comet

4 Advanced RAG Algorithms to Optimize Retrieval

Words By Paul Iusztin and Decoding ML May 10, 2024

*Welcome to **Lesson 5 of 11** in our free course series, **LLM Twin: Building Your Production-Ready AI Replica**. You'll learn how to use LLMs, vector DVs, and LLMOps best practices to design, train, and deploy a production ready "LLM twin" of yourself. This AI character will write like you, incorporating your style, personality, and voice into an LLM. For a full overview of course objectives and prerequisites, start with Lesson 1.*

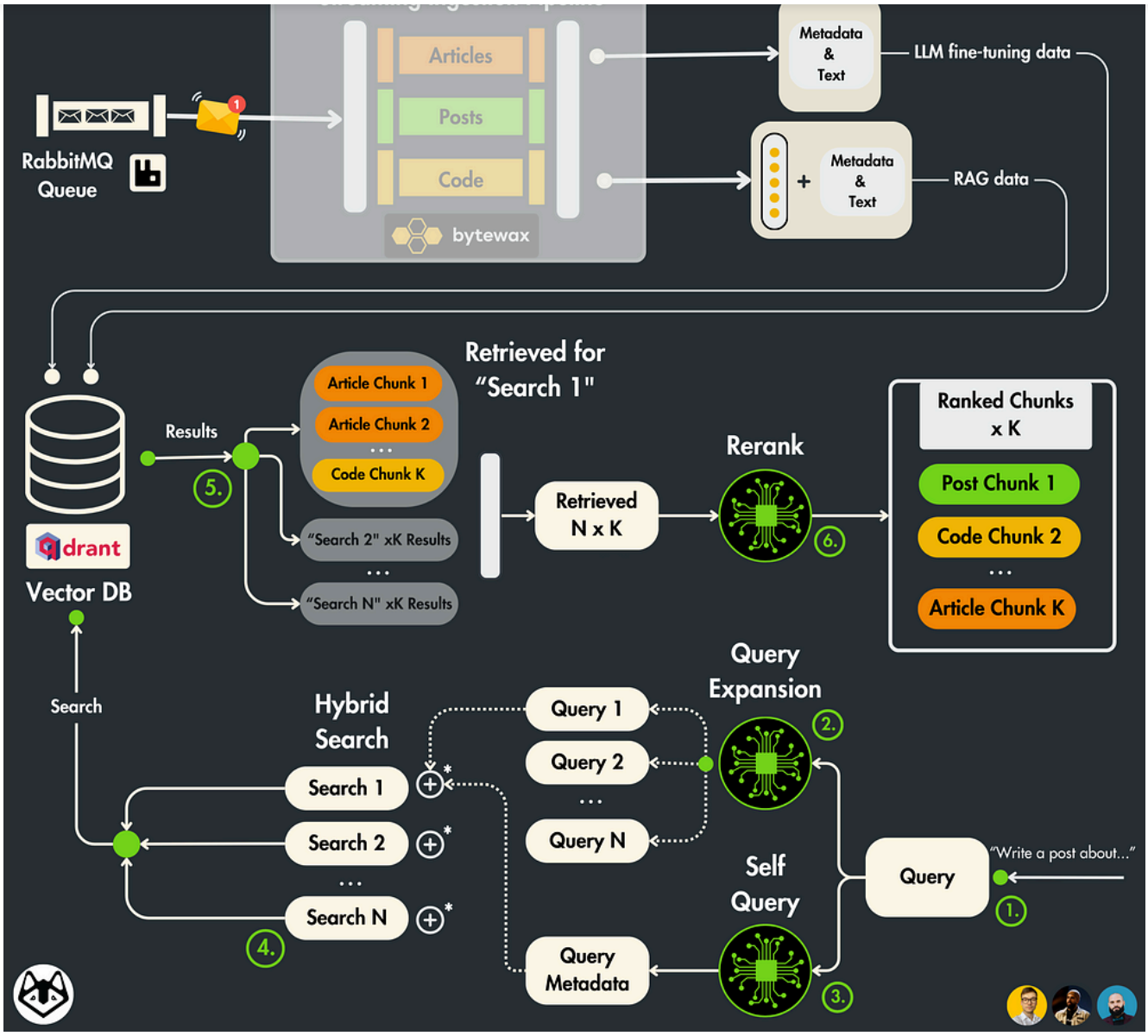
In **Lesson 5**, we will focus on building an advanced retrieval module used for RAG.

We will show you how to implement 4 **retrieval** and **post-retrieval advanced optimization techniques** to **improve** the **accuracy** of your **RAG retrieval step**.

In this lesson, we will focus only on the retrieval part of the RAG system.

