Large Language Models for Information Retrieval: A Survey

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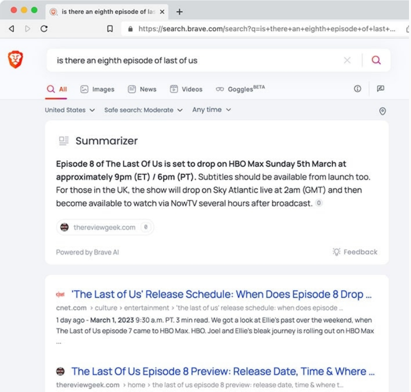
Today, do you search on Google or ask ChatGPT?

Introduction

- Traditional IR: retrieve and rank documents.
- LLM-powered IR: understand, summarize, and answer.
- Tools like Bing, Brave, Perplexity, and Gemini integrate LLMs to deliver instant summaries.
- **Users now expect answers, not just links.**



Example: Brave Search summarizing results via LLM.

Why This Survey Matters

- LLMs are transforming not just how we generate language, but how we **access and retrieve information**.
- Classical IR relies on indexing and keyword matching — effective, but limited in understanding intent.
- In contrast, LLMs enable:
    - semantic understanding,
    - multi-turn conversational context,
    - and end-to-end answer generation.

From IR Pipeline to LLM-enhanced Modules

- This survey focuses on how LLMs enhance the four core components of IR:
    1. **Query Rewriter**
    2. **Retriever**
    3. **Reranker**
    4. **Reader**
- Each module faces new opportunities — and new challenges — with the advent of LLMs.

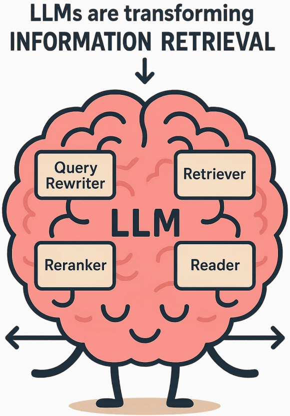


Illustration of modular IR pipeline adapted to LLMs. AI generated.

Background

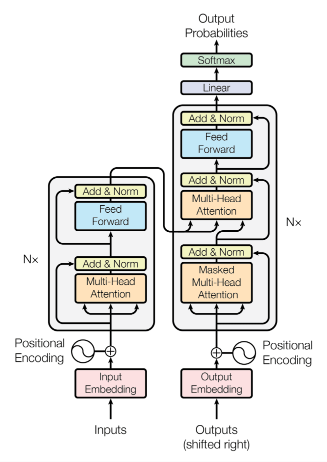
From Classical IR to Neural Retrieval

- Traditional IR systems[1] rely on:
  - keyword matching (e.g., Boolean models [1], BM25 [2]),
  - vector space models (cosine similarity),
  - statistical models (language models).
- Neural IR improves by leveraging:
  - learned dense embeddings,
  - pre-trained language models (e.g., BERT [3]).
- LLMs extend this further: beyond matching, toward **understanding and generation**.

[1] Lectures 3.1-3.4, BDDM A.A. 2024/25, F. **Bertini**

Large Language Models: A Quick Overview

- LLMs are transformer-based models [4] with billions of parameters.
- Key types:
  - **Encoder-only** – understanding
  - **Decoder-only** – generation
  - **Encoder-decoder** – flexible
- Learning styles:
  - **In-context learning**
  - **Fine-tuning**
  - **RAG (retrieval-augmented generation)**



Source: Vaswani et al., "Attention Is All You Need", 2017.

Query Rewriting

- First step in the IR pipeline: improve the quality of the user query.
- Classical techniques: query expansion, pseudo-relevance feedback.
- LLMs allow rewriting queries using:
  - **Prompting**: zero/few-shot style reformulation.
  - **Fine-tuning**: domain-specific transformations.
  - **Knowledge distillation**: compress LLM behavior into smaller models.
- Particularly useful in:
  - *ad-hoc* search with ambiguous queries,
  - *multi-turn* conversational search.

Query2Doc: Few-shot Pseudo-Document Generation

- Query2Doc [5] reframes query rewriting as **text generation**.
- It uses **few-shot prompting** (in-context learning) to guide the LLM.
- Prompt examples are drawn from the MSMARCO dataset [6].
- The model generates a *pseudo-document* that simulates a relevant passage, used to retrieve real documents more effectively.

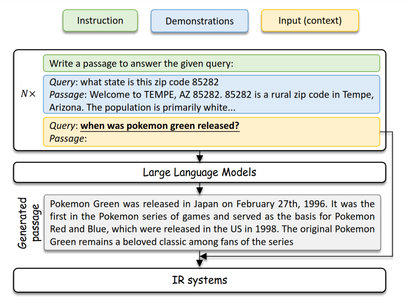


Figure from the original paper.

- **Concept drift** [7, 8, 9]:
  - LLMs may inject unrelated details when rewriting queries.
  - This can dilute the core intent of the original question.
  - Often caused by the LLM's tendency to be verbose or over-informative.
- **Retrieval performance degradation** [10]:
  - Expansion improves weak retrievers, but often **harms stronger ones**.
  - Expansion may help align queries with the expected format when the corpus diverges from the training distribution.
- **Key takeaway:**
  - Query rewriting must be **target-aware** and retriever-aware.
  - More rewriting $\neq$ better results.

