Generative Information Retrieval

ECIR 2024 tutorial

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https://ecir2024-generativeir.github.io/

March 28, 2024

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About the presenters

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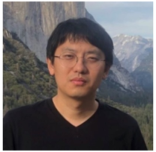

Zhaochun Ren

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Jiafeng Guo

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Maarten de Rijke

Faculty

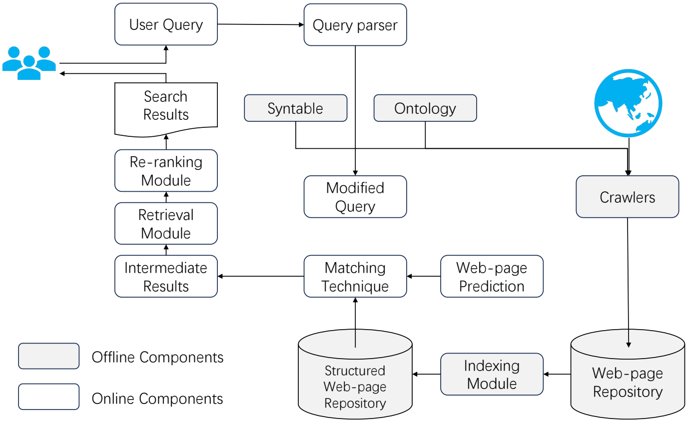
@UvA

Information retrieval

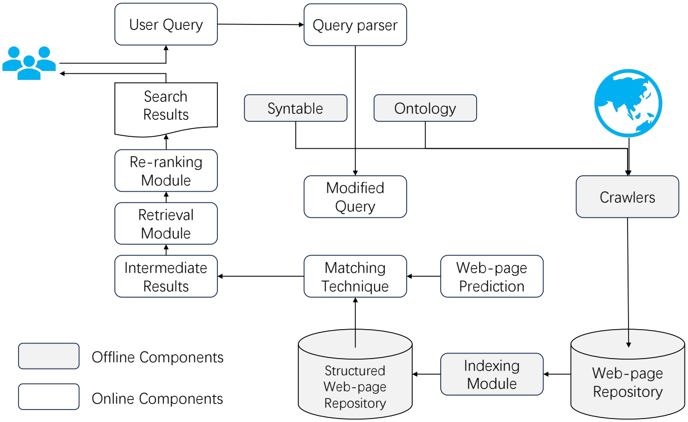
Information retrieval (IR) is the activity of obtaining information system resources that are relevant to an information need from a collection of those resources.

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

Complex architecture design behind search engines

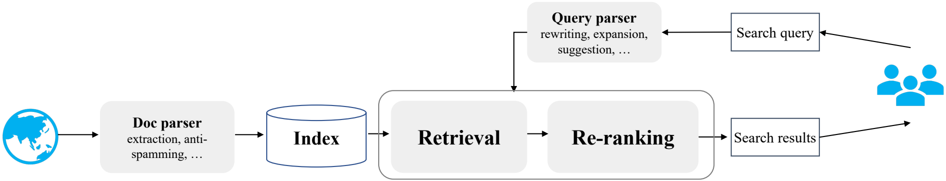


Complex architecture design behind search engines



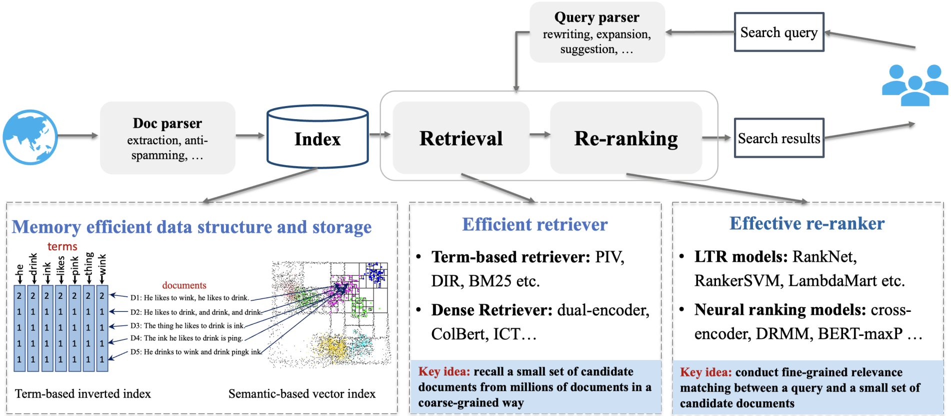
- **Advantages**:
  - Pipelined paradigm has withstood the test of time
  - Advanced machine learning and deep learning approaches applied to many components of modern systems

Core pipelined paradigm: Index-Retrieval-Ranking



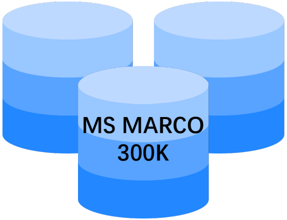
- Index: Build an index for each document in the entire corpus
- Retriever: Find an initial set of candidate documents for a query
- Re-ranker: Determine the relevance degree of each candidate

Index-Retrieval-Ranking: Disadvantages



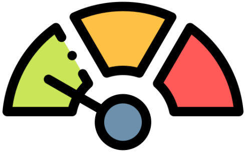
- **Effectiveness**: Heterogeneous ranking components are usually difficult to be optimized in an end-to-end way towards the global objective

Index-Retrieval-Ranking: Disadvantages



Big storage

GTR (Dense retrieval)
Memory size 1430MB



Slow inference speed

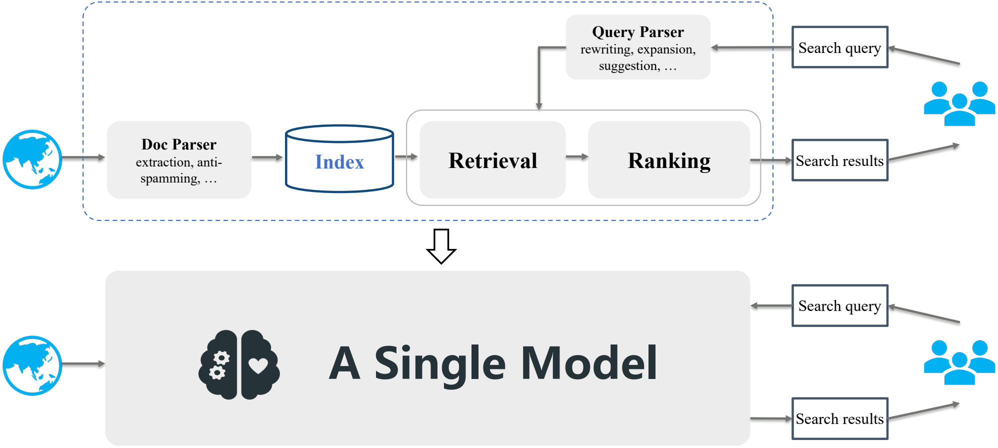
GTR (Dense retrieval)
Online latency 1.97s

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

Source: [Sun et al., 2023]

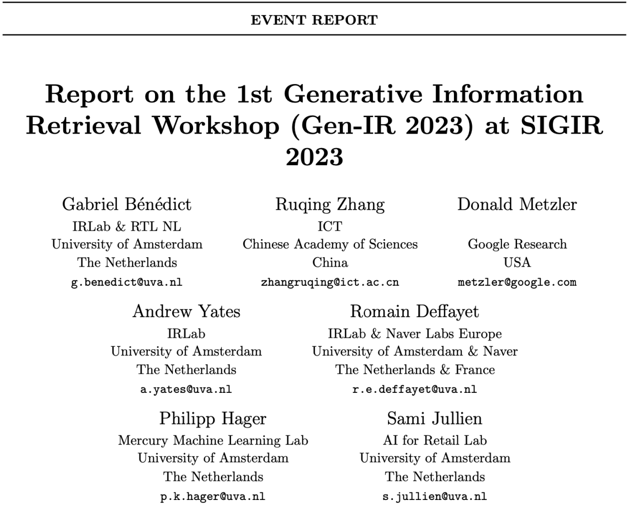
What if we replaced the pipelined architecture with a single consolidated model that efficiently and effectively encodes all of the information contained in the corpus?

Opinion paper: A single model for IR



Source: [Metzler et al., 2021]

Report on the 1st Generative Information Retrieval Workshop at SIGIR 2023



https://coda.io/@sigir/gen-ir

Generative language models

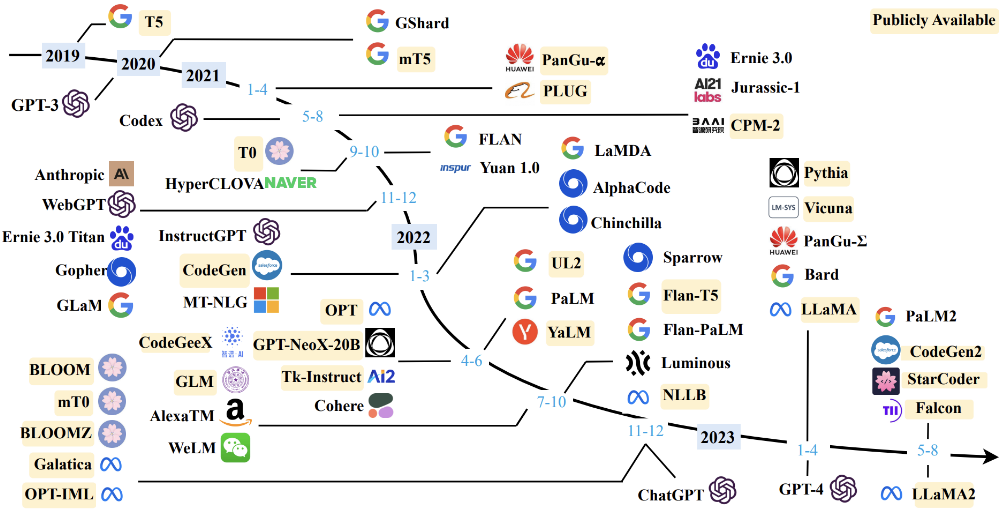


Image source: [Zhao et al., 2023]

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

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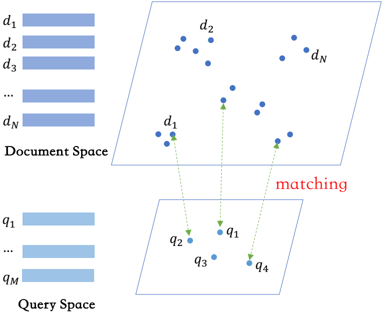
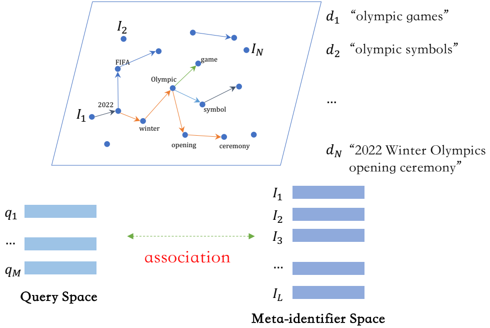
- **Input**: A sequence of query words
- **Output**: A sequence of document identifiers

Neural IR models: Discriminative vs. Generative

Discriminative



Generative



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

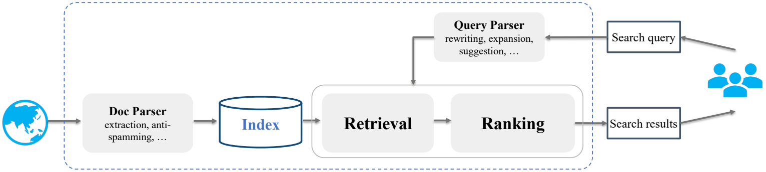
(probabilistic ranking principle)

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

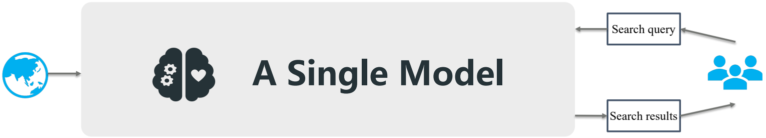
(query likelihood)

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

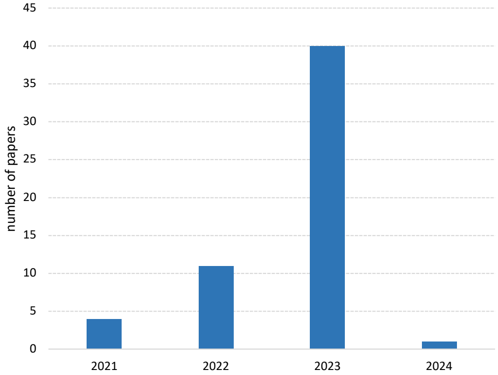
Why generative retrieval?

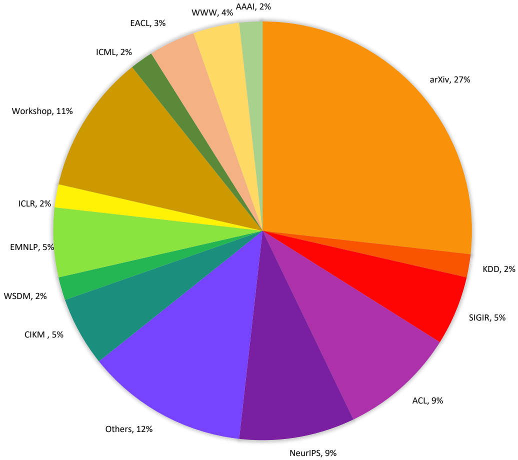
	Dense retrieval	Generative retrieval
Memory size (MS MARCO 300K)	GTR 1430MB	GenRet 860MB
Online latency	GTR 1.97s	GenRet 0.16s

- **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 March 13, 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)
  - **Problem definitions**
  - **Docid design**
  - **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
09:00-09:10	Section 1: Introduction	Maarten de Rijke
09:10-09:30	Section 2: Definitions & Preliminaries	Zhaochun Ren
09:30-10:10	Section 3: Docid design	Yubao Tang

15min coffee break

Time	Section	Presenter
10:25-11:00	Section 4: Training approaches	Zhaochun Ren
11:00-11:20	Section 5: Inference strategies	Yubao Tang
11:20-11:30	Section 6: Applications	Yubao Tang
11:30-11:50	Section 7: Challenges & Opportunities	Maarten de Rijke
11:50-12:00	Q & A	All

Section 2:
Definitions & Preliminaries

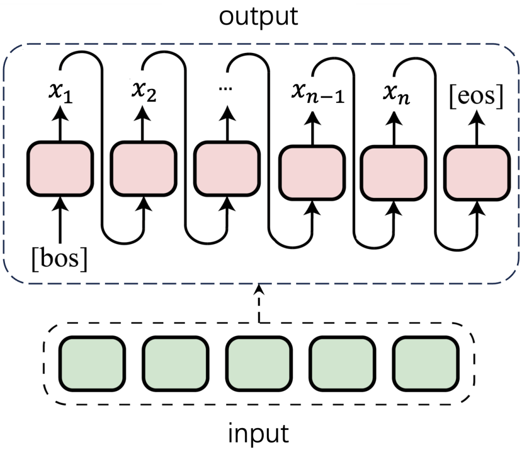
Generative retrieval: Definition

Generative retrieval (GR) aims to directly generate the identifiers of information resources (e.g., docids) that are relevant to an information need (e.g., an input query) in an autoregressive fashion

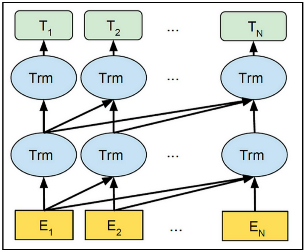
"Transformer Memory as a Differentiable Search Index". Tay et al. [2022]; "Autoregressive Entity Retrieval". De Cao et al. [2021]

Autoregressive formulation

$$P(x_n | x_1, x_2, \ldots, x_{n-1})$$



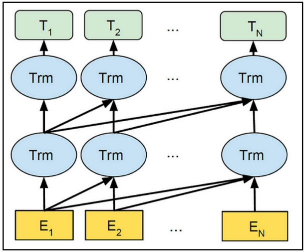
Autoregressive models



Decoder-only

Image source: Kenton and Toutanova [2019] and Retrieval-based Language Models and Applications

Autoregressive models



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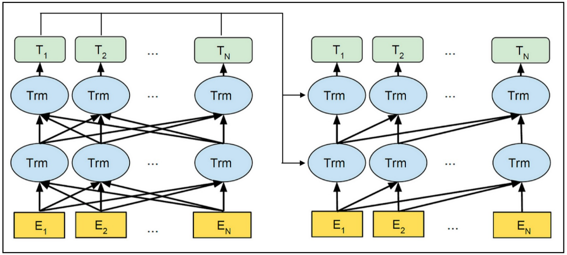

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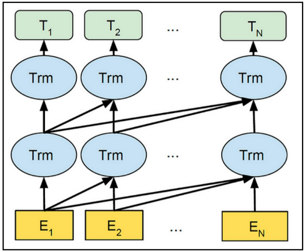

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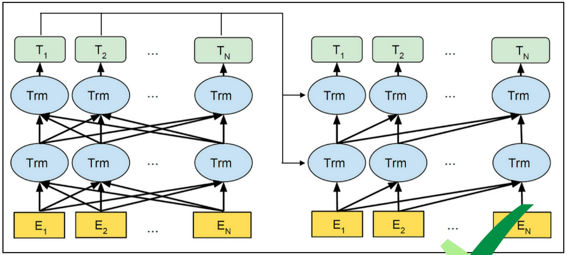


Encoder-decoder

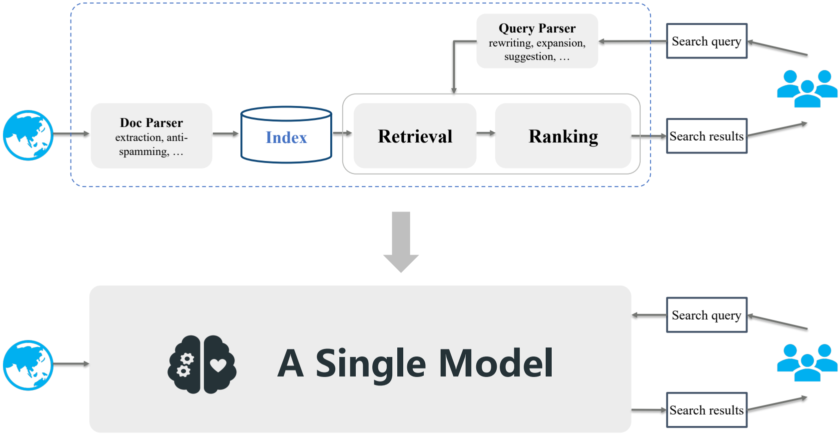
Image source: Kenton and Toutanova [2019] and Retrieval-based Language Models and Applications

Generative retrieval: Definition

GR usually exploits a Seq2Seq encoder-decoder architecture to generate a ranked list of docids for an input query, in an autoregressive fashion

"Transformer Memory as a Differentiable Search Index". Tay et al. [2022]; "Autoregressive Entity Retrieval". De Cao et al. [2021]

Revisit the key idea



Two basic operations in GR

- Indexing: To **memorize information about each document**, a GR model should learn to associate the content of each document with its corresponding docid

Source: [Tay et al., 2022]

Two basic operations in GR

- Indexing: To **memorize information about each document**, a GR model should learn to associate the content of each document with its corresponding docid
- Retrieval: Given an input query, a GR model should **return a ranked list of candidate docids** by autoregressively generating the docid string

Source: [Tay et al., 2022]

Indexing: Formulation

Given:

- A corpus of documents D;
- A corresponding docid set I_D;

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The indexing task directly takes each original document $d \in D$ as input and generates its docid $id \in I_D$ as output in a straightforward Seq2Seq fashion, i.e.,

$$\mathcal{L}_{Indexing}(D, I_D; \theta) = -\sum_{d \in D} \log P(id \mid d; \theta),$$

where θ denotes the model parameters, and $P(id \mid d; \theta)$ is the likelihood of each docid id given the document d

Retrieval: Formulation

Given:

- A query set Q;
- A set of relevant docids I_Q;

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The retrieval task aims to generate a ranked list of relevant docids $id^q \in I_Q$ in response to a query $q \in Q$ with the indexed information, i.e.,

$$\mathcal{L}_{Retrieval}(Q, I_Q; \theta) = -\sum_{q \in Q} \sum_{id^q \in I_Q} \log P(id^q \mid q; \theta),$$

where $P(id^q \mid q; \theta)$ is the likelihood of each relevant docid id^q given the query q

Training

Following the above two basic operations, i.e., indexing and retrieval, a single model can be optimized directly in an end-to-end manner towards a global objective,

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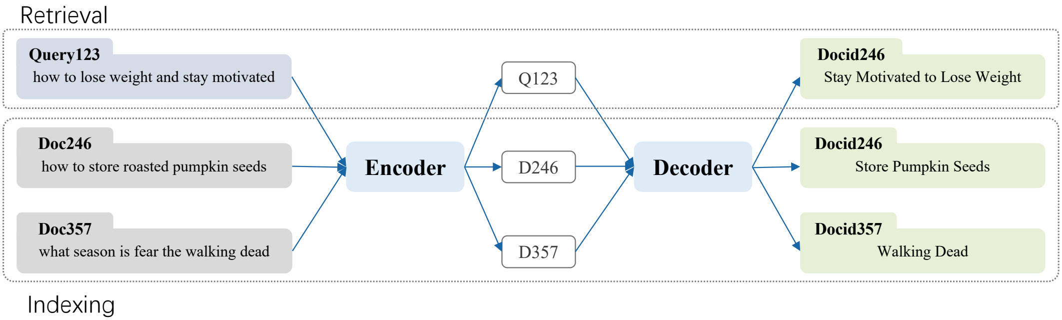
$$\mathcal{L}_{Global}(Q, D, I_D, I_Q; \theta) = \mathcal{L}_{Indexing}(D, I_D; \theta) + \mathcal{L}_{Retrieval}(Q, I_Q; \theta)$$

Training: An example



Joint learning the indexing and retrieval tasks

Inference

- Once such a GR model is learned, it can be used to generate candidate docids for a test query q_t, all within a single, unified model,

$$w_t = GR_\theta(q_t, w_0, w_1, \ldots, w_{t-1}),$$

where w_t is the t-th token in the docid string and the generation stops when decoding a special EOS token

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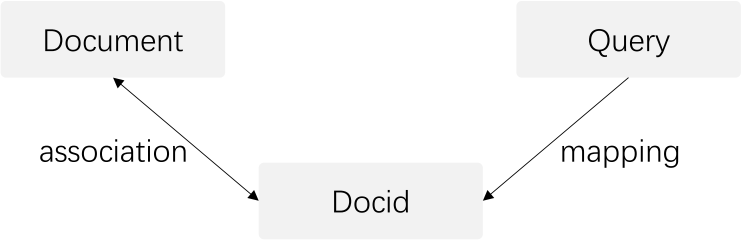
  where w_t is the t-th token in the docid string and the generation stops when decoding a special EOS token
- The docids generated with the top-K highest likelihood (joint probability of generated tokens within a docid) form a ranking list in descending order

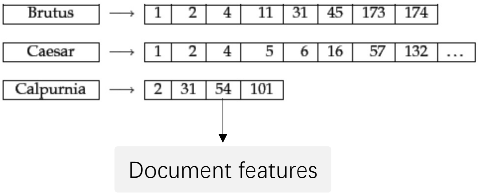
Research questions (1): Docid design



Unfortunately, there is no natural identifier for each document!

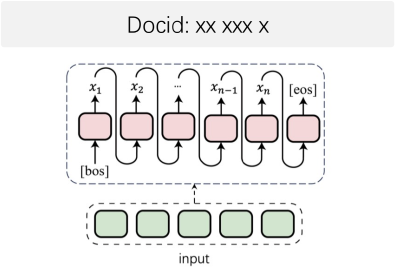
Research questions (1): Docid design

Traditional information retrieval



As an entry

Generative retrieval



For generation

Image source: Information retrieval book

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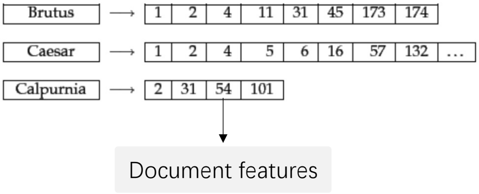

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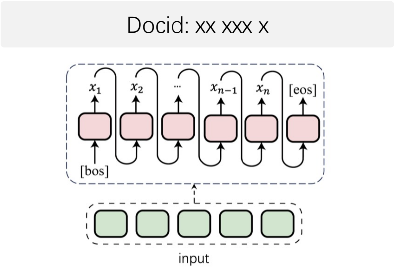


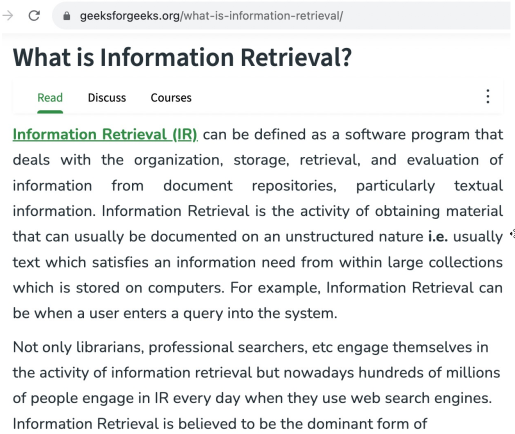
For generation

How to design docids for documents?

