# CSCE 670 - Information Storage and Retrieval

## Lecture 16: Neural Ranking, Dense Passage Retrieval

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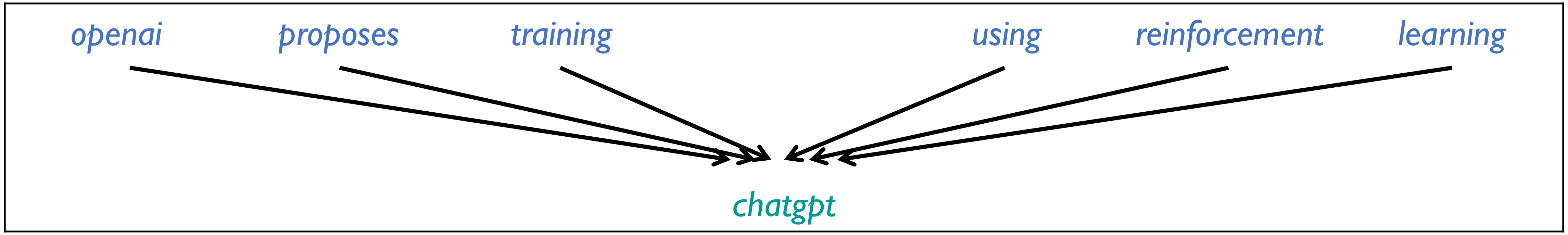
Course Website: https://yuzhang-teaching.github.io/CSCE670-F25.html

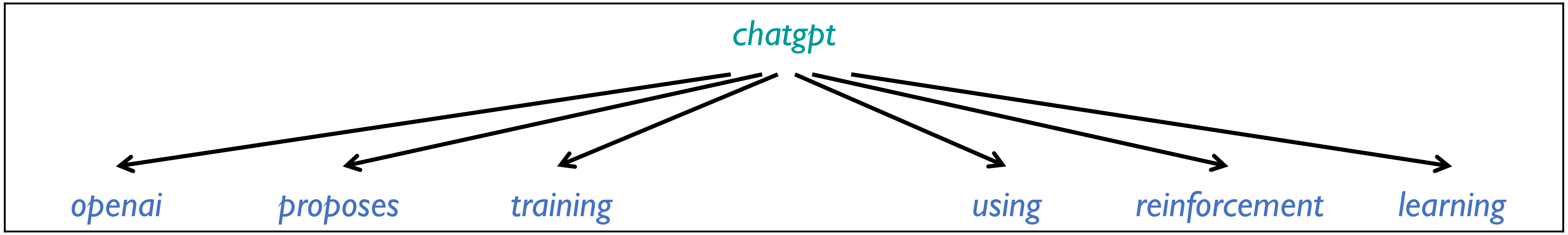
Adapted from the slides by Prof. James Caverlee

## Recap: word2vec

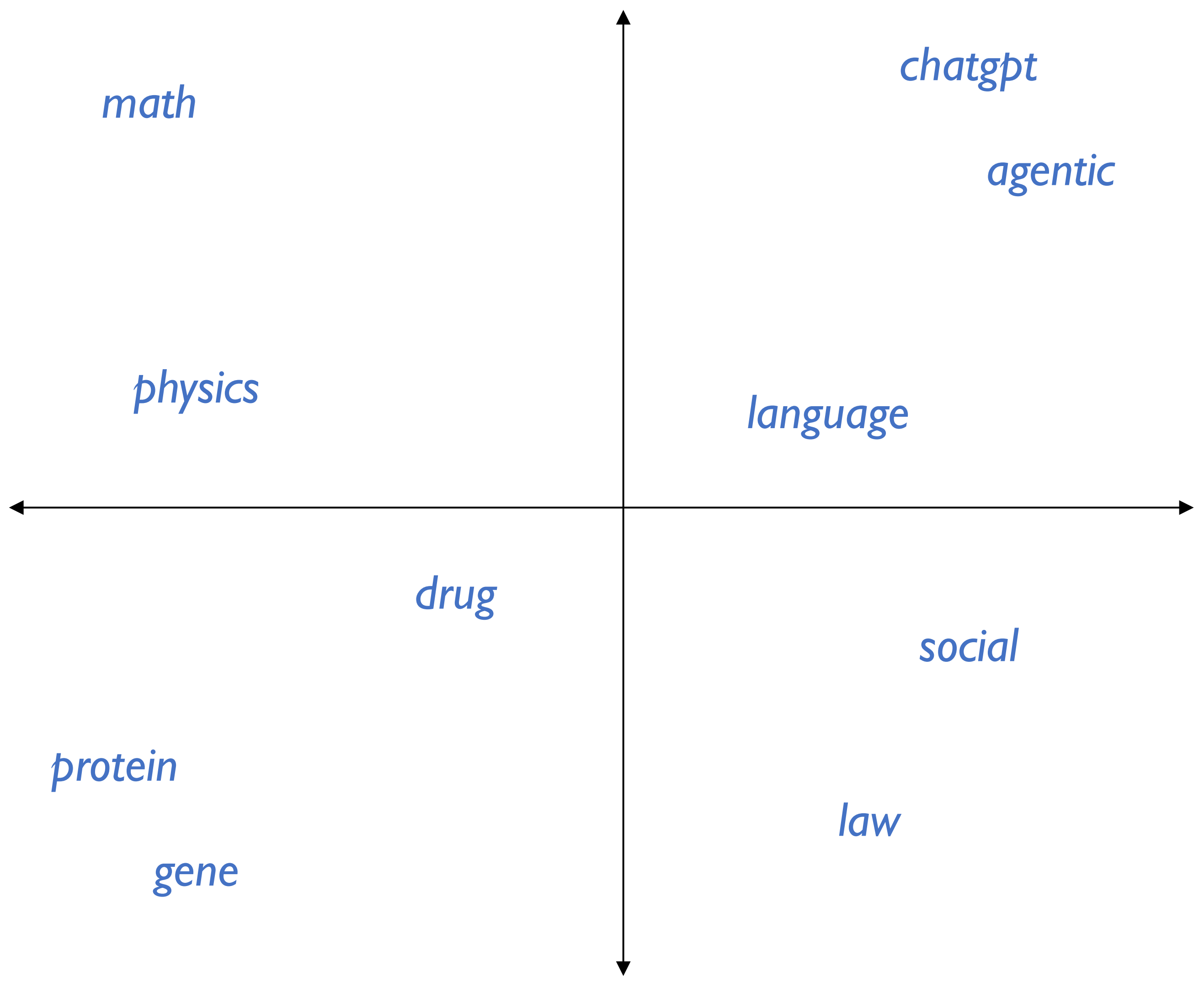
- Continuous Bag-of-Words (CBOW): using context to predict word



- Skip-Gram: using word to predict context



## Words are now distributed in the vector space in this way!



But how to use word embeddings to improve search?

## Simplest Solution: Taking the Average/Sum

- Query $q$:"*large language models*"

$$\boldsymbol{e}_q = \frac{1}{|q|}\sum_{w \in q} \boldsymbol{e}_w = \frac{1}{3}\left(\boldsymbol{e}_{\text{large}} + \boldsymbol{e}_{\text{language}} + \boldsymbol{e}_{\text{models}}\right)$$

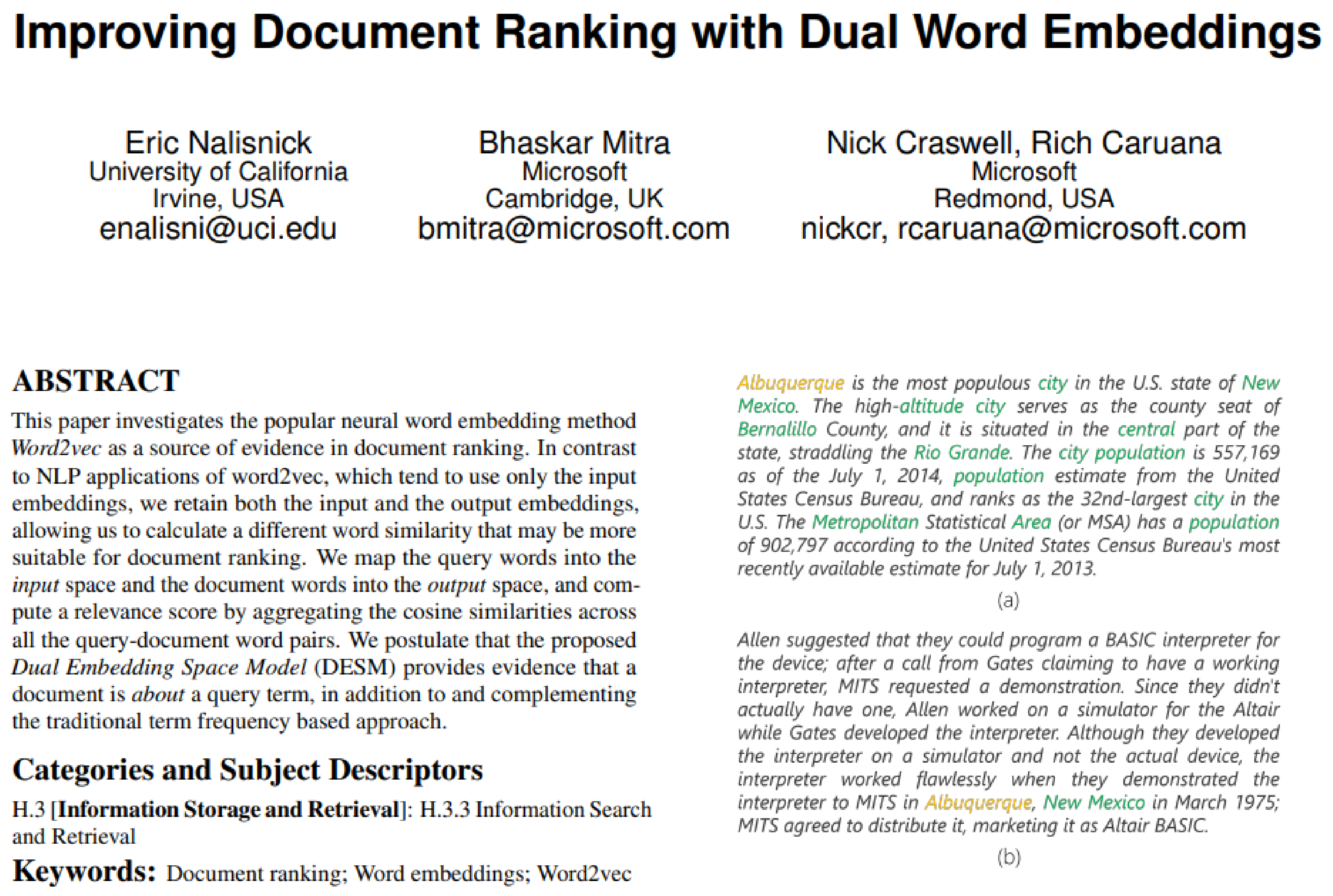
- Document $d$:"*openai proposes training chatgpt using reinforcement learning*"

$$\boldsymbol{e}_d = \frac{1}{|d|}\sum_{w \in d} \boldsymbol{e}_w = \frac{1}{7}\left(\boldsymbol{e}_{\text{openai}} + \boldsymbol{e}_{\text{proposes}} + \boldsymbol{e}_{\text{training}} + \cdots\right)$$

- Skip out-of-vocabulary words (if there are any)
- Can also take the sum instead of the average

- $\text{score}(q, d) = \cos(\boldsymbol{e}_q, \boldsymbol{e}_d)$ or $\boldsymbol{e}_q^T \boldsymbol{e}_d$

## DESM [Nalisnick et al., WWW 2016]



# Improving Document Ranking with Dual Word Embeddings

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## ABSTRACT

This paper investigates the popular neural word embedding method *Word2vec* as a source of evidence in document ranking. In contrast to NLP applications of word2vec, which tend to use only the input embeddings, we retain both the input and the output embeddings, allowing us to calculate a different word similarity that may be more suitable for document ranking. We map the query words into the *input* space and the document words into the *output* space, and compute a relevance score by aggregating the cosine similarities across all the query-document word pairs. We postulate that the proposed *Dual Embedding Space Model* (DESM) provides evidence that a document is *about* a query term, in addition to and complementing the traditional term frequency based approach.

