RAJALAKSHMI ENGINEERING COLLEGE
An AUTONOMOUS Institution
Affiliated to ANNA UNIVERSITY, Chennai

FUNDAMENTALS OF DATA SCIENCE

Laboratory Record Notebook

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Year / Branch / Section: IInd Year - CSE ‘A’ - B.E

University Register No: 230701048

College Roll No: 230701048

Semester: III

Academic Year: 2024-2025

In [ ]:
```
# Name of the Experiment : Pandas Buit in function
 # EX NO : 01
# Register Number : 230701048
# Name : AWINTHIKA SANTHANAM
```

In [1]:
```
import pandas as pd
import numpy as np
#               ---               Part               1:               Pandas               ---               #

# Create a sample DataFrame with multiple columns and rows
data = {
    'Name': ['Alice', 'Bob', 'Charlie', 'David', 'Eva'],
    'Age': [25, 30, 35, 40, 45],
    'Salary': [50000, 60000, 70000, 80000, 90000],
    'Department': ['HR', 'IT', 'Finance', 'Marketing', 'Sales']
}

df = pd.DataFrame(data) # Display the DataFrame
print("Original DataFrame:")
print(df)
print("-" * 50)
# Access specific rows and columns using `iloc` (index-based slicing)
print("Sliced DataFrame using iloc (index-based slicing):")
print(df.iloc[1:4])  # Slicing rows 1 to 3 (0-indexed)
print("-" * 50)
# Access specific rows and columns using `loc` (label-based slicing)
print("Sliced DataFrame using loc (label-based slicing):")
print(df.loc[1:3])  # Slicing rows 1 to 3 (inclusive)
print("-" * 50)
# Access specific column(s)
print("Accessing 'Age' column:")
print(df['Age'])
print("-" * 50)
# Select multiple columns
print("Accessing multiple columns 'Name' and 'Salary':")
print(df[['Name', 'Salary']])
print("-" * 50)
# Filter DataFrame based on condition
print("Filtering DataFrame where Age > 30:")
print(df[df['Age'] > 30])
print("-" * 50)
# Add a new column with calculated values
df['Salary_in_K'] = df['Salary'] / 1000
print("DataFrame with new 'Salary_in_K' column:")
print(df)
print("-" * 50)

# Number of dimensions (ndim) of the DataFrame
print("Number of dimensions of DataFrame:")
print(df.ndim)  # Should return 2 (since it's a DataFrame)
print("-" * 50)
# --- Part 2: NumPy --- # # Create a NumPy 2D array
arr = np.array([[1, 2, 3], [4, 5, 6], [7, 8, 9]])
# Display the original NumPy array
print("Original NumPy array:")
print(arr)
print("-" * 50)
# Reshaping the array to 1D using reshape()
reshaped_arr = arr.reshape(-1)
print("Reshaped NumPy array (1D):")
print(reshaped_arr)
print("-" * 50)

# Flatten the array using ravel()
raveled_arr = arr.ravel()
print("Raveled NumPy array:")
```

```
print(raveled_arr) print("-" * 50)
# Number of dimensions (ndim) of the NumPy array
print("Number of dimensions of NumPy array:")
print(arr.ndim)  # Should return 2 (since it's a 2D array)
print("-" * 50)
# Array slicing (slicing rows and columns)
print("Array slicing - Select rows 1 and 2, columns 0 and 1:")
print(arr[1:3, 0:2])  # Slicing rows 1 to 2, and columns 0 to 1
print("-" * 50)
# Transpose the array
transposed_arr = arr.T
print("Transposed NumPy array:")
print(transposed_arr)
print("-" * 50)

# Operations on NumPy array (addition, multiplication)
print("Element-wise addition (arr + 10):")
print(arr + 10)
print("-" * 50)
print("Element-wise multiplication (arr * 2):")
print(arr * 2)
print("-" * 50)

#    ---    Part    3:    Combining    Pandas    and    NumPy    ---    #

# Convert DataFrame column to NumPy array
numpy_salary = df['Salary'].to_numpy()
print("Converted 'Salary' column from DataFrame to NumPy array:")
print(numpy_salary)
print("-" * 50)

# Perform a NumPy operation on the 'Salary' column of the DataFrame
new_salaries = numpy_salary * 1.1  # Increase salary by 10%
df['Updated_Salary'] = new_salaries
print("DataFrame with updated salaries (10% increase):")
print(df)
print("-" * 50)
# Create a NumPy array from multiple columns of the DataFrame
salary_dept_arr = df[['Salary', 'Department']].to_numpy()
print("NumPy array from 'Salary' and 'Department' columns of DataFrame:")
print(salary_dept_arr)
print("-" * 50)

# --- End of Program ---
```

OUTPUT

```
Original DataFrame:
      Name  Age  Salary Department
0    Alice   25   50000         HR
1      Bob   30   60000         IT
2  Charlie   35   70000    Finance
3    David   40   80000  Marketing
4      Eva   45   90000      Sales
--------------------------------------------------
Sliced DataFrame using iloc (index-based slicing):
      Name  Age  Salary Department
1      Bob   30   60000         IT
2  Charlie   35   70000    Finance
3    David   40   80000  Marketing
--------------------------------------------------
Sliced DataFrame using loc (label-based slicing):
      Name  Age  Salary Department
1      Bob   30   60000         IT
2  Charlie   35   70000    Finance
3    David   40   80000  Marketing
--------------------------------------------------
Accessing 'Age' column:
0    25
1    30
2    35
3    40
4    45
Name: Age, dtype: int64
--------------------------------------------------
Accessing multiple columns 'Name' and 'Salary':
      Name  Salary
0    Alice   50000
1      Bob   60000
2  Charlie   70000
```

3   David   80000 4   Eva   90000 --
------   Filtering   DataFrame   where   Age   >   30:
Name Age Salary Department 2 Charlie   35   70000   Finance
3   David   40   80000 Marketing 4   Eva   45   90000   Sales --------
----
DataFrame with new 'Salary_in_K' column:
Name Age Salary Department Salary_in_K
0 Alice 25 50000 HR 50.0
1 Bob 30 60000 IT 60.0
2 Charlie 35 70000 Finance 70.0
3 David 40 80000 Marketing 80.0
4 Eva 45 90000 Sales 90.0 ---------------------------------------
----------- Number of dimensions of DataFrame: 2 -------------------------
----------------------- Original NumPy array: [[1 2 3] [4 5 6] [7 8 9]] -------
-- Reshaped NumPy array (1D):
[1 2 3 4 5 6 7 8 9] ---
Raveled NumPy array: [1 2 3 4 5 6 7 8 9] ---------------------------------------
----------- Number of dimensions of NumPy array: 2 -----------------------
------------------------- Array slicing -
Select rows 1 and 2, columns 0 and 1: [[4 5] [7 8]] -------------------------
----------------------- Transposed NumPy array: [[1 4 7] [2 5 8] [3 6 9]] ---
--- Element-wise addition (arr + 10):
[[11 12 13] [14 15 16] [17 18 19]] ---
Element-wise multiplication (arr * 2): [[2 4 6] [8 10 12] [14 16 18]] -----
----
Converted 'Salary' column from DataFrame to NumPy array:
[50000 60000 70000 80000 90000] --
------- DataFrame with updated salaries (10% increase):
Name Age Salary Department Salary_in_K Updated_Salary
0 Alice 25 50000 HR 50.0 55000.0
1 Bob 30 60000 IT 60.0 66000.0
2 Charlie 35 70000 Finance 70.0 77000.0
3 David 40 80000 Marketing 80.0 88000.0
4 Eva 45 90000 Sales 90.0 99000.0 ---------------------

NumPy array from 'Salary' and 'Department' columns of DataFrame:
[[50000 'HR'] [60000 'IT'] [70000 'Finance'] [80000 'Marketing']
[90000 'Sales']] --

In [3]:

```python
import pandas as pd

# Create a DataFrame
data = {
    'Name': ['Alice', 'Bob', 'Charlie', 'David'],
    'Age': [24, 27, 22, 32],
    'City': ['New York', 'Los Angeles', 'Chicago', 'Houston']
}
df = pd.DataFrame(data)

# Display first few rows
print("Head of DataFrame:")
print(df.head())

# Display last few rows
print("\nTail of DataFrame:")
print(df.tail())

# Summary statistics
print("\nSummary Statistics:")
print(df.describe())

# Information about DataFrame
print("\nDataFrame Info:")
df.info()
```

OUTPUT

```
Head of DataFrame:
      Name  Age         City
0    Alice   24     New York
1      Bob   27  Los Angeles
2  Charlie   22      Chicago
3    David   32      Houston
Tail of DataFrame:
      Name  Age         City
0    Alice   24     New York
1      Bob   27  Los Angeles
2  Charlie   22      Chicago
3    David   32      Houston
Summary Statistics:
             Age
count   4.000000
mean   26.250000
std     4.349329
min    22.000000
25%    23.500000
50%    25.500000
75%    28.250000
max    32.000000
DataFrame Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4 entries, 0 to 3
Data columns (total 3 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   Name    4 non-null      object
 1   Age     4 non-null      int64
 2   City    4 non-null      object
dtypes: int64(1), object(2)
memory usage: 228.0+ bytes
```

In [5]:

```
import numpy as np

# Create a NumPy array
arr = np.array([1, 2, 3, 4, 5, 6, 7, 8, 9])
# Slice array (from index 2 to 7, with a step of 2)
sliced_arr = arr[2:8:2]
print("Sliced Array:", sliced_arr)
```

```
Sliced Array: [3 5 7]
```

In [7]:

```
# Create a 2D array
arr_2d = np.array([[1, 2, 3], [4, 5, 6]])
# Flatten the array
flat_arr = arr_2d.ravel()
print("Flattened Array:", flat_arr)
```

```
Flattened Array: [1 2 3 4 5 6]
```

In [9]:

```
# Reshape 1D array into a 3x3 matrix
reshaped_arr = arr.reshape(3, 3)
print("Reshaped Array (3x3):\n", reshaped_arr)
```

```
Reshaped Array (3x3):
 [[1 2 3]
 [4 5 6]
 [7 8 9]]
```

In [11]:

```
# Check the number of dimensions
print("Number of Dimensions:", arr.ndim)
print("Number of Dimensions (2D array):", arr_2d.ndim)
```

```
Number of Dimensions: 1
Number of Dimensions (2D array): 2
```

In [13]:
```
import numpy as np

# Create an array
arr = np.array([1, 2, 3, 4, 5, 6, 7, 8, 9])
# Array slicing
sliced_arr = arr[2:8:2]
print("Sliced Array:", sliced_arr)

# Ravel (flatten the array)
arr_2d = np.array([[1, 2, 3], [4, 5, 6]])
flat_arr = arr_2d.ravel()
print("Flattened Array:", flat_arr)
# Reshape
reshaped_arr = arr.reshape(3, 3)
print("Reshaped Array (3x3):\n", reshaped_arr)

# Number of dimensions
print("Number of Dimensions (original array):", arr.ndim)
print("Number of Dimensions (2D array):", arr_2d.ndim)
```

```
Sliced Array: [3 5 7]
Flattened Array: [1 2 3 4 5 6]
Reshaped Array (3x3):
 [[1 2 3]
 [4 5 6]
 [7 8 9]]
Number of Dimensions (original array): 1
Number of Dimensions (2D array): 2
```

In [15]:
```
# Name of the Experiment : Outlier detection
# EX NO : 02
# Register Number : 230701048
#Name : AWINTHIKA SANTHANAM
```

In [17]:
```
#sample calculation for low range(lr) , upper range (ur),percentile
import numpy as np
array=np.random.randint(1,100,16) # randomly generate 16 numbers between 1 to 100
array
```

Out[17]:
```
array([76, 47, 16, 24, 21, 95,  8, 19, 25,  8, 65, 21, 85, 64, 45, 19])
```

In [21]:
```
array.mean()
```

Out[21]:
```
39.875
```

In [23]:
```
np.percentile(array,25)
```

Out[23]:
```
19.0
```

In [25]:
```
np.percentile(array,50)
```

Out[25]:
```
24.5
```

In [27]:
```
np.percentile(array,75)
```

Out[27]:
```
64.25
```

In [29]:
```
np.percentile(array,100)
```

Out[29]:
```
95.0
```

In [33]:
```
def outDetection(array):
    sorted(array)
    Q1,Q3=np.percentile(array,[25,75])
    IQR=Q3-Q1
    lr=Q1-(1.5*IQR)
    ur=Q3+(1.5*IQR)
    return lr,ur
```

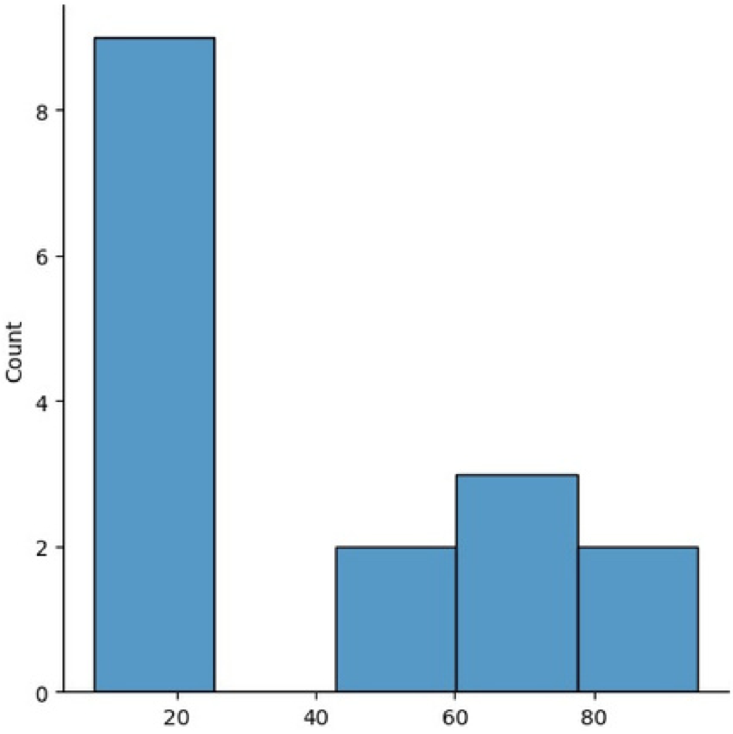
In [35]:
```
lr,ur=outDetection(array)
```

