```
"""

1. Implement and demonstrate the FIND-S algorithm for finding the

most specific hypothesis based on a given set of training data samples.

Read the training data from a .CSV file

"""

import csv

a = []

with open('enjoysport.csv', 'r') as csvfile:

    next(csvfile)

    for row in csv.reader(csvfile):

        a.append(row)

    print(a)



print("\nThe total number of training instances are : ",len(a))



num_attribute = len(a[0])-1



print("\nThe initial hypothesis is : ")

hypothesis = ['0']*num_attribute

print(hypothesis)



for i in range(0, len(a)):

    if a[i][num_attribute] == 'yes':
```

```
        print ("\nInstance ", i+1, "is", a[i], " and is Positive Instance")

        for j in range(0, num_attribute):

            if hypothesis[j] == '0' or hypothesis[j] == a[i][j]:

                hypothesis[j] = a[i][j]

            else:

                hypothesis[j] = '?'

        print("The hypothesis for the training instance", i+1, " is: " , hypothesis, "\n")



    if a[i][num_attribute] == 'no':

        print ("\nInstance ", i+1, "is", a[i], " and is Negative Instance Hence Ignored")

        print("The hypothesis for the training instance", i+1, " is: " , hypothesis, "\n")



print("\nThe Maximally specific hypothesis for the training instance is ", hypothesis)
```

Output:

```
File  Edit  Shell  Debug  Options  Window  Help
Python 3.10.4 (tags/v3.10.4:9d38120, Mar 23 2022, 23:13:41) [MSC v.1929 64 bit (AMD64)] on win32
Type "help", "copyright", "credits" or "license()" for more information.
>>>
============== RESTART: C:\machine learning programs\lab\sample.py ============
[['sunny', 'warm', 'normal', 'strong', 'warm', 'same', 'yes'], ['sunny', 'warm', 'high', 'strong', 'warm', 'same', 'yes'], ['rainy', 'cold', 'high', 'strong', 'warm', 'change', 'no'], ['sunny', 'warm', 'high', 'strong', 'cool', 'change', 'yes']]

The total number of training instances are :  4

The initial hypothesis is :
['0', '0', '0', '0', '0', '0']

Instance  1 is ['sunny', 'warm', 'normal', 'strong', 'warm', 'same', 'yes']  and is Positive Instance
The hypothesis for the training instance 1  is:  ['sunny', 'warm', 'normal', 'strong', 'warm', 'same']


Instance  2 is ['sunny', 'warm', 'high', 'strong', 'warm', 'same', 'yes']  and is Positive Instance
The hypothesis for the training instance 2  is:  ['sunny', 'warm', '?', 'strong', 'warm', 'same']


Instance  3 is ['rainy', 'cold', 'high', 'strong', 'warm', 'change', 'no']  and is Negative Instance Hence Ignored
The hypothesis for the training instance 3  is:  ['sunny', 'warm', '?', 'strong', 'warm', 'same']


Instance  4 is ['sunny', 'warm', 'high', 'strong', 'cool', 'change', 'yes']  and is Positive Instance
The hypothesis for the training instance 4  is:  ['sunny', 'warm', '?', 'strong', '?', '?']


The Maximally specific hypothesis for the training instance is  ['sunny', 'warm', '?', 'strong', '?', '?']
>>>
```

2. **For a given set of training data examples stored in a .CSV file, implement and demonstrate the Candidate-Elimination algorithm in python to output a description of the set of all hypotheses consistent with the training examples.**

```
import numpy as np
import pandas as pd

data = pd.read_csv(path+'/enjoysport.csv')
concepts = np.array(data.iloc[:,0:-1])
print("\nInstances are:\n",concepts)
target = np.array(data.iloc[:,-1])
print("\nTarget Values are: ",target)

def learn(concepts, target):
  specific_h = concepts[0].copy()
  print("\nInitialization of specific_h and genearal_h")
  print("\nSpecific Boundary: ", specific_h)
  general_h = [["?" for i in range(len(specific_h))] for i in range(len(specific_h))]
  print("\nGeneric Boundary: ",general_h)

  for i, h in enumerate(concepts):
    print("\nInstance", i+1 , "is ", h)
    if target[i] == "yes":
      print("Instance is Positive ")
      for x in range(len(specific_h)):
        if h[x]!= specific_h[x]:
          specific_h[x] ='?'
          general_h[x][x] ='?'

    if target[i] == "no":
      print("Instance is Negative ")
      for x in range(len(specific_h)):
        if h[x]!= specific_h[x]:
          general_h[x][x] = specific_h[x]
        else:
          general_h[x][x] = '?'

    print("Specific Bundary after ", i+1, "Instance is ", specific_h)
    print("Generic Boundary after ", i+1, "Instance is ", general_h)
    print("\n")
```

Output:

```
================================================= RESTART: C:

Instances are:
 [['sunny' 'warm' 'normal' 'strong' 'warm' 'same']
 ['sunny' 'warm' 'high' 'strong' 'warm' 'same']
 ['rainy' 'cold' 'high' 'strong' 'warm' 'change']
 ['sunny' 'warm' 'high' 'strong' 'cool' 'change']]

Target Values are:  ['yes' 'yes' 'no' 'yes']
>
```

3. **Write a program to demonstrate the working of the decision tree based ID3 algorithm. Use an appropriate data set for building the decision tree and apply this knowledge to classify a new sample.**

```
#Import libraries and read data using read_csv() function. Remove the target from the data and store
#attributes in the features variable.

import pandas as pd
import math
import numpy as np

data = pd.read_csv("Dataset/4-dataset.csv")
features = [feat for feat in data]
features.remove("answer")
# Create a class named Node with four members children, value, isLeaf and pred.
class Node:
    def __init__(self):
        self.children = []
        self.value = ""
        self.isLeaf = False
        self.pred = ""
# Define a function called entropy to find the entropy oof the dataset
def entropy(examples):
    pos = 0.0
    neg = 0.0
    for _, row in examples.iterrows():
        if row["answer"] == "yes":
            pos += 1
        else:
            neg += 1
    if pos == 0.0 or neg == 0.0:
        return 0.0
    else:
        p = pos / (pos + neg)
        n = neg / (pos + neg)
        return -(p * math.log(p, 2) + n * math.log(n, 2))
# Define a function named info_gain to find the gain of the attribute
def info_gain(examples, attr):
    uniq = np.unique(examples[attr])
    #print ("\n",uniq)
    gain = entropy(examples)
    #print ("\n",gain)
    for u in uniq:
        subdata = examples[examples[attr] == u]
        #print ("\n",subdata)
        sub_e = entropy(subdata)
        gain -= (float(len(subdata)) / float(len(examples))) * sub_e
        #print ("\n",gain)
    return gain
# Define a function named ID3 to get the decision tree for the given dataset
def ID3(examples, attrs):
    root = Node()

    max_gain = 0
    max_feat = ""
    for feature in attrs:
```

```
        #print ("\n",examples)
        gain = info_gain(examples, feature)
        if gain > max_gain:
            max_gain = gain
            max_feat = feature
    root.value = max_feat
    #print ("\nMax feature attr",max_feat)
    uniq = np.unique(examples[max_feat])
    #print ("\n",uniq)
    for u in uniq:
        #print ("\n",u)
        subdata = examples[examples[max_feat] == u]
        #print ("\n",subdata)
        if entropy(subdata) == 0.0:
            newNode = Node()
            newNode.isLeaf = True
            newNode.value = u
            newNode.pred = np.unique(subdata["answer"])
            root.children.append(newNode)
        else:
            dummyNode = Node()
            dummyNode.value = u
            new_attrs = attrs.copy()
            new_attrs.remove(max_feat)
            child = ID3(subdata, new_attrs)
            dummyNode.children.append(child)
            root.children.append(dummyNode)

    return root
# Define a function named printTree to draw the decision tree
def printTree(root: Node, depth=0):
    for i in range(depth):
        print("\t", end="")
    print(root.value, end="")
    if root.isLeaf:
        print(" -> ", root.pred)
    print()
    for child in root.children:
        printTree(child, depth + 1)
# Define a function named classify to classify the new example
def classify(root: Node, new):
    for child in root.children:
        if child.value == new[root.value]:
            if child.isLeaf:
                print ("Predicted Label for new example", new," is:", child.pred)
                exit
            else:
                classify (child.children[0], new)
# Finally, call the ID3, printTree and classify functions
root = ID3(data, features)
print("Decision Tree is:")
printTree(root)
```

```
print ("------------------")

new = {"outlook":"sunny", "temperature":"hot", "humidity":"normal", "wind":"strong"}
classify (root, new)
```

Output:

```
Decision Tree is:
outlook
        overcast ->  ['yes']

        rain
                wind
                        strong ->  ['no']

                        weak ->  ['yes']

        sunny
                humidity
                        high ->  ['no']

                        normal ->  ['yes']

------------------
Predicted Label for new example {'outlook': 'sunny', 'temperature': 'hot', 'humidity': 'normal', 'wind': 'strong'}  is: ['yes']
```

4. **Build an Artificial Neural Network by implementing the Backpropagation algorithm and test the same using appropriate data sets.**

```
"""
Created on Fri Jan 27 08:29:18 2023

@author: GEOMOL GEORGE
"""

import numpy as np

X = np.array(([2, 9], [1, 5], [3, 6]), dtype=float)
y = np.array(([92], [86], [89]), dtype=float)
X = X/np.amax(X,axis=0) #maximum of X array longitudinally
y = y/100

#Sigmoid Function
def sigmoid (x):
   return 1/(1 + np.exp(-x))

#Derivative of Sigmoid Function
def derivatives_sigmoid(x):
   return x * (1 - x)

#Variable initialization
epoch=5 #Setting training iterations
lr=0.1 #Setting learning rate

inputlayer_neurons = 2 #number of features in data set
hiddenlayer_neurons = 3 #number of hidden layers neurons
output_neurons = 1 #number of neurons at output layer
#weight and bias initialization

wh=np.random.uniform(size=(inputlayer_neurons,hiddenlayer_neurons))
bh=np.random.uniform(size=(1,hiddenlayer_neurons))
```

```
wout=np.random.uniform(size=(hiddenlayer_neurons,output_neurons))
bout=np.random.uniform(size=(1,output_neurons))

#draws a random range of numbers uniformly of dim x*y
for i in range(epoch):
    #Forward Propogation
    hinp1=np.dot(X,wh)
    hinp=hinp1 + bh
    hlayer_act = sigmoid(hinp)
    outinp1=np.dot(hlayer_act,wout)
    outinp= outinp1+bout
    output = sigmoid(outinp)

    #Backpropagation
    EO = y-output
    outgrad = derivatives_sigmoid(output)
    d_output = EO * outgrad
    EH = d_output.dot(wout.T)
    hiddengrad = derivatives_sigmoid(hlayer_act)#how much hidden layer wts contributed to error
    d_hiddenlayer = EH * hiddengrad

    wout += hlayer_act.T.dot(d_output) *lr   # dotproduct of nextlayererror and currentlayerop
    wh += X.T.dot(d_hiddenlayer) *lr

    print ("-----------Epoch-", i+1, "Starts----------")
    print("Input: \n" + str(X))
    print("Actual Output: \n" + str(y))
    print("Predicted Output: \n" ,output)
    print ("-----------Epoch-", i+1, "Ends----------\n")

print("Input: \n" + str(X))
print("Actual Output: \n" + str(y))
print("Predicted Output: \n" ,output)
```

