Natural Language Processing with Deep Learning

Lecture 10 – Text classification 6: BERT part two

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December 15, 2023

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Paderborn University
We focus on Trustworthy Human Language Technologies

www.trusthlt.org

Motivation

Last time we started with the transformer and BERT, but we

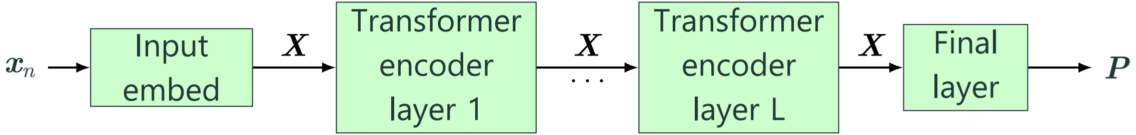
- skipped some important architectural details
- were unprecise with some graphical representation
- did not talk about pre-training and fine-tuning

Let's fix that today!

After this lecture you should be able to build BERT

BERT — Encoder architecture in detail

Transformer encoder (BERT)



As usual, green boxes are functions with trainable parameters

BERT (encoding-only transformer, forward pass)

function ETRANSFORMER($\boldsymbol{x}; \boldsymbol{\mathcal{W}}$)
    $\ldots$

Input:

$\boldsymbol{x}$ — $\boldsymbol{x} \in V^*$, a sequence of token IDs

$\boldsymbol{\mathcal{W}}$ — all trainable parameters

Output:

Typically an embedding vector for each input token

Or: $\boldsymbol{P} \in (0,1)^{\ell_{\mathsf{x}} \times N_{\mathsf{V}}}$, where each row of $\boldsymbol{P}$ is a distribution over the vocabulary

Input embeddings

The cat sat $\boldsymbol{x}_n = \begin{pmatrix} 21 & 11987 & 5438 \end{pmatrix}$

$$\begin{bmatrix} 21 & 11987 & 5438 \end{bmatrix} \xrightarrow{\boldsymbol{x}_n} \boxed{\text{Input embeddings}} \xrightarrow{\boldsymbol{X}} \begin{bmatrix} \cdots & \boldsymbol{e}_1 & \cdots \\ \cdots & \boldsymbol{e}_2 & \cdots \\ \cdots & \boldsymbol{e}_3 & \cdots \end{bmatrix}$$

BERT (encoding-only transformer, forward pass)

```
function ETRANSFORMER(x; W)
    ℓ ← length(x)
    for t ∈ [ℓ] : e_t ← W_e[x[t], :] + W_p[t, :]        ▷ Token emb. + positional emb.
    X ← Stack row-wise[e_1, e_2, . . . e_ℓ]
    . . .
```

function $\textsc{ETransformer}(\boldsymbol{x}; \boldsymbol{\mathcal{W}})$

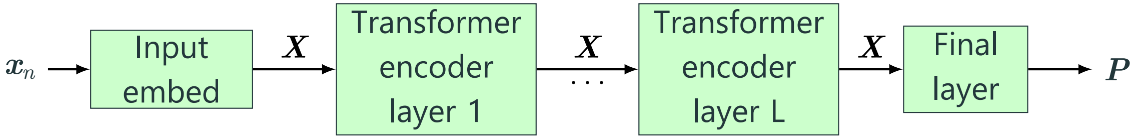
$\ell \leftarrow \text{length}(\boldsymbol{x})$

for $t \in [\ell] : \boldsymbol{e}_t \leftarrow \boldsymbol{W_e}[x[t], :] + \boldsymbol{W_p}[t, :]$ ▷ Token emb. + positional emb.

$\boldsymbol{X} \leftarrow$ Stack row-wise$[\boldsymbol{e}_1, \boldsymbol{e}_2, \ldots \boldsymbol{e}_\ell]$

$\ldots$

Transformer encoder (BERT)



The transformer encoder layer is repeated L-times (each with different parameters)

BERT (encoding-only transformer, forward pass)

function ETRANSFORMER($\boldsymbol{x}; \boldsymbol{\mathcal{W}}$)

  $\ell \leftarrow \text{length}(\boldsymbol{x})$

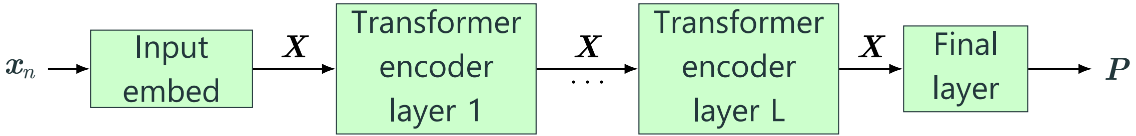
  for $t \in [\ell] : \boldsymbol{e}_t \leftarrow \boldsymbol{W_e}[x[t], :] + \boldsymbol{W_p}[t, :]$ ▷ Token emb. + positional emb.

