Fine-tuning and information retrieval with LMs

NLP Week 9

Thanks to Dan Jurafsky for most of the slides this week!

Plan for today

1. Contextualized embeddings
2. Fine-tuning for classification
3. Fine-tuning for sequence labeling
4. Practical considerations for fine-tuning
5. Information retrieval powered by language models
6. *Group exercises*

Problem with static embeddings (word2vec)

They are **static**! The embedding for a word doesn't reflect how its meaning changes in context.

```
The chicken didn't cross the road because it was too tired
```

What is the meaning represented in the static embedding for "it"?

Contextual Embeddings

- **Intuition:** a representation of meaning of a word should be different in different contexts!
- **Contextual Embedding:** each word has a different vector that expresses different meanings depending on the surrounding words
- **How to compute contextual embeddings?**
  - Deep neural networks
  - Bi-LSTMs
  - Self-attention

Contextual Embeddings

`The chicken didn't cross the road because it _____`

What should be the properties of "it"?

`The chicken didn't cross the road because it was too` **`tired`**
`The chicken didn't cross the road because it was too` **`wide`**

At this point in the sentence, it's probably referring to either the chicken or the street

Levesque et al. 2012 - The Winograd Schema Challenge

Word sense

Words are ambiguous

A **word sense** is a discrete representation of one aspect of meaning

mouse^{1} : .... a *mouse* controlling a computer system in 1968.
mouse^{2} : .... a quiet animal like a *mouse*
bank^{1} : ...a *bank* can hold the investments in a custodial account ...
bank^{2} : ...as agriculture burgeons on the east *bank*, the river ...

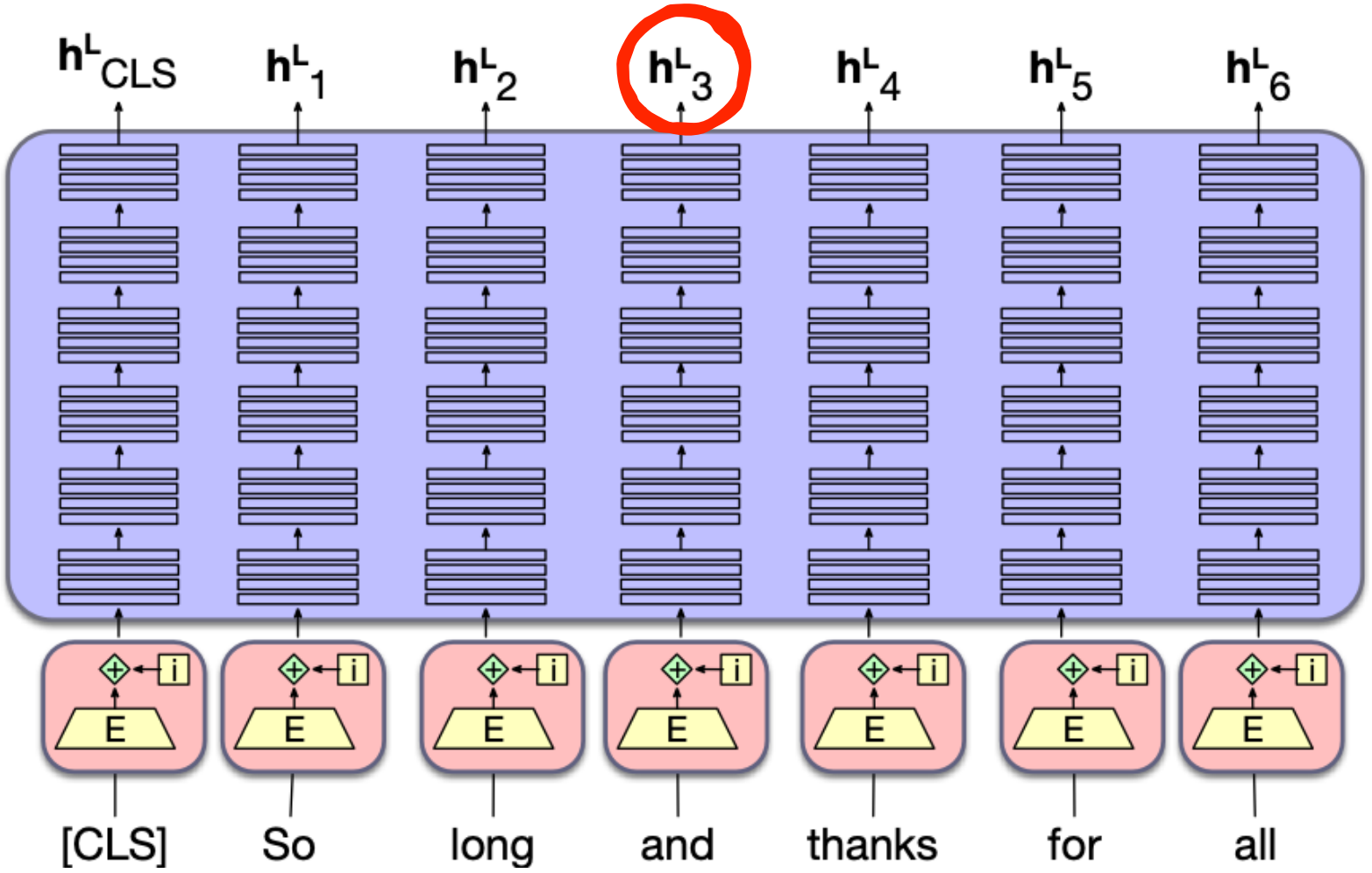
Contextual embeddings offer a continuous high-dimensional model of meaning that is more fine grained than discrete senses.

Static vs Contextual Embeddings

Static embeddings represent **word types** (dictionary entries)

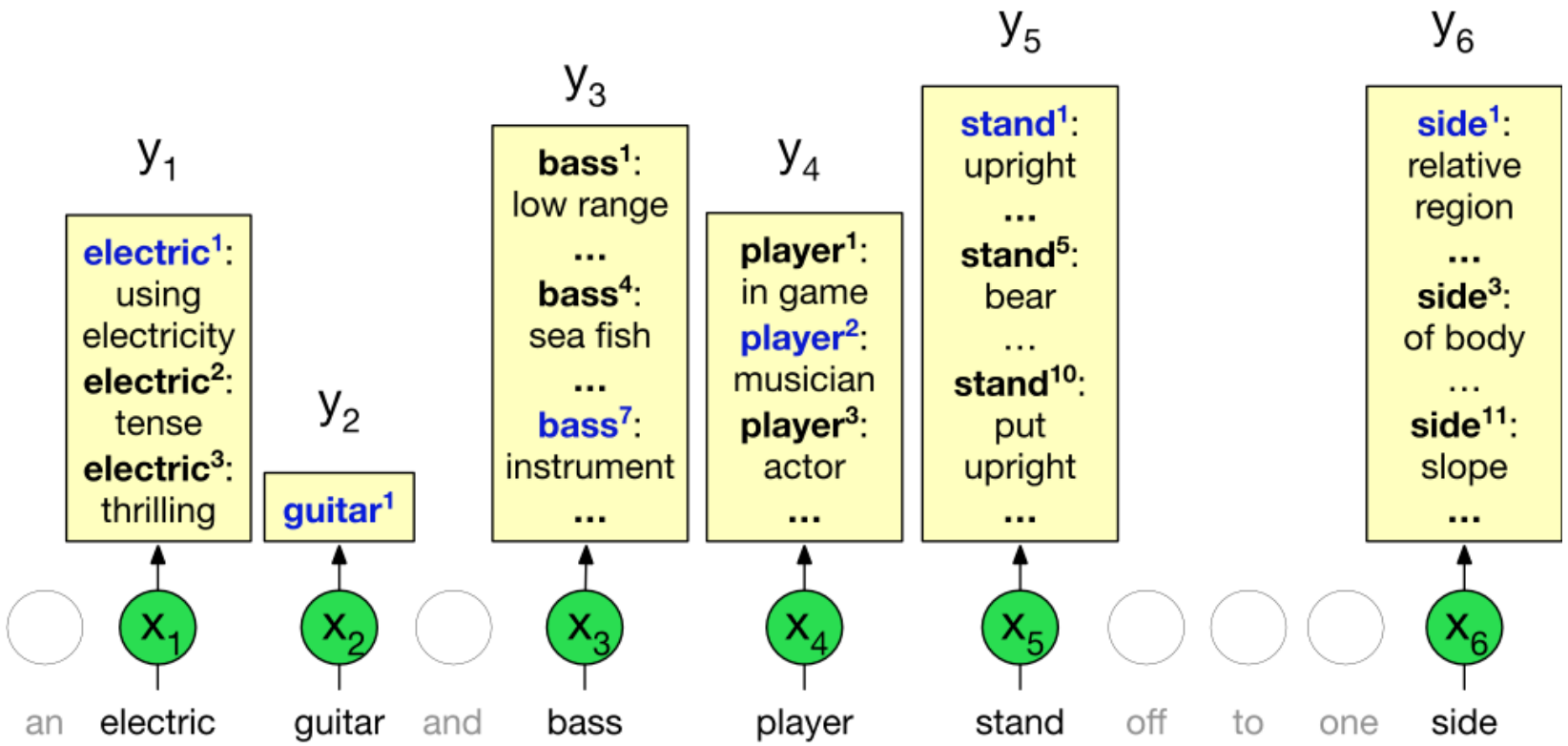
Contextual embeddings represent **word instances** (one for each time the word occurs in any context/sentence)

Contextual Embeddings from BERT



Word sense disambiguation (WSD)

The task of selecting the correct sense for a word.



1-nearest neighbor algorithm for WSD

Melamud et al (2016), Peters et al (2018)

