Module 4 Introduction - Retrieval Augmented Generation Evaluation and Observability

The module "Retrieval Augmented Generation Evaluation and Observability" provides a comprehensive exploration of advanced techniques and tools in the field of AI, focusing on enhancing chatbots and question-answering systems through Retrieval-Augmented Generation (RAG) systems. It explores the critical aspects of evaluating these systems, emphasizing the importance of faithfulness, relevance, and the prevention of hallucinations in AI responses. The module introduces tools like the FaithfulnessEvaluator and RAGAS, along with the Golden Context Dataset, offering insights into effective evaluation methodologies, including indexing, embedding, and generation metrics. Additionally, the module covers the LangChain framework and the LangSmith platform, providing practical knowledge on building and testing LLM-powered applications. Students will learn about the components of LangChain, such as Models, Vector Stores, and Chains, and the functionalities of the LangChain Hub.

vRAG - Metrics & Evaluation

In this lesson, you will learn about Retrieval-Augmented Generation (RAG) systems and their evaluation metrics, with a focus on improving chatbots and question-answering systems. The lesson introduces you to different approaches to analysis, the importance of faithfulness and answer relevancy, nuances of indexing and embedding metrics, and generation metrics aimed at preventing hallucinations in AI responses. It discusses the significance of the FaithfulnessEvaluator tool for checking the alignment of AI responses with retrieved context and introduces RAGAS and the Golden Context Dataset for system evaluation. Additionally, real-world setups for assessing and improving RAG systems are explored through examples of community-based tools, including comprehensive evaluation of retrieval metrics, holistic approach evaluations, and the custom RAG pipeline evaluation.

LangSmith and LangChain Fundamentals for LLM Applications

In this lesson, you will learn about the fundamentals of the LangChain framework and the newly introduced LangSmith platform to build and test LLM-powered applications. We will review LangChain components, such as Models, Vector Stores, and Chains, as well as principles of the LangChain Hub, including prompt exploration and versioning for collaborative prompt development. The lesson will guide you through setting up the LangSmith environment, creating an API key, and basics of prompt versioning and tracing. You will also learn how to use LangServe to deploy applications as a REST API and go through the process of reading and processing data from a webpage, storing it into Deep Lake vector store, and using prompts from the LangChain Hub to build a QuestionAnswering Chain application.

RAG - Metrics & Evaluation

Introduction

So far, we've observed that LLMs' response generation ability is improved by incorporating context from a vector database, a typical design approach used in RAG systems for chatbots and question-answering systems. RAG applications strive to produce factually grounded outputs supported by the context they retrieve. Creating an evaluation pipeline for these systems is crucial, as it allows for measuring the effectiveness of the added techniques. The evaluation process should focus on ensuring that the output meaningfully incorporates the context, avoiding mere repetition, and aiming to create responses that are comprehensive, non-repetitive, and devoid of redundancy.

RAG Metrics

A holistic approach in RAG system evaluation is to present a detailed assessment of individual components and the system as a whole. Setting the baseline values for elements like chunking logic and embedding models and then examining each part independently and in an end-to-end manner is key for understanding the impact of modifications on the system's overall performance. The holistic modules don't always need ground-truth labels, as they can be evaluated based on the query, context, response, and LLM interpretations.

Here are five metrics commonly used to evaluate RAG systems:

- **Correctness**: Checks if the answer generated matches the reference answer for the given query (labels required). The accuracy of the generated answer is verified by comparing it directly to a reference answer provided for the question.
- **Faithfulness**: Determines if the answer is accurate and doesn't contain fabrication, relative to the retrieved contexts. The faithfulness metric evaluates the integrity of the answer, ensuring it faithfully represents the information in the retrieved context by checking that the answer is accurate and free from distortions or fabrications that could misrepresent the source material.
- **Context Relevancy**: Measures the relevance of the retrieved context and the resulting answer to the original query. It does so by ensuring that the system only retrieves information in a way that is pertinent to the user's request.
- **Guideline Adherence**: Determines if the predicted answer follows a set of guidelines and whether the response meets predefined criteria, encompassing stylistic, factual, and ethical standards, so the answer responds to the query while also aligning with specific established norms.
- **Embedding Semantic Similarity:** Calculates the similarity score between embeddings of the generated answer and the reference answer (reference labels required).

The analysis starts broadly, focusing on the overarching goal of RAG applications to produce helpful outputs supported by contextually relevant facts from the retrievers. It is then narrowed down to specific evaluation metrics, including faithfulness, answer relevancy, and the Sensibleness and Specificity Average (SSA), focusing on avoiding hallucination in responses. Google's SSA metric evaluates open-domain chatbot responses for sensibleness (contextual coherence) and specificity (detailed and direct

responses). Initially involving human evaluators, this approach aims to ensure outputs are comprehensive yet not overly vague.
A high faithfulness score does not guarantee high relevance. For example, an answer that accurately reflects the context but lacks direct relevance to the question would score lower in answer relevance, especially if it includes incomplete or redundant information.

Faithfulness Evaluator

Avoiding vague responses is essential, but preventing LLMs from “hallucinating” is equally crucial. Hallucination refers to generating responses not grounded in factual content or context. LlamaIndex's `FaithfulnessEvaluator` assesses responses based on their alignment with the retrieved context, measuring this aspect. Faithfulness evaluation considers whether the response matches the retrieved context, aligns with the query, and adheres to the reference answer or guidelines. The result returns a boolean value indicating whether the response passed the accuracy and faithfulness checks.
To execute the following codes, we must initially install the necessary libraries. This can be done using the Python package manager. Afterward, set the API keys for both OpenAI and the Activeloop service, as we will access indexes from a dataset hosted on Deep Lake. Remember to replace the placeholders with your API keys.
The code for this lesson is also available through a Colab notebook, where you can follow along.
Copy

```
pip install -q llama-index==0.9.14.post3 deeplake==3.8.12 openai==1.3.8 cohere==4.37
```

Shell command to install the required libraries.

Copy

```
import os


os.environ["OPENAI_API_KEY"] = "<YOUR_OPENAI_KEY>"
os.environ["ACTIVELOOP_TOKEN"] = "<YOUR_ACTIVELOOP_TOKEN>"
```

Code to set the environment variables we need.

