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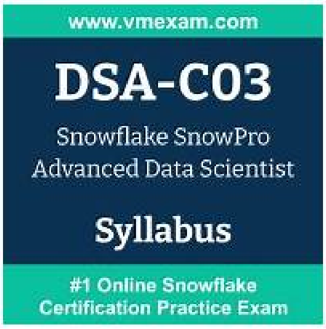

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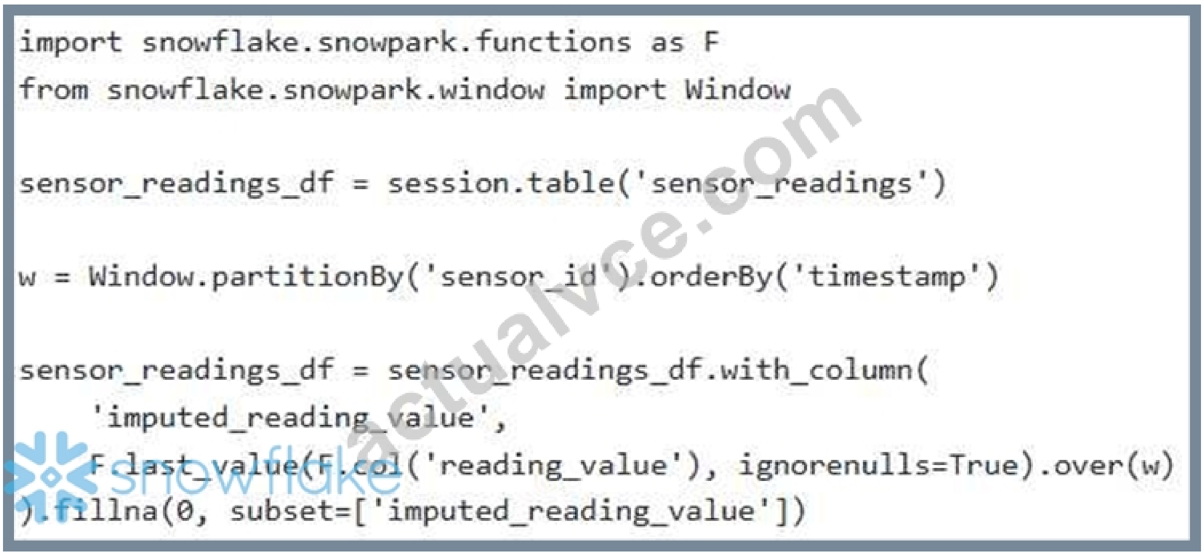
Snowflake SnowPro Advanced: Data Scientist Certification Exam Sample Questions (Q258-Q263):

NEW QUESTION # 258
You are working with a Snowflake table named 'sensor readingS containing IoT sensor data'. The table has columns 'sensor id' , 'timestamp' , and 'reading value'. You observe that the 'reading value' column contains a significant number of missing values (represented as NULL). To prepare this data for a time series analysis, you need to impute these missing values. You have decided

to use the 'LOCF' (Last Observation Carried Forward) method, filling the NULL values with the most recent non-NULL value for each sensor. In addition to LOCF, you also want to handle the scenario where a sensor has NULL values at the beginning of its data stream (i.e., no previous observation to carry forward). For these initial NULLs, you want to use a fixed default value of 0. Which of the following approaches, using either Snowpark for Python or a combination of Snowpark and SQL, correctly implements this LOCF imputation with a default value?

- A.



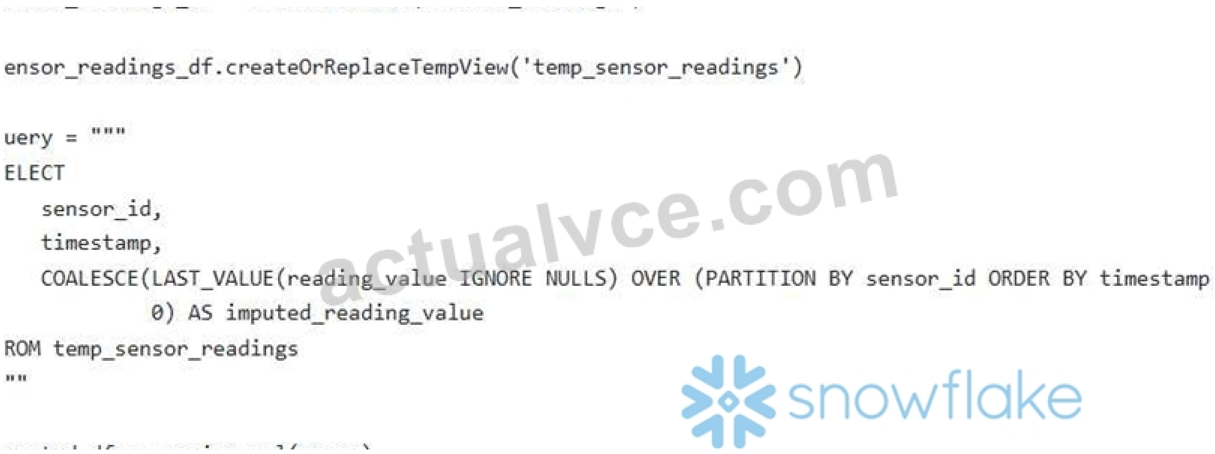
```
import snowflake.snowpark.functions as F
from snowflake.snowpark.window import Window

sensor_readings_df = session.table('sensor_readings')

w = Window.partitionBy('sensor_id').orderBy('timestamp')

sensor_readings_df = sensor_readings_df.with_column(
    'imputed_reading_value',
    F.last_value(F.col('reading_value'), ignorenulls=True).over(w)
).fillna(0, subset=['imputed_reading_value'])
```

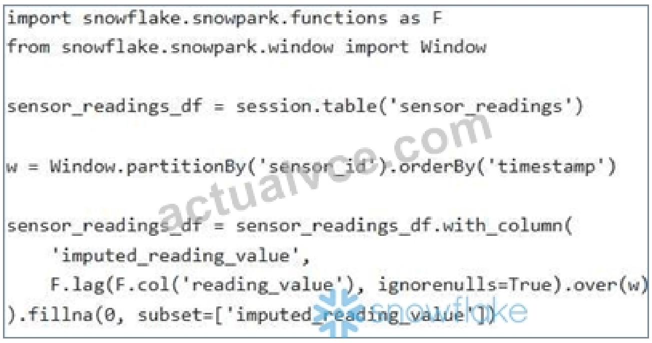
- B. All of the above
- C.



```
ensor_readings_df.createOrReplaceTempView('temp_sensor_readings')

uery = """
ELECT
    sensor_id,
    timestamp,
    COALESCE(LAST_VALUE(reading_value IGNORE NULLS) OVER (PARTITION BY sensor_id ORDER BY timestamp
              0) AS imputed_reading_value
ROM temp_sensor_readings
""
```

- D.



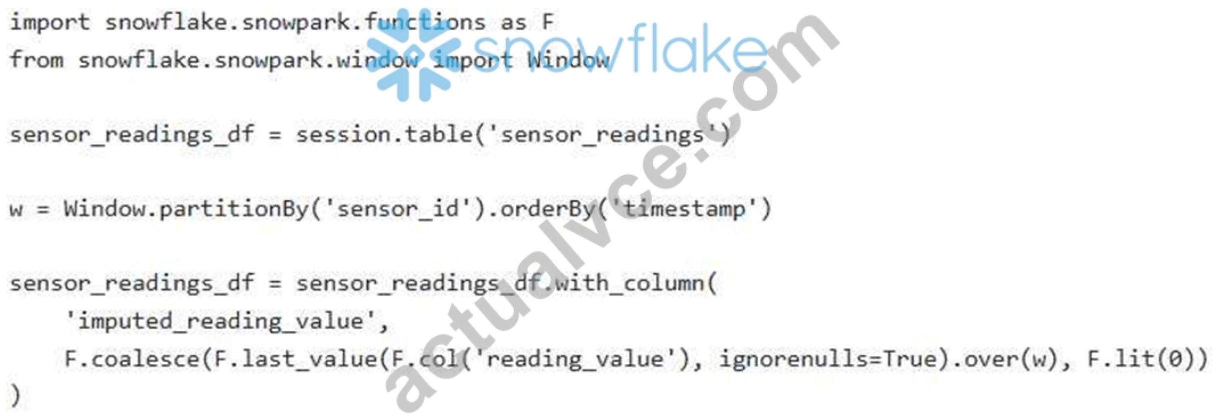
```
import snowflake.snowpark.functions as F
from snowflake.snowpark.window import Window

sensor_readings_df = session.table('sensor_readings')

w = Window.partitionBy('sensor_id').orderBy('timestamp')

sensor_readings_df = sensor_readings_df.with_column(
    'imputed_reading_value',
    F.lag(F.col('reading_value'), ignorenulls=True).over(w)
).fillna(0, subset=['imputed_reading_value'])
```

