### Information Retrieval

Sept 30, 2025 @ Introduction to Human Language Technology

Eugene Yang <a href="mailto:eugene.yang@jhu.edu">eugene.yang@jhu.edu</a>

Slides borrowed from SIGIR24 Tutorial "Neural Methods for Cross-Language Information Retrieval"

# What is Information Retrieval? (relevant)

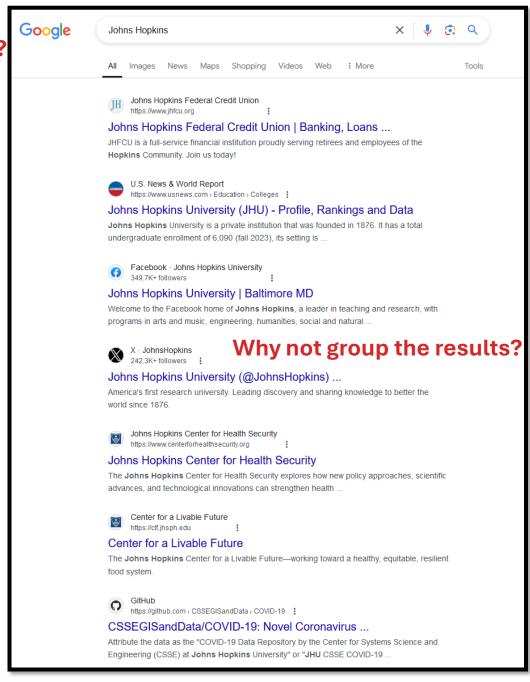
Retrieve information from a storage based on user's information need

# Don't we have Google?

Yes, but Google is not all.

#### What if I'm looking for the person?

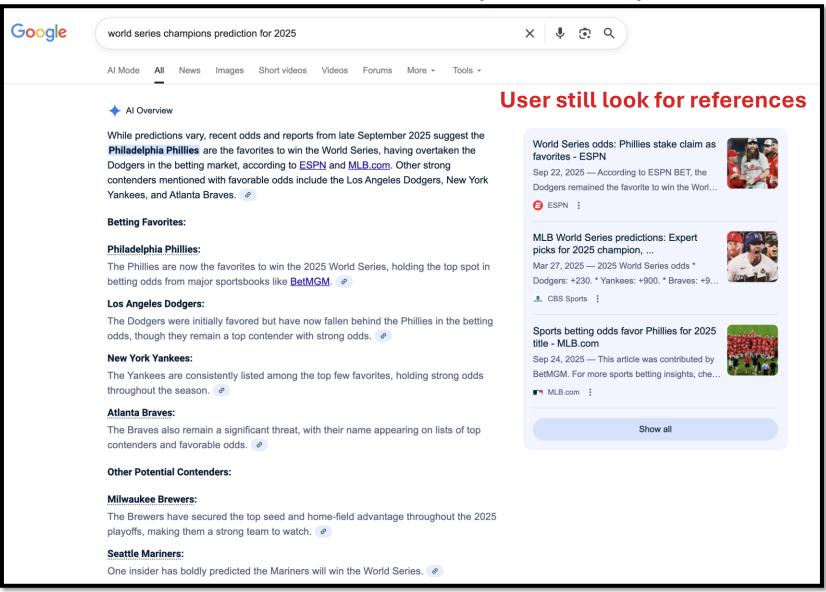




#### Why not read my mind?

Why asking me to read?

#### Still need to understand the intent (it's about MLB)



Still need retrieval for source information

### Google Search is just one implementation

Google trained us well!

- Even faster?
- Smarter?
- Cross language?

### Hard Matching Problem

- Text to text
  - Search in notes
  - Cross language search
  - Cross domain search
- Text to other modalities
  - Image search
  - Video search

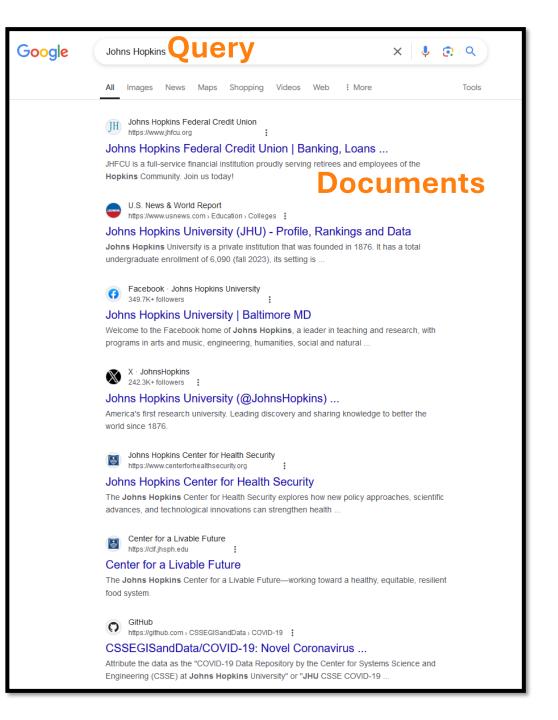
### Different Search Process

- Iterative search
  - e.g., electronic discovery and systematic review
- Conversational search
  - Alexa search
- Recommendation systems
  - Implicit queries

### Core Problem

- Rank relevant document at top
- Do it fast

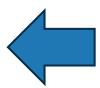
**Ranked List** 



### Design Space

#### **Effectiveness**

- Definition of relevancy
- How to model relevancy



#### **Downstream Customer**

- Human or LLM?
- What kind of presentation?

### **Efficiency**

- How fast
- Fast at what stage

### Agenda

- What is information retrieval?
- Retrieval modeling and pipeline
  - statistical and neural
- Evaluation
- Retrieval-Augmented Generation
- Research problems

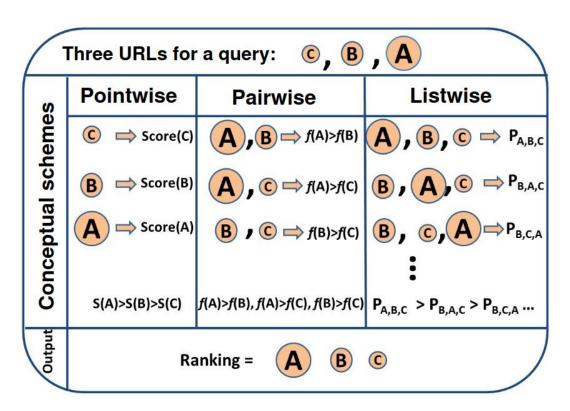
# Retrieval Modeling and Pipeline

Modeling relevancy and do it fast

### Three main modeling strategies

- Pointwise
- Pairwise
- Listwise

And combinations of them



https://medium.com/vptech/learning-to-rank-at-veepee-ed420fd828e5

### Statistical Models

$$score(D, Q) = \sum$$
 How important the term is x How often the term appear in the D For each query term

$$score(D, Q) = \sum$$
 Inverted document frequency x Term frequency

For each query term

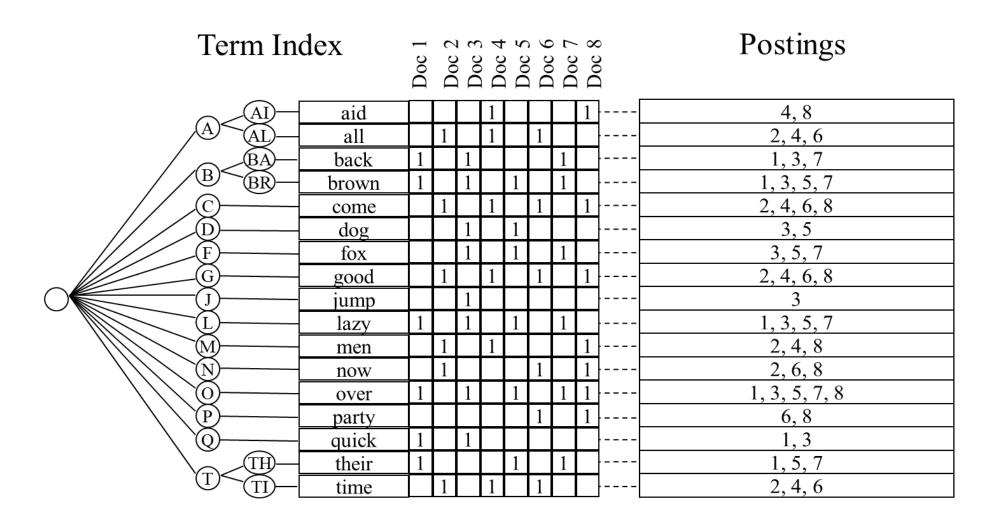
TF-IDF
$$score(D, Q) = \sum_{i=1}^{n} log \frac{N}{n_t} \times log(f(q_i, D) + 1)$$

$$extstyleset{ extstyleset} extstyleset{ extst$$

### How to make it fast?

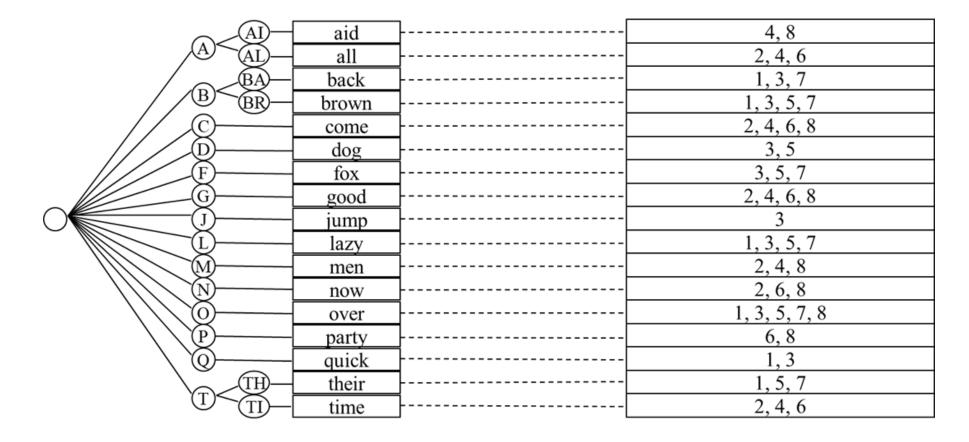
- "Fast" in responding to queries
- Better data structure
- Preprocess the data

### Inverted Index



### Inverted Index

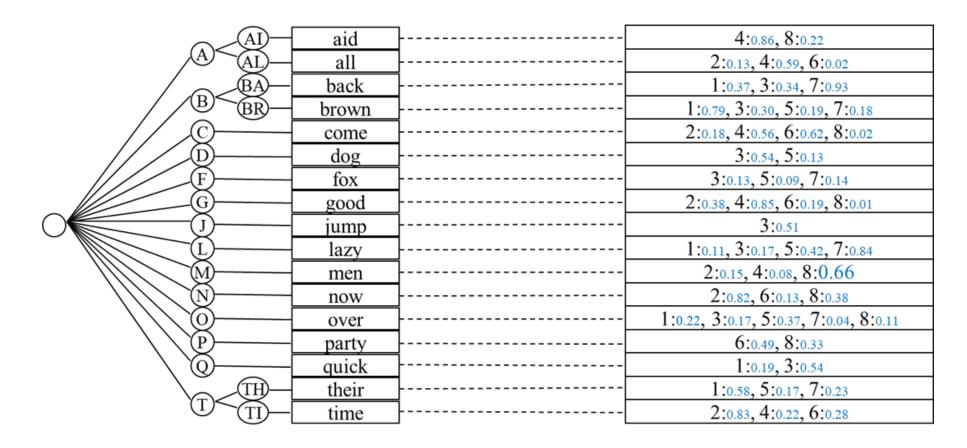
Term Index Postings



### Inverted Index

Term Index

### **Postings**



### Two-Stage System

- Offline preprocessing and indexing
  - Define retrieval unit
  - Tokenization
  - Build the inverted index
- Online query serving
  - Traverse the inverted index and score it



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Apache Lucene is distributed under a commercially friendly Apache Software license

#### Elasticsearch

### The heart of the free and open Elastic Stack

 ${\it Elastic search is a distributed, RESTful search and analytics engine, scalable data}$ 

store, and vector database capable of addressin the heart of the Elastic Stack, it centrally store fine-tuned relevancy, and powerful an



Download Elastic

#### Welcome to Apache Lucene

The Apache Lucene™ project develops open-source search software. The project releases a core search library, named Lucene™ core, as well as PyLucene, a python binding for Lucene.

Lucene Core is a Java library providing powerful indexing and search features, as well as spellchecking, hit highlighting and advanced analysis/tokenization capabilities. The PyLucene sub project provides Python bindings for Lucene Core.

#### Latest Lucene Core News

Apache Lucene™ 8.11.4 available (24.Sep)

Apache Lucene™ 9.11.1 available (27.Jun)

Apache Lucene™ 9.11.0 available (06.Jun)

#### Projects

Lucene Core (Java)
PyLucene
Open Relevance
(Discontinued)

#### About

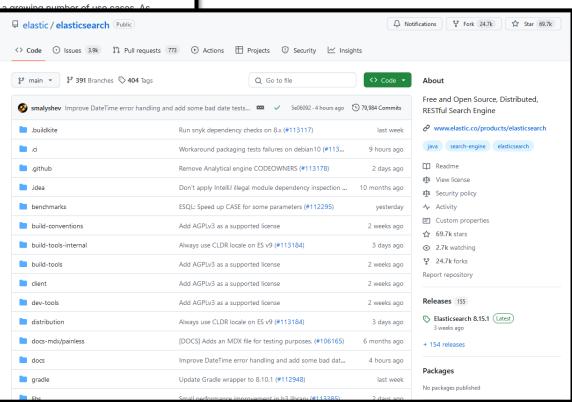
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TLP News

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Code of Conduct



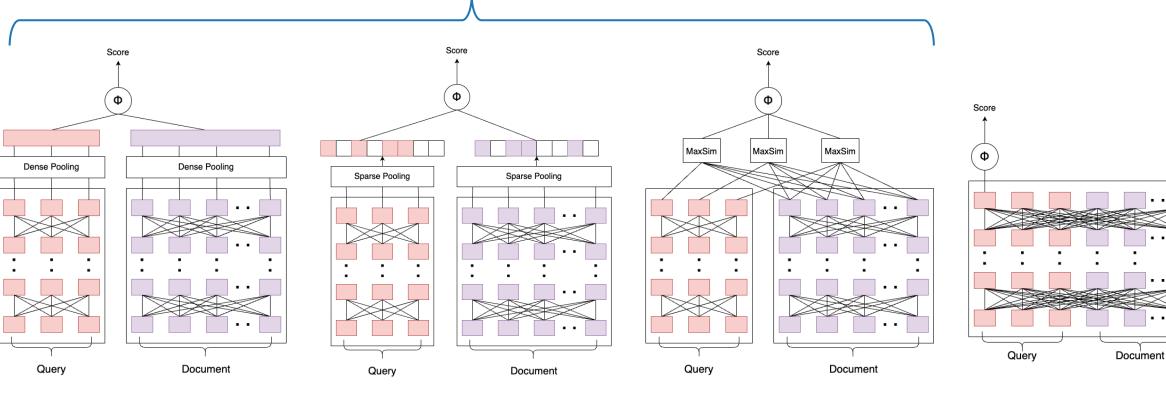
ANNOUNCEMENT: The Solr™ sub project has moved to a separate Top Level Project (TLP). All things Solr can now be found at https://solr.apache.org/. Mailing lists and git repositories have changed, please see details on the Solr website.



## Can we go beyond surface forms?

neural language models





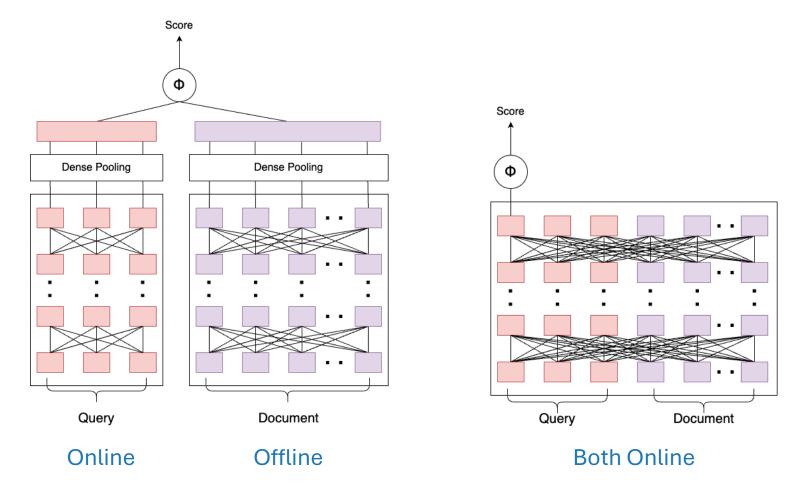
One Dense Vector Per Sequence e.g., DPR

One <u>Sparse</u> Vector Per Sequence e.g., SPLADE

Bi-Encoder

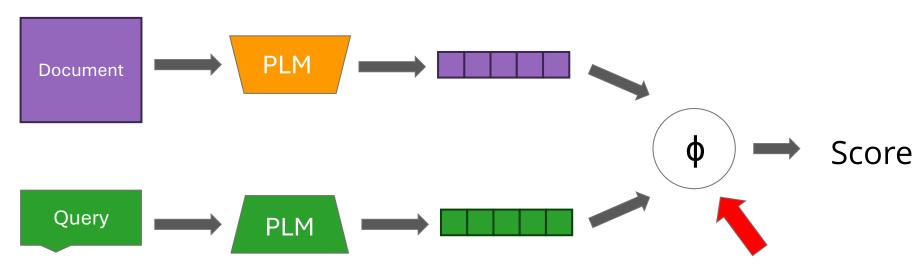
Multiple Dense Vectors Per Sequence e.g., ColBERT

