Review, State-of-the-arts, and Few-Last-Words

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Temu-Balik Informasi, Fasilkom UI

Renungan: Temu-Balik Informasi?

- Jadi, apa inti dari kuliah Temu-Balik Informasi?
- Apa yang Anda pelajari? Dan apa kaitan kuliah ini dengan kuliah-kuliah/keilmuan CS yang lain?
- Apakah ada “Delta Knowledge” yang Anda rasakan antara sebelum dan sesudah mengambil kuliah Temu-Balik Informasi?

Sparse Retrieval?

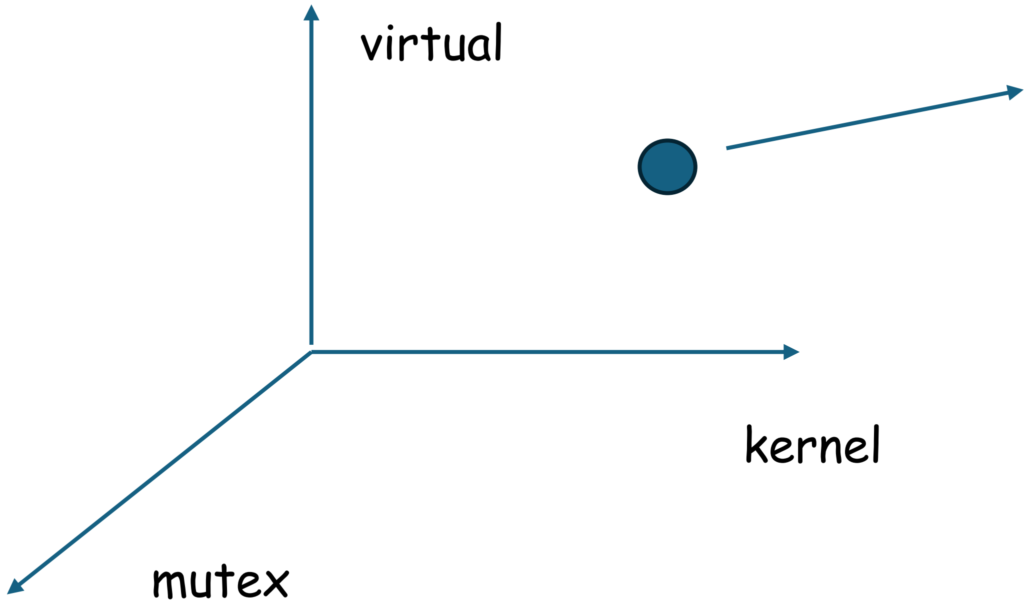
- Inverted Index adalah struktur data utama yang menyimpan **pemetaan term-term dengan dokumen-dokumen** yang mengandung term tersebut.
- Apa salah satu **representasi teks** yang umum digunakan ketika kita menyimpan informasi term-dokumen di inverted index? **Bag-of-Words!**
- Apa ciri dari representasi **Bag-of-Words?**

Sparse Retrieval?

- Apa kaitan **Bag-of-Words** dengan **Vector Space Model**?
- Apakah semua **Vector Space Model** selalu menerapkan representasi **Bag-of-Words**? Contoh?
- Sebaliknya, apakah konsep representasi **Bag-of-Words** **"selalu"** merupakan **Vector Space Model**? Contoh?

Sparse Retrieval?

- Apa kaitan **Bag-of-Words** dengan **Vector Space Model**?
- Beberapa **Vector Space Model** berbasis **Bag-of-Words**!



2 kali kata kernel, 1 kali kata virtual, 0 kata mutex

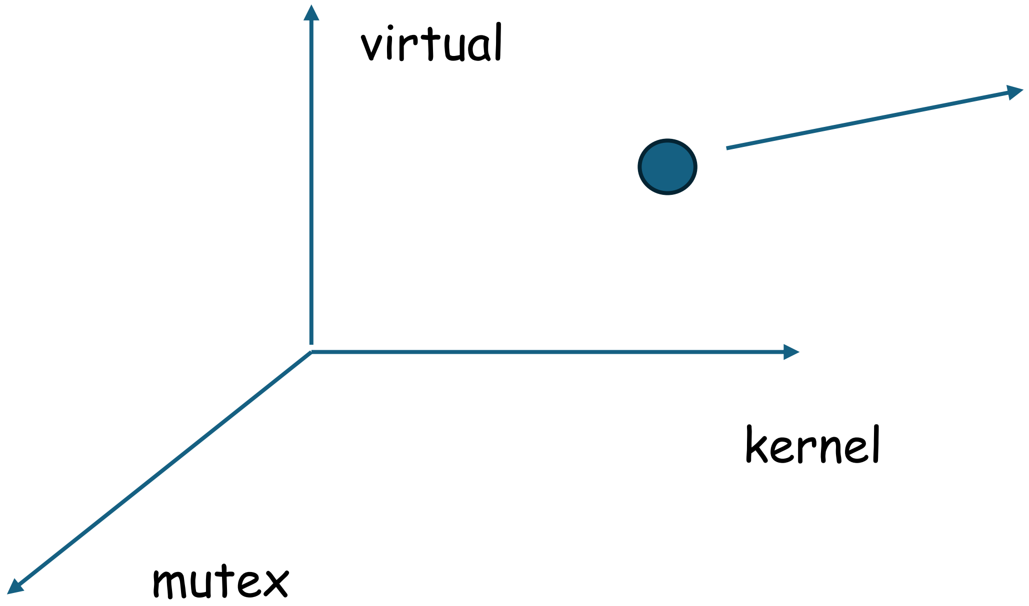
$$\begin{bmatrix} 2 \\ 1 \\ 0 \end{bmatrix}$$

Ini Namanya **Sparse Vector**

Mengapa?

Sparse Retrieval?

- Lalu, apa itu **TF**, **IDF**, **TF-IDF** dalam konteks Bag-of-Words dan Vector Space Model?

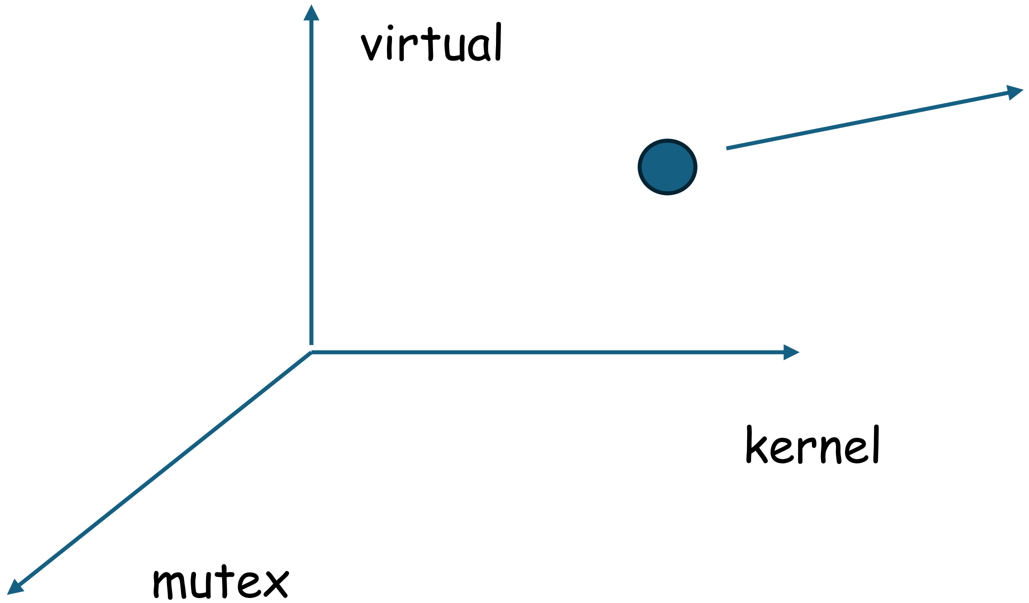


2 kali kata kernel, 1 kali kata virtual, 0 kata mutex

$$\begin{bmatrix} 2 \\ 1 \\ 0 \end{bmatrix}$$

Sparse Retrieval?

- Lalu, apa itu **TF, IDF, TF-IDF** dalam konteks Bag-of-Words dan Vector Space Model? ---> hanyalah **skema pembobotan** saja …



Misal, IDF(kernel) = 0.2, IDF(virtual) = 0.8

2 kali kata kernel, 1 kali kata virtual, 0 kata mutex

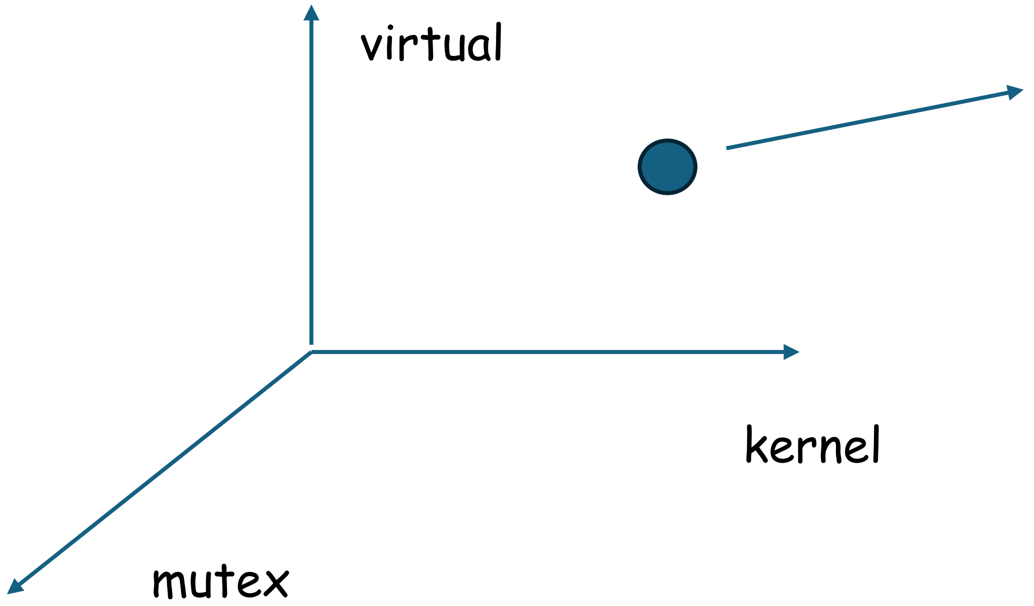
$$\begin{bmatrix} 2 \\ 1 \\ 0 \end{bmatrix} \qquad \begin{bmatrix} 0.4 \\ 0.8 \\ 0 \end{bmatrix}$$

Raw TF   TF-IDF

Dan yang lainnya …

Sparse Retrieval?

