Natural Language Understanding, Generation, and Machine Translation

Lecture 10: Pretrained Language Models

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The Story so Far

Bert Architecture

Masked Training

Pre-training and Finetuning Bert

Reading: [Devlin et al.2019].

The Story so Far

Self-attention

Self-attention is what we get when compute attention over the input sequence. Let $\mathbf{x}_1, \ldots, \mathbf{x}_t$ be the input vectors and $\mathbf{y}_1, \ldots, \mathbf{y}_t$ be the output vectors:

$$\mathbf{y}_i = \sum_j w_{ij} \mathbf{x}_j$$

We now compute the attention weight as the dot-product of each input token with every other token.

$$w'_{ij} = \mathbf{x}_i \cdot \mathbf{x}_j$$
$$\mathbf{w}_i = \text{softmax}(\mathbf{w}'_i)$$

Note that the attention weight is now called $\mathbf{w}'$ and the attention distribution $\mathbf{w}$ (rather than $\mathbf{a}$ and α).

Self-attention

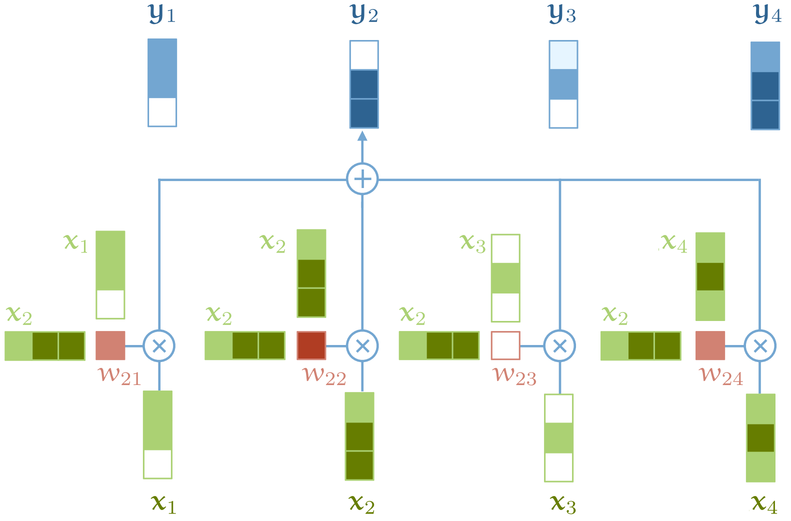
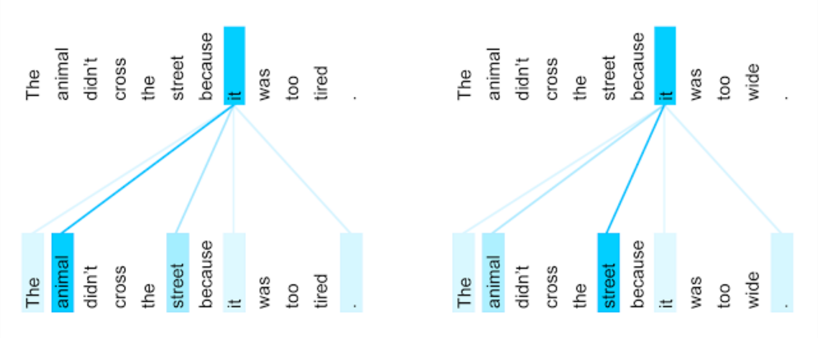


Figure from [Bloem2019].

Multi-head Attention

Multi-head attention is able to jointly attend to different parts of the input. If we just have a single head, have to average.

For example, one head could attend to the subject of a verb, another one to its object. Or different heads could attend to different referents of a pronoun.



The Transformer

The multi-head self attention mechanism needs to be integrated into a larger architecture to be useful:

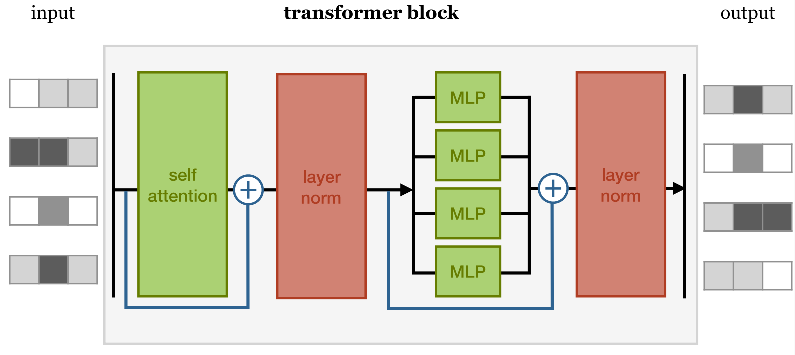


Figure from [Bloem2019].

