Notebook

February 25, 2025

1 *Merged Jupyter Notebook*

from file: PMRP_1

2 OM CHOKSI 23AIML010 PMRP DAY 1 ASSIGNMENT 1

2.1 Question 1

Separate the given list based on the data types. List1 = [“Aakash”, 90, 77, “B”, 3.142,12]

[2]:
```
List1 = ["Aakash", 90, 77, "B", 3.142,12]
string = []
inte = []
flo = []
for i in List1:
    if type(i) == str:
        string.append(i)
    elif type(i) == int:
        inte.append(i)
    else:
        flo.append(i)
print(f"strings are {string}\ninteger are {inte}\nfloat are {flo}")
```

```
strings are ['Aakash', 'B']
integer are [90, 77, 12]
float are [3.142]
```

2.2 Question 2

Consider you are collecting data from students on their heights (in cms) containing numbers as 140,145,153, etc. Use Numpy library and randomly generate 50 such numbers in the range 150 to 180. Which data type would you use list or array to store such data? Calculate measures of central tendency of this data stored in list as well as array.

[3]:
```
import numpy as np
import statistics as st

height = np.random.randint(150,180,50)
```

```
print(height)
print(type(height))


mean=np.mean(height)
median=np.median(height)
mode=st.mode(height)
std=np.std(height)
var=np.var(height)

print(f"Mean of given data: {mean}")
print(f"Median of given data: {median}")
print(f"Mode of given data: {mode}")
print(f"Standard deviation of given data: {std}")
print(f"Variance of given data: {var}")
```

```
[155 153 155 177 169 174 154 156 161 158 153 158 156 155 153 155 170 164
 165 160 173 155 152 175 172 175 172 170 163 153 161 177 160 177 165 151
 152 171 156 169 153 178 173 172 157 171 172 170 155 152]
<class 'numpy.ndarray'>
Mean of given data: 163.06
Median of given data: 161.0
Mode of given data: 155
Standard deviation of given data: 8.755364070100113
Variance of given data: 76.6564
```

2.3 OPTIONAL QUESTION

find mode of given range using maths basic formulas

[5]:
```
import numpy as np

height = np.random.randint(150, 180, 50)


freq = {}
mode = None
max_count = 0

for h in height:
    if h in freq:
        freq[h] += 1
    else:
        freq[h] = 1

for key in freq:
    if freq[key] > max_count:
        max_count = freq[key]
```

```
        mode = key

print("Mode:", mode)
```

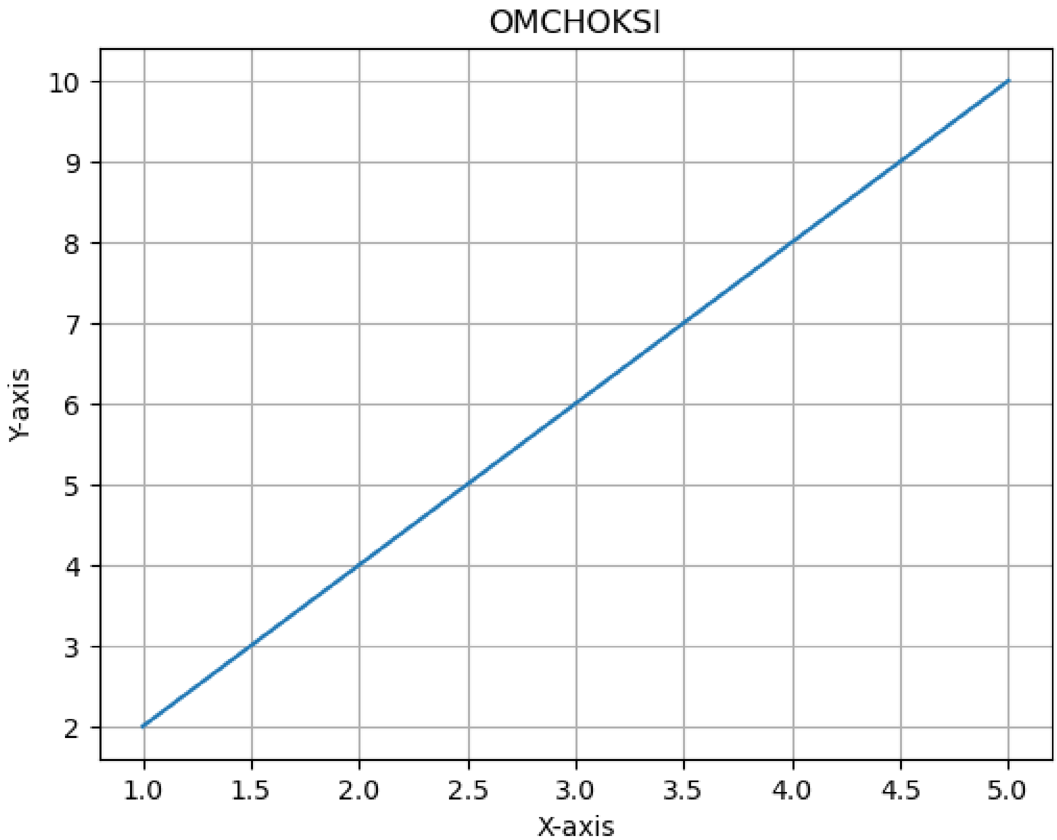
```
Mode: 154
```

2.4 Question 3

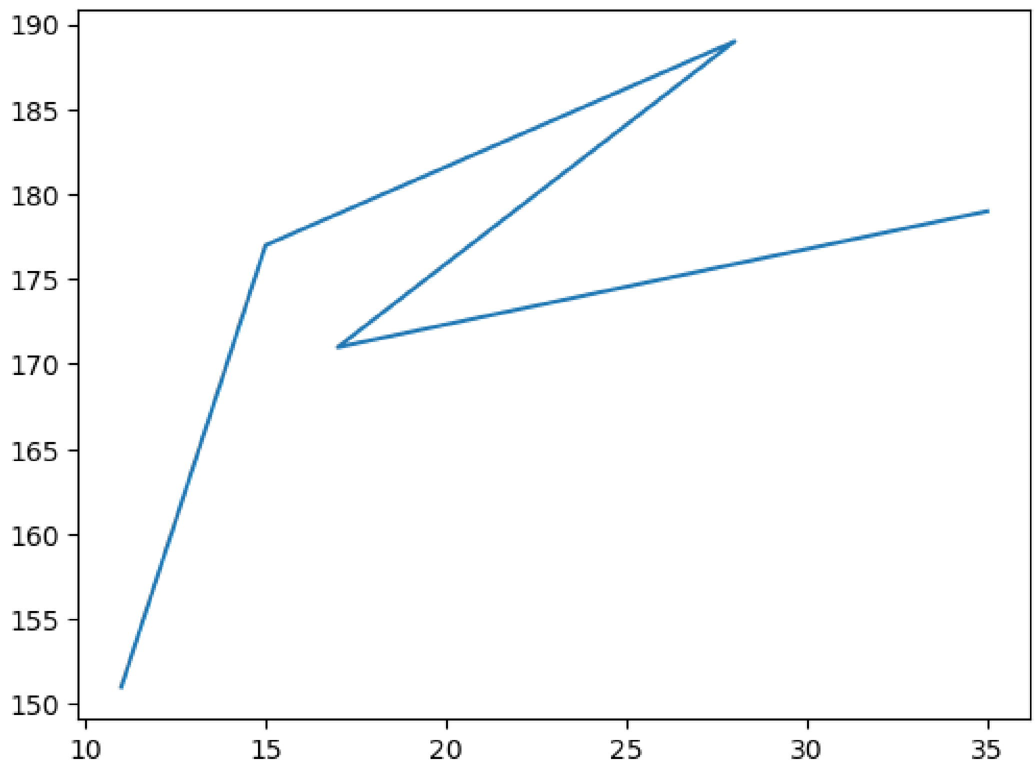
Part 1:-

Create the function that will plot simple line chart for any given data.

[7]:
```
import matplotlib.pyplot as plt
def linePLOT(x,y):
  plt.plot(x,y)
  plt.xlabel("X-axis")
  plt.ylabel("Y-axis")
  plt.title("OMCHOKSI")
  plt.grid(True)
  plt.show()

x=[1,2,3,4,5]
y=[2,4,6,8,10]
linePLOT(x,y)

data1 = np.random.randint(1, 50, 5)
data2 = np.random.randint(150, 200, 5)
plt.plot(data1, data2)
```



[7]: [<matplotlib.lines.Line2D at 0x19632b65d90>]



2.5 Question 3

Part 2:-

Create the recursive function for finding out factorial of a given number

[10]:
```
def fact(n):
    if n == 1:
        return 1
    return n * fact(n - 1)

n = int(input())
print(fact(n))
```

```
10
```

```
3628800
```

2.6 Question 3

Part 3:-

Create generator function for Fibonacci series and print out first 10 numbers.

[13]:
```
def fibonacci_generator(n):
    x, y = 0, 1
    for _ in range(n):
        yield x
        x,y=y,x+y
fib_gen = fibonacci_generator(10)
for num in fib_gen:
    print(num)
```

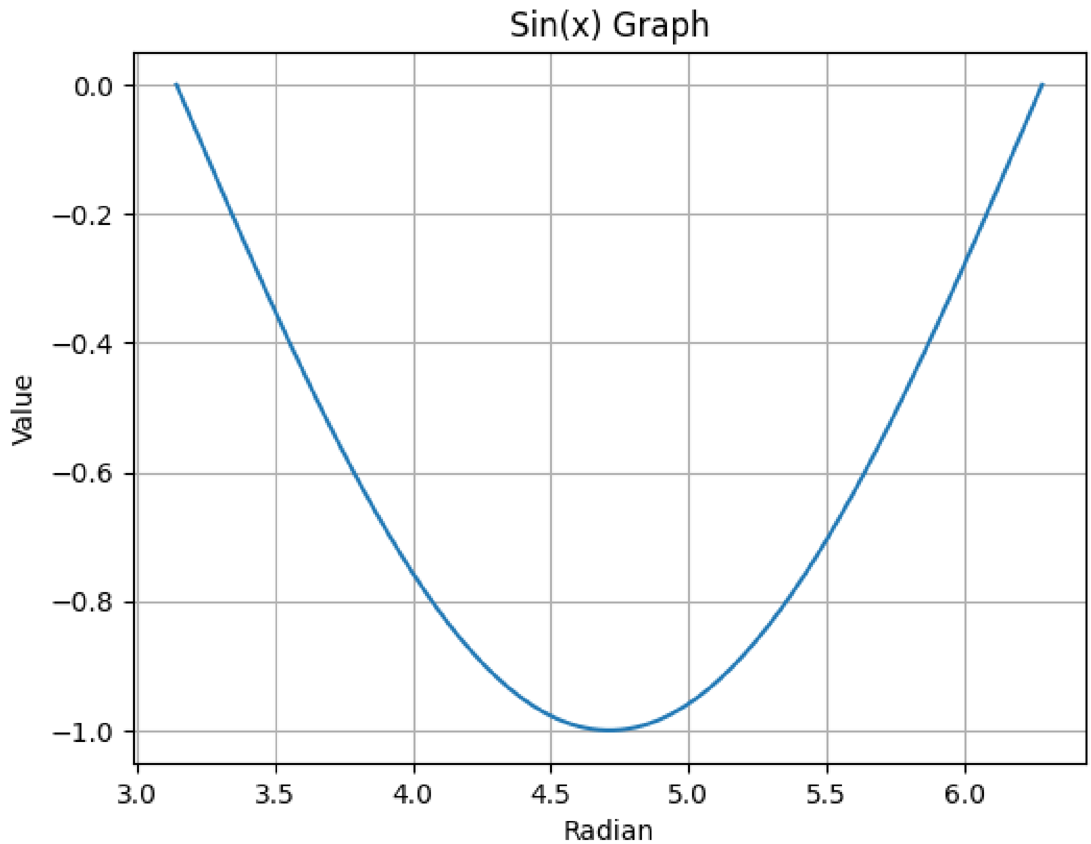
```
0
1
1
2
3
5
8
13
21
34
```

2.7 Question 3

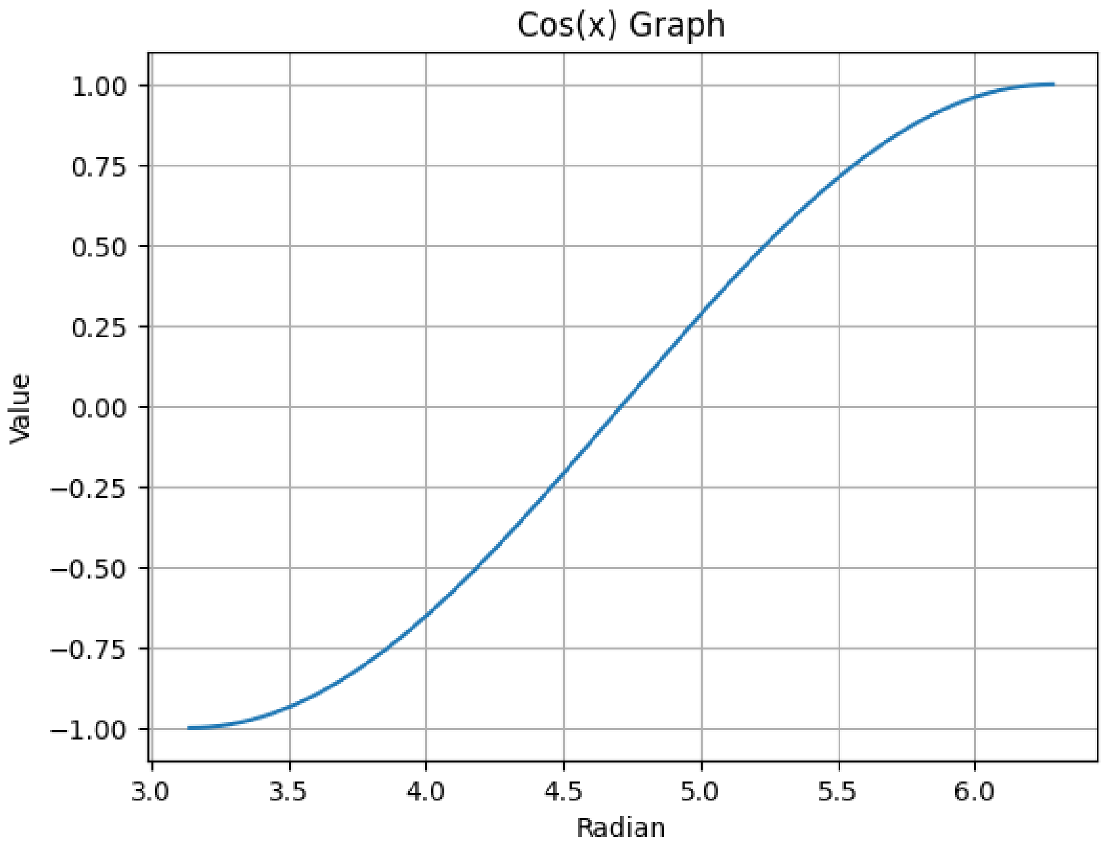
Part 4:-

Plot the graphs for trigonometric functions sin, cos, tan, cot, sec & cosec for the values pi to 2pi.

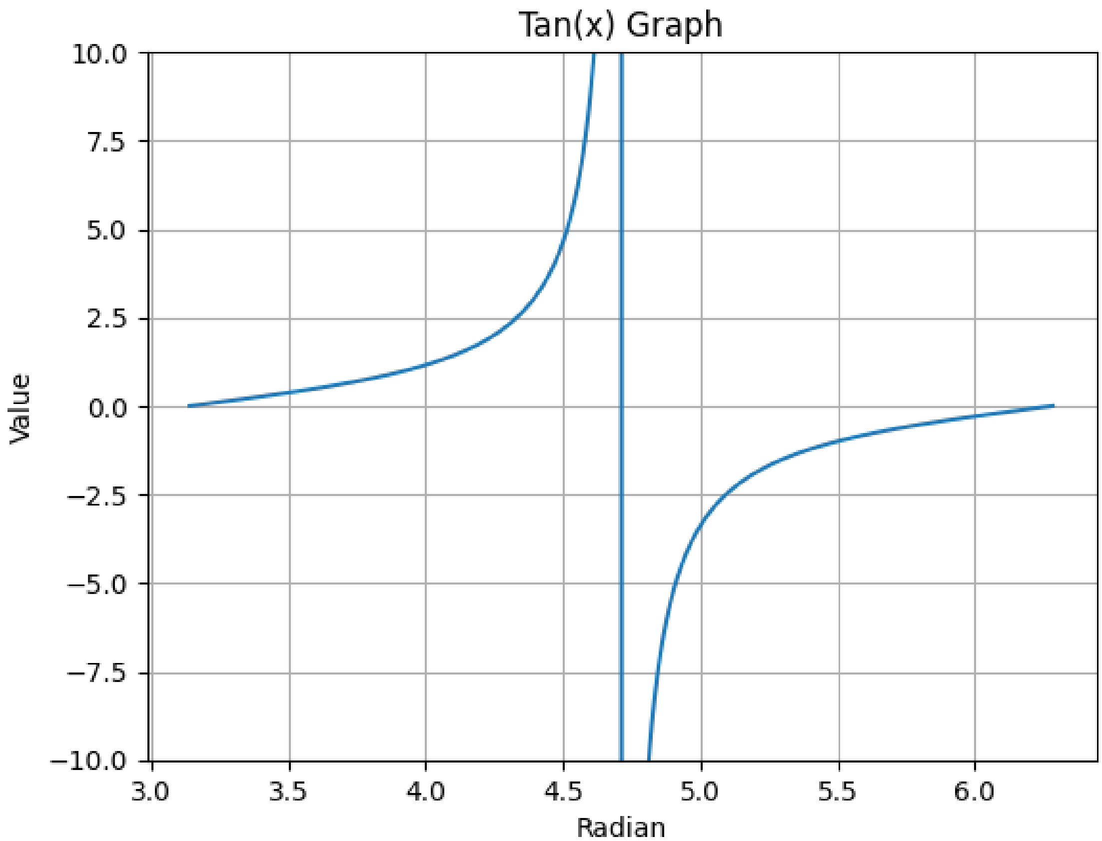
[57]:
```
import math
x = np.linspace(math.pi, 2 * math.pi, 10000)
y = np.sin(x)
plt.grid()
plt.xlabel("Radian")
plt.ylabel("Value")
plt.title("Sin(x) Graph")
plt.plot(x, y)
plt.show()
```



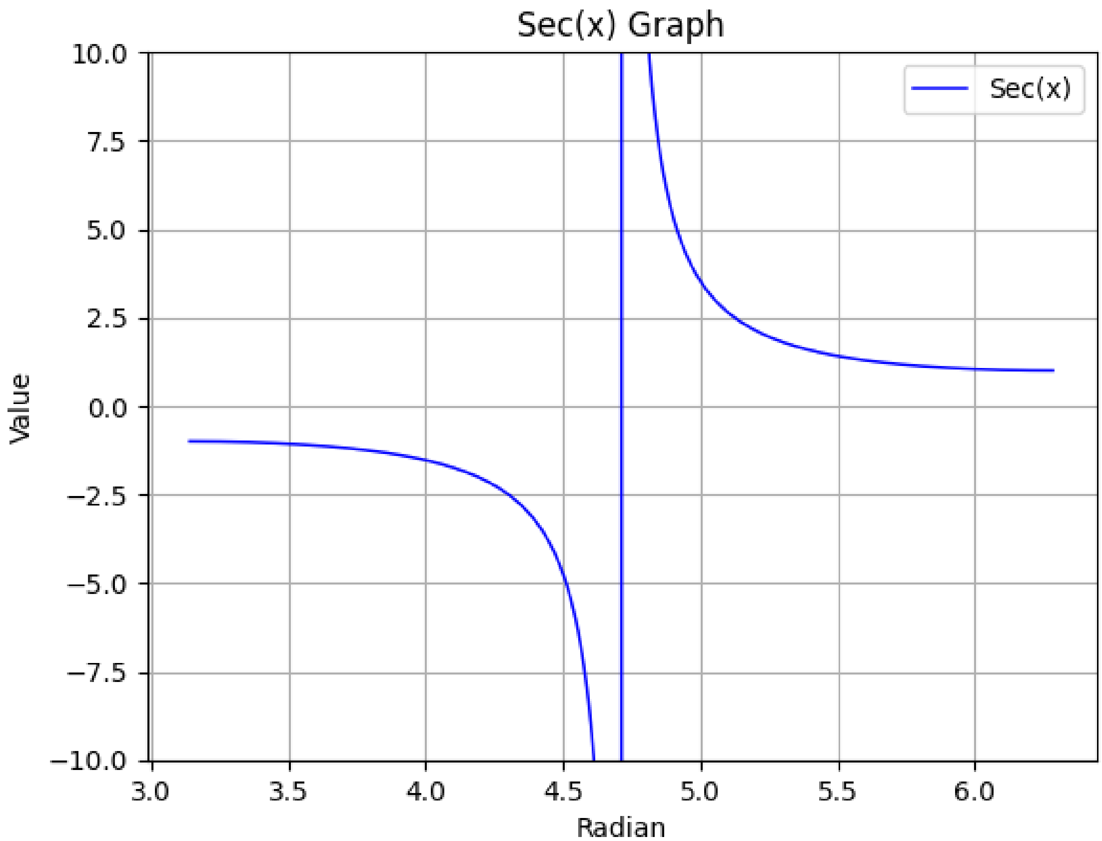
[58]:
```
import math
x = np.linspace(math.pi, 2 * math.pi, 10000)
y = np.cos(x)
plt.grid()
plt.xlabel("Radian")
plt.ylabel("Value")
plt.title("Cos(x) Graph")
plt.plot(x, y)
plt.show()
```



