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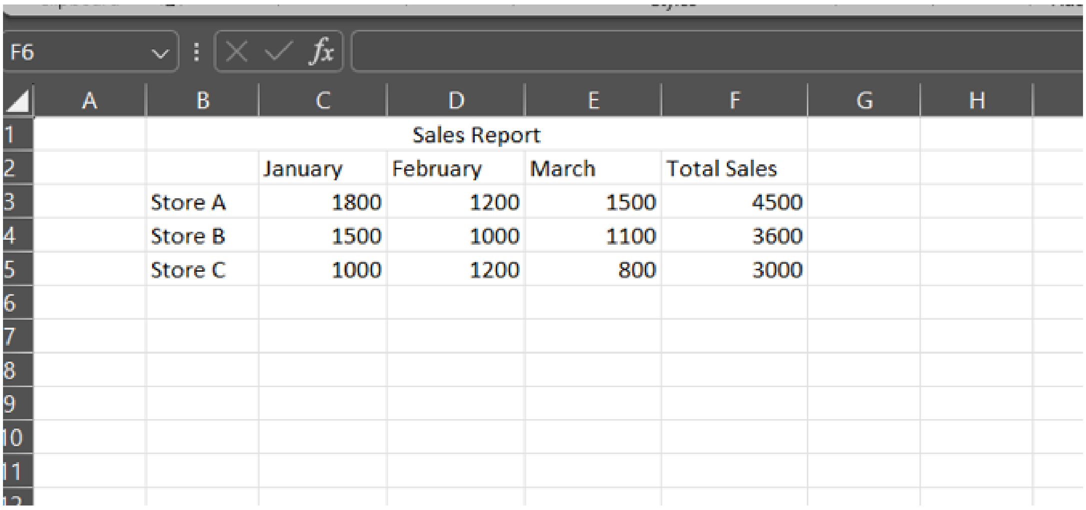
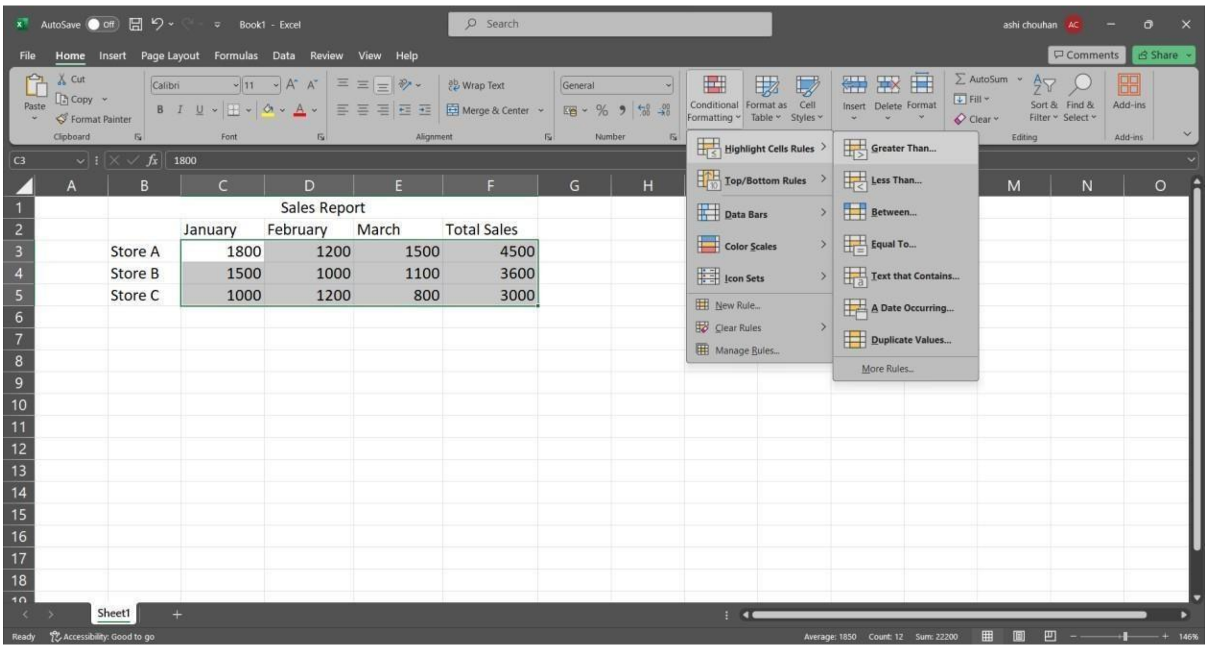
PRACTICAL NO. – 1

A. **Perform conditional formatting on a dataset using various criteria.**

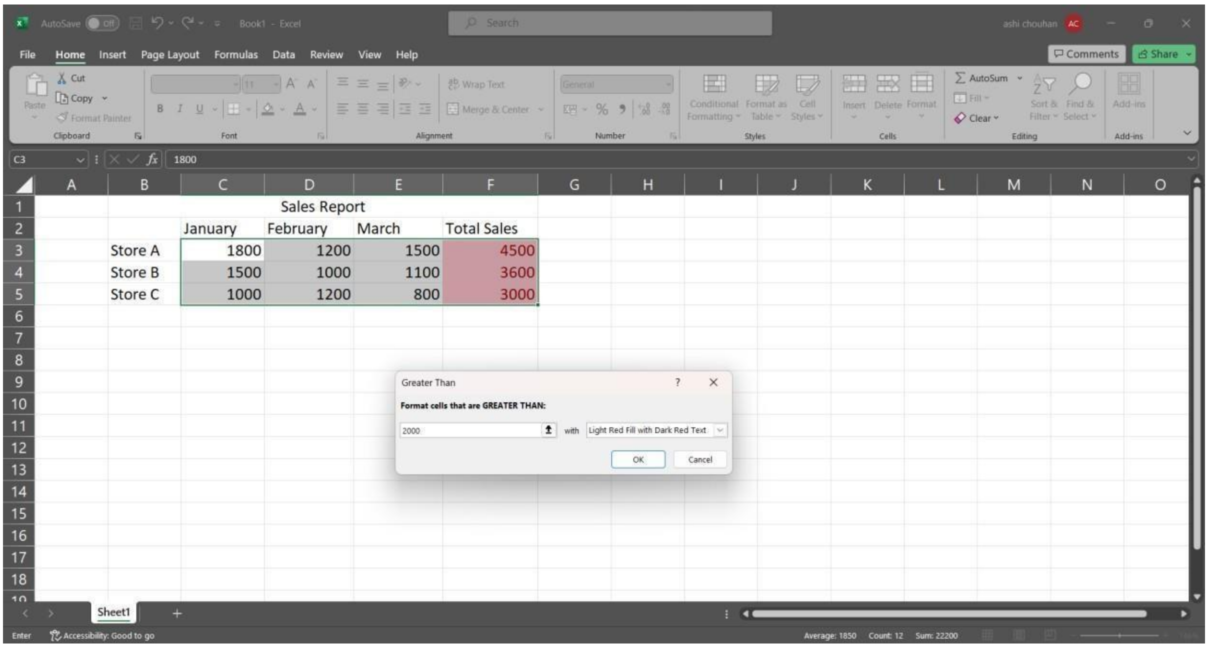


Steps

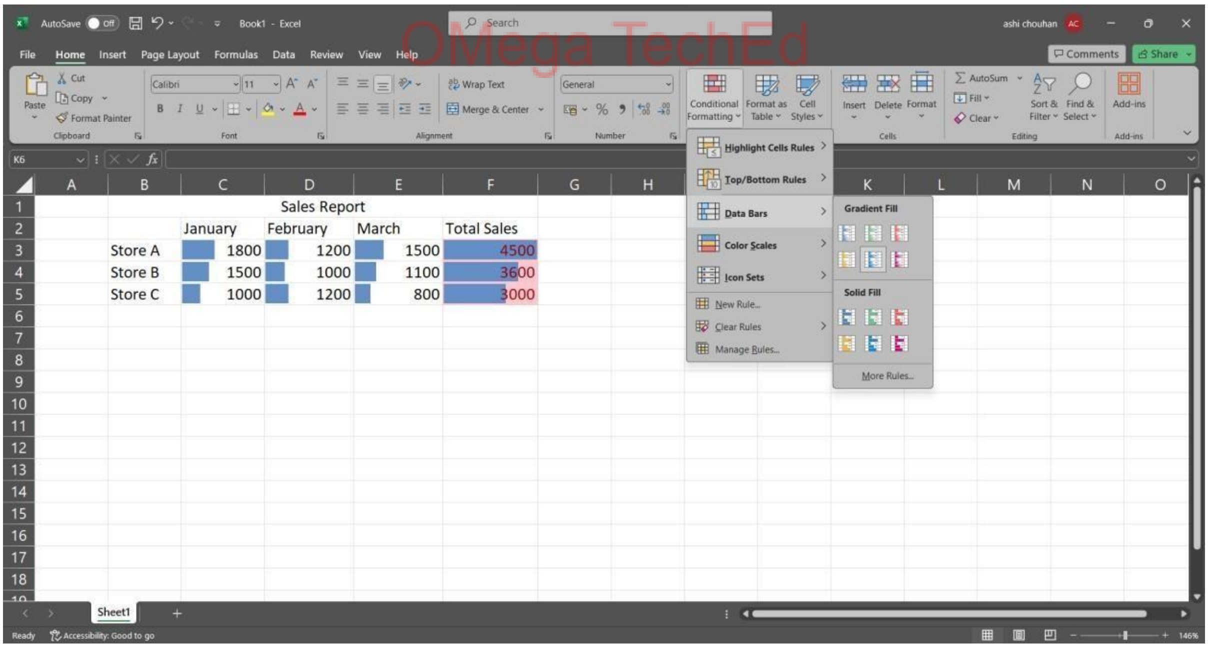
Step 1: Go to conditional formatting > Greater Than



Step 2: Enter the greater than filter value for example 2000.



Step 3: Go to Data Bars > Solid Fill in conditional formatting.

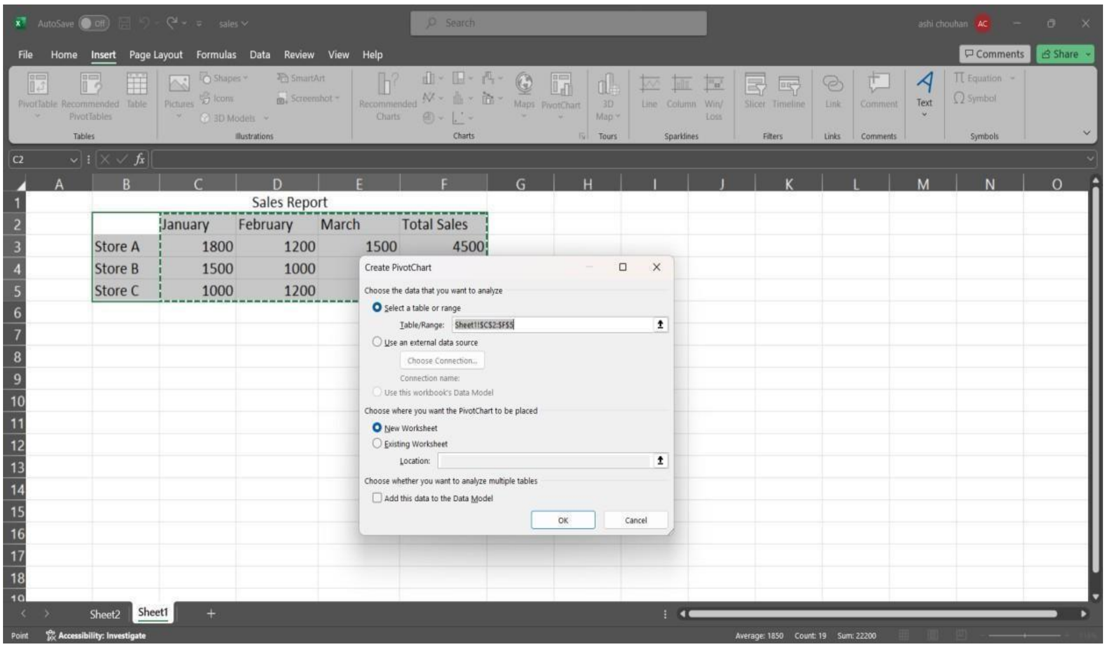


B. **Create a pivot table to analyse and summarize data.**

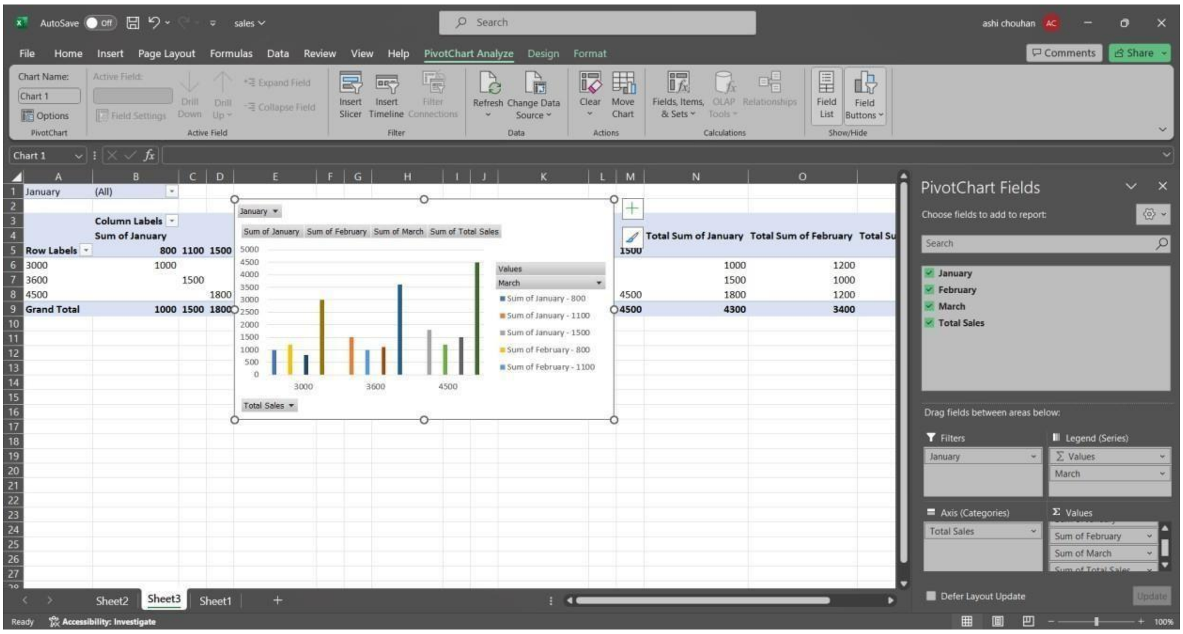
Steps

Step1: - Select the entire table and go to Insert Tab PivotChart > Pivotchart

Step2:- Select "New Worksheet" in the create pivot chart window.



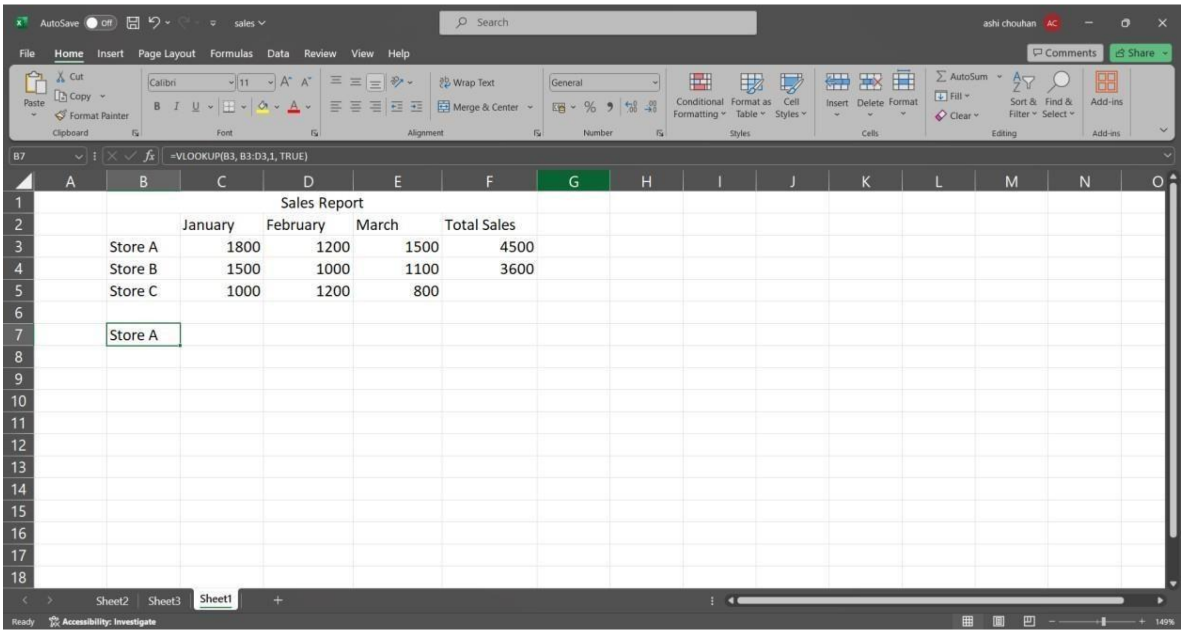
Step 3: Select and drag attributes in the below boxes.



C. **Use VLOOKUP function to retrieve information from a different worksheet or table.**

Steps

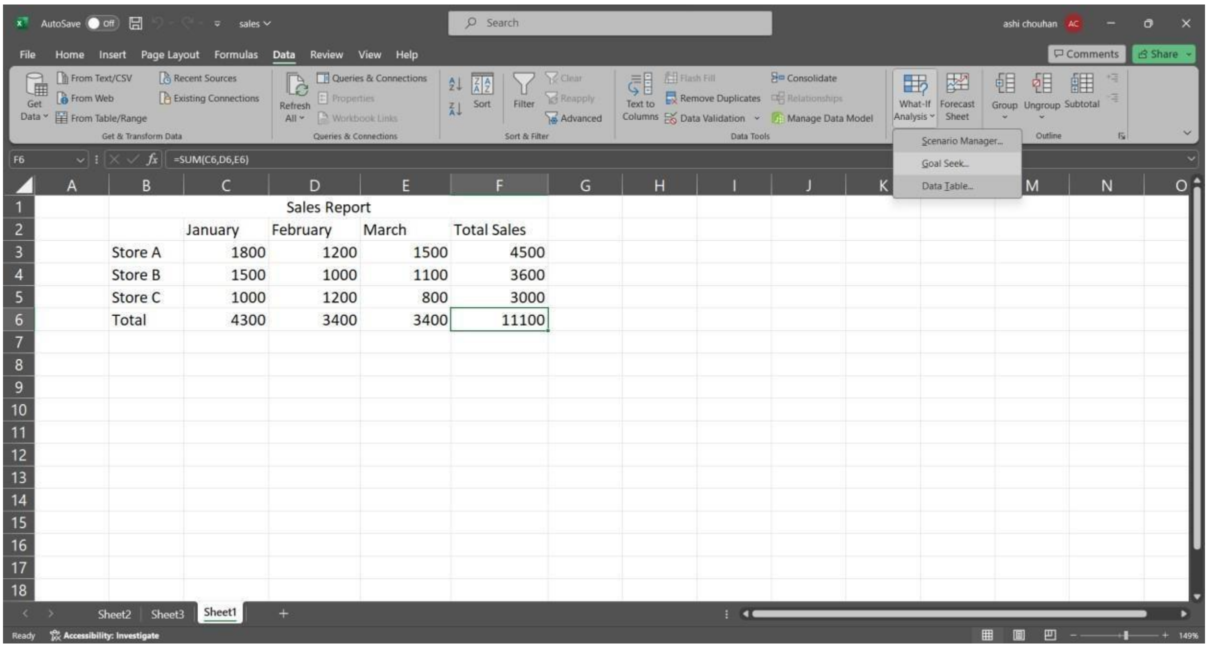
Step 1: click on an empty cell and type the following command.
=VLOOKUP(B3, B3:D3,1, TRUE)



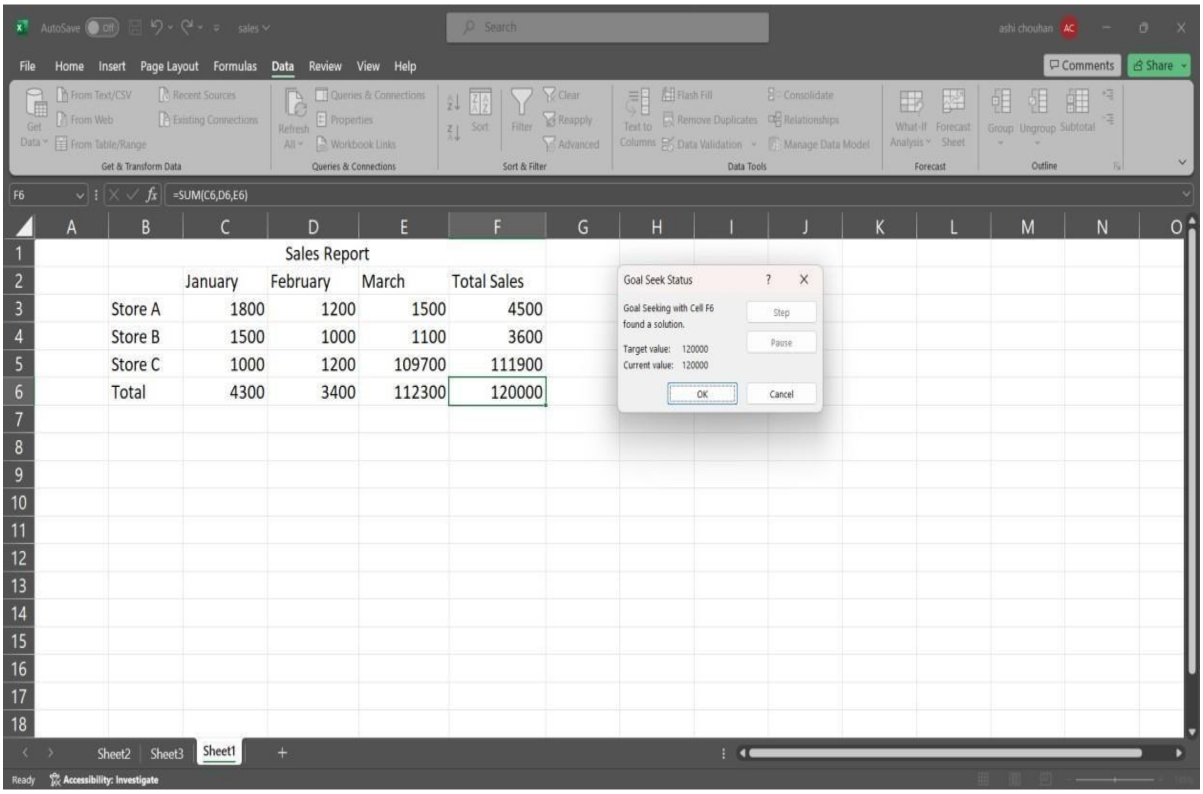
D. Perform what-if analysis using Goal Seek to determine input values for desired output.

