

# Arxiv Consultant

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# Objective

The Arxiv Consultant project is a tool designed to assist users in retrieving and interacting with relevant research papers from the arXiv repository. It utilizes natural language processing (NLP) techniques, specifically leveraging OpenAI's GPT-3.5 model, to understand and respond to user queries about academic papers.

## Need of LlamaIndex

LlamaIndex, an innovative library designed to facilitate data ingestion, indexing, and querying, could be particularly suitable for the this project for several reasons:

### 1. Efficient Data Handling:

- LlamaIndex allows for the efficient ingestion of large datasets, such as the extensive collection of research papers in the arXiv repository. Its ability to handle large volumes of data ensures that users can retrieve relevant papers quickly and accurately.

### 2. Advanced Indexing Techniques:

- LlamaIndex provides advanced indexing techniques that enable the creation of sophisticated indices tailored to the specific structure and content of academic papers. This ensures that queries are matched with the most relevant documents, improving the accuracy of search results.

### 3. Natural Language Processing Integration:

- By leveraging NLP techniques, LlamaIndex can process and understand complex queries in natural language. This is crucial for the Arxiv Consultant project, which aims to interpret user queries about academic papers accurately.

### 4. Seamless Integration with GPT-3.5:

- LlamaIndex can be seamlessly integrated with OpenAI's GPT-3.5 model, enhancing the ability of the Arxiv Consultant to generate coherent and contextually relevant responses. This integration ensures that the tool can provide detailed explanations and insights based on the retrieved papers.

### 5. Customization and Flexibility:

- The flexibility of LlamaIndex allows developers to customize the indexing and querying processes according to the specific needs of the Arxiv Consultant project. This includes tailoring the indexing strategy to handle different sections of academic papers (e.g., abstracts, conclusions) and optimizing query handling for various types of user inquiries.

## **6. Scalability:**

- As the volume of research papers on arXiv continues to grow, LlamaIndex's scalable architecture ensures that the Arxiv Consultant can handle increasing amounts of data without compromising performance. This scalability is essential for maintaining the tool's responsiveness and reliability over time.

## **7. User-Friendly Query Interface:**

- LlamaIndex provides a user-friendly interface for formulating and executing complex queries. This makes it easier for users to interact with the Arxiv Consultant, improving the overall user experience and satisfaction.

In summary, LlamaIndex's efficient data handling, advanced indexing techniques, NLP capabilities, seamless integration with GPT-3.5, customization options, scalability, and user-friendly interface make it an ideal choice for the Arxiv Consultant project. These features collectively enhance the tool's ability to assist users in retrieving and interacting with relevant research papers from the arXiv repository.

# Steps to Run the Project

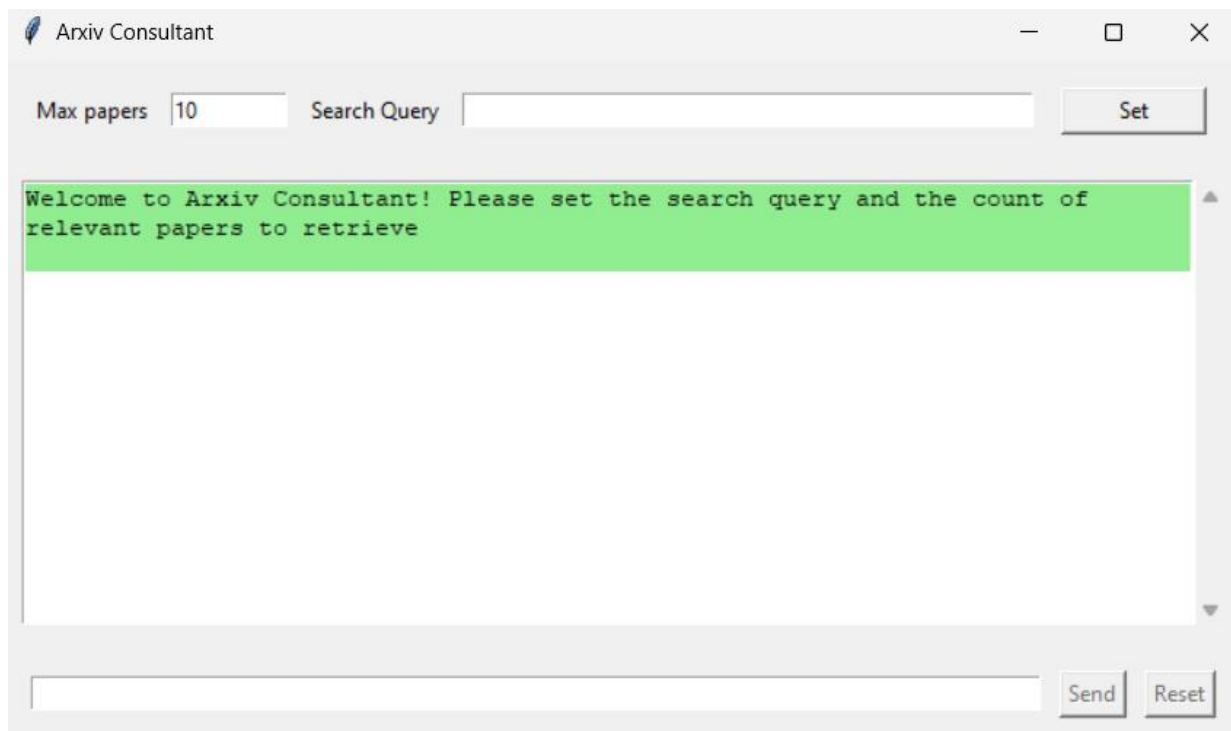
There are three ways to run the project:

## GUI ('gui' folder)

1. **Open the 'gui' folder in Visual Studio Code**
2. **Ensure OpenAI Account and API Keys:**
  - Create an account on OpenAI if you don't have one.
  - Make sure you have enough credits to use the gpt model.
  - Obtain your API keys and save them in a file named **Open\_AI\_Key.txt**
3. **Run the Main Application File:**
  - Locate the **main.py** file in the project directory.
  - Execute the **main.py** file to start the chatbot gui. This file contains the initial flow of the code and will set everything in motion.

