

Generative Information Retrieval



The Web Conference 2024 tutorial – Section 1

**Yubao Tang^a, Ruqing Zhang^a, Zhaochun Ren^b, Weiwei Sun^c, Jiafeng Guo^a and
Maarten de Rijke^d**

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

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^a Institute of Computing Technology, Chinese Academy of Sciences & UCAS

^b Leiden University

^c Shandong University

^d University of Amsterdam

About presenters



Yubao Tang
PhD student
@ICT, CAS



Ruqing Zhang
Faculty
@ICT, CAS



Zhaochun Ren
Faculty
@LEI



Weiwei Sun
MSc student
@SDU



Jiafeng Guo
Faculty
@ICT, CAS



Maarten de Rijke
Faculty
@UvA

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.

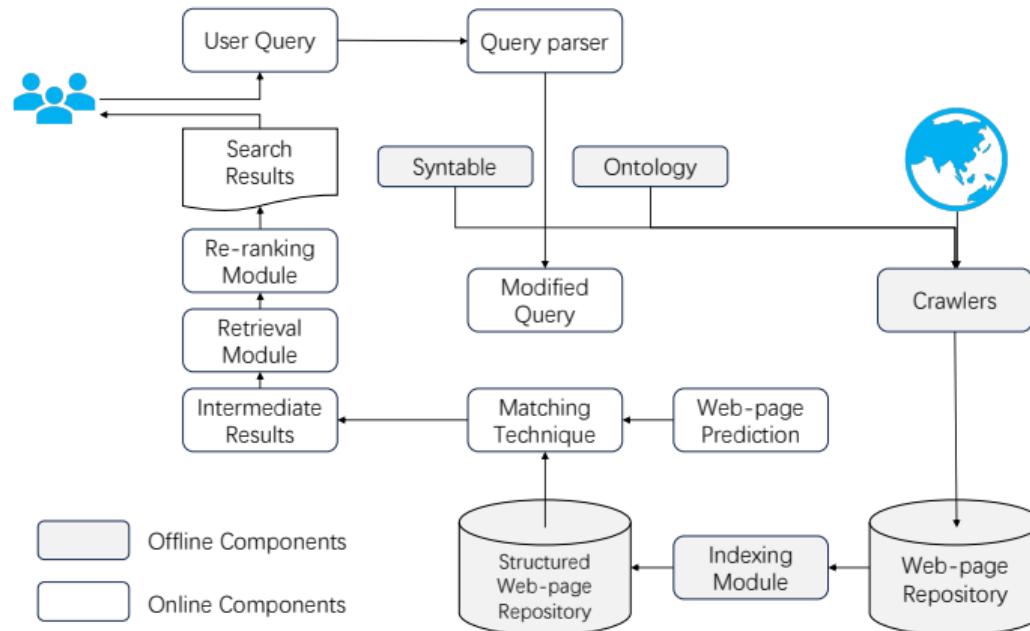


Given: User query (keywords, question, image, ...)

