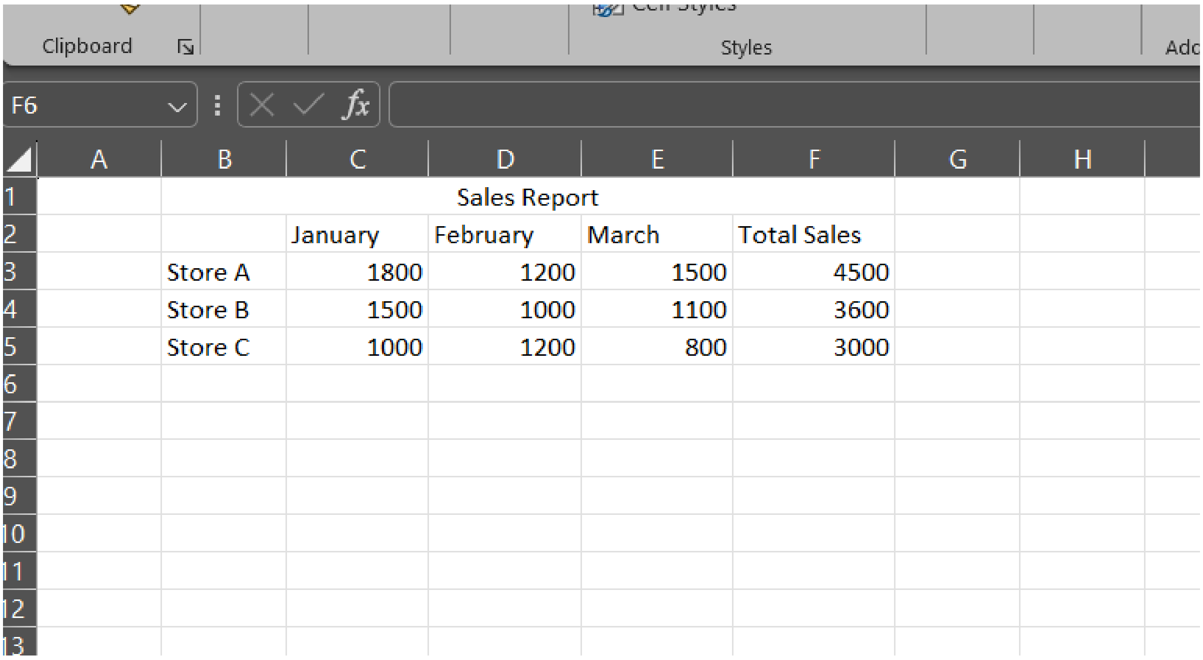
PRACTICAL 1

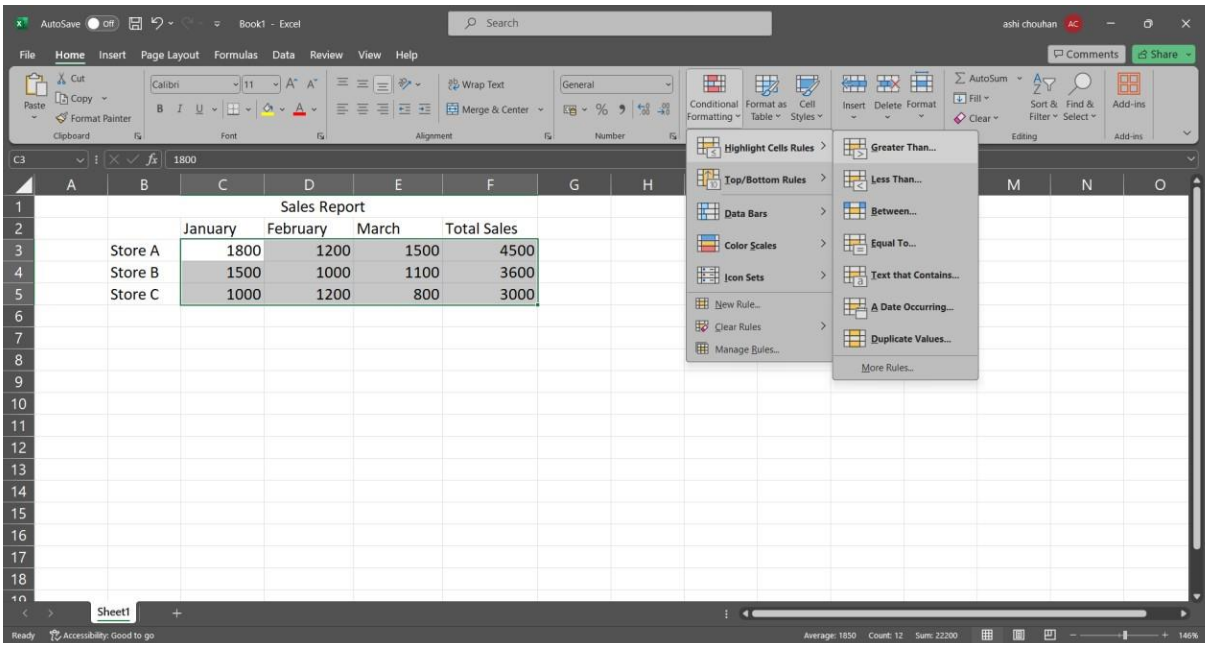
Introduction to Excel

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

