

Lecture 07: Context based models, BERT overview

Radoslav Neychev

MADE, Moscow
21.04.2021

1. OpenAI Transformer
2. ELMo
3. BERT
4. GPT-2 & GPT-3
5. Q & A

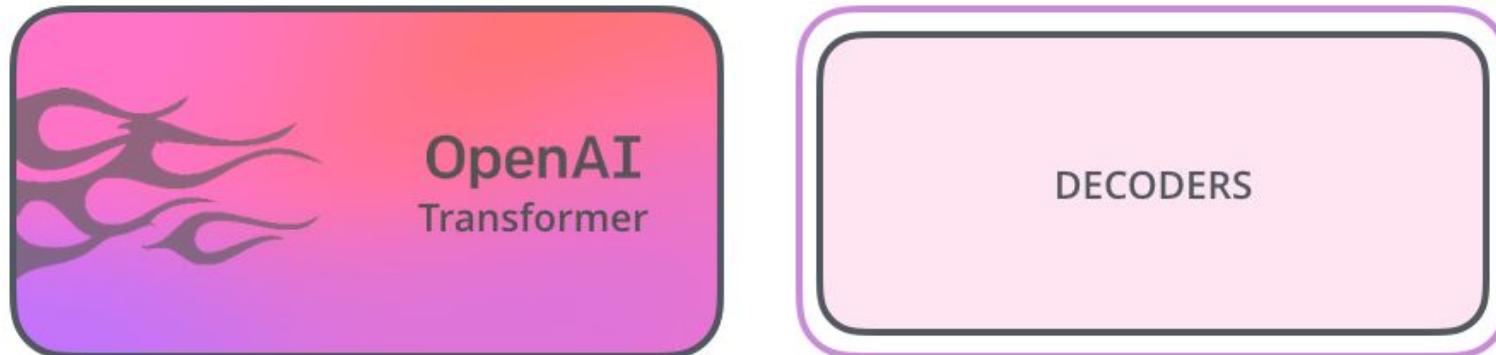
Based on: <http://web.stanford.edu/class/cs224n/slides/cs224n-2019-lecture13-contextual-representations.pdf>
<https://jalammar.github.io/illustrated-transformer/>
<http://jalammar.github.io/illustrated-bert/>
<https://medium.com/mlreview/understanding-building-blocks-of-ulmfit-818d3775325b>



OpenAI Transformer: Pre-training Decoder for Language Modeling

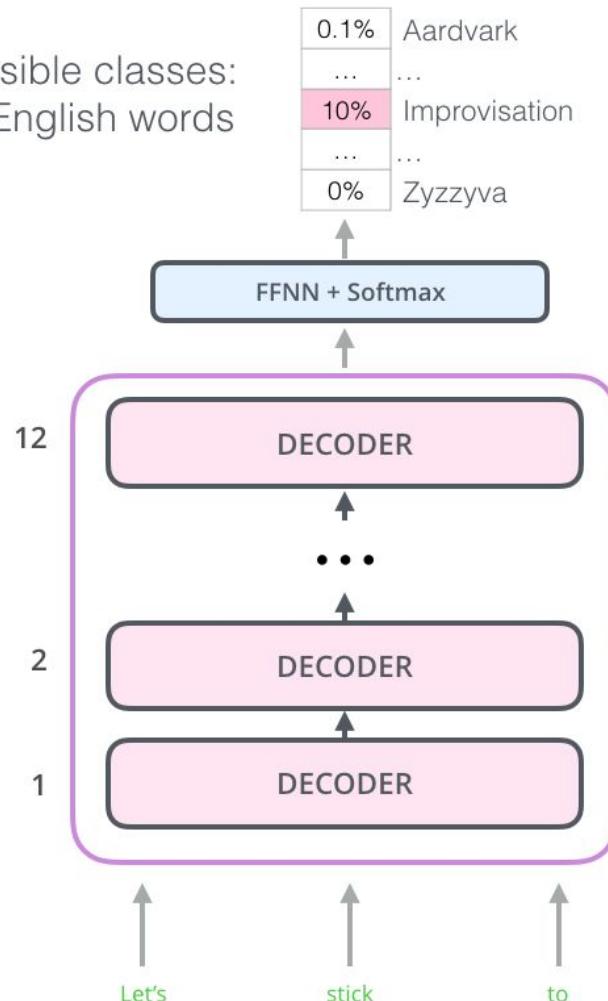
OpenAI Transformer

- The Encoder-Decoder structure of the transformer made it perfect for machine translation
- But what about sentence classification?
- **Main goal: pre-train a language model that can be fine-tuned for other tasks**



OpenAI Transformer

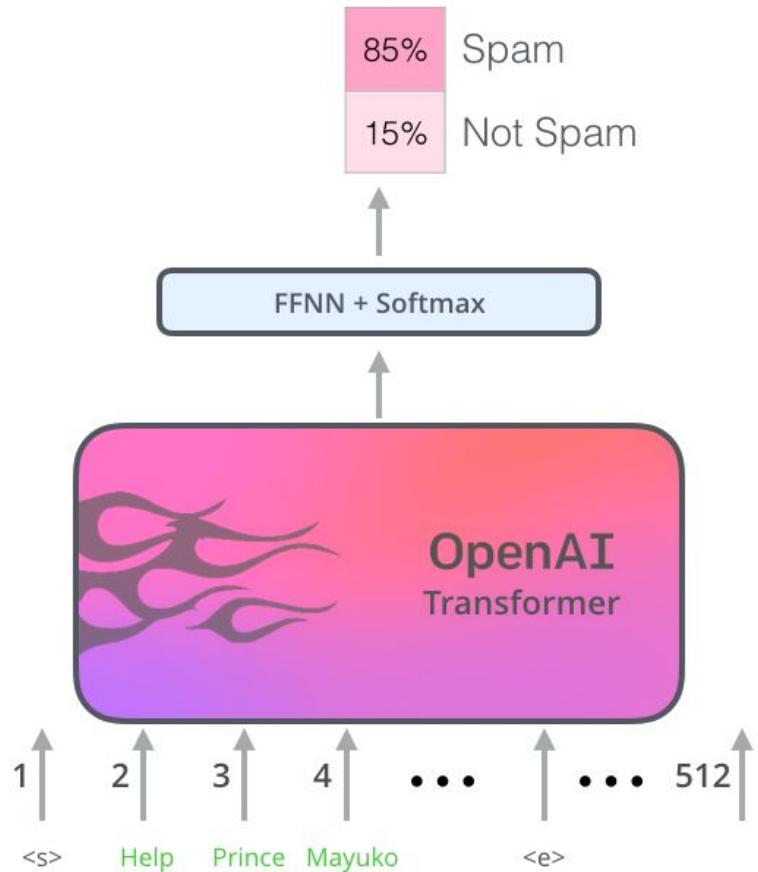
Possible classes:
All English words



Differences from vanilla Transformer:

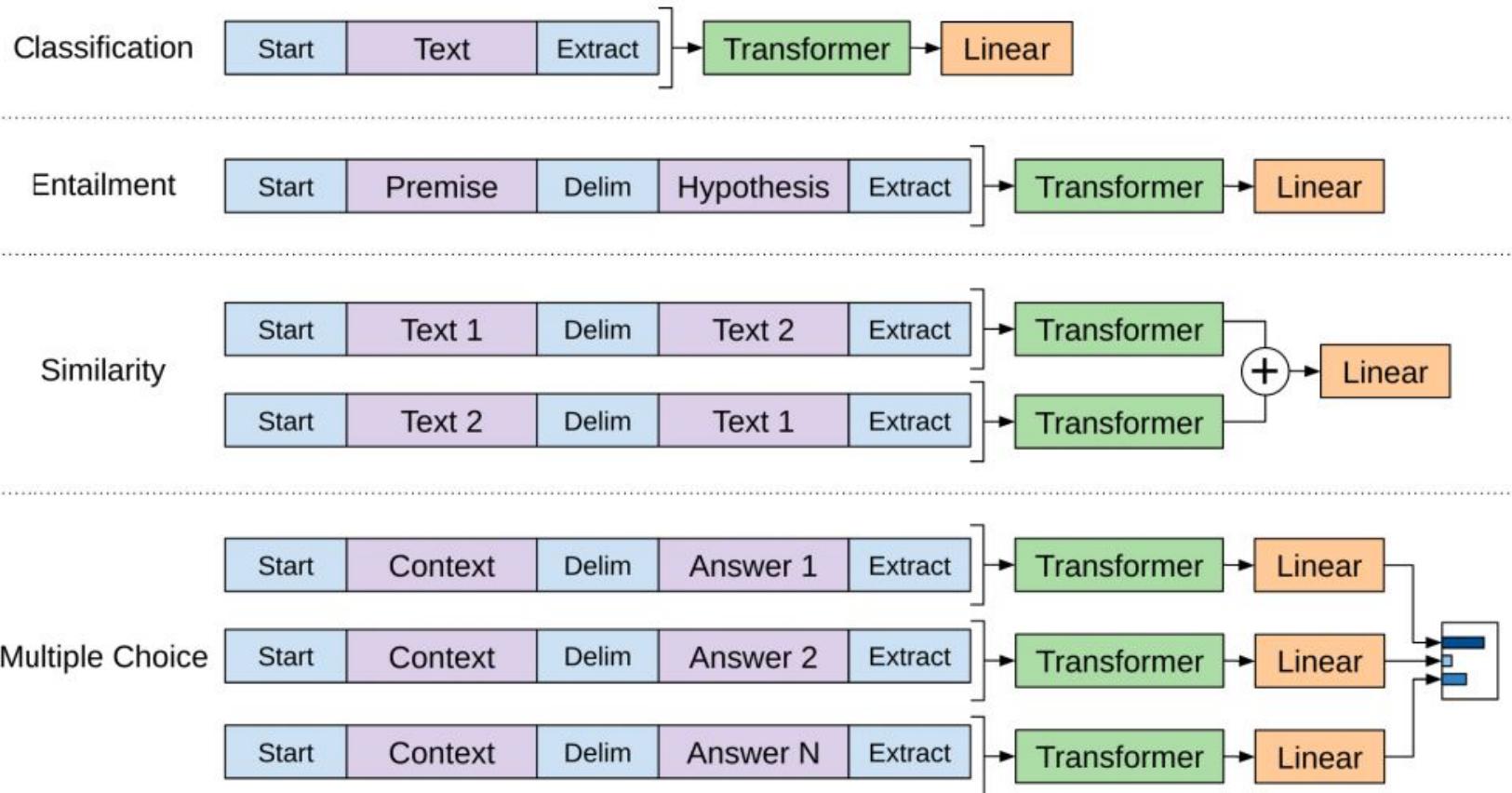
- no encoder
- decoder layers would not have the encoder-decoder attention sublayer
- Pre-train the model on predicting the next word using massive (unlabeled) datasets

OpenAI Transformer



- During pre-training phase layers have been tuned to reasonably handle language
- Now let's use it for downstream tasks (e.g. sentence classification)

Input transformations for different tasks





ELMo: context that matters

ELMo: contextualized word embeddings

“Why not give it an embedding based on the context it’s used in – to both capture the word meaning in that context as well as other contextual information?”



Peters et. al., 2017, McCann et. al., 2017,
Peters et. al., 2018 in the ELMo paper

ELMo – deep contextualized
word representations

What does it stand for?



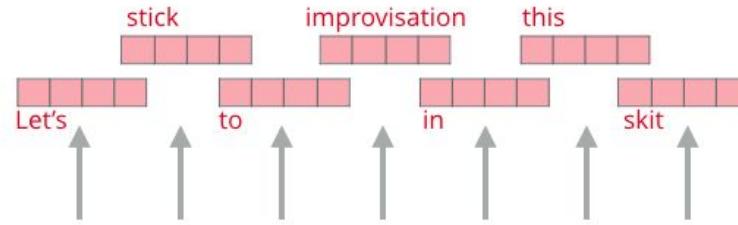
1. Expedited Labour Market Opinion
2. Electric Light Machine Organization
3. Enough Let's Move On
4. Embeddings from Language Models

ELMo: contextualized word embeddings



ELMo: Contextualized word embeddings

ELMo
Embeddings



- uses a bi-directional LSTM trained on Language Modeling task
- a model can learn without labels

Words to embed



Bidirectional Language Models (biLMs)

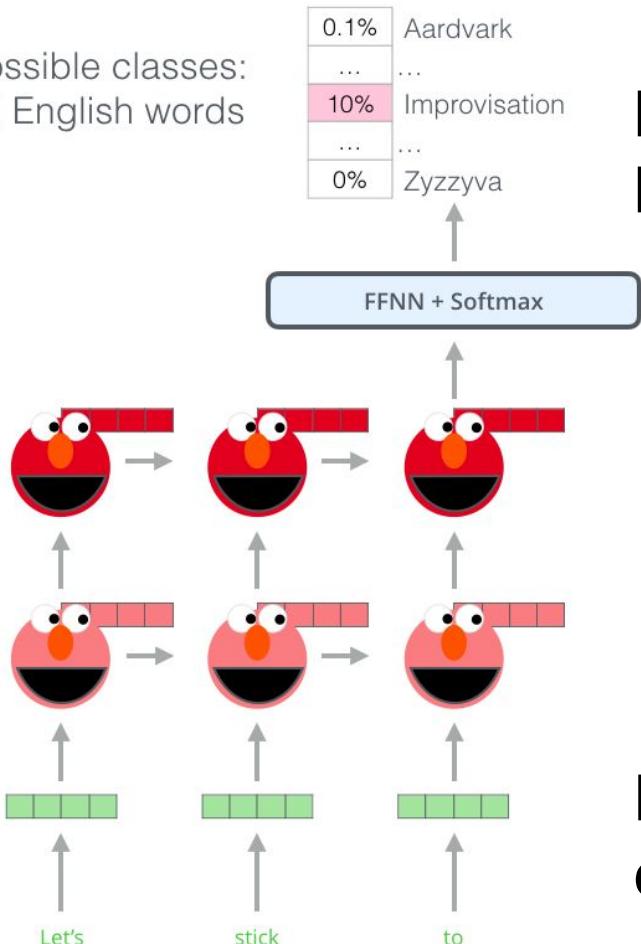
Possible classes:
All English words

Output
Layer

LSTM
Layer #2

LSTM
Layer #1

Embedding



biLMs consist of forward and backward LMs:

- Forward:

$$p(t_1, t_2, \dots, t_N) = \prod_{k=1}^N p(t_k | t_1, t_2, \dots, t_{k-1})$$

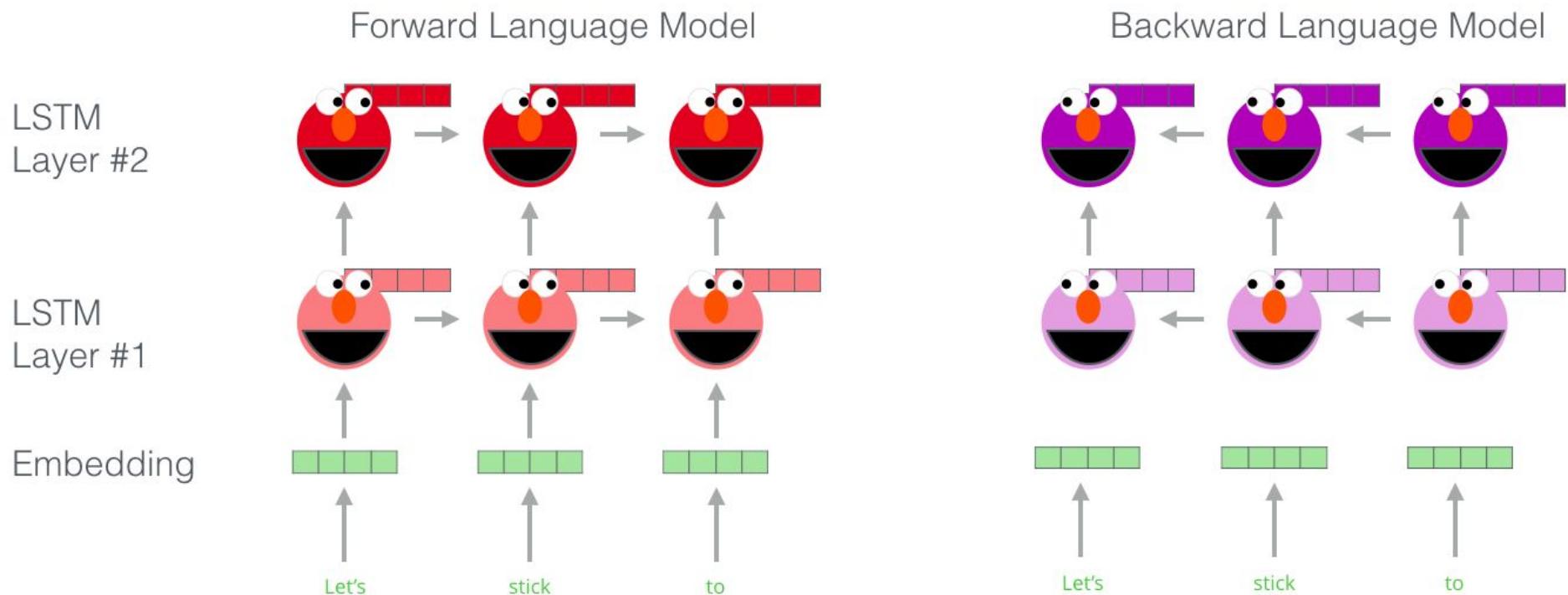
- Backward:

$$p(t_1, t_2, \dots, t_N) = \prod_{k=1}^N p(t_k | t_{k+1}, t_{k+2}, \dots, t_N)$$

