



Transformers

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Outline

- **Encoder-Only / Decoder-Only**
- **Huggingface Transformer - Provides pretrained models, tools and APIs for using transformer based architectures.**

Encoder-Only | BERT

Bidirectional Encoder Representations from Transformers (BERT) - Google.

Model Architecture

- Transformer Encoder

What is Special About It

- Mask Language Modeling & Next Sentence Prediction
- Downstream task adaptation

BERT's primary goal is to create contextualized word embeddings, meaning it captures the meaning of a word based on its context in the sentence.

BERT's embeddings are dynamic and depend on the **words surrounding the target word**.

How BERT Achieves This Goal:

To achieve contextualized embeddings, BERT is trained using two key tasks:

1. Next Sentence Prediction (NSP):

- a. What is NSP? The model is given two sentences, and it must predict whether the second sentence logically follows the first sentence or if it is a random sentence.
- b. Why? This task helps BERT understand relationships between sentences, which is useful for downstream tasks like question answering, text classification, or sentence similarity.

2. Masked Language Model (MLM):

- a. What is MLM? In this task, random words in the input sentence are masked (replaced with [MASK]), and the model is trained to predict those masked words based on the context provided by the other words in the sentence.
- b. Why? By doing this, BERT learns how words relate to each other in context. It helps the model understand how different words fit together, which is essential for producing rich, context-aware word representations.

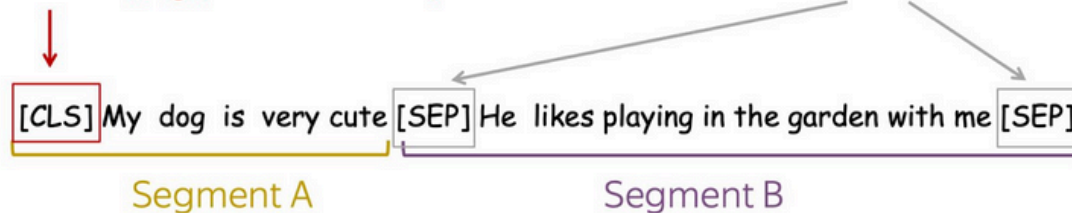
BERT - Pretrain | Inputs

Training Input: 1) pairs of sentence; 2) [CLS] token; 3) [SEP] token

[CLS]: Special token

- Training time: predict if sentences are consecutive or not (Next Sentence Prediction /NSP objective)
- Test time: downstream tasks (e.g., classification)

[SEP]: Special token-separator



Training on pairs of sentences: either consecutive or random (50%/50%)

Embedding

Training time: predict if sentences are consecutive (NSP objective)

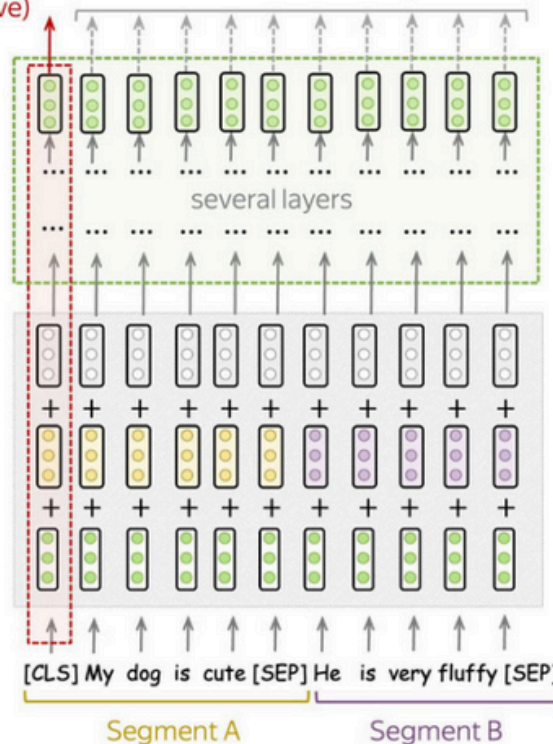
Test time: classification

- 1) Token
- 2) Segment
- 3) Position

Model
(Transformer encoder)

