Lectures on Natural Language Processing

8. Pretrained Language Models

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Review: Conditional Language Models

- Language model (LM) conditioning on $x = (x_1 \dots x_T)$

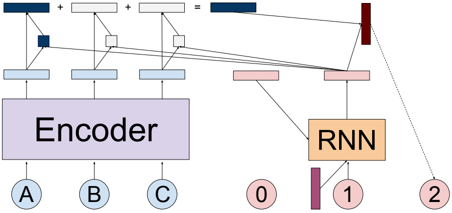
$$p_\theta(y_1 \dots y_{T'}|x) = \prod_{t'=1}^{T'+1} p_\theta(y_{t'}|x, y_{<t'})$$

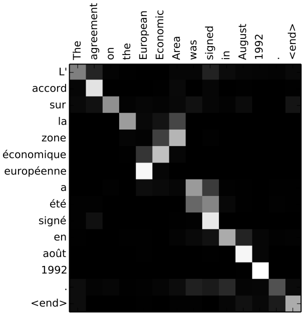
- Learnable modules
  - **Encoder. enc**$_\theta : \mathcal{V}^T \rightarrow \mathbb{R}^{T \times d}$ contextualizes source token embeddings of x (e.g., BiLSTM, Transformer encoder)
  - **Decoder. dec**$_\theta : \mathbb{R}^{T \times d} \times \mathcal{V}^{t'-1} \rightarrow \mathbb{R}^V$ computes logits for next word given source encodings and target history via attention to source encodings (e.g., recurrent, Transformer decoder)
- Encoder-decoder/sequence-to-sequence (seq2seq): Train encoder & decoder jointly to optimize a function of

$$p_\theta(y_{t'}|x, y_{<t'}) = \mathrm{softmax}_{y_{t'}}(\mathbf{dec}_\theta(\mathbf{enc}_\theta(x), y_{<t'}))$$

Review: Stepwise Cross-Attention

- Example: RNN decoder with input feeding





- Learns to attend to right source positions, without supervision. Visualization for translating English to French (Bahdanau et al., 2016)
- Transformer decoder (Vaswani et al., 2017): No recurrent or convolutional layers, entirely based on attention with a position-shared feedforward

The Unknown Word Problem

- Target text may contain rare words like
  - Proper names: Lausanne, Cesar, Guilaume, ...
  - Numbers/values: 103, 95, 42, 3.141592, 3.141593, ...
- Decoder needs these in target vocab $\mathcal{V}$ to generate at all!
  - Note target vocab may be distinct from source vocab $\mathcal{V}_{\mathrm{src}}$ in general (e.g., translation)
- Brute-force: Include all word types in $\mathcal{V}$? Not practical
  - By Zipf's Law, most words will have extremely low probabilities
  - Never enough: Guilaumé? 3.141594? Not seen in training data
- Simple/naive approach: Threshold vocab by frequency
  - Keep top-k (e.g., $k = 100000$) most frequent types in $\mathcal{V}$ and replace all other types ("OOV") with special token $\langle \mathrm{unk} \rangle$ in training
  - Problem: Model predicts $\langle \mathrm{unk} \rangle$ at test time (e.g., "$\langle \mathrm{unk} \rangle$ and $\langle \mathrm{unk} \rangle$ have a blue car in $\langle \mathrm{unk} \rangle$").
  - Can be postprocessed, but can we do better?

Copy Mechanism

- Idea: Unknown target words likely to be **copied** from source sentence somewhere
- Example: translation (Gulcehre et al., 2016)

French: Guillaume et Cesar ont une voiture bleue a Lausanne.

Copy Copy Copy

English: Guillaume and Cesar have a blue car in Lausanne.

- Example: data-to-text generation (Wiseman et al., 2017)

TEAM	WIN	LOSS	PTS
Heat	11	12	103
Hawk	7	15	95

The Atlanta Hawks defeated the Miami Heat, 103-95, at Philips Arena on Wednesday...

- Approaches: Data pre-processing, attention-based
- Non-copy approaches
  - Subword tokenization (e.g., BPE): No "unknown" words, but sequences longer and may still benefit from copy mechanism
  - Scaling softmax to accommodate bigger $\mathcal{V}$ (e.g., hierarchical softmax, sampling-based methods)

Data Pre-Processing Approach

Addressing the Rare Word Problem in Neural Machine Translation (Luong et al., 2015)

- Original data: Apply an unsupervised aligner to get alignments
  - The ecotax portico in Pont-de-Buis
  - Le portique écotaxe de Pont-de-Buis
- Conventional pre-processing
  - The $\langle \text{unk} \rangle$ portico in $\langle \text{unk} \rangle$
  - Le $\langle \text{unk} \rangle$ $\langle \text{unk} \rangle$ de $\langle \text{unk} \rangle$
- Copyable Model pre-processing
  - The $\langle \text{unk} \rangle_1$ portico in $\langle \text{unk} \rangle_2$
  - Le $\langle \text{unk} \rangle_\varnothing$ $\langle \text{unk} \rangle_1$ de $\langle \text{unk} \rangle_2$

  Can't align to known words in the source sentence
- Positional Unknown Model pre-processing
  - The $\langle \text{unk} \rangle$ portico in $\langle \text{unk} \rangle$
  - Le $\langle \text{unk} \rangle_1$ $\langle \text{unk} \rangle_{-1}$ de $\langle \text{unk} \rangle_0$

  i-th target token $\langle \text{unk} \rangle_k$ aligned to $(i+k)$-th source token

