

Transfer learning with Transformer networks

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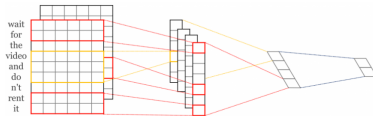
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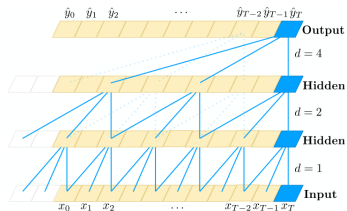
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Traditional architectures for NLP

CNN



Dilated CNN



RNN

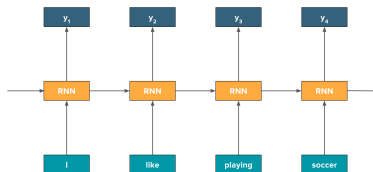


Image from <https://techblog.gumgum.com/articles/deep-learning-for-natural-language-processing-part-2-rnns> and

<http://www.wildml.com/2015/11/understanding-convolutional-neural-networks-for-nlp/>

Attention mechanisms

Concept

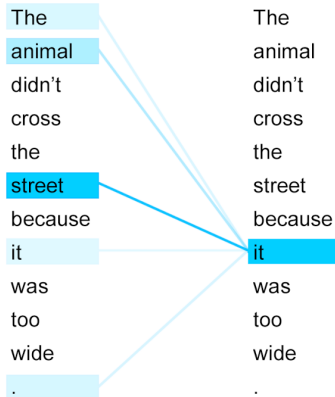
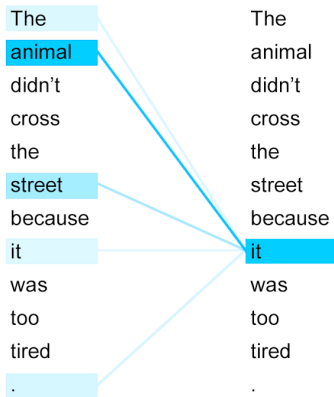
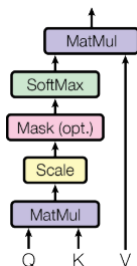


Image from <https://ai.googleblog.com/2017/08/transformer-novel-neural-network.html>

Attention mechanisms

Scaled Dot-Product Attention

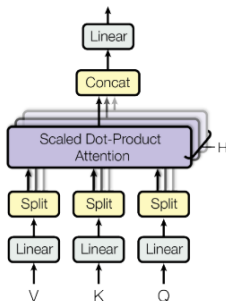


Q is the query vector, K is the key vector and V value vector.

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

Attention mechanisms

Multi-Head Attention



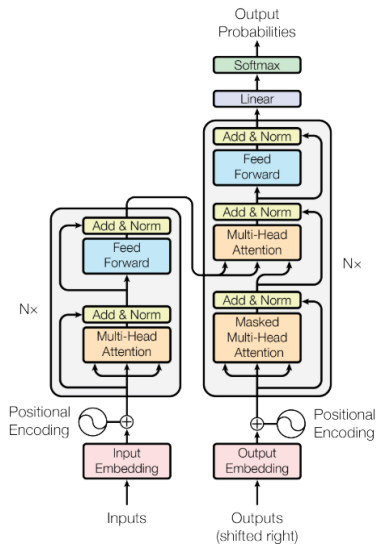
$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, \dots, \text{head}_h)$$

$$\text{where } \text{head}_i = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V)$$

where the projections W_i^Q , W_i^K and W_i^V are parameter matrices.

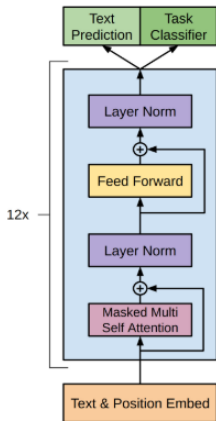
Transformer network

Original transformer



Transformer network

OpenAI multi-layer decoder



W_e is the token embedding matrix

W_p is the position embedding matrix

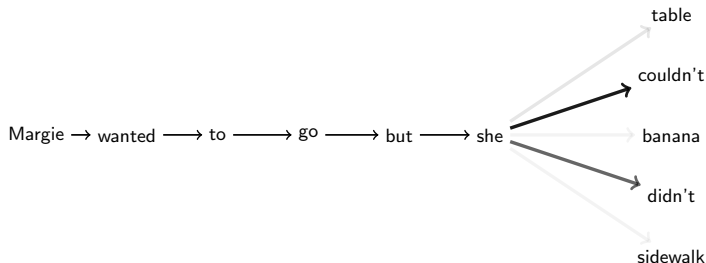
$$h_0 = UW_e + W_p$$

$$h_i = \text{transformer_block}(h_{i-1}) \forall i \in [1, n]$$

The *Text Prediction* and *Task classifier* heads take h_n as input.

