Databricks-Certified-Professional-Data-Engineer Dumps

Databricks Certified Data Engineer Professional Exam

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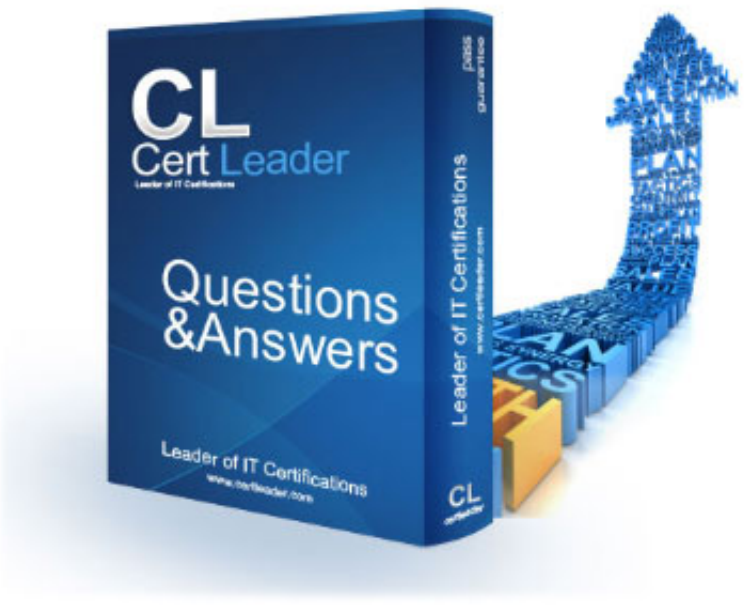

NEW QUESTION 1
A Databricks job has been configured with 3 tasks, each of which is a Databricks notebook. Task A does not depend on other tasks. Tasks B and C run in parallel, with each having a serial dependency on Task A.
If task A fails during a scheduled run, which statement describes the results of this run?

A. Because all tasks are managed as a dependency graph, no changes will be committed to the Lakehouse until all tasks have successfully been completed.
B. Tasks B and C will attempt to run as configured; any changes made in task A will be rolled back due to task failure.
C. Unless all tasks complete successfully, no changes will be committed to the Lakehouse; because task A failed, all commits will be rolled back automatically.
D. Tasks B and C will be skipped; some logic expressed in task A may have been committed before task failure.
E. Tasks B and C will be skipped; task A will not commit any changes because of stage failure.

Answer: D

Explanation:
When a Databricks job runs multiple tasks with dependencies, the tasks are executed in a dependency graph. If a task fails, the downstream tasks that depend on it are skipped and marked as Upstream failed. However, the failed task may have already committed some changes to the Lakehouse before the failure occurred, and those changes are not rolled back automatically. Therefore, the job run may result in a partial update of the Lakehouse. To avoid this, you can use the transactional writes feature of Delta Lake to ensure that the changes are only committed when the entire job run succeeds.
Alternatively, you can use the Run if condition to configure tasks to run even when some or all of their dependencies have failed, allowing your job to recover from failures and
continue running. References:
? transactional writes: https://docs.databricks.com/delta/delta- intro.html#transactional-writes
? Run if: https://docs.databricks.com/en/workflows/jobs/conditional-tasks.html

NEW QUESTION 2
An upstream source writes Parquet data as hourly batches to directories named with the current date. A nightly batch job runs the following code to ingest all data from the previous day as indicated by the date variable:

```
(spark.read
  .format("parquet")
  .load(f"/mnt/raw_orders/{date}")
  .dropDuplicates(["customer_id", "order_id"])
  .write
  .mode("append")
  .saveAsTable("orders")
)
```

Assume that the fields customer_id and order_id serve as a composite key to uniquely identify each order.
If the upstream system is known to occasionally produce duplicate entries for a single order
hours apart, which statement is correct?

A. Each write to the orders table will only contain unique records, and only those records without duplicates in the target table will be written.
B. Each write to the orders table will only contain unique records, but newly written records may have duplicates already present in the target table.
C. Each write to the orders table will only contain unique records; if existing records with the same key are present in the target table, these records will be overwritten.
D. Each write to the orders table will only contain unique records; if existing records with the same key are present in the target table, the operation will tail.
E. Each write to the orders table will run deduplication over the union of new and existing records, ensuring no duplicate records are present.

Answer: B

Explanation:
This is the correct answer because the code uses the dropDuplicates method to remove any duplicate records within each batch of data before writing to the orders table. However, this method does not check for duplicates across different batches or in the target table, so it is possible that newly written records may have duplicates already present in the target table. To avoid this, a better approach would be to use Delta Lake and perform an upsert operation using mergeInto.
Verified References: [Databricks Certified Data Engineer Professional], under “Delta Lake” section; Databricks Documentation, under “DROP DUPLICATES” section.

NEW QUESTION 3
A junior data engineer has been asked to develop a streaming data pipeline with a grouped aggregation using DataFrame df. The pipeline needs to calculate the average humidity and average temperature for each non-overlapping five-minute interval. Events are recorded once per minute per device.
Streaming DataFrame df has the following schema:
"device_id INT, event_time TIMESTAMP, temp FLOAT, humidity FLOAT" Code block:
Choose the response that correctly fills in the blank within the code block to complete this task.

A. to_interval("event_time", "5 minutes").alias("time")
B. window("event_time", "5 minutes").alias("time")
C. "event_time"
D. window("event_time", "10 minutes").alias("time")
E. lag("event_time", "10 minutes").alias("time")

Answer: B

Explanation:
This is the correct answer because the window function is used to group streaming data by time intervals. The window function takes two arguments: a time column and a window duration. The window duration specifies how long each window is, and must be a multiple of 1 second. In this case, the window duration is “5 minutes”, which means each window will cover a non-overlapping five-minute interval. The window function also returns a struct column with two fields: start

and end, which represent the start and end time of each window. The alias function is used to rename the struct column as “time”. Verified References: [Databricks Certified Data Engineer Professional], under “Structured Streaming” section; Databricks Documentation, under “WINDOW” section. https://www.databricks.com/blog/2017/05/08/event-time-aggregation-watermarking-apache-sparks-structured-streaming.html

NEW QUESTION 4
A junior data engineer is working to implement logic for a Lakehouse table named silver_device_recordings. The source data contains 100 unique fields in a highly nested JSON structure.
The silver_device_recordings table will be used downstream to power several production monitoring dashboards and a production model. At present, 45 of the 100 fields are being used in at least one of these applications.
The data engineer is trying to determine the best approach for dealing with schema declaration given the highly-nested structure of the data and the numerous fields.
Which of the following accurately presents information about Delta Lake and Databricks that may impact their decision-making process?

A. The Tungsten encoding used by Databricks is optimized for storing string data; newly- added native support for querying JSON strings means that string types are always most efficient.
B. Because Delta Lake uses Parquet for data storage, data types can be easily evolved by just modifying file footer information in place.
C. Human labor in writing code is the largest cost associated with data engineering workloads; as such, automating table declaration logic should be a priority in all migration workloads.
D. Because Databricks will infer schema using types that allow all observed data to be processed, setting types manually provides greater assurance of data quality enforcement.
E. Schema inference and evolution on .Databricks ensure that inferred types will always accurately match the data types used by downstream systems.

Answer: D

Explanation:
This is the correct answer because it accurately presents information about Delta Lake and Databricks that may impact the decision-making process of a junior data engineer who is trying to determine the best approach for dealing with schema declaration given the highly-nested structure of the data and the numerous fields. Delta Lake and Databricks support schema inference and evolution, which means that they can automatically infer the schema of a table from the source data and allow adding new columns or changing column types without affecting existing queries or pipelines. However, schema inference and evolution may not always be desirable or reliable, especially when dealing with complex or nested data structures or when enforcing data quality and consistency across different systems. Therefore, setting types manually can provide greater assurance of data quality enforcement and avoid potential errors or conflicts due to incompatible or unexpected data types. Verified References: [Databricks Certified Data Engineer Professional], under “Delta Lake” section; Databricks Documentation, under “Schema inference and partition of streaming DataFrames/Datasets” section.

NEW QUESTION 5
A data engineer needs to capture pipeline settings from an existing in the workspace, and use them to create and version a JSON file to create a new pipeline.
Which command should the data engineer enter in a web terminal configured with the Databricks CLI?

A. Use the get command to capture the settings for the existing pipeline; remove the pipeline_id and rename the pipeline; use this in a create command
B. Stop the existing pipeline; use the returned settings in a reset command
C. Use the alone command to create a copy of an existing pipeline; use the get JSON command to get the pipeline definition; save this to git
D. Use list pipelines to get the specs for all pipelines; get the pipeline spec from the return results parse and use this to create a pipeline

Answer: A

Explanation:
The Databricks CLI provides a way to automate interactions with Databricks services. When dealing with pipelines, you can use the databricks pipelines get --pipeline-id command to capture the settings of an existing pipeline in JSON format. This JSON can then be modified by removing the pipeline_id to prevent conflicts and renaming the pipeline to create a new pipeline. The modified JSON file can then be used with the databricks pipelines create command to create a new pipeline with those settings. References:
? Databricks Documentation on CLI for Pipelines: Databricks CLI - Pipelines

NEW QUESTION 6
A Delta Lake table in the Lakehouse named customer_parsams is used in churn prediction by the machine learning team. The table contains information about customers derived from a number of upstream sources. Currently, the data engineering team populates this table nightly by overwriting the table with the current valid values derived from upstream data sources.
Immediately after each update succeeds, the data engineer team would like to determine the difference between the new version and the previous of the table.
Given the current implementation, which method can be used?