Image source: Information retrieval book

Research questions (1): Docid design

- Possible design choices

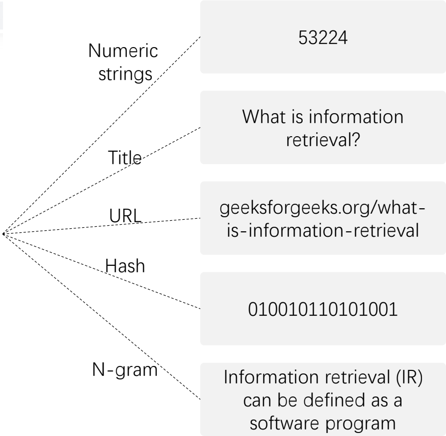

geeksforgeeks.org/what-is-information-retrieval/

What is Information Retrieval?

Read Discuss Courses

Information Retrieval (IR) can be defined as a software program that deals with the organization, storage, retrieval, and evaluation of information from document repositories, particularly textual information. Information Retrieval is the activity of obtaining material that can usually be documented on an unstructured nature **i.e.** usually text which satisfies an information need from within large collections which is stored on computers. For example, Information Retrieval can be when a user enters a query into the system.

Not only librarians, professional searchers, etc engage themselves in the activity of information retrieval but nowadays hundreds of millions of people engage in IR every day when they use web search engines. Information Retrieval is believed to be the dominant form of



Document source: Geeksforgeeks

Challenges of docid design

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  - Long (e.g., 728 hash code) vs. Short docids (e.g., n-grams)
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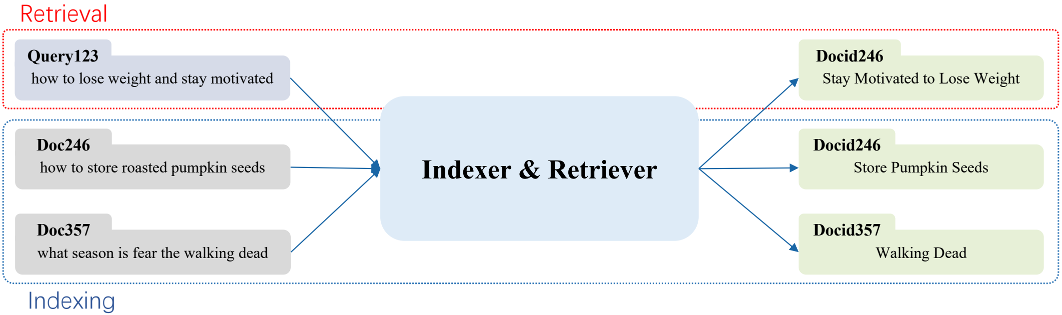
We will tackle these questions in Section 3!

Research questions (2): Training approaches



Joint learning process of the indexing and retrieval tasks

Challenges of training approaches

- **How to memorize the whole corpus effectively and efficiently?**
  - Rich information in documents
  - Limited labeled data

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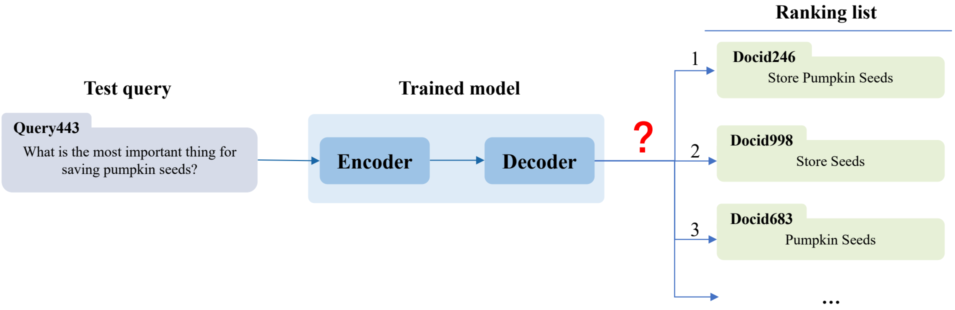
Research questions (3): Inference strategies



The generation process is different from general language generation

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Research questions (4): Applications

How to employ generative retrieval models in different downstream tasks?

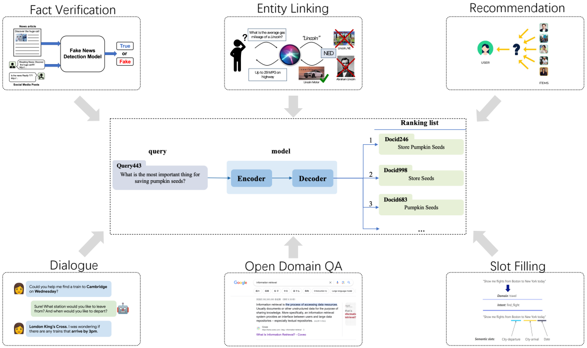
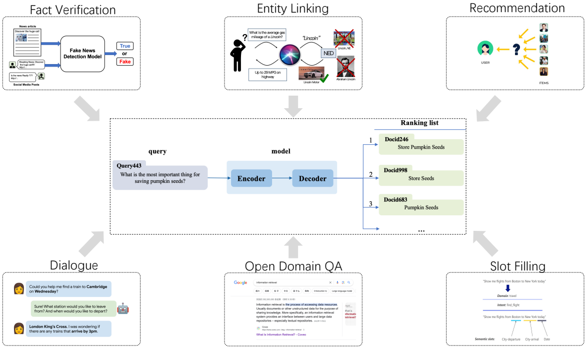


Image source: Murayama [2021], Stanford blog, Froomle AI, Google, Zero-shot blog, and Heck and Heck [2020]

Research questions (4): Applications

How to employ generative retrieval models in different downstream tasks?



We will tackle this question in Section 6!

Image source: Murayama [2021], Stanford blog, Froomle AI, Google, Zero-shot blog, and Heck and Heck [2020]

Section 3:
Docid design

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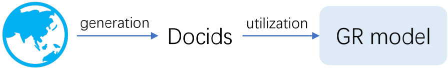
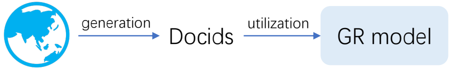
- Would the choices of different docids affect the model performance (effectiveness, capacity, etc.)?

Categorization of docids

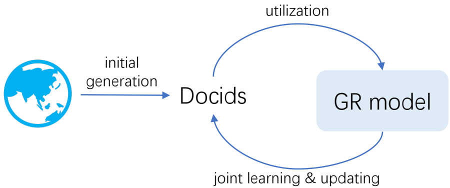


- Pre-defined static docids

Categorization of docids



- Pre-defined static docids

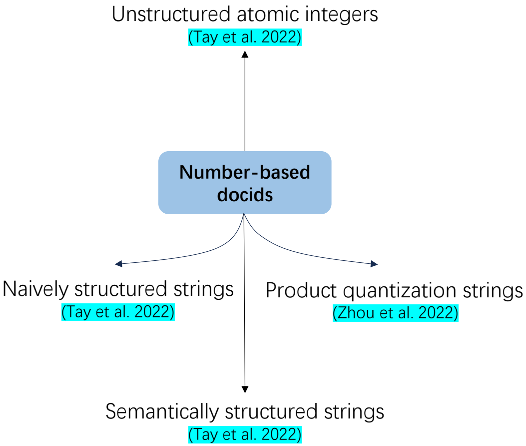


- Learnable docids

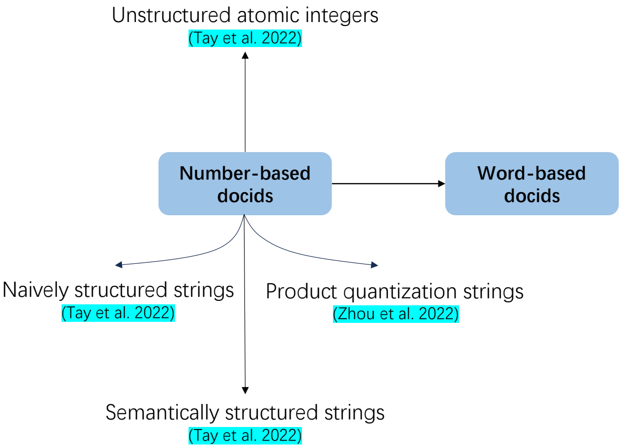
Roadmap of pre-defined static docids

Number-based docids

Roadmap of pre-defined static docids



Roadmap of pre-defined static docids



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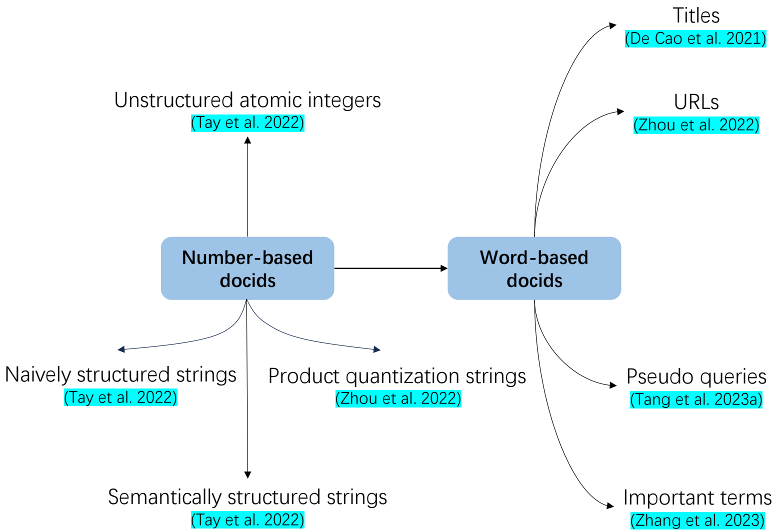

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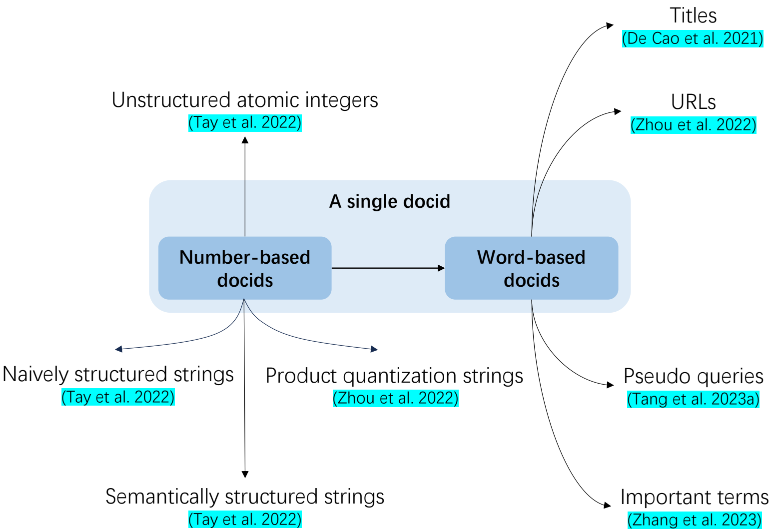

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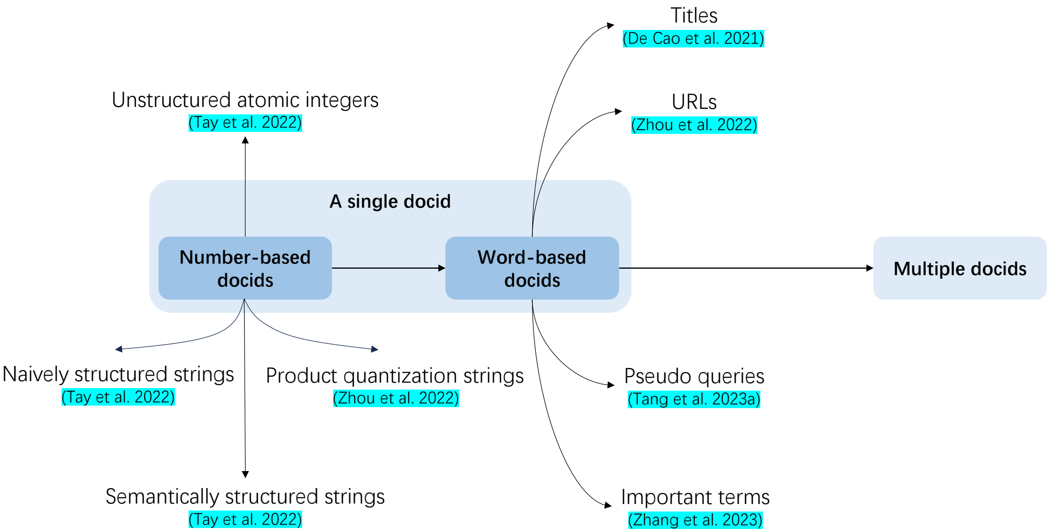

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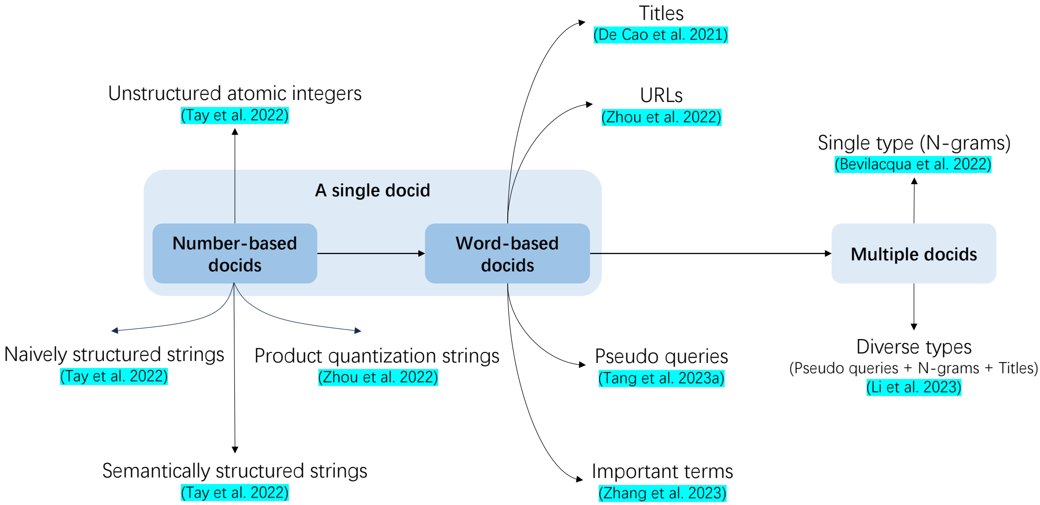
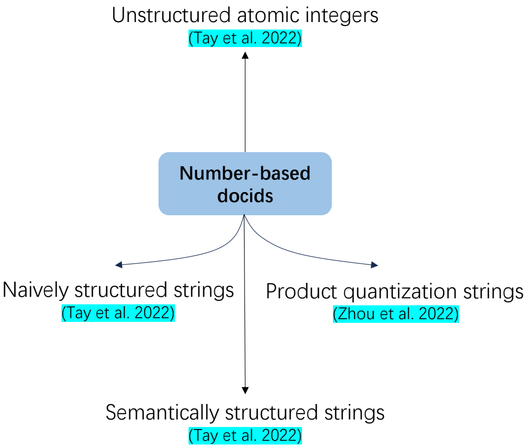


A single docid: Number-based



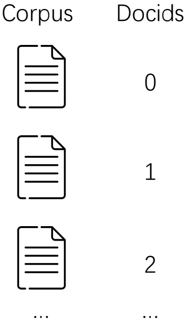
Number-based: Unstructured atomic integers

- An arbitrary (and possibly random) unique integer identifier

Source: [Tay et al., 2022]

Number-based: Unstructured atomic integers

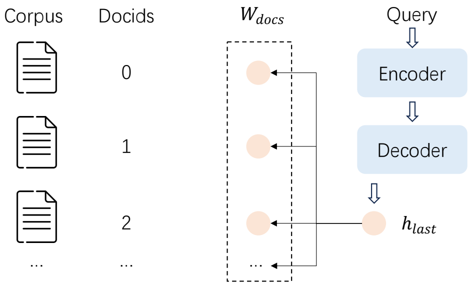
- An arbitrary (and possibly random) unique integer identifier



Source: [Tay et al., 2022]

Number-based: Unstructured atomic integers

- **Decoding formulation**: learn a probability distribution over the docid embeddings, i.e., emitting one logit for each unique docid

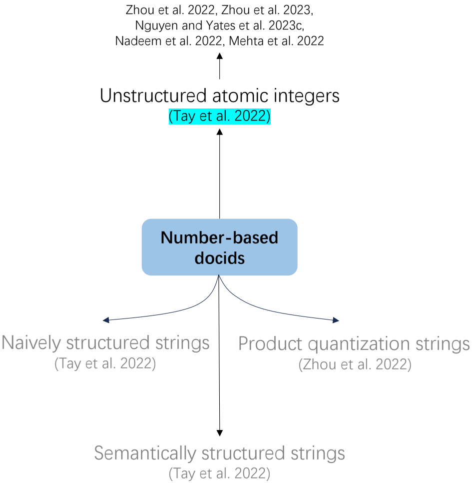


$$O = \mathrm{Softmax}([W_{docs}]^T h_{last}),$$

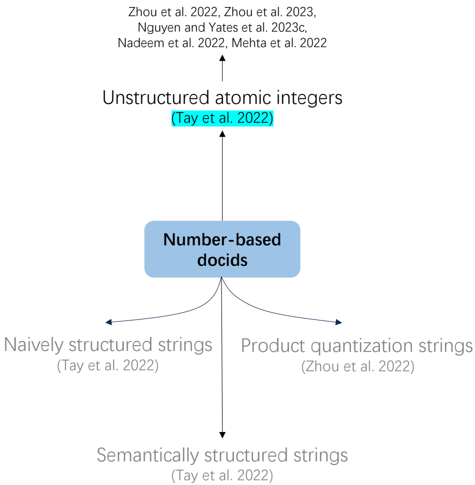
where $[W_{docs}]$ is the document embedding matrix, and h_{last} is the last layer's hidden state of the decoder

Source: [Tay et al., 2022]

Unstructured atomic integers and subsequent work



Unstructured atomic integers and subsequent work



Easy to build: analogous to the output layer in standard language model

Unstructured atomic integers: obvious constraints

👎 The need to learn embeddings for each individual docid

Unstructured atomic integers: obvious constraints

- The need to learn embeddings for each individual docid
- The need for the large softmax output space

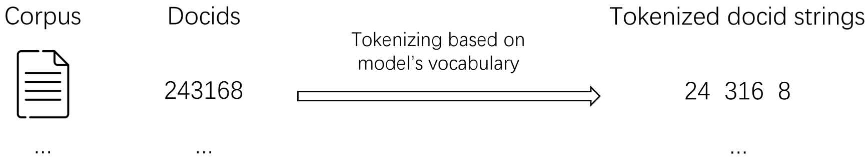
Unstructured atomic integers: obvious constraints

- 👎 The need to learn embeddings for each individual docid
- 👎 The need for the large softmax output space

It is challenging to be used on large corpora!

Number-based: Naively structured strings

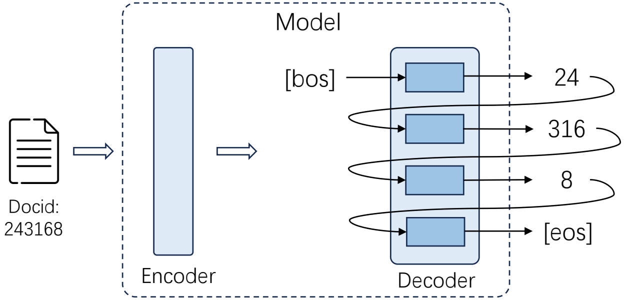
- Treat arbitrary unique integers as tokenizable strings



Source: [Tay et al., 2022]

Number-based: Naively structured strings

- **Decoding formulation**: Generating a docid string in a token-by-token manner



Source: [Tay et al., 2022]

Naively structured strings and subsequent work

Zhou et al. 2022, Zhou et al. 2023,
Nguyen and Yates et al. 2023c,
Nadeem et al. 2022, Mehta et al. 2022

Unstructured atomic integers
(Tay et al. 2022)

Number-based docids

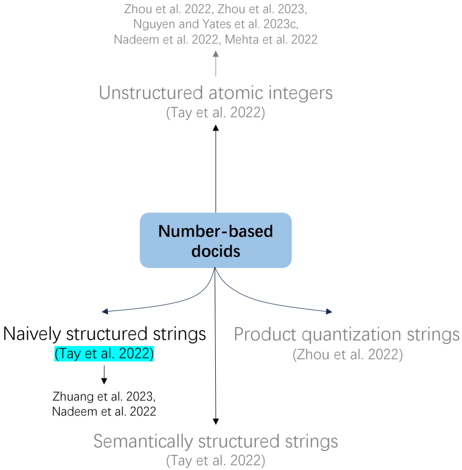
Naively structured strings
(Tay et al. 2022)

Zhuang et al. 2023,
Nadeem et al. 2022

Product quantization strings
(Zhou et al. 2022)

Semantically structured strings
(Tay et al. 2022)

Naively structured strings and subsequent work



Such a way frees the limitation for the **corpus size** that comes with unstructured atomic docid

Naively structured strings: obvious constraints

👎 Identifiers are assigned in an arbitrary manner

Naively structured strings: obvious constraints

- Identifiers are assigned in an arbitrary manner
- The docid space lacks semantic structure

Number-based: Semantically structured strings

Properties:

- The docid should capture some information about the semantics of its associated document

Source: [Tay et al., 2022]

Number-based: Semantically structured strings

Properties:

- The docid should capture some information about the semantics of its associated document
- The docid should be structured in a way that the search space is effectively reduced after each decoding step

Source: [Tay et al., 2022]

Number-based: Semantically structured strings

Properties:

- The docid should capture some information about the semantics of its associated document
- The docid should be structured in a way that the search space is effectively reduced after each decoding step

↓

Semantically similar documents share identifier prefixes

Source: [Tay et al., 2022]

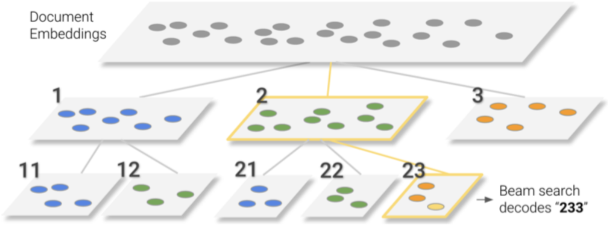
Number-based: Semantically structured strings

- A hierarchical clustering algorithm over document embeddings to induce a decimal tree

Source: [Tay et al., 2022]

Number-based: Semantically structured strings

- A hierarchical clustering algorithm over document embeddings to induce a decimal tree



Source: [Tay et al., 2022]

Semantically structured strings and subsequent work

Zhou et al. 2022, Zhou et al. 2023,
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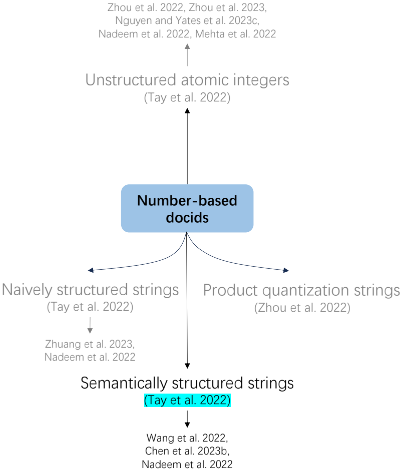
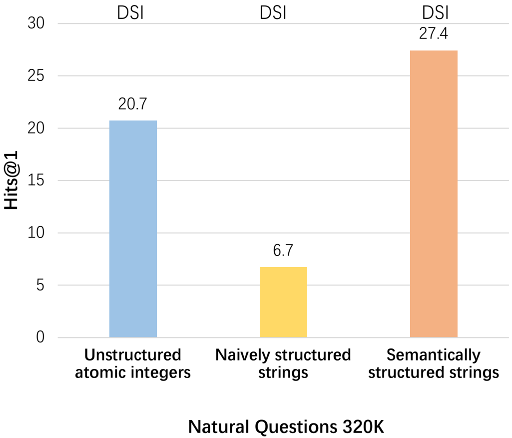
Wang et al. 2022,
Chen et al. 2023b,
Nadeem et al. 2022