## Categories and Subject Descriptors

H.3 [**Information Storage and Retrieval**]: H.3.3 Information Search and Retrieval

**Keywords:** Document ranking; Word embeddings; Word2vec

*Albuquerque is the most populous city in the U.S. state of New Mexico. The high-altitude city serves as the county seat of Bernalillo County, and it is situated in the central part of the state, straddling the Rio Grande. The city population is 557,169 as of the July 1, 2014, population estimate from the United States Census Bureau, and ranks as the 32nd-largest city in the U.S. The Metropolitan Statistical Area (or MSA) has a population of 902,797 according to the United States Census Bureau's most recently available estimate for July 1, 2013.*

(a)

*Allen suggested that they could program a BASIC interpreter for the device; after a call from Gates claiming to have a working interpreter, MITS requested a demonstration. Since they didn't actually have one, Allen worked on a simulator for the Altair while Gates developed the interpreter. Although they developed the interpreter on a simulator and not the actual device, the interpreter worked flawlessly when they demonstrated the interpreter to MITS in Albuquerque, New Mexico in March 1975; MITS agreed to distribute it, marketing it as Altair BASIC.*

(b)

## Dual Embedding Space Model

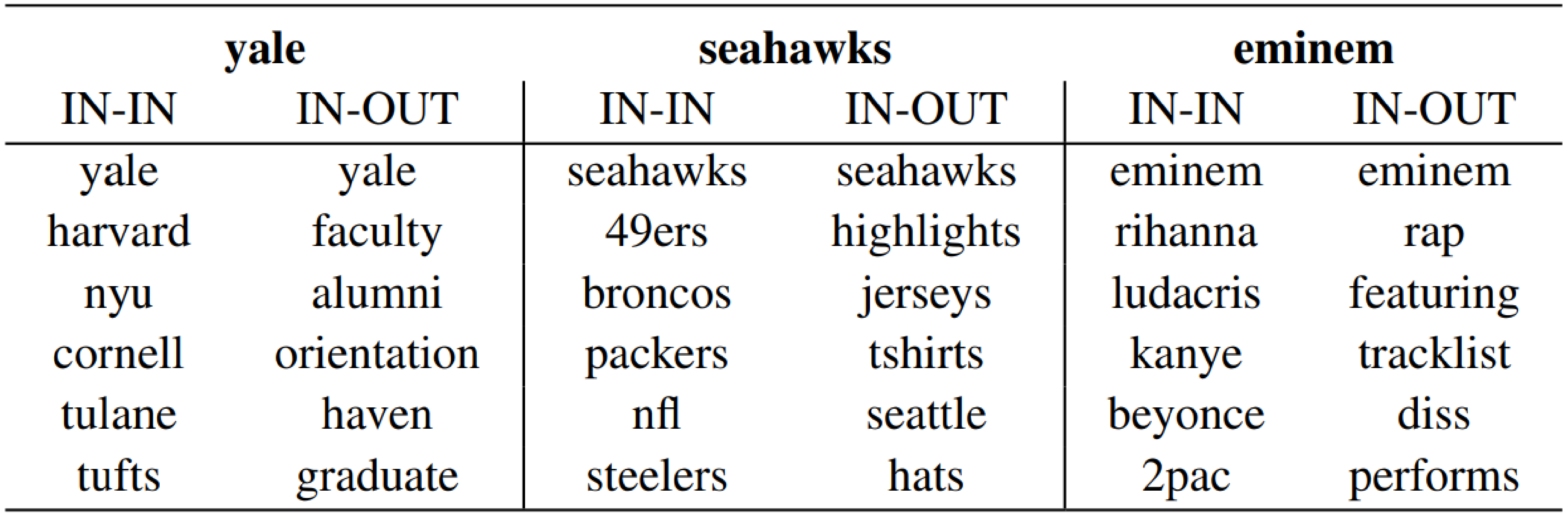
- Idea: Each word $w$ can have two embeddings
  - $\boldsymbol{e}_w$: when $w$ serves as the "word" in embedding learning
  - $\tilde{\boldsymbol{e}}_w$: when $w$ serves as the "context" in embedding learning
- The learning objective of Skip-Gram becomes

$$\max_{\{\boldsymbol{e}_v, \tilde{\boldsymbol{e}}_v | v \in \mathcal{V}\}} \sum_{d \in D} \sum_{w \in d} \sum_{x \in \mathrm{Context}(w)} \frac{\exp(\boldsymbol{e}_w^T \tilde{\boldsymbol{e}}_x)}{\sum_{v \in \mathcal{V}} \exp(\boldsymbol{e}_w^T \tilde{\boldsymbol{e}}_v)}$$

- Analogy:
  - If you factorize a user-item matrix, you get user embeddings and item embeddings in the same space
  - If you factorize a word-word matrix, you get word embeddings (as the word) and word embeddings (as the context) in the same space

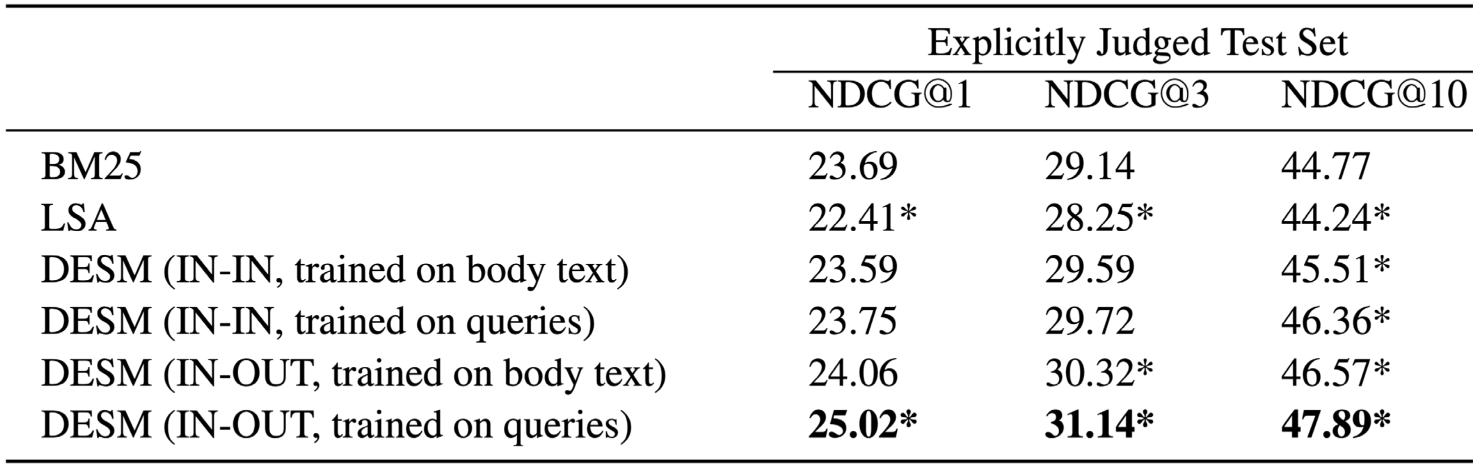
## How to use Dual Embeddings?

- Strategy 1 (“IN-IN”): Discard $\tilde{\boldsymbol{e}}_w$
  - score$(w, x) = \boldsymbol{e}_w^T \boldsymbol{e}_x$
- Strategy 2 (“IN-OUT”): Keep both $\boldsymbol{e}_w$ and $\tilde{\boldsymbol{e}}_w$
  - score$(w, x) = \boldsymbol{e}_w^T \tilde{\boldsymbol{e}}_x$



| **yale** | | **seahawks** | | **eminem** | |
|---|---|---|---|---|---|
| IN-IN | IN-OUT | IN-IN | IN-OUT | IN-IN | IN-OUT |
| yale | yale | seahawks | seahawks | eminem | eminem |
| harvard | faculty | 49ers | highlights | rihanna | rap |
| nyu | alumni | broncos | jerseys | ludacris | featuring |
| cornell | orientation | packers | tshirts | kanye | tracklist |
| tulane | haven | nfl | seattle | beyonce | diss |
| tufts | graduate | steelers | hats | 2pac | performs |

## Which strategy is better?



| | Explicitly Judged Test Set | | |
|---|---|---|---|
| | NDCG@1 | NDCG@3 | NDCG@10 |
| BM25 | 23.69 | 29.14 | 44.77 |
| LSA | 22.41* | 28.25* | 44.24* |
| DESM (IN-IN, trained on body text) | 23.59 | 29.59 | 45.51* |
| DESM (IN-IN, trained on queries) | 23.75 | 29.72 | 46.36* |
| DESM (IN-OUT, trained on body text) | 24.06 | 30.32* | 46.57* |
| DESM (IN-OUT, trained on queries) | **25.02*** | **31.14*** | **47.89*** |

- Why?
  - Assume the query is "*yale*". Which of the following sentence is more relevant?
  - "*He has collaborated with researchers from Yale, Harvard, NYU, and Cornell on several interdisciplinary projects.*"
  - "*Many Yale faculty members are proud alumni who continue to mentor current graduate students.*"

## Similarity Calculation in DESM

- Precompute document embedding

$$\tilde{\boldsymbol{e}}_d = \frac{1}{|d|} \sum_{w \in d} \frac{\tilde{\boldsymbol{e}}_w}{\|\tilde{\boldsymbol{e}}_w\|}$$

- Average the similarity between each query word and the document

$$\text{score}(q, d) = \frac{1}{|q|} \sum_{w \in q} \cos(\boldsymbol{e}_w, \tilde{\boldsymbol{e}}_d)$$

- Any more complicated solutions?

## Experiments

- Train word2vec (CBOW) from either
  - 600 million Bing queries
  - 342 million web document sentences
- Test on 7,741 randomly sampled Bing queries
  - 5-level evaluation (Perfect, Excellent, Good, Fair, Bad)
- Two approaches
  - Use DESM model to rerank top results from BM25
  - Use DESM alone or a mixture model of it and BM25

## Ranking All Documents

- DESM alone performs poorly
- Even BM25 + DESM does not significantly outperform BM25
  - Recall the "Neural Hype" mentioned in the lecture of BM25

| | Explicitly Judged Test Set | | |
|---|---|---|---|
| | NDCG@1 | NDCG@3 | NDCG@10 |
| BM25 | 21.44 | 26.09 | 37.53 |
| LSA | 04.61* | 04.63* | 04.83* |
| DESM (IN-IN, trained on body text) | 06.69* | 06.80* | 07.39* |
| DESM (IN-IN, trained on queries) | 05.56* | 05.59* | 06.03* |
| DESM (IN-OUT, trained on body text) | 01.01* | 01.16* | 01.58* |
| DESM (IN-OUT, trained on queries) | 00.62* | 00.58* | 00.81* |
| BM25 + DESM (IN-IN, trained on body text) | 21.53 | 26.16 | 37.48 |
| BM25 + DESM (IN-IN, trained on queries) | **21.58** | 26.20 | 37.62 |
| BM25 + DESM (IN-OUT, trained on body text) | 21.47 | 26.18 | 37.55 |
| BM25 + DESM (IN-OUT, trained on queries) | 21.54 | **26.42*** | **37.86*** |

## Reranking Top-$k$ Results by BM25

- Better at reranking somewhat relevant documents by judging their fine-grained relevance to the query

| | Explicitly Judged Test Set | | |
|---|---|---|---|
| | NDCG@1 | NDCG@3 | NDCG@10 |
| BM25 | 23.69 | 29.14 | 44.77 |
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## Questions?

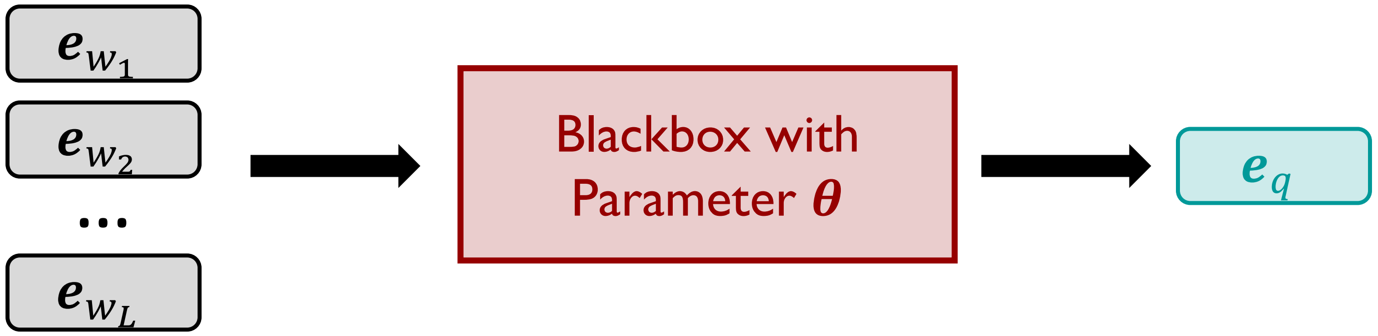
## Learning to Rank with Word Embeddings

- DESM does not use any relevant $(q, d)$ pairs to train the ranker!
  - Self-supervised word embedding learning + similarity computation (without any learnable parameters)

- What we have some relevant $(q, d)$ pairs to perform training (i.e., learning to rank)?
  - Parameters?
  - Learning objective?
  - Optimization technique? – Will not go into detail here. You can think of it as gradient descent, although in reality it involves more sophisticated tricks

# Learning to Rank with Word Embeddings

- Parameters: How to aggregate word embeddings to query / document embedding?
  - $\boldsymbol{e}_q = \mathrm{f}_{\boldsymbol{\theta}}(\{\boldsymbol{e}_w | w \in q\}),\ \boldsymbol{e}_d = \mathrm{f}_{\boldsymbol{\theta}}(\{\tilde{\boldsymbol{e}}_w | w \in d\})$
  - $\boldsymbol{\theta}$ denotes all parameters of the model



