CMPT 825: Natural Language Processing

Contextualized Word Embeddings

Spring 2020
2020-03-17

Adapted from slides from Danqi Chen and Karthik Narasimhan
(with some content from slides from Chris Manning and Abigail See)

Course Logistics

- Online lectures from now on! Everyone stay safe!
- HW4 due Tuesday 3/24
- Project Milestone due Tuesday 3/31

Course Logistics

Remaining lectures (tentative)

- Contextual word embeddings and Transformers

- Parsing:
  - Dependency Parsing
  - Constituency Parsing
  - Semantic Parsing

- CNNs for NLP

- Applications: Question Answering, Dialogue, Coreference, Grounding

Overview

Contextualized Word Representations

- ELMo = **E**mbeddings from **L**anguage **Mo**dels

Deep contextualized word representations

https://arxiv.org › cs

by ME Peters - 2018 - Cited by 1683 - Related articles

Deep contextualized word representations. ... Our **word** vectors are learned functions of the internal states of a **deep** bidirectional language model (biLM), which is pre-trained on a large text corpus.

- BERT = **B**idirectional **E**ncoder **R**epresentations from **T**ransformers

BERT: Pre-training of Deep Bidirectional Transformers for ...

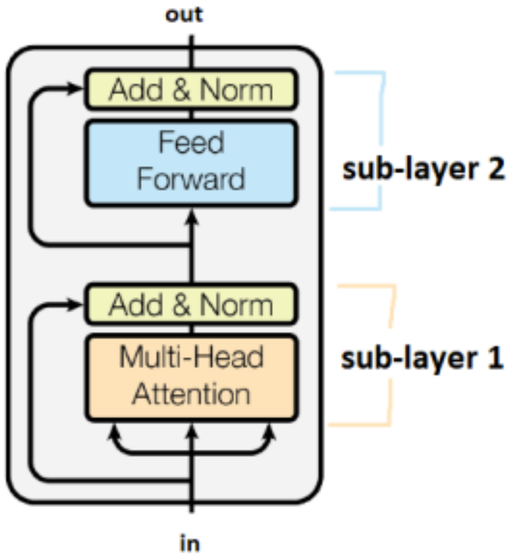
https://arxiv.org › cs

by J Devlin - 2018 - Cited by 2259 - Related articles

Oct 11, 2018 - Unlike recent language representation models, **BERT** is designed to pre-train deep ... As a result, the pre-trained **BERT** model can be fine-tuned with just one additional output ... Which authors of this **paper** are endorsers?

Overview

- Transformers

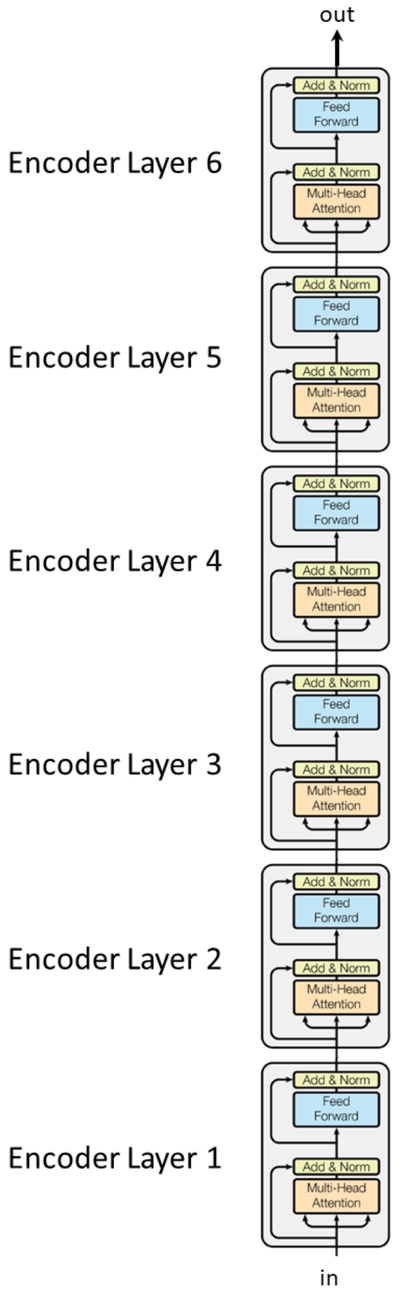


Attention Is All You Need

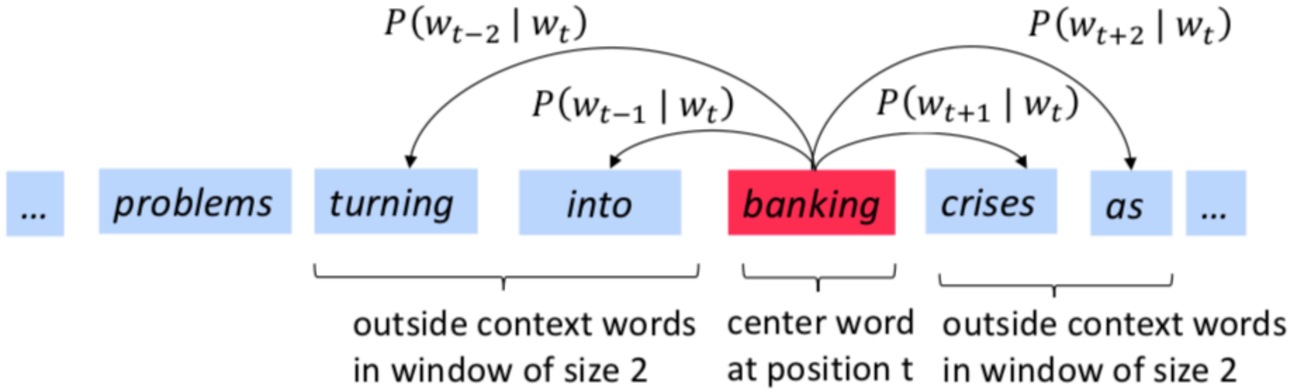
https://arxiv.org › cs ▾

by A Vaswani - 2017 - Cited by 4323 - Related articles

Jun 12, 2017 - **Attention Is All You Need**. The dominant sequence transduction models are based on complex recurrent or convolutional neural networks in an encoder-decoder configuration. The best performing models also connect the encoder and decoder through an **attention** mechanism.



Recap: word2vec



word = “sweden”

Word	Cosine distance
norway	0.760124
denmark	0.715460
finland	0.620022
switzerland	0.588132
belgium	0.585835
netherlands	0.574631
iceland	0.562368
estonia	0.547621
slovenia	0.531408

What's wrong with word2vec?

- One vector for each word type

$$v(\text{bank}) = \begin{pmatrix} -0.224 \\ 0.130 \\ -0.290 \\ 0.276 \end{pmatrix}$$

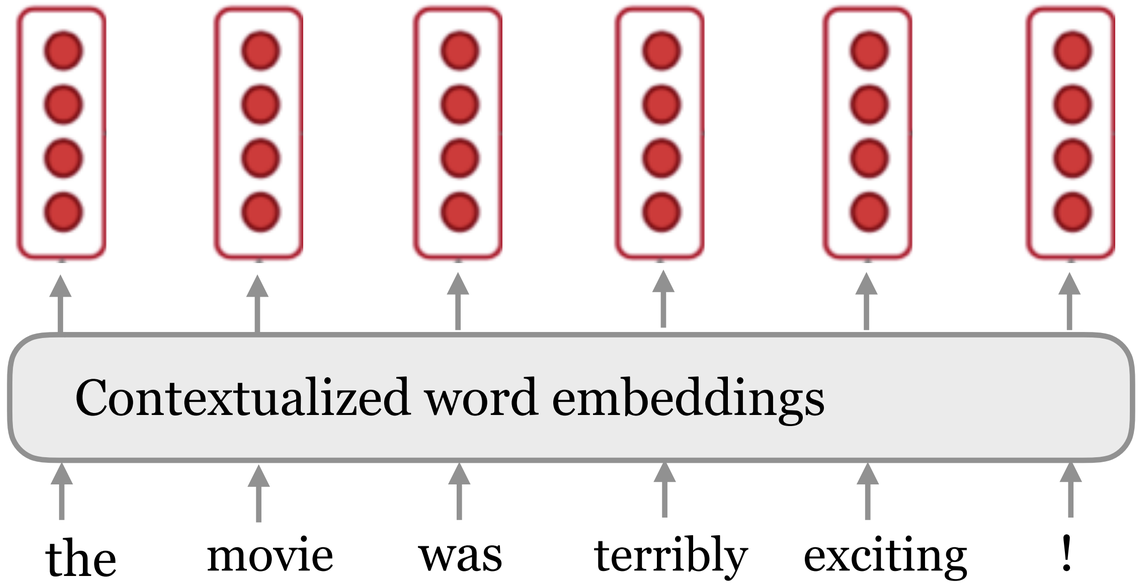
- Complex characteristics of word use: semantics, syntactic behavior, and connotations

- Polysemous words, e.g., bank, mouse

mouse^1 : .... a *mouse* controlling a computer system in 1968.
mouse^2 : .... a quiet animal like a *mouse*
bank^1 : ...a *bank* can hold the investments in a custodial account ...
bank^2 : ...as agriculture burgeons on the east *bank*, the river ...

Contextualized word embeddings

Let's build a vector for each word conditioned on its **context**!



$$f : (w_1, w_2, \ldots, w_n) \longrightarrow \mathbf{x}_1, \ldots, \mathbf{x}_n \in \mathbb{R}^d$$

Contextualized word embeddings

	Source	Nearest Neighbors
GloVe	play	playing, game, games, played, players, plays, player, Play, football, multiplayer
biLM (from ELMo)	Chico Ruiz made a spectacular play on Alusik 's grounder {...}	Kieffer , the only junior in the group , was commended for his ability to hit in the clutch , as well as his all-round excellent play .
	Olivia De Havilland signed to do a Broadway play for Garson {...}	{...} they were actors who had been handed fat roles in a successful play , and had talent enough to fill the roles competently , with nice understatement .

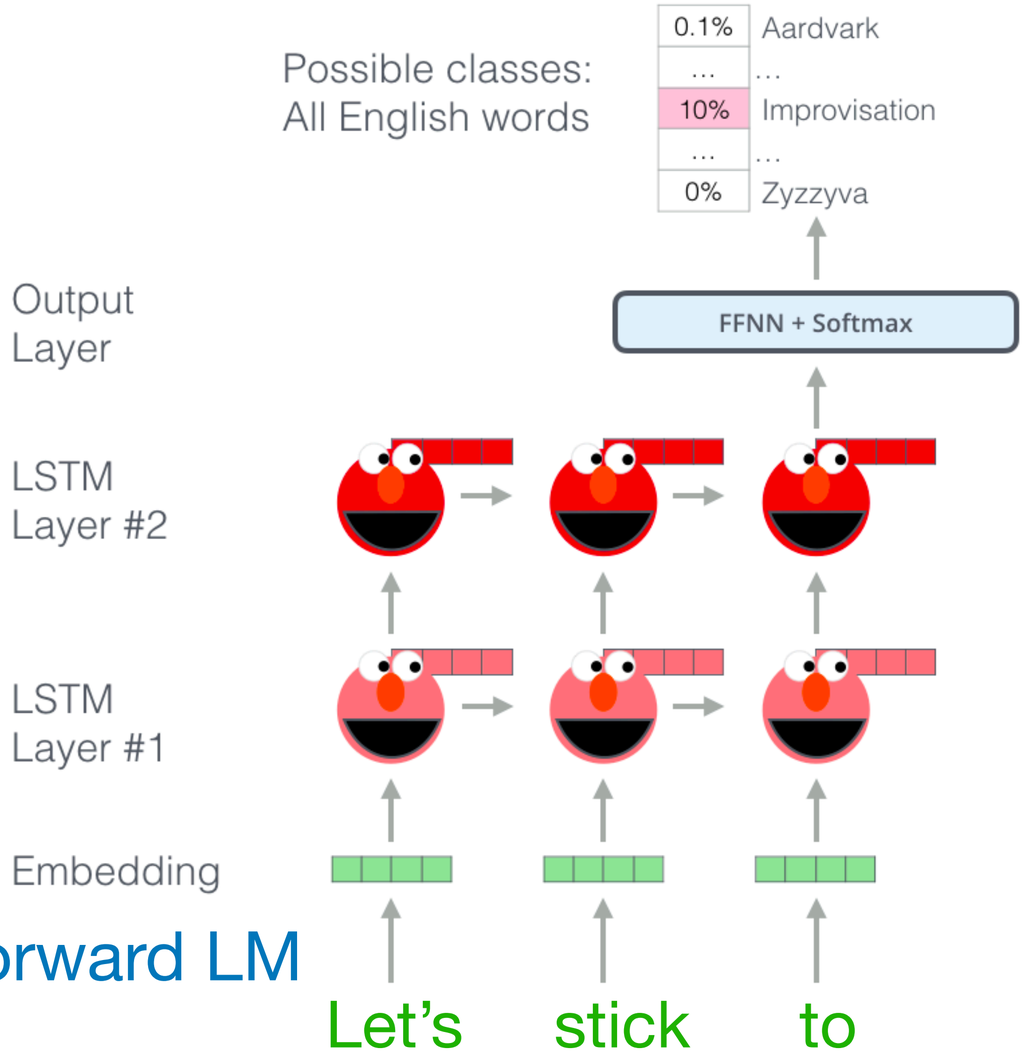
(Peters et al, 2018): Deep contextualized word representations

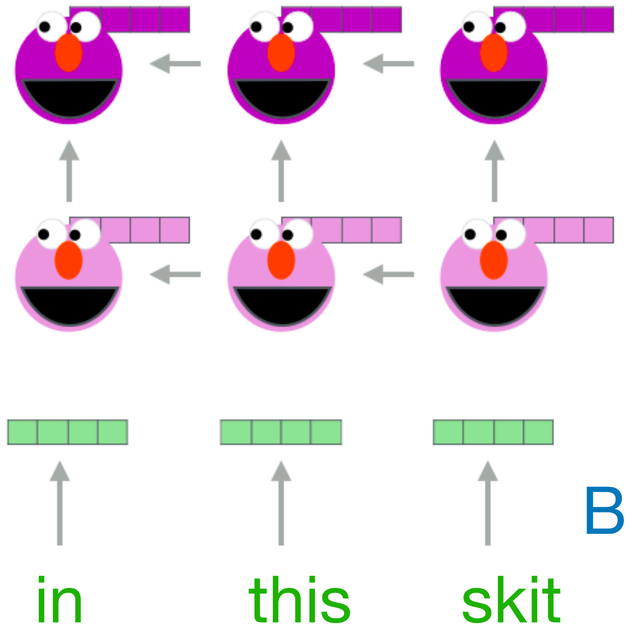
ELMo

- NAACL'18: Deep contextualized word representations
- Key idea:
  - Train an LSTM-based language model on some large corpus
  - Use the hidden states of the LSTM for each token to compute a vector representation of each word

Pretrain LM

ELMo





tokens in the sentence

LSTM parameters

$$\sum_{k=1}^{N} \left(\log p(t_k \mid t_1, \ldots, t_{k-1}; \Theta_x, \overrightarrow{\Theta}_{LSTM}, \Theta_s) + \log p(t_k \mid t_{k+1}, \ldots, t_N; \Theta_x, \overleftarrow{\Theta}_{LSTM}, \Theta_s) \right)$$

