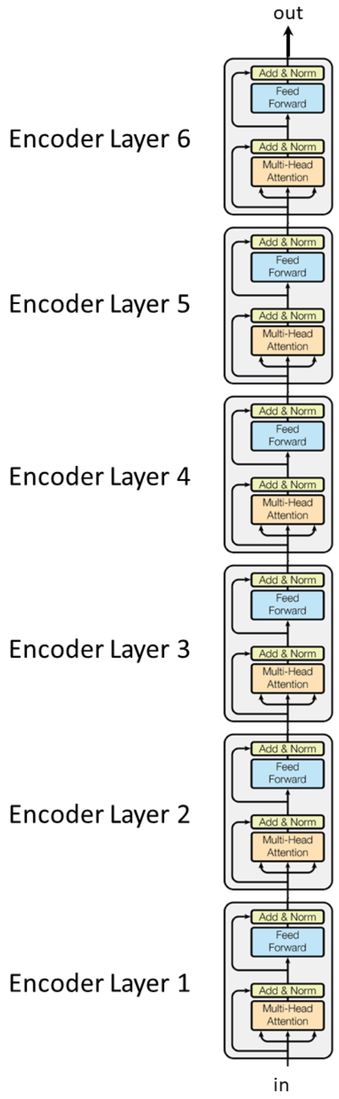
COS 484

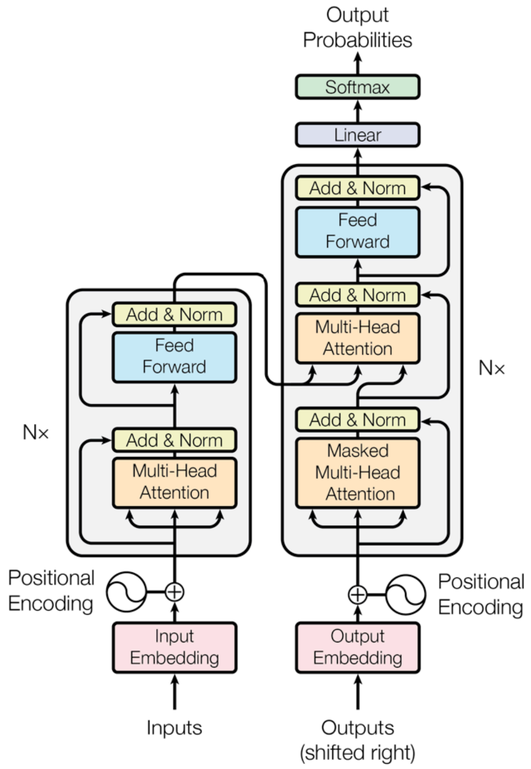
Natural Language Processing

L15: Contextualized Embeddings and Pre-training

Spring 2022

Recap: Transformer





- Both encoder and decoder consist of *N* layers
- Each encoder layer has two sub-layers
  - Multi-head **self**-attention
  - FeedForward
- Each decoder layer has three sub-layers
  - Masked multi-head **self**-attention
  - Multi-head **cross**-attention
  - FeedForward
- Decoder: generate output probabilities for predicting next word

Vaswani et al., 2017: Attention Is All You Need

Transformers: machine translation

Model	BLEU		Training Cost (FLOPs)	
	EN-DE	EN-FR	EN-DE	EN-FR
ByteNet [15]	23.75			
Deep-Att + PosUnk [32]		39.2		$1.0 \cdot 10^{20}$
GNMT + RL [31]	24.6	39.92	$2.3 \cdot 10^{19}$	$1.4 \cdot 10^{20}$
ConvS2S [8]	25.16	40.46	$9.6 \cdot 10^{18}$	$1.5 \cdot 10^{20}$
MoE [26]	26.03	40.56	$2.0 \cdot 10^{19}$	$1.2 \cdot 10^{20}$
Deep-Att + PosUnk Ensemble [32]		40.4		$8.0 \cdot 10^{20}$
GNMT + RL Ensemble [31]	26.30	41.16	$1.8 \cdot 10^{20}$	$1.1 \cdot 10^{21}$
ConvS2S Ensemble [8]	26.36	**41.29**	$7.7 \cdot 10^{19}$	$1.2 \cdot 10^{21}$
Transformer (base model)	27.3	38.1	**$3.3 \cdot 10^{18}$**	
Transformer (big)	**28.4**	**41.0**	$2.3 \cdot 10^{19}$	

Vaswani et al., 2017: Attention Is All You Need

- ELMo = **E**mbeddings from **L**anguage **Mo**dels
- GPT = **G**enerative **P**re-**T**raining
- BERT = **B**idirectional **E**ncoder **R**epresentations from **T**ransformers

Deep contextualized word representations
ME Peters, M Neumann, M Iyyer, M Gardner… - arXiv preprint arXiv …, 2018 - arxiv.org
We introduce a new type of deep contextualized word representation that models both (1) complex characteristics of word use (eg, syntax and semantics), and (2) how these uses vary across linguistic contexts (ie, to model polysemy). Our word vectors are learned functions of …
☆ Cited by 6367 Related articles All 20 versions »

Bert: Pre-training of **deep bidirectional transformers** for **language understanding**
J Devlin, MW Chang, K Lee, K Toutanova - arXiv preprint arXiv …, 2018 - arxiv.org
We introduce a new **language** representation model called BERT, which stands for **Bidirectional** Encoder Representations from **Transformers**. Unlike recent **language** representation models, BERT is designed to pre-train **deep bidirectional** representations …
☆ Cited by 17552 Related articles All 26 versions »

[PDF] Improving language understanding by **generative pre-training**
A **Radford**, K Narasimhan, T Salimans, I Sutskever - **2018** - cs.ubc.ca
Natural language understanding comprises a wide range of diverse tasks such as textual entailment, question answering, semantic similarity assessment, and document classification. Although large unlabeled text corpora are abundant, labeled data for learning these specific tasks is scarce, making it challenging for discriminatively trained models to perform adequately. We demonstrate that large gains on these tasks can be realized by generative pre-training of a language model on a diverse corpus of unlabeled text, followed …
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Today's key concepts

- Contextualized word embeddings
- Transformer-based language models
- Pre-training and fine-tuning

What's wrong with word2vec?

- One vector for each word type

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

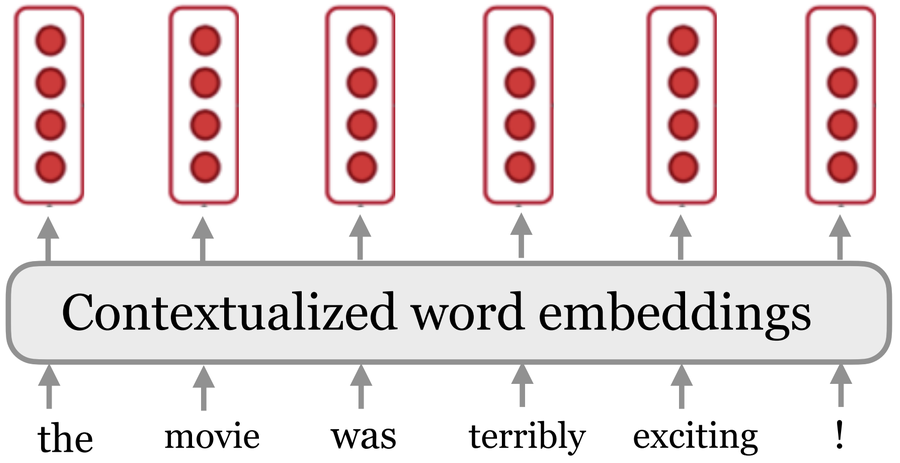
- Complex characteristics of word use: syntax and semantics