Retriever

- The retriever selects candidate documents likely to be relevant to a query.
- **Classical methods**:
  - Sparse retrievers — keyword-based (e.g., BM25 [2]).
  - Dense retrievers — neural representations (e.g., DPR [11]).
- **LLMs improve retrieval** in two complementary ways:
  1. **Data augmentation** — generate synthetic queries and labels for dense retrievers.
  2. **Model enhancement** — build better retrievers using LLM architectures.

LLMs for Data Augmentation in Retrieval

- **Motivation:** manual annotation of training data is expensive and domain-specific.
- LLMs can generate synthetic training signals:
  - **Pseudo-query generation:** generate questions for existing documents (e.g., InPairs [12] + GPT-3 [13]).
  - **Relevance label generation:** assign soft relevance scores to query-document pairs (e.g., ART [14]), used as training targets for dense retrievers.
- Enables few-shot and zero-shot retrieval training across domains.

- LLMs can serve as the **retriever itself**, not just as a data generator.
- Three main approaches:
  1. **Dense retrievers:** use LLMs as encoders to map queries and documents into vector space (e.g., GTR [15], RepLLaMA [16])
  2. **Task-aware retrievers:** prepend task-specific instructions to queries to guide retrieval (e.g., TART [17])
  3. **Generative retrievers:** LLM decodes document identifiers directly from queries (e.g., DSI [18], LLM-URL [19])
- These models leverage LLMs' semantic understanding for more accurate and flexible retrieval.

Reranker

Reranker: Second-pass Filtering

- The reranker receives the candidate documents from the retriever.
- It refines the ranking by evaluating the **query-document relevance** more precisely.
- With LLMs, three usage paradigms emerge:
    1. Supervised rerankers
    2. Unsupervised rerankers
    3. LLM-assisted data augmentation
- **Goal:** assign better scores → improve top-ranked results.

- LLMs are fine-tuned on labeled datasets (e.g., MSMARCO) to learn relevance signals.
- Three architectural types:
  1. **Encoder-only:** monoBERT [20] uses the embedding for scoring (`[CLS] query [SEP] document [SEP]`).
  2. **Encoder-decoder:** T5 [21] generates a classification token (`true`/`false`).
  3. **Decoder-only:** RankLLaMA [22] formats input as a prompt (`query: {query} document: {document} [EOS]`) and uses the last token's embedding.
- Loss functions: cross-entropy, pairwise, listwise.

Unsupervised Reranking with LLMs

- Large LLMs (10B+ params) make fine-tuning difficult, so prompting is used for unsupervised reranking.
- Three main methods:
  1. **Pointwise**: Score each query-document pair independently. **Open-source models required**: to access the logits of the ”YES” and ”NO” tokens.
  2. **Listwise**: rank a list of documents at once; better accuracy but costly and sensitive to input order.
  3. **Pairwise**: compare document pairs to build ranking; good accuracy but computationally expensive.
- Prompt engineering and few-shot examples improve results.

Reader

- The reader generates answers from top-ranked documents retrieved by the IR system.
- Reader models differ in how they interact with the retrieval process:
  1. **Passive Readers** — receive documents from the IR system and generate answers.
     - ⋆ *Once-Retrieval* (e.g., RAG [23]): retrieve once at the beginning.
     - ⋆ *Periodic-Retrieval* (e.g., RETRO [24]): retrieve during generation (every n tokens).
     - ⋆ *Aperiodic-Retrieval* (e.g., FLARE [25]): retrieve when confidence is low.

LLM-Based Reader: Typologies and Strategies II

2. **Active Readers** — LLMs autonomously decide when and what to retrieve.
   - Formulate follow-up queries (e.g., Self-Ask [26]);
   - Build reasoning chains across retrieval iterations;
3. **Compressors** — reduce retrieved content to fit LLM input limits.
   - *Extractive* (e.g., LeanContext [27]) or *abstractive* (e.g., TCRA [28]) compression.

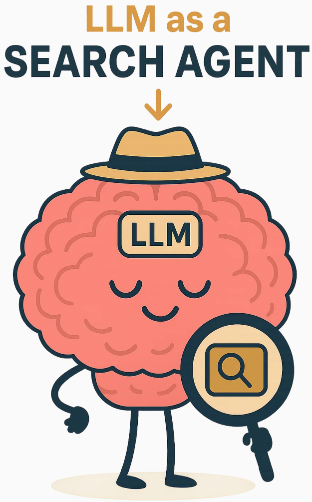
- These strategies balance accuracy, interactivity, and computational efficiency.

Retrieval-Augmented Generation (RAG)

- **RAG** [23] integrates a retriever and a generator in a single architecture.
- At inference time:
  - A retriever selects top-k documents given a query.
  - A generator (LLM) conditions on both query and documents to produce an answer.
- Advantages:
  - Combines factual grounding (retriever) with fluent generation (LLM).
  - Allows open-book reasoning with up-to-date information.
- Limitation: risk of hallucinating content not grounded in the retrieved passages.

Search Agents

- **Goal:** mimic human browsing to search, interpret, and synthesize autonomously.
- **WebGPT** [29]
  - Answers questions via web browsing
  - Cites sources; reward model encourages factuality
- **ReAct** [30]
  - Interleaves *Thought* and *Action*
  - Generates reasoning steps and search commands



LLM as a search agent. AI generated.

Conclusion

Looking Ahead: Future Directions

- **Query rewriting**: improve personalization and reward-aware reformulation.
- **Retriever**: reduce latency, support multimodal and updatable indexes.
- **Reranker**: enhance online efficiency and adapt to diverse ranking tasks.
- **Reader**: increase factuality and snippet selection to avoid hallucinations.
- **Evaluation**: go beyond relevance—measure generation quality and faithfulness.

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