In **Lesson 4**, we showed you how to clean, chunk, embed, and load social media data to a Qdrant vector DB (the ingestion part of RAG).

In future lessons, we will integrate this retrieval module into the inference pipeline for a full-fledged RAG system.



Retrieval Python Module Architecture

We **assume** you are **already familiar** with what a **naive RAG looks like. If not**, **check out this article** from Decoding ML, where we **present** in a **2-minute** read **what** a **naive RAG looks like.**

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> 🔗 ***Check out the code on GitHub [1] and support us with a*** ⭐

1. Overview of advanced RAG optimization techniques

A production RAG system is split into **3 main components**:

- **ingestion:** clean, chunk, embed, and load your data to a vector DB
- **retrieval:** query your vector DB for context
- **generation:** attach the retrieved context to your prompt and pass it to an LLM

The **ingestion component** sits in the *feature pipeline*, while the **retrieval** and **generation components** are implemented inside the *inference pipeline*.

You can **also use** the **retrieval** and **generation components** in your *training pipeline* to fine-tune your LLM further on domain-specific prompts.

You can apply advanced techniques to optimize your RAG system for ingestion, retrieval and generation.

That being said, there are 3 main types of advanced RAG techniques:

- **Pre-retrieval optimization** [ingestion]: tweak how you create the chunks
- **Retrieval optimization** [retrieval]: improve the queries to your vector DB
- **Post-retrieval optimization** [retrieval]**:** process the retrieved chunks to filter out the noise

> ***The generation step can be improved through fine-tuning or prompt engineering, which will be explained in future lessons.***

The **pre-retrieval optimization techniques** are explained in Lesson 4.

2. Advanced RAG techniques applied to the LLM twin

Retrieval optimization

We will combine 3 techniques:

- Query Expansion
- Self Query
- Filtered vector search

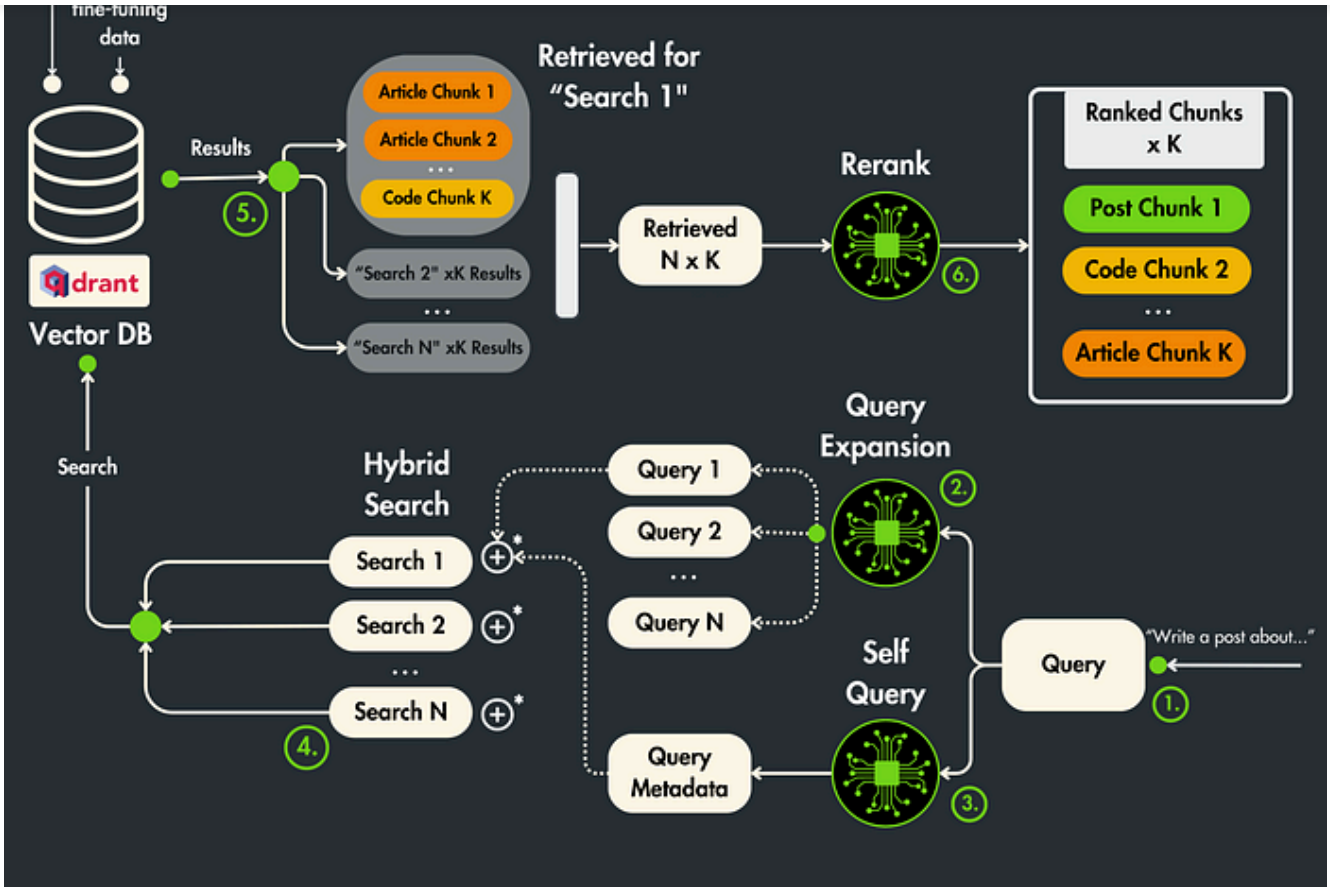
Post-retrieval optimization

We will **use** the **rerank** pattern **using GPT-4** and **prompt engineering** instead of Cohere or an open-source re-ranker cross-encoder [4].

I don't want to spend too much time on the theoretical aspects. There are plenty of articles on that.

*So, we will **jump** straight to **implementing** and **integrating** these techniques in our LLM twin system.*

But before seeing the code, let's clarify a few things ↓



Advanced RAG architecture

2.1 Important Note!

We will show you a **custom implementation** of the **advanced techniques** and **NOT use LangChain.**

Our primary **goal** is to **build** your **intuition** about how they **work behind the scenes**. However, we will **attach LangChain's equivalent** so you can use them in your apps.

Customizing LangChain can be a **real headache**. Thus, understanding what happens behind its utilities can help you build real-world applications.

Also, it is **critical** to **know** that if you don't ingest the data using LangChain, you cannot use their retrievals either, as they expect the data to be in a specific format.

We haven't used LangChain's ingestion function in Lesson 4 either (the feature pipeline that loads data to Qdrant) as we want to do everything "by hand".

But since we discovered Qdrant, we loved it.

Why?

- It is built in Rust.
- Apache-2.0 license — open-source 🔥
- It has a great and intuitive Python SDK.
- It has a freemium self-hosted version to build PoCs for free.
- It supports unlimited document sizes, and vector dims of up to 645536.
- It is production-ready. Companies such as Disney, Mozilla, and Microsoft already use it.
- It is one of the most popular vector DBs out there.

To put that in perspective, Pinecone, one of its biggest competitors, supports only documents with up to 40k tokens and vectors with up to 20k dimensions.... and a proprietary license.

I could go on and on...

...but if you are **curious to find out more**, *check out Qdrant* ←

3. Retrieval optimization (1): Query expansion

The problem

In a typical retrieval step, you query your vector DB using a single point.

The issue with that approach is that by **using** a **single vector**, you **cover** only a **small area** of your **embedding space**.

Thus, if your embedding doesn't contain all the required information, your retrieved context will not be relevant.

What if we **could query** the **vector DB** with **multiple data points** that are semantically related?

That is what the **"Query expansion"** technique is doing!

