UNIVERSITY OF MUMBAI
INSTITUTE OF DISTANCE AND OPEN LEARNING (IDOL)

PRACTICAL JOURNAL IN PAPER - I

RESEARCH IN COMPUTING

SUBMITTED BY
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APPLICATION ID :6647
SEAT NO:508144

MASTERS OF SCIENCE IN INFORMATION TECHNOLOGY PART-1
SEMESTER-1

ACADEMIC YEAR
2022-2023

INSTITUTE OF DISTANCE AND OPEN LEARNING
IDOL BUILDING, VIDYANAGRI,
SANTACRUZ(EAST), MUMBAI-400 098

CONDUCTED AT
RIZVI COLLEGE OF ARTS, SCIENCE AND COMMERCE
BANDRA(W), MUMBAI- 400050

UNIVERSITY OF MUMBAI
INSTITUTE OF DISTANCE AND OPEN LEARNING (IDOL)

Dr. Shankar Dayal Sharma Bhavan, Kalina Vidyanagri, Santacruz(E), Mumbai-400 098

Certificate

This is to certify that

Mr. **Pramod Radheshyam Sharma**, Application ID: **6647**, Seat No: **508144** - from Rizvi College of Arts, Science and Commerce Bandra(W), Mumbai 400 050 has successfullycompleted practical Paper **I** titled **RESEARCH IN COMPUTING** for M.sc (IT) Part1 semester 1 in the academic year 2022-2023.

M.sc (IT) Co-Ordinator, IDOL

External Examiner

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Sr. No	Practical Aim	Signature
1	a. Write a program for obtaining descriptive statistics of data. b. Import data from different data sources (from Excel, csv, mysql, sql server, oracle to R/Python/Excel)	
2	a. Design a survey form for a given case study, collect the primary data and analyze it b. Perform suitable analysis of given secondary data.	
3	a. Perform testing of hypothesis using one sample t-test. b. Perform testing of hypothesis using two sample t-test. c. Perform testing of hypothesis using paired t- test.	
4	a. Perform testing of hypothesis using chi- squared goodness-of-fit test. b. Perform testing of hypothesis using chi- squared Test of Independence	
5	a. Perform testing of hypothesis using Z-test.	
6	a. Perform testing of hypothesis using one-way ANOVA. b. Perform testing of hypothesis using two-way ANOVA c. Perform testing of hypothesis using multivariate ANOVA (MANOVA).	
7	a. Perform the Random sampling for the givendata and analyse it. b. Perform the Stratified sampling for the givendata and analyse it.	
8	a. Compute different types of correlation.	
9	a. Perform linear regression for prediction. b. Perform polynomial regression for prediction.	
10	a. Perform multiple linear regression. b. Perform Logistic regression.	

Practical 1

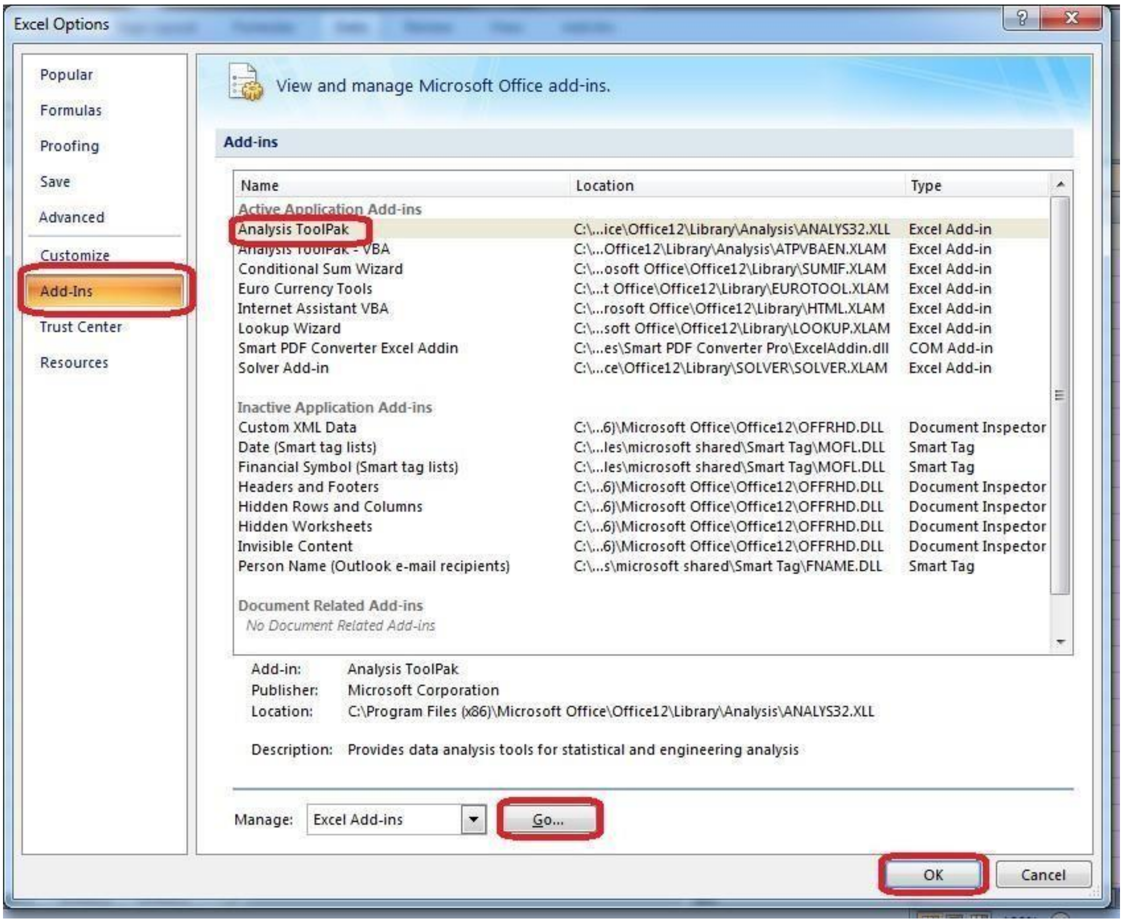
A. Write a program for obtaining descriptive statistics of data.

```
########################################################################
#Practical 1A: Write a python program on descriptive statistics analysis.
########################################################################import
pandas as pd
#Create a Dictionary of series
d = {'Age':pd.Series([25,26,25,23,30,29,23,34,40,30,51,46]),
'Rating':pd.Series([4.23,3.24,3.98,2.56,3.20,4.6,3.8,3.78,2.98,4.80,4.10,3.65])}
#Create a DataFrame df =
pd.DataFrame(d)print(df)
print('############ Sum ########## ')
print (df.sum())
print('############ Mean ########## ')
print (df.mean())
print('############ Standard Deviation ########## ')print
(df.std())
print('############ Descriptive Statistics ########## ')print
(df.describe())
```

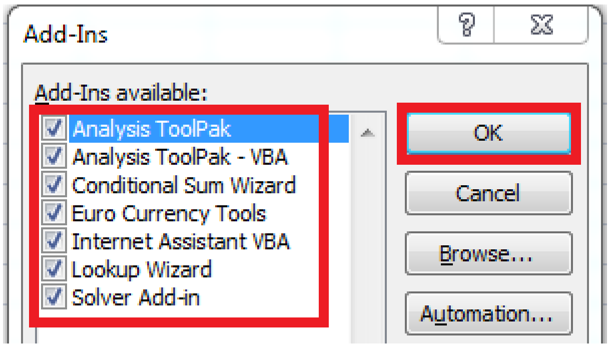
Output:

```
    Age  Rating
0    25    4.23
1    26    3.24
2    25    3.98
3    23    2.56
4    30    3.20
5    29    4.60
6    23    3.80
7    34    3.78
8    40    2.98
9    30    4.80
10   51    4.10
11   46    3.65
############  Sum ##########
Age        382.00
Rating      44.92
dtype: float64
############  Mean ##########
Age        31.833333
Rating      3.743333
dtype: float64
############  Standard Deviation ##########
Age        9.232682
Rating     0.661628
dtype: float64
############  Descriptive Statistics ##########
             Age     Rating
count  12.000000  12.000000
mean   31.833333   3.743333
std     9.232682   0.661628
min    23.000000   2.560000
25%    25.000000   3.230000
50%    29.500000   3.790000
75%    35.500000   4.132500
max    51.000000   4.800000
```

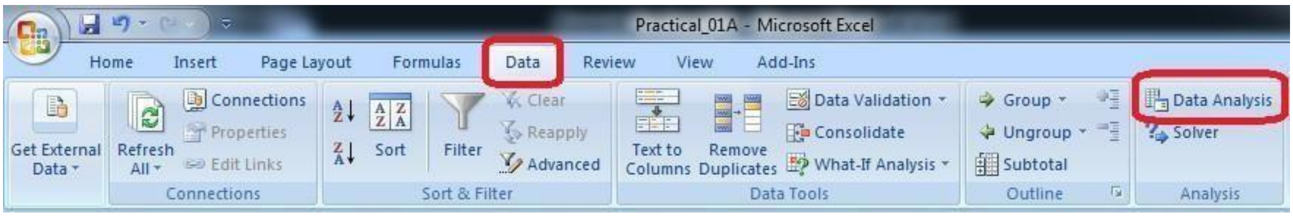
Using Excel



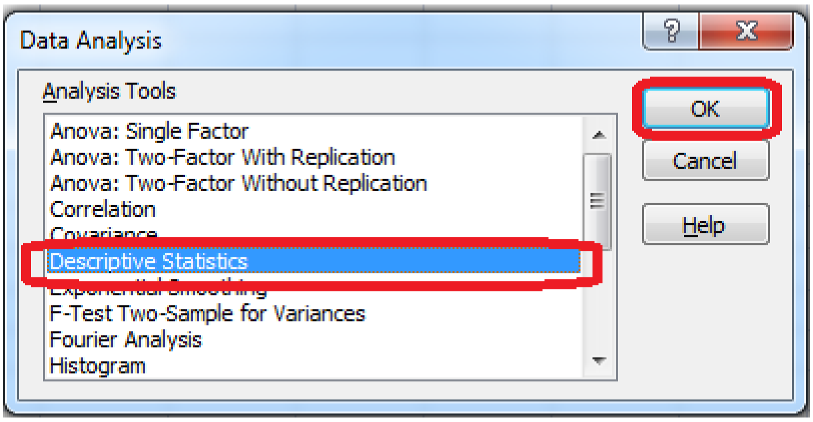
Excel Options
Popular
Formulas
Proofing
Save
Advanced
Customize
Add-Ins
Trust Center
Resources
View and manage Microsoft Office add-ins.
Add-ins
Name
Location
Type
Active Application Add-ins
Analysis ToolPak
Conditional Sum Wizard
Euro Currency Tools
Internet Assistant VBA
Lookup Wizard
Smart PDF Converter Excel Addin
Solver Add-in
Inactive Application Add-ins
Custom XML Data
Date (Smart tag lists)
Financial Symbol (Smart tag lists)
Headers and Footers
Hidden Rows and Columns
Hidden Worksheets
Invisible Content
Person Name (Outlook e-mail recipients)
Document Related Add-ins
No Document Related Add-ins
Add-in: Analysis ToolPak
Publisher: Microsoft Corporation
Location: C:\Program Files (x86)\Microsoft Office\Office12\Library\Analysis\ANALYS32.XLL
Description: Provides data analysis tools for statistical and engineering analysis
Manage: Excel Add-ins
Go...
OK
Cancel



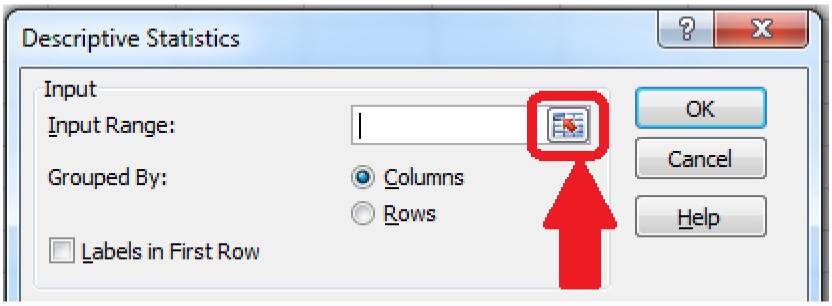
Add-Ins
Add-Ins available:
Analysis ToolPak
Analysis ToolPak - VBA
Conditional Sum Wizard
Euro Currency Tools
Internet Assistant VBA
Lookup Wizard
Solver Add-in
OK
Cancel
Browse...
Automation...



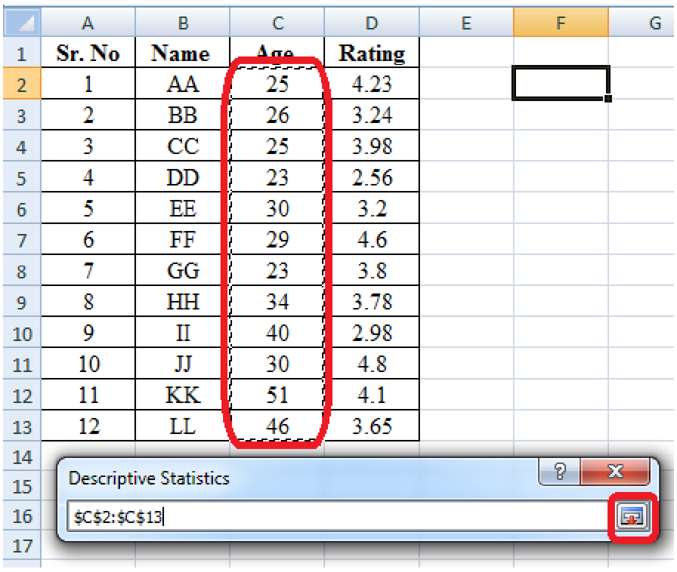
Practical_01A - Microsoft Excel
Home
Insert
Page Layout
Formulas
Data
Review
View
Add-Ins
Get External Data
Refresh All
Connections
Properties
Edit Links
Sort
Filter
Clear
Reapply
Advanced
Text to Columns
Remove Duplicates
Data Validation
Consolidate
What-If Analysis
Group
Ungroup
Subtotal
Data Analysis
Solver
Connections
Sort & Filter
Data Tools
Outline
Analysis



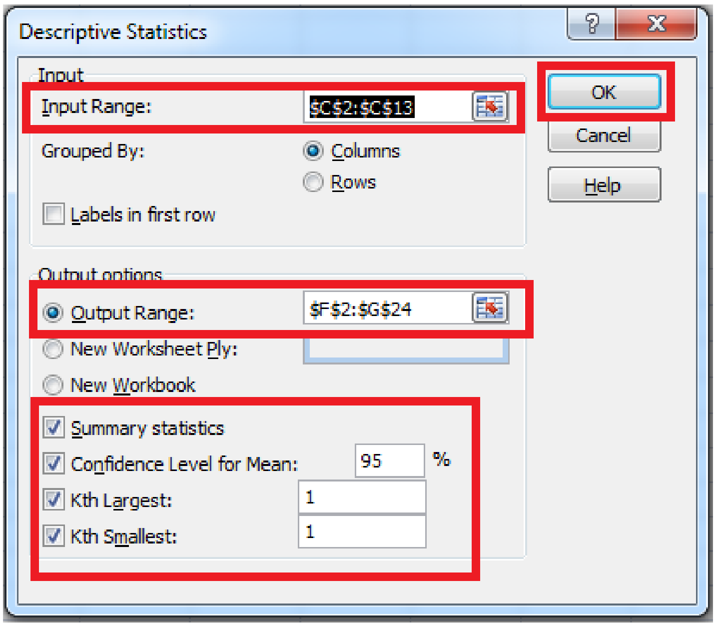
\



Select the data range from the excel worksheet.



