Smarter Retrieval, Better Generation: Improving RAG Systems

David S. Batista

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About Me

Lisbon, Portugal

About Me

Lisbon, Portugal

Berlin, Germany

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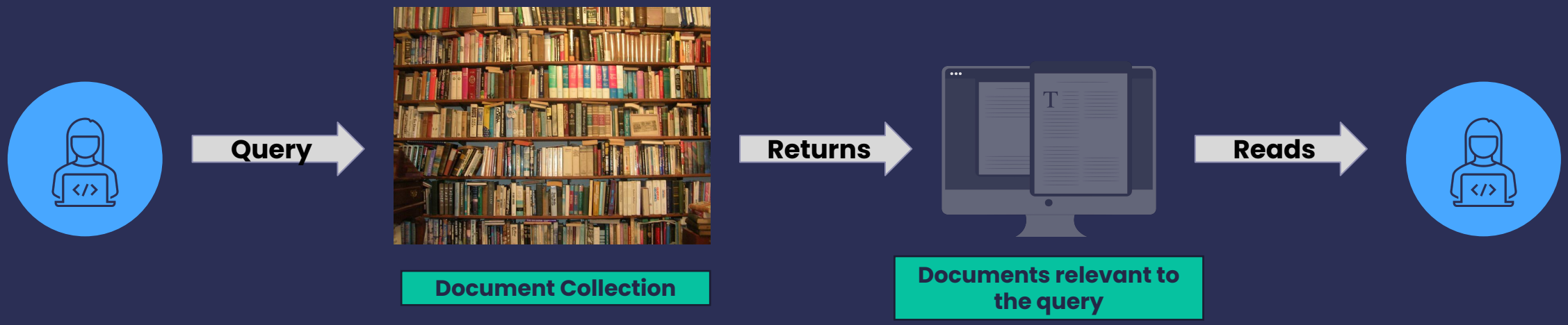
haystack
by deepset

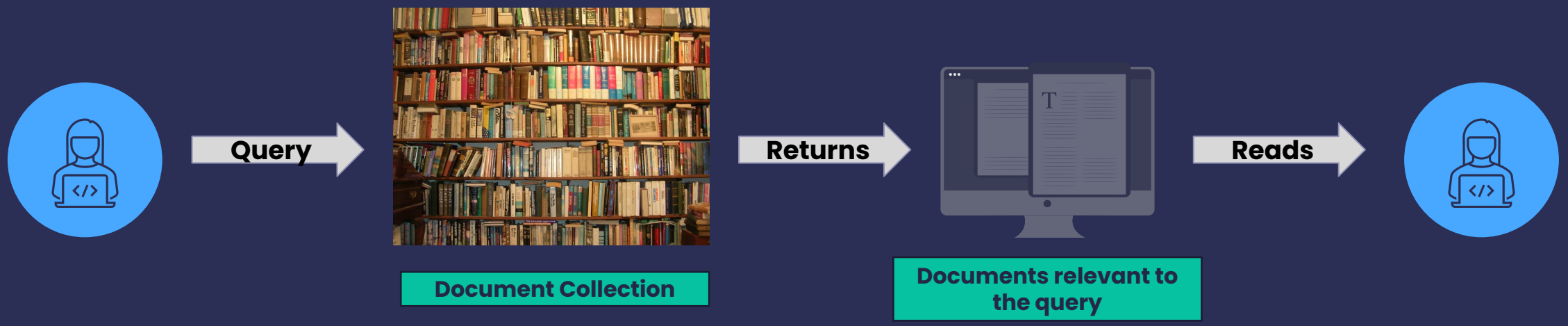
open source framework for building LLM applications, retrieval-augmented generative pipelines search systems that work over large document collections

Berlin, Germany

From classic Information Systems to RAG

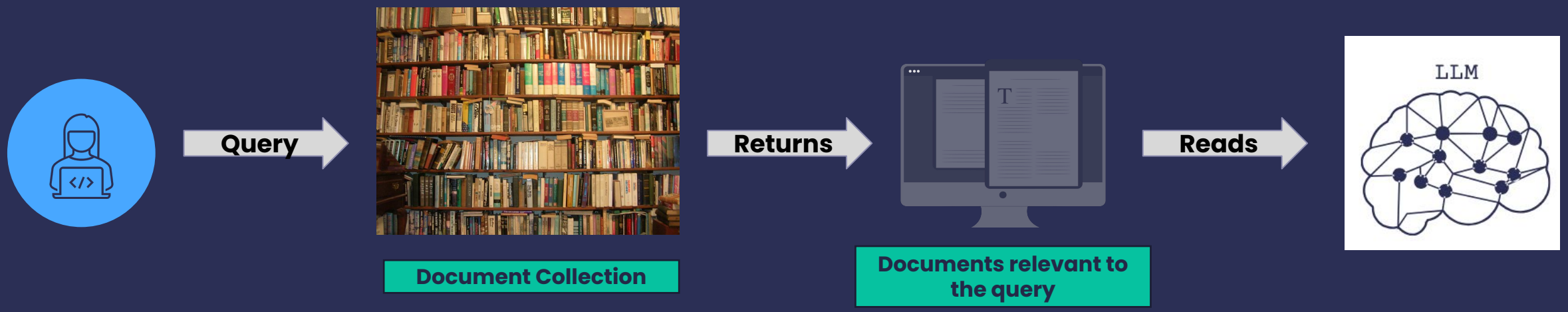


From classic Information Systems to RAG



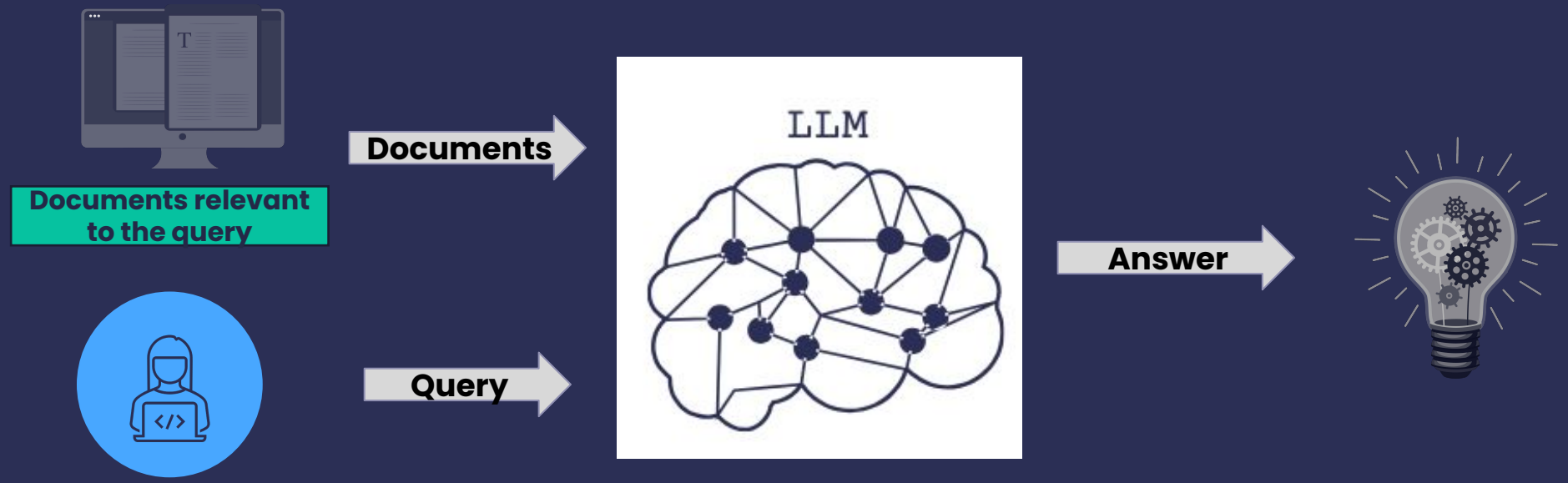
- Return a list of documents or snippets, requiring users to read through multiple results to find the information they need
- A complex or nuanced query requires a deeper understanding of the context and relationships between different pieces of information

