RAG (Retrieval Augmented Generation) Cheatsheet

Stages in RAG:

1. **Loading:**
   - Import your data (text files, PDFs, databases, APIs) using LlamaHub's extensive range of connectors.
2. **Indexing:**
   - Create searchable data structures, primarily through vector embeddings and metadata strategies, enabling efficient context retrieval.
3. **Storing:**
   - Securely store your indexed data and metadata for quick access without the need to re-index.
4. **Querying:**
   - Utilize LLMs and LlamaIndex data structures for diverse querying techniques, including sub-queries and hybrid strategies.
5. **Evaluation:**
   - Continuously assess the effectiveness of your pipeline to ensure accuracy, faithfulness, and response speed.

Application Types:

1. **Query Engines:**
   - For direct question-answering over your data.
2. **Chat Engines:**
   - Enables conversations with your data for an interactive experience.
3. **Agents:**
   - Automated decision-makers that interact with external tools, adaptable for complex tasks.

Key Concepts:

1. **Nodes and Documents:**
   Fundamental units in LlamaIndex, where Documents encapsulate data sources and Nodes represent data "chunks" with associated metadata.
   1. **Connectors:**
      Bridge various data sources into the RAG framework, transforming them into Nodes and Documents.
   1. **Indexes:**
      The backbone of RAG, enabling the storage of vector embeddings in a vector store along with crucial metadata.
   1. **Embeddings:**
      Numerical representations of data, facilitating the relevance filtering process.
   1. **Retrievers:**
      Define efficient retrieval strategies, ensuring the relevancy and efficiency of data retrieval.
   1. **Routers:**
      Manage the selection of appropriate retrievers based on query specifics and metadata.
   1. **Node Postprocessors:**
      Apply transformations or re-ranking logic to refine the set of retrieved nodes.
   1. **Response Synthesizers:**
      Craft responses from the LLM, utilizing user queries and retrieved text chunks for enriched answers.