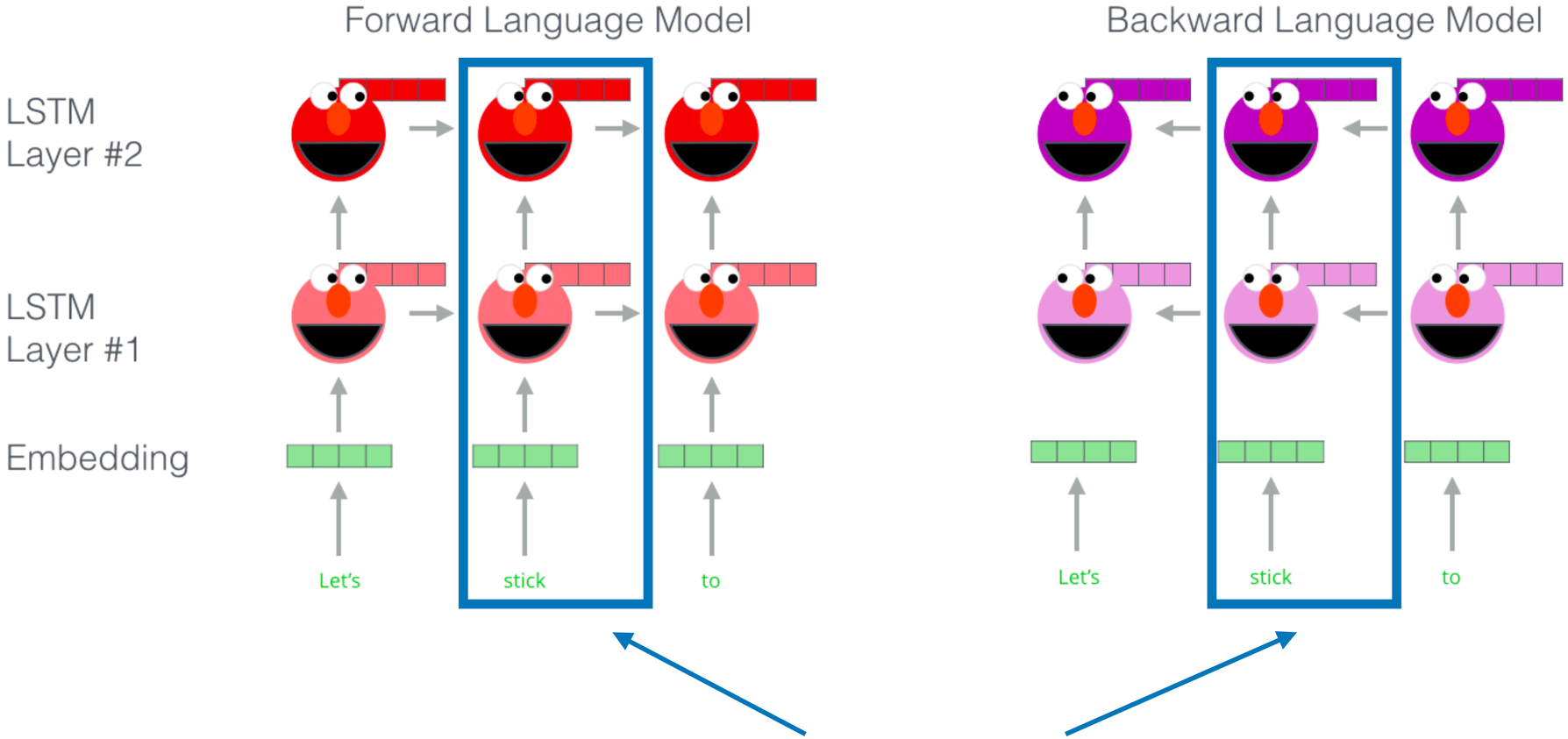
input tokens

softmax

(figure credit: Jay Alammar http://jalammar.github.io/illustrated-bert/)

ELMo

After training LM

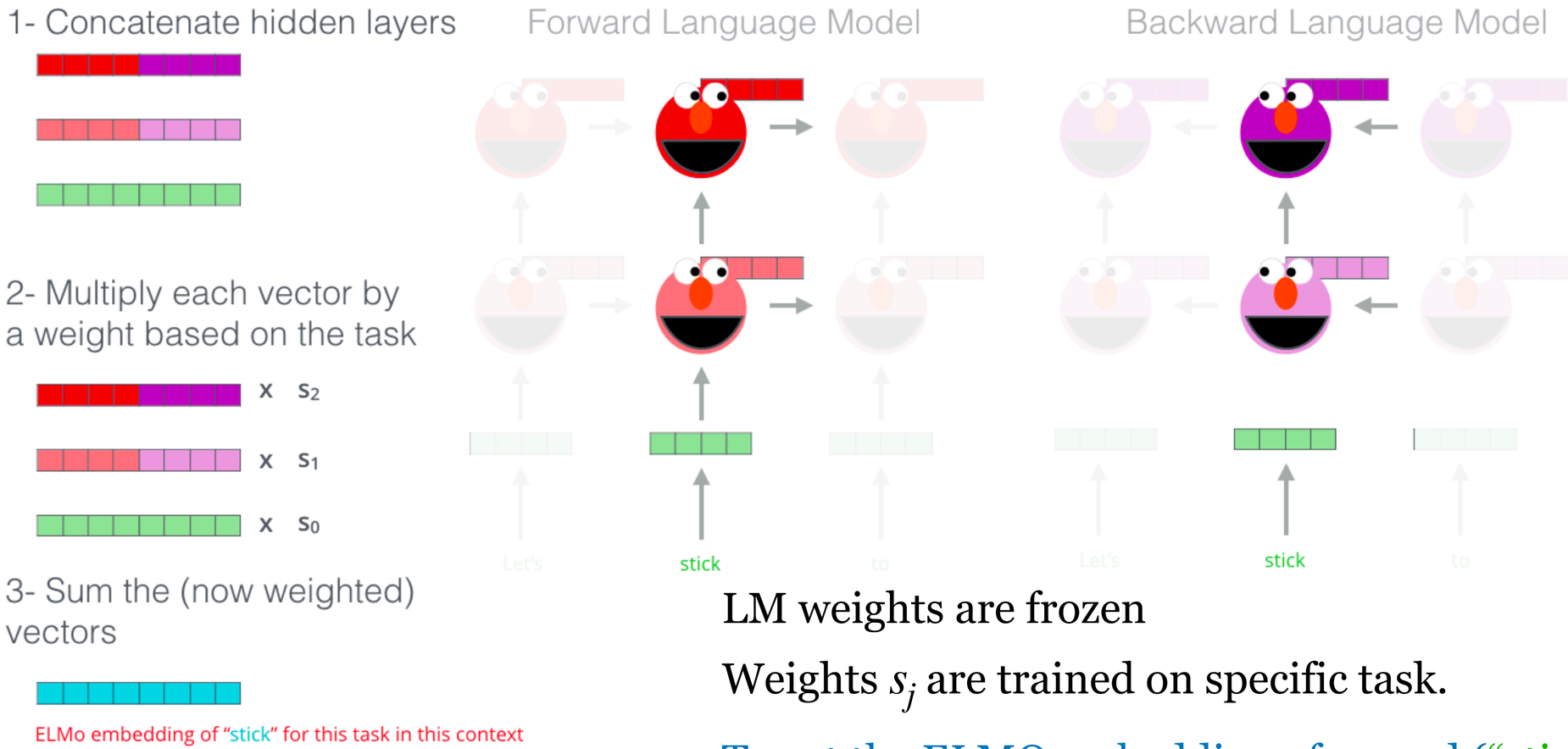


To get the ELMO embedding of a word ("stick"):

Concatenate forward and backward embeddings and take weighted sum of layers

(figure credit: Jay Alammar http://jalammar.github.io/illustrated-bert/)

ELMo



LM weights are frozen

Weights s_j are trained on specific task.

To get the ELMO embedding of a word ("stick"):

Concatenate forward and backward embeddings and take weighted sum of layers

(figure credit: Jay Alammar http://jalammar.github.io/illustrated-bert/)

Summary: How to get ELMo embedding?

$$
\begin{aligned}
R_k &= \{\mathbf{x}_k^{LM}, \overrightarrow{\mathbf{h}}_{k,j}^{LM}, \overleftarrow{\mathbf{h}}_{k,j}^{LM} \mid j = 1, \ldots, L\} \\
&= \{\mathbf{h}_{k,j}^{LM} \mid j = 0, \ldots, L\},
\end{aligned}
$$

← L is # of layers

Token representation → $\mathbf{h}_{k,0}^{LM} = \mathbf{x}_k^{LM}, \mathbf{h}_{k,j}^{LM} = [\overrightarrow{\mathbf{h}}_{k,j}^{LM}; \overleftarrow{\mathbf{h}}_{k,j}^{LM}]$ ← hidden states

$$
\mathbf{ELMo}_k^{task} = E(R_k; \Theta^{task}) = \gamma^{task} \sum_{j=0}^{L} s_j^{task} \mathbf{h}_{k,j}^{LM}
$$

- γ^{task}: allows the task model to scale the entire ELMo vector
- s_j^{task}: softmax-normalized weights across layers
- To use: plug ELMo into any (neural) NLP model: freeze all the LMs weights and change the input representation to:

$$
[\mathbf{x}_k; \mathbf{ELMo}_k^{task}]
$$

(could also insert into higher layers)

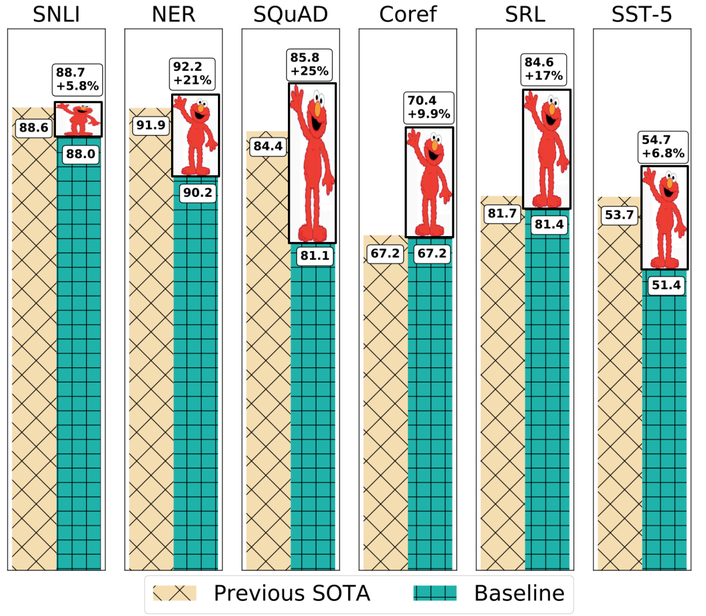
More details

- Forward and backward LMs: 2 layers each
- Use character CNN to build initial word representation
  - 2048 char n-gram filters and 2 highway layers, 512 dim projection
- User 4096 dim hidden/cell LSTM states with 512 dim projections to next input
- A residual connection from the first to second layer
- Trained 10 epochs on 1B Word Benchmark

Experimental results

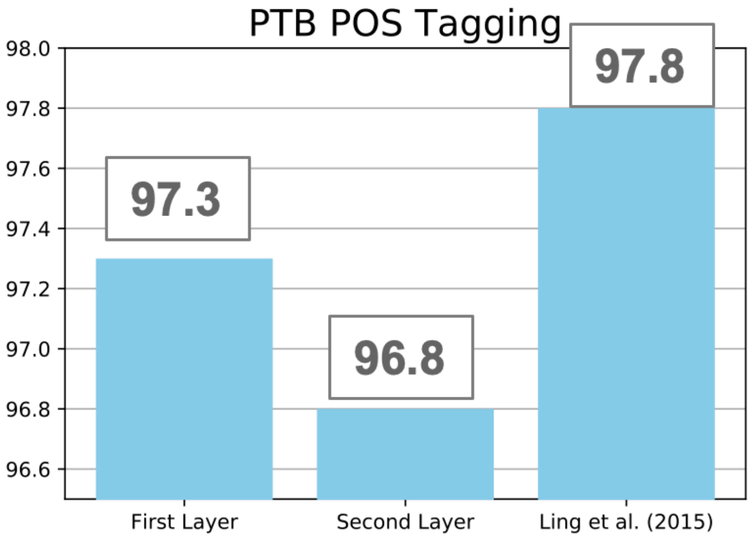
Task	Previous SOTA		Our baseline	ELMo + baseline	Increase (absolute/ relative)
SQuAD	Liu et al. (2017)	84.4	81.1	85.8	4.7 / 24.9%
SNLI	Chen et al. (2017)	88.6	88.0	88.7 ± 0.17	0.7 / 5.8%
SRL	He et al. (2017)	81.7	81.4	84.6	3.2 / 17.2%
Coref	Lee et al. (2017)	67.2	67.2	70.4	3.2 / 9.8%
NER	Peters et al. (2017)	91.93 ± 0.19	90.15	92.22 ± 0.10	2.06 / 21%
SST-5	McCann et al. (2017)	53.7	51.4	54.7 ± 0.5	3.3 / 6.8%

- SQuAD: question answering
- SNLI: natural language inference
- SRL: semantic role labeling
- Coref: coreference resolution
- NER: named entity recognition
- SST-5: sentiment analysis



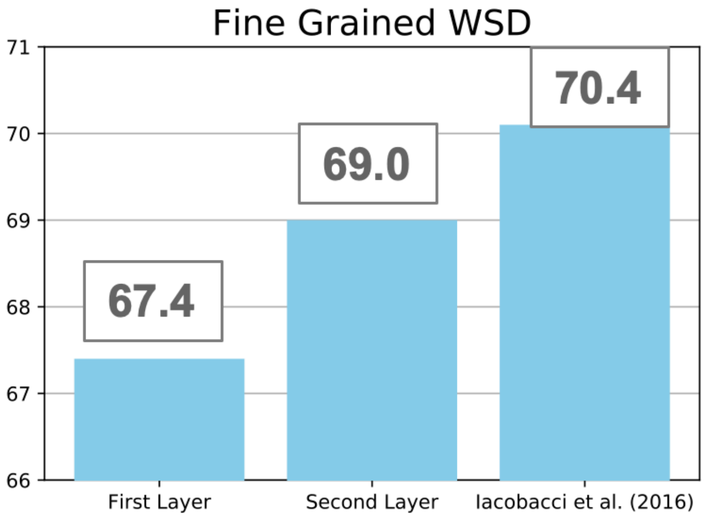
Intrinsic Evaluation

syntactic information



First Layer > Second Layer

semantic information



Second Layer > First Layer

syntactic information is better represented at lower layers
while semantic information is captured at higher layers

Use ELMo in practice

https://allennlp.org/elmo

Pre-trained ELMo Models

Model	Link(Weights/Options File)		# Parameters (Millions)	LSTM Hidden Size/Output size	# Highway Layers>
Small	weights	options	13.6	1024/128	1
Medium	weights	options	28.0	2048/256	1
Original	weights	options	93.6	4096/512	2
Original (5.5B)	weights	options	93.6	4096/512	2

```
from allennlp.modules.elmo import Elmo, batch_to_ids

options_file = "https://allennlp.s3.amazonaws.com/models/elmo/2x409
weight_file = "https://allennlp.s3.amazonaws.com/models/elmo/2x4096_

# Compute two different representation for each token.
# Each representation is a linear weighted combination for the
# 3 layers in ELMo (i.e., charcnn, the outputs of the two BiLSTM))
elmo = Elmo(options_file, weight_file, 2, dropout=0)

# use batch_to_ids to convert sentences to character ids
sentences = [['First', 'sentence', '.'], ['Another', '.']]
character_ids = batch_to_ids(sentences)

embeddings = elmo(character_ids)
```

Also available in TensorFlow

BERT

- First released in Oct 2018.
- NAACL'19: BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

How is BERT different from ELMo?

#1. Unidirectional context vs bidirectional context

#2. LSTMs vs Transformers (will talk later)

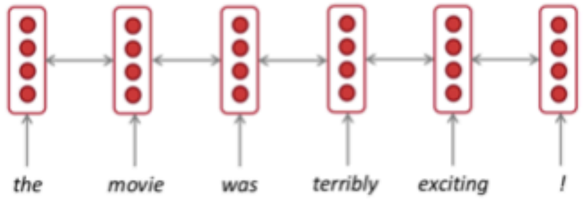
#3. The weights are not frozen, called fine-tuning

Bidirectional encoders

- Language models only use left context or right context (although ELMo used two independent LMs from each direction).
- Language understanding is bidirectional

Bidirectional RNNs

Bidirectionality is important in language representations:

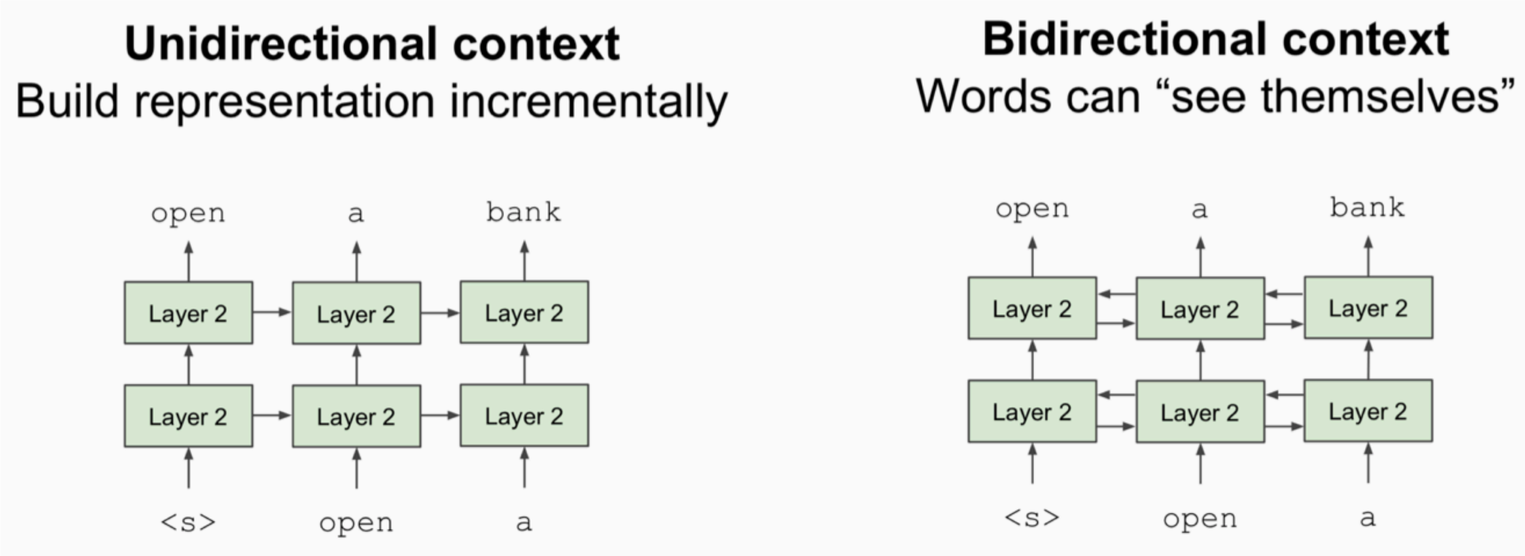


terribly:
- left context "the movie was"
- right context "exciting !"

