



# 自然語言處理與應用

## Natural Language Processing and Applications

**Retrieval-Augmented Generation  
(RAG)**

Instructor: 林英嘉 (Ying-Jia Lin)  
2025/05/19



[Course GitHub](#)



[Slido # NLP\\_0519](#)

# 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. 



**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. 

(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).

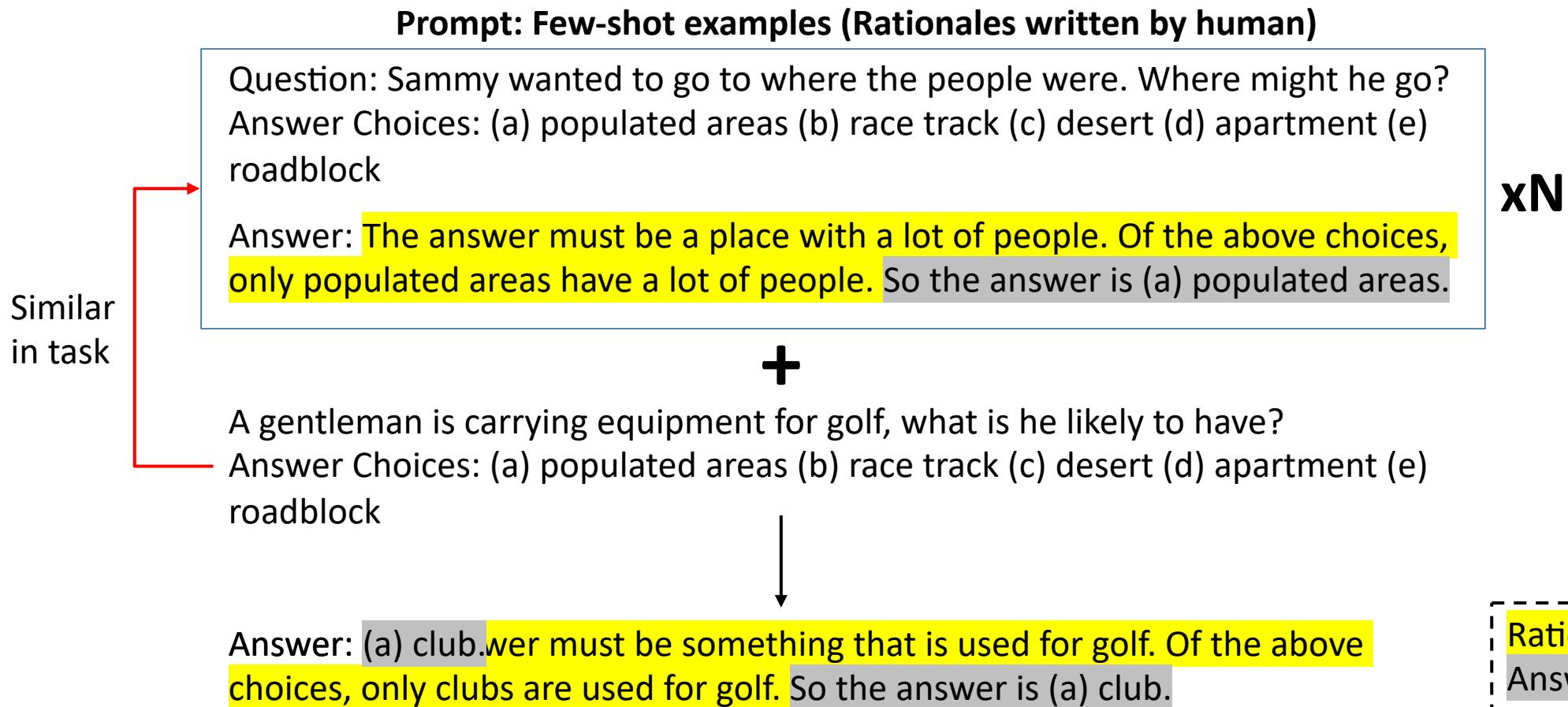
# Solutions to Mitigating Hallucinations

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- 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.



# Retrieval-Augmented Generation (RAG)

# Information Retrieval

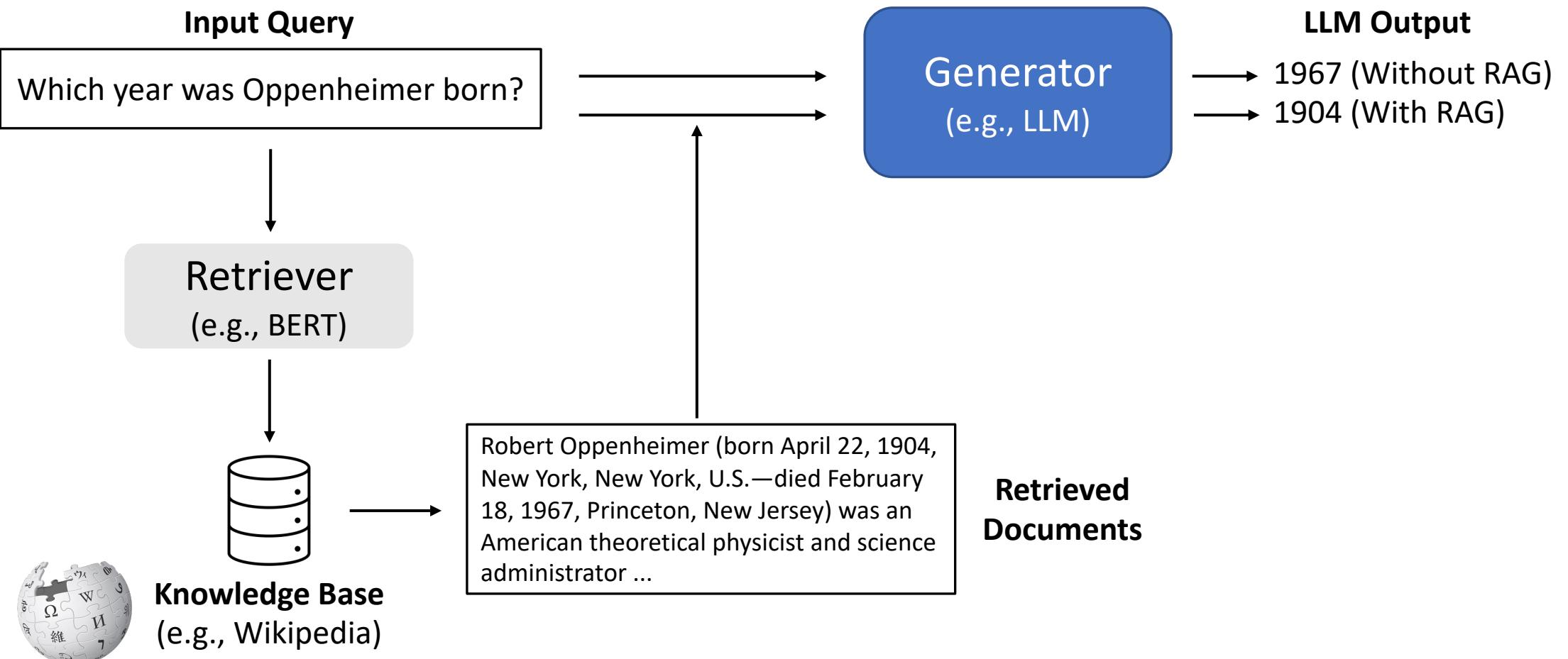
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- Retrieval: get relevant information from a pool (like a search engine)



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

# Retrieval-Augmented Generation (RAG)



# Why do we need RAG?

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- LLMs have profound parameterized knowledge that makes them useful in responding to general prompts.
- However, LLMs are error-prone due to 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.

# Retrievers for RAG

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- A retriever is aimed at searching relevant documents based on an input query.
- A retriever plays an important role for enhancing 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 comes from other encoder models or the retriever itself..

# Task: Open-domain question answering (ODQA)

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- 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

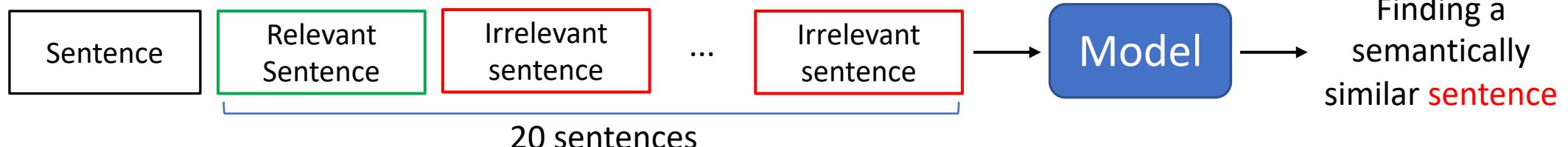
# Retrievers for RAG

- 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).