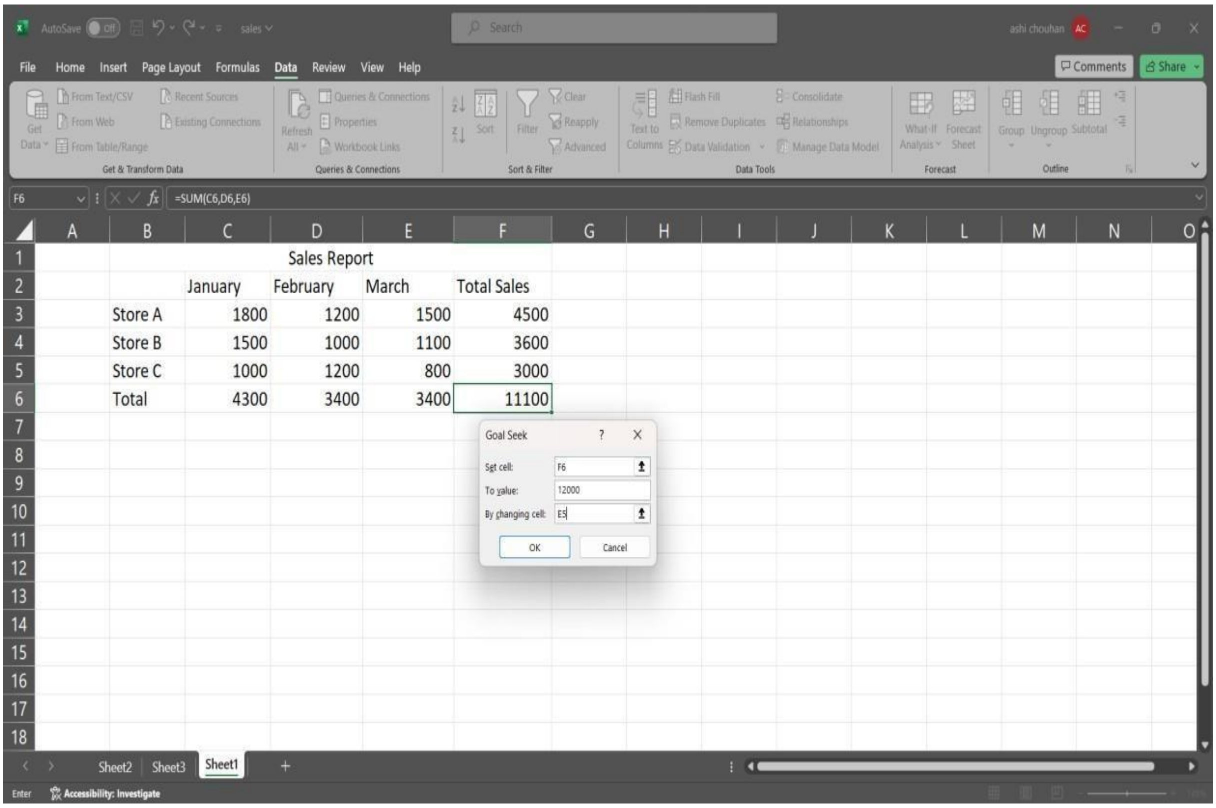
Steps

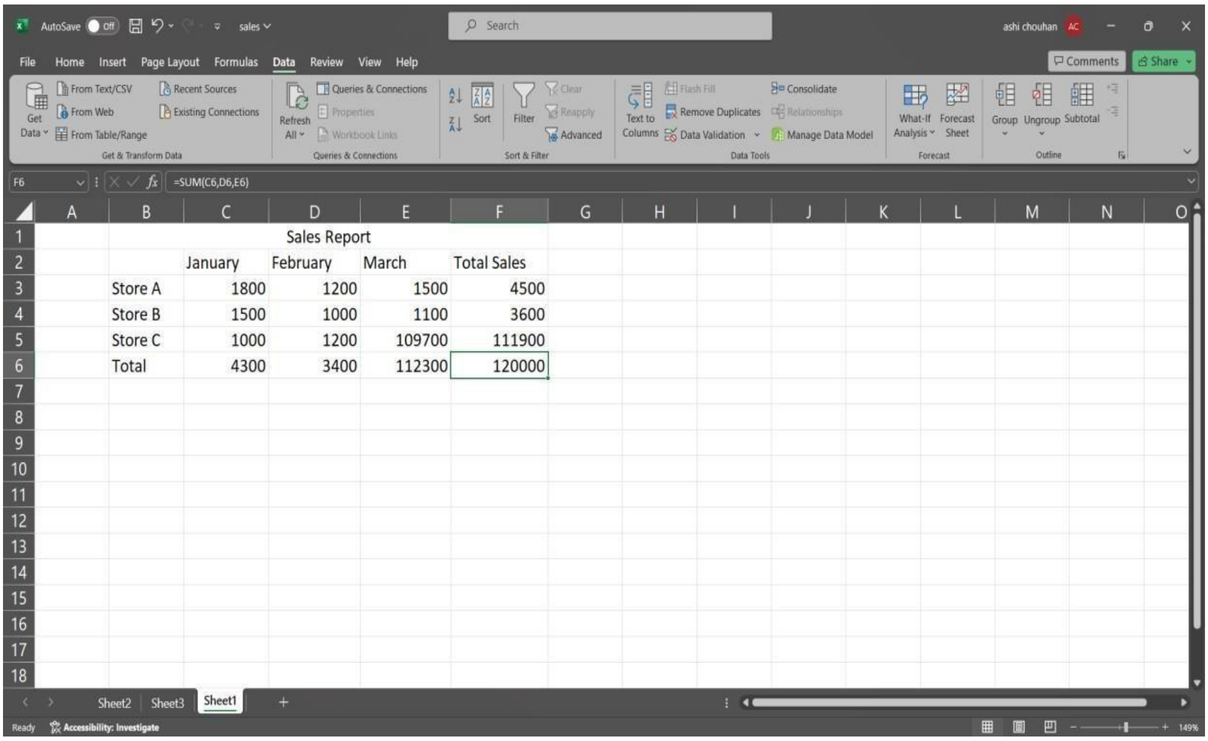
Step 1: In the Data tab go to the what if analysis>Goal seek.



Step 2: Fill the information in the window accordingly and click ok.


Sales Report
January February March Total Sales
Store A 1800 1200 1500 4500
Store B 1500 1000 1100 3600
Store C 1000 1200 109700 111900
Total 4300 3400 112300 120000
=SUM(C6,D6,E6)
Goal Seek Status
Goal Seeking with Cell F6 found a solution.
Target value: 120000
Current value: 120000
OK
Cancel
Sheet2 Sheet3 Sheet1


=SUM(C6,D6,E6)
Sales Report
January
February
March
Total Sales
Store A 1800 1200 1500 4500
Store B 1500 1000 1100 3600
Store C 1000 1200 800 3000
Total 4300 3400 3400 11100
Goal Seek
Set cell: F6
To value: 12000
By changing cell: E5
OK
Cancel


=SUM(C6,D6,E6)
Sales Report
January
February
March
Total Sales
Store A 1800 1200 1500 4500
Store B 1500 1000 1100 3600
Store C 1000 1200 109700 111900
Total 4300 3400 112300 120000

PRACTICAL NO. 2

AIM:- Data Frames and Basic Data Pre-Processing

A. Read Data from CSV and JSON files into a data frame.

SOURCE CODE:-

```
#Read data from a csv file
import pandas as pd
df = pd.read_csv('Student_Marks.csv')
print("Our dataset")
print(df)
```

OUTPUT:-

```
================ RESTART: D:\Notes\sem-6\data science\prac2
Our dataset
    number_courses  time_study   Marks
0                3       4.508  19.202
1                4       0.096   7.734
2                4       3.133  13.811
3                6       7.909  53.018
4                8       7.811  55.299
..             ...         ...     ...
95               6       3.561  19.128
96               3       0.301   5.609
97               4       7.163  41.444
98               7       0.309  12.027
99               3       6.335  32.357

[100 rows x 3 columns]
>>>
```

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SOURCE CODE:-

#Reading data from a JSON Import

pandas as pd

data=pd.read_json('dataset.json')

print(data)

OUTPUT:-

```
>>>
================ RESTART: D:/Notes/sem-6/data science/p:
    fruit    size   color
0   Apple   Large     Red
1  Banana  Medium  Yellow
2  Orange   Small  Orange
>>>
```

B. Perform basic data pre-processing tasks such as handling missing values and outliers code:

1. #Replacing NA values using fillna()
   Import pandas as pd
   df = pd.read_csv('titanic.csv')
   Print(df)
   df.head(10)
   print("Dataset after filling NA values with 0:") df2 =
   df.fillna(value = 0)
   print(df2)

   OUTPUT:-

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```
================ RESTART: D:/Notes/sem-6/data science/prac2c.py =======
     PassengerId  Pclass  ... Cabin Embarked
0            892     3.0  ...   NaN        Q
1            893     3.0  ...   NaN        S
2            894     2.0  ...   NaN        Q
3            895     3.0  ...   NaN        S
4            896     NaN  ...   NaN        S
..           ...     ...  ...   ...      ...
413         1305     3.0  ...   NaN        S
414         1306     1.0  ...  C105        C
415         1307     3.0  ...   NaN        S
416         1308     3.0  ...   NaN        S
417         1309     3.0  ...   NaN        C

[418 rows x 11 columns]
Dataset after filling NA values with 0 :
     PassengerId  Pclass  ... Cabin Embarked
0            892     3.0  ...     0        Q
1            893     3.0  ...     0        S
2            894     2.0  ...     0        Q
3            895     3.0  ...     0        S
4            896     0.0  ...     0        S
..           ...     ...  ...   ...      ...
413         1305     3.0  ...     0        S
414         1306     1.0  ...  C105        C
415         1307     3.0  ...     0        S
416         1308     3.0  ...     0        S
417         1309     3.0  ...     0        C

[418 rows x 11 columns]
>>>
```

2. #Dropping NA values using dropna()
Import pandas as pd
df= pd.read_csv('titanic.csv')
print(df)
df.head(10)
print("Dataset after dropping NA values:") df.dropna(inplace = True)
print(df)

OUTPUT:-

```
================ RESTART: D:/Notes/sem-6/data science/prac2c.py ================
     PassengerId  Pclass  ... Cabin Embarked
0            892     3.0  ...   NaN        Q
1            893     3.0  ...   NaN        S
2            894     2.0  ...   NaN        Q
3            895     3.0  ...   NaN        S
4            896     NaN  ...   NaN        S
..           ...     ...  ...   ...      ...
413         1305     3.0  ...   NaN        S
414         1306     1.0  ...  C105        C
415         1307     3.0  ...   NaN        S
416         1308     3.0  ...   NaN        S
417         1309     3.0  ...   NaN        C

[418 rows x 11 columns]
Dataset after dropping NA values:
     PassengerId  Pclass  ...            Cabin Embarked
12           904     1.0  ...              B45        S
14           906     1.0  ...              E31        S
24           916     1.0  ...  B57 B59 B63 B66        C
26           918     1.0  ...              B36        C
28           920     1.0  ...              A21        S
..           ...     ...  ...              ...      ...
404         1296     1.0  ...              D40        C
405         1297     2.0  ...              D38        C
407         1299     1.0  ...              C80        C
411         1303     1.0  ...              C78        Q
414         1306     1.0  ...             C105        C

[87 rows x 11 columns]
>>>
```

C. Manipulate and transform data using functions like

filtering, sorting, and grouping Code:

SOURCE CODE:-

import pandas as pd #

Load iris dataset

iris = pd.read_csv('Iris.csv')

Filtering data based on a

condition setosa = iris[iris['Species'] ==

'setosa'] print("Setosa samples:")

print(setosa.head())

Sorting data

sorted_iris =

iris.sort_values(by='SepalLengthCm',ascendin g=False)

print("\nSorted iris dataset:")

print(sorted_iris.head())

Grouping data grouped_species =

iris.groupby('Species').mean() print("\nMean

measurements for each species:")

print(grouped_species)

OUTPUT:-

```
================ RESTART: D:/Notes/sem-6/data science/prac2b.py ================
Setosa samples:
Empty DataFrame
Columns: [Id, SepalLengthCm, SepalWidthCm, PetalLengthCm, PetalWidthCm, Species]
Index: []

Sorted iris dataset:
      Id  SepalLengthCm  ...  PetalWidthCm         Species
131  132            7.9  ...           2.0  Iris-virginica
135  136            7.7  ...           2.3  Iris-virginica
122  123            7.7  ...           2.0  Iris-virginica
117  118            7.7  ...           2.2  Iris-virginica
118  119            7.7  ...           2.3  Iris-virginica

[5 rows x 6 columns]

Mean measurements for each species:
                    Id  SepalLengthCm  ...  PetalLengthCm  PetalWidthCm
Species                                ...
Iris-setosa       25.5          5.006  ...          1.464         0.244
Iris-versicolor   75.5          5.936  ...          4.260         1.326
Iris-virginica   125.5          6.588  ...          5.552         2.026

[3 rows x 5 columns]
>>
```

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PRACTICAL NO. 3

AIM:- Feature Scaling and Dummification

A. Apply feature-scaling techniques like standardization and normalization to numerical features.

SOURCE CODE:-

```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler,
StandardScaler #
Load dataset
df = pd.read_csv('wine.csv', header=None, usecols=[0, 1,
2], skiprows=1)
df.columns = ['classlabel', 'Alcohol', 'Malic Acid'] #
Display original DataFrame
print("Original DataFrame:")
print(df)
# Apply Min-Max Scaling min_max_scaler
= MinMaxScaler() df[['Alcohol', 'Malic
Acid']] =
min_max_scaler.fit_transform(df[['Alcohol', 'Malic Acid']])
print("\nDataFrame after Min-Max Scaling:") print(df)
# Apply Standard Scaling standard_scaler =
StandardScaler() df[['Alcohol', 'Malic Acid']]
=
standard_scaler.fit_transform(df[['Alcohol', 'Malic Acid']])
print("\nDataFrame after Standard Scaling:") print(df)
```

OUTPUT:-

```
= RESTART: D:/Notes/sem-6/data science/prac3b.py
Original DataFrame:
     classlabel  Alcohol  Malic Acid
0             1    14.23        1.71
1             1    13.20        1.78
2             1    13.16        2.36
3             1    14.37        1.95
4             1    13.24        2.59
..          ...      ...         ...
173           3    13.71        5.65
174           3    13.40        3.91
175           3    13.27        4.28
176           3    13.17        2.59
177           3    14.13        4.10

[178 rows x 3 columns]

 Dataframe after MinMax Scaling
     classlabel   Alcohol  Malic Acid
0             1  0.842105    0.191700
1             1  0.571053    0.205534
2             1  0.560526    0.320158
3             1  0.878947    0.239130
4             1  0.581579    0.365613
..          ...       ...         ...
173           3  0.705263    0.970356
174           3  0.623684    0.626482
175           3  0.589474    0.699605
176           3  0.563158    0.365613
177           3  0.815789    0.664032

[178 rows x 3 columns]

 Dataframe after Standard Scaling
```

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```
177           3  0.815789    0.664032

[178 rows x 3 columns]

 Dataframe after Standard Scaling
     classlabel   Alcohol  Malic Acid
0             1  1.518613   -0.562250
1             1  0.246290   -0.499413
2             1  0.196879    0.021231
3             1  1.691550   -0.346811
4             1  0.295700    0.227694
..          ...       ...         ...
173           3  0.876275    2.974543
174           3  0.493343    1.412609
175           3  0.332758    1.744744
176           3  0.209232    0.227694
177           3  1.395086    1.583165

[178 rows x 3 columns]
>>>
```

B. Perform feature Dummification to convert categorical variables into numerical representations.

SOURCE CODE:-

import pandas as pd

from sklearn.preprocessing import LabelEncoder # Load the dataset

iris = pd.read_csv("Iris.csv") print(iris)

Apply Label Encoding le = LabelEncoder()

iris['code'] = le.fit_transform(iris['Species'])

print(iris)

OUTPUT:-

```
================ RESTART: D:/Notes/sem-6/data science/prac3a.py ================
      Id  SepalLengthCm  ...  PetalWidthCm         Species
0      1            5.1  ...           0.2     Iris-setosa
1      2            4.9  ...           0.2     Iris-setosa
2      3            4.7  ...           0.2     Iris-setosa
3      4            4.6  ...           0.2     Iris-setosa
4      5            5.0  ...           0.2     Iris-setosa
..   ...            ...  ...           ...             ...
145  146            6.7  ...           2.3  Iris-virginica
146  147            6.3  ...           1.9  Iris-virginica
147  148            6.5  ...           2.0  Iris-virginica
148  149            6.2  ...           2.3  Iris-virginica
149  150            5.9  ...           1.8  Iris-virginica

[150 rows x 6 columns]
      Id  SepalLengthCm  SepalWidthCm  ...  PetalWidthCm         Species code
0      1            5.1           3.5  ...           0.2     Iris-setosa    0
1      2            4.9           3.0  ...           0.2     Iris-setosa    0
2      3            4.7           3.2  ...           0.2     Iris-setosa    0
3      4            4.6           3.1  ...           0.2     Iris-setosa    0
4      5            5.0           3.6  ...           0.2     Iris-setosa    0
..   ...            ...           ...  ...           ...             ...  ...
145  146            6.7           3.0  ...           2.3  Iris-virginica    2
146  147            6.3           2.5  ...           1.9  Iris-virginica    2
147  148            6.5           3.0  ...           2.0  Iris-virginica    2
148  149            6.2           3.4  ...           2.3  Iris-virginica    2
149  150            5.9           3.0  ...           1.8  Iris-virginica    2

[150 rows x 7 columns]
>>>
```

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PRACTICAL NO. – 4

AIM:- Hypothesis Testing

SOURCE CODE:-

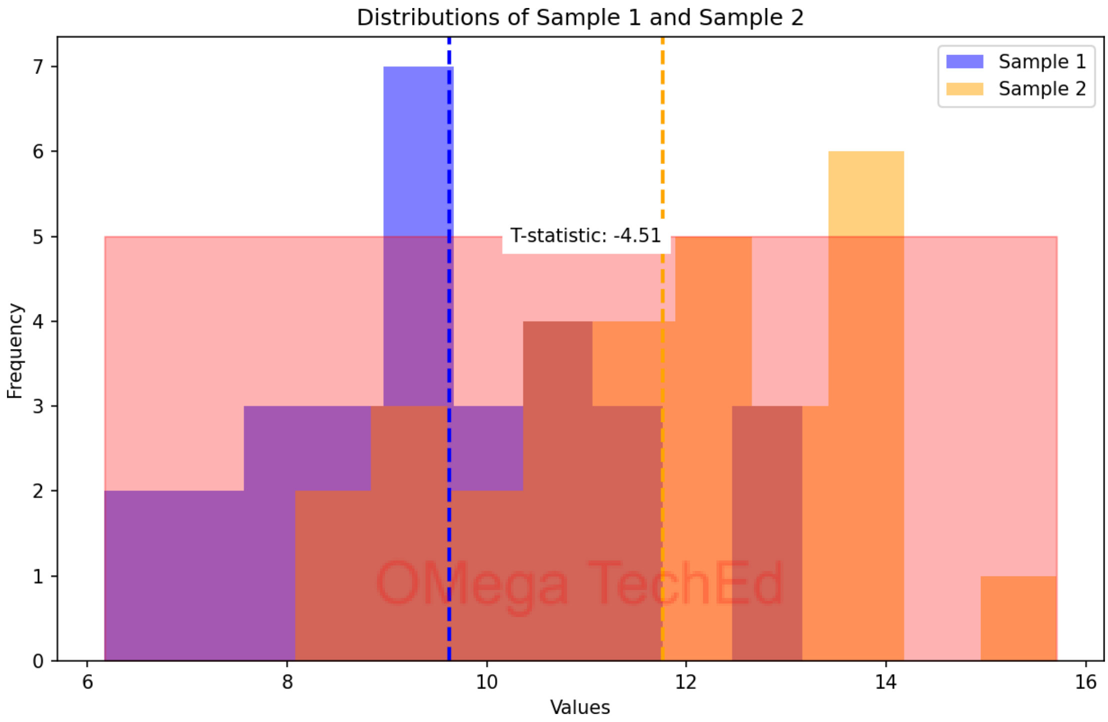
```
import numpy as np from
scipy import stats
import matplotlib.pyplot as plt

# Generate two samples for demonstration purposes np.random.seed(42)
sample1 = np.random.normal(loc=10, scale=2, size=30) sample2 =
np.random.normal(loc=12, scale=2, size=30)

# Perform a two-sample t-test
t_statistic, p_value = stats.ttest_ind(sample1, sample2)

# Set the significance level alpha
= 0.05

print("Results of Two-Sample t-test:")
print(f'T-statistic: {t_statistic}') print(f'P-
value: {p_value}')
print(f"Degrees of Freedom: {len(sample1) + len(sample2) - 2}")
```

```
# Plot the distributions
plt.figure(figsize=(10, 6))
plt.hist(sample1, alpha=0.5, label='Sample 1', color='blue')
plt.hist(sample2, alpha=0.5, label='Sample 2', color='orange')
plt.axvline(np.mean(sample1), color='blue', linestyle='dashed',
linewidth=2)
plt.axvline(np.mean(sample2), color='orange', linestyle='dashed', linewidth=2)
plt.title('Distributions of Sample 1 and Sample 2') plt.xlabel('Values')
plt.ylabel('Frequency')
plt.legend()

# Highlight the critical region if null hypothesis is rejected if
p_value < alpha:
    critical_region = np.linspace(min(sample1.min(), sample2.min()),
max(sample1.max(), sample2.max()), 1000)
    plt.fill_between(critical_region, 0, 5, color='red', alpha=0.3,
label='Critical Region')
    plt.text(11, 5, f'T-statistic: {t_statistic:.2f}', ha='center', va='center', color='black',
backgroundcolor='white')

# Show the plot
plt.show()
```

```
# Draw Conclusions if
p_value < alpha:
    if np.mean(sample1) > np.mean(sample2):
        print("Conclusion: There is significant evidence to reject the null hypothesis.")
        print("Interpretation: The mean of Sample 1 is significantly higher than
that of Sample 2.")
    else:
        print("Conclusion: There is significant evidence to reject the null hypothesis.")
        print("Interpretation: The mean of Sample 2 is significantly higher than
that of Sample 1.")
else:
    print("Conclusion: Fail to reject the null hypothesis.") print("Interpretation:
    There is not enough evidence to claim a
significant difference between the means.")
```

