RAGing against the machine

A brief introduction to Retrieval Augmented Generation

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Who am I?

- Ph.D. in Computational Linguistics from Gothenburg University.
- Leading the AI development on the SVEA project

SVEA

SWEDEN

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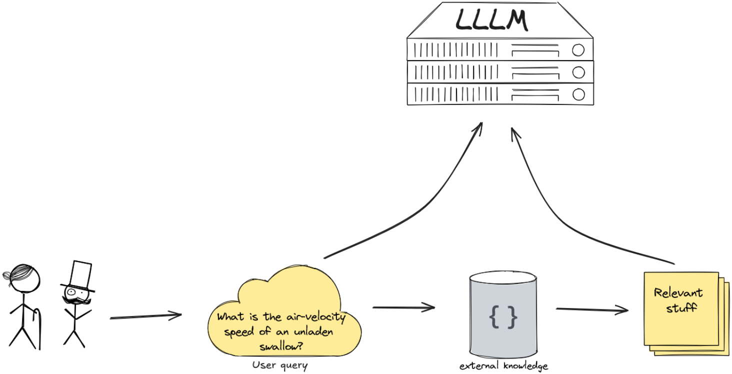
- The how: Retrieval Augmented Generation (LLM + database)

Retrieval Augmented Generation (RAG)



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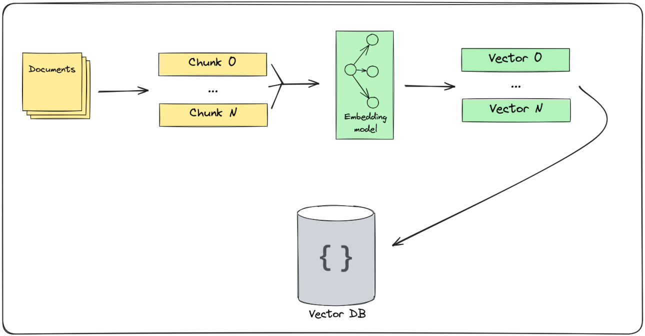
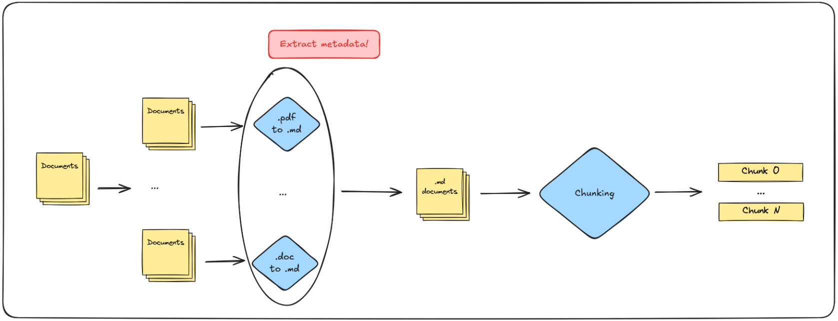
- Why a vector database?
  1. We can construct specialized retrievers for our data
  2. We can filter the data based on meta-knowledge of the data
  3. We can **update** the knowledge database
  4. It's fast!

Creating a vector database



Garbage in, garbage out

Preparing documents



Preprocessing documents

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- Filter the data so the relevant information is **easy** to encode
  - Remove **bös**, clean/fix parsing errors, manage multi-modal information, …

