

Bert_Review (1)

August 26, 2020

0.1 Bert

0.1.1 01 what is Bert?

1. Bert Architecture
2. State of Art

0.1.2 02 Bert Architecture

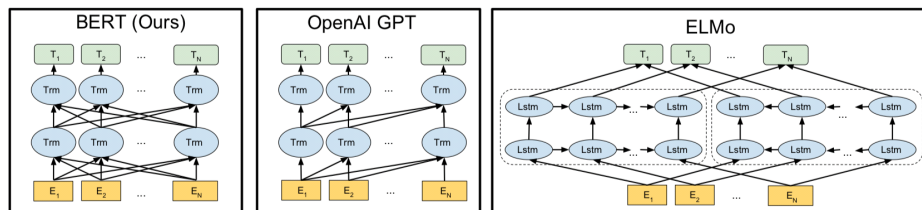
1. Pre-training task
2. Input Embedding
3. Encoding
4. Fine-tuning

1. RNN () : hidden layer /
2. LSTM : RNN hidden state cell state
3. Transformer (Encoder-Decoder): RNN base Encoding () Decoding ()
4. Attention: Transformer
5. Bert : Transformer Encoder Self Attention (Bi-directional) ,

0.2 BERT (Bi-directional Encoder Representation from Transformers)

Purpose: /

- ELMO
- ELMO : Uni-directional LSTM Model



alt text

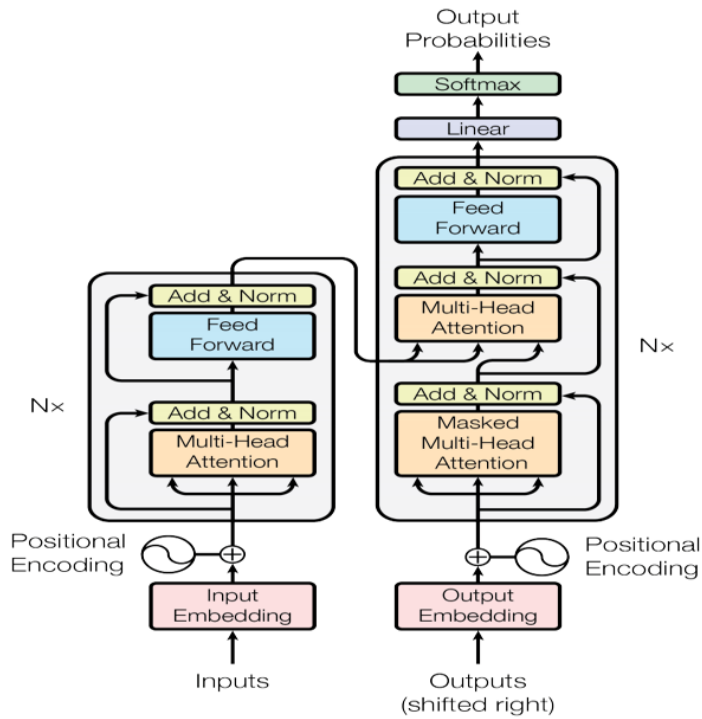


Figure 1: The Transformer - model architecture.

alt text

- GPT : left to right, and right to left transformer model
- NLP 11 state of art
- SQuAD
- Transfer Learning Fine -tuning .
- Transformer
 - Encoder
 - Speed, Accuracy , Long-term decedency

0.3 BERT ARCHITECTURE

‘Attention is All’ Transformer Encoding

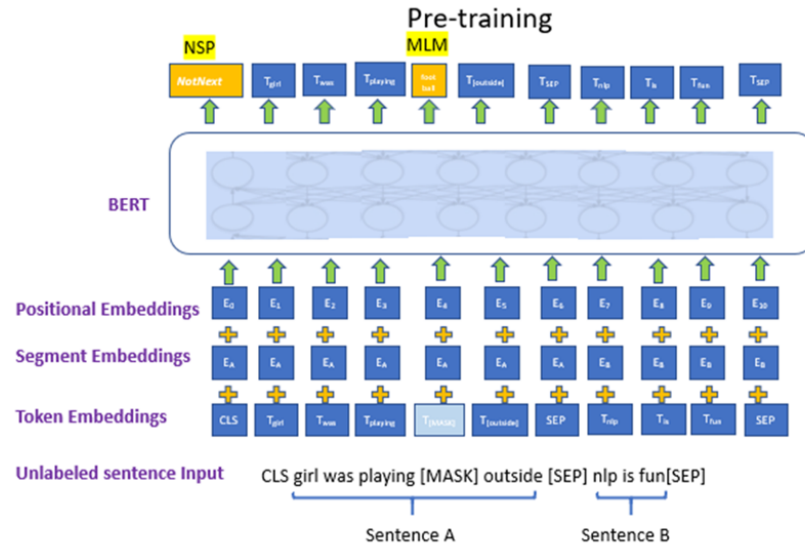
1. Pre-training task
2. Fine-Tuning

2 : * Bert-Base (L=12, H=768, A=12) * Bert-Large(L=24, H=1024, A=16) * Base

0.4 1. Pre - training

0.4.1 1. pre-training tasks

- * Masked Language Modelling
 - * 15% <MASK>



alt text

- * 80% ['MASK'] Token
- * 10% Random , 10%
- * , mask ,
- * Next Sentence Prediction
 - * B A
 - * 50%
 - * B A IsNext , NotNext
 - *) Input = [CLS] the man went to [MASK] store [SEP] he bought a gallon [MASK] milk [SEP]
 - *) Input = [CLS] the man [MASK] to the store [SEP] penguin [MASK] are flight ##less b

0.4.2 2. Embedding :

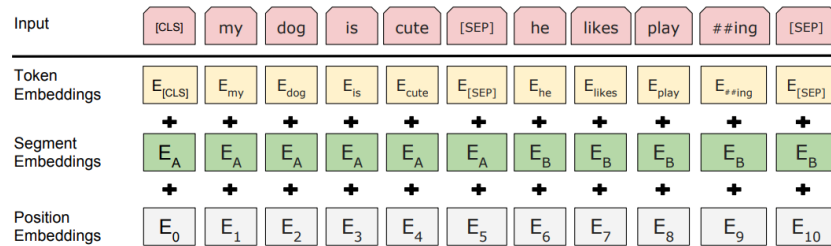


Figure 2: BERT input representation. The input embeddings is the sum of the token embeddings, the segmentation embeddings and the position embeddings.

Token Vectorize

Input = Token Embedding + Segment Embedding + Position Embedding

- Position Encoding Postion embedding
- Token : Vector
- Segment : / (0, 1 etc)
- Position: /

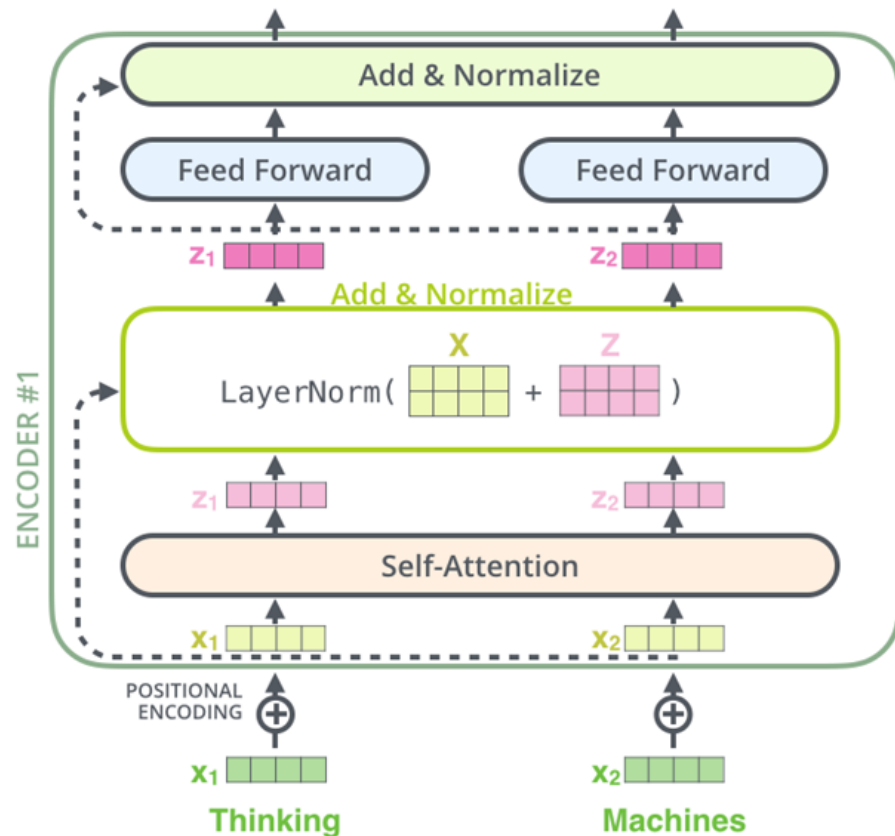
- : 3
 - (Base 768 Vector Large 1024)
 - + + 768 vector Embedding

0.4.3 3. Encoding Layers

	query		key		score	softmax
dog	0.3 -0.2 0.4	•	0.5 -0.9 0.2	The	= 0.4	0.4
dog	0.3 -0.2 0.4	•	1.1 -0.3 0.5	dog	= 0.6	0.5
dog	0.3 -0.2 0.4	•	-1.0 0.3 -0.7	ran	= -0.6	0.1

1. Multi-Head Attention: / 1. 768 input vector 12 head 64 Vector Q,K,V . 2. Q K vector .) dog Q [0.3, -0.2 0.4] * 'The' K [0.5, -0.9, 0.2] = 0.4 3. soft max 0~1 scaling Score) [0.4 0.6 -0.6] -> [0.4 0.5 0.1] 4. softmax(score) V vector (64) 5. 12 Head 12 64 vector sum 768 vector

Encoding Layer N Layer



2. Add & Normalize

- ResNet : Embedding input vector Self-Attention Normalize

- Normalize: , Layer Stabilize

0.5 2. Fine-Tuning

- Bert Tasks:
 - Text similarity : text corpus Binary Classification
 - Reply Matching : text corpus Binary Classification
 - Intent Classification : / classification
 - * Sentiment Analysis
 - * Question and Answer
 - * Name Entity Recognition
- Feature-based vs. Fine-tuning
 - Feature-based approach : task network Feature , network (ELMO)
 - Fine-tuning approach : Pre-trained parameter downstream task
 - * NER: Pretrained Bert CONLL (NNP Person, Organization Labelling system)
 - Labelling Supervised Learning

In []: