CS 533: Natural Language Processing

# Natural Language Understanding, Pretrained Language Models

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# 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)

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

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

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

- 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: $\approx 70$

# 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

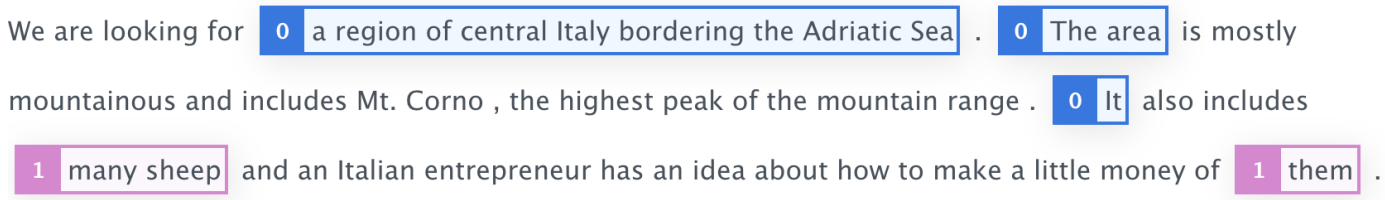
**Example 3**
**Question:** why does queen elizabeth sign her name elizabeth r
**Wikipedia Page:** Royal_sign-manual
**Long answer:** The royal sign-manual usually consists of the sovereign's regnal name (without number, if otherwise used), followed by the letter R for Rex (King) or Regina (Queen). Thus, 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




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

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

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

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

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

- 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 develop general language understanding capabilities
- 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: What task in NLP can we 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): CBOW With Negative Sampling

- 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 $x_{\text{mid}}$. 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...

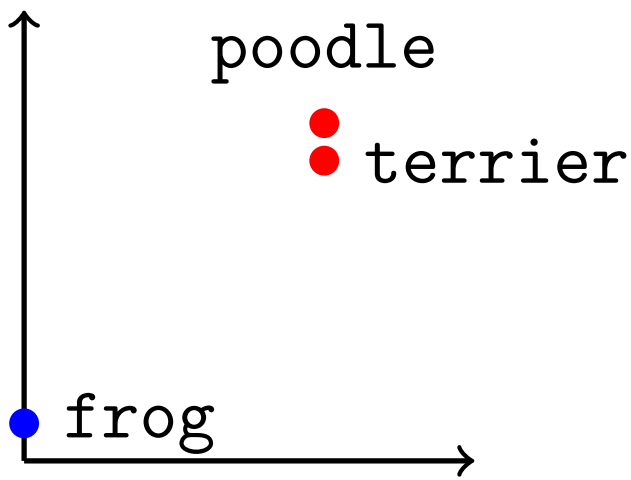
...love your terrier...

...schnauzer, or terrier...

...frog is an amphibian...

...frog from predators...

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




$$||\text{poodle} - \text{terrier}|| \ll ||\text{poodle} - \text{frog}||$$

"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 non-neural word embedding techniques: GloVe (Pennington et al., 2014), spectral (Stratos et al., 2015)
  - All based on modeling distributional similarity between words by compressing context, have similar quality

# Nearest Neighbor Examples

Top-8 words with highest cosine similarity using spectral word embeddings

| rochester | seattle | yahoo | starbucks | lol |
|---|---|---|---|---|
| binghamton | tacoma | linkedin | dunkin | yeah |
| albany | portland | msn | mcdonalds | heh |
| hartford | washington | facebook | mcdonald's | kidding |
| utica | denver | digg | domino's | thats |
| syracuse | oakland | aol | applebee's | damn |
| elmira | baltimore | google | 7-eleven | ahh |
| bridgeport | chicago | friendster | kfc | gosh |
| newark | cleveland | orkut | walmart | kinda |

| smile | frown | 1 | 1945 | second |
|---|---|---|---|---|
| smiles | frowns | 2 | 1944 | third |
| smiling | frowned | 3 | 1943 | fourth |
| grin | disapprove | 4 | 1942 | fifth |
| wide-eyed | cringe | 5 | 1941 | first |
| laugh | discourages | 6 | 1946 | sixth |
| cheerful | overreact | 8 | 1940 | seventh |
| eyes | detest | 7 | 1939 | eighth |
| grinning | forbid | 9 | 1947 | ninth |