Semantically structured strings and subsequent work



- 👍 The document semantics can be incorporated in the decoding process
- 👍 It is not limited by the size of the corpus

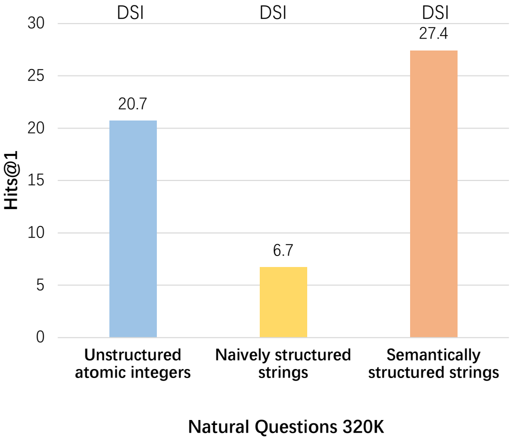
Performance comparisons [Tay et al., 2022]



Data source: Tay et al. [2022]

- Backbone: T5-base
- Observations: imbuing the docid space with semantic structure can lead to better retrieval capabilities

Performance comparisons [Tay et al., 2022]



- Backbone: T5-base
- Observations: imbuing the docid space with semantic structure can lead to better retrieval capabilities

This is only about "identifiers"

Later sections will discuss the performance compared to traditional IR models

Data source: Tay et al. [2022]

Number-based: Product quantization strings

- Product quantization (PQ) is a technique used for vector compression

Image source: Product Quantization for Similarity Search

Number-based: Product quantization strings

- Product quantization (PQ) is a technique used for vector compression
- An original vector is represented by a short code composed of its subspace quantization indices

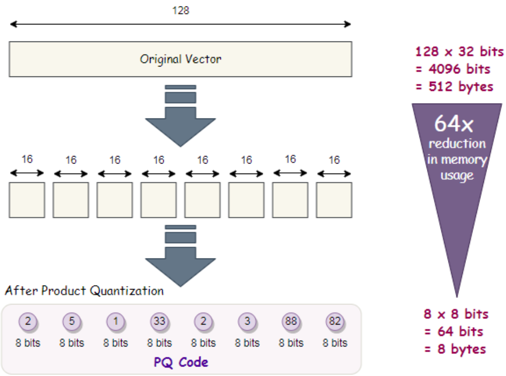


Image source: Product Quantization for Similarity Search

Number-based: Product quantization strings

Given all D-dimensional embedding vectors of documents [Zhou et al., 2022],

"Ultron: An ultimate retriever on corpus with a model-based indexer". Zhou et al. [2022]

Number-based: Product quantization strings

Given all D-dimensional embedding vectors of documents [Zhou et al., 2022],

- Divide the D-dimensional space into m groups

"Ultron: An ultimate retriever on corpus with a model-based indexer". Zhou et al. [2022]

Number-based: Product quantization strings

Given all D-dimensional embedding vectors of documents [Zhou et al., 2022],

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- Perform K-means clustering on each group to obtain k cluster centers

"Ultron: An ultimate retriever on corpus with a model-based indexer". Zhou et al. [2022]

Number-based: Product quantization strings

Given all D-dimensional embedding vectors of documents [Zhou et al., 2022],

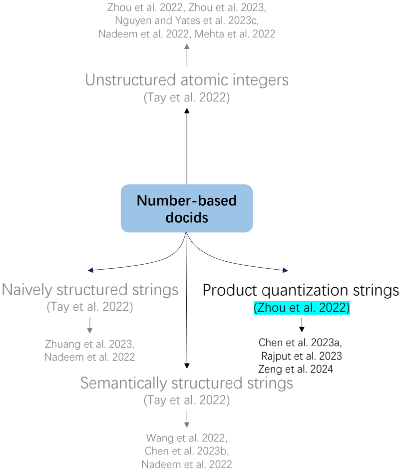
- Divide the D-dimensional space into m groups
- Perform K-means clustering on each group to obtain k cluster centers
- Each embedding vector can be represented as a set of m cluster identifiers. For each document d, its product quantization string identifier id_{PQ} can be defined,

$$id_{PQ} = PQ(Encoder(d)),$$

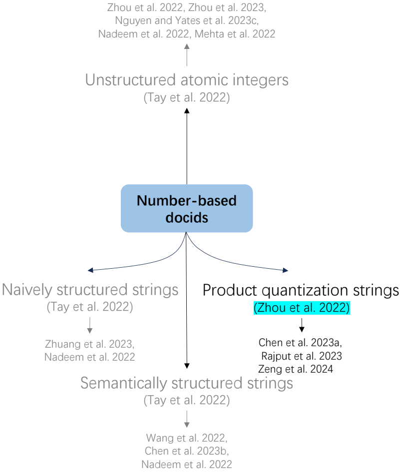
where $Encoder(\cdot)$ can be implemented by different language models

"Ultron: An ultimate retriever on corpus with a model-based indexer". Zhou et al. [2022]

Product quantization strings and subsequent work

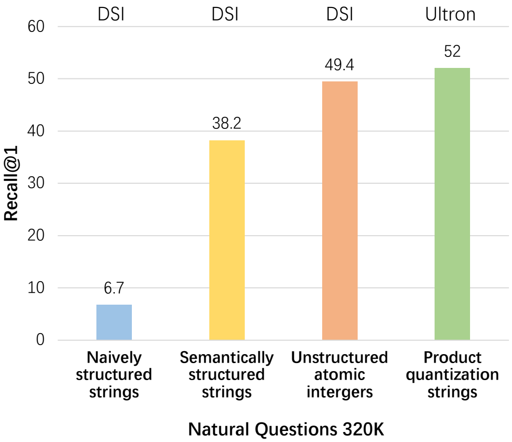


Product quantization strings and subsequent work



- Preserving dense vector semantics in a smaller space
- Capturing local semantic information

Performance comparisons



- Backbone: T5-base
- Observations: Product quantization string identifiers improves over structured semantic identifiers

Data source: Wang et al. [2023]

Number-based docids: Summary

Docids based on integers are easy to build

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- Docids based on integers are easy to build
- Unstructured atomic integers and naively/semantically structured strings can maintain uniqueness

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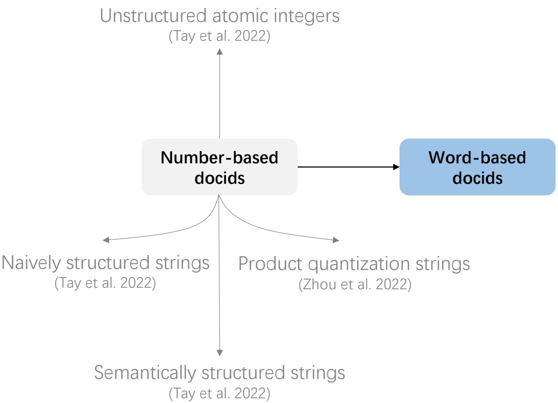
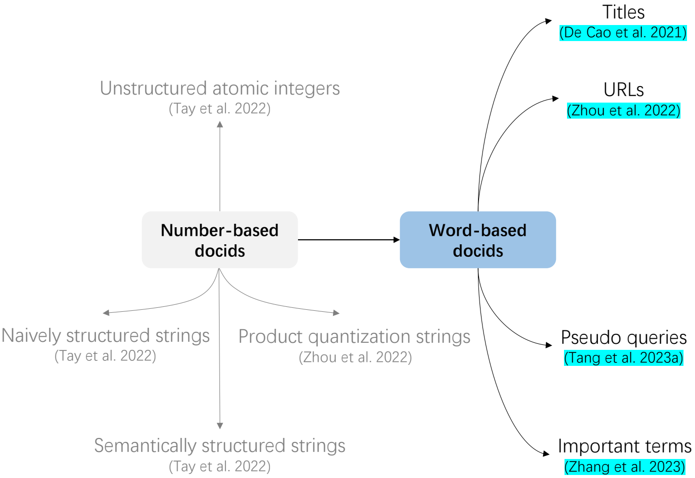
Number-based docids: Summary

- Docids based on integers are easy to build
- Unstructured atomic integers and naively/semantically structured strings can maintain uniqueness
- Number-based docids are composed of unreadable numbers
- It is challenging to interpret the model's understanding of the corpus

A single docid: Word-based



A single docid: Word-based



A single docid: Word-based

The fundamental inspiration

- The query is usually keyword-based natural language, which can be challenging to map into a numeric string, while mapping it to words would be more intuitive

A single docid: Word-based

The fundamental inspiration

- The query is usually keyword-based natural language, which can be challenging to map into a numeric string, while mapping it to words would be more intuitive
- Elaboration Strategies in human learning encoding and recall for humans: natural language vs. integer-based strings

Word-based: Titles

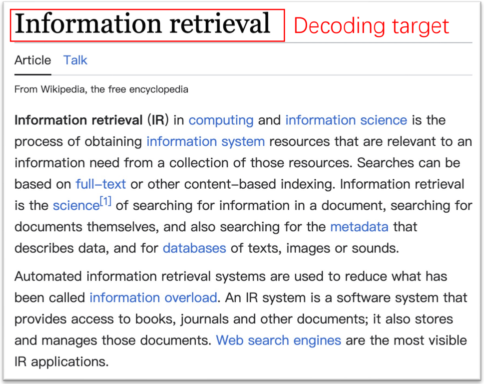
- Document titles: be able to summarize the main content

Image source: Wikipedia and CNN

"Autoregressive Entity Retrieval". De Cao et al. [2021]

Word-based: Titles

- Document titles: be able to summarize the main content


Information retrieval

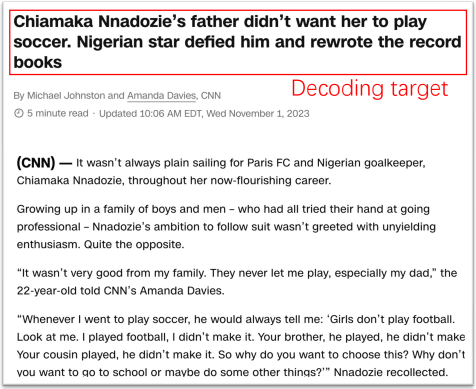
Decoding target

Article Talk

From Wikipedia, the free encyclopedia

Information retrieval (**IR**) in computing and information science is the process of obtaining information system resources that are relevant to an information need from a collection of those resources. Searches can be based on full–text or other content–based indexing. Information retrieval is the science[1] of searching for information in a document, searching for documents themselves, and also searching for the metadata that describes data, and for databases of texts, images or sounds.

Automated information retrieval systems are used to reduce what has been called information overload. An IR system is a software system that provides access to books, journals and other documents; it also stores and manages those documents. Web search engines are the most visible IR applications.


Chiamaka Nnadozie's father didn't want her to play soccer. Nigerian star defied him and rewrote the record books

Decoding target

By Michael Johnston and Amanda Davies, CNN

5 minute read · Updated 10:06 AM EDT, Wed November 1, 2023

(CNN) — It wasn't always plain sailing for Paris FC and Nigerian goalkeeper, Chiamaka Nnadozie, throughout her now-flourishing career.

Growing up in a family of boys and men – who had all tried their hand at going professional – Nnadozie's ambition to follow suit wasn't greeted with unyielding enthusiasm. Quite the opposite.

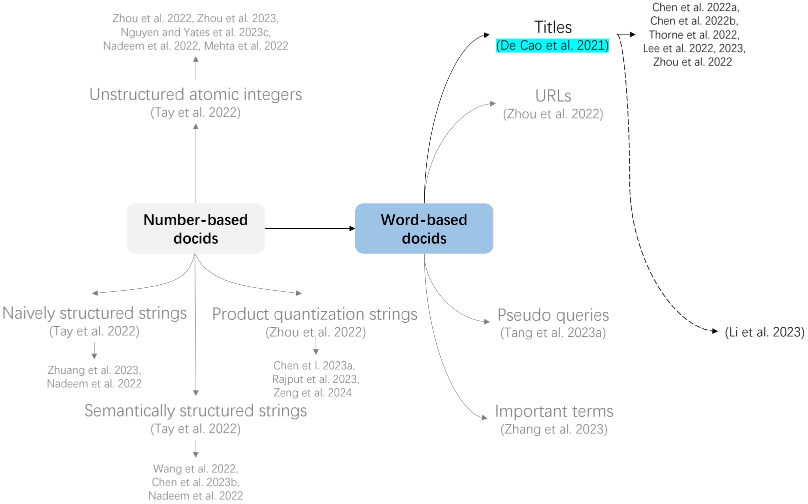
"It wasn't very good from my family. They never let me play, especially my dad," the 22-year-old told CNN's Amanda Davies.

"Whenever I went to play soccer, he would always tell me: 'Girls don't play football. Look at me. I played football, I didn't make it. Your brother, he played, he didn't make Your cousin played, he didn't make it. So why do you want to choose this? Why don't you want to go to school or maybe do some other things?'" Nnadozie recollected.

Image source: Wikipedia and CNN

"Autoregressive Entity Retrieval". De Cao et al. [2021]

Titles and subsequent work



Titles: Obvious constraints

👎 Depending on certain special document metadata

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Titles: Obvious constraints

- 👎 Depending on certain special document metadata
- 👎 The titles may be duplicated (i.e., web datasets), and require further investigation
- 👎 Time-consuming step of producing titles and requiring increasingly sophisticated domain knowledge

For a while, mainly evaluated on Wikipedia-based tasks (with well-written titles)!

Wikipedia-based tasks

Fact Verification
De Cao et al. 2021, Chen et al. 2022b, Chen et al. 2022a, Thorne et al. 2022, Lee et al. 2023

Entity Linking
De Cao et al. 2021, Chen et al. 2022b, Lee et al. 2023

Slot Filling
De Cao et al. 2021, Chen et al. 2022b, Lee et al. 2023

Open Domain QA
De Cao et al. 2021, Chen et al. 2022b, Zhou et al. 2022, Lee et al. 2023

Dialogue
De Cao et al. 2021, Chen et al. 2022b, Lee et al. 2023

Multi-hop retrieval
Lee et al. 2022

Word-based: URLs

- The URL of a document contains certain semantic information and can uniquely correspond to this document

Image source: Geeksforgeeks

"TOME: A Two-stage Approach for Model-based Retrieval". Ren et al. [2023]

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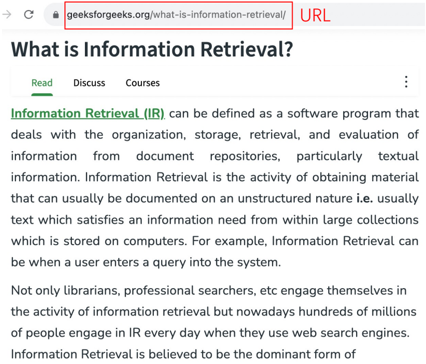

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Word-based: URLs

https://en.wikipedia.org/wiki/Nevada

⇓ tokenize

https :// en . Wikipedia . org / wiki / N e vada

- Ren et al. [2023] solely utilized tokenized URLs as the identifier

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Word-based: URLs

https://en.wikipedia.org/wiki/Nevada

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- Ren et al. [2023] solely utilized tokenized URLs as the identifier
- The tokenized symbols of URLs are well aligned with the vocabulary of the generative language model, thereby enhancing the generative capacity

"TOME: A Two-stage Approach for Model-based Retrieval". Ren et al. [2023]

Word-based: URLs

- However, not all URLs provide sufficient semantic information

"Ultron: An ultimate retriever on corpus with a model-based indexer". Zhou et al. [2022]

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- Zhou et al. [2022] proposed to combine the URL and the document title as docids to guarantee both the uniqueness and semantics of the identifiers

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Word-based: URLs

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For a while, mainly evaluated on Web search datasets (with available URLs)!

"Ultron: An ultimate retriever on corpus with a model-based indexer". Zhou et al. [2022]

Web search datasets

MS MARCO
Nguyen et al. 2016

Natural Questions
Kwiatkowski et al. 2019

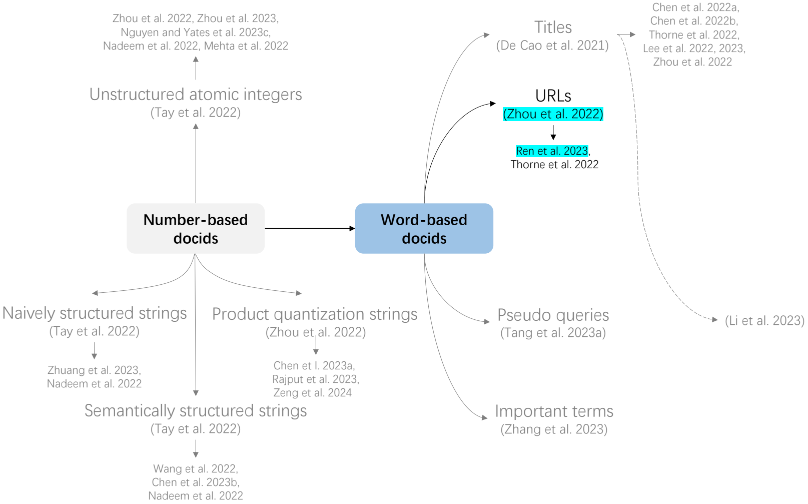
Trec-CAR
Dietz et al. 2017

Robust04
Voorhees et al. 2004

ClueWeb09-B
Clarke et al. 2010

Gov2
Clarke et al. 2004

URLs and subsequent work



If the special document metadata is not available

It is necessary to design automatic docid generation techniques

Word-based: Pseudo queries

- Doc2Query technique: pseudo queries are likely to be representative or related to the contents of documents

"Semantic-Enhanced Differentiable Search Index Inspired by Learning Strategies". Tang et al. [2023a]

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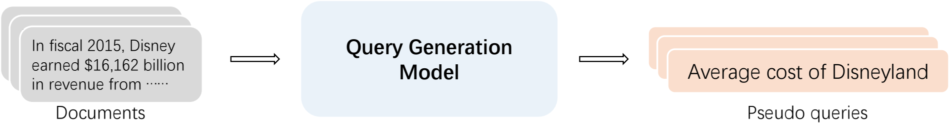

"Semantic-Enhanced Differentiable Search Index Inspired by Learning Strategies". Tang et al. [2023a]

Word-based: Pseudo queries

- Docid repetition problem
    - Tang et al. [2023a] uses the top 1 generated query as the docid for each document
    - Based on statistics, about 5% and 3% docids of documents are not unique in MS MARCO and Natural questions datasets, respectively
    - It is reasonable that different documents may share the same docid if they share very similar essential information

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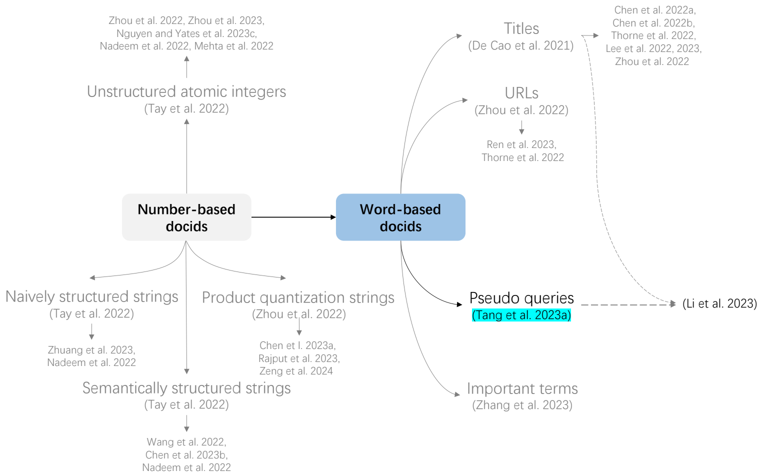
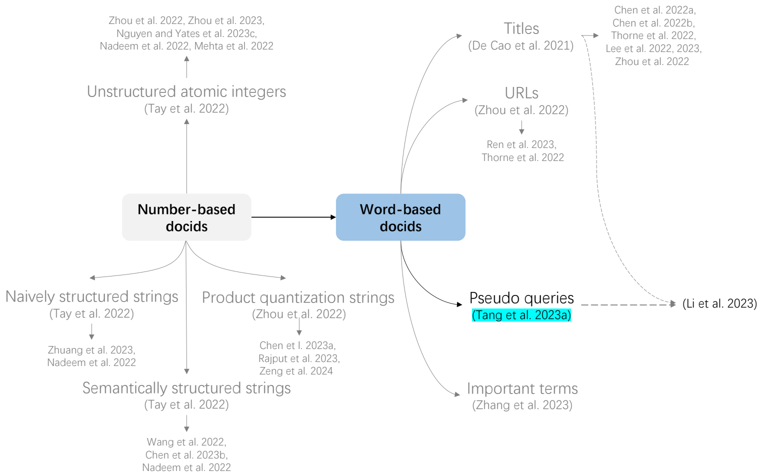
  - Based on statistics, about 5% and 3% docids of documents are not unique in MS MARCO and Natural questions datasets, respectively
  - It is reasonable that different documents may share the same docid if they share very similar essential information
- Countermeasure
  - If a docid corresponds to multiple documents, return all of them in a random order, while keeping the relative order of documents corresponding to other docids

"Semantic-Enhanced Differentiable Search Index Inspired by Learning Strategies". Tang et al. [2023a]

Pseudo queries and subsequent work



Pseudo queries and subsequent work



Without the requirements of certain document metadata, e.g., titles and URLs

False pruning [Zhang et al., 2023]

Titles, URLs and pseudo queries:

"Term-Sets Can Be Strong Document Identifiers For Auto-Regressive Search Engines". Zhang et al. [2023]

False pruning [Zhang et al., 2023]

Titles, URLs and pseudo queries:

- One pre-defined sequence

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Titles, URLs and pseudo queries:

- One pre-defined sequence
- The requirement for the exact generation
- The targeted document will be missed from the retrieval result if a false prediction about its identifier is made in any step of the generation process

"Term-Sets Can Be Strong Document Identifiers For Auto-Regressive Search Engines". Zhang et al. [2023]

The permutation of docids becomes critical

Word-based: Important terms [Zhang et al., 2023]

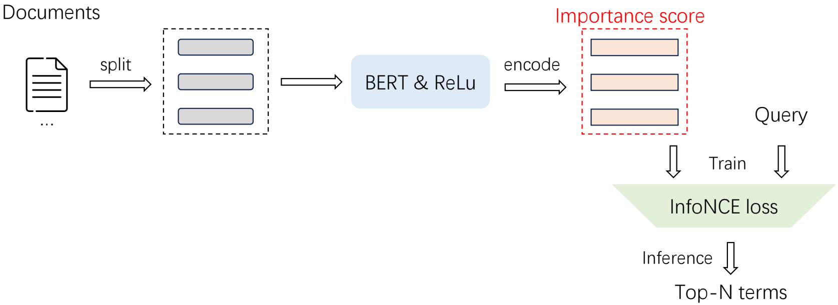
- **Any permutation** of the **term set** will be a **valid** identification for the corresponding document

Word-based: Important terms [Zhang et al., 2023]

- **Any permutation** of the **term set** will be a **valid** identification for the corresponding document
- Important terms: A set of document terms that have high importance scores

Important terms: AutoTSG [Zhang et al., 2023]

- Importance scores: The relevance scores of terms with respect to the query



"Term-Sets Can Be Strong Document Identifiers For Auto-Regressive Search Engines". Zhang et al. [2023]

Important terms: AutoTSG [Zhang et al., 2023]

Docid repetition problem

- If the number of terms is sufficiently large, all documents within the corpus can be unique

"Term-Sets Can Be Strong Document Identifiers For Auto-Regressive Search Engines". Zhang et al. [2023]

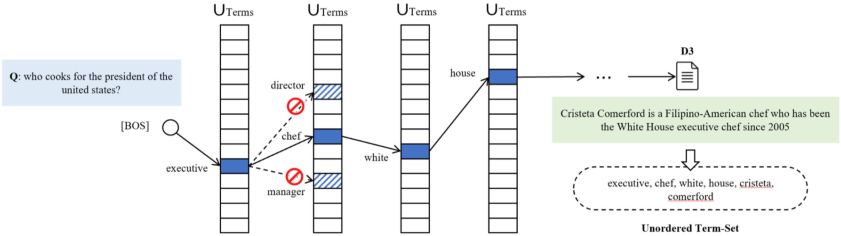
Important terms: AutoTSG [Zhang et al., 2023]

Docid repetition problem

- If the number of terms is sufficiently large, all documents within the corpus can be unique
- For a moderate-scale corpus like Natural Questions, specifying 12 terms is already sufficient to ensure uniqueness