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

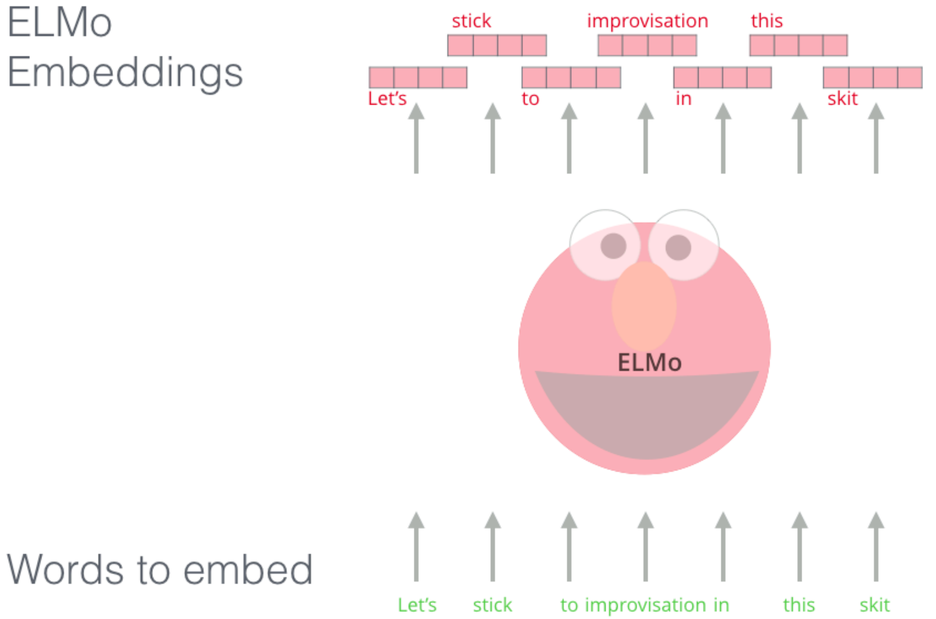
mouse^{1} : .... a *mouse* controlling a computer system in 1968.
mouse^{2} : .... a quiet animal like a *mouse*
bank^{1} : ...a *bank* can hold the investments in a custodial account ...
bank^{2} : ...as agriculture burgeons on the east *bank*, the river ...

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

Sent #1: Chico Ruiz made a spectacular **play** on Alusik's grounder {. . . } $v(\text{play}) = ?$

Sent #2: Olivia De Havilland signed to do a Broadway **play** for Garson {. . . } $v(\text{play}) = ?$

Sent #3: Kieffer was commended for his ability to hit in the clutch , as well as his all-round excellent **play** {. . . } $v(\text{play}) = ?$

Sent #4: {. . . } they were actors who had been handed fat roles in a successful **play** {. . . } $v(\text{play}) = ?$

Sent #5: Concepts **play** an important role in all aspects of cognition {. . . } $v(\text{play}) = ?$

Contextualized word embeddings

	Source	Nearest Neighbors
GloVe	play	playing, game, games, played, players, plays, player, Play, football, multiplayer
biLM	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 .

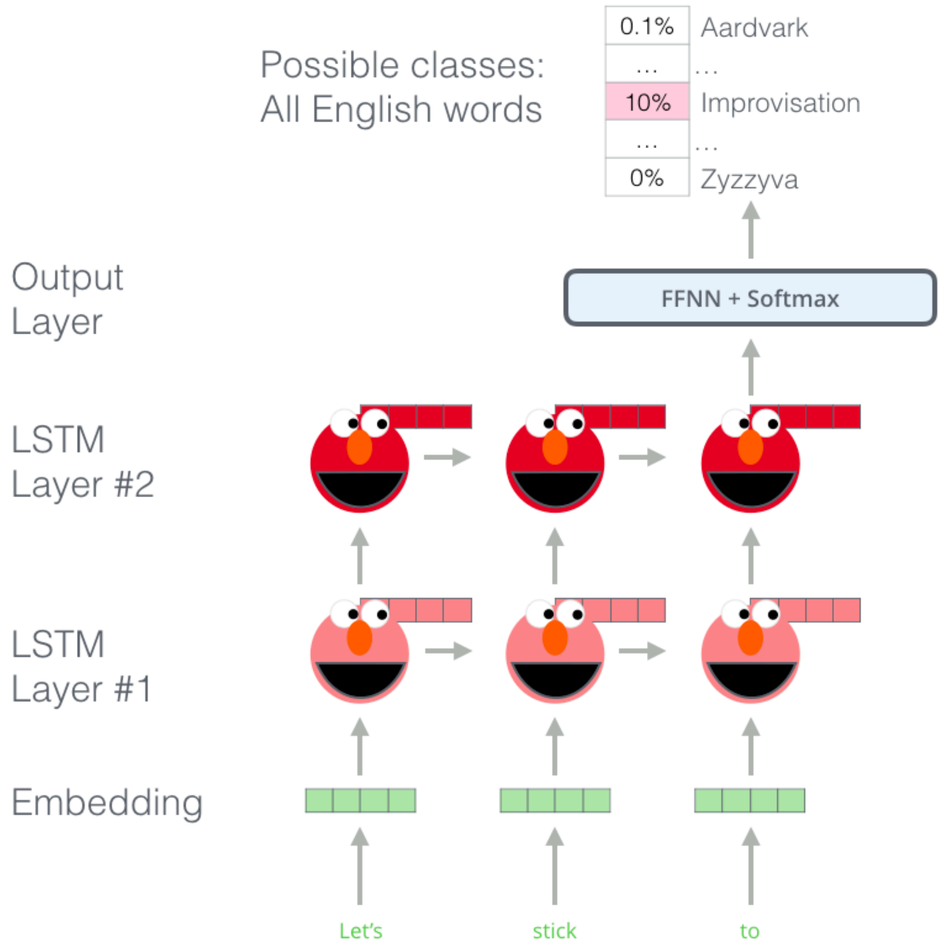
(Peters et al, 2018): Deep contextualized word representations

How can we get these contextualized embeddings?

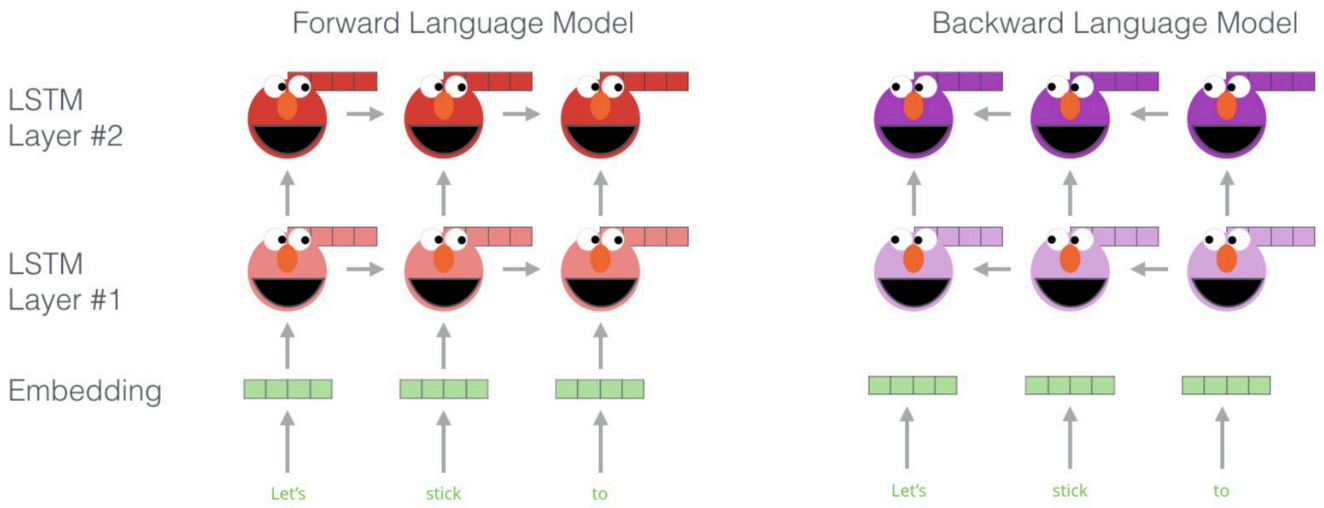
The key idea of ELMo:

- Train *two* stacked LSTM-based language models on a **large** corpus
- Use the **hidden states** of the LSTMs for each token to compute a vector representation of each word

Q: Why use the hidden representations of language models?



