Generative Information Retrieval

The Web Conference 2024 tutorial – Section 4

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

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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

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

Stationary scenarios

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

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

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

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Limitation (1): Single document granularity

$$
\begin{aligned}
\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)
\end{aligned}
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"Semantic-Enhanced Differentiable Search Index Inspired by Learning Strategies". Tang et al. [2023a]

Limitation (1): Single document granularity

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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

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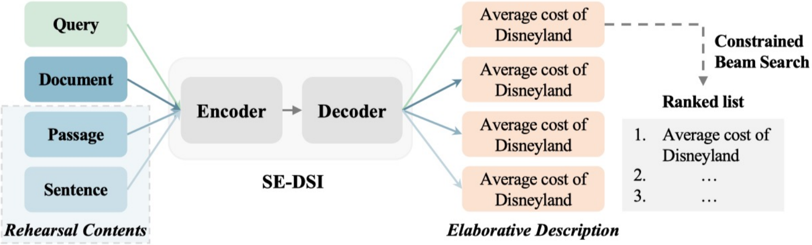
$$\mathcal{L}_{Indexing}(D, I_D; \theta) = -(\sum_{d \in D} \log P(id \mid d; \theta) + \sum_{p \in d} \log P(id \mid p; \theta) + \sum_{s \in d} \log P(id \mid s; \theta))$$

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

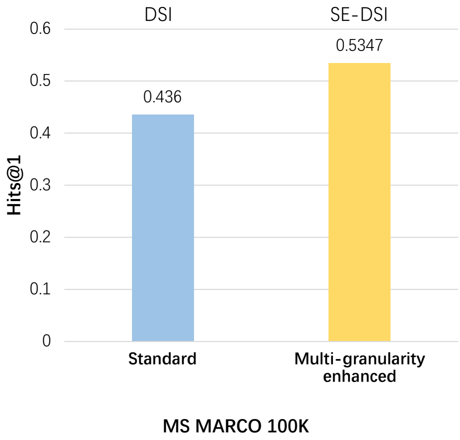
Supervised learning: Multi-granularity enhanced

- 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



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

Data source: Tang et al. [2023a]

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) \\
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"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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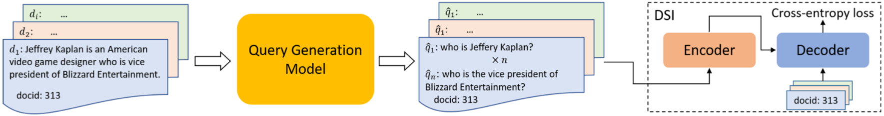
Long document in indexing vs. Short query in retrieval

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

↓

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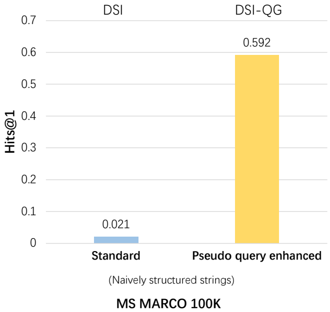

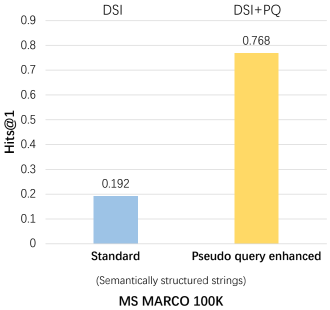

- Backbone: T5-base
- Using only pseudo synthetic queries to docid during indexing is an effective training strategy on MS MARCO [Pradeep et al., 2023]

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

Limitation (3): Limited labeled data

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

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

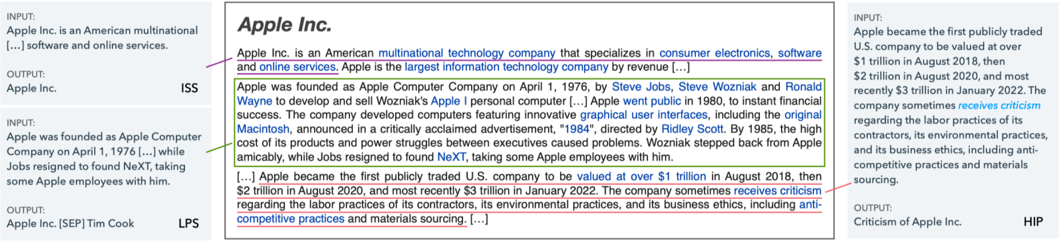
What should we do if there is no or few labeled query-docid pairs?

