Stat 2332 Final Project

Coded in Jupyter(Python)

Q1: Read the Final.csv data from D2L to R and Python and denote this data by d1.

import numpy as np

import pandas as pd

#q1

d1 = pd.read_csv("final.csv")

Q2: How many observations (number of rows) and Variables (columns) in the d1 data?

np.shape(d1)

Output: 17842 rows, 28 columns

Q3: How many variables are numerical/continuous and how many are them are integers/discrete?

d1.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 17842 entries, 0 to 17841
Data columns (total 28 columns):
    Column
               Non-Null Count Dtype
                17842 non-null object
    ΙD
                17842 non-null int64
    SW
    MOI
               17842 non-null int64
    YOI
               17842 non-null int64
    DOICMC
               17842 non-null int64
    RMOB
                17842 non-null int64
    RYOB
               17842 non-null int64
    RDOBCMC
               17842 non-null int64
                17842 non-null int64
    RCA
    Region
                17842 non-null int64
10
               17842 non-null int64
   TPR
 11
    DPR
               17842 non-null int64
 12
               17842 non-null
                              int64
    NV
13
    HEL
               17842 non-null int64
14
   Has Radio 17842 non-null int64
15 Has TV
               17842 non-null int64
16
    Religion
               17842 non-null int64
17
                17842 non-null int64
    WΙ
                              float64
 18
    MOFB
                12335 non-null
 19
    YOB
                12335 non-null float64
               16025 non-null float64
20
    DOBCMC
```

```
DOFBCMC
 21
                 16025 non-null float64
 22
     AOR
                 16025 non-null
                                 float64
 23
    MTFBI
                 16025 non-null
                                 float64
 24
                                float64
    DSOUOM.CMC 10279 non-null
 25 RW
                17842 non-null int64
 26
                 17842 non-null
    RH
                                 int64
 27
     RBMI
                17842 non-null
                                 int64
dtypes: float64(7), int64(20), object(1)
memory usage: 3.8+ MB
```

Q4: Delete ID variable from the d1 data

d1.dtypes

del d1['ID']

d1.info()

```
RangeIndex: 17842 entries, 0 to 17841
Data columns (total 27 columns):
                Non-Null Count
     Column
                                 Dtype
     SW
                 17842 non-null
                                 int64
    MOI
                17842 non-null
                                int64
                17842 non-null
    YOI
                                int64
                17842 non-null
                                int64
    DOICMC
                17842 non-null
                                int64
    RMOB
    RYOB
                17842 non-null
                                int64
    RDOBCMC
                17842 non-null
                               int64
                17842 non-null int64
    RCA
                17842 non-null int64
    Region
                17842 non-null
                                int64
    TPR
    DPR
                17842 non-null
                                int64
 11
    NV
                17842 non-null
                                int.64
 12
    HEL
                17842 non-null
                                int64
 13
    Has Radio
                17842 non-null
                                int64
    Has TV
                17842 non-null int64
 14
    Religion
15
                17842 non-null int64
                17842 non-null int64
16
    WΙ
                                float64
17
    MOFB
                12335 non-null
18
    YOB
                12335 non-null
                                float64
                16025 non-null
 19
    DOBCMC
                                float64
 20
                16025 non-null
    DOFBCMC
                                float64
 21
                 16025 non-null
    AOR
                                float64
 22
    MTFBI
                16025 non-null float64
 23
    DSOUOM.CMC 10279 non-null float64
 24
                17842 non-null
                                 int64
    RW
 25
                17842 non-null
                                int64
 26
     RBMI
                17842 non-null
                                int64
dtypes: float64(7), int64(20)
```

```
memory usage: 3.7 MB
```

Q5: Report the number of missing values for the variables MOFB, YOB, and AOR.

```
temp = d1[['MOFB', 'YOB', 'AOR']].copy()
num_nan = temp.isna().sum()
print(num_nan)
```

Output:

```
MOFB 5507
YOB 5507
AOR 1817
dtype: int64
```

Q6: Create d2 data from d1 data by selecting variables RMOB, WI, RCA, Religion, Region, AOR, HEL, DOBCMC, DOFBCMC, MTFBI, RW, RH, and RBMI variables.

Output:

```
RangeIndex: 17842 entries, 0 to 17841
Data columns (total 13 columns):
    Column Non-Null Count Dtype
     RMOB 17842 non-null int64
     WI 17842 non-null int64 RCA 17842 non-null int64
     Religion 17842 non-null int64
     Region 17842 non-null int64
    AOR 16025 non-null float64
HEL 17842 non-null int64
DOBCMC 16025 non-null float64
 6
     DOFBCMC 16025 non-null float64
     MTFBI 16025 non-null float64
               17842 non-null int64
 11
     RH
               17842 non-null int64
     RBMI
                17842 non-null int64
dtypes: float64(4), int64(9)
```

Q7: Delete rows that have missing values for any variable in the d2 data and denote this new data by d3.

