BERT and The History Behind It

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Agenda

1. Some typical NLP tasks.
2. Sequence to sequence learning (Seq2Seq).
3. Transformer.
4. BERT.

Some typical NLP tasks

- Named entity recognition (NER), intent classification, slot filling (chatbots, virtual assistants):

Sentence	*show*	*flights*	*from*	*Boston*	*To*	*New*	*York*	*today*
Slots/Concepts	O	O	O	B-dept	O	B-arr	I-arr	B-date
Named Entity	O	O	O	B-city	O	B-city	I-city	O
Intent	*Find_Flight*							
Domain	*Airline Travel*							

Identify known entities in a given text, classify the intent.

G. Mesnil et al. Using Recurrent Neural Networks for Slot Filling in Spoken Language Understanding.

Some typical NLP tasks

- Question answering:

context: Beyoncé Giselle Knowles-Carter (/biːˈjɒnseɪ/ bee-YON-say) (born September 4, 1981) is an American singer, songwriter, record producer and actress. Born and raised in Houston, Texas, she performed in various singing and dancing competitions as a child, and rose to fame in the late 1990s as lead singer of R&B girl-group Destiny's Child. Managed by her father, Mathew Knowles, the group became one of the world's best-selling girl groups of all time. Their hiatus saw the release of Beyoncé's debut album, Dangerously in Love (2003), which established her as a solo artist worldwide, earned five Grammy Awards and featured the Billboard Hot 100 number-one singles "Crazy in Love" and "Baby Boy".
question: What was the name of Beyoncé's first solo album?
answer: Dangerously in Love

- Neural machine translation (NMT):

Je m'appelle Daniil → My name is Daniil

Stanford Question Answering Dataset (SQuAD).

Tweet sentiment extraction

Given a tweet and sentiment, predict words subsequence, which responsible for the sentiment.

tweet: I`d have responded, if I were going
sentiment: neutral
answer: I`d have responded, if I were going

tweet: Sooo SAD I will miss you here in San Diego!!!
sentiment: negative
answer: Sooo SAD

tweet: I really really like the song Love Story by Taylor Swift
sentiment: positive
answer: like

tweet: I`m sorry.
sentiment: negative
answer: I`m sorry.

tweet: is back home now gonna miss every one
sentiment: negative
answer: onna

tweet: hm... Both of us I guess...
sentiment: neutral
answer: hm... Both of us I guess...

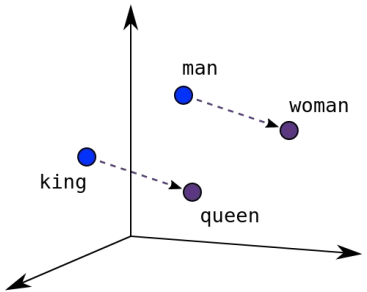
Kaggle Tweet Sentiment Extraction Challenge.

From words to vectors

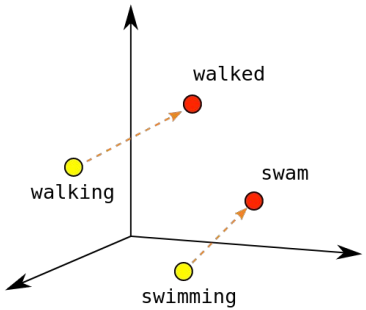
Q: How to map words to vectors?

From words to vectors

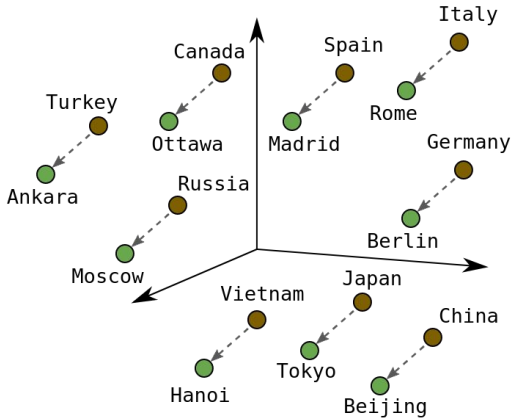
- One-hot encoding.
- Word2vec, GloVe.
- Embedding layer.



Male-Female



Verb Tense



Country-Capital

https://developers.google.com/machine-learning/crash-course/embeddings/translating-to-a-lower-dimensional-space.

Slide name is hidden

1. $W^{hx}x$ = ?

Slide name is hidden

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2. sigm($W^{hx}x$) = ?

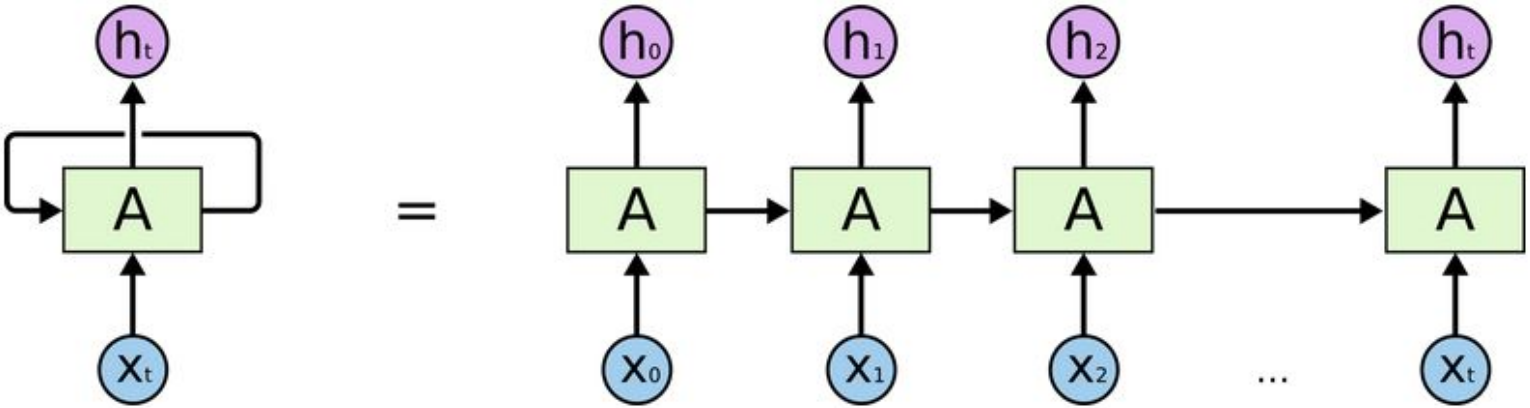
Slide name is hidden

1. $W^{hx}x$ = FC.
2. sigm($W^{hx}x$) = FC + activation.
3. sigm($W^{hx}x_t + W^{hh}h_{t-1}$) = ?

Recurrent neural network

1. $W^{hx}x$ = FC.
2. sigm($W^{hx}x$) = FC + activation.
3. sigm($W^{hx}x_t + W^{hh}h_{t-1}$) = h_t, recurrent unit.

y = $W^{yh}h_t$ - output, e.g. logits for intent classification.



C.Olah. Understanding LSTM Networks.