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., 2022]: 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. [2022]

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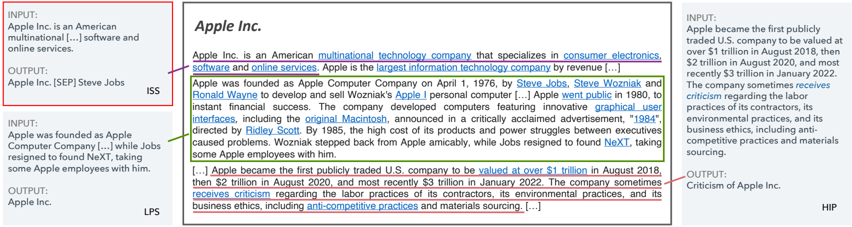

Inner Sentence Selection (ISS):

- 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"

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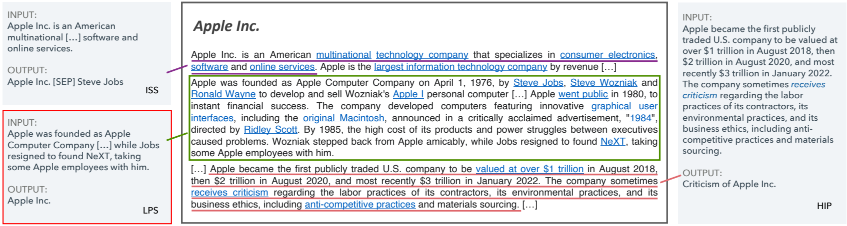

Lead Paragraph Selection (LPS):

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

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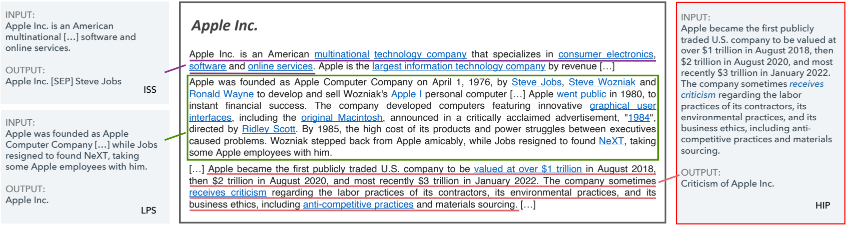
CorpusBrain [Chen et al., 2022]: Pre-training



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

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CorpusBrain [Chen et al., 2022]: 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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CorpusBrain [Chen et al., 2022]: 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
- **Fine-tuning**: CorpusBrain is fine-tuned using the processed data (in a Seq2Seq pair format) in downstream tasks

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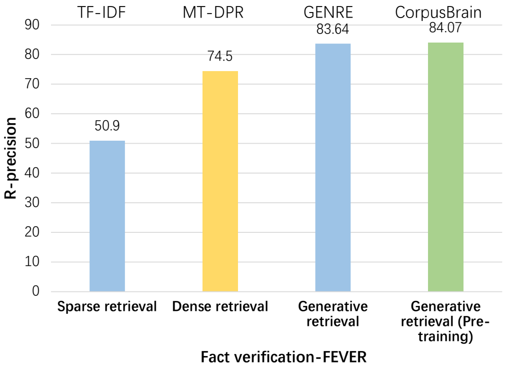
- **Fine-tuning**: CorpusBrain is fine-tuned using the processed data (in a Seq2Seq pair format) in downstream tasks
- **Test**: Given a test query, the fine-tuned CorpusBrain utilizes constrained beam search to decode relevant docids

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

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

Limitation (4): Pointwise optimization for GR

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

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

Limitation (4): Pointwise optimization for GR

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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

Limitation (4): Pointwise optimization for GR

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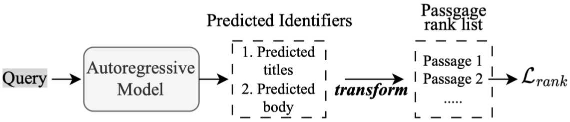
Pairwise and listwise optimization strategies for GR are necessary!