A. Parse the Delta Lake transaction log to identify all newly written data files.
B. Execute DESCRIBE HISTORY customer_churn_params to obtain the full operation metrics for the update, including a log of all records that have been added or modified.
C. Execute a query to calculate the difference between the new version and the previous version using Delta Lake’s built-in versioning and time travel functionality.
D. Parse the Spark event logs to identify those rows that were updated, inserted, or deleted.

Answer: C

Explanation:
Delta Lake provides built-in versioning and time travel capabilities, allowing users to query previous snapshots of a table. This feature is particularly useful for understanding changes between different versions of the table. In this scenario, where the table is overwritten nightly, you can use Delta Lake's time travel feature to execute a query comparing the latest version of the table (the current state) with its previous version. This approach effectively identifies the differences (such as new, updated, or deleted records) between the two versions. The other options do not provide a straightforward or efficient way to directly compare different versions of a Delta Lake table.
References:
? Delta Lake Documentation on Time Travel: Delta Time Travel
? Delta Lake Versioning: Delta Lake Versioning Guide

NEW QUESTION 7

A data engineer is testing a collection of mathematical functions, one of which calculates the area under a curve as described by another function.
Which kind of the test does the above line exemplify?

A. Integration
B. Unit
C. Manual
D. functional

Answer: B

Explanation:
A unit test is designed to verify the correctness of a small, isolated piece of
code, typically a single function. Testing a mathematical function that calculates the area under a curve is an example of a unit test because it is testing a specific, individual function to ensure it operates as expected.
References:
? Software Testing Fundamentals: Unit Testing

NEW QUESTION 8
In order to prevent accidental commits to production data, a senior data engineer has instituted a policy that all development work will reference clones of Delta Lake tables. After testing both deep and shallow clone, development tables are created using shallow clone.
A few weeks after initial table creation, the cloned versions of several tables implemented as Type 1 Slowly Changing Dimension (SCD) stop working. The transaction logs for the source tables show that vacuum was run the day before.
Why are the cloned tables no longer working?

A. The data files compacted by vacuum are not tracked by the cloned metadata; running refresh on the cloned table will pull in recent changes.
B. Because Type 1 changes overwrite existing records, Delta Lake cannot guarantee data consistency for cloned tables.
C. The metadata created by the clone operation is referencing data files that were purged as invalid by the vacuum command
D. Running vacuum automatically invalidates any shallow clones of a table; deep clone should always be used when a cloned table will be repeatedly queried.

Answer: C

Explanation:
In Delta Lake, a shallow clone creates a new table by copying the metadata of the source table without duplicating the data files. When the vacuum command is run on the source table, it removes old data files that are no longer needed to maintain the transactional log's integrity, potentially including files referenced by the shallow clone's metadata. If these files are purged, the shallow cloned tables will reference non-existent data files, causing them to stop working properly. This highlights the dependency of shallow clones on the source table's data files and the impact of data management operations like vacuum on these clones.References: Databricks documentation on Delta Lake, particularly the sections on cloning tables (shallow and deep cloning) and data retention with the vacuum command (https://docs.databricks.com/delta/index.html).

NEW QUESTION 9
The Databricks CLI is use to trigger a run of an existing job by passing the job_id parameter. The response that the job run request has been submitted successfully includes a filed run_id.
Which statement describes what the number alongside this field represents?

A. The job_id is returned in this field.
B. The job_id and number of times the job has been are concatenated and returned.
C. The number of times the job definition has been run in the workspace.
D. The globally unique ID of the newly triggered run.

Answer: D

Explanation:
When triggering a job run using the Databricks CLI, the run_id field in the response represents a globally unique identifier for that particular run of the job. This run_id is distinct from the job_id. While the job_id identifies the job definition and is constant across all runs of that job, the run_id is unique to each execution and is used to track and query the status of that specific job run within the Databricks environment. This distinction allows users to manage and reference individual executions of a job directly.

NEW QUESTION 10
A junior data engineer has been asked to develop a streaming data pipeline with a grouped aggregation using DataFrame df. The pipeline needs to calculate the average humidity and average temperature for each non-overlapping five-minute interval. Incremental state information should be maintained for 10 minutes for late-arriving data.
Streaming DataFrame df has the following schema:
"device_id INT, event_time TIMESTAMP, temp FLOAT, humidity FLOAT" Code block:
Choose the response that correctly fills in the blank within the code block to complete this task.

A. withWatermark("event_time", "10 minutes")
B. awaitArrival("event_time", "10 minutes")
C. await("event_time + ‘10 minutes'")
D. slidingWindow("event_time", "10 minutes")
E. delayWrite("event_time", "10 minutes")

Answer: A

Explanation:
The correct answer is A. withWatermark(“event_time”, “10 minutes”). This is because the question asks for incremental state information to be maintained for 10 minutes for late-arriving data. The withWatermark method is used to define the watermark for late data. The watermark is a timestamp column and a threshold that tells the system
how long to wait for late data. In this case, the watermark is set to 10 minutes. The other options are incorrect because they are not valid methods or syntax for watermarking in Structured Streaming. References:
? Watermarking: https://docs.databricks.com/spark/latest/structured-streaming/watermarks.html

? Windowed aggregations: https://docs.databricks.com/spark/latest/structured-streaming/window-operations.html

NEW QUESTION 10
A Structured Streaming job deployed to production has been experiencing delays during peak hours of the day. At present, during normal execution, each microbatch of data is processed in less than 3 seconds. During peak hours of the day, execution time for each microbatch becomes very inconsistent, sometimes exceeding 30 seconds. The streaming write is currently configured with a trigger interval of 10 seconds.
Holding all other variables constant and assuming records need to be processed in less than 10 seconds, which adjustment will meet the requirement?

A. Decrease the trigger interval to 5 seconds; triggering batches more frequently allows idle executors to begin processing the next batch while longer running tasks from previous batches finish.
B. Increase the trigger interval to 30 seconds; setting the trigger interval near the maximum execution time observed for each batch is always best practice to ensure no records are dropped.
C. The trigger interval cannot be modified without modifying the checkpoint directory; to maintain the current stream state, increase the number of shuffle partitions to maximize parallelism.
D. Use the trigger once option and configure a Databricks job to execute the query every 10 seconds; this ensures all backlogged records are processed with each batch.
E. Decrease the trigger interval to 5 seconds; triggering batches more frequently may prevent records from backing up and large batches from causing spill.

Answer: E

Explanation:
The adjustment that will meet the requirement of processing records in less than 10 seconds is to decrease the trigger interval to 5 seconds. This is because triggering batches more frequently may prevent records from backing up and large batches from causing spill. Spill is a phenomenon where the data in memory exceeds the available capacity and has to be written to disk, which can slow down the processing and increase the execution time1. By reducing the trigger interval, the streaming query can process smaller batches of data more quickly and avoid spill. This can also improve the latency and throughput of the streaming job2.
The other options are not correct, because:
? Option A is incorrect because triggering batches more frequently does not allow idle executors to begin processing the next batch while longer running tasks from previous batches finish. In fact, the opposite is true. Triggering batches more frequently may cause concurrent batches to compete for the same resources and cause contention and backpressure2. This can degrade the performance and stability of the streaming job.
? Option B is incorrect because increasing the trigger interval to 30 seconds is not a good practice to ensure no records are dropped. Increasing the trigger interval means that the streaming query will process larger batches of data less frequently, which can increase the risk of spill, memory pressure, and timeouts12. This can also increase the latency and reduce the throughput of the streaming job.
? Option C is incorrect because the trigger interval can be modified without modifying the checkpoint directory. The checkpoint directory stores the metadata and state of the streaming query, such as the offsets, schema, and configuration3. Changing the trigger interval does not affect the state of the streaming query, and does not require a new checkpoint directory. However, changing the number of shuffle partitions may affect the state of the streaming query, and may require a new checkpoint directory4.
? Option D is incorrect because using the trigger once option and configuring a Databricks job to execute the query every 10 seconds does not ensure that all backlogged records are processed with each batch. The trigger once option means that the streaming query will process all the available data in the source and then stop5. However, this does not guarantee that the query will finish processing within 10 seconds, especially if there are a lot of records in the source. Moreover, configuring a Databricks job to execute the query every 10 seconds may cause overlapping or missed batches, depending on the execution time of the query.
References: Memory Management Overview, Structured Streaming Performance Tuning Guide, Checkpointing, Recovery Semantics after Changes in a Streaming Query, Triggers

NEW QUESTION 12
A junior data engineer has manually configured a series of jobs using the Databricks Jobs UI. Upon reviewing their work, the engineer realizes that they are listed as the "Owner" for each job. They attempt to transfer "Owner" privileges to the "DevOps" group, but cannot successfully accomplish this task.
Which statement explains what is preventing this privilege transfer?

A. Databricks jobs must have exactly one owner; "Owner" privileges cannot be assigned to a group.
B. The creator of a Databricks job will always have "Owner" privileges; this configuration cannot be changed.
C. Other than the default "admins" group, only individual users can be granted privileges on jobs.
D. A user can only transfer job ownership to a group if they are also a member of that group.
E. Only workspace administrators can grant "Owner" privileges to a group.

