Attention and Transformers

Deep Learning

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Pre-Word2Vec

- A word embedding technique (word represented by a vector)
- Model probability of neighboring words given a center word

$$\arg\max_{\theta} \prod_{t=1}^{T} \prod_{-m \le j \le m, j \ne 0} p(w_{t+j} | w_t; \theta)$$

$$= \arg\min_{\theta} \left[-\frac{1}{T} \sum_{t=1}^{T} \sum_{-m \le j \le m, j \ne 0} \log p(w_{t+j} | w_t; \theta) \right]$$

$$p(o|c) = \text{softmax}(u_o^\top v_c)$$

Word2Vec

- "Distributed representations of words and phrases and their compositionality" (Mikolov et al. 2013)
  - Try to reduce computational complexity
  - Also referred to as the skip-gram model

$$J_t(\theta) = -\left[\log \sigma(u_o^\top v_c) + \sum_{j \sim p(w)} \log(1 - \sigma(u_j^\top v_c))\right]$$

- Alternative model
  - Continuous bag of words (CBOW): model in an opposite manner. Model center word probability with surrounding words

Latent semantic analysis

- Word2Vec uses a window and goes through entire document
- Latent semantic analysis (aka topic model) looks into co-occurence count instead
  - Lower complexity
  - Simply generate vector using SVD

GloVe

- Combine the idea of window and cooccurence counting
- By Pennington, Socher, Manning (2014)

$$J(\theta) = \frac{1}{2} \sum_{i,j} f(p_{i,j})(u_i^\top v_j - \log p_{i,j})^2$$

Evaluating word vector

- Intrinsic (intermediate task):
  - Word vector analogy: man to woman = king to ?
  - Word vector distances and their correlation with human judgments
- Extrinsic (real-world task):
  - Name entity recognition
  - Machine translation

Fun word2vec analogies

Expression	Nearest token
Paris - France + Italy	Rome
bigger - big + cold	colder
sushi - Japan + Germany	bratwurst
Cu - copper + gold	Au
Windows - Microsoft + Google	Android
Montreal Canadians - Montreal + Toronto	Toronto Maple Leafs

Richard Socher

Evaluation datasets

- Word vector analogies: syntactic and semantic examples
  http://code.google.com/p/word2vec/source/browse/trunk/questions-words.txt
- Distances correlated with human judgments
  http://www.cs.technion.ac.il/ gabr/resources/data/wordsim353/

Name Entity Recognition (NER)

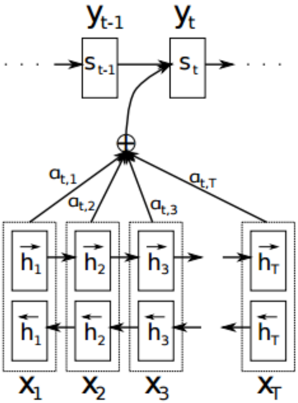
- Goal: try to predict whether a given word in a sentence is a name and its category
  - Person (PER)
  - Organization (ORG)
  - Location (LOC)
  - Miscellaneous (MISC)
- For example,
  - John lives in Oklahoma and studies at the University of Oklahoma
  - The Republicans will repeal the Affordable Care Act

Problem with RNNs

- Seq2seq models require RNNs to memorize the entire sentence before translating it. It works great for short sentences but performance drops significantly for long sentences
- RNNs are relatively hard and computationally very expensive to train

Attention for language translation

Bahdanau et al. 2014 (Bengio's group)



- The original model summarizes the input with a single vector c
- Different output position probably more relevant to a part of the input

$$s_t = f(s_{t-1}, y_{t-1}, c_t)$$
$$p(y_t | y_{t-1}, \cdots, y_1, x) = g(s_t, y_{t-1}, c_t)$$

with

$$c_t = \sum_j \alpha_{t,j} h_j, \qquad \alpha_{t,j} = \frac{\exp(e_{t,j})}{\sum_k \exp(e_{t,k})}$$

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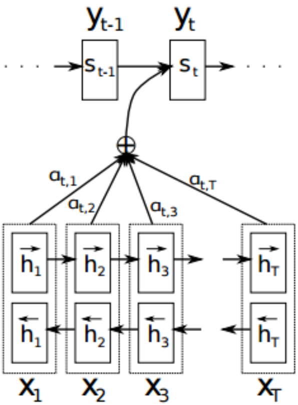

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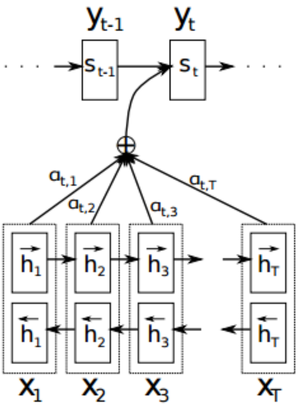