Recurrent neural network

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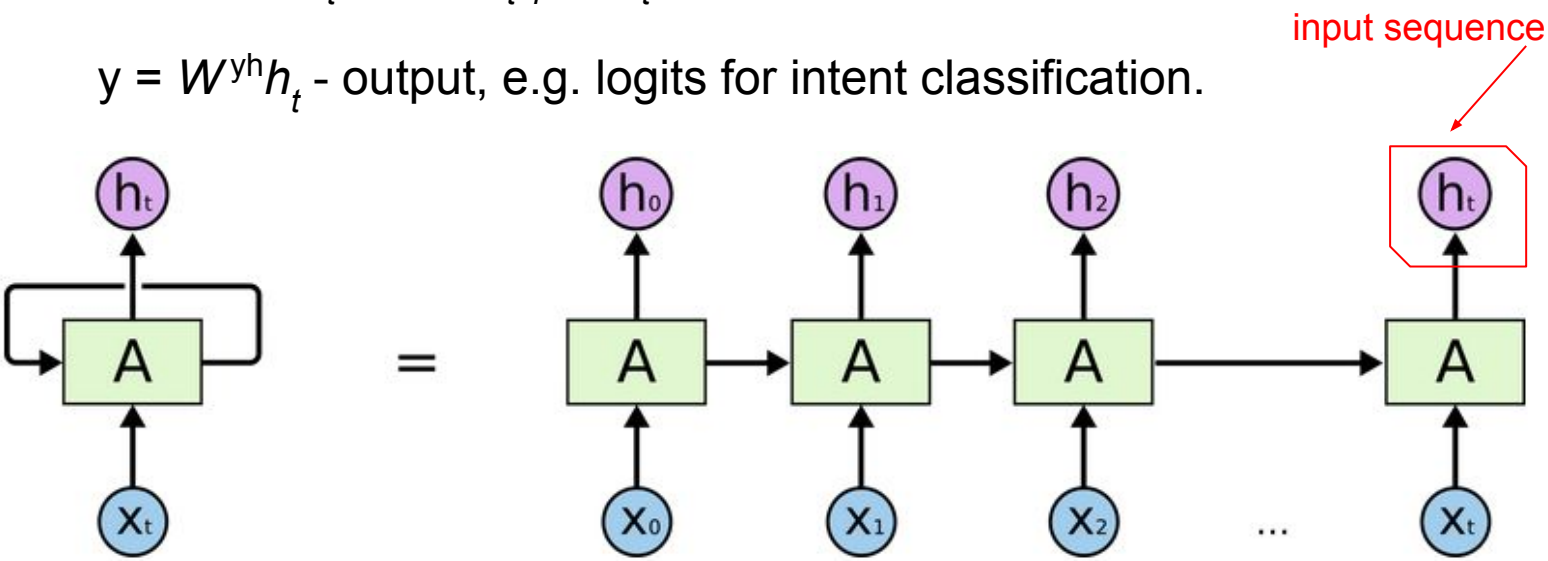
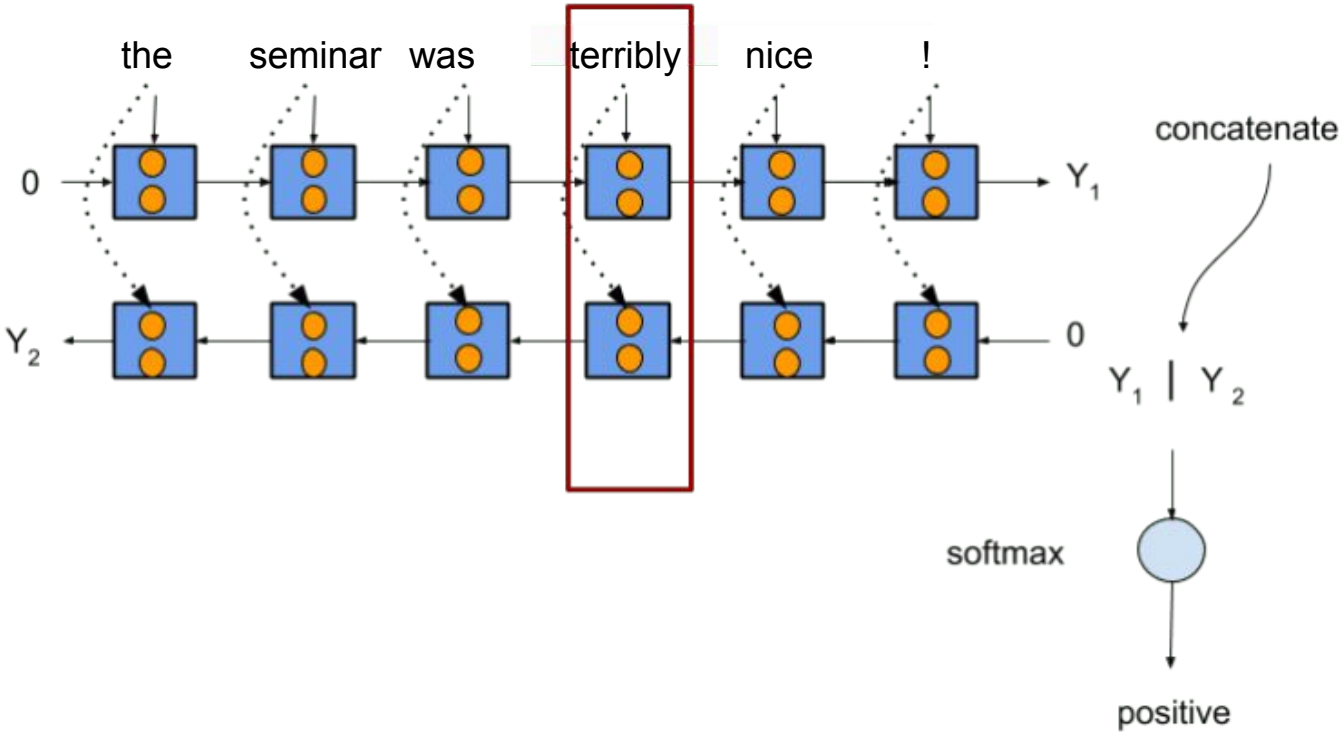


C.Olah. Understanding LSTM Networks.

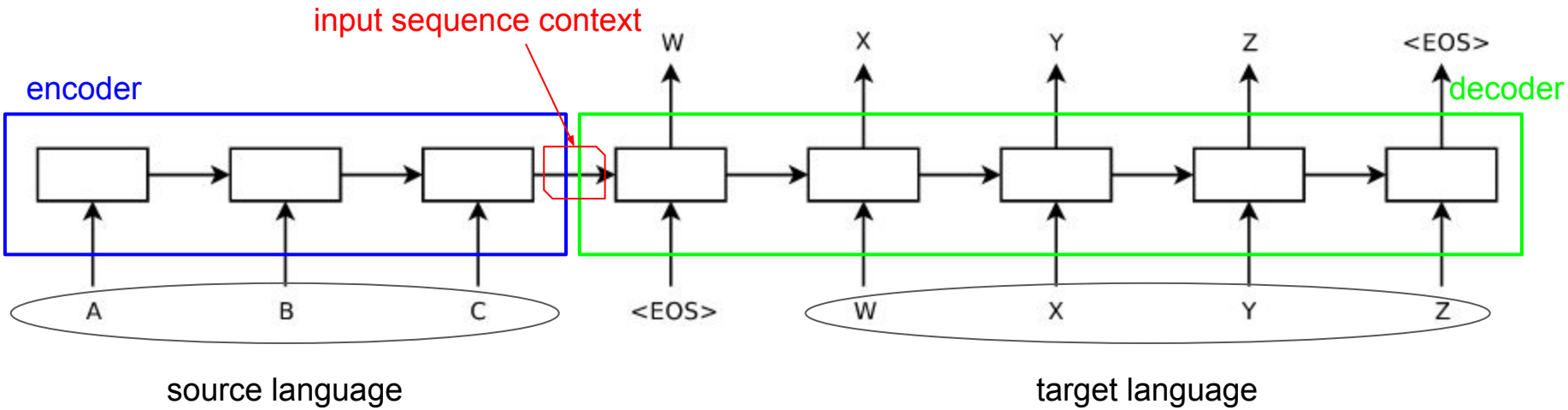
Bidirectional recurrent neural network

Consider review: “The seminar was terribly nice!”, the task is to predict sentiment.



Bidirectional LSTM using Keras.

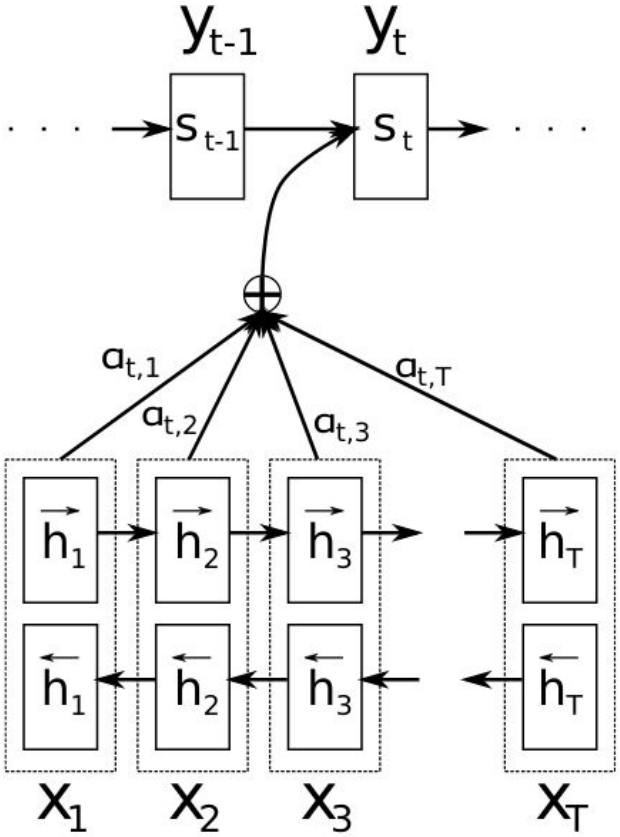
Seq2Seq: text translation



Encoder and decoder are RNNs (LSTM, GRU).

I.Sutskever et al. Sequence to Sequence Learning with Neural Networks.

