Generative Information Retrieval

SIGIR 2024 tutorial – Section 2

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https://generative-ir.github.io/

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Section 2:
Definitions & Preliminaries

SCAN ME

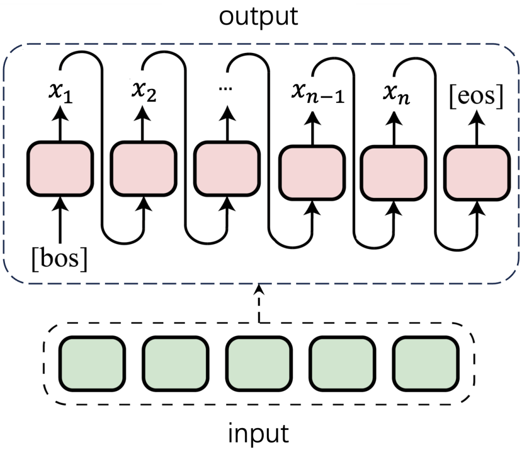
Generative retrieval: Definition

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

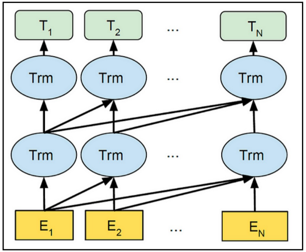
"Transformer Memory as a Differentiable Search Index". Tay et al. [2022]; "Autoregressive Entity Retrieval". De Cao et al. [2021]

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

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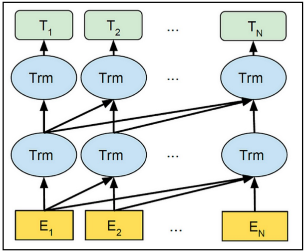

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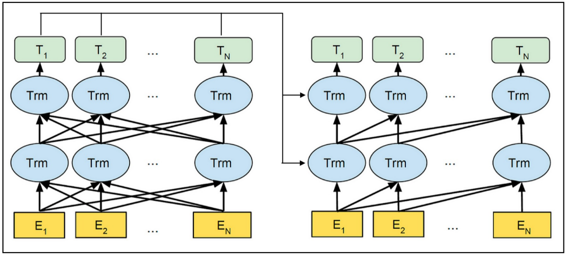

Encoder-decoder

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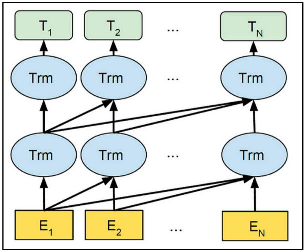

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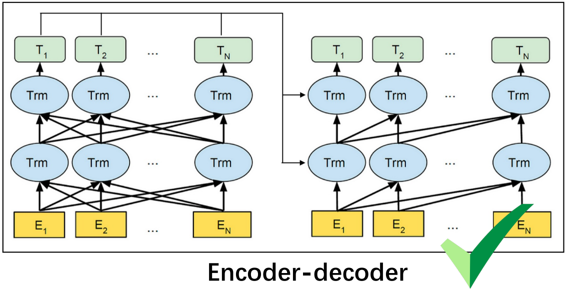


Encoder-decoder

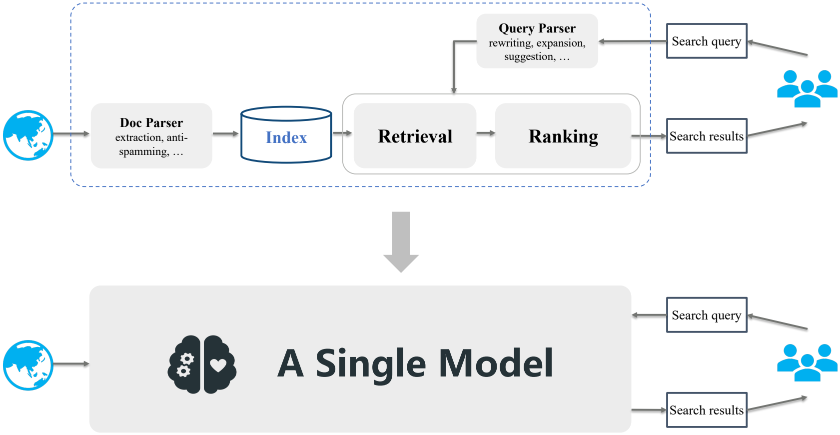
Image source: Kenton and Toutanova [2019] and Retrieval-based Language Models and Applications

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]