Attention-Based Approaches

- Data pre-processing approach: Simple and effective (1-2 points improvement over strong NMT baselines)
- Limitations
  - Requires an external word aligner in the pipeline
  - Fixed-size window ($\langle \mathrm{unk} \rangle_{-7} \ldots \langle \mathrm{unk} \rangle_{7}$), can't handle copy from far away in source sequence
- Idea: Make the model learn *when* and *what* to copy without supervision, by attention
- Pointer networks (Vinyals et al., 2015): Only what to copy
- CopyNet (Gu et al., 2016): Both when and what to copy, applied on summarization
- Concurrent work by Gulcehre et al., 2016: Different modeling details, applied on both translation and summarization
- When to copy: Modeled by a "switching network" (learned jointly)

Conditional LM with a Copy Mechanism

- Single training example now consists of

$$x = (x_1 \dots x_T) \qquad y = (y_1 \dots y_{T'}) \qquad z = (z_1 \dots z_{T'})$$

  where $z_{t'} \in \{0, 1\}$ is 1 iff $y_{t'}$ is copied from x
- Assume for now that z is observed
  - E.g., set $z_{t'} = 1$ if $y_{t'}$ appears in x somewhere.
- Conditional LM with a copy mechanism

$$p_\theta(y, z|x) = \prod_{t'=1}^{T'+1} p_\theta(y_{t'}, z_{t'}|x, y_{<t'}, z_{<t'})$$

- Further decomposition by the chain rule

$$p_\theta(y_t, z_{t'}|x, y_{<t'}, z_{<t'}) = \underbrace{p_\theta(z_{t'}|x, y_{<t'}, z_{<t'})}_{\text{“switching network”}} \times p_\theta(y_{t'}|x, y_{<t'}, z_{\leq t'})$$

Parameterization

- Switching network

$$p_\theta(1|x, y_{<t'}, z_{<t'}) = \sigma\left(f_\theta(x, y_{<t'}, z_{<t'})\right)$$
$$p_\theta(0|x, y_{<t'}, z_{<t'}) = 1 - \sigma\left(f_\theta(x, y_{<t'}, z_{<t'})\right)$$

$f_\theta(x, y_{<t'}, z_{<t'}) \in \mathbb{R}$ computed from current state

- If $z_{t'} = 1$, "dynamic LM" with vocab $\{w \in x\}$

$$p_\theta(y_{t'} = w|x, y_{<t'}, z_{\leq t'}) = \sum_{t=1:\ x_t = w}^{T} \underbrace{A^\theta_{t,t'}}_{\text{attention from } t'\text{-th target to } t\text{-th source}}$$

- If $z_{t'} = 0$, vocab $\mathcal{V}$

$$p_\theta(y_{t'} = w|x, y_{<t'}, z_{\leq t'}) = \underbrace{p_\theta(y_{t'} = w|x, y_{<t'})}_{\text{usual next word probability}}$$

Supervised vs Unsupervised Loss

- Supervised training: Maximize $\log p_\theta(y, z|x)$ in training data
  - Inference: At each step t', consider all

$$p_\theta(w, 1|x, y_{<t'}, z_{<t'}) \qquad \forall w \in x$$
$$p_\theta(w, 0|x, y_{<t'}, z_{<t'}) \qquad \forall w \in \mathcal{V}$$

- Unsupervised training: Maximize $\log p_\theta(y|x)$ in training data

$$\begin{aligned} p_\theta(y_{t'}|x, y_{<t'}) &= \sum_{z \in \{0,1\}} p_\theta(y_{t'}, z|x, y_{<t'}) \\ &= \sigma\left(f_\theta(x, y_{<t'}, z_{<t'})\right) \left(\sum_{t=1:\ x_t = y_{t'}}^{T} A^\theta_{t,t'} \right) + \\ &\quad (1 - \sigma\left(f_\theta(x, y_{<t'}, z_{<t'})\right)) p_\theta(y_{t'} = w|x, y_{<t'}) \end{aligned}$$

Switching network f_θ trained without supervision, inference remains the same

Illustration

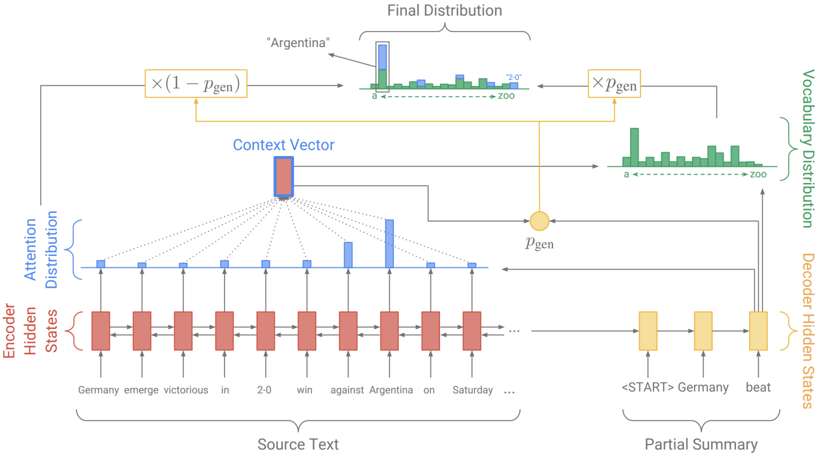
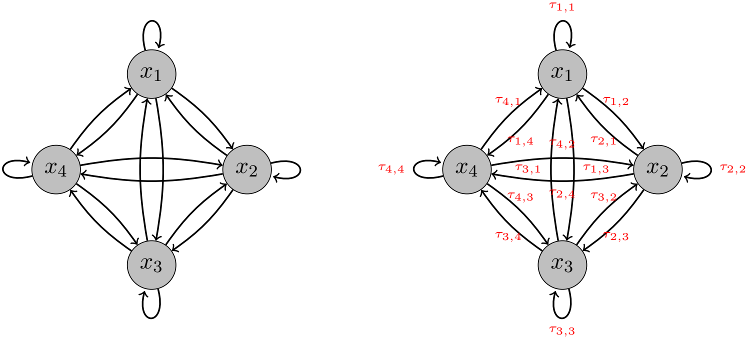