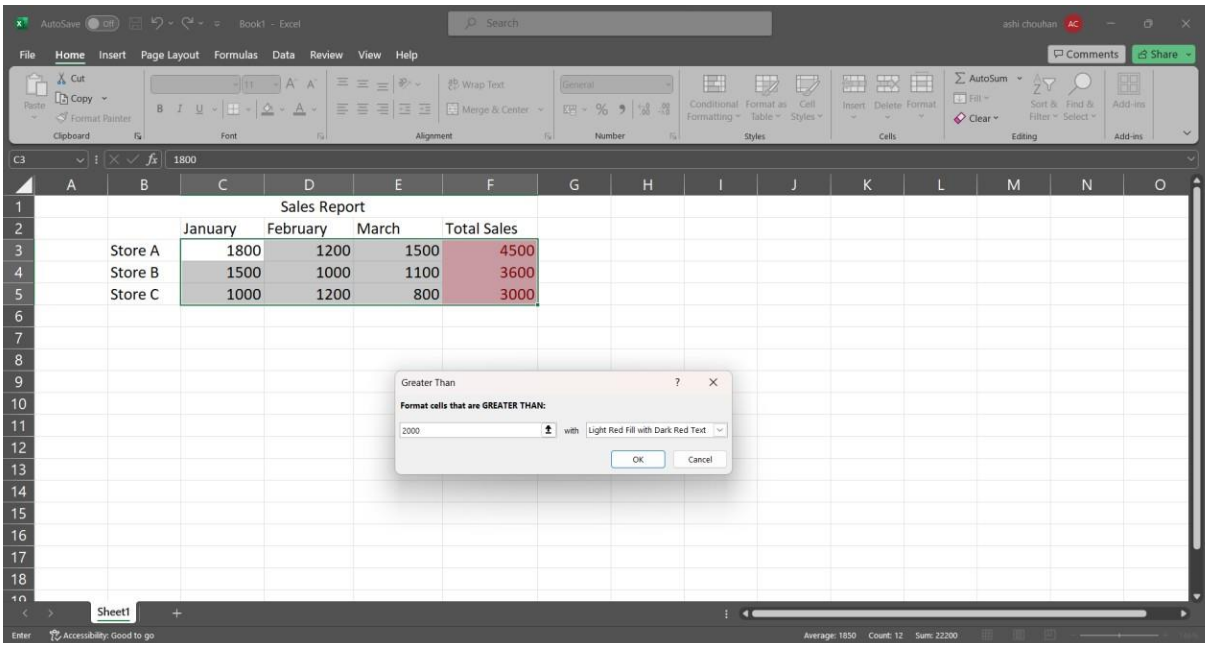


Steps

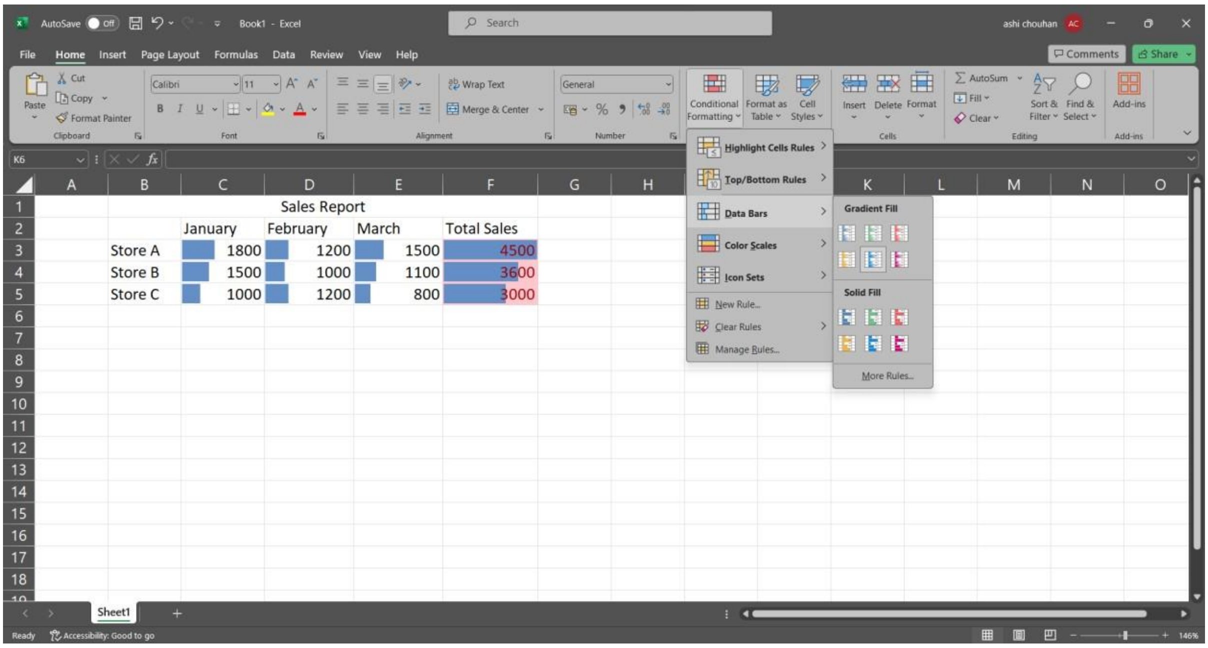
Step 1: Go to conditional formatting > Greater Than