In [37]:
```
lr,ur
```

Out[37]:
```
(-48.875, 132.125)
```

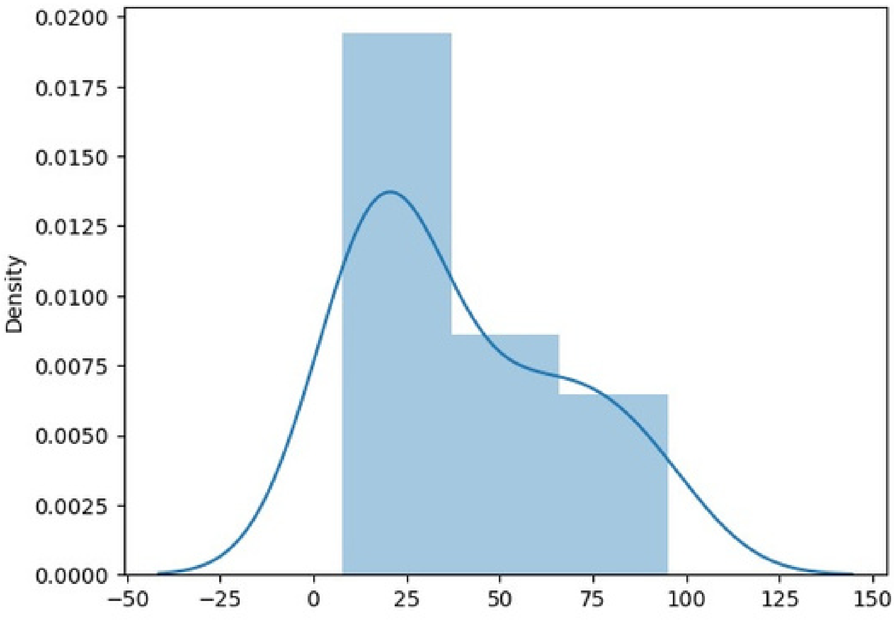
In [39]:
```
import seaborn as sns
%matplotlib inline
sns.displot(array)
```

Out[39]: <seaborn.axisgrid.FacetGrid at 0x2737269b470>



In [41]:
```
sns.distplot(array)
```

Out[41]: <Axes: ylabel='Density'>



In [43]:
```
new_array=array[(array>lr) & (array<ur)]
new_array
```

Out[43]: array([76, 47, 16, 24, 21, 95, 8, 19, 25, 8, 65, 21, 85, 64, 45, 19])

In [45]:
```
lr1,ur1=outDetection(new_array)
lr1,ur1
```

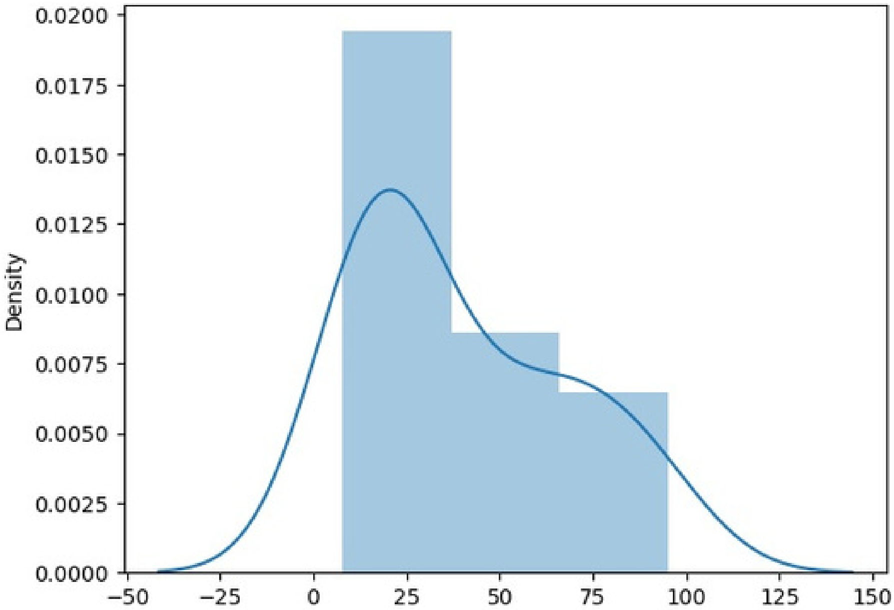
Out[45]: (-48.875, 132.125)

In [47]:
```
final_array=new_array[(new_array>lr1) & (new_array<ur1)]
final_array
```

Out[47]: array([76, 47, 16, 24, 21, 95, 8, 19, 25, 8, 65, 21, 85, 64, 45, 19])

In [49]:
```
sns.distplot(final_array)
```

Out[49]:



In [25]:
```
# Name of the Experiment : Missing and inappropriate data
# EX NO : 03 #Register Number : 230701059 #
Name : M N CHANDNI # Date : 19/08/2024
```

In [42]:
```
import numpy as np
import pandas as pd
# Upload Hotel.csv and convert it into DataFrame
df = pd.read_csv("Hotel_Dataset.csv")
print("Original DataFrame:")
print(df)
# From the dataframe, identify duplicate rows (i.e., row 9)
print("\nChecking for duplicates:")
print(df.duplicated())

# The info() method prints information about the DataFrame, including the number of columns, column data types,
print("\nDataFrame Information:")
df.info()

# Remove duplicate rows
df.drop_duplicates(inplace=True)
print("\nDataFrame after removing duplicates:")
print(df)
# Reset index after dropping duplicate rows
print("\nResetting index after removing duplicates:")
df.reset_index(drop=True, inplace=True)
print(df)
# Use axis=1 to drop 'Age_Group.1' column from the DataFrame (if it exists)
df.drop(['Age_Group.1'], axis=1, inplace=True, errors='ignore')
print("\nDataFrame after dropping 'Age_Group.1' column:")
```

```
print(df)

# Correcting negative values in CustomerID, Bill, and EstimatedSalary using loc to avoid chained assignment
df.loc[df.CustomerID < 0, 'CustomerID'] = np.nan
df.loc[df.Bill < 0, 'Bill'] = np.nan
df.loc[df.EstimatedSalary < 0, 'EstimatedSalary'] = np.nan
print("\nDataFrame after replacing negative values with NaN:")
print(df)
# Replacing invalid 'NoOfPax' values (<1 or >20) with NaN using loc
df.loc[(df['NoOfPax'] < 1) | (df['NoOfPax'] > 20), 'NoOfPax'] = np.nan
print("\nDataFrame after replacing invalid 'NoOfPax' values with NaN:")
print(df)
# Show unique values of 'Age_Group', 'Hotel' and 'FoodPreference'
print("\nUnique values in 'Age_Group' column:")
print(df.Age_Group.unique())

print("\nUnique values in 'Hotel' column:")
print(df.Hotel.unique())
print("\nUnique values in 'FoodPreference' column:")
print(df.FoodPreference.unique())
# Replace incorrect or inconsistent values in 'Hotel' column using loc
df.loc[df.Hotel == 'Ibys', 'Hotel'] = 'Ibis'
print("\nDataFrame after replacing 'Ibys' with 'Ibis' in 'Hotel' column:")
print(df)
# Replace values in 'FoodPreference' column using loc
df.loc[df.FoodPreference.isin(['Vegetarian', 'veg']), 'FoodPreference'] = 'Veg'
df.loc[df.FoodPreference == 'non-Veg', 'FoodPreference'] = 'Non-Veg'
print("\nDataFrame after replacing inconsistent values in 'FoodPreference' column:")
print(df)

# Fill missing values in numerical columns with mean (for continuous) and median (for discrete) using loc
df.loc[:, 'EstimatedSalary'] = df['EstimatedSalary'].fillna(round(df['EstimatedSalary'].mean()))
df.loc[:, 'NoOfPax'] = df['NoOfPax'].fillna(round(df['NoOfPax'].median()))
df.loc[:, 'Rating(1-5)'] = df['Rating(1-5)'].fillna(round(df['Rating(1-5)'].median()))
df.loc[:, 'Bill'] = df['Bill'].fillna(round(df['Bill'].mean()))

# Fill missing values in categorical columns (if needed) with the mode
df.loc[:, 'Age_Group'] = df['Age_Group'].fillna(df['Age_Group'].mode()[0])
df.loc[:, 'Hotel'] = df['Hotel'].fillna(df['Hotel'].mode()[0])
df.loc[:, 'FoodPreference'] = df['FoodPreference'].fillna(df['FoodPreference'].mode()[0])
# Display final cleaned DataFrame
print("\nFinal cleaned DataFrame:")
print(df)

# Save the cleaned DataFrame to a new CSV file
df.to_csv("Cleaned_Hotel_Dataset.csv", index=False)
```

OUTPUT

```
Original DataFrame:
   CustomerID Age_Group  Rating(1-5)      Hotel FoodPreference  Bill  \
0           1     20-25            4       Ibis            veg  1300
1           2     30-35            5  LemonTree        Non-Veg  2000
2           3     25-30            6     RedFox            Veg  1322
3           4     20-25           -1  LemonTree            Veg  1234
4           5       35+            3       Ibis     Vegetarian   989
5           6       35+            3       Ibys        Non-Veg  1909
6           7       35+            4     RedFox     Vegetarian  1000
7           8     20-25            7  LemonTree            Veg  2999
8           9     25-30            2       Ibis        Non-Veg  3456
9           9     25-30            2       Ibis        Non-Veg  3456
10         10     30-35            5     RedFox        non-Veg -6755

    NoOfPax  EstimatedSalary Age_Group.1
0         2            40000       20-25
1         3            59000       30-35
2         2            30000       25-30
3         2           120000       20-25
4         2            45000         35+
5         2           122220         35+
6        -1            21122         35+
7       -10           345673       20-25
8         3           -99999       25-30
9         3           -99999       25-30
10        4            87777       30-35
Checking for duplicates:
0     False
1     False
2     False
```

