Using the Transformer

BERT – Architecture

Learning goals

- Understand the use of the transformer encoder in this model
- Understand the architectural components

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2013 - word2vec

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01/2018

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An embedding layer at the bottom of the network was complemented by three AWD-LSTM layers (Merity et al., 2017) and a softmax layer for pre-training.

A **Unidirectional contextual** model since no biLSTMs are used.

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Compared to ELMo it is just **unidirectionally contextual**, since it uses only the decoder side of the Transformer. On the other hand it is **end-to-end trainable** (cf. ULMFiT) and embeddings do not have to be extracted like in the case of ELMo.

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October 2018 - BERT

BERT (**Devlin et al., 2018**) is a bidirectional contextual embedding model purely relying on Self-Attention by using multiple **Transformer encoder** blocks.

BERT (and its successors) rely on the **Masked Language Modelling objective** during pre-training on huge unlabelled corpora of text.

CONTEXT: ULMFIT AND GPT

Shortcomings of ELMo:

- No adaption of the Embeddings to target domain/task
- Sequential nature of LSTMs: Not fully parallelizable

Alleviations/Alternatives:

- ULMFiT ▸ Howard and Ruder, 2018 is a uni-directional LSTM which is fine-tuned as a whole model on data from the target domain/task.
- GPT ▸ Radford et al., 2018 is a Transformer decoder which is fine-tuned as a whole model on data from the target domain/task.

BERT: KEY FACTS

***B**idirectional **E**ncoder **R**epresentations from **T**ransformers:*

- Bidirectionally contextual model

  $\rightarrow$ The embeddings of a single token depend on its left- and on its right-side context (similar to ELMo, but better)

- Introduces new self-supervised objective(s)

  $\rightarrow$ MLM as *necessity* for the architecture to work

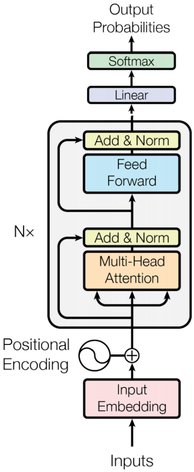
  $\rightarrow$ Next-Sentence-Prediction as complementary objective (cf. next section)

- Completely replaces recurrent architectures by Self-Attention
  $+$ simultaneously includes bidirectionality into the embeddings
  $+$ fine-tuned as a whole

BERT: KEY FACTS

- Transformer *encoder* as backbone of the architecture
- 110M (340M) parameters in total for $BERT_{Base}$ ($BERT_{Large}$)
  - 12 (24) Transformer encoder blocks
  - Embedding size of $E = 768$ (1024)
  - Hidden layer size $H = E$
  - $A = H/64 = 12$ (16) attention heads
  - Feed-forward size is set to $4H$

CORE OF BERT – THE TRANSFORMER ENCODER



Source: Vaswani et al. (2017)

A REMARK ON "CAUSALITY"

Causality is an issue!

- Goal: Learn contextual representations for words/tokens
- *Self-Supervision:* Input and target sequence are the same
  $\rightarrow$ We modify the input to create a meaningful task
- ⚠ Unconstrained Self-Attention makes using the LM objective infeasible
- **Question:** Why is this the case?

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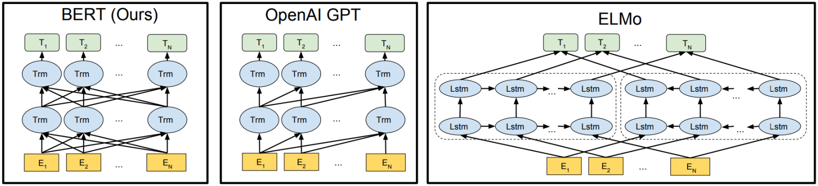
- **Question:** Why is this the case?

  Bidirectionality at a lower layer would allow a word to see itself at later hidden layers
  $\rightarrow$ The model would be allowed to cheat!
  $\rightarrow$ This would not lead to meaningful internal representations

ELMO VS. GPT VS. BERT



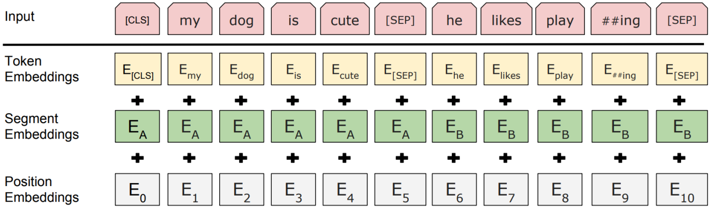
Source: Devlin et al. (2018)

Major architectural differences:

- ELMo uses two separate unidirectional models to achieve bidirectionality $\rightarrow$ Only "*shallow*" bidirectionality
- GPT is not bidirectional, thus no issues concerning causality
- BERT combines the best of both worlds:

$$\textit{Self-Attention} + (\textit{Deep})\ \textit{Bidirectionality}$$

INPUT EMBEDDINGS



Source: Devlin et al. (2018)

- Two concatenated sentences as input
- WordPiece tokenization (Wu et al., 2016) for the inputs
  $\rightarrow$ Vocabulary of 30.000 tokens
- Learned segment $+$ position embeddings
- Special `[CLS]` and `[SEP]` tokens