LSTM predicts next word in both directions to build biLMs

ELMo: main pipeline

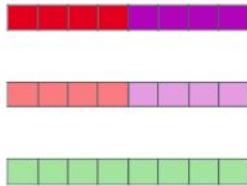
Embedding of “stick” in “Let’s stick to” - Step #1



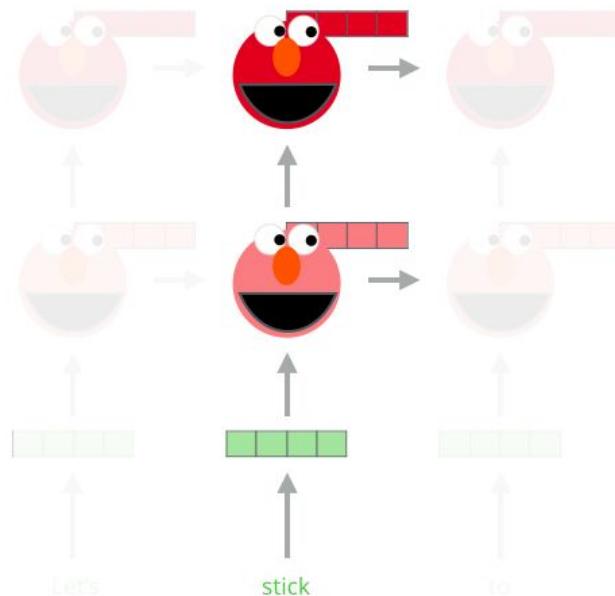
ELMo: main pipeline

Embedding of “stick” in “Let’s stick to” - Step #2

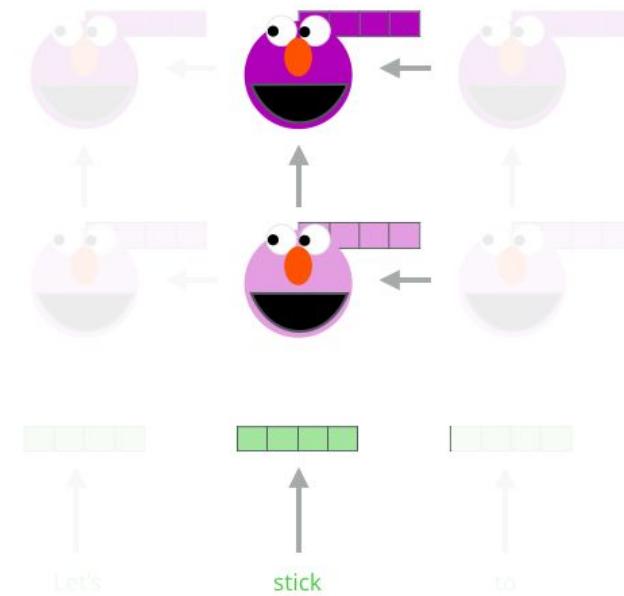
1- Concatenate hidden layers



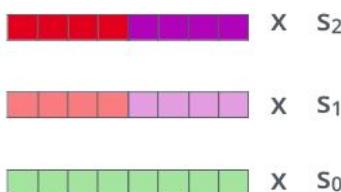
Forward Language Model



Backward Language Model



2- Multiply each vector by a weight based on the task



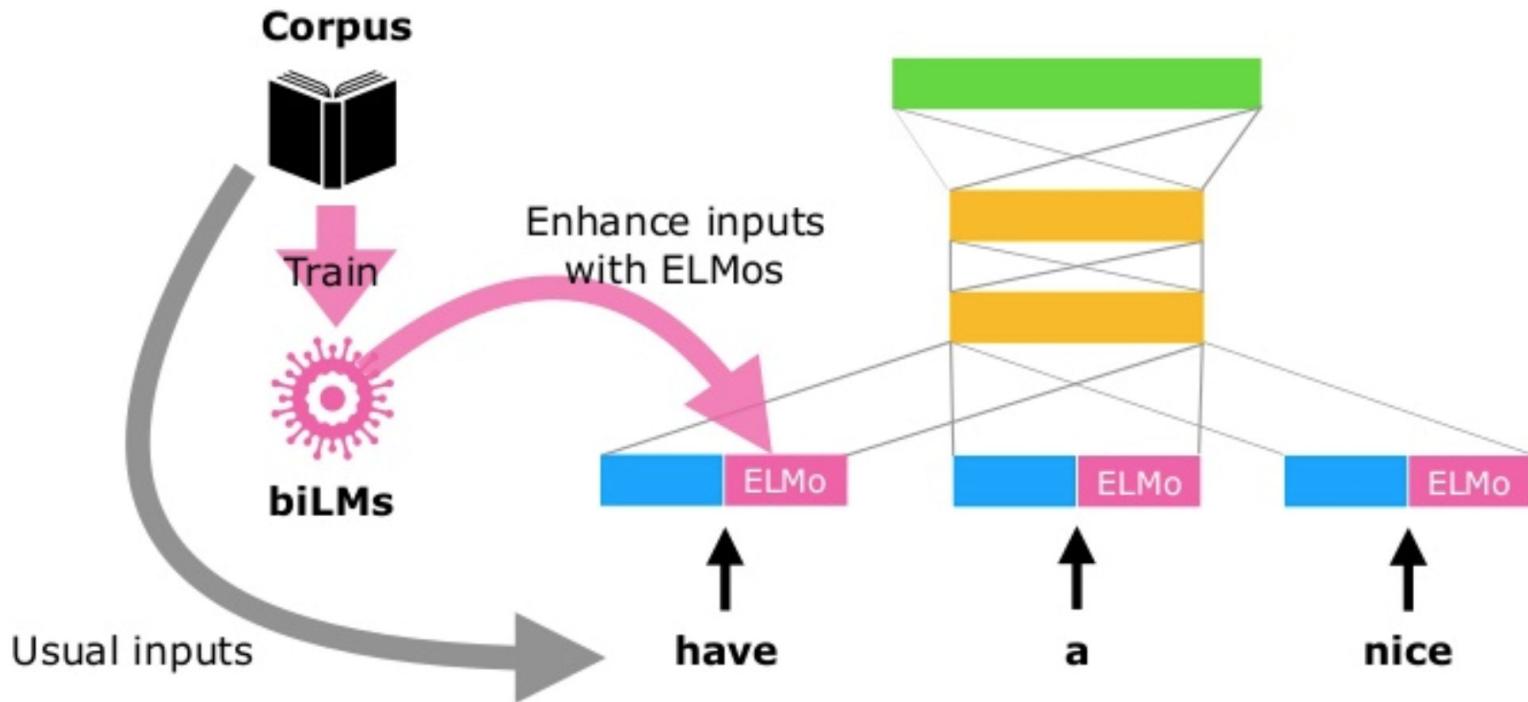
3- Sum the (now weighted) vectors



ELMo embedding of “stick” for this task in this context

ELMo represents a word as a linear combination of corresponding hidden layers

ELMo can be integrated to almost all neural NLP tasks with simple concatenation to the embedding layer



- Pretrained ELMo models: <http://allennlp.org/elmo>
- AllenNLP is a library on the top of PyTorch
- Higher levels seems to catch semantics while lower layer probably capture syntactic features



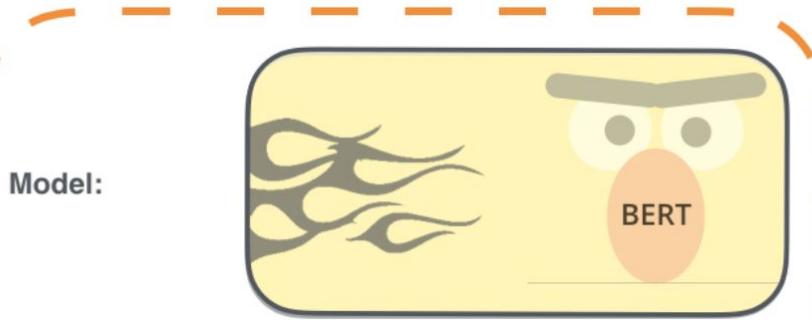
BERT

Bidirectional Encoder Representations from Transformers

1 - Semi-supervised training on large amounts of text (books, wikipedia..etc).

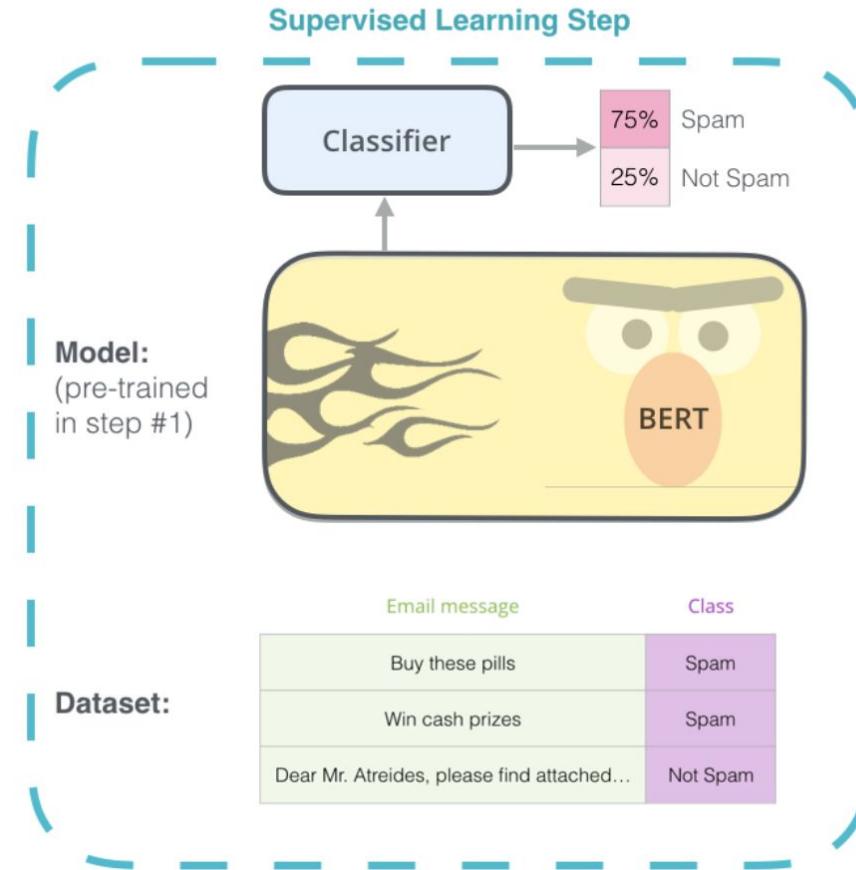
The model is trained on a certain task that enables it to grasp patterns in language. By the end of the training process, BERT has language-processing abilities capable of empowering many models we later need to build and train in a supervised way.

Semi-supervised Learning Step



2 - Supervised training on a specific task with a labeled dataset.

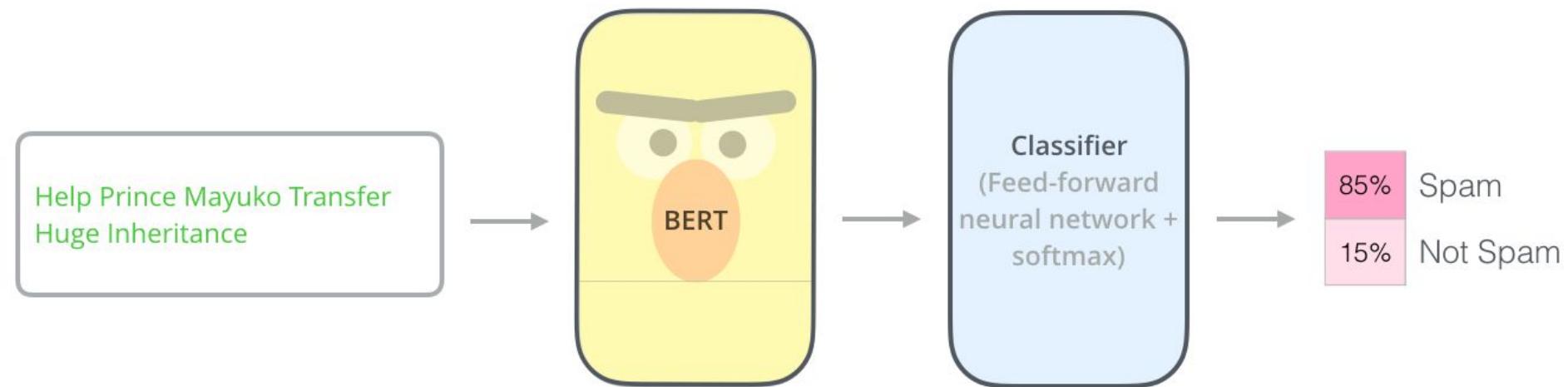
Supervised Learning Step



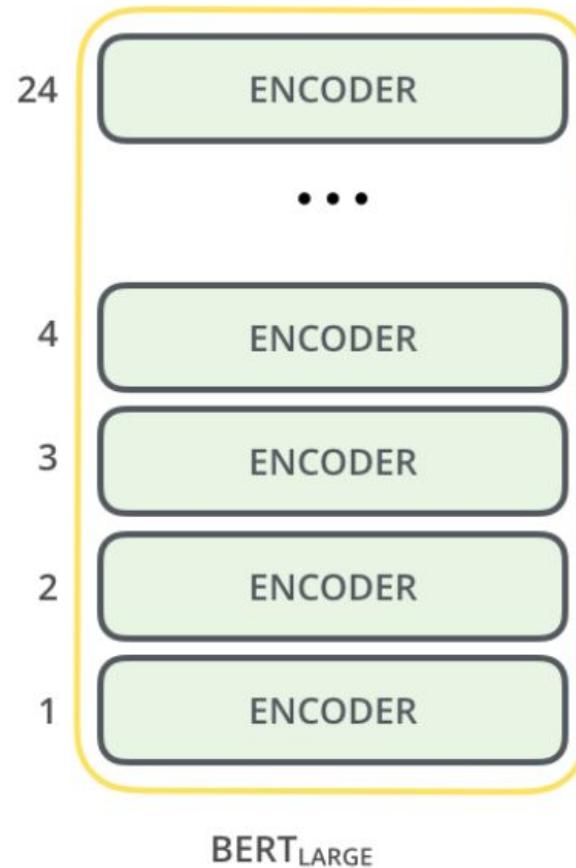
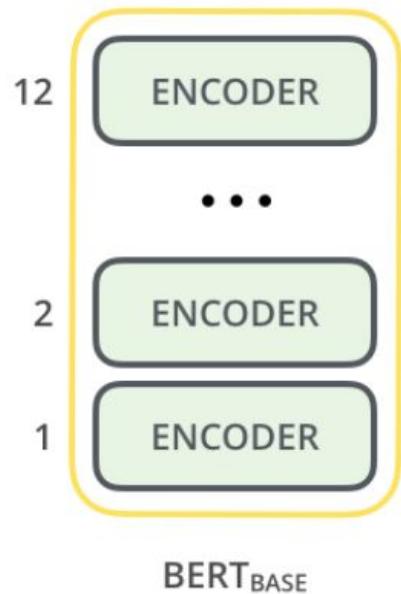
BERT