Image credit: See et al. (2017)

Self-Attention as a Fully Connected Directed Graph

- Self-attention viewed as a fully connected directed graph
- Natural generalization: Incorporate edge types in the model



- Example edge types: Relative positions, relation between table cells (e.g., cell-column, cell-row)

Relation-Aware Self-Attention (Shaw et al., 2018)

- Extra parameters (relation bias) in the multi-head attention module
  - $b^K_{\tau} \in \mathbb{R}^{d/H}$ for every relation type τ
  - $b^V_{\tau} \in \mathbb{R}^{d/H}$ for every relation type τ
- Self-attention weight from $x_{t'}$ to x_t with relation $\tau_{t',t}$ under head h

$$l^h_{t',t} = \frac{q^h_{t'} \cdot (k^h_t + b^K_{\tau_{t',t}})}{d/H}$$

Probabilities: $(\alpha^h_{t',1} \ldots \alpha^h_{t',T}) = \mathrm{softmax}(l^h_{t',1} \ldots l^h_{t',T})$

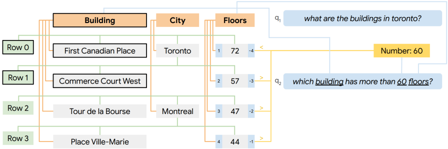
- Answer value

$$a^h_{t'} = \sum_{t=1}^{T} \alpha^h_{t,t'} \left(v^h_t + b^V_{\tau_{t',t}} \right)$$

- Relation bias is shared across all heads. Efficient batch computation still possible

Applications of Relation-Aware Self-Attention

- Relative position encoding (Shaw et al., 2018)
  - Original Transformer: Add constant (or learnable) absolute position embeddings at input vectors
  - Now: For some k (e.g., $k = 8$), use $2k + 1$ relation types representing local distances
  - Tokens beyond window clipped to k or $-k$
  - Can entirely replace additive position embeddings, even modest improvement
  - Value bias b^V_τ found unnecessary given key bias b^T_τ (for MT)
- Relation between tokens in structured input (Müller et al., 2019)
  - Task: question answering from a table (represented as a flat sequence of words)
  - Idea: Distinguish relations between table cells, row header, column header, question, etc.



Natural Language Understanding (NLU) Tasks

- Tasks that (1) cannot be solved by just using word-level patterns (must use logic, predicate/argument structure, etc.), (2) require "common sense" outside task-specific supervision
- Tasks not considered NLU
  - Topic classification: Bag-of-words linear classifier works fine
  - Short translation: Mapping self-contained, no need for much external knowledge
- Tasks considered NLU
  - Sentiment analysis: A few instances do require genuine language understanding
  - Natural language inference (NLI): "If Liz likes John, is it the case that Liz loves John?"
  - Question answering: "Why does Queen Elizabeth sign her name Elizabeth R?"
  - Coreference resolution: "The trophy doesn't fit in the suitcase because [it]'s too big."

Natural Language Inference (NLI)

- Can be framed as sentence-pair classification
  - **Input.** (Premise, Hypothesis)
  - **Output.** Entailment (E), contradiction (C), or neutral (N)
- Examples (Bowman et al., 2015)

(A soccer game with multiple males playing., Some men are playing a sport.) $\rightarrow$ E

(A black race car starts up in front of a crowd of people., A man is driving down a lonely road.) $\rightarrow$ C

(An older and younger man smiling., Two men are smiling and laughing at the cats playing on the floor.) $\rightarrow$ N

- MNLI (Williams et al., 2018): 393k training instances, 20k test
  - Annotation by crowdsourcing (relatively easy for humans)
  - Human accuracy: 92
  - CBOW-based classifier accuracy: 56
  - BiLSTM-based classifier accuracy: ≈ 70

Question Answering (QA)

- Can be framed as predicting an answer span in a passage given a passage-question pair
- Early work: SQuAD dataset (Rajpurkar et al., 2016)
- **Input.**
  - Passage: "In meteorology, precipitation is any product of the condensation of atmospheric water vapor that falls under gravity. The main forms of precipitation include drizzle, rain, sleet, snow, graupel and hail ..."
  - Question: "What causes precipitation to fall?"
- **Output.** Span $(17, 18)$, corresponding to "gravity"
- Typical architecture: Joint encoding of passage & question, then softmax over passage positions
- Many challenges in defining QA tasks
  - Unlike MT, difficult to obtain *natural* data. SQuAD asked annotators to create questions answerable by passage
  - Spurious occurrences of answer string (e.g., "three" can appear in irrelevant context)

Example: Natural Questions Dataset (Kwiatkowski et al., 2019)

Example 1
Question: what color was john wilkes booth's hair
Wikipedia Page: John_Wilkes_Booth
Long answer: Some critics called Booth "the handsomest man in America" and a "natural genius", and noted his having an "astonishing memory"; others were mixed in their estimation of his acting. He stood 5 feet 8 inches (1.73 m) tall, had jet-black hair , and was lean and athletic. Noted Civil War reporter George Alfred Townsend described him as a "muscular, perfect man" with "curling hair, like a Corinthian capital".