"Term-Sets Can Be Strong Document Identifiers For Auto-Regressive Search Engines". Zhang et al. [2023]

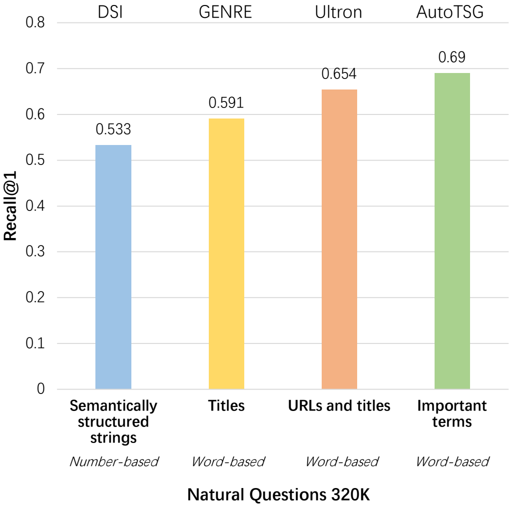
Important terms: AutoTSG [Zhang et al., 2023]



- Any permutation of the term-set identifier will lead to the retrieval of the corresponding document

"Term-Sets Can Be Strong Document Identifiers For Auto-Regressive Search Engines". Zhang et al. [2023]

Performance comparisons



Data source: Zhang et al. [2023]

- Backbone: T5-base
- Using important term sets obtained through relevance matching as docids help represent the important information of the document
- This method also mitigates the issue of false pruning

Word-based docids: Summary

👍 Semantically related to the content of the document

Word-based docids: Summary

- Semantically related to the content of the document
- Good interpretability

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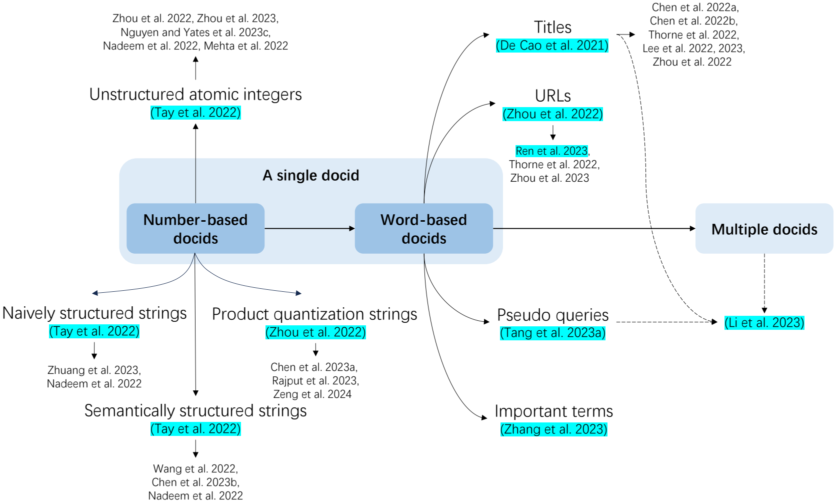
- 👎 Rely on metadata or labeled data

Word-based docids: Summary

- 👍 Semantically related to the content of the document
- 👍 Good interpretability
- 👎 Rely on metadata or labeled data
- 👎 May lead to duplication

A single docid: Summary



A single docid: Summary

The design of a single docid is relatively straightforward

A single docid: Summary

- The design of a single docid is relatively straightforward
- The GR model may easily learn the one-to-one mapping relationship

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A single docid: Summary

- 👍 The design of a single docid is relatively straightforward
- 👍 The GR model may easily learn the one-to-one mapping relationship
- 👎 Single identifiers are typically short strings, providing limited information about the document
- 👎 A single type of identifier only represents a document from one view; and might be insufficient to effectively capture the entirety of the document's content

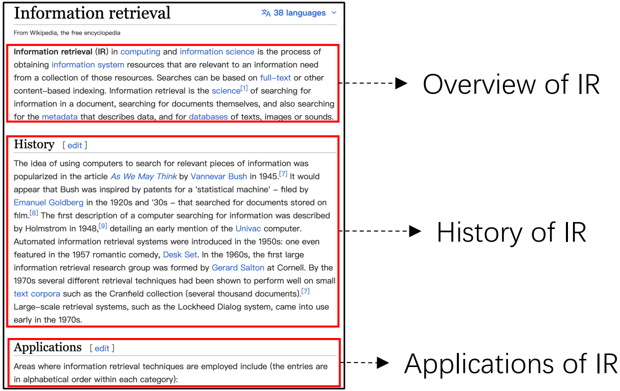
Multiple docids

- Multiple identifiers can provide complementary information from different views

Image source: Wikipedia

Multiple docids

- Multiple identifiers can provide complementary information from different views



Information retrieval

38 languages

From Wikipedia, the free encyclopedia

Information retrieval (**IR**) in computing and information science is the process of obtaining information system resources that are relevant to an information need from a collection of those resources. Searches can be based on full-text or other content-based indexing. Information retrieval is the science[1] of searching for information in a document, searching for documents themselves, and also searching for the metadata that describes data, and for databases of texts, images or sounds.

History [edit]

The idea of using computers to search for relevant pieces of information was popularized in the article *As We May Think* by Vannevar Bush in 1945.[7] It would appear that Bush was inspired by patents for a 'statistical machine' – filed by Emanuel Goldberg in the 1920s and '30s – that searched for documents stored on film.[8] The first description of a computer searching for information was described by Holmstrom in 1948,[9] detailing an early mention of the Univac computer. Automated information retrieval systems were introduced in the 1950s: one even featured in the 1957 romantic comedy, Desk Set. In the 1960s, the first large information retrieval research group was formed by Gerard Salton at Cornell. By the 1970s several different retrieval techniques had been shown to perform well on small text corpora such as the Cranfield collection (several thousand documents).[7] Large-scale retrieval systems, such as the Lockheed Dialog system, came into use early in the 1970s.

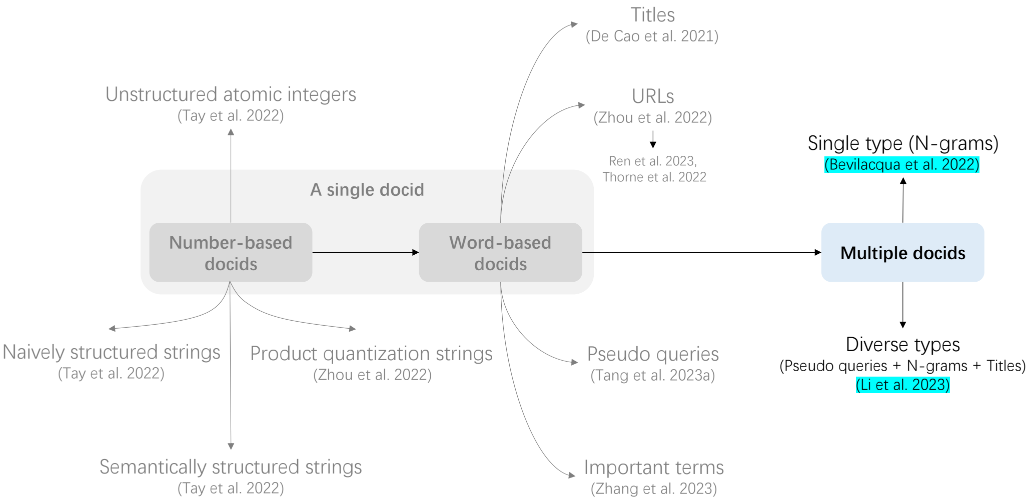
Applications [edit]

Areas where information retrieval techniques are employed include (the entries are in alphabetical order within each category):

Multi-view information

Image source: Wikipedia

Multiple docids



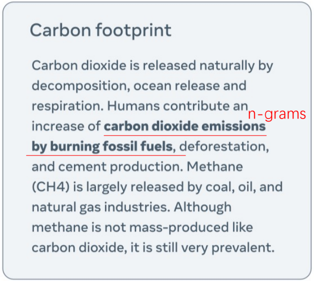
Multiple docids: Single type (N-grams) [Bevilacqua et al., 2022]

- All n-grams (i.e., substrings) in a document are treated as its possible identifiers

"Autoregressive Search Engines: Generating Substrings as Document Identifiers". Bevilacqua et al. [2022]

Multiple docids: Single type (N-grams) [Bevilacqua et al., 2022]

- All n-grams (i.e., substrings) in a document are treated as its possible identifiers
- Part of n-grams as identifiers during training: Only the terms from the document that have **a high overlap with the query** are chosen as the target docids



Carbon footprint

Carbon dioxide is released naturally by decomposition, ocean release and respiration. Humans contribute an increase of **carbon dioxide emissions by burning fossil fuels**, deforestation, and cement production. Methane (CH4) is largely released by coal, oil, and natural gas industries. Although methane is not mass-produced like carbon dioxide, it is still very prevalent.

"Autoregressive Search Engines: Generating Substrings as Document Identifiers". Bevilacqua et al. [2022]

Multiple docids: Single type (N-grams) [Bevilacqua et al., 2022]

Docid repetition problem

- A heuristic scoring function is designed to address this during inference

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Docid repetition problem

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We will discuss this in Section 5!

"Autoregressive Search Engines: Generating Substrings as Document Identifiers". Bevilacqua et al. [2022]

Multiple docids: Single type (Important n-grams) [Chen et al., 2023b]

- The **important n-grams** occurring in a document as its identifiers

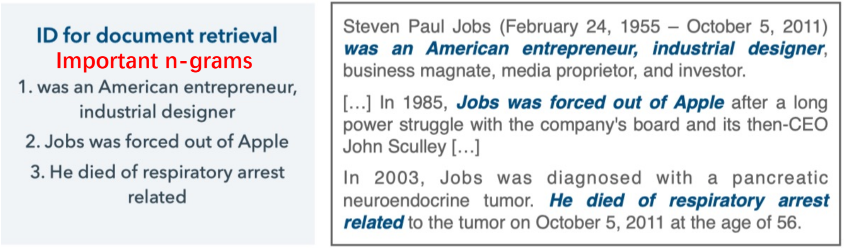
"A Unified Generative Retriever for Knowledge-Intensive Language Tasks via Prompt Learning". Chen et al. [2023b]

Multiple docids: Single type (Important n-grams) [Chen et al., 2023b]

- The **important n-grams** occurring in a document as its identifiers
- N-gram importance
  - Step 1: The query and its relevant document are concatenated with special delimiter tokens as a single input sequence
  - Step 2: Feed it into the original BERT model to get the [CLS] vector
  - Step 3: The token importance is computed by averaging the [CLS]-token attention weights
  - Step 4: The importance for the n-gram is the average of these tokens' importance

"A Unified Generative Retriever for Knowledge-Intensive Language Tasks via Prompt Learning". Chen et al. [2023b]

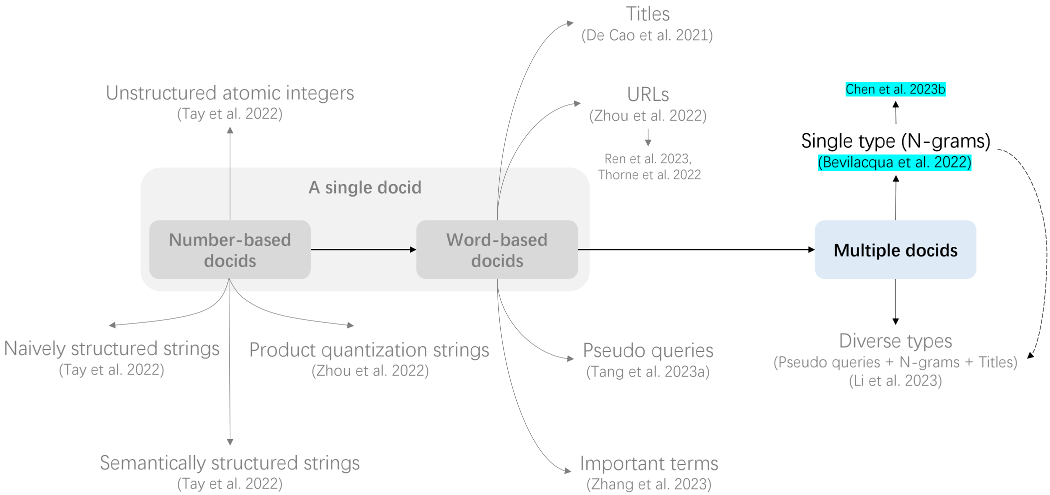
Single type (Important n-grams) [Chen et al., 2023b]: An example



- Countermeasure for docid repetition problem: Similar to Bevilacqua et al. [2022]

"A Unified Generative Retriever for Knowledge-Intensive Language Tasks via Prompt Learning". Chen et al. [2023b]

Single type (N-grams) and subsequent work



Multiple docids: Diverse types (MINDER) [Li et al., 2023d]

Query: Who is the singer of *does he love you?*

↑**Relevant**

Passage (*https://en.wikipedia.org/wiki/Does_He_Love_You*)

"Does He Love You" is a song written by Sandy Knox and Billy Stritch, and recorded as a duet by American country music artists Reba McEntire and Linda Davis. It was released in August 1993 as the first single from Reba's album "Greatest Hits Volume Two". It is one of country music's several songs about a love triangle. "Does He Love You" was written in 1982 by Billy Stritch. ......

Multiview Identifiers

Title: Does He Love You

Substrings: "Does He Love You" is a song ..., recorded as a duet by American country music artists Reba McEntire and Linda Davis, ...

Pseudo-queries:

Who wrote the song does he love you?

Who sings does he love you?

When was does he love you released by reba?

What is the first song in the album "Greatest Hits Volume Two" about?

- Three views of identifiers

"Multiview Identifiers Enhanced Generative Retrieval". Li et al. [2023d]

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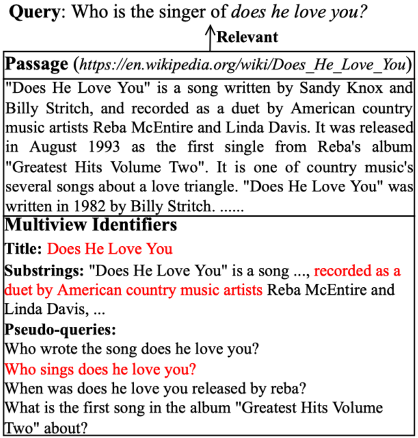

- Three views of identifiers
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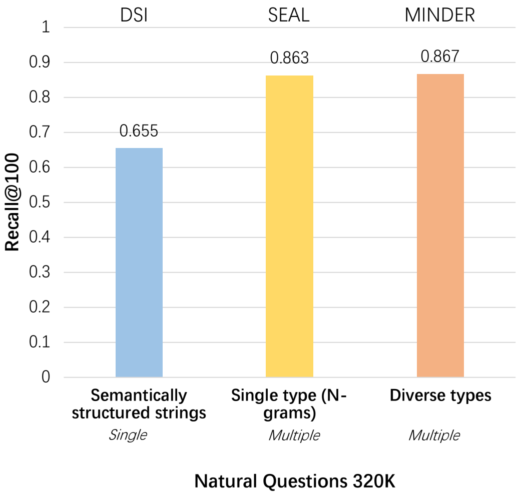
- Three views of identifiers
  - Title: Indicate the subject of a document
  - Substrings (N-grams): Be also semantically related
  - Pseudo-queries: Integrate multiple segments and contextualized information

"Multiview Identifiers Enhanced Generative Retrieval". Li et al. [2023d]

Performance comparisons



Data source: Li et al. [2023d]

- Backbone: BART-large
- Results: Using multiple docids for a document yields better results than using a single docid

Multiple docids: Summary

👍 Multiple docids can provide a more comprehensive representation of the document, assisting the model in gaining a multifaceted understanding

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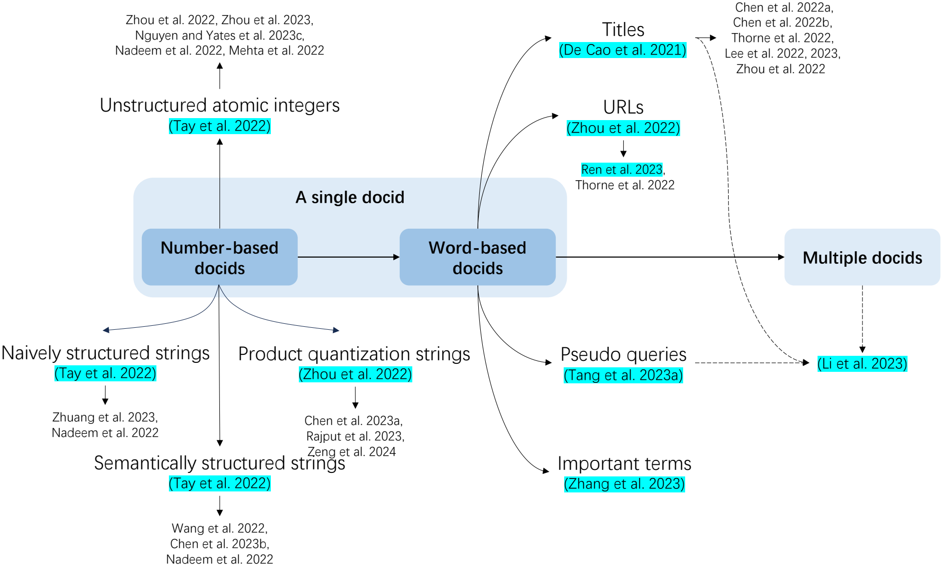
- 👍 Multiple docids can provide a more comprehensive representation of the document, assisting the model in gaining a multifaceted understanding
- 👍 Similar docids across different documents can reflect the similarity between the documents
- 👎 GR models with the increased identifier numbers demand more memory usage and inference time compared to GR models with single identifiers
- 👎 It is challenging to design discriminative multiple identifiers for a document

Pre-defined static docids: Summary



Pre-defined static docids: Summary

Docid type		Construction	Uniqueness	The degree of semantic connection to the document	Relying on labeled data	Relying on metadata
A single docid: Number-based	Unstructured atomic integers (Tay et al. 2022)	Easy	Yes	None	No	No
	Naively structured strings (Tay et al. 2022)	Easy	Yes	None	No	No
	Semantically structured strings (Tay et al. 2022)	Moderate	Yes	Weak	No	No
	Product quantization strings (Zhou et al. 2022)	Moderate	No	Moderate	No	No
A single docid: Word-based	Titles (De Cao et al. 2021)	Easy	No	Strong	No	Yes
	URLs (Zhou et al. 2022, Ren et al. 2023)	Easy	Yes	Strong	No	Yes
	Pseudo queries (Tang et al. 2023a)	Moderate	No	Strong	Yes	No
	Important terms (Zhang et al. 2023)	Hard	Yes	Strong	Yes	No
Multiple docids	Single type: N-grams (Bevilacqua et al. 2022)	Easy	No	Moderate	No	No
	Diverse types (Li et al. 2023)	Moderate	No	Strong	Yes	Yes

Pre-defined static docids: Obvious constrains

They are fixed and not learnable by training on the retrieval tasks

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Not specifically optimized for retrieval tasks

Pre-defined static docids: Obvious constrains

They are fixed and not learnable by training on the retrieval tasks

- 👎 Not specifically optimized for retrieval tasks
- 👎 Difficult to learn semantics and relationships between documents

How to design learnable docids tailored for retrieval tasks?

Learnable docids

- **Repeatable docids**:
  - GenRet [Sun et al., 2023] learns to tokenize documents into short discrete representations via a discrete auto-encoding, jointly training with the retrieval task
  - ASI [Yang et al., 2023] combines both the end-to-end learning of docids for existing and new documents and the end-to-end document retrieval based joint optimization

Learnable docids

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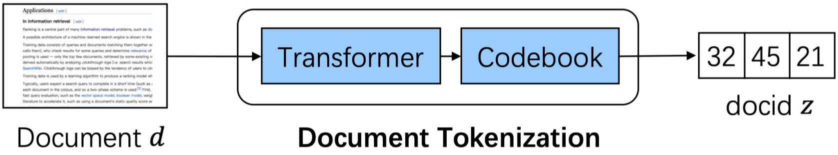
  - ASI [Yang et al., 2023] combines both the end-to-end learning of docids for existing and new documents and the end-to-end document retrieval based joint optimization
- **Unique docids**:
  - NOVO [Wang et al., 2023] uses unique n-gram sets identifying each document and can be generated in any order and can be optimized through retrieval tasks

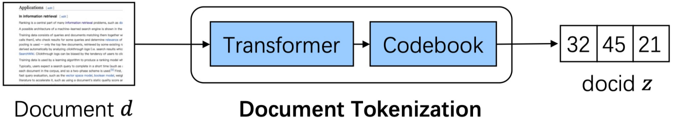
Repeatable learnable docids: GenRet [Sun et al., 2023]



- Docid: A sequence of discrete numbers is the docid for a given document converted by a document tokenization model
- Training: Jointly training with a document tokenization task, reconstruction task and retrieval task

"Learning to Tokenize for Generative Retrieval". Sun et al. [2023]

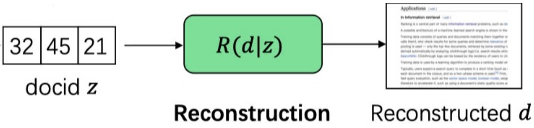
Repeatable learnable docids: GenRet [Sun et al., 2023]



- Document tokenization task: Produce docids for documents

"Learning to Tokenize for Generative Retrieval". Sun et al. [2023]

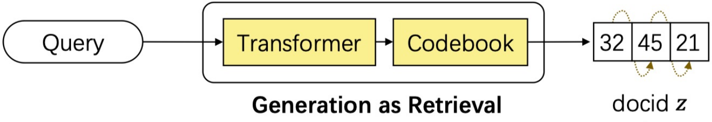
Repeatable learnable docids: GenRet [Sun et al., 2023]



- Reconstruction task: Learn to reconstruct a document based on a docid

"Learning to Tokenize for Generative Retrieval". Sun et al. [2023]

Repeatable learnable docids: GenRet [Sun et al., 2023]



- Retrieval task: Generate relevant docids directly for a query

"Learning to Tokenize for Generative Retrieval". Sun et al. [2023]

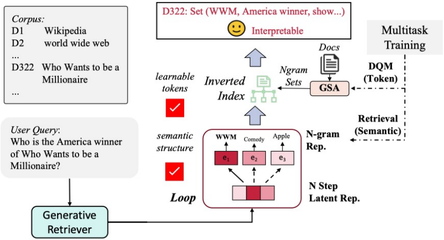
Repeatable learnable docids: GenRet [Sun et al., 2023]

Docid repetition problem

- All corresponding documents are retrieved and shuffled in an arbitrary order

"Learning to Tokenize for Generative Retrieval". Sun et al. [2023]

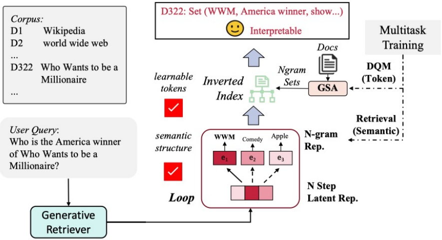
Unique learnable docids: NOVO [Wang et al., 2023]



- Docid: Unique n-grams sets of the documents obtained from global self-attention

"NOVO: Learnable and Interpretable Document Identifiers for Model-Based IR". Wang et al. [2023]

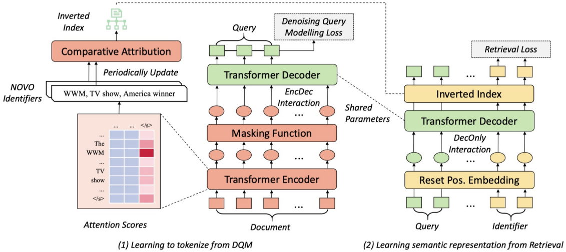
Unique learnable docids: NOVO [Wang et al., 2023]



- Docid: Unique n-grams sets of the documents obtained from global self-attention
- Decoding: A document can be retrieved by generating its n-grams in the sets in any order

"NOVO: Learnable and Interpretable Document Identifiers for Model-Based IR". Wang et al. [2023]

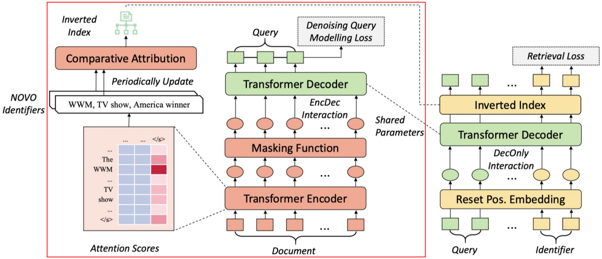
Unique learnable docids: NOVO [Wang et al., 2023]



