2026 Databricks-Generative-AI-Engineer-Associate: Efficient Latest Databricks Certified Generative AI Engineer Associate Test Format

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

Topic	Details
Topic 1	• Governance: Generative AI Engineers who take the exam get knowledge about masking techniques, guardrail techniques, and legal • licensing requirements in this topic.
Topic 2	• 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.
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.
Topic 4	• 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.

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Quiz Databricks-Generative-AI-Engineer-Associate - Databricks Certified

Generative AI Engineer Associate Newest Latest Test Format

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Databricks Certified Generative AI Engineer Associate Sample Questions (Q60-Q65):

NEW QUESTION # 60
A Generative AI Engineer has been asked to design an LLM-based application that accomplishes the following business objective: answer employee HR questions using HR PDF documentation.
Which set of high level tasks should the Generative AI Engineer's system perform?

- A. Split HR documentation into chunks and embed into a vector store. Use the employee question to retrieve best matched chunks of documentation, and use the LLM to generate a response to the employee based upon the documentation retrieved.
- B. Calculate averaged embeddings for each HR document, compare embeddings to user query to find the best document. Pass the best document with the user query into an LLM with a large context window to generate a response to the employee.
- C. Create an interaction matrix of historical employee questions and HR documentation. Use ALS to factorize the matrix and create embeddings. Calculate the embeddings of new queries and use them to find the best HR documentation. Use an LLM to generate a response to the employee question based upon the documentation retrieved.
- D. Use an LLM to summarize HR documentation. Provide summaries of documentation and user query into an LLM with a large context window to generate a response to the user.

Answer: A

Explanation:
To design an LLM-based application that can answer employee HR questions using HR PDF documentation, the most effective approach is option D. Here's why:
* Chunking and Vector Store Embedding:HR documentation tends to be lengthy, so splitting it into smaller, manageable chunks helps optimize retrieval. These chunks are then embedded into avector store(a database that stores vector representations of text). Each chunk of text is transformed into an embeddingusing a transformer-based model, which allows for efficient similarity-based retrieval.
* Using Vector Search for Retrieval:When an employee asks a question, the system converts their query into an embedding as well. This embedding is then compared with the embeddings of the document chunks in the vector store. The most semantically similar chunks are retrieved, which ensures that the answer is based on the most relevant parts of the documentation.
* LLM to Generate a Response:Once the relevant chunks are retrieved, these chunks are passed into the LLM, which uses them as context to generate a coherent and accurate response to the employee's question.
* Why Other Options Are Less Suitable:
* A (Calculate Averaged Embeddings): Averaging embeddings might dilute important information. It doesn't provide enough granularity to focus on specific sections of documents.
* B (Summarize HR Documentation): Summarization loses the detail necessary for HR-related queries, which are often specific. It would likely miss the mark for more detailed inquiries.
* C (Interaction Matrix and ALS): This approach is better suited for recommendation systems and not for HR queries, as it's focused on collaborative filtering rather than text-based retrieval.
Thus, option D is the most effective solution for providing precise and contextual answers based on HR documentation.

NEW QUESTION # 61
A Generative Al Engineer is building a system which will answer questions on latest stock news articles.
Which will NOT help with ensuring the outputs are relevant to financial news?

- A. Increase the compute to improve processing speed of questions to allow greater relevancy analysis C Implement a profanity filter to screen out offensive language

- B. Implement a comprehensive guardrail framework that includes policies for content filters tailored to the finance sector.
- C. Incorporate manual reviews to correct any problematic outputs prior to sending to the users

Answer: A

Explanation:
In the context of ensuring that outputs are relevant to financial news, increasing compute power (option B) does not directly improve the relevance of the LLM-generated outputs. Here's why:
Compute Power and Relevancy:
Increasing compute power can help the model process inputs faster, but it does not inherently improve the relevance of the answers. Relevancy depends on the data sources, the retrieval method, and the filtering mechanisms in place, not on how quickly the model processes the query.
What Actually Helps with Relevance:
Other methods, like content filtering, guardrails, or manual review, can directly impact the relevance of the model's responses by ensuring the model focuses on pertinent financial content. These methods help tailor the LLM's responses to the financial domain and avoid irrelevant or harmful outputs.
Why Other Options Are More Relevant:
A (Comprehensive Guardrail Framework): This will ensure that the model avoids generating content that is irrelevant or inappropriate in the finance sector.
C (Profanity Filter): While not directly related to financial relevancy, ensuring the output is clean and professional is still important in maintaining the quality of responses.
D (Manual Review): Incorporating human oversight to catch and correct issues with the LLM's output ensures the final answers are aligned with financial content expectations.
Thus, increasing compute power does not help with ensuring the outputs are more relevant to financial news, making option B the correct answer.

