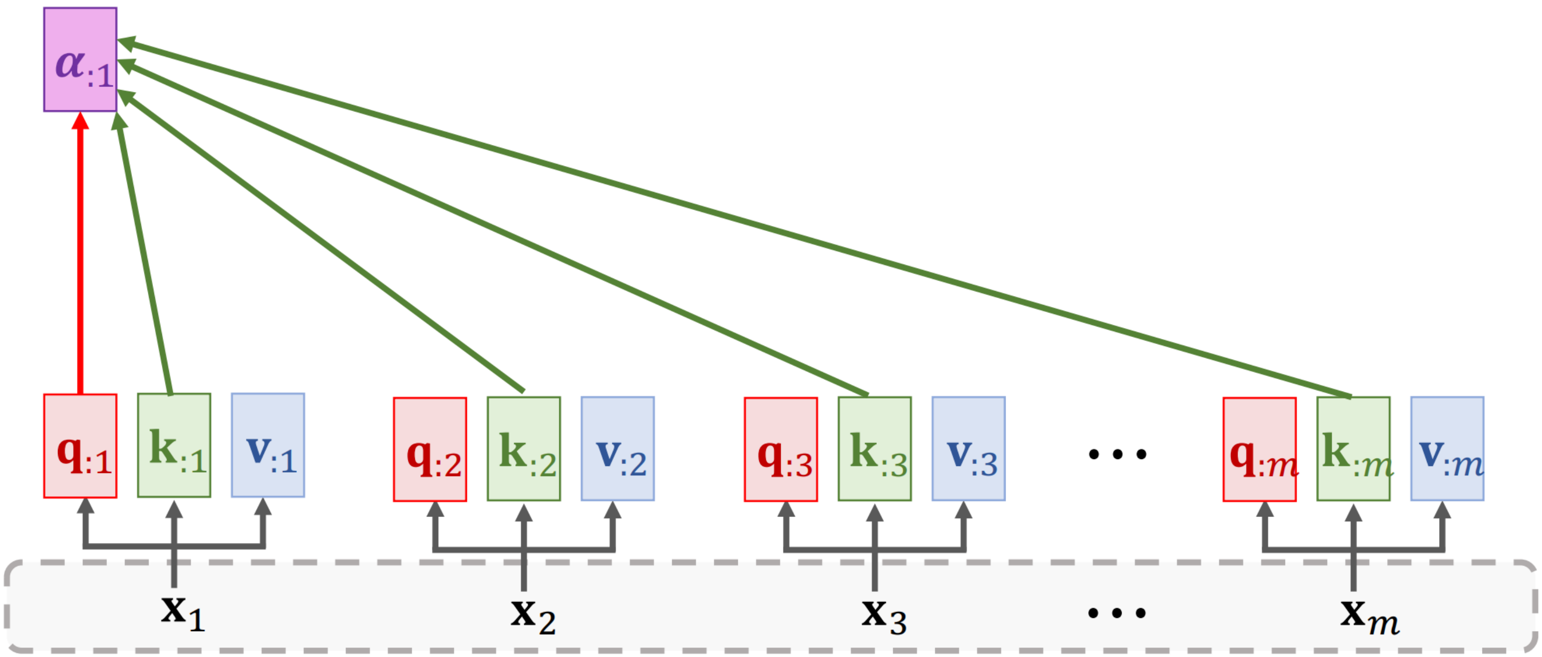
Inputs:

$\mathbf{x}_1 \quad \mathbf{x}_2 \quad \mathbf{x}_3 \quad \cdots \quad \mathbf{x}_m$

