الجامعة السورية الخاصة
SYRIAN PRIVATE UNIVERSITY

الذكاء الصنعي العملي | كلية الهندسة | المحاضرة 5

LLM in practice
Retrieval-Augmented-Generation (RAG)

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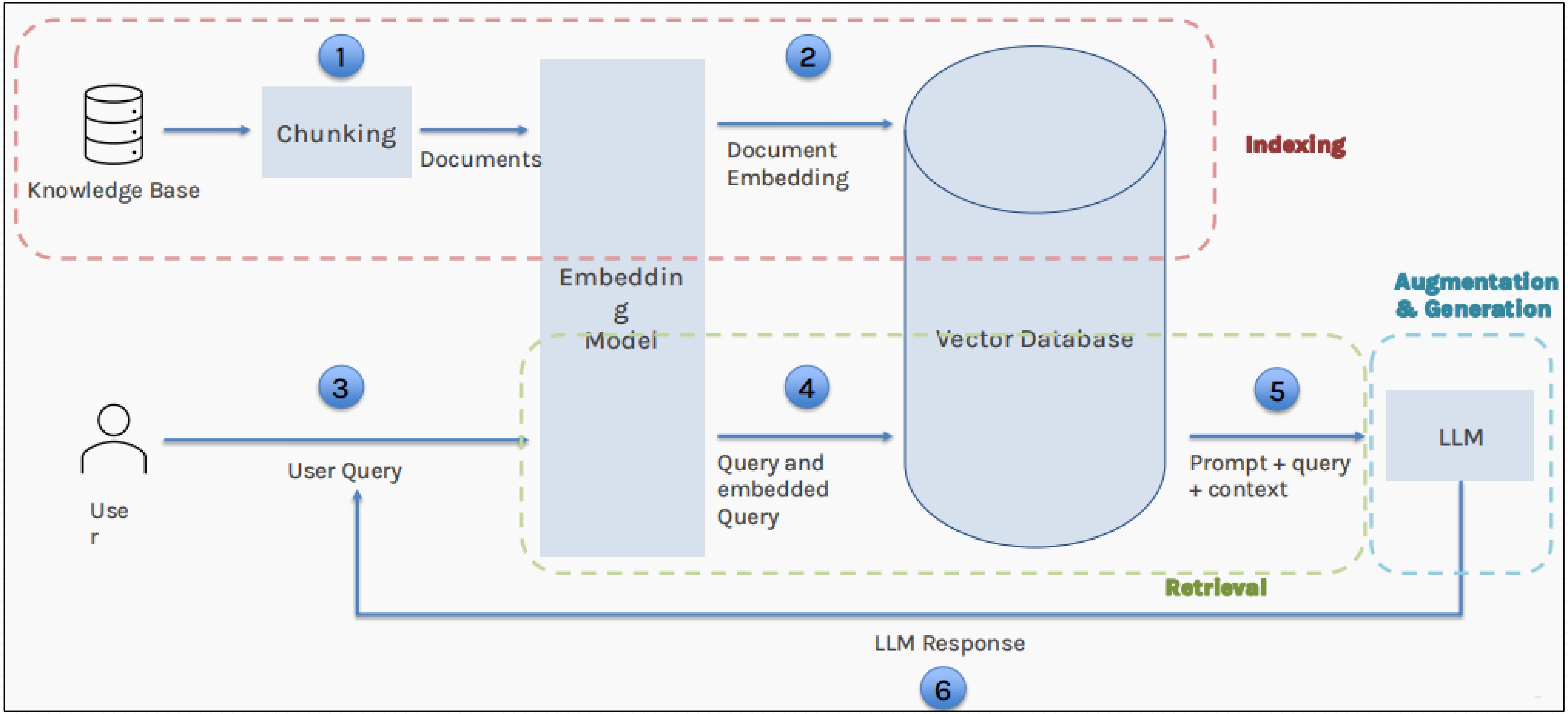
Retrieval-Augmented-Generation (RAG)

- RAG stands for Retrieval-Augmented-Generation.
- It is technique that improves the performance of a LLM, especially for tasks that require accurate and detailed information.
- **Benefits of RAG:**
  - Increased Accuracy: By incorporating external knowledge.
  - Contextual Relevance: RAG allows LLMs to tailor responses to specific contexts and user needs.
  - Up-to-Date Information: RAG can access and utilize the latest information from external sources.
  - Customization: RAG enables organizations to integrate their specific knowledge bases and data into LLM applications.
  - Improved Reliability: Users can verify the sources of information used by RAG models, enhancing trust in their responses.

