Using the Transformer

BERT – Pre-training & Fine-Tuning

Learning goals

- Understand the two pre-training tasks
- Learn how samples are constructed
- Understand the pre-training process
- Understand the fine-tuning procedure
- Learn the differences between token- and sequence classification

MASKED LANGUAGE MODELING (MLM)

First remark:

- It has nothing to do with 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

MASKED LANGUAGE MODELING (MLM) CTD.

- **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:**

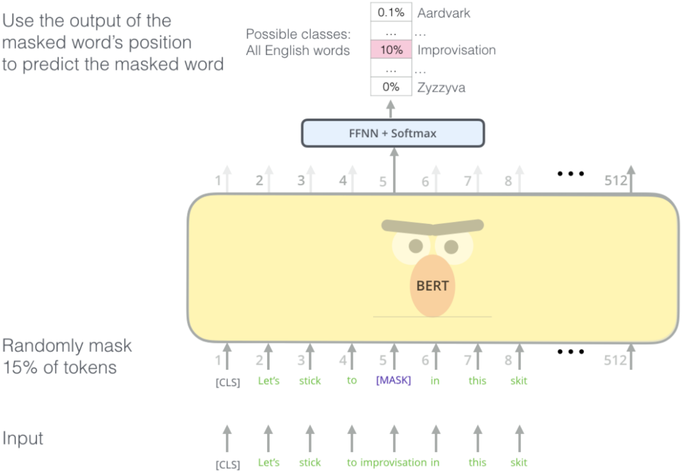
  $(\textit{fox}, \textit{lazy})$

MASKED LANGUAGE MODELING (MLM) CTD.

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  Predict 15% of the tokens of which only 80% have been replaced by `[MASK]`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:
    `The quick brown fox` $\rightarrow$ `The quick brown [MASK]`
  - 10% of the selected tokens:
    `The quick brown fox` $\rightarrow$ `The quick brown went`
  - 10% of the selected tokens:
    `The quick brown fox` $\rightarrow$ `The quick brown fox`

MASKED LANGUAGE MODELING (MLM) CTD.



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)

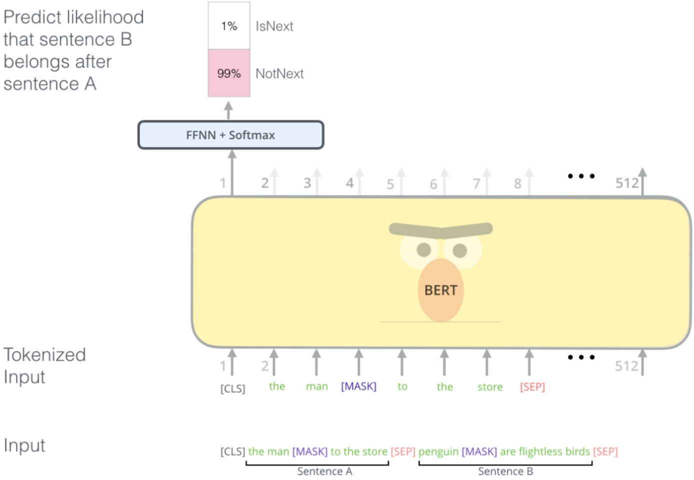
  *50% of the time the second sentence is the actual next sentence, 50% of the time it is a randomly sampled sentence

- **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

NEXT SENTENCE PREDICTION (NSP) CTD.



Source: *Jay Alammar*

PRE-TRAINING BERT

Ingredients:

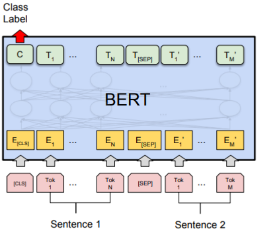
- Massive lexical resources (BooksCorpus + Eng. Wikipedia) $\rightarrow$ 13 GB in total
- Train for approximately* 40 epochs
- 4 (16) Cloud TPUs for 4 days for the BASE (LARGE) variant
- Loss function:

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

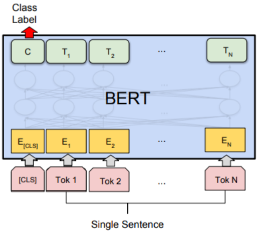
*1.000.000 steps on batches of 256 sequences with a sequence length of 512 tokens

- 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: Learn positional embeddings for all positions)

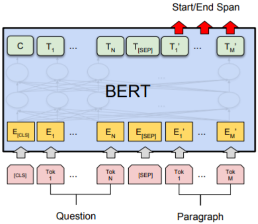
FINE-TUNING BERT



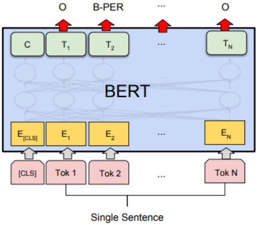
(a) Sentence Pair Classification Tasks:
MNLI, QQP, QNLI, STS-B, MRPC,
RTE, SWAG



(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. (2018)

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**

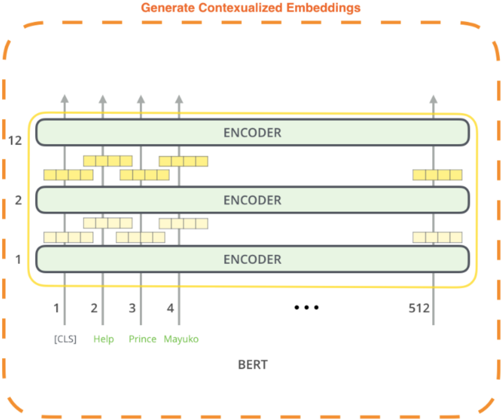
Source: Devlin et al. (2018)

- Performance of BERT on the ▸ GLUE Benchmark
- Beats all of the previous state-of-the-art models
- In the meantime: Other models better than BERT

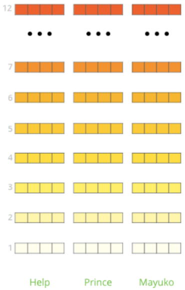
FINE-TUNING DETAILS

- 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. (2018)