3 False 4 False 5 False 6 False 7 False 8 False 9 True 10 False dtype: bool DataFrame Information: <class 'pandas.core.frame.DataFrame'> RangeIndex: 11 entries, 0 to 10 Data columns (total 9 columns): # Column Non-Null Count Dtype --- ------ -------------- ----- 0 CustomerID 11 non-null int64 1 Age_Group 11 non-null object 2 Rating(1-5) 11 non-null int64 3 Hotel 11 non-null object 4 FoodPreference 11 non-null object 5 Bill 11 non-null int64 6 NoOfPax 11 non-null int64 7 EstimatedSalary 11 non-null int64 8 Age_Group.1 11 non-null object dtypes: int64(5), object(4) memory usage: 924.0+ bytes DataFrame after removing duplicates: CustomerID Age_Group Rating(1-5) Hotel FoodPreference Bill \ 0 1 20-25 4 Ibis veg 1300 1 2 30-35 5 LemonTree Non-Veg 2000 2 3 25-30 6 RedFox Veg 1322 3 4 20-25 -1 LemonTree Veg 1234 4 5 35+ 3 Ibis Vegetarian 989 5 6 35+ 3 Ibys Non-Veg 1909 6 7 35+ 4 RedFox Vegetarian 1000 7 8 20-25 7 LemonTree Veg 2999 8 9 25-30 2 Ibis Non-Veg 3456 10 10 30-35 5 RedFox non-Veg -6755 NoOfPax EstimatedSalary Age_Group.1 0 2 40000 20-25 1 3 59000 30-35 2 2 30000 25-30 3 2 120000 20-25 4 2 45000 35+ 5 2 122220 35+ 6 -1 21122 35+ 7 -10 345673 20-25 8 3 -99999 25-30 10 4 87777 30-35 Resetting index after removing duplicates: CustomerID Age_Group Rating(1-5) Hotel FoodPreference Bill NoOfPax \ 0 1 20-25 4 Ibis veg 1300 2 1 2 30-35 5 LemonTree Non-Veg 2000 3 2 3 25-30 6 RedFox Veg 1322 2 3 4 20-25 -1 LemonTree Veg 1234 2 4 5 35+ 3 Ibis Vegetarian 989 2 5 6 35+ 3 Ibys Non-Veg 1909 2 6 7 35+ 4 RedFox Vegetarian 1000 -1 7 8 20-25 7 LemonTree Veg 2999 -10 8 9 25-30 2 Ibis Non-Veg 3456 3 9 10 30-35 5 RedFox non-Veg -6755 4 EstimatedSalary Age_Group.1 0 40000 20-25 1 59000 30-35 2 30000 25-30 3 120000 20-25 4 45000 35+ 5 122220 35+ 6 21122 35+ 7 345673 20-25 8 -99999 25-30 9 87777 30-35 DataFrame after dropping 'Age_Group.1' column: CustomerID Age_Group Rating(1-5) Hotel FoodPreference Bill NoOfPax \ 0 1 20-25 4 Ibis veg 1300 2 1 2 30-35 5 LemonTree Non-Veg 2000 3 2 3 25-30 6 RedFox Veg 1322 2 3 4 20-25 -1 LemonTree Veg 1234 2 4 5 35+ 3 Ibis Vegetarian 989 2 5 6 35+ 3 Ibys Non-Veg 1909 2 6 7 35+ 4 RedFox Vegetarian 1000 -1 7 8 20-25 7 LemonTree Veg 2999 -10 8 9 25-30 2 Ibis Non-Veg 3456 3 9 10 30-35 5 RedFox non-Veg -6755 4 EstimatedSalary 0 40000 1 59000 2 30000 3 120000 4 45000 5 122220 6 21122 7 345673 8 -99999 9 87777 DataFrame after replacing negative values with NaN: CustomerID Age_Group Rating(1-5) Hotel FoodPreference Bill \ 0 1.0 20-25 4 Ibis veg 1300.0 1 2.0 30-35 5 LemonTree Non-Veg 2000.0 2 3.0 25-30 6 RedFox Veg 1322.0 3 4.0 20-25 -1 LemonTree Veg 1234.0 4 5.0 35+ 3 Ibis Vegetarian 989.0 5 6.0 35+ 3 Ibys Non-Veg 1909.0 6 7.0 35+ 4 RedFox Vegetarian 1000.0 7 8.0 20-25 7 LemonTree Veg 2999.0 8 9.0 25-30 2 Ibis Non-Veg 3456.0 9 10.0 30-35 5 RedFox non-Veg NaN NoOfPax EstimatedSalary 0 2 40000.0 1 3 59000.0 2 2 30000.0 3 2 120000.0 4 2 45000.0 5 2 122220.0 6 -1 21122.0 7 -10 345673.0 8 3 NaN 9 4 87777.0 DataFrame after replacing invalid 'NoOfPax' values with NaN: CustomerID Age_Group Rating(1-5) Hotel FoodPreference Bill \ 0 1.0 20-25 4 Ibis veg 1300.0 1 2.0 30-35 5 LemonTree Non-Veg 2000.0 2 3.0 25-30 6 RedFox Veg 1322.0 3 4.0 20-25 -1 LemonTree Veg 1234.0 4 5.0 35+ 3 Ibis Vegetarian 989.0 5 6.0 35+ 3 Ibys Non-Veg 1909.0 6 7.0 35+ 4 RedFox Vegetarian 1000.0 7 8.0 20-25 7 LemonTree Veg 2999.0 8 9.0 25-30 2 Ibis Non-Veg 3456.0 9 10.0 30-35 5 RedFox non-Veg NaN NoOfPax EstimatedSalary 0 2.0 40000.0 1 3.0 59000.0 2 2.0 30000.0 3 2.0 120000.0 4 2.0 45000.0 5 2.0 122220.0 6 NaN 21122.0 7 NaN 345673.0 8 3.0 NaN 9 4.0 87777.0 Unique values in 'Age_Group' column: ['20-25' '30-35' '25-30' '35+'] Unique values in 'Hotel' column: ['Ibis' 'LemonTree' 'RedFox' 'Ibys'] Unique values in 'FoodPreference' column: ['veg' 'Non-Veg' 'Veg' 'Vegetarian' 'non-Veg'] DataFrame after replacing 'Ibys' with 'Ibis' in 'Hotel' column: CustomerID Age_Group Rating(1-5) Hotel FoodPreference Bill \ 0 1.0 20-25 4 Ibis veg 1300.0 1 2.0 30-35 5 LemonTree Non-Veg 2000.0

```
2          3.0      25-30             6      RedFox             Veg  1322.0     3          4.0      20-
25                          -1      LemonTree                              Veg      1234.0
4               5.0           35+                    3            Ibis         Vegetarian     989.0
5              6.0           35+                   3           Ibis             Non-Veg   1909.0
6         7.0       35+            4      RedFox      Vegetarian  1000.0     7          8.0      20-
25                  7    LemonTree                   Veg    2999.0       8               9.0       25-
30                  2           Ibis             Non-Veg    3456.0       9             10.0       30-
35          5     RedFox       non-Veg     NaN

   NoOfPax  EstimatedSalary
0      2.0         40000.0
1      3.0         59000.0
2      2.0         30000.0
3      2.0        120000.0
4      2.0         45000.0
5      2.0        122220.0
6      NaN         21122.0
7      NaN        345673.0
8      3.0             NaN
9      4.0         87777.0

DataFrame after replacing inconsistent values in 'FoodPreference' column:
   CustomerID Age_Group  Rating(1-5)      Hotel FoodPreference    Bill  \
0         1.0     20-25            4       Ibis            Veg  1300.0
1         2.0     30-35            5  LemonTree        Non-Veg  2000.0
2         3.0     25-30            6     RedFox            Veg  1322.0
3         4.0     20-25           -1  LemonTree            Veg  1234.0
4         5.0       35+            3       Ibis            Veg   989.0
5         6.0       35+            3       Ibis        Non-Veg  1909.0
6         7.0       35+            4     RedFox            Veg  1000.0
7         8.0     20-25            7  LemonTree            Veg  2999.0
8         9.0     25-30            2       Ibis        Non-Veg  3456.0
9        10.0     30-35            5     RedFox        Non-Veg     NaN
   NoOfPax  EstimatedSalary
0      2.0         40000.0
1      3.0         59000.0
2      2.0         30000.0
3      2.0        120000.0
4      2.0         45000.0
5      2.0        122220.0
6      NaN         21122.0
7      NaN        345673.0
8      3.0             NaN
9      4.0         87777.0

Final cleaned DataFrame:
   CustomerID Age_Group  Rating(1-5)      Hotel FoodPreference    Bill  \
0         1.0     20-25            4       Ibis            Veg  1300.0
1         2.0     30-35            5  LemonTree        Non-Veg  2000.0
2         3.0     25-30            6     RedFox            Veg  1322.0
3         4.0     20-25           -1  LemonTree            Veg  1234.0
4         5.0       35+            3       Ibis            Veg   989.0
5         6.0       35+            3       Ibis        Non-Veg  1909.0
6         7.0       35+            4     RedFox            Veg  1000.0
7         8.0     20-25            7  LemonTree            Veg  2999.0
8         9.0     25-30            2       Ibis        Non-Veg  3456.0
9        10.0     30-35            5     RedFox        Non-Veg  1801.0
   NoOfPax  EstimatedSalary
0      2.0         40000.0
1      3.0         59000.0
2      2.0         30000.0
3      2.0        120000.0
4      2.0         45000.0
5      2.0        122220.0
6      2.0         21122.0
7      2.0        345673.0
8      3.0         96755.0
9      4.0         87777.0
```

In [38]:
```python
# Name of the Experiment : Data Preprocessing
# EX NO : 04
#  Register Number : 230701048
#  Name : AWINTHIKA SANTHANA
# Date : 27/08/2024
```

In [56]:
```python
import numpy as np
import pandas as pd
# Create a sample dataset
data = {
  'Country': ['France', 'Spain', 'Germany', 'Spain', 'Germany', 'France', 'Spain', 'France', 'France', 'France
```

```python
'Age': [44, 27, 30, 38, 40, 35, 38, 48, 50, 37],
'Salary': [72000, 48000, 54000, 61000, 63778, 58000, 52000, 79000, 83000, 67000],
'Purchased': ['No', 'Yes', 'No', 'No', 'Yes', 'Yes', 'No', 'Yes', 'No', 'Yes'] } # Create DataFrame df = pd.DataFrame(data)
# Display the original dataset print("Original DataFrame:") print(df) # Handling missing values (if any)
df['Country'] = df['Country'].fillna(df['Country'].mode()[0]) # Fill missing 'Country' with mode
df['Age'] = df['Age'].fillna(df['Age'].median()) # Fill missing 'Age' with median
df['Salary'] = df['Salary'].fillna(round(df['Salary'].mean())) # Fill missing 'Salary' with mean # One-hot encode the 'Country' column
df_encoded = pd.concat([pd.get_dummies(df['Country']), df[['Age', 'Salary', 'Purchased']]], axis=1)
# Handle the downcasting warning for 'Purchased' column
# Option 1: Setting the option to suppress downcasting warning pd.set_option('future.no_silent_downcasting', True)
# Replace the 'Purchased' column ('Yes'/'No' to 1/0)
df_encoded['Purchased'] = df_encoded['Purchased'].replace(['No', 'Yes'], [0, 1]) # Display the processed DataFrame
print("\nProcessed DataFrame:") print(df_encoded) # Additional Operations (to showcase more code)
# Calculate summary statistics summary_stats = df_encoded.describe()
# Group by countries and calculate mean of 'Age' and 'Salary'
country_grouped = df_encoded.groupby(['France', 'Germany', 'Spain']).agg({'Age': 'mean', 'Salary': 'mean'})
# Handle missing values (replacing 'Purchased' with the mode)
df_encoded['Purchased'] = df_encoded['Purchased'].fillna(df_encoded['Purchased'].mode()[0])
# Display the summary and grouped data print("\nSummary Statistics:") print(summary_stats)
print("\nCountry Grouped by Average Age and Salary:") print(country_grouped)
# Resetting the option to avoid future warnings pd.reset_option('future.no_silent_downcasting')
```

output

Original DataFrame: Country Age Salary Purchased 0 France 44 72000 No 1 Spain 27 48000 Yes 2 Germany 30 54000 No 3 Spain 38 61000 No 4 Germany 40 63778 Yes 5 France 35 58000 Yes 6 Spain 38 52000 No 7 France 48 79000 Yes 8 France 50 83000 No 9 France 37 67000 Yes

Processed DataFrame:

```
 France Germany Spain Age Salary Purchased
0 True False False 44 72000 0
1 False False True 27 48000 1
2 False True False 30 54000 0
3 False False True 38 61000 0
4 False True False 40 63778 1
5 True False False 35 58000 1
6 False False True 38 52000 0
7 True False False 48 79000 1
8 True False False 50 83000 0
9 True False False 37 67000 1
```

Summary Statistics:

```
 Age Salary
count 10.000000 10.000000
mean 38.700000 63777.800000
std 7.257946 11564.099406
min 27.000000 48000.000000
25% 35.500000 55000.000000
50% 38.000000 62389.000000
75% 43.000000 70750.000000
max 50.000000 83000.000000
```

Country Grouped by Average Age and Salary:

```
 Age Salary
France Germany Spain
False False True 34.333333 53666.666667
 True False 35.000000 58889.000000
True False False 42.800000 71800.000000
```

In [52]:

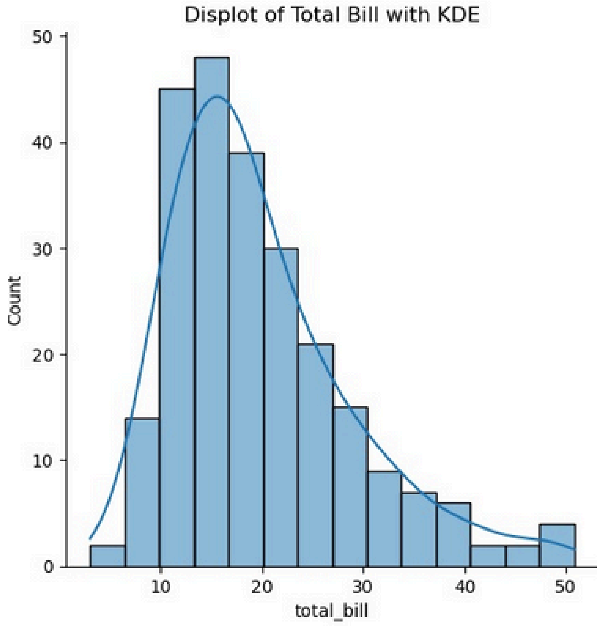
```python
# Name of the Experiment : EDA-Quantitative and Qualitative plots
# EX NO : 05
#  Register Number : 230701048
#  Name : awinthika santhanam
# Date : 03/09/2024
```

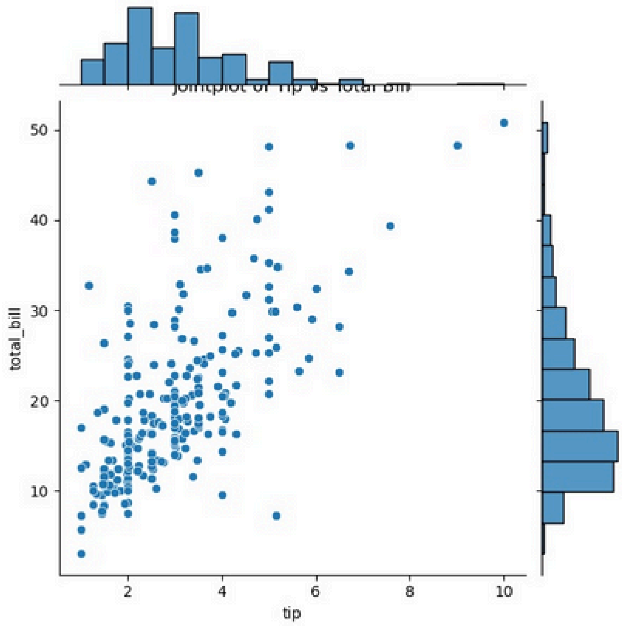
In [61]:

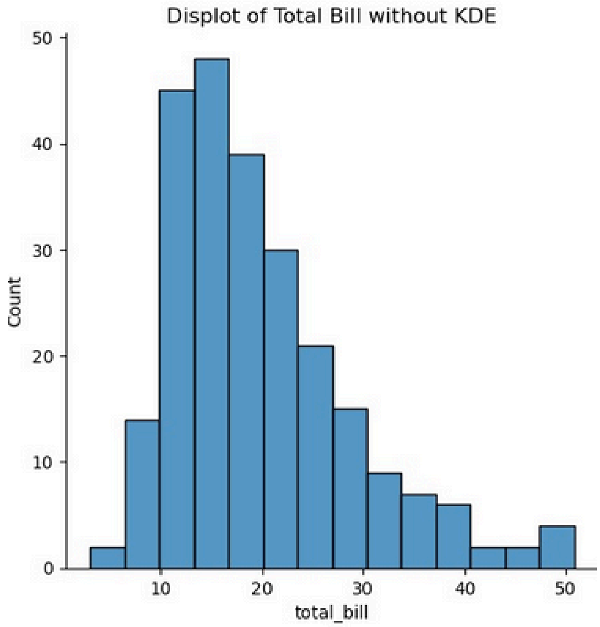
```python
import seaborn as sns
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
# Load the 'tips' dataset from seaborn
tips = sns.load_dataset('tips')
# Display the first few rows of the dataset
print(tips.head())
# Visualization 1: Displot with KDE for the 'total_bill' column
sns.displot(tips.total_bill, kde=True)
plt.title("Displot of Total Bill with KDE")
plt.show()
# Visualization 2: Displot without KDE for the 'total_bill' column
sns.displot(tips.total_bill, kde=False)
plt.title("Displot of Total Bill without KDE")
plt.show()
# Visualization 3: Jointplot for 'tip' vs 'total_bill'
sns.jointplot(x=tips.tip, y=tips.total_bill)
plt.title("Jointplot of Tip vs Total Bill")
plt.show()
# Visualization 4: Jointplot with regression line for 'tip' vs 'total_bill'
sns.jointplot(x=tips.tip, y=tips.total_bill, kind="reg")
plt.title("Jointplot with Regression of Tip vs Total Bill")
plt.show()
# Visualization 5: Jointplot with hexbin for 'tip' vs 'total_bill'
sns.jointplot(x=tips.tip, y=tips.total_bill, kind="hex")
```

