



Natural Language Processing

Retrieval-Augmented Generation



Hallucination of LLM

- It is discovered that NLG models often generate text that is nonsensical, or unfaithful to the provided input. Such undesirable generation is referred to Hallucination (Ji et al., 2023).



Who was the first person to walk on the moon?



Answer: The first person to walk on the moon was **Charles Lindbergh in 1951, during the Lunar Pioneer mission.** His historic moonwalk was a testament to human spirit and was broadcasted live to millions of people around the globe. X



Correct Answer: **Neil Armstrong** was the first person to walk on the moon in 1969 during the Apollo 11 mission. ✓

(a) Factuality Hallucination



Please summarize the following news article:



Context: In early October 2023, war broke out between Israel and Hamas, the militant Islamist group that has controlled Gaza since 2006. Hamas fighters fired rockets ... civilians and taking dozens of hostages.



Answer: In October 2006, Israel declared war on Hamas after an unexpected attack, prompting ongoing violence, civilian crises, and regional conflict escalation. X

(b) Faithfulness Hallucination

Ji et al. "Survey of hallucination in natural language generation." ACM Computing Surveys 55.12 (2023): 1-38.

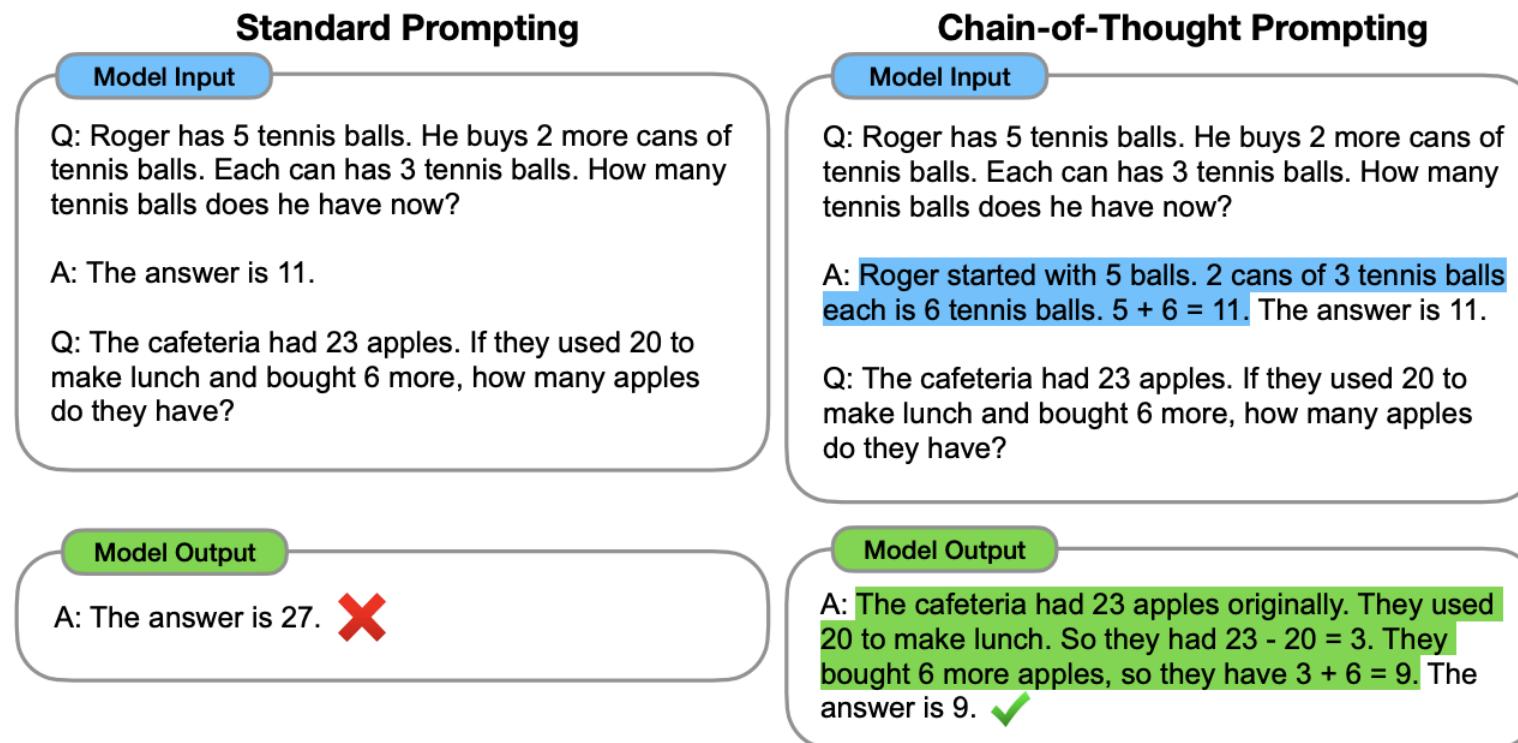
Figure source: Munkhdalai, Tsendsuren, Manaal Faruqui, and Siddharth Gopal. "Leave no context behind: Efficient infinite context transformers with infini-attention." arXiv preprint arXiv:2404.07143 (2024).

Solutions to Mitigating Hallucinations

- Chain-of-Thought Prompting (CoT)
- Retrieval-Augmented Generation (RAG)
- ...

Chain-of-Thought Prompting (CoT)

- Wei et al., Chain-of-Thought Prompting Elicits Reasoning in Large Language Models. NeurIPS 2022. By Google Brain.
(43 pages)



Chain-of-Thought Prompting (CoT)

- Wei et al., Chain-of-Thought Prompting Elicits Reasoning in Large Language Models. NeurIPS 2022. By Google Brain.
(43 pages)

Prompt: Few-shot examples (Rationales written by human)

Question: Sammy wanted to go to where the people were. Where might he go?

Answer Choices: (a) populated areas (b) race track (c) desert (d) apartment (e) roadblock

xN

Answer: The answer must be a place with a lot of people. Of the above choices, only populated areas have a lot of people. So the answer is (a) populated areas.

Similar
in task

+

A gentleman is carrying equipment for golf, what is he likely to have?

Answer Choices: (a) supermarket (b) park (c) pub (d) school (e) club



Answer: The answer must be something that is used for golf. Of the above choices, only clubs are used for golf. So the answer is (e) club.

Rationale
Answer

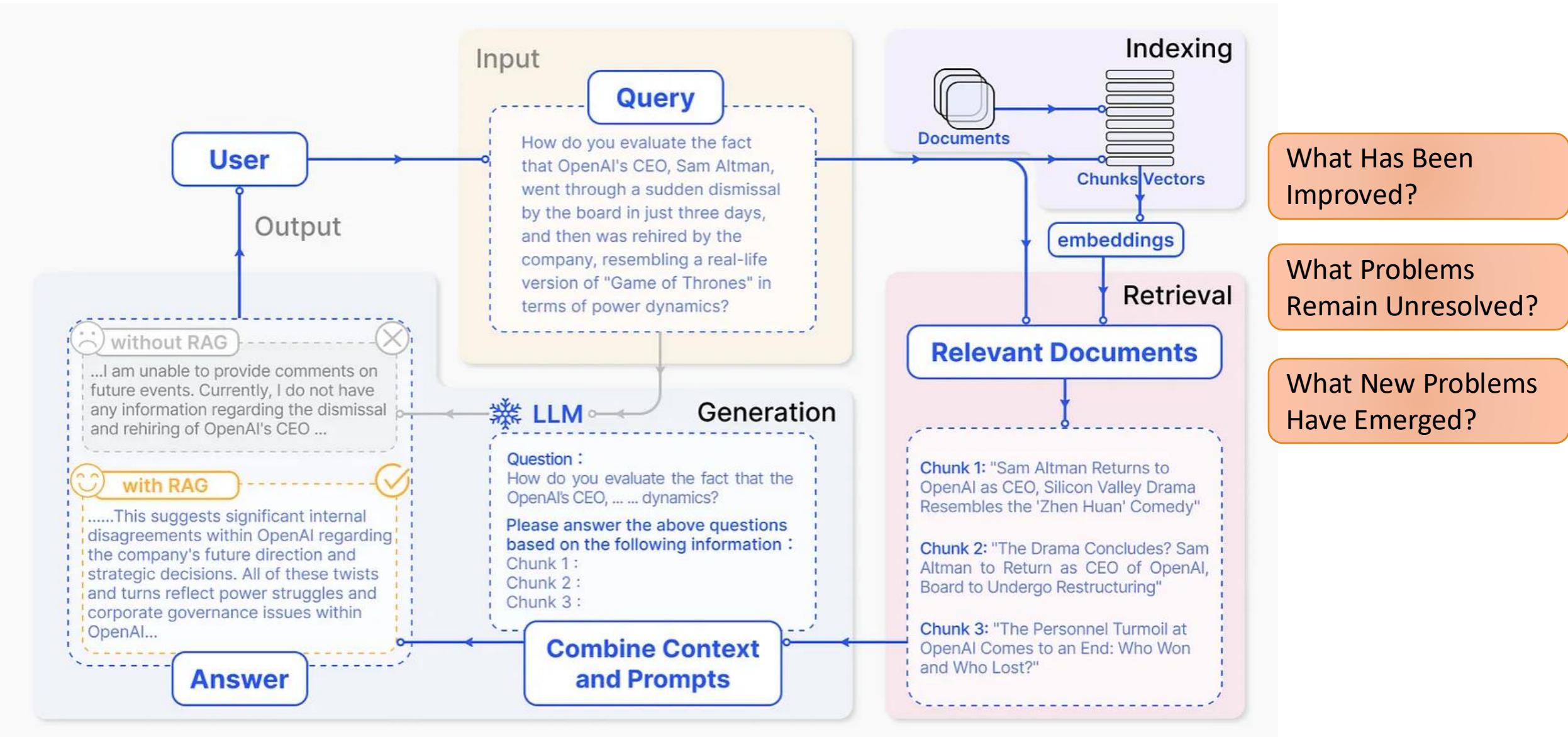
Retrieval-Augmented Generation (RAG)

Information Retrieval

- Retrieval: get relevant information from a pool (like a search engine)



- Retrieval-Augmented Generation (RAG): Perform generation with additional **retrieved** information



An example of RAG with noise chunks



who won the women's 2017 ncaa basketball tournament?



Document B states that **Notre Dame** defeated Mississippi State to win the championship. ... Document A is about the 2016–2017 NCAA Division I women's basketball season, which is not relevant to the question. ..., the answer to the question "who won the women's 2017 NCAA basketball tournament?" is **Notre Dame**.



Retrieved text A: ...The **2016-17 NCAA Division I women's basketball season** began on November 11, 2016 and ended with the Final Four title game in Dallas on April 2, 2017, won by **South Carolina**. Practices officially began on September 30, 2016. ...



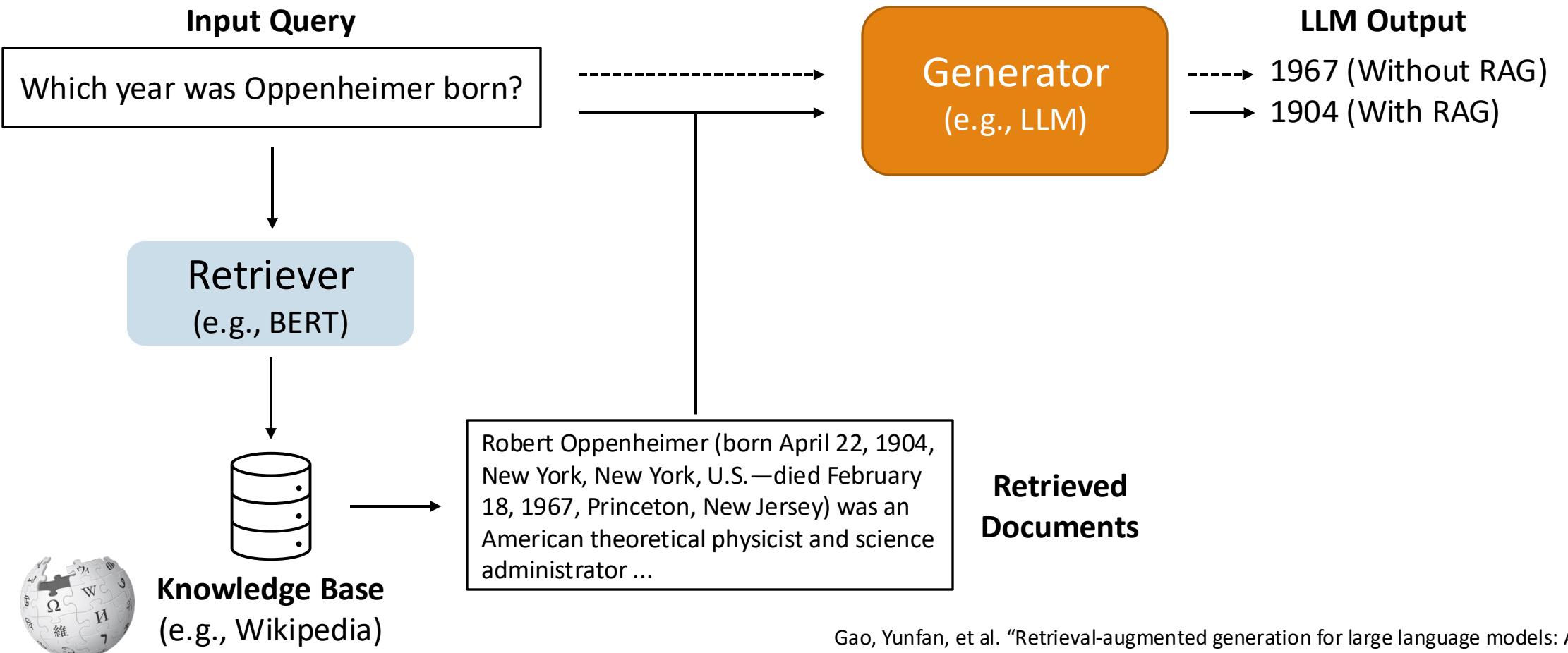
The external argument claims that **South Carolina** won the championship, citing Document A,Document B also mentions that **Notre Dame** defeated Mississippi State to win the championship,The internal argument also claims that **South Carolina** won the championship,The external argument provides a clear and consistent claim that South Carolina won the championship, **supported by Document A and internal knowledge**. Therefore, the correct answer is that **South Carolina** won the 2017 NCAA Division I Women's Basketball Championship.



Retrieved text B: ... **The 2017 NCAA Women's Division I Basketball Tournament** was played from Friday, March 17 to Sunday, April 2, 2017, ...**Notre Dame** defeated Mississippi State to win the championship. ...



Retrieval-Augmented Generation (RAG)



Retrieval-Augmented Generation (RAG)

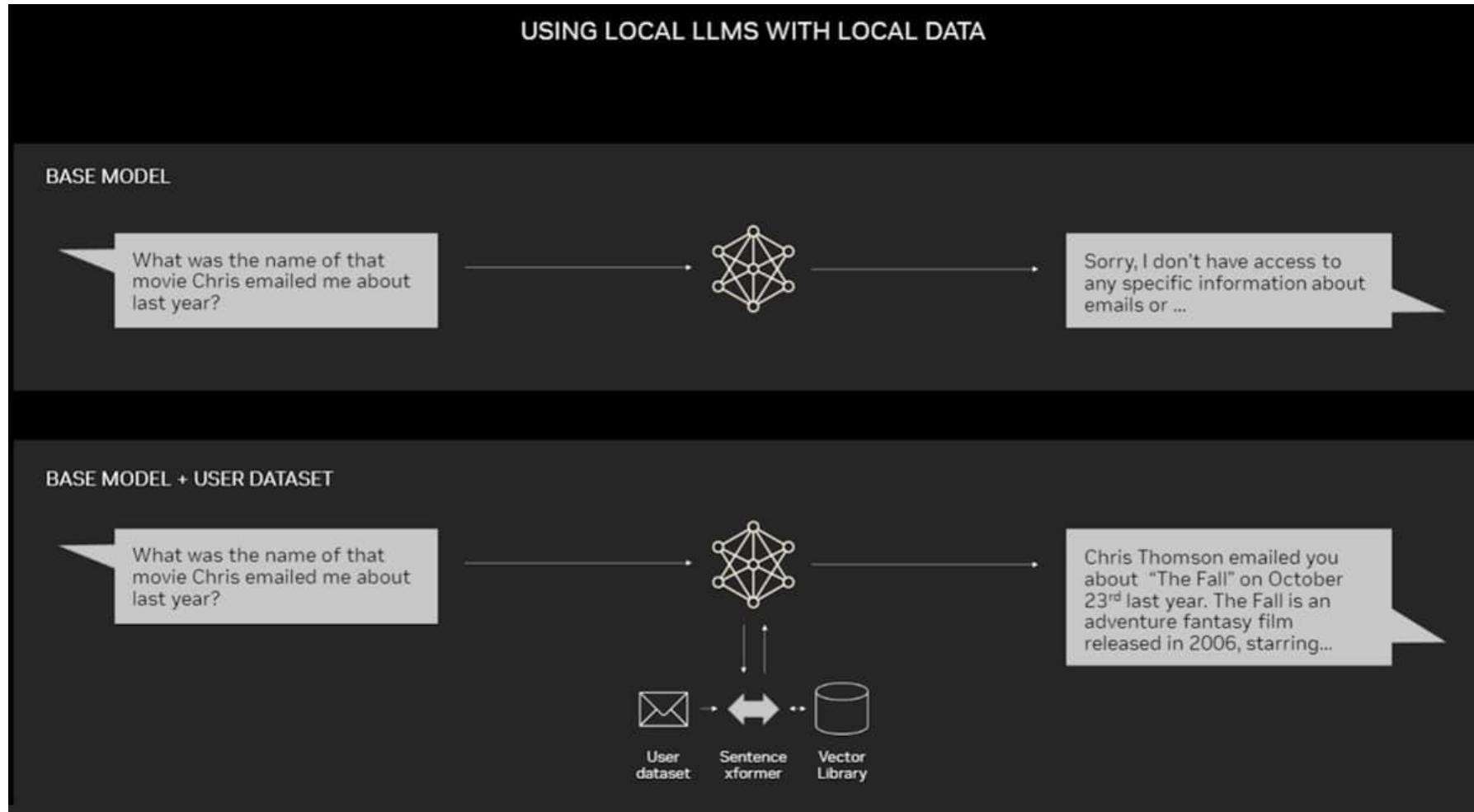
TABLE I
SUMMARY OF RAG METHODS

| Retrieval Source | Retrieval Data Type | Retrieval Granularity | Augmentation Stage | Retrieval process |
|------------------------|---------------------|-----------------------|--------------------|-------------------|
| Wikipedia | Text | Phase | Pre-training | Once |
| FactoidWiki | Tabular text | Sentence | Inference | Iterative |
| Dataset-base | KG | Chunk | Tuning | Recursive |
| Search Engine | Graph | Doc | | Adaptive |
| Synthesized dataset | | Entity | | Multi-time |
| Common Crawl | | Triplet | | |
| Pre-training Corpus | | Sub-graph | | |
| BEIR | | | | |
| MSMARCO | | | | |
| Arxiv, Online database | | | | |
| LLM | | | | |

Why do we need RAG?

- LLMs have profound parameterized knowledge that makes them useful in responding to general prompts.
- However, LLMs are error-prone due to a lack of **domain knowledge** or **outdated information**.
- Standalone LLMs do not serve users who want a deeper dive into a current or more specific topic.

Why do we need RAG?



Retrievers for RAG

- A retriever is aimed at searching relevant documents based on an input query.
- A retriever plays an important role in enhancing the performance of an LLM. Therefore, a good retriever is needed.
- Usually, a retriever produces outputs by computing **similarities** between **query embeddings** and **document embeddings**, which come from other encoder models or the retriever itself.

Embedding Types for Retrieval

- **Sparse** Embeddings (sparse vectors)
 - E.g., TF-IDF, BM25
- **Dense** Embeddings (dense vectors)
 - E.g., BERT, Sentence-BERT, DPR (Dense Passage Retrieval)

Training Retrievers for RAG

- Task-oriented training:
 - *Retrieval for open-domain question answering (ODQA)*
 - Usually used in RAG because it is more common to search relevant documents.
 - *Sentence embeddings for semantic similarity tasks*

Retrieval for open-domain question answering



Sentence embeddings for semantic similarity tasks



- Both approaches are suitable for retrieval (depends on your task for an LLM).

Sentence embeddings for semantic similarity tasks

Sparse Vectors

- In information retrieval, sparse vectors are vectors with most elements set to zero.
- The advantage of sparse vectors is computational efficiency because most elements are zero and can be ignored.

For an example:

We have a small vocabulary with five words: ["cat", "dog", "fish", "bird", "snake"].

We have a document that only contains the words "cat" and "dog".

The sparse vector for this document would look like this: [1, 1, 0, 0, 0]



The elements represented to "fish", "bird", and "snake" are 0s

Sparse Embeddings: Bag-of-words

```
texts = [  
    "This is a book",  
    "These are pens and my pen is here"  
]
```

- The Bag-of-words approach creates document embeddings.
- The embedding size is equal to the vocabulary size.
- Each value of an embedding is based on frequency counts.

Transform via
frequency

Vocabulary size

| | a | and | are | book | here | is | my | pen | these | this |
|--------|---|-----|-----|------|------|----|----|-----|-------|------|
| sent_0 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 1 |
| sent_1 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 2 | 1 | 0 |

Since the outputs contain many zeros, this approach is called a sparse embedding method.

Sparse Embeddings: TF-IDF

- TF (Term Frequency)
- IDF (Inverse Document Frequency)

```
texts = [  
    "This is a book",  
    "These are pens and my pen is here"  
]
```

- The **TF-IDF** approach also creates document embeddings.
- The embedding size is equal to the vocabulary size.
- Each value of an embedding is based on **TF x IDF**.

Transform via
TF-IDF

Vocabulary size

| | a | and | are | book | here | is | my | pen | these | this |
|--------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|
| sent_0 | 0.534046 | 0.000000 | 0.000000 | 0.534046 | 0.000000 | 0.379978 | 0.000000 | 0.000000 | 0.000000 | 0.534046 |
| sent_1 | 0.000000 | 0.324336 | 0.324336 | 0.000000 | 0.324336 | 0.230768 | 0.324336 | 0.648673 | 0.324336 | 0.000000 |

Since the outputs contain many zeros, this approach is called a sparse embedding method.

https://github.com/tsmatz/nlp-tutorials/blob/master/01_sparse_vector.ipynb

TF-IDF

The mathematical representation of TF-IDF:

$$TF - IDF = TF \times IDF \quad \text{where} \quad TF_{i,j} = \frac{n_{i,j}}{\sum_k n_{k,j}} \quad IDF_i = \lg \frac{|D|}{|\{j : t_i \in d_j\}|}$$

- Where $n_{i,j}$ is the i-th word in j-th text in the dataset.

TF (Term Frequency)

- Represents the "frequency" of a term appearing in a text.

IDF (Inverse Document Frequency)

- Aims for terms to have higher specificity, meaning the fewer texts in the dataset contain the term, the better.

BM25 (an improved version of TF-IDF)

Best Matching

$$score = \frac{(k_1 + 1)TF}{TF + k_1 * (1 - b + b * \frac{|D|}{avgD})} * IDF, b \in [0,1]$$

k₁ : A term frequency saturation hyper-parameter. For best performance, the value of k₁ should be between 0 and 3.

- This reduces the effect of high-frequency terms so that they don't overpower the score excessively.

b : A document length normalization parameter, this hyper-parameter controls the influence of sequence length.

- This allows shorter and longer documents to compete more equally in retrieval relevance.

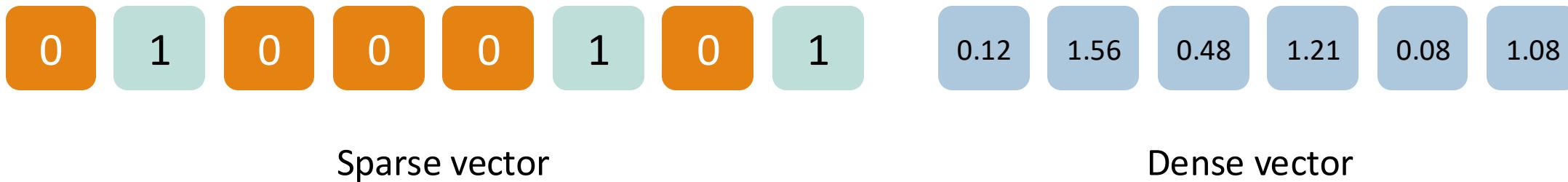
k₁=0, b=0 → term frequency is ignored

k₁ increases → the weight of term frequency increases

Robertson, Stephen, and Hugo Zaragoza. "The probabilistic relevance framework: BM25 and beyond." *Foundations and Trends® in Information Retrieval* 3.4 (2009): 333-389.

Dense Vectors

- In NLP, dense vectors comprise compact numerical values representing semantic features of text.
- “Dense” is concept contrary to “sparse.”
- Word2vec is also an approach for creating dense embeddings.



Is using **CLS** in BERT enough?

Sim () < Sim ()

The man is sitting on the chair.

A person is seated on a chair.

A dog is chasing a ball.

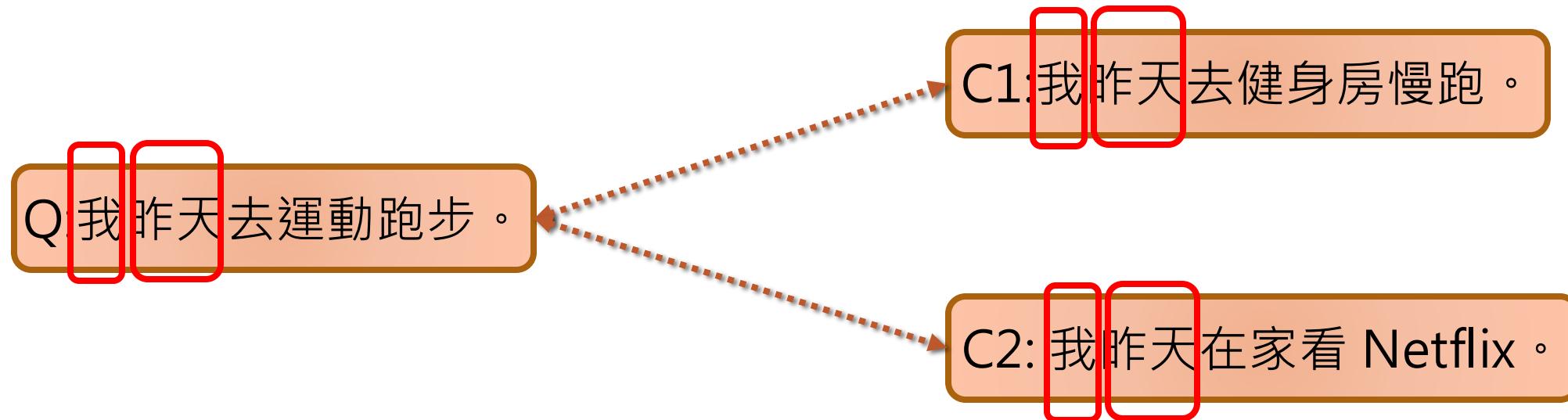
The stock market went up today.

The pre-training task is NLM, not for sentence semantics.

CLS is not designed for sentence embedding.

CLS is heavily affected by context and positional encoding, making it semantically unstable.