# Limitations of Pretrained Word Embeddings

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

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

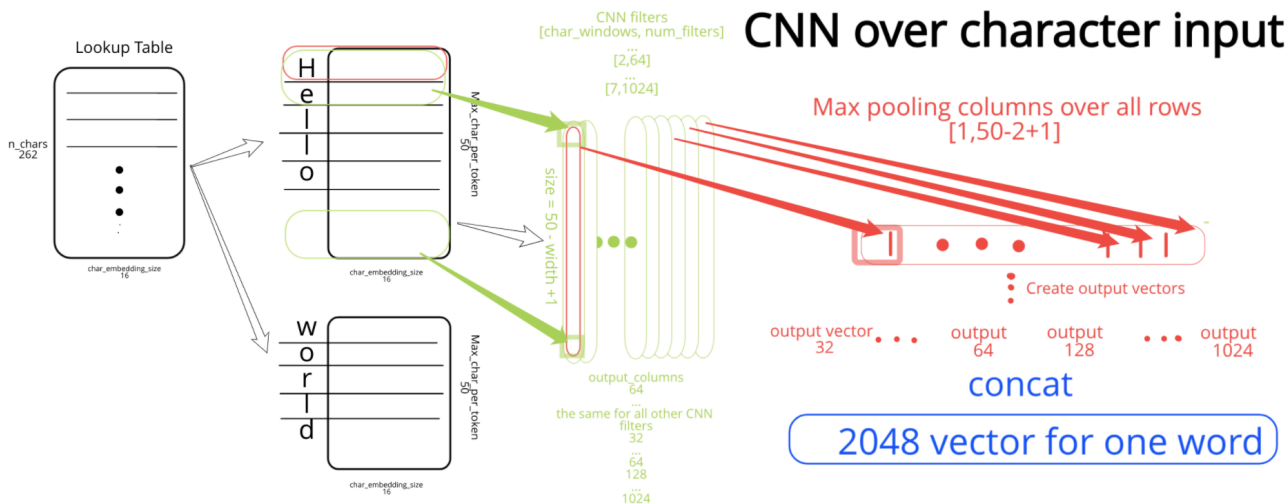
- Can use contextualizer on top like BiLSMs in finetuning, but no transfer learning for that module
- Not helpful when downstream task has enough training data
  - Example: MT, similar performance with random vs pretrained word embeddings
- Intuition: Generic word similarity is useful, but definitely not enough for general language understanding
- Natural next step: Transfer an entire LM, rather than just lookup tables
  - 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

