Neural Networks for Text

Instructor: Alan Ritter

Slides Adapted from Graham Neubig and Greg Durrett

An Example Prediction Problem: Sentence Classification

I hate this movie

very good
good
neutral
bad
very bad

I love this movie

very good
good
neutral
bad
very bad

A First Try: Bag of Words (BOW)

What do Our Vectors Represent?

- Each word has its own 5 elements corresponding to [very good, good, neutral, bad, very bad]
- “hate” will have a high value for “very bad”, etc.

Build It, Break It

I don’t love this movie

very good
good
neutral
bad
very bad

There’s nothing I don’t love about this movie

very good
good
neutral
bad
very bad

Combination Features

- Does it contain “don’t” and “love”?
- Does it contain “don’t”, “i”, “love”, and “nothing”?

Basic Idea of Neural Networks (for NLP Prediction Tasks)

1.10.0 ▼

Search Docs

Notes [+]

Language Bindings [+]

Python API [-]

torch
torch.nn
torch.nn.functional
torch.Tensor
Tensor Attributes
Tensor Views
torch.autograd
torch.cuda

EMBEDDING

Embedding

CLASS `torch.nn.Embedding(num_embeddings, embedding_dim, padding_idx=None, max_norm=None, norm_type=2.0, scale_grad_by_freq=False, sparse=False, _weight=None, device=None, dtype=None)` [SOURCE]

A simple lookup table that stores embeddings of a fixed dictionary and size.

This module is often used to store word embeddings and retrieve them using indices. The input to the module is a list of indices, and the output is the corresponding word embeddings.

Parameters

- **num_embeddings** (*int*) – size of the dictionary of embeddings
- **embedding_dim** (*int*) – the size of each embedding vector
- **padding_idx** (*int, optional*) – If specified, the entries at `padding_idx` do not contribute to the

1.10.0 ▼

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Parameters

- **num_em**
- **embeddi**
- **padding_**

```
>>> # an Embedding module containing 10 tensors of size 3
>>> embedding = nn.Embedding(10, 3)
>>> # a batch of 2 samples of 4 indices each
>>> input = torch.LongTensor([[1,2,4,5],[4,3,2,9]])
>>> embedding(input)
tensor([[[-0.0251, -1.6902,  0.7172],
         [-0.6431,  0.0748,  0.6969],
         [ 1.4970,  1.3448, -0.9685],
         [-0.3677, -2.7265, -0.1685]],

        [[ 1.4970,  1.3448, -0.9685],
         [ 0.4362, -0.4004,  0.9400],
         [-0.6431,  0.0748,  0.6969],
         [ 0.9124, -2.3616,  1.1151]]])
```

Continuous Bag of Words (CBOW)

What do Our Vectors Represent?

- Each vector has “features” (e.g. is this an animate object? is this a positive word, etc.)
- We sum these features, then use these to make predictions
- Still no combination features: only the expressive power of a linear model, but dimension reduced

Deep CBOW

What do Our Vectors Represent?

- Now things are more interesting!
- We can learn feature combinations (a node in the second layer might be “feature 1 AND feature 5 are active”)
- e.g. capture things such as “not” AND “hate”

Sentiment Analysis

Deep Averaging Networks: feedforward neural network on average of word embeddings from input

Iyyer et al. (2015)

Sentiment Analysis

Model	RT	SST fine	SST bin	IMDB	Time (s)
DAN-ROOT	—	46.9	85.7	—	**31**
DAN-RAND	77.3	45.4	83.2	88.8	136
DAN	80.3	47.7	86.3	89.4	136
NBOW-RAND	76.2	42.3	81.4	88.9	91
NBOW	79.0	43.6	83.6	89.0	91
BiNB	—	41.9	83.1	—	—
NBSVM-bi	79.4	—	—	91.2	—
RecNN*	77.7	43.2	82.4	—	—
RecNTN*	—	45.7	85.4	—	—
DRecNN	—	49.8	86.6	—	431
TreeLSTM	—	**50.6**	86.9	—	—
DCNN*	—	48.5	86.9	89.4	—
PVEC*	—	48.7	87.8	**92.6**	—
CNN-MC	**81.1**	47.4	**88.1**	—	2,452
WRRBM*	—	—	—	89.2	—

Iyyer et al. (2015)

Bag-of-words

Wang and Manning (2012)

Tree RNNs / CNNS / LSTMS

Kim (2014)

Bag of n-grams

Time Delay Neural Networks

(Waibel et al. 1989)