# Vectors (embeddings) in this semester

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Retriever

**Word Embeddings**

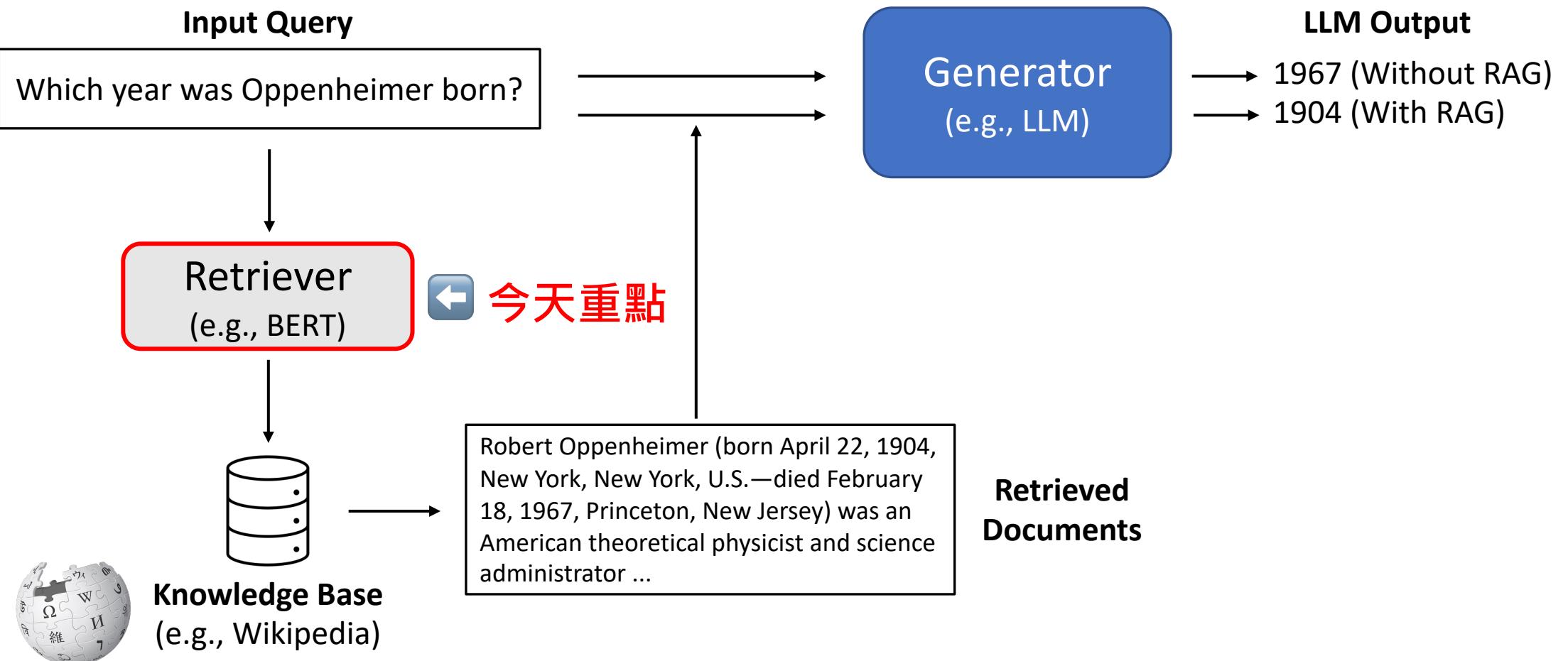
One-hot Encodings / PMI / LSA (week 2)  
Word2vec / GloVe (week 3)

Retriever

**Document  
Embeddings**

Bag-of-words / TF-IDF (week 2)  
DPR / ... (week 14)

# Retrieval-Augmented Generation (RAG)

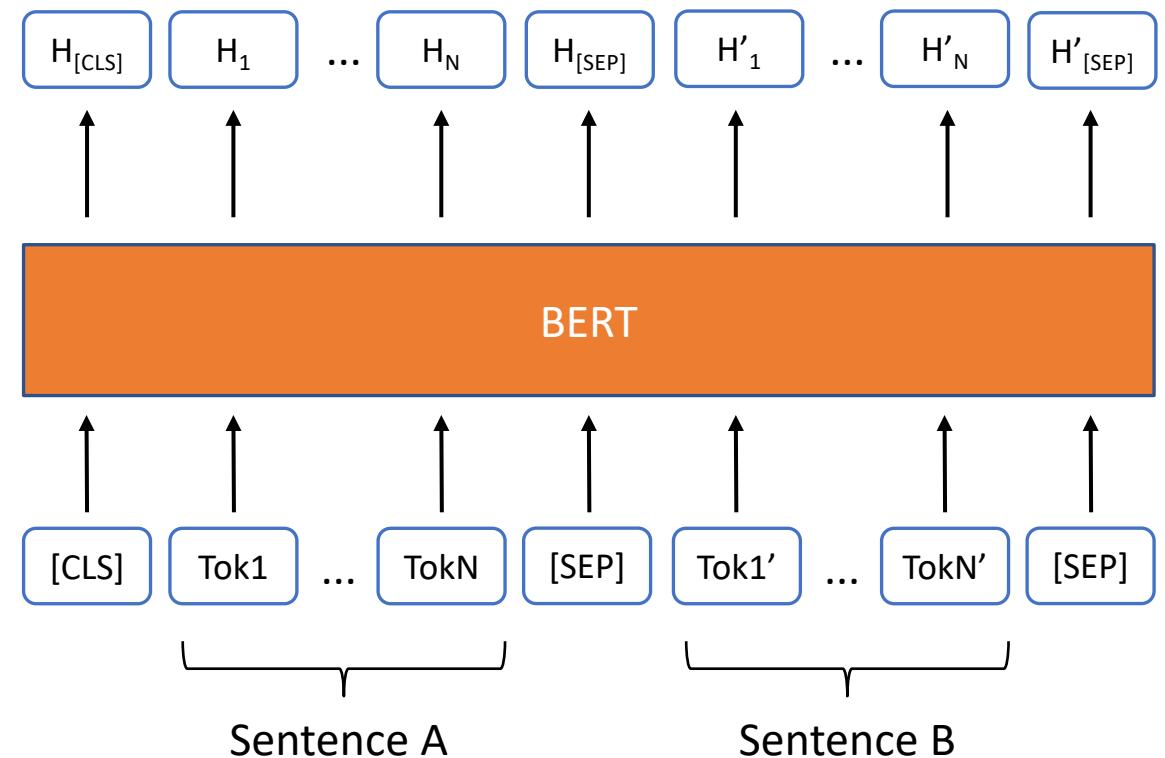


# Sentence embeddings for semantic similarity tasks

# BERT as a Cross Encoder

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- 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.



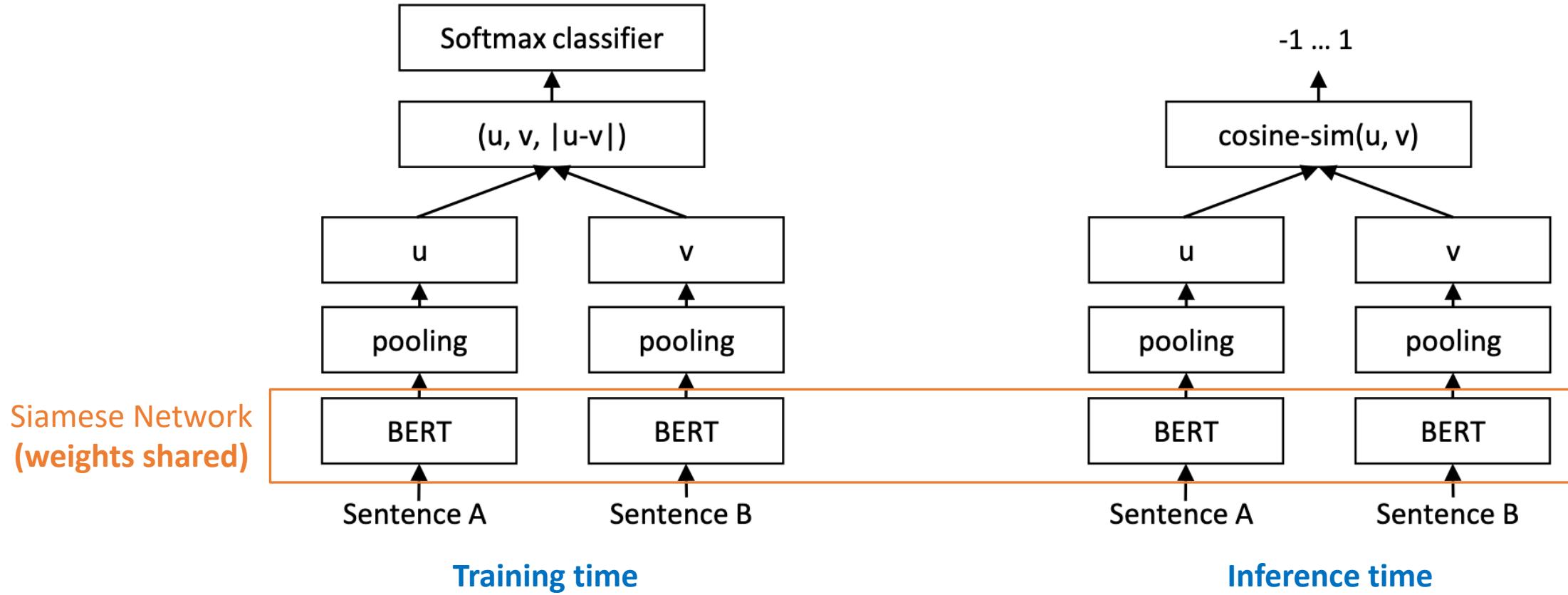
# Cross-encoder 速度問題



- For 10,000 sentence pairs:
  - Cross encoders:  $n \cdot (n-1)/2 = 49,995,000$  inference times