RAG



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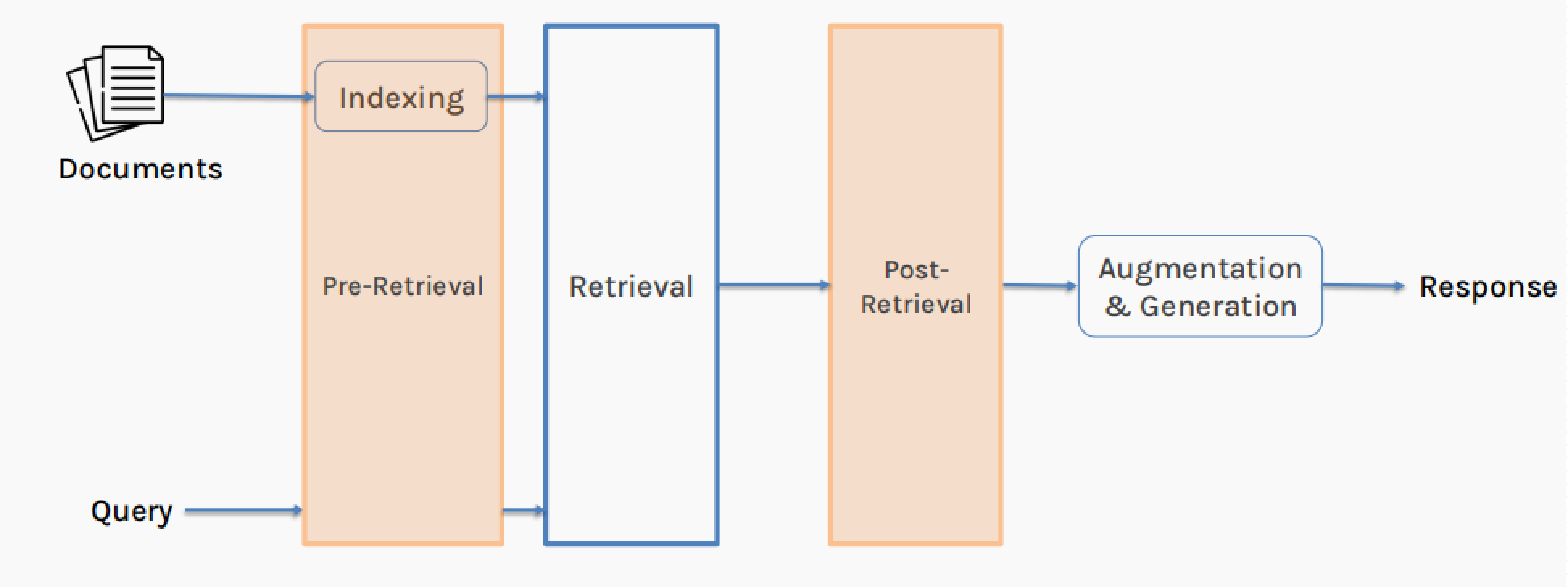
RAG



The Pre-Retrieval Phase deals with:
- Chunking the data
- Converting the chunks into embeddings
- Handling the embeddings

The Post-Retrieval phase deals with polishing what was obtained from the retriever.

Pre-Retrieval Optimization (Improve the chunking process)

Let's take another example

Advancements in Transfer Learning for NLP

Abstract:
"Transfer learning has become a crucial technique in NLP. This paper explores recent advancements, including fine-tuning pre-trained models like BERT and GPT-3, and domain adaptation methods. Our experiments demonstrate significant improvements in performance across various NLP tasks."