<u>These are soft 2-grams!</u>

Convolutional Networks

(LeCun et al. 1997)

Parameter extraction performs a 2D sweep, not 1D

$1_{\times 1}$	$1_{\times 0}$	$1_{\times 1}$	0	0
$0_{\times 0}$	$1_{\times 1}$	$1_{\times 0}$	1	0
$0_{\times 1}$	$0_{\times 0}$	$1_{\times 1}$	1	1
0	0	1	1	0
0	1	1	0	0

Image

4		

Convolved Feature

$1_{\times 1}$	$1_{\times 0}$	$1_{\times 1}$	0	0
$0_{\times 0}$	$1_{\times 1}$	$1_{\times 0}$	1	0
$0_{\times 1}$	$0_{\times 0}$	$1_{\times 1}$	1	1
0	0	1	1	0
0	1	1	0	0

Image

4		

Convolved Feature

CNNs for Text

(Collobert and Weston 2011)

- 1D convolution ≈ Time Delay Neural Network
  - But often uses terminology/functions borrowed from image processing
- Two main paradigms:
  - **Context window modeling:** For tagging, etc. get the surrounding context before tagging
  - **Sentence modeling:** Do convolution to extract n-grams, pooling to combine over whole sentence

CNNs for Sentence Modeling

(Collobert and Weston 2011)

Sentence Classification

Model	MR	SST-1	SST-2	Subj	TREC	CR	MPQA
CNN-multichannel	81.1	47.4	**88.1**	93.2	92.2	**85.0**	89.4
NBSVM (Wang and Manning, 2012)	79.4	–	–	93.2	–	81.8	86.3

Kim (2014)

Sentence Classification

movie review
sentiment

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question type classification

- Also effective at document-level text classification

Kim (2014)

RNN Basics

RNN Motivation

- Feedforward NNs can't handle variable length input: each position in the feature vector has fixed semantics

the movie was great

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- These don't look related (*great* is in two different orthogonal subspaces)

- Instead, we need to:

1) Process each word in a uniform way

2) …while still exploiting the context that that token occurs in

RNN Abstraction

- Cell that takes some input **x**, has some hidden state **h**, and updates that hidden state and produces output **y** (all vector-valued)

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Elman Networks

Elman (1990)

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$$\mathbf{h}_t = \tanh(W\mathbf{x}_t + V\mathbf{h}_{t-1} + \mathbf{b}_h)$$

- Updates hidden state based on input and current hidden state

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- Long history! (invented in the late 1980s)

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it was my favorite movie of 2016, though it wasn't without problems -> +

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- "Correct" parameter update is to do a better job of remembering the sentiment of *favorite*

Vanishing Gradient

http://colah.github.io/posts/2015-08-Understanding-LSTMs/

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LSTMs

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LSTMs

- Gradient still diminishes, but in a controlled way and generally by less — usually initialize forget gate = 1 to remember everything to start

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What do RNNs produce?

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- Encoding of the sentence — can pass this a decoder or make a classification decision about the sentence
- Encoding of each word — can pass this to another layer to make a prediction (can also pool these to get a different sentence encoding)
- RNN can be viewed as a transformation of a sequence of vectors into a sequence of context-dependent vectors

Training RNNs

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- Example: sentiment analysis

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- Loss terms filter back through network
- Example: language modeling (predict next word given context)

Applications

What can LSTMs model?

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- Sentiment
  - Encode one sentence, predict
- Language models
  - Move left-to-right, per-token prediction

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  - Encode one sentence, predict
- Language models
  - Move left-to-right, per-token prediction
- Translation
  - Encode sentence + then decode, use token predictions for attention weights (later in the course)

Visualizing LSTMs

Karpathy et al. (2015)

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- Train *character* LSTM language model (predict next character based on history) over two datasets: War and Peace and Linux kernel source code

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- Counter: know when to generate \n

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- Visualize activations of specific cells to see what they track
- Binary switch: tells us if we're in a quote or not

Karpathy et al. (2015)

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```
#ifdef CONFIG_AUDITSYSCALL
static inline int audit_match_class_bits(int class, u32 *mask)
{
  int i;
  if (classes[class]) {
    for (i = 0; i < AUDIT_BITMASK_SIZE; i++)
      if (mask[i] & classes[class][i])
        return 0;
  }
  return 1;
}
```

Karpathy et al. (2015)

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- Stack: activation based on indentation

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- Train *character* LSTM language model (predict next character based on history) over two datasets: War and Peace and Linux kernel source code
- Visualize activations of specific cells to see what they track
- Uninterpretable: probably doing double-duty, or only makes sense in the context of another activation