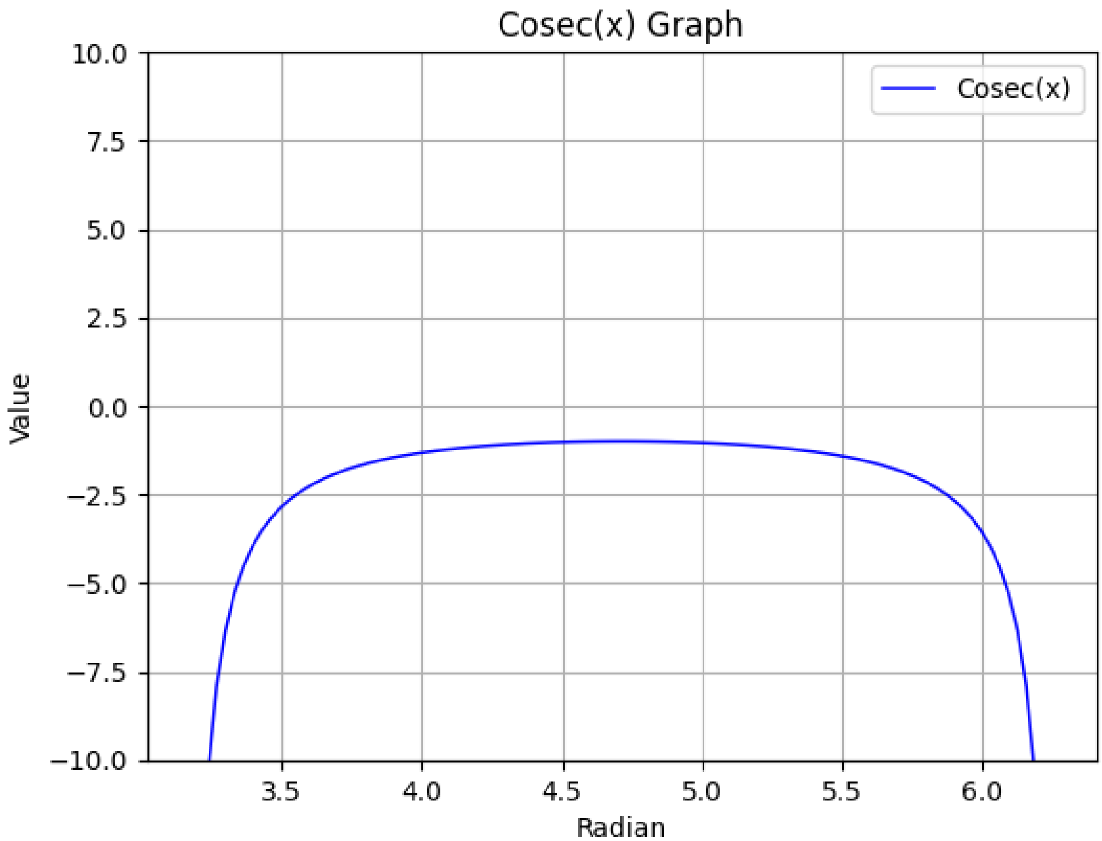
[59]:
```
import math
x = np.linspace(math.pi, 2 * math.pi, 10000)
y = np.tan(x)
plt.grid()
plt.xlabel("Radian")
plt.ylabel("Value")
plt.title("Tan(x) Graph")
plt.ylim(-10, 10)
plt.plot(x, y)
plt.show()
```



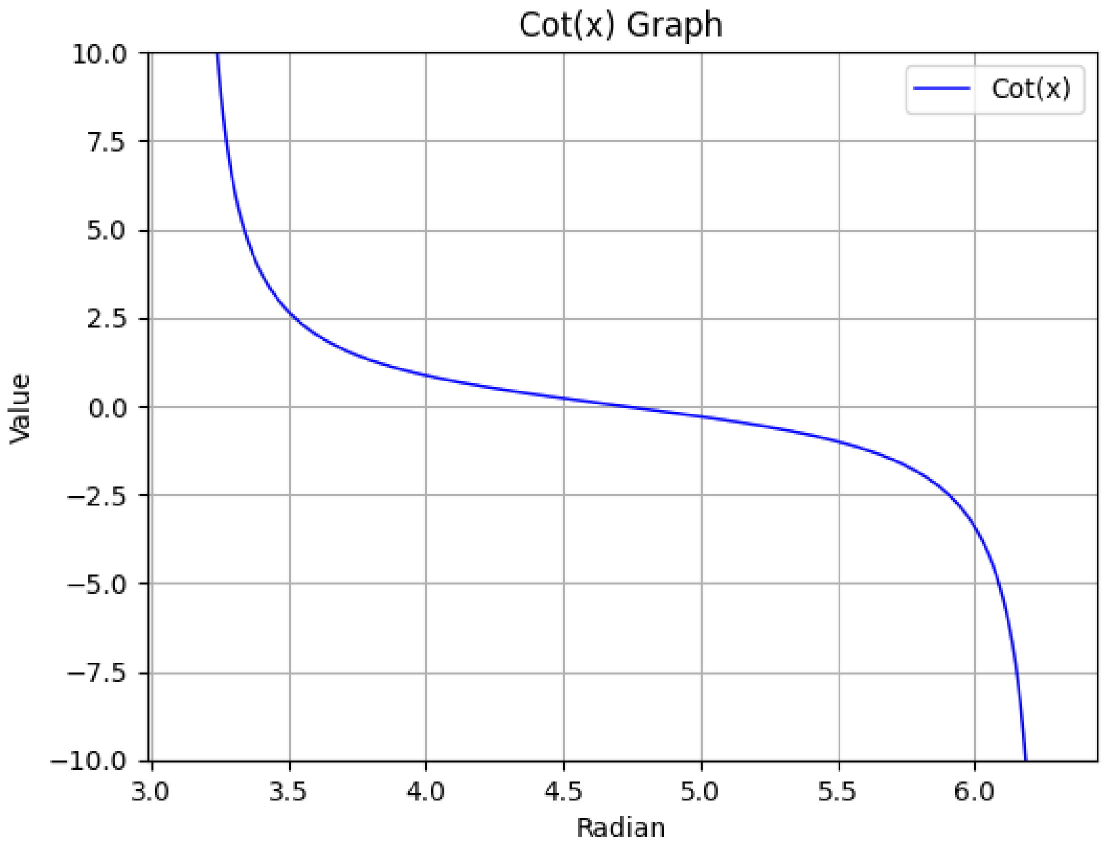
[60]:
```
import math
x = np.linspace(math.pi, 2 * math.pi, 10000)
y = 1 / np.cos(x)
y[np.abs(np.cos(x)) < 1e-5] = np.nan
plt.grid()
plt.xlabel("Radian")
plt.ylabel("Value")
plt.title("Sec(x) Graph")
plt.plot(x, y, linewidth = 1.1, color = 'blue', label = "Sec(x)")
plt.legend()
plt.ylim(-10, 10)
plt.show()
```



[61]:
```
import math
x = np.linspace(math.pi, 2 * math.pi, 100)
y = 1 / np.sin(x)
y[np.abs(np.sin(x)) < 1e-5] = np.nan
plt.grid()
plt.xlabel("Radian")
plt.ylabel("Value")
plt.title("Cosec(x) Graph")
plt.plot(x, y, linewidth = 1.1, color = 'blue', label = "Cosec(x)")
plt.legend()
plt.ylim(-10, 10)
plt.show()
```



[62]:
```
import math
x = np.linspace(math.pi, 2 * math.pi, 10000)
y = 1 / np.tan(x)
y[np.abs(np.tan(x)) < 1e-5] = np.nan
plt.grid()
plt.xlabel("Radian")
plt.ylabel("Value")
plt.title("Cot(x) Graph")
plt.plot(x, y, linewidth = 1.1, color = 'blue', label = "Cot(x)")
plt.legend()
plt.ylim(-10, 10)
plt.show()
```



2.8 Question 4

Consider you want create dataset with ages of people in your surroundings. Use input method to ask user their age, store those ages in appropriate data type. Apply error handling that will not accept more than 130 or less than 0 inputs, raise appropriate prompts to guide users.

[63]:
```
def coll():
    ages = []

    while True:
        usr = input("Enter Age of the person\nEnter q to exit")

        if usr == 'q':
            break
        try:
            usr = int(usr)
            if(usr < 0 or usr > 130):
                print("Invalid input")
            else:
                ages.append(usr)
```

```python
        except ValueError:
            print("Invallid input")
    return ages
use = coll()
print(use)
```

```
Enter Age of the person
Enter q to exit 5
Enter Age of the person
Enter q to exit q
```

```
[5]
```

2.9 Question 5

Create class as Employees with inputs as name, department and salary. Salary should be encapsulated.

