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## DEA-C02 Test Score Report, Valid DEA-C02 Test Pass4sure

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## Snowflake SnowPro Advanced: Data Engineer (DEA-C02) Sample Questions (Q83-Q88):

### NEW QUESTION # 83

A data engineer is tasked with creating a Snowpark Python UDF to perform sentiment analysis on customer reviews. The UDF, named 'analyze\_sentiment', takes a string as input and returns a string indicating the sentiment ('Positive', 'Negative', or 'Neutral'). The engineer wants to leverage a pre-trained machine learning model stored in a Snowflake stage called 'models'. Which of the following code snippets correctly registers and uses this UDF?

```

J from snowflake.snowpark import Session import snowflake.snowpark.functions as F def analyze_sentiment(review: str) -> str: # Load model from
stage 'models' here (implementation omitted) # Assume 'model' is loaded correctly return model.predict([review])[0] session =
Session.builder.configs(connection_parameters).create() session.udf.register(analyze_sentiment, name='analyze_sentiment', packages=['snowflake-ml-
python']) df = session.createDataFrame(['Great product!', 'Terrible service'], schema=['review']) df.select(F.col('review'),
F.call_udf('analyze_sentiment', F.col('review')).alias('sentiment')).show()

O from snowflake.snowpark import Session import snowflake.snowpark.functions as F def analyze_sentiment(session: Session, review: str) -> str: #
Load model from stage 'models' here (implementation omitted) # Assume 'model' is loaded correctly return model.predict([review])[0] session =
Session.builder.configs(connection_parameters).create() session.udf.register(analyze_sentiment, return_type='StringType', input_types=['Session',
'StringType'], name='analyze_sentiment', packages=['snowflake-ml-python']) df = session.createDataFrame(['Great product!', 'Terrible service'],
schema=['review']) df.select(F.col('review'), F.call_udf('analyze_sentiment', session, F.col('review')).alias('sentiment')).show()

O from snowflake.snowpark import Session import snowflake.snowpark.functions as F def analyze_sentiment(review: str) -> str: # Load model from
stage 'models' here (implementation omitted) # Assume 'model' is loaded correctly return model.predict([review])[0] session =
Session.builder.configs(connection_parameters).create() session.add_packages('snowflake-ml-python') session.udf.register(analyze_sentiment,
return_type='StringType', input_types=['StringType'], name='analyze_sentiment') df = session.createDataFrame(['Great product!', 'Terrible service'],
schema=['review']) df.select(F.col('review'), F.call_udf('analyze_sentiment', F.col('review')).alias('sentiment')).show()

) from snowflake.snowpark import Session import snowflake.snowpark.functions as F @F.udf(return_type='StringType', input_types=['StringType'],
packages=['snowflake-ml-python']) def analyze_sentiment(review: str) -> str: # Load model from stage 'models' here (implementation omitted) # Assume
'model' is loaded correctly return model.predict([review])[0] session = Session.builder.configs(connection_parameters).create() df =
session.createDataFrame(['Great product!', 'Terrible service'], schema=['review']) df.select(F.col('review'),
analyze_sentiment(F.col('review')).alias('sentiment')).show()

) from snowflake.snowpark import Session import snowflake.snowpark.functions as F def analyze_sentiment(review: str) -> str: # Load model from
stage 'models' here (implementation omitted) # Assume 'model' is loaded correctly return model.predict([review])[0] session =
Session.builder.configs(connection_parameters).create() session.udf.register(func=analyze_sentiment, name='analyze_sentiment',
return_type=StringType(), input_types=[StringType()], packages=['snowflake-ml-python']) df = session.createDataFrame(['Great product!', 'Terrible
service'], schema=['review']) df.select(F.col('review'), F.call_udf('analyze_sentiment', F.col('review')).alias('sentiment')).show()

```

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

**Answer: E**

**Explanation:**

The most concise and recommended way to define a Snowpark UDF in Python is using the `@F.udf` decorator. This decorator automatically handles registration with Snowflake and simplifies the code. It also correctly specifies the 'return\_type', 'input\_types', and required packages'. Options A, B, C and E are either missing the decorator or have issues with specifying input types or session usage. The `session.add_packages` is not a proper way to define packages used by UDFs and 'StringType' is not imported from 'snowflake.snowpark.types', so the correct way is to set `return_type` and `input_types` within the decorator.