output:

```
-----------Epoch- 1 Starts----------
Input:
[[0.66666667 1.        ]
 [0.33333333 0.55555556]
 [1.         0.66666667]]
Actual Output:
[[0.92]
 [0.86]
 [0.89]]
Predicted Output:
 [[0.93250493]
 [0.92457935]
 [0.93337352]]
-----------Epoch- 1 Ends----------
```

```
-----------Epoch- 2 Starts----------
Input:
[[0.66666667 1.        ]
 [0.33333333 0.55555556]
 [1.         0.66666667]]
Actual Output:
[[0.92]
 [0.86]
 [0.89]]
Predicted Output:
 [[0.93241372]
 [0.92448608]
 [0.93328291]]
-----------Epoch- 2 Ends----------

-----------Epoch- 3 Starts----------
Input:
[[0.66666667 1.        ]
 [0.33333333 0.55555556]
 [1.         0.66666667]]
Actual Output:
[[0.92]
 [0.86]
 [0.89]]
Predicted Output:
 [[0.9323225 ]
 [0.92439282]
 [0.93319229]]
-----------Epoch- 3 Ends----------

-----------Epoch- 4 Starts----------
Input:
[[0.66666667 1.        ]
 [0.33333333 0.55555556]
 [1.         0.66666667]]
Actual Output:
[[0.92]
 [0.86]
 [0.89]]
Predicted Output:
 [[0.93223127]
 [0.92429955]
 [0.93310166]]
-----------Epoch- 4 Ends----------

-----------Epoch- 5 Starts----------
Input:
[[0.66666667 1.        ]
```

```
 [0.33333333 0.55555556]
 [1.        0.66666667]]
Actual Output:
[[0.92]
 [0.86]
 [0.89]]
Predicted Output:
 [[0.93214003]
 [0.92420629]
 [0.93301102]]
-----------Epoch- 5 Ends----------

Input:
[[0.66666667 1.        ]
 [0.33333333 0.55555556]
 [1.        0.66666667]]
Actual Output:
[[0.92]
 [0.86]
 [0.89]]
Predicted Output:
 [[0.93214003]
 [0.92420629]
 [0.93301102]]
```

5. **Write a program for Implementation of K-Nearest Neighbors (K-NN) in Python**

```
"""
Created on Fri Jan 27 09:32:02 2023
KNN
@author: GEOMOL GEORGE
"""
import numpy as np
import pandas as pd

dataset = pd.read_csv("D:/GEO/BE COURSES/LAB/DATASET/knn1 (1).csv")
"""
The breast cancer dataset has the following features: Sample code number, Clump Thickness, Uniformity of Cell Size,
Uniformity of Cell Shape, Marginal Adhesion, Single Epithelial Cell Size, Bare Nuclei, Bland Chromatin,
 Normal Nucleoli, Mitosis, Class.
"""
X = dataset.iloc[:, :-1].values
y = dataset.iloc[:, -1].values
dataset.shape
#splitting the dataset into the Training set and Test set
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20, random_state = 42)
#Feature Scaling
"""
Feature scaling is the process of converting the data into a given range.
In this case, the standard scalar technique is used.
```

"""
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
#Training the K-Nearest Neighbors (K-NN) Classification model on the Training set
"""
Once the dataset is scaled, next, the K-Nearest Neighbors (K-NN) classifier algorithm is used to create a model.
The hyperparameters such as n_neighbors, metric, and p are set to 5, Minkowski, and 2 respectively.
The remaining hyperparameters are set to default values.
"""
from sklearn.neighbors import KNeighborsClassifier
classifier = KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', p = 2)

classifier.fit(X_train, y_train)
"""
Display the results (confusion matrix and accuracy)
Here evaluation metrics such as confusion matrix and accuracy are used to evaluate the performance of the model built using a decision tree classifier.
"""
from sklearn.metrics import confusion_matrix, accuracy_score
y_pred = classifier.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
print(cm)
accuracy_score(y_test, y_pred)

```
================
[[78  1]
 [ 5 53]]
>
```

6. **Write a program to implement Naïve Bayes algorithm in python and to display the results using confusion matrix and accuracy. Java/Python ML library classes can be used for this problem.**

-*- coding: utf-8 -*-
"""
Created on Fri Jan 27 11:28:03 2023

@author: GEOMOL GEORGE

Implementation of Naive Bayes in Python – Machine Learning
In this tutorial, we will understand the Implementation of Naive Bayes in Python – Machine Learning.

Importing the Necessary libraries
To begin the implementation first we will import the necessary libraries
like NumPy for numerical computation and pandas for reading the dataset.
"""
import numpy as np
import pandas as pd
#Importing the dataset
"""
Next, we import or read the dataset. Click here to download the breast cancer dataset used in this implementation.
After reading the dataset, divide the dataset into concepts and targets. Store the concepts into X and

```
 targets into y.
"""
dataset = pd.read_csv("D:/GEO/BE COURSES/LAB/DATASET/breastcancer.csv")
X = dataset.iloc[:, :-1].values
y = dataset.iloc[:, -1].values
"""
Splitting the dataset into the Training set and Test set
Once the dataset is read into the memory, next, divide the dataset into two parts, training and
testing using the train_test_split function from sklearn.
 The test_size and random_state attributes are set to 0.25 and 0 respectively.
 You can change these attributes as per your requirements.
"""
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state = 0)

#Feature Scaling
"""
Feature scaling is the process of converting the data into a min-max range. In this case,
 the standard scalar method is used.
"""
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
"""
Training the Naive Bayes Classification model on the Training set
Once the dataset is scaled, next, the Naive Bayes classifier algorithm is used to create a model.
The GaussianNB function is imported from sklearn.naive_bayes library. The hyperparameters such as kernel,
and random_state to linear, and 0 respectively. The remaining hyperparameters of the support vector machine
 algorithm are set to default values.
"""
from sklearn.naive_bayes import GaussianNB
classifier = GaussianNB()
classifier.fit(X_train, y_train)

#Naive Bayes classifier model
GaussianNB(priors=None, var_smoothing=1e-09)

#Display the results (confusion matrix and accuracy)
"""
Here evaluation metrics such as confusion matrix and accuracy are used to evaluate the performance of
the model built using a decision tree classifier.
"""
from sklearn.metrics import confusion_matrix, accuracy_score
y_pred = classifier.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
print(cm)
accuracy_score(y_test, y_pred)
```

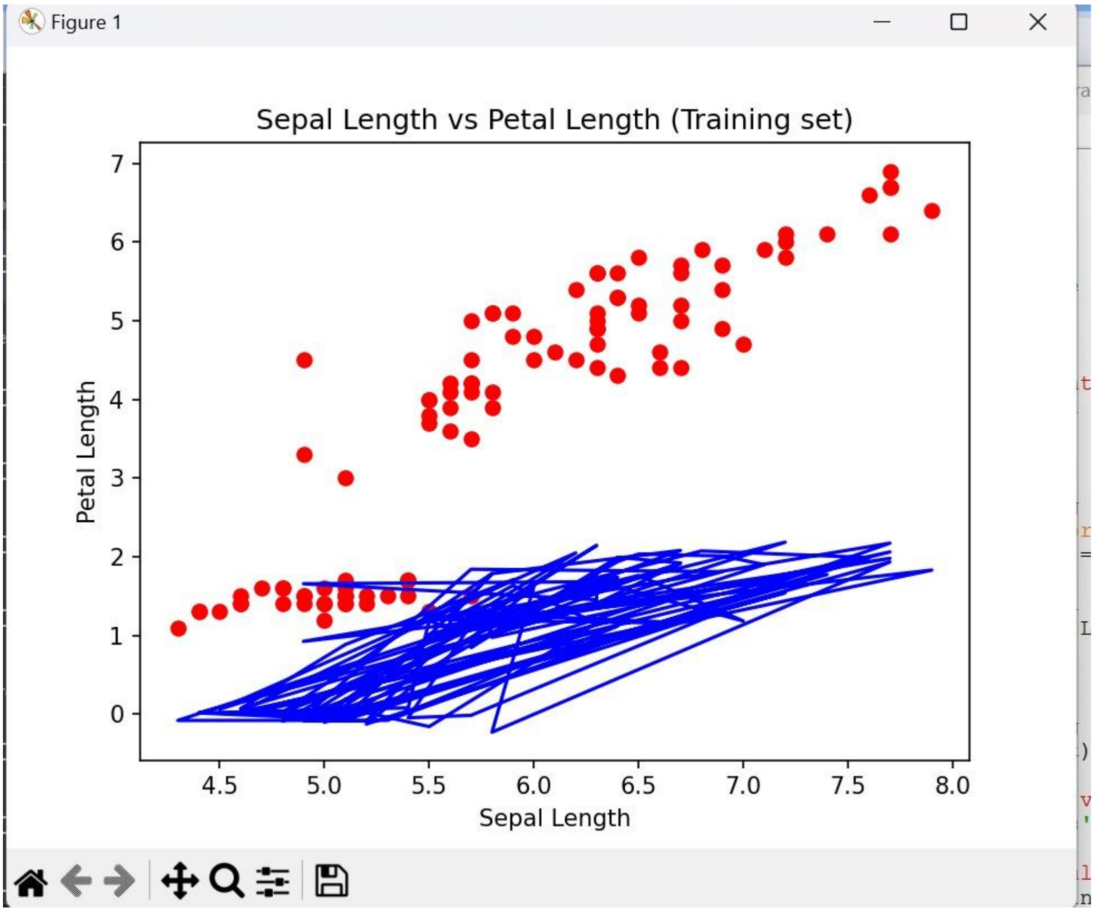
output:

```
=============== RESTART
[[99  8]
 [ 2 62]]
>>>
```