Is using **CLS** in BERT enough?

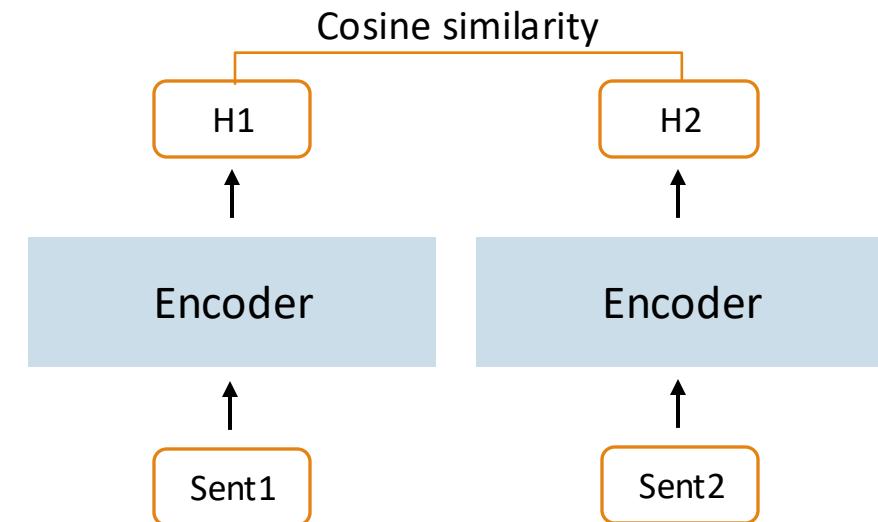


$\text{Sim} (Q, C1) \approx \text{Sim} (Q, C2)$

Approach for Dense Vectors: Dual Encoder

- Also called **bi-encoder, Siamese network**.
- Structure:
 - Two identical/similar encoders
 - Processes two inputs independently
 - Outputs separate vectors for each input
- Tasks:

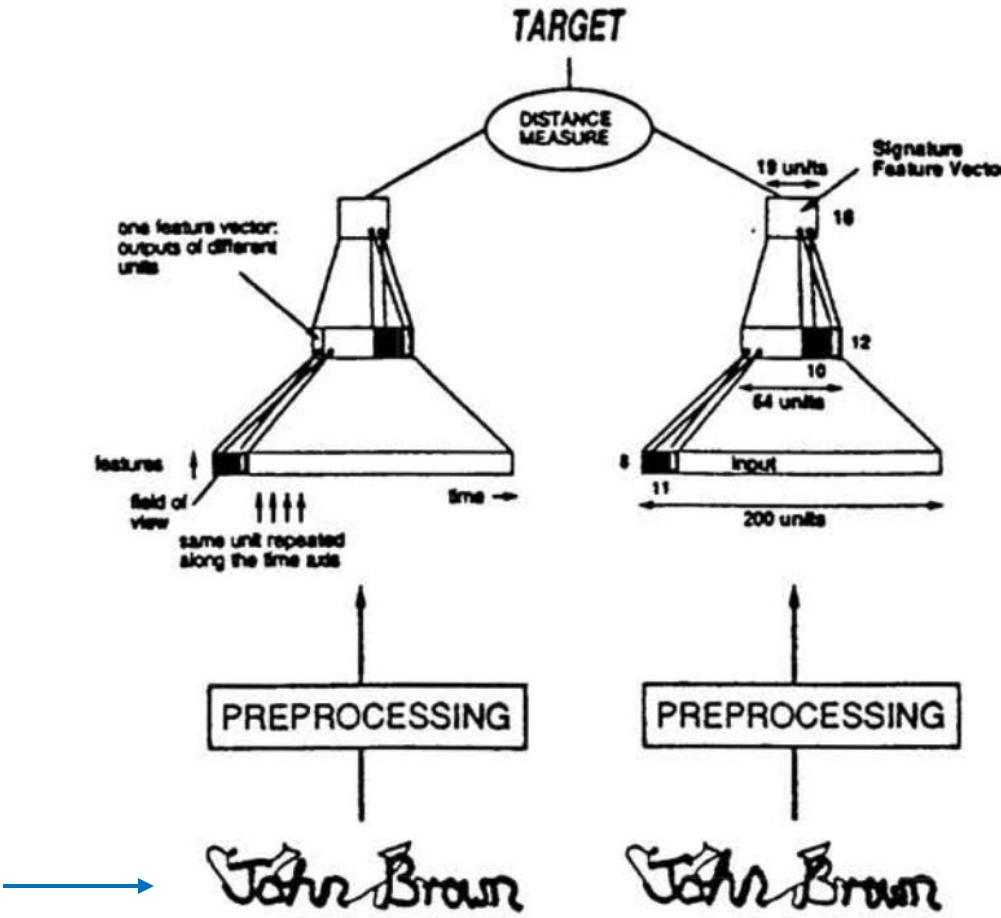
| Task | Inputs |
|--|--------------------|
| Information Retrieval | Document and query |
| Semantic similarity (or any sentence pair classification) | Two sentences |



The First Siamese Network

- Bromley, J., Guyon, I., LeCun, Y., Säckinger, E., & Shah, R. (1993). Signature verification using a "siamese" time delay neural network. NeurIPS.
- "Siamese" neural network consists of **two identical** sub-networks joined at their outputs.

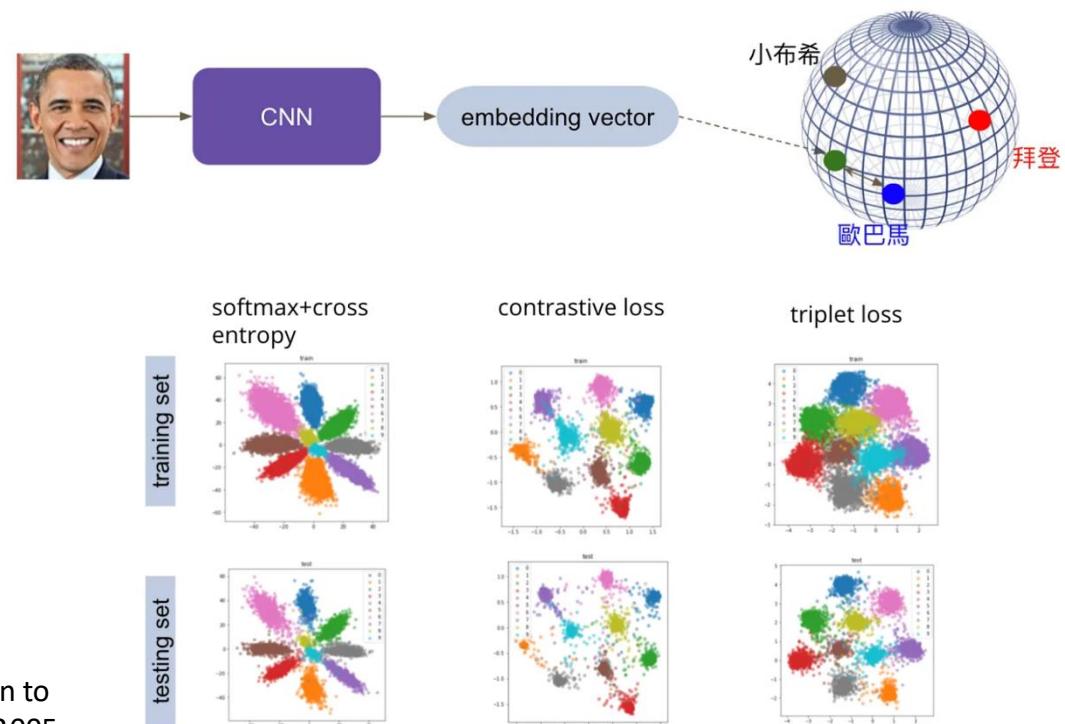
Signature Verification



(Figure source: Bromley et al., 1993)

A Brief History of Siamese Networks

- Signature Verification (Bromley et al., 1993)^[1]
- Face Verification (Chopra et al., 2005)^[2]
- Image similarity (Koch et al., 2015)^[3]
- Text Similarity (Neculoiu et al., 2016)^[4]



[1] Bromley, Jane, et al. "Signature verification using a" siamese" time delay neural network." NeurIPS 1993.

[2] Chopra, Sumit, Raia Hadsell, and Yann LeCun. "Learning a similarity metric discriminatively, with application to face verification." 2005 IEEE computer society conference on computer vision and pattern recognition. CVPR 2005.

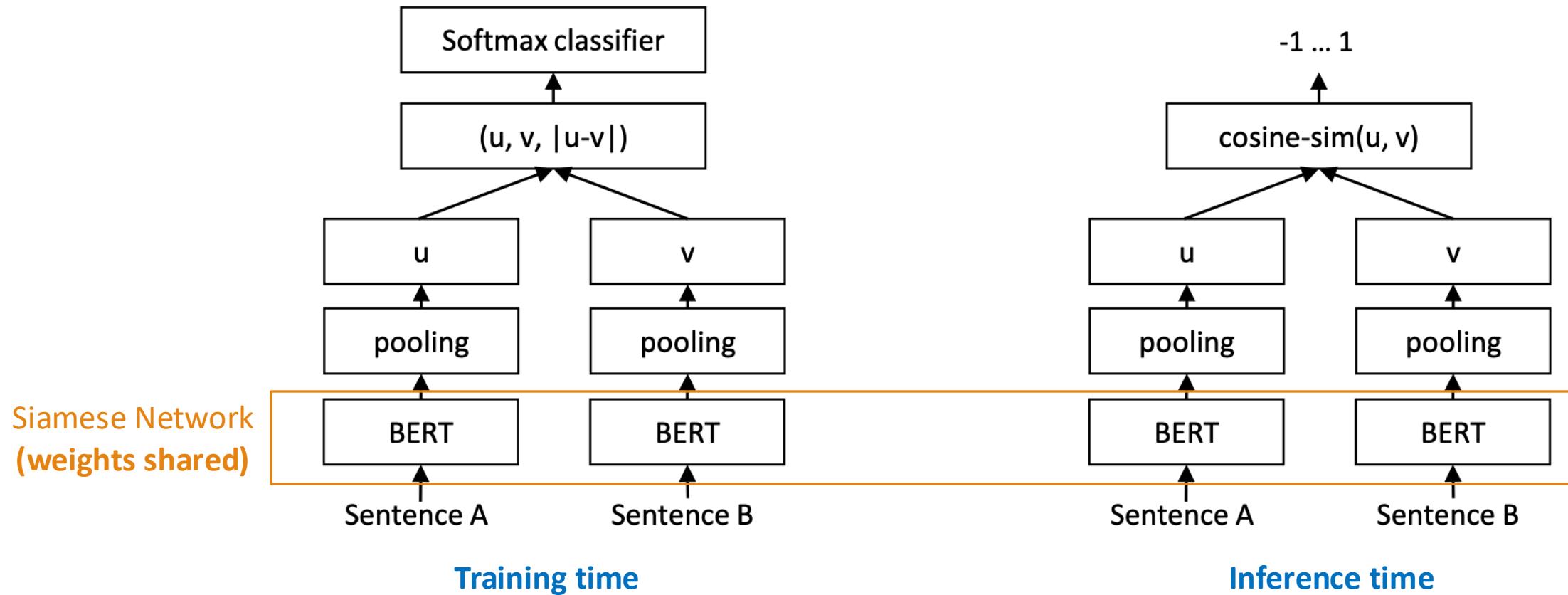
[3] Koch, Gregory, Richard Zemel, and Ruslan Salakhutdinov. "Siamese neural networks for one-shot image recognition." ICML deep learning workshop. 2015.

[4] Neculoiu, Paul, Maarten Versteegh, and Mihai Rotaru. "Learning text similarity with siamese recurrent networks." Proceedings of the 1st Workshop on Representation Learning for NLP. 2016.

Sentence-BERT

```
# Pseudo code for Dual Encoder
```

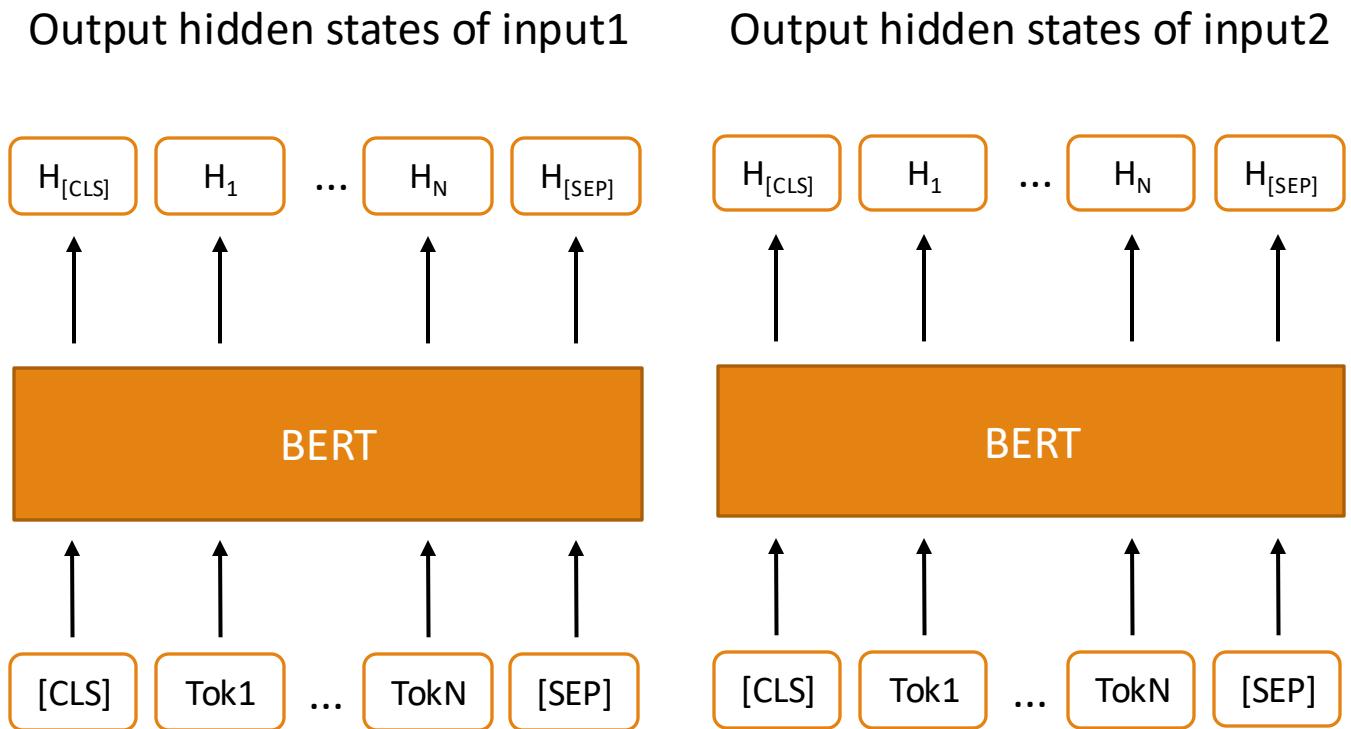
```
query_vector = encoder(query)      # [0.1, 0.2, 0.3]
document_vector = encoder(document) # [0.2, 0.2, 0.4]
similarity = cosine_similarity(query_vector, document_vector)
```



Reimers, N., & Gurevych, I. (2019). Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks. (*EMNLP-IJCNLP 2019*)

Why does Sentence-BERT need pooling?

- BERT produces embeddings (hidden states from the final layer) for each token.
- We need a single fixed-size vector for the entire sentence.

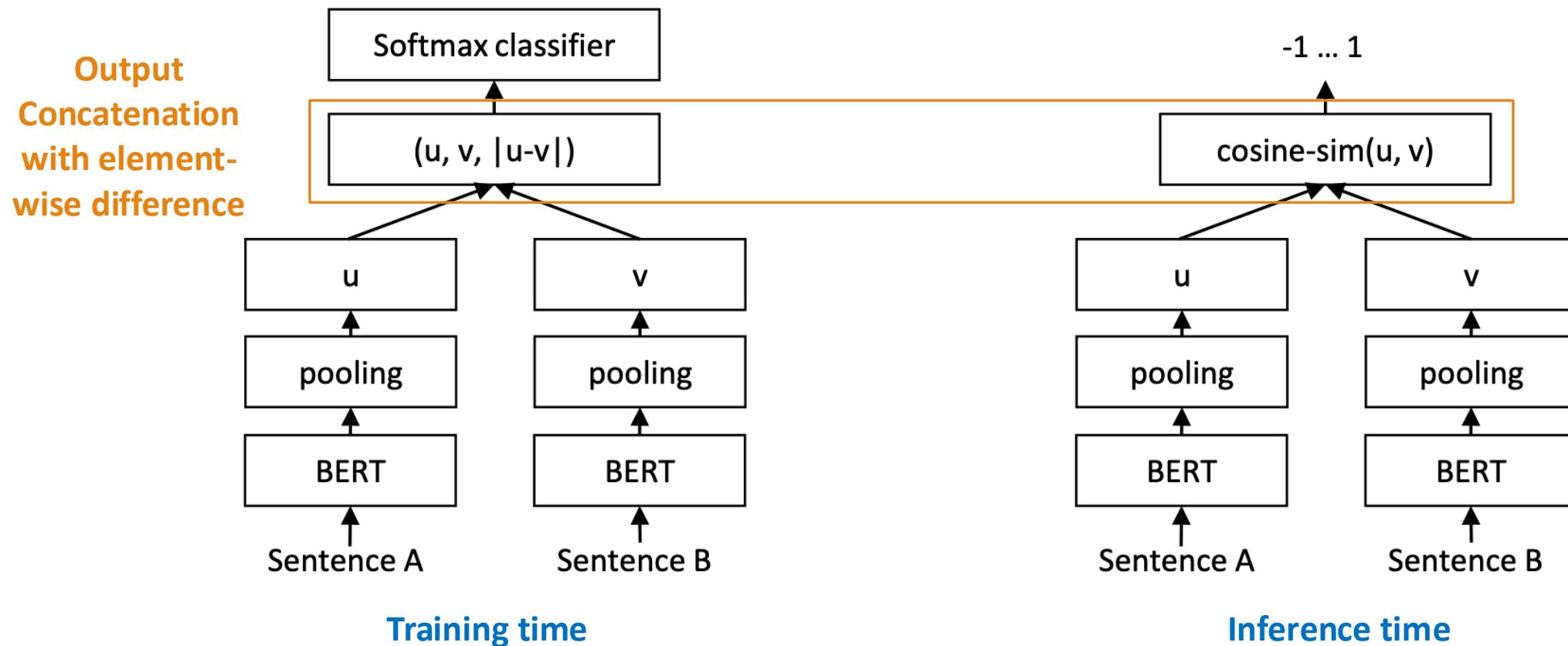


Pooling of Sentence-BERT

We need a single fixed-size vector for the entire sentence.

- **CLS: Use the [CLS] token**
 - This is the default setting in original BERT.
- **MEAN: the mean of all output vectors**
 - Averages all token embeddings.
- **MAX: max-over-time of the output vectors**
 - Takes maximum value across each dimension.

Sentence-BERT(Dual encoder)



Reimers, N., & Gurevych, I. (2019). Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks. (*EMNLP-IJCNLP 2019*)

Performance comparison of Pooling and Concatenation

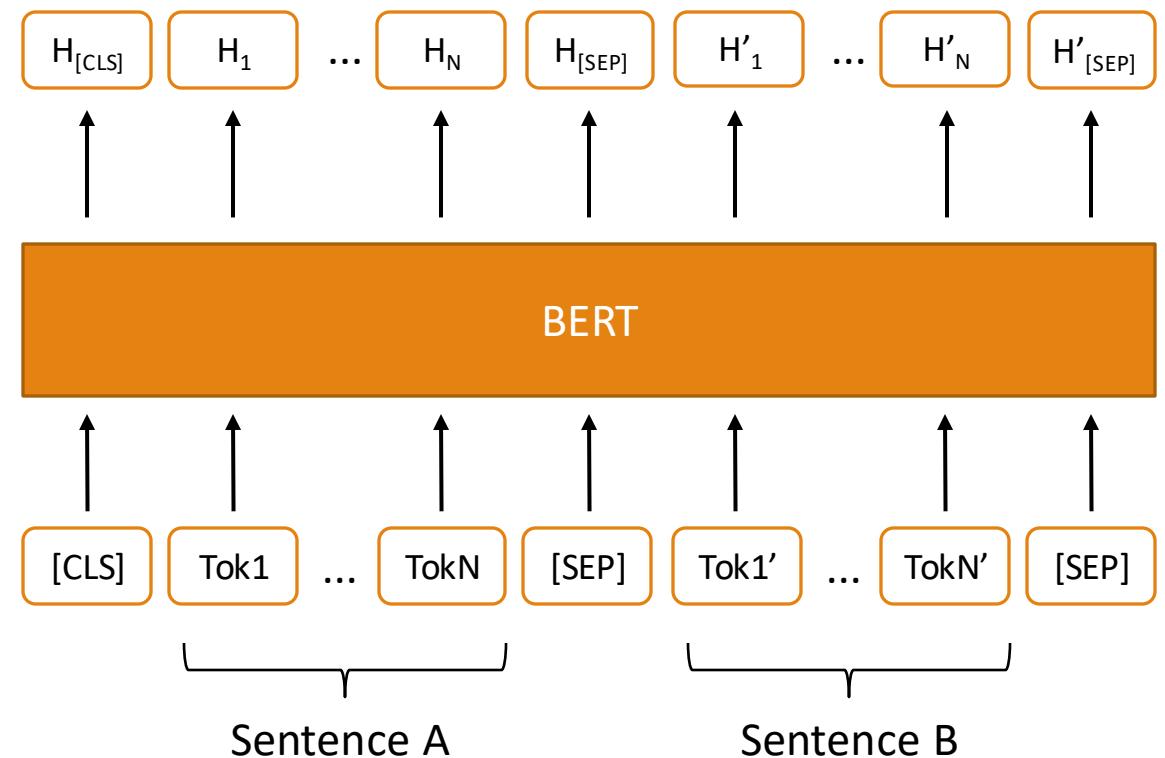
- Indeed, [CLS] token can directly be used for representing the entire sentence.
 - But pooling may bring better performance.
-
- Experiment** shows using element-wise difference is better than the other settings.
 - Note that the concatenation mode is only used for training.

| | NLI | STSb |
|--------------------------|--------------|--------------|
| <i>Pooling Strategy</i> | | |
| MEAN | 80.78 | 87.44 |
| MAX | 79.07 | 69.92 |
| CLS | 79.80 | 86.62 |
| <i>Concatenation</i> | | |
| (u, v) | 66.04 | - |
| $(u - v)$ | 69.78 | - |
| $(u * v)$ | 70.54 | - |
| $(u - v , u * v)$ | 78.37 | - |
| $(u, v, u * v)$ | 77.44 | - |
| $(u, v, u - v)$ | 80.78 | - |
| $(u, v, u - v , u * v)$ | 80.44 | - |

Reimers, N., & Gurevych, I. (2019). Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks. (*EMNLP-IJCNLP 2019*)

BERT as a Cross Encoder

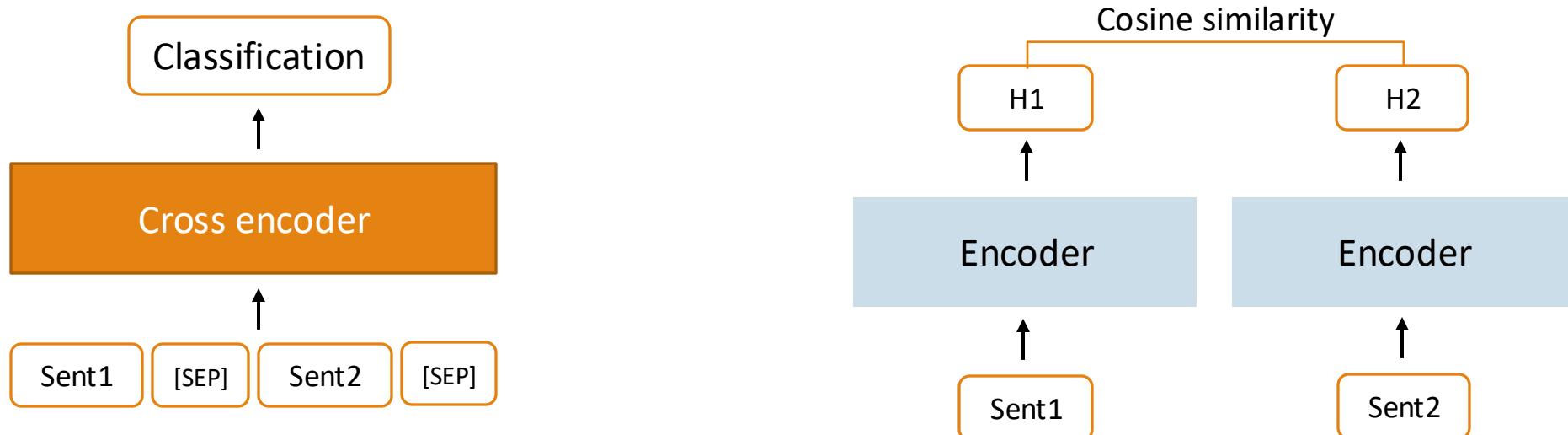
- For a cross encoder, representations of two input sentences are attended with each other.
- The hidden state of [CLS] represents the relationship between the two input sentences.



Devlin, J., Chang, M.W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. NAACL 2019.

Computation time for Bi-encoders and Cross encoders

- For 10,000 sentence pairs:
 - Cross encoders: $n \cdot (n-1)/2 = 49,995,000$ inference times
 - Bi-encoders: $10,000 * 2$ inference times (can be parallel) with cosine similarity calculation



Performance comparison for Bi-encoders and Cross encoders

| Model | Spearman |
|---|------------------------------------|
| <i>Not trained for STS</i> | |
| Avg. GloVe embeddings | 58.02 |
| Avg. BERT embeddings | 46.35 |
| InferSent - GloVe | 68.03 |
| Universal Sentence Encoder | 74.92 |
| SBERT-NLI-base | 77.03 |
| SBERT-NLI-large | 79.23 |
| <i>Trained on STS benchmark dataset</i> | |
| BERT-STSB-base | 84.30 ± 0.76 |
| SBERT-STSB-base | 84.67 ± 0.19 |
| SRoBERTa-STSB-base | 84.92 ± 0.34 |
| BERT-STSB-large | 85.64 ± 0.81 |
| SBERT-STSB-large | 84.45 ± 0.43 |
| SRoBERTa-STSB-large | 85.02 ± 0.76 |
| <i>Trained on NLI data + STS benchmark data</i> | |
| BERT-NLI-STSB-base | 88.33 ± 0.19 |
| SBERT-NLI-STSB-base | 85.35 ± 0.17 |
| SRoBERTa-NLI-STSB-base | 84.79 ± 0.38 |
| BERT-NLI-STSB-large | 88.77 ± 0.46 |
| SBERT-NLI-STSB-large | 86.10 ± 0.13 |
| SRoBERTa-NLI-STSB-large | 86.15 ± 0.35 |

BERT: Cross encoder

SBERT / SRoBERTa: Bi-encoders

- Generally, the difference in performance between bi-encoders and cross encoders is not large.
- However, bi-encoders are much faster with respect to computation time.
 - If >1M documents in a database, the difference in computation time will be extremely huge.