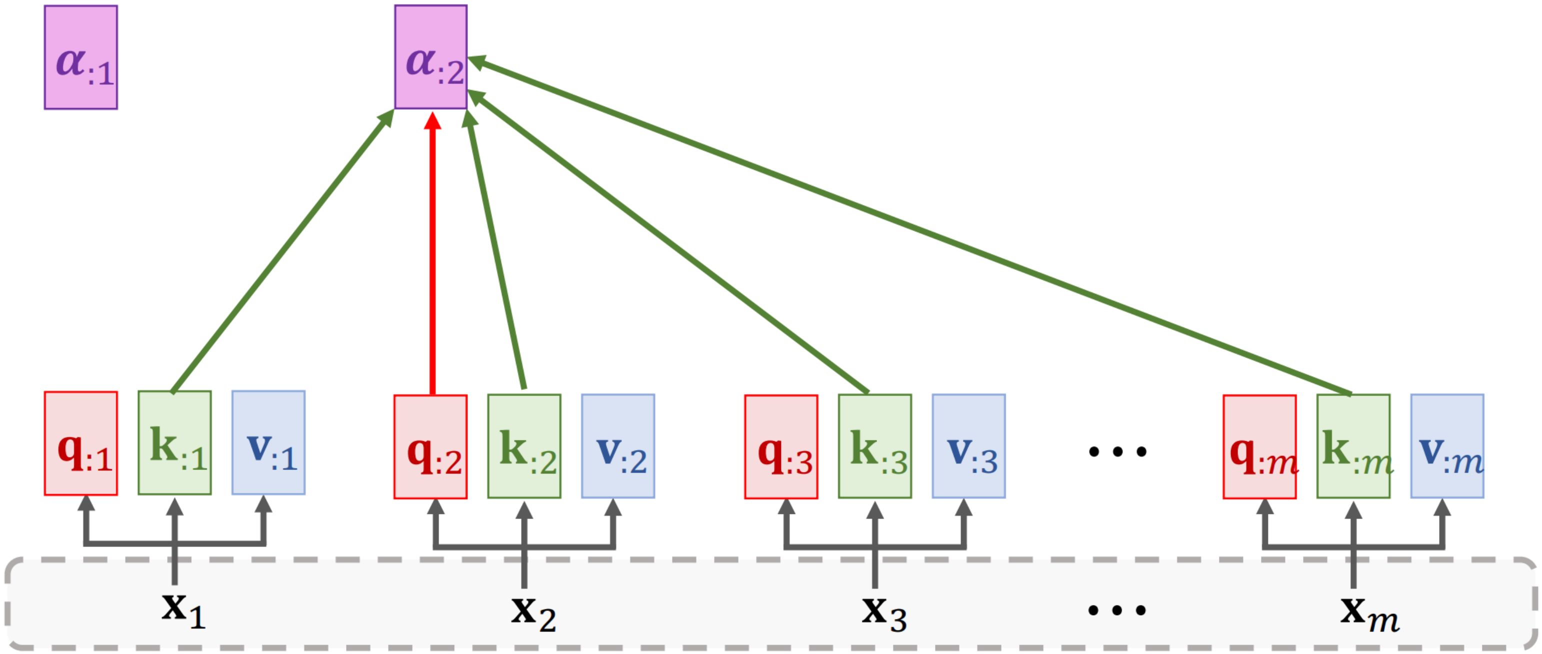
Self-attention



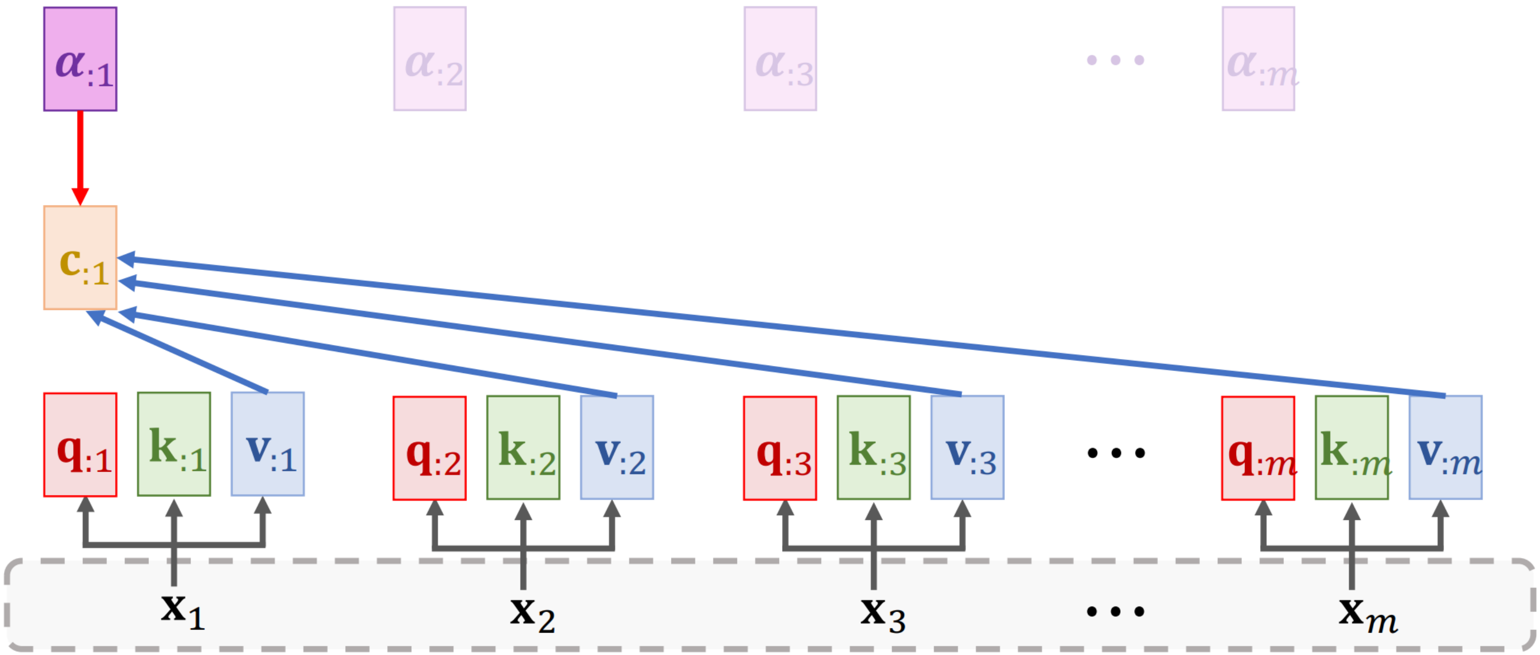
Self-attention



Self-attention

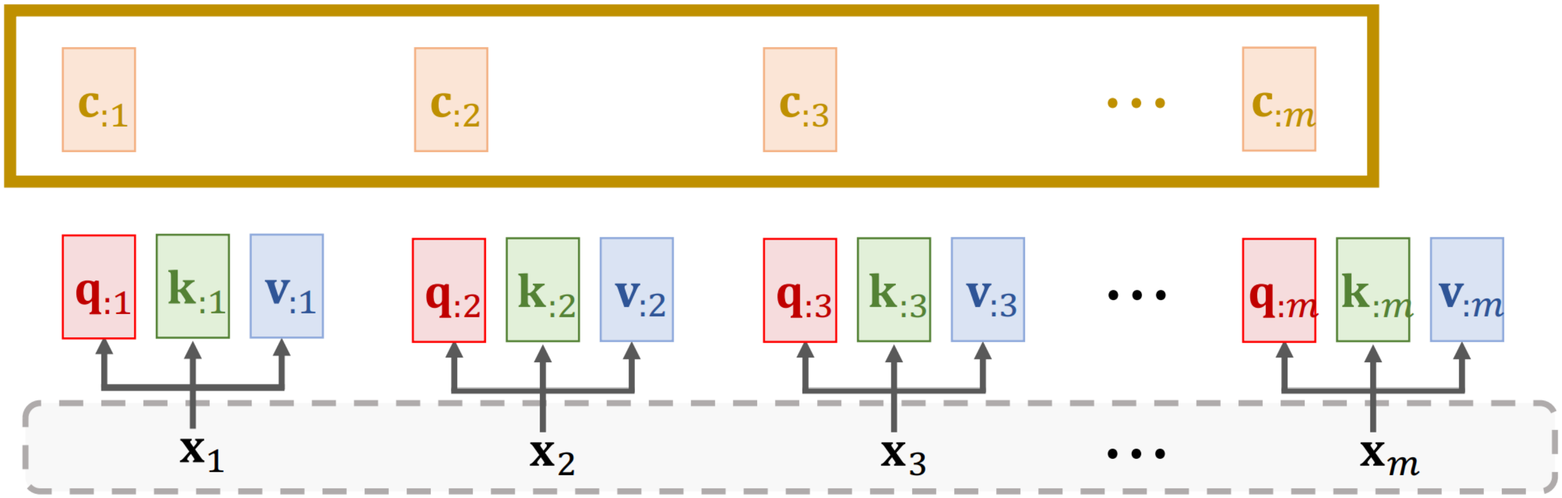


Self-attention



Self-attention

Output of self-attention layer:



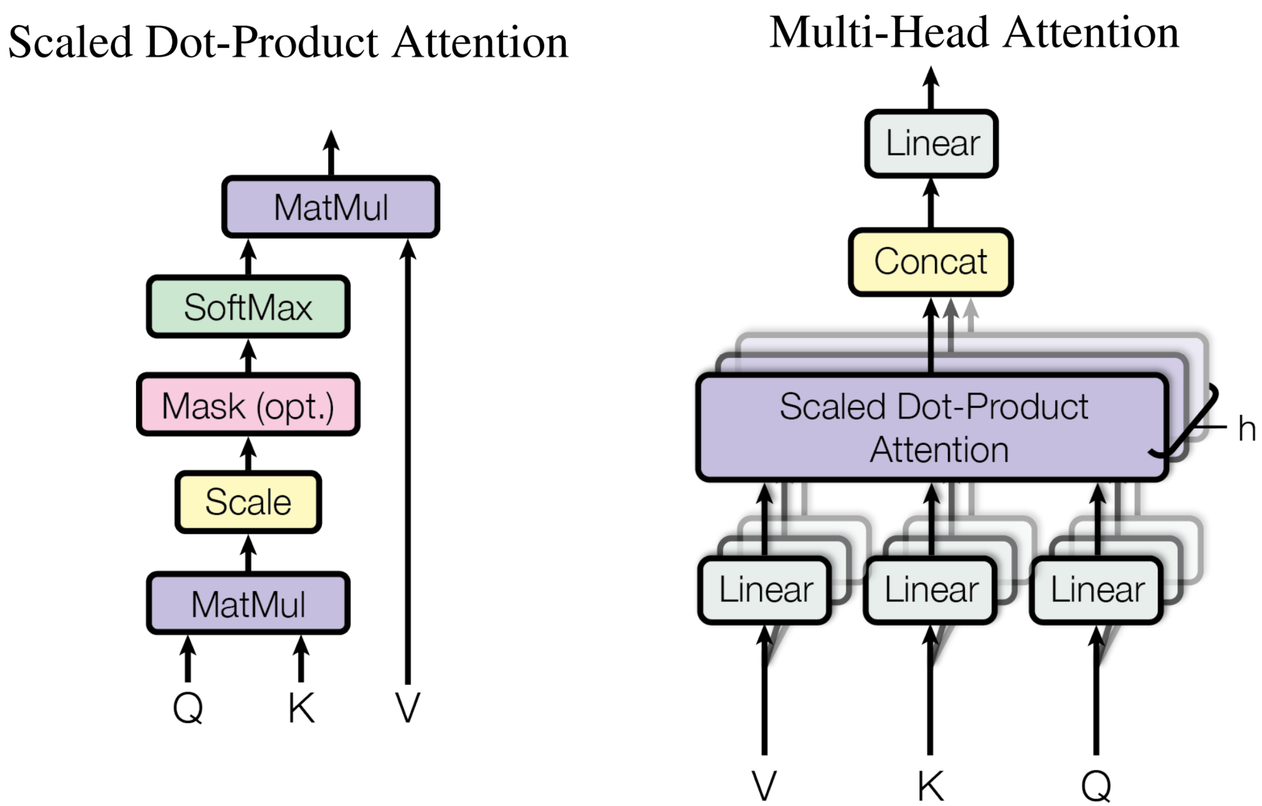
Multi-head attention

- **Project Q, K, V for h times -> self-attention -> concat**
- **Allow model focus on different subspace**

$$\mathrm{MultiHead}(Q, K, V) = \mathrm{Concat}(\mathrm{head_1}, ..., \mathrm{head_h})W^O$$
$$\text{where } \mathrm{head_i} = \mathrm{Attention}(QW_i^Q, KW_i^K, VW_i^V)$$

$$\mathrm{Attention}(Q, K, V) = \mathrm{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$