  $\boldsymbol{X} \leftarrow \text{Stack row-wise}[\boldsymbol{e}_1, \boldsymbol{e}_2, \ldots \boldsymbol{e}_\ell]$

  for $l = 1, 2, \ldots, L$ **do**

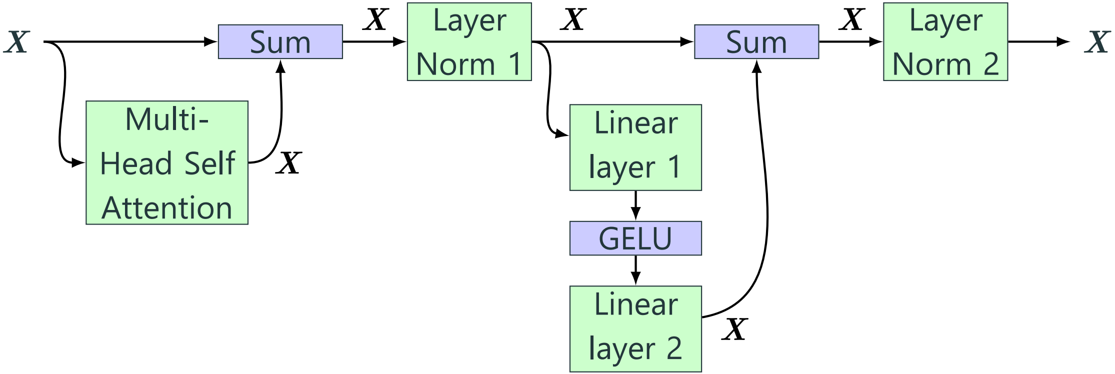
    $\ldots$

Transformer encoder (BERT)



Let's look at a single transformer encoder layer

Transformer encoder layer (BERT)



Let's focus on Multi-Head Self Attention

BERT (encoding-only transformer, forward pass)

function ETRANSFORMER($\boldsymbol{x}; \mathcal{W}$)

  $\ell \leftarrow \text{length}(\boldsymbol{x})$

  for $t \in [\ell]$: $\boldsymbol{e}_t \leftarrow \boldsymbol{W}_{\boldsymbol{e}}[x[t], :] + \boldsymbol{W}_{\boldsymbol{p}}[t, :]$ ▷ Token emb. + positional emb.

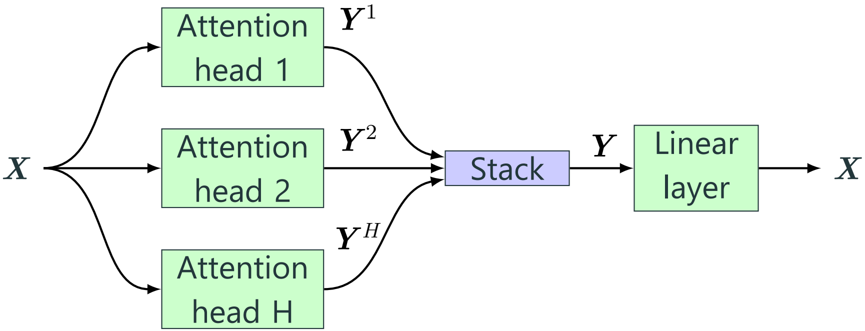
  $\boldsymbol{X} \leftarrow \text{Stack row-wise}[\boldsymbol{e}_1, \boldsymbol{e}_2, \ldots \boldsymbol{e}_\ell]$

  for $l = 1, 2, \ldots, L$ **do**

    $\boldsymbol{X} \leftarrow \boldsymbol{X} + \text{MHATTENTION}(\boldsymbol{X} | \mathcal{W}_l)$ ▷ Multi-head att., residual conn

    $\ldots$

Multi-head unmasked self-attention (BERT)



Multi-head bidirectional / unmasked self-attention

Input: $\boldsymbol{X} \in \mathbb{R}^{\ell_\mathsf{x} \times d_\mathsf{x}}$, vector representations of the sequence of length ℓ_x

Output: $\tilde{\boldsymbol{V}} \in \mathbb{R}^{\ell_\mathsf{x} \times d_\mathsf{out}}$, updated vector representations of tokens in $\boldsymbol{X}$

Hyper-param: H, number of attention heads

Params for each $h \in [H]$: $\boldsymbol{\mathcal{W}}^h_{\boldsymbol{qkv}}$:

- $\boldsymbol{W}^h_{\boldsymbol{q}}, \boldsymbol{W}^h_{\boldsymbol{k}} \in \mathbb{R}^{d_\mathsf{x} \times d_\mathsf{attn}}$, $\boldsymbol{b}^h_{\boldsymbol{q}}, \boldsymbol{b}^h_{\boldsymbol{k}} \in \mathbb{R}^{d_\mathsf{attn}}$, $\boldsymbol{W}_{\boldsymbol{v}} \in \mathbb{R}^{d_\mathsf{x} \times d_\mathsf{mid}}$, $\boldsymbol{b}_{\boldsymbol{v}} \in \mathbb{R}^{d_\mathsf{mid}}$
- $\boldsymbol{W}_{\boldsymbol{o}} \in \mathbb{R}^{H \cdot d_\mathsf{mid} \times d_\mathsf{out}}$, $\boldsymbol{b}_{\boldsymbol{o}} \in \mathbb{R}^{d_\mathsf{out}}$

```
function MHAttention(X; W)
    for h ∈ [H] do
        Y^h ← Attention(X; W^h_qkv)                ▷ Y^h ∈ R^{ℓx × dmid}
    Y ← [Y^1; Y^2; ...; Y^H]                       ▷ Y ∈ R^{ℓx × H·dmid}
    return Ṽ = Y W_o + b_o
```

function $\text{MHAttention}(\boldsymbol{X}; \boldsymbol{\mathcal{W}})$

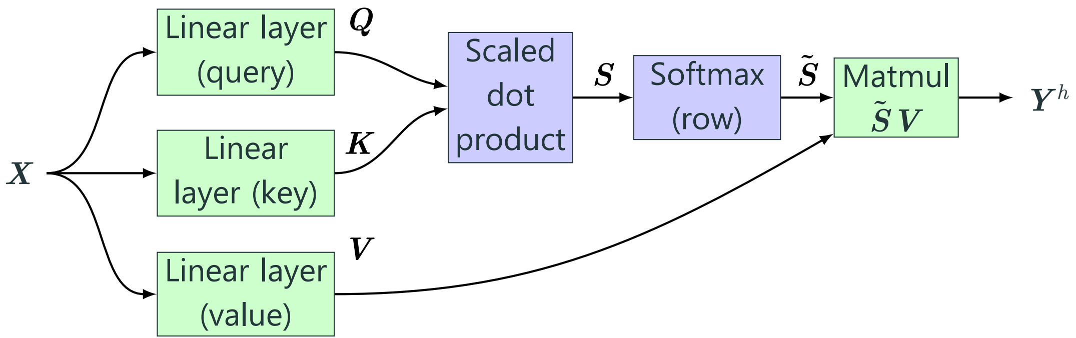
  for $h \in [H]$ **do**

    $\boldsymbol{Y}^h \leftarrow \text{Attention}(\boldsymbol{X}; \boldsymbol{\mathcal{W}}^h_{\boldsymbol{qkv}})$ $\triangleright\ \boldsymbol{Y}^h \in \mathbb{R}^{\ell_\mathsf{x} \times d_\mathsf{mid}}$

  $\boldsymbol{Y} \leftarrow [\boldsymbol{Y}^1; \boldsymbol{Y}^2; \ldots; \boldsymbol{Y}^H]$ $\triangleright\ \boldsymbol{Y} \in \mathbb{R}^{\ell_\mathsf{x} \times H \cdot d_\mathsf{mid}}$

  return $\tilde{\boldsymbol{V}} = \boldsymbol{Y}\boldsymbol{W}_{\boldsymbol{o}} + \boldsymbol{b}_{\boldsymbol{o}}$

Single unmasked self-attention head (BERT)



Bidirectional / unmasked self-attention (recap from last lecture)

Input: $\boldsymbol{X} \in \mathbb{R}^{\ell_\mathsf{x} \times d_\mathsf{x}}$, vector representations of the sequence of length ℓ_x

Output: $\tilde{\boldsymbol{V}} \in \mathbb{R}^{\ell_\mathsf{x} \times d_\mathsf{out}}$, updated vector representations of tokens in $\boldsymbol{X}$

Params $\boldsymbol{\mathcal{W}}_{\boldsymbol{qkv}}$: $\boldsymbol{W_q}, \boldsymbol{W_k} \in \mathbb{R}^{d_\mathsf{x} \times d_\mathsf{attn}}$, $\boldsymbol{b_q}, \boldsymbol{b_k} \in \mathbb{R}^{d_\mathsf{attn}}$, $\boldsymbol{W_v} \in \mathbb{R}^{d_\mathsf{x} \times d_\mathsf{out}}$, $\boldsymbol{b_v} \in \mathbb{R}^{d_\mathsf{out}}$

function ATTENTION($\boldsymbol{X}; \boldsymbol{\mathcal{W}}_{\boldsymbol{qkv}}$)

$\boldsymbol{Q} \leftarrow \boldsymbol{X}\boldsymbol{W_q} +_{\text{(rows)}} \boldsymbol{b_q}$ ▷ Query $\in \mathbb{R}^{\ell_\mathsf{x} \times d_\mathsf{attn}}$