Methodology:
"We fine-tuned BERT and GPT-3 models on specific NLP tasks, adapting them to different domains. Domain adaptation involved additional pre-training on domain-specific data. Our approach leverages the pre-trained knowledge and adapts it to new tasks, achieving higher accuracy and efficiency."

Results:
"The results indicate a 20% increase in accuracy for domain-specific tasks using our fine-tuning and domain adaptation techniques. We observed substantial performance gains compared to baseline models."

Now, if we do character splitting for chunks (chunk size=200), we get:

Chunk 1:
Recent techniques in transfer learning for NLP Abstract: Transfer learning has become a crucial technique in NLP. This paper explores recent advancements, including fine-tuning pre-trained models like BERT and GPT-3, and **dom**

Chunk 2:
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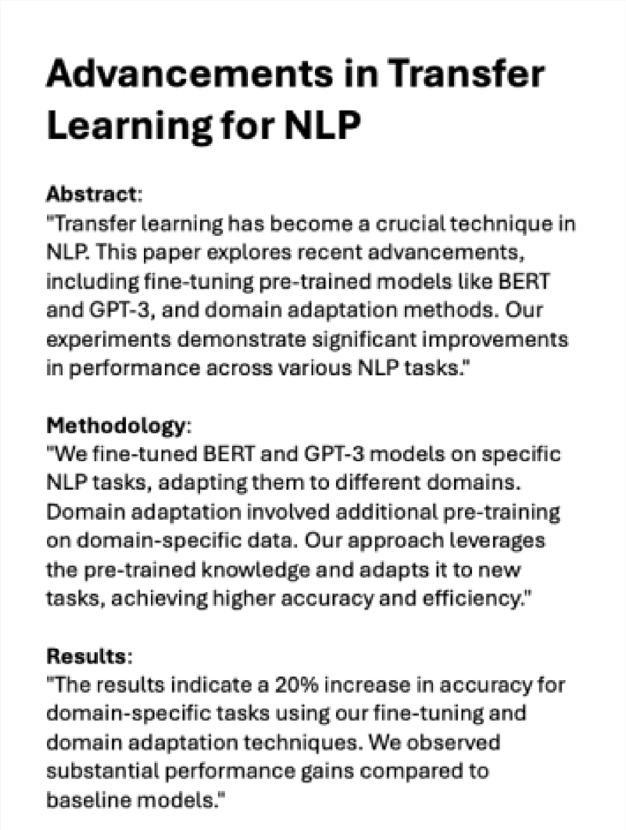
Pre-Retrieval Optimization (Improve the chunking process)

Better Approach!
Semantic chunking

Let's take another example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The optimal way to do it would be:

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Chunk 2:
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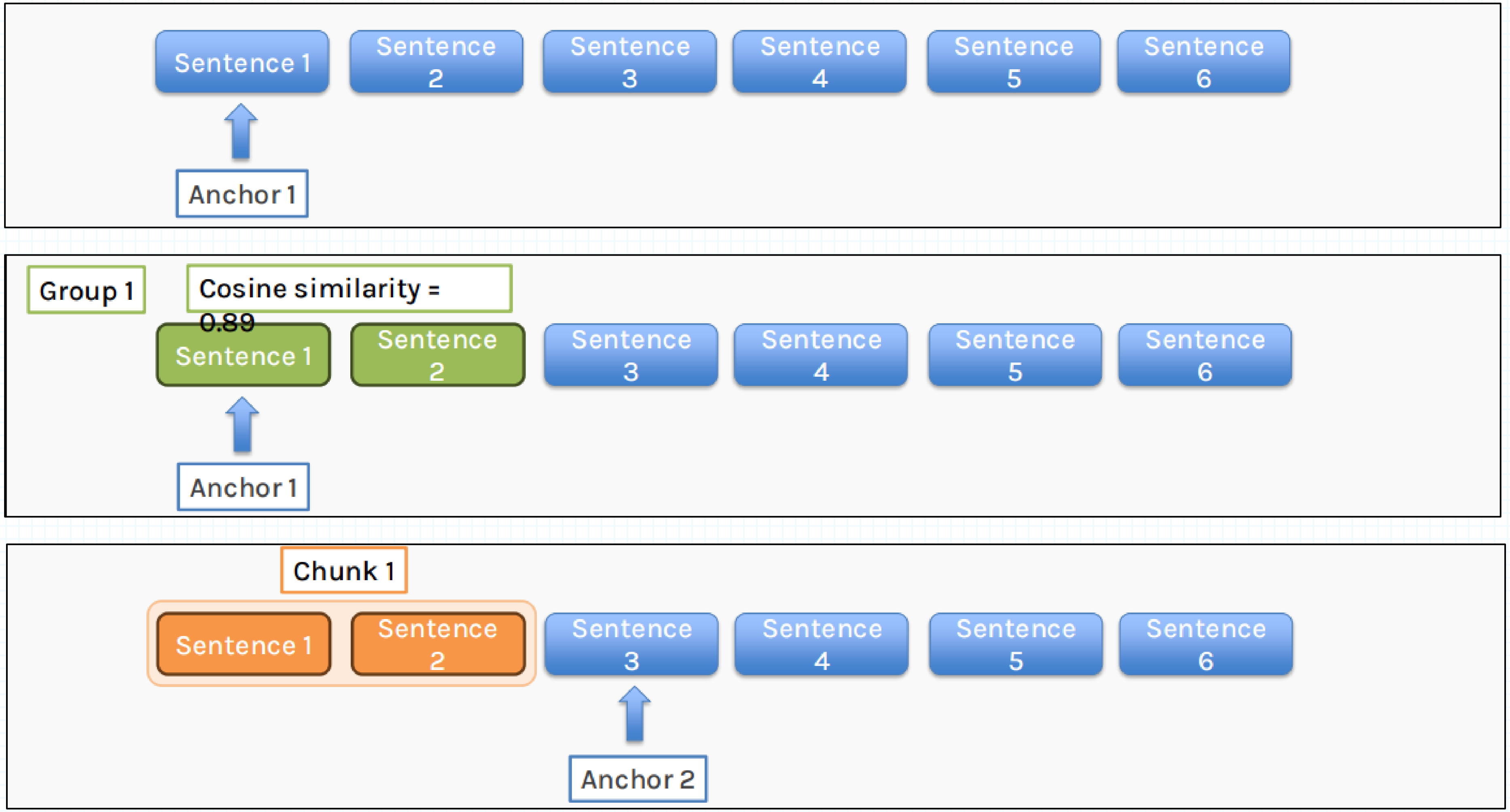
Pre-Retrieval Optimization (Improve the chunking process)

- **Semantic Chunking – Steps**
  - Splitting: We split the document to sentences using separators(.,?,!).
  - Grouping: Select anchor sentences and choose how many sentences to consider at either side of the anchor (window size).
  - Similarity Check: Calculate the distance between the group of sentences (e.g.: cosine similarity).
  - Chunking: Chunk together the similar sentences.

Pre-Retrieval Optimization (Improve the chunking process)

Semantic Chunking



Pre-Retrieval Optimization (Improve the chunking process)