How can we get these contextualized embeddings?



words in the sentence

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

input embeddings = output embeddings

How to get ELMo embeddings?

input embeddings

hidden states

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

# of layers

$$
\mathbf{h}_{k,0}^{lM} = \mathbf{x}_k^{LM}, \mathbf{h}_{k,j}^{LM} = [\overrightarrow{\mathbf{h}}_{k,j}^{LM}; \overleftarrow{\mathbf{h}}_{k,j}^{LM}]
$$

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

- γ^{task}: allows the task model to scale the entire ELMo vector
- s_j^{task}: softmax-normalized weights across layers

Both are parameters to be learned

How to get ELMo embeddings?

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

Q: Why use both forward and backward language models?

Because it is important to model both left and right context!

Bidirectionality is VERY crucial in language understanding tasks!

Q: Why use the weighted average of different layers instead of just the top layer?

Because different layers are expected to encode different information.

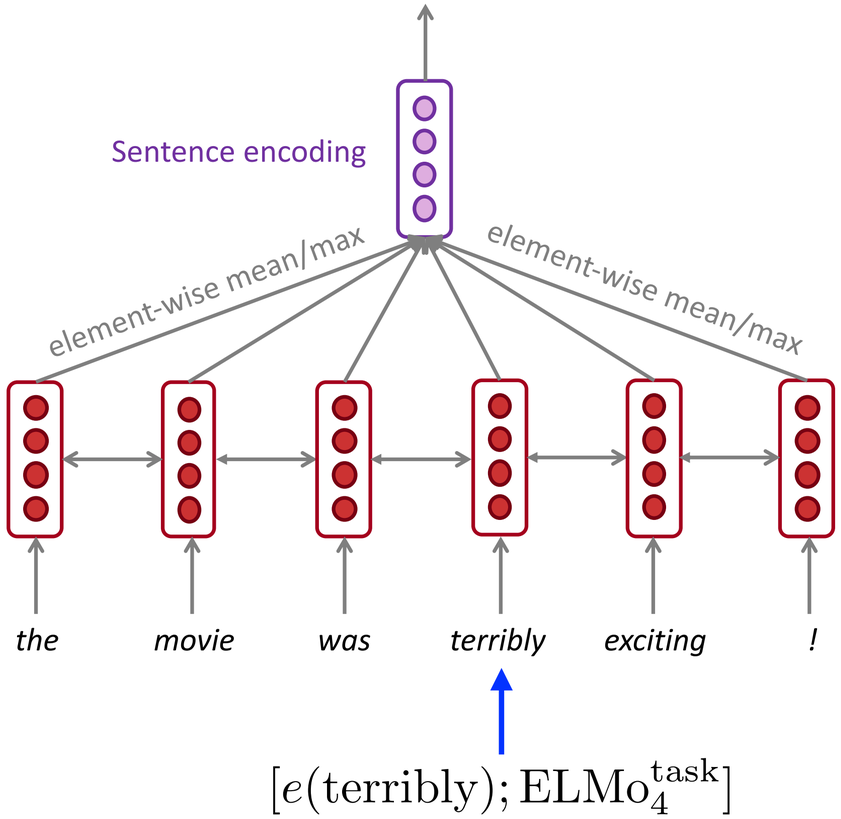
We will see some examples soon!

ELMo: pre-training and the use

- Data: 10 epoches on 1B Word Benchmark (trained on **single sentences**)
- **Pre-training** time: 2 weeks on 3 NVIDIA GTX 1080 GPUs
  - Much lower time cost if we used V100s / Google's TPUs but still hundreds of dollars in compute cost to train once
  - Larger BERT models trained on more data costs $10k+
- How to apply ELMo in practice?
  - Take the embeddings $f : (w_1, w_2, \ldots, w_n) \longrightarrow \mathbf{x}_1, \ldots, \mathbf{x}_n \in \mathbb{R}^d$ and feed them into any neural models just like word2vec
  - The LM's hidden states are *fixed* and not updated during the downstream use (only the scaling and softmax weights are learned)
  - Common practice: concatenate word2vec/GloVe with ELMo

ELMo: pre-training and the use

Example: A BiLSTM model for sentiment classification



What is pre-training?

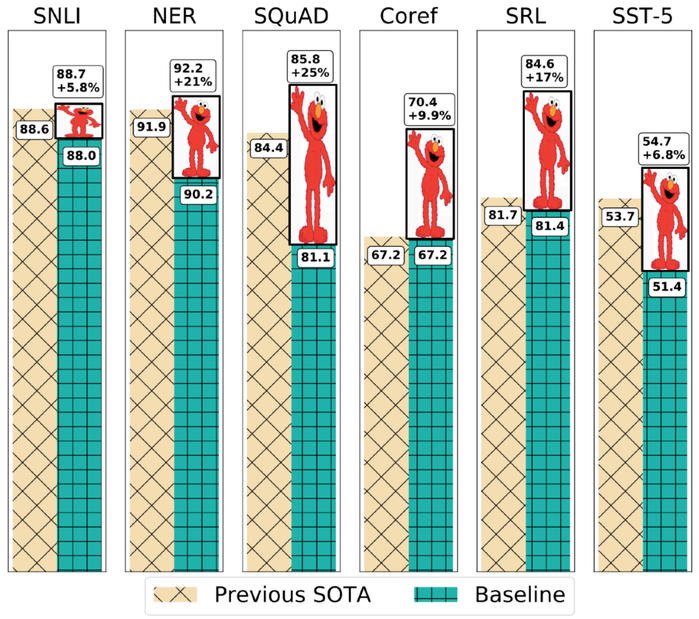
- “Pre-train” a model on a large dataset for task X, then “fine-tune” it on a dataset for task Y
- Key idea: X is somewhat related to Y, so a model that can do X will have some good neural representations for Y as well
- ImageNet pre-training is huge in computer vision: learning generic visual features for recognizing objects
- Word2vec can be seen as pre-training: learn vectors with the skip-gram objective on large dataset (task X), then use them as a part of a neural network for sentiment classification or any other task (task Y)

Slide credit: Greg Durrett

ELMo: Experimental results

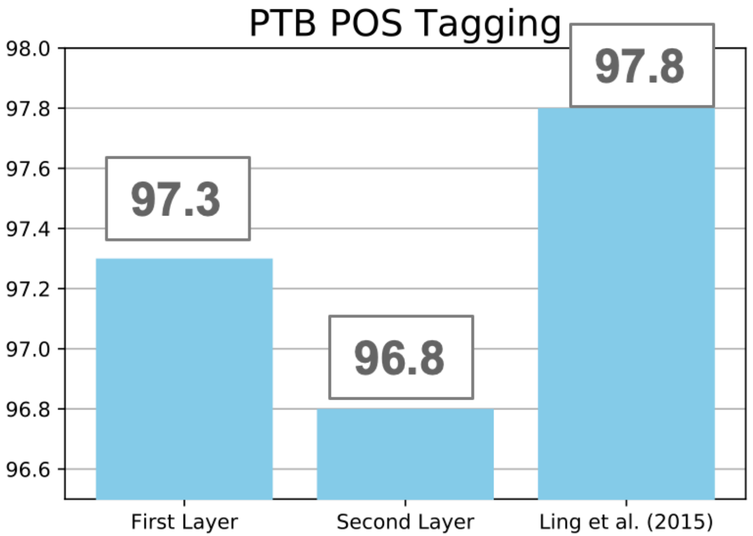
Task	Previous SOTA		Our baseline	ELMo + baseline	Increase (absolute/ relative)
SQuAD	Liu et al. (2017)	84.4	81.1	85.8	4.7 / 24.9%
SNLI	Chen et al. (2017)	88.6	88.0	88.7 ± 0.17	0.7 / 5.8%
SRL	He et al. (2017)	81.7	81.4	84.6	3.2 / 17.2%
Coref	Lee et al. (2017)	67.2	67.2	70.4	3.2 / 9.8%
NER	Peters et al. (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%