[64]:
```python
class Employees:
    def __init__(self, name, department, salary):
        self.name = name
        self.department = department
        self.__salary = salary
    def setsalary(self, slary):
        self.__salary = slary
    def getsalary(self):
        return self.__salary
    def print(self):
        print(f"The Employee name is {self.name}\nThe department is {self.
 ↪department}\nThe salary is {self.__salary}")
e1 = Employees("Yash", "AIML", 100000000)
e1.print()
```

```
The Employee name is Yash
The department is AIML
The salary is 100000000
```

2.10 Question 6

Create two 3d arrays as matrices. Perform matrix operations (Addition, Multiplication, dot product, inverse, determinant) on those matrices. Explain identity matrix, multiply each matrix with identity matrix and record the observation. (All operations should be done with Numpy library)

[65]:
```python
import numpy as np

arr1 = np.array([[[1, 2], [3, 4]], [[5, 6], [7, 8]]])
arr2 = np.array([[[9, 10], [11, 12]], [[13, 14], [15, 16]]])

print("Matrix Addition:\n", arr1 + arr2)
```

```python
print("\nElement-wise Multiplication:\n", arr1 * arr2)
print("\nDot Product:\n", np.matmul(arr1, arr2))
print("\nInverse of arr1:\n", np.linalg.inv(arr1))
print("\nDeterminants of arr1:\n", np.linalg.det(arr1))
print("\nIdentity Matrix:\n", np.eye(2))
print("\narr1 multiplied with Identity Matrix:\n", np.array([np.dot(np.eye(2),␣
 ↪mat) for mat in arr1]))
```

```
Matrix Addition:
 [[[10 12]
  [14 16]]

 [[18 20]
  [22 24]]]

Element-wise Multiplication:
 [[[  9  20]
  [ 33  48]]

 [[ 65  84]
  [105 128]]]

Dot Product:
 [[[ 31  34]
  [ 71  78]]

 [[155 166]
  [211 226]]]

Inverse of arr1:
 [[[-2.   1. ]
  [ 1.5 -0.5]]

 [[-4.   3. ]
  [ 3.5 -2.5]]]

Determinants of arr1:
 [-2. -2.]

Identity Matrix:
 [[1. 0.]
 [0. 1.]]

arr1 multiplied with Identity Matrix:
 [[[1. 2.]
  [3. 4.]]

 [[5. 6.]
```

```
  [7. 8.]]]
```

from file: PMRP_2

23AIML010 OM CHOKSI PMRP ASSIGNMENT 2

[46]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

1. Find out the outliers in each numerical column
2. Find out gender distribution in this data.
3. What is average daily usage of data? Explore gender wise and device wise variation in average usage of data.
4. Which device have highest popularity based on Age and Gender?

WE WILL LOAD CSV FILE AND GET BASIC DESCRIPTION OF DATA

[47]:
```
data1 =  pd.read_csv("data.csv")
data.head(),data.describe(),data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 6 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   Age          200 non-null    int64
 1   Sex          200 non-null    object
 2   BP           200 non-null    object
 3   Cholesterol  200 non-null    object
 4   Na_to_K      200 non-null    float64
 5   Drug         200 non-null    object
dtypes: float64(1), int64(1), object(4)
memory usage: 9.5+ KB
```

[47]:
```
(    Age Sex      BP Cholesterol  Na_to_K   Drug
 0   23   F    HIGH        HIGH   25.355  drugY
 1   47   M     LOW        HIGH   13.093  drugC
 2   47   M     LOW        HIGH   10.114  drugC
 3   28   F  NORMAL        HIGH    7.798  drugX
 4   61   F     LOW        HIGH   18.043  drugY,
                Age     Na_to_K
 count  200.000000  200.000000
 mean    44.315000   16.084485
 std     16.544315    7.223956
 min     15.000000    6.269000
 25%     31.000000   10.445500
 50%     45.000000   13.936500
 75%     58.000000   19.380000
```

```
max      74.000000   38.247000,
None)
```

Find out the outliers in each numerical column using pandas

[48]:
```python
def detect_outliers(data1, column):
    Q1 = data1[column].quantile(0.25)
    Q3 = data1[column].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    outliers = data1[(data1[column] < lower_bound) | (data1[column] >
 ↪upper_bound)]
    return outliers


numerical_columns = data1.select_dtypes(include=np.number).columns

outliers_dict = {col: detect_outliers(data1, col) for col in numerical_columns}

for col, outliers in outliers_dict.items():
    print(f"Outliers in {col}:\n", outliers)
```

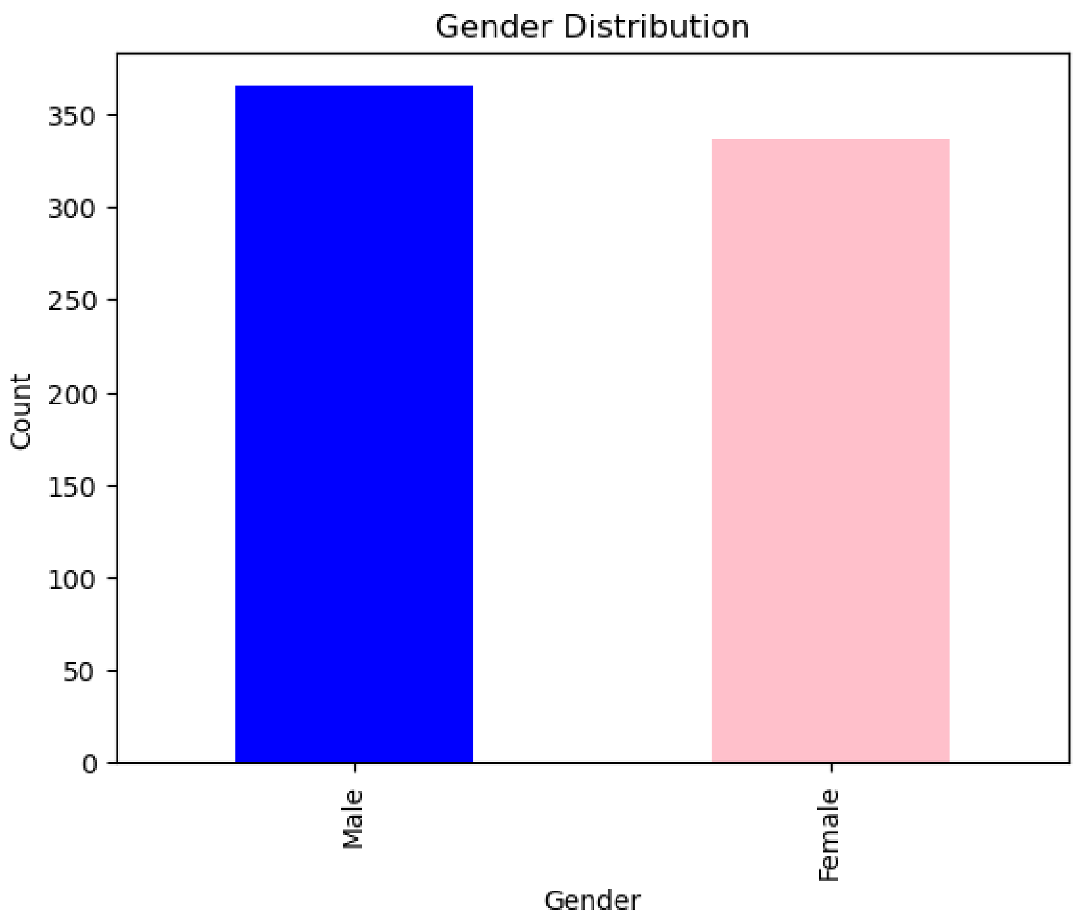
```
Outliers in User ID:
 Empty DataFrame
Columns: [User ID, Device Model, Operating System, App Usage Time (min/day),
Screen On Time (hours/day), Battery Drain (mAh/day), Number of Apps Installed,
Data Usage (MB/day), Age, Gender, User Behavior Class]
Index: []
Outliers in App Usage Time (min/day):
 Empty DataFrame
Columns: [User ID, Device Model, Operating System, App Usage Time (min/day),
Screen On Time (hours/day), Battery Drain (mAh/day), Number of Apps Installed,
Data Usage (MB/day), Age, Gender, User Behavior Class]
Index: []
Outliers in Screen On Time (hours/day):
 Empty DataFrame
Columns: [User ID, Device Model, Operating System, App Usage Time (min/day),
Screen On Time (hours/day), Battery Drain (mAh/day), Number of Apps Installed,
Data Usage (MB/day), Age, Gender, User Behavior Class]
Index: []
Outliers in Battery Drain (mAh/day):
 Empty DataFrame
Columns: [User ID, Device Model, Operating System, App Usage Time (min/day),
Screen On Time (hours/day), Battery Drain (mAh/day), Number of Apps Installed,
Data Usage (MB/day), Age, Gender, User Behavior Class]
Index: []
Outliers in Number of Apps Installed:
```

```
 Empty DataFrame
Columns: [User ID, Device Model, Operating System, App Usage Time (min/day),
Screen On Time (hours/day), Battery Drain (mAh/day), Number of Apps Installed,
Data Usage (MB/day), Age, Gender, User Behavior Class]
Index: []
Outliers in Data Usage (MB/day):
 Empty DataFrame
Columns: [User ID, Device Model, Operating System, App Usage Time (min/day),
Screen On Time (hours/day), Battery Drain (mAh/day), Number of Apps Installed,
Data Usage (MB/day), Age, Gender, User Behavior Class]
Index: []
Outliers in Age:
 Empty DataFrame
Columns: [User ID, Device Model, Operating System, App Usage Time (min/day),
Screen On Time (hours/day), Battery Drain (mAh/day), Number of Apps Installed,
Data Usage (MB/day), Age, Gender, User Behavior Class]
Index: []
Outliers in User Behavior Class:
 Empty DataFrame
Columns: [User ID, Device Model, Operating System, App Usage Time (min/day),
Screen On Time (hours/day), Battery Drain (mAh/day), Number of Apps Installed,
Data Usage (MB/day), Age, Gender, User Behavior Class]
Index: []
```