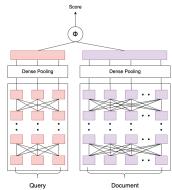
Joint Encoder e.g., monoBERT



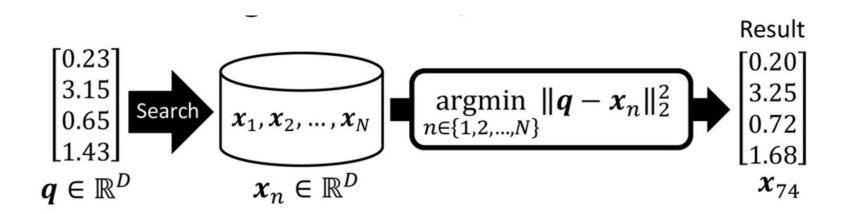
Separate query and document processing

### One Vector per Query, One Vector per Document



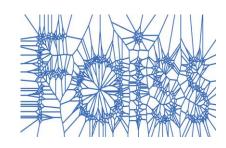


### Nearest Vectors aka Neighbors

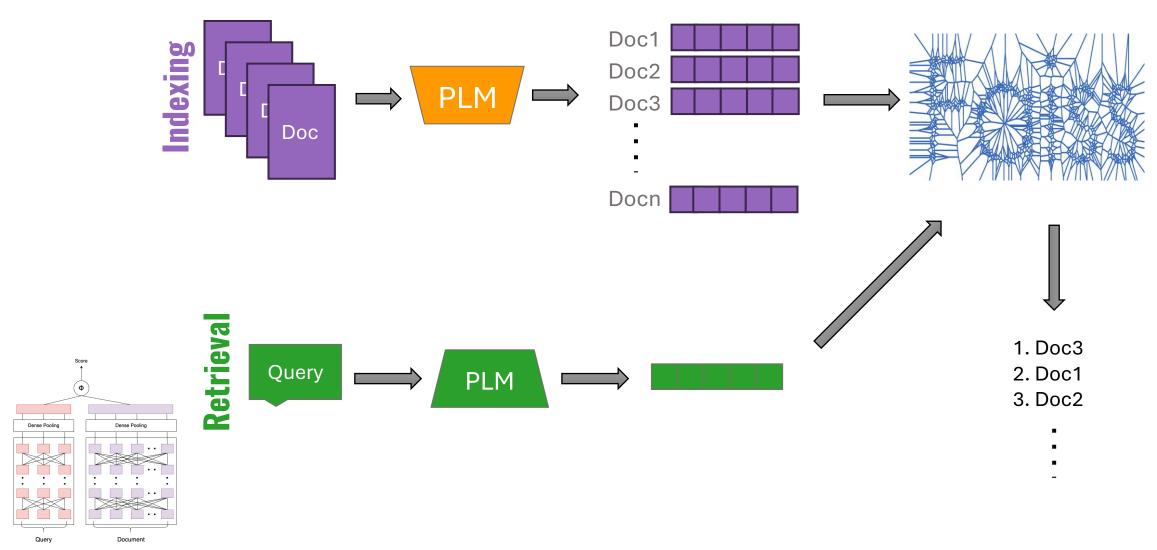


- Linear Search
  - Slow (scales linearly in size of document collection)
- Approximate Methods (e.g., Product Quantization) → ANN
  - Faster Search

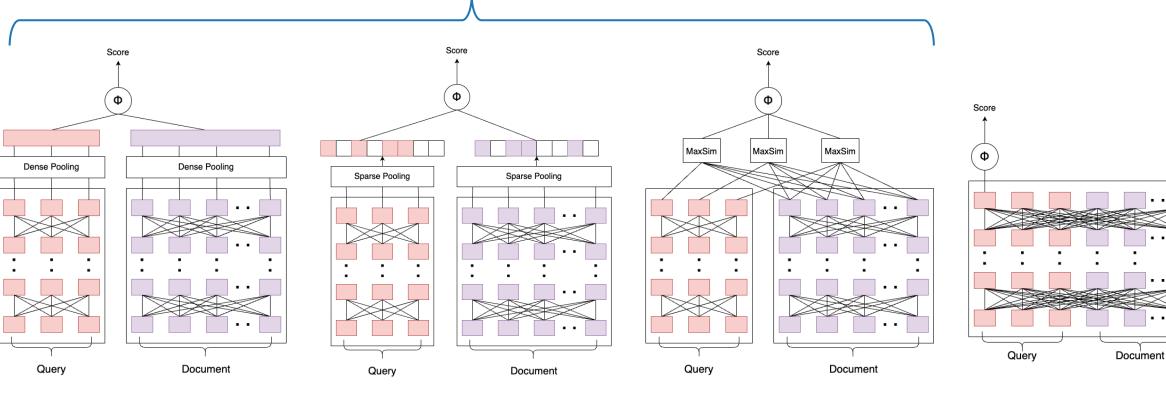




### **DPR Indexing and Retrieval**







One Dense Vector Per Sequence e.g., DPR

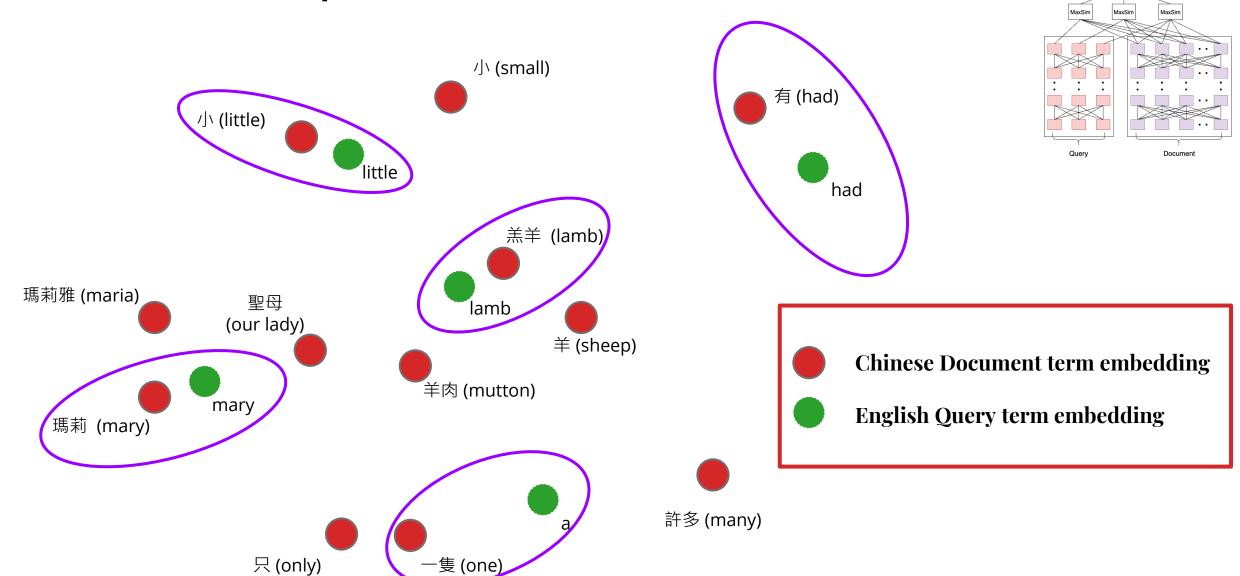
One <u>Sparse</u> Vector Per Sequence e.g., SPLADE

