Multilingual BERT

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Outline

Contextual Word Embeddings

BERT as a Transformer

How is BERT trained?

Many languages at once

Exercise

Where do contextual embeddings come from?

Outline

Contextual Word Embeddings

A very general timeline

The general idea has always been to turn a word into a dense vector of real value. Theoretical works generally stress a connection with the distributional hypothesis (Harris, 1954; Firth, 1957)

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- first *contextualized* neural embeddings 2017

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  - Also entails that existing word embeddings benchmarks may not be appropriate
- Unlike sentence encoders, which merge together in a single vector all the semantics of the sentence, contextualized embedding algorithm assign to each token a representation that is a function of the entire input sentence.

Contextual Word Embeddings

What changed: fine-tuning vs. feature-based models

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1. Fine-tuning: Achieving state-of-the-art performance on multiple tasks by simply fine-tuning the embeddings model.

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2. Contrasts with previous non-contextualized embeddings which were most of the time used as additional features for more complex, often task-specific models
   NB: still possible with contextualized representations

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- So many studies on BERT that we coined the term “Bertology”

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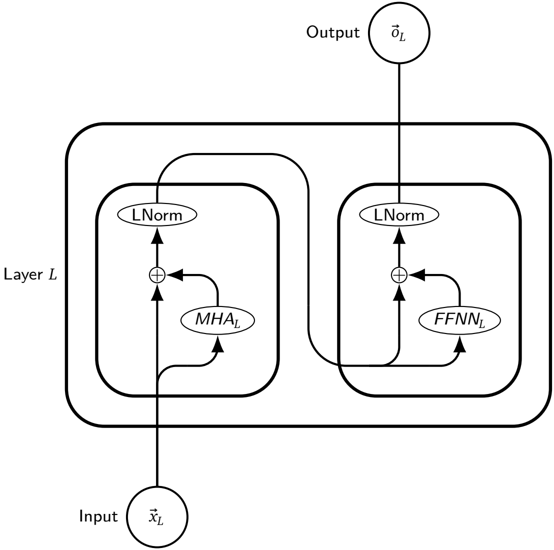
- Layer-normalization employs two learned parameters, a bias $\vec{b}$ and a gain $\vec{g}$:

$$\text{LayerNorm}(\vec{x}) = \vec{g} \odot \frac{\vec{x} - \mu_{\vec{x}}}{\sigma_{\vec{x}}} + \vec{b}$$

  where $\mu_{\vec{x}}$ is the mean of the components of $\vec{x}$, and $\sigma_{\vec{x}}$ the standard deviation, and $\odot$ is element-wise multiplication

BERT as a Transformer

Transformer Layer at a glance



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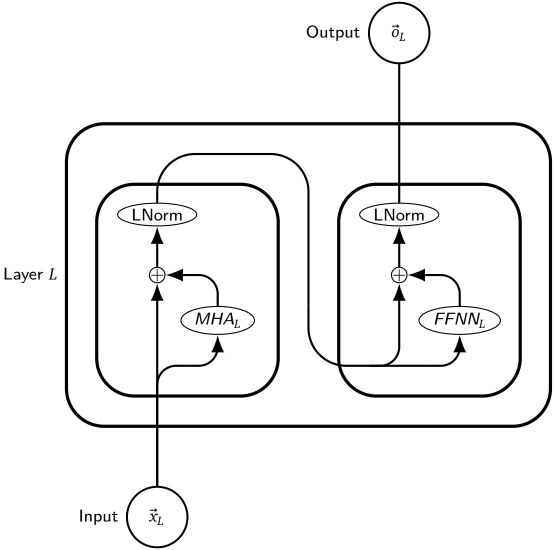

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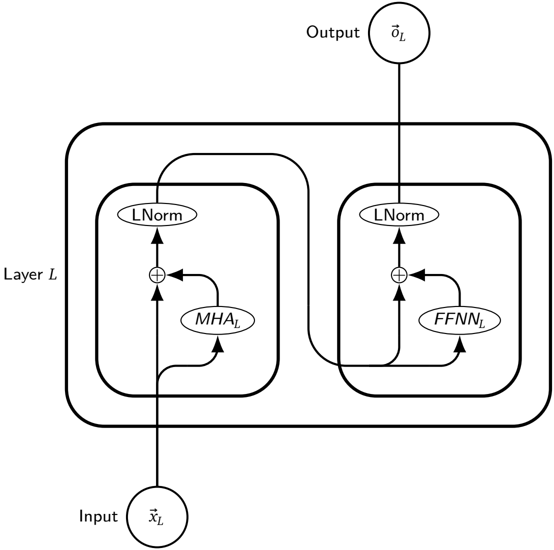