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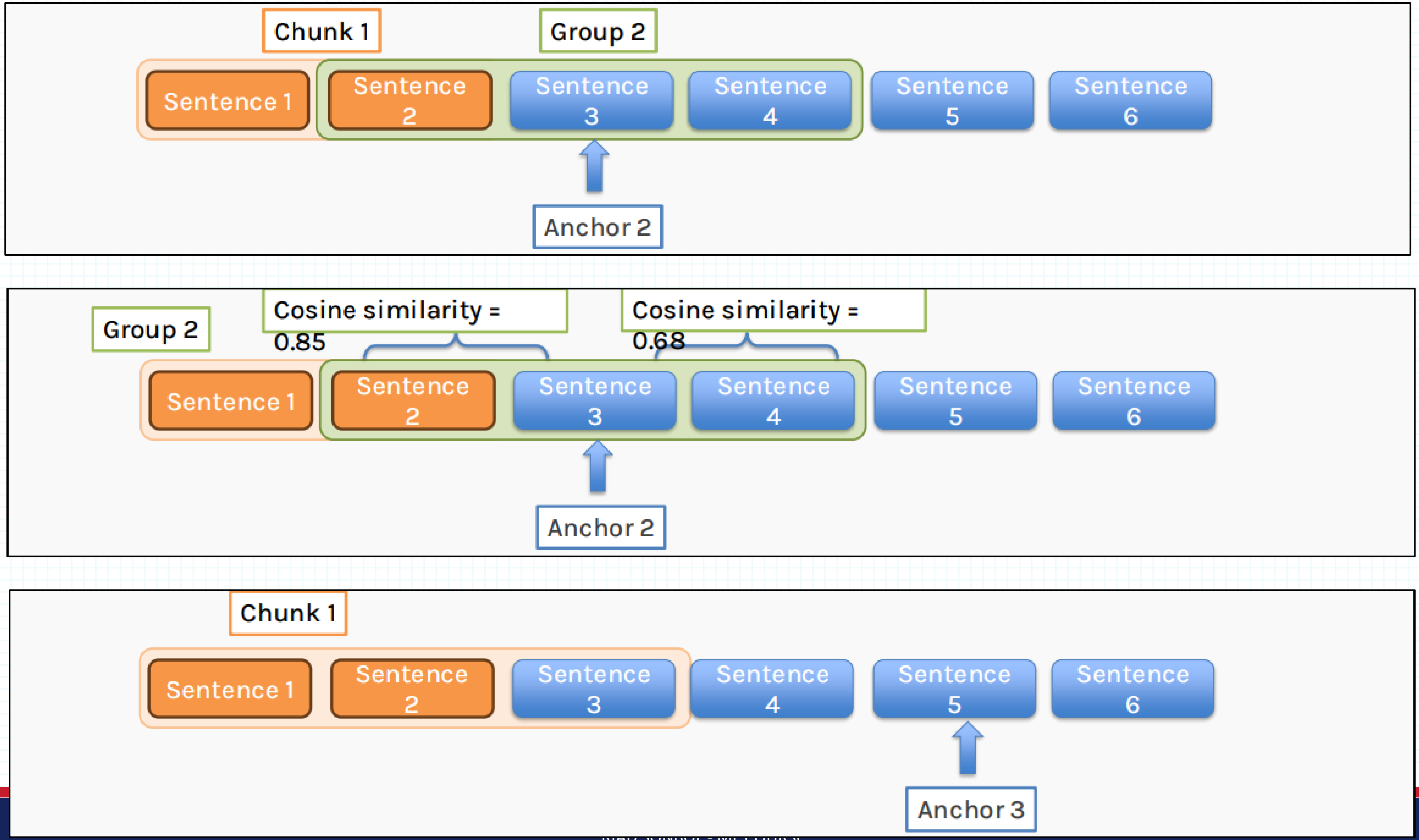
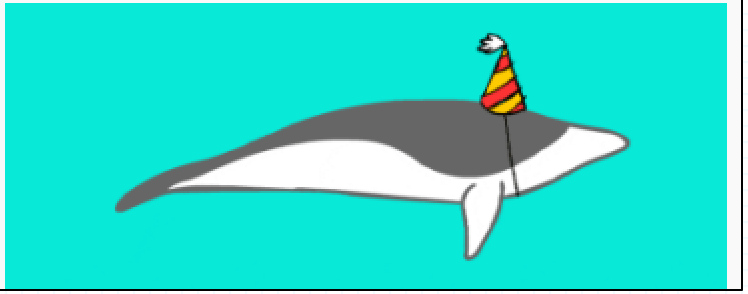