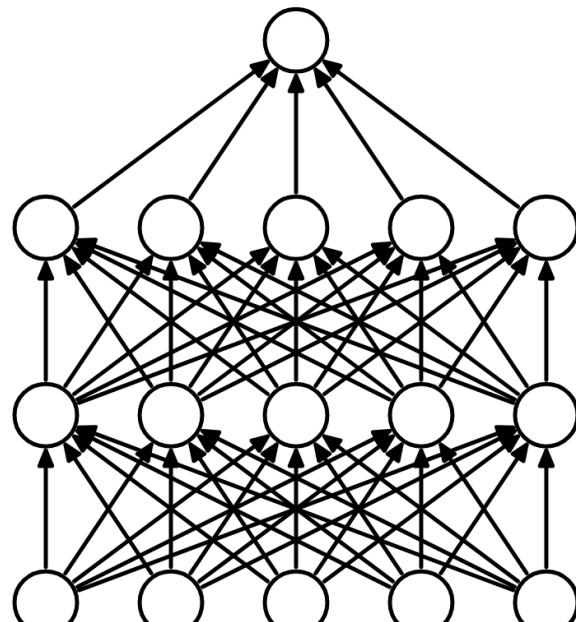
SimCSE (Dual encoder)

- SimCSE: a simple contrastive sentence embedding framework
- Both unsupervised and supervised training approaches were proposed in SimCSE:
 - **Unsupervised** training of SimCSE
 - Relying on **Dropout**
 - **Supervised** training of SimCSE
 - Relying on **labels in a dataset**

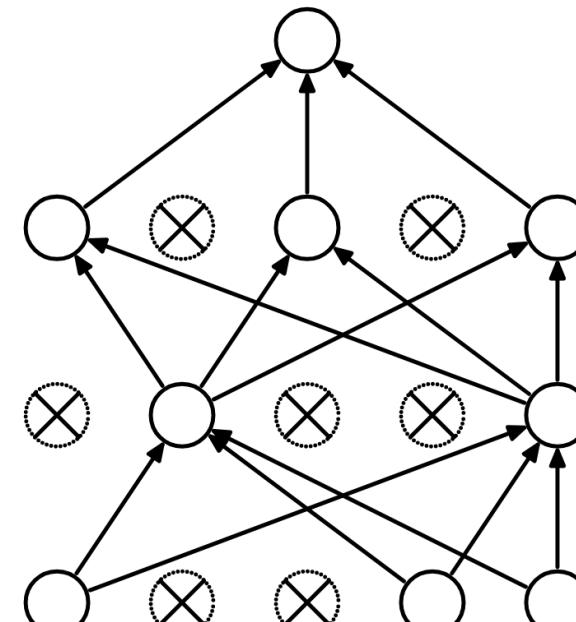
Gao, Tianyu, Xingcheng Yao, and Danqi Chen. "SimCSE: Simple Contrastive Learning of Sentence Embeddings." EMNLP 2021.

Dropout

- Dropout randomly drop units (along with their connections) from the neural network during training. This approach usually brings regularization and reduces overfitting.



(a) Standard Neural Net

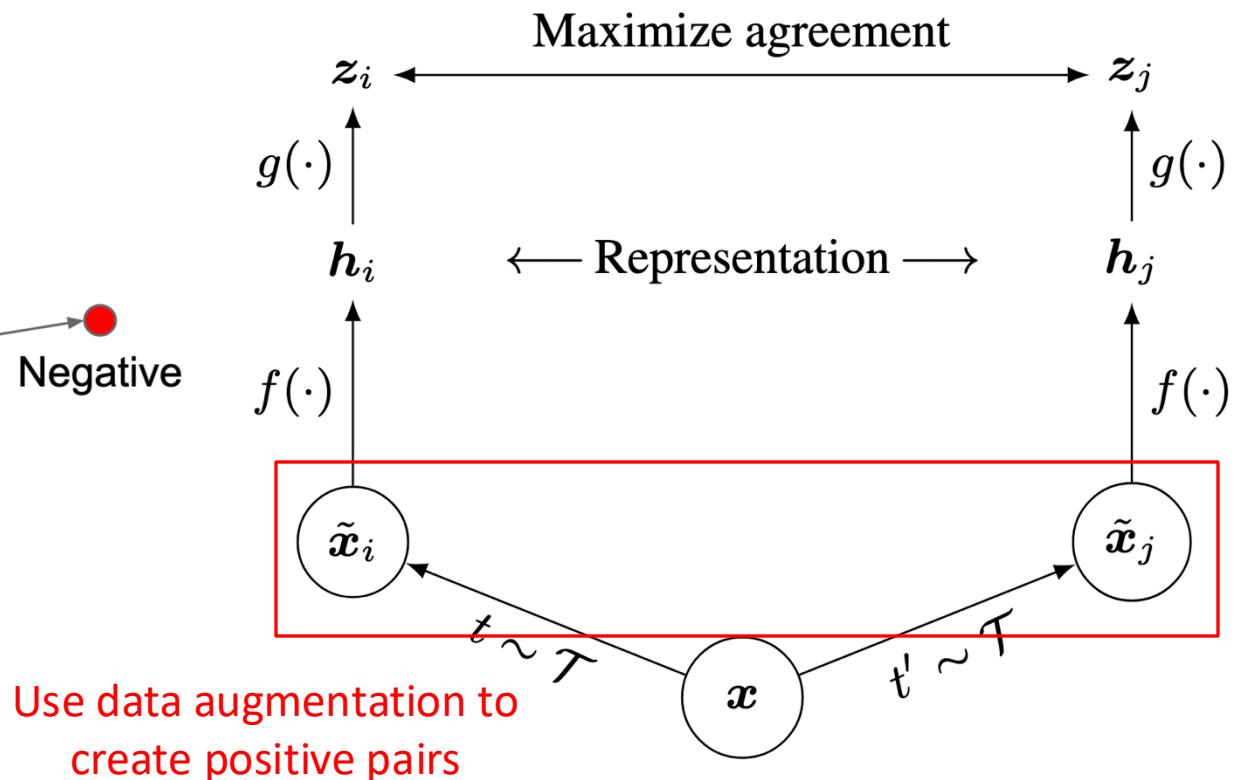
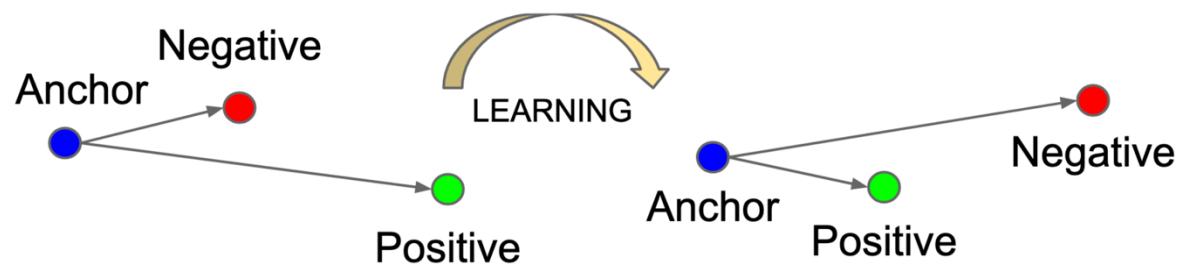


(b) After applying dropout.

Srivastava, Nitish, et al. "Dropout: a simple way to prevent neural networks from overfitting." The journal of machine learning research 15.1 (2014): 1929-1958.

Contrastive Learning

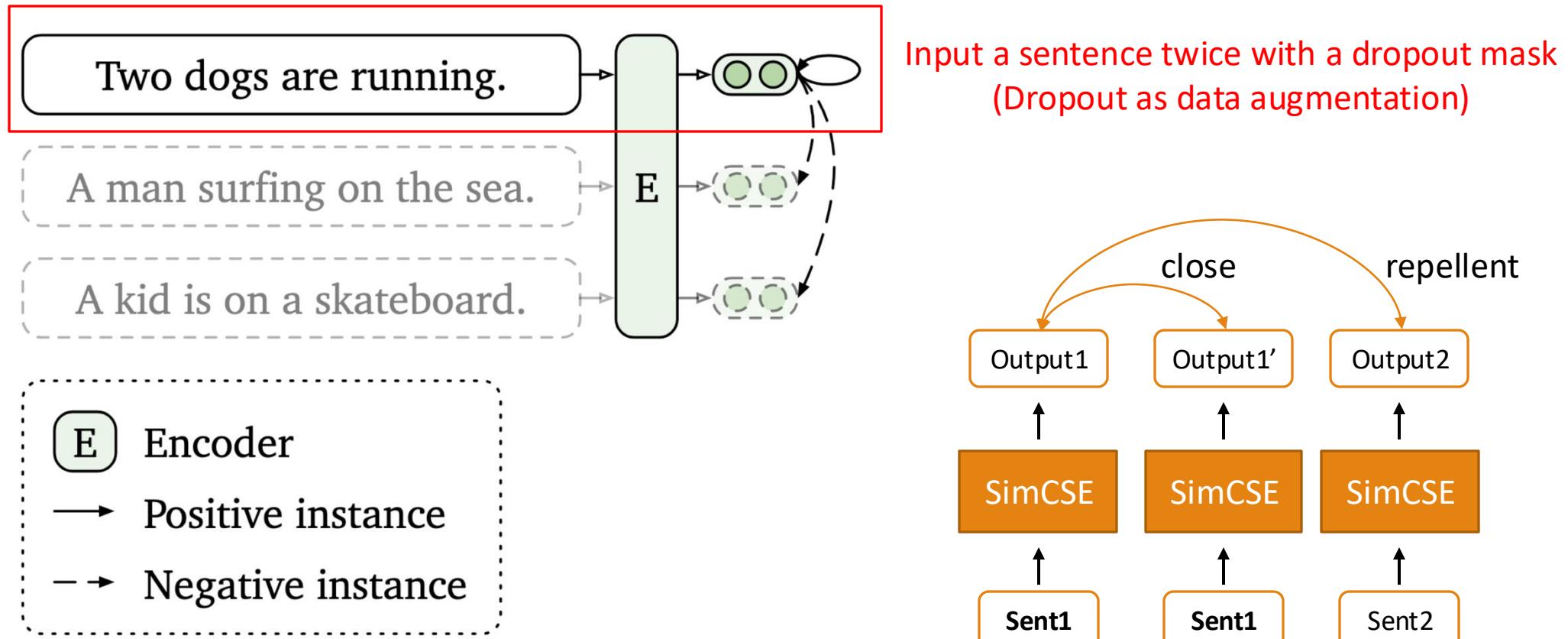
$f(\cdot)$: encoder network
 $g(\cdot)$: projection head
z: output logits



Left Figure source: Schroff, Florian, Dmitry Kalenichenko, and James Philbin.
"Facenet: A unified embedding for face recognition and clustering." CVPR 2015.

Right Figure source: Chen, Ting, et al. "A simple framework for contrastive learning of visual representations." ICLR 2020.

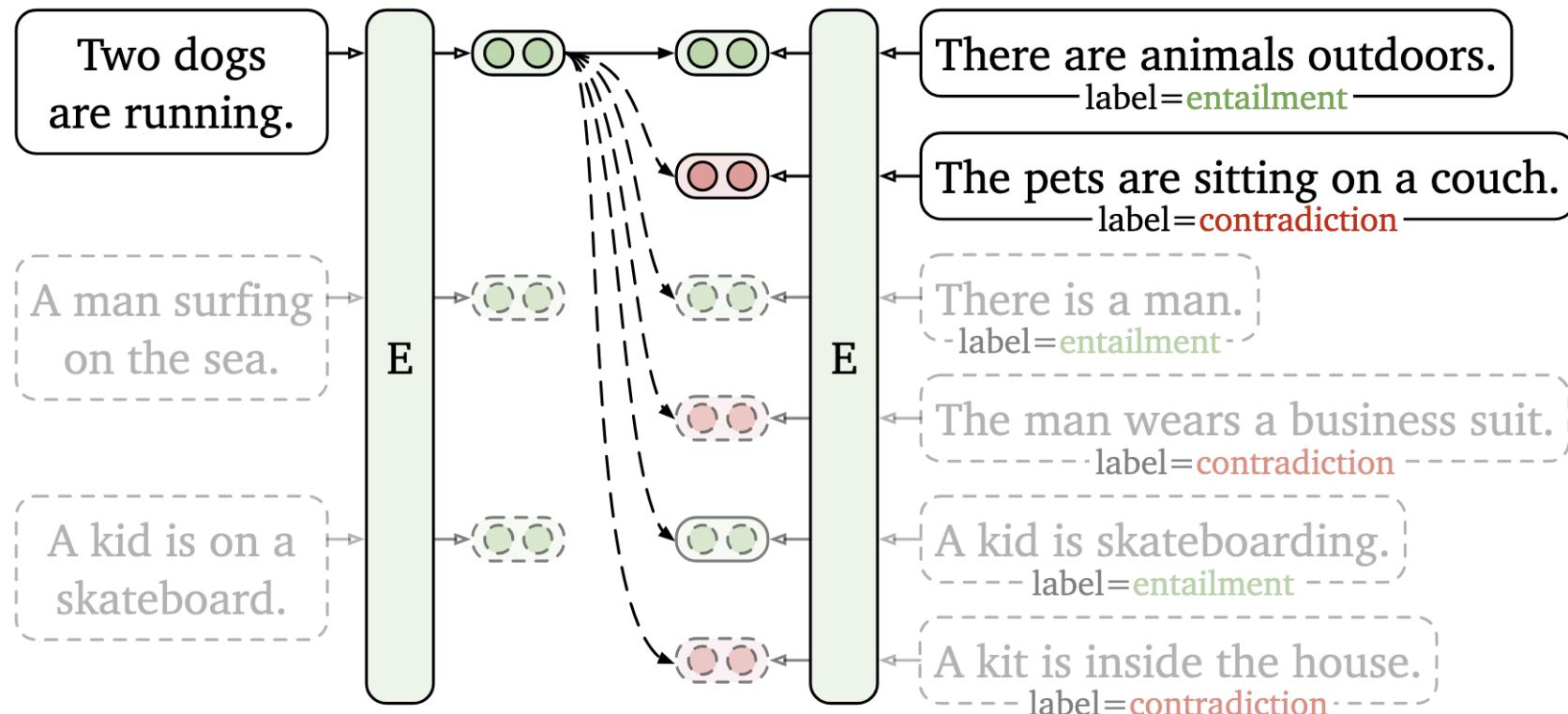
Unsupervised training of SimCSE



Gao, Tianyu, Xingcheng Yao, and Danqi Chen. "SimCSE: Simple Contrastive Learning of Sentence Embeddings." EMNLP 2021.

Supervised training of SimCSE

- Supervised training of SimCSE relies on labels in a dataset to define positives and negatives.



Gao, Tianyu, Xingcheng Yao, and Danqi Chen. "SimCSE: Simple Contrastive Learning of Sentence Embeddings." EMNLP 2021.

SimCSE outperforms Sentence-BERT

- SimCSE outperforms Sentence-BERT on semantic similarity tasks.

| Model | STS12 | STS13 | STS14 | STS15 | STS16 | STS-B | SICK-R | Avg. |
|-------------------------------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|
| <i>Supervised models</i> | | | | | | | | |
| SRoBERTa _{base} ♣ | 71.54 | 72.49 | 70.80 | 78.74 | 73.69 | 77.77 | 74.46 | 74.21 |
| SRoBERTa _{base} -whitening | 70.46 | 77.07 | 74.46 | 81.64 | 76.43 | 79.49 | 76.65 | 76.60 |
| * SimCSE-RoBERTa _{base} | 76.53 | 85.21 | 80.95 | 86.03 | 82.57 | 85.83 | 80.50 | 82.52 |
| * SimCSE-RoBERTa _{large} | 77.46 | 87.27 | 82.36 | 86.66 | 83.93 | 86.70 | 81.95 | 83.76 |

Retrieval for open-domain question answering (ODQA)

Open-domain question answering (ODQA)

- Given a question x such as “What is the currency of the UK?”, a model must output the correct answer string y , “pound”.
- The “open” part of ODQA refers to the fact that the model does not receive a pre-identified document that is known to contain the answer.
- ODQA is like Reading comprehension (RC) tasks, such as SQuAD, but no relevant articles provided.

(Example of SQuAD)

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... Precipitation forms as smaller droplets coalesce via collision with other rain drops or ice crystals within a cloud. Short, intense periods of rain in scattered locations are called “showers”.

What causes precipitation to fall?
gravity

Guu, Kelvin, et al. "Retrieval augmented language model pre-training." ICML 2020.

Rajpurkar, P., Zhang, J., Lopyrev, K., & Liang, P. (2016). SQuAD: 100,000+ Questions for Machine Comprehension of Text. EMNLP 2016.

Dense Passage Retrieval (DPR)

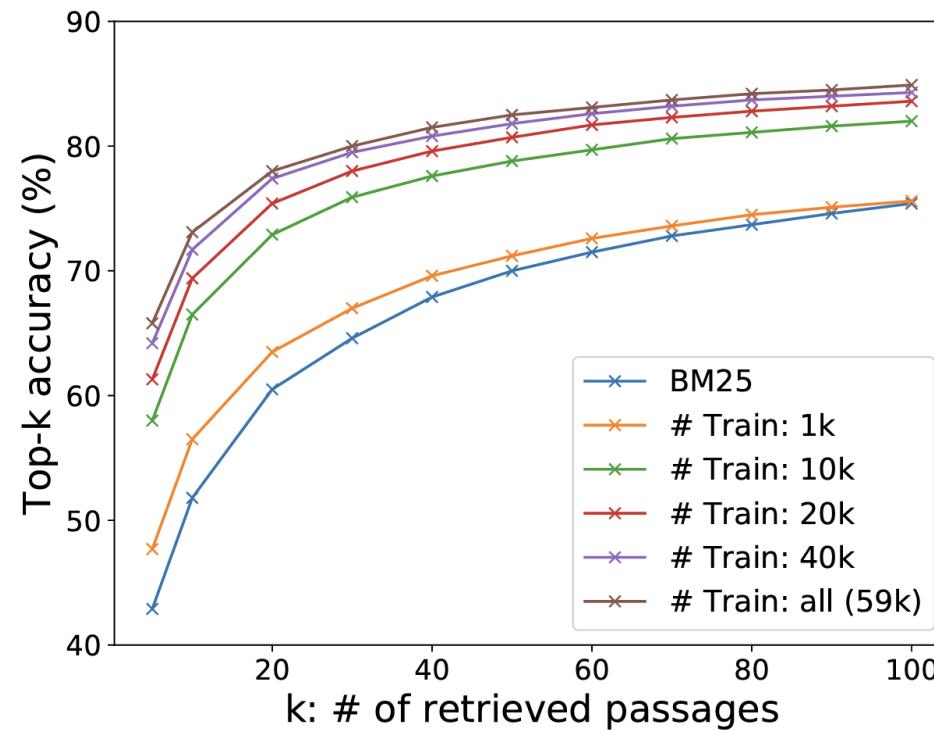
- Dense retrieval focuses on **semantic similarity**
- Passages and questions are embedded into dense vectors
- Dense vectors enable better matching for related words or phrases
(e.g., “the body of water” matched with “sea”)

| Question | Passage received by BM25 | Passage retrieved by DPR |
|--|---|--|
| What is the body of water between England and Ireland? | Title:British Cycling ... England is not recognised as a region by the UCI, and there is no English cycling team outside the Commonwealth Games. For those occasions, British Cycling selects and supports the England team. Cycling is represented on the Isle of Man by the Isle of Man Cycling Association. Cycling in Northern Ireland is organised under Cycling Ulster, part of the all-Ireland governing body Cycling Ireland . Until 2006, a rival governing body existed, ... | Title: Irish Sea ... Annual traffic between Great Britain and Ireland amounts to over 12 million passengers and of traded goods. The Irish Sea is connected to the North Atlantic at both its northern and southern ends. To the north, the connection is through the North Channel between Scotland and Northern Ireland and the Malin Sea. The southern end is linked to the Atlantic through the St George's Channel between Ireland and Pembrokeshire, and the Celtic Sea. ... |

Karpukhin et al., 2020. Dense Passage Retrieval for Open-Domain Question Answering, EMNLP 2020.

Dense Passage Retrieval (DPR)

- Outperforms **BM25** using only 1000 training data!



Dense Passage Retrieval (DPR)

- After training, two **BERT-based encoders** can **independently** encode question (**q**) and passage (**p**) into dense vectors.
- **Similarity** between question and passage = **dot product** between their embeddings
$$\text{sim}(q, p) = E_Q(q)^\top E_P(p).$$

q : question text

p : passage text

E_Q : BERT model that outputs question representation

E_p : BERT model that outputs passage representation

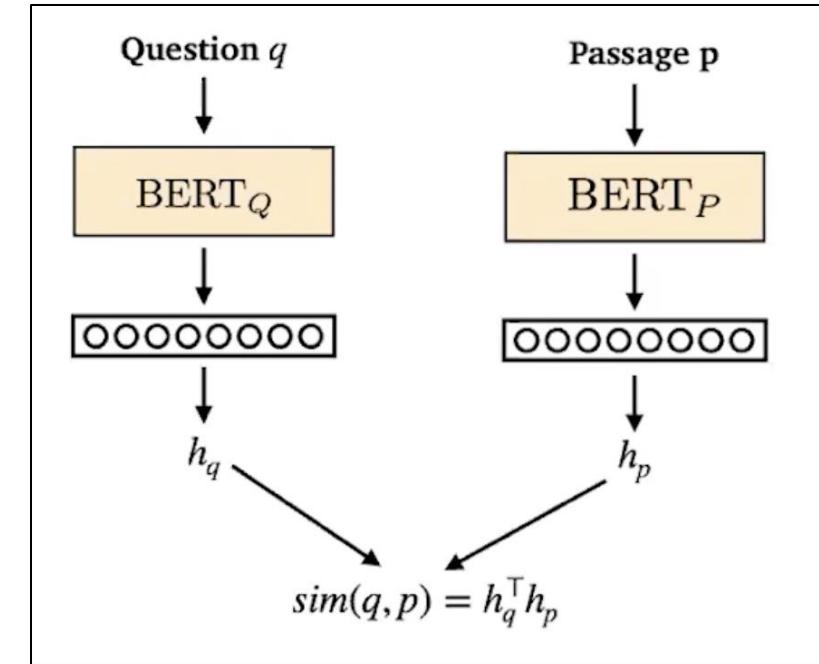


Image source: [Stanford CS224N Lecture 12 - Question Answering](#)

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

Dense Passage Retrieval (DPR)

Training the encoders

- Goal: **Relevant** pairs of questions and passages will have **smaller distance** than the irrelevant ones
- Training data

$$\mathcal{D} = \{\langle q_i, p_i^+, [p_{i,1}^-, \dots, p_{i,n}^-] \rangle\}_{i=1}^m$$

Question Relevant Passage *n* Irrelevant Passages *m* training instances

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

Dense Passage Retrieval (DPR)

Training the encoders

- Base model: bert-base-uncased
- Loss function: Negative log-likelihood of the positive passage

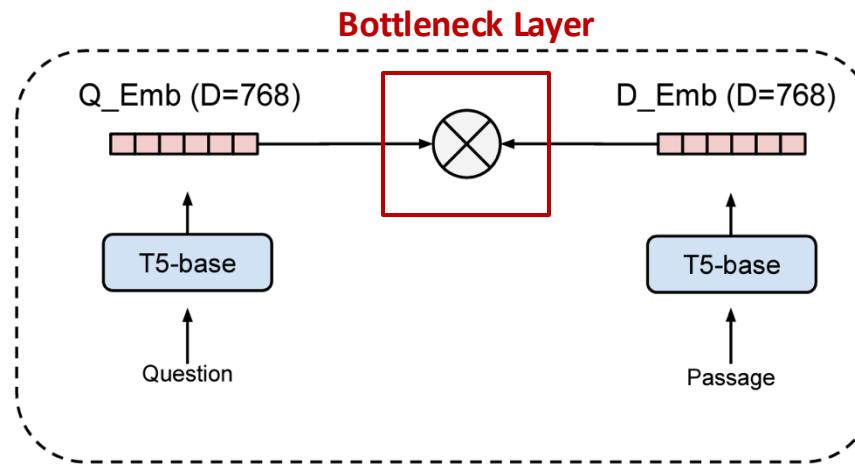
$$L(q_i, p_i^+, p_{i,1}^-, \dots, p_{i,n}^-) = -\log \frac{e^{\text{sim}(q_i, p_i^+)}}{e^{\text{sim}(q_i, p_i^+)} + \sum_{j=1}^n e^{\text{sim}(q_i, p_{i,j}^-)}}.$$

- **Maximize** the similarity between \mathbf{q}_i and \mathbf{p}_i^+
- **Minimize** the similarity between non-relevant pairs (\mathbf{q}_i and $\mathbf{p}_{i,j}^-$)

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

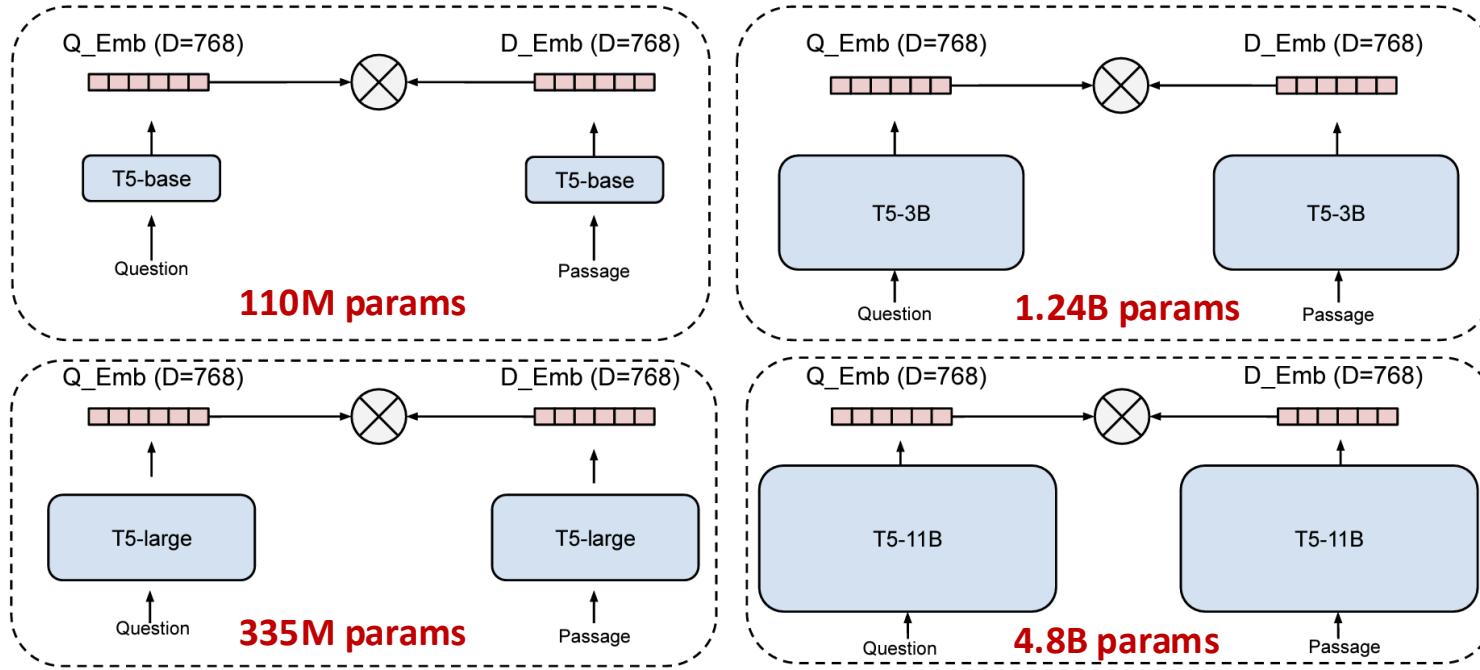
Limitations of Dual Encoders

- Often fail to generalize to other domains for retrieval tasks
- **Bottleneck layer** of dual encoders (simple dot-product or cosine similarity)
might not be powerful enough to capture semantic relevance?



