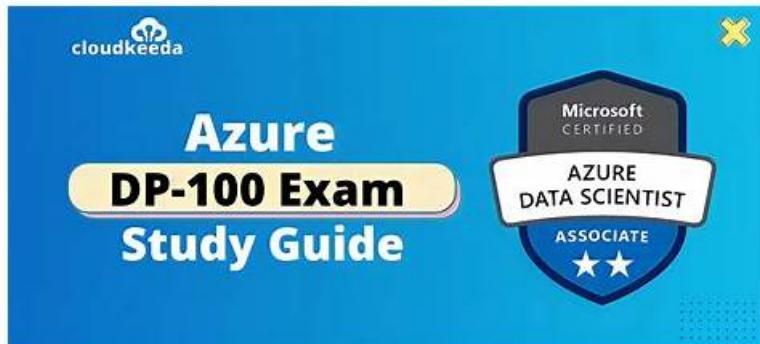


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This exam will provide substantial career growth for data scientist-related job roles. If anyone's job profile demands natural language processing and predictive analysis, s/he can aim at this exam to access needed expertise.

Microsoft Designing and Implementing a Data Science Solution on Azure Sample Questions (Q139-Q144):

NEW QUESTION # 139

You run an experiment that uses an AutoMLConfig class to define an automated machine learning task with a maximum of ten model training iterations. The task will attempt to find the best performing model based on a metric named accuracy.

You submit the experiment with the following code:

You need to create Python code that returns the best model that is generated by the automated machine learning task. Which code

segment should you use?

- A.
- B.
- C.
- D.

Answer: C

Explanation:

Explanation

The `get_output` method returns the best run and the fitted model.

Reference:

<https://notebooks.azure.com/azureml/projects/azureml-getting-started/html/how-to-use-azureml/automated-mach>

NEW QUESTION # 140

You are creating a machine learning model that can predict the species of a penguin from its measurements.

You have a file that contains measurements for free species of penguin in comma delimited format.

The model must be optimized for area under the received operating characteristic curve performance metric averaged for each class.

You need to use the Automated Machine Learning user interface in Azure Machine Learning studio to run an experiment and find the best performing model.

Which five actions should you perform in sequence? To answer, move the appropriate actions from the list of actions to the answer area and arrange them in the correct order.

Actions

- Select the **Regression** task type.
- Set the Primary metric configuration setting to **AUC Weighted**.
- Create and select a new dataset by uploading the comma-delimited file of penguin data.
- Select the **Classification** task type.
- Set the Primary metric configuration setting to **Accuracy**.
- Configure the automated machine learning run by selecting the experiment name, target column, and compute target.
- Run the automated machine learning experiment and review the results.

Answer area

Microsoft

Up and down arrows for reordering the list.

Answer:

Explanation:

Actions

- Select the **Regression** task type.
- Set the Primary metric configuration setting to **AUC Weighted**.
- Create and select a new dataset by uploading the comma-delimited file of penguin data.
- Select the **Classification** task type.
- Set the Primary metric configuration setting to **Accuracy**.
- Configure the automated machine learning run by selecting the experiment name, target column, and compute target.
- Run the automated machine learning experiment and review the results.

Answer area

- 1 Create and select a new dataset by uploading the comma-delimited file of penguin data.
- 2 Select the **Classification** task type.
- 3 Set the Primary metric configuration setting to **Accuracy**.
- 4 Configure the automated machine learning run by selecting the experiment name, target column, and compute target.
- 5 Run the automated machine learning experiment and review the results.

Microsoft

Up and down arrows for reordering the list.

Explanation

Actions

- Select the **Regression** task type.
- Set the Primary metric configuration setting to **AUC Weighted**.

Answer area

- 1 Create and select a new dataset by uploading the comma-delimited file of penguin data.
- 2 Select the **Classification** task type.
- 3 Set the Primary metric configuration setting to **Accuracy**.
- 4 Configure the automated machine learning run by selecting the experiment name, target column, and compute target.
- 5 Run the automated machine learning experiment and review the results.

Microsoft

NEW QUESTION # 141

You create an Azure Machine Learning workspace. You train an MLflow-formatted regression model by using tabular structured data.

You must use a Responsible AI dashboard to assess the model.

You need to use the Azure Machine Learning studio UI to generate the Responsible A dashboard.

What should you do first?

- A. Register the model with the workspace.
- B. Create the model explanations.
- C. Convert the model from the MLflow format to a custom format.
- D. Deploy the model to a managed online endpoint.

Answer: C

NEW QUESTION # 142

You create an Azure Machine Learning workspace.

You need to detect data drift between a baseline dataset and a subsequent target dataset by using the DataDriftDetector class.

How should you complete the code segment? To answer, select the appropriate options in the answer area.