OUTPUT:-

```
Results of Two-Sample t-test:
T-statistic: -4.512913234547555
P-value: 3.176506547470154e-05
Degrees of Freedom: 58
```



SOURCE CODE:-

```
import numpy as
np import pandas
as pd
import matplotlib.pyplot as plt
import seaborn as sb
import warnings
from scipy import stats


# Suppress warnings
warnings.filterwarnings('ignore')


# Load dataset
df = sb.load_dataset('mpg')
```

```
print(df)

# Describe horsepower and model year columns
print(df['horsepower'].describe())
print(df['model_year'].describe())

# Categorize horsepower into bins
bins = [0, 75, 150, 240]
df['horsepower_new'] = pd.cut(df['horsepower'], bins=bins, labels=['l', 'm',
'h']) c = df['horsepower_new']
print(c)

# Categorize model year into bins
ybins = [69, 72, 74, 84]
labels = ['t1', 't2', 't3']
df['modelyear_new'] = pd.cut(df['model_year'], bins=ybins, labels=labels)
newyear = df['modelyear_new']
print(newyear)

# Create a contingency table
df_chi = pd.crosstab(df['horsepower_new'], df['modelyear_new'])
print(df_chi)

# Perform chi-square test
chi2_stat, p_value, dof, expected =
```

```
stats.chi2_contingency(df_chi) print(f'Chi-Square Statistic:
{chi2_stat}')
print(f'P-value: {p_value}')
print(f'Degrees of Freedom: {dof}')
print(f'Expected Frequencies:\n{expected}')
```

OUTPUT:-

```
==================== RESTART: E:/all notes/DS/prac_4.1.py ====================
      mpg  cylinders  ...  origin                       name
0    18.0          8  ...     usa  chevrolet chevelle malibu
1    15.0          8  ...     usa          buick skylark 320
2    18.0          8  ...     usa         plymouth satellite
3    16.0          8  ...     usa              amc rebel sst
4    17.0          8  ...     usa                ford torino
..    ...        ...  ...     ...                        ...
393  27.0          4  ...     usa            ford mustang gl
394  44.0          4  ...  europe                  vw pickup
395  32.0          4  ...     usa              dodge rampage
396  28.0          4  ...     usa                ford ranger
397  31.0          4  ...     usa                 chevy s-10

[398 rows x 9 columns]
count    392.000000
mean     104.469388
std       38.491160
min       46.000000
25%       75.000000
50%       93.500000
75%      126.000000
max      230.000000
```

```
Name: horsepower, dtype: float64
count    398.000000
mean      76.010050
std        3.697627
min       70.000000
25%       73.000000
50%       76.000000
75%       79.000000
max       82.000000
Name: model_year, dtype: float64
0      m
1      h
2      m
3      m
4      m
      ..
393    m
394    l
395    m
396    m
397    m
```

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```
Name: horsepower_new, Length: 398, dtype: category
Categories (3, object): ['l' < 'm' < 'h']
0      t1
1      t1
2      t1
3      t1
4      t1
       ..
393    t3
394    t3
395    t3
396    t3
397    t3
Name: modelyear_new, Length: 398, dtype: category
Categories (3, object): ['t1' < 't2' < 't3']
modelyear_new   t1  t2   t3
horsepower_new
l                9  14   76
m               49  41  158
h               26  11    8
(54.95485392447537, 3.320518009555984e-11, 4, array([[ 21.21428571,  16.66836735,  61.11734694]
,
       [ 53.14285714,  41.75510204, 153.10204082],
       [  9.64285714,   7.57653061,  27.78061224]]))
```

PRACTICAL NO. – 5

AIM:- ANOVA(Analysis of Variance)

SOURCE CODE:-

```
import numpy as np import
pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb
import warnings
from scipy import stats
from statsmodels.stats.multicomp import pairwise_tukeyhsd

# Suppress warnings
warnings.filterwarnings('ignore')

# Load dataset
df = sb.load_dataset('mpg')
print(df)

# Describe horsepower and model year columns
print(df['horsepower'].describe()) print(df['model_year'].describe())

# Categorize horsepower into bins bins =
[0, 75, 150, 240]
```

```
df['horsepower_new'] = pd.cut(df['horsepower'], bins=bins, labels=['l', 'm', 'h'])

c = df['horsepower_new'] print(c)


# Categorize model year into bins ybins =

[69, 72, 74, 84]

labels = ['t1', 't2', 't3']

df['modelyear_new'] = pd.cut(df['model_year'], bins=ybins,
labels=labels)

newyear = df['modelyear_new']

print(newyear)


# Create a contingency table

df_chi = pd.crosstab(df['horsepower_new'], df['modelyear_new']) print(df_chi)


# Perform chi-square test

chi2_stat, p_value, dof, expected = stats.chi2_contingency(df_chi)

print(f'Chi-Square Statistic: {chi2_stat}')

print(f'P-value: {p_value}') print(f'Degrees of

Freedom: {dof}')

print(f'Expected Frequencies:\n{expected}')
```

```
# Define groups for ANOVA
group1 = [23, 25, 29, 34, 30]
group2 = [19, 20, 22, 24, 25]
group3 = [15, 18, 20, 21, 17]
group4 = [28, 24, 26, 30, 29]

# Combine data into a DataFrame
data = pd.DataFrame({'value': group1 + group2 + group3 + group4, 'group':
                   ['Group1'] * len(group1) + ['Group2'] *
len(group2) +
                         ['Group3'] * len(group3) + ['Group4'] *
len(group4)})

# Perform one-way ANOVA
f_statistics, p_value_anova = stats.f_oneway(group1, group2, group3, group4)
print("\nOne-way ANOVA:")
print("F-statistics:", f_statistics)
print("P-value:", p_value_anova)

# Perform Tukey-Kramer post-hoc test
tukey_results = pairwise_tukeyhsd(data['value'], data['group'])
print("\nTukey-Kramer post-hoc test:")
print(tukey_results)
```

OUTPUT:-

```
one-way ANOVA:
F-statistics: 12.139872842870115
p-value 0.00021465200901629603

Tukey-Kramer post-hoc test:
 Multiple Comparison of Means - Tukey HSD, FWER=0.05
=====================================================
group1 group2 meandiff p-adj   lower    upper  reject
-----------------------------------------------------
Group1 Group2     -6.2  0.024 -11.6809 -0.7191   True
Group1 Group3    -10.0 0.0004 -15.4809 -4.5191   True
Group1 Group4     -0.8 0.9747  -6.2809  4.6809  False
Group2 Group3     -3.8 0.2348  -9.2809  1.6809  False
Group2 Group4      5.4 0.0542  -0.0809 10.8809  False
Group3 Group4      9.2  0.001   3.7191 14.6809   True
-----------------------------------------------------
```

PRACTICAL NO. – 6

AIM:- Regression and its Types SOURCE

CODE:-

```
import numpy as np import
pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb
import warnings
from scipy import stats
from statsmodels.stats.multicomp import pairwise_tukeyhsd from
sklearn.datasets import fetch_california_housing
from sklearn.model_selection import train_test_split from
sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score

# Suppress warnings
warnings.filterwarnings('ignore')

# Load dataset
df = sb.load_dataset('mpg')
print(df)

# Describe horsepower and model year columns
```

```
print(df['horsepower'].describe()) print(df['model_year'].describe())

# Categorize horsepower into bins bins =
[0, 75, 150, 240]
df['horsepower_new'] = pd.cut(df['horsepower'], bins=bins, labels=['l', 'm', 'h'])
c = df['horsepower_new'] print(c)

# Categorize model year into bins ybins =
[69, 72, 74, 84]
labels = ['t1', 't2', 't3']
df['modelyear_new'] = pd.cut(df['model_year'], bins=ybins,
labels=labels)
newyear = df['modelyear_new']
print(newyear)

# Create a contingency table
df_chi = pd.crosstab(df['horsepower_new'], df['modelyear_new']) print(df_chi)

# Perform chi-square test
chi2_stat, p_value, dof, expected = stats.chi2_contingency(df_chi)
```

```
print(f'Chi-Square Statistic: {chi2_stat}')
print(f'P-value: {p_value}') print(f'Degrees of
Freedom: {dof}')
print(f'Expected Frequencies:\n{expected}')

# Define groups for ANOVA
group1 = [23, 25, 29, 34, 30]
group2 = [19, 20, 22, 24, 25]
group3 = [15, 18, 20, 21, 17]
group4 = [28, 24, 26, 30, 29]

# Combine data into a DataFrame
data = pd.DataFrame({'value': group1 + group2 + group3 + group4, 'group':
                    ['Group1'] * len(group1) + ['Group2'] *
len(group2) +
                            ['Group3'] * len(group3) + ['Group4'] *
len(group4)})

# Perform one-way ANOVA
f_statistics, p_value_anova = stats.f_oneway(group1, group2, group3, group4)
print("\nOne-way ANOVA:")
print("F-statistics:", f_statistics)
print("P-value:", p_value_anova)
```

```
# Perform Tukey-Kramer post-hoc test
tukey_results = pairwise_tukeyhsd(data['value'], data['group'])
print("\nTukey-Kramer post-hoc test:")
print(tukey_results)

# Load California housing dataset
housing = fetch_california_housing()
housing_df = pd.DataFrame(housing.data,
columns=housing.feature_names)
print(housing_df)

# Add target variable housing_df['PRICE'] =
housing.target

# Select feature and target
X = housing_df[['AveRooms']] y =
housing_df['PRICE']

# Split dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Train linear regression model model =
LinearRegression()
```

model.fit(X_train, y_train)

Evaluate model

mse = mean_squared_error(y_test, model.predict(X_test)) r2 =

r2_score(y_test, model.predict(X_test))

print("Mean Squared Error:", mse)

print("R-squared:", r2) print("Intercept:",

model.intercept_) print("Coefficient:",

model.coef_) **OUTPUT:-**

```
===
       MedInc  HouseAge  AveRooms  ...  AveOccup  Latitude  Longitude
0      8.3252      41.0  6.984127  ...  2.555556     37.88    -122.23
1      8.3014      21.0  6.238137  ...  2.109842     37.86    -122.22
2      7.2574      52.0  8.288136  ...  2.802260     37.85    -122.24
3      5.6431      52.0  5.817352  ...  2.547945     37.85    -122.25
4      3.8462      52.0  6.281853  ...  2.181467     37.85    -122.25
...       ...       ...       ...  ...       ...       ...        ...
20635  1.5603      25.0  5.045455  ...  2.560606     39.48    -121.09
20636  2.5568      18.0  6.114035  ...  3.122807     39.49    -121.21
20637  1.7000      17.0  5.205543  ...  2.325635     39.43    -121.22
20638  1.8672      18.0  5.329513  ...  2.123209     39.43    -121.32
20639  2.3886      16.0  5.254717  ...  2.616981     39.37    -121.24

[20640 rows x 8 columns]
Mean Squared Error: 1.2923314440807299
R-squared: 0.013795337532284901
Intercept: 1.654762268596842
Coefficient: [0.07675559]
>
```

SOURCE CODE:-

import numpy as np import

pandas as pd

import matplotlib.pyplot as plt

import seaborn as sb import
warnings
from scipy import stats
from statsmodels.stats.multicomp import pairwise_tukeyhsd from
sklearn.datasets import fetch_california_housing
from sklearn.model_selection import train_test_split from
sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score

# Suppress warnings
warnings.filterwarnings('ignore')

# Load dataset
df = sb.load_dataset('mpg')
print(df)

# Describe horsepower and model year columns
print(df['horsepower'].describe()) print(df['model_year'].describe())

Categorize horsepower into bins bins = [0,
75, 150, 240]

```
df['horsepower_new'] = pd.cut(df['horsepower'], bins=bins, labels=['l', 'm', 'h'])
c = df['horsepower_new'] print(c)

# Categorize model year into bins ybins =
[69, 72, 74, 84]
labels = ['t1', 't2', 't3']
df['modelyear_new'] = pd.cut(df['model_year'], bins=ybins, labels=labels)
newyear = df['modelyear_new']
print(newyear)

# Create a contingency table
df_chi = pd.crosstab(df['horsepower_new'], df['modelyear_new'])
print(df_chi)

# Perform chi-square test
chi2_stat, p_value, dof, expected = stats.chi2_contingency(df_chi)
print(f'Chi-Square Statistic: {chi2_stat}') print(f'P-
value: {p_value}')
```

```
print(f'Degrees of Freedom: {dof}') print(f'Expected
Frequencies:\n{expected}')

# Define groups for ANOVA group1 = [23,
25, 29, 34, 30]
group2 = [19, 20, 22, 24, 25]
group3 = [15, 18, 20, 21, 17]
group4 = [28, 24, 26, 30, 29]

# Combine data into a DataFrame
data = pd.DataFrame({'value': group1 + group2 + group3 + group4,
                     'group': ['Group1'] * len(group1) + ['Group2'] * len(group2) +
                              ['Group3'] * len(group3) + ['Group4'] *
len(group4)})

# Perform one-way ANOVA
f_statistics, p_value_anova = stats.f_oneway(group1, group2, group3, group4)
print("\nOne-way ANOVA:") print("F-
statistics:", f_statistics) print("P-value:",
p_value_anova)
```

Perform Tukey-Kramer post-hoc test

tukey_results = pairwise_tukeyhsd(data['value'], data['group']) print("\nTukey-Kramer post-hoc test:")

print(tukey_results)

Load California housing dataset housing =

fetch_california_housing()

housing_df = pd.DataFrame(housing.data, columns=housing.feature_names)

print(housing_df)

Add target variable housing_df['PRICE'] =

housing.target

Multiple Linear Regression

X = housing_df.drop('PRICE', axis=1) y =

housing_df['PRICE']

Split dataset into training and testing sets

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

```
# Train linear regression model model =
LinearRegression() model.fit(X_train,
y_train)

# Make predictions
y_pred = model.predict(X_test)

# Evaluate model
mse = mean_squared_error(y_test, y_pred) r2 =
r2_score(y_test, y_pred)
print("Mean Squared Error:", mse) print("R-
squared:", r2) print("Intercept:",
model.intercept_) print("Coefficient:",
model.coef_)
```

OUTPUT:-

```
========================= RESTART: E:\all notes\DS\prac_6_single.py =====================
       MedInc  HouseAge  AveRooms  ...  AveOccup  Latitude  Longitude
0      8.3252      41.0  6.984127  ...  2.555556     37.88    -122.23
1      8.3014      21.0  6.238137  ...  2.109842     37.86    -122.22
2      7.2574      52.0  8.288136  ...  2.802260     37.85    -122.24
3      5.6431      52.0  5.817352  ...  2.547945     37.85    -122.25
4      3.8462      52.0  6.281853  ...  2.181467     37.85    -122.25
...       ...       ...       ...  ...       ...       ...        ...
20635  1.5603      25.0  5.045455  ...  2.560606     39.48    -121.09
20636  2.5568      18.0  6.114035  ...  3.122807     39.49    -121.21
20637  1.7000      17.0  5.205543  ...  2.325635     39.43    -121.22
20638  1.8672      18.0  5.329513  ...  2.123209     39.43    -121.32
20639  2.3886      16.0  5.254717  ...  2.616981     39.37    -121.24

[20640 rows x 8 columns]
Mean Squared Error: 1.2923314440807299
R-squared: 0.013795337532284901
Intercept: 1.654762268596842
Coefficient: [0.07675559]
Mean Squared Error: 0.5558915986952441
R-squared: 0.575787706032451
Intercept: -37.02327770606414
Coefficient: [ 4.48674910e-01  9.72425752e-03 -1.23323343e-01  7.83144907e-01
 -2.02962058e-06 -3.52631849e-03 -4.19792487e-01 -4.33708065e-01]
```

PRACTICAL NO. – 7

AIM:- Logistic Regression and Decision Tree SOURCE CODE:-

```
import numpy as np import
pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb
import warnings
from scipy import stats
from statsmodels.stats.multicomp import pairwise_tukeyhsd from
sklearn.datasets import fetch_california_housing, load_iris from
sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression,
LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import mean_squared_error, r2_score, accuracy_score,
precision_score, recall_score, classification_report


# Suppress warnings
warnings.filterwarnings('ignore')


# Load dataset
df = sb.load_dataset('mpg')
print(df)
```

```
# Describe horsepower and model year columns

print(df['horsepower'].describe()) print(df['model_year'].describe())


# Categorize horsepower into bins bins =

[0, 75, 150, 240]

df['horsepower_new'] = pd.cut(df['horsepower'], bins=bins, labels=['l', 'm', 'h'])

c = df['horsepower_new'] print(c)


# Categorize model year into bins ybins =

[69, 72, 74, 84]

labels = ['t1', 't2', 't3']

df['modelyear_new'] = pd.cut(df['model_year'], bins=ybins,
labels=labels)

newyear = df['modelyear_new']

print(newyear)


# Create a contingency table

df_chi = pd.crosstab(df['horsepower_new'], df['modelyear_new']) print(df_chi)
```

```
# Perform chi-square test
chi2_stat, p_value, dof, expected = stats.chi2_contingency(df_chi)
print(f'Chi-Square Statistic: {chi2_stat}')
print(f'P-value: {p_value}') print(f'Degrees of
Freedom: {dof}')
print(f'Expected Frequencies:\n{expected}')

# Define groups for ANOVA
group1 = [23, 25, 29, 34, 30]
group2 = [19, 20, 22, 24, 25]
group3 = [15, 18, 20, 21, 17]
group4 = [28, 24, 26, 30, 29]

# Combine data into a DataFrame
data = pd.DataFrame({'value': group1 + group2 + group3 + group4, 'group':
                    ['Group1'] * len(group1) + ['Group2'] *
len(group2) +
                             ['Group3'] * len(group3) + ['Group4'] *
len(group4)})

# Perform one-way ANOVA
f_statistics, p_value_anova = stats.f_oneway(group1, group2, group3, group4)
print("\nOne-way ANOVA:")
print("F-statistics:", f_statistics)
```

```
print("P-value:", p_value_anova)

# Perform Tukey-Kramer post-hoc test
tukey_results = pairwise_tukeyhsd(data['value'], data['group'])
print("\nTukey-Kramer post-hoc test:")
print(tukey_results)

# Load California housing dataset housing =
fetch_california_housing()
housing_df = pd.DataFrame(housing.data,
columns=housing.feature_names)
print(housing_df)

# Add target variable housing_df['PRICE'] =
housing.target

# Multiple Linear Regression
X = housing_df.drop('PRICE', axis=1) y =
housing_df['PRICE']

# Split dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
# Train linear regression model model =
LinearRegression() model.fit(X_train,
y_train)

# Make predictions
y_pred = model.predict(X_test)

# Evaluate model
mse = mean_squared_error(y_test, y_pred) r2 =
r2_score(y_test, y_pred)
print("Mean Squared Error:", mse)
print("R-squared:", r2) print("Intercept:",
model.intercept_) print("Coefficient:",
model.coef_)

# Load the Iris dataset and classification problem iris =
load_iris()
iris_df = pd.DataFrame(data=np.c_[iris['data'], iris['target']],
columns=iris['feature_names'] + ['target'])
binary_df = iris_df[iris_df['target'] != 2] X =
binary_df.drop('target', axis=1)
y = binary_df['target']

# Split the data into training and testing sets
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Train a logistic regression model and evaluate its performance
logistic_model = LogisticRegression() logistic_model.fit(X_train,
y_train)
y_pred_logistic = logistic_model.predict(X_test)

print("\nLogistic Regression Metrics")
print("Accuracy:", accuracy_score(y_test, y_pred_logistic))
print("Precision:", precision_score(y_test, y_pred_logistic))
print("Recall:", recall_score(y_test, y_pred_logistic))
print("\nClassification Report") print(classification_report(y_test,
y_pred_logistic))

# Train a decision tree model and evaluate its performance decision_tree_model =
DecisionTreeClassifier() decision_tree_model.fit(X_train, y_train)
y_pred_tree = decision_tree_model.predict(X_test)

print("\nDecision Tree Metrics")
print("Accuracy:",      accuracy_score(y_test,      y_pred_tree))
print("Precision:",      precision_score(y_test,      y_pred_tree))
print("Recall:", recall_score(y_test, y_pred_tree))
```

print("\nClassification Report")

print(classification_report(y_test, y_pred_tree))

OUTPUT:-

```
Logistic Regression Metrics
Accuracy:  1.0
Precision: 1.0
Recall:    1.0

Classification Report
              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00        12
         1.0       1.00      1.00      1.00         8

    accuracy                           1.00        20
   macro avg       1.00      1.00      1.00        20
weighted avg       1.00      1.00      1.00        20


Decision Tree Metrics
Accuracy:  1.0
Precision: 1.0
Recall:    1.0
```

PRACTICAL NO. – 8

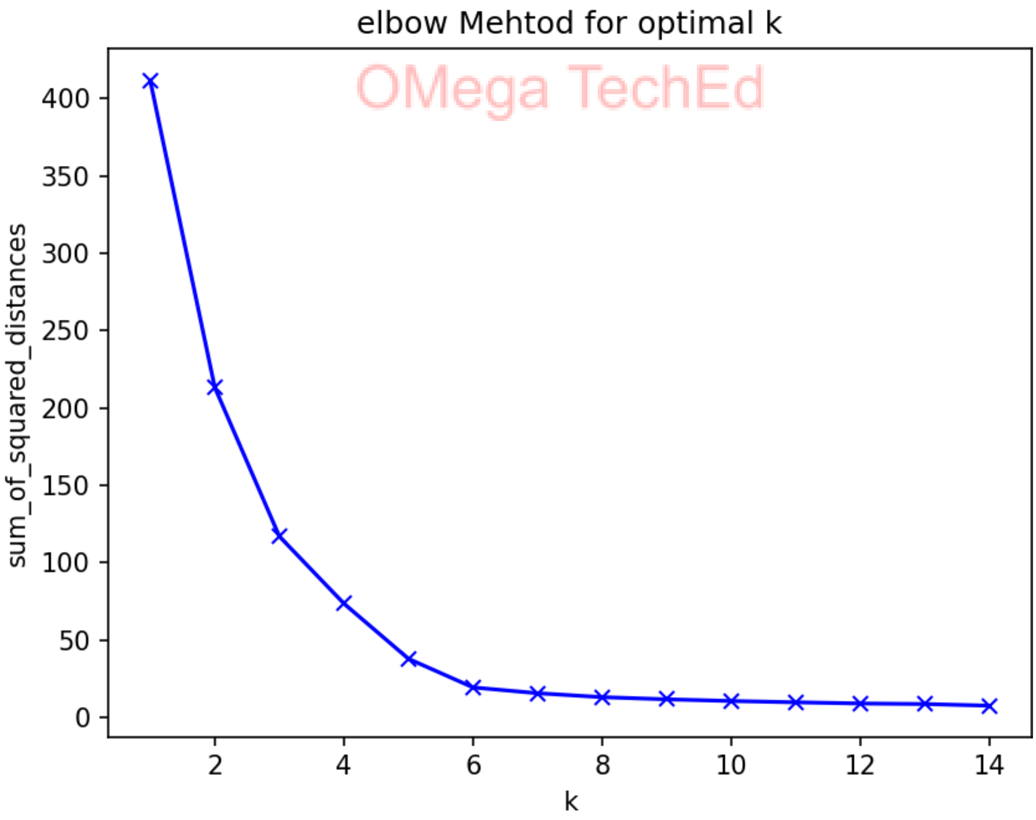
AIM:- K-MEANS CLUSTERING SOURCE

CODE:-

```
import pandas as pd

from sklearn.preprocessing import MinMaxScaler from

sklearn.cluster import KMeans

import matplotlib.pyplot as plt


# Load dataset data

=

pd.read_csv("C:\\Users\\Reape\\Downloads\\wholesale\\wholesale.csv ")

data.head()


# Define categorical and continuous features categorical_features =

['Channel', 'Region']

continuous_features = ['Fresh', 'Milk', 'Grocery', 'Frozen',
'Detergents_Paper', 'Delicassen']

data[continuous_features].describe()


# Convert categorical variables into dummy variables for col in

categorical_features:

    dummies = pd.get_dummies(data[col], prefix=col) data =

    pd.concat([data, dummies], axis=1)
```

```
    data.drop(col, axis=1, inplace=True)

data.head()

# Scale the data
mms = MinMaxScaler()
mms.fit(data)
data_transformed = mms.transform(data)

# Elbow Method to find optimal k
sum_of_squared_distances = []
K = range(1, 15)
for k in K:
    km = KMeans(n_clusters=k) km =
    km.fit(data_transformed)
    sum_of_squared_distances.append(km.inertia_)

# Plot the Elbow Method
plt.plot(K,      sum_of_squared_distances,      'bx-')
plt.xlabel('k')
plt.ylabel('Sum    of    Squared    Distances')
plt.title('Elbow    Method    for    Optimal    k')
plt.show()
```

OUTPUT:-


elbow Mehtod for optimal k
OMega TechEd
sum_of_squared_distances
400
350
300
250
200
150
100
50
0
2
4
6
8
10
12
14
k

PRACTICAL NO. 9

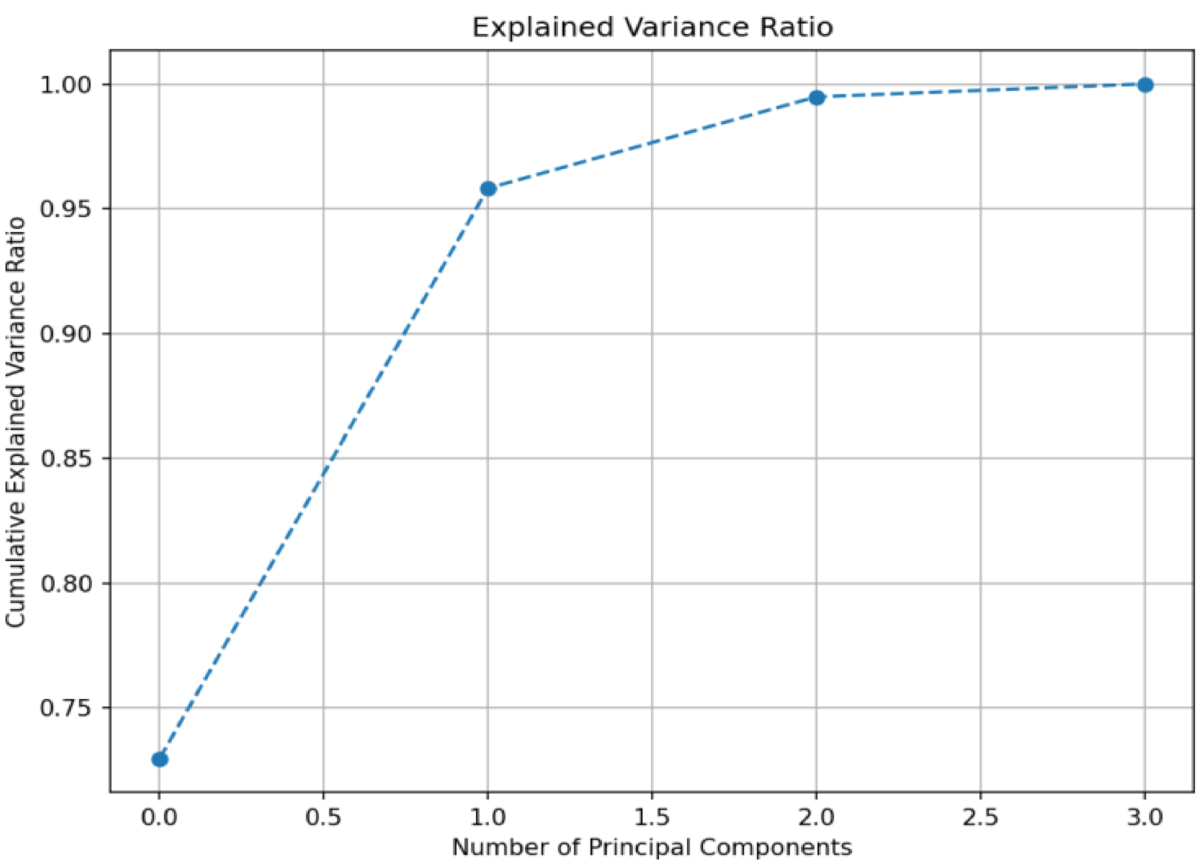
AIM:- Principal Component Analysis (PCA) SOURCE CODE:-

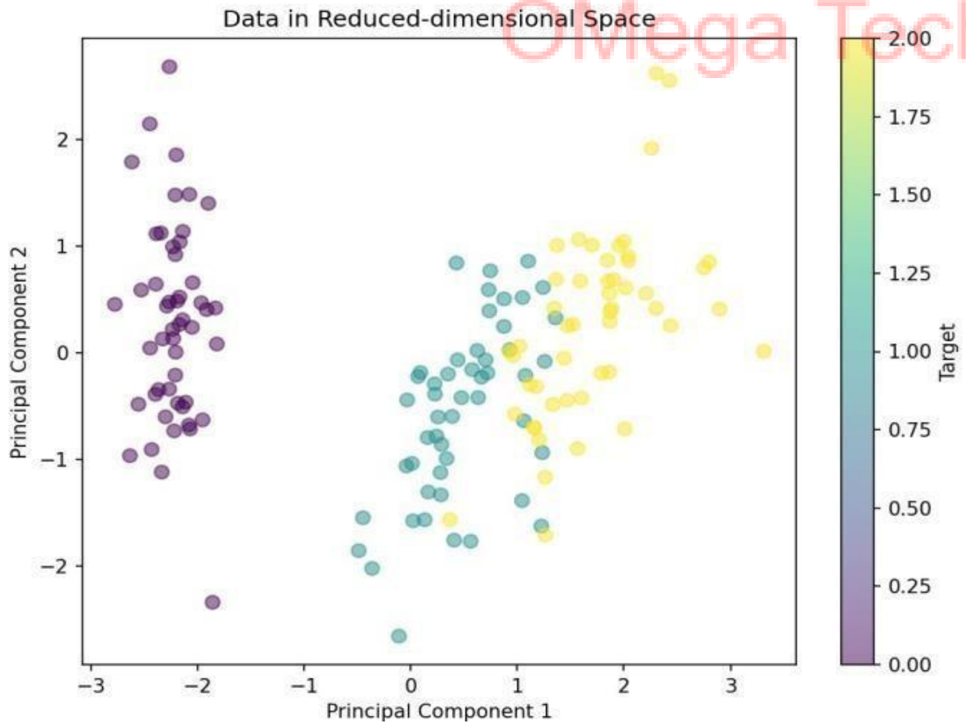
```
import pandas as pd import

numpy as np

import matplotlib.pyplot as plt

from sklearn.datasets import load_iris

from sklearn.preprocessing import StandardScaler from

sklearn.decomposition import PCA


# Load the Iris dataset iris

= load_iris()

iris_df = pd.DataFrame(data=np.c_[iris['data'], iris['target']],
columns=iris['feature_names'] + ['target'])


# Separate features and target

X = iris_df.drop('target', axis=1) y =

iris_df['target']


# Standardize the features scaler

= StandardScaler()

X_scaled = scaler.fit_transform(X)


# Apply PCA
```

```
pca = PCA()

X_pca = pca.fit_transform(X_scaled) explained_variance_ratio =
pca.explained_variance_ratio_

# Plot cumulative explained variance
plt.figure(figsize=(8, 6))
plt.plot(np.cumsum(explained_variance_ratio), marker='o',
linestyle='--')
plt.title('Explained Variance Ratio') plt.xlabel('Number of
Principal Components') plt.ylabel('Cumulative Explained
Variance Ratio') plt.grid(True)
plt.show()

# Determine the number of components to explain 95% variance
cumulative_variance_ratio = np.cumsum(explained_variance_ratio) n_components =
np.argmax(cumulative_variance_ratio >= 0.95) + 1
print(f"Number of principal components to explain 95% variance:
{n_components}")

# Reduce dimensions using selected number of components pca =
PCA(n_components=n_components)
X_reduced = pca.fit_transform(X_scaled)
```

```
# Scatter plot of the reduced data
plt.figure(figsize=(8, 6))
plt.scatter(X_reduced[:, 0], X_reduced[:, 1], c=y, cmap='viridis', s=50, alpha=0.5)
plt.title('Data in Reduced-dimensional Space') plt.xlabel('Principal
Component 1')
plt.ylabel('Principal Component 2')
plt.colorbar(label='Target') plt.show()
```

OUTPUT:-






