arXiv Chatbot

A RAG-based model to query arXiv papers

Erdos Deep Learning Bootcamp June - Aug 2024



Outline

- Introduction
- RAG + LLM pipeline
- App design and web deployment
- Summary, Demo and future Work

RAG + Large Language Model (LLM) Intro

Ideal for:

- Research and academic fields needing precise, trustworthy information.
- Niche questions that require specific, detailed answers.

What is RAG?

- Retrieval Augmented Generation
- Combines real-time data retrieval with user query to generate answers.

How It Works

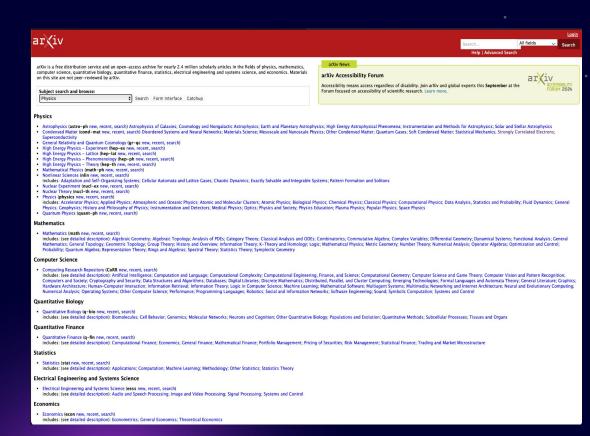
- Data Retrieval: Fetches relevant, real-time information from external sources based on semantic search.
- LLM Processing: Generates accurate and contextualized responses using the retrieved data.

Why Use RAG + LLM?

- Reduces Errors: Minimizes hallucinations common in standard Al models.
- Up-to-Date: Provides the latest information, unlike static pre-trained models.
- Citable Sources: Delivers responses with verifiable references.
- Flexible: Can be adapted to any database

What is <u>arXiv</u>

- Research papers spanning 8 major disciplines
- 2.4 million articles
- Data goldmine for recent and factual information in science
- Multiple use cases combining it with a LLM



Why arXiv with RAG + LLM?

Quick Retrieval Without Manual Searching:

- **Automated Paper Retrieval:** With RAG + LLM, users can bypass the need to manually search for papers by entering specific keywords or topics. The model automatically pulls relevant papers from arXiv.
- **Semantic Search:** Instead of relying on traditional keyword searches, RAG uses a semantic search approach, ensuring that the papers retrieved are not just keyword matches, but contextually relevant to the query.

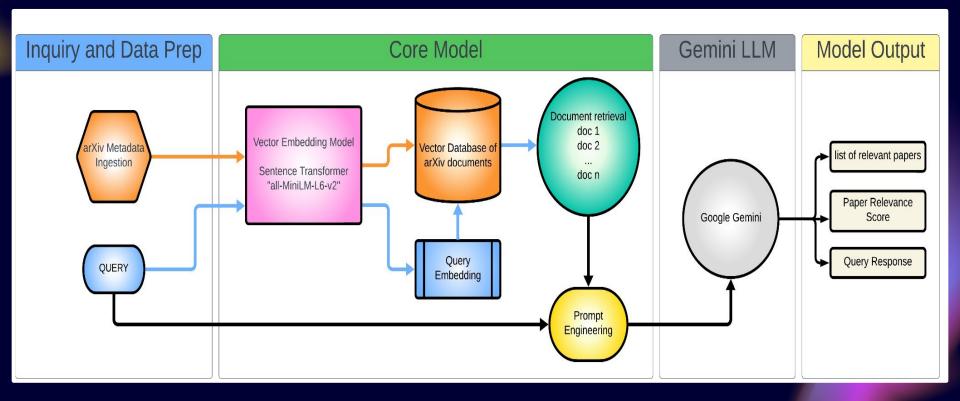
Instant Access to the Latest Research:

- **Real-Time Data Fetching:** The RAG pipeline is connected to arXiv's live database, allowing for immediate access to all query-relevant publications.
- **Dynamic Updating:** As new papers are added to arXiv, RAG + LLM can seamlessly incorporate them, ensuring that users always receive the latest research without needing to manually check for updates.

Simplifying Complex Queries:

- **Contextual Understanding:** RAG's ability to understand the context of a query means that it can retrieve documents that are highly relevant, even for complex or niche topics.
- **Efficient Document Ranking:** The pipeline ranks the documents based on their relevance to the query, presenting the most pertinent papers first, i.e. those with the highest relevance score.

Pipeline



Document preparation

- User input a topic such as "quantum physics", "dolphins", author name, ...
- 100 document summaries (title, author, abstract, identifier etc) are loaded using the arXivLoader module from langchain-community, based on traditional keyword matching approach.

Sentence Transformer

- Creates a high dimensional vector for each document summary. Document summaries longer than N tokens are truncated.
- We use a pre-trained sentence transformer model all-MinilM-L6-v2, which encodes a maximum of 256 tokens, with vector embedding dimension d=384.
- Typical arXiv document abstract length is ~200 words, compatible with all-MiniLM-L6-v2.

