Databricks

Exam Questions Databricks-Certified-Professional-Data-Engineer

Databricks Certified Data Engineer Professional Exam

NEW QUESTION 1
Review the following error traceback:
Which statement describes the error being raised?

A. The code executed was PvSoark but was executed in a Scala notebook.
B. There is no column in the table named heartrateheartrateheartrate
C. There is a type error because a column object cannot be multiplied.
D. There is a type error because a DataFrame object cannot be multiplied.
E. There is a syntax error because the heartrate column is not correctly identified as a column.

Answer: E

Explanation:
The error being raised is an AnalysisException, which is a type of exception that occurs when Spark SQL cannot analyze or execute a query due to some logical or semantic error1. In this case, the error message indicates that the query cannot resolve the column name 'heartrateheartrateheartrate' given the input columns 'heartrate' and 'age'. This means that there is no column in the table named 'heartrateheartrateheartrate', and the query is invalid. A possible cause of this error is a typo or a copy-paste mistake in the query. To fix this error, the query should use a valid column name that exists in the table, such as 'heartrate'.
References: AnalysisException

NEW QUESTION 2
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 3
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 4
What statement is true regarding the retention of job run history?

A. It is retained until you export or delete job run logs
B. It is retained for 30 days, during which time you can deliver job run logs to DBFS or S3
C. t is retained for 60 days, during which you can export notebook run results to HTML
D. It is retained for 60 days, after which logs are archived
E. It is retained for 90 days or until the run-id is re-used through custom run configuration

Answer: C

NEW QUESTION 5
A junior member of the data engineering team is exploring the language interoperability of Databricks notebooks. The intended outcome of the below code is to register a view of all sales that occurred in countries on the continent of Africa that appear in the geo_lookup table.
Before executing the code, running SHOW TABLES on the current database indicates the database contains only two tables: geo_lookup and sales.

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

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

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

A. Both commands will succee
B. Executing show tables will show that countries at and sales at have been registered as views.
C. Cmd 1 will succee
D. Cmd 2 will search all accessible databases for a table or view named countries af: if this entity exists, Cmd 2 will succeed.
E. Cmd 1 will succeed and Cmd 2 will fail, countries at will be a Python variable representing a PySpark DataFrame.
F. Both commands will fai
G. No new variables, tables, or views will be created.
H. Cmd 1 will succeed and Cmd 2 will fail, countries at will be a Python variable containing a list of strings.

Answer: E

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

NEW QUESTION 6
A Delta Lake table representing metadata about content posts from users has the following schema:
user_id LONG, post_text STRING, post_id STRING, longitude FLOAT, latitude FLOAT, post_time TIMESTAMP, date DATE
This table is partitioned by the date column. A query is run with the following filter: longitude < 20 & longitude > -20
Which statement describes how data will be filtered?

A. Statistics in the Delta Log will be used to identify partitions that might Include files in the filtered range.
B. No file skipping will occur because the optimizer does not know the relationship between the partition column and the longitude.
C. The Delta Engine will use row-level statistics in the transaction log to identify the flies that meet the filter criteria.
D. Statistics in the Delta Log will be used to identify data files that might include records in the filtered range.
E. The Delta Engine will scan the parquet file footers to identify each row that meets the filter criteria.

Answer: D

Explanation:
This is the correct answer because it describes how data will be filtered when a query is run with the following filter: longitude < 20 & longitude > -20. The query is run on a Delta Lake table that has the following schema: user_id LONG, post_text STRING, post_id STRING, longitude FLOAT, latitude FLOAT, post_time TIMESTAMP, date DATE. This table is partitioned by the date column. When a query is run on a partitioned Delta Lake table, Delta Lake uses statistics in the Delta Log to identify data files that might include records in the filtered range. The statistics include information such as min and max values for each column in each data file. By using these statistics, Delta Lake can skip reading data files that do not match the filter condition, which can improve query performance and reduce I/O costs. Verified References: [Databricks Certified Data Engineer Professional], under “Delta Lake” section; Databricks Documentation, under “Data skipping” section.

NEW QUESTION 7
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 8
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 9
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

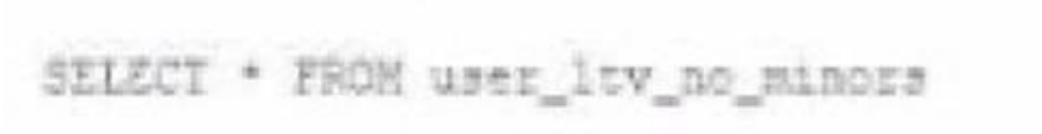
NEW QUESTION 10
A table named user_ltv is being used to create a view that will be used by data analysis on various teams. Users in the workspace are configured into groups, which are used for setting up data access using ACLs.
The user_ltv table has the following schema:

```
email STRING, age INT, ltv INT

The following view definition is executed:

CREATE VIEW user_ltv_no_minors AS
SELECT email, age, ltv
FROM user_ltv
WHERE
  CASE
    WHEN is_member("auditing") THEN TRUE
    ELSE age >= 18
  END
```

An analyze who is not a member of the auditing group executing the following query:



Which result will be returned by this query?