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



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

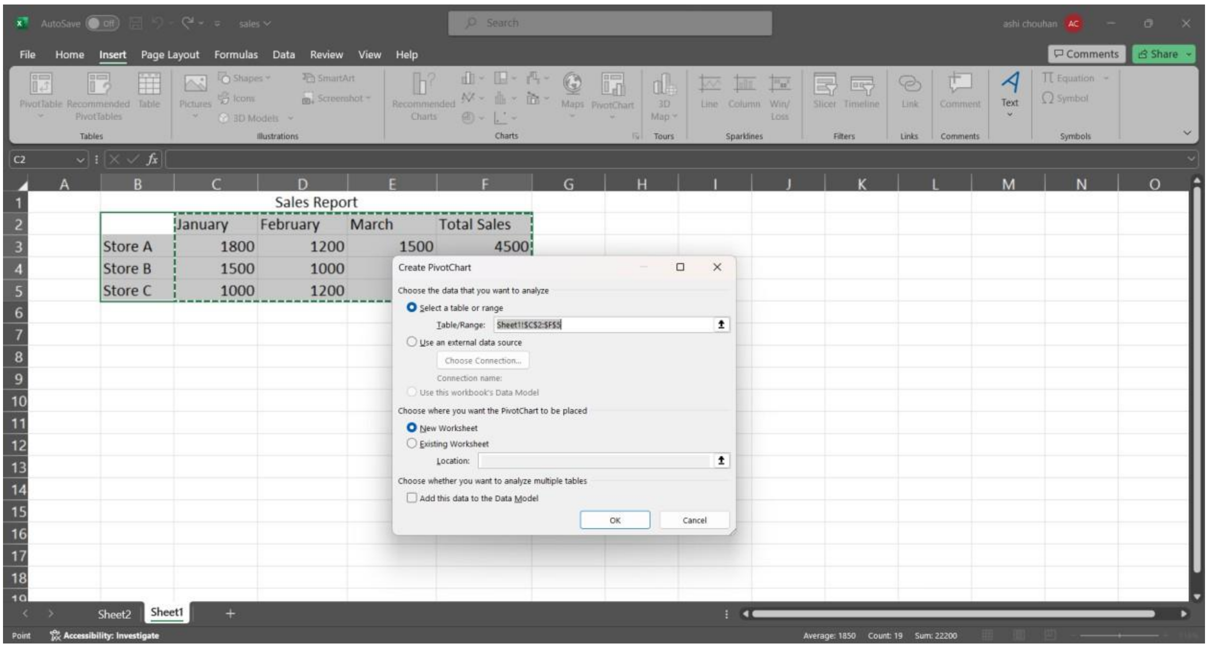


B. Create a pivot table to analyse and summarize data.

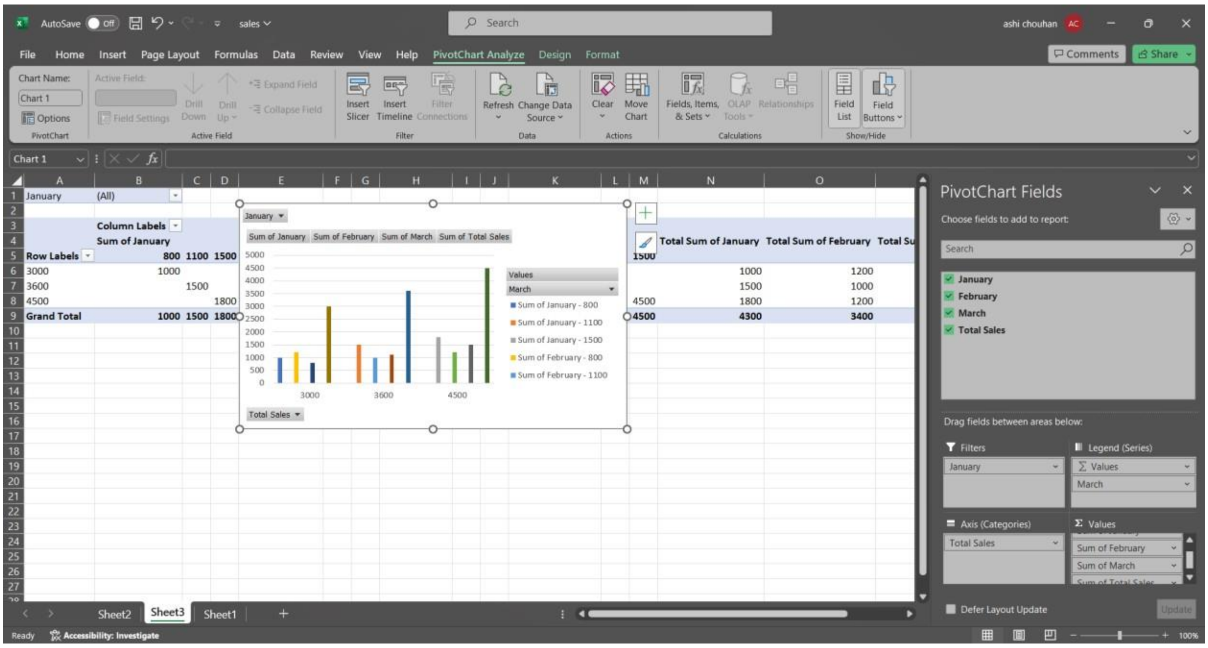
Steps

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

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

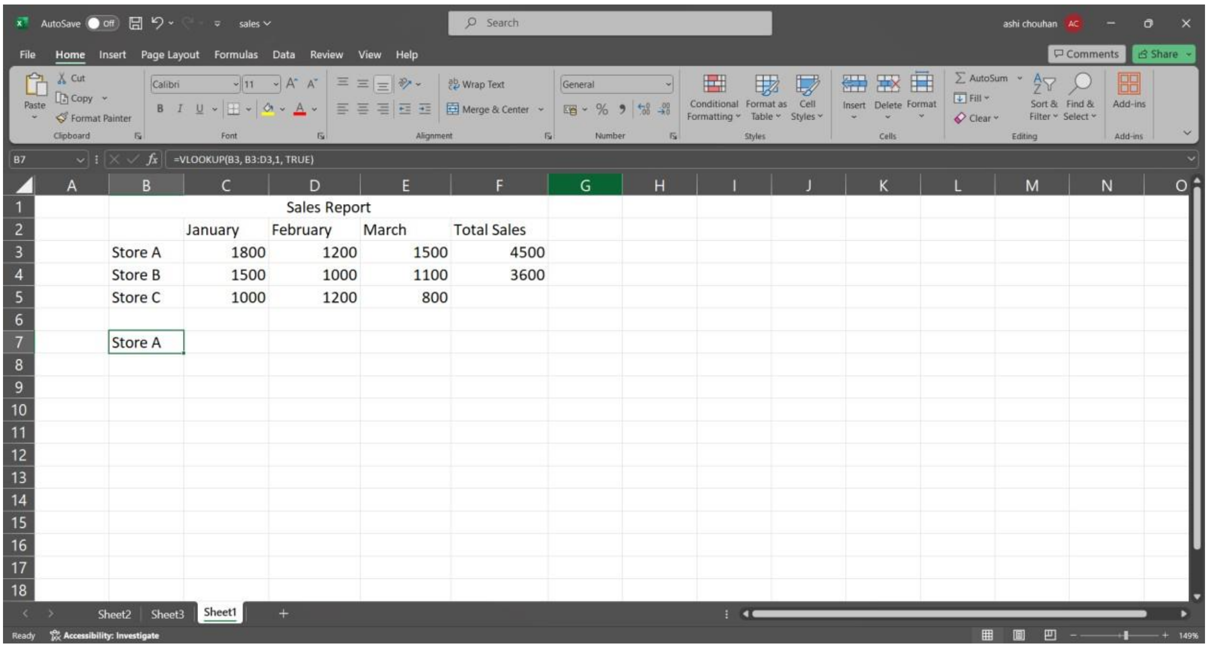


Step 3: Select and drag attributes in the below boxes.

