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

Topic	Details

Topic 1	• 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.
Topic 2	• Evaluation and Monitoring: This topic is all about selecting an LLM choice and key metrics. Moreover, Generative AI Engineers learn about evaluating model performance. Lastly, the topic includes sub-topics about inference logging and usage of Databricks features.
Topic 3	• Governance: Generative AI Engineers who take the exam get knowledge about masking techniques, guardrail techniques, and legal • licensing requirements in this topic.

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Databricks Certified Generative AI Engineer Associate Sample Questions (Q40-Q45):

NEW QUESTION # 40

A Generative AI Engineer is building an LLM to generate article summaries in the form of a type of poem, such as a haiku, given the article content. However, the initial output from the LLM does not match the desired tone or style. Which approach will NOT improve the LLM's response to achieve the desired response?

- A. Fine-tune the LLM on a dataset of desired tone and style
- B. Provide the LLM with a prompt that explicitly instructs it to generate text in the desired tone and style
- **C. Use a neutralizer to normalize the tone and style of the underlying documents**
- D. Include few-shot examples in the prompt to the LLM

Answer: C

Explanation:

The task at hand is to improve the LLM's ability to generate poem-like article summaries with the desired tone and style. Using a neutralizer to normalize the tone and style of the underlying documents (option B) will not help improve the LLM's ability to generate the desired poetic style. Here's why:

* **Neutralizing Underlying Documents:** A neutralizer aims to reduce or standardize the tone of input data. However, this contradicts the goal, which is to generate text with a specific tone and style (like haikus). Neutralizing the source documents will strip away the richness of the content, making it harder for the LLM to generate creative, stylistic outputs like poems.

* **Why Other Options Improve Results:**

* **A (Explicit Instructions in the Prompt):** Directly instructing the LLM to generate text in a specific tone and style helps align the output with the desired format (e.g., haikus). This is a common and effective technique in prompt engineering.

* **C (Few-shot Examples):** Providing examples of the desired output format helps the LLM understand the expected tone and structure, making it easier to generate similar outputs.

* **D (Fine-tuning the LLM):** Fine-tuning the model on a dataset that contains examples of the desired tone and style is a powerful way to improve the model's ability to generate outputs that match the target format.

Therefore, using a neutralizer (option B) is not an effective method for achieving the goal of generating stylized poetic summaries.

NEW QUESTION # 41

A Generative AI 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. Add a classifier for user queries that predicts which book will best contain the answer. Use this to filter retrieval.
- B. Change embedding models and compare performance.
- C. 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.
- D. 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.
- E. 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.

Answer: C,D

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 D 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.

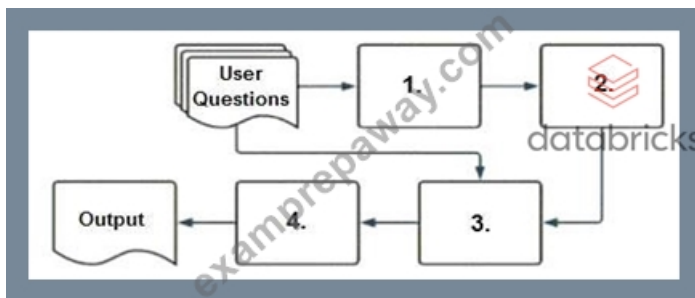
* This metric could be a qualitative judgment on how closely the retrieved information matches the user's intent.

* 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 # 42

A company has a typical RAG-enabled, customer-facing chatbot on its website.



Select the correct sequence of components a user's questions will go through before the final output is returned. Use the diagram above for reference.

- A. 1.context-augmented prompt, 2.vector search, 3.embedding model, 4.response-generating LLM
- B. 1.response-generating LLM, 2.context-augmented prompt, 3.vector search, 4.embedding model
- C. 1.response-generating LLM, 2.vector search, 3.context-augmented prompt, 4.embedding model
- D. 1.embedding model, 2.vector search, 3.context-augmented prompt, 4.response-generating LLM

Answer: D

Explanation:

To understand how a typical RAG-enabled customer-facing chatbot processes a user's question, let's go through the correct sequence as depicted in the diagram and explained in option A:

* Embedding Model (1): The first step involves the user's question being processed through an embedding model. This model converts the text into a vector format that numerically represents the text. This step is essential for allowing the subsequent vector search to operate effectively.

* Vector Search (2): The vectors generated by the embedding model are then used in a vector search mechanism. This search identifies the most relevant documents or previously answered questions that are stored in a vector format in a database.

* Context-Augmented Prompt (3): The information retrieved from the vector search is used to create a context-augmented prompt. This step involves enhancing the basic user query with additional relevant information gathered to ensure the generated response is as accurate and informative as possible.