NEW QUESTION # 62
A generative AI engineer is deploying an AI agent authored with MLflow's ChatAgent interface for a retail company's customer support system on Databricks. The agent must handle thousands of inquiries daily, and the engineer needs to track its performance and quality in real-time to ensure it meets service-level agreements. Which metrics are automatically captured by default and made available for monitoring when the agent is deployed using the Mosaic AI Agent Framework?

- A. Operational metrics like request volume, latency, and errors
- B. Both operational and quality metrics
- C. No metrics are automatically captured
- D. Quality metrics like correctness and guideline adherence

Answer: A

Explanation:
When deploying an agent via the Mosaic AI Agent Framework (which leverages Databricks Model Serving), operational metrics are captured automatically by default. These include system-level telemetry such as the number of requests per second (volume), the time taken for the model to respond (latency), and the rate of 4xx/5xx HTTP errors. These are essential for monitoring Service Level Agreements (SLAs). However, Quality metrics (B), such as correctness, groundedness, or adherence to custom guidelines, cannot be determined "automatically" by the serving infrastructure because they require either human feedback or an LLM-as-a-judge evaluation (using Databricks Agent Evaluation). While Databricks makes it easy to generate quality metrics using the mlflow.evaluate API or the inference table, they are not "default operational metrics" that appear without additional evaluation configuration.

NEW QUESTION # 63
A Generative AI Engineer is creating an agent-based LLM system for their favorite monster truck team. The system can answer text based questions about the monster truck team, lookup event dates via an API call, or query tables on the team's latest standings.
How could the Generative AI Engineer best design these capabilities into their system?

- A. Instruct the LLM to respond with "RAG", "API", or "TABLE" depending on the query, then use text parsing and conditional statements to resolve the query.
- B. Write a system prompt for the agent listing available tools and bundle it into an agent system that runs a number of calls to solve a query.
- C. Build a system prompt with all possible event dates and table information in the system prompt. Use a RAG architecture to lookup generic text questions and otherwise leverage the information in the system prompt.

- D. Ingest PDF documents about the monster truck team into a vector store and query it in a RAG architecture.

Answer: B

Explanation:
In this scenario, the Generative AI Engineer needs to design a system that can handle different types of queries about the monster truck team. The queries may involve text-based information, API lookups for event dates, or table queries for standings. The best solution is to implement a tool-based agent system.
Here's how option B works, and why it's the most appropriate answer:
System Design Using Agent-Based Model:
In modern agent-based LLM systems, you can design a system where the LLM (Large Language Model) acts as a central orchestrator. The model can "decide" which tools to use based on the query. These tools can include API calls, table lookups, or natural language searches. The system should contain a system prompt that informs the LLM about the available tools.
System Prompt Listing Tools:
By creating a well-crafted system prompt, the LLM knows which tools are at its disposal. For instance, one tool may query an external API for event dates, another might look up standings in a database, and a third may involve searching a vector database for general text-based information. The agent will be responsible for calling the appropriate tool depending on the query.
Agent Orchestration of Calls:
The agent system is designed to execute a series of steps based on the incoming query. If a user asks for the next event date, the system will recognize this as a task that requires an API call. If the user asks about standings, the agent might query the appropriate table in the database. For text-based questions, it may call a search function over ingested data. The agent orchestrates this entire process, ensuring the LLM makes calls to the right resources dynamically.
Generative AI Tools and Context:
This is a standard architecture for integrating multiple functionalities into a system where each query requires different actions. The core design in option B is efficient because it keeps the system modular and dynamic by leveraging tools rather than overloading the LLM with static information in a system prompt (like option D).
Why Other Options Are Less Suitable:
A (RAG Architecture): While relevant, simply ingesting PDFs into a vector store only helps with text-based retrieval. It wouldn't help with API lookups or table queries.
C (Conditional Logic with RAG/API/TABLE): Although this approach works, it relies heavily on manual text parsing and might introduce complexity when scaling the system.
D (System Prompt with Event Dates and Standings): Hardcoding dates and table information into a system prompt isn't scalable. As the standings or events change, the system would need constant updating, making it inefficient.
By bundling multiple tools into a single agent-based system (as in option B), the Generative AI Engineer can best handle the diverse requirements of this system.

