Generative pre-training of transformer networks

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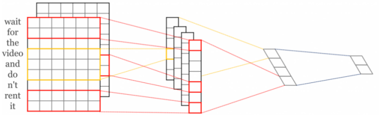
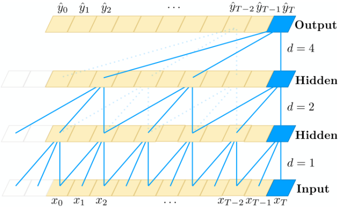
Traditional DL architectures for NLP

CNN



Dilated CNN



RNN

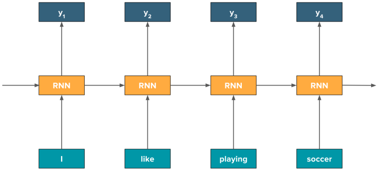


Image from https://techblog.gumgum.com/articles/deep-learning-for-natural-language-processing-part-2-rnns and

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

Attention mechanisms

Concept

A woman is throwing a frisbee in a park.

A dog is standing on a hardwood floor.

A stop sign is on a road with a mountain in the background.

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.

Input sentence	elle	alla	à	la	plage
Key	subject	verb	filler	filler	location
Value	*she*	*to go, past tense*	-	-	*beach*

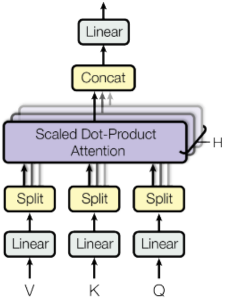
Output sentence	she	went	to	the	**?????**
Query	subject	verb	filler	filler	location

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

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

Attention mechanisms

Multi-Head Attention

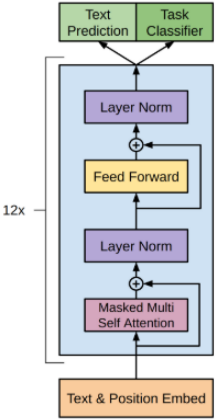


$$\begin{aligned} \mathrm{MultiHead}(Q, K, V) &= \mathrm{Concat}(\mathrm{head}_1, \ldots, \mathrm{head}_h) \\ \text{where} \quad \mathrm{head}_i &= \mathrm{Attention}(QW_i^Q, KW_i^K, VW_i^V) \end{aligned}$$

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

Transformer network

OpenAI multi-layer decoder



W_e is the token embedding matrix

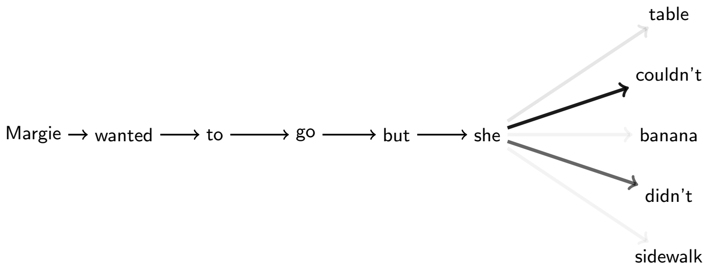
W_p is the position embedding matrix

$$h_0 = UW_e + W_p$$
$$h_l = \text{transformer\_block}(h_{l-1}) \forall i \in [1, n]$$

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

Unsupervised pre-training task

Language modeling



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

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

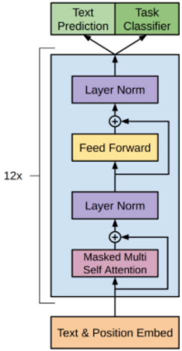
Dataset BooksCorpus (7000 books, $\sim$ 800M words, $\sim$ 5GB of text),

Duration 1 month,

Hardware 8 GPUs.

Supervised fine-tuning

Multitask learning



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

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

Language modeling loss

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

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

Classification loss

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

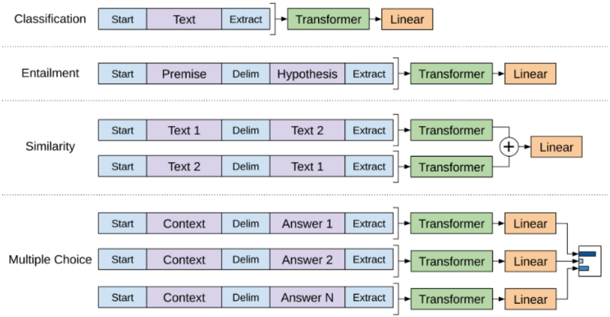
Final loss

Results on standard datasets

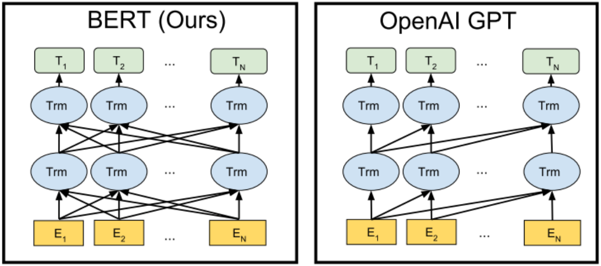
New state of the art on the following tasks:

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

Input formatting



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.

Google's BERT produces 11 new SOTAs on top of the 9 of OpenAI's GPT.

References

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- 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: Github repo for IMDB sentiment analysis with GPT
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- 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).

- Github repo for these slides.