- A simple (but overly ideal) example:
  - Assume all queries and documents have 10 words (e.g., $q$ is $w_1 w_2 \ldots w_{10}$)
  - $\boldsymbol{e}_q = \sum_{i=1}^{10} \theta_i \boldsymbol{e}_{w_i}$

# Learning to Rank with Word Embeddings

- Parameters: How to aggregate word embeddings to query / document embedding?
  - In reality:

hidden states

$h^{(t)} = \sigma\left(W_h h^{(t-1)} + W_e e^{(t)} + b_1\right)$

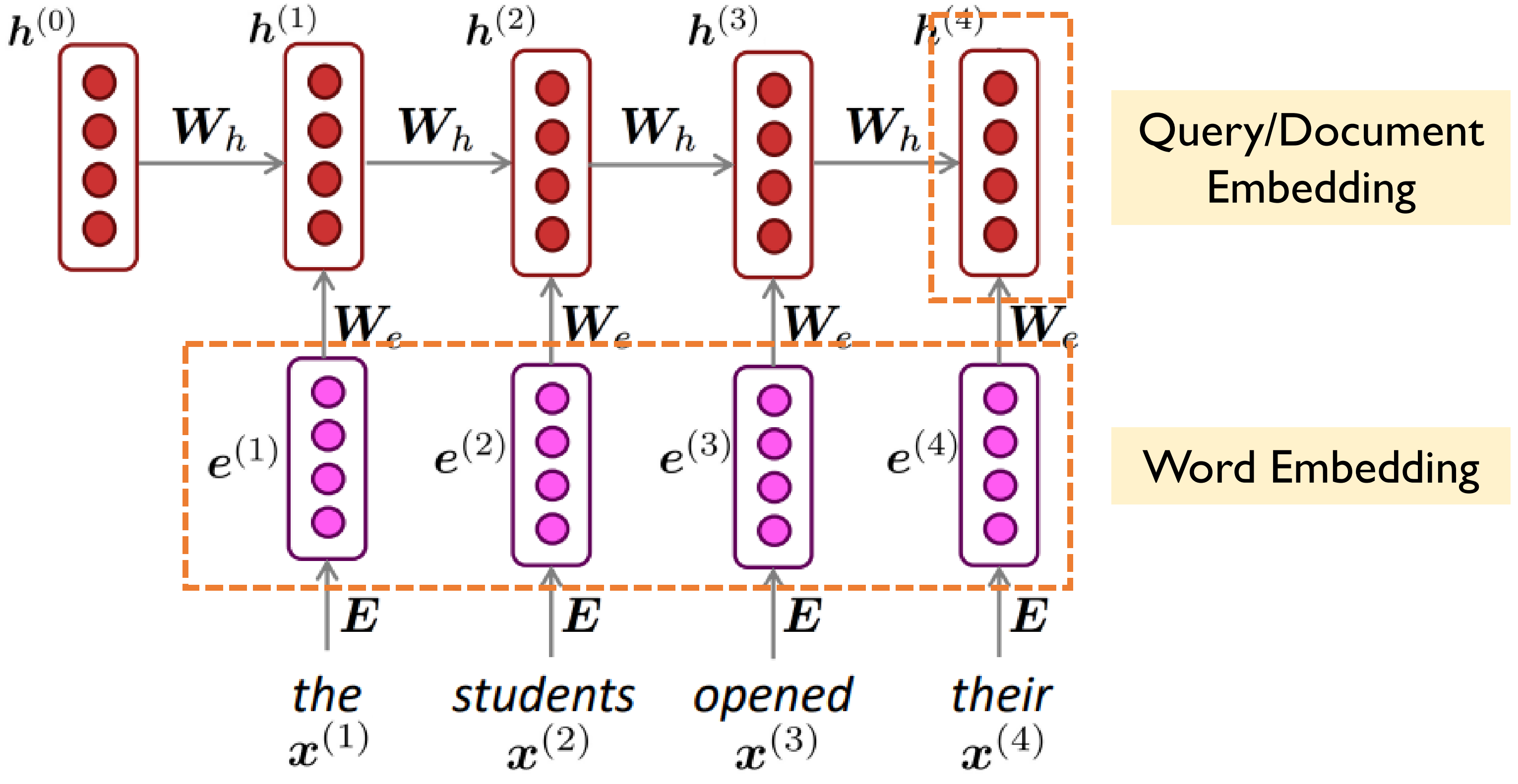
$h^{(0)}$ is the initial hidden state

word embeddings

$e^{(t)} = E x^{(t)}$

words / one-hot vectors

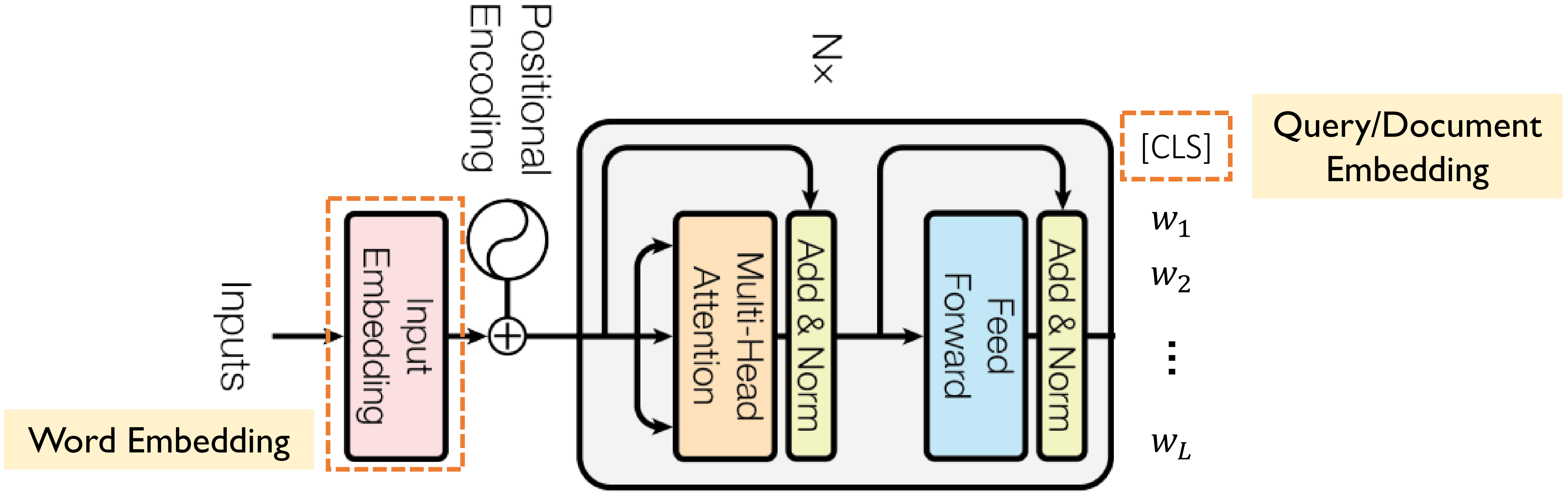
$x^{(t)} \in \mathbb{R}^{|V|}$



Recurrent Neural Network: https://web.stanford.edu/class/cs224n/slides/cs224n-spr2024-lecture05-rnnlm.pdf

## Learning to Rank with Word Embeddings

- Parameters: How to aggregate word embeddings to query / document embedding?
  - In reality:

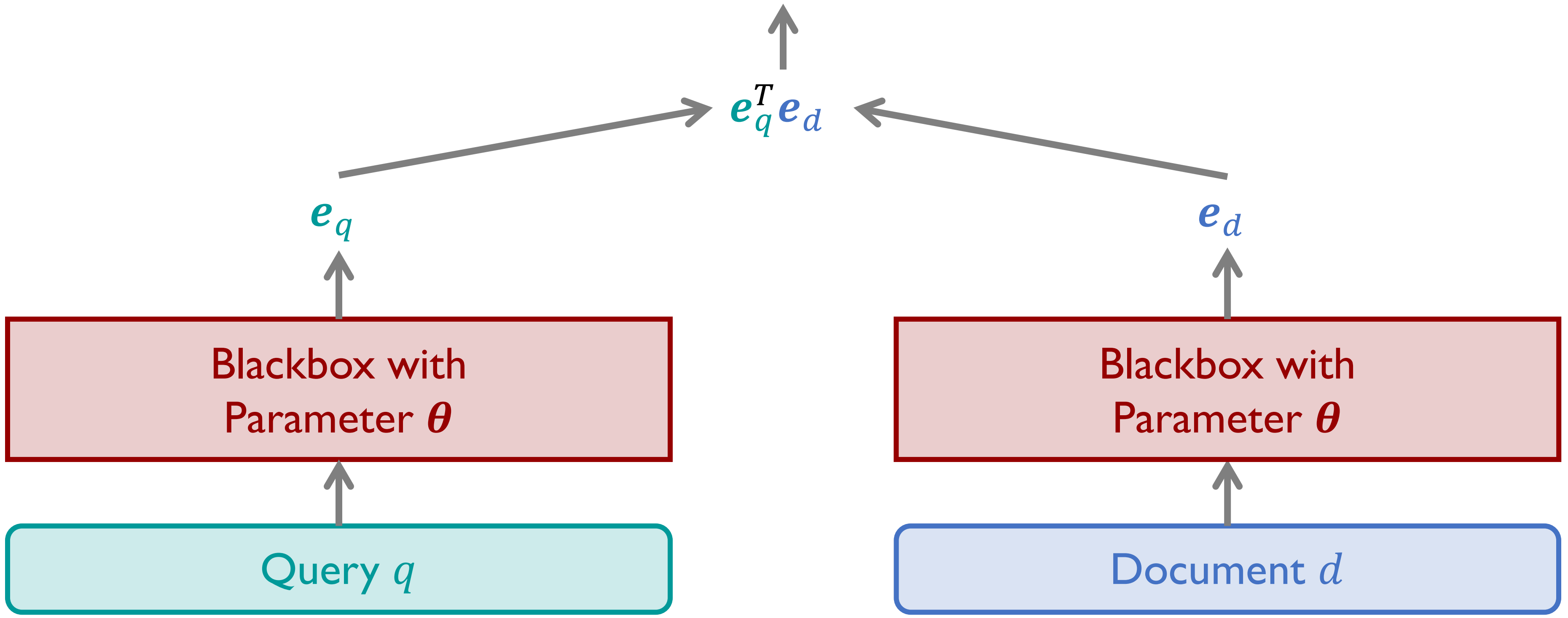


Transformer Encoder / BERT: https://arxiv.org/pdf/1706.03762

## Learning to Rank with Word Embeddings

- Learning objective: A simple strategy is binary classification (i.e., whether $q$ and $d$ is relevant)

$$\hat{y}_{q,d} = p(\text{relevant}|q,d) = \text{Sigmoid}\left(\boldsymbol{e}_q^T \boldsymbol{e}_d\right) = \frac{1}{1 + \exp(-\boldsymbol{e}_q^T \boldsymbol{e}_d)}$$


$\boldsymbol{e}_q^T \boldsymbol{e}_d$
$\boldsymbol{e}_q$
$\boldsymbol{e}_d$
Blackbox with Parameter $\boldsymbol{\theta}$
Blackbox with Parameter $\boldsymbol{\theta}$
Query $q$
Document $d$

## Learning to Rank with Word Embeddings

- Learning objective: A simple strategy is binary classification (i.e., whether $q$ and $d$ is relevant)