Answer: E

Explanation:
The reason why the junior data engineer cannot transfer “Owner” privileges to the “DevOps” group is that Databricks jobs must have exactly one owner, and the owner must be an individual user, not a group. A job cannot have more than one owner, and a job cannot have a group as an owner. The owner of a job is the user who created the job, or the user who was assigned the ownership by another user. The owner of a job has the highest level of permission on the job, and can grant or revoke permissions to other users or groups. However, the owner cannot transfer the ownership to a group, only to another user. Therefore, the junior data engineer’s attempt to transfer “Owner” privileges to the “DevOps” group is not possible. References:
? Jobs access control: https://docs.databricks.com/security/access-control/table-acls/index.html
? Job permissions: https://docs.databricks.com/security/access-control/table-acls/privileges.html#job-permissions

NEW QUESTION 13
The data engineering team is migrating an enterprise system with thousands of tables and views into the Lakehouse. They plan to implement the target architecture using a series of bronze, silver, and gold tables. Bronze tables will almost exclusively be used by production data engineering workloads, while silver tables will be used to support both data engineering and machine learning workloads. Gold tables will largely serve business intelligence and reporting purposes. While personal identifying information (PII) exists in all tiers of data, pseudonymization and anonymization rules are in place for all data at the silver and gold levels.
The organization is interested in reducing security concerns while maximizing the ability to collaborate across diverse teams.
Which statement exemplifies best practices for implementing this system?

A. Isolating tables in separate databases based on data quality tiers allows for easy permissions management through database ACLs and allows physical separation ofdefault storage locations for managed tables.
B. Because databases on Databricks are merely a logical construct, choices around database organization do not impact security or discoverability in the Lakehouse.

C. Storinq all production tables in a single database provides a unified view of all data assets available throughout the Lakehouse, simplifying discoverability by granting all users view privileges on this database.
D. Working in the default Databricks database provides the greatest security when working with managed tables, as these will be created in the DBFS root.
E. Because all tables must live in the same storage containers used for the database they're created in, organizations should be prepared to create between dozens and thousands of databases depending on their data isolation requirements.

Answer: A

Explanation:
This is the correct answer because it exemplifies best practices for implementing this system. By isolating tables in separate databases based on data quality tiers, such as bronze, silver, and gold, the data engineering team can achieve several benefits. First, they can easily manage permissions for different users and groups through database ACLs, which allow granting or revoking access to databases, tables, or views. Second, they can physically separate the default storage locations for managed tables in each database, which can improve performance and reduce costs. Third, they can provide a clear and consistent naming convention for the tables in each database, which can improve discoverability and usability. Verified References: [Databricks Certified Data Engineer Professional], under “Lakehouse” section; Databricks Documentation, under “Database object privileges” section.

NEW QUESTION 17
A Delta Lake table was created with the below query:
Consider the following query:
DROP TABLE prod.sales_by_store -
If this statement is executed by a workspace admin, which result will occur?

A. Nothing will occur until a COMMIT command is executed.
B. The table will be removed from the catalog but the data will remain in storage.
C. The table will be removed from the catalog and the data will be deleted.
D. An error will occur because Delta Lake prevents the deletion of production data.
E. Data will be marked as deleted but still recoverable with Time Travel.

Answer: C

Explanation:
When a table is dropped in Delta Lake, the table is removed from the catalog and the data is deleted. This is because Delta Lake is a transactional storage layer that provides ACID guarantees. When a table is dropped, the transaction log is updated to reflect the deletion of the table and the data is deleted from the underlying storage. References:
? https://docs.databricks.com/delta/quick-start.html#drop-a-table
? https://docs.databricks.com/delta/delta-batch.html#drop-table

NEW QUESTION 20
The business reporting tem requires that data for their dashboards be updated every hour. The total processing time for the pipeline that extracts transforms and load the data for their pipeline runs in 10 minutes.
Assuming normal operating conditions, which configuration will meet their service-level agreement requirements with the lowest cost?

A. Schedule a jo to execute the pipeline once and hour on a dedicated interactive cluster.
B. Schedule a Structured Streaming job with a trigger interval of 60 minutes.
C. Schedule a job to execute the pipeline once hour on a new job cluster.
D. Configure a job that executes every time new data lands in a given directory.

Answer: C

Explanation:
Scheduling a job to execute the data processing pipeline once an hour on a new job cluster is the most cost-effective solution given the scenario. Job clusters are ephemeral in nature; they are spun up just before the job execution and terminated upon completion, which means you only incur costs for the time the cluster is active. Since the total processing time is only 10 minutes, a new job cluster created for each hourly execution minimizes the running time and thus the cost, while also fulfilling the requirement for hourly data updates for the business reporting team's dashboards.
References:
? Databricks documentation on jobs and job clusters: https://docs.databricks.com/jobs.html

NEW QUESTION 23
A junior member of the data engineering team is exploring the language interoperability of Databricks notebooks. The intended outcome of the below code is to register a view of all sales that occurred in countries on the continent of Africa that appear in the geo_lookup table.
Before executing the code, running SHOW TABLES on the current database indicates the database contains only two tables: geo_lookup and sales.

```
Cmd 1
%python
countries_af = [x[0] for x in
spark.table("geo_lookup").filter("continent='AF'").select("country").collect()]

Cmd 2
%sql
CREATE VIEW sales_af AS
  SELECT *
  FROM sales
  WHERE city IN countries_af
  AND CONTINENT = "AF"
```

Which statement correctly describes the outcome of executing these command cells in order in an interactive notebook?

A. Both commands will succee
B. Executing show tables will show that countries at and sales at have been registered as views.
C. Cmd 1 will succee
D. Cmd 2 will search all accessible databases for a table or view named countries af: if this entity exists, Cmd 2 will succeed.
E. Cmd 1 will succeed and Cmd 2 will fail, countries at will be a Python variable representing a PySpark DataFrame.

F. Both commands will fai
G. No new variables, tables, or views will be created.
H. Cmd 1 will succeed and Cmd 2 will fail, countries at will be a Python variable containing a list of strings.

Answer: E

Explanation:
This is the correct answer because Cmd 1 is written in Python and uses a list comprehension to extract the country names from the geo_lookup table and store them in a Python variable named countries af. This variable will contain a list of strings, not a PySpark DataFrame or a SQL view. Cmd 2 is written in SQL and tries to create a view named sales af by selecting from the sales table where city is in countries af. However, this command will fail because countries af is not a valid SQL entity and cannot be used in a SQL query. To fix this, a better approach would be to use spark.sql() to execute a SQL query in Python and pass the countries af variable as a parameter. Verified References: [Databricks Certified Data Engineer Professional], under “Language Interoperability” section; Databricks Documentation, under “Mix languages” section.

NEW QUESTION 27
A developer has successfully configured credential for Databricks Repos and cloned a remote Git repository. Hey don not have privileges to make changes to the main branch, which is the only branch currently visible in their workspace.
Use Response to pull changes from the remote Git repository commit and push changes to a branch that appeared as a changes were pulled.

A. Use Repos to merge all differences and make a pull request back to the remote repository.
B. Use repos to merge all difference and make a pull request back to the remote repository.
C. Use Repos to create a new branch commit all changes and push changes to the remote Git repertory.
D. Use repos to create a fork of the remote repository commit all changes and make a pull request on the source repository

Answer: C

Explanation:
In Databricks Repos, when a user does not have privileges to make changes directly to the main branch of a cloned remote Git repository, the recommended approach is to create a new branch within the Databricks workspace. The developer can then make changes in this new branch, commit those changes, and push the new branch to the remote Git repository. This workflow allows for isolated development without affecting the main branch, enabling the developer to propose changes via a pull request from the new branch to the main branch in the remote repository. This method adheres to common Git collaboration workflows, fostering code review and collaboration while ensuring the integrity of the main branch.
References:
? Databricks documentation on using Repos with Git: https://docs.databricks.com/repos.html

NEW QUESTION 31
When evaluating the Ganglia Metrics for a given cluster with 3 executor nodes, which indicator would signal proper utilization of the VM's resources?

A. The five Minute Load Average remains consistent/flat
B. Bytes Received never exceeds 80 million bytes per second
C. Network I/O never spikes
D. Total Disk Space remains constant
E. CPU Utilization is around 75%

Answer: E

Explanation:
In the context of cluster performance and resource utilization, a CPU utilization rate of around 75% is generally considered a good indicator of efficient resource usage. This level of CPU utilization suggests that the cluster is being effectively used without being overburdened or underutilized.
? A consistent 75% CPU utilization indicates that the cluster's processing power is being effectively employed while leaving some headroom to handle spikes in workload or additional tasks without maxing out the CPU, which could lead to performance degradation.
? A five Minute Load Average that remains consistent/flat (Option A) might indicate underutilization or a bottleneck elsewhere.
? Monitoring network I/O (Options B and C) is important, but these metrics alone don't provide a complete picture of resource utilization efficiency.
? Total Disk Space (Option D) remaining constant is not necessarily an indicator of proper resource utilization, as it's more related to storage rather than computational efficiency.
References:
? Ganglia Monitoring System: Ganglia Documentation
? Databricks Documentation on Monitoring: Databricks Cluster Monitoring

NEW QUESTION 34
The data science team has created and logged a production using MLFlow. The model accepts a list of column names and returns a new column of type DOUBLE. The following code correctly imports the production model, load the customer table containing the customer_id key column into a Dataframe, and defines the feature columns needed for the model.

```
model = mlflow.pyfunc.spark_udf (spark,
model_uri="models:/churn/prod")

df = spark.table("customers")

columns = ["account_age", "time_since_last_seen", "app_rating"]
```

Which code block will output DataFrame with the schema'' customer_id LONG, predictions DOUBLE''?