	A	B	C	D	E	F	G
1	Sr. No	Name	Age	Rating			
2	1	AA	25	4.23			
3	2	BB	26	3.24			
4	3	CC	25	3.98			
5	4	DD	23	2.56			
6	5	EE	30	3.2			
7	6	FF	29	4.6			
8	7	GG	23	3.8			
9	8	HH	34	3.78			
10	9	II	40	2.98			
11	10	JJ	30	4.8			
12	11	KK	51	4.1			
13	12	LL	46	3.65			



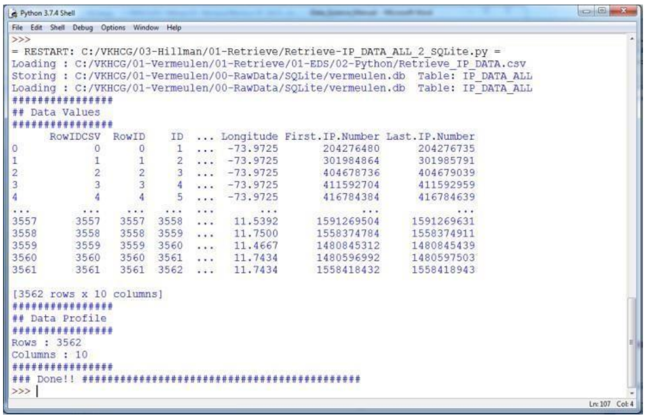
Output:

	A	B	C	D	E	F	G
1	**Sr. No**	**Name**	**Age**	**Rating**			
2	1	AA	25	4.23		*Column1*	
3	2	BB	26	3.24			
4	3	CC	25	3.98		Mean	31.83333
5	4	DD	23	2.56		Standard Error	2.665246
6	5	EE	30	3.2		Median	29.5
7	6	FF	29	4.6		Mode	25
8	7	GG	23	3.8		Standard Deviation	9.232682
9	8	HH	34	3.78		Sample Variance	85.24242
10	9	II	40	2.98		Kurtosis	0.24931
11	10	JJ	30	4.8		Skewness	1.135089
12	11	KK	51	4.1		Range	28
13	12	LL	46	3.65		Minimum	23
14						Maximum	51
15						Sum	382
16						Count	12
17						Largest(1)	51
18						Smallest(1)	23
19						Confidence Level(95.0%)	5.866167

B. Import data from different data sources (from Excel, csv, mysql, sqlserver, oracle to R/Python/Excel)

SQLite:

```
import sqlite3 as sqimport
pandas as pd
####################################################################
Base='C:/VKHCG'
sDatabaseName=Base + '/01-Vermeulen/00-RawData/SQLite/vermeulen.db' conn =
sq.connect(sDatabaseName)
####################################################################
sFileName='C:/VKHCG/01-Vermeulen/01-Retrieve/01-EDS/02-
Python/Retrieve_IP_DATA.csv'
print('Loading :',sFileName)
IP_DATA_ALL_FIX=pd.read_csv(sFileName,header=0,low_memory=False)
IP_DATA_ALL_FIX.index.names = ['RowIDCSV'] sTable='IP_DATA_ALL'
print('Storing :',sDatabaseName,' Table:',sTable)
IP_DATA_ALL_FIX.to_sql(sTable, conn, if_exists="replace") print('Loading
:',sDatabaseName,' Table:',sTable) TestData=pd.read_sql_query("select * from
IP_DATA_ALL;", conn)print('################')
print('## Data Values')
print('################')
print(TestData)
print('################')
print('## Data Profile')
print('################')
print('Rows :',TestData.shape[0])
print('Columns :',TestData.shape[1])
print('################')
print('### Done!! ############################################')
```



```
>>>
= RESTART: C:/VKHCG/03-Hillman/01-Retrieve/Retrieve-IP_DATA_ALL_2_SQLite.py =
Loading : C:/VKHCG/01-Vermeulen/01-Retrieve/01-EDS/02-Python/Retrieve_IP_DATA.csv
Storing : C:/VKHCG/01-Vermeulen/00-RawData/SQLite/vermeulen.db  Table: IP_DATA_ALL
Loading : C:/VKHCG/01-Vermeulen/00-RawData/SQLite/vermeulen.db  Table: IP_DATA_ALL
################
## Data Values
################
      RowIDCSV  RowID    ID  ... Longitude First.IP.Number Last.IP.Number
0            0      0     1  ...  -73.9725       204276480      204276735
1            1      1     2  ...  -73.9725       301984864      301985791
2            2      2     3  ...  -73.9725       404678736      404679039
3            3      3     4  ...  -73.9725       411592704      411592959
4            4      4     5  ...  -73.9725       416784384      416784639
...        ...    ...   ...  ...       ...             ...            ...
3557      3557   3557  3558  ...   11.5392      1591269504     1591269631
3558      3558   3558  3559  ...   11.7500      1558374784     1558374911
3559      3559   3559  3560  ...   11.4667      1480845312     1480845439
3560      3560   3560  3561  ...   11.7434      1480596992     1480597503
3561      3561   3561  3562  ...   11.7434      1558418432     1558418943

[3562 rows x 10 columns]
################
## Data Profile
################
Rows : 3562
Columns : 10
################
### Done!! ############################################
>>> |
```

MySQL:

Open MySql

Create a database –DataScience‖

Create a python file and add the following code:

################# Connection With MySQL ######################

importmysql.connector

conn = mysql.connector.connect(host='localhost',

database='DataScience',

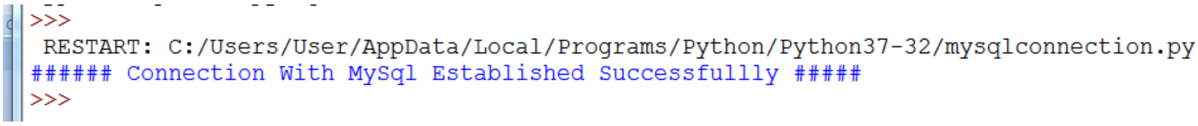
user='root', password='root')

conn.connect

if(conn.is_connected):

print('###### Connection With MySql Established Successfullly ##### ')else:

print('Not Connected -- Check Connection Properites')



```
>>>
 RESTART: C:/Users/User/AppData/Local/Programs/Python/Python37-32/mysqlconnection.py
###### Connection With MySql Established Successfullly #####
>>>
```

Microsoft Excel

#################Retrieve-Country-Currency.py # -*-

coding: utf-8 -*-

importos

import pandas as pd

Base='C:/VKHCG'

sFileDir=Base + '/01-Vermeulen/01-Retrieve/01-EDS/02-Python'#if not os.path.exists(sFileDir):

```
#os.makedirs(sFileDir)
CurrencyRawData = pd.read_excel('C:/VKHCG/01-Vermeulen/00-RawData/Country_Currency.xlsx')sColumns
= ['Country or territory', 'Currency', 'ISO-4217']
CurrencyData = CurrencyRawData[sColumns]
CurrencyData.rename(columns={'Country or territory': 'Country', 'ISO-4217':
'CurrencyCode'}, inplace=True) CurrencyData.dropna(subset=['Currency'],inplace=True)
CurrencyData['Country'] = CurrencyData['Country'].map(lambda x: x.strip())
CurrencyData['Currency'] = CurrencyData['Currency'].map(lambda x: x.strip())
CurrencyData['CurrencyCode'] = CurrencyData['CurrencyCode'].map(lambda x:x.strip())
print(CurrencyData)
print('~~~~~~ Data from Excel Sheet Retrived Successfully ~~~~~~~ ')sFileName=sFileDir +
'/Retrieve-Country-Currency.csv' CurrencyData.to_csv(sFileName, index = False)
```

OUTPUT:

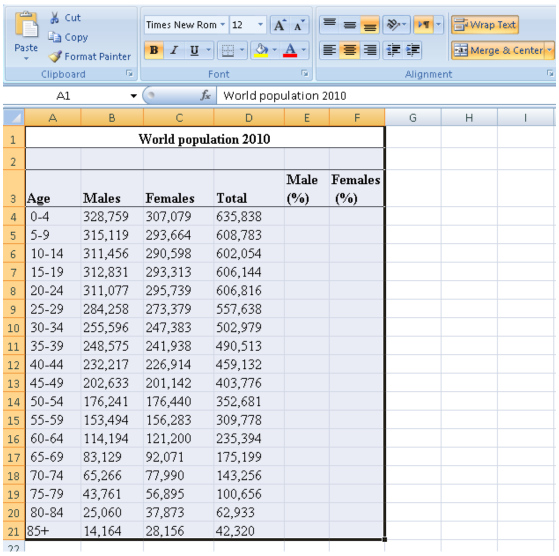
```
Python 3.7.4 Shell
File  Edit  Shell  Debug  Options  Window  Help
Python 3.7.4 (tags/v3.7.4:e09359112e, Jul  8 2019, 19:29:22) [MSC v.1916 32 bit
(Intel)] on win32
Type "help", "copyright", "credits" or "license()" for more information.
>>>
==== RESTART: C:/VKHCG/04-Clark/01-Retrieve/Retrieve-Country-Currency.py ====
                        Country              Currency CurrencyCode
1                   Afghanistan        Afghan afghani          AFN
2     Akrotiri and Dhekelia (UK)         European euro          EUR
3        Aland Islands (Finland)         European euro          EUR
4                       Albania          Albanian lek          ALL
5                       Algeria        Algerian dinar          DZD
..                          ...                   ...          ...
271           Wake Island (USA)  United States dollar          USD
272  Wallis and Futuna (France)             CFP franc          XPF
274                       Yemen          Yemeni rial          YER
276                      Zambia        Zambian kwacha          ZMW
277                    Zimbabwe  United States dollar          USD

[253 rows x 3 columns]
~~~~~~ Data from Excel Sheet Retrived Successfully ~~~~~~~
>>> |
Ln: 20  Col: 4
```

Practical 2

Perform analysis of given secondary data.

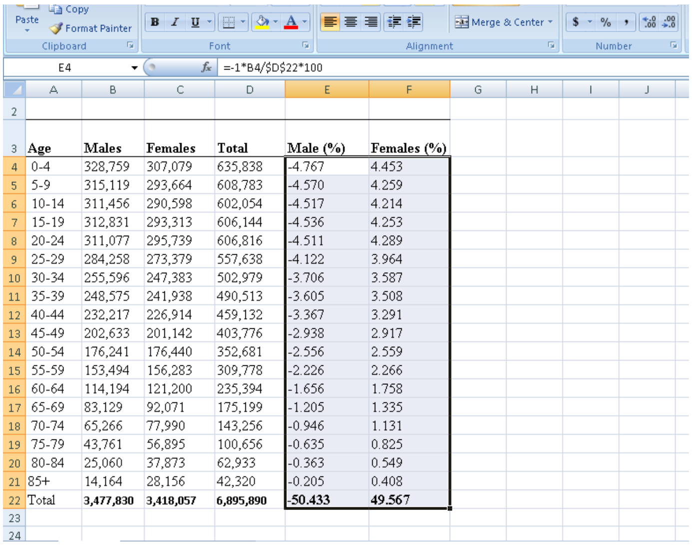
1. **Determine your research question** – Knowing exactly what you are looking for.
2. **Locating data**– Knowing what is out there and whether you can gain access to it. A quick Internet search, possibly with the help of a librarian, will reveal a wealth of options.
3. **Evaluating relevance of the data** – Considering things like the data‘s original purpose, when it was collected, population, sampling strategy/sample, data collection protocols, operationalization of concepts, questions asked, and form/shape of the data.
4. **Assessing credibility of the data** – Establishing the credentials of the original researchers, searching for full explication of methods including any problems encountered, determining how consistent the data is with data from other sources, anddiscovering whether the data has been used in any credible published research.
5. **Analysis –** This will generally involve a range of statistical processes.

Example: Analyze the given Population Census Data for Planning and Decision Making byusing the size and composition of populations.



World population 2010					
Age	Males	Females	Total	Male (%)	Females (%)
0-4	328,759	307,079	635,838		
5-9	315,119	293,664	608,783		
10-14	311,456	290,598	602,054		
15-19	312,831	293,313	606,144		
20-24	311,077	295,739	606,816		
25-29	284,258	273,379	557,638		
30-34	255,596	247,383	502,979		
35-39	248,575	241,938	490,513		
40-44	232,217	226,914	459,132		
45-49	202,633	201,142	403,776		
50-54	176,241	176,440	352,681		
55-59	153,494	156,283	309,778		
60-64	114,194	121,200	235,394		
65-69	83,129	92,071	175,199		
70-74	65,266	77,990	143,256		
75-79	43,761	56,895	100,656		
80-84	25,060	37,873	62,933		
85+	14,164	28,156	42,320		

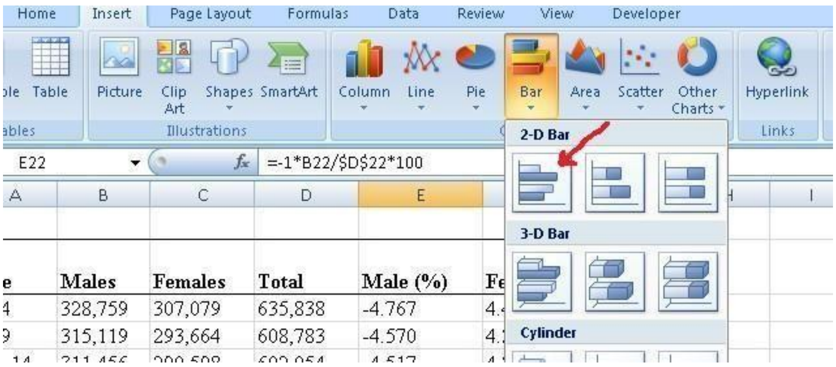
Put the cursor in cell **B22** and click on the **AutoSum** and then click **Enter**. This will calculatethe total population. Then copy the formula in cell **D22** across the row **22.**To calculate the percent of males in cell **E4**, enter the formula **=-1*100*B4/$D$22** . And copy the formula in cell **E4** down to cell **E21.** To calculate the percent of females in cell **F4**, enter the formula =**100*C4/$D$22**. Copy the formula in cell **F4** down to cell **F21.**



	Age	Males	Females	Total	Male (%)	Females (%)
4	0-4	328,759	307,079	635,838	-4.767	4.453
5	5-9	315,119	293,664	608,783	-4.570	4.259
6	10-14	311,456	290,598	602,054	-4.517	4.214
7	15-19	312,831	293,313	606,144	-4.536	4.253
8	20-24	311,077	295,739	606,816	-4.511	4.289
9	25-29	284,258	273,379	557,638	-4.122	3.964
10	30-34	255,596	247,383	502,979	-3.706	3.587
11	35-39	248,575	241,938	490,513	-3.605	3.508
12	40-44	232,217	226,914	459,132	-3.367	3.291
13	45-49	202,633	201,142	403,776	-2.938	2.917
14	50-54	176,241	176,440	352,681	-2.556	2.559
15	55-59	153,494	156,283	309,778	-2.226	2.266
16	60-64	114,194	121,200	235,394	-1.656	1.758
17	65-69	83,129	92,071	175,199	-1.205	1.335
18	70-74	65,266	77,990	143,256	-0.946	1.131
19	75-79	43,761	56,895	100,656	-0.635	0.825
20	80-84	25,060	37,873	62,933	-0.363	0.549
21	85+	14,164	28,156	42,320	-0.205	0.408
22	Total	3,477,830	3,418,057	6,895,890	-50.433	49.567

To build the population pyramid, we need to choose a horizontal bar chart with two series ofdata (% male and % female) and the age labels in column A as the **Category X-axis** labels. Highlight the range **A3:A21**, hold down the CTRL key and highlight the range **E3:F21**

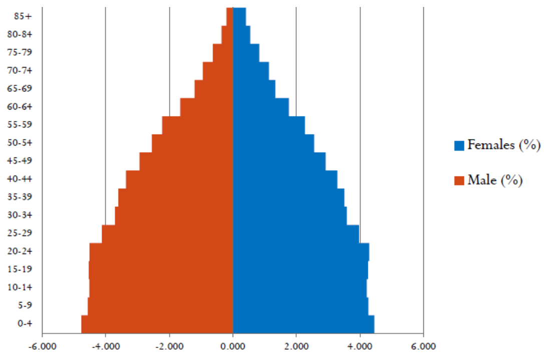
Under **inset** tab, under horizontal bar charts select **clustered bar chart**



Put the tip of your mouse arrow on the **Y-axis** (vertical axis) so it says ―Category Axis‖, right click and chose **Format Axis**

Choose **Axis options** tab and set the major and minor tick mark type to **None**, Axis labels to **Low**, and click **OK**.

Click on any of the bars in your pyramid, click right and select ―format data series‖. Set the **Overlap** to **100** and **Gap Width** to **0**. Click **OK**.



Practical 3

A. Perform testing of hypothesis using one sample t-test.

One sample t-test : The One Sample T Test determines whether the sample mean is statistically different from a known or hypothesised population mean. The One Sample T Test is a parametric test.

Program Code:

```
# -*- coding: utf-8 -*- fromscipy.stats
import ttest_1sampimportnumpy as np
ages = np.genfromtxt('ages.csv')
print(ages)
ages_mean = np.mean(ages)
print(ages_mean)
tset, pval = ttest_1samp(ages, 30)print('p-
values - ',pval)

if pval< 0.05:    # alpha value is 0.05
        print(" we are rejecting null hypothesis")
else:
        print("we are accepting null hypothesis")
```

Output:

```
In [4]: runfile('K:/Research In Computing/Practical Material/Programs/
Practical_05/Prac_3A.py', wdir='K:/Research In Computing/Practical Material/
Programs/Practical_05')
[20. 30. 25. 13. 16. 17. 34. 35. 38. 42. 43. 45. 48. 49. 50. 51. 54. 55.
 56. 59. 61. 62. 18. 22. 29. 30. 31. 39. 52. 53. 67. 36. 47. 54. 40. 40.
 35. 22. 59. 58. 30. 43. 22. 45. 21. 59. 51. 47. 25. 58. 50. 23. 24. 45.
 37. 59. 28. 28. 48. 42. 54. 36. 36. 24. 26. 24. 50. 48. 34. 44. 56. 55.
 35. 33. 39. 53. 34. 28. 56. 24. 21. 29. 28. 58. 35. 57. 26. 25. 59. 56.
 22. 57. 48. 33. 23. 26. 57. 32. 53. 31. 35. 44. 54. 25. 31. 58. 26. 32.
 26. 50. 41. 49. 26. 33. 34. 24. 43. 42. 51. 36. 38. 38. 40. 38. 56. 39.
 23. 33. 53. 30. 38.]
39.47328244274809
p-values -  5.362905195437013e-14
 we are rejecting null hypothesis
```

B. Write a program for t-test comparing two means for independent samples.

The T distribution provides a good way to perform one sample tests on the mean when the population variance is not known provided the population is normal or the sample is sufficiently large so that the Central Limit Theorem applies.

Two Sample Test

Example: A college Principal informed classroom teachers that some of their students showed Unusual potential for intellectual gains. One months later the students identified to teachers as having potential for unusual intellectual gains showed significantly greater gainsperformance on a test said to measure IQ than did students who were not so identified. Below are the data for the students:

Experimental	**Comparison**	
35	2	
40	27	
12	38	
15	31	
21	1	
14	19	
46	1	
10	34	
28	3	
48	1	
16	2	
30	3	
32	2	
48	1	
31	2	
22	1	
12	3	
39	29	
19	37	
25	2	
27.15	11.95	Mean
12.51	14.61	Sd

Experimental Data

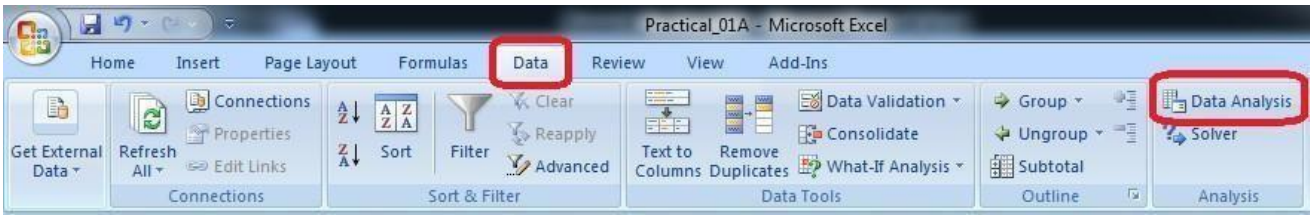
To calculate Standard Mean go to cell A22 and type =SUM(A2:A21)/20

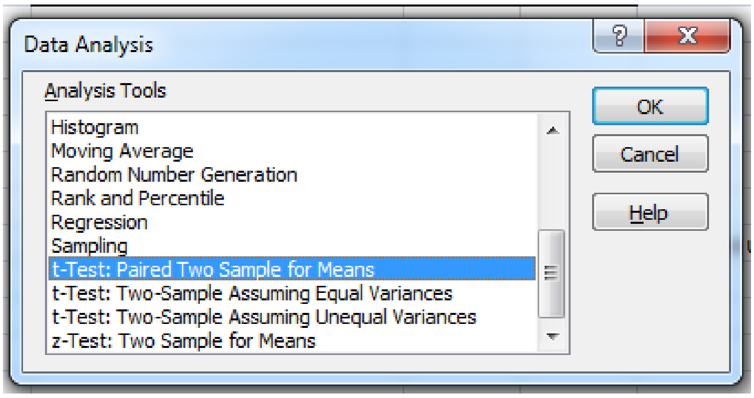
To calculate Standard Deviation go to cell A23 and type =STDEV(A2:A21)

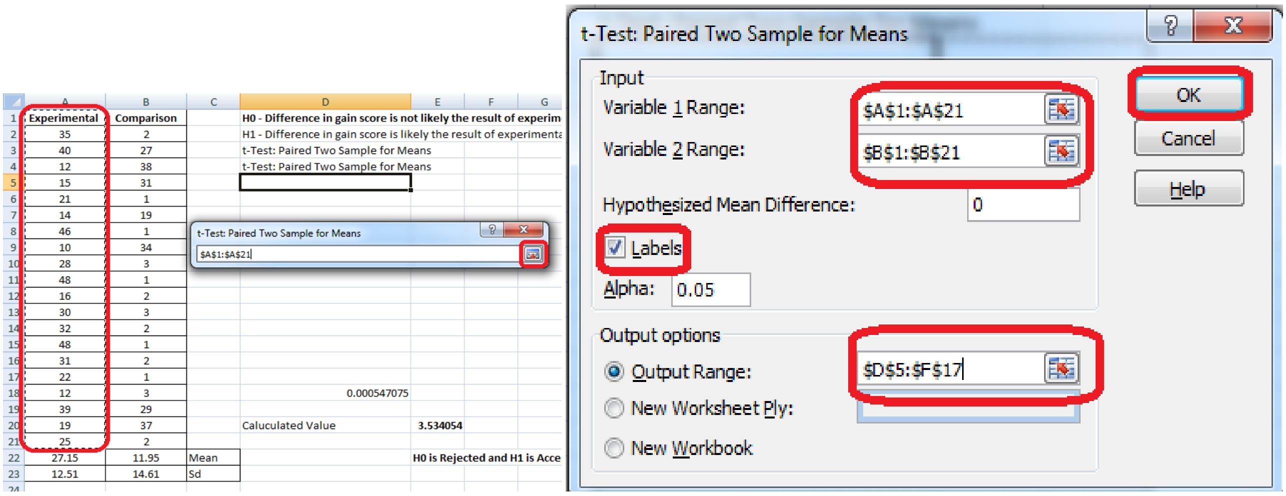
Comparison Data

To calculate Standard Mean go to cell B22 and type =SUM(B2:B21)/20

To calculate Standard Deviation go to cell B23 and type =STDEV(B2:B21) To find T-Test Statistics go to data ☐ Data Analysis







To caluculate the T-Test square value go to cell E20 and type =(A22-B22)/SQRT((A23*A23)/COUNT(A2:A21)+(B23*B23)/COUNT(A2:A21))

Now go to cell E20 and type =IF(E20<E12,"H0 is Accepted", "H0 is Rejected and H1 is Accepted")

Our calculated value is larger than the tabled value at alpha = .01, so we reject the null Hypothesis and accept the alternative hypothesis, namely, that the difference in gain scores is likely the resultof the experimental treatment and not the result of chance variation.

Output:

	A	B	C	D	E	F	G	H	I	J	K
1	**Experimental**	**Comparison**		**H0 - Difference in gain score is not likely the result of experimental treatment.**							
2	35	2		H1 - Difference in gain score is likely the result of experimental treatment and not the result of change variation.							
3	40	27		t-Test: Paired Two Sample for Means							
4	12	38		t-Test: Paired Two Sample for Means							
5	15	31		t-Test: Paired Two Sample for Means							
6	21	1									
7	14	19			*Experimental*	*Comparison*					
8	46	1		Mean	27.15	11.95					
9	10	34		Variance	156.45	213.5236842					
10	28	3		Observations	20	20					
11	48	1		Pearson Correlation	-0.395904927						
12	16	2		Hypothesized Mean Difference	0						
13	30	3		df	19						
14	32	2		t Stat	2.996289153						
15	48	1		P(T<=t) one-tail	0.003711226						
16	31	2		t Critical one-tail	1.729132792						
17	22	1		P(T<=t) two-tail	0.007422452						
18	12	3		t Critical two-tail	2.09302405						
19	39	29									
20	19	37		Caluculated Value	**3.534053898**						
21	25	2									
22	27.15	11.95	Mean		**H0 is Rejected and H1 is Accepted**						
23	12.51	14.61	Sd								

Using Python importnumpy as

```
np fromscipy import stats
fromnumpy.random import randnN = 20
#a = [35,40,12,15,21,14,46,10,28,48,16,30, 32,48,31,22,12,39,19,25]
#b = [2,27,31,38,1,19,1,34,3,1,2,1,3,1,2,1,3,29,37,2]
a = 5 * randn(100) + 50b = 5 *
randn(100) + 51var_a =
a.var(ddof=1) var_b =
b.var(ddof=1)
s = np.sqrt((var_a + var_b)/2)
t = (a.mean() - b.mean())/(s*np.sqrt(2/N))df = 2*N
- 2
#p-value after comparison with the tp = 1 -
stats.t.cdf(t,df=df)
print("t = " + str(t)) print("p = "
+ str(2*p))if t> p :
print('Mean of two distribution are differnt and significant')else:
print('Mean of two distribution are same and not significant')
```

Output:

```
In [9]: runfile('E:/Research In Computing/Programs/
Practical_04/Program_4B.py', wdir='E:/Research In
Computing/Programs/Practical_04')
t = -1.051463820987354
p = 1.700313560478936
Mean of two distribution are same and not significant

In [10]: runfile('E:/Research In Computing/Programs/
Practical_04/Program_4B.py', wdir='E:/Research In
Computing/Programs/Practical_04')
t = 0.46409515960993775
p = 0.6452274090296801
Mean of two distribution are differnt and significant
```

A. Perform testing of hypothesis using paired t-test.

The paired sample t-test is also called dependent sample t-test. It‘s an univariate test that tests fora significant difference between 2 related variables. An example of this is if you where t

collect the blood pressure for an individual before and after some treatment, condition, or time point. The data set contains blood pressure readings before and after an intervention. These are variables ―bp_before‖ and ―bp_after‖.

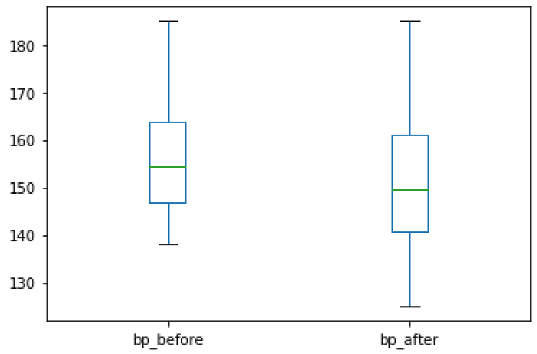
The hypothesis being test is:

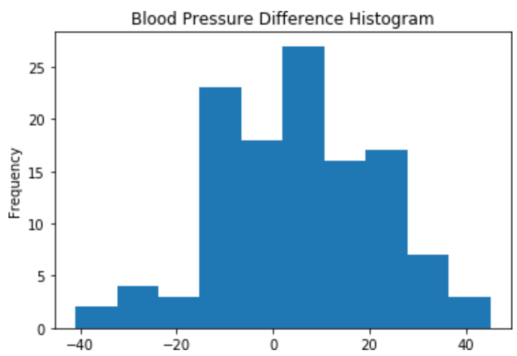
- **H0** - The mean difference between sample 1 and sample 2 is equal to 0.
- **H0** - The mean difference between sample 1 and sample 2 is not equal to 0

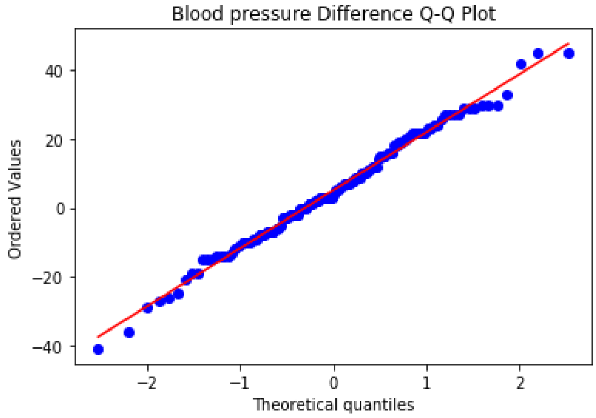
Program Code:

```
# -*- coding: utf-8 -*-
Created on Mon Dec 16 19:49:23 2019from
scipy import stats
import matplotlib.pyplot as pltimport
pandas as pd
df = pd.read_csv("blood_pressure.csv") print(df[['bp_before','bp_after']].describe())

#First let‘s check for any significant outliers in#each of
the variables.
df[['bp_before', 'bp_after']].plot(kind='box')# This
saves the plot as a png file
plt.savefig('boxplot_outliers.png')

# make a histogram to differences between the two scores.
df['bp_difference'] = df['bp_before'] - df['bp_after']

df['bp_difference'].plot(kind='hist', title= 'Blood Pressure Difference Histogram')#Again,
this saves the plot as a png file
plt.savefig('blood pressure difference histogram.png')
stats.probplot(df['bp_difference'], plot= plt) plt.title('Blood
pressure Difference Q-Q Plot') plt.savefig('blood pressure
difference qq plot.png') stats.shapiro(df['bp_difference'])
stats.ttest_rel(df['bp_before'], df['bp_after'])
```

Output:








```
In [21]: runfile('K:/Research In Computing/Practical
Material/Programs/Practical_03/Practical_03C.py', wdir='K:/
Research In Computing/Practical Material/Programs/
Practical_03')
        bp_before    bp_after
count  120.000000  120.000000
mean   156.450000  151.358333
std     11.389845   14.177622
min    138.000000  125.000000
25%    147.000000  140.750000
50%    154.500000  149.500000
75%    164.000000  161.000000
max    185.000000  185.000000
0.0011297914644840823
Ttest_relResult(statistic=3.3371870510833657,
pvalue=0.0011297914644840823)
reject null hypothesis
```

A paired sample t-test was used to analyze the blood pressure before and after the intervention to test if the intervention had a significant affect on the blood pressure. The blood pressure before the intervention was higher (156.45 ± 11.39 units) compared to the blood pressure postintervention (151.36 ± 14.18 units); there was a statistically significant decrease in blood pressure ($t(119)=3.34$, $p= 0.0011$) of 5.09 units.

Practical 4

A. Perform testing of hypothesis using chi-squared goodness-of-fit test. Problem

Ansystem administrator needs to upgrade the computers for his division. He wants to know what sort of computer system his workers prefer. He gives three choices: Windows, Mac, or Linux. Test the hypothesis or theory that an equal percentage ofthe population prefers each type of computer system .

System	O	Ei	$\sum \frac{(O_i - E_i)^2}{Ei}$
Windows	20	**33.33 %**	
Mac	60	**33.33 %**	
Linux	20	**33.33 %**	

H0 : The population distribution of the variable is the same as the proposed distribution

HA : The distributions are different

To calculate the Chi –Squred value for Windows go to cell D2 and type =((B2-C2)*(B2-C2))/C2

To calculate the Chi –Squred value for Mac go to cell D3 and type =((B3-C3)*(B3-C3))/C3

To calculate the Chi –Squred value for Mac go to cell D3 and type =((B4-C4)*(B4-C4))/C4

Go to Cell D5 for $\sum \frac{(O_i - E_i)^2}{Ei}$ and type=SUM(D2:D4)

To get the table value for Chi-Square for α = 0.05 and dof = 2, go to cell D7 and type =CHIINV(0.05,2)

At cell D8 type =IF(D5>D7, "H0 Accepted","H0 Rejected")

Output:

	A	B	C	D	E	F
1	System	O	Ei	$\sum \frac{(O_i - E_i)^2}{Ei}$		
2	Windows	20	33.33	5.333333		H0 : The population distribution of the variable is the same as the proposed distribution
3	Mac	60	33.33	21.33333		H1 - : The distributions are different
4	Linux	20	33.33	5.333333		
5	Total	100	100	32		
6						
7			Table Value	**5.991465**		
8			H0 Accepted			

B. Perform testing of hypothesis using chi-squared test of independence.

In a study to understatnd the permormacne of M. Sc. IT Part -1 class, a college selects a randomsample of 100 students. Each student was asked his grade obtained in B. Sc. IT. The sampleisas given below

Sr. No	Roll No	Student's Name	Gen	Grade
1	1	Gaborone	m	O
2	2	Francistown	m	O
3	5	Niamey	m	O
4	13	Maxixe	m	O
5	16	Tema	m	O
6	17	Kumasi	m	O
7	34	Blida	m	O
8	35	Oran	m	O
9	38	Saefda	m	O
10	42	Constantine	m	O
11	43	Annaba	m	O
12	45	Bejaefa	m	O
13	48	Medea	m	O
14	49	Djelfa	m	O
15	50	Tipaza	m	O
16	51	Bechar	m	O
17	54	Mostaganem	m	O
18	55	Tiaret	m	O
19	56	Bouira	m	O
20	59	Tebessa	m	O
21	61	El Harrach	m	O
22	62	Mila	m	O
23	65	Fouka	m	O
24	66	El Eulma	m	O
25	68	SidiBel Abbes	m	O
26	69	Jijel	m	O
27	70	Guelma	m	O
28	85	Khemis El Khechna	m	O
29	87	Bordj El Kiffan	m	O
30	88	Lakhdaria	m	O
31	6	Maputo	m	D
32	12	Lichinga	m	D
33	15	Ressano Garcia	m	D
34	19	Accra	m	D
35	27	Wa	m	D
36	28	Navrongo	m	D
37	37	Mascara	m	D
38	44	Batna	m	D
39	57	El Biar	m	D
40	60	Boufarik	m	D
41	63	OuedRhiou	m	D
42	64	Souk Ahras	m	D
43	71	Dar El Befda	m	D
44	86	Birtouta	m	D
45	18	Takoradi	m	C
46	22	Cape Coast	m	C
47	29	Kwabeng	m	C
48	30	Algiers	m	C
49	31	Laghouat	m	C
50	39	Relizane	m	C
51	52	Setif	m	C
52	53	Biskra	m	C
53	67	Kolea	m	C
54	100	AefnFakroun	m	C
55	26	Nima	m	B
56	32	TiziOuzou	m	B
57	33	Chlef	m	B
58	89	M'sila	m	A
59	96	Heliopolis	m	A
60	97	Berrouaghia	m	A
61	98	Sougueur	m	A
62	3	Maun	f	O
63	7	Tete	f	O
64	9	Chimoio	f	O
65	11	Pemba	f	O
66	14	Chibuto	f	O
67	25	Mampong	f	O
68	36	Tlemcen	f	O
69	40	Adrar	f	O
70	41	Tindouf	f	O
71	46	Skikda	f	O
72	47	Ouargla	f	O
73	10	Matola	f	D
74	20	Legon	f	D
75	21	Sunyani	f	D
76	72	Teenas	f	D
77	73	Kouba	f	D
78	75	HussenDey	f	D
79	77	Khenchela	f	D
80	82	HassiBahbah	f	D
81	84	Baraki	f	D
82	91	Boudouaou	f	D
83	95	Tadjenanet	f	D
84	4	Molepolole	f	C
85	8	Quelimane	f	C
86	23	Bolgatanga	f	C
87	58	Mohammadia	f	C
88	83	Merouana	f	C
89	24	Ashaiman	f	B
90	76	N'gaous	f	B
91	90	Bab El Oued	f	B
92	92	BordjMenael	f	B
93	93	Ksar El Boukhari	f	B
94	74	Reghaa	f	A
95	78	Cheria	f	A
96	79	Mouzaa	f	A
97	80	Meskiana	f	A
98	81	Miliana	f	A
99	94	Sig	f	A
100	99	Kadiria	f	A

Null Hypothesis - H0 : The performance of girls students is same as boys students.
Alternate Hypothesis - H1 : The performance of boys and girls students are different.
Open Excel Workbook

	O	A	B	C	D	Total	$\sum \frac{(O_i - E_i)^2}{Ei}$
Girls	11	7	5	5	11	**39**	6.075
Boys	30	4	3	10	14	**61**	6.075
Total	41	11	8	15	25	**100**	**12.150**
Ei	**20.5**	**5.5**	**4**	**7.5**	**12.5**	**50**	

Prepare a contingency table as shown above.
To calculate Girls Students with _O‘ Grade
Go to Cell N6 and type =COUNTIF($J$2:$K$40,"O")

To calculate Girls Students with _A‘ Grade
Go to Cell O6 and type =COUNTIF($J$2:$K$40,"A")

To calculate Girls Students with _B‘ Grade
Go to Cell P6 and type =COUNTIF($J$2:$K$40,"B")

To calculate Girls Students with _C‘ Grade
Go to Cell Q6 and type =COUNTIF($J$2:$K$40,"C")

To calculate Girls Students with _D‘ Grade
Go to Cell R6 and type =COUNTIF($J$2:$K$40,"D")

To calculate Boys Students with _O‘ Grade
Go to Cell N7 and type =COUNTIF($D$2:$E$62,"O")
To calculate Boys Students with _A‘ Grade
Go to Cell O7 and type =COUNTIF($D$2:$E$62,"A")
To calculate Boys Students with _B‘ Grade
Go to Cell P7 and type =COUNTIF($D$2:$E$62,"B")
To calculate Boys Students with _C‘ Grade
Go to Cell Q7 and type =COUNTIF($D$2:$E$62,"C")
To calculate Boys Students with _D‘ Grade
Go to Cell R7 and type =COUNTIF($D$2:$E$62,"D")

To calculated the expected value Ei
Go to Cell N9 and type =N8/2
Go to Cell O9 and type =O8/2
Go to Cell P9 and type =P8/2
Go to Cell Q9 and type =Q8/2
Go to Cell R9 and type =R8/2
Go to Cell S6 and calculate total girl students = SUM(N6:R6)
Go to Cell S7 and calculate total girl students = SUM(N7:R7)

Now Calculate

Go to cell **T6** and type

=SUM((N6-$N$9)^2/$N$9,(O6-$O$9)^2/$O$9,(P6-$P$9)^2/$P$9,(Q6-Q$9)^2/$Q$9, (R6-$R$9)^2/$R$9)

Go to cell **T7** and type

=SUM((N7-$N$9)^2/$N$9,(O7-$O$9)^2/$O$9,(P7-$P$9)^2/$P$9,(Q7-Q$9)^2/$Q$9, (R7-$R$9)^2/$R$9)

To get the table value go to cell T11 and type **=CHIINV(0.05,4)**

Go to cell O13 and type =IF(T8>=T11," H0 is Accepted", "H0 is Rejected")

M	N	O	P	Q	R	S	T
H0 : Performance of boys and girls are equal							
Frequency Table							$(O_i - E_i)^2$
	O	**A**	**B**	**C**	**D**	**Total**	**Ei**
Girls	11	7	5	5	11	**39**	6.075
Boys	30	4	3	10	14	**61**	6.075
Total	41	11	8	15	25	**100**	**12.150**
Ei	**20.5**	**5.5**	**4**	**7.5**	**12.5**	**50**	
Critcal Value of α =0.05 for df = (2-1) * (5-1)							9.487729
Decesion		**H0 is Accepted**					

Using Python

```
importnumpy as np import
pandas as pd importscipy.stats as
statsnp.random.seed(10)
stud_grade = np.random.choice(a=["O","A","B","C","D"],
                              p=[0.20, 0.20 ,0.20, 0.20, 0.20], size=100)
stud_gen = np.random.choice(a=["Male","Female"], p=[0.5, 0.5], size=100)mscpart1
= pd.DataFrame({"Grades":stud_grade, "Gender":stud_gen}) print(mscpart1)
stud_tab = pd.crosstab(mscpart1.Grades, mscpart1.Gender, margins=True)
stud_tab.columns = ["Male", "Female", "row_totals"]
stud_tab.index = ["O", "A", "B", "C", "D", "col_totals"]observed
= stud_tab.iloc[0:5, 0:2 ]
print(observed)
expected = np.outer(stud_tab["row_totals"][0:5],
stud_tab.loc["col_totals"][0:2]) / 100 print(expected)
chi_squared_stat = (((observed-expected)**2)/expected).sum().sum()
print('Calculated : ',chi_squared_stat)

crit = stats.chi2.ppf(q=0.95, df=4)
print('Table Value : ',crit)

ifchi_squared_stat>= crit:print('H0
is Accepted ') else:
print('H0 is Rejected ')
```

Output :

```
In [1]: runfile('E:/Research In Computing/Programs/
Practical_03/ChiSquaer.py', wdir='E:/Research In
Computing/Programs/Practical_03')
   Grades  Gender
0       C  Female
1       O  Female
2       C    Male
3       C    Male
4       B  Female
..    ...     ...
95      B    Male
96      D  Female
97      B  Female
98      A    Male
99      B    Male

[100 rows x 2 columns]
   Male  Female
O    11      12
A     9      13
B     7      11
C    10       8
D    12       7
[[11.27 11.73]
 [10.78 11.22]
 [ 8.82  9.18]
 [ 8.82  9.18]
 [ 9.31  9.69]]
Calculated :  3.158915138993211
Table Value :  9.487729036781154
H0 is Rejected
```

Practical 5

Perform testing of hypothesis using Z-test.

Use a Z test if:

- Your sample size is greater than 30. Otherwise, use a t test.
- Data points should be independent from each other. In other words, one data point isn‘trelated or doesn‘t affect another data point.
- Your data should be normally distributed. However, for large sample sizes (over 30)this doesn‘t always matter.
- Your data should be randomly selected from a population, where each item has an equalchance of being selected.
- Sample sizes should be equal if at all possible.

Ho - Blood pressure has a mean of 156 units

Program Code for one-sample Z test.

```
from statsmodels.stats import weightstats as stestsimport
pandas as pd
from scipy import stats
df = pd.read_csv("blood_pressure.csv")
df[['bp_before','bp_after']].describe() print(df)
ztest ,pval = stests.ztest(df['bp_before'], x2=None, value=156)
print(float(pval))

if pval<0.05:
   print("reject null hypothesis")else:
   print("accept null hypothesis")
```

Output:

```
In [26]: runfile('K:/Research In Computing/Practical
Material/Programs/Practical_05/Z_Test_One_Sample.py',
wdir='K:/Research In Computing/Practical Material/Programs/
Practical_05')
     patient  gender agegrp  bp_before  bp_after
0          1    Male  30-45        143       153
1          2    Male  30-45        163       170
2          3    Male  30-45        153       168
3          4    Male  30-45        153       142
4          5    Male  30-45        146       141
..       ...     ...    ...        ...       ...
115      116  Female    60+        152       152
116      117  Female    60+        161       152
117      118  Female    60+        165       174
118      119  Female    60+        149       151
119      120  Female    60+        185       163

[120 rows x 5 columns]
0.6651614730255063
accept null hypothesis
```

Two-sample Z test- In two sample z-test , similar to t-test here we are checking two independent data groups and deciding whether sample mean of two group is equal or not.

H0 : mean of two group is 0

H1 : mean of two group is not 0

```
# -*- coding: utf-8 -*-
"""
```

Created on Mon Dec 16 20:42:17 2019@author:
MyHome """

import pandas as pd
from statsmodels.stats import weightstats as stestsdf =
pd.read_csv("blood_pressure.csv")
df[['bp_before','bp_after']].describe()
print(df)

ztest ,pval = stests.ztest(df['bp_before'], x2=df['bp_after'], value=0,alternative='two-sided')
print(float(pval))

if pval<0.05:
    print("reject null hypothesis")else:
    print("accept null hypothesis")

```
In [29]: runfile('K:/Research In Computing/Practical
Material/Programs/Practical_05/Z_Test_Two_Sample.py',
wdir='K:/Research In Computing/Practical Material/Programs/
Practical_05')
     patient  gender agegrp  bp_before  bp_after
0          1    Male  30-45        143       153
1          2    Male  30-45        163       170
2          3    Male  30-45        153       168
3          4    Male  30-45        153       142
4          5    Male  30-45        146       141
..       ...     ...    ...        ...       ...
115      116  Female    60+        152       152
116      117  Female    60+        161       152
117      118  Female    60+        165       174
118      119  Female    60+        149       151
119      120  Female    60+        185       163

[120 rows x 5 columns]
0.002162306611369422
reject null hypothesis
```

Practical 6

A. Perform testing of hypothesis using One-way ANOVA.

ANOVA ASSUMPTIONS

- The dependent variable (SAT scores in our example) should be continuous.
- The independent variables (districts in our example) should be two or more categorical groups.
- There must be different participants in each group with no participant being in morethan one group. In our case, each school cannot be in more than one district.
- The dependent variable should be approximately normally distributed for eachcategory.
- Variances of each group are approximately equal.

From our data exploration, we can see that the average SAT scores are quite different foreach district. Since we have five different groups, we cannot use the t-test, use the 1-wayANOVA test anyway just to understand the concepts.

H0 - There are no significant differences between the groups' mean SATscores.

$$\mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5$$

H1 - There is a significant difference between the groups' mean SATscores.

If there is at least one group with a significant difference with another group,the null hypothesis will be rejected.

import pandas as pd importnumpy as
np importmatplotlib.pyplot as plt
importseaborn as sns fromscipy
import stats

data = pd.read_csv("scores.csv")
data.head()
data['Borough'].value_counts()
############### There is no total score column, have to create it. ########In addition, find the mean score of the each district across all schools.

data['total_score'] = data['Average Score (SAT Reading)'] + \
data['Average Score (SAT Math)'] + \
data['Average Score (SAT Writing)']
data = data[['Borough', 'total_score']].dropna()
x = ['Brooklyn', 'Bronx', 'Manhattan', 'Queens', 'Staten Island']district_dict =
{}

#Assigns each test score series to a dictionary keyfor district in x:

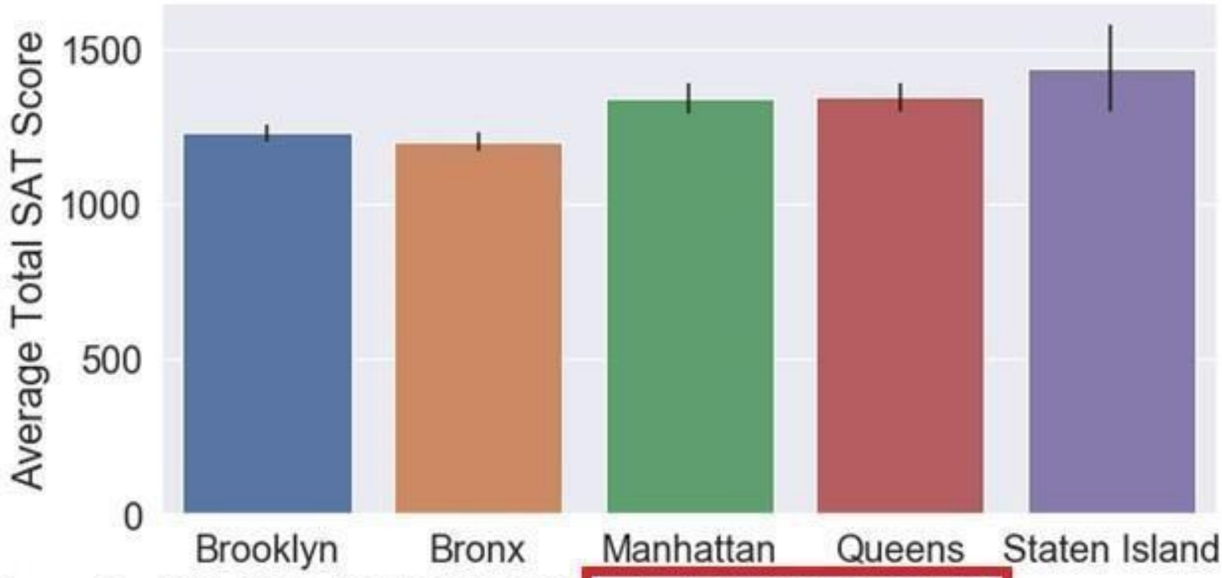
```
district_dict[district] = data[data['Borough'] == district]['total_score']y = []
yerror = []
#Assigns the mean score and 95% confidence limit to each districtfor
district in x:
y.append(district_dict[district].mean())
yerror.append(1.96*district_dict[district].std()/np.sqrt(district_dict[district].shap e[0]))
print(district + '_std : {}'.format(district_dict[district].std()))

sns.set(font_scale=1.8)
fig = plt.figure(figsize=(10,5))
ax = sns.barplot(x, y, yerr=yerror)
ax.set_ylabel('Average Total SAT Score')
plt.show()
```

###################### Perform 1-way ANOVA