Bi-Encoder

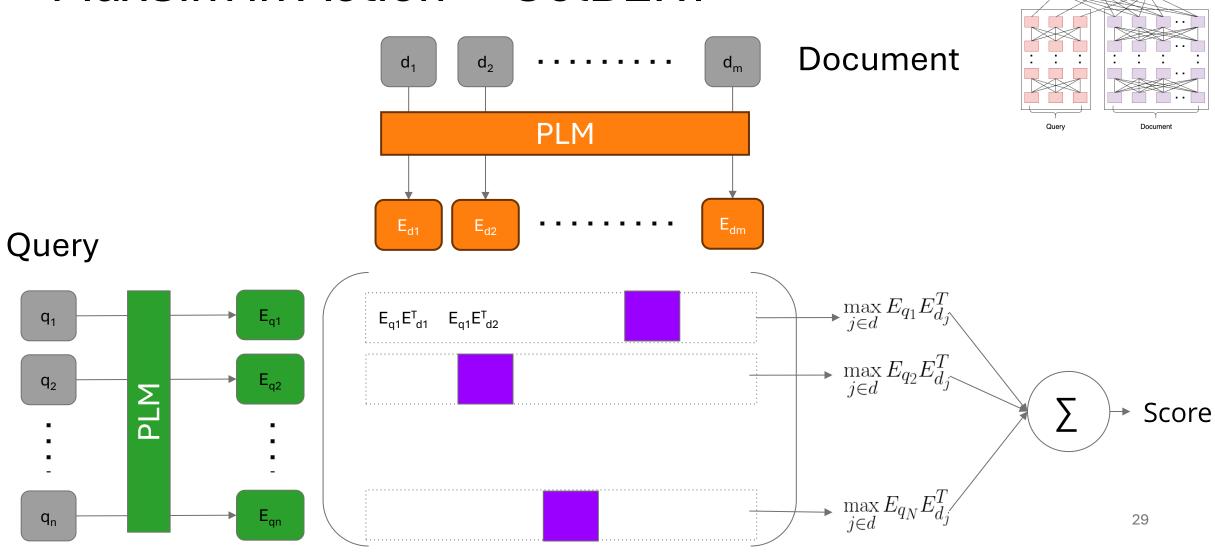
Multiple Dense Vectors Per Sequence e.g., ColBERT

Joint Encoder e.g., monoBERT

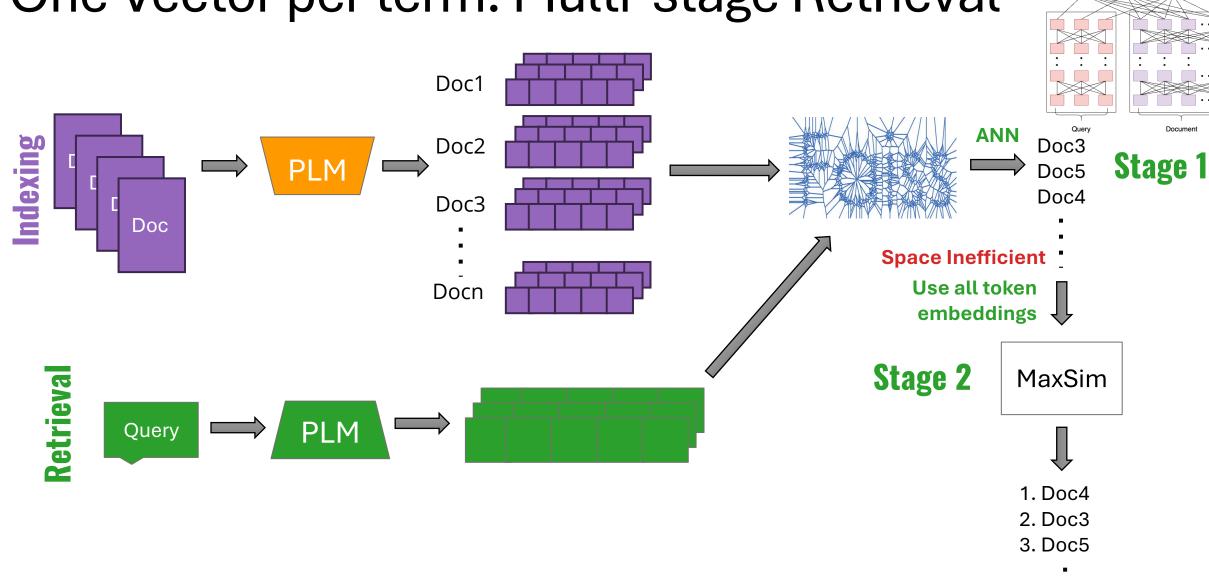
### One Vector per Term: MaxSim



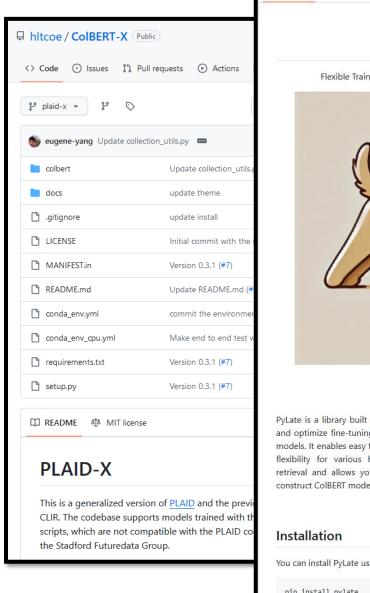
### MaxSim in Action -- ColBERT

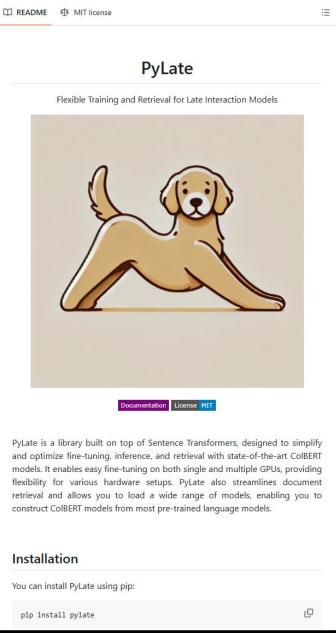


### One Vector per term: Multi-stage Retrieval



30

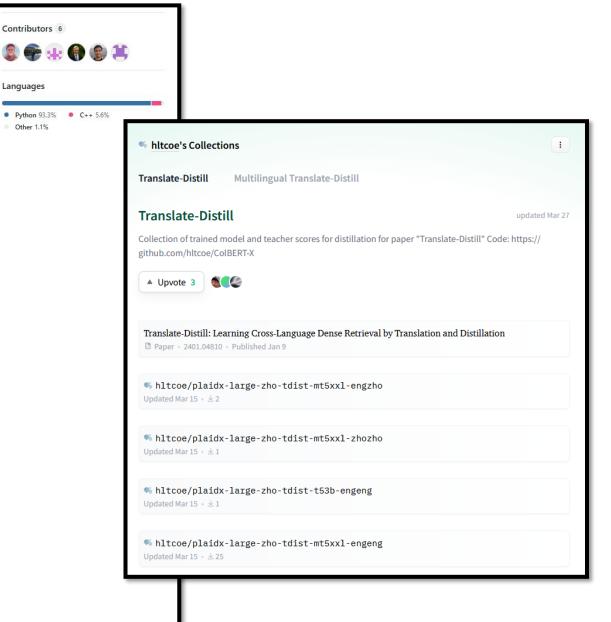




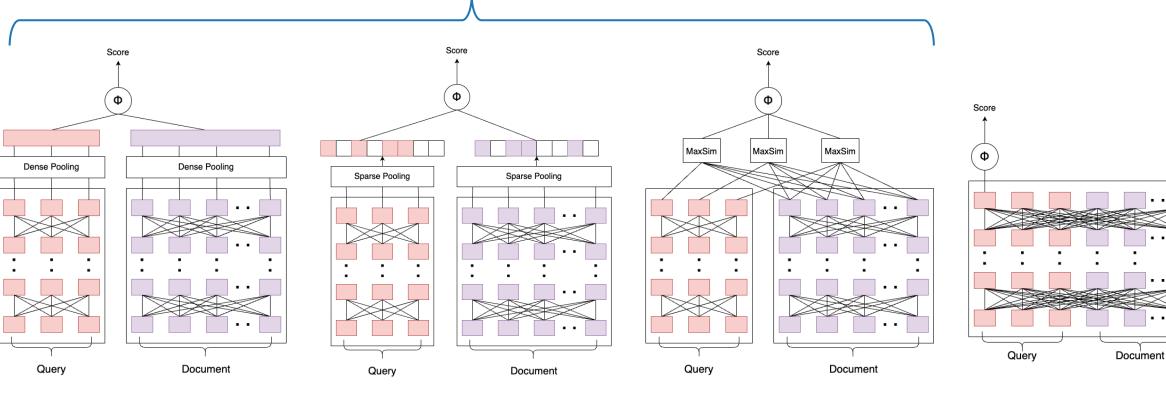
Contributors 6

Languages

Other 1.1%







One Dense Vector Per Sequence e.g., DPR

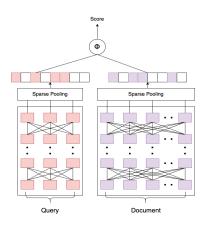
One <u>Sparse</u> Vector Per Sequence e.g., SPLADE