```
/* Unpack a filter field's string representation from user-space
 * buffer. */
char *audit_unpack_string(void **bufp, size_t *remain, size_t len)
{
  char *str;
  if (!*bufp || (len == 0) || (len > *remain))
    return ERR_PTR(-EINVAL);
  /* Of the currently implemented string fields, PATH_MAX
   * defines the longest valid length.
   */
```

Karpathy et al. (2015)

CNNs vs. LSTMs

n x k

the movie was good

CNNs vs. LSTMs

CNNs vs. LSTMs

O(n) x c

c filters,
m x k each

n x k

CNNs vs. LSTMs

CNNs vs. LSTMs

CNNs vs. LSTMs

- Both LSTMs and convolutional layers transform the input using context
- LSTM: “globally” looks at the entire sentence (but local for many problems)
- CNN: local depending on filter width + number of layers

Text-to-Text Generation

Encoder-Decoder

- Encode a sequence into a fixed-sized vector

Sutskever et al. (2014)

Encoder-Decoder

- Encode a sequence into a fixed-sized vector

- Now use that vector to produce a series of tokens as output from a separate LSTM *decoder*

Sutskever et al. (2014)

Model

- Generate next word conditioned on previous word as well as hidden state

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- W size is |vocab| x |hidden state|, softmax over entire vocabulary

$$P(y_i|\mathbf{x}, y_1, \ldots, y_{i-1}) = \text{softmax}(W\bar{h})$$

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$$P(y_i|\mathbf{x}, y_1, \ldots, y_{i-1}) = \text{softmax}(W\bar{h})$$

$$P(\mathbf{y}|\mathbf{x}) = \prod_{i=1}^{n} P(y_i|\mathbf{x}, y_1, \ldots, y_{i-1})$$

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Decoder has separate parameters from encoder, so this can learn to be a language model (produce a plausible next word given current one)

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- Decoder is advanced one state at a time until [STOP] is reached

Implementing seq2seq Models

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- Encoder: consumes sequence of tokens, produces a vector. Analogous to encoders for classification/tagging tasks

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- Encoder: consumes sequence of tokens, produces a vector. Analogous to encoders for classification/tagging tasks
- Decoder: separate module, single cell. Takes two inputs: hidden state (vector *h* or tuple (*h*, *c*)) and previous token. Outputs token + new state

Training

- Objective: maximize $\sum_{(\mathbf{x},\mathbf{y})} \sum_{i=1}^{n} \log P(y_i^* | \mathbf{x}, y_1^*, \ldots, y_{i-1}^*)$
- One loss term for each target-sentence word, feed the correct word regardless of model's prediction

Attention

Problems with Seq2seq Models

- Encoder-decoder models like to repeat themselves:

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Un garçon joue dans la neige → A boy plays in the snow **boy plays boy plays**

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- Need some notion of input coverage or what input words we've translated

Problems with Seq2seq Models

- Unknown words:

en: The *ecotax* portico in *Pont-de-Buis* , . . . [truncated] . . . , was taken down on Thursday morning

fr: Le *portique* *écotaxe* de *Pont-de-Buis* , . . . [truncated] . . . , a été *démonté* jeudi matin

nn: Le `unk` de `unk` à `unk` , . . . [truncated] . . . , a été pris le jeudi matin

- No matter how much data you have, you'll need some mechanism to copy a word like Pont-de-Buis from the source to target

Problems with Seq2seq Models

- Bad at long sentences: 1) a fixed-size representation doesn't scale; 2) LSTMs still have a hard time remembering for really long periods of time

RNNsearch: introduces attention mechanism to give "variable-sized" representation

Bahdanau et al. (2014)

Aligned Inputs

- Suppose we knew the source and target would be word-by-word translated

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the movie was great

le film était bon

Aligned Inputs

- Suppose we knew the source and target would be word-by-word translated
- Can look at the corresponding input word when translating — this could scale!

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- How can we achieve this without hardcoding it?

Attention

Attention

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Attention

...
the
movie
was
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the
movie
was
great
the
movie
was
great
<s>
le

Attention

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Attention

- At each decoder state, compute a distribution over source inputs based on current decoder state

Attention

- At each decoder state, compute a distribution over source inputs based on current decoder state
- Use that in output layer

Attention

- For each decoder state, compute weighted sum of input states

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Attention

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$$e_{ij} = f(\bar{h}_i, h_j)$$

- Unnormalized scalar weight

Attention

- For each decoder state, compute weighted sum of input states

$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{j'} \exp(e_{ij'})}$$

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Attention