- Docids are learned by the denoising query modeling task and retrieval task jointly

"NOVO: Learnable and Interpretable Document Identifiers for Model-Based IR". Wang et al. [2023]

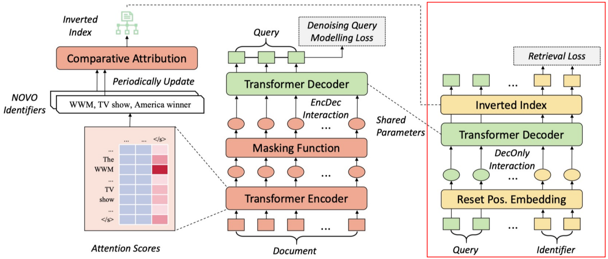
Unique learnable docids: NOVO [Wang et al., 2023]



- Denoising query modeling task: By learning to generate queries with noisy documents, n-grams that are more relevant to the query are may be filtered out

"NOVO: Learnable and Interpretable Document Identifiers for Model-Based IR". Wang et al. [2023]

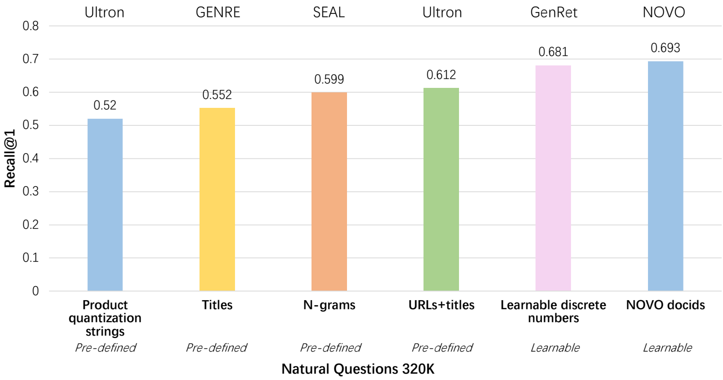
Unique learnable docids: NOVO [Wang et al., 2023]



- Retrieval task: The model learns the mapping from the query to relevant docids to update docid semantics

"NOVO: Learnable and Interpretable Document Identifiers for Model-Based IR". Wang et al. [2023]

Performance comparisons



- Backbone: T5-base
- Results: Two learnable docids yields better results than partial pre-defined static docids

Data source: Wang et al. [2023]

Learnable docids: Summary

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- 👍 A learnable approach can enable number-based docids like those in GenRet [Sun et al., 2023] to perform well
- 👎 It relies on complex task design for learning
- 👎 The learning process is complex, as docids change and require iterative learning

Docid design: Summary

- **Shall we use randomize numbers as the docids?**
  - Random number strings can serve as docids, but their effectiveness is limited

Docid design: Summary

- **Shall we use randomize numbers as the docids?**
  - Random number strings can serve as docids, but their effectiveness is limited
- **How to construct proper docids for the documents?**
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Docid design: Summary

- **Shall we use randomize numbers as the docids?**
  - Random number strings can serve as docids, but their effectiveness is limited
- **How to construct proper docids for the documents?**
  - Designing predefined or learnable docids based on the semantics of the documents
- **Would the choices of different docids affect the model performance(effectiveness, capacity, etc.)?**
  - The length and quantity of docids both impact the effectiveness of the model's performance
  - The influence on capacity is yet to be explored

Docid design: Summary

Docid type				
Pre-defined	Single	Number-based	- Simplified construction	- Low interpretability - Moderate performance
		Word-based	- High interpretability - Good performance	- Single-perspective representation of documents
	Multiple		- Comprehensive document representations - Better performance	- Slightly more complex construction
Learnable			- Adapting to GR objectives - Best performance	- Complex learning process

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</table>

Based on these docids

Model training → **Section 4!**

Model inference → **Section 5!**

Coffee break

Section 4:
Training approaches

Revisit the definition of generative retrieval

GR usually exploits a Seq2Seq encoder-decoder architecture to generate a ranked list of docids for an input query, in an autoregressive fashion

Standard training objective

The common used training objective for both indexing and retrieval is maximum likelihood estimation (MLE):

$$
\begin{aligned}
\mathcal{L}_{Global}(Q, D, I_D, I_Q; \theta) &= \mathcal{L}_{Indexing}(D, I_D; \theta) + \mathcal{L}_{Retrieval}(Q, I_Q; \theta) \\
&= -\sum_{d \in D} \log P(id \mid d; \theta) - \sum_{q \in Q} \sum_{id^q \in I_Q} \log P(id^q \mid q; \theta)
\end{aligned}
$$

Different learning scenarios based on the corpus

$$\begin{aligned}\mathcal{L}_{Global}(Q, \underline{D}, I_D, I_Q; \theta) &= \mathcal{L}_{Indexing}(\underline{D}, I_D; \theta) + \mathcal{L}_{Retrieval}(Q, I_Q; \theta) \\ &= -\sum_{d \in \underline{D}} \log P(id \mid d; \theta) - \sum_{q \in Q} \sum_{id^q \in I_Q} \log P(id^q \mid q; \theta)\end{aligned}$$

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- **Stationary scenarios**: The document collection is fixed
- **Dynamic scenarios**: Information changes and new documents emerge incrementally over time

Stationary scenarios

$$\mathcal{L}_{Global}(Q, D, I_D, I_Q; \theta) = \mathcal{L}_{Indexing}(D, I_D; \theta) + \mathcal{L}_{Retrieval}(Q, I_Q; \theta)$$
$$= -\sum_{d \in D} \log P(id \mid d; \theta) - \sum_{q \in Q} \sum_{id^q \in I_Q} \log P(id^q \mid q; \theta)$$

According to the availability of labeled data, the training approaches in stationary scenarios can be generally classified into:

- **Supervised learning methods**
- **Pre-training methods**

Supervised learning: Basic training method

- Learn the indexing task first, and then learn retrieval tasks
  - Step 1: $\mathcal{L}_{Indexing}(D, I_D; \theta) = -\sum_{d \in D} \log P(id \mid d; \theta)$
  - Step 2: $\mathcal{L}_{Retrieval}(Q, I_Q; \theta) = -\sum_{q \in Q} \sum_{id^q \in I_Q} \log P(id^q \mid q; \theta)$

"Transformer Memory as a Differentiable Search Index". Tay et al. [2022]

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- Learn indexing and retrieval tasks simultaneously in a multitask fashion

$$
\begin{aligned}
\mathcal{L}_{Global}(Q, D, I_D, I_Q; \theta) &= \mathcal{L}_{Indexing}(D, I_D; \theta) + \mathcal{L}_{Retrieval}(Q, I_Q; \theta) \\
&= -\sum_{d \in D} \log P(id \mid d; \theta) - \sum_{q \in Q} \sum_{id^q \in I_Q} \log P(id^q \mid q; \theta)
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\end{aligned}
$$

"Transformer Memory as a Differentiable Search Index". Tay et al. [2022]

Supervised learning: Multitask learning via MLE

- For a single docid representing a document
  - Indexing: Learn the relationships between document-docid pairs
  - Retrieval: Pair the query and the docid of each relevant document, and learn the relationships between query-docid pairs

Supervised learning: Multitask learning via MLE

- For a single docid representing a document
  - Indexing: Learn the relationships between document-docid pairs
  - Retrieval: Pair the query and the docid of each relevant document, and learn the relationships between query-docid pairs
- For multiple docids representing a document
  - Indexing: Pair the document and its each corresponding docid, and then learn the relationships between document-docid pairs
  - Retrieval: Pair the query and each docid of each relevant document, and learn the relationships between query-docid pairs

Limitation (1): Single document granularity

$$\mathcal{L}_{Global}(Q, D, I_D, I_Q; \theta) = \underline{\mathcal{L}_{Indexing}(D, I_D; \theta)} + \mathcal{L}_{Retrieval}(Q, I_Q; \theta)$$
$$= -\sum_{d \in D} \log P(id \mid \underline{d}; \theta) - \sum_{q \in Q} \sum_{id^q \in I_Q} \log P(id^q \mid q; \theta)$$

"Semantic-Enhanced Differentiable Search Index Inspired by Learning Strategies". Tang et al. [2023a]

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$$= -\sum_{d \in D} \log P(id \mid \underline{d}; \theta) - \sum_{q \in Q} \sum_{id^q \in I_Q} \log P(id^q \mid q; \theta)$$

When indexing, memorizing each document at a single granularity, e.g., first L tokens or the full text, is insufficient, especially for long documents with rich semantics.

"Semantic-Enhanced Differentiable Search Index Inspired by Learning Strategies". Tang et al. [2023a]

Supervised learning: Multi-granularity enhanced

- Given a document, the important passages p and sentences s are selected to augment the indexing data

"Semantic-Enhanced Differentiable Search Index Inspired by Learning Strategies". Tang et al. [2023a]

Supervised learning: Multi-granularity enhanced

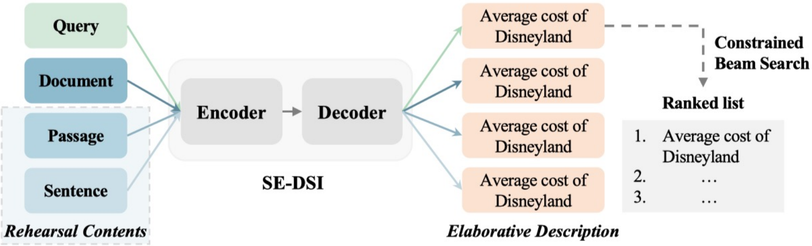
- Given a document, the important passages p and sentences s are selected to augment the indexing data

$$\mathcal{L}_{Indexing}(D, I_D; \theta) = -(\sum_{d \in D} \log P(id \mid d; \theta) + \sum_{p \in d} \log P(id \mid p; \theta) + \sum_{s \in d} \log P(id \mid s; \theta))$$

"Semantic-Enhanced Differentiable Search Index Inspired by Learning Strategies". Tang et al. [2023a]

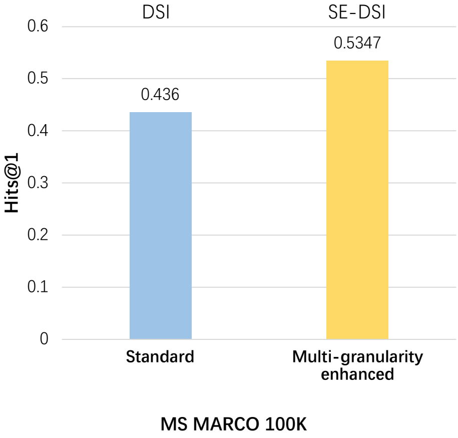
Supervised learning: Multi-granularity enhanced

- Leading-style: Directly use the leading passages and sentences
- Summarization-style: Leverage the document summarization technique, e.g., TextRank, to highlight important parts



"Semantic-Enhanced Differentiable Search Index Inspired by Learning Strategies". Tang et al. [2023a]

Comparisons



Data source: Tang et al. [2023a]

- Backbone: T5-base
- Multi-granularity representations of documents can comprehensively encode the documents, and further contribute to the retrieval

Limitation (2): The gap between indexing and retrieval

$$\begin{aligned}\mathcal{L}_{Global}(Q, D, I_D, I_Q; \theta) &= \mathcal{L}_{Indexing}(\underline{D}, I_D; \theta) + \mathcal{L}_{Retrieval}(\underline{Q}, I_Q; \theta)\\ &= -\sum_{d \in D} \log P(id \mid \underline{d}; \theta) - \sum_{q \in Q} \sum_{id^q \in I_Q} \log P(id^q \mid \underline{q}; \theta)\end{aligned}$$

"Bridging the Gap Between Indexing and Retrieval for Differentiable Search Index with Query Generation". Zhuang et al. [2023]

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Long document in indexing vs. Short query in retrieval

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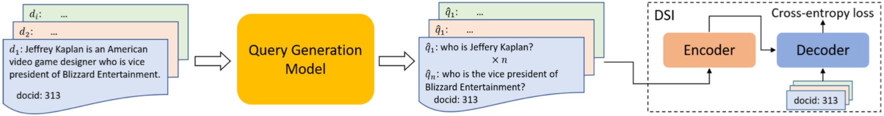
$$

Long document in indexing vs. Short query in retrieval

The data distribution mismatch that occurs between the indexing and retrieval

"Bridging the Gap Between Indexing and Retrieval for Differentiable Search Index with Query Generation". Zhuang et al. [2023]

Supervised learning: Pseudo query enhanced



Using a set of pseudo queries *pq* generated from the document as the inputs of the indexing task

"Bridging the Gap Between Indexing and Retrieval for Differentiable Search Index with Query Generation". Zhuang et al. [2023]

Supervised learning: Pseudo query enhanced

$$\mathcal{L}_{Indexing}(D, I_D; \theta) = -\sum_{d \in D} \log P(id \mid \underline{d}; \theta)$$

$$\downarrow$$

$$\mathcal{L}_{Indexing}(D, I_D; \theta) = -\sum_{pq \in D} \log P(id \mid \underline{pq}; \theta)$$

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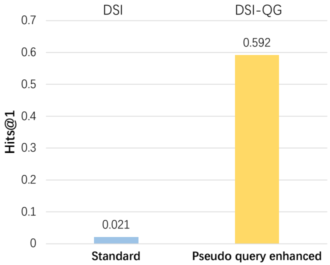
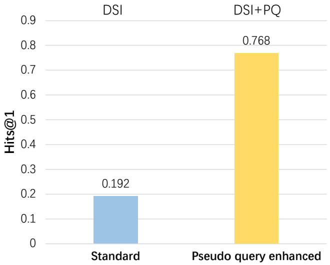


(Naively structured strings)

MS MARCO 100K



(Semantically structured strings)

MS MARCO 100K

- Backbone: T5-base
- Using only pseudo synthetic queries to docid during indexing is an effective training strategy on MS MARCO [Pradeep et al., 2023]

Data source: Pradeep et al. [2023], Zhuang et al. [2023]

Limitation (3): Limited labeled data

$$\mathcal{L}_{Global}(Q, D, I_D, I_Q; \theta) = \mathcal{L}_{Indexing}(D, I_D; \theta) + \boxed{\mathcal{L}_{Retrieval}(Q, I_Q; \theta)} \; ?$$

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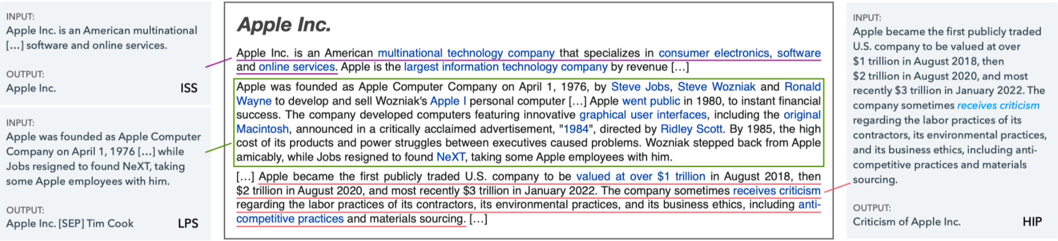
What should we do if there is no or few labeled query-docid pairs?

Pre-training methods

Constructing pseudo query-docid pairs (PQ, I_Q^P) for the pre-training retrieval task

$$\mathcal{L}_{Pre-train}(PQ, D, I_D, I_Q^P; \theta) = \mathcal{L}_{Indexing}(D, I_D; \theta) + \underline{\mathcal{L}_{Retrieval}(PQ, I_Q^P; \theta)}$$

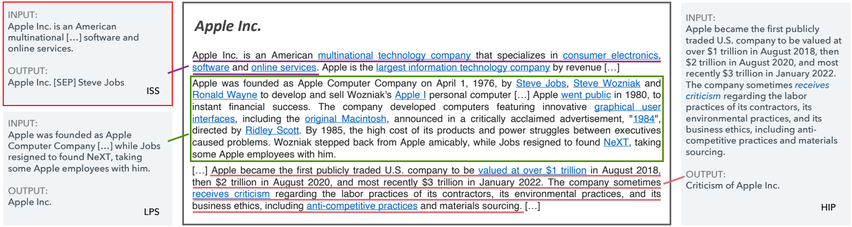
CorpusBrain [Chen et al., 2022b]: Pre-training



Based on Wikipedia, three pre-training retrieval tasks are constructed

"CorpusBrain: Pre-train a Generative Retrieval Model for Knowledge-Intensive Language Tasks". Chen et al. [2022b]

CorpusBrain [Chen et al., 2022b]: Pre-training

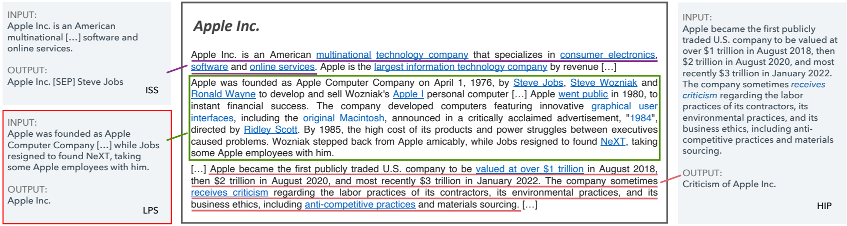


Inner Sentence Selection (ISS):

- Pseudo query (PQ): Randomly selected inner sentence from its document
- Docid (I_Q^P): Concatenated relevant document titles, i.e., "title [SEP] title [SEP] title"

"CorpusBrain: Pre-train a Generative Retrieval Model for Knowledge-Intensive Language Tasks". Chen et al. [2022b]

CorpusBrain [Chen et al., 2022b]: Pre-training

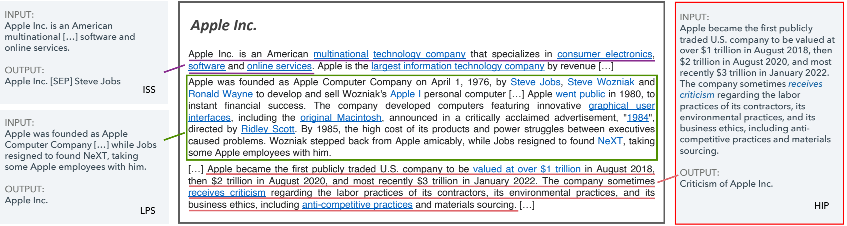


Lead Paragraph Selection (LPS):

- Pseudo query (PQ): A (lead) paragraph is sampled from the document
- Docid (I_Q^P): Concatenated relevant document titles

"CorpusBrain: Pre-train a Generative Retrieval Model for Knowledge-Intensive Language Tasks". Chen et al. [2022b]

CorpusBrain [Chen et al., 2022b]: Pre-training



Hyperlink Identifier Prediction (HIP):

- Pseudo query (PQ): The anchor context, i.e., the surrounding contextual information in the anchor's corresponding sentence
- Docid (I_Q^P): The document title of the destination page

"CorpusBrain: Pre-train a Generative Retrieval Model for Knowledge-Intensive Language Tasks". Chen et al. [2022b]

CorpusBrain [Chen et al., 2022b]: Training and inference

- **Pre-training**: Based on the three pre-training tasks, a large number of pseudo pairs of query and document identifiers are constructed. All the tasks are formulated by a standard seq2seq objective for the pre-training

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- **Fine-tuning**: CorpusBrain is fine-tuned using the processed data (in a Seq2Seq pair format) in downstream tasks

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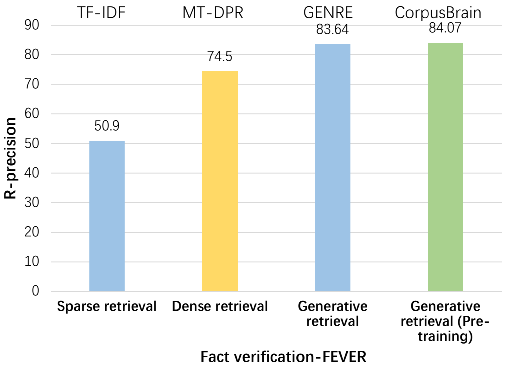
- **Fine-tuning**: CorpusBrain is fine-tuned using the processed data (in a Seq2Seq pair format) in downstream tasks
- **Test**: Given a test query, the fine-tuned CorpusBrain utilizes constrained beam search to decode relevant docids

"CorpusBrain: Pre-train a Generative Retrieval Model for Knowledge-Intensive Language Tasks". Chen et al. [2022b]

CorpusBrain [Chen et al., 2022b]: Performance



- In the KILT leaderboard, Corpusbrain achieved first place in 5 of them, second place in 1 task, and third place in 4 tasks, outperforming traditional pipelined approaches

"CorpusBrain: Pre-train a Generative Retrieval Model for Knowledge-Intensive Language Tasks". Chen et al. [2022b]

Challenge (4): Pointwise optimization for GR

$$\begin{aligned}\mathcal{L}_{Global}(Q, D, I_D, I_Q; \theta) &= \mathcal{L}_{Indexing}(D, I_D; \theta) + \underline{\mathcal{L}_{Retrieval}(Q, I_Q; \theta)} \\ &= -\sum_{d \in D} \log P(id \mid d; \theta) \underline{- \sum_{q \in Q} \sum_{id^q \in I_Q} \log P(id^q \mid q; \theta)}\end{aligned}$$

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- It assumes the likelihood for each relevant docid is independent of the other docids in the list for a query
- Ranking is a prediction task on list of objects

Challenge (4): Pointwise optimization for GR

$$\begin{aligned}\mathcal{L}_{Global}(Q, D, I_D, I_Q; \theta) &= \mathcal{L}_{Indexing}(D, I_D; \theta) + \underline{\mathcal{L}_{Retrieval}(Q, I_Q; \theta)} \\ &= -\sum_{d \in D} \log P(id \mid d; \theta) \underline{- \sum_{q \in Q} \sum_{id^q \in I_Q} \log P(id^q \mid q; \theta)}\end{aligned}$$

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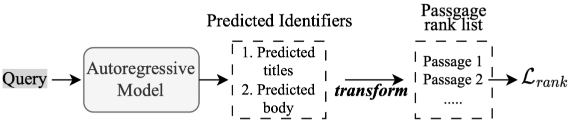
Pairwise and listwise optimization strategies for GR are necessary!