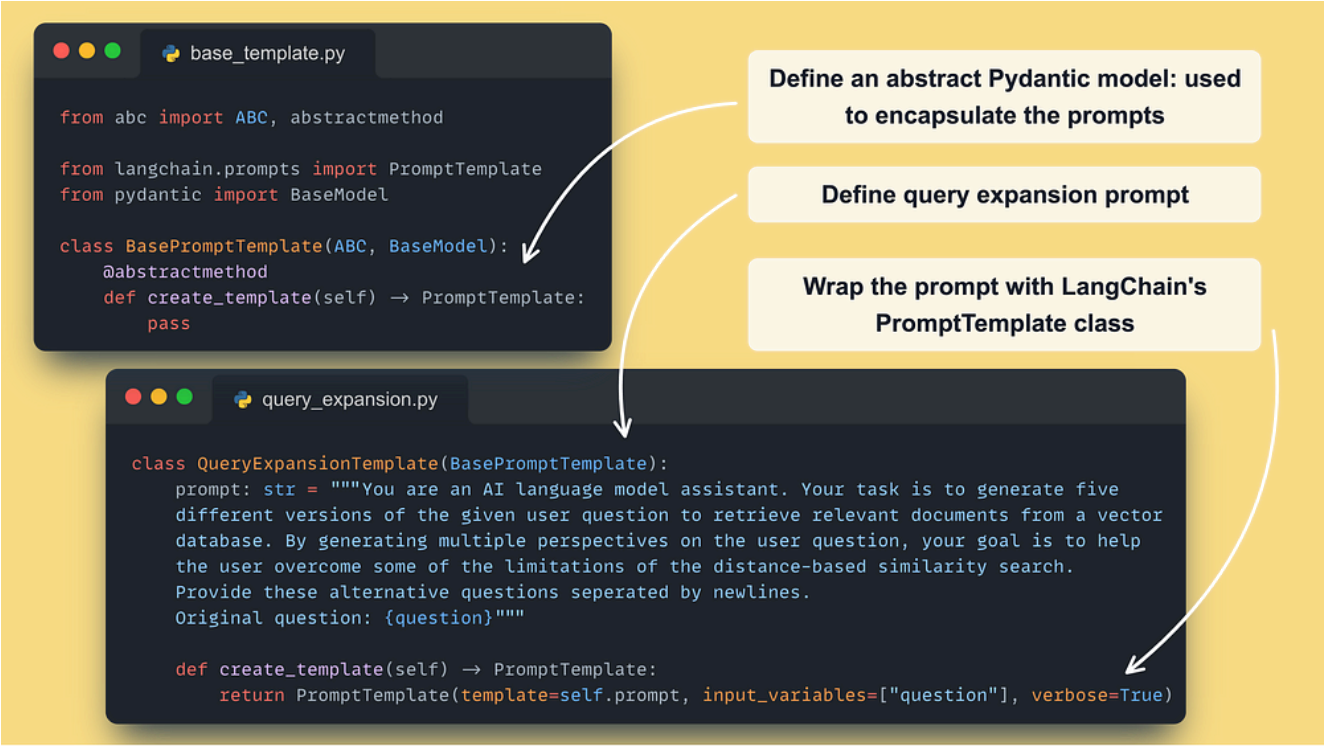
You use an LLM to generate multiple queries based on your initial query.

These queries should contain multiple perspectives of the initial query.

Thus, when embedded, they hit different areas of your embedding space that are still relevant to our initial question.

You can do query expansion with a detailed zero-shot prompt.

Here is our simple & custom solution ↓



Query expansion template → GitHub Code ←

> ***Here is LangChain's MultiQueryRetriever class [5] (their equivalent).***

4. Retrieval optimization (2): Self query

The problem

When embedding your query, you cannot guarantee that all the aspects required by your use case are present in the embedding vector.

The issue is that by embedding the query prompt, you can never be sure that the tags are represented in the embedding vector or have enough signal when computing the distance against other vectors.

The solution

What if you could extract the tags within the query and use them along the embedded query?

That is what self-query is all about!

You use an LLM to extract various metadata fields that are critical for your business use case (e.g., tags, author ID, number of comments, likes, shares, etc.)

In our custom solution, we are extracting just the author ID. Thus, a zero-shot prompt engineering technique will do the job.

But, when extracting multiple metadata types, you should also use few-shot learning to optimize the extraction step.

Self-queries work hand-in-hand with vector filter searches, which we will explain in the next section.

Here is our solution ↓

Self-query template → GitHub Code ←

> ***Here is LangChain's SelfQueryRetriever class [6] equivalent and this is an example using Qdrant [8].***

5. Retrieval optimization (3): Hybrid & filtered vector search

The problem

Embeddings are great for capturing the general semantics of a specific chunk.

But they are not that great for querying specific keywords.

For example, if we want to retrieve article chunks about LLMs from our Qdrant vector DB, embeddings would be enough.

However, if we want to query for a specific LLM type (e.g., LLama 3), using only similarities between embeddings won't be enough.

Thus, embeddings are not great for finding exact phrase matching for specific terms.

The solution

It is not defined which algorithms are combined, but the most standard strategy for hybrid search is to combine the traditional keyword-based search and modern vector search.

How are these combined?

*The **first method** is to merge the similarity scores of the 2 techniques as follows:*

```
hybrid_score = (1 - alpha) * sparse_score + alpha *
dense_score
```

Where **alpha** takes a value between [0, 1], with:

- **alpha = 1**: Vector Search
- **alpha = 0**: Keyword search

Also, the similarity scores are defined as follows:

- **sparse_score:** is the result of the *keyword search* that, behind the scenes, uses a BM25 algorithm [7] that sits on top of TF-IDF.
- **dense_score:** is the result of the *vector search* that most commonly uses a similarity metric such as cosine distance

*The **second method** uses the vector search technique as usual and applies a filter based on your keywords on top of the metadata of retrieved results.*

> → ***This is also known as filtered vector search.***

In this use case, the **similar score** is **not changed based** on the **provided keywords**.

It is just a fancy word for a simple filter applied to the metadata of your vectors.

- the **first method** combines the similarity score between the keywords and vectors using the alpha parameter;
- the **second method** is a simple filter on top of your vector search.