Short answer: jet-black

Example 2
Question: can you make and receive calls in airplane mode
Wikipedia Page: Airplane_mode
Long answer: Airplane mode, aeroplane mode, flight mode, offline mode, or standalone mode is a setting available on many smartphones, portable computers, and other electronic devices that, when activated, suspends radio-frequency signal transmission by the device, thereby disabling Bluetooth, telephony, and Wi-Fi. GPS may or may not be disabled, because it does not involve transmitting radio waves.

Short answer: BOOLEAN:NO

Example 3
Question: why does queen elizabeth sign her name elizabeth r
Wikipedia Page: Royal_sign-manual
Long answer: The royal sign-manual usually consists of the sovereign's regnal name (without number, if otherwise used), followed by the letter R for Rex (King) or Regina (Queen). Thus, the signs-manual of both Elizabeth I and Elizabeth II read Elizabeth R. When the British monarch was also Emperor or Empress of India, the sign manual ended with R I, for Rex Imperator or Regina Imperatrix (King-Emperor/Queen-Empress).

Short answer: NULL

- 307k training instances, 7.8k evaluation
- **Input.** (Question, Wikipedia Page)
- Questions: Real Google queries
- **Output.**
  1. Long answer: Either a paragraph that answers the question, or not-answerable
  2. Short answer: Either a short span (e.g., entity), yes/no, or null
- F1 evaluation (long answer, dev)
  - Human: 73.4
  - DocumentQA (BiRNN/attention, init with pretrained word embeddings): 46.1

Coreference Resolution (Coref)

- General coref: Identify and cluster mentions based on referenced entities

  We are looking for [0 a region of central Italy bordering the Adriatic Sea] . [0 The area] is mostly mountainous and includes Mt. Corno , the highest peak of the mountain range . [0 It] also includes [1 many sheep] and an Italian entrepreneur has an idea about how to make a little money of [1 them] .

- Simplification: Winograd Schema Challenge (WSC) (Levesque et al., 2011)
  - The drain is clogged with hair. It has to be <u>cleaned</u>.
  - The drain is clogged with hair. It has to be <u>removed</u>.
- Reduction to NLI (WNLI)

$$\left(\text{The drain is clogged with hair.}, \text{The hair has to be cleaned}\right) \rightarrow \mathsf{C}$$

$$\left(\text{The drain is clogged with hair.}, \text{The drain has to be cleaned}\right) \rightarrow \mathsf{E}$$

$$\left(\text{The drain is clogged with hair.}, \text{The hair has to be removed}\right) \rightarrow \mathsf{E}$$

$$\left(\text{The drain is clogged with hair.}, \text{The drain has to be removed}\right) \rightarrow \mathsf{C}$$

- WNLI: 634 training instances, 146 test
  - Human accuracy 96
  - Any neural model trained from scratch: 65.1 (random)

Other NLU Tasks

- **Sentence similarity**: Formulated as sentence-pair regression

$$(\text{A person is combing a cat hair.}, \text{A person is brushing a cat.}) \rightarrow 4.4$$
$$(\text{A man is cutting up a potato.}, \text{A man is cutting up carrots.}) \rightarrow 2.4$$
$$(\text{A boy is riding a horse.}, \text{A monkey is riding a bus.}) \rightarrow 0.4$$

  - STS-B dataset: 7k training examples, 1.4k test.
  - Performance (correlation): Human 92.7, BiLSTM 65-70
- **Linguistic acceptability**: Single-sentence binary classification (grammatical vs ungrammatical)

$$\text{She voted for herself.} \rightarrow 1$$
$$\text{Maryann should leaving.} \rightarrow 0$$
$$\text{Kim persuaded it to rain.} \rightarrow 0$$
$$\text{Books were sent to each other by the students.} \rightarrow 0$$

  - CoLA (Warstadt et al., 2018): 8.5k training examples, 1k test.
  - Performance (correlation): Human 66.4, BiLSTM 15

NLU Benchmarks

- Collection of tasks for testing NLU capabilities of a system
- Example: GLUE (Wang et al, 2018)

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

- Only train/dev data released: System submits predictions online to receive test performance
- Single score by macro-average
  - Human GLUE score: 87.1
  - BiLSTM GLUE score: 63.7
- Typically consider simple classification/regression tasks
  - Complex tasks like full-fledged QA and coref not included, must be considered additionally

Need for Transfer Learning

- NLU tasks, and other downstream tasks, supply limited supervision ($\approx 300k$ labeled examples at most)
- We can't train a model from scratch for each task and expect it to work well!
- Solution: **Transfer Learning**
  - Use knowledge aquired to solve task A to help better solve a related task B
- In particular: **Unsupervised** transfer learning
  - A doesn't need supervision
  - Form of semi-supervised learning (lots of unlabeled data, small labeled data)
- Central question: Is there any task in NLP that we can train a model for with no annotation, yet it's closly related to many downstream tasks?

