Databricks

Exam Questions Databricks-Certified-Professional-Data-Engineer

Databricks Certified Data Engineer Professional Exam

NEW QUESTION 1
The business intelligence team has a dashboard configured to track various summary metrics for retail stories. This includes total sales for the previous day alongside totals and averages for a variety of time periods. The fields required to populate this dashboard have the following schema:
For Demand forecasting, the Lakehouse contains a validated table of all itemized sales updated incrementally in near real-time. This table named products_per_order, includes the following fields:
Because reporting on long-term sales trends is less volatile, analysts using the new dashboard only require data to be refreshed once daily. Because the dashboard will be queried interactively by many users throughout a normal business day, it should return results quickly and reduce total compute associated with each materialization.
Which solution meets the expectations of the end users while controlling and limiting possible costs?

A. Use the Delta Cache to persists the products_per_order table in memory to quickly the dashboard with each query.
B. Populate the dashboard by configuring a nightly batch job to save the required to quickly update the dashboard with each query.
C. Use Structure Streaming to configure a live dashboard against the products_per_order table within a Databricks notebook.
D. Define a view against the products_per_order table and define the dashboard against this view.

Answer: D

Explanation:
Given the requirement for daily refresh of data and the need to ensure quick response times for interactive queries while controlling costs, a nightly batch job to pre- compute and save the required summary metrics is the most suitable approach.
? By pre-aggregating data during off-peak hours, the dashboard can serve queries quickly without requiring on-the-fly computation, which can be resource-intensive and slow, especially with many users.
? This approach also limits the cost by avoiding continuous computation throughout the day and instead leverages a batch process that efficiently computes and stores the necessary data.
? The other options (A, C, D) either do not address the cost and performance requirements effectively or are not suitable for the use case of less frequent data refresh and high interactivity.
References:
? Databricks Documentation on Batch Processing: Databricks Batch Processing
? Data Lakehouse Patterns: Data Lakehouse Best Practices

NEW QUESTION 2
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

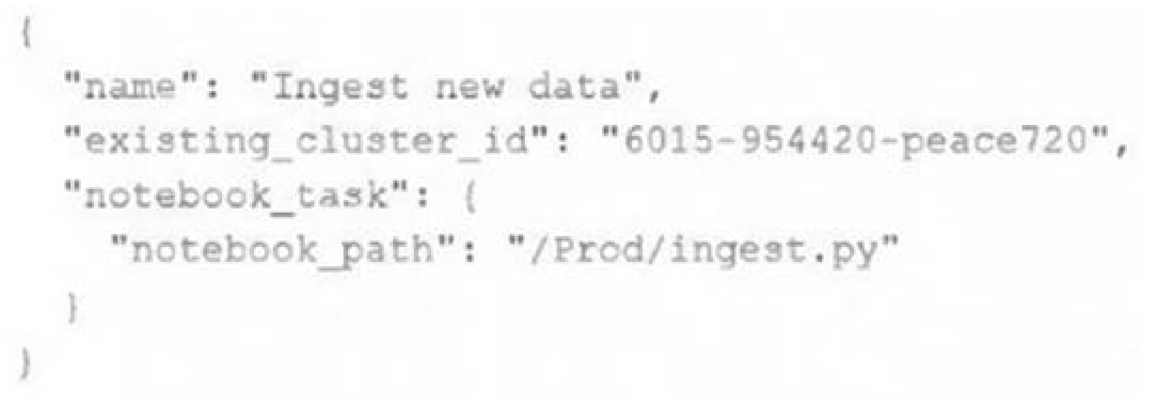
NEW QUESTION 3
The data architect has mandated that all tables in the Lakehouse should be configured as external Delta Lake tables.
Which approach will ensure that this requirement is met?

A. Whenever a database is being created, make sure that the location keyword is used
B. When configuring an external data warehouse for all table storag
C. leverage Databricks for all ELT.
D. Whenever a table is being created, make sure that the location keyword is used.
E. When tables are created, make sure that the external keyword is used in the create table statement.
F. When the workspace is being configured, make sure that external cloud object storage has been mounted.

Answer: C

Explanation:
This is the correct answer because it ensures that this requirement is met. The requirement is that all tables in the Lakehouse should be configured as external Delta Lake tables. An external table is a table that is stored outside of the default warehouse directory and whose metadata is not managed by Databricks. An external table can be created by using the location keyword to specify the path to an existing directory in a cloud storage system, such as DBFS or S3. By creating external tables, the data engineering team can avoid losing data if they drop or overwrite the table, as well as leverage existing data without moving or copying it. Verified References: [Databricks Certified Data Engineer Professional], under “Delta Lake” section; Databricks Documentation, under “Create an external table” section.

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
A data engineer is configuring a pipeline that will potentially see late-arriving, duplicate records.
In addition to de-duplicating records within the batch, which of the following approaches allows the data engineer to deduplicate data against previously processed records as it is inserted into a Delta table?

A. Set the configuration delta.deduplicate = true.
B. VACUUM the Delta table after each batch completes.
C. Perform an insert-only merge with a matching condition on a unique key.
D. Perform a full outer join on a unique key and overwrite existing data.
E. Rely on Delta Lake schema enforcement to prevent duplicate records.

Answer: C

Explanation:
To deduplicate data against previously processed records as it is inserted into a Delta table, you can use the merge operation with an insert-only clause. This allows you to insert new records that do not match any existing records based on a unique key, while ignoring duplicate records that match existing records. For example, you can use the following syntax:
MERGE INTO target_table USING source_table ON target_table.unique_key = source_table.unique_key WHEN NOT MATCHED THEN INSERT *
This will insert only the records from the source table that have a unique key that is not present in the target table, and skip the records that have a matching key. This way, you can avoid inserting duplicate records into the Delta table.
References:
? https://docs.databricks.com/delta/delta-update.html#upsert-into-a-table-using- merge
? https://docs.databricks.com/delta/delta-update.html#insert-only-merge

NEW QUESTION 6
A Delta Lake table was created with the below query:
Realizing that the original query had a typographical error, the below code was executed: ALTER TABLE prod.sales_by_stor RENAME TO prod.sales_by_store
Which result will occur after running the second command?

A. The table reference in the metastore is updated and no data is changed.
B. The table name change is recorded in the Delta transaction log.
C. All related files and metadata are dropped and recreated in a single ACID transaction.
D. The table reference in the metastore is updated and all data files are moved.
E. A new Delta transaction log Is created for the renamed table.