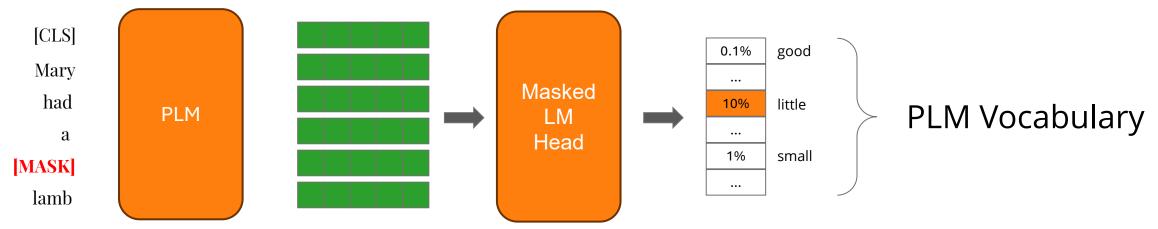
Bi-Encoder

Multiple Dense Vectors Per Sequence e.g., ColBERT

Joint Encoder e.g., monoBERT

### High-dimensional Vector: Masked LM





### Learned Sparse Retrieval

### Baltimore Orioles clinch playoff berth for 2nd straight season

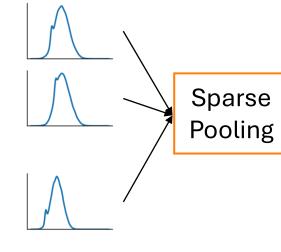
The Baltimore Orioles are headed to the playoffs in consecutive years for the first time since the 1990s, clinching no worse than a wild-card berth with a 5-3 win over the New York Yankees paired with Minnesota's loss to Miami



PLM







Predicted Vocabulary

baltimore (1.2)

orioles (2.5)

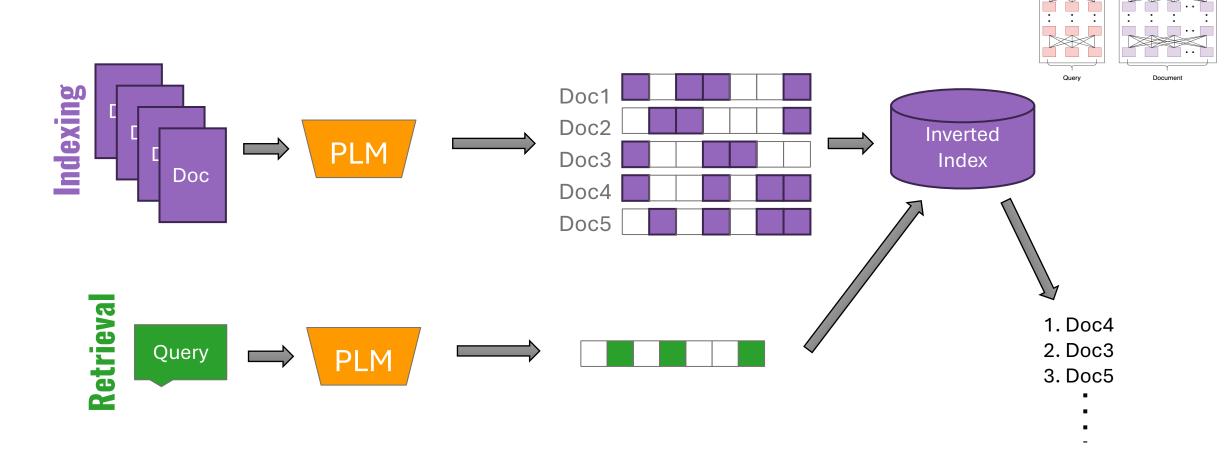
season (0.2)

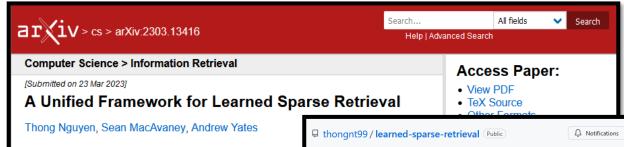
berth (0.9)

playoff (1.9)

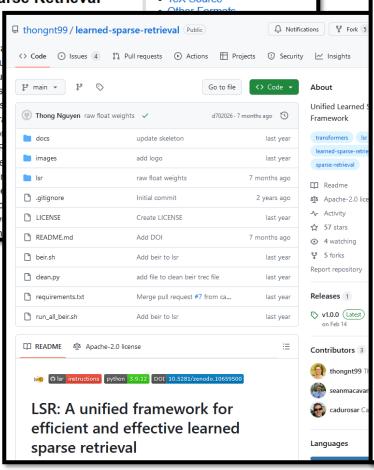
Baltimore Orioles' Anthony Santander runs the bases after hitting a home run during the sixth inning of a baseball game against the New York Yankees, Tuesday, Sept. 24, 2024, in New York. (AP Photo/Bryan Woolston)

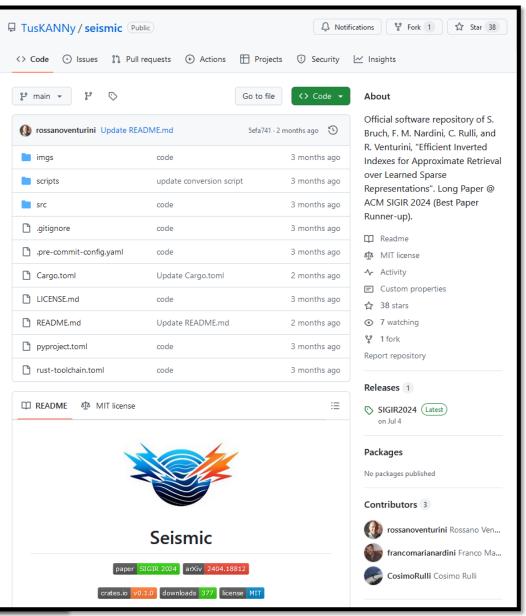
### SPLADE Search Pipeline



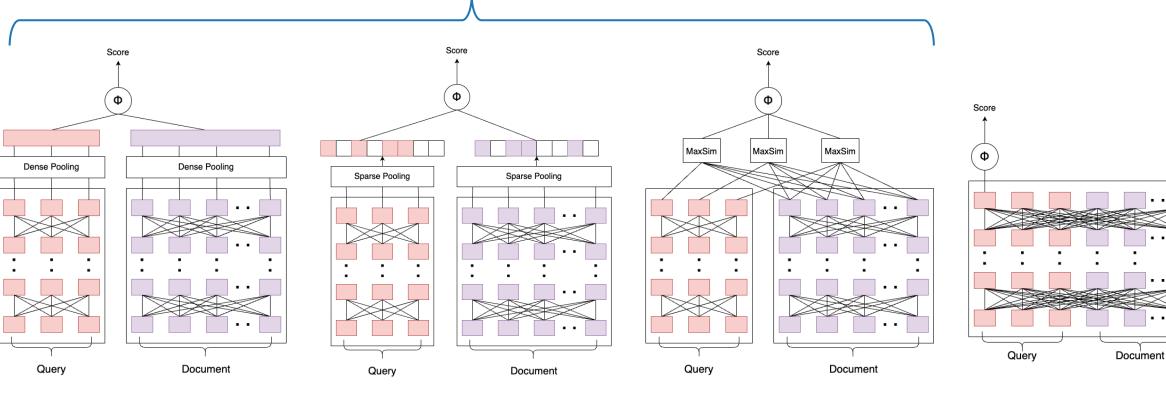


Learned sparse retrieval (LSR) is a family of first-stage retrieval to generate sparse lexical representations of queries and documented index. Many LSR methods have been recently introduce achieving state-of-the-art performance on MSMarco. Despite such architectures, many LSR methods show substantial differences efficiency. Differences in the experimental setups and configured difficult to compare the methods and derive insights. In this works methods and identify key components to establish an LSR LSR methods under the same perspective. We then reproduce using a common codebase and re-train them in the same environt to quantify how components of the framework affect effectivenes that (1) including document term weighting is most important for effectiveness, (2) including query weighting has a small positive document expansion and query expansion have a cancellation









One Dense Vector Per Sequence e.g., DPR

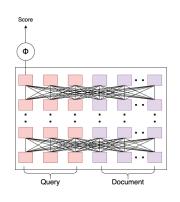
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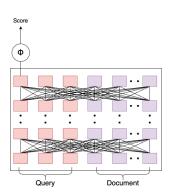
Multiple Dense Vectors Per Sequence e.g., ColBERT