Why are LMs unidirectional?

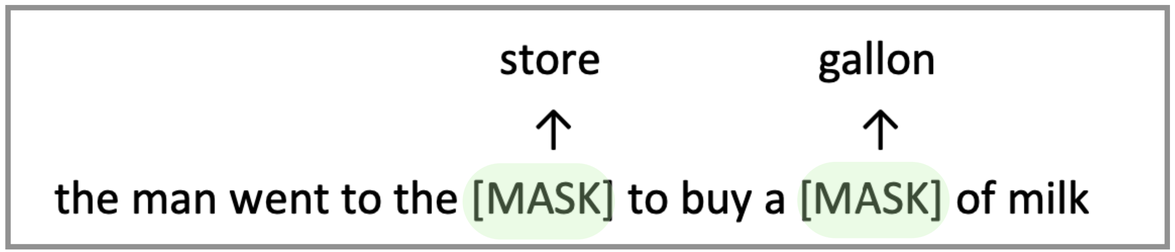
Bidirectional encoders

- Language models only use left context or right context (although ELMo used two independent LMs from each direction).
- Language understanding is bidirectional



Masked language models (MLMs)

- Solution: Mask out 15% of the input words, and then predict the masked words



- Too little masking: too expensive to train
- Too much masking: not enough context

Masked language models (MLMs)

A little more complex

(don't always replace with `[MASK]`):

Example: `my dog is hairy`, we replace the word hairy

- 80% of time: replace word with `[MASK]` token

  `my dog is [MASK]`

- 10% of time: replace word with random word

  `my dog is apple`

- 10% of time: keep word unchanged to bias representation toward actual observed word

  `my dog is hairy`

Because `[MASK]` is never seen when BERT is used…

Next sentence prediction (NSP)

Always sample two sentences, predict whether the second sentence is followed after the first one.

Input = `[CLS] the man went to [MASK] store [SEP]`

`he bought a gallon [MASK] milk [SEP]`

Label = `IsNext`

Input = `[CLS] the man [MASK] to the store [SEP]`

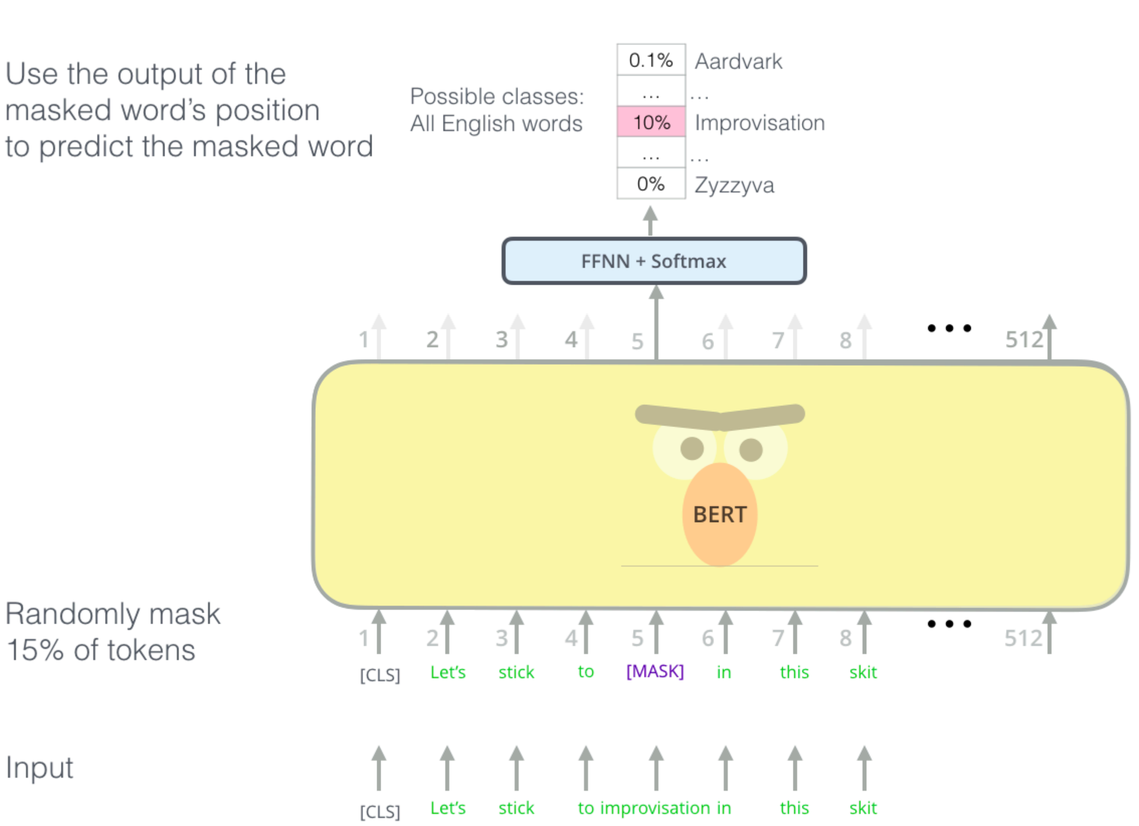
`penguin [MASK] are flight ##less birds [SEP]`

Label = `NotNext`

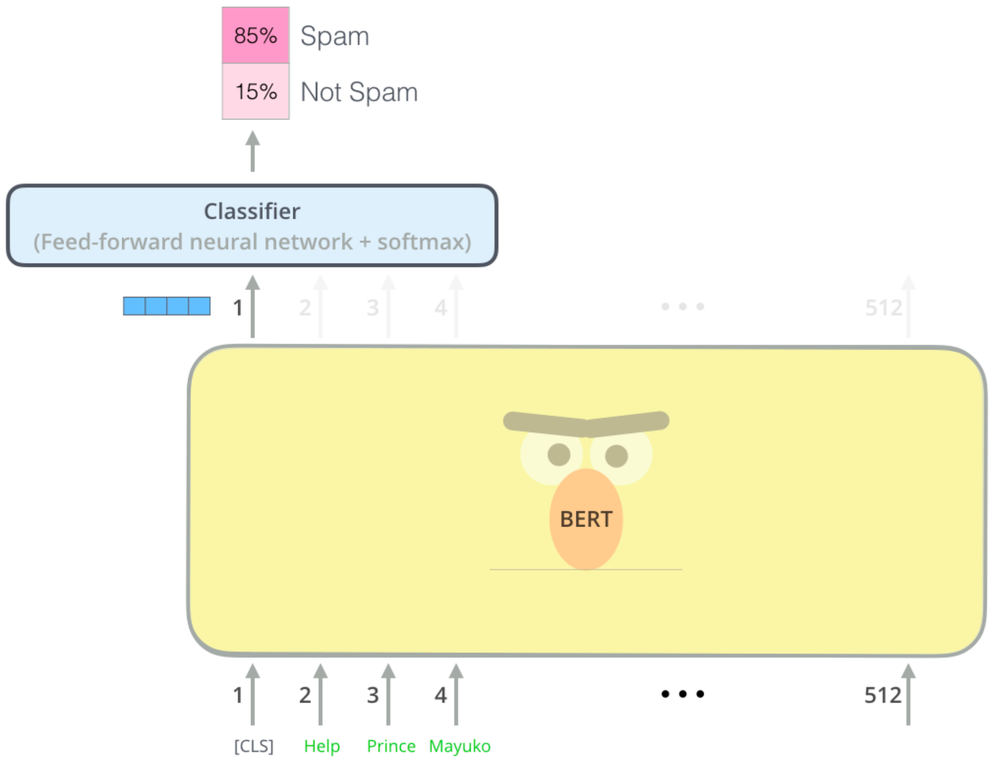
Recent papers show that NSP is not necessary…

(Joshi*, Chen* et al, 2019) :SpanBERT: Improving Pre-training by Representing and Predicting Spans
(Liu et al, 2019): RoBERTa: A Robustly Optimized BERT Pretraining Approach

Pre-training and fine-tuning



Pre-training

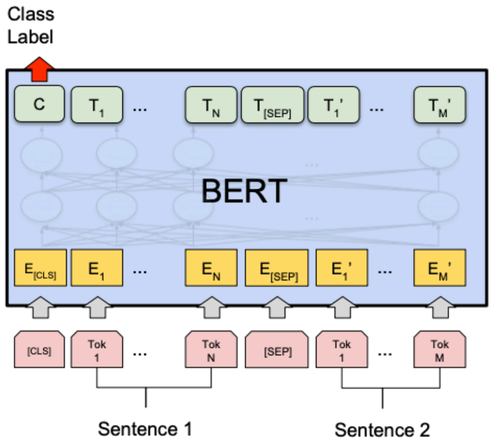


Fine-tuning

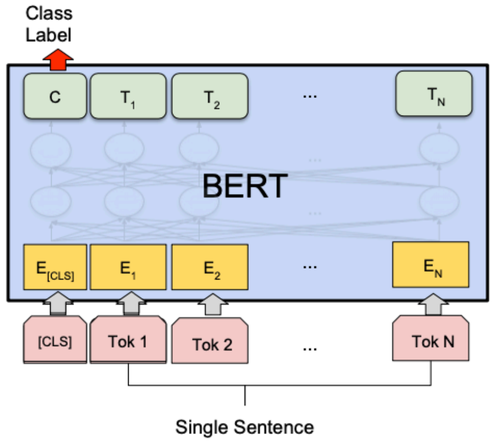
(figure credit: Jay Alammar http://jalammar.github.io/illustrated-bert/)

Key idea: all the weights are fine-tuned on downstream tasks

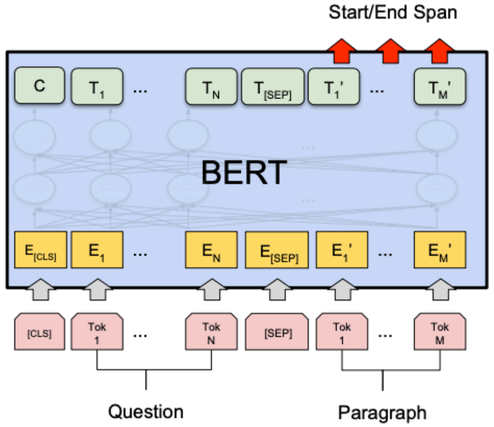
Applications



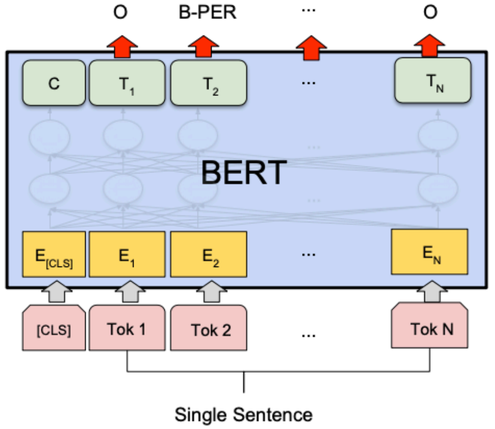
(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG



(b) Single Sentence Classification Tasks: SST-2, CoLA



(c) Question Answering Tasks: SQuAD v1.1

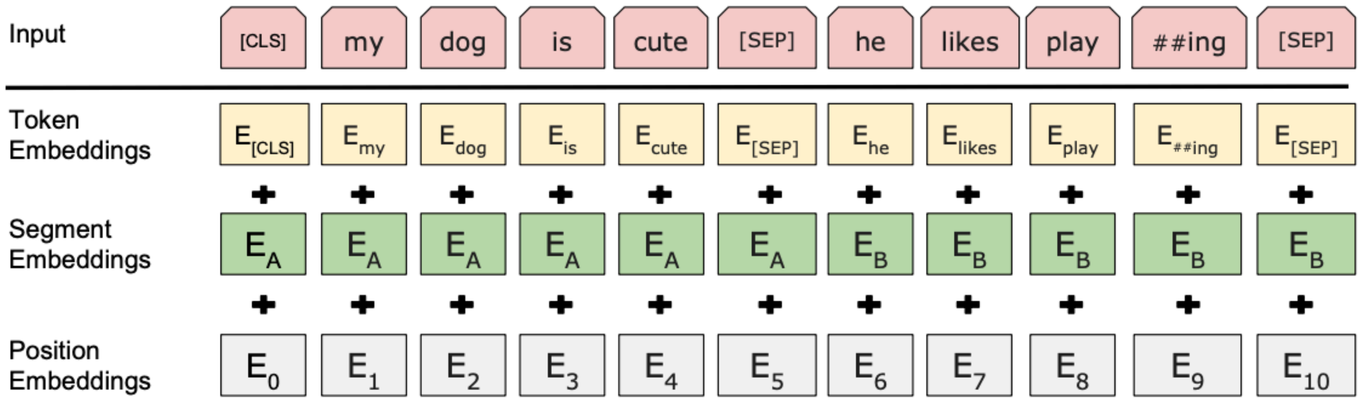


(d) Single Sentence Tagging Tasks: CoNLL-2003 NER

(figure credit: Jay Alammar http://jalammar.github.io/illustrated-bert/)

More details

- Input representations



- Use word pieces instead of words: playing => play ##ing
- Trained 40 epochs on Wikipedia (2.5B tokens) + BookCorpus (0.8B tokens)
- Released two model sizes: BERT_base, BERT_large

Experimental results

BiLSTM: 63.9

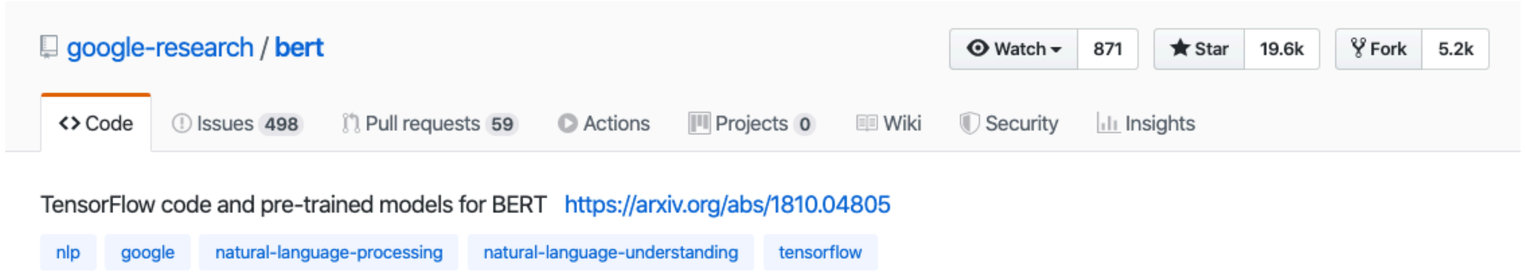
System	MNLI-(m/mm) 392k	QQP 363k	QNLI 108k	SST-2 67k	CoLA 8.5k	STS-B 5.7k	MRPC 3.5k	RTE 2.5k	**Average** -
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.9	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	88.1	91.3	45.4	80.0	82.3	56.0	75.2
$\text{BERT}_{\text{BASE}}$	84.6/83.4	71.2	90.1	93.5	52.1	85.8	88.9	66.4	79.6
$\text{BERT}_{\text{LARGE}}$	**86.7/85.9**	**72.1**	**91.1**	**94.9**	**60.5**	**86.5**	**89.3**	**70.1**	**81.9**