Ni et al., 2022. Large Dual Encoders Are Generalizable Retrievers, EMNLP 2022.

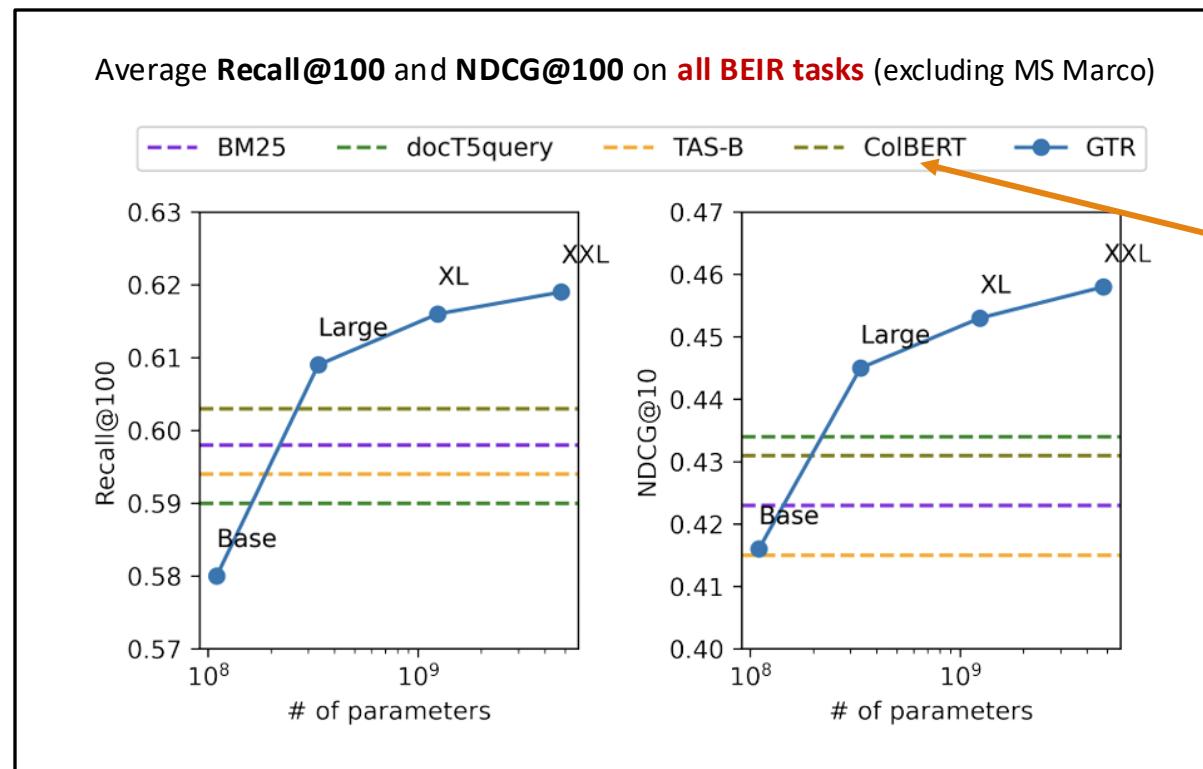
Generalizable T5-based Retriever (GTR)



Can scaling up dual encoder model size *improve the retrieval performance*, while keeping the bottleneck layers **fixed**?

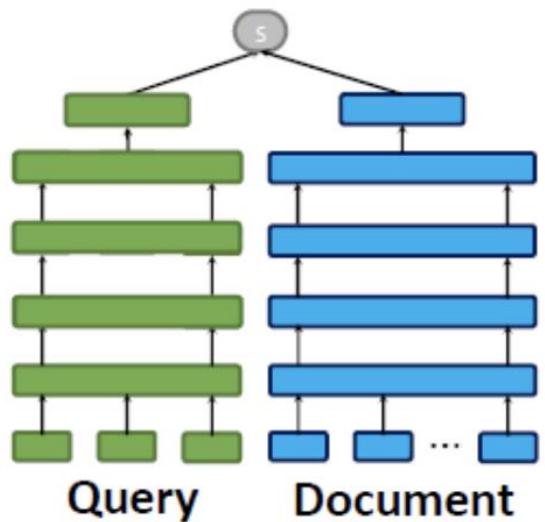
Generalizable T5-based Retriever (GTR)

- Scaling up *consistently improves* dual encoders' **out-of-domain** performance.

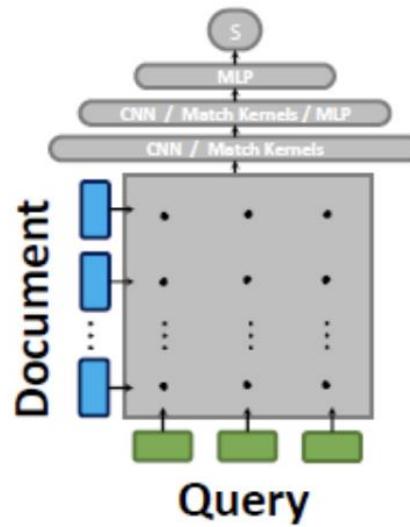


ColBERT: Efficient and Effective Passage Search via Contextualized Late Interaction over BERT, SIGIR 2020

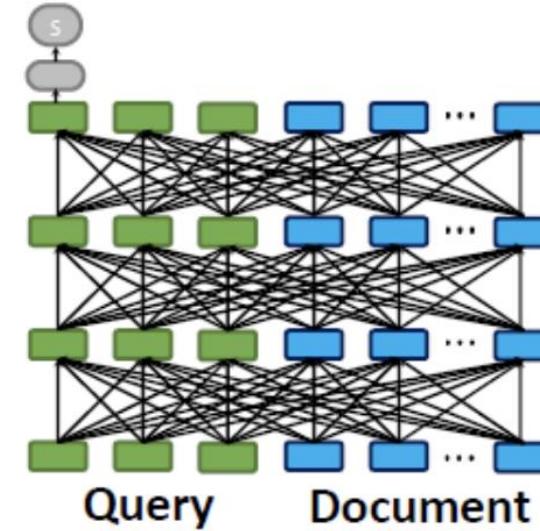
Interactions of Query and Document



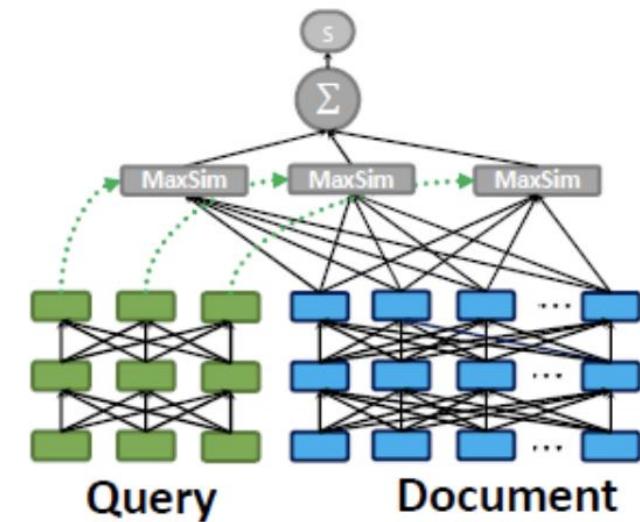
(a) Representation-based Similarity
(e.g., DSSM, SNRM)



(b) Query-Document Interaction
(e.g., DRMM, KNRM, Conv-KNRM)



(c) All-to-all Interaction
(e.g., BERT)

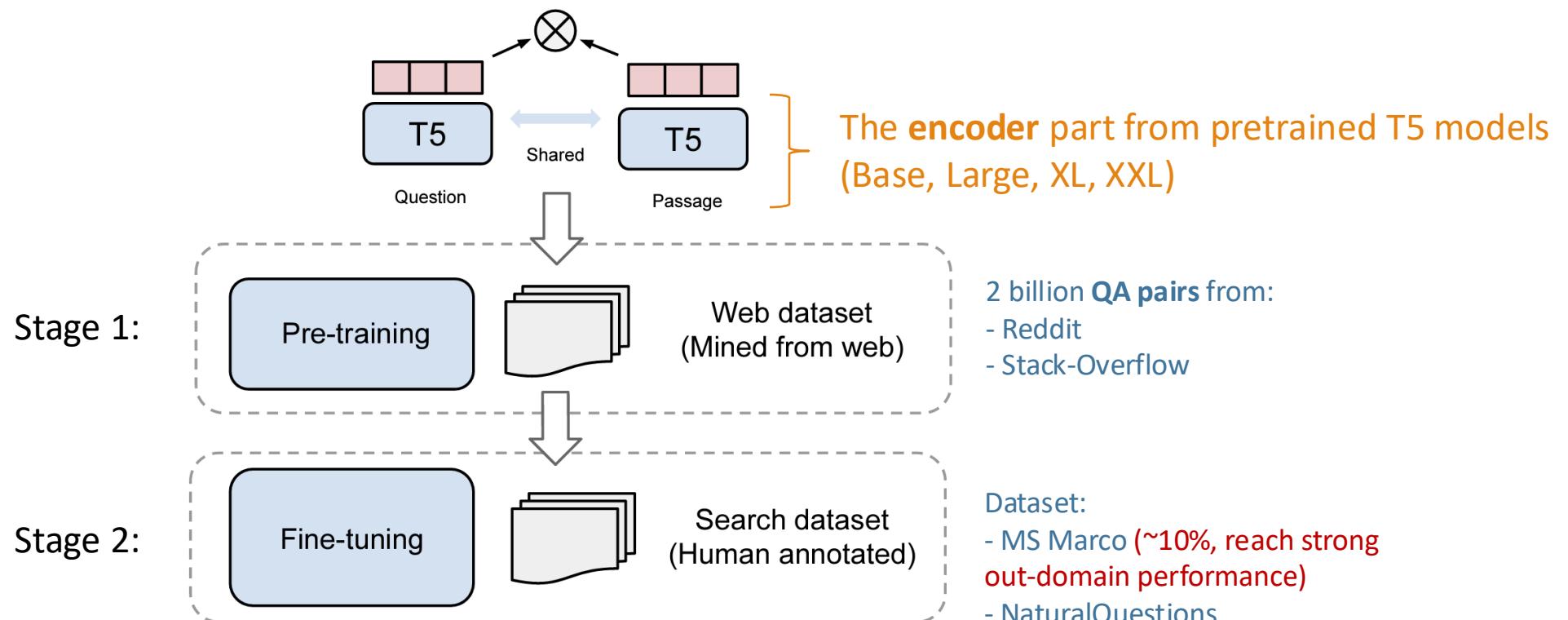


(d) Late Interaction
(i.e., the proposed ColBERT)

ColBERT: Efficient and Effective Passage Search via Contextualized Late Interaction over BERT, SIGIR 2020

Generalizable T5-based Retriever (GTR)

Multi-stage training for GTR



MS MARCO: A Human Generated MArine Reading COmprehension Dataset

- Machine Reading Comprehension (MRC) dataset
 - by Microsoft 2016, which was adapted in 2018 for retrieval.
- 8.8 M passages from the Web to 1M real-world queries.
- Each query is associated with sparse relevance judgments of one (or very few) documents marked as relevant and no documents explicitly indicated as irrelevant.
- three different tasks
 - (i) predict if a question is answerable given a set of context passages, and extract and synthesize the answer as a human would
 - (ii) generate a well-formed answer (if possible) based on the context passages that can be understood with the question and passage context
 - (iii) rank a set of retrieved passages given a question.

Generalizable T5-based Retriever (GTR)

- **Data efficiency:** Only needs **10%** of MS Marco *supervised data* to achieve the best **out-of-domain** performance!

| | | *GTR w/o Pre-training | | *GTR w/ Pre-training + Fine-tuning | | |
|---------------|--|-----------------------|--|------------------------------------|--------------|----------------|
| | | GTR-FT | | GTR | | |
| Ratio of data | | Large | XL | Large | XL | XXL |
| | | | NDCG@10 on MS Marco | | | *in-domain |
| 10% | | 0.402 | 0.397 | 0.428 | 0.426 | - |
| 100% | | <u>0.415</u> | <u>0.418</u> | <u>0.430</u> | <u>0.439</u> | <u>0.430</u> |
| | | | Zero-shot average NDCG@10 w/o MS Marco | | | *out-of-domain |
| 10% | | 0.413 | 0.418 | 0.452 | 0.462 | 0.465 |
| 100% | | 0.412 | 0.433 | 0.445 | 0.453 | 0.458 |

Summary Parameter Sharing

| | BERT (Devlin et al., NAACL 2019) | Sentence-BERT (Reimers et al., EMNLP 2019) | SimCSE (Gao et al., EMNLP 2021) | DPR (Karpukhin et al., EMNLP 2020) | GTR (Ni et al., EMNLP 2022) |
|----------------|---|---|--|---|--|
| Encoder Type | Cross | Dual | Dual | Dual | Dual |
| Weight Sharing | Nan | Yes | Yes | No (Separate Query Encoder and Passage Encoder) | Yes |

BEIR: A Heterogeneous Benchmark for Zero-shot Evaluation of Information Retrieval Models

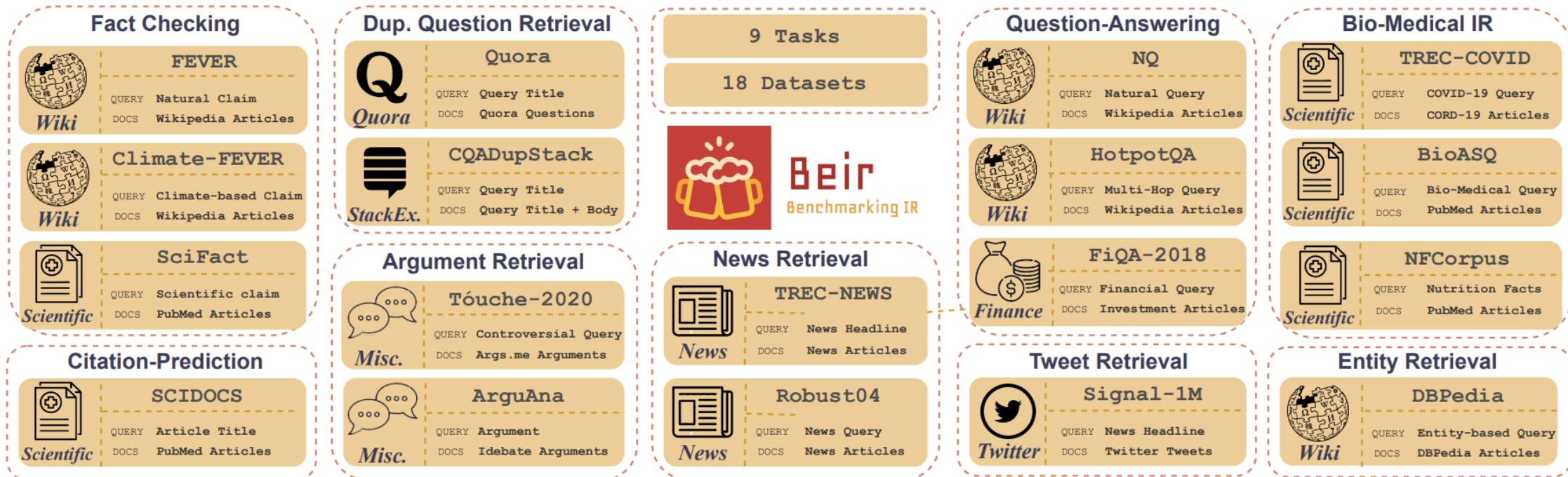


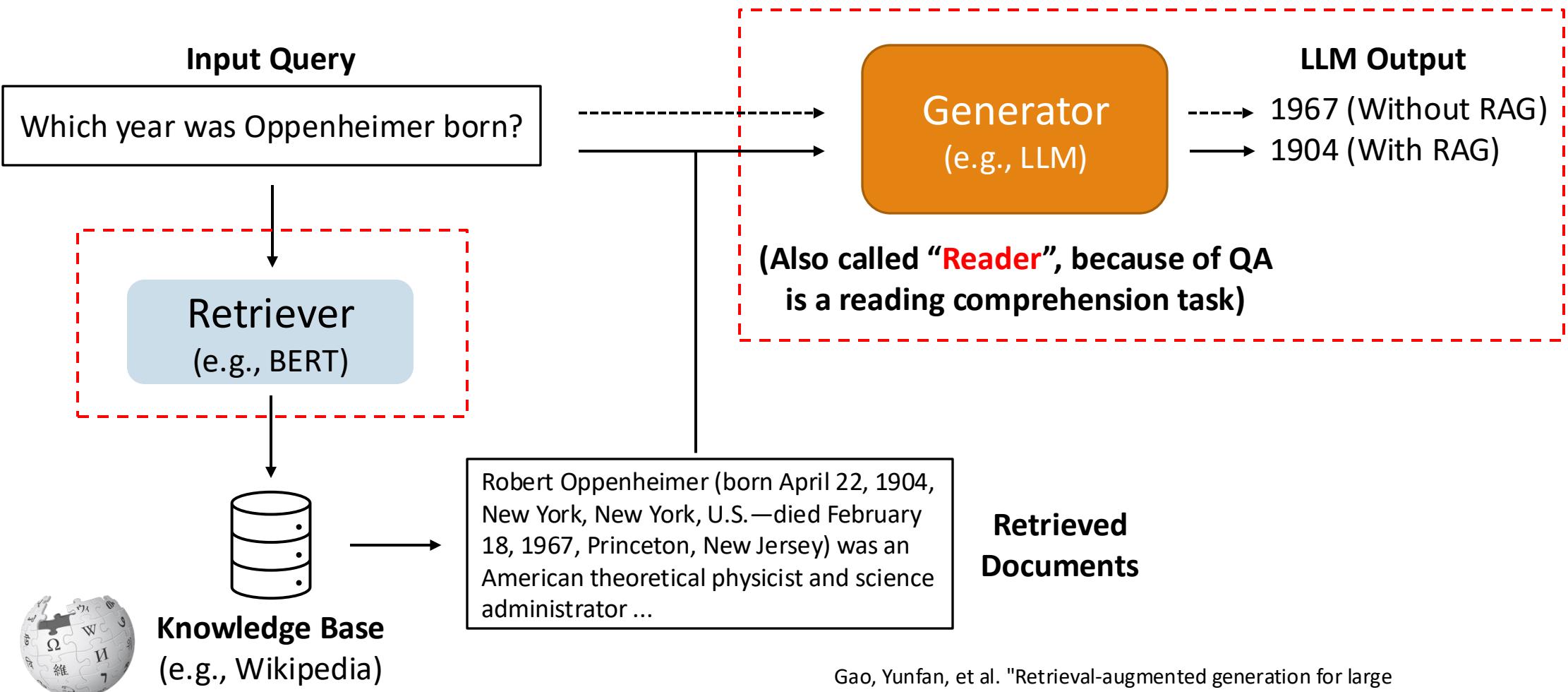
Figure 1: An overview of the diverse tasks and datasets in BEIR benchmark.

BEIR: A Heterogeneous Benchmark for Zero-shot Evaluation of Information Retrieval Models

| Model (→) | Lexical | | | | Sparse | | | | Dense | | | | Late-Interaction | | Re-ranking | |
|---------------------------|-------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|---------|--|------------------|--|------------|--|
| | Dataset (↓) | BM25 | DeepCT | SPARTA | docT5query | DPR | ANCE | TAS-B | GenQ | ColBERT | BM25+CE | | | | | |
| MS MARCO | 0.228 | 0.296 [‡] | 0.351 [‡] | 0.338 [‡] | 0.177 | 0.388 [‡] | 0.408 [‡] | 0.408 [‡] | 0.401 [‡] | 0.413 [‡] | | | | | | |
| TREC-COVID | 0.656 | 0.406 | 0.538 | 0.713 | 0.332 | 0.654 | 0.481 | 0.619 | 0.677 | 0.757 | | | | | | |
| BioASQ | 0.465 | 0.407 | 0.351 | 0.431 | 0.127 | 0.306 | 0.383 | 0.398 | 0.474 | 0.523 | | | | | | |
| NFCorpus | 0.325 | 0.283 | 0.301 | 0.328 | 0.189 | 0.237 | 0.319 | 0.319 | 0.305 | 0.350 | | | | | | |
| NQ | 0.329 | 0.188 | 0.398 | 0.399 | 0.474 [‡] | 0.446 | 0.463 | 0.358 | 0.524 | 0.533 | | | | | | |
| HotpotQA | 0.603 | 0.503 | 0.492 | 0.580 | 0.391 | 0.456 | 0.584 | 0.534 | 0.593 | 0.707 | | | | | | |
| FiQA-2018 | 0.236 | 0.191 | 0.198 | 0.291 | 0.112 | 0.295 | 0.300 | 0.308 | 0.317 | 0.347 | | | | | | |
| Signal-1M (RT) | 0.330 | 0.269 | 0.252 | 0.307 | 0.155 | 0.249 | 0.289 | 0.281 | 0.274 | 0.338 | | | | | | |
| TREC-NEWS | 0.398 | 0.220 | 0.258 | 0.420 | 0.161 | 0.382 | 0.377 | 0.396 | 0.393 | 0.431 | | | | | | |
| Robust04 | 0.408 | 0.287 | 0.276 | 0.437 | 0.252 | 0.392 | 0.427 | 0.362 | 0.391 | 0.475 | | | | | | |
| ArguAna | 0.315 | 0.309 | 0.279 | 0.349 | 0.175 | 0.415 | 0.429 | 0.493 | 0.233 | 0.311 | | | | | | |
| Touché-2020 | 0.367 | 0.156 | 0.175 | 0.347 | 0.131 | 0.240 | 0.162 | 0.182 | 0.202 | 0.271 | | | | | | |
| CQADupStack | 0.299 | 0.268 | 0.257 | 0.325 | 0.153 | 0.296 | 0.314 | 0.347 | 0.350 | 0.370 | | | | | | |
| Quora | 0.789 | 0.691 | 0.630 | 0.802 | 0.248 | 0.852 | 0.835 | 0.830 | 0.854 | 0.825 | | | | | | |
| DBpedia | 0.313 | 0.177 | 0.314 | 0.331 | 0.263 | 0.281 | 0.384 | 0.328 | 0.392 | 0.409 | | | | | | |
| SCIDOCS | 0.158 | 0.124 | 0.126 | 0.162 | 0.077 | 0.122 | 0.149 | 0.143 | 0.145 | 0.166 | | | | | | |
| FEVER | 0.753 | 0.353 | 0.596 | 0.714 | 0.562 | 0.669 | 0.700 | 0.669 | 0.771 | 0.819 | | | | | | |
| Climate-FEVER | 0.213 | 0.066 | 0.082 | 0.201 | 0.148 | 0.198 | 0.228 | 0.175 | 0.184 | 0.253 | | | | | | |
| SciFact | 0.665 | 0.630 | 0.582 | 0.675 | 0.318 | 0.507 | 0.643 | 0.644 | 0.671 | 0.688 | | | | | | |
| Avg. Performance vs. BM25 | - 27.9% | - 20.3% | + 1.6% | - 47.7% | - 7.4% | - 2.8% | - 3.6% | + 2.5% | + 11% | | | | | | | |

From Retrievers to QA

From now we focus on the full QA pipeline.

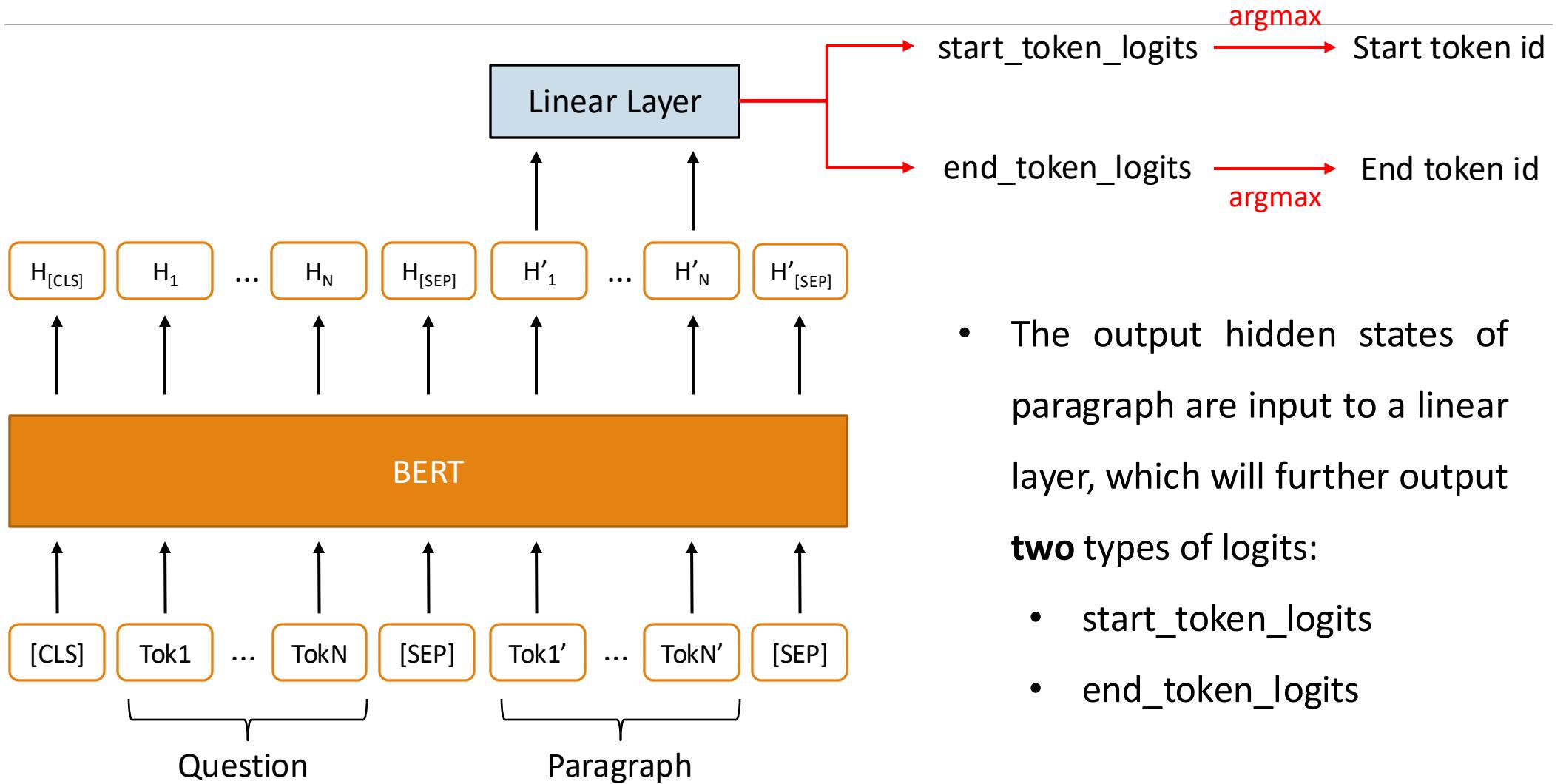


Open-domain QA with retrievers

- The QA model is an encoder (e.g., BERT).
 - ORQA
 - REALM
- The QA model is a generator (e.g., BART).