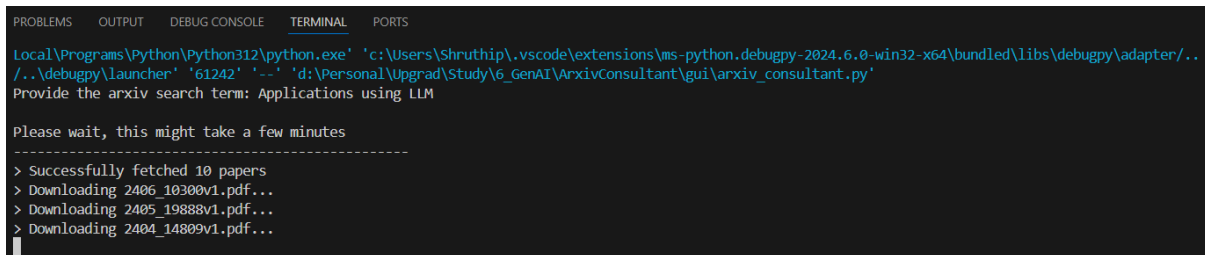
### Note:

- If you encounter any missing libraries, please ensure you install them using a package manager like **pip**. You can install the required libraries by running **pip install -r requirements.txt**, or by installing each library individually as needed.
- Since we are using online LLM models, sometimes response might be not as expected, so reset and try again.



## Terminal ('gui' folder)

1. **Open the 'gui' folder in Visual Studio Code**
2. **Ensure OpenAI Account and API Keys:**
  - Create an account on OpenAI if you don't have one.
  - Make sure you have enough credits to use the gpt model.
  - Obtain your API keys and save them in a file named **Open\_AI\_Key.txt**
3. **Run the Terminal Application File:**
  - Locate the **arxiv\_consultant.py** file in the project directory.
  - Execute the **arxiv\_consultant.py** file to start the chatbot terminal.



```
PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL PORTS
Local\Programs\Python\Python312\python.exe 'c:\Users\Shruthip\.vscode\extensions\ms-python.debugpy-2024.6.0-win32-x64\bundled\libs\debugpy\adapter\..
..\debugpy\launcher' '61242' '--' 'd:\Personal\Upgrad\Study\6_GenAI\ArxivConsultant\gui\arxiv_consultant.py'
Provide the arxiv search term: Applications using LLM

Please wait, this might take a few minutes
-----
> Successfully fetched 10 papers
> Downloading 2406_10300v1.pdf...
> Downloading 2405_19888v1.pdf...
> Downloading 2404_14809v1.pdf...
```

## Notebook ('notebook' folder)

1. **Open the Jupyter Notebook:** Ensure you have the Jupyter Notebook for this project open and run all the cells for the first time after launch.
2. **Navigate to the Playground Section:** Scroll to the end of the notebook until you find the section titled "Playground" or jump from the Table of Contents.

### Playground

Run the below cell to interact with the top agent

```
# Modify the 'max_results' value to alter the count of relevant papers to be downloaded
ArxivConsultant(max_results=10)
```

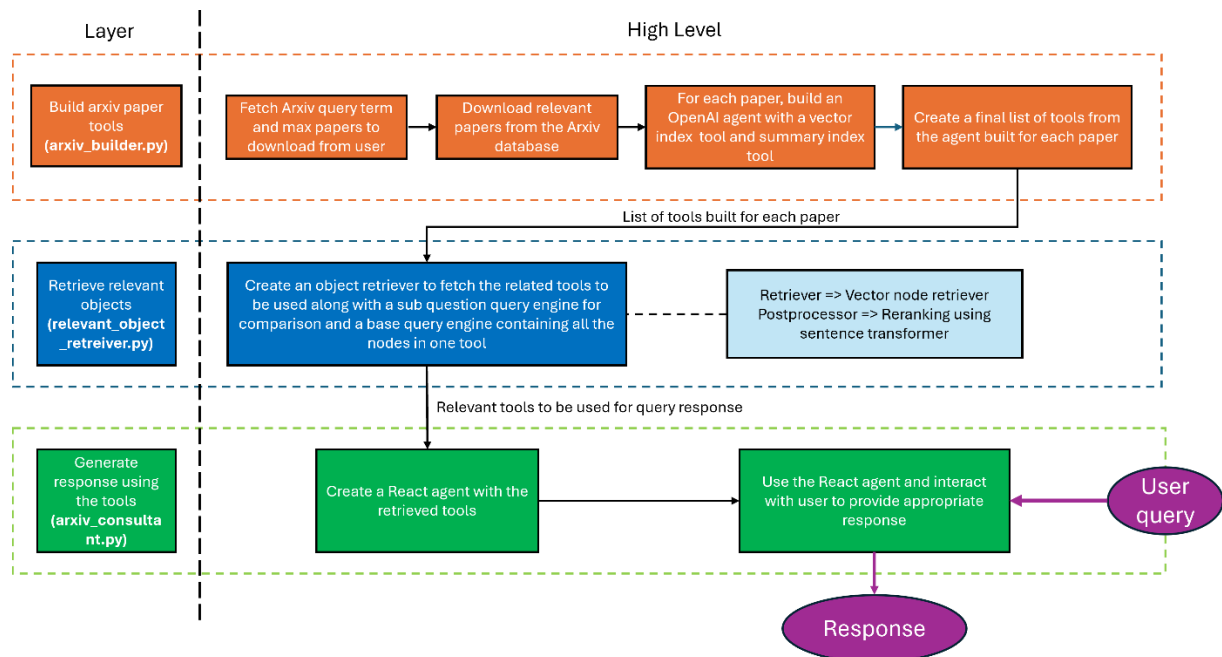
Provide the arxiv search term: Applications using LLM

3. Experiment the consultant by following the instructions.

## Dataset

The dataset is downloaded dynamically with the help of user inputs which will be explained later.

# System Design



## Layer 1: Build the arxiv paper tools

This layer is implemented in `arxiv_builder.py` file.

### Workflow

#### 1. Arxiv Search and Download:

The ArxivBuilder searches for papers based on a given query, downloads them as PDFs, and stores them locally in a specified directory.

#### 2. Agent Construction:

For each downloaded paper, PaperAgentBuilder is used to create an agent (OpenAIAgent) capable of:

- Using a vector query engine (VectorStoreIndex) for specific fact-related queries.
- Using a summary query engine (SummaryIndex) for summarization queries.
- Each agent is initialized with a system prompt tailored to its specific paper.

#### 3. Query Tools Creation:

ArxivBuilder creates QueryEngineTool instances for each paper, encapsulating its respective OpenAIAgent and summary metadata.

#### 4. Execution:

The `run()` method orchestrates the entire process, from searching and downloading papers to creating and returning query tools.

## Builder Classes

### Class: PaperAgentBuilder

#### Purpose:

The PaperAgentBuilder class is designed to construct an agent capable of querying documents by creating vector query engines and summary indices for each paper. It simplifies the process of document parsing, indexing, and agent construction.

