#### WEEK-4

#### CORRELATION MATRIX

#### **OBJECTIVE:**

Write a python program to load the dataset and understand the input data

Dataset: Pima Indians Diabetes Dataset

https://www.kaggle.com/uciml/pima-indians-diabetes-database#diabetes.csv

Library: Scipy

- a) Load data, describe the given data and identify missing, outlier data items
- b) Find correlation among all attributes
- c) Visualize correlation matrix

### **RESOURCES:**

- a) Python 3.7.0
- b) Install: pip installer, pandas, SciPy library

#### **PROCEDURE:**

- 1. Create: Open a new file in Python shell, write a program and save the program with .py extension.
- 2. Execute: Go to Run -> Run module (F5)

#### **PROGRAM LOGIC:**

a) Load data

import pandas as pd

importnumpy as np

importmatplotlib as plt

%matplotlib inline

# #Reading the dataset in a dataframe using Pandas

df = pd.read\_csv("C:/Users/admin/Documents/diabetes.csv")

# #describe the given data

print(df. describe())

#### #Display first 10 rows of data

print(df.head(10))

#### **#Missing values**

#### In Pandas missing data is represented by two values:

**None**: None is a Python singleton object that is often used for missing data in Python code.

NaN :NaN (an acronym for Not a Number), is a special floating-point value recognized by all systems

- isnull()
- notnull()
- dropna()
- fillna()
- replace()
- interpolate()

# # identify missing items

print(df.isnull())

```
#outlier data items
  Methods
  Z-score method
  Modified Z-score method
  IQR method
  #Z-score function defined in scipy library to detect the outliers
  importnumpy as np
  defoutliers_z_score(ys):
  threshold = 3
  mean_y = np.mean(ys)
  stdev_y = np.std(ys)
  z_scores = [(y - mean_y) / stdev_y for y in ys]
  returnnp.where(np.abs(z_scores) > threshold)
b) Find correlation among all attributes
  # importing pandas as pd
  import pandas as pd
  # Making data frame from the csv file
  df = pd.read_csv("nba.csv")
  # Printing the first 10 rows of the data frame for visualization
  df[:10]
  # To find the correlation among columns
  # using pearson method
  df.corr(method ='pearson')
  # using 'kendall' method.
  df.corr(method ='kendall')
c) Visualize correlation matrix
  INPUT/OUTPUT:
  import pandas as pd
  df = pd.read_csv("C:/Users/admin/Documents/diabetes.csv")
  print(df. describe())
  print(df.head(10))
```

#### Pregnancies Glucose ... Age Outcome 768.000000 768.000000 768.000000 768.000000 3.845052 120.894531 33.240885 0.348958 3.369578 31.972618 11.760232 0.476951 0.000000 0.000000 21.000000 0.000000 24.000000 0.000000 0.000000 age Outcome count mean std min 1.000000 99.000000 ... 24.000000 0.000000 25% 3.000000 3.000000 117.000000 ... 29.000000 6.000000 140.250000 ... 41.000000 17.000000 199.000000 ... 81.000000 50% 0.000000 75% 1.000000 max 1.000000 [8 rows x 9 columns] Pregnancies Glucose BloodPressure ... DiabetesPedigreeFunction Age Outcome 6 148 72 ... 0.627 50 1 148 0 66 ... 85 0.351 1 85 8 183 1 89 0 137 5 116 3 78 10 115 2 197 8 125 1 2 64 ... 0.672 32 3 66 ... 0.167 21 4 33 40 . . . 2.288 1 74 ... 5 0.201 30 50 ... 6 0.248 26 29 7 0 ... 0 0.134 70 ... 96 ... 8 0.158 53 54 9 0.232 1

[10 rows x 9 columns]

#### WEEK -5

#### DATA PREPROCESSING - HANDLING MISSING VALUES

#### **OBJECTIVE:**

Write a python program to impute missing values with various techniques on given dataset.

- a) Remove rows/ attributes
- b) Replace with mean or mode
- c) Write a python program to perform transformation of data using Discretization (Binning) and normalization (MinMaxScaler or MaxAbsScaler) on given dataset.

https://www.kaggle.com/uciml/pima-indians-diabetes-database#diabetes.csv Library: Scipy

# **RESOURCES:**

- a) Python 3.7.0
- b) Install: pip installer, pandas, SciPy library

#### **PROCEDURE:**

- 1. Create: Open a new file in Python shell, write a program and save the program with .py extension.
- 2. Execute: Go to Run -> Run module (F5)

#### **PROGRAM LOGIC:**

# filling missing value using fillna()

df.fillna(0)

# filling a missing value with previous value

df.fillna(method ='pad')

#Filling null value with the next ones

df.fillna(method ='bfill')

# filling a null values using fillna()

data["Gender"].fillna("No Gender", inplace = True)

# will replace Nan value in dataframe with value -99

data.replace(to\_replace = np.nan, value = -99)

#### # Remove rows/ attributes

# using dropna() function to remove rows having one Nan

df.dropna()

# using dropna() function to remove rows with all Nan

df.dropna(how = 'all')

# using dropna() function to remove column having one Nan

df.dropna(axis = 1)

# # Replace with mean or mode

 $mean_y = np.mean(ys)$ 

#### # Perform transformation of data using Discretization (Binning)

Binning can also be used as a discretization technique. Discretization refers to the process of converting or partitioning continuous attributes, features or variables to discretized or nominal attributes/ features/ variables/ intervals.