NEW QUESTION # 64
A Generative AI Engineer is building a Generative AI system that suggests the best matched employee team member to newly scoped projects. The team member is selected from a very large team. The match should be based upon project date availability and how well their employee profile matches the project scope. Both the employee profile and project scope are unstructured text.
How should the Generative Al Engineer architect their system?

- A. Create a tool for finding available team members given project dates. Embed all project scopes into a vector store, perform a retrieval using team member profiles to find the best team member.
- B. Create a tool to find available team members given project dates. Create a second tool that can calculate a similarity score for a combination of team member profile and the project scope. Iterate through the team members and rank by best score to select a team member.
- C. Create a tool for finding available team members given project dates. Embed team profiles into a vector store and use the project scope and filtering to perform retrieval to find the available best matched team members.
- D. Create a tool for finding team member availability given project dates, and another tool that uses an LLM to extract keywords from project scopes. Iterate through available team members' profiles and perform keyword matching to find the best available team member.

Answer: C

Explanation:
Problem Context: The problem involves matching team members to new projects based on two main factors:
Availability: Ensure the team members are available during the project dates.
Profile-Project Match: Use the employee profiles (unstructured text) to find the best match for a project's scope (also unstructured text).

The two main inputs are the employee profiles and project scopes, both of which are unstructured. This means traditional rule-based systems (e.g., simple keyword matching) would be inefficient, especially when working with large datasets.
Explanation of Options: Let's break down the provided options to understand why D is the most optimal answer.
Option A suggests embedding project scopes into a vector store and then performing retrieval using team member profiles. While embedding project scopes into a vector store is a valid technique, it skips an important detail: the focus should primarily be on embedding employee profiles because we're matching the profiles to a new project, not the other way around.
Option B involves using a large language model (LLM) to extract keywords from the project scope and perform keyword matching on employee profiles. While LLMs can help with keyword extraction, this approach is too simplistic and doesn't leverage advanced retrieval techniques like vector embeddings, which can handle the nuanced and rich semantics of unstructured data. This approach may miss out on subtle but important similarities.
Option C suggests calculating a similarity score between each team member's profile and project scope. While this is a good idea, it doesn't specify how to handle the unstructured nature of data efficiently. Iterating through each member's profile individually could be computationally expensive in large teams. It also lacks the mention of using a vector store or an efficient retrieval mechanism.
Option D is the correct approach. Here's why:
Embedding team profiles into a vector store: Using a vector store allows for efficient similarity searches on unstructured data. Embedding the team member profiles into vectors captures their semantics in a way that is far more flexible than keyword-based matching.
Using project scope for retrieval: Instead of matching keywords, this approach suggests using vector embeddings and similarity search algorithms (e.g., cosine similarity) to find the team members whose profiles most closely align with the project scope.
Filtering based on availability: Once the best-matched candidates are retrieved based on profile similarity, filtering them by availability ensures that the system provides a practically useful result.
This method efficiently handles large-scale datasets by leveraging vector embeddings and similarity search techniques, both of which are fundamental tools in Generative AI engineering for handling unstructured text.
Technical Reference:
Vector embeddings: In this approach, the unstructured text (employee profiles and project scopes) is converted into high-dimensional vectors using pretrained models (e.g., BERT, Sentence-BERT, or custom embeddings). These embeddings capture the semantic meaning of the text, making it easier to perform similarity-based retrieval.
Vector stores: Solutions like FAISS or Milvus allow storing and retrieving large numbers of vector embeddings quickly. This is critical when working with large teams where querying through individual profiles sequentially would be inefficient.
LLM Integration: Large language models can assist in generating embeddings for both employee profiles and project scopes. They can also assist in fine-tuning similarity measures, ensuring that the retrieval system captures the nuances of the text data.
Filtering: After retrieving the most similar profiles based on the project scope, filtering based on availability ensures that only team members who are free for the project are considered.
This system is scalable, efficient, and makes use of the latest techniques in Generative AI, such as vector embeddings and semantic search.

NEW QUESTION # 65
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