- Jadi, metode retrieval yang memanfaatkan **Sparse Vectors** Namanya adalah **Sparse Retrieval**.



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2 kali kata kernel, 1 kali kata virtual, 0 kata mutex

$$\begin{bmatrix} 2 \\ 1 \\ 0 \end{bmatrix} \qquad \begin{bmatrix} 0.4 \\ 0.8 \\ 0 \end{bmatrix}$$

Raw TF — TF-IDF

Dan yang lainnya …

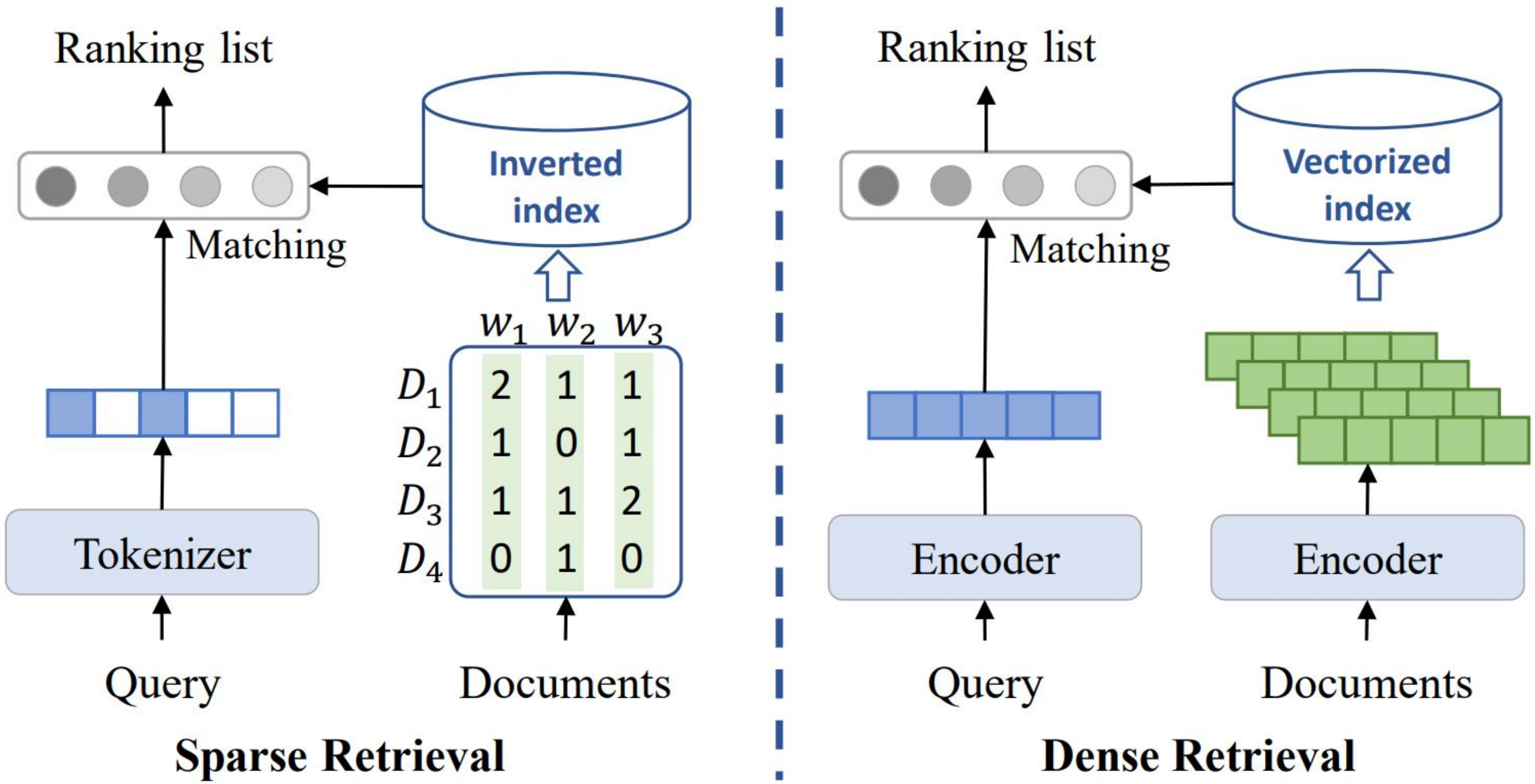
Sparse Retrieval?

- Salah satu **Sparse Retrieval** scoring algorithm adalah **BM25**.

$$BM25(D,Q) = \sum_{i=1}^{n} IDF(q_i) \frac{f(q_i, D)(k_1 + 1)}{f(q_i, D) + k_1(1 - b + b\frac{|D|}{avgdl})}$$

- Keunggulan dibandingkan Teknik yang berbasis ML:
  - Indexing and Retrieval Speed
  - Explainability: **The meaning of sparse vector is obvious**. We can easily check why particular entity was retrieved for particular query and what terms had the greatest impact.

Sparse Retrieval vs Dense Retrieval



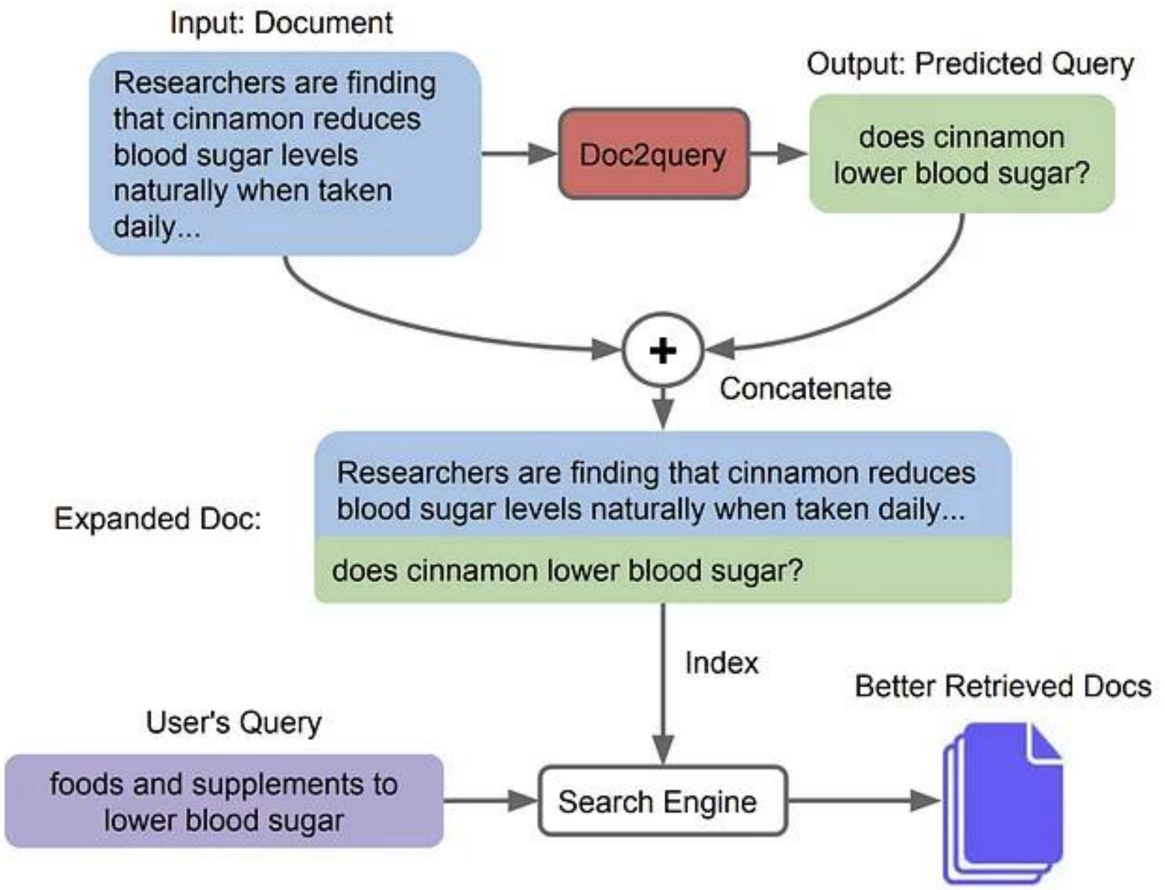
https://blog.reachsumit.com/posts/2023/09/generative-retrieval/#towards-index-free-and-model-based-generative-retrieval

Bisakah Deep Learning digunakan untuk Sparse Retrieval Model?

Ataukah Deep Learning hanya untuk Dense Retrieval Model?