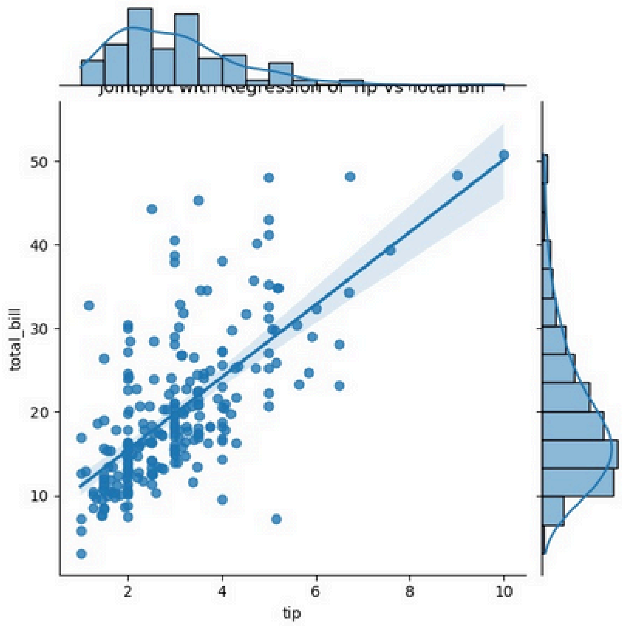
```
plt.title("Hexbin Jointplot of Tip vs Total Bill")
plt.show()

# Visualization 6: Pairplot of all numerical columns
sns.pairplot(tips)
plt.title("Pairplot of Numerical Columns")
plt.show()
# Visualization 7: Pairplot with hue based on 'time'
sns.pairplot(tips, hue='time')
plt.title("Pairplot with Hue on Time")
plt.show()
# Visualization 8: Pairplot with hue based on 'day'
sns.pairplot(tips, hue='day')
plt.title("Pairplot with Hue on Day")
plt.show()
# Visualization 9: Heatmap of correlation matrix for numerical columns
sns.heatmap(tips.corr(numeric_only=True), annot=True)
plt.title("Heatmap of Correlation Matrix")
plt.show()
# Visualization 10: Boxplot for 'total_bill'
sns.boxplot(tips.total_bill)
plt.title("Boxplot of Total Bill")
plt.show()
# Visualization 11: Boxplot for 'tip'
sns.boxplot(tips.tip)
plt.title("Boxplot of Tip")
plt.show()
# Visualization 12: Countplot of 'day'
sns.countplot(tips.day)
plt.title("Countplot of Day")
plt.show()
# Visualization 13: Countplot of 'sex'
sns.countplot(tips.sex)
plt.title("Countplot of Sex")
plt.show()
# Visualization 14: Pie chart of 'sex' value counts
tips.sex.value_counts().plot(kind='pie', autopct='%1.1f%%', startangle=90)
plt.title("Pie Chart of Sex Distribution")
plt.ylabel('')  # Hide the 'sex' label
plt.show()

# Visualization 15: Bar chart of 'sex' value counts
tips.sex.value_counts().plot(kind='bar')
plt.title("Bar Chart of Sex Distribution")
plt.show()
# Visualization 16: Countplot for 'day' based on 'time'=='Dinner'
sns.countplot(tips[tips.time=='Dinner']['day'])
plt.title("Countplot of Day for Dinner Time")
plt.show()
```

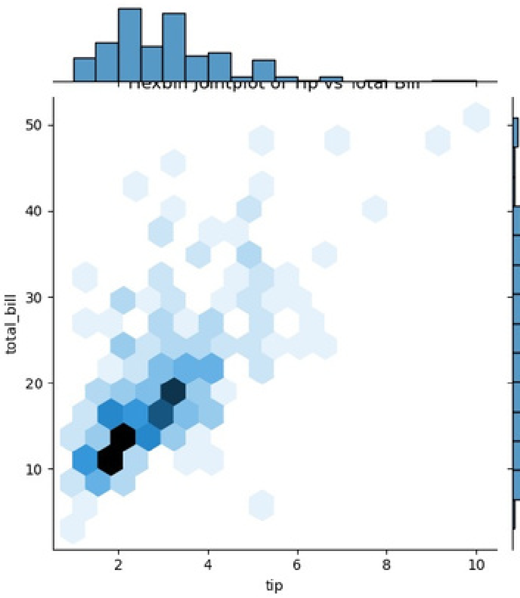
	total_bill	tip	sex	smoker	day	time	size
0	16.99	1.01	Female	No	Sun	Dinner	2
1	10.34	1.66	Male	No	Sun	Dinner	3
2	21.01	3.50	Male	No	Sun	Dinner	3
3	23.68	3.31	Male	No	Sun	Dinner	2
4	24.59	3.61	Female	No	Sun	Dinner	4