Unsupervised pre-training task

Language modeling



$$P(u) = \text{softmax}(h_n W_e^T)$$

$$L_1(\mathcal{U}) = \sum_i \log P(u_i | u_{i-k}, \dots, u_{i-1}; \Theta)$$

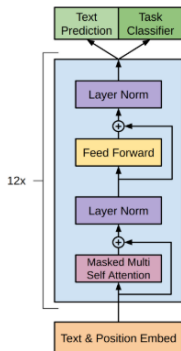
Dataset BooksCorpus (7000 books, ~ 800M words, ~ 5GB of text),

Duration 1 month,

Hardware 8 GPUs.

Supervised fine-tuning

Multitask learning



$$P(u) = \text{softmax}(h_n W_e^T)$$

$$L_1(\mathcal{U}) = \sum_i \log P(u_i | u_{i-k}, \dots, u_{i-1}; \Theta)$$

Language modeling loss

$$P(y | x^1, \dots, x^m) = \text{softmax}(h_n^m W_y)$$

$$L_2(\mathcal{C}) = \sum_{(x,y)} P(y | x^1, \dots, x^m)$$

Classification loss

$$L_3(\mathcal{C}) = L_2(\mathcal{C}) + \lambda * L_1(\mathcal{C})$$

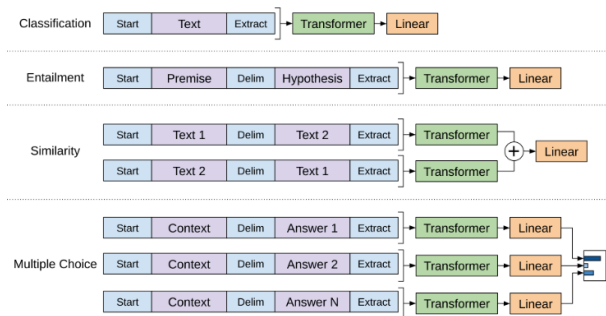
Final loss

Results on standard datasets

New state of the art on the following tasks:

- Textual Entailment
 - ▶ SNLI 89.3 → 89.9
 - ▶ MNLI Matched 80.6 → 82.1
 - ▶ MNLI Mismatched 80.1 → 81.4
 - ▶ SciTail 83.3 → 88.3
 - ▶ QNLI 82.3 → 88.1
- Semantic Similarity
 - ▶ STS-B 81.0 → 82.0
 - ▶ QQP 66.1 → 70.3
- Reading Comprehension
 - ▶ RACE 53.3 → 59.0
- Commonsense Reasoning
 - ▶ ROCStories 77.6 → 86.5
 - ▶ COPA 71.2 → 78.6
- Linguistic Acceptability
 - ▶ CoLA 35.0 → 45.4
- Multi-Task Benchmark
 - ▶ GLUE 68.9 → 72.8

Input formatting



Two possible input shape:

- (batch_idx, token_idx, 2)
- (batch_idx, sequence_idx, token_idx, 2)

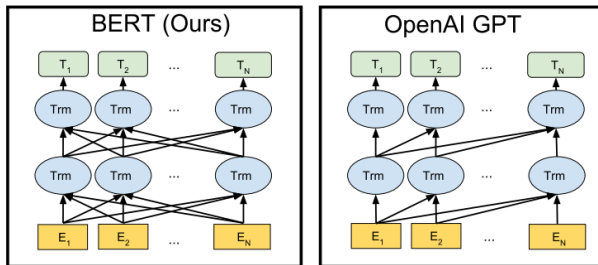
The 2 is there to select either the token embedding or its corresponding position embedding.

Input formatting

```
def transform_imdb(X, encoder, max_len, n_vocab, n_special,
                   n_ctx):
    n_batch    = len(X)
    xmb        = np.zeros((n_batch, n_ctx, 2), dtype = np.int32)
    mmb        = np.zeros((n_batch, n_ctx), dtype = np.float32)
    start      = encoder['_start_']
    clf_token   = encoder['_classify_']
    for i, x in enumerate(X):
        x_with_tokens = [start] + x[:max_len] + [clf_token]
        l_x           = len(x_with_tokens)
        xmb[i, :l_x, 0] = x_with_tokens
        mmb[i, :l_x]    = 1
    pos_emb_start = n_vocab + n_special
    xmb[:, :, 1] = np.arange(
        pos_emb_start,
        pos_emb_start + n_ctx
    )

    return xmb, mmb
```

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



BERT is an improvement on the GPT. The main differences are:

- Bidirectional training,
- Different pre-training tasks (masked language model and next sentence prediction),
- Trained on a much bigger corpus (BookCorpus + **Wikipedia**),
- $3 \times$ as many parameters for the large version,
- Pre-trained model for 102 languages.

BERT produces 11 new states of the art.

References

- Vaswani, Ashish, et al. "Attention is all you need." Advances in Neural Information Processing Systems. 2017.
- Radford, Alec, et al. "Improving language understanding by generative pre-training." [URL](#) [Article](#) [pdf link](#) [Blog post](#) (2018).
- Devlin, Jacob, et al. "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding." arXiv preprint [arXiv:1810.04805](#) (2018).