```
print(stats.f_oneway(
district_dict['Brooklyn'], district_dict['Bronx'], \
district_dict['Manhattan'], district_dict['Queens'], \
district_dict['Staten Island']
))
districts = ['Brooklyn', 'Bronx', 'Manhattan', 'Queens', 'Staten Island']
ss_b = 0
for d in districts:
ss_b += district_dict[d].shape[0] * \
np.sum((district_dict[d].mean() - data['total_score'].mean())**2)
ss_w = 0
for d in districts:
ss_w += np.sum((district_dict[d] - district_dict[d].mean())**2)
msb = ss_b/4
msw = ss_w/(len(data)-5)
f=msb/msw
print('F_statistic: {}'.format(f))

ss_t = np.sum((data['total_score']-data['total_score'].mean())**2)
eta_squared = ss_b/ss_t
        print('eta_squared: {}'.format(eta_squared))
```

Output:

```
In [37]: runfile('E:/Research In Computing/Programs/Practical_05/Annova.py', wdir='E:/Research In Computing/Programs/Practical_05')
Brooklyn_std : 154.8684270520867
Bronx_std : 150.39390071890668
Manhattan_std : 230.2941395363782
Queens_std : 195.25289850192115
Staten Island_std : 222.30359621222706
```




```
F_onewayResult(statistic=12.733085029201668, pvalue=1.0161974965566023e-09)
F_statistic: 12.733085029201687
eta_squared: 0.12099887621529214
```

Since the resulting p value is less than 0.05. The null hypothesis is rejected and conclude thatthere is a significant difference between the SAT scores for each district.

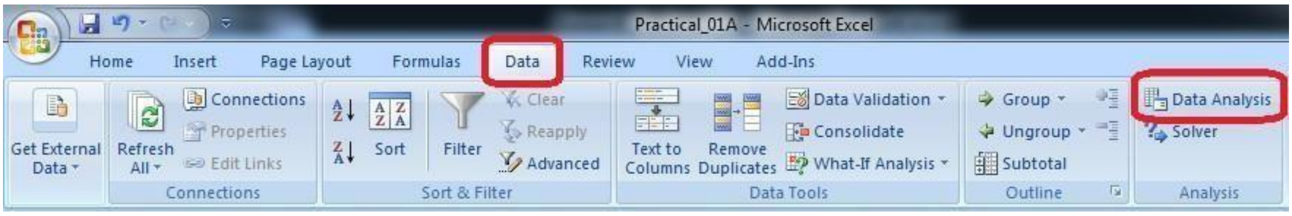
Using Excel

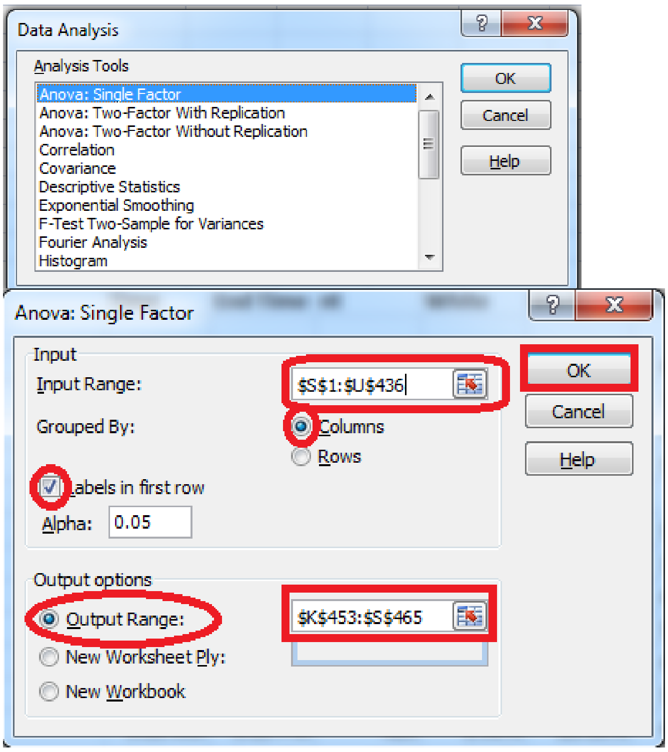
H0 - There are no significant differences between the Subject's mean SAT scores.

$$\mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5$$

H1 - There is a significant difference between the Subject's mean SAT scores.

To perform ANOVA go to data □Data Analysis





Input Range : $S$1:$U$436*(Select columns to be analyzed in group)*

Output Range :$K$453:$S$465*(Can be any Range)*

Anova: Single Factor						
SUMMARY						
Groups	*Count*	*Sum*	*Average*	*Variance*		
Average Score (SAT Math)	375	162354	432.944	5177.144		
Average Score (SAT Reading)	375	159189	424.504	3829.267		
Average Score (SAT Writing)	375	156922	418.4587	4166.522		
ANOVA						
Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	39700.57	2	19850.28	4.520698	0.01108	3.003745
Within Groups	4926677	1122	4390.977			
Total	4966377	1124				

Since the resulting p value is less than 0.05. The null hypothesis (H0) is rejected and conclude at there is a significant difference between the SAT scores for each subject.

B:Perform testing of hypothesis using Two-way ANOVA.

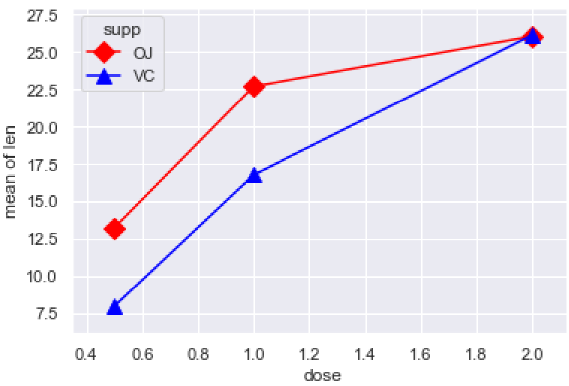
Program Code:

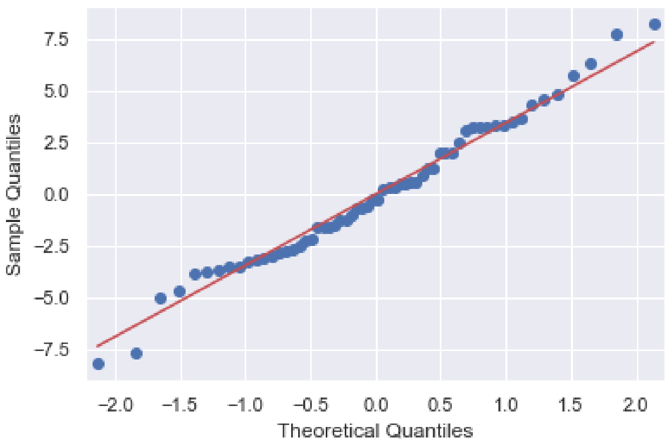
```
import pandas as pd
import statsmodels.api as sm
from statsmodels.formula.api import ols
from statsmodels.stats.anova import anova_lm
from statsmodels.graphics.factorplots import interaction_plot
import matplotlib.pyplot as plt
from scipy import stats

def eta_squared(aov):
aov['eta_sq'] = 'NaN'
aov['eta_sq'] = aov[:-1]['sum_sq']/sum(aov['sum_sq'])
return aov

def omega_squared(aov):
mse = aov['sum_sq'][-1]/aov['df'][-1]
aov['omega_sq'] = 'NaN'
aov['omega_sq'] = (aov[:-1]['sum_sq']-(aov[:-1]['df']*mse))/(sum(aov['sum_sq'])+mse)
return aov

datafile = "ToothGrowth.csv"
data = pd.read_csv(datafile)
fig  =  interaction_plot(data.dose,  data.supp,  data.len,
colors=['red','blue'], markers=['D','^'], ms=10)
N = len(data.len)
df_a  =  len(data.supp.unique())  -  1
df_b  =  len(data.dose.unique())  -  1
df_axb = df_a*df_b
df_w = N - (len(data.supp.unique())*len(data.dose.unique()))
grand_mean = data['len'].mean()
#Sum of Squares A – supp
ssq_a = sum([(data[data.supp ==l].len.mean()-grand_mean)**2 for l in data.supp])
#Sum of Squares B – supp
ssq_b = sum([(data[data.dose ==l].len.mean()-grand_mean)**2 for l in data.dose])
#Sum of Squares Total
ssq_t = sum((data.len - grand_mean)**2)vc
= data[data.supp == 'VC']
oj = data[data.supp == 'OJ']
vc_dose_means = [vc[vc.dose == d].len.mean() for d in vc.dose]
oj_dose_means = [oj[oj.dose == d].len.mean() for d in oj.dose]
ssq_w = sum((oj.len - oj_dose_means)**2) +sum((vc.len - vc_dose_means)**2)
ssq_axb = ssq_t-ssq_a-ssq_b-ssq_w
ms_a = ssq_a/df_a           #Mean Square A
ms_b = ssq_b/df_b                     #Mean
Square B
ms_axb = ssq_axb/df_axb           #Mean Square AXB
ms_w = ssq_w/df_w
f_a = ms_a/ms_wf_b = ms_b/ms_w
```

```
f_axb = ms_axb/ms_w
p_a = stats.f.sf(f_a, df_a, df_w)
p_b = stats.f.sf(f_b, df_b, df_w)
p_axb = stats.f.sf(f_axb, df_axb, df_w)
results = {'sum_sq':[ssq_a, ssq_b, ssq_axb, ssq_w],
'df':[df_a, df_b, df_axb, df_w],
'F':[f_a, f_b, f_axb, 'NaN'],
'PR(>F)':[p_a, p_b, p_axb, 'NaN']}
columns=['sum_sq', 'df', 'F', 'PR(>F)']

aov_table1 = pd.DataFrame(results, columns=columns,
index=['supp', 'dose',
'supp:dose', 'Residual'])
formula = 'len ~ C(supp) + C(dose) + C(supp):C(dose)'
model = ols(formula, data).fit()
aov_table = anova_lm(model, typ=2)
eta_squared(aov_table)
omega_squared(aov_table)
print(aov_table.round(4))
res = model.resid
fig = sm.qqplot(res, line='s')
plt.show()
```

Output:

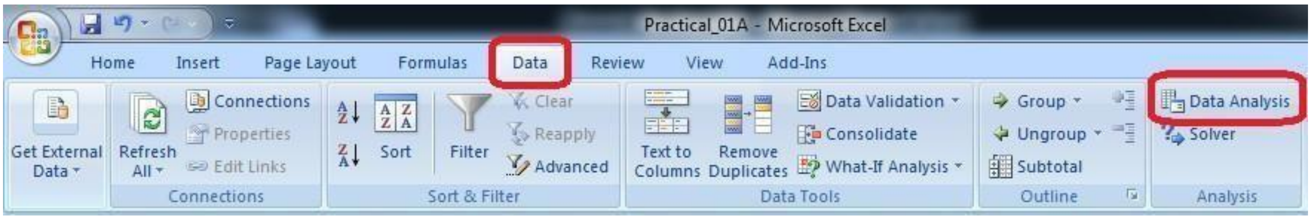
```
In [40]: runfile('K:/Research In Computing/Practical Material/Programs/
Practical_06/Annova_2_Way.py', wdir='K:/Research In Computing/Practical
Material/Programs/Practical_06')
                    sum_sq    df       F  PR(>F)  eta_sq  omega_sq
C(supp)           205.3500   1.0  15.572  0.0002  0.0595    0.0555
C(dose)          2426.4343   2.0  92.000  0.0000  0.7029    0.6926
C(supp):C(dose)   108.3190   2.0   4.107  0.0219  0.0314    0.0236
Residual          712.1060  54.0     NaN     NaN     NaN       NaN
```

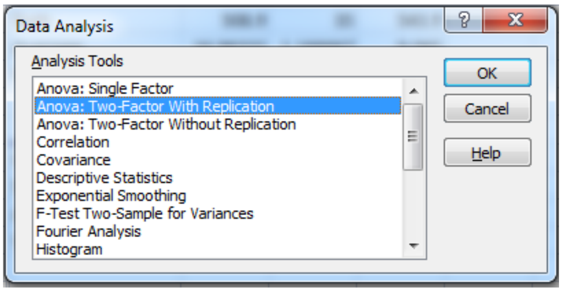


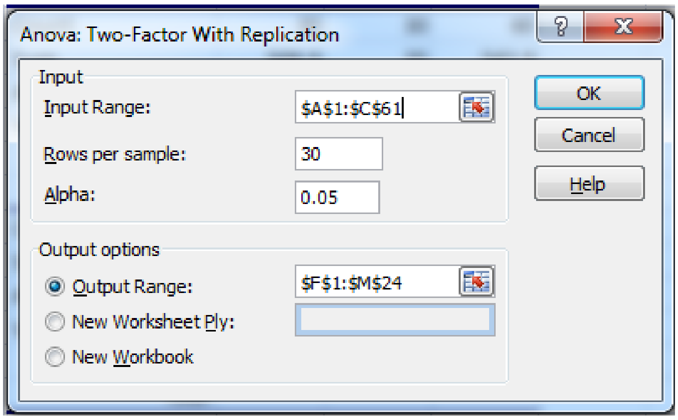


Using Excel:

Go to Data tab Data Analysis







Input Range - $A$1:$C$61
Rows Per Sample – 30 (Beacause 30 Patients are given each dose)
Alpha – 0.05
Output Range - $F$1:$M$24

Output:

Anova: Two-Factor With Replication						
SUMMARY	len	dose	Total			
1						
Count	30	30	60			
Sum	508.9	35	543.9			
Average	16.96333	1.166667	9.065			
Variance	68.32723	0.402299	97.22333			
31						
Count	30	30	60			
Sum	619.9	35	654.9			
Average	20.66333	1.166667	10.915			
Variance	43.63344	0.402299	118.2854			
Total						
Count	60	60				
Sum	1128.8	70				
Average	18.81333	1.166667				
Variance	58.51202	0.39548				
ANOVA						

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	102.675	1	102.675	3.642079	0.058808	3.922879
Columns	9342.145	1	9342.145	331.3838	8.55E-36	3.922879
Interaction	102.675	1	102.675	3.642079	0.058808	3.922879
Within	3270.193	116	28.19132			
Total	12817.69	119				

P-value = 0.0588079 columns in the ANOVA Source of Variation table at the bottom of the Output. Because the p- values for both medicine dose and interaction are less than our significance level, the factors are statistically significant. On the other hand, the interaction effect is not significant because its p-value (0.0588) is greater than our significance level. Because the interaction effect is not significant, we can focus on only the main effects and not consider the interaction effect of the dose.

B. Perform testing of hypothesis using MANOVA. Code:

```
import pandas as pd
fromstatsmodels.multivariate.manova import MANOVA
df = pd.read_csv('iris.csv', index_col=0)
df.columns = df.columns.str.replace(".", "_")
df.head()
print('~~~~~~~~~ Data Set ~~~~~~~~~')
print(df)
maov = MANOVA.from_formula('Sepal_Length + Sepal_Width + \
Petal_Length + Petal_Width ~ Species', data=df)
print('~~~~~~~~~ MANOVA Test Result ~~~~~~~~~')
print(maov.mv_test())
```

Output:

```
In [42]: runfile('E:/Research In Computing/Programs/Practical_10/Manova_Test.py', wdir='E:/Research
In Computing/Programs/Practical_10')
~~~~~~~~~ Data Set ~~~~~~~~~
     Sepal_Length  Sepal_Width  Petal_Length  Petal_Width    Species
1             5.1          3.5           1.4          0.2     setosa
2             4.9          3.0           1.4          0.2     setosa
3             4.7          3.2           1.3          0.2     setosa
4             4.6          3.1           1.5          0.2     setosa
5             5.0          3.6           1.4          0.2     setosa
..            ...          ...           ...          ...        ...
146           6.7          3.0           5.2          2.3  virginica
147           6.3          2.5           5.0          1.9  virginica
148           6.5          3.0           5.2          2.0  virginica
149           6.2          3.4           5.4          2.3  virginica
150           5.9          3.0           5.1          1.8  virginica

[150 rows x 5 columns]
~~~~~~~~~ MANOVA Test Result ~~~~~~~~~
                   Multivariate linear model
================================================================

----------------------------------------------------------------
       Intercept         Value  Num DF  Den DF   F Value  Pr > F
----------------------------------------------------------------
          Wilks' lambda  0.0170 4.0000 144.0000 2086.7720 0.0000
         Pillai's trace  0.9830 4.0000 144.0000 2086.7720 0.0000
 Hotelling-Lawley trace 57.9659 4.0000 144.0000 2086.7720 0.0000
    Roy's greatest root 57.9659 4.0000 144.0000 2086.7720 0.0000
----------------------------------------------------------------

----------------------------------------------------------------
        Species          Value  Num DF  Den DF   F Value  Pr > F
----------------------------------------------------------------
          Wilks' lambda  0.0234 8.0000 288.0000  199.1453 0.0000
         Pillai's trace  1.1919 8.0000 290.0000   53.4665 0.0000
 Hotelling-Lawley trace 32.4773 8.0000 203.4024  582.1970 0.0000
    Roy's greatest root 32.1919 4.0000 145.0000 1166.9574 0.0000
================================================================
```

Practical 7

A. Perform the Random sampling for the given data and analyse it. Example 1:

From a population of 10 women and 10 men as given in the table in Figure 1 onthe left below, create a random sample of 6 people for Group 1 and a periodic sample consistingof every 3rd woman for Group 2. You need to run the sampling data analysis tool twice, once to create Group 1 and again to create Group 2. For Group 1 you select all 20 population cells as the Input Range and Randomas the Sampling Method with 6 for the Random Number of Samples. For Group 2 you select the 10 cells in the Women column as Input Range and Periodic with Period 3.

Open existing excel sheet with population dataSample

Sheet looks as given below:

	A	B	C	D	E	F	G	H	I	J	K
1	Sr. No	Roll No	Student's Name	Gender	Grade		Sr. No	Roll No	Student's Name	Gender	Grade
2	1	1	Gaborone	m	O		62	3	Maun	f	O
3	2	2	Francistown	m	O		63	7	Tete	f	O
4	3	5	Niamey	m	O		64	9	Chimoio	f	O
5	4	13	Maxixe	m	O		65	11	Pemba	f	O
6	5	16	Tema	m	O		66	14	Chibuto	f	O
7	6	17	Kumasi	m	O		67	25	Mampong	f	O
8	7	34	Blida	m	O		68	36	Tlemcen	f	O
9	8	35	Oran	m	O		69	40	Adrar	f	O
10	9	38	Saefda	m	O		70	41	Tindouf	f	O
11	10	42	Constantine	m	O		71	46	Skikda	f	O
12	11	43	Annaba	m	O		72	47	Ouargla	f	O
13	12	45	Bejaefa	m	O		73	10	Matola	f	D
14	13	48	Medea	m	O		74	20	Legon	f	D
15	14	49	Djelfa	m	O		75	21	Sunyani	f	D
16	15	50	Tipaza	m	O		76	72	Teenas	f	D
17	16	51	Bechar	m	O		77	73	Kouba	f	D
18	17	54	Mostaganem	m	O		78	75	Hussen Dey	f	D
19	18	55	Tiaret	m	O		79	77	Khenchela	f	D
20	19	56	Bouira	m	O		80	82	Hassi Bahbah	f	D
21	20	59	Tebessa	m	O		81	84	Baraki	f	D
22	21	61	El Harrach	m	O		82	91	Boudouaou	f	D
23	22	62	Mila	m	O		83	95	Tadjenanet	f	D
24	23	65	Fouka	m	O		84	4	Molepolole	f	C

Output:

O	P
Male	Female
A	A
A	A
A	A
B	A
C	B
C	C
D	C
D	C
D	C
D	C
D	D
D	A
D	B
D	B
O	D
O	D

B. Perform the Stratified sampling for the given data and analyse it.

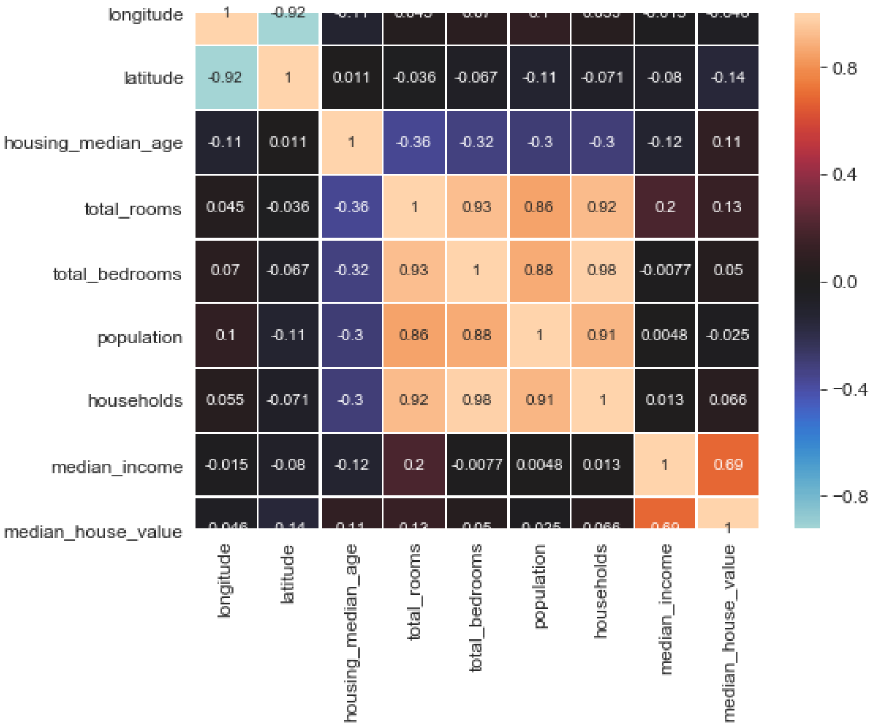
we are to carry out a **hypothetical** housing quality survey across Lagos state, Nigeria. And we looking at a total of 5000 houses (hypothetically). We don‘t just go to one local government and select 5000 houses, rather we ensure that the 5000 houses are a representative of the whole20 local government areas Lagos state is comprised of. This is called stratified sampling. The population is divided into homogenous strata and the right number of instances is sampled fromeach stratum to guarantee that the test-set (which in this case is the 5000 houses) is a representative of the overall population. If we used random sampling, there would be a significant chance of having bias in the survey results.

Program Code:

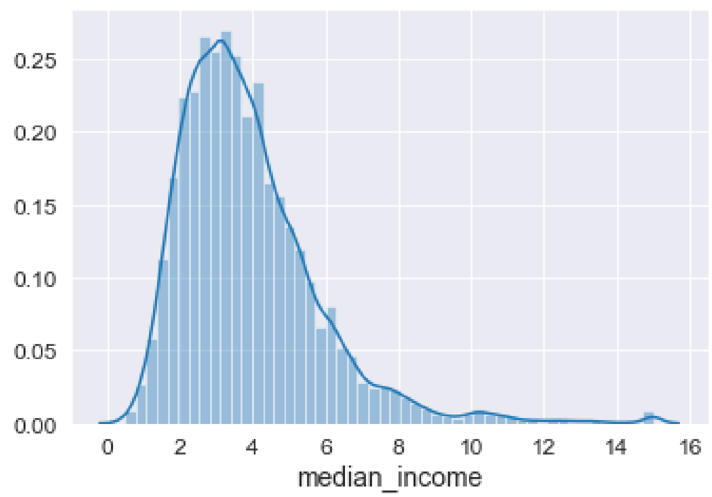
```
import pandas as pd
importnumpy as np

importmatplotlib
importmatplotlib.pyplot as plt

plt.rcParams['axes.labelsize'] = 14
plt.rcParams['xtick.labelsize'] = 12
plt.rcParams['ytick.labelsize'] = 12

importseaborn as sns color =
sns.color_palette()
sns.set_style('darkgrid')

importsklearn
fromsklearn.model_selection import train_test_split

housing =pd.read_csv('housing.csv')
print(housing.head())
print(housing.info())

 #creating a heatmap of the attributes in the dataset
correlation_matrix = housing.corr()
plt.subplots(figsize=(8,6))
sns.heatmap(correlation_matrix, center=0, annot=True, linewidths=.3)


corr =housing.corr()
print(corr['median_house_value'].sort_values(ascending=False))

sns.distplot(housing.median_income)plt.show()
```

Output:

```
In [28]: runfile('J:/Research In Computing/Practical Material/Programs/Practical_05/
Stratified_Sample.py', wdir='J:/Research In Computing/Practical Material/Programs/Practical_05')
   longitude  latitude  ...  median_house_value  ocean_proximity
0    -122.23     37.88  ...            452600.0         NEAR BAY
1    -122.22     37.86  ...            358500.0         NEAR BAY
2    -122.24     37.85  ...            352100.0         NEAR BAY
3    -122.25     37.85  ...            341300.0         NEAR BAY
4    -122.25     37.85  ...            342200.0         NEAR BAY

[5 rows x 10 columns]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 10 columns):
longitude             20640 non-null float64
latitude              20640 non-null float64
housing_median_age    20640 non-null float64
total_rooms           20640 non-null float64
total_bedrooms        20433 non-null float64
population            20640 non-null float64
households            20640 non-null float64
median_income         20640 non-null float64
median_house_value    20640 non-null float64
ocean_proximity       20640 non-null object
dtypes: float64(9), object(1)
memory usage: 1.6+ MB
None
median_house_value    1.000000
median_income         0.688075
total_rooms           0.134153
housing_median_age    0.105623
households            0.065843
total_bedrooms        0.049686
population           -0.024650
longitude            -0.045967
latitude             -0.144160
Name: median_house_value, dtype: float64
```



There‘s a ton of information we can mine from the heatmap above, a couple of strongly positively correlated features and a couple of negatively correlated features. Take a look at the small bright box right in the middle of the heatmap from total_rooms on the left ‘y-axis‘ till households and note how bright the box is as well as the highly positively correlated attributes, also note that median_income is the most correlated feature to the target which is median_house_value.



From the image above, we can see that most median incomes are clustered between \$20,000 and \$50,000 with some outliers going far beyond \$60,000 making the distribution skew to the right.

Practical 8

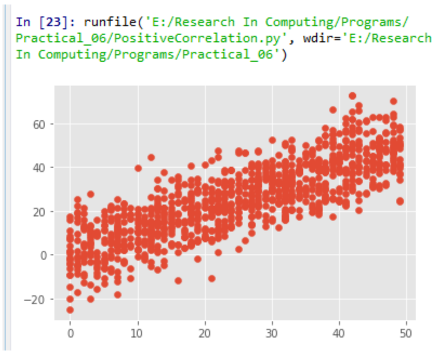
Write a program for computing different correlation.

Positive Correlation:

Code:

```
importnumpy as np
importmatplotlib.pyplot as plt
np.random.seed(1)
# 1000 random integers between 0 and 50
x = np.random.randint(0, 50, 1000)
# Positive Correlation with some noisey =
x + np.random.normal(0, 10, 1000)
np.corrcoef(x, y)
matplotlib.style.use('ggplot') plt.scatter(x,
y)
plt.show()
```

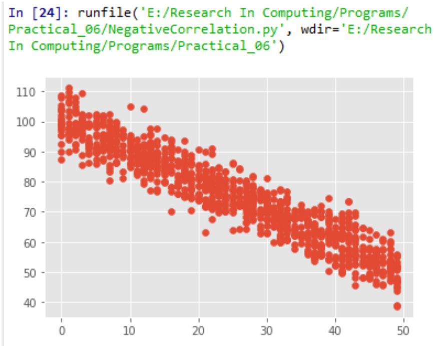
Output:



Negative Correlation:

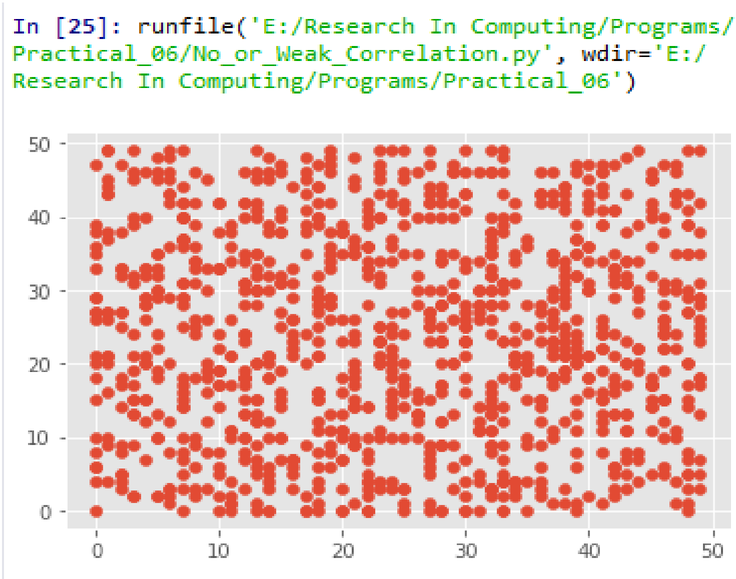
```
import numpy as np
import matplotlib.pyplot as
plt
np.random.seed(1)
# 1000 random integers between 0 and 50
x = np.random.randint(0, 50, 1000)
# Negative Correlation with some noise
y = 100 - x + np.random.normal(0, 5,
1000)np.corrcoef(x, y)
plt.scatter(x, y)plt.show()
```

Output:



No/Weak Correlation: importnumpy
as np importmatplotlib.pyplot as plt
np.random.seed(1)
x = np.random.randint(0, 50, 1000)
y = np.random.randint(0, 50, 1000)
np.corrcoef(x, y)
plt.scatter(x, y)
plt.show()

Output:



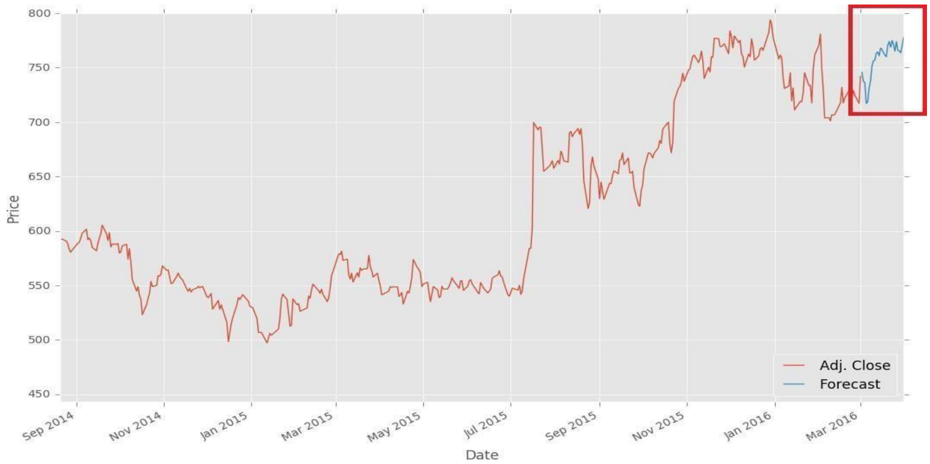
Practical 9

A. Write a program to Perform linear regression for prediction.

```
# -*- coding: utf-8 -*-
import Quandl, math
import numpy as np
import pandas as pd
from sklearn import preprocessing, cross_validation, svm
from sklearn.linear_model import LinearRegression import
matplotlib.pyplot as plt
from matplotlib import style
import datetime
style.use('ggplot')
df = Quandl.get("WIKI/GOOGL")
df = df[['Adj. Open', 'Adj. High', 'Adj. Low', 'Adj. Close', 'Adj. Volume']]
df['HL_PCT'] = (df['Adj. High'] - df['Adj. Low']) / df['Adj. Close'] * 100.0
df['PCT_change'] = (df['Adj. Close'] - df['Adj. Open']) / df['Adj. Open'] * 100.0

df = df[['Adj. Close', 'HL_PCT', 'PCT_change', 'Adj. Volume']]
forecast_col = 'Adj. Close'
df.fillna(value=-99999, inplace=True)
forecast_out = int(math.ceil(0.01 * len(df)))
df['label'] = df[forecast_col].shift(-forecast_out)

X = np.array(df.drop(['label'], 1))X
= preprocessing.scale(X) X_lately
=  X[-forecast_out:]
X = X[:-forecast_out]

df.dropna(inplace=True)y
= np.array(df['label'])
X_train, X_test, y_train, y_test = cross_validation.train_test_split(X, y, test_size=0.2)clf
= LinearRegression(n_jobs=-1)
clf.fit(X_train, y_train)
confidence = clf.score(X_test, y_test)

forecast_set = clf.predict(X_lately)
df['Forecast'] = np.nan

last_date = df.iloc[-1].name
last_unix = last_date.timestamp()
one_day = 86400
next_unix = last_unix + one_day

for i in forecast_set:
next_date = datetime.datetime.fromtimestamp(next_unix)
next_unix += 86400
df.loc[next_date] = [np.nan for _ in range(len(df.columns)-1)]+[i]

df['Adj. Close'].plot()
```

```
df['Forecast'].plot()
plt.legend(loc=4)
plt.xlabel('Date')
plt.ylabel('Price')
plt.show()
```

Output:



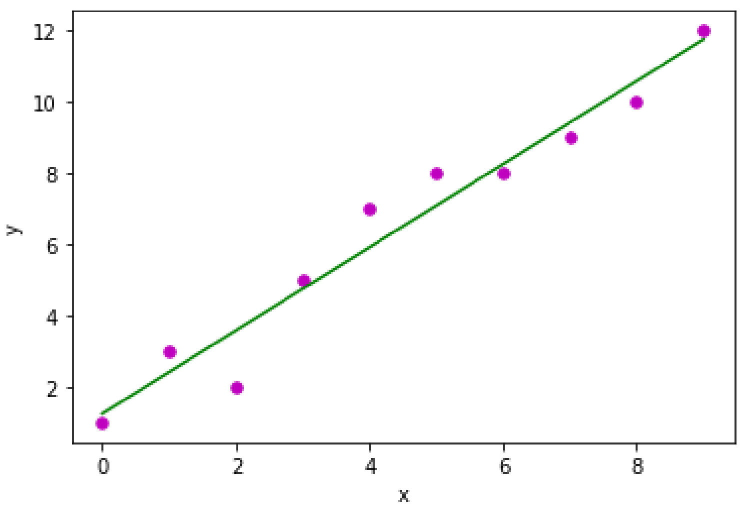
B. Perform polynomial regression for prediction.

