BERT
AI2 made ELMo in spring 2018, GPT (transformer-based ELMo) was released in summer 2018, BERT came out October 2018

Four major changes compared to ELMo:

- Transformers instead of LSTMs
- Bidirectional model with “Masked LM” objective instead of standard LM
- Fine-tune instead of freeze at test time
- Operates over word pieces (byte pair encoding)
ELMo is a unidirectional model (as is GPT): we can concatenate two unidirectional models, but is this the right thing to do?

ELMo reprs look at each direction in isolation; BERT looks at them jointly.

A stunning ballet dancer, Copeland is one of the best performers to see live.

Devlin et al. (2019)
How to learn a “deeply bidirectional” model? What happens if we just replace an LSTM with a transformer?

You could do this with a “one-sided” transformer, but this “two-sided” model can cheat.
Masked Language Modeling

- How to prevent cheating? Next word prediction fundamentally doesn't work for bidirectional models, instead do *masked language modeling*.

- BERT formula: take a chunk of text, mask out 15% of the tokens, and try to predict them.

Devlin et al. (2019)
Next “Sentence” Prediction

- Input: [CLS] Text chunk 1 [SEP] Text chunk 2
- 50% of the time, take the true next chunk of text, 50% of the time take a random other chunk. Predict whether the next chunk is the “true” next
- BERT objective: masked LM + next sentence prediction

Input: [CLS] Text chunk 1 [SEP] Text chunk 2

NotNext:

Madagascar enjoyed like

Transformer

... Transformer


Devlin et al. (2019)
BERT Architecture

- BERT Base: 12 layers, 768-dim per wordpiece token, 12 heads. Total params = 110M
- BERT Large: 24 layers, 1024-dim per wordpiece token, 16 heads. Total params = 340M
- Positional embeddings and segment embeddings, 30k word pieces
- This is the model that gets \textit{pre-trained} on a large corpus

Devlin et al. (2019)
What can BERT do?

- Artificial [CLS] token is used as the vector to do classification from
- Sentence pair tasks (entailment): feed both sentences into BERT
- BERT can also do tagging by predicting tags at each word piece

Devlin et al. (2019)
What can BERT do?

Entails (first sentence implies second is true)

- How does BERT model this sentence pair stuff?
- Transformers can capture interactions between the two sentences, even though the NSP objective doesn’t really cause this to happen
What can BERT NOT do?

- BERT **cannot** generate text (at least not in an obvious way)
  
  - Can fill in MASK tokens, but can’t generate left-to-right (well, you could put MASK at the end repeatedly, but this is slow)

- Masked language models are intended to be used primarily for “analysis” tasks
Fine-tuning BERT

- Fine-tune for 1-3 epochs, batch size 2-32, learning rate 2e-5 - 5e-5
- Large changes to weights up here (particularly in last layer to route the right information to [CLS])
- Smaller changes to weights lower down in the transformer
- Small LR and short fine-tuning schedule mean weights don’t change much
- More complex “triangular learning rate” schemes exist

(b) Single Sentence Classification Tasks: SST-2, CoLA
## Fine-tuning BERT

<table>
<thead>
<tr>
<th>Pretraining</th>
<th>Adaptation</th>
<th>NER CoNLL 2003</th>
<th>SA SST-2</th>
<th>Nat. lang. inference MNLI</th>
<th>Semantic textual similarity SICK-E</th>
<th>Semantic textual similarity SICK-R</th>
<th>MRPC</th>
<th>STS-B</th>
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<tbody>
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<td>🍁</td>
<td>-</td>
<td>81.8</td>
<td>62.9</td>
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<td>86.6</td>
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<td>86.3</td>
<td>86.1</td>
<td>76.0</td>
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<td>🔥</td>
<td>91.9</td>
<td>91.2</td>
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<td>75.5</td>
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<td></td>
<td>Δ=🔥-🍁</td>
<td>0.2</td>
<td>-0.6</td>
<td>-3.2</td>
<td>-3.3</td>
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<td>-1.3</td>
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<td>🔥</td>
<td>92.4</td>
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<tr>
<td></td>
<td>Δ=🔥-🍁</td>
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<td>0.5</td>
<td>0.0</td>
<td>1.0</td>
<td>2.3</td>
<td>6.7</td>
<td>4.2</td>
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</tbody>
</table>

- BERT is typically better if the whole network is fine-tuned, unlike ELMo

Peters, Ruder, Smith (2019)
## Evaluation: GLUE

<table>
<thead>
<tr>
<th>Corpus</th>
<th>Train</th>
<th>Test</th>
<th>Task</th>
<th>Metrics</th>
<th>Domain</th>
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</thead>
<tbody>
<tr>
<td>CoLA</td>
<td>8.5k</td>
<td>1k</td>
<td>acceptability</td>
<td>Matthews corr.</td>
<td>misc.</td>
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<tr>
<td>SST-2</td>
<td>67k</td>
<td>1.8k</td>
<td>sentiment</td>
<td>acc.</td>
<td>movie reviews</td>
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<td></td>
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<tr>
<td><strong>Single-Sentence Tasks</strong></td>
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<tr>
<td>MRPC</td>
<td>3.7k</td>
<td>1.7k</td>
<td>paraphrase</td>
<td>acc./F1</td>
<td>news</td>
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<tr>
<td>STS-B</td>
<td>7k</td>
<td>1.4k</td>
<td>sentence similarity</td>
<td>Pearson/Spearman corr.</td>
<td>misc.</td>
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<tr>
<td>QQP</td>
<td>364k</td>
<td>391k</td>
<td>paraphrase</td>
<td>acc./F1</td>
<td>social QA questions</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td><strong>Similarity and Paraphrase Tasks</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>MNLI</td>
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<td>20k</td>
<td>NLI</td>
<td>matched acc./mismatched acc.</td>
<td>misc.</td>
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<tr>
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<td>5.4k</td>
<td>QA/NLI</td>
<td>acc.</td>
<td>Wikipedia</td>
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<tr>
<td>RTE</td>
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<td>3k</td>
<td>NLI</td>
<td>acc.</td>
<td>news, Wikipedia</td>
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<td>WNL1</td>
<td>634</td>
<td>146</td>
<td>coreference/NLI</td>
<td>acc.</td>
<td>fiction books</td>
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</tbody>
</table>
### Results