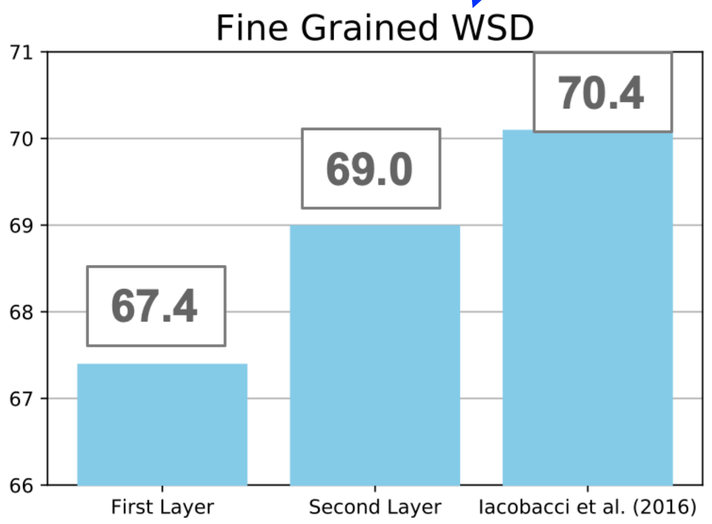
- SQuAD: question answering
- SNLI: natural language inference
- SRL: semantic role labeling
- Coref: coreference resolution
- NER: named entity recognition
- SST-5: sentiment analysis



What information does ELMo encode?

WSD = word sense disambiguation





First Layer > Second Layer

Second Layer > First Layer

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

Use ELMo models

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

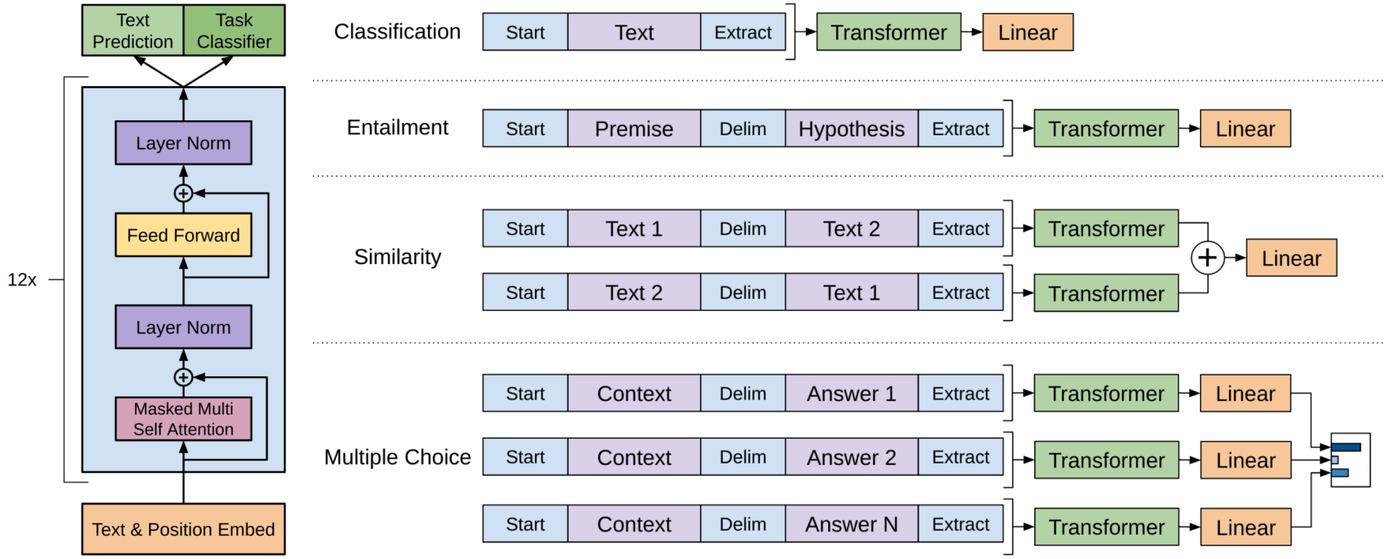
```
from allennlp.modules.elmo import Elmo, batch_to_ids

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)
```

Pre-training is expensive but it only needs to be done once!

People can download the pre-trained models and use them in their downstream applications.

Generative Pre-Training (GPT)

- Use Transformers instead of LSTMs
- Trained on longer segments of text (**512 word-piece tokens**), not just single sentences
  - Capture longer-range dependencies
- Use language modeling as a pre-training objective
- “Fine-tune” the entire set of model parameters on various downstream tasks
  - Use task-specific prompt formats

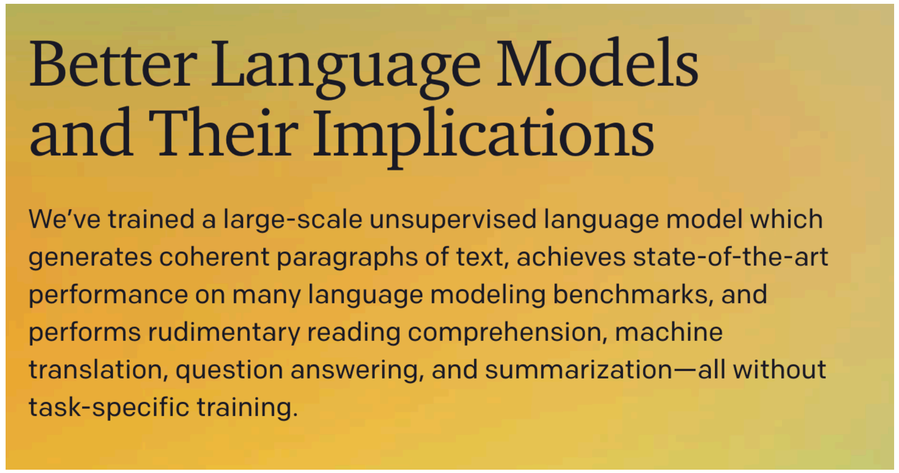


Results on downstream tasks

Method	Classification		Semantic Similarity			GLUE
	CoLA (mc)	SST2 (acc)	MRPC (F1)	STSB (pc)	QQP (F1)	
Sparse byte mLSTM [16]	-	**93.2**	-	-	-	-
TF-KLD [23]	-	-	**86.0**	-	-	-
ECNU (mixed ensemble) [60]	-	-	-	81.0	-	-
Single-task BiLSTM + ELMo + Attn [64]	35.0	90.2	80.2	55.5	66.1	64.8
Multi-task BiLSTM + ELMo + Attn [64]	18.9	91.6	83.5	72.8	63.3	68.9
Finetuned Transformer LM (ours)	**45.4**	91.3	82.3	**82.0**	**70.3**	**72.8**

Scaling up GPT to GPT-2

- Train GPT language model on 40 GB of internet text
- Really good generative model of language
- Surprising zero-shot abilities



Generation examples

SYSTEM PROMPT (HUMAN-WRITTEN)

A train carriage containing controlled nuclear materials was stolen in Cincinnati today. Its whereabouts are unknown.