Answer: A

Explanation:
The query uses the CREATE TABLE USING DELTA syntax to create a Delta Lake table from an existing Parquet file stored in DBFS. The query also uses the LOCATION keyword to specify the path to the Parquet file as /mnt/finance_eda_bucket/tx_sales.parquet. By using the LOCATION keyword, the query creates an external table, which is a table that is stored outside of the default warehouse directory and whose metadata is not managed by Databricks. An external table can be created from an existing directory in a cloud storage system, such as DBFS or S3, that contains data files in a supported format, such as Parquet or CSV.
The result that will occur after running the second command is that the table reference in the metastore is updated and no data is changed. The metastore is a service that stores metadata about tables, such as their schema, location, properties, and partitions. The metastore allows users to access tables using SQL commands or Spark APIs without knowing their physical location or format. When renaming an external table using the ALTER TABLE RENAME TO command, only the table reference in the metastore is updated with the new name; no data files or directories are moved or changed in the storage system. The table will still point to the same location and use the same format as before. However, if renaming a managed table, which is a table whose metadata and data are both managed by Databricks, both the table reference in the metastore and the data files in the default warehouse directory are moved and renamed accordingly.
Verified References: [Databricks Certified Data Engineer Professional], under “Delta Lake” section; Databricks Documentation, under “ALTER TABLE RENAME TO” section; Databricks Documentation, under “Metastore” section; Databricks Documentation, under “Managed and external tables” section.

NEW QUESTION 7

Which statement describes the correct use of pyspark.sql.functions.broadcast?

A. It marks a column as having low enough cardinality to properly map distinct values to available partitions, allowing a broadcast join.
B. It marks a column as small enough to store in memory on all executors, allowing a broadcast join.
C. It caches a copy of the indicated table on attached storage volumes for all active clusters within a Databricks workspace.
D. It marks a DataFrame as small enough to store in memory on all executors, allowing a broadcast join.
E. It caches a copy of the indicated table on all nodes in the cluster for use in all future queries during the cluster lifetime.

Answer: D

Explanation:
https://spark.apache.org/docs/3.1.3/api/python/reference/api/pyspark.sql.functions.broadca st.html
The broadcast function in PySpark is used in the context of joins. When you mark a DataFrame with broadcast, Spark tries to send this DataFrame to all worker nodes so that it can be joined with another DataFrame without shuffling the larger DataFrame across the nodes. This is particularly beneficial when the DataFrame is small enough to fit into the memory of each node. It helps to optimize the join process by reducing the amount of data that needs to be shuffled across the cluster, which can be a very expensive operation in terms of computation and time.
The pyspark.sql.functions.broadcast function in PySpark is used to hint to Spark that a DataFrame is small enough to be broadcast to all worker nodes in the cluster. When this hint is applied, Spark can perform a broadcast join, where the smaller DataFrame is sent to each executor only once and joined with the larger DataFrame on each executor. This can significantly reduce the amount of data shuffled across the network and can improve the performance of the join operation.
In a broadcast join, the entire smaller DataFrame is sent to each executor, not just a specific column or a cached version on attached storage. This function is particularly useful when one of the DataFrames in a join operation is much smaller than the other, and can fit comfortably in the memory of each executor node.
References:
? Databricks Documentation on Broadcast Joins: Databricks Broadcast Join Guide
? PySpark API Reference: pyspark.sql.functions.broadcast

NEW QUESTION 8
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 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
Which REST API call can be used to review the notebooks configured to run as tasks in a multi-task job?

A. /jobs/runs/list
B. /jobs/runs/get-output
C. /jobs/runs/get
D. /jobs/get
E. /jobs/list

Answer: D

Explanation:
This is the correct answer because it is the REST API call that can be used to review the notebooks configured to run as tasks in a multi-task job. The REST API is an interface that allows programmatically interacting with Databricks resources, such as clusters, jobs, notebooks, or tables. The REST API uses HTTP methods, such as GET, POST, PUT, or DELETE, to perform operations on these resources. The /jobs/get endpoint is a GET method that returns information about a job given its job ID. The information includes the job settings, such as the name, schedule, timeout, retries, email notifications, and tasks. The tasks are the units of work that a job executes. A task can be a notebook task, which runs a notebook with specified parameters; a jar task, which runs a JAR uploaded to DBFS with specified main class and arguments; or a python task, which runs a Python file uploaded to DBFS with specified parameters. A multi-task job is a job that has more than one task configured to run in a specific order or in parallel. By using the /jobs/get endpoint, one can review the notebooks configured to run as tasks in a multi-

task job.
Verified References: [Databricks Certified Data Engineer Professional], under “Databricks Jobs” section; Databricks Documentation, under “Get” section; Databricks Documentation, under “JobSettings” section.

NEW QUESTION 10
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 18
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 19
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 22
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 25
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 29
What is a method of installing a Python package scoped at the notebook level to all nodes in the currently active cluster?

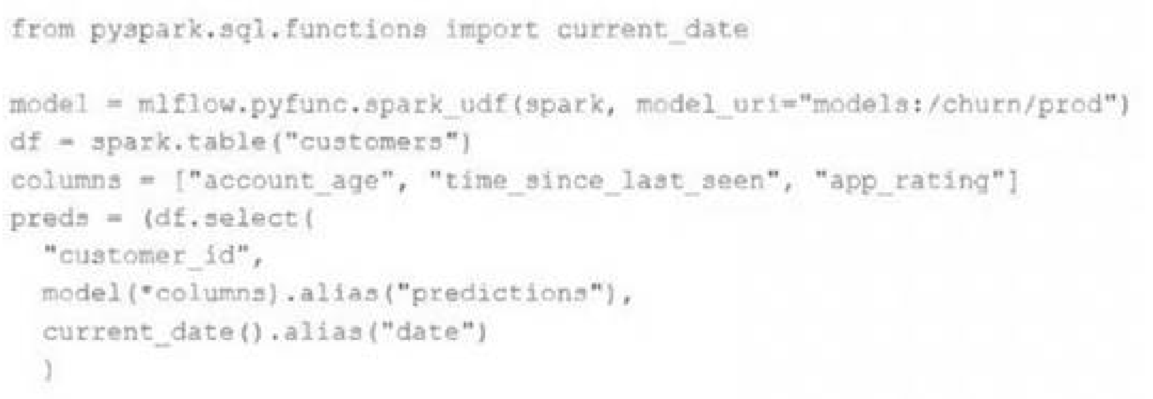
A. Use &Pip install in a notebook cell
B. Run source env/bin/activate in a notebook setup script
C. Install libraries from PyPi using the cluster UI
D. Use &sh install in a notebook cell