At training time, take a sense-labeled corpus like SEMCOR

Run corpus through BERT to get contextual embedding for each token

- E.g., pooling representations from last 4 BERT transformer layer

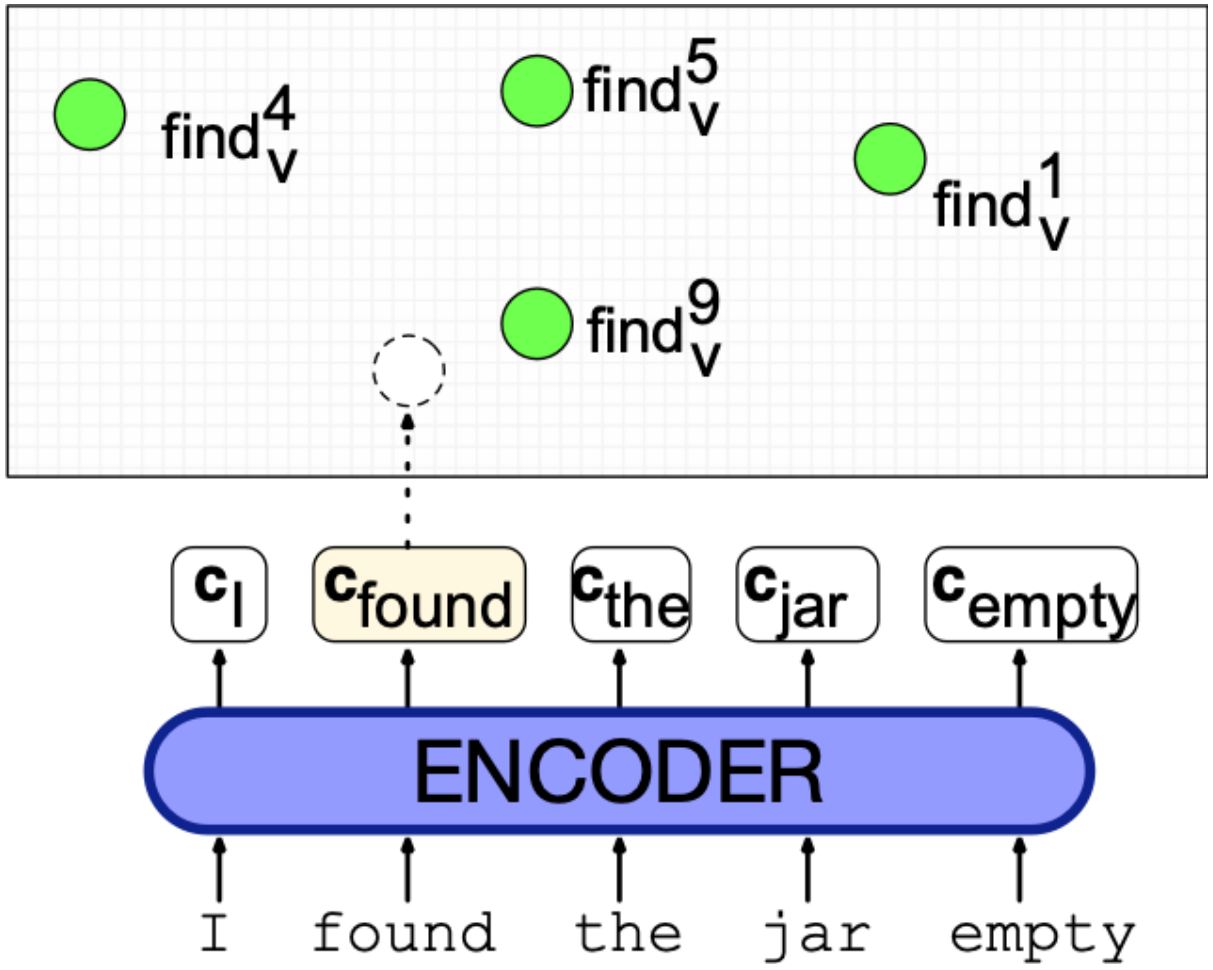
Then for each sense s of word w for n tokens of that sense, pool embeddings:

$$\mathbf{v}_s = \frac{1}{n}\sum_{i=0}^{n}\mathbf{v}_i \quad \forall \mathbf{v}_i \in \text{tokens}(s)$$

At test time, given a token of a target word *t*, compute contextual embedding t and choose its nearest neighbor sense from training set

$$\text{sense}(t) = \underset{s \in \text{senses}(t)}{\text{argmax}}\ \text{cosine}(\mathbf{t}, \mathbf{v}_s)$$

1-nearest neighbor algorithm for WSD



Similarity and contextual embeddings

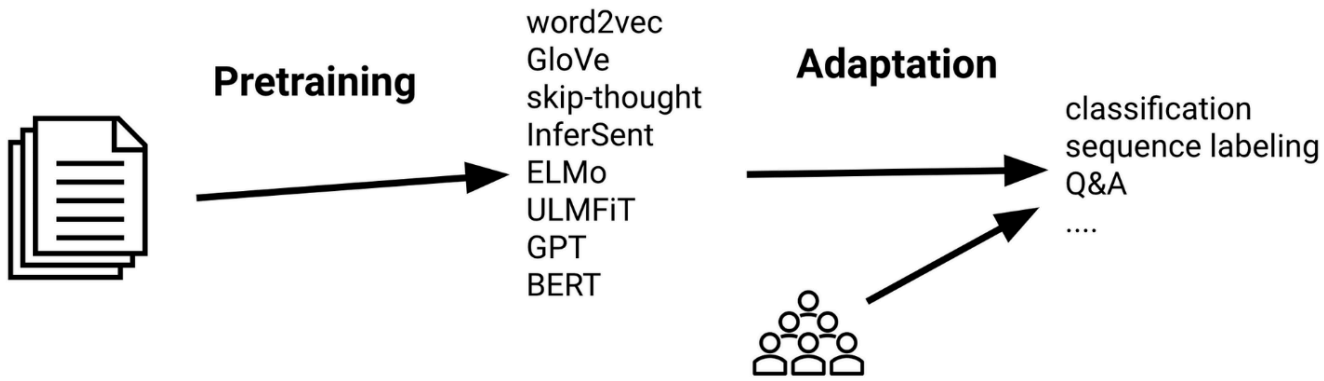
- We generally use cosine as for static embeddings
- But some issues:
  - Contextual embeddings tend to be **anisotropic:** all point in roughly the same direction so have high inherent cosines (Ethayarajh 2019)
  - Cosine measure are dominated by a small number of "rogue" dimensions with very high values (Timkey and van Schijndel 2021)
  - Cosine tends to underestimate human judgments on similarity of word meaning for very frequent words (Zhou et al., 2022)

Fine-tuning pre-trained models

- Recap: Basic ingredients for training ML models
  - A model $p_\theta(y \mid \mathbf{x})$
  - A dataset $\mathscr{D} = \{(\mathbf{x}_i, \mathbf{y}_i)\}_{i=1}^n$
  - An objective function, e.g., cross-entropy loss
  - A learning algorithm: gradient descent

Fine-tuning pre-trained models

- So far, models where initialized randomly, i.e., $\theta \sim \mathcal{N}(\mu, \sigma)$
- Fine-tuning → Initialize weights from a pre-trained model
- Why should this work? → Transfer learning
  - Pre-training encodes useful information about language
  - This is helpful for various NLP downstream tasks



Howard & Ruder (2018) - Universal Language Model Fine-tuning for Text Classification

Ruder (2019) - The State of Transfer Learning in NLP

Fine-tuning pre-trained models

- Nowadays, fine-tuning means many things
  - Adaptation to a single task, e.g., classification
  - Continual pre-training
  - Language adaptation
  - Instruction fine-tuning
  - Safety fine-tuning, RLHF
  - Post-training
  - Mid-training
  - Reinforcement fine-tuning
  - etc.

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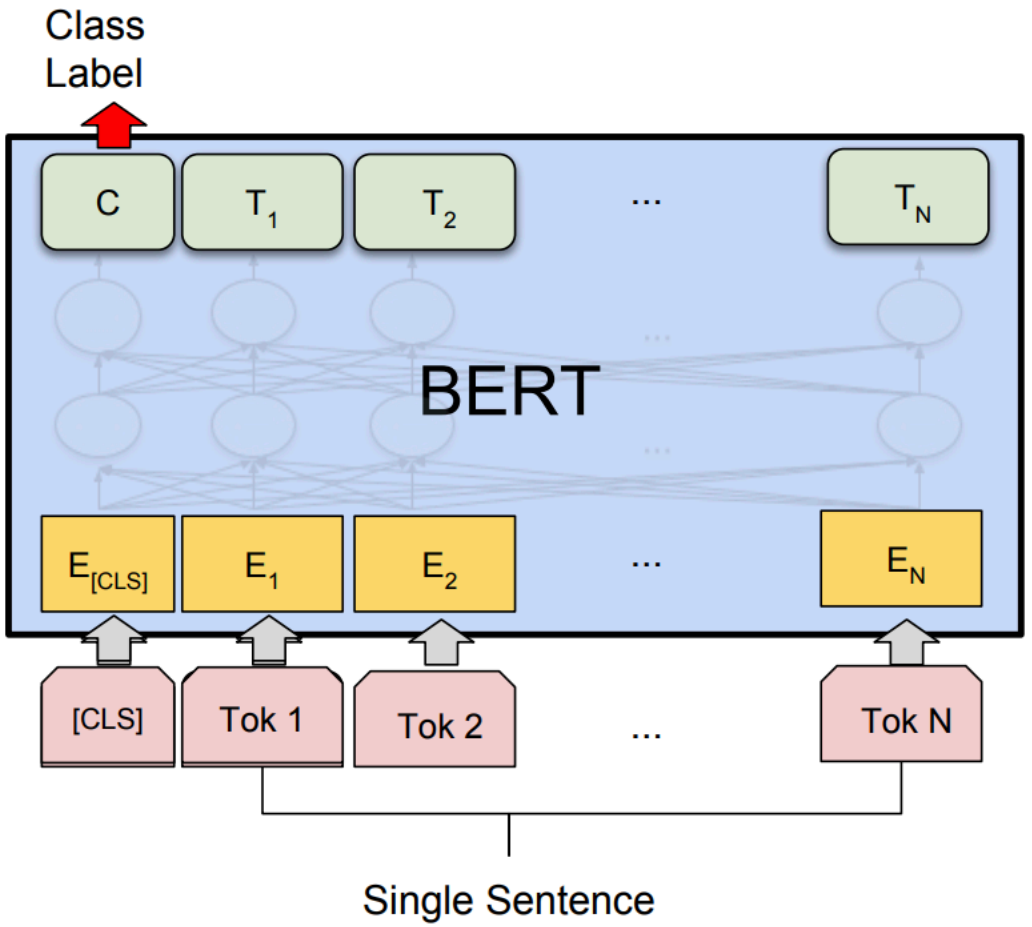
Using BERT for classification



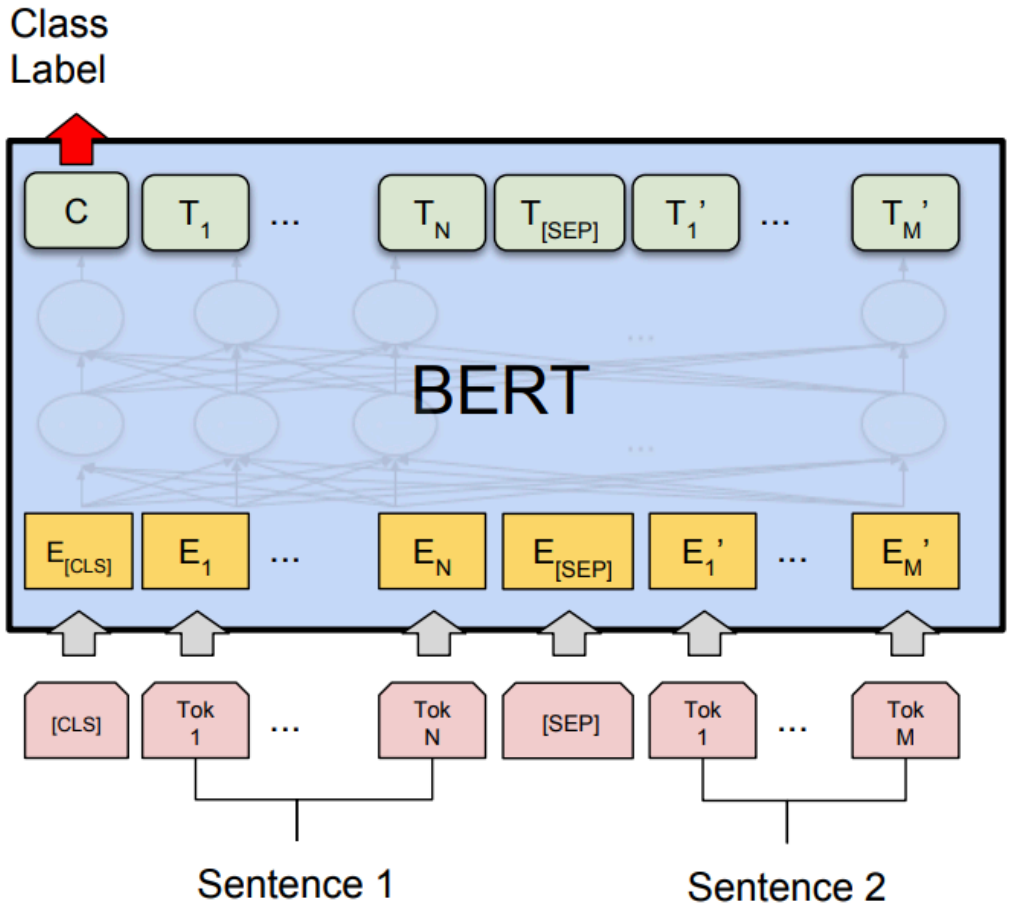
Devlin et al. 2018 - BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

Sentence classification

Assign a label to a single sentences:

- **Sentiment analysis** (does a given sentence have positive or negative sentiment?)
- **Acceptability judgements** (is a given sentence grammatical?)
- **Hate speech detection** (e.g, does a given sentence express hate or encourages violence?)

