Lecture No. 1

■ Summary

- The video is part of a series focusing on "rag" and will practically create a rag-based system using "lang chain".
- The problem statement is about creating a chat system through which users can discuss various YouTube videos in real-time.
- The system can be created as a Chrome plugin or a Streamlet website, depending on the us er's knowledge of HTML, CSS, and JavaScript.

■ Key Terms and Concepts

- rag-based system
- lang chain
- YouTube chat system
- Chrome plugin
- Streamlet website
- HTML
- CSS
- JavaScript

■ Review Questions

- 1. What was the problem statement discussed in the video?
- 2. What are the different ways in which the chat system can be designed?
- 3. What knowledge is needed to create the chat system as a Chrome plugin?
- 4. What is the alternative approach to creating the chat system if one does not know HTML, CSS, and JavaScript?
- 5. Why is the chat system considered a useful solution for engaging with YouTube videos?

■ Summary

- Focus on building a RAG system and making it inside a Google Colab notebook.
- Use tools like Streamlet and Langchain for loading the video transcript.
- Steps include loading the transcript, dividing it into chunks, generating embeddings, cr eating a retriever, merging relevant chunks with the query, and sending the prompt to LLM for response generation.

■ Key Terms and Concepts

- Streamlet
- Google Colab notebook
- RAG system (Retrieval-augmented generation)

■ Review Questions

- 1. What are the key steps in building a RAG system?
- 2. What tools can be used for loading the transcript of a video?
- 3. What are the main features of a retriever in the RAG system architecture?

■ Summary

- The tutorial explains a step-by-step process of using an API to load the transcript of a YouTube video.
- To achieve this, it involves obtaining the video ID, retrieving the transcript via the Y ouTube transcript API, and processing the transcript data.
- The time stamp and the duration of text visibility on the screen are shown using Python code.

- YouTube transcript API
- Video ID
- Python API usage
- Retrieving the transcript

- Text visibility and duration
- Timestamp-based transcript loading

- 1. What are the key steps involved in using the YouTube transcript API to retrieve a video 's transcript?
- 2. How is the ID of a YouTube video obtained for transcript retrieval?
- 3. What is the significance of the try-accept block in the Python code?
- 4. What information is available in the API-converted transcript related to text visibilit y and duration?
- 5. In what ways did the speaker find this approach to be the best for obtaining video tran scripts?

■ Summary

- Converting a transcript into smaller chunks
- Joining the smaller chunks
- Loading the Hindi transcript for the video
- Using a text splitter to divide the transcript into smaller chunks
- Using a vector store to store the chunks as vectors

- Transcript
- Text splitter
- Recursive character text splitter
- Chunk size and overlap
- Embedding model
- Open AI embeddings
- Vector store

- 1. How is the transcript converted into smaller chunks?
- 2. What are the functions used to manipulate the transcript and join the chunks?
- 3. What kind of embedding model is used to convert the smaller chunks into vectors?
- 4. What purpose does the vector store serve in this process?

■ Summary

- The video explains the process of using vector embeddings and indexing to create a retri ever for document retrieval.
- The retriever embeds a query and searches for the closest matching vectors in the vector store.
- Once the retriever finds the closest vectors, it retrieves the corresponding documents.

■ Key Terms and Concepts

- Vector store
- Embedding and storing chunks
- Creating a retriever
- Retrieval process
- Similarity search
- Prop template
- Retrieved documents

■ Review Questions

- 1. How does the retriever search for matching vectors in the vector store?
- 2. What is the purpose of the prop template in the argumentation part?
- 3. What happens in the retrieval step? How is it associated with the retriever?
- 4. Explain the process of retrieving documents using the retriever and the query.

■ Summary

- Need to concatenate page content from multiple documents
- Custom code to concatenate page content from each document
- Invoking the custom code with context and final prop
- Generating an answer from the invoked LLM

■ Key Terms and Concepts

- Concatenation of page content
- Custom code
- Invocation of code with context and final prop
- Answer generation from the LLM
- Chaining multiple steps for automation

■ Review Questions

- 1. What is the purpose of invoking the custom code with context and final prop?
- 2. How can we automate and streamline the process of calling each step separately?
- 3. What are the key concepts involved in generating an answer from the invoked LLM?