Answer: C

Explanation:
Installing a Python package scoped at the notebook level to all nodes in the currently active cluster in Databricks can be achieved by using the Libraries tab in the cluster UI. This interface allows you to install libraries across all nodes in the cluster. While the %pip command in a notebook cell would only affect the driver node, using the cluster UI ensures that the package is installed on all nodes.
References:

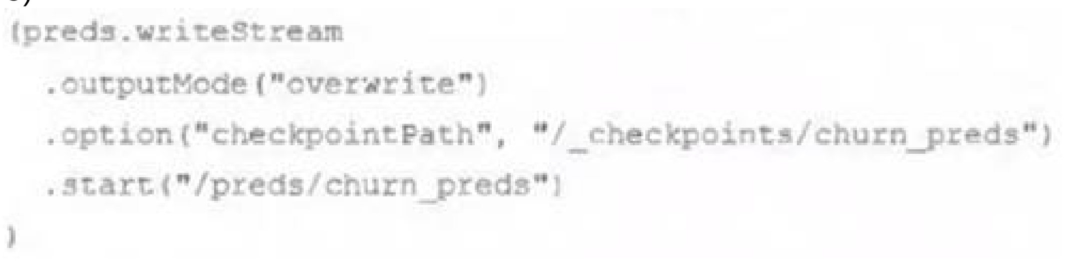
? Databricks Documentation on Libraries: Libraries

NEW QUESTION 33
The data science team has created and logged a production model using MLflow. The following code correctly imports and applies the production model to output the predictions as a new DataFrame named preds with the schema "customer_id LONG, predictions DOUBLE, date DATE".



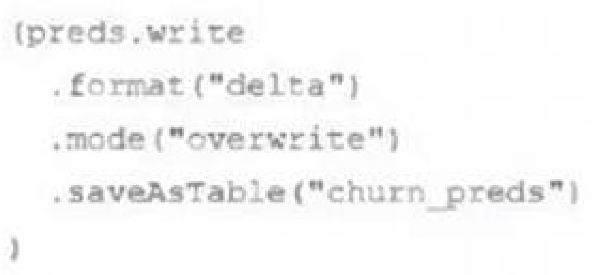
```
from pyspark.sql.functions import current_date

model = mlflow.pyfunc.spark_udf(spark, model_uri="models:/churn/prod")
df = spark.table("customers")
columns = ["account_age", "time_since_last_seen", "app_rating"]
preds = (df.select(
  "customer_id",
  model(*columns).alias("predictions"),
  current_date().alias("date")
  )
```

The data science team would like predictions saved to a Delta Lake table with the ability to compare all predictions across time. Churn predictions will be made at most once per day.
Which code block accomplishes this task while minimizing potential compute costs?
A) preds.write.mode("append").saveAsTable("churn_preds")
B) preds.write.format("delta").save("/preds/churn_preds")
C)



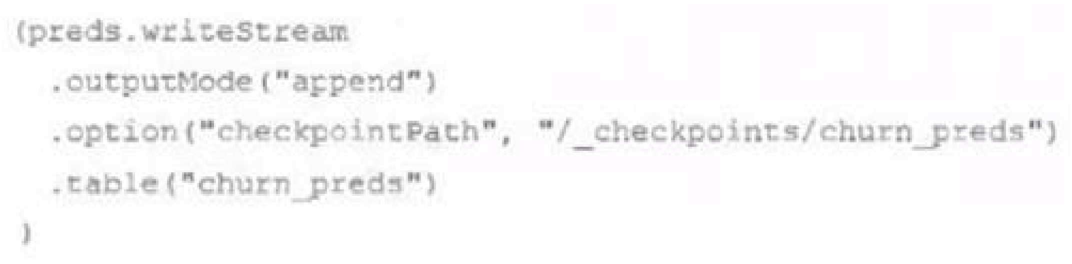
```
(preds.writeStream
  .outputMode("overwrite")
  .option("checkpointPath", "/_checkpoints/churn_preds")
  .start("/preds/churn_preds")
)
```

D)



```
(preds.write
  .format("delta")
  .mode("overwrite")
  .saveAsTable("churn_preds")
)
```

E)



```
(preds.writeStream
  .outputMode("append")
  .option("checkpointPath", "/_checkpoints/churn_preds")
  .table("churn_preds")
 )
```

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

Answer: A

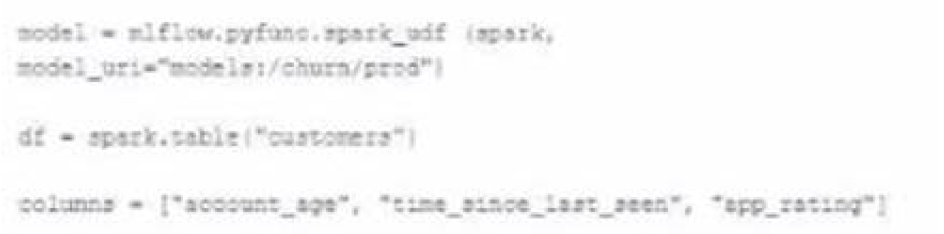
NEW QUESTION 37
A data architect has designed a system in which two Structured Streaming jobs will concurrently write to a single bronze Delta table. Each job is subscribing to a different topic from an Apache Kafka source, but they will write data with the same schema. To keep the directory structure simple, a data engineer has decided to nest a checkpoint directory to be shared by both streams.
The proposed directory structure is displayed below:
Which statement describes whether this checkpoint directory structure is valid for the given scenario and why?

A. No; Delta Lake manages streaming checkpoints in the transaction log.
B. Yes; both of the streams can share a single checkpoint directory.
C. No; only one stream can write to a Delta Lake table.
D. Yes; Delta Lake supports infinite concurrent writers.
E. No; each of the streams needs to have its own checkpoint directory.

Answer: E

Explanation:
This is the correct answer because checkpointing is a critical feature of Structured Streaming that provides fault tolerance and recovery in case of failures. Checkpointing stores the current state and progress of a streaming query in a reliable storage system, such as DBFS or S3. Each streaming query must have its own checkpoint directory that is unique and exclusive to that query. If two streaming queries share the same checkpoint directory, they will interfere with each other and cause unexpected errors or data loss. Verified References: [Databricks Certified Data Engineer Professional], under
“Structured Streaming” section; Databricks Documentation, under “Checkpointing” section.