Document retrieval accuracy (KPI)

- We use relevance score to measure document retrieval accuracy.
- It is obtained from the cosine similarity between vector embeddings of the user query and document summaries.
- A score close to 1 means high relevance.
- Including entirety of document summaries improves the relevance score to 0.5~0.8
 - Upper end achieved by more precise user queries

```
query = ['research articles about graphene']
   documents = [
        'Phases and phase transitions in a dimerized spin-12 XXZ chain ',
        'Strongly interacting Hofstadter states in magic-angle twisted bilayer graphene',
       'Constraints imposed by symmetry on pairing operators for the iron pnictides',
       'Interplay between tetragonal magnetic order, stripe magnetism, and superconductivity in
       iron-based materials',
       'Visualizing the nonlinear coupling between strain and electronic nematicity in the iron
       pnictides by elasto-scanning tunneling spectroscopy',
       'Strong-coupling expansion of multi-band interacting models: Mapping onto the transverse-field
       J1-J2 Ising model'
   model = SentenceTransformer("all-MiniLM-L6-v2")
   doc_embedding = model.encode(documents)
   query embedding = model.encode(query)
   scores = model.similarity(query embedding,doc embedding)
   for i in range(len(documents)):
       print(documents[i]+': '+ f'{scores[0][i].item():.2f}')
 ✓ 0.5s
Phases and phase transitions in a dimerized spin-12 XXZ chain: 0.13
Strongly interacting Hofstadter states in magic-angle twisted bilayer graphene 0.47
Constraints imposed by symmetry on pairing operators for the iron pnictides: 0.12
Interplay between tetragonal magnetic order, stripe magnetism, and superconductivity in iron-based
materials: 0.13
Visualizing the nonlinear coupling between strain and electronic nematicity in the iron pnictides by
elasto-scanning tunneling spectroscopy: 0.21
Strong-coupling expansion of multi-band interacting models: Mapping onto the transverse-field J1-J2 Ising
model: 0.10
```

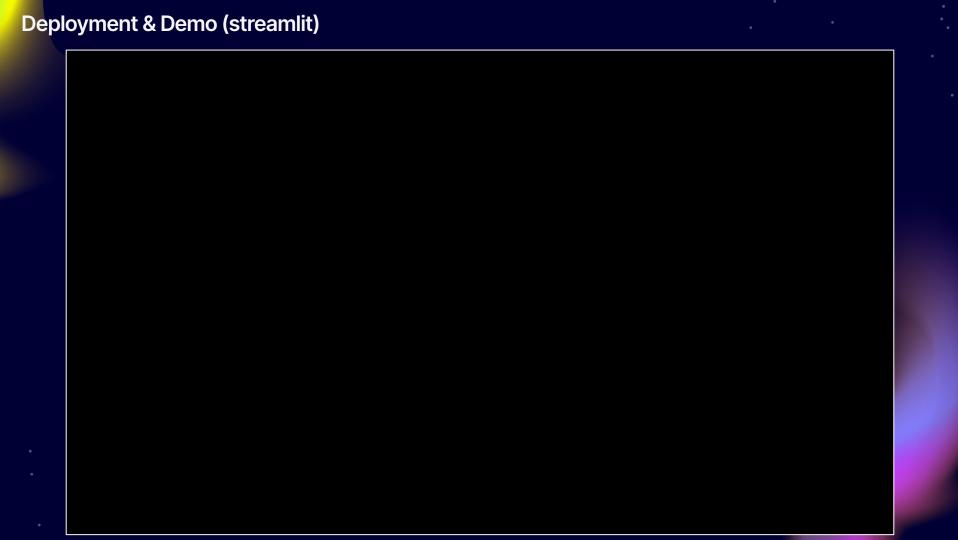
Prompt Engineering

```
prompt = """
   You are a question—answer bot that provides answers in the scientific domain.
   Given the provided context: {rag_context}
   Answer user's question "{query}" on the topic of {user_input}.
   When answering the question, try to make use of arxiv_specifiers provided in the context.\n
"""
```

Choice of Commercial LLM

Gemini:

- We use Gemini, a family of large language models developed by Google.
- This is the language model that is used to generate answers to the users queries.
- Gemini advertises as being capable of complex reasoning and offers an easy to obtain API, and has a large free query allowance of up to 1500.



Project summary

- We stress tested our RAG+LLM pipeline on a broad spectrum of topics covered by arXiv.org. The
 results are generally satisfactory in the eyes of team members who are domain experts
- The retrieved documents have relevance scores in the 0.5 to 0.8 range. Higher scores are typically obtained if the user query contains keywords that are also in the document summaries.
- The final generated response is contextualized with the retrieved documents, providing accurate answers while also citing relevant sources.
- The pipeline is deployed as a web app at https://erdos-arxiv-chatbot.streamlit.app/, which has a clean user interface, and instructions on how to use it.

Future Work

- The future work will revolve around two aspects: improvements to the core RAG module, and adding new features.
- These improvements and new features include
 - Pre-built vector database
 - Whole document ingestion
 - Customized sentence LLM
 - Bibliography construction
 - Abstract Generation

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