Doc2Query

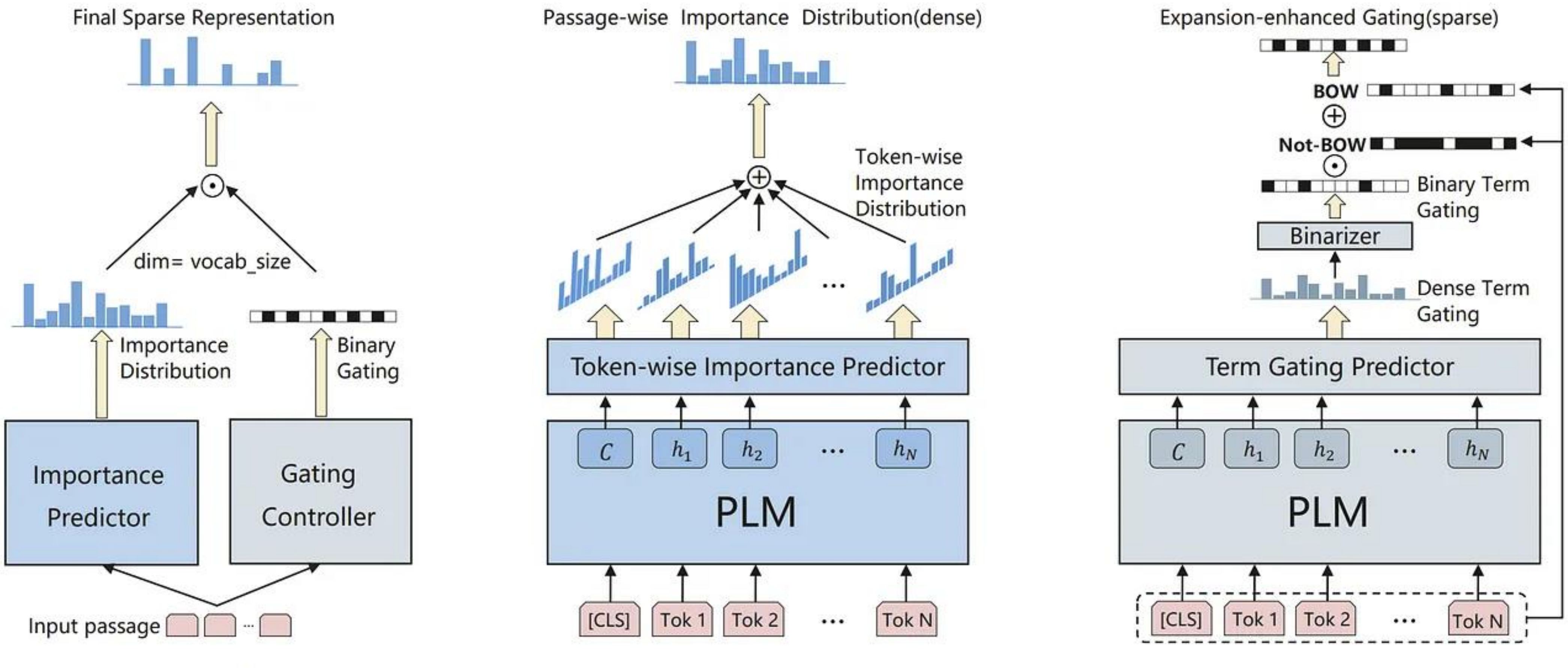
It is a simple method that **predicts which queries will be issued** for a given document and then expands it with those predictions with a sequence-to-sequence neural network, trained using datasets consisting of pairs of query and relevant documents.



[Rodrigo Nogueira et al., Document Expansion by Query Prediction, 2019, arXiv:1904.08375]

SparTerm

Framework called SparTerm directly **learns sparse text representations** in the full vocabulary space.



(a) SparTerm Model (b) Importance Predictor (c) Gating Controller

[Yang Bai et al., SparTerm: Learning Term-based Sparse Representation for Fast Text Retrieval, 2020, arXiv:2010.00768]

Review Lagi …

Language Model & Embedding

- Apa itu **Language Model**?

- Sebutkan beberapa jenis **Language Model**?
  - Unigram Language Model?
  - Bigram Language Model?
  - Causal Language Model? Untuk apa?
  - Masked Language Model? Untuk apa?
  - Skip-Gram Language Model? Untuk apa?

- Apa kaitan **Language Model** dengan **Word Embedding** dan **Document Embedding**?

Singular Value Decomposition

- Apa itu **SVD**?
- Apa itu **Latent Semantic Analysis**?
- Ketika SVD diterapkan kepada Term-Document matrix, apa isi dari U, Σ, dan V^T?

Transformers, Encoders & Decoders

- Apa itu **Transformers**?
- Apa perbedaan **Transformers** dengan **Recurrent Units** seperti LSTMs, GRUs, dsb?
- Apa itu **Encoders**? **Decoders**?

Transformers, Encoders & Decoders

- Apa perbedaan **Fine-Tuning** dan **Pre-Training**?

- Bagaimana Pre-Train Encoder?
- Kapan dan Bagaimana Fine-Tune Encoder?

- Bagaimana Pre-Train Decoder?
- Kapan Fine-Tune Decoder? Bagaimana?

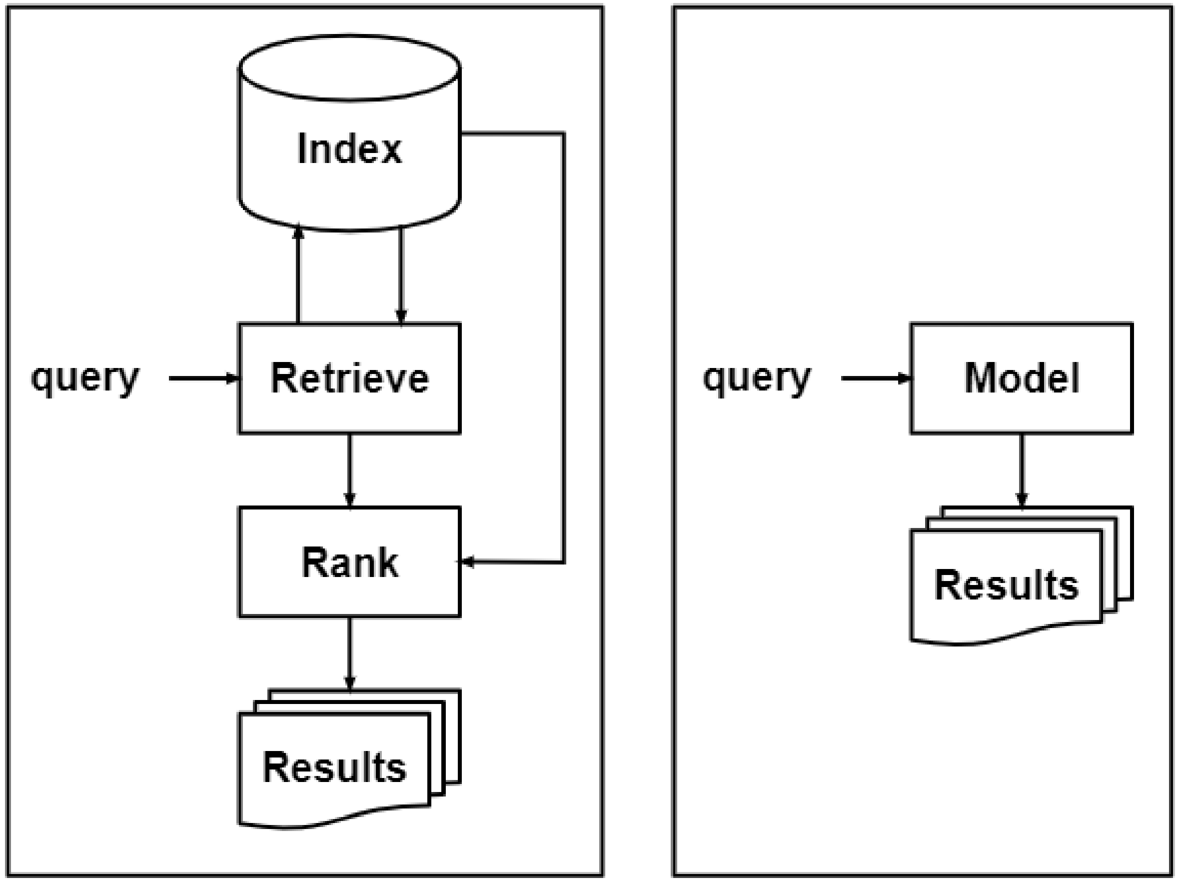
Future Directions?

- Index-Retrieve-Then-Rank Paradigm
  - Sparse Retrieval
  - Dense Retrieval

- Index-Free and Model-Based **Generative Retrieval**
  - Some researchers define this notion as **Autoregressive Search Engine**, **Differentiable Search Index**, or **Neural Corpus Indexer**

https://blog.reachsumit.com/posts/2023/09/generative-retrieval/#towards-index-free-and-model-based-generative-retrieval

Sparse & Dense Retrieval VS Generative Retrieval



(a) Retrieve-then-rank **(b)** Unified retrieve-and-rank

Generative Retrieval

- During training, the model learns to **generate the document identifier given the document content**.
- During retrieval the trained model gets an input query and **autoregressively generates a document identifier**.

https://blog.reachsumit.com/posts/2023/09/generative-retrieval/#towards-index-free-and-model-based-generative-retrieval