Pretrained Neural Language Models

- Family of neural LMs "pretrained" on a **large** quantity of unlabeled text
- Given a downstream task, copy the pretrained LM weights and "finetune" them on a small quantity of labeled data
  - Variations possible: Hold pretrained weights fixed, only train a new classification layer
- We don't necessarily care about pretraining itself, as long as the resulting model is useful for downstream tasks.
  - Flexibility in designing the pretraining objective
- Some landmarks: Word2vec, ELMo, BERT, GPTs
  - Initial works like word2vec only considered pretraining word embeddings
  - Later works consider pretraining an entire LM capable of producing *contextual* word embeddings

Word2Vec (Mikolov et al., 2013)

- Given vocab $\mathcal{V}$ and dimension d, learn
  - Word embedding matrix: $W = [w_1 \dots w_{|\mathcal{V}|}] \in \mathbb{R}^{d \times |\mathcal{V}|}$
  - Context word embedding matrix: $C = [c_1 \dots c_{|\mathcal{V}|}] \in \mathbb{R}^{d \times |\mathcal{V}|}$
- Training: Draw a random n-grams $(x_1 \dots x_n)$ from a corpus with middel word x_{mid}. Set

$$c_{\text{cbow}} = \frac{1}{n-1} \sum_{i=1:\ i \neq \text{mid}}^{n} c_{x_i}$$

Draw K random words $x_1^{\text{neg}} \dots x_K^{\text{neg}} \sim q$ where q is some distribution over $\mathcal{V}$ (e.g., empirical unigram distribution). Take a gradient step on the single-example loss

$$\widehat{J}_{\text{single}}(W, C) = -\log \sigma(w_{x_{\text{mid}}}^\top c_{\text{cbow}}) - \sum_{k=1}^{K} \log \sigma(-w_{x_k^{\text{neg}}}^\top c_{\text{cbow}})$$

Distributional Word Representations

`... this dog is a poodle ...`

`...love my poodle ...`

`...poodle and schnauzer ...`

`...terrier is a dog ...`

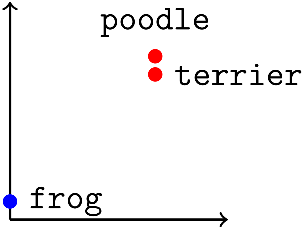
`...love your terrier ...`

`...schnauzer, or terrier ...`

`...frog is an amphibian ...`

`...frog from predators ...`

`...cold-blooded, a frog ...`



$$\left\|\texttt{poodle} - \texttt{terrier}\right\| \ll \left\|\texttt{poodle} - \texttt{frog}\right\|$$

"You shall know a word by the company it keeps." -Firth

Word2Vec in Practice

- Can be viewed as a stripped down LM
  - Predict what the middle word is given a bag of context words
  - Approximate cross-entropy loss by negative sampling (must specify number of negatives, e.g., $K = 5$)
- Efficient training, CPU friendly, parallelizable over corpus with asynchronous updates
  - Only a few hours to train on the entire Wikipedia corpus (3 billion tokens, vocab size $> 100k$)
- Once trained, use $w_x \in \mathbb{R}^d$ as embedding of word $x \in \mathcal{V}$
  - Typically discard context embeddings c_x
- In a downstream task, initialize word embeddings with w_x
  - Significant improvement over randomly initialized word embeddings if labeled data is small
  - E.g., CoNLL 2003 NER performance using BiLSTM-CRF (Lample et al., 2016): $83.6 \rightarrow 90.9$
- Other word embedding techniques: GloVe (Pennington et al., 2014), spectral (Stratos et al., 2015)

Limitations of Pretrained Word Embeddings

- **Non-contextual**: "saw" below gets the same word embedding

```
the man saw the cut
the saw cut the man
```

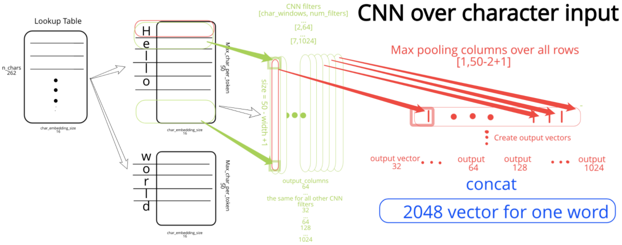
- Can use contextualizer on top like BiLSMs in finetuning, but no transfer learning for that module
- Not helpful when downstream task has enough training data
  - Example: MT, similar performance with random vs pretrained word embeddings
- Natural next step: **Transfer an entire LM**, rather than just word embeddings
  - Took a while before this happened because of "word embedding inertia"
  - Word embeddings are so simple and easy to train, interpretable, reliably effective
  - Much harder to transfer a contextual encoder

ELMo (Peters et al., 2017)

- **E**mbeddings from **L**anguage **Mo**dels
- One of the first truly successful pretrained LMs for transfer learning, building on earlier works like
  - CoVe (McCann et al., 2017): Transfer learning by MT
  - TagLM (Peters et al., 2017): Transfer learning also by bidirectional LM. ELMo uses more layers and better techniques
- Character-level input
  - Run CNN over characters instead of having a static embedding for each word
  - Prediction is still word level
- Backward LM that encodes context to the right, trained jointly
- Light-weight scheme to tailor ELMo embeddings for downstream tasks without finetuning ELMo itself

Character-Level Input

- Each word w treated as a sequence of characters $c \in \mathcal{C}$ where $|\mathcal{C}| = 262$ (UTF-8 encoding)
- Character embedding dimension 16: input matrix $C \in \mathbb{R}^{262 \times 16}$
- CNN filter sizes 1–7 with increasing filter numbers (32... 1024) and max pooling: Outputs $u_w \in \mathbb{R}^{2048}$



(Image credit: Petr Lorenc)

- Final word rep: $v_w = \text{Feedforward}(\text{Highway}^2(u_w)) \in \mathbb{R}^{512}$
  - This is the input to LSTMs, shared between forward/backward LMs