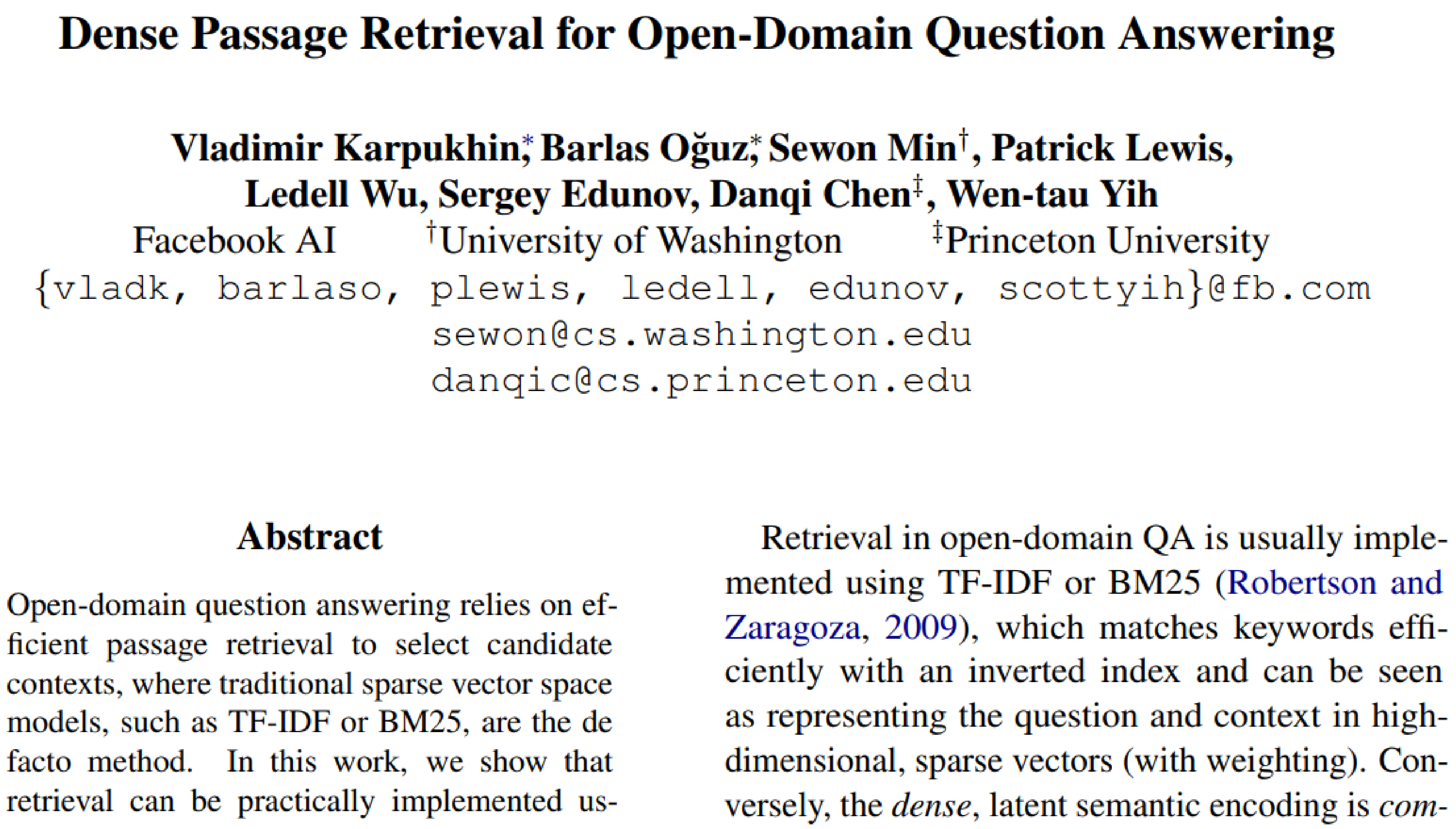
$$\hat{y}_{q,d} = p(\text{relevant}|q,d) = \text{Sigmoid}\left(\boldsymbol{e}_q^T \boldsymbol{e}_d\right) = \frac{1}{1+\exp(-\boldsymbol{e}_q^T \boldsymbol{e}_d)}$$

  - If $q$ and $d$ are relevant, then the ground truth $y_{q,d} = 1$
  - If $q$ and $d$ are irrelevant, then the ground truth $y_{q,d} = 0$
  - Cross-entropy loss: $\mathcal{L} = -y_{q,d}\log\hat{y}_{q,d} - \left(1 - y_{q,d}\right)\log(1 - \hat{y}_{q,d})$

  - Pulling relevant $\boldsymbol{e}_q$ and $\boldsymbol{e}_d$ closer
  - Pushing irrelevant $\boldsymbol{e}_q$ and $\boldsymbol{e}_d$ apart

  - Is this strategy pointwise or pairwise learning to rank?
  - What if we want to perform pairwise learning to rank?

## Dense Passage Retrieval [Karpukhin et al., EMNLP 2020]



**Dense Passage Retrieval for Open-Domain Question Answering**

**Vladimir Karpukhin**[*], **Barlas Oğuz**[*], **Sewon Min**[†], **Patrick Lewis,**
**Ledell Wu, Sergey Edunov, Danqi Chen**[‡], **Wen-tau Yih**
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**Abstract**

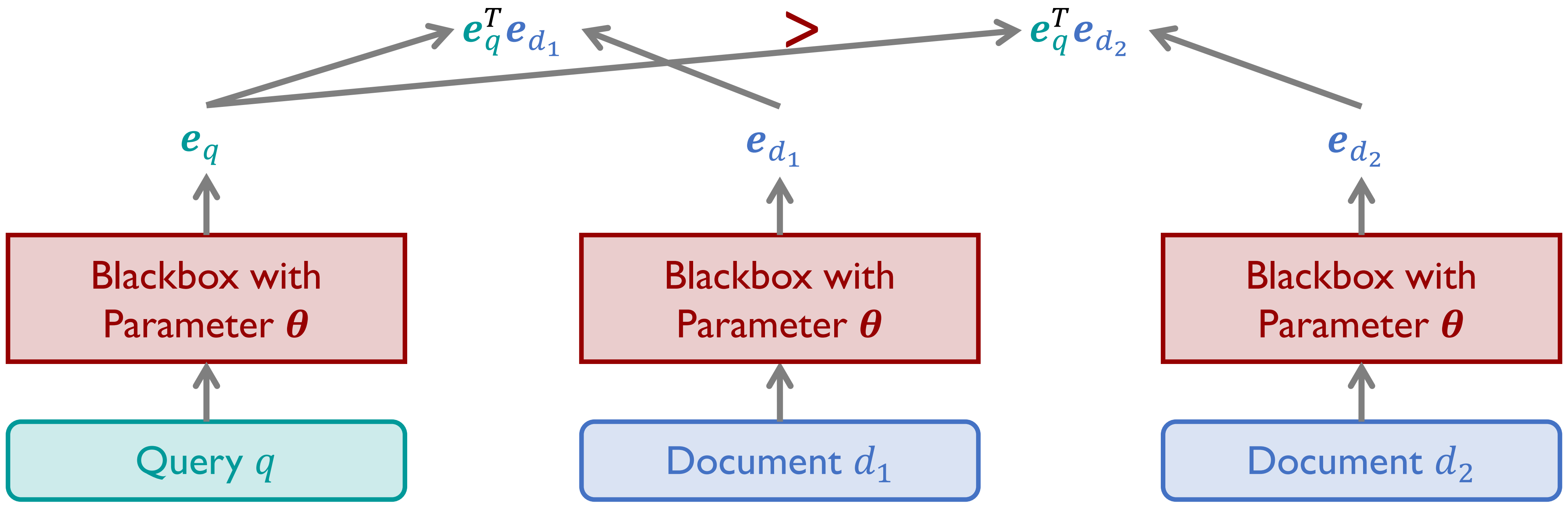
Open-domain question answering relies on efficient passage retrieval to select candidate contexts, where traditional sparse vector space models, such as TF-IDF or BM25, are the de facto method. In this work, we show that retrieval can be practically implemented us-

Retrieval in open-domain QA is usually implemented using TF-IDF or BM25 (Robertson and Zaragoza, 2009), which matches keywords efficiently with an inverted index and can be seen as representing the question and context in high-dimensional, sparse vectors (with weighting). Conversely, the *dense*, latent semantic encoding is *com-*

## Learning to Rank with Word Embeddings

- Learning objective (Pairwise): Given a query $q$ and two documents $d_1$ and $d_2$, the ground truth tells us that $d_1$ is more relevant to $q$ than $d_2$

$$\text{Sigmoid}\left(\boldsymbol{e}_q^T\boldsymbol{e}_{d_1} - \boldsymbol{e}_q^T\boldsymbol{e}_{d_2}\right) = \frac{\exp(\boldsymbol{e}_q^T\boldsymbol{e}_{d_1})}{\exp\left(\boldsymbol{e}_q^T\boldsymbol{e}_{d_1}\right) + \exp\left(\boldsymbol{e}_q^T\boldsymbol{e}_{d_2}\right)}$$

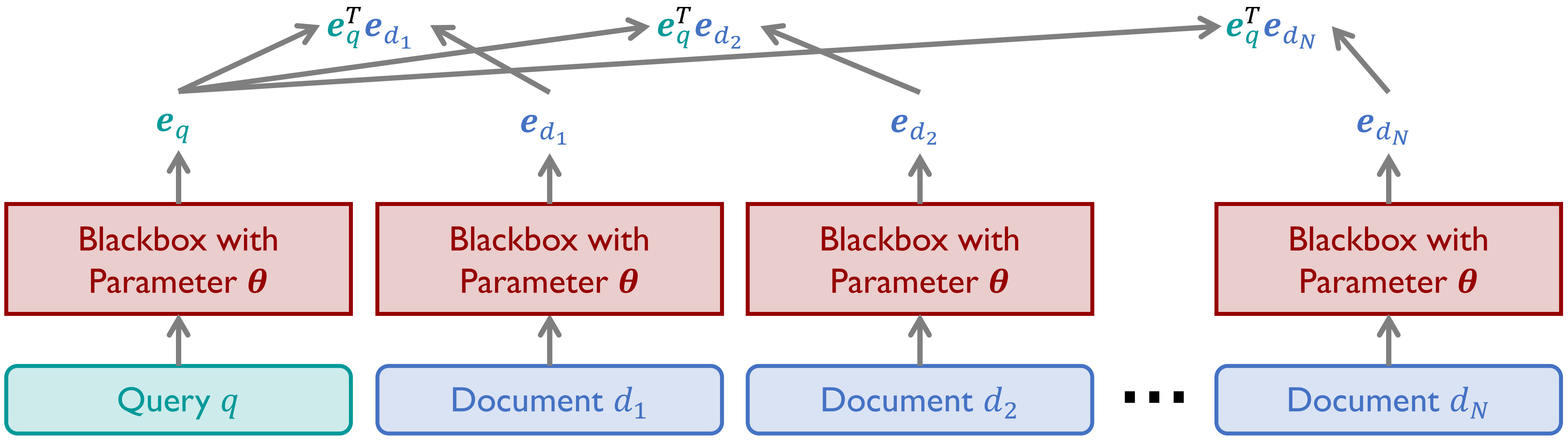


$\boldsymbol{e}_q^T\boldsymbol{e}_{d_1}$
>
$\boldsymbol{e}_q^T\boldsymbol{e}_{d_2}$
$\boldsymbol{e}_q$
$\boldsymbol{e}_{d_1}$
$\boldsymbol{e}_{d_2}$
Blackbox with Parameter $\boldsymbol{\theta}$
Blackbox with Parameter $\boldsymbol{\theta}$
Blackbox with Parameter $\boldsymbol{\theta}$
Query $q$
Document $d_1$
Document $d_2$

# Learning to Rank with Word Embeddings

- Learning objective: Given a query $q$ and $N$ documents $(d_1, d_2, \dots, d_N)$, the ground truth tells us that $d_1$ is the most relevant to $q$ among these documents

$$\frac{\exp(\boldsymbol{e}_q^T \boldsymbol{e}_{d_1})}{\sum_{i=1}^{N} \exp(\boldsymbol{e}_q^T \boldsymbol{e}_{d_i})}$$



$\boldsymbol{e}_q^T \boldsymbol{e}_{d_1}$
$\boldsymbol{e}_q^T \boldsymbol{e}_{d_2}$
$\boldsymbol{e}_q^T \boldsymbol{e}_{d_N}$
$\boldsymbol{e}_q$
$\boldsymbol{e}_{d_1}$
$\boldsymbol{e}_{d_2}$
$\boldsymbol{e}_{d_N}$
Blackbox with Parameter $\boldsymbol{\theta}$
Blackbox with Parameter $\boldsymbol{\theta}$
Blackbox with Parameter $\boldsymbol{\theta}$
Blackbox with Parameter $\boldsymbol{\theta}$
Query $q$
Document $d_1$
Document $d_2$
…
Document $d_N$

## Contrastive Learning

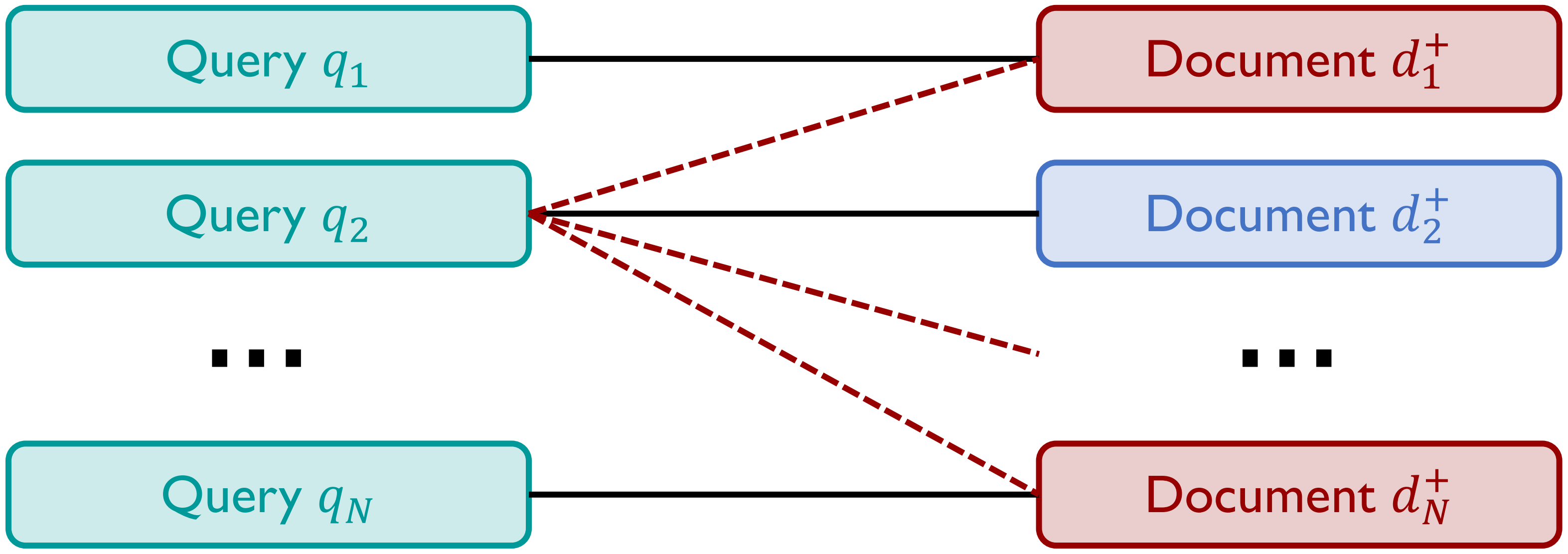
- A query $q$
- A positive sample $d^+$
- One or more negative samples $d_1^-, d_2^-, \dots, d_{N-1}^-$
- Learning objective:

$$\max \frac{\exp\big(\mathrm{score}(q, d^+)\big)}{\exp\big(\mathrm{score}(q, d^+)\big) + \sum_{i=1}^{N-1} \exp\big(\mathrm{score}(q, d_i^-)\big)}$$