```
d3 = d2.dropna()
```

```
d3 = d2.dropna()
print(d3.isna())
                           RCA Religion Region
False False False
False False
                                                                                    DOFBCMC \
          RMOB
                    WI
                                                          AOR
                                                                   HEL DOBCMC
                                                False False
False False
False False
         False False
False False
                         False
                                                                           False
                                                                 False
                                                                                      False
                          False
                                                                           False
                                                                                      False
                                                                 False
         False
                 False
                          False
                                      False
                                                                 False
                                                                           False
                                                                                      False
         False
                 False
                          False
                                      False
                                                False
                                                        False
                                                                 False
                                                                           False
                                                                                      False
4
         False
                 False
                          False
                                      False
                                                False
                                                        False
                                                                 False
                                                                           False
                                                                                      False
... ... ... ... ... 17837 False False
                                      ...
False
                                                False False
                                                                ...
False
                                                                                      ...
False
                                                                           ...
False
                         False
False
17838 False False
                                      False
False
                                                False False
False False
                                                                 False
                                                                           False
                                                                                      False
False
17839
         False
                 False
                                                                 False
                                                                           False
17840 False False
17841 False False
                                      False
False
                                                False False False
False False False
                                                                                      False
False
                          False
                                                                           False
                          False
                                                                           False
         MTFBI RW RH RBMI
False False False
         False False
                         False
                                  False
         False
                 False
                          False
                                  False
                 False
                          False
         False
                                  False
                 False
                         False False
         False
... ...
17837 False
                 ...
False
                         ...
False
                                  ...
False
 17838
         False
                 False
                          False
                                  False
17839
         False
                 False
                          False
                                  False
        False
False
                False
False
                                  False
False
 17840
                          False
                          False
17841
[16025 rows x 13 columns]
```

Q8: Find the summary statistics of the d3 data.

d3.describe()

output:

	RMO B	WI	RCA	Relig ion	Regi on	AOR	HEL	DOB CMC	DOF BCM C	MTF BI	RW	RH	RBMI
c o u nt	1602 5.000 000												
m e a n	6.437 067	3.128 799	31.84 1373	1.120 562	3.934 727	17.90 2902	1.210 109	1252. 6493 60	1174. 1900 78	35.43 6505	702.4 7756 6	1700. 9552 57	2343. 2044 31
st d	3.491 742	1.424 111	8.886 835	0.356 198	1.901 758	3.323 532	0.930 617	75.32 4979	107.3 1785 2	83.80 8245	1398. 1235 57	1263. 8574 53	1243. 5694 93
m in	1.000	1.000	13.00 0000	1.000	1.000	11.00 0000	0.000	921.0 0000 0	893.0 0000 0	0.000	229.0 0000 0	1044. 0000 00	1245. 0000 00

	RMO B	wı	RCA	Relig ion	Regi on	AOR	HEL	DOB CMC	DOF BCM C	MTF BI	RW	RH	RBMI
2 5 %	3.000 000	2.000	24.00 0000	1.000	2.000	16.00 0000	0.000	1212. 0000 00	1091. 0000 00	12.00 0000	423.0 0000 0	1474. 0000 00	1876. 0000 00
5 0 %	6.000 000	3.000	31.00 0000	1.000	4.000 000	17.00 0000	1.000	1273. 0000 00	1188. 0000 00	22.00 0000	482.0 0000 0	1510. 0000 00	2114. 0000 00
7 5 %	10.00 0000	4.000 000	39.00 0000	1.000 000	6.000 000	19.00 0000	2.000 000	1311. 0000 00	1264. 0000 00	38.00 0000	556.0 0000 0	1547. 0000 00	2420. 0000 00
m a x	12.00 0000	5.000 000	49.00 0000	4.000 000	7.000 000	40.00 0000	3.000	1344. 0000 00	1344. 0000 00	996.0 0000 0	9999. 0000 00	9999. 0000 00	9999. 0000 00

Q9: Add a new variable in the d3 data by finding the average of DOBCMC, DOFBCMC and MTFBI.

```
x = ['DOBCMC', 'DOFBCMC', 'MTFBI']
d3["average"] = d3[x].mean(axis = 1)
d3['average']
```

output:

```
0 813.333333

1 907.000000

2 867.666667

3 793.666667

4 860.333333

...

17837 815.000000

17838 870.333333

17840 737.333333

17841 885.333333
```

Q10: Create a new variable named "Newreligion" by recoding '1' as '1' and rest as '2' from the Religion Variable.

