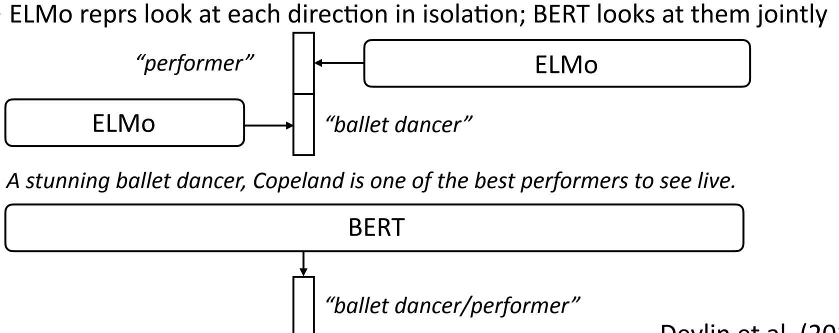
BERT

BERT

- AI2 made ELMo in spring 2018, GPT (transformer-based ELMo) was released in summer 2018, BERT came out October 2018
- Four major changes compared to ELMo:
  - Transformers instead of LSTMs
  - Bidirectional model with “Masked LM” objective instead of standard LM
  - Fine-tune instead of freeze at test time
  - Operates over word pieces (byte pair encoding)

BERT

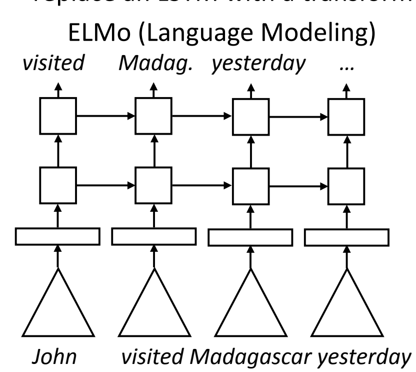
- ELMo is a unidirectional model (as is GPT): we can concatenate two unidirectional models, but is this the right thing to do?
- ELMo reprs look at each direction in isolation; BERT looks at them jointly

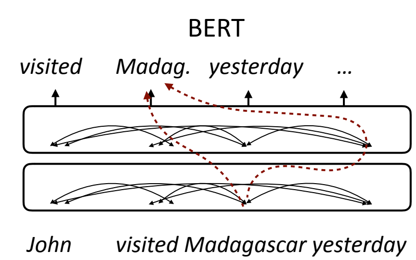


Devlin et al. (2019)

BERT

- How to learn a “deeply bidirectional” model? What happens if we just replace an LSTM with a transformer?

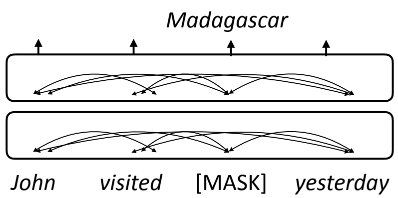




- You could do this with a “one-sided” transformer, but this “two-sided” model can cheat

Masked Language Modeling

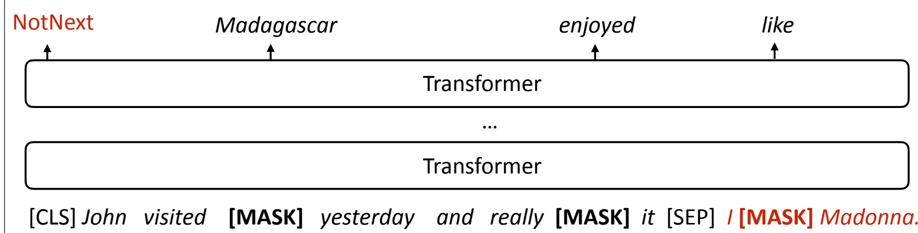
- How to prevent cheating? Next word prediction fundamentally doesn't work for bidirectional models, instead do *masked language modeling*
- BERT formula: take a chunk of text, mask out 15% of the tokens, and try to predict them



Devlin et al. (2019)

Next "Sentence" Prediction

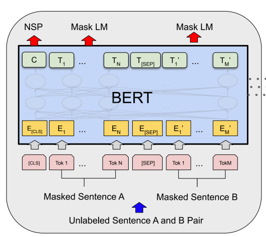
- Input: [CLS] Text chunk 1 [SEP] Text chunk 2
- 50% of the time, take the true next chunk of text, 50% of the time take a random other chunk. Predict whether the next chunk is the "true" next
- BERT objective: masked LM + next sentence prediction

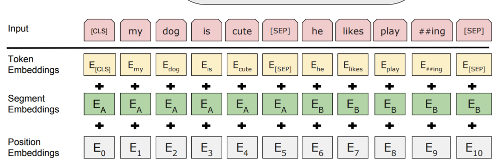


Devlin et al. (2019)