- Different choices of $\mathrm{score}(q, d)$
  - $\mathrm{score}(q, d) = \boldsymbol{e}_q^T \boldsymbol{e}_d$
  - $\mathrm{score}(q, d) = \frac{\cos(\boldsymbol{e}_q, \boldsymbol{e}_d)}{\tau}$
    - $\tau$ is a hyperparameter that is usually smaller than 1 (e.g., 0.05)

## Contrastive Learning

- In-batch negative samples
  - Feed $N$ (query, positive document) pairs together as a batch into GPU
  - No need to explicitly sample negative documents for each query
  - The positive documents of other queries in the same batch will be used as negative documents of the current query

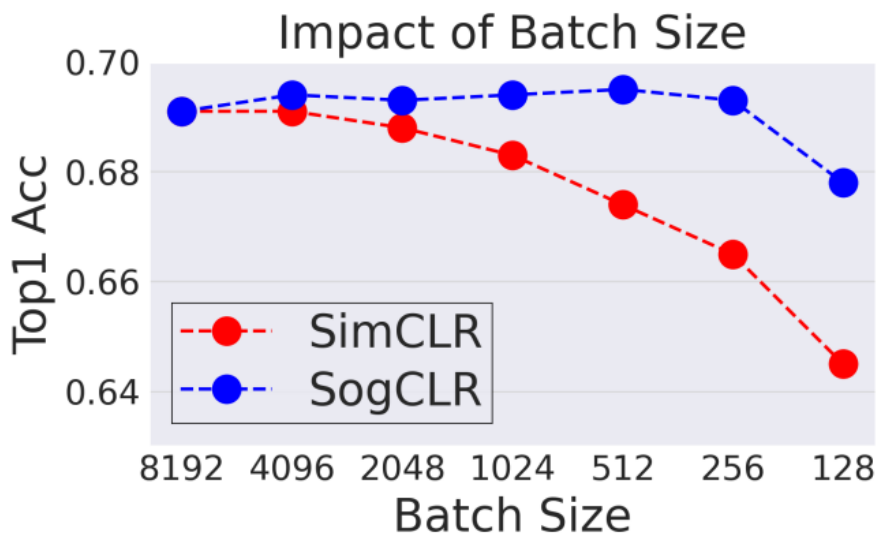


## Contrastive Learning

- The performance of contrastive learning improves as the batch size $N$ increases
- For Dense Passage Retrieval,

| $N$ | 8 | 32 | 128 |
|---|---|---|---|
| Performance | 80.8 | 82.1 | 83.1 |

- In other contrastive learning studies,

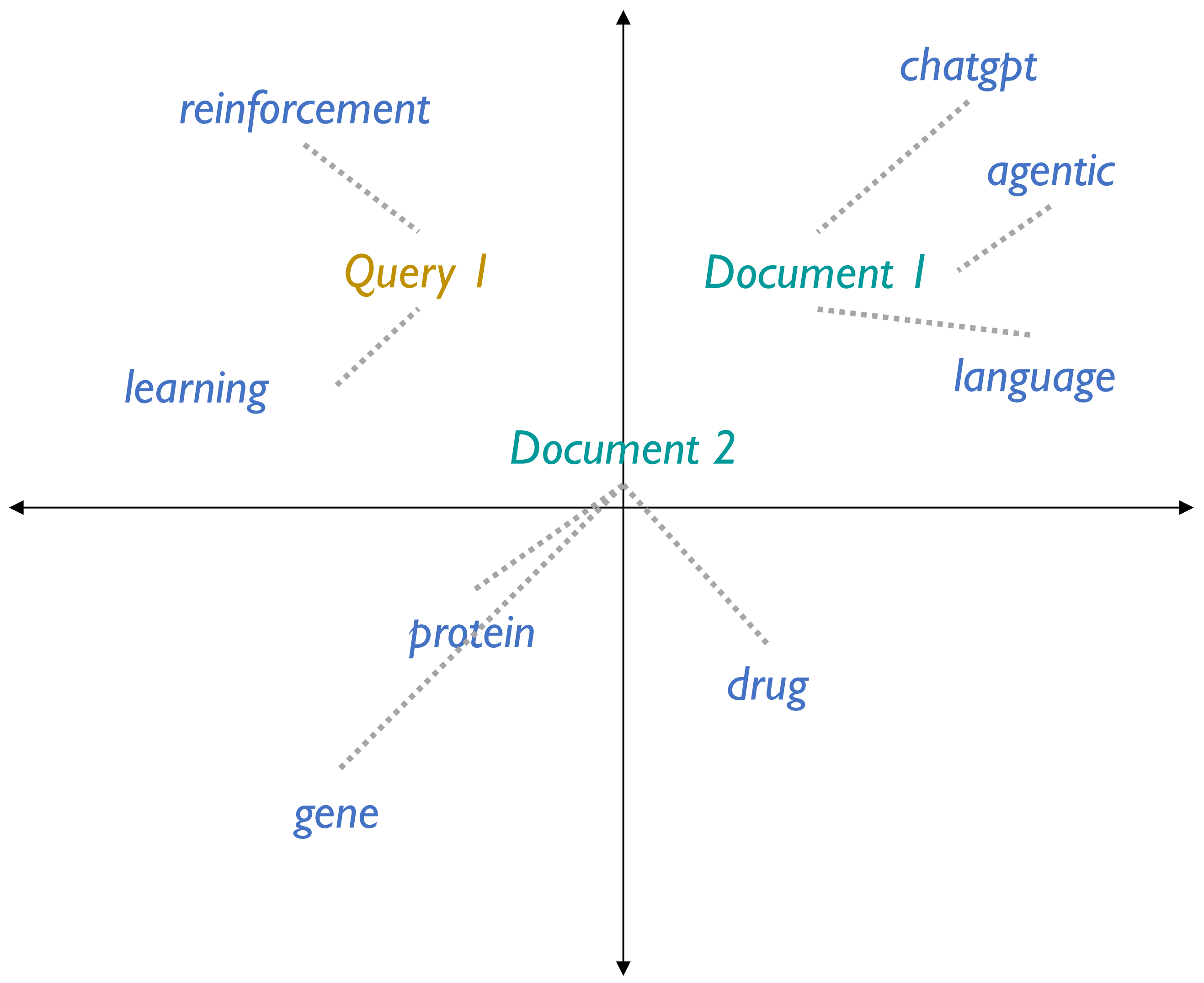


## Contrastive Learning

- Contrastive learning can be applied to scenarios far beyond retrieval
- Example 1: Citation Recommendation
  - Query: A research paper
  - Positive Document: A research paper cited by the query paper
  - Usage: When you write a new paper, the model can suggest possible citations

- Example 2: Community Question Answering
  - Query: A question from Stack Overflow
  - Positive Document: The answer with the most upvotes
  - Usage: When you post a new question on Stack Overflow, the model can suggest possible existing answers

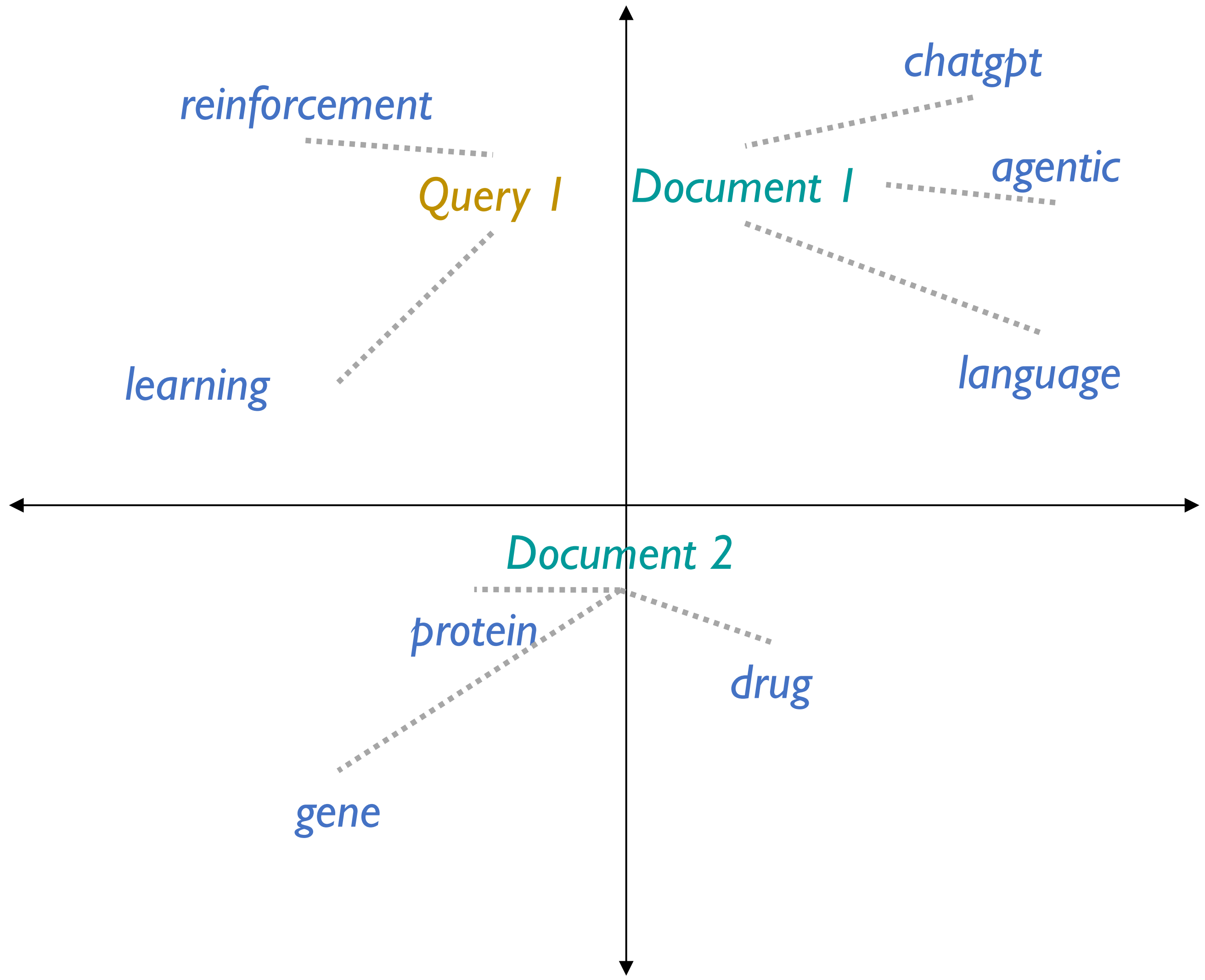
# Visualization of the Contrastive Learning Process



Suppose *Document 1* is the positive document of *Query 1*; *Document 2* is a negative document of *Query 1*.

