Natural Language Processing
Big Picture

• Central to human intelligence.
• Tremendous practical value.
• Colossal developments recently.
Goal of This Tutorial

• Basic NLP literacy.
• Getting up to date with recent developments.
  ▶ Architectures
  ▶ Language tasks
  ▶ Tremendous developments in the field recently!
• Know where to look at if you’re starting an NLP project
Language Models

• A statistical model that assigns probabilities to the words in a sentences.
• **Most commonly**: Given previous words, what should the next one be?
• **Neural language model**: Model the probability of words given others using neural networks.
Which architecture is most suitable?
Recurrent Architectures

- We can use recurrent architectures.
- LSTM, GRU ...
- Great for variable length inputs, like sentences.
What are some of the problems with recurrent architectures?

- Not parallelizable across instances.
- Cannot model long dependences.
- Optimization difficulties (vanishing gradients).
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We’d like an architectural primitive that is:

- Ideally feed-forward
- Can facilitate between-token interactions
- Can model long dependences easily.

Attention to the rescue!

- There are many forms of attention. Today we’ll focus on scaled dot product attention.
Attention

- Three inputs: queries, keys and values.
- "Return a combination of the values based on the similarities between keys and queries”.
- Dimensionalities:
  - $Q \in \mathbb{R}^{n_q \times d_{kq}}$
  - $K \in \mathbb{R}^{n_{kv} \times d_{kq}}$
  - $V \in \mathbb{R}^{n_{kv} \times d_v}$

$$A(Q, K, V) = V(\text{softmax}(\frac{K^T Q}{d_{kq}}))$$ (1)
Quiz!

• True of False: The dimensionality of queries have to match the dimensionality of the keys.
Quiz!

- True or False: The dimensionality of queries have to match the dimensionality of the keys. **TRUE**
- True or False: The number of keys have to match the number of values.
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Quiz!

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- True or False: The number of keys have to match the number of values. **TRUE**
- True or False: The number of keys have to match the number of queries. **FALSE**
Quiz!

• True or False: The dimensionality of queries have to match the dimensionality of the keys. TRUE

• True or False: The number of keys have to match the number of values. TRUE

• True or False: The number of keys have to match the number of queries. FALSE

• Dimensionalities:
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We need to make two central decisions:

• How do we compute similarity?
• How do we ’normalize’ the similarity scores amongst values?
Attention

- **Similarity**: Dot product between keys and queries.
- **Interesting theorem**: In high dimensions, two randomly sampled vectors are almost always approximately perpendicular to each other.
- **Normalization**: Softmax along the keys/values!
- **Result**: Scaled dot product attention.
- We get the following attention mechanism:

\[
A(Q, K, V) = V(softmax\left(\frac{K^T Q}{d_{kq}}\right)) \tag{2}
\]

\(^1\)From, lets say, a isotropic multivariate Gaussian distribution.
Scaled Dot-Product Attention

- MatMul
- SoftMax
- Mask (opt.)
- Scale
- MatMul

Q → K → V
• What is self-attention?
• What is self-attention?
• Use the same tensor for keys, values and queries!
• What is self-attention?
• Use the same tensor for keys, values and queries!
• What are the keys/queries/values in a self attention layer processing sentence
Self-Attention

- What is self-attention?
- Use the same tensor for keys, values and queries!
- What are the keys/queries/values in a self attention layer processing sentence
- The features corresponding to each token!
Lingering question: What is learned in an attention layer?

- The space in which the similarities are computed.
- The transformations on the values.

What if we’d like to have different notions of similarity on the same set of tokens?

Multi head attention to the rescue!
Properties of the transformer architecture:

- Fully feed forward.
- Equivariance properties of scaled dot product attention (important):
  - How does the output change if we permute the order of queries? (equivariance)
  - How does the output change if we permute the key-value pairs in unison? (invariance)

Exercise: How about self-attention?
Table 1: Maximum path lengths, per-layer complexity and minimum number of sequential operations for different layer types. $n$ is the sequence length, $d$ is the representation dimension, $k$ is the kernel size of convolutions and $r$ the size of the neighborhood in restricted self-attention.