BERT Architecture

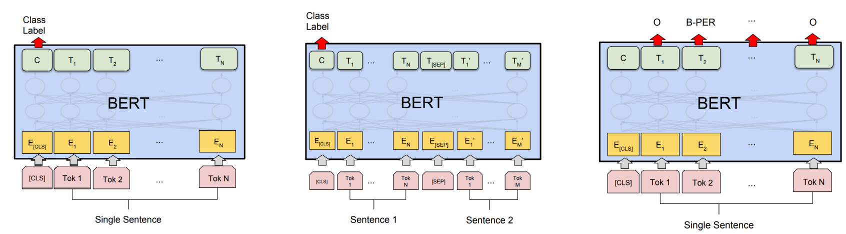
- BERT Base: 12 layers, 768-dim per wordpiece token, 12 heads. Total params = 110M
- BERT Large: 24 layers, 1024-dim per wordpiece token, 16 heads. Total params = 340M
- Positional embeddings and segment embeddings, 30k word pieces
- This is the model that gets **pre-trained** on a large corpus





Devlin et al. (2019)

What can BERT do?



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

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

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

- Artificial [CLS] token is used as the vector to do classification from
- Sentence pair tasks (entailment): feed both sentences into BERT
- BERT can also do tagging by predicting tags at each word piece

Devlin et al. (2019)

What can BERT do?

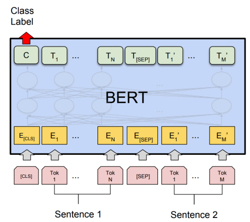
Entails (first sentence implies second is true)

Transformer

...

Transformer

[CLS] A boy plays in the snow [SEP] A boy is outside



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

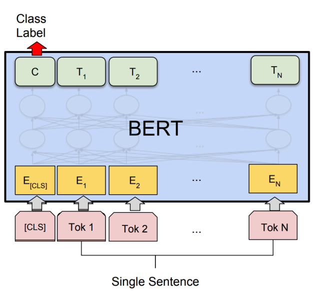
- How does BERT model this sentence pair stuff?
- Transformers can capture interactions between the two sentences, even though the NSP objective doesn't really cause this to happen

What can BERT NOT do?

- BERT **cannot** generate text (at least not in an obvious way)
  - Can fill in MASK tokens, but can't generate left-to-right (well, you could put MASK at the end repeatedly, but this is slow)
- Masked language models are intended to be used primarily for "analysis" tasks

Fine-tuning BERT

- Fine-tune for 1-3 epochs, batch size 2-32, learning rate 2e-5 - 5e-5



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

- Large changes to weights up here (particularly in last layer to route the right information to [CLS])
- Smaller changes to weights lower down in the transformer
- Small LR and short fine-tuning schedule mean weights don't change much
- More complex "triangular learning rate" schemes exist

Fine-tuning BERT

Pretraining	Adaptation	NER CoNLL 2003	SA SST-2	Nat. lang. inference MNLI	Nat. lang. inference SICK-E	Semantic textual similarity SICK-R	Semantic textual similarity MRPC	Semantic textual similarity STS-B
Skip-thoughts	❄️	-	81.8	62.9	-	86.6	75.8	71.8
ELMo	❄️	91.7	**91.8**	**79.6**	**86.3**	**86.1**	**76.0**	**75.9**
	🔥	**91.9**	91.2	76.4	83.3	83.3	74.7	75.5
	Δ=🔥-❄️	0.2	-0.6	-3.2	-3.3	-2.8	-1.3	-0.4
BERT-base	❄️	92.2	93.0	**84.6**	84.8	86.4	78.1	82.9
	🔥	**92.4**	**93.5**	**84.6**	**85.8**	**88.7**	**84.8**	**87.1**
	Δ=🔥-❄️	0.2	0.5	0.0	1.0	2.3	6.7	4.2

- BERT is typically better if the whole network is fine-tuned, unlike ELMo

Peters, Ruder, Smith (2019)

Evaluation: GLUE

Corpus	|Train|	|Test|	Task	Metrics	Domain
			Single-Sentence Tasks		
CoLA	8.5k	**1k**	acceptability	Matthews corr.	misc.
SST-2	67k	1.8k	sentiment	acc.	movie reviews
			Similarity and Paraphrase Tasks		
MRPC	3.7k	1.7k	paraphrase	acc./F1	news
STS-B	7k	1.4k	sentence similarity	Pearson/Spearman corr.	misc.
QQP	364k	**391k**	paraphrase	acc./F1	social QA questions
			Inference Tasks		
MNLI	393k	**20k**	NLI	matched acc./mismatched acc.	misc.
QNLI	105k	5.4k	QA/NLI	acc.	Wikipedia
RTE	2.5k	3k	NLI	acc.	news, Wikipedia
WNLI	634	**146**	coreference/NLI	acc.	fiction books