Bidirectional Language Modeling

- **Forward LM**
  - Two-layer LSTM cell: Input dim 512, cell state dim 4096 but hidden state dim projected back to 512
- **Backward LM**: Same architecture but distinct parameters
- Shared classification layer $W \in \mathbb{R}^{512 \times V}$ where $V = 793471$ vocab extracted from 1 Billion Word Benchmark dataset
- Loss: Sum of forward and backward LM losses

$$\widehat{J}_x(\theta) = -\sum_{t=1}^{T} \Big(\log p(x_t | x_{<t}; \theta_{\text{cnn}}, \theta_{\text{forward}}, \theta_{\text{softmax}}) + \log p(x_t | x_{>t}; \theta_{\text{cnn}}, \theta_{\text{backward}}, \theta_{\text{softmax}}) \Big)$$

The ELMo Embeddings

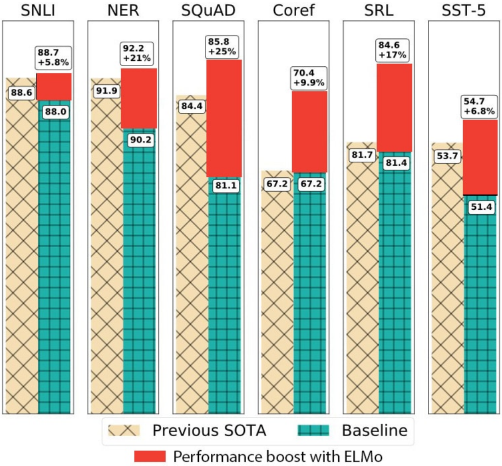
- ELMo parameters frozen after pretraining
- Given sentence $x_1 \ldots x_T$, running ELMo yields
  1. Word reps $v_{x_1} \ldots v_{x_T} \in \mathbb{R}^{512}$ from CNN, can be precomputed
  2. Forward LSTM hidden states $\vec{h}_1^{(l)} \ldots \vec{h}_T^{(l)} \in \mathbb{R}^{512}$ for each layer $l = 1, 2$ where $\vec{h}_t^{(l)}$ is a function of $x_{\leq t}$
  3. Backward LSTM hidden states $\overleftarrow{h}_1^{(l)} \ldots \overleftarrow{h}_T^{(l)} \in \mathbb{R}^{512}$ for each layer $l = 1, 2$ where $\vec{h}_t^{(l)}$ is a function of $x_{\geq t}$
- 1024-dimensional contextual embedding of t-th word

$$\textbf{ELMo}_t = \gamma \left(\alpha_0 \begin{bmatrix} v_{x_t} \\ v_{x_t} \end{bmatrix} + \alpha_1 \begin{bmatrix} \vec{h}_t^{(1)} \\ \overleftarrow{h}_t^{(1)} \end{bmatrix} + \alpha_2 \begin{bmatrix} \vec{h}_t^{(2)} \\ \overleftarrow{h}_t^{(2)} \end{bmatrix} \right)$$

  Introducing learnable scalar parameters $\gamma, \alpha_l \in \mathbb{R}$ to scale embeddings from different layers for target task
- In a downstream task, just concatenate with initial word embedding
  - E.g., Input to RNN is word embeddings concat with $\textbf{ELMo}_t$.

Results

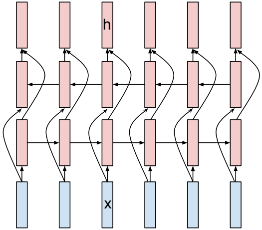
- 10 epochs on 1B Word Benchmark (2 weeks on 3 GPUs)
  - 800 milion tokens of news data, vocab size $800k$
- Append ELMo embeddings at input in various baseline models



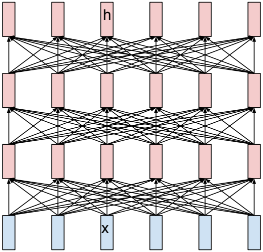
(Image credit: Isha Salian)

Limitations of ELMo

- **ELMo**$_t \in \mathbb{R}^{1024}$ encodes both left/right context, but shallowly bidirectional



(not bidirectional until later)



(deeply bidirectional)

- Only transferring frozen contextual embeddings
  - Must train task-specific encoders like LSTMs on top
- How can we pretrain an LM that's deeply bidirectional and almost "sufficient" on its own?

BERT (Devlin et al., 2019)

- **B**idirectional **E**ncoder **R**epresentations from **T**ransformers
- Insight: Pretrain an LM in such a way that it's "almost" the same as how it'll be used for downstream tasks
- How do we use an NLP model for downtream tasks?
  1. Apply powerful transformation on tokens to get contextual token embeddings.
  2. Add a linear classifier on top.
- We want to pretrain an LM for 1, without limiting it to forward or backward token prediction
- Central question: How can we do language modeling while "seeing" the whole input text?

Masked Language Modeling (MLM)

- Mask out tokens (wordpieces) at random

  the man went to the [MASK] to buy a [MASK] of milk

  The model receives the input above and predict what the missing words are: "store", "gallon"
  - Crucially, can use context to the right all the time!
- Need to be careful
  - Too little masking: too expensive to train
  - Too much masking: not enough context
  - Test time: no [MASK] input, so training should also handle no [MASK] input sometimes
- BERT masking scheme: Given input text,
  - Choose 15% of tokens uniformly at random
  - For each chosen token, replace it with [MASK] 80% of the time, a random token 10% of the time, and leave it unchanged 10% of the time.