```
d3["NewReligion"] = d3['Religion']
d3.loc[d3['NewReligion'] != 1] = 2
```



Q11: Find the frequency table for the Region variable

pd.crosstab(index = d3["Region"], columns = "count")

Output:



Q12: Find the joint frequency table for the variables Region and Religion.

pd.crosstab(index = d3["Region"], columns = d3["Religion"])

Output:



Q13: Find the mean values of AOR variable corresponding to each label of Region variable.

d3_byRegion = d3.groupby('Region')

d3_byRegion.mean().transpose()

Region	1	2	3	4	5	6	7
RMOB	6.354686	4.507001	6.384165	6.560870	6.449176	6.478950	6.435484
wı	2.873665	2.725495	3.361544	3.221256	3.065934	2.671405	3.241935
RCA	31.672598	18.311685	31.759360	32.107246	32.120421	31.494806	31.887097
Religion	1.000000	1.436987	1.000000	1.000000	1.000000	1.000000	1.000000
AOR	17.781139	10.943747	17.880265	17.566667	17.607601	17.279388	18.572903
HEL	1.358244	1.579189	1.169267	1.276329	1.180861	1.137233	0.978710
DOBCMC	1255.581851	714.960406	1254.570203	1240.954589	1242.006868	1250.049754	1273.264516
DOFBCMC	1173.952550	667.447851	1175.865835	1167.916425	1166.230769	1171.449426	1181.184516
MTFBI	33.395611	19.965476	35.419657	32.613527	41.543498	35.294150	36.478710
RW	961.041518	414.558909	704.145086	664.336232	702.423077	515.057408	658.692258
RH	1946.447805	970.093433	1690.661076	1653.341063	1707.211538	1550.246583	1670.567742
RBMI	2545.765718	1340.294785	2346.479719	2348.993720	2355.123168	2159.464735	2268.927742
average	820.976671	467.457911	821.951898	813.828180	816.593712	818.931110	830.309247
NewReligion	1.000000	1.436987	1.000000	1.000000	1.000000	1.000000	1.000000

Q14: Find the variances of AOR variable corresponding to each label of Religion variable.

d3_byReligion = d3.groupby('Religion')

d3_byReligion.std().transpose()

Religion	1	2
RMOB	3.494648	0.0
WI	1.423346	0.0
RCA	8.874438	0.0
Region	1.880966	0.0
AOR	3.273809	0.0
HEL	0.926591	0.0
DOBCMC	74.201189	0.0
DOFBCMC	107.415022	0.0
MTFBI	83.961840	0.0
RW	1402.118068	0.0
RH	1267.567788	0.0
RBMI	1247.216736	0.0
average	62.029359	0.0
NewReligion	0.000000	0.0

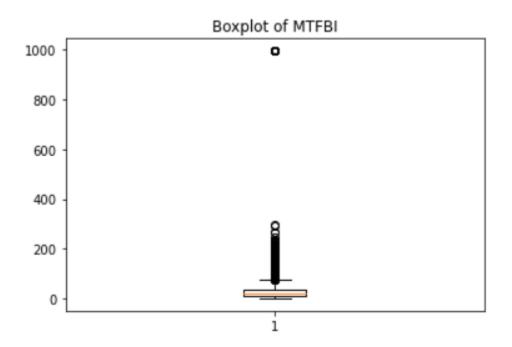
Q15: Draw a boxplot for the MTFBI variable.

import matplotlib.pyplot as plt

y = d3['MTFBI']

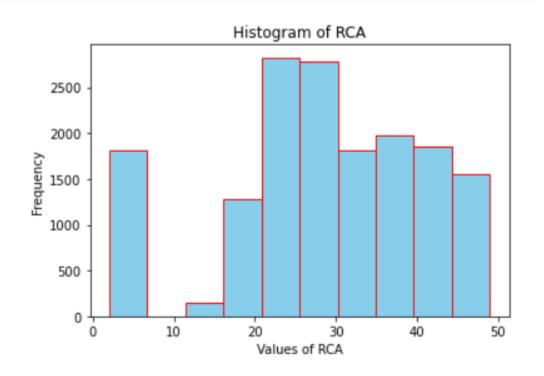
plt.boxplot(y)

plt.title("Boxplot of MTFBI")



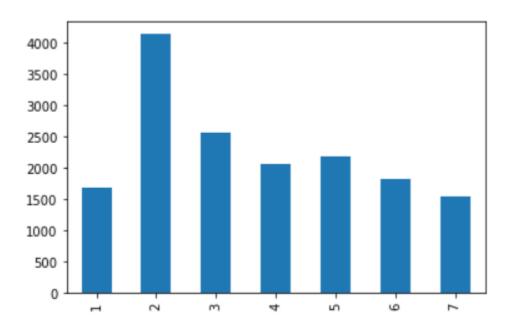
Q16: Draw a histogram for the RCA variable.