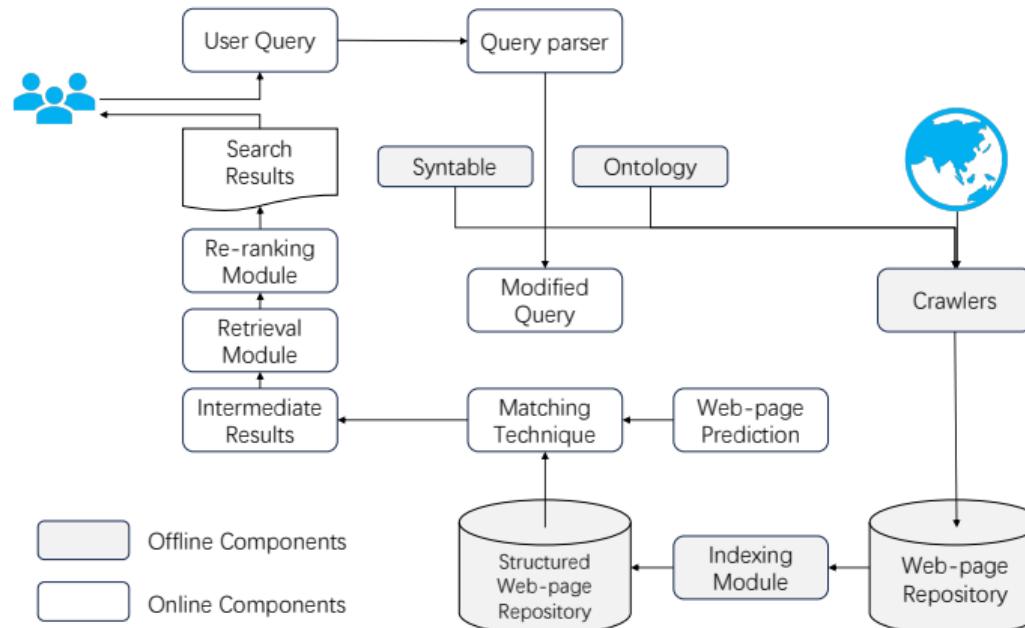
Rank: Information objects (passages, documents, images, products, ...)

Ordered by: Relevance scores

Complex architecture design behind search engines



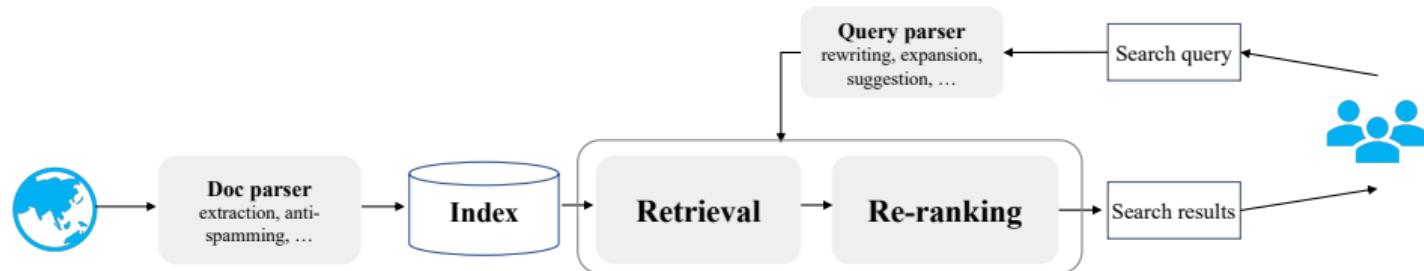
Complex architecture design behind search engines