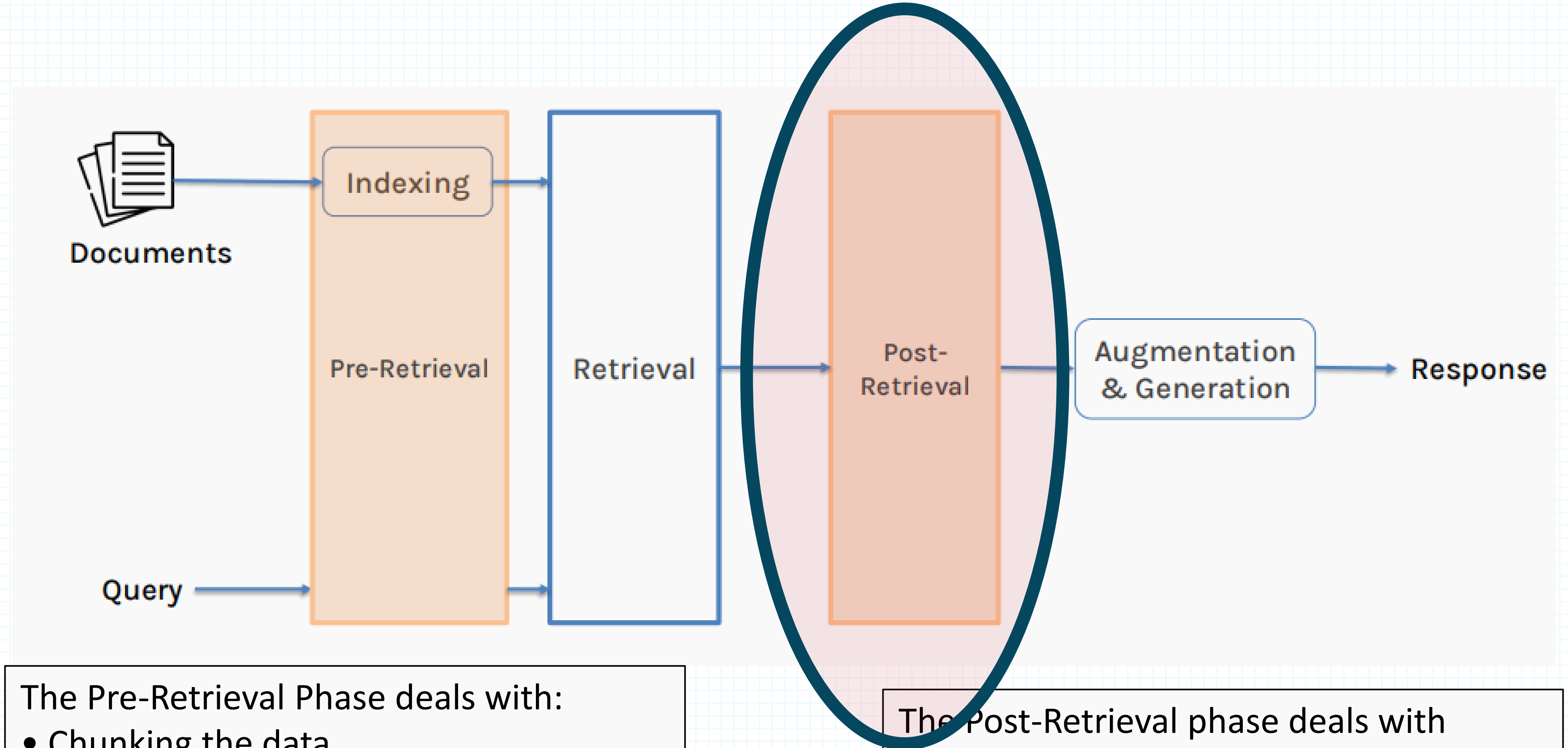
Pre-Retrieval Optimization (Query Manipulation)

- 2 problems can come up when it comes to queries provided by a user:
  - The query is 'cluttered': This can be due to it being sprinkled with a lot of irrelevant information.
  - The query is ambiguous: The query doesn't have sufficient information
- Example:

❓Original Query	We have an essay due tomorrow. We have to write about some animal. I love penguins. I could write bout them. But I could also write about dolphins. Are they animals? Maybe. Let's do dolphins. Where do they live, for example?
🧠Rewritten query	Where do dolphins live?