```
Number of principal components to explain 95% variance: 2
```

PRACTICAL NO. – 10

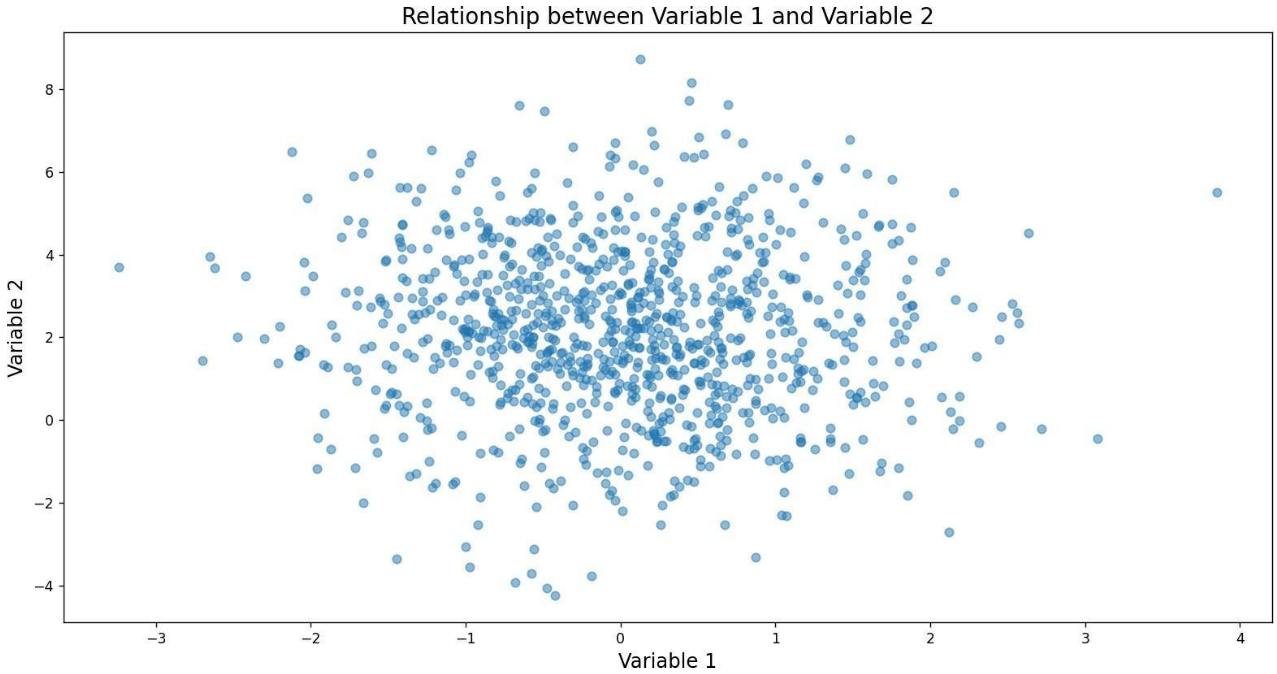
AIM:-Data Visualization and Storytelling SOURCE CODE:-

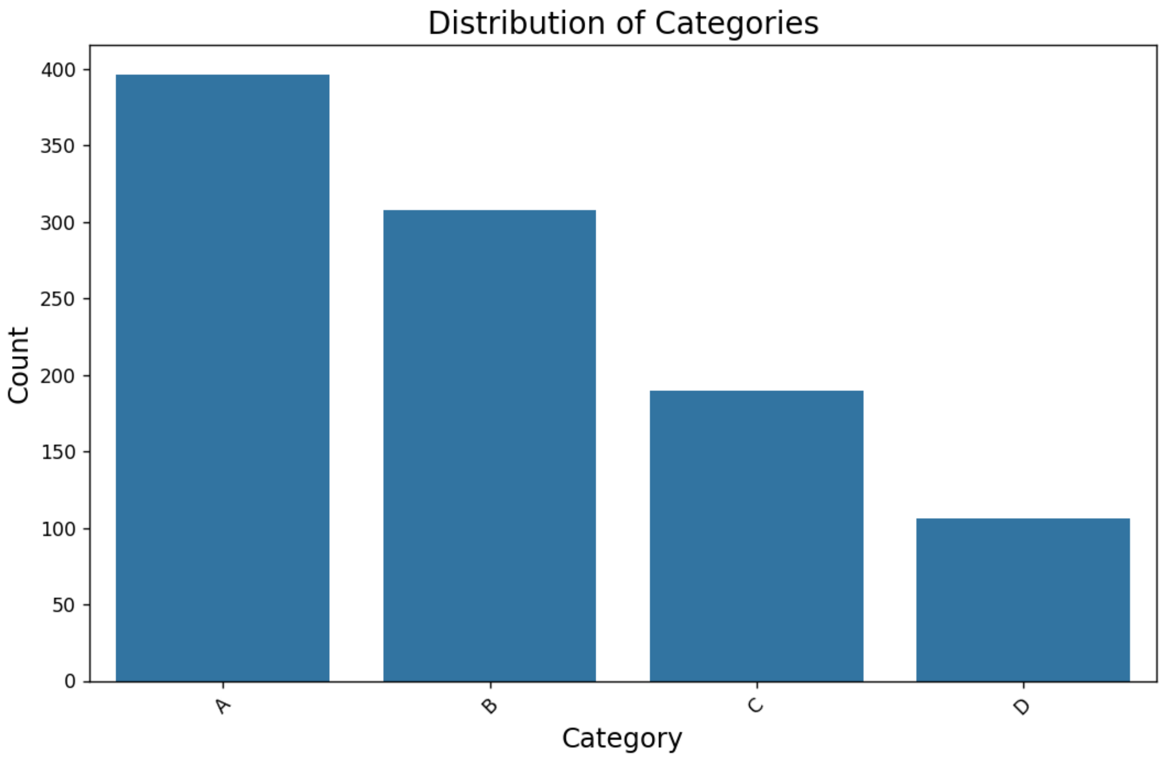
```
import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns

import numpy as np


# Generate random data

np.random.seed(42)  # Set a seed for reproducibility


# Create a DataFrame with random data data

= pd.DataFrame({

    'variable1': np.random.normal(0, 1, 1000),

    'variable2': np.random.normal(2, 2, 1000) + 0.5 *
np.random.normal(0, 1, 1000),

    'variable3': np.random.normal(-1, 1.5, 1000),

    'category': pd.Series(np.random.choice(['A', 'B', 'C', 'D'], size=1000, p=[0.4,
0.3, 0.2, 0.1]),

                            dtype='category')

})


# Create a scatter plot to visualize the relationship between two variables
```

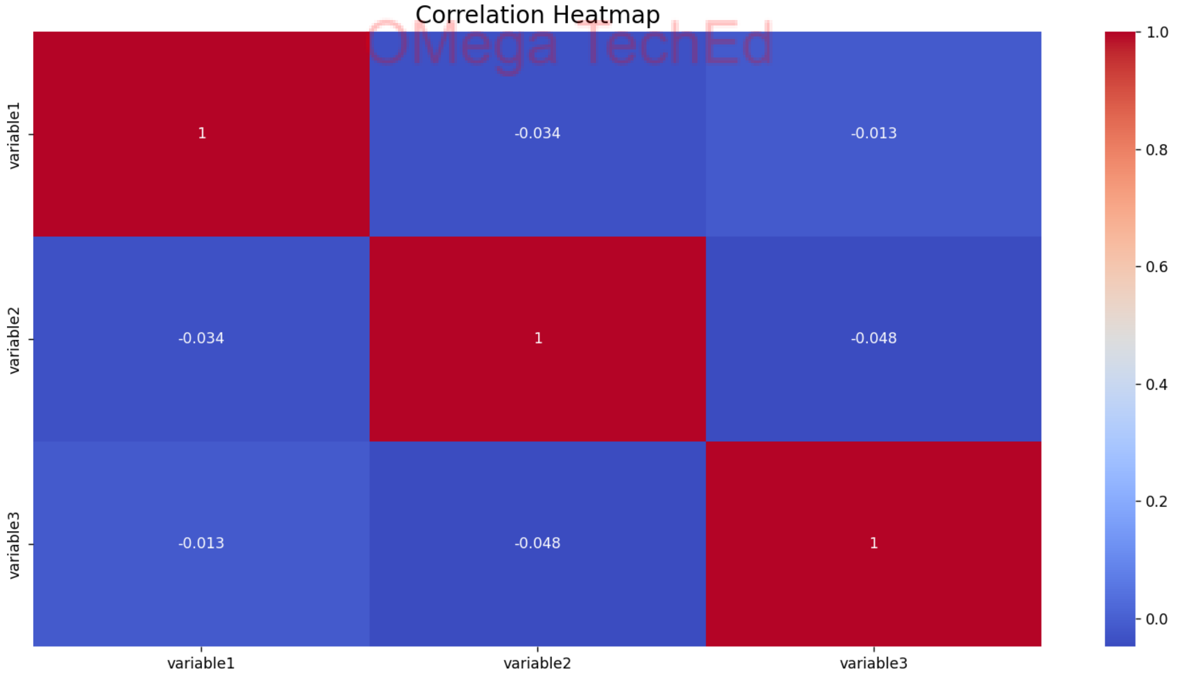
```
plt.figure(figsize=(10, 6))
plt.scatter(data['variable1'], data['variable2'], alpha=0.5) plt.title('Relationship
between Variable 1 and Variable 2', fontsize=16) plt.xlabel('Variable 1',
fontsize=14)
plt.ylabel('Variable 2', fontsize=14) plt.show()

# Create a bar chart to visualize the distribution of a categorical variable
plt.figure(figsize=(10, 6)) sns.countplot(x='category',
data=data) plt.title('Distribution of Categories',
fontsize=16) plt.xlabel('Category', fontsize=14)
plt.ylabel('Count', fontsize=14) plt.xticks(rotation=45)
plt.show()

# Create a heatmap to visualize the correlation between numerical variables
plt.figure(figsize=(10, 8))
numerical_cols = ['variable1', 'variable2', 'variable3']
sns.heatmap(data[numerical_cols].corr(), annot=True,
cmap='coolwarm')
plt.title('Correlation Heatmap', fontsize=16)
plt.show()
```

```
# Data Storytelling
print("Title: Exploring the Relationship between Variable 1 and Variable 2")

print("\nThe scatter plot (Figure 1) shows the relationship between Variable 1
and Variable 2.")

print("\nScatter Plot")
print("Figure 1: Scatter Plot of Variable 1 and Variable 2")

print("\nTo better understand the distribution of the categorical variable
'category', we created a ")

print("\nBar Chart")
print("Figure 2: Distribution of Categories")

print("\nAdditionally, we explored the correlation between numerical variables using a
heatmap")

print("\nHeatmap")
print("Figure 3: Correlation Heatmap")

print("\nIn summary, the visualizations and analysis provide insights into the
relationships")
```

OUTPUT:-


Relationship between Variable 1 and Variable 2
Variable 2
Variable 1
8
6
4
2
0
−2
−4
−3
−2
−1
0
1
2
3
4


Distribution of Categories
Count
Category
400
350
300
250
200
150
100
50
0
A
B
C
D



= RESTART: D:/pract 10.py
Title: Exploring the Relationship between Variable 1 and Variable 2

The scatter plot (Figure 1) shows the relationship between Variable 1 and Variable 2.

Scatter Plot
Figure 1: Scatter Plot of Variable 1 and Variable 2

To better understand the distribution of the categorical variable 'category', we created a

Bar Chart
Figure 2: Distribution of Categories

Additionally, we explored the correlation between numerical variables using a heatmap

Heatmap
Figure 3: Correlation Heatmap

In summary, the visualizations and analysis provide insights into the relationships