From classic Information Systems to RAG

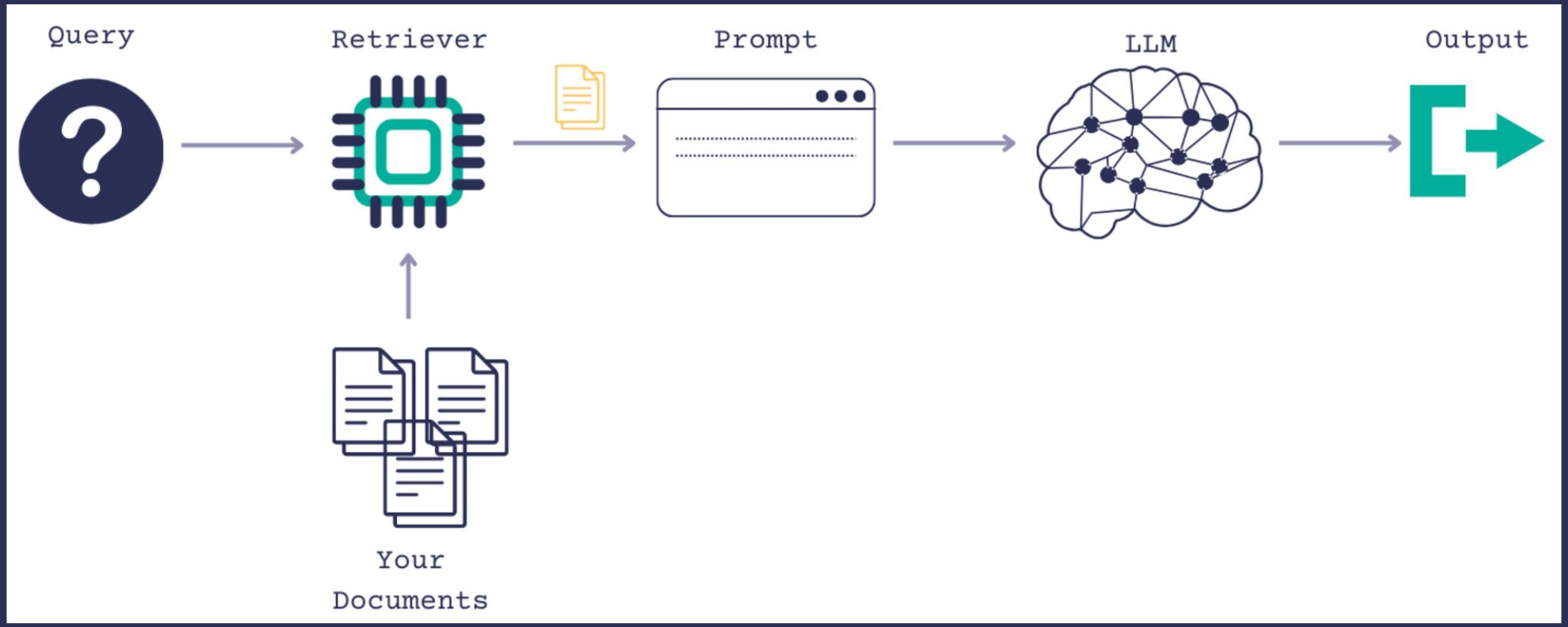


- What if, instead the user sifting through the results, we build a prompt composed by retrieved snippets together with the query and feed it to an LLM?

From classic Information Systems to RAG

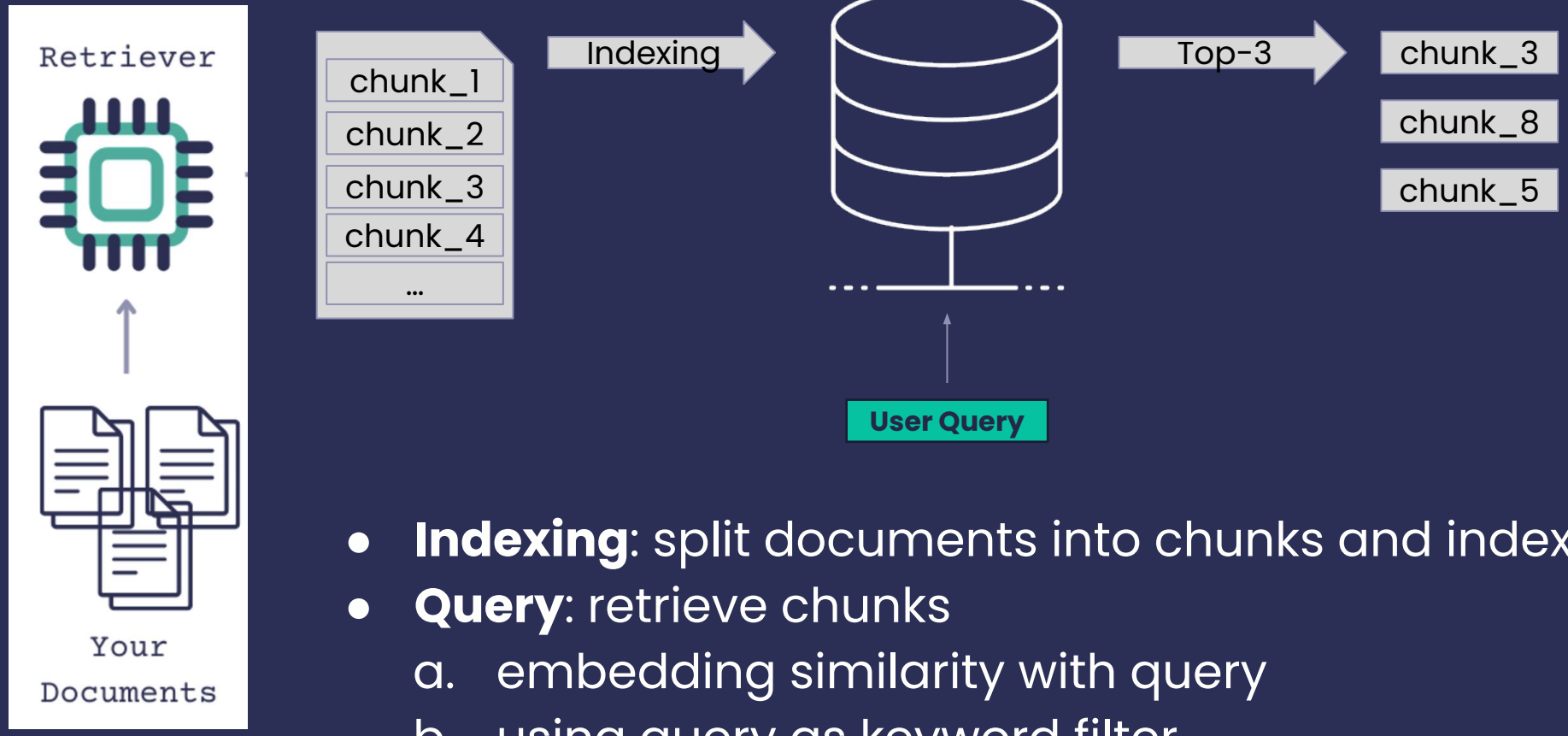


RAG - Retrieval Augmented Generation



RAG - Retrieval Step

Motivation - Baseline Retrieval



- **Indexing**: split documents into chunks and index in a vector db
- **Query**: retrieve chunks
  a. embedding similarity with query
  b. using query as keyword filter
- **Ranking**: rank by similarity with the query