Using BERT for sentence pair classification



Devlin et al. 2018 - BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

Sequence-Pair classification

Assign a label to pairs of sentences:

- **Paraphrase detection** (are the two sentences paraphrases of each other?)
- **Logical entailment** (does sentence A logically entail sentence B?)
- **Discourse coherence** (how coherent is sentence B as a follow-on to sentence A?)

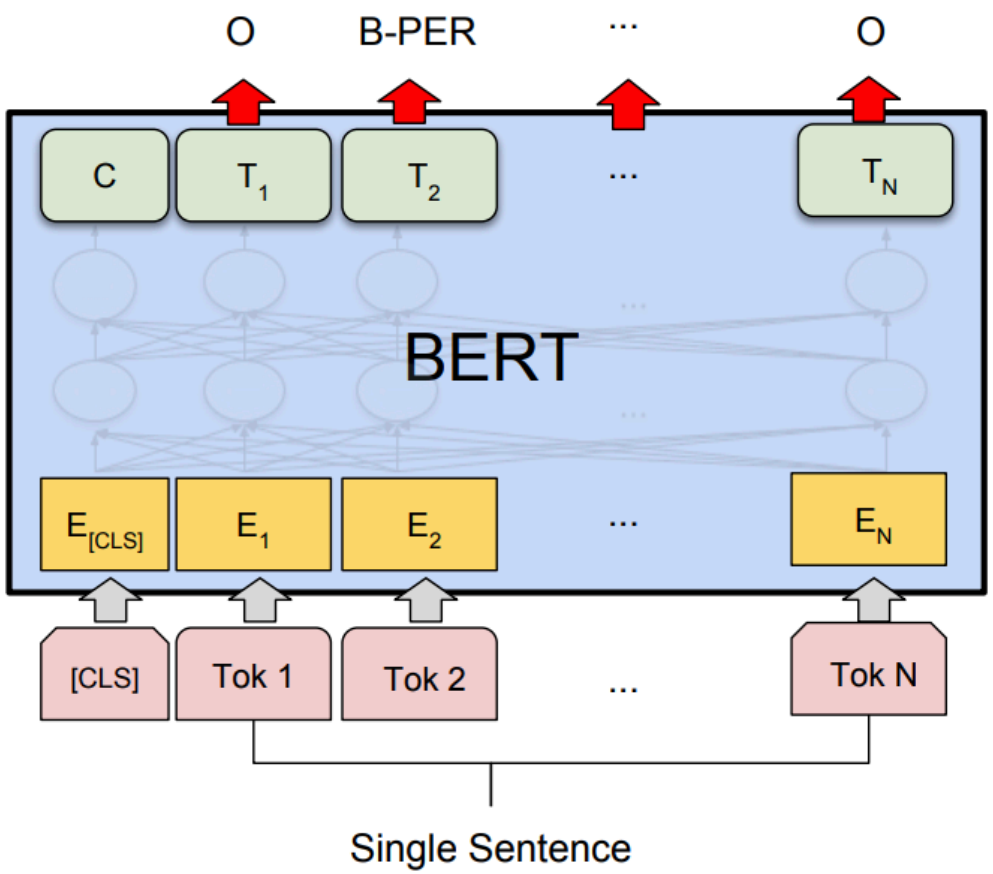
Example: Natural Language Inference

Pairs of sentences are given one of 3 labels

- `Neutral`
  - a: Jon walked back to the town to the smithy.
  - b: Jon traveled back to his hometown.
- `Contradicts`
  - a: Tourist Information offices can be very helpful.
  - b: Tourist Information offices are never of any help.
- `Entails`
  - a: I'm confused.
  - b: Not all of it is very clear to me.

How? —> pass the premise/hypothesis pairs through BERT and use the output vector for the [CLS] token as the input to the classification head .

Using BERT for sequence labeling



Devlin et al. 2018 - BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

Using BERT for sequence labeling

Assign a label from a small fixed set of labels to each token in the sequence.

- Named entity recognition
- Part of speech tagging

Named Entity Recognition

A **named entity** is anything that can be referred to with a proper name: a person, a location, an organization

Named entity recognition (NER): find spans of text that constitute proper names and tag the type of the entity

Type	Tag	Sample Categories	Example sentences
People	PER	people, characters	**Turing** is a giant of computer science.
Organization	ORG	companies, sports teams	The **IPCC** warned about the cyclone.
Location	LOC	regions, mountains, seas	**Mt. Sanitas** is in **Sunshine Canyon**.
Geo-Political Entity	GPE	countries, states	**Palo Alto** is raising the fees for parking.

Named Entity Recognition

Citing high fuel prices, [ORG **United Airlines**] said [TIME **Friday**] it has increased fares by [MONEY **$6**] per round trip on flights to some cities also served by lower-cost carriers. [ORG **American Airlines**], a unit of [ORG **AMR Corp.**], immediately matched the move, spokesman [PER **Tim Wagner**] said. [ORG **United**], a unit of [ORG **UAL Corp.**], said the increase took effect [TIME **Thursday**] and applies to most routes where it competes against discount carriers, such as [LOC **Chicago**] to [LOC **Dallas**] and [LOC **Denver**] to [LOC **San Francisco**].

BIO Tagging

Ramshaw and Marcus (1995)

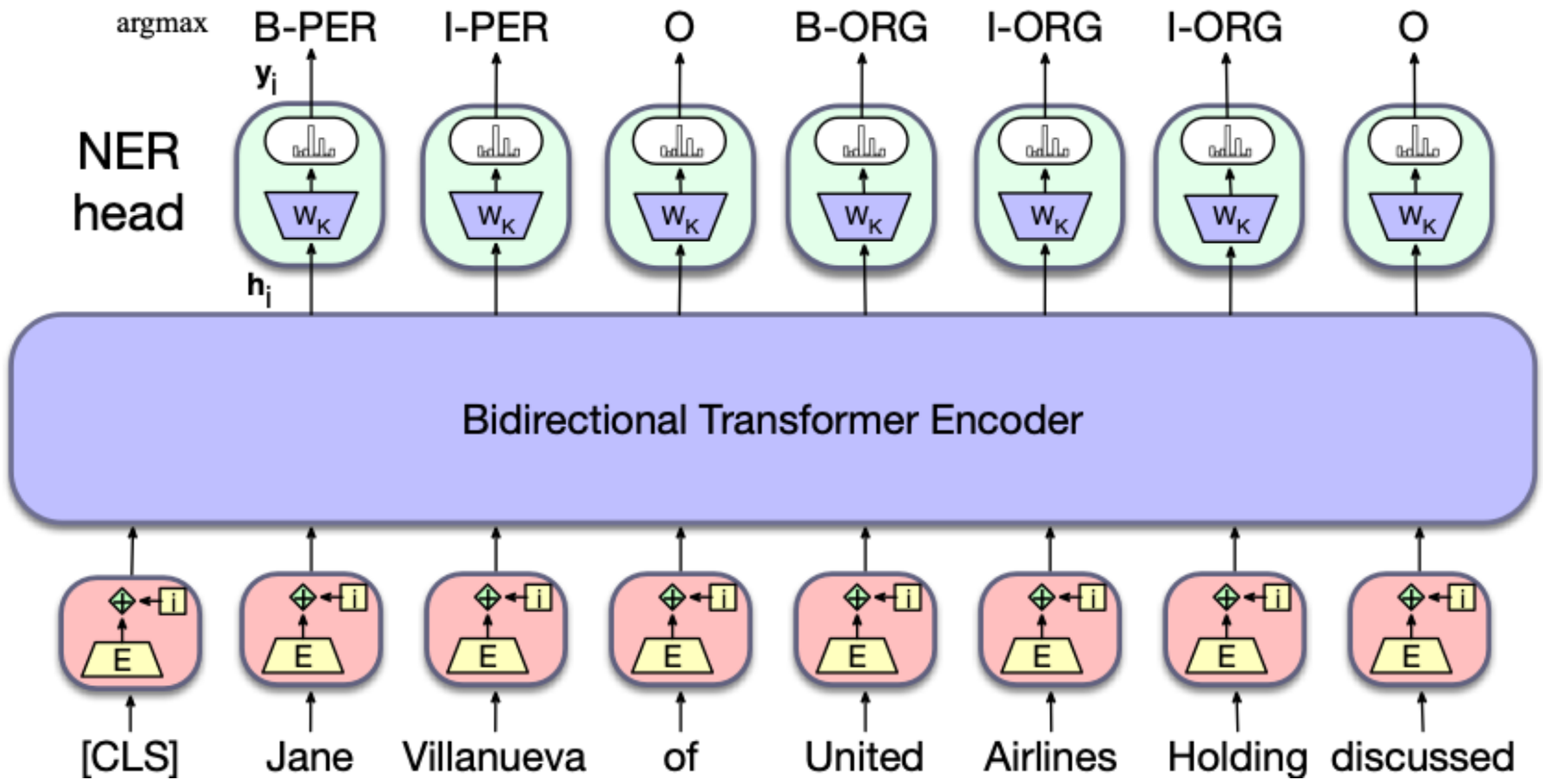
A method that lets us turn a segmentation task (finding boundaries of entities) into a classification task

[PER **Jane Villanueva**] of [ORG **United**] , a unit of [ORG **United Airlines Holding**] , said the fare applies to the [LOC **Chicago**] route.

Words	IO Label	BIO Label	BIOES Label
Jane	I-PER	B-PER	B-PER
Villanueva	I-PER	I-PER	E-PER
of	O	O	O
United	I-ORG	B-ORG	B-ORG
Airlines	I-ORG	I-ORG	I-ORG
Holding	I-ORG	I-ORG	E-ORG
discussed	O	O	O
the	O	O	O
Chicago	I-LOC	B-LOC	S-LOC
route	O	O	O
.	O	O	O

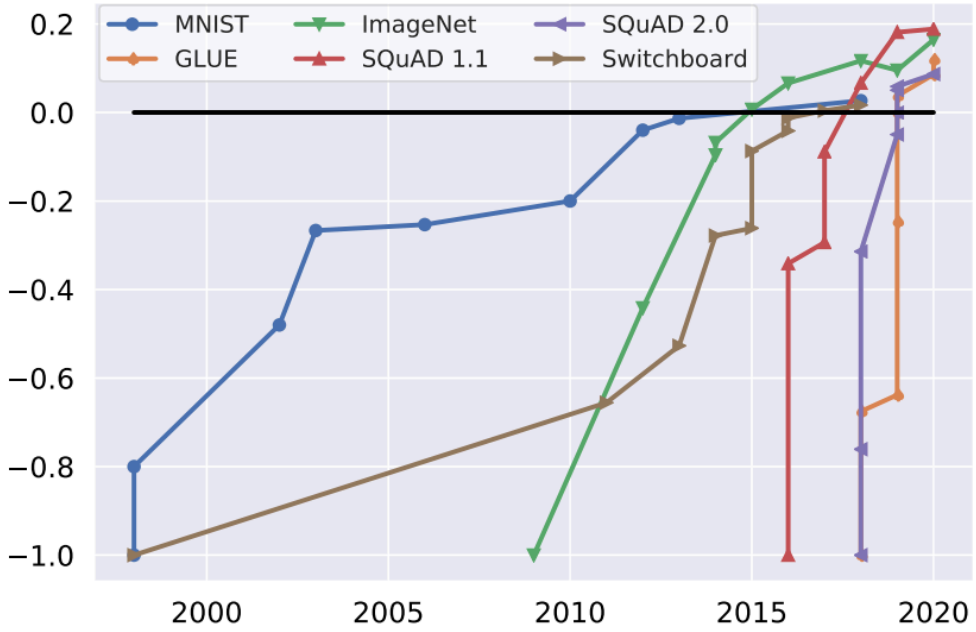
Sequence labeling

$$\mathbf{y_i} = \text{softmax}(\mathbf{h_i^L W_K})$$
$$\mathbf{t_i} = \text{argmax}_k(\mathbf{y}_i)$$



Evaluating pre-trained language models

- How good are fine-tuning language models?
- Glue, SuperGLUE, SQuAD, MasakhaNER, etc.



