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Exam : DP-100

Title : Designing and
Implementing a Data
Science Solution on Azure

Version : DEMO

1. Topic 1, 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 shared 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 stow.
- 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.

You need to resolve the local machine learning pipeline performance issue.

What should you do?

- A. Increase Graphic Processing Units (GPUs).
- B. Increase the learning rate.
- C. Increase the training iterations,
- D. Increase Central Processing Units (CPUs).

Answer: A

2.DRAG DROP

You need to modify the inputs for the global penalty event model to address the bias and variance issue. Which three 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	Answer area
Build ratios.	
Bin the new data.	
Add a K-Means clustering module with 10 clusters.	
Select the behavior data.	
Select the location data.	
Perform a Primary Component Analysis (PCA).	

Answer:

Actions	Answer area
Build ratios.	Select the behavior data.
Bin the new data.	Add a K-Means clustering module with 10 clusters.
Add a K-Means clustering module with 10 clusters.	Perform a Primary Component Analysis (PCA).
Select the behavior data.	
Select the location data.	
Perform a Primary Component Analysis (PCA).	

3.You need to select an environment that will meet the business and data requirements.

Which environment should you use?

- A. Azure HDInsight with Spark MLlib
- B. Azure Cognitive Services
- C. Azure Machine Learning Studio
- D. Microsoft Machine Learning Server

Answer: D

4.DRAG DROP

You need to define a process for penalty event detection.

Which three 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	Answer area
Build the global model using Microsoft Cognitive Toolkit (CNTK).	
Import the global model and build a local model using Microsoft Cognitive Toolkit (CNTK).	
Export the global model using Neural Network Exchange Format (NNEF).	
Import the global model and build the local model using PyTorch.	
Build the global model using PyTorch.	
Build the global model using TensorFlow.	
Import the global model and build the local model using TensorFlow.	
Export the global model using the Open Neural Network Exchange (ONNX) format.	

Answer:

Actions	Answer area
Build the global model using Microsoft Cognitive Toolkit (CNTK).	Build the global model using PyTorch.
Import the global model and build a local model using Microsoft Cognitive Toolkit (CNTK).	Export the global model using Neural Network Exchange Format (NNEF).
Export the global model using Neural Network Exchange Format (NNEF).	Import the global model and build the local model using TensorFlow.
Import the global model and build the local model using PyTorch.	
Build the global model using PyTorch.	
Build the global model using TensorFlow.	
Import the global model and build the local model using TensorFlow.	
Export the global model using the Open Neural Network Exchange (ONNX) format.	

5.DRAG DROP

You need to define a process for penalty event detection.

Which three 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	Answer area
Standardize to mono audio clips.	
Vary the length of sliding windows between modeling epochs.	
Vary the length of frequency bands between modeling epochs.	
Use an Inverse Fourier transform on frequency changes over time.	
Use a Fast Fourier transform on frequency changes over time.	
Standardize to stereo audio clips.	

Answer:

Actions	Answer area
Standardize to mono audio clips.	Vary the length of frequency bands between modeling epochs.
Vary the length of sliding windows between modeling epochs.	Standardize to mono audio clips.
Vary the length of frequency bands between modeling epochs.	Use an Inverse Fourier transform on frequency changes over time.
Use an Inverse Fourier transform on frequency changes over time.	
Use a Fast Fourier transform on frequency changes over time.	
Standardize to stereo audio clips.	