Paper Review #3

BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

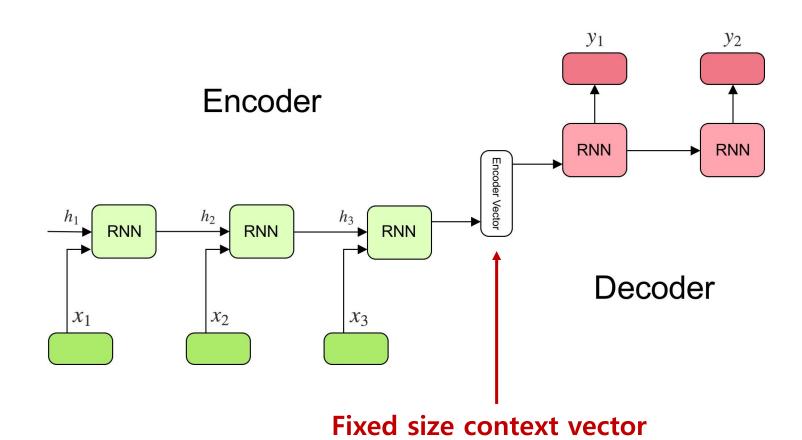
Dept. of Computer Science & Engineering 201502755 Meeyun Kim

Contents

- 1. Introduction
- 2. About BERT
- 3. Results

1. Introduction

RNN based Encoder & Decoder

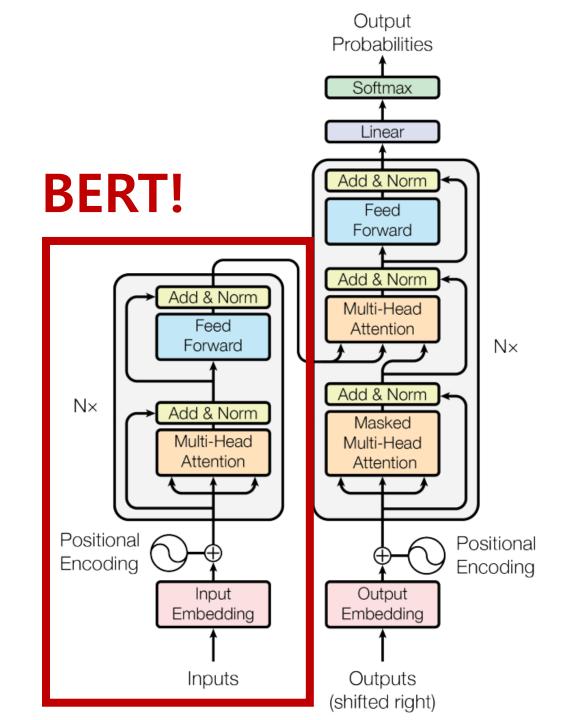


Transformer

- Encoder + Decoder

- Without RNN, Only Attention!

Adopt Parallelization
 → Dot Production



2. About BERT

1) What is BERT?

Bidirectional Encoder Representations from Transformers

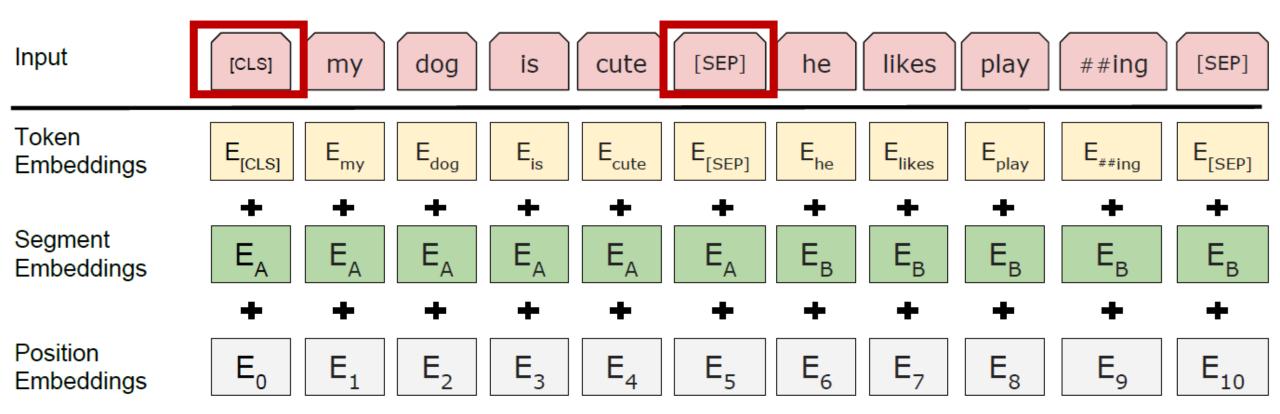
cf> OpenAl GPT -> Decoder (left-to-right, unidirectional)