Pairwise optimization: LTRGR [Li et al., 2023c]

- Step 1: Initial training with pointwise optimization
- Step 2: Based on the trained initial model, perform pairwise optimization

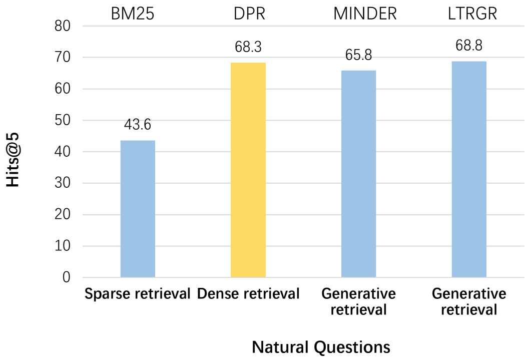


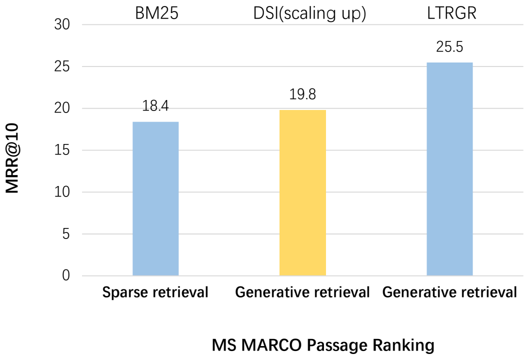
$$max(0, s(q, d_-) - s(q, d_+) + m),$$

where d_- and d_+ are negative and positive documents, and m is the margin

"Learning to Rank in Generative Retrieval". Li et al. [2023c]

LTRGR [Li et al., 2023c]: Performance



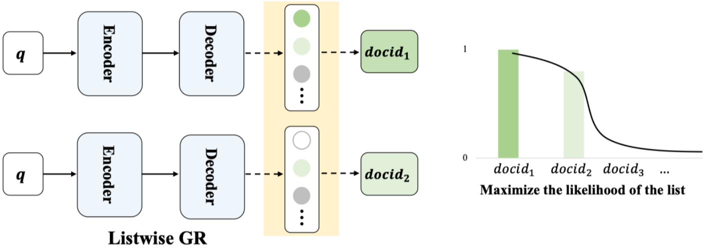


"Learning to Rank in Generative Retrieval". Li et al. [2023c]

Listwise optimization: [Tang et al., 2023b]

Training with position-aware ListMLE

- View the docid ranking problem as a sequential learning process, with each step targeting to maximize the corresponding stepwise probability distribution



"Listwise Generative Retrieval Models via a Sequential Learning Process". Tang et al. [2023b]

Listwise optimization: [Tang et al., 2023b]

Given:

- A query q
- Its ground-truth docid list $\pi_q = [id^{(1)}, id^{(2)}, \ldots]$, in descending order of relevance, where $id^{(1)}$ is the docid ranked at the first position, and $id^{(2)}$ is the docid ranked at the second position, and so on

"Listwise Generative Retrieval Models via a Sequential Learning Process". Tang et al. [2023b]

Sequential learning process

Step 1: Maximize the following top-1 positional conditional probability:

$$P(id^{(1)} \mid q; \theta) = \frac{\exp(\tilde{P}(id^{(1)} \mid q; \theta))}{\sum_{j=1}^{n} \exp(\tilde{P}(id^{(j)} \mid q; \theta))},$$

where $\tilde{P}(id^{(i)} \mid q; \theta) = \frac{\log P(id^{(i)} | q; \theta)}{|id^{(i)}|}$, and $P(id^{(i)} \mid q; \theta)$ is the generated likelihood of the i-th relevant docid $id^{(i)}$ for q

"Listwise Generative Retrieval Models via a Sequential Learning Process". Tang et al. [2023b]

Sequential learning process

Step 2: For $i = 2, \ldots, n$, maximize the following i-th positional conditional probability given the preceding top $i-1$ docids,

$$P(id^{(i)} \mid q, id^{(1)}, \ldots, id^{(i-1)}; \theta) = \frac{\exp(\tilde{P}(id^{(i)} \mid q; \theta))}{\sum_{j=i}^{n} \exp(\tilde{P}(id^{(j)} \mid q; \theta))}$$

The learning process ends at step $n+1$

"Listwise Generative Retrieval Models via a Sequential Learning Process". Tang et al. [2023b]

Listwise loss with position importance

- Listwise probability with position importance

$$\begin{aligned}
&\min_{\theta} -\log P(\pi_q \mid q; \theta) \\
&\quad = -\alpha(1) \log P(id^{(1)} \mid q; \theta) - \sum_{i=2}^{n} \alpha(i) \log P\left(id^{(i)} \mid q, id^{(1)}, \ldots, id^{(i-1)}; \theta\right),
\end{aligned}$$

where the weight $\alpha(\cdot)$ is a decreasing function

- Listwise loss function incorporating the probability based on Plackett-Luce model

$$\mathcal{L}_{List}(q, \pi_q; \theta) = \sum_{i=1}^{n} \alpha(i) \left(-\tilde{P}(id^{(i)} \mid q; \theta) + \log \left(\sum_{k=i}^{n} \exp(\tilde{P}(id^{(k)} \mid q; \theta)) \right) \right)$$

"Listwise Generative Retrieval Models via a Sequential Learning Process". Tang et al. [2023b]

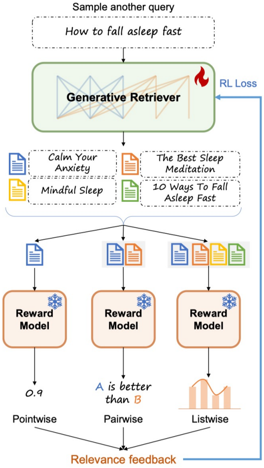
Multiple optimization: GenRRL [Zhou et al., 2023]

Based on reinforce learning framework

- train a linear reward model
- train a GR model with pointwise, pairwise and listwise optimization strategies

"Enhancing Generative Retrieval with Reinforcement Learning from Relevance Feedback". Zhou et al. [2023]

Multiple optimization: GenRRL [Zhou et al., 2023]



- Pointwise optimization:
  $-\sum_i (R(q, id_i) - b) \sum_t \log P(w_t^i \mid w_{<t}, q)$,
  where R is a reward model, and b is a baseline

"Enhancing Generative Retrieval with Reinforcement Learning from Relevance Feedback". Zhou et al. [2023]

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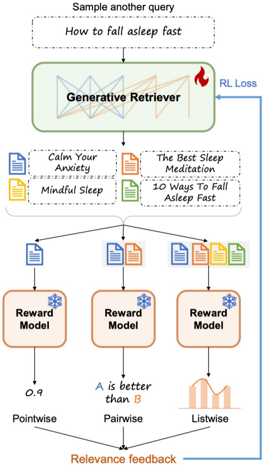

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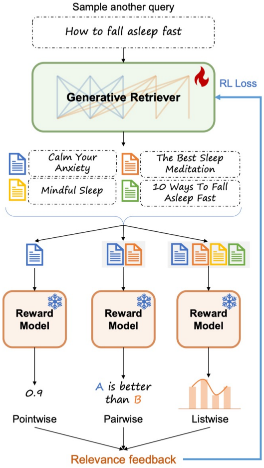
  where R is a reward model, and b is a baseline
- Pairwise optimization:
  $-\sum_{(id_i, id_j)} (R(q, id_i) \log p_{ij} + R(q, id_j) \log p_{ji}$,
  where $p_{ij} = |P(w_t^i \mid q) - P(w_t^j \mid q)|$

"Enhancing Generative Retrieval with Reinforcement Learning from Relevance Feedback". Zhou et al. [2023]

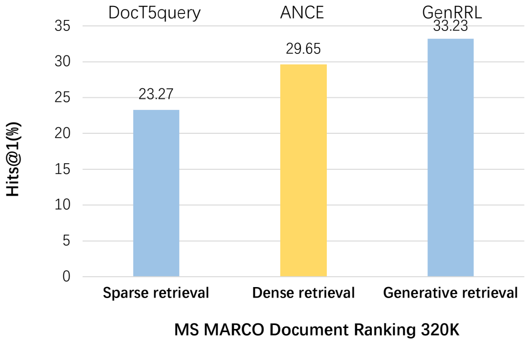
Multiple optimization: GenRRL [Zhou et al., 2023]

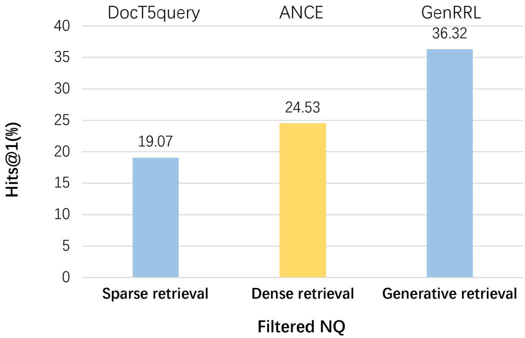


- Pointwise optimization:
  $-\sum_i (R(q, id_i) - b) \sum_t \log P(w_t^i \mid w_{<t}, q)$,
  where R is a reward model, and b is a baseline
- Pairwise optimization:
  $-\sum_{(id_i, id_j)} (R(q, id_i) \log p_{ij} + R(q, id_j) \log p_{ji}$,
  where $p_{ij} = |P(w_t^i \mid q) - P(w_t^j \mid q)|$
- Listwise optimization:
  $-\sum_{id_i \in C} R(q, id_i) \log \frac{\exp(P(w_t^i | q))}{\sum_j \exp(P(w_t^j | q))}$

"Enhancing Generative Retrieval with Reinforcement Learning from Relevance Feedback". Zhou et al. [2023]

GenRRL [Zhou et al., 2023]: Performance





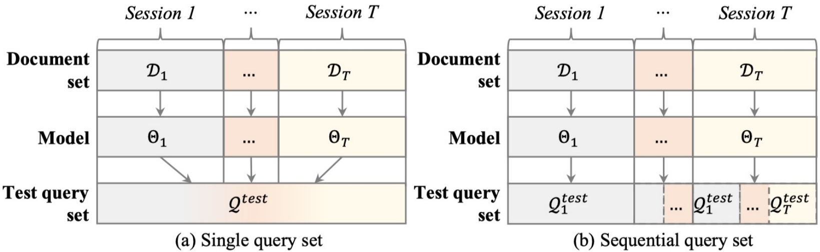
"Enhancing Generative Retrieval with Reinforcement Learning from Relevance Feedback". Zhou et al. [2023]

Dynamic scenarios

$$\begin{aligned}\mathcal{L}_{Global}(Q, \underline{D}, I_D, I_Q; \theta) &= \mathcal{L}_{Indexing}(\underline{D}, I_D; \theta) + \mathcal{L}_{Retrieval}(Q, I_Q; \theta) \\ &= -\sum_{d \in \underline{D}} \log P(id \mid d; \theta) - \sum_{q \in Q} \sum_{id^q \in I_Q} \log P(id^q \mid q; \theta)\end{aligned}$$

Information changes and new documents emerge incrementally over time

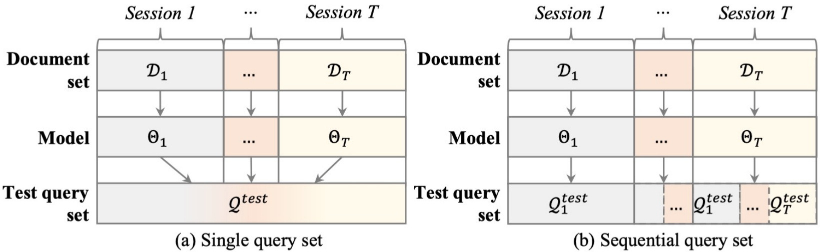
Continual learning task: Formulation



- **Initial model**: A large-scale base document set D_0 and sufficiently many labeled query-document pairs

Image source: Chen et al. [2023a]

Continual learning task: Formulation



- **Initial model**: A large-scale base document set D_0 and sufficiently many labeled query-document pairs
- **New datasets**: T new datasets $D_1, \ldots, D_T$, from T sessions arriving in a sequential manner, which are only composed of newly encountered documents without queries related to these documents

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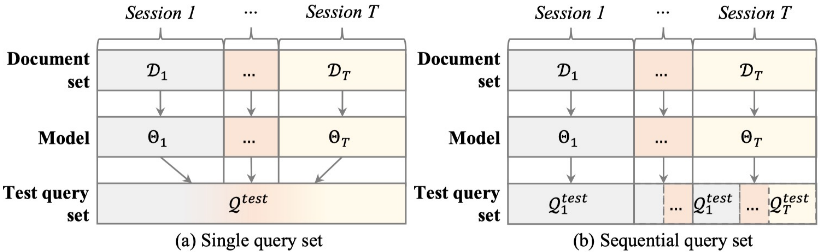
Continual learning task: Formulation



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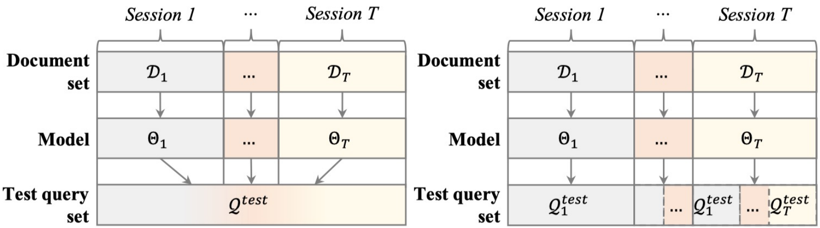
- **New datasets**: T new datasets $D_1, \ldots, D_T$, from T sessions arriving in a sequential manner, which are only composed of newly encountered documents without queries related to these documents
- **Model update**: The new dataset D_t and previous datasets $D_0, \ldots, D_{t-1}$

Image source: Chen et al. [2023a]

Continual learning task: Evaluation



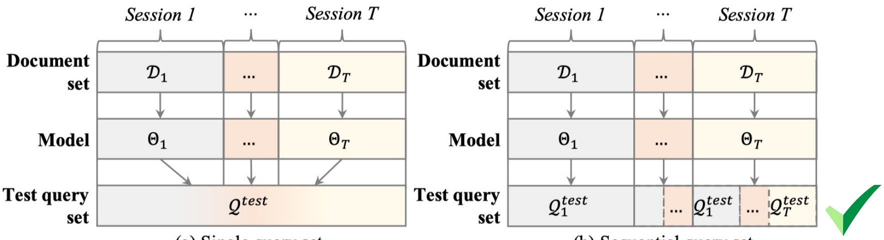
(a) Single query set (b) Sequential query set

Two types of test query set for performance evaluation:

- **Single query set**: There is only one test query set, and their relevant documents arrive in different sessions
- **Sequential query set**: The test query set is specific for each session, and the relevant documents appear in existing sessions

Image source: Chen et al. [2023a]

Continual learning task: Evaluation



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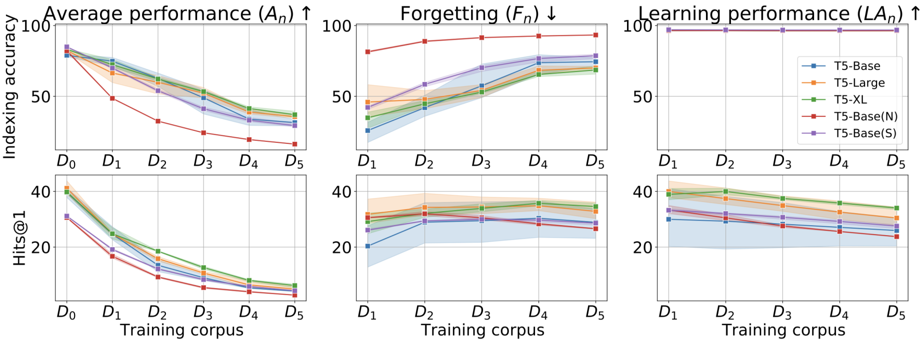


The GR model undergoes severe forgetting under continual indexing of new documents

Image source: Mehta et al. [2022]

"DSI++: Updating Transformer Memory with New Documents". Mehta et al. [2022]

Challenges of continual learning for GR

- How to incrementally index new documents with low computational and memory costs?

Challenges of continual learning for GR

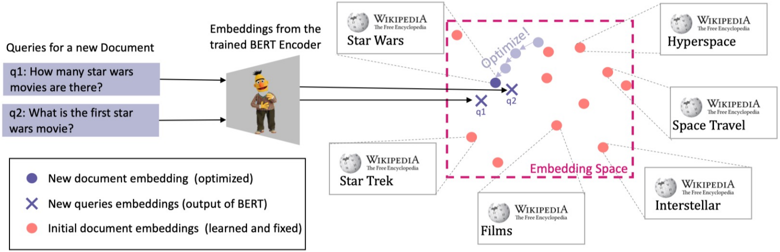
- How to incrementally index new documents with low computational and memory costs?
- How to prevent catastrophic forgetting for previously indexed documents and maintain the retrieval ability?

IncDSI [Kishore et al., 2023]

- Docid: unique atomic integers
- Constrained optimization problem: find the optimal document vector for a new document, do not modify any other existing document vectors and do not require broader updates to the query encoder

"IncDSI: Incrementally Updatable Document Retrieval". Kishore et al. [2023]

IncDSI [Kishore et al., 2023]: Incrementally indexing new documents



- Constrained optimization:
  - The new document is scored higher than all the existing documents for the its representative query embedding

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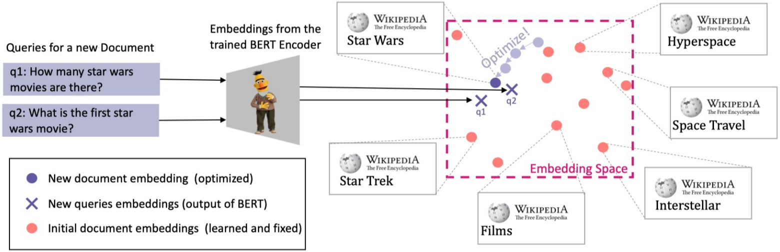
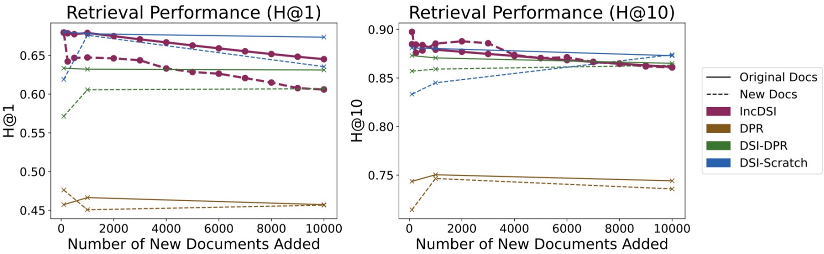


- Constrained optimization:
  - The new document is scored higher than all the existing documents for the its representative query embedding
  - The new document is scored lower than all the existing documents for other representative query embedding

"IncDSI: Incrementally Updatable Document Retrieval". Kishore et al. [2023]

IncDSI [Kishore et al., 2023]: Effectiveness



- The H@10 for the original documents is nearly constant during indexing, although the Hits@1 for the original documents does degrade slowly over time

"IncDSI: Incrementally Updatable Document Retrieval". Kishore et al. [2023]

IncDSI [Kishore et al., 2023]: Limitations

- It needs learn a embedding for each document, resulting high computational costs
- It may not address the catastrophic forgetting problem

"IncDSI: Incrementally Updatable Document Retrieval". Kishore et al. [2023]

DSI++ [Mehta et al., 2022]: Incrementally indexing new documents

- Docids: The new documents are assigned unstructured atomic integers as docids, and the GR model learns new embeddings for each of them

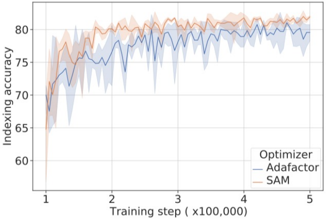
"DSI++: Updating Transformer Memory with New Documents". Mehta et al. [2022]

DSI++ [Mehta et al., 2022]: Incrementally indexing new documents

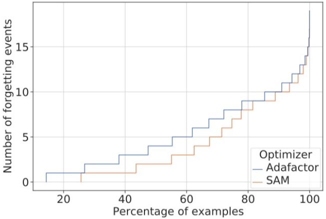
- Docids: The new documents are assigned unstructured atomic integers as docids, and the GR model learns new embeddings for each of them
- Modifying the training dynamics: Since flatter minima implicitly alleviate forgetting, optimizing for flatter loss basins using Sharpness-Aware Minimization (SAM) as an objective allows the model to stably memorize more documents

"DSI++: Updating Transformer Memory with New Documents". Mehta et al. [2022]

DSI++ [Mehta et al., 2022]: Incrementally indexing new documents



(a) Indexing accuracy during memorization



(b) Cumulative histogram of forgetting events

- SAM outperforms Adafactor in terms of the overall indexing accuracy
- SAM undergoes less severe fluctuations during the course of training

Image source: Mehta et al. [2022]

"DSI++: Updating Transformer Memory with New Documents". Mehta et al. [2022]

DSI++ [Mehta et al., 2022]: Preventing catastrophic forgetting

- Generative memory: Train a query generator model to sample pseudo-queries for previously seen documents and supplement the query-docid pairs during continual indexing

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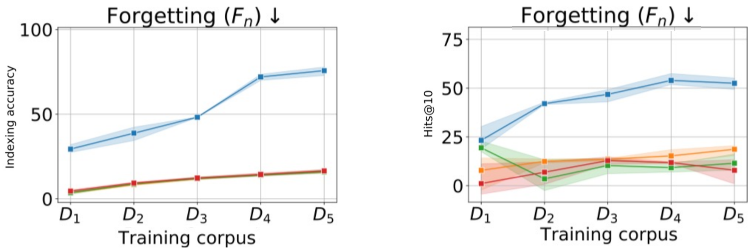
DSI++ [Mehta et al., 2022]: Preventing catastrophic forgetting

- Generative memory: Train a query generator model to sample pseudo-queries for previously seen documents and supplement the query-docid pairs during continual indexing
- It reduces the forgetting, and improves average Hits@10 by +21.1% over baselines



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Limitations of DSI++

- Learning embeddings for each individual new docid from scratch incurs prohibitively high computational costs

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Limitations of DSI++

- Learning embeddings for each individual new docid from scratch incurs prohibitively high computational costs
- The relationships between new and old documents may not be easily obtained from randomly-selected exemplars

"DSI++: Updating Transformer Memory with New Documents". Mehta et al. [2022]

CLEVER [Chen et al., 2023a]: Incrementally indexing new documents

Incremental product quantization (PQ) codes as identifiers: Update a partial quantization codebook according to two adaptive thresholds

"Continual Learning for Generative Retrieval over Dynamic Corpora". Chen et al. [2023a]

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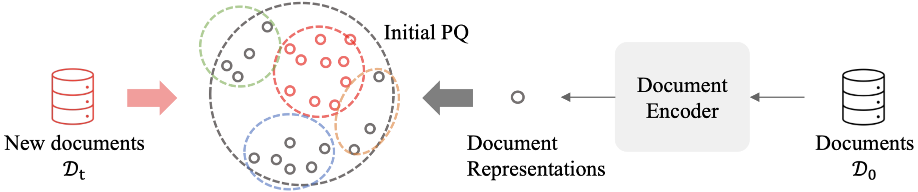
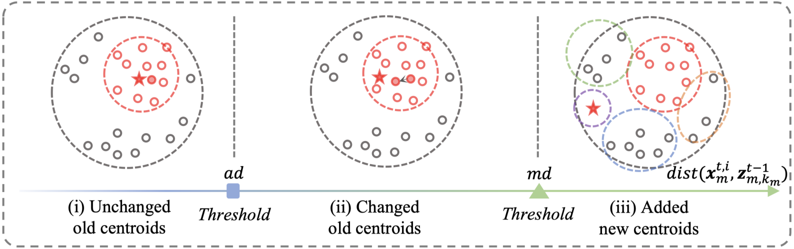


- Build base PQ
  - Centroids are obtained via clustering over document representations
  - Document representations are learned with a bootstrapped training process

"Continual Learning for Generative Retrieval over Dynamic Corpora". Chen et al. [2023a]

CLEVER [Chen et al., 2023a]: Incremental product quantization



- Update adaptively
  - Dynamic thresholds: Average distance (ad); maximum distance (md)
  - Three types of update for centroid representation: Depend on contributions to centroid update

"Continual Learning for Generative Retrieval over Dynamic Corpora". Chen et al. [2023a]

CLEVER [Chen et al., 2023a]: Preventing catastrophic forgetting

Memory-augmented learning mechanism: Form meaningful connections between old and new documents

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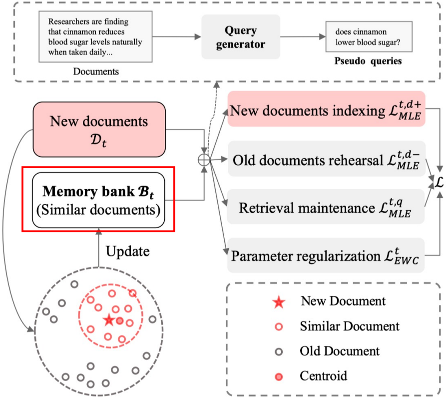
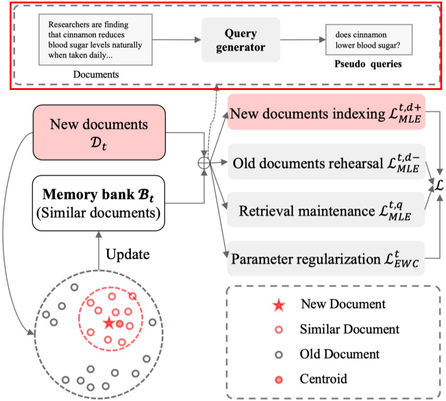


- **Dynamic memory bank**: Construct a memory bank with similar documents for each new session and replay the process of indexing them alongside the indexing of new documents

"Continual Learning for Generative Retrieval over Dynamic Corpora". Chen et al. [2023a]

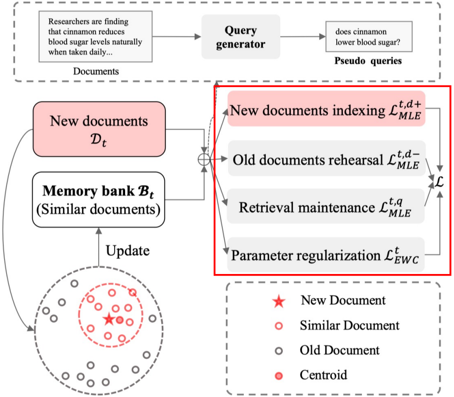
CLEVER [Chen et al., 2023a]: Memory-augmented learning mechanism



- **Pseudo query-docid pairs**: Train a query generator model to sample pseudo-queries for documents and supplement the query-docid pairs during indexing

"Continual Learning for Generative Retrieval over Dynamic Corpora". Chen et al. [2023a]

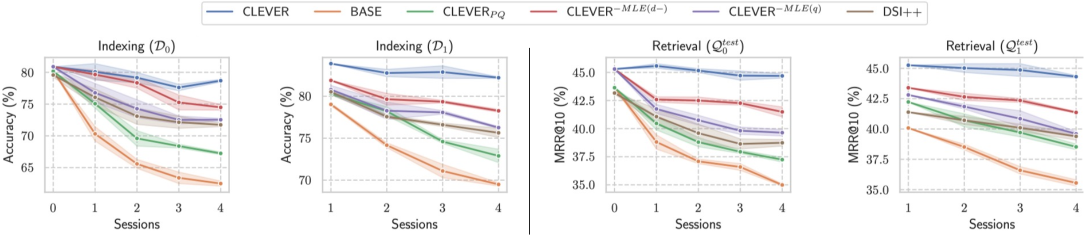
CLEVER [Chen et al., 2023a]: Memory-augmented learning mechanism



- **Sequentially training**: new documents indexing, old document rehearsal, retrieval maintenance losses and an elastic weight consolidation (EWC) loss as a regularization term

"Continual Learning for Generative Retrieval over Dynamic Corpora". Chen et al. [2023a]

CLEVER [Chen et al., 2023a]: Performance



Indexing ($D_0 \rightarrow D_1$)

Retrieval ($Q_0^{test} \rightarrow Q_1^{test}$)

- CLEVER almost avoids catastrophic forgetting on both indexing and retrieval tasks, showing its effectiveness in a dynamic setting

Image source: Chen et al. [2023a]

"Continual Learning for Generative Retrieval over Dynamic Corpora". Chen et al. [2023a]

Limitations in large-scale corpus

- Existing GR models only perform well on artificially-constructed and small-scale collections
- Zeng et al. [2024] introduced the RIPOR framework, designed to improve the performance of generative retrieval models for MS MARCO dataset, with 8.8M passages and 532K training queries

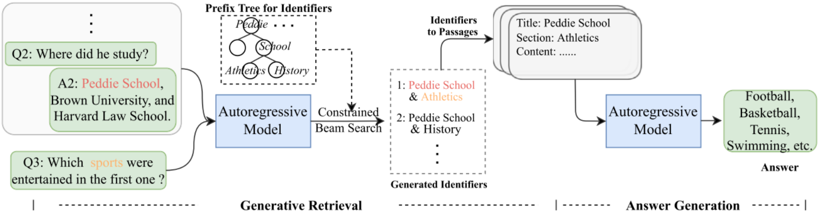
It is necessary to explore the capacity of GR models to larger corpus

"Scalable and Effective Generative Information Retrieval". Zeng et al. [2024]

Retrieval tasks and question answering (QA) tasks can assist each other

How to apply generative retrieval in question answering?