How does this fit into our architecture?

Remember that during the self-query step, we extracted the **author_id** as an exact field that we have to match.

Thus, we will search for the **author_id** using the keyword search algorithm and attach it to the 5 queries generated by the query expansion step.

*As we want the **most relevant chunks** from a **given author,** it makes the most sense to use a **filter using** the **author_id** as follows (**filtered vector search**)* ↓

```
self._qdrant_client.search(
      collection_name="vector_posts",
      query_filter=models.Filter(
          must=[
              models.FieldCondition(
                  key="author_id",
                  match=models.MatchValue(
                      value=metadata_filter_value,
                  ),
              )
          ]
      ),

query_vector=self._embedder.encode(generated_query).tolist(),
      limit=k,
)
```

The only **question** you have to **ask yourself** is whether we want to **use** a simple **vector search filter** or the more complex **hybrid search** strategy.

> ***Note that LangChain's SelfQueryRetriever class combines the self-query and hybrid search techniques behind the scenes, as can be seen in their Qdrant example [8]. That is why we wanted to build everything from scratch.***

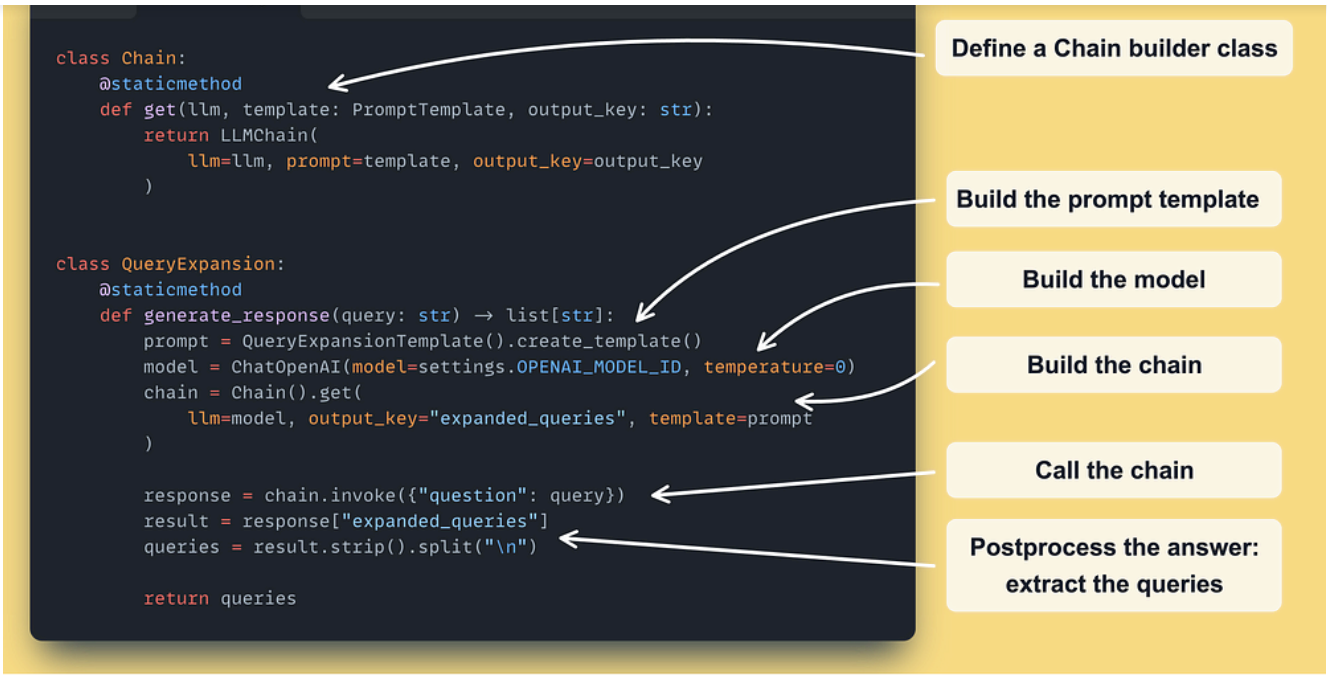
6. Implement the advanced retrieval Python class

*Now that you've understood the **advanced retrieval optimization techniques** we're using, let's **combine** them into a **Python retrieval class**.*

Here is what the main retriever function looks like ↓

VectorRetriever: main retriever function → GitHub ←

> ***Using a Python ThreadPoolExecutor is extremely powerful for addressing I/O bottlenecks, as these types of operations are not blocked by Python's GIL limitations.***



Query expansion chains wrapper → GitHub ←

The *SelfQuery* class looks very similar — access it here [1] ←.