For example, attribute values can be discretized by applying equal-width or equal-frequency binning, and then replacing each bin value by the bin mean or median, as in smoothing by bin means or smoothing by bin medians, respectively. Then the continuous values can be converted to a nominal or discretized value which is same as the value of their corresponding bin.

There are basically two types of binning approaches –

**Equal width (or distance) binning :** The simplest binning approach is to partition the range of the variable into k equal-width intervals. The interval width is simply the range [A, B] of the variable divided by k, w = (B-A) / k

```
Thus, i^{th} interval range will be [A + (i-1)w, A + iw] where i = 1, 2, 3 \dots k
```

Skewed data cannot be handled well by this method.

**Equal depth (or frequency) binning :** In equal-frequency binning we divide the range [A, B] of the variable into intervals that contain (approximately) equal number of points; equal frequency may not be possible due to repeated values.

There are three approaches to perform smoothing –

**Smoothing by bin means**: In smoothing by bin means, each value in a bin is replaced by the mean value of the bin.

**Smoothing by bin median :** In this method each bin value is replaced by its bin median value.

**Smoothing by bin boundary:** In smoothing by bin boundaries, the minimum and maximum values in a given bin are identified as the bin boundaries. Each bin value is then replaced by the closest boundary value.

Example:

Sorted data for price(in dollar): 2, 6, 7, 9, 13, 20, 21, 25, 30

```
Partition using equal frequency approach:
Bin 1: 2, 6, 7
Bin 2: 9, 13, 20
Bin 3 : 21, 24, 30
Smoothing by bin mean :
Bin 1: 5, 5, 5
Bin 2: 14, 14, 14
Bin 3 : 25, 25, 25
Smoothing by bin median :
Bin 1: 6, 6, 6
Bin 2: 13, 13, 13
Bin 3 : 24, 24, 24
Smoothing by bin boundary :
Bin 1: 2, 7, 7
Bin 2: 9, 9, 20
Bin 3 : 21, 21, 30
```

# import numpy as np import math

# from sklearn.datasets import load\_iris from sklearn import datasets, linear\_model, metrics

```
# load iris data set
dataset = load iris()
a = dataset.data
b = np.zeros(150)
# take 1st column among 4 column of data set
for i in range (150):
  b[i]=a[i,1]
b=np.sort(b) #sort the array
# create bins
bin1=np.zeros((30,5))
bin2=np.zeros((30,5))
bin3=np.zeros((30,5))
# Bin mean
for i in range (0,150,5):
  k=int(i/5)
  mean=(b[i] + b[i+1] + b[i+2] + b[i+3] + b[i+4])/5
  for j in range(5):
     bin1[k,j]=mean
print("Bin Mean: \n",bin1)
# Bin boundaries
for i in range (0,150,5):
  k=int(i/5)
  for j in range (5):
     if (b[i+j]-b[i]) < (b[i+4]-b[i+j]):
       bin2[k,j]=b[i]
     else:
       bin2[k,j]=b[i+4]
print("Bin Boundaries: \n",bin2)
# Bin median
for i in range (0,150,5):
  k=int(i/5)
  for j in range (5):
     bin3[k,j]=b[i+2]
print("Bin Median: \n",bin3)
```

### **OUTPUT:**

Bin Mean:	Bin Boundaries:	Bin Median:
[[2.18 2.18 2.18 2.18 2.18]	[[2. 2.3 2.3 2.3 2.3]	[[2.2 2.2 2.2 2.2 2.2]
[2.34 2.34 2.34 2.34 2.34]	[2.3 2.3 2.3 2.4 2.4]	[2.3 2.3 2.3 2.3 2.3]
[2.48 2.48 2.48 2.48 2.48]	[2.4 2.5 2.5 2.5 2.5]	[2.5 2.5 2.5 2.5 2.5]
[2.52 2.52 2.52 2.52 2.52]	[2.5 2.5 2.5 2.5 2.6]	[2.5 2.5 2.5 2.5 2.5]
[2.62 2.62 2.62 2.62 2.62]	[2.6 2.6 2.6 2.6 2.7]	[2.6 2.6 2.6 2.6 2.6]

