#### AZURE MACHINE LEARNING ASSIGNMENT – 1

NISHA - 2211566 - AI&ML

Use the feature engineering process for building a regression model using bike rental demand data. In machine learning predictions, effective feature engineering will lead to a more accurate model. The Bike Rental dataset is based on real data from the capital Bikeshare company, which operates a bike rental network in Washington DC in the United States. The dataset contains 17,379 rows and 17 columns, each row representing the number of bike rentals within a specific hour of a day in the years 2011 or 2012. Weather conditions (such as temperature, humidity, and wind speed) were included in this raw feature set, and the dates were categorized as holiday v/s weekdays etc.

The field to predict is "cnt" which contains a count value ranging from 1 to 977, representing the number of bike rentals within a specific hour. Our main goal is to construct effective features in the training data, so we build two models using the same algorithm, but with two different datasets. Using the Split Data Module in the visual designer, we split the input data such a way that the training data contains records for the year 2011, and the testing data, records for 2012. Both datasets have the same raw data at the origin, but we added different additional features to each training set.

- Set A = weather + holiday + weekday + weekend features for the predicted day
- Set B = number of bikes that were rented in each of the previous 12 hours

We are building two training datasets by combining the feature set as follows:

- Training set 1 : feature set A only.
- Training set 2: feature sets A+B

# Steps....

- 1. Download bike-rental-hour.csv and create a blob object and copy URL.
- 2. Create a new data asset and name it **BikeRentalHourly** and with Type as File and choose **From web files** and give the copied URL from previous step as **Web URL**.
- 3. Open Pipeline Authoring Editor and Setup Compute Target.
- 4. Drag and drop on the canvas, the available BikeRentalHourly dataset under the Data.
- 5. Drag and drop the **Edit Metadata module** (Component/Data transformation category), connect the module to the dataset, and double click on the **Edit MetaData** to open Edit Metadata details

- 6. Click on the Edit column and the season and weathersit columns.
- 7. Drag and drop the **Select Columns in Dataset** (Data transformation category), connect the module to the Edit Metadata module, and double click on the **Select Columns in the Dataset**.
- 8. Click Edit Columns, Configure the Select Columns in Dataset module as follows:

Include: All columns

Select +

Exclude Columns names: instant, dteday, casual, registered.

Select Save

9. Drag and drop the Execute Python Script module (Python Language Category) and connect it with the Select Columns in Dataset. (Make sure the connector is connected to the very first input of the Execute Python Script module)

Use Python script to append a new set of features to the dataset: number of bikes that were rented in each of the previous 12 hours. Feature set B captures very recent demand for the bikes. This will be the B set in the described feature engineering approach. The script adds 12 new columns to the dataset containing the number of bikes that were rented in each of the previous 12 hours.

10. Use the **Split Data** module ( Data Transformation module) and connect its input with output from the **Select Columns in Dataset** module. Use the following configurations:

Splitting mode : Relative Expression Relational Expression: \"y" == 0

- 11. Select the **Split Data** module block and use the menu buttons to Copy and Paste it on the Canvas. Connect the second one to the output of the Python Script execution step, which is the featured B set.
- 12. Drag and drop **Select columns in Dataset module** (Data transformation category), create four identical modules to exclude the yr column from all the outputs.
- 13. Drag and drop Boosted Decision Tree Regression module (Machine Learning Algorithms, Regression category)
- 14. Drag and drop **Train model** module (Model training category) and enter the cnt column in the Label column field.
- 15. Link the Boosted Decision Tree Regression module as the first input and the training dataset as the second input to the Train Model module.
- 16. Use two Score Model modules (Model Scoring and Evaluation category) and link it to the two Score Model modules.
- 17. Drag and drop the Evaluate Model module (Model Scoring and evaluation category) and link it to the two Score Model modules.

18. Select Submit to open the Setup pipeline run editor. In the Setup pipeline run editor, select Experiment, Create new and provide a New experiment name.

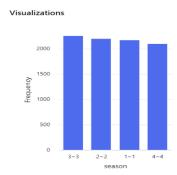
# Results:-

Observe the values for the Mean\_Absolute\_Error, RMSE and R- Squared and other metrics. The first values corresponds to the model trained on feature set A. The second values corresponds to the model trained on the feature sets A + B.

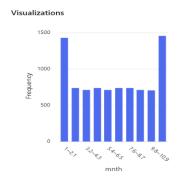
Using simple feature engineering to derive new features from the existing data set allows the model to better understand the dynamics of the data and hence, produce a better prediction.