# Sentence-BERT

```
# Pseudo code for Bi-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)
```

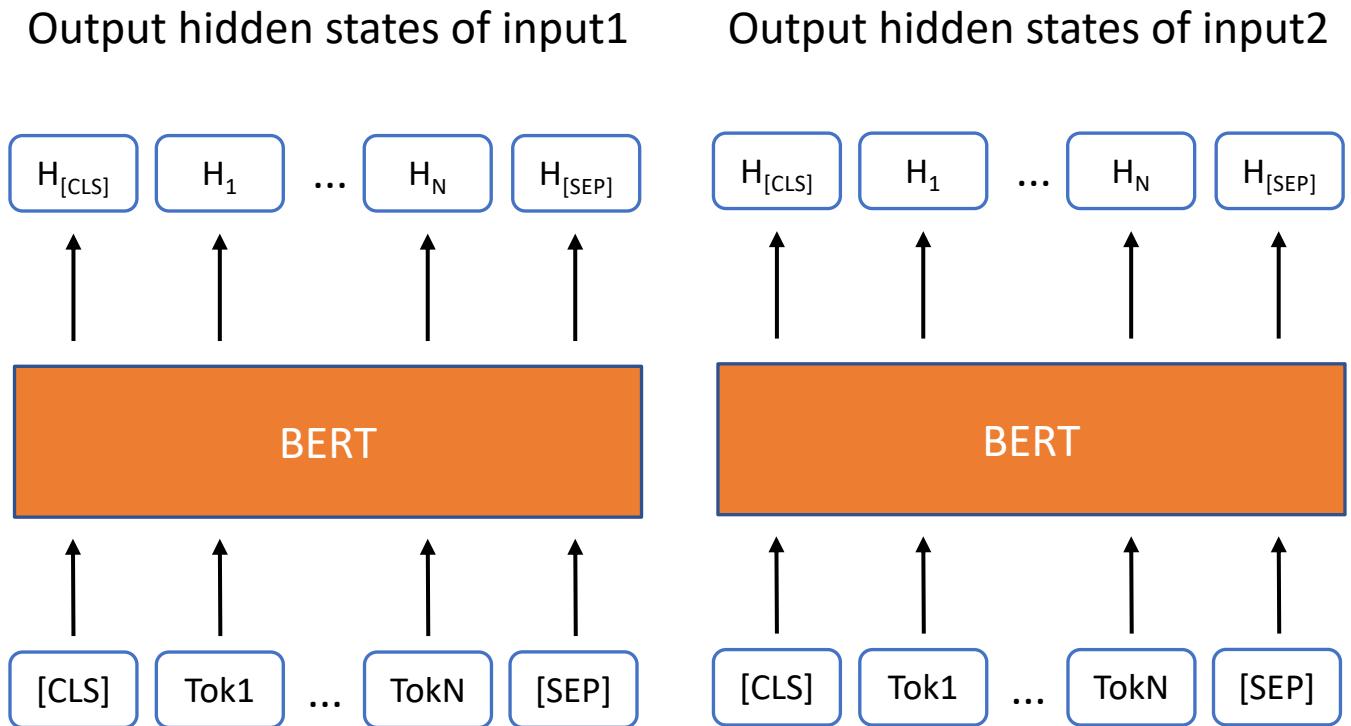


Reimers, N., & Gurevych, I. (2019). Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks. (*EMNLP-IJCNLP 2019*)

# Why does Sentence-BERT need pooling?

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- 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

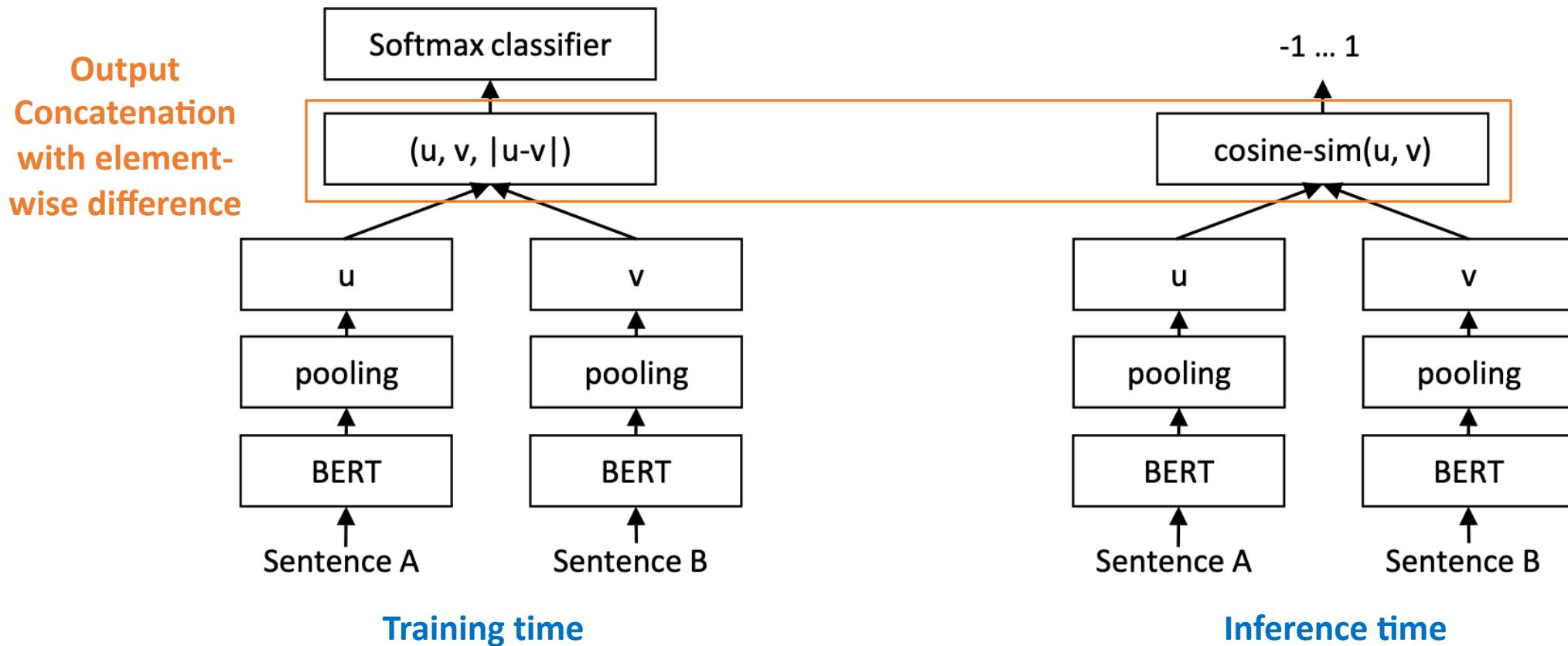
---

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.

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

# Sentence-BERT (Bi-encoder)



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

# Performance comparison of Pooling and Concatenation

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- 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.

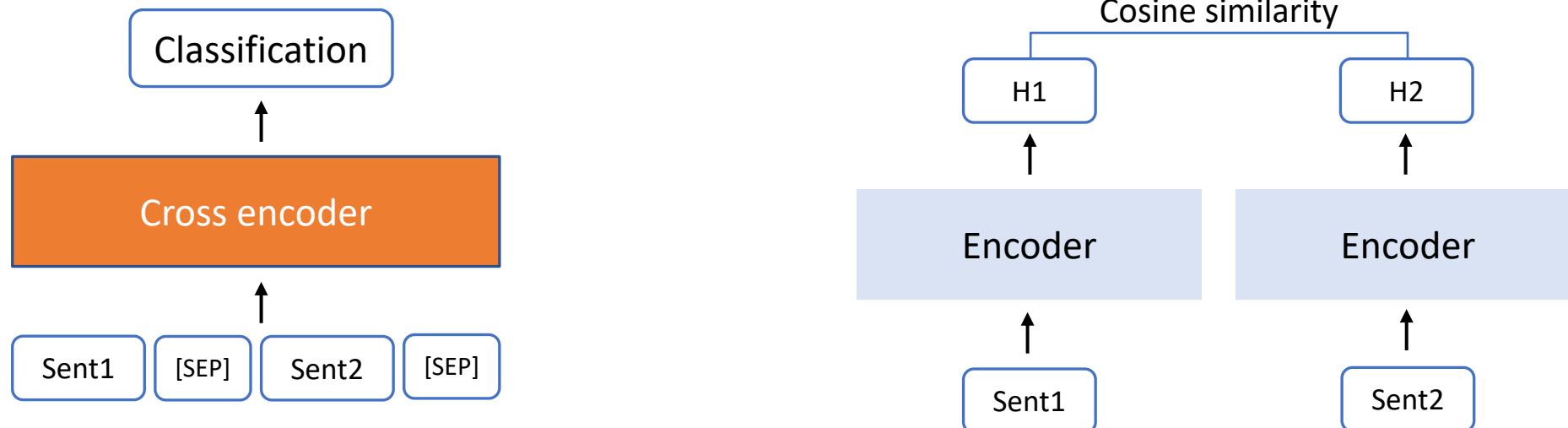
	<b>NLI</b>	<b>STSb</b>
<i>Pooling Strategy</i>		
MEAN	<b>80.78</b>	<b>87.44</b>
MAX	79.07	69.92
CLS	79.80	86.62
<i>Concatenation</i>		
$(u, v)$	66.04	-
$( u - v )$	69.78	-
$(u * v)$	70.54	-
$( u - v , u * v)$	78.37	-
$(u, v, u * v)$	77.44	-
$(u, v,  u - v )$	<b>80.78</b>	-
$(u, v,  u - v , u * v)$	80.44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