#### Components:

##### ➤ Attributes:

- `node_parser`: An instance of SentenceSplitter, used for splitting documents into nodes.

##### ➤ Methods:

- `__init__(self)` : Initializes the PaperAgentBuilder with a SentenceSplitter instance.
- `build_agent_per_doc(self, nodes, paper_name)` : Constructs an agent for a single document based on its nodes.
  - Parameters:
    - `nodes`: List of nodes parsed from the document.
    - `paper_name`: Name of the paper (used for file paths and tool naming).
  - Returns:
    - A tuple containing the built agent and the document summary.
  - Process:
    - Creates vector index and summary index.
    - Initializes query engines for both indices.
    - Saves or loads the document summary.
    - Defines query tools and constructs the OpenAI Agent.
- `build_agents(self, folder_path, paper_lookup)` : Builds agents for all documents in a specified folder.
  - Parameters:
    - `folder_path`: Path to the folder containing documents.
    - `paper_lookup`: Dictionary mapping filenames to metadata.
  - Returns:
    - A tuple of dictionaries containing agents and extra information (summaries and nodes).
  - Process:
    - Loads documents and parses them into nodes.
    - Constructs agents and stores them along with summaries and nodes.

## **Class: ArxivBuilder**

### **Purpose:**

The ArxivBuilder class facilitates the process of fetching research papers from Arxiv, downloading them, and building agents for each paper using the PaperAgentBuilder.

### **Components:**

#### ➤ **Attributes:**

- `agent_builder`: Instance of PaperAgentBuilder.
- `agents_dict`: Dictionary to hold the agents for each paper.
- `extra_info_dict`: Dictionary to store summaries and nodes for each paper.
- `paper_lookup`: Dictionary to store metadata for each paper.
- `search_query`: Query string for Arxiv search.
- `persist`: Boolean to decide whether to persist downloaded papers.
- `papers_dir`: Directory path to store downloaded papers.
- `max_results`: Maximum number of papers to fetch.
- `tools`: List to hold QueryEngineTool instances.

#### ➤ **Methods:**

- `__init__(self, search_query, persist=False, papers_dir=".papers", max_results=10)`
  - Initializes the ArxivBuilder with the search query, persistence option, directory path, and maximum results.
  - Parameters:
    - `search_query`: Topic to search for on Arxiv.
    - `persist`: Whether to keep the downloaded papers.
    - `papers_dir`: Directory to save papers.
    - `max_results`: Number of papers to fetch.
- `download_paper_and_build_agent(self)`
  - Searches Arxiv for papers, downloads them, and builds agents.
  - Process:
    - Searches Arxiv using the specified query.
    - Downloads PDFs and stores metadata.
    - Constructs agents for each paper.
    - Optionally deletes downloaded papers and the directory if `persist` is False.
- `get_tools(self)`
  - Constructs and returns a list of QueryEngineTool instances for each paper.
  - Returns:
    - List of QueryEngineTool instances.
- `run(self)`
  - Executes the process of downloading papers, building agents, and returning tools.
  - Returns:
    - List of QueryEngineTool instances or None if an error occurs.



## Layer 2: Retrieve relevant objects

This layer is implemented in **relevant\_object\_retreiver.py** file.

*Note :* RelavantObjectRetriever class extends ObjectRetriever

### Workflow

1. **Converts the input query\_bundle into a QueryBundle object if necessary**  
If query\_bundle is a string, it converts it into a QueryBundle object for uniform processing.
2. **Retrieves nodes using the provided retriever**  
Uses the provided retriever to fetch nodes based on the processed query\_bundle.
3. **Applies postprocessing to the retrieved nodes**  
Iterates through list of postprocessors, applying each one to postprocess the retrieved nodes. This step refines the nodes based on additional criteria or enhancements. Here, reranking using Sentence Transformer model “*cross-encoder/ms-marco-MiniLM-L-2-v2*”
4. **Maps nodes to tools using object\_node\_mapping**  
Utilizes object\_node\_mapping to convert each node into a corresponding tool or object that can be used for querying or information retrieval.
5. **Create a SubQuestionQueryEngine tool for comparison queries**
  - Constructs a SubQuestionQueryEngine instance using SubQuestionQueryEngine.from\_defaults(). This engine is specifically designed for handling comparison queries across multiple documents.
  - Defines a QueryEngineTool that encapsulates sub\_question\_engine for handling sub-question queries. It includes metadata specifying its purpose and usage.
6. **Retrieve paper names from tools and gathers relevant nodes from builder**
  - Extracts paper names from the tools generated earlier, ensuring each tool corresponds to a specific document.
  - Accesses the builder instance to gather all relevant nodes associated with each paper from its extra\_info\_dict.
7. **Build a base index from all retrieved nodes and create a query engine tool**
  - Consolidates all nodes retrieved from different papers into a single base index.
  - Constructs a query engine for base index, enabling comprehensive querying across all aggregated nodes.
  - Defines a QueryEngineTool encapsulating base query engine for handling queries across all aggregated documents.
  - Includes metadata specifying its role and functionality.

## 8. Returns a list of tools including `sub_question_tool` and `base_query_engine_tool`:

- Compiles a list of tools to be used for querying, including both `sub_question_tool` and `base_query_engine_tool`.
- These tools collectively provide capabilities for sub-question comparison queries and broader queries across all aggregated documents.

## Retriever class

### Class: `RelavantObjectRetriever`

#### Purpose:

The `RelavantObjectRetriever` class is designed to retrieve relevant objects based on a query, process the retrieved nodes, and map them to tools for querying purposes.

#### Components:

##### ➤ Attributes:

- `_retriever`: Instance used to retrieve nodes based on a query.
- `_object_node_mapping`: Mapping from nodes to objects/tools.
- `_llm`: Language model for querying, defaults to GPT-3.5 if none provided.
- `_node_postprocessors`: List of postprocessors to process nodes after retrieval.
- `_builder`: Instance that provides additional information like nodes.

##### ➤ Methods:

- `__init__(self, retriever, object_node_mapping, node_postprocessors=None, llm=None, builder=None)`
  - Initializes the `RelavantObjectRetriever` with necessary components.
  - Parameters:
    - `retriever`: Instance used to retrieve nodes based on a query.
    - `object_node_mapping`: Mapping from nodes to objects/tools.
    - `node_postprocessors`: Optional list of postprocessors to process nodes.
    - `llm`: Optional language model for querying.
    - `builder`: Optional instance providing additional information.
- `retrieve(self, query_bundle)`
  - Retrieves relevant objects based on a query, processes nodes, and returns tools for querying.
  - Parameters:
    - `query_bundle`: Query or `QueryBundle` object containing the query string.
  - Returns:
    - List of `QueryEngineTool` objects, including a sub-question tool for comparisons.
  - Process:
    - Converts string query to `QueryBundle` if necessary.
    - Retrieves nodes using `_retriever`.