LlamaIndex SingleStore LangChain OpenAI

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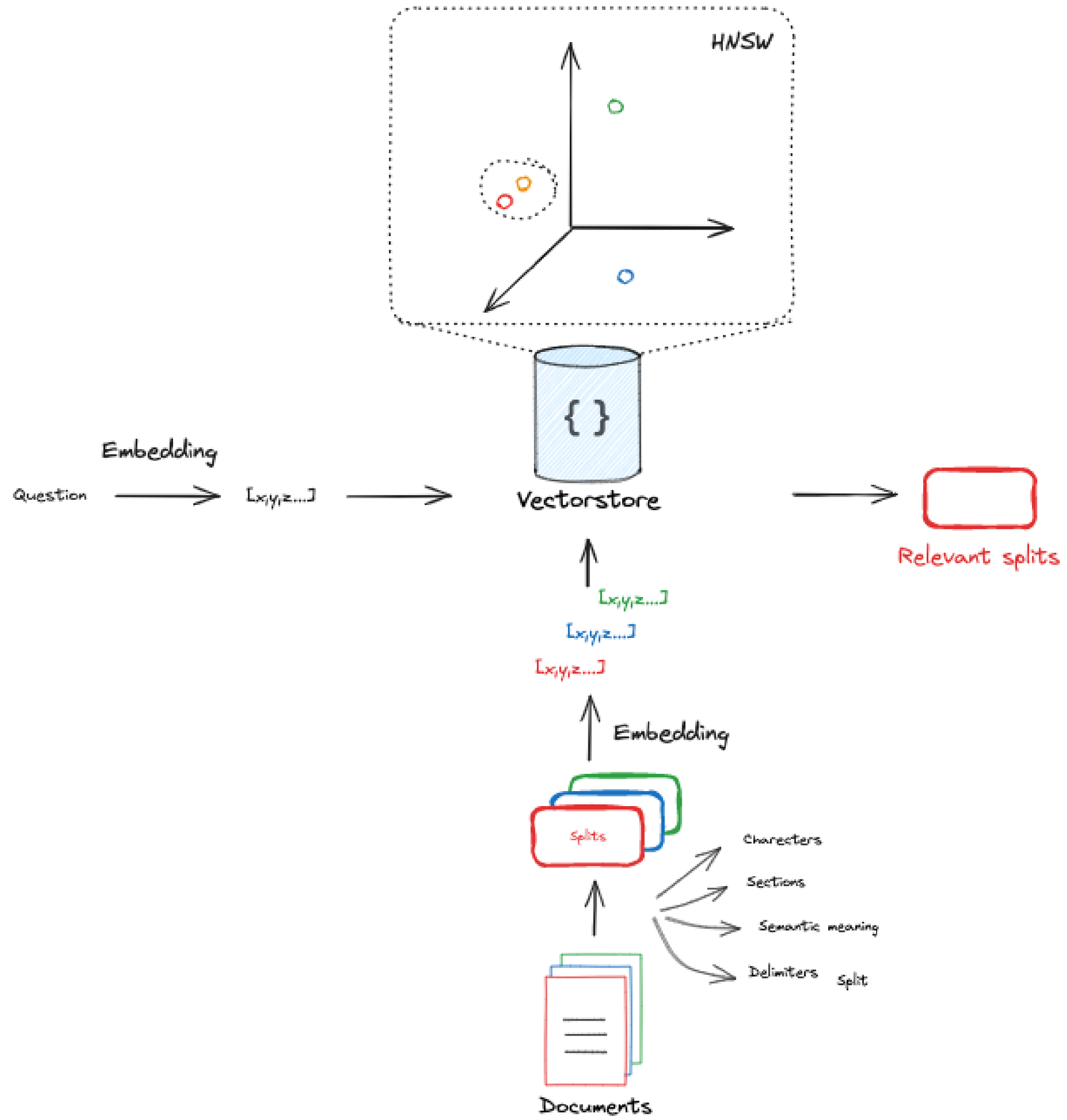
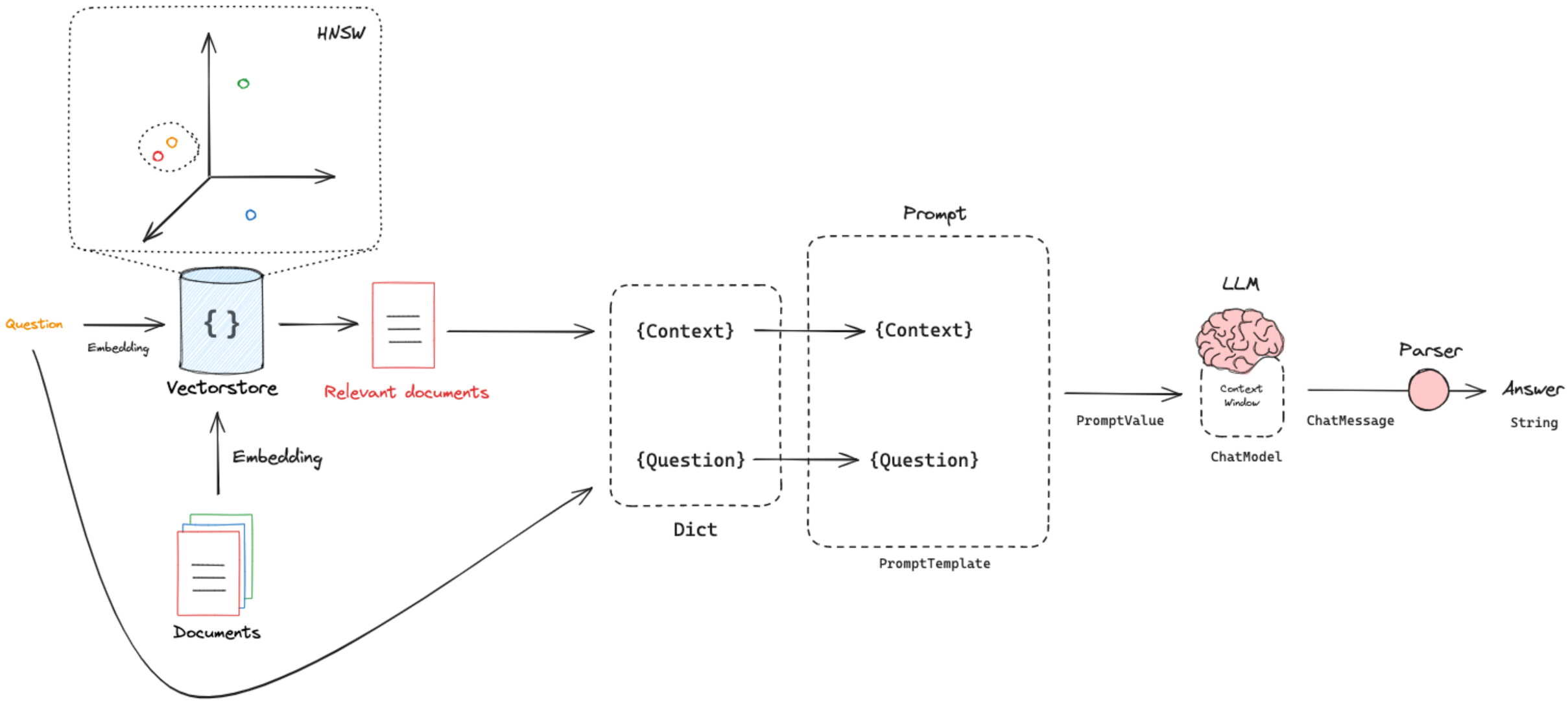
Indexing:



https://github.com/langchain-ai/rag-from-scratch/blob/main/rag_from_scratch_1_to_4.ipynb

Generation:



https://github.com/langchain-ai/rag-from-scratch/blob/main/rag_from_scratch_1_to_4.ipynb

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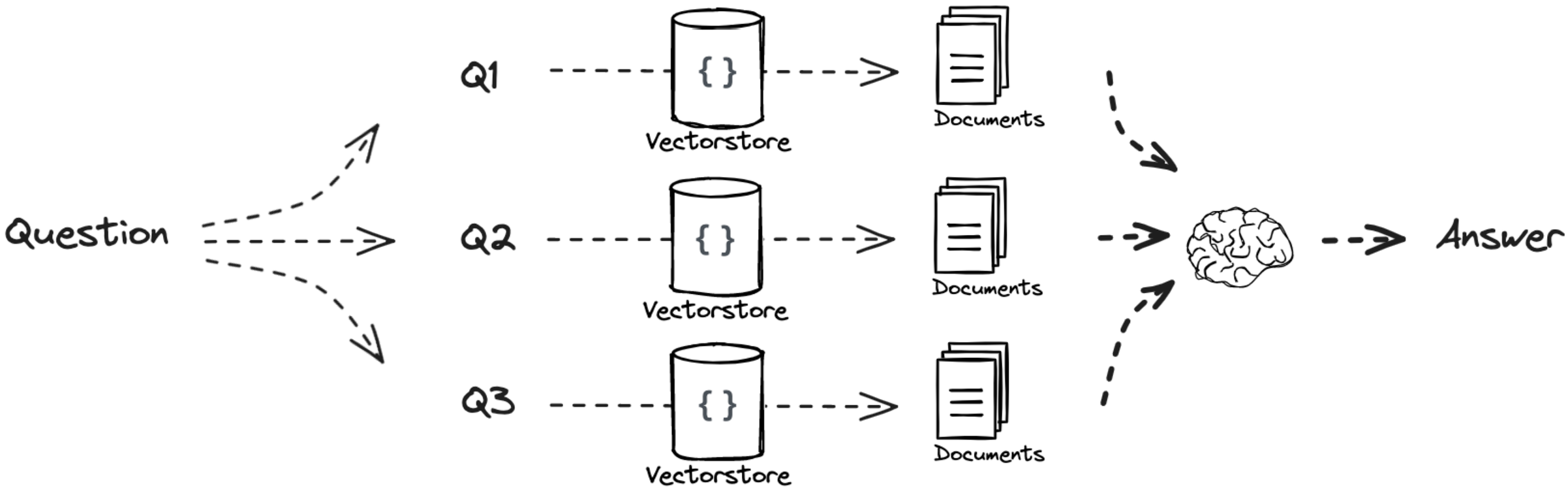
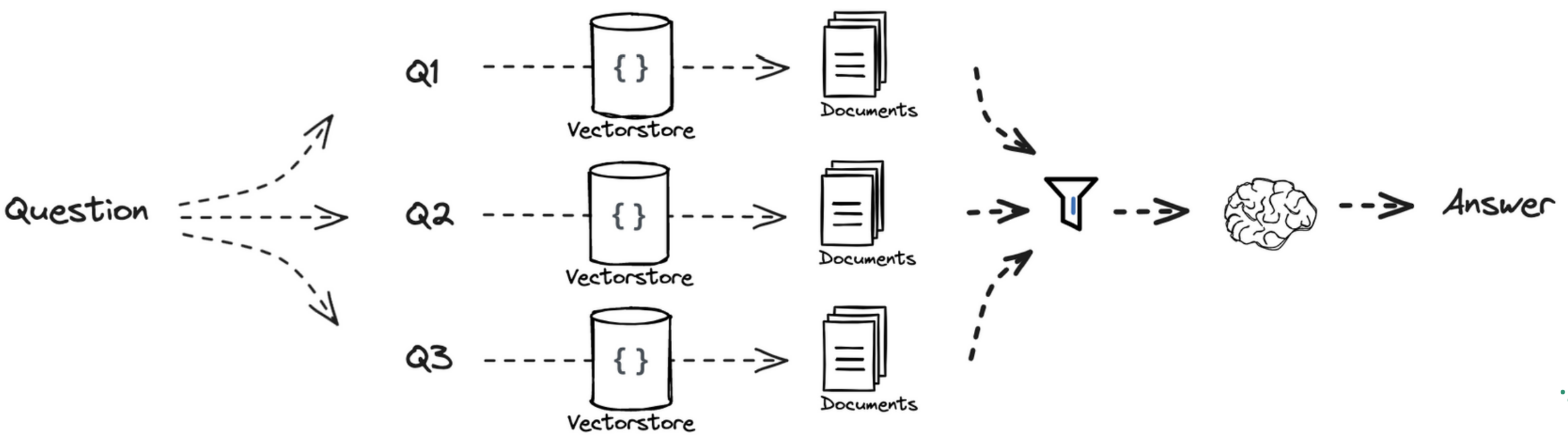
Multi Query:



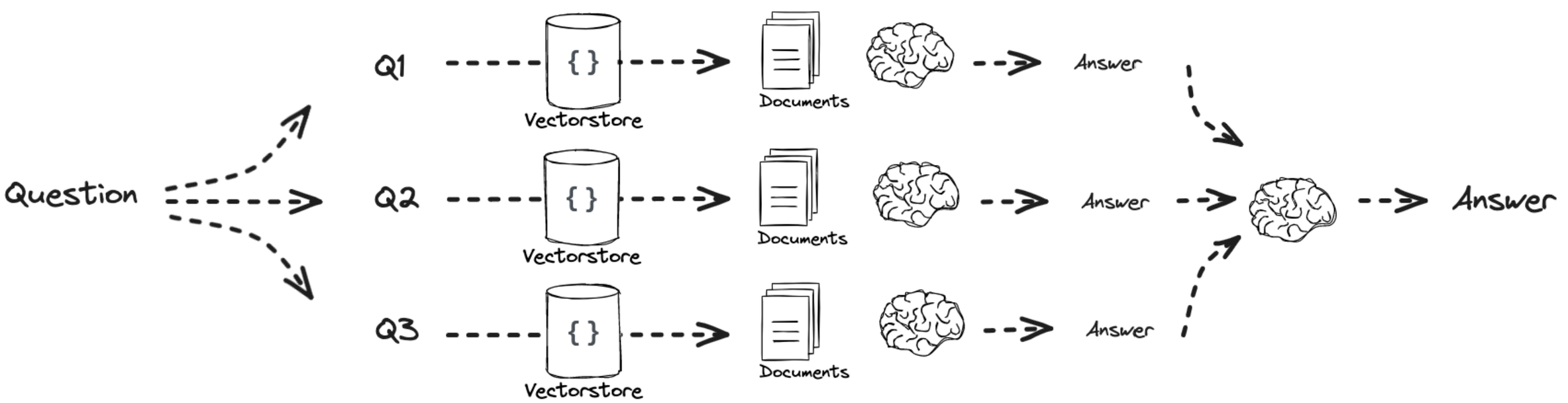
https://python.langchain.com/docs/modules/data_connection/retrievers/MultiQueryRetriever

