Exam Questions Databricks-Certified-Professional-Data-Engineer

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
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 3
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 4
A junior data engineer has configured a workload that posts the following JSON to the Databricks REST API endpoint 2.0/jobs/create.

```
{
  "name": "Ingest new data",
  "existing_cluster_id": "6015-954420-peace720",
  "notebook_task": {
    "notebook_path": "/Prod/ingest.py"
  }
}
```

Assuming that all configurations and referenced resources are available, which statement describes the result of executing this workload three times?

A. Three new jobs named "Ingest new data" will be defined in the workspace, and they will each run once daily.
B. The logic defined in the referenced notebook will be executed three times on new clusters with the configurations of the provided cluster ID.
C. Three new jobs named "Ingest new data" will be defined in the workspace, but no jobs will be executed.
D. One new job named "Ingest new data" will be defined in the workspace, but it will not be executed.
E. The logic defined in the referenced notebook will be executed three times on the referenced existing all purpose cluster.

Answer: E

Explanation:
This is the correct answer because the JSON posted to the Databricks REST API endpoint 2.0/jobs/create defines a new job with a name, an existing cluster id, and a notebook task. However, it does not specify any schedule or trigger for the job execution. Therefore, three new jobs with the same name and configuration will be created in the workspace, but none of them will be executed until they are manually triggered or scheduled. Verified References: [Databricks Certified Data Engineer Professional], under “Monitoring & Logging” section; [Databricks Documentation], under “Jobs API - Create” section.

NEW QUESTION 5
Incorporating unit tests into a PySpark application requires upfront attention to the design of your jobs, or a potentially significant refactoring of existing code.
Which statement describes a main benefit that offset this additional effort?

A. Improves the quality of your data
B. Validates a complete use case of your application
C. Troubleshooting is easier since all steps are isolated and tested individually
D. Yields faster deployment and execution times
E. Ensures that all steps interact correctly to achieve the desired end result

Answer: A

NEW QUESTION 6
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 7
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 8
An hourly batch job is configured to ingest data files from a cloud object storage container where each batch represent all records produced by the source system in a given hour. The batch job to process these records into the Lakehouse is sufficiently delayed to ensure no late-arriving data is missed. The user_id field represents a unique key for the data, which has the following schema:
user_id BIGINT, username STRING, user_utc STRING, user_region STRING, last_login BIGINT, auto_pay BOOLEAN, last_updated BIGINT
New records are all ingested into a table named account_history which maintains a full record of all data in the same schema as the source. The next table in the system is named account_current and is implemented as a Type 1 table representing the most recent value for each unique user_id.
Assuming there are millions of user accounts and tens of thousands of records processed hourly, which implementation can be used to efficiently update the described account_current table as part of each hourly batch job?

A. Use Auto Loader to subscribe to new files in the account history directory; configure a Structured Streaminq trigger once job to batch update newly detected files into the account current table.
B. Overwrite the account current table with each batch using the results of a query against the account history table grouping by user id and filtering for the max value of last updated.
C. Filter records in account history using the last updated field and the most recent hour processed, as well as the max last iogin by user id write a merge statement to update or insert the most recent value for each user id.
D. Use Delta Lake version history to get the difference between the latest version of account history and one version prior, then write these records to account current.
E. Filter records in account history using the last updated field and the most recent hour processed, making sure to deduplicate on username; write a merge statement to update orinsert themost recent value for each username.

Answer: C

Explanation:
This is the correct answer because it efficiently updates the account current table with only the most recent value for each user id. The code filters records in account history using the last updated field and the most recent hour processed, which means it will only process the latest batch of data. It also filters by the max last login by user id, which means it will only keep the most recent record for each user id within that batch. Then, it writes a merge statement to update or insert the most recent value for each user id into account current, which means it will perform an upsert operation based on the user id column. Verified References: [Databricks Certified Data Engineer Professional], under “Delta Lake” section; Databricks Documentation, under “Upsert into a table using merge” section.

NEW QUESTION 9
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 10
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 10
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 14
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 for highly selective joins on a number of fields, and will also be leveraged by the machine learning team to filter on a handful of relevant fields, in total, 15 fields have been identified that will often be used for filter and join logic.
The data engineer is trying to determine the best approach for dealing with these nested fields before declaring the table schema.
Which of the following accurately presents information about Delta Lake and Databricks that may Impact their decision-making process?

A. Because Delta Lake uses Parquet for data storage, Dremel encoding information for nesting can be directly referenced by the Delta transaction log.
B. 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.
C. Schema inference and evolution on Databricks ensure that inferred types will always accurately match the data types used by downstream systems.
D. By default Delta Lake collects statistics on the first 32 columns in a table; these statistics are leveraged for data skipping when executing selective queries.

Answer: D

Explanation:
Delta Lake, built on top of Parquet, enhances query performance through data skipping, which is based on the statistics collected for each file in a table. For tables with a large number of columns, Delta Lake by default collects and stores statistics only for the first 32 columns. These statistics include min/max values and null counts, which are used to optimize query execution by skipping irrelevant data files. When dealing with highly nested JSON structures, understanding this behavior is crucial for schema design, especially when determining which fields should be flattened or prioritized in the table structure to leverage data skipping efficiently for performance optimization.References: Databricks documentation on Delta Lake optimization techniques, including data skipping and statistics collection (https://docs.databricks.com/delta/optimizations/index.html).

NEW QUESTION 17
The data governance team has instituted a requirement that all tables containing Personal Identifiable Information (PH) must be clearly annotated. This includes adding column comments, table comments, and setting the custom table property "contains_pii" = true.
The following SQL DDL statement is executed to create a new table:
Which command allows manual confirmation that these three requirements have been met?

A. DESCRIBE EXTENDED dev.pii test
B. DESCRIBE DETAIL dev.pii test
C. SHOW TBLPROPERTIES dev.pii test
D. DESCRIBE HISTORY dev.pii test
E. SHOW TABLES dev

Answer: A

Explanation:
This is the correct answer because it allows manual confirmation that these three requirements have been met. The requirements are that all tables containing Personal Identifiable Information (PII) must be clearly annotated, which includes adding column comments, table comments, and setting the custom table property “contains_pii” = true. The DESCRIBE EXTENDED command is used to display detailed information about a table, such as its schema, location, properties, and comments. By using this command on the dev.pii_test table, one can verify that the table has been created with the correct column comments, table comment, and custom table property as specified in the SQL DDL statement. Verified References: [Databricks Certified Data Engineer Professional], under “Lakehouse” section; Databricks Documentation, under “DESCRIBE EXTENDED” section.

NEW QUESTION 20
A production workload incrementally applies updates from an external Change Data Capture feed to a Delta Lake table as an always-on Structured Stream job. When data was initially migrated for this table, OPTIMIZE was executed and most data files were resized to 1 GB. Auto Optimize and Auto Compaction were both turned on for the streaming production job. Recent review of data files shows that most data files are under 64 MB, although each partition in the table contains at least 1 GB of data and the total table size is over 10 TB.
Which of the following likely explains these smaller file sizes?

A. Databricks has autotuned to a smaller target file size to reduce duration of MERGE operations
B. Z-order indices calculated on the table are preventing file compactionC Bloom filler indices calculated on the table are preventing file compaction
C. Databricks has autotuned to a smaller target file size based on the overall size of data in the table
D. Databricks has autotuned to a smaller target file size based on the amount of data in each partition

Answer: A

Explanation:
This is the correct answer because Databricks has a feature called Auto Optimize, which automatically optimizes the layout of Delta Lake tables by coalescing small files into larger ones and sorting data within each file by a specified column. However, Auto Optimize also considers the trade-off between file size and merge performance, and may choose a smaller target file size to reduce the duration of merge operations, especially for streaming workloads that frequently update existing records. Therefore, it is possible that Auto Optimize has autotuned to a smaller target file size based on the characteristics of the streaming production job. Verified References: [Databricks Certified Data Engineer Professional], under “Delta Lake” section; Databricks Documentation, under “Auto Optimize” section. https://docs.databricks.com/en/delta/tune-file-size.html#autotune-table 'Autotune file size based on workload'

NEW QUESTION 23
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 24
The Databricks workspace administrator has configured interactive clusters for each of the data engineering groups. To control costs, clusters are set to terminate after 30 minutes of inactivity. Each user should be able to execute workloads against their assigned clusters at any time of the day.
Assuming users have been added to a workspace but not granted any permissions, which of the following describes the minimal permissions a user would need to start and attach to an already configured cluster.

A. "Can Manage" privileges on the required cluster
B. Workspace Admin privileges, cluster creation allowe
C. "Can Attach To" privileges on the required cluster
D. Cluster creation allowe
E. "Can Attach To" privileges on the required cluster
F. "Can Restart" privileges on the required cluster
G. Cluster creation allowe
H. "Can Restart" privileges on the required cluster

Answer: D

Explanation:
https://learn.microsoft.com/en-us/azure/databricks/security/auth-authz/access-control/cluster-acl
https://docs.databricks.com/en/security/auth-authz/access-control/cluster-acl.html

NEW QUESTION 29
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"}]
```

How would the following update be handled?

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 32
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 34
A junior developer complains that the code in their notebook isn't producing the correct results in the development environment. A shared screenshot reveals that while they're using a notebook versioned with Databricks Repos, they're using a personal branch that contains old logic. The desired branch named dev-2.3.9 is not available from the branch selection dropdown.
Which approach will allow this developer to review the current logic for this notebook?

A. Use Repos to make a pull request use the Databricks REST API to update the current branch to dev-2.3.9
B. Use Repos to pull changes from the remote Git repository and select the dev-2.3.9 branch.
C. Use Repos to checkout the dev-2.3.9 branch and auto-resolve conflicts with the current branch
D. Merge all changes back to the main branch in the remote Git repository and clone the repo again
E. Use Repos to merge the current branch and the dev-2.3.9 branch, then make a pull request to sync with the remote repository

Answer: B

Explanation:
This is the correct answer because it will allow the developer to update their local repository with the latest changes from the remote repository and switch to the desired branch. Pulling changes will not affect the current branch or create any conflicts, as it will only fetch the changes and not merge them. Selecting the dev-2.3.9 branch from the dropdown will checkout that branch and display its contents in the notebook. Verified References: [Databricks Certified Data Engineer Professional], under “Databricks Tooling” section; Databricks Documentation, under “Pull changes from a remote repository” section.

NEW QUESTION 38
A data engineer, User A, has promoted a new pipeline to production by using the REST API to programmatically create several jobs. A DevOps engineer, User B, has configured an external orchestration tool to trigger job runs through the REST API. Both users authorized the REST API calls using their personal access tokens.
Which statement describes the contents of the workspace audit logs concerning these events?

A. Because the REST API was used for job creation and triggering runs, a Service Principal will be automatically used to identity these events.
B. Because User B last configured the jobs, their identity will be associated with both the job creation events and the job run events.
C. Because these events are managed separately, User A will have their identity associated with the job creation events and User B will have their identity associated with the job run events.
D. Because the REST API was used for job creation and triggering runs, user identity will not be captured in the audit logs.
E. Because User A created the jobs, their identity will be associated with both the job creation events and the job run events.

Answer: C

Explanation:
The events are that a data engineer, User A, has promoted a new pipeline to production by using the REST API to programmatically create several jobs, and a DevOps engineer, User B, has configured an external orchestration tool to trigger job runs through the REST API. Both users authorized the REST API calls using their personal access tokens. The workspace audit logs are logs that record user activities in a Databricks workspace, such as creating, updating, or deleting objects like clusters, jobs, notebooks, or tables. The workspace audit logs also capture the identity of the user who performed each activity, as well as the time and details of the activity. Because these events are managed separately, User A will have their identity associated with the job creation events and User B will have their identity associated with the job run events in the workspace audit logs. Verified References: [Databricks Certified Data Engineer Professional], under “Databricks Workspace” section; Databricks Documentation, under “Workspace audit logs” section.

NEW QUESTION 43
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 48
The data engineer is using Spark's MEMORY_ONLY storage level.
Which indicators should the data engineer look for in the spark UI's Storage tab to signal that a cached table is not performing optimally?

A. Size on Disk is> 0
B. The number of Cached Partitions> the number of Spark Partitions
C. The RDD Block Name included the '' annotation signaling failure to cache
D. On Heap Memory Usage is within 75% of off Heap Memory usage

Answer: C

Explanation:
In the Spark UI's Storage tab, an indicator that a cached table is not performing optimally would be the presence of the _disk annotation in the RDD Block Name. This annotation indicates that some partitions of the cached data have been spilled to disk because there wasn't enough memory to hold them. This is suboptimal because accessing data from disk is much slower than from memory. The goal of caching is to keep data in memory for fast access, and a spill to disk means that this goal is not fully achieved.

NEW QUESTION 49
A DLT pipeline includes the following streaming tables:
Raw_lot ingest raw device measurement data from a heart rate tracking device. Bgm_stats incrementally computes user statistics based on BPM measurements from raw_lot.
How can the data engineer configure this pipeline to be able to retain manually deleted or updated records in the raw_iot table while recomputing the downstream table when a pipeline update is run?

A. Set the skipChangeCommits flag to true on bpm_stats
B. Set the SkipChangeCommits flag to true raw_lot
C. Set the pipelines, reset, allowed property to false on bpm_stats
D. Set the pipelines, reset, allowed property to false on raw_iot

Answer: D

Explanation:
In Databricks Lakehouse, to retain manually deleted or updated records in the raw_iot table while recomputing downstream tables when a pipeline update is run, the property pipelines.reset.allowed should be set to false. This property prevents the system from resetting the state of the table, which includes the removal of the history of changes, during a pipeline update. By keeping this property as false, any changes to the raw_iot table, including manual deletes or updates, are retained, and recomputation of downstream tables, such as bpm_stats, can occur with the full history of data changes intact. References:
? Databricks documentation on DLT pipelines: https://docs.databricks.com/data-engineering/delta-live-tables/delta-live-tables-overview.html

NEW QUESTION 50
The marketing team is looking to share data in an aggregate table with the sales organization, but the field names used by the teams do not match, and a number of marketing specific fields have not been approval for the sales org.
Which of the following solutions addresses the situation while emphasizing simplicity?

A. Create a view on the marketing table selecting only these fields approved for the sales team alias the names of any fields that should be standardized to the sales naming conventions.
B. Use a CTAS statement to create a derivative table from the marketing table configure a production jon to propagation changes.
C. Add a parallel table write to the current production pipeline, updating a new sales table that varies as required from marketing table.
D. Create a new table with the required schema and use Delta Lake's DEEP CLONE functionality to sync up changes committed to one table to the corresponding table.

Answer: A

Explanation:
Creating a view is a straightforward solution that can address the need for field name standardization and selective field sharing between departments. A view allows for presenting a transformed version of the underlying data without duplicating it. In this scenario, the view would only include the approved fields for the sales team and rename any fields as per their naming conventions.
References:
? Databricks documentation on using SQL views in Delta Lake: https://docs.databricks.com/delta/quick-start.html#sql-views

NEW QUESTION 53
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. Can run
D. Can Read

Answer: D

Explanation:
Granting a user 'Can Read' permissions on a notebook within Databricks allows them to view the notebook's content without the ability to execute or edit it. This level of permission ensures that the new team member can review the production logic for learning or auditing purposes without the risk of altering the notebook's code or affecting production data and workflows. This approach aligns with best practices for maintaining security and integrity in production environments, where strict access controls are essential to prevent unintended modifications.References: Databricks documentation on access control and permissions for notebooks within the workspace (https://docs.databricks.com/security/access-control/workspace-acl.html).

NEW QUESTION 57
The data architect has mandated that all tables in the Lakehouse should be configured as external (also known as "unmanaged") Delta Lake tables.
Which approach will ensure that this requirement is met?

A. When a database is being created, make sure that the LOCATION keyword is used.
B. When configuring an external data warehouse for all table storage, leverage Databricks for all ELT.
C. When data is saved to a table, make sure that a full file path is specified alongside the Delta format.
D. When tables are created, make sure that the EXTERNAL keyword is used in the CREATE TABLE statement.
E. When the workspace is being configured, make sure that external cloud object storage has been mounted.

Answer: D

Explanation:
To create an external or unmanaged Delta Lake table, you need to use the EXTERNAL keyword in the CREATE TABLE statement. This indicates that the table is not managed by the catalog and the data files are not deleted when the table is dropped. You also need to provide a LOCATION clause to specify the path where the data files are stored. For example:
CREATE EXTERNAL TABLE events (date DATE, eventId STRING, eventType STRING, data STRING) USING DELTA LOCATION '/mnt/delta/events';
This creates an external Delta Lake table named events that references the data files in the '/mnt/delta/events' path. If you drop this table, the data files will remain intact and you can recreate the table with the same statement.
References:
? https://docs.databricks.com/delta/delta-batch.html#create-a-table
? https://docs.databricks.com/delta/delta-batch.html#drop-a-table

NEW QUESTION 62
Which statement regarding spark configuration on the Databricks platform is true?

A. Spark configuration properties set for an interactive cluster with the Clusters UI will impact all notebooks attached to that cluster.
B. When the same spar configuration property is set for an interactive to the same interactive cluster.
C. Spark configuration set within an notebook will affect all SparkSession attached to the same interactive cluster
D. The Databricks REST API can be used to modify the Spark configuration properties for an interactive cluster without interrupting jobs.

Answer: A

Explanation:
When Spark configuration properties are set for an interactive cluster using the Clusters UI in Databricks, those configurations are applied at the cluster level. This means that all notebooks attached to that cluster will inherit and be affected by these configurations. This approach ensures consistency across all executions within that cluster, as the Spark configuration properties dictate aspects such as memory allocation, number of executors, and other vital execution parameters. This centralized configuration management helps maintain standardized execution environments across different notebooks, aiding in debugging and performance optimization.
References:
? Databricks documentation on configuring clusters: https://docs.databricks.com/clusters/configure.html

NEW QUESTION 65
An upstream system is emitting change data capture (CDC) logs that are being written to a cloud object storage directory. Each record in the log indicates the change type (insert, update, or delete) and the values for each field after the change. The source table has a primary key identified by the field pk_id.
For auditing purposes, the data governance team wishes to maintain a full record of all values that have ever been valid in the source system. For analytical purposes, only the most recent value for each record needs to be recorded. The Databricks job to ingest these records occurs once per hour, but each individual record may have changed multiple times over the course of an hour.
Which solution meets these requirements?

A. Create a separate history table for each pk_id resolve the current state of the table by running a union all filtering the history tables for the most recent state.
B. Use merge into to insert, update, or delete the most recent entry for each pk_id into abronze table, then propagate all changes throughout the system.
C. Iterate through an ordered set of changes to the table, applying each in turn; rely on Delta Lake's versioning ability to create an audit log.
D. Use Delta Lake's change data feed to automatically process CDC data from an external system, propagating all changes to all dependent tables in the Lakehouse.
E. Ingest all log information into a bronze table; use merge into to insert, update, or delete the most recent entry for each pk_id into a silver table to recreate the current table state.

Answer: B

Explanation:
This is the correct answer because it meets the requirements of maintaining a full record of all values that have ever been valid in the source system and recreating the current table state with only the most recent value for each record. The code ingests all log information into a bronze table, which preserves the raw CDC data as it is. Then, it uses merge into to perform an upsert operation on a silver table, which means it will insert new records or update or delete existing records based on the change type and the pk_id columns. This way, the silver table will always reflect the current state of the source table, while the bronze table will keep the history of all changes. Verified References: [Databricks Certified Data Engineer Professional], under "Delta Lake" section; Databricks Documentation, under "Upsert into a table using merge" section.

NEW QUESTION 70
The data architect has decided that once data has been ingested from external sources into the
Databricks Lakehouse, table access controls will be leveraged to manage permissions for all production tables and views.
The following logic was executed to grant privileges for interactive queries on a production database to the core engineering group.
GRANT USAGE ON DATABASE prod TO eng; GRANT SELECT ON DATABASE prod TO eng;
Assuming these are the only privileges that have been granted to the eng group and that these users are not workspace administrators, which statement describes their privileges?

A. Group members have full permissions on the prod database and can also assign permissions to other users or groups.
B. Group members are able to list all tables in the prod database but are not able to see the results of any queries on those tables.
C. Group members are able to query and modify all tables and views in the prod database,but cannot create new tables or views.
D. Group members are able to query all tables and views in the prod database, but cannot create or edit anything in the database.
E. Group members are able to create, query, and modify all tables and views in the prod database, but cannot define custom functions.

Answer: D

Explanation:
The GRANT USAGE ON DATABASE prod TO eng command grants the eng group the permission to use the prod database, which means they can list and access the tables and views in the database. The GRANT SELECT ON DATABASE prod TO eng command grants the eng group the permission to select data from the tables and views in the prod database, which means they can query the data using SQL or DataFrame API. However, these commands do not grant the eng group any other permissions, such as creating, modifying, or deleting tables and views, or defining custom functions. Therefore, the eng group members are able to query all tables and views in the prod database, but cannot create or edit anything in the database. References:

? Grant privileges on a database: https://docs.databricks.com/en/security/auth-authz/table-acls/grant-privileges-database.html
? Privileges you can grant on Hive metastore objects: https://docs.databricks.com/en/security/auth-authz/table-acls/privileges.html

NEW QUESTION 74
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 75
A Delta Lake table representing metadata about content from user has the following schema:
Based on the above schema, which column is a good candidate for partitioning the Delta Table?

A. Date
B. Post_id
C. User_id
D. Post_time

Answer: A

Explanation:
Partitioning a Delta Lake table improves query performance by organizing data into partitions based on the values of a column. In the given schema, the date column is a good candidate for partitioning for several reasons:
? Time-Based Queries: If queries frequently filter or group by date, partitioning by the date column can significantly improve performance by limiting the amount of data scanned.
? Granularity: The date column likely has a granularity that leads to a reasonable number of partitions (not too many and not too few). This balance is important for optimizing both read and write performance.
? Data Skew: Other columns like post_id or user_id might lead to uneven partition sizes (data skew), which can negatively impact performance.
Partitioning by post_time could also be considered, but typically date is preferred due to its more manageable granularity.
References:
? Delta Lake Documentation on Table Partitioning: Optimizing Layout with Partitioning

NEW QUESTION 78
A table is registered with the following code:
Both users and orders are Delta Lake tables. Which statement describes the results of querying recent_orders?

A. All logic will execute at query time and return the result of joining the valid versions of the source tables at the time the query finishes.
B. All logic will execute when the table is defined and store the result of joining tables to the DBFS; this stored data will be returned when the table is queried.
C. Results will be computed and cached when the table is defined; these cached results will incrementally update as new records are inserted into source tables.
D. All logic will execute at query time and return the result of joining the valid versions of the source tables at the time the query began.
E. The versions of each source table will be stored in the table transaction log; query results will be saved to DBFS with each query.

Answer: B

NEW QUESTION 79
Which Python variable contains a list of directories to be searched when trying to locate required modules?

A. importlib.resource path
B. ,sys.path
C. os-path
D. pypi.path
E. pylib.source

Answer: B

NEW QUESTION 81

The data governance team is reviewing code used for deleting records for compliance with GDPR. They note the following logic is used to delete records from the Delta Lake table named users.

```
DELETE FROM users
WHERE user_id IN
   (SELECT user_id FROM delete_requests)
```

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

A. Yes; Delta Lake ACID guarantees provide assurance that the delete command succeeded fully and permanently purged these records.
B. No; the Delta cache may return records from previous versions of the table until the cluster is restarted.
C. Yes; the Delta cache immediately updates to reflect the latest data files recorded to disk.
D. No; the Delta Lake delete command only provides ACID guarantees when combined with the merge into command.
E. No; files containing deleted records may still be accessible with time travel until a vacuum command is used to remove invalidated data files.

Answer: E

Explanation:
The code uses the DELETE FROM command to delete records from the users table that match a condition based on a join with another table called delete_requests, which contains all users that have requested deletion. The DELETE FROM command deletes records from a Delta Lake table by creating a new version of the table that does not contain the deleted records. However, this does not guarantee that the records to be deleted are no longer accessible, because Delta Lake supports time travel, which allows querying previous versions of the table using a timestamp or version number. Therefore, files containing deleted records may still be accessible with time travel until a vacuum command is used to remove invalidated data files from physical storage. Verified References: [Databricks Certified Data Engineer Professional], under “Delta Lake” section; Databricks Documentation, under “Delete from a table” section; Databricks Documentation, under “Remove files no longer referenced by a Delta table” section.

NEW QUESTION 86
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 87
Which configuration parameter directly affects the size of a spark-partition upon ingestion of data into Spark?

A. spark.sql.files.maxPartitionBytes
B. spark.sql.autoBroadcastJoinThreshold
C. spark.sql.files.openCostInBytes
D. spark.sql.adaptive.coalescePartitions.minPartitionNum
E. spark.sql.adaptive.advisoryPartitionSizeInBytes

Answer: A

Explanation:
This is the correct answer because spark.sql.files.maxPartitionBytes is a configuration parameter that directly affects the size of a spark-partition upon ingestion of data into Spark. This parameter configures the maximum number of bytes to pack into a single partition when reading files from file-based sources such as Parquet, JSON and ORC. The default value is 128 MB, which means each partition will be roughly 128 MB in size, unless there are too many small files or only one large file. Verified References: [Databricks Certified Data Engineer Professional], under “Spark Configuration”
section; Databricks Documentation, under “Available Properties - spark.sql.files.maxPartitionBytes” section.

NEW QUESTION 92
The data engineering team has configured a Databricks SQL query and alert to monitor the values in a Delta Lake table. The recent_sensor_recordings table contains an identifying sensor_id alongside the timestamp and temperature for the most recent 5 minutes of recordings.
The below query is used to create the alert:

```
SELECT MEAN(temperature), MAX(temperature), MIN(temperature)
FROM recent_sensor_recordings
GROUP BY sensor_id
```

The query is set to refresh each minute and always completes in less than 10 seconds. The alert is set to trigger when mean (temperature) > 120. Notifications are triggered to be sent at most every 1 minute.
If this alert raises notifications for 3 consecutive minutes and then stops, which statement must be true?

A. The total average temperature across all sensors exceeded 120 on three consecutive executions of the query
B. The recent_sensor_recordingstable was unresponsive for three consecutive runs of the query
C. The source query failed to update properly for three consecutive minutes and then restarted
D. The maximum temperature recording for at least one sensor exceeded 120 on three consecutive executions of the query
E. The average temperature recordings for at least one sensor exceeded 120 on three consecutive executions of the query

Answer: E

Explanation:
This is the correct answer because the query is using a GROUP BY clause on the sensor_id column, which means it will calculate the mean temperature for each sensor separately. The alert will trigger when the mean temperature for any sensor is greater than 120, which means at least one sensor had an average temperature above 120 for three consecutive minutes. The alert will stop when the mean temperature for all sensors drops below 120. Verified References: [Databricks Certified Data Engineer Professional], under “SQL Analytics” section; Databricks Documentation, under “Alerts” section.

NEW QUESTION 96
A nightly job ingests data into a Delta Lake table using the following code:

```
from pyspark.sql.functions import current_timestamp, input_file_name, col
from pyspark.sql.column import Column

def ingest_daily_batch(time_col: Column, year:int, month:int, day:int):
    (spark.read
        .format("parquet")
        .load(f"/mnt/daily_batch/{year}/{month}/{day}")
        .select("*",
                time_col.alias("ingest_time"),
                input_file_name().alias("source_file")
               )
        .write
        .mode("append")
        .saveAsTable("bronze")
    )
```

The next step in the pipeline requires a function that returns an object that can be used to manipulate new records that have not yet been processed to the next table in the pipeline.
Which code snippet completes this function definition? def new_records():

A. return spark.readStream.table("bronze")
B. return spark.readStream.load("bronze")C.

```
return (spark.read
        .table("bronze")
        .filter(col("ingest_time") == current_timestamp())
    )
```

D.return spark.read.option("readChangeFeed", "true").table ("bronze")
C.

```
return (spark.read
    .table("bronze")
    .filter(col("source_file") == f"/mnt/daily_batch/{year}/{month}/{day}")
  )
```

Answer: E

Explanation:
https://docs.databricks.com/en/delta/delta-change-data-feed.html

NEW QUESTION 100
Which is a key benefit of an end-to-end test?

A. It closely simulates real world usage of your application.
B. It pinpoint errors in the building blocks of your application.
C. It provides testing coverage for all code paths and branches.
D. It makes it easier to automate your test suite

Answer: A

Explanation:
End-to-end testing is a methodology used to test whether the flow of an application, from start to finish, behaves as expected. The key benefit of an end-to-end

test is that it closely simulates real-world, user behavior, ensuring that the system as a whole operates correctly.
References:
? Software Testing: End-to-End Testing

NEW QUESTION 101
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 103
Where in the Spark UI can one diagnose a performance problem induced by not leveraging predicate push-down?

A. In the Executor's log file, by gripping for "predicate push-down"
B. In the Stage's Detail screen, in the Completed Stages table, by noting the size of data read from the Input column
C. In the Storage Detail screen, by noting which RDDs are not stored on disk
D. In the Delta Lake transaction lo
E. by noting the column statistics
F. In the Query Detail screen, by interpreting the Physical Plan

Answer: E

Explanation:
This is the correct answer because it is where in the Spark UI one can diagnose a performance problem induced by not leveraging predicate push-down. Predicate push-down is an optimization technique that allows filtering data at the source before loading it into memory or processing it further. This can improve performance and reduce I/O costs by avoiding reading unnecessary data. To leverage predicate push-down, one should use supported data sources and formats, such as Delta Lake, Parquet, or JDBC, and use filter expressions that can be pushed down to the source. To diagnose a performance problem induced by not leveraging predicate push-down, one can use the Spark UI to access the Query Detail screen, which shows information about a SQL query executed on a Spark cluster. The Query Detail screen includes the Physical Plan, which is the actual plan executed by Spark to perform the query. The Physical Plan shows the physical operators used by Spark, such as Scan, Filter, Project, or Aggregate, and their input and output statistics, such as rows and bytes. By interpreting the Physical Plan, one can see if the filter expressions are pushed down to the source or not, and how much data is read or processed by each operator. Verified References: [Databricks Certified Data Engineer Professional], under “Spark Core” section; Databricks Documentation, under “Predicate pushdown” section; Databricks Documentation, under “Query detail page” section.

NEW QUESTION 106
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 108
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 112
Each configuration below is identical to the extent that each cluster has 400 GB total of RAM, 160 total cores and only one Executor per VM.
Given a job with at least one wide transformation, which of the following cluster configurations will result in maximum performance?

A. • Total VMs; 1• 400 GB per Executor• 160 Cores / Executor
B. • Total VMs: 8• 50 GB per Executor• 20 Cores / Executor
C. • Total VMs: 4• 100 GB per Executor• 40 Cores/Executor
D. • Total VMs:2• 200 GB per Executor• 80 Cores / Executor

Answer: B

Explanation:
This is the correct answer because it is the cluster configuration that will result in maximum performance for a job with at least one wide transformation. A wide transformation is a type of transformation that requires shuffling data across partitions, such as join, groupBy, or orderBy. Shuffling can be expensive and time-consuming, especially if there are too many or too few partitions. Therefore, it is important to choose a cluster configuration that can balance the trade-off between parallelism and network overhead. In this case, having 8 VMs with 50 GB per executor and 20 cores per executor will create 8 partitions, each with enough memory and CPU resources to handle the shuffling efficiently. Having fewer VMs with more memory and cores per executor will create fewer partitions, which will reduce parallelism and increase the size of each shuffle block. Having more VMs with less memory and cores per executor will create more partitions, which will increase parallelism but also increase the network overhead and the number of shuffle files. Verified References: [Databricks Certified Data Engineer Professional], under “Performance Tuning” section; Databricks Documentation, under “Cluster configurations” section.

NEW QUESTION 115
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