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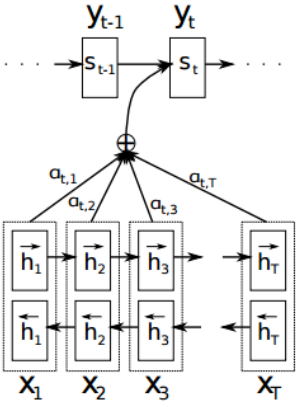

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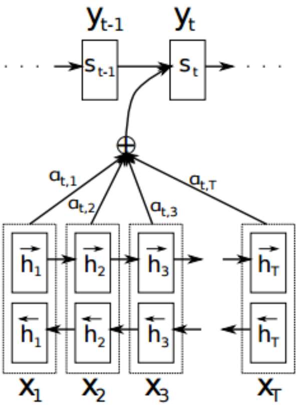

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$$s_t = f(s_{t-1}, y_{t-1}, \color{red}{c_t})$$
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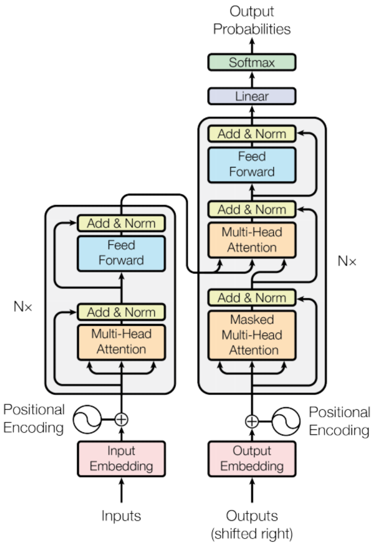
Transformer



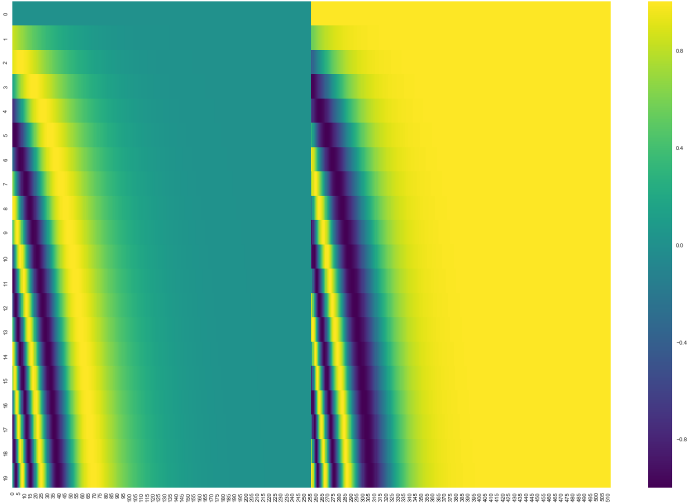
Transformer

$$\text{Multihead}(Q,K,V) = W_0 \text{concat}(\text{Head}_1, \cdots, \text{Head}_n)$$

$$\text{where } \text{Head}_i = \text{Attention}(W_i^Q Q, W_i^K K, W_i^V V)$$

$$\text{Attention}(q,k,v) = \text{softmax}\left(\frac{q^\top k}{\sqrt{d_k}}\right) v$$

Positional encoding



GPT/GPT-2

- GPT means generative pre-training
- Language model from OpenAI
- If we only care about building a model (not translation), only need decoders
- Can be use for different task with little refinement (transfer learning)

GPT applications

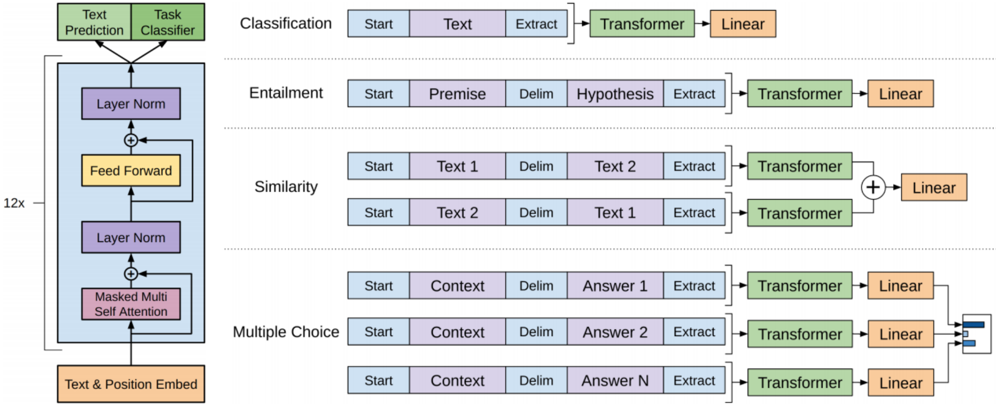


Figure 1: **(left)** Transformer architecture and training objectives used in this work. **(right)** Input transformations for fine-tuning on different tasks. We convert all structured inputs into token sequences to be processed by our pre-trained model, followed by a linear+softmax layer.