NEW QUESTION 38
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 43
A CHECK constraint has been successfully added to the Delta table named activity_details using the following logic:
A batch job is attempting to insert new records to the table, including a record where latitude = 45.50 and longitude = 212.67.
Which statement describes the outcome of this batch insert?

A. The write will fail when the violating record is reached; any records previously processed will be recorded to the target table.
B. The write will fail completely because of the constraint violation and no records will be inserted into the target table.
C. The write will insert all records except those that violate the table constraints; the violating records will be recorded to a quarantine table.
D. The write will include all records in the target table; any violations will be indicated in the boolean column named valid_coordinates.
E. The write will insert all records except those that violate the table constraints; the violating records will be reported in a warning log.

Answer: B

Explanation:
The CHECK constraint is used to ensure that the data inserted into the table meets the specified conditions. In this case, the CHECK constraint is used to ensure that the latitude and longitude values are within the specified range. If the data does not meet the specified conditions, the write operation will fail completely and no records will be inserted into the target table. This is because Delta Lake supports ACID transactions, which means that either all the data is written or none of it is written. Therefore, the batch insert will fail when it encounters a record that violates the constraint, and the target table will not be updated. References:
? Constraints: https://docs.delta.io/latest/delta-constraints.html
? ACID Transactions: https://docs.delta.io/latest/delta-intro.html#acid-transactions

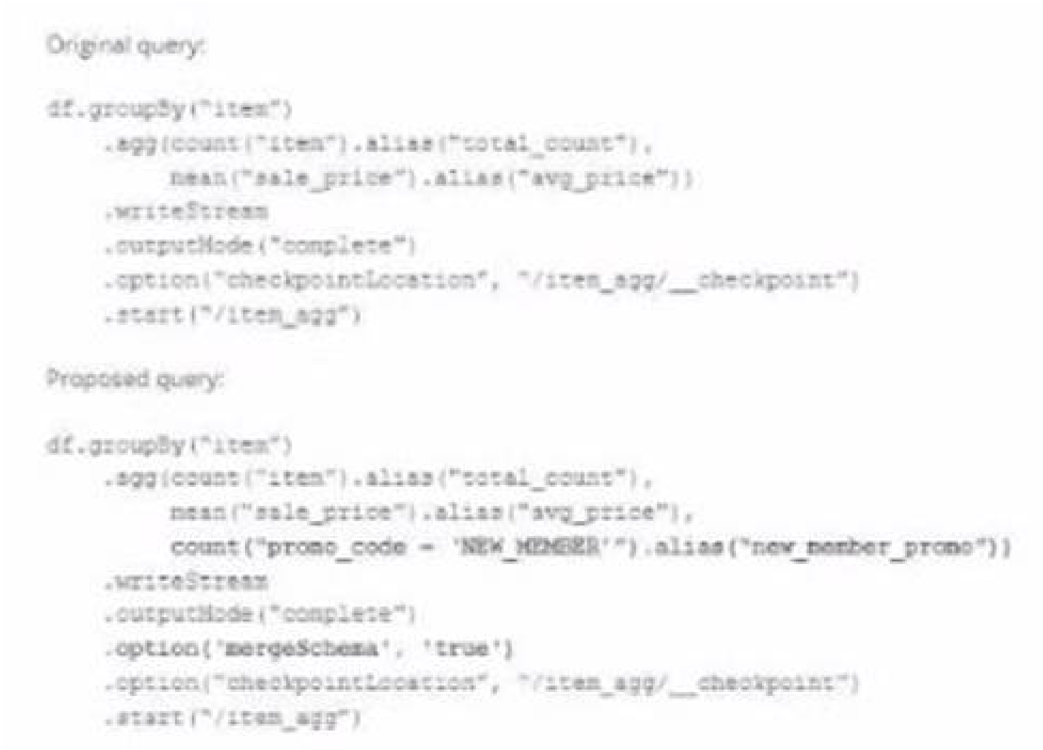
NEW QUESTION 46
A production workload incrementally applies updates from an external Change Data Capture feed to a Delta Lake table as an always-on Structured Stream job. When data was initially migrated for this table, OPTIMIZE was executed and most data files were resized to 1 GB. Auto Optimize and 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 51
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

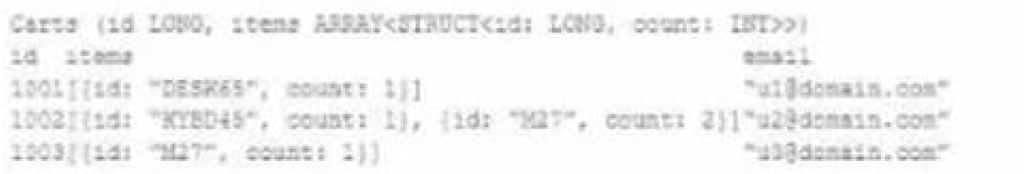
NEW QUESTION 54
A Data engineer wants to run unit's tests using common Python testing frameworks on python functions defined across several Databricks notebooks currently used in production.
How can the data engineer run unit tests against function that work with data in production?

A. Run unit tests against non-production data that closely mirrors production
B. Define and unit test functions using Files in Repos
C. Define units test and functions within the same notebook
D. Define and import unit test functions from a separate Databricks notebook

Answer: A

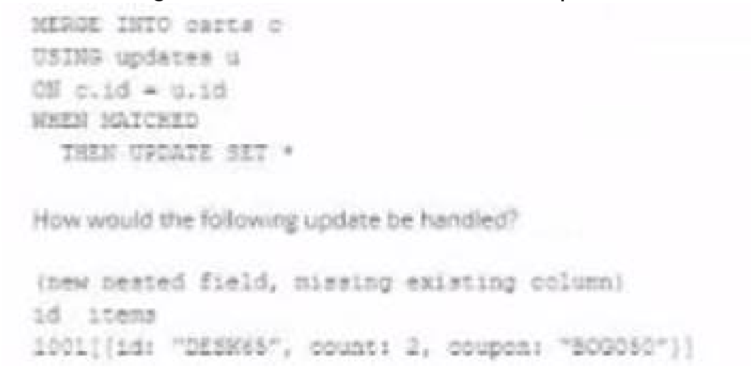
Explanation:
The best practice for running unit tests on functions that interact with data is to use a dataset that closely mirrors the production data. This approach allows data engineers to validate the logic of their functions without the risk of affecting the actual production data. It's important to have a representative sample of production data to catch edge cases and ensure the functions will work correctly when used in a production environment.
References:
? Databricks Documentation on Testing: Testing and Validation of Data and Notebooks