- For each decoder state, compute weighted sum of input states

$$c_i = \sum_j \alpha_{ij} h_j$$

$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{j'} \exp(e_{ij'})}$$

$$e_{ij} = f(\bar{h}_i, h_j)$$

- Weighted sum of input hidden states (vector)

- Unnormalized scalar weight

Attention

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Attention

- For each decoder state, compute weighted sum of input states

$$P(y_i|\mathbf{x}, y_1, \ldots, y_{i-1}) = \mathrm{softmax}(W[c_i; \bar{h}_i])$$

$$c_i = \sum_j \alpha_{ij} h_j$$

- Weighted sum of input hidden states (vector)

$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{j'} \exp(e_{ij'})}$$

$$e_{ij} = f(\bar{h}_i, h_j)$$

- Unnormalized scalar weight

Attention

- For each decoder state, compute weighted sum of input states

- No attn: $P(y_i|\mathbf{x}, y_1, \ldots, y_{i-1}) = \text{softmax}(W\bar{h}_i)$

$$P(y_i|\mathbf{x}, y_1, \ldots, y_{i-1}) = \text{softmax}(W[c_i; \bar{h}_i])$$

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Luong et al. (2015)

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$$e_{ij} = f(\bar{h}_i, h_j)$$

$$f(\bar{h}_i, h_j) = \tanh(W[\bar{h}_i, h_j])$$

- Bahdanau+ (2014): additive

Luong et al. (2015)

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Luong et al. (2015)

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- Luong+ (2015): bilinear

Luong et al. (2015)

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$$f(\bar{h}_i, h_j) = \bar{h}_i^\top W h_j$$

- Luong+ (2015): bilinear

- Note that this all uses outputs of hidden layers

Luong et al. (2015)

What can attention do?

Luong et al. (2015)

What can attention do?

- Learning to copy — how might this work?

Luong et al. (2015)

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Luong et al. (2015)

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- Learning to copy — how might this work?

- LSTM can learn to count with the right weight matrix

Luong et al. (2015)

What can attention do?

- Learning to copy — how might this work?

- LSTM can learn to count with the right weight matrix

- This is effectively position-based addressing

Luong et al. (2015)

Attention

The
agreement
on
the
European
Economic
Area
was
signed
in
August
1992
.
<end>
L'
accord
sur
la
zone
économique
européenne
a
été
signé
en
août
1992
.
<end>

Attention

- Encoder hidden states capture contextual source word identity

Attention

- Encoder hidden states capture contextual source word identity
- Decoder hidden states are now mostly responsible for selecting what to attend to

Attention

- Encoder hidden states capture contextual source word identity
- Decoder hidden states are now mostly responsible for selecting what to attend to
- Doesn't take a complex hidden state to walk monotonically through a sentence and spit out word-by-word translations

Transformers for MT

Self-Attention

- Each word forms a “query” which then computes attention over each word

Vaswani et al. (2017)

Self-Attention

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Vaswani et al. (2017)

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$$\alpha_{i,j} = \mathrm{softmax}(x_i^\top x_j)$$ scalar

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- Multiple "heads" analogous to different convolutional filters. Use parameters W_k and V_k to get different attention values + transform vectors

Vaswani et al. (2017)

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Vaswani et al. (2017)

Self-Attention

- Each word forms a "query" which then computes attention over each word

$$\alpha_{i,j} = \mathrm{softmax}(x_i^\top x_j) \quad \text{scalar}$$

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- Multiple "heads" analogous to different convolutional filters. Use parameters W_k and V_k to get different attention values + transform vectors

$$\alpha_{k,i,j} = \mathrm{softmax}(x_i^\top W_k x_j) \qquad x'_{k,i} = \sum_{j=1}^{n} \alpha_{k,i,j} V_k x_j$$

Vaswani et al. (2017)

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Vaswani et al. (2017)

Transformers

- Augment word embedding with position embeddings, each dim is a sine/cosine wave of a different frequency. Closer points = higher dot products
- Works essentially as well as just encoding position as a one-hot vector

Vaswani et al. (2017)

Transformers

- Encoder and decoder are both transformers
- Decoder consumes the previous generated token (and attends to input), but has *no recurrent state*

Vaswani et al. (2017)

Transformers

Model	BLEU	
	EN-DE	EN-FR
ByteNet [18]	23.75	
Deep-Att + PosUnk [39]		39.2
GNMT + RL [38]	24.6	39.92
ConvS2S [9]	25.16	40.46
MoE [32]	26.03	40.56
Deep-Att + PosUnk Ensemble [39]		40.4
GNMT + RL Ensemble [38]	26.30	41.16
ConvS2S Ensemble [9]	26.36	**41.29**
Transformer (base model)	27.3	38.1
Transformer (big)	**28.4**	**41.8**

- Big = 6 layers, 1000 dim for each token, 16 heads, base = 6 layers + other params halved

Vaswani et al. (2017)

Visualization

Vaswani et al. (2017)

Visualization

Vaswani et al. (2017)

Transformer Implementations

https://nlp.seas.harvard.edu/2018/04/03/attention.html

harvardnlp

Members PI Code Publications

The Annotated Transformer

Apr 3, 2018