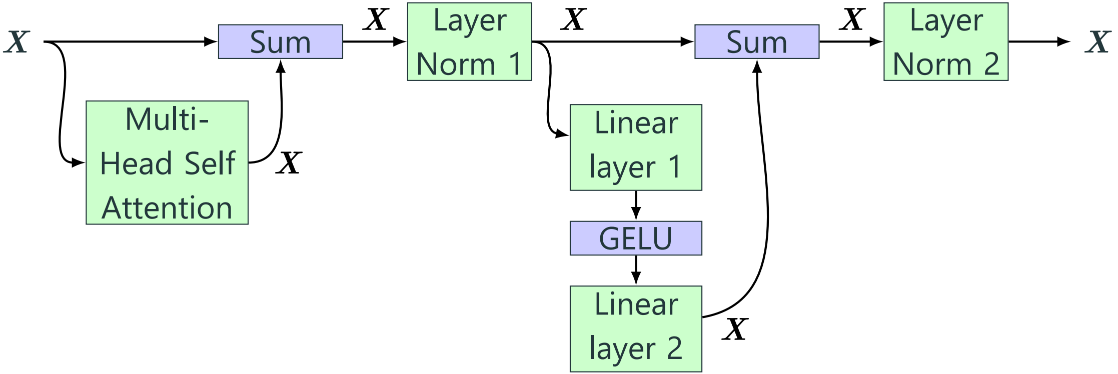
$\boldsymbol{K} \leftarrow \boldsymbol{X}\boldsymbol{W_k} +_{\text{(rows)}} \boldsymbol{b_k}$ ▷ Key $\in \mathbb{R}^{\ell_\mathsf{x} \times d_\mathsf{attn}}$

$\boldsymbol{V} \leftarrow \boldsymbol{X}\boldsymbol{W_v} +_{\text{(rows)}} \boldsymbol{b_v}$ ▷ Value $\in \mathbb{R}^{\ell_\mathsf{x} \times d_\mathsf{out}}$

$\boldsymbol{S} \leftarrow \frac{1}{\sqrt{d_\mathsf{attn}}} (\boldsymbol{Q}\boldsymbol{K}^\top)$ ▷ Scaled score $\in \mathbb{R}^{\ell_\mathsf{x} \times \ell_\mathsf{x}}$

return $\tilde{\boldsymbol{V}} = \mathrm{softmax}_{\text{row}}(\boldsymbol{S})\,\boldsymbol{V}$

Transformer encoder layer (BERT)



Let's add Layer Normalization and GELU

Simplifying notation: Perform LayerNorm on each row

Recall: LayerNorm

Input: $\boldsymbol{e} \in \mathbb{R}^d$ (output of a layer), Output: $\hat{e} \in \mathbb{R}^d$

Params: $\boldsymbol{\gamma}, \boldsymbol{\beta} \in \mathbb{R}^d$, trainable element-wise scale and offset

function LayerNorm($\boldsymbol{e} | \boldsymbol{\gamma}, \boldsymbol{\beta}$)
    $m \leftarrow \frac{1}{d} \sum_{i=1}^{d} \boldsymbol{e}[i]$ ▷ 'Sample mean' of $\boldsymbol{e}$
    $v \leftarrow \frac{1}{d} \sum_{i=1}^{d} (\boldsymbol{e}[i] - m)^2$ ▷ 'Sample variance' of $\boldsymbol{e}$
    return $\hat{e} = \frac{e-m}{\sqrt{v}} \odot \boldsymbol{\gamma} + \boldsymbol{\beta}$ ▷ Offset and scale

function LayerNormEachRow($\boldsymbol{X} \in \mathbb{R}^{m \times n} | \boldsymbol{\gamma}, \boldsymbol{\beta}$)
    for $t \in [m]$ **do**
        $\boldsymbol{X}[t, :] \leftarrow$ LayerNorm$(\boldsymbol{X}[t, :] | \boldsymbol{\gamma}, \boldsymbol{\beta})$
    return $\boldsymbol{X}$

GELU — Gaussian Error Linear Units

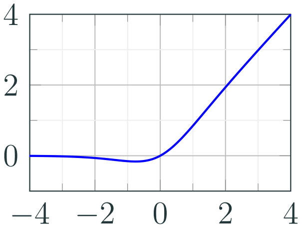
Recall: CDF $\Phi(x)$ of standard normal $X \sim \mathcal{N}(0;1)$

$$\Phi(x) = \Pr(X \leq x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{x} \exp\left(\frac{-t^2}{2}\right) \mathrm{d}t$$

D. Hendrycks and K. Gimpel (2016). ***Gaussian Error Linear Units (GELUs)***. arXiv: `1606.08415`

For vectors $\boldsymbol{x} \in \mathbb{R}^n$, GELU$(\boldsymbol{x})$ is applied element-wise

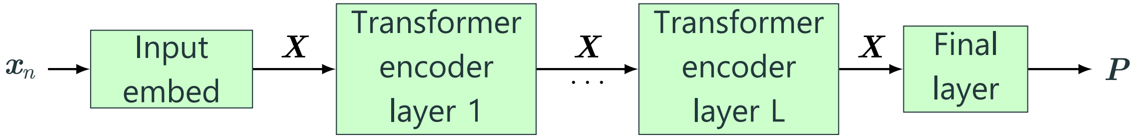
$$\begin{aligned} \text{GELU}(x) &= x \cdot \Phi(x) \\ &\approx x \cdot \sigma(1.702x) \qquad \text{(if speed > exactness)} \end{aligned}$$