7. Write a program to implement Linear Regression (LR) algorithm in python

```
"""
```

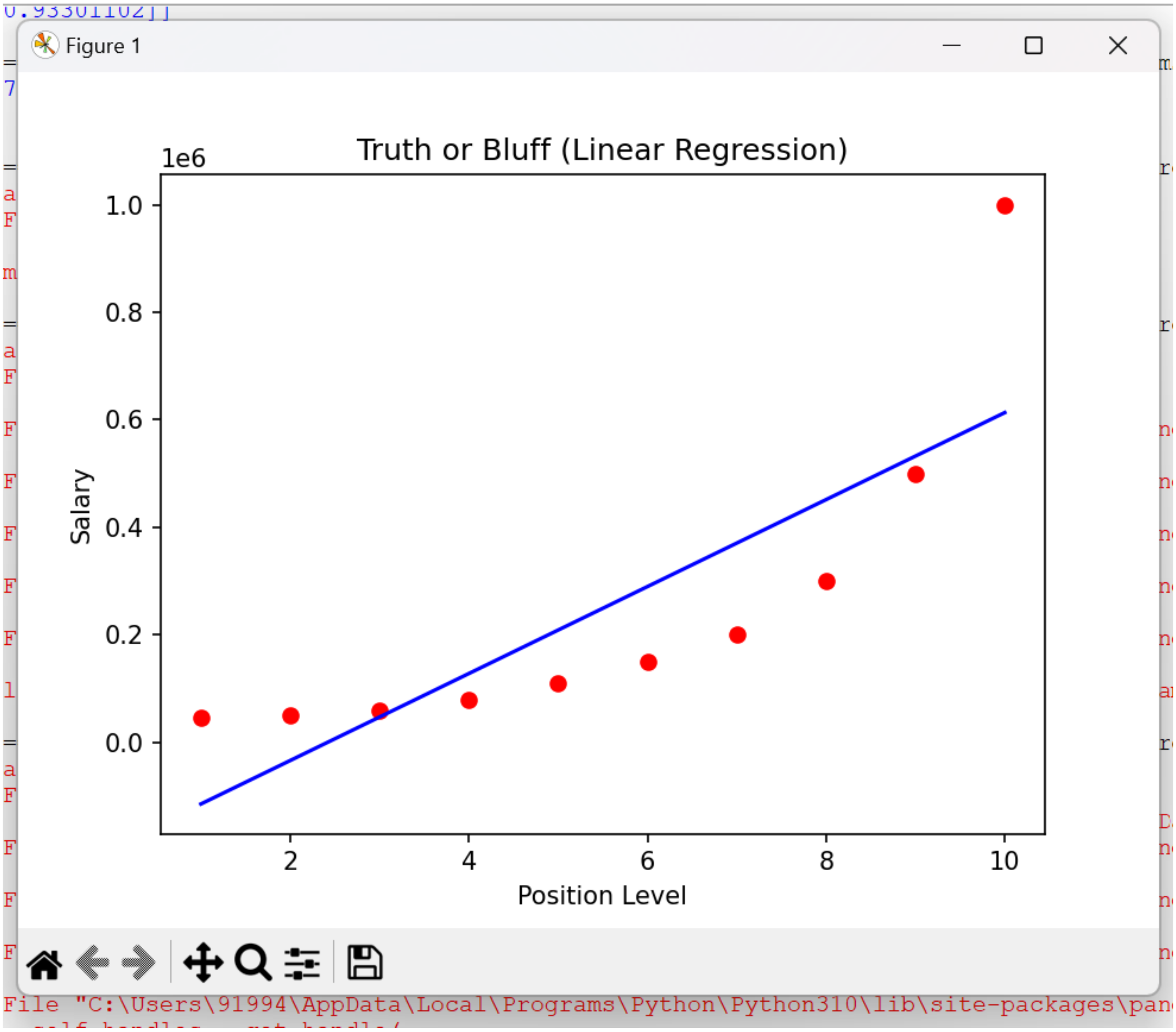
```
Created on Fri Jan 27 12:10:19 2023

@author: GEOMOL GEORGE
"""

import numpy as np
import matplotlib.pyplot as plt
import pandas as pd

dataset = pd.read_csv('D:/GEO/BE COURSES/LAB/DATASET/Salary_Data.csv')
X = dataset.iloc[:, :-1].values
y = dataset.iloc[:, -1].values

dataset.head()

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 1/3, random_state = 0)


from sklearn.linear_model import LinearRegression
regressor = LinearRegression()
regressor.fit(X_train, y_train)

LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)

y_pred = regressor.predict(X_test)
pd.DataFrame(data={'Actuals': y_test, 'Predictions': y_pred})


#Visualising the Training set results Here scatter plot is used to visualize the results.

plt.scatter(X_train, y_train, color = 'red')
plt.plot(X_train, regressor.predict(X_train), color = 'blue')
plt.title('Salary vs Experience (Training set)')
plt.xlabel('Years of Experience')
plt.ylabel('Salary')
plt.show()
```



8. Implementation Of Linear And Polynomial Regression In Python

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
dataset = pd.read_csv('D:/GEO/BE COURSES/LAB/DATASET/Position_Salaries.csv')
X = dataset.iloc[:, 1:-1].values
y = dataset.iloc[:, -1].values
"""
Training the Linear Regression model on the Whole dataset
A Linear regression algorithm is used to create a model.
 A LinearRegression function is imported from sklearn.linear_model library.
 """

from sklearn.linear_model import LinearRegression
lin_reg = LinearRegression()
lin_reg.fit(X, y)

#Linear Regression classifier model
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
"""
Training the Polynomial Regression model on the Whole dataset
A polynomial regression algorithm is used to create a model.
"""
from sklearn.preprocessing import PolynomialFeatures
poly_reg = PolynomialFeatures(degree = 4)
X_poly = poly_reg.fit_transform(X)
lin_reg_2 = LinearRegression()
lin_reg_2.fit(X_poly, y)
```

```
#Polynomial Regression classifier model
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
"""
Visualising the Linear Regression results
Here scatter plot is used to visualize the results. The title of the plot is set to Truth or Bluff
(Linear Regression), xlabel is set to Position Level , and ylabel is set to Salary.
"""
plt.scatter(X, y, color = 'red')
plt.plot(X, lin_reg.predict(X), color = 'blue')
plt.title('Truth or Bluff (Linear Regression)')
plt.xlabel('Position Level')
plt.ylabel('Salary')
plt.show()
#Visualising the Polynomial Regression results
"""
The title of the plot is set to Truth or Bluff (Polynomial Regression), xlabel is set to Position level,
 and ylabel is set to Salary.
"""
plt.scatter(X, y, color = 'red')
plt.plot(X, lin_reg_2.predict(poly_reg.fit_transform(X)), color = 'blue')
plt.title('Truth or Bluff (Polynomial Regression)')
plt.xlabel('Position level')
plt.ylabel('Salary')
plt.show()
```



9. **Write a program to implement Logistic Regression (LR) algorithm in python**

```
"""
Created on Fri Jan 27 11:53:58 2023

@author: GEOMOL GEORGE
"""
"""
Implementation of Logistic Regression (LR) in Python – Machine Learning
In this tutorial, we will understand the Implementation of Logistic Regression (LR) in Python – Machine
Learning.
Importing the libraries
"""
import numpy as np
import pandas as pd

#"Importing the dataset
"""
After importing the necessary libraries, next, we import or read the dataset.
 Click here to download the breast cancer dataset used in this implementation.
 The breast cancer dataset has the following features:
```

```
 Sample code number, Clump Thickness, Uniformity of Cell Size, Uniformity of Cell Shape, Marginal Adhesion,
 Single Epithelial Cell Size, Bare Nuclei, Bland Chromatin, Normal Nucleoli, Mitosis, Class.
"""


# divide the dataset into concepts and targets. Store the concepts into X and targets into y.
dataset = pd.read_csv("D:/GEO/BE COURSES/LAB/DATASET/breastcancer.csv")
X = dataset.iloc[:, :-1].values
y = dataset.iloc[:, -1].values

#Splitting the dataset into the Training set and Test
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.30, random_state = 2)

#Feature Scaling
"""
Feature scaling is the process of converting the data into a given range. In this case, the standard scalar technique is used.
from sklearn.preprocessing import StandardScaler
"""
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
"""
Training the Logistic Regression (LR) Classification model on the Training set
Once the dataset is scaled, next, the Logistic Regression (LR) classifier algorithm is used to create a model.
The hyperparameters such as random_state to 0 respectively.
 The remaining hyperparameters Logistic Regression (LR) are set to default values.
 """
from sklearn.linear_model import LogisticRegression
classifier = LogisticRegression(random_state = 0)
classifier.fit(X_train, y_train)
#Logistic Regression (LR) classifier model
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='warn', n_jobs=None, penalty='l2',
                   random_state=0, solver='warn', tol=0.0001, verbose=0,
                   warm_start=False)
#Display the results (confusion matrix and accuracy)
"""
Here evaluation metrics such as confusion matrix and accuracy are used to evaluate the performance of the model
built using a decision tree classifier.
"""
from sklearn.metrics import confusion_matrix, accuracy_score
y_pred = classifier.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
print(cm)
accuracy_score(y_test, y_pred)
```

```
====================================
[[117   8]
 [  6  74]]
Accuracy: 0.9317073170731708
>
```

10. Python Program to Implement Estimation & MAximization Algorithm

Program:

```
"""

Created on Fri Jan 27 13:13:36 2023

@author: GEOMOL GEORGE

Python Program to Implement  Estimation & MAximization Algorithm

"""



#from sklearn.cluster import KMeans

from sklearn.mixture import GaussianMixture

import sklearn.metrics as metrics

import pandas as pd

import numpy as np

import matplotlib.pyplot as plt


names = ['Sepal_Length','Sepal_Width','Petal_Length','Petal_Width', 'Class']


dataset = pd.read_csv("D:/GEO/BE COURSES/LAB/DATASET/8-dataset.csv", names=names)


X = dataset.iloc[:, :-1]


label = {'Iris-setosa': 0,'Iris-versicolor': 1, 'Iris-virginica': 2}


y = [label[c] for c in dataset.iloc[:, -1]]
```

```
plt.figure(figsize=(14,7))

colormap=np.array(['red','lime','black'])


# REAL PLOT

plt.subplot(1,3,1)

plt.title('Real')

plt.scatter(X.Petal_Length,X.Petal_Width,c=colormap[y])



# GMM PLOT

gmm=GaussianMixture(n_components=3, random_state=0).fit(X)

y_cluster_gmm=gmm.predict(X)

plt.subplot(1,3,3)

plt.title('GMM Classification')

plt.scatter(X.Petal_Length,X.Petal_Width,c=colormap[y_cluster_gmm])


print('The accuracy score of EM: ',metrics.accuracy_score(y, y_cluster_gmm))

print('The Confusion matrix of EM:\n ',metrics.confusion_matrix(y, y_cluster_gmm)
```

OUTPUT:

```
The accuracy score of EM:  0.36666666666666664
->
```

11. **There are three credit scores that banks and credit card companies use to label their customers: Good, Standard, Poor A person with a good credit score will get loans from any bank and financial institution. Write a program for the task of Credit Score Classification, we need a labelled dataset with credit scores.**

```
"""

Credit Score Classification
```

There are three credit scores that banks and credit card companies use to label their customers:

Good

Standard

Poor

A person with a good credit score will get loans from any bank and financial institution. For the task of Credit Score Classification, we need a labelled dataset with credit scores.

"""

import pandas as pd

import numpy as np

import plotly.express as px

import plotly.graph_objects as go

import plotly.io as pio

pio.templates.default = "plotly_white"

import plotly.io as io

io.renderers.default='browser'

data = pd.read_csv('D:/GEO/BE COURSES/LAB/DATASET/Credit-Score-Data/Credit Score Data/train.csv')

print(data.head())

print(data.info())

#the dataset has any null values or not:

print(data.isnull().sum())

#The dataset doesn’t have any null values. As this dataset is labelled, let’s have a look at the Credit_Score column values:

data["Credit_Score"].value_counts()

data.shape

#Data Exploration

"""

The dataset has many features that can train a Machine Learning model for credit score classification.

Let's explore all the features one by one.

I will start by exploring the occupation feature to know if the occupation of the person affects credit scores:

""""

```
fig = px.box(data,
             x="Occupation",
             color="Credit_Score",
             title="Credit Scores Based on Occupation",
             color_discrete_map={'Poor':'red',
                                 'Standard':'yellow',
                                 'Good':'green'})
fig.show()
```

""""

There's not much difference in the credit scores of all occupations mentioned in the data. Now let's explore

whether the Annual Income of the person impacts your credit scores or not:

""""

```
fig = px.box(data,
             x="Credit_Score",
             y="Annual_Income",
             color="Credit_Score",
             title="Credit Scores Based on Annual Income",
             color_discrete_map={'Poor':'red',
                                 'Standard':'yellow',
                                 'Good':'green'})
fig.update_traces(quartilemethod="exclusive")
fig.show()
```

```
"""
 let’s explore whether the monthly in-hand salary impacts credit scores or not:
"""
fig = px.box(data,
             x="Credit_Score",
             y="Monthly_Inhand_Salary",
             color="Credit_Score",
             title="Credit Scores Based on Monthly Inhand Salary",
             color_discrete_map={'Poor':'red',
                                 'Standard':'yellow',
                                 'Good':'green'})
fig.update_traces(quartilemethod="exclusive")
fig.show()


fig = px.box(data,
             x="Credit_Score",
             y="Num_Bank_Accounts",
             color="Credit_Score",
             title="Credit Scores Based on Number of Bank Accounts",
             color_discrete_map={'Poor':'red',
                                 'Standard':'yellow',
                                 'Good':'green'})
fig.update_traces(quartilemethod="exclusive")
fig.show()
# impact on credit scores based on the number of credit cards you have:
fig = px.box(data,
             x="Credit_Score",
```