Now the final step is to call Qdrant for each query generated by the query expansion step ↓

VectorRetriever: main search function → GitHub ←

*Note that we have **3 types of data**: posts, articles, and code repositories.*

The most performant method is to use multi-indexing techniques, which allow you to query multiple types of data at once.

But at the time I am writing this article, this is not a solved problem at the production level.

Thus, we gathered data from each collection individually and kept the best-retrieved results using rerank.

Which is the final step of the article.

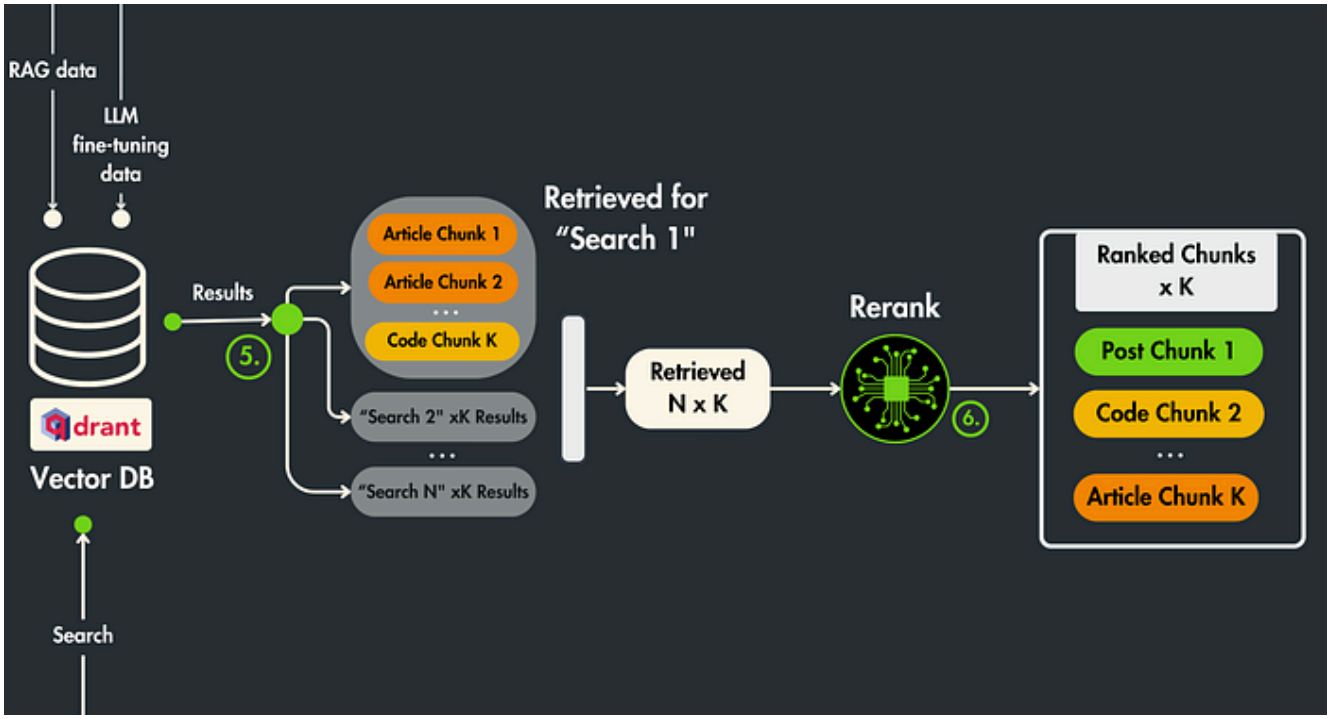
7. Post-retrieval optimization: Rerank using GPT-4

We made a **different search** in the Qdrant vector DB for **N prompts generated** by the **query expansion step**.

Each search returns **K results**.

Thus, we **end up with N x K chunks**.

In our particular case, **N = 5** & **K = 3.** Thus, we end up with 15 chunks.



Post-retrieval optimization: rerank

- **add noise:** the retrieved context might be irrelevant
- **make the prompt bigger:** results in higher costs & the LLM is usually biased in looking only at the first and last pieces of context. Thus, if you add a big context, there is a big chance it will miss the essence.
- **unaligned with your question:** the chunks are retrieved based on the query and chunk embedding similarity. The issue is that the embedding model is not tuned to your particular question, which might result in high similarity scores that are not 100% relevant to your question.

The solution

We will use **rerank** to order all the **N x K** chunks based on their relevance relative to the initial question, where the first one will be the most relevant and the last chunk the least.

Ultimately, we will pick the TOP K most relevant chunks.

Rerank works really well when combined with query expansion.