■ Summary

- The learning journey involves understanding how to create and manage a chain in the invoke function
- A chain can trigger an entire pipeline automatically, with every step executing and prod ucing an output that serves as input for the next step
- The structure of the chain includes a simple linear flow and two parallel chains
- The construction of a parallel chain involves using Runnable Parallel and defining keys in a dictionary to handle context and question, with the processing being a part of the chain

- Invoke function
- Pipeline automation
- Structure of the chain
- Simple linear flow
- Parallel chains
- Runnable Parallel
- Context and question keys
- Dictionary
- Processing within the chain

- 1. What is the purpose of the invoke function in managing a chain?
- 2. How is the overall pipeline triggered and executed automatically in the chain structure
- 3. What tools or components are involved in creating a parallel chain?
- 4. How is the processing of documents integrated into the chain structure?
- 5. What are the key elements in defining a dictionary within the parallel chain?

■ Summary

- The code implements a chain system to perform indexing, retrieval, and generation.
- A Runnable lambda is used to execute the chain.
- The chain is tested using parallel chain invoke and returns a dictionary with context an d question keys.
- Key Terms and Concepts
- Runnable lambda
- Parallel chain invoke

- Dictionary
- Context and question keys
- Main chain

- 1. What is the purpose of the Runnable lambda in the chain system?
- 2. Explain the testing process of the chain with parallel chain invoke.
- 3. What information does the returned dictionary contain?
- 4. How is the main chain connected to the parallel chain?

■ Summary

- UI-based enhancements for a rack system can be made
- Running a rack system inside a Google Collab notebook, requiring manual user intervention
- Final product can be improved to appear as a website or Chrome plugin
- Evaluation of rack systems is critical for industry-grade systems
- Libraries like Rags and Langmith are used for evaluating rack systems

- UI-based enhancements
- Google Collab notebook
- Chrome plugin
- Evaluation of rack systems
- Rags and Langmith libraries
- Faithfulness, relevance, and context precision in evaluation
- Auto-generated transcripts and their errors
- Document ingestion, document splitting, and vector storage

- Semantic chunker for text splitting
- Vector store libraries like FYERS
- Industry-grade rack systems

- 1. How can a rack system be improved to appear as a website or a Chrome plugin?
- 2. Why is the evaluation of rack systems important in an industry-grade context?
- 3. What are some important evaluation metrics for rack systems?
- 4. How can auto-generated transcript errors be fixed?
- 5. What are the key stages in the document ingestion process for a rack system?

■ Summary

- Different stages of retrieval in a vector store system
- Tasks before retrieval such as pre-retrieval and multi-query generation
- Domain aware routing for complex rack systems
- Performing reranking in retrieval to improve performance
- Post-retrieval tasks such as contextual compression and answer grounding
- Context window optimization

- Vector store
- Cloud-based solution
- Pine cone type solution
- Pre-retrieval
- Multi-query generation
- Domain aware routing
- Reranking

- Contextual compression
- Prompt templating
- Answer grounding
- Context window optimization

- 1. What are the different stages of retrieval in a vector store system?
- 2. How can multi-query generation be beneficial in the retrieval process?
- 3. What is domain aware routing and when is it used?
- 4. How does reranking in retrieval improve performance?
- 5. Explain the concept of answer grounding and its importance in retrieval.

■ Summary

- LLMs process a certain number of tokens in the input
- Context window optimization involves trimming the context to ensure it does not cross the window limitation
- LLM generates the answer, also allowing for citations and guard railing
- Multimodal rack system processes text, images, and videos
- Agentic rack system operates as an Al agent, not just a chatbot
- Memory-based rack system can be personalized based on past interactions

- LLMs
- Context window optimization
- Multimodal rack system
- Agentic rack system
- Memory-based rack system

- Guard railing
- Advanced Rag

- 1. What is the purpose of context window optimization in LLMs?
- 2. How does the multimodal rack system differ from the agentic rack system?
- 3. What is the concept of guard railing in relation to LLM output?
- 4. How does the memory-based rack system personalize interactions based on past conversations?
- 5. What is the significance of Advanced Rag in the industry?

■ Summary

- Advanced Rag systems will be covered in a separate playlist called Advanced Rag after the Lang Chain playlist is completed.
- The goal of the video was to explain how to create a simple functional rack system.
- Key Terms and Concepts
- Lang Chain playlist
- Advanced Rag
- Functional rack system

■ Review Questions

- 1. When will the Advanced Rag systems be covered?
- 2. What was the goal of the video?
- 3. What will be covered in the separate playlist called Advanced Rag?