JNAN VIKAS MANDAL'S

PADMASHREE DR. R.T.DOSHI DEGREE COLLEGE OF INFORMATION TECHNOLOGY

MOHANLAL RAICHAND MEHTA COLLEGE OF COMMERCE

DIWALIMAA DEGREE COLLEGE OF SCIENCE

CERTIFICATE

This is to certify that the **Mr/Miss.** ____________________________,
having roll number _____ of T.Y.B.Sc.(CS) Semester-VI has completed the practical work in the subject of **DATA SCIENCE** during the Academic year 2024-2025 under the guidance of **Mrs. Vinaya Deshmukh** being the partial requirement for the fulfilment of the curriculum of Degree of Bachelor of Science in Computer Science, **University of Mumbai.**

Place: Airoli **Date:**

Sign of Subject Incharge Sign of External Examiner

Sign of Incharge / H.O.D

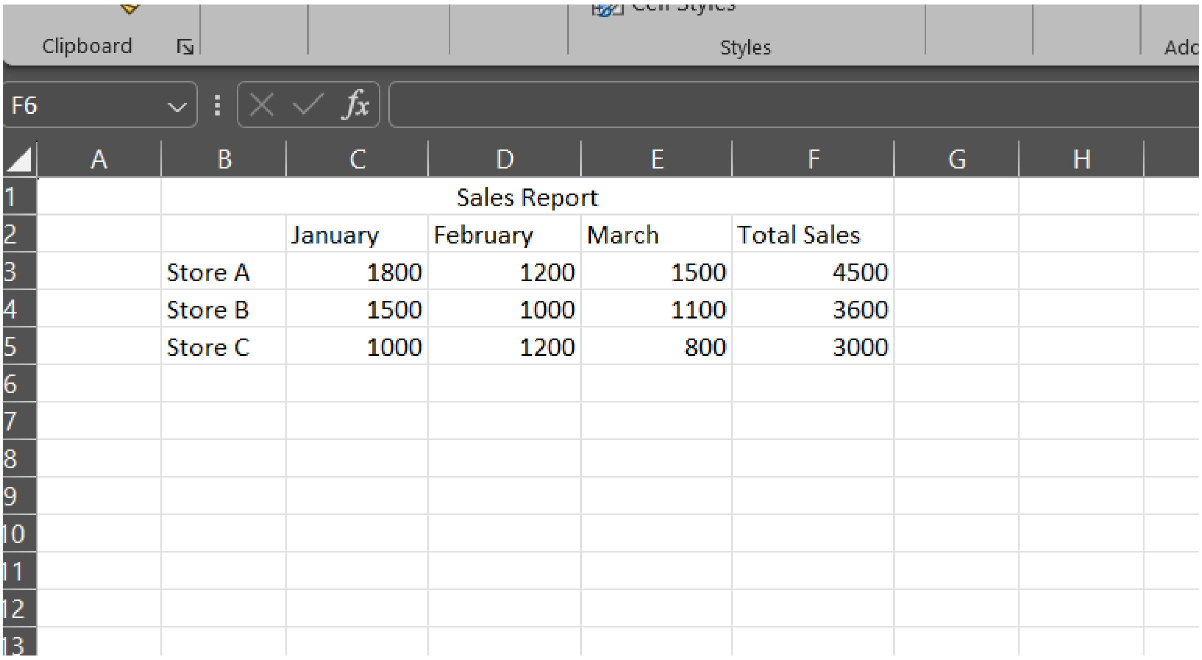
INDEX

Sr. No.	Practical	Date	Sign
1	Introduction to Excel	13/01/2025	
2	Data Frames and Basic Data Pre-processing	20/01/2025	
3	Feature Scaling and Dummification	27/01/2025	
4	Hypothesis Testing	03/02/2025	
5	ANOVA (Analysis of Variance)	10/02/2025	
6	Regression and its Types.	17/02/2025	
7	Logistic Regression and Decision Tree	24/02/2025	
8	K -Means clustering	03/03/2025	
9	Storytelling	10/03/2025	

