# **Using the Transformer**

# BERT (Devlin et al., 2018)



#### Learning goals

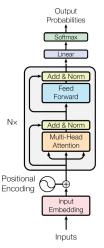
- Understand the use of the transformer encoder in this model
- Understand the iarchitectural components

## KEY FACTS ON BERT DEVLIN ET AL. (2018)

#### Bidirectional Encoder Representations from Transformers:

- Bidirectionally contextual model
- Introduces new self-supervised objective(s)
- Completely replaces recurrent architectures by Self-Attention + simultaneously able to include bidirectionality
- Transformer encoder as backbone of the architecture
  - 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
  - $\rightarrow$  110M (340M) parameters in total for *BERT*<sub>Base</sub> (*BERT*<sub>Large</sub>)

## **CORE OF BERT – THE TRANSFORMER ENCODER**



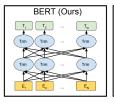
Source: Vaswani et al. (2017)

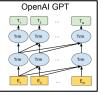
#### A REMARK ON "CAUSALITY"

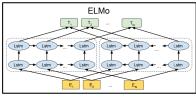
#### Causality is an issue!

- Goal: Learn contextual representations for words/tokens
- Self-Supervision: Input and target sequence are the same
  - ightarrow We modify the input to create a meaningful task
- Unconstrained Self-Attention makes using the LM objective infeasible
- Bidirectionality at a lower layer would allow a word to see itself at later hidden layers
  - → The model would be allowed to cheat!
  - ightarrow This would not lead to meaningful internal representations

### **ELMO VS. GPT VS. BERT**







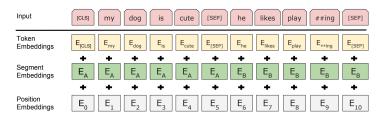
Source: Devlin et al. (2018)

#### Major architectural differences:

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

Self-Attention + (Deep) Bidirectionality

### INPUT EMBEDDINGS



Source: Devlin et al. (2018)

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