Generative Retrieval

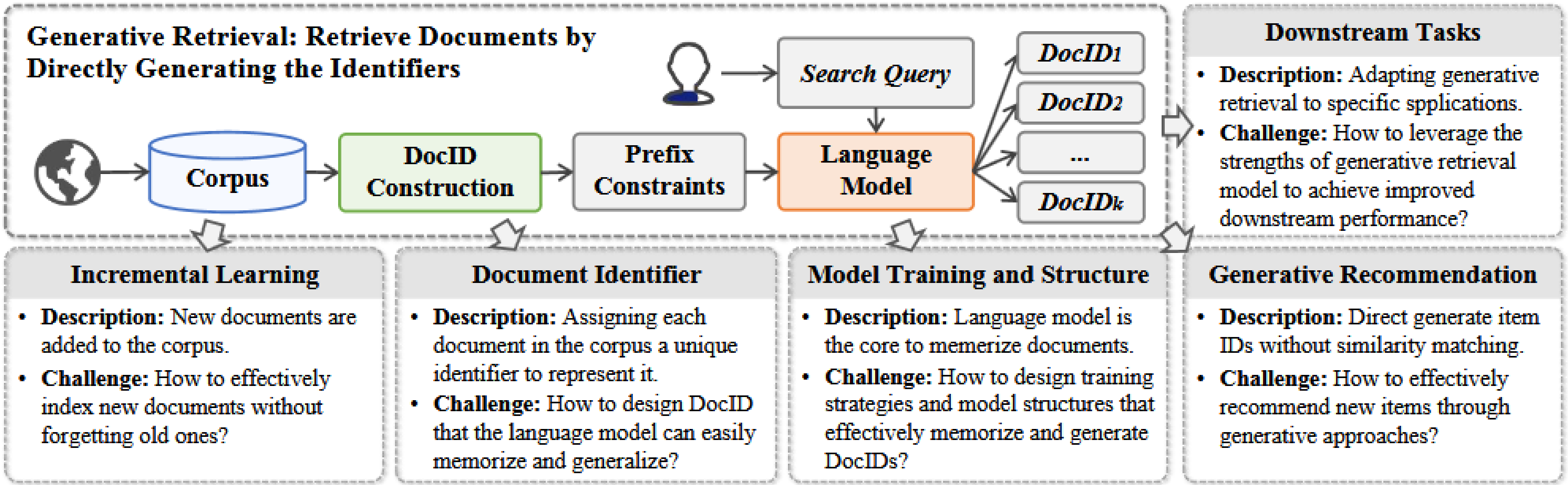
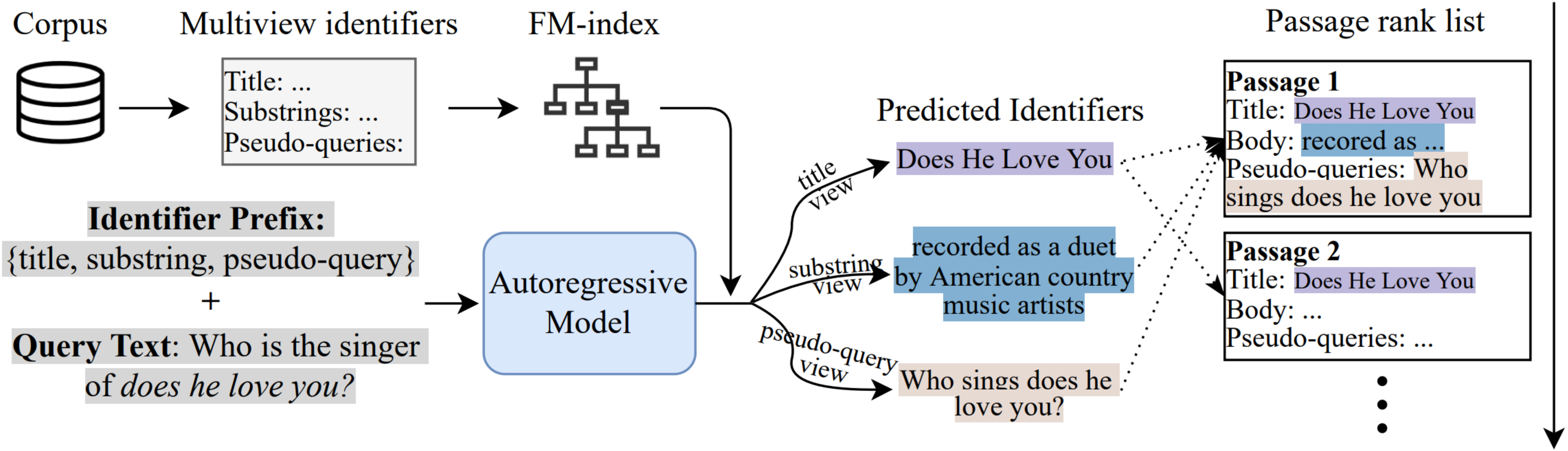


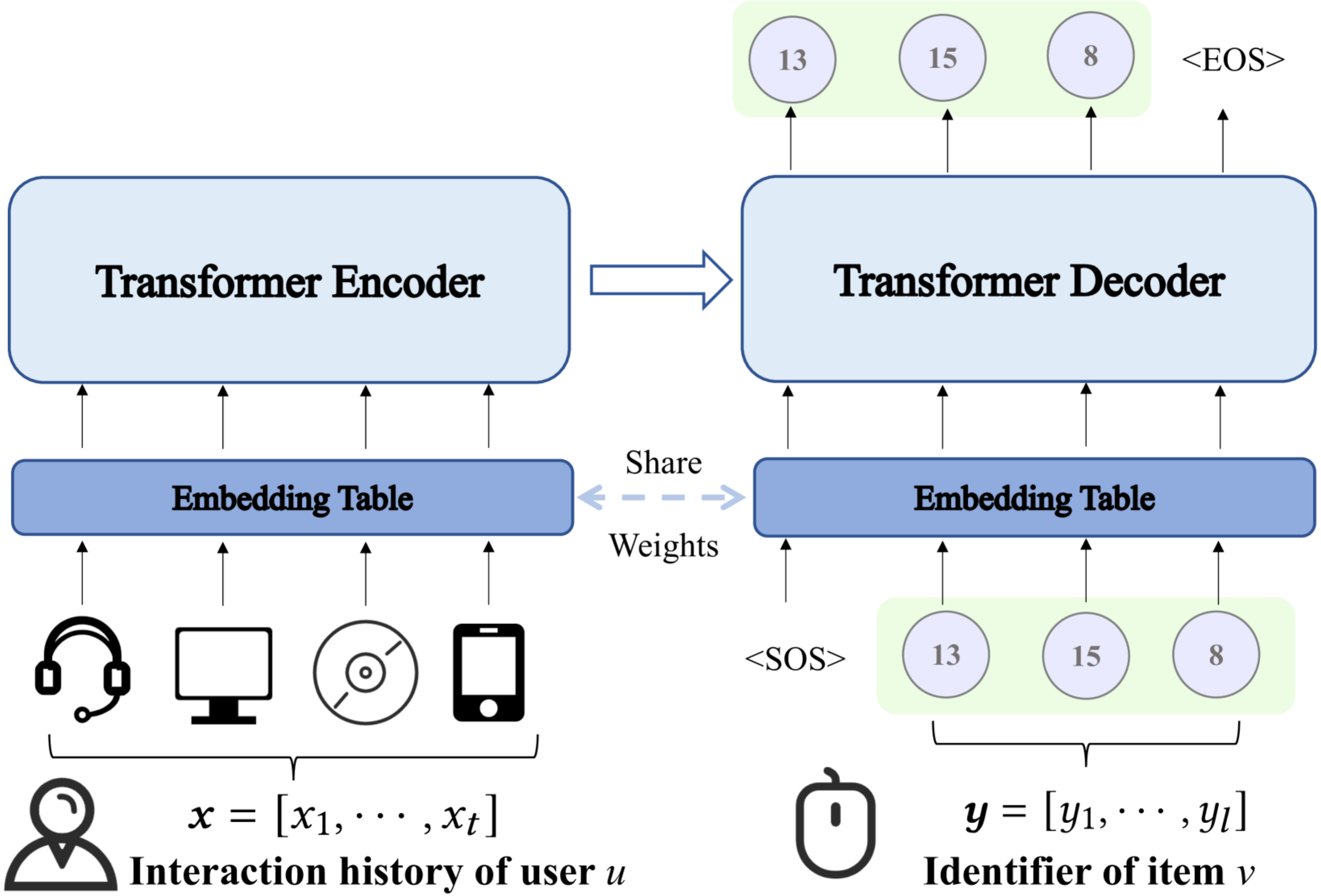
Fig. 4. A conceptual framework for a generative retrieval system, with a focus on challenges in incremental learning, identifier construction, model training and structure, and integration with downstream tasks and recommendation systems.

https://arxiv.org/pdf/2404.14851

Generative Retrieval: Contoh: MINDER



Li, Y., Yang, N., Wang, L., Wei, F., & Li, W. (2023). Multiview Identifiers Enhanced Generative Retrieval. *Annual Meeting of the Association for Computational Linguistics.*



https://arxiv.org/abs/2309.13375

Generative Retrieval --> Direct QA / Direct Information Accessing

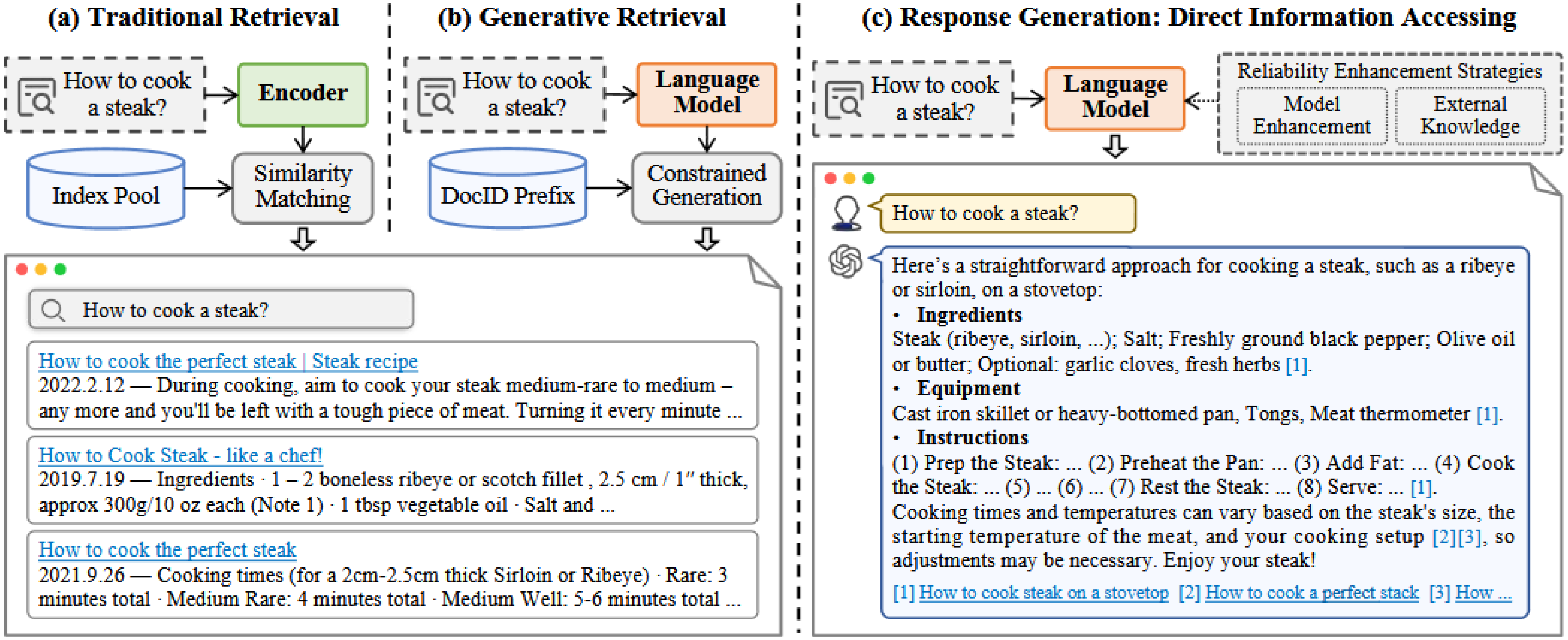


Fig. 1. Exploring IR Evolution: From Traditional to Generative Methods - This diagram illustrates the shift from traditional similarity-based document matching (a) to GenIR techniques. Current GenIR methods can be categorized into two types: generative retrieval (b), which retrieves documents by directly generating relevant DocIDs constrained by a DocID prefix tree; and response generation (c), which directly generates reliable and user-centric answers.

