Databricks-Generative-AI-Engineer-Associate Valid Exam Book - Databricks-Generative-AI-Engineer-Associate Latest Exam Pattern

Exam : **Databricks Generative AI Engineer Associate**

Title : Databricks Certified Generative AI Engineer Associate

https://www.passcert.com/Databricks-Generative-AI-Engineer-Associate.html

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Practice tests are also a core part of the ExamsReviews product. We recognize that retention of information is crucial, and interactive learning tools, such as practice exams are provided to help students retain the information they have learned. These Databricks-Generative-AI-Engineer-Associate Practice Tests simulate the actual exam conditions and provide applicants with an accurate assessment of their readiness for the test.

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	• 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	• 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 4	• 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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Our Databricks-Generative-AI-Engineer-Associate exam materials have helped many people improve their soft power. They are now more efficient than their colleagues, so they have received more attention from their leaders. We are all ordinary professional people. We must show our strength to show that we are worth the opportunity. Using Databricks-Generative-AI-Engineer-Associate practice engine may be the most important step for you to improve your strength. You know, like the butterfly effect, one of your choices may affect your life. And our Databricks-Generative-AI-Engineer-Associate Exam Questions will be the right exam tool for you to pass the Databricks-Generative-AI-Engineer-Associate exam and obtain the dreaming certification.

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

NEW QUESTION # 40
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 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.
- B. 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.
- C. 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.
- D. 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.

Answer: D

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 # 41
A Generative AI Engineer at an automotive company would like to build a question-answering chatbot to help customers answer specific questions about their vehicles. They have:
A catalog with hundreds of thousands of cars manufactured since the 1960s Historical searches with user queries and successful matches Descriptions of their own cars in multiple languages They have already selected an open-source LLM and created a test set of user queries. They need to discard techniques that will not help them build the chatbot. Which do they discard?

- A. Implementing metadata filtering based on car models and years
- B. Fine-tuning an embedding model on automotive terminology
- C. Adding few-shot examples for response generation
- D. Setting chunk size to match the model's context window to maximize coverage

Answer: D

Explanation:
According to Generative AI engineering standards for Retrieval-Augmented Generation (RAG), chunking strategy is a critical optimization variable. Setting the chunk size to match the model's maximum context window (e.g., 4k or 8k tokens) is a poor practice and should be discarded. Large chunks introduce significant "noise" into the LLM's context, as only a small portion of a massive chunk usually contains the answer to a specific query. This leads to the "lost in the middle" phenomenon where LLMs struggle to extract relevant information from bloated contexts. Furthermore, large chunks reduce the precision of the vector search. Standard best practices involve using smaller, semantically meaningful chunks (typically 256-512 tokens) with overlap to maintain context. In contrast, metadata filtering (B) is essential for narrowing searches to specific car years, fine-tuning embeddings (C) improves retrieval accuracy for domain-specific technical terms, and few-shot examples (D) guide the LLM's output format and tone.

NEW QUESTION # 42
A Generative Al Engineer is deciding between using LSH (Locality Sensitive Hashing) and HNSW (Hierarchical Navigable Small

World) for indexing their vector database Their top priority is semantic accuracy Which approach should the Generative Al Engineer use to evaluate these two techniques?

- A. Compare the Bilingual Evaluation Understudy (BLEU) scores of returned results for a representative sample of test inputs
- B. Compare the cosine similarities of the embeddings of returned results against those of a representative sample of test inputs
- C. Compare the Recall-Onented-Understudy for Gistmg Evaluation (ROUGE) scores of returned results for a representative sample of test inputs
- D. Compare the Levenshtein distances of returned results against a representative sample of test inputs