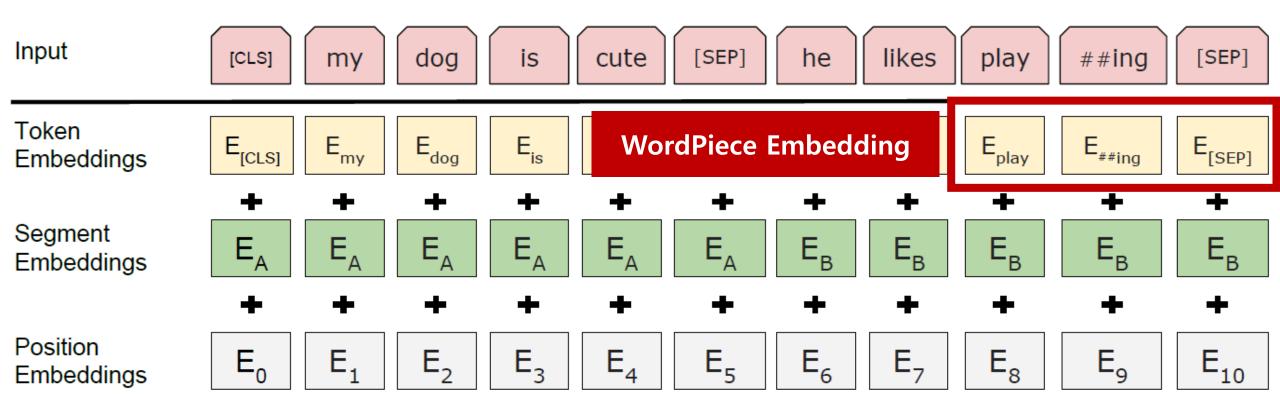
2) Model Architecture

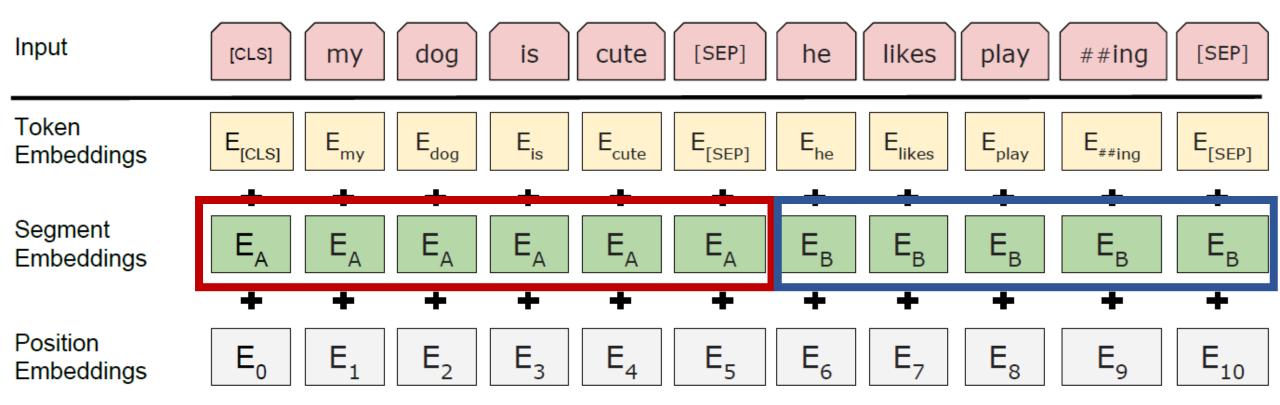
- BERT_{BASE}: L=12, H=768, A=12, Total Parameters=110M
- BERT_{LARGE}: L=24, H=1024, A=16, Total Parameters=340M

