Announcements

- A4 due today
- A5 out today, due Tuesday
- Final project out Tuesday

Recap: Machine Translation

Today

- ELMo
- BERT
- BERT results
- Applying BERT
ELMo

What is pre-training?

- “Pre-train” a model on a large dataset for task X, then “fine-tune” it on a dataset for task Y
- Key idea: X is somewhat related to Y, so a model that can do X will have some good neural representations for Y as well
- ImageNet pre-training is huge in computer vision: learn generic visual features for recognizing objects
- GloVe can be seen as pre-training: learn vectors with the skip-gram objective on large data (task X), then fine-tune them as part of a neural network for sentiment/any other task (task Y)

GloVe is insufficient

- GloVe uses a lot of data but in a weak way
- Having a single embedding for each word is wrong
  - they swing the bats  they see the bats
- Identifying discrete word senses is hard, doesn’t scale. Hard to identify how many senses each word has
- How can we make our word embeddings more context-dependent?

Context-dependent Embeddings

- Train a neural language model to predict the next word given previous words in the sentence, use the hidden states (output) at each step as word embeddings
- This is the key idea behind ELMo: language models can allow us to form useful word representations in the same way word2vec did

Peters et al. (2018)
ELMo

- CNN over each word => RNN
- Representation of visited (plus vectors from another LM running backwards)
- Peters et al. (2018)

- Use the embeddings as a drop-in replacement for GloVe
- Huge gains across many high-profile tasks: NER, question answering, semantic role labeling (similar to parsing), etc.
- But what if the pre-training isn’t only the embeddings?

ELMo

- 4096-dim LSTMs
- 2048 CNN filters projected down to 512-dim

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

BERT

- 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)
BERT

• 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

ELMo

"ballet dancer"

ELMo

"performer"

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

BERT

"ballet dancer/performer"

Devlin et al. (2019)

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

Madagascar

John visited [MASK] yesterday

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

NotNext

Madagascar

Transformer

like


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 pre-trained on a large corpus

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

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

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
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
- Often requires tricky learning rate schedules (“triangular” learning rates with warmup periods)

BERT Results

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

Evaluation: GLUE

<table>
<thead>
<tr>
<th>Corpus</th>
<th>Train</th>
<th>Test</th>
<th>Task</th>
<th>Metrics</th>
<th>Domain</th>
</tr>
</thead>
<tbody>
<tr>
<td>CoLA</td>
<td>8.5k</td>
<td>1k</td>
<td>sentiment</td>
<td>Matthews corr.</td>
<td>misc, movie reviews</td>
</tr>
<tr>
<td>SST-2</td>
<td>67k</td>
<td>1.8k</td>
<td>acceptability</td>
<td>acc.</td>
<td></td>
</tr>
<tr>
<td>MRPC</td>
<td>3.7k</td>
<td>1.7k</td>
<td>paraphrase</td>
<td>acc./F1</td>
<td>news</td>
</tr>
<tr>
<td>STS-B</td>
<td>7k</td>
<td>1.4k</td>
<td>sentence similarity</td>
<td>Pearson/Spearman corr.</td>
<td>misc</td>
</tr>
<tr>
<td>QQP</td>
<td>364k</td>
<td>391k</td>
<td>paraphrase</td>
<td>acc./F1</td>
<td>social QA questions</td>
</tr>
</tbody>
</table>

Inference Tasks

<table>
<thead>
<tr>
<th>MNLI</th>
<th>NLI</th>
<th>Matched acc./mismatched acc.</th>
<th>misc.</th>
</tr>
</thead>
<tbody>
<tr>
<td>QNLI</td>
<td>QA/NLI</td>
<td>acc.</td>
<td>Wikipedia</td>
</tr>
<tr>
<td>RTE</td>
<td>NLI</td>
<td>acc.</td>
<td>news, Wikipedia</td>
</tr>
<tr>
<td>WNLI</td>
<td>coreference/NLI</td>
<td>acc.</td>
<td>fiction books</td>
</tr>
</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>
</tr>
</thead>
<tbody>
<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>
</tr>
<tr>
<td>BERTBASE</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>BERTLARGE</td>
<td>86.7/85.9</td>
<td>72.1</td>
<td>91.1</td>
<td>94.9</td>
<td>60.5</td>
<td>86.5</td>
<td>89.3</td>
<td>70.1</td>
<td>81.9</td>
</tr>
</tbody>
</table>