Input
Features

Output
Prediction



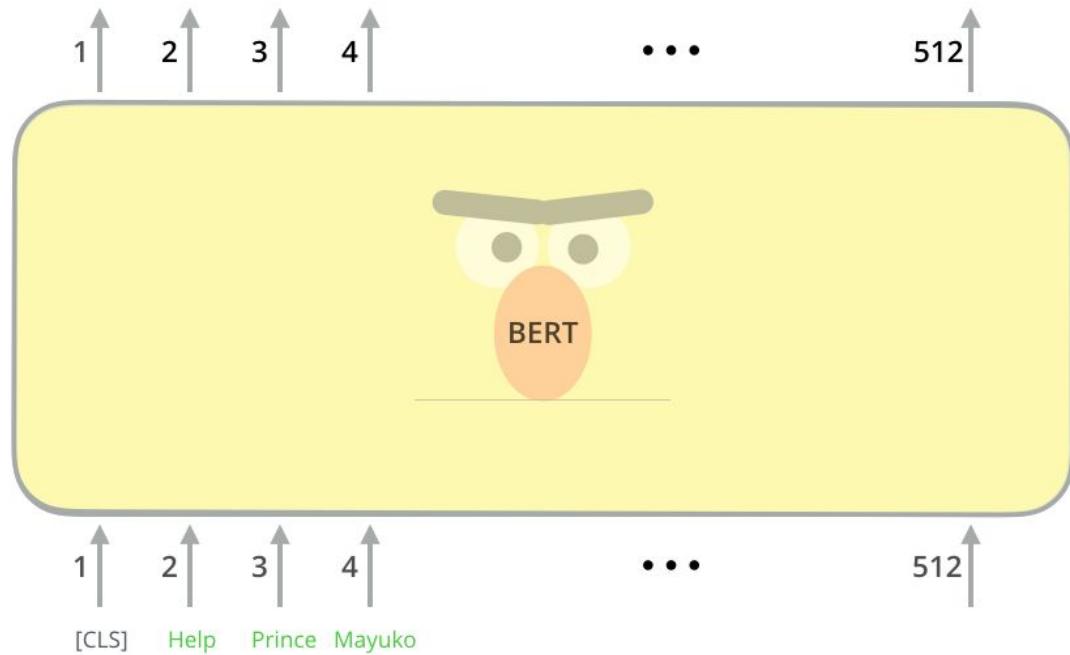
BERT: base and large



BERT vs. Transformer

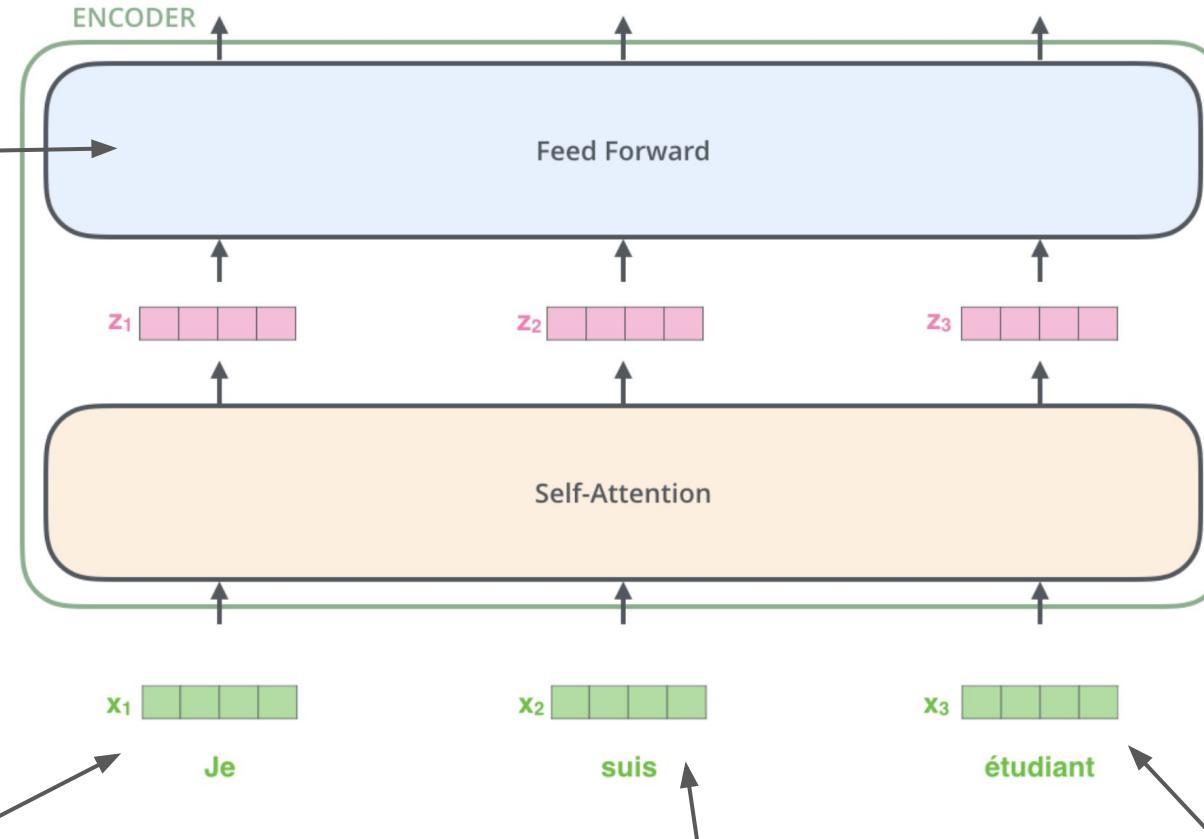
	 THE TRANSFORMER	 BERT	
		Base BERT	Large BERT
Encoders	6	12	24
Units in FFN	512	768	1024
Attention Heads	8	12	16

Model inputs



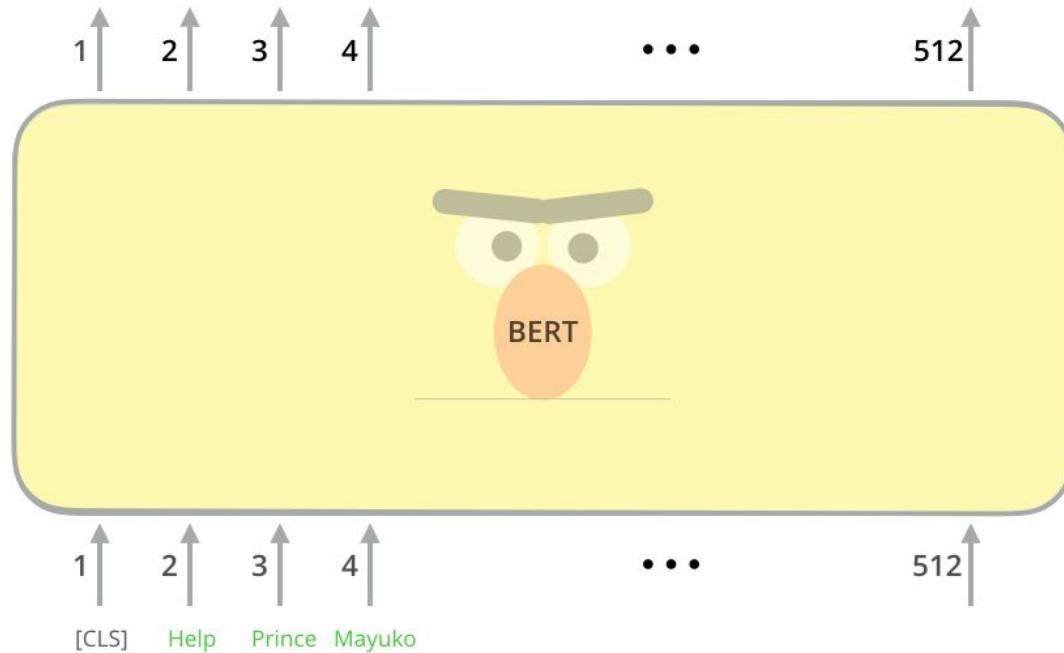
Transformer Block in BERT

Can be parallelized



the word in each position flows through its own path in the encoder

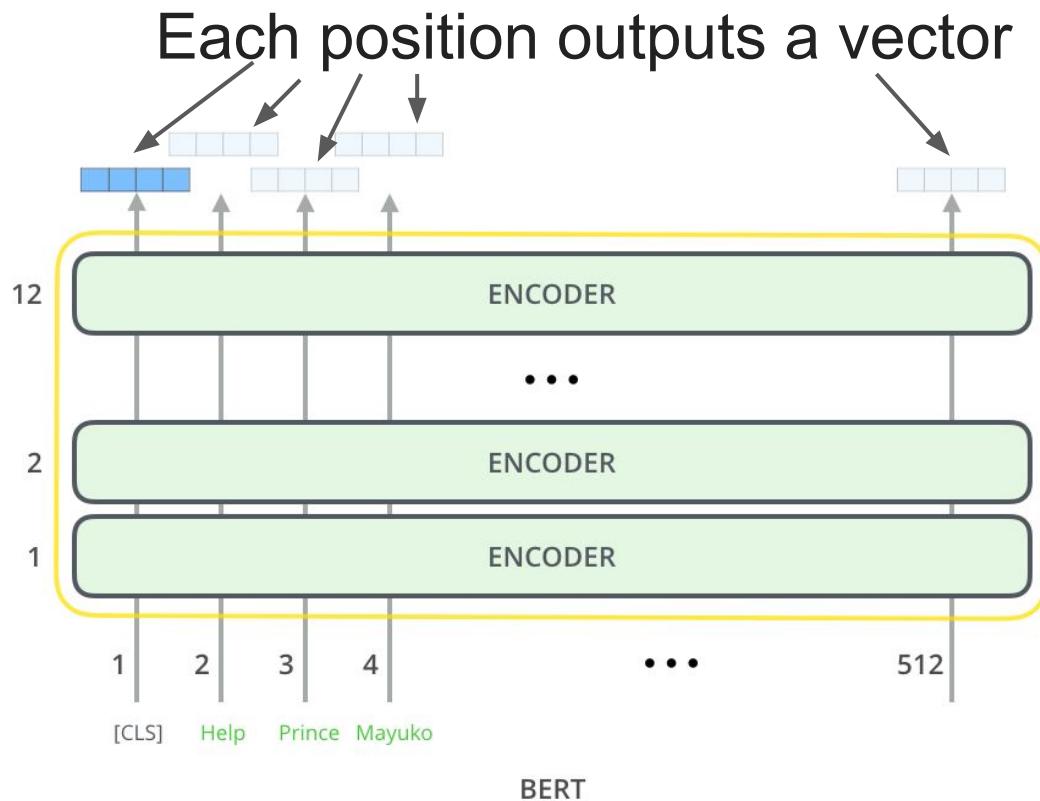
Model inputs



Identical to the Transformer up until this point

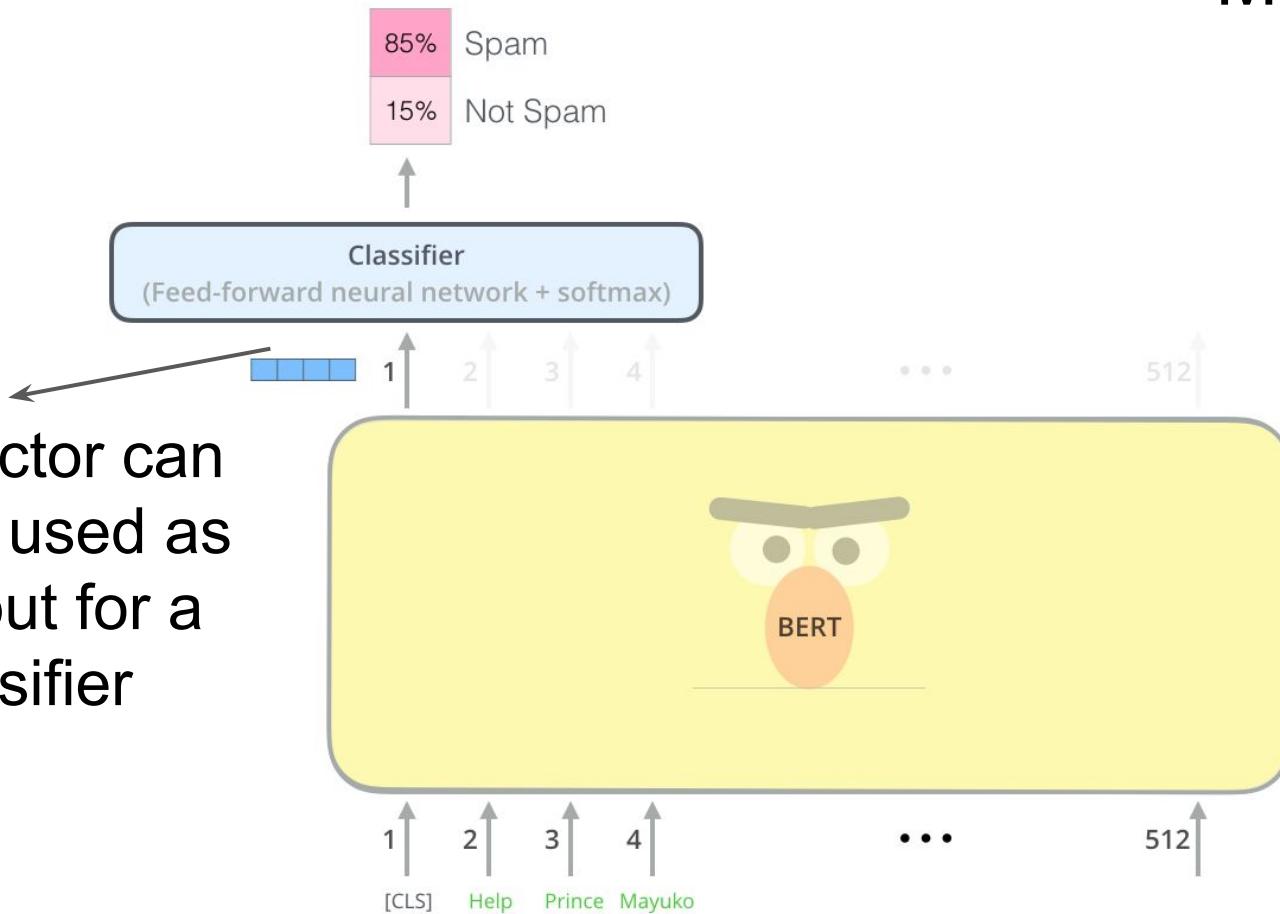
Why is BERT so special?