```
from IPython.display import Image
Image(filename='images/aiayn.png')
```

Attention Is All You Need

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Transformer Implementations

https://github.com/pytorch/fairseq

README.md

FAIRSEQ

license MIT | release v0.10.2 | build passing | docs passing

Fairseq(-py) is a sequence modeling toolkit that allows researchers and developers to train custom models for translation, summarization, language modeling and other text generation tasks.

We provide reference implementations of various sequence modeling papers:

▶ List of implemented papers

What's New:

- March 2021 Added full parameter and optimizer state sharding + CPU offloading
- February 2021 Added LASER training code
- December 2020: Added Adaptive Attention Span code
- December 2020: GottBERT model and code released
- November 2020: Adopted the Hydra configuration framework

Pretraining / ELMo

Recall: Context-dependent Embeddings

- How to handle different word senses? One vector for *balls*

- Train a neural language model to predict the next word given previous words in the sentence, use its internal representations as word vectors

Peters et al. (2018)

ELMo

- CNN over each word => RNN

Representation of *visited* (plus vectors from backwards LM)

4096-dim LSTMs w/ 512-dim projections

2048 CNN filters projected down to 512-dim

Peters et al. (2018)

How to apply ELMo?

- Take those embeddings and feed them into whatever architecture you want to use for your task
- *Frozen* embeddings: update the weights of your network but keep ELMo's parameters frozen
- *Fine-tuning*: backpropagate all the way into ELMo when training your model

Peters, Ruder, Smith (2019)

Results: Frozen ELMo

Task	Previous SOTA		Our baseline	ELMo + baseline	Increase (absolute/ relative)
SQuAD	Liu et al. (2017)	84.4	81.1	85.8	4.7 / 24.9%
SNLI	Chen et al. (2017)	88.6	88.0	88.7 ± 0.17	0.7 / 5.8%
SRL	He et al. (2017)	81.7	81.4	84.6	3.2 / 17.2%
Coref	Lee et al. (2017)	67.2	67.2	70.4	3.2 / 9.8%
NER	Peters et al. (2017)	91.93 ± 0.19	90.15	92.22 ± 0.10	2.06 / 21%
SST-5	McCann et al. (2017)	53.7	51.4	54.7 ± 0.5	3.3 / 6.8%

- Massive improvements across 5 benchmark datasets: question answering, natural language inference, semantic role labeling (discussed later in the course), coreference resolution, named entity recognition, and sentiment analysis

How to apply ELMo?

Pretraining	Adaptation	NER CoNLL 2003	SA SST-2	Nat. lang. inference MNLI	SICK-E	Semantic textual similarity SICK-R	MRPC	STS-B
Skip-thoughts	❄️	-	81.8	62.9	-	86.6	75.8	71.8
ELMo	❄️	91.7	**91.8**	**79.6**	**86.3**	**86.1**	**76.0**	**75.9**
	🔥	**91.9**	91.2	76.4	83.3	83.3	74.7	75.5
	Δ=🔥-❄️	0.2	-0.6	-3.2	-3.3	-2.8	-1.3	-0.4

- How does frozen (❄️) vs. fine-tuned (🔥) compare?
- Recommendations:

Conditions			Guidelines
Pretrain	Adapt.	Task	
Any	❄️	Any	Add many task parameters
Any	🔥	Any	Add minimal task parameters ⚠️ Hyper-parameters
Any	Any	Seq. / clas.	❄️ and 🔥 have similar performance
ELMo	Any	Sent. pair	use ❄️
BERT	Any	Sent. pair	use 🔥

Peters, Ruder, Smith (2019)

Why is language modeling a good objective?

- "Impossible" problem but bigger models seem to do better and better at distributional modeling (no upper limit yet)
- Successfully predicting next words requires modeling lots of different effects in text

Context: My wife refused to allow me to come to Hong Kong when the plague was at its height and –" "Your wife, Johanne? You are married at last ?" Johanne grinned. "Well, when a man gets to my age, he starts to need a few home comforts.
Target sentence: After my dear mother passed away ten years ago now, I became _____.
Target word: lonely