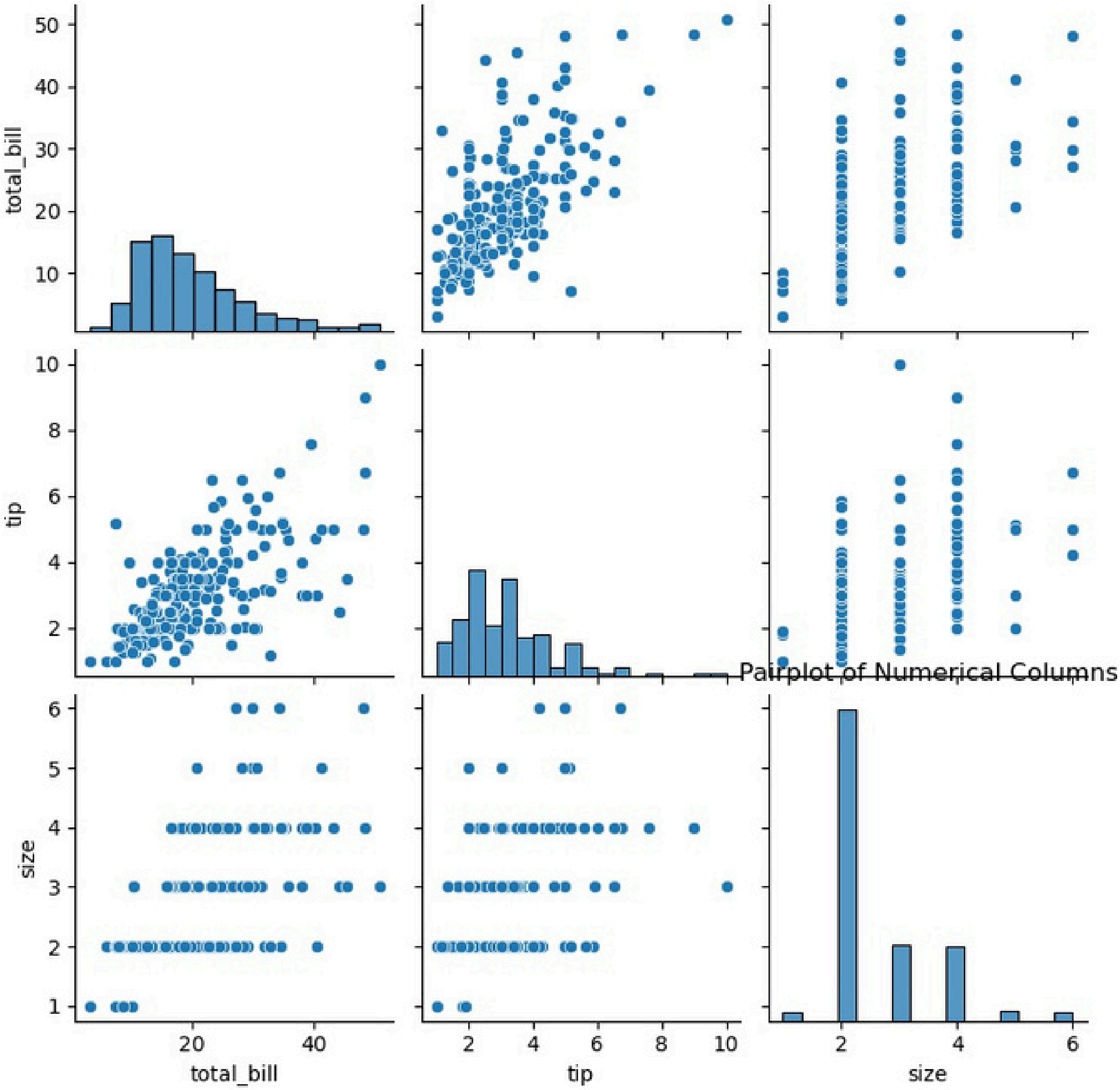

Displot of Total Bill with KDE
Count
total_bill

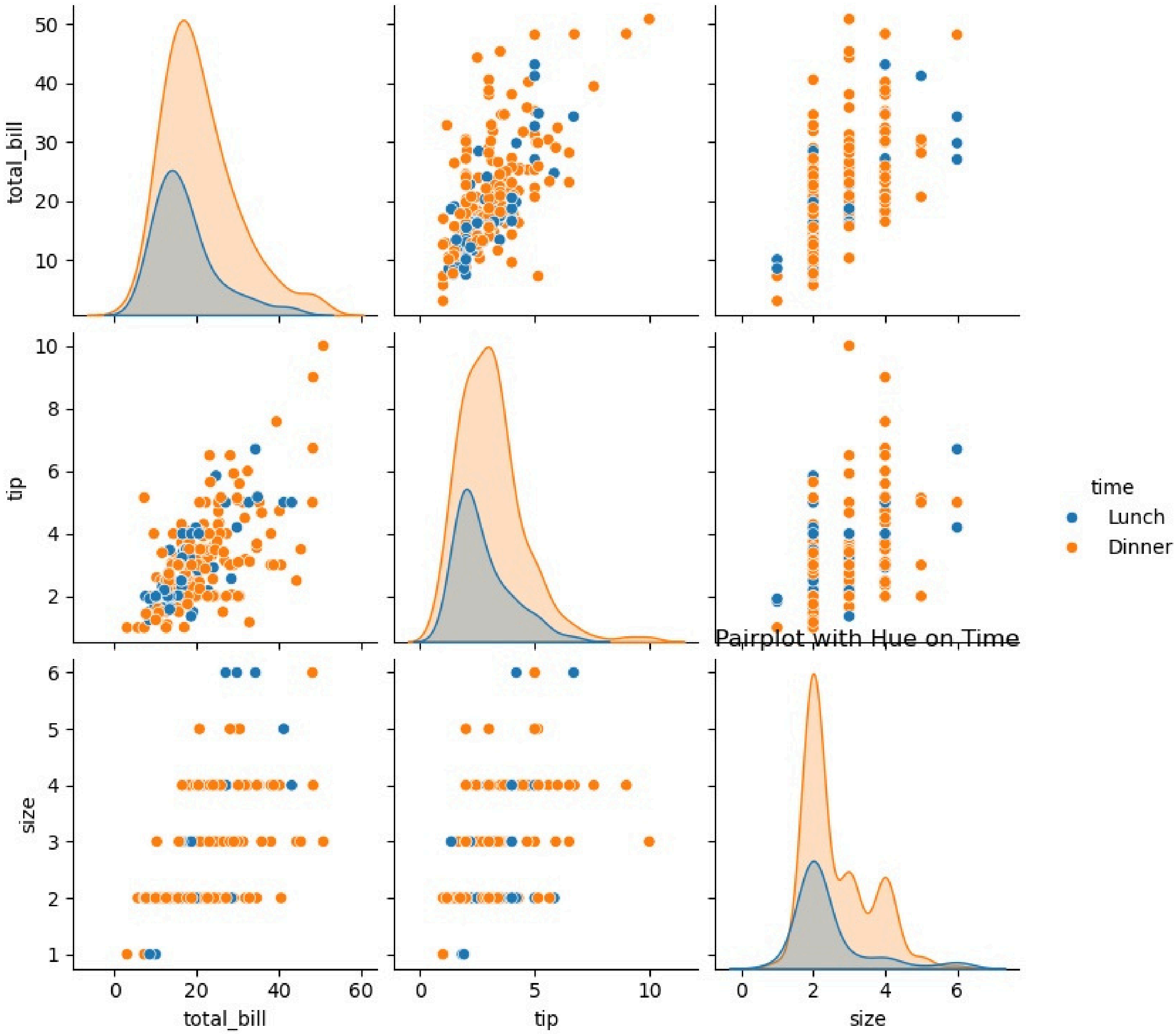

total_bill
tip


Displot of Total Bill without KDE
Count
total_bill

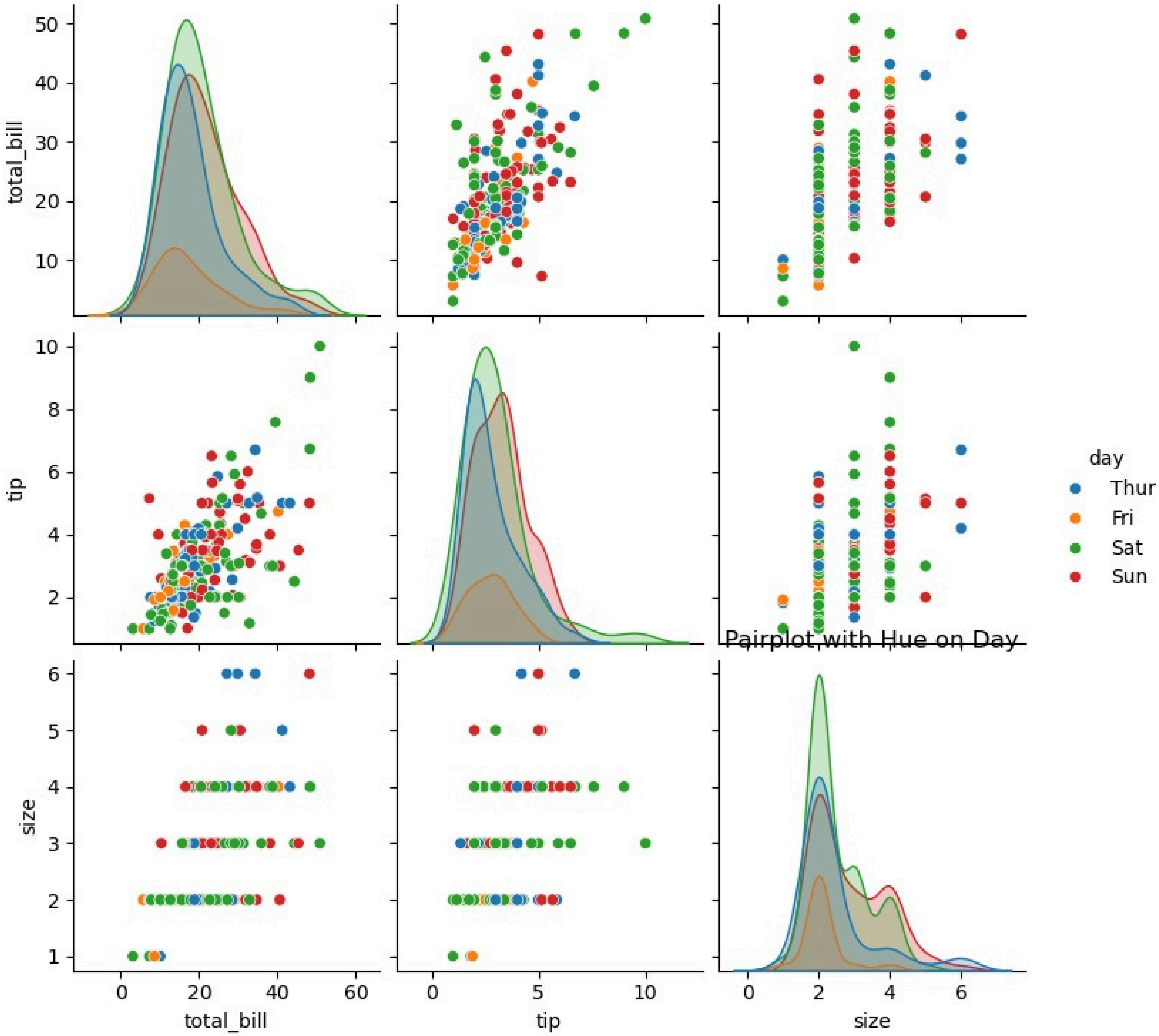

total_bill
tip


Hexbin Jointplot of Tip vs Total Bill
total_bill
50
40
30
20
10
2
4
6
8
10
tip

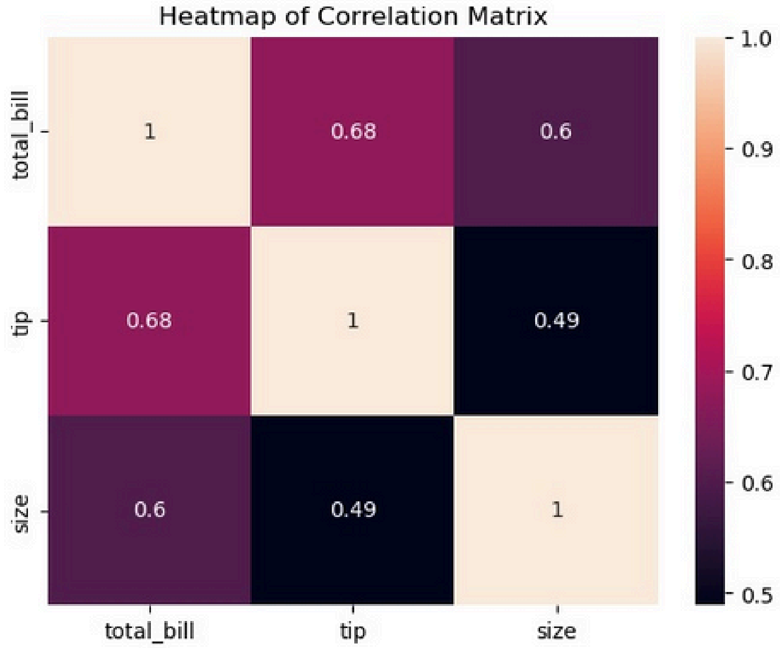

Pairplot of Numerical Columns
total_bill
tip
size
50
40
30
20
10
10
8
6
4
2
6
5
4
3
2
1
20
40
2
4
6
8
10
2
4
6
total_bill
tip
size

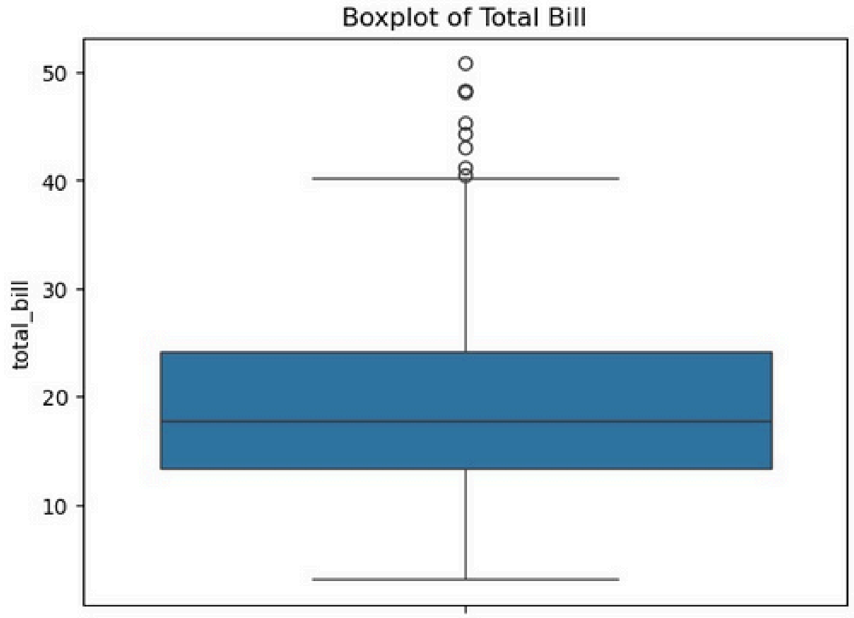


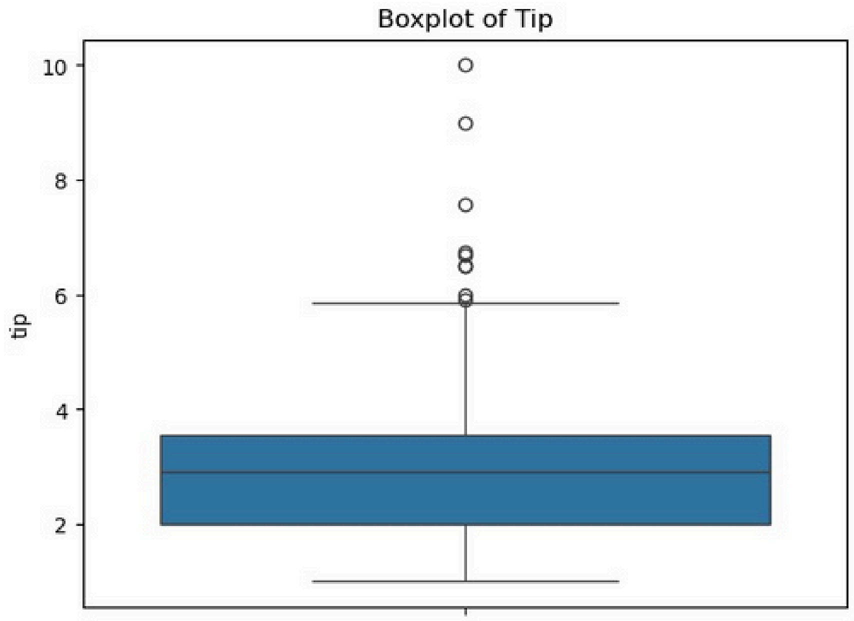
Pairplot with Hue on Time
total_bill
tip
size
time
Lunch
Dinner

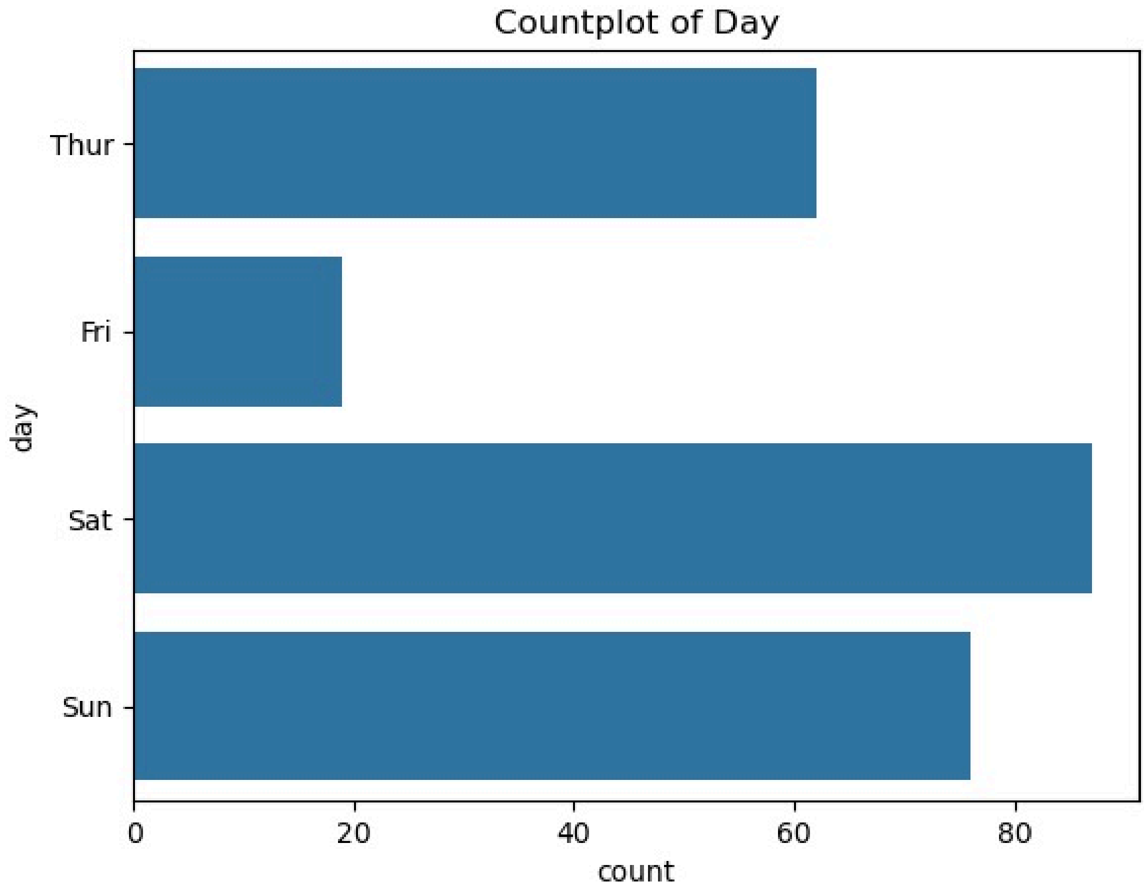


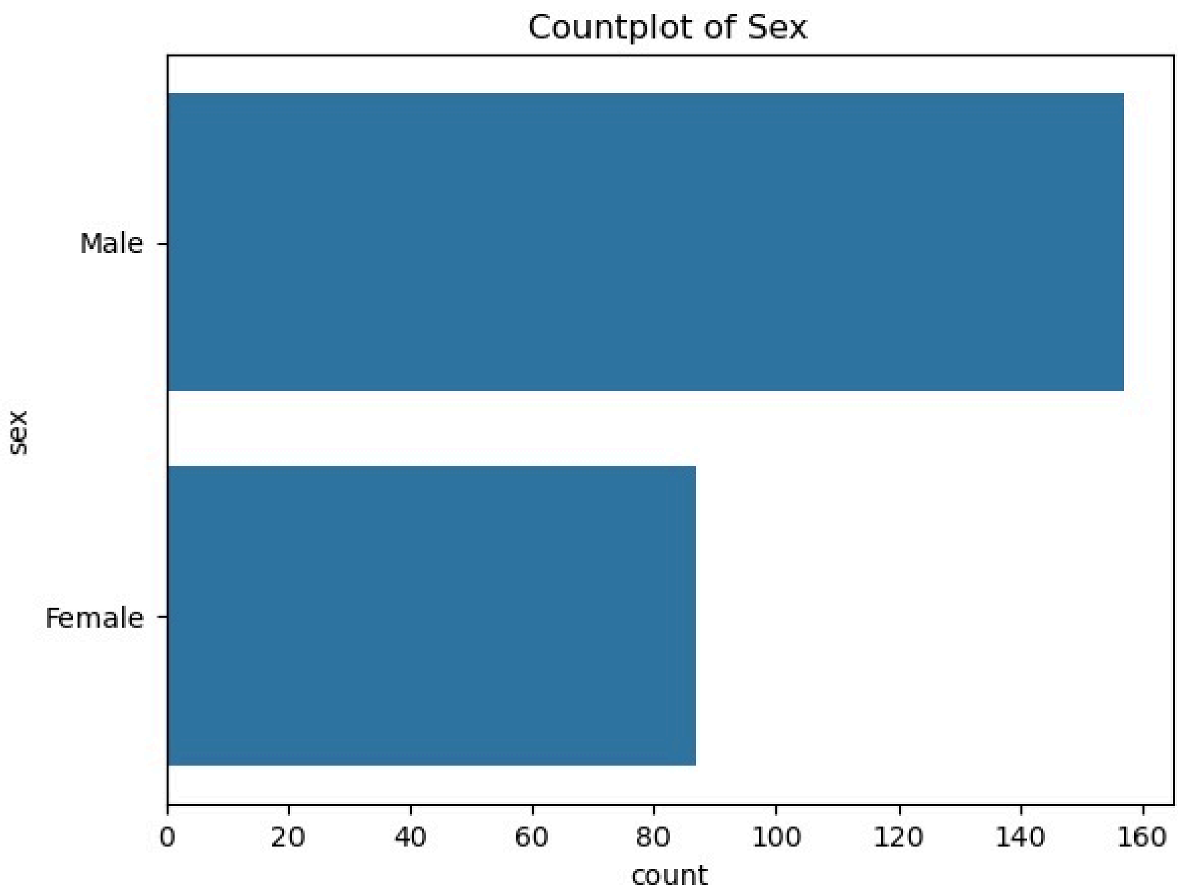
Pairplot with Hue on Day
total_bill
tip
size
day
Thur
Fri
Sat
Sun

