BERT-Base Transformer Forward Pass

Ana Marasović

Initialize:

```
W_T \in \mathbb{R}^{\text{vocab size} \times d} = \mathbb{R}^{\text{vocab size} \times 768} \dots \text{token embeddings}
W_P \in \mathbb{R}^{\text{max input length} \times d} = \mathbb{R}^{512 \times 768} \dots \text{positional embeddings}
h \in \{1, \dots, n_{\text{heads}}\}, n_{\text{heads}} = 12
l \in \{1, \dots, n_{\text{layers}}\}, n_{\text{layers}} = 12
W_{h,l}^Q \in \mathbb{R}^{d \times d_q} = \mathbb{R}^{768 \times 64} \dots \text{query } weight \text{ matrices}
W_{h,l}^K \in \mathbb{R}^{d \times d_k} = \mathbb{R}^{768 \times 64} \dots \text{key } weight \text{ matrices}
W_{h,l}^{V} \in \mathbb{R}^{d \times d_q} = \mathbb{R}^{768 \times 64} \dots \text{ value } weight \text{ matrices}
W_{t}^{ffnn} \in \mathbb{R}^{d \times d_{ffnn}} = \mathbb{R}^{768 \times 3072} \dotsfeedforward layer's weight matrix
b_l^{ffnn} \in \mathbb{R}^{1 \times d_{ffnn}} = \mathbb{R}^{1 \times 3072} \dots feedforward layer's bias vector
W_l^{out} \in \mathbb{R}^{d_{ffnn} \times d} = \mathbb{R}^{3072 \times 768} \dotsoutput layer's weight matrix
b_l^{out} \in \mathbb{R}^{1 \times d} = \mathbb{R}^{1 \times 768} \dots output layer's bias vector
W^{final} \in \mathbb{R}^{d \times d} = \mathbb{R}^{768 \times 768} \dotsfinal layer's weight matrix
I = (i_1, \dots, i_{512}) \in \mathbb{N}_0^{1 \times \text{max input length}} = \mathbb{N}_0^{1 \times 512} \dots \text{input vocab indices}
T = \mathsf{lookup}(W_T, I) \in \mathbb{R}^{\max \text{ input length} \times d} = \mathbb{R}^{512 \times 768} \dots \text{ input token embeddings}
X = T + W_P \in \mathbb{R}^{\text{max input length} \times d} = \mathbb{R}^{512 \times 768} \dots \text{input embeddings}
Z_0 = X
```

Forward algorithmm:

```
 \begin{array}{l} \text{for } (\ l=1; \ l \leq n_{layers} = 12; \ l++ \ ) \ \{ \\ \text{for } (\ h=1; \ h \leq n_{heads} = 12; \ h++ \ ) \ \{ \\ \\ Q_{h,l} = Z_{l-1}W_{h,l}^Q \in \mathbb{R}^{\max \text{ input len} \times d_q} = \mathbb{R}^{512 \times 64} \dots \text{ query matrix } \\ K_{h,l} = Z_{l-1}W_{h,l}^K \in \mathbb{R}^{\max \text{ input len} \times d_k} = \mathbb{R}^{512 \times 64} \dots \text{ key matrix } \\ V_{h,l} = Z_{l-1}W_{h,l}^V \in \mathbb{R}^{\max \text{ input len} \times d_v} = \mathbb{R}^{512 \times 64} \dots \text{ value matrix } \\ A_{h,l} = \operatorname{Softmax}(\frac{Q_{h,l}K_{h,l}^T}{\sqrt{d_k}}) \in \mathbb{R}^{\max \text{ input len} \times \max \text{ input len}} = \mathbb{R}^{512 \times 512} \\ Z_{h,l} = A_{h,l}V_{h,l} \in \mathbb{R}^{\max \text{ input len} \times d_v} = \mathbb{R}^{512 \times 64} \\ \} \\ \tilde{Z}_l = \operatorname{concat}(Z_{1,l}, \dots, Z_{n_{\operatorname{heads}},l}) \in \mathbb{R}^{\max \text{ input len} \times (d_v \cdot n_{\operatorname{heads}})} = \mathbb{R}^{512 \times (64 \cdot 12)} = \mathbb{R}^{512 \times 768} \\ \tilde{Z}_l = \operatorname{LayerNorm}(Z_{l-1} + \tilde{Z}_l) \in \mathbb{R}^{512 \times 768} \\ Z_l^{out} = Z_l^{ffnn}W_l^{out} + b_l^{out} \in \mathbb{R}^{\max \text{ input len} \times d} = \mathbb{R}^{512 \times 768} \\ Z_l = \operatorname{LayerNorm}(\tilde{Z}_l + Z_l^{out}) \in \mathbb{R}^{512 \times 768} \\ Z_l = \operatorname{LayerNorm}(\tilde{Z}_l + Z_l^{out}) \in \mathbb{R}^{512 \times 768} \\ \} \\ \end{cases}
```

Pass $\tanh(W^{final}Z_{n_{\text{layers}}}[0,:])$ to the final Softmax that predicts the class, where $Z_{n_{\text{layers}}}[0,:]$ is the hidden state corresponding to the first token.