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

# Computation time for Bi-encoders and Cross encoders

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- 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



# SimCSE (Bi-encoder)

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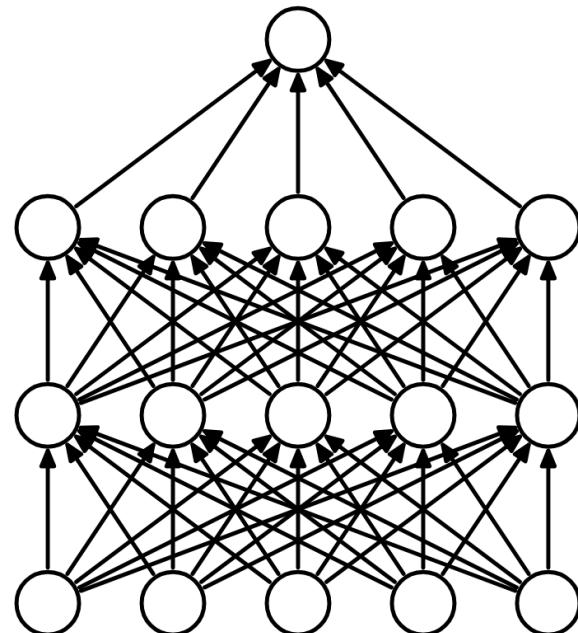
- SimCSE: a simple contrastive sentence embedding framework
- Both unsupervised and supervised training approaches were proposed in SimCSE:
  - **Unsupervised** training of SimCSE
    - Relying on **Dropout**
  - **Supervised** training of SimCSE
    - Relying on **labels in a dataset**

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

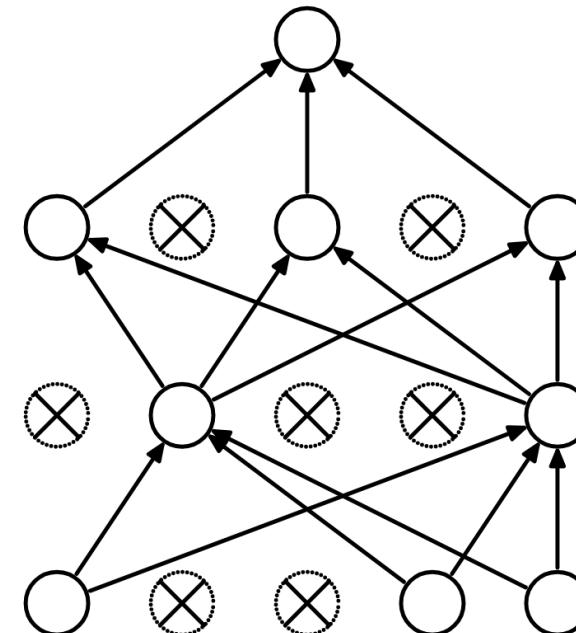
# Dropout

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



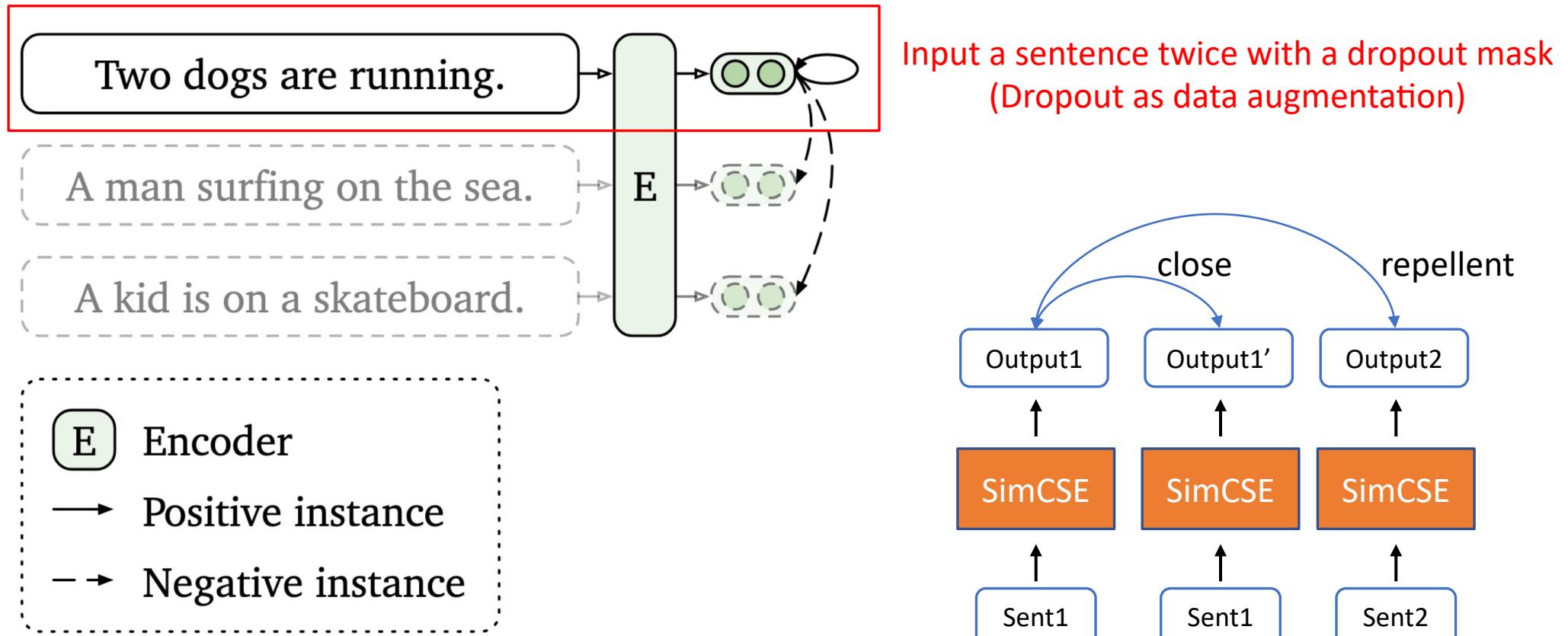
(a) Standard Neural Net



(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.

# Unsupervised training of SimCSE

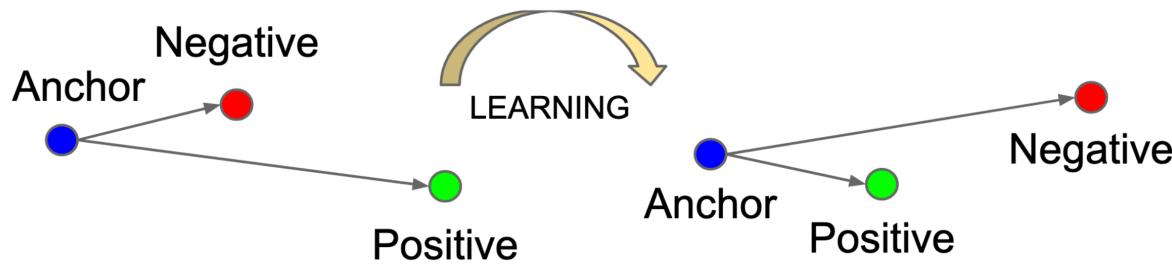


Gao, Tianyu, Xingcheng Yao, and Danqi Chen. "SimCSE: Simple Contrastive Learning of Sentence Embeddings." EMNLP 2021.

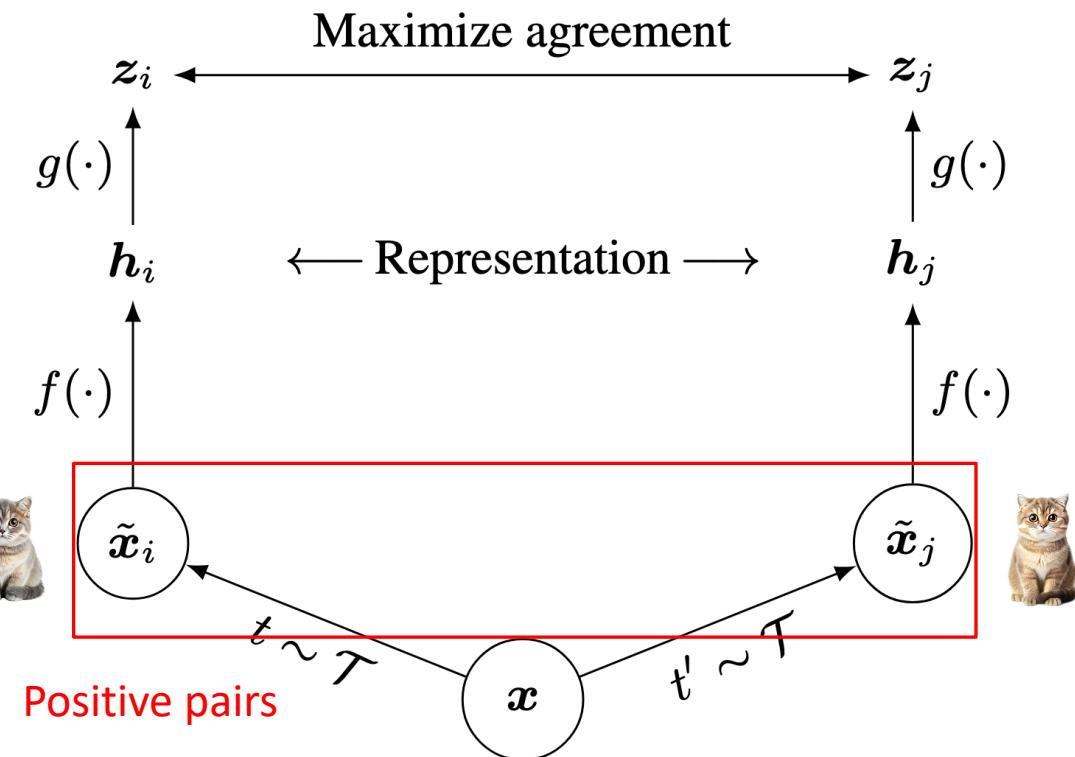
# Contrastive Learning in Images

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

- The concept of contrastive learning is to maximize the agreement of positive pairs [1][2].
- A model will be able to learn the connections among similar data and dissimilar data.



