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Databricks Databricks-Generative-AI-Engineer-Associate Exam Syllabus Topics:

Topic	Details
Topic 1	• Design Applications: The topic focuses on designing a prompt that elicits a specifically formatted response. It also focuses on selecting model tasks to accomplish a given business requirement. Lastly, the topic covers chain components for a desired model input and output.

Topic 2	• Application Development: In this topic, Generative AI Engineers learn about tools needed to extract data, Langchain • similar tools, and assessing responses to identify common issues. Moreover, the topic includes questions about adjusting an LLM's response, LLM guardrails, and the best LLM based on the attributes of the application.
Topic 3	• Assembling and Deploying Applications: In this topic, Generative AI Engineers get knowledge about coding a chain using a pyfunc mode, coding a simple chain using langchain, and coding a simple chain according to requirements. Additionally, the topic focuses on basic elements needed to create a RAG application. Lastly, the topic addresses sub-topics about registering the model to Unity Catalog using MLflow.

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Databricks Certified Generative AI Engineer Associate Sample Questions (Q64-Q69):

NEW QUESTION # 64
A Generative AI Engineer at a legal firm is designing a RAG system to analyze historical legal cases. The system needs to process millions of court opinions and legal documents, already organized by time and topic, to track how interpretations of specific laws have evolved over time. All of these documents are in plain-text. The engineer needs to choose a chunking method that would most effectively preserve continuity and the temporal nature of the cases. Which method do they choose?

- A. Implement windowed summarization with overlapping chunks.
- B. Implement sentence level embeddings with each chunk tagged with the time to enable metadata filtering.
- C. Implement paragraph level embeddings with each chunk.
- D. Implement a hierarchical tree structure, like RAPTOR, to group similar legal concepts.

Answer: A

Explanation:
In the context of legal document analysis where the "evolution of interpretation" is the primary goal, preserving narrative continuity is paramount. Windowed summarization with overlapping chunks is the most effective method for this use case. Overlapping (e.g., 10-15% of the chunk size) ensures that sentences or concepts split at the boundary of one chunk are preserved in the next, preventing the loss of critical context that often occurs in legal jargon. Furthermore, windowed summarization allows the system to condense long-form court opinions into manageable parts while maintaining the chronological "thread" of the argument. While sentence-level embeddings with metadata (D) are useful for filtering, they often lack the sufficient context required to understand the nuances of a legal ruling. A windowed approach provides the LLM with enough surrounding text to understand the "why" behind a legal evolution, rather than just the "when."

NEW QUESTION # 65
Which indicator should be considered to evaluate the safety of the LLM outputs when qualitatively assessing LLM responses for a translation use case?

- A. The similarity to the previous language
- B. The latency of the response and the length of text generated
- C. The accuracy and relevance of the responses

- D. The ability to generate responses in code

Answer: C

Explanation:
* Problem Context: When assessing the safety and effectiveness of LLM outputs in a translation use case, it is essential to ensure that the translations accurately and relevantly convey the intended message. The evaluation should focus on how well the LLM understands and processes different languages and contexts.
* Explanation of Options:
* Option A: The ability to generate responses in code- This is not relevant to translation quality or safety.
* Option B: The similarity to the previous language- While ensuring that translations preserve the original's intent is important, this doesn't directly address the overall quality or safety of the translation.
* Option C: The latency of the response and the length of text generated- These operational metrics are less critical in assessing the qualitative aspects of translation safety.
* Option D: The accuracy and relevance of the responses- This is crucial in translation to ensure that the translated content is true to the original in meaning and appropriateness. Accuracy and relevance directly impact the effectiveness and safety of translations, especially in sensitive or nuanced contexts.
Thus,Option Dis the most important indicator when evaluating the safety of LLM outputs in translation, focusing on the core aspects that determine the utility and trustworthiness of translated content.

NEW QUESTION # 66
A Generative AI Engineer I using the code below to test setting up a vector store:
Assuming they intend to use Databricks managed embeddings with the default embedding model, what should be the next logical function call?

- A. vsc.create_direct_access_index()
- B. vsc.similarity_search()
- C. vsc.get_index()
- D. vsc.create_delta_sync_index()

Answer: D

Explanation:
Context: The Generative AI Engineer is setting up a vector store using Databricks' VectorSearchClient. This is typically done to enable fast and efficient retrieval of vectorized data for tasks like similarity searches.
Explanation of Options:
* Option A: vsc.get_index(): This function would be used to retrieve an existing index, not create one, so it would not be the logical next step immediately after creating an endpoint.
* Option B: vsc.create_delta_sync_index(): After setting up a vector store endpoint, creating an index is necessary to start populating and organizing the data. The create_delta_sync_index() function specifically creates an index that synchronizes with a Delta table, allowing automatic updates as the data changes. This is likely the most appropriate choice if the engineer plans to use dynamic data that is updated over time.
* Option C: vsc.create_direct_access_index(): This function would create an index that directly accesses the data without synchronization. While also a valid approach, it's less likely to be the next logical step if the default setup (typically accommodating changes) is intended.
* Option D: vsc.similarity_search(): This function would be used to perform searches on an existing index; however, an index needs to be created and populated with data before any search can be conducted.
Given the typical workflow in setting up a vector store, the next step after creating an endpoint is to establish an index, particularly one that synchronizes with ongoing data updates, henceOption B.