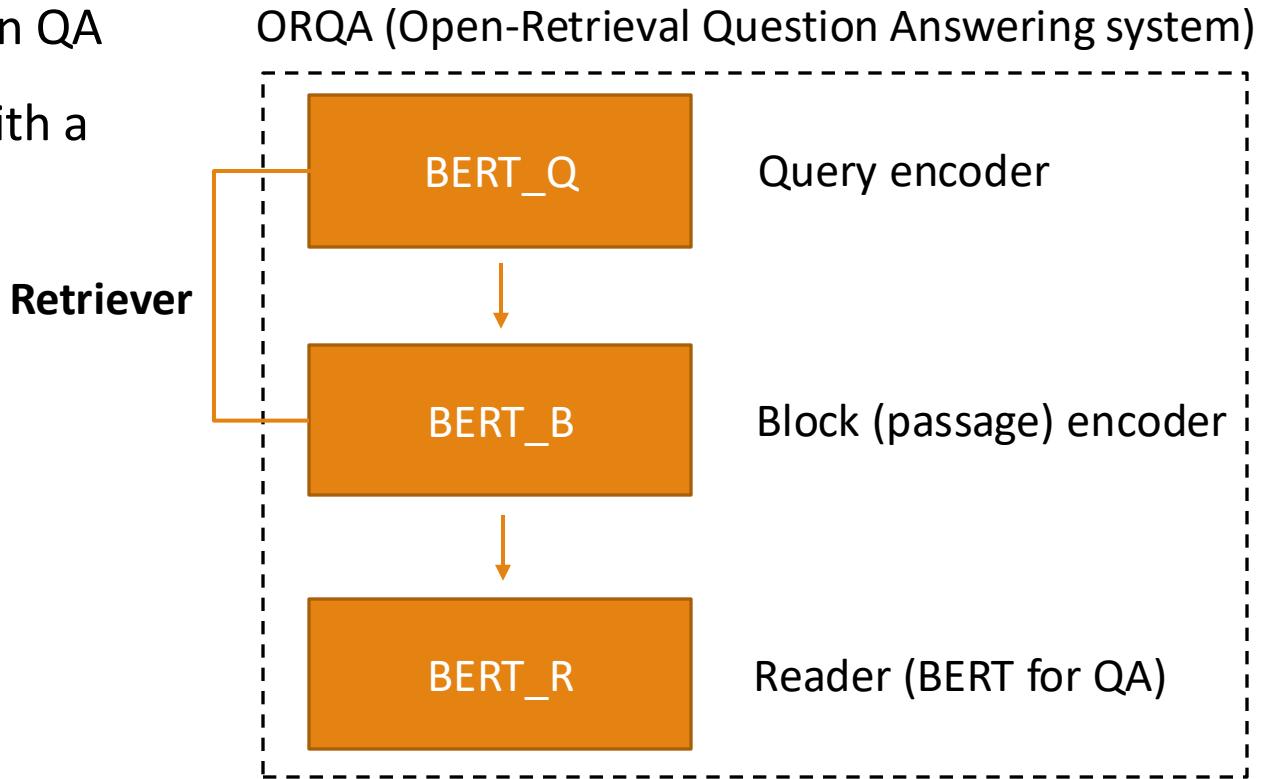
QA model is an encoder (e.g., BERT)

BERT for QA (Reading Comprehension)



ORQA (Open-Retrieval Question Answering system)

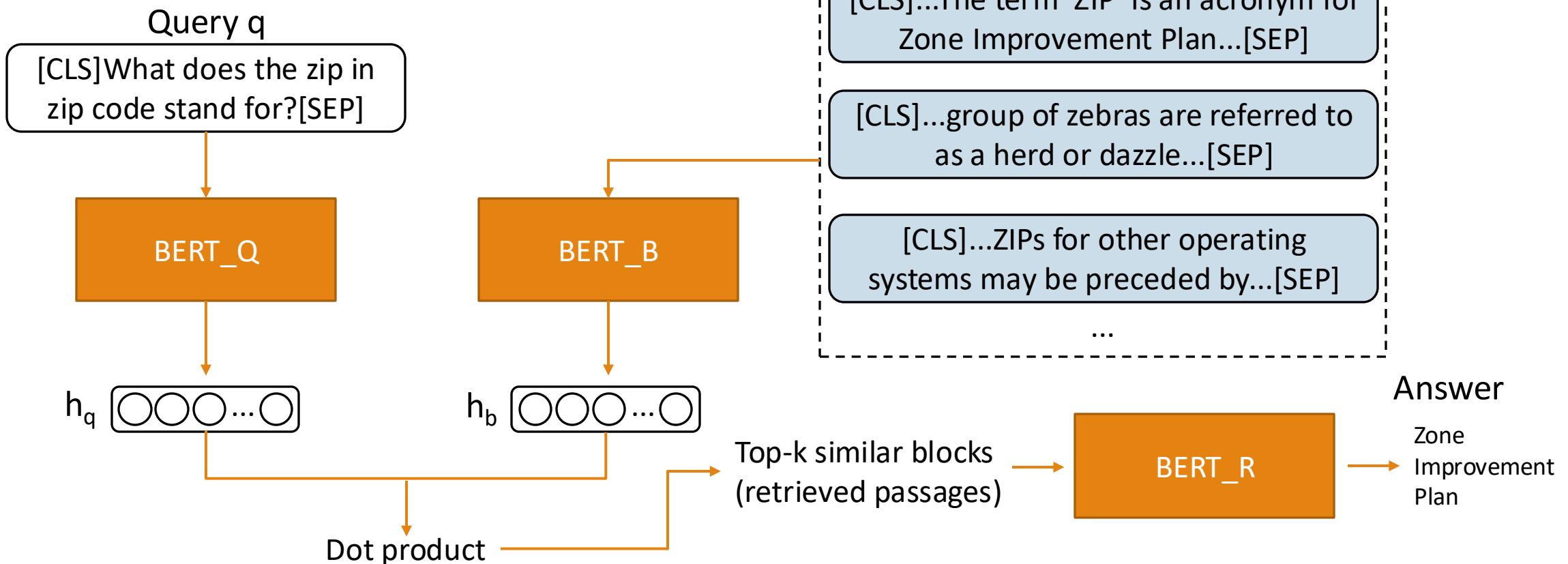
- Leverage **BERTs** for open-domain QA
- Extend BERT for QA to **ODQA** with a retriever model



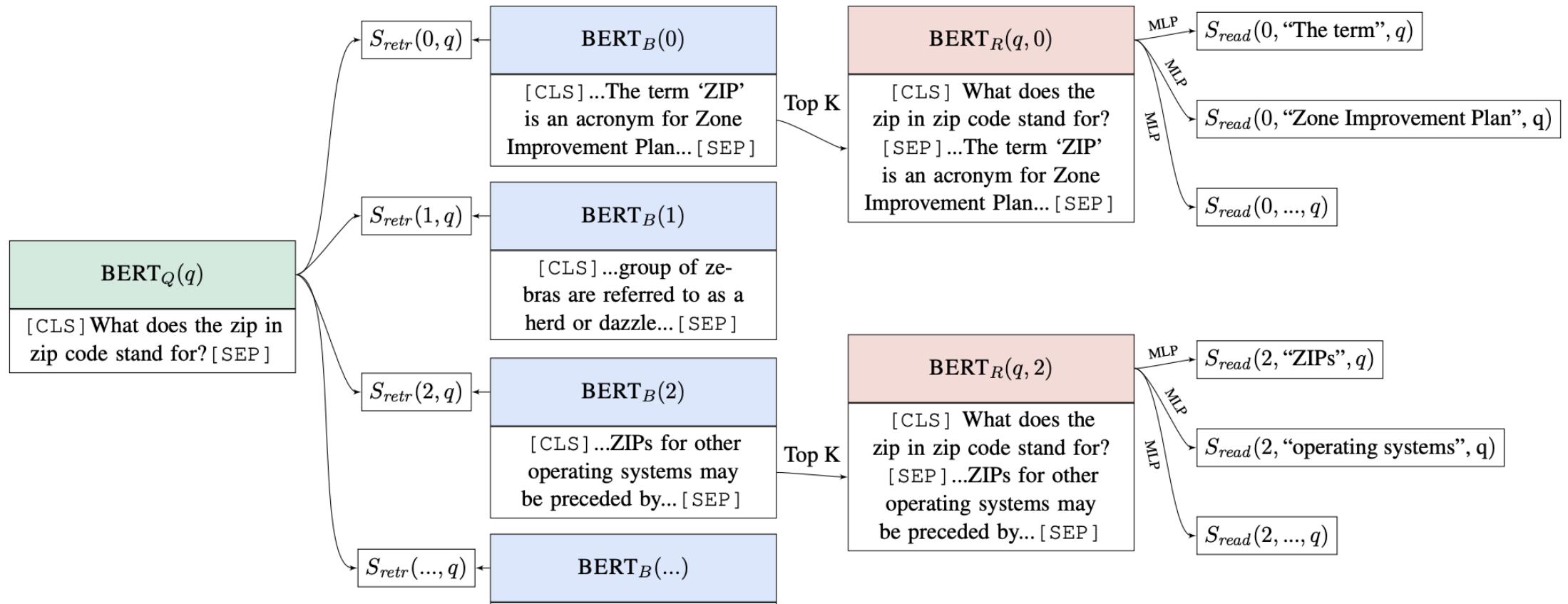
Lee, Kenton, Ming-Wei Chang, and Kristina Toutanova. "Latent Retrieval for Weakly Supervised Open Domain Question Answering." ACL 2019.

ORQA (Open-Retrieval Question Answering system)

- Leverage **BERTs** for open-domain QA



ORQA (Open-Retrieval Question Answering system)



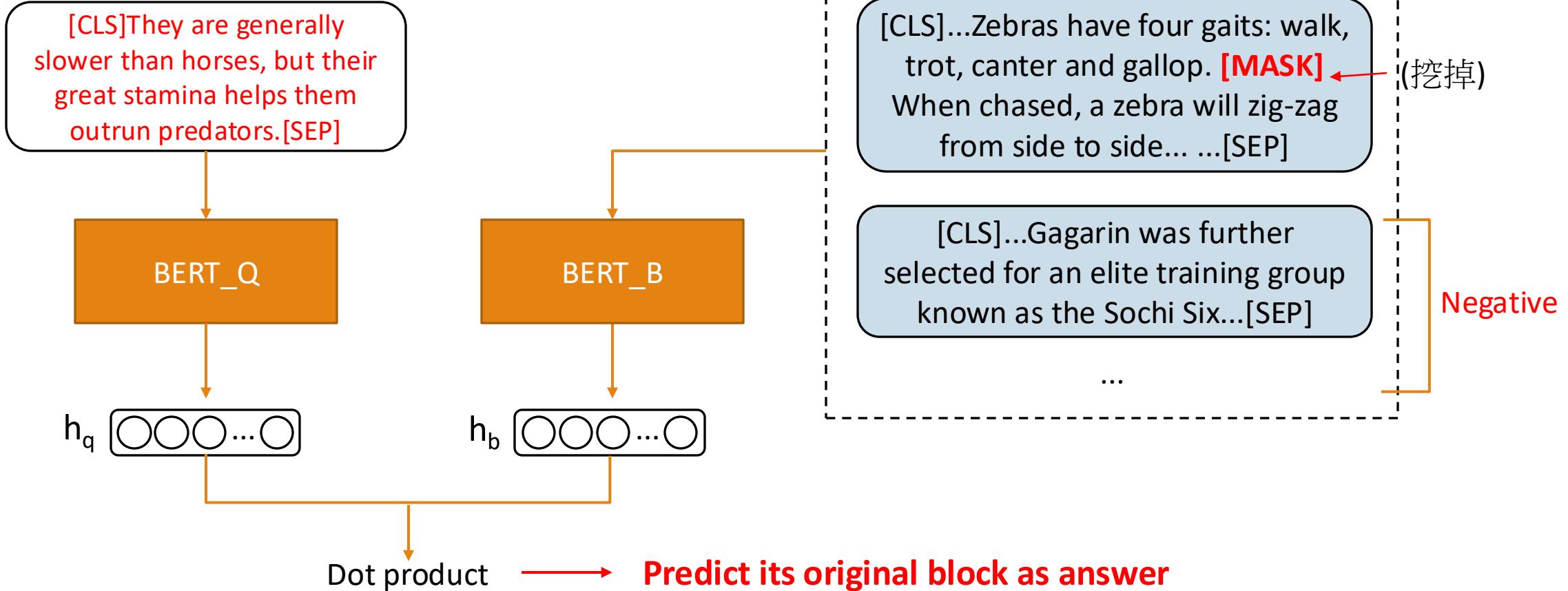
Inverse Cloze Task for Pre-training a Retriever

- Cloze task: predict masked token from a corrupted context
- **Inverse cloze task (ICT): predict a corrupted context from a randomly sampled sentence (unsupervised)**
 - This is a **continual** pre-training (CP) task starting from the pre-trained BERT model in **ORQA**.

Lee, Kenton, Ming-Wei Chang, and Kristina Toutanova. "Latent Retrieval for Weakly Supervised Open Domain Question Answering." ACL 2019.

ICT for Pre-training a Retriever

[MASK] from an evidence block



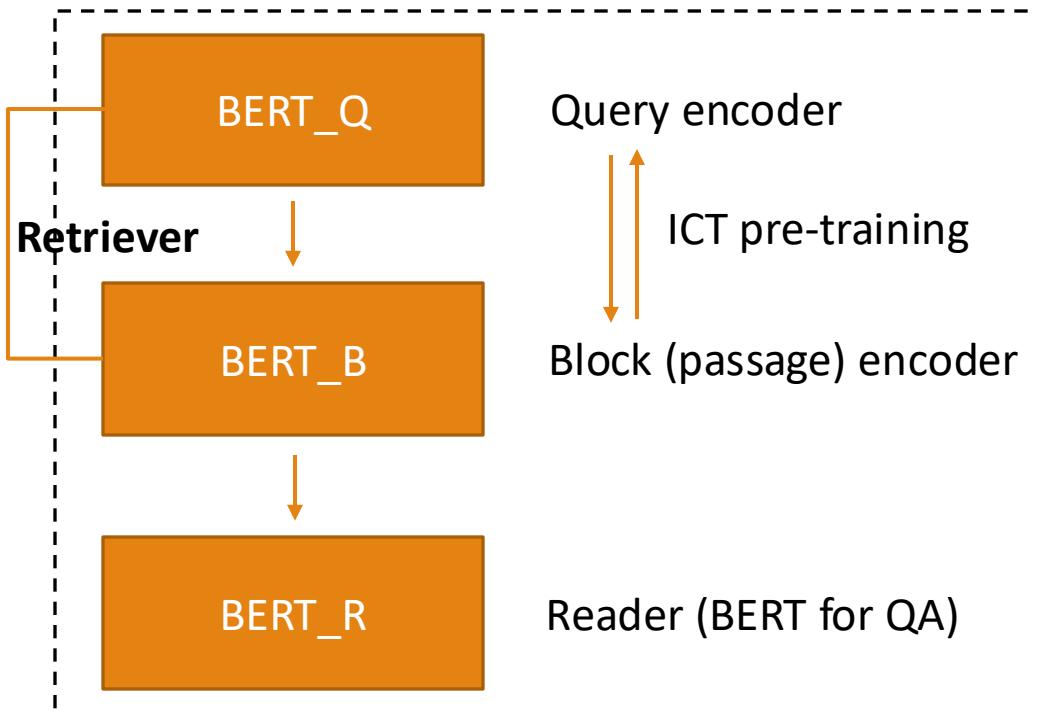
ICT for Pre-training a Retriever

- Cloze task: predict masked token from a corrupted context
- **Inverse cloze task (ICT): predict a corrupted context from a randomly sampled sentence**
 - This is a **continual** pre-training (CP) task starting from the pre-trained BERT model in **ORQA**.
- Model to train:
 - Pre-training stage: BERT_Q and BERT_B
 - **Fine-tuning stage: BERT_Q and BERT_R**

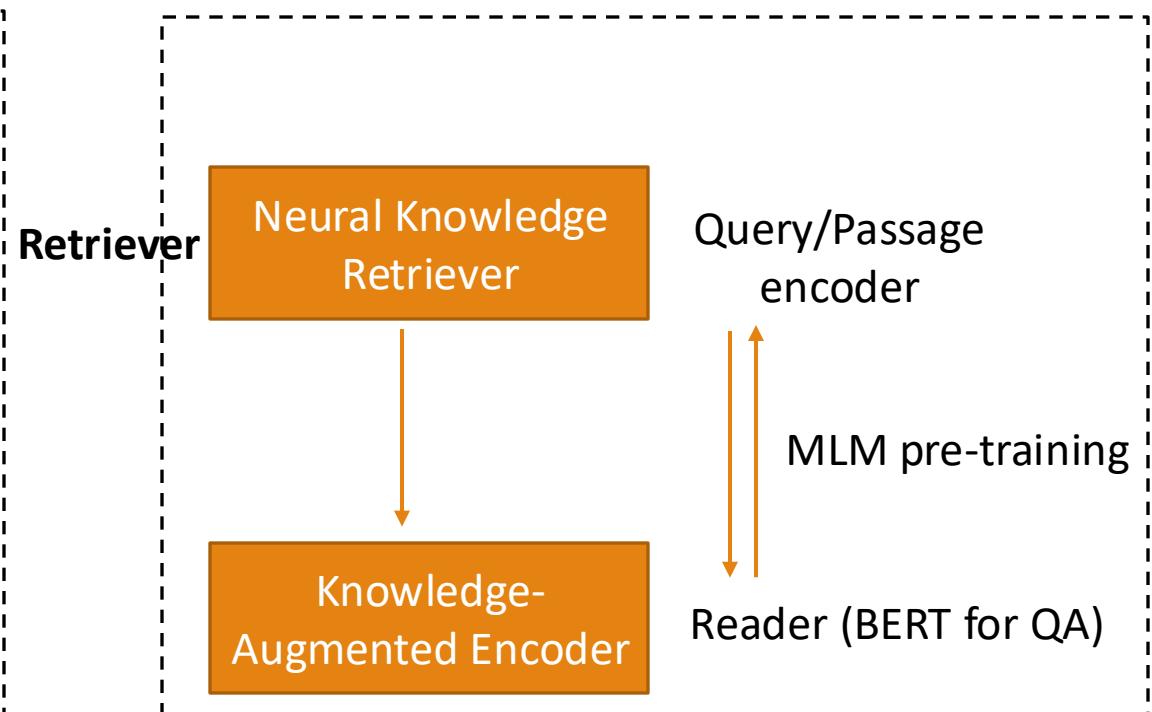
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REALM (Retrieval-Augmented Language Model Pre-Training)

ORQA (Open-Retrieval Question Answering system)



REALM (Retrieval-Augmented Language Model Pre-Training)

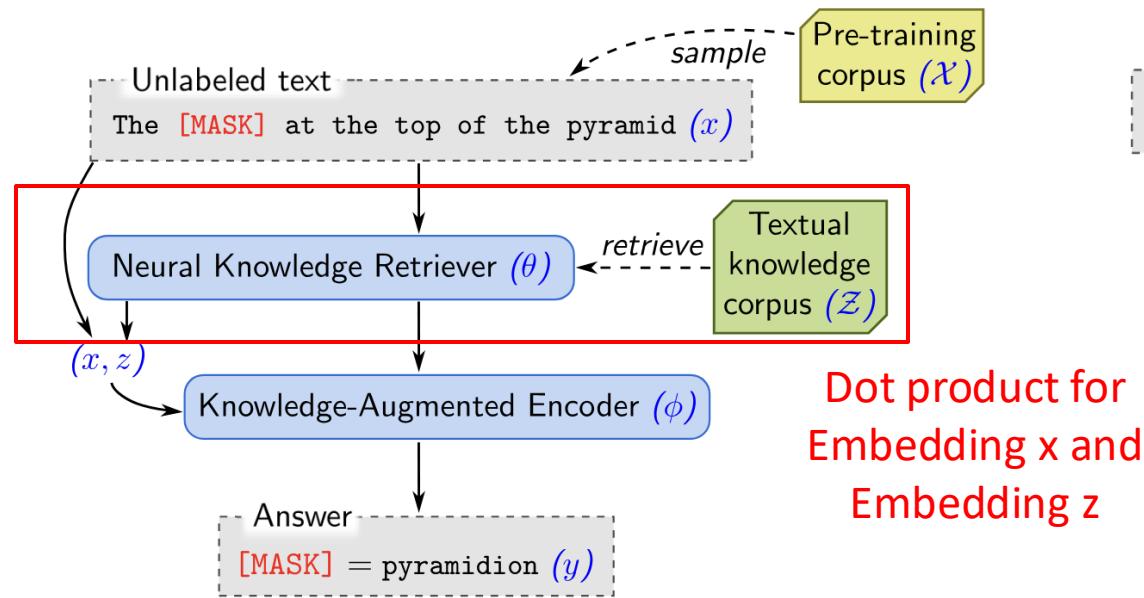


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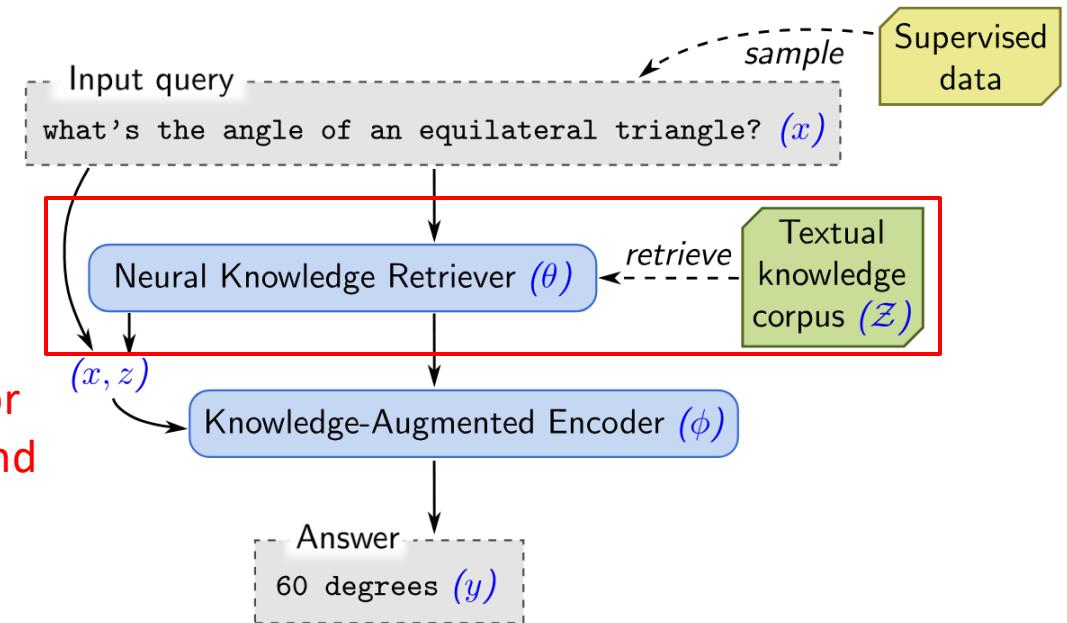
Guu, Kelvin, et al. "Retrieval augmented language model pre-training." ICML 2020.