<table>
<thead>
<tr>
<th>Layer Type</th>
<th>Complexity per Layer</th>
<th>Sequential Operations</th>
<th>Maximum Path Length</th>
</tr>
</thead>
<tbody>
<tr>
<td>Self-Attention</td>
<td>$O(n^2 \cdot d)$</td>
<td>$O(1)$</td>
<td>$O(1)$</td>
</tr>
<tr>
<td>Recurrent</td>
<td>$O(n \cdot d^2)$</td>
<td>$O(n)$</td>
<td>$O(n)$</td>
</tr>
<tr>
<td>Convolutional</td>
<td>$O(k \cdot n \cdot d^2)$</td>
<td>$O(1)$</td>
<td>$O(log_k(n))$</td>
</tr>
<tr>
<td>Self-Attention (restricted)</td>
<td>$O(r \cdot n \cdot d)$</td>
<td>$O(1)$</td>
<td>$O(n/r)$</td>
</tr>
</tbody>
</table>
What’s next?

• Brief intro to self-supervised learning
• BERT (i.e. Self-supervised training of language models)
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• Brief intro to self supervised learning
• BERT (i.e. Self-supervised training of language models)
Three types of learning:

- Supervised learning
- Reinforcement learning
- Unsupervised/self-supervised learning:
  - When the label is in the data itself!
  - Possible to make use of large amounts of data with no additional labelling efforts.
Examples of self-supervised learning:

- Predict next frame in a video.
- Image completion.
- Auto-encoding tasks.
- Rotation prediction.
- Predicting next word from previous ones.
• Can we use large amounts of text data to pretrain language models?

- Previous approaches:
  - ELMO (Peters et al., 2017): Bidirectional, but shallow.
  - GPT (Radford et al., 2018): Deep, but unidirectional.
  - BERT (Devlin et al., 2018): Deep and bidirectional!
• Can we use large amounts of text data to pretrain language models?

• Considerations:
  ▶ How can we fuse both left-right and right-left context?
  ▶ How can we facilitate non-trivial interactions between input tokens?
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Previous approaches:

- **ELMO** (Peters. et. al., 2017): Bidirectional, but shallow.
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- **BERT** (Devlin et. al., 2018): Deep and bidirectional!
• The BERT workflow includes:
  ▶ Pretrain on generic, self-supervised tasks, using large amounts of data (like all of Wikipedia)
  ▶ Fine-tune on specific tasks with limited, labelled data.
• The pretraining tasks (will talk about this in more detail later):
  ▶ Masked Language Modelling (to learn contextualized token representations)
  ▶ Next Sentence Prediction (summary vector for the whole input)
BERT Architecture

Pre-training

Fine-Tuning

MNLI

SQuAD

Start/End Span

Question Answer Pair

Question

Paragraph

Masked Sentence A

Masked Sentence B

Unlabeled Sentence A and B Pair

[CLS] Tok 1 ... Tok N [SEP] Tok 1 ... TokM

C T₁ ... Tₙ T_{[SEP]} T₁' ... Tₘ'

E_{[CLS]} E₁ ... Eₙ E_{[SEP]} E₁' ... Eₘ'

NSP Mask LM Mask LM

BERT

BERT
BERT Architecture

Properties

• Two input sequences.
  ▶ Many NLP tasks have two inputs (question answering, paraphrase detection, entailment detection etc. )

• Computes embeddings
  ▶ Both token, position and segment embeddings.
  ▶ Special start and separation tokens.

• Architecture
  ▶ Basically the same as transformer encoder.

• Outputs:
  ▶ Contextualized token representations.
  ▶ Special tokens for context.
How we tokenize the inputs is very important!
BERT uses the WordPiece tokenizer (Wu et. al. 2016)
(Aside) Tokenizers

• Tokenizers have to balance the following:
  ► Being comprehensive (rare words? translation to different languages)
  ► Total number of tokens
  ► How semantically meaningful each token is.