Model outputs

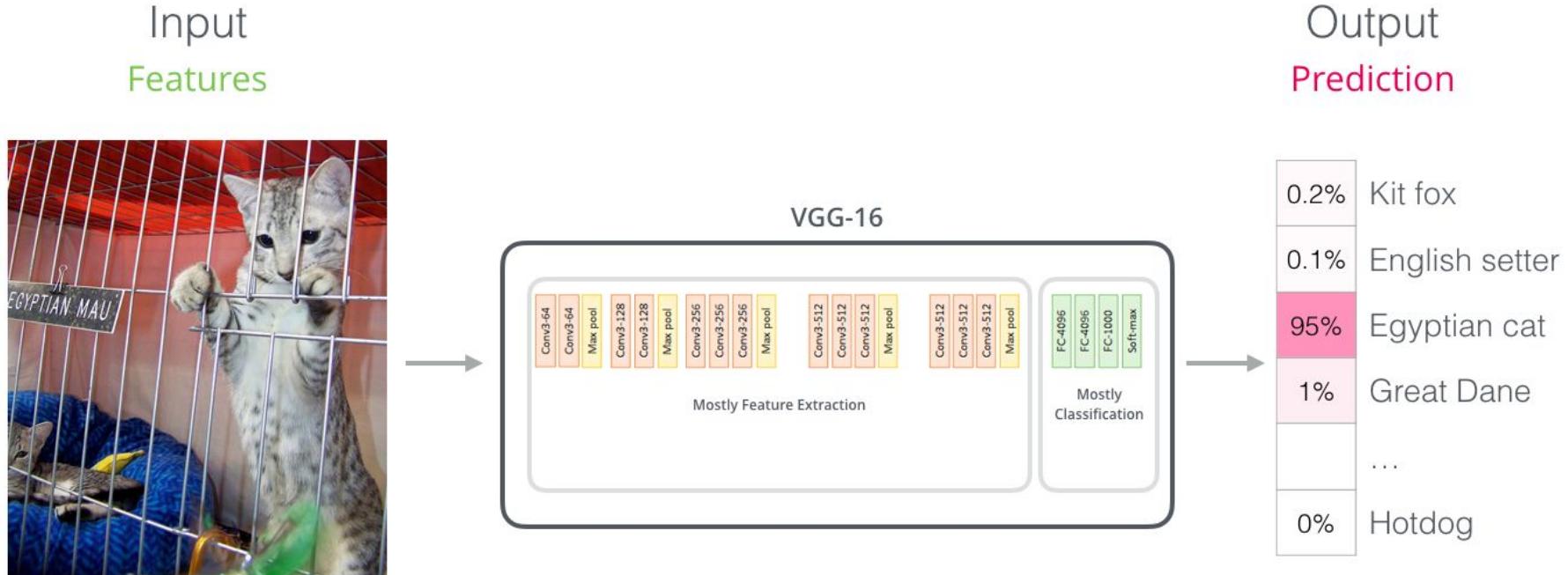


For sentence classification we focus on the first position
(that we passed [CLS] token to)

Model inputs

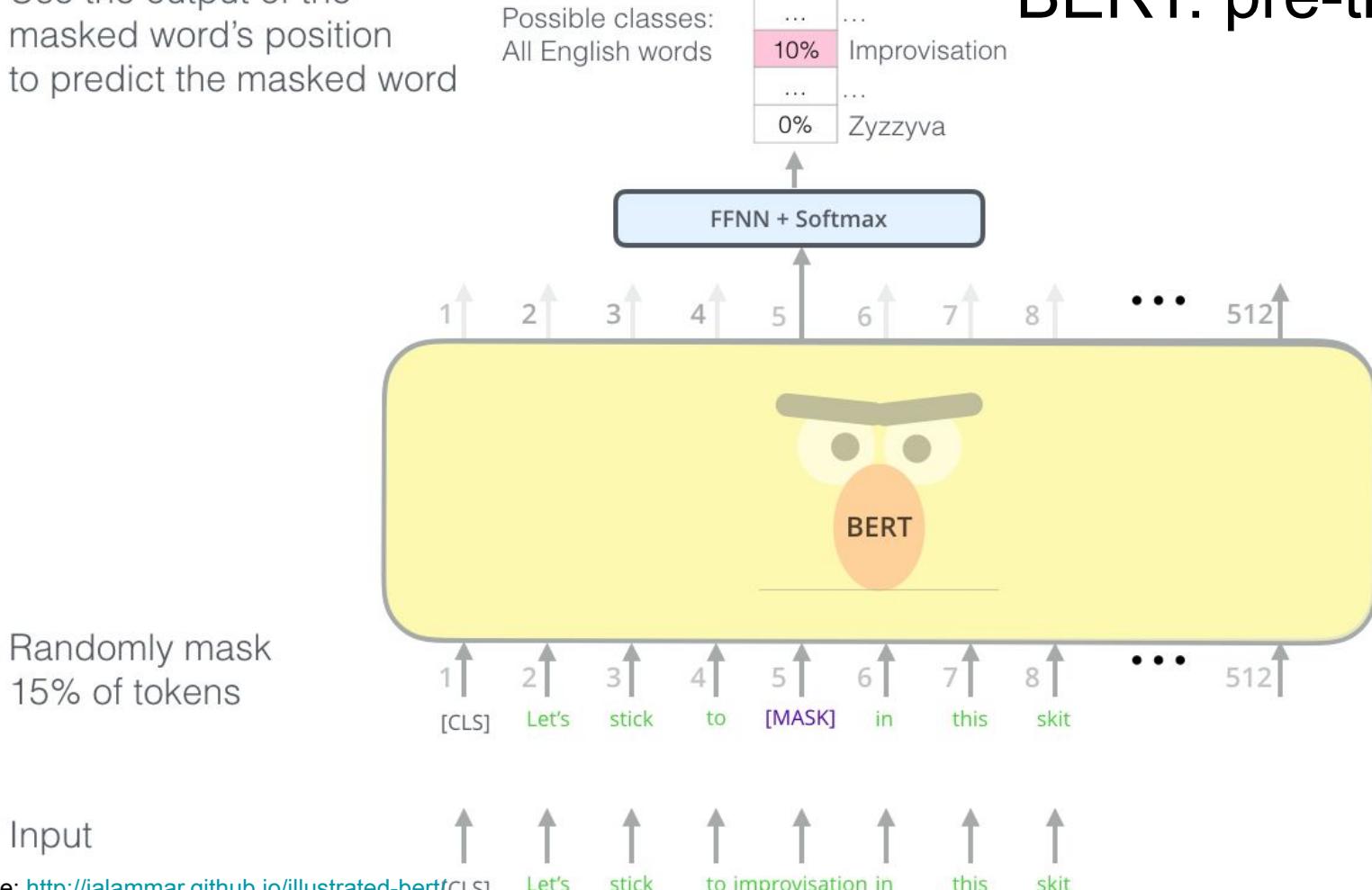


Similar to CNN concept!



BERT: pre-training

Use the output of the masked word's position to predict the masked word



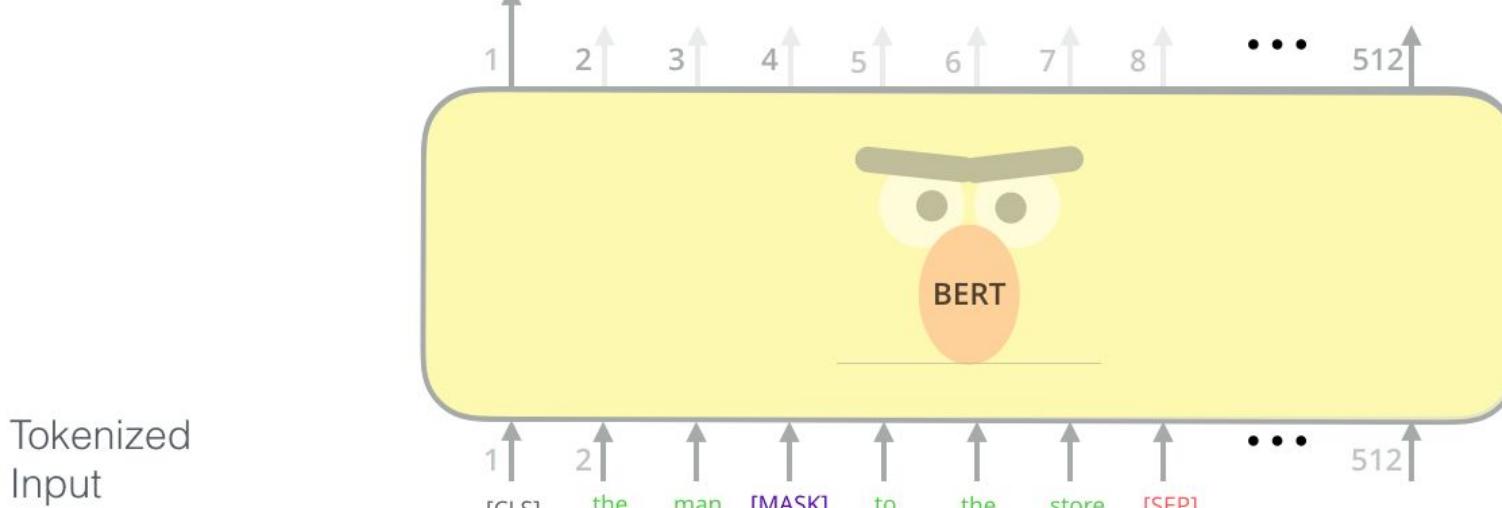
Input

BERT: pre-training

- “Masked Language Model” approach
- To make BERT better at handling relationships between multiple sentences, the pre-training process includes an additional task:
“Given two sentences (A and B), is B likely to be the sentence that follows A, or not?”

BERT: pre-training

Predict likelihood
that sentence B
belongs after
sentence A



Tokenized
Input

Input

[CLS] the man [MASK] to the store [SEP] penguin [MASK] are flightless birds [SEP]

Sentence A

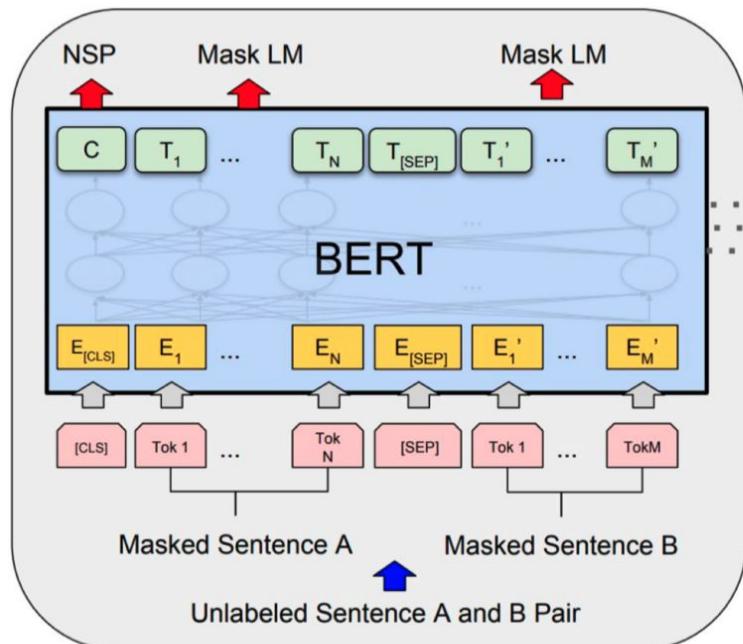
Sentence B

BERT: input data format

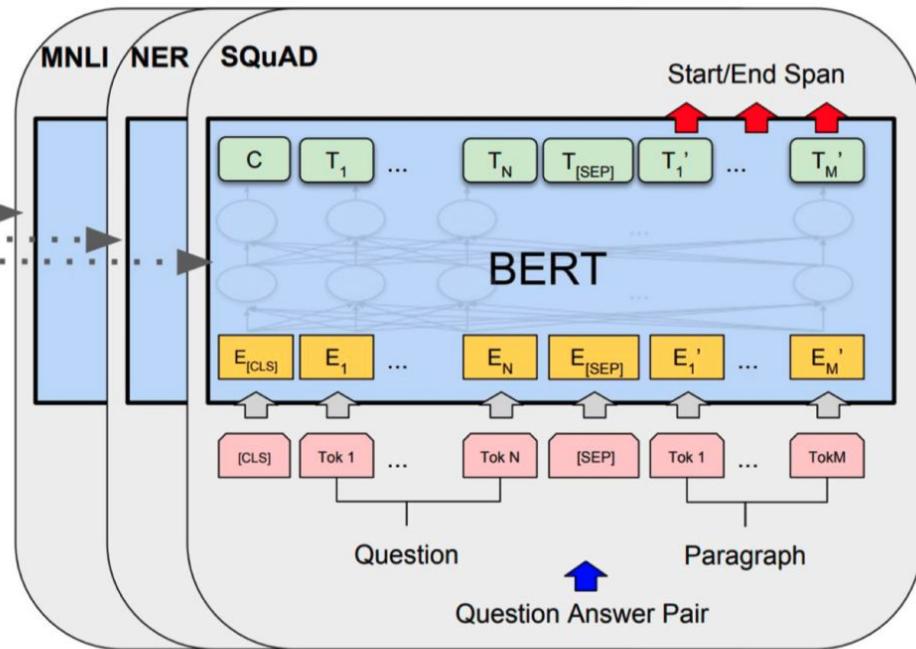
For each tokenized input sentence, we need to create:

- **input ids**: a sequence of integers identifying each input token to its index number in the BERT tokenizer vocabulary
- **segment mask**: a sequence of 1s and 0s used to identify whether the input is one sentence or two sentences long. For one sentence inputs, this is simply a sequence of 0s. For two sentence inputs, there is a 0 for each token of the first sentence, followed by a 1 for each token of the second sentence
- **attention mask**: a sequence of 1s and 0s, with 1s for all input tokens and 0s for all padding tokens

BERT: fine-tuning for different tasks

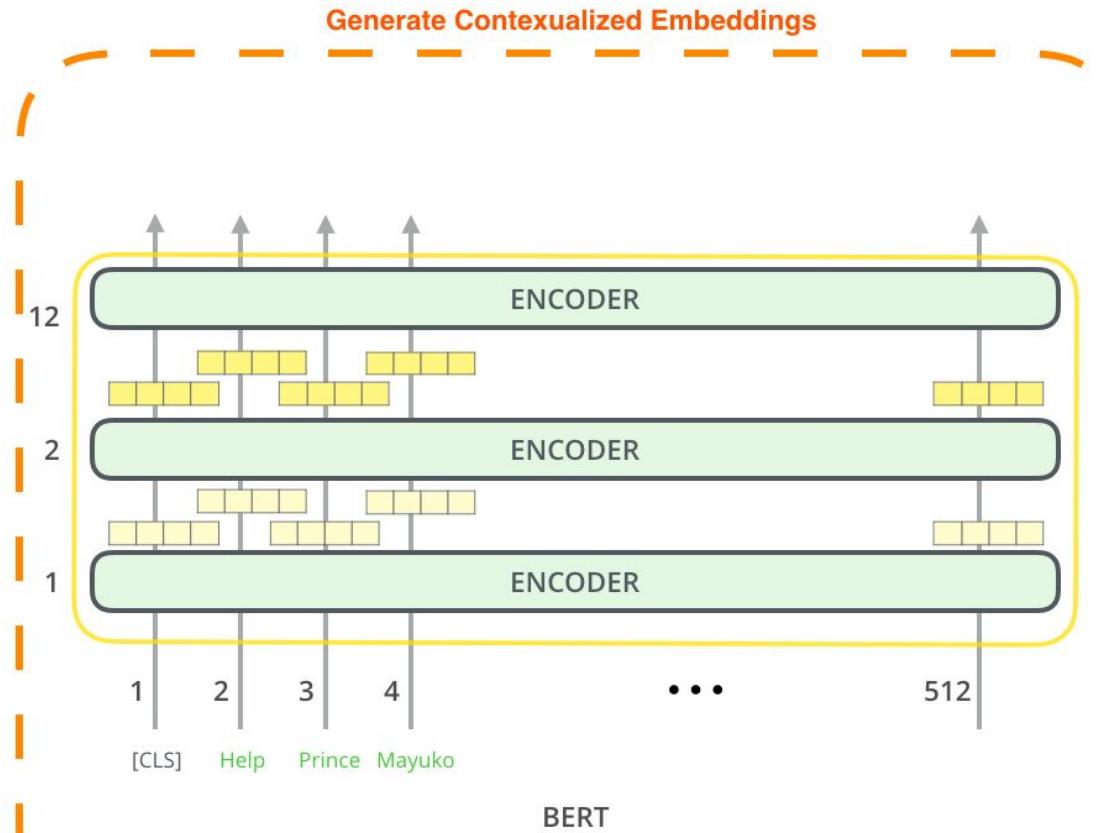


Pre-training

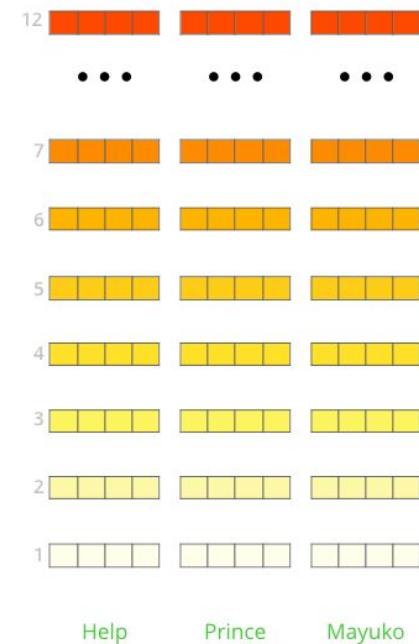


Fine-Tuning

BERT for feature extraction



The output of each encoder layer along each token's path can be used as a feature representing that token.