https://arxiv.org/pdf/2404.14851

Retrieval-Augmented Generation (RAG)

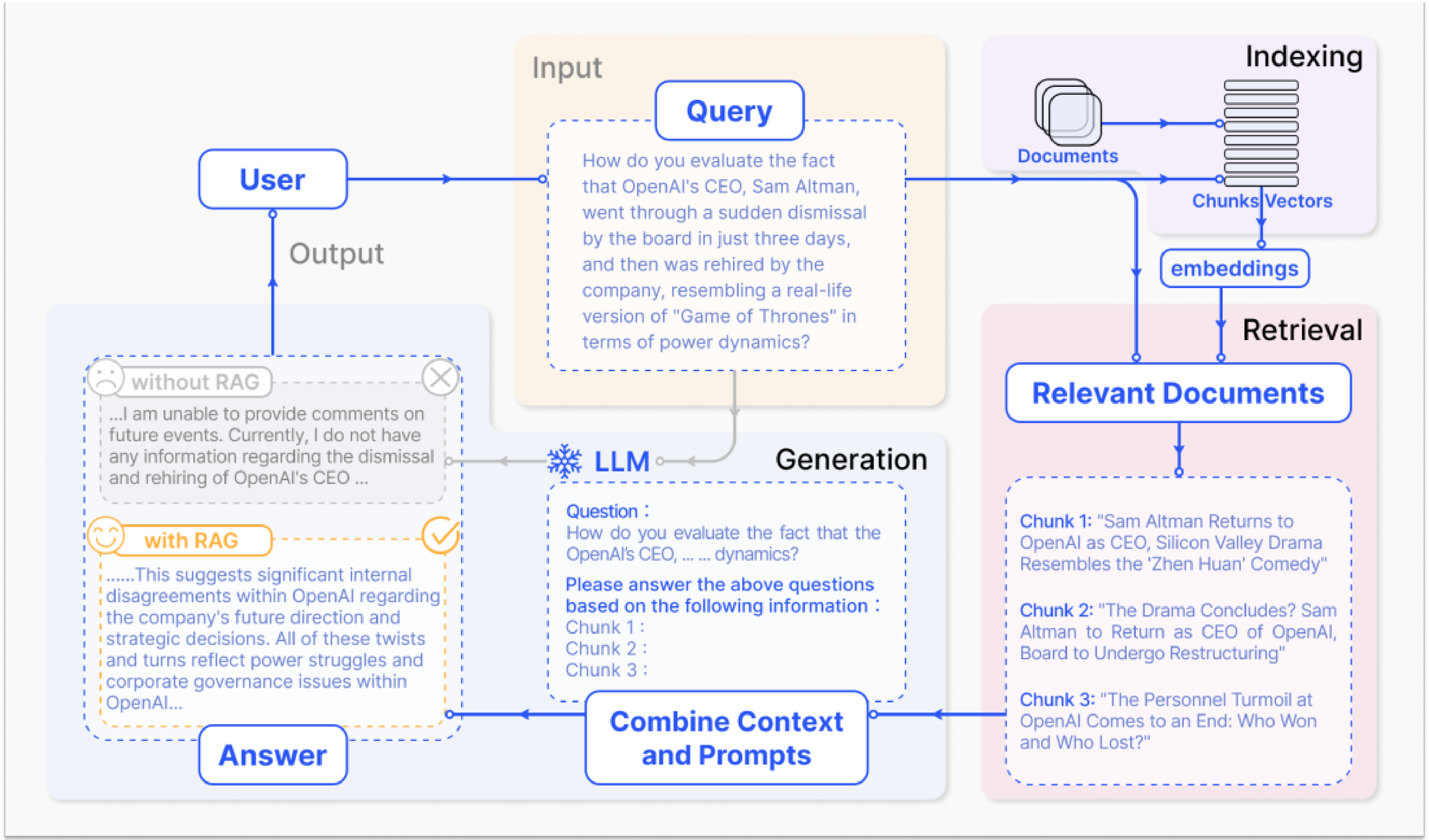
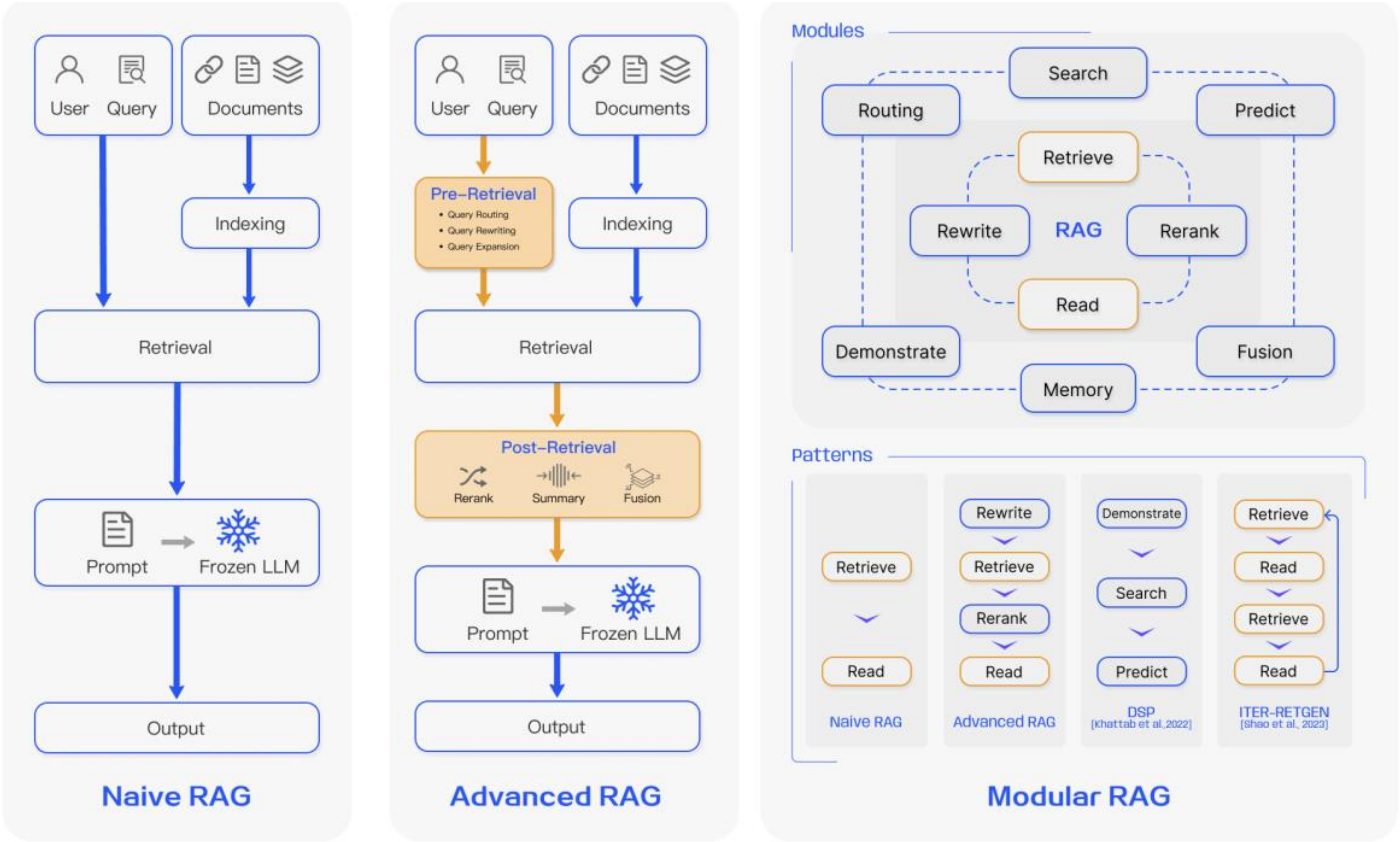


Fig. 2. A representative instance of the RAG process applied to question answering. It mainly consists of 3 steps. 1) Indexing. Documents are split into chunks, encoded into vectors, and stored in a vector database. 2) Retrieval. Retrieve the Top k chunks most relevant to the question based on semantic similarity. 3) Generation. Input the original question and the retrieved chunks together into LLM to generate the final answer.

https://arxiv.org/abs/2312.10997

Retrieval-Augmented Generation (RAG)