2. Find out gender distribution in this data.

[49]:
```
gender_distribution = data1['Gender'].value_counts()
print("Gender Distribution:")
print(gender_distribution)

gender_distribution.plot(kind='bar', color=['blue', 'pink'], title='Gender␣
↪Distribution')
plt.xlabel('Gender')
plt.ylabel('Count')
plt.show()
```

```
Gender Distribution:
Gender
Male      365
Female    336
Name: count, dtype: int64
```

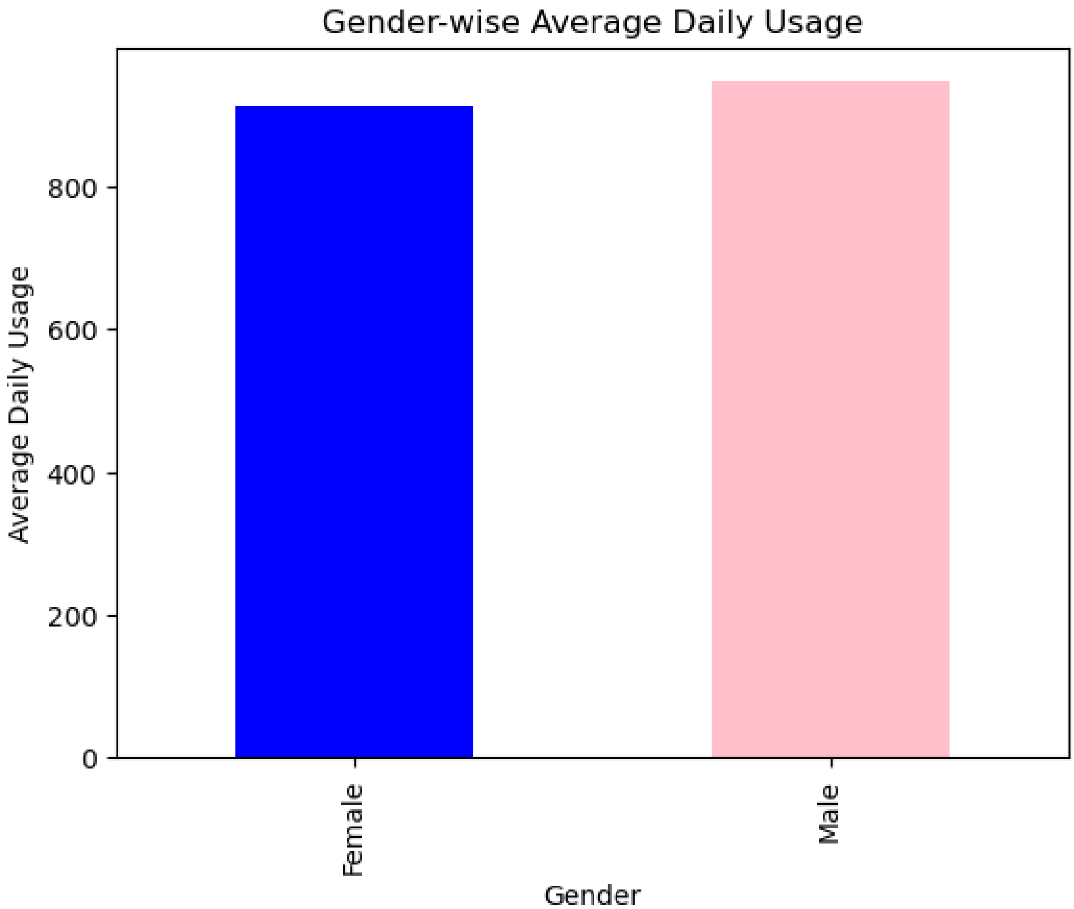


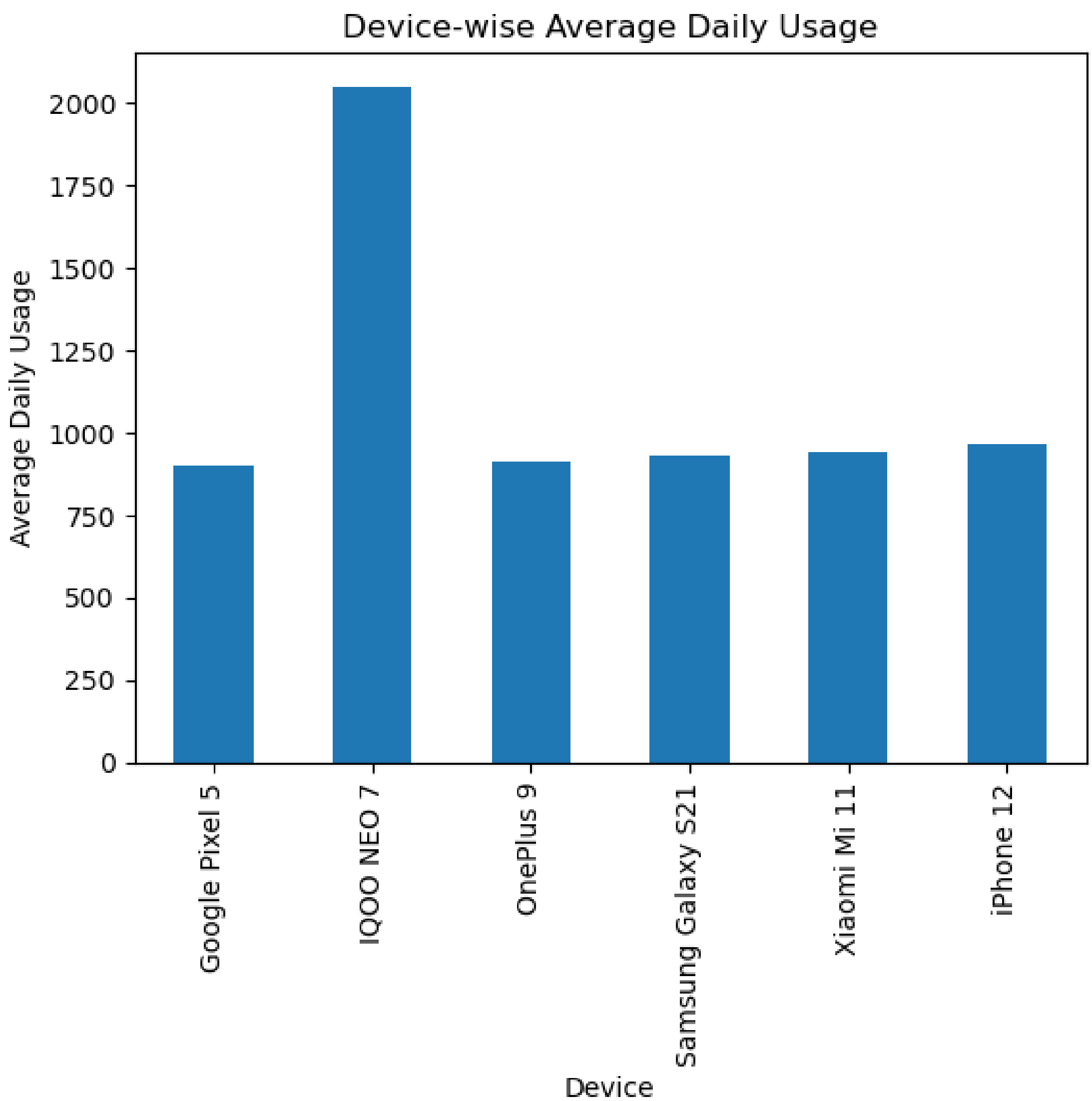
3. What is average daily usage of data? Explore gender wise and device wise variation in average usage of data.