• This is an activate area of research.
Pretraining tasks

- Masked Language Modelling (i.e. Cloze Task (Taylor, 1953))
- Next sentence prediction
• Mask 15% of the input tokens. (i.e. replace with a dummy masking token)
• Run the model, obtain the embeddings for the masked tokens.
• Using these embeddings, try to predict the missing token.
• ”I love to eat peanut ___ and jam. ” Can you guess what’s missing?
This procedure forces the model to encode context information in the features of all of the tokens.
Next Sentence Prediction

• Goal is to summarize the complete context (i.e. the two segments) in a single feature vector.

• Procedure for generating data
  ▶ Pick a sentence from the training corpus and feed it as ”segment A”.
  ▶ With 50% probability, pick the following sentence and feed that as ”segment B”.
  ▶ With 50% probability, pick the a random sentence and feed it as ”segment B”.

• Using the features for the context token, predict whether segment B is the following sentence of segment A.

• Turns out to be a very effective pretraining technique!
Fine Tuning

Procedure:

- Add a final layer on top of BERT representations.
- Train the whole network on the fine-tuning dataset.
- Pre-training time: In the order of days on TPUs.
- Fine tuning task: Takes only a few hours max.
<table>
<thead>
<tr>
<th>System</th>
<th>MNLI-(m/mm)</th>
<th>QQP</th>
<th>QNLI</th>
<th>SST-2</th>
<th>CoLA</th>
<th>STS-B</th>
<th>MRPC</th>
<th>RTE</th>
<th>Average</th>
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<tbody>
<tr>
<td></td>
<td>392k</td>
<td>363k</td>
<td>108k</td>
<td>67k</td>
<td>8.5k</td>
<td>5.7k</td>
<td>3.5k</td>
<td>2.5k</td>
<td>-</td>
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<tr>
<td>Pre-OpenAI SOTA</td>
<td>80.6/80.1</td>
<td>66.1</td>
<td>82.3</td>
<td>93.2</td>
<td>35.0</td>
<td>81.0</td>
<td>86.0</td>
<td>61.7</td>
<td>74.0</td>
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<tr>
<td>BiLSTM+ELMo+Attn</td>
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<td>64.8</td>
<td>79.8</td>
<td>90.4</td>
<td>36.0</td>
<td>73.3</td>
<td>84.9</td>
<td>56.8</td>
<td>71.0</td>
</tr>
<tr>
<td>OpenAI GPT</td>
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<td>70.3</td>
<td>87.4</td>
<td>91.3</td>
<td>45.4</td>
<td>80.0</td>
<td>82.3</td>
<td>56.0</td>
<td>75.1</td>
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<tr>
<td>BERT&lt;sub&gt;BASE&lt;/sub&gt;</td>
<td>84.6/83.4</td>
<td>71.2</td>
<td>90.5</td>
<td>93.5</td>
<td>52.1</td>
<td>85.8</td>
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<td>66.4</td>
<td>79.6</td>
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<td>72.1</td>
<td>92.7</td>
<td>94.9</td>
<td>60.5</td>
<td>86.5</td>
<td>89.3</td>
<td>70.1</td>
<td>82.1</td>
</tr>
</tbody>
</table>

Table 1: GLUE Test results, scored by the evaluation server (https://gluebenchmark.com/leaderboard). The number below each task denotes the number of training examples. The “Average” column is slightly different than the official GLUE score, since we exclude the problematic WNLI set. BERT and OpenAI GPT are single-model, single task. F1 scores are reported for QQP and MRPC, Spearman correlations are reported for STS-B, and accuracy scores are reported for the other tasks. We exclude entries that use BERT as one of their components.
The transformer section of this tutorial is influenced by the fantastic talk by Lukasz Kaiser on transformers: https://www.youtube.com/watch?v=rBCqOTEfxvgt=1704s