Position Encodings

We choose a function $f : \mathbb{N} \to \mathbb{R}^k$ that maps positions to real valued vectors, and let the network learn how to interpret these.

The choice of encoding function is a hyperparameter. [Vaswani et al.2017] use:

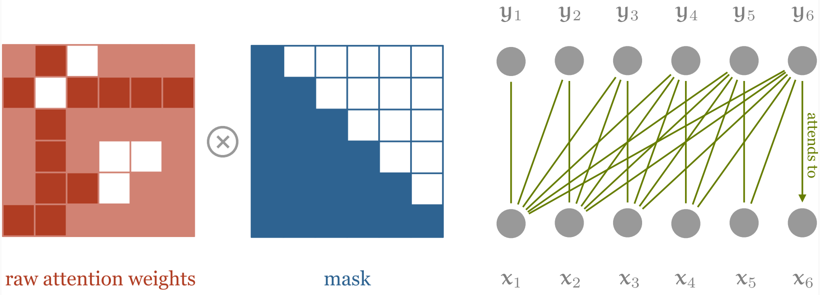
$$PE_{(pos,2i)} = \sin(pos/10000^{2i/k})$$
$$PE_{(pos,2i+1)} = \cos(pos/10000^{2i/k})$$

where *pos* is the position and i is an index over dimensions.

The positions encoding is then added to the input embedding (both are of dimensionality k).

Masking

We apply a mask to the matrix of dot products, before the softmax is applied. This disables all elements above the diagonal:



The model can no longer look forward and just copy the upcoming input; it behaves like an RNN!

Figure from [Bloem2019].

From Transformers to Embeddings

- In lecture 8, we saw how we can stack transformers and use them for *classification.* We apply mean pooling to the output and map it onto a class vector.
- We can also use transformers for *sequence prediction.* For this we need to mask some of the input.
- In lecture 9, we saw how we can derive *embeddings* from neural language models.
- Using transformers, we can build language models that represent context very well: *contextualized embeddings.*
- These language models can be used for feature extraction, but also in a *pre-training/finetuning* setup.

Bert Architecture

Bert Architecture

Bert (Bidirectional Encoder Representations from Transformers):

- designed for pre-training deep bidirectional representations from unlabeled text;
- conditions on left and right context in all layers;
- pre-trained model can be finetuned with one additional output layer for many tasks (e.g., NLI, QA, sentiment);
- for many tasks, no modifications to the Bert architecture are required;
- [Devlin et al.2019] report SotA results on 11 tasks using pre-training/finetuning approach.

Bert Architecture

Bert uses bidirectional transformer representations. This is shown to be superior to competing architectures:

- GPT [Radford et al.2018] also uses transformers, but is only trained left-to-right;
- Elmo [Peters et al.2018] uses shallow concatenation of independently trained left-to-right and right-to-left LSTMs.

Main attraction of Bert: *pre-training/finetuning* approach (though this is also present in GPT).

Bert Architecture

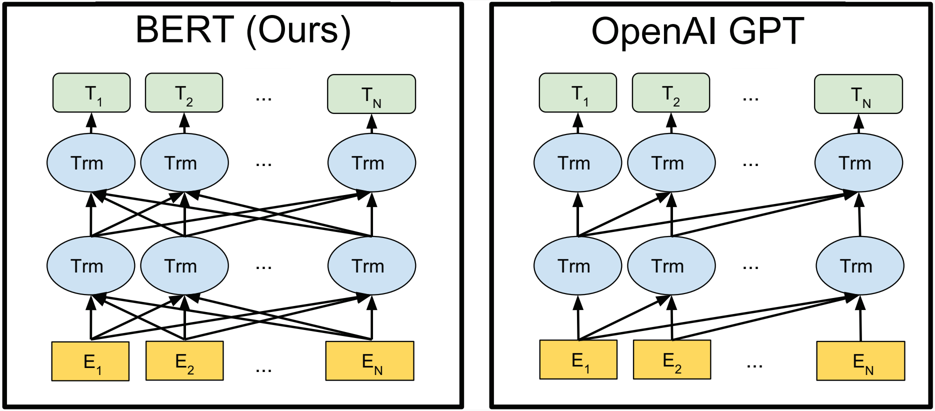


Figure from [Devlin et al.2019].