A. Model, predict (df, columns)
B. Df, map (lambda k:midel (x [columns]) ,select (''customer_id predictions'')
C. D
D. Select (''customer_id''. Model (''columns) alias (''predictions'')
E. Df.apply(model, columns). Select (''customer_id, prediction''

Answer: A

Explanation:
Given the information that the model is registered with MLflow and assuming predict is the method used to apply the model to a set of columns, we use the model.predict() function to apply the model to the DataFrame df using the specified columns. The model.predict() function is designed to take in a DataFrame and a list of column names as arguments, applying the trained model to these features to produce a predictions column. When working with PySpark, this predictions column needs to be selected alongside the customer_id to create a new DataFrame with the schema customer_id LONG, predictions DOUBLE.
References:
? MLflow documentation on using Python function models: https://www.mlflow.org/docs/latest/models.html#python-function-python
? PySpark MLlib documentation on model prediction: https://spark.apache.org/docs/latest/ml-pipeline.html#pipeline

NEW QUESTION 39
When scheduling Structured Streaming jobs for production, which configuration automatically recovers from query failures and keeps costs low?

A. Cluster: New Job Cluster; Retries: Unlimited;Maximum Concurrent Runs: Unlimited
B. Cluster: New Job Cluster; Retries: None;Maximum Concurrent Runs: 1
C. Cluster: Existing All-Purpose Cluster; Retries: Unlimited;Maximum Concurrent Runs: 1
D. Cluster: Existing All-Purpose Cluster; Retries: Unlimited;Maximum Concurrent Runs: 1
E. Cluster: Existing All-Purpose Cluster; Retries: None;Maximum Concurrent Runs: 1

Answer: D

Explanation:
The configuration that automatically recovers from query failures and keeps costs low is to use a new job cluster, set retries to unlimited, and set maximum concurrent runs to 1. This configuration has the following advantages:
? A new job cluster is a cluster that is created and terminated for each job run. This means that the cluster resources are only used when the job is running, and no idle costs are incurred. This also ensures that the cluster is always in a clean state and has the latest configuration and libraries for the job1.
? Setting retries to unlimited means that the job will automatically restart the query in case of any failure, such as network issues, node failures, or transient errors. This improves the reliability and availability of the streaming job, and avoids data loss or inconsistency2.
? Setting maximum concurrent runs to 1 means that only one instance of the job can run at a time. This prevents multiple queries from competing for the same resources or writing to the same output location, which can cause performance degradation or data corruption3.
Therefore, this configuration is the best practice for scheduling Structured Streaming jobs for production, as it ensures that the job is resilient, efficient, and consistent.
References: Job clusters, Job retries, Maximum concurrent runs

NEW QUESTION 44
A distributed team of data analysts share computing resources on an interactive cluster with autoscaling configured. In order to better manage costs and query throughput, the workspace administrator is hoping to evaluate whether cluster upscaling is caused by many concurrent users or resource-intensive queries.
In which location can one review the timeline for cluster resizing events?

A. Workspace audit logs
B. Driver's log file
C. Ganglia
D. Cluster Event Log
E. Executor's log file

Answer: C

NEW QUESTION 45
The downstream consumers of a Delta Lake table have been complaining about data quality issues impacting performance in their applications. Specifically, they have complained that invalid latitude and longitude values in the activity_details table have been breaking their ability to use other geolocation processes.
A junior engineer has written the following code to add CHECK constraints to the Delta Lake table:

```
ALTER TABLE activity_details
ADD CONSTRAINT valid_coordinates
CHECK (
  latitude >= -90 AND
  latitude <= 90 AND
  longitude >= -180 AND
  longitude <= 180);
```

A senior engineer has confirmed the above logic is correct and the valid ranges for latitude and longitude are provided, but the code fails when executed.
Which statement explains the cause of this failure?

A. Because another team uses this table to support a frequently running application, two- phase locking is preventing the operation from committing.
B. The activity details table already exists; CHECK constraints can only be added during initial table creation.
C. The activity details table already contains records that violate the constraints; all existing data must pass CHECK constraints in order to add them to an existing table.
D. The activity details table already contains records; CHECK constraints can only be added prior to inserting values into a table.
E. The current table schema does not contain the field valid coordinates; schema evolution will need to be enabled before altering the table to add a constraint.

Answer: C

Explanation:

The failure is that the code to add CHECK constraints to the Delta Lake table fails when executed. The code uses ALTER TABLE ADD CONSTRAINT commands to add two CHECK constraints to a table named activity_details. The first constraint checks if the latitude value is between -90 and 90, and the second constraint checks if the longitude value is between -180 and 180. The cause of this failure is that the activity_details table already contains records that violate these constraints, meaning that they have invalid latitude or longitude values outside of these ranges. When adding CHECK constraints to an existing table, Delta Lake verifies that all existing data satisfies the constraints before adding them to the table. If any record violates the constraints, Delta Lake throws an exception and aborts the operation. Verified References: [Databricks Certified Data Engineer Professional], under “Delta Lake” section; Databricks Documentation, under “Add a CHECK constraint to an existing table” section. https://docs.databricks.com/en/sql/language-manual/sql-ref-syntax-ddl-alter-table.html#add-constraint

NEW QUESTION 50
The data engineering team maintains a table of aggregate statistics through batch nightly updates. This includes total sales for the previous day alongside totals and averages for a variety of time periods including the 7 previous days, year-to-date, and quarter-to-date. This table is named store_saies_summary and the schema is as follows:
The table daily_store_sales contains all the information needed to update store_sales_summary. The schema for this table is: store_id INT, sales_date DATE, total_sales FLOAT If daily_store_sales is implemented as a Type 1 table and the total_sales column might be adjusted after manual data auditing, which approach is the safest to generate accurate reports in the store_sales_summary table?

A. Implement the appropriate aggregate logic as a batch read against the daily_store_salestable and overwrite the store_sales_summary table with each Update.
B. Implement the appropriate aggregate logic as a batch read against the daily_store_sales table and append new rows nightly to the store_sales_summary table.
C. Implement the appropriate aggregate logic as a batch read against the daily_store_sales table and use upsert logic to update results in the store_sales_summary table.
D. Implement the appropriate aggregate logic as a Structured Streaming read against the daily_store_sales table and use upsert logic to update results in the store_sales_summary table.
E. Use Structured Streaming to subscribe to the change data feed for daily_store_sales and apply changes to the aggregates in the store_sales_summary table with each update.

Answer: E

Explanation:
The daily_store_sales table contains all the information needed to update store_sales_summary. The schema of the table is:
store_id INT, sales_date DATE, total_sales FLOAT
The daily_store_sales table is implemented as a Type 1 table, which means that old values are overwritten by new values and no history is maintained. The total_sales column might be adjusted after manual data auditing, which means that the data in the table may change over time.
The safest approach to generate accurate reports in the store_sales_summary table is to use Structured Streaming to subscribe to the change data feed for daily_store_sales and apply changes to the aggregates in the store_sales_summary table with each update. Structured Streaming is a scalable and fault-tolerant stream processing engine built on Spark SQL. Structured Streaming allows processing data streams as if they were tables or DataFrames, using familiar operations such as select, filter, groupBy, or join. Structured Streaming also supports output modes that specify how to write the results of a streaming query to a sink, such as append, update, or complete. Structured Streaming can handle both streaming and batch data sources in a unified manner.
The change data feed is a feature of Delta Lake that provides structured streaming sources that can subscribe to changes made to a Delta Lake table. The change data feed captures both data changes and schema changes as ordered events that can be processed by downstream applications or services. The change data feed can be configured with different options, such as starting from a specific version or timestamp, filtering by operation type or partition values, or excluding no-op changes.
By using Structured Streaming to subscribe to the change data feed for daily_store_sales, one can capture and process any changes made to the total_sales column due to manual data auditing. By applying these changes to the aggregates in the store_sales_summary table with each update, one can ensure that the reports are always consistent and accurate with the latest data. Verified References: [Databricks Certified Data Engineer Professional], under “Spark Core” section; Databricks Documentation, under “Structured Streaming” section; Databricks Documentation, under “Delta Change Data Feed” section.

NEW QUESTION 55
A data team's Structured Streaming job is configured to calculate running aggregates for item sales to update a downstream marketing dashboard. The marketing team has introduced a new field to track the number of times this promotion code is used for each item. A junior data engineer suggests updating the existing query as follows: Note that proposed changes are in bold.

Original query:

```
df.groupBy("item")
    .agg(count("item").alias("total_count"),
         mean("sale_price").alias("avg_price"))
    .writeStream
    .outputMode("complete")
    .option("checkpointLocation", "/item_agg/__checkpoint")
    .start("/item_agg")
```

Proposed query:

```
df.groupBy("item")
    .agg(count("item").alias("total_count"),
         mean("sale_price").alias("avg_price"),
         count("promo_code = 'NEW_MEMBER'").alias("new_member_promo"))
    .writeStream
    .outputMode("complete")
    .option('mergeSchema', 'true')
    .option("checkpointLocation", "/item_agg/__checkpoint")
    .start("/item_agg")
```

Which step must also be completed to put the proposed query into production?