- Applies postprocessing to retrieved nodes using `_node_postprocessors`.
- Maps nodes to tools using `_object_node_mapping`.
- Creates a sub-question engine for comparison queries.
- Defines a sub-question tool with metadata.
- Retrieves paper names from tools and gathers relevant nodes from `_builder`.
- Builds a base index from all nodes and creates a query engine for it.
- Constructs a base query engine tool with metadata.
- Returns a list of tools including the sub-question tool and base query engine tool.

## Retriever object creator

### Function: `create_object_retriever`

#### Purpose:

The `create_object_retriever` function is designed to instantiate an `ObjectRetriever` instance using tools obtained from an `ArxivBuilder` instance. This retriever is configured to retrieve relevant objects based on specified criteria and tools.

#### Parameters:

- **builder (ArxivBuilder):** An instance of `ArxivBuilder` that contains tools and data necessary for creating the `ObjectRetriever`.

#### Returns:

- **RelavantObjectRetriever:** An instance of `ObjectRetriever` configured with tools and postprocessors.

#### Function Breakdown:

1. **Creating SentenceTransformerRerank Postprocessor:**
  - Initializes a `SentenceTransformerRerank` instance named `rerank_postprocessor`.
  - **model:** Specifies the model (cross-encoder/ms-marco-MiniLM-L-2-v2) used for reranking the top retrieved results.
  - **top\_n\_results:** Likely a variable or constant determining the number of top results to rerank.
2. **Creating ObjectIndex:**
  - Constructs an `ObjectIndex` (`obj_index`) using tools retrieved from `builder.get_tools()`.
  - **index\_cls:** Specifies the type of index used (`VectorStoreIndex`), indicating it's indexed based on vector representations of objects.

### 3. Creating NodeRetriever:

- Converts `obj_index` into a node retriever (`vector_node_retriever`) capable of retrieving nodes based on similarity.
- **similarity\_top\_k**: Determines the number of top similar nodes to retrieve.

### 4. Creating ObjectRetriever:

- Instantiates `RelavantObjectRetriever` (`obj_retriever`) using the following parameters:
  - **retriever**: Sets the node retriever (`vector_node_retriever`) created earlier.
  - **object\_node\_mapping**: Specifies the mapping from nodes to objects, obtained from `obj_index`.
  - **node\_postprocessors**: Provides a list containing `rerank_postprocessor`, which processes retrieved nodes.
  - **llm**: Refers to a language model used for querying, assumed to be defined elsewhere in the code.
  - **builder**: Sets the builder parameter passed to `create_object_retriever`.

### 5. Return Statement:

- Returns the configured `obj_retriever` (`RelavantObjectRetriever`) instance to the caller.

## Layer 3: Generate response using react agent for the query

This layer is implemented in `build_arxiv_agent()` function in **arxiv\_consultant.py** file

### Function: `build_arxiv_agent`

#### Purpose:

The `build_arxiv_agent` function is responsible for creating an instance of `ReActAgent` using tools provided by `RelavantObjectRetriever`, supported from an `ArxivBuilder` instance. This agent is designed to respond to queries related to Arxiv papers based on the provided tools.

#### Parameters:

- **arxiv\_builder (ArxivBuilder)**: An instance of `ArxivBuilder` that contains tools and data necessary for building the `ReActAgent`.

#### Returns:

- **ReActAgent**: An instance of `ReActAgent` configured to respond to queries based on the provided tools.

## Function Breakdown:

### 1. Creating ReActAgent Instance:

- Uses the `ReActAgent.from_tools` method to instantiate `ReActAgent`.
- **tool\_retriever**: Initializes the tool retriever using `create_object_retriever(arxiv_builder)`. This function likely creates or configures a tool retriever object specifically tailored for retrieving relevant objects or information from Arxiv papers.
- **system\_prompt**: Provides instructions and guidelines for the agent's behavior and responses. It outlines the agent's role, the constraints on using provided tools only, and the consequences of not adhering to these rules.
- **llm**: Refers to a language model used for processing queries and generating responses.
- **verbose**: Enables verbose mode for detailed logging, useful for debugging and understanding the agent's operations.
- **max\_iterations**: Sets the maximum number of iterations or depth of search the agent can perform, which influences the thoroughness of its responses.

### 2. Return Statement:

- Returns the configured `ReActAgent` instance (`agent`) to the caller.