```
r = d3['RCA']
plt.hist(r, color = "skyblue", ec = "red")
plt.title("Histogram of RCA")
plt.xlabel("Values of RCA")
plt.ylabel("Frequency")
```



Q17: Draw a bar chart for the Region variable

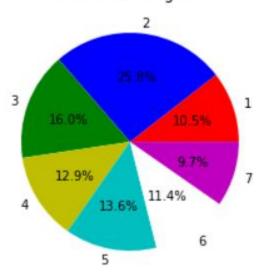
 ${\tt d3['Region'].value_counts(sort = False).plot.bar()}$



Q18: Draw a pie chart for the Region variable

Output:

Pie chart of Regions

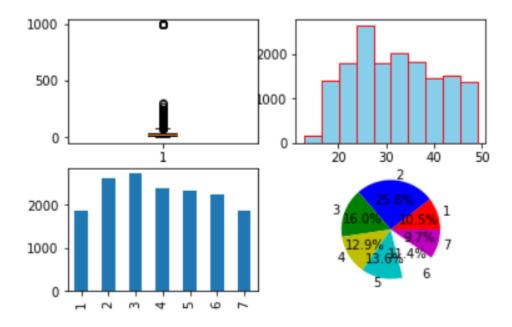


Q19: Put above four figures (question 15 to question 18) in a 2 by 2 grid

```
b = d3['MTFBI']
h = d3['RCA']
reg = d3['Region']
ba = d3['Region'].value_counts(sort = False)
labels = ['1', '2', '3', '4', '5', '6', '7']
cols = ['r', 'b', 'g', 'y', 'c', 'w', 'm']
sizes = ['1686', '4142', '2564', '2070', '2184', '1829', '1550']
```

plt.subplot(2,2,2)

```
plt.hist(h, color = "skyblue", ec = "red")
plt.subplot(2,2,1)
plt.boxplot(b)
plt.subplot(2,2,3)
d3['Region'].value_counts(sort = False).plot.bar()
plt.subplot(2,2,4)
plt.pie(sizes, explode = None, labels = labels, autopct = '%1.1f%%', colors = cols)
```



Q20: Split the d3 data by WI variable and denote it by d4

Output:

Q21: For each split data in d4 write a single loop to find the mean, minimum, maximum, standard deviation of MTFBI.

import statistics as ss
ds = [rows for _, rows in d4]
datalist = []
for i in range(len(ds)):

WI	MTF	BI mean	MTFBI	min	MTFBI	Max	MTFBI	Varia	nce	MTFBI	Media	n
0	1	37.29508	8 8	0	. 0	996	. 0	7890.	2678	41		22.0
0	2	21.97579	94	0	. 0	996	. 0	4433.	4643	18		8.0
0	3	34.08464	46	0	. 0	996	. 0	6400.	7666	59		22.0
0	4	34.8145	76	0	. 0	996	. 0	7217.	25790	9		22.0
0	5	36.2525	77	0	. 0	996	. 0	6859.	6871	71		23.0

Q22: Conduct a one sample mean test of hypothesis to check whether MTFBI has a mean of 30 or not.

import scipy.stats as st

st.stats.ttest_1samp(d3.MTFBI, 30)

Output: Ttest_1sampResult(statistic=2.8121680810452396, pvalue=0.004926859651115069)

Q23: Conduct a normality test of the MTFBI variable

import scipy

scipy.stats.shapiro(d3.MTFBI)

Output: ShapiroResult(statistic=0.24056196212768555, pvalue=0.0)

Q24: Check the equality of mean for MTFBI variable corresponding to two labels of "Newreligion" variable.

scipy.stats.ttest_ind(d3[d3.NewReligion == 1].MTFBI, d3[d3.NewReligion == 2].MTFBI)

Output: Ttest indResult(statistic=17.0063732678908, pvalue=2.698791769280193e-64)

Q25: Find the correlation matrix of the variables DOBCMC, DOFBCMC, AOR, MTFBI, RW, RH and RBMI from the d3 data.