Seq2Seq: text translation with attention



Own context vector c_i for each target y_i.

$$c_i = \sum_{j=1}^{T_x} \alpha_{ij} h_j$$

$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{k=1}^{T_x} \exp(e_{ik})}$$

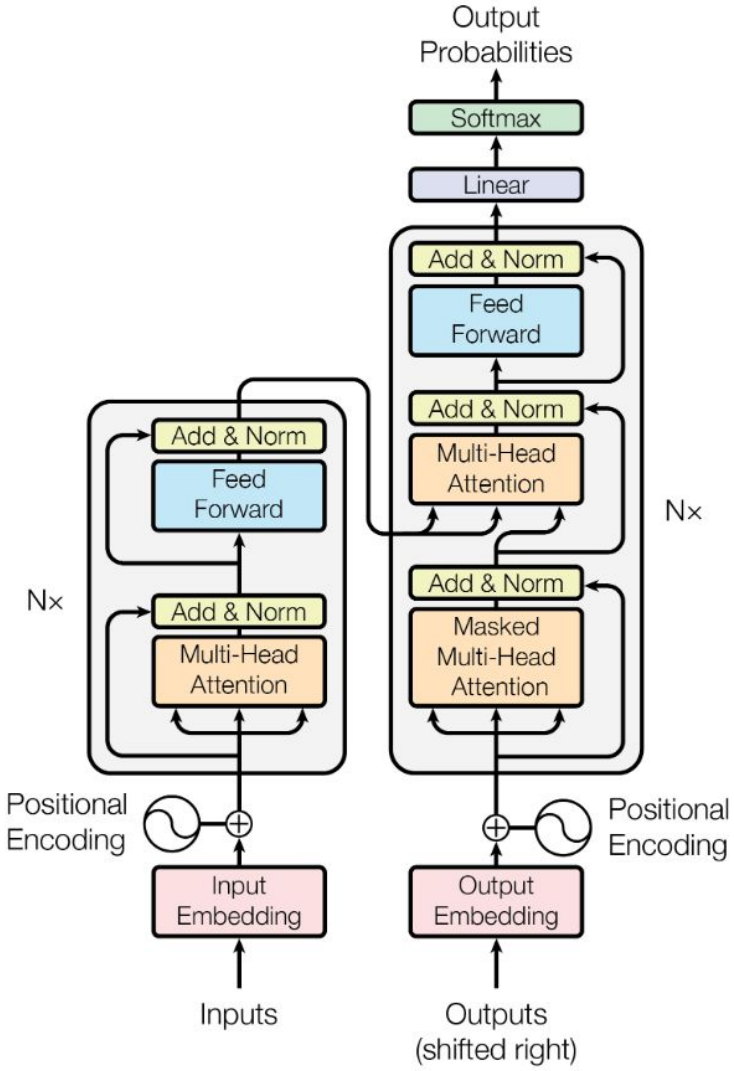
$$e_{ij} = a(s_{i-1}, h_j)$$

a(s, h) - model (fc) which scores how well the inputs around position j and the output at position i match.

D. Bahdanau et al. Neural Machine Translation by Jointly Learning to Align and Translate.

Transformer

Looks simple, huh?



A. Vaswani et al. Attention Is All You Need.

Transformer

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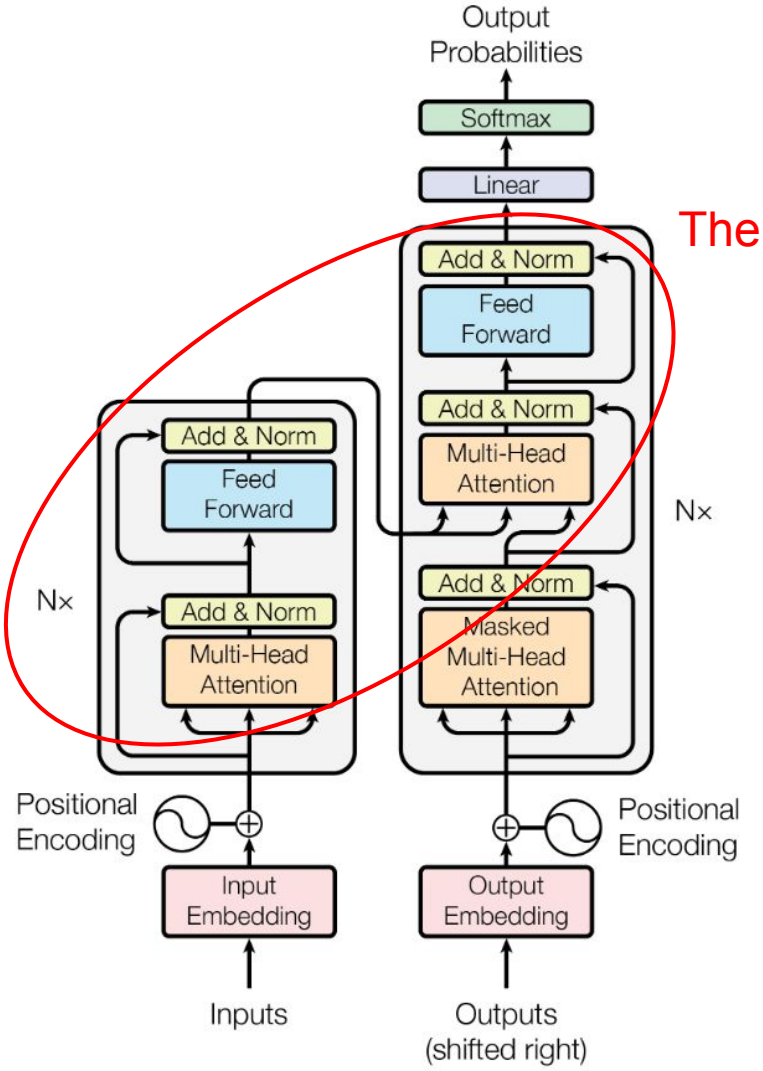
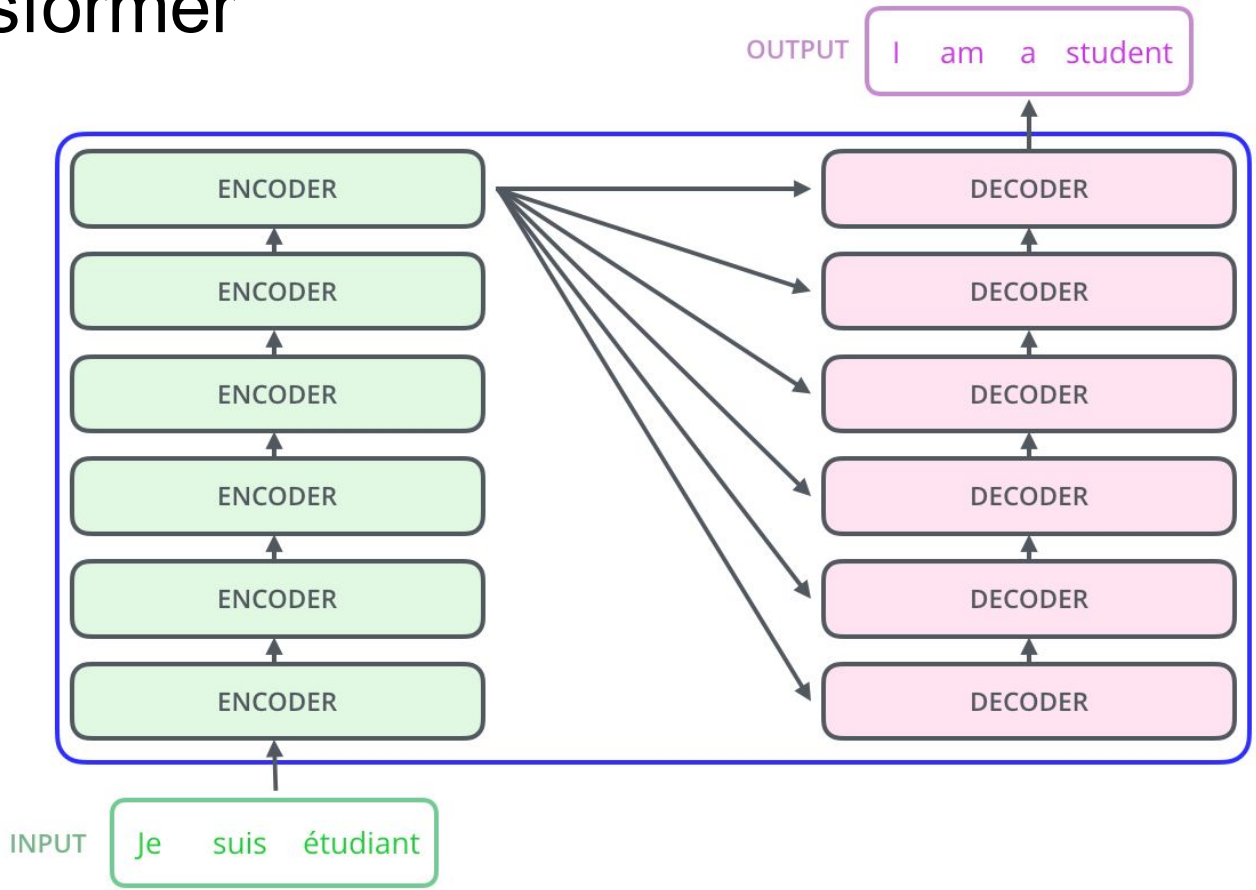