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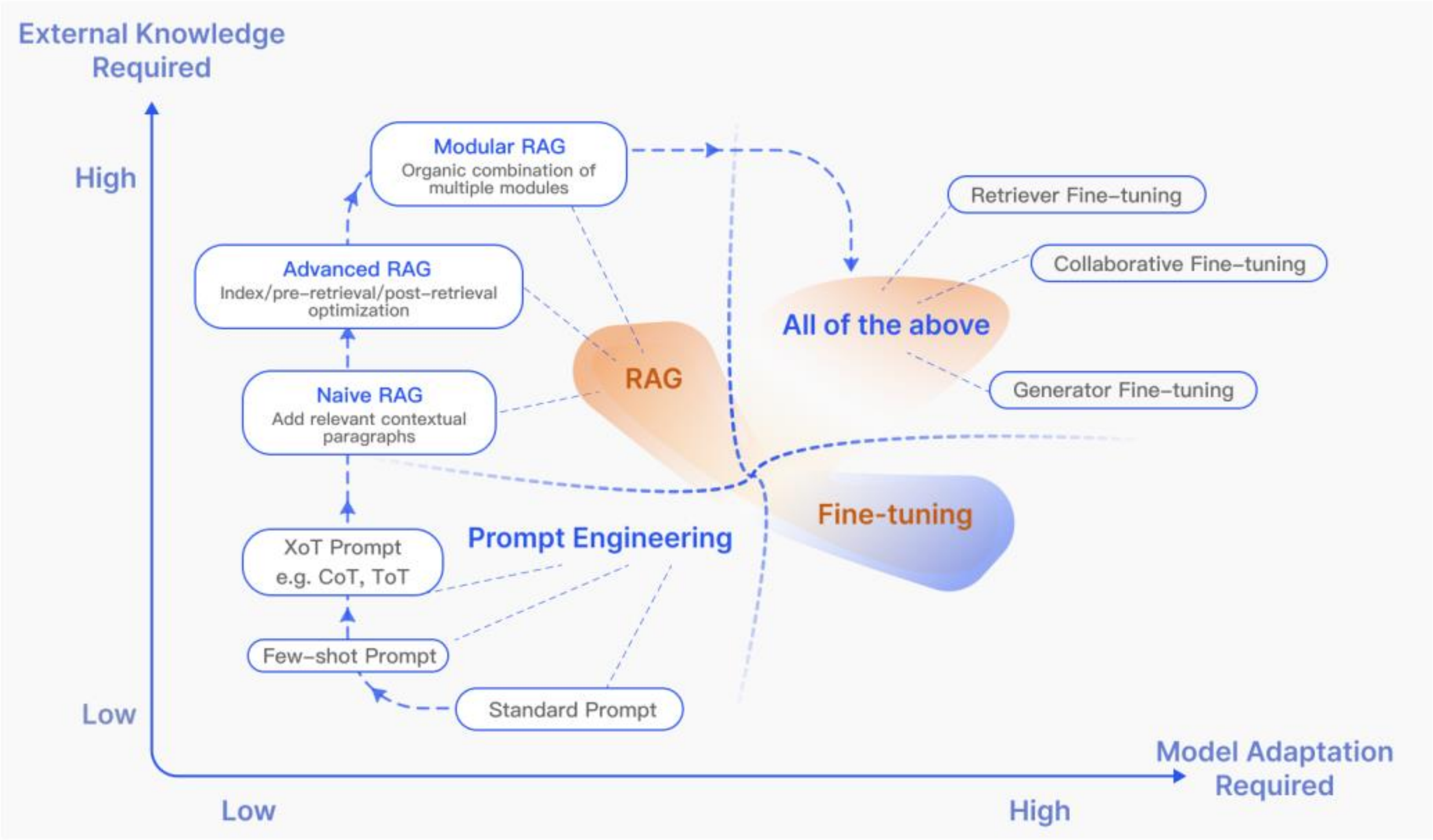

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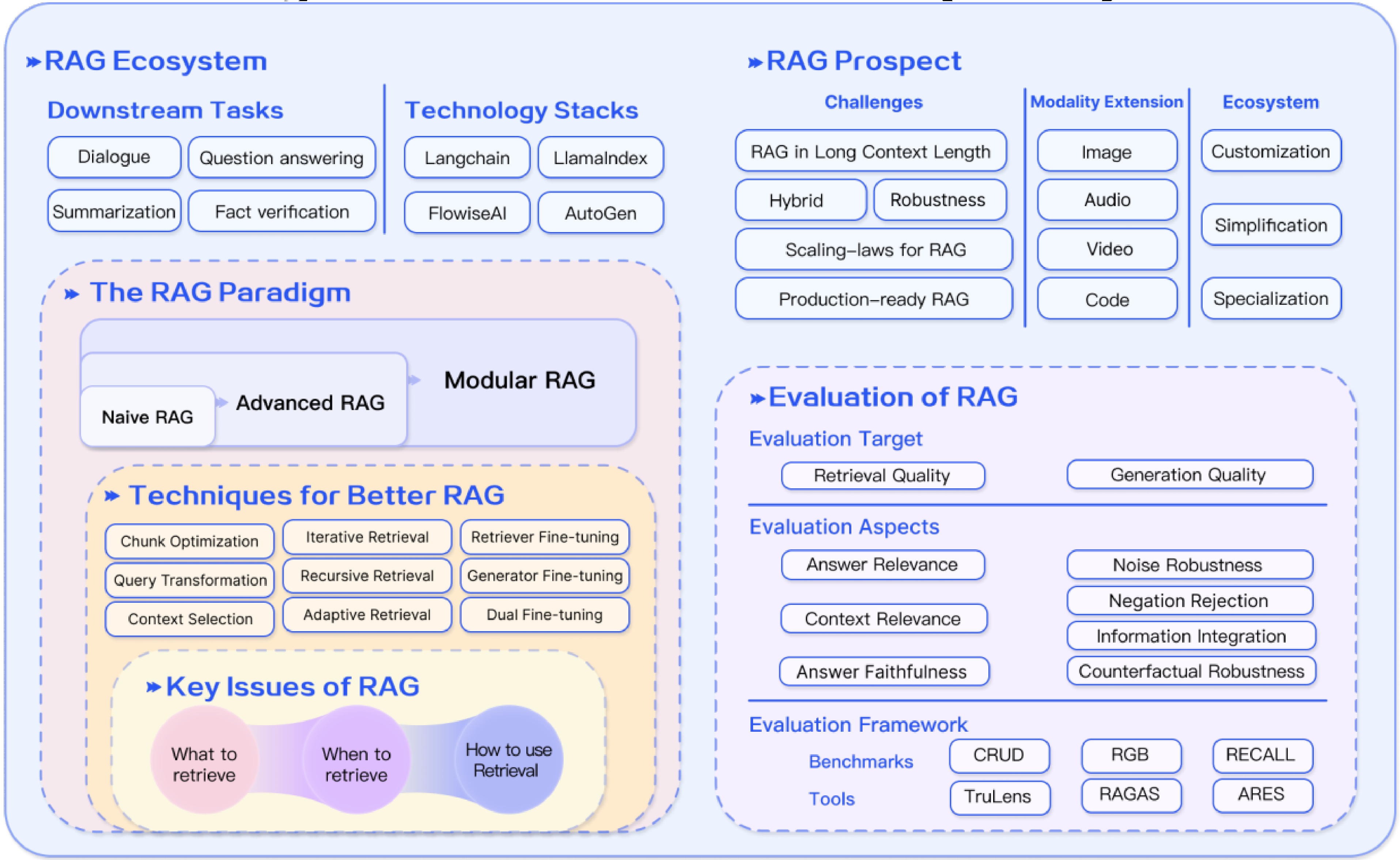


https://arxiv.org/abs/2312.10997

Summary: Manfaat LLMs untuk IR

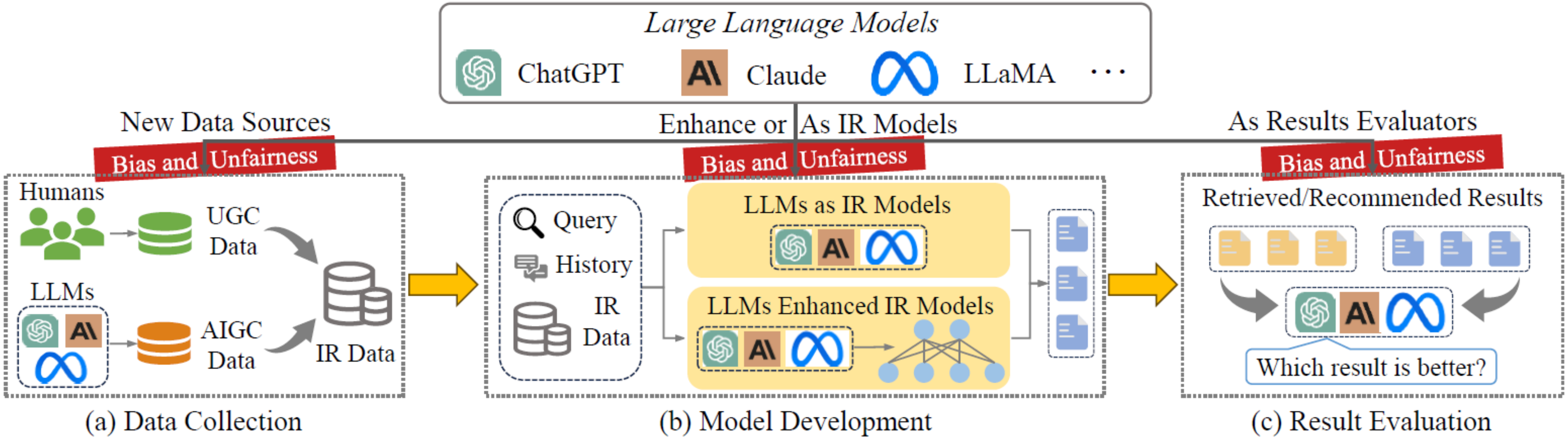


Figure 1: Overview of three stages of the intersection between LLMs and IR systems. (a) LLMs-generated content as new data sources for IR. (b) Incorporating LLMs to enhance or as IR models. (c) Adopting LLMs as results evaluators in IR systems.

https://arxiv.org/pdf/2404.11457

Bias & Fairness

Are your LLM-based IR biased or unfair?