<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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</thead>
<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>
</tr>
<tr>
<td>BiLSTM+ELMo+Attn</td>
<td>76.4/76.1</td>
<td>64.8</td>
<td>79.9</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>
<td>82.1/81.4</td>
<td>70.3</td>
<td>88.1</td>
<td>91.3</td>
<td>45.4</td>
<td>80.0</td>
<td>82.3</td>
<td>56.0</td>
<td>75.2</td>
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<tr>
<td>(\text{BERT}_{\text{BASE}})</td>
<td>84.6/83.4</td>
<td>71.2</td>
<td>90.1</td>
<td>93.5</td>
<td>52.1</td>
<td>85.8</td>
<td>88.9</td>
<td>66.4</td>
<td>79.6</td>
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<tr>
<td>(\text{BERT}_{\text{LARGE}})</td>
<td><strong>86.7/85.9</strong></td>
<td><strong>72.1</strong></td>
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<td><strong>94.9</strong></td>
<td><strong>60.5</strong></td>
<td><strong>86.5</strong></td>
<td><strong>89.3</strong></td>
<td><strong>70.1</strong></td>
<td><strong>81.9</strong></td>
</tr>
</tbody>
</table>

- Huge improvements over prior work (even compared to ELMo)
- Effective at “sentence pair” tasks: textual entailment (does sentence A imply sentence B), paraphrase detection

Devlin et al. (2018)
RoBERTa

- “Robustly optimized BERT”
- 160GB of data instead of 16 GB
- Dynamic masking: standard BERT uses the same MASK scheme for every epoch, RoBERTa recomputes them
- New training + more data = better performance

<table>
<thead>
<tr>
<th>Model</th>
<th>data</th>
<th>bsz</th>
<th>steps</th>
<th>SQuAD (v1.1/2.0)</th>
<th>MNLI-m</th>
<th>SST-2</th>
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</thead>
<tbody>
<tr>
<td>RoBERTa</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>with BOOKS + WIKI</td>
<td>16GB</td>
<td>8K</td>
<td>100K</td>
<td>93.6/87.3</td>
<td>89.0</td>
<td>95.3</td>
</tr>
<tr>
<td>+ additional data (§3.2)</td>
<td>160GB</td>
<td>8K</td>
<td>100K</td>
<td>94.0/87.7</td>
<td>89.3</td>
<td>95.6</td>
</tr>
<tr>
<td>+ pretrain longer</td>
<td>160GB</td>
<td>8K</td>
<td>300K</td>
<td>94.4/88.7</td>
<td>90.0</td>
<td>96.1</td>
</tr>
<tr>
<td>+ pretrain even longer</td>
<td>160GB</td>
<td>8K</td>
<td>500K</td>
<td>94.6/89.4</td>
<td>90.2</td>
<td>96.4</td>
</tr>
<tr>
<td>BERTLARGE with BOOKS + WIKI</td>
<td>13GB</td>
<td>256</td>
<td>1M</td>
<td>90.9/81.8</td>
<td>86.6</td>
<td>93.7</td>
</tr>
</tbody>
</table>

Liu et al. (2019)
Using BERT

- Huggingface Transformers: big open-source library with most pre-trained architectures implemented, weights available

- Lots of standard models...

  Model architectures

- Transformers currently provides the following NLU/NLG architectures:

  2. **GPT** (from OpenAI) released with the paper *Improving Language Understanding*.
  3. **GPT-2** (from OpenAI) released with the paper *Language Models are Unintended Generators of Unintended Bias*.
  4. **Transformer-XL** (from Google/CMU) released with the paper *Transformer Fixed-Length Context*.
  5. **XLNet** (from Google/CMU) released with the paper *XLNet: Generalized Understanding*.
  6. **XLM** (from Facebook) released together with the paper *Cross-lingual Li and Alexis Conneau*.
  7. **RoBERTa** (from Facebook), released together with the paper a *Robustly*.

  and “community models”

  - mrm8488/spanbert-large-finetuned-tacred
  - mrm8488/xlm-multi-finetuned-xquadv1
  - nlpaueb/bert-base-greek-uncased-v1
  - nlptown/bert-base-multilingual-uncased-sentiment
  - patrickvonplaten/reformer-crime-and-punish
  - redwiedergabe/bert-base-historical-german-rw-cased
  - roberta-base
  - severinsimmler/literary-german-bert
  - seyonec/ChemBERTa-zinc-base-v1

  ...
Heads on transformers learn interesting and diverse things: content heads (attend based on content), positional heads (based on position), etc.

Clark et al. (2019)
What does BERT learn?

- **Direct objects** attend to their verbs
  - 86.8% accuracy at the `dobj` relation

- **Noun modifiers** (e.g., determiners) attend to their noun
  - 94.3% accuracy at the `det` relation

- Still way worse than what supervised systems can do, but interesting that this is learned organically

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**Clark et al. (2019)¶**

- **Coreferent** mentions attend to their antecedents
  - 65.1% accuracy at linking the head of a coreferent mention to the head of an antecedent

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