```
columns = ["DOBCMC","DOFBCMC","AOR","MTFBI","RW","RH", "RBMI"]
c1=d3[columns]
import matplotlib.pyplot as plt
plt.matshow(c1.corr())
```

correltion matrix

c1.corr()

Output:



Q27: Fit a multiple regression model by considering MTFBI as dependent variable and AOR, RW, Region as independent variables

#q27

import statsmodels.tools as sm

from statsmodels.api import OLS

y=d3.MTFBI

x=d3[['AOR','RW','Region']]

x1=sm.add_constant(x)

model = OLS(y, x1).fit()

model.summary()

Dep. Variable: MTFBI R-squared: 0.030 Model: OLS Adj. R-squared: 0.030 Method: Least Squares F-statistic: 168.0 Date: Mon, 06 Dec 2021 Prob (F-statistic): 3.15e-107 Time: 19:57:45 Log-Likelihood: -92669. No. Observations: 16025 AIC: 1.853e+05 Df Residuals: 16021 BIC: 1.854e+05 Df Model: 3 3 Covariance Type: nonrobust coef std err t P> t [0.025 0.975] const -7.0307 1.966 -3.577 0.000 -10.883 -3.178 AOR 2.3469 0.111 21.051 0.000 2.128 2.565 RW -0.0004 0.000 -0.876 0.381 -0.001 0.001 Region 0.4137 0.346 1.196 0.232 -0.264 1.092 Omnibus: 26291.859 Durbin-Watson: 1.995 Prob(Omnibus): 0.000 Jarque-Bera (JB): 12555518.901	t[126]: OLS Regression R	esults					
Method: Least Squares F-statistic: 168.0 Date: Mon, 06 Dec 2021 Prob (F-statistic): 3.15e-107 Time: 19:57:45 Log-Likelihood: -92669 No. Observations: 16025 AIC: 1.853e+05 Df Model: 3 Covariance Type: nonrobust const -7.0307 1.966 -3.577 0.000 -10.883 -3.178 AOR 2.3469 0.111 21.051 0.000 2.128 2.565 RW -0.004 0.000 -0.871 -0.001 0.001 Region 0.4137 0.346 1.196 0.232 -0.264 1.092 Omnibus: 26291.859 Durbin-Watson: 1.995 <th colspan<="" th=""><td>Dep. Variabl</td><td>e:</td><td>MTFB</td><td>I F</td><td>R-squared:</td><td>0.030</td></th>	<td>Dep. Variabl</td> <td>e:</td> <td>MTFB</td> <td>I F</td> <td>R-squared:</td> <td>0.030</td>	Dep. Variabl	e:	MTFB	I F	R-squared:	0.030
Date: Mon, 06 Dec 2021 Prob (F-statistic): 3.15e-107 Time: 19:57:45 Log-Likelihood: -92669. No. Observations: 16025 AIC: 1.853e+05 Df Residuals: 16021 BIC: 1.854e+05 Df Model: 3 Covariance Type: nonrobust coef std err t P> t [0.025 0.975] const -7.0307 1.966 -3.577 0.000 -10.883 -3.178 AOR 2.3469 0.111 21.051 0.000 2.128 2.565 RW -0.0004 0.000 -0.876 0.381 -0.001 0.001 Region 0.4137 0.346 1.196 0.232 -0.264 1.092 Omnibus: 26291.859 Durbin-Watson: 1.995 Prob(Omnibus): 0.000 Jarque-Bera (JB): 12555518.901	Mode	d:	OLS	Adj. F	R-squared:	0.030	
Time: 19:57:45 Log-Likelihood: -92669. No. Observations: 16025 AIC: 1.853e+05 Df Residuals: 16021 BIC: 1.854e+05 Df Model: 3 Covariance Type: nonrobust coef std err t P> t [0.025 0.975] const -7.0307 1.966 -3.577 0.000 -10.883 -3.178 AOR 2.3469 0.111 21.051 0.000 2.128 2.565 RW -0.0004 0.000 -0.876 0.381 -0.001 0.001 Region 0.4137 0.346 1.196 0.232 -0.264 1.092 Omnibus: 26291.859 Durbin-Watson: 1.995 Prob(Omnibus): 0.000 Jarque-Bera (JB): 12555518.901	Metho	d: Lea	ast Squares	s I	F-statistic:	168.0	
No. Observations: 16025 AIC: 1.853e+05 Df Residuals: 16021 BIC: 1.854e+05 Df Model: 3 Covariance Type: nonrobust coef std err t P> t [0.025 0.975] const -7.0307 1.966 -3.577 0.000 -10.883 -3.178 AOR 2.3469 0.111 21.051 0.000 2.128 2.565 RW -0.0004 0.000 -0.876 0.381 -0.001 0.001 Region 0.4137 0.346 1.196 0.232 -0.264 1.092 Omnibus: 26291.859 Durbin-Watson: 1.995 Prob(Omnibus): 0.000 Jarque-Bera (JB): 12555518.901	Dat	e: Mon, 0	6 Dec 2021	1 Prob (F	-statistic):	3.15e-107	