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

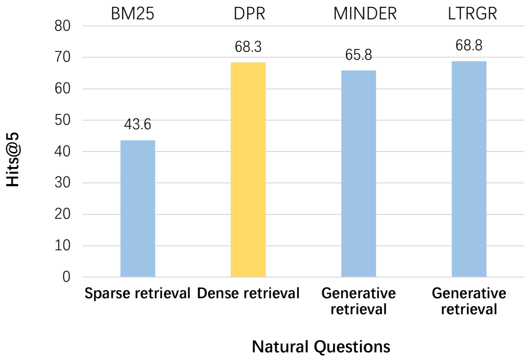


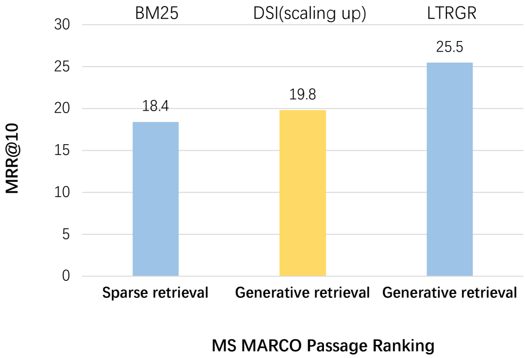
$$max(0, s(q, d_-) - s(q, d_+) + m),$$

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



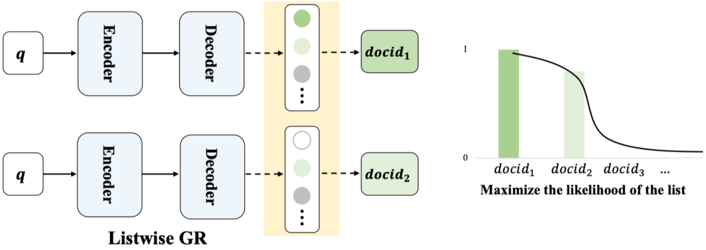


"Learning to Rank in Generative Retrieval". Li et al. [2023c]

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 $\tilde{P}(id^{(i)} \mid q; \theta) = \frac{\log \prod_{t \in [1, |id^{(i)}|]} P(w_t | q, w_{<t}; \theta)}{|id^{(i)}|}$ (without considering the ranking order information), 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

$$\min_{\theta} -\log P(\pi_q \mid q; \theta)$$

$$= -\alpha(1)\log P(id^{(1)} \mid q; \theta) - \sum_{i=2}^{n} \alpha(i) \log P\left(id^{(i)} \mid q, id^{(1)}, \ldots, id^{(i-1)}; \theta\right),$$

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]

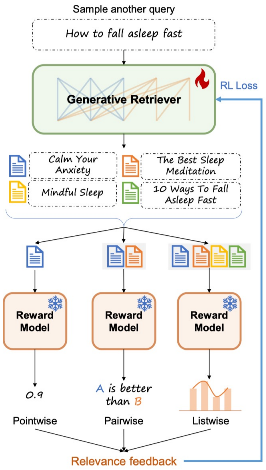
Multiple optimization: GenRRL [Zhou et al., 2023]

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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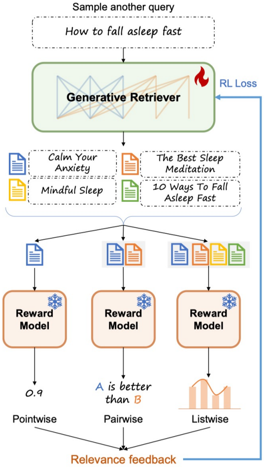

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- Pairwise optimization:
  $-\sum_{(id_i, id_j)} (R(q, id_i) \log p_{ij} + R(q, id_j) \log p_{ji}$,
  where $p_{ij} = |P(w_t^i \mid q) - P(w_t^j \mid q)|$