```
            y="Num_Credit_Card",
            color="Credit_Score",
            title="Credit Scores Based on Number of Credit cards",
            color_discrete_map={'Poor':'red',
                                'Standard':'yellow',
                                'Good':'green'})
fig.update_traces(quartilemethod="exclusive")
fig.show()

fig = px.box(data,
            x="Credit_Score",
            y="Interest_Rate",
            color="Credit_Score",
            title="Credit Scores Based on the Average Interest rates",
            color_discrete_map={'Poor':'red',
                                'Standard':'yellow',
                                'Good':'green'})
fig.update_traces(quartilemethod="exclusive")
fig.show()

data["Credit_Mix"] = data["Credit_Mix"].map({"Standard": 1,
                              "Good": 2,
                              "Bad": 0})
from sklearn.model_selection import train_test_split
x = np.array(data[["Annual_Income", "Monthly_Inhand_Salary",
                 "Num_Bank_Accounts", "Num_Credit_Card",
                 "Interest_Rate", "Num_of_Loan",
                 "Delay_from_due_date", "Num_of_Delayed_Payment",
```

```
                    "Credit_Mix", "Outstanding_Debt",
                    "Credit_History_Age", "Monthly_Balance"]])
y = np.array(data[["Credit_Score"]])
xtrain, xtest, ytrain, ytest = train_test_split(x, y,
                                                test_size=0.33,
                                                random_state=42)
from sklearn.ensemble import RandomForestClassifier
model = RandomForestClassifier()
model.fit(xtrain, ytrain)
print("Credit Score Prediction : ")
a = float(input("Annual Income: "))
b = float(input("Monthly Inhand Salary: "))
c = float(input("Number of Bank Accounts: "))
d = float(input("Number of Credit cards: "))
e = float(input("Interest rate: "))
f = float(input("Number of Loans: "))
g = float(input("Average number of days delayed by the person: "))
h = float(input("Number of delayed payments: "))
i = input("Credit Mix (Bad: 0, Standard: 1, Good: 3) : ")
j = float(input("Outstanding Debt: "))
k = float(input("Credit History Age: "))
l = float(input("Monthly Balance: "))

features = np.array([[a, b, c, d, e, f, g, h, i, j, k, l]])
print("Predicted Credit Score = ", model.predict(features))
```

Output:

```
   ID  Customer_ID  ...  Monthly_Balance Credit_Score
```

```
0  5634        3392  ...      312.494089       Good
1  5635        3392  ...      284.629162       Good
2  5636        3392  ...      331.209863       Good
3  5637        3392  ...      223.451310       Good
4  5638        3392  ...      341.489231       Good

[5 rows x 28 columns]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 28 columns):
 #   Column                    Non-Null Count   Dtype
---  ------                    --------------   -----
 0   ID                        100000 non-null  int64
 1   Customer_ID               100000 non-null  int64
 2   Month                     100000 non-null  int64
 3   Name                      100000 non-null  object
 4   Age                       100000 non-null  float64
 5   SSN                       100000 non-null  float64
 6   Occupation                100000 non-null  object
 7   Annual_Income             100000 non-null  float64
 8   Monthly_Inhand_Salary     100000 non-null  float64
 9   Num_Bank_Accounts         100000 non-null  float64
 10  Num_Credit_Card           100000 non-null  float64
 11  Interest_Rate             100000 non-null  float64
 12  Num_of_Loan               100000 non-null  float64
 13  Type_of_Loan              100000 non-null  object
 14  Delay_from_due_date       100000 non-null  float64
 15  Num_of_Delayed_Payment    100000 non-null  float64
```

