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Snowflake SnowPro Advanced: Data Scientist Certification Exam Sample Questions (Q222-Q227):

NEW QUESTION # 222
You are building a data science pipeline in Snowflake to predict customer churn. The pipeline includes a Python UDF that uses a pre- trained scikit-learn model stored as a binary file in a Snowflake stage. The UDF needs to load this model for prediction. You've

encountered an issue where the UDF intermittently fails, seemingly related to resource limits when multiple concurrent queries invoke the UDF. Which of the following strategies would best optimize the UDF for concurrency and resource efficiency, minimizing the risk of failure?

- A. Load the scikit-learn model inside the UDF function on every invocation to ensure the latest version is used.
- B. Increase the memory allocated to the Snowflake warehouse to accommodate multiple UDF invocations.
- C. Implement a global, lazy-loaded cache for the scikit-learn model within the UDF's module. The model is loaded only once during the first invocation and shared across subsequent calls. Protect the loading process with a lock to prevent race conditions in concurrent environments.
- D. Utilize Snowflake's session-level caching by storing the loaded model in 'session.get('model')' to be reused across multiple UDF calls within the same session. Reload the model if 'session.get('model')' is None.
- E. Load the scikit-learn model outside the UDF function in the global scope of the module so that all invocations share the same loaded model instance. Use the 'context.getExecutionContext(Y to track execution, making sure it is thread safe.

Answer: C

Explanation:
Option D provides the most efficient and robust solution. Loading the model only once (lazy loading) reduces overhead. A global cache ensures reusability. A lock is crucial to prevent race conditions during the initial loading in a concurrent environment. Option A is inefficient due to repeated loading. Option B is problematic because Snowflake UDFs do not directly support global variables in a thread-safe manner. Option C is incorrect as 'session.get' is not a valid Snowflake API for Python UDFs and lacks thread safety. Option E, while potentially helpful, doesn't address the underlying inefficiency of repeatedly loading the model.

NEW QUESTION # 223
You are building a model training pipeline in Snowflake using Snowpark Python. You want to leverage a pre-trained model from Hugging Face Transformers for a text classification task, fine-tuning it with your own labeled data stored in a Snowflake table named 'training_data'. You've chosen the 'transformers' library and plan to use a 'transformers.pipeline' for inference. Which of the following code snippets, when integrated into your Snowpark Python application, will correctly download the pre trained model and tokenizer, prepare the data, perform fine-tuning, and then save the fine-tuned model to a Snowflake stage?

```
○ from snowflake.snowpark import Session import transformers def train_model(session: Session, model_name: str, stage_name: str, table_name: str):
model = transformers.AutoModelForSequenceClassification.from_pretrained(model_name) tokenizer =
transformers.AutoTokenizer.from_pretrained(model_name) training_data = session.table(table_name).to_pandas() trainer =
transformers.Trainer(model=model, train_dataset=training_data, tokenizer=tokenizer) trainer.train() model.save_pretrained(f'@{stage_name}')
tokenizer.save_pretrained(f'@{stage_name}')
```

```
○ from snowflake.snowpark import Session from transformers import AutoModelForSequenceClassification, AutoTokenizer, Trainer, TrainingArguments def
train_model(session: Session, model_name: str, stage_name: str, table_name: str): model =
AutoModelForSequenceClassification.from_pretrained(model_name) tokenizer = AutoTokenizer.from_pretrained(model_name) training_data =
session.table(table_name) training_args = TrainingArguments(output_dir='tmp_results', evaluation_strategy='epoch') trainer = Trainer(model=model,
args=training_args, train_dataset=training_data.to_pandas(), tokenizer=tokenizer) trainer.train() trainer.save_model(f'@{stage_name}')
```

```
○ from snowflake.snowpark import Session import torch from transformers import AutoModelForSequenceClassification, AutoTokenizer, Trainer,
TrainingArguments, TextClassificationPipeline def train_model(session: Session, model_name: str, stage_name: str, table_name: str): model =
AutoModelForSequenceClassification.from_pretrained(model_name) tokenizer = AutoTokenizer.from_pretrained(model_name) training_data =
session.table(table_name).to_pandas() training_args = TrainingArguments(output_dir='tmp_results', evaluation_strategy='epoch') trainer =
Trainer(model=model, args=training_args, train_dataset=training_data, tokenizer=tokenizer) trainer.train() trainer.save_model(f'@{stage_name}') #
Create a pipeline for inference and upload it to the stage pipeline = TextClassificationPipeline(model=model, tokenizer=tokenizer,
device=torch.device('cuda' if torch.cuda.is_available() else 'cpu')) session.add_dependency(f'@{stage_name}')
```

```
○ from snowflake.snowpark import Session from transformers import AutoModelForSequenceClassification, AutoTokenizer, Trainer, TrainingArguments def
train_model(session: Session, model_name: str, stage_name: str, table_name: str): model =
AutoModelForSequenceClassification.from_pretrained(model_name) tokenizer = AutoTokenizer.from_pretrained(model_name) training_data =
session.table(table_name).to_pandas() training_args = TrainingArguments(output_dir='/tmp', evaluation_strategy='epoch') trainer =
Trainer(model=model, args=training_args, train_dataset=training_data, tokenizer=tokenizer) trainer.train() trainer.save_model(f'@{stage_name}')
```

```
○ from snowflake.snowpark import Session from transformers import AutoModelForSequenceClassification, AutoTokenizer, Trainer, TrainingArguments def
train_model(session: Session, model_name: str, stage_name: str, table_name: str): model =
AutoModelForSequenceClassification.from_pretrained(model_name) tokenizer = AutoTokenizer.from_pretrained(model_name) training_data =
session.table(table_name).to_pandas() training_args = TrainingArguments(output_dir='./results', evaluation_strategy='epoch') trainer =
Trainer(model=model, args=training_args, train_dataset=training_data, tokenizer=tokenizer) trainer.train() trainer.save_model(f'@{stage_name}')
```