BERT (encoding-only transformer, forward pass)

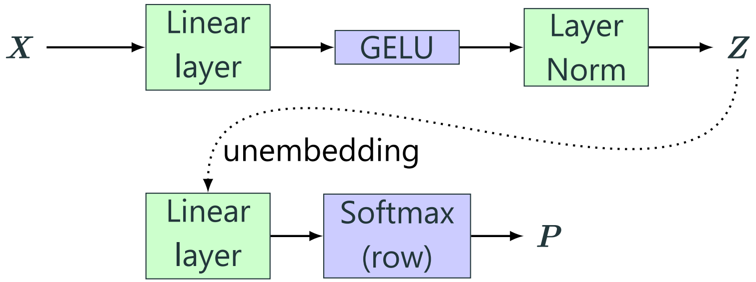
function $\text{ETRANSFORMER}(\boldsymbol{x}; \mathcal{W})$
  $\ell \leftarrow \text{length}(\boldsymbol{x})$
  for $t \in [\ell]$: $\boldsymbol{e}_t \leftarrow \boldsymbol{W_e}[x[t], :] + \boldsymbol{W_p}[t, :]$ ▷ Token emb. + positional emb.
  $\boldsymbol{X} \leftarrow \text{Stack row-wise}[\boldsymbol{e}_1, \boldsymbol{e}_2, \dots \boldsymbol{e}_\ell]$
  for $l = 1, 2, \dots, L$ **do**
    $\boldsymbol{X} \leftarrow \boldsymbol{X} + \text{MHATTENTION}(\boldsymbol{X} | \mathcal{W}_l)$ ▷ Multi-head att., residual conn
    $\boldsymbol{X} \leftarrow \text{LAYERNORMPERROW}(\boldsymbol{X} | \boldsymbol{\gamma}_l^1, \boldsymbol{\beta}_l^1)$
    $\boldsymbol{X} \leftarrow \boldsymbol{X} + \left(\text{GELU}(\boldsymbol{X}\boldsymbol{W}_l^{\text{mlp1}} +_{\text{(row)}} \boldsymbol{b}_l^{\text{mlp1}})\,\boldsymbol{W}_l^{\text{mlp2}} +_{\text{(row)}} \boldsymbol{b}_l^{\text{mlp2}}\right)$ ▷ MLP
    $\boldsymbol{X} \leftarrow \text{LAYERNORMPERROW}(\boldsymbol{X} | \boldsymbol{\gamma}_l^2, \boldsymbol{\beta}_l^2)$
  $\dots$

Transformer encoder (BERT)



Let’s look at the final layers

Final layer (BERT)



BERT (encoding-only transformer, forward pass)

function $\text{ETRANSFORMER}(\boldsymbol{x}; \boldsymbol{\mathcal{W}})$

$\ell \leftarrow \text{length}(\boldsymbol{x})$

for $t \in [\ell] : \boldsymbol{e}_t \leftarrow \boldsymbol{W_e}[x[t], :] + \boldsymbol{W_p}[t, :]$ ▷ Token emb. + positional emb.

$\boldsymbol{X} \leftarrow \text{Stack row-wise}[\boldsymbol{e}_1, \boldsymbol{e}_2, \ldots \boldsymbol{e}_\ell]$

for $l = 1, 2, \ldots, L$ **do**

$\boldsymbol{X} \leftarrow \boldsymbol{X} + \text{MHATTENTION}(\boldsymbol{X} | \boldsymbol{\mathcal{W}}_l)$ ▷ Multi-head att., residual conn

$\boldsymbol{X} \leftarrow \text{LAYERNORMPERROW}(\boldsymbol{X} | \boldsymbol{\gamma}_l^1, \boldsymbol{\beta}_l^1)$

$\boldsymbol{X} \leftarrow \boldsymbol{X} + \left(\text{GELU}(\boldsymbol{X} \boldsymbol{W}_l^{\text{mlp1}} +_{\text{(row)}} \boldsymbol{b}_l^{\text{mlp1}}) \boldsymbol{W}_l^{\text{mlp2}} +_{\text{(row)}} \boldsymbol{b}_l^{\text{mlp2}} \right)$ ▷ MLP

$\boldsymbol{X} \leftarrow \text{LAYERNORMPERROW}(\boldsymbol{X} | \boldsymbol{\gamma}_l^2, \boldsymbol{\beta}_l^2)$

$\boldsymbol{X} \leftarrow \text{GELU}(\boldsymbol{X} \boldsymbol{W_f} +_{\text{(row)}} \boldsymbol{b_f})$

$\boldsymbol{X} \leftarrow \text{LAYERNORMPERROW}(\boldsymbol{X} | \boldsymbol{\gamma}_l, \boldsymbol{\beta}_l)$

return $\boldsymbol{P} = \text{softmax}(\boldsymbol{X} \boldsymbol{W_u})$ ▷ Project to vocab., probabilities