```
 16  Changed_Credit_Limit      100000 non-null  float64
 17  Num_Credit_Inquiries      100000 non-null  float64
 18  Credit_Mix                100000 non-null  object
 19  Outstanding_Debt          100000 non-null  float64
 20  Credit_Utilization_Ratio  100000 non-null  float64
 21  Credit_History_Age        100000 non-null  float64
 22  Payment_of_Min_Amount     100000 non-null  object
 23  Total_EMI_per_month       100000 non-null  float64
 24  Amount_invested_monthly   100000 non-null  float64
 25  Payment_Behaviour         100000 non-null  object
 26  Monthly_Balance           100000 non-null  float64
 27  Credit_Score              100000 non-null  object
dtypes: float64(18), int64(3), object(7)
memory usage: 21.4+ MB
None
ID                          0
Customer_ID                 0
Month                       0
Name                        0
Age                         0
SSN                         0
Occupation                  0
Annual_Income               0
Monthly_Inhand_Salary       0
Num_Bank_Accounts           0
Num_Credit_Card             0
Interest_Rate               0
Num_of_Loan                 0
```

Type_of_Loan 0

Delay_from_due_date 0

Num_of_Delayed_Payment 0

Changed_Credit_Limit 0

Num_Credit_Inquiries 0

Credit_Mix 0

Outstanding_Debt 0

Credit_Utilization_Ratio 0

Credit_History_Age 0

Payment_of_Min_Amount 0

Total_EMI_per_month 0

Amount_invested_monthly 0

Payment_Behaviour 0

Monthly_Balance 0

Credit_Score 0

dtype: int64

Warning (from warnings module):

File "C:\machine learning programs\lab\11th.py", line 111

model.fit(xtrain, ytrain)

DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples,), for example using ravel().