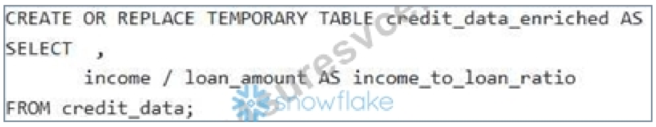
- A. Option E
- B. Option D
- C. Option A
- D. Option B
- E. Option C

Answer: D

Explanation:
The correct answer is B. It correctly uses the 'transformers' library with Snowpark Python. It downloads the model and tokenizer using and 'AutoTokenizer.from_pretrained'. TrainingArguments are configured with output_dir and evaluation_strategy. It reads training data using session.table. Trainer properly configured and finally Trainer saves the trained model in specified 'stage_name' . Option A is incorrect because it missing 'TrainingArgumentS configuration and uses general function, which may not be optimal for the Trainer setup. Option C is incorrect because incorrect use case. Option D and E is incorrect because 'TrainingArguments' output_dir is local folder that cannot be written by Trainer.

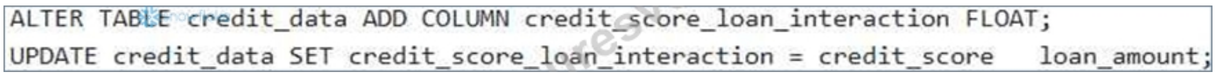
NEW QUESTION # 224
Consider you are working on a credit risk scoring model using Snowflake. You have a table 'credit data' with the following schema: 'customer id', 'age', 'income', 'credit_score', 'loan_amount', 'loan_duration', 'defaulted'. You want to create several new features using Snowflake SQL to improve your model. Which combination of the following SQL statements will successfully create features for age groups, income-to-loan ratio, and interaction between credit score and loan amount using SQL in Snowflake? Choose all that apply.

- A.

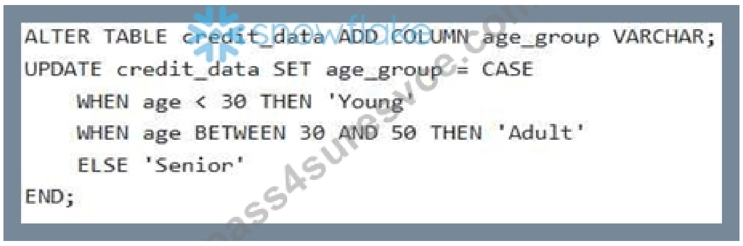


```
CREATE OR REPLACE TEMPORARY TABLE credit_data_enriched AS
SELECT  ,
       income / loan_amount AS income_to_loan_ratio
FROM credit_data;
```

- B.