REALM (Retrieval-Augmented Language Model Pre-Training)

Unsupervised pre-training with masked language modeling (MLM)



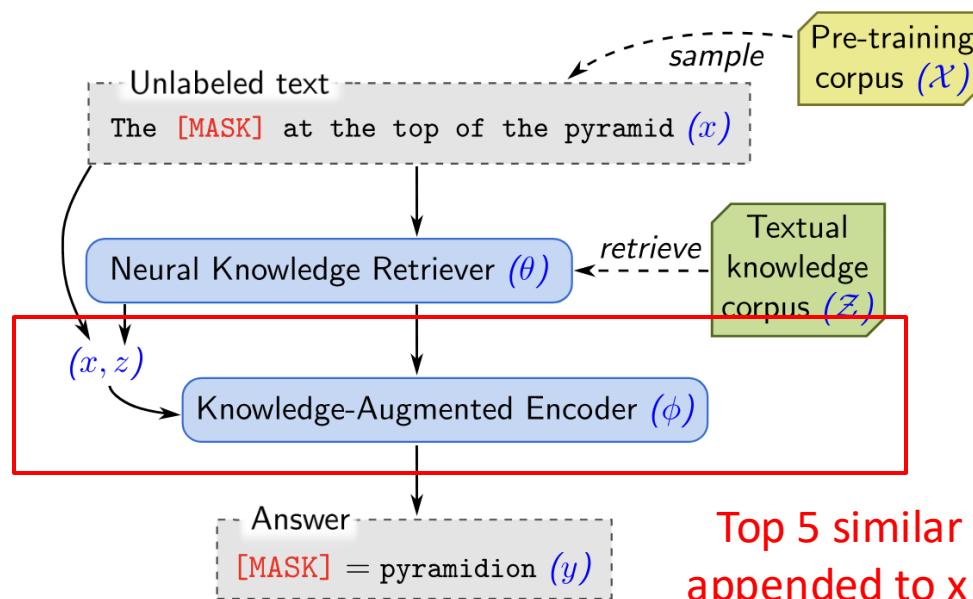
Fine-tuning on open-domain QA



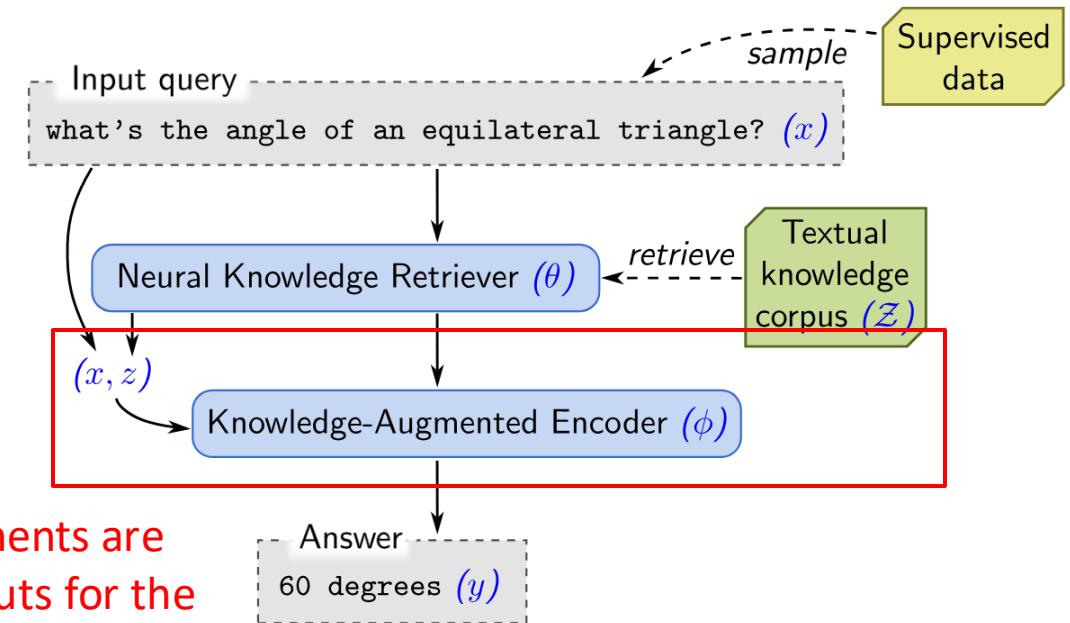
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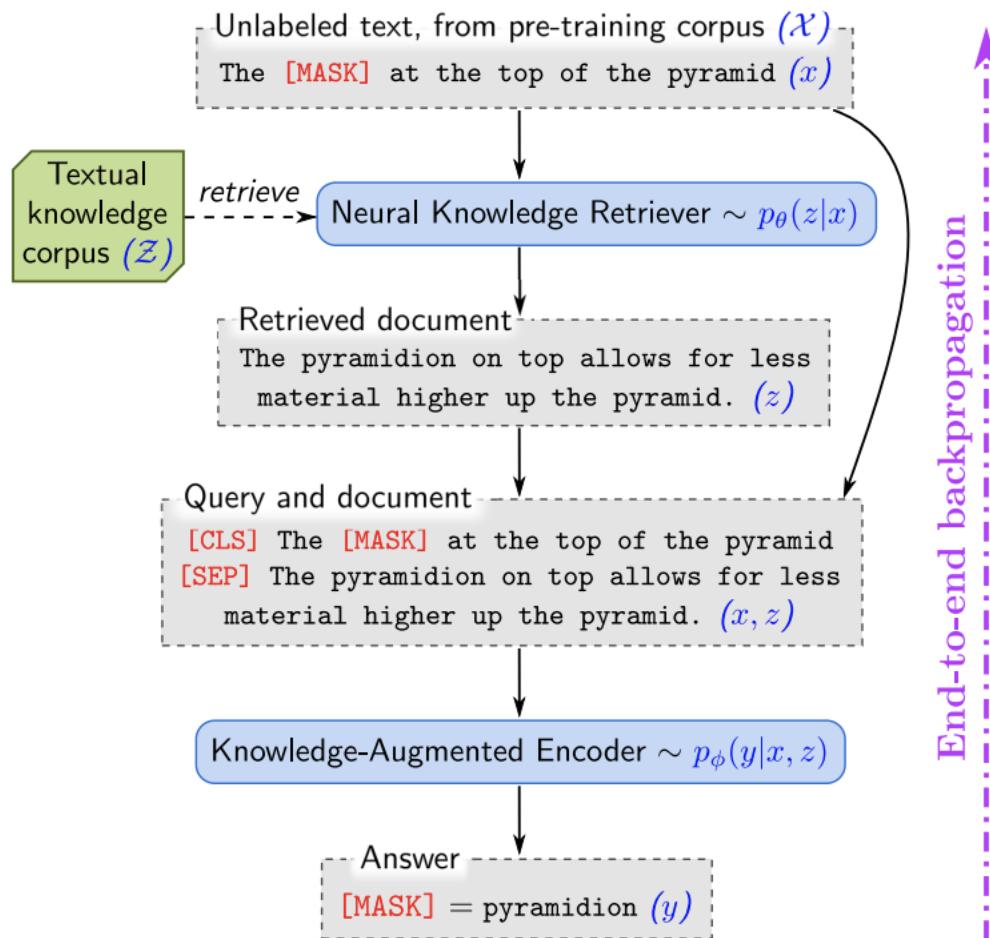
Fine-tuning on open-domain QA



Top 5 similar documents are appended to x as inputs for the Knowledge-Augmented Encoder

Guu, Kelvin, et al. "Retrieval augmented language model pre-training." ICML 2020.

REALM (Retrieval-Augmented Language Model Pre-Training)



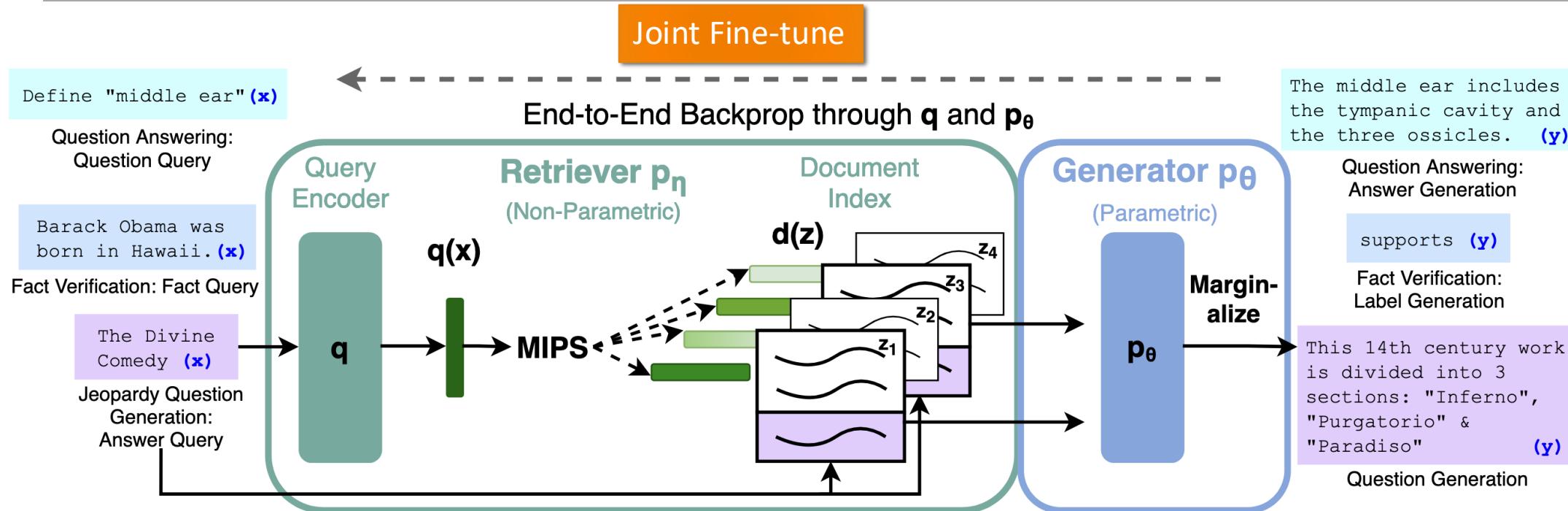
- Through the MLM loss, gradients are backpropagated not only to update the **language model's parameters** but also the **retriever's encoder parameters**.
- The retriever gradually learns **which types of documents** are most **helpful** for the language model's predictions.

Some issues

- The corpus is big. (all of Wikipedia)
 - Index in embedding level
- \mathcal{X} contain [MASK]
- End-to-end training

QA model is a generator (e.g., BART)

Retrieval-Augmented Generation (RAG)



- This approach is the first RAG paper.
- No pre-training is involved. Only fine-tuning on open-domain QA.
- MIPS: Maximum Inner-Product Search (speed-up approach, supported by indexing packages like FAISS.)

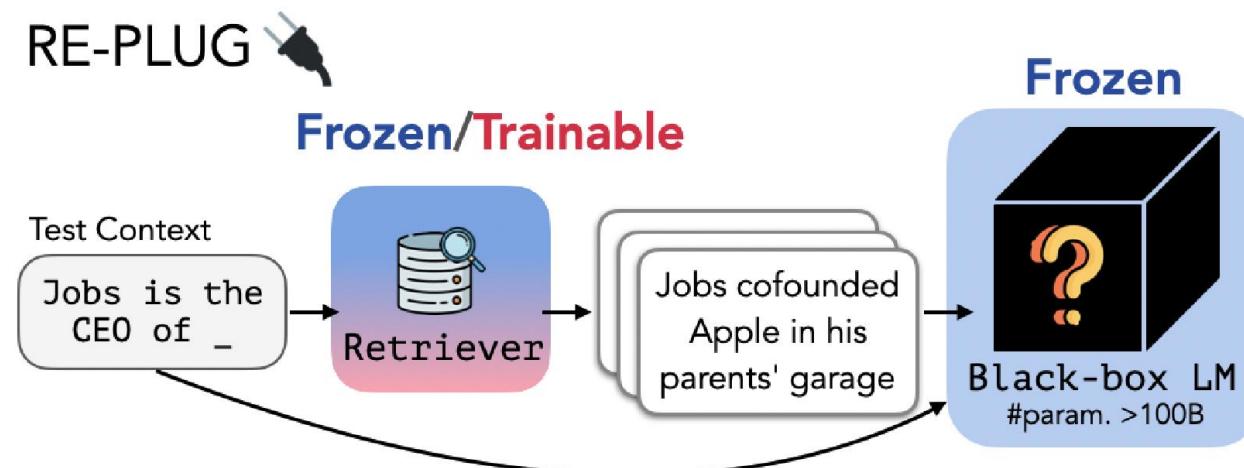
Also Read **FiD (Fusion-in-Decoder)** "Leveraging Passage Retrieval with Generative Models for Open Domain Question Answering." *arXiv preprint arXiv:2007.01282*, 2020, EACL 2021.

Lewis, Patrick, et al. "Retrieval-augmented generation for knowledge-intensive nlp tasks." NeurIPS 2020.

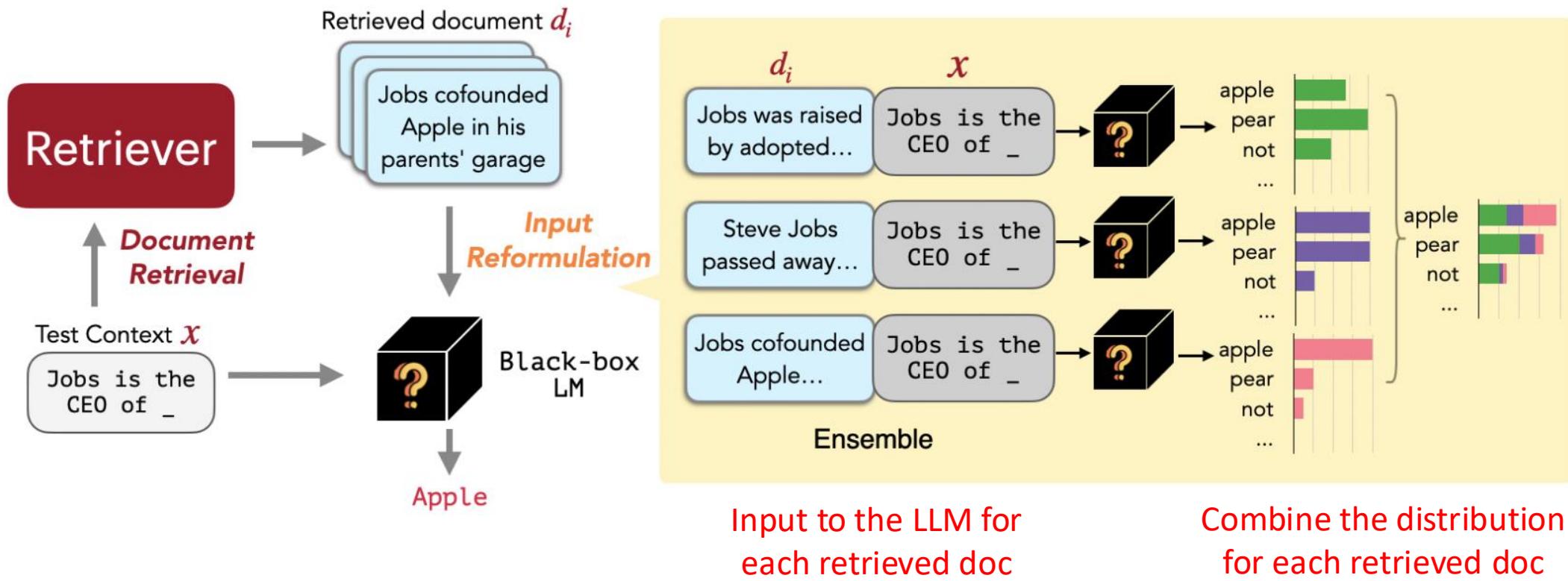
RAG with an LLM as the generator

Shi, Weijia, et al. "REPLUG: Retrieval-Augmented Black-Box Language Models." NAACL 2024.

- Due to a very large number of parameters, LLM is hard to train.
- **REPLUG (Retrieve and Plug)** proposes to train an LLM in the RAG framework.



REPLUG (at Inference Time)

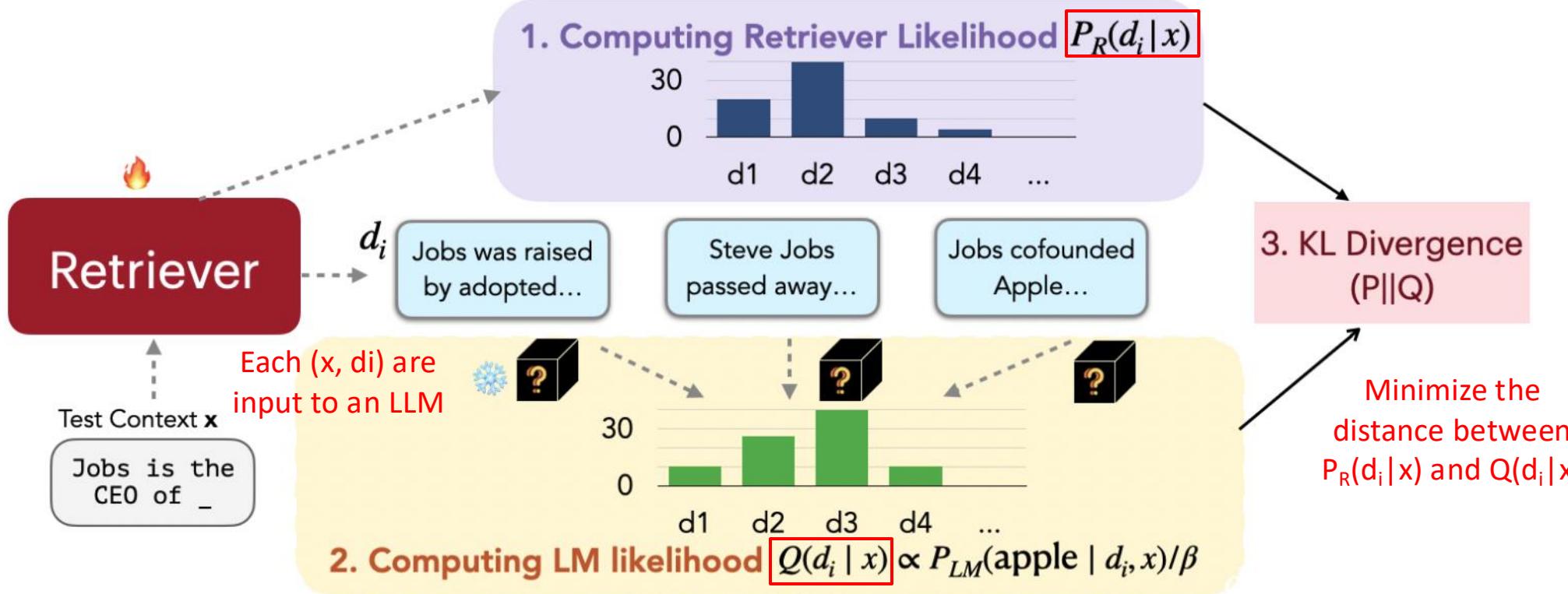


Shi, Weijia, et al. "REPLUG: Retrieval-Augmented Black-Box Language Models." NAACL 2024.

Training REPLUG with a Frozen LLM

REPLUG LSR (LM-Supervised Retrieval)

Train the retriever to retrieve the documents that are most helpful for the language model to generate good answers.



Shi, Weijia, et al. "REPLUG: Retrieval-Augmented Black-Box Language Models." NAACL 2024.

Comparison between REPLUG and REPLUG LSR

Why use BPB to evaluate REPLUG?

| Model | # Parameters | Original | + REPLUG | Gain % | + REPLUG LSR | Gain % | |
|----------------------|--------------|----------|----------|--------|--------------|--------|-----|
| GPT-2 | Small | 117M | 1.33 | 1.26 | 5.3 | 1.21 | 9.0 |
| | Medium | 345M | 1.20 | 1.14 | 5.0 | 1.11 | 7.5 |
| | Large | 774M | 1.19 | 1.15 | 3.4 | 1.09 | 8.4 |
| | XL | 1.5B | 1.16 | 1.09 | 6.0 | 1.07 | 7.8 |
| GPT-3 (black-box) | Ada | 350M | 1.05 | 0.98 | 6.7 | 0.96 | 8.6 |
| | Babbage | 1.3B | 0.95 | 0.90 | 5.3 | 0.88 | 7.4 |
| | Curie | 6.7B | 0.88 | 0.85 | 3.4 | 0.82 | 6.8 |
| | Davinci | 175B | 0.80 | 0.77 | 3.8 | 0.75 | 6.3 |

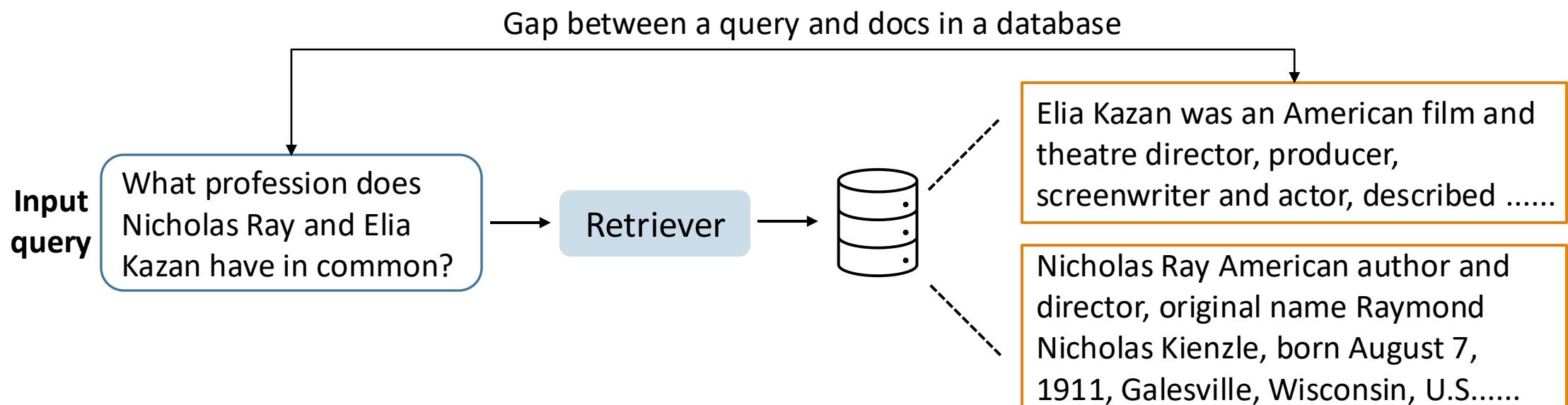
Table 1: **Both REPLUG and REPLUG LSR consistently enhanced the performance of different language models.** Bits per byte (BPB) of the Pile using GPT-3 and GPT-2 family models (Original) and their retrieval-augmented versions (+REPLUG and +REPLUG LSR). The gain % shows the relative improvement of our models compared to the original language model.

Recent RAG Developments

| Type | Method | Paper | Venue Year |
|--|-----------------|--|------------|
| Enhancing Retrieval | Query Rewriting | Query Rewriting in Retrieval-Augmented Large Language Models | EMNLP 2023 |
| | HyDE | Precise Zero-Shot Dense Retrieval without Relevance Labels | ACL 2023 |
| Enhancing RAG | RetRobust | Making Retrieval-Augmented Language Models Robust to Irrelevant Context | ICLR 2024 |
| | RAFT | RAFT: Adapting Language Model to Domain Specific RAG | COLM 2024 |
| | Self-RAG | Self-RAG: Learning to Retrieve, Generate, and Critique through Self-Reflection | ICLR 2024 |
| | RAAT | Enhancing Noise Robustness of Retrieval-Augmented Language Models with Adaptive Adversarial Training | ACL 2024 |
| Enhancing RAG with Continual Retrieval | FLARE | Active Retrieval Augmented Generation | EMNLP 2023 |

Query Rewriting

- Motivation:
 - There is inevitably a gap between the input text and the knowledge that is really needed to query.

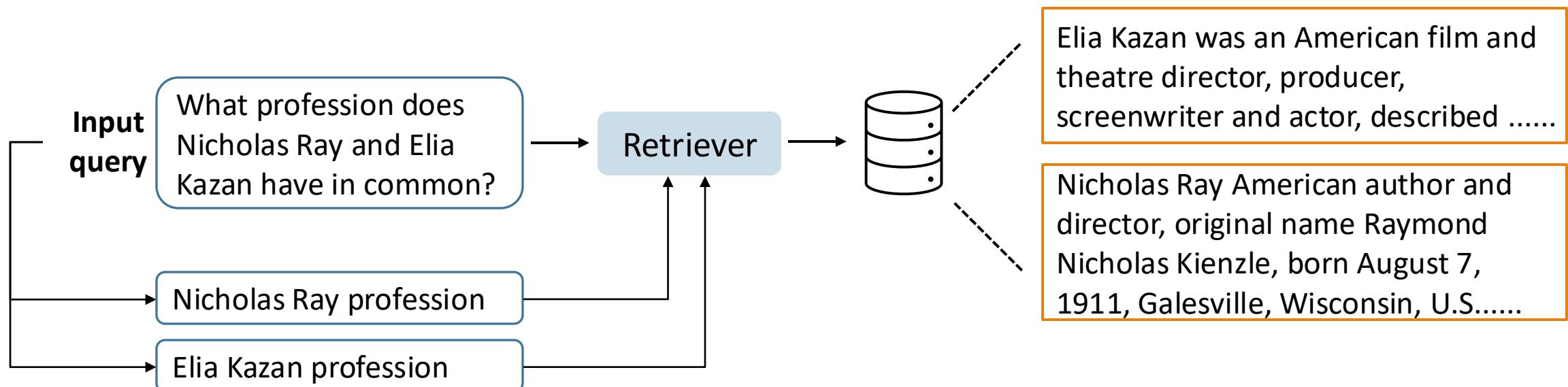


Ma, Xinbei, et al. "Query Rewriting in Retrieval-Augmented Large Language Models." EMNLP 2023.

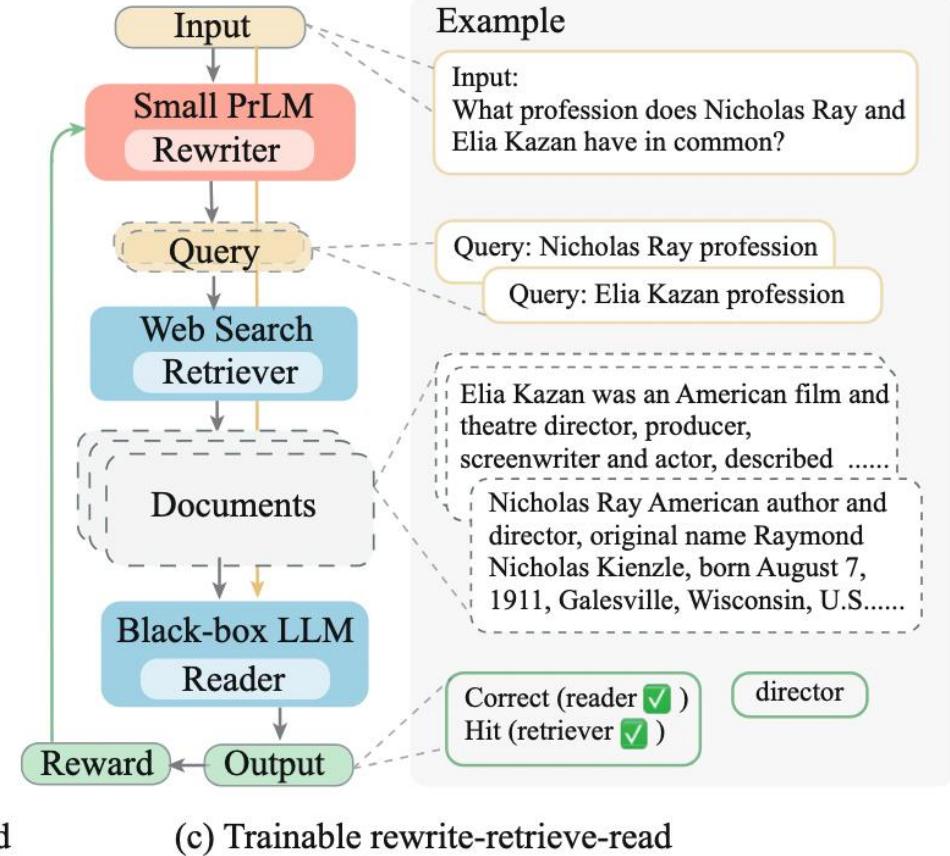
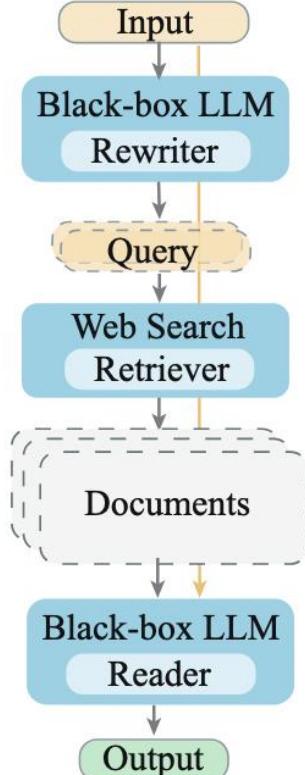
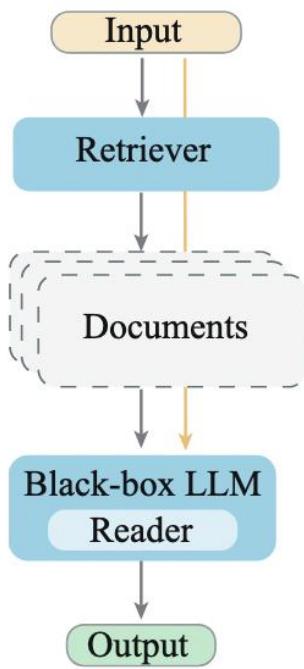
Query Rewriting

Ma, Xinbei, et al. "Query Rewriting in Retrieval-Augmented Large Language Models." EMNLP 2023.

- Motivation:
 - There is inevitably a gap between the input text and the knowledge that is really needed to query.



Query Rewriting – Approach



(a) Retrieve-then-read (b) Rewrite-retrieve-read

(c) Trainable rewrite-retrieve-read

Ma, Xinbei, et al. "Query Rewriting in Retrieval-Augmented Large Language Models." EMNLP 2023.