Wang et al. (2019)

Results

System	MNLI-(m/mm)	QQP	QNLI	SST-2	CoLA	STS-B	MRPC	RTE	**Average**
	392k	363k	108k	67k	8.5k	5.7k	3.5k	2.5k	-
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**

- Huge improvements over prior work (even compared to ELMo)
- Effective at "sentence pair" tasks: textual entailment (does sentence A imply sentence B), paraphrase detection

Devlin et al. (2018)

RoBERTa

- "Robustly optimized BERT"
- 160GB of data instead of 16 GB
- Dynamic masking: standard BERT uses the same MASK scheme for every epoch, RoBERTa recomputes them

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

- New training + more data = better performance

Liu et al. (2019)

Using BERT

- Huggingface Transformers: big open-source library with most pre-trained architectures implemented, weights available
- Lots of standard models…

Model architectures

🤗 Transformers currently provides the following NLU/NLG architectures:

1. **BERT** (from Google) released with the paper BERT: Pre-training of Deep Understanding by Jacob Devlin, Ming-Wei Chang, Kenton Lee and Krist
2. **GPT** (from OpenAI) released with the paper Improving Language Under Radford, Karthik Narasimhan, Tim Salimans and Ilya Sutskever.
3. **GPT-2** (from OpenAI) released with the paper Language Models are Un Jeffrey Wu*, Rewon Child, David Luan, Dario Amodei** and Ilya Sutskev
4. **Transformer-XL** (from Google/CMU) released with the paper Transform Fixed-Length Context by Zihang Dai*, Zhilin Yang*, Yiming Yang, Jaime
5. **XLNet** (from Google/CMU) released with the paper XLNet: Generalized Understanding by Zhilin Yang*, Zihang Dai*, Yiming Yang, Jaime Carbon
6. **XLM** (from Facebook) released together with the paper Cross-lingual L and Alexis Conneau.
7. **RoBERTa** (from Facebook), released together with the paper a Robustly

…

and "community models"

`mrm8488/spanbert-large-finetuned-tacred`

`mrm8488/xlm-multi-finetuned-xquadv1`

`nlpaueb/bert-base-greek-uncased-v1`

`nlptown/bert-base-multilingual-uncased-sentiment`

`patrickvonplaten/reformer-crime-and-punish`

`redewiedergabe/bert-base-historical-german-rw-cased`

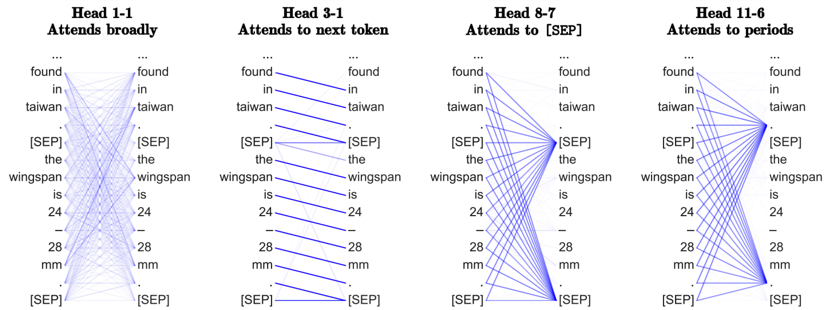
`roberta-base`

`severinsimmler/literary-german-bert`

`seyonec/ChemBERTa-zinc-base-v1`

…

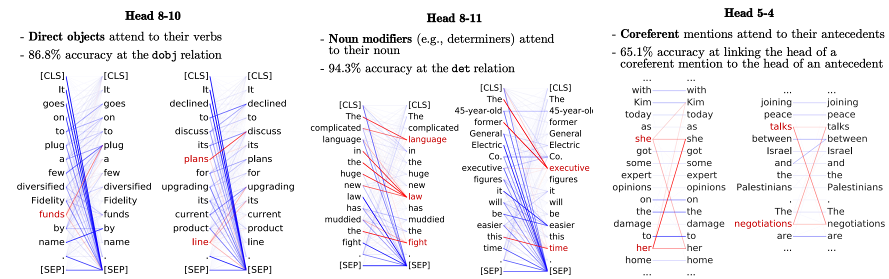
What does BERT learn?



- Heads on transformers learn interesting and diverse things: content heads (attend based on content), positional heads (based on position), etc.

Clark et al. (2019)

What does BERT learn?



- Still way worse than what supervised systems can do, but interesting that this is learned organically

Clark et al. (2019)