Credit Score Prediction :

Annual Income: 50000

Monthly Inhand Salary: 2000

Number of Bank Accounts: 3

Number of Credit cards: 2

Interest rate: 3.5

Number of Loans: 0

Average number of days delayed by the person: 0

Number of delayed payments: 0

Credit Mix (Bad: 0, Standard: 1, Good: 3) : 23

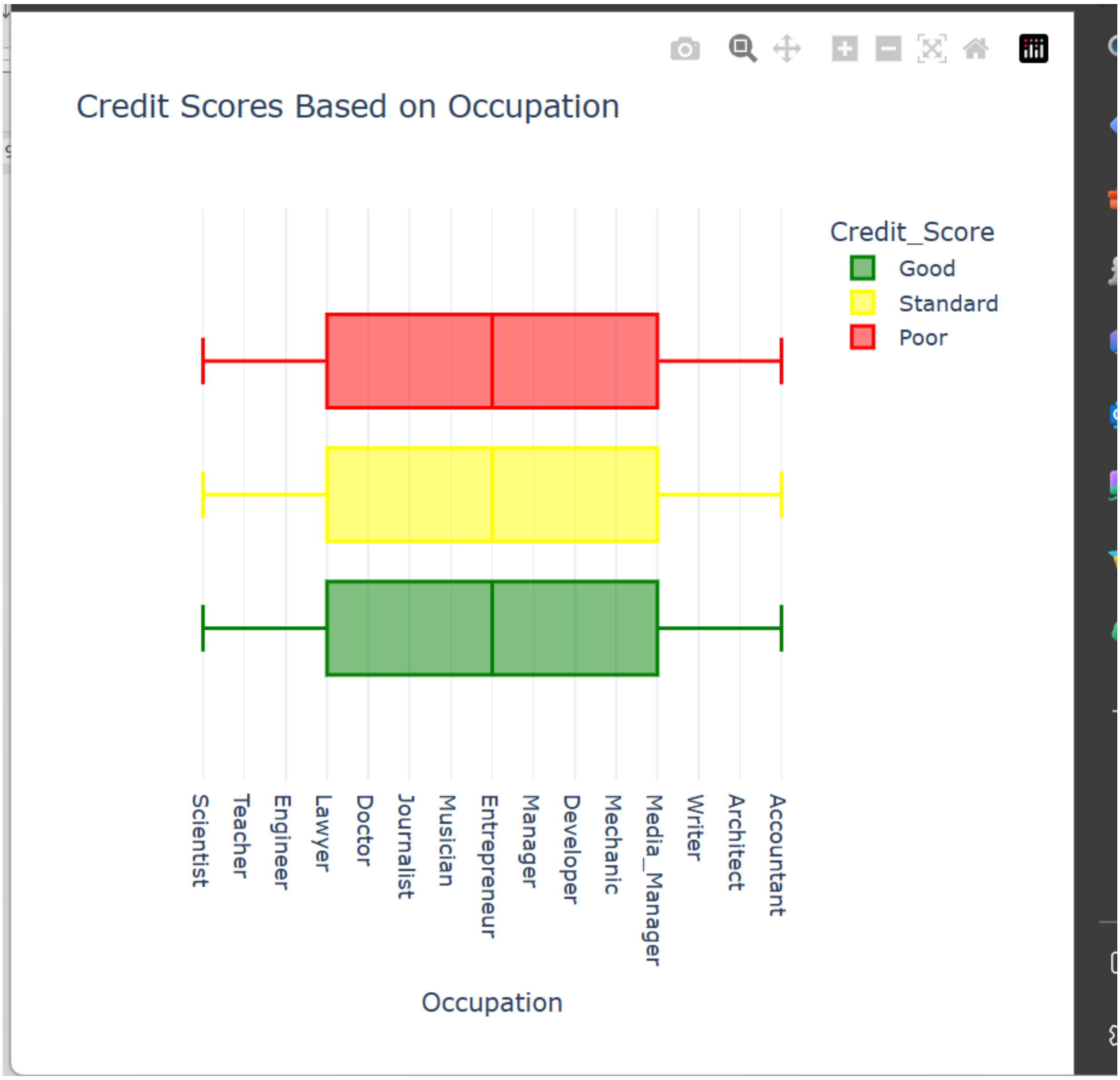
Outstanding Debt: 2

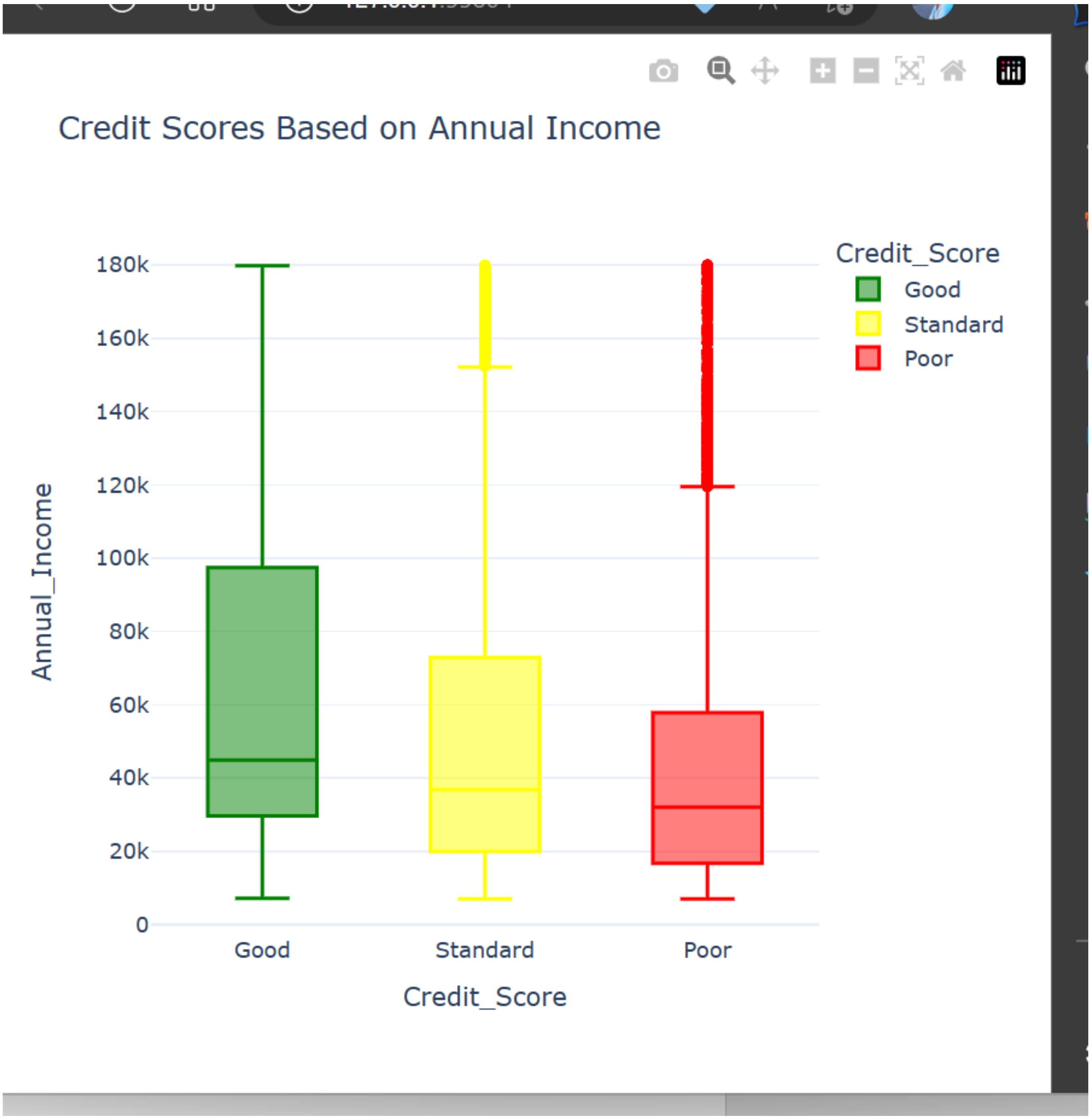
Credit History Age: 4

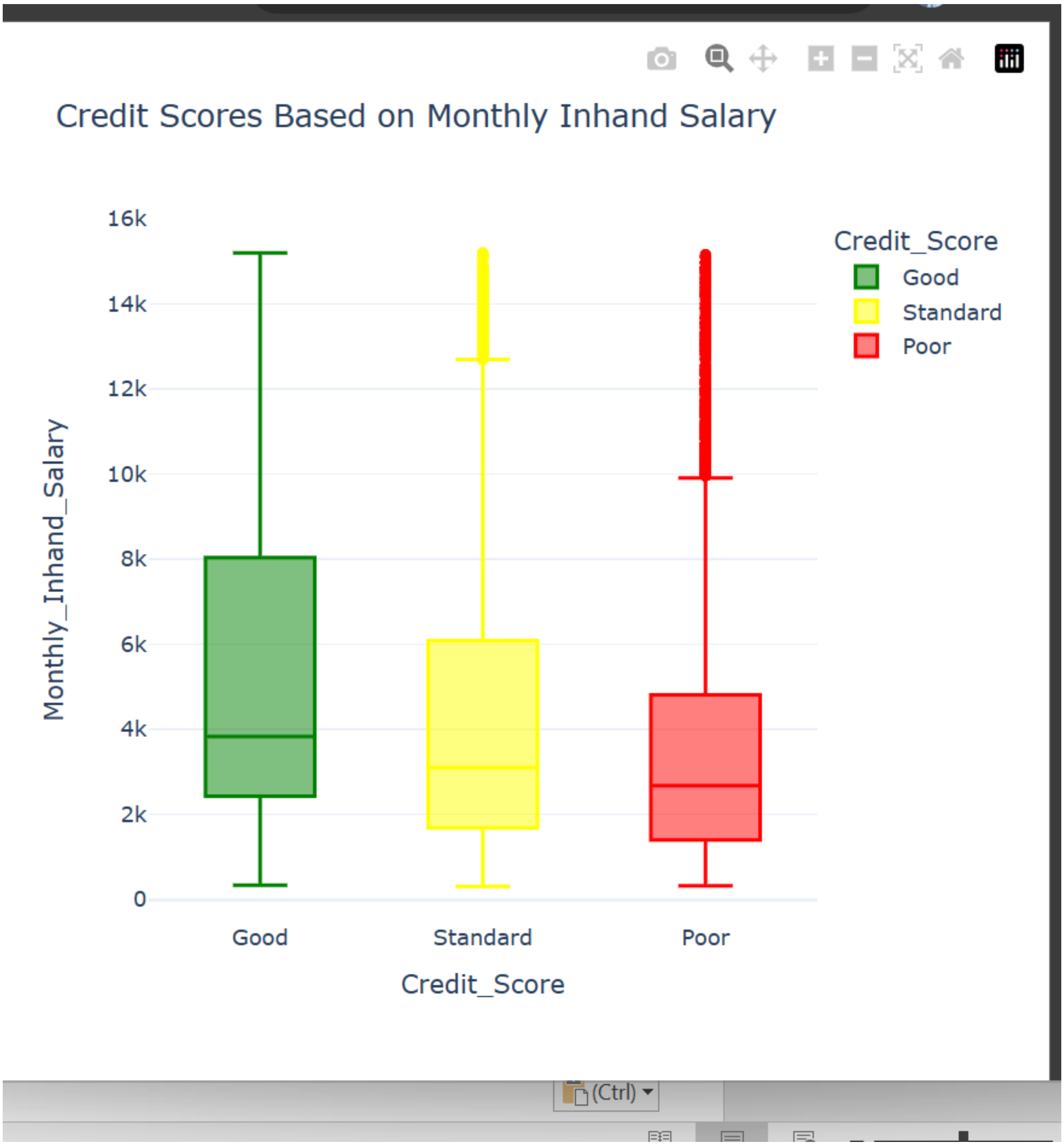
Monthly Balance: 1600

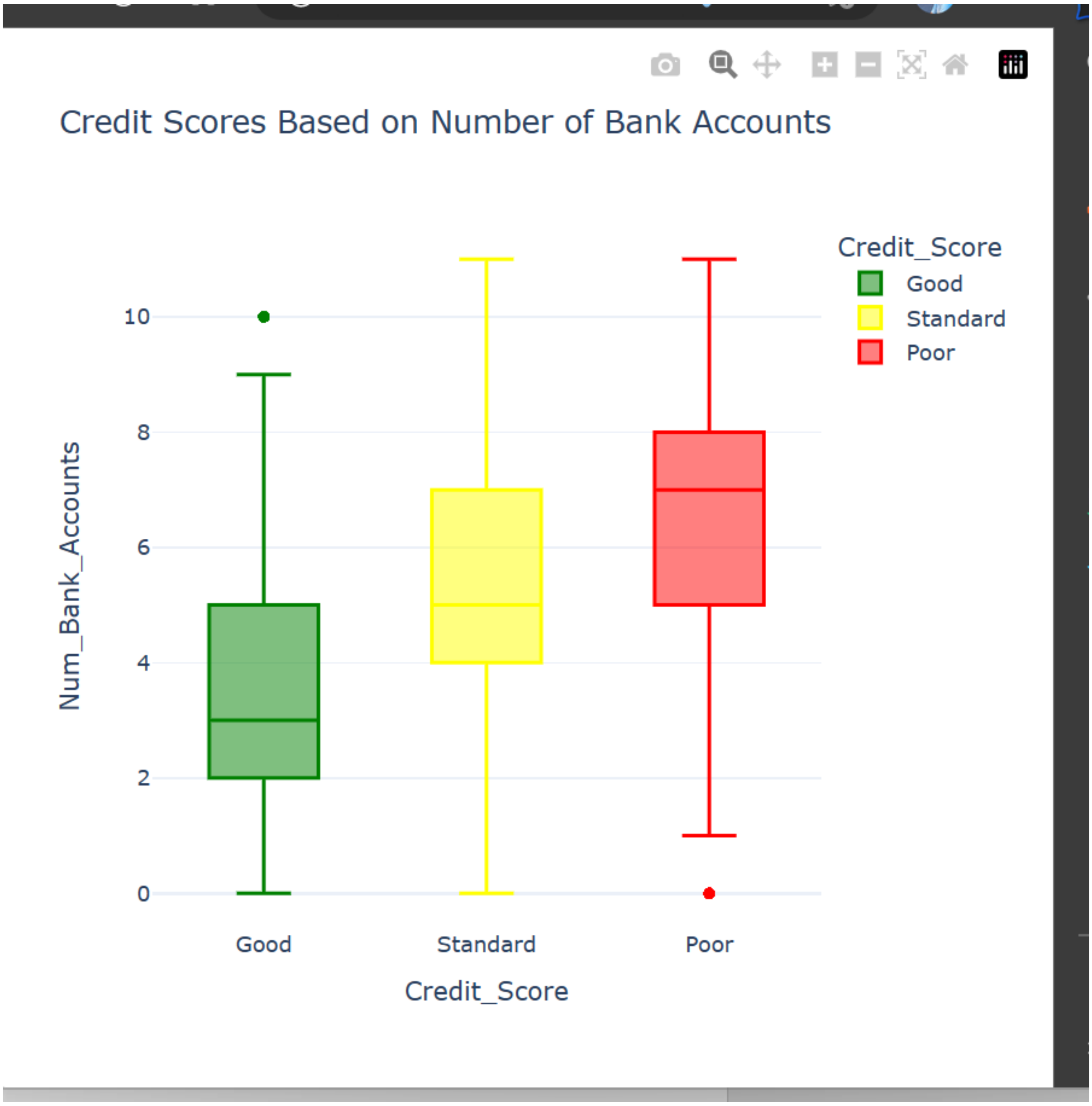
Predicted Credit Score = ['Good']

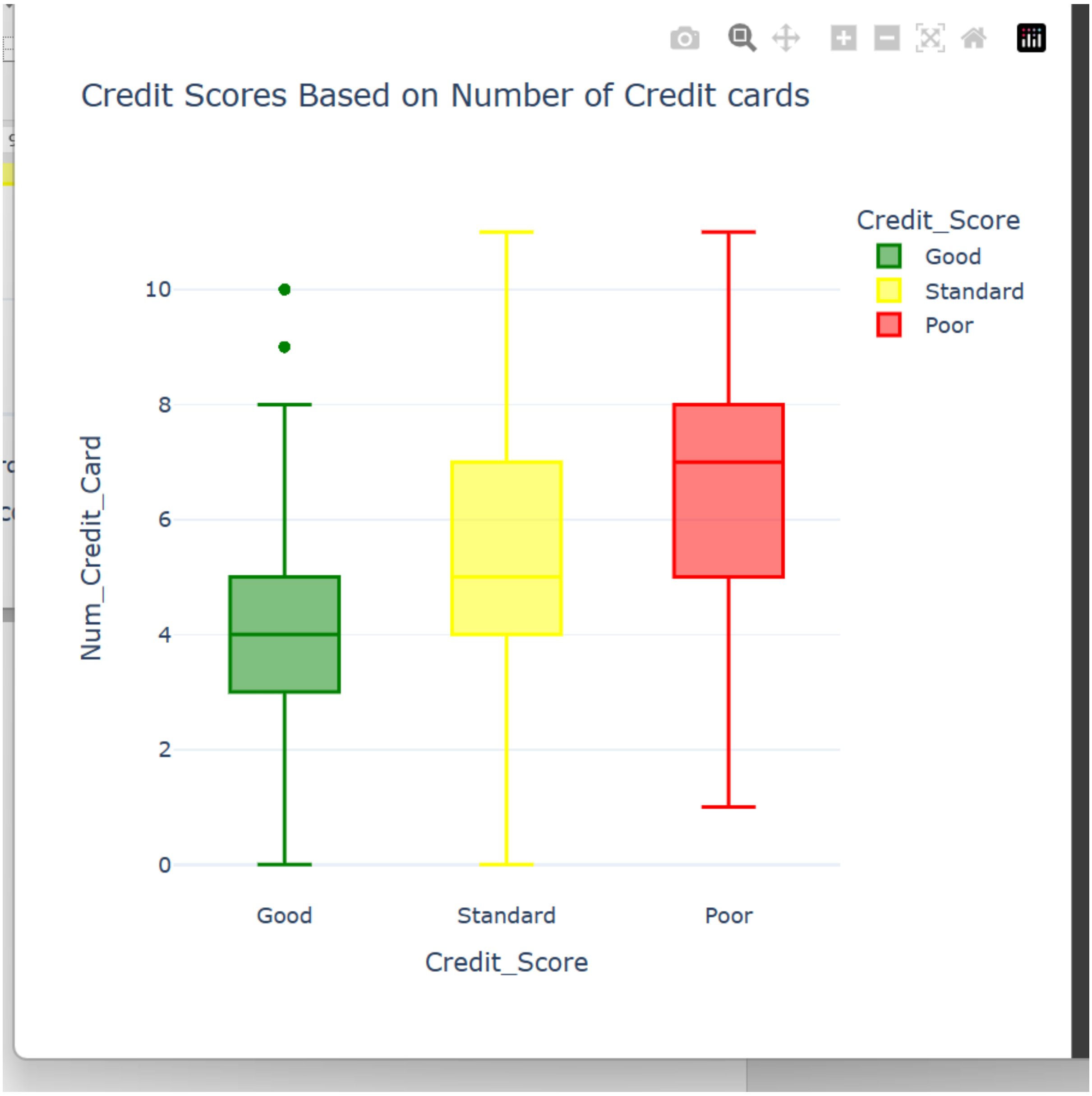
Graphs:

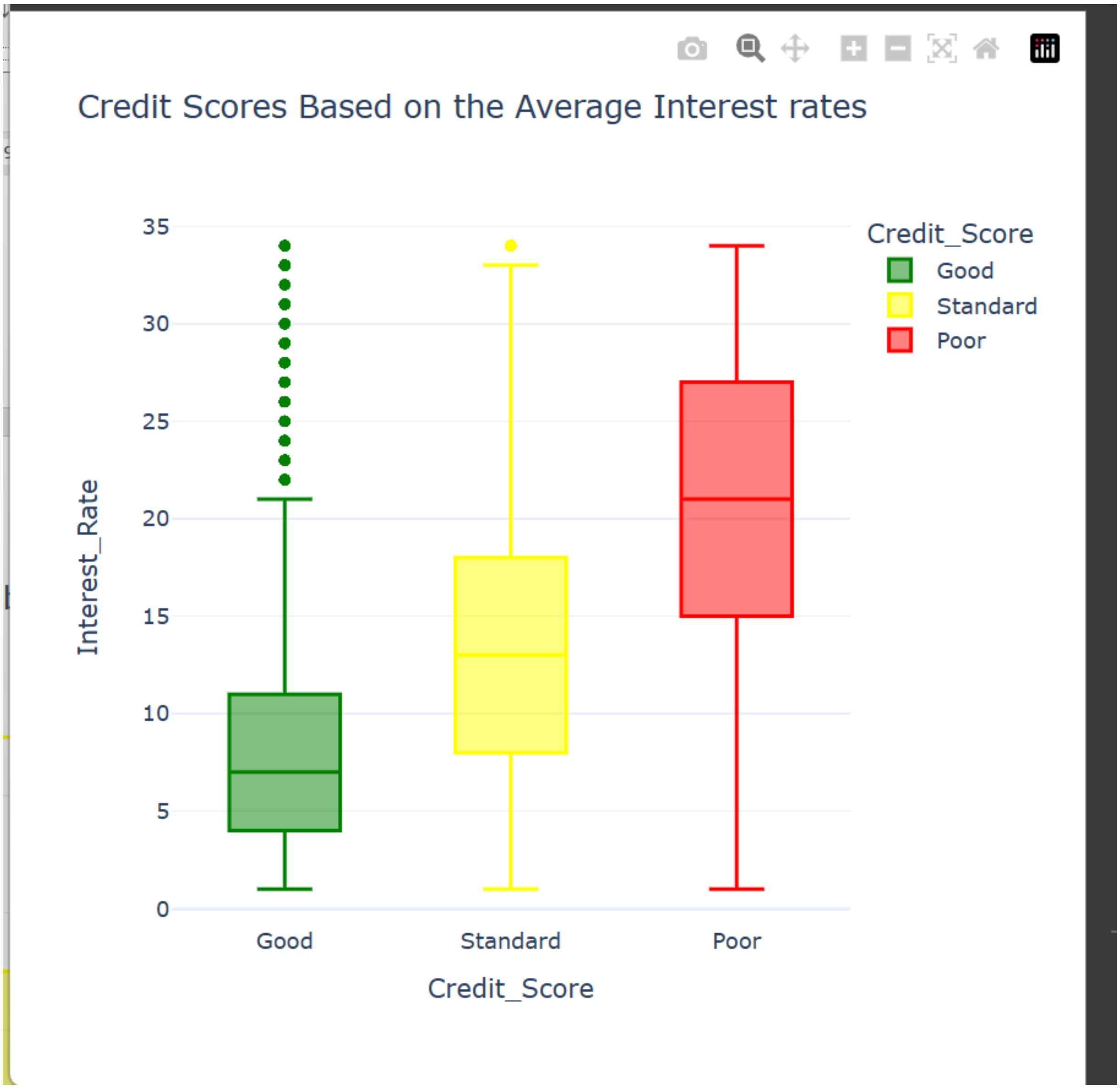



Credit Scores Based on Annual Income
Credit_Score
Good
Standard
Poor
180k
160k
140k
120k
100k
80k
60k
40k
20k
0
Annual_Income
Good
Standard
Poor
Credit_Score


Credit Scores Based on Monthly Inhand Salary
16k
14k
12k
10k
8k
6k
4k
2k
0
Monthly_Inhand_Salary
Good
Standard
Poor
Credit_Score
Credit_Score
Good
Standard
Poor
(Ctrl)


Credit Scores Based on Number of Bank Accounts
Credit_Score
Good
Standard
Poor
Num_Bank_Accounts
0
2
4
6
8
10
Good
Standard
Poor
Credit_Score


Credit Scores Based on Number of Credit cards
Credit_Score
Good
Standard
Poor
Num_Credit_Card
10
8
6
4
2
0
Good
Standard
Poor
Credit_Score



12. Iris Flower Classification using KNN

"""

Created on Tue Jan 24 09:37:46 2023

@author: GEOMOL GEORGE

Iris Flower Classification using Python

"""

import pandas as pd

import matplotlib.pyplot as plt

import numpy as np

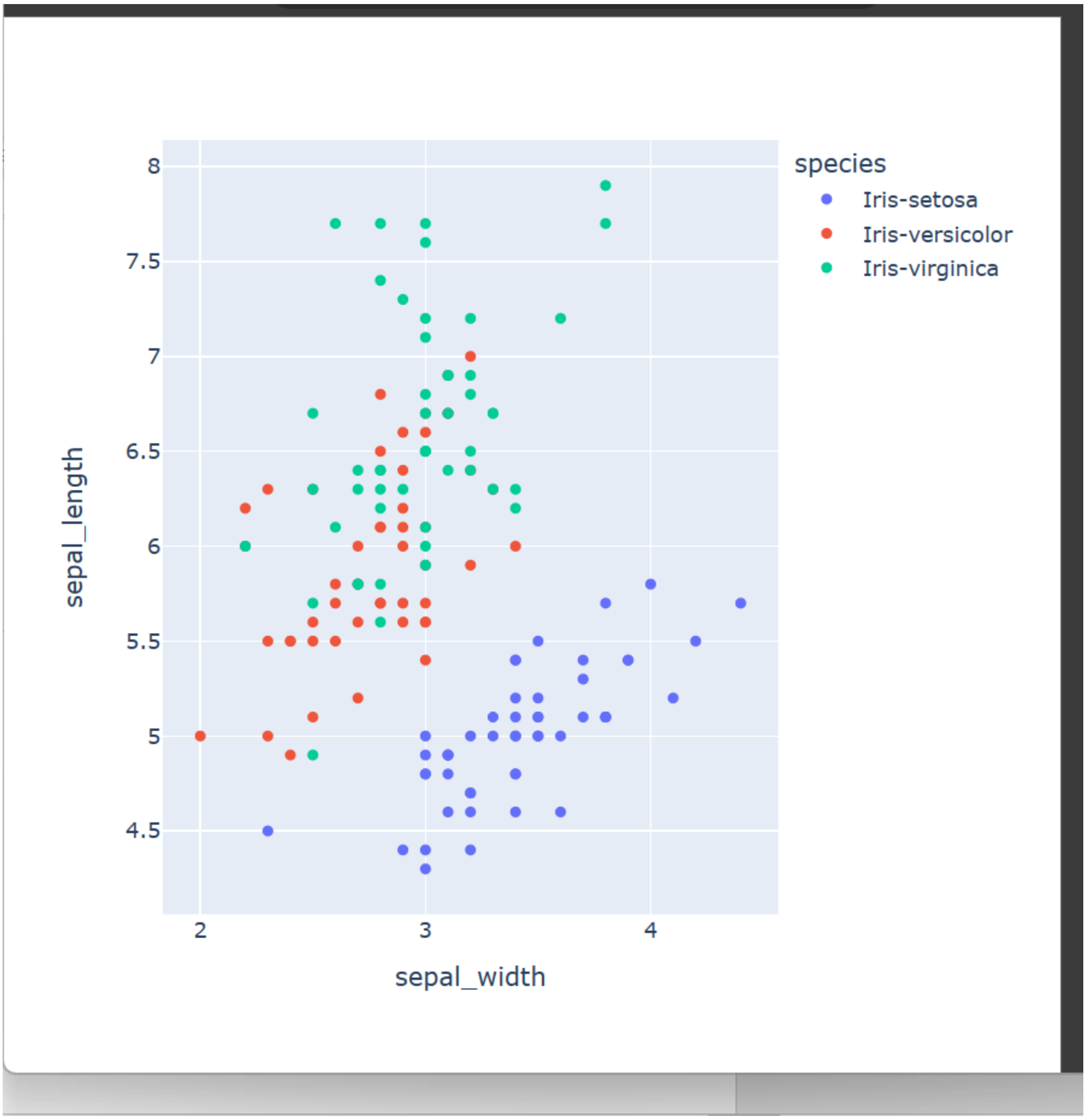
iris = pd.read_csv("D:/GEO/BE COURSES/LAB/DATASET/IRIS.csv")

#first five rows of this dataset:

```
print(iris.head())

print(iris.describe())

#The target labels of this dataset are present in the species column, let’s have a quick look at the target labels:


print("Target Labels", iris["species"].unique())

#plot the data using a scatter plot which will plot the iris species according to the sepal length and sepal width:


import plotly.io as io

io.renderers.default='browser'


import plotly.express as px

fig = px.scatter(iris, x="sepal_width", y="sepal_length", color="species")

fig.show()

#Iris Classification Model


x = iris.drop("species", axis=1)

y = iris["species"]

from sklearn.model_selection import train_test_split

x_train, x_test, y_train, y_test = train_test_split(x, y,test_size=0.2,random_state=0)


from sklearn.neighbors import KNeighborsClassifier

knn = KNeighborsClassifier(n_neighbors=1)

knn.fit(x_train, y_train)


x_new = np.array([[6, 2.9, 1, 0.2]])

prediction = knn.predict(x_new) print

("Prediction: {}".format(prediction))
```

Output:

```
   sepal_length  sepal_width  petal_length  petal_width      species
0           5.1          3.5           1.4          0.2  Iris-setosa
1           4.9          3.0           1.4          0.2  Iris-setosa
2           4.7          3.2           1.3          0.2  Iris-setosa
3           4.6          3.1           1.5          0.2  Iris-setosa
4           5.0          3.6           1.4          0.2  Iris-setosa
       sepal_length  sepal_width  petal_length  petal_width
count    150.000000   150.000000    150.000000   150.000000
mean       5.843333     3.054000      3.758667     1.198667
std        0.828066     0.433594      1.764420     0.763161
min        4.300000     2.000000      1.000000     0.100000
25%        5.100000     2.800000      1.600000     0.300000
50%        5.800000     3.000000      4.350000     1.300000
75%        6.400000     3.300000      5.100000     1.800000
max        7.900000     4.400000      6.900000     2.500000
Target Labels ['Iris-setosa' 'Iris-versicolor' 'Iris-virginica']
```



13. **Car Price Prediction Model using Python**

"""

Created on Tue Jan 24 10:02:09 2023

@author: GEOMOL GEORGE

car price prediction

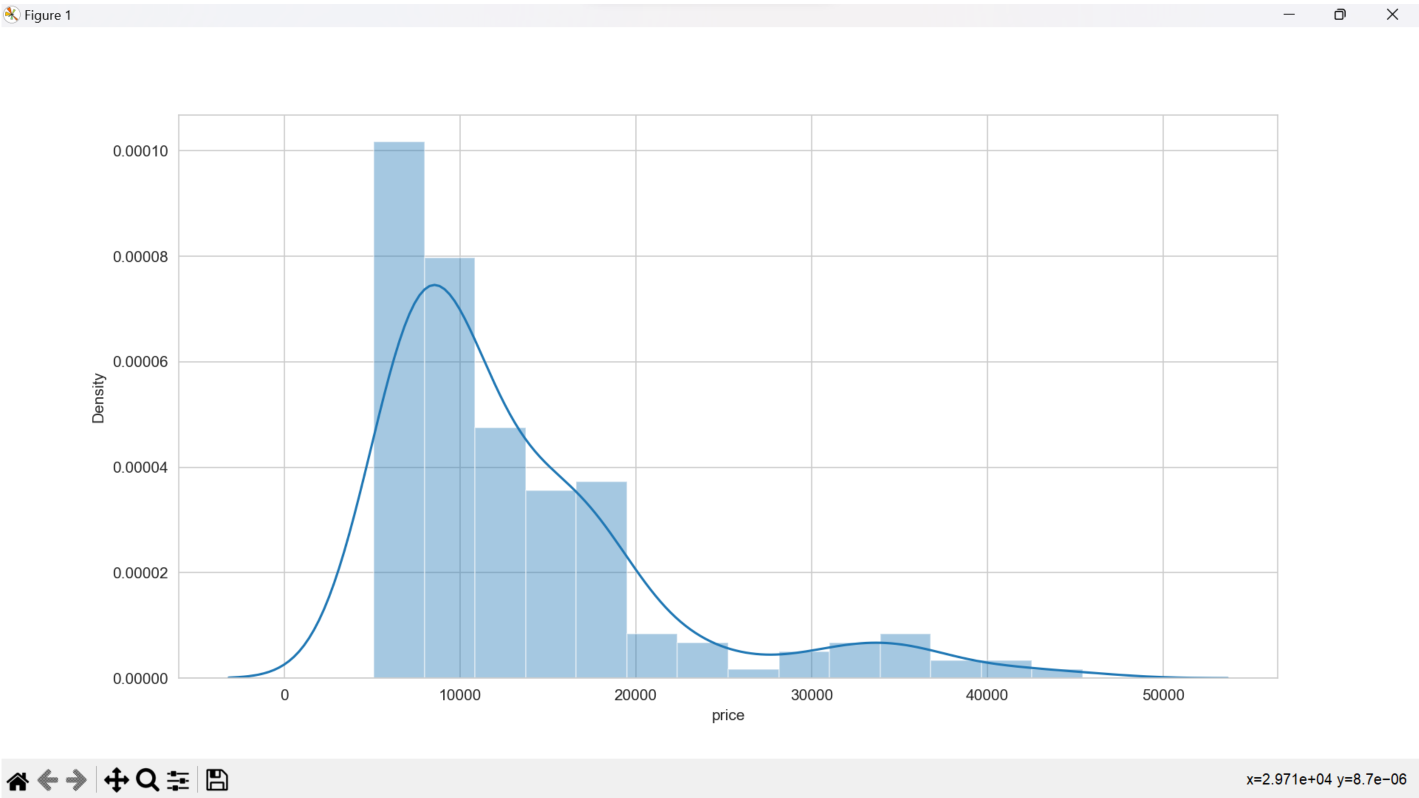
"""

import numpy as np

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeRegressor

data = pd.read_csv("D:/GEO/BE COURSES/LAB/DATASET/CarPrice.csv")
data.head()
data.shape
data.isnull().sum()
#So this dataset doesn’t have any null values, now let’s look at some of the other important insights to get
#an idea of what kind of data we’re dealing with:
data.info()
data.describe()
data.CarName.unique()

sns.set_style("whitegrid")
plt.figure(figsize=(15, 10))
sns.distplot(data.price)
plt.show()

#Now let’s have a look at the correlation among all the features of this dataset:

print(data.corr())



plt.figure(figsize=(20, 15))
correlations = data.corr()
sns.heatmap(correlations, cmap="coolwarm", annot=True)
plt.show()

#Training a Car Price Prediction Model
predict = "price"
data = data[["symboling", "wheelbase", "carlength",
```

```
        "carwidth", "carheight", "curbweight",
        "enginesize", "boreratio", "stroke",
        "compressionratio", "horsepower", "peakrpm",
        "citympg", "highwaympg", "price"]]
x = np.array(data.drop([predict], 1))
y = np.array(data[predict])

from sklearn.model_selection import train_test_split
xtrain, xtest, ytrain, ytest = train_test_split(x, y, test_size=0.2)

from sklearn.tree import DecisionTreeRegressor
model = DecisionTreeRegressor()
model.fit(xtrain, ytrain)
predictions = model.predict(xtest)

from sklearn.metrics import mean_absolute_error
model.score(xtest, predictions)
```

```
================================================= RESTART: C:\mach:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205 entries, 0 to 204
Data columns (total 26 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   car_ID            205 non-null    int64
 1   symboling         205 non-null    int64
 2   CarName           205 non-null    object
 3   fueltype          205 non-null    object
 4   aspiration        205 non-null    object
 5   doornumber        205 non-null    object
 6   carbody           205 non-null    object
 7   drivewheel        205 non-null    object
 8   enginelocation    205 non-null    object
 9   wheelbase         205 non-null    float64
 10  carlength         205 non-null    float64
 11  carwidth          205 non-null    float64
 12  carheight         205 non-null    float64
 13  curbweight        205 non-null    int64
 14  enginetype        205 non-null    object
 15  cylindernumber    205 non-null    object
 16  enginesize        205 non-null    int64
 17  fuelsystem        205 non-null    object
 18  boreratio         205 non-null    float64
 19  stroke            205 non-null    float64
 20  compressionratio  205 non-null    float64
 21  horsepower        205 non-null    int64
 22  peakrpm           205 non-null    int64
 23  citympg           205 non-null    int64
 24  highwaympg        205 non-null    int64
 25  price             205 non-null    float64
dtypes: float64(8), int64(8), object(10)
memory usage: 41.8+ KB
```



14. House Price Prediction using Machine Learning in Python

```
# -*- coding: utf-8 -*-
"""
Created on Mon Jan 23 11:39:55 2023

@author: GEOMOL GEORGE
"""
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

dataset = pd.read_excel("HousePricePrediction.xlsx")

# Printing first 5 records of the dataset
print(dataset.head(5))

dataset.shape

obj = (dataset.dtypes == 'object')
object_cols = list(obj[obj].index)
print("Categorical variables:",len(object_cols))

int_ = (dataset.dtypes == 'int')
num_cols = list(int_[int_].index)
print("Integer variables:",len(num_cols))

fl = (dataset.dtypes == 'float')
fl_cols = list(fl[fl].index)
print("Float variables:",len(fl_cols))



plt.figure(figsize=(12, 6))
sns.heatmap(dataset.corr(),
                        cmap = 'BrBG',
                        fmt = '.2f',
                        linewidths = 2,
                        annot = True)

unique_values = []
```

```
for col in object_cols:
  unique_values.append(dataset[col].unique().size)
plt.figure(figsize=(10,6))
plt.title('No. Unique values of Categorical Features')
plt.xticks(rotation=90)
sns.barplot(x=object_cols,y=unique_values)

plt.figure(figsize=(18, 36))
plt.title('Categorical Features: Distribution')
plt.xticks(rotation=90)
index = 1

for col in object_cols:
	y = dataset[col].value_counts()
	plt.subplot(11, 4, index)
	plt.xticks(rotation=90)
	sns.barplot(x=list(y.index), y=y)
	index += 1

dataset.drop(['Id'],
			axis=1,
			inplace=True)

dataset['SalePrice'] = dataset['SalePrice'].fillna(dataset['SalePrice'].mean())

new_dataset = dataset.dropna()

new_dataset.isnull().sum()



from sklearn.preprocessing import OneHotEncoder

s = (new_dataset.dtypes == 'object')
object_cols = list(s[s].index)
print("Categorical variables:")
print(object_cols)
print('No. of. categorical features: ',len(object_cols))
```

```
OH_encoder = OneHotEncoder(sparse=False)
OH_cols = pd.DataFrame(OH_encoder.fit_transform(new_dataset[object_cols]))
OH_cols.index = new_dataset.index
OH_cols.columns = OH_encoder.get_feature_names()
df_final = new_dataset.drop(object_cols, axis=1)
df_final = pd.concat([df_final, OH_cols], axis=1)



from sklearn.metrics import mean_absolute_error
from sklearn.model_selection import train_test_split

X = df_final.drop(['SalePrice'], axis=1)
Y = df_final['SalePrice']

# Split the training set into
# training and validation set
X_train, X_valid, Y_train, Y_valid = train_test_split(X, Y, train_size=0.8, test_size=0.2, random_state=0)
#Model and Accuracy
#svm

from sklearn import svm
from sklearn.svm import SVC
from sklearn.metrics import mean_absolute_percentage_error

model_SVR = svm.SVR()
model_SVR.fit(X_train,Y_train)
Y_pred = model_SVR.predict(X_valid)

print(mean_absolute_percentage_error(Y_valid, Y_pred))
#Random forest

from sklearn.ensemble import RandomForestRegressor

model_RFR = RandomForestRegressor(n_estimators=10)
model_RFR.fit(X_train, Y_train)
Y_pred = model_RFR.predict(X_valid)

mean_absolute_percentage_error(Y_valid, Y_pred)
```

```
#LinearRegression
from sklearn.linear_model import LinearRegression

model_LR = LinearRegression()
model_LR.fit(X_train, Y_train)
Y_pred = model_LR.predict(X_valid)

print(mean_absolute_percentage_error(Y_valid, Y_pred))
```

```
==================================================== RESTART: C:\machin
   Id  MSSubClass MSZoning  ...  BsmtFinSF2 TotalBsmtSF SalePrice
0   0          60       RL  ...         0.0       856.0  208500.0
1   1          20       RL  ...         0.0      1262.0  181500.0
2   2          60       RL  ...         0.0       920.0  223500.0
3   3          70       RL  ...         0.0       756.0  140000.0
4   4          60       RL  ...         0.0      1145.0  250000.0

[5 rows x 13 columns]
Categorical variables: 4
Integer variables: 0
Float variables: 3
```