Input

Training on pairs of sentences: either consecutive or random (50%/50%)

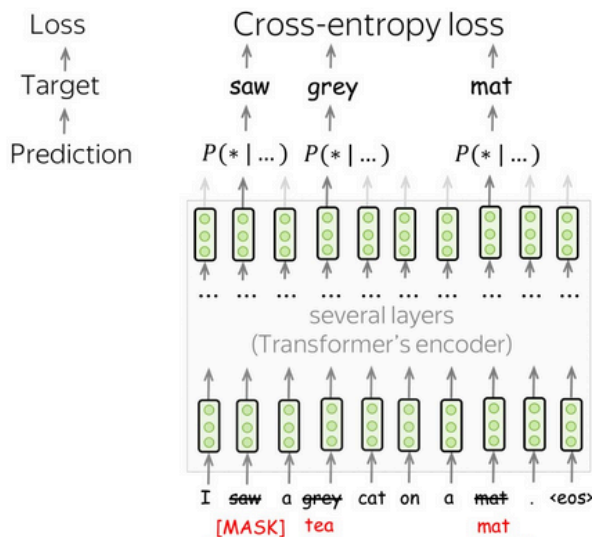


positions
0 1 2 3 4 ...

segments
A A A A A A B B B B B

tokens
[CLS] My dog is ...

BERT - Pretrain | Inputs



At each training step:

- pick randomly 15% of tokens
- replace each of the chosen tokens with something
- predict original chosen tokens

BERT - Pretrain | Objective

Next Sentence Prediction (NSP)

Input: [CLS] the man went to [MASK] store [SEP] he bought a gallon [MASK] milk [SEP]

Label: isNext

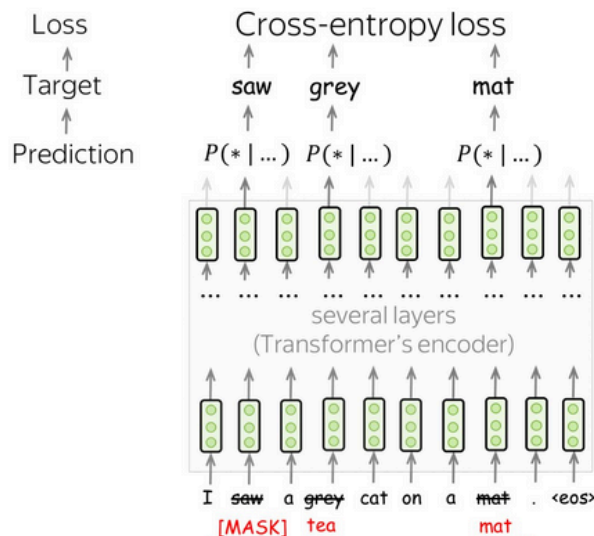
Input: [CLS] the man went to [MASK] store [SEP] penguin [MASK] are flight ##less birds [SEP]

Label: notNext

BERT - Pretrain | Objective

Masked Language Modeling (MLM)

Output layer of MLM - Output Linear Layer: Generates logits for vocabulary.



At each training step:

- pick randomly 15% of tokens
- replace each of the chosen tokens with something
- predict original chosen tokens

- [MASK], with $p = 80\%$
- Random token, with $p = 10\%$
- Original token, with $p = 10\%$

During training:

Masked tokens: Predicted tokens are compared to original tokens.

Loss calculation: Cross-entropy loss calculated for each masked token.

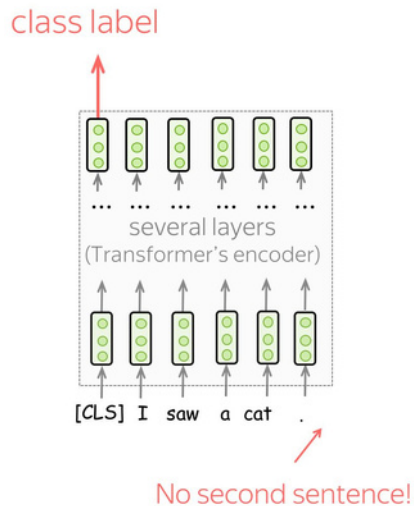
Backpropagation: Gradients computed to update model weights.