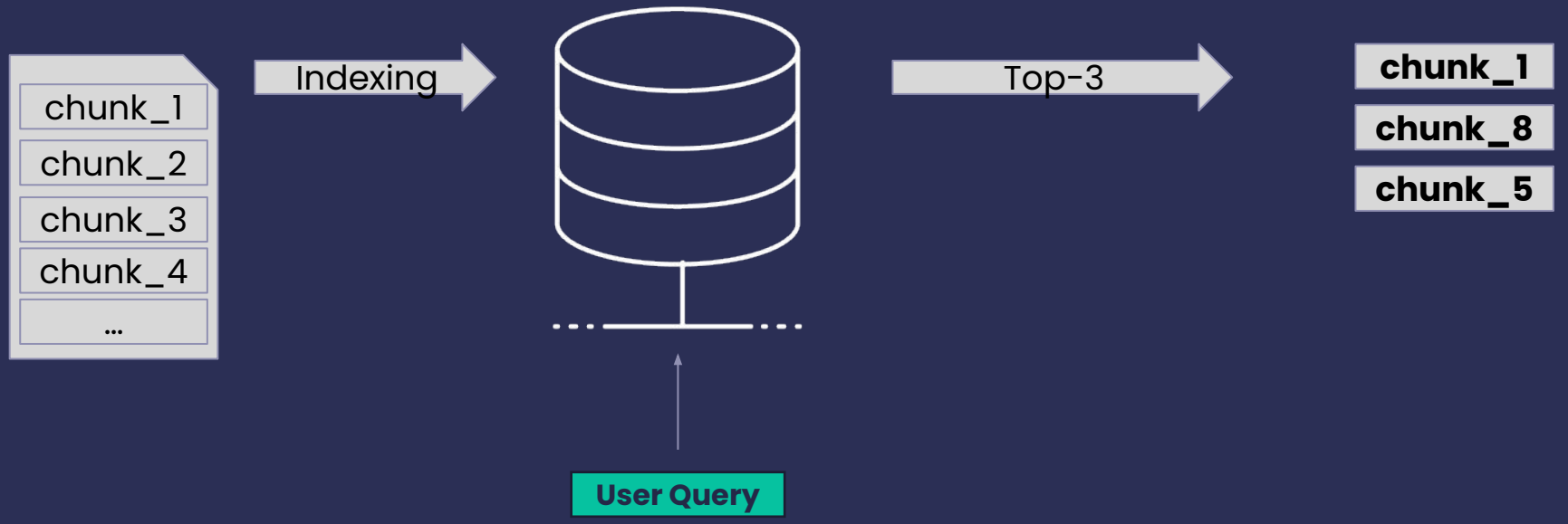
Outline

1. Classic Retrieval Techniques
2. LLM-based Retrieval Techniques
3. Comparative Summary
4. Experiment

Classical Techniques

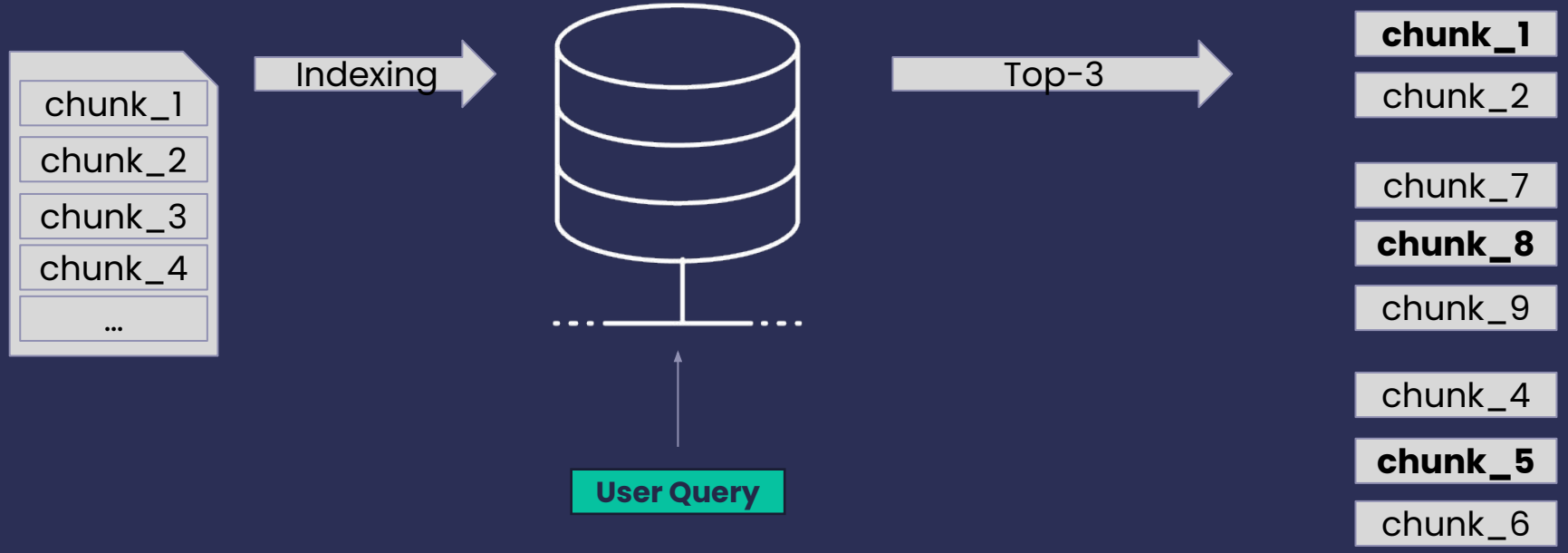
- Sentence-Window Retrieval
- Auto-Merging Retrieval
- Maximum Marginal Relevance
- Hybrid Retrieval (with/ Reciprocal Rank fusion)

Sentence-Window Retrieval



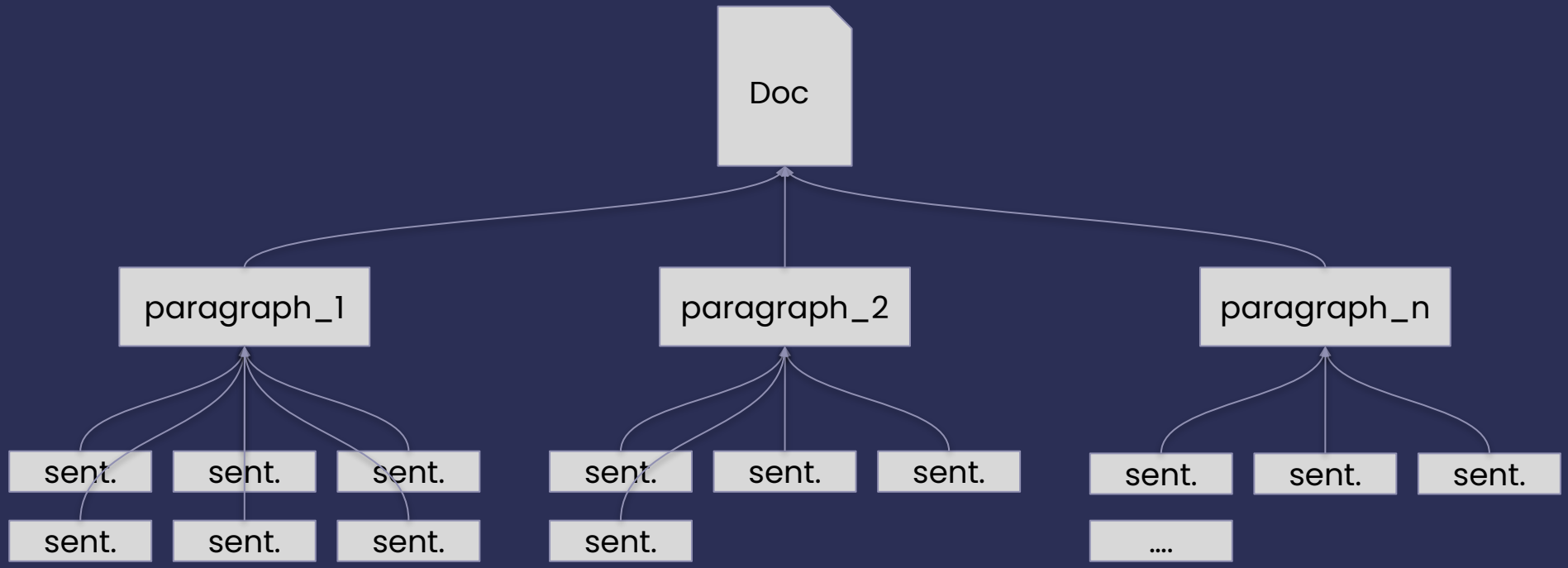
- Retrieve the chunks before and after the matching chunk