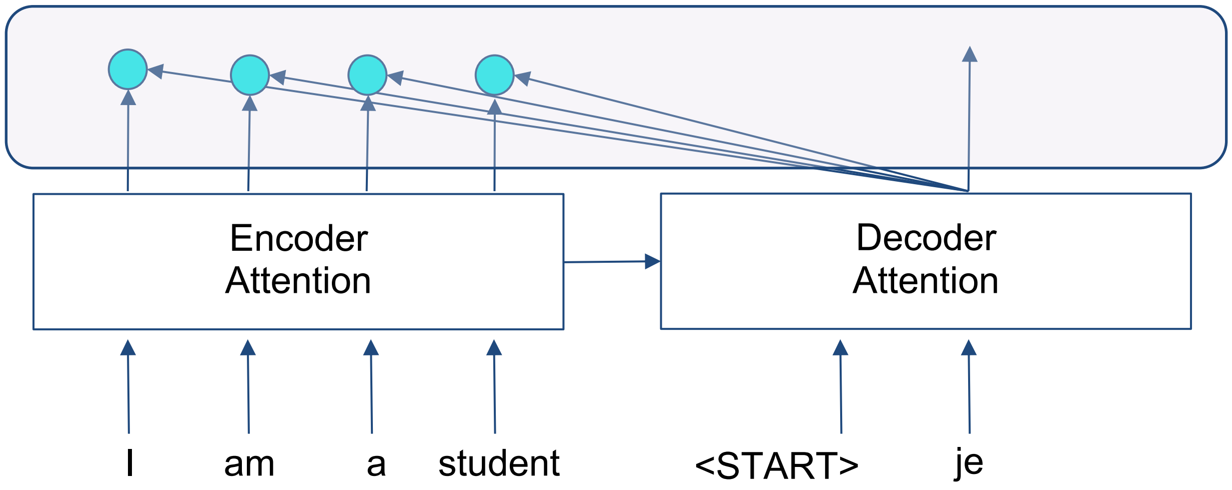
Multi-head attention



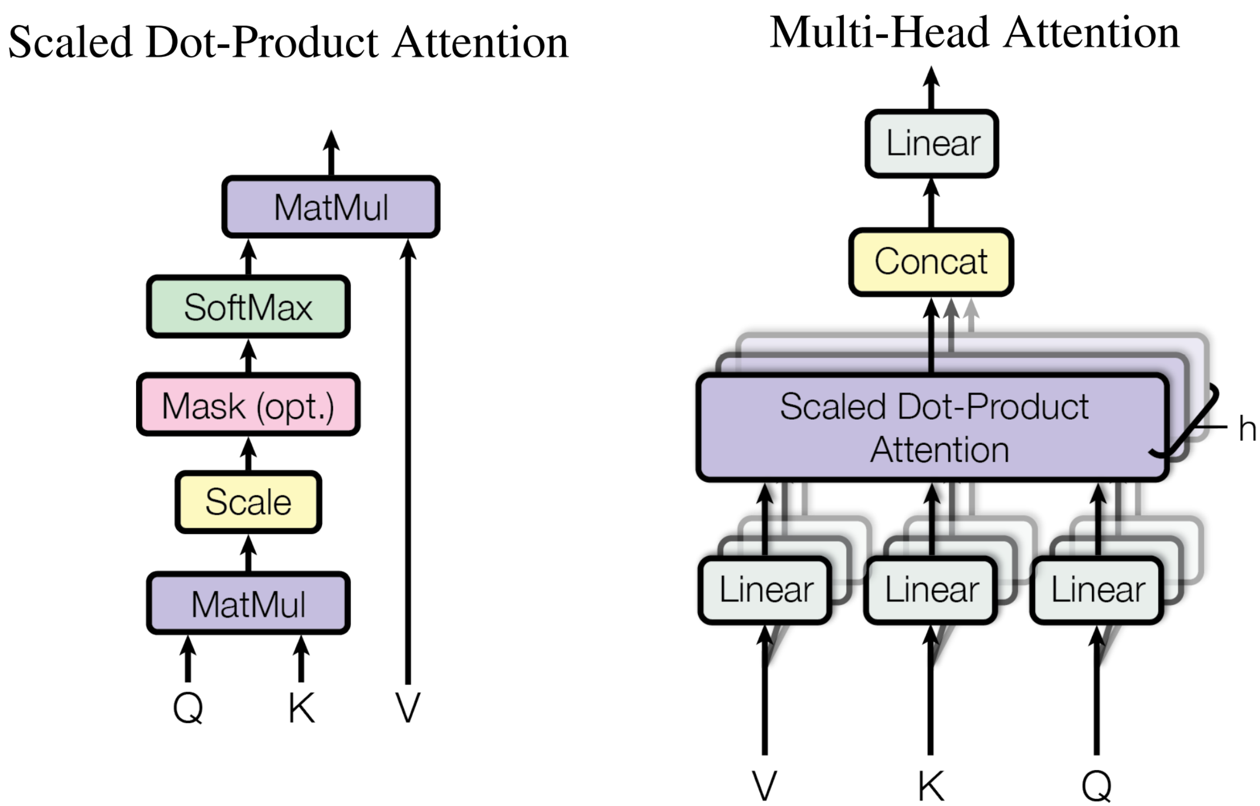
- Q, K, V of self-attention: embedding of input tokens or outputs from previous attention layers

Cross-attention

- ❖ **RNN part is replaced in both Encoder and Decoder by self-attention**
- ❖ **What is next?**
  - Decoder attention with encoder contexts



Cross-attention



- Q: Output of decoder self-attention
- K, V of cross attention: Encoder output
- Query which source token is important to the current target token

Feed-forward

- **Dense layers after self-attention/cross-attention**

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

Transformer: Overview

- ❖ Seq2seq: Encoder + Decoder
- ❖ Encoder: Self-attention
- ❖ Decoder: Self-attention + Cross-attention

- Stack N times for each (attention + feed-forward)

