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

## Paper Presentation

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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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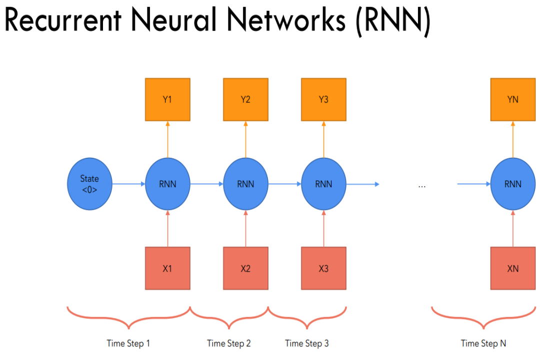


Figure 1: Workflow of RNN: *photo credit, Umar Jamil*

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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

1. Background
2. Introducing Transformer
   - Attention is all you need.
3. BERT

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# Transformer Architecture

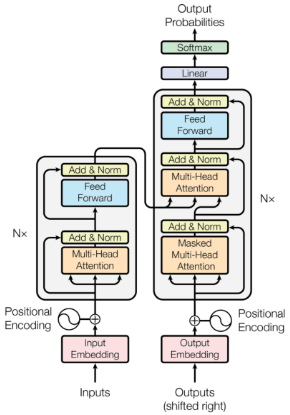


Figure 2: Transformer Model: *photo credit, Attention paper*

# The Encoder

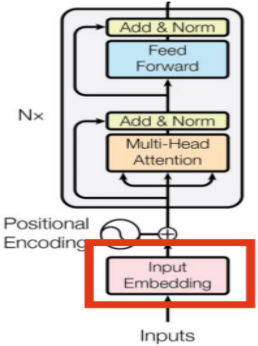


Figure 3: Transformer Model: *photo credit, Attention paper*

# Input Embedding


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

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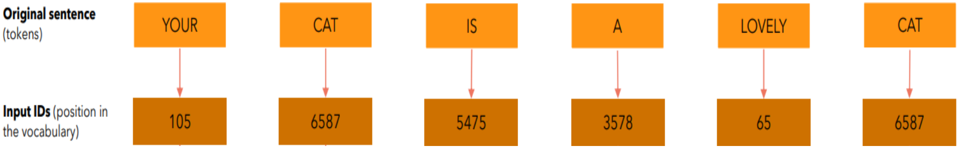



Figure 5: Document Representation

# Input Embedding

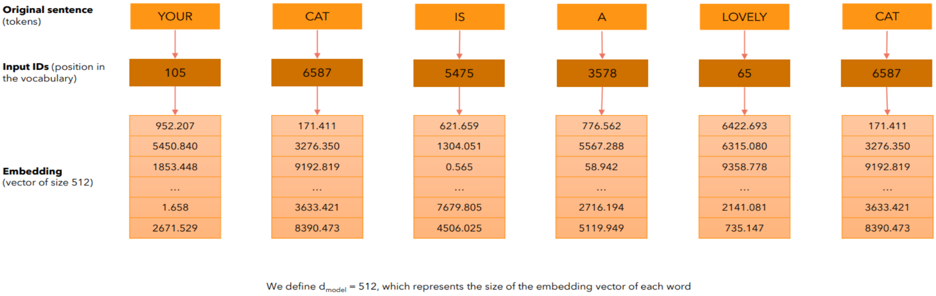
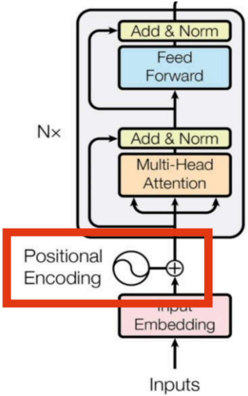



Figure 6: Document Representation

# Positional Embedding



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

iii Position encoding portray patterns learned by the model.