[50]:
```
average_daily_usage = data1['Data Usage (MB/day)'].mean()
print(f"Overall Average Daily Usage: {average_daily_usage}")

gender_avg_usage = data1.groupby('Gender')['Data Usage (MB/day)'].mean()
device_avg_usage = data1.groupby('Device Model')['Data Usage (MB/day)'].mean()

print("Gender-wise Average Daily Usage:")
print(gender_avg_usage)

print("Device-wise Average Daily Usage:")
print(device_avg_usage)

gender_avg_usage.plot(kind='bar', color=['blue', 'pink'], title='Gender-wise␣
↪Average Daily Usage')
plt.xlabel('Gender')
```

```python
plt.ylabel('Average Daily Usage')
plt.show()

device_avg_usage.plot(kind='bar', title='Device-wise Average Daily Usage')
plt.xlabel('Device')
plt.ylabel('Average Daily Usage')
plt.show()
```

```
Overall Average Daily Usage: 931.3380884450785
Gender-wise Average Daily Usage:
Gender
Female    914.321429
Male      947.002740
Name: Data Usage (MB/day), dtype: float64
Device-wise Average Daily Usage:
Device Model
Google Pixel 5         897.704225
IQOO NEO 7            2048.000000
OnePlus 9              911.120301
Samsung Galaxy S21     931.872180
Xiaomi Mi 11           940.164384
iPhone 12              965.506849
Name: Data Usage (MB/day), dtype: float64
```


Gender-wise Average Daily Usage
Average Daily Usage
0
200
400
600
800
Female
Male
Gender

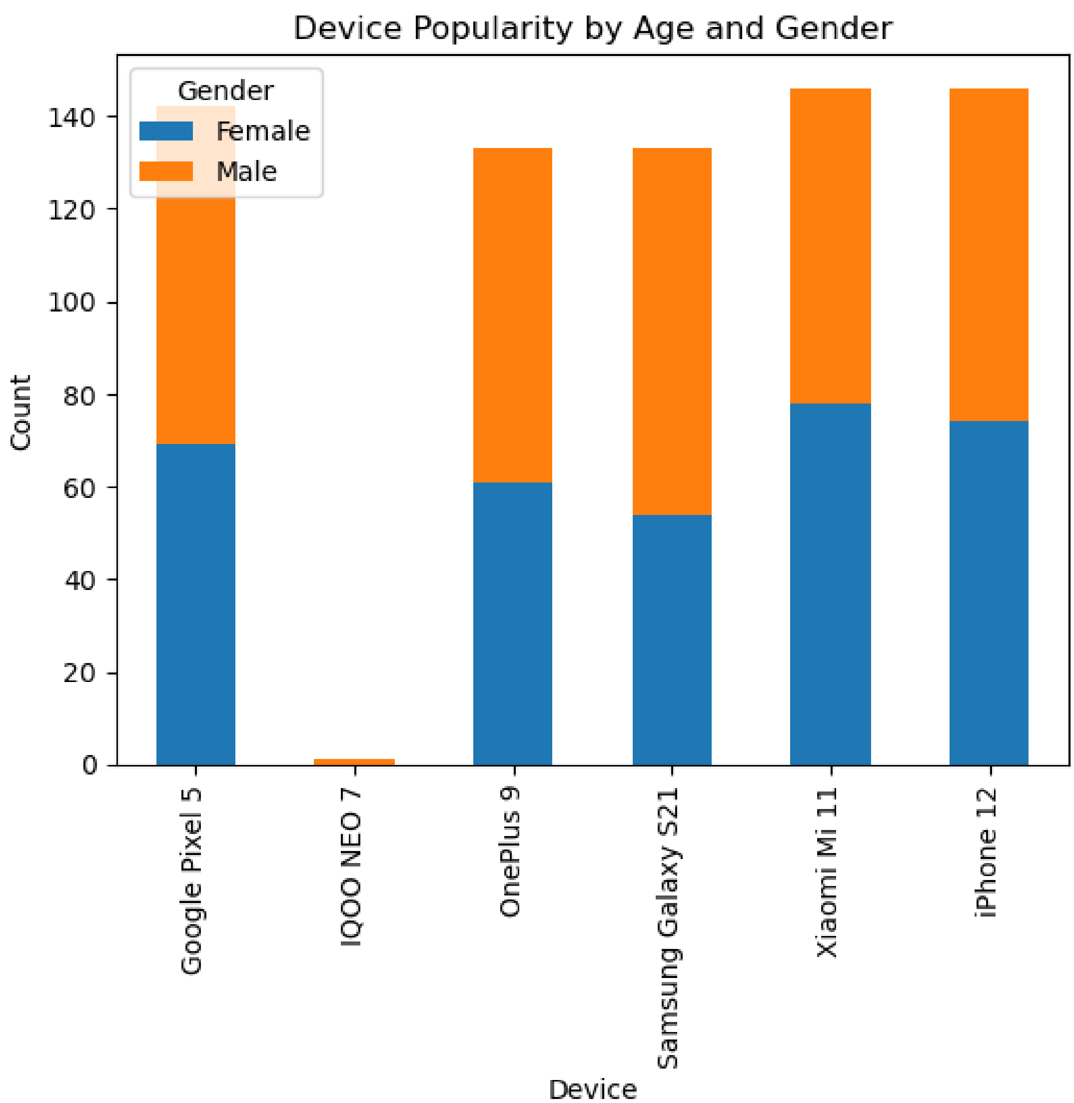


4. Which device have highest popularity based on Age and Gender?

[51]:
```
pAgedevice = data1.groupby(['Age', 'Gender'])['Device Model'].agg(lambda x: x.
    ↪mode().iloc[0])
pAgedevice

device_popularity = data1.groupby(['Device Model', 'Gender'])['Age'].count()
highest_popularity = device_popularity.idxmax()
print(f"Device with highest popularity based on Age and Gender:␣
    ↪{highest_popularity}")

popularity_pivot = data1.pivot_table(index='Device Model', columns='Gender',␣
    ↪values='Age', aggfunc='count')
```

```
popularity_pivot.plot(kind='bar', stacked=True, title='Device Popularity by Age and Gender')
plt.xlabel('Device')
plt.ylabel('Count')
plt.show()
```

```
Device with highest popularity based on Age and Gender: ('Samsung Galaxy S21',
'Male')
```



CLASSWORK PMRP

Plot Distribution curve for Age along with histogram. Calculate Q1,Q2,Q3 and IQR without using np.percentile function. Calculate lower and upper bound values. Plot box plot as well for Age. Calculate frequency table as well for age column. Ranges for this can be in multiple of 10, e.g. 10-20,20-30,etc..