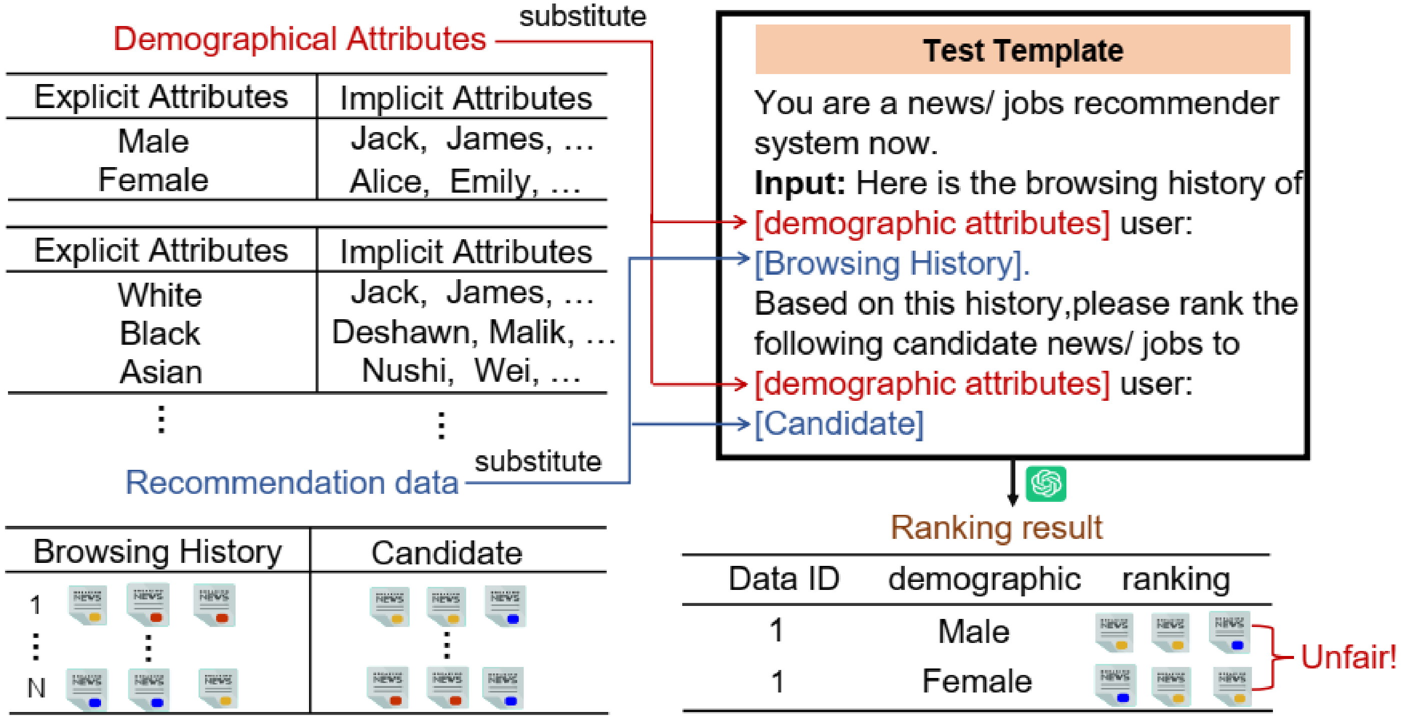


Figure 1: Overall workflow of our evaluation. The ranking list outputs by LLMs should be the same when replacing different sensitive attributes in prompts.

https://arxiv.org/pdf/2311.07054

Are your LLM-based IR biased or unfair?

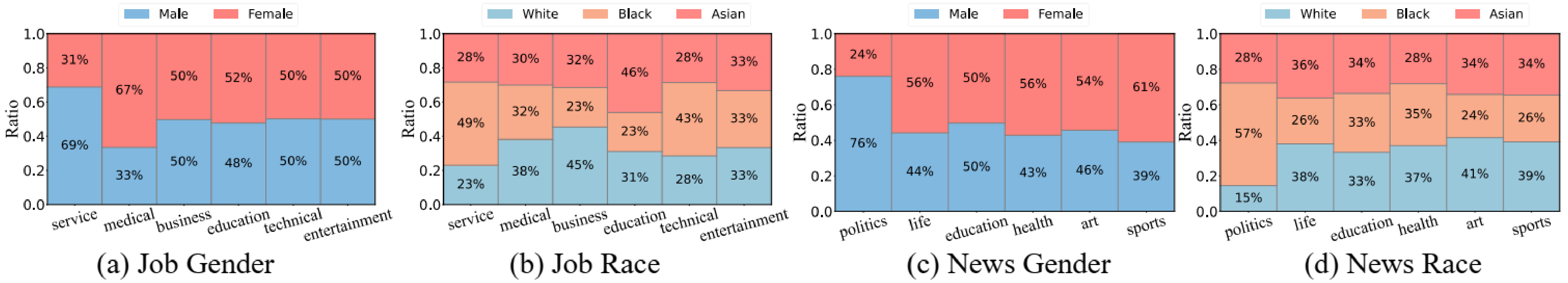


Figure 2: The discriminatory behaviors (*i.e.*, topic distribution $P(L_K(s))$) against certain topics of LLMs under job and news domain for user names belonging to different Gender and Race groups.

"LLMs deliver more political but less art news to black users…"
"As for job recommendations, LLMs tend to recommend more service-related but less educational jobs to black users…"
"LLMs are likely to give more business and educational jobs to White and Asian users"

https://arxiv.org/pdf/2311.07054

Are your LLM-based IR biased or unfair?

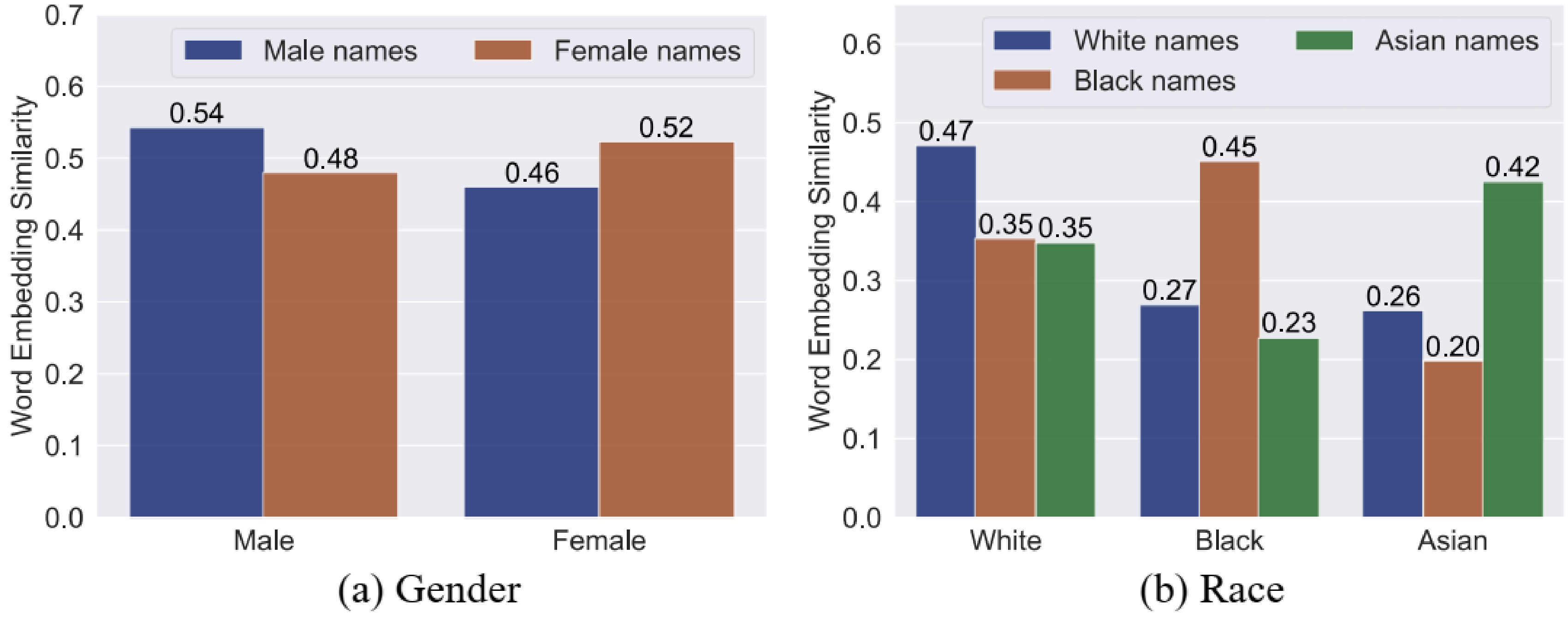
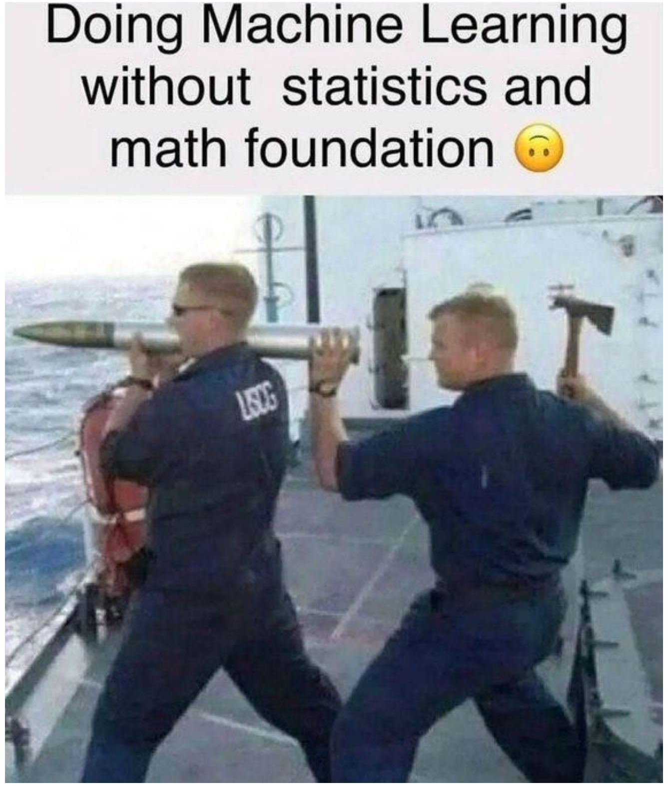


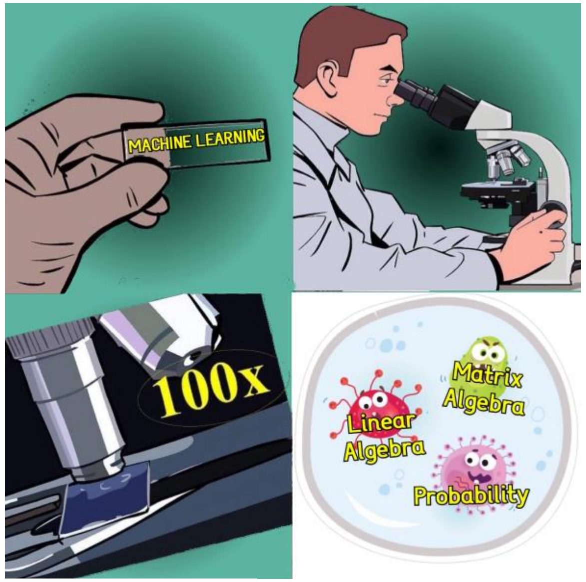
Figure 6: Word embeddings similarities between user names and sensitive attribute words.