A natural flow when using rerank is as follows:

Search for >K chunks >>> Reorder using rerank >>> Take top K

Thus, when combined with query expansion, we gather potential useful context from multiple points in space rather than just looking for more than K samples in a single location.

Now the flow looks like:

Search for N x K chunks >>> Reoder using rerank >>> Take top K

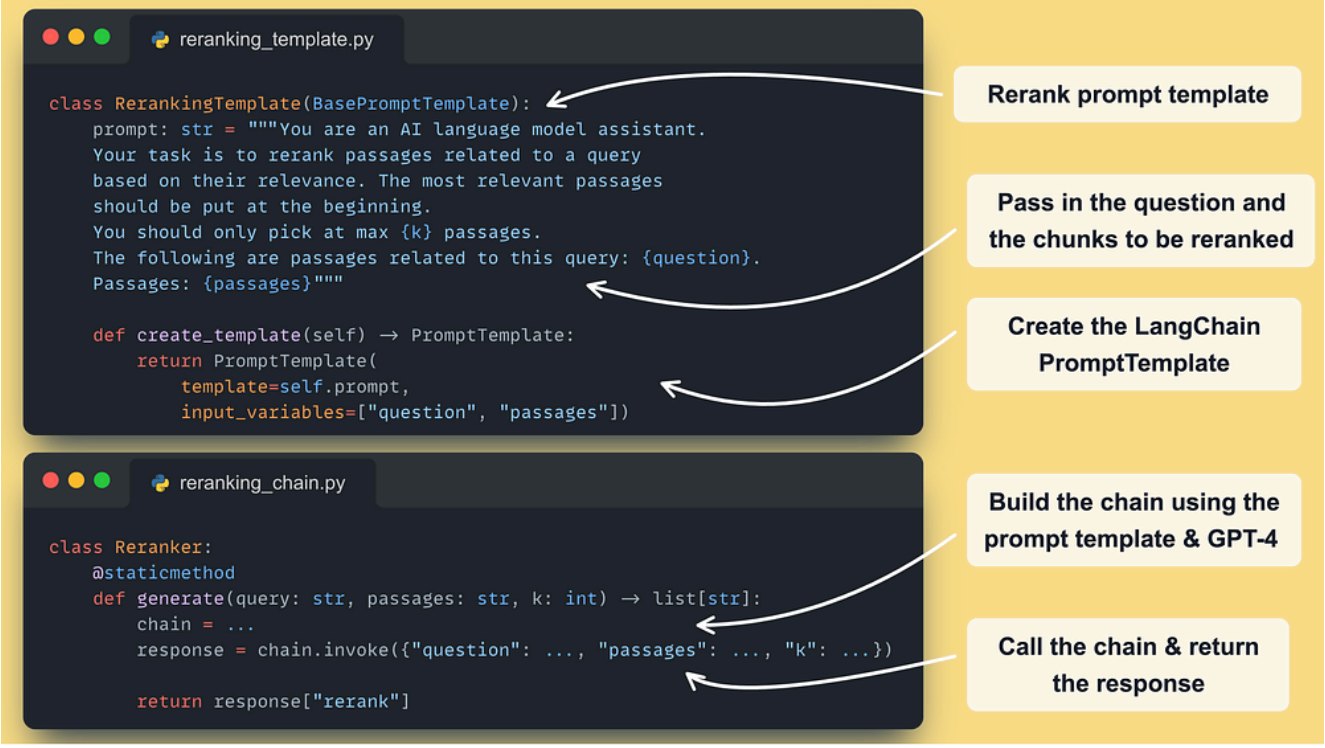
A typical solution for reranking is to use open-source Bi-Encoders from sentence transformers [4].

These solutions take both the question and context as input and return a score from 0 to 1.

If you want to see how to **apply rerank using open-source algorithms**, check out this **hands-on article** from Decoding ML.

