Databricks Databricks-Generative-AI-Engineer-Associate Actual Test & Top Databricks-Generative-AI-Engineer-Associate Questions

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The web-based format gives results at the end of every Databricks Databricks-Generative-AI-Engineer-Associate practice test attempt and points the mistakes so you can get rid of them before the final attempt. This online format of the Databricks Certified Generative AI Engineer Associate (Databricks-Generative-AI-Engineer-Associate) practice exam works well with Android, Mac, Windows, iOS, and Linux operating systems.

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

Topic	Details
Topic 1	• 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 2	• Governance: Generative AI Engineers who take the exam get knowledge about masking techniques, guardrail techniques, and legal • licensing requirements in this topic.
Topic 3	• 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 4	• Data Preparation: Generative AI Engineers covers a chunking strategy for a given document structure and model constraints. The topic also focuses on filter extraneous content in source documents. Lastly, Generative AI Engineers also learn about extracting document content from provided source data and format.

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Generally speaking, preparing for the Databricks-Generative-AI-Engineer-Associate exam is a very hard and even some suffering process. Because time is limited, sometimes we have to spare time to do other things to review the exam content, which makes the preparation process full of pressure and anxiety. But from the point of view of customers, our Databricks-Generative-AI-Engineer-Associate Actual Exam will not let you suffer from this. We have a high pass rate of our Databricks-Generative-AI-Engineer-Associate study materials as 98% to 100%. Our Databricks-Generative-AI-Engineer-Associate learning quiz will be your best choice.

Databricks Certified Generative AI Engineer Associate Sample Questions (Q61-Q66):

NEW QUESTION # 61
A Generative Al Engineer is working with a retail company that wants to enhance its customer experience by automatically handling common customer inquiries. They are working on an LLM-powered Al solution that should improve response times while maintaining a personalized interaction. They want to define the appropriate input and LLM task to do this.
Which input/output pair will do this?

- A. Input: Customer reviews; Output Group the reviews by users and aggregate per-user average rating, then respond
- B. Input: Customer service chat logs; Output Group the chat logs by users, followed by summarizing each user's interactions, then respond
- C. Input: Customer reviews: Output Classify review sentiment
- D. Input: Customer service chat logs; Output: Find the answers to similar questions and respond with a summary

Answer: D

Explanation:
The task described in the question involves enhancing customer experience by automatically handling common customer inquiries using an LLM-powered AI solution. This requires the system to process input data (customer inquiries) and generate personalized, relevant responses efficiently. Let's evaluate the options step-by-step in the context of Databricks Generative AI Engineer principles, which emphasize leveraging LLMs for tasks like question answering, summarization, and retrieval-augmented generation (RAG).
* Option A: Input: Customer reviews; Output: Group the reviews by users and aggregate per-user average rating, then respond
* This option focuses on analyzing customer reviews to compute average ratings per user. While this might be useful for sentiment analysis or user profiling, it does not directly address the goal of handling common customer inquiries or improving response times for personalized interactions. Customer reviews are typically feedback data, not real-time inquiries requiring immediate responses.
* Databricks Reference: Databricks documentation on LLMs (e.g., "Building LLM Applications with Databricks") emphasizes that LLMs excel at tasks like question answering and conversational responses, not just aggregation or statistical analysis of reviews.
* Option B: Input: Customer service chat logs; Output: Group the chat logs by users, followed by summarizing each user's interactions, then respond
* This option uses chat logs as input, which aligns with customer service scenarios. However, the output-grouping by users and summarizing interactions-focuses on user-specific summaries rather than directly addressing inquiries. While summarization is an LLM capability, this approach lacks the specificity of finding answers to common questions, which is central to the problem.
* Databricks Reference: Per Databricks' "Generative AI Cookbook," LLMs can summarize text, but for customer service, the emphasis is on retrieval and response generation (e.g., RAG workflows) rather than user interaction summaries alone.
* Option C: Input: Customer service chat logs; Output: Find the answers to similar questions and respond with a summary
* This option uses chat logs (real customer inquiries) as input and tasks the LLM with identifying answers to similar questions, then providing a summarized response. This directly aligns with the goal of handling common inquiries efficiently while maintaining personalization (by referencing past interactions or similar cases). It leverages LLM capabilities like semantic search, retrieval, and response generation, which are core to Databricks' LLM workflows.
* Databricks Reference: From Databricks documentation ("Building LLM-Powered Applications," 2023), an exact extract states:"For customer support use cases, LLMs can be used to retrieve relevant answers from historical data like chat logs and generate concise, contextually appropriate responses."This matches Option C's approach of finding answers and summarizing them.
* Option D: Input: Customer reviews; Output: Classify review sentiment
* This option focuses on sentiment classification of reviews, which is a valid LLM task but unrelated to handling customer inquiries or improving response times in a conversational context.
It's more suited for feedback analysis than real-time customer service.