- **Advantages:**

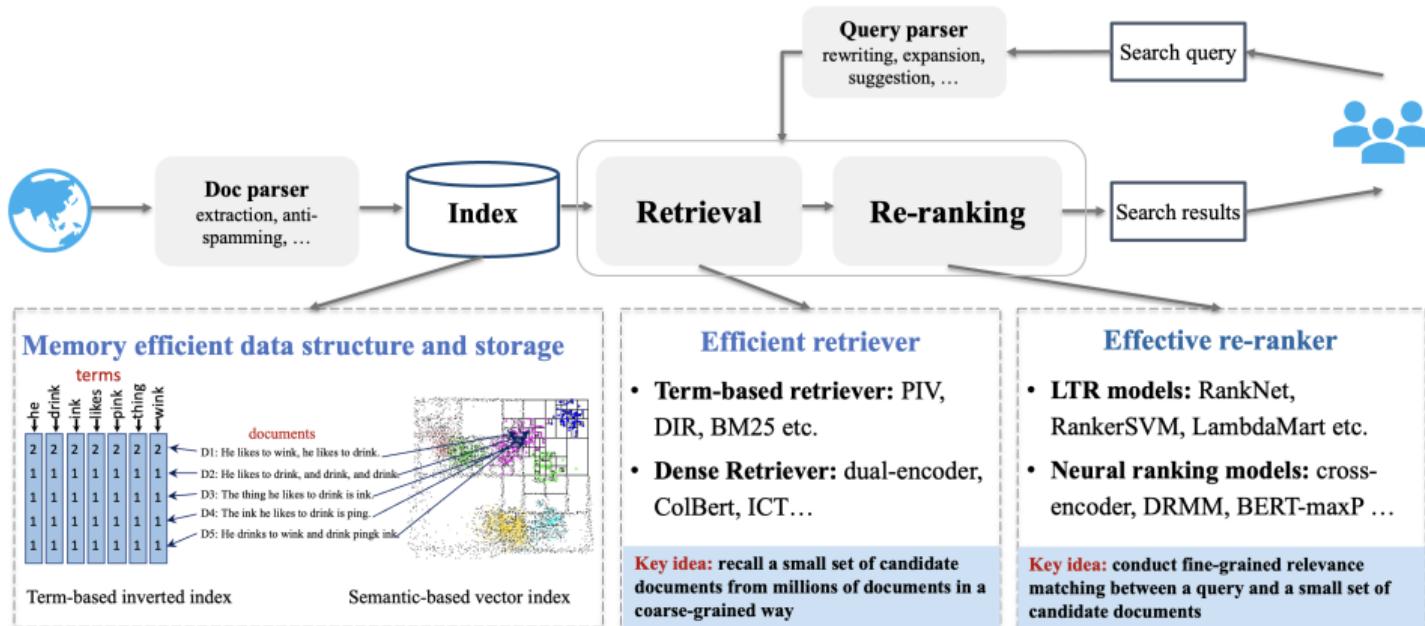
- Pipelined paradigm has withstood the test of time
- Advanced machine learning and deep learning approaches applied to many components of modern systems

Core pipelined paradigm: Index-Retrieval-Ranking



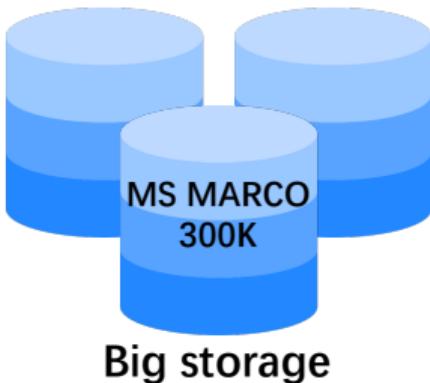
- Index: Build an index for each document in the entire corpus
- Retriever: Find an initial set of candidate documents for a query
- Re-ranker: Determine the relevance degree of each candidate