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

# The ELMo Embeddings

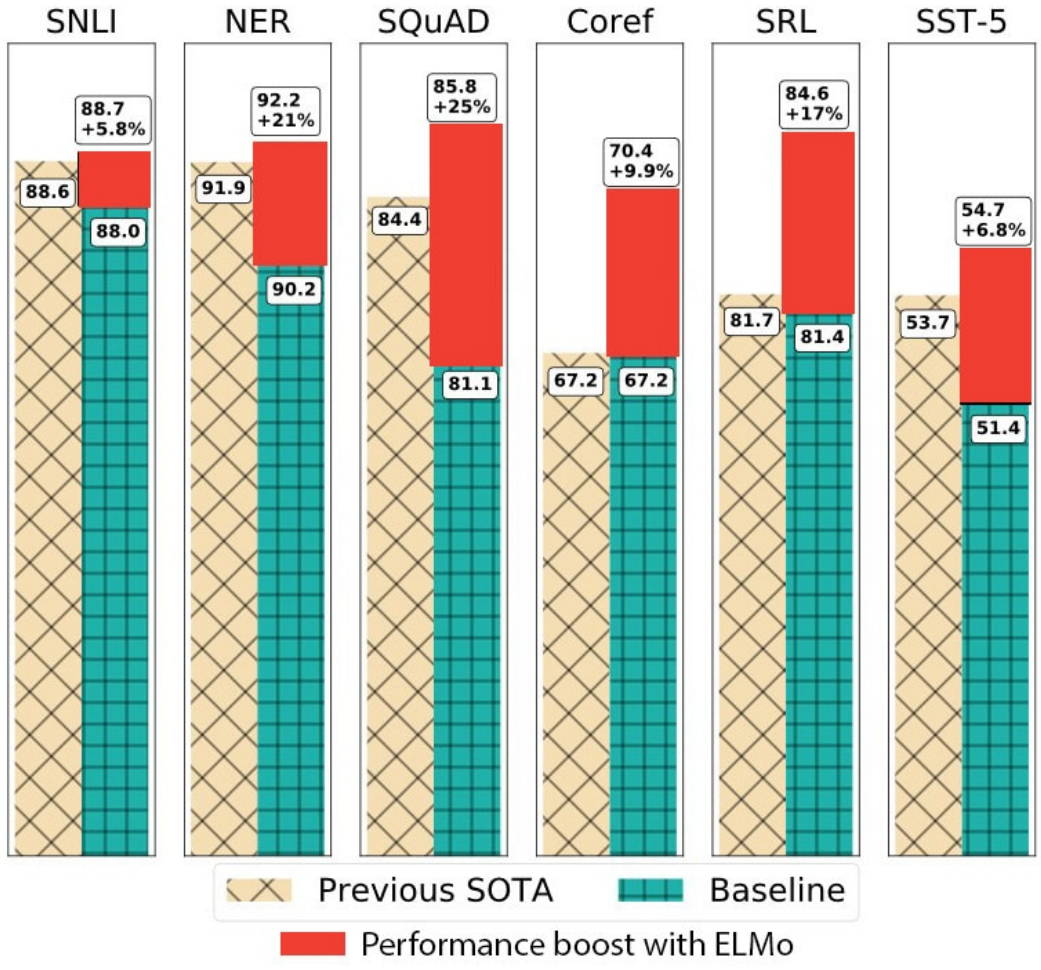
- ELMo parameters frozen after pretraining
- Given sentence $x_1 \dots x_T$, running ELMo yields
  1. Word reps $v_{x_1} \dots v_{x_T} \in \mathbb{R}^{512}$ from CNN, can be precomputed
  2. Forward LSTM hidden states $\vec{h}_1^{(l)} \dots \vec{h}_T^{(l)} \in \mathbb{R}^{512}$ for each layer $l = 1,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

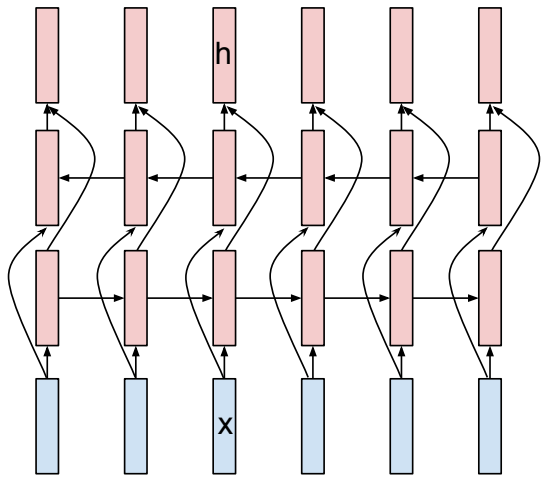
- 10 epochs on 1B Word Benchmark (2 weeks on 3 GPUs)
  - 800 milion tokens of news data, vocab size $800k$
- Append ELMo embeddings at input in various baseline models