The same blocks structure

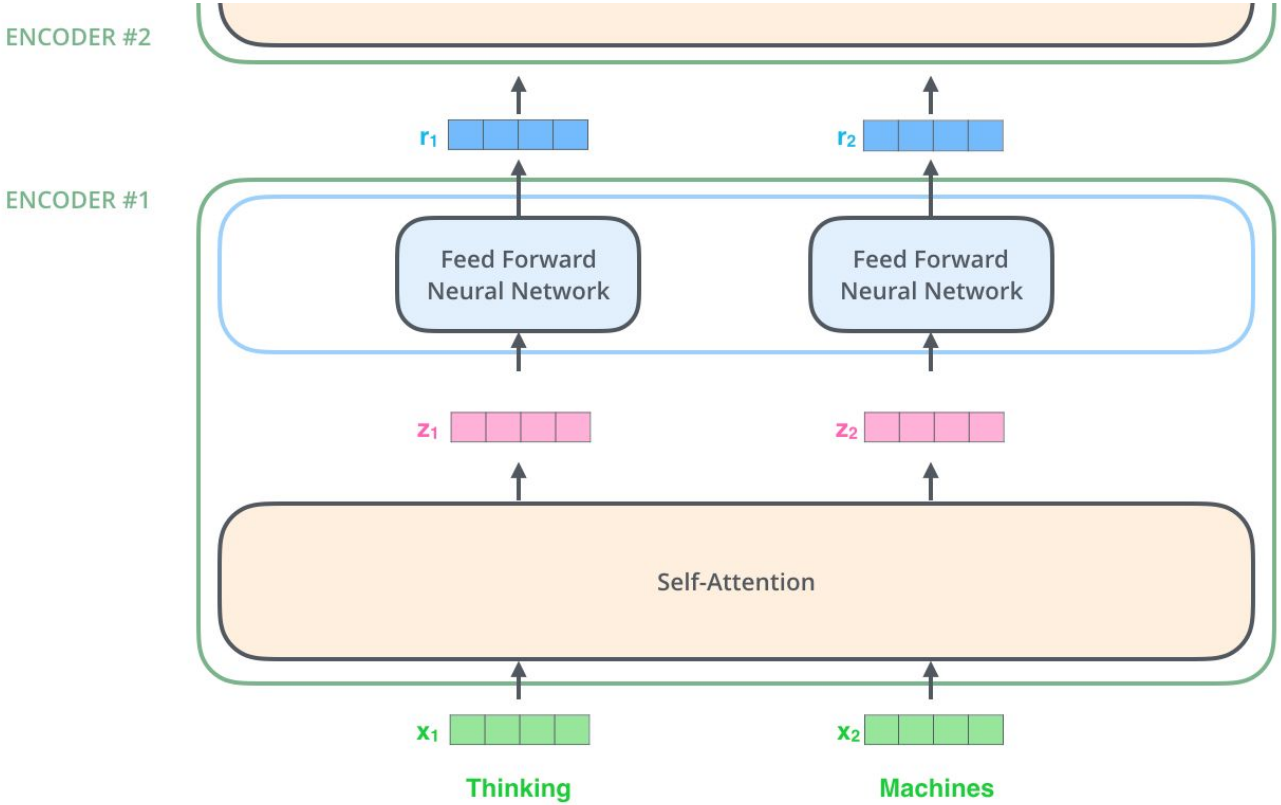
A. Vaswani et al. Attention Is All You Need.

Transformer



The illustrated transformer, https://jalammar.github.io/illustrated-transformer/.

Transformer: encoder



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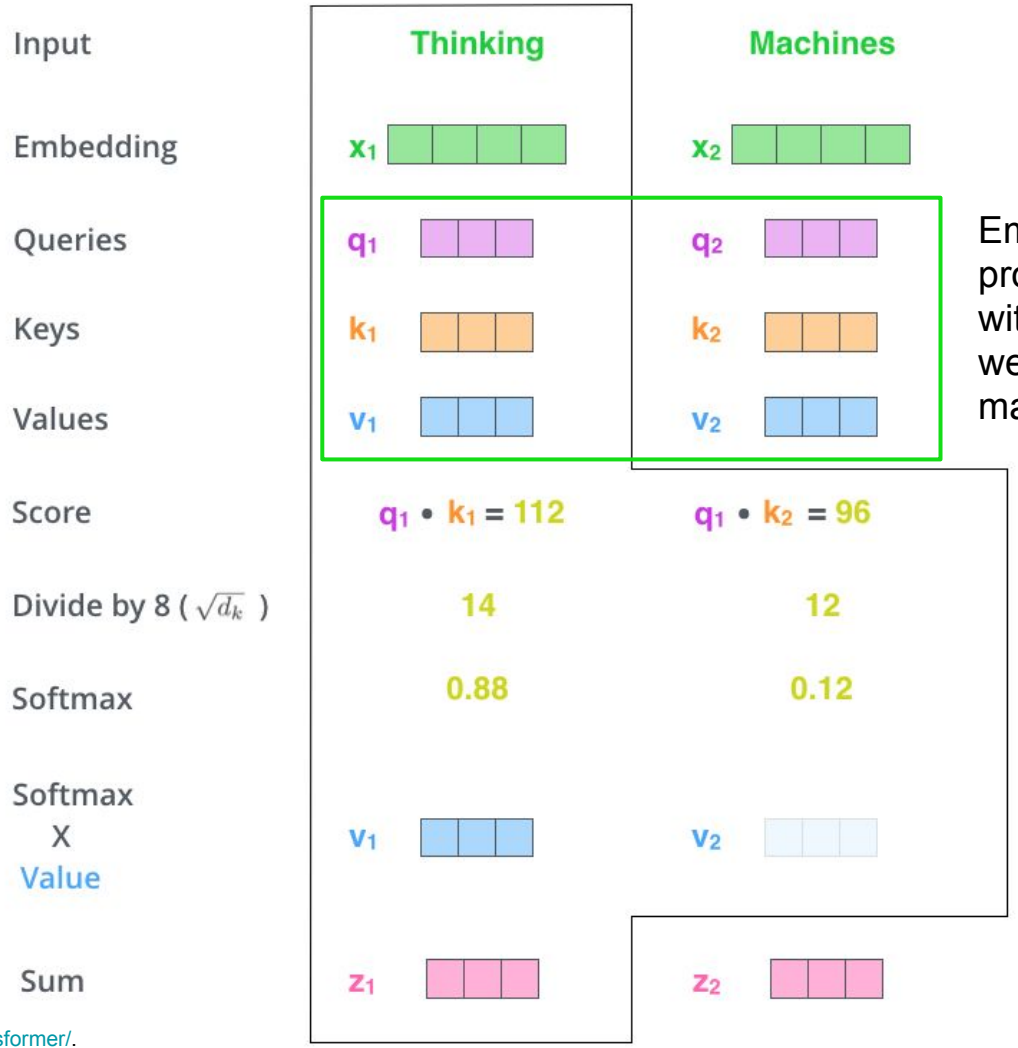
Transformer: self-attention

Input: $X = (x_1; x_2; \ldots; x_{max\_num\_words})$,
$X \in R^{max\_num\_words \times embedding\_dim}$