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**



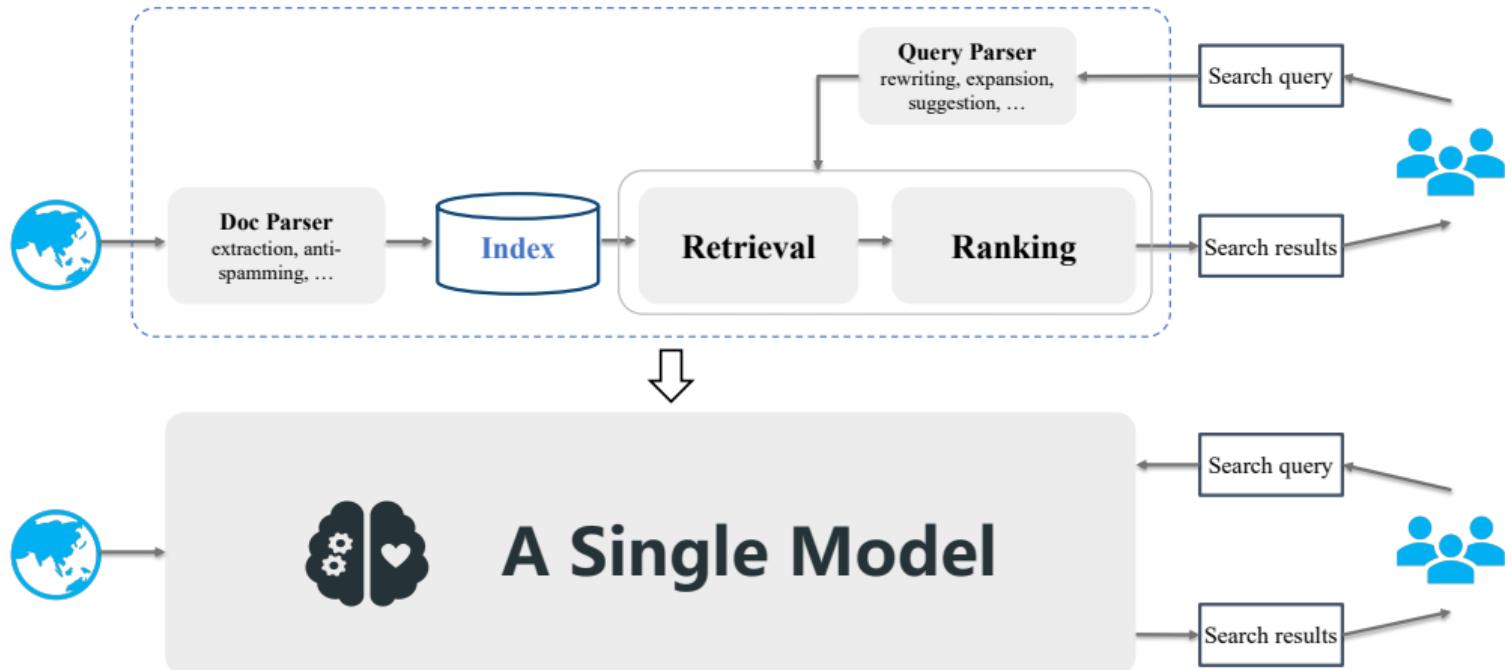
Slow inference speed

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

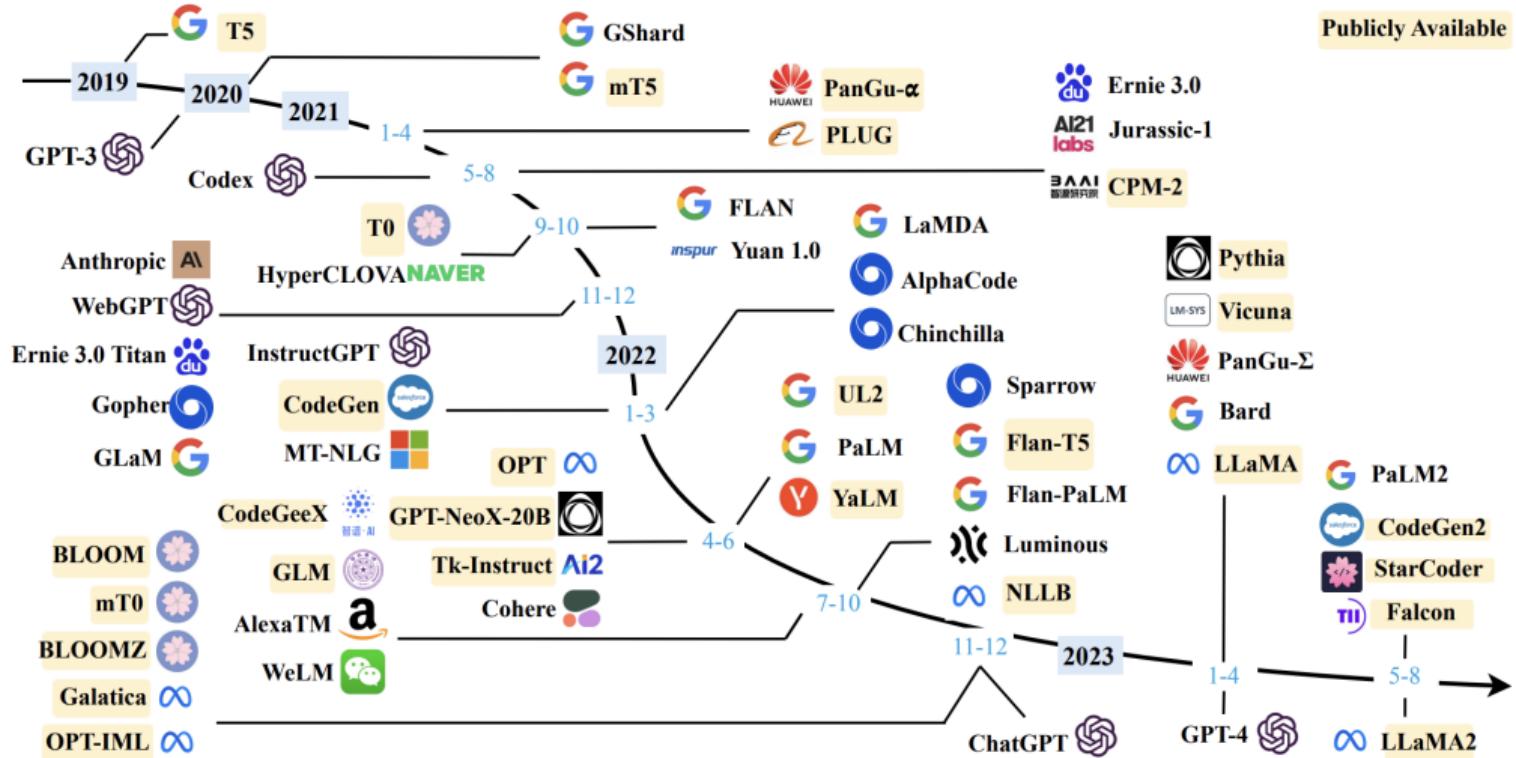
- **Efficiency:** A large document index is needed to search over the corpus, leading to significant memory consumption and computational overhead

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



Generative language models



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

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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

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

Neural IR models: Discriminative vs. Generative

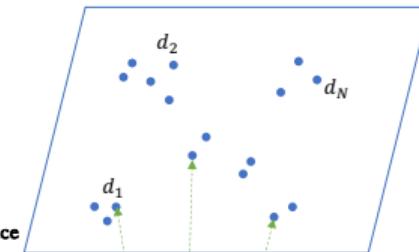
Discriminative

d_1
 d_2
 d_3
...
 d_N

Document Space

q_1
...
 q_M

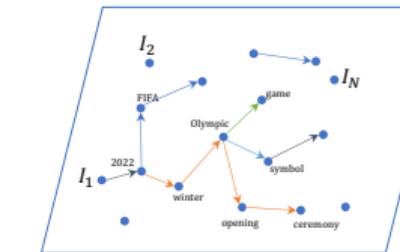
Query Space



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

(probabilistic ranking principle)

Generative



d_1 "olympic games"
 d_2 "olympic symbols"
...
 d_N "2022 Winter Olympics opening ceremony"