Benefits:

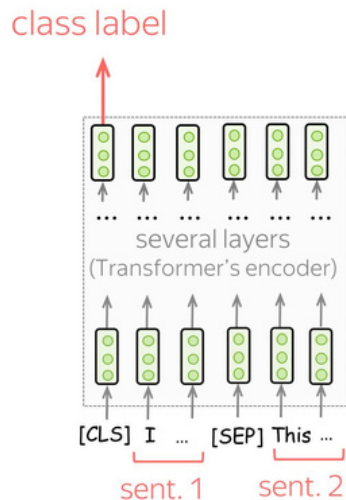
- 1.Contextual understanding: BERT learns to represent tokens in context.
- 2.Improved language modeling: Better handling of out-of-vocabulary tokens.
- 3.Transfer learning: Fine-tuning benefits from pre-trained MLM.

BERT - Finetune | Tasks

Single sentence classification

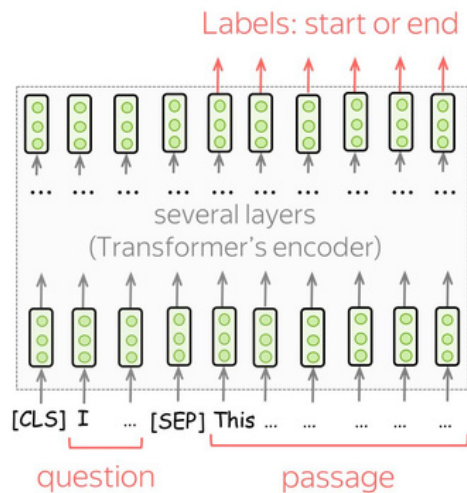


Sentence Pair Classification

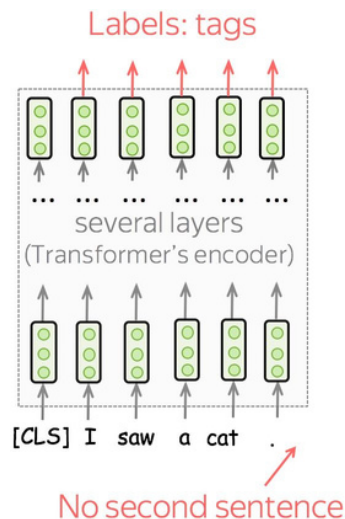


BERT - Finetune | Tasks

Question Answering



Single sentence tagging



Decoder-Only | GPT

Generative Pretrained Transformer (GPT) - OpenAI

Model Architecture

- Transformer **Decoder**

What is Special About It

1. Autoregressive Language Modeling - Predict next token given previous tokens.
2. Downstream task adaptation.

Mathematically:

$$P(\text{token}_n \mid \text{token}_1, \text{token}_2, \dots, \text{token}_{\{n-1\}})$$

Key features:

- **Unsupervised Learning:** Trained on large corpus without labeled data.
- **Generative Capabilities:** Generates coherent text.
- **Transfer Learning:** Fine-tunes for downstream tasks.

Downstream Task Adaptation

GPT's adaptation:

- **Language Translation:** Generate translations.
- **Text Summarization:** Summarize long texts.
- **Chatbots:** Engage in conversations.

GPT - Pretrain | Inputs

Training Input: 1) sentences; 2) [PAD] / [EOS] token

Sentences: Sequential text data.

[PAD] token: Padding token for fixed-length sequences.

[EOS] token: End-of-sequence token.