Answer: B

Explanation:
The task is to choose between LSH and HNSW for a vector database index, prioritizing semantic accuracy. The evaluation must assess how well each method retrieves semantically relevant results. Let's evaluate the options.
Option A: Compare the cosine similarities of the embeddings of returned results against those of a representative sample of test inputs Cosine similarity measures semantic closeness between vectors, directly assessing retrieval accuracy in a vector database. Comparing returned results' embeddings to test inputs' embeddings evaluates how well LSH or HNSW preserves semantic relationships, aligning with the priority.
Databricks Reference: "Cosine similarity is a standard metric for evaluating vector search accuracy" ("Databricks Vector Search Documentation," 2023).
Option B: Compare the Bilingual Evaluation Understudy (BLEU) scores of returned results for a representative sample of test inputs BLEU evaluates text generation (e.g., translations), not vector retrieval accuracy. It's irrelevant for indexing performance.
Databricks Reference: "BLEU applies to generative tasks, not retrieval" ("Generative AI Cookbook").
Option C: Compare the Recall-Oriented-Understudy for Gisting Evaluation (ROUGE) scores of returned results for a representative sample of test inputs ROUGE is for summarization evaluation, not vector search. It doesn't measure semantic accuracy in retrieval.
Databricks Reference: "ROUGE is unsuited for vector database evaluation" ("Building LLM Applications with Databricks").
Option D: Compare the Levenshtein distances of returned results against a representative sample of test inputs Levenshtein distance measures string edit distance, not semantic similarity in embeddings. It's inappropriate for vector-based retrieval.
Databricks Reference: No specific support for Levenshtein in vector search contexts.
Conclusion: Option A (cosine similarity) is the correct approach, directly evaluating semantic accuracy in vector retrieval, as recommended by Databricks for Vector Search assessments.

NEW QUESTION # 43
A Generative Al Engineer is deciding between using LSH (Locality Sensitive Hashing) and HNSW (Hierarchical Navigable Small World) for indexing their vector database Their top priority is semantic accuracy Which approach should the Generative Al Engineer use to evaluate these two techniques?

- A. Compare the Bilingual Evaluation Understudy (BLEU) scores of returned results for a representative sample of test inputs
- B. Compare the cosine similarities of the embeddings of returned results against those of a representative sample of test inputs
- C. Compare the Recall-Onented-Understudy for Gistmg Evaluation (ROUGE) scores of returned results for a representative sample of test inputs
- D. Compare the Levenshtein distances of returned results against a representative sample of test inputs

Answer: B

Explanation:
The task is to choose between LSH and HNSW for a vector database index, prioritizing semantic accuracy.
The evaluation must assess how well each method retrieves semantically relevant results. Let's evaluate the options.
* Option A: Compare the cosine similarities of the embeddings of returned results against those of a representative sample of test inputs
* Cosine similarity measures semantic closeness between vectors, directly assessing retrieval accuracy in a vector database. Comparing returned results' embeddings to test inputs' embeddings evaluates how well LSH or HNSW preserves semantic relationships, aligning with the priority.
* Databricks Reference:"Cosine similarity is a standard metric for evaluating vector search accuracy"("Databricks Vector Search Documentation," 2023).
* Option B: Compare the Bilingual Evaluation Understudy (BLEU) scores of returned results for a representative sample of test inputs
* BLEU evaluates text generation (e.g., translations), not vector retrieval accuracy. It's irrelevant for indexing performance.
* Databricks Reference:"BLEU applies to generative tasks, not retrieval"("Generative AI Cookbook").
* Option C: Compare the Recall-Oriented-Understudy for Gisting Evaluation (ROUGE) scores of returned results for a

representative sample of test inputs
* ROUGE is for summarization evaluation, not vector search. It doesn't measure semantic accuracy in retrieval.
* Databricks Reference:"ROUGE is unsuited for vector database evaluation"("Building LLM Applications with Databricks").
* Option D: Compare the Levenshtein distances of returned results against a representative sample of test inputs
* Levenshtein distance measures string edit distance, not semantic similarity in embeddings. It's inappropriate for vector-based retrieval.
* Databricks Reference: No specific support for Levenshtein in vector search contexts.
Conclusion: Option A (cosine similarity) is the correct approach, directly evaluating semantic accuracy in vector retrieval, as recommended by Databricks for Vector Search assessments.

NEW QUESTION # 44
A Generative Al Engineer is tasked with developing an application that is based on an open source large language model (LLM). They need a foundation LLM with a large context window.
Which model fits this need?

- A. DistilBERT
- B. DBRX
- C. MPT-30B
- D. Llama2-70B

Answer: D

Explanation:
* Problem Context: The engineer needs an open-source LLM with a large context window to develop an application.
* Explanation of Options:
* Option A: DistilBERT: While an efficient and smaller version of BERT, DistilBERT does not provide a particularly large context window.
* Option B: MPT-30B: This model, while large, is not specified as being particularly notable for its context window capabilities.
* Option C: Llama2-70B: Known for its large model size and extensive capabilities, including a large context window. It is also available as an open-source model, making it ideal for applications requiring extensive contextual understanding.
* Option D: DBRX: This is not a recognized standard model in the context of large language models with extensive context windows.
Thus,Option C(Llama2-70B) is the best fit as it meets the criteria of having a large context window and being available for open-source use, suitable for developing robust language understanding applications.

NEW QUESTION # 45
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