Sentence-Window Retrieval



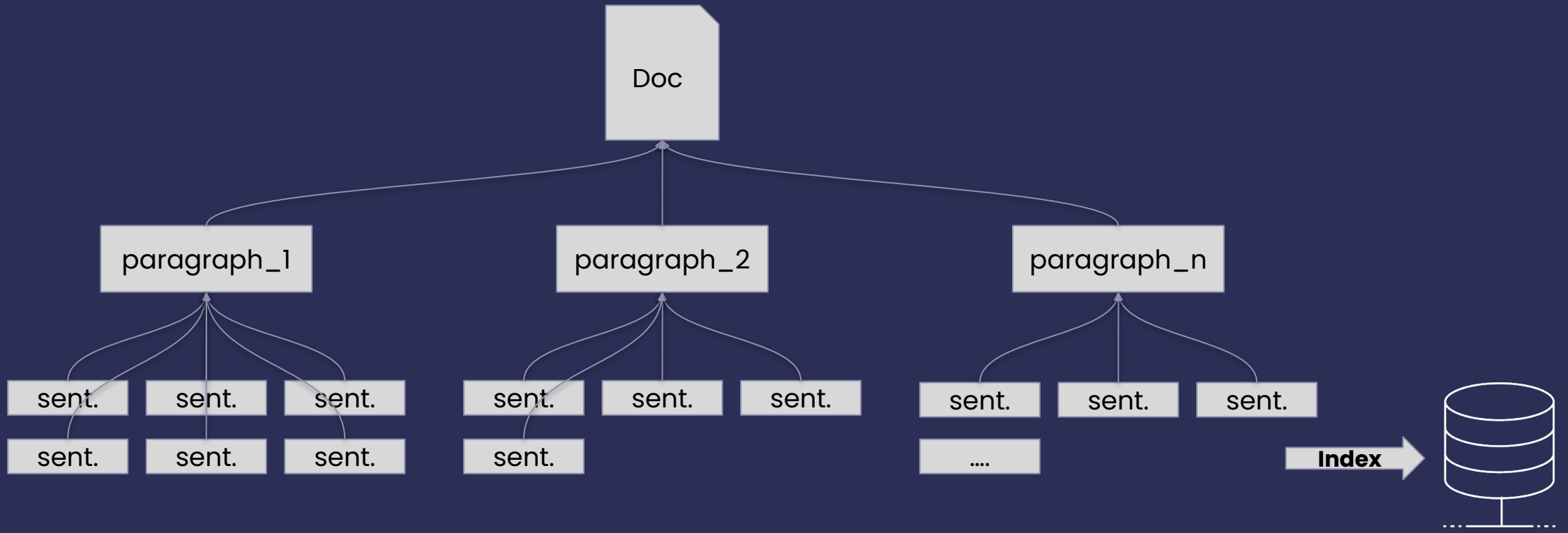
- Retrieve the chunks before and after the matching chunk
- A simple way to gather more context
- Indexing needs to preserve the order of the chunks

Auto-Merging Retrieval



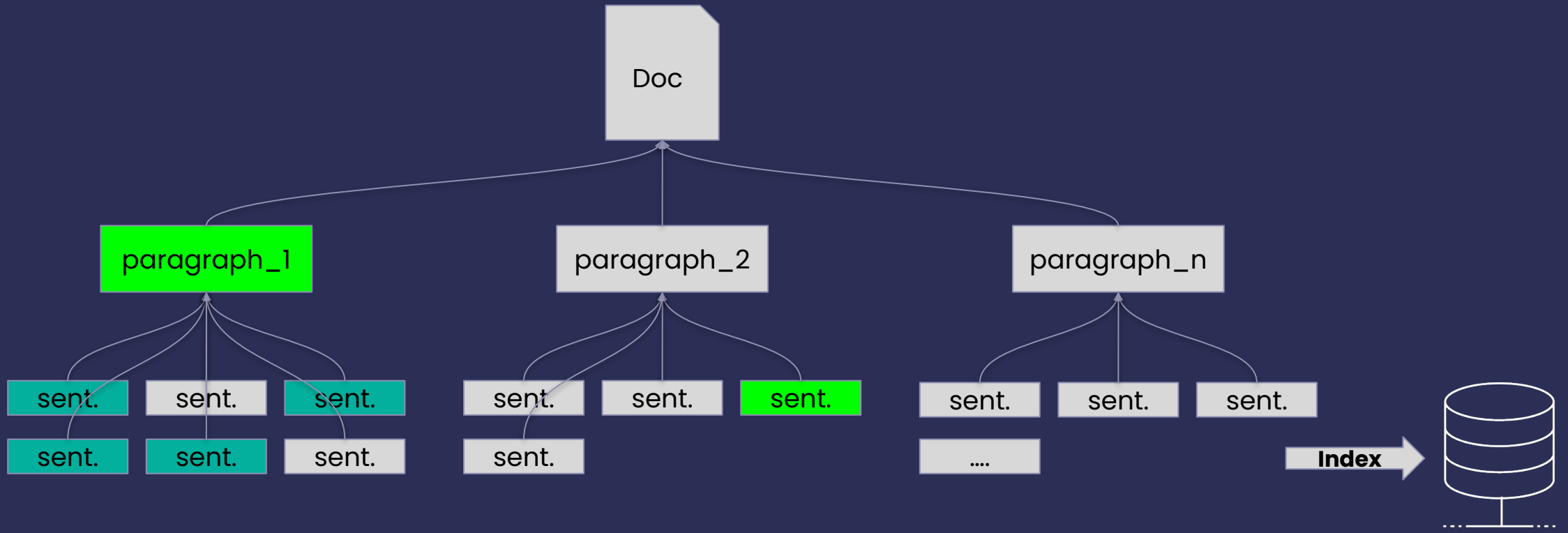
- Transform documents into an Hierarchical Tree structure

Auto-Merging Retrieval



- Transform documents into an Hierarchical Tree structure
- Children chunks/sentences are index and used for retrieval

Auto-Merging Retrieval



- With a threshold of 0.5
  - The paragraph_1 is returned, instead of 4 sentences
  - Plus, the one sentence from paragraph_2
- A whole paragraph might be more informative than individual chunks

Maximum Marginal Relevance (MMR)

- Classical retrieval ranks the retrieved documents by relevance similarity to the user query
- What about scenarios with a high number of relevant documents, but also highly redundant or containing partially or fully duplicative information?
- We need to consider how novel is a document compared to the already retrieved docs

Maximum Marginal Relevance (MMR)

$$\text{MMR} = \arg\max_{d_i \in D \setminus R} [\lambda \cdot \text{Sim}_1(d_i, q) - (1 - \lambda) \cdot \max_{d_j \in R} \text{Sim}_2(d_i, d_j)]$$

Each retrieved document is scored

Maximum Marginal Relevance (MMR)

$$\lambda \cdot \text{Sim}_1(d_i, q)$$

Each retrieved document is scored:

- Similarity between a candidate document and the query

Maximum Marginal Relevance (MMR)

$$- (1 - \lambda) \cdot \max_{d_j \in R} \text{Sim}_2(d_i, d_j)]$$

Each retrieved document is scored:

- Find maximum similarity between a candidate document and any previously selected document.
- Maximize the similarity to already selected documents and then subtracting it - penalize documents that are too similar to what's already been selected.

Maximum Marginal Relevance (MMR)

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- **λ** balances between these two terms

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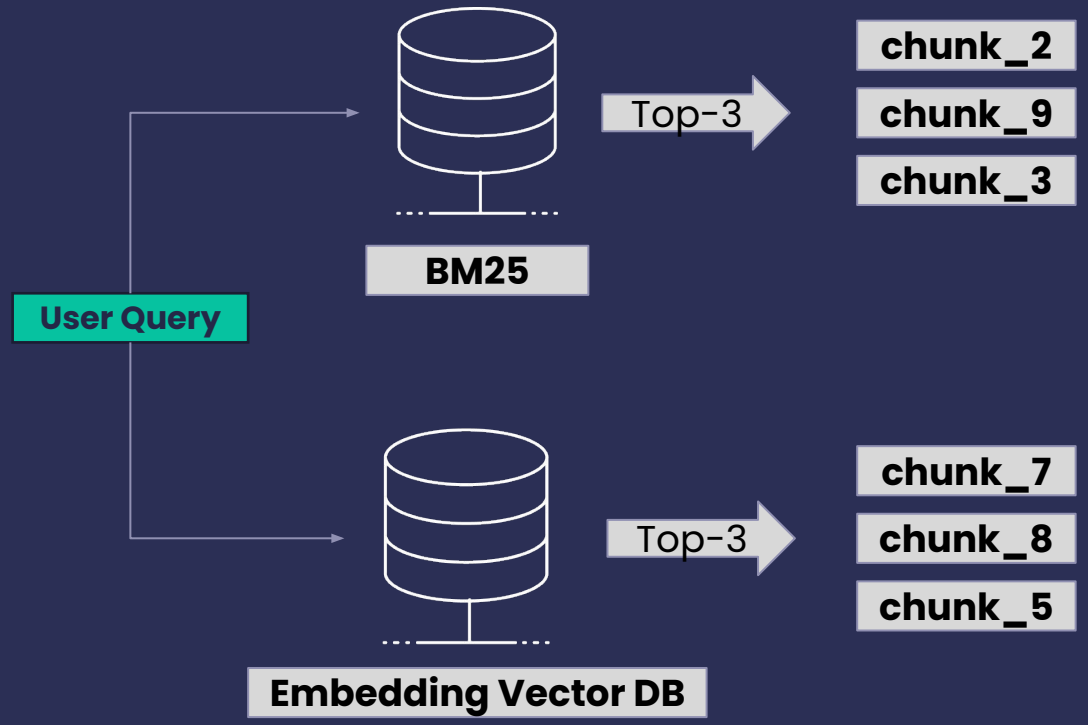
Hybrid Retrieval + Reranking