- LAMBADA dataset (Papernot et al., 2016): explicitly targets world knowledge and very challenging LM examples
- Coreference, Winograd schema, and much more

Why is language modeling a good objective?

Zhang and Bowman (2018)

Why did this take time to catch on?

- Earlier version of ELMo by the same authors in 2017, but it was only evaluated on tagging tasks, gains were 1% or less
- Required: training on lots of data, having the right architecture, significant hyperparameter tuning

Probing ELMo

- From each layer of the ELMo model, attempt to predict something: POS tags, word senses, etc.
- Higher accuracy => ELMo is capturing that thing more nicely

Model	F_1
WordNet 1st Sense Baseline	65.9
Raganato et al. (2017a)	69.9
Iacobacci et al. (2016)	**70.1**
CoVe, First Layer	59.4
CoVe, Second Layer	*64.7*
biLM, First layer	67.4
biLM, Second layer	*69.0*

Table 5: All-words fine grained WSD F_1. For CoVe and the biLM, we report scores for both the first and second layer biLSTMs.

Model	Acc.
Collobert et al. (2011)	97.3
Ma and Hovy (2016)	97.6
Ling et al. (2015)	**97.8**
CoVe, First Layer	*93.3*
CoVe, Second Layer	92.8
biLM, First Layer	*97.3*
biLM, Second Layer	96.8

Table 6: Test set POS tagging accuracies for PTB. For CoVe and the biLM, we report scores for both the first and second layer biLSTMs.

BERT

Recall: Self-Attention

- Each word forms a "query" which then computes attention over each word

$$\alpha_{i,j} = \mathrm{softmax}(x_i^\top x_j)$$ scalar

$$x'_i = \sum_{j=1}^{n} \alpha_{i,j} x_j$$ vector = sum of scalar * vector

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Recall: Transformers

- Augment word embedding with position embeddings, each dim is a sine/cosine wave of a different frequency. Closer points = higher dot products
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Vaswani et al. (2017)

BERT

- AI2 made ELMo in spring 2018, GPT was released in summer 2018, BERT came out October 2018
- Three major changes compared to ELMo:
  - Transformers instead of LSTMs (transformers in GPT as well)
  - Bidirectional <=> Masked LM objective instead of standard LM
  - Fine-tune instead of freeze at test time

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

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

Devlin et al. (2019)

BERT

- How to learn a "deeply bidirectional" model? What happens if we just replace an LSTM with a transformer?

ELMo (Language Modeling)

BERT

- Transformer LMs have to be "one-sided" (only attend to previous tokens), not what we want

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, predict 15% of the tokens
  - For 80% (of the 15%), replace the input token with [MASK]
  - For 10%, replace w/random
  - For 10%, keep same

John	*visited*	[MASK]	*yesterday*
John	*visited*	**of**	*yesterday*
John	*visited*	Madagascar	*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

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

Devlin et al. (2019)

What can BERT do?

(b) Single Sentence Classification Tasks: SST-2, CoLA

(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG

(d) Single Sentence Tagging Tasks: CoNLL-2003 NER

- CLS token is used to provide classification decisions
- 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?

(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG

- 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)
  - Not an autoregressive model, can do weird things like stick a [MASK] at the end of a string, fill in the mask, and repeat
- 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

(b) Single Sentence Classification Tasks: SST-2, CoLA

- 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

Fine-tuning BERT