- E.



```
import snowflake.snowpark.functions as F
from snowflake.snowpark.window import Window

sensor_readings_df = session.table('sensor_readings')

w = Window.partitionBy('sensor_id').orderBy('timestamp')

sensor_readings_df = sensor_readings_df.with_column(
    'imputed_reading_value',
    F.coalesce(F.last_value(F.col('reading_value'), ignorenulls=True).over(w), F.lit(0))
)
```

Answer: A,C,E

Explanation:
Options A, B, and C all correctly implement LOCF imputation with a default value of 0 for initial NULLs. Option A first uses ignorenulls=TrueV within a window to perform LOCF and then uses 'fillnas to replace any remaining NULLs (the initial NULLs) with 0. Option B is the most concise, using 'coalesce' to combine the LOCF result with the default value of 0. 'coalesce' returns the first non-NULL value in a list of expressions. Option C implements the same logic using SQL within Snowpark. The function performs LOCF, and 'COALESCE provides the default value. Option D uses 'F.lag' , which retrieves the previous value, not the last value carried forward. Therefore, it will not perform LOCF correctly.

NEW QUESTION # 259
A Data Scientist is designing a machine learning model to predict customer churn for a telecommunications company. They have access to various data sources, including call logs, billing information, customer demographics, and support tickets, all residing in separate Snowflake tables. The data scientist aims to minimize bias and ensure data quality during the data collection phase. Which of the following strategies would be MOST effective for collecting and preparing the data for model training?

- A. Use Snowflake's Data Marketplace to supplement the existing data with external datasets, regardless of their relevance to the churn prediction problem.
- B. Create a single, wide table by performing a series of INNER JOINs on all tables using customer ID as the primary key. Handle missing values by imputing with the mean for numerical columns and 'Unknown' for categorical columns.
- C. Perform exploratory data analysis (EDA) on each table to identify relevant features and potential biases. Use feature selection techniques to reduce dimensionality. Implement robust data validation checks to ensure data quality and consistency before joining the tables. Handle missing values strategically based on the specific column and its potential impact on the model.
- D. Directly use all available columns from each table without any preprocessing to avoid introducing bias.
- E. Randomly select a subset of data from each table to reduce computational complexity and speed up model training.

Answer: C

Explanation:
Option C is the MOST effective because it emphasizes a thorough and rigorous approach to data collection and preparation. It highlights the importance of EDA for identifying relevant features and biases, feature selection for dimensionality reduction, data validation for ensuring data quality, and strategic handling of missing values. This approach helps to minimize bias, improve model performance, and ensure the reliability of the churn prediction model. The other options are flawed because they either ignore potential biases and data quality issues (A), use a simplistic approach to handling missing values (B), compromise data representativeness (D), or introduce potentially irrelevant data (E).

NEW QUESTION # 260
You're developing a fraud detection system in Snowflake. You're using Snowflake Cortex to generate embeddings from transaction descriptions, aiming to cluster similar fraudulent transactions. Which of the following approaches are MOST effective for optimizing the performance and cost of generating embeddings for a large dataset of millions of transaction descriptions using Snowflake Cortex, especially considering the potential cost implications of generating embeddings at scale? Select two options.

- A. Use a Snowflake Task to incrementally generate embeddings only for new transactions that have been added since the last embedding generation run.

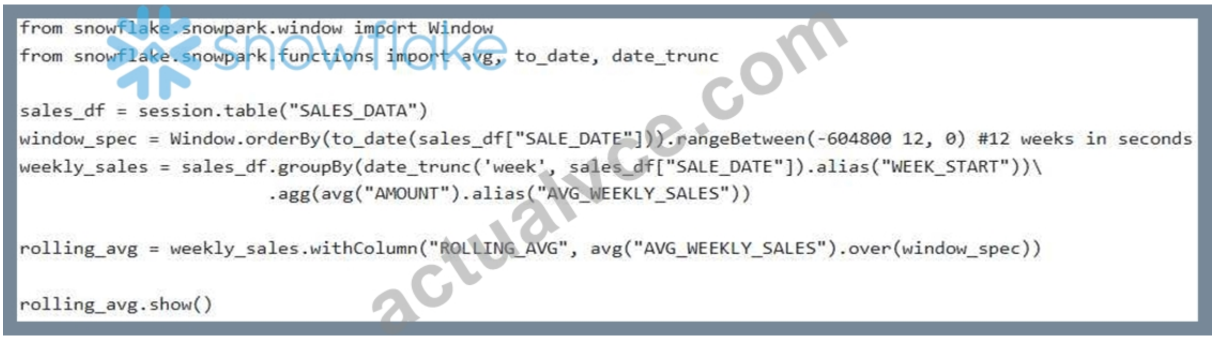
- B. Generate embeddings using snowflake-cortex-embed-text function, using the OPENAI embedding model
- C. Create a materialized view containing pre-computed embeddings for all transaction descriptions.
- D. Generate embeddings on the entire dataset every day to capture all potential fraudulent transactions and ensure the model is always up-to-date.
- E. Implement caching mechanism based on a hash of transaction description if transaction description does not change then no need to recompute the emebeddings again.