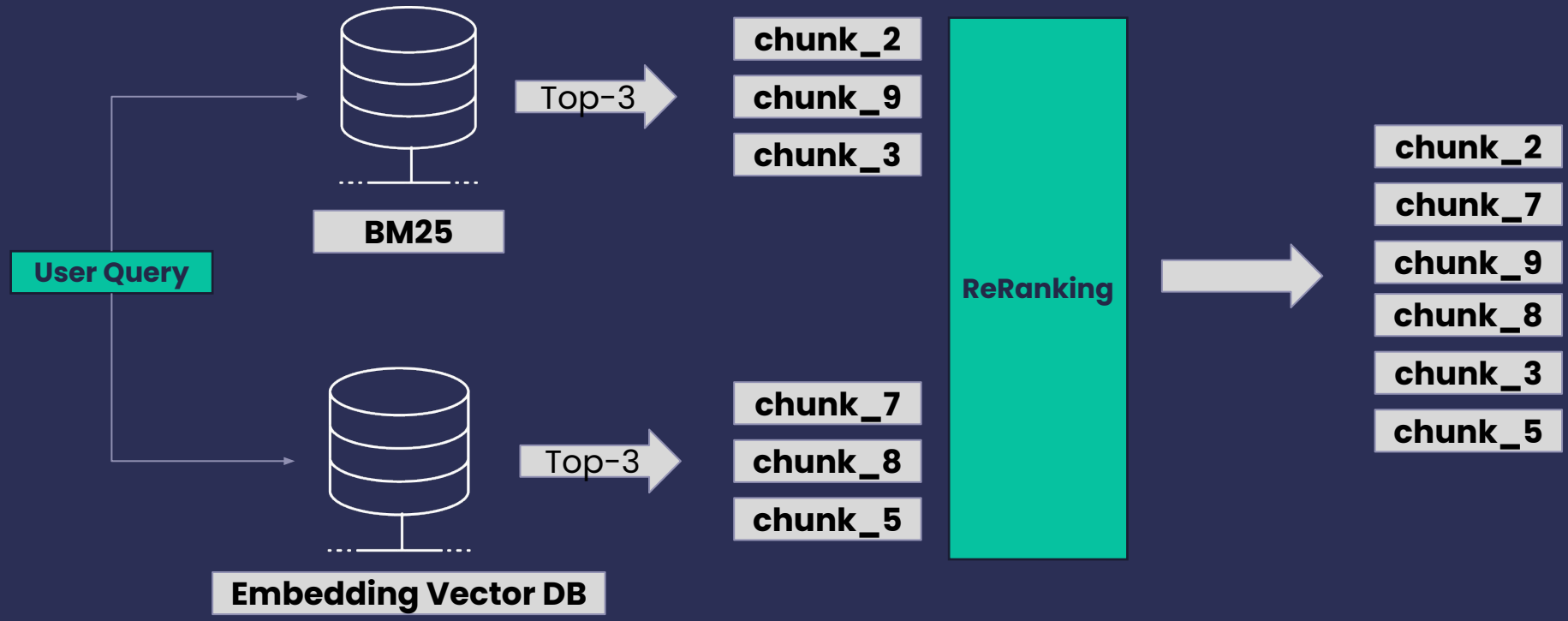
- Combines multiple search techniques
- keyword-based (BM25)

Hybrid Retrieval + Reranking



- Combines multiple search techniques
- keyword-based (BM25) and semantic-based (embedding vector)

Hybrid Retrieval + Reranking



- Combines multiple search techniques
- keyword-based (BM25) and semantic-based (embedding vector)
- Rank-merge results

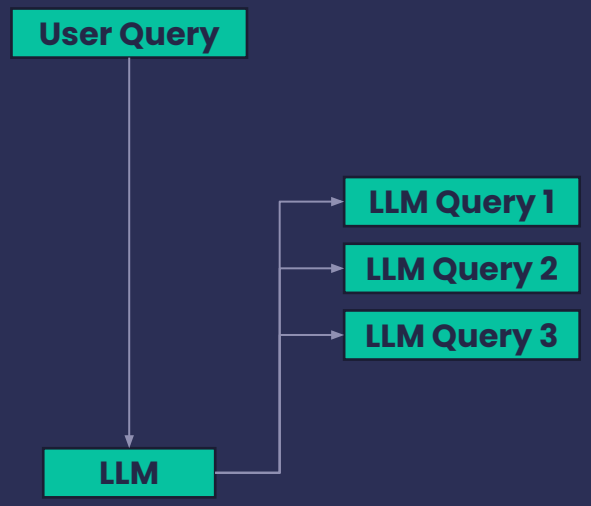
Classical Techniques

- ~~Sentence-Window Retrieval~~
- ~~Auto-Merging Retrieval~~
- ~~Maximum Marginal Relevance~~
- ~~Hybrid Retrieval (with/ Reciprocal Rank fusion)~~

LLM-based Techniques

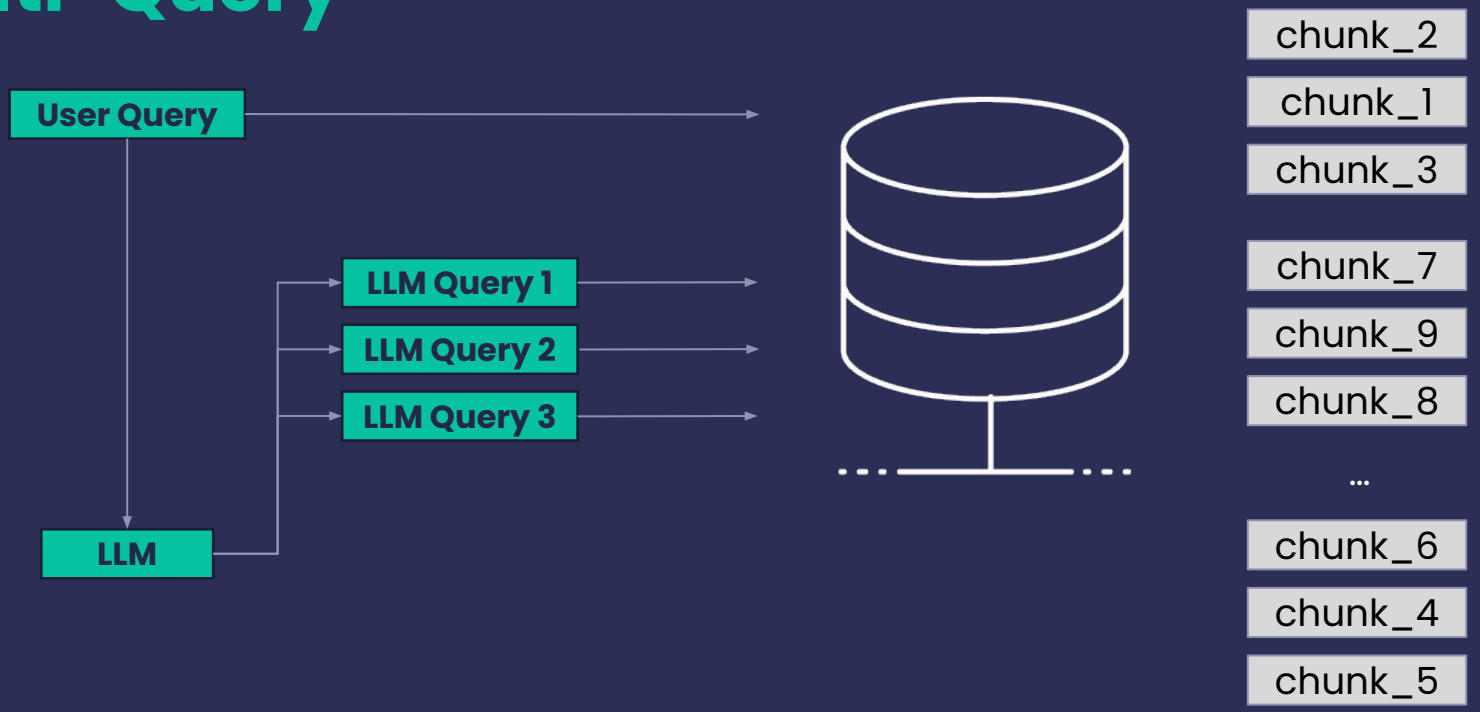
- Multi-Query
- Hypothetical Document Embeddings - HyDE
- Document Summary Indexing

