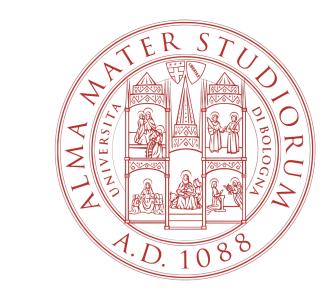
Query My Library! Question-Answering with Open-Source LLMs and Local Books

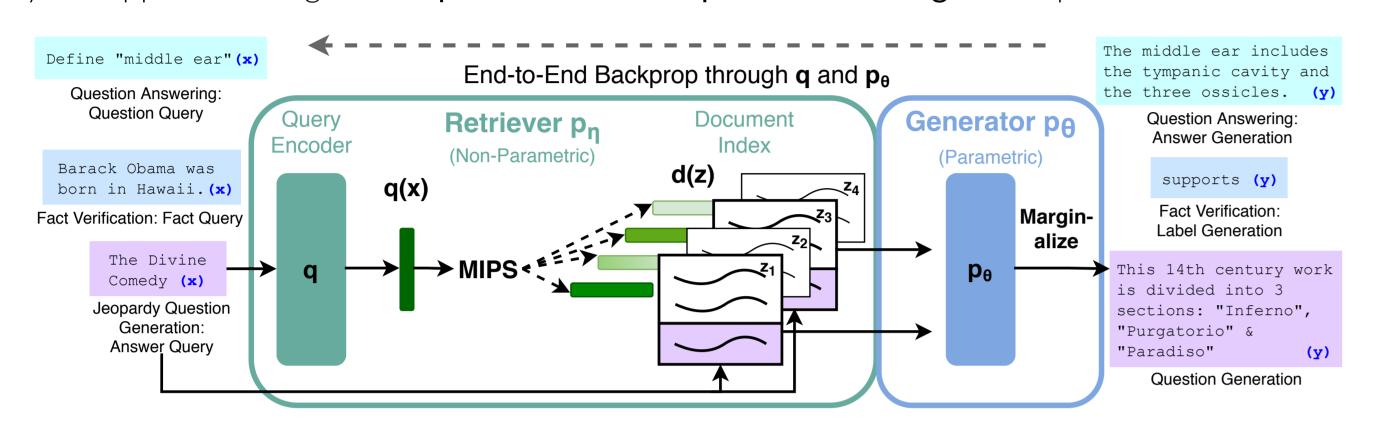
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Introduction

Suppose an avid reader with an extensive bookshelf struggles to fully grasp challenging ideas in complex texts. Could we facilitate their learning by integrating an assistant to help them study? I explore the use of Transformers that leverage **agent planning** pipelines and **RAG engines** for a hybrid approach using both **supervised** and **unsupervised learning** techniques.