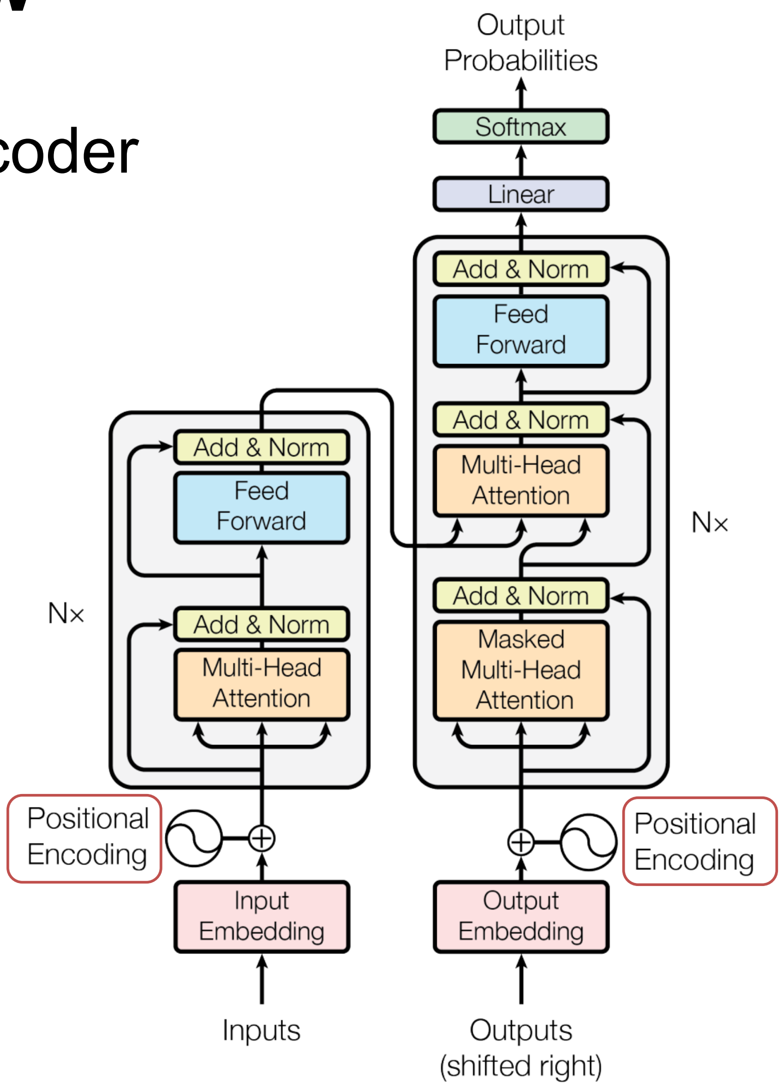


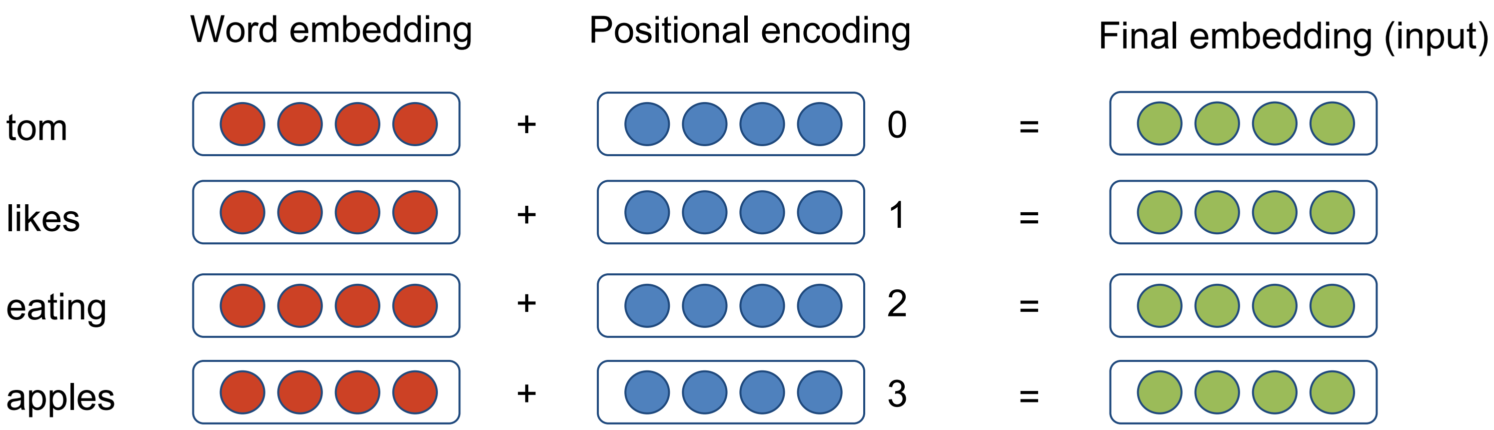
Figure 1: The Transformer - model architecture.

Positional Encoding

- Self-attention does not consider ordering in a sequence

$$\mathrm{Attention}(Q,K,V) = \mathrm{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$

- “tom likes eating apples” = “apples like eating tom”
- Add position information in word embedding



Fixed or trainable

BERT

- **B**idirectional **E**ncoder **R**epresentations from **T**ransformers
- Kenton, et al. "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding." NAACL 2019.

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

Bert: **Pre-training** of **deep bidirectional** transformers for language understanding
J Devlin, MW Chang, K Lee, K Toutanova - arXiv preprint arXiv …, 2018 - arxiv.org
… **deep** bidirectionality of **BERT** by evaluating two **pretraining** objectives using exactly the same **pretraining** … No NSP: A **bidirectional** model which is trained using the "masked LM" (MLM) …
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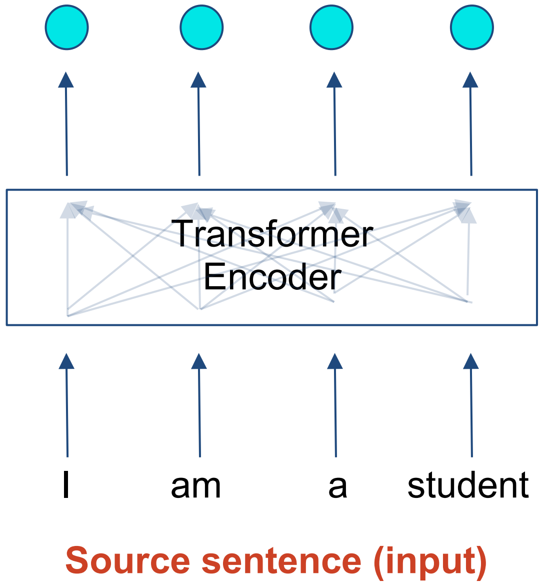
BERT

- Goals:
  - Provide a universal pretrained language model
  - Easily fine-tune on downstream tasks
- Contribution: Lead the scheme of “Pre-training + fine-tuning” in NLP

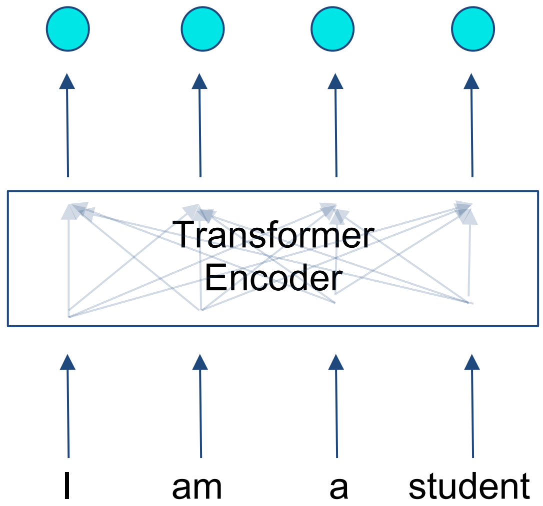
BERT: Structure

- Transformer Encoder
- Why bidirectional?
    - Every token can see previous and following tokens

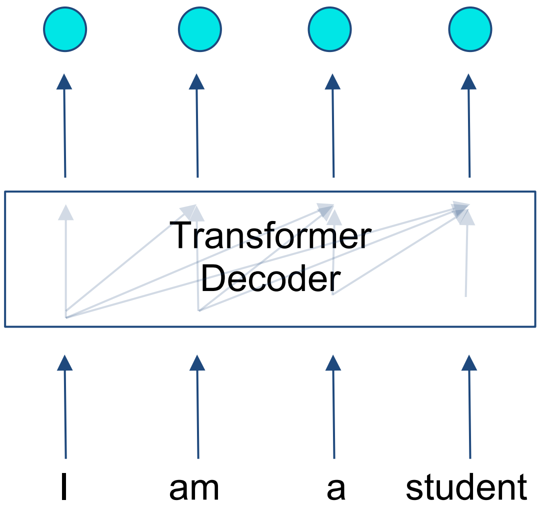


BERT: Structure

- ❖ Bidirectional (Encoder)
  - Every token can see previous and following tokens
- ❖ Recursive (Decoder), such as GPT
  - Every token can only see previous tokens