But which one should we use?

BERT for feature extraction

What is the best contextualized embedding for “**Help**” in that context?

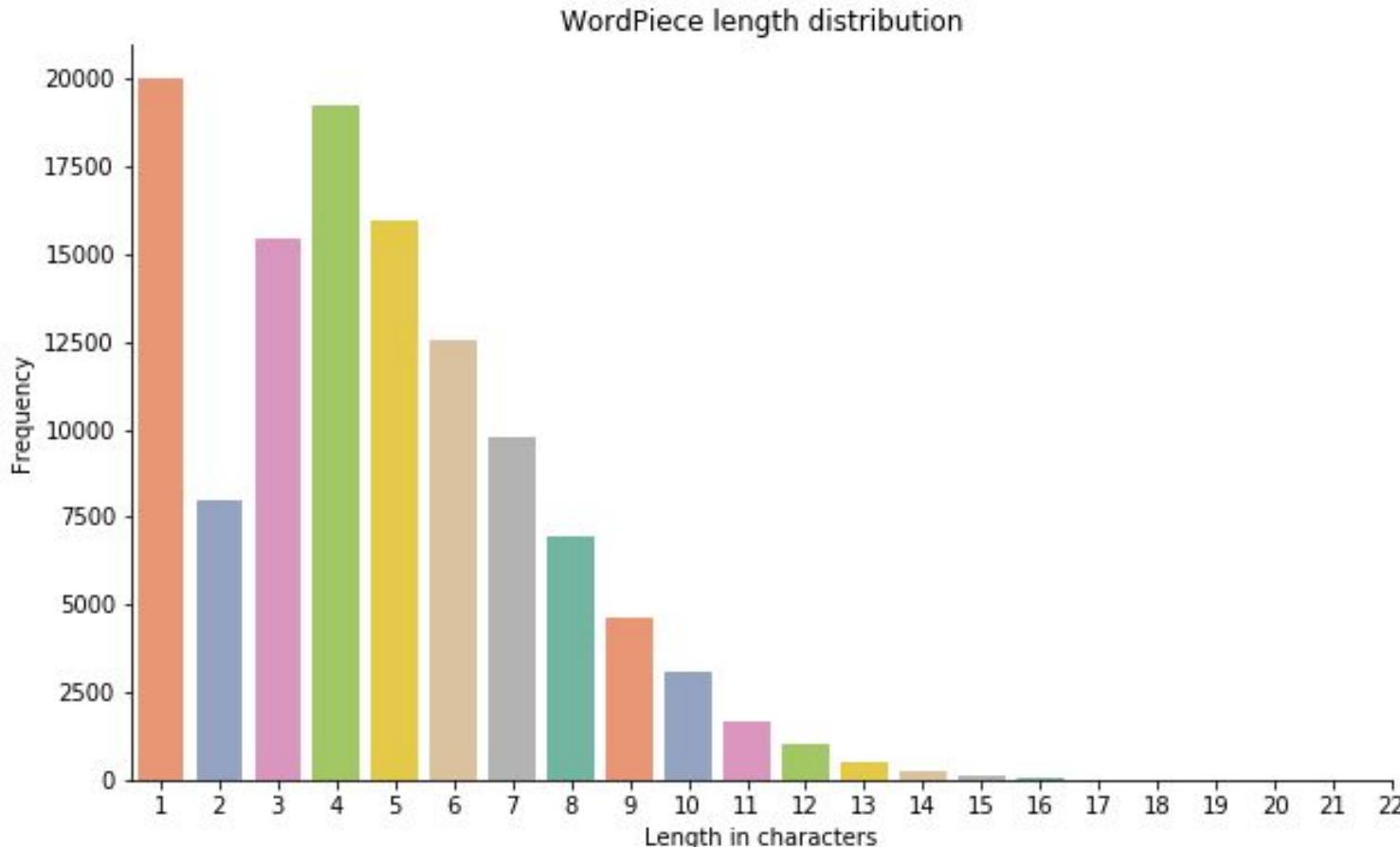
For named-entity recognition task CoNLL-2003 NER

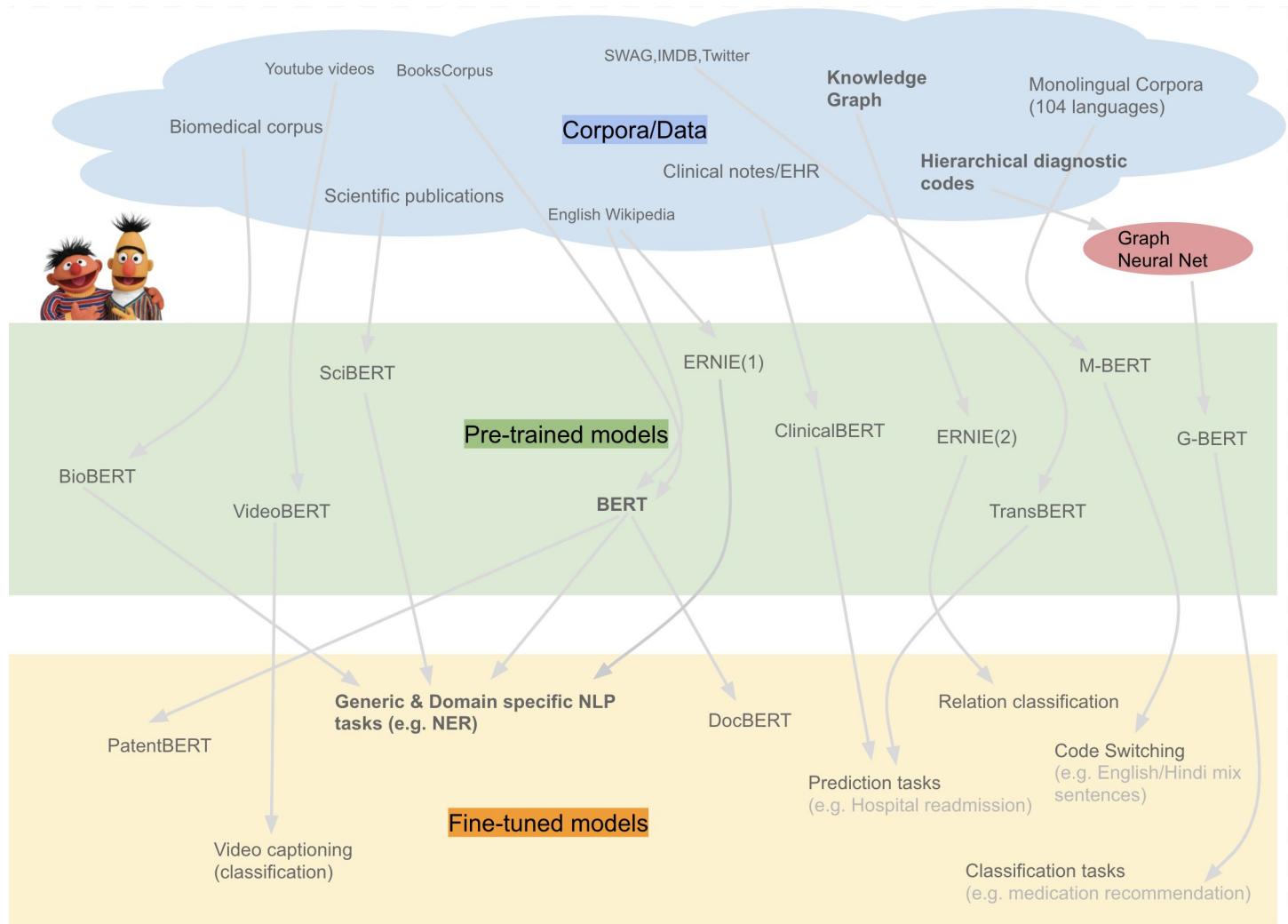
			Dev F1 Score	
12		First Layer	Embedding	91.0
• • •		Last Hidden Layer		94.9
7				
6		Sum All 12 Layers		95.5
5				
4		Second-to-Last Hidden Layer		95.6
3				
2		Sum Last Four Hidden		95.9
1				
		Concat Last Four Hidden		96.1
Help				

Example: Unaffable -> un, ##aff, ##able

- Single model for 104 languages with a large shared vocabulary (119,547 [WordPiece](#) model)
- Non-word-initial units are prefixed with ##
- The first 106 symbols: constants like PAD and UNK
- 36.5% of the vocabulary are non-initial word pieces
- The alphabet consists of 9,997 unique characters that are defined as word-initial (C) and continuation symbols (##C), which together make up 19,994 word pieces
- The rest are multi character word pieces of various length.

BERT: tokenization





BERT: overview

- [BERT repo](#)
- [Try out BERT on TPU](#)
- [WordPieces Tokenizer](#)
- [PyTorch Implementation of BERT](#)

GPT-2 & GPT-3

- Transformer-based architecture
- trained to predict the **next** word
- 1.5 billion parameters
- Trained on 8 million web-pages



On language tasks (question answering, reading comprehension, summarization, translation) works well **WITHOUT** fine-tuning

GPT-2: question answering

EXAMPLES

Who wrote the book the origin of species?

Correct answer: *Charles Darwin*

Model answer: Charles Darwin

What is the largest state in the U.S. by land mass?

Correct answer: *Alaska*

Model answer: California

GPT-2: language modeling

EXAMPLE

Both its sun-speckled shade and the cool grass beneath were a welcome respite after the stifling kitchen, and I was glad to relax against the tree's rough, brittle bark and begin my breakfast of buttery, toasted bread and fresh fruit. Even the water was tasty, it was so clean and cold. It almost made up for the lack of...

Correct answer: coffee

Model answer: food

GPT-2: machine translation

EXAMPLE

French sentence:

Un homme a expliqué que l'opération gratuite qu'il avait subie pour soigner une hernie lui permettrait de travailler à nouveau.

Reference translation:

One man explained that the free hernia surgery he'd received will allow him to work again.

Model translation:

A man told me that the operation gratuity he had been promised would not allow him to travel.

New AI fake text generator may be too dangerous to ... - The Guardian

<https://www.theguardian.com/.../elon-musk-backed-ai-writes-convincing-news-fiction>

4 days ago - The Elon Musk-backed nonprofit company OpenAI declines to release research publicly for fear of misuse. The creators of a revolutionary AI system that can write news stories and works of fiction – dubbed "deepfakes for text" – have taken the unusual step of not releasing ...

OpenAI built a text generator so good, it's considered too dangerous to ...

<https://techcrunch.com/2019/02/17/openai-text-generator-dangerous/> ▾

12 hours ago - A storm is brewing over a new language model, built by non-profit artificial intelligence research company OpenAI, which it says is so good at ...

The AI Text Generator That's Too Dangerous to Make Public | WIRED

<https://www.wired.com/story/ai-text-generator-too-dangerous-to-make-public/> ▾

4 days ago - In 2015, car-and-rocket man Elon Musk joined with influential startup backer Sam Altman to put artificial intelligence on a new, more open ...

Elon Musk-backed AI Company Claims It Made a Text Generator ...

<https://gizmodo.com/elon-musk-backed-ai-company-claims-it-made-a-text-gener-183...> ▾

Elon Musk-backed AI Company Claims It Made a Text Generator That's Too Dangerous to Release · Rhett Jones · Friday 12:15pm · Filed to: OpenAI Filed to: ...

Scientists have made an AI that they think is too dangerous to ...

<https://www.weforum.org/.../amazing-new-ai-churns-out-coherent-paragraphs-of-text/> ▾

3 days ago - Sample outputs suggest that the AI system is an extraordinary step forward, producing text rich with context, nuance and even something ...

New AI Fake Text Generator May Be Too Dangerous To ... - Slashdot

<https://news.slashdot.org/.../new-ai-fake-text-generator-may-be-too-dangerous-to-rele...> ▾

3 days ago - An anonymous reader shares a report: The creators of a revolutionary AI system that can write news stories and works of fiction – dubbed ...

GPT-2: fake news and hype

Top stories



OpenAI built a text generator so good, it's considered too dangerous to release

TechCrunch

11 hours ago



Elon Musk's AI company created a fake news generator it's too scared to make public

BGR.com

9 hours ago



The AI That Can Write A Fake News Story From A Handful Of Words

NDTV.com

2 hours ago

When Is Technology Too Dangerous to Release to the Public?

Slate · 2 days ago



Scientists Developed an AI So Advanced They Say It's Too Dangerous to Release

ScienceAlert · 6 days ago



Different models (2019)