* Databricks Reference: Databricks' "Generative AI Engineer Guide" notes that sentiment analysis is a common LLM task, but it's not highlighted for real-time conversational applications like customer support.
Conclusion: Option C is the best fit because it uses relevant input (chat logs) and defines an LLM task (finding answers and summarizing) that meets the requirements of improving response times and maintaining personalized interaction. This aligns with Databricks' recommended practices for LLM-powered customer service solutions, such as retrieval-augmented generation (RAG) workflows.

NEW QUESTION # 62
A Generative AI Engineer received the following business requirements for an external chatbot.
The chatbot needs to know what types of questions the user asks and routes to appropriate models to answer the questions. For example, the user might ask about upcoming event details. Another user might ask about purchasing tickets for a particular event.
What is an ideal workflow for such a chatbot?

- A. There should be two different chatbots handling different types of user queries.
- B. The chatbot should only process payments
- C. The chatbot should only look at previous event information
- D. The chatbot should be implemented as a multi-step LLM workflow. First, identify the type of question asked, then route the question to the appropriate model. If it's an upcoming event question, send the query to a text-to-SQL model. If it's about ticket purchasing, the customer should be redirected to a payment platform.

Answer: D

Explanation:
* Problem Context: The chatbot must handle various types of queries and intelligently route them to the appropriate responses or systems.
* Explanation of Options:
* Option A: Limiting the chatbot to only previous event information restricts its utility and does not meet the broader business requirements.
* Option B: Having two separate chatbots could unnecessarily complicate user interaction and increase maintenance overhead.
* Option C: Implementing a multi-step workflow where the chatbot first identifies the type of question and then routes it accordingly is the most efficient and scalable solution. This approach allows the chatbot to handle a variety of queries dynamically, improving user experience and operational efficiency.
* Option D: Focusing solely on payments would not satisfy all the specified user interaction needs, such as inquiring about event details.
Option Coffers a comprehensive workflow that maximizes the chatbot's utility and responsiveness to different user needs, aligning perfectly with the business requirements.

NEW QUESTION # 63
A Generative AI Engineer is creating an LLM-powered application that will need access to up-to-date news articles and stock prices.
The design requires the use of stock prices which are stored in Delta tables and finding the latest relevant news articles by searching the internet.
How should the Generative AI Engineer architect their LLM system?

- A. Query the Delta table for volatile stock prices and use an LLM to generate a search query to investigate potential causes of the stock volatility.
- B. Use an LLM to summarize the latest news articles and lookup stock tickers from the summaries to find stock prices.
- C. Create an agent with tools for SQL querying of Delta tables and web searching, provide retrieved values to an LLM for generation of response.
- D. Download and store news articles and stock price information in a vector store. Use a RAG architecture to retrieve and generate at runtime.

Answer: C

Explanation:
To build an LLM-powered system that accesses up-to-date news articles and stock prices, the best approach is tocreate an agentthat has access to specific tools (option D).
* Agent with SQL and Web Search Capabilities:By using an agent-based architecture, the LLM can interact with external tools. The agent can query Delta tables (for up-to-date stock prices) via SQL and perform web searches to retrieve the latest news articles.

This modular approach ensures the system can access both structured (stock prices) and unstructured (news) data sources dynamically.
* Why This Approach Works:
* SQL Queries for Stock Prices: Delta tables store stock prices, which the agent can query directly for the latest data.
* Web Search for News: For news articles, the agent can generate search queries and retrieve the most relevant and recent articles, then pass them to the LLM for processing.
* Why Other Options Are Less Suitable:
* A (Summarizing News for Stock Prices): This convoluted approach would not ensure accuracy when retrieving stock prices, which are already structured and stored in Delta tables.
* B (Stock Price Volatility Queries): While this could retrieve relevant information, it doesn't address how to obtain the most up-to-date news articles.
* C (Vector Store): Storing news articles and stock prices in a vector store might not capture the real-time nature of stock data and news updates, as it relies on pre-existing data rather than dynamic querying.
Thus, using an agent with access to both SQL for querying stock prices and web search for retrieving news articles is the best approach for ensuring up-to-date and accurate responses.

NEW QUESTION # 64
A Generative AI Engineer is developing a chatbot designed to assist users with insurance-related queries. The chatbot is built on a large language model (LLM) and is conversational. However, to maintain the chatbot's focus and to comply with company policy, it must not provide responses to questions about politics. Instead, when presented with political inquiries, the chatbot should respond with a standard message:
"Sorry, I cannot answer that. I am a chatbot that can only answer questions around insurance." Which framework type should be implemented to solve this?