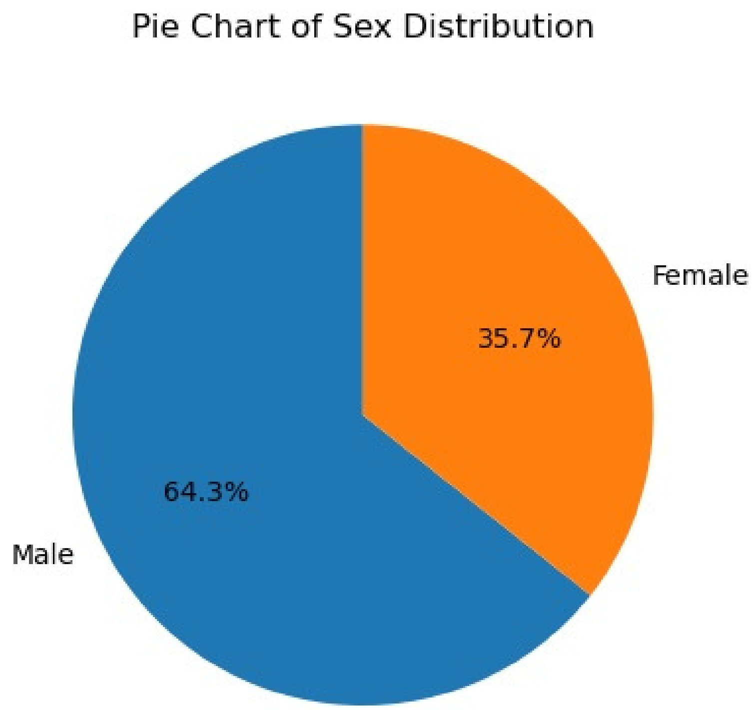

Heatmap of Correlation Matrix
total_bill
tip
size
1
0.68
0.6
0.68
1
0.49
0.6
0.49
1
1.0
0.9
0.8
0.7
0.6
0.5


Boxplot of Total Bill
total_bill
50
40
30
20
10

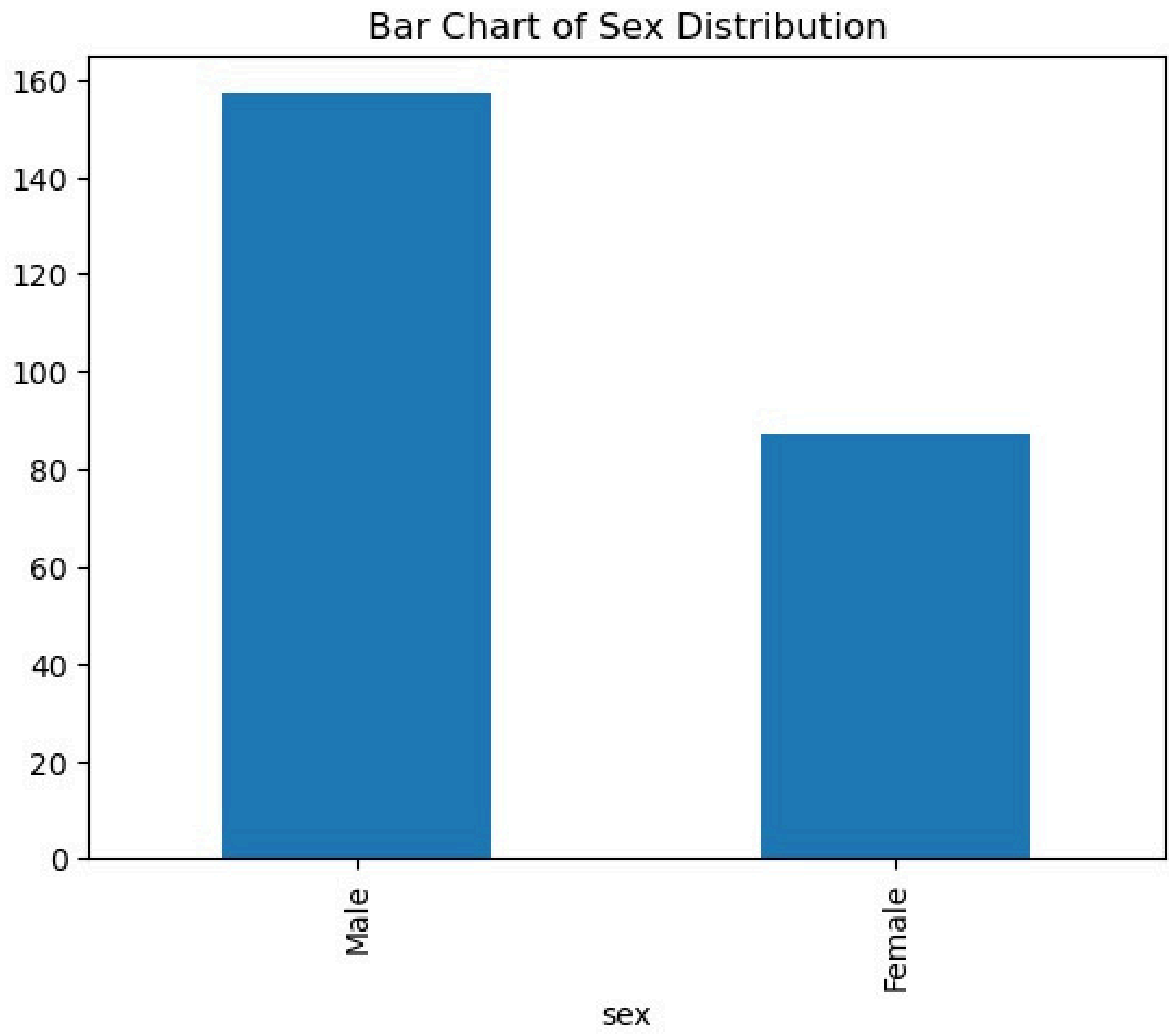

Boxplot of Tip
tip
10
8
6
4
2


Countplot of Day
Thur
Fri
Sat
Sun
day
0
20
40
60
80
count

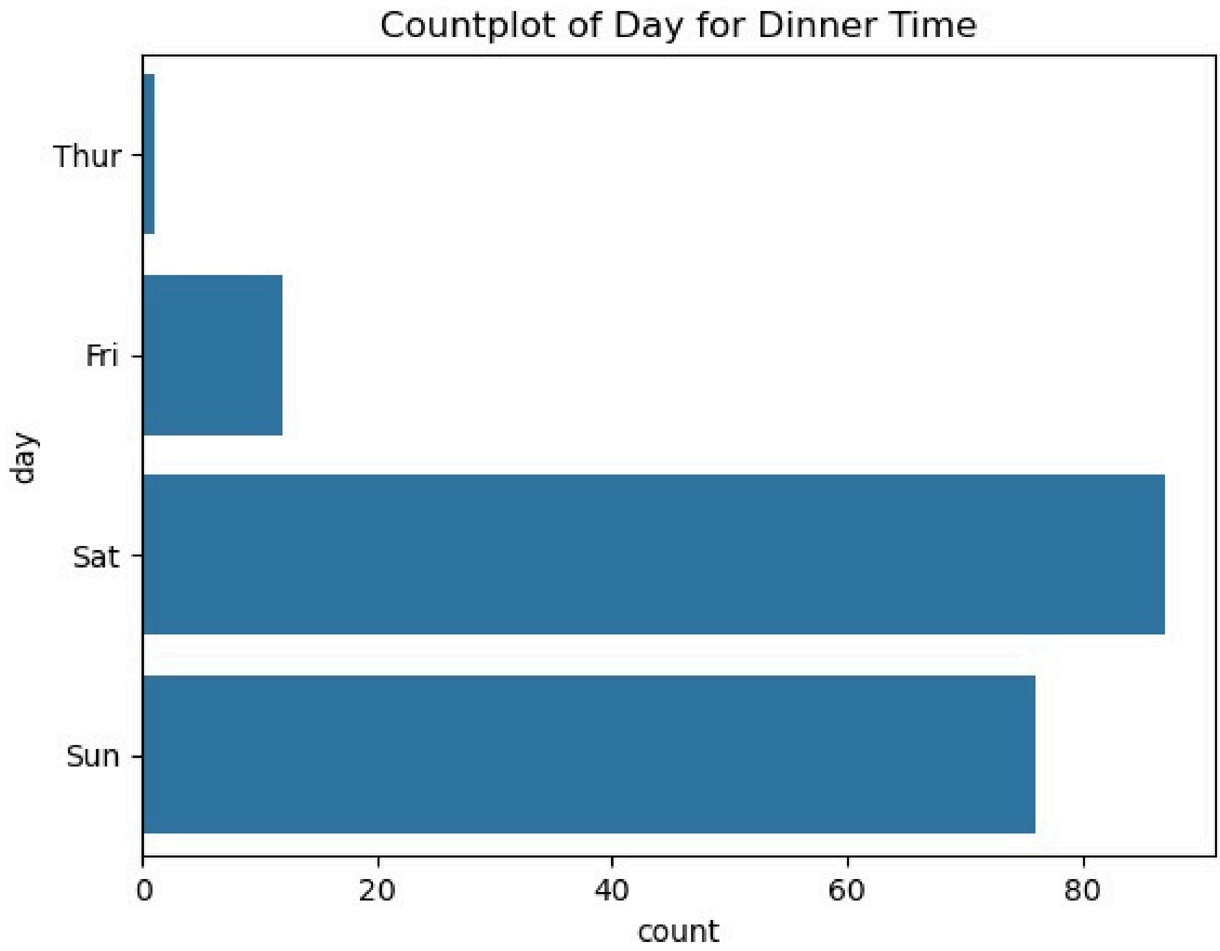

Countplot of Sex
Male
Female
sex
0
20
40
60
80
100
120
140
160
count



Pie Chart of Sex Distribution
Female
35.7%
64.3%
Male

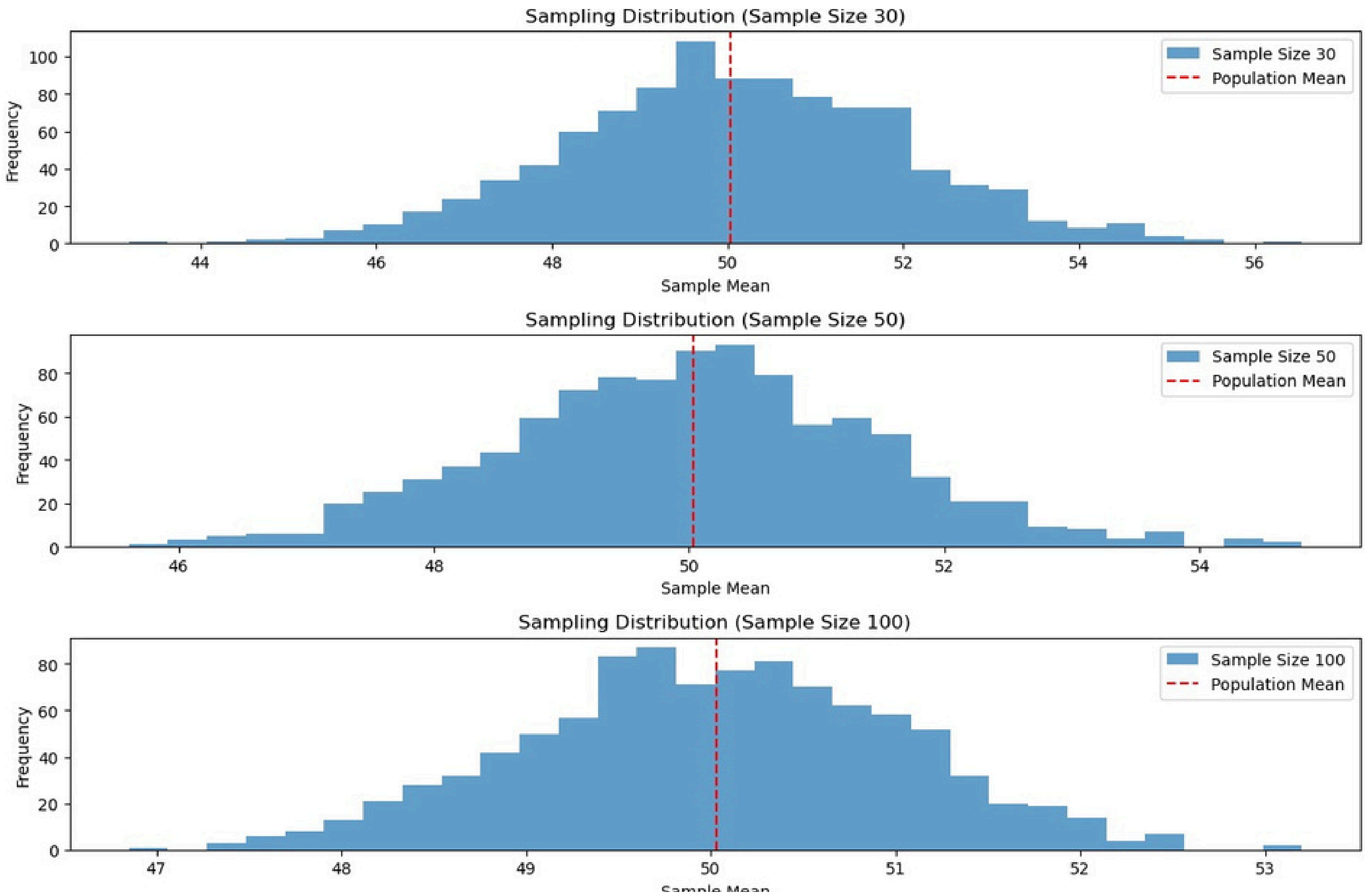


Bar Chart of Sex Distribution
160
140
120
100
80
60
40
20
0
Male
Female
sex


Countplot of Day for Dinner Time
Thur
Fri
Sat
Sun
day
0
20
40
60
80
count

In [54]:
```
# Name of the Experiment : Random Sampling and Sampling Distribution # EX NO : 06
#Register Number : 230701048 # Name : awinthika santhanam # Date :10/09/2024
```

In [63]:
```
import numpy as np
import matplotlib.pyplot as plt
# Step 1: Generate a population (e.g., normal distribution)
population_mean = 50
population_std = 10
population_size = 100000
population = np.random.normal(population_mean, population_std, population_size)

# Step 2: Random sampling
sample_sizes = [30, 50, 100]  # Different sample sizes to consider
num_samples = 1000  # Number of samples for each sample size
sample_means = {}
# Loop through each sample size
for size in sample_sizes:
    sample_means[size] = []
    for _ in range(num_samples):
        sample = np.random.choice(population, size=size, replace=False)
        sample_means[size].append(np.mean(sample))
# Step 3: Plotting sampling distributions
plt.figure(figsize=(12, 8))
# Loop through sample sizes and plot each distribution
for i, size in enumerate(sample_sizes):
    plt.subplot(len(sample_sizes), 1, i + 1)
    plt.hist(sample_means[size], bins=30, alpha=0.7, label=f'Sample Size {size}')
    plt.axvline(np.mean(population), color='red', linestyle='dashed', linewidth=1.5,
                label='Population Mean')
    plt.title(f'Sampling Distribution (Sample Size {size})')
    plt.xlabel('Sample Mean')
    plt.ylabel('Frequency')
    plt.legend()
# Adjust layout for better readability and show the plot
plt.tight_layout()
plt.show()
```