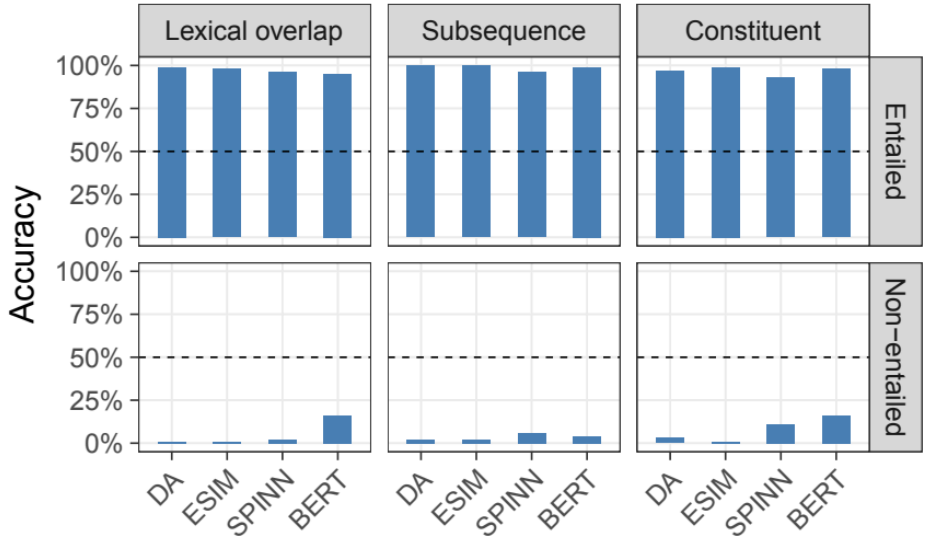
Performance (relative to human performance) saturation over time

Kiela et al. (2021) - Dynabench: Rethinking Benchmarking in NLP

Practical considerations: Out-of-domain generalization

- Do models *truly* learn the task they are supposed to learn?
- What happens if we evaluate models *outside the training distribution?*
- Models can learn shortcuts present in the training data

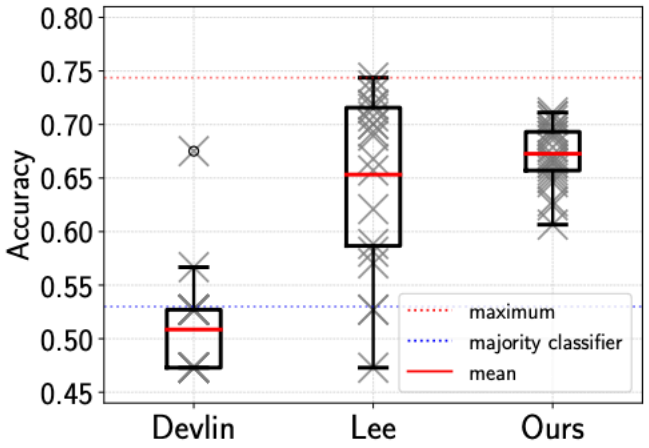
McCoy et al. (2019) - Right for the Wrong Reasons: Diagnosing Syntactic Heuristics in Natural Language Inference



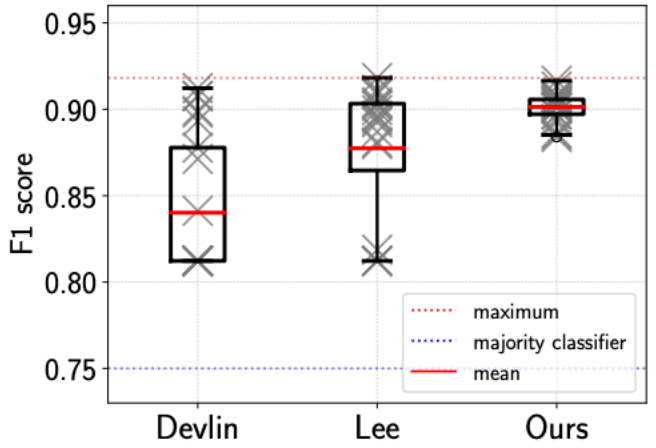
Heuristic	Premise	Hypothesis	Label
Lexical overlap heuristic	The banker near the judge saw the actor.	The banker saw the actor.	E
	The lawyer was advised by the actor.	The actor advised the lawyer.	E
	The doctors visited the lawyer.	The lawyer visited the doctors.	N
	The judge by the actor stopped the banker.	The banker stopped the actor.	N

Practical considerations: Fine-tuning (in)stability

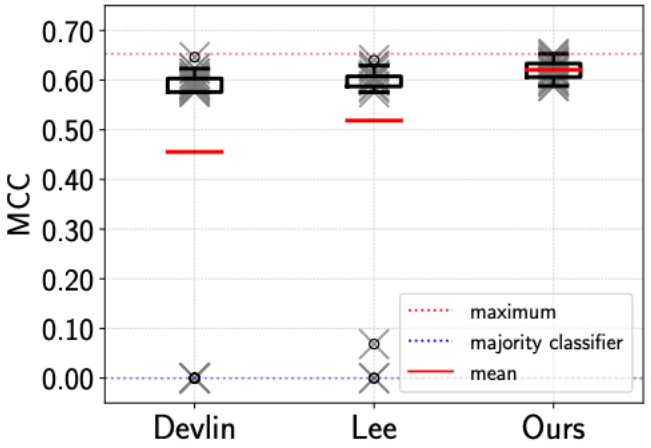
- Repeat fine-tuning many times and change only the data order + weights of the classification layer
- Substantial variations in task performance



(a) RTE



(b) MRPC

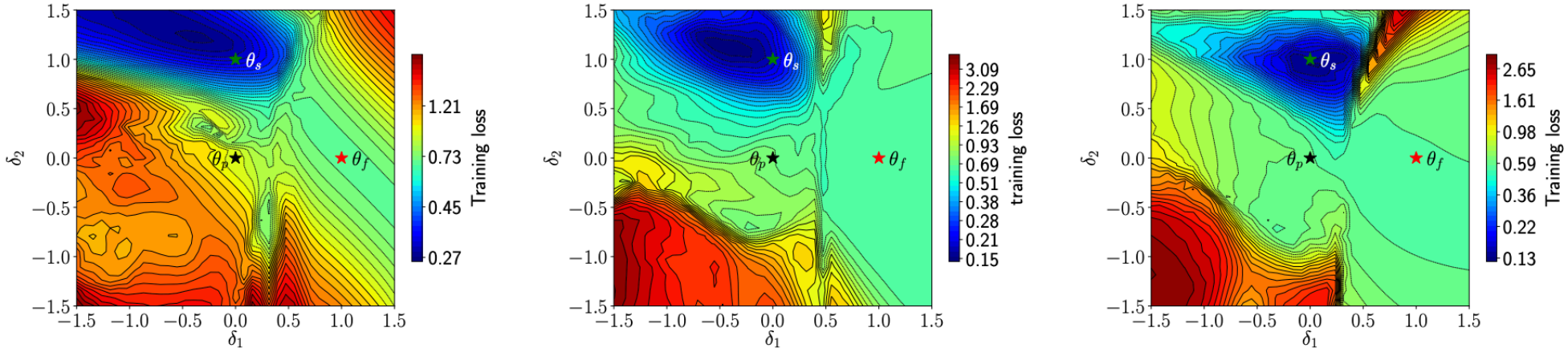


(c) CoLA

Mosbach et al. (2021) - On the Stability of Fine-tuning BERT: Misconceptions, Explanations, and Strong Baselines

Practical considerations: Fine-tuning (in)stability

- Fine-tuning can fail due to optimization problems
- You have to choose your step-size (learning rate) carefully



(a) RTE (b) MRPC (c) CoLA

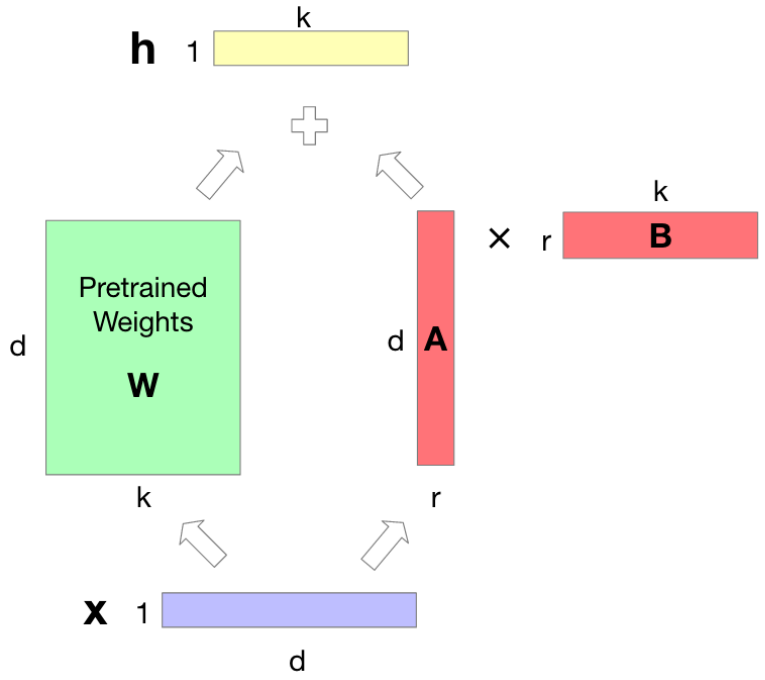
Mosbach et al. (2021) - On the Stability of Fine-tuning BERT: Misconceptions, Explanations, and Strong Baselines

Practical considerations: Parameter-efficient fine-tuning

- As models grow in size, fine-tuning can be expensive both in memory and time
- But do we really need to fine-tune all weights of a pre-trained model?
- There exist many method for fine-tuning only a subset of the weights and these models often achieve very similar performance compare to fine-tuning all weights

