

# Generative pre-training of transformer networks

Grégory Châtel

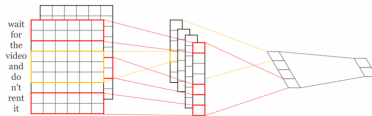
Disaitek  
Intel Software Innovator

@rodgzilla  
[github.com/rodgzilla](https://github.com/rodgzilla)

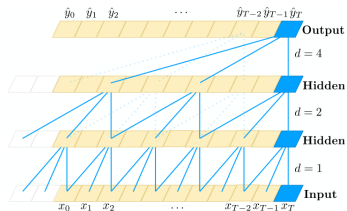
11/17/2018

# Traditional architectures for NLP

CNN



Dilated CNN



RNN

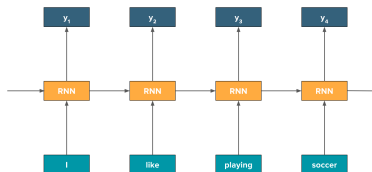


Image from <https://techblog.gumgum.com/articles/deep-learning-for-natural-language-processing-part-2-rnns> and

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

# Attention mechanisms

## Concept

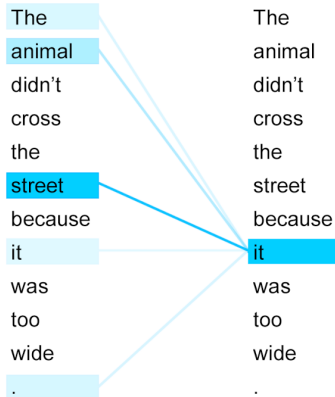
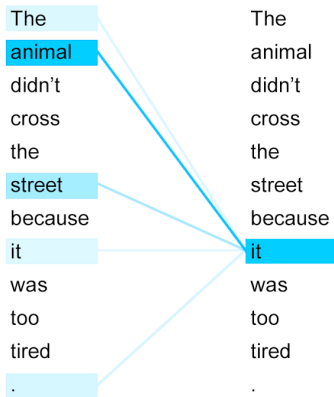


Image from <https://ai.googleblog.com/2017/08/transformer-novel-neural-network.html>

# Attention mechanisms

## Scaled Dot-Product Attention

To compute the next word in the translation, the attention mechanism creates a vector using the source sentence and what has been generated so far.

<b>Input sentence</b>	elle	alla	à	la	plage
<b>Key</b>	subject	verb	filler	filler	location
<b>Value</b>	she	go, past tense	-	-	beach

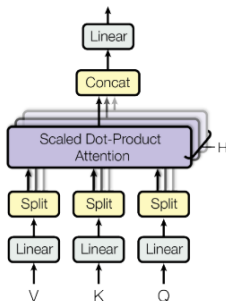
<b>Output sentence</b>	she	went	to	the	?????
<b>Query</b>	subject	verb	filler	filler	location

$Q$ ,  $K$  and  $V$  are respectively the query, key and value vectors.

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

# Attention mechanisms

## Multi-Head Attention



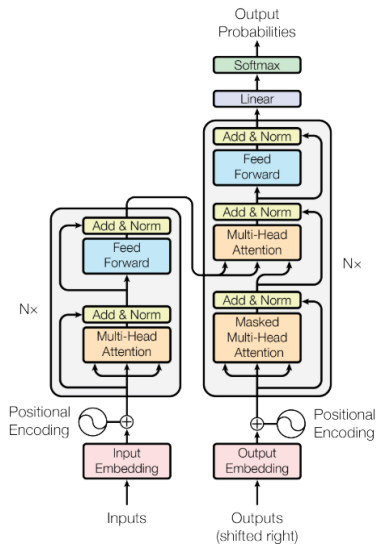
$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, \dots, \text{head}_h)$$

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

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

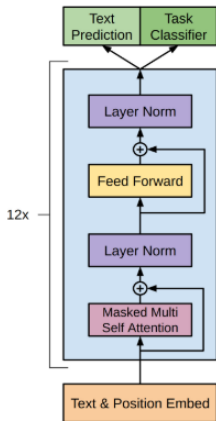
# Transformer network

## Original transformer



# Transformer network

OpenAI multi-layer decoder



$W_e$  is the token embedding matrix

$W_p$  is the position embedding matrix

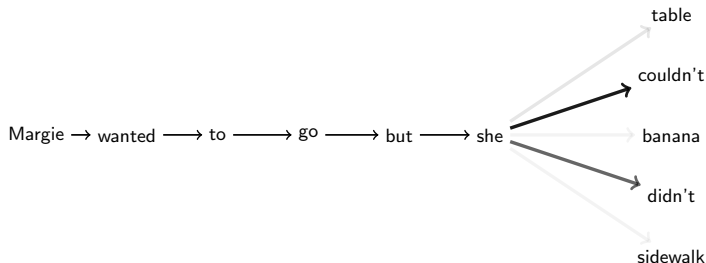
$$h_0 = UW_e + W_p$$

$$h_l = \text{transformer\_block}(h_{l-1}) \forall i \in [1, n]$$

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),

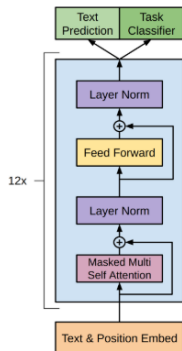
**Duration** 1 month,

**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

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

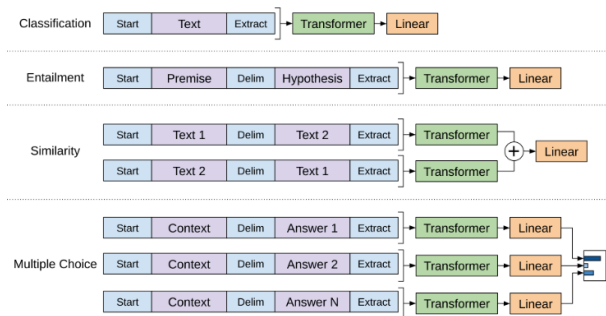
Final loss

## 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)

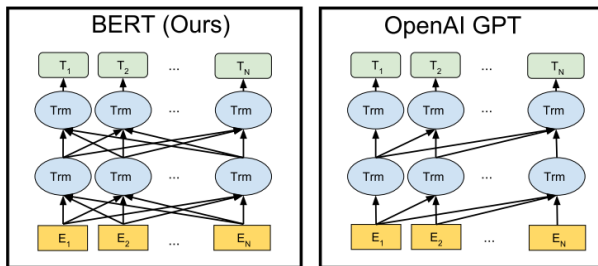
The 2 is there to select either the token embedding or its corresponding position embedding.

## 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 (800M words) + **Wikipedia (2500M words)**),
- $3 \times$  as many parameters for the large version,
- Pre-trained model for 102 languages.

BERT produces 11 new states of the art.

# References

- Tensorflow GPT: <https://github.com/openai/finetune-transformer-lm>
- Tensorflow BERT: <https://github.com/google-research/bert>
- PyTorch GPT: <https://github.com/huggingface/pytorch-openai-transformer-lm>
- PyTorch BERT: <https://github.com/huggingface/pytorch-pretrained-BERT>
- IMDB movie review classification:  
[https://github.com/rodgzilla/pytorch-openai-transformer-lm/tree/movie\\_reviews\\_classification](https://github.com/rodgzilla/pytorch-openai-transformer-lm/tree/movie_reviews_classification)
- Bai, Shaojie, J. Zico Kolter, and Vladlen Koltun. "An empirical evaluation of generic convolutional and recurrent networks for sequence modeling." arXiv preprint arXiv:1803.01271 (2018).
- 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).