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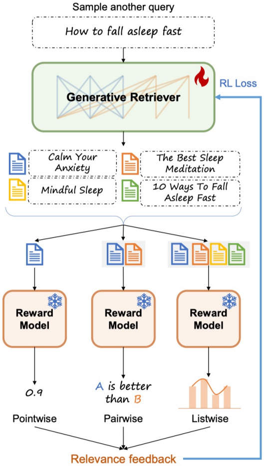
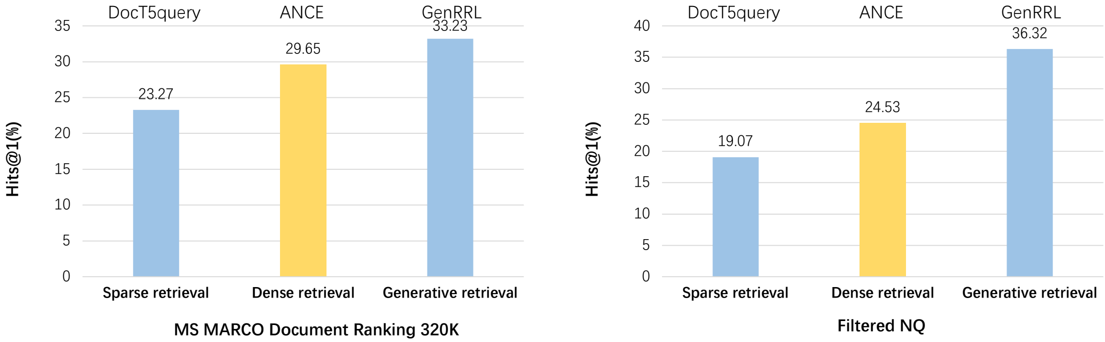


- Pointwise optimization:
  $-\sum_i (R(q, id_i) - b) \sum_t \log P(w_t^i \mid w_{<t}, q)$,
  where R is a reward model, and b is a baseline
- Pairwise optimization:
  $-\sum_{(id_i, id_j)} (R(q, id_i) \log p_{ij} + R(q, id_j) \log p_{ji}$,
  where $p_{ij} = |P(w_t^i \mid q) - P(w_t^j \mid q)|$
- Listwise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

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

GenRRL [Zhou et al., 2023]: Performance



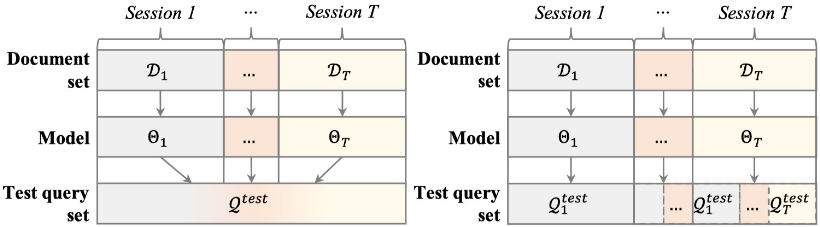
"Enhancing Generative Retrieval with Reinforcement Learning from Relevance Feedback". Zhou et al. [2023]

Dynamic scenarios

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

Information changes and new documents emerge incrementally over time

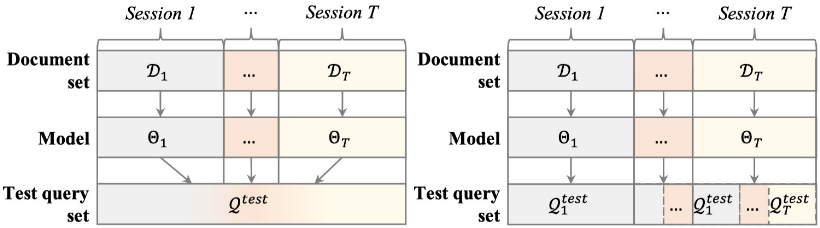
Continual learning task: Formulation



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

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

Image source: Chen et al. [2023]



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

- **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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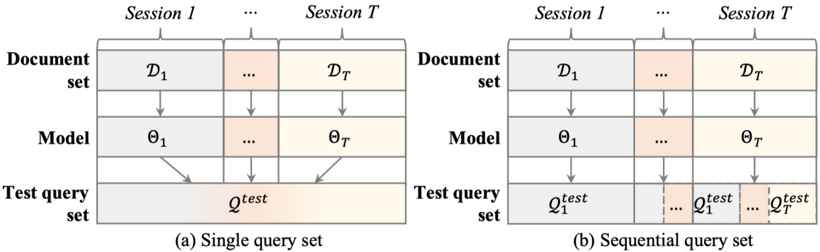
Continual learning task: Formulation