Details of BERT

- Wordpiece tokenization: Vocab size $30k$ (cased/uncased)
- **Transformer encoder**
  - bert-base: 12 layers, 12 attention heads, 110m parameters
  - bert-large: 24 layers, 16 attention heads, 340m parameters
- Input: Sentence pair (marked at input by additive embeddings), will predict consecutive (50% random) in addition to MLM
- Introduced atomic special tokens
  - **[CLS]**: First token used for sent pair classification
  - **[SEP]**: Separater between sentences
  - **[MASK]**: Mask token
- Pretrained on BooksCorpus ($800m$ tokens) + English Wikipedia ($2.5b$ tokens)
  - Batch size 256 seqs of 512 tokens: $128k$ tokens per batch
  - $1m$ updates: 40 epochs over $3.3b$ tokens
  - Adam with weight decay, linear LR warmup step $10k$, dropout 0.1, gelu activation
  - Other tricks: E.g., train on length-128 for 90% steps first

MLM (Next Sentence Prediction Omitted)

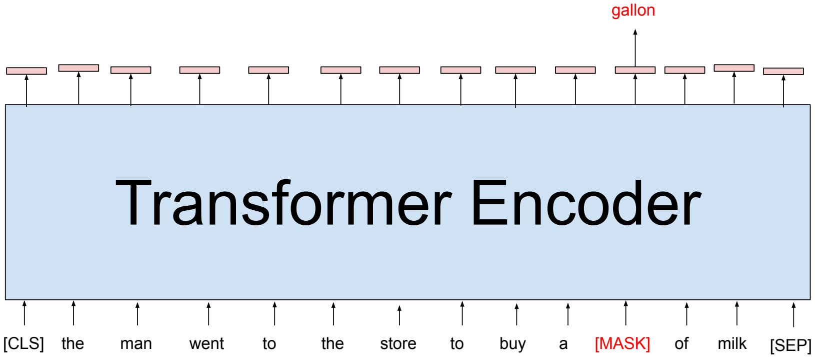
[CLS] the man went to the store to buy a gallon of milk [SEP]

MLM (Next Sentence Prediction Omitted)

[CLS] the man went to the store to buy a gallon of milk [SEP]

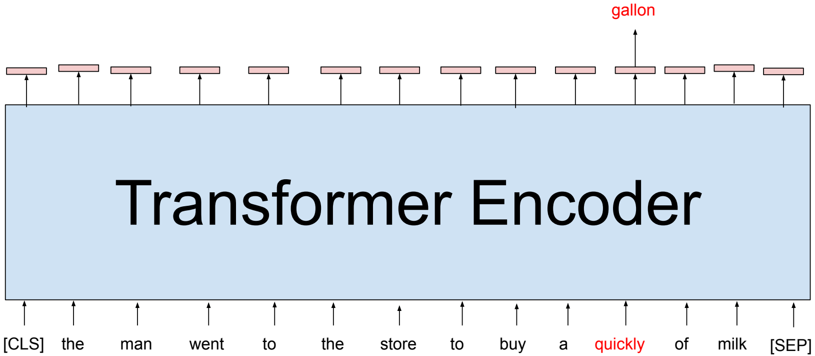
15% of tokens selected at random

MLM (Next Sentence Prediction Omitted)



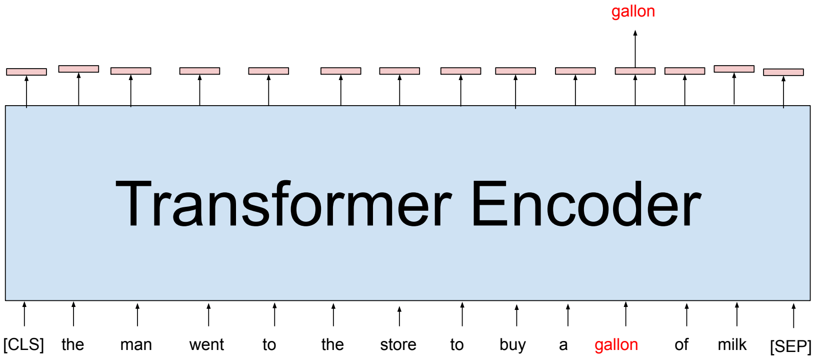
80% of time, a selected token is replaced with [MASK]

MLM (Next Sentence Prediction Omitted)



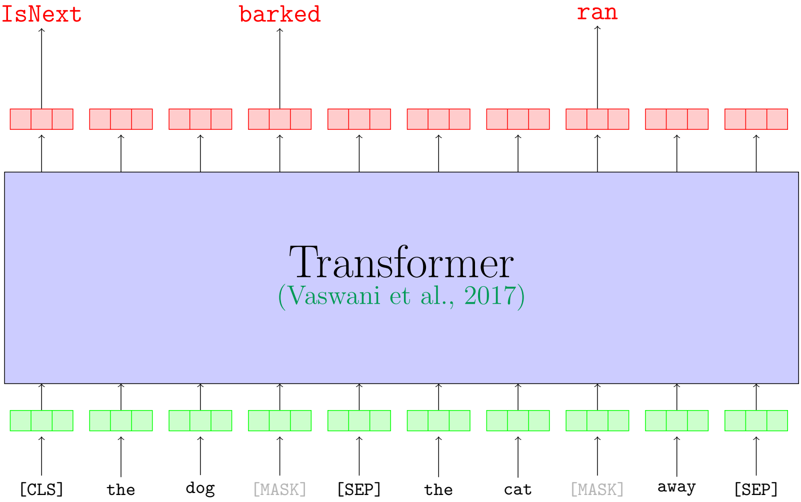
10% of time, a selected token is replaced with a random token

MLM (Next Sentence Prediction Omitted)



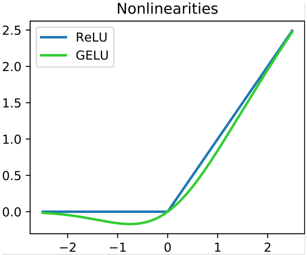
10% of time, a selected token is left alone