BERT parameters and hyperparameters

Hyperparameters: $\ell_{\mathsf{max}}, L, H, d_{\mathsf{e}}, d_{\mathsf{mlp}}, d_{\mathsf{f}} \in \mathbb{N}$

Parameters:

$\boldsymbol{W_e} \in \mathbb{R}^{N_{\mathsf{V}} \times d_{\mathsf{e}}}$, $\boldsymbol{W_p} \in \mathbb{R}^{\ell_{\mathsf{max}} \times d_{\mathsf{e}}}$, the token and positional embedding matrices

For $l \in [L]$: $\boldsymbol{\mathcal{W}}_l$, multi-head attention parameters for layer l:

- $\boldsymbol{\gamma}_l^1, \boldsymbol{\beta}_l^1, \boldsymbol{\gamma}_l^2, \boldsymbol{\beta}_l^2$, two sets of layer-norm parameters
- $\boldsymbol{W}_l^{\mathsf{mlp1}} \in \mathbb{R}^{d_{\mathsf{e}} \times d_{\mathsf{mlp}}}$, $\boldsymbol{b}_l^{\mathsf{mlp1}} \in \mathbb{R}^{d_{\mathsf{mlp}}}$
- $\boldsymbol{W}_l^{\mathsf{mlp2}} \in \mathbb{R}^{d_{\mathsf{mlp}} \times d_{\mathsf{e}}}$, $\boldsymbol{b}_l^{\mathsf{mlp2}} \in \mathbb{R}^{d_{\mathsf{e}}}$

$\boldsymbol{W_f} \in \mathbb{R}^{d_{\mathsf{e}} \times d_{\mathsf{f}}}$, $\boldsymbol{b_f} \in \mathbb{R}^{d_{\mathsf{f}}}$, $\boldsymbol{\gamma}, \boldsymbol{\beta} \in \mathbb{R}^{d_{\mathsf{f}}}$, the final linear projection and layer-norm parameters.

$\boldsymbol{W_u} \in \mathbb{R}^{d_{\mathsf{e}} \times N_{\mathsf{V}}}$, the unembedding matrix

Input and pre-training

BERT — Encoder architecture in detail

Input and pre-training

Pre-training

Downstream tasks and fine-tuning

BERT: Tokenization

Tokenizing into a multilingual WordPiece inventory

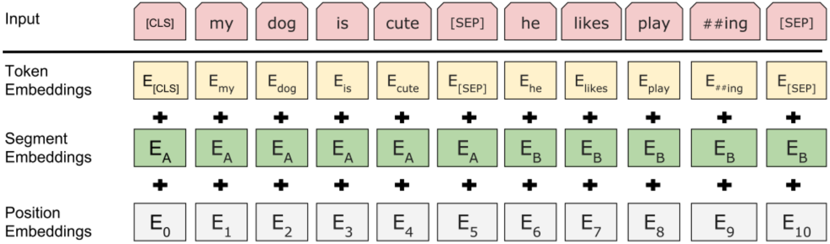
- Recall that WordPiece units are sub-word units
- 30,000 WordPiece units (newer models 110k units, 100 languages)

Implications: BERT can ”consume” any language

BERT: Input representation

- Each WordPiece token from the input is represented by a **WordPiece embedding** (randomly initialized)
- Each position from the input is associated with a **positional embedding** (also randomly initialized)
- Input length limited to **512** WordPiece tokens, using <PAD>ding
- Special tokens
    - The fist token is always a special token **[CLS]**
    - If the task involves two sentences (e.g., NLI), these two sentences are separated by a special token **[SEP]**; also special two **segment position embeddings**

BERT: Input representation summary



Pre-training

BERT — Encoder architecture in detail
Input and pre-training
Pre-training
Downstream tasks and fine-tuning

BERT: Self-supervised multi-task pre-training

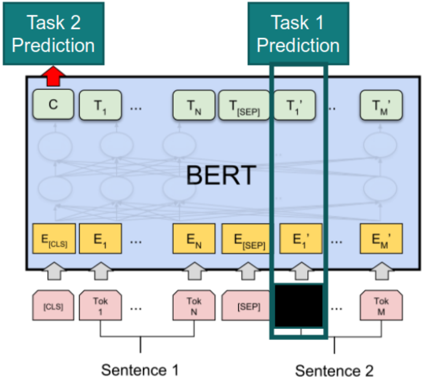
Prepare two auxiliary tasks that need no labeled data

Task 1: Cloze-test task

- Predict the masked WordPiece unit (multi-class, 30k classes)

Task 2: Consecutive segment prediction

- Did the second text segment appeared after the first segment? (binary)



BERT: Pre-training data generation

Take the entire Wikipedia (in 100 languages; 2,5 billion words)

To generate a single training instance, sample two segments (max combined length 512 WordPiece tokens)