Multi-Query



- Expand a user query into *n* similar queries reflecting the original intent
- ..or break-down a complex query into individual questions

Multi-Query



- Expand a user query into *n* similar queries reflecting the original intent
- ..or break-down a complex query into individual questions
- Each new query is used for an individual retrieval processes

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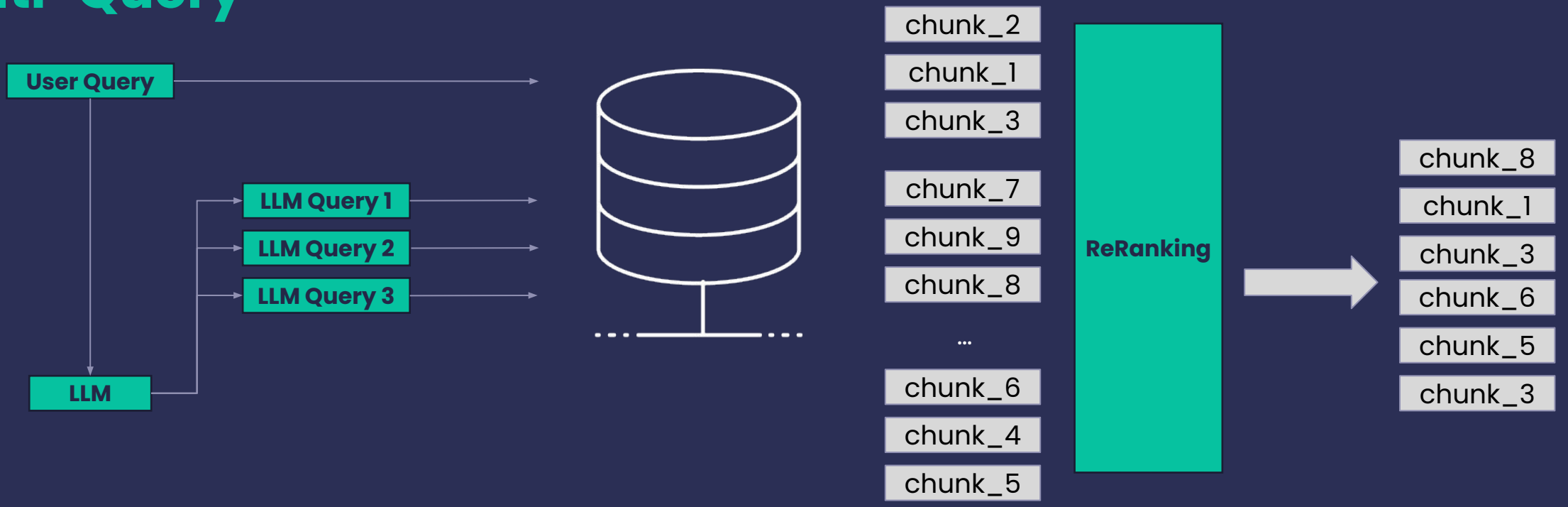
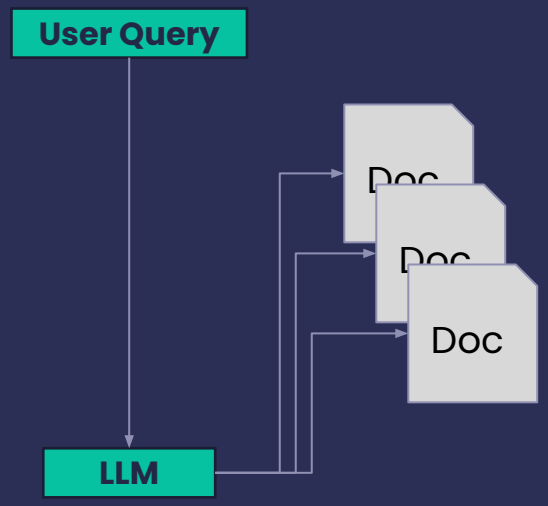


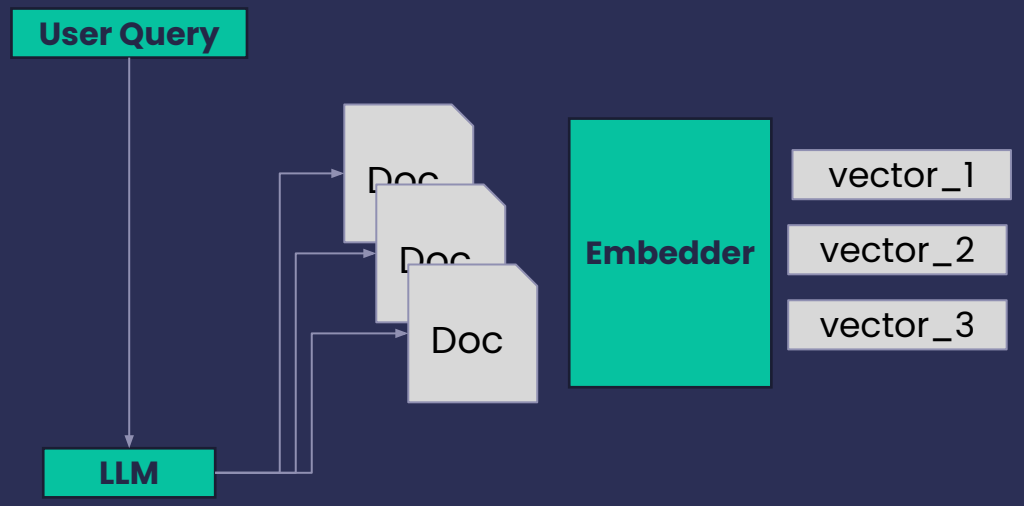
- Expand a user query into *n* similar queries reflecting the original intent
- ..or break-down a complex query into individual questions
- Each new query is used for an individual retrieval processes
- Re-ranking process over all retrieved chunks

Hypothetical Document Embeddings – HyDE



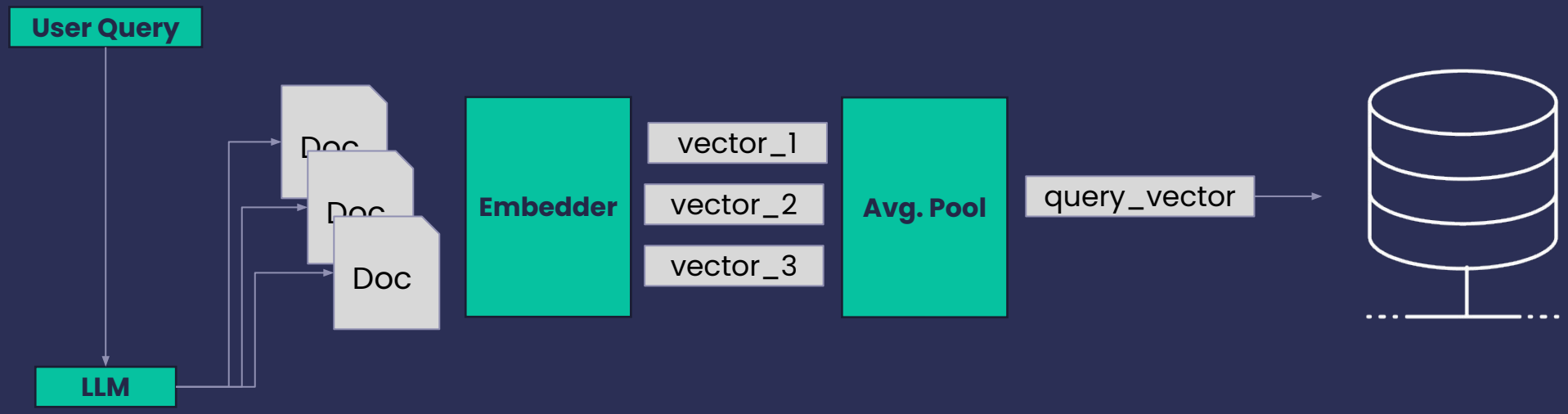
- Given a user query, use a LLM to generate *n* "hypothetical" (short) documents whose content would ideally answer the query

