**MULTIVARIATE STATISTICS(LAB)**

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**1. LOGISTIC REGRESSION**

**import pandas as pd**

**import numpy as np**

**import matplotlib.pyplot as plt**

**import os**

**from sklearn.model\_selection import train\_test\_split**

**from sklearn.linear\_model import LogisticRegression**

**from sklearn.metrics import confusion\_matrix**

**os.chdir("C:/Users/Dell/Downloads")**

**data=pd.read\_csv('Telecom\_Data.csv')**

**data.info()**

**# regressor variables**

**x = data.iloc[:, 0:20].values**

**#print(x)**

**# regressed variables**

**y = data.iloc[:, 20].values**

**#print(y)**

**xtrain, xtest, ytrain, ytest = train\_test\_split(x, y, test\_size = 0.25, random\_state = 0)**

**classifier = LogisticRegression(random\_state = 0)**

**classifier.fit(xtrain, ytrain)**

**#y\_pred = classifier.predict(xtest)**

**#cm = confusion\_matrix(ytest, y\_pred)**

**#print ("Confusion Matrix : \n", cm)**

**2. TAKING DUPLICATE DATASET**

**import pandas as pd**

**import numpy as np**

**import os**

**import seaborn as sns**

**import matplotlib.pyplot as plt**

**os.chdir("C:/Users/Dell/Downloads")**

**iris = pd.read\_csv('Iris.csv')**

**print(iris.head())**

**print(iris.describe())**

**sns.countplot(x='Species', data = iris)**

**plt.show()**

**#sns.scatterplot('SepalLengthCm','SepalWidthCm', hue='Species',data = iris)**

**#plt.show()**

**#sns.pairplot(iris.drop(['Id'],axis =1), hue= 'Species', height= 2)**

**#plt.show()**

**#sns.heatmap(iris.corr(), data = iris)**

**#plt.show()**

**#x= iris.corr(method= 'pearson')**

**#print(x)**

**#sns.heatmap(iris.corr(method='pearson').drop(['Id'],axis=1).drop(['Id'],axis=0))**

**3.CLUSTERING**

**from sklearn.datasets import load\_iris**

**from sklearn.cluster import AgglomerativeClustering**

**import numpy as np**

**import pandas as pd**

**import matplotlib.pyplot as plt**

**from scipy.cluster.hierarchy import dendrogram, linkage**

**import os**

**os.chdir("C:/Users/Dell/Downloads")**

**dataset = pd.read\_csv('CarPrice\_Assignment\_FA.csv')**

**dataset.drop(['car\_ID','CarName'],axis=1,inplace=True)**

**dataset.info()**

**df = dataset.iloc[:, [8,9]].values**

**Z = linkage(df, method = "ward")**

**dendro = dendrogram(Z)**

**plt.title('Dendogram')**

**plt.ylabel('Euclidean distance')**

**plt.show()**

**ac = AgglomerativeClustering(n\_clusters=4, affinity="euclidean", linkage="ward")**

**labels = ac.fit\_predict(df)**

**plt.figure(figsize = (8,5))**

**plt.scatter(df[labels == 0,0] , df[labels == 0,1], c= 'red')**

**plt.scatter(df[labels == 1,0] , df[labels == 1,1], c= 'blue')**

**plt.scatter(df[labels == 2,0] , df[labels == 2,1], c= 'green')**

**plt.scatter(df[labels == 3,0] , df[labels == 3,1], c= 'black')**

**plt.scatter(df[labels == 4,0] , df[labels == 4,1], c= 'orange')**

**plt.show()**

**4. EDA AND LINEAR REGRESSION**

**# EDA and linear regression for two pair of variables**

**import pandas as pd**

**import numpy as np**

**import os**

**import seaborn as sns**

**import matplotlib.pyplot as plt**

**from sklearn import linear\_model**

**from sklearn import datasets**

**import sklearn**

**os.chdir("C:/Users/Dell/Downloads")**

**mtcars=pd.read\_csv('CarPrice\_Assignment.csv')**

**#print(mtcars.describe())**

**mtcars.info()**

**# 1. EDA and visualisation**

**#print(mtcars.describe())**

**#sns.countplot('doornumber',data=mtcars)**

**#plt.show()**

**#plt.hist('cylindernumber',data = mtcars)**

**#plt.show()**

**#x= mtcars.corr(method= 'pearson')**

**#print(x)**

**#sns.heatmap(mtcars.corr(method='pearson').drop(['car\_ID','symboling'],axis=1).drop(['car\_ID','symboling'],axis=0),data=mtcars)**

**#sns.show()**

**#df = pd.DataFrame(mtcars,columns=['cylindernumber','horsepower'])**

**#plt.bar(df['cylindernumber'], df['horsepower'])**

**#plt.title('Cylinder number vs Horsepower', fontsize=14)**

**#plt.xlabel('CYlinder Number', fontsize=14)**

**#plt.ylabel('Horse Power', fontsize=14)**

**#plt.show()**

**#sns.pairplot(mtcars)**

**#plt.show()**

**#sns.boxplot(y='compressionratio',x='fueltype',data=mtcars)**

**#plt.show()**

**#2. Regression on one variable**

**#(a) Regression on one variable for negative correlation**

**#X=mtcars[['highwaympg']]**

**#Y=mtcars[['horsepower']]**

**#reg=linear\_model.LinearRegression()**

**#reg.fit(X,Y)**

**#print(reg.coef\_)**

**#sns.regplot(X,Y)**

**#plt.show()**

**#(b) Regression on one variable for positive correlation**

**X=mtcars[['wheelbase']]**

**Y=mtcars[['carlength']]**

**reg=linear\_model.LinearRegression()**

**reg.fit(X,Y)**

**print(reg.coef\_)**

**print(reg.intercept\_) #IMP**

**sns.regplot(X,Y)**

**plt.show()**

**#(c) Regression on one variable with no correlation**

**#X=mtcars[['stroke']]**

**#Y=mtcars[['price']]**

**#reg=linear\_model.LinearRegression()**

**#reg.fit(X,Y)**

**#print(reg.coef\_)**

**#sns.regplot(X,Y)**

**#plt.show()**

**#3. Regression on multiple variables**

**X=mtcars[['horsepower','curbweight']]**

**Y=mtcars[['price']]**

**reg=linear\_model.LinearRegression()**

**reg.fit(X,Y)**

**print(reg.coef\_)**

**# complete credit to the internet for the below code**

**df2 = pd.DataFrame(mtcars,columns=['horsepower','curbweight','price'])**

**import statsmodels.formula.api as smf**

**model = smf.ols(formula='price ~ horsepower + curbweight', data=df2)**

**results\_formula = model.fit()**

**results\_formula.params**

**## Prepare the data for Visualization**

**x\_surf, y\_surf = np.meshgrid(np.linspace(df2.horsepower.min(), df2.horsepower.max(), 100),np.linspace(df2.curbweight.min(), df2.curbweight.max(), 100))**