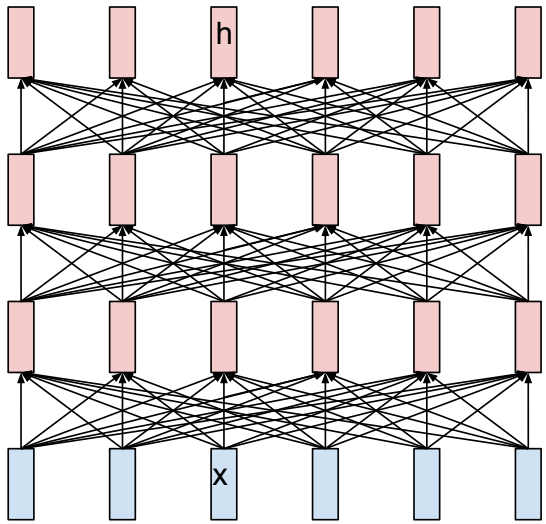

(Image credit: Isha Salian)

# 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

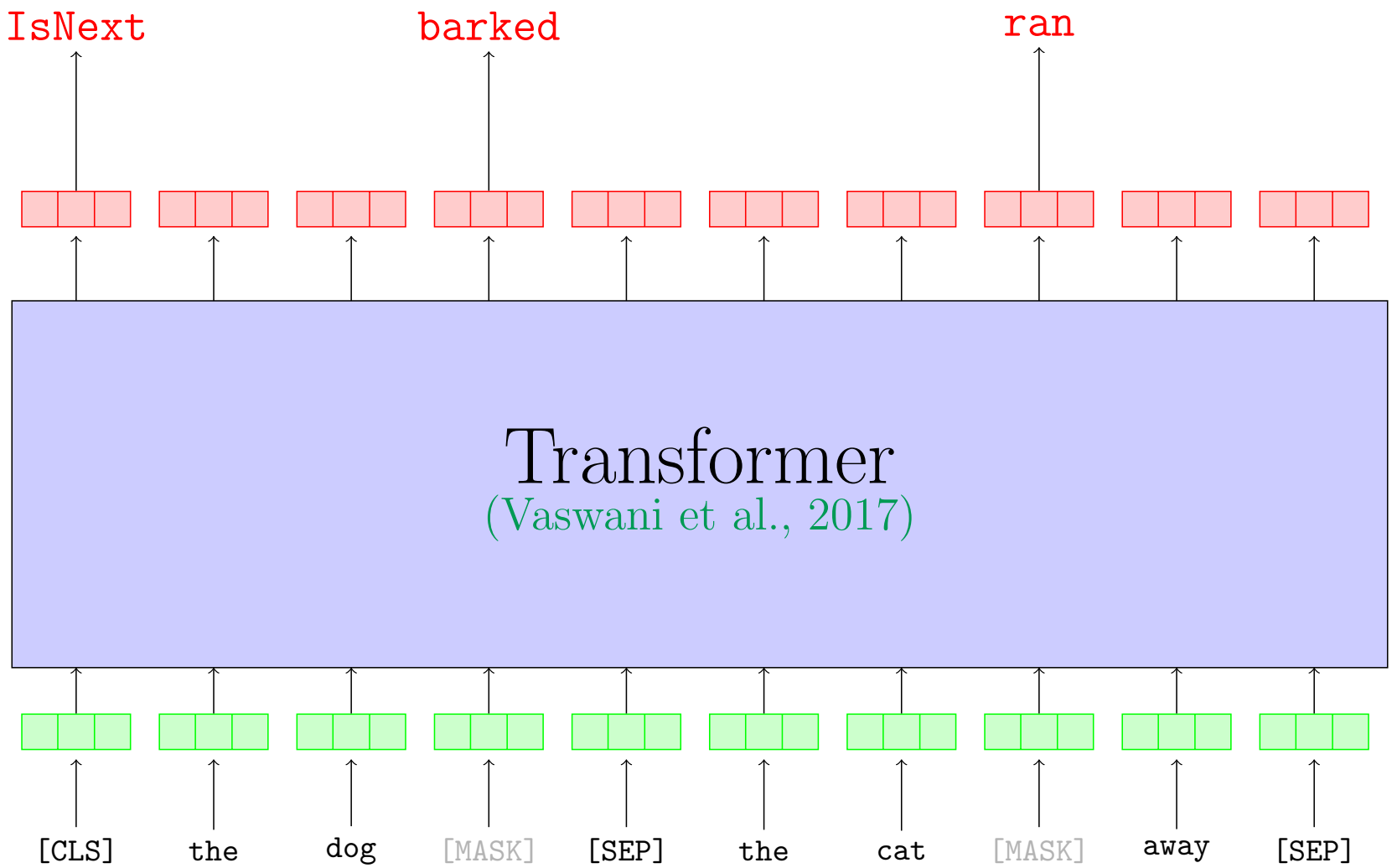
  the man went to the [MASK] to buy a [MASK] of milk