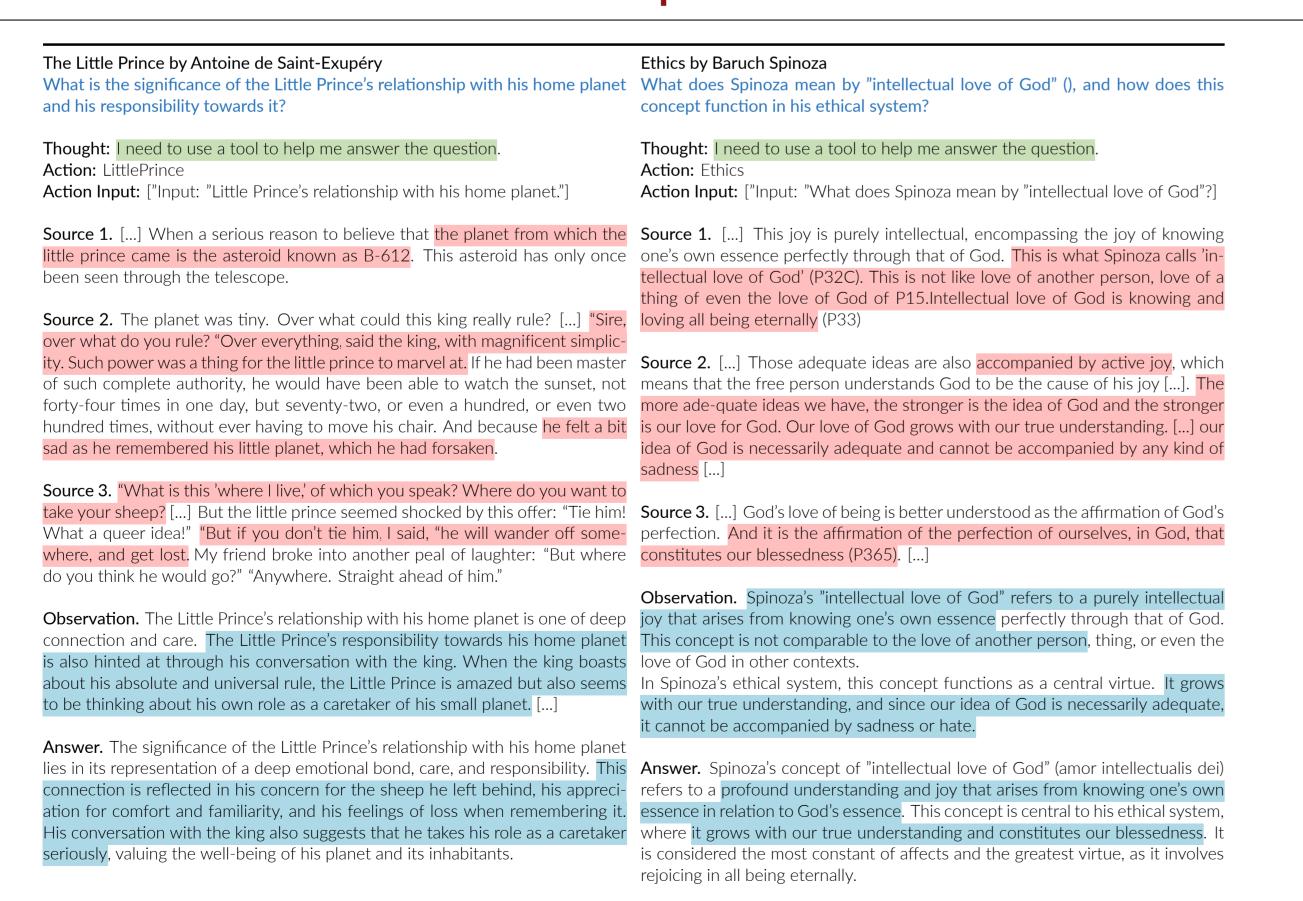


Problem Statement

Figure 1. The RAG Architecture. Taken from [3].

- Identify the Problem: Traditional LLMs struggle with knowledge-intensive tasks, such as specialized domain questions, fact verification, or Jeopardy-style questions.
- Put it into context: Answering questions about books may exhibit these limitations.
- Find the root cause: The model often fails to locate precise book passages, leading to incomplete or inaccurate answers.
- Ideal outcome: Provide the model with relevant information to generate accurate responses.
- Propose a solution: Develop a method to expand prompts with essential information and iteratively refine answers for accuracy.

Results: Generated Responses with Citations



Methods: How is the Vector Store generated?

- **Book Set:** We have N books, labeled as b_1, b_2, \ldots, b_N .
- Page Segmentation: Each book b_i is divided into pages. Let's call the k-th page of book i as $p_{i,k}$.
- Semantic Chunking: For each page $p_{i,k}$, we create multiple chunks of text based on semantic meaning. Let's call these chunks $c_{i,k,1}, c_{i,k,2}, \ldots$ We then use an embedding function f (as described in [4]) to convert each chunk into a 384-dimensional vector: $e_{i,k,l} = f(c_{i,k,l})$. Here, $e_{i,k,l}$ is the embedding of the l-th chunk from the k-th page of the i-th book.
- Vector Database: We collect all these embeddings to create a vector database D, as described in [1].
- User Query: When a user submits a query q, we: 1. Convert the query to an embedding using the same function: $e_q = f(q)$.
- 2. Use an SVM to find the top 3 closest matches in our database D.

Why use two embedding models?

- Query Embedding [1]. Small (33M parameters) yet powerful model optimized for applications where low latency is a requirement.
- Semantic Chunking [4]. Comparatively, larger model (109M parameters) designed for semantic search. It seeks to improve search accuracy by understanding the semantic meaning of the search query and the corpus to search over.

Model Name	Use case	Dimensions	Size	Suitable Score Function
BAAI/bge-small-en-v1.5 [1]	querying	384	33M	SVM [2]
multi-qa-mpnet-base-dot-v1 [4] ser	nantic nodes	768	109M	dot-product

Table 1. Properties of the embedding models used to create semantic nodes and to generate the vector store.

Analysis: 2-Dimensional Cluster Visualization

- PCA. Is a linear dimension reduction technique that seeks to maximize variance and preserves large pairwise distances. In other words, items that are different end up far apart.
- t-SNE. It differs from PCA by preserving only small pairwise distances or local similarities. Gives an intuition on how data is arranged in higher dimensions.