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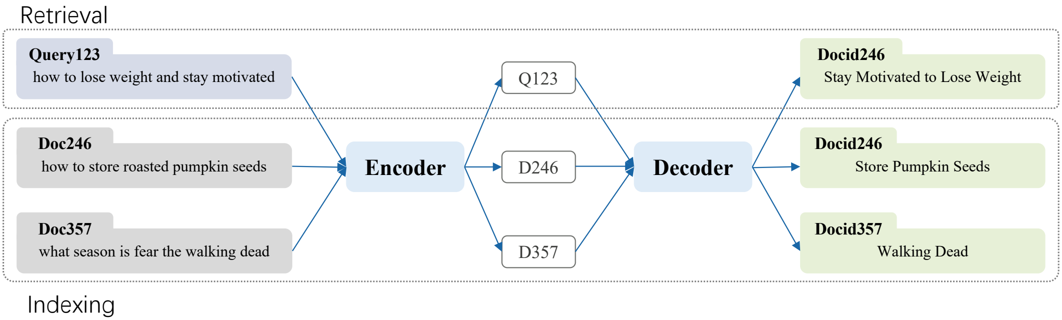
$$\mathcal{L}_{Global}(Q, D, I_D, I_Q; \theta) = \mathcal{L}_{Indexing}(D, I_D; \theta) + \mathcal{L}_{Retrieval}(Q, I_Q; \theta)$$

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,

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

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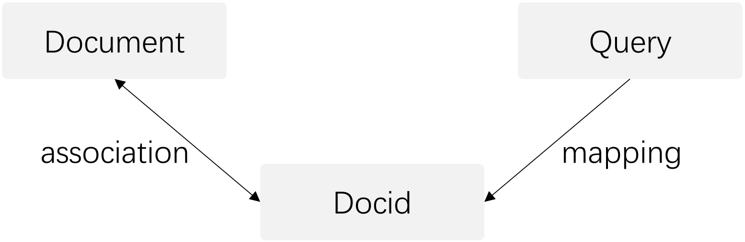
where w_t is the t-th token in the docid string and the generation stops when decoding a special EOS token
- The docids generated with the top-K highest likelihood (joint probability of generated tokens within a docid) form a ranking list in descending order

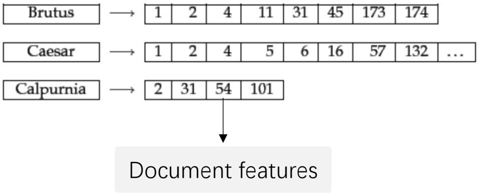
Research questions (1): Docid design



Unfortunately, there is no natural identifier for each document!

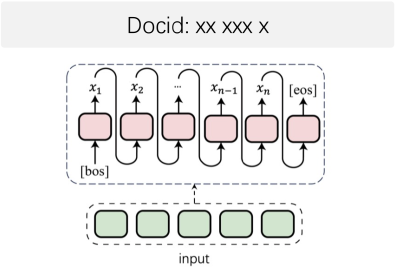
Research questions (1): Docid design

Traditional information retrieval



As an entry

Generative retrieval



For generation

Image source: Information retrieval book

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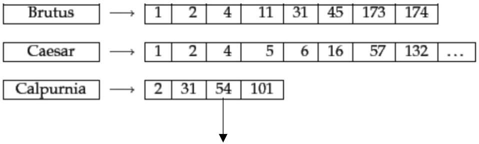
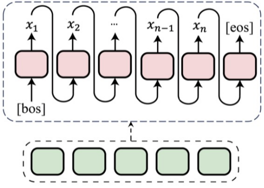


Document features

As an entry

Generative retrieval

Docid: xx xxx x



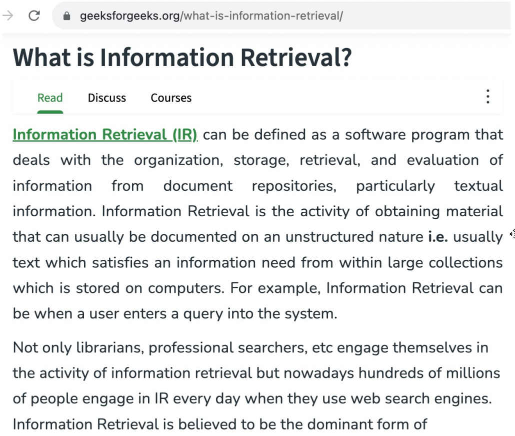
For generation

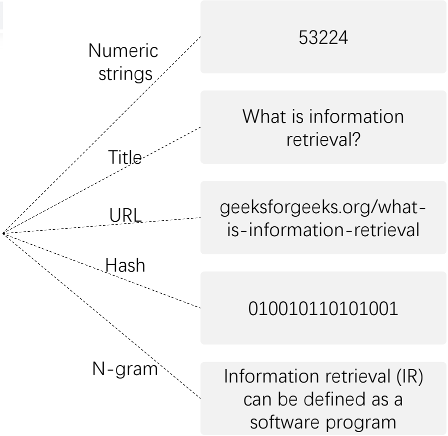
How to design docids for documents?