- Many implementation apply layer-norm before the layer function (MHA or FFN)
- In any event, there exists a path from input to output passing only by residual connections and layer norms

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Multi-Head Attention

- The first sub-layer applies scaled-dot self-attention:

$$\text{Attention}(Q,K,V) = \text{Softmax}(\frac{Q \cdot K^T}{\sqrt{d_K}})V$$

NB: dot product can be seen as a measure of similarity: $\vec{u} \cdot \vec{v} = \|\vec{u}\|_2 \ \|\vec{v}\|_2 \ \cos(\vec{u}, \vec{v})$

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- ... combined with multi-head attention, ie. each attention sublayer has A learned linear projections for queries Q, keys K and values V

$$\text{MultiHead}(Q,K,V) = W_{\text{MHA}} \cdot \Big(\bigoplus_{a}^{A} \text{Attention}(W_q^a Q, W_k^a K, W_v^a V)\Big)$$

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  - Softmax$(\ldots)V$ is a weighted average that strongly favors the most similar elements

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Layer Wiring

- The second sub-layer is a feed forward network, composed of two linear transformations with a rectified linear unit activation in between :

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- In other words the position encoding vectors are **fixed**.

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Training procedure is deeply tied to input format.

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BERT input format

- To convert a sequence of tokens to a BERT input format:
  1. tokens are first embedded
  2. 'positional encodings' $\vec{p(i)}$ mark the position i of the token
  3. 'Segment encodings' $\vec{\mathtt{seg}}_A$, $\vec{\mathtt{seg}}_B$ mark which sentence tokens belong to
  4. 3 special tokens: `[SEP]` for sentence boundaries, `[CLS]` and `[MASK]` for performing the actual training
- Given the example "*My dog barks. It is a pooch.*", the actual input would be:

$$\begin{aligned}
\vec{\mathtt{[CLS]}} + \vec{p(0)} + \vec{\mathtt{seg}}_A, &\quad \vec{My} + \vec{p(1)} + \vec{\mathtt{seg}}_A,\\
\vec{dog} + \vec{p(2)} + \vec{\mathtt{seg}}_A, &\quad \vec{barks} + \vec{p(3)} + \vec{\mathtt{seg}}_A,\\
\vec{.} + \vec{p(4)} + \vec{\mathtt{seg}}_A, &\quad \vec{\mathtt{[SEP]}} + \vec{p(5)} + \vec{\mathtt{seg}}_A,\\
\vec{It} + \vec{p(6)} + \vec{\mathtt{seg}}_B, &\quad \vec{is} + \vec{p(7)} + \vec{\mathtt{seg}}_B,\\
\vec{a} + \vec{p(8)} + \vec{\mathtt{seg}}_B, &\quad \vec{pooch} + \vec{p(9)} + \vec{\mathtt{seg}}_B,\\
\vec{.} + \vec{p(10)} + \vec{\mathtt{seg}}_B, &\quad \vec{\mathtt{[SEP]}} + \vec{p(11)} + \vec{\mathtt{seg}}_B
\end{aligned}$$

- During training, some tokens at random will be masked using $\vec{\mathtt{[MASK]}}$.
- Positional encodings are only there for technical reasons, so we can safely ignore them.

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- In a given sentence a word (or a group of words) will be blanked out
- Subjects will then be tasked with filling in said blanks.

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- The "Cloze Test", also known as "Gap-Fill", "Cloze deletion test", "Fill in the blanks"...
- In a given sentence a word (or a group of words) will be blanked out
- Subjects will then be tasked with filling in said blanks.
- It is mostly used as learning exercises to assess **reading proficiency** and **mastery of grammar**.

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- It has also been used jointly with eye-tracking.

How is BERT trained?