q_1
...
 q_M

Query Space

I_1
 I_2
 I_3
...
 I_L

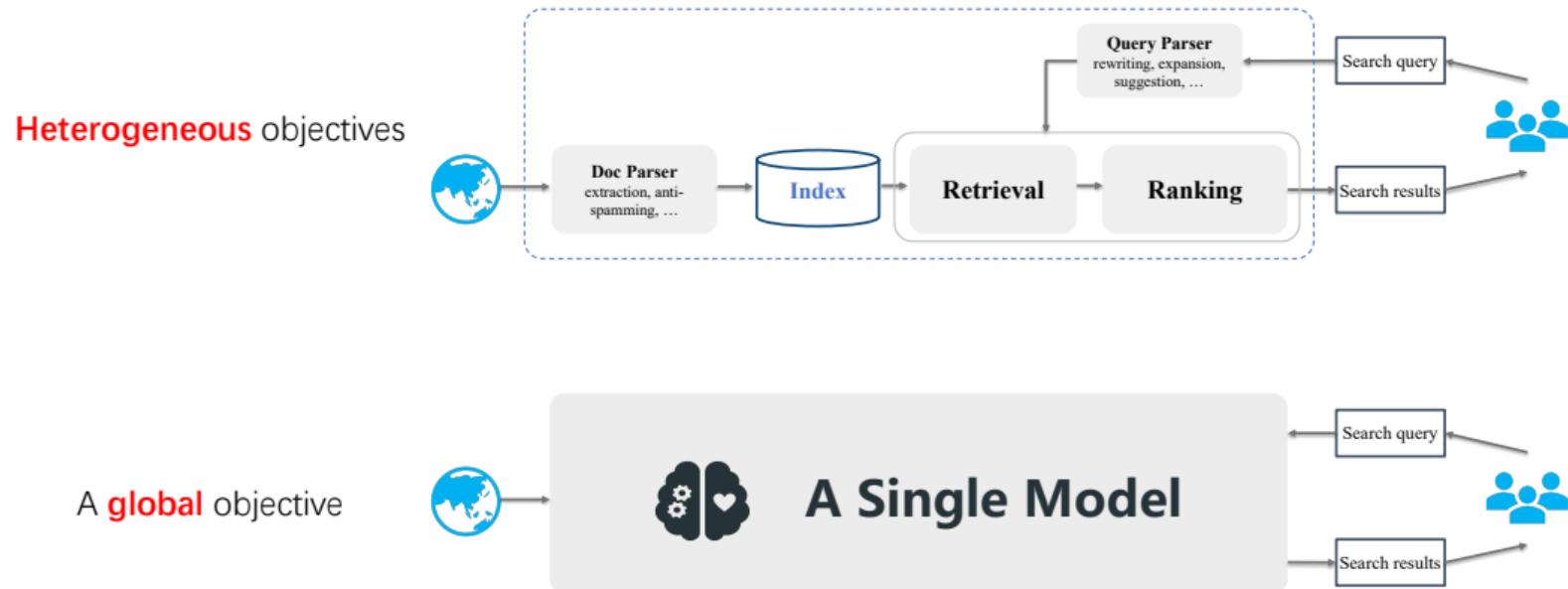
Meta-identifier Space

association

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

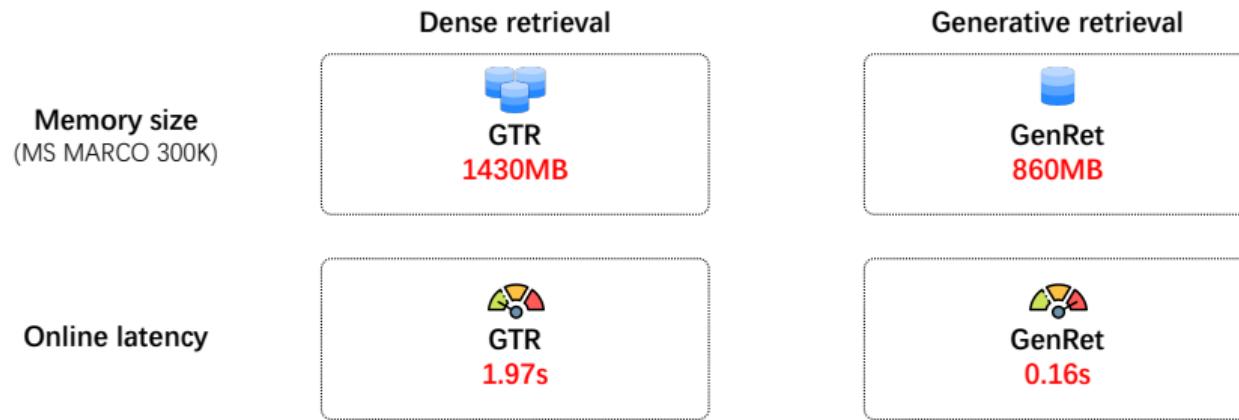
(query likelihood)

Why generative retrieval?