# Positional Embedding

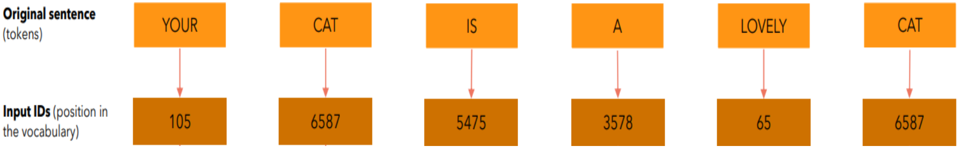



Figure 8: Document Representation

# Positional Embedding

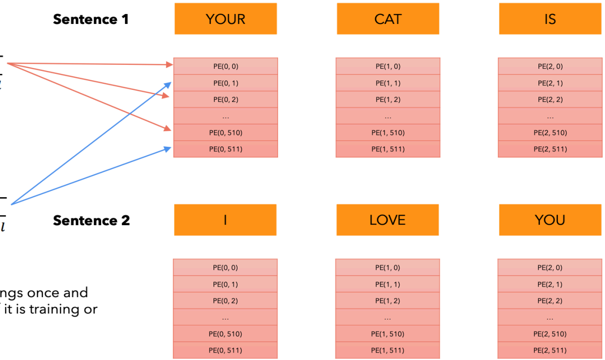
| Original sentence | YOUR | CAT | IS | A | LOVELY | CAT |
|---|---|---|---|---|---|---|
| **Embedding** (vector of size 512) | 952.207 | 171.411 | 621.659 | 776.562 | 6422.693 | 171.411 |
| | 5450.840 | 3276.350 | 1304.051 | 5567.288 | 6315.080 | 3276.350 |
| | 1853.448 | 9192.819 | 0.565 | 58.942 | 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

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

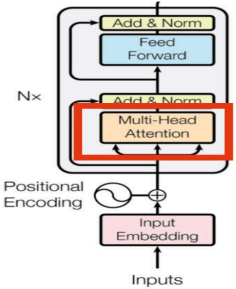
$$PE(pos, 2i+1) = \cos \frac{pos}{10000^{\frac{2i}{d_{model}}}}$$




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.

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

$$\text{softmax}\left(\frac{\underset{(6,\,512)}{\mathbf{Q}} \times \underset{(512,\,6)}{\mathbf{K^T}}}{\sqrt{512}}\right) =$$

| | 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

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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

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

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

Figure 14: Multi-Head Attention

# Multi-Head Attention Mechanism - DECODER

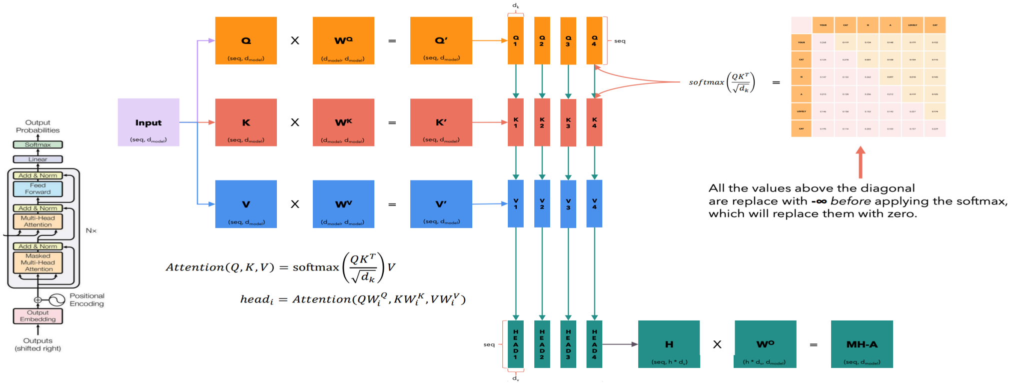


Figure 15: Masked Multi-head Attention computation

# Motivation

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

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iii 4096 hidden size of feed-forward layer

iv 1024 embedding size

# BERT Training

Two ways of training;

