# Generative Information Retrieval

## The Web Conference 2024 tutorial

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https://TheWebConf2024-generative-IR.github.io

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# About presenters

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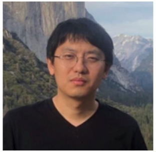

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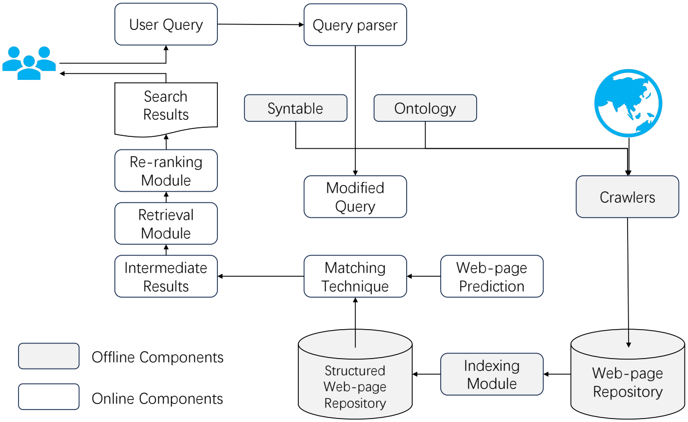
# Information retrieval

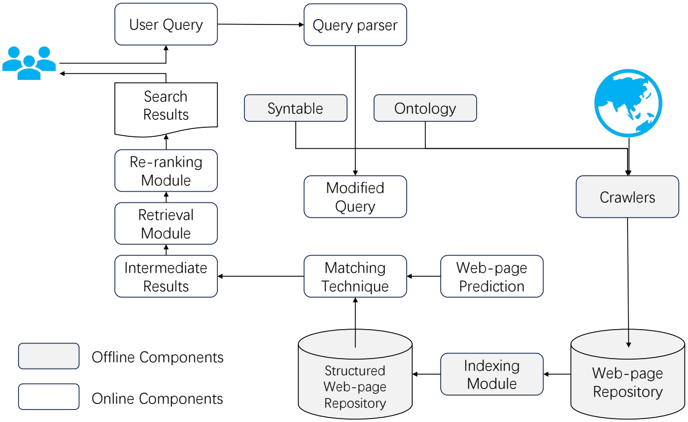
Information retrieval (IR) is the activity of obtaining information system resources that are relevant to an information need from a collection of those resources.


**Given**: User query (keywords, question, image, . . . )
**Rank**: Information objects (passages, documents, images, products, . . . )
**Ordered by**: Relevance scores

# Complex architecture design behind search engines

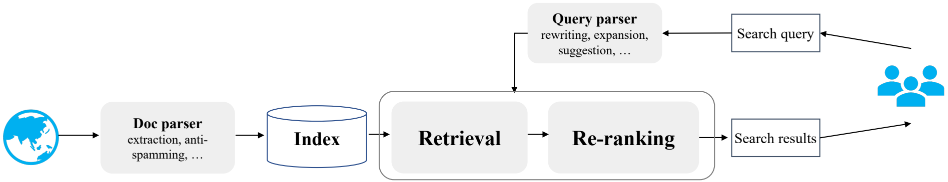


# Complex architecture design behind search engines



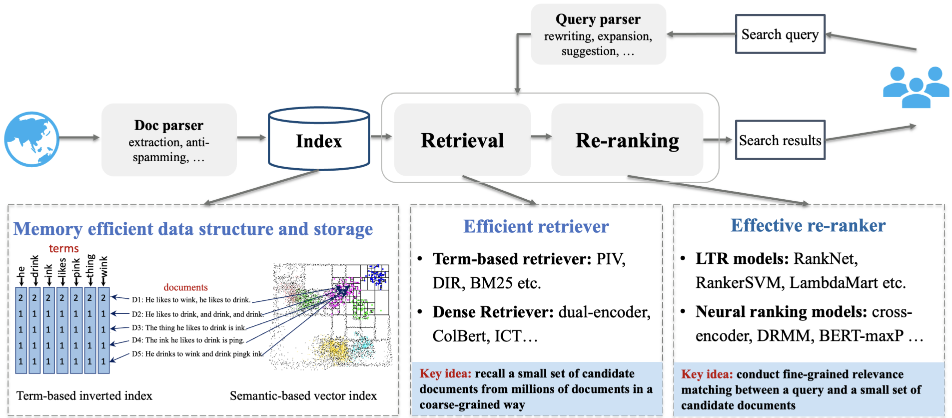

- **Advantages**:
  - Pipelined paradigm has withstood the test of time
  - Advanced machine learning and deep learning approaches applied to many components of modern systems