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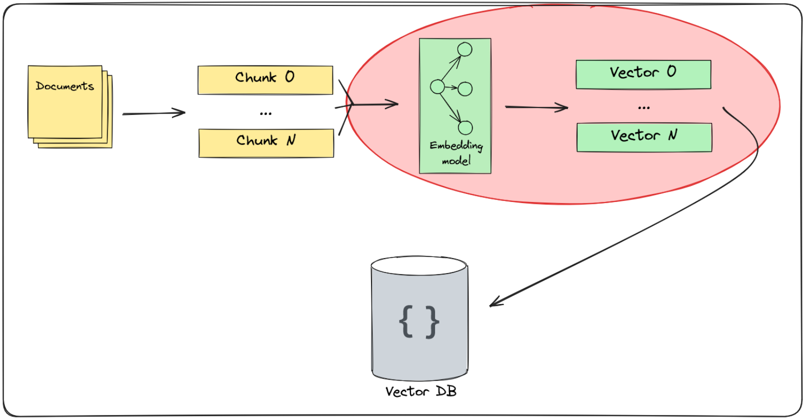
- Hierarchical chunking: Identify a tree structure based on e.g. headers, paragraph-breaks

Embedding chunks



Embedding chunks

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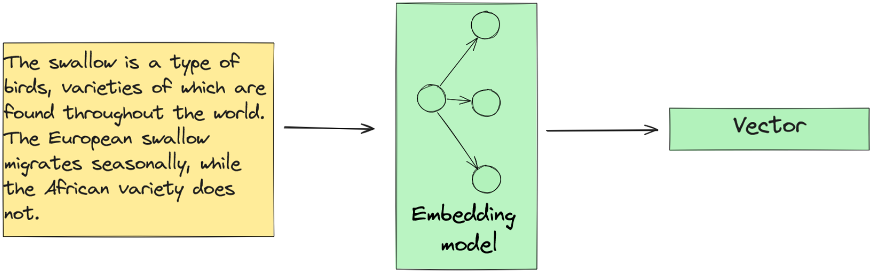
  - A model specifically designed to **encode** information
  - Much smaller than LLLMs (~ 100-600 million parameters)

Embedding model



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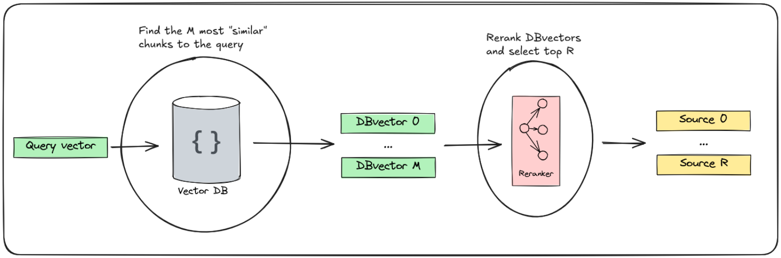
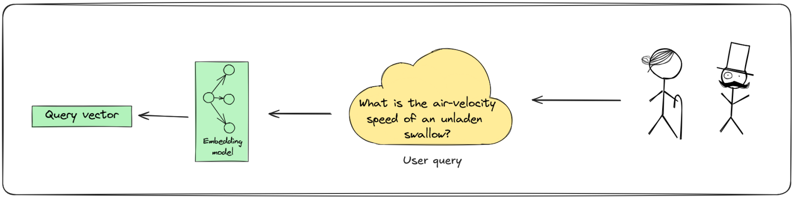
- We have full control of the level of specialization
- Optimize the trade-off between speed (smaller models) and efficiency (larger models)

Obtaining results from a vector database

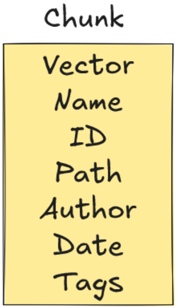


Question embedding



Indexing

- A vector database contains chunks, and their fields:



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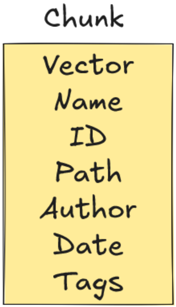
- What do we search for?



Indexing

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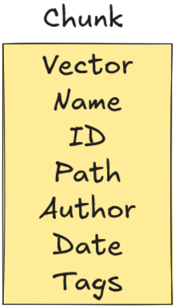
  Semantic and contextual similarity of a chunk to the query!