Sampling Distribution (Sample Size 30)
Sample Size 30
Population Mean
Frequency
Sample Mean
Sampling Distribution (Sample Size 50)
Sample Size 50
Population Mean
Frequency
Sample Mean
Sampling Distribution (Sample Size 100)
Sample Size 100
Population Mean
Frequency

In [65]:

```
#Name of the Experiment : Z-Test
# EX NO : 07 #
#Register Number : 230701048
#Name : awinthika santhanam
```

In [67]:

```
import numpy as np
import scipy.stats as stats
# Define the sample data (hypothetical weights in grams)
sample_data = np.array([152, 148, 151, 149, 147, 153, 150, 148, 152,
                        149, 151, 150, 149, 152, 151, 148, 150, 152, 149,
                        150, 148, 153, 151, 150, 149, 152, 148, 151, 150, 153])
# Population mean under the null hypothesis
population_mean = 150
# Calculate sample statistics
sample_mean = np.mean(sample_data)
sample_std = np.std(sample_data, ddof=1)  # Using sample standard deviation

# Number of observations
n = len(sample_data)
# Calculate the Z-statistic
z_statistic = (sample_mean - population_mean) / (sample_std / np.sqrt(n))
# Calculate the p-value (two-tailed test)
p_value = 2 * (1 - stats.norm.cdf(np.abs(z_statistic)))
# Print results
print(f"Sample Mean: {sample_mean:.2f}")
print(f"Z-Statistic: {z_statistic:.4f}")
print(f"P-Value: {p_value:.4f}")
# Decision based on the significance level
alpha = 0.05
if p_value < alpha:
    print("Reject the null hypothesis: The average weight is significantly different from 150 grams.")
else:
    print("Fail to reject the null hypothesis: There is no significant difference in average weight from 150 gra
```

output

```
Sample Mean: 150.20
Z-Statistic: 0.6406
P-Value: 0.5218
Fail to reject the null hypothesis: There is no significant difference in average weight from 150 grams.
```

In [13]:
```
# Name of the Experiment : T-Test
# EX NO : 08 #
Register Number : 230701048 # Name :
AWINTHIKA SANTHANAM
```

In [69]:
```
import numpy as np
import scipy.stats as stats
# Set a random seed for reproducibility
np.random.seed(42)
# Generate hypothetical sample data (IQ scores)
sample_size = 25
sample_data = np.random.normal(loc=102, scale=15, size=sample_size)  # Mean IQ of 102, SD of 15

# Population mean under the null hypothesis
population_mean = 100
# Calculate sample statistics
sample_mean = np.mean(sample_data)
sample_std = np.std(sample_data, ddof=1)  # Using sample standard deviation

# Number of observations
n = len(sample_data)
# Calculate the T-statistic and p-value using a one-sample t-test
t_statistic, p_value = stats.ttest_1samp(sample_data, population_mean)
# Print results
print(f"Sample Mean: {sample_mean:.2f}")
print(f"T-Statistic: {t_statistic:.4f}")
print(f"P-Value: {p_value:.4f}")
# Decision based on the significance level
alpha = 0.05
if p_value < alpha:
   print("Reject the null hypothesis: The average IQ score is significantly different from 100.")
else:
   print("Fail to reject the null hypothesis: There is no significant difference in average IQ score from 100."
```

```
Sample Mean: 99.55
T-Statistic: -0.1577
P-Value: 0.8760
Fail to reject the null hypothesis: There is no significant difference in average IQ score from 100.
```

In [15]:
```
# Name of the Experiment : Annova TEST
# EX NO : 09
# Register Number : 230701048
# Student Name : AWI THIKA SANTHANAM
```

In [71]:
```
import numpy as np
import scipy.stats as stats
from statsmodels.stats.multicomp import pairwise_tukeyhsd

# Set a random seed for reproducibility
np.random.seed(42)
# Generate hypothetical growth data for three treatments (A, B, C)
n_plants = 25
# Growth data (in cm) for Treatment A, B, and C
growth_A = np.random.normal(loc=10, scale=2, size=n_plants)
growth_B = np.random.normal(loc=12, scale=3, size=n_plants)
growth_C = np.random.normal(loc=15, scale=2.5, size=n_plants)
# Combine all data into one array
all_data = np.concatenate([growth_A, growth_B, growth_C])
# Treatment labels for each group
treatment_labels = ['A'] * n_plants + ['B'] * n_plants + ['C'] * n_plants
# Perform one-way ANOVA
f_statistic, p_value = stats.f_oneway(growth_A, growth_B, growth_C)
# Print results
print("Treatment A Mean Growth:", np.mean(growth_A))
print("Treatment B Mean Growth:", np.mean(growth_B))
print("Treatment C Mean Growth:", np.mean(growth_C))
print()
print(f"F-Statistic: {f_statistic:.4f}")
print(f"P-Value: {p_value:.4f}")

# Decision based on the significance level

alpha = 0.05
if p_value < alpha:
    print("Reject the null hypothesis: There is a significant difference in mean growth rates among the three tr
else:
    print("Fail to reject the null hypothesis: There is no significant difference in mean growth rates among the

# Additional: Post-hoc analysis (Tukey's HSD) if ANOVA is significant
if p_value < alpha:
    tukey_results = pairwise_tukeyhsd(all_data, treatment_labels, alpha=0.05)
    print("\nTukey's HSD Post-hoc Test:")
    print(tukey_results)
```

OUTPUT

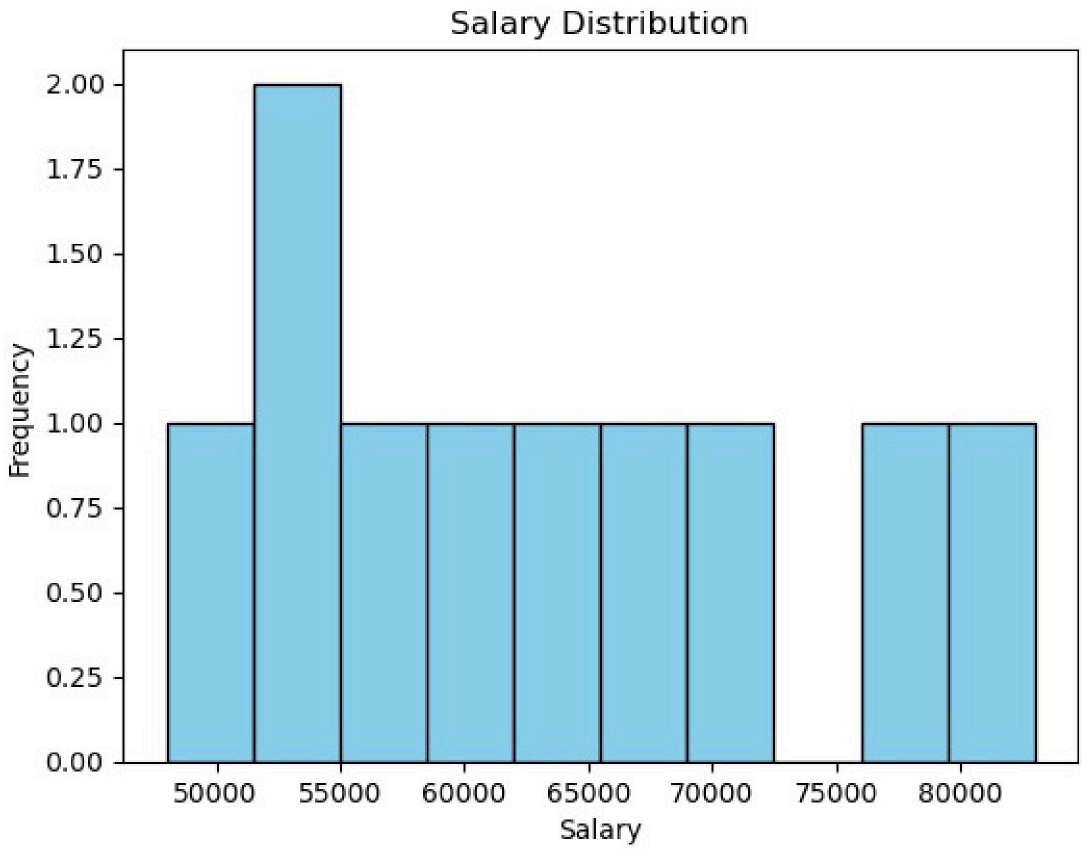
```
Treatment A Mean Growth: 9.672983882683818
Treatment B Mean Growth: 11.137680744437432
Treatment C Mean Growth: 15.265234904828972

F-Statistic: 36.1214
P-Value: 0.0000
Reject the null hypothesis: There is a significant difference in mean growth rates among the three treatments.

Tukey's HSD Post-hoc Test:
Multiple Comparison of Means - Tukey HSD, FWER=0.05
====================================================
group1 group2 meandiff p-adj   lower  upper  reject
----------------------------------------------------
     A      B   1.4647 0.0877 -0.1683 3.0977  False
     A      C   5.5923    0.0  3.9593 7.2252   True
     B      C   4.1276    0.0  2.4946 5.7605   True
----------------------------------------------------
```

In [17]:
```
# Name of the Experiment : Feature Scaling
# EX NO : 10
# Register Number : 230701048
# Name : AWINTHIKA SANTHANAM
```

In [77]:
```
import numpy as np
import pandas as pd
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OneHotEncoder, StandardScaler, MinMaxScaler
from statsmodels.stats.multicomp import pairwise_tukeyhsd
import matplotlib.pyplot as plt
# Sample dataset
data = {
    'Country': ['France', 'Spain', 'Germany', 'Spain', 'Germany', 'France', 'Spain', 'France', 'France', 'France
    'Age': [44, 27, 30, 38, 40, 35, 38, 48, 50, 37],
    'Salary': [72000, 48000, 54000, 61000, 65000, 58000, 52000, 79000, 83000, 67000],
    'Purchased': ['No', 'Yes', 'No', 'No', 'Yes', 'Yes', 'No', 'Yes', 'No', 'Yes']
}

# Create DataFrame
df = pd.DataFrame(data)
# Display the first few rows of the dataset
print("Original Data:")
print(df)

# Handle missing values
# Fill missing 'Country' with the mode (most frequent value)
df['Country'] = df['Country'].fillna(df['Country'].mode()[0])

# Separate features and labels
features = df.iloc[:, :-1].values
labels = df.iloc[:, -1].values

# Use SimpleImputer to handle missing values for 'Age' and 'Salary'
age_imputer = SimpleImputer(strategy="mean")
salary_imputer = SimpleImputer(strategy="mean")

# Impute missing values
features[:, 1] = age_imputer.fit_transform(features[:, [1]]).flatten()
features[:, 2] = salary_imputer.fit_transform(features[:, [2]]).flatten()

# OneHotEncoder for 'Country' column
oh = OneHotEncoder(sparse_output=False)
country_encoded = oh.fit_transform(features[:, [0]])

# Combine the encoded 'Country' values with the rest of the features
final_features = np.concatenate((country_encoded, features[:, 1:]), axis=1)
# Standardize the features using StandardScaler
scaler = StandardScaler()
standardized_features = scaler.fit_transform(final_features)
# Normalize the features using MinMaxScaler mms = MinMaxScaler(feature_range=(0, 1))
normalized_features = mms.fit_transform(final_features)
# Display the final processed features
print("\nProcessed Features (Standardized):")
print(standardized_features)

print("\nProcessed Features (Normalized):")
print(normalized_features)
# Plotting the processed data (just an example with a histogram for 'Salary')
plt.hist(df['Salary'], bins=10, color='skyblue', edgecolor='black')
plt.title('Salary Distribution')
plt.xlabel('Salary')
plt.ylabel('Frequency')
plt.show()
# Perform One-Way ANOVA to compare the mean 'Salary' across countries
from scipy import stats
f_stat, p_value = stats.f_oneway(df[df['Country'] == 'France']['Salary'],
                                 df[df['Country'] == 'Spain']['Salary'],
                                 df[df['Country'] == 'Germany']['Salary'])

print("\nANOVA Results:")
print(f"F-Statistic: {f_stat:.4f}, P-Value: {p_value:.4f}")
# Decision based on significance level
alpha = 0.05
if p_value < alpha:
    print("Reject the null hypothesis: There is a significant difference in mean Salary across countries.")
else:
    print("Fail to reject the null hypothesis: There is no significant difference in mean Salary across countrie
# Perform Tukey's HSD test if ANOVA is significant
if p_value < alpha:
    tukey_results = pairwise_tukeyhsd(df['Salary'], df['Country'], alpha=0.05)
    print("\nTukey's HSD Post-hoc Test Results:")
    print(tukey_results)
```

OUTPUT

```
Original Data:
   Country  Age  Salary Purchased
0   France   44   72000        No
1    Spain   27   48000       Yes
2  Germany   30   54000        No
3    Spain   38   61000        No
4  Germany   40   65000       Yes
5   France   35   58000       Yes
6    Spain   38   52000        No
7   France   48   79000       Yes
8   France   50   83000        No
9   France   37   67000       Yes
Processed Features (Standardized):
[[ 1.         -0.5        -0.65465367  0.76973439  0.7379204 ]
 [-1.         -0.5         1.52752523 -1.69922498 -1.44851041]
 [-1.          2.         -0.65465367 -1.26352627 -0.90190271]
 [-1.         -0.5         1.52752523 -0.10166303 -0.26419372]
 [-1.          2.         -0.65465367  0.18880278  0.10021141]
 [ 1.         -0.5        -0.65465367 -0.53736175 -0.53749758]
 [-1.         -0.5         1.52752523 -0.10166303 -1.08410528]
 [ 1.         -0.5        -0.65465367  1.35066601  1.37562939]
 [ 1.         -0.5        -0.65465367  1.64113182  1.74003452]
 [ 1.         -0.5        -0.65465367 -0.24689594  0.28241398]]

Processed Features (Normalized):
[[1.         0.         0.         0.73913043 0.68571429]
 [0.         0.         1.         0.         0.        ]
 [0.         1.         0.         0.13043478 0.17142857]
 [0.         0.         1.         0.47826087 0.37142857]
 [0.         1.         0.         0.56521739 0.48571429]
 [1.         0.         0.         0.34782609 0.28571429]
 [0.         0.         1.         0.47826087 0.11428571]
 [1.         0.         0.         0.91304348 0.88571429]
 [1.         0.         0.         1.         1.        ]
 [1.         0.         0.         0.43478261 0.54285714]]
```