Answer: A,E

Explanation:
Option B is a better approach compared to option A to generate embeddings because its incrementally generate embeddings for new transactions. Option E is also an important approach where if transaction description remains same for the embeddings will not be re-computed. Materialized view is not suited for API integrations like those using Snowflake Cortex. Option D is technically correct, but doesn't address the optimization and cost concerns. Option A Regenerating embeddings for the entire dataset daily is computationally expensive and can quickly lead to high costs, especially with Snowflake Cortex. The best approach is to use caching and compute only for a new transaction description. So correct answer is B and E.

NEW QUESTION # 261
You are analyzing sales data in Snowflake using Snowpark to identify seasonality. You have a table named 'SALES DATA with columns 'SALE DATE (TIMESTAMP NTZ) and 'AMOUNT (NUMBER). You want to calculate the rolling average sales for each week over a period of 12 weeks using a Snowpark DataFrame. Which of the following Snowpark code snippets correctly implements this calculation?

- A.



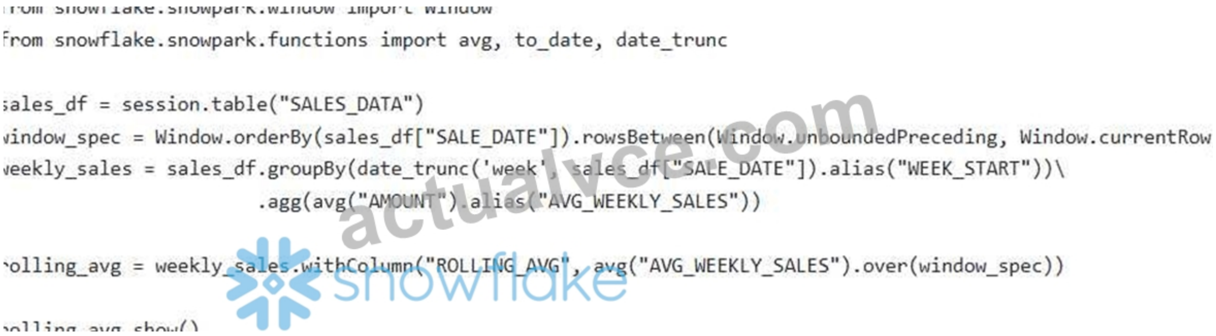
```
from snowflake.snowpark.window import Window
from snowflake.snowpark.functions import avg, to_date, date_trunc

sales_df = session.table("SALES_DATA")
window_spec = Window.orderBy(to_date(sales_df["SALE_DATE"])).rangeBetween(-604800 12, 0) #12 weeks in seconds
weekly_sales = sales_df.groupBy(date_trunc('week', sales_df["SALE_DATE"]).alias("WEEK_START"))\
                      .agg(avg("AMOUNT").alias("AVG_WEEKLY_SALES"))

rolling_avg = weekly_sales.withColumn("ROLLING_AVG", avg("AVG_WEEKLY_SALES").over(window_spec))

rolling_avg.show()
```

- B.

