

Lab experiments

Experiment 1:

Setting up the Python environment and libraries-Jupyter Notebook:
code:

```
1.print("Hello, Jupyter Notebook!")
```

O/P:Hello, Jupyter Notebook!

```
2.import ipywidgets as widgets
from IPython.display import display

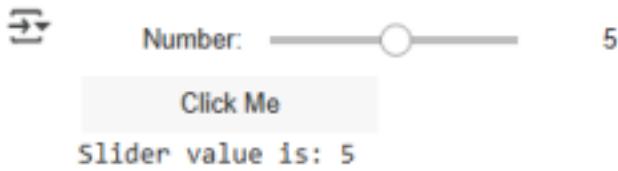
slider = widgets.IntSlider(value=5, min=0, max=10, step=1,
description='Number:')
display(slider)

button = widgets.Button(description="Click Me")
display(button)

def on_click(b):
    print(f"Slider value is: {slider.value}")

button.on_click(on_click)
```

O/P:



Experiment - 2:

EDA-Data Import and Export:

Code:

```
import pandas as pd
from sqlalchemy import create_engine
import sqlite3
import requests
```

```

import matplotlib.pyplot as plt

# Load CSV
df_csv = pd.read_csv("/content/gender_submission.csv")
print("CSV Data:\n", df_csv.head())

# Export to Excel
excel_path = "titanic_full.xlsx"
df_csv.to_excel(excel_path, index=False)
print(f"Entire CSV exported to: {excel_path}")

# Read Excel file and preview
df_excel = pd.read_excel("/content/titanic_full.xlsx")
print("Excel Data Preview:")
display(df_excel.head()) # ✓ Now appears in a nice box

# SQL setup and query
engine = create_engine("sqlite:///memory:")
df_csv.to_sql("titanic", engine, if_exists="replace", index=False)

query = """
SELECT Survived, COUNT(*) AS count
FROM titanic
GROUP BY Survived
"""

df_sql = pd.read_sql_query(query, engine)
print("SQL Query Result:\n", df_sql)
# Web scraping
url = "https://en.wikipedia.org/wiki/Titanic"
try:
    tables = pd.read_html(url)
    print("\nWeb Scraped Table Example:\n", tables[0].head())
except:
    print("\nUnable to scrape table from the web.")

# Plot survival count
df_sql.plot(kind='bar', x='Survived', y='count', legend=False,
color=['red', 'green'])
plt.title("Titanic Survival Count")
plt.xlabel("Survived (0 = No, 1 = Yes)")
plt.ylabel("Number of Passengers")
plt.xticks(rotation=0)
plt.grid(axis='y')

```

```

plt.tight_layout()
plt.show()

# Export SQL result to Excel
df_sql.to_excel("titanic_survival_summary.xlsx", index=False)
print("Survival summary exported to: titanic_survival_summary.xlsx")

```

Output:

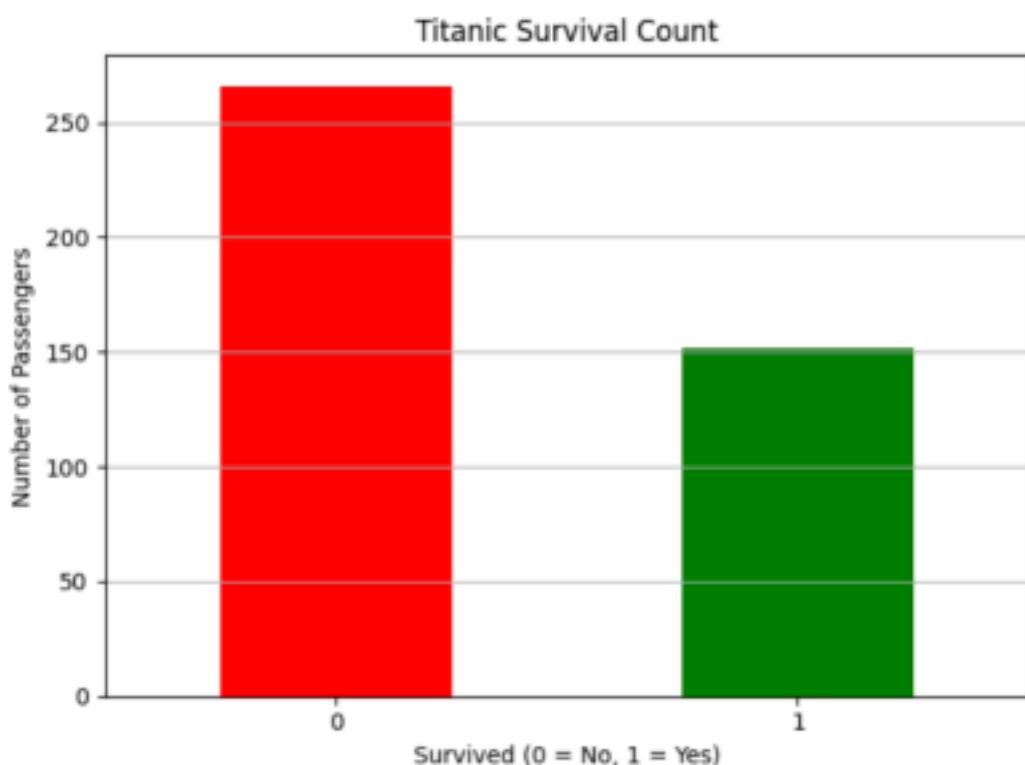
```

SQL Query Result:
   Survived  count
0          0    266
1          1    152