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

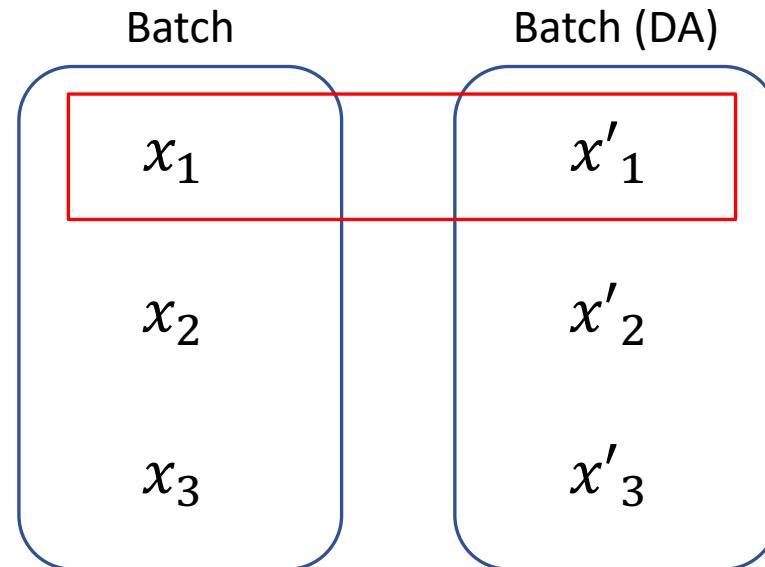
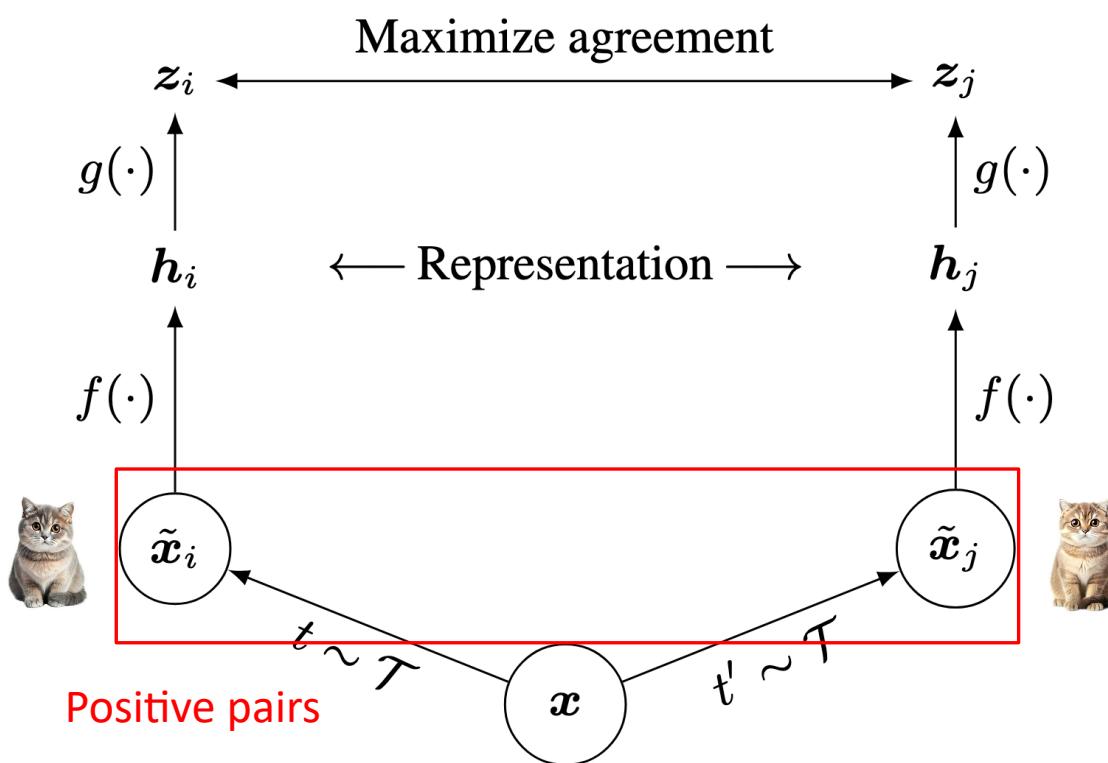


[2] Right Figure source: Chen, Ting, et al. "A simple framework for contrastive learning of visual representations." ICLR 2020.

# Contrastive Learning Loss (1)

DA: data augmentation

假設 Batch\_size 為  $N$



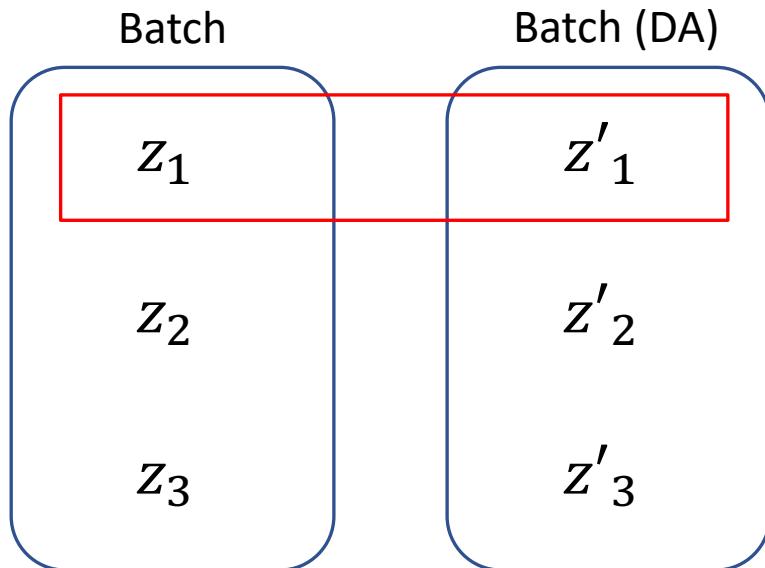
以  $x_1$  為例：  
正樣本對 ->  $(x_1, x'_1)$   
負樣本對 ->  $(x_1, x'_2) \backslash (x_1, x'_3) \backslash (x_1, x_2) \backslash (x_1, x_3)$