# Visualization of the Contrastive Learning Process

Contrastive learning pulls relevant (*query*, *document*) closer and pushes irrelevant (*query*, *document*) apart

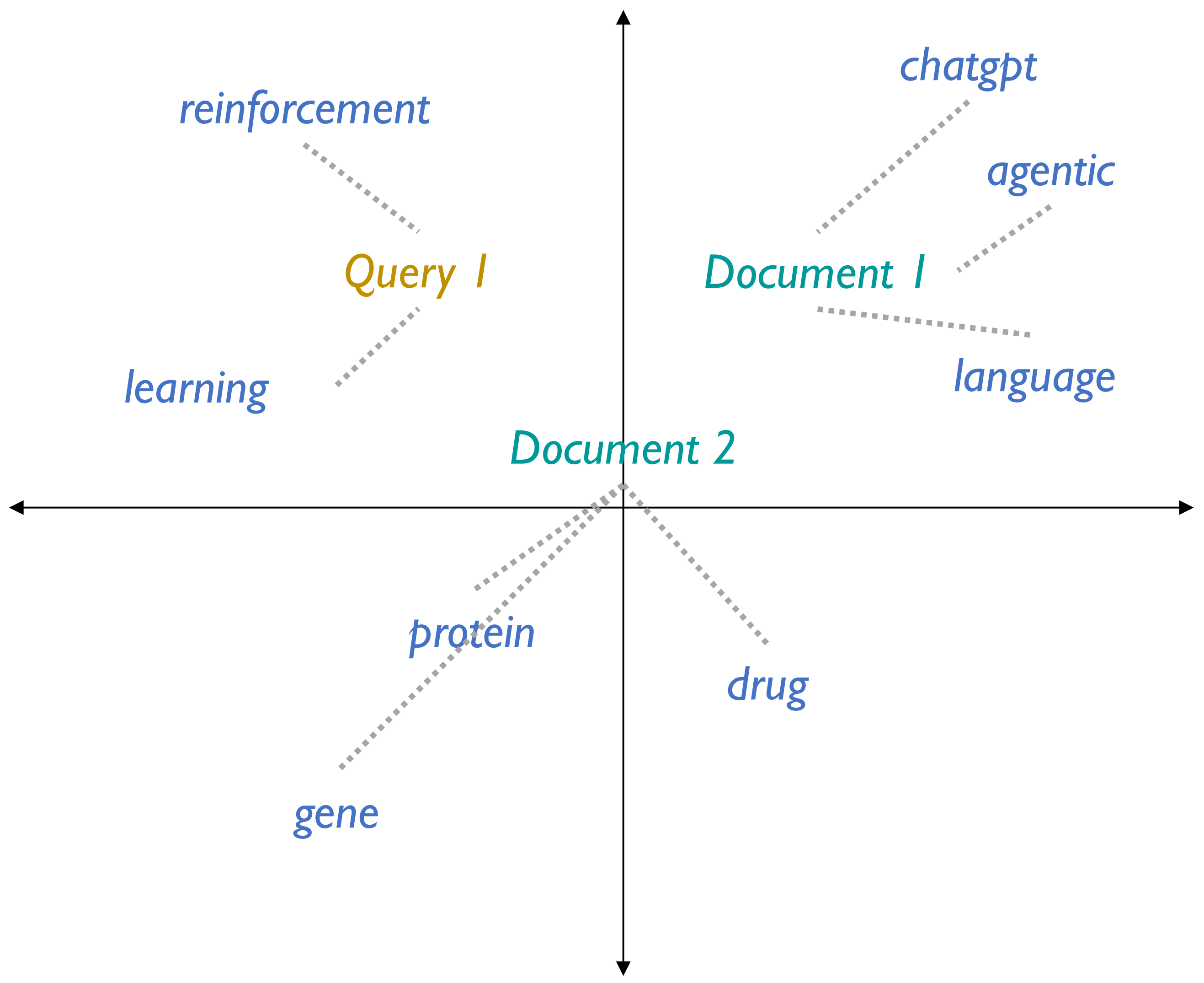


But word embeddings do not change because they are not part of the model parameters $\theta$

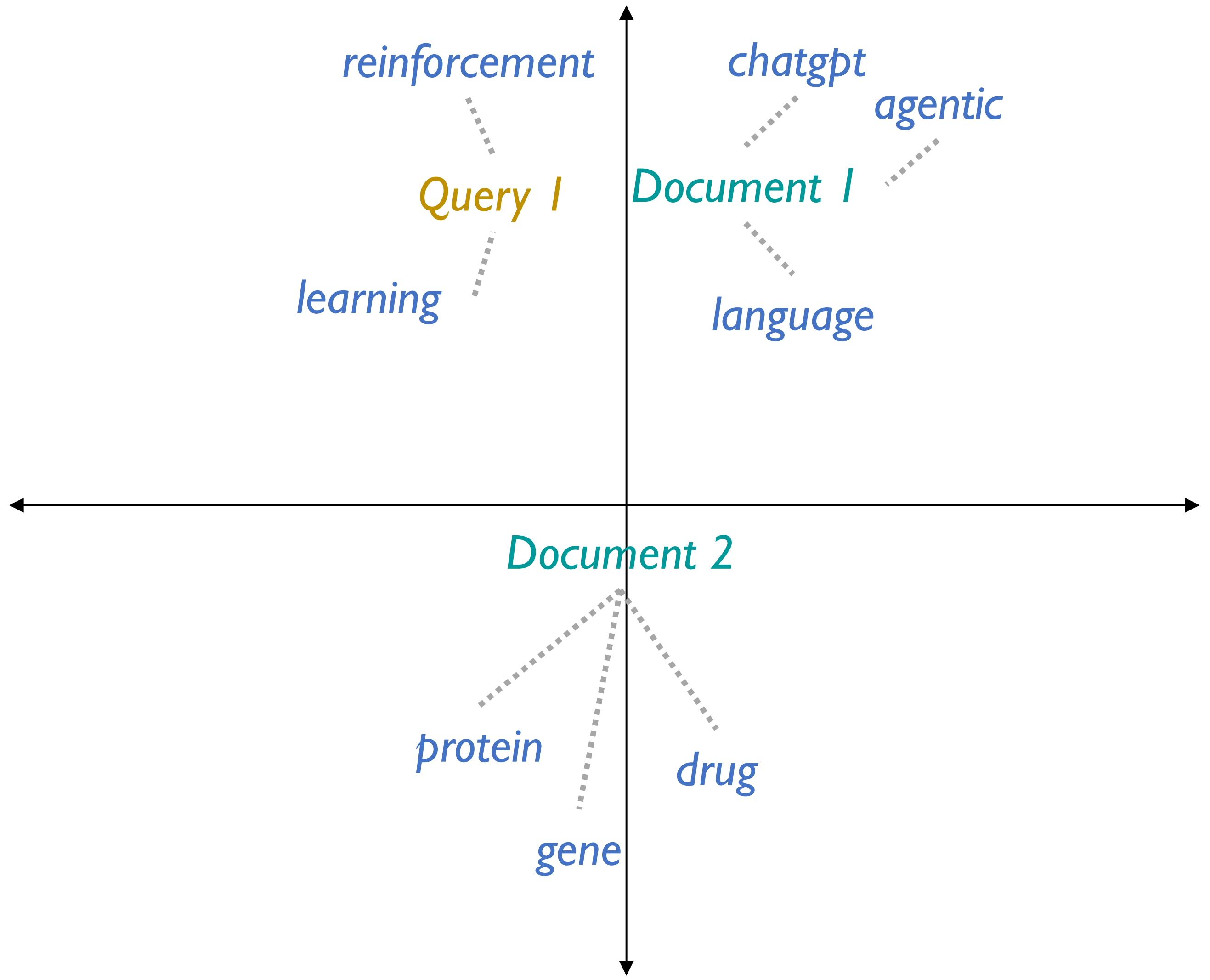
Can we also include word embeddings as model parameters?

## Visualization of the Contrastive Learning Process

Before update



## Visualization of the Contrastive Learning Process



After the model is trained on this sample, word embeddings are updated as well!

In practice, word embeddings will be included as model parameters if the training data (for contrastive learning) is large enough or domain-specific

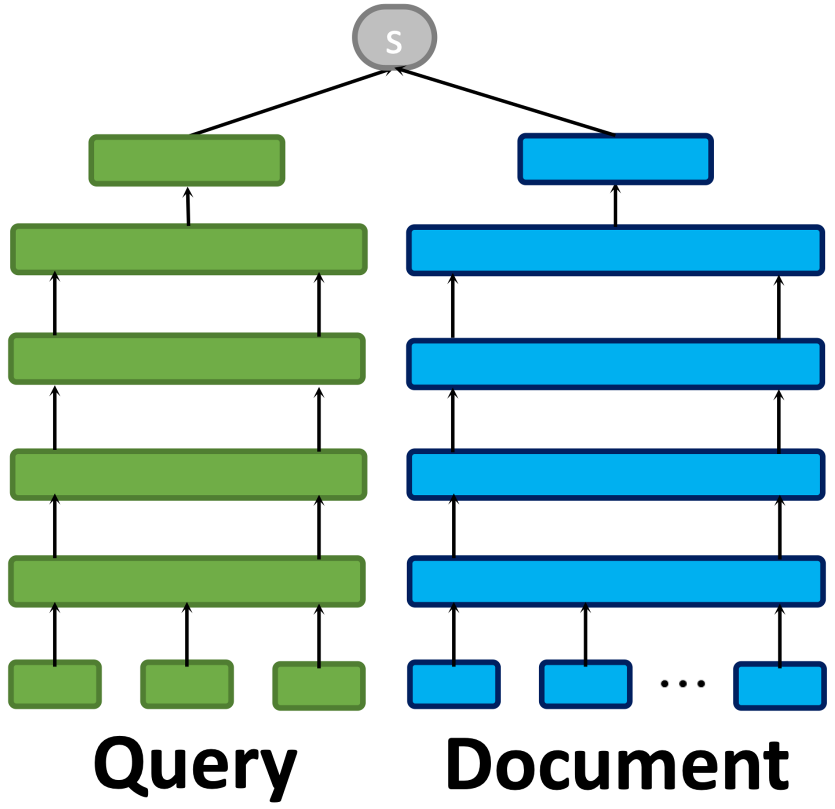
Questions?

## Modeling Query-Document Interaction

- We have introduced
  - Average of word2vec
  - Dense Passage Retrieval (contrastive learning)

- They independently encode the query and the document into vectors and calculate their similarity.

- However, the importance of a query word may vary across different documents; the importance of a document word may also vary across different queries.



## Modeling Query-Document Interaction

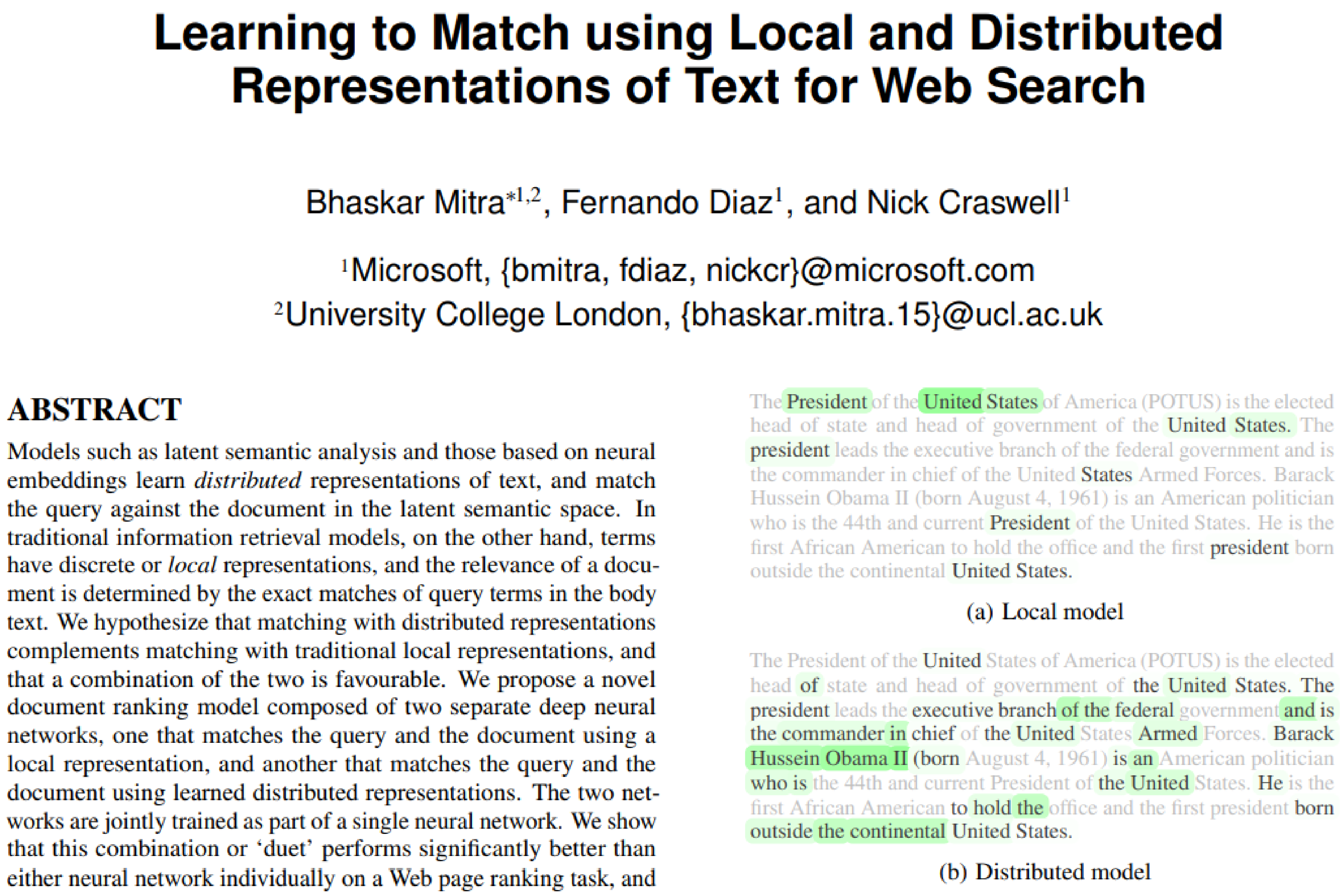
- Document: "*a comprehensive survey of scientific large language models and their applications in scientific discovery*"

