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There may be a lot of people feel that the preparation process for exams is hard and boring, and hard work does not necessarily mean good results, which is an important reason why many people are afraid of examinations. Today, our Databricks-Generative-AI-Engineer-Associate study materials will radically change this. High question hit rate makes you no longer aimless when preparing for the exam, so you just should review according to the content of our Databricks-Generative-AI-Engineer-Associate Study Materials prepared for you.

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

Topic	Details
Topic 1	• 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 2	• 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 3	• 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.

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Frankly speaking, it is difficult to get the Databricks-Generative-AI-Engineer-Associate certificate without help. Usually, the time

you invest to prepare the exam is long. Now, all of your worries can be wiped out because of our Databricks-Generative-AI-Engineer-Associate exam questions. Some people worry about that some difficult knowledge is hard to understand or the Databricks-Generative-AI-Engineer-Associate test guide is not suitable for them. Actually, the difficult parts of the exam have been simplified, which will be easy for you to understand. Also, there will be examples, simulations and charts to make explanations vivid. In order to aid you to memorize the Databricks Certified Generative AI Engineer Associate exam cram better, we have integrated knowledge structure. You will clearly know what you are learning and which part you need to learn carefully. You will regret if you give up challenging yourself.

Databricks Certified Generative AI Engineer Associate Sample Questions (Q66-Q71):

NEW QUESTION # 66
A Generative Al Engineer is developing a RAG application and would like to experiment with different embedding models to improve the application performance.
Which strategy for picking an embedding model should they choose?

- A. Pick an embedding model with multilingual support to support potential multilingual user questions
- B. Pick the most recent and most performant open LLM released at the time
- C. Pick an embedding model trained on related domain knowledge
- D. pick the embedding model ranked highest on the Massive Text Embedding Benchmark (MTEB) leaderboard hosted by HuggingFace

Answer: C

Explanation:
The task involves improving a Retrieval-Augmented Generation (RAG) application's performance by experimenting with embedding models. The choice of embedding model impacts retrieval accuracy,which is critical for RAG systems. Let's evaluate the options based on Databricks Generative AI Engineer best practices.
* Option A: Pick an embedding model trained on related domain knowledge
* Embedding models trained on domain-specific data (e.g., industry-specific corpora) produce vectors that better capture the semantics of the application's context, improving retrieval relevance. For RAG, this is a key strategy to enhance performance.
* Databricks Reference:"For optimal retrieval in RAG systems, select embedding models aligned with the domain of your data" ("Building LLM Applications with Databricks," 2023).
* Option B: Pick the most recent and most performant open LLM released at the time
* LLMs are not embedding models; they generate text, not embeddings for retrieval. While recent LLMs may be performant for generation, this doesn't address the embedding step in RAG. This option misunderstands the component being selected.
* Databricks Reference: Embedding models and LLMs are distinct in RAG workflows:
"Embedding models convert text to vectors, while LLMs generate responses"("Generative AI Cookbook").
* Option C: Pick the embedding model ranked highest on the Massive Text Embedding Benchmark (MTEB) leaderboard hosted by HuggingFace
* The MTEB leaderboard ranks models across general tasks, but high overall performance doesn't guarantee suitability for a specific domain. A top-ranked model might excel in generic contexts but underperform on the engineer's unique data.
* Databricks Reference: General performance is less critical than domain fit:"Benchmark rankings provide a starting point, but domain-specific evaluation is recommended"("Databricks Generative AI Engineer Guide").
* Option D: Pick an embedding model with multilingual support to support potential multilingual user questions
* Multilingual support is useful only if the application explicitly requires it. Without evidence of multilingual needs, this adds complexity without guaranteed performance gains for the current use case.
* Databricks Reference:"Choose features like multilingual support based on application requirements"("Building LLM-Powered Applications").
Conclusion: Option A is the best strategy because it prioritizes domain relevance, directly improving retrieval accuracy in a RAG system-aligning with Databricks' emphasis on tailoring models to specific use cases.

NEW QUESTION # 67
A Generative AI Engineer is designing a RAG application for answering user questions on technical regulations as they learn a new sport.
What are the steps needed to build this RAG application and deploy it?

- A. Ingest documents from a source -> Index the documents and save to Vector Search -> User submits queries against an LLM -> LLM retrieves relevant documents -> LLM generates a response -> Evaluate model -> Deploy it using Model

Serving

- B. User submits queries against an LLM -> Ingest documents from a source -> Index the documents and save to Vector Search -> LLM retrieves relevant documents -> LLM generates a response -> Evaluate model -> Deploy it using Model Serving
- C. Ingest documents from a source -> Index the documents and save to Vector Search -> Evaluate model -> Deploy it using Model Serving
- D. Ingest documents from a source -> Index the documents and saves to Vector Search -> User submits queries against an LLM -> LLM retrieves relevant documents -> Evaluate model -> LLM generates a response -> Deploy it using Model Serving

Answer: A

Explanation:
The Generative AI Engineer needs to follow a methodical pipeline to build and deploy a Retrieval-Augmented Generation (RAG) application. The steps outlined in option B accurately reflect this process:
Ingest documents from a source: This is the first step, where the engineer collects documents (e.g., technical regulations) that will be used for retrieval when the application answers user questions.
Index the documents and save to Vector Search: Once the documents are ingested, they need to be embedded using a technique like embeddings (e.g., with a pre-trained model like BERT) and stored in a vector database (such as Pinecone or FAISS). This enables fast retrieval based on user queries.
User submits queries against an LLM: Users interact with the application by submitting their queries. These queries will be passed to the LLM.
LLM retrieves relevant documents: The LLM works with the vector store to retrieve the most relevant documents based on their vector representations.
LLM generates a response: Using the retrieved documents, the LLM generates a response that is tailored to the user's question.
Evaluate model: After generating responses, the system must be evaluated to ensure the retrieved documents are relevant and the generated response is accurate. Metrics such as accuracy, relevance, and user satisfaction can be used for evaluation.
Deploy it using Model Serving: Once the RAG pipeline is ready and evaluated, it is deployed using a model-serving platform such as Databricks Model Serving. This enables real-time inference and response generation for users.
By following these steps, the Generative AI Engineer ensures that the RAG application is both efficient and effective for the task of answering technical regulation questions.