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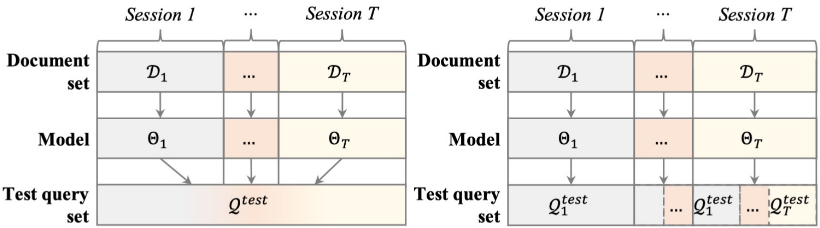
- **New datasets**: T new datasets $D_1, \ldots, D_T$, from T sessions arriving in a sequential manner, which are only composed of newly encountered documents without queries related to these documents
- **Model update**: The new dataset D_t and previous datasets $D_0, \ldots, D_{t-1}$

Image source: Chen et al. [2023]

Continual learning task: Evaluation



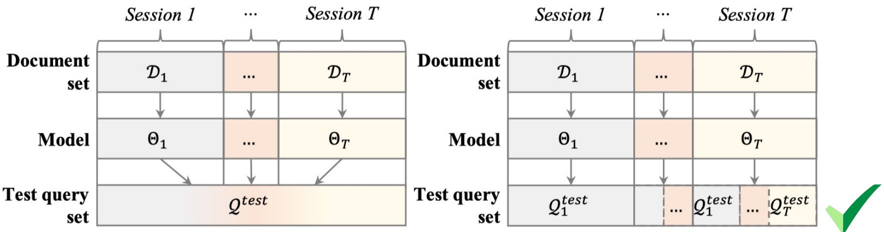
(a) Single query set (b) Sequential query set

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. [2023]

Continual learning task: Evaluation



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Catastrophic forgetting

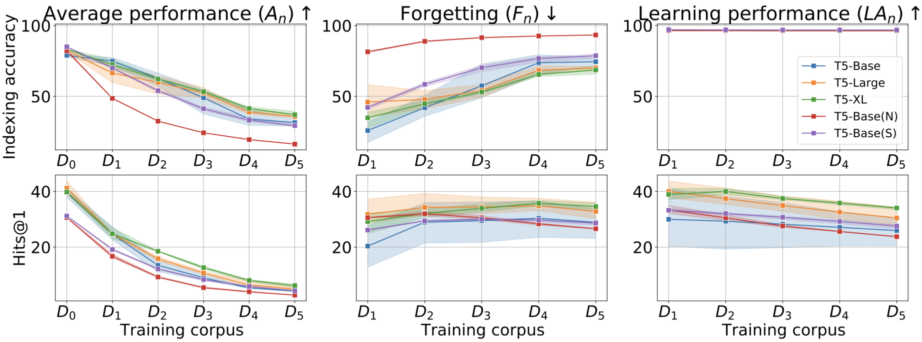


Image source: Mehta et al. [2022]

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

"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

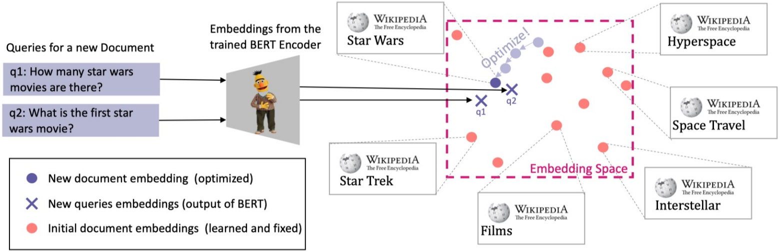
- How to incrementally index new documents with low computational and memory costs?
- How to prevent catastrophic forgetting for previously indexed documents and maintain the retrieval ability?

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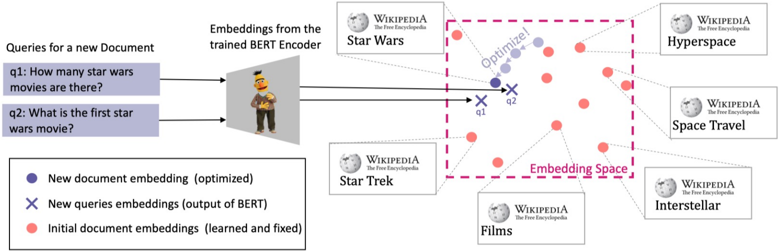
IncDSI [Kishore et al., 2023]: Incrementally indexing new documents