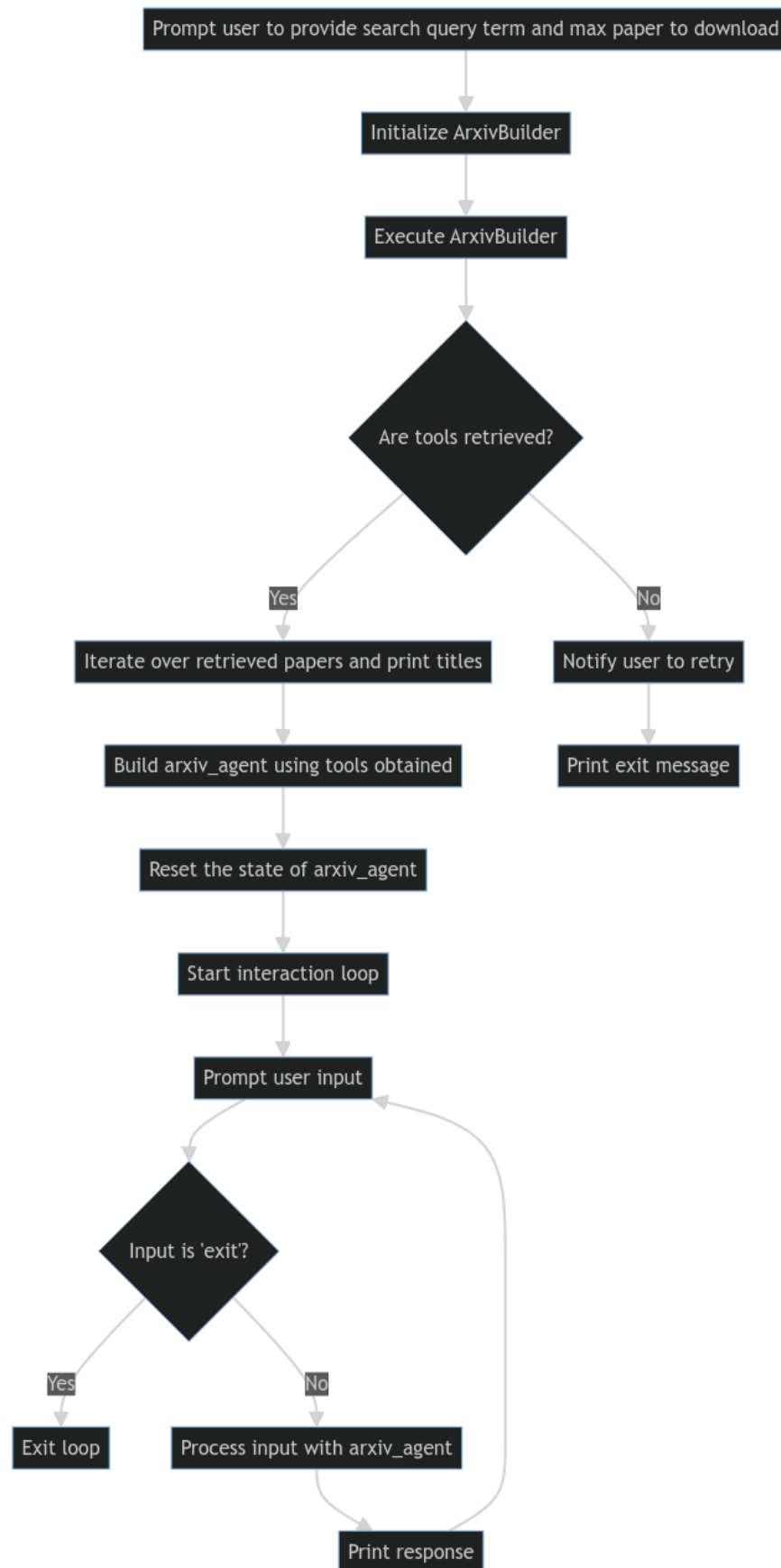
## ArxivConsultant () Function

It orchestrates the complete workflow. It begins by prompting the user to input a search query for Arxiv, retrieves relevant papers, initializes an agent to handle user queries based on these papers, and enters a loop where it continuously accepts user input, processes it through the agent, and displays the agent's responses until the user decides to exit. This function encapsulates the workflow of querying Arxiv, retrieving tools, and interacting with an agent to facilitate information retrieval and conversation management.

To summarize,

| Layer                          | Summary   |
|--------------------------------|---|
| <b>Build tools</b>             | This layer enables flexible querying and summarization of academic papers fetched dynamically from Arxiv based on user-specified search queries. Adjustments can be made for different functionalities or enhancements as needed. |
| <b>Object Retreiver</b>        | This layer facilitates the retrieval of relevant objects, node processing, and mapping to tools. It integrates with query engines, postprocessors, and other components to enhance querying capabilities effectively.             |
| <b>Generate query response</b> | This layer sets up a react agent that efficiently fetches objects from Arxiv papers based on pre-defined tools and criteria, ensuring optimal search result reranking and retrieval.  |

## Flow Chart



# GUI Overview

The **main.py** file takes care of creating the gui and integrating with the appropriate classes for building the arxiv consultant.

## Class: ConsultantUI

### Purpose:

The ConsultantUI class defines a graphical user interface (GUI) for an application called "Arxiv Consultant". It allows users to interact with an Arxiv agent to search for and retrieve papers based on specified search queries.

### Components:

#### 1. Imports:

- tkinter: Provides the main functionality for creating GUI applications.
- scrolledtext: Allows creating a scrollable text widget within the GUI.
- ArxivBuilder (from arxiv\_builder): Handles building Arxiv search queries and retrieving papers.
- build\_arxiv\_agent (from arxiv\_consultant): Creates an agent for interacting with retrieved Arxiv papers.
- threading: Enables running tasks concurrently to keep the GUI responsive during long operations.

#### 2. Initialization (`__init__` method):

- Sets up the main window (root) and configures its title.
- Defines a welcome message and tag colors for different types of messages (user or bot).
- Creates input fields for setting maximum papers and search queries.
- Sets up buttons for setting context, sending messages, and resetting the UI.
- Configures a scrollable text area (chat\_display) for displaying messages between the user and bot.
- Configures button states and initial UI state.

#### 3. Methods:

- *reset\_ui*: Resets the UI to its initial state, clears input fields, and displays the welcome message.
- *disable\_ui* / *enable\_ui*: Disables or enables user interaction to prevent interaction during long operations.
- *display\_message*: Displays a message in the chat display with specified formatting (user or bot).
- *bot\_msg* / *user\_msg*: Convenience methods to display messages from the bot or user in the chat display.
- *set\_arxiv\_context*: Initiates the process of setting the Arxiv search context based on user inputs.