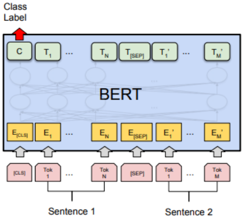
BERT

- "Bidirectional Encoder Representations from Transformers": encoder only model
- Quite a bit larger model size
  - Base model: 12 encoder blocks (layers), embedding (hidden) size 768, 12 heads (110M in total)
  - Large model: 24 encoder blocks, embedding size 1024, 16 heads (340M in total)
  - In contrast, the original transformer model has 6 encoder and 6 decoder blocks, 512 embedding size, and 8 heads

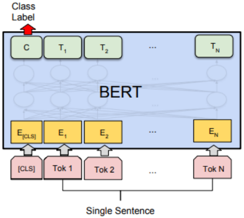
BERT Pretraining

- The main idea is bidirectional. It is obvious but we can train such model with the original task
- The authors pre-train BERT with the following tasks
  - Mask LM (MLM)
  - Next Sentence Prediction (NSP)
    - 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

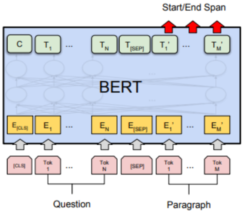
BERT finetuning/applications



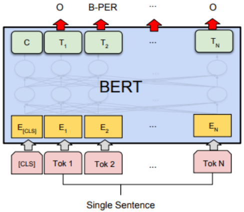
(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG



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



(c) Question Answering Tasks: SQuAD v1.1



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

BERT Positional encoding

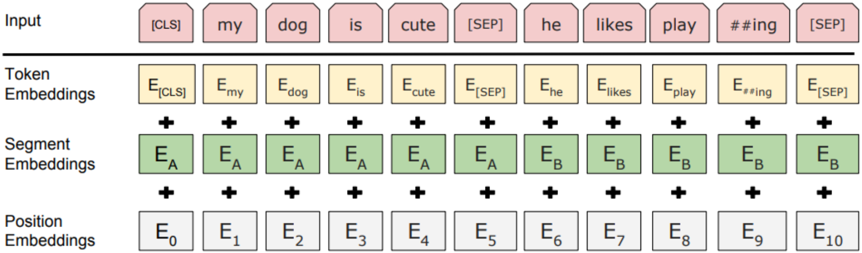


Figure 2: BERT input representation. The input embeddings are the sum of the token embeddings, the segmentation embeddings and the position embeddings.

Comparison

	BERT	RoBERTa	DistilBERT	XLNet
Size (millions)	**Base**: 110 **Large**: 340	**Base**: 110 **Large**: 340	**Base**: 66	**Base**: ~110 **Large**: ~340
Training Time	**Base**: 8 x V100 x 12 days* **Large:** 64 TPU Chips x 4 days (or 280 x V100 x 1 days*)	**Large:** 1024 x V100 x 1 day; 4-5 times more than BERT.	**Base**: 8 x V100 x 3.5 days; 4 times less than BERT.	**Large:** 512 TPU Chips x 2.5 days; 5 times more than BERT.
Performance	Outperforms state-of-the-art in Oct 2018	2-20% improvement over BERT	3% degradation from BERT	2-15% improvement over BERT
Data	16 GB BERT data (Books Corpus + Wikipedia). 3.3 Billion words.	160 GB (16 GB BERT data + 144 GB additional)	16 GB BERT data. 3.3 Billion words.	**Base**: 16 GB BERT data **Large**: 113 GB (16 GB BERT data + 97 GB additional). 33 Billion words.
Method	BERT (Bidirectional Transformer with MLM and NSP)	BERT without NSP**	BERT Distillation	Bidirectional Transformer with Permutation based modeling

https://towardsdatascience.com/bert-roberta-distilbert-xlnet-which-one-to-use-3d5ab82ba5f8

Objective: create function to preserve permutation invariance (used in stacked capsule autoencoder)

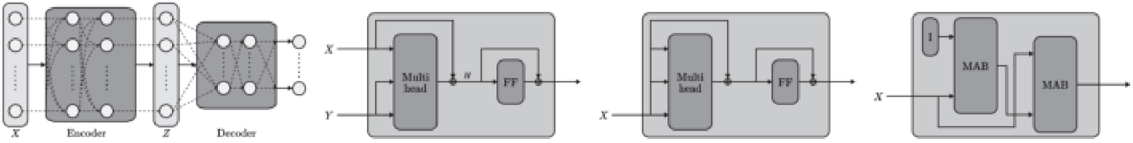
- Encoder: SAB(SAB(X))
- Decoder: rFF(SAB(PMA(Z)))

rFF: row-wise feedforward layer

SAB(X):= MAB(X,X)

PMA(Z):= MAB(S,rFF(Z)), where S is a learnable set of k seed vectors

MAB(X,Y):=LayerNorm(H+rFF(H)), where H=LayerNorm(X+Multihead(X,Y,Y;w)) and w is learnable parameter



(a) Our model (b) MAB (c) SAB (d) ISAB