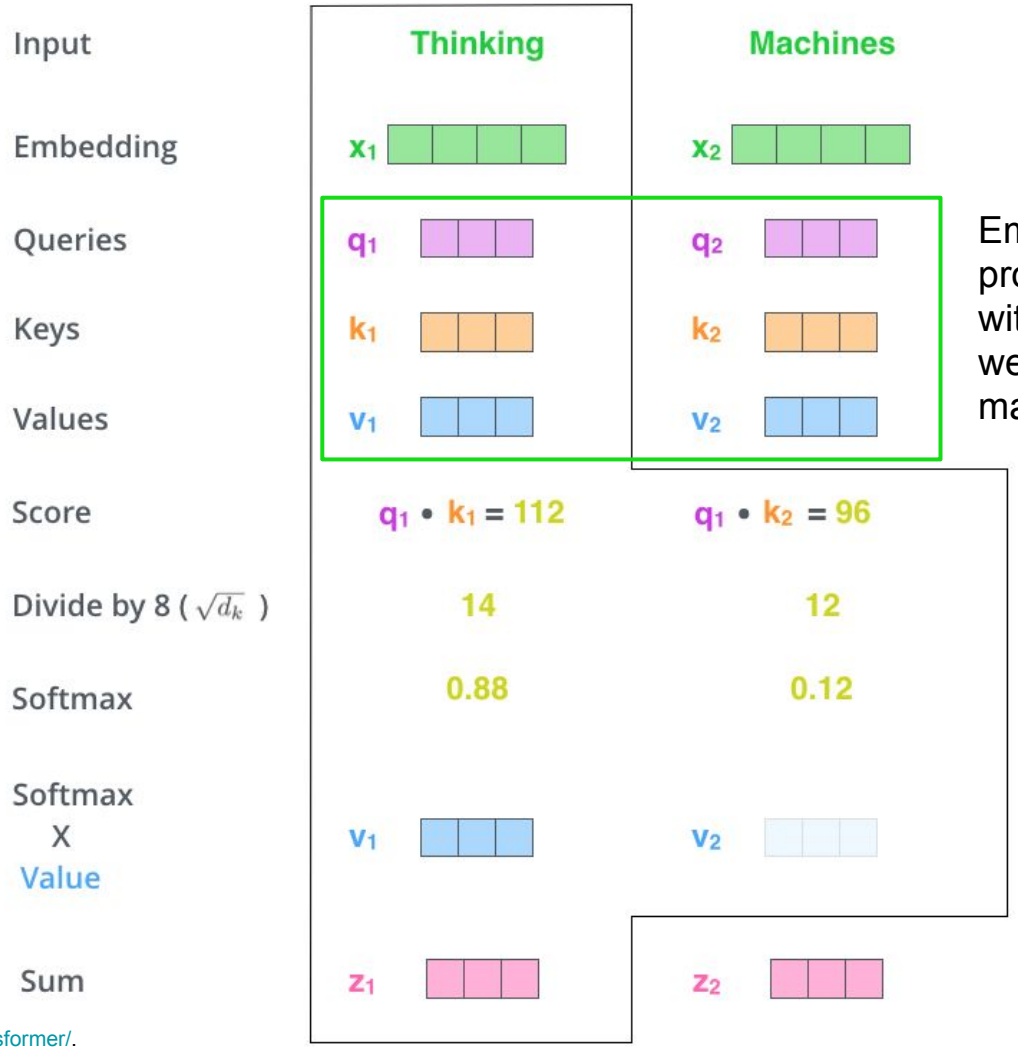


Embedding projections with learnable weights (just matmul)

The illustrated transformer, https://jalammar.github.io/illustrated-transformer/.

Transformer: self-attention

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



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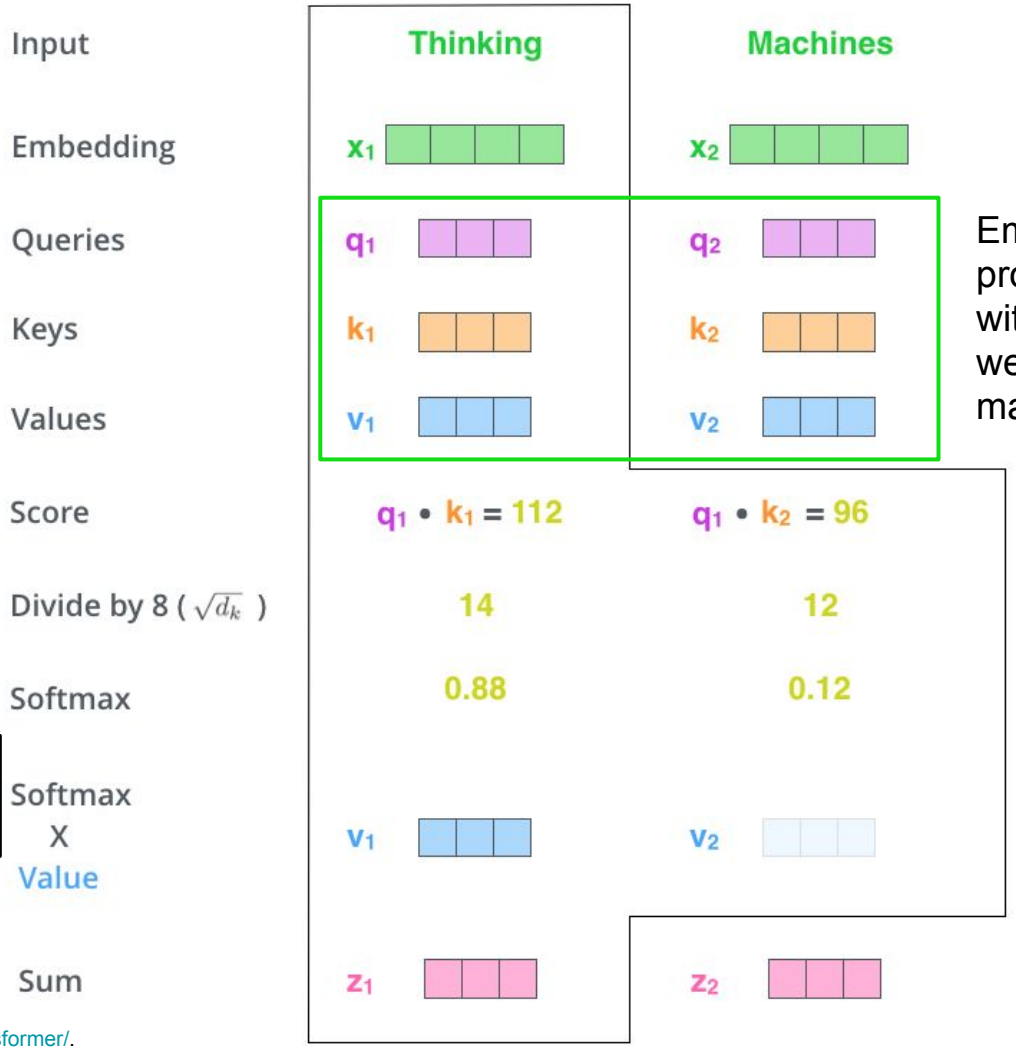
$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

It is bidirectional.



Embedding projections with learnable weights (just matmul)

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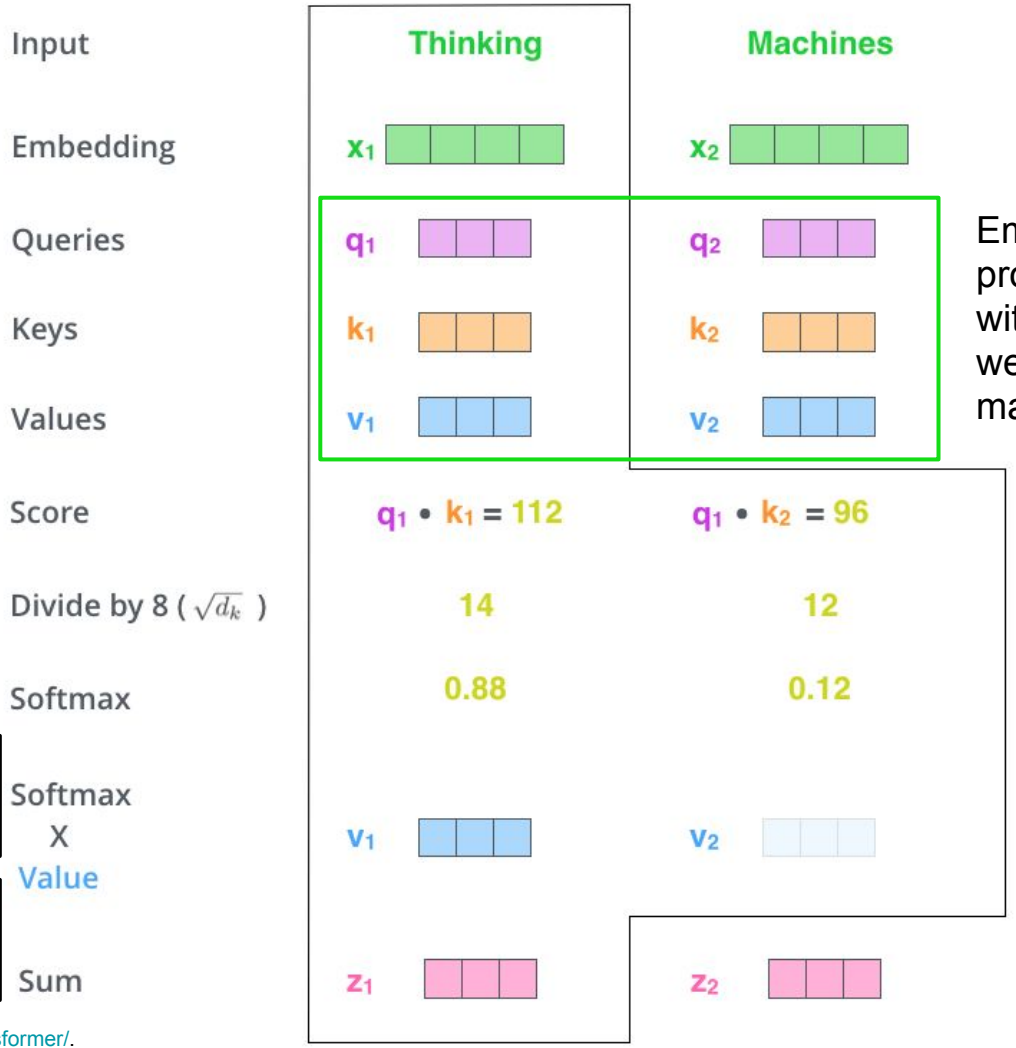
Transformer: self-attention

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

It is bidirectional.