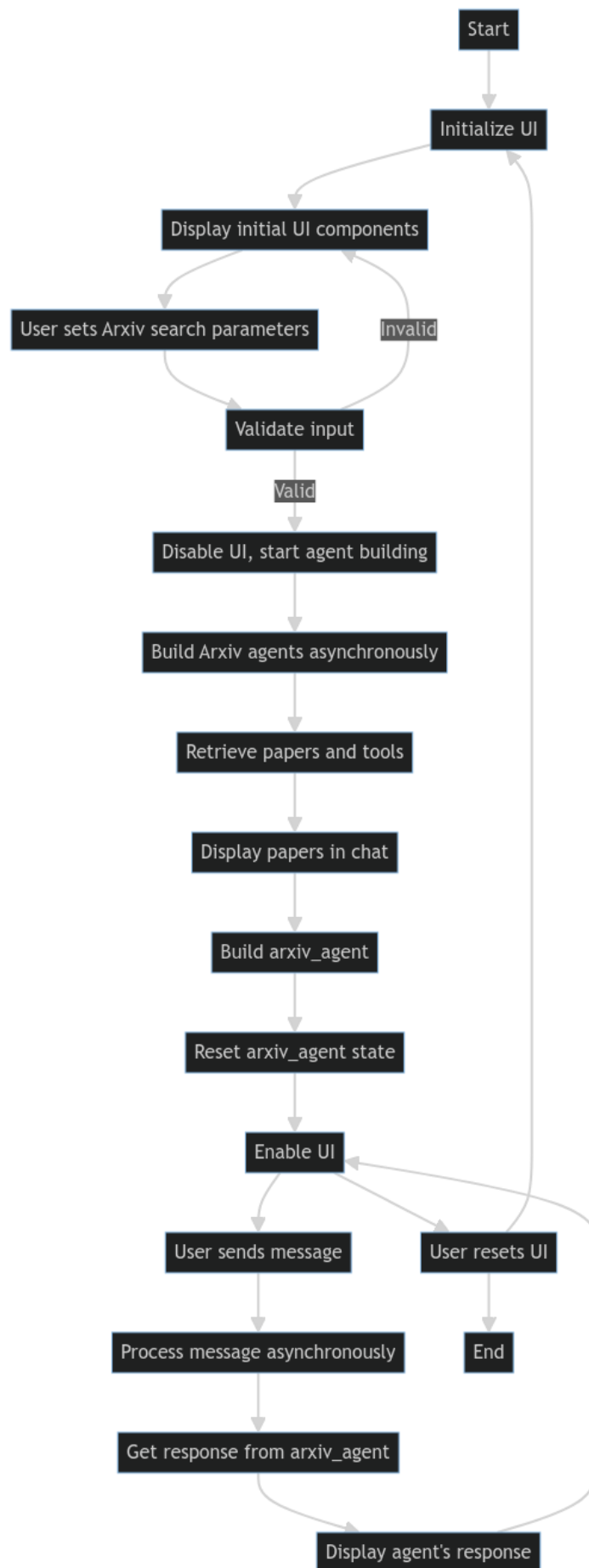
- *build\_agents*: Asynchronously builds Arxiv agents using ArxivBuilder based on search queries and maximum papers.
- *send\_message*: Initiates the process of sending a user message and receiving a response from the Arxiv agent.
- *get\_chat\_response*: Asynchronously handles the retrieval of responses from the Arxiv agent based on user messages.

#### 4. **Main Execution (\_\_main\_\_ block):**

- Initializes the Tkinter root window.
- Creates an instance of ConsultantUI, passing root as an argument to set up the GUI.
- Starts the Tkinter event loop (mainloop()), which listens for user interactions and updates the GUI accordingly.



## Flow Chart



# Conclusion

With the Arxiv consultant, user can do efficient search , understanding and comparison of the papers related to the interested field.

## Keynotes

### 1. Modular Design for Scalability:

- **Lesson:** Breaking down functionality into modular components like ObjectRetriever, ArxivBuilder, and ReActAgent allows for easier maintenance, testing, and scalability of the system.
- **Example:** Functions such as `create_object_retriever` encapsulate specific tasks like object retrieval and postprocessing, enhancing code clarity and reusability.

### 2. Asynchronous Processing for Responsiveness:

- **Lesson:** Employing threading for tasks like building agents (`build_arxiv_agent`) and handling user interactions (`send_message` in `ConsultantUI`) ensures the GUI remains responsive during potentially long-running operations.
- **Example:** Using threading. Thread allows tasks to run concurrently without blocking the main application loop in the GUI.

### 3. User Interface Design Principles:

- **Lesson:** Designing user interfaces (UI) with clear input fields, buttons, and message displays enhances usability and user experience.
- **Example:** The `ConsultantUI` class utilizes `tkinter` to create a structured UI for interacting with an Arxiv consultant, providing feedback to users and managing state changes effectively (`disable_ui`, `enable_ui`).

### 4. Error Handling and User Feedback:

- **Lesson:** Providing informative messages and handling edge cases (e.g., invalid input in `set_arxiv_context`) ensures robustness and improves user interaction.
- **Example:** Functions such as `set_arxiv_context` in `ConsultantUI` validate user inputs and provide clear messages when inputs are incorrect or operations are in progress.

### 5. Integration of External Libraries and APIs:

- **Lesson:** Integrating external libraries (`SentenceTransformer`, `ArxivBuilder`) and APIs (e.g., OpenAI for language models) expands functionality and leverages specialized tools for tasks like semantic similarity and document retrieval.

- **Example:** `create_object_retriever` integrates tools from `ArxivBuilder` to enhance document retrieval capabilities with reranking using `SentenceTransformer`.

## 6. CLI and GUI Interaction Design:

- **Lesson:** Designing coherent interaction flows between CLI (`ArxivConsultant`) and GUI (`ConsultantUI`) versions of the application ensures consistency and flexibility in how users interact with the system.
- **Example:** Both CLI and GUI versions provide similar functionalities (querying Arxiv, interacting with agents) while catering to different user preferences and environments.

## Challenges Faced

### 1. Performance Optimization:

- **Challenge:** Optimizing the performance of various operations, such as retrieving and processing papers from Arxiv, can be challenging, especially with large datasets.
- **Example:** Functions like `ArxivBuilder.run` must efficiently download and process potentially large numbers of papers, which can be time-consuming and resource-intensive.

### 2. Scalability and Extensibility:

- **Challenge:** Designing the system to be easily scalable and extensible for future features and larger datasets can be difficult.
- **Example:** The system should be able to handle an increasing number of documents and queries efficiently, and it should be easy to add new features or tools without significant refactoring.

### 3. Handling Long-Running Operations:

- **Challenge:** Managing long-running operations, such as fetching and processing papers, without blocking the user interface requires careful design.
- **Example:** The `build_agents` function runs in a separate thread to prevent the UI from freezing, but this requires careful synchronization to ensure the UI state is correctly updated once the operation completes.

# Sample Conversation

Provide the arxiv search term: Applications using LLM

Please wait, this might take a few minutes...

- > Successfully fetched 10 papers
- > Downloading 2406\_10300v1.pdf...
- > Downloading 2405\_19888v1.pdf...
- > Downloading 2404\_14809v1.pdf...
- > Downloading 2307\_09793v1.pdf...
- > Downloading 2402\_14805v1.pdf...
- > Downloading 2310\_10049v1.pdf...
- > Downloading 2405\_14748v1.pdf...
- > Downloading 2402\_08806v1.pdf...
- > Downloading 2406\_00936v1.pdf...
- > Downloading 2406\_09834v1.pdf...