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

# Contrastive Learning Loss (2)

$z$  為模型輸出的 representation

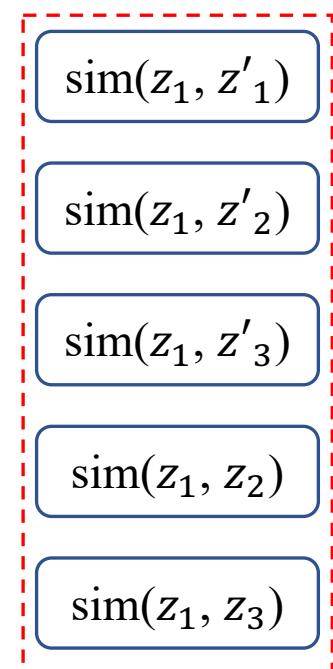
假設 Batch\_size 為  $N$



以  $x_1$  為例：

正樣本對 ->  $(z_1, z'_1)$

負樣本對 ->  $(z_1, z'_2)$ 、 $(z_1, z'_3)$ 、 $(z_1, z_2)$ 、 $(z_1, z_3)$



取 Softmax  
後之機率

0.3

0.2

0.1

0.1

0.3

正確答案

1

0

0

0

0



Cross-entropy

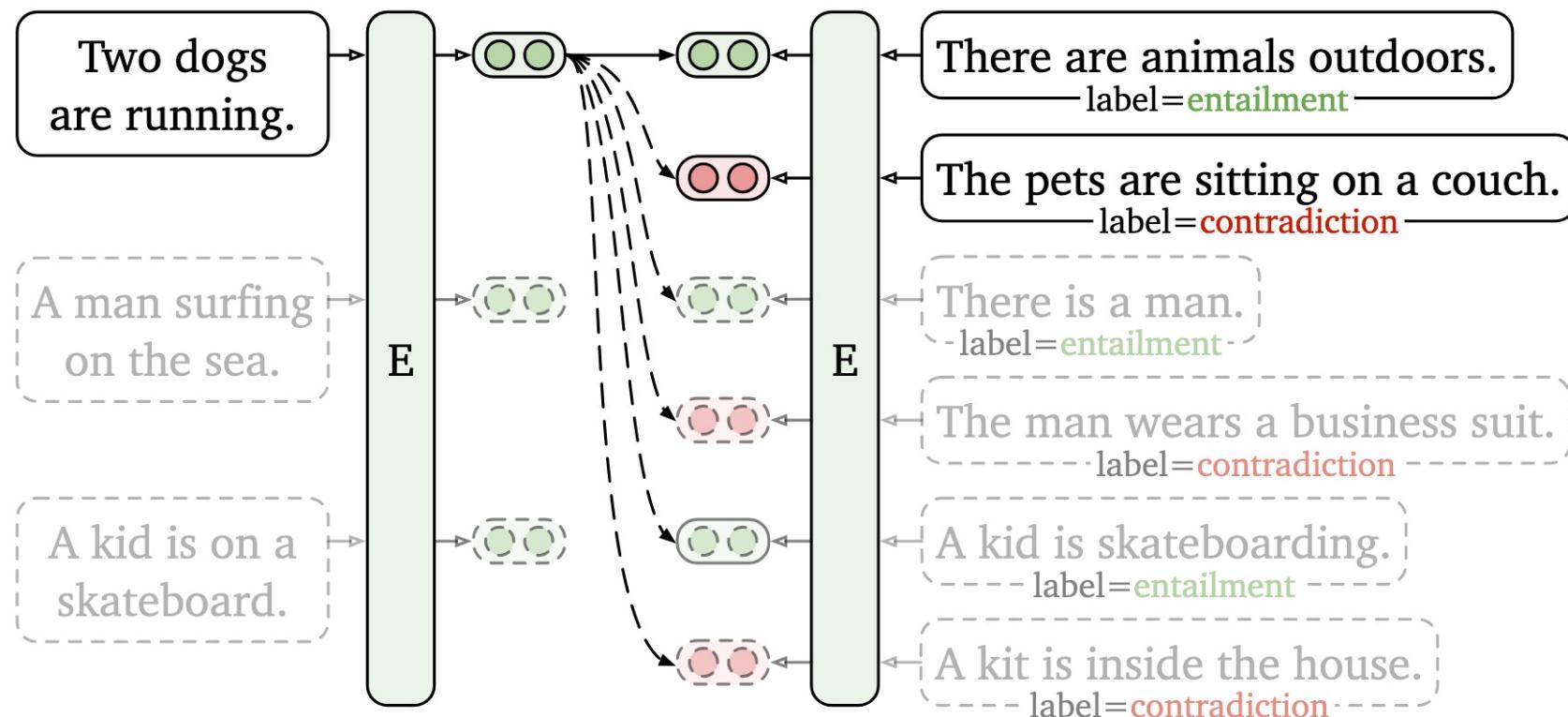
相當於在做  $2N-1$  個類別之分類任務

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

Cross-entropy:  $\mathcal{L}_i = -\log P(Y = y_i | X = x_i)$

# 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.

# Retrieval for open-domain question answering (ODQA)

# Dense Passage Retrieval (DPR)

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- 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 ... <b>England</b> 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 <b>England</b> team. Cycling is represented on the Isle of Man by the Isle of Man Cycling Association. Cycling in Northern <b>Ireland</b> is organised under Cycling Ulster, part of the all-Ireland governing <b>body</b> Cycling <b>Ireland</b> . Until 2006, a rival governing <b>body</b> existed, ...	Title: Irish Sea ... Annual traffic between Great Britain and <b>Ireland</b> amounts to over 12 million passengers and of traded goods. <b>The Irish Sea</b> 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 <b>Ireland</b> 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)

- 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

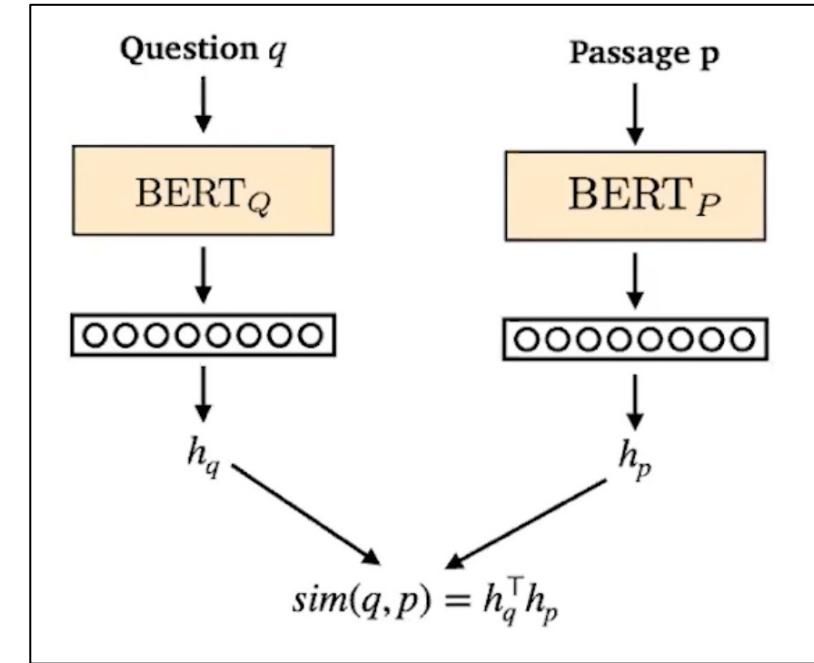


Image source: [Stanford CS224N Lecture 12 - Question Answering](#)

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

# Dense Passage Retrieval (DPR)

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## 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. EMNLP 2020.

# 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. EMNLP 2020.

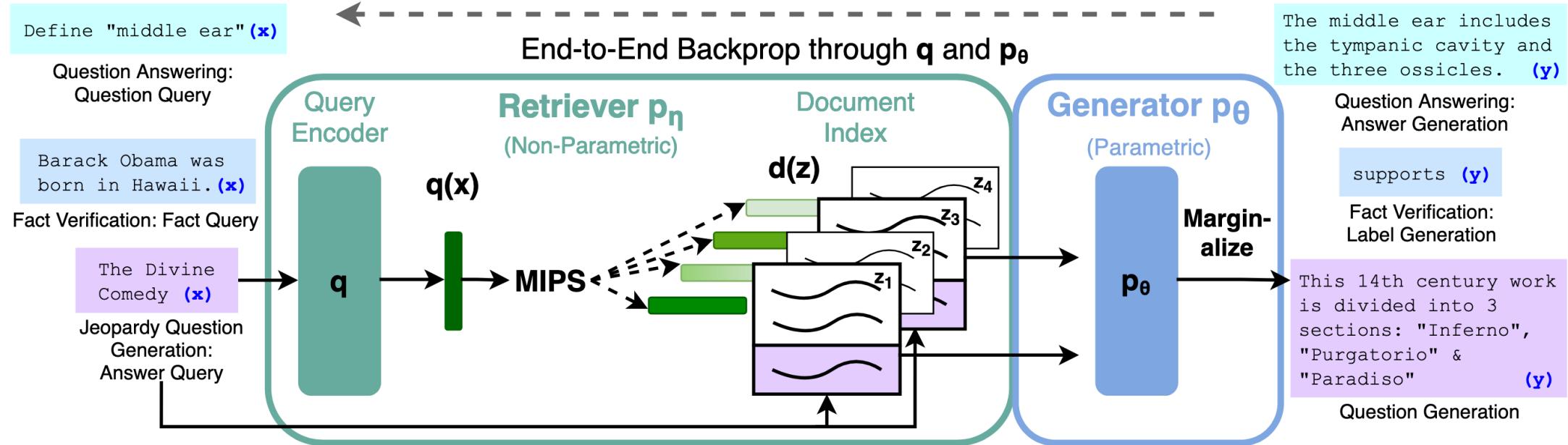
# Summary Parameter Sharing

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	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)
Encoder Type	Cross-encoder	Bi-encoder	Bi-encoder	Dual encoder
Weight Sharing	Nan	Yes	Yes	No (Separate Query Encoder and Passage Encoder)

# Complete RAG

# 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.)

# Challenges in Modern RAG

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- 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

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

# Capabilities that LLMs Should Have in RAG

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## 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

---

## Noise 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

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## 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,...**