Implementing the Cloze Test as an objective

- The idea behind BERT is to train the Transformer architecture to do well on Cloze Test: if it can find the correct parameters to solve a reading exercise, then it's probably a decent textual representation.

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This use of the Cloze Test as a training task was dubbed by the authors the 'Masked Language Model' task, or MLM for short.

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- This objective entails that BERT can only be trained on a corpus of coherent documents, and not on corpora composed of shuffled sentences
- This second objective supposedly helps on QA and NLI downstream tasks.
- There are serious concerns about the usefulness of this task, newer implementations of BERT don’t necessarily use it.

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- The prediction is done using a simple linear classifier.

Outline

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"Multilingual BERT" model was trained on the 100 largest wikipedia dumps

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5. restart from 2.; loop until T reaches a certain size

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- Chinese characters in multilingual BERT are considered as distinct tokens, since Chinese doesn't use whitespaces.
- all other language characters are lowercased and accent diacritics are removed
- to avoid over- or under-representing languages when training the model and computing BPE, a sampling ratio per language is defined:

$$\hat{P}(L) = \frac{P(L)^S}{\sum_{L'} P(L')^S}$$

with $P(L)$ the original magnitude of the language L in the corpus, and S a smoothing factor (in the case of multilingual BERT, $S = 0.7$).

NB: The result is that more frequent languages are sampled less, whereas less frequent languages are sampled more.

Outline

Bertology 101: Studying the Stability of the BERT Semantic Space

Testing BERT on a similarity benchmark

In this exercise, you will be comparing BERT embeddings drawn from two different corpora on a word-type similarity benchmark.

1. Download data

- **Python code for loading BERT:** Download the original repository using `git clone https://github.com/google-research/bert.git`. *It is highly recommended to use a dedicated virtual environment, eg. using `python3 -m venv bert-venv`.*
- **Download the model itself:** All information pertaining to this step should be on the github you installed in the previous step.
- **Retrieving a similarity benchmark:** Download the MEN dataset from https://staff.fnwi.uva.nl/e.bruni/MEN, and retrieve the file `MEN_dataset_natural_form_full`. It contains space-separated triples, composed of two words and a similarity rating.
- **Retrieve sentence corpora:** BERT embeddings are computed "on the fly", so there is no file containing the exact embeddings (unlike word2vec for instance). As a result, you need sentences corpora to compute embeddings from: retrieve the two pre-parsed corpora from the lecture's github (derived from Wikipedia and OpenSubtitles).

2. Retrieve word type representation

- **Retrieve word token embeddings:** Use the script `extract_features.py` from Google's BERT github. **Carefully read the README file for this github**. You only need the output from the last layer (use `--layers=-1`. This script should produce a JSON output that contains all the required information.
- **Compute word type representations:** Parse the output file from the previous step to retrieve individual tokens paired with their embeddings. You can then compute the average embedding for a given word type to retrieve a word type representation.

Tip: *do not retrieve all embeddings before computing the average for a given word type: instead, compute the sum of token embeddings as you parse them, and divide by the number of tokens for that word type.*

3. Compare embeddings from the two corpora

- **Using the MEN benchmark:**
  - Make sure you computed word-token representations: the script `extract_features.py` produces outputs associated to *word-pieces*.
  - For each triple from the MEN dataset, retrieve the word-type representations of the two paired words (as derived from the first of the two corpora)
  - Compute their cosine. This should result in a series of similarity measurements.
  - Compute the Spearman correlation of cosine measurements and human similarity ratings from MEN (i.e., compare the cosine with the third item from the triple).
  - Repeat the process, this time using embeddings from the second of the two copora.
- **Directly compare the embeddings of the two corpora:**
  - This time, you can directly compare embeddings of word-pieces.
  - Compute the average type representations for each word-piece embedding in the first corpus; repeat on the second corpus.
  - Compare directly the vectors component-wise using a related sample t-test over the two sets of vectors (use the scipy function scipy.stats.ttest_rel).
  - Probe the structure of the two vector spaces for the two corpora: a) select a random sub-sample of word-pieces, b) compute their pairwise distances (Euclidean or cosine) in both corpora, c) compute a t-test using these two related series of measurements.
- **What do you conclude from these experiments?**
  - How do you interpret them?
  - Are there unclear/uncertain points remaining?
  - How would you try to clarify them?

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