A. All columns will be displayed normally for those records that have an age greater than 18; records not meeting this condition will be omitted.
B. All columns will be displayed normally for those records that have an age greater than 17; records not meeting this condition will be omitted.
C. All age values less than 18 will be returned as null values all other columns will be returned with the values in user_ltv.
D. All records from all columns will be displayed with the values in user_ltv.

Answer: A

Explanation:
Given the CASE statement in the view definition, the result set for a user not in the auditing group would be constrained by the ELSE condition, which filters out records based on age. Therefore, the view will return all columns normally for records with an age greater than 18, as users who are not in the auditing group will not satisfy the is_member('auditing') condition. Records not meeting the age > 18 condition will not be displayed.

NEW QUESTION 10
Spill occurs as a result of executing various wide transformations. However, diagnosing spill requires one to proactively look for key indicators.
Where in the Spark UI are two of the primary indicators that a partition is spilling to disk?

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

Answer: B

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

NEW QUESTION 11
A Spark job is taking longer than expected. Using the Spark UI, a data engineer notes that the Min, Median, and Max Durations for tasks in a particular stage show the minimum and median time to complete a task as roughly the same, but the max duration for a task to be roughly 100 times as long as the minimum.
Which situation is causing increased duration of the overall job?

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

Answer: D

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

NEW QUESTION 16
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 20
Assuming that the Databricks CLI has been installed and configured correctly, which Databricks CLI command can be used to upload a custom Python Wheel to object storage mounted with the DBFS for use with a production job?

A. configure
B. fs
C. jobs
D. libraries
E. workspace

Answer: B

Explanation:
The libraries command group allows you to install, uninstall, and list libraries on Databricks clusters. You can use the libraries install command to install a custom Python Wheel on a cluster by specifying the --whl option and the path to the wheel file. For example, you can use the following command to install a custom Python Wheel named mylib-0.1-py3-none-any.whl on a cluster with the id 1234-567890-abcde123:
databricks libraries install --cluster-id1234-567890-abcde123--whldbfs:/mnt/mylib/mylib-0.1-py3-none-any.whl
This will upload the custom Python Wheel to the cluster and make it available for use with a production job. You can also use the libraries uninstall command to uninstall a library from a cluster, and the libraries list command to list the libraries installed on a cluster. References:
? Libraries CLI (legacy): https://docs.databricks.com/en/archive/dev-tools/cli/libraries-cli.html
? Library operations: https://docs.databricks.com/en/dev- tools/cli/commands.html#library-operations
? Install or update the Databricks CLI: https://docs.databricks.com/en/dev- tools/cli/install.html

NEW QUESTION 23
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 26
The following code has been migrated to a Databricks notebook from a legacy workload:

```
%sh
git clone https://github.com/foo/data_loader;
python ./data_loader/run.py;
mv ./output /dbfs/mnt/new_data
```

The code executes successfully and provides the logically correct results, however, it takes over 20 minutes to extract and load around 1 GB of data.
Which statement is a possible explanation for this behavior?

A. %sh triggers a cluster restart to collect and install Gi
B. Most of the latency is related to cluster startup time.
C. Instead of cloning, the code should use %sh pip install so that the Python code can get executed in parallel across all nodes in a cluster.
D. %sh does not distribute file moving operations; the final line of code should be updated to use %fs instead.
E. Python will always execute slower than Scala on Databrick
F. The run.py script should be refactored to Scala.
G. %sh executes shell code on the driver nod
H. The code does not take advantage of the worker nodes or Databricks optimized Spark.

Answer: E

Explanation:
https://www.databricks.com/blog/2020/08/31/introducing-the-databricks-web- terminal.html
The code is using %sh to execute shell code on the driver node. This means that the code is not taking advantage of the worker nodes or Databricks optimized Spark. This is why the code is taking longer to execute. A better approach would be to use Databricks libraries and APIs to read and write data from Git and DBFS, and to leverage the parallelism and performance of Spark. For example, you can use the Databricks Connect feature to run your Python code on a remote Databricks cluster, or you can use the Spark Git Connector to read data from Git repositories as Spark DataFrames.

NEW QUESTION 29
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 31
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 34
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 36
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 39
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 44
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 48
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 51
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 55

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