Open Domain Question Answering

Project Guide: Dr. Rajendra Prasath

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Project code: B25RP03

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Introduction

A system that answers questions without domain restrictions using information from a large corpus

How It Works:

Question Understanding - Preprocessing, Normalization, Semantic understanding

Document Retrieval - BM25, DPR, Hybrid Retrieval

Passage Ranking - TF-IDF Scoring, BERT based models.

Answer Extraction - Extractive Models(BERT) , Generative Models(GPT)

Key Components:

Retriever

Reader

Knowledge Source

Introduction

- Existing Paradigms:
  - -Retrieve-then-read: Relies on external corpora (e.g., Wikipedia).
  - -Generate-then-read: Uses LLMs to generate virtual documents.
- Limitations:
  - -Retrieve-then-read may miss diverse evidence.
  - -Generate-then-read may lack factual accuracy.

Recent works:

1) **Retrieve-then-Read Paradigm**

- Two-stage pipeline: Retriever fetches documents; Reader generates answers.
- Sparse (exact-match): BM25 [1]
- Dense (learned): DPR [2], RocketQA [3], ColBERT [4], ART [5]
- Readers: T5 [6], InstructGPT [7]

2) **Generate-then-Read Paradigm**

- LLMs as generative retrievers [9, 10, 11].
- Generative Retrieval: LLMs create pseudo-documents [8]
- GenRead: Cluster-based evidence generation [9]

Recent works:

3) **LLM Capabilities**

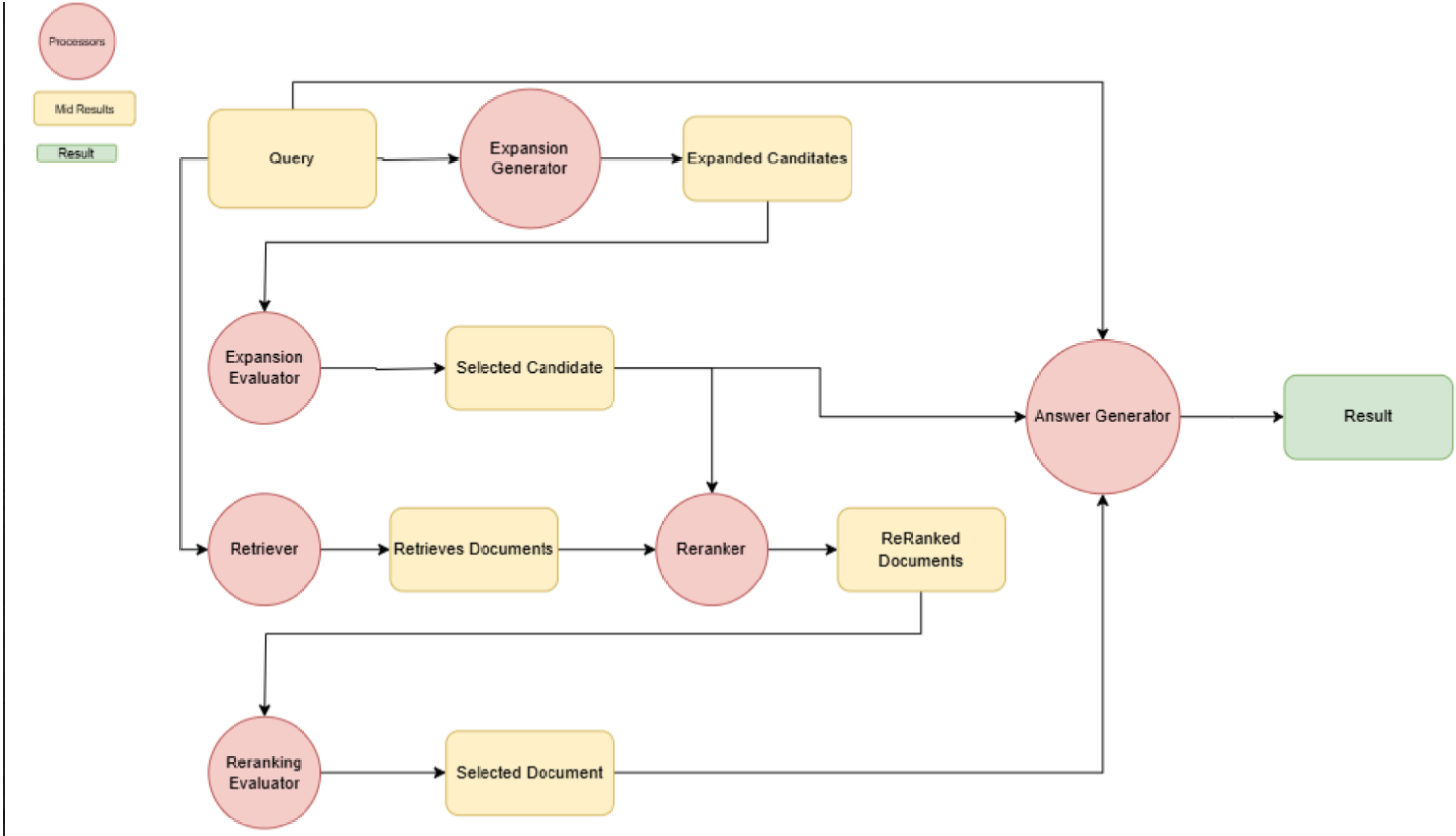
- Few/Zero-Shot Generation: GPT-3 [10], PaLM [11]
- Self-Verification/Refinement: Reflexion [12]
- LLM Reranking: Listwise scoring [13]