A. Increase the shuffle partitions to account for additional aggregates
B. Specify a new checkpointlocation
C. Run REFRESH TABLE delta, /item_agg'
D. Remove .option (mergeSchema', true') from the streaming write

Answer: B

Explanation:
When introducing a new aggregation or a change in the logic of a Structured Streaming query, it is generally necessary to specify a new checkpoint location. This is because the checkpoint directory contains metadata about the offsets and the state of the aggregations of a streaming query. If the logic of the query changes, such as including a new aggregation field, the state information saved in the current checkpoint would not be compatible with the new logic, potentially leading to incorrect results or failures. Therefore, to accommodate the new field and ensure the streaming job has the correct starting point and state information for aggregations, a new checkpoint location should be specified. References:
? Databricks documentation on Structured Streaming:
https://docs.databricks.com/spark/latest/structured-streaming/index.html
? Databricks documentation on streaming checkpoints: https://docs.databricks.com/spark/latest/structured- streaming/production.html#checkpointing

NEW QUESTION 59
The following table consists of items found in user carts within an e-commerce website.

```
Carts (id LONG, items ARRAY<STRUCT<id: LONG, count: INT>>)
id  items                                              email
1001[{id: "DESK65", count: 1}]                         "u1@domain.com"
1002[{id: "KYBD45", count: 1}, {id: "M27", count: 2}]"u2@domain.com"
1003[{id: "M27", count: 1}]                            "u3@domain.com"
```

The following MERGE statement is used to update this table using an updates view, with schema evaluation enabled on this table.

```
MERGE INTO carts c
USING updates u
ON c.id = u.id
WHEN MATCHED
  THEN UPDATE SET *
```

How would the following update be handled?

```
(new nested field, missing existing column)
id  items
1001[{id: "DESK65", count: 2, coupon: "BOGO50"}]
```

A. The update is moved to separate "restored" column because it is missing a column expected in the target schema.
B. The new restored field is added to the target schema, and dynamically read as NULL for existing unmatched records.
C. The update throws an error because changes to existing columns in the target schema are not supported.
D. The new nested field is added to the target schema, and files underlying existing records are updated to include NULL values for the new field.

Answer: D

Explanation:
With schema evolution enabled in Databricks Delta tables, when a new field is added to a record through a MERGE operation, Databricks automatically modifies the table schema to include the new field. In existing records where this new field is not present, Databricks will insert NULL values for that field. This ensures that the schema remains consistent across all records in the table, with the new field being present in every record, even if it is NULL for records that did not originally include it.
References:
? Databricks documentation on schema evolution in Delta Lake: https://docs.databricks.com/delta/delta-batch.html#schema-evolution

NEW QUESTION 63
The data engineering team maintains the following code:

```
import pyspark.sql.functions as F

(spark.table("silver_customer_sales")
  .groupBy("customer_id")
  .agg(
    F.min("sale_date").alias("first_transaction_date"),
    F.max("sale_date").alias("last_transaction_date"),
    F.mean("sale_total").alias("average_sales"),
    F.countDistinct("order_id").alias("total_orders"),
    F.sum("sale_total").alias("lifetime_value")
  ).write
  .mode("overwrite")
  .table("gold_customer_lifetime_sales_summary")
)
```

Assuming that this code produces logically correct results and the data in the source table has been de-duplicated and validated, which statement describes what will occur when this code is executed?

A. The silver_customer_sales table will be overwritten by aggregated values calculated from all records in the gold_customer_lifetime_sales_summary table as a batch job.
B. A batch job will update the gold_customer_lifetime_sales_summary table, replacing only those rows that have different values than the current version of the table, using customer_id as the primary key.
C. The gold_customer_lifetime_sales_summary table will be overwritten by aggregated values calculated from all records in the silver_customer_sales table as a batch job.
D. An incremental job will leverage running information in the state store to update aggregate values in the gold_customer_lifetime_sales_summary table.
E. An incremental job will detect if new rows have been written to the silver_customer_sales table; if new rows are detected, all aggregates will be recalculated and used to overwrite the gold_customer_lifetime_sales_summary table.

Answer: C

Explanation:
This code is using the pyspark.sql.functions library to group the silver_customer_sales table by customer_id and then aggregate the data using the minimum sale date, maximum sale total, and sum of distinct order ids. The resulting aggregated data is then written to the gold_customer_lifetime_sales_summary table, overwriting any existing data in that table. This is a batch job that does not use any incremental or streaming logic, and does not perform any merge or update operations. Therefore, the code will overwrite the gold table with the aggregated values from the silver table every time it is executed. References:
? https://docs.databricks.com/spark/latest/dataframes-datasets/introduction-to-dataframes-python.html
? https://docs.databricks.com/spark/latest/dataframes-datasets/transforming-data- with-dataframes.html
? https://docs.databricks.com/spark/latest/dataframes-datasets/aggregating-data- with-dataframes.html

NEW QUESTION 67
A data engineer wants to join a stream of advertisement impressions (when an ad was shown) with another stream of user clicks on advertisements to correlate when impression led to monitizable clicks.

```
In the code below, impressions is a streaming DataFrame with a watermark ("event_time", "10 minutes")
.groupBy(
window("event_time", "5 minutes"),
"id")
.count()
).     withWatermark("event_time", 2 hours)
impressions.join(clicks, expr("clickAdId = impressionAdId"), "inner")
```

Which solution would improve the performance?
A)

```
Joining on event time constraint: clickTime == impressionTime using a leftOuter join
```

B)

```
Joining on event time constraint: clickTime >= impressionTime - interval 3 hours and removing
watermarks
```

C)

```
Joining on event time constraint: clickTime + 3 hours < impressionTime - 2 hours
```

D)

```
Joining on event time constraint: clickTime >= impressionTime AND clickTime <= impressionTime +
interval 1 hour
```

A. Option A
B. Option B
C. Option C
D. Option D

Answer: A

Explanation:
When joining a stream of advertisement impressions with a stream of user clicks, you want to minimize the state that you need to maintain for the join. Option A suggests using a left outer join with the condition that clickTime == impressionTime, which is suitable for correlating events that occur at the exact same time. However, in a real-world scenario, you would likely need some leeway to account for the delay between an impression and a possible click. It's important to design the join condition and the window of time considered to optimize performance while still capturing the relevant user interactions. In this case, having the watermark can help with state management and avoid state growing unbounded by discarding old state data that's unlikely to match with new data.

NEW QUESTION 68
A team of data engineer are adding tables to a DLT pipeline that contain repetitive expectations for many of the same data quality checks.
One member of the team suggests reusing these data quality rules across all tables defined for this pipeline.
What approach would allow them to do this?

A. Maintain data quality rules in a Delta table outside of this pipeline's target schema, providing the schema name as a pipeline parameter.
B. Use global Python variables to make expectations visible across DLT notebooks included in the same pipeline.
C. Add data quality constraints to tables in this pipeline using an external job with access to pipeline configuration files.
D. Maintain data quality rules in a separate Databricks notebook that each DLT notebook of file.

Answer: A

Explanation:
Maintaining data quality rules in a centralized Delta table allows for the reuse of these rules across multiple DLT (Delta Live Tables) pipelines. By storing these rules outside the pipeline's target schema and referencing the schema name as a pipeline parameter, the team can apply the same set of data quality checks to different tables within the pipeline. This approach ensures consistency in data quality validations and reduces redundancy in code by not having to replicate the same rules in each DLT notebook or file. References:
? Databricks Documentation on Delta Live Tables: Delta Live Tables Guide

NEW QUESTION 70
Spill occurs as a result of executing various wide transformations. However, diagnosing spill requires one to proactively look for key indicators.
Where in the Spark UI are two of the primary indicators that a partition is spilling to disk?

A. Stage's detail screen and Executor's files
B. Stage's detail screen and Query's detail screen
C. Driver's and Executor's log files
D. Executor's detail screen and Executor's log files

Answer: B

Explanation:

In Apache Spark's UI, indicators of data spilling to disk during the execution of wide transformations can be found in the Stage's detail screen and the Query's detail screen. These screens provide detailed metrics about each stage of a Spark job, including information about memory usage and spill data. If a task is spilling data to disk, it indicates that the data being processed exceeds the available memory, causing Spark to spill data to disk to free up memory. This is an important performance metric as excessive spill can significantly slow down the processing.
References:
? Apache Spark Monitoring and Instrumentation: Spark Monitoring Guide
? Spark UI Explained: Spark UI Documentation

NEW QUESTION 73
A Spark job is taking longer than expected. Using the Spark UI, a data engineer notes that the Min, Median, and Max Durations for tasks in a particular stage show the minimum and median time to complete a task as roughly the same, but the max duration for a task to be roughly 100 times as long as the minimum.
Which situation is causing increased duration of the overall job?

A. Task queueing resulting from improper thread pool assignment.
B. Spill resulting from attached volume storage being too small.
C. Network latency due to some cluster nodes being in different regions from the source data
D. Skew caused by more data being assigned to a subset of spark-partitions.
E. Credential validation errors while pulling data from an external system.

Answer: D

Explanation:
This is the correct answer because skew is a common situation that causes increased duration of the overall job. Skew occurs when some partitions have more data than others, resulting in uneven distribution of work among tasks and executors. Skew can be caused by various factors, such as skewed data distribution, improper partitioning strategy, or join operations with skewed keys. Skew can lead to performance issues such as long-running tasks, wasted resources, or even task failures due to memory or disk spills. Verified References: [Databricks Certified Data Engineer Professional], under "Performance Tuning" section; Databricks Documentation, under "Skew" section.