# Core pipelined paradigm: Index-Retrieval-Ranking



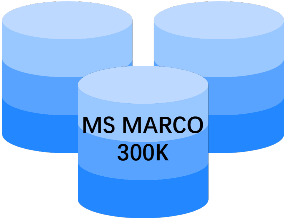

- Index: Build an index for each document in the entire corpus
- Retriever: Find an initial set of candidate documents for a query
- Re-ranker: Determine the relevance degree of each candidate

# Index-Retrieval-Ranking: Disadvantages



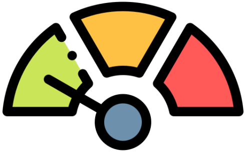

- **Effectiveness**: Heterogeneous ranking components are usually difficult to be optimized in an end-to-end way towards the global objective

# Index-Retrieval-Ranking: Disadvantages




**Big storage**

**GTR (Dense retrieval)**
**Memory size 1430MB**



**Slow inference speed**

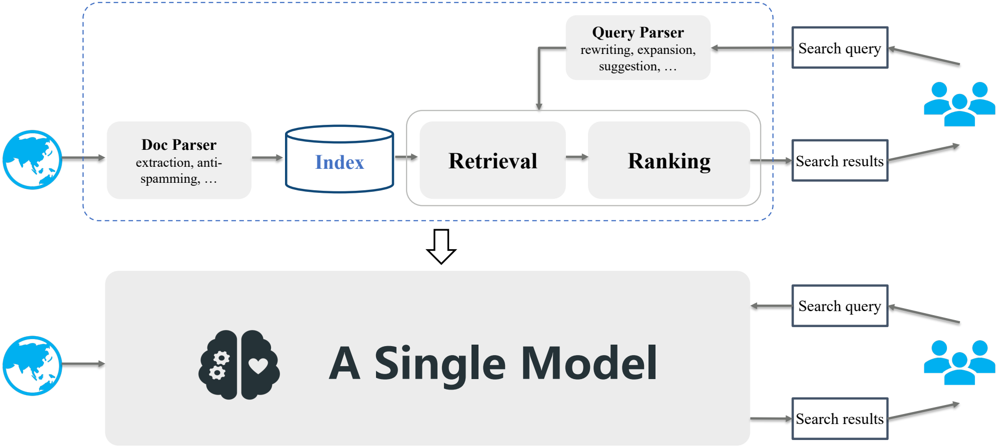
**GTR (Dense retrieval)**
**Online latency 1.97s**

- **Efficiency**: A large document index is needed to search over the corpus, leading to significant memory consumption and computational overhead

Source: [Sun et al., 2023]

**What if we replaced the pipelined architecture with a single consolidated model that efficiently and effectively encodes all of the information contained in the corpus?**

# Opinion paper: A single model for IR




Source: [Metzler et al., 2021]

