BERT

Pre-training & Fine-Tuning

Learning goals

- Know the pre-training tasks
- How to construct samples
- Understand the pre-training
- Gain understanding of the fine-tuning procedure
- Differences between token- and sequence classification

MASKED LANGUAGE MODELING (MLM)

First remark:

- Distinguish from *Masked Self-Attenion*
  $\rightarrow$ Masked Self-Attention is an architectural detail in the decoder of the Transformer, i.e. used by e.g. GPT
- Masked Self-Attention as a way to prevent causality issues in a Transformer decoder
- MLM is a self-supervised *modeling objective* introduced to couple Self-Attention and (deep) bidirectionality without violating causality

MLM (2)

- **Training objective:**

  Given a sentence, predict `[MASK]`ed tokens

- **Generation of samples:**

  Randomly replace* a fraction of the words by `[MASK]`

  *Sample 15% of the tokens; replace 80% of them by `[MASK]`, 10% by a random token & leave 10% unchanged

- **Input:**

The	quick	brown	`[MASK]`	jumps	over	the	`[MASK]`	dog	.

- **Targets:**

  $(fox, \; lazy)$

MLM (3)

- ⚠ But 20% of the samples will look different!
  → 10% replaced by a random token; 10% left unchanged
- **Input (first case):**

The	quick	brown	`orange`	jumps	over	the	`is`	dog	.

- **Targets (first case):**

$$(\textit{fox}, \ \textit{lazy})$$

- **Input (second case):**

The	quick	brown	`fox`	jumps	over	the	`lazy`	dog	.

- **Targets (second case):**

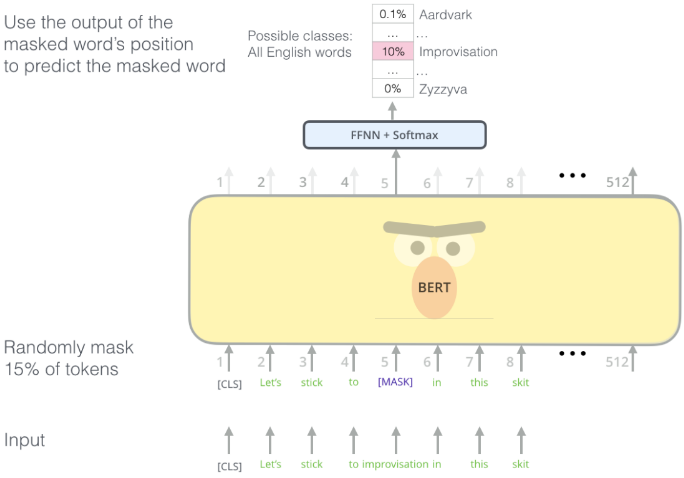
$$(\textit{fox}, \ \textit{lazy})$$

MLM (4)

Discrepancy between pre-training & fine-tuning:

- `[MASK]`-token as central part of pre-training procedure
- `[MASK]`-token does not occur during fine-tuning
- **Modified pre-training task:**
  Predict 15% of the tokens of which only 80% have been replaced by `[MASK]`
  - 80% of the selected tokens are actually `[MASK]`ed
  - 10% of the selected tokens: The model has to “understand“ that the word needs to be *replaced*
  - 10% of the selected tokens: The model has to “understand“ that the word needs to be *kept*
- This ensures overlap between the kind data seen during pre-training and during fine-tuning

MLM (5)



Source: Jay Alammar

NEXT SENTENCE PREDICTION (NSP)

- **Training objective:**

  Given two sentences, predict whether s_2 follows s_1

- **Generation of samples:**

  Randomly sample* negative examples (cf. word2vec)

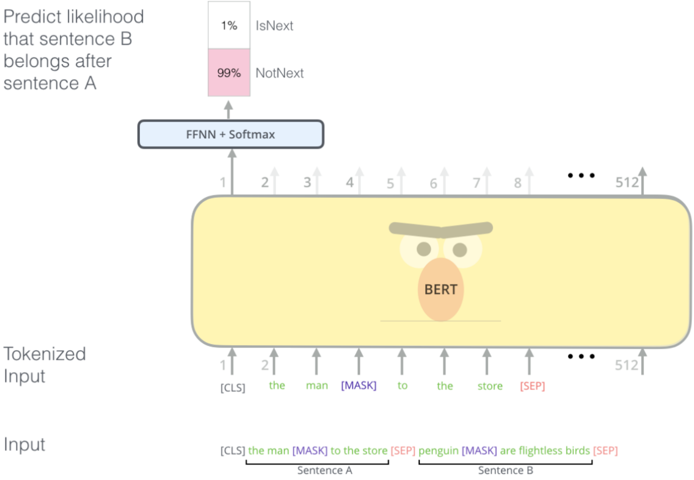
  *50% of the time the second sentence is the actual next sentence, 50% of the time it is a randomly sampled sentence

- **Full Input:**

[CLS]	The	[MASK]	is	quick	.	[SEP]	
It	jumps	over	the	[MASK]	dog	.	[SEP]

- `[CLS]` token as sequence representation for classification
- `[SEP]` token for separation of the two input sequences

NSP (2)



Source: Jay Alammar

PRE-TRAINING BERT

Setup:

- 13 GB of text (BooksCorpus $+$ Eng. Wikipedia)
  $\rightarrow$ Back then: **huge**; Now: rather **small**
- Train for approximately* 40 epochs
- 4 (16) Cloud TPUs for 4 days for the BASE (LARGE) variant
- Loss function:

$$Loss_{BERT} = Loss_{MLM} + Loss_{NSP}$$

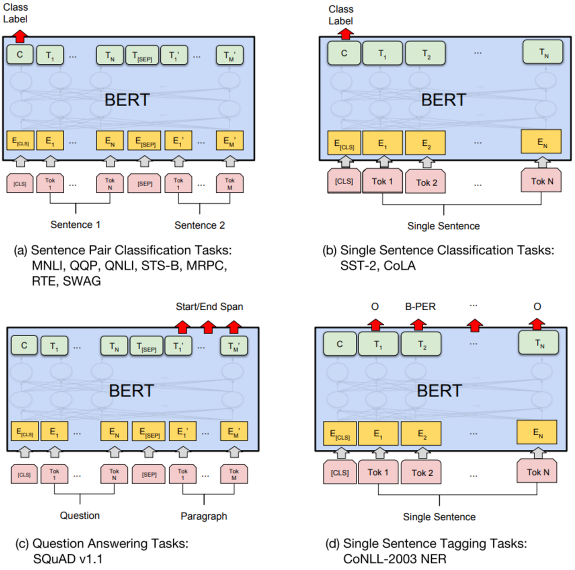
*1.000.000 steps on batches of 256 sequences with a sequence length of 512 tokens

PRE-TRAINING BERT

Sequence lengths:

- For their experiments:
  - Pre-train w/ sequence length 128 for 90% of the steps
  - Pre-train w/ sequence length 512 for 10% of the steps
- *Reason:* Positional embeddings
  - Learned, not sinusoidal (as opposed to the original Transformer)
  - Training on long sequences necessary to learn them well
  - **But:** Training expensive, hence this “compromise“

FINE-TUNING BERT



(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

▸ Source: Devlin et al., 2019

FINE-TUNING BERT

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	79.8	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	87.4	91.3	45.4	80.0	82.3	56.0	75.1
$\text{BERT}_{\text{BASE}}$	84.6/83.4	71.2	90.5	93.5	52.1	85.8	88.9	66.4	79.6
$\text{BERT}_{\text{LARGE}}$	**86.7/85.9**	**72.1**	**92.7**	**94.9**	**60.5**	**86.5**	**89.3**	**70.1**	**82.1**

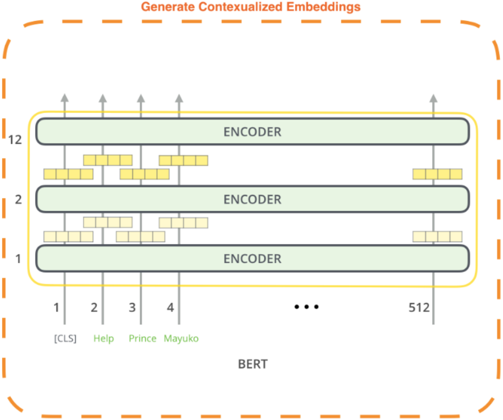
Source: Devlin et al., 2019

- Performance of BERT on the GLUE Benchmark Wang et al., 2018
- Beats all of the previous state-of-the-art models
- In the meantime: Other models (way) better than BERT

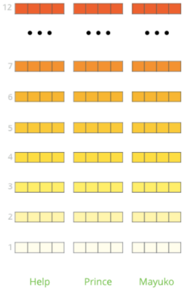
FINE-TUNING DETAILS

- Relatively cheap compared to pre-training:
  - $<$ 1 hour on a single Cloud TPU
  - "a few hours" on a GPU
- Recommendations for hyperparameters:
  - **Batch Size:** 16, 32
  - **Adam learning rate:** 5e-5, 3e-5, 2e-5
  - **#epochs:** 2, 3, 4
  - **Dropout probability:** 0.1
- Data sets w/ > 100k labeled examples rather insensitive to hyperparameters

FEATURE EXTRACTION FROM BERT



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?

Source: Jay Alammar

FEATURE EXTRACTION FROM BERT

System	Dev F1	Test F1
ELMo (Peters et al., 2018a)	95.7	92.2
CVT (Clark et al., 2018)	-	92.6
CSE (Akbik et al., 2018)	-	**93.1**
Fine-tuning approach		
$\text{BERT}_{\text{LARGE}}$	96.6	92.8
$\text{BERT}_{\text{BASE}}$	96.4	92.4
Feature-based approach ($\text{BERT}_{\text{BASE}}$)		
Embeddings	91.0	-
Second-to-Last Hidden	95.6	-
Last Hidden	94.9	-
Weighted Sum Last Four Hidden	95.9	-
Concat Last Four Hidden	96.1	-
Weighted Sum All 12 Layers	95.5	-

Table 7: CoNLL-2003 Named Entity Recognition results. Hyperparameters were selected using the Dev set. The reported Dev and Test scores are averaged over 5 random restarts using those hyperparameters.

Source: Devlin et al., 2019