  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

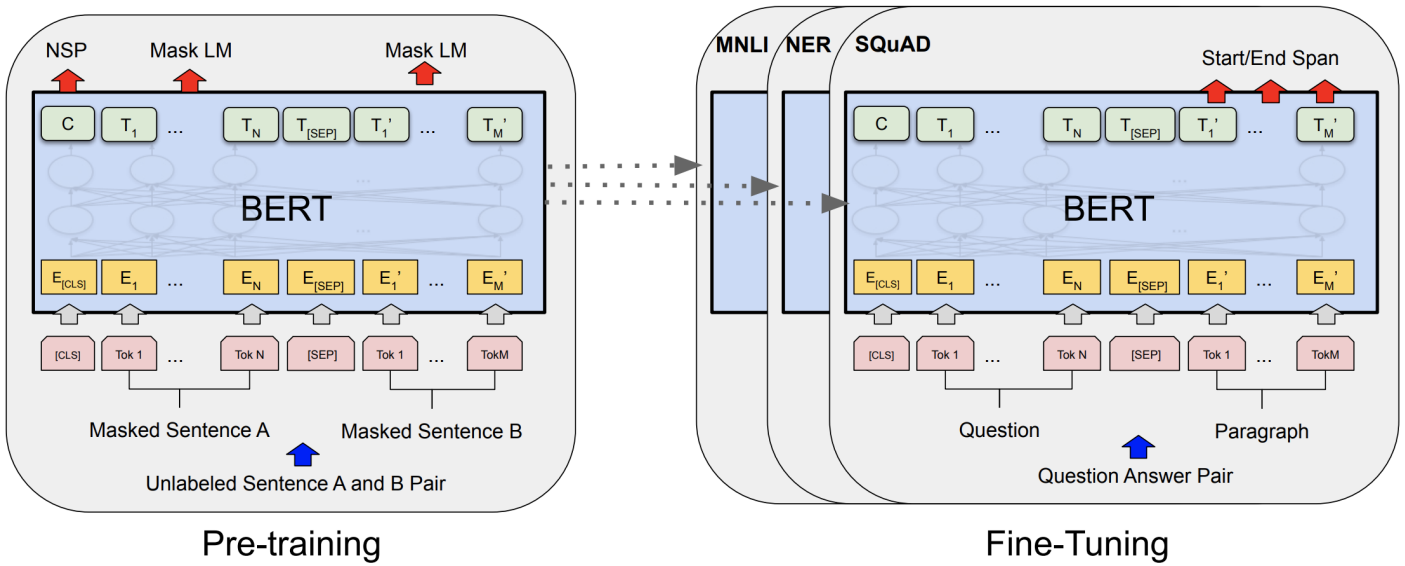
- Wordpiece tokenization: Vocab size $30k$ (cased/uncased versions)
- **Transformer encoder**
  - bert-base: 12 layers, 12 attention heads, 110m parameters
  - bert-large: 24 layers, 16 attention heads, 340m parameters
- Input: Sentence pair (marked at input by additive embeddings), predict consecutive (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