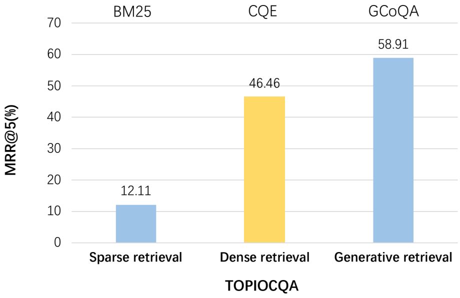
GCoQA [Li et al., 2023b]

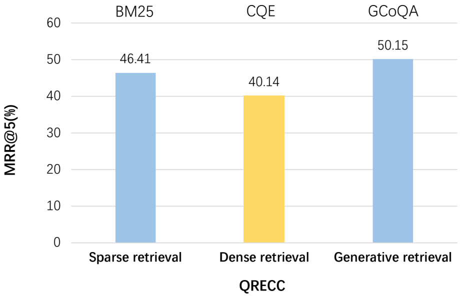


- Step 1: **Document retrieval** with a GR model
- Step 2: **Answer generation** with another autoregressive model

"Generative retrieval for conversational question answering". Li et al. [2023b]

GCoQA [Li et al., 2023b]: Performance



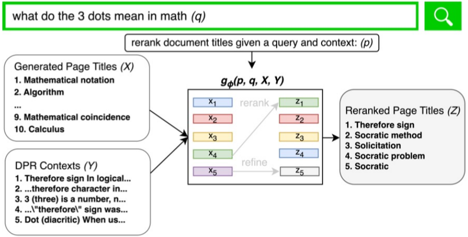


"Generative retrieval for conversational question answering". Li et al. [2023b]

Limitations

- The GR may not account for contextual information
- The retrieval can't be tuned for the downstream readers as decoding the docid is a non-differentiable operation

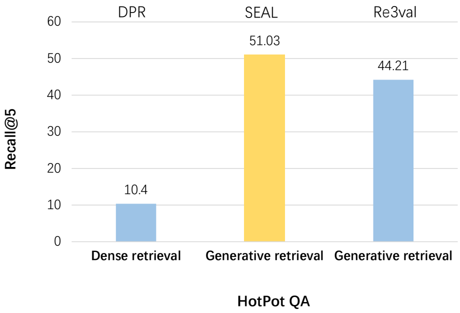
Re3val [Song et al., 2024]

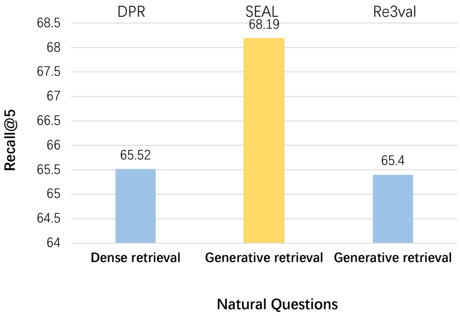


- Step 1: Relevant titles generation using a GR model
- Step 2: Retrieved titles reranking using a cross-encoder
- Step 3: Context retrieval for titles using BM25
- Step 4: Answer generation using an generative model

"Re3val: Reinforced and Reranked Generative Retrieval". Li et al. [2023a]

Re3val [Song et al., 2024]: Performance



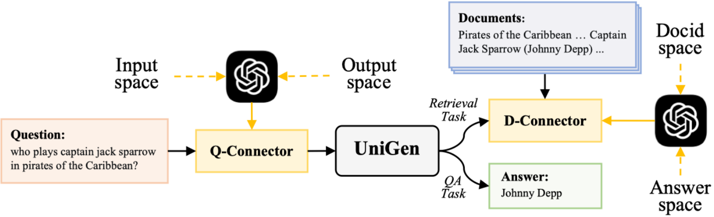


"Re3val: Reinforced and Reranked Generative Retrieval". Li et al. [2023a]

Limitation

Generative document retrieval and grounded answer generation rely on separate retrieval and reader module, which may hinder simultaneous optimization

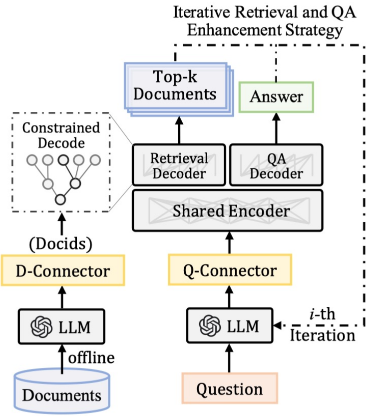
UniGen [Li et al., 2023a]



- Joint learning for GR and QA
- Connectors generated by LLMs bridge the gaps between the input space and output space

"UniGen: A Unified Generative Framework for Retrieval and Question Answering with Large Language Models". Li et al. [2023a]

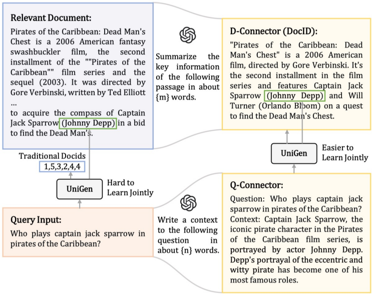
UniGen [Li et al., 2023a]: Architecture



- A shared encoder and two distinct decoders for GR and QA

"UniGen: A Unified Generative Framework for Retrieval and Question Answering with Large Language Models". Li et al. [2023a]

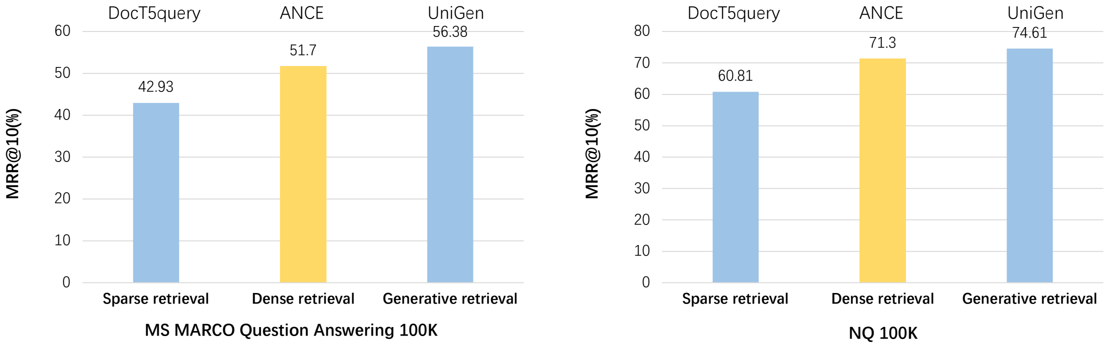
UniGen [Li et al., 2023a]



- Use LLMs to generate a query context and document summary, serving as bridges between query inputs, documents, and answer outputs

"UniGen: A Unified Generative Framework for Retrieval and Question Answering with Large Language Models". Li et al. [2023a]

UniGen [Li et al., 2023a]: Performance



"UniGen: A Unified Generative Framework for Retrieval and Question Answering with Large Language Models". Li et al. [2023a]

A look back

Training approaches				
Standard approach (Tay et al. 2022)			- Simple	- Moderate performance
Stationary	Multi-granularity enhanced (Tang et al. 2023a)		- Enhancing the memorization ability	- Requiring extra tools for selecting important paragraphs or sentences
	Pseudo query enhanced (Zhuang et al. 2023)		- Reducing the gap between training and inference	- Depending on labeled data
	Pre-training based (Chen et al. 2022b)		- Addressing the issue of no or limited labeled data	- Depending on the quality of pre-training corpora and task design
	Pairwise optimization (Li et al., 2023c)		- Enhancing the relevance signals	- Multi-stage training
	Multiple optimization (Zhou et al., 2023)		- Fully utilize relevance signals	- Rely on various external algorithms
Dynamic	IncDSI (Kishore et al.2023)	Unstructured atomic integers & constrained optimization	- Simple design & high efficiency	- Moderate performance - Ignore catastrophic forgetting
	DSI++ (Mehta et al. 2022)	Unstructured atomic integers & experience replay	- Simple design - Good performance	- High computational cost - Difficult to capture the relationship between old and new corpora
	CLEVER (Chen et al. 2023a)	Incremental product quantization & memory-augmented learning	- High efficiency - Better at capturing the relationship between old and new corpora - Better performance	- More complicated docid implementation - Extra memory bank
Apply GR in QA	GCoQA (Li et al. 2023a)		- Large model knowledge is introduced	- Data preprocessing incurs high costs - Separate retrieval and reader module
	Re3val (Song et al., 2024)		- A cross-encoder is introduced	As above
	UniGen (Li et al., 2023a)		- Joint optimization for GR and QA	- The generation process of the retriever and reader is not explicitly connected
Large-scale corpora	PIPOR (Zeng et al. 2023)		- The optimization considers the docid structure	- The optimization process is complex

Revisit: Challenges of training approaches

- **How to memorize the whole corpus effectively and efficiently?**

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  - Pre-training
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  - Low computational and memory costs
  - Maintaining the retrieval ability

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Model inference $\rightarrow$ **Section 5!**

Section 5:
Inference strategies

Roadmap of inference strategies

- A **single identifier** to represent a document:
  - Constrained beam search with a prefix tree
  - Constrained greedy search with the inverted index

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- A **single identifier** to represent a document:
  - Constrained beam search with a prefix tree
  - Constrained greedy search with the inverted index
- **Multiple identifiers** to represent a document
  - Constrained beam search with the FM-index
  - Scoring functions to aggregate the contributions of several identifiers

Single identifier: Constrained beam search with a prefix tree

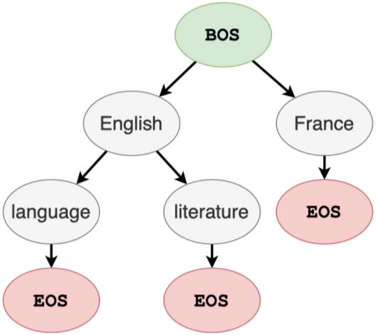
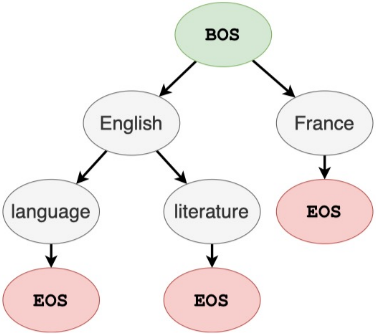


Image source: De Cao et al. [2021]

- For docids considering order of tokens
- **Applicable docids**: Naively structured strings, semantically structured strings, product quantization strings, titles, n-grams, URLs and pseudo queries

"Autoregressive Entity Retrieval". De Cao et al. [2021]

Single identifier: Constrained beam search with a prefix tree

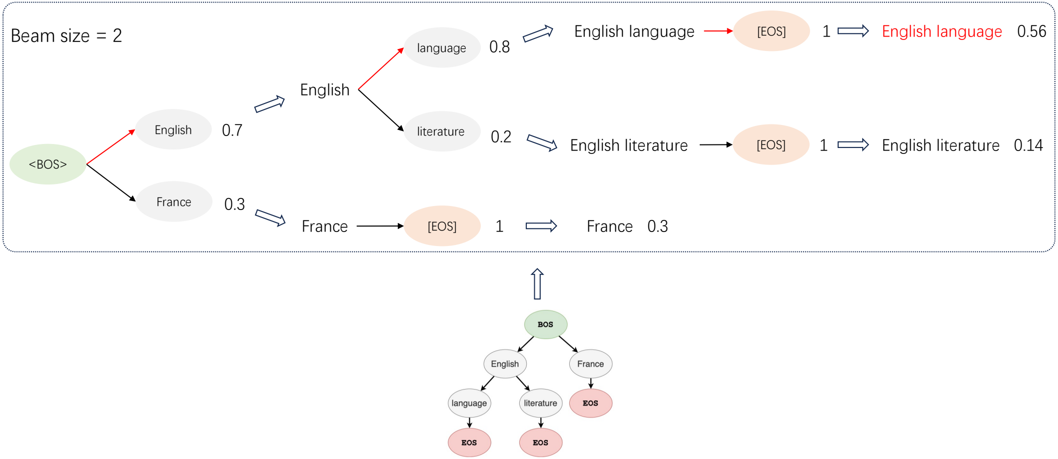


“Autoregressive Entity Retrieval”. De Cao et al. [2021]

Image source: De Cao et al. [2021]

- For docids considering order of tokens
- **Applicable docids**: Naively structured strings, semantically structured strings, product quantization strings, titles, n-grams, URLs and pseudo queries
- Prefix tree: Nodes are annotated with tokens from the predefined candidate set. For each node, its children indicate all the allowed continuations from the prefix defined traversing the tree from the root to it

Example



Beam size = 2
<BOS>
English
0.7
France
0.3
English
language
0.8
literature
0.2
English language
[EOS]
1
English language 0.56
English literature
[EOS]
1
English literature 0.14
France
[EOS]
1
France 0.3
BOS
English
France
language
literature
EOS
EOS
EOS

Single identifier: Constrained greedy search with the inverted index

- Applicable docids: Important terms

"Term-Sets Can Be Strong Document Identifiers For Auto-Regressive Search Engines". Zhang et al. [2023]

Single identifier: Constrained greedy search with the inverted index

- Applicable docids: Important terms
- Inverted index table: Enable the generation in any permutations (unordered docids) are constructed

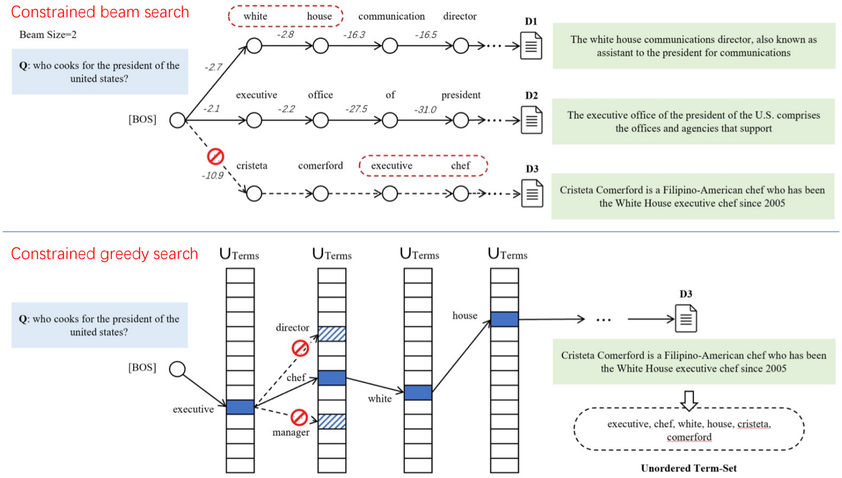
"Term-Sets Can Be Strong Document Identifiers For Auto-Regressive Search Engines". Zhang et al. [2023]

Single identifier: Constrained greedy search with the inverted index

- Applicable docids: Important terms
- Inverted index table: Enable the generation in any permutations (unordered docids) are constructed
- Generation process: The model is expected to produce docids of the highest generation likelihood. At each step of generation, the terms from the inverted index table which give rise to the top-K generation likelihood are greedily selected

"Term-Sets Can Be Strong Document Identifiers For Auto-Regressive Search Engines". Zhang et al. [2023]

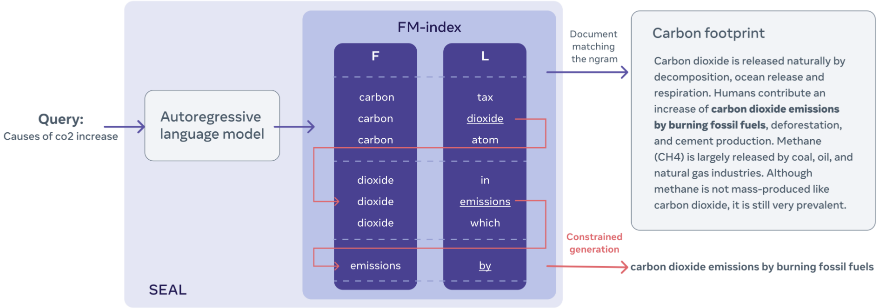
Constrained beam search vs. Constrained greedy search



"Term-Sets Can Be Strong Document Identifiers For Auto-Regressive Search Engines". Zhang et al. [2023]

Image source: Zhang et al. [2023]

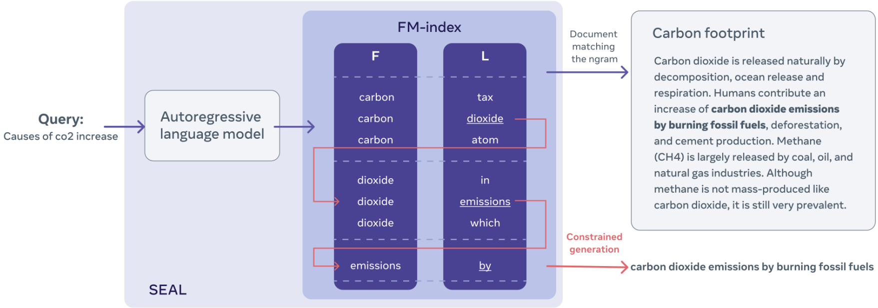
Multiple identifiers: Constrained beam search with the FM-index



- Applicable docids: N-grams based docids

"Autoregressive Search Engines: Generating Substrings as Document Identifiers". Bevilacqua et al. [2022]

Multiple identifiers: Constrained beam search with the FM-index



- Applicable docids: N-grams based docids
- FM-index: An index combining the Burrows-Wheeler Transform (BWT) with a few small auxiliary data structures

"Autoregressive Search Engines: Generating Substrings as Document Identifiers". Bevilacqua et al. [2022]

FM-index: N-gram level scores

Given an input query q, we obtain the weight of each predicted n-gram n:

$$score(n, q) = \max\left(0, \log \frac{P(n|q)(1 - P(n))}{P(n)(1 - P(n|q))}\right),$$

where $P(n|q)$ is the probability of the generative model decoding n conditioned on q, and $p(n)$ denotes the unconditional n-gram probability.

"Autoregressive Search Engines: Generating Substrings as Document Identifiers". Bevilacqua et al. [2022]

N-gram level to document level scores

How to aggregate the contribution of multiple generated n-gram identifiers to its corresponding documents?

Aggregation functions: SEAL [Bevilacqua et al., 2022]

The document-level rank score combines the n-gram level rank score $score(n, q)$ and coverage weight $cover(n, K)$:

$$score(d, q) = \sum_{n \in K^d} score(n, q)^{\alpha} \times cover(n, K),$$

where K denotes all the generated n-grams, K^d is the subset of n-grams in K that appear in d , α is a hyperparameter

"Autoregressive Search Engines: Generating Substrings as Document Identifiers". Bevilacqua et al. [2022]

Aggregation functions: SEAL [Bevilacqua et al., 2022]

For docid repetition problem

- Coverage weight $cover(n, K)$: Avoid the overscoring of very repetitive documents, where many similar n-grams are matched

$$cover(n, K) = 1 - \beta + \beta \frac{|set(n) \backslash C(n, K)|}{|set(n)|},$$

where β is a hyperparameter, $set(n)$ is the set of tokens in n, and $C(n, K)$ is the union of all tokens in K with top-g highest scores

"Autoregressive Search Engines: Generating Substrings as Document Identifiers". Bevilacqua et al. [2022]

Aggregation functions: MINDER [Li et al., 2023d]

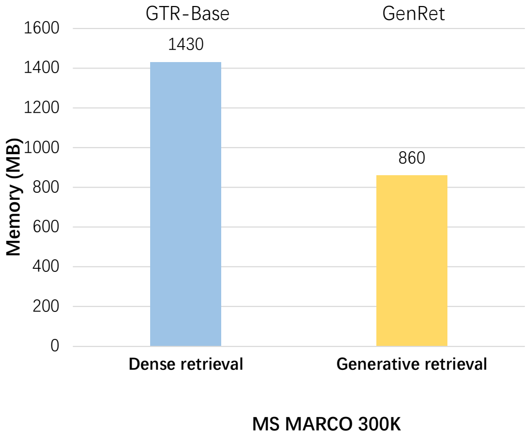
The document-level rank score: Sum of the scores of its covered docid

$$score(q, d) = \sum_{i_d \in I_d} P(i_d|q),$$

where $P(i_d|q)$ is the generated likelihood score of the docid i_d of the document d. And I_d denotes the docids generated for d

"Multiview Identifiers Enhanced Generative Retrieval".Li et al. [2023d]

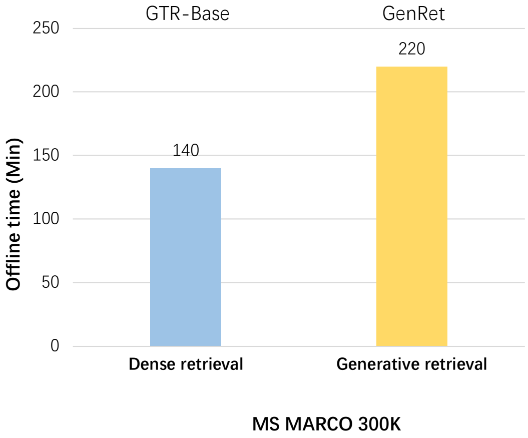
Inference efficiency: Memeory footprint



- The memory footprint of the GR model GenRet is smaller than that of the traditional dense retrieval method GTR, e.g., 1.6 times

Data source: Sun et al. [2023]

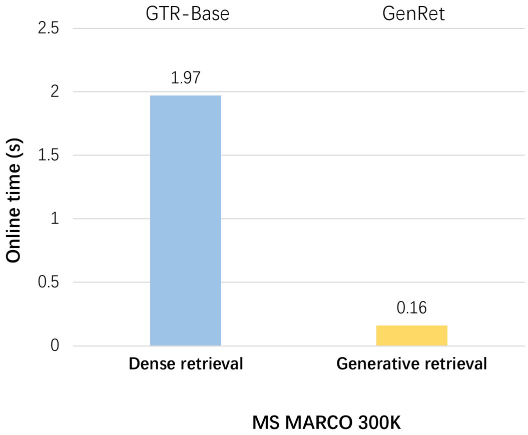
Inference efficiency: Offline latency



- GenRet takes a longer time for offline indexing, as the use of auxiliary models. GTR's offline time consumption comes from document encoding

Data source: Sun et al. [2023]

Inference efficiency: Online latency



- Compared with the traditional dense retrieval model GTR, the GR model GenRet is faster, e.g., 12 times

Data source: Sun et al. [2023]

A look back

Inference strategies			
A single docid	Constrained beam search with prefix tree (De Cao et al. 2021)	- Simple	- It cannot generate in an unordered manner
	Constrained greedy search with inverted index (Zhang et al. 2023)	- It can generate in any permutations of docids	- It may require handling a significant amount of duplicate terms
Multiple docids	Constrained beam search with FM-index (Bevilacqua et al. 2022)	- It can store all the information of documents - The contributions of multiple docids comprehensively are considered	- It cannot generate in an unordered manner - Complex construction - Complex aggregation functions
	Scoring functions (Li et al. 2023)	- The contributions of multiple docids comprehensively are considered - Simple aggregation functions	- Depending on design

Revisit: Challenges of model inference

- **How to generate valid docids?**

Revisit: Challenges of model inference

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  - Constrained generation mechanism based on prefix tree, inverted index table or FM-index

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  - One-by-one generation based on likelihood probabilities

Limitations

- Dependency on prior knowledge: Some heuristic scoring functions may require prior knowledge or manually designed rules

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Applications $\rightarrow$ **Section 6!**

Section 6: Applications

A range of target tasks

Fact Verification
De Cao et al. 2021, Chen et al. 2022b, Chen et al. 2022a, Thorne et al. 2022, Lee et al. 2023

Open Domain QA
De Cao et al. 2021, Chen et al. 2022b, Zhou et al. 2022, Lee et al. 2023

Entity Linking
De Cao et al. 2021, Chen et al. 2022b, Lee et al. 2023

Knowledge-intensive language tasks

A range of target tasks

Fact Verification
De Cao et al. 2021, Chen et al. 2022b, Chen et al. 2022a, Thorne et al. 2022, Lee et al. 2023

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De Cao et al. 2021, Chen et al. 2022b, Zhou et al. 2022, Lee et al. 2023

Entity Linking
De Cao et al. 2021, Chen et al. 2022b, Lee et al. 2023

Multi-hop retrieval
Lee et al. 2022

Recommendation
Si et al. 2023, Rajput et al. 2023

Code retrieval
Naddem et al. 2022

More retrieval tasks

A range of target tasks

Fact Verification
De Cao et al. 2021, Chen et al. 2022b, Chen et al. 2022a, Thorne et al. 2022, Lee et al. 2023

Open Domain QA
De Cao et al. 2021, Chen et al. 2022b, Zhou et al. 2022, Lee et al. 2023

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Recommendation
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Naddem et al. 2022

Official site retrieval
Tang et al. 2023a

Industry retrieval tasks

How to adapt a GR model for a task?