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

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

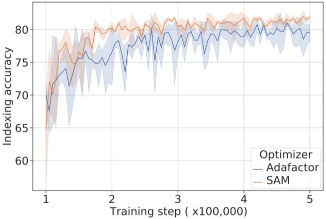
"DSI++: Updating Transformer Memory with New Documents". Mehta et al. [2022]

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

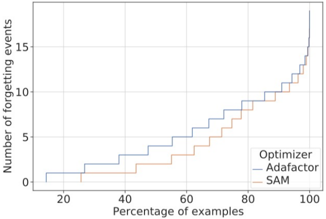
- Docids: The new documents are assigned unstructured atomic integers as docids, and the GR model learns new embeddings for each of them
- Modifying the training dynamics: Since flatter minima implicitly alleviate forgetting, optimizing for flatter loss basins using Sharpness-Aware Minimization (SAM) 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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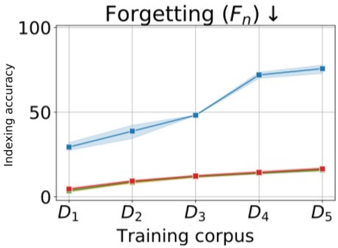
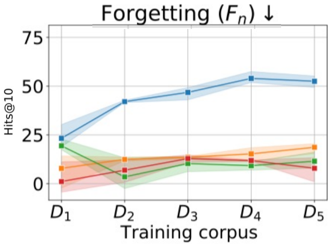
DSI++ [Mehta et al., 2022]: Preventing catastrophic forgetting

- 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





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

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., 2023]: 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. [2023]

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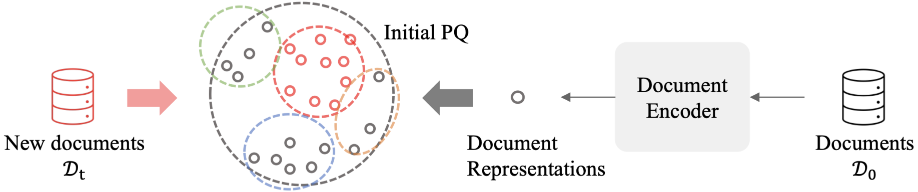
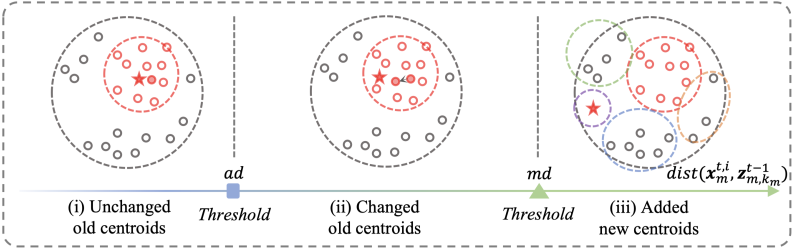


- Build base PQ
  - Centroids are obtained via clustering over document representations
  - Document representations are learned with a bootstrapped training process

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

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

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

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

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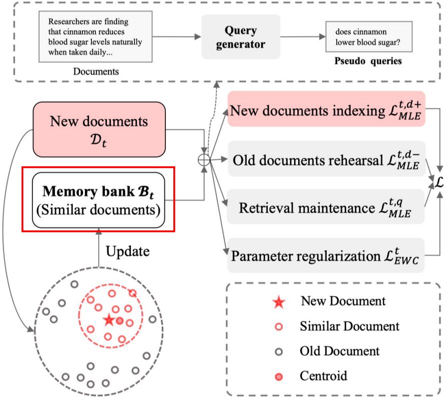
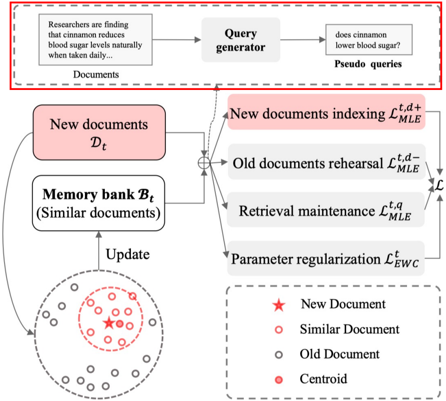