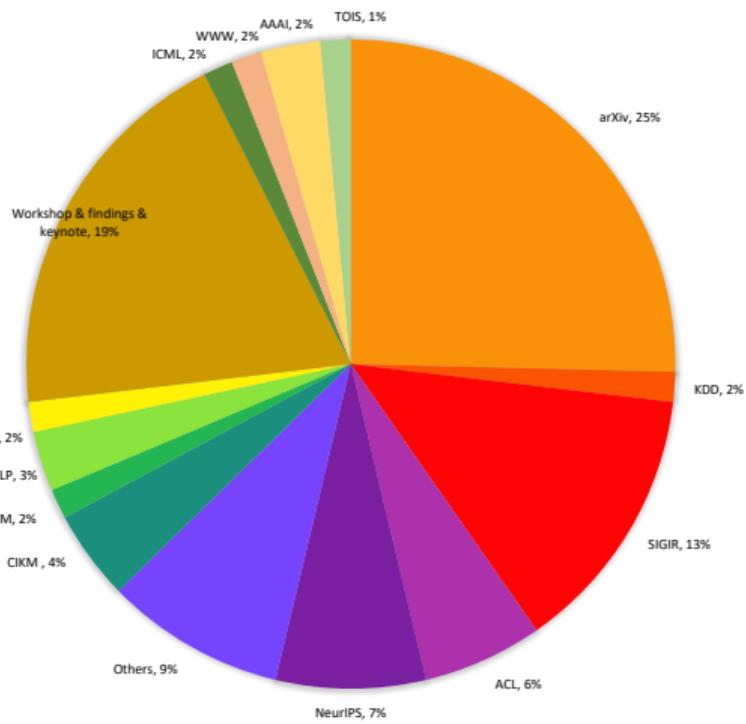
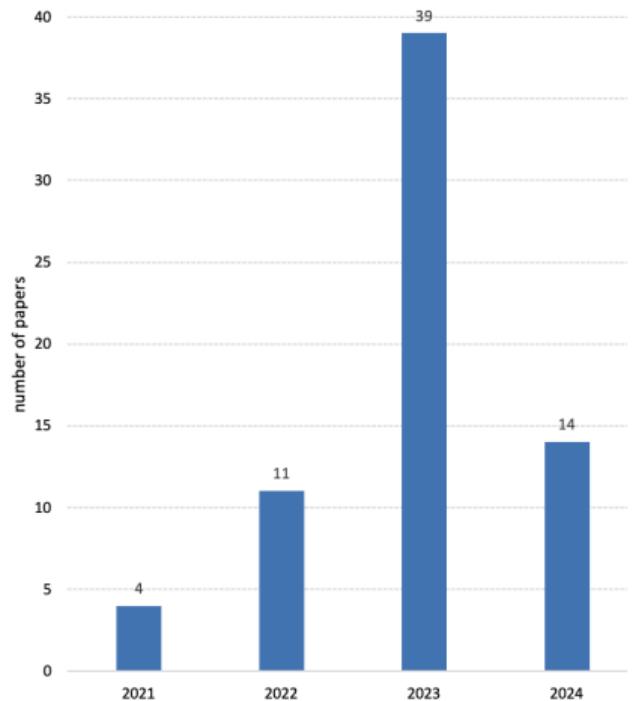
- **Effectiveness:** Knowledge of all documents in corpus is encoded into model parameters, which can be optimized directly in an end-to-end manner

Why generative retrieval?



- **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

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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- We will cover key developments on generative information retrieval (mostly 2021–2024)
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 - **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/19lAeVzPkh20Ly855tKDkz1uv-1pHV_9GxfntiTJPUG/.
- 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.