BERT Pretraining



Aside: GELU (Hendrycks and Gimpel, 2016)

- GPT-1 and BERT popularized GELU (Gaussian Error Linear Unit) as the choice of nonlinear function in transformers



$$\mathrm{GELU}(x) = x \underbrace{\Pr_{z \sim \mathcal{N}(0,1)}(z \leq x)}_{\text{Gaussian CDF: } \Phi(x)}$$

- Simple implementation w/ numerical approximation (Page, 1977):
  $\Phi(x) = \frac{1}{2}(1 + \mathrm{erf}(\frac{x}{\sqrt{2}})) \approx \frac{1}{2}(1 + \tanh(\sqrt{\frac{2}{\pi}}(x + 0.044715x^3)))$
- Switching ReLU with GELU usually gives a small but consistent improvement

Motivation for GELU

- ReLU performs deterministic thresholding (at zero)

$$\mathrm{ReLU}(x) = \max(0, x) = x\mathbb{1}(0 \leq x)$$

- We can consider stochastic thresholding, drawing $z \sim \mathcal{N}(0, 1)$

$$\mathrm{GELU}_z(x) = x\mathbb{1}(z \leq x)$$

  "Dropout", with input-dynamic instead of static probability

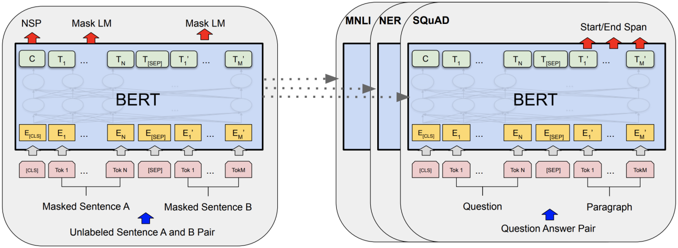
- GELU: "Expected dropout"

$$\mathrm{GELU}(x) = \mathop{\mathbf{E}}_{z \sim \mathcal{N}(0,1)} [x\mathbb{1}(z \leq x)] = x\Phi(x)$$

- Keeps the general shape of ReLU and its benefits (sparse activation, monotonic gradients), but is smooth and "more nonlinear"

Using Pretrained BERT

- Add a light-weight classification layer for each task
- **Finetune.** Instead of holding BERT parameters frozen, jointly optimize them all along with added layer

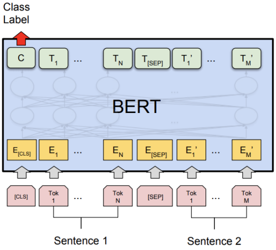


Pre-training

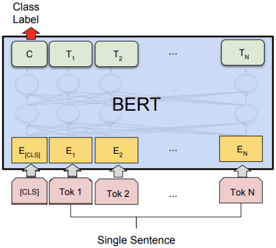
Fine-Tuning

- Not very sensitive to input representation, sensible choices
  - Sentence pair: "[CLS] s1 [SEP] s2"
  - Single sentecne: "[CLS] s"
- Importantly, often just works with one of a small number of hyperparameter configurations!
  - Batch size: 16, 32, dropout: 0.1, learning rate (Adam): $5e{-}5$, $3e{-}5$, $2e{-}5$, 3-10 epochs

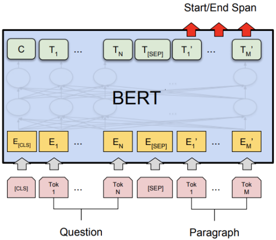
BERT-Based Architectures for Downstream Tasks



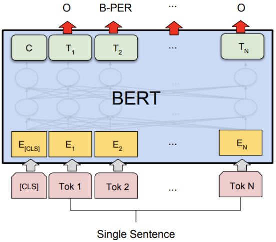
(a) Sentence Pair Classification Tasks:
MNLI, QQP, QNLI, STS-B, MRPC,
RTE, SWAG



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

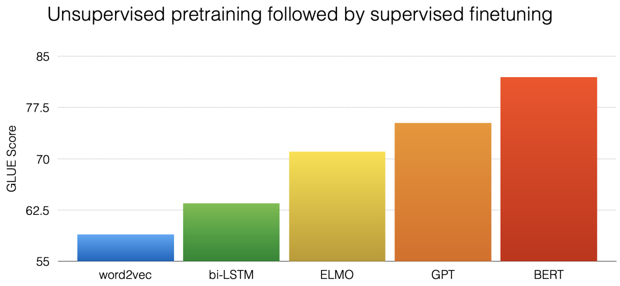


(c) Question Answering Tasks:
SQuAD v1.1



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

The Era of Pretrained Language Models



(Image credit: Graves and Ranzato)

- The success of BERT started an era of large-scale pretrained language models, in particular trained by MLM
  - RoBERTa (Liu et al., 2019), ALBERT (Lan et al., 2019), T5 (Raffel et al., 2019), ...
- GLUE score: human 87.1, transformer 90.3 (T5)
  - Recall: WNLI seems to require common sense. Human accuracy 95.9. Transformer accuracy 95.9 (ERNIE).

The Unreasonable Effectiveness of Pretrained Transformers

- Game of scale/engineering: Marginal changes in approach/architecture/loss
  - T5 has 5 billion parameters, trained on 1 trillion tokens
- Explosion of research around pretrained transformer LMs/MLMs
  - What information does a pretrained language model contain?
  - How can we make training more data-efficient (e.g., ELECTRA (Clark et al., 2020))?
  - How can we train multi-lingual transformers effectively?
  - And many more