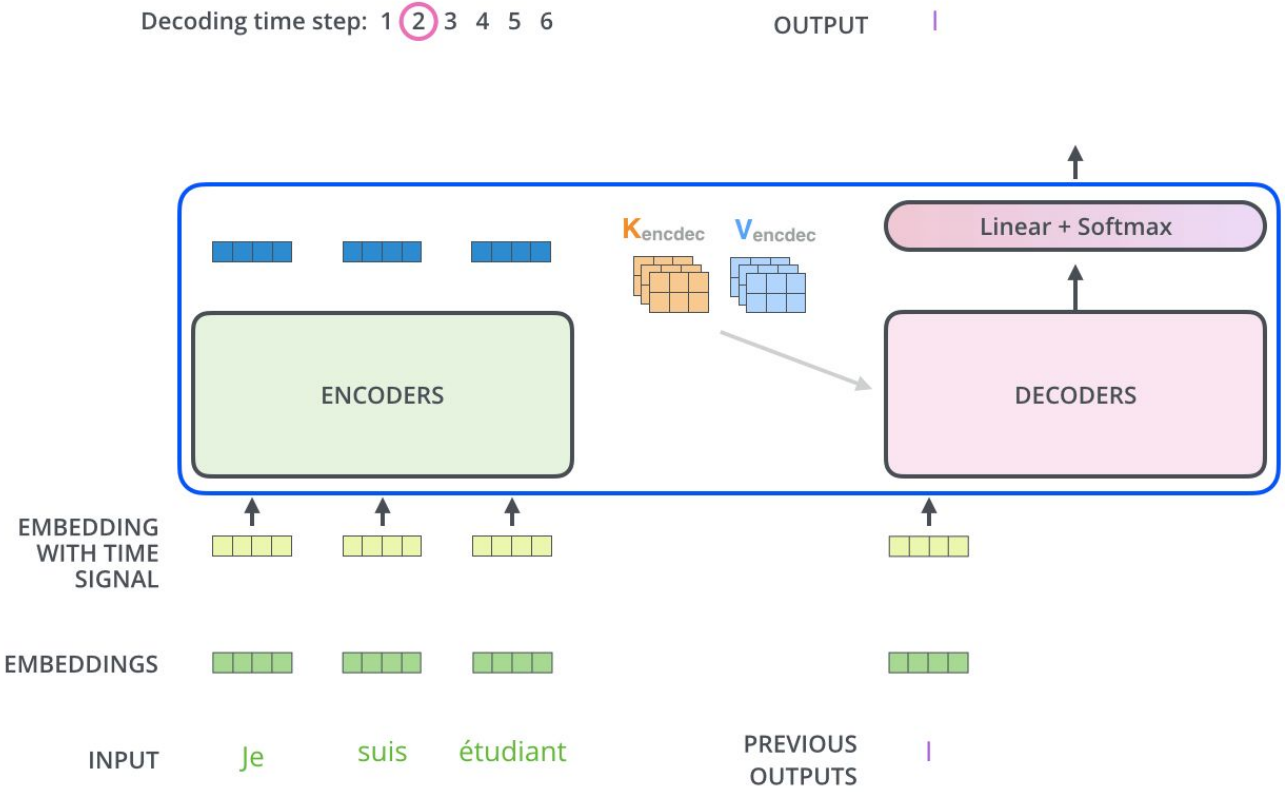
It is multi-headed.



Embedding projections with learnable weights (just matmul)

The illustrated transformer, https://jalammar.github.io/illustrated-transformer/.

Transformer: decoder



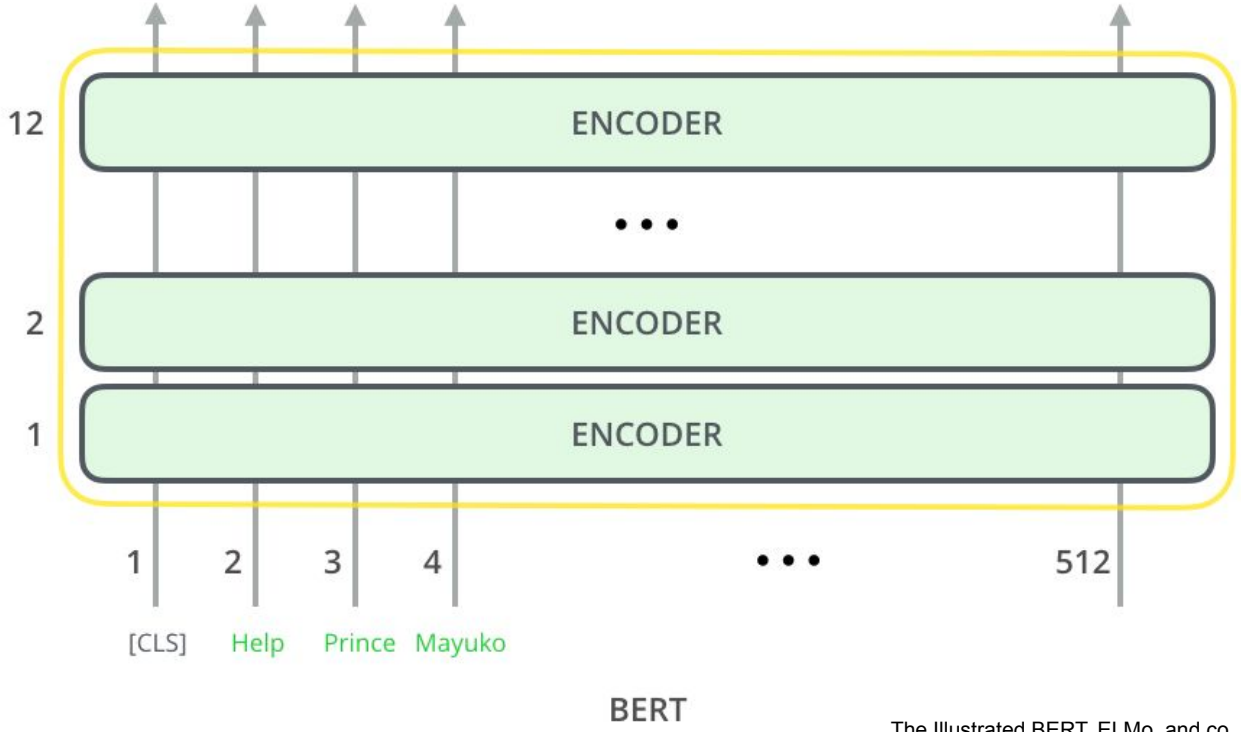
The illustrated transformer, https://jalammar.github.io/illustrated-transformer/.

BERT: Bidirectional Encoder Representations from Transformers

How many transformers in BERT?