Query Rewriting – Prompt for the LLMs

Direct prompt

Answer the question in the following format, end the answer with '***'. {demonstration} Question: {*x*} Answer:

Reader prompt in retrieval-augment pipelines

Answer the question in the following format, end the answer with '***'. {demonstration} Question: {*doc*} {*x*} Answer:

Prompts for LLM as a frozen rewriter

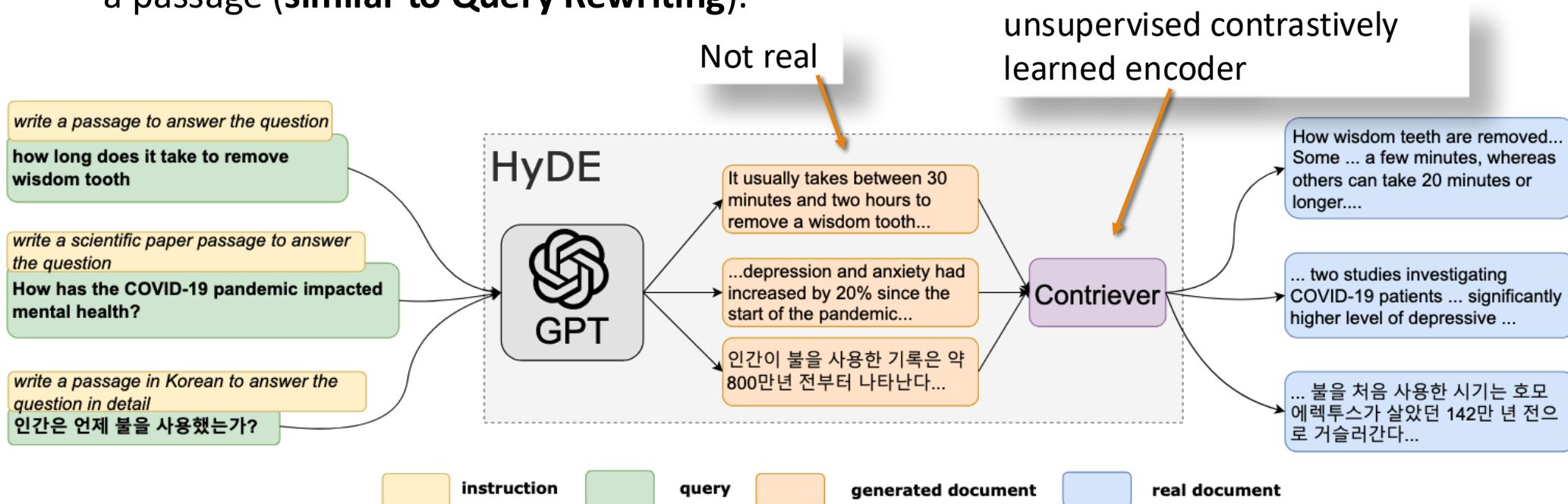
Open-domain QA: Think step by step to answer this question, and provide search engine queries for knowledge that you need. Split the queries with ';' and end the queries with '***'. {demonstration} Question: {*x*} Answer:

Multiple choice QA: Provide a better search query for web search engine to answer the given question, end the queries with '***'. {demonstration} Question: {*x*} Answer:

Table 1: Prompt lines used for the LLMs.

Hypothetical Document Embeddings (HyDE)

- Use an LLM (InstructGPT) to perform query transformations by asking the LLM to write a passage (**similar to Query Rewriting**).



適合各種任務與Query嗎？

Gao, Luyu, et al. "Precise Zero-Shot Dense Retrieval without Relevance Labels." ACL 2023.

HyDE can be better than Query Rewriting for retrieval tasks

| Method | TREC DL19 | | | | | TREC DL20 | | | | |
|------------------------|--------------|--------------|--------------|--------------|-------------|--------------|--------------|--------------|--------------|-------------|
| | mAP | nDCG@10 | R@50 | R@1k | Latency | mAP | nDCG@10 | R@50 | R@1k | Latency |
| <i>unsupervised</i> | | | | | | | | | | |
| BM25 | 30.13 | 50.58 | 38.32 | 75.01 | 0.07 | 28.56 | 47.96 | 46.18 | 78.63 | 0.29 |
| Contriever | 23.99 | 44.54 | 37.54 | 74.59 | 3.06 | 23.98 | 42.13 | 43.81 | 75.39 | 0.98 |
| <i>supervised</i> | | | | | | | | | | |
| LLM-Embedder | 44.66 | 70.20 | 49.06 | 84.48 | <u>2.61</u> | 45.60 | 68.76 | 61.36 | 84.41 | <u>0.71</u> |
| + Query Rewriting | 44.56 | 67.89 | 51.45 | 85.35 | <u>7.80</u> | 45.16 | 65.62 | 59.63 | 83.45 | <u>2.06</u> |
| + Query Decomposition | 41.93 | 66.10 | 48.66 | 82.62 | 14.98 | 43.30 | 64.95 | 57.74 | 84.18 | 2.01 |
| + HyDE | 50.87 | 75.44 | 54.93 | 88.76 | 7.21 | 50.94 | 73.94 | 63.80 | 88.03 | 2.14 |
| + Hybrid Search | 47.14 | 72.50 | 51.13 | <u>89.08</u> | 3.20 | 47.72 | 69.80 | <u>64.32</u> | <u>88.04</u> | 0.77 |
| + HyDE + Hybrid Search | 52.13 | <u>73.34</u> | 55.38 | 90.42 | 11.16 | 53.13 | <u>72.72</u> | 66.14 | 90.67 | 2.95 |

Table 7: Results for different retrieval methods on TREC DL19/20. The best result for each method is made bold and the second is underlined.

RetRobust: Making Retrieval-Augmented Language Models Robust to Irrelevant Context

Q: Who is the actor playing Jason on general hospital?

Large Language Model (no retrieval)



The answer is: Steve Burton



Retrieval Augmented Language Model



E: Jason Gerhardt (born April 21, 1974) is an American actor. He is known for playing the role of Cooper Barrett in General Hospital and Zack Kilmer in Mistresses.

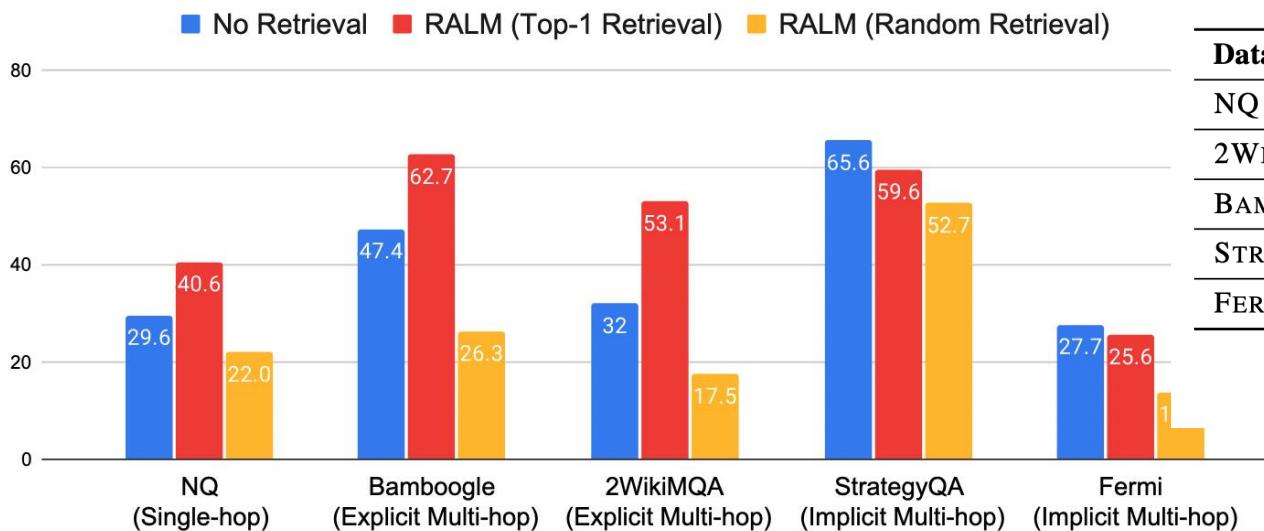
The answer is: Jason Gerhardt



RALM: Retrieval Augmented Language Model

Yoran, Ori, et al. "Making Retrieval-Augmented Language Models Robust to Irrelevant Context." ICLR 2024.

RetRobust: Making Retrieval-Augmented Language Models Robust to Irrelevant Context



| Dataset | Type | Example |
|------------|------------|---|
| NQ | Single-hop | What episode of law and order svu is mike tyson in? |
| 2WIKIMQA | Explicit | Where was the place of death of Isabella Of Bourbon's father? |
| BAMBOOGLE | Explicit | What is the maximum airspeed (in km/h) of the third fastest bird? |
| STRATEGYQA | Implicit | Can Arnold Schwarzenegger deadlift an adult Black rhinoceros? |
| FERMI | Implicit | How many high fives has Lebron James given/received? |

Table 1: The QA datasets in our experiments.

Retrieval augmentation can boost performance, but it also hurts performance on StrategyQA and Fermi, and random contexts reduce performance dramatically.

StrategyQA:

Did Aristotle Use a Laptop? A Question Answering Benchmark with Implicit Reasoning Strategies (EMNLP 2021)

Each question requires several unstated reasoning steps to answer, and those intermediate facts are not explicitly mentioned in the question itself.

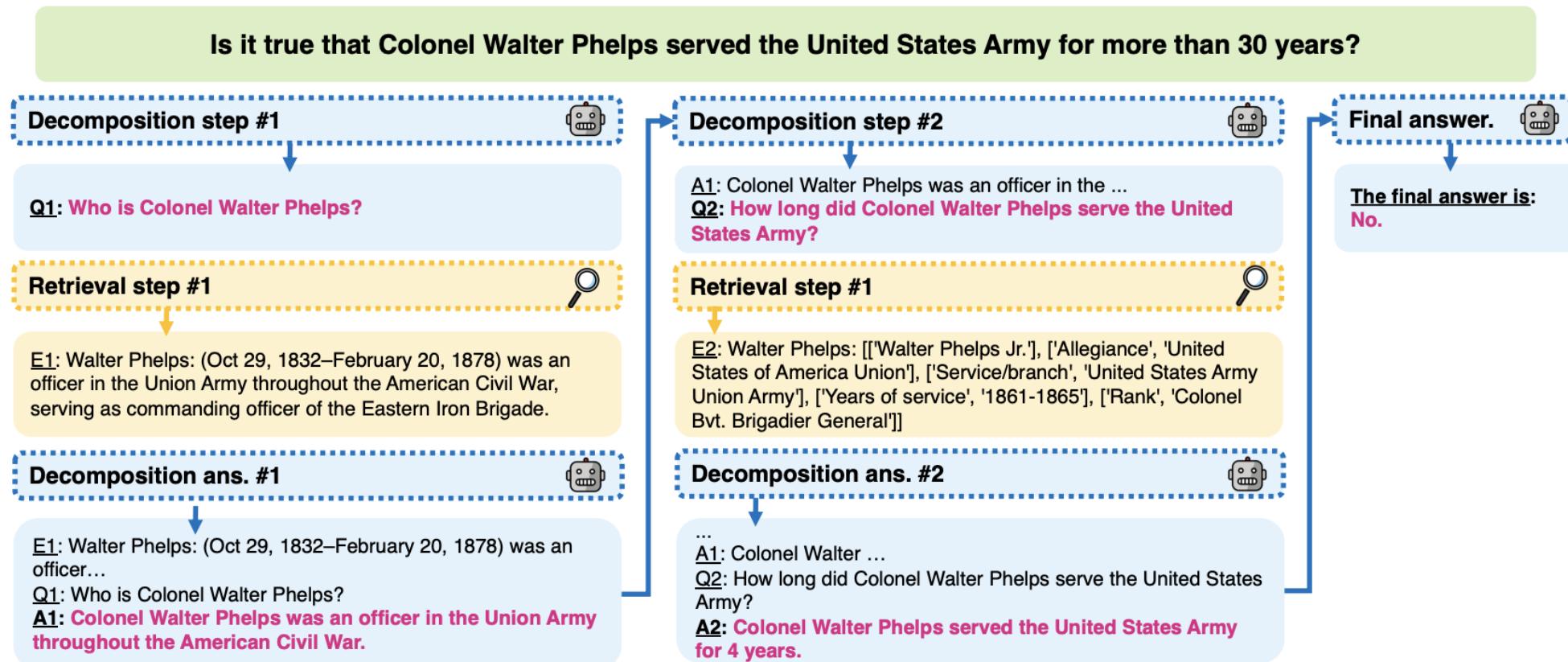
Could a crocodile run a marathon?

- A marathon is about **42 kilometers long**.
- Running requires sustained terrestrial movement.
- Crocodiles are semi-aquatic animals and **cannot run long distances** on land.
- Therefore, the answer is **No**.

Would the Eiffel Tower cast a shadow at night?

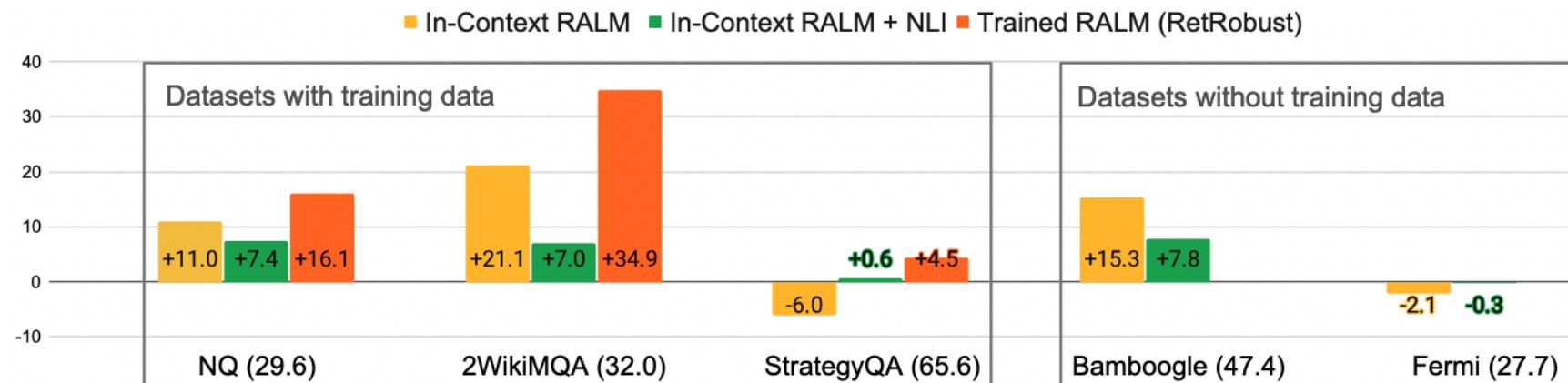
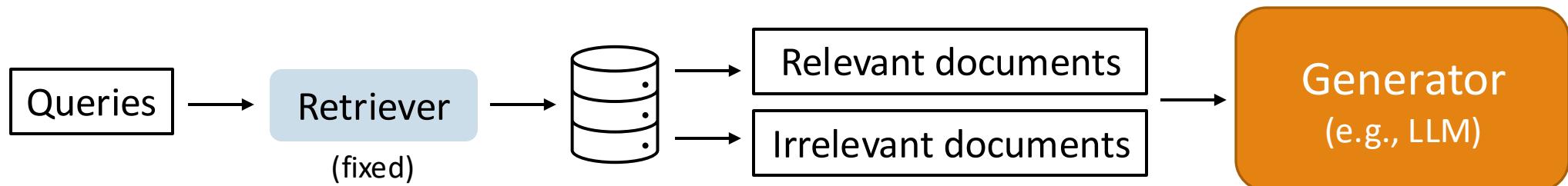
Could an elephant fit inside an average car?

RetRobust: Making Retrieval-Augmented Language Models Robust to Irrelevant Context



RetRobust: Making Retrieval-Augmented Language Models Robust to Irrelevant Context

Train the generator on QA tasks with both relevant and irrelevant retrieved documents.

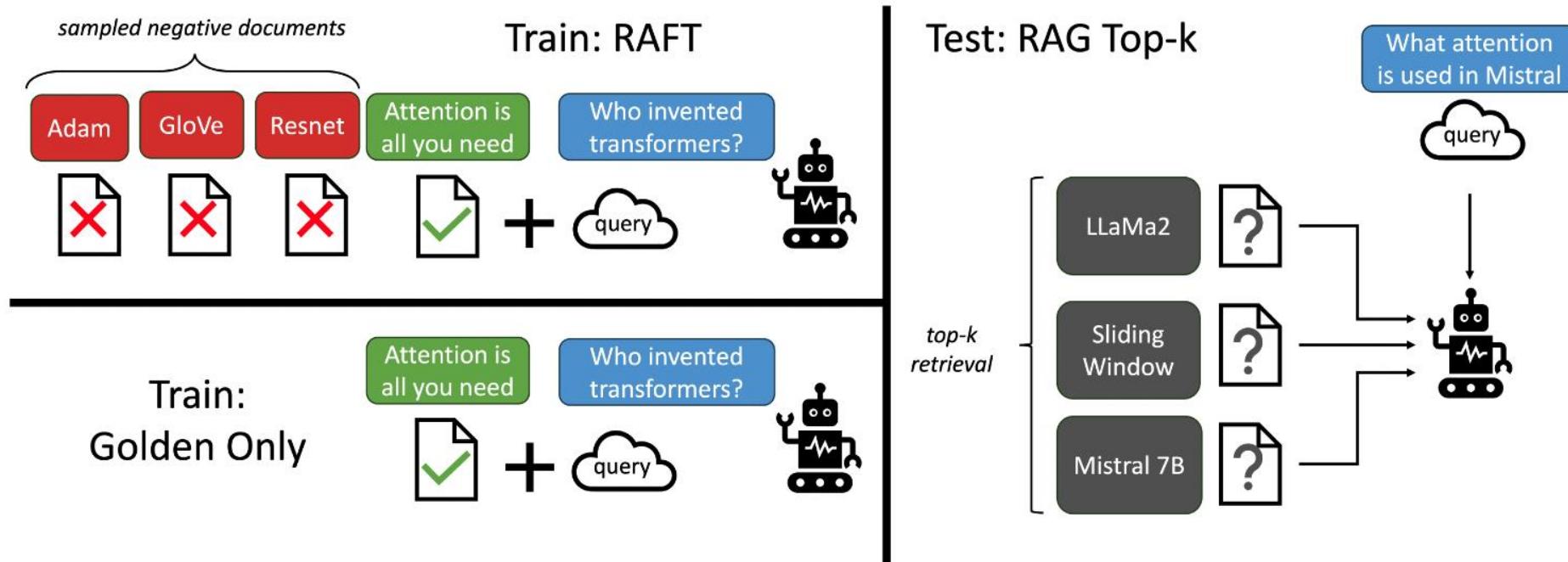


Yoran, Ori, et al. "Making Retrieval-Augmented Language Models Robust to Irrelevant Context." ICLR 2024.

RAFT: Adapting LLM to RAG

(Retrieval-Augmented Fine-Tuning)

- In this work, the retriever is fixed. An LLM is trainable.
- Both correct and incorrect documents are included during training.



Matei Zaharia, Tianjun Zhang, Shishir G. Patil, Naman Jain, Sheng Shen, and Ion Stoica. "RAFT: Adapting Language Model to Domain Specific RAG." COLM 2024.

Difference between RetRobust and RAFT

**RAFT uses CoT Answer
(answer with rationales).**

Question: The Oberoi family is part of a hotel company that has a head office in what city?

context: [The Oberoi family is an Indian family that is famous for its involvement in hotels, namely through The Oberoi Group]...[It is located in city center of Jakarta, near Mega Kuningan, adjacent to the sister JW Marriott Hotel. It is operated by The Ritz-Carlton Hotel Company. The complex has two towers that comprises a hotel and the Airlangga Apartment respectively]...[The Oberoi Group is a hotel company with its head office in Delhi.]

Instruction: Given the question, context and answer above, provide a logical reasoning for that answer. Please use the format of: ##Reason: {reason}
##Answer: {answer}.

CoT Answer: ##Reason: The document ##begin_quote## The Oberoi family is an Indian family that is famous for its involvement in hotels, namely through The Oberoi Group. ##end_quote## establishes that the Oberoi family is involved in the Oberoi group, and the document ##begin_quote## The Oberoi Group is a hotel company with its head office in Delhi. ##end_quote## establishes the head office of The Oberoi Group. Therefore, the Oberoi family is part of a hotel company whose head office is in Delhi. ##Answer: Delhi



EMNLP 2023
Carnegie Mellon University
Active Retrieval Augmented
Generation

Problem Formation

- For a naïve retrieval augmented generation:

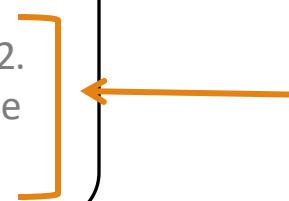


Query: Generate a summary
about Joe Biden



Redundant information (Noise) may confuse
the language model and make the generation
wrong.

1. Joseph Robinette Biden Jr. was born on November 20, 1942
2. Neilia Hunter Biden, the first wife of Joe Biden, was born on July 28, 1942.
3. I started thinking as I was coming over here, why is it that Joe Biden is the
first in his family ever to go to a university?



Noise

Methodology

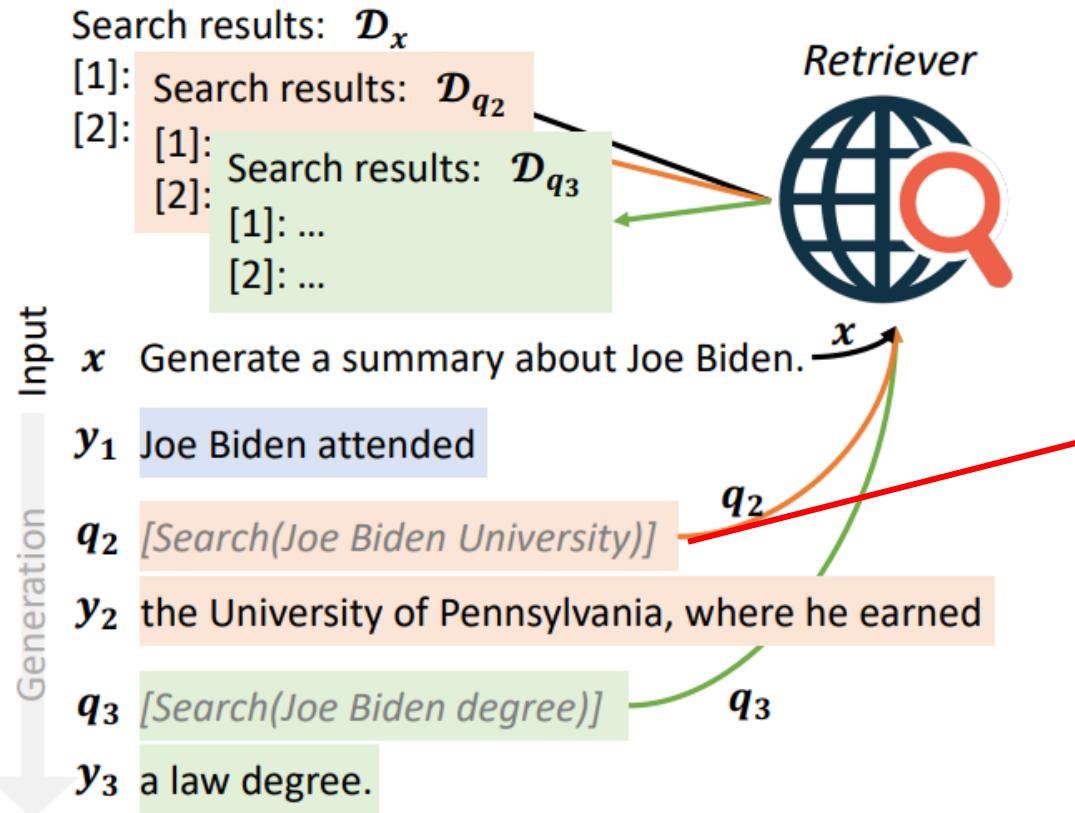
In retrieval-augmented generation, it is crucial to determine:

- **What to retrieve:** Selecting relevant and useful information.
- **When to retrieve:** Identifying the appropriate timing for retrieval.

The retrieved information should:

- Be essential for the model's generation process.
- Directly address the model's specific needs.

What to retrieve

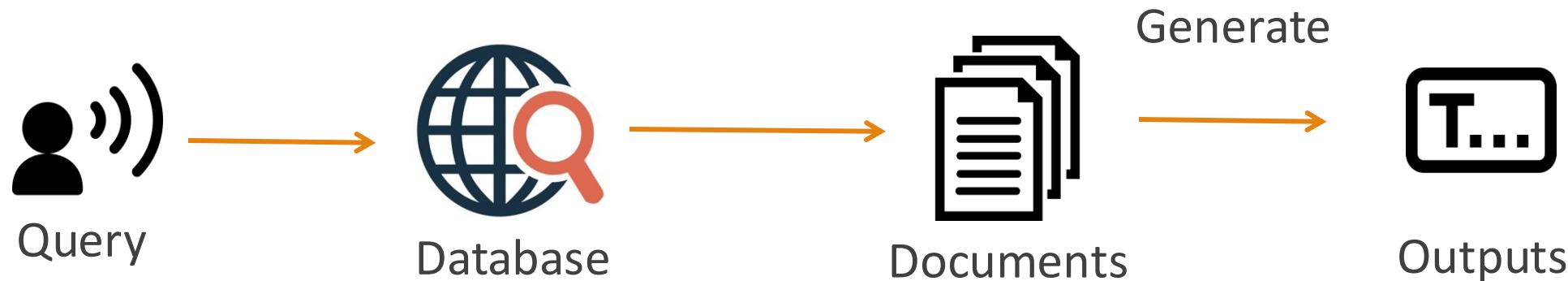


1. LMs should only retrieve information when they do not have the necessary knowledge to avoid unnecessary or inappropriate retrieval.
2. the retrieval queries should reflect the intents of future generations

Output = concat(y_1, y_2, y_3, \dots)

When to retrieve

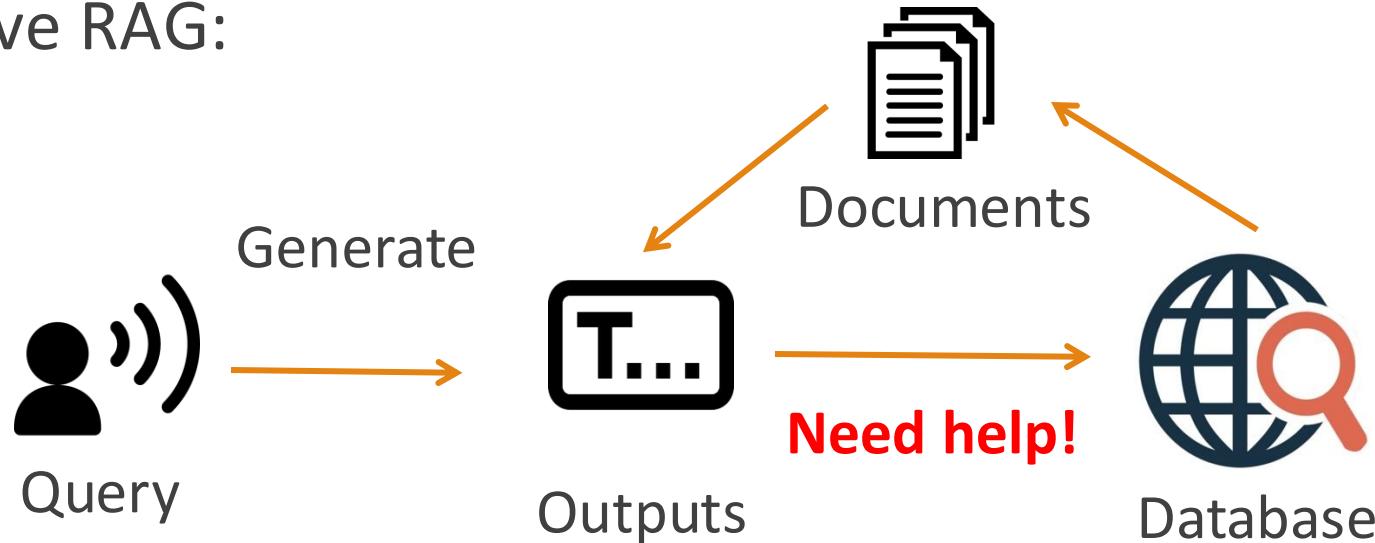
For traditional RAG:



The documents are retrieved based on the input query before generation.