Pretraining	Adaptation	NER CoNLL 2003	SA SST-2	Nat. lang. inference MNLI	SICK-E	Semantic textual similarity SICK-R	MRPC	STS-B
Skip-thoughts	❄️	-	81.8	62.9	-	86.6	75.8	71.8
ELMo	❄️	91.7	**91.8**	**79.6**	**86.3**	**86.1**	**76.0**	**75.9**
	🔥	**91.9**	91.2	76.4	83.3	83.3	74.7	75.5
	Δ=🔥-❄️	0.2	-0.6	-3.2	-3.3	-2.8	-1.3	-0.4
BERT-base	❄️	92.2	93.0	**84.6**	84.8	86.4	78.1	82.9
	🔥	**92.4**	**93.5**	**84.6**	**85.8**	**88.7**	**84.8**	**87.1**
	Δ=🔥-❄️	0.2	0.5	0.0	1.0	2.3	6.7	4.2

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

Peters, Ruder, Smith (2019)

Evaluation: GLUE

Corpus	|Train|	|Test|	Task	Metrics	Domain
			Single-Sentence Tasks		
CoLA	8.5k	**1k**	acceptability	Matthews corr.	misc.
SST-2	67k	1.8k	sentiment	acc.	movie reviews
			Similarity and Paraphrase Tasks		
MRPC	3.7k	1.7k	paraphrase	acc./F1	news
STS-B	7k	1.4k	sentence similarity	Pearson/Spearman corr.	misc.
QQP	364k	**391k**	paraphrase	acc./F1	social QA questions
			Inference Tasks		
MNLI	393k	**20k**	NLI	matched acc./mismatched acc.	misc.
QNLI	105k	5.4k	QA/NLI	acc.	Wikipedia
RTE	2.5k	3k	NLI	acc.	news, Wikipedia
WNLI	634	**146**	coreference/NLI	acc.	fiction books

Wang et al. (2019)

Results

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	79.9	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	88.1	91.3	45.4	80.0	82.3	56.0	75.2
$\text{BERT}_{\text{BASE}}$	84.6/83.4	71.2	90.1	93.5	52.1	85.8	88.9	66.4	79.6
$\text{BERT}_{\text{LARGE}}$	**86.7/85.9**	**72.1**	**91.1**	**94.9**	**60.5**	**86.5**	**89.3**	**70.1**	**81.9**

- 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

Model	data	bsz	steps	SQuAD (v1.1/2.0)	MNLI-m	SST-2
RoBERTa						
with BOOKS + WIKI	16GB	8K	100K	93.6/87.3	89.0	95.3
+ additional data (§3.2)	160GB	8K	100K	94.0/87.7	89.3	95.6
+ pretrain longer	160GB	8K	300K	94.4/88.7	90.0	96.1
+ pretrain even longer	160GB	8K	500K	**94.6/89.4**	**90.2**	**96.4**
$\text{BERT}_{\text{LARGE}}$						
with BOOKS + WIKI	13GB	256	1M	90.9/81.8	86.6	93.7

- New training + more data = better performance

Liu et al. (2019)

v4.5.0 ▼

transformers

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Transformers

State-of-the-art Natural Language Processing for Pytorch and TensorFlow 2.0.

🤗 Transformers (formerly known as *pytorch-transformers* and *pytorch-pretrained-bert*) provides general-purpose architectures (BERT, GPT-2, RoBERTa, XLM, DistilBert, XLNet…) for Natural Language Understanding (NLU) and Natural Language Generation (NLG) with over 32+ pretrained models in 100+ languages and deep interoperability between TensorFlow 2.0 and PyTorch.

This is the documentation of our repository transformers.

GPT/GPT2

OpenAI GPT/GPT2

- "ELMo with transformers" (works better than ELMo)
- Train a single unidirectional transformer LM on long contexts
- GPT2: trained on 40GB of text collected from upvoted links from reddit
- 1.5B parameters — by far the largest of these models trained as of March 2019

Parameters	Layers	d_{model}
117M	12	768
345M	24	1024
762M	36	1280
1542M	48	1600

- Because it's a language model, we can **generate** from it

Radford et al. (2019)

OpenAI GPT2

SYSTEM PROMPT (HUMAN-WRITTEN)	*Miley Cyrus was caught shoplifting from Abercrombie and Fitch on Hollywood Boulevard today.*
MODEL COMPLETION (MACHINE-WRITTEN, SECOND TRY)	The 19-year-old singer was caught on camera being escorted out of the store by security guards. The singer was wearing a black hoodie with the label 'Blurred Lines' on the front and 'Fashion Police' on the back. Scroll down for video Shoplifting: Miley Cyrus was caught shoplifting from Abercrombie and Fitch on Hollywood Boulevard today (pictured) The singer was wearing a black hoodie with the label 'Blurred Lines' on the front and 'Fashion Police' on the back The singer was also wearing a pair of black-rimmed glasses, a black jacket, black jeans and black sandals. She was carrying a pair of black and white striped gloves and a small black bag.