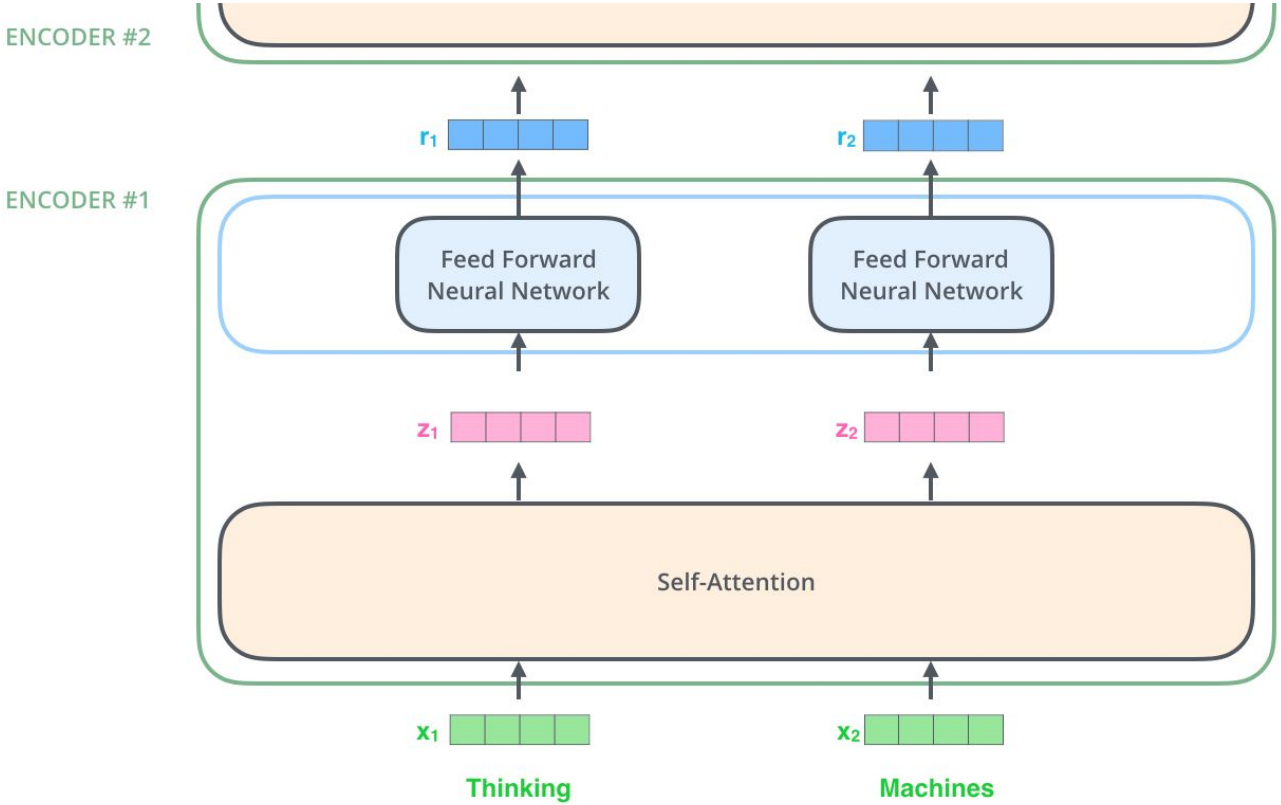
38 parrots, YouTube.

BERT: Bidirectional Encoder Representations from Transformers



The Illustrated BERT, ELMo, and co, http://jalammar.github.io/illustrated-bert/.

Transformer: encoder



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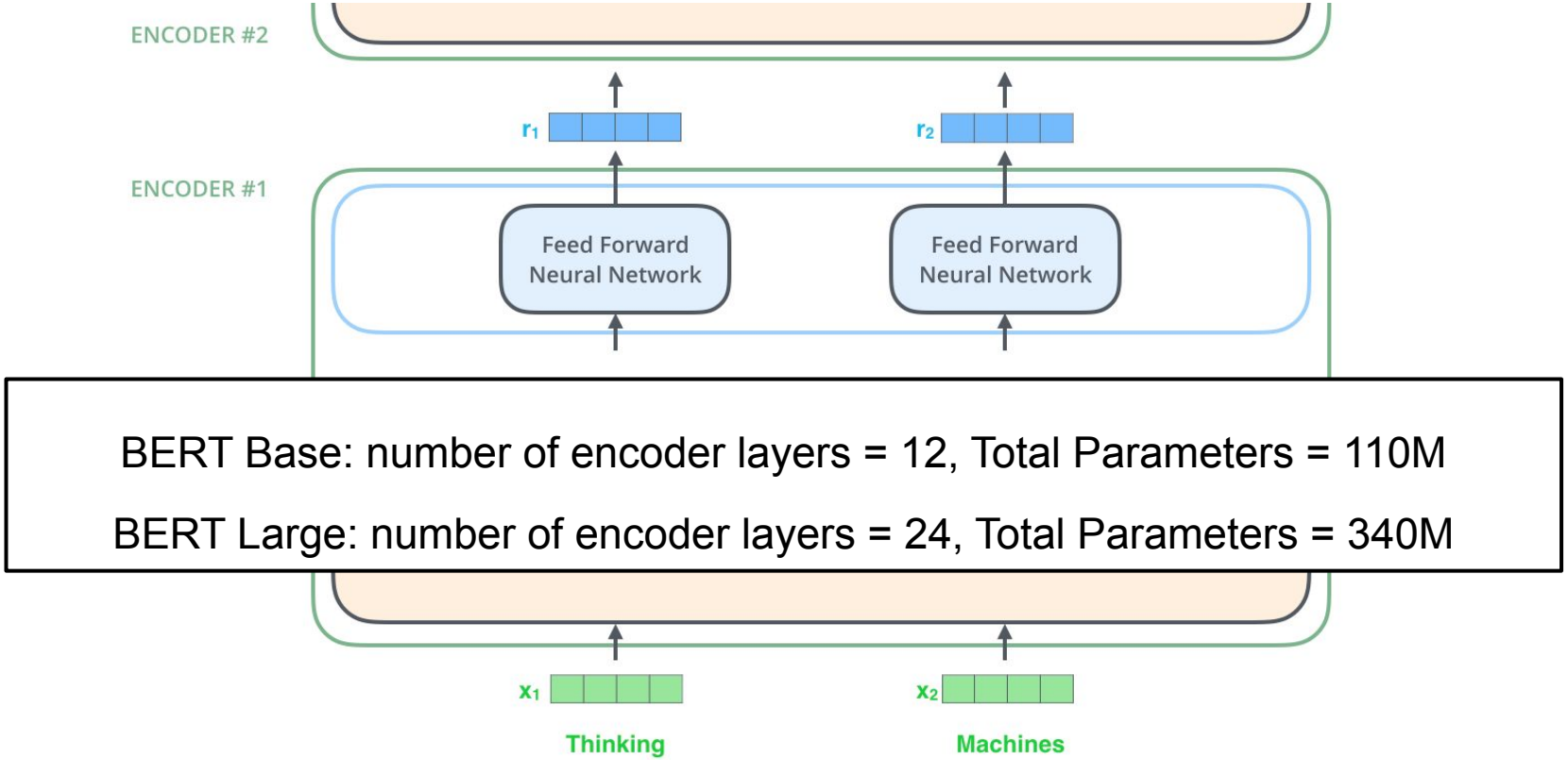


BERT Base: number of encoder layers = 12, Total Parameters = 110M

BERT Large: number of encoder layers = 24, Total Parameters = 340M

The illustrated transformer, https://jalammar.github.io/illustrated-transformer/.

BERT text mapping example

Tokenizer: split text into subwords.

```
from transformers import BertTokenizer, RobertaTokenizer
if __name__ == '__main__':
    sentence = 'On the way to Malaysia...no internet access to Twit'
    for tokenizer_class, tokenizer_name in zip(
            [BertTokenizer, RobertaTokenizer],
            ['bert-base-uncased', 'roberta-base']):
        tokenizer = tokenizer_class.from_pretrained(tokenizer_name)
        tokens = tokenizer.tokenize(sentence)
        print('{}:'.format(tokenizer_name))
        print(tokens)
bert-base-uncased:
['on', 'the', 'way', 'to', 'malaysia', '.', '.', '.', 'no', 'internet', 'access', 'to', 't', '##wi', '##t']
roberta-base:
['On', 'Ġthe', 'Ġway', 'Ġto', 'ĠMalaysia', '...', 'no', 'Ġinternet', 'Ġaccess', 'Ġto', 'ĠTw', 'it']
```

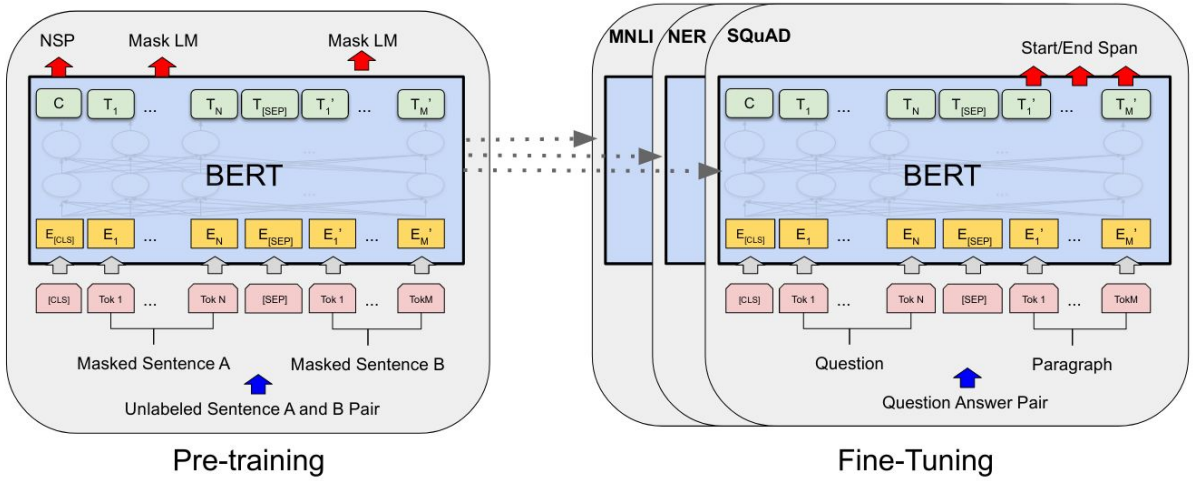
BERT: pre-training

Masked language modeling:

- Mask some percentage of the input tokens at random, and then predict those masked tokens.