- Query: "*chatgpt*"
- Document: "*a comprehensive survey of scientific large language models and their applications in scientific discovery*"

- Query: "*drug discovery*"
- Document: "*a comprehensive survey of scientific large language models and their applications in scientific discovery*"

- Capture interactions between each query word and each document word when predicting their relevance

# Duet [Mitra et al., WWW 2017]



Learning to Match using Local and Distributed Representations of Text for Web Search

Bhaskar Mitra*[1,2], Fernando Diaz[1], and Nick Craswell[1]

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[2]University College London, {bhaskar.mitra.15}@ucl.ac.uk

**ABSTRACT**

Models such as latent semantic analysis and those based on neural embeddings learn *distributed* representations of text, and match the query against the document in the latent semantic space. In traditional information retrieval models, on the other hand, terms have discrete or *local* representations, and the relevance of a document is determined by the exact matches of query terms in the body text. We hypothesize that matching with distributed representations complements matching with traditional local representations, and that a combination of the two is favourable. We propose a novel document ranking model composed of two separate deep neural networks, one that matches the query and the document using a local representation, and another that matches the query and the document using learned distributed representations. The two networks are jointly trained as part of a single neural network. We show that this combination or 'duet' performs significantly better than either neural network individually on a Web page ranking task, and

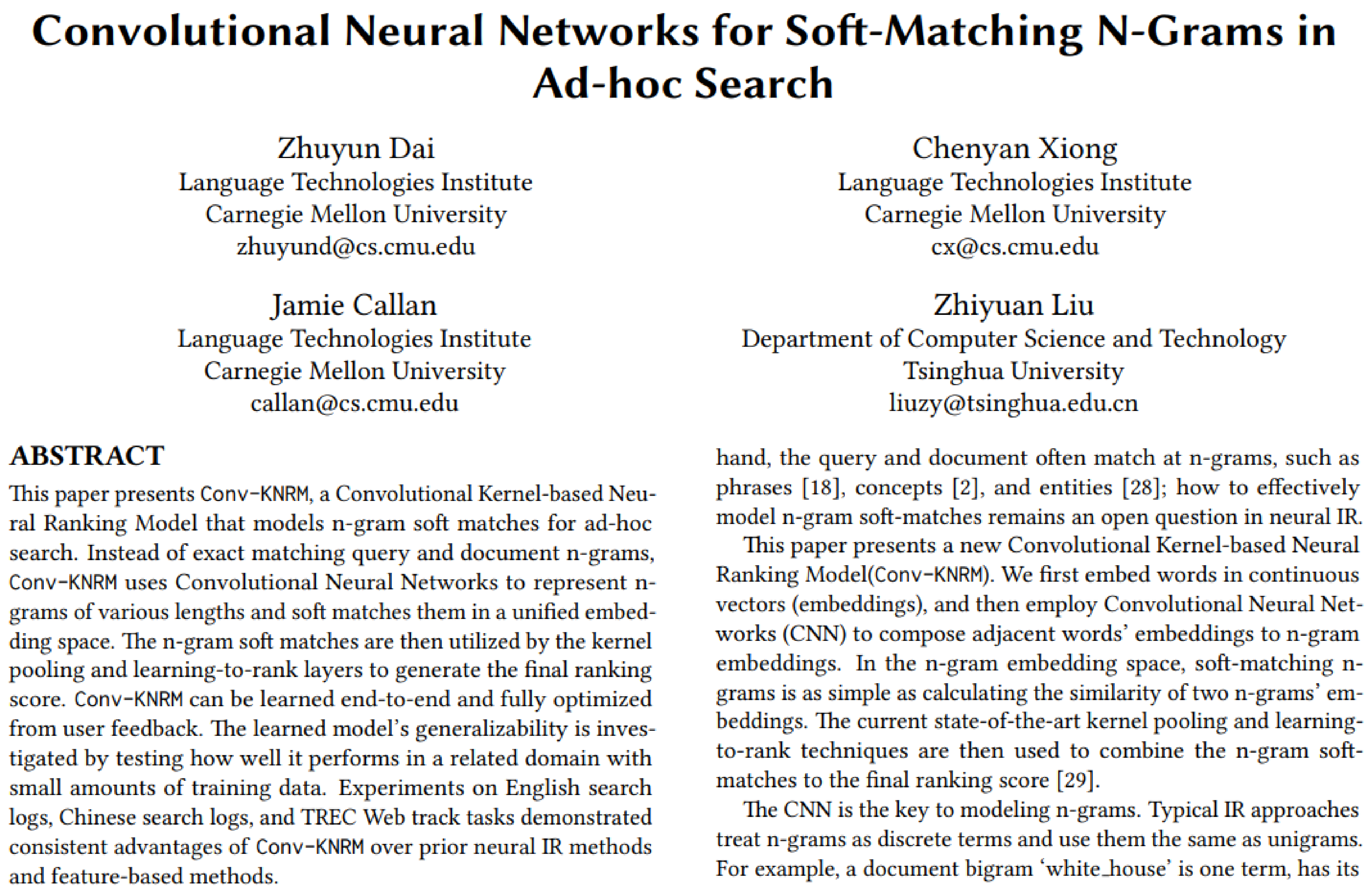
The President of the United States of America (POTUS) is the elected head of state and head of government of the United States. The president leads the executive branch of the federal government and is the commander in chief of the United States Armed Forces. Barack Hussein Obama II (born August 4, 1961) is an American politician who is the 44th and current President of the United States. He is the first African American to hold the office and the first president born outside the continental United States.

(a) Local model

The President of the United States of America (POTUS) is the elected head of state and head of government of the United States. The president leads the executive branch of the federal government and is the commander in chief of the United States Armed Forces. Barack Hussein Obama II (born August 4, 1961) is an American politician who is the 44th and current President of the United States. He is the first African American to hold the office and the first president born outside the continental United States.

(b) Distributed model

# Conv-KNRM [Dai et al., WSDM 2018]



## Convolutional Neural Networks for Soft-Matching N-Grams in Ad-hoc Search

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### ABSTRACT

This paper presents Conv-KNRM, a Convolutional Kernel-based Neural Ranking Model that models n-gram soft matches for ad-hoc search. Instead of exact matching query and document n-grams, Conv-KNRM uses Convolutional Neural Networks to represent n-grams of various lengths and soft matches them in a unified embedding space. The n-gram soft matches are then utilized by the kernel pooling and learning-to-rank layers to generate the final ranking score. Conv-KNRM can be learned end-to-end and fully optimized from user feedback. The learned model's generalizability is investigated by testing how well it performs in a related domain with small amounts of training data. Experiments on English search logs, Chinese search logs, and TREC Web track tasks demonstrated consistent advantages of Conv-KNRM over prior neural IR methods and feature-based methods.

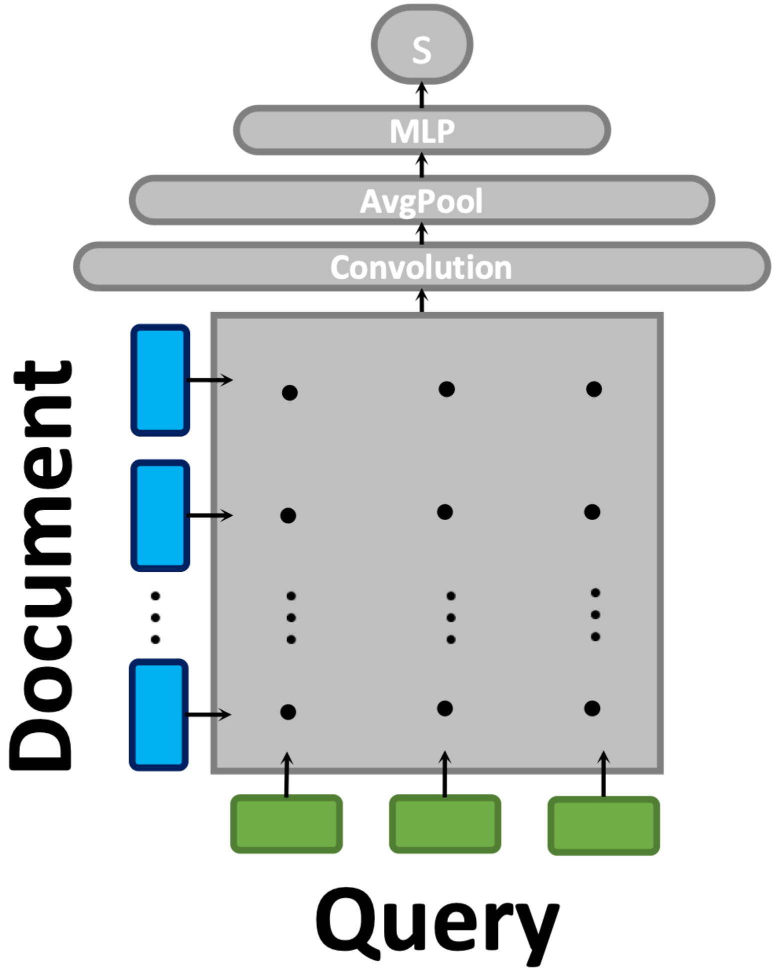
hand, the query and document often match at n-grams, such as phrases [18], concepts [2], and entities [28]; how to effectively model n-gram soft-matches remains an open question in neural IR.

This paper presents a new Convolutional Kernel-based Neural Ranking Model(Conv-KNRM). We first embed words in continuous vectors (embeddings), and then employ Convolutional Neural Networks (CNN) to compose adjacent words' embeddings to n-gram embeddings. In the n-gram embedding space, soft-matching n-grams is as simple as calculating the similarity of two n-grams' embeddings. The current state-of-the-art kernel pooling and learning-to-rank techniques are then used to combine the n-gram soft-matches to the final ranking score [29].

The CNN is the key to modeling n-grams. Typical IR approaches treat n-grams as discrete terms and use them the same as unigrams. For example, a document bigram 'white_house' is one term, has its

# Modeling Query-Document Interaction

- Step 1: Get the embedding (e.g., word2vec) of each query word and each document word
- Step 2: Build a query-document interaction matrix (e.g., store the cosine similarity of each pair of words)
- Step 3: Reduce this dense matrix to a score using convolution layers and linear layers
  - Imagine how binary image classification is performed (i.e., predicting whether an image is a cat or a dog from its pixel matrix)
  - We are predicting whether a query-document pair is relevant from its interaction matrix
- Step 4: Learn these neural layers from training data



## But …

- Query-Document Interaction models are expensive!
- We cannot aggregate embeddings of document words until we see the query!
- By contrast,
  - For simple average:
    - $\boldsymbol{e}_q = \frac{1}{|q|}\sum_{w\in q}\boldsymbol{e}_w, \quad \boldsymbol{e}_d = \frac{1}{|d|}\sum_{w\in d}\boldsymbol{e}_w, \quad \text{score}(q,d) = \cos(\boldsymbol{e}_q, \boldsymbol{e}_d)$ or $\boldsymbol{e}_q^T\boldsymbol{e}_d$
    - We can precompute $\boldsymbol{e}_d$ for all documents

  - For DESM,
    - $\tilde{\boldsymbol{e}}_d = \frac{1}{|d|}\sum_{w\in d}\frac{\tilde{e}_w}{\|\tilde{e}_w\|}, \quad \text{score}(q,d) = \frac{1}{|q|}\sum_{w\in q}\cos(\boldsymbol{e}_w, \tilde{\boldsymbol{e}}_d)$
    - We can precompute $\tilde{\boldsymbol{e}}_d$ for all documents

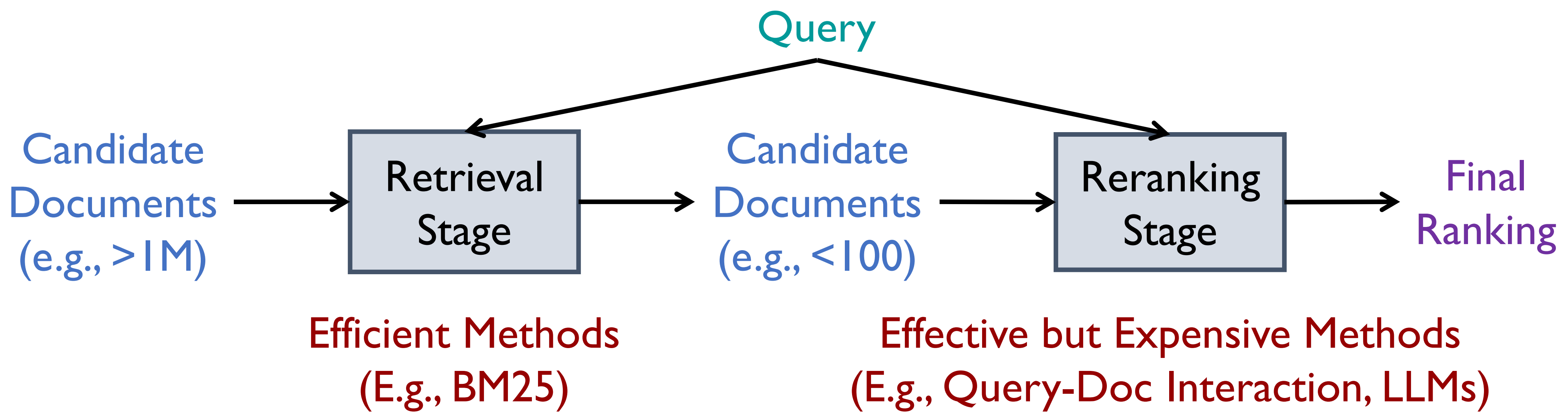
## But …

- Query-Document Interaction models are expensive!
- We cannot aggregate embeddings of document words until we see the query!
- By contrast,
  - For Dense Passage Retrieval:
    - $\boldsymbol{e}_q = \mathrm{f}_{\boldsymbol{\theta}}(\{\boldsymbol{e}_w | w \in q\}), \quad \boldsymbol{e}_d = \mathrm{f}_{\boldsymbol{\theta}}(\{\tilde{\boldsymbol{e}}_w | w \in d\}), \quad \mathrm{score}(q, d) = \boldsymbol{e}_q^T \boldsymbol{e}_d$
    - We can precompute $\boldsymbol{e}_d$ for all documents

- Imagine you have 1,000 queries and 1,000 documents:
  - How many times do you need to call $\mathrm{f}_{\boldsymbol{\theta}}(\cdot)$ to obtain the score between each query and each document?
  - How many times do you need to call a Query-Document Interaction model to obtain the score between each query and each document?