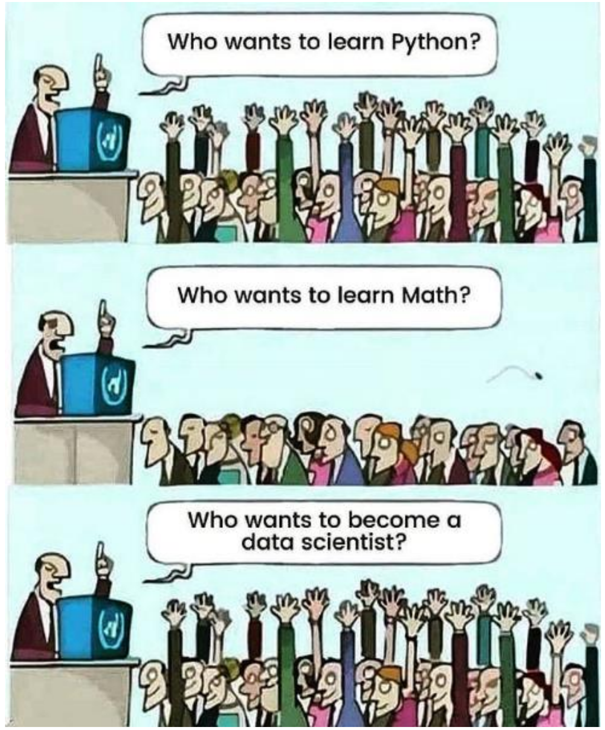
https://arxiv.org/pdf/2311.07054

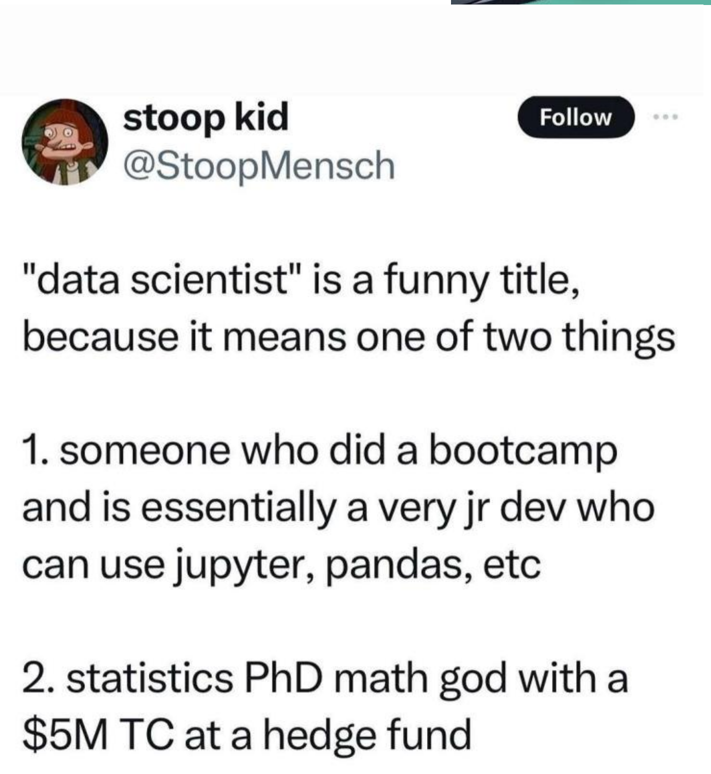
Few Last Words

Jangan tertipu (baca: "FOMO") dengan *buzz words*: AI, LLMs, Deep Learning, GenAI, Data Science, Big Data, …





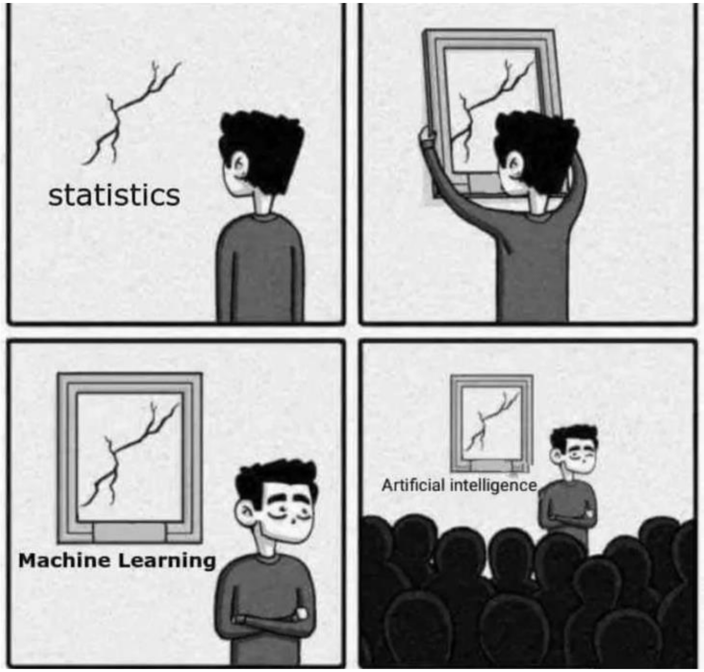



stoop kid
@StoopMensch
Follow

"data scientist" is a funny title, because it means one of two things

1. someone who did a bootcamp and is essentially a very jr dev who can use jupyter, pandas, etc

2. statistics PhD math god with a $5M TC at a hedge fund



Tanpa malu, meme-meme ini diperoleh dari Google Search.

MABA CS UI

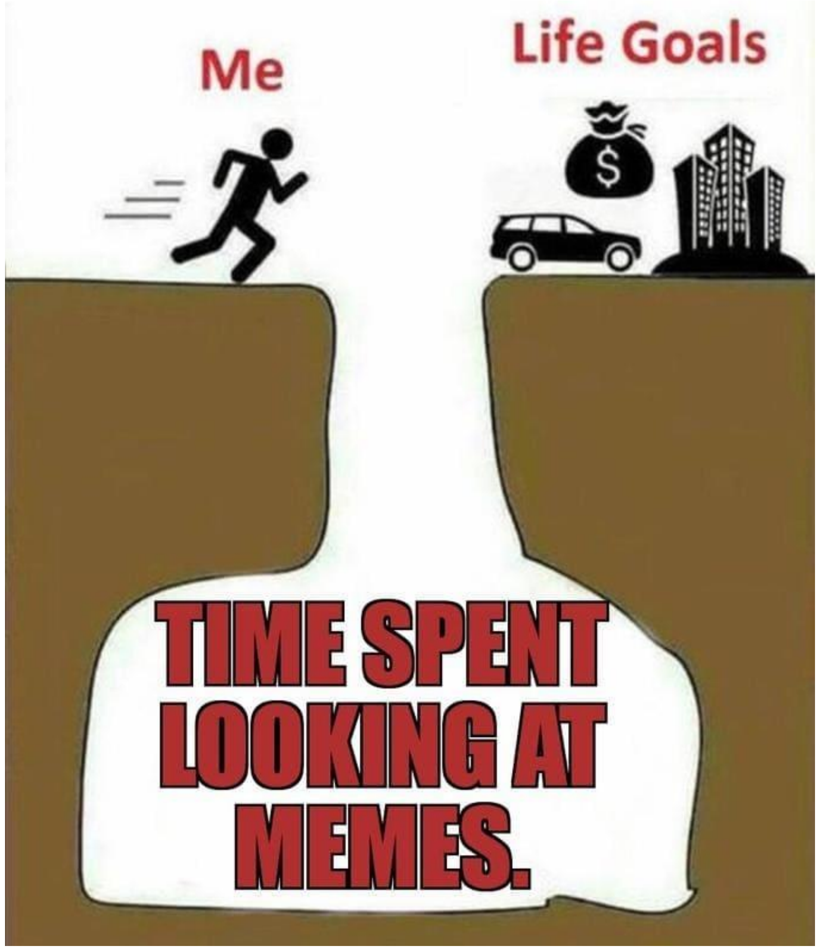
LULUS

Tanpa malu, meme-meme ini diperoleh dari Google Search.

Lupakan AI, Lupakan LLMs, Lupakan Deep Learning, dan semuanya ……… untuk sementara waktu.

Mari sejenak renungkan pertanyaan mendasar: **untuk apa Anda kuliah di Fasilkom UI**? Apa rencana 5-10 tahun kedepan? …

Life should be goal-directed (and yes, this is only my opinion; you may disagree with this).



Dan saya sudah **buang-buang waktu sekitar 1.5 jam** untuk cari meme buat presentasi kuliah hari ini.

Tanpa malu, meme-meme ini diperoleh dari Google Search.