1. Pre-training

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2. Fine-tuning

# BERT Training

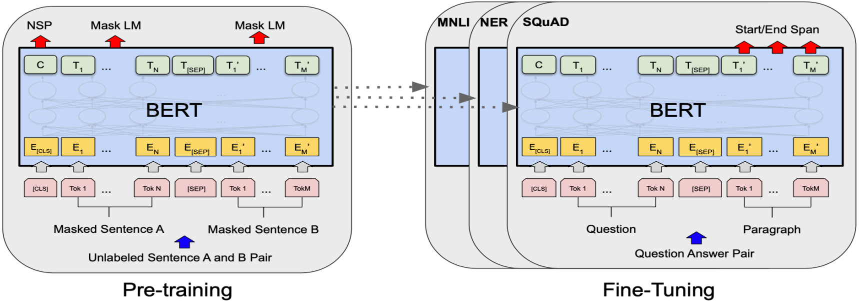


Figure 16: BERT Training

# BERT: Pre-training tasks

## Masked Language Modeling (MLM)

- Randomly masks 15% of the tokens.

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- Randomly masks 15% of the tokens.
- Predicts the masked tokens using bidirectional context.

# Masked Language Modeling (MLM)

**SENTENCE: The cat sat on the mat**

**80% of the time [MASK] token —-> The [MASK] sat on the mat.**

**10% of the time random token —-> The ant sat on the mat.**

**10% of the time unchanged token —-> The cat sat on the mat.**

Figure 17: BERT: MLM Pre-training

# Masked Language Modeling (MLM)

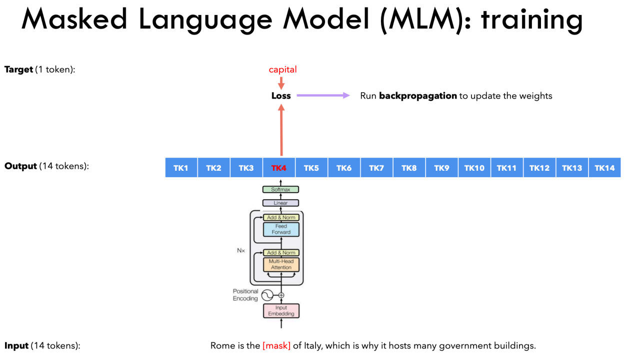


Figure 18: BERT: MLM Pre-training

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## Next Sentence Prediction (NSP)

- Determines if a second sentence follows logically from the first.
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- 50% of the B is the actual sentence, 50% is a random sentence.
- Classification setup; *IsNEXT, NotNEXT*