# Generative language models

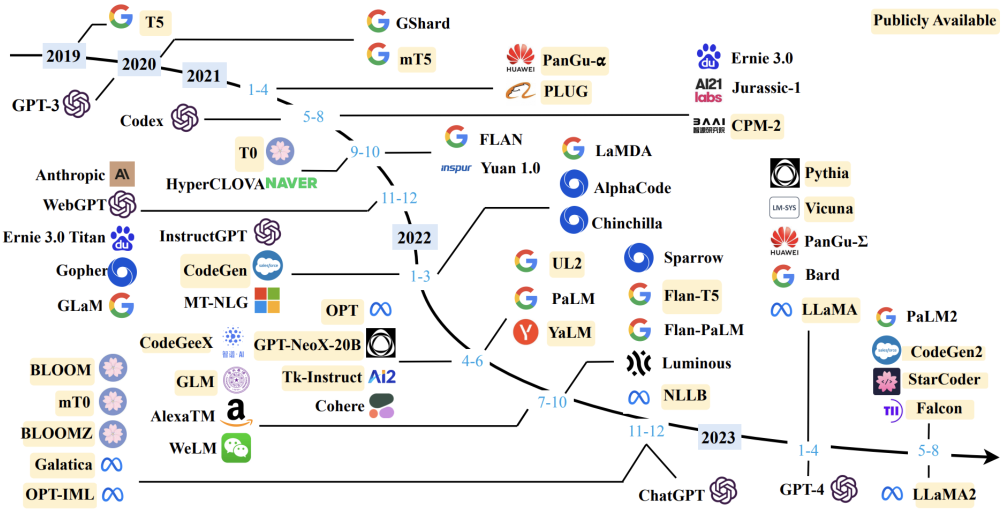



Image source: [Zhao et al., 2023]

# Two families of generative retrieval

- Closed-book: The language model is the **only source** of knowledge leveraged during generation, e.g.,
  - Capturing document ids in the language models
  - Language models as retrieval agents via prompting
- Open-book: The language model can draw on **external memory** prior to, during and after generation, e.g.,
  - Retrieval augmented generation of answers
  - Tool-augmented generation of answers

Source: [Najork, 2023]

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# Closed-book generative retrieval

The IR task can be formulated as a sequence-to-sequence (Seq2Seq) generation problem

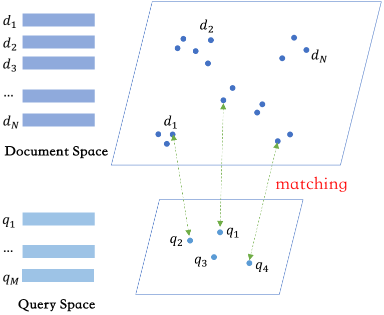
## Closed-book generative retrieval

The IR task can be formulated as a sequence-to-sequence (Seq2Seq) generation problem

- **Input**: A sequence of query words
- **Output**: A sequence of document identifiers

# Neural IR models: Discriminative vs. Generative

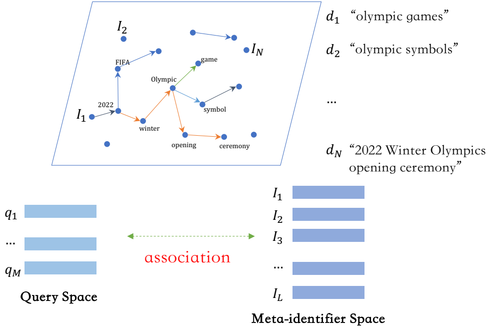
***Discriminative***




$$p(R = 1|q, d) \approx \quad \dots \quad \approx argmax\ s(\vec{q}, \vec{d})$$

( probabilistic ranking principle)

***Generative***

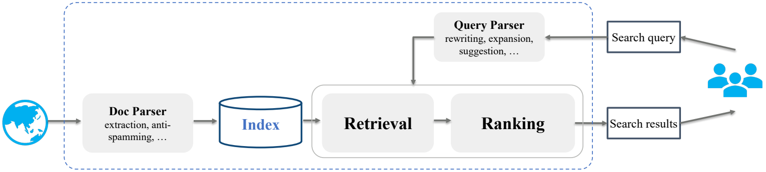



$$p(q|d) \approx p(docID|q) = argmax\ \mathrm{p}((I_1, \dots, I_k)|q)$$

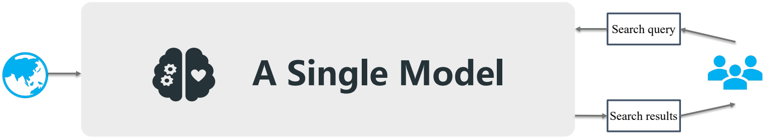
( query likelihood)

# Why generative retrieval?

**Heterogeneous** objectives




A **global** objective




- **Effectiveness**: Knowledge of all documents in corpus is encoded into model parameters, which can be optimized directly in an end-to-end manner

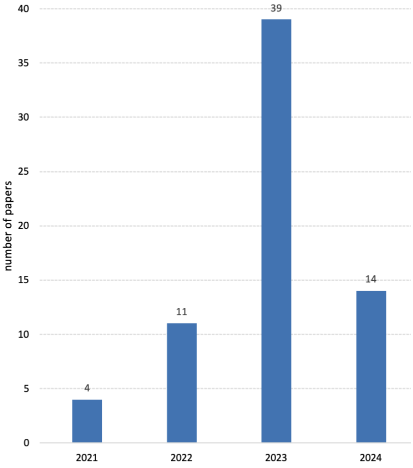
# Why generative retrieval?