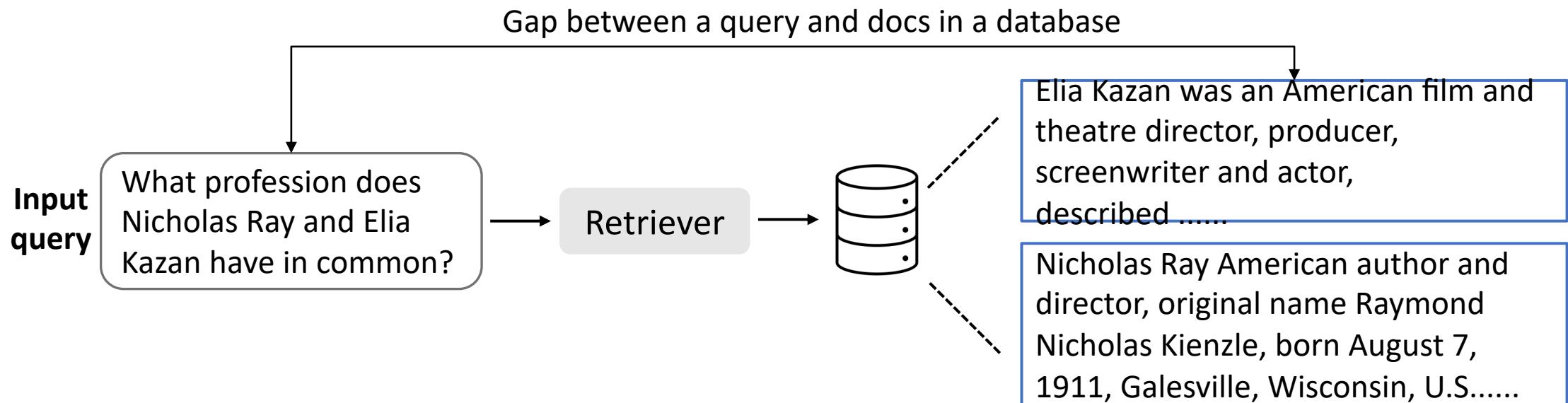
Retrieval Augmented Generation



**May 18 and March 1.**

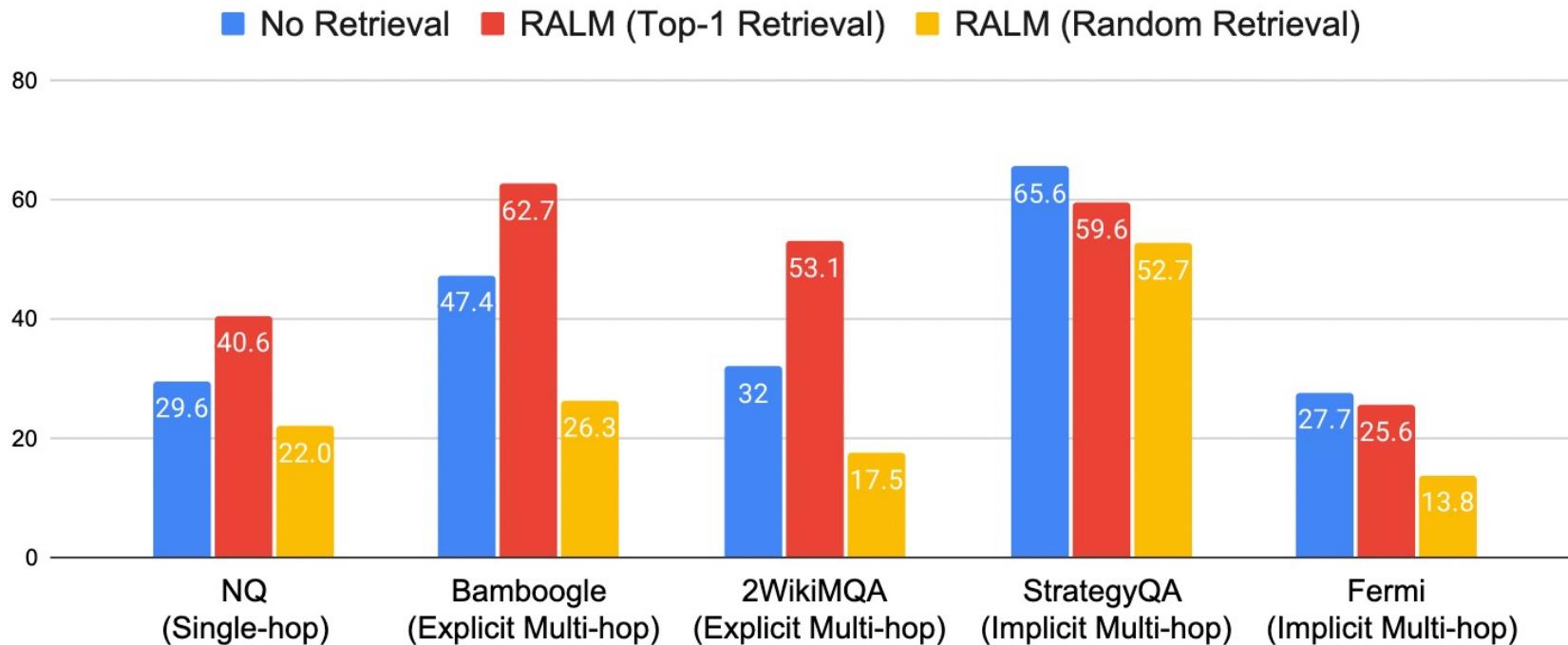
# Query Rewriting

- 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.

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

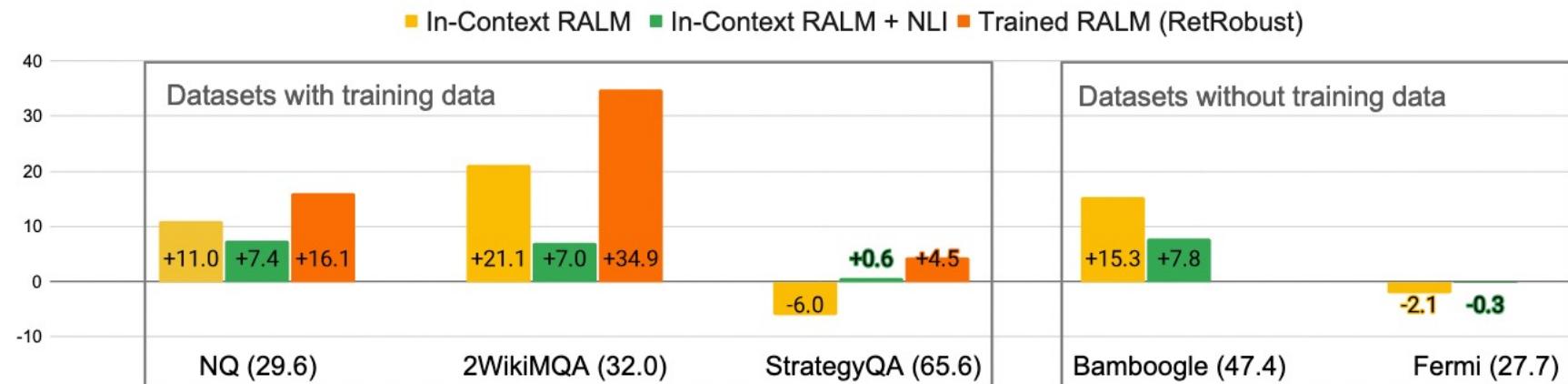
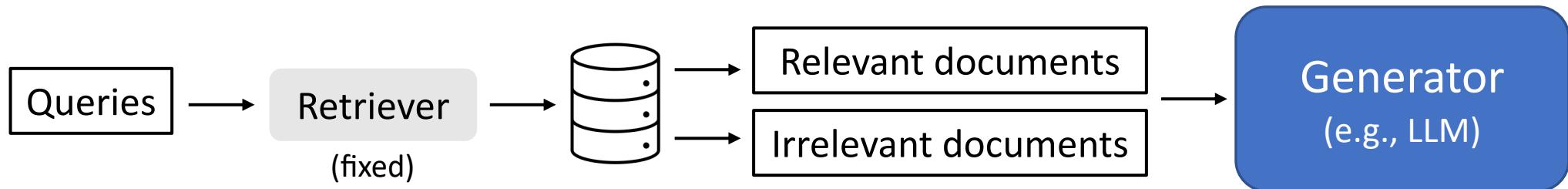


Retrieval augmentation can boost performance, but it also hurts performance on StrategyQA and Fermi, and random contexts reduce performance dramatically.