15. NAÏVE IRIS CLASSIFICATION

```
# -*- coding: utf-8 -*-
"""
Created on Tue Jan 24 11:44:42 2023

@author: GEOMOL GEORGE
"""


from sklearn.naive_bayes import GaussianNB
from sklearn.naive_bayes import MultinomialNB
from sklearn import datasets
from sklearn.metrics import confusion_matrix

iris = datasets.load_iris()
gnb = GaussianNB()
mnb = MultinomialNB()

y_pred_gnb = gnb.fit(iris.data, iris.target).predict(iris.data)

cnf_matrix_gnb = confusion_matrix(iris.target, y_pred_gnb)

print(cnf_matrix_gnb)
y_pred_mnb = mnb.fit(iris.data, iris.target).predict(iris.data)
cnf_matrix_mnb = confusion_matrix(iris.target, y_pred_mnb)
print(cnf_matrix_mnb)
```

```
============================
[[50  0  0]
 [ 0 47  3]
 [ 0  3 47]]
[[50  0  0]
 [ 0 46  4]
 [ 0  3 47]]
>
```

16. Comparison of Classification Algorithms

```
"""
Created on Wed Jan 25 13:10:08 2023

@author: GEOMOL GEORGE
Comparison of Classification Algorithms
"""

import numpy
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import BernoulliNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import PassiveAggressiveClassifier
from sklearn.metrics import classification_report

iris= pd.read_csv("D:/GEO/BE COURSES/LAB/DATASET/IRIS.csv")
print(iris.head())

x = iris.drop("species", axis=1)
y = iris["species"]
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y,test_size=0..10,random_state=42)

#x = np.array(data[["Age", "EstimatedSalary"]])
#y = np.array(data[["Purchased"]])

#xtrain, xtest, ytrain, ytest = train_test_split(x, y, test_size=0.10, random_state=42)
decisiontree = DecisionTreeClassifier()
logisticregression = LogisticRegression()
knearestclassifier = KNeighborsClassifier()
#svm_classifier = SVC()
bernoulli_naiveBayes = BernoulliNB()
passiveAggressive = PassiveAggressiveClassifier()

knearestclassifier.fit(x_train, y_train)
decisiontree.fit(x_train, y_train)
logisticregression.fit(x_train, y_train)
passiveAggressive.fit(x_train, y_train)

data1 = {"Classification Algorithms": ["KNN Classifier", "Decision Tree Classifier",
                                 "Logistic Regression", "Passive Aggressive Classifier"],
     "Score": [knearestclassifier.score(x,y), decisiontree.score(x, y),
              logisticregression.score(x, y), passiveAggressive.score(x,y) ]}
score = pd.DataFrame(data1)
```

score

```
>>
====================================================== RESTART: C:\machine le
   sepal_length  sepal_width  petal_length  petal_width      species
0           5.1          3.5           1.4          0.2  Iris-setosa
1           4.9          3.0           1.4          0.2  Iris-setosa
2           4.7          3.2           1.3          0.2  Iris-setosa
3           4.6          3.1           1.5          0.2  Iris-setosa
4           5.0          3.6           1.4          0.2  Iris-setosa

Warning (from warnings module):
```

17. Mobile Price Classification using Python

```
"""
Created on Wed Jan 25 13:32:56 2023

@author: GEOMOL GEORGE
Mobile Price Classification using Python
"""

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
sns.set()

import plotly.io as io
io.renderers.default='browser'

data = pd.read_csv("D:/GEO/BE COURSES/LAB/DATASET/mobile_prices.csv")
print(data.head())
plt.figure(figsize=(12, 10))
sns.heatmap(data.corr(), annot=True, cmap="coolwarm", linecolor='white', linewidths=1)

#data preparation
x = data.iloc[:, :-1].values
y = data.iloc[:, -1].values
x = StandardScaler().fit_transform(x)
```

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.20, random_state=0)

Logistic Regression algorithm provided by Scikit-learn:

from sklearn.linear_model import LogisticRegression

lreg = LogisticRegression()

lreg.fit(x_train, y_train)

y_pred = lreg.predict(x_test)

#accuracy of the model:

accuracy = accuracy_score(y_test, y_pred) * 100

print("Accuracy of the Logistic Regression Model: ",accuracy)

#predictions made by the model:

print(y_pred)

#Let's have a look at the number of mobile phones classified for each price range:

(unique, counts) = np.unique(y_pred, return_counts=True)

price_range = np.asarray((unique, counts)).T

print(price_range)

```
>>>
==================================================== RESTART: C:\machine learning programs\lab\17th.py ====
   battery_power  blue  clock_speed  ...  touch_screen  wifi  price_range
0            842     0          2.2  ...             0     1            1
1           1021     1          0.5  ...             1     0            2
2            563     1          0.5  ...             1     0            2
3            615     1          2.5  ...             0     0            2
4           1821     1          1.2  ...             1     0            1

[5 rows x 21 columns]
Accuracy of the Logistic Regression Model:  95.5
[3 0 2 2 3 0 0 3 3 1 1 3 0 2 3 0 3 2 2 1 0 0 3 1 2 2 3 1 3 1 1 0 2 0 2 3 0
 0 3 3 3 1 3 3 1 3 0 1 3 1 1 3 0 3 0 2 2 2 0 3 3 1 3 2 1 2 3 2 2 2 3 2 1 0
 1 3 2 2 1 2 3 3 3 0 0 0 2 1 2 3 1 2 2 1 0 3 3 3 0 3 1 1 3 1 3 2 2 3 2 3 3
 0 0 1 3 3 0 0 1 0 0 3 2 2 1 2 1 1 0 2 1 3 3 3 3 3 3 2 0 1 1 2 1 3 0 3 0 0
 2 0 1 1 1 1 3 0 0 3 1 3 2 1 3 1 2 3 3 2 1 0 3 1 2 3 3 0 2 2 3 1 2 1 0 1 2
 2 2 0 3 3 1 1 0 2 3 0 1 2 2 0 3 3 3 1 2 3 3 3 0 0 0 2 3 3 0 0 1 3 2 3 3 3
 0 0 2 3 3 1 0 2 0 0 0 3 2 1 2 2 1 1 0 2 3 3 0 0 1 3 3 1 3 0 3 1 1 0 2 3 3
 2 0 0 1 2 3 2 2 3 2 1 0 3 3 2 1 3 2 2 2 1 0 2 2 1 0 0 2 2 2 3 0 1 3 0 2 2
 3 0 2 0 1 1 3 0 0 2 3 1 2 0 2 0 3 0 3 3 2 3 1 2 2 1 1 1 0 1 0 3 1 0 3 0 0
 1 3 0 3 1 1 0 1 3 0 2 1 1 2 1 1 0 2 0 0 3 1 2 3 2 2 0 3 2 2 1 3 2 3 3 3 0
 2 0 3 0 1 1 2 3 1 3 1 2 0 1 2 3 0 0 1 3 0 3 0 2 2 1 1 0 2 0]
[[  0  95]
 [  1  90]
 [  2  97]
 [  3 118]]
```

18. Perceptron IRIS classiification

"""

Created on Tue Jan 24 10:51:21 2023

Perceptron IRIS classiification

@author: GEOMOL GEORGE

```
"""

from sklearn import datasets
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.linear_model import Perceptron
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score

iris = datasets.load_iris()
X = iris.data[:, [2, 3]]
y = iris.target

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.3, random_state=1, stratify=y)

sc = StandardScaler()
sc.fit(X_train)
X_train_std = sc.transform(X_train)
X_test_std = sc.transform(X_test)

ppn = Perceptron(eta0=0.1, random_state=1)
ppn.fit(X_train_std, y_train)

y_pred = ppn.predict(X_test_std)

print('Accuracy: %.3f' % accuracy_score(y_test, y_pred))
print('Accuracy: %.3f' % ppn.score(X_test_std, y_test))
```

```
=============================================
Accuracy: 0.978
Accuracy: 0.978
>>
```

19.Implementation of Naive Bayes in Python – Machine Learning

```
"""
Created on Fri Jan 27 11:28:03 2023

@author: GEOMOL GEORGE
```

Implementation of Naive Bayes in Python – Machine Learning

In this tutorial, we will understand the Implementation of Naive Bayes in Python – Machine Learning.

Importing the Necessary libraries

```
"""
import numpy as np
import pandas as pd
#Importing the dataset
"""
```

Next, we import or read the dataset. Click here to download the breast cancer dataset used in this implementation

```
"""
dataset = pd.read_csv("D:/GEO/BE COURSES/LAB/DATASET/breastcancer.csv")
X = dataset.iloc[:, :-1].values
y = dataset.iloc[:, -1].values
"""
```

Splitting the dataset into the Training set and Test set

Once the dataset is read into the memory, next, divide the dataset into two parts, training and testing using the train_test_split function from sklearn.

The test_size and random_state attributes are set to 0.25 and 0 respectively.

You can change these attributes as per your requirements.

```
"""
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state = 0)

#Feature Scaling
"""
```

Feature scaling is the process of converting the data into a min-max range. In this case, the standard scalar method is used.

```
"""
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
"""
```

Training the Naive Bayes Classification model on the Training set

The GaussianNB function is imported from sklearn.naive_bayes library. The hyperparameters such as kernel, and random_state to linear, and 0 respectively. The remaining hyperparameters of the support vector machine algorithm are set to default values.

```
"""
from sklearn.naive_bayes import GaussianNB
classifier = GaussianNB()
classifier.fit(X_train, y_train)

#Naive Bayes classifier model
GaussianNB(priors=None, var_smoothing=1e-09)

#Display the results (confusion matrix and accuracy)
"""
Here evaluation metrics such as confusion matrix and accuracy are used to evaluate the performance of
the model built using a decision tree classifier.
"""
from sklearn.metrics import confusion_matrix, accuracy_score
y_pred = classifier.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
print(cm)
accuracy_score(y_test, y_pred)
```

```
=====================
[[99  8]
 [ 2 62]]
>>
```

20.Future Sales Prediction using Python

```
"""
Created on Tue Jan 24 13:52:17 2023

@author: GEOMOL GEORGE
Future Sales Prediction using Python
"""

import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
import plotly.io as io
io.renderers.default='browser'

data = pd.read_csv("D:/GEO/BE COURSES/LAB/DATASET/futuresale prediction.csv")
```

```
print(data.head())



print(data.sample(5))
print(data.isnull().sum())
import plotly.express as px
import plotly.graph_objects as go
figure = px.scatter(data_frame = data, x="Sales",
            y="TV", size="TV", trendline="ols")
figure.show()
figure = px.scatter(data_frame = data, x="Sales",
            y="Newspaper", size="Newspaper", trendline="ols")
figure.show()
figure = px.scatter(data_frame = data, x="Sales",
            y="Radio", size="Radio", trendline="ols")
figure.show()
correlation = data.corr()
print(correlation["Sales"].sort_values(ascending=False))
x = np.array(data.drop(["Sales"], 1))
y = np.array(data["Sales"])
xtrain, xtest, ytrain, ytest = train_test_split(x, y,
                            test_size=0.2,
                            random_state=42)
model = LinearRegression()
model.fit(xtrain, ytrain)
print(model.score(xtest, ytest))
features = [[TV, Radio, Newspaper]]
features = np.array([[230.1, 37.8, 69.2]])
print(model.predict(features))
```

```
==================================================
      TV  Radio  Newspaper  Sales
0  230.1   37.8       69.2   22.1
1   44.5   39.3       45.1   10.4
2   17.2   45.9       69.3   12.0
3  151.5   41.3       58.5   16.5
4  180.8   10.8       58.4   17.9
        TV  Radio  Newspaper  Sales
5      8.7   48.9       75.0    7.2
101  296.4   36.3      100.9   23.8
110  225.8    8.2       56.5   18.4
154  187.8   21.1        9.5   20.6
53   182.6   46.2       58.7   21.2
TV           0
Radio        0
Newspaper    0
Sales        0
dtype: int64
```