## NEW QUESTION # 84

A financial institution is using Snowflake to store transaction data for millions of customers. The data is stored in a table named 'TRANSACTIONS' with columns such as 'TRANSACTION ID', 'CUSTOMER ID', 'TRANSACTION DATE', 'TRANSACTION\_AMOUNT', and 'MERCHANT CATEGORY'. Analysts are running complex analytical queries that often involve filtering transactions by 'TRANSACTION\_DATE', 'MERCHANT\_CATEGORY', and 'TRANSACTION\_AMOUNT' ranges. These queries are experiencing performance bottlenecks. The data team wants to leverage query acceleration service to improve performance without significantly altering the existing query patterns. Which of the following actions or combination of actions would be MOST beneficial, considering the constraints and the nature of the queries? (Select TWO)

- A. Create separate virtual warehouses dedicated to reporting queries and ad-hoc queries respectively. Enable query acceleration only for the warehouse running reporting queries.
- B. Create materialized views pre-aggregating the transaction data by 'MERCHANT\_CATEGORY' and 'TRANSACTION\_DATE', and enable query acceleration on the virtual warehouse.
- C. Enable Automatic Clustering on the 'TRANSACTIONS' table, ordering the keys as 'TRANSACTION\_DATE', 'MERCHANT\_CATEGORY', 'CUSTOMER\_ID'. Then, enable query acceleration on the virtual warehouse.
- D. Enable Search Optimization Service for the 'TRANSACTIONS' table, specifically targeting the 'MERCHANT\_CATEGORY' column. Enable query acceleration on the virtual warehouse.
- E. Increase the size of the virtual warehouse used for running the queries and enable query acceleration on the warehouse without further modifications.

**Answer: C,D**

**Explanation:**

Enabling Automatic Clustering on 'TRANSACTIONS' with the specified key order ('TRANSACTION DATES, 'MERCHANT\_CATEGORY', 'CUSTOMER\_ID') aligns the data layout with common query patterns, allowing Snowflake to efficiently prune irrelevant data during query execution. This drastically improves query performance. Enabling Search Optimization on the 'MERCHANT\_CATEGORY' further enhances query performance by creating search access paths that enable faster lookups and filtering based on merchant category. Simply increasing the warehouse size (option A) may provide some improvement, but it's less targeted and potentially less cost-effective than optimizing the data organization. While dedicated warehouses (option C) can improve concurrency, they do not address the underlying performance bottleneck related to data access. Materialized views (option E) can be beneficial, but they require careful design and maintenance, and they might not be flexible enough for ad-hoc queries with varying filter conditions. Clustering and search optimization provide a more general and efficient solution in this scenario.

### NEW QUESTION # 85

You have a Snowpark DataFrame 'df\_products' with columns 'product id', 'category', and 'price'. You need to perform the following transformations in a single, optimized query using Snowpark Python: 1. Filter for products in the 'Electronics' or 'Clothing' categories. 2. Group the filtered data by category. 3. Calculate the average price for each category. 4. Rename the aggregated column to 'average\_price'. Which of the following code snippets demonstrates the most efficient way to achieve this?

```

☐ df_products.filter((df_products['category'] == 'Electronics') | (df_products['category'] == 'Clothing')).groupBy('category').agg(avg(df_products['price']).alias('average_price')).show()

☐ from snowflake.snowpark.functions import col, avg df_products.filter(col('category').isin(['Electronics', 'Clothing'])).groupBy(col('category')).agg(avg(col('price')).as_('average_price')).show()

☐ df_products.where(df_products.category.isin(['Electronics', 'Clothing'])).groupBy(df_products.category).agg(mean(df_products.price).name('average_price')).show()

☐ from snowflake.snowpark.functions import col, avg df_products.filter(col('category').isin(['Electronics', 'Clothing'])).groupBy('category').agg(avg('price').alias('average_price')).show()

☐ from snowflake.snowpark.functions import col, avg df_products.where(col('category').isin(['Electronics', 'Clothing'])).groupBy('category').agg(avg('price').alias('average_price')).to_pandas()

```

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

**Answer: A**

Explanation:

Option B is the most efficient and correct. It uses 'col()' from 'snowflake.snowpark.functions' to properly reference the 'category' and 'price' columns, uses 'isin()' for a more concise and efficient filtering of multiple category values, groups by the category using 'groupBy()' and calculates the average price with 'avg(col('price')).as\_('average\_price')'. Option A, C, and D are syntactically incorrect or less efficient ways to accomplish the same task within Snowpark. Option E is incorrect because it utilizes 'to\_pandas()' which returns the result as a Pandas DataFrame rather than a Snowpark DataFrame, failing to adhere to the Snowpark environment. While Option D is very similar, it lacks the proper syntax for specifying column references with 'col('category')' in the groupBy and 'col('price')' in the avg function.

### NEW QUESTION # 86

You have a 'SALES' table and a 'PRODUCTS' table. The 'SALES' table contains daily sales transactions, including 'SALE DATE', 'PRODUCT ID', and 'QUANTITY'. The 'PRODUCTS' table contains 'PRODUCT' and 'CATEGORY'. You need to create a materialized view to track the total quantity sold per category daily, optimized for fast query performance. You anticipate frequent updates to the 'SALES' table but infrequent changes to the 'PRODUCTS' table. Which of the following strategies would provide the MOST efficient materialized view implementation, considering both data freshness and query performance?

- A. Create a standard materialized view that joins 'SALES' and 'PRODUCTS', grouping by 'SALE\_DATE' and 'CATEGORY', and defining a clustering key on 'CATEGORY'.
- B. Create a standard materialized view that joins 'SALES' and 'PRODUCTS', grouping by 'SALE\_DATE' and 'CATEGORY', and defining a clustering key on 'SALE\_DATE' and 'CATEGORY'.
- C. Create a standard materialized view that joins 'SALES' and 'PRODUCTS', grouping by 'SALE\_DATE' and

'CATEGORY' without any specific clustering key.

- **D. Create a standard materialized view that joins 'SALES' and 'PRODUCTS' , grouping by 'SALE\_DATE and 'CATEGORY', and defining a clustering key on 'SALE DATE.**
- E. Create two materialized views: one for daily sales by product and another joining the first with 'PRODUCTS' to aggregate by category. Cluster the first view by 'SALE DATE' and the second by 'CATEGORY'.

**Answer: D**

Explanation:

Option B is most efficient. Clustering the materialized view on 'SALE\_DATE will significantly improve query performance when filtering or grouping by date, which is a common operation in time-series data. Although frequent updates will affect the maintenance costs of the materialized view, querying on date will be very efficient. Option A is less efficient due to the lack of clustering. Option C may not be the best choice if filtering/grouping primarily occurs on date. Option D is also good, but Option B is better if most of the query filter is on SALE DATE. Option E introduces complexity and two refreshes may create a delay in data available.

#### NEW QUESTION # 87

You have a large dataset of JSON documents stored in AWS S3, each document representing a customer order. You want to ingest these documents into Snowflake using Snowpipe and transform the nested 'address' field into separate columns in your target table. Considering data volume, complexity, and cost efficiency, which approach is MOST suitable?

- A. Create an external table on the S3 bucket and then use CREATE TABLE AS SELECT (CTAS) to transform the data.
- B. Use Snowpipe with a user-defined function (UDF) written in Python to parse the JSON and flatten the 'address' field.
- **C. Use Snowpipe to ingest the raw JSON data into a VARIANT column, then create a view that flattens the 'address' field.**
- D. Use a COPY INTO statement with a transform clause to flatten the 'address' field during ingestion.
- E. Pre-process the JSON documents using an external compute service (e.g., AWS Lambda) to flatten the 'address' field before ingesting into Snowflake via Snowpipe.

**Answer: C**

Explanation:

Using Snowpipe to ingest into a VARIANT column and then creating a view is generally the most cost-effective and flexible approach for handling semi- structured data and performing transformations in Snowflake. CTAS involves full table scans and is less efficient for ongoing ingestion. COPY INTO with transforms has limitations for complex nested structures. Pre-processing with Lambda adds complexity and cost. UDFs can be expensive for large datasets compared to Snowflake's native JSON processing capabilities.

#### NEW QUESTION # 88

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