Joint Encoder e.g., monoBERT

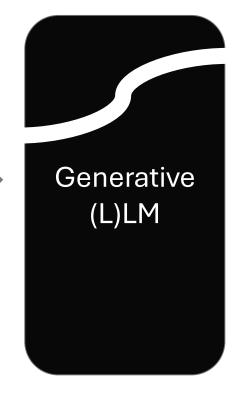
### Cross-Encoder as Reranker







Query: What does Mary have Doc: Mary had a little lamb. Relevant:

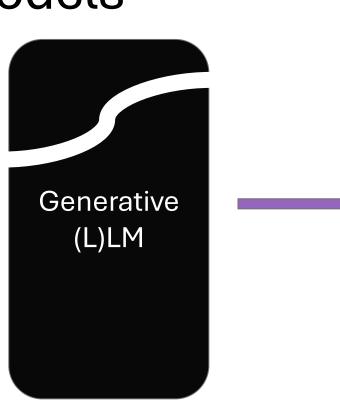


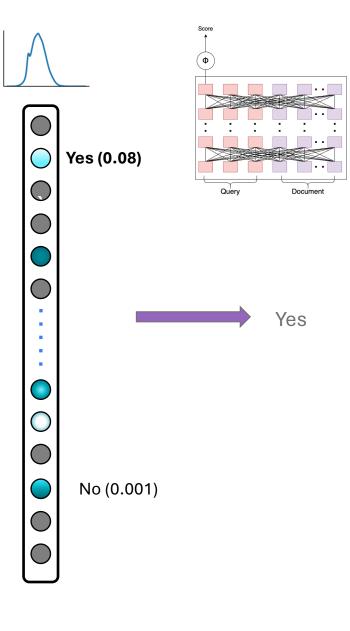
e.g, Qwen3

Not a number!

Yes

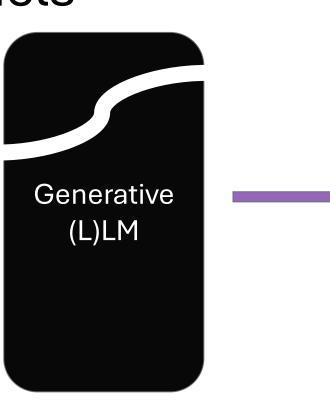
Query: What does Mary have Doc: Mary had a little lamb. Relevant:

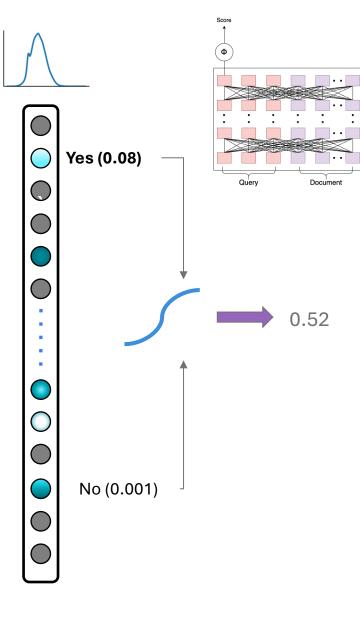




#### **Pointwise score**

Query: What does Mary have Doc: Mary had a little lamb. Relevant:

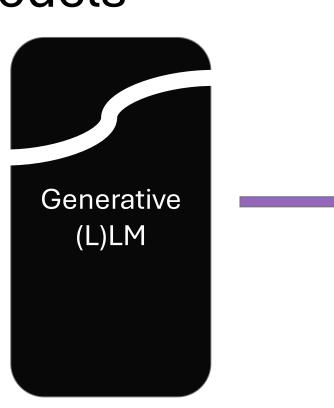


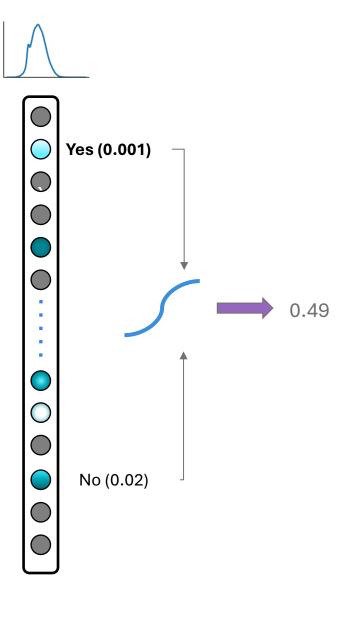


#### **Pairwise score**

Query: What does Mary have Doc0: JHU is in Baltimore Doc1: Mary had a little lamb.

Relevant:

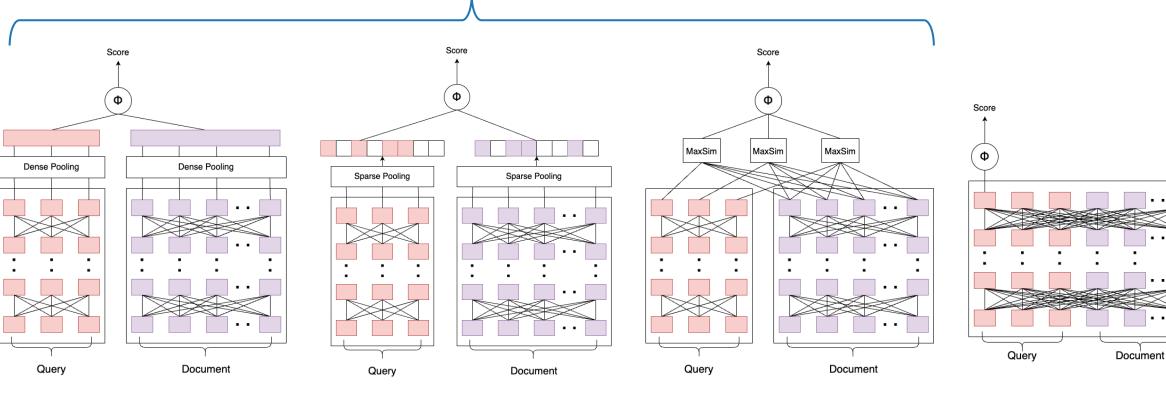




### Many kinds of LLM-based Rerankers

	Generative Model	Reasoning Model
Pointwise	MonoT5 RankLlama	Rank1
Pairwise	DuoT5	
Listwise/Setwise	RankGPT RankZephyr	Rank-K ReasonRank





One Dense Vector Per Sequence e.g., DPR

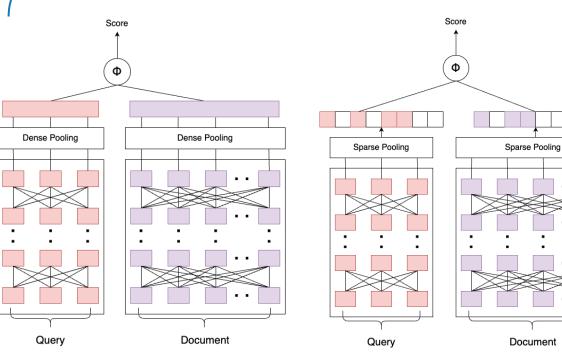
One <u>Sparse</u> Vector Per Sequence e.g., SPLADE

Bi-Encoder

Multiple Dense Vectors Per Sequence e.g., ColBERT

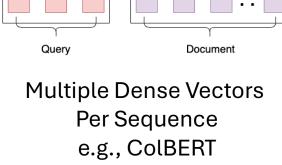
Joint Encoder e.g., monoBERT





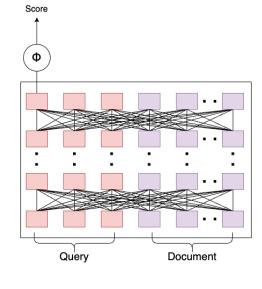
One <u>Sparse</u> Vector Per Sequence e.g., SPLADE