4) **Prompt Optimization**

Improving how we ask questions to get better answers from LLMs.

- APE: Iterative prompt search[14] (Tries many prompts and picks the best one)
- DLN: Learnable-prompt parameters [15] (Learns the best prompts automatically.)

Architecture



Proposed Framework

- Three-Step Process:

  -Query Expansion: Generate background context using LLMs.

  -Document Selection: Retrieve and rerank documents.

  -Answer Generation: Produce the final answer.

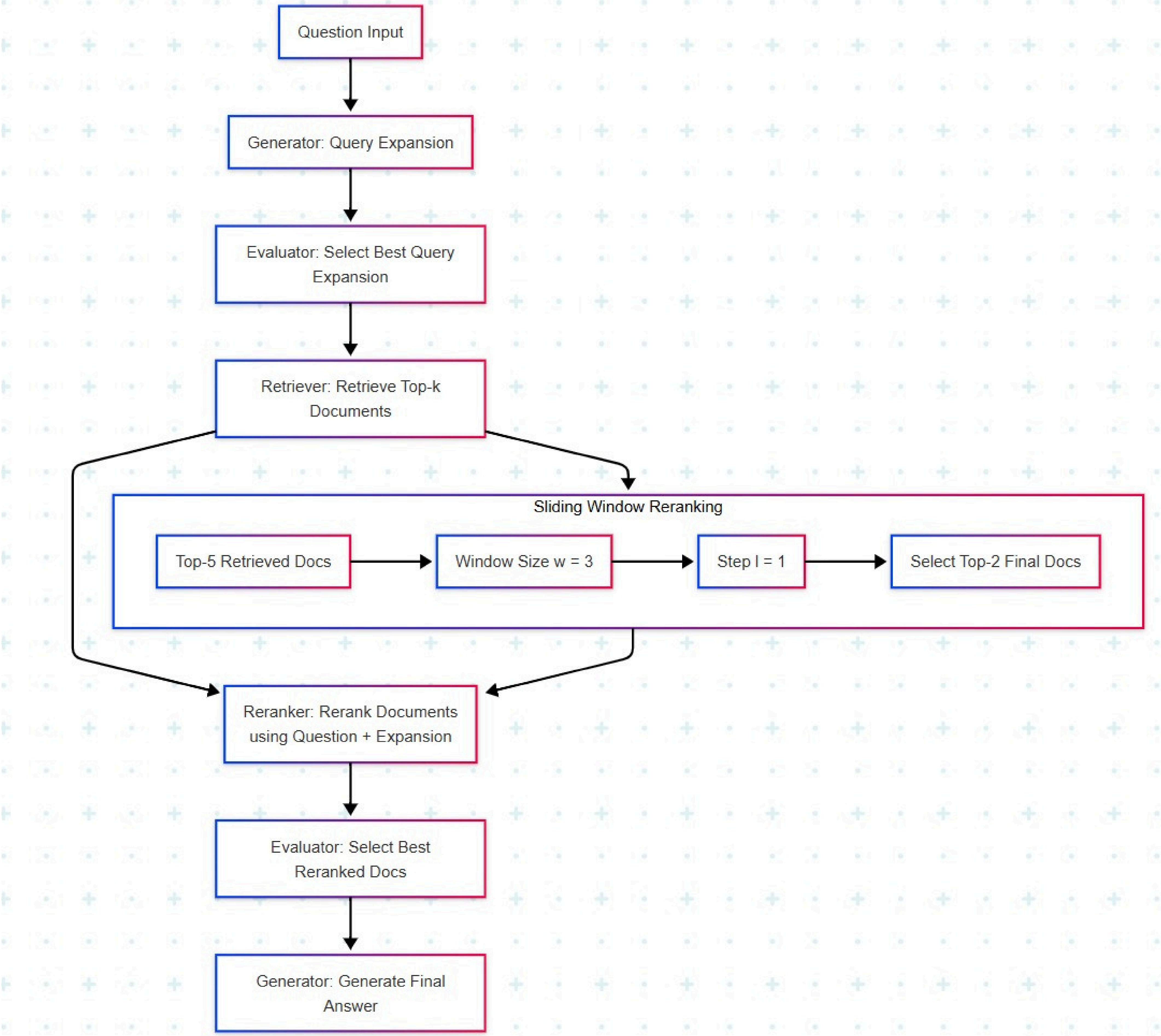
- Multi-Role LLMs:

  -Generator: Expands queries.

  -Reranker: Prioritizes documents.

  -Evaluator: Refines outputs via feedback.

Pipeline



Question Input
Generator: Query Expansion
Evaluator: Select Best Query Expansion
Retriever: Retrieve Top-k Documents
Sliding Window Reranking
Top-5 Retrieved Docs
Window Size w = 3
Step l = 1
Select Top-2 Final Docs
Reranker: Rerank Documents using Question + Expansion
Evaluator: Select Best Reranked Docs
Generator: Generate Final Answer

Methodology Details

Query expansion:

1. Generate background context using LLMs.
    - Example:
        - Question: "Who invented the telephone?"
        - Expansion: "Background: The telephone was patented in 1876. Key inventors include Alexander Graham Bell and Elisha Gray."

2. LLM as Generator (G_e):

$$e = G_e(q;\theta_e)$$

    - Input: Question (q) + prompt (θ_e).
    - Output: Expansion (e) with key details.

Methodology Details

Document selection:

1. Process:
   - question("When was the first iPhone released?")
   - Fine Reranking: LLM reranks top-k docs (k=10) via sliding window (window=20, step=10).

     -"The first iPhone debuted on June 29, 2007." (Score: 0.98)

     -"Apple Inc. was founded in 1976." (Score: 0.45)
2. LLM as Reranker (Rd):

   $$d = Rd(q, e; \theta d)$$

   - Input: Question (q) + Expansion (e) + Optimized prompt (θd).
   - Output: Top-k reranked documents (d).