Image source: Information retrieval book

Research questions (1): Docid design

- Possible design choices





Document source: Geeksforgeeks

Challenges of docid design

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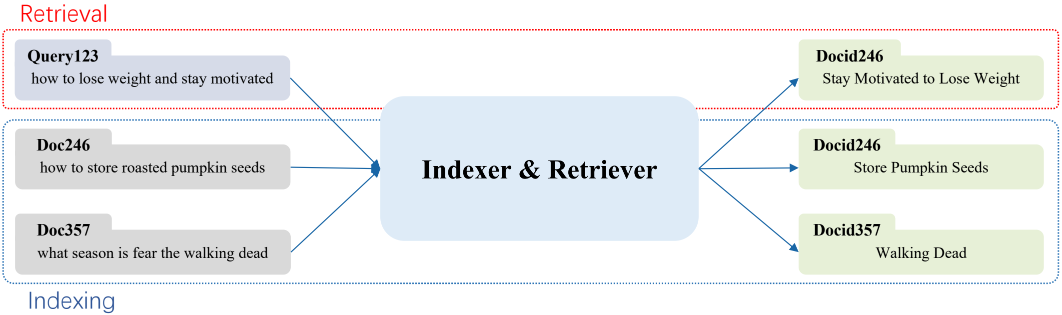
We will tackle these questions in Section 3!

Research questions (2): Training approaches



Joint learning process of the indexing and retrieval tasks

Challenges of training approaches

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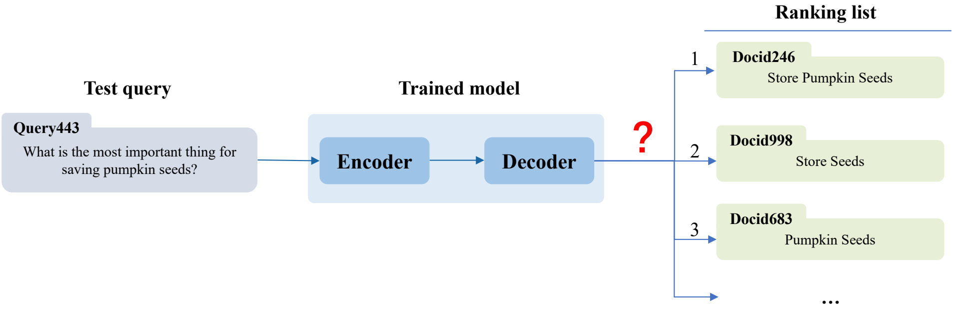
Research questions (3): Inference strategies



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?

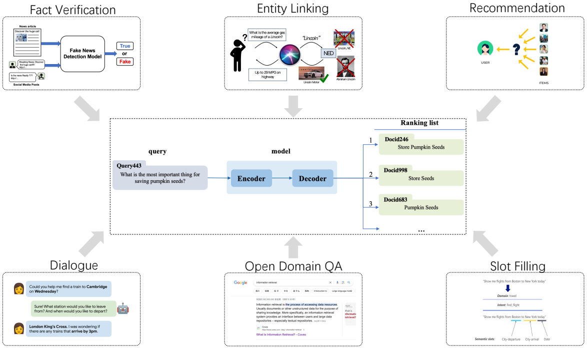

Image source: Murayama [2021], Stanford blog, Froomle AI, Google, Zero-shot blog, and Heck and Heck [2020]

Research questions (4): Applications

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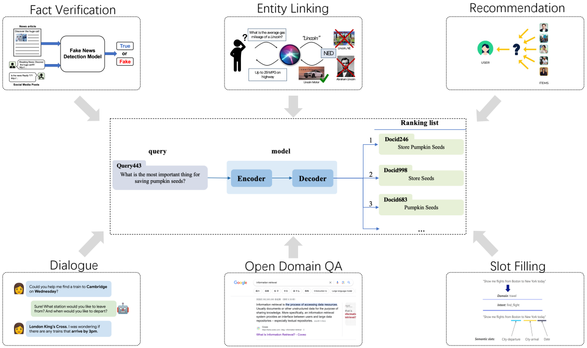

We will tackle this question in Section 6!

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

References

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