MODEL COMPLETION (MACHINE-WRITTEN, FIRST TRY)

The incident occurred on the downtown train line, which runs from Covington and Ashland stations.

In an email to Ohio news outlets, the U.S. Department of Energy said it is working with the Federal Railroad Administration to find the thief.

"The theft of this nuclear material will have significant negative consequences on public and environmental health, our workforce and the economy of our nation," said Tom Hicks, the U.S. Energy Secretary, in a statement. "Our top priority is to secure the theft and ensure it doesn't happen again."

The stolen material was taken from the University of Cincinnati's Research Triangle Park nuclear research site, according to a news release from Department officials.

The Nuclear Regulatory Commission did not immediately release any information.

According to the release, the U.S. Department of Energy's Office of Nuclear Material Safety and Security is leading that team's investigation.

"The safety of people, the environment and the nation's nuclear stockpile is our highest priority," Hicks said. "We will get to the bottom of this and make no excuses.

SYSTEM PROMPT (HUMAN-WRITTEN)

In a shocking finding, scientist discovered a herd of unicorns living in a remote, previously unexplored valley, in the Andes Mountains. Even more surprising to the researchers was the fact that the unicorns spoke perfect English.

MODEL COMPLETION (MACHINE-WRITTEN, 10 TRIES)

The scientist named the population, after their distinctive horn, Ovid's Unicorn. These four-horned, silver-white unicorns were previously unknown to science.

Now, after almost two centuries, the mystery of what sparked this odd phenomenon is finally solved.

Dr. Jorge Pérez, an evolutionary biologist from the University of La Paz, and several companions, were exploring the Andes Mountains when they found a small valley, with no other animals or humans. Pérez noticed that the valley had what appeared to be a natural fountain, surrounded by two peaks of rock and silver snow.

Pérez and the others then ventured further into the valley. "By the time we reached the top of one peak, the water looked blue, with some crystals on top," said Pérez.

Pérez and his friends were astonished to see the unicorn herd. These creatures could be seen from the air without having to move too much to see them – they were so close they could touch their horns.

While examining these bizarre creatures the scientists discovered that the creatures also spoke some fairly regular English. Pérez stated, "We can see, for example, that they have a common 'language,' something like a dialect or dialectic."

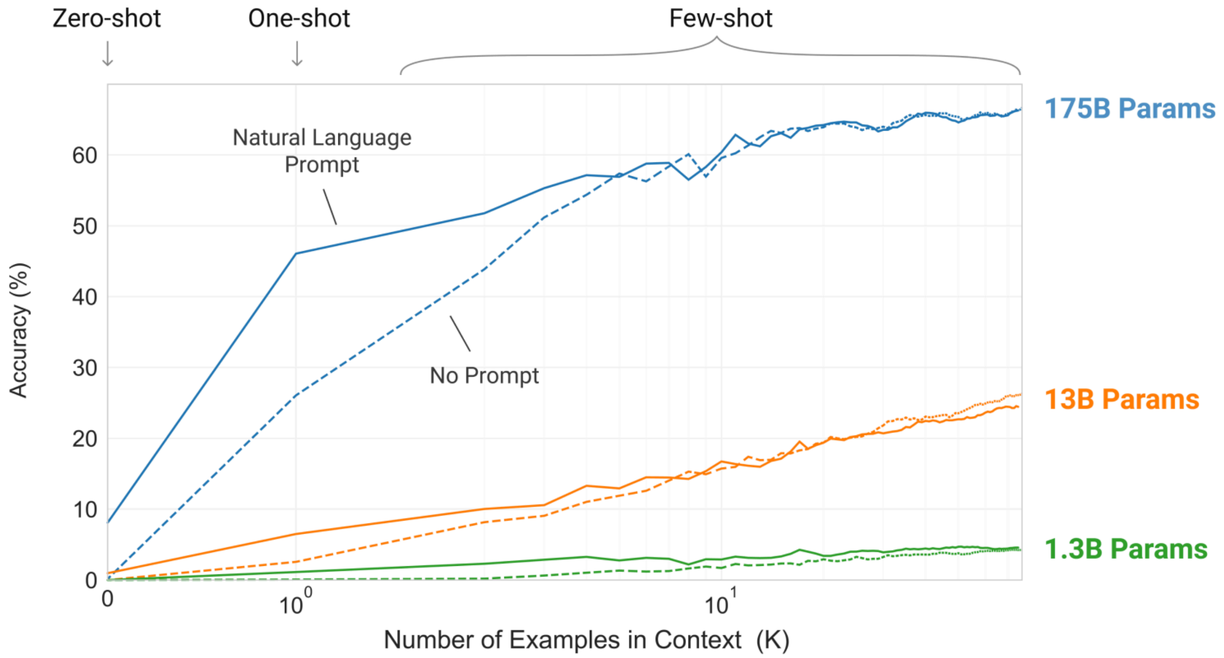
Dr. Pérez believes that the unicorns may have originated in Argentina, where the animals were believed to be descendants of a lost race of people who lived there before the arrival of humans in those parts of South America.

Zero-shot task performance

DATASET	METRIC	OUR RESULT	PREVIOUS RECORD	HUMAN
Winograd Schema Challenge	accuracy (+)	**70.70%**	63.7%	92%+
LAMBADA	accuracy (+)	**63.24%**	59.23%	95%+
LAMBADA	perplexity (–)	**8.6**	99	~1-2
Children's Book Test Common Nouns (validation accuracy)	accuracy (+)	**93.30%**	85.7%	96%
Children's Book Test Named Entities (validation accuracy)	accuracy (+)	**89.05%**	82.3%	92%
Penn Tree Bank	perplexity (–)	**35.76**	46.54	unknown
WikiText-2	perplexity (–)	**18.34**	39.14	unknown
enwik8	bits per character (–)	**0.93**	0.99	unknown
text8	bits per character (–)	**0.98**	1.08	unknown
WikiText-103	perplexity (–)	**17.48**	18.3	unknown

Scaling even further - GPT-3

- Massive language model - 175 billion parameters
- Very impressive zero-shot capabilities
- Adapt models to downstream tasks through natural language ‘prompting’



GPT-3

- In-context ‘learning’: Provide the model with a few input-output examples relevant to the task
- No updates to parameters of the model
- Started a new direction around ‘prompt engineering’

Zero-shot

The model predicts the answer given only a natural language description of the task. No gradient updates are performed.

```
1  Translate English to French:        ← task description
2  cheese =>                           ← prompt
```

GPT-3

- In-context ‘learning’: Provide the model with a few input-output examples relevant to the task
- No updates to parameters of the model
- Started a new direction around ‘prompt/context engineering’
  - Alternative to fine-tuning models

One-shot

In addition to the task description, the model sees a single example of the task. No gradient updates are performed.

```
1  Translate English to French:        ← task description
2  sea otter => loutre de mer          ← example
3  cheese =>                           ← prompt
```

Few-shot

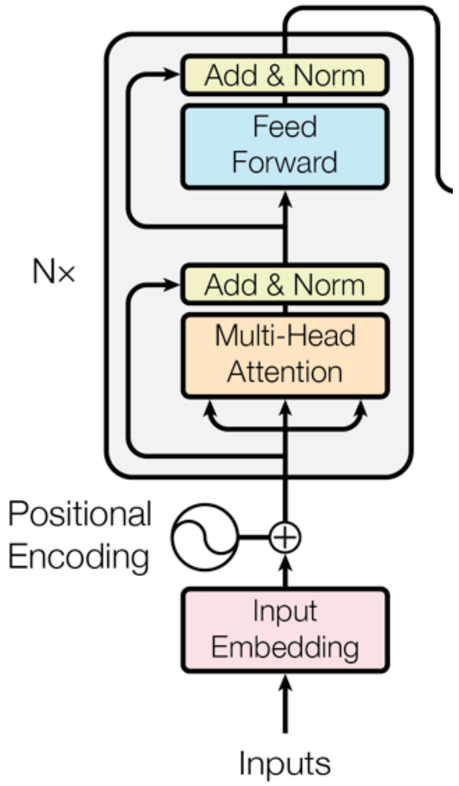
In addition to the task description, the model sees a few examples of the task. No gradient updates are performed.

```
1  Translate English to French:        ← task description
2  sea otter => loutre de mer          ← examples
3  peppermint => menthe poivrée        ←
4  plush girafe => girafe peluche      ←
5  cheese =>                           ← prompt
```