# Illustration of BERT



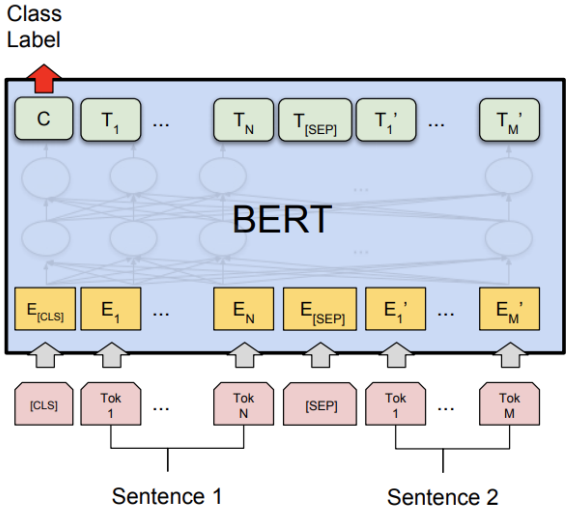
# Using Pretrained BERT

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

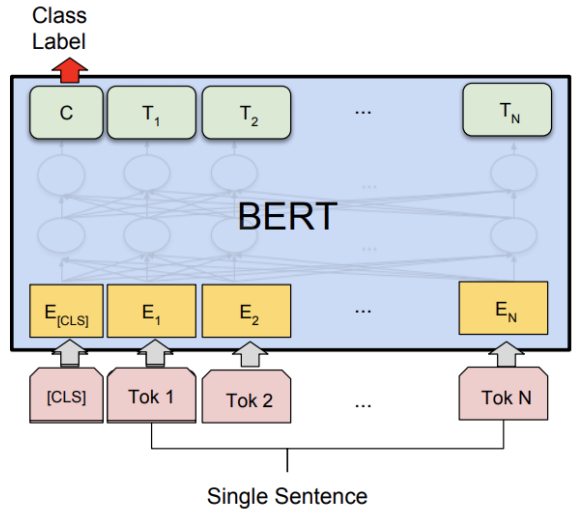



- Not very sensitive to input representation, sensible choices
  - Sentence pair: "[CLS] s1 [SEP] s2"
  - Single sentecne: "[CLS] s"
- Importantly, often just works with one of a small number of hyperparameter configurations!
  - Batch size: 16, 32, dropout: 0.1, learning rate (Adam): $5e{-}5$, $3e{-}5$,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

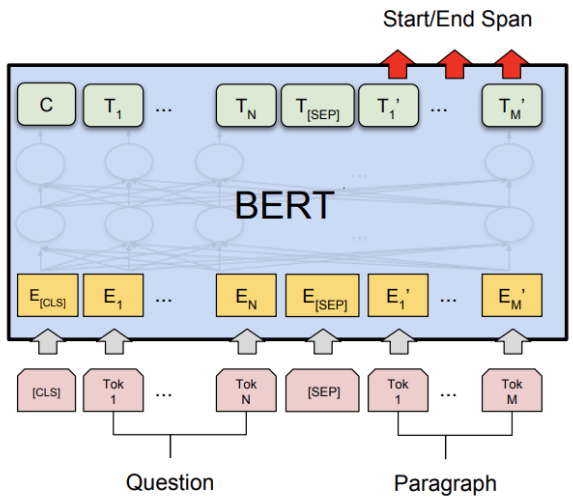
# BERT-Based Architectures for Downstream Tasks