slide credit: OpenAI

Open Questions

1) How novel is the stuff being generated? (Is it just doing nearest neighbors on a large corpus?)

2) How do we understand and distill what is learned in this model?

3) How do we harness these priors for conditional generation tasks (summarization, generate a report of a basketball game, etc.)

4) Is this technology dangerous? (OpenAI has only released 774M param model, not 1.5B yet)

Grover

- Sample from a large language model conditioned on a domain, date, authors, and headline
- Humans rank Grover-generated propaganda as more realistic than real "fake news"
- Fine-tuned Grover can detect Grover propaganda easily — authors argue for releasing it for this reason
- NOTE: Not a GAN, discriminator trained separately from the generator

Discriminator size		Unpaired Accuracy, Generator size 1.5B	355M	124M	Paired Accuracy, Generator size 1.5B	355M	124M
	Chance		50.0			50.0	
1.5B	GROVER-Mega	**92.0**	**98.5**	**99.8**	**97.4**	**100.0**	**100.0**
355M	GROVER-Large	**80.8**	**91.2**	**98.4**	**89.0**	**96.9**	**100.0**
	BERT-Large	73.1	75.9	97.5	84.1	91.5	99.9
	GPT2	70.1	78.0	90.3	78.8	87.0	96.8
124M	GROVER-Base	**70.1**	**80.0**	**89.2**	77.5	88.2	95.7
	BERT-Base	67.2	76.6	84.1	**80.0**	**89.5**	**96.2**
	GPT2	66.2	71.9	83.5	72.5	79.6	89.6
11M	FastText	63.8	65.6	69.7	65.9	69.0	74.4

Zellers et al. (2019)

Pre-Training Cost (with Google/AWS)

- BERT: Base $500, Large $7000
- Grover-MEGA: $25,000
- XLNet (BERT variant): $30,000 — $60,000 (unclear)
- This is for a single pre-training run…developing new pre-training techniques may require many runs
- *Fine-tuning* these models can typically be done with a single GPU (but may take 1-3 days for medium-sized datasets)

https://syncedreview.com/2019/06/27/the-staggering-cost-of-training-sota-ai-models/

Pushing the Limits

- NVIDIA: trained 8.3B parameter GPT model (5.6x the size of GPT-2)
- Arguable these models are still underfit: larger models still get better held-out perplexities

NVIDIA blog (Narasimhan, August 2019)

Google T5

Number of tokens	Repeats	GLUE	CNNDM	SQuAD	SGLUE	EnDe	EnFr	EnRo
★ Full dataset	0	**83.28**	**19.24**	**80.88**	**71.36**	**26.98**	**39.82**	**27.65**
2^{29}	64	**82.87**	**19.19**	**80.97**	**72.03**	**26.83**	**39.74**	**27.63**
2^{27}	256	82.62	**19.20**	79.78	69.97	**27.02**	**39.71**	27.33
2^{25}	1,024	79.55	18.57	76.27	64.76	26.38	39.56	26.80
2^{23}	4,096	76.34	18.33	70.92	59.29	26.37	38.84	25.81

- Colossal Cleaned Common Crawl: 750 GB of text
- We still haven't hit the limit of bigger data being useful

Raffel et al. (October 23, 2019)

((((yoav' ()ل)()ل))) @yoavgo · Jul 17, 2020

GPT-3 update: I got contacted by @gdb who sent me an invite! excited to try it out. thanks Greg!

13 76 334

((((yoav' ()ل)()ل)))
@yoavgo

Replying to @yoavgo

some code stuff, the context sensitivity is very impressive.
(my prompt is up to lst[-1])

Playground

in the python programming language:

Q: take the first item from a list
A: lst[0]
Q: take the last item from a list
A: lst[-1]

Q: verify that the list has at least 4 items
A: len(lst) > 4
Q: verify that the list has 5 items or more
A: len(lst) >= 5
Q: verify that the list has 3 items
A: len(lst) == 3

BART

- Sequence-to-sequence BERT variant: permute/make/delete tokens, then predict full sequence autoregressively
- For downstream tasks: feed document into both encoder + decoder, use decoder hidden state as output
- Good results on dialogue, summarization tasks

Lewis et al. (October 30, 2019)