number of parameters, millions

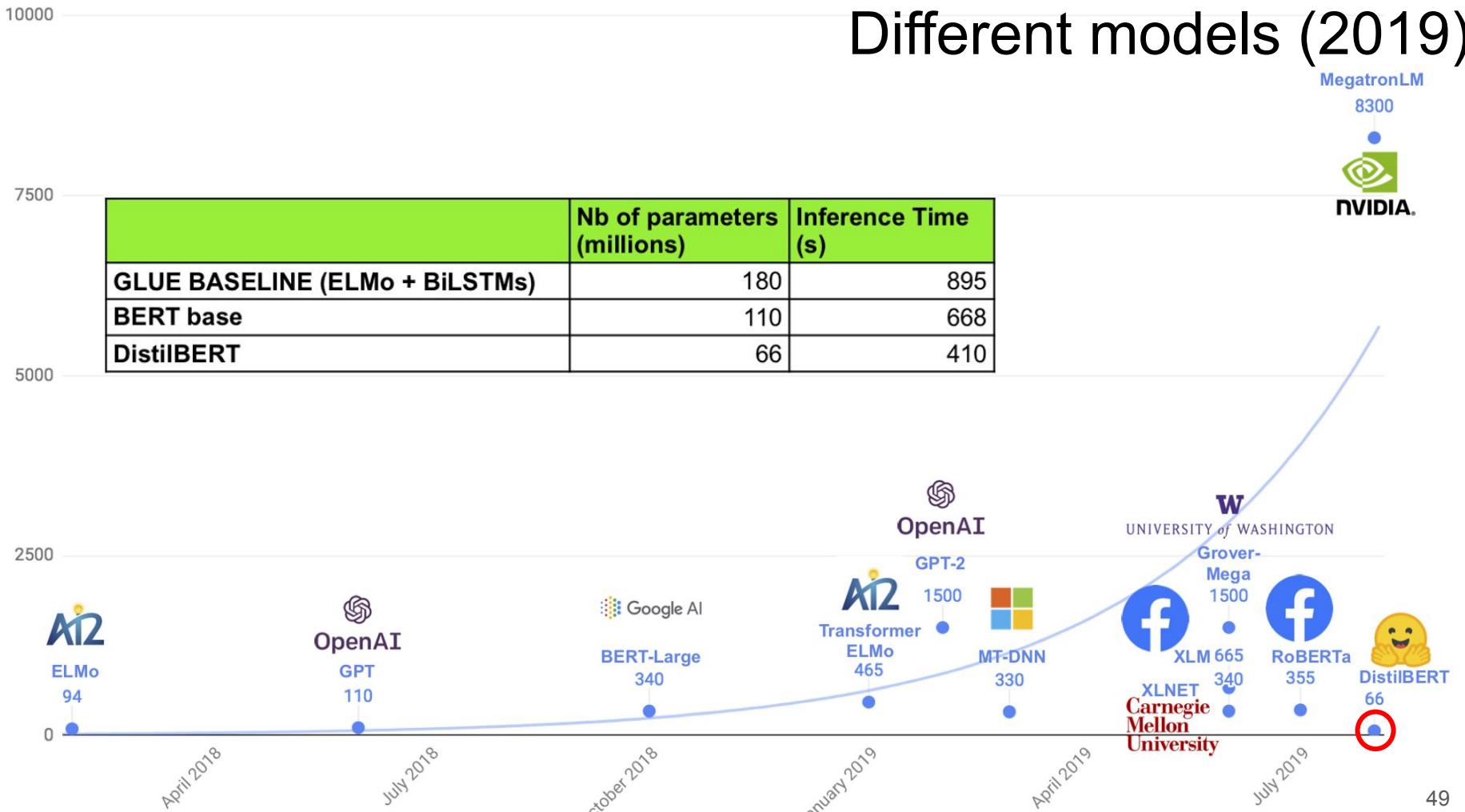
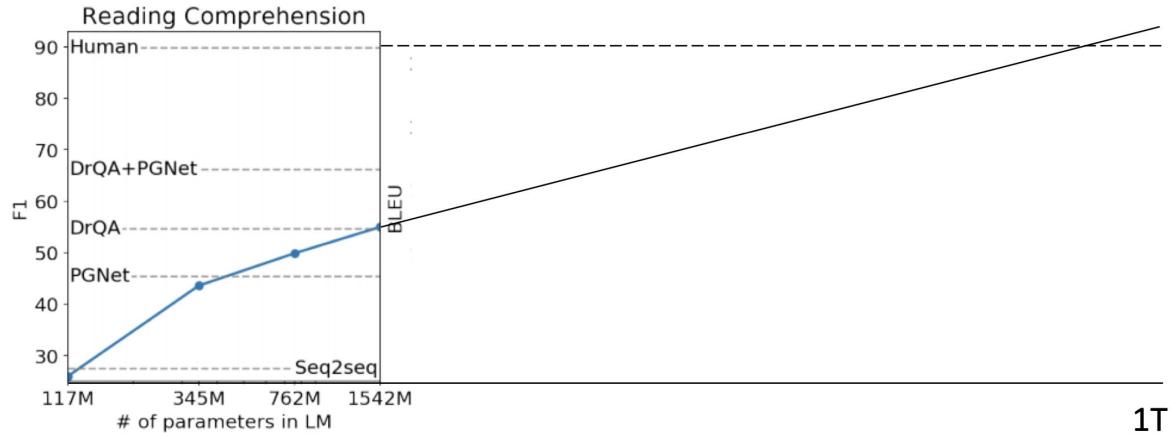
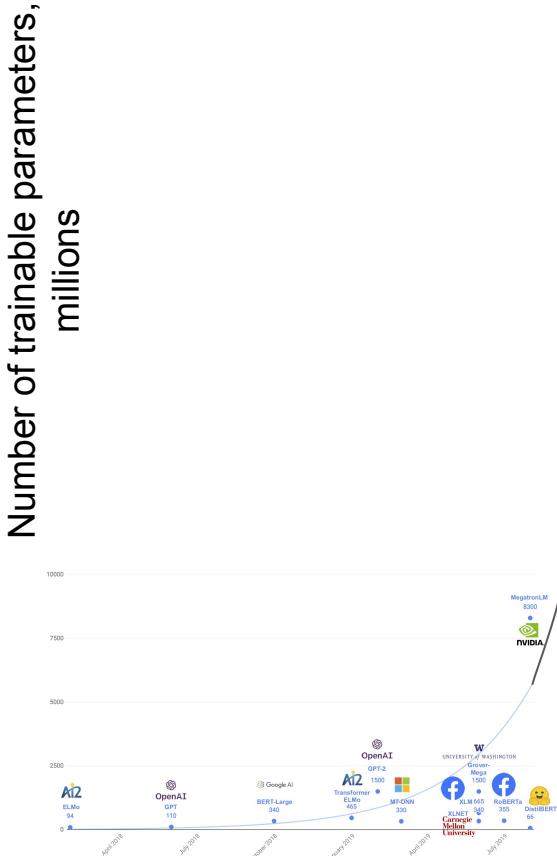


Image source: [Smaller, faster, cheaper, lighter: Introducing DistilBERT, a distilled version of BERT](#)

New achievements: GPT-3

GPT-3, May 2020

Proportions are not preserved for visual sake



Hypothesis from Stanford CS224N Lecture 20 (2019)

- GPT-2: 1.5 billion parameters
- GPT-3: **175 billion** parameters



Geoffrey Hinton @geoffreyhinton · Jun 10

Extrapolating the spectacular performance of GPT3 into the future suggests that the answer to life, the universe and everything is just 4.398 trillion parameters.

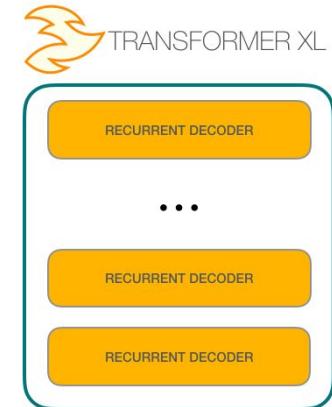
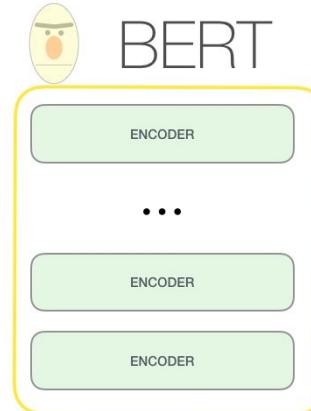
62

643

3.4K



- Transformer
- OpenAI Transformer
- ELMO
- BERT
- BERTology
- GPT
- GPT-2
- GPT-3



- Transfer learning caused a giant leap in Computer Vision and Natural Language Processing
 - Which domain is next?
- Using pre-trained BERT might be a good idea in many tasks
 - Or even using DistillBERT
- Better problem statement leads to better results
 - What information is hidden within the data and can be retrieved?

Backup

ULM-fit: Universal Language Model Fine-tuning for Text Classification

ULMFiT: architecture

- Encoder: AWD-LSTM (ASGD
Weight-Dropped LSTM)

```
SequentialRNN(  
    (0): MultiBatchEncoder(  
        (module): AWD_LSTM(  
            (encoder): Embedding(60003, 300, padding_idx=1)  
            (encoder_dp): EmbeddingDropout(  
                (emb): Embedding(60003, 300, padding_idx=1)  
            )  
            (rnns): ModuleList(  
                (0): WeightDropout(  
                    (module): LSTM(300, 1150, batch_first=True)  
                )  
                (1): WeightDropout(  
                    (module): LSTM(1150, 1150, batch_first=True)  
                )  
                (2): WeightDropout(  
                    (module): LSTM(1150, 300, batch_first=True)  
                )  
            )  
            (input_dp): RNNDropout()  
            (hidden_dps): ModuleList(  
                (0): RNNDropout()  
                (1): RNNDropout()  
                (2): RNNDropout()  
            )  
        )  
    )  
    (1): PoolingLinearClassifier(  
        (layers): Sequential(  
            (0): BatchNorm1d(900, eps=1e-05, momentum=0.1, affine=True,  
track_running_stats=True)  
            (1): Dropout(p=0.4)  
            (2): Linear(in_features=900, out_features=50, bias=True)  
            (3): ReLU(inplace)  
            (4): BatchNorm1d(50, eps=1e-05, momentum=0.1, affine=True,  
track_running_stats=True)  
            (5): Dropout(p=0.1)  
            (6): Linear(in_features=50, out_features=2, bias=True)  
        )  
    )  
)
```

What's the main difference from all the other Sesame street models?

What's the main difference from all the other Sesame street models?



ULMFiT: architecture

- Encoder: AWD-LSTM (ASGD Weight-Dropped LSTM)
- AWD-LSTM literally has dropout at all the possible layers as long as it makes sense.

```
SequentialRNN(  
    (0): MultiBatchEncoder(  
        (module): AWD_LSTM(  
            (encoder): Embedding(60003, 300, padding_idx=1)  
            (encoder_dp): EmbeddingDropout(  
                (emb): Embedding(60003, 300, padding_idx=1)  
            )  
            (rnns): ModuleList(  
                (0): WeightDropout(  
                    (module): LSTM(300, 1150, batch_first=True)  
                )  
                (1): WeightDropout(  
                    (module): LSTM(1150, 1150, batch_first=True)  
                )  
                (2): WeightDropout(  
                    (module): LSTM(1150, 300, batch_first=True)  
                )  
            )  
            (input_dp): RNNDropout()  
            (hidden_dps): ModuleList(  
                (0): RNNDropout()  
                (1): RNNDropout()  
                (2): RNNDropout()  
            )  
        )  
    )  
    (1): PoolingLinearClassifier(  
        (layers): Sequential(  
            (0): BatchNorm1d(900, eps=1e-05, momentum=0.1, affine=True,  
track_running_stats=True)  
            (1): Dropout(p=0.4)  
            (2): Linear(in_features=900, out_features=50, bias=True)  
            (3): ReLU(inplace)  
            (4): BatchNorm1d(50, eps=1e-05, momentum=0.1, affine=True,  
track_running_stats=True)  
            (5): Dropout(p=0.1)  
            (6): Linear(in_features=50, out_features=2, bias=True)  
        )  
    )  
)
```

ULMFiT: encoder dropout

1. **Encoder Dropout (*EmbeddingDropout()*):** Zeroing embedding vectors randomly.

ENCODER DROPOUT				
	before dropout			after dropout
token	d1	d2	...	token
I	0.399	0.75379	0.62616	I
love	0.88533	0.29449	0.15856	love
cats	0.48927	0.04071	0.21427	cats
dogs	0.72918	0.86882	0.77136	dogs

ULMFiT: input dropout

2. Input Dropout (`RNNDropout()`): Zeroing embedding lookup outputs randomly.

INPUT DROPOUT				
batch: [I love cats, I love dogs]				
				before dropout
I	0	0	0	
love	0.88533	0.29449	0.15856	
cats	0.48927	0.04071	0.21427	
				after dropout
I	0	0	0	
love	0	0.29449	0.15856	
cats	0	0.04071	0.21427	
				before dropout
I	0	0	0	
love	0.88533	0.29449	0.15856	
dogs	0.72918	0.86882	0.77136	
				after dropout
I	0	0	0	
love	0.88533	0.29449	0	
dogs	0.72918	0.86882	0	

ULMFiT: dropout

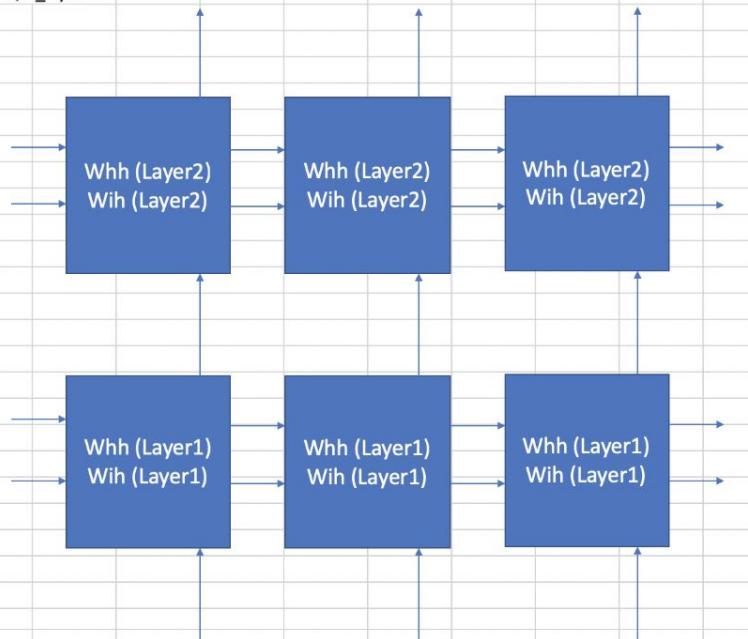
3. Weight Dropout(*WeightDropout()*) : Apply dropout to LSTM weights.

Random dropout at hidden-to-hidden weights for each LSTM layer

```
rnn = nn.LSTM(5,10,1, bidirectional=False, batch_first=True)  
WeightDropout(rnn, weight_p=0.5, layer_names=['weight_hh_10'])
```

ULMFiT: weight dropout

WEIGHT DROPOUT
 $n_{hid}=5, n_{layers}=2$



I	I
0	0
0	0
0	0

love	love
0	0.88533
0.29449	0.29449
0.15856	0

cats	dogs
0	0.72918
0.04071	0.86882
0.21427	0

before dropout

Whh (Layer1)				
0.30546	0.94294	0.66715	0.5655	0.31191
0.06246	0.36674	0.35672	0.53357	0.04652
0.84278	0.17049	0.92283	0.97827	0.67913
0.94699	0.02277	0.79537	0.09479	0.16284
0.34098	0.09256	0.69661	0.22605	0.57153
0.09455	0.78172	0.48226	0.82222	0.25151
0.92516	0.50419	0.82879	0.67049	0.84304
0.11741	0.09362	0.69367	0.5633	0.34755
0.98025	0.73131	0.21491	0.86319	0.31456
0.0289	0.90899	0.30697	0.75105	0.62107
0.96808	0.4712	0.77992	0.83567	0.09754
0.15539	0.94866	0.51977	0.51167	0.08723
0.10944	0.88881	0.74007	0.96823	0.03516
0.62014	0.4363	0.02097	0.61126	0.30466
0.10465	0.02462	0.2334	0.25372	0.54579
0.14384	0.962	0.70157	0.39285	0.41064
0.42081	0.64236	0.06941	0.41805	0.78772
0.45229	0.9871	0.49831	0.17108	0.48868
0.42142	0.66105	0.53273	0.30901	0.45095
0.33421	0.77472	0.33966	0.42693	0.4567

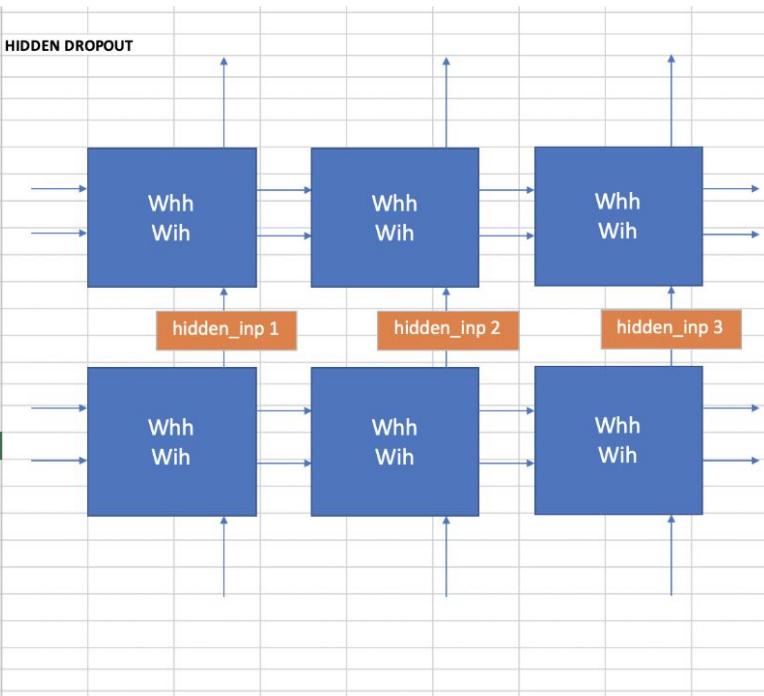
after dropout

Whh (Layer1)				
0.30546	0	0.66715	0.5655	0
0	0.36674	0.35672	0.53357	0.04652
0.84278	0.17049	0.92283	0.97827	0.67913
0.94699	0.02277	0.79537	0.09479	0.16284
0.34098	0.09256	0.69661	0.22605	0.57153
0	0.78172	0.48226	0.82222	0.25151
0	0.50419	0	0.67049	0.84304
0	0.09362	0.69367	0.5633	0
0.98025	0.73131	0	0	0.31456
0	0	0.30697	0.75105	0.62107
0	0	0.77992	0.83567	0.09754
0.15539	0	0.51977	0.51167	0.08723
0.10944	0.88881	0.74007	0.96823	0.03516
0.62014	0.4363	0.02097	0.61126	0.30466
0.10465	0.02462	0.2334	0	0.54579
0	0.962	0.70157	0	0.41064
0	0	0.06941	0.41805	0.78772
0.45229	0.9871	0.49831	0	0.48868
0.42142	0.66105	0.53273	0.30901	0.45095
0	0.77472	0.33966	0.42693	0.4567

same word, different vectors

ULMFiT: hidden dropout

4. Hidden Dropout (`RNNDropout()`): Zeroing outputs of LSTM layers. This dropout is applied except for the last LSTM layer output.