Source sentence (input)
Bidirectional



Source sentence (input)
Recursive

BERT

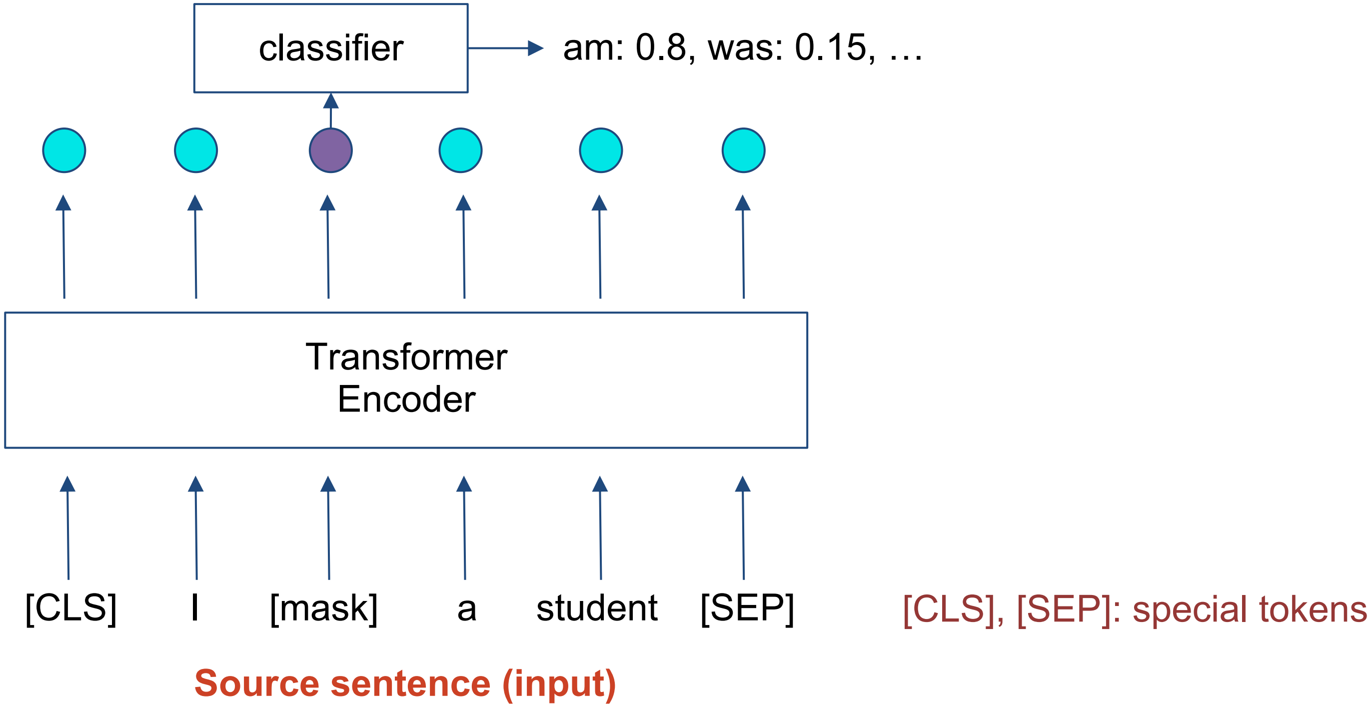
- Pretraining Goals:
  - Let the model understand natural languages
- Tasks:
  - Masked token prediction
  - Next sentence prediction

Masked Token Prediction

❖ Randomly mask some tokens in the dataset

- Mask rate: 15%

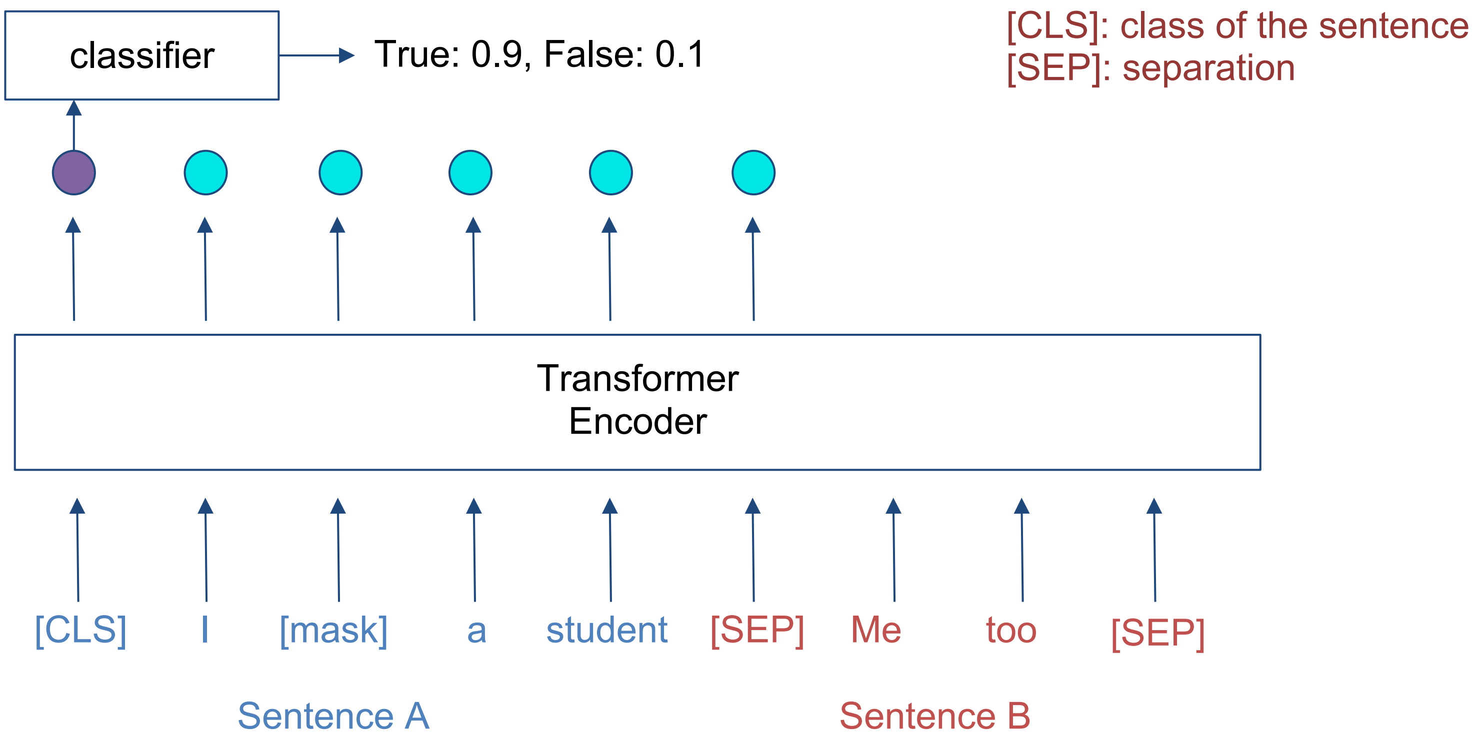
❖ Let the model predict the masked tokens in a sentence