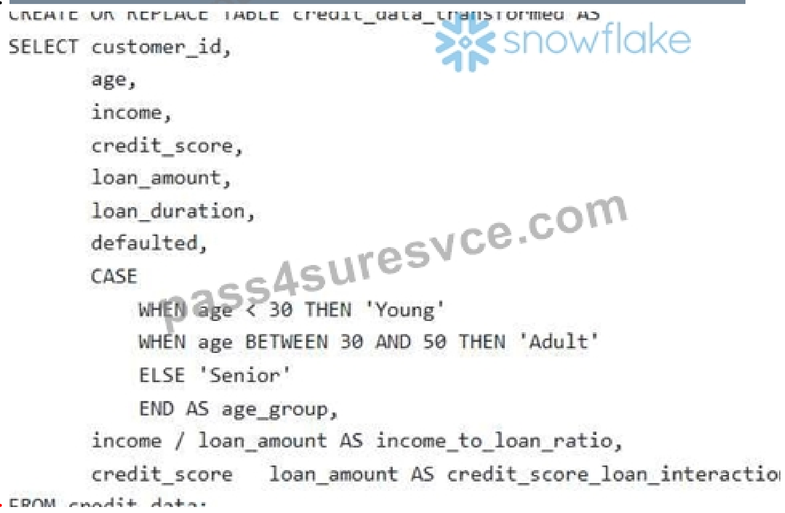


```
ALTER TABLE credit_data ADD COLUMN credit_score_loan_interaction FLOAT;
UPDATE credit_data SET credit_score_loan_interaction = credit_score   loan_amount;
```



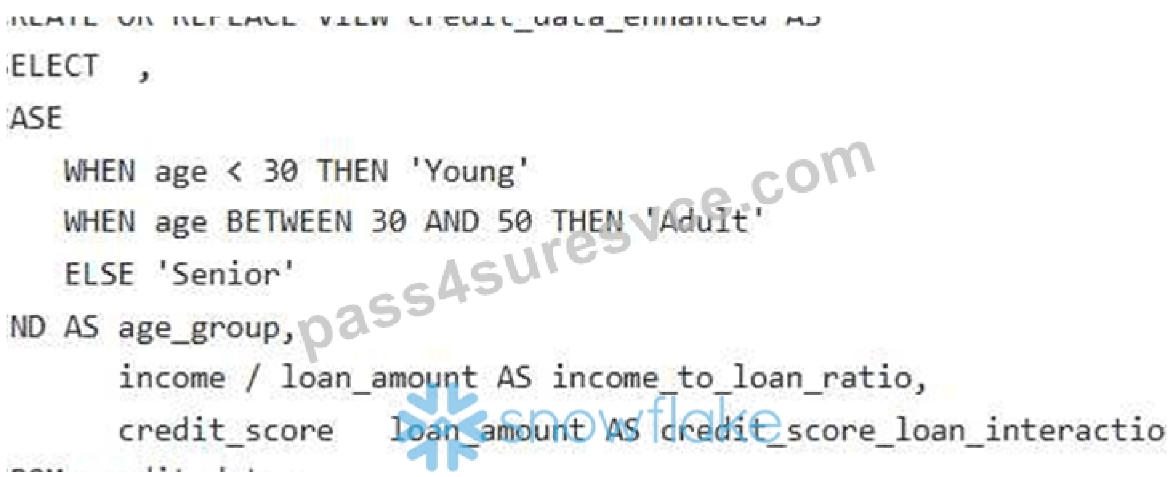
```
ALTER TABLE credit_data ADD COLUMN age_group VARCHAR;
UPDATE credit_data SET age_group = CASE
    WHEN age < 30 THEN 'Young'
    WHEN age BETWEEN 30 AND 50 THEN 'Adult'
    ELSE 'Senior'
END;
```

- C.



```
CREATE OR REPLACE TABLE credit_data_transformed AS
SELECT customer_id,
       age,
       income,
       credit_score,
       loan_amount,
       loan_duration,
       defaulted,
       CASE
           WHEN age < 30 THEN 'Young'
           WHEN age BETWEEN 30 AND 50 THEN 'Adult'
           ELSE 'Senior'
           END AS age_group,
       income / loan_amount AS income_to_loan_ratio,
       credit_score   loan_amount AS credit_score_loan_interactio
FROM credit_data;
```

- D.



```
REATE OR REPLACE VIEW credit_data_enhanced AS
ELECT  ,
ASE
    WHEN age < 30 THEN 'Young'
    WHEN age BETWEEN 30 AND 50 THEN 'Adult'
    ELSE 'Senior'
ND AS age_group,
        income / loan_amount AS income_to_loan_ratio,
        credit_score   loan_amount AS credit_score_loan_interactio
```

- E.