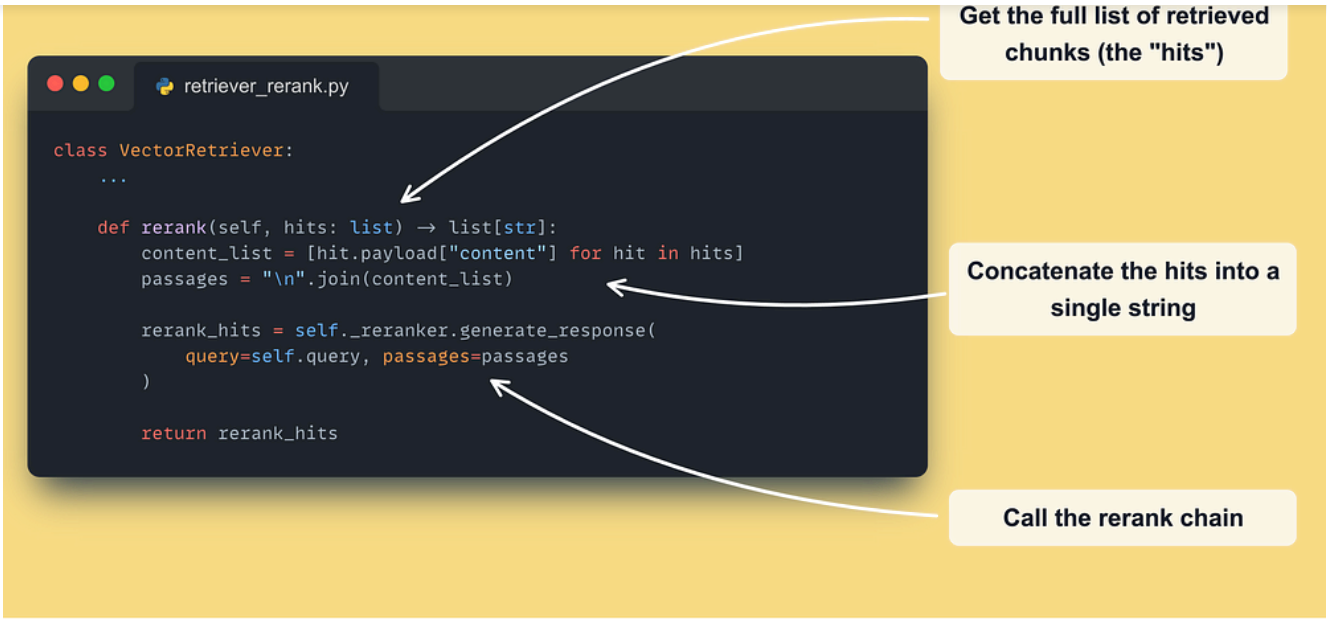
Now let's see our implementation using GPT-4 & prompt engineering.

Similar to what we did for the expansion and self-query chains, we define a template and a chain builder ↓



Rerank chain → GitHub ←

Here is how we integrate the rerank chain into the retriever:



Retriever: rerank step → GitHub ←

...and that's it!

> ***Note that this is an experimental process. Thus, you can further tune your prompts for better results, but the primary idea is the same.***

8. How to use the retrieval

The last step is to run the whole thing.

But there is a catch.

As we said in the beginning the retriever will not be used as a standalone component in the LLM system.

*It will be used as a **layer** between the **data** and the **Qdrant vector DB** by the:*

- **training pipeline** to retrieve raw data for fine-tuning (we haven't shown that as it's a straightforward search operation — no RAG involved)
- **inference pipeline** to do RAG

→ That is why, for this lesson, there is no infrastructure involved!

But, to test the retrieval, we wrote a simple script ↓

Retriever testing entry point → GitHub ←

Look at how easy it is to call the whole chain with our custom retriever—no fancy LangChain involved!

*Now, to **call** this **script**, **run** the following **Make command**:*

```
make local-test-retriever
```

...and that's it!

In future lessons, we will learn to integrate it into the training & inference pipelines.

> ***→ Check out the LLM Twin GitHub repository and try it yourself! ... Of course, don't forget to give it a ⭐ to stay updated with the latest changes.***

Conclusion

Congratulations!

In **Lesson 5**, you learned to **build** an **advanced RAG retrieval module** optimized for searching posts, articles, and code repositories from

comet

First, you learned about where the RAG pipeline can be optimized:

- pre-retrieval
- retrieval
- post-retrieval

After you learn how to build from scratch (without using LangChain's utilities) the following advanced RAG retrieval & post-retrieval optimization techniques:

- query expansion
- self query
- hybrid search
- rerank

Ultimately, you understood where the retrieval component sits in an RAG production LLM system, where the code is shared between multiple microservices and doesn't sit in a single Notebook.

*In **Lesson 6**, we will move to the training pipeline and show you how to automatically transform the data crawled from LinkedIn, Substack, Medium, and GitHub into an instruction dataset using GPT-4 to fine-tune your LLM Twin.*

See you there! 🤗

> 🔗 ***Check out the code on GitHub [1] and support us with a*** ⭐

References

Literature

[1] Your LLM Twin Course — GitHub Repository (2024), Decoding ML GitHub Organization

[2] Bytewax, Bytewax Landing Page

[3] Qdrant, Qdrant Documentation

[5] MultiQueryRetriever, LangChain's Documentation

[6] Self-querying, LangChain's Documentation

[7] Okapi BM25, Wikipedia

[8] Qdrant Self Query Example, LangChain's Documentation

Images

If not otherwise stated, all images are created by the author.

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