NEW QUESTION 78
A data engineer wants to reflector the following DLT code, which includes multiple definition with very similar code:

```
@dlt.table(name=f"t1_dataset")
def t1_dataset():
    return spark.read.table(t1)

@dlt.table(name=f"t2_dataset")
def t2_dataset():
    return spark.read.table(t2)

@dlt.table(name=f"t3_dataset")
def t3_dataset():
    return spark.read.table(t3)

...
```

In an attempt to programmatically create these tables using a parameterized table definition, the data engineer writes the following code.

```
tables = ["t1", "t2", "t3"]

for t in tables:
    @dlt.table(name=f"{t}_dataset")
        def new_table():
```

The pipeline runs an update with this refactored code, but generates a different DAG showing incorrect configuration values for tables.
How can the data engineer fix this?

A. Convert the list of configuration values to a dictionary of table settings, using table names as keys.
B. Convert the list of configuration values to a dictionary of table settings, using different input the for loop.
C. Load the configuration values for these tables from a separate file, located at a path provided by a pipeline parameter.
D. Wrap the loop inside another table definition, using generalized names and properties to replace with those from the inner table

Answer: A

Explanation:
The issue with the refactored code is that it tries to use string interpolation to dynamically create table names within the dlc.table decorator, which will not correctly interpret the table names. Instead, by using a dictionary with table names as keys and their configurations as values, the data engineer can iterate over the dictionary items and use the keys (table names) to properly configure the table settings. This way, the decorator can correctly recognize each table name, and the corresponding configuration settings can be applied appropriately.

NEW QUESTION 81
What is the first of a Databricks Python notebook when viewed in a text editor?

A. %python
B. % Databricks notebook source

C. -- Databricks notebook source
D. //Databricks notebook source

Answer: B

Explanation:
When viewing a Databricks Python notebook in a text editor, the first line indicates the format and source type of the notebook. The correct option is % Databricks notebook source, which is a magic command that specifies the start of a Databricks notebook source file.

NEW QUESTION 86
The data science team has requested assistance in accelerating queries on free form text from user reviews. The data is currently stored in Parquet with the below schema:
item_id INT, user_id INT, review_id INT, rating FLOAT, review STRING
The review column contains the full text of the review left by the user. Specifically, the data science team is looking to identify if any of 30 key words exist in this field.
A junior data engineer suggests converting this data to Delta Lake will improve query performance.
Which response to the junior data engineer s suggestion is correct?

A. Delta Lake statistics are not optimized for free text fields with high cardinality.
B. Text data cannot be stored with Delta Lake.
C. ZORDER ON review will need to be run to see performance gains.
D. The Delta log creates a term matrix for free text fields to support selective filtering.
E. Delta Lake statistics are only collected on the first 4 columns in a table.

Answer: A

Explanation:
Converting the data to Delta Lake may not improve query performance on free text fields with high cardinality, such as the review column. This is because Delta Lake collects statistics on the minimum and maximum values of each column, which are not very useful for filtering or skipping data on free text fields. Moreover, Delta Lake collects statistics on the first 32 columns by default, which may not include the review column if the table has more columns. Therefore, the junior data engineer's suggestion is not correct. A better approach would be to use a full-text search engine, such as Elasticsearch, to index and query the review column. Alternatively, you can use natural language processing techniques, such as tokenization, stemming, and lemmatization, to preprocess the review column and create a new column with normalized terms that can be used for filtering or skipping data. References:
? Optimizations: https://docs.delta.io/latest/optimizations-oss.html
? Full-text search with Elasticsearch: https://docs.databricks.com/data/data- sources/elasticsearch.html
? Natural language processing: https://docs.databricks.com/applications/nlp/index.html

NEW QUESTION 87
The DevOps team has configured a production workload as a collection of notebooks scheduled to run daily using the Jobs UI. A new data engineering hire is onboarding to the team and has requested access to one of these notebooks to review the production logic.
What are the maximum notebook permissions that can be granted to the user without allowing accidental changes to production code or data?

A. Can Manage
B. Can Edit
C. No permissions
D. Can Read
E. Can Run

Answer: C

Explanation:
This is the correct answer because it is the maximum notebook permissions that can be granted to the user without allowing accidental changes to production code or data. Notebook permissions are used to control access to notebooks in Databricks workspaces. There are four types of notebook permissions: Can Manage, Can Edit, Can Run, and Can Read. Can Manage allows full control over the notebook, including editing, running, deleting, exporting, and changing permissions. Can Edit allows modifying and running the notebook, but not changing permissions or deleting it. Can Run allows executing commands in an existing cluster attached to the notebook, but not modifying or exporting it. Can Read allows viewing the notebook content, but not running or modifying it. In this case, granting Can Read permission to the user will allow them to review the
production logic in the notebook without allowing them to make any changes to it or run any commands that may affect production data. Verified References: [Databricks Certified Data Engineer Professional], under "Databricks Workspace" section; Databricks Documentation, under "Notebook permissions" section.

NEW QUESTION 91
Which statement describes integration testing?

A. Validates interactions between subsystems of your application
B. Requires an automated testing framework
C. Requires manual intervention
D. Validates an application use case
E. Validates behavior of individual elements of your application

Answer: D

Explanation:
This is the correct answer because it describes integration testing. Integration testing is a type of testing that validates interactions between subsystems of your application, such as modules, components, or services. Integration testing ensures that the subsystems work together as expected and produce the correct outputs or results. Integration testing can be done at different levels of granularity, such as component integration testing, system integration testing, or end-to-end testing. Integration testing can help detect errors or bugs that may not be found by unit testing, which only validates behavior of individual elements of your application. Verified References: [Databricks Certified Data Engineer Professional], under "Testing" section; Databricks Documentation, under "Integration testing" section.

NEW QUESTION 96
The security team is exploring whether or not the Databricks secrets module can be leveraged for connecting to an external database.
After testing the code with all Python variables being defined with strings, they upload the password to the secrets module and configure the correct permissions for the currently active user. They then modify their code to the following (leaving all other variables unchanged).

```
password = dbutils.secrets.get(scope="db_creds", key="jdbc_password")

print(password)

df = (spark
  .read
  .format("jdbc")
  .option("url", connection)
  .option("dbtable", tablename)
  .option("user", username)
  .option("password", password)
  )
```

Which statement describes what will happen when the above code is executed?

A. The connection to the external table will fail; the string "redacted" will be printed.
B. An interactive input box will appear in the notebook; if the right password is provided, the connection will succeed and the encoded password will be saved to DBFS.
C. An interactive input box will appear in the notebook; if the right password is provided, the connection will succeed and the password will be printed in plain text.
D. The connection to the external table will succeed; the string value of password will be printed in plain text.
E. The connection to the external table will succeed; the string "redacted" will be printed.

Answer: E

Explanation:
This is the correct answer because the code is using the dbutils.secrets.get method to retrieve the password from the secrets module and store it in a variable. The secrets module allows users to securely store and access sensitive information such as passwords, tokens, or API keys. The connection to the external table will succeed because the password variable will contain the actual password value. However, when printing the password variable, the string “redacted” will be displayed instead of the plain text password, as a security measure to prevent exposing sensitive information in notebooks. Verified References: [Databricks Certified Data Engineer Professional], under “Security & Governance” section; Databricks Documentation, under “Secrets” section.

NEW QUESTION 101
The data engineering team has configured a job to process customer requests to be forgotten (have their data deleted). All user data that needs to be deleted is stored in Delta Lake tables using default table settings.
The team has decided to process all deletions from the previous week as a batch job at 1am each Sunday. The total duration of this job is less than one hour.
Every Monday at 3am, a batch job executes a series of VACUUM commands on all Delta Lake tables throughout the organization.
The compliance officer has recently learned about Delta Lake's time travel functionality. They are concerned that this might allow continued access to deleted data.
Assuming all delete logic is correctly implemented, which statement correctly addresses this concern?

A. Because the vacuum command permanently deletes all files containing deleted records, deleted records may be accessible with time travel for around 24 hours.
B. Because the default data retention threshold is 24 hours, data files containing deleted records will be retained until the vacuum job is run the following day.
C. Because Delta Lake time travel provides full access to the entire history of a table, deleted records can always be recreated by users with full admin privileges.
D. Because Delta Lake's delete statements have ACID guarantees, deleted records will be permanently purged from all storage systems as soon as a delete job completes.
E. Because the default data retention threshold is 7 days, data files containing deleted records will be retained until the vacuum job is run 8 days later.

Answer: E

Explanation:
https://learn.microsoft.com/en-us/azure/databricks/delta/vacuum

NEW QUESTION 105
The view updates represents an incremental batch of all newly ingested data to be inserted or updated in the customers table.
The following logic is used to process these records.
Which statement describes this implementation?

A. The customers table is implemented as a Type 3 table; old values are maintained as a new column alongside the current value.
B. The customers table is implemented as a Type 2 table; old values are maintained but marked as no longer current and new values are inserted.
C. The customers table is implemented as a Type 0 table; all writes are append only with no changes to existing values.
D. The customers table is implemented as a Type 1 table; old values are overwritten by new values and no history is maintained.
E. The customers table is implemented as a Type 2 table; old values are overwritten and new customers are appended.

Answer: A

Explanation:
The logic uses the MERGE INTO command to merge new records from the view updates into the table customers. The MERGE INTO command takes two arguments: a target table and a source table or view. The command also specifies a condition to match records between the target and the source, and a set of actions to perform when there is a match or not. In this case, the condition is to match records by customer_id, which is the primary key of the customers table. The actions are to update the existing record in the target with the new values from the source, and set the current_flag to false to indicate that the record is no longer current; and to insert a new record in the target with the new values from the source, and set the current_flag to true to indicate that the record is current. This means that old values are maintained but marked as no longer current and new values are inserted, which is the definition of a Type 2 table. Verified References: [Databricks Certified Data Engineer Professional], under “Delta Lake” section; Databricks Documentation, under “Merge Into (Delta Lake on Databricks)” section.

NEW QUESTION 110

Two of the most common data locations on Databricks are the DBFS root storage and external object storage mounted with dbutils.fs.mount().
Which of the following statements is correct?

A. DBFS is a file system protocol that allows users to interact with files stored in object storage using syntax and guarantees similar to Unix file systems.
B. By default, both the DBFS root and mounted data sources are only accessible to workspace administrators.
C. The DBFS root is the most secure location to store data, because mounted storage volumes must have full public read and write permissions.
D. Neither the DBFS root nor mounted storage can be accessed when using %sh in a Databricks notebook.
E. The DBFS root stores files in ephemeral block volumes attached to the driver, while mounted directories will always persist saved data to external storage between sessions.

Answer: A

Explanation:
DBFS is a file system protocol that allows users to interact with files stored in object storage using syntax and guarantees similar to Unix file systems1. DBFS is not a physical file system, but a layer over the object storage that provides a unified view of data across different data sources1. By default, the DBFS root is accessible to all users in the workspace, and the access to mounted data sources depends on the permissions of the storage account or container2. Mounted storage volumes do not need to have full public read and write permissions, but they do require a valid connection string or access key to be provided when mounting3. Both the DBFS root and mounted storage can be accessed when using %sh in a Databricks notebook, as long as the cluster has FUSE enabled4. The DBFS root does not store files in ephemeral block volumes attached to the driver, but in the object storage associated with the workspace1. Mounted directories will persist saved data to external storage between sessions, unless they are unmounted or deleted3. References: DBFS, Work with files on Azure Databricks, Mounting cloud object storage on Azure Databricks, Access DBFS with FUSE

NEW QUESTION 111
Which statement describes Delta Lake optimized writes?

A. A shuffle occurs prior to writing to try to group data together resulting in fewer files instead of each executor writing multiple files based on directory partitions.
B. Optimized writes logical partitions instead of directory partitions partition boundaries are only represented in metadata fewer small files are written.
C. An asynchronous job runs after the write completes to detect if files could be further compacted; yes, an OPTIMIZE job is executed toward a default of 1 GB.
D. Before a job cluster terminates, OPTIMIZE is executed on all tables modified during the most recent job.

Answer: A

Explanation:
Delta Lake optimized writes involve a shuffle operation before writing out data to the Delta table. The shuffle operation groups data by partition keys, which can lead to a reduction in the number of output files and potentially larger files, instead of multiple smaller files. This approach can significantly reduce the total number of files in the table, improve read performance by reducing the metadata overhead, and optimize the table storage layout, especially for workloads with many small files.
References:
? Databricks documentation on Delta Lake performance tuning: https://docs.databricks.com/delta/optimizations/auto-optimize.html

NEW QUESTION 116
A data architect has heard about lake's built-in versioning and time travel capabilities. For auditing purposes they have a requirement to maintain a full of all valid street addresses as they appear in the customers table.
The architect is interested in implementing a Type 1 table, overwriting existing records with new values and relying on Delta Lake time travel to support long-term auditing. A data engineer on the project feels that a Type 2 table will provide better performance and scalability.
Which piece of information is critical to this decision?

A. Delta Lake time travel does not scale well in cost or latency to provide a long-term versioning solution.
B. Delta Lake time travel cannot be used to query previous versions of these tables because Type 1 changes modify data files in place.
C. Shallow clones can be combined with Type 1 tables to accelerate historic queries for long-term versioning.
D. Data corruption can occur if a query fails in a partially completed state because Type 2 tables requiresSetting multiple fields in a single update.

Answer: A

Explanation:
Delta Lake's time travel feature allows users to access previous versions of a table, providing a powerful tool for auditing and versioning. However, using time travel as a long-term versioning solution for auditing purposes can be less optimal in terms of cost and performance, especially as the volume of data and the number of versions grow. For maintaining a full history of valid street addresses as they appear in a customers table, using a Type 2 table (where each update creates a new record with versioning) might provide better scalability and performance by avoiding the overhead associated with accessing older versions of a large table. While Type 1 tables, where existing records are overwritten with new values, seem simpler and can leverage time travel for auditing, the critical piece of information is that time travel might not scale well in cost or latency for long- term versioning needs, making a Type 2 approach more viable for performance and scalability.References:
? Databricks Documentation on Delta Lake's Time Travel: Delta Lake Time Travel
? Databricks Blog on Managing Slowly Changing Dimensions in Delta Lake: Managing SCDs in Delta Lake

NEW QUESTION 118
Which distribution does Databricks support for installing custom Python code packages?

A. sbt
B. CRAN
C. CRAM
D. nom
E. Wheels
F. jars

Answer: D

NEW QUESTION 122
A Databricks SQL dashboard has been configured to monitor the total number of records present in a collection of Delta Lake tables using the following query

pattern:
SELECT COUNT (*) FROM table -
Which of the following describes how results are generated each time the dashboard is updated?

A. The total count of rows is calculated by scanning all data files
B. The total count of rows will be returned from cached results unless REFRESH is run
C. The total count of records is calculated from the Delta transaction logs
D. The total count of records is calculated from the parquet file metadata
E. The total count of records is calculated from the Hive metastore

Answer: C

Explanation:
https://delta.io/blog/2023-04-19-faster-aggregations-metadata/#:~:text=You%20can%20get%20the%20number,a%20given%20Delta%20table%20version.

NEW QUESTION 123
A junior data engineer on your team has implemented the following code block.

```
MERGE INTO events
USING new_events
ON events.event_id = new_events.event_id
WHEN NOT MATCHED
  INSERT *
```

The view new_events contains a batch of records with the same schema as the events Delta table. The event_id field serves as a unique key for this table.
When this query is executed, what will happen with new records that have the same event_id as an existing record?

A. They are merged.
B. They are ignored.
C. They are updated.
D. They are inserted.
E. They are deleted.

Answer: B

Explanation:
This is the correct answer because it describes what will happen with new records that have the same event_id as an existing record when the query is executed. The query uses the INSERT INTO command to append new records from the view new_events to the table events. However, the INSERT INTO command does not check for duplicate values in the primary key column (event_id) and does not perform any update or delete operations on existing records. Therefore, if there are new records that have the same event_id as an existing record, they will be ignored and not inserted into the table events. Verified References: [Databricks Certified Data Engineer Professional], under “Delta Lake” section; Databricks Documentation, under “Append data using INSERT INTO” section.
"If none of the WHEN MATCHED conditions evaluate to true for a source and target row pair that matches the merge_condition, then the target row is left unchanged." https://docs.databricks.com/en/sql/language-manual/delta-merge-into.html#:~:text=If%20none%20of%20the%20WHEN%20MATCHED%20conditions%20evaluate%20to%20true%20for%20a%20source%20and%20target%20row%20pair%20that%20matches%20the%20merge_condition%2C%20then%20the%20target%20row%20is%20l eft%20unchanged.

NEW QUESTION 127
The data governance team is reviewing user for deleting records for compliance with GDPR. The following logic has been implemented to propagate deleted requests from the
user_lookup table to the user aggregate table.

```
(spark.read
  .format("delta")
  .option("readChangeData", True)
  .option("startingTimestamp", '2021-08-22 00:00:00')
  .option("endingTimestamp", '2021-08-29 00:00:00')
  .table("user_lookup")
  .createOrReplaceTempView("changes"))

spark.sql("""
  DELETE FROM user_aggregates
  WHERE user_id IN (
    SELECT user_id
    FROM changes
    WHERE _change_type='delete'
    )
""")
```

Assuming that user_id is a unique identifying key and that all users have requested deletion have been removed from the user_lookup table, which statement describes whether successfully executing the above logic guarantees that the records to be deleted from the user_aggregates table are no longer accessible and why?

A. No: files containing deleted records may still be accessible with time travel until a BACUM command is used to remove invalidated data files.

B. Yes: Delta Lake ACID guarantees provide assurance that the DELETE command successed fully and permanently purged these records.
C. No: the change data feed only tracks inserts and updates not deleted records.
D. No: the Delta Lake DELETE command only provides ACID guarantees when combined with the MERGE INTO command

Answer: A

Explanation:
The DELETE operation in Delta Lake is ACID compliant, which means that once the operation is successful, the records are logically removed from the table. However, the underlying files that contained these records may still exist and be accessible via time travel to older versions of the table. To ensure that these records are physically removed and compliance with GDPR is maintained, a VACUUM command should be used to clean up these data files after a certain retention period. The VACUUM command will remove the files from the storage layer, and after this, the records will no longer be accessible.

NEW QUESTION 130
Which of the following is true of Delta Lake and the Lakehouse?