- For Task 2, replace the second segment randomly in 50% (negative samples)
- For Task 1, choose random 15% of the tokens, and in 80% replace with a [MASK]

BERT: Pre-training data – Simplified example

Input = [CLS] the man went to [MASK] store [SEP]

he bought a gallon [MASK] milk [SEP]

Label = IsNext

Input = [CLS] the man [MASK] to the store [SEP]

penguin [MASK] are flight ##less birds [SEP]

Label = NotNext

- <PAD>ding is missing
- The actual segments are longer and not necessarily sentences (just spans)
- The WordPiece tokens match full words here

BERT: pre-training by masked language modeling

function ETRAINING($\{\boldsymbol{x}_n\}_{n=1}^{N_{\text{data}}}$ seqs, $\boldsymbol{\theta}$ init. params; $p_{\text{mask}} \in (0, 1)$, N_{epochs}, η)
    for $i \in [N_{\text{epochs}}]$ **do**
        for $n \in [N_{\text{data}}]$ **do**
            $\ell \leftarrow \text{length}(\boldsymbol{x}_n)$
            for $t \in [\ell]$ **do**
                $\tilde{\boldsymbol{x}}_n[t] \leftarrow$ `<mask_token>` with prob. p_{mask}, otherwise $\boldsymbol{x}_n[t]$
            $\tilde{T} \leftarrow \{t \in [\ell] : \tilde{\boldsymbol{x}}_n[t] =$ `<mask_token>`$\}$ ▷ Indices of masked tokens
            $\boldsymbol{P}_{\boldsymbol{\theta}} \leftarrow$ ETRANSFORMER$(\tilde{\boldsymbol{x}}_n | \boldsymbol{\theta})$
            $\text{loss}_{\boldsymbol{\theta}} \leftarrow -\sum_{t \in \tilde{T}} \log \boldsymbol{P}_{\boldsymbol{\theta}}[t, \boldsymbol{x}_n[t]]$
            $\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} - \eta \cdot \nabla \text{loss}_{\boldsymbol{\theta}}$
    return $\boldsymbol{\theta}$

Simple example explaining lines 6–7 (masking)

$\begin{pmatrix}\text{The} & \text{cat} & \text{sat}\end{pmatrix} \to \boldsymbol{x}_n = \begin{pmatrix}21 & 11987 & 5438\end{pmatrix}$ (Indices in V)

Random masking (index of `<mask_token>` = 50001):

1. For $t = 1$, the random outcome is "mask"
2. For $t = 2$, the random outcome is "keep"
3. For $t = 3$, the random outcome is "mask"

$$\tilde{\boldsymbol{x}}_n = \begin{pmatrix}50001 & 11987 & 50001\end{pmatrix}, \tilde{T} = \{1, 3\}$$

Explaining line 9 (negative log likelihood)

$\begin{pmatrix}\text{The} & \text{cat} & \text{sat}\end{pmatrix} \to \boldsymbol{x}_n = \begin{pmatrix}21 & 11987 & 5438\end{pmatrix}, \tilde{\boldsymbol{x}}_n = \begin{pmatrix}50001 & 11987 & 50001\end{pmatrix}, \tilde{T} = \{1, 3\}$

$\boldsymbol{P_\theta} \leftarrow \text{ETRANSFORMER}(\tilde{\boldsymbol{x}}_n | \boldsymbol{\theta})$

$$\boldsymbol{P_\theta} = \begin{pmatrix} 0.001 & 0.0007 & \dots & 0.0003 \\ 0.0013 & 0.0065 & \dots & 0.0001 \\ 0.079 & 0.015 & \dots & 0.0001 \end{pmatrix}$$

$\boldsymbol{P_\theta} \in (0, 1)^{\ell_\mathsf{x} \times N_\mathsf{V}}$, where each row of $\boldsymbol{P}$ is a distribution over the vocabulary

Explaining line 9 (negative log likelihood), $t = 1$

$\boldsymbol{x}_n = (21, 11987, 5438)$, $\tilde{\boldsymbol{x}}_n = (50001, 11987, 50001)$, $\tilde{T} = \{1, 3\}$

$$\boldsymbol{P_\theta} = \begin{pmatrix} 0.001 & \dots & 0.0041_{21} & \dots 0.0003 \\ \vdots & & & \end{pmatrix}$$

For $t = 1$, the model should learn to predict "The" (index 21)

Gold: $\boldsymbol{y} = (0, 0, \dots, 1_{21}, \dots, 0) \in \mathbb{R}^{N_\text{V}}$

Pred: $\hat{\boldsymbol{y}} = \boldsymbol{P_\theta}[1, :] = (0.001, \dots, 0.0041_{21}, \dots 0.0003) \in \mathbb{R}^{N_\text{V}}$

Categorical cross entropy loss (Lec. 4)