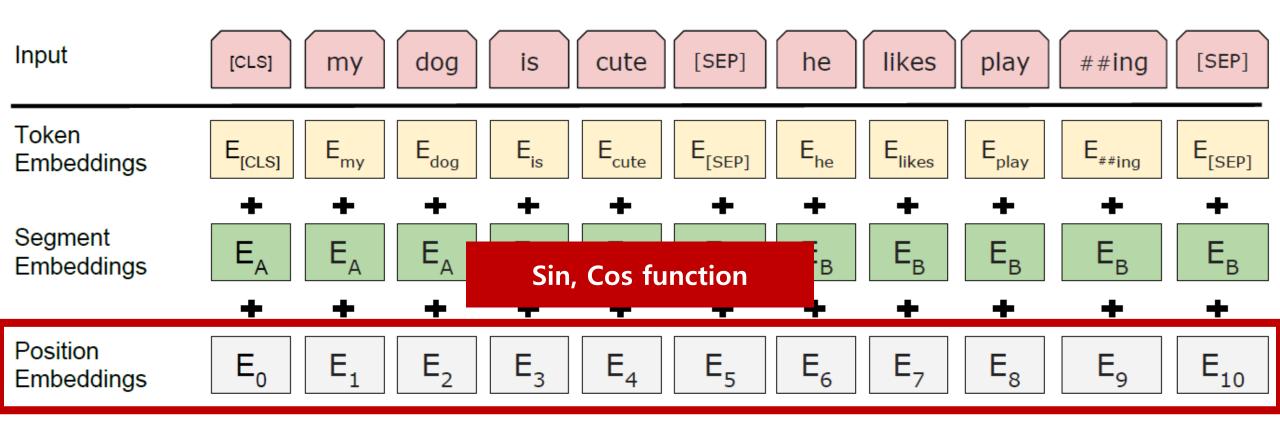
(number of layers - L, the hidden size - H, the number of self-attention heads - A)

- BookCorpus(800M words) + English Wikipedia(2,500M words)







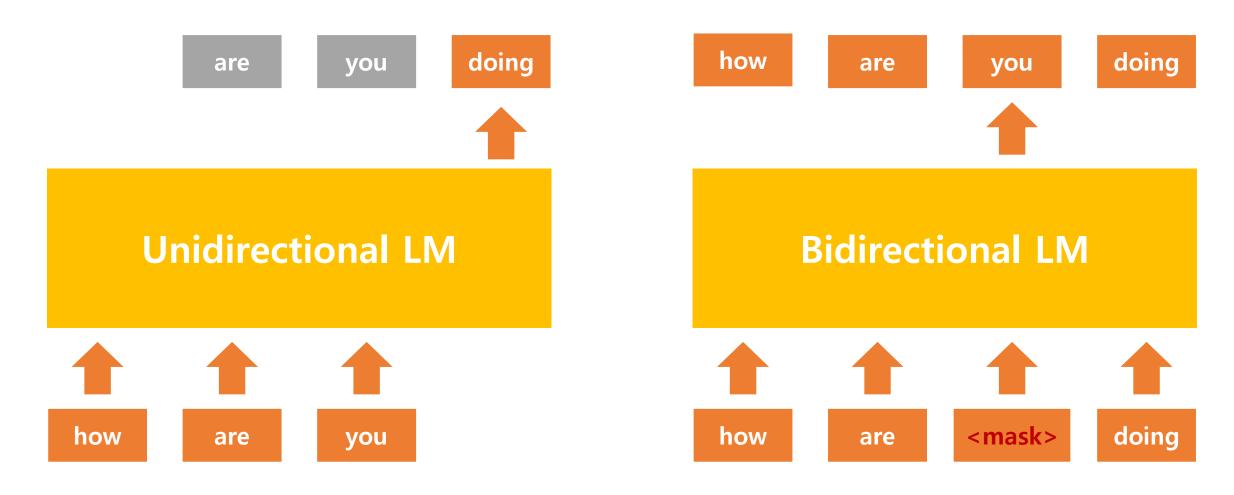


- 1) Outputs different value for each position
- 2) No limit on input

(1) Masked Language Model(MLM) (2) Next sentence prediction

(1) Masked Language Model(MLM)

Unidirectional(Traditional) LM vs Bidirectional(Masked) LM(BERT)



- (1) Masked Language Model(MLM) (Cont'd)
- Generator chooses 15% of the token positions at random for prediction:

→ **80%** : [MASK] token

→ 10% : Random token

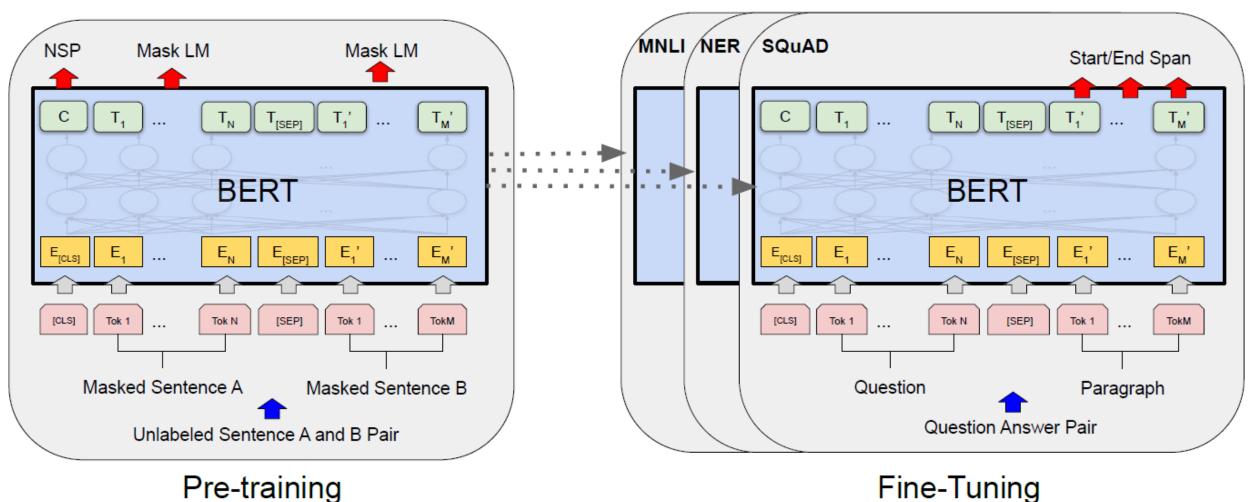
→ 10% : Unchanged token

- (2) Next Sentence prediction
- for task understanding relationship between two sentences(like QA)
- Binarized next sentence prediction task



- → 50%: B is the actual next sentence(labeled as IsNext)
- → Remaining 50%: B is a random sentence(labeled as NotNext)

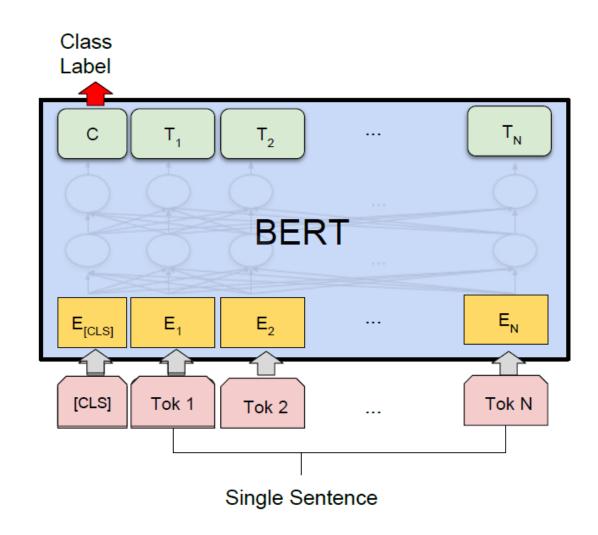
BERT = Pre-training + Fine-tuning



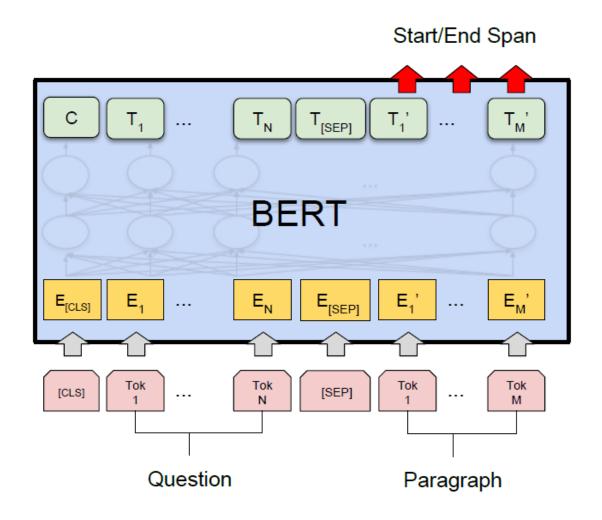
Fine-Tuning

Class Label BERT Tok [CLS] Sentence 1 Sentence 2

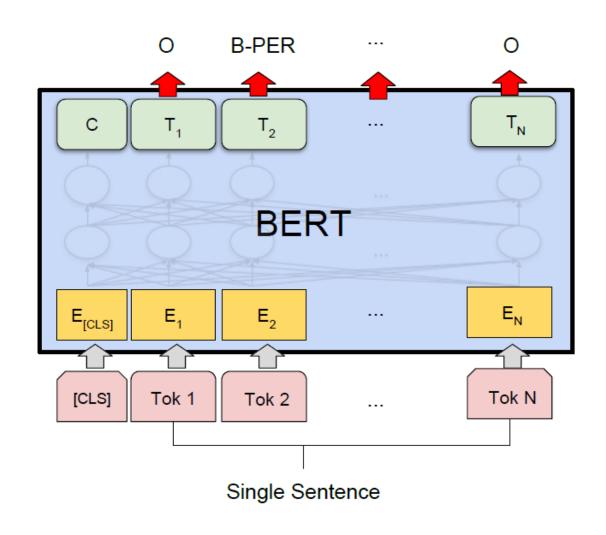
(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG



(b) Single Sentence Classification Tasks: SST-2, CoLA



(c) Question Answering Tasks: SQuAD v1.1



(d) Single Sentence Tagging Tasks: CoNLL-2003 NER

3. Result

1) GLUE Results

Dataset	Description	Data example	Metric
CoLA	Is the sentence grammatical or ungrammatical?	"This building is than that one." = Ungrammatical	Matthews
SST-2	Is the movie review positive, negative, or neutral?	"The movie is funny , smart , visually inventive , and most of all , alive ." = .93056 (Very Positive)	Accuracy
MRPC	Is the sentence B a paraphrase of sentence A?	A) "Yesterday, Taiwan reported 35 new infections, bringing the total number of cases to 418." B) "The island reported another 35 probable cases yesterday, taking its total to 418." = A Paraphrase	Accuracy / F1
STS-B	How similar are sentences A and B?	A) "Elephants are walking down a trail." B) "A herd of elephants are walking along a trail." = 4.6 (Very Similar)	Pearson / Spearman
QQP	Are the two questions similar?	A) "How can I increase the speed of my internet connection while using a VPN?" B) "How can Internet speed be increased by hacking through DNS?" = Not Similar	Accuracy / F1
MNLI-mm	Does sentence A entail or contradict sentence B?	A) "Tourist Information offices can be very helpful." B) "Tourist Information offices are never of any help." = Contradiction	Accuracy
QNLI	Does sentence B contain the answer to the question in sentence A?	A) "What is essential for the mating of the elements that create radio waves?" B) "Antennas are required by any radio receiver or transmitter to couple its electrical connection to the electromagnetic field." = Answerable	Accuracy
RTE	Does sentence A entail sentence B?	A) "In 2003, Yunus brought the microcredit revolution to the streets of Bangladesh to support more than 50,000 beggars, whom the Grameen Bank respectfully calls Struggling Members." B) "Yunus supported more than 50,000 Struggling Members." = Entailed	Accuracy
WNLI	Sentence B replaces sentence A's ambiguous pronoun with one of the nouns - is this the correct noun?	A) "Lily spoke to Donna, breaking her concentration." B) "Lily spoke to Donna, breaking Lily's concentration." = Incorrect Referent	Accuracy

1) GLUE Results

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
BERT _{BASE}	84.6/83.4	71.2	90.5	93.5	52.1	85.8	88.9	66.4	79.6
$BERT_{LARGE}$	86.7/85.9	72.1	92.7	94.9	60.5	86.5	89.3	70.1	82.1

- GLUE → sequence classification task
- BERT achieves SOTA

2) SQuAD v1.1 Results

- SQuAD → Question Answering task
- **BERT**_{LARGE} achieves **SOTA** (with wide margin)

System	D	ev	Test				
•	EM	F1	EM	F1			
Top Leaderboard System	s (Dec	10th,	2018)				
Human	-	-	82.3	91.2			
#1 Ensemble - nlnet	-	-	86.0	91.7			
#2 Ensemble - QANet	-	-	84.5	90.5			
Published							
BiDAF+ELMo (Single)	-	85.6	-	85.8			
R.M. Reader (Ensemble)	81.2	87.9	82.3	88.5			
Ours							
BERT _{BASE} (Single)	80.8	88.5	-	-			
BERT _{LARGE} (Single)	84.1	90.9	-	-			
BERT _{LARGE} (Ensemble)	85.8	91.8	-	-			
BERT _{LARGE} (Sgl.+TriviaQA)	84.2	91.1	85.1	91.8			
BERT _{LARGE} (Ens.+TriviaQA)	86.2	92.2	87.4	93.2			

3) SWAG Results

- SWAG → grounded common-sense inference task
- **BERT**_{LARGE} achieves **SOTA** (with wide margin)

System	Dev	Test
ESIM+GloVe ESIM+ELMo OpenAI GPT		52.7 59.2 78.0
BERT _{BASE} BERT _{LARGE}	81.6 86.6	86.3
Human (expert) [†] Human (5 annotations) [†]	-	85.0 88.0

4) Ablation Studies

(1) Effect of Pre-training Tasks

	Dev Set					
Tasks	MNLI-m	QNLI	MRPC	SST-2	SQuAD	
	(Acc)	(Acc)	(Acc)	(Acc)	(F1)	
BERT _{BASE}	84.4	88.4	86.7	92.7	88.5	
No NSP	83.9	84.9	86.5	92.6	87.9	
LTR & No NSP	82.1	84.3	77.5	92.1	77.8	
+ BiLSTM	82.1	84.1	75.7	91.6	84.9	

4) Ablation Studies

(2) Effect of Model Size

Hyperparams				Dev Set Accuracy				
#L	#H	#A	LM (ppl)	MNLI-m	MRPC	SST-2		
3	768	12	5.84	77.9	79.8	88.4		
6	768	3	5.24	80.6	82.2	90.7		
6	768	12	4.68	81.9	84.8	91.3		
12	768	12	3.99	84.4	86.7	92.9		
12	1024	16	3.54	85.7	86.9	93.3		
24	1024	16	3.23	86.6	87.8	93.7		