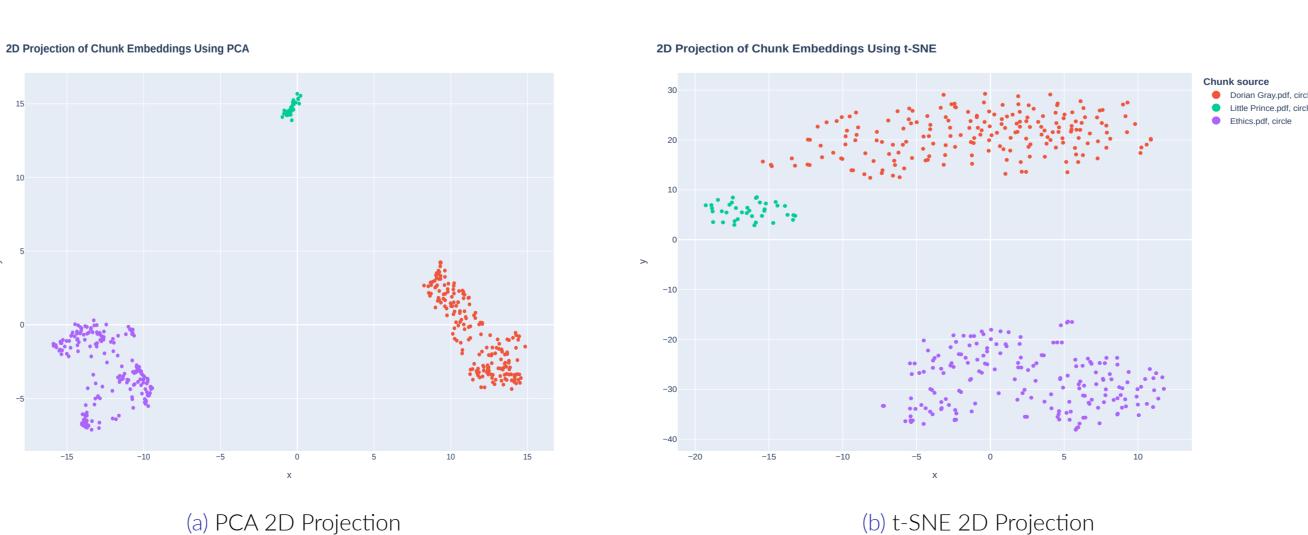


Figure 2. Three clusters: The Picture of Dorian Gray (red), The Little Prince (green), Ethics (purple).

Pairwise Heatmap Embeddings

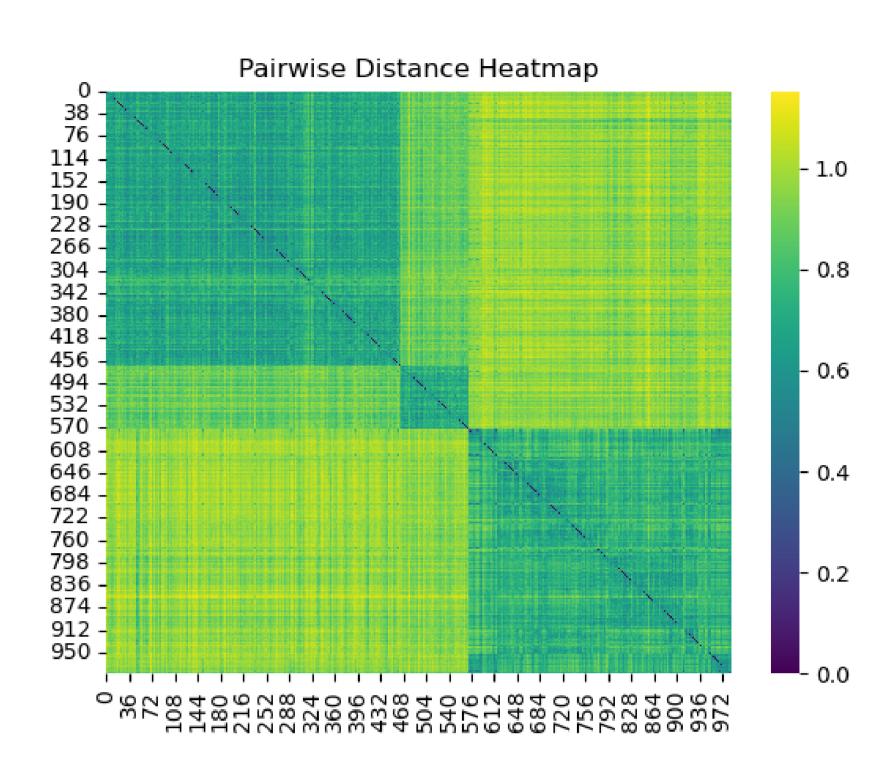


Figure 3. Upper left corner: The Picture of Dorian Gray, Middle: The Little Prince, Bottom Right: Ethics.

- Dark colors represent lower pairwise distances, indicating more similar pairings.
- Lighter colors represent higher pairwise distances, indicating less similar pairings.

Conclusion

- Local and remote inference. The model generally requires strong LLMs such as *Llama 3* in order to adequately use complex planning pipelines. Fortunately, Llama 3 is available for free both locally and remotely through the HuggingFace API.
- Future models. Due to the fact that the Librarian is usable both locally and via remote inference, the project is likely to scale well as stronger open-source models become available.

Future Work

- Integrate with other services. Use other resources made available through the LlamaIndex hub, including the ability to search Wikipedia or to query the arXiv knowledge database.
- Enable Multi-agent workflows. Allow users to interact with multiple agents by asking and answering questions and engaging in interactive conversations[5].

References

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https://github.com/atomwalk12/librarian