PRACTICAL 1

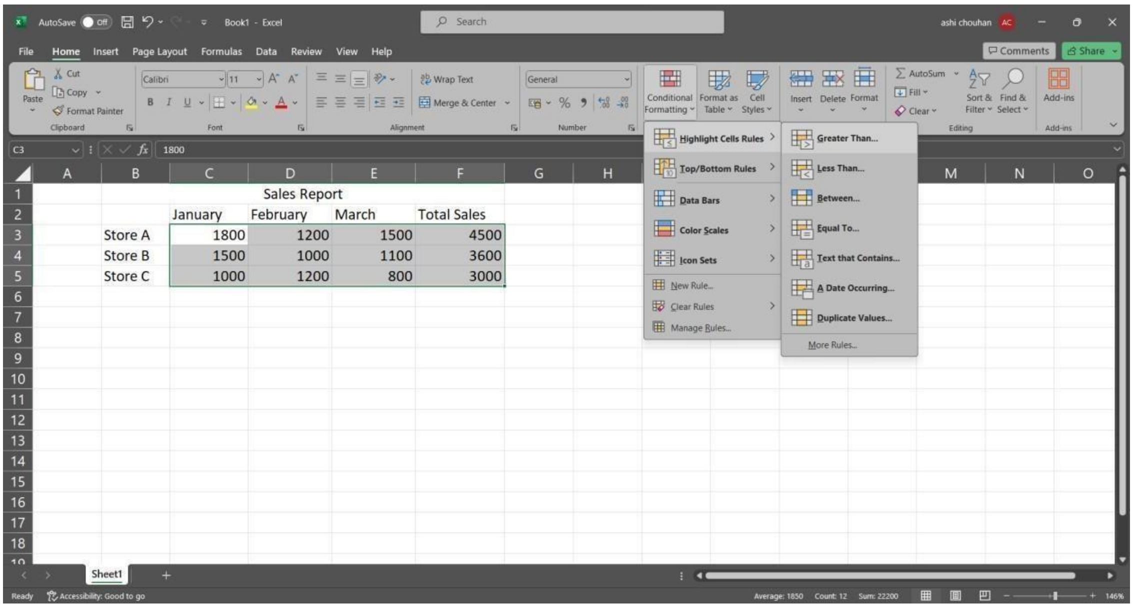
Introduction to Excel

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

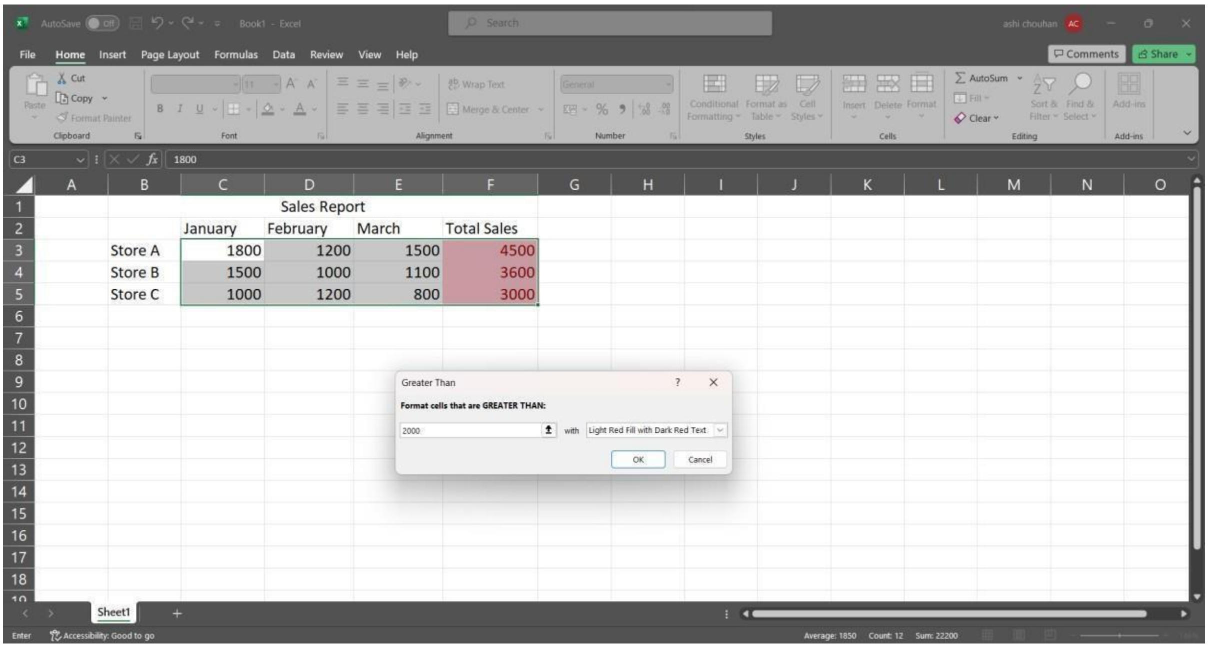


Steps

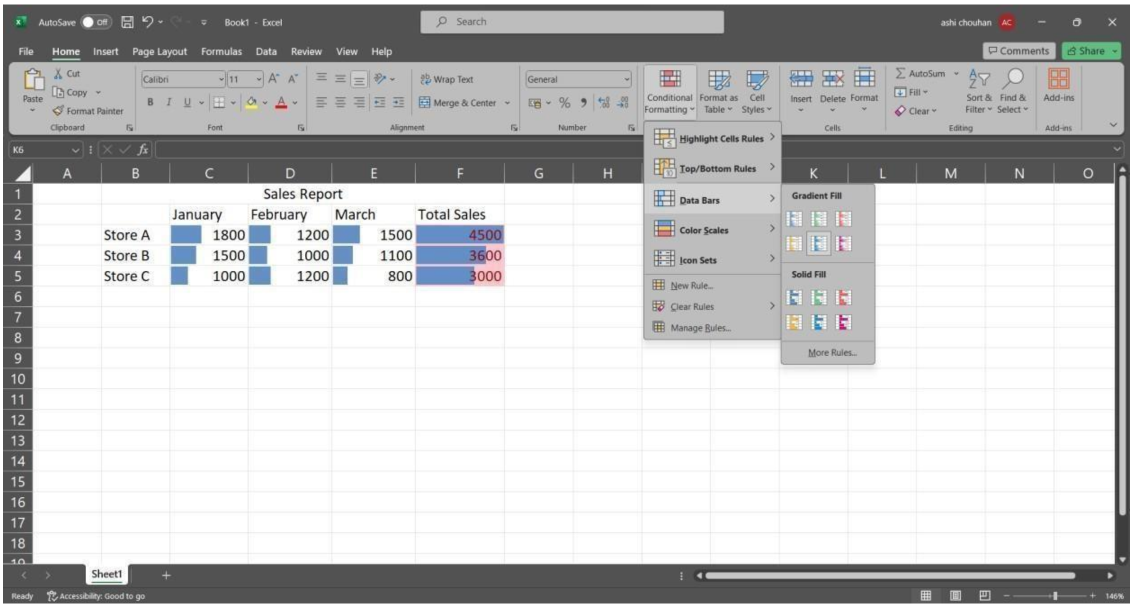
Step 1: Go to conditional formatting > Greater Than



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



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

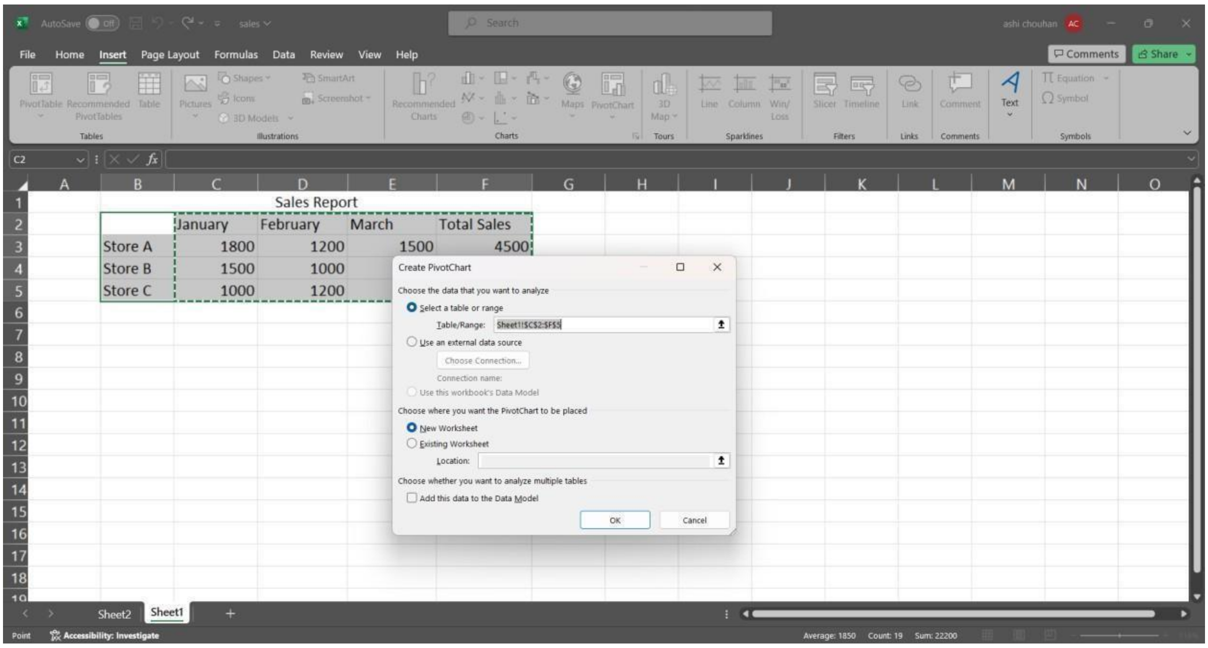


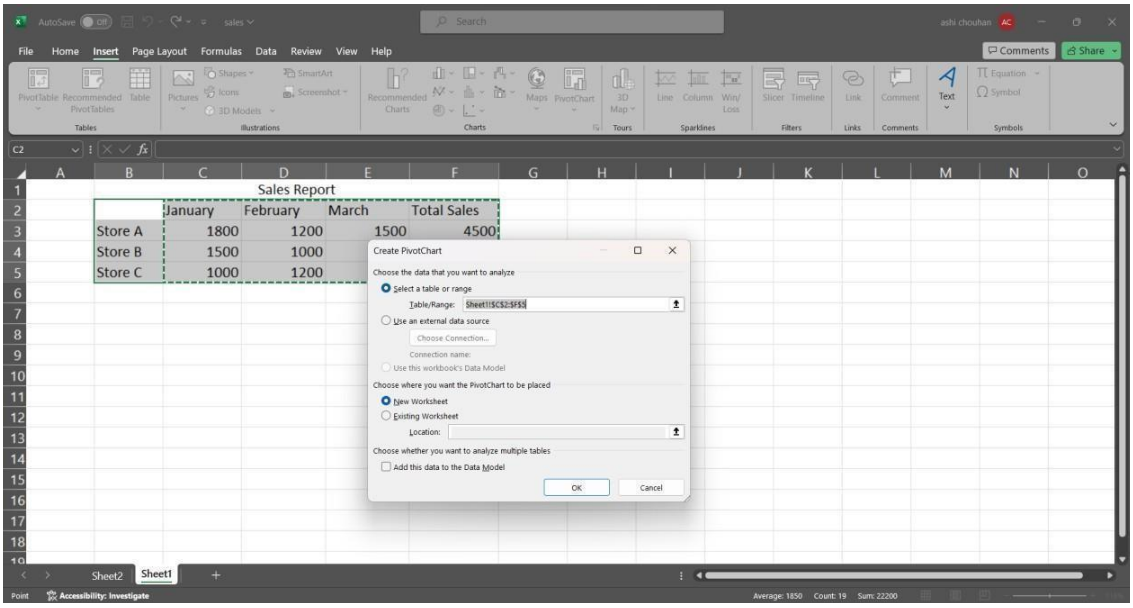
B. Create a pivot table to analyse and summarize data.

Steps

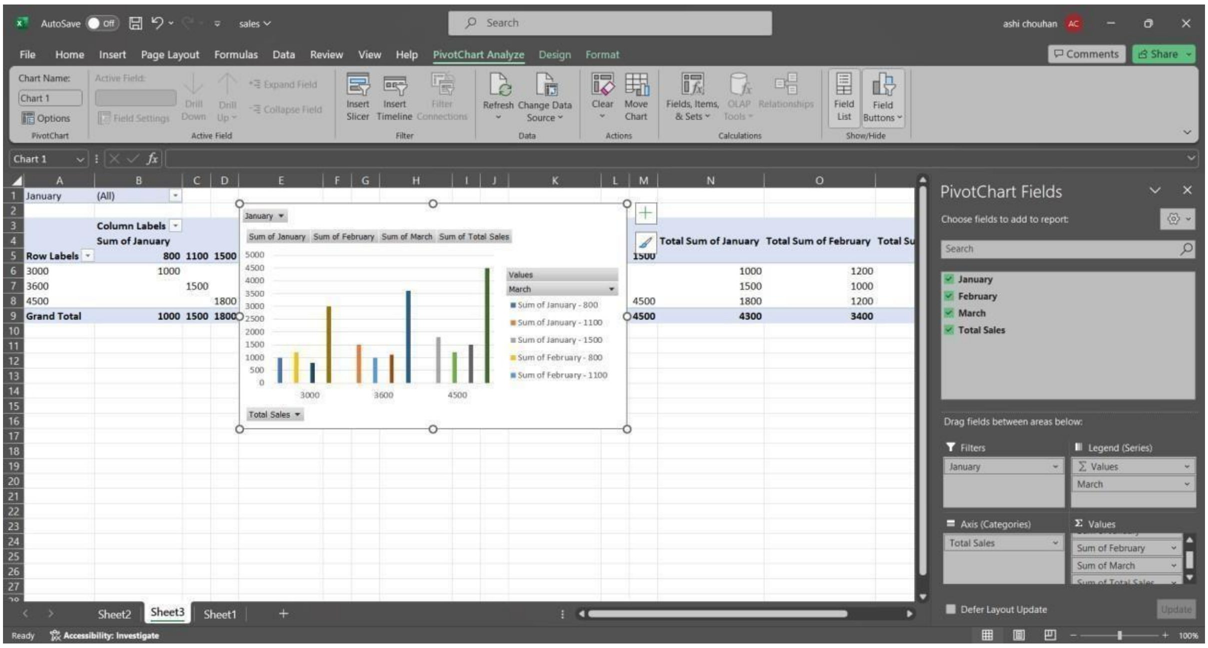
Step 1: select the entire table and go to Insert tab PivotChart > Pivotchart

Step 2: Select “New worksheet” in the create pivot chart window.





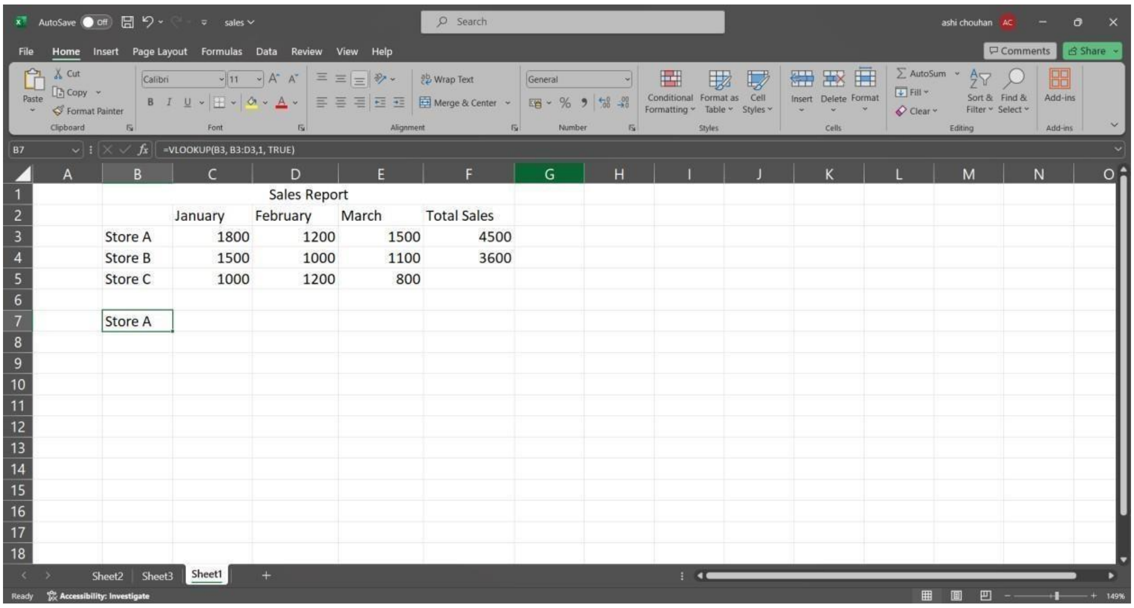
Step 3: Select and drag attributes in the below boxes.



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.

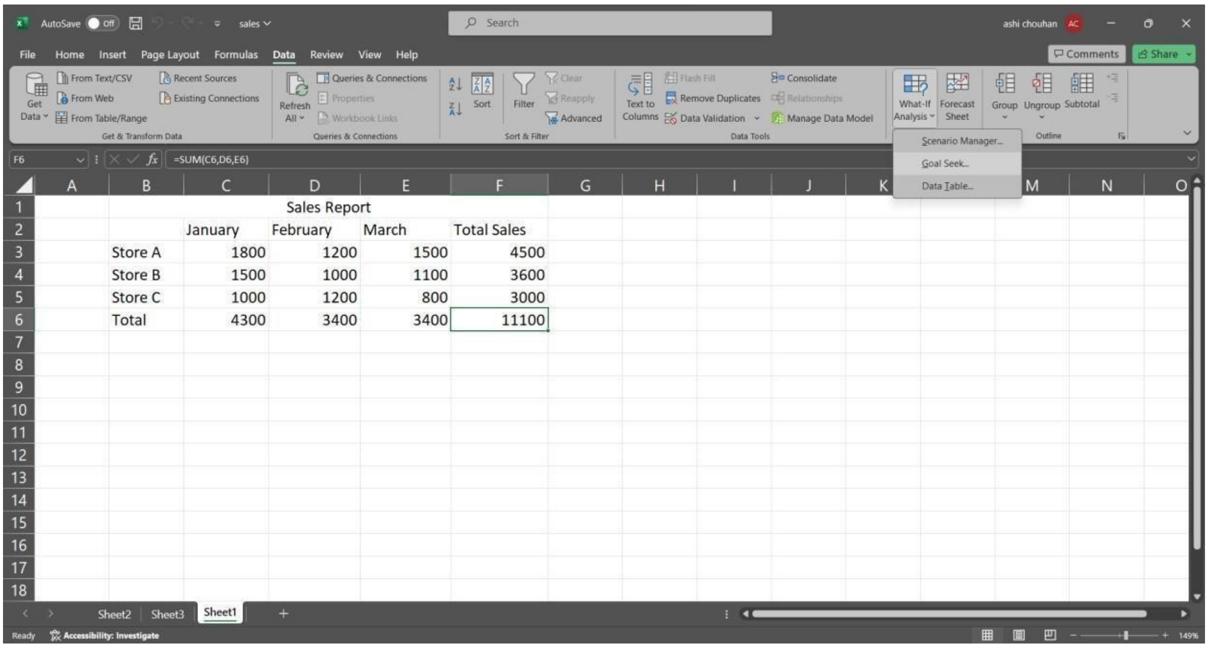
=VLOOKUP(B3, B3:D3,1, TRUE)



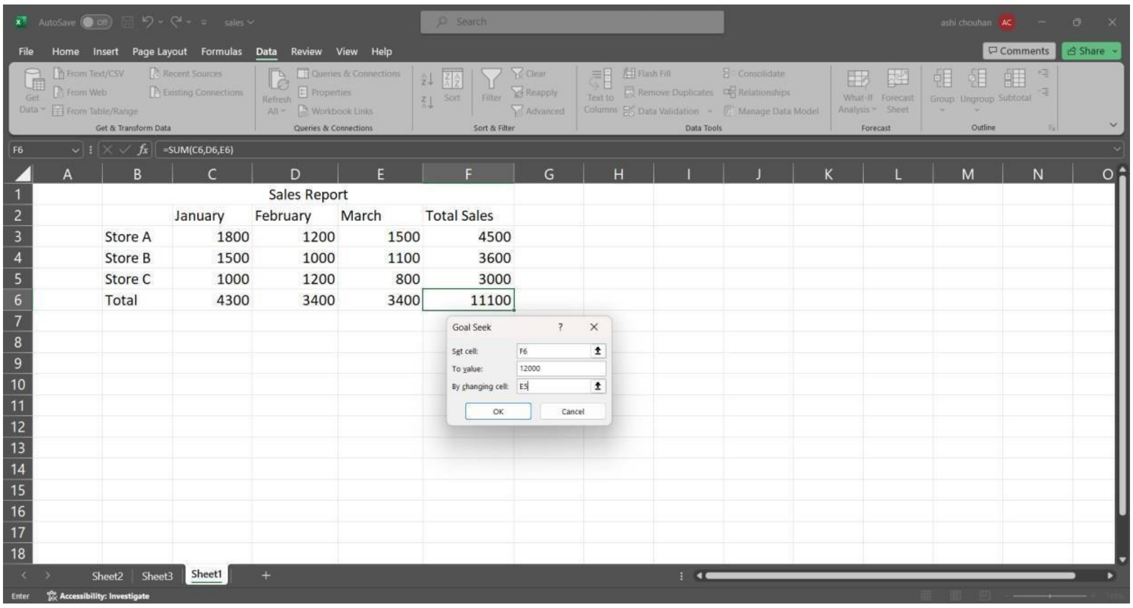
D. Perform what-if analysis using Goal Seek to determine input values for desiredoutput.

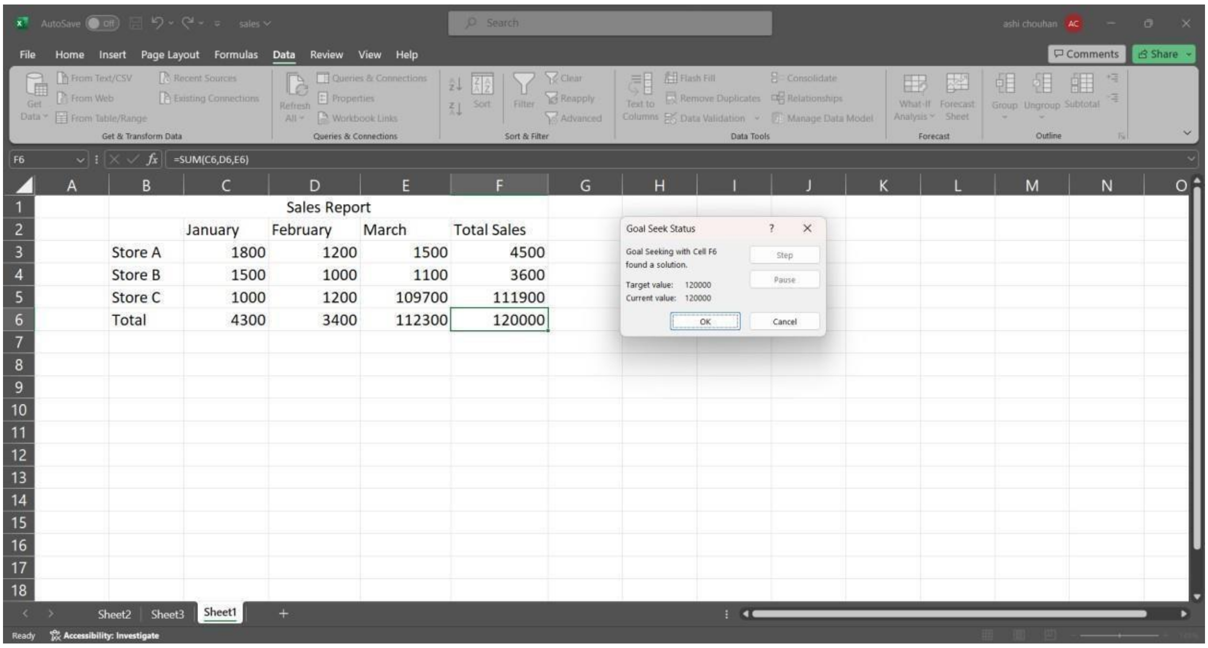
Steps

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

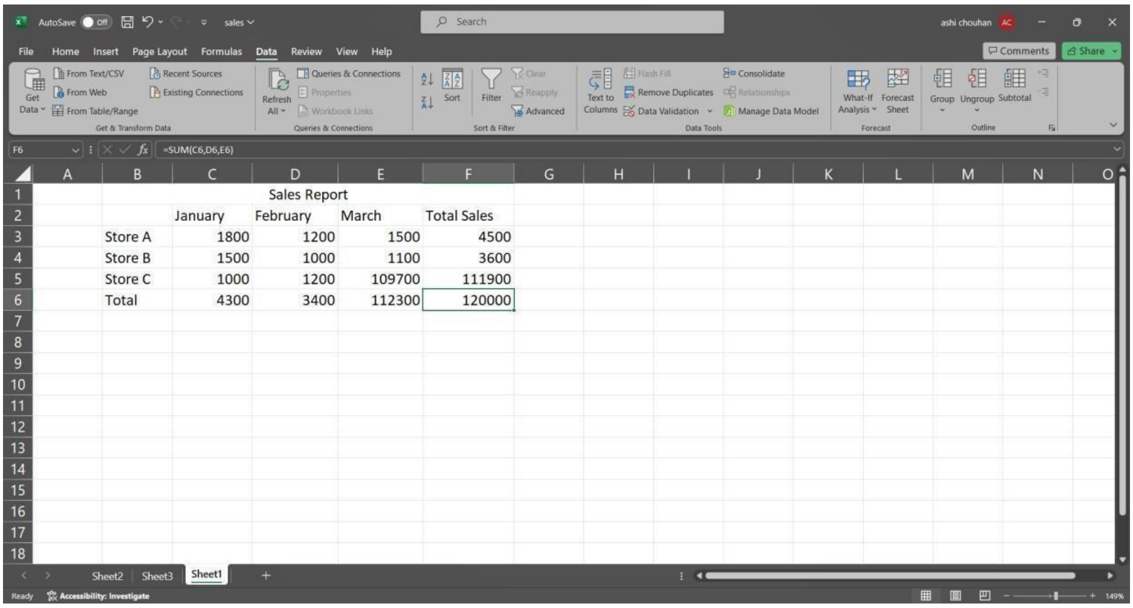


Step 2: Fill the information in the window accordingly and click ok.





	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



	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 2

Data Frames and Basic Data Pre-processing

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

(1)

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

```
================ 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]
>>>
```

(2)

```
# Reading data from a JSON file
import pandas as pd
data = pd.read_json('dataset.json')
print(data)
```

```
>>>
================ 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)

```
================ 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)
```

```
================ 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:

```
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', ascending=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)
```

```
================ 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]
>>>
```

PRACTICAL 3

Feature Scaling and Dummification

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

Code:

```
# Standardization and normalization
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.preprocessing
import MinMaxScaler, StandardScaler
df = pd.read_csv('wine.csv', header=None, usecols=[0, 1, 2],
skiprows=1) df.columns = ['classlabel', 'Alcohol', 'Malic Acid']
print("Original DataFrame:")
print(df) scaling=MinMaxScaler()
scaled_value=scaling.fit_transform(df[['Alcohol','Malic
Acid']])
df[['Alcohol','Malic Acid']]=scaled_value
print("\n Dataframe after MinMax Scaling")
print(df)
scaling=StandardScaler()
scaled_standardvalue=scaling.fit_transform(df[['Alcohol','Mali
c Acid']]) df[['Alcohol','Malic Acid']]=scaled_standardvalue
print("\n Dataframe after Standard Scaling")
print(df)
```

```
= 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
```


```
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.

Code:

```
import pandas as pd
iris=pd.read_csv("Iris.csv")
print(iris)
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
iris['code']=le.fit_transform(iris.Species)
print(iris)
```

```
================ 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]
>>>
```

PRACTICAL 4

Hypothesis Testing

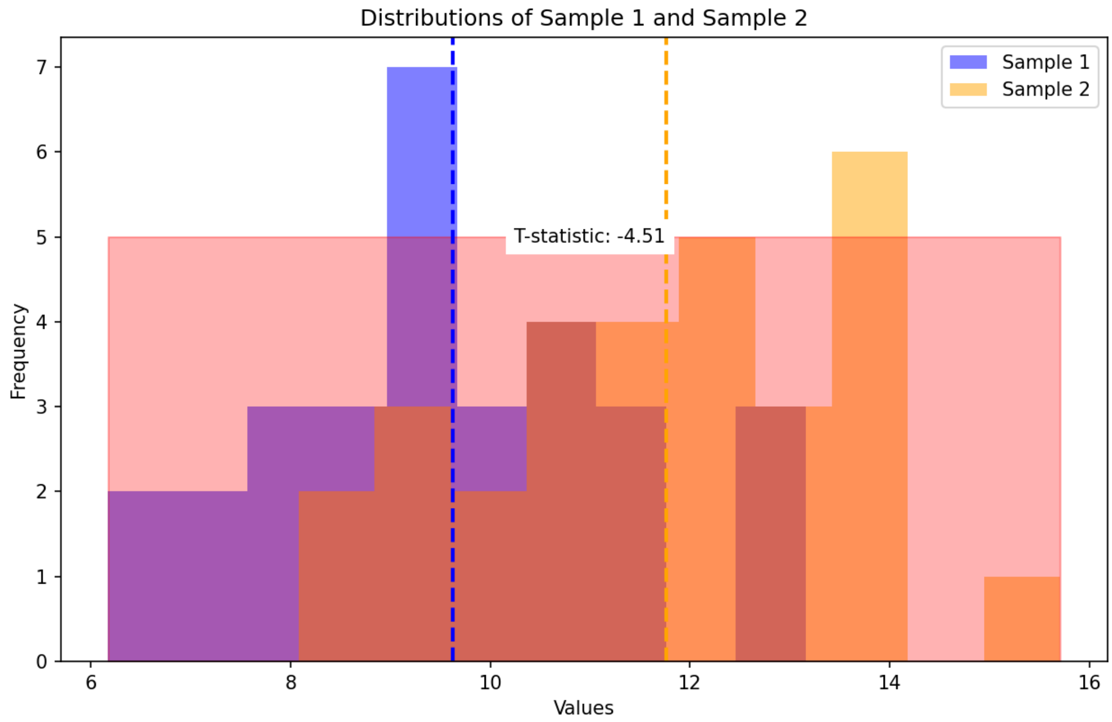
Conduct a hypothesis test using appropriate statistical tests (e.g., t-test, chi-square test)

```
# t-test
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
```




```
#chi-test
import pandas as pd
import numpy as np
import matplotlib as plt
import seaborn as sb
import warnings
from scipy import stats
warnings.filterwarnings('ignore')
df=sb.load_dataset('mpg')
print(df)
print(df['horsepower'].describe())
print(df['model_year'].describe())
```

```
bins=[0,75,150,240]
df['horsepower_new']=pd.cut(df['horsepower'],bins=bins,labels=['l','
m','h'])
c=df['horsepower_new']
print(c)
ybins=[69,72,74,84]
label=['t1','t2','t3']
df['modelyear_new']=pd.cut(df['model_year'],bins=ybins,labels=lab
el)
newyear=df['modelyear_new']
print(newyear)
df_chi=pd.crosstab(df['horsepower_new'],df['modelyear_new'])
print(df_chi)
print(stats.chi2_contingency(df_chi))
```

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
```

```
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]]))
```

Conclusion: There is sufficient evidence to reject the null hypothesis, indicating that there is a significant association between 'horsepower_new' and 'modelyear_new' categories.

PRACTICAL 5

ANOVA (Analysis of Variance)

Perform one-way ANOVA to compare means across multiple groups.

Conduct post-hoc tests to identify significant differences between group means.

```
import pandas as pd import scipy.stats as stats

from statsmodels.stats.multicomp import pairwise_tukeyhsd

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

all_data = group1 + group2 + group3 + group4
group_labels = ['Group1'] * len(group1) + ['Group2'] * len(group2)
+ ['Group3'] * len(group3) + ['Group4'] * len(group4)

f_statistics, p_value = stats.f_oneway(group1, group2, group3,
group4)
print("one-way ANOVA:")
print("F-statistics:", f_statistics)
print("p-value", p_value)

tukey_results = pairwise_tukeyhsd(all_data, group_labels)
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 6

Regression and its Types.

```
import numpy as np
import pandas as pd
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

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

housing_df['PRICE'] = housing.target

X = housing_df[['AveRooms']] y = housing_df['PRICE']

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

model = LinearRegression()

model.fit(X_train, y_train)

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_)

##############################################
```

```
#Multiple Liner Regression

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

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

model = LinearRegression()

model.fit(X_train,y_train)

y_pred = model.predict(X_test)

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 7

Logistic Regression and Decision Tree

```
import numpy as np
import pandas as pd

from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score,
classification_report

# Load the Iris dataset and create a binary 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("Logistic 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
```

```
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
```

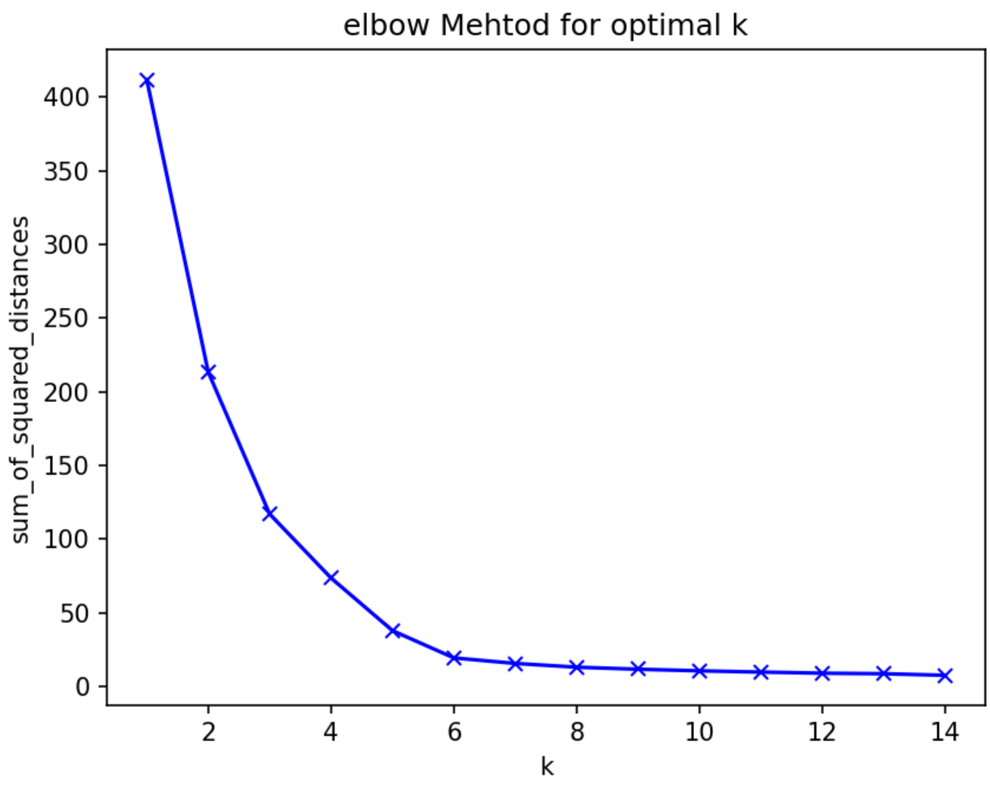
PRACTICAL 8

K-Means clustering

```
import pandas as pd


from sklearn.preprocessing
import MinMaxScaler from sklearn.cluster
import KMeans
import matplotlib.pyplot as plt


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


categorical_features = ['Channel', 'Region']
continuous_features = ['Fresh', 'Milk', 'Grocery', 'Frozen',
'Detergents_Paper', 'Delicassen']
data[continuous_features].describe()


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()


mms = MinMaxScaler()
mms.fit(data)
data_transformed = mms.transform(data)
```

```
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_)
plt.plot(K, sum_of_squared_distances, 'bx-')
plt.xlabel('k')
plt.ylabel('sum_of_squared_distances')
plt.title('elbow Mehtod for optimal k')
plt.show()
```

Output:



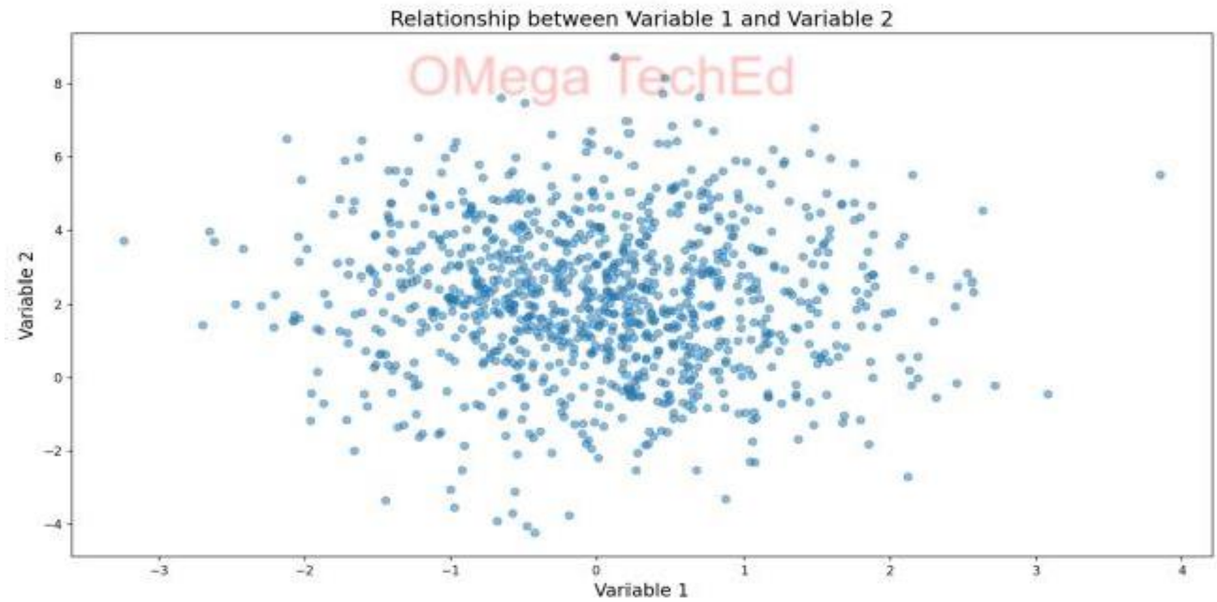
Practical 9

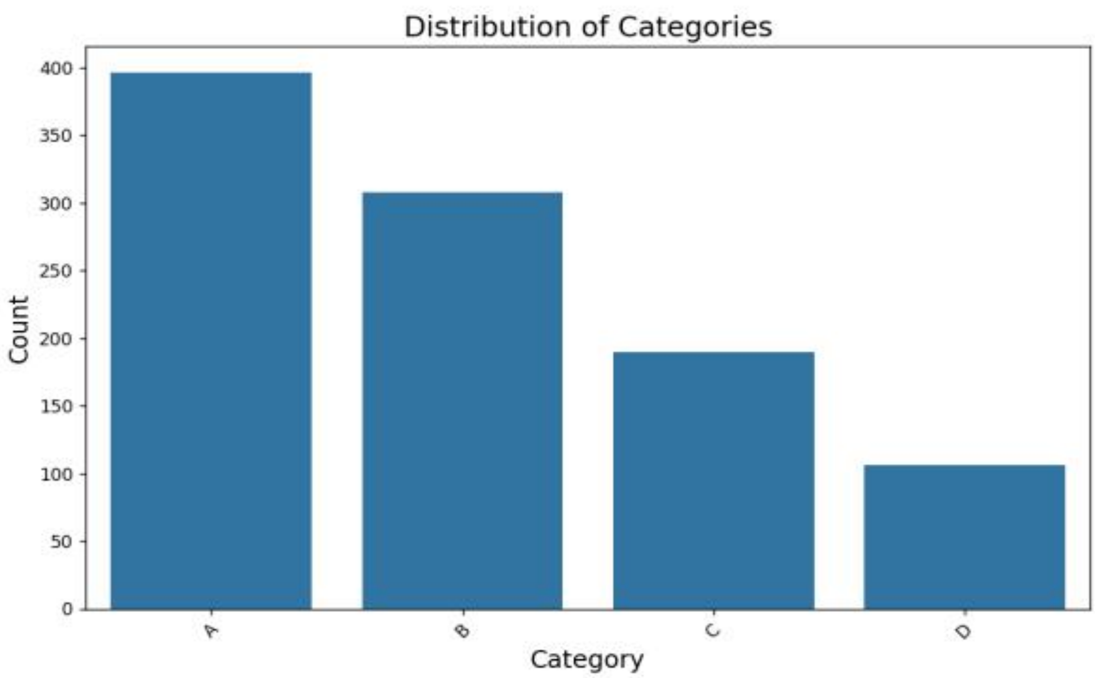
Data Visualization and Storytelling

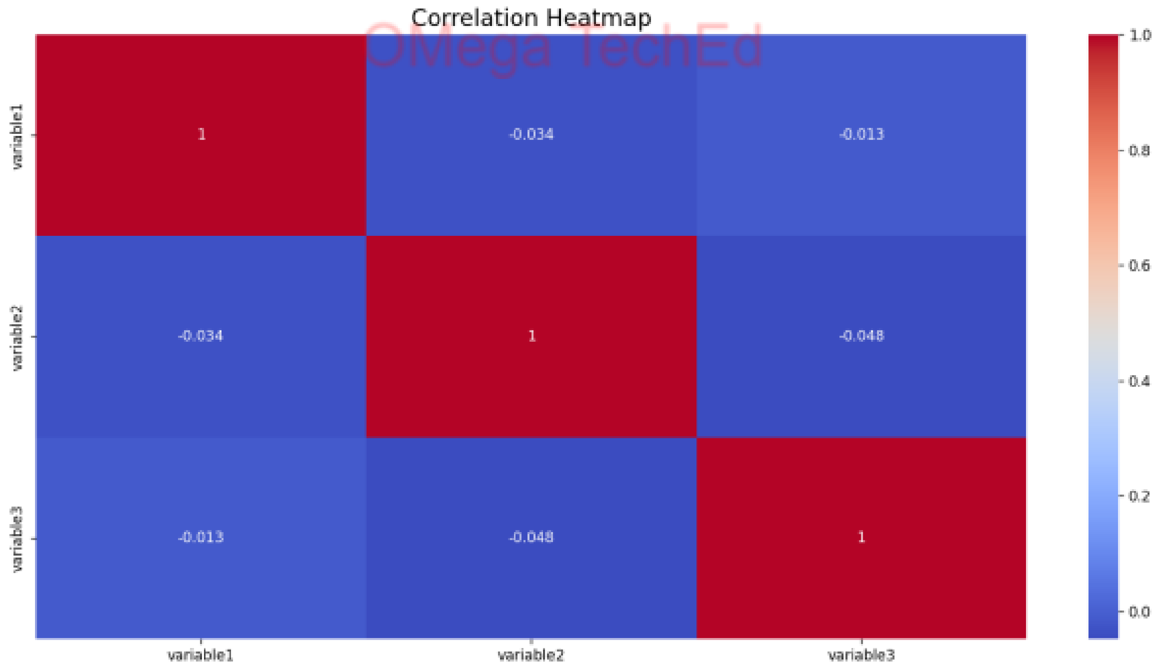
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
# Generate random data
np.random.seed(42) # Set a seed for reproducibility
# Create a DataFrame with random data
data = pd.DataFrame({
'variable1': np.random.normal(0, 1, 1000),
'variable2': np.random.normal(2, 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:-






Correlation Heatmap
variable1
variable2
variable3
1
-0.034
-0.013
-0.034
1
-0.048
-0.013
-0.048
1
variable1
variable2
variable3
1.0
0.8
0.6
0.4
0.2
0.0