# SCORED DATASETS - Exploring the Data sets.

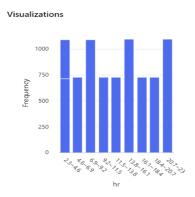
season	
Statistics	
Mean	-
Median	-
Min	-
Max	-
Standard deviation	-
Unique values	4
Missing values	0
Feature type	Categorical Feature



mnth	
Statistics	
Mean	6.5019
Median	7
Min	1
Max	12
Standard deviation	3.4491
Unique values	12
Missing values	0
Feature type	Numeric Feature



Statistics		
Mean	11.5202	
Median	12	
Min	0	
Max	23	
Standard deviation	6.9212	
Unique values	24	
Missing values	0	
Feature type	Numeric Feature	



## holiday

#### Statistics

 Mean
 0.0299

 Median
 0

 Min
 0

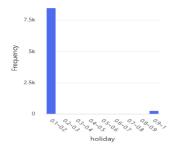
 Max
 1

 Standard deviation
 0.1703

 Unique values
 2

 Missing values
 0

Feature type Numeric Feature



#### weekday

#### Statistics

 Mean
 2.9947

 Median
 3

 Min
 0

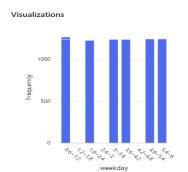
 Max
 6

 Standard deviation
 2.0053

 Unique values
 7

 Missing values
 0

Feature type Numeric Feature



#### workingday

#### Statistics

 Mean
 0.6817

 Median
 1

 Min
 0

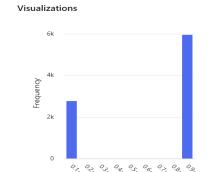
 Max
 1

 Standard deviation
 0.4658

 Unique values
 2

 Missing values
 0

Feature type Numeric Feature



workingday

## weathersit

#### Statistics

 Mean

 Median

 Min

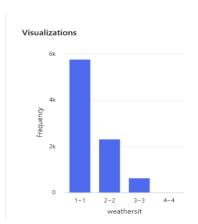
 Max

 Standard deviation

 Unique values
 4

 Missing values
 0

Feature type Categorical Feature



#### temp

#### Statistics

Missing values

 Mean
 0.5048

 Median
 0.52

 Min
 0.02

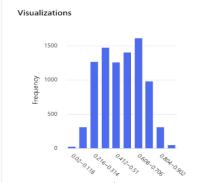
 Max
 1

 Standard deviation
 0.1868

 Unique values
 50

Feature type Numeric Feature

0



temp

#### atemp

#### Statistics

 Mean
 0.4825

 Median
 0.4848

 Min
 0.0152

 Max
 0.9242

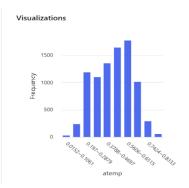
 Standard deviation
 0.1666

 Unique values
 61

 Missing values
 0

Feature type Numeric Feature

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#### hum

#### Statistics

 Mean
 0.6112

 Median
 0.61

 Min
 0.16

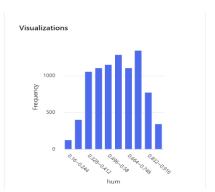
 Max
 1

 Standard deviation
 0.1882

 Unique values
 81

 Missing values
 0

Feature type Numeric Feature



#### windspeed

#### Statistics

 Mean
 0.189

 Median
 0.1642

 Min
 0

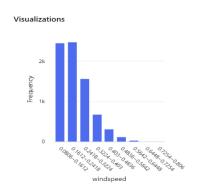
 Max
 0.806

 Standard deviation
 0.1215

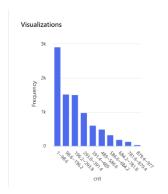
 Unique values
 26

 Missing values
 0

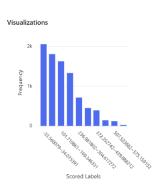
Feature type Numeric Feature



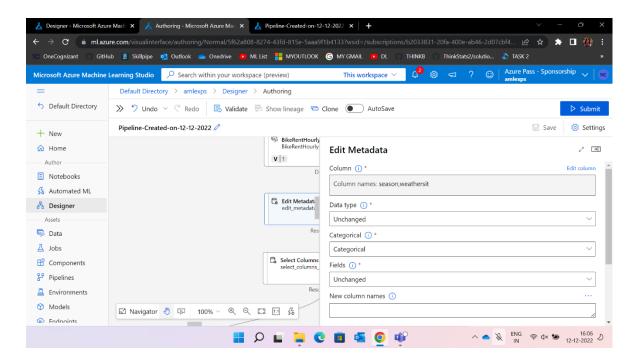
# Statistics 234.6664 Median 191 Min 1 Max 977 Standard deviation 208.9109 Unique values 866 Missing values 0 Feature type Numeric Label