Wang et al. (2019)

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

Liu et al. (2019)

<table>
<thead>
<tr>
<th>Model</th>
<th>data</th>
<th>bs</th>
<th>steps</th>
<th>SQuAD (v1.1/2.0)</th>
<th>MNLIm</th>
<th>SST-2</th>
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</thead>
<tbody>
<tr>
<td>RoBERTa</td>
<td>160GB</td>
<td>8K</td>
<td>100K</td>
<td>93.687.3</td>
<td>89.0</td>
<td>95.3</td>
</tr>
<tr>
<td>with Books + Wiki</td>
<td>160GB</td>
<td>8K</td>
<td>100K</td>
<td>94.087.7</td>
<td>93.3</td>
<td>95.6</td>
</tr>
<tr>
<td>+ additional data (3.2)</td>
<td>160GB</td>
<td>8K</td>
<td>300K</td>
<td>94.488.7</td>
<td>90.0</td>
<td>96.1</td>
</tr>
<tr>
<td>+ pretrain longer</td>
<td>160GB</td>
<td>8K</td>
<td>500K</td>
<td>94.889.4</td>
<td>90.2</td>
<td>96.4</td>
</tr>
<tr>
<td>+ pretrain even longer</td>
<td>160GB</td>
<td>8K</td>
<td>500K</td>
<td>94.889.4</td>
<td>90.2</td>
<td>96.4</td>
</tr>
</tbody>
</table>

**ELECTRA**

- Discriminator to *detect* replaced tokens rather than a generator to actually *predict* what those tokens are
- More efficient, strong performance

Clark et al. (2020)

**DeBERTa**

- Slightly better variant

He et al. (2021)

\[
A_{i,j} = \{H_i, P_{ij}\} \times \{H_j, P_{ji}\}^T
\]

\[
= H_iH_j^T + H_iP_{ji} + P_{ij}H_j^T + P_{ij}P_{ji}^T
\]

That is, the attention weight of a word pair can be computed as a sum of four attention scores using disentangled matrices on their contents and positions as *content-to-content*, *content-to-position*, *position-to-content*, and *position-to-position*.

**Using BERT**

- HuggingFace Transformers: big open-source library with most pre-trained architectures implemented, weights available
- Lots of standard models...

1. BERT (from Google, released with the paper BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding by Jacob Devlin, Ming-Wei Chang, Kenton Lee and Kristina Toutanova.)
2. GPT (from OpenAI, released with the paper Improving Language Understanding Using Contrastive Learning by Karen Hao,2) Dario Amodei, and Ilya Sutskever.
3. GPT-2 (from OpenAI, released with the paper Language Models are Self-Supervised by Jeffrey Wu, Reia Bird, David Luan, Dario Amodei, and Ilya Sutskever.
4. DeBERTa, released with the paper DeBERTa: Pre-training Large Language Models from Scratch by Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Yonghui Wu, Zhochen Yang, Quanfu Fan, Guodong Hua, Minsheng Lu, Zhou Han, Wei Du, Jianfeng Zhang, Feifei Chen, and Jianfeng Gao.
5. ELECTRA (from Google, released with the paper ELECTRA: Efficiently Learning Distractor-free Representation via Adversarial pre-training by Zhilin Yang, Zihang Dai, Yinhan Yang, Jaime Carbonell, Omer Levy, and Noam Shazeer.)
6. RoBERTa, released together with the paper a Robustly Optimized Pretrained Language Understanding Model, Liu et al. (2019).

... and “community models”

- m4disa/squad-bert-base-finetuned-turkqa
- m4disa/mbert-multilingual-finetuned
- alpaca/htlm-bert-base-1.1
- patrickjamieson/reformer-finetuned
- redwhitedev/bert-base-multilingual-uncased-finetuned
- roberta-base
- nllb/100langs/bert-base-12langs
- nllb/bert-base-12langs
- nllb/bert-base-12langs
- nllb/100langs/bert-base-12langs
- nllb/100langs/roberta-base
What does BERT learn?