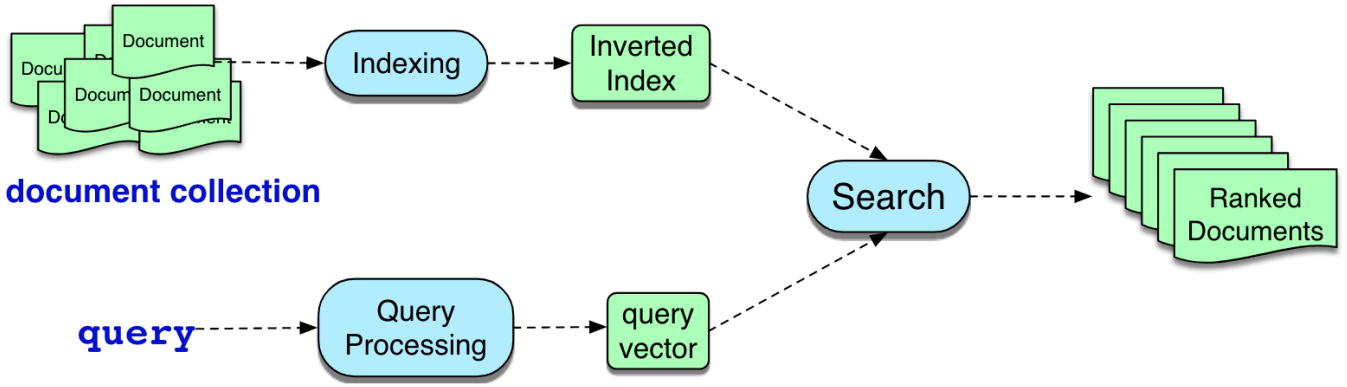
LoRA

- Low-rank adaptation (LoRA) is a widely used parameter-efficient fine-tuning method (PEFT)
- Fine-tuning introduces changes to the models weights $\mathbf{W}' = \mathbf{W} + \Delta\mathbf{W}$
- Let's assume $\Delta\mathbf{W}$ is low rank
- Parameterize $\Delta\mathbf{W} = \mathbf{AB}$
- Now learn only $\mathbf{A}$ and $\mathbf{B}$



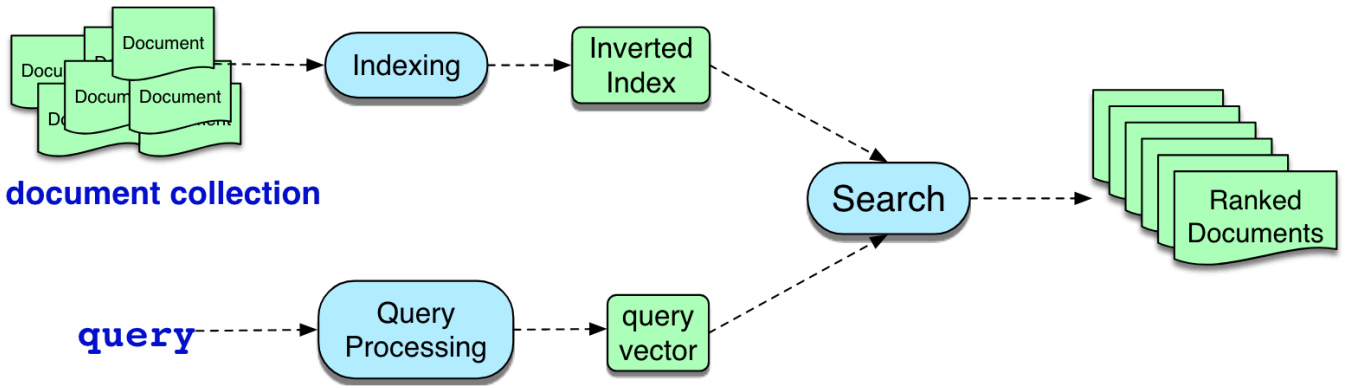
Information retrieval

- Retrieve *media* based on a user's *information need*
- We consider a special case of IR: **ad-hoc retrieval**
- A user provides a question to a system, which then returns one or more documents from a collection of documents



Information retrieval

- **Document**: the unit of text that the IR system indexes
- **Collection**: set of documents
- **Term**: a word (or paragraph) that occurs in the collection
- **Query**: information need expressed as a set of terms



Recall from Week 5

Embedding types

- **There are three main types of embeddings used in NLP and they are created using three different methods:**

  1. Sparse embeddings and term-document frequency

  2. Dense embeddings and Word2Vec algorithms

  3. Contextual word embeddings and language modeling

Recall from Week 5

Term frequency (tf) in the tf-idf algorithm

We could imagine using raw count:

$$\text{tf}_{t,d} = \text{count}(t,d)$$

But instead of using raw count, we usually squash a bit:

$$\text{tf}_{t,d} = \begin{cases} 1 + \log_{10} \text{count}(t,d) & \text{if } \text{count}(t,d) > 0 \\ 0 & \text{otherwise} \end{cases}$$

Recall from Week 5

Inverse document frequency (idf)

$$\text{idf}_t = \log_{10}\left(\frac{N}{\text{df}_t}\right)$$

df_t *is* the number of documents *t* occurs in.

(note this is not collection frequency: total count across all documents)

N is the total number of documents in the collection

tf-idf scoring

- Weighted value for each term

$$w_{t,d} = \text{tf}_{t,d} \times \text{idf}_f$$

- How do we score queries and documents?

$$\text{score}(q, d) = \cos(\mathbf{q}, \mathbf{d}) = \frac{\mathbf{q} \cdot \mathbf{d}}{|\mathbf{q}||\mathbf{d}|}$$

tf-idf scoring

$$\text{score}(q,d) = \cos(\mathbf{q},\mathbf{d}) = \frac{\mathbf{q}\cdot\mathbf{d}}{|\mathbf{q}||\mathbf{d}|}$$

- Rewrite the dot-product as a sum of products

$$\text{score}(q,d) = \sum_{t\in\mathbf{q}} \frac{\text{tf-idf}(t,q)}{\sqrt{\sum_{q_i\in q}\text{tf-idf}^2(q_i,q)}} \cdot \frac{\text{tf-idf}(t,d)}{\sqrt{\sum_{d_i\in d}\text{tf-idf}^2(d_i,d)}}$$

tf-idf scoring

$$\text{score}(q,d) = \sum_{t \in \mathbf{q}} \frac{\text{tf-idf}(t,q)}{\sqrt{\sum_{q_i \in q} \text{tf-idf}^2(q_i,q)}} \cdot \frac{\text{tf-idf}(t,d)}{\sqrt{\sum_{d_i \in d} \text{tf-idf}^2(d_i,d)}}$$

Query:	sweet love
Doc 1:	Sweet sweet nurse! Love?
Doc 2:	Sweet sorrow
Doc 3:	How sweet is love?
Doc 4:	Nurse!

	Query					
word	**cnt**	**tf**	**df**	**idf**	**tf-idf**	**n'lized** = tf-idf/$\lvert q \rvert$
sweet	1	1	3	0.125	0.125	0.383
nurse	0	0	2	0.301	0	0
love	1	1	2	0.301	0.301	0.924
how	0	0	1	0.602	0	0
sorrow	0	0	1	0.602	0	0
is	0	0	1	0.602	0	0
$\lvert q \rvert = \sqrt{.125^2 + .301^2} = .326$						

tf-idf scoring

$$\text{score}(q,d) = \sum_{t \in \mathbf{q}} \frac{\text{tf-idf}(t,q)}{\sqrt{\sum_{q_i \in q} \text{tf-idf}^2(q_i,q)}} \cdot \frac{\text{tf-idf}(t,d)}{\sqrt{\sum_{d_i \in d} \text{tf-idf}^2(d_i,d)}}$$

Query:	sweet love
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	Document 1					Document 2				
word	**cnt**	**tf**	**tf-idf**	**n'lized**	**× q**	**cnt**	**tf**	**tf-idf**	**n'lized**	**×q**
sweet	2	1.301	0.163	0.357	**0.137**	1	1.000	0.125	0.203	**0.0779**
nurse	1	1.000	0.301	0.661	0	0	0	0	0	0
love	1	1.000	0.301	0.661	**0.610**	0	0	0	0	**0**
how	0	0	0	0	0	0	0	0	0	0
sorrow	0	0	0	0	0	1	1.000	0.602	0.979	0
is	0	0	0	0	0	0	0	0	0	0
$\lvert d_1 \rvert = \sqrt{.163^2 + .301^2 + .301^2} = .456$						$\lvert d_2 \rvert = \sqrt{.125^2 + .602^2} = .615$				
Cosine: $\sum$ of column:					**0.747**	Cosine: $\sum$ of column:				**0.0779**

BM25

$$\text{idf}_t = \log_{10}\left(\frac{N}{\text{df}_t}\right)$$

- Introduce parameters k and b

$$\text{score}(q,d) = \sum_{t \in q} \overbrace{\log\left(\frac{N}{df_t}\right)}^{\text{IDF}} \overbrace{\frac{tf_{t,d}}{k\left(1-b+b\left(\frac{|d|}{|d_{\text{avg}}|}\right)\right)+tf_{t,d}}}^{\text{weighted tf}}$$

Information retrieval

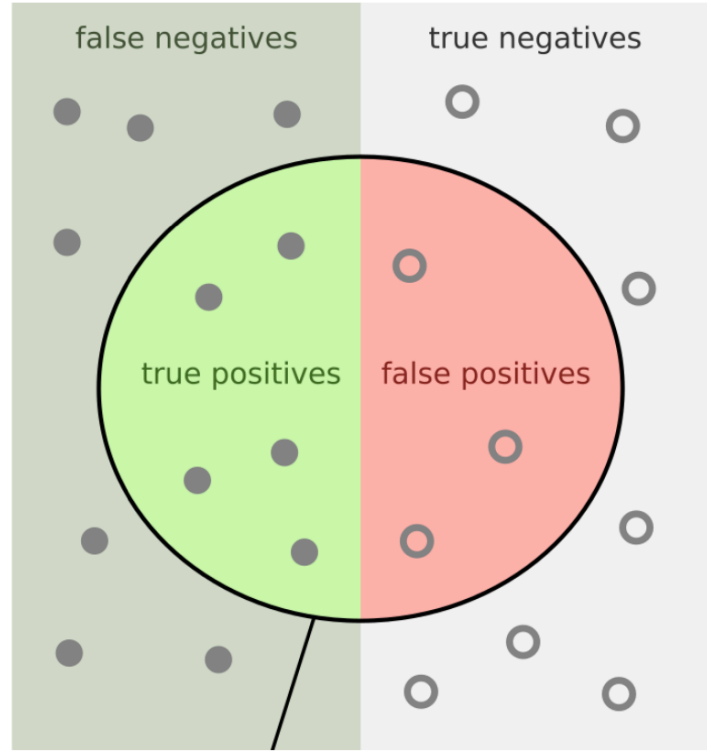
- Efficiently find documents that contain terms of interest
- **Inverted index**
  - Dictionary: list of terms (+ document frequency)
  - Postings list: list of document ids that contain the term (+ term frequency in each of the documents)

Query:	sweet love
Doc 1:	Sweet sweet nurse! Love?
Doc 2:	Sweet sorrow
Doc 3:	How sweet is love?
Doc 4:	Nurse!

how {1}	→	3 [1]
is {1}	→	3 [1]
love {2}	→	1 [1] → 3 [1]
nurse {2}	→	1 [1] → 4 [1]
sorry {1}	→	2 [1]
sweet {3}	→	1 [2] → 2 [1] → 3 [1]

Precision and Recall

- Heuristic classifiers tend to have high **precision** but very low **recall.**
- **Classifier accuracy is measured with precision and recall:**



How many relevant items are retrieved?

Recall = $\frac{\text{■}}{\text{■}}$

How many retrieved items are relevant?