Here's an example illustrating how to evaluate a single response for faithfulness.
Copy

```
from llama_index import ServiceContext
from llama_index.llms import OpenAI


# build service context
llm = OpenAI(model="gpt-4", temperature=0.0)
service_context = ServiceContext.from_defaults(llm=llm)
```

```
from llama_index.vector_stores import DeepLakeVectorStore

from llama_index.storage.storage_context import StorageContext

from llama_index import VectorStoreIndex


vector_store =
DeepLakeVectorStore(dataset_path="hub://genai360/LlamaIndex_paulgraham_essay",
overwrite=False)

storage_context = StorageContext.from_defaults(vector_store=vector_store)


index = VectorStoreIndex.from_vector_store(

    vector_store, storage_context=storage_context

)


from llama_index.evaluation import FaithfulnessEvaluator


# define evaluator

evaluator = FaithfulnessEvaluator(service_context=service_context)


# query index

query_engine = index.as_query_engine()

response = query_engine.query(

    "What does Paul Graham do?"

)


eval_result = evaluator.evaluate_response(response=response)


print( "> response:", response )


print( "> evaluator result:", eval_result.passing )
```

The sample code.

Copy

```
> response: Paul Graham is involved in various activities. He is a writer and has
given talks on topics such as starting a startup. He has also worked on software
development, including creating software for generating websites and building online
stores. Additionally, he has been a studio assistant for a beloved teacher who is a
painter.
```

```
> evaluator result: True
```

The output.

Most of the previously mentioned code should be recognizable, as it involves generating an index from the Deep Lake vector store, using this index to query the LLM, and conducting the evaluation procedure. The query engine processes the question, and its response is then forwarded to the evaluator for analysis. Let's focus on the evaluation process, which starts by setting up an evaluator to assess the accuracy of responses based on the service context.

- The code initializes a `FaithfulnessEvaluator`, a tool designed to assess the accuracy of responses generated by the language model (GPT-4 in this case).
- The evaluator uses the `service_context` created earlier, which includes the configured GPT-4 model. This context provides the necessary environment and parameters for the language model to function.
- The primary role of the `FaithfulnessEvaluator` is to determine how closely the language model's responses adhere to accurate and reliable information. It uses a set of criteria or algorithms to compare the generated responses against known factual data or expected outputs.

The evaluator then checks the response for its faithfulness to factual information. This means it evaluates whether the response accurately and reliably reflects historical facts about the queried topic. The result of this evaluation (`eval_result`) is then checked to see if it meets the standards of accuracy set by the evaluator, indicated by `eval_result.passing`. The result returns a boolean value indicating whether the response passed the accuracy and faithfulness checks.

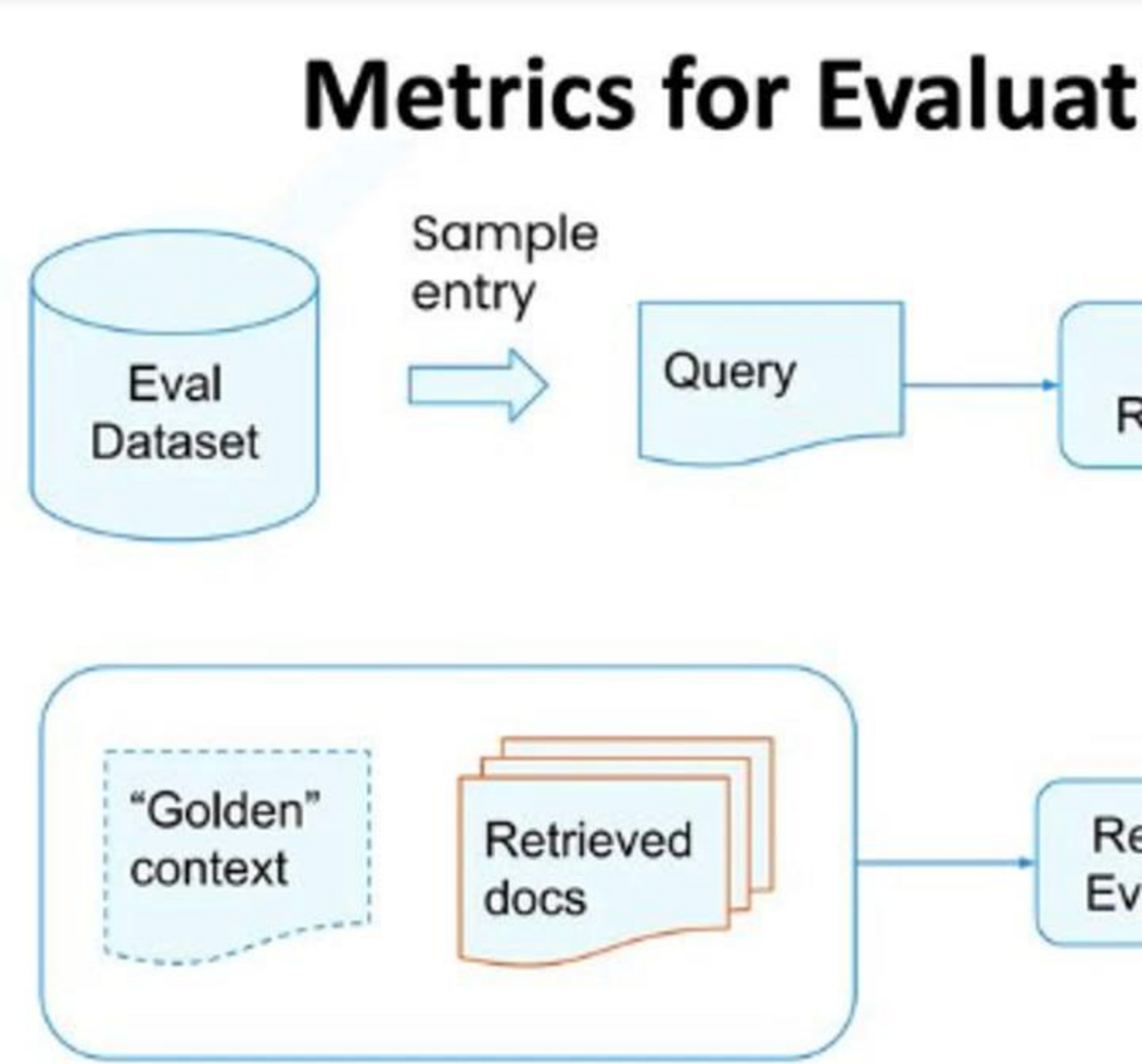
Retrieval Evaluation Metrics

The evaluation of retrieval in RAG systems involves determining the relevance of documents to specific queries.

✴

RAG system outputs need to encompass three critical aspects: factual accuracy, direct relevance to the query, and inclusion of essential contextual information.

In information retrieval, the main goal is to identify unstructured data that meets a specific information requirement within a database.



the evaluation metrics of retrieval in RAG systems.