	before dropout									
I	0.11587	0.89354	0.18537	0.13159	0.04328	0.36997	0.68241	0.21505	0.07696	0.1405
love	0.51854	0.94156	0.80541	0.49411	0.44335	0.31453	0.20678	0.95815	0.70224	0.2766
cats	0.41255	0.70882	0.76667	0.93813	0.89034	0.1676	0.92944	0.32216	0.11675	0.99425

	after dropout										
hidden_inp 1	I	0.11587	0	0.18537	0.13159	0	0.36997	0.68241	0	0	0.1405
hidden_inp 2	love	0.51854	0	0.80541	0.49411	0	0.31453	0.20678	0	0	0.2766
hidden_inp 3	cats	0.41255	0	0.76667	0.93813	0	0.1676	0.92944	0	0	0.99425

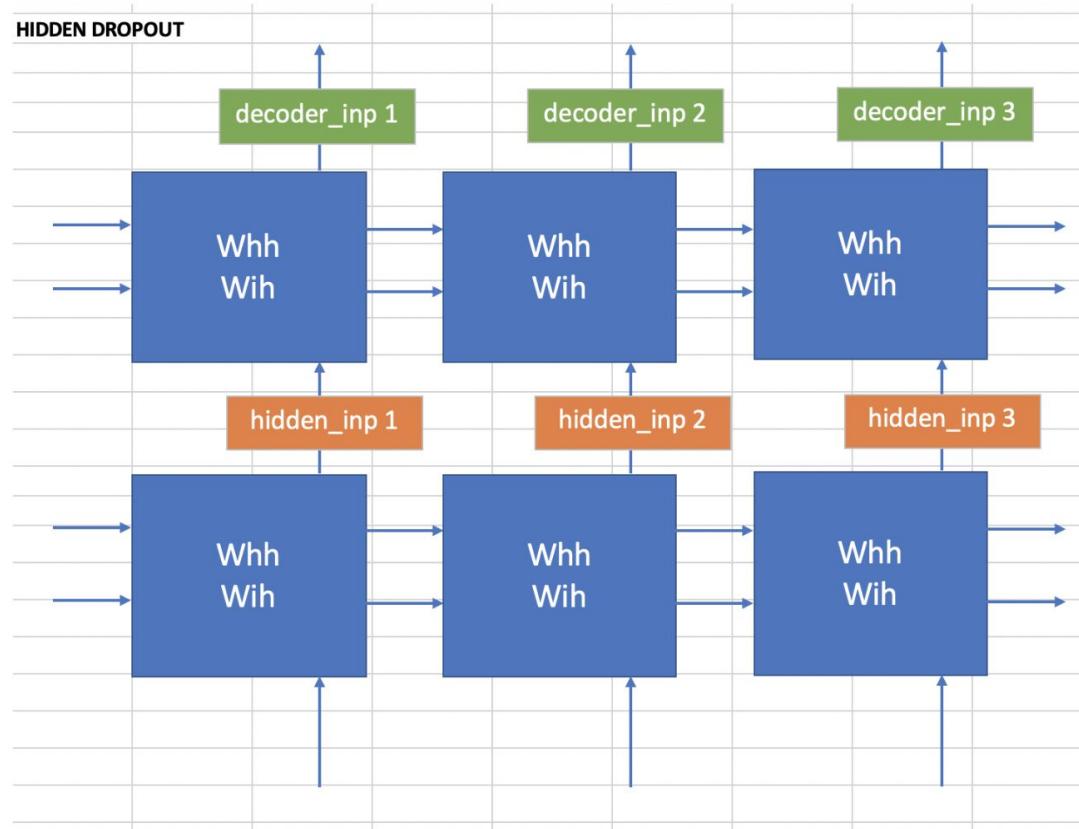
	before dropout									
I	0.90644	0.01673	0.38366	0.86887	0.26845	0.332	0.93804	0.34769	0.83711	0.66387
love	0.82539	0.09143	0.32444	0.35099	0.64491	0.79199	0.24797	0.56466	0.46948	0.33358
dogs	0.38805	0.56548	0.1424	0.31113	0.11645	0.36759	0.73068	0.05727	0.7315	0.01498

	after dropout										
hidden_inp 1	I	0	0	0.38366	0.86887	0	0.332	0	0.34769	0.83711	0.66387
hidden_inp 2	love	0	0	0.32444	0.35099	0	0.79199	0	0.56466	0.46948	0.33358
hidden_inp 3	dogs	0	0	0.1424	0.31113	0	0.36759	0	0.05727	0.7315	0.01498

ULMFiT: output dropout

5. Output Dropout

(*RNNDropout()*): Zeroing final sequence outputs from encoder before feeding it to decoder.



Variable Length BPTT

Fixed window to back-propagate will always have the same words contributing for the update with same weight of gradients flowing from last word to the first

Let's randomize windows selected at each step!

More about BPTT: <https://machinelearningmastery.com/gentle-introduction-backpropagation-time/>

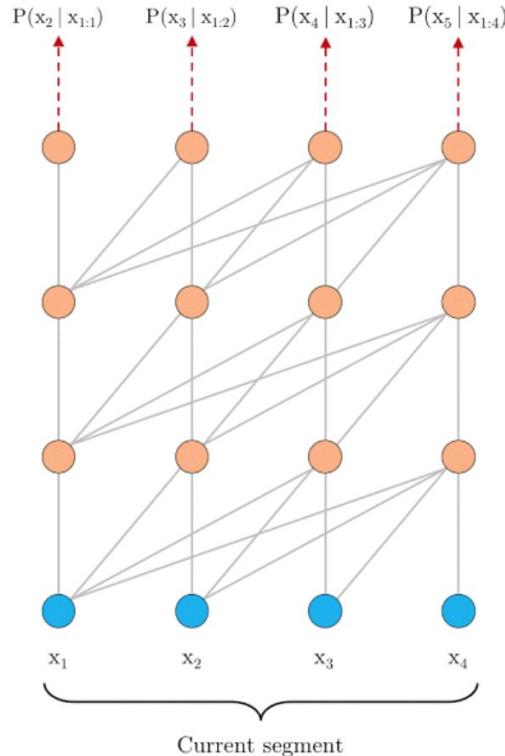
Transformer-XL

- Vanilla Transformer works with a fixed-length context at training time. That's why:
 - the algorithm is not able to model dependencies that are longer than a fixed length.
 - the segments usually do not respect the sentence boundaries, resulting in context fragmentation which leads to inefficient optimization.

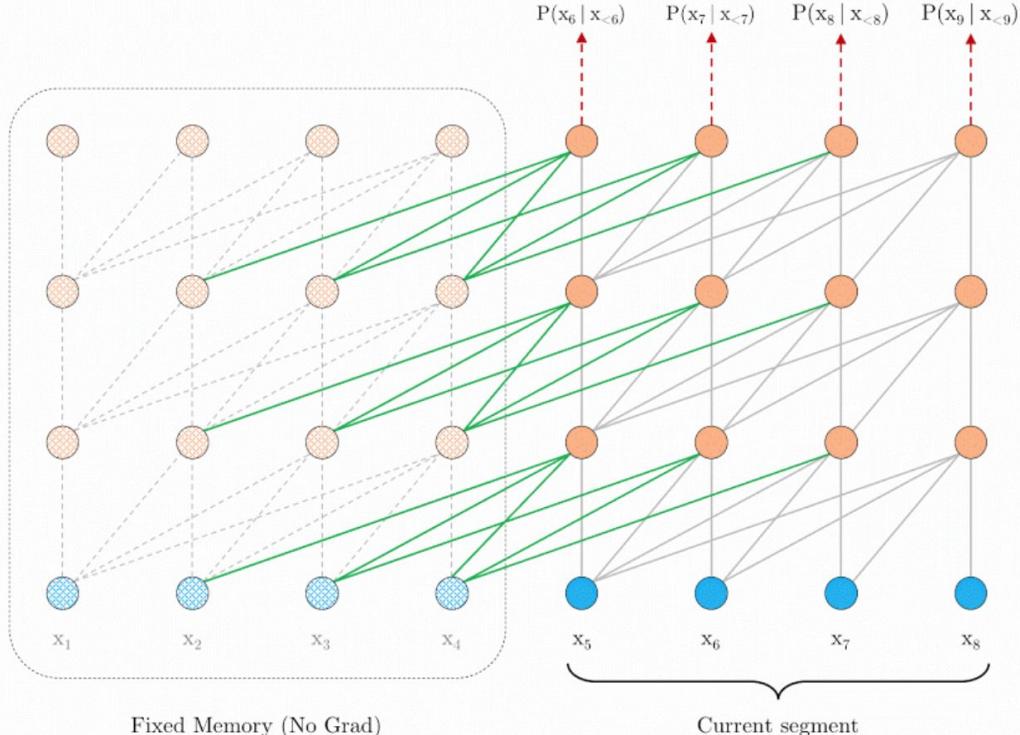
Segment-level Recurrence

- During training, the representations computed for the previous segment are fixed and cached to be reused as an extended context when the model processes the next new segment.
- Contextual information is now able to flow across segment boundaries.
- Recurrence mechanism also resolves the context fragmentation issue, providing necessary context for tokens in the front of a new segment.

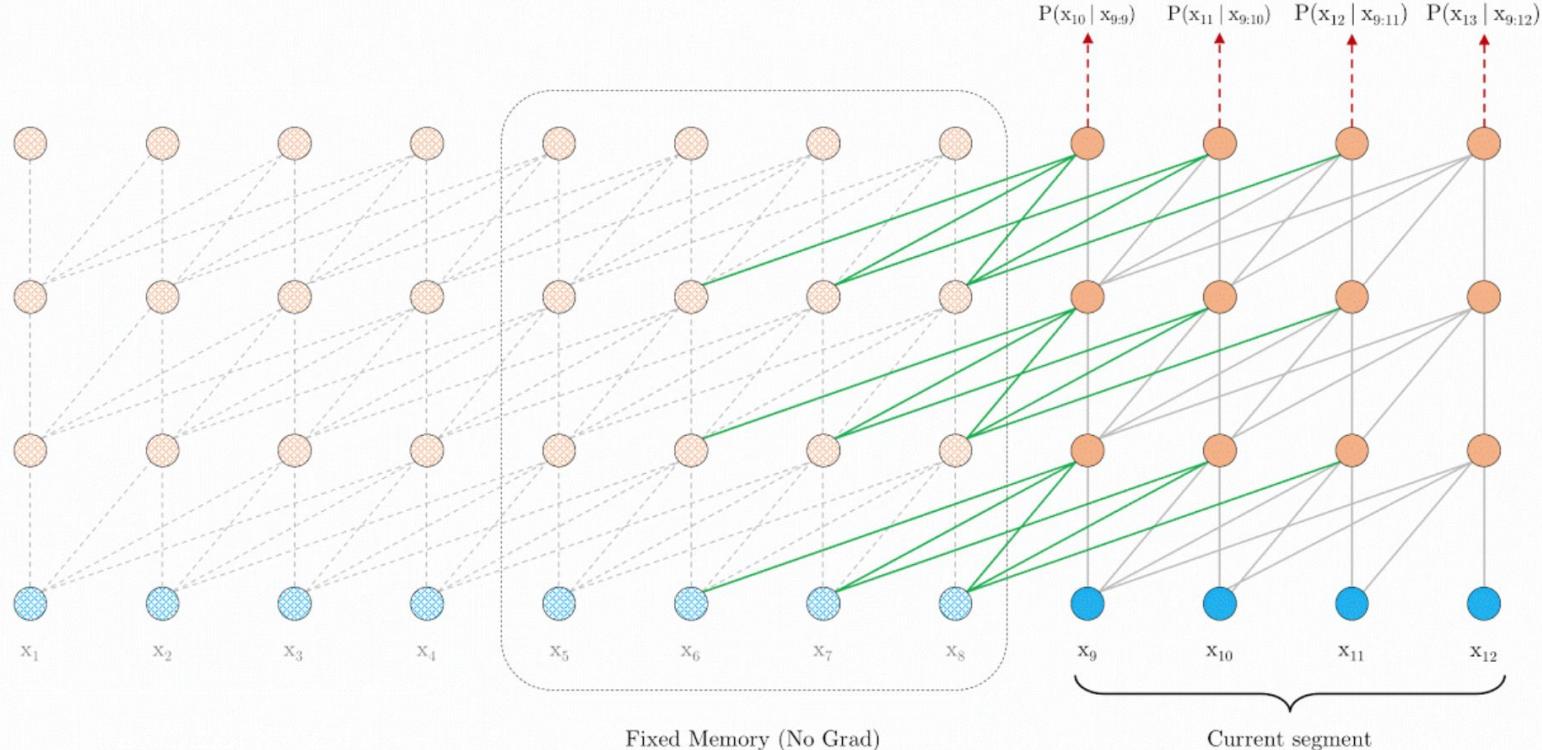
Segment-level Recurrence



Segment-level Recurrence



Segment-level Recurrence



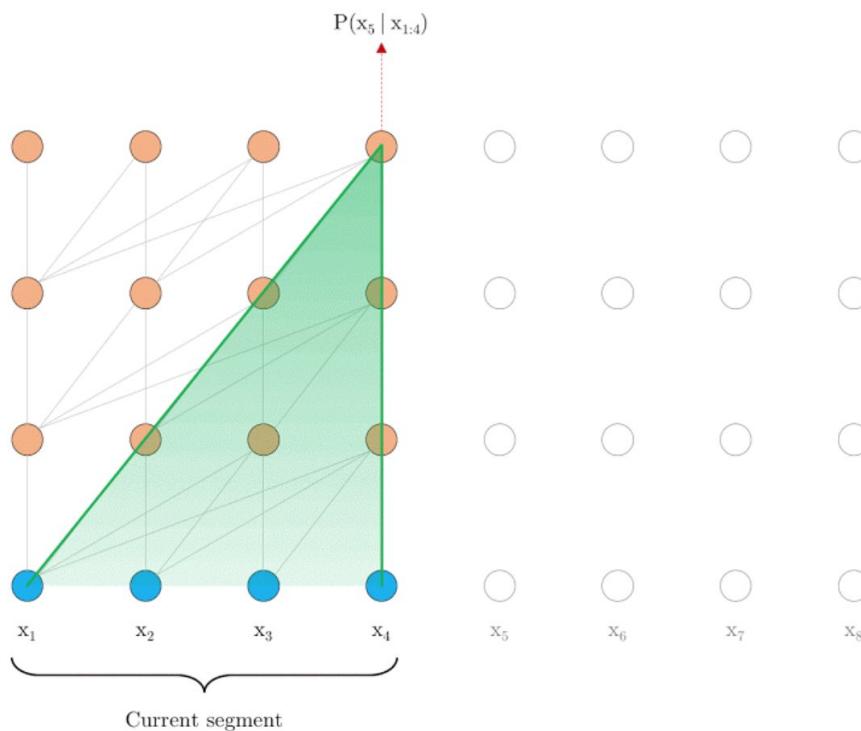
Relative Positional Encodings

- Fixed embeddings with learnable transformations instead of learnable embeddings

As a result:

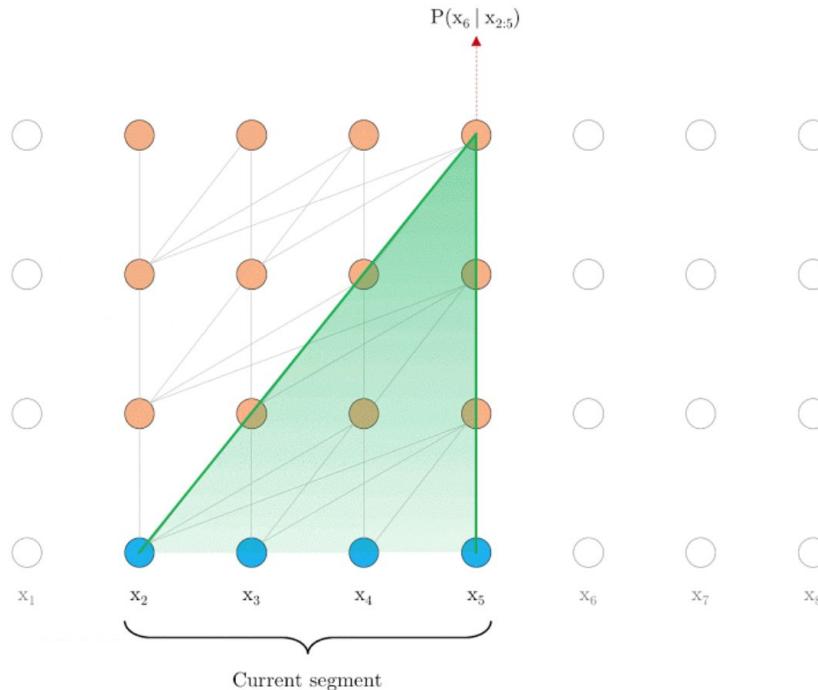
- more generalizable to longer sequences at test time
- longer effective context

Vanilla Transformer vs. Transformer-XL



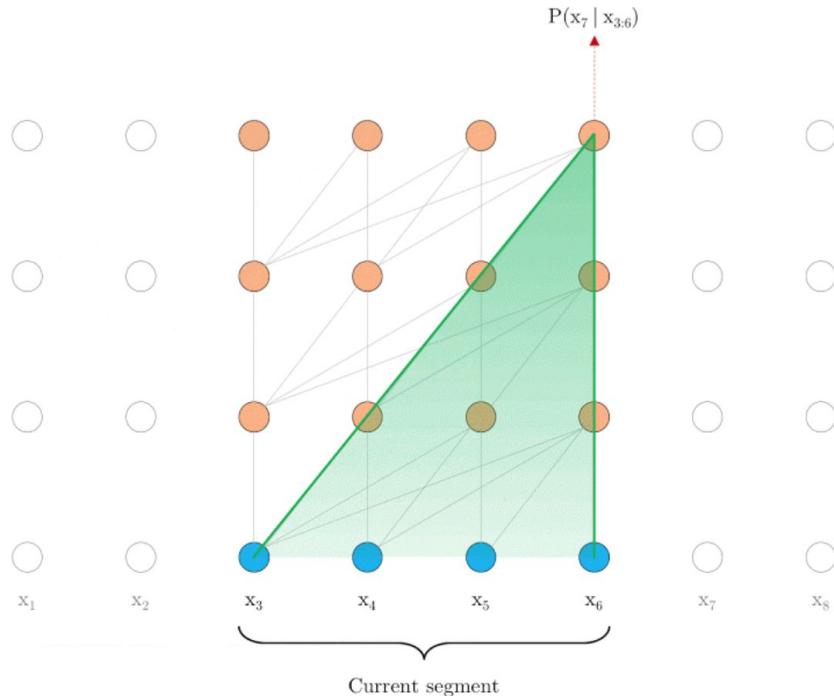
Vanilla Transformer with a fixed-length context at evaluation time

Vanilla Transformer vs. Transformer-XL



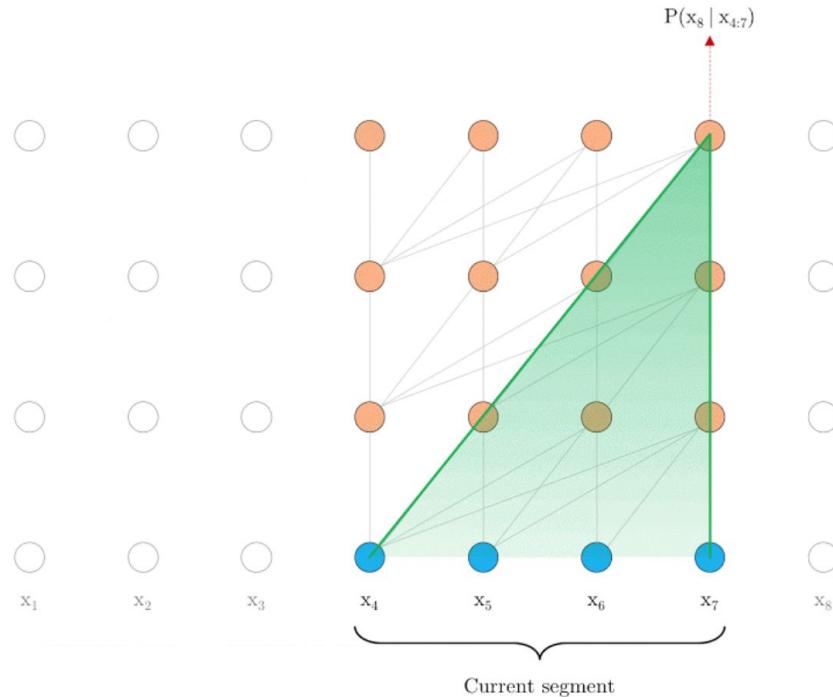
Vanilla Transformer with a fixed-length context at evaluation time

Vanilla Transformer vs. Transformer-XL



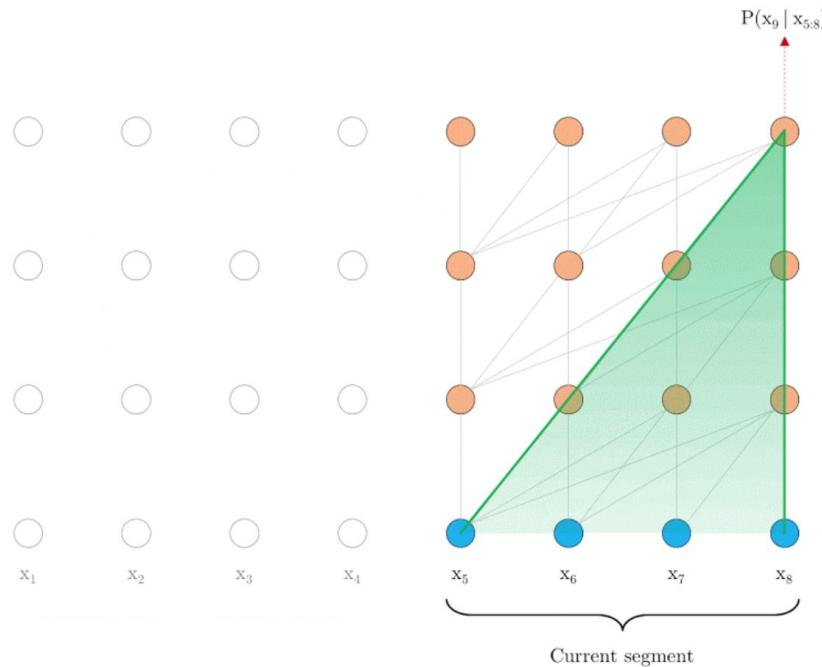
Vanilla Transformer with a fixed-length context at evaluation time

Vanilla Transformer vs. Transformer-XL



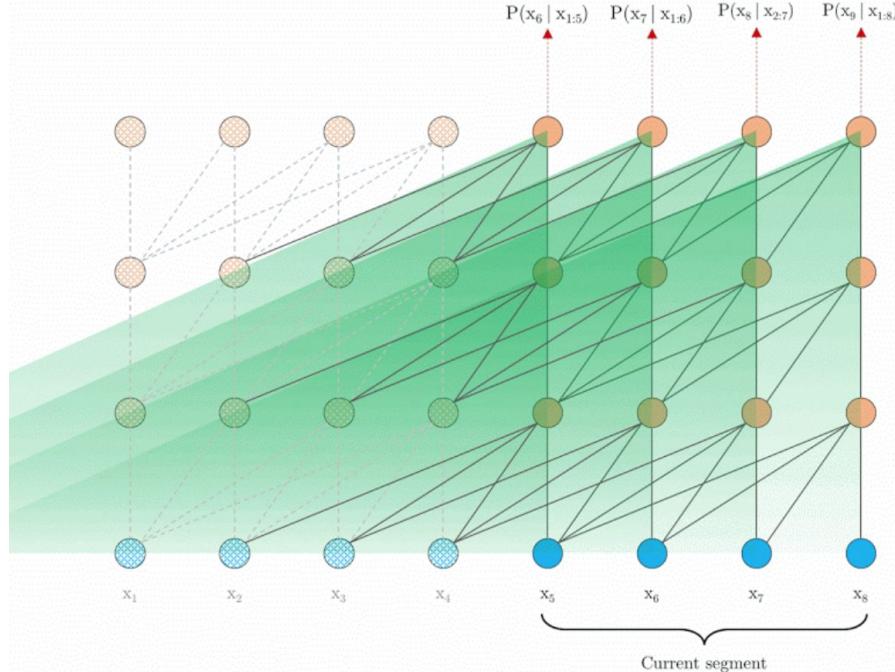
Vanilla Transformer with a fixed-length context at evaluation time

Vanilla Transformer vs. Transformer-XL



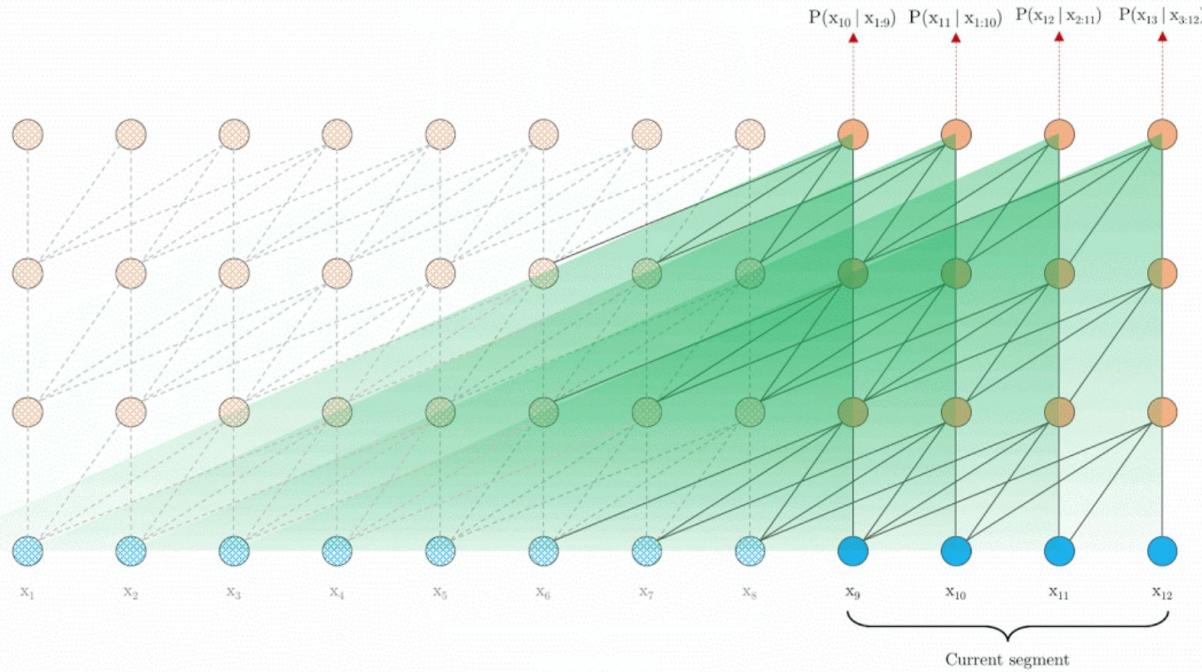
Vanilla Transformer with a fixed-length context at evaluation time

Vanila Transformer vs. Transformer-XL



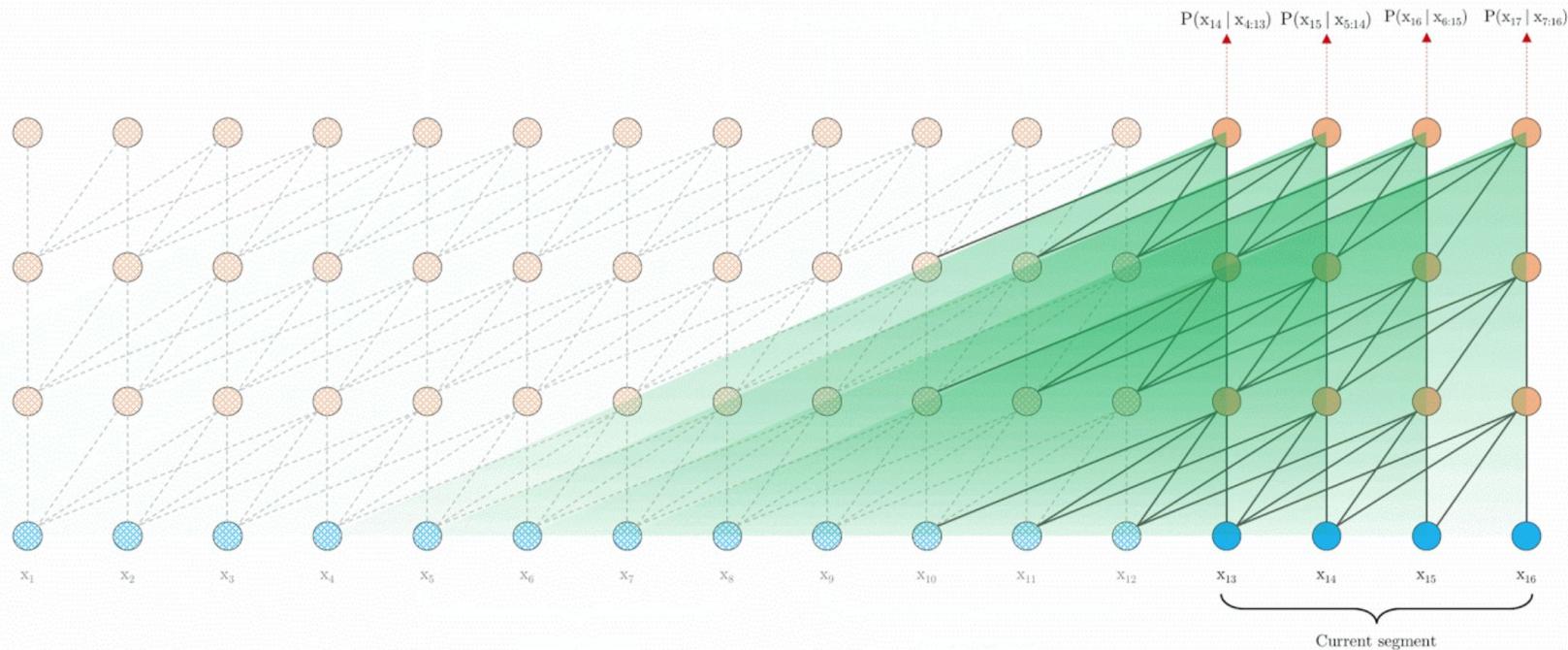
Transformer-XL with segment-level recurrence at evaluation time

Vanila Transformer vs. Transformer-XL



Transformer-XL with segment-level recurrence at evaluation time

Vanila Transformer vs. Transformer-XL



Transformer-XL with segment-level recurrence at evaluation time

Vanila Transformer vs. Transformer-XL

- Transformer-XL learns dependency that is about 80% longer than RNNs and 450% longer than vanilla Transformers
- Transformer-XL is up to 1,800+ times faster than a vanilla Transformer during evaluation on language modeling tasks, because no re-computation is needed