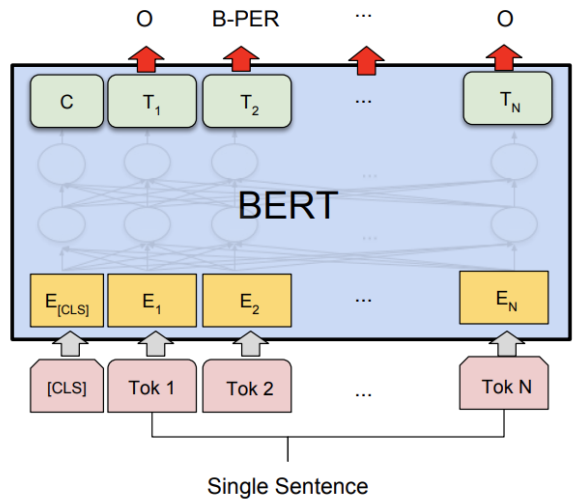

(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG




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

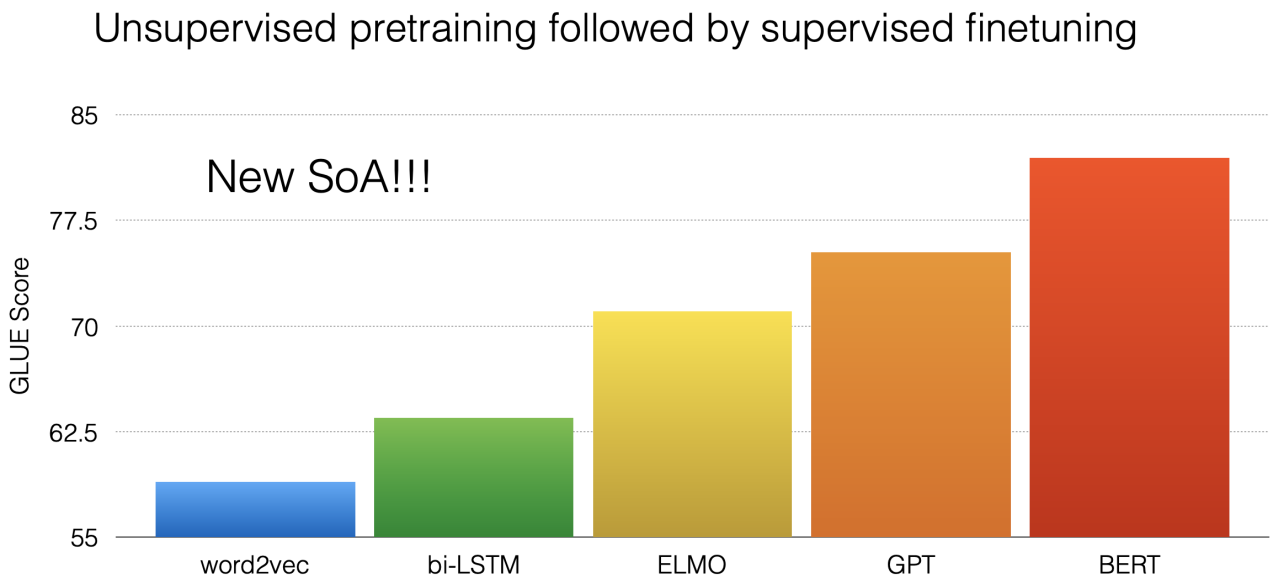



(c) Question Answering Tasks: SQuAD v1.1




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

# The Era of Pretrained Language Models




(Image credit: Graves and Ranzato)

- GPT: Transformer LM (use last hidden state)
- 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), ...

# 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
- 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).
- Weird situation
  - Before: How can we make it work?
  - Now: *How can it work so well???*
- Explosion of research around pretrained transformer LMs/MLMs
  - What information does a pretrained MLM contain? How can it even seem to solve the Winograd challenge?
  - 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