Metrics for evaluating a retriever include Mean Reciprocal Rank (MRR), Hit Rate, MAP and NDCG.

- **MRR** measures the retrieval system's ability to return the best result as high up in the ranking as possible.
- **Hit Rate** evaluates the presence of relevant items within the top results returned, which is crucial where users only consider the first few results.

- **MAP (Mean Average Precision)**: is a measure of ranking quality across multiple queries. MAP calculates the mean of the average precisions for each query, where the average precision is computed as the mean of the precision scores after each relevant document is retrieved.
- **NDCG (Normalized Discounted Cumulative Gain)**: This metric evaluates the ranking of documents based on their relevance, giving more importance to relevant documents that appear higher in the ranking. It is normalized so that the perfect ranking's score is 1, allowing for comparison across different sets of queries.

The `RetrieverEvaluator` is a more advanced technique from LlamaIndex, which can calculate metrics such as Mean Reciprocal Rank (MRR) and Hit Rate. It is designed to evaluate the efficacy of a retrieval system, which retrieves data pertinent to user queries from a database or index. This class assesses the retriever's performance in relation to specific questions and expected results, providing benchmarks for evaluation.
Inferred from the evaluator's definition, it's necessary to compile an evaluation dataset comprising the contents, a collection of questions, and corresponding nodes that serve as references for answering these questions. The `generate_question_context_pairs` function in LlamaIndex can take care of generating an evaluation dataset. The rest of the process involves passing a query and using the dataset as a reference to ensure the chatbot retrieves the right documents. Please read the following tutorial for an example.

While the single-query evaluation is presented, the practical implementation in real-world scenarios often requires batch evaluations. A large set of queries and expected results are extracted from the retriever to determine its overall reliability. In batch testing, the retriever undergoes an assessment involving many queries and their corresponding expected results. Systematically querying the retriever with these varied inputs and evaluating its outputs against predefined correct answers is the method employed to measure its consistency accurately.

Golden Context Dataset

The Golden Context dataset would consist of carefully selected queries paired with an ideally matched set of sources that contain the answers. Optionally, it could also include the perfect answers that are expected to be generated by the LLM. For our purposes, 177 representative user queries have been manually curated. For each query, the most relevant source within our documentation has been diligently identified so that these sources directly address the queries in question. The Golden Context Dataset serves as our benchmark for precision evaluation. The dataset is structured around 'question' and 'source' pairings.
To create a Golden Dataset, gather a set of realistic customer questions and pair them with expert answers, then use this dataset to compare against responses from a language model for quality assurance, ensuring the LLM's answers align closely with the expert ones for accuracy and relevance. If you want to learn more about the dataset's creation, follow the link in the resources section.
Once the golden dataset is ready, the next step is to use it to measure the quality of LLM responses. After each evaluation, metrics like the following will be available to quantify the user experience. For example:

Similarity	Relevance	Coherence	Grounded-ness
3.7	77	88	69

⚠
Note: While synthetic question generation has benefits, it's not recommended for evaluating metrics related to real-world user experiences. Questions used in such evaluations should ideally mirror what actual users might ask, something not typically achieved with questions generated by an LLM. Hand-crafting questions with a focus on the users' perspective is advised for a more accurate reflection.

Community-Based Evaluation Tools

LlamaIndex incorporates various evaluation tools designed to foster community engagement and collaborative endeavors. The devices are structured to support a shared process of assessing and enhancing the system, empowering users and developers to play an active role in the evaluation. Through the use of tools shaped by community input, LlamaIndex creates a collaborative environment where constant feedback is smoothly incorporated, contributing to continual development.
Notable tools in this ecosystem include:

- Ragas: Another key tool that provides a framework for evaluating and integrating with LlamaIndex, offering detailed metrics.
- DeepEval: A tool designed for in-depth evaluation, facilitating comprehensive assessments of various aspects of the system.

Evaluating with Ragas

The evaluation process involves importing specific metrics from Ragas, such as *faithfulness, answer relevancy, context precision, context recall, and harmfulness.*
When evaluating using Ragas, the following elements are essential:

- **Query Engine**: This is the primary component and acts as the core of the evaluation process, where its performance is assessed.
- **Metrics**: Ragas provides a range of metrics specifically designed to evaluate a nuanced assessment of the engine's capabilities.
- **Questions**: A curated set of questions is required, which are used to probe the engine's ability to retrieve and generate accurate responses.

We must first set up a query engine to demonstrate how to use the Ragas library, which involves loading a document. For this, we will use the contents of the "New York City" Wikipedia page as our source document. Additionally, installing two more libraries is necessary: one for processing the webpage content and the other for the evaluation library itself.
Copy

```
pip install html2text==2020.1.16 ragas==0.0.22
```

The sample code.

At this point, we can use the `SimpleWebPageReader` class by providing a URL as its argument to load the content. These documents can then create the index and the query engine. Then, it is possible to ask questions about the document!
Copy

```
from llama_index.readers.web import SimpleWebPageReader

from llama_index import VectorStoreIndex, ServiceContext


documents = SimpleWebPageReader(html_to_text=True).load_data(
["https://en.wikipedia.org/wiki/New_York_City"] )


vector_index = VectorStoreIndex.from_documents(

    documents, service_context=ServiceContext.from_defaults(chunk_size=512)

)


query_engine = vector_index.as_query_engine()


response_vector = query_engine.query("How did New York City get its name?")


print(response_vector)
```

The sample code.

Copy

```
New York City got its name in honor of the Duke of York, who later became King James
II of England. The Duke of York was appointed as the proprietor of the former
territory of New Netherland, including the city of New Amsterdam, when England seized
it from Dutch control.
```

The output.

Returning to our goal of evaluating the models, the next step involves composing a series of questions, ideally derived from the original document, to ensure a more accurate performance assessment.
Copy

```
eval_questions = [

    "What is the population of New York City as of 2020?",

    "Which borough of New York City has the highest population?",

    "What is the economic significance of New York City?",

    "How did New York City get its name?",

    "What is the significance of the Statue of Liberty in New York City?",
```

```
]


eval_answers = [
    "8,804,000",  # incorrect answer
    "Queens",  # incorrect answer
    "New York City's economic significance is vast, as it serves as the global financial capital, housing Wall Street and major financial institutions. Its diverse economy spans technology, media, healthcare, education, and more, making it resilient to economic fluctuations. NYC is a hub for international business, attracting global companies, and boasts a large, skilled labor force. Its real estate market, tourism, cultural industries, and educational institutions further fuel its economic prowess. The city's transportation network and global influence amplify its impact on the world stage, solidifying its status as a vital economic player and cultural epicenter.",
    "New York City got its name when it came under British control in 1664. King Charles II of England granted the lands to his brother, the Duke of York, who named the city New York in his own honor.",
    "The Statue of Liberty in New York City holds great significance as a symbol of the United States and its ideals of liberty and peace. It greeted millions of immigrants who arrived in the U.S. by ship in the late 19th and early 20th centuries, representing hope and freedom for those seeking a better life. It has since become an iconic landmark and a global symbol of cultural diversity and freedom.",
]


eval_answers = [[a] for a in eval_answers]
```

The sample code.