Model	**data**	**bsz**	**steps**	**SQuAD** (v1.1/2.0)	**MNLI-m**	**SST-2**
RoBERTa						
with BOOKS + WIKI	16GB	8K	100K	93.6/87.3	89.0	95.3
+ additional data (§3.2)	160GB	8K	100K	94.0/87.7	89.3	95.6
+ pretrain longer	160GB	8K	300K	94.4/88.7	90.0	96.1
+ pretrain even longer	160GB	8K	500K	**94.6/89.4**	**90.2**	**96.4**
$\text{BERT}_{\text{LARGE}}$						
with BOOKS + WIKI	13GB	256	1M	90.9/81.8	86.6	93.7
$\text{XLNet}_{\text{LARGE}}$						
with BOOKS + WIKI	13GB	256	1M	94.0/87.8	88.4	94.4
+ additional data	126GB	2K	500K	94.5/88.8	89.8	95.6

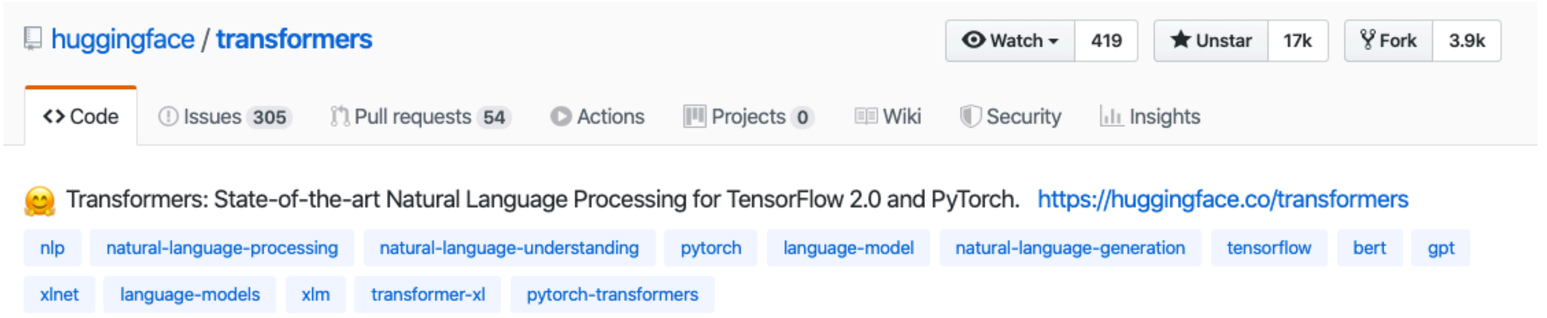
(Wang et al, 2018): GLUE: A Multi-Task Benchmark and Analysis Platform for Natural Language Understanding

Use BERT in practice

TensorFlow: https://github.com/google-research/bert



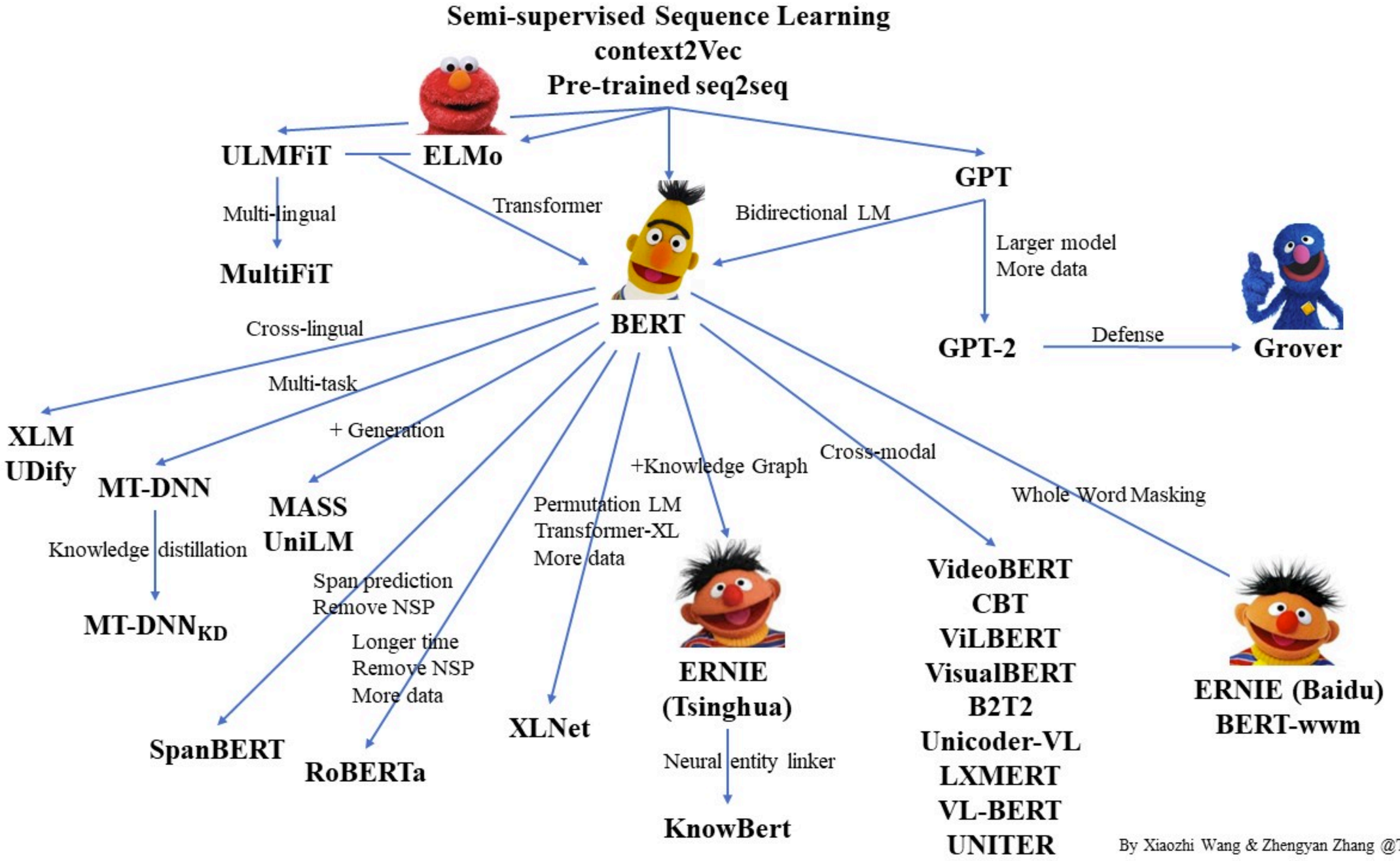
PyTorch: https://github.com/huggingface/transformers



Contextualized word embeddings in context

- TagLM (Peters et, 2017)
- CoVe (McCann et al. 2017)
- ULMfit (Howard and Ruder, 2018)
- **ELMo (Peters et al, 2018)**
- OpenAI GPT (Radford et al, 2018)
- **BERT (Devlin et al, 2018)**
- OpenAI GPT-2 (Radford et al, 2019)
- XLNet (Yang et al, 2019)
- SpanBERT (Joshi et al, 2019)
- RoBERTa (Liu et al, 2019)
- ALBERT (Lan et al, 2019)
- …

https://github.com/huggingface/transformers


Semi-supervised Sequence Learning
context2Vec
Pre-trained seq2seq
ULMFiT
ELMo
Multi-lingual
MultiFiT
Transformer
BERT
Bidirectional LM
GPT
Larger model
More data
GPT-2
Defense
Grover
Cross-lingual
XLM
UDify
Multi-task
MT-DNN
Knowledge distillation
MT-DNN$_{KD}$
+ Generation
MASS
UniLM
Span prediction
Remove NSP
SpanBERT
Longer time
Remove NSP
More data
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
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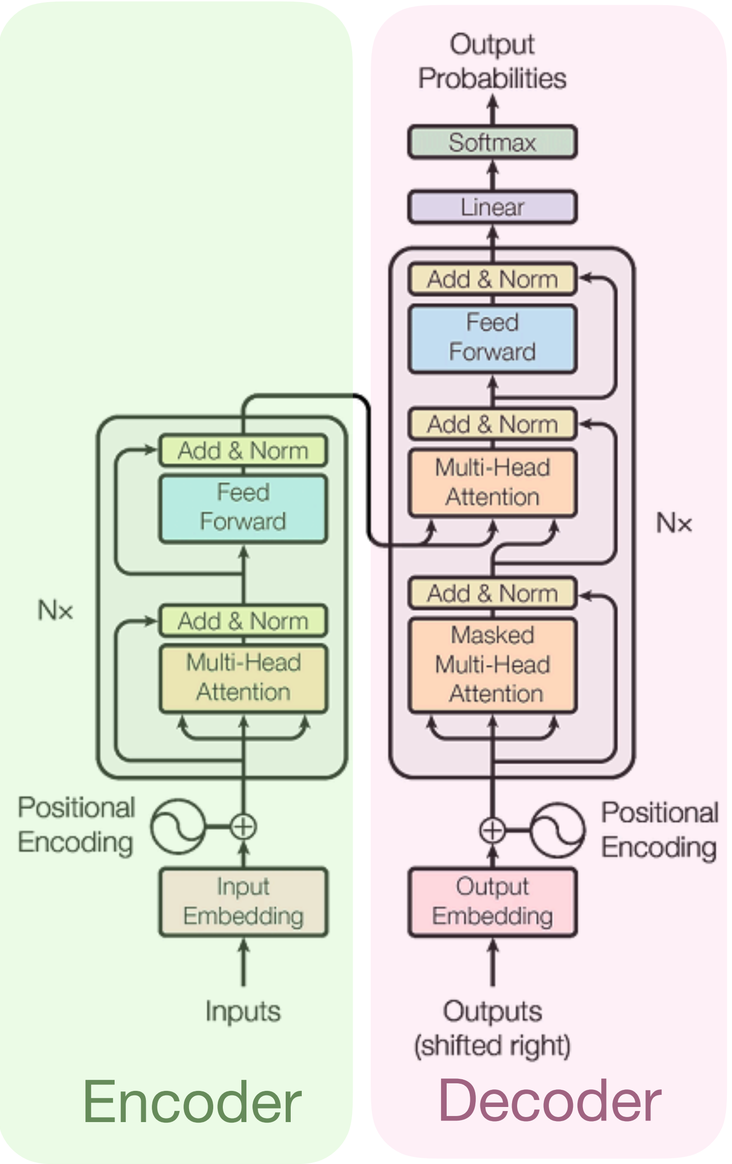
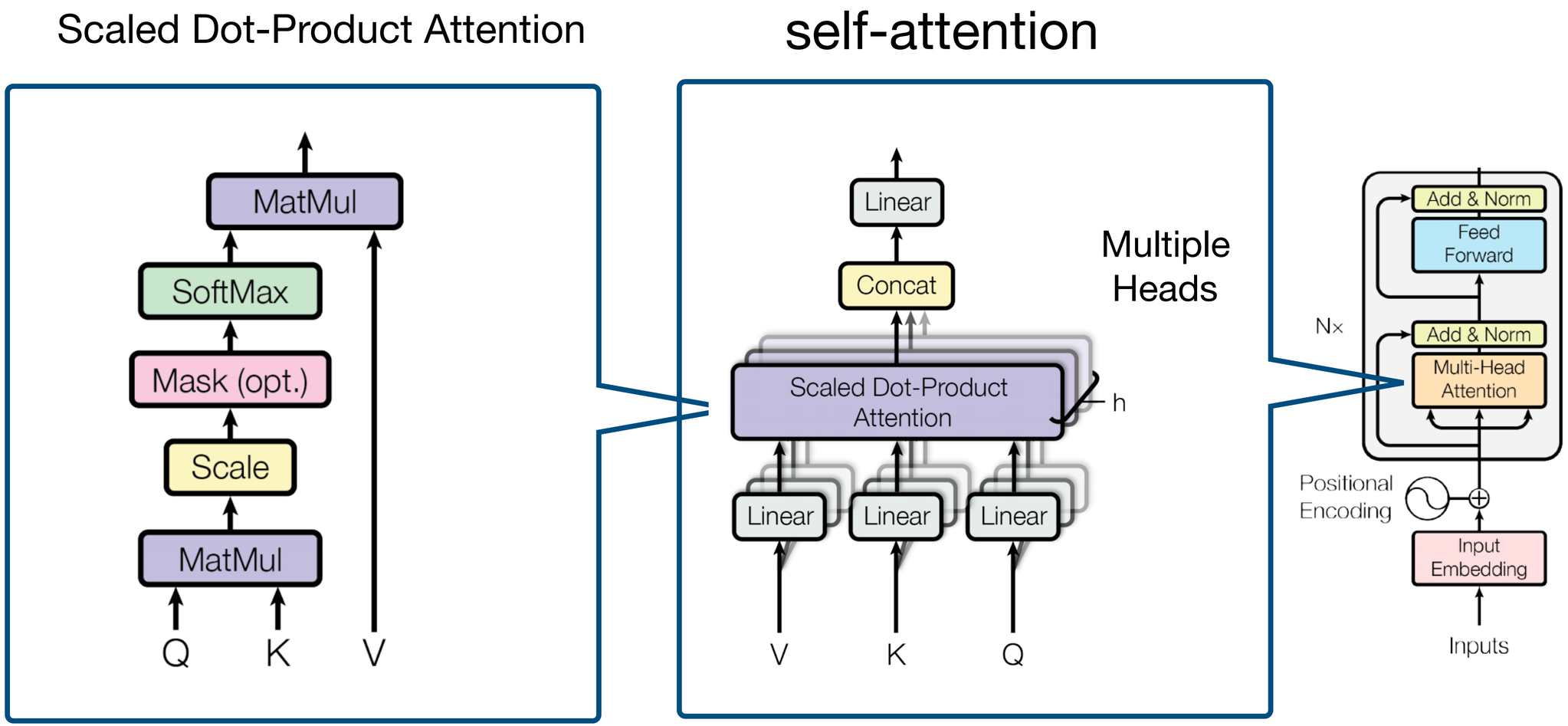
Transformers

Transformers

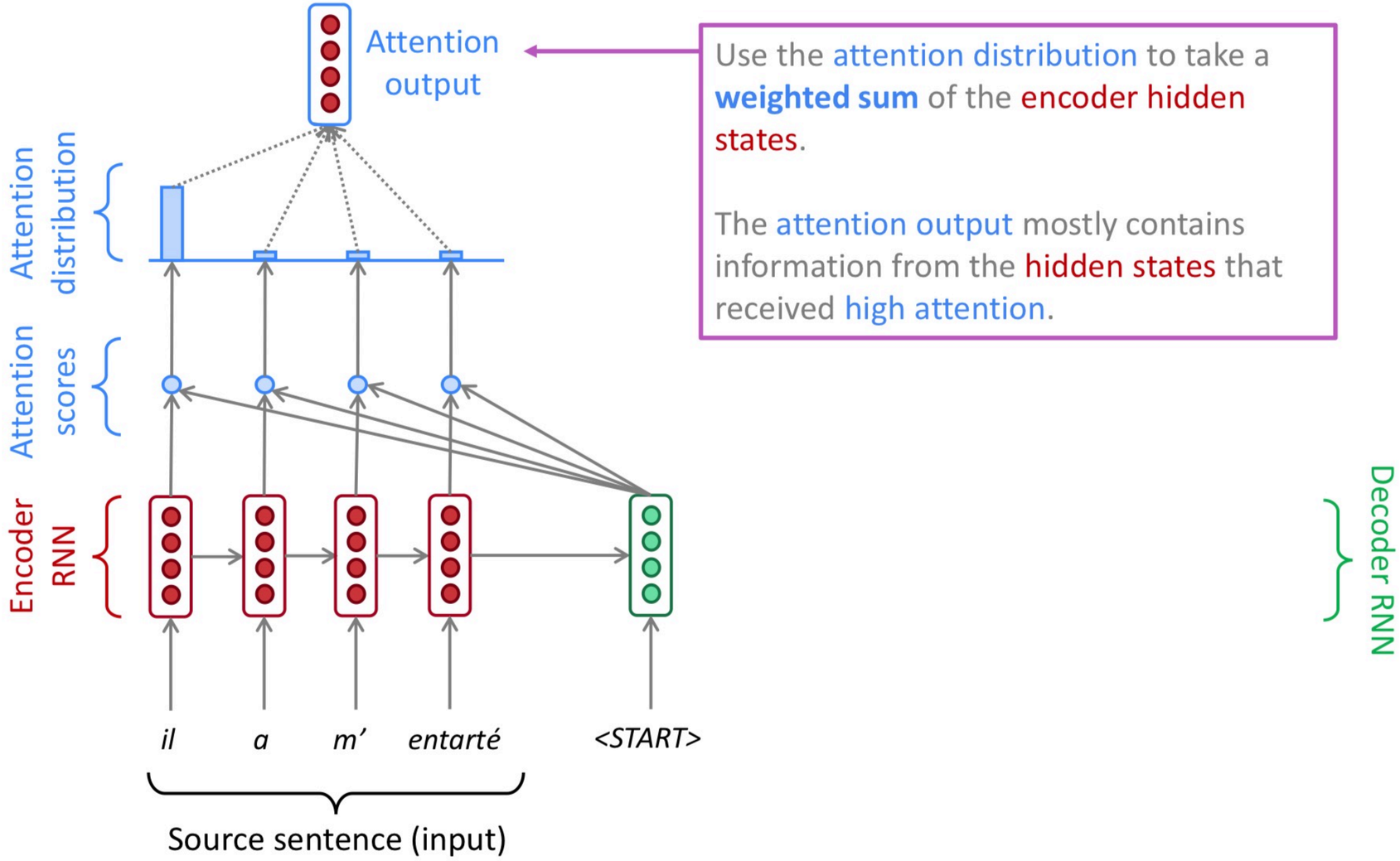
- NIPS'17: Attention is All You Need
- Originally proposed for NMT (encoder-decoder framework)
- Used as the base model of BERT (encoder only)
- Key idea: **Multi-head self-attention**
- No recurrence structure any more so it trains much faster



Multi-head self-attention



Recall: attention



Use the attention distribution to take a **weighted sum** of the encoder hidden states.