```

Web Scrapped Table Example:

| | 0 | 1 |
|---|---|---|
| 0 | RMS Titanic departing Southampton for the only... | \ |
| 1 | Location of Titanic wreck | |
| 2 | History | |
| 3 | United Kingdom | |
| 4 | Name | |
| | | 1 |
| 0 | RMS Titanic departing Southampton for the only... | |
| 1 | Location of Titanic wreck | |
| 2 | History | |
| 3 | United Kingdom | |
| 4 | RMS Titanic | |



Survival summary exported to: titanic_survival_summary.xlsx

EXPERIMENT - 3

EDA-Data Cleaning:

CODE:

```
# ❓❓ Step 1: Import required libraries
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler, MinMaxScaler

# ❓❓ Step 2: Create a sample DataFrame
data = {
    'Name': ['Alice', 'Bob', 'Charlie', np.nan, 'Eve', 'Alice'],
    'Age': [25, np.nan, 30, 22, 29, 25],
    'Salary': [50000, 60000, 55000, 52000, np.nan, 50000],
    'Department': ['HR', 'IT', 'IT', 'HR', 'Finance', 'HR'] }
df = pd.DataFrame(data)
print("❓❓ Original DataFrame:\n")
print(df)

# ❓❓ Step 3: Detect missing values
print("\n❓❓ Missing values before cleaning:")
print(df.isnull().sum())

# ❓❓ Step 4: Fill missing values using forward fill (new
syntax) df.fillna(inplace=True)

# ❓❓ Step 5: Drop any remaining rows with missing
values df.dropna(inplace=True)

# ❓❓ Step 6: Show missing values after cleaning
print("\n✓ Missing values after filling and dropping:")
print(df.isnull().sum())

# ❓❓ Step 7: Remove duplicate rows
print("\n❓❓ Duplicate rows before removal:", df.duplicated().sum())
df.drop_duplicates(inplace=True)
print("✓ Duplicate rows after removal:", df.duplicated().sum())

# ❓❓ Step 8: Remove unnecessary columns
df.drop(columns=['Name'], inplace=True)

# ❓❓ Step 9: Show data types before conversion
print("\n❓❓ Data types before conversion:")
```

```

print(df.dtypes)

# ❓ Step 10: Convert data types for consistency
df['Age'] = df['Age'].astype(int)
df['Salary'] = df['Salary'].astype(int)

# ❓ Step 11: Show data types after conversion
print("\n✓ Data types after conversion:")
print(df.dtypes)

# ❓ Step 12: Normalize numerical columns
numeric_cols = df.select_dtypes(include=[np.number]).columns.tolist()
print("\n❓ Numeric columns to normalize:", numeric_cols)

# Standardization (Z-score)
scaler_std = StandardScaler()
df_standardized = df.copy()
df_standardized[numeric_cols] =
scaler_std.fit_transform(df_standardized[numeric_cols])

# Min-Max Scaling (0-1 range)
scaler_mm = MinMaxScaler()
df_minmax = df.copy()
df_minmax[numeric_cols] = scaler_mm.fit_transform(df_minmax[numeric_cols])

# ❓ Step 13: Save cleaned data to CSV
df.to_csv("cleaned_data.csv", index=False)
df_standardized.to_csv("standardized_data.csv", index=False)
df_minmax.to_csv("minmax_scaled_data.csv", index=False)

# ❓ Step 14: Final Outputs
print("\n✓ Final Cleaned DataFrame:\n")
print(df)

print("\n✓ Standardized DataFrame:\n")
print(df_standardized)

print("\n✓ Min-Max Scaled DataFrame:\n")
print(df_minmax)

print("\n❓ Files saved: cleaned_data.csv,
standardized_data.csv, minmax_scaled_data.csv")

```

OUTPUT:

The screenshot shows a Jupyter Notebook interface with several code cells and their outputs. The code cells are collapsed, indicated by a minus sign icon.