- Docid design
- Training approach
- Inference strategy

Knowledge-intensive language tasks

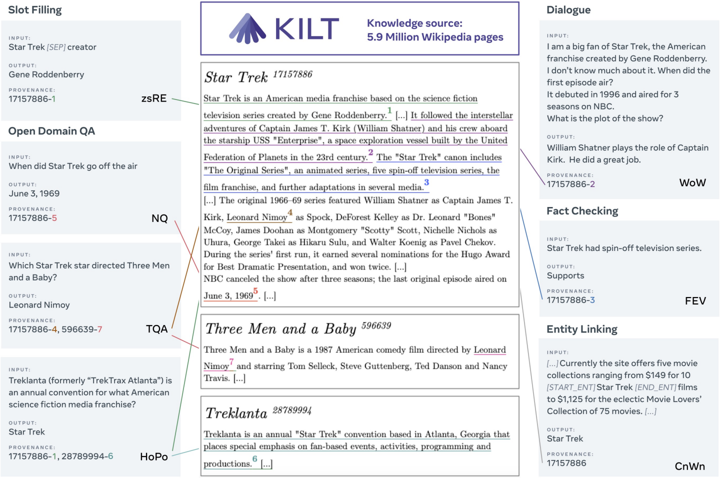
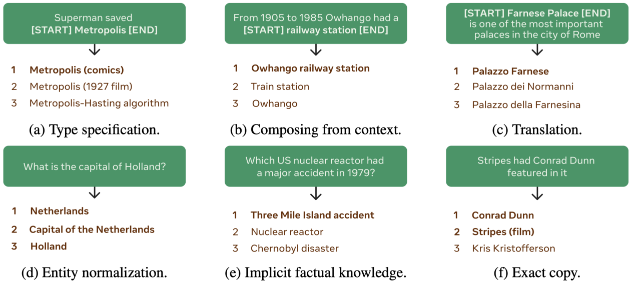


Image source: KILT

KILT example: GENRE [De Cao et al., 2021]



- Entity retrieval: Entity disambiguation, document retrieval, and etc
- Corpus: Wikipedia
- Input: Query
- Output: Destination/ relevant pages' title

"Autoregressive Entity Retrieval". De Cao et al. [2021]

KILT example: GENRE [De Cao et al., 2021]

- **Docid**: Titles
- **Training**: MLE objective with document-title and query-title pairs
- **Inference**: Constrained beam search with a prefix tree

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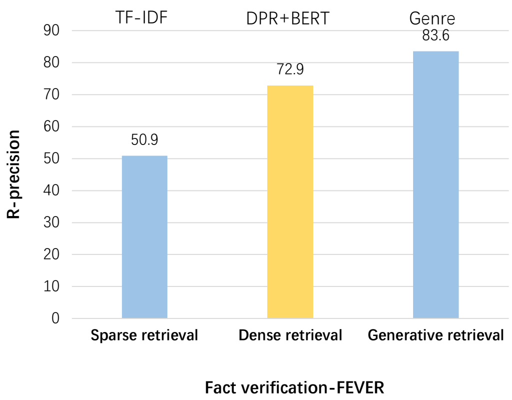
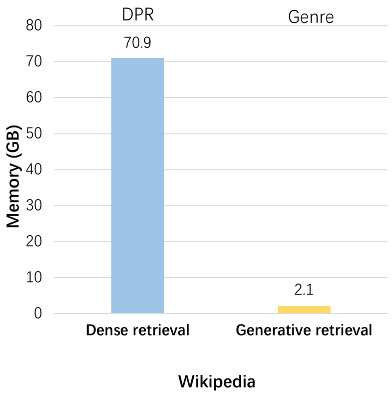
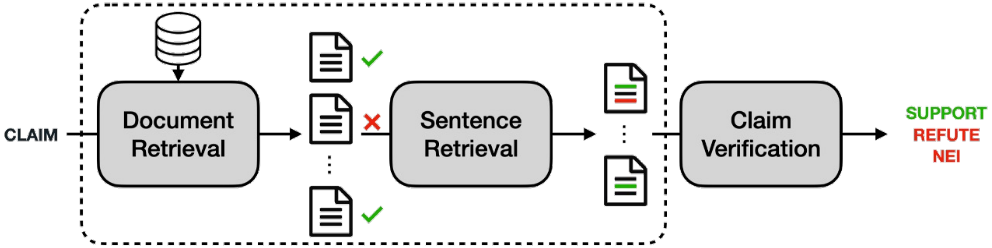




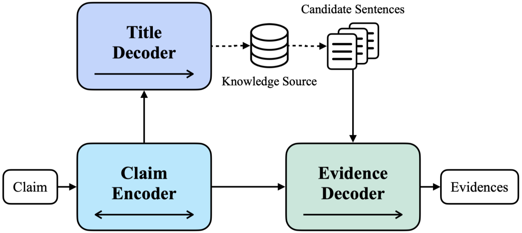
"Autoregressive Entity Retrieval". De Cao et al. [2021]

KILT example: GERE [Chen et al., 2022a]

- Fact verification: Verify a claim using multiple evidential sentences from trustworthy corpora
  - Input: Claim
  - Output: Support/Refute/Not enough information



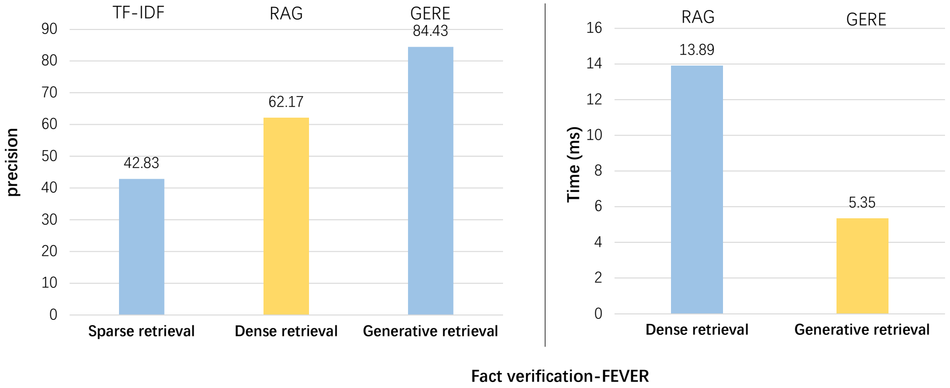
KILT example: GERE [Chen et al., 2022a]



- **Docid**: Titles
- **Training**: MLE objective with claim-title and claim-evidence pairs
- **Inference**: Constrained beam search with a prefix tree

"GERE: Generative evidence retrieval for fact verification". Chen et al. [2022a]

KILT example: GERE [Chen et al., 2022a]



"GERE: Generative evidence retrieval for fact verification". Chen et al. [2022a]

Multi-hop retrieval [Lee et al., 2022]

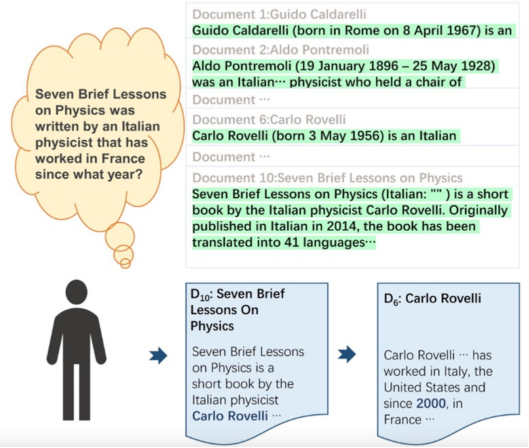
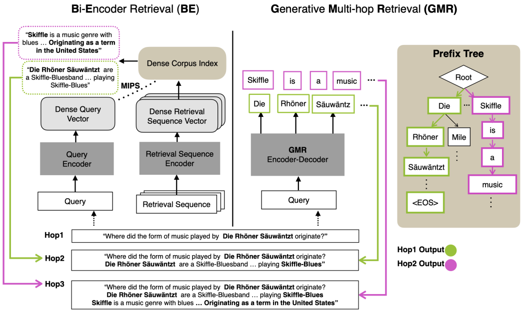


Image source: Memory enhances ChatGPT performance in multi-hop QA

"Generative multi-hop retrieval". Lee et al. [2022]

- Multi-hop retrieval
  - One needs to retrieve multiple documents that together provide sufficient evidence to answer the query
  - Previously retrieved items are appended to the query while iterating through multiple hops

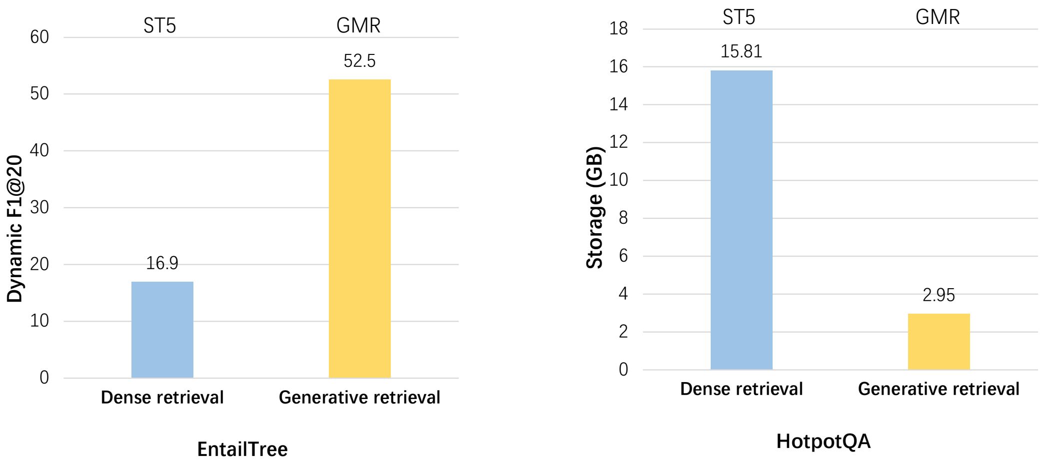
Multi-hop retrieval [Lee et al., 2022]



- **Docid**: Word-based answer
- **Jointly training**:
  - Indexing: Randomly select the first m words of the document as input and predict the remaining words with MLE
  - Retrieval: Learn pseudo query-answer pairs with MLE
- **Inference**: Constrained beam search with a prefix tree

"Generative multi-hop retrieval". Lee et al. [2022]

Multi-hop retrieval [Lee et al., 2022]



"Generative multi-hop retrieval". Lee et al. [2022]

Item recommendation [Rajput et al., 2023]

- Sequential recommendation: Help users discover content of interest and are ubiquitous in various recommendation domains
  - Input: User history
  - Output: Next item identifier

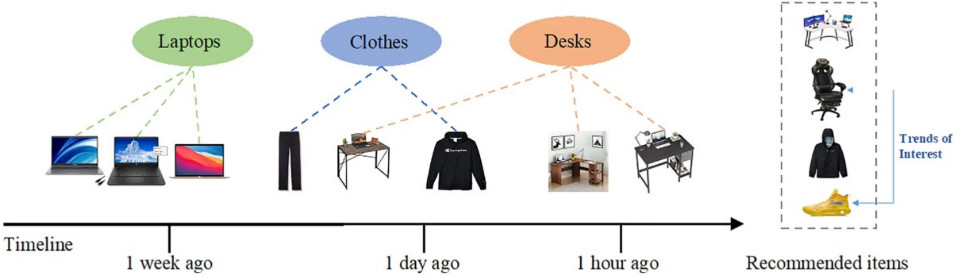
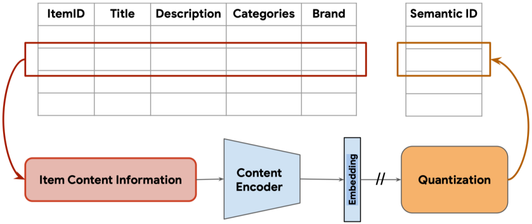


Image source: Ma et al. [2023]

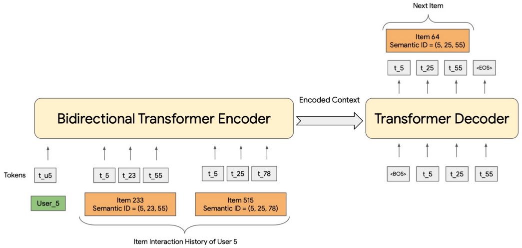
Item recommendation [Rajput et al., 2023]



- **Docid**: Product quantization strings
- **Docid training**: Train a residual-quantized variational autoencoder model with a docid reconstruction loss and a multi-stage quantization loss

"Recommender Systems with Generative Retrieval". Rajput et al. [2023]

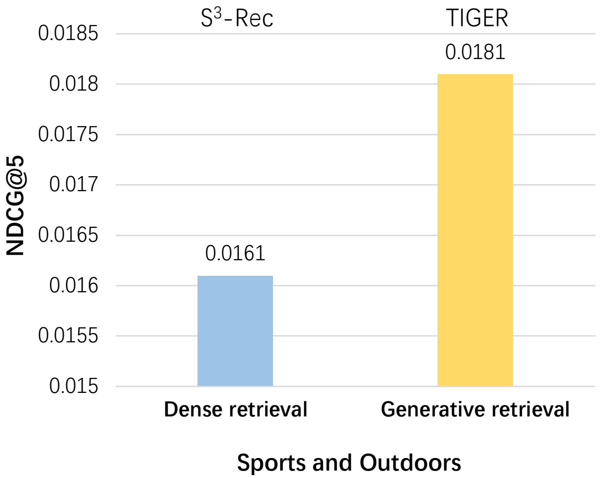
Item recommendation [Rajput et al., 2023]



- **Recommendation training**
  - Construct item sequences for every user by sorting chronologically the items they have interacted with
  - Given item sequences, the recommender system's task is to predict the next item with MLE
- **Inference**: Beam search

"Recommender Systems with Generative Retrieval". Rajput et al. [2023]

Item recommendation [Rajput et al., 2023]



"Recommender Systems with Generative Retrieval". Rajput et al. [2023]

Code retrieval [Nadeem et al., 2022]

- Code retrieval: A model takes natural language queries as input and, in turn, relevant code samples from a database are returned
  - Input: Query
  - Output: Relevant code samples

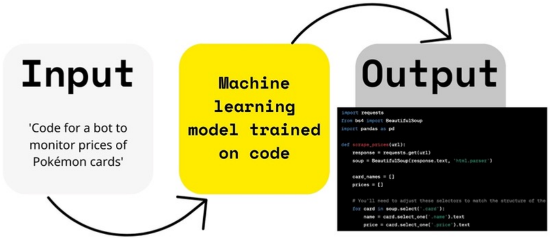
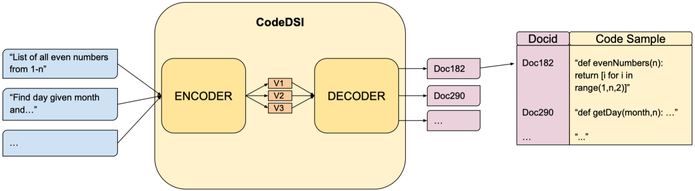


Image source: AI Code Generation Models: The Big List

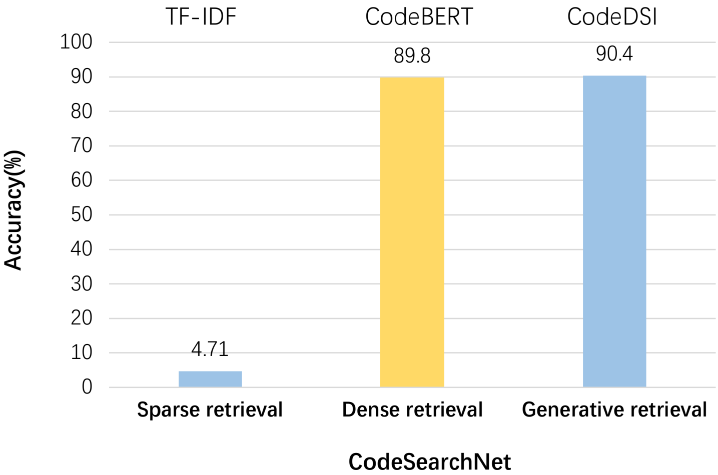
Code retrieval [Nadeem et al., 2022]



- **Docid**: Naively structured strings/ semantically structured strings
- **Training**: Standard indexing loss with code-docid pairs and retrieval loss with query-docid pairs
- **Inference**: Beam search

"CodeDSI: Differentiable Code Search".Nadeem et al. [2022]

Code retrieval [Nadeem et al., 2022]



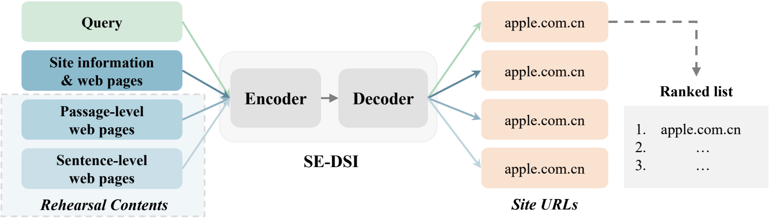
"CodeDSI: Differentiable Code Search". Nadeem et al. [2022]

Official site retrieval [Tang et al., 2023a]

- Official sites: Web pages that have been operated by universities, departments, or other administrative units

"Semantic-Enhanced Differentiable Search Index Inspired by Learning Strategies". Tang et al. [2023a]

Official site retrieval [Tang et al., 2023a]

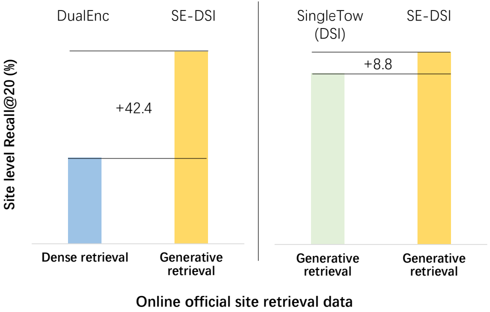


- **Docid**: Unique site URLs
- **Jointly training**:
  - Indexing: Learn site information (site name/ site domain/ ICP record) - docid pairs, web pages-docid pairs, and important web pages-docid pairs with MLE
  - Retrieval: Learn query - docid pairs with MLE
- **Inference**: Constrained beam search with a prefix tree

"Semantic-Enhanced Differentiable Search Index Inspired by Learning Strategies". Tang et al. [2023a]

Official site retrieval [Tang et al., 2023a]

Online retrieval performance:



Inference comparison:

- Memory footprint: SE-DSI's memory is reduced by about 31 times compared to RepBERT
- Inference speed: SE-DSI's speed is significantly improved by about 2.5 times compared to RepBERT

"Semantic-Enhanced Differentiable Search Index Inspired by Learning Strategies". Tang et al. [2023a]

Applications: limitations

- Generalizing to ultra-large-scale corpora remains a challenge
- How to adapt to the significant dynamic changes in large-scale corpora for online applications

Section 7:
Challenges & Opportunities

Tutorial summary

- **Definition & preliminaries**
- **Generative retrieval: docid design**
  - Single docids: number-based and word-based identifiers
  - Multiple docids: single type and diverse types
- **Generative retrieval: training approaches**
  - Stationary scenarios: supervised learning and pre-training
  - Dynamic scenarios
- **Generative retrieval: inference strategies**
  - Single docids: constrained greedy search, constrained beam search and FM-index
  - Multiple docids: aggregation functions
- **Generative retrieval: applications**

Pros of generative retrieval

Information retrieval in the era of language models

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Information retrieval in the era of language models

- Encode the global information in corpus; optimize in an end-to-end way
- The semantic-level association extending beyond mere signal-level matching

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Information retrieval in the era of language models

- Encode the global information in corpus; optimize in an end-to-end way
- The semantic-level association extending beyond mere signal-level matching
- Constraint decoding over thousand-level vocabulary
- Internal index which eliminates large-scale external index

Cons of generative retrieval: Scalability

- Large-scale real-word corpus
  - Current research can generalize from corpora of hundreds of thousands to millions
  - How to accurately memorize vast amounts of real complex data?

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  - How to keep such GR models up-to-date?
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  - How to unify different search tasks into a single generative form?
  - How to capture task specifications while obtaining the shared knowledge?
- Combining GR with retrieval-augmented generation (RAG)
  - How to integrate GR with RAG to enhance the effectiveness of both?

Cons of generative retrieval: Controllability

For an issue, it is often unclear what modeling knobs one should turn to fix the model's behavior

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- Interpretability
  - Black-box neural models
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  - Model editing: how to accurately and conveniently modify training data or tune hyperparameters in the loss function?
- Robustness
  - When a new technique enters into the real-world application, it is critical to know not only how it works in average, but also how would it behave in abnormal situations

Cons of generative retrieval: User-centered

Searching is a socially and contextually situated activity with diverse set of goals and needs for support that must not be boiled down to a combination of text matching and text generating algorithms [Shah and Bender, 2022]

Source: [Shah and Bender, 2022]

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- Human information seeking behavior
- Transparency
- Provenance
- Accountability

Source: [Shah and Bender, 2022]

Cons of generative retrieval: Performance

The current performance of GR can only be compared to the index-retrieval stage of traditional methods, and it has not yet achieved the additional improvement provided by re-ranking

So much to do ...

- 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.,
  - Retrieve-augmented generation of answers
  - Tool-augmented generation of answers

So much to do . . .

Cater for long-term effects

- How to combine the short-term relevance goal with long-term goals such as diversity

Source: [Deffayet et al., To appear, Zhou et al., 2023]

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Address needs of interactive environments

- Interactive systems must operate under high degrees of uncertainty
  - User feedback, non-stationarity, exogenous factor, user preferences, . . .

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Searching/recommending slates of items

- Interface of many search/recommendation platforms requires showing combinations of results to users on the same page
- Different combinations may lead to different short vs. long-term outcomes
- Problem thus becomes combinatorial in nature, intractable for most applications

Source: [Deffayet et al., To appear, Zhou et al., 2023]

Resources and sharing

Sharing more than code

- Models
- ...

Reducing compute resources

So much to do . . .

Re-invent information retrieval in the age of large language models!

Q & A

Thank you for joining us today!

All materials are available at

https://ecir2024-generativeir.github.io/

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