Bert Architecture

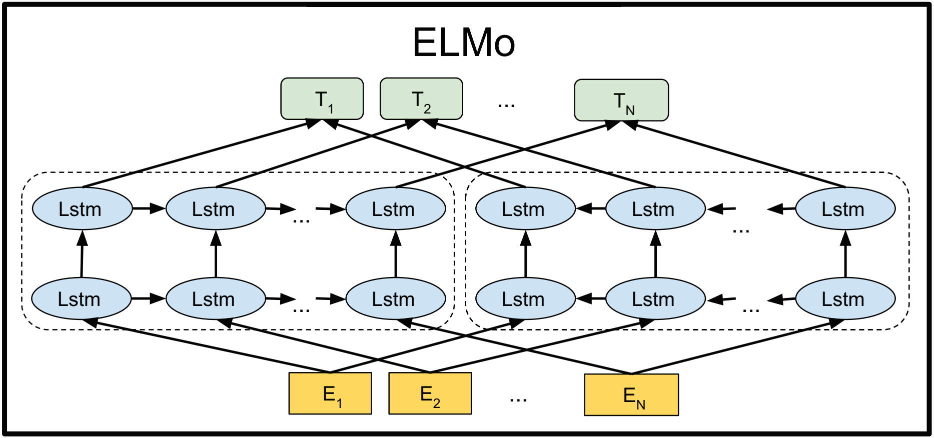


Figure from [Devlin et al.2019].

Bert Architecture

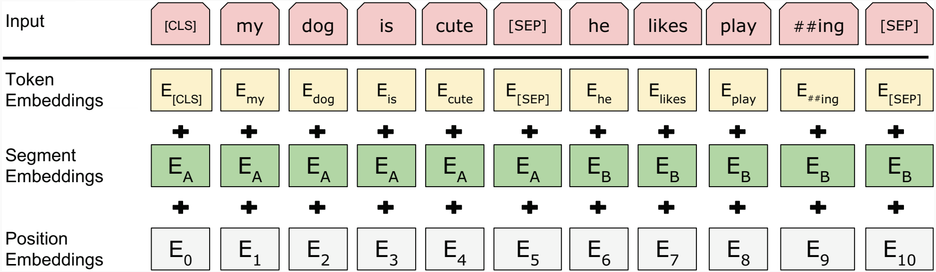
Basic Bert architecture:

- multi-layer bidirectional transformer [Vaswani et al.2017];
- L: layers (transformer blocks); H: dimensionality of hidden layer, A: number of self-attention heads;
- Bert Base: $L = 12$, $H = 768$, $A = 12$, 110M parameters;
- Bert Large: $L = 24$, $H = 1024$, $A = 16$, 340M parameters.

Input/Output Representation

- Input sequence: can be $\langle$Question, Answer$\rangle$ pair, single sentence, or any other string of tokens;
- 30,000 token vocabulary, represented as WordPiece embeddings (handles OOV words);
- first token is always `[CLS]`: aggregate sentence representation for classification tasks;
- sentence pairs separated by `[SEP]` token; and by segment embeddings;
- token position represented by position embeddings.

Bert Architecture



E: input embedding, C: final hidden vector of `[CLS]`; T_i: final hidden vector for the i-th input token.

Note: C and T_i used in subsequent slides.

Figure from [Devlin et al.2019].

Masked Training

Masked Language Model

Important departure from previous embedding models (including GPT and Elmo):

Don't train the model to predict the next word, but train it to predict the whole context.

- Problem: how can we prevent *trivial copying* via the self-attention mechanism?
- Solution: mask 15% of the tokens in the input sequence; train the model to predict these.

Masked Language Model

Problem: masking creates mismatch between pre-training and finetuning: `[MASK]` token is not seen during fine-tuning. Solution:

- do not always replace masked words with `[MASK]`, instead choose 15% of token positions at random for prediction;
- if i-th token is chosen, we replace the i-th token with:
  1. the `[MASK]` token 80% of the time;
  2. a random token 10% of the time;
  3. the unchanged i-th token 10% of the time.
- Now use T_i to predict original token with cross entropy loss.