```
importnumpy as np
importmatplotlib.pyplot as plt

defestimate_coef(x, y):
# number of observations/pointsn =
np.size(x)

# mean of x and y vector
m_x, m_y = np.mean(x), np.mean(y)

# calculating cross-deviation and deviation about xSS_xy =
np.sum(y*x) - n*m_y*m_x
SS_xx = np.sum(x*x) - n*m_x*m_x

# calculating regression coefficientsb_1 =
SS_xy / SS_xx
b_0 = m_y - b_1*m_x

return(b_0, b_1)

defplot_regression_line(x, y, b):
# plotting the actual points as scatter plot
plt.scatter(x, y, color = "m",
marker = "o", s = 30)

# predicted response vectory_pred = b[0] + b[1]*x
```

```
        # plotting the regression line plt.plot(x,
        y_pred, color = "g")

        # putting labels
        plt.xlabel('x')
        plt.ylabel('y')

        # function to show plot
        plt.show()

def main():
        # observations
        x = np.array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
        y = np.array([1, 3, 2, 5, 7, 8, 8, 9, 10, 12])

        # estimating coefficientsb =
        estimate_coef(x, y)
        print("Estimated coefficients:\nb_0 = {} b_1 = {}".format(b[0], b[1]))

        # plotting regression line
        plot_regression_line(x, y, b)

if__name__== " main ":main()
```

Output:

```
In [22]: runfile('E:/Research In Computing/Programs/
Practical_07/Practical_7B.py', wdir='E:/Research In
Computing/Programs/Practical_07')
Estimated coefficients:
b_0 = 1.2363636363636363  b_1 = 1.1696969696969697
```



Practical 10

A. Write a program for multiple linear regression analysis.

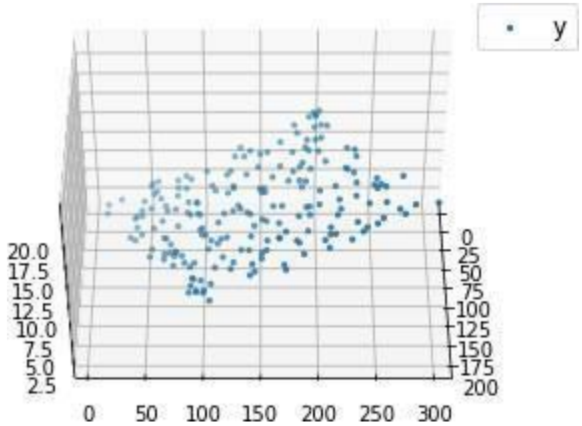
Step #1: Data Pre Processing

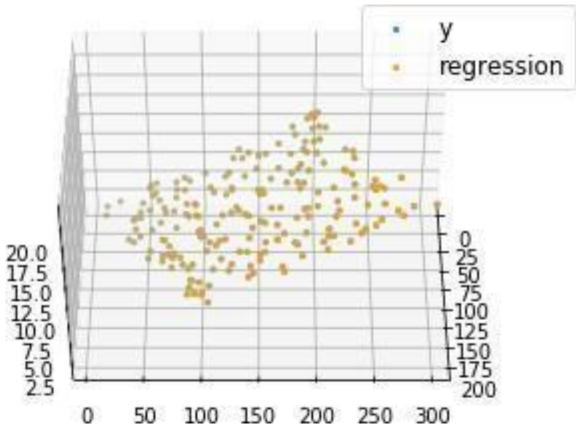
a) Importing The Libraries.
b) Importing the Data Set.
c) Encoding the Categorical Data.
d) Avoiding the Dummy Variable Trap.
e) Splitting the Data set into Training Set and Test Set.**Step #2:** Fitting Multiple Linear Regression to the Training set**Step #3:** Predicting the Test set results.

```
importnumpy as np
importmatplotlib as mpl
from mpl_toolkits.mplot3d import Axes3D
importmatplotlib.pyplot as plt
defgenerate_dataset(n):
    x = []
    y = []
    random_x1 = np.random.rand()
    random_x2 = np.random.rand() fori in
    range(n):
        x1 = i
        x2 = i/2 + np.random.rand()*n
        x.append([1, x1, x2])
        y.append(random_x1 * x1 + random_x2 * x2 + 1)
    returnnp.array(x), np.array(y)
x, y = generate_dataset(200)
mpl.rcParams['legend.fontsize'] = 12fig =
plt.figure()
ax = fig.gca(projection ='3d')
ax.scatter(x[:, 1], x[:, 2], y, label ='y', s = 5)
ax.legend()
ax.view_init(45, 0)
plt.show() defmse(coef, x,
y):
    returnnp.mean((np.dot(x, coef) - y)**2)/2def
gradients(coef, x, y):
    returnnp.mean(x.transpose()*(np.dot(x, coef) - y), axis = 1)
defmultilinear_regression(coef, x, y, lr, b1 = 0.9, b2 = 0.999, epsilon = 1e-8):
    prev_error = 0
    m_coef = np.zeros(coef.shape)v_coef =
    np.zeros(coef.shape)
    moment_m_coef = np.zeros(coef.shape)
    moment_v_coef = np.zeros(coef.shape)t = 0
    while True:
        error = mse(coef, x, y)
        if abs(error - prev_error) <= epsilon:break
    prev_error = error
```

```
                grad = gradients(coef, x, y)t += 1
                m_coef = b1 * m_coef + (1-b1)*grad v_coef =
                b2 * v_coef + (1-b2)*grad**2moment_m_coef =
                m_coef / (1-b1**t) moment_v_coef = v_coef /
                (1-b2**t)

                delta = ((lr / moment_v_coef**0.5 + 1e-8) *
                                (b1 * moment_m_coef + (1-b1)*grad/(1-b1**t)))coef =
                np.subtract(coef, delta)
            returncoef
     coef = np.array([0, 0, 0])
c = multilinear_regression(coef, x, y, 1e-1)fig =
plt.figure()
ax = fig.gca(projection ='3d') ax.scatter(x[:,
1], x[:, 2], y, label ='y',
                                s = 5, color ="dodgerblue")
ax.scatter(x[:, 1], x[:, 2], c[0] + c[1]*x[:, 1] + c[2]*x[:, 2],
                                        label ='regression', s = 5, color ="orange")
ax.view_init(45, 0)
ax.legend() plt.show()
```

Output:





B. Perform logistic regression analysis.

Logistic regression is a classification method built on the same concept as linear regression. With linear regression, we take linear combination of explanatory variables plus an interceptterm to arrive at a prediction.

In this example we will use a logistic regression model to predict survival.

Program Code:

```
import os
import  numpy  as  np  import
pandas      as      pd      import
matplotlib
import matplotlib.pyplot as pltimport
scipy.stats as stats
from sklearn import linear_model from
sklearn import preprocessingfrom sklearn
import metrics

matplotlib.style.use('ggplot')
plt.figure(figsize=(9,9))

def sigmoid(t):                          # Define the sigmoid functionreturn
    (1/(1 + np.e**(-t)))

plot_range = np.arange(-6, 6, 0.1)y_values

= sigmoid(plot_range) # Plot curve
plt.plot(plot_range, # X-axis range
         y_values,          # Predicted values
         color="red")
titanic_train = pd.read_csv("titanic_train.csv")     # Read the data char_cabin =
titanic_train["Cabin"].astype(str)                        # Convert cabin to str new_Cabin
= np.array([cabin[0] for cabin in char_cabin]) # Take first letter

titanic_train["Cabin"] = pd.Categorical(new_Cabin) # Save the new cabin var# Impute

median Age for NA Age values
new_age_var  =  np.where(titanic_train["Age"].isnull(),  #  Logical  check28,  #
                 Value if check is true titanic_train["Age"])       # Value if check
                 is false

titanic_train["Age"] = new_age_var label_encoder =

preprocessing.LabelEncoder()# Convert Sex variable to

numeric
encoded_sex = label_encoder.fit_transform(titanic_train["Sex"])

# Initialize logistic regression model
        log_model = linear_model.LogisticRegression()
```

```
# Train the model
log_model.fit(X = pd.DataFrame(encoded_sex),y =
          titanic_train["Survived"])

# Check trained model intercept
print(log_model.intercept_)

# Check trained model coefficients
print(log_model.coef_)

# Make predictions
preds = log_model.predict_proba(X= pd.DataFrame(encoded_sex))preds =
pd.DataFrame(preds)
preds.columns = ["Death_prob", "Survival_prob"]

# Generate table of predictions vs Sex pd.crosstab(titanic_train["Sex"],
preds.ix[:, "Survival_prob"])

# Convert more variables to numeric
encoded_class = label_encoder.fit_transform(titanic_train["Pclass"])
encoded_cabin = label_encoder.fit_transform(titanic_train["Cabin"])

train_features = pd.DataFrame([encoded_class,
                      encoded_cabin, encoded_sex,
                      titanic_train["Age"]]).T

# Initialize logistic regression model
log_model = linear_model.LogisticRegression()

# Train the model log_model.fit(X =
train_features ,
          y = titanic_train["Survived"])

# Check trained model intercept
print(log_model.intercept_)

# Check trained model coefficients
print(log_model.coef_)

# Make predictions
preds = log_model.predict(X= train_features)

# Generate table of predictions vs actual pd.crosstab(preds,titanic_train["Survived"])

log_model.score(X = train_features ,
        y = titanic_train["Survived"])
```

```
metrics.confusion_matrix(y_true=titanic_train["Survived"], # True labels
                    y_pred=preds) # Predicted labels

# View summary of common classification metrics
print(metrics.classification_report(y_true=titanic_train["Survived"],
                        y_pred=preds) )

# Read and prepare test data
titanic_test = pd.read_csv("titanic_test.csv")    # Read the data char_cabin =

titanic_test["Cabin"].astype(str)                      # Convert cabin to str

new_Cabin = np.array([cabin[0] for cabin in char_cabin]) # Take first letter

titanic_test["Cabin"] = pd.Categorical(new_Cabin) # Save the new cabin var# Impute

median Age for NA Age values
new_age_var  =  np.where(titanic_test["Age"].isnull(),  #  Logical  check28,  #
                Value if check is true titanic_test["Age"])        # Value if check
                is false

titanic_test["Age"] = new_age_var

# Convert test variables to match model features
encoded_sex = label_encoder.fit_transform(titanic_test["Sex"])
encoded_class = label_encoder.fit_transform(titanic_test["Pclass"])
encoded_cabin = label_encoder.fit_transform(titanic_test["Cabin"])

test_features = pd.DataFrame([encoded_class,
                        encoded_cabin,encoded_sex,titanic_test["Age"]]).T

# Make test set predictions
test_preds = log_model.predict(X=test_features)

# Create a submission for Kaggle
submission = pd.DataFrame({"PassengerId":titanic_test["PassengerId"],
                    "Survived":test_preds})

# Save submission to CSV submission.to_csv("tutorial_logreg_submission.csv",
            index=False)       # Do not save index values

    print(pd)
```

Output:

Survival_prob	0.193110906347	0.729443792051
Sex		
female	0	312
male	577	0

The table shows that the model predicted a survival chance of roughly 19% for males and 73% for females.

```
             precision    recall  f1-score   support

          0       0.82      0.85      0.83       549
          1       0.74      0.70      0.72       340

avg / total       0.79      0.79      0.79       889
```

For the Titanic competition, accuracy is the scoring metric used to judge the competition, so we don't have to worry too much about other metrics.

Survived	0	1
row_0		
0	467	103
1	82	237

The table above shows the classes our model predicted vs. true values of the Survived variable.

This logistic regression model has an accuracy score of 0.75598 which is actually worse thanthe accuracy of the simplistic women survive, men die model (0.76555).

Example 2:

The dataset is related to direct marketing campaigns (phone calls) of a Portuguese banking institution. The classification goal is to predict whether the client will subscribe (1/0) to a termdeposit (variable y). The dataset provides the bank customers‘ information. It includes 41,188records and 21 fields.

Input variables

1. **age** (numeric)
2. **job :** type of job (categorical: –admin‖, –blue-collar‖, –entrepreneur‖, –housemaid‖, –management‖, –retired‖, –self-employed‖, –services‖, –student‖, –technician‖, –unemployed‖, –unknown‖)
3. **marital :** marital status (categorical: –divorced‖, –married‖, –single‖, –unknown‖)

4. **education** (categorical: –basic.4y‖, –basic.6y‖, –basic.9y‖, –high.school‖, –illiterate‖, –professional.course‖, –university.degree‖, –unknown‖)
5. **default:** has credit in default? (categorical: –no‖, –yes‖, –unknown‖)
6. **housing:** has housing loan? (categorical: –no‖, –yes‖, –unknown‖)
7. **loan:** has personal loan? (categorical: –no‖, –yes‖, –unknown‖)
8. **contact:** contact communication type (categorical: –cellular‖, –telephone‖)
9. **month:** last contact month of year (categorical: –jan‖, –feb‖, –mar‖, …, –nov‖, –dec‖)
10. **day_of_week:** last contact day of the week (categorical: –mon‖, –tue‖, –wed‖, –thu‖, –fri‖)
11. **duration:** last contact duration, in seconds (numeric). Important note: this attribute highly affects the output target (e.g., if duration=0 then y='no'). The duration is not known before a call is performed, also, after the end of the call, y is obviously known.Thus, this input should only be included for benchmark purposes and should be discarded if the intention is to have a realistic predictive model
12. **campaign:** number of contacts performed during this campaign and for this client (numeric, includes last contact)
13. **pdays:** number of days that passed by after the client was last contacted from a previous campaign (numeric; 999 means client was not previously contacted)
14. **previous:** number of contacts performed before this campaign and for this client (numeric)
15. **poutcome:** outcome of the previous marketing campaign (categorical: –failure‖, –nonexistent‖, –success‖)
16. **emp.var.rate:** employment variation rate — (numeric)
17. **cons.price.idx:** consumer price index — (numeric)
18. **cons.conf.idx**: consumer confidence index — (numeric)
19. **euribor3m:** euribor 3 month rate — (numeric)
20. **nr.employed:** number of employees — (numeric)

Predict variable (desired target):
y — has the client subscribed a term deposit?(binary: —1‖, means —Yes‖, —0‖ means —No‖)

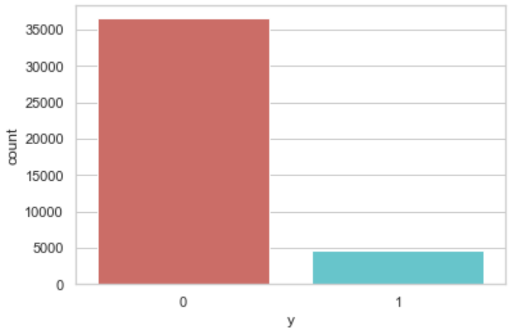
Program Code:

```
# -*- coding: utf-8 -*-
import pandas as pd
import numpy as np
from sklearn import preprocessing
import matplotlib.pyplot as plt
plt.rc("font", size=14)
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
import seaborn as sns
sns.set(style="white")
sns.set(style="whitegrid", color_codes=True)
data = pd.read_csv('bank.csv', header=0) data =
data.dropna()
print(data.shape)
print(list(data.columns))
data['education'].unique()
data['education']=np.where(data['education'] =='basic.9y', 'Basic', data['education'])
data['education']=np.where(data['education'] =='basic.6y', 'Basic', data['education'])
data['education']=np.where(data['education'] =='basic.4y', 'Basic', data['education'])
data['education'].unique()
data['y'].value_counts()
```

```
sns.countplot(x='y', data=data, palette='hls')
plt.show();
plt.savefig('Practical10B-plot.jpeg')

count_no_sub = len(data[data['y']==0])
count_sub = len(data[data['y']==1])
pct_of_no_sub = count_no_sub/(count_no_sub+count_sub)
print("percentage of no subscription is", pct_of_no_sub*100)
pct_of_sub = count_sub/(count_no_sub+count_sub)
print("percentage of subscription", pct_of_sub*100)

data.groupby('y').mean()
data.groupby('job').mean() data.groupby('marital').mean()
data.groupby('education').mean()

########### Purchase Frequency for Job Title
pd.crosstab(data.job,data.y).plot(kind='bar')
plt.title('Purchase Frequency for Job Title')
plt.xlabel('Job')
plt.ylabel('Frequency of Purchase')
plt.savefig('purchase_fre_job')

###################### Marital Status vs Purchase
table=pd.crosstab(data.marital,data.y)
table.div(table.sum(1).astype(float), axis=0).plot(kind='bar', stacked=True)
plt.title('Stacked Bar Chart of Marital Status vs Purchase') plt.xlabel('Marital
Status')
plt.ylabel('Proportion of Customers')
plt.savefig('mariral_vs_pur_stack')

############     Education vs Purchase
table=pd.crosstab(data.education,data.y) table.div(table.sum(1).astype(float),
axis=0).plot(kind='bar', stacked=True)plt.title('Stacked Bar Chart of
Education vs Purchase') plt.xlabel('Education')
plt.ylabel('Proportion of Customers')
plt.savefig('edu_vs_pur_stack')

pd.crosstab(data.day_of_week,data.y).plot(kind='bar')
plt.title('Purchase Frequency for Day of Week')
plt.xlabel('Day of Week')
plt.ylabel('Frequency of Purchase')plt.savefig('pur_dayofweek_bar')
########## Purchase Frequency for Month
pd.crosstab(data.month,data.y).plot(kind='bar')
plt.title('Purchase Frequency for Month')
plt.xlabel('Month')
plt.ylabel('Frequency of Purchase')
plt.savefig('pur_fre_month_bar')

############# Age Purchase frequency pattern
data.age.hist()
plt.title('Histogram of Age')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.savefig('hist_age')
```

Output: -

```
In [47]: runfile('K:/Research In Computing/Practical Material/Progra
Practical_10/Practical_10B.py', wdir='K:/Research In Computing/Pract
Material/Programs/Practical_10')
(41188, 21)
['age', 'job', 'marital', 'education', 'default', 'housing', 'loan',
'contact', 'month', 'day_of_week', 'duration', 'campaign', 'pdays',
'previous', 'poutcome', 'emp_var_rate', 'cons_price_idx',
'cons_conf_idx', 'euribor3m', 'nr_employed', 'y']
```



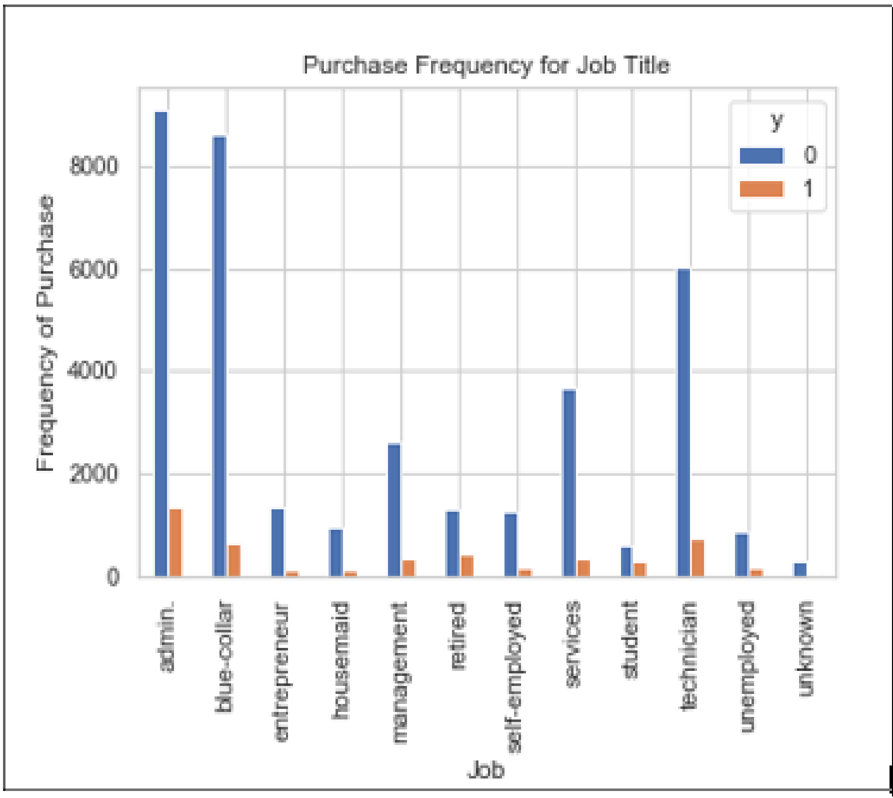

```
percentage of no subscription is 88.73458288821988
percentage of subscription 11.265417111780131
```

PERCENTAGE OF NO SUBSCRIPTION IS 88.73458288821988

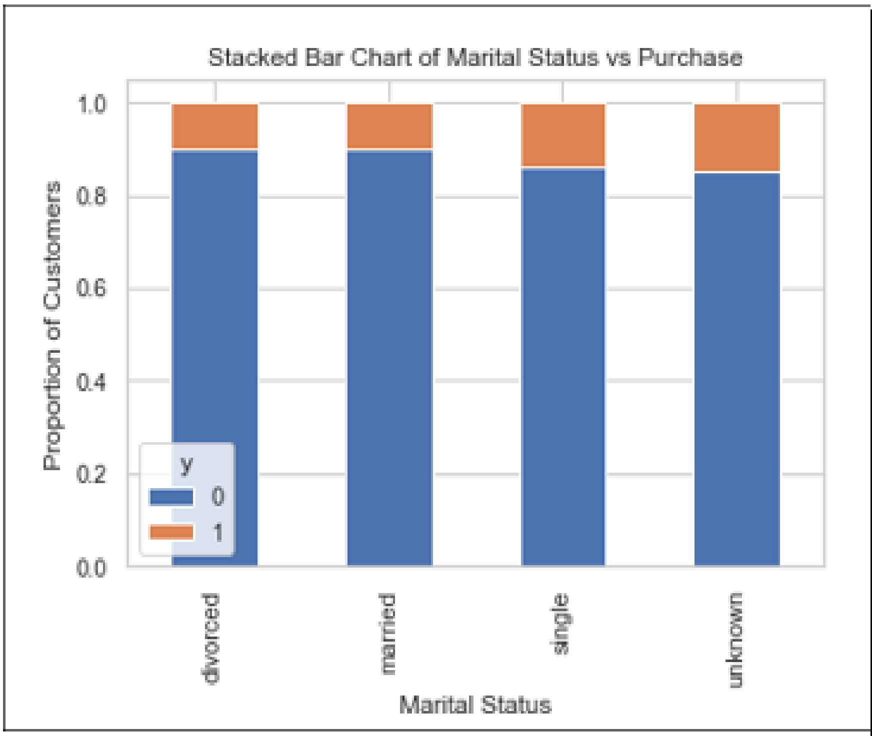
PERCENTAGE OF SUBSCRIPTION 11.265417111780131

Our classes are imbalanced, and the ratio of no-subscription to subscription instances is 89:11.

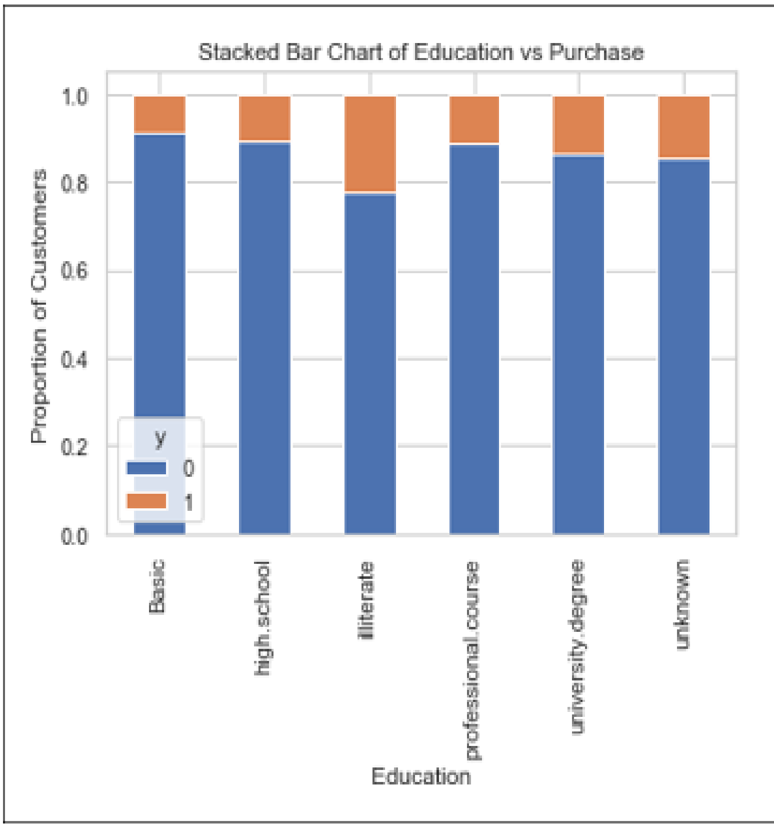
- The average age of customers who bought the term deposit is higher thanthat of the customers who didn't.
- The pdays (days since the customer waslast contacted) is understandably lower for the customers who bought it. The lower the pdays, the better the memory of the last call and hence the



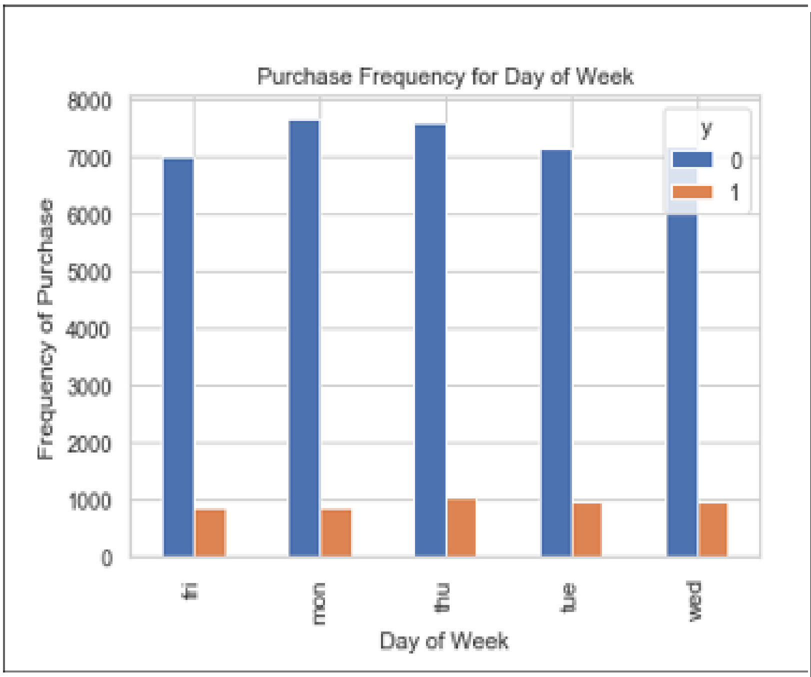
The frequency of purchase of the deposit depends a great deal on the job title. Thus, the job title can be a good predictor of the outcome variable.



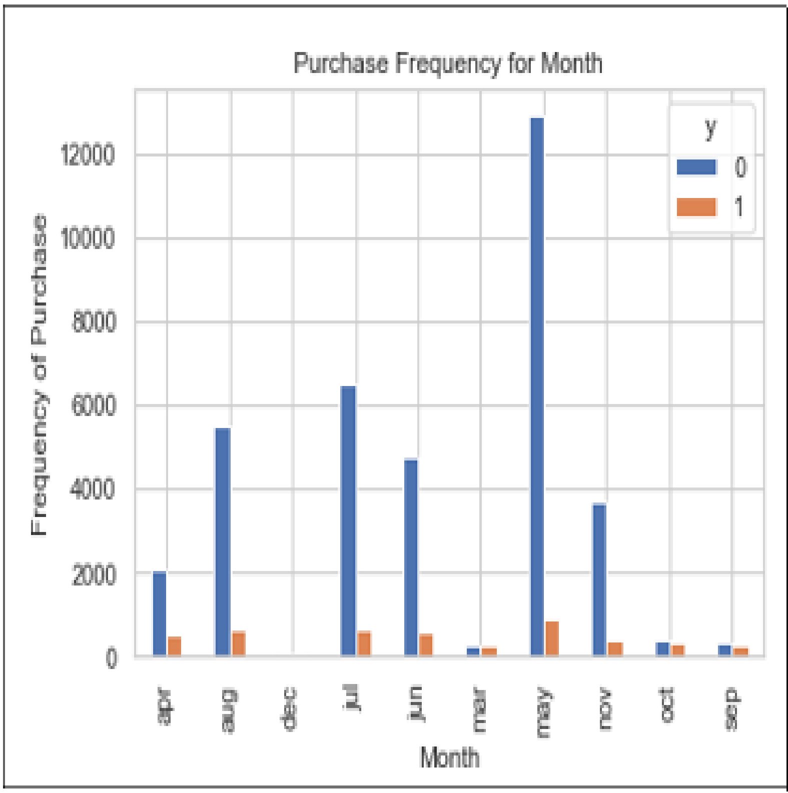
The marital status does not seem a strong predictor for the outcome variable.



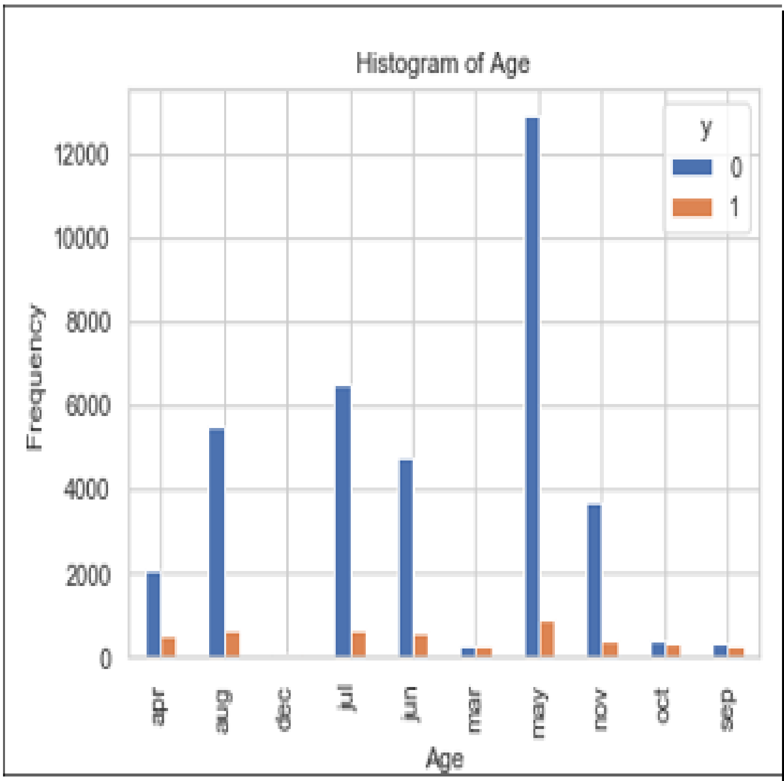
Education seems a good predictor of the outcome variable.



Day of week may not be a good predictor of the outcome.



Month might be a good predictor of the outcome variable.



Most of the customers of the bank in this dataset are in the age range of 30–40.