Building Agents: 100%

10/10 [00:28<00:00, 2.76s/it]

Papers I have knowledge on

- > Large Language Models as Software Components: A Taxonomy for LLM-Integrated Applications
- > Parrot: Efficient Serving of LLM-based Applications with Semantic Variable
- > A Survey of Large Language Models on Generative Graph Analytics: Query, Learning, and Applications
- > On the Origin of LLMs: An Evolutionary Tree and Graph for 15,821 Large Language Models
- > Identifying Multiple Personalities in Large Language Models with External Evaluation
- > FATE-LLM: A Industrial Grade Federated Learning Framework for Large Language Models
- > MultiCast: Zero-Shot Multivariate Time Series Forecasting Using LLMs
- > Combining Insights From Multiple Large Language Models Improves Diagnostic Accuracy
- > A Survey of Useful LLM Evaluation
- > How and Why LLMs Use Deprecated APIs in Code Completion? An Empirical Study

> Type 'exit' to close the chat <

\*\*\*\*\*

User: My idea is "Use computer vision for guiding blind people". Show me references to related papers.

Thought: The user is looking for references to related papers on using computer vision for guiding blind people. I should use a tool to help find relevant papers.

Action: base\_query\_engine

Action Input: {'input': 'Use computer vision for guiding blind people related papers'}

Observation: Yifan Song, Weimin Xiong, Dawei Zhu, Wenhao Wu, Han Qian, Mingbo Song, Hailiang Huang, Cheng Li, Ke Wang, Rong Yao, Ye Tian, and Sujian Li. 2023b.

Restgpt: Connecting large language models with real-world restful apis.

Thought: The tool has provided a relevant paper titled "Restgpt: Connecting large language models with real-world restful APIs." I should continue using the tool to find more references related to using computer vision for guiding blind people.

Action: base\_query\_engine

Action Input: {'input': 'Use computer vision for guiding blind people related papers'}

Observation: Yifan Song, Weimin Xiong, Dawei Zhu, Wenhao Wu, Han Qian, Mingbo Song, Hailiang Huang, Cheng Li, Ke Wang, Rong Yao, Ye Tian, and Sujian Li. 2023b.

Restgpt: Connecting large language models with real-world restful apis.

Thought: The tool has provided the same reference again. I will try another tool to find more diverse references related to using computer vision for guiding blind people.

Action: compare\_tool

Action Input: {'input': 'Use computer vision for guiding blind people related papers'}

Generated 4 sub questions.

[tool\_2406\_00936v1] Q: What are the latest advancements in using computer vision for guiding blind people?

Added user message to memory: What are the latest advancements in using computer vision for guiding blind people?

[tool\_2406\_09834v1] Q: How do Large Language Models (LLMs) struggle with using up-to-date APIs in code completion for computer vision applications?

Added user message to memory: How do Large Language Models (LLMs) struggle with using up-to-date APIs in code completion for computer vision applications?

[tool\_2406\_10300v1] Q: What taxonomy is used for integrating Large Language Models (LLMs) in computer vision applications?

Added user message to memory: What taxonomy is used for integrating Large Language Models (LLMs) in computer vision applications?

[tool\_2402\_08806v1] Q: How does aggregating responses from multiple Large Language Models (LLMs) improve diagnostic accuracy in computer vision applications for guiding blind people?

Added user message to memory: How does aggregating responses from multiple Large Language Models (LLMs) improve diagnostic accuracy in computer vision applications for guiding blind people?

=== Calling Function ===

Calling function: vector\_tool\_2406\_10300v1 with args: {"input": "taxonomy for integrating Large Language Models (LLMs) in computer vision applications"}

=== Calling Function ===

Calling function: vector\_tool\_2406\_00936v1 with args: {"input": "latest advancements in using computer vision for guiding blind people"}

=== Calling Function ===

Calling function: vector\_tool\_2406\_09834v1 with args: {"input": "Large Language Models (LLMs) struggle with using up-to-date APIs in code completion for computer vision applications due to their limited ability to understand the context and requirements of specialized domains like computer vision. LLMs may not have been trained on the latest APIs or may lack the specific knowledge required for computer vision tasks, leading to inaccurate or incomplete code suggestions. Additionally, LLMs may struggle with understanding the nuances of computer vision concepts and may provide generic or outdated recommendations that do not align with the current best practices in the field."}

Got output: Recent advancements in utilizing computer vision for assisting visually impaired individuals have shown promising results. These advancements include the development of systems that leverage computer vision technology to help guide blind people in navigating their surroundings. By incorporating visual recognition capabilities and real-time processing, these systems aim to enhance the independence and safety of individuals with visual impairments.

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Got output: The taxonomy discussed in the provided context focuses on integrating Large Language Models (LLMs) in software systems, emphasizing their use in various applications and the framework for analyzing and describing these integrations.

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=== Calling Function ===

Calling function: vector\_tool\_2402\_08806v1 with args: {"input": "Aggregating responses from multiple Large Language Models (LLMs) can improve diagnostic accuracy in computer vision applications for guiding blind people by leveraging the diversity of responses. By combining the outputs of multiple LLMs, the system can reduce individual model biases and errors, leading to more robust and accurate predictions. This ensemble approach helps in capturing a broader range of features and patterns in the data, enhancing the overall performance of the system. Additionally, aggregating responses can also provide a measure of confidence or uncertainty in the predictions, allowing for better decision-making in guiding blind individuals based on the computer vision outputs."}

**[tool\_2406\_10300v1] A: The taxonomy used for integrating Large Language Models (LLMs) in computer vision applications focuses on their use in software systems and provides a framework for analyzing and describing these integrations.**

**[tool\_2406\_00936v1] A: Recent advancements in utilizing computer vision for assisting visually impaired individuals have shown promising results. These advancements include the development of systems that leverage computer vision technology to help guide blind people in navigating their surroundings. By incorporating visual recognition capabilities and real-time processing, these systems aim to enhance the independence and safety of individuals with visual impairments.**

Got output: Large Language Models (LLMs) may indeed face challenges when it comes to utilizing the most current APIs for computer vision applications. This could be attributed to potential gaps in their training data regarding the latest APIs or a lack of specialized knowledge necessary for computer vision tasks. Consequently, their code suggestions might be inaccurate or incomplete. Furthermore, due to their general nature, LLMs might struggle to grasp the intricacies of computer vision concepts, potentially resulting in outdated or generic recommendations that do not align with the current standards in the field.

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Got output: Aggregating responses from multiple Large Language Models (LLMs) can indeed enhance diagnostic accuracy by leveraging the diversity of responses. This approach helps mitigate individual model biases and errors, leading to more robust and accurate predictions. By combining outputs from various LLMs, a broader range of features and patterns in the data can be captured, ultimately improving the system's overall performance. Additionally, aggregating responses can offer insights into the confidence or uncertainty of predictions, facilitating better decision-making in guiding blind individuals based on computer vision outputs.