NEW QUESTION 55
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"}]
```

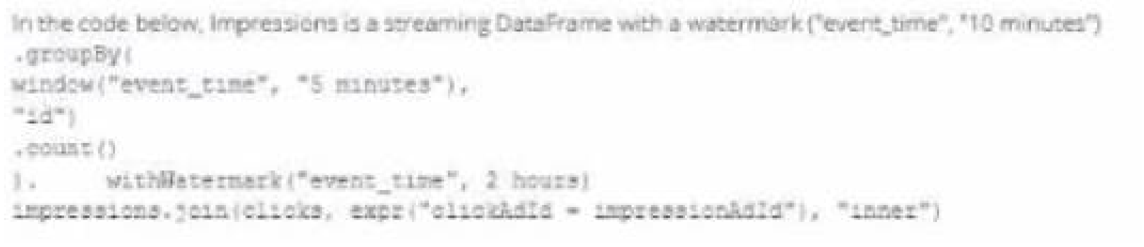
How would the following update be handled?

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 59
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 60
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 63
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 68
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.

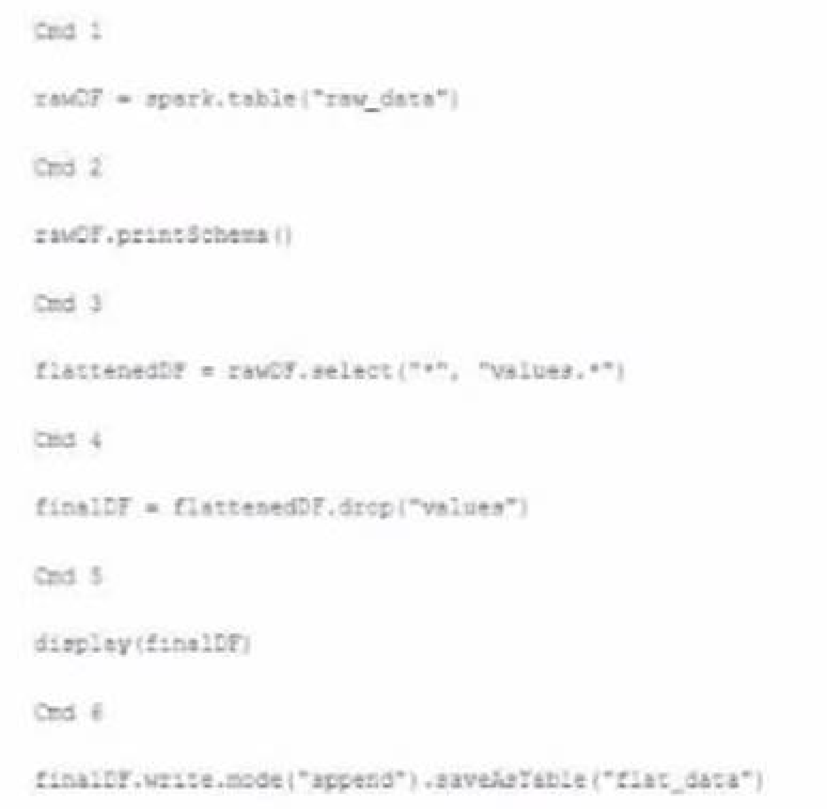
NEW QUESTION 71
The data engineer team has been tasked with configured connections to an external database that does not have a supported native connector with Databricks. The external database already has data security configured by group membership. These groups map directly to user group already created in Databricks that represent various teams within the company.
A new login credential has been created for each group in the external database. The Databricks Utilities Secrets module will be used to make these credentials available to Databricks users.
Assuming that all the credentials are configured correctly on the external database and group membership is properly configured on Databricks, which statement describes how teams can be granted the minimum necessary access to using these credentials?

A. ''Read'' permissions should be set on a secret key mapped to those credentials that will be used by a given team.
B. No additional configuration is necessary as long as all users are configured as administrators in the workspace where secrets have been added.
C. "Read" permissions should be set on a secret scope containing only those credentials that will be used by a given team.
D. "Manage" permission should be set on a secret scope containing only those credentials that will be used by a given team.

Answer: C

Explanation:
In Databricks, using the Secrets module allows for secure management of sensitive information such as database credentials. Granting 'Read' permissions on a secret key that maps to database credentials for a specific team ensures that only members of that team can access these credentials. This approach aligns with the principle of least privilege, granting users the minimum level of access required to perform their jobs, thus enhancing security.
References:
? Databricks Documentation on Secret Management: Secrets

NEW QUESTION 75
A member of the data engineering team has submitted a short notebook that they wish to schedule as part of a larger data pipeline. Assume that the commands provided below produce the logically correct results when run as presented.



```
Cmd 1

rawDF = spark.table("raw_data")

Cmd 2

rawDF.printSchema()

Cmd 3

flattenedDF = rawDF.select("*", "values.*")

Cmd 4

finalDF = flattenedDF.drop("values")

Cmd 5

display(finalDF)