[2.7 2.7 2.7 2.7 2.7]	[2.7 2.7 2.7 2.7 2.7]	[2.7 2.7 2.7 2.7 2.7]
[2.74 2.74 2.74 2.74 2.74]	[2.7 2.7 2.7 2.8 2.8]	[2.7 2.7 2.7 2.7 2.7]
[2.8 2.8 2.8 2.8 2.8]	[2.8 2.8 2.8 2.8 2.8]	[2.8 2.8 2.8 2.8 2.8]
[2.8 2.8 2.8 2.8 2.8]	[2.8 2.8 2.8 2.8 2.8]	[2.8 2.8 2.8 2.8 2.8]
[2.86 2.86 2.86 2.86 2.86]	[2.8 2.8 2.9 2.9 2.9]	[2.9 2.9 2.9 2.9]
[2.9 2.9 2.9 2.9 2.9]	[2.9 2.9 2.9 2.9 2.9]	[2.9 2.9 2.9 2.9 2.9]
[2.96 2.96 2.96 2.96 2.96]	[2.9 2.9 3. 3. 3. ]	[3. 3. 3. 3. 3.]
[3. 3. 3. 3. ]	[3. 3. 3. 3. 3.]	[3. 3. 3. 3. 3.]
[3. 3. 3. 3. ]	[3. 3. 3. 3. 3.]	[3. 3. 3. 3. 3.]
[3. 3. 3. 3. 3. ]	[3. 3. 3. 3. 3.]	[3. 3. 3. 3. 3.]
[3. 3. 3. 3. ]	[3. 3. 3. 3. 3.]	[3. 3. 3. 3. ]
[3.04 3.04 3.04 3.04 3.04]	[3. 3. 3. 3.1 3.1]	[3. 3. 3. 3. 3.]
[3.1 3.1 3.1 3.1 3.1]	[3.1 3.1 3.1 3.1 3.1]	[3.1 3.1 3.1 3.1 3.1]
[3.12 3.12 3.12 3.12 3.12]	[3.1 3.1 3.1 3.1 3.2]	[3.1 3.1 3.1 3.1 3.1]
[3.2 3.2 3.2 3.2 3.2]	[3.2 3.2 3.2 3.2 3.2]	[3.2 3.2 3.2 3.2 3.2]
[3.2 3.2 3.2 3.2 3.2]	[3.2 3.2 3.2 3.2 3.2]	[3.2 3.2 3.2 3.2 3.2]
[3.26 3.26 3.26 3.26 3.26]	[3.2 3.2 3.3 3.3 3.3]	[3.3 3.3 3.3 3.3 3.3]
[3.34 3.34 3.34 3.34 3.34]	[3.3 3.3 3.4 3.4]	[3.3 3.3 3.3 3.3 3.3]
[3.4 3.4 3.4 3.4 3.4]	[3.4 3.4 3.4 3.4 3.4]	[3.4 3.4 3.4 3.4 3.4]
[3.4 3.4 3.4 3.4 3.4]	[3.4 3.4 3.4 3.4 3.4]	[3.4 3.4 3.4 3.4 3.4]
[3.5 3.5 3.5 3.5 3.5]	[3.5 3.5 3.5 3.5 3.5]	[3.5 3.5 3.5 3.5 3.5]
[3.58 3.58 3.58 3.58 3.58]	[3.5 3.6 3.6 3.6 3.6]	[3.6 3.6 3.6 3.6 3.6]
[3.74 3.74 3.74 3.74 3.74]	[3.7 3.7 3.7 3.8 3.8]	[3.7 3.7 3.7 3.7 3.7]
[3.82 3.82 3.82 3.82 3.82]	[3.8 3.8 3.8 3.8 3.9]	[3.8 3.8 3.8 3.8 3.8]
[4.12 4.12 4.12 4.12 4.12]]	[3.9 3.9 3.9 4.4 4.4]]	[4.1 4.1 4.1 4.1 ]]

#### # Perform transformation of data using normalization (MinMaxScaler or MaxAbsScaler) on given dataset.

In preprocessing, standardization of data is one of the transformation task. Standardization is scaling features to lie between a given minimum and maximum value, often between zero and one, or so that the maximum absolute value of each feature is scaled to unit size. This can be achieved using MinMaxScaler or MaxAbsScaler, respectively.

The motivation to use this scaling include robustness to very small standard deviations of features and preserving zero entries in sparse data.

#### Example to scale a toy data matrix to the [0, 1] range:

```
from sklearn.preprocessing import MinMaxScaler
data = [[-1, 2], [-0.5, 6], [0, 10], [1, 18]]
scaler = MinMaxScaler()
print(scaler.fit(data))
MinMaxScaler()
print("data:\n",scaler.data_max_)
print("Transformed data:\n",scaler.transform(data))

OUTPUT
MinMaxScaler(copy=True, feature_range=(0, 1))
data:
[ 1. 18.]
Transformed data:
[ [0. 0. ]
[ [0.25 0.25]
[ [0.5 0.5 ]
```

[1. 1.]]