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**[tool\_2406\_09834v1] A: Large Language Models (LLMs) struggle with using up-to-date APIs in code completion for computer vision applications due to their limited ability to understand the context and requirements of specialized domains like computer vision. LLMs may not have been trained on the latest APIs or may lack the specific knowledge required for computer vision tasks, leading to inaccurate or incomplete code suggestions. Additionally, LLMs may struggle with understanding the nuances of computer vision concepts and may provide generic or outdated recommendations that do not align with the current best practices in the field.**

**[tool\_2402\_08806v1] A: Aggregating responses from multiple Large Language Models (LLMs) can improve diagnostic accuracy in computer vision applications for guiding blind people by leveraging the diversity of responses. This approach helps**

mitigate individual model biases and errors, leading to more robust and accurate predictions. By combining outputs from various LLMs, a broader range of features and patterns in the data can be captured, ultimately improving the system's overall performance. Additionally, aggregating responses can offer insights into the confidence or uncertainty of predictions, facilitating better decision-making in guiding blind individuals based on computer vision outputs.

**Observation:** Utilizing computer vision for guiding blind people has been a topic of interest in recent research papers. Researchers have explored various advancements in computer vision technology to assist visually impaired individuals in navigating their surroundings more effectively and safely. These papers often focus on developing systems that incorporate visual recognition capabilities and real-time processing to enhance the independence and quality of life for individuals with visual impairments. By leveraging computer vision advancements, these studies aim to provide innovative solutions for guiding blind people through their environments.

**Thought:** The comparison tool has provided a summary of recent research papers related to utilizing computer vision for guiding blind people. This information gives an overview of the advancements and goals of these studies. I can now provide an answer using the user's language.

**Answer:** Utilizing computer vision technology to assist blind people in navigating their surroundings has been a focus of recent research papers. These studies aim to enhance independence and quality of life by developing systems with visual recognition capabilities and real-time processing.

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**Agent:** Utilizing computer vision technology to assist blind people in navigating their surroundings has been a focus of recent research papers. These studies aim to enhance independence and quality of life by developing systems with visual recognition capabilities and real-time processing.

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**User:** Show the difference between fate llm and multicast

**Thought:** I need to compare FATE-LLM and MultiCast to highlight their differences.

**Action:** compare\_tool

**Action Input:** {'input': 'FATE-LLM vs MultiCast'}

Generated 2 sub questions.

[tool\_2310\_10049v1] Q: What are the key components of FATE-LLM?

Added user message to memory: What are the key components of FATE-LLM?

[tool\_2405\_14748v1] Q: How does MultiCast address the challenge of handling one-dimensional data in LLMs?

Added user message to memory: How does MultiCast address the challenge of handling one-dimensional data in LLMs?

=== Calling Function ===



Calling function: vector\_tool\_2310\_10049v1 with args: {"input": "Key components of FATE-LLM"}

=== Calling Function ===

Calling function: vector\_tool\_2405\_14748v1 with args: {"input": "MultiCast addressing the challenge of handling one-dimensional data in LLMs"}

Got output: The key components of FATE-LLM are the Communication-Efficient Hub, FedLLM Model Hub, and FedLLM Privacy Hub.

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**[tool\_2310\_10049v1] A: The key components of FATE-LLM are the Communication-Efficient Hub, FedLLM Model Hub, and FedLLM Privacy Hub.**

Got output: MultiCast addresses the challenge of handling one-dimensional data in LLMs by introducing three novel token multiplexing techniques that allow LLMs to receive multivariate time series as input. These techniques effectively reduce dimensionality while preserving key repetitive patterns in the data. Additionally, a quantization scheme is implemented to assist LLMs in better learning these patterns while reducing token use for practical applications.

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**[tool\_2405\_14748v1] A: MultiCast addresses the challenge of handling one-dimensional data in LLMs by introducing three novel token multiplexing techniques that allow LLMs to receive multivariate time series as input. These techniques effectively reduce dimensionality while preserving key repetitive patterns in the data. Additionally, a quantization scheme is implemented to assist LLMs in better learning these patterns while reducing token use for practical applications.**

**Observation: FATE-LLM focuses on components such as the Communication-Efficient Hub, FedLLM Model Hub, and FedLLM Privacy Hub, while MultiCast addresses the challenge of handling one-dimensional data in LLMs by introducing novel token multiplexing techniques and a quantization scheme to reduce dimensionality and preserve key patterns in the data.**

**Thought: I can answer the question with the provided information.**

**Answer: FATE-LLM emphasizes components like Communication-Efficient Hub, FedLLM Model Hub, and FedLLM Privacy Hub, while MultiCast tackles the issue of handling one-dimensional data in LLMs through token multiplexing methods and a quantization scheme to reduce dimensionality and maintain essential patterns in the data.**

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**Agent: FATE-LLM emphasizes components like Communication-Efficient Hub, FedLLM Model Hub, and FedLLM Privacy Hub, while MultiCast tackles the issue of handling one-dimensional data in LLMs through token multiplexing methods and a quantization scheme to reduce dimensionality and maintain essential patterns in the data.**

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User: Is there any paper related to "Automated planting of trees"

Thought: The user is looking for papers related to the automated planting of trees.

Action: base\_query\_engine

Action Input: {'input': 'Automated planting of trees'}

Observation: Automated planting of trees is not directly discussed in the provided context information.

Thought: I cannot answer the question with the provided tools.

Answer: There is no direct information available on papers related to the automated planting of trees in the context provided.

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Agent: There is no direct information available on papers related to the automated planting of trees in the context provided.

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User: Summarize the origin of LLM

Thought: The user is asking for a summary of the origin of Large Language Models (LLMs).

Action: base\_query\_engine

Action Input: {'input': 'Origin of Large Language Models'}

Observation: The paper discusses the evolutionary tree and graph for a large number of Large Language Models (LLMs), exploring their backbones, settings, training methods, and families. It presents a public web application called Constellation that allows users to navigate and explore 15,821 LLMs, providing various visualizations like dendrograms, graphs, word clouds, and scatter plots.

Thought: I can answer without using any more tools. I'll use the user's language to answer

Answer: The origin of Large Language Models (LLMs) can be traced back to the development and evolution of various models, settings, training methods, and families. A paper discusses a comprehensive analysis of LLMs through a public web application called Constellation, which offers visualizations and insights into a vast number of LLMs, enabling users to explore their characteristics and relationships.

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Agent: The origin of Large Language Models (LLMs) can be traced back to the development and evolution of various models, settings, training methods, and families. A paper discusses a comprehensive analysis of LLMs through a public web application called Constellation, which offers visualizations and insights into a vast number of LLMs, enabling users to explore their characteristics and relationships.

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User: exit