- 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?

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

Clark et al. (2019)

Applying BERT

- Compared to ELMo, BERT is very good at sentence-pair tasks
  - Paraphrase detection
  - Semantic textual similarity
  - Textual entailment
  - Question answering (not really a sentence pair, but it’s a pair of inputs)

- The final project will focus on when these models fail to learn the right things on these tasks. For now: crash course on these tasks + datasets
Natural Language Inference

<table>
<thead>
<tr>
<th>Premise</th>
<th>Hypothesis</th>
</tr>
</thead>
<tbody>
<tr>
<td>A boy plays in the snow</td>
<td>entails</td>
</tr>
<tr>
<td>A man inspects the uniform of a figure</td>
<td>contradicts</td>
</tr>
<tr>
<td>An older and younger man smiling</td>
<td>neutral</td>
</tr>
</tbody>
</table>

- Long history of this task: “Recognizing Textual Entailment” challenge in 2006 (Dagan, Glickman, Magnini)
- Early datasets: small (hundreds of pairs), very ambitious (lots of world knowledge, temporal reasoning, etc.)

SNLI Dataset

- Show people captions for (unseen) images and solicit entailed / neural / contradictory statements
- >500,000 sentence pairs
- One possible architecture:
  - 300D BiLSTM: 83% accuracy (Liu et al., 2016)
  - One of the first big successes of LSTM-based classifiers (sentiment results were more marginal)

MNLI Dataset

- Drawn from multiple genres of text

<table>
<thead>
<tr>
<th>Premise</th>
<th>Label</th>
<th>Hypothesis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fiction</td>
<td></td>
<td>Ca’dsan knew the Old One very well</td>
</tr>
<tr>
<td>Letters</td>
<td></td>
<td>Hundreds of students will benefit from your generosity.</td>
</tr>
<tr>
<td>Telephone Speech</td>
<td></td>
<td>August is a black out month for vacations in the company</td>
</tr>
<tr>
<td>9/11 Report</td>
<td></td>
<td>People formed a line at the end of Pennsylvania Avenue</td>
</tr>
</tbody>
</table>

How do models do it?

- Transformers can easily learn to spot words or short phrases that are transformed
- But, models are often overly sensitive to lexical overlap

Williams et al. (2018)
Question Answering

- Many types of QA:
  - We’ll focus on factoid questions being answered from text
    - E.g., “What was Marie Curie the first female recipient of?” — unlikely you would have this answer in a database
    - Not appropriate: “When was Marie Curie born?” — probably answered in a DB
    - Not appropriate: “Why did World War II start?” — no simple answer

SQuAD

Q: What was Marie Curie the first female recipient of?

Passage: One of the most famous people born in Warsaw was Marie Skłodowska-Curie, who achieved international recognition for her research on radioactivity and was the first female recipient of the Nobel Prize. Famous musicians include Władysław Szpilman and Frédéric Chopin. Though Chopin was born in the village of Żelazowa Wola, about 60 km (37 mi) from Warsaw, he moved to the city with his family when he was seven months old. Casimir Pulaski, a Polish general and hero of the American Revolutionary War, was born here in 1745.

Answer = Nobel Prize

- Assume we know a passage that contains the answer. More recent work has shown how to retrieve these effectively (will discuss when we get to QA)

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Passage: One of the most famous people born in Warsaw was Marie Skłodowska-Curie, who achieved international recognition for her research on radioactivity and was the first female recipient of the Nobel Prize. Famous musicians include Władysław Szpilman and Frédéric Chopin. Though Chopin was born in the village of Żelazowa Wola, about 60 km (37 mi) from Warsaw, he moved to the city with his family when he was seven months old. Casimir Pulaski, a Polish general and hero of the American Revolutionary War, was born here in 1745.

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QA with BERT

What was Marie Curie the first female recipient of? [SEP] One of the most famous people born in Warsaw was Marie ...
Takeaways

‣ Pre-trained models and BERT are very powerful for a range of NLP tasks

‣ These models have enabled big advances in NLI and QA specifically

‣ Next time: final project introduction. Idea of dataset artifacts ("bad" patterns memorized by the model that hurt its ability to generalize) and what we can do about them