Answer: D,E

Explanation:
Options D and E are correct. Option D creates a VIEW that dynamically calculates all three features without modifying the underlying table. A view is the correct and recommended usage. Option E creates a new table with all the features including the new engineered features. Option A creates a column and updates it, but this is inefficient compared to creating the feature directly in a single SELECT statement (Option E). B createa a temporary table but does not contain all three features. Option C, it only addresses the interaction feature, not age_group or income to loan ratio.

NEW QUESTION # 225
You're tasked with building an image classification model on Snowflake to identify defective components on a manufacturing assembly line using images captured by high-resolution cameras. The images are stored in a Snowflake table named 'ASSEMBLY LINE IMAGES', with columns including 'image_id' (INT), 'image_data' (VARIANT containing binary image data), and 'timestamp' (TIMESTAMP NTZ). You have a pre-trained image classification model (TensorFlow/PyTorch) saved in Snowflake's internal stage. To improve inference speed and reduce data transfer overhead, which approach provides the MOST efficient way to classify these images using Snowpark Python and UDFs?

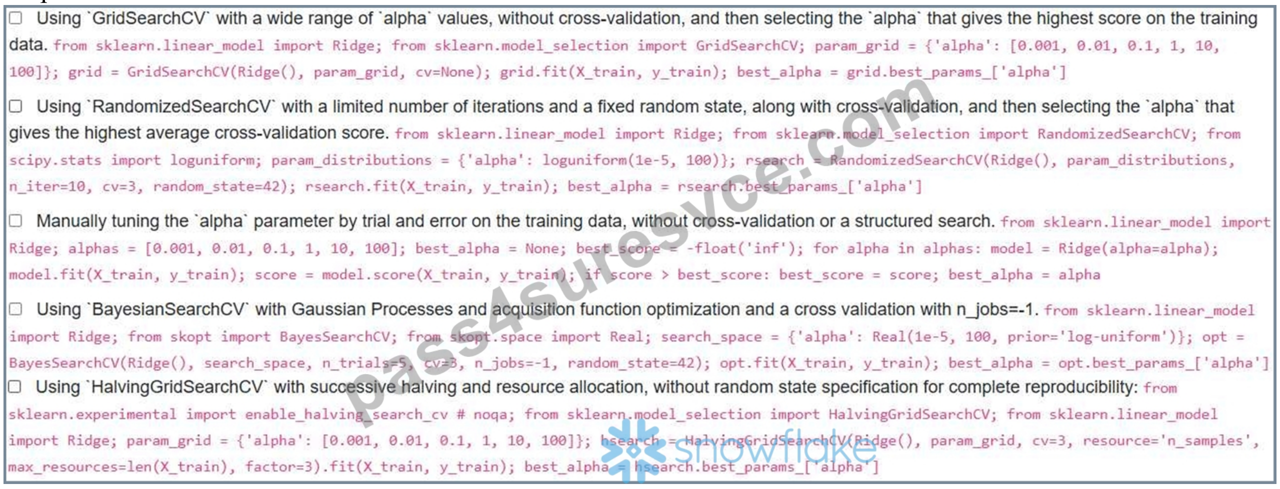
- A. Create a Python UDF that loads the entire table into memory, preprocesses the images, loads the pre-trained model, and performs classification for all images in a single execution.
- B. Create a Python UDF that takes a single 'image_id' as input, retrieves the corresponding 'image_data' from the table, preprocesses the image, loads the pre-trained model, performs classification, and returns the result. This UDF will be called for each image individually.
- C. Use Snowflake's external function feature to offload the image classification task to a serverless function hosted on AWS Lambda, passing the and 'image_icf to the function for processing.
- D. Create a vectorized Python UDF that takes a batch of 'image_id' values as input, retrieves the corresponding 'image_data' from the 'ASSEMBLY LINE IMAGES table using a JOIN, preprocesses the images in a vectorized manner, loads the pre-trained model once at the beginning, performs classification on the batch, and returns the results.
- E. Create a Java UDF that loads the pre-trained model and preprocesses the images. Call this Java UDF from a Python UDF to perform the image classification. Since Java is faster than Python, this will optimize performance.