- Data types after conversion:**

| | Age | Salary | Department |
|---|-----|--------|------------|
| 0 | 25 | 50000 | HR |
| 1 | 25 | 60000 | IT |
| 2 | 30 | 55000 | IT |
| 3 | 22 | 52000 | HR |
| 4 | 29 | 52000 | Finance |
- Numeric columns to normalize: ['Age', 'Salary']**
- Final Cleaned DataFrame:**

| | Age | Salary | Department |
|---|-----------|-----------|------------|
| 0 | -0.410152 | -1.089725 | HR |
| 1 | -0.410152 | 1.777972 | IT |
| 2 | 1.298813 | 0.344124 | IT |
| 3 | -1.435530 | -0.516185 | HR |
| 4 | 0.057028 | -0.516185 | Finance |
- Standardized DataFrame:**

| | Age | Salary | Department |
|---|--------|--------|------------|
| 0 | 0.375 | 0.0 | HR |
| 1 | 0.375 | 1.0 | IT |
| 2 | 1.000 | 0.5 | IT |
| 3 | 0.000 | 0.2 | HR |
| 4 | -0.875 | 0.2 | Finance |
- Min-Max Scaled DataFrame:**

| | Age | Salary | Department |
|---|------|--------|------------|
| 0 | 0.0 | 0.0 | HR |
| 1 | 0.0 | 1.0 | IT |
| 2 | 1.0 | 0.5 | IT |
| 3 | 0.0 | 0.2 | HR |
| 4 | -1.0 | 0.2 | Finance |
- Original DataFrame:**

| | Name | Age | Salary | Department |
|---|---------|------|---------|------------|
| 0 | Alice | 25.0 | 50000.0 | HR |
| 1 | Bob | NaN | 60000.0 | IT |
| 2 | Charlie | 30.0 | 55000.0 | IT |
| 3 | David | 22.0 | 52000.0 | HR |
| 4 | Eve | 29.0 | NaN | Finance |
| 5 | Alice | 25.0 | 50000.0 | HR |
- Missing values before cleaning:**

| Name | Age | Salary | Department |
|---------|------|---------|------------|
| Alice | 25.0 | 50000.0 | HR |
| Bob | NaN | 60000.0 | IT |
| Charlie | 30.0 | 55000.0 | IT |
| David | 22.0 | 52000.0 | HR |
| Eve | 29.0 | NaN | Finance |
| Alice | 25.0 | 50000.0 | HR |
- Missing values after filling and dropping:**

| Name | Age | Salary | Department |
|---------|------|---------|------------|
| Alice | 25.0 | 50000.0 | HR |
| Bob | NaN | 60000.0 | IT |
| Charlie | 30.0 | 55000.0 | IT |
| David | 22.0 | 52000.0 | HR |
| Eve | 29.0 | NaN | Finance |
- Duplicate rows before removal: 1**
- Duplicate rows after removal: 0**
- Data types before conversion:**

| | Age | Salary | Department |
|---|-----|--------|------------|
| 0 | 25 | 50000 | HR |
| 1 | 25 | 60000 | IT |
| 2 | 30 | 55000 | IT |
| 3 | 22 | 52000 | HR |
| 4 | 29 | 52000 | Finance |
- Data types after conversion:**

| | Age | Salary | Department |
|---|------|---------|------------|
| 0 | 25.0 | 50000.0 | HR |
| 1 | 25.0 | 60000.0 | IT |
| 2 | 30.0 | 55000.0 | IT |
| 3 | 22.0 | 52000.0 | HR |
| 4 | 29.0 | 52000.0 | Finance |

EXPERIMENT - 4:

EDA-Data Inspection and Analysis:

CODE:

```
# ?? Step 1: Import necessary libraries
import pandas as pd
import numpy as np

# ?? Step 2: Create a sample DataFrame
data = {
    'Name': ['Alice', 'Bob', 'Charlie', 'David', 'Eve'],
    'Age': [25, 30, 22, 28, 35],
    'Salary': [50000, 60000, 52000, 58000, 65000],
```

```

'Department': ['HR', 'IT', 'HR', 'Finance', 'IT'] }
df = pd.DataFrame(data)

# ?? Step 3: View and inspect the DataFrame
print("?? First 5 rows of the
DataFrame:\n") print(df.head())

print("\n?? Info about DataFrame:")
print(df.info())

print("\n?? Shape of DataFrame:", df.shape)
print("\n?? Column Names:",
df.columns.tolist())

# ?? Step 4: Filter and subset data using
conditions print("\n?? Employees with Salary >
55000:") high_salary = df[df['Salary'] > 55000]
print(high_salary)

print("\n??      Employees      from      IT
Department:")      it_employees      =
df[df['Department']]      ==      'IT'
print(it_employees)

# ?? Step 5: Descriptive statistics - Central Tendency
print("\n?? Mean Age:", df['Age'].mean())
print("?? Median Age:", df['Age'].median())
print("?? Mode Age:", df['Age'].mode()[0])

# ?? Step 6: Descriptive statistics - Dispersion
range_age = df['Age'].max() - df['Age'].min()
print("\n?? Range of Age:", range_age)

print("?? Variance of Age:", df['Age'].var())
print("?? Standard Deviation of Age:", df['Age'].std())

range_salary = df['Salary'].max() - df['Salary'].min()
print("\n?? Range of Salary:", range_salary)

print("?? Variance of Salary:", df['Salary'].var())
print("?? Standard Deviation of Salary:", df['Salary'].std())

```

OUTPUT:

```

Shape of DataFrame: (5, 4)
Column Names: ['Name', 'Age', 'Salary', 'Department']
Employees with Salary > 55000:
   Name  Age  Salary Department
0  Bob   30   60000      IT
1  David  28   58000  Finance
2  Eve    35   65000      IT

Employees from IT Department:
   Name  Age  Salary Department
0  Bob   30   60000      IT
1  Eve   35   65000      IT

Mean Age: 28.0
Median Age: 28.0
Mode Age: 22

Range of Age: 13
Variance of Age: 24.5
Standard Deviation of Age: 4.949747468305833

Range of Salary: 15000
Variance of Salary: 37000000.0
Standard Deviation of Salary: 6082.76253829822

```

First 5 rows of the DataFrame:

| | Name | Age | Salary | Department |
|---|---------|-----|--------|------------|
| 0 | Alice | 25 | 50000 | HR |
| 1 | Bob | 30 | 60000 | IT |
| 2 | Charlie | 22 | 52000 | HR |
| 3 | David | 28 | 58000 | Finance |
| 4 | Eve | 35 | 65000 | IT |

Info about DataFrame:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5 entries, 0 to 4
Data columns (total 4 columns):
 # Column Non-Null Count Dtype

 0 Name 5 non-null object
 1 Age 5 non-null int64
 2 Salary 5 non-null int64
 3 Department 5 non-null object
dtypes: int64(2), object(2)
memory usage: 202.0+ bytes
None

Shape of DataFrame: (5, 4)

Column Names: ['Name', 'Age', 'Salary', 'Department']

Employees with Salary > 55000:

| | Name | Age | Salary | Department |
|---|-------|-----|--------|------------|
| 0 | Bob | 30 | 60000 | IT |
| 3 | David | 28 | 58000 | Finance |
| 4 | Eve | 35 | 65000 | IT |

Exp 5:

EDA-DATA VISUALIZATION USING MATPLOTLIB

CODE:

```

import matplotlib.pyplot as plt

from sklearn.datasets import load_iris

import numpy as np

# Load Iris dataset (built-in)

iris = load_iris()

```

```
data = iris.data

feature_names = iris.feature_names

# Take first feature (sepal length) and second feature (sepal width)

sepal_length = data[:, 0]

sepal_width = data[:, 1]

# ----

# 1. Line Chart

# ----

plt.figure(figsize=(6,4))

plt.plot(sepal_length[:30], sepal_width[:30], marker='o', linestyle='--',
color='blue')

plt.title("Line Chart - Sepal Length vs Sepal Width")

plt.xlabel("Sepal Length (first 30 samples)")

plt.ylabel("Sepal Width")

plt.grid(True)

plt.show()

# ----
```

```
# 2. Bar Chart

# ----

# Average sepal length by species

species = iris.target

unique_species = np.unique(species)

avg_sepal_length = [sepal_length[species == s].mean() for s in unique_species]

plt.figure(figsize=(6,4))

plt.bar(iris.target_names, avg_sepal_length, color=['red', 'green', 'blue'])

plt.title("Bar Chart - Avg Sepal Length per Species")

plt.xlabel("Species")

plt.ylabel("Average Sepal Length")

plt.show()

# -----


# 3. Histogram

# -----


plt.figure(figsize=(6,4))

plt.hist(sepal_length, bins=20, color='purple', edgecolor='black')

plt.title("Histogram - Sepal Length Distribution")
```

```
plt.xlabel("Sepal Length")  
  
plt.ylabel("Frequency")  
  
plt.show()
```

OUTPUT:

