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

Paper Presentation

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1. Background
2. Introducing Transformer
3. BERT

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Prerequisite

- Knowledge of recurrent neural networks and how they work.

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- Attention is all you need paper.

Introduction

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- For problems like language modeling and machine translation.

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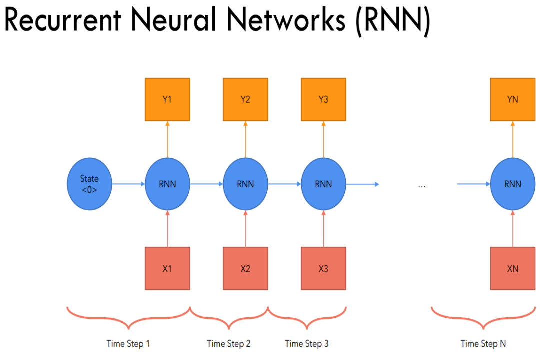

Figure 1: Workflow of RNN: *photo credit, Umar Jamil*

Introduction

- Problem as sequence length increases;

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i Slow computation

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ii Varnishing and Exploding gradients

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i Slow computation

ii Varnishing and Exploding gradients

iii Difficulty in accessing information from longer past time step

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Transformer Architecture

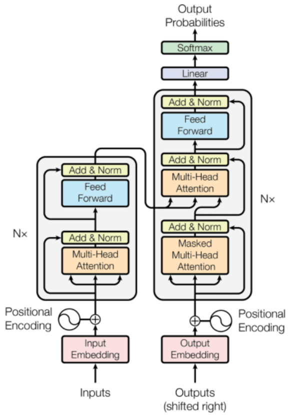


Figure 2: Transformer Model: *photo credit, Attention paper*

The Encoder

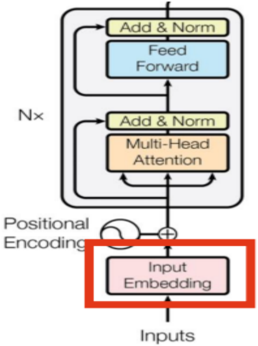


Figure 3: Transformer Model: *photo credit, Attention paper*

Input Embedding

Figure 4: Document Representation: *photo credit, Umar Jamil*

Input Embedding

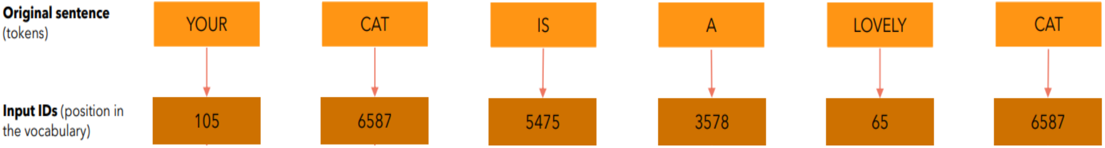


Figure 5: Document Representation

Input Embedding

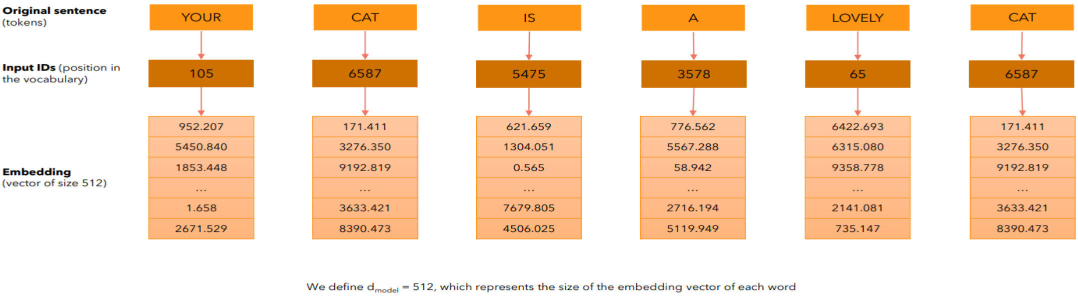
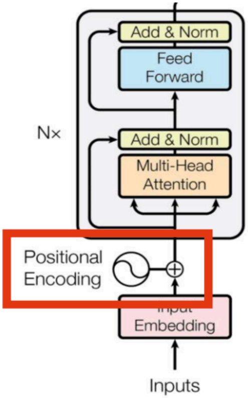


Figure 6: Document Representation

Positional Embedding



Positional Embedding

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  i Position of each word in the document.

  ii Treating words that are close as "close" and distant as "distant"

  iii Position encoding portray patterns learned by the model.

Positional Embedding

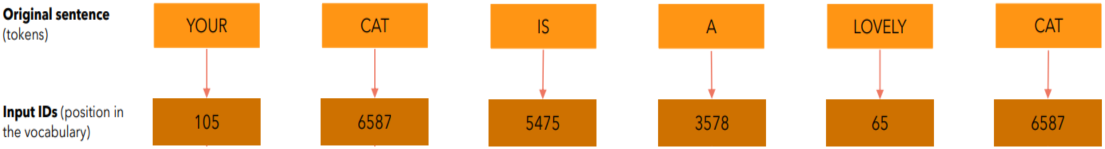


Figure 8: Document Representation

Positional Embedding

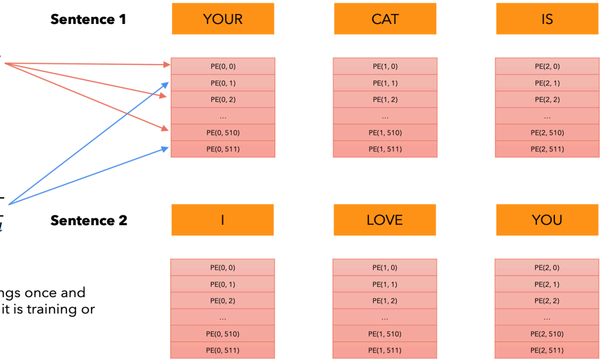
Original sentence	YOUR	CAT	IS	A	LOVELY	CAT
Embedding (vector of size 512)	952.207	171.411	621.659	776.562	6422.693	171.411
	5450.840	3276.350	1304.051	5567.288	6315.080	3276.350
	1853.448	9192.819	0.565	58.942	9358.778	9192.819
	...	...	...	...	...	...
	1.658	3633.421	7679.805	2716.194	2141.081	3633.421
	2671.529	8390.473	4506.025	5119.949	735.147	8390.473
	+	+	+	+	+	+
Position Embedding (vector of size 512). Only computed once and reused for every sentence during training and inference.	...	1664.068	...	...	...	1281.458
	...	8080.133	...	...	...	7902.890
	...	2620.399	...	...	...	912.970
	...	...	...	...	...	3821.102
	...	9386.405	...	...	...	1659.217
	...	3120.159	...	...	...	7018.620
	=	=	=	=	=	=
Encoder Input (vector of size 512)	...	1835.479	...	...	...	1452.869
	...	11356.483	...	...	...	11179.24
	...	11813.218	...	...	...	10105.789
	...	...	...	...	...	...
	...	13019.826	...	...	...	5292.638
	...	11510.632	...	...	...	15409.093

Figure 9: Document Representation

Positional Embedding Calculation

$$PE(pos, 2i) = \sin \frac{pos}{10000^{\frac{2i}{d_{model}}}}$$

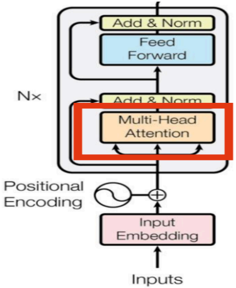
$$PE(pos, 2i+1) = \cos \frac{pos}{10000^{\frac{2i}{d_{model}}}}$$



We only need to compute the positional encodings once and then reuse them for every sentence, no matter if it is training or inference.

Figure 10: Document Representation

Attention Mechanism



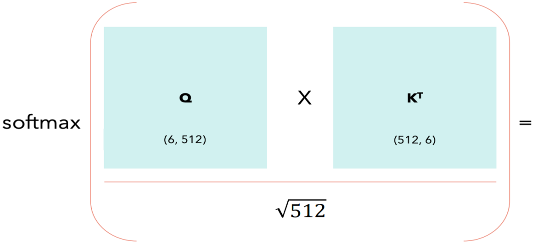
Attention Mechanism

Self-Attention allows the model to relate words to each other.

In this simple case we consider the sequence length **seq** = 6 and $\mathbf{d_{model}} = \mathbf{d_k} = 512$.

The matrices **Q**, **K** and **V** are just the input sentence.

$$Attention(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$



	YOUR	CAT	IS	A	LOVELY	CAT	Σ
YOUR	0.268	0.119	0.134	0.148	0.179	0.152	1
CAT	0.124	0.278	0.201	0.128	0.154	0.115	1
IS	0.147	0.132	0.262	0.097	0.218	0.145	1
A	0.210	0.128	0.206	0.212	0.119	0.125	1
LOVELY	0.146	0.158	0.152	0.143	0.227	0.174	1
CAT	0.195	0.114	0.203	0.103	0.157	0.229	1

* all values are random.

Figure 12: Self Attention computation

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(6, 6)

X

V

(6, 512)

=

Attention

(6, 512)

Each row in this matrix captures not only the meaning (given by the embedding) or the position in the sentence (represented by the positional encodings) but also each word's interaction with other words.

Figure 13: Self Attention computation

Properties of Self Atention

- No requires no parameter(s)

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- Can switch off word interactions. etc

Self-Attention Computation

$$softmax(\mathbf{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{N} e^{z_j}}$$

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Attention Mechanism

$$Attention(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

$$MultiHead(Q, K, V) = Concat(head_1 \ \dots head_h)W^O$$
$$head_i = Attention(QW_i^Q, KW_i^K, VW_i^V)$$

Figure 14: Multi-Head Attention

Multi-Head Attention Mechanism - DECODER

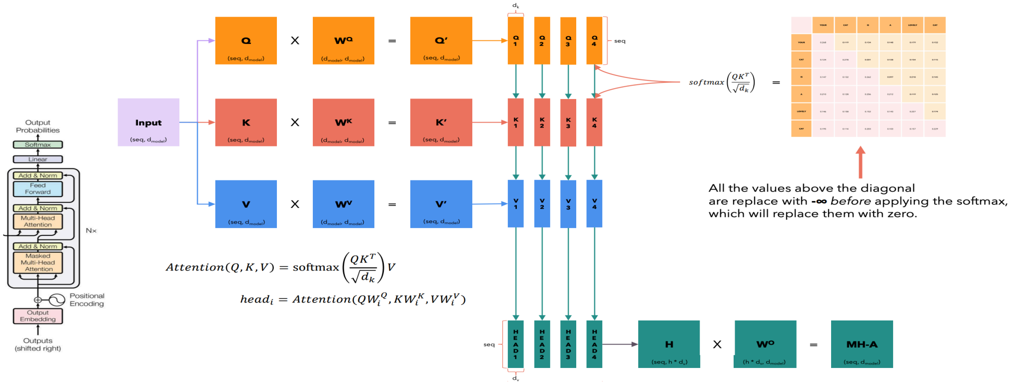

Figure 15: Masked Multi-head Attention computation

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Motivation

- Existing models like OpenAI GPT were unidirectional.

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- Understanding context in both directions was a challenge.

Goal

- To build a model that fully leverages context from both directions for improved language understanding.

Model Architecture

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    ii 12 attention heads
    iii 3072 hidden size of feed-forward layer
    iv 768 embedding size

Model Architecture

- **BERT-large:**

Model Architecture

- **BERT-large:**

i 24 encoder layers

Model Architecture

- **BERT-large:**

i 24 encoder layers

ii 16 attention heads

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iii 4096 hidden size of feed-forward layer

Model Architecture

- **BERT-large:**

i 24 encoder layers

ii 16 attention heads

iii 4096 hidden size of feed-forward layer

iv 1024 embedding size

BERT Training

Two ways of training;

1. Pre-training

BERT Training

Two ways of training;

1. Pre-training
2. Fine-tuning

BERT Training

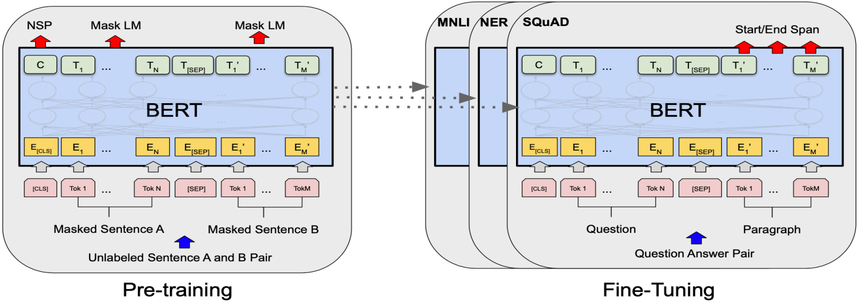

Figure 16: BERT Training

BERT: Pre-training tasks

Masked Language Modeling (MLM)

- Randomly masks 15% of the tokens.

BERT: Pre-training tasks

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- Predicts the masked tokens using bidirectional context.

Masked Language Modeling (MLM)

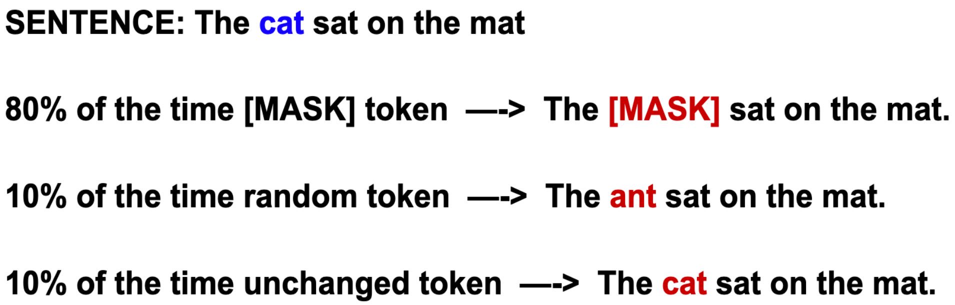

Figure 17: BERT: MLM Pre-training

Masked Language Modeling (MLM)

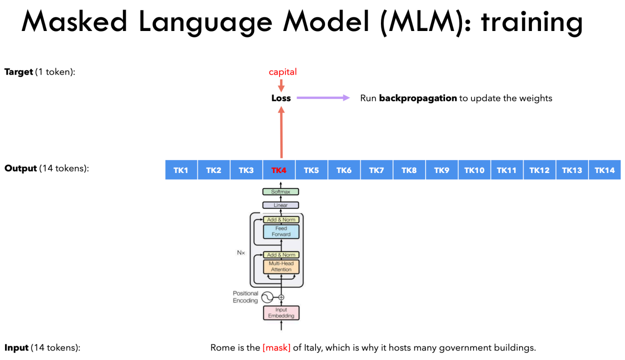

Figure 18: BERT: MLM Pre-training

BERT: Pre-training tasks

Next Sentence Prediction (NSP)

- Determines if a second sentence follows logically from the first.

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Next Sentence Prediction (NSP)

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- Sentence pair tasks; (sentence A, sentence B)
- 50% of the B is the actual sentence, 50% is a random sentence.
- Classification setup; *IsNEXT, NotNEXT*

Next Sentence Prediction (NSP)

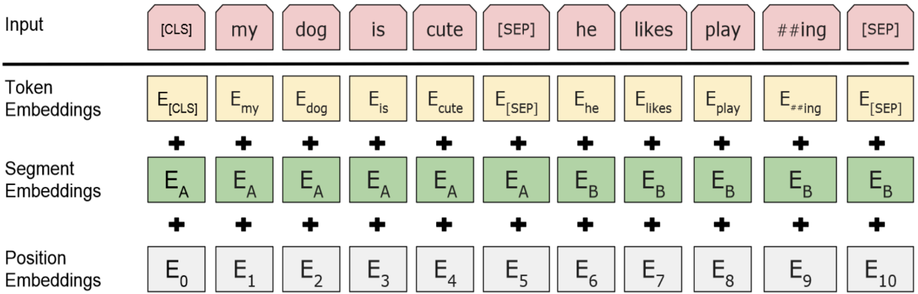

Figure 19: BERT: NSP Pre-training

Next Sentence Prediction (NSP)

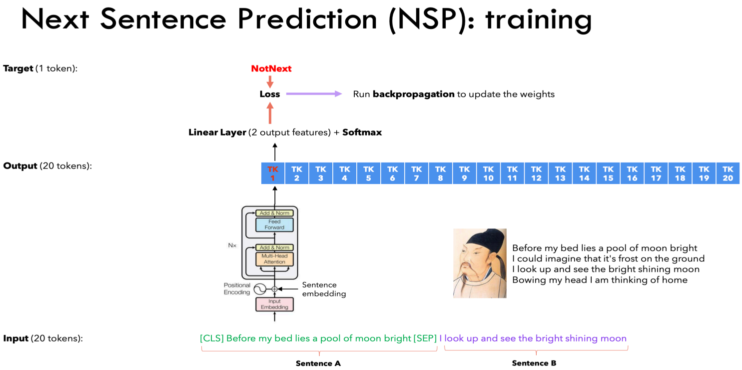

Figure 20: BERT: NSP Pre-training

BERT: Fine-tuning tasks

Text Classification Task

Text Classification: training

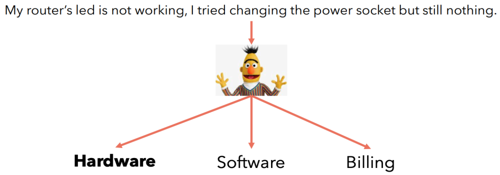

Figure 21: BERT: Fine-tuning for classification task

Text Classification Task

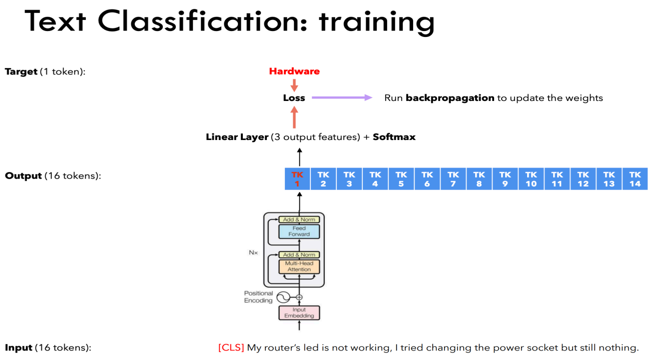

Figure 22: BERT: Fine-tuning for classification task

BERT: Fine-tuning tasks

Question Answering Task

Question Answering: sentence A and B

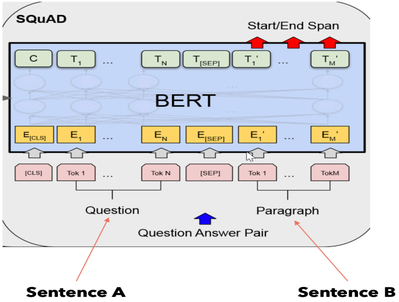

Figure 23: BERT: Fine-tuning for question answering task

Question Answering Task

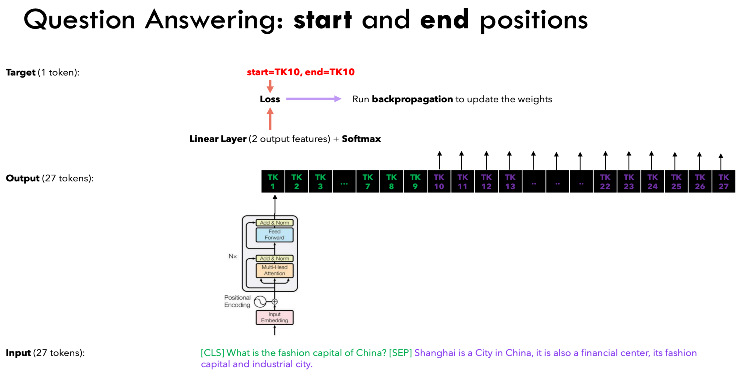

Figure 24: BERT: Fine-tuning for question answering task

Experiment & 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
$\text{BERT}_{\text{BASE}}$	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**

Figure 25: Experiment and results

Limitations

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- Limited understanding of rare or out-of-distribution words

Conclusions

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- BERT revolutionized NLP with bidirectional transformers.
- Future improvements focus on efficiency (e.g., DistilBERT) and domain-specific adaptations (e.g., BioBERT).

Thank You