NOTE: Each correct selection is worth one point.

```
from azureml.core import Workspace, Dataset
from datetime import datetime

ws = Workspace.from_config()
dset = Dataset.get_by_name(ws, 'target')
baseline = target.time_before(datetime(2021, 2, 1))
features = ['windAngle', 'windSpeed', 'temperature', 'stationName']

monitor = DataDriftDetector.
     (ws, 'drift-monitor', baseline,
     backfill
     create_from_datasets
     create_from_model
     target, compute_target='cpu-cluster', frequency='Week', feature_list=None,
     drift_threshold=.6, latency=24)

monitor = DataDriftDetector.get_by_name(ws, 'drift-monitor')
monitor = monitor.update(feature_list=features)
complete = monitor.
     (datetime(2021, 1, 1), datetime.today())
     backfill
     list
     update
```



Answer:

Explanation:

```

from azureml.core import Workspace, Dataset
from datetime import datetime

ws = Workspace.from_config()
dset = Dataset.get_by_name(ws, 'target')
baseline = target.time_before(datetime(2021, 2, 1))
features = ['windAngle', 'windSpeed', 'temperature', 'stationName']

monitor = DataDriftDetector. 
(ws, 'drift-monitor', baseline,
    backfill
    create from datasets
    create from model)

target, compute_target='cpu-cluster', frequency='Week', feature_list=None,
drift_threshold=.6, latency=24)

monitor = DataDriftDetector.get_by_name(ws, 'drift-monitor')
monitor = monitor.update(feature_list=features)
complete = monitor. 
(datetime(2021, 1, 1), datetime.today())
    backfill
    list
    update

```

Reference:

[https://docs.microsoft.com/en-us/python/api/azureml-datadrift/azureml.datadrift.datadriftdetector\(class\)](https://docs.microsoft.com/en-us/python/api/azureml-datadrift/azureml.datadrift.datadriftdetector(class))

Topic 2, Overview

Current environment

Requirements

* Media used for penalty event detection will be provided by consumer devices. Media may include images and videos captured during the sporting event and snared using social media. The images and videos will have varying sizes and formats.

* The data available for model building comprises of seven years of sporting event media. The sporting event media includes: recorded videos, transcripts of radio commentary, and logs from related social media feeds captured during the sporting events.

* Crowd sentiment will include audio recordings submitted by event attendees in both mono and stereo formats.

Advertisements

* Ad response models must be trained at the beginning of each event and applied during the sporting event.

* Market segmentation models must optimize for similar ad response history.

* Sampling must guarantee mutual and collective exclusivity local and global segmentation models that share the same features.

* Local market segmentation models will be applied before determining a user's propensity to respond to an advertisement.

* Data scientists must be able to detect model degradation and decay.

* Ad response models must support non linear boundaries features.

* The ad propensity model uses a cut threshold is 0.45 and retrains occur if weighted Kappa deviates from 0.1 +/- 5%.

* The ad propensity model uses cost factors shown in the following diagram:

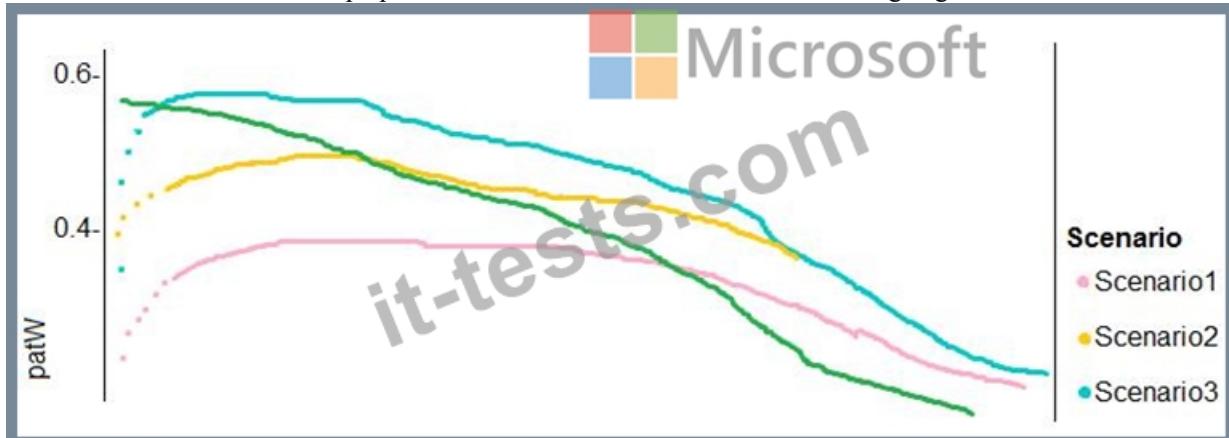
		Actual	
		1	0
Predicted	0	1	2
	1	2	1

The ad propensity model uses proposed cost factors shown in the following diagram:

		Actual	
		1	0
Predicted	0	1	5
	1	5	1



Performance curves of current and proposed cost factor scenarios are shown in the following diagram:



Penalty detection and sentiment

Findings

- * Data scientists must build an intelligent solution by using multiple machine learning models for penalty event detection.
- * Data scientists must build notebooks in a local environment using automatic feature engineering and model building in machine learning pipelines.
- * Notebooks must be deployed to retrain by using Spark instances with dynamic worker allocation
- * Notebooks must execute with the same code on new Spark instances to recode only the source of the data.
- * Global penalty detection models must be trained by using dynamic runtime graph computation during training.
- * Local penalty detection models must be written by using BrainScript.
- * Experiments for local crowd sentiment models must combine local penalty detection data.
- * Crowd sentiment models must identify known sounds such as cheers and known catch phrases. Individual crowd sentiment models will detect similar sounds.
- * All shared features for local models are continuous variables.
- * Shared features must use double precision. Subsequent layers must have aggregate running mean and standard deviation metrics

Available segments

During the initial weeks in production, the following was observed:

- * Ad response rates declined.
- * Drops were not consistent across ad styles.
- * The distribution of features across training and production data are not consistent.

Analysis shows that of the 100 numeric features on user location and behavior, the 47 features that come from location sources are being used as raw features. A suggested experiment to remedy the bias and variance issue is to engineer 10 linearly uncorrected features.

Penalty detection and sentiment

- * Initial data discovery shows a wide range of densities of target states in training data used for crowd sentiment models.
- * All penalty detection models show inference phases using a Stochastic Gradient Descent (SGD) are running too slow.
- * Audio samples show that the length of a catch phrase varies between 25%-47%, depending on region.
- * The performance of the global penalty detection models show lower variance but higher bias when comparing training and validation sets. Before implementing any feature changes, you must confirm the bias and variance using all training and validation cases.

NEW QUESTION # 143

You are a data scientist creating a linear regression model.

You need to determine how closely the data fits the regression line.

Which metric should you review?

- A. Recall
- B. Mean absolute error
- C. Coefficient of determination
- D. Root Mean Square Error
- E. Precision

Answer: B

Explanation:

Topic 2, Case Study 1

Overview

You are a data scientist in a company that provides data science for professional sporting events. Models will be global and local market data to meet the following business goals:

*Understand sentiment of mobile device users at sporting events based on audio from crowd reactions.

*Access a user's tendency to respond to an advertisement.

*Customize styles of ads served on mobile devices.

*Use video to detect penalty events.

Current environment

Requirements

* Media used for penalty event detection will be provided by consumer devices. Media may include images and videos captured during the sporting event and snared using social media. The images and videos will have varying sizes and formats.

* The data available for model building comprises of seven years of sporting event media. The sporting event media includes: recorded videos, transcripts of radio commentary, and logs from related social media feeds captured during the sporting events.

*Crowd sentiment will include audio recordings submitted by event attendees in both mono and stereo Formats.

Advertisements

* Ad response models must be trained at the beginning of each event and applied during the sporting event.

* Market segmentation models must optimize for similar ad response history.

* Sampling must guarantee mutual and collective exclusivity local and global segmentation models that share the same features.

* Local market segmentation models will be applied before determining a user's propensity to respond to an advertisement.

* Data scientists must be able to detect model degradation and decay.

* Ad response models must support non linear boundaries features.

* The ad propensity model uses a cut threshold is 0.45 and retrains occur if weighted Kappa deviates from 0.1

+/-5%.

* The ad propensity model uses cost factors shown in the following diagram:

		Actual	
		1	0
Predicted	0	1	2
	1	2	1

- The ad propensity model uses proposed cost factors shown in the following diagram:

		Actual	
		1	0
Predicted	0	1	5
	1	5	1

- Performance curves of current and proposed cost factor scenarios are shown in the following diagram:



Penalty detection and sentiment

Findings

- Data scientists must build an intelligent solution by using multiple machine learning models for penalty event detection.
- Data scientists must build notebooks in a local environment using automatic feature engineering and model building in machine learning pipelines.
- Notebooks must be deployed to retrain by using Spark instances with dynamic worker allocation.
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- All shared features for local models are continuous variables.
- Shared features must use double precision. Subsequent layers must have aggregate running mean and standard deviation metrics Available.

Segments

During the initial weeks in production, the following was observed:

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- The distribution of features across training and production data are not consistent.

Analysis shows that of the 100 numeric features on user location and behavior, the 47 features that come from location sources are being used as raw features. A suggested experiment to remedy the bias and variance issue is to engineer 10 linearly uncorrected features.

Penalty detection and sentiment

- Initial data discovery shows a wide range of densities of target states in training data used for crowd sentiment models.
- All penalty detection models show inference phases using a Stochastic Gradient Descent (SGD) are running too slow.
- Audio samples show that the length of a catch phrase varies between 25%-47%, depending on region.
- The performance of the global penalty detection models show lower variance but higher bias when comparing training and

validation sets. Before implementing any feature changes, you must confirm the bias and variance using all training and validation cases.

NEW QUESTION # 144

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