RAG-Fusion:



https://github.com/langchain-ai/langchain/blob/master/cookbook/rag_fusion.ipynb

Decomposition:



https://arxiv.org/pdf/2205.10625.pdf

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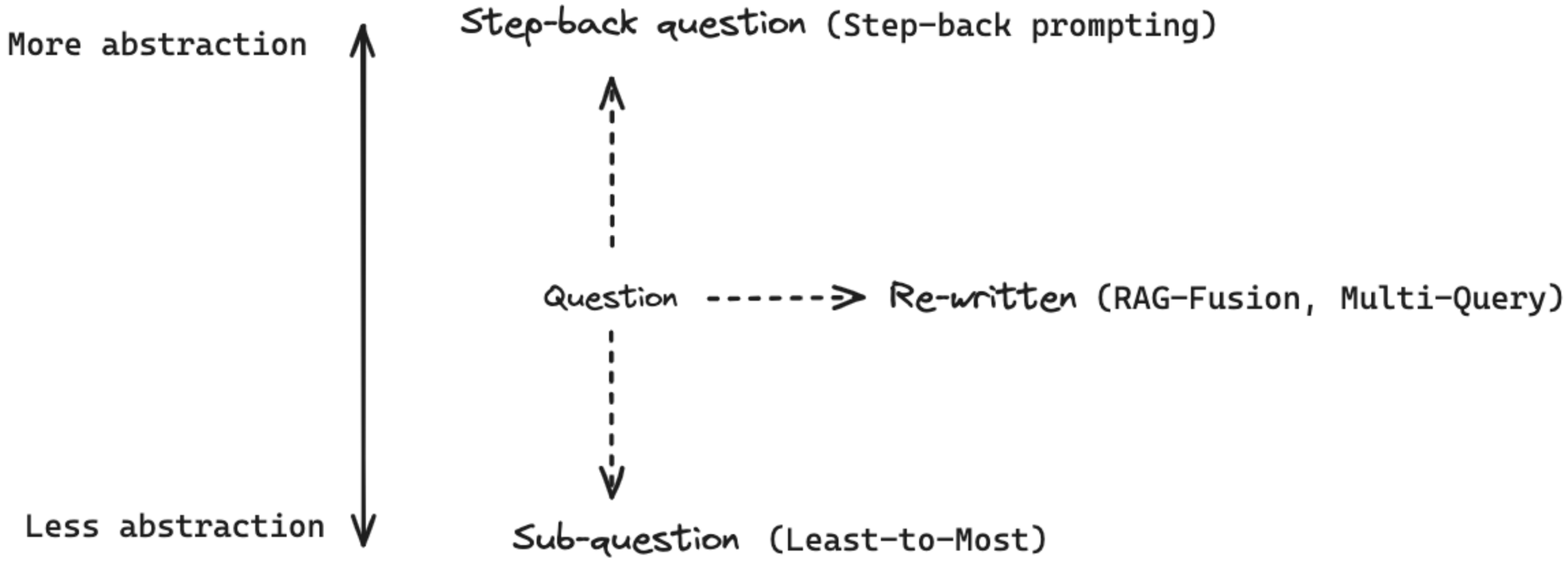
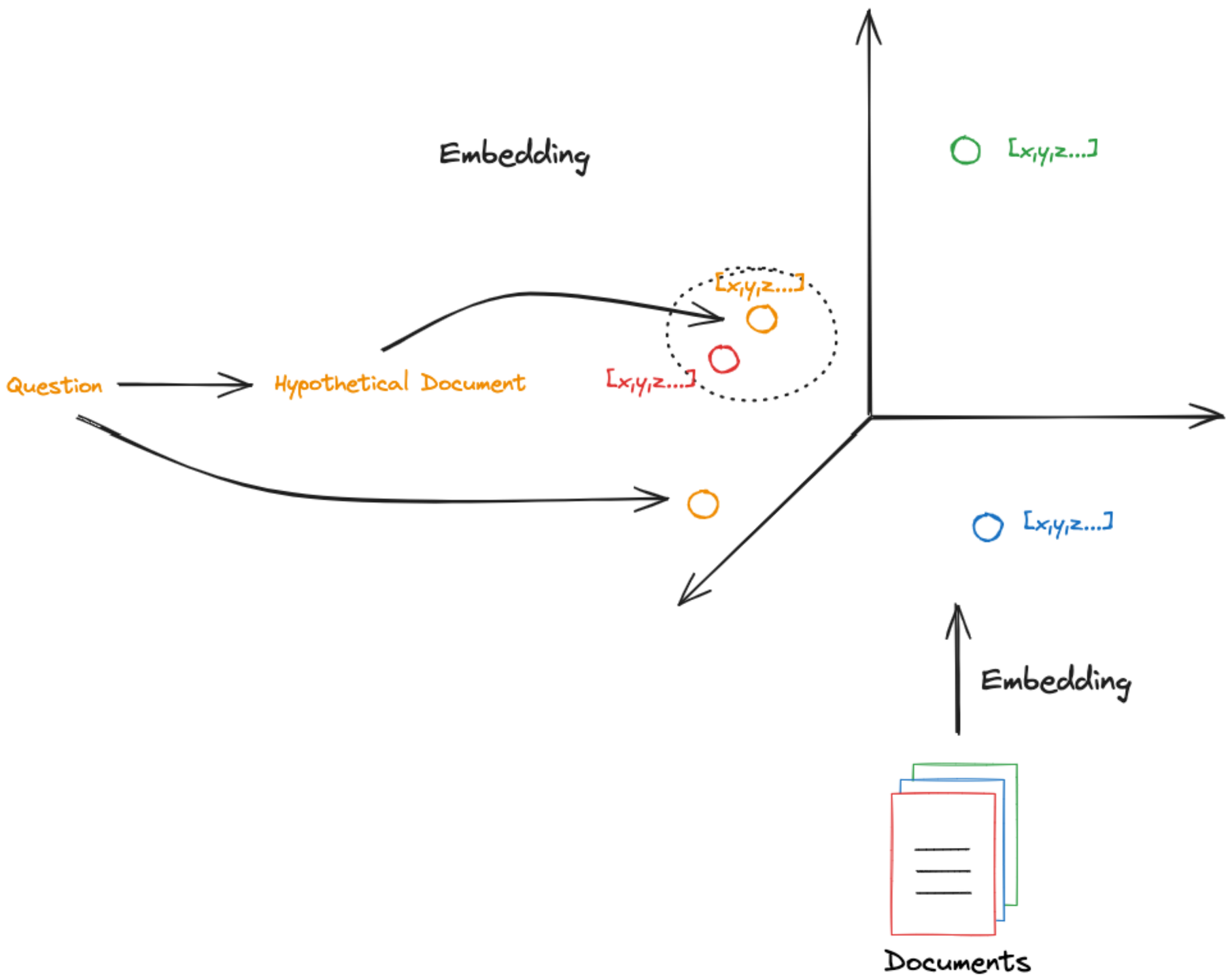
Step Back:



https://arxiv.org/pdf/2310.06117.pdf

HyDE:



https://arxiv.org/abs/2212.10496

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Techniques and Tools:

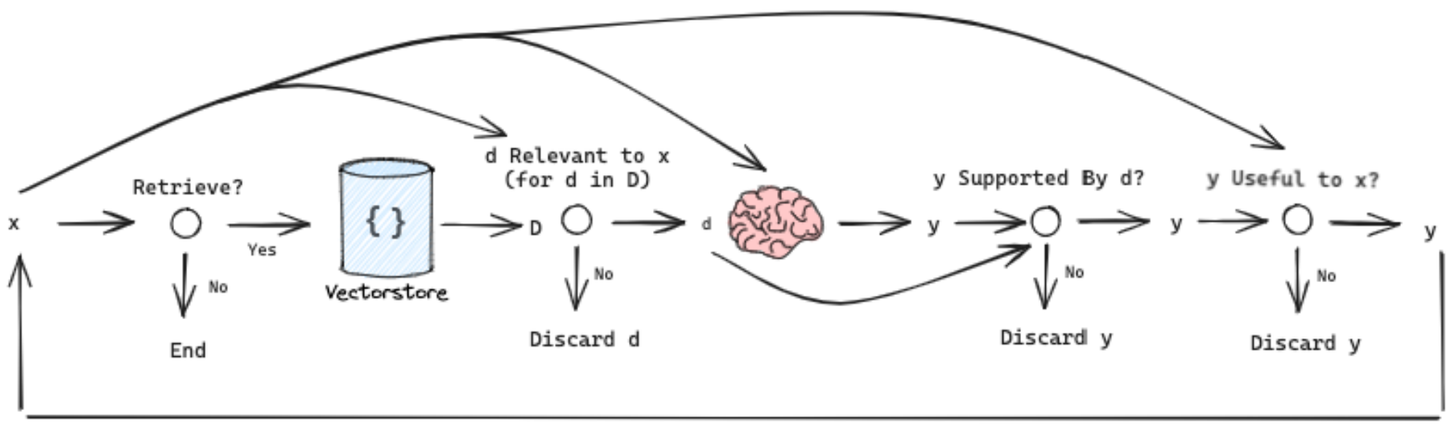
1. **Data Ingestion and Querying:**
   - Using tools like LlamaIndex for processing and querying data from various sources into the model's prompt.
2. Chunk Size Optimization:
   - **Adjusting the size of data chunks for efficient processing and retrieval, improving response quality.**
3. Metadata Filtering:
   - Enhancing retrieval by adding structured context to data, utilizing vector database capabilities for more relevant results.
4. Fine-Tuning Embeddings:
   - Customizing embedding models to better match query context with relevant data, improving precision and recall.
5. Advanced Retrieval Algorithms:
   - Implementing sophisticated retrieval methods like recursive retrieval and parent-child chunk retrieval to enhance context understanding and response accuracy.