Precision = $\frac{\text{■}}{\text{■}}$

Recall = TP / (**FN** +TP) Precision = TP / (**FP** +TP)

Precision and recall in IR

- Each document is either relevant or not relevant
- **Precision**: Fraction of retrieved documents that are relevant
- **Recall**: Fraction of all relevant documents that are retrieved
- Let T be the set of returned documents, R are the relevant documents in T, N are the irrelevant documents in T, U are all relevant documents in the collection

$$Precision = \frac{|R|}{|T|} \qquad Recall = \frac{|R|}{|U|}$$

Evaluation of information retrieval systems

- We care about the rank of the target document(s)
- **Precision@k:** fraction of relevant documents seen at a particular rank k
- **Recall@k:** fraction of relevant documents found at a particular rank k

Rank	Judgment	Precision_{Rank}	Recall_{Rank}
1	R	1.0	.11
2	N	.50	.11
3	R	.66	.22
4	N	.50	.22
5	R	.60	.33
6	R	.66	.44
7	N	.57	.44
8	R	.63	.55
9	N	.55	.55
10	N	.50	.55

Evaluation of information retrieval systems

- **Mean average precision** (MAP)
  - Iterate over the ranked list top to bottom
  - Note the precision **only** at positions where a relevant item has been encountered
  - Average these precisions over the return set
  - Formally: Let R_r be the set of relevant documents at or above rank r
  - **Average precision**:

$$\mathrm{AP} = \frac{1}{|R_r|} \sum_{d \in R_r} \mathrm{Precision}_r(d)$$

    - $\mathrm{Precision}_r(d)$ precision measured at rank where d was found

Evaluation of information retrieval systems

- **Mean average precision** (MAP)
  - **Average precision**:

$$\mathrm{AP} = \frac{1}{|R_r|} \sum_{d \in R_r} \mathrm{Precision}_r(d)$$

    - $\mathrm{Precision}_r(d)$ precision measured at rank where d was found
- Given a set of queries Q:

$$\mathrm{MAP} = \frac{1}{|Q|} \sum_{q \in Q} \mathrm{AP}(q)$$

Evaluation of information retrieval systems

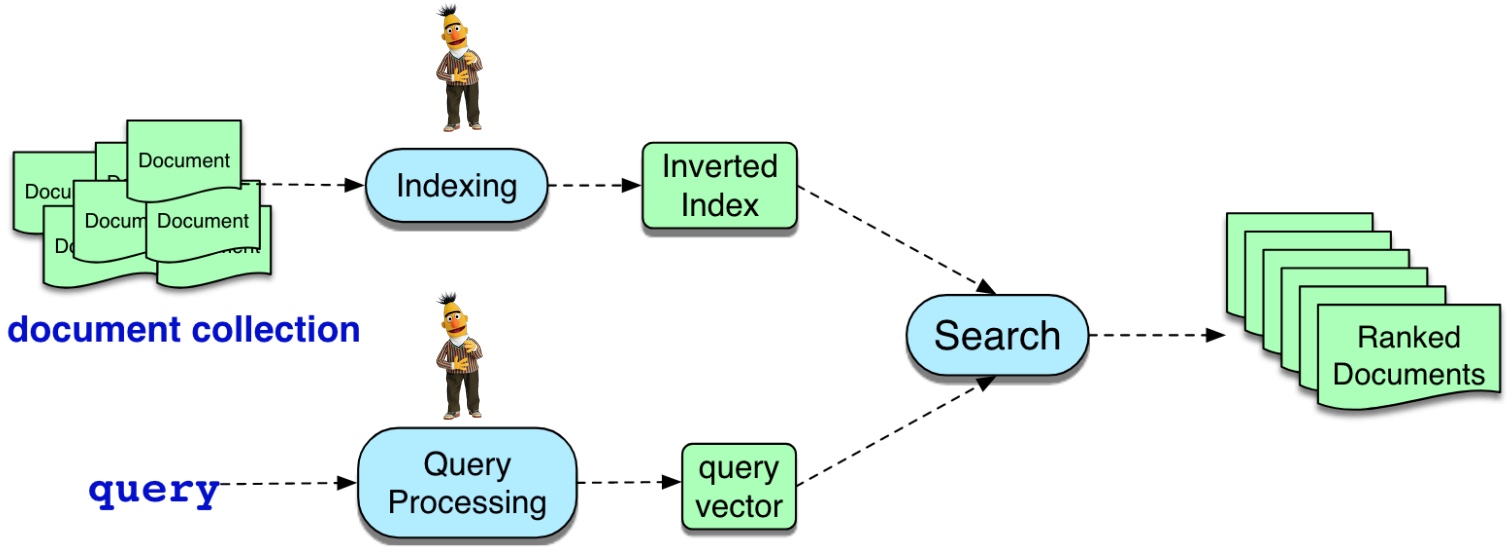
- **Mean average precision** (MAP)

$$\text{MAP} = \frac{1}{|Q|} \sum_{q \in Q} \text{AP}(q)$$

Rank	Judgment	Precision_{Rank}	Recall_{Rank}
1	R	1.0	.11
2	N	.50	.11
3	R	.66	.22
4	N	.50	.22
5	R	.60	.33
6	R	.66	.44
7	N	.57	.44
8	R	.63	.55
9	N	.55	.55
10	N	.50	.55

- Relevant docs at: 1, 3, 5, 6, 8
- Precisions: 1.0, 0.66, 0.60, 0.66, 0.63
- AP = (1.0 + 0.66 + 0.60 + 0.66 + 0.63) / 5 = 3.55 / 5 = 0.71

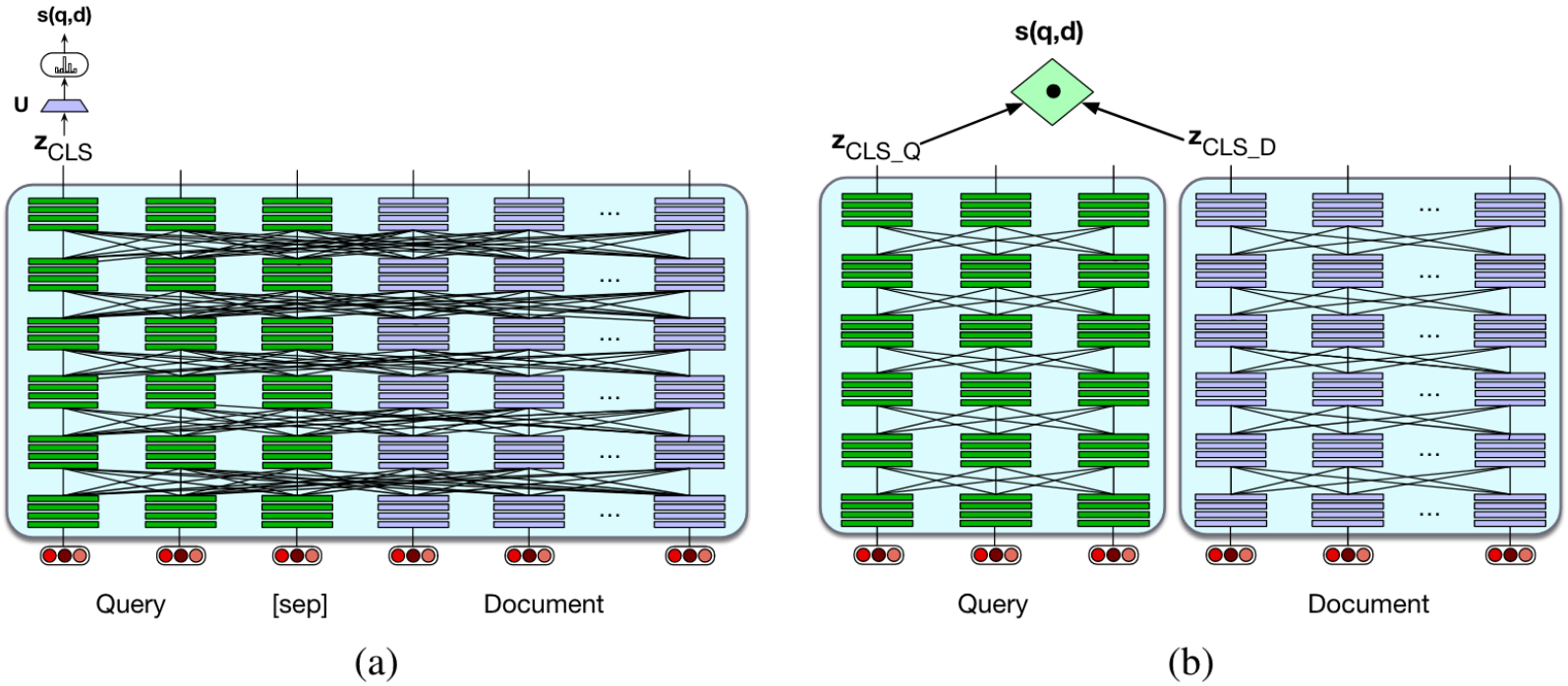
Information retrieval with pre-trained LMs



- Instead of using word-count vectors, use dense vectors from pre-trained language models, e.g., BERT

Information retrieval with pre-trained LMs

- Two potential ways to index queries and documents
  - Jointly encode query and each document
  - Bi-encoder: encode query and documents independently