Bi-Encoder



MaxSim

MaxSim



e.g., Rank1

Joint Encoder

**More Effective** 

**More Efficient (at Query Time)** 

One Dense Vector

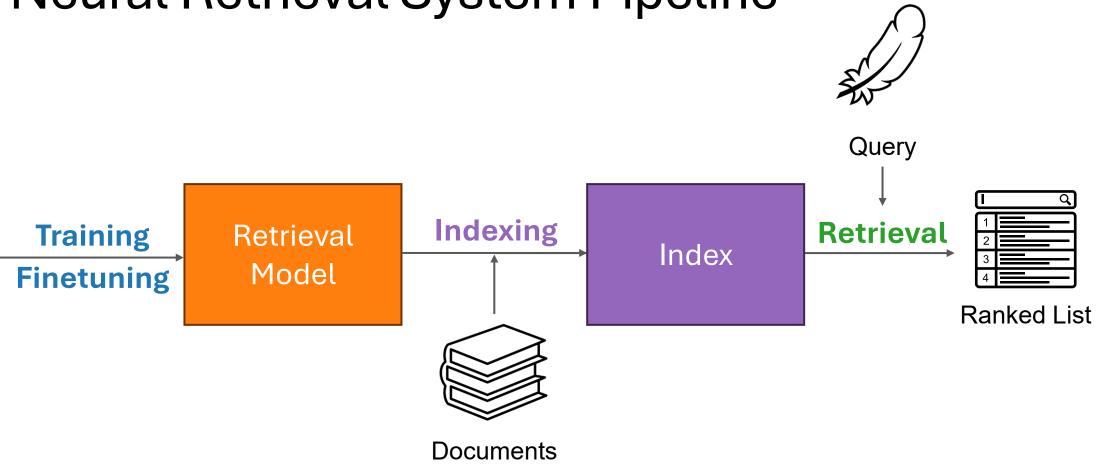
Per Sequence

e.g., DPR

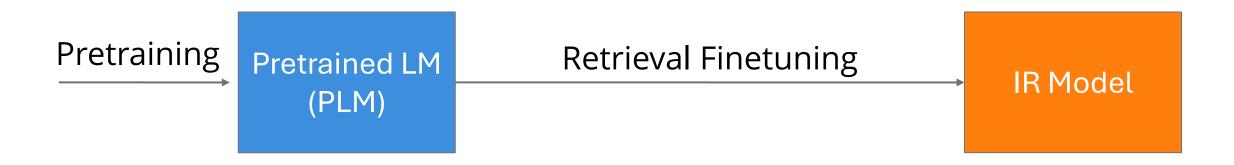
### Retrieve-and-Rerank System Combinations



### Neural Retrieval System Pipeline



### PLM to IR Model



- Align the representation
- Model "relevancy"

### Evaluation

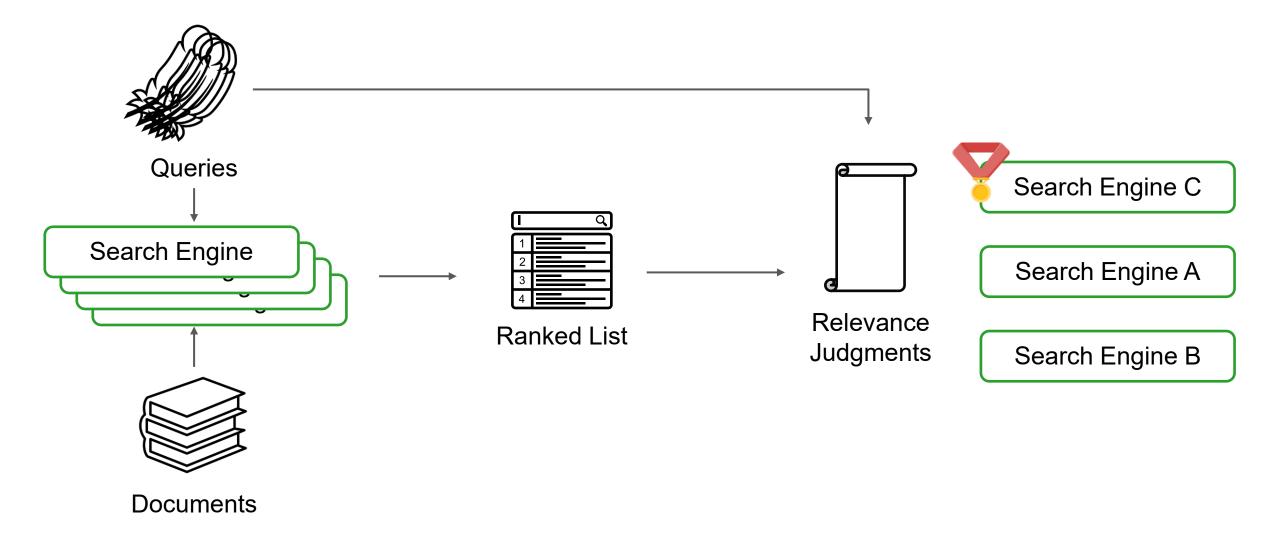
Which system is better?

## What is Information Retrieval? (relevant)

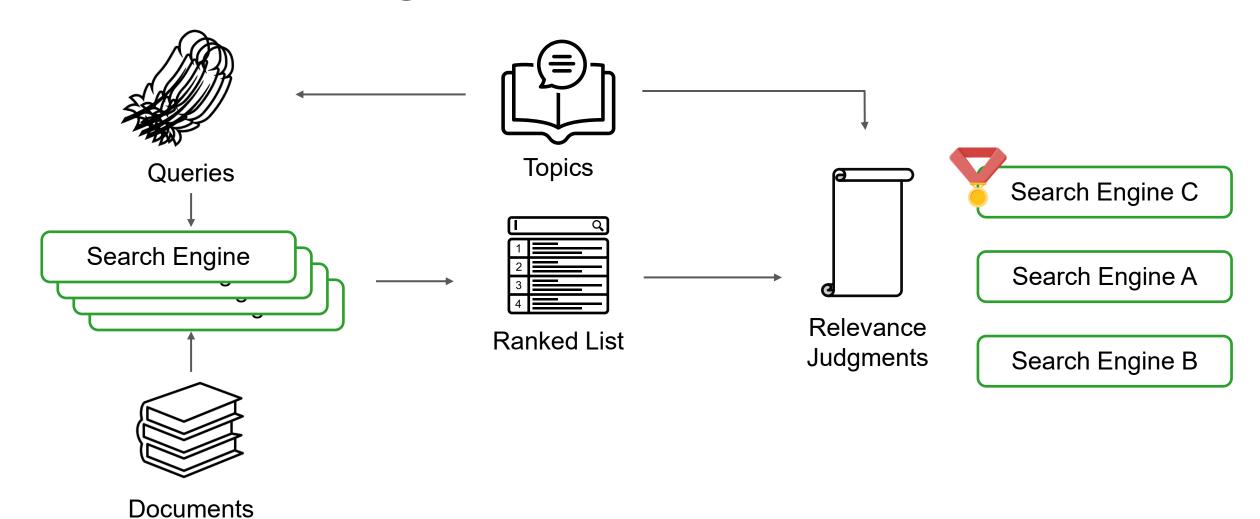
Retrieve information from a storage based on user's information need