Challenges and Solutions:

- **Missing Data:**
  Addressed by expanding the document corpus or integrating external knowledge bases.
- **The issue with Ranking:**
  Overcome by using advanced retrieval techniques like rerankers.
- **Consolidation Issues:**
  Solved by employing strategies that ensure relevant documents are included in the final context.
- **Formatting Issues:**
  Addressed by ensuring the system correctly interprets and responds to format-specific queries.
- **Incorrect Specifics and Incomplete Answers:**
  Mitigated by adjusting the detail level of responses to match user queries.
- **Extraction Challenges:**
  Overcome by refining the system's ability to accurately extract information from the selected context.

Self-RAG

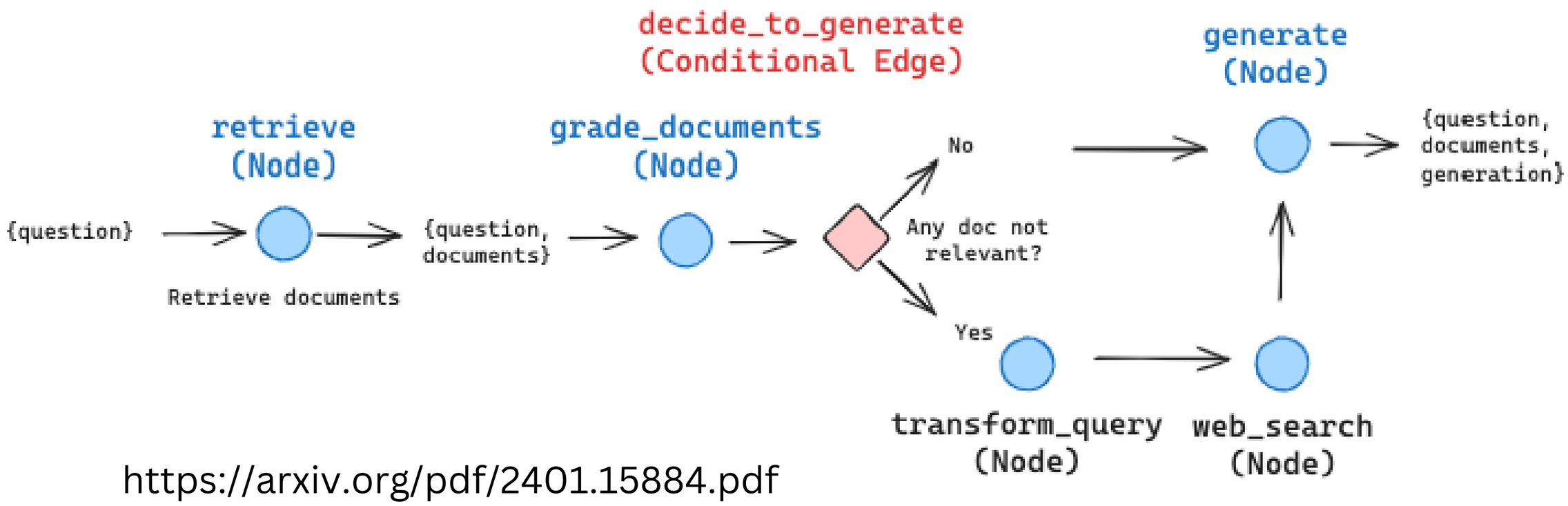
Self-reflection can enhance RAG, enabling correction of poor quality retrieval or generations.



https://arxiv.org/abs/2310.11511

Corrective RAG

Corrective-RAG (CRAG) is a recent paper that introduces an interesting approach for self-reflective RAG.



https://arxiv.org/pdf/2401.15884.pdf

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