Cmd 6

finalDF.write.mode("append").saveAsTable("flat_data")
```

Which command should be removed from the notebook before scheduling it as a job?

A. Cmd 2
B. Cmd 3
C. Cmd 4
D. Cmd 5
E. Cmd 6

Answer: E

Explanation:
Cmd 6 is the command that should be removed from the notebook before scheduling it as a job. This command is selecting all the columns from the finalDF dataframe and displaying them in the notebook. This is not necessary for the job, as the finalDF dataframe is already written to a table in Cmd 7. Displaying the dataframe in the notebook will only consume resources and time, and it will not affect the output of the job. Therefore, Cmd 6 is redundant and should be removed.
The other commands are essential for the job, as they perform the following tasks:
? Cmd 1: Reads the raw_data table into a Spark dataframe called rawDF.
? Cmd 2: Prints the schema of the rawDF dataframe, which is useful for debugging and understanding the data structure.
? Cmd 3: Selects all the columns from the rawDF dataframe, as well as the nested columns from the values struct column, and creates a new dataframe called flattenedDF.
? Cmd 4: Drops the values column from the flattenedDF dataframe, as it is no longer needed after flattening, and creates a new dataframe called finalDF.
? Cmd 5: Explains the physical plan of the finalDF dataframe, which is useful for optimizing and tuning the performance of the job.
? Cmd 7: Writes the finalDF dataframe to a table called flat_data, using the append mode to add new data to the existing table.

NEW QUESTION 78
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 80
A production cluster has 3 executor nodes and uses the same virtual machine type for the driver and executor.
When evaluating the Ganglia Metrics for this cluster, which indicator would signal a bottleneck caused by code executing on the driver?

A. The five Minute Load Average remains consistent/flat
B. Bytes Received never exceeds 80 million bytes per second
C. Total Disk Space remains constant
D. Network I/O never spikes
E. Overall cluster CPU utilization is around 25%

Answer: E

Explanation:
This is the correct answer because it indicates a bottleneck caused by code executing on the driver. A bottleneck is a situation where the performance or capacity of a system is limited by a single component or resource. A bottleneck can cause slow execution, high latency, or low throughput. A production cluster has 3 executor nodes and uses the same virtual machine type for the driver and executor. When evaluating the Ganglia Metrics for this cluster, one can look for indicators that show how the cluster resources are being utilized, such as CPU, memory, disk, or network. If the overall cluster CPU utilization is around 25%, it means that only one out of the four nodes (driver + 3 executors) is using its full CPU capacity, while the other three nodes are idle or underutilized. This suggests that the code executing on the driver is taking too long or consuming too much CPU resources, preventing the executors from receiving tasks or data to process. This can happen when the code has driver-side operations that are not parallelized or distributed, such as collecting large amounts of data to the driver, performing complex calculations on the driver, or using non-Spark libraries on the driver. Verified References: [Databricks Certified Data Engineer Professional], under “Spark Core” section; Databricks Documentation, under “View cluster status and event logs - Ganglia metrics” section; Databricks Documentation, under “Avoid collecting large RDDs” section.
In a Spark cluster, the driver node is responsible for managing the execution of the Spark application, including scheduling tasks, managing the execution plan, and interacting with the cluster manager. If the overall cluster CPU utilization is low (e.g., around 25%), it may indicate that the driver node is not utilizing the available resources effectively and might be a bottleneck.

NEW QUESTION 85
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 88
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.

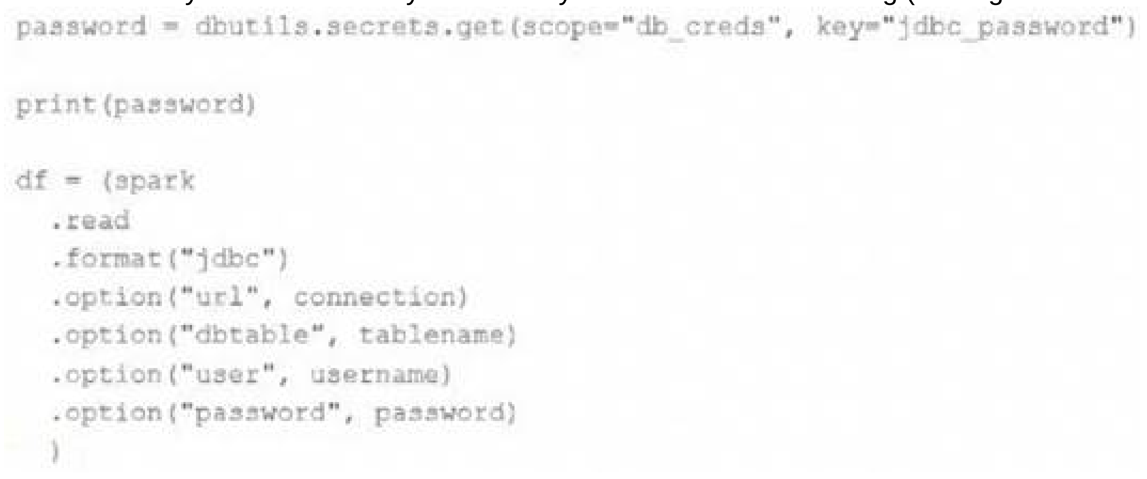
NEW QUESTION 91
Which statement describes integration testing?

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?

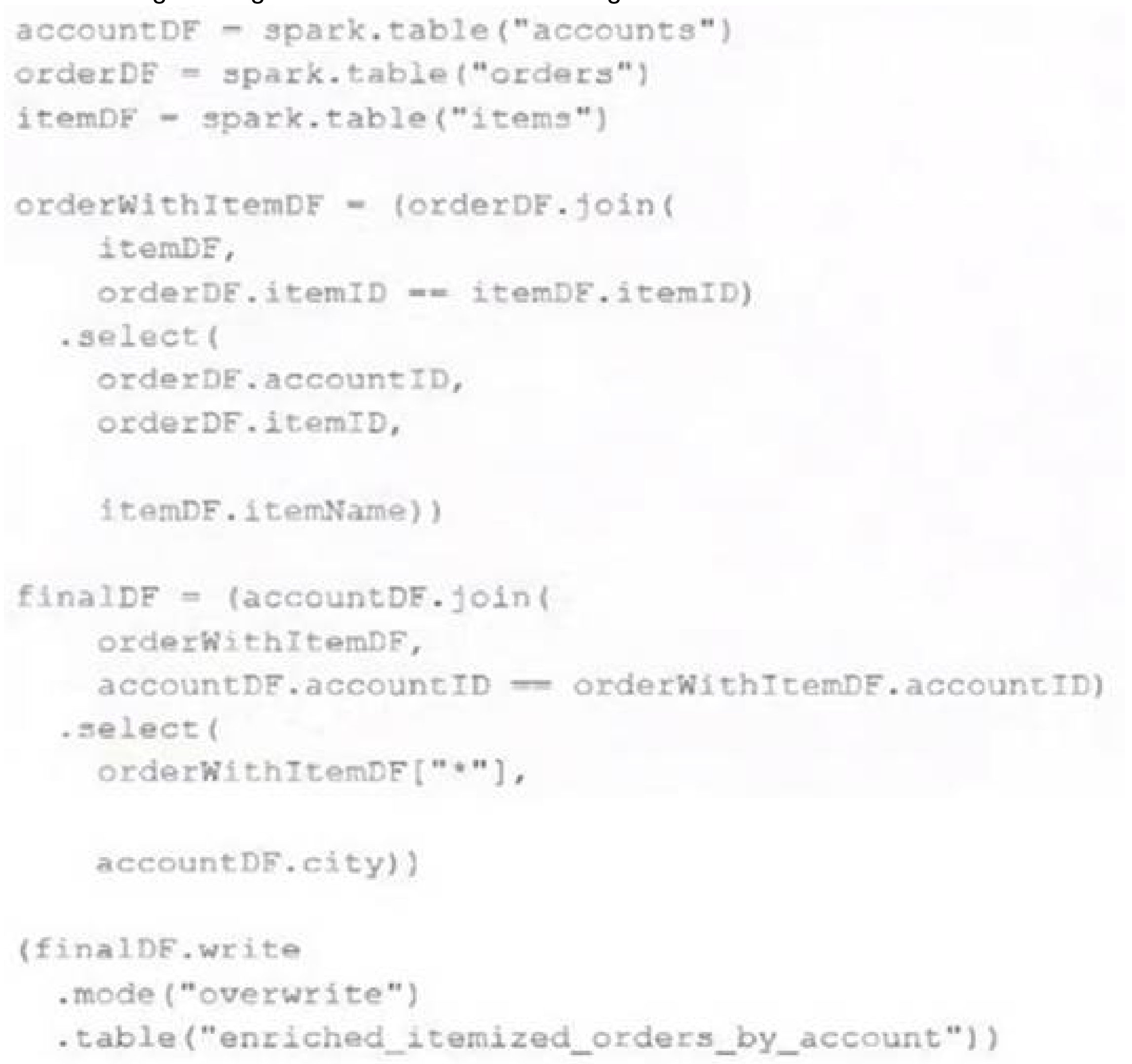
A. The connection to the external table will fail; the string "redacted" will be printed.
B. An interactive input box will appear in the notebook; if the right password is provided, the connection will succeed and the encoded password will be saved to DBFS.
C. An interactive input box will appear in 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 100
The data engineering team maintains the following code:



```
accountDF = spark.table("accounts")
orderDF = spark.table("orders")
itemDF = spark.table("items")

orderWithItemDF = (orderDF.join(
    itemDF,
    orderDF.itemID == itemDF.itemID)
  .select(
    orderDF.accountID,
    orderDF.itemID,

    itemDF.itemName))

finalDF = (accountDF.join(
    orderWithItemDF,
    accountDF.accountID == orderWithItemDF.accountID)
  .select(
    orderWithItemDF["*"],

    accountDF.city))

(finalDF.write
  .mode("overwrite")
  .table("enriched_itemized_orders_by_account"))
```

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

A. A batch job will update the enriched_itemized_orders_by_account table, replacing only those rows that have different values than the current version of the table, using accountID as the primary key.
B. The enriched_itemized_orders_by_account table will be overwritten using the current valid version of data in each of the three tables referenced in the join logic.
C. An incremental job will leverage information in the state store to identify unjoined rows in the source tables and write these rows to the enriched_iteinized_orders_by_account table.
D. An incremental job will detect if new rows have been written to any of the source tables; if new rows are detected, all results will be recalculated and used to overwrite the enriched_itemized_orders_by_account table.
E. No computation will occur until enriched_itemized_orders_by_account is queried; upon query materialization, results will be calculated using the current valid version of data in each of the three tables referenced in the join logic.

Answer: B

Explanation:
This is the correct answer because it describes what will occur when this code is executed. The code uses three Delta Lake tables as input sources: accounts, orders, and order_items. These tables are joined together using SQL queries to create a view called new_enriched_itemized_orders_by_account, which contains information about each order item and its associated account details. Then, the code uses write.format(“delta”).mode(“overwrite”) to overwrite a target table called enriched_itemized_orders_by_account using the data from the view. This means that every time this code is executed, it will replace all existing data in the target table with new data based on the current valid version of data in each of the three input tables. Verified References: [Databricks Certified Data Engineer Professional], under “Delta Lake” section; Databricks Documentation, under “Write to Delta tables” section.

NEW QUESTION 101
A data engineer is performing a join operating to combine values from a static userlookup table with a streaming DataFrame streamingDF.
Which code block attempts to perform an invalid stream-static join?

A. userLookup.join(streamingDF, ["userid"], how="inner")
B. streamingDF.join(userLookup, ["user_id"], how="outer")
C. streamingDF.join(userLookup, ["user_id"], how="left")
D. streamingDF.join(userLookup, ["userid"], how="inner")
E. userLookup.join(streamingDF, ["user_id"], how="right")

Answer: E

Explanation:
In Spark Structured Streaming, certain types of joins between a static DataFrame and a streaming DataFrame are not supported. Specifically, a right outer join where the static DataFrame is on the left side and the streaming DataFrame is on the right side is not valid. This is because Spark Structured Streaming cannot handle scenarios where it has to wait for new rows to arrive in the streaming DataFrame to match rows in the static DataFrame. The other join types listed (inner, left, and full outer joins) are supported in streaming-static DataFrame joins.
References:
? Structured Streaming Programming Guide: Join Operations
? Databricks Documentation on Stream-Static Joins: Databricks Stream-Static Joins

NEW QUESTION 104
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 107
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.

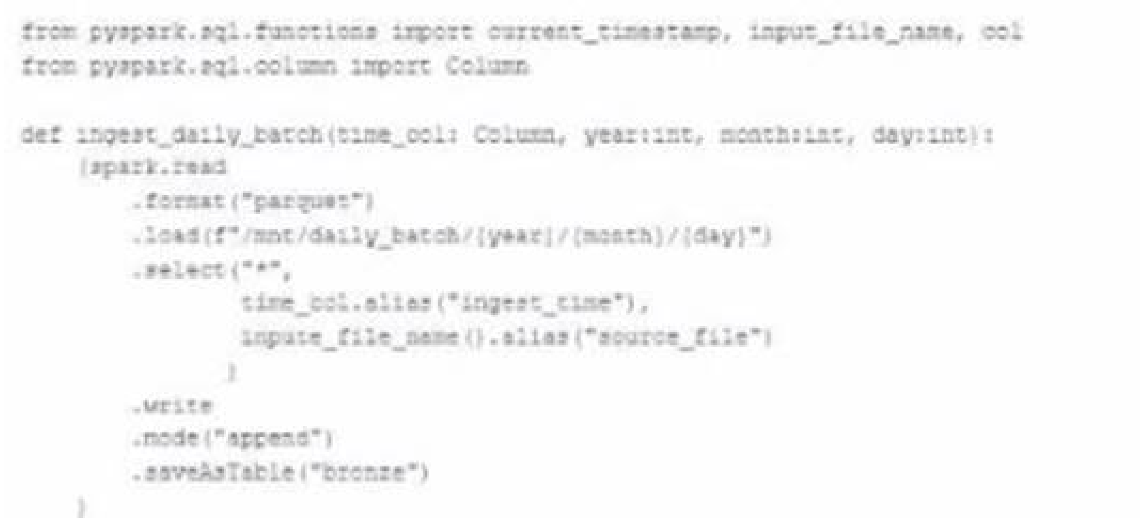
NEW QUESTION 111
A data architect has heard about lake's built-in versioning and time travel capabilities. For auditing purposes they have a requirement to maintain a full of all valid street addresses as they appear in the customers table.
The architect is interested in implementing a Type 1 table, 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

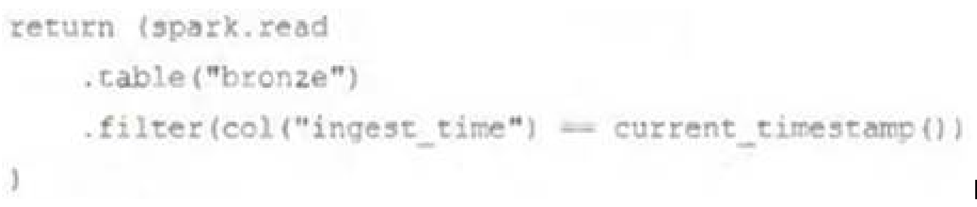
NEW QUESTION 116
A nightly job ingests data into a Delta Lake table using the following code:



```
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"),
                inpute_file_name().alias("source_file")
               )
        .write
        .mode("append")
        .saveAsTable("bronze")
    )
```

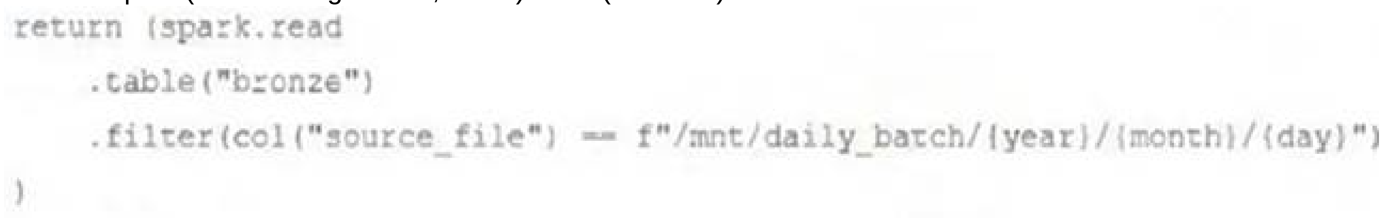
The next step in the pipeline requires a function that returns an object that can be used to manipulate new records that have not yet been processed to the next table in the pipeline.
Which code snippet completes this function definition? def new_records():

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

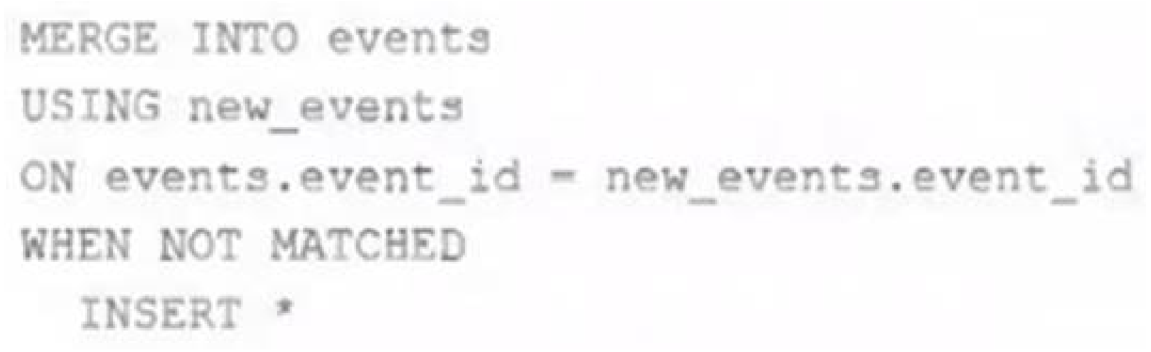
NEW QUESTION 117
A Databricks SQL dashboard has been configured to monitor the total number of records present in a collection of Delta Lake tables using the following query pattern:
SELECT COUNT (*) FROM table -
Which of the following describes how results are generated each time the dashboard is updated?

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 121
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 123
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 125
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 130
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 131
All records from an Apache Kafka producer are being ingested into a single Delta Lake table with the following schema:
key BINARY, value BINARY, topic STRING, partition LONG, offset LONG, timestamp LONG
There are 5 unique topics being ingested. Only the "registration" topic contains Personal Identifiable Information (PII). The company wishes to restrict access to PII. The company also wishes to only retain records containing PII in this table for 14 days after initial ingestion. However, for non-PII information, it would like to retain these records indefinitely.
Which of the following solutions meets the requirements?

A. All data should be deleted biweekly; Delta Lake's time travel functionality should be leveraged to maintain a history of non-PII information.
B. Data should be partitioned by the registration field, allowing ACLs and delete statements to be set for the PII directory.
C. Because the value field is stored as binary data, this information is not considered PII and no special precautions should be taken.
D. Separate object storage containers should be specified based on the partition field, allowing isolation at the storage level.
E. Data should be partitioned by the topic field, allowing ACLs and delete statements to leverage partition boundaries.

Answer: B

Explanation:
Partitioning the data by the topic field allows the company to apply different access control policies and retention policies for different topics. For example, the company can use the Table Access Control feature to grant or revoke permissions to the registration topic based on user roles or groups. The company can also use the DELETE command to remove records from the registration topic that are older than 14 days, while keeping the records from other topics indefinitely. Partitioning by the topic field also improves the performance of queries that filter by the topic field, as they can skip reading irrelevant partitions. References:
? Table Access Control: https://docs.databricks.com/security/access-control/table-
acls/index.html
? DELETE: https://docs.databricks.com/delta/delta-update.html#delete-from-a-table

NEW QUESTION 134
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