Generative Information Retrieval

The Web Conference 2024 tutorial – Section 5

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

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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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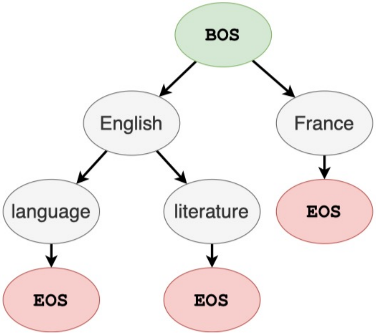
Multiple identifiers to represent a document

- 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



"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

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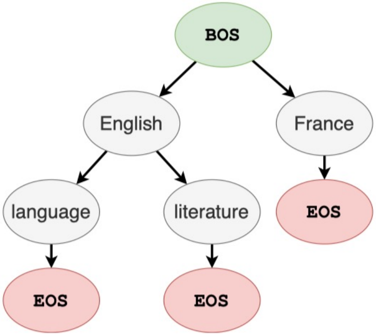

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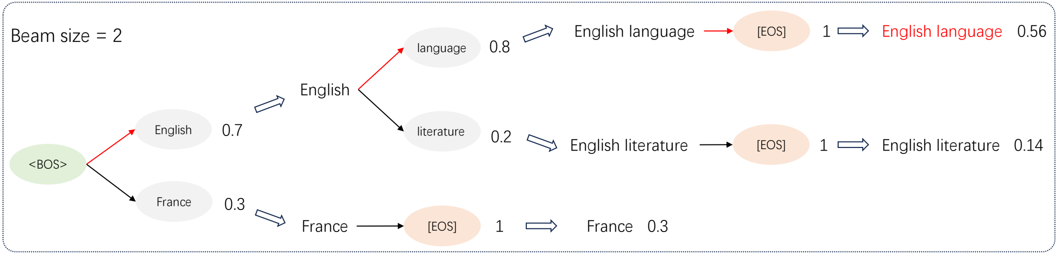
Prefix tree: Nodes are annotated with tokens from the predefined candidate set. For each node, its children indicate all the allowed continuations from the prefix defined traversing the tree from the root to it

Example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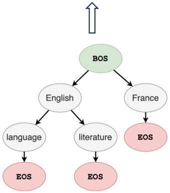
BOS
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Single identifier: Constrained greedy search with the inverted index

Applicable docids: Important terms

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

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Applicable docids: Important terms

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

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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

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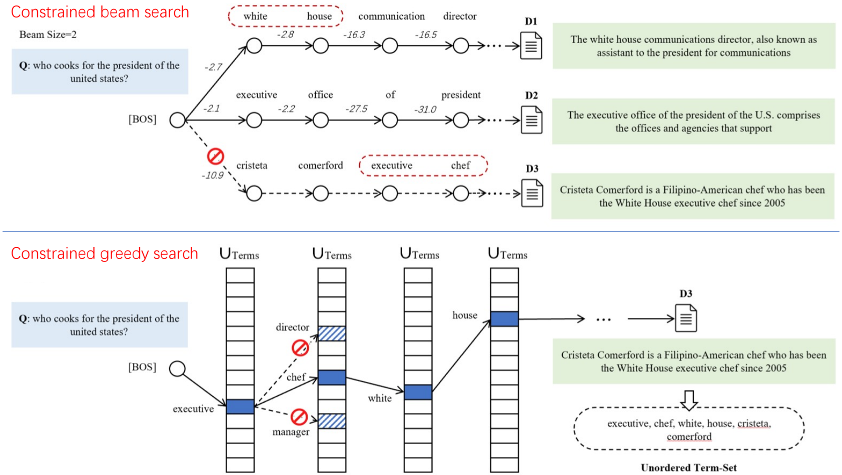
Constrained beam search vs. Constrained greedy search



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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]

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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 identi ers to its corresponding documents?

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

The document-level rank score combines the n-gram level rank score $\mathrm{score}(n; q)$ and coverage weight $\mathrm{cover}(n; K)$:

$$\mathrm{score}(d; q) = \sum_{n \in K^{d}} \mathrm{score}(n; q) \quad \mathrm{cover}(n; K);$$

where K denotes all the generated n-grams, K^{d} is the subset of n-grams in K that appear in d, 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 $\mathrm{cover}(n, K)$: Avoid the overscoring of very repetitive documents, where many similar n-grams are matched

$$\mathrm{cover}(n, K) = 1 \qquad + \frac{|\mathrm{set}(n) \setminus C(n, K)|}{|\mathrm{set}(n)|},$$

where is a hyperparameter, $\mathrm{set}(n)$ 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., 2023]

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

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

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. [2023]

Inference e ciency: 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 e ciency: O ine latency

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

Data source: Sun et al. [2023]

Inference e ciency: 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

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How to generate a ranked list of docids for a query?

- One-by-one generation based on likelihood probabilities

References

References i

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