The attention output mostly contains information from the hidden states that received high attention.

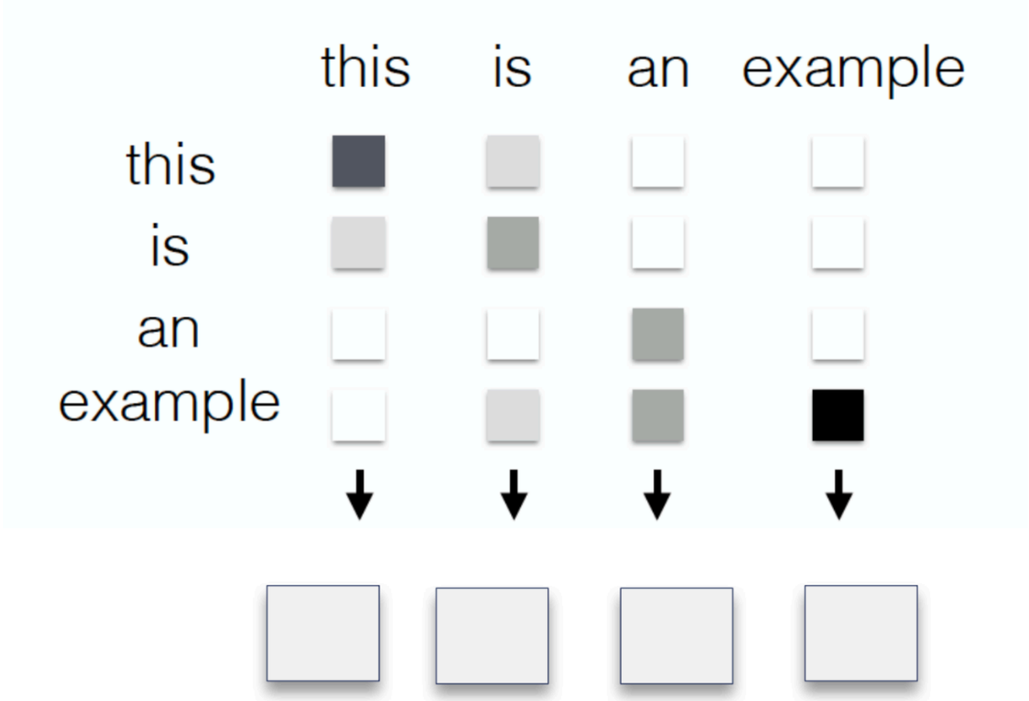
(slide credit: Abigail See)

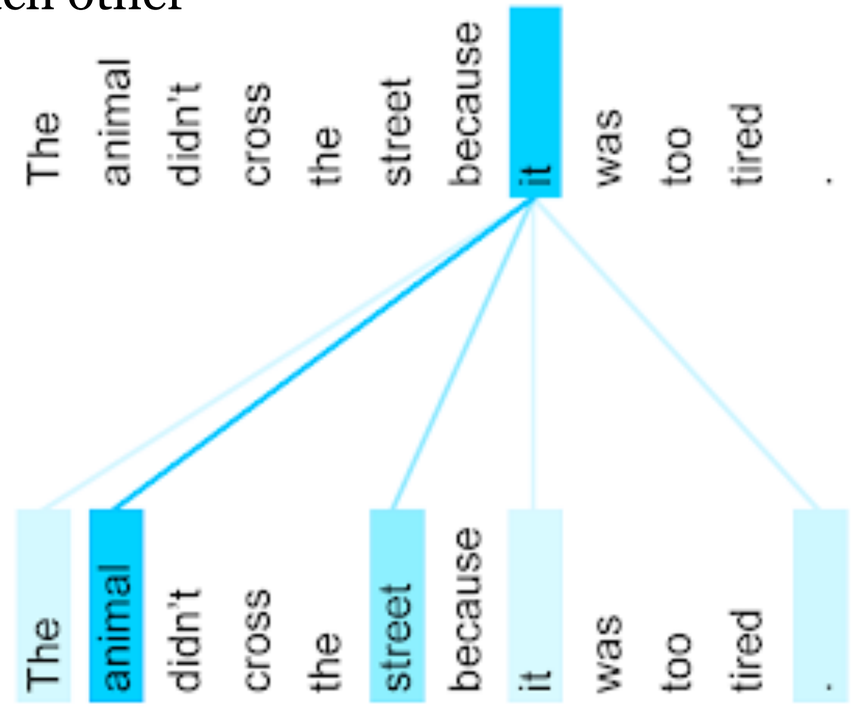
Self Attention

(also referred to as Intra-Attention)

- **Self-attention**: let's use each word as query and compute the attention with all the other words

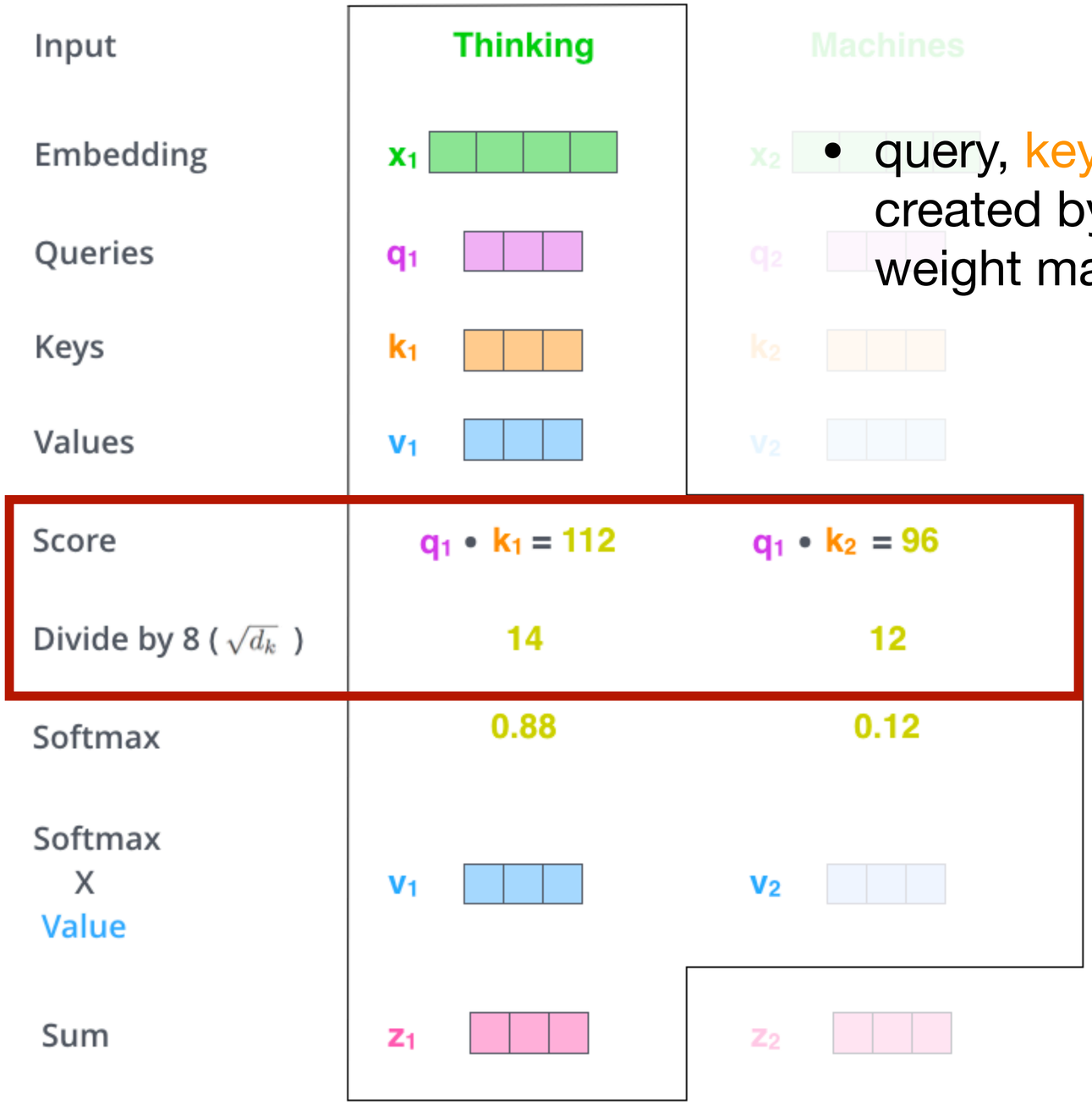
  = the word vectors themselves select each other





General definition of attention

- **Attention** is a general concept
  - Given query q and a set of key-value pairs (K,V)
  - **Attention** is a way to compute a **weighted sum** of the values dependent on the query and the corresponding keys.
  - Query determines what values to focus on, the query “attends” to the values
  - All of these (key value query) are represented using **vectors**
    - These vectors are created by multiplying embedding by trained weight matrices.



- query, key, and value vectors created by multiplying learned weight matrices with embedding

- Can be any kind of attention function
- For transformers, this is the scaled dot-product attention

(figure credit: Jay Alammar http://jalammar.github.io/illustrated-transformer/)

Recall: types of attention

- Assume encoder hidden states $h_1, h_2, \ldots, h_n$ and decoder hidden state z

1. **Dot-product attention** (assumes equal dimensions for a and b):

$$g(h_i, z) = z^T h_i \in \mathbb{R}$$

more efficient (matrix multiplication)

Simplest (no extra parameters)
requires z and h_i to be same size

2. **Bilinear / multiplicative attention:**

$$g(h_i, z) = z^T W h_i \in \mathbb{R}, \text{ where } W \text{ is a weight matrix}$$

More flexible than dot-product (W is trainable)

3. **Additive attention (essentially MLP):**

$$g(h_i, z) = v^T \tanh\left(W_1 h_i + W_2 z\right) \in \mathbb{R}$$

where W_1, W_2 are weight matrices and v is a weight vector

Perform better for larger dimensions

Scaled dot-product attention

- Assume encoder hidden states $h_1, h_2, \ldots, h_n$ and decoder hidden state z

1. **Dot-product attention** (assumes equal dimensions for a and b):

$$g(h_i, z) = z^T h_i \in \mathbb{R}$$

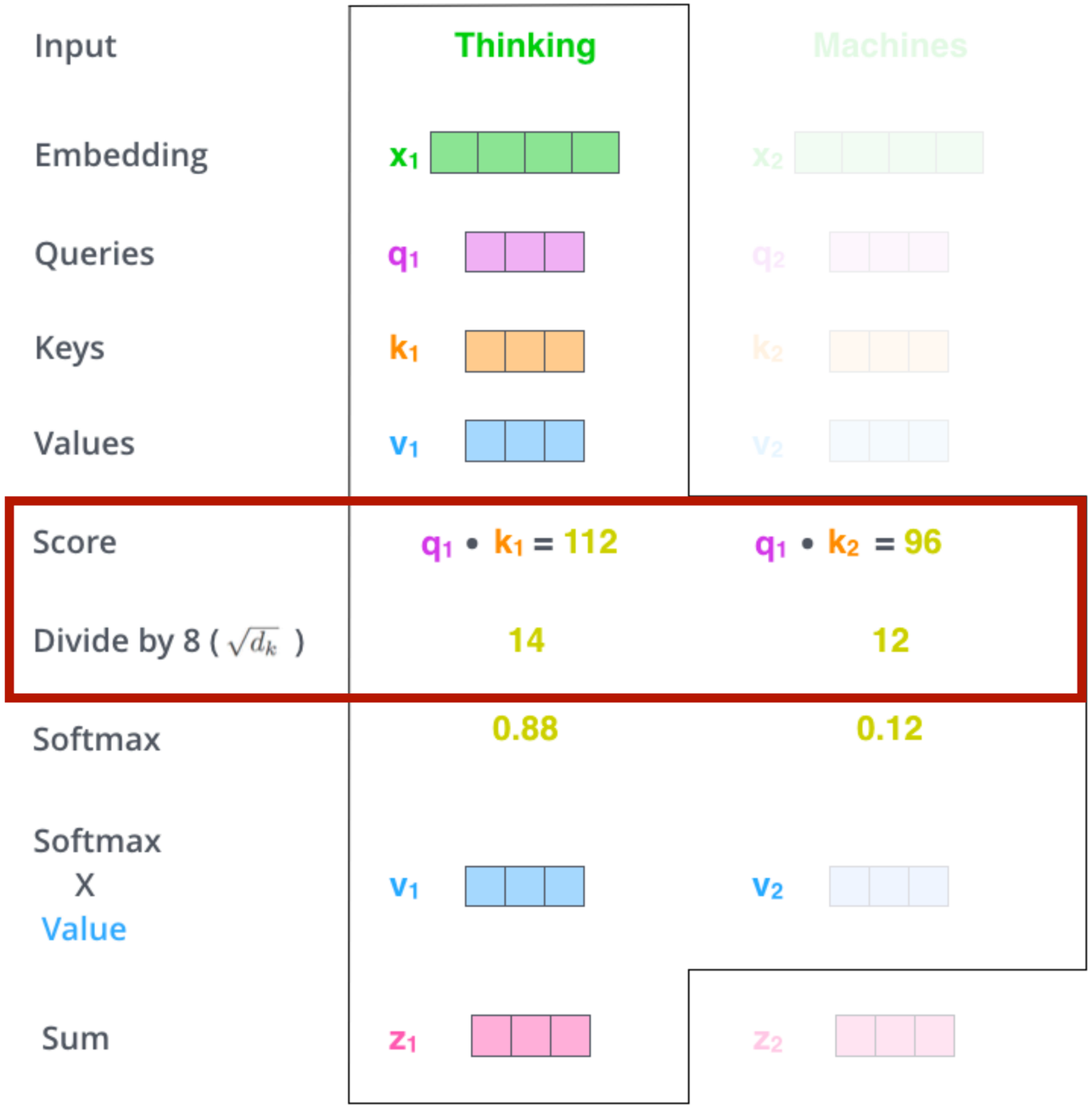
Perform poorly for large d
Softmax has small gradient