Methodology Details

Answer Generation:

1. Inputs:
   - Question (q): "Who invented the telephone?"
   - Expansion (e): "Background: The telephone was patented in 1876. Key inventors include Alexander Graham Bell and Elisha Gray."
   - Reranked Docs (d):
     a. "Alexander Graham Bell was awarded the first US patent for the telephone in 1876."
     b. "Elisha Gray filed a patent caveat the same day but lost the legal battle."
2. LLM as Reader ($\boldsymbol{Ga}$):

$$a = Ga(q, e, d; \theta a)$$

   - Prompt (θa): "Summarize the most accurate answer from the evidence."
   - Output (a): "Alexander Graham Bell invented the telephone, patented in 1876."

Output from Our Implementation

Query expansion:

Question: "what did james k polk do before he was president?"

"expansion_candidates":
["<think> Okay, so I need to figure out what James K. Polk did before he became president. I remember that he was a U.S. President, probably in the 19th century, but I'm not exactly sure of the details. Let me start by recalling what I know about him. I think he ....

"expansion_scores": [
0.6969156523537555,
0.6915215483794672,
0.6989462438269207,
0.6916691048144472,
0.6928344002802335,
0.6957589557604544,
0.6937911983566307,
0.687763436870264,
0.6911557235482523,
0.6908004897383319],

Like this 10 passages are generated, then expansion scores are calculated.

LLM Used: deepseek-r1-distill-llama-70b
Embedding model that we used: all-MiniLM-L6-v2

Output from Our Implementation

Document selection:

"ctxs": [
  {"text": "Entity: James K. Polk (ID: m.042f1)"},
  {"text": "Entity: United States Representative (ID: m.02_bcst)"},
  {"text": "Entity: Governor of Tennessee (ID: m.04x_n9q)"},
  {"text": "Entity: Speaker of the United States House of Representatives (ID: m.0cgqx)"}
]

"reranking_scores": [0.569273014141989, 0.569273014141989, 0.569273115222647]

Output from Our Implementation

Answer Generation:

"answers": [
  "Speaker of the United States House of Representatives (ID: m.0cgqx)",
  "Governor of Tennessee (ID: m.04x_n9q)",
  "United States Representative (ID: m.02_bcst)"
]

Experimental Results

- Datasets:
  -WebQsp
- Metrics:
  -Recall, precision, f1

Recall Metrics:

Top-k	Recall(%)
Top-2	63.20
Top-4	83.15
Top-8	91.24

Precision Metrics:

Top-k	Precision(%)
Top-2	49.73
Top-4	46.15
Top-8	33.20

F1 Score Metrics:

Top-k	F1 Score(%)
Top-2	48.89
Top-4	49.24
Top-8	38.26

Comparision with other results

Our work's results surpassed the results existing methods:

On WebQ dataset:

Recall:

Method	**Top-2**	**Top-4**	**Top-8**
GenRead-sampling [9]	58.02	64.67	69.59
GenRead-clustering [9]	61.17	67.47	72.00
Our Implementation	63.20	83.15	91.24