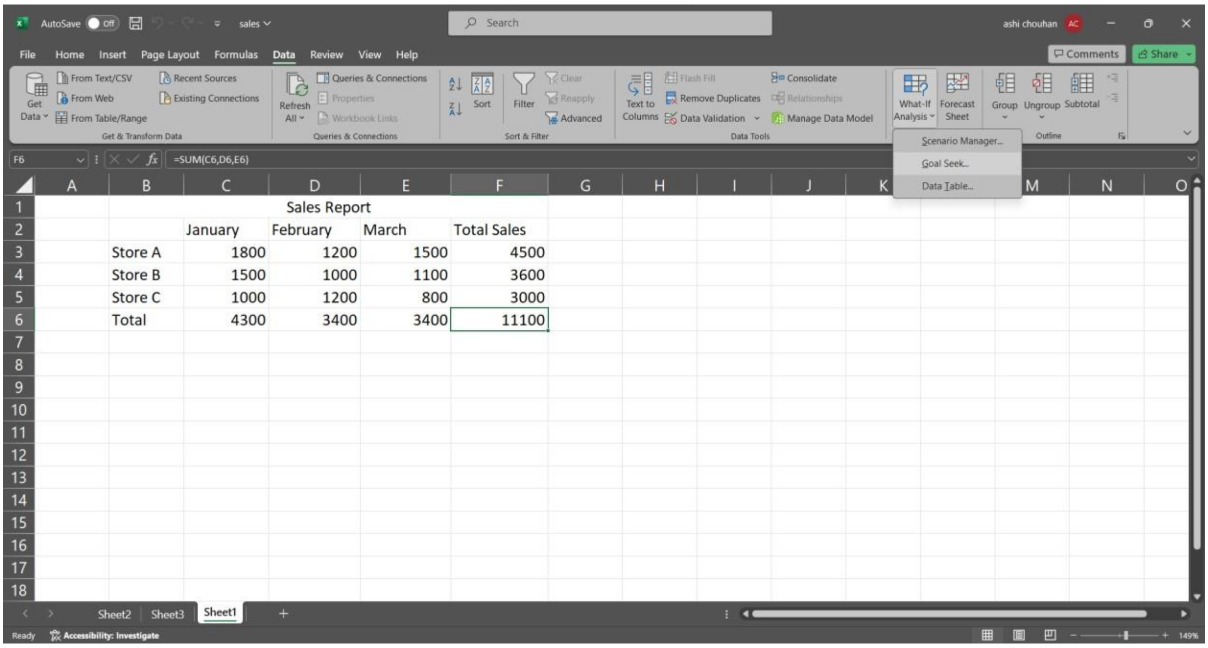


C. Use VLOOKUP function to retrieve information from a different worksheet or table.
   Steps:
   Step 1: click on an empty cell and type the following command.

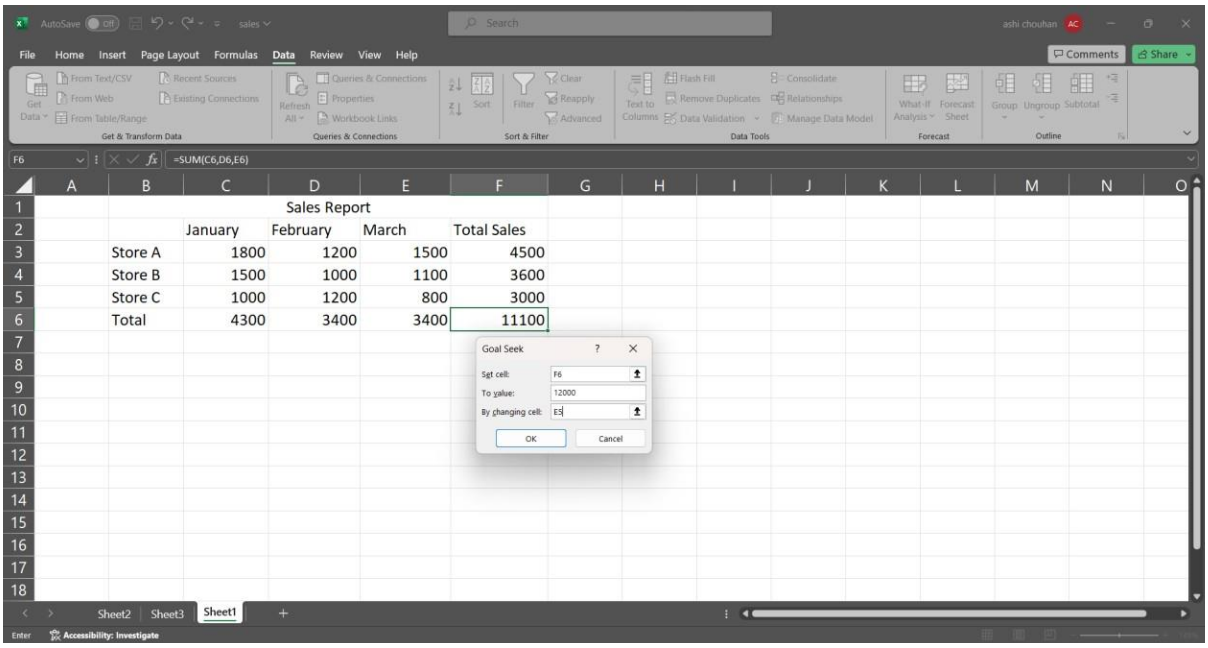
=VLOOKUP(B3, B3:D3,1, TRUE)