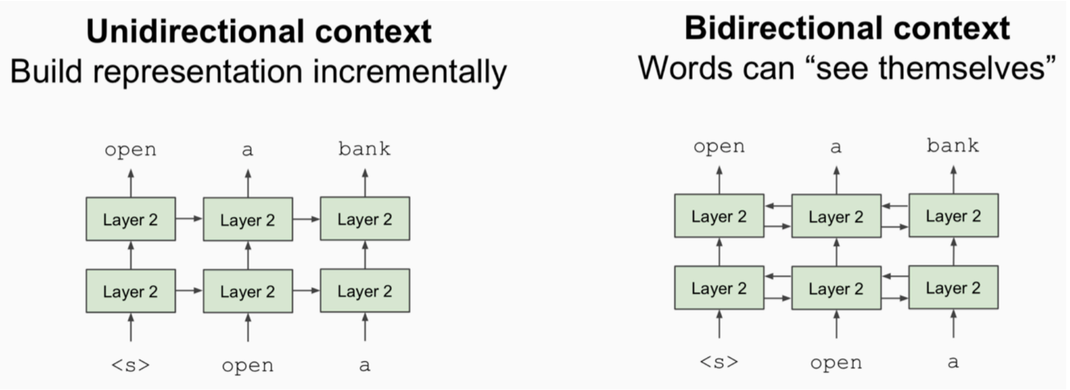
What is BERT?

- Use a bidirectional encoder instead of a unidirectional Transformer language model
- Two new pre-training objectives:
  - **Masked language model (MLM)**
  - Next sentence prediction (NSP)
    - Later work shows that NSP hurts performance, so we omit it here
- Use entire set of BERT parameters for fine-tuning, instead of word embeddings

Bidirectional encoder



- Let's use a Transformer encoder with self-attention
- Language models only use left context or right context (although ELMo used two independent LMs from each direction).



- If the word "a" is already seen, what to predict then?
- How can we build good representations that allow us to see both sides?

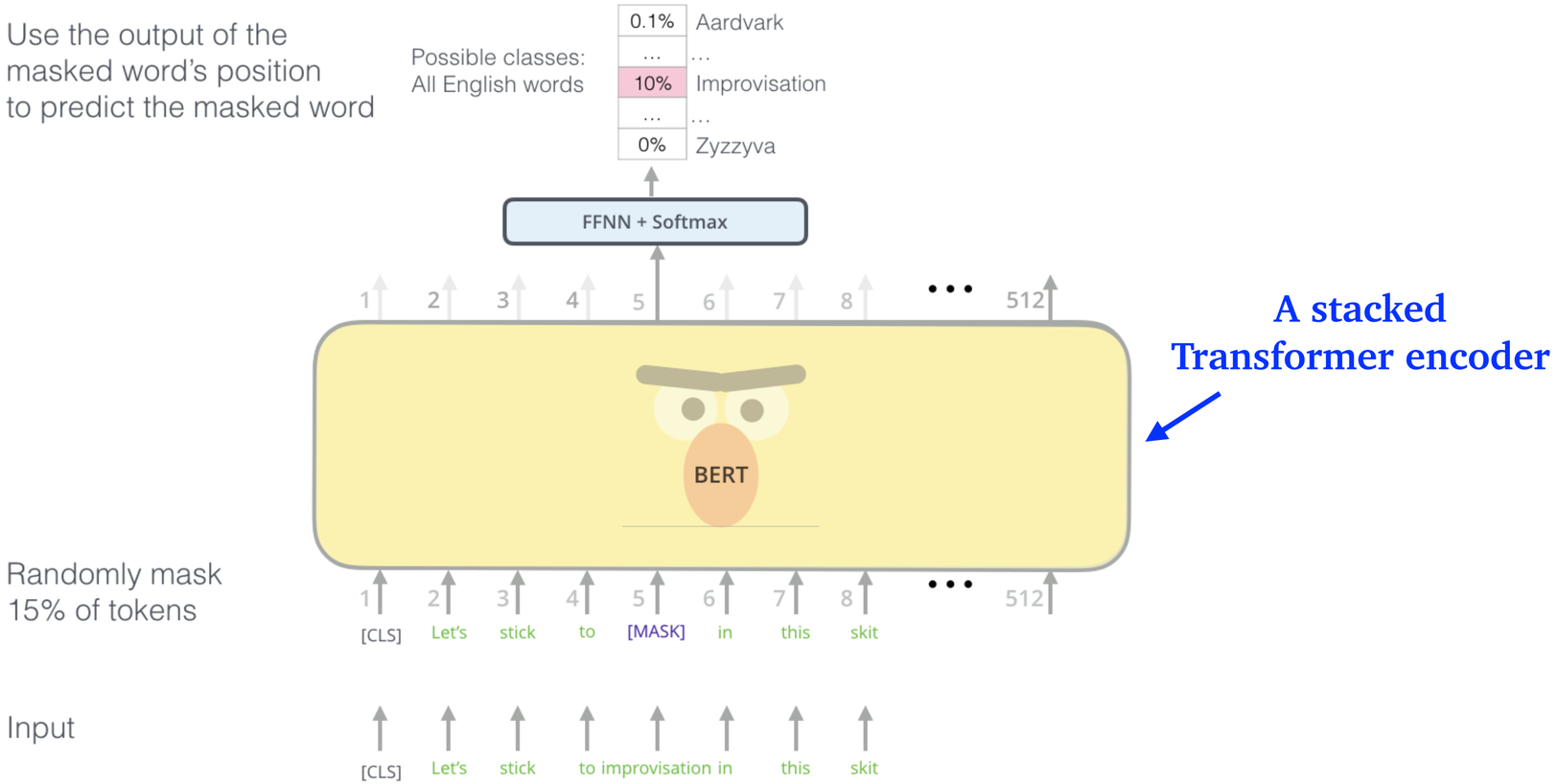
Key idea: masked language model (MLM)

- Solution: let's mask out 15% of the input words, and then predict the masked words

Q: Why 15%?

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

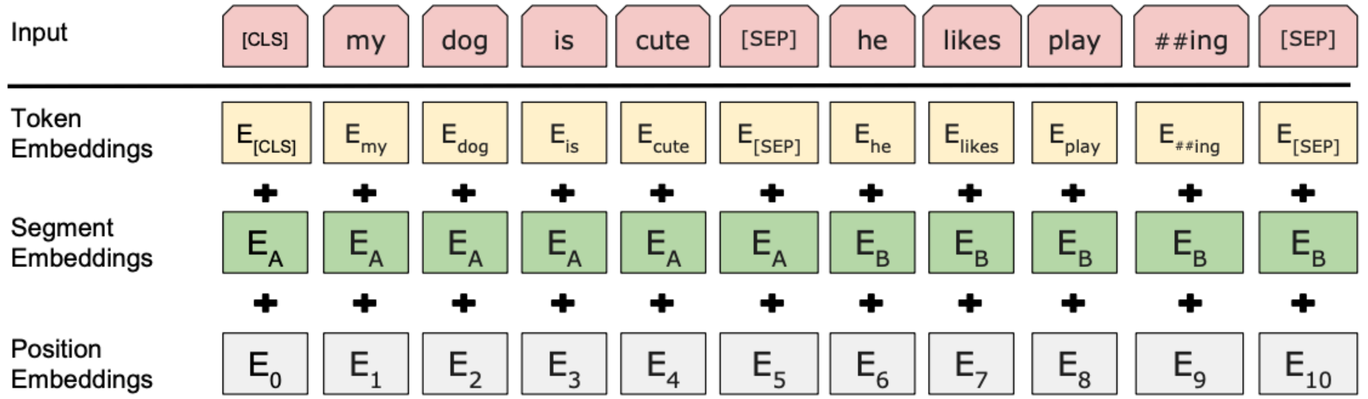
Key idea: masked language model (MLM)



Caveat: the actual sampling process is a bit more complicated than this. Check out the paper for details!