Masked Language Model

Why this masking scheme?

- if we always use [MASK] token, the model would not have to learn good representation for other words;
- if we only use [MASK] token or random word, model would learn that observed word is never correct;
- if we only use [MASK] token or observed word, model would just learn to trivially copy.

Secondary Task: Next Sentence Prediction

- Bert is designed to be used for tasks such a question answering (QA) and natural language inference (NLI) that require sentence pairs;
- Bert uses a special mechanism to capture this: pre-training on next sentence prediction task;
- generate training data: chose two sentences A and B, such that 50% of the time B is the actual next sentence of A, and 50% of the time a randomly selected sentence.

Pre-training and Finetuning Bert

Pre-training and Finetuning Bert

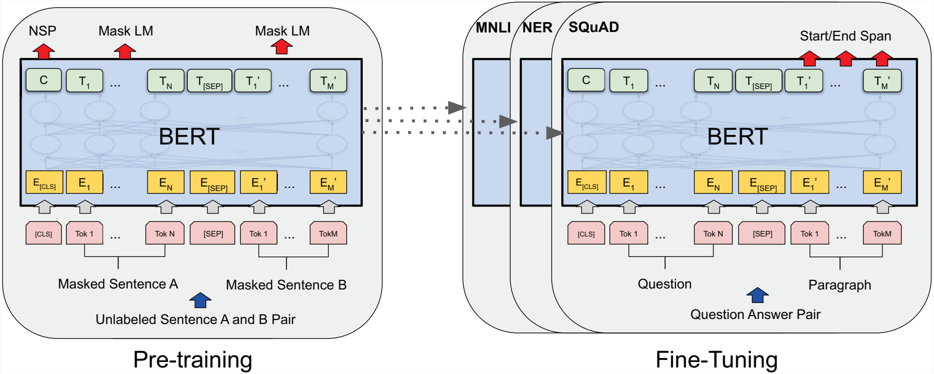


Figure from [Devlin et al.2019].

Pre-training and Finetuning Bert

- Pre-training on BooksCorpus (800M words) and English Wikipedia (2,500M words);
- to finetune for a new task, we plug task-specific inputs and outputs into Bert and re-train its parameters;
- input: designed to be two sentences:
  1. sentence pairs in paraphrasing;
  2. hypothesis-premise pairs in entailment;
  3. question-passage pairs in question answering;
  4. text-$\emptyset$ pair in text classification or sequence tagging;
- output:
  1. sequence of tokens in tasks such as QA (mark answer span);
  2. sequence of labels in tagging tasks such as NER;
  3. `[CLS]` representation is fed into an output layer for classification, such as entailment or sentiment.
- appendix of [Devlin et al.2019] gives examples.

Bert Results: Glue Benchmark

System	MNLI-(m/mm)	QQP	QNLI	SST-2	CoLA	STS-B	MRPC	RTE	**Average**
	392k	363k	108k	67k	8.5k	5.7k	3.5k	2.5k	-
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.8	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	87.4	91.3	45.4	80.0	82.3	56.0	75.1
$\text{BERT}_{\text{BASE}}$	84.6/83.4	71.2	90.5	93.5	52.1	85.8	88.9	66.4	79.6
$\text{BERT}_{\text{LARGE}}$	**86.7/85.9**	**72.1**	**92.7**	**94.9**	**60.5**	**86.5**	**89.3**	**70.1**	**82.1**

Glue is a mixture of various natural language understanding tasks: MNLI, QNLI, WNLI: natural language inference; QQP: question equivalence; SST-2: sentiment; CoLA: linguistic acceptability; STS-B: semantic similarity; MRPC: paraphrasing; RTE: entailment.