NEW QUESTION # 67
A Generative Al Engineer has created a RAG application to look up answers to questions about a series of fantasy novels that are being asked on the author's web forum. The fantasy novel texts are chunked and embedded into a vector store with metadata (page number, chapter number, book title), retrieved with the user's query, and provided to an LLM for response generation. The Generative AI Engineer used their intuition to pick the chunking strategy and associated configurations but now wants to more methodically choose the best values.
Which TWO strategies should the Generative AI Engineer take to optimize their chunking strategy and parameters? (Choose two.)

- A. Choose an appropriate evaluation metric (such as recall or NDCG) and experiment with changes in the chunking strategy, such as splitting chunks by paragraphs or chapters.
  Choose the strategy that gives the best performance metric.
- B. Change embedding models and compare performance.
- C. Add a classifier for user queries that predicts which book will best contain the answer. Use this to filter retrieval.
- D. Pass known questions and best answers to an LLM and instruct the LLM to provide the best token count. Use a summary statistic (mean, median, etc.) of the best token counts to choose chunk size.
- E. Create an LLM-as-a-judge metric to evaluate how well previous questions are answered by the most appropriate chunk. Optimize the chunking parameters based upon the values of the metric.

Answer: A,E

Explanation:
To optimize a chunking strategy for a Retrieval-Augmented Generation (RAG) application, the Generative AI Engineer needs a structured approach to evaluating the chunking strategy, ensuring that the chosen configuration retrieves the most relevant information and leads to accurate and coherent LLM responses. Here's why C and E are the correct strategies:
Strategy C: Evaluation Metrics (Recall, NDCG)
Define an evaluation metric: Common evaluation metrics such as recall, precision, or NDCG (Normalized Discounted Cumulative Gain) measure how well the retrieved chunks match the user's query and the expected response.
Recall measures the proportion of relevant information retrieved.
NDCG is often used when you want to account for both the relevance of retrieved chunks and the ranking or order in which they are retrieved.
Experiment with chunking strategies: Adjusting chunking strategies based on text structure (e.g., splitting by paragraph, chapter, or a fixed number of tokens) allows the engineer to experiment with various ways of slicing the text. Some chunks may better align with the user's query than others.
Evaluate performance: By using recall or NDCG, the engineer can methodically test various chunking strategies to identify which one yields the highest performance. This ensures that the chunking method provides the most relevant information when embedding and retrieving data from the vector store.
Strategy E: LLM-as-a-Judge Metric
Use the LLM as an evaluator: After retrieving chunks, the LLM can be used to evaluate the quality of answers based on the chunks provided. This could be framed as a "judge" function, where the LLM compares how well a given chunk answers previous user queries.
Optimize based on the LLM's judgment: By having the LLM assess previous answers and rate their relevance and accuracy, the engineer can collect feedback on how well different chunking configurations perform in real-world scenarios.
This metric could be a qualitative judgment on how closely the retrieved information matches the user's intent.
Tune chunking parameters: Based on the LLM's judgment, the engineer can adjust the chunk size or structure to better align with the LLM's responses, optimizing retrieval for future queries.
By combining these two approaches, the engineer ensures that the chunking strategy is systematically evaluated using both quantitative (recall/NDCG) and qualitative (LLM judgment) methods. This balanced optimization process results in improved retrieval relevance and, consequently, better response generation by the LLM.

NEW QUESTION # 68
A Generative Al Engineer is building a production-ready LLM system which replies directly to customers. The solution makes use of the Foundation Model API via provisioned throughput. They are concerned that the LLM could potentially respond in a toxic or otherwise unsafe way. They also wish to perform this with the least amount of effort.
Which approach will do this?

- A. Add some LLM calls to their chain to detect unsafe content before returning text
- B. Add a regex expression on inputs and outputs to detect unsafe responses.
- C. Ask users to report unsafe responses
- D. Host Llama Guard on Foundation Model API and use it to detect unsafe responses

Answer: D

Explanation:
The task is to prevent toxic or unsafe responses in an LLM system using the Foundation Model API with minimal effort. Let's assess the options.
Option A: Host Llama Guard on Foundation Model API and use it to detect unsafe responses Llama Guard is a safety-focused model designed to detect toxic or unsafe content. Hosting it via the Foundation Model API (a Databricks service) integrates seamlessly with the existing system, requiring minimal setup (just deployment and a check step), and leverages provisioned

throughput for performance.
Databricks Reference: "Foundation Model API supports hosting safety models like Llama Guard to filter outputs efficiently" ("Foundation Model API Documentation," 2023).
Option B: Add some LLM calls to their chain to detect unsafe content before returning text Using additional LLM calls (e.g., prompting an LLM to classify toxicity) increases latency, complexity, and effort (crafting prompts, chaining logic), and lacks the specificity of a dedicated safety model.
Databricks Reference: "Ad-hoc LLM checks are less efficient than purpose-built safety solutions" ("Building LLM Applications with Databricks").
Option C: Add a regex expression on inputs and outputs to detect unsafe responses Regex can catch simple patterns (e.g., profanity) but fails for nuanced toxicity (e.g., sarcasm, context-dependent harm), requiring significant manual effort to maintain and update rules.
Databricks Reference: "Regex-based filtering is limited for complex safety needs" ("Generative AI Cookbook").
Option D: Ask users to report unsafe responses
User reporting is reactive, not preventive, and places burden on users rather than the system. It doesn't limit unsafe outputs proactively and requires additional effort for feedback handling.
Databricks Reference: "Proactive guardrails are preferred over user-driven monitoring" ("Databricks Generative AI Engineer Guide").
Conclusion: Option A (Llama Guard on Foundation Model API) is the least-effort, most effective approach, leveraging Databricks' infrastructure for seamless safety integration.

NEW QUESTION # 69
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