Df Residuals: 16021 BIC: 1.854e+05 Df Model: 3 Covariance Type: nonrobust coef std err t P> t [0.025 0.975] const -7.0307 1.966 -3.577 0.000 -10.883 -3.178 AOR 2.3469 0.111 21.051 0.000 2.128 2.565 RW -0.0004 0.000 -0.876 0.381 -0.001 0.001 Region 0.4137 0.346 1.196 0.232 -0.264 1.092 Omnibus: 26291.859 Durbin-Watson: 1.995 Prob(Omnibus): 0.000 Jarque-Bera (JB): 12555518.901	Tim	e:	19:57:49	5 Log-L	ikelihood:	-92669.	
Df Model: 3 Covariance Type: nonrobust coef std err t P> t [0.025 0.975] const -7.0307 1.966 -3.577 0.000 -10.883 -3.178 AOR 2.3469 0.111 21.051 0.000 2.128 2.565 RW -0.0004 0.000 -0.876 0.381 -0.001 0.001 Region 0.4137 0.346 1.196 0.232 -0.264 1.092 Omnibus: 26291.859 Durbin-Watson: 1.995 Prob(Omnibus): 0.000 Jarque-Bera (JB): 12555518.901	No. Observation	8:	1602	5	AIC:	1.853e+05	
Covariance Type: nonrobust coef std err t P> t [0.025] 0.975] const -7.0307 1.966 -3.577 0.000 -10.883 -3.178 AOR 2.3469 0.111 21.051 0.000 2.128 2.565 RW -0.0004 0.000 -0.876 0.381 -0.001 0.001 Region 0.4137 0.346 1.196 0.232 -0.264 1.092 Omnibus: 26291.859 Durbin-Watson: 1.995 Prob(Omnibus): 0.000 Jarque-Bera (JB): 12555518.901	Df Residual	8:	16021	1	BIC:	1.854e+05	
coef std err t P> t [0.025] 0.975] const -7.0307 1.966 -3.577 0.000 -10.883 -3.178 AOR 2.3469 0.111 21.051 0.000 2.128 2.565 RW -0.0004 0.000 -0.876 0.381 -0.001 0.001 Region 0.4137 0.346 1.196 0.232 -0.264 1.092 Omnibus: 26291.859 Durbin-Watson: 1.995 Prob(Omnibus): 0.000 Jarque-Bera (JB): 12555518.901	Df Mode	d:	:	3			
const -7.0307 1.966 -3.577 0.000 -10.883 -3.178 AOR 2.3469 0.111 21.051 0.000 2.128 2.565 RW -0.0004 0.000 -0.876 0.381 -0.001 0.001 Region 0.4137 0.346 1.196 0.232 -0.264 1.092 Omnibus: 26291.859 Durbin-Watson: 1.995 Prob(Omnibus): 0.000 Jarque-Bera (JB): 12555518.901	Covariance Typ	e:	nonrobus	t			
AOR 2.3469 0.111 21.051 0.000 2.128 2.565 RW -0.0004 0.000 -0.876 0.381 -0.001 0.001 Region 0.4137 0.346 1.196 0.232 -0.264 1.092 Omnibus: 26291.859 Durbin-Watson: 1.995 Prob(Omnibus): 0.000 Jarque-Bera (JB): 12555518.901	coef	std err	t	P> t [0.	025 0.975	ı	
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Region 0.4137 0.346 1.196 0.232 -0.264 1.092 Omnibus: 26291.859 Durbin-Watson: 1.995 Prob(Omnibus): 0.000 Jarque-Bera (JB): 12555518.901	AOR 2.3469	0.111	21.051 0	.000 2.	128 2.565	5	
Omnibus: 26291.859 Durbin-Watson: 1.995 Prob(Omnibus): 0.000 Jarque-Bera (JB): 12555518.901	RW -0.0004	0.000	-0.876 0	.381 -0.	001 0.001	ı	
Prob(Omnibus): 0.000 Jarque-Bera (JB): 12555518.901	Region 0.4137	0.346	1.196 0	.232 -0.	264 1.092	2	
	Omnibus:	26291.85	9 Durb	in-Watsor	1:	1.995	
Skew: 11 269 Prob(IR): 0.00	Prob(Omnibus):	0.00	0 Jarque	-Bera (JB): 1255551	8.901	
3KCW. 11.203 110D(3D). 0.00	Skew:	11.26	9	Prob(JB):	0.00	
Kurtosis: 138.262 Cond. No. 4.70e+03	Kurtosis:	138.26	2	Cond. No	5. 4.7	0e+03	

Q28 – 32: Simulate one data from the following equation y=50+10X+20U+100N+E. Where X is binomial with n=20, p=.70. U is uniform between 15 and 30 (inclusive). N is normal with mean 0 and standard deviation 5. E is random uniform between -1 and 1. True mean is 640. True variance is 257920. Repeat the procedure 100 times and check the true mean with the simulated mean. Repeat the procedure 100 times and check the true variance with the simulated variance. Repeat the procedure 500 times and check the true mean with the simulated mean. Repeat the procedure 500 times and check the true variance with the simulated variance.

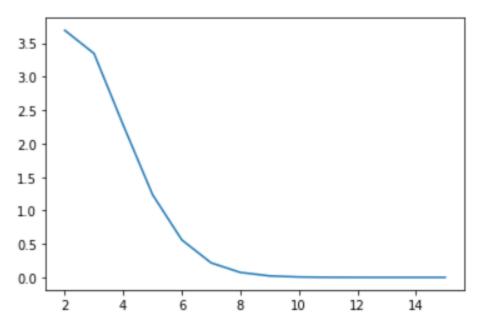
```
import numpy as np
import pandas as pd
import scipy.stats as stats
import statsmodels.stats.api as sms
#q28
def sim(n):
    x = np.random.binomial(20,.70,n)
    u = np.random.normal(0,5,n)
```