2. **Scaled dot-product attention:**

$$g(h_i, z) = \frac{z^T h_i}{\sqrt{d}} \in \mathbb{R}$$

Maybe will perform well
for larger dimensions

Scaling factor: d = dimension of hidden state



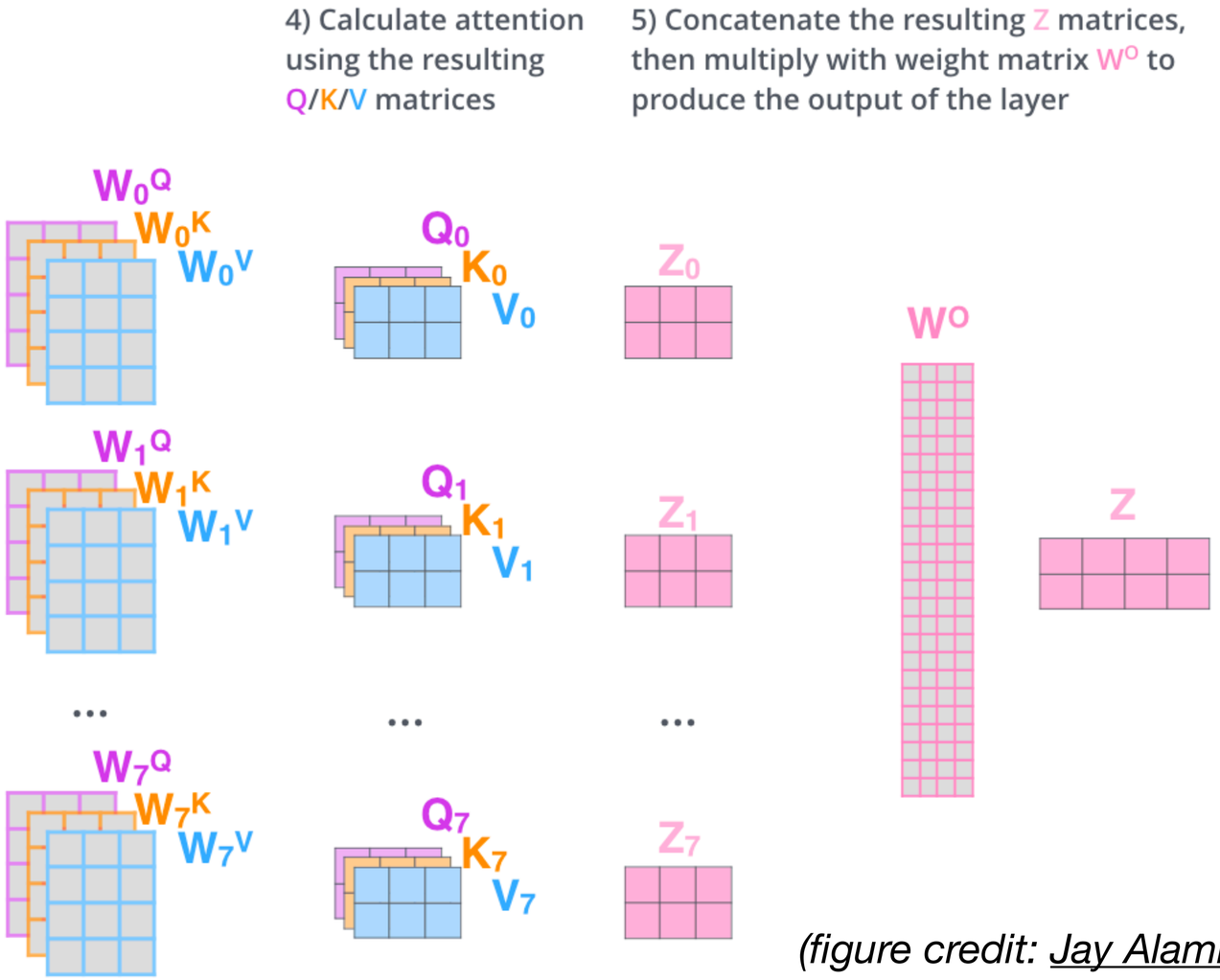
- Can be any kind of attention function
- For transformers, this is the scaled dot-product attention

- Final vector of attended values for “Thinking” as the query

(figure credit: Jay Alammar http://jalammar.github.io/illustrated-transformer/)

Multiple heads

- Multiple (different) representations for each query, key, and values
- Different weight matrices —> different vectors
- Different ways for the words to interact with each other



(figure credit: Jay Alammar http://jalammar.github.io/illustrated-transformer/)

Summary: Multi-head Self Attention

- **Attention**: a query q and a set of key-value (k_i, v_i) pairs to an output
- Dot-product attention:

$$A(q, K, V) = \sum_i \frac{e^{q \cdot k_i}}{\sum_j e^{q \cdot k_j}} v_i$$

$$K, V \in \mathbb{R}^{n \times d}, q \in \mathbb{R}^d$$

- If we have multiple queries:

$$A(Q, K, V) = \text{softmax}(QK^\intercal)V$$

$$Q \in \mathbb{R}^{n_Q \times d}, K, V \in \mathbb{R}^{n \times d}$$

- **Self-attention**: let's use each word as query and compute the attention with all the other words

  = the word vectors themselves select each other

Summary: Multi-head Self Attention

- Scaled Dot-Product Attention:

$$A(Q, K, V) = \text{softmax}(\frac{QK^\intercal}{\sqrt{d}})V$$

- Input: $X \in \mathbb{R}^{n \times d_{in}}$

$$A(XW^Q, XW^K, XW^V) \in \mathbb{R}^{n \times d}$$

$$W^Q, W^K, W^V \in \mathbb{R}^{d_{in} \times d}$$

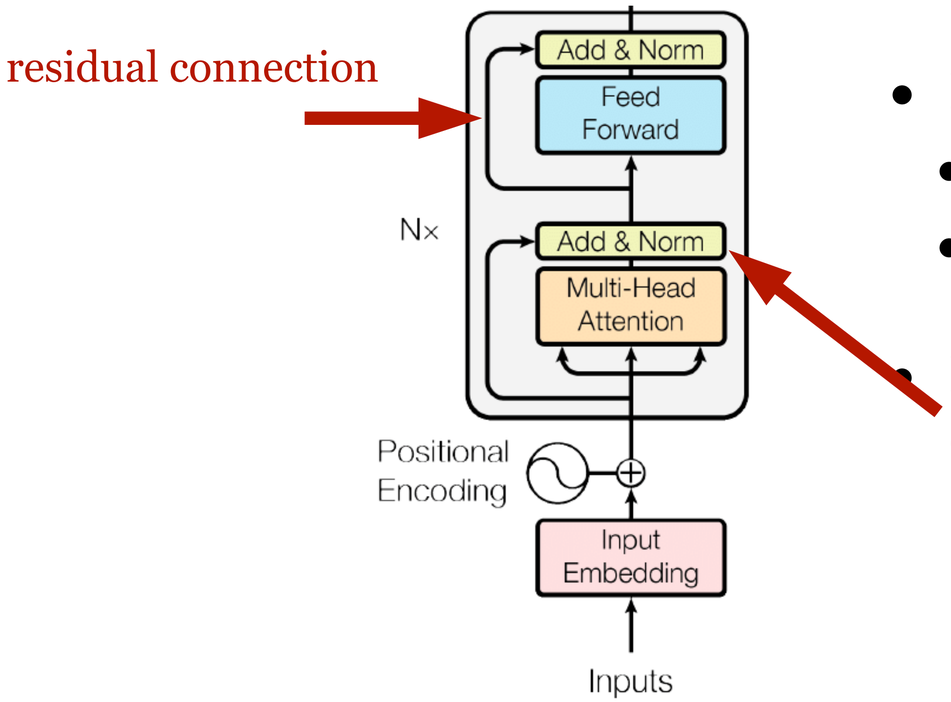
- Multi-head attention: using more than one head is always useful..

$$A(Q, K, V) = \text{Concat}(\text{head}_1, \ldots, \text{head}_h)W^O$$

$$\text{head}_i = A(XW_i^Q, XW_i^K, XW_i^V)$$

In practice, $h = 8, d = d_{out}/h, W^O = d_{out} \times d_{out}$

Putting it all together

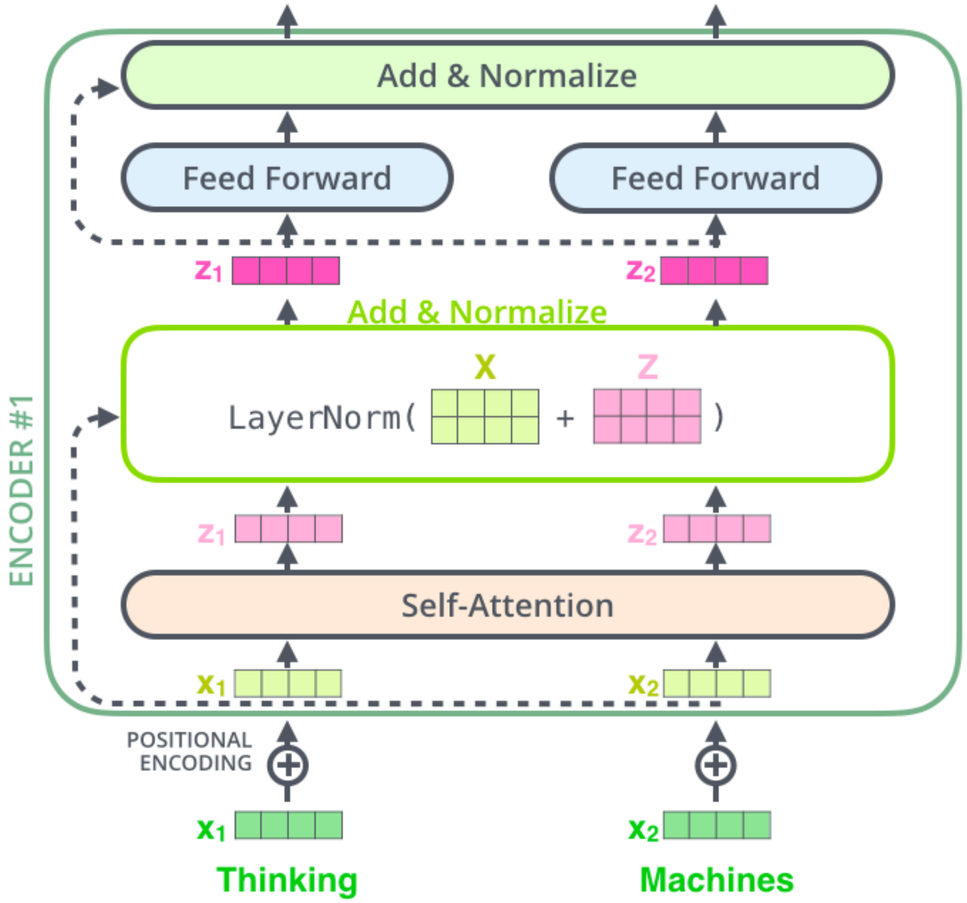


- Each Transformer block has two sub-layers
  - Multi-head attention
  - 2-layer feedforward NN (with ReLU)
- Each sublayer has a residual connection and a layer normalization

$$\text{LayerNorm}(x + \text{SubLayer}(x))$$

(Ba et al, 2016): Layer Normalization

Residual connections and Layer Normalization



(figure credit: Jay Alammar http://jalammar.github.io/illustrated-transformer/)

LayerNorm

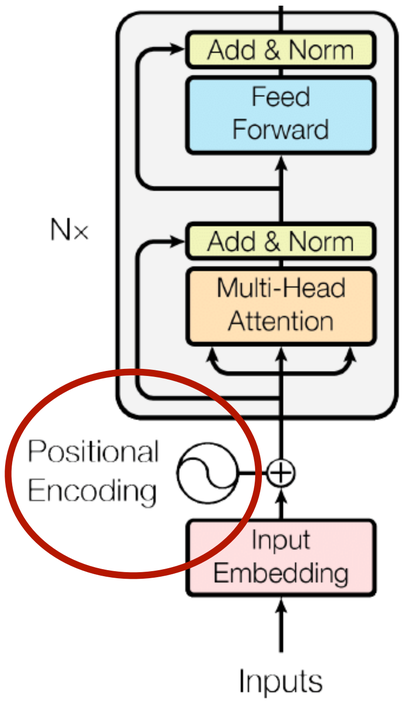
- changes input features to have mean 0 and variance 1 per layer.
- Adds two more parameters

$$\mu^l = \frac{1}{H}\sum_{i=1}^{H} a_i^l \qquad \sigma^l = \sqrt{\frac{1}{H}\sum_{i=1}^{H}(a_i^l - \mu^l)^2}$$

$$h_i = f\left(\frac{g_i}{\sigma_i}(a_i - \mu_i) + b_i\right)$$

(Ba et al, 2016): Layer Normalization

Putting it all together



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$$\text{LayerNorm}(x + \text{SubLayer}(x))$$

- Input layer has a positional encoding

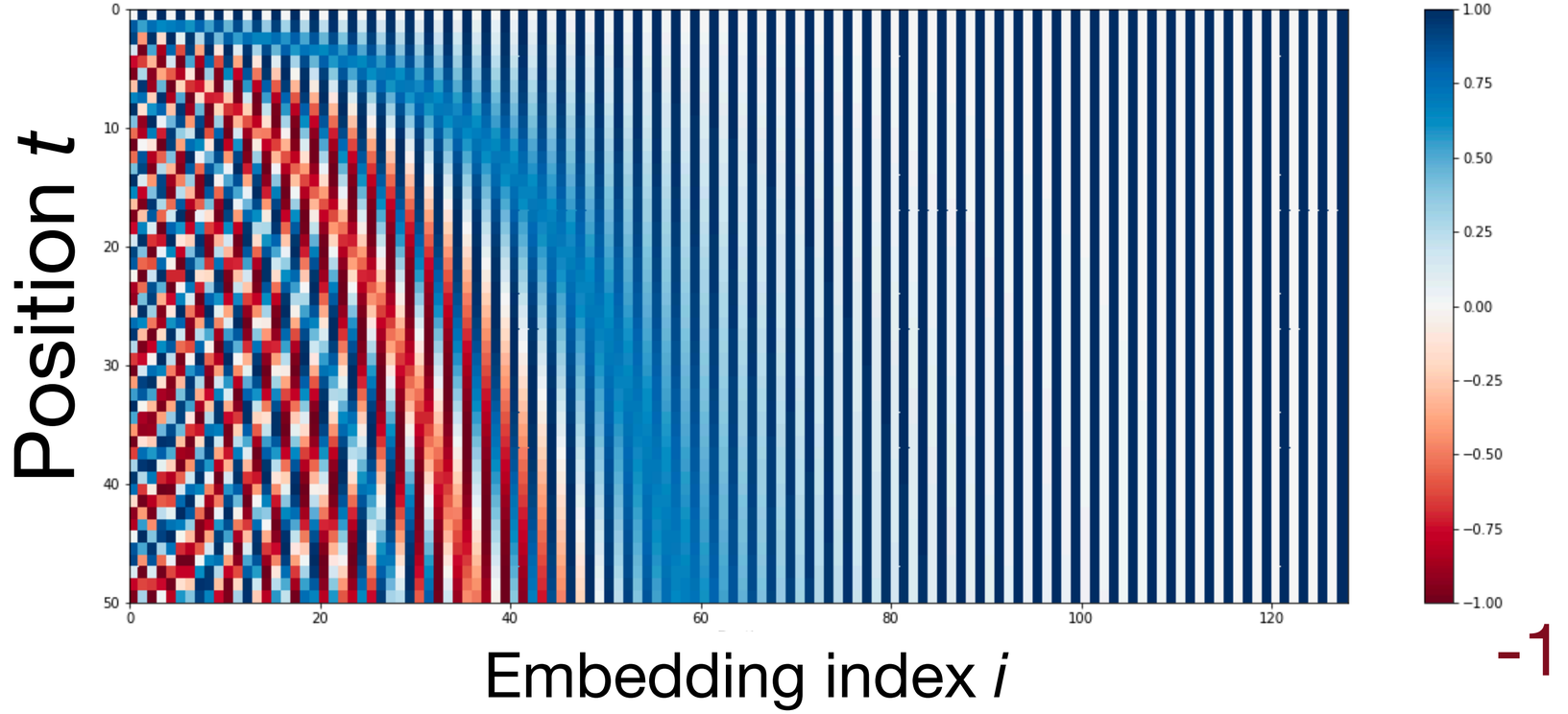
(Ba et al, 2016): Layer Normalization

Positional encoding

$$\overrightarrow{p_t}^{(i)} = f(t)^{(i)} := \begin{cases} \sin(\omega_k . t), & \text{if } i = 2k \\ \cos(\omega_k . t), & \text{if } i = 2k+1 \end{cases}$$

$$\omega_k = \frac{1}{10000^{2k/d}}$$

$$\overrightarrow{p_t} = \begin{bmatrix} \sin(\omega_1 . t) \\ \cos(\omega_1 . t) \\ \\ \sin(\omega_2 . t) \\ \cos(\omega_2 . t) \\ \\ \vdots \\ \\ \sin(\omega_{d/2} . t) \\ \cos(\omega_{d/2} . t) \end{bmatrix}_{d \times 1}$$