NEW QUESTION # 68
A Generative Al Engineer has built an LLM-based system that will automatically translate user text between two languages. They now want to benchmark multiple LLM's on this task and pick the best one. They have an evaluation set with known high quality translation examples. They want to evaluate each LLM using the evaluation set with a performant metric.
Which metric should they choose for this evaluation?

- A. ROUGE metric
- B. NDCG metric
- C. BLEU metric
- D. RECALL metric

Answer: C

Explanation:
The task is to benchmark LLMs for text translation using an evaluation set with known high-quality examples, requiring a performant metric. Let's evaluate the options.
Option A: ROUGE metric
ROUGE (Recall-Oriented Understudy for Gisting Evaluation) measures overlap between generated and reference texts, primarily for summarization. It's less suited for translation, where precision and word order matter more.
Databricks Reference: "ROUGE is commonly used for summarization, not translation evaluation" ("Generative AI Cookbook," 2023).
Option B: BLEU metric
BLEU (Bilingual Evaluation Understudy) evaluates translation quality by comparing n-gram overlap with reference translations, accounting for precision and brevity. It's widely used, performant, and appropriate for this task.
Databricks Reference: "BLEU is a standard metric for evaluating machine translation, balancing accuracy and efficiency" ("Building LLM Applications with Databricks").
Option C: NDCG metric
NDCG (Normalized Discounted Cumulative Gain) assesses ranking quality, not text generation. It's irrelevant for translation

evaluation.
Databricks Reference: "NDCG is suited for ranking tasks, not generative output scoring" ("Databricks Generative AI Engineer Guide").
Option D: RECALL metric
Recall measures retrieved relevant items but doesn't evaluate translation quality (e.g., fluency, correctness). It's incomplete for this use case.
Databricks Reference: No specific extract, but recall alone lacks the granularity of BLEU for text generation tasks.
Conclusion: Option B (BLEU) is the best metric for translation evaluation, offering a performant and standard approach, as endorsed by Databricks' guidance on generative tasks.

NEW QUESTION # 69
A Generative AI Engineer developed an LLM application using the provisioned throughput Foundation Model API. Now that the application is ready to be deployed, they realize their volume of requests are not sufficiently high enough to create their own provisioned throughput endpoint. They want to choose a strategy that ensures the best cost-effectiveness for their application.
What strategy should the Generative AI Engineer use?

- A. Throttle the incoming batch of requests manually to avoid rate limiting issues
- B. Deploy the model using pay-per-token throughput as it comes with cost guarantees
- C. Switch to using External Models instead
- D. Change to a model with a fewer number of parameters in order to reduce hardware constraint issues

Answer: B

Explanation:
* Problem Context: The engineer needs a cost-effective deployment strategy for an LLM application with relatively low request volume.
* Explanation of Options:
* Option A: Switching to external models may not provide the required control or integration necessary for specific application needs.
* Option B: Using a pay-per-token model is cost-effective, especially for applications with variable or low request volumes, as it aligns costs directly with usage.
* Option C: Changing to a model with fewer parameters could reduce costs, but might also impact the performance and capabilities of the application.
* Option D: Manually throttling requests is a less efficient and potentially error-prone strategy for managing costs.
OptionBis ideal, offering flexibility and cost control, aligning expenses directly with the application's usage patterns.

NEW QUESTION # 70
A Generative Al Engineer is creating an LLM system that will retrieve news articles from the year 1918 and related to a user's query and summarize them. The engineer has noticed that the summaries are generated well but often also include an explanation of how the summary was generated, which is undesirable.
Which change could the Generative Al Engineer perform to mitigate this issue?

- A. Revisit their document ingestion logic, ensuring that the news articles are being ingested properly.
- B. Tune the chunk size of news articles or experiment with different embedding models.
- C. Provide few shot examples of desired output format to the system and/or user prompt.
- D. Split the LLM output by newline characters to truncate away the summarization explanation.

Answer: C

Explanation:
To mitigate the issue of the LLM including explanations of how summaries are generated in its output, the best approach is to adjust the training or prompt structure. Here's why Option D is effective:
* Few-shot Learning: By providing specific examples of how the desired output should look (i.e., just the summary without explanation), the model learns the preferred format. This few-shot learning approach helps the model understand not only what content to generate but also how to format its responses.
* Prompt Engineering: Adjusting the user prompt to specify the desired output format clearly can guide the LLM to produce summaries without additional explanatory text. Effective prompt design is crucial in controlling the behavior of generative models.
Why Other Options Are Less Suitable:
* A: While technically feasible, splitting the output by newline and truncating could lead to loss of important content or create

awkward breaks in the summary.
* B: Tuning chunk sizes or changing embedding models does not directly address the issue of the model's tendency to generate explanations along with summaries.
* C: Revisiting document ingestion logic ensures accurate source data but does not influence how the model formats its output.
By using few-shot examples and refining the prompt, the engineer directly influences the output format, making this approach the most targeted and effective solution.

NEW QUESTION # 71
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