# Next Sentence Prediction (NSP)

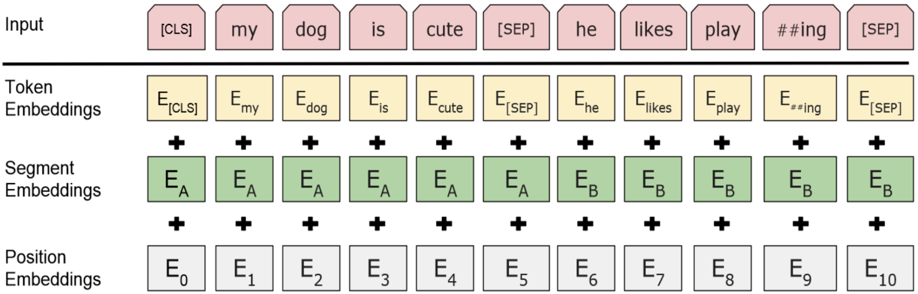


Figure 19: BERT: NSP Pre-training

# Next Sentence Prediction (NSP)

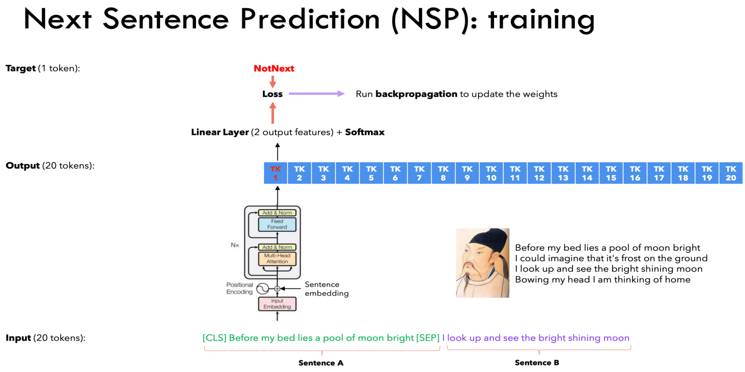


Figure 20: BERT: NSP Pre-training

# BERT: Fine-tuning tasks

## Text Classification Task

### Text Classification: training

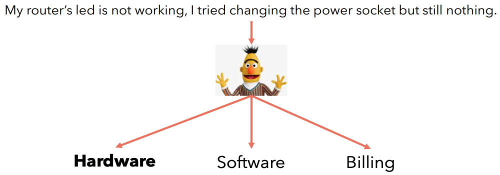


Figure 21: BERT: Fine-tuning for classification task

# Text Classification Task

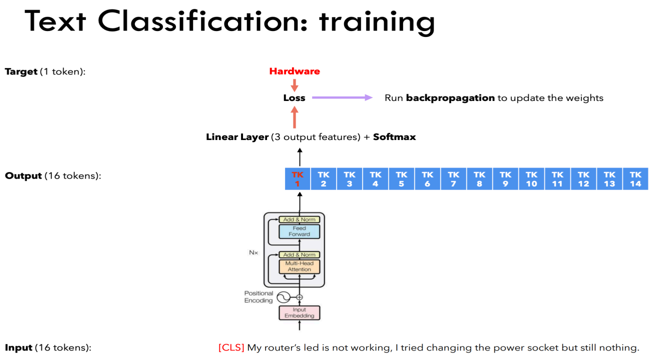


Figure 22: BERT: Fine-tuning for classification task

# BERT: Fine-tuning tasks

## Question Answering Task

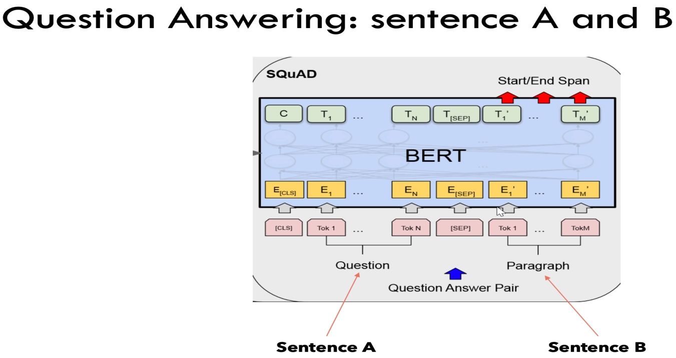


Figure 23: BERT: Fine-tuning for question answering task

# Question Answering Task

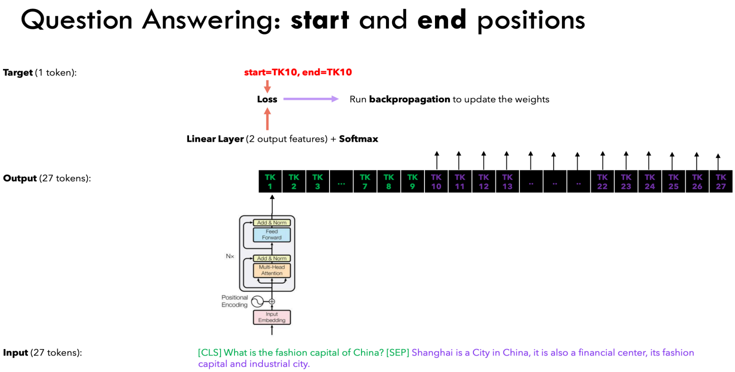


Figure 24: BERT: Fine-tuning for question answering task

# 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

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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*