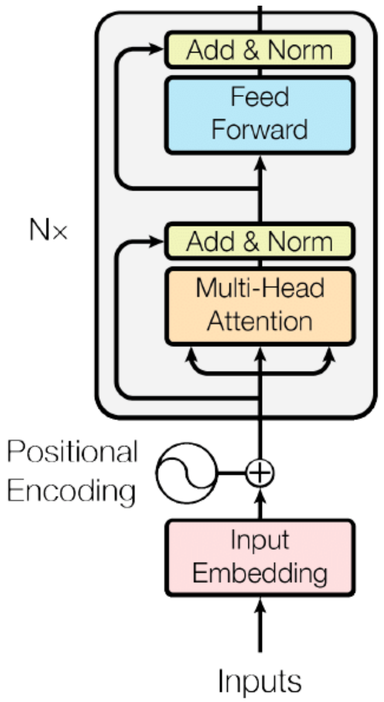


t = position

d = embedding dimension

i = embedding index (0 to d-1)

Putting it all together

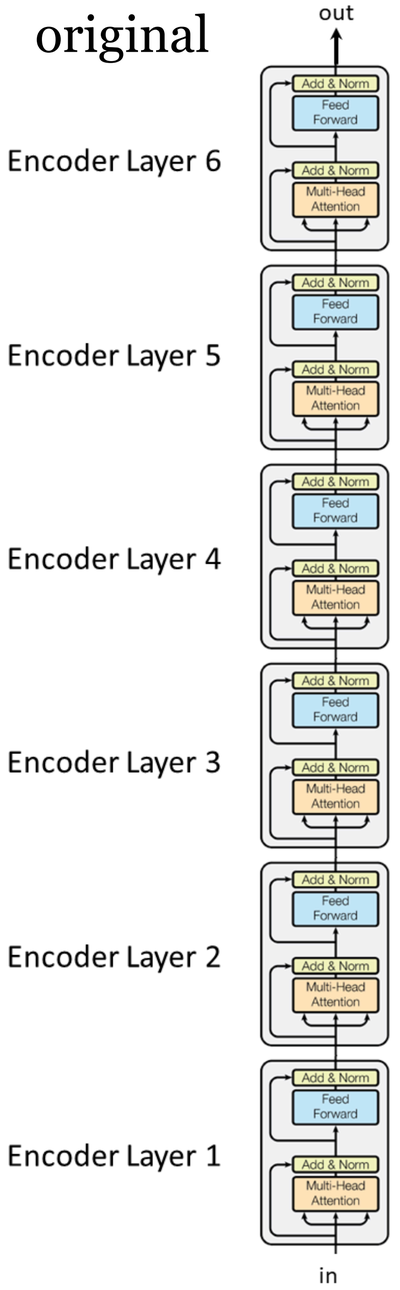


- Each Transformer block has two sub-layers
  - Multi-head attention
  - 2-layer feedforward NN (with ReLU)
- Each sublayer has a residual connection and a layer normalization

$$\text{LayerNorm}(x + \text{SubLayer}(x))$$

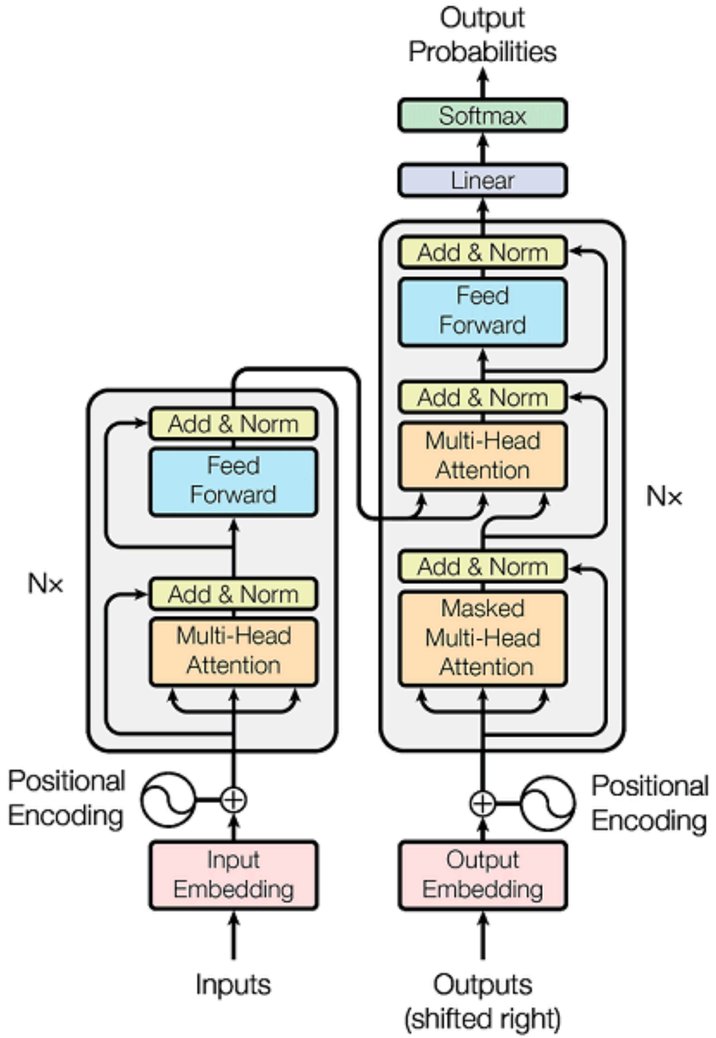
- Input layer has a positional encoding
- Input embedding is byte pair encoding (BPE)

- BERT_base: 12 layers, 12 heads, hidden size = 768, 110M parameters
- BERT_large: 24 layers, 16 heads, hidden size = 1024, 340M parameters



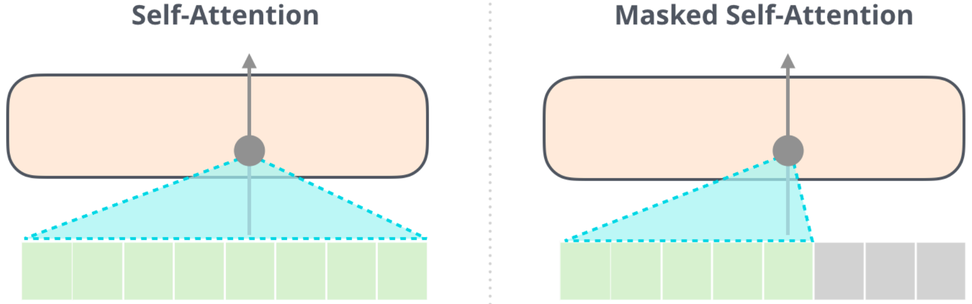
(Ba et al, 2016): Layer Normalization

Transformer decoder



- Encoder-Decoder Attention, where queries come from previous decoder layer and keys and values come from output of encoder

- Masked decoder self-attention on previously generated outputs



(figure credit: Jay Alammar http://jalammar.github.io/illustrated-gpt2/)

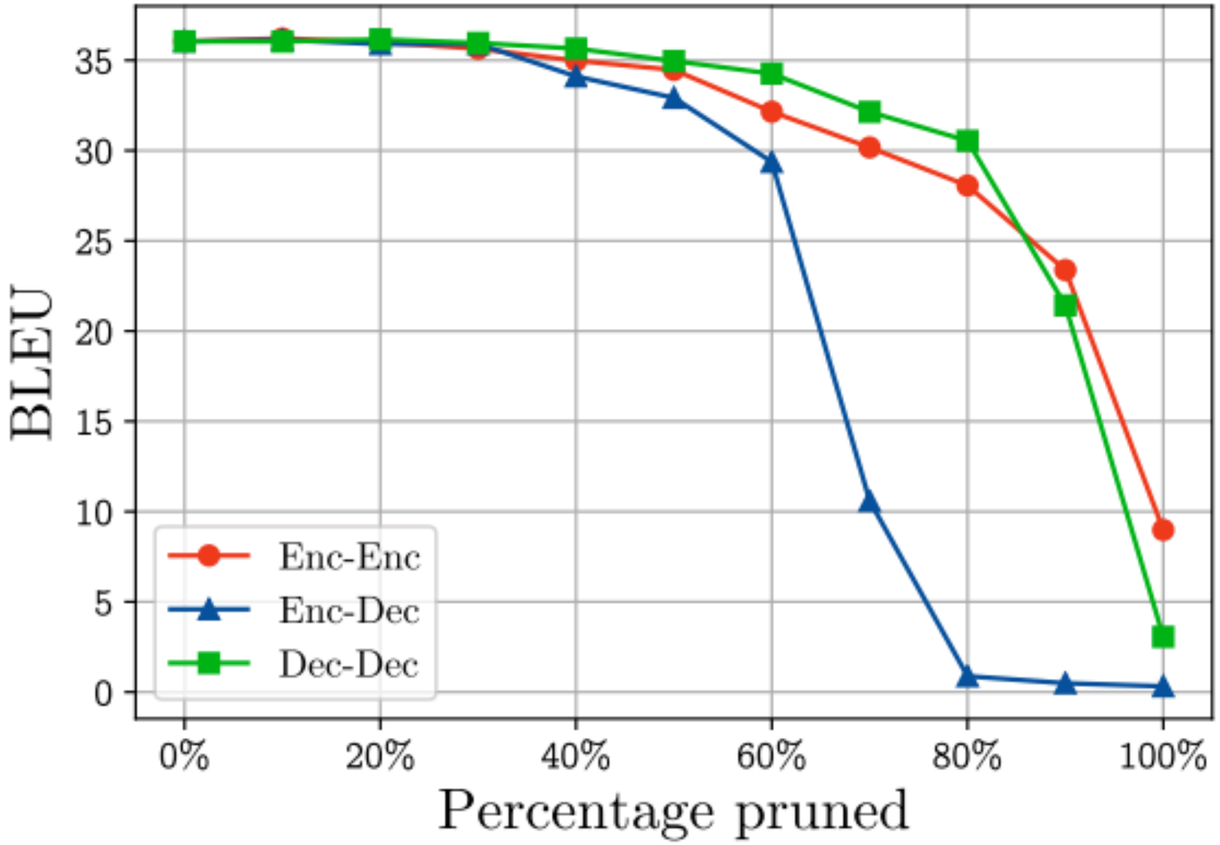
- also 6 layers (in original paper)

Do we need all these heads?

3 types of attention: Enc-Enc, Enc-Dec, Dec-Dec

6 layers, 16 heads each layer for each type

- Can we prune away some of the heads of a trained model during test time?



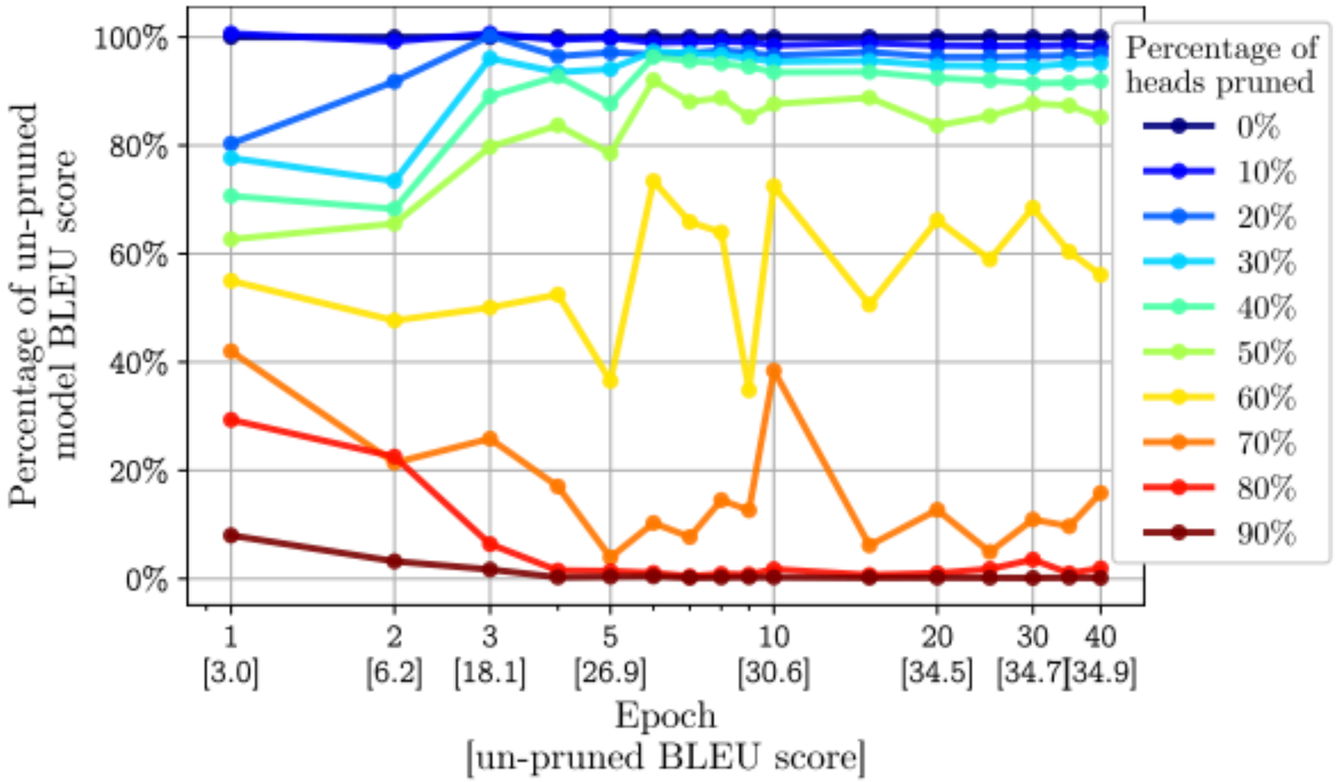
Are Sixteen Heads Really Better than One?
Michel, Levy, and Neubig, NeurIPS 2019

Do we need all these heads?

3 types of attention: Enc-Enc, Enc-Dec, Dec-Dec

6 layers, 16 heads each layer for each type

- Can we train a good MT model with less heads?



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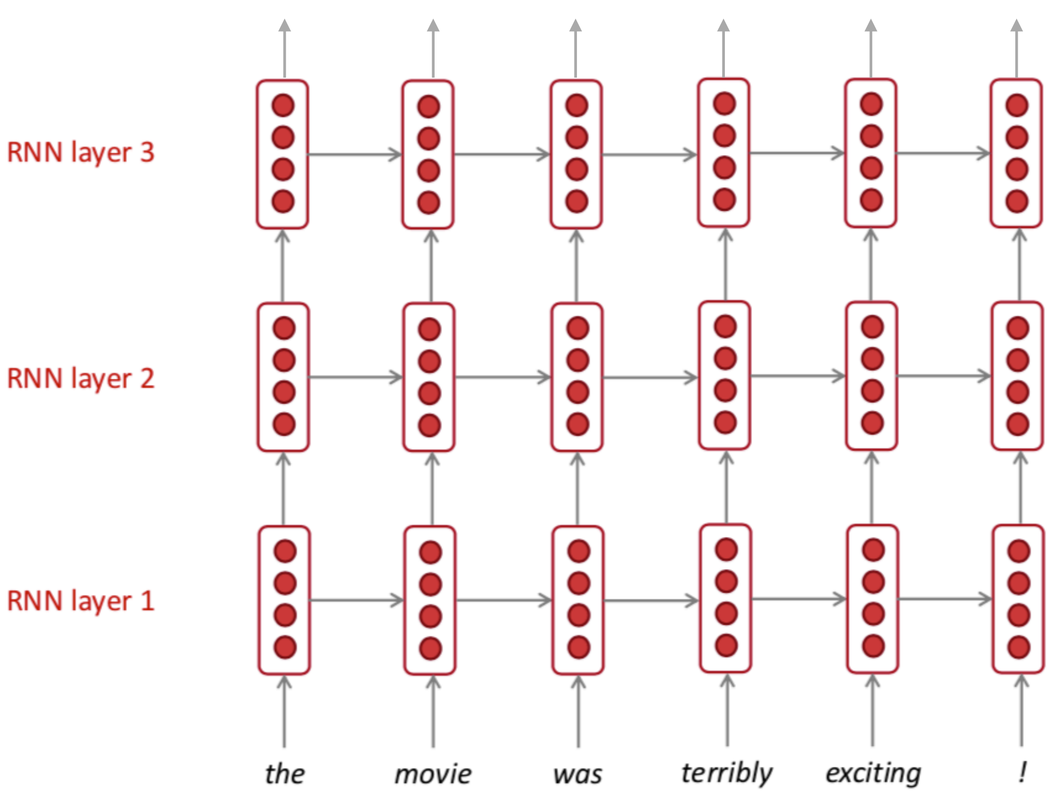
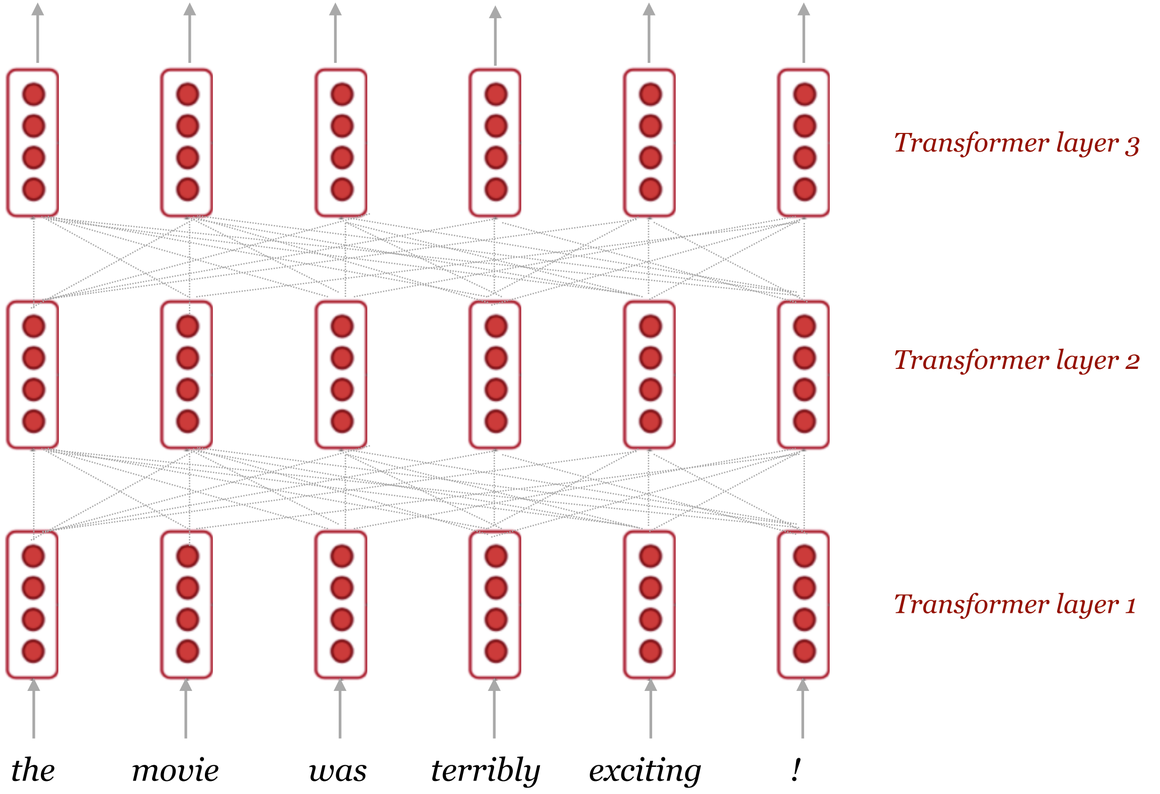
RNNs vs Transformers