- A. Safety Guardrail
- B. Contextual Guardrail
- C. Compliance Guardrail
- D. Security Guardrail

Answer: A

Explanation:
In this scenario, the chatbot must avoid answering political questions and instead provide a standard message for such inquiries. Implementing aSafety Guardrailis the appropriate solution for this:
* What is a Safety Guardrail?Safety guardrails are mechanisms implemented in Generative AI systems to ensure the model behaves within specific bounds. In this case, it ensures the chatbot does not answer politically sensitive or irrelevant questions, which aligns with the business rules.
* Preventing Responses to Political Questions:The Safety Guardrail is programmed to detect specific types of inquiries (like political questions) and prevent the model from generating responses outside its intended domain. When such queries are detected, the guardrail intervenes and provides a pre-defined response: "Sorry, I cannot answer that. I am a chatbot that can only answer questions around insurance."
* How It Works in Practice:The LLM system can include aclassification layeror trigger rules based on specific keywords related to politics. When such terms are detected, the Safety Guardrail blocks the normal generation flow and responds with the fixed message.
* Why Other Options Are Less Suitable:
* B (Security Guardrail): This is more focused on protecting the system from security vulnerabilities or data breaches, not controlling the conversational focus.
* C (Contextual Guardrail): While context guardrails can limit responses based on context, safety guardrails are specifically about ensuring the chatbot stays within a safe conversational scope.
* D (Compliance Guardrail): Compliance guardrails are often related to legal and regulatory adherence, which is not directly relevant here.
Therefore, aSafety Guardrailis the right framework to ensure the chatbot only answers insurance-related queries and avoids political discussions.

NEW QUESTION # 65
A Generative AI Engineer is testing a simple prompt template in LangChain using the code below, but is getting an error.

```
from langchain.chains import LLMChain
from langchain_community.llms import OpenAI
from langchain_core.prompts import PromptTemplat

prompt_template = "Tell me a {adjective} joke"

prompt = PromptTemplate(
    input_variables=["adjective"],
    template=prompt_template

llm = LLMChain(prompt=prompt)
llm.generate([{"adjective": "funny"}])
```

Assuming the API key was properly defined, what change does the Generative AI Engineer need to make to fix their chain?

- A.
```
prompt_template = "Tell me a {adjective} joke"

prompt = PromptTemplate(
    input_variables=["adjective"],
    template=prompt_template

llm = LLMChain(llm=OpenAI(), prompt=prompt)
llm.generate([{"adjective": "funny"}])
```
- B.
```
prompt_template = "Tell me a {adjective} joke"

prompt = PromptTemplate(
    input_variables=["adjective"],
    template=prompt_template
    llm=OpenAI()
)

llm = LLMChain(prompt=prompt)
```
- C.
```
prompt_template = "Tell me a {adjective} joke"

prompt = PromptTemplate(
    input_variables=["adjective"],
    template=prompt_template
)

llm = LLMChain(prompt=prompt)
llm.generate("funny")
```
- D.
```
prompt_template = "Tell me a {adjective} joke"

prompt = PromptTemplate(
    input_variables=["adjective"],
    template=prompt_template
)

llm = LLMChain(prompt=prompt.format("funny"))
llm.generate()
```

Answer: B

Explanation:
To fix the error in the LangChain code provided for using a simple prompt template, the correct approach is Option C. Here's a detailed breakdown of why Option C is the right choice and how it addresses the issue:
* Proper Initialization: In Option C, the LLMChain is correctly initialized with the LLM instance specified as OpenAI(), which likely represents a language model (like GPT) from OpenAI. This is crucial as it specifies which model to use for generating responses.

* Correct Use of Classes and Methods:
* The PromptTemplate is defined with the correct format, specifying that adjective is a variable within the template. This allows dynamic insertion of values into the template when generating text.
* The prompt variable is properly linked with the PromptTemplate, and the final template string is passed correctly.
* The LLMChain correctly references the prompt and the initialized OpenAI() instance, ensuring that the template and the model are properly linked for generating output.
Why Other Options Are Incorrect:
* Option A: Misuses the parameter passing in generate method by incorrectly structuring the dictionary.
* Option B: Incorrectly uses prompt.format method which does not exist in the context of LLMChain and PromptTemplate configuration, resulting in potential errors.
* Option D: Incorrect order and setup in the initialization parameters for LLMChain, which would likely lead to a failure in recognizing the correct configuration for prompt and LLM usage.
Thus, Option C is correct because it ensures that the LangChain components are correctly set up and integrated, adhering to proper syntax and logical flow required by LangChain's architecture. This setup avoids common pitfalls such as type errors or method misuses, which are evident in other options.

NEW QUESTION # 66
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