Hypothetical Document Embeddings – HyDE



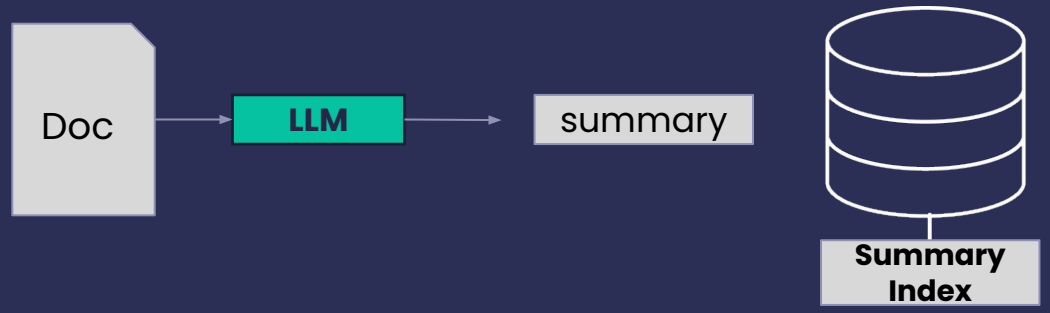
- Given a user query, use a LLM to generate *n* "hypothetical" (short) documents whose content would ideally answer the query
- Each of the *n* documents is embedded into a vector

Hypothetical Document Embeddings – HyDE



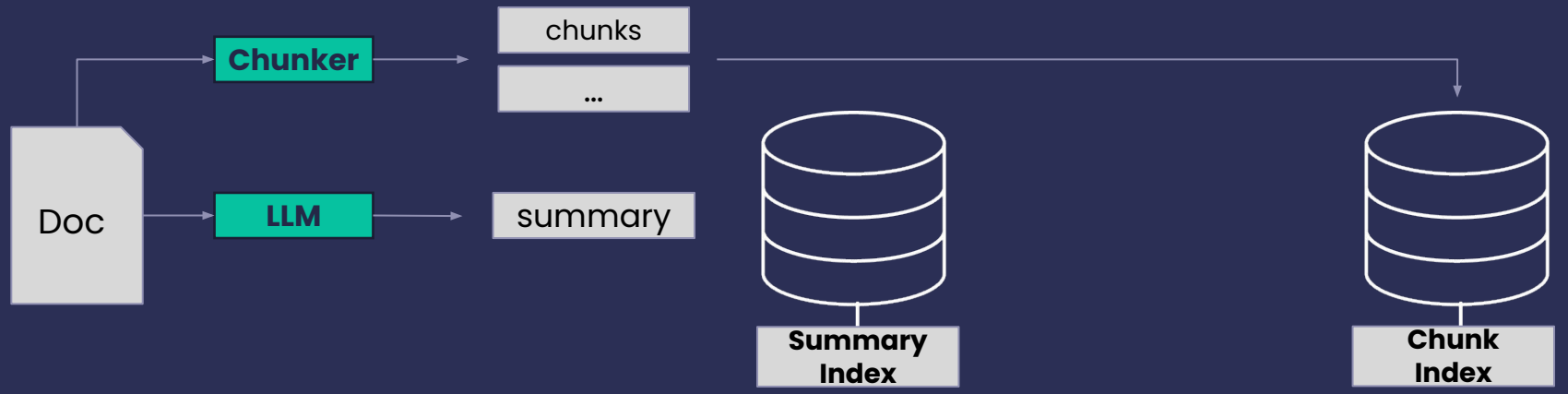
- Given a user query, use a LLM to generate *n* "hypothetical" (short) documents whose content would ideally answer the query
- Each of the *n* documents is embedded into a vector
- You perform an average pooling generating a new query embedding used to search for similar documents instead of the original query

Document Summary Indexing



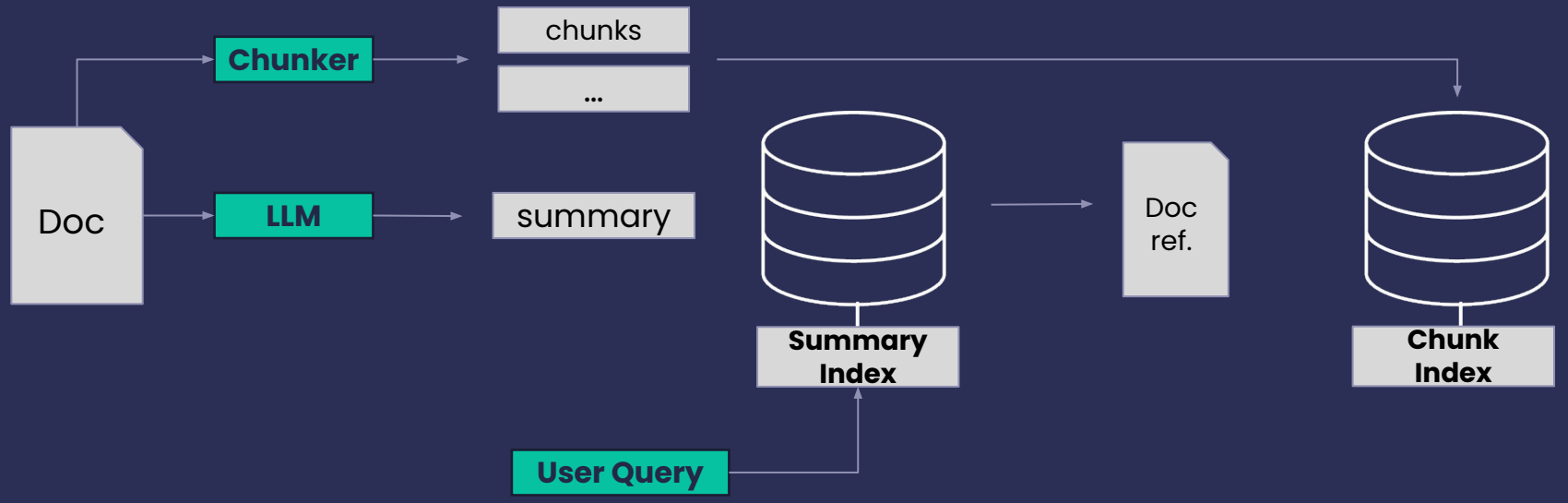
- **Summary Index:** generate a summary for each document with an LLM

Document Summary Indexing



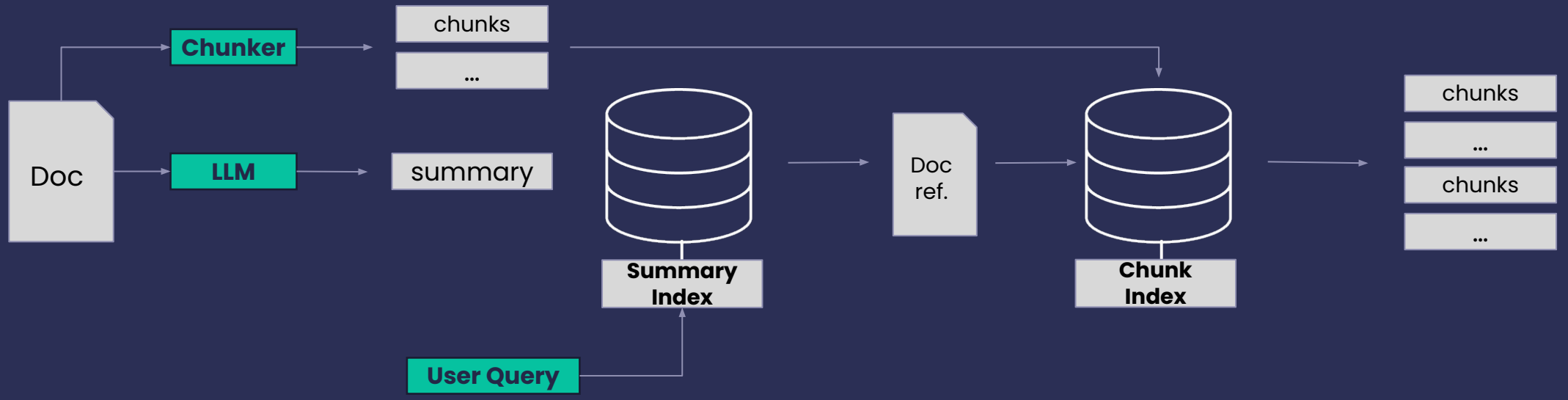
- **Summary Index:** generate a summary for each document with an LLM
- **Chunk Index:** split each document up into chunks