RNN



Transformer

Useful Resources

nn.Transformer:

```
>>> transformer_model = nn.Transformer(nhead=16, num_encoder_layers=12)
>>> src = torch.rand((10, 32, 512))
>>> tgt = torch.rand((20, 32, 512))
>>> out = transformer_model(src, tgt)
```

nn.TransformerEncoder:

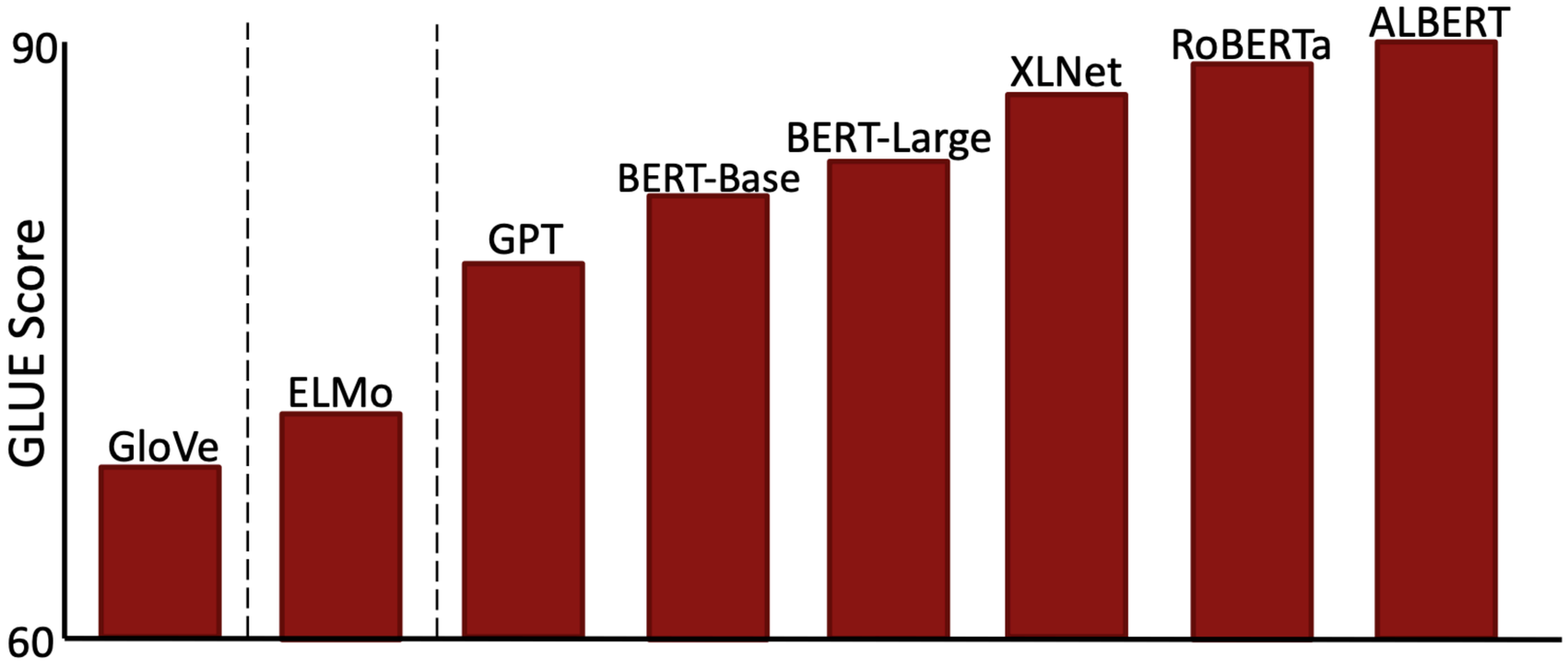
```
>>> encoder_layer = nn.TransformerEncoderLayer(d_model=512, nhead=8)
>>> transformer_encoder = nn.TransformerEncoder(encoder_layer, num_layers=6)
>>> src = torch.rand(10, 32, 512)
>>> out = transformer_encoder(src)
```

The Annotated Transformer:

http://nlp.seas.harvard.edu/2018/04/03/attention.html

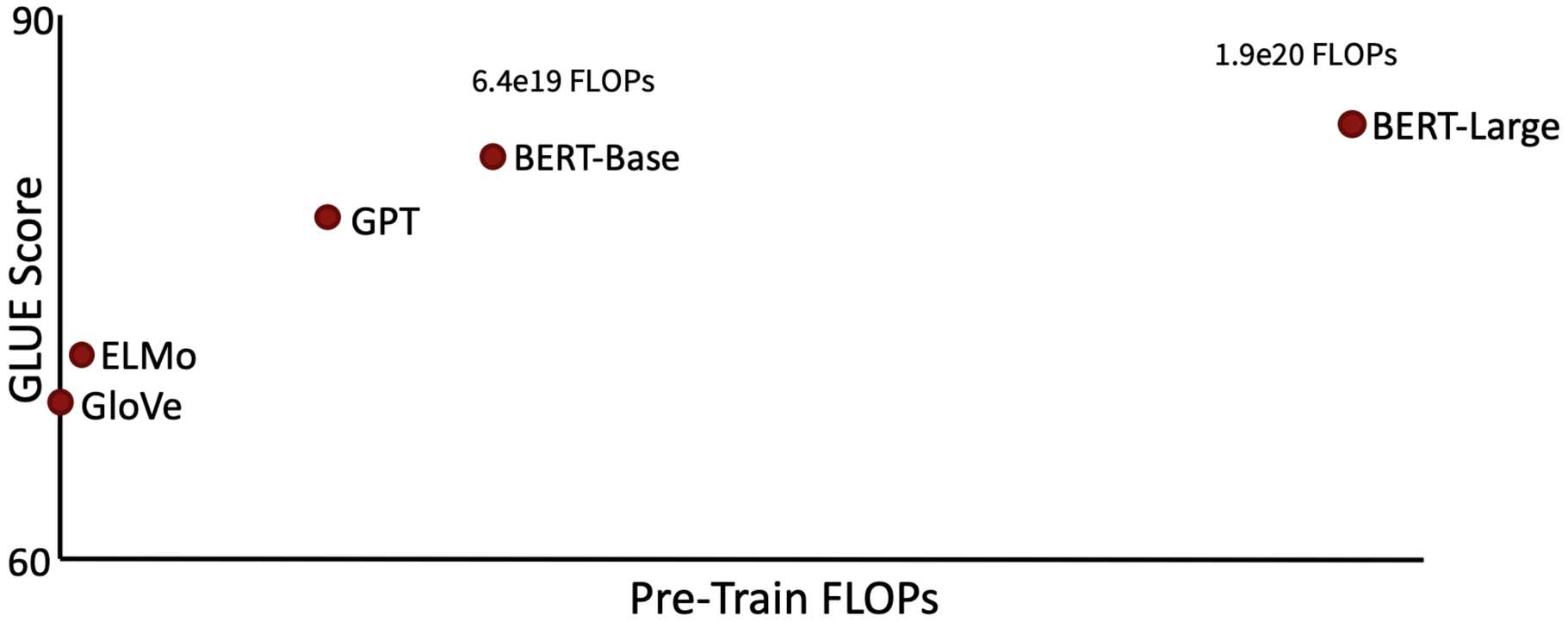
A Jupyter notebook which explains how Transformer works line by line in PyTorch!

NLP progress so far



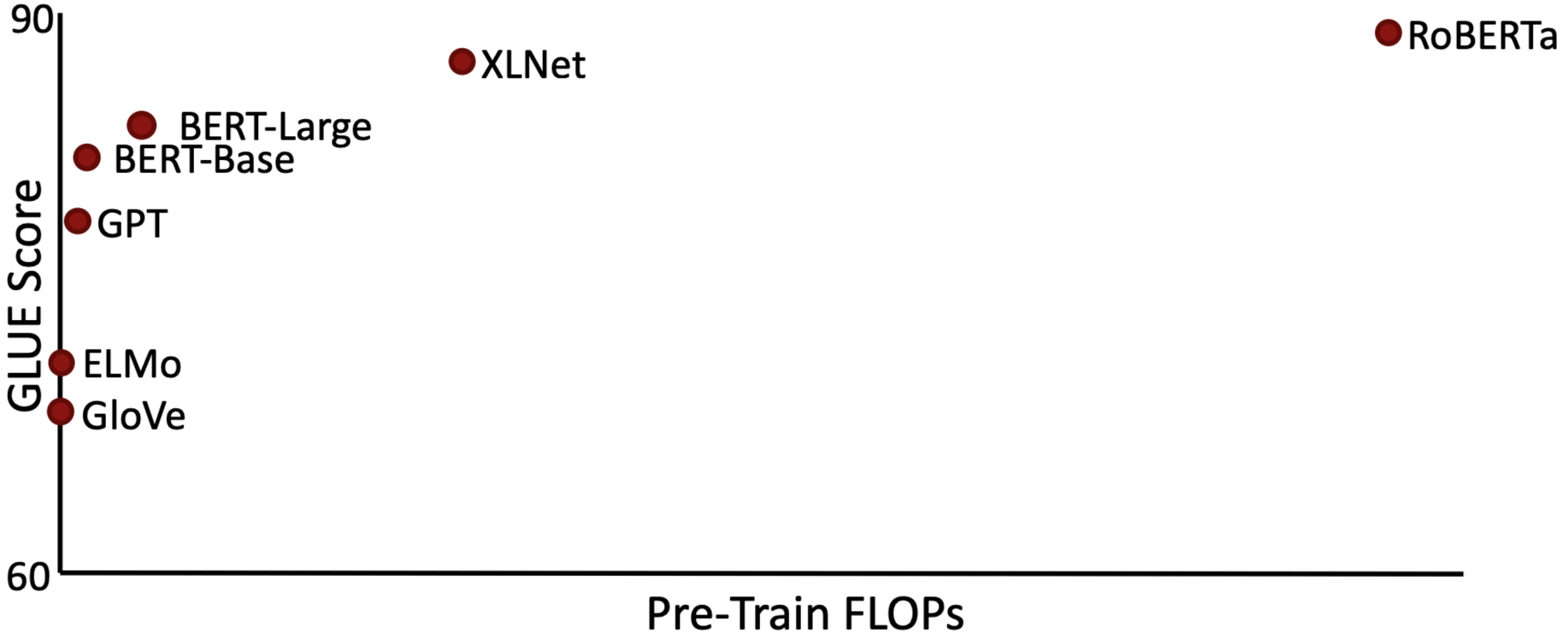
Over 3x reduction in error in 2 years, “superhuman” performance

(slide credit: Stanford CS224N, Chris Manning)



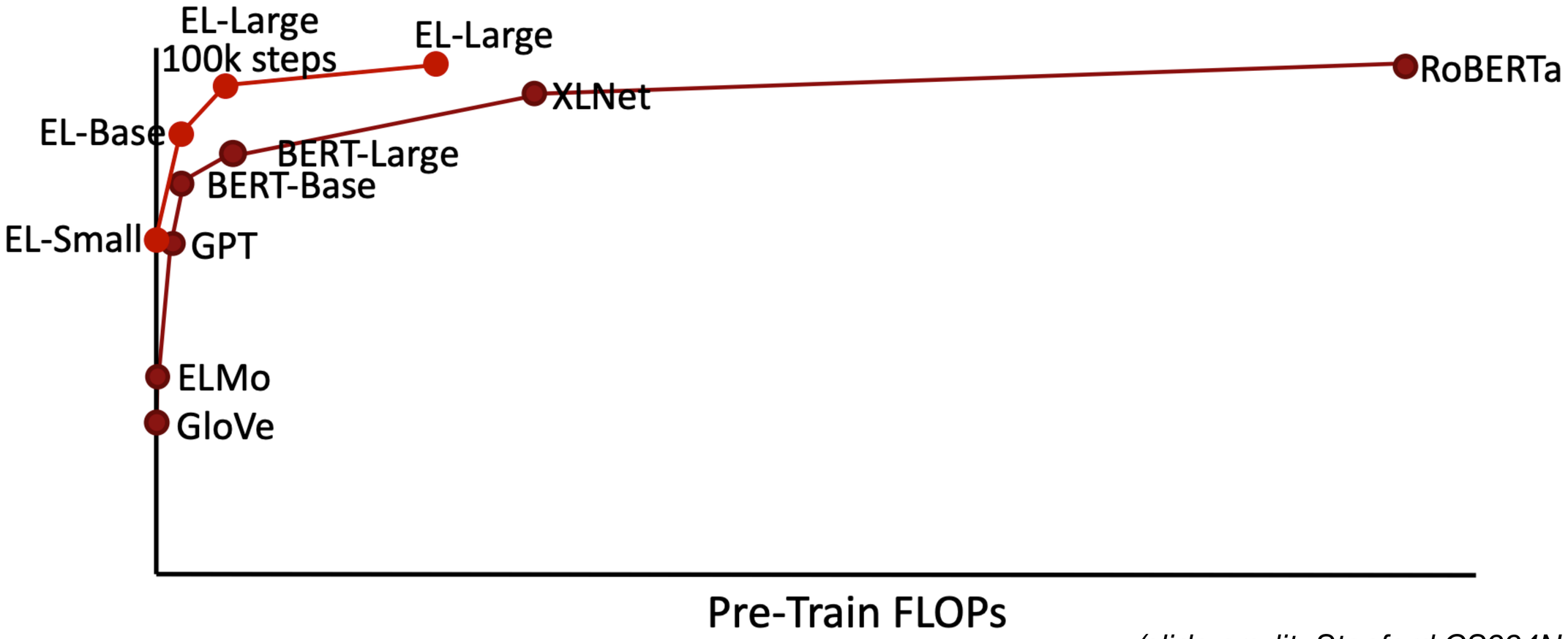
BERT-Large uses 60x more compute than ELMo

(slide credit: Stanford CS224N, Chris Manning)



RoBERTa uses 16x more compute than BERT-Large

(slide credit: Stanford CS224N, Chris Manning)



(slide credit: Stanford CS224N, Chris Manning)

Have fun with using ELMo or BERT in your final project :)