```
N = np.random.uniform(15,30,n)
  E = np.random.uniform(-1, 1, n)
  y= 50 + 10*x + 20 * u + 100 * N + E
  y1=pd.DataFrame(y)
  return y1
a = sim(1000)
# mean and variance
np.mean(a)
np.var(a)
stats.ttest_1samp(a,1000)
# repeating 100 times
B=100
repeat=[sim(1000) for i in range(B)]
alldata=pd.concat(repeat)
# computing mean and variance from simulated data
simulated_mean=np.mean(alldata)
simulated_variance=np.var(alldata)
# Theoretical Mean and Variance
theoretical_mean= 640
theoretical_variance= 257920
# difference between them
#29
print("100 iterations mean: ", abs(simulated_mean-theoretical_mean))
#30
print("100 iterations variance: " , abs(simulated_variance-theoretical_variance))
```

```
repeat=[sim(1000) for i in range(C)]
alldata=pd.concat(repeat)
# computing mean and variance from simulated data
simulated_mean=np.mean(alldata)
simulated_variance=np.var(alldata)
# Theoretical Mean and Variance
theoretical_mean= 640
theoretical_variance= 257920
# difference between them
#31
print("500 iterations mean: " , abs(simulated_mean-theoretical_mean))
#32
print("500 iterations variance: ", abs(simulated_variance-theoretical_variance))
Output:
100 iterations mean: 0 1798.40595
dtype: float64
100 iterations variance: 0 59598.103901
dtype: float64
500 iterations mean: 0 1800.528569
dtype: float64
500 iterations variance: 0 59601.945352
Q33: For five values of x=1:5, y=2:6, and z=3:7, compute 5 values for f(x)=e^x-\log[0(x^2)]
(5+y)
import math
def fun(x, y, z):
  return (math.exp(x) - math.log(z^{**2}))/(5+y)
x = 1
y = 2
z = 3
for i in range(5):
```

```
print(fun(x,y,z))
 x += 1
 y += 1
 z += 1
Output:
0.07443675016040364
0.5770584220863586
1.8740734553688299
5.1014631094688125
13.138303527678726
Q34: Solve the following system of linear equations: 70x+100y+40z=900; 120x+450y+340z=1000;
230x+230y+1230z=3000
a=np.array([[70,100,40],[120,450,340],[230,230,1230]])
b=np.array([900,1000,3000])
x=np.linalg.solve(a,b)
print(x)
Output:
[15.53852758 -1.8270015 -0.12491951]
Q35: Find the inverse of the following matrix: A=(20, 30, 30
                                          20,80,120
                                          40,90,360)
a = np.array([[20, 30, 30],
      [20, 80, 120],
      [40, 90, 360]])
print(np.linalg.inv(a))
Output:
   0.07317073 -0.03292683 0.00487805]
 [-0.0097561]
                  0.02439024 - 0.00731707
 [-0.00569106 -0.00243902 0.00406504]]
```

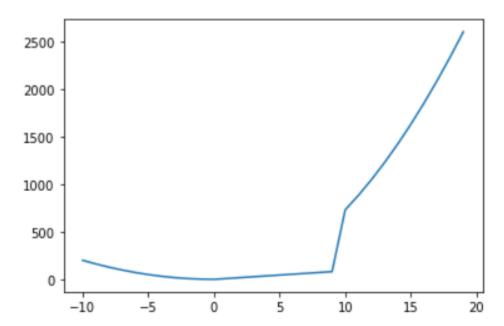
```
Q36: Suppose b=(10
                 20
                 30).
Then find (A'A)^-1 A'b. Here A' means A transpose.
a_2 = a.transpose()
b = np.array([[10],
       [20],
       [30]])
v1 = np.linalg.inv(a_2.dot(a))
v2 = a_2.dot(b)
print(v1.dot(v2))
Output:
[[0.2195122]
 [0.17073171]
 [0.01626016]]
Q37: Draw the graph for the function f(x) = e^x/x!; for 2 \le x \le 15.
import numpy as np
from matplotlib import pyplot as plt
def f(x):
  return math.exp(x) / math.factorial(x)
x = [2,3,4,5,6,7,8,9,10,11,12,13,14,15]
y = []
for i in range(len(x)):
  y.append(f(x[i]))
plt.plot(x,y)
plt.show()
Output:
```



Q38: Draw the graph for the step functions Consider the continuous function

```
f(x)={2x^2+e^x+3; if x<0}
9x+log (20); if 0≤x<10
7x^2+5x-17;I f10≤x.
def g(x):
  out = 0
  if x < 0:
    out = 2 * (x**2) + math.exp(x) + 3
  elif x >= 0 and x < 10:
    out = 9 * x + math.log(20)
  else:
    out = 7 * (x**2) + 5 * x - 17
  return out
x = [i \text{ for } i \text{ in range}(-10, 20)]
y = []
for i in range(len(x)):
  y.append(g(x[i]))
```

```
plt.plot(x, y)
plt.show()
```



Q39: Find the areas of 10 circles, which have radii 10:19. The Area of a circle is given πr^2 .