When to retrieve

For Active RAG:



The documents are retrieved only when the language model **needs help**.

The definition of "need help"

Language models are often well-calibrated, meaning that **low probability or confidence** typically reflects a lack of knowledge.

This paper define a threshold $\theta \in [0, 1]$, when the probability of next token prediction is lower than θ , a retrieval is triggered.

$$\mathbf{y}_t = \begin{cases} \hat{\mathbf{s}}_t & \text{if all tokens of } \hat{\mathbf{s}}_t \text{ have probs } \geq \theta \\ \mathbf{s}_t = \text{LM}([\mathcal{D}_{\mathbf{q}_t}, \mathbf{x}, \mathbf{y}_{<t}]) & \text{otherwise} \end{cases}$$

There is no need to perform retrieval.

↑

Use $\hat{\mathbf{s}}_t$ to perform a **next** retrieval

Generation

Query: Generate a summary about Joe Biden

Outputs: Joe Biden attended [Search(*Joe Biden University*)]

Low Confidence!

Search & Generate

the University of Pennsylvania, where he earned [Search(*Joe Biden degree*)]

Low Confidence!

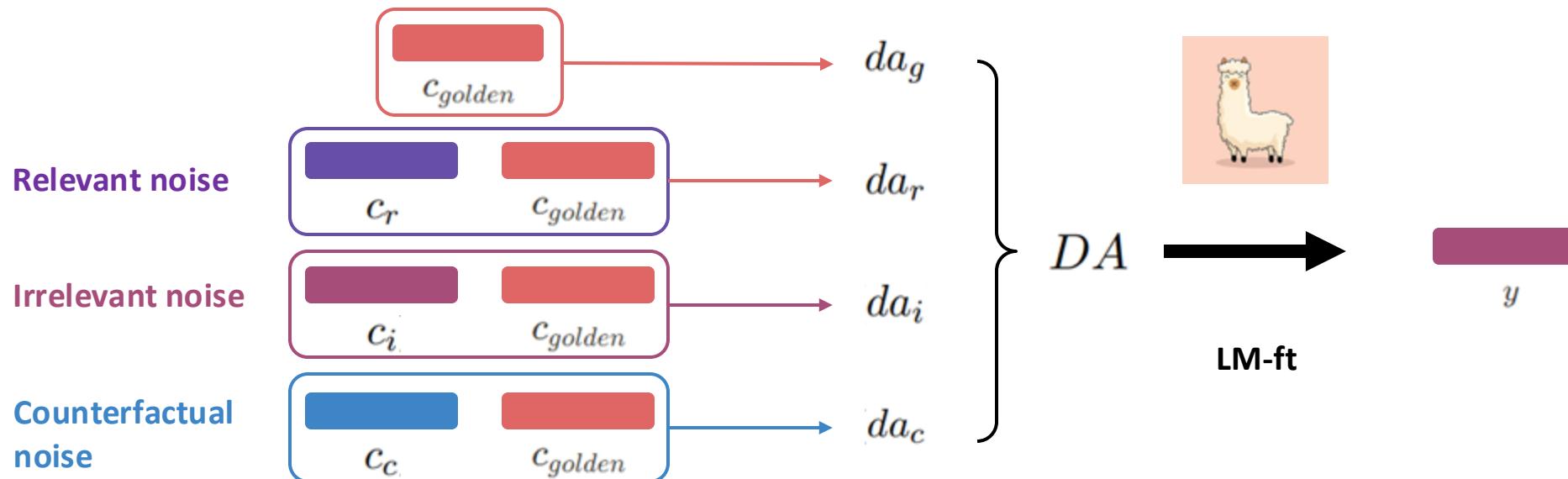
Search & Generate

a law degree.

RAAT

Adaptive Adversarial Training

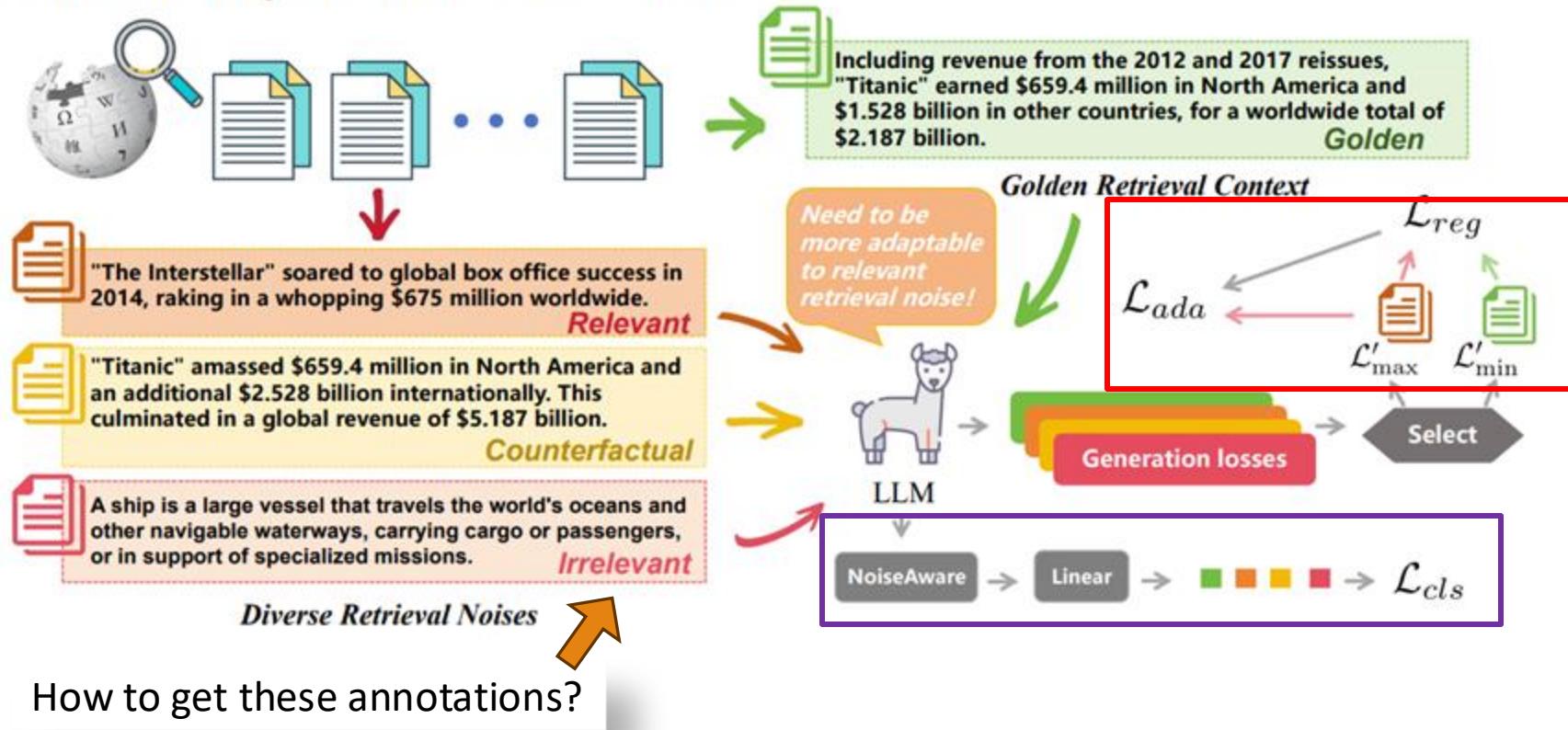
- Recently, several studies have attempted to **enhance the noise robustness of RALMs through noisy training**, which involves incorporating retrieved noisy contexts into fine-tuning data.



Fang, Feiteng, et al. "Enhancing Noise Robustness of Retrieval-Augmented Language Models with Adaptive Adversarial Training." ACL 2024.

RAAT

How much money did the film "Titanic" make?



Adaptive learning maximizes input manipulation and minimizes by fine-tuning to enhance model robustness.

An auxiliary task enhances RALMs' robustness by detecting and addressing retrieval noise.

Fang, Feiteng, et al. "Enhancing Noise Robustness of Retrieval-Augmented Language Models with Adaptive Adversarial Training." ACL 2024.

RAAT Conclusion

| Method | Golden Only | | Golden & c_i | | Golden & c_r | | Golden & c_c | | Avg | |
|---------------------------|--------------|--------------|----------------|--------------|----------------|--------------|----------------|--------------|--------------|--------------|
| | F1 | EM | F1 | EM | F1 | EM | F1 | EM | F1 | EM |
| LLaMA2 _{7B} | 65.56 | 51.80 | 56.14 | 42.87 | 53.10 | 39.73 | 51.81 | 38.37 | 56.68 | 43.19 |
| Qwen _{7B} | 62.57 | 47.07 | 61.48 | 46.06 | 55.50 | 40.50 | 53.26 | 36.90 | 58.20 | 42.63 |
| LLaMA2 _{13B} | 69.27 | 55.00 | 63.25 | 49.47 | 62.27 | 47.97 | 62.07 | 47.17 | 64.22 | 49.90 |
| Qwen _{14B} | 67.45 | 51.43 | 66.71 | 51.20 | 61.88 | 46.16 | 58.65 | 41.30 | 63.67 | 47.52 |
| LLaMA2 _{70B} | 71.43 | 56.56 | 70.05 | 55.13 | 65.97 | 51.33 | 63.91 | 48.27 | 67.84 | 52.82 |
| ChatGPT _{3.5} | 73.98 | 60.50 | 72.24 | 60.30 | 70.65 | 56.89 | 69.00 | 54.64 | 71.47 | 58.10 |
| RALM _{golden} | 80.31 | 74.03 | 79.33 | 72.73 | 73.26 | 66.33 | 73.08 | 65.40 | 76.50 | 69.62 |
| RetRobust | 80.10 | 73.80 | 79.25 | 72.97 | 74.81 | 68.30 | 75.46 | 68.43 | 77.41 | 70.88 |
| RALM _{retrieved} | 80.04 | 73.40 | 81.09 | 74.80 | 75.99 | 69.10 | 73.10 | 65.67 | 77.55 | 70.74 |
| RALM _{multiple} | 85.47 | 80.17 | 85.27 | 81.20 | 83.07 | 78.33 | 83.25 | 79.23 | 84.27 | 79.73 |
| RAAT | 87.15 | 83.07 | 86.80 | 82.73 | 85.14 | 81.00 | 86.29 | 82.10 | 86.35 | 82.23 |

Table 2: Experimental results on our RAG-Bench benchmark. “Golden Only” denotes a scenario where LLMs only consult the golden retrieval context. In “Golden & $c_i/c_r/c_c$ ”, LLMs consider both the golden retrieval context and *irrelevant retrieval noise/relevant retrieval noise/counterfactual retrieval noise*.

Fang, Feiteng, et al. “Enhancing Noise Robustness of Retrieval-Augmented Language Models with Adaptive Adversarial Training.” ACL 2024.

RAAT Conclusion

1. Investigated **retrieval noises** in RALMs and categorized them into **three distinct types**, reflecting real-world environments.
2. Introduced **RAAT** as a solution to address the noise robustness challenges faced by RALMs, which leveraged **adaptive adversarial learning** and **multi-task learning** to enhance the model's capability.
3. **Established a benchmark** to verify the effectiveness of RAAT based on three open-domain QA datasets.

Q: 物理意義上學到了什麼?

Fang, Feiteng, et al. "Enhancing Noise Robustness of Retrieval-Augmented Language Models with Adaptive Adversarial Training." ACL 2024.

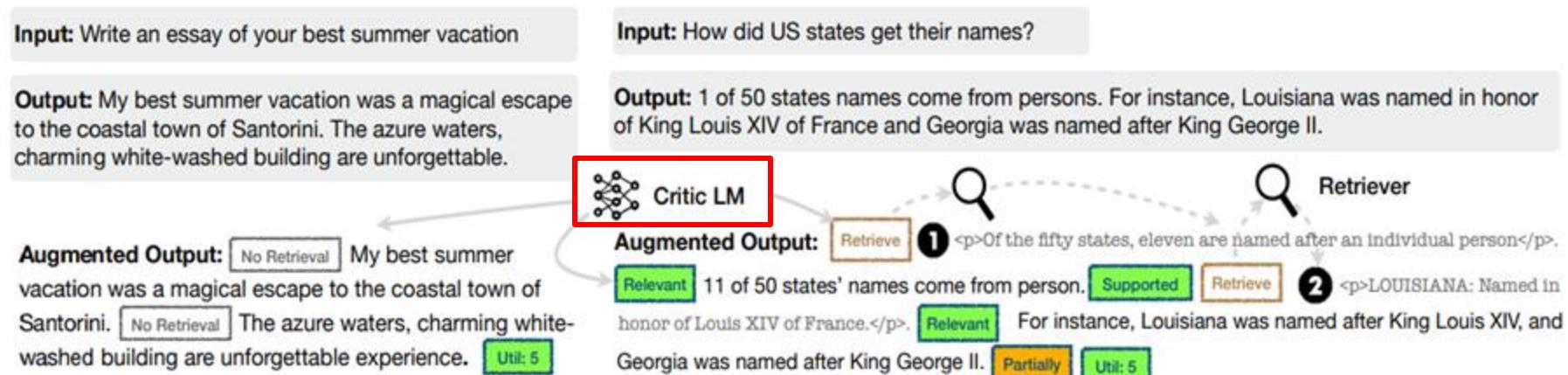


Self-RAG

self-critique & self-reflect

Self-RAG (Training)

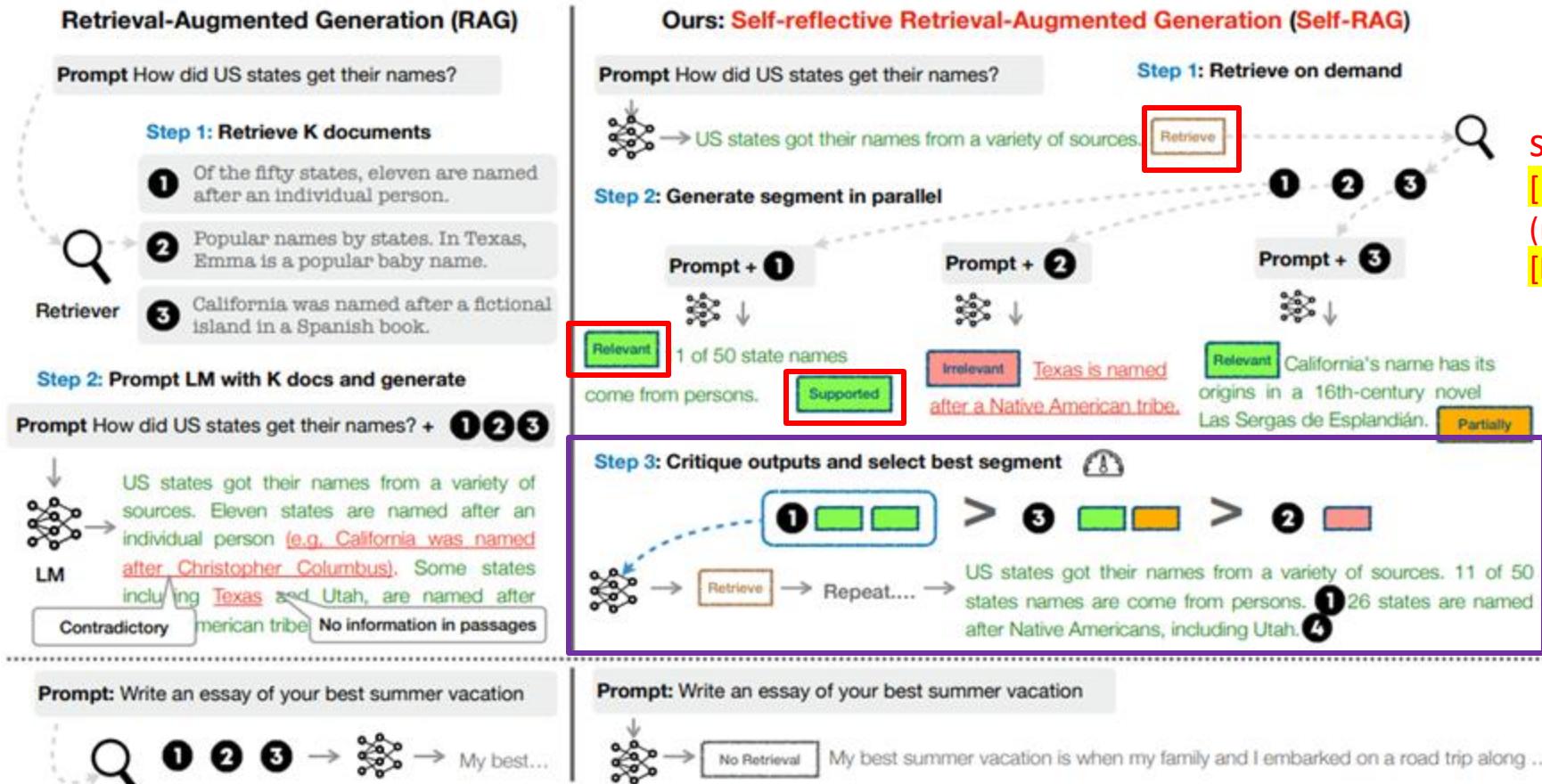
- Supervised data is created by prompting GPT-4 for reflection tokens, distilled into a critic model with token-specific definitions and inputs.
- Thus, they use critic model to collect training data for Generator.



Asai, Akari, et al. "Self-rag: Learning to retrieve, generate, and critique through self-reflection." ICLR 2024.

Self-RAG

Self-RAG (Inference)



Asai, Akari, et al. "Self-rag: Learning to retrieve, generate, and critique through self-reflection." ICLR 2024.

self-reflection:
[Retrieve], [IsRel], [IsSup]
(response supported by d),
[IsUse] (useful response)

obtain the top-B
segment
continuations at
each timestamp

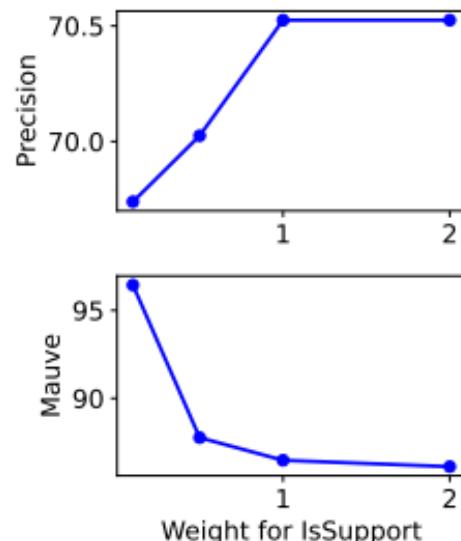
Self-RAG

| LM | Short-form | | Closed-set | | Long-form generations (with citations) | | | | | |
|------------------------------------|----------------|--------------|--------------|--------------|--|-------------|-------------|---------------|-------------|-------------|
| | PopQA (acc) | TQA (acc) | Pub (acc) | ARC (acc) | Bio (FS) | (em) | (rg) | ASQA (mau) | (pre) | (rec) |
| <i>LMs with proprietary data</i> | | | | | | | | | | |
| Llama2-c _{13B} | 20.0 | 59.3 | 49.4 | 38.4 | 55.9 | 22.4 | 29.6 | 28.6 | — | — |
| Ret-Llama2-c _{13B} | 51.8 | 59.8 | 52.1 | 37.9 | 79.9 | 32.8 | 34.8 | 43.8 | 19.8 | 36.1 |
| ChatGPT | 29.3 | 74.3 | 70.1 | 75.3 | 71.8 | 35.3 | 36.2 | 68.8 | — | — |
| Ret-ChatGPT | 50.8 | 65.7 | 54.7 | 75.3 | — | 40.7 | 39.9 | 79.7 | 65.1 | 76.6 |
| Perplexity.ai | — | — | — | — | 71.2 | — | — | — | — | — |
| <i>Baselines without retrieval</i> | | | | | | | | | | |
| Llama2 _{7B} | 14.7 | 30.5 | 34.2 | 21.8 | 44.5 | 7.9 | 15.3 | 19.0 | — | — |
| Alpaca _{7B} | 23.6 | 54.5 | 49.8 | 45.0 | 45.8 | 18.8 | 29.4 | 61.7 | — | — |
| Llama2 _{13B} | 14.7 | 38.5 | 29.4 | 29.4 | 53.4 | 7.2 | 12.4 | 16.0 | — | — |
| Alpaca _{13B} | 24.4 | 61.3 | 55.5 | 54.9 | 50.2 | 22.9 | 32.0 | 70.6 | — | — |
| CoVE _{65B} * | — | — | — | — | 71.2 | — | — | — | — | — |
| <i>Baselines with retrieval</i> | | | | | | | | | | |
| Toolformer* _{6B} | — | 48.8 | — | — | — | — | — | — | — | — |
| Llama2 _{7B} | 38.2 | 42.5 | 30.0 | 48.0 | 78.0 | 15.2 | 22.1 | 32.0 | 2.9 | 4.0 |
| Alpaca _{7B} | 46.7 | 64.1 | 40.2 | 48.0 | 76.6 | 30.9 | 33.3 | 57.9 | 5.5 | 7.2 |
| Llama2-FT _{7B} | 48.7 | 57.3 | 64.3 | 65.8 | 78.2 | 31.0 | 35.8 | 51.2 | 5.0 | 7.5 |
| SAIL* _{7B} | — | — | 69.2 | 48.4 | — | — | — | — | — | — |
| Llama2 _{13B} | 45.7 | 47.0 | 30.2 | 26.0 | 77.5 | 16.3 | 20.5 | 24.7 | 2.3 | 3.6 |
| Alpaca _{13B} | 46.1 | 66.9 | 51.1 | 57.6 | 77.7 | 34.8 | 36.7 | 56.6 | 2.0 | 3.8 |
| Our SELF-RAG_{7B} | 54.9 | 66.4 | 72.4 | 67.3 | 81.2 | 30.0 | 35.7 | 74.3 | 66.9 | 67.8 |
| Our SELF-RAG_{13B} | 55.8 | 69.3 | 74.5 | 73.1 | 80.2 | 31.7 | 37.0 | 71.6 | 70.3 | 71.3 |

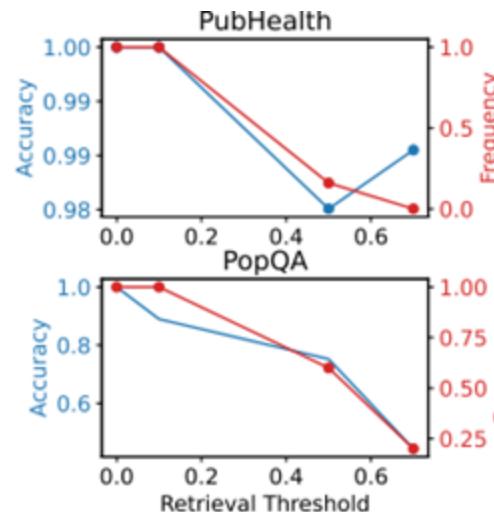
Asai, Akari, et al. "Self-rag: Learning to retrieve, generate, and critique through self-reflection." ICLR 2024.

Self-RAG

- Reflection token settings balance precision versus fluency and accuracy versus retrieval frequency.



(b) Customization



(c) Retrieval

Asai, Akari, et al. "Self-rag: Learning to retrieve, generate, and critique through self-reflection." ICLR 2024.

Self-RAG Conclusion

1. It introduces **SELF-RAG**, a new framework to enhance the quality and factuality of LLMs through **retrieval on demand** and **self-reflection**.
2. SELF-RAG trains an LM to learn to **retrieve**, **generate**, and **critique text passages and its own generation** by **predicting the next tokens** from its original vocabulary as well as newly added special tokens, called **reflection tokens**.
3. SELF-RAG further enables the **tailoring of LM behaviors** at test time by leveraging reflection tokens.

Asai, Akari, et al. "Self-rag: Learning to retrieve, generate, and critique through self-reflection." ICLR 2024.

Challenges in Modern RAG

- A significant amount of **noise information** even fake news in the content available on the Internet.
- Currently, there is **a lack of comprehensive understanding** of how each model can improve performance through information retrieval.

Type of Noises

- Relevant (semantically similar) but not contain the answer
- Counterfactual information
- Irrelevant information
- Black box digestion
- ...

Capabilities that LLMs Should Have in RAG

Noise Robustness

- LLMs must be able to **extract** the necessary information from documents despite there are noisy documents.

Question

Who was awarded the **2022** Nobel prize in literature?

External documents contain noises

The Nobel Prize in Literature for **2022** is awarded to the French author **Annie Ernaux**, “for the courage and clinical acuity ...

The Nobel Prize in Literature for **2021** is awarded to the novelist **Abdulrazak Gurnah**, born in Zanzibar and active in ...

Retrieval Augmented Generation



Annie Ernaux

Capabilities that LLMs Should Have in RAG

Negative Rejection

- In real-world situations, the search engine often fails to retrieve documents containing the answers.
- It is important for the model to have the capability to **reject recognition** and **avoid generating misleading content**.

Question

Who was awarded the **2022** Nobel prize in literature?

External documents contain noises

The Nobel Prize in Literature for **2021** is awarded to the novelist **Abdulrazak Gurnah**, born in Zanzibar and active in ...

The **2020** Nobel Laureate in Literature, poet **Louise Glück**, has written both poetry and essays about poetry. Since her...

Retrieval Augmented Generation



I can not answer the question because of the insufficient information in documents.

Capabilities that LLMs Should Have in RAG

Information Integration

- In many cases, **the answer to a question may be contained in multiple documents.**
- To provide better answers to complex questions, it is necessary for LLMs to have the ability to integrate information.

Question

When were the **ChatGPT app for iOS** and **ChatGPT api** launched?

External documents contain noises

On **May 18th**, 2023, OpenAI introduced its own **ChatGPT app for iOS...**

That changed **on March 1**, when OpenAI announced **the release of API access to ChatGPT and Whisper,...**

Retrieval Augmented Generation



May 18 and March 1.

Capabilities that LLMs Should Have in RAG

Counterfactual Robustness

- In the real world, there is an abundance of false information on the internet.
- LLMs should **identify risks of known factual errors** in the retrieved documents when the LLMs are given warnings about potential risks in the retrieved information through instruction.

Question

Which city hosted the Olympic games in **2004**?

External documents contain noises

The 2004 Olympic Games returned home to **New York**, birthplace of the ...

After leading all voting rounds, **New York** easily defeated Rome in the fifth and final vote ...

Retrieval Augmented Generation

There are factual errors in the provided documents. **The answer should be Athens.**