Answer: D

Explanation:
Option C offers the most efficient solution. Vectorized UDFs allow processing batches of data at once, significantly reducing overhead compared to processing each image individually (Option B). Loading the model once per batch avoids redundant model loading. Option A is highly inefficient as it attempts to load the entire table into memory. While Java can be faster in certain scenarios, the complexity of calling a Java UDF from a Python UDF (Option D) will likely introduce more overhead than benefits. External functions (Option E) introduce network latency and are generally less efficient than in-database processing, unless there's a specific need for external resources or specialized hardware that Snowflake doesn't offer.

NEW QUESTION # 226
You are developing a churn prediction model using Snowpark Python and Scikit-learn. After initial model training, you observe significant overfitting. Which of the following hyperparameter tuning strategies and code snippets, when implemented within a

Snowflake Python UDF, would be MOST effective to address overfitting in a Ridge Regression model and how can you implement a reproducible model with minimal code?



☐ Using `GridSearchCV` with a wide range of `alpha` values, without cross-validation, and then selecting the `alpha` that gives the highest score on the training data. `from sklearn.linear_model import Ridge; from sklearn.model_selection import GridSearchCV; param_grid = {'alpha': [0.001, 0.01, 0.1, 1, 10, 100]}; grid = GridSearchCV(Ridge(), param_grid, cv=None); grid.fit(X_train, y_train); best_alpha = grid.best_params_['alpha']`

☐ Using `RandomizedSearchCV` with a limited number of iterations and a fixed random state, along with cross-validation, and then selecting the `alpha` that gives the highest average cross-validation score. `from sklearn.linear_model import Ridge; from sklearn.model_selection import RandomizedSearchCV; from scipy.stats import loguniform; param_distributions = {'alpha': loguniform(1e-5, 100)}; rsearch = RandomizedSearchCV(Ridge(), param_distributions, n_iter=10, cv=3, random_state=42); rsearch.fit(X_train, y_train); best_alpha = rsearch.best_params_['alpha']`

☐ Manually tuning the `alpha` parameter by trial and error on the training data, without cross-validation or a structured search. `from sklearn.linear_model import Ridge; alphas = [0.001, 0.01, 0.1, 1, 10, 100]; best_alpha = None; best_score = -float('inf'); for alpha in alphas: model = Ridge(alpha=alpha); model.fit(X_train, y_train); score = model.score(X_train, y_train); if score > best_score: best_score = score; best_alpha = alpha`

☐ Using `BayesianSearchCV` with Gaussian Processes and acquisition function optimization and a cross validation with n_jobs=-1. `from sklearn.linear_model import Ridge; from skopt import BayesSearchCV; from skopt.space import Real; search_space = {'alpha': Real(1e-5, 100, prior='log-uniform')}; opt = BayesSearchCV(Ridge(), search_space, n_trials=5, cv=3, n_jobs=-1, random_state=42); opt.fit(X_train, y_train); best_alpha = opt.best_params_['alpha']`

☐ Using `HalvingGridSearchCV` with successive halving and resource allocation, without random state specification for complete reproducibility: `from sklearn.experimental import enable_halving_search_cv # noqa; from sklearn.model_selection import HalvingGridSearchCV; from sklearn.linear_model import Ridge; param_grid = {'alpha': [0.001, 0.01, 0.1, 1, 10, 100]}; hsearch = HalvingGridSearchCV(Ridge(), param_grid, cv=3, resource='n_samples', max_resources=len(X_train), factor=3).fit(X_train, y_train); best_alpha = hsearch.best_params_['alpha']`

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

Answer: A,D

Explanation:
Options B and D are correct because they employ techniques to mitigate overfitting. Option B uses ' RandomizedSearchCV' with cross-validation and a fixed 'random_state' , making the search reproducible and preventing overfitting by evaluating performance on multiple validation sets. Option D leverages 'BayesianSearchCV' , which uses a probabilistic model to efficiently explore the hyperparameter space, also with cross-validation and a fixed random state making search reproducible. Both methods aim to find a balance between model complexity and generalization ability. Option A is incorrect because it does not use cross-validation, which is crucial for preventing overfitting. Option C is incorrect because manual tuning without a systematic search and cross-validation is prone to bias and overfitting. Finally, option E is incorrect because while using a modern algorithm, it lacks a random state, making it difficult to reproduce the outcome.

NEW QUESTION # 227
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