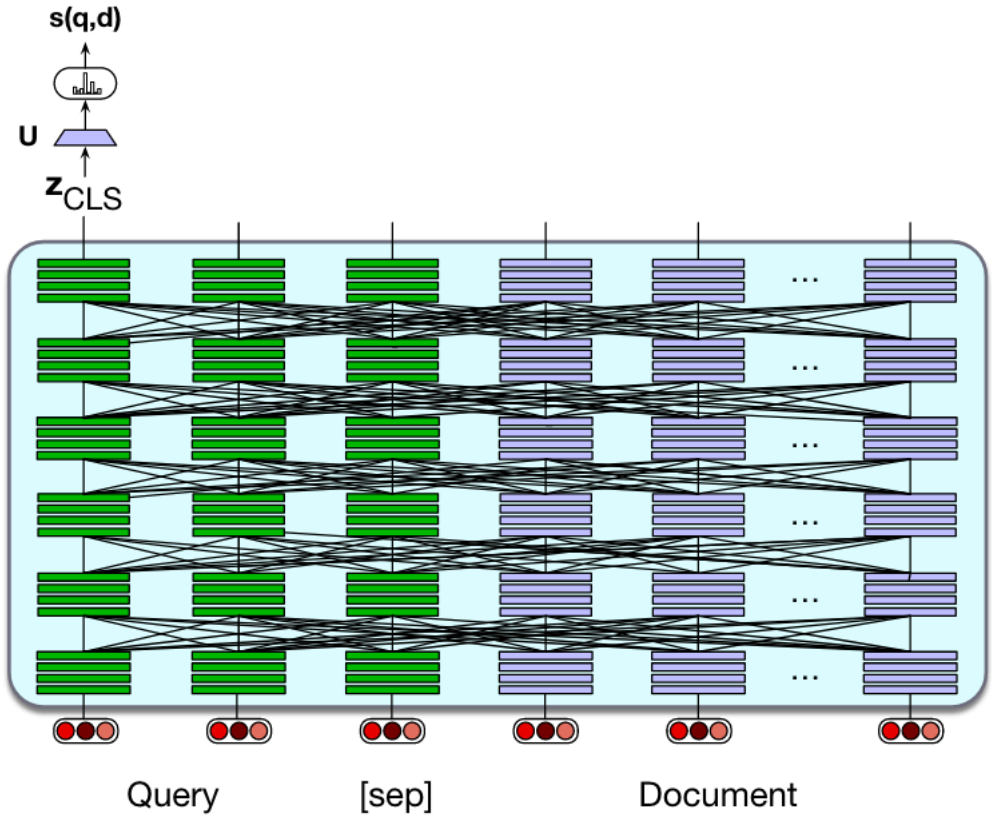


Information retrieval with pre-trained LMs

- Jointly encode query and every document

$$\mathbf{z} = \text{BERT}(q; [\text{SEP}]; d)[\text{CLS}]$$

$$\text{score}(\mathbf{z}) = \text{softmax}(\mathbf{U}\mathbf{z})$$

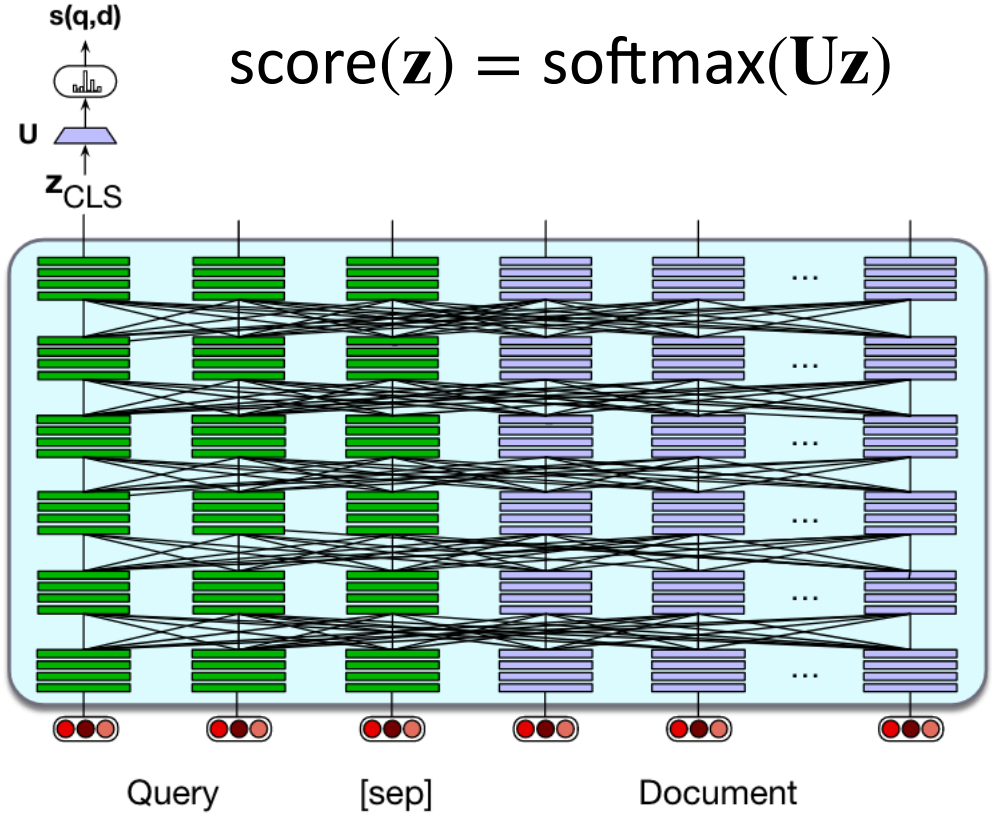


Information retrieval with pre-trained LMs

- This approach is expensive
- Need to re-encode every document for each query
- This quickly becomes impractical when dealing with large document collections

$$\mathbf{z} = \text{BERT}(q; [\text{SEP}]; d)[\text{CLS}]$$

$$\text{score}(\mathbf{z}) = \text{softmax}(\mathbf{U}\mathbf{z})$$



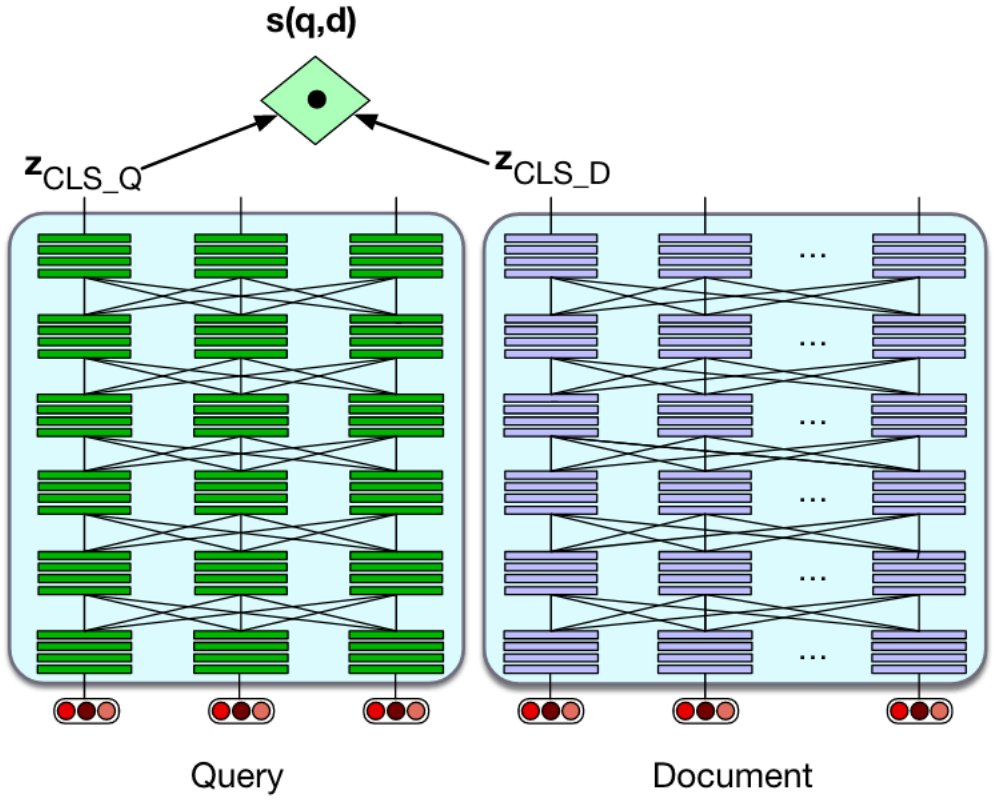
Information retrieval with pre-trained LMs

- **Bi-encoder**: encode queries and documents independently

$$\mathbf{z}_q = \text{BERT}_{\text{query}}(q)[\text{CLS}]$$

$$\mathbf{z}_d = \text{BERT}_{\text{doc}}(d)[\text{CLS}]$$

$$\text{score}(q, d) = \mathbf{z}_q \cdot \mathbf{z}_d$$



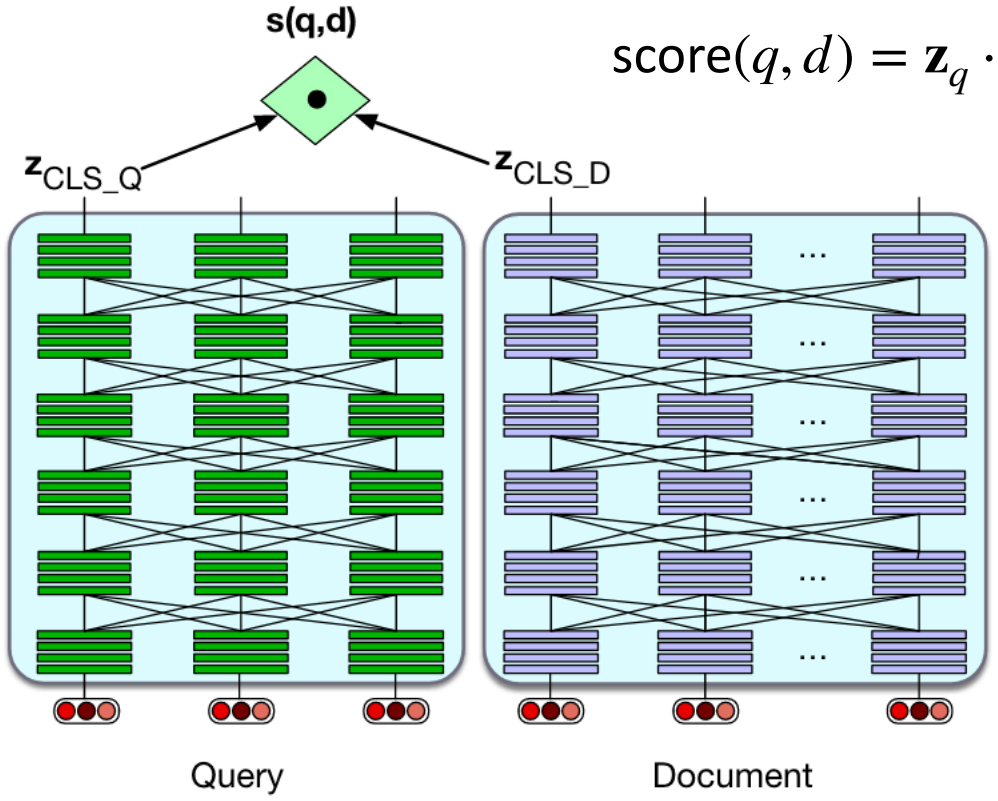
Information retrieval with pre-trained LMs

- Documents are encoded in advance
- When a new query comes in, we only have to encode that query
- Much more efficient but tends to give worse results
- Question: How to combine the two approaches?

$$\mathbf{z}_q = \text{BERT}_{\text{query}}(q)[\text{CLS}]$$

$$\mathbf{z}_d = \text{BERT}_{\text{doc}}(d)[\text{CLS}]$$

$$\text{score}(q, d) = \mathbf{z}_q \cdot \mathbf{z}_d$$



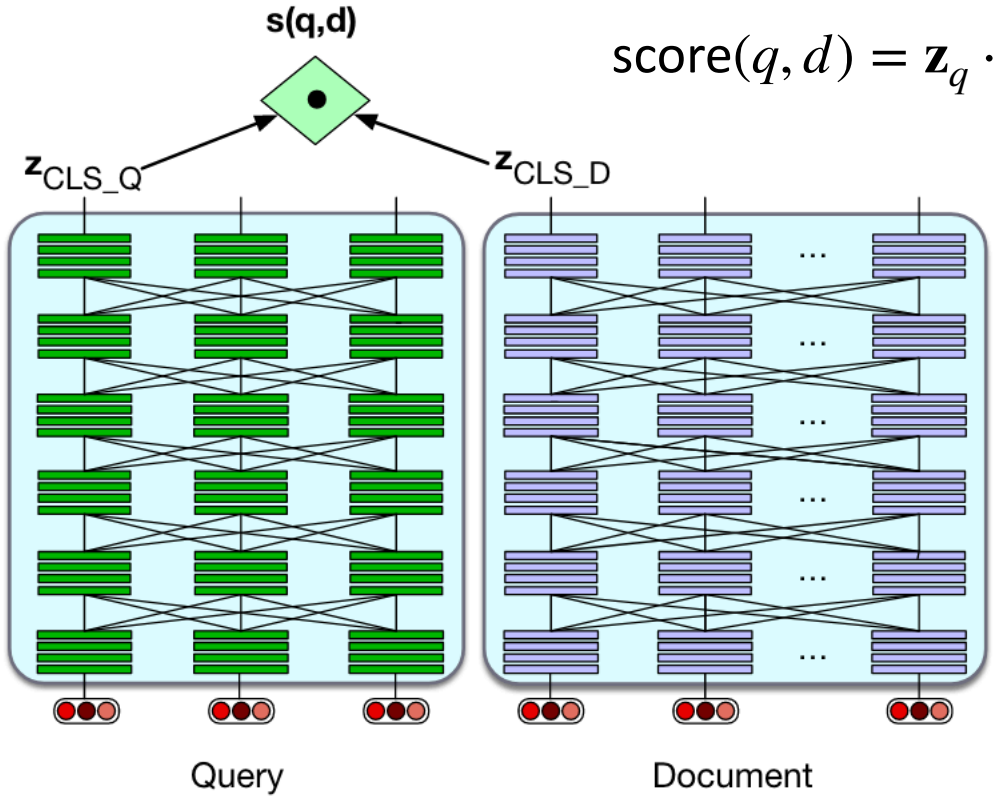
Information retrieval with pre-trained LMs