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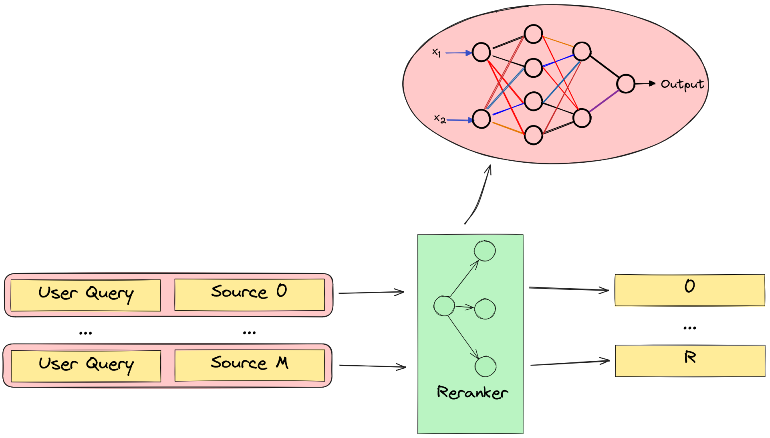
  - The initial search results are fast, but fuzzy
  - The LLM is sensitive to the order of chunks

Reranking



x_1
x_2
Output
User Query
Source 0
...
...
User Query
Source M
Reranker
0
...
R

Retrieval mantra

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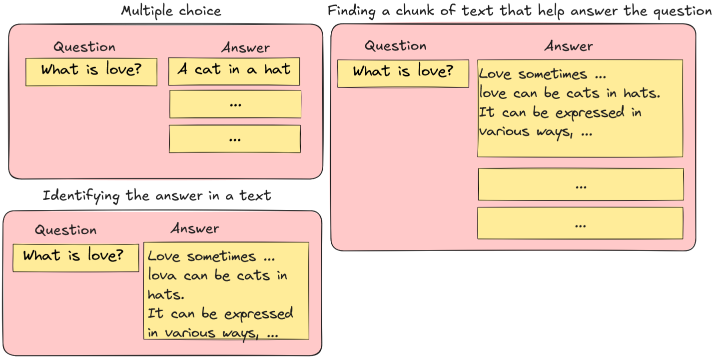
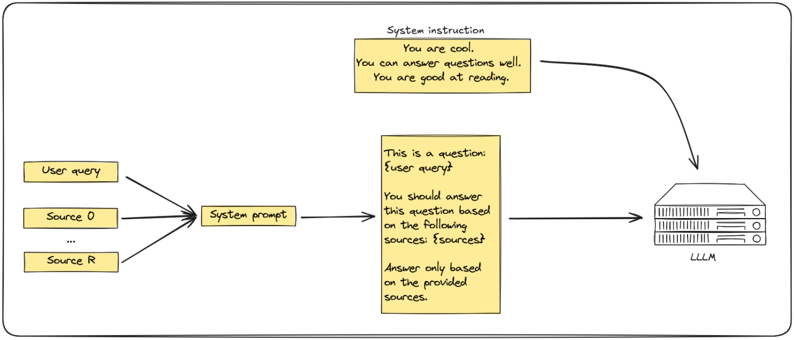
  - The search should contain chunks with the same topic, domain, …
- Reranking should maximize contextual fit
  - How well does the chunk answer the question?

Adapting embeddings models to data



Generating a response



Some resources

- Presentation/demo repo: `https://github.com/adamlek/intro-to-RAG`
- Embedding models: `https://cohere.com/blog/embedding-models`
- LLamaIndex: `https://www.llamaindex.ai/`
- Text cleaning: `https://www.analyticsvidhya.com/blog/2022/01/text-cleaning-methods-in-nlp/`
- Rag Evaluation: `https://cloud.google.com/blog/products/ai-machine-learning/optimizing-rag-retrieval`, `https://qdrant.tech/blog/rag-evaluation-guide/`