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## Snowflake SnowPro Advanced: Data Scientist Certification Exam Sample Questions (Q225-Q230):

### NEW QUESTION # 225

You are tasked with building a machine learning model in Python using data stored in Snowflake. You need to efficiently load a large table (100GB+) into a Pandas DataFrame for model training, minimizing memory footprint and network transfer time. You are using the Snowflake Connector for Python. Which of the following approaches would be MOST efficient for loading the data, considering potential memory limitations on your client machine and the need for data transformations during the load process?

- A. Use 'snowsql' to unload the table to a local CSV file, then load the CSV file into a Pandas DataFrame.
- B. Create a Snowflake view with the necessary transformations, and then load the view into a Pandas DataFrame using 'pd.read\_sql()'.

- C. Use the 'COPY INTO' command to unload the table to an Amazon S3 bucket and then use boto3 in your python script to fetch data from s3 and load into pandas dataframe.
- D. Load the entire table into a Pandas DataFrame using with a simple 'SELECT FROM my\_table' query and then perform data transformations in Pandas.
- E. Utilize the 'execute\_stream' method of the Snowflake cursor to fetch data in chunks, apply transformations in each chunk, and append to a larger DataFrame or process iteratively without creating a large in-memory DataFrame.

**Answer: E**

Explanation:

Option C is the most efficient. 'execute\_stream' allows you to fetch data in chunks, preventing out-of-memory errors with large tables. You can perform transformations on each chunk, reducing the memory footprint. Loading the entire table at once (A) is inefficient for large datasets. Using ssnowsqr (B) or 'COPY INTO' (E) adds an extra step of unloading and reloading, increasing the time taken. Creating a Snowflake view (D) is a good approach for pre-processing but might not fully address memory issues during the final load into Pandas, especially if the view still contains a large amount of data.

### NEW QUESTION # 226

A data scientist is analyzing sales data in Snowflake to identify seasonal trends. The 'SALES TABLE' contains columns 'SALE DATE' (DATE) and 'SALE\_AMOUNT' (NUMBER). They want to calculate the average daily sales amount for each month and year in the dataset. Which of the following SQL queries will correctly achieve this, while also handling potential NULL values in 'SALE\_AMOUNT'?

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

**Answer: C,D,E**

Explanation:

Options B, D and E correctly calculate the average daily sales for each month and year. Options B uses 'COALESCE' to replace NULL SALE\_AMOUNT values with 0 before calculating the average. Option D utilizes ' NVL', which is a synonym for COALESCE in Snowflake. Option E uses ZEROIFNULL' which is another way to handle NULL values. Option A does not handle NULL values, potentially skewing the average. Option C incorrectly uses 'TO\_CHAR which results in string format for date, but that is fine, it also tries to use 'IFF which is acceptable to handle Null, but SIFF function may lead to string conversion issues when calculating the average.

### NEW QUESTION # 227

You are building a real-time fraud detection system using Snowpark ML and Dynamic Tables. The raw transaction data arrives continuously in a Snowflake stream. You need to create a data science pipeline that continuously transforms the data, trains a model, and scores new transactions in near real-time. Which combination of Snowflake features provides the BEST solution for achieving low latency and high throughput for this fraud detection system? Select all that apply:

- A. Snowflake Tasks with a 'WHEN SYSTEM\$STREAM HAS clause to incrementally process new transactions from the stream and update feature tables.
- B. Snowpark ML User-Defined Functions (UDFs) to apply the fraud detection model to incoming transactions, executed using Snowflake's vectorized engine for optimal performance.
- C. Scheduled Snowflake tasks to retrain the model every hour based on the most recent transaction data.
- D. Snowpipe with Auto-Ingest to load the raw transaction data into a staging table before processing it with Dynamic Tables.
- E. Dynamic Tables to continuously transform the raw transaction data into features required by the model, with 'WAREHOUSE SIZE set to 'X-LARGE to ensure sufficient compute resources.

**Answer: A,B,E**

Explanation:

Options A, B, and C are the best choices for low-latency, high-throughput fraud detection. Option A: Using Snowflake Tasks with the 'WHEN SYSTEM\$STREAM HAS DATA()' clause ensures that tasks only run when there is new data in the stream, enabling incremental processing and reducing unnecessary computations. Option B: Dynamic Tables automatically update as the underlying

data changes, providing continuously transformed features. Increasing the 'WAREHOUSE SIZE' ensures enough compute resources are available. Option C: Snowpark ML UDFs allow you to score incoming transactions in near real-time, leveraging Snowflake's vectorized engine for fast performance. Option D introduces a delay of one hour for model retraining, which is not ideal for a real-time system. Furthermore, regularly scheduling retrain tasks and rerunning them when data is available from stream is not most efficient processing paradigm. While option E is relevant, the question focuses on the transformation, model scoring and data processing parts of a real time data science pipeline, for which A, B, and C are more directly connected.

#### NEW QUESTION # 228

You are using the NetworkX library in Snowpark Python to analyze social network data stored in a Snowflake table named 'USER CONNECTIONS', which has columns 'USER ID' and 'CONNECTED USER' representing connections between users. You want to find the users with the highest 'betweenness centrality' to identify influential nodes in the network. Which Snowpark Python code snippet would correctly calculate and display the top 5 users with the highest betweenness centrality?

- A. ☐
- B. ☐
- C. ☐
- D. ☐
- E. ☒

**Answer: E**

Explanation:

Option A is the most efficient and correct approach. It leverages for directly creating the graph from a Pandas DataFrame (converted from the Snowpark DataFrame), calculates betweenness centrality using NetworkX, creates a Pandas DataFrame for results, and then sorts and displays the top 5 users. Options B iterates through the rows, which is less efficient, and attempts to create a Snowpark DataFrame from the betweenness dictionary, which isn't the most efficient output mechanism in this context. Option C is almost correct but uses 'nlargest' which is also valid. Option D uses which is slower and less efficient than Option E is very close but includes the parameter which is unnecessary for this specific operation since it's the initial creation of the betweenness df and the index isn't crucial to be reset. So while it functions it is redundant.

#### NEW QUESTION # 229

You're building a regression model using Snowpark Python to predict house prices. After initial training, you observe that the model consistently overestimates the prices of high-value houses and underestimates the prices of low-value houses. Given the options below, which optimization metric, along with code snippet to calculate it using Snowpark, would be most effective in addressing this specific issue?

- A. Mean Absolute Error MAE - as it is sensitive to outliers and will penalize large errors more heavily.  
☐
- B. Mean Squared Error (MSE) - as it is less sensitive to outliers than RMSE.  
☐
- C. Adjusted R-squared - as it penalizes the addition of irrelevant features, improving the model's generalization ability.  
☐
- D. Root Mean Squared Error (RMSE) - as it gives more weight to larger errors, making it suitable for addressing the underestimation/overestimation problem.  
☒
- E. R-squared - as it measures the proportion of variance explained, directly addressing how well the model fits the data across all price ranges.  
☐

**Answer: D**

Explanation:

RMSE is the most effective metric in this scenario. Since the model consistently underestimates low values and overestimates high values, larger errors (the difference between predicted and actual prices) are occurring in these ranges. RMSE penalizes larger errors more heavily than MAE, making it more sensitive to these discrepancies and driving the model to improve its predictions for both high and low-value houses. The code snippet demonstrates how to calculate RMSE using Snowpark Python.