Next sentence prediction:

- Understand the relationship between two sentences. Binary classification if in a given sentences pair the second sentence follows the first.



J. Devlin et al. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding.

BERT: fine-tuning

```
class TweetModel(transformers.BertPreTrainedModel):
    def __init__(self, conf):
        super().__init__(conf)
        self.bert = transformers.BertModel.from_pretrained('bert-base-uncased', config=conf)
        self.drop_out = nn.Dropout(0.1)
        self.l0 = nn.Linear(768 * 2, 2)

    def forward(self, tokens_ids, mask, tokens_type_ids):
        last_hidden_state, pooler_output, hidden_states = self.bert(
            tokens_ids,
            attention_mask=mask,
            token_type_ids=tokens_type_ids
        )
```

BERT: fine-tuning

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```

Input text tokens
(batch_size x max_tokens_num)

BERT: fine-tuning

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```

Mask with 1 at positions of real tokens and 0 for padding
(batch_size x max_tokens_num)

BERT: fine-tuning

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```

Mask to identify different input sequences with 0 for 1st and 1 for 2nd sequence (batch_size x max_tokens_num)

BERT: fine-tuning

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        )
```

Last encoder output
(batch_size x max_tokens_num x embedding_dim)

BERT: fine-tuning

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        )
```

Processed last encoder output for the 1st token
(batch_size x embedding_dim)

BERT: fine-tuning

```python
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        )
```

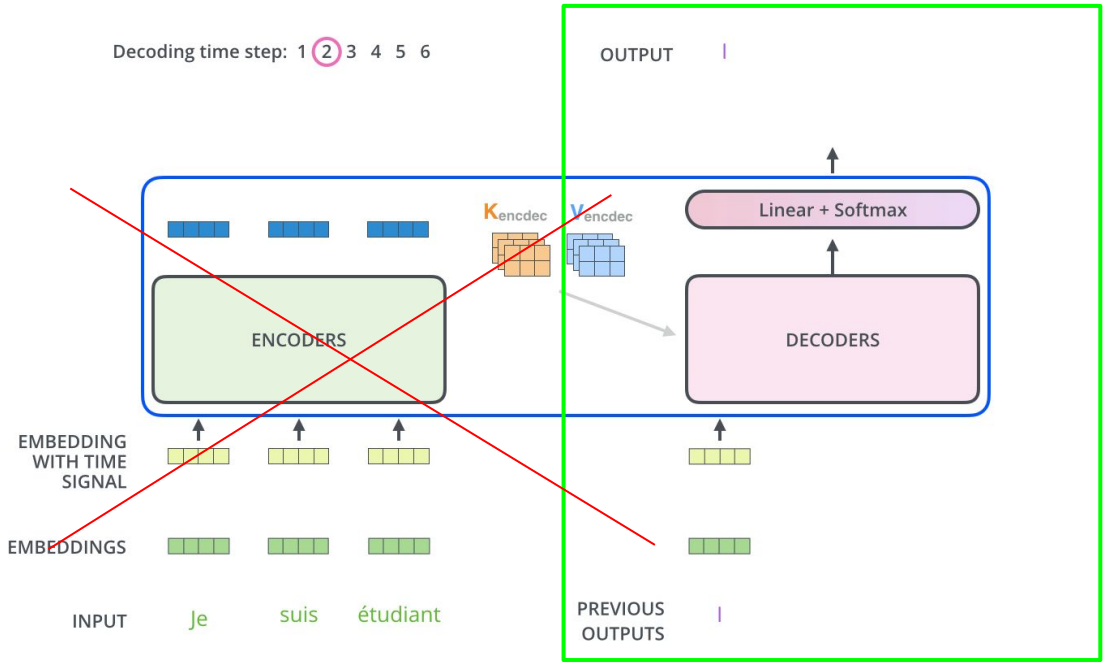
Output from embeddings and all encoders
Tuple of tensors (batch_size x max_tokens_num x embedding_dim)

GPT: Improving Language Understanding by Generative Pre-Training

GPT: Improving Language Understanding by Generative Pre-Training

It is a decoder from transformer.

Try it out (GPT-2): https://demo.allennlp.org/next-token-lm?text=Lobachevsky



GPT: Improving Language Understanding by Generative Pre-Training

It is a decoder from transformer.

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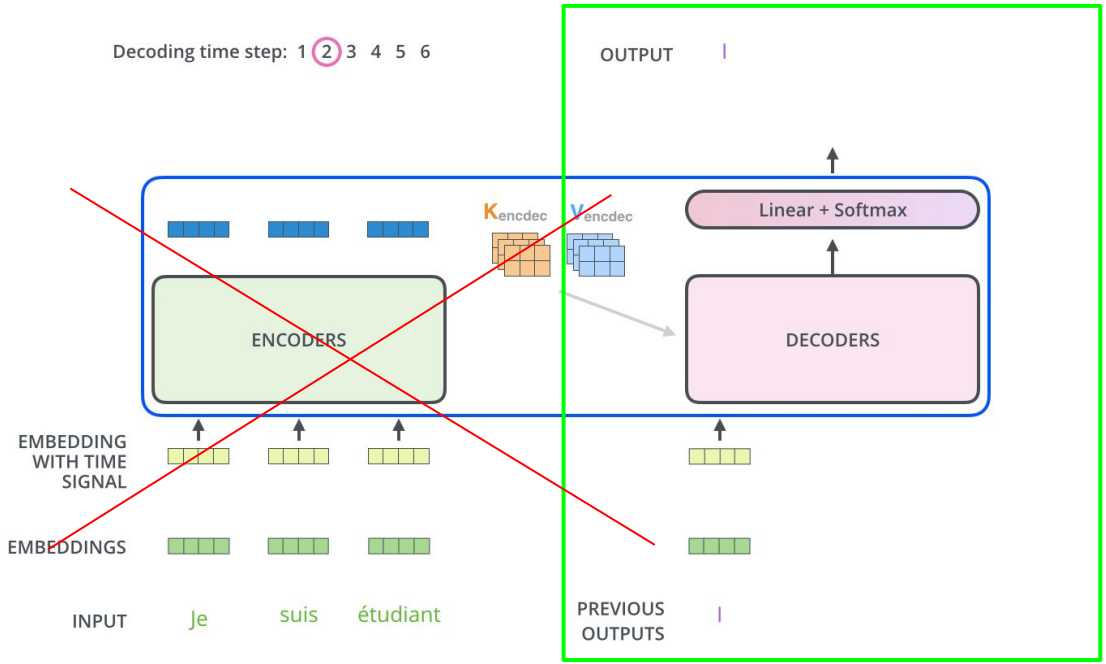
GPT-3 has 175B parameters.



Summary

- Seq2Seq: encode all input text into single context vector.
- Attention: make context vector adaptive to position of output word.
- Self-attention: shorten distance between words.
- BERT: large scale pre-training.

Thank you for the attention!

- https://towardsdatascience.com/lost-in-translation-found-by-transformer-46a16bf6418f
- https://towardsdatascience.com/bert-for-dummies-step-by-step-tutorial-fb90890ffe03
- https://mccormickml.com/2019/07/22/BERT-fine-tuning/
- https://www.analyticsvidhya.com/blog/2019/06/understanding-transformers-nlp-state-of-the-art-models/
- http://jalammar.github.io/illustrated-gpt2/
- https://pytorch.org/tutorials/intermediate/seq2seq_translation_tutorial.html
- https://lilianweng.github.io/lil-log/2018/06/24/attention-attention.html
- https://ai.googleblog.com/2020/03/more-efficient-nlp-model-pre-training.html
- https://huggingface.co/transformers/