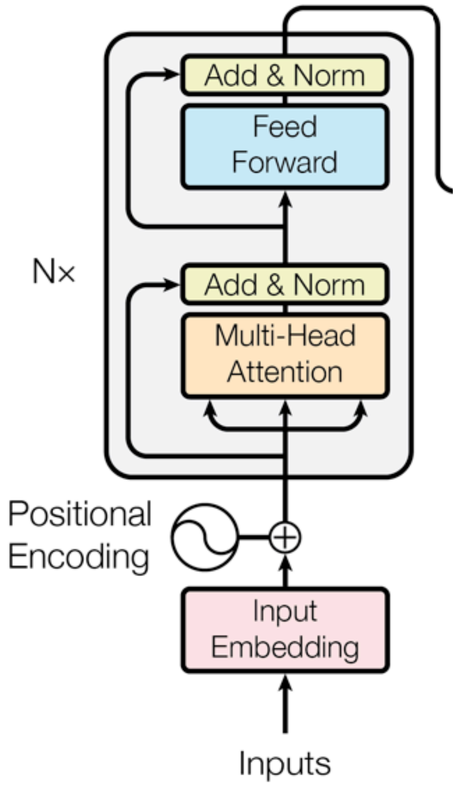
BERT: pre-training

- Input representations



- Segment length: 512 BPE (=byte pair encoding) tokens
- Trained 40 epochs on Wikipedia (2.5B tokens) + BookCorpus (0.8B tokens)
- Released two model sizes: BERT_base, BERT_large

BERT: model sizes



- **BERT$_{BASE}$**: L=12, H=768, A=12, Total Parameters=110M
- **BERT$_{LARGE}$**: L=24, H=1024, A=16, Total Parameters=340M

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

BERT: ablation studies

Tasks	Dev Set MNLI-m (Acc)	QNLI (Acc)	MRPC (Acc)	SST-2 (Acc)	SQuAD (F1)
$\text{BERT}_{\text{BASE}}$	84.4	88.4	86.7	92.7	88.5
No NSP	83.9	84.9	86.5	92.6	87.9
LTR & No NSP	82.1	84.3	77.5	92.1	77.8
+ BiLSTM	82.1	84.1	75.7	91.6	84.9

Unidirectional LMs

Table 5: Ablation over the pre-training tasks using the $\text{BERT}_{\text{BASE}}$ architecture. "No NSP" is trained without the next sentence prediction task. "LTR & No NSP" is trained as a left-to-right LM without the next sentence prediction, like OpenAI GPT. "+ BiLSTM" adds a randomly initialized BiLSTM on top of the "LTR + No NSP" model during fine-tuning.

Hyperparams				Dev Set Accuracy		
#L	#H	#A	LM (ppl)	MNLI-m	MRPC	SST-2
3	768	12	5.84	77.9	79.8	88.4
6	768	3	5.24	80.6	82.2	90.7
6	768	12	4.68	81.9	84.8	91.3
12	768	12	3.99	84.4	86.7	92.9
12	1024	16	3.54	85.7	86.9	93.3
24	1024	16	3.23	86.6	87.8	93.7

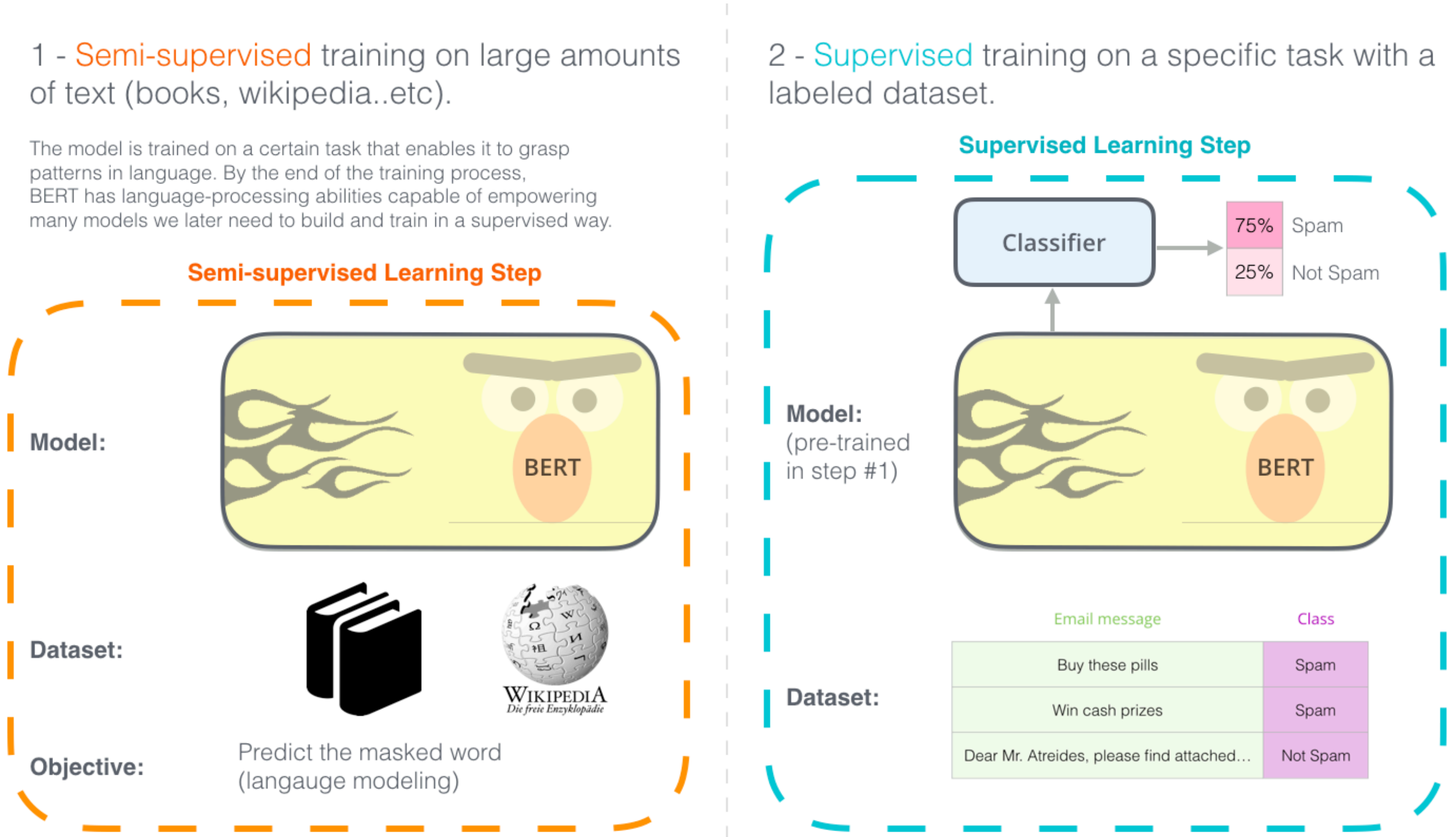
Table 6: Ablation over BERT model size. #L = the number of layers; #H = hidden size; #A = number of attention heads. "LM (ppl)" is the masked LM perplexity of held-out training data.

The bigger, the better..