Document Summary Indexing



- **Summary Index:** generate a summary for each document with an LLM
- **Chunk Index:** split each document up into chunks
- Use the **Summary Index** to retrieve top-k relevant documents to the query

Document Summary Indexing



- **Summary Index:** generate a summary for each document with an LLM
- **Chunk Index:** split each document up into chunks
- Use the **Summary Index** to retrieve top-k relevant documents to the query
- Using the document(s) reference retrieve the most relevant chunks

Summary

	Custom Index Structure	ReRanking	Query Rewriting	Combining multiple sources	Relies on a LLM
Sentence-Window Retrieval	X				
Auto-Merging Retrieval	X				
Maximum Margin Relevance		X			
Hybrid Retrieval				X	
Multi-Query			X		X
Hypothetical Document Embeddings			X		X
Document Summary Indexing	X			X	X

Comparative Experiment

- "ARAGOG: Advanced RAG Output Grading" M Eibich, S Nagpal, A Fred-Ojala arXiv preprint, 2024

- **Dataset:**
  - ArXiv preprints covering topics around Transformers and LLMs
  - 13 PDF papers (https://huggingface.co/datasets/jamescalam/ai-arxiv)
  - 107 questions and answers generated with the assistance of an LLM
  - All questions and answers were manually validated and corrected

- **Experiment:**
  - Run the questions over each retrieval technique
  - Compare ground-truth answer with generated answer
  - Semantic Answer Similarity: cos sim embeddings of both answers

Comparative Experiment: ARAGOG

	Semantic Answer Similarity	Specific Parameters
Sentence-Window Retrieval	0.688	window=3
Auto-Merging Retrieval	0.619	threshold=0.5, block_sizes={10, 5}
Maximum Margin Relevance	0.607	lambda_threshold=0.5
Hybrid Retrieval	0.701	join_mode="concatenate"
Multi-Query	0.692	n_variations=3
Hypothetical Document Embeddings	0.642	nr_completions=3
Document Summary Indexing	0.731	-

- sentence-transformers/all-MiniLM-L6-v2
- chunk_size = 15
- split_by = "sentence"
- top_k = 3

LLM

OpenAI: gpt-4o-mini

Takeaways

- Build a dataset for our use case - **50~100 annotated questions**
- Start with the simple RAG approach and set it as your baseline
- Start by exploring “cheap” and simple techniques
- **Sentence-Window Retriever** and **Hybrid Retrieval -** good results and no need for complexing indexing or an LLM
- If none of these produces satisfying results then, explore indexing/retrieval methods based on LLMs

Haystack Implementations

Sentence-Window Retrieval	haystack.components.retrievers.SentenceWindowRetriever
Auto-Merging Retrieval	haystack.components.retrievers.AutoMergingRetriever haystack.components.preprocessors.HierarchicalDocumentSplitter
Maximum Margin Relevance	haystack.components.rankers.SentenceTransformersDiversityRanker
Hybrid Retrieval w/ ReRanking	haystack.components.retrievers.InMemoryEmbeddingRetriever haystack.components.retrievers.InMemoryBM25Retriever haystack.components.joiners.DocumentJoiner (ranking techniques)
Multi-Query	https://github.com/davidsbatista/haystack-retrieval https://haystack.deepset.ai/blog/query-expansion https://haystack.deepset.ai/blog/query-decomposition
Hypothetical Document Embeddings	https://haystack.deepset.ai/blog/optimizing-retrieval-with-hyde
Document Summary Indexing	https://github.com/davidsbatista/haystack-retrieval

Haystack Implementations - SuperComponents

Sentence-Window Retrieval	haystack.components.retrievers.SentenceWindowRetriever
Auto-Merging Retrieval	haystack.components.retrievers.AutoMergingRetriever haystack.components.preprocessors.HierarchicalDocumentSplitter
Maximum Margin Relevance	haystack.components.rankers.SentenceTransformersDiversityRanker
Hybrid Retrieval w/ ReRanking	**Will be soon available as a SuperComponent!**
Multi-Query	**Can be built as a SuperComponent!**
Hypothetical Document Embeddings	**Can be built as a SuperComponent!**
Document Summary Indexing	**Can be built as a SuperComponent!**

SuperComponent in Haystack 2.12.0!

- wrap complex pipelines into reusable (super)components
- easy to reuse them across applications
- Initialize a SuperComponent with a pipeline

References

- "The use of MMR, diversity-based reranking for reordering documents and producing summaries" J Carbonell, J Goldstein - ACM SIGIR 1998
- "ARAGOG: Advanced RAG Output Grading" M Eibich, S Nagpal, A Fred-Ojala arXiv preprint, 2024
- "Advanced RAG: Query Expansion" - Haystack Blog, 2024
- "Advanced RAG: Query Decomposition & Reasoning" - Haystack Blog, 2024
- "Precise Zero-Shot Dense Retrieval without Relevance Labels" Luyu Gao, Xueguang Ma, Jimmy Lin, and Jamie Callan- *ACL 2023*
- "A New Document Summary Index for LLM-powered QA Systems", Jerry Liu 2023

Code and experiments

Haystack

Code + Slides

www.davidsbatista.net

Comparative Experiment

- HotpotQA: A Dataset for Diverse, Explainable Multi-hop Question Answering Zhilin Yang, Peng Qi, Saizheng Zhang, Yoshua Bengio, William Cohen, Ruslan Salakhutdinov, Christopher D. Manning

- **Dataset:**
  - Question-Answering dataset over Wikipedia articles
  - Very short answers, e.g.:
    - *'Who is older Glenn Hughes or Ross Lynch?'*
    - *'Are Gin and tonic and Paloma both cocktails based on tequila?'*
  - Select the first 100 questions from `hotpot_train_v1.1.json`

- **Experiment:**
  - Evaluate the retrievers: Precision, Recall and Fallout
  - Evaluate generated answer: Semantic Answer Similarity

Comparative Experiment: HotpotQA

	Recall	Precision	Fall-out	Semantic Answer Similarity	Parameters
Sentence-Window Retrieval	0.73	0.49	0.51	0.688	window=3
Auto-Merging Retrieval	0.36	0.26	0.74	0.376	0
Maximum Margin Relevance	0.73	0.48	0.52	0.500	lambda_threshold=0.75
Hybrid Retrieval	0.81	0.40	0.60	0.512	join_mode="concatenate"
Multi-Query	0.75	0.36	0.64	0.515	n_variations=3
Hypothetical Document Embeddings	0.77	0.53	0.47	0.529	nr_completions=3
Document Summary Indexing	0.72	0.47	0.53	0.514	0

- sentence-transformers/all-MiniLM-L6-v2
- chunk_size = 15
- split_by = "sentence"
- top_k = 3

LLM

OpenAI: gpt-4o-mini

Maximum Marginal Relevance (MMR)

$$\text{MMR} = \arg\max_{d_i \in D \setminus R} [\lambda \cdot \text{Sim}_1(d_i, q) - (1 - \lambda) \cdot \max_{d_j \in R} \text{Sim}_2(d_i, d_j)]$$

- D is the set of all candidate documents
- R is the set of already selected documents
- q is the query
- Sim_1 is the similarity function between a document and the query
- Sim_2 is the similarity function between two documents
- d_i and d_j are documents in D and R respectively
- λ is a parameter that controls the trade-off between relevance and diversity

Number of LLM calls

- **Multi-Query:**
  - Each query results in 2 LLM calls
- **Hypothetical Document Embeddings**
  - Each query results in 2 LLM calls
- **Document Summary Indexing**
  - Dependent on the detail parameter
  - LLM_calls = 1 + detail * (X / minimum_chunk_size - 1)