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

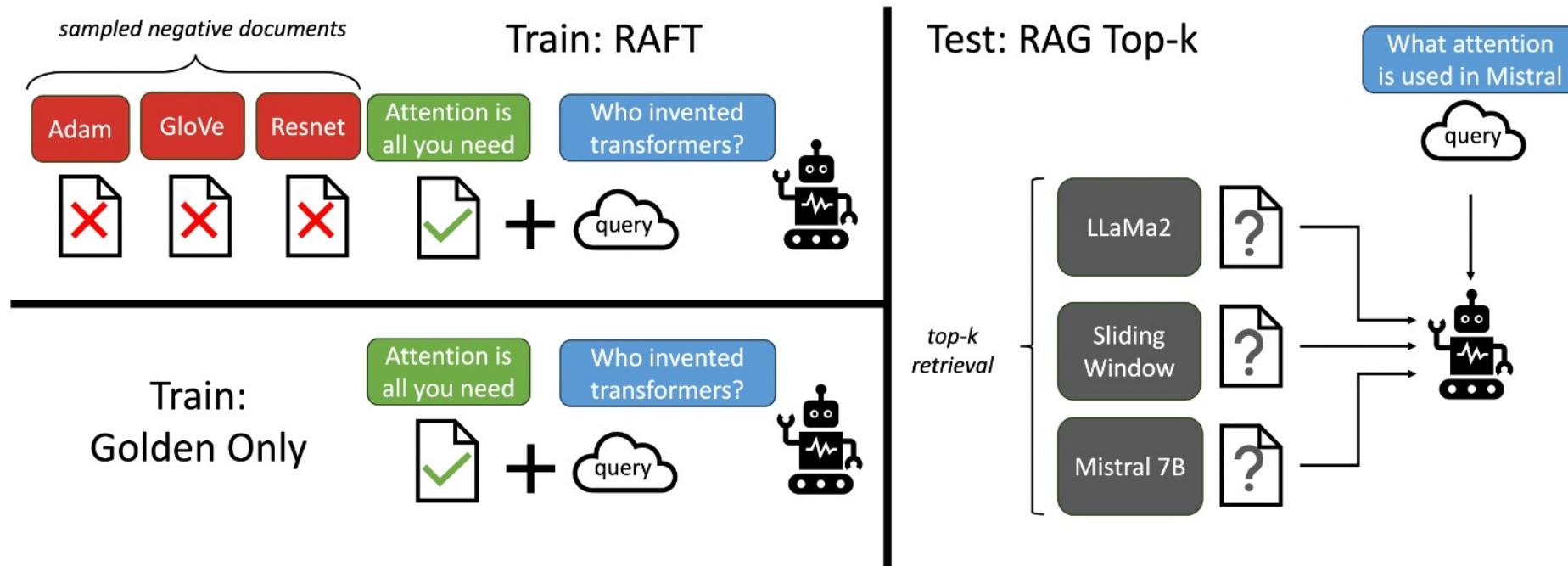
Train the generator on QA tasks with both relevant and irrelevant retrieved documents.



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

# RAFT: Adapting LLM to RAG

- 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

Context 包含錯誤資訊

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}.

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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

# Capabilities that LLMs Should Have in RAG

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## 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



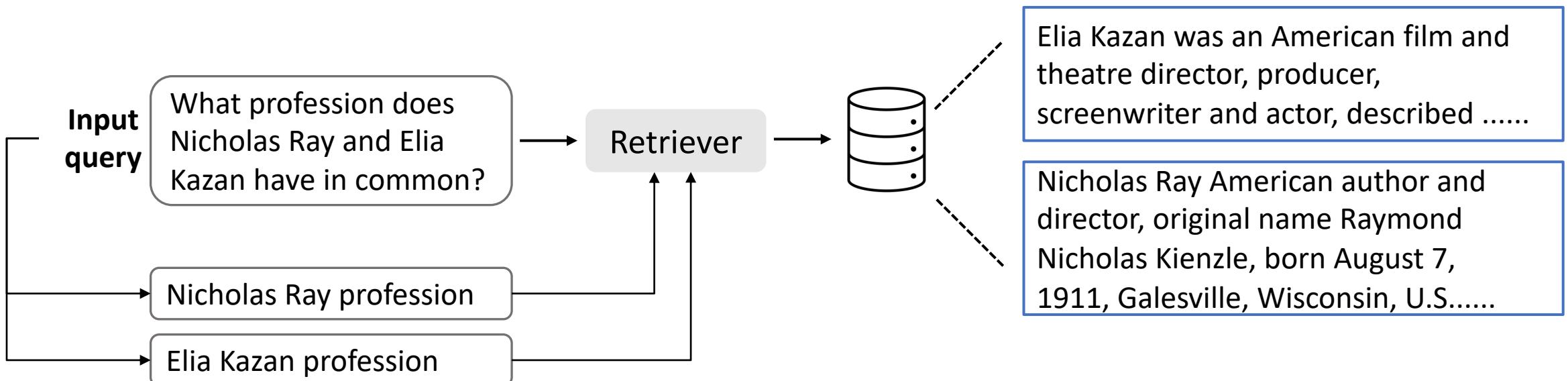
There are factual errors in the provided documents. **The answer should be Athens.**

# Other Techniques for Boosting RAG Performance

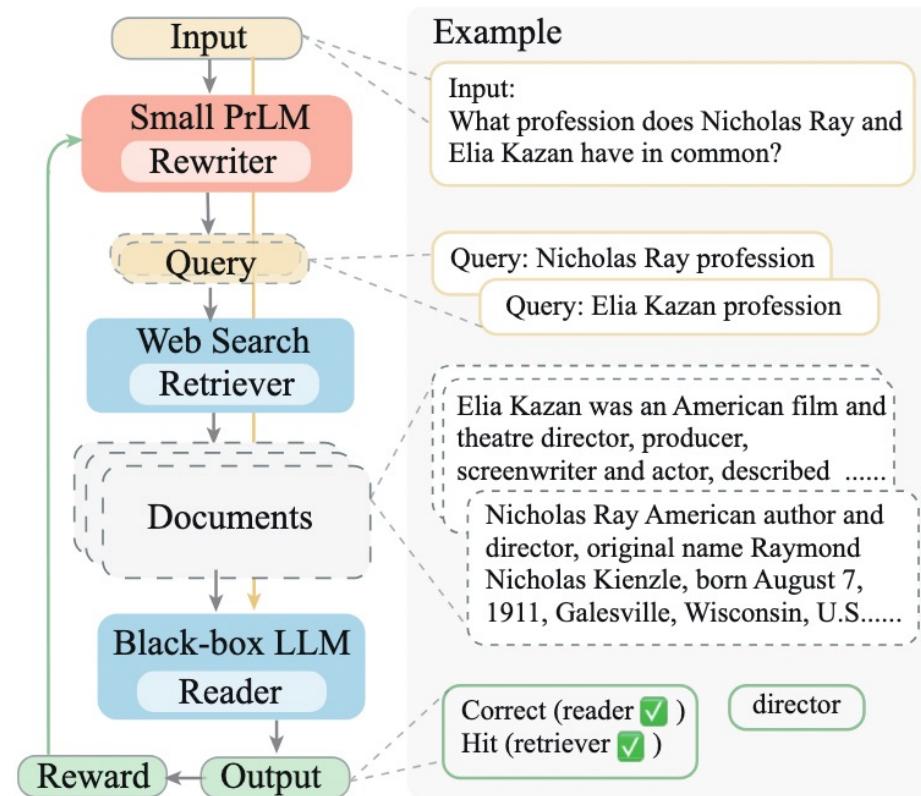
# Query Rewriting

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



# Query Rewriting – Prompt for the LLMs

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## Direct prompt

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

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## Reader prompt in retrieval-augment pipelines

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

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## Prompts for LLM as a frozen rewriter

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*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:

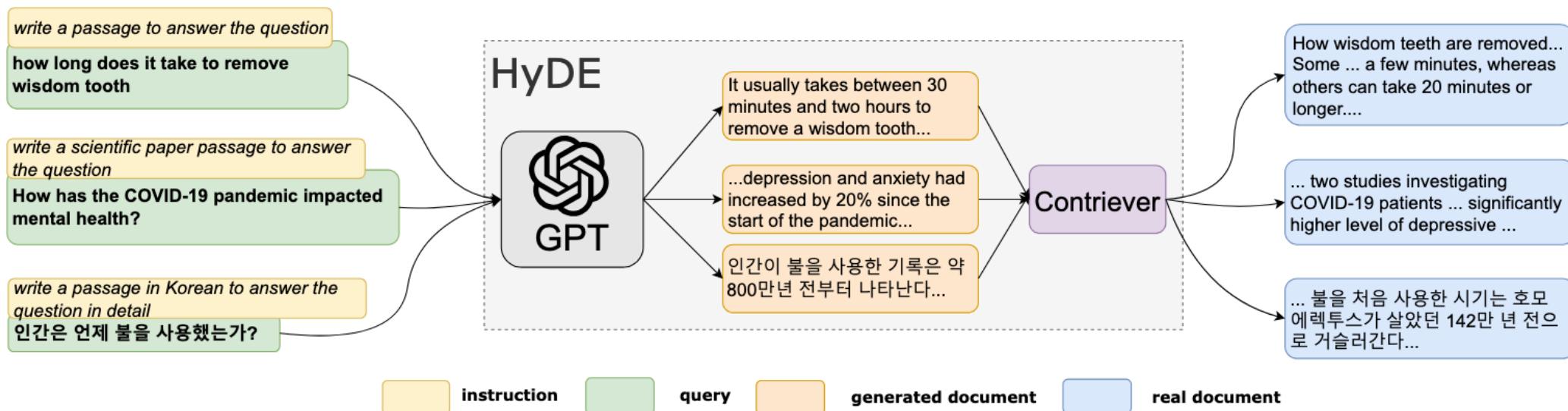
*Multiple choice QA*: Provide a better search query for web search engine to answer the given question, end the queries with '\*\*\*'. {demonstration} Question: {*x*} Answer:

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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**).



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

# HyDE can be better than Query Rewriting for retrieval tasks

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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	<b>0.07</b>	28.56	47.96	46.18	78.63	<b>0.29</b>
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	<b>75.44</b>	54.93	88.76	7.21	50.94	<b>73.94</b>	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	<b>52.13</b>	<u>73.34</u>	<b>55.38</b>	<b>90.42</b>	11.16	<b>53.13</b>	<u>72.72</u>	<b>66.14</b>	<b>90.67</b>	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.

# Recent RAG Developments

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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

Thank you!

Instructor: 林英嘉

 yjlin@cgu.edu.tw

TA: 吳宣毅

 m1161007@cgu.edu.tw