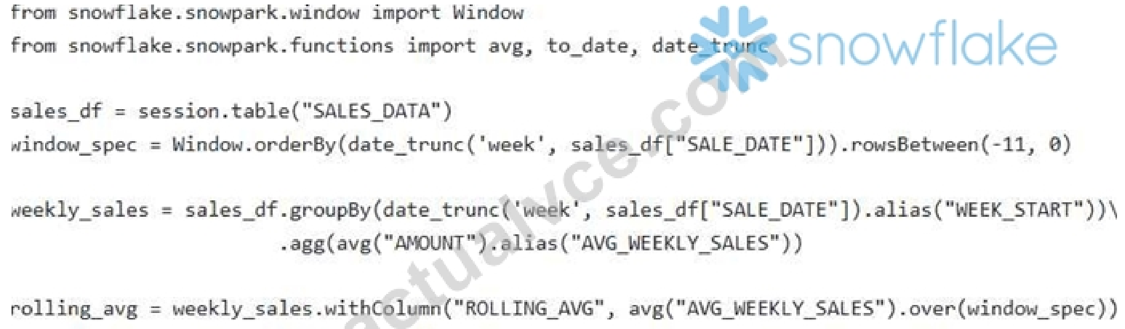


```
from snowflake.snowpark.window import Window
from snowflake.snowpark.functions import avg, to_date, date_trunc

sales_df = session.table("SALES_DATA")
window_spec = Window.orderBy(sales_df["SALE_DATE"]).rowsBetween(Window.unboundedPreceding, Window.currentRow
weekly_sales = sales_df.groupBy(date_trunc('week', sales_df["SALE_DATE"]).alias("WEEK_START"))\
                      .agg(avg("AMOUNT").alias("AVG_WEEKLY_SALES"))

rolling_avg = weekly_sales.withColumn("ROLLING_AVG", avg("AVG_WEEKLY_SALES").over(window_spec))

rolling_avg.show()
```



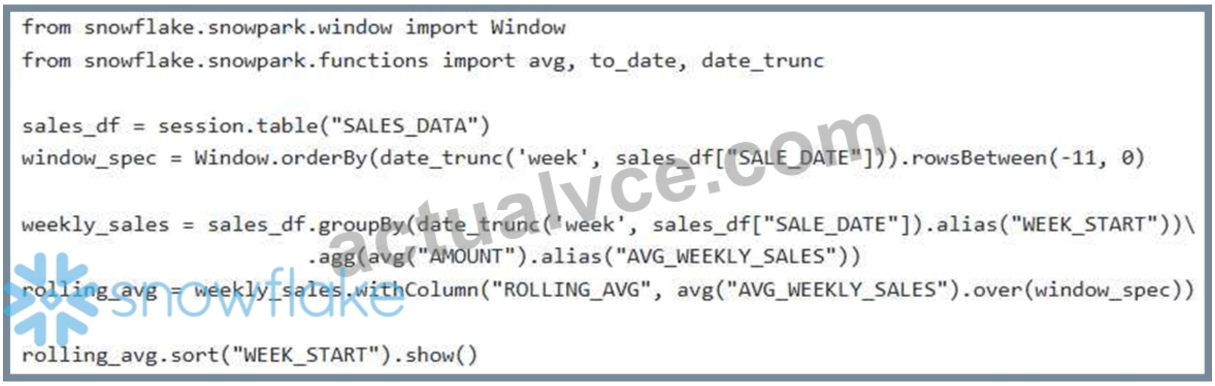
```
from snowflake.snowpark.window import Window
from snowflake.snowpark.functions import avg, to_date, date_trunc

sales_df = session.table("SALES_DATA")
window_spec = Window.orderBy(date_trunc('week', sales_df["SALE_DATE"])).rowsBetween(-11, 0)

weekly_sales = sales_df.groupBy(date_trunc('week', sales_df["SALE_DATE"]).alias("WEEK_START"))\
                      .agg(avg("AMOUNT").alias("AVG_WEEKLY_SALES"))

rolling_avg = weekly_sales.withColumn("ROLLING_AVG", avg("AVG_WEEKLY_SALES").over(window_spec))
```

- C. rolling_avg.show()
- D.



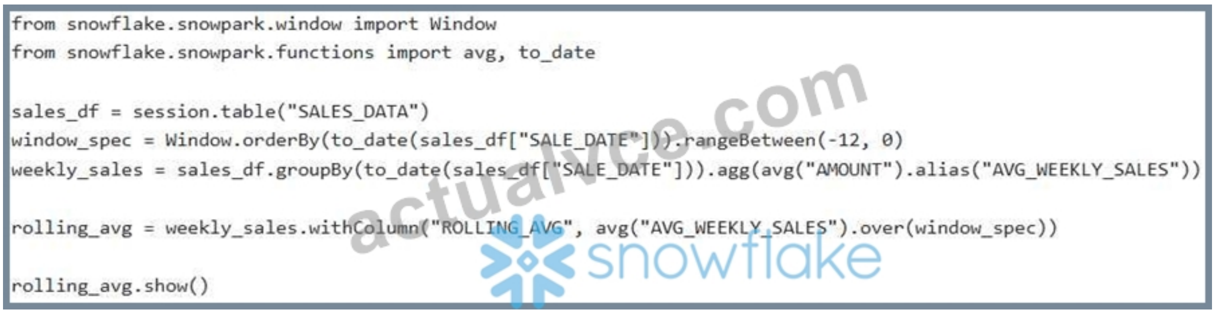
```
from snowflake.snowpark.window import Window
from snowflake.snowpark.functions import avg, to_date, date_trunc

sales_df = session.table("SALES_DATA")
window_spec = Window.orderBy(date_trunc('week', sales_df["SALE_DATE"])).rowsBetween(-11, 0)

weekly_sales = sales_df.groupBy(date_trunc('week', sales_df["SALE_DATE"]).alias("WEEK_START"))\
                        .agg(avg("AMOUNT").alias("AVG_WEEKLY_SALES"))
rolling_avg = weekly_sales.withColumn("ROLLING_AVG", avg("AVG_WEEKLY_SALES").over(window_spec))

rolling_avg.sort("WEEK_START").show()
```

- E.



```
from snowflake.snowpark.window import Window
from snowflake.snowpark.functions import avg, to_date

sales_df = session.table("SALES_DATA")
window_spec = Window.orderBy(to_date(sales_df["SALE_DATE"])).rangeBetween(-12, 0)
weekly_sales = sales_df.groupBy(to_date(sales_df["SALE_DATE"])).agg(avg("AMOUNT").alias("AVG_WEEKLY_SALES"))

rolling_avg = weekly_sales.withColumn("ROLLING_AVG", avg("AVG_WEEKLY_SALES").over(window_spec))

rolling_avg.show()
```

Answer: C,D

Explanation:
Options B and E are correct. They both calculate the 12 week rolling average grouped by week correctly and will display the average. Option B is the more correct of the two, because it does not require the user to sort the result to get the appropriate rolling average. Option A is incorrect because rangeBetween with seconds is not appropriate for weekly aggregation and calculation. Option C is incorrect because to_date would truncate the time component, grouping everything with the same date. Option D calculates a cumulative average since the beginning of the dataset

NEW QUESTION # 262
You are building an image classification model within Snowflake to categorize satellite imagery based on land use types (residential, commercial, industrial, agricultural). The images are stored as binary data in a Snowflake table 'SATELLITE IMAGES. You plan to use a pre-trained convolutional neural network (CNN) from a library like TensorFlow via Snowpark Python UDFs. The model requires images to be resized and normalized before prediction. You have a Python UDF named that takes the image data and model as input and returns the predicted class. What steps are crucial to ensure optimal performance and scalability of the image classification process within Snowflake, considering the volume and velocity of incoming satellite imagery?

- A. Implement image resizing and normalization directly within the 'classify_image' Python UDF using libraries like OpenCV. Ensure the UDF is vectorized to process images in batches and leverage Snowpark's optimized data transfer capabilities.
- B. Utilize Snowflake's external functions to call an image processing service hosted on AWS Lambda or Azure Functions for image resizing and normalization, then pass the processed images to the 'classify_image' UDF.
- C. Use a combination of Snowpark Python UDFs for preprocessing tasks like resizing and normalization, and leverage Snowflake's GPU-accelerated warehouses (if available) to expedite the inference step within the 'classify_image' UDF. Ensure the model weights are efficiently cached.
- D. Load the entire 'SATELLITE IMAGES table into the UDF for processing, allowing the UDF to handle all image resizing, normalization, and classification tasks sequentially.
- E. Pre-process the images outside of Snowflake using a separate data pipeline and store the resized and normalized images in a new Snowflake table before running the 'classify_image' UDE

Answer: A,C

Explanation:
Options B and E represent the most effective strategies. Option B emphasizes in-database processing with a vectorized 'DF and optimized data transfer. Option E highlights the use of 'DFs for preprocessing and leverages GPU acceleration for the computationally intensive inference step, along with efficient model weight caching. Option A introduces unnecessary complexity with external functions, which can add latency. Option C requires additional data storage and management outside of the core

classification process. Option D is inefficient because loading the entire table into the 'DF is not scalable and will likely cause performance issues. Vectorizing the 'DF allows for batch processing, which significantly improves throughput. GPU acceleration further enhances the speed of model inference, and caching the model prevents repeated loading, saving computational resources.

NEW QUESTION # 263

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