- **Dynamic memory bank**: Construct a memory bank with similar documents for each new session and replay the process of indexing them alongside the indexing of new documents

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

CLEVER [Chen et al., 2023]: 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

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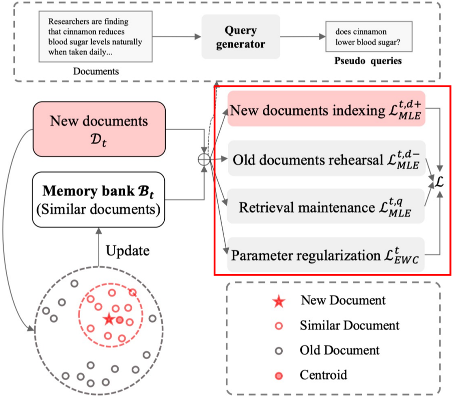
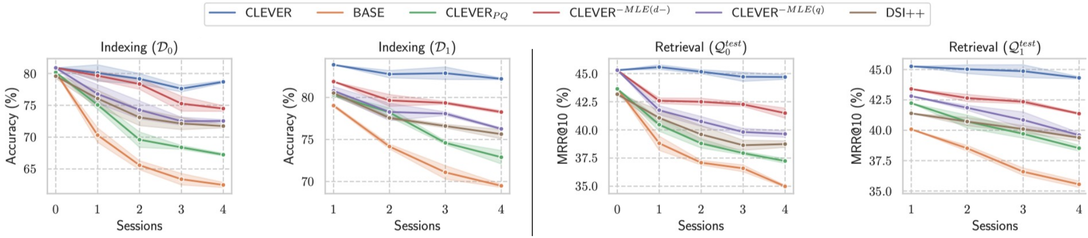


- **Sequentially training**: new documents indexing, old document rehearsal, retrieval maintenance losses and an elastic weight consolidation (EWC) loss as a regularization term

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

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

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

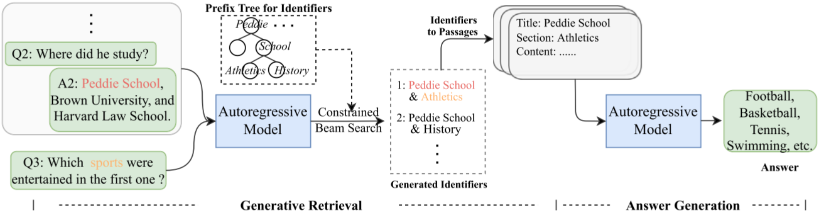
Combination of GR and retrieval-agumented generation (RAG)

How to jointly train the GR model and QA model?

$$\mathcal{L}_{QA}(Q^*, I_D^*, D^*, A; \psi) = -\sum_{q^* \in Q^*, id \in I_D, d \in D, a \in A} \log f(a|q^*, id, d; \psi),$$

where Q^* is the query set of the downstream task, I_D^* are the docids retrieved by a GR model, D^* are the corresponding documents, a is an answer in the answer set A, f is the QA function and ψ is the model parameters

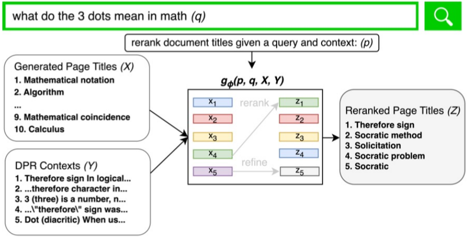
GCoQA [Li et al., 2023b]



- 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]

Re3val [Song et al., 2024]



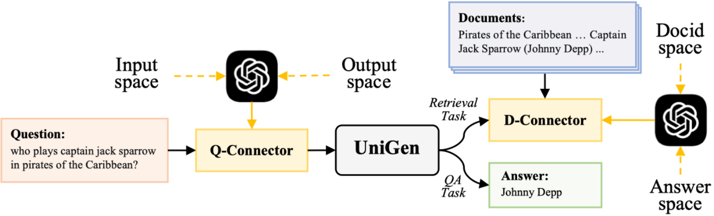
- Step 1: Relevant titles generation using a GR model
- Step 2: Retrieved titles reranking using a cross-encoder
- Step 3: Context retrieval for titles using BM25
- Step 4: Answer generation using an generative model

"Re3val: Reinforced and Reranked Generative Retrieval". Song et al. [2024]