This stage is the setup phase of the evaluation process. QueryEngine's proficiency is assessed based on how effectively it processes and responds to these specific questions, utilizing the answers as a standard for measuring performance. We need to import the metrics from the Ragas library.
Copy

```
from ragas.metrics import (
    faithfulness,
    answer_relevancy,
    context_precision,
    context_recall,
)
from ragas.metrics.critique import harmfulness


metrics = [
```

```
    faithfulness,
    answer_relevancy,
    context_precision,
    context_recall,
    harmfulness,
]
```

The `metrics` list compiles the metrics into a collection, which can then be used in the evaluation process to assess various aspects of the `QueryEngine`'s performance. The results, which include scores for each metric, can be further analyzed.
Finally, let's run the evaluation:
Copy

```
from ragas.llama_index import evaluate


result = evaluate(query_engine, metrics, eval_questions, eval_answers)


# print the final scores
print(result)
```

The sample code.

Copy

```
evaluating with [faithfulness]
100%|██████████| 1/1 [00:16<00:00, 16.95s/it]
evaluating with [answer_relevancy]
100%|██████████| 1/1 [00:03<00:00,  3.54s/it]
evaluating with [context_precision]
100%|██████████| 1/1 [00:02<00:00,  2.73s/it]
evaluating with [context_recall]
100%|██████████| 1/1 [00:07<00:00,  7.06s/it]
evaluating with [harmfulness]
100%|██████████| 1/1 [00:02<00:00,  2.16s/it]


{'faithfulness': 0.8000, 'answer_relevancy': 0.7634, 'context_precision': 0.6000,
'context_recall': 0.8667, 'harmfulness': 0.0000}
```

The output.

The metrics analysis quantifies different aspects of the RAG system's performance:

1. `faithfulness`: **0.8000**

- measures how accurately the system's responses adhere to the factual content of the source material. A score of 0.7 indicates *relatively high* faithfulness, meaning the responses are mostly accurate and true to the source.

2. `answer_relevancy`: **0.7634**
   - measures how relevant the system's responses are to the given queries. A high score of 0.955 suggests that the majority of the system's responses are *closely aligned* with the queries' intent.
3. `context_precision`: **0.6000**
   - evaluates the precision of the context used by the system to generate responses. A lower score of 0.2335 indicates that the context used *often includes irrelevant* information.
4. `context_recall`: **0.8667**
   - measures the recall rate of relevant context determined by the system. A high score of 0.98 suggests that the system is *very effective* in retrieving most of the relevant context.
5. `harmfulness`: **0.0000**
   - measures the system for harmful or inappropriate content generation. A score of 0 implies that *no harmful content* was generated in the evaluated responses.

The Custom RAG Pipeline Evaluation

For a practical evaluation of a custom RAG system, it is essential to employ a range of assessment benchmarks instrumental in assessing various facets of the RAG system, such as its effectiveness and reliability. The variety of measures guarantees a detailed evaluation and in-depth insight into the system's overall capabilities. This section involves developing a tailored evaluation pipeline, beginning with loading a dataset, forming an evaluation dataset from its contents, and then calculating the metrics we have previously discussed. Initially, we download the text file to serve as the dataset.
Copy

```
wget 'https://raw.githubusercontent.com/idontcalculate/data-repo/main/venus_transmission.txt'
```

The sample code.

Copy

```
--2023-12-18 20:21:53--  https://raw.githubusercontent.com/idontcalculate/data-repo/main/venus_transmission.txt

Resolving raw.githubusercontent.com (raw.githubusercontent.com)... 185.199.108.133, 185.199.109.133, 185.199.110.133, ...

Connecting to raw.githubusercontent.com (raw.githubusercontent.com)|185.199.108.133|:443... connected.

HTTP request sent, awaiting response... 200 OK

Length: 19241 (19K) [text/plain]

Saving to: ‘venus_transmission.txt’


venus_transmission. 100%[===================>]  18.79K  --.-KB/s    in 0.001s
```

```
2023-12-18 20:21:53 (32.6 MB/s) - ‘venus_transmission.txt’ saved [19241/19241]
```

The output.

Then, the text file can be loaded as a `Document` object, identifiable by LlamaIndex.
Copy

```
from llama_index import SimpleDirectoryReader


reader = SimpleDirectoryReader(input_files=["/content/venus_transmission.txt"])


docs = reader.load_data()

print(f"Loaded {len(docs)} docs")
```

The sample code.

Copy

```
Loaded 1 docs
```

The output.

The `SimpleNodeParser`, in this context, converts documents into a structured format known as nodes and serves for customization in parsing documents, specifically in terms of defining the chunk size, managing overlap, and incorporating metadata. Each chunk of the document is treated as a node. In this case, the parser is set with a `chunk_size` of 512, meaning each node will consist of 512 characters from the original document. These chunks can then be used to generate the indexes.
Copy

```
from llama_index.node_parser import SimpleNodeParser

from llama_index import VectorStoreIndex


# Build index with a chunk_size of 512

node_parser = SimpleNodeParser.from_defaults(chunk_size=512)

nodes = node_parser.get_nodes_from_documents(docs)

vector_index = VectorStoreIndex(nodes)
```

The sample code.

The indexes can now be used as a query engine to query a specific question concerning the source document.
Copy

```
query_engine = vector_index.as_query_engine()
```

```
response_vector = query_engine.query("What was The first beings to inhabit the
planet?")

print( response_vector.response )
```

The sample code.

Copy

```
The first beings to inhabit the planet were a dinoid and reptoid race from two
different systems outside our solar system.
```

The output.

The response generated by the query engine is stored in `response_vector`. So, the document is processed into nodes, indexed, and then queried using a language model. To investigate the response further, we can use the `.source_nodes` key to access the retrieved document from the index used to answer the question.
Copy

```
# First retrieved node

response_vector.source_nodes[0].get_text()
```

The sample code.