# Which system retrieve more relevant information?

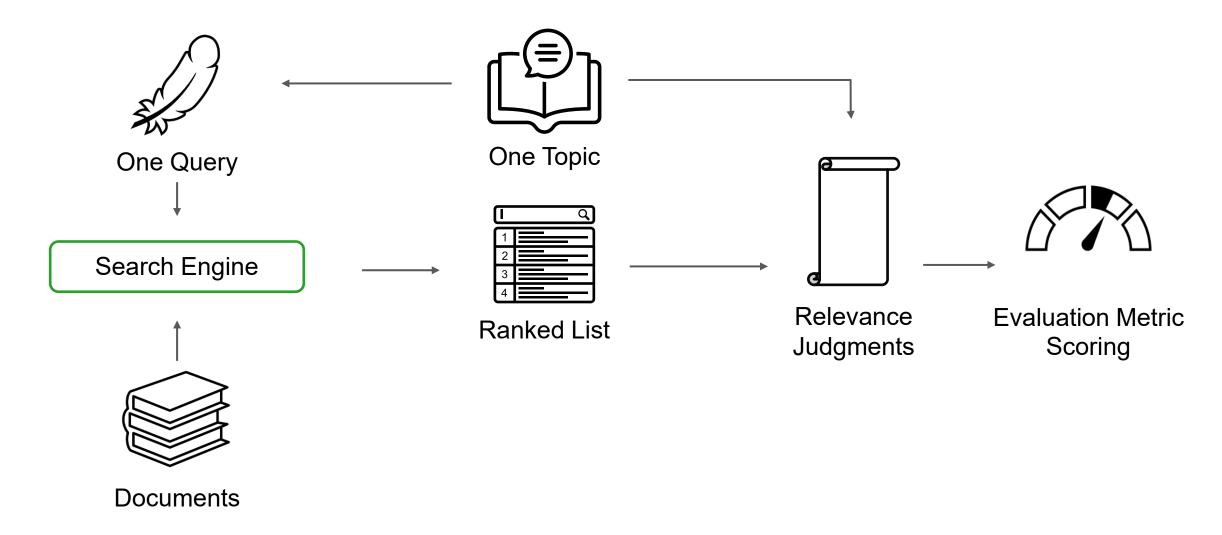
### Cranfield Paradigm Evaluation



### Cranfield Paradigm Evaluation



### Cranfield Paradigm Evaluation



### IR-Specific Issues

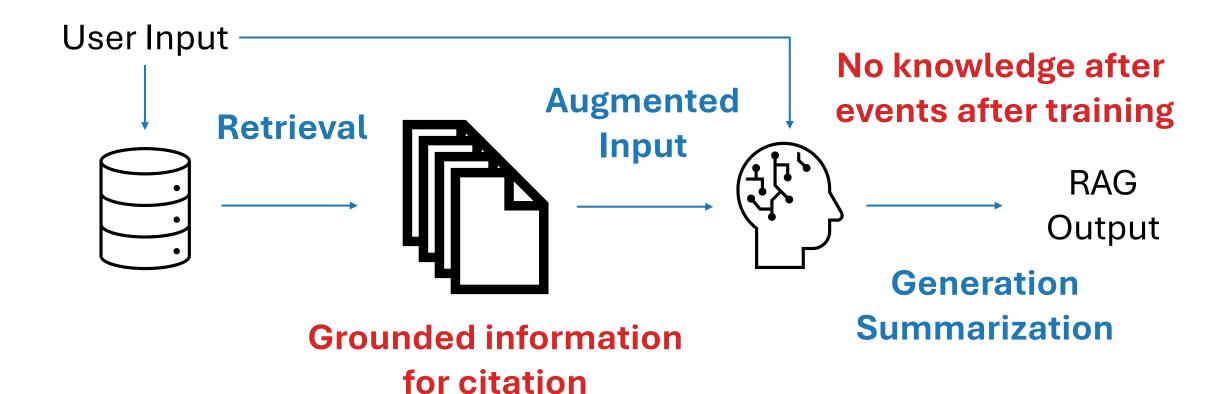
- Topics vs Queries
  - Clear intent vs an expression of such intent
- Relevant vs related
  - Fulfilling the information need or not
- Relevance Judgements vs Labels
  - Opinion vs "fact"
- Ranked retrieval metrics
  - Measuring the quality/effectiveness of a ranked list

### IR Metrics



- Effective Metrics
  - Mean Average Precision
  - Normalized Discounted Cumulative Gain
  - Recall@k
- Efficiency Metrics
  - Indexing time
  - Index disk space
  - Query latency (average search time per query)

### Retrieval Augmented Generation



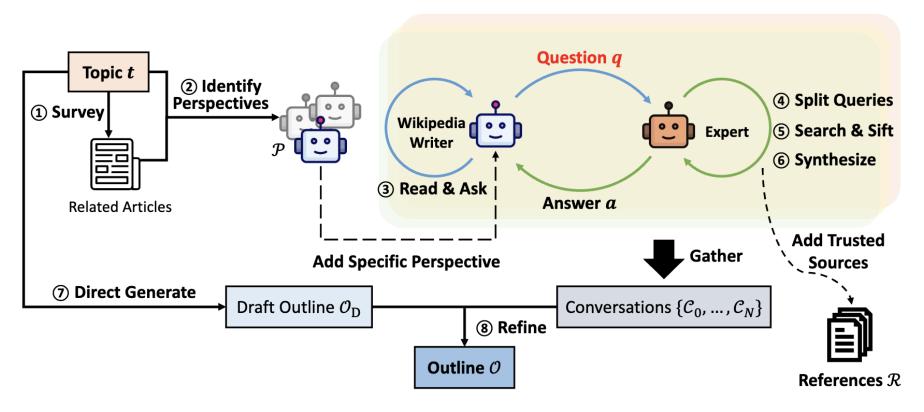
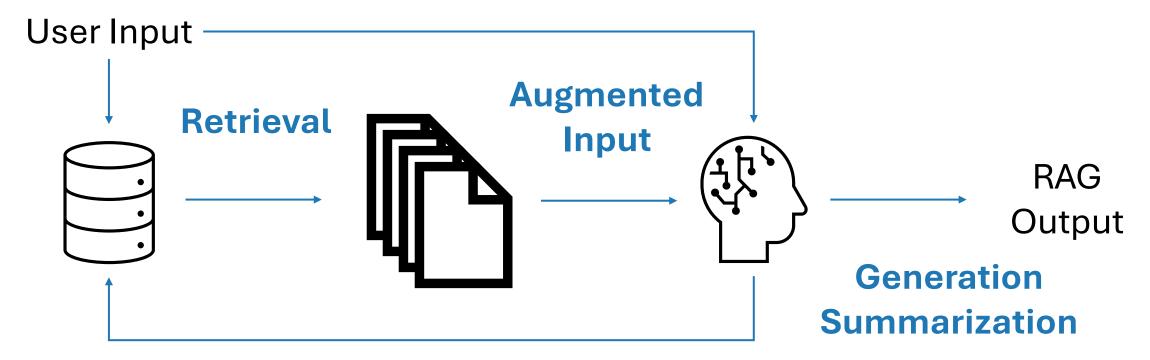


Figure 2: The overview of STORM that automates the pre-writing stage. Starting with a given topic, STORM identifies various perspectives on covering the topic by surveying related Wikipedia articles (1-2). It then simulates conversations between a Wikipedia writer who asks questions guided by the given perspective and an expert grounded on trustworthy online sources (3-6). The final outline is curated based on the LLM's intrinsic knowledge and the gathered conversations from different perspectives (7-8).

Shao, Yijia, et al. "Assisting in Writing Wikipedia-like Articles From Scratch with Large Language Models." Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers). 2024.

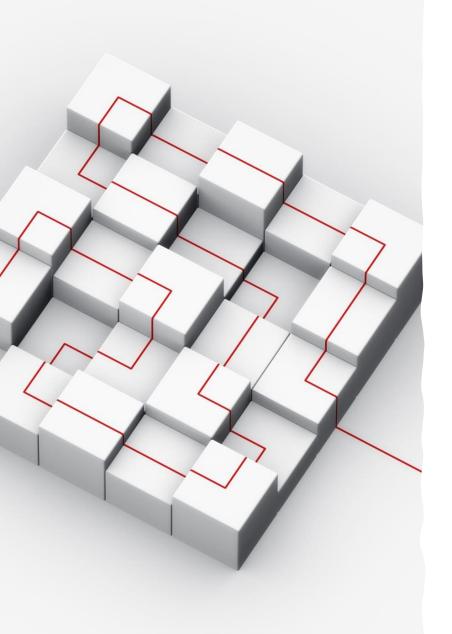
### A Green Field

- How the pipeline should be designed?
  - Predefined one or agentic system?
- Short vs long input from user
- How to make the response to be more useful?
  - Graphical or just text?
- How to interact with human?



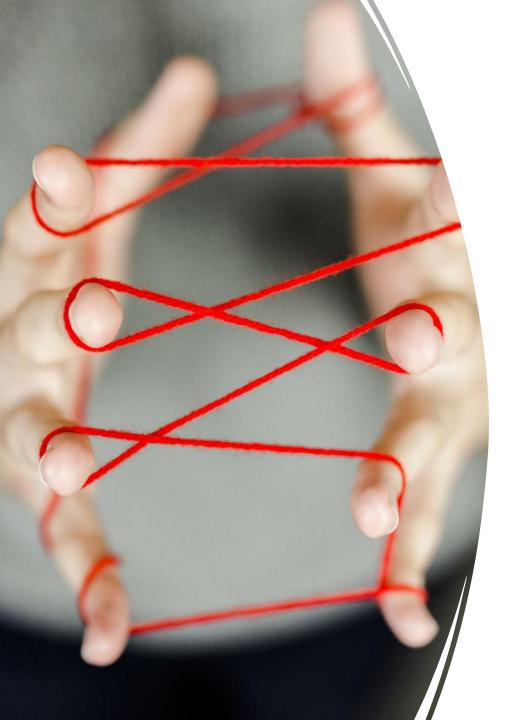
Feedback Loop

### State of IR Research



### Better Retrieval Models

- More effective
  - Better/larger neural models
  - Better architecture?
  - Under harder setup, e.g., scholar search, multilingual, cross-modal, etc
- More efficient
  - Faster at query time
  - Less resource footprint, e.g., memory, storage, compute, etc
- Other qualities
  - Fairness, diversity, etc



# Other Retrieval Problems

- Conversational
  - Guessing intent, finding the "right" information to serve
- Iterative/interactive/human-in-theloop
  - Rounds of interactions
- Generative
  - Returning a piece of text



### Evaluation

- What to measure
  - and when would it fail
- How to measure
  - Generative text? Citations?
- "Better" evaluation collection
  - Not necessarily larger