$L(\hat{\boldsymbol{y}}, \boldsymbol{y}) := - \sum_{k=1}^{K} \boldsymbol{y}_{[k]} \log \left(\hat{\boldsymbol{y}}_{[k]} \right)$
$= -1 \cdot \log(\hat{\boldsymbol{y}}[21]) = -\log(\boldsymbol{P_\theta}[1, 21])$
$= -\log(\boldsymbol{P_\theta}[1, \boldsymbol{x}_n[1]]) = -\log(\boldsymbol{P_\theta}[t, \boldsymbol{x}_n[t]])$

Explaining line 9 (negative log likelihood), $t = 3$

$\boldsymbol{x}_n = (21, 11987, 5438)$, $\tilde{\boldsymbol{x}}_n = (50001, 11987, 50001)$, $\tilde{T} = \{1, 3\}$

$$\boldsymbol{P_\theta} = \begin{pmatrix} \vdots & \ldots & \ldots & \end{pmatrix}$$

For $t = 3$, the model should learn to predict "sat" (id 5438)

Categorical cross entropy loss

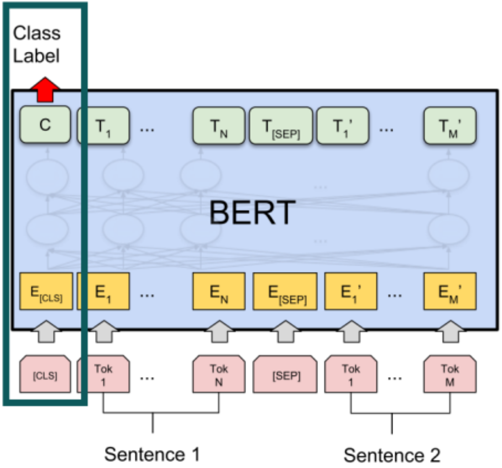
$L(\hat{\boldsymbol{y}}, \boldsymbol{y}) := -\sum_{k=1}^{K} \boldsymbol{y}_{[k]} \log \left(\hat{\boldsymbol{y}}_{[k]} \right)$
$= -1 \cdot \log(\hat{\boldsymbol{y}}[5438]) = -\log(\boldsymbol{P_\theta}[3, 5438]) = -\log(\boldsymbol{P_\theta}[t, \boldsymbol{x}_n[t]])$

Sum over all masked token positions in $\tilde{T}$ gives us line 9:

$$\text{loss}_{\boldsymbol{\theta}} \leftarrow -\sum_{t \in \tilde{T}} \log \boldsymbol{P_\theta}[t, \boldsymbol{x}_n[t]]$$

Downstream tasks and fine-tuning

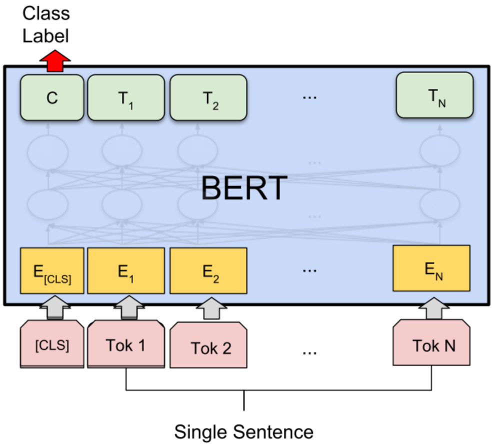
BERT: Representing various NLP tasks



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

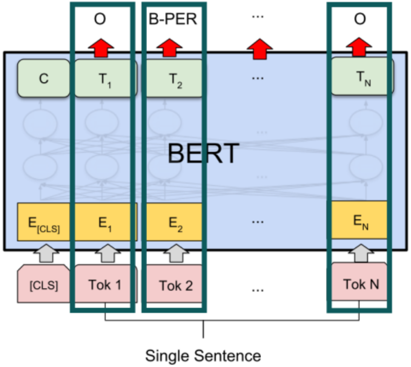
That explains the special [CLS] token at sequence start

BERT: Representing various NLP tasks



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

BERT: Representing various NLP tasks



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

Not conditioned on surrounding predictions

BERT pre-training time

Pretraining BERT took originally 4 days on 64 TPUs[1]

Once pre-trained, transfer and "fine-tune" on your small-data task and get competitive results

P. Izsak, M. Berchansky, and O. Levy (2021). **"How to Train BERT with an Academic Budget".** In: *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*. Online and Punta Cana, Dominican Republic: Association for Computational Linguistics, pp. 10644–10652

[1]Can be done more efficiently, see, e.g., Izsak, Berchansky, and Levy (2021)

Recap

A. Rogers, O. Kovaleva, and A. Rumshisky (2020). **"A Primer in BERTology: What We Know About How BERT Works".** In: *Transactions of the Association for Computational Linguistics* 8, pp. 842–866

BERT stays on the shoulders of many clever concepts and techniques, mastered into a single model

What do we know about how BERT works?

"BERTology has clearly come a long way, but it is fair to say we still have more questions than answers about how BERT works." — Rogers, Kovaleva, and Rumshisky (2020)[2]

[2]Highly recommended reading!

License and credits

Credits

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