Limitation

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

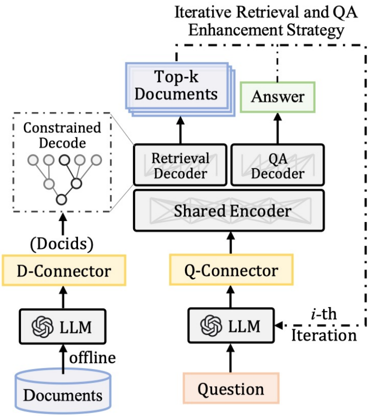
UniGen [Li et al., 2023a]



- Joint learning for GR and QA

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

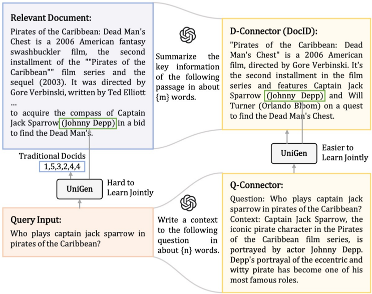
UniGen [Li et al., 2023a]: Architecture



- 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

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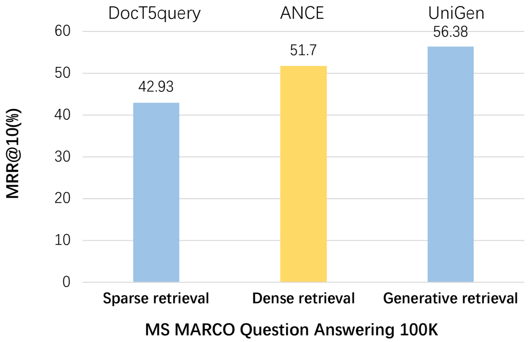
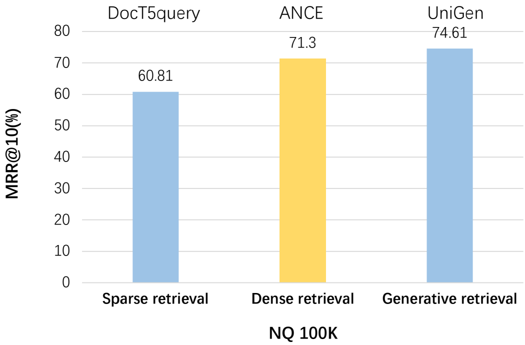
UniGen [Li et al., 2023a]: Performance





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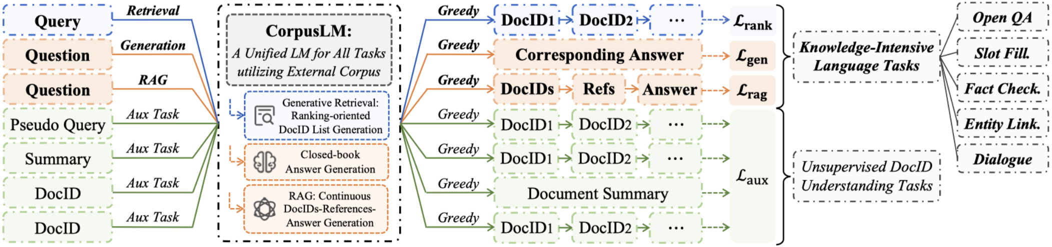
CorpusLM [Li et al., 2024]



- a unified language model that leverages external corpus to tackle various knowledge-intensive tasks by integrating GR, closed-book generation, and RAG through a unified greedy decoding process

"CorpusLM: Towards a Unified Language Model on Corpus for Knowledge-Intensive Tasks". Li et al. [2024]

Limitations in large-scale corpus

- Existing GR models only perform well on artificially-constructed and small-scale collections
- Zeng et al. [2024a] and Zeng et al. [2024b] introduced RIPOR and PAG, designed to improve the performance of GR models for MS MARCO dataset, with 8.8M passages.

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

"Scalable and Effective Generative Information Retrieval". Zeng et al. [2024a] & Planning Ahead in Generative Retrieval: Guiding Autoregressive Generation through Simultaneous Decoding Zeng et al. [2024b]

Revisit: Challenges of training approaches

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

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- **How to handle a dynamically evolving document collection?**
  - Low computational and memory costs
  - Maintaining the retrieval ability

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