## Retrieval-Reranking Paradigm

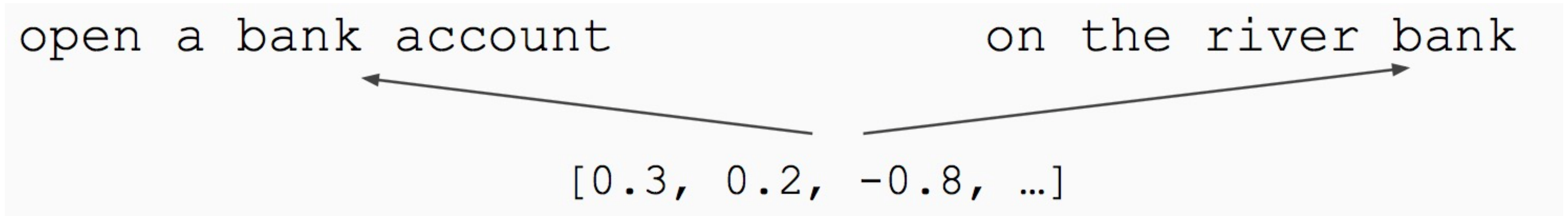
- We want to use effective but expensive ranking models …
- … only for a more fine-grained ranking of the most relevant documents.



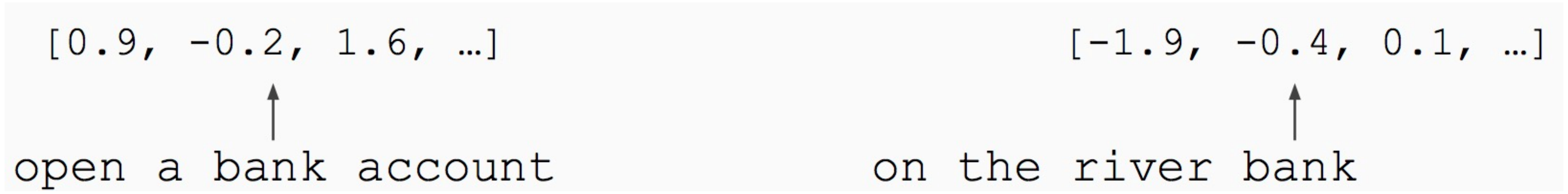
Query
Candidate Documents (e.g., >1M)
Retrieval Stage
Candidate Documents (e.g., <100)
Reranking Stage
Final Ranking
Efficient Methods (E.g., BM25)
Effective but Expensive Methods (E.g., Query-Doc Interaction, LLMs)

## Limitations of word2vec-based Ranking

- Word embeddings are applied in a context-free manner!



- Is it possible to have different vectors of the same word given different contexts?



# Transformer [Vaswani et al., NIPS 2017]

Attention Is All You Need

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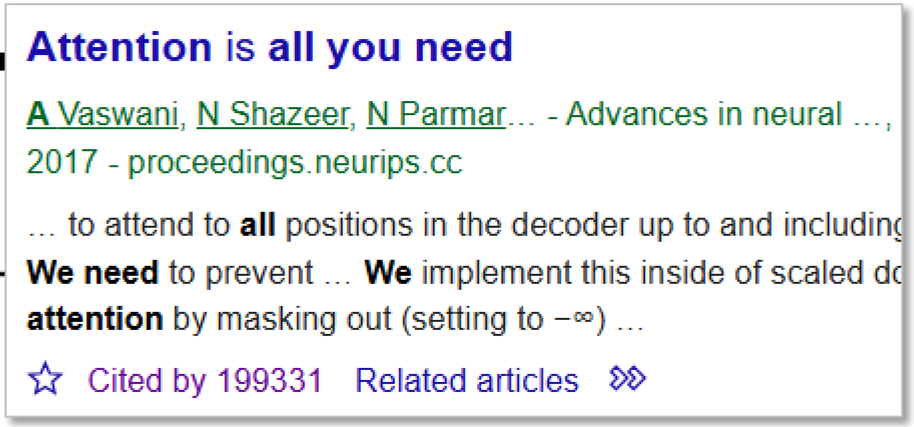

Attention is all you need

A Vaswani, N Shazeer, N Parmar… - Advances in neural …, 2017 - proceedings.neurips.cc

… to attend to **all** positions in the decoder up to and including

**We need** to prevent … **We** implement this inside of scaled do

**attention** by masking out (setting to −∞) …

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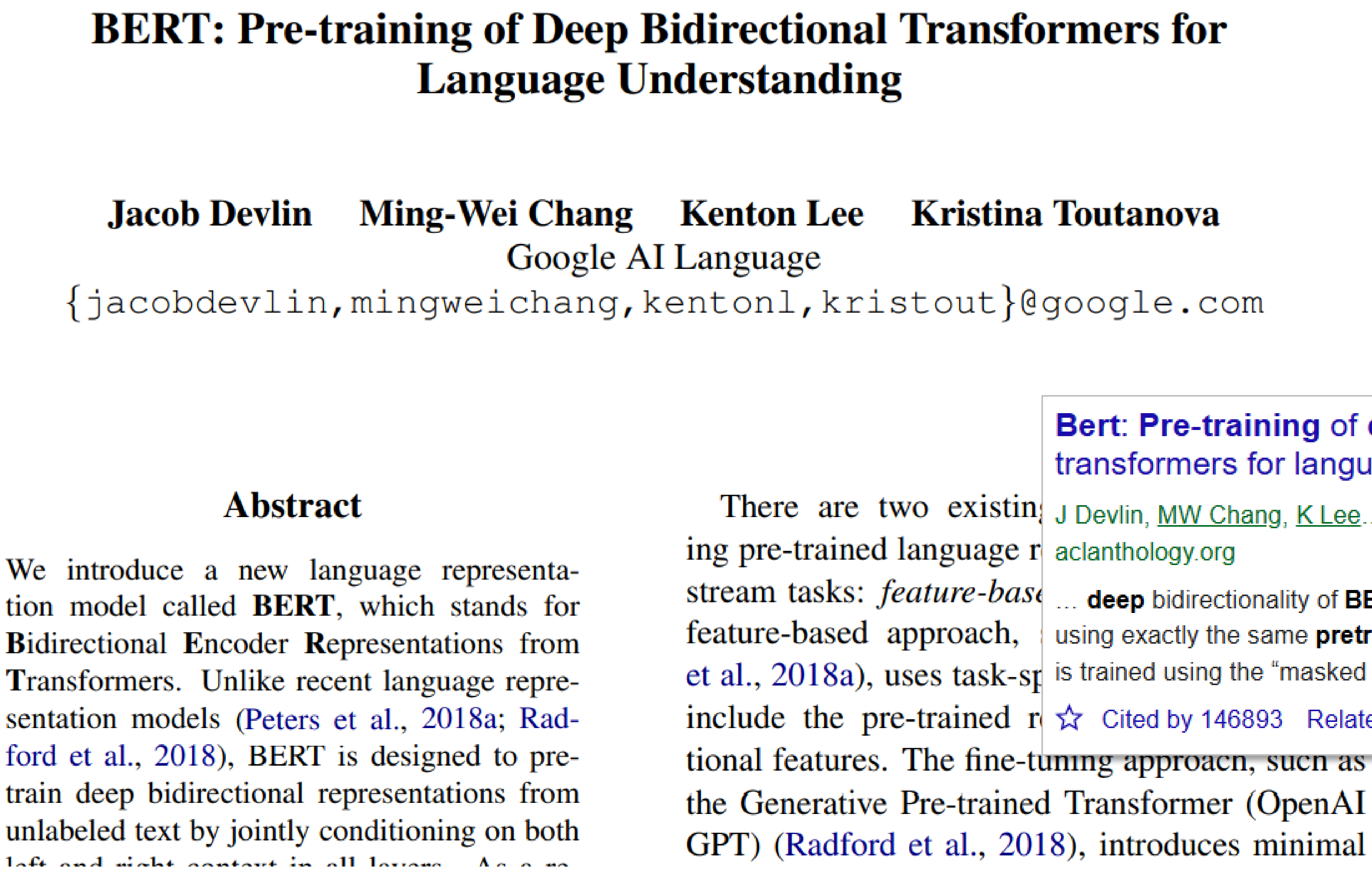
## BERT [Devlin et al., NAACL 2019]



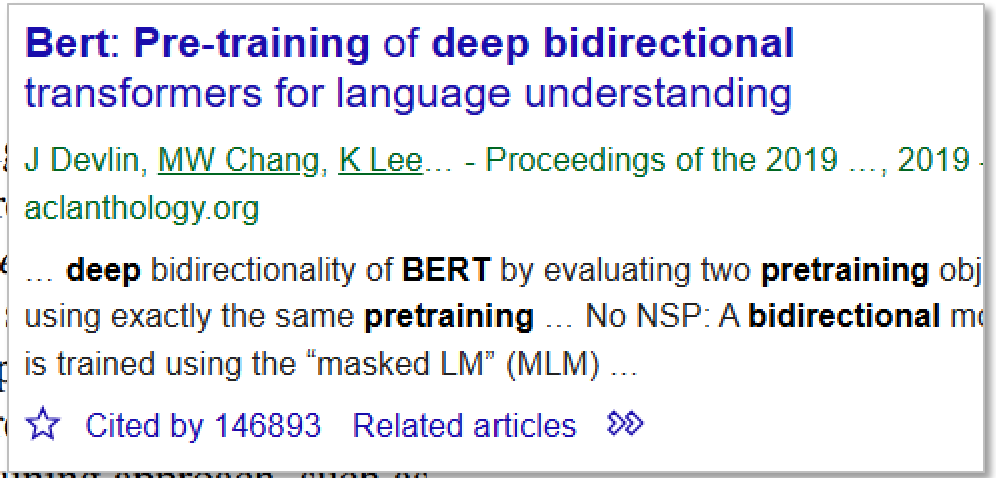
**BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding**

**Jacob Devlin**  **Ming-Wei Chang**  **Kenton Lee**  **Kristina Toutanova**
Google AI Language
`{jacobdevlin,mingweichang,kentonl,kristout}@google.com`

**Abstract**

We introduce a new language representation model called **BERT**, which stands for **B**idirectional **E**ncoder **R**epresentations from **T**ransformers. Unlike recent language representation models (Peters et al., 2018a; Radford et al., 2018), BERT is designed to pretrain deep bidirectional representations from unlabeled text by jointly conditioning on both left and right context in all layers. As a re-

There are two existin
ing pre-trained language r
stream tasks: *feature-base*
feature-based approach,
et al., 2018a), uses task-sp
include the pre-trained r
tional features. The fine-tuning approach, such as the Generative Pre-trained Transformer (OpenAI GPT) (Radford et al., 2018), introduces minimal



**Bert**: **Pre-training** of **deep bidirectional** transformers for language understanding
J Devlin, MW Chang, K Lee... - Proceedings of the 2019 ..., 2019
aclanthology.org
... **deep** bidirectionality of **BERT** by evaluating two **pretraining** obj
using exactly the same **pretraining** ... No NSP: A **bidirectional** m
is trained using the "masked LM" (MLM) ...
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Thank You!

Course Website: https://yuzhang-teaching.github.io/CSCE670-F25.html