- Documents are encoded in advance
- When a new query comes in, we only have to encode that query
- Much more efficient but tends to give worse results
- Question: How to combine the two approaches?
  - **Re-ranking**

$$\mathbf{z}_q = \text{BERT}_{\text{query}}(q)[\text{CLS}]$$

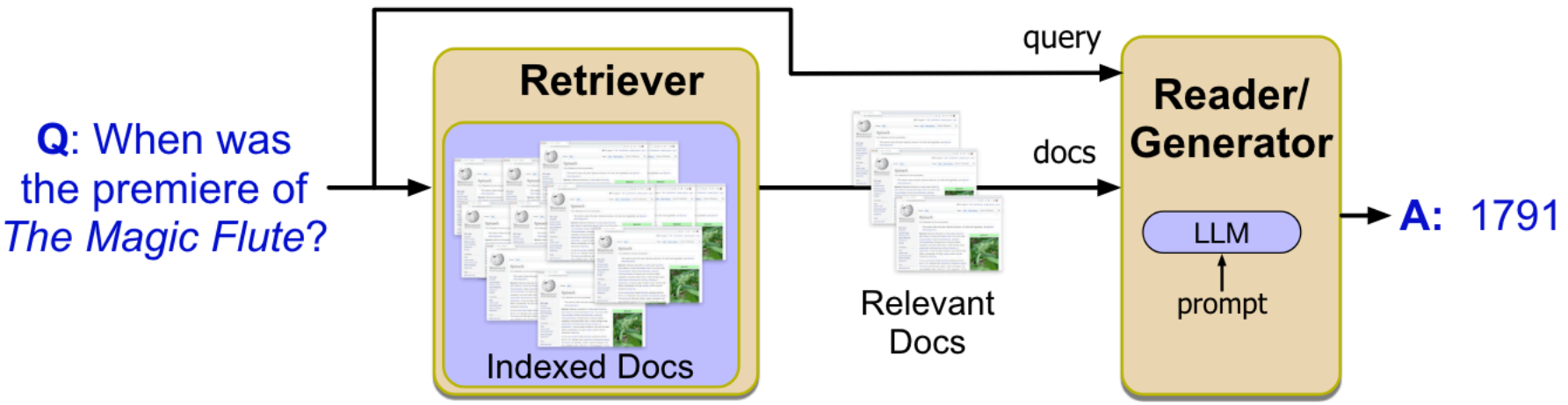
$$\mathbf{z}_d = \text{BERT}_{\text{doc}}(d)[\text{CLS}]$$

$$\text{score}(q, d) = \mathbf{z}_q \cdot \mathbf{z}_d$$



Information retrieval with pre-trained LMs

- Question Answering (QA) as a retrieval problem
- Find supporting documents for a query
- Extract or generate an answer based on the top-k docs



Information retrieval with pre-trained LMs

- Consider the document on the right
- There exist many queries for which this document might be relevant
  - When was HEC founded?
  - Can I do a PhD at HEC?
  - What's Viger Square?
  - Etc.
- Ideally, all of this needs to be encoded in the document representation

HEC Montréal (French: *Hautes études commerciales de Montréal*; English: *High Commercial Studies of Montreal*) is a bilingual public business school located in Montreal, Quebec, Canada. Founded in 1907, HEC Montréal is the graduate business school of the Université de Montréal and is the first established school of management in Canada.[2][3]

HEC Montréal offers undergraduate, graduate, and post-graduate programs, including Bachelor of Business Administration (BBA), Master of Science in Administration (MSc), Master of Management (MM), Master of Business Administration (MBA), and PhD in Administration, in addition to a joint Executive MBA program with McGill University.

HEC Montréal was founded in 1907 by the Board of Trade of Metropolitan Montreal. Its initial building in Viger Square is now called the Gilles Hocquart Building.[2]

In 1988, a group of HEC students established Jeux du Commerce, where more than 1300 students from 14 universities in Eastern Canada gather annually for academic, social, and sports events.[4][5] A similar competition has been established in Western Canada called JDC West.

As of 2021, the centenary of the HEC Montréal Alumni Association, the school had over 100,000 alumni.[6]

How to improve dense retrieval?

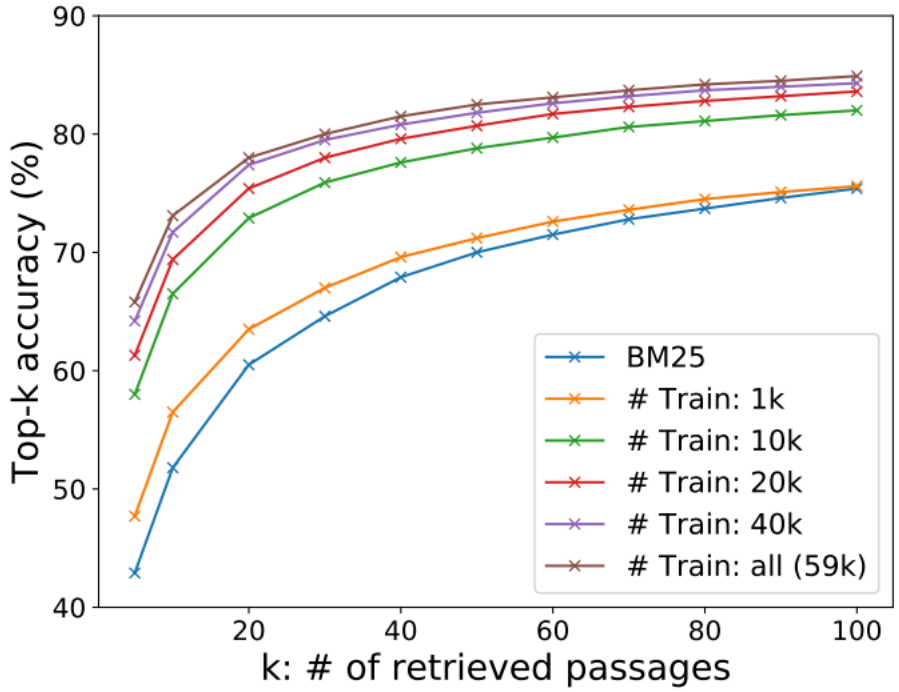
- Use a collection $\{(q_i, d_i^+, d_i^-)\}_{i=1}^n$ of queries paired with positive and negative documents
- Learn an implicit relevance definition based on this collection via **contrastive learning**
- Intuition: move positive documents close to query, push negative documents away from query

$$\mathcal{L}(q_i, d_i^+, \{d_{i,j}^-\}_{j=1}^k) = \frac{\exp(\mathbf{q} \cdot \mathbf{d}_i^+)}{\exp(\mathbf{q_i} \cdot \mathbf{d_i}^+) + \sum_{j=1}^k \exp(\mathbf{q}_i \cdot \mathbf{d}_{i,j}^-)}$$

Karpukhin et al. (2020) - Dense Passage Retrieval for Open-Domain Question Answering

Dense Passage Retrieval for Open-Domain QA

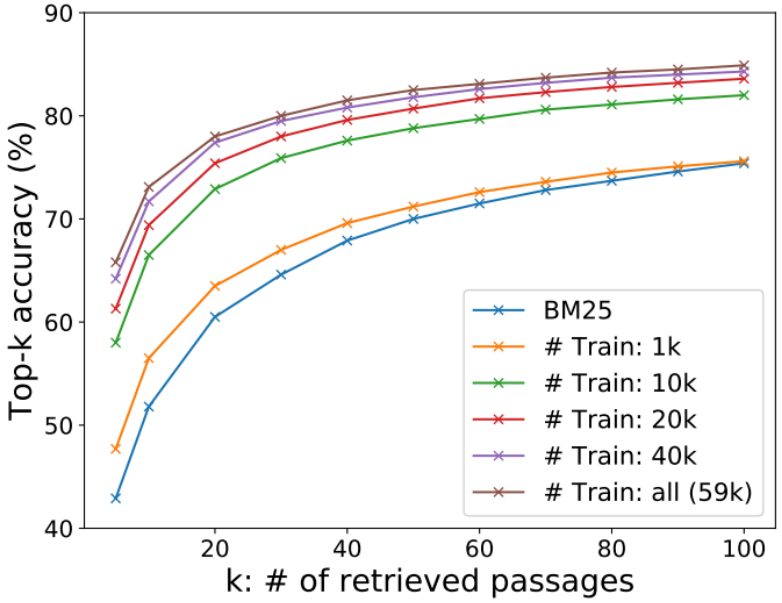
- How does it compare to BM25?

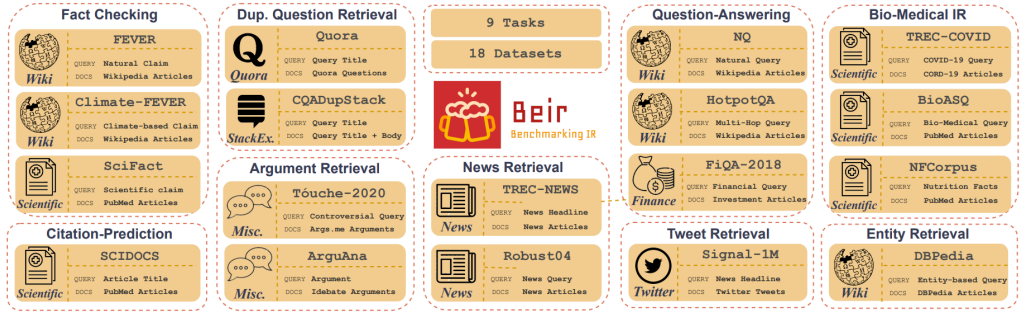


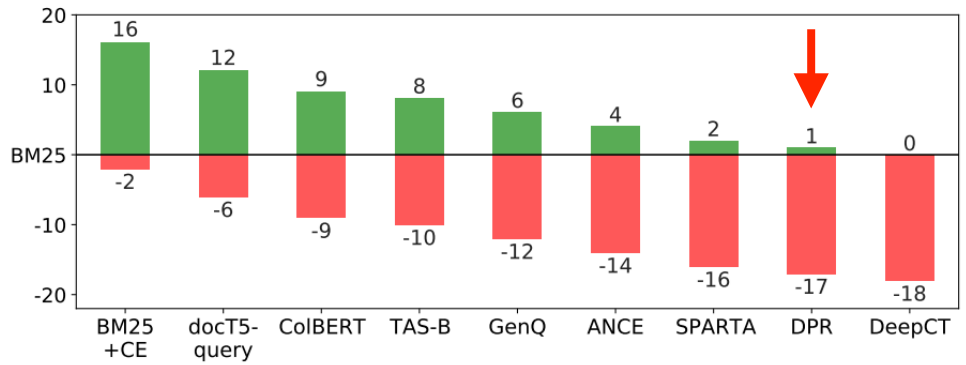
Karpukhin et al. (2020) - Dense Passage Retrieval for Open-Domain Question Answering

Dense Passage Retrieval for Open-Domain QA

- What happens outside of the training distribution?
- Question: what could be the reason?







Thakur et al. (2021) - BEIR: A Heterogenous Benchmark for Zero-shot Evaluation of Information Retrieval Models

Practical considerations

- How to efficiently search over dense representations?
  - Approximate nearest neighbour search
  - Fast embedding search (FAISS) on GPUs

[15 minute break]