Naïve RAG



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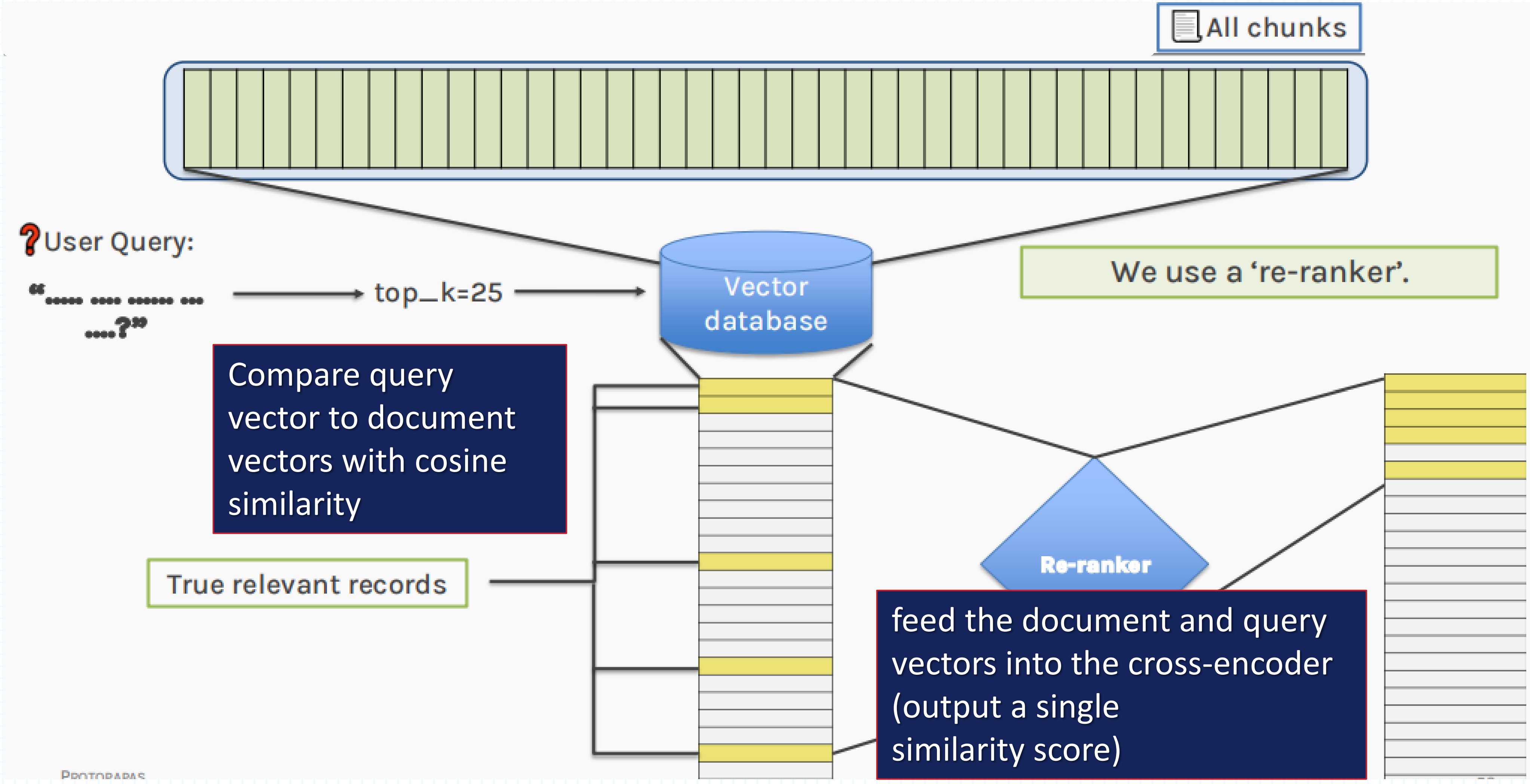
Post-Retrieval – Re-ranking