* Response-Generating LLM (4): Finally, the context-augmented prompt is fed into a response-generating large language model (LLM). This LLM uses the prompt to generate a coherent and contextually appropriate answer, which is then delivered as the final output to the user.

Why Other Options Are Less Suitable:

* B, C, D: These options suggest incorrect sequences that do not align with how a RAG system typically processes queries. They misplace the role of embedding models, vector search, and response generation in an order that would not facilitate effective information retrieval and response generation.

Thus, the correct sequence is embedding model, vector search, context-augmented prompt, response-generating LLM, which is option A.

NEW QUESTION # 43

A Generative AI Engineer is setting up a Databricks Vector Search that will lookup news articles by topic within 10 days of the date specified. An example query might be "Tell me about monster truck news around January 5th 1992". They want to do this with the least amount of effort.

How can they set up their Vector Search index to support this use case?

- A. Create separate indexes by topic and add a classifier model to appropriately pick the best index.
- B. Pass the query directly to the vector search index and return the best articles.
- C. Split articles by 10-day blocks and return the block closest to the query.
- D. Include metadata columns for article date and topic to support metadata filtering.

Answer: D

Explanation:

The task is to set up a Databricks Vector Search index for news articles, supporting queries like "monster truck news around January 5th, 1992," with minimal effort. The index must filter by topic and a 10-day date range. Let's evaluate the options.

* Option A: Split articles by 10-day blocks and return the block closest to the query

* Pre-splitting articles into 10-day blocks requires significant preprocessing and index management (e.g., one index per block). It's effort-intensive and inflexible for dynamic date ranges.

* Databricks Reference: "Static partitioning increases setup complexity; metadata filtering is preferred" ("Databricks Vector Search

Documentation").

- * Option B: Include metadata columns for article date and topic to support metadata filtering
 - * Adding date and topic as metadata in the Vector Search index allows dynamic filtering (e.g., date $\pm$ 5 days, topic = "monster truck") at query time. This leverages Databricks' built-in metadata filtering, minimizing setup effort.
 - * Databricks Reference: "Vector Search supports metadata filtering on columns like date or category for precise retrieval with minimal preprocessing" ("Vector Search Guide," 2023).
 - * Option C: Pass the query directly to the vector search index and return the best articles
 - * Passing the full query (e.g., "Tell me about monster truck news around January 5th, 1992") to Vector Search relies solely on embeddings, ignoring structured filtering for date and topic. This risks inaccurate results without explicit range logic.
 - * Databricks Reference: "Pure vector similarity may not handle temporal or categorical constraints effectively" ("Building LLM Applications with Databricks").
 - * Option D: Create separate indexes by topic and add a classifier model to appropriately pick the best index
 - * Separate indexes per topic plus a classifier model adds significant complexity (index creation, model training, maintenance), far exceeding "least effort." It's overkill for this use case.
 - * Databricks Reference: "Multiple indexes increase overhead; single-index with metadata is simpler" ("Databricks Vector Search Documentation").
- Conclusion: Option B is the simplest and most effective solution, using metadata filtering in a single Vector Search index to handle date ranges and topics, aligning with Databricks' emphasis on efficient, low-effort setups.

NEW QUESTION # 44

A Generative AI Engineer is creating an LLM-based application. The documents for its retriever have been chunked to a maximum of 512 tokens each. The Generative AI Engineer knows that cost and latency are more important than quality for this application. They have several context length levels to choose from. Which will fulfill their need?

- **A. context length 512: smallest model is 0.13GB and embedding dimension 384**
- B. context length 514; smallest model is 0.44GB and embedding dimension 768
- C. context length 32768: smallest model is 14GB and embedding dimension 4096
- D. context length 2048: smallest model is 11GB and embedding dimension 2560

Answer: A

Explanation:

When prioritizing cost and latency over quality in a Large Language Model (LLM)-based application, it is crucial to select a configuration that minimizes both computational resources and latency while still providing reasonable performance. Here's why Dis is the best choice:

- * Context length: The context length of 512 tokens aligns with the chunk size used for the documents (maximum of 512 tokens per chunk). This is sufficient for capturing the needed information and generating responses without unnecessary overhead.
- * Smallest model size: The model with a size of 0.13GB is significantly smaller than the other options.

This small footprint ensures faster inference times and lower memory usage, which directly reduces both latency and cost.

- * Embedding dimension: While the embedding dimension of 384 is smaller than the other options, it is still adequate for tasks where cost and speed are more important than precision and depth of understanding.

This setup achieves the desired balance between cost-efficiency and reasonable performance in a latency- sensitive, cost-conscious application.

NEW QUESTION # 45

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