A. Because Parquet compresses data row by ro
B. strings will only be compressed when a character is repeated multiple times.
C. Delta Lake automatically collects statistics on the first 32 columns of each table which are leveraged in data skipping based on query filters.
D. Views in the Lakehouse maintain a valid cache of the most recent versions of source tables at all times.
E. Primary and foreign key constraints can be leveraged to ensure duplicate values are never entered into a dimension table.
F. Z-order can only be applied to numeric values stored in Delta Lake tables

Answer: B

Explanation:
https://docs.delta.io/2.0.0/table-properties.html
Delta Lake automatically collects statistics on the first 32 columns of each table, which are leveraged in data skipping based on query filters1. Data skipping is a performance optimization technique that aims to avoid reading irrelevant data from the storage layer1. By collecting statistics such as min/max values, null counts, and bloom filters, Delta Lake can efficiently prune unnecessary files or partitions from the query plan1. This can significantly improve the query performance and reduce the I/O cost.
The other options are false because:
? Parquet compresses data column by column, not row by row2. This allows for better compression ratios, especially for repeated or similar values within a column2.
? Views in the Lakehouse do not maintain a valid cache of the most recent versions of source tables at all times3. Views are logical constructs that are defined by a SQL query on one or more base tables3. Views are not materialized by default, which means they do not store any data, but only the query definition3. Therefore, views always reflect the latest state of the source tables when queried3. However, views can be cached manually using the CACHE TABLE or CREATE TABLE AS SELECT commands.
? Primary and foreign key constraints can not be leveraged to ensure duplicate values are never entered into a dimension table. Delta Lake does not support enforcing primary and foreign key constraints on tables. Constraints are logical rules that define the integrity and validity of the data in a table. Delta Lake relies on the application logic or the user to ensure the data quality and consistency.
? Z-order can be applied to any values stored in Delta Lake tables, not only numeric values. Z-order is a technique to optimize the layout of the data files by sorting them on one or more columns. Z-order can improve the query performance by clustering related values together and enabling more efficient data skipping. Z-order can be applied to any column that has a defined ordering, such as numeric, string, date, or boolean values.
References: Data Skipping, Parquet Format, Views, [Caching], [Constraints], [Z-Ordering]

NEW QUESTION 133
A small company based in the United States has recently contracted a consulting firm in India to implement several new data engineering pipelines to power artificial intelligence applications. All the company's data is stored in regional cloud storage in the United States.
The workspace administrator at the company is uncertain about where the Databricks workspace used by the contractors should be deployed.
Assuming that all data governance considerations are accounted for, which statement accurately informs this decision?

A. Databricks runs HDFS on cloud volume storage; as such, cloud virtual machines must be deployed in the region where the data is stored.
B. Databricks workspaces do not rely on any regional infrastructure; as such, the decision should be made based upon what is most convenient for the workspace administrator.
C. Cross-region reads and writes can incur significant costs and latency; whenever possible, compute should be deployed in the same region the data is stored.
D. Databricks leverages user workstations as the driver during interactive development; as such, users should always use a workspace deployed in a region they are physically near.
E. Databricks notebooks send all executable code from the user's browser to virtual machines over the open internet; whenever possible, choosing a workspace region near the end users is the most secure.

Answer: C

Explanation:
This is the correct answer because it accurately informs this decision. The decision is about where the Databricks workspace used by the contractors should be deployed. The contractors are based in India, while all the company’s data is stored in regional cloud storage in the United States. When choosing a region for deploying a Databricks workspace, one of the important factors to consider is the proximity to the data sources and sinks. Cross-region reads and writes can incur significant costs and latency due to network bandwidth and data transfer fees. Therefore, whenever possible, compute should be deployed in the same region the data is stored to optimize performance and reduce costs. Verified References: [Databricks Certified Data Engineer Professional], under “Databricks Workspace” section; Databricks Documentation, under “Choose a region” section.

NEW QUESTION 138
An external object storage container has been mounted to the location /mnt/finance_eda_bucket.
The following logic was executed to create a database for the finance team:
After the database was successfully created and permissions configured, a member of the finance team runs the following code:
If all users on the finance team are members of the finance group, which statement describes how the tx_sales table will be created?

A. A logical table will persist the query plan to the Hive Metastore in the Databricks control plane.
B. An external table will be created in the storage container mounted to /mnt/finance eda bucket.
C. A logical table will persist the physical plan to the Hive Metastore in the Databricks control plane.
D. An managed table will be created in the storage container mounted to /mnt/finance eda bucket.

E. A managed table will be created in the DBFS root storage container.

Answer: A

Explanation:
https://docs.databricks.com/en/lakehouse/data-objects.html

NEW QUESTION 140
The view updates represents an incremental batch of all newly ingested data to be inserted or updated in the customers table.
The following logic is used to process these records.
MERGE INTO customers USING (
SELECT updates.customer_id as merge_ey, updates .* FROM updates
UNION ALL
SELECT NULL as merge_key, updates .* FROM updates JOIN customers
ON updates.customer_id = customers.customer_id
WHERE customers.current = true AND updates.address <> customers.address
) staged_updates
ON customers.customer_id = mergekey
WHEN MATCHED AND customers. current = true AND customers.address <> staged_updates.address THEN
UPDATE SET current = false, end_date = staged_updates.effective_date WHEN NOT MATCHED THEN
INSERT (customer_id, address, current, effective_date, end_date)
VALUES (staged_updates.customer_id, staged_updates.address, true, staged_updates.effective_date, null)
Which statement describes this implementation?

A. The customers table is implemented as a Type 2 table; old values are overwritten and new customers are appended.
B. The customers table is implemented as a Type 1 table; old values are overwritten by new values and no history is maintained.
C. The customers table is implemented as a Type 2 table; old values are maintained but marked as no longer current and new values are inserted.
D. The customers table is implemented as a Type 0 table; all writes are append only with no changes to existing values.

Answer: C

Explanation:
The provided MERGE statement is a classic implementation of a Type 2 SCD in a data warehousing context. In this approach, historical data is preserved by keeping old records (marking them as not current) and adding new records for changes. Specifically, when a match is found and there's a change in the address, the existing record in the customers table is updated to mark it as no longer current (current = false), and an end date is assigned (end_date = staged_updates.effective_date). A new record for the customer is then inserted with the updated information, marked as current. This method ensures that the full history of changes to customer information is maintained in the table, allowing for time-based analysis of customer data.References: Databricks documentation on implementing SCDs using Delta Lake and the MERGE statement (https://docs.databricks.com/delta/delta-update.html#upsert-into-a-table-using-merge).

NEW QUESTION 145
Which statement describes Delta Lake Auto Compaction?

A. An asynchronous job runs after the write completes to detect if files could be further compacted; if yes, an optimize job is executed toward a default of 1 GB.
B. Before a Jobs cluster terminates, optimize is executed on all tables modified during the most recent job.
C. Optimized writes use logical partitions instead of directory partitions; because partition boundaries are only represented in metadata, fewer small files are written.
D. Data is queued in a messaging bus instead of committing data directly to memory; all data is committed from the messaging bus in one batch once the job is complete.
E. An asynchronous job runs after the write completes to detect if files could be further compacted; if yes, an optimize job is executed toward a default of 128 MB.

Answer: E

Explanation:
This is the correct answer because it describes the behavior of Delta Lake Auto Compaction, which is a feature that automatically optimizes the layout of Delta Lake tables by coalescing small files into larger ones. Auto Compaction runs as an asynchronous job after a write to a table has succeeded and checks if files within a partition can be further compacted. If yes, it runs an optimize job with a default target file size of 128 MB. Auto Compaction only compacts files that have not been compacted previously. Verified References: [Databricks Certified Data Engineer Professional], under “Delta Lake” section; Databricks Documentation, under “Auto Compaction for Delta Lake on Databricks” section.
"Auto compaction occurs after a write to a table has succeeded and runs synchronously on the cluster that has performed the write. Auto compaction only compacts files that haven’t been compacted previously."
https://learn.microsoft.com/en-us/azure/databricks/delta/tune-file-size

NEW QUESTION 147
A new data engineer notices that a critical field was omitted from an application that writes its Kafka source to Delta Lake. This happened even though the critical field was in the Kafka source. That field was further missing from data written to dependent, long-term storage. The retention threshold on the Kafka service is seven days. The pipeline has been in production for three months.
Which describes how Delta Lake can help to avoid data loss of this nature in the future?

A. The Delta log and Structured Streaming checkpoints record the full history of the Kafkaproducer.
B. Delta Lake schema evolution can retroactively calculate the correct value for newly added fields, as long as the data was in the original source.
C. Delta Lake automatically checks that all fields present in the source data are included in the ingestion layer.
D. Data can never be permanently dropped or deleted from Delta Lake, so data loss is not possible under any circumstance.
E. Ingestine all raw data and metadata from Kafka to a bronze Delta table creates a permanent, replayable history of the data state.

Answer: E

Explanation:
This is the correct answer because it describes how Delta Lake can help to avoid data loss of this nature in the future. By ingesting all raw data and metadata from Kafka to a bronze Delta table, Delta Lake creates a permanent, replayable history of the data state that can be used for recovery or reprocessing in case of errors or omissions in downstream applications or pipelines. Delta Lake also supports schema evolution, which allows adding new columns to existing tables without

affecting existing queries or pipelines. Therefore, if a critical field was omitted from an application that writes its Kafka source to Delta Lake, it can be easily added later and the data can be reprocessed from the bronze table without losing any information. Verified References: [Databricks Certified Data Engineer Professional], under “Delta Lake” section; Databricks Documentation, under “Delta Lake core features” section.

NEW QUESTION 149

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