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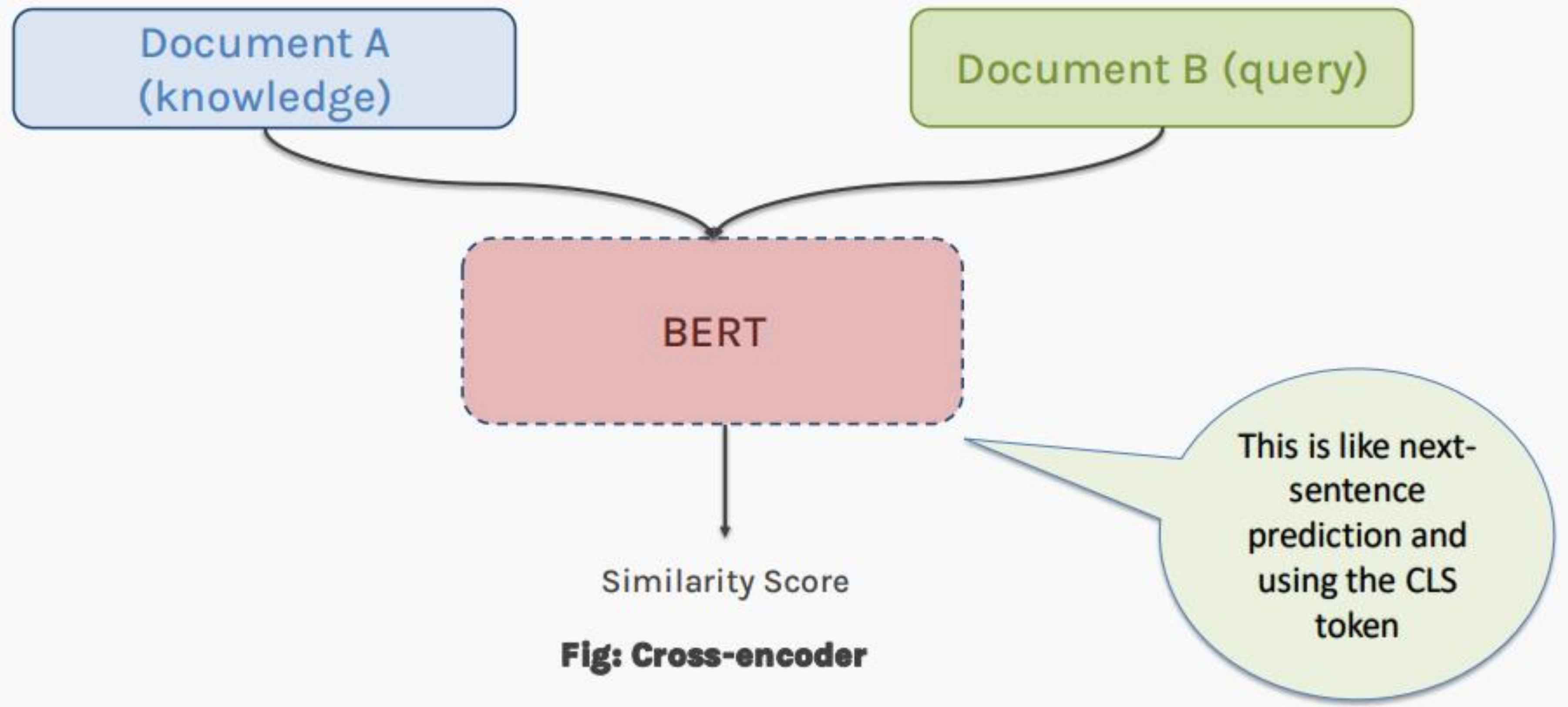

Fig: Cross-encoder