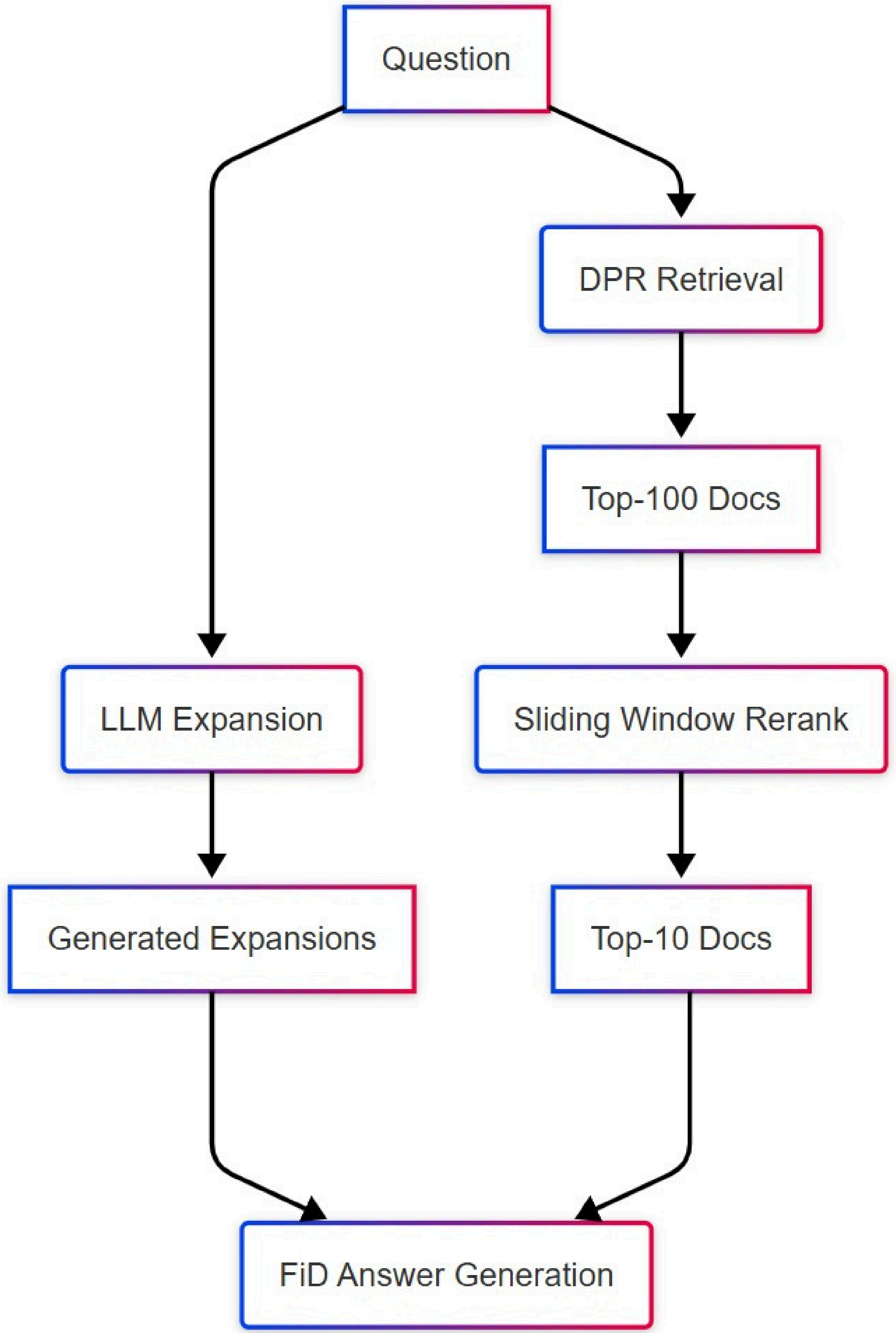
Future Work

Hybrid Retrieval-Augmented Generation (RAG)

Current system uses only LLM-generated expansions.

Combine LLM-generated virtual docs with retrieved evidence to enhance accuracy & coverage.

Retrieve passages from large knowledge sources (e.g., Wikipedia) using sparse (BM25) or dense (DPR) retrievers to ensure factual accuracy.



Future Work

Prompt Optimzation algorithm: [14],[15]

- Goal: Automatically refine prompts for better performance.
- Approach:
  -Treat prompts as learnable parameters.
  -Use variational inference to optimize prompts.
  -Update prompts based on evaluator feedback.

Example:

Step	Initial Prompt	Optimized Prompt
Query Expansion	Generate a document about X.	List key facts, dates, and people related to X.
Document Reranking	Rank these by relevance.	Prioritize docs with direct quotes or numbers.

Future Work

- Test the Impact of Components:

  -Without generator

  -Without reranker

  -Without evaluator

  -Without prompt optimization

- Evaluate it on different ODQA datasets:

  - Currently evaluated on only Webqsp.
  - Evaluate it on NQ, TriviaQA

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Thank you