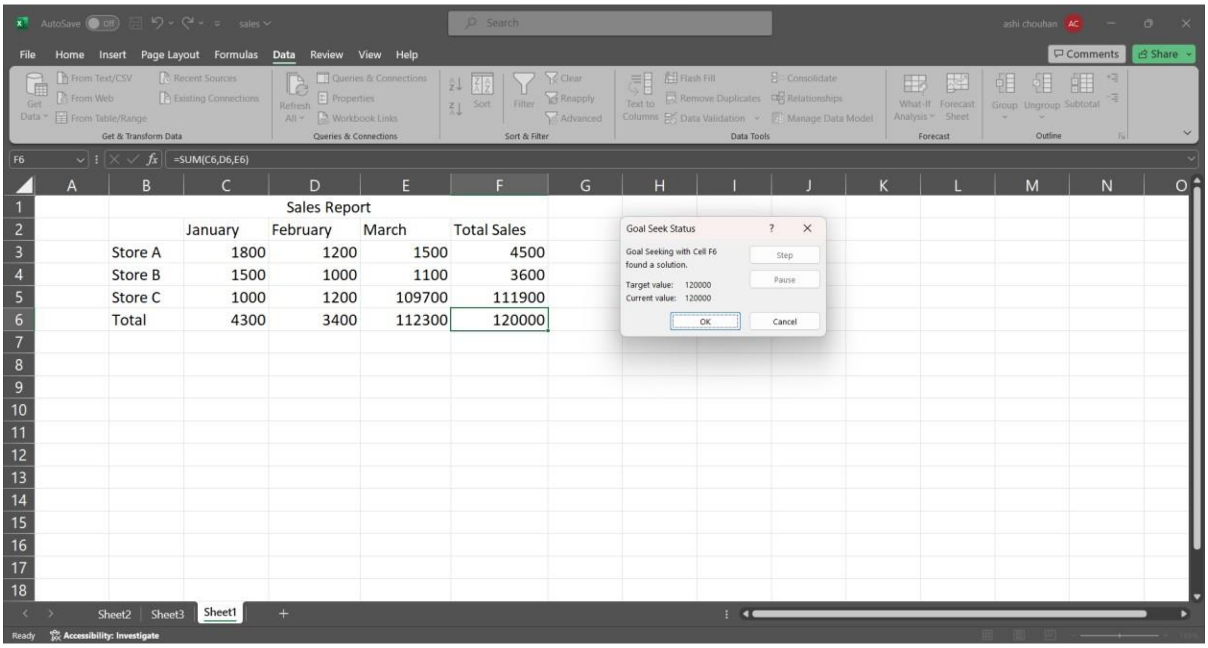


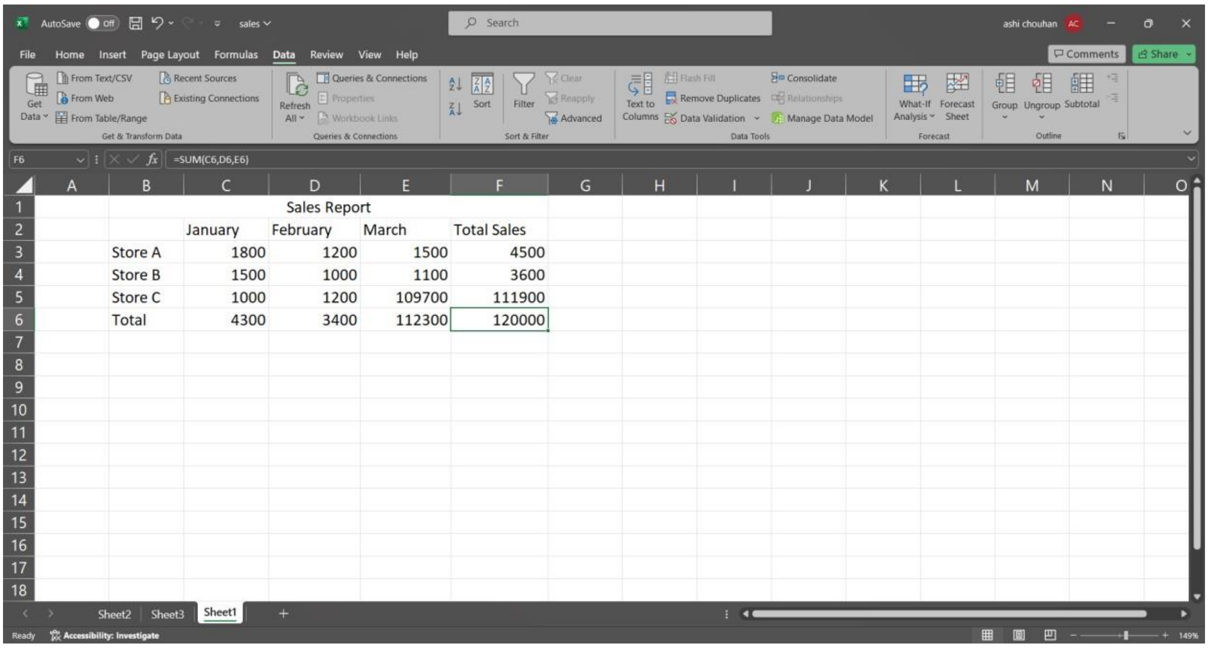
D. Perform what-if analysis using Goal Seek to determine input values for desired output.
Steps-
Step 1: In the Data tab go to the what if analysis>Goal seek.



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


AutoSave
Off
sales
Search
ashi chouhan
Comments
Share
File
Home
Insert
Page Layout
Formulas
Data
Review
View
Help
F6
=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
Sheet2
Sheet3
Sheet1
Enter
Accessibility: Investigate


AutoSave
Off
sales
Search
ashi chouhan
Comments
Share
File
Home
Insert
Page Layout
Formulas
Data
Review
View
Help
F6
=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
Goal Seek Status
Goal Seeking with Cell F6
found a solution.
Target value: 120000
Current value: 120000
Step
Pause
OK
Cancel
Sheet2
Sheet3
Sheet1
Ready
Accessibility: Investigate



		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','Malic 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)

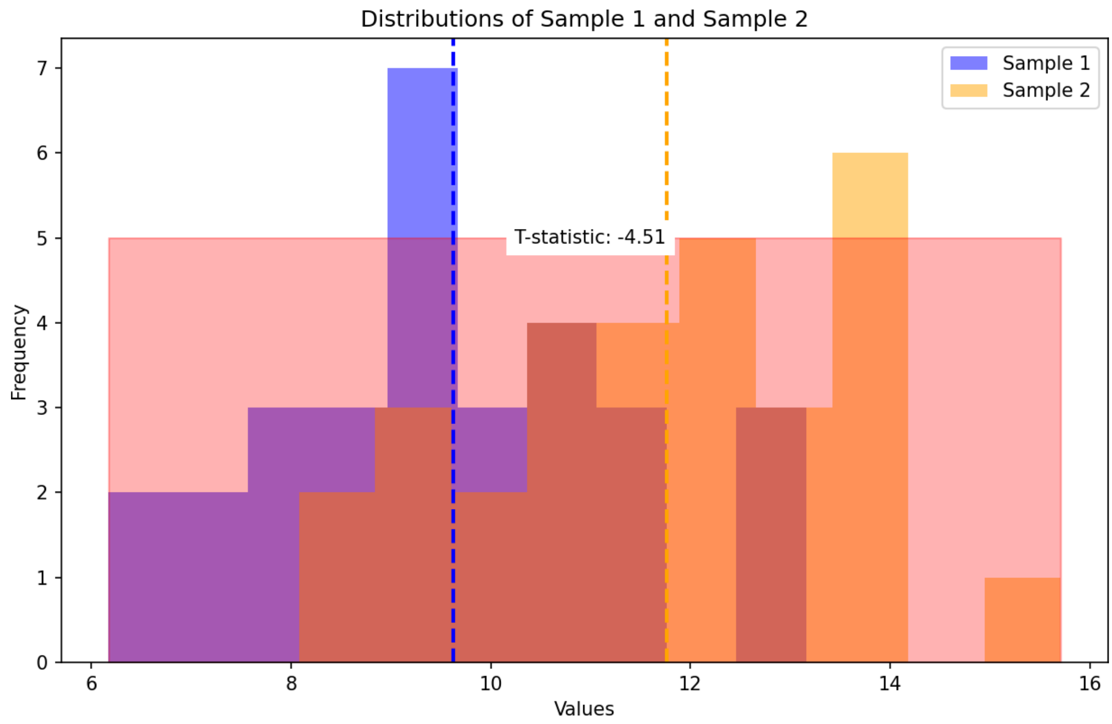
```
# t-test
import numpy as np
from scipy import stats
import matplotlib.pyplot as plt

# 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:

```
================================ RESTART: E:/all not
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=label)
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:-

```
RESTART: E:/all notes/DS/
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
```

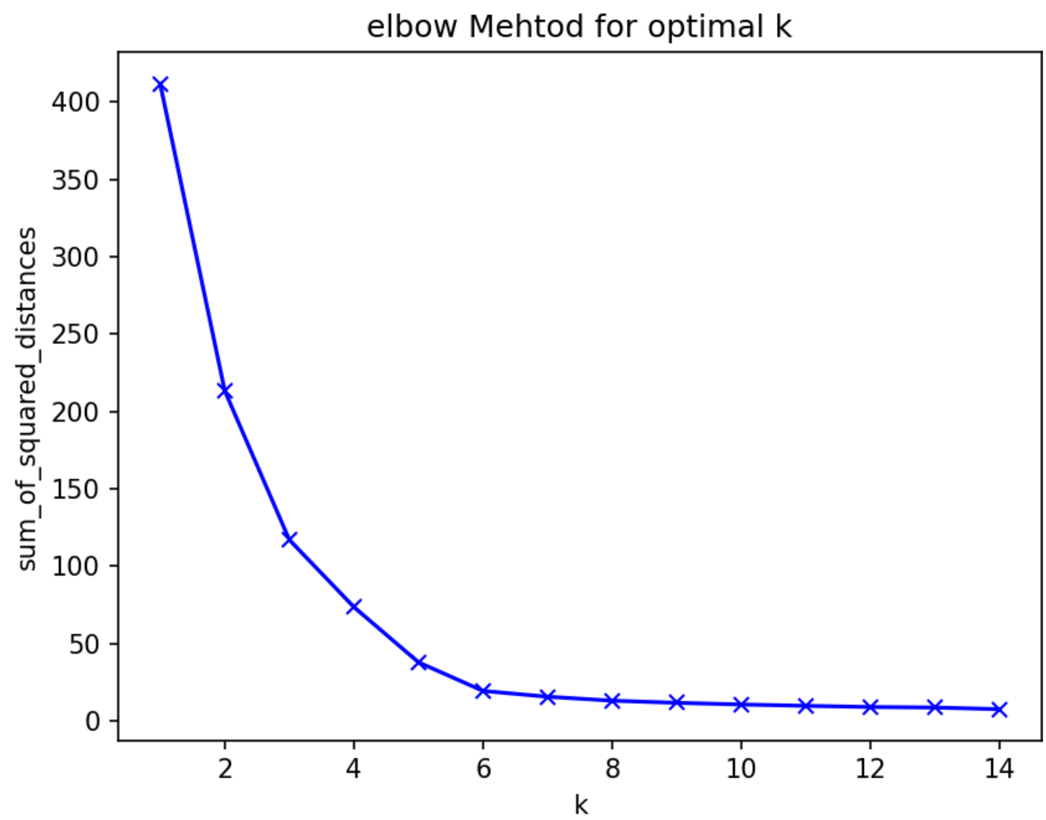
Practical 8

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:



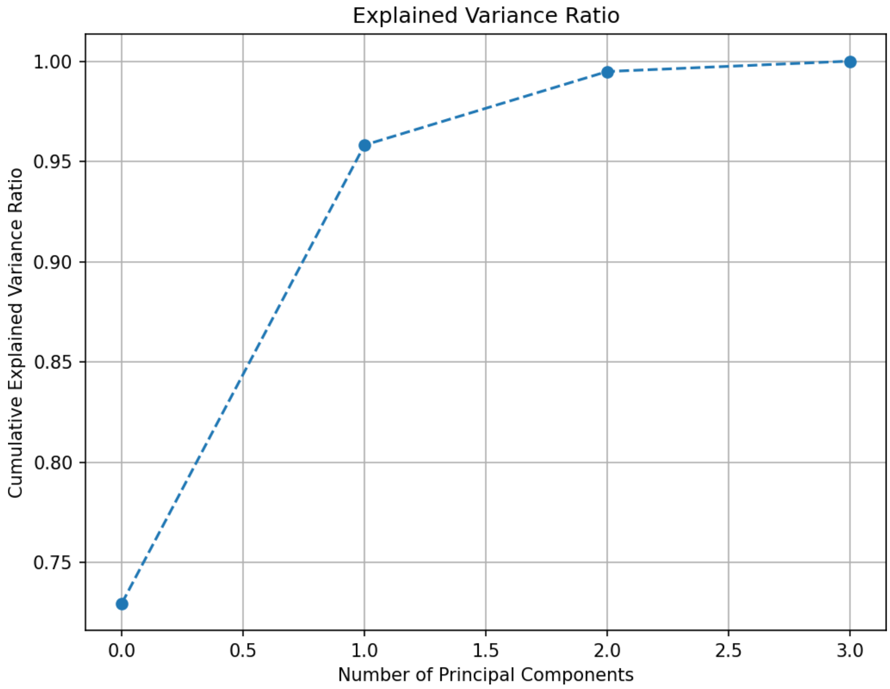
Practical 9

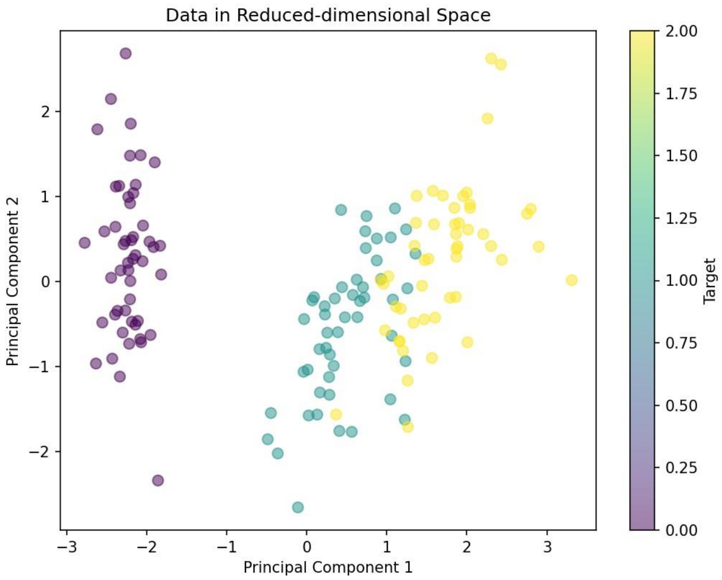
Principal Component Analysis (PCA)

```
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

iris = load_iris()
iris_df = pd.DataFrame(data=np.c_[iris['data'], iris['target']], columns=iris['feature_names'] + ['target'])
X = iris_df.drop('target', axis=1)
y = iris_df['target']

scaler =  StandardScaler()
X_scaled = scaler.fit_transform(X)

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

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()

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}")

pca = PCA(n_components=n_components)
X_reduced = pca.fit_transform(X_scaled)

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:






```
============================== RESTART: E:/all notes/DS/pr
Number of principal components to explain 95% variance: 2
```

Practical 10

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. We can observe a positive correlation, indicating that as Variable 1 increases, Variable 2 tends to increase as well. However, there is a considerable amount of scatter, suggesting that other factors may influence this relationship.")
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 bar chart (Figure 2). The chart reveals that Category A has the highest frequency, followed by Category B, Category C, and Category D. This information could be useful for further analysis or decision-making processes.")
```

print("\nBar Chart")

print("Figure 2: Distribution of Categories")

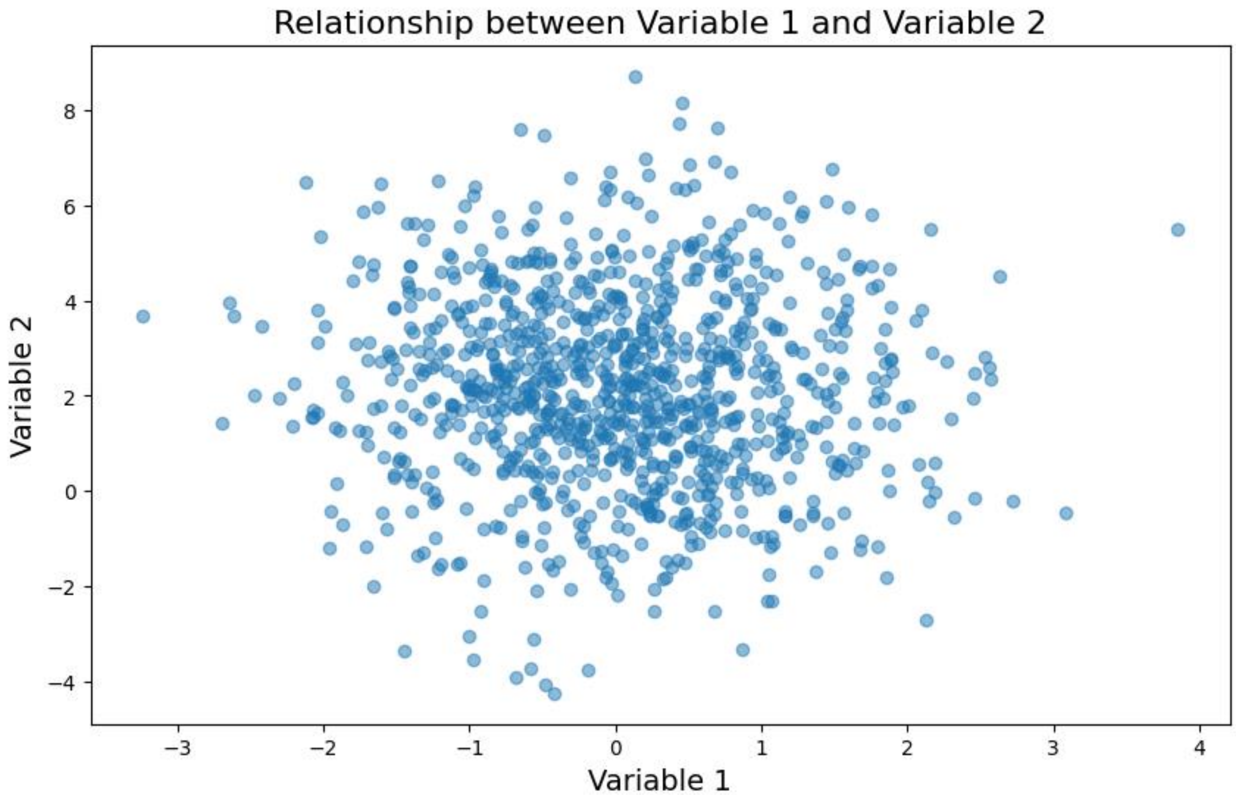
print("\nAdditionally, we explored the correlation between numerical variables using a heatmap (Figure 3). The heatmap shows that Variable 1 and Variable 2 have a strong positive correlation, confirming the observation from the scatter plot. However, we can also see that Variable 3 has a moderate negative correlation with both Variable 1 and Variable 2, suggesting that it may have an opposing effect on the relationship between the first two variables.")