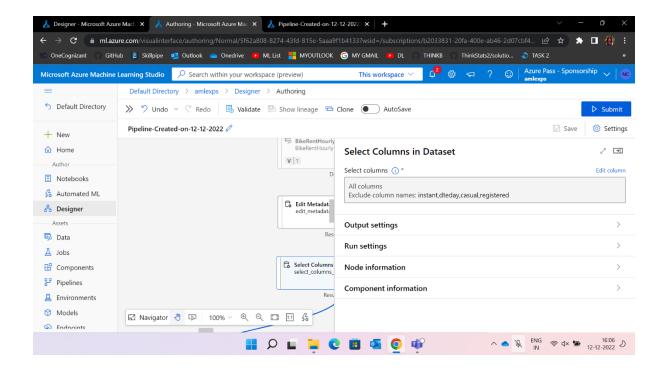




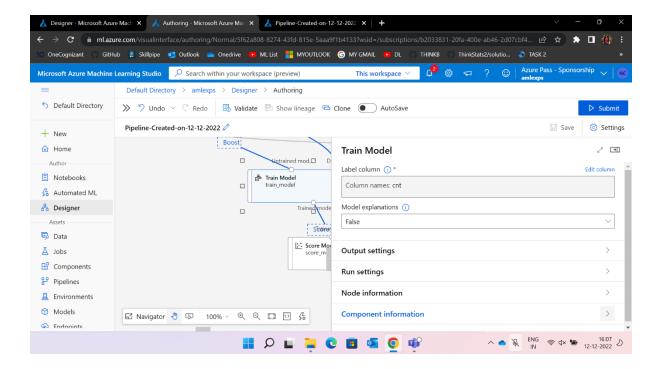


# **EDIT METADATA**

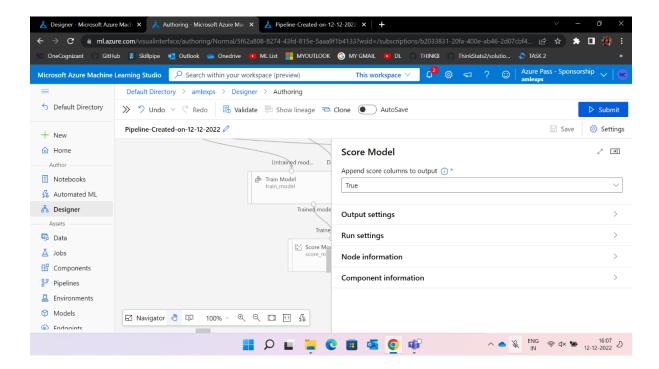




## TRAIN MODEL



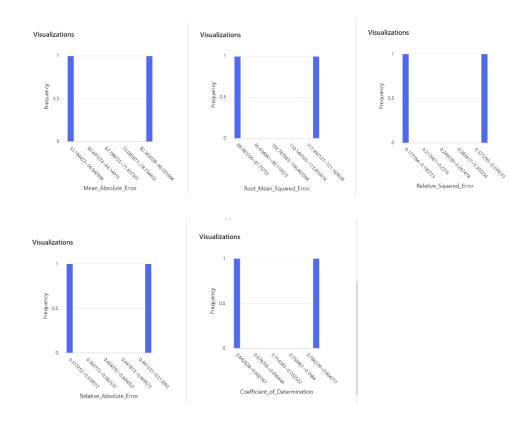
# **SCORE MODEL**



# **EVALUATION RESULT –**

Coefficient_of_Determination		Relative_Absolute_Error		Relative_Squared_Error	
Statistics		Statistics		Statistics	
Mean	0.7325	Mean	0.4261	Mean	0.2675
Median	0.7325	Median	0.4261	Median	0.2675
Min	0.6428	Min	0.3173	Min	0.1778
Max	0.8222	Max	0.5349	Max	0.3572
Standard deviation	0.1268	Standard deviation	0.1539	Standard deviation	0.1268
Unique values	2	Unique values	2	Unique values	2
Missing values	0	Missing values	0	Missing values	0
Feature type	Numeric Feature	Feature type	Numeric Feature	Feature type	Numeric Feature

Root_Mean_Squared_Error		Mean_Absolute_Error		
Statistics		Statistics		
Mean	106.4636	Mean	71.4373	
Median	106.4636	Median	71.4373	
Min	88.081	Min	53.1944	
Max	124.8461	Max	89.6802	
Standard deviation	25.9969	Standard deviation	25.7993	
Unique values	2	Unique values	2	
Missing values	0	Missing values	0	
Feature type	Numeric Feature	Feature type	Numeric Feature	



# RUNNED MODEL :- Successfully runned!