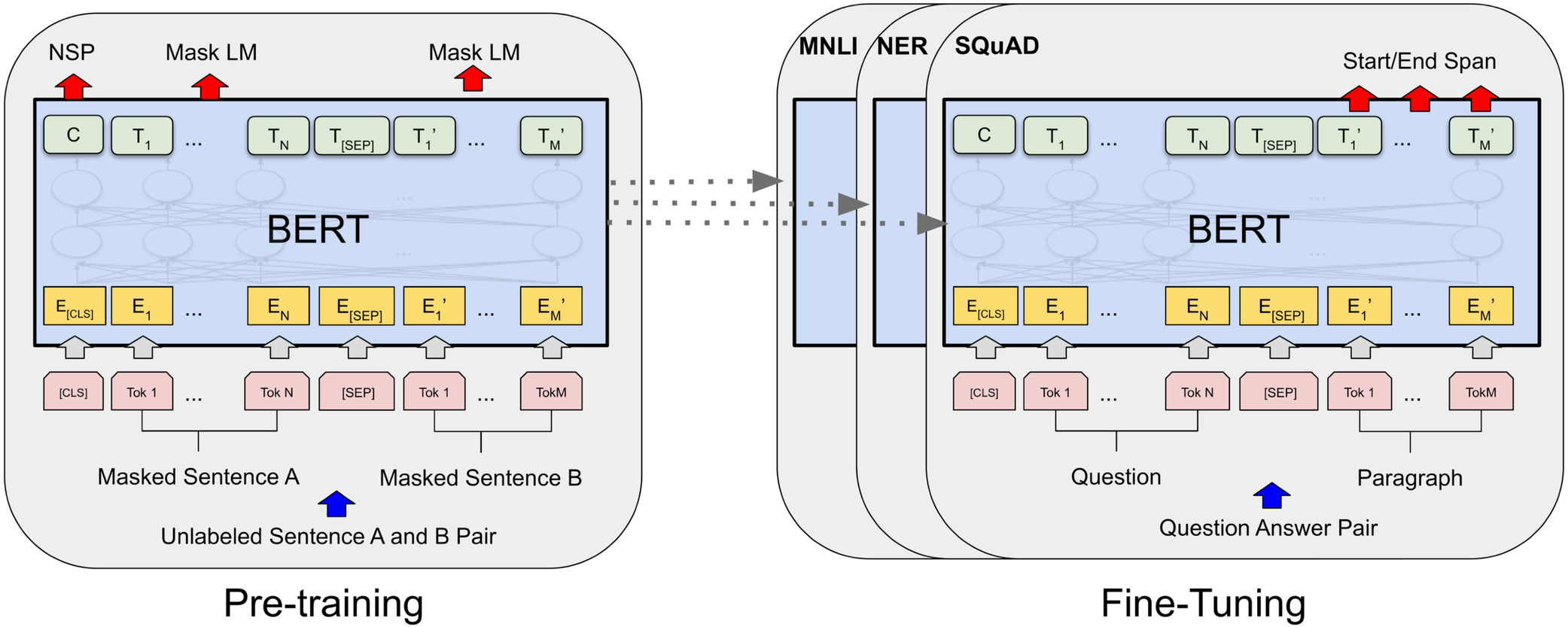
(Devlin et al., 2019) BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

How to use BERT?

Key idea: instead of use BERT to produce contextualized word embeddings, keep all the parameters and **fine-tune** them for downstream tasks

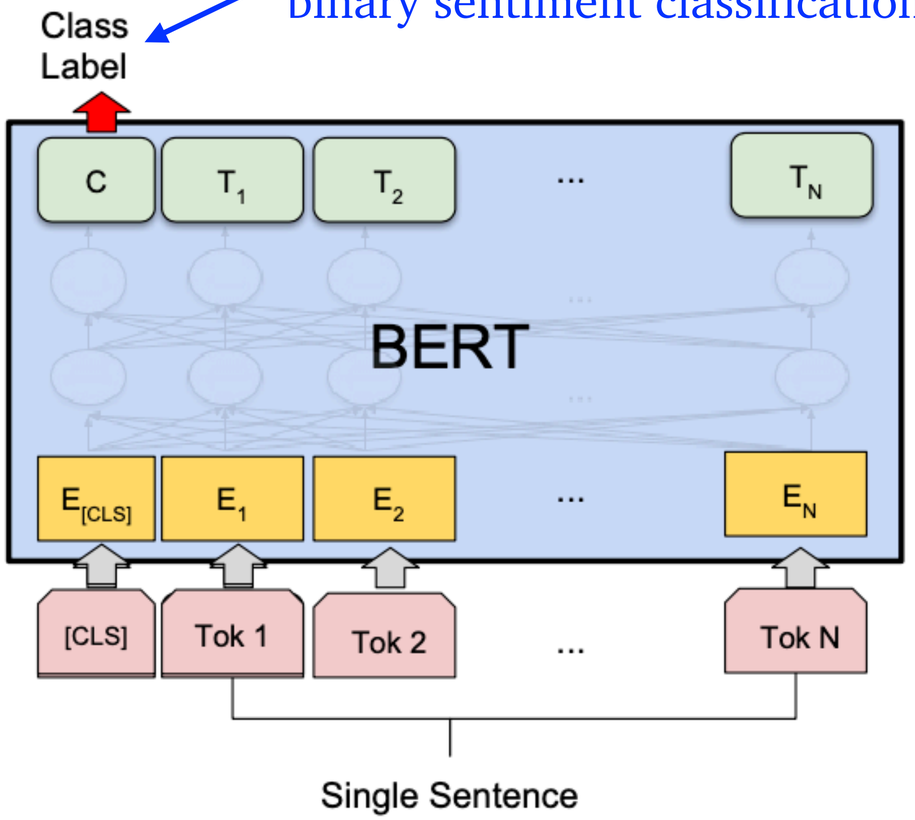


How to use BERT?



Example: sentiment classification

We just need to introduce $2H$ parameters for binary sentiment classification!



All the parameters will be learned together (original BERT parameters + new classifier parameters)

BERT: experimental results

BiLSTM: 63.9

unidirectional

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

Use BERT models

https://github.com/huggingface/transformers

Transformers

State-of-the-art Natural Language Processing for PyTorch and TensorFlow 2.0

```
export TASK_NAME=mrpc

python run_glue.py \
  --model_name_or_path bert-base-cased \
  --task_name $TASK_NAME \
  --do_train \
  --do_eval \
  --max_seq_length 128 \
  --per_device_train_batch_size 32 \
  --learning_rate 2e-5 \
  --num_train_epochs 3 \
  --output_dir /tmp/$TASK_NAME/
```

	H=128	H=256	H=512	H=768
L=2	**2/128 (BERT-Tiny)**	2/256	2/512	2/768
L=4	4/128	**4/256 (BERT-Mini)**	**4/512 (BERT-Small)**	4/768
L=6	6/128	6/256	6/512	6/768
L=8	8/128	8/256	**8/512 (BERT-Medium)**	8/768
L=10	10/128	10/256	10/512	10/768
L=12	12/128	12/256	12/512	**12/768 (BERT-Base)**

Model	Score	CoLA	SST-2	MRPC	STS-B	QQP	MNLI-m	MNLI-mm	QNLI(v2)	R
BERT-Tiny	64.2	0.0	83.2	81.1/71.1	74.3/73.6	62.2/83.4	70.2	70.3	81.5	57
BERT-Mini	65.8	0.0	85.9	81.1/71.8	75.4/73.3	66.4/86.2	74.8	74.3	84.1	57
BERT-Small	71.2	27.8	89.7	83.4/76.2	78.8/77.0	68.1/87.0	77.6	77.0	86.4	61
BERT-Medium	73.5	38.0	89.6	86.6/81.6	80.4/78.4	69.6/87.9	80.0	79.1	87.7	62

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