Feature Extraction vs. Finetuning: Named Entity Recognition

System	Dev F1	Test F1
ELMo (Peters et al., 2018a)	95.7	92.2
CVT (Clark et al., 2018)	-	92.6
CSE (Akbik et al., 2018)	-	**93.1**
Fine-tuning approach		
$\text{BERT}_{\text{LARGE}}$	96.6	92.8
$\text{BERT}_{\text{BASE}}$	96.4	92.4
Feature-based approach ($\text{BERT}_{\text{BASE}}$)		
Embeddings	91.0	-
Second-to-Last Hidden	95.6	-
Last Hidden	94.9	-
Weighted Sum Last Four Hidden	95.9	-
Concat Last Four Hidden	96.1	-
Weighted Sum All 12 Layers	95.5	-

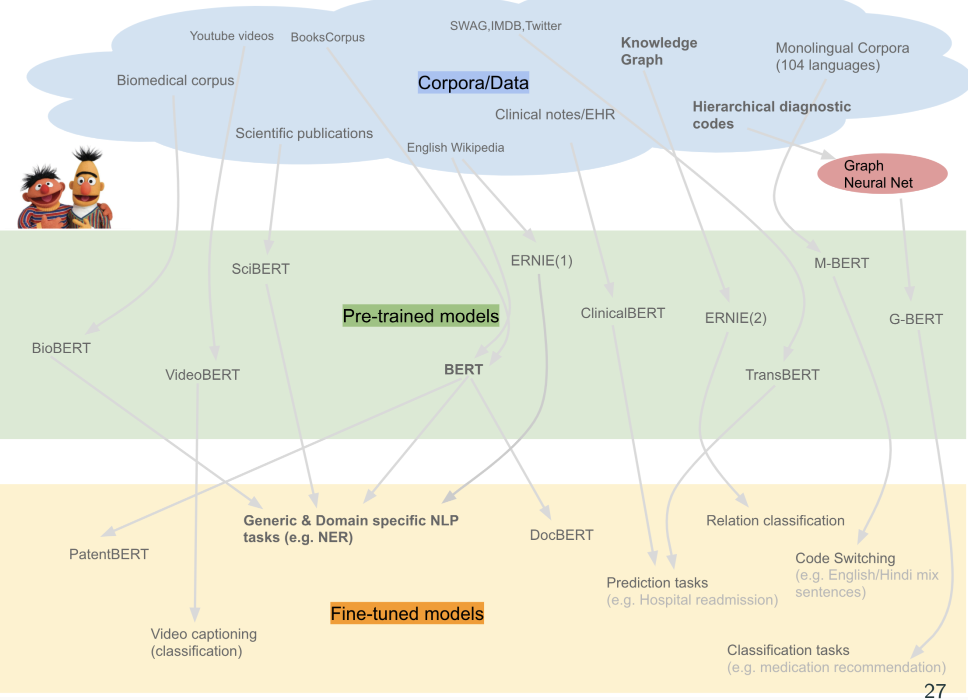
Bert and the State of the Art

The current state of the art in NLP owes a lot to Bert (and many subsequent large language models):

- pre-training a large language model and then fine-tuning or prompting is state of the art for many NLP tasks
- pre-training requires lots of resources! Estimate for Bert (Tim Dettmers): 4 GPUs (RTX 2080Ti) for 100 days
- fine-tuning existing model is relatively quick, but fitting model in GPU memory can be a challenge
- getting new state of the art results with ever-larger models and data is a game that will continue, but only few can play
- positive (for everybody else): we also need smart ideas for architectures, objective functions, evaluation, etc.

Summary

- Bert is a contextualized language model that uses a deep, bidirectional transformer architecture;
- it is pre-trained on unlabeled text using masking and next sentence prediction;
- it is designed for finetuning with minimal architectural modifications;
- the input uses sentence pairs; the output can be sentences, labels, classification decisions, depending on task;
- Bert-based models are state of the art on many NLP tasks.
- There are many variants of Bert ...


Corpora/Data
Youtube videos
BooksCorpus
SWAG,IMDB,Twitter
Knowledge Graph
Monolingual Corpora (104 languages)
Biomedical corpus
Clinical notes/EHR
Hierarchical diagnostic codes
Scientific publications
English Wikipedia
Graph Neural Net
Pre-trained models
SciBERT
ERNIE(1)
M-BERT
ClinicalBERT
ERNIE(2)
G-BERT
BioBERT
VideoBERT
BERT
TransBERT
Fine-tuned models
Generic & Domain specific NLP tasks (e.g. NER)
DocBERT
Relation classification
PatentBERT
Code Switching
(e.g. English/Hindi mix sentences)
Prediction tasks
(e.g. Hospital readmission)
Video captioning (classification)
Classification tasks
(e.g. medication recommendation)

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