Next Sentence Prediction

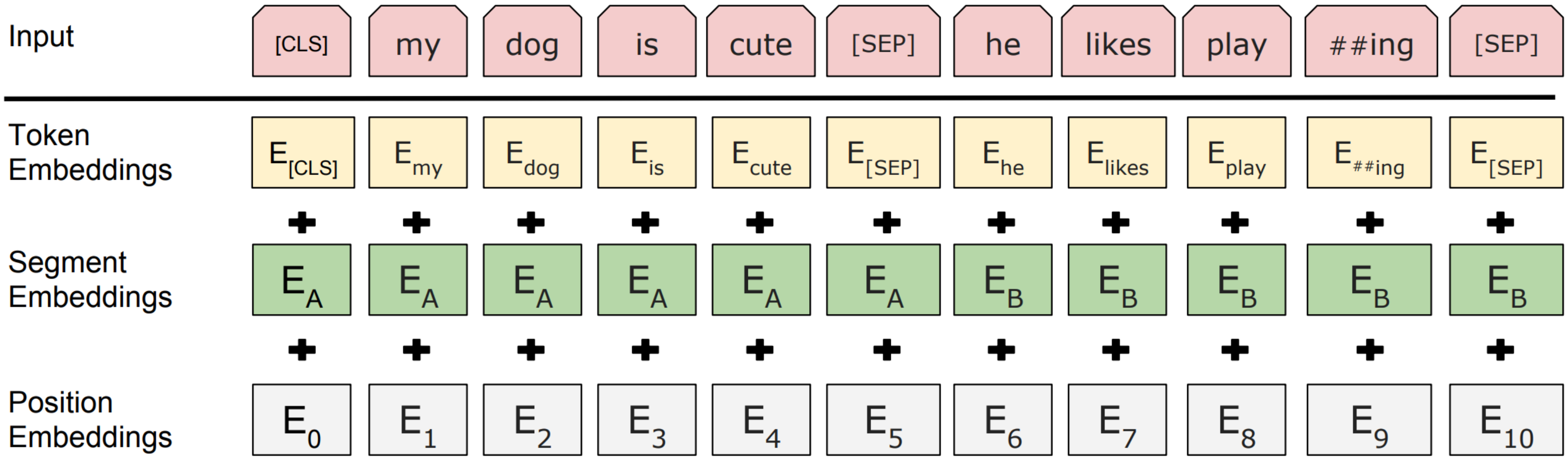
❖ Given two sentences A and B, let the model predict whether B is the next sentence of A