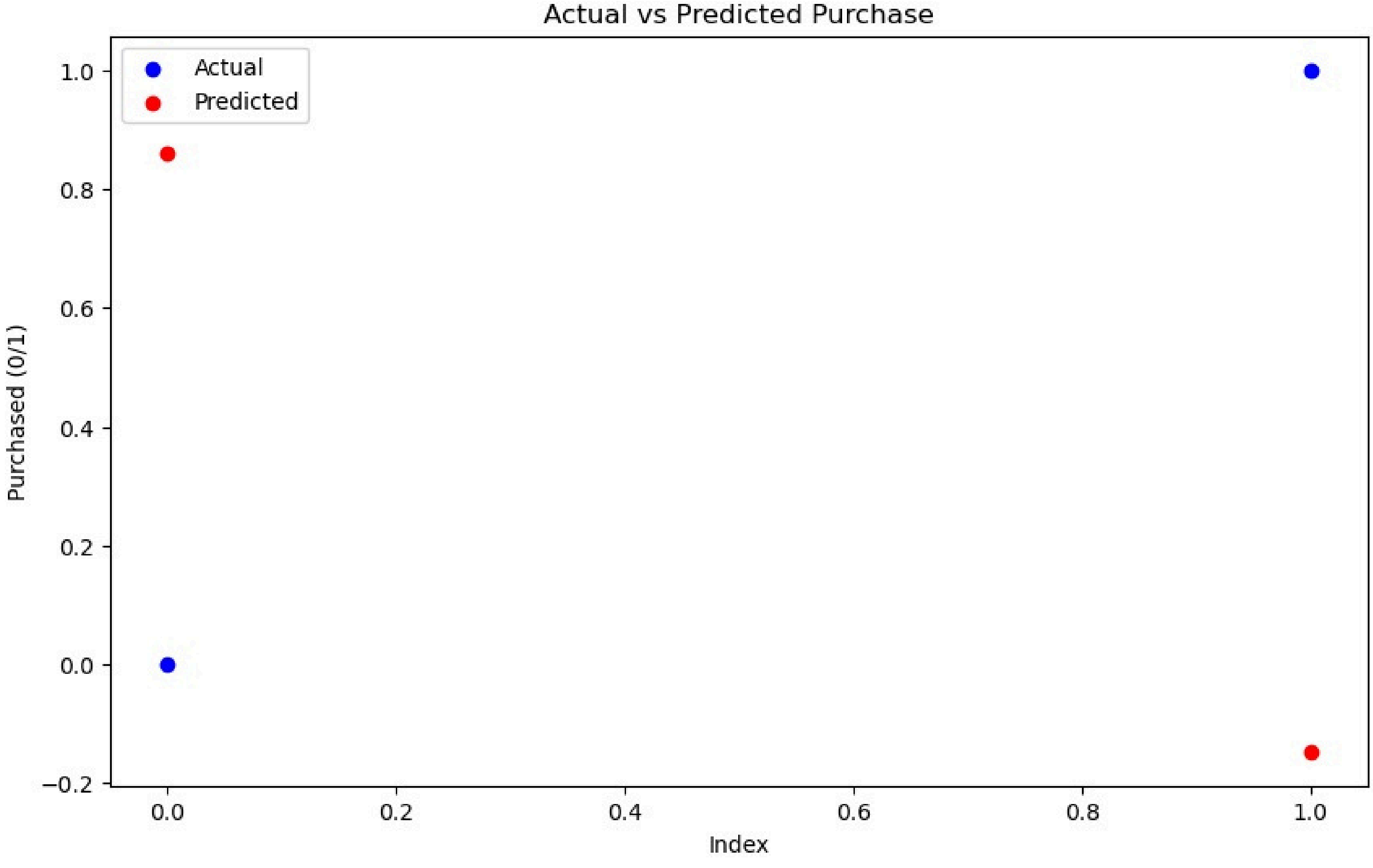


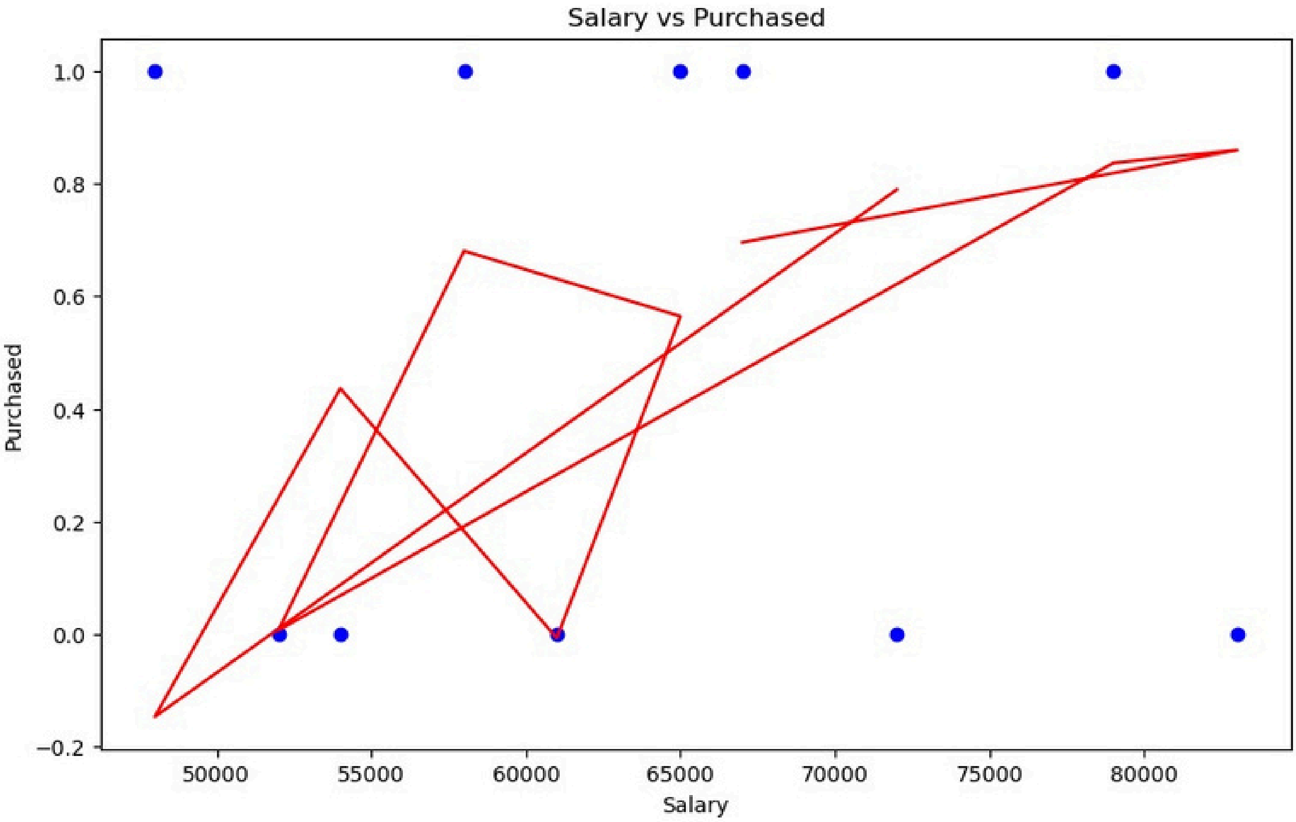

```
ANOVA Results:
F-Statistic: 4.3100, P-Value: 0.0602
Fail to reject the null hypothesis: There is no significant difference in mean Salary across countries.
```

In [19]:
```
# Name of the Experiment : Linear Regression
# EX NO : 11
# Register Number : 230701048
# Name : AWINTHIKA SANTHANAM
```

In [81]:
```
# Importing necessary libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_squared_error, r2_score
# Sample dataset
data = {
    'Country': ['France', 'Spain', 'Germany', 'Spain', 'Germany', 'France', 'Spain', 'France', 'France', 'France
    'Age': [44, 27, 30, 38, 40, 35, 38, 48, 50, 37],
    'Salary': [72000, 48000, 54000, 61000, 65000, 58000, 52000, 79000, 83000, 67000],
    'Purchased': ['No', 'Yes', 'No', 'No', 'Yes', 'Yes', 'No', 'Yes', 'No', 'Yes']
}

# Create DataFrame
df = pd.DataFrame(data)
# Handle missing values (if any)
df['Country'] = df['Country'].fillna(df['Country'].mode()[0])  # Filling missing countries
df['Age'] = df['Age'].fillna(df['Age'].mean())  # Filling missing age
df['Salary'] = df['Salary'].fillna(df['Salary'].mean())  # Filling missing salary
# Encoding 'Country' (categorical to numerical using OneHotEncoding)
from sklearn.preprocessing import OneHotEncoder
# Encode the 'Country' feature
encoder = OneHotEncoder(sparse_output=False)  # Updated parameter
country_encoded = encoder.fit_transform(df[['Country']])

# Combine the encoded 'Country' with 'Age' and 'Salary'
X = np.concatenate((country_encoded, df[['Age', 'Salary']].values), axis=1)
# Convert 'Purchased' to numeric (0 for 'No', 1 for 'Yes')
df['Purchased'] = df['Purchased'].map({'No': 0, 'Yes': 1})
y = df['Purchased'].values

# Split the dataset into training and testing sets (80% training, 20% testing) X_train, X_test, y_train, y_test =
train_test_split(X, y, test_size=0.2, random_state=42)
# Feature scaling (standardization)
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
# Initialize and train the Linear Regression model
model = LinearRegression()
model.fit(X_train, y_train)
# Make predictions
y_pred = model.predict(X_test)
# Evaluate the model
mse = mean_squared_error(y_test, y_pred) # Mean Squared Error
rmse = np.sqrt(mse) # Root Mean Squared Error
r2 = r2_score(y_test, y_pred) # R-squared score

 # Output evaluation metrics
 print(f"Mean Squared Error: {mse:.4f}")
 print(f"Root Mean Squared Error: {rmse:.4f}")
 print(f"R-squared: {r2:.4f}")
 # Visualize the comparison of predicted vs actual values
 plt.figure(figsize=(10, 6))
 plt.scatter(range(len(y_test)), y_test, color='blue', label='Actual')
 plt.scatter(range(len(y_test)), y_pred, color='red', label='Predicted')
 plt.title('Actual vs Predicted Purchase')
 plt.xlabel('Index')
 plt.ylabel('Purchased (0/1)')
 plt.legend()
 plt.show()

 # Optional: Visualizing the regression line for Salary vs Purchased
 plt.figure(figsize=(10, 6))
 plt.scatter(df['Salary'], df['Purchased'], color='blue')
 plt.plot(df['Salary'], model.predict(scaler.transform(np.concatenate((encoder.transform(df[['Country']]), df[['A
 plt.title('Salary vs Purchased')
 plt.xlabel('Salary')
 plt.ylabel('Purchased')
 plt.show()
```

Mean Squared Error: 1.0261
Root Mean Squared Error: 1.0130
R-squared: -3.1044




Salary vs Purchased
Purchased
Salary
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
50000
55000
60000
65000
70000
75000
80000

In [21]:
```
# Name of the Experiment : Logistic Regression # EX NO : 12
#Register Number : 230701048 # Name : AWINTHIKA SANTHANAM
```

In [101…
```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification_report
# Corrected dataset with equal-length lists
data = {
    "User ID": [15624510, 15810944, 15668575, 15603246, 15804002, 15683016, 15707098, 15686536, 15621310, 156823
              15746732, 15680352, 15820022, 15636760, 15717341, 15755018, 15691863, 15706071, 15654296, 157550
    "Gender": ['Male', 'Male', 'Female', 'Female', 'Male', 'Female', 'Male', 'Female', 'Male', 'Female',
              'Male', 'Female', 'Female', 'Male', 'Female', 'Male', 'Female', 'Male', 'Female', 'Male'],
    "Age": [19, 35, 26, 27, 19, 30, 35, 38, 28, 25, 35, 31, 35, 32, 34, 36, 46, 51, 50, 36],
    "EstimatedSalary": [19000, 20000, 43000, 57000, 76000, 85000, 150000, 60000, 62000, 55000,
                        90000, 50000, 58000, 45000, 80000, 33000, 41000, 23000, 20000, 33000],
    "Purchased": [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0]
}

# Convert the dictionary to a DataFrame
df = pd.DataFrame(data)
# Display the DataFrame to ensure it's correct
print("Dataset:\n", df.head())
# Preprocessing the data
df['Gender'] = df['Gender'].map({'Male': 0, 'Female': 1})  # Encoding 'Gender'
# Features and labels
features = df[['Gender', 'Age', 'EstimatedSalary']].values
labels = df['Purchased'].values

# Split the dataset into training and testing sets
x_train, x_test, y_train, y_test = train_test_split(features, labels, test_size=0.2, random_state=0)
# Standardize the features
scaler = StandardScaler()
x_train = scaler.fit_transform(x_train)
x_test = scaler.transform(x_test)

 # Train the Logistic Regression model
 model = LogisticRegression()
 model.fit(x_train, y_train)
 # Evaluate the model
 train_score = model.score(x_train, y_train)
 test_score = model.score(x_test, y_test)

 print(f"\nTraining Accuracy: {train_score:.4f}")
 print(f"Testing Accuracy: {test_score:.4f}")
 # Classification report
 y_pred = model.predict(x_test)
 print("\nClassification Report:\n", classification_report(y_test, y_pred))

 # Predicting on the entire dataset (for the sake of example)
 y_pred_full = model.predict(features)
 print("\nFull dataset predictions:\n", y_pred_full)
```

OUTPUT

```
Dataset:
    User ID  Gender  Age  EstimatedSalary  Purchased
0  15624510    Male   19            19000          0
1  15810944    Male   35            20000          0
2  15668575  Female   26            43000          0
3  15603246  Female   27            57000          0
4  15804002    Male   19            76000          0

Training Accuracy: 0.9375
Testing Accuracy: 1.0000
Classification Report:
              precision    recall  f1-score   support
           0       1.00      1.00      1.00         3
           1       1.00      1.00      1.00         1
    accuracy                           1.00         4
   macro avg       1.00      1.00      1.00         4
weighted avg       1.00      1.00      1.00         4



Full dataset predictions:
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
```