Copy

```
They had heard of this beautiful new planet. At this time, Earth had two moons to
harmonize the weather conditions and control the tides of the large bodies of water.

The first beings to inhabit the planet were a dinoid and reptoid race from two
different systems outside our solar system. They were intelligent and walked on two
legs like humans and were war-like considering themselves to be superior to all other
life forms. In the past, the four races of humans had conflicts with them before they
outgrew such behavior. They arrived on Earth to rob it of its minerals and valuable
gems. Soon they had created a terrible war. They were joined by re-

1

enforcements from their home planets. One set up its base on one of the Earth's
moons, the other on Earth. It was a terrible war with advanced nuclear and laser
weapons like you see in your science fiction movies. It lasted very long. Most of the
life forms lay in singed waste and the one moon was destroyed. No longer interested
in Earth, they went back to their planets leaving their wounded behind, they had no
use for them.

The four races sent a few forces to see if they could help the wounded dinoids and
reptilians and to see what they could do to repair the Earth. They soon found that
due to the nuclear radiation it was too dangerous on Earth before it was cleared.
Even they had to remain so as not to contaminate their own planets.

Due to the radiation, the survivors of the dinoids and reptoids mutated into the
Dinosaurs and giant reptilians you know of in your history. The humans that were
trapped there mutated into what you call Neanderthals.

The Earth remained a devastated ruin, covered by a huge dark nuclear cloud and what
vegetation was left was being devoured by the giant beings, also humans and animals
by some. It was this way for hundreds of years before a giant comet crashed into one
```

of the oceans and created another huge cloud. This created such darkness that the radiating heat of the Sun could not interact with Earth's gravitational field and an ice age was created. This destroyed the mutated life forms and gave the four races the chance to cleanse and heal the Earth with technology and their energy.

Once again, they brought various forms of life to the Earth, creating again a paradise, except for extreme weather conditions and extreme tidal activities.

The output.

We can index the second item on the list to view the content of the second node that contributed to the generation of the content.
Copy

```
# Second retrieved node

response_vector.source_nodes[1].get_text()
```

The sample code.

Copy

Due to the radiation, the survivors of the dinoids and reptoids mutated into the Dinosaurs and giant reptilians you know of in your history. The humans that were trapped there mutated into what you call Neanderthals.

The Earth remained a devastated ruin, covered by a huge dark nuclear cloud and what vegetation was left was being devoured by the giant beings, also humans and animals by some. It was this way for hundreds of years before a giant comet crashed into one of the oceans and created another huge cloud. This created such darkness that the radiating heat of the Sun could not interact with Earth's gravitational field and an ice age was created. This destroyed the mutated life forms and gave the four races the chance to cleanse and heal the Earth with technology and their energy.

Once again, they brought various forms of life to the Earth, creating again a paradise, except for extreme weather conditions and extreme tidal activities.

During this time they realized that their planets were going into a natural dormant stage that they would not be able to support physical life. So they decided to colonize the Earth with their own people. They were concerned about the one moon, because it is creating earthquakes and tidal waves and storms and other difficulties for the structure of the Earth. They knew how to drink fluids to protect and balance themselves. These were the first colonies like Atlantis and Lemuria.

The rest of the people stayed on their planets to await their destiny. They knew that they would perish and die. They had made the decision only to bring the younger generation with some spiritual teachers and elders to the Earth. The planet was too small for all of them. But they had no fear of death.

They had once again created a paradise. They were instructed to build special temples here as doorways to the other dimensions. Because of the aggressive beings, the temples were hidden for future times when they will be important. There they could do their meditations and the higher beings.

They were informed to build two shields around the Earth out of ice particles to balance the influence of the one moon. They created a tropical climate for the Earth. There were no deserts at that time. They have special crystals for these doorways and they were able to lower their vibration to enter through these doorways. The news spread of the beautiful planet.

The output.

You can view the textual information from the second node that the query engine found relevant, providing additional context or information in response to the query. This helps understand the breadth of knowledge the query engine pulls from and how different parts of the indexed documents contribute to the overall response.
As previously mentioned, our task involves creating an evaluation dataset. This essentially entails generating a series of questions and their respective answers, all in relation to the content we have loaded. The `generate_question_context_pairs` class leverages the LLM to create questions based on the content of each node: For each node, two questions will be created, resulting in a dataset where each item consists of a context (the node's text) and a corresponding set of questions. The Q&A dataset will serve us to evaluate the capabilities of an RAG system in question generation and context understanding tasks. You can see the first ten questions in the output.
Copy

```
from llama_index.llms import OpenAI
from llama_index.evaluation import generate_question_context_pairs


# Define an LLM
llm = OpenAI(model="gpt-3.5-turbo")


qa_dataset = generate_question_context_pairs(
    nodes,
    llm=llm,
    num_questions_per_chunk=2
)


queries = list(qa_dataset.queries.values())
print( queries[0:10] )
```

The sample code.

Copy

```
100%|██████████| 13/13 [00:31<00:00,  2.46s/it]


['Explain the role of different alien races in the history of our solar system
according to the information provided. How did these races contribute to the
transformation process and why was Earth considered a special planet?', 'Describe the
advanced abilities and technology possessed by the Masters and beings mentioned in
the context. How did their understanding of creation and their eternal nature shape
their perspective on life and death?', 'How did the four races of humans demonstrate
their mastery of creativity and what were the potential consequences of using this
```

power for selfish reasons?', 'Describe the initial state of Earth before it became a planet and how the four races of humans contributed to its transformation into a unique paradise.', 'How did the arrival of the dinoid and reptoid races on Earth lead to a devastating war? Discuss the reasons behind their conflict with the four races of humans and the impact it had on the planet.', "Explain the process of mutation that occurred among the survivors of the dinoids and reptoids, resulting in the emergence of dinosaurs and Neanderthals. Discuss the role of nuclear radiation and its effects on the Earth's environment and living organisms.", 'How did the survivors of the dinoids and reptoids mutate into the dinosaurs and giant reptilians we know of in history? Explain the role of radiation in this process.', 'Describe the events that led to the creation of an ice age on Earth. How did this ice age affect the mutated life forms and provide an opportunity for the four races to cleanse and heal the Earth?', 'Explain the purpose and significance of building special temples as doorways to other dimensions in the context of the given information. How did these temples serve the people and protect them from the dark forces?', 'Discuss the actions taken by the colonies in response to the war declared by another race of humans. How did the colonies ensure the preservation of their knowledge and technology, and what measures did they take to protect themselves from the dark forces?', 'How did the inhabitants of Lemuria and Atlantis ensure that their knowledge and technology would not be misused by the dark forces?', 'What measures were taken by the controlling forces to prevent the people from communicating with other dimensions and remembering their past lives or the hidden temples?', 'How has the manipulation and control of human beings by the rich and powerful impacted society throughout history? Discuss the role of religion, race, and power in perpetuating this control and the potential consequences for humanity.', 'Explain the role of the Galactic Brotherhood and other spiritually evolved beings in the transformation of Earth. How have they worked to change the energy of the planet and its inhabitants? Discuss the potential risks they aim to mitigate, such as genetic manipulation and the use of destructive technologies.', "Explain the role of the Galactic Brotherhood in the transformation of the planet's energy and the introduction of new technologies. How are different beings, such as the Spiritual Hierarchy, Ascended Masters, and nature spirits, cooperating in this process?", 'Discuss the significance of the hidden temples and the space ships in the frequency change of the Earth. How do these elements contribute to the gradual transformation and what effects do they have on the environment?', 'Explain the concept of chakras and their role in the transformation process described in the context information. How do chakras relate to the abilities of mental telepathy, intuition, and past life recollection?', "Discuss the significance of the Earth's future purpose as mentioned in the context information. How does it differ from its past role? How does the concept of yin and yang, as well as the negative and positive energies, tie into this transformation?", 'How does the concept of division into good and bad energies contribute to the perpetuation of negative forces and selfishness among individuals?', 'Discuss the shift in power dynamics from feminine qualities to male energy in societies after genetic manipulation. How does the future vision of equal and balanced male and female powers impact the purpose of Earth for human beings?', 'How has the balance of feminine and masculine energies shifted throughout human history, and what is the envisioned future for this balance on Earth?', 'In the future described in the context information, how will individuals govern themselves and what role will manmade laws play in society?', 'How does the concept of obeying spiritual laws contribute to living in harmony on other planets for millions of years? Provide examples or evidence from the context information to support your answer.', 'According to the context information, what are some key aspects of the future living style and awareness on Earth after the transformation is complete? How do these aspects differ from the current state of existence?', "How does the concept of eternity and the ability to overcome time and aging impact one's perspective on

```
life and the enjoyment of experiences?", 'In what ways can individuals create a
balance and harmony within themselves, and why is it important for them to do so?']
```

The output.

The `RetrieverEvaluator` class can now use this QA dataset to evaluate the retriever's performance. It queries each question using the retriever and evaluates which chunks are returned as the answer. The higher MRR and Hit rate numbers represent the retriever's ability to identify the chunk with the correct answer.

Copy

```python
from llama_index.evaluation import RetrieverEvaluator


retriever = vector_index.as_retriever(similarity_top_k=2)


retriever_evaluator = RetrieverEvaluator.from_metric_names(
    ["mrr", "hit_rate"], retriever=retriever
)


# Evaluate
eval_results = await retriever_evaluator.aevaluate_dataset(qa_dataset)


def display_results(name, eval_results):
    """Display results from evaluate."""

    metric_dicts = []
    for eval_result in eval_results:
        metric_dict = eval_result.metric_vals_dict
        metric_dicts.append(metric_dict)


    full_df = pd.DataFrame(metric_dicts)


    hit_rate = full_df["hit_rate"].mean()
    mrr = full_df["mrr"].mean()


    metric_df = pd.DataFrame(
        {"Retriever Name": [name], "Hit Rate": [hit_rate], "MRR": [mrr]}
    )
```

```
    return metric_df


display_results("OpenAI Embedding Retriever", eval_results)
```

The sample code.

Copy

	Retriever Name	Hit Rate	MRR
0	OpenAI Embedding Retriever	0.884615	0.730769

The output.

We can now enhance our analysis of the application's performance by including additional metrics like faithfulness and relevancy. To achieve this, we utilize a subset of the generated Q&A dataset and create instances of both GPT-3.5 and GPT-4. It's advisable to employ a more advanced model like GPT-4 for evaluation purposes while using the less expensive model for the generation process.
Copy

```
# gpt-3.5-turbo
gpt35 = OpenAI(temperature=0, model="gpt-3.5-turbo")
service_context_gpt35 = ServiceContext.from_defaults(llm=gpt35)


# gpt-4
gpt4 = OpenAI(temperature=0, model="gpt-4")
service_context_gpt4 = ServiceContext.from_defaults(llm=gpt4)


vector_index = VectorStoreIndex(nodes, service_context = service_context_gpt35)
query_engine = vector_index.as_query_engine()


eval_query = queries[10]
response_vector = query_engine.query(eval_query)


print( "> eval_query: ", eval_query )
print( "> response_vector:", response_vector )
```

The sample code.

Copy

```
> eval_query:  How did the colonies respond to the declaration of war by the dark forces, and what measures did they take to protect their knowledge and technology?

> response_vector: The colonies did not fight back against the dark forces when they declared war. Instead, they sent most of their people into hiding in order to rebuild the colonies later. They also destroyed everything to ensure that their knowledge and technology would not fall into the hands of the dark forces. Additionally, Lemuria and Atlantis were destroyed by their inhabitants to prevent the misuse of their knowledge and technology by the dark forces.
```

The output.

Now, we can establish the evaluator classes responsible for measuring each metric. We'll then use a sample response to determine if it meets the test criteria.

Copy

```
from llama_index.evaluation import RelevancyEvaluator

from llama_index.evaluation import FaithfulnessEvaluator


relevancy_gpt4 = RelevancyEvaluator(service_context=service_context_gpt4)

faithfulness_gpt4 = FaithfulnessEvaluator(service_context=service_context_gpt4)


# Compute faithfulness evaluation


eval_result = faithfulness_gpt4.evaluate_response(response=response_vector)

# check passing parameter in eval_result if it passed the evaluation.

print( eval_result.passing )


# Relevancy evaluation

eval_result = relevancy_gpt4.evaluate_response(

    query=eval_query, response=response_vector

)

# You can check passing parameter in eval_result if it passed the evaluation.

print( eval_result.passing )
```

The sample code.

Copy

```
True

True
```

The output.

We must perform a for-loop to feed each sample from the evaluation dataset and get the appropriate results. In this situation, we can use the LlamaIndex `BatchEvalRunner` class, which runs the evaluation process in batches and concurrently. It means the evaluation can be done faster.

Copy

```
#Batch Evaluator:

#BatchEvalRunner to compute multiple evaluations in batch wise manner.


from llama_index.evaluation import BatchEvalRunner


# Let's pick top 10 queries to do evaluation

batch_eval_queries = queries[:10]


# Initiate BatchEvalRunner to compute FaithFulness and Relevancy Evaluation.

runner = BatchEvalRunner(

    {"faithfulness": faithfulness_gpt4, "relevancy": relevancy_gpt4},

    workers=8,

)


# Compute evaluation

eval_results = await runner.aevaluate_queries(

    query_engine, queries=batch_eval_queries

)


# get faithfulness score

faithfulness_score = sum(result.passing for result in eval_results['faithfulness']) /
len(eval_results['faithfulness'])

# get relevancy score

relevancy_score = sum(result.passing for result in eval_results['faithfulness']) /
len(eval_results['relevancy'])


print( "> faithfulness_score", faithfulness_score )

print( "> relevancy_score", relevancy_score )
```

The sample code.

Copy

```
> faithfulness_score 1.0

> relevancy_score 1.0
```

The output.

The batch processing method helps in quickly assessing the system's performance over a range of different queries. A faithfulness score of 1.0 signifies that the generated answers contain no hallucinations and are entirely based on retrieved context. Additionally, the Relevance score of 1.0 suggests that the answers generated consistently align with the retrieved context and the queries.

Conclusion

This lesson has guided us through constructing and assessing an RAG pipeline using LlamaIndex, concentrating mainly on evaluating the retrieval system and the responses generated within the pipeline. Assessing LLMs and chatbots presents a challenge due to the subjective nature of their outputs. Perceptions of what constitutes a great response can vary significantly from one person to another. Therefore, examining various facets of an RAG application and evaluating each aspect individually based on specific metrics is prudent.
>> Notebook.

RESOURCES:

- Response Evaluation
- Retrieval Evaluation
- **openai-cookbook-eval**
  github.com

- **llamaindex**
  Evaluating - LlamaIndex □ 0.9.15
  docs.llamaindex.ai

- **golden-dataset**
  github.com

- **RAGAS**
  github.com

- `RagEvaluatorPack`

  Downloading a LlamaDataset from LlamaHub - LlamaIndex □ 0.9.15.post2
  docs.llamaindex.ai

LangSmith Introduction

In this lesson, we will recap LangChain components, review its essential concepts, and discuss how to use the newly introduced LangSmith platform. Additionally, we will create a basic Large Language Model application to understand its capabilities better.

LangChain Recap

LangChain is a specialized framework designed for building LLM-powered applications. It streamlines the development of intelligent, responsive LLMs and Libraries for handling chains and agents with integrated components. It also offers Templates for deployable task-specific architectures and LangSmith for debugging in a testing environment. The key features of LangChain, like Models, Vector Stores, Chains, etc., have been explained in detail in the previous lesson.

While LangChain is suitable for prototyping, LangSmith enables an environment for debugging, testing, and optimizing LLM apps.

LangChain Hub

LangChain Hub is a centralized repository for community-sourced prompts tailored to various use cases like classification or summarization. The Hub supports both public contributions and private organizational use, fostering a collaborative development environment. The platform's version control system enables users to track prompt modifications and maintain consistency across applications.

The Hub offers features like **Prompt Exploration**, ideal for fresh interactions with language models or specific prompts to achieve particular objectives. It also simplifies the process of finding and utilizing effective prompts for various models. Additionally, the user can share, modify, and track prompt versions with **Prompt Versioning**. It allows for the easy management of different versions of prompts, a highly relevant feature in real-world projects where reverting to earlier versions may be necessary. The user-friendly interface of the Hub allows for prompt testing, customization, and iteration in a playground environment.

Discover, version control, and experiment with different prompts for LangChain and LLMs directly in your browser: docs.smith.langchain.com.

LangSmith

LangSmith provides an environment for evaluating and monitoring the quality of LLM outputs. An integral part of its functionality includes metadata monitoring, token usage, and execution time, which are crucial for resource management.

This platform facilitates the refinement of new chains and tools, potentially enhancing their efficiency and performance. Users can create diverse testing environments tailored to specific needs, enabling thorough evaluation under various conditions. Additionally,

the service provides visualization tools that can aid in identifying response patterns and trends, thereby supporting a deeper understanding and assessment of performance. Lastly, the platform supports tracing the runs associated with an active instance and testing and evaluating any prompts or answers generated.
LangSmith is designed with user-friendliness in mind. The platform offers a range of tutorials and documentation to help you get started.
The setup for LangChain requires installing the necessary libraries and configuring the required environment variables, which we will cover in the following section. For certain functionalities like tracing, you need to have a LangSmith account. Please follow the steps outlined below to set up a new account.

- Head over to the LangSmith website and sign up for an account. You can use various supported login methods.
- Once your account is set up, go to the settings page. Here, you'll find the option to create an API key.
- Click the 'Generate API Key' button to receive your API key.

Versioning

You can commit a prompt after implementing and debugging your chain. Add this prompt under your handle's namespace to view it in the Hub.
Copy

```
from langchain import hub

from langchain.prompts.chat import ChatPromptTemplate


prompt = ChatPromptTemplate.from_template("tell me a joke about {topic}")


handle = "<YOUR_USERNAME>"

hub.push(f"{handle}/rag", prompt)Copy
```

The sample code.

During evaluation, if you come up with a better idea after trying the prompt, you can push the updated prompt to the same key to "commit" a new version of the prompt. For instance, let's add a system message to the prompt.
Copy

```
# You may try making other changes and saving them in a new commit.

from langchain import schema


prompt.messages.insert(0,

   schema.SystemMessage(

       content="You are a precise, autoregressive question-answering system."

   )
```

```
)Copy
```

The sample code.

With the saved changes, we can analyze how the change reflects the model performance. The newest version of the prompt is saved as the latest version.
Copy

```
# Pushing to the same prompt "repo" will create a new commit

hub.push(f"{handle}/rag-prompt", prompt)Copy
```

The sample code.

Tracing

LangSmith allows users to review the inputs and outputs of each element in the chain by simplifying the process of logging runs for your LLM applications. This feature is useful when debugging your application or understanding the behavior of specific components. The following section will explore the optional environment variables that enable the tracing feature. For more information, you can visit the documentation.

Serving (LangServe)

LangServe helps developers deploy LangChain-powered applications and chains as a REST API. It is integrated with FastAPI, which makes the process of creating API endpoints easy and accessible. It is possible to quickly deploy applications by using the `langserve` package. The deployment process is out of the scope of this course. However, you can learn more about the process from the Github repository.

QuestionAnswering Chain & LangChain Hub

The next steps are loading data from a webpage, splitting it into smaller chunks, transforming them into embeddings, storing them on the Deep Lake vector store, and utilizing the prompt templates from the LangSmith Hub.
Before exploring the code, installing the essential libraries from the Python package (pip) manager is necessary.
Copy

```
pip install -q langchain==0.0.346 openai==1.3.7 tiktoken==0.5.2 cohere==4.37
deeplake==3.8.11 langchainhub==0.1.14Copy
```

The sample command.

The next step is to set the API keys in the environment for OpenAI, utilized in the embedding generation process, and the Activeloop key, required for storing data in the cloud.
Copy

```
import os
```

```
os.environ["OPENAI_API_KEY"] = "<YOUR_OPENAI_API_KEY>"

os.environ["ACTIVELOOP_TOKEN"] = "<YOUR_ACTIVELOOP_API_KEY>"Copy
```

The sample code.

You can optionally use the following environment variables to keep track of the runs in the LangSmith dashboard under the projects section.
Copy

```
os.environ["LANGCHAIN_TRACING_V2"]=True

os.environ["LANGCHAIN_ENDPOINT"]="https://api.smith.langchain.com"

os.environ["LANGCHAIN_API_KEY"]="<YOUR_LANGSMITH_API_KEY>"

os.environ["LANGCHAIN_PROJECT"]="langsmith-intro" # if not specified, defaults to
"default"Copy
```

The sample code.

Now, we can read the content of a webpage using the `WebBaseLoader` class. It will return a single instance of the `Document` class containing all the textual information from the mentioned address. Subsequently, the lengthy text is divided into smaller segments of 500 characters each, with no overlap, resulting in 130 chunks.
Copy

```
from langchain.document_loaders import WebBaseLoader

from langchain.text_splitter import RecursiveCharacterTextSplitter


# Loading

loader = WebBaseLoader("https://lilianweng.github.io/posts/2023-06-23-agent/")

data = loader.load()

print(len(data))


# Split

text_splitter = RecursiveCharacterTextSplitter(chunk_size=500, chunk_overlap=0)

all_splits = text_splitter.split_documents(data)

print(len(all_splits))Copy
```

The sample code.

Copy

```
1

130
```

The output.

Chunks can be saved to the Deep Lake vector store through LangChain integration. The DeepLake class handles converting texts into embeddings via OpenAI's API and then stores these results in the cloud. The dataset can be loaded from the GenAI360 course organization, or you can use your organization name (which defaults to your username) to create the dataset. Note that this task incurs the associated costs of using OpenAI endpoints.
Copy

```
from langchain.embeddings import OpenAIEmbeddings

from langchain.vectorstores import DeepLake


vectorstore = DeepLake.from_documents(

                                                all_splits,


        dataset_path="hub://genai360/langsmith_intro",

                                                embedding=OpenAIEmbeddings(),
overwrite=False)Copy
```

The sample code.

Copy

```
Your Deep Lake dataset has been successfully created!

Creating 130 embeddings in 1 batches of size 130:: 100%|██████████| 1/1 [00:05<00:00,
5.81s/it] dataset (path='hub://genai360/langsmith_intro', tensors=['text',
'metadata', 'embedding', 'id'])


  tensor      htype       shape      dtype  compression

  -------    -------     -------    -------  -------

   text       text      (130, 1)      str     None

 metadata     json      (130, 1)      str     None

 embedding  embedding  (130, 1536)  float32   None

    id         text      (130, 1)      str     NoneCopy
```

The output.

Once the data is processed, we can retrieve a prompt from the LangChain hub, which provides a `ChatPromptTemplate` instance. This eliminates the need for designing a prompt through trial and error, allowing us to build upon already tested implementations. The following code tagged a specific prompt version so future changes would not impact the active deployment version.
Copy

```
from langchain import hub
```

```
prompt = hub.pull("rlm/rag-prompt:50442af1")

print(prompt)Copy
```

The sample code.

Copy

```
ChatPromptTemplate(input_variables=['context', 'question'],
messages=[HumanMessagePromptTemplate(prompt=PromptTemplate(input_variables=['context'
, 'question'], template="You are an assistant for question-answering tasks. Use the
following pieces of retrieved context to answer the question. If you don't know the
answer, just say that you don't know. Use three sentences maximum and keep the answer
concise.\nQuestion: {question} \nContext: {context} \nAnswer:"))])
```

The output.

Finally, we can employ the `RetrievalQA` chain to fetch related documents from the database and utilize the `ChatOpenAI` model to use these documents to generate our final response.

Copy

```
# LLM

from langchain.chains import RetrievalQA

from langchain.chat_models import ChatOpenAI


llm = ChatOpenAI(model_name="gpt-3.5-turbo", temperature=0)


# RetrievalQA

qa_chain = RetrievalQA.from_chain_type(

    llm,

    retriever=vectorstore.as_retriever(),

    chain_type_kwargs={"prompt": prompt}

)


question = "What are the approaches to Task Decomposition?"

result = qa_chain({"query": question})

result["result"]Copy
```

The sample code.

Copy

```
The approaches to task decomposition include using LLM with simple prompting, task-
specific instructions, and human inputs.
```

The output.

Prompt versioning supports ongoing experimentation and collaboration, effectively preventing the accidental deployment of chain components that haven't been sufficiently validated.

Conclusion

In this lesson, we discussed how to use the LangChain Hub to store and share prompts for a retrieval QA chain. The Hub is a centralized location to manage, version, and share prompts. LangSmith excels in diagnosing errors, comparing prompt effectiveness, assessing output quality, and tracking key metadata like token usage and execution time for optimizing LLM applications.

The platform also provides a detailed analysis of how different prompts affected the LLM performance. The intuitive UI and the valuable insights the platform offers make the iterative process of refining LLMs more transparent and manageable. It's evident that the LangSmith platform, even in its beta phase, has the potential to be a significant tool for developers aiming to leverage the full potential of LLMs.

LangSmith provides an immediate functionality to sift through your runs and presents metrics. These metrics are essential for quickly assessing latency and the total token count throughout your application.

>> Notebook.

RESOURCES:

- hub-examples: LangSmith cookbook

  github.com
  github.com

- the art of LangSmith article
  - **The Art of LangSmithing**
  - A guide to testing, evaluating, and monitoring LLM calls for production using LangSmith.
  - betterprogramming.pub

Building Fullstack Applications with LlamaIndex: LlamaPacks & more

https://youtu.be/wV4ajKStYSc

Technical Report: Boosting Cosine Similarity & Retrieval Accuracy with Intel CPUs & Deep Memory

https://github.com/activeloopai/deeplake