```
def circ_area(r):
    return math.pi * r**2

for i in range(10, 20):
    print("Area of circle with radius " + str(i))
    print(round(circ_area(i),2))
```

```
Area of circle with radius 10
314.16
Area of circle with radius 11
380.13
Area of circle with radius 12
452.39
Area of circle with radius 13
530.93
Area of circle with radius 14
615.75
Area of circle with radius 15
```

```
706.86
Area of circle with radius 16
804.25
Area of circle with radius 17
907.92
Area of circle with radius 18
1017.88
Area of circle with radius 19
1134.11
```

Q40: Find sum(1/logx) for x = 2 to 10000

```
def h(x):
    return 1/(math.log(x))

sum = 0

for i in range(2, 10000):
    sum += h(i)

print(sum)
```

Output:

1245.839690648031

Q41: Find sum(i $^10/3+j$) for i = 1 to 30 and j = 1 to 10

```
sum = 0
for i in range(30):
    for j in range(10):
        sum += (i ** 10)/ (3 + j)
print(sum)
```

Output:

def f(x):

2134775903297949.8

Q42: Compute the integral \int from 0 to positive infinity for equation: $x^15 * e^-40xdx$.

from scipy.integrate import quad

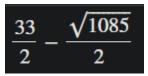
```
return (x ** 15) * (math.exp(-(40 * x)))
res, err = quad(f, 0, math.inf)
print(res, err)
Output:
3.044666888955981e-14 2.76644736276991e-14
Q43: Compute the integral \int from 0 to 1 for equation: x^150 * (1-x)^30dx
def g(x):
  return (x ** 150) * (math.pow(1-x,30))
res,err = quad(g, 0, 1)
print(res, err)
Output:
4.167698831230213e-37 6.182522311694294e-37
Q44: For five values of x=1:5, y=2:6, and z=3:7, compute 5 values for f(x)=e^x-\log (z^2)
(5+y)
import math
def fun(x, y, z):
  return (math.exp(x) - math.log(z^{**2}))/(5+y)
x = 1
y = 2
z = 3
for i in range(5):
  print(fun(x,y,z))
  x += 1
  y += 1
  z += 1
```

```
0.07443675016040364
0.5770584220863586
1.8740734553688299
5.1014631094688125
13.138303527678726
```

Q45: Solve the equation $x^2-33x+1=0$.

```
import sympy as sym solution = sym.solve('x**2 - 33 * x + 1','x') solution[0]
```

Output:



Q47: If \$40 is invested today for 50 years with interest rate .10, the find the total amount of money in 50 years. The formula is $p*(1+r)^t$. p=40, t=50, and r=.10.

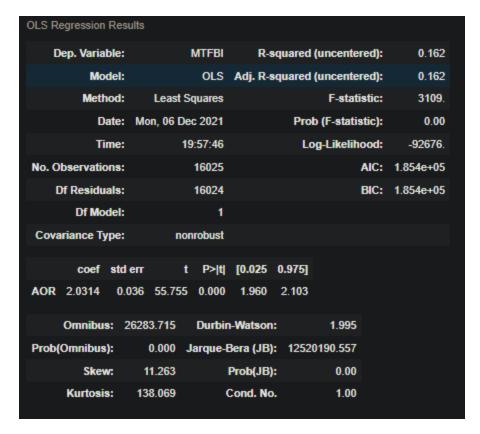
```
def interest(p, t, r):
    return p * ((1 + r) ** t)
print(interest(40, 50, 0.1))
```

Output:

4695.634115187831

Q48: Fit a simple regression model by using MTFBI as dependent variable and AOR as independent variable.

```
import statsmodels.api as sm
model = sm.OLS(d3.MTFBI, d3.AOR).fit()
predictions = model.predict(d3.AOR)
model.summary()
```



Q49: Check whether AOR and MTFBI are correlated or not.

import scipy

if p > 0.05:

scipy.stats.pearsonr(d3.AOR, d3.MTFBI)

Output:

```
(0.1742337620135717, 1.9819270155456687e-109)
```

Q50: Check whether variance of AOR is 10 or not.

```
def chi_sq_test_for_variance(variable, h0):
    sample_variance = variable.var()
    n = variable.notnull().sum()
    degrees_of_freedom = n - 1
    x_sq_stat = (n-1) * sample_variance / h0
    p = stats.chi2.cdf(x_sq_stat, degrees_of_freedom)
```

```
p = 1 - p
  return (x_sq_stat,p,degrees_of_freedom)
aor_variance = round(d3["AOR"].var(),2)
x_sq_stat,pval,dof = chi_sq_test_for_variance(d3["AOR"], h0 = 10)
print(round(x_sq_stat, 2),pval,dof)
```

55214.29 0.0 16024