Example:

My dog is very cute. He likes playing in the garden with me [EOS] [PAD] ... [PAD]

Embedding:

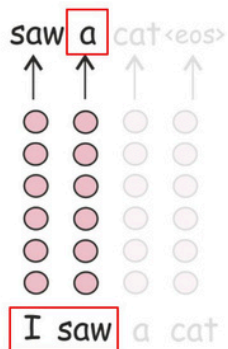
Token embeddings + positional embeddings

GPT - Pretrain | Objective

Autoregressive Language Modeling

Language Modeling

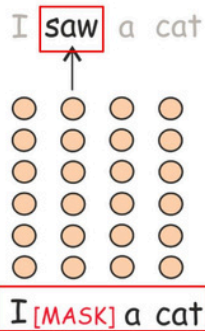
- Target: next token
- Prediction: $P(* | \text{I saw})$



left-to-right, does
not see future

Masked Language Modeling

- Target: current token (the true one)
- Prediction: $P(* | \text{I [MASK] a cat})$



sees the whole text, but
something is corrupted

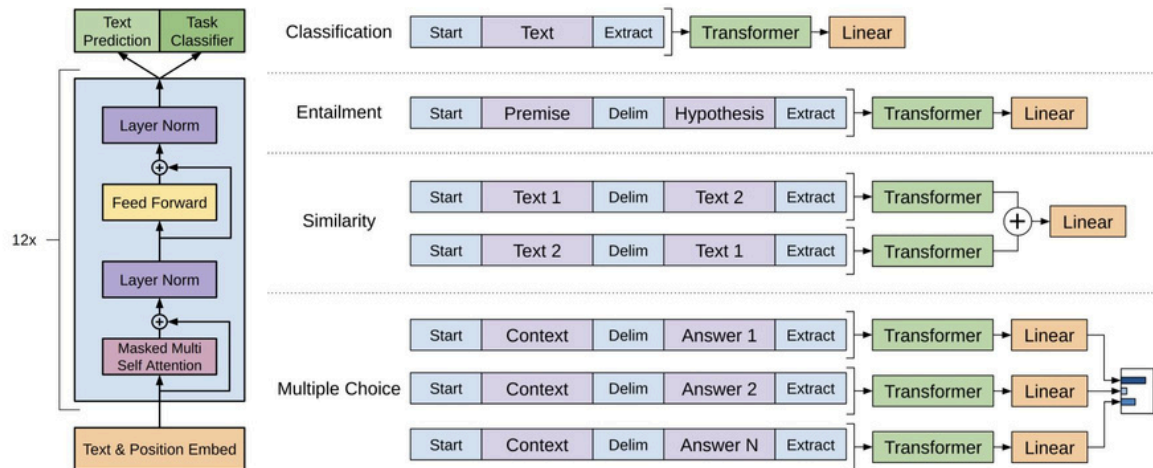
$$P(\text{token}_n | \text{token}_1, \text{token}_2, \dots, \text{token}_{\{n-1\}})$$

$$P(\text{token}_i | \text{token}_1, \dots, \text{token}_{\{i-1\}}, [\text{MASK}], \text{token}_{\{i+1\}}, \dots)$$

GPT - Finetune | NLU Tasks

GPT for Natural Language Understanding (NLU) Tasks

- You can train an additional linear head on top of the final transformer block activation vector.



Encoder-Decoder | T5

Text-to-Text Transfer Transformer (T5) Model Architecture

- Transformer Encoder & Decoder

What is Special About It

- pretraining on multi-task mixture of unsupervised and supervised tasks (converted to Text-to-Text format)

Resources

- Encoder-Only (BERT)
 - <https://github.com/JonasGeiping/cramming>
- Decoder-Only (GPT)
 - <https://github.com/karpathy/nanoGPT>
- Encoder-Decoder (T5)
 - <https://github.com/PiotrNawrot/nanoT5>

Summary

- Encoder-Only (BERT)

- Decoder-Only (GPT)

- Encoder-Decoder (T5)

Acknowledgement

This presentation is adapted from Elena (Lena) Voita's NLP Course | For You
(https://lena-voita.github.io/nlp_course.html)