**onlyX = pd.DataFrame({'horsepower': x\_surf.ravel(), 'curbweight': y\_surf.ravel()})**

**fittedY=results\_formula.predict(exog=onlyX)**

**## convert the predicted result in an array**

**fittedY=np.array(fittedY)**

**# Visualize the Data for Multiple Linear Regression**

**fig = plt.figure()**

**ax = fig.add\_subplot(111, projection='3d')**

**ax.scatter(df2['horsepower'],df2['curbweight'],df2['price'],c='red', marker='o', alpha=0.5)**

**ax.plot\_surface(x\_surf,y\_surf,fittedY.reshape(x\_surf.shape), color='b', alpha=0.3)**

**ax.set\_xlabel('Horsepower')**

**ax.set\_ylabel('Curbweight')**

**ax.set\_zlabel('Price')**

**plt.show()**

**5. FACTOR ANALYSIS**

**import pandas as pd**

**from sklearn.datasets import load\_iris**

**from factor\_analyzer import FactorAnalyzer**

**from factor\_analyzer.factor\_analyzer import calculate\_bartlett\_sphericity**

**from factor\_analyzer.factor\_analyzer import calculate\_kmo**

**import matplotlib.pyplot as plt**

**import os**

**import seaborn as sns**

**import numpy as np**

**os.chdir("C:/Users/DellDownloads")**

**df=pd.read\_csv('CarPrice\_Assignment\_FA.csv')**

**df.info()**

**df.drop(['car\_ID','CarName'],axis=1,inplace=True)**

**df.info()**

**# Converting the categorical data into continous was done manually using FIND AND REPLACE in MS Excel.**

**# Checking the correlation**

**#x= df.corr(method= 'pearson')**

**#print(x)**

**#sns.heatmap(df.corr(method='pearson'),data=df)**

**#plt.show()**

**# Bartlett’s test**

**#chi\_square\_value,p\_value=calculate\_bartlett\_sphericity(df)**

**#print(chi\_square\_value, p\_value)**

**# Not sure how to interpret this.**

**# Kaiser-Meyer-Olkin (KMO) Test**

**kmo\_all,kmo\_model=calculate\_kmo(df)**

**print(kmo\_model)**

**# KMO values range between 0 and 1. Value of KMO less than 0.5 is considered inadequate.**

**# The overall KMO for our data is 0.78, which is pretty good.**

**# This value indicates that we can proceed with our planned factor analysis.**

**#Choosing the number of factors**

**# Create factor analysis object and perform factor analysis**

**#fa = FactorAnalyzer()**

**#fa.analyze(df, 25, rotation=None)**

**#Check Eigenvalues**

**#ev, v = fa.get\_eigenvalues()**

**#print(ev)**

**fa = FactorAnalyzer()**

**fa.fit(df)**

**eigen\_values, vectors = fa.get\_eigenvalues()**

**print(vectors)**

**# 3 eigen values are greater than 1 therefore,**

**# NUMBER OF FACTORS = 3**

**# Create scree plot using matplotlib**

**plt.scatter(range(1,df.shape[1]+1),vectors)**

**plt.plot(range(1,df.shape[1]+1),vectors)**

**plt.title('Scree Plot')**

**plt.xlabel('Factors')**

**plt.ylabel('Eigenvalue')**

**plt.grid()**

**plt.show()**

**# It is understandable from the scree plot that the number of factors 3 or 4.**

**# Create factor analysis object and perform factor analysis**

**fa = FactorAnalyzer()**

**fa.set\_params(n\_factors=6, rotation='varimax')**

**fa.fit(df)**

**loadings = fa.loadings\_**

**print(loadings)**

**# Get variance of each factors**

**print(fa.get\_factor\_variance())**

**# It is in the below format**

**# Factor 1 Factor2 Factor3**

**# SS Loadings**

**# Proportion Var**

**# Cummulative Var**

**# Total 58% cumulative Variance is explained by the 3 factors.**

**6. HYPOTHESIS TESTING**

**getwd()**

**data=read.csv("CarPrice\_Assignment.csv")**

**mean(data$curbweight)**

**# H0: Mean curbweight = 2550**

**# H1: Mean curbweight > 2550**

**t.test(data$curbweight,mu=2550,alternative ='two.sided',conf.level=0.95)**

**7.MATRICES AND VECTORS**

**import numpy as np**

**X=np.array([[1,2,3],[3,2,1],[9,10,7]])**

**print(X)**

**Y=np.array([[1,2,3],[3,2,1],[9,10,7]]).T**

**print(X)**

**A=np.array([[0]\*3])**

**print(A)**

**print(np.zeros((4,8)))**

**print(np.ones(4))**

**print(X)**

**print(Y)**

**print(X+Y)**

**print(np.shape(X))**

**I=np.array([[10,20,30,40,50,60,70]])**

**print(I)**

**print(I[0,1],I[0,3],I[0,6])**

**print(np.shape(I))**

**print(I.T)**

**V=np.array([[1,2,3,4,5],[6,7,8,9,10],[11,12,13,14,15],[16,17,18,19,20]])**

**print(V)**

**print(np.shape(V))**

**print(V.T)**

**print(V[:,0])**

**print(V[0,:])**

**print(np.zeros(7))**

**print(np.ones(3))**

**8.QUESTIONS AND ANSWERS**

**import numpy as np**

**# 1. Define and print a 6 dimentional vector**

**X=np.array([[1,2,3,4,5,6]])**

**print(X)**

**# 2. Print the transpose of the above vector**

**print(X.T)**

**# 3. Define two non square matrices such that they can be mulplied.**

**X=np.array([[1,2],[3,4],[5,6]])**

**Y=np.array([[1,2,3],[4,5,6]])**

**# 4. Print the shape of the above matrices\**

**print(np.shape(X), np.shape(Y))**

**# 5. Print the product of above two matrices (do so without using the inbuilt functions).**

**Z=np.array([np.zeros(3)]\*3)**

**for i in range(len(X)):**

**for j in range(len(Y[1])):**

**for k in range(len(Y)):**

**Z[i][j] += X[i][k] \* Y[k][j]**

**print(Z)**

**# 6. Define two non square matrices of same order and print their sum.**

**A=np.array([[1,2,3],[4,5,6]])**

**B=np.array([[-1,-2,-3],[-4,-5,-6]])**

**print(A+B)**

**# 7. Define a square matrix A.**

**A=np.array([[7,2,4],[4,9,6],[7,8,9]])**

**# 8. Print the transpose of A.**

**print(A.T)**

**# 9. Print the identity matrix of the above order I.**

**I=np.array([[1,0,0],[0,1,0],[0,0,1]])**

**print(I)**

**# 10. Verify A.I = I.A for matrix multiplication.**

**X=A@I**

**print("A.I = ",X)**

**Y=I@A**

**print("I.A = ",Y)**

**print(" Therefore, A.I = I.A")**

**# 11. Define another square matrix of the same order as A.**

**B=np.array([[2,5,7],[3,6,3],[0,1,9]])**

**# 12. Print the product of the matrices as matrix multiplication**

**print(A@B)**

**# 13. Print the product of the matrices by element wise multiplication**

**print(np.multiply(A,B))**

**# 14. Calculate and print the inverse of A. (Use linalg)**

**d=np.linalg.det(A)**

**print("Determinant = ",d)**

**if d!=0:**

**print("Inverse of A = ",np.linalg.inv(A))**

**else:**

**print("Inverse does not exist")**