- True/False = 50% / 50%



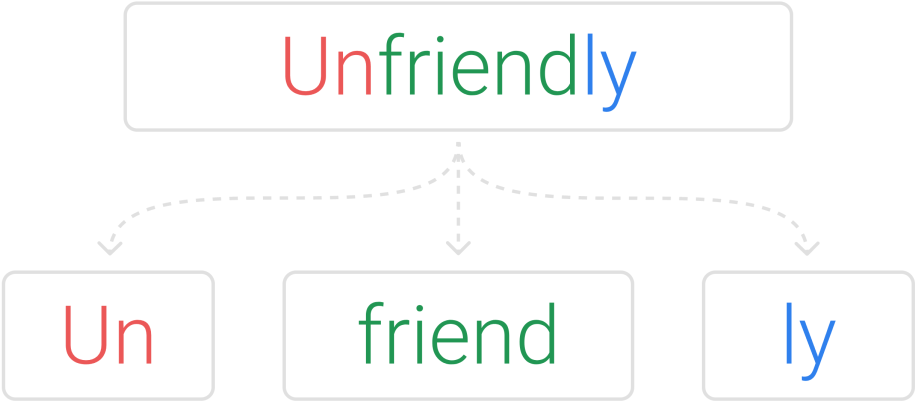
Positional Encoding

- Word embedding
- Segment embedding
- Position Embedding



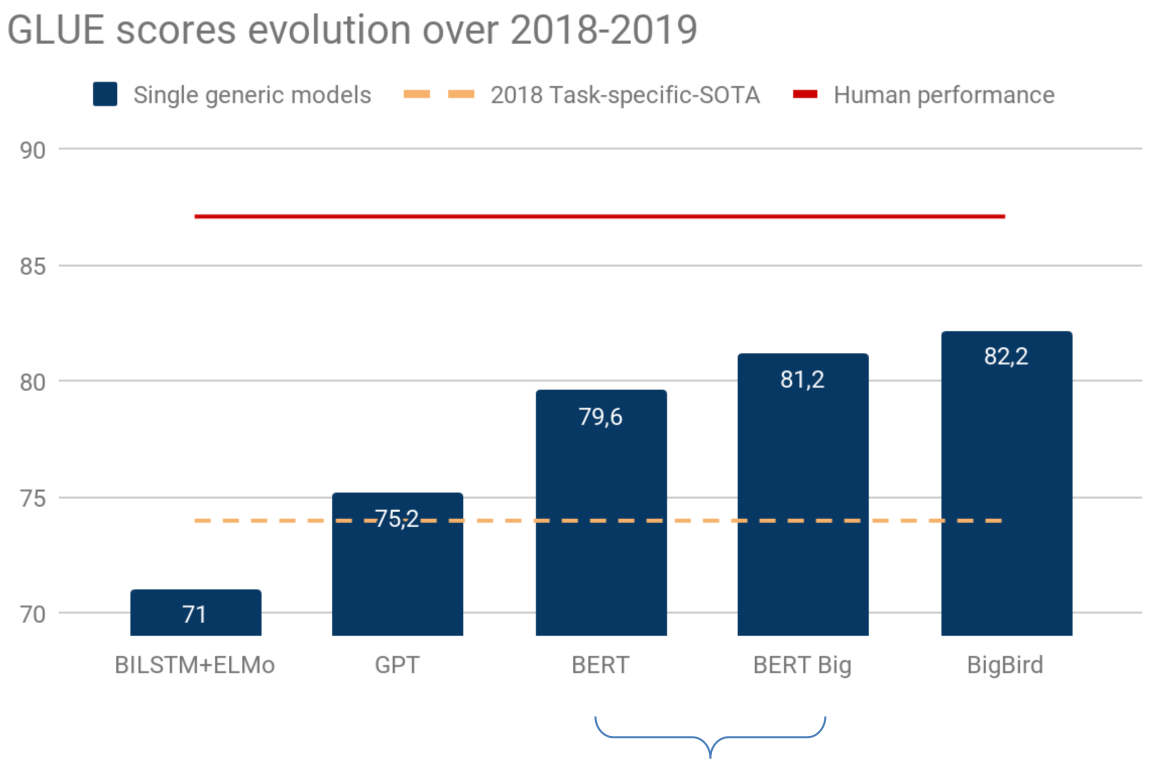
Tokenization

❖ Wordpiece: frequent subword

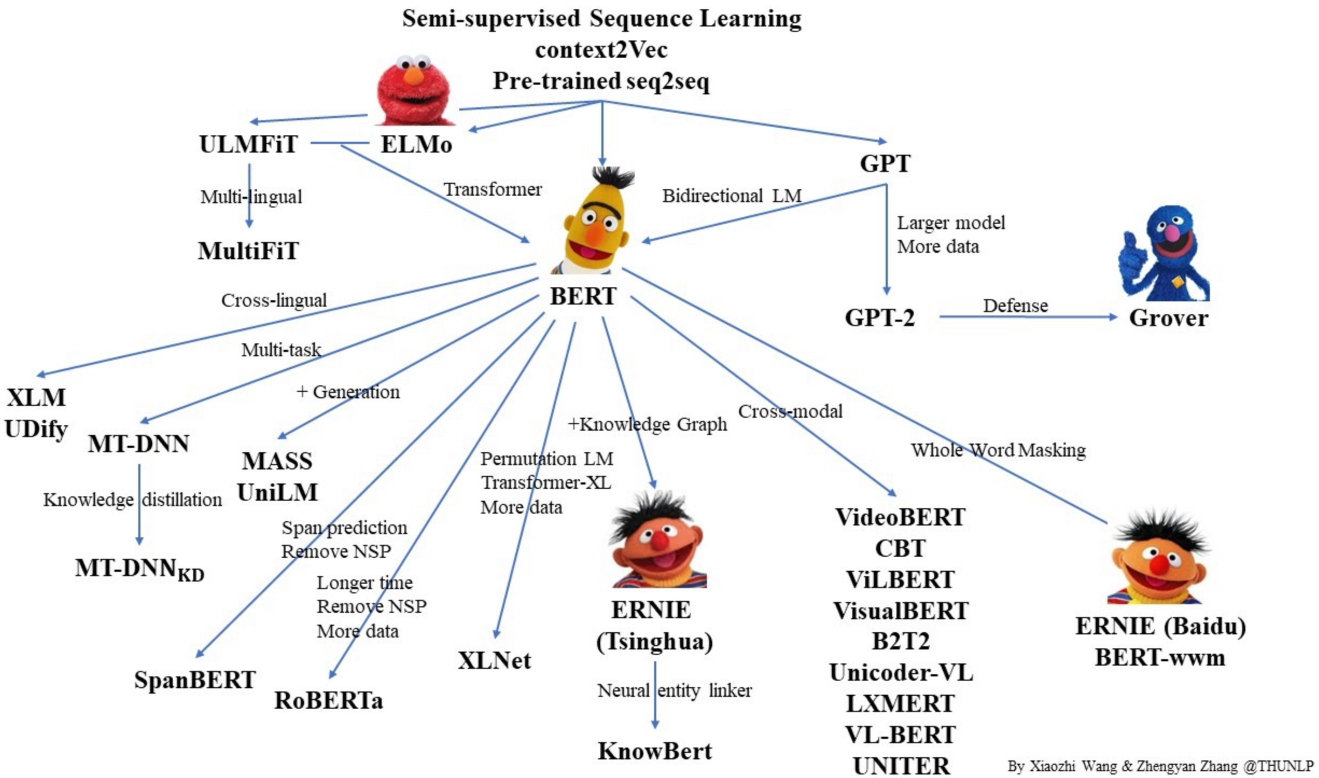


BERT Performance using GLUE

❖ GLUE: The General Language Understanding Evaluation benchmark on various tasks



BERT Family



Semi-supervised Sequence Learning
context2Vec
Pre-trained seq2seq
ULMFiT
ELMo
GPT
Transformer
Bidirectional LM
Multi-lingual
MultiFiT
Larger model
More data
BERT
GPT-2
Defense
Grover
Cross-lingual
Multi-task
XLM
UDify
MT-DNN
+ Generation
MASS
UniLM
Knowledge distillation
MT-DNN$_{KD}$
Span prediction
Remove NSP
Longer time
Remove NSP
More data
SpanBERT
RoBERTa
Permutation LM
Transformer-XL
More data
XLNet
+Knowledge Graph
ERNIE
(Tsinghua)
Neural entity linker
KnowBert
Cross-modal
VideoBERT
CBT
ViLBERT
VisualBERT
B2T2
Unicoder-VL
LXMERT
VL-BERT
UNITER
Whole Word Masking
ERNIE (Baidu)
BERT-wwm
By Xiaozhi Wang & Zhengyan Zhang @THUNLP

Q & A