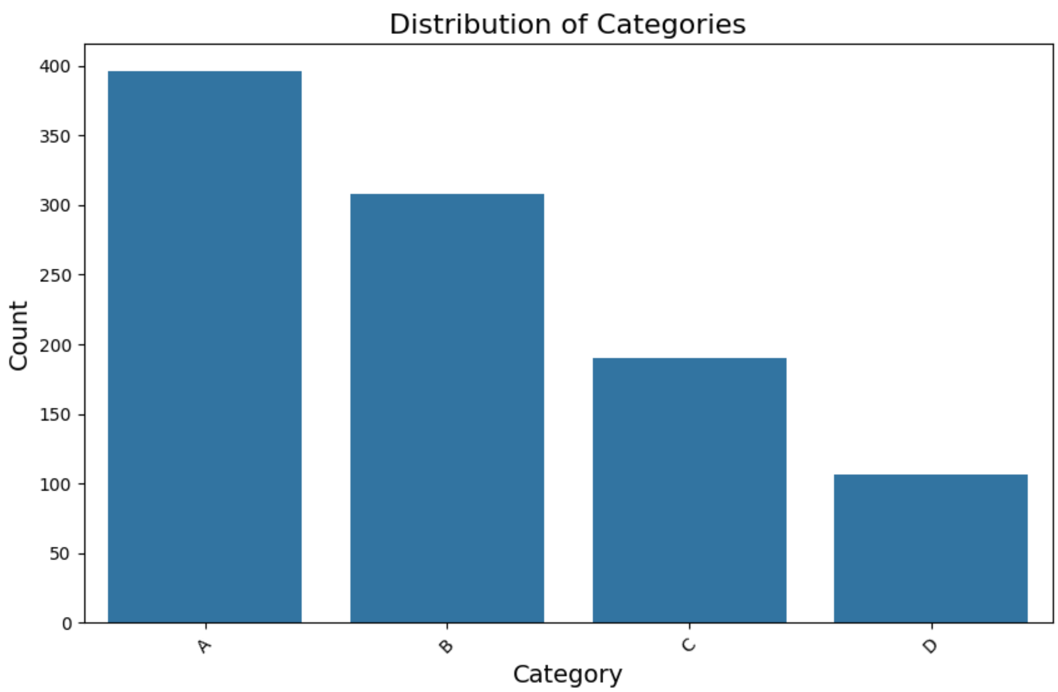
print("\nHeatmap")

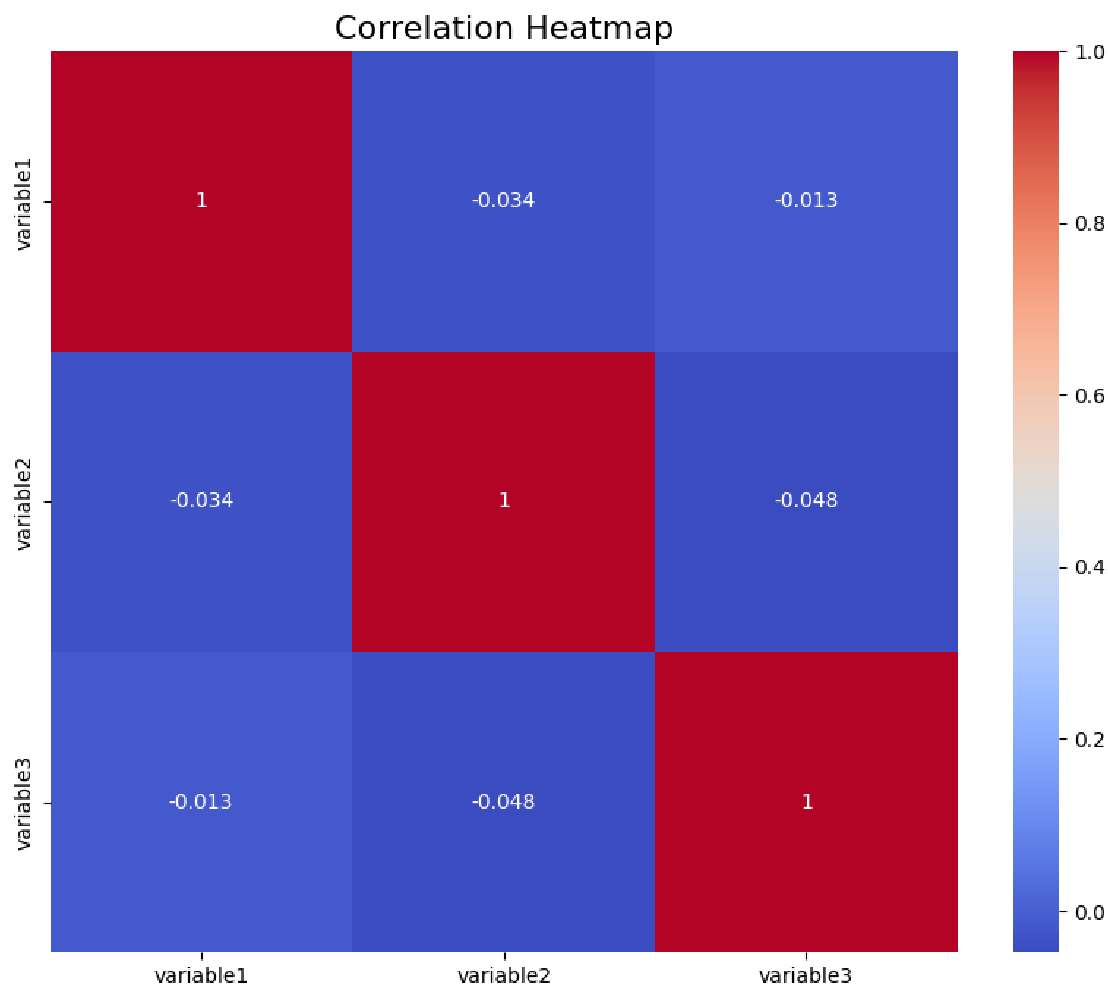
print("Figure 3: Correlation Heatmap")

print("\nIn summary, the visualizations and analysis provide insights into the relationships between variables, the distribution of categories, and the correlations between numerical variables. These findings can be used to inform further analysis, decision-making, or to generate new hypotheses for investigation.")

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



Title: Exploring the Relationship between Variable 1 and Variable 2

The scatter plot (Figure 1) shows the relationship between Variable 1 and Variable 2. We can observe a positive correlation, indicating that as Variable 1 increases, Variable 2 tends to increase as well. However, there is a considerable amount of scatter, suggesting that other factors may influence this relationship.

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). The chart reveals that Category A has the highest frequency, followed by Category B, Category C, and Category D. This information could be useful for further analysis or decision-making processes.

Bar Chart
Figure 2: Distribution of Categories

Additionally, we explored the correlation between numerical variables using a heatmap (Figure 3). The heatmap shows that Variable 1 and Variable 2 have a strong positive correlation, confirming the observation from the scatter plot. However, we can also see that Variable 3 has a moderate negative correlation with both Variable 1 and Variable 2, suggesting that it may have an opposing effect on the relationship between the first two variables.

Heatmap
Figure 3: Correlation Heatmap

In summary, the visualizations and analysis provide insights into the relationships between variables, the distribution of categories, and the correlations between numerical variables. These findings can be used to inform further analysis, decision-making, or to generate new hypotheses for investigation.