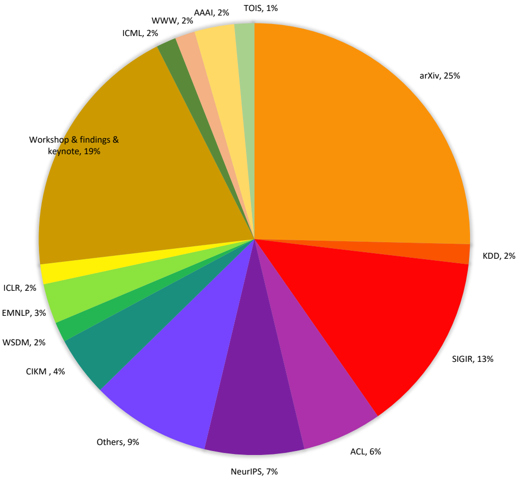
| | Dense retrieval | Generative retrieval |
|---|---|---|
| **Memory size** (MS MARCO 300K) | **GTR** **1430MB** | **GenRet** **860MB** |
| **Online latency** | **GTR** **1.97s** | **GenRet** **0.16s** |

- **Efficiency**: Main memory computation of GR is the storage of document identifiers and model parameters
- Heavy retrieval process is replaced with a light generative process over the vocabulary of identifiers

Data source: [Sun et al., 2023]

# Statistics of related publications




The data statistics cover up to May 11, 2024.

## Goals of the tutorial

- We will cover key developments on generative information retrieval (mostly 2021–2024)
  - **Problem definitions**
  - **Docid design**
  - **Training approaches**
  - **Inference strategies**
  - **Applications**

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  - **Training approaches**
  - **Inference strategies**
  - **Applications**
- We are still far from understanding how to best develop generative IR architecture compared to traditional pipelined IR architecture:
  - Taxonomies of existing research and key insights
  - Our perspectives on the **current challenges** & **future directions**

# Schedule

| Time | Section | Presenter |
|---|---|---|
| 13:30-13:50 | Section 1: Introduction | Maarten de Rijke |
| 13:50-14:20 | Section 2: Definitions & Preliminaries | Zhaochun Ren |
| 14:20-15:00 | Section 3: Docid design | Yubao Tang |
| |   15min coffee break | |
| 15:15-15:55 | Section 4: Training approaches | Weiwei Sun |
| 15:55-16:15 | Section 5: Inference strategies | Weiwei Sun |
| 16:15-16:35 | Section 6: Applications | Yubao Tang |
| 16:35-16:50 | Section 7: Challenges & Opportunities | Maarten de Rijke |
| 16:50-17:00 | Q & A | All |

# References

# References i


D. Metzler, Y. Tay, D. Bahri, and M. Najork. Rethinking search: Making domain experts out of dilettantes. *SIGIR Forum*, 55(1):1–27, 2021.

M. Najork. Generative information retrieval (slides), 2023. URL https://docs.google.com/presentation/d/191AeVzPkh20Ly855tKDkz1uv-1pHV_9GxfntiTJPUug/.

W. Sun, L. Yan, Z. Chen, S. Wang, H. Zhu, P. Ren, Z. Chen, D. Yin, M. de Rijke, and Z. Ren. Learning to tokenize for generative retrieval. In *Thirty-seventh Conference on Neural Information Processing Systems*, 2023.

W. X. Zhao, K. Zhou, J. Li, T. Tang, X. Wang, Y. Hou, Y. Min, B. Zhang, J. Zhang, Z. Dong, et al. A survey of large language models. *arXiv preprint arXiv:2303.18223*, 2023.