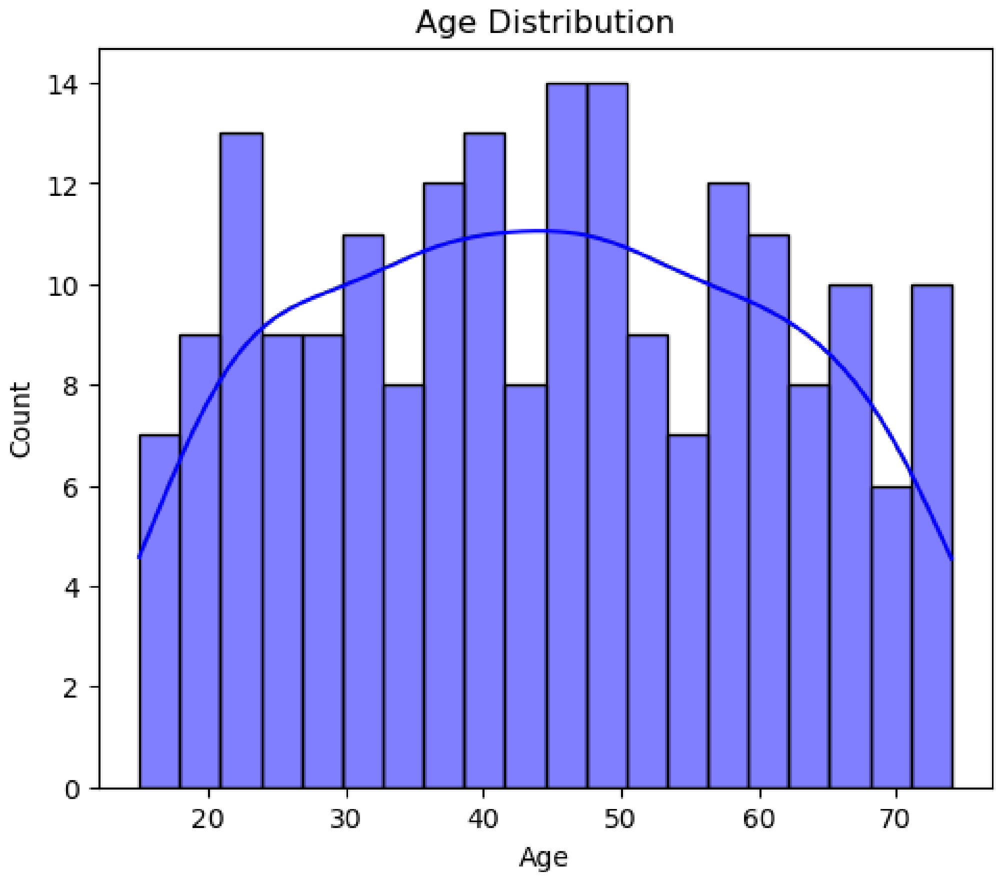
[52]:
```
data2=pd.read_csv("drug200.csv")
data2.head(),data.info(),data.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 6 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   Age          200 non-null    int64
 1   Sex          200 non-null    object
 2   BP           200 non-null    object
 3   Cholesterol  200 non-null    object
 4   Na_to_K      200 non-null    float64
 5   Drug         200 non-null    object
dtypes: float64(1), int64(1), object(4)
memory usage: 9.5+ KB
```

[52]:
```
(   Age Sex      BP Cholesterol  Na_to_K   Drug
 0   23   F    HIGH        HIGH   25.355  drugY
 1   47   M     LOW        HIGH   13.093  drugC
 2   47   M     LOW        HIGH   10.114  drugC
 3   28   F  NORMAL        HIGH    7.798  drugX
 4   61   F     LOW        HIGH   18.043  drugY,
 None,
               Age     Na_to_K
 count  200.000000  200.000000
 mean    44.315000   16.084485
 std     16.544315    7.223956
 min     15.000000    6.269000
 25%     31.000000   10.445500
 50%     45.000000   13.936500
 75%     58.000000   19.380000
 max     74.000000   38.247000)
```

1.Plot Distribution curve for Age along with histogram.

[53]:
```
plt.figure(figsize=(6, 5))
sns.histplot(data2["Age"], kde=True, color='blue',bins=20)
plt.title('Age Distribution')
plt.show()
```



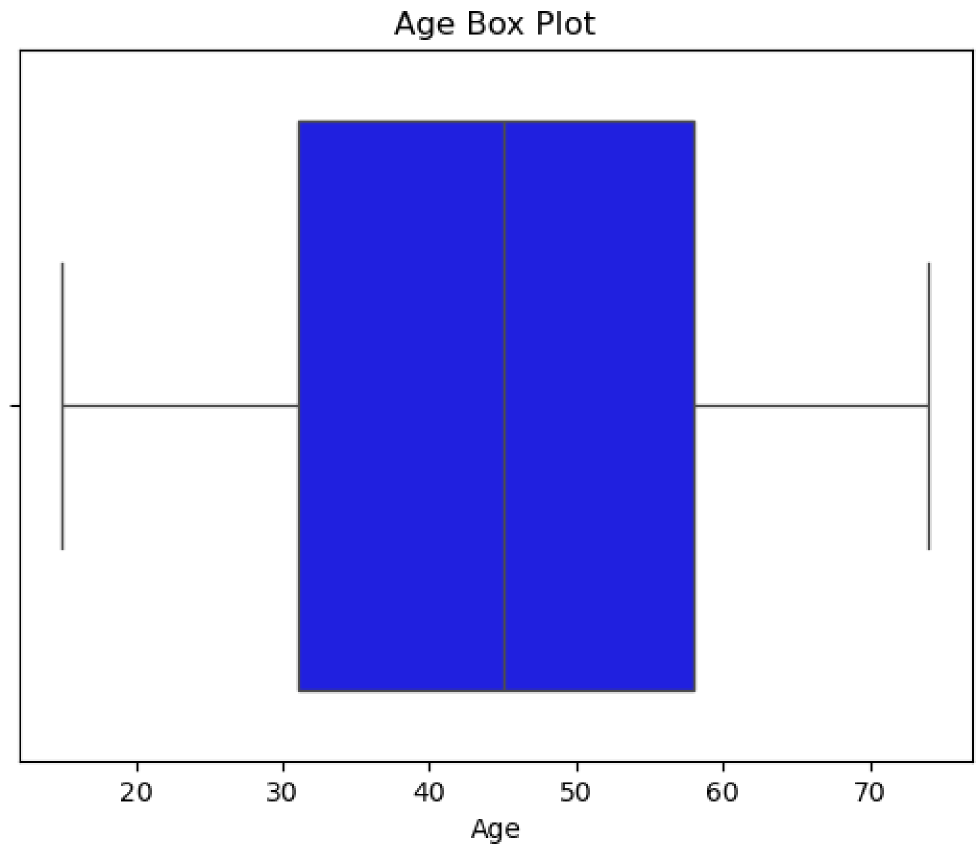
2.Calculate Q1,Q2,Q3 and IQR without using np.percentile function. Calculate lower and upper bound values.

[54]:
```
def q_vals(col):
    q1 = col.sort_values().iloc[len(col) // 4]
    q2 = col.median()
    q3 = col.sort_values().iloc[(len(col) * 3) // 4]
    iqr = q3 - q1
    lb = q1 - 1.5 * iqr
    ub = q3 + 1.5 * iqr
    return q1, q2, q3, iqr, lb, ub

q1, q2, q3, iqr, lb, ub = q_vals(data2["Age"])

print(f"Q1: {q1}, Q2: {q2}, Q3: {q3}, IQR: {iqr}, LB: {lb}, UB: {ub}")
```

```
Q1: 31, Q2: 45.0, Q3: 58, IQR: 27, LB: -9.5, UB: 98.5
```

Plot box plot as well for Age.

[55]:
```
sns.boxplot(x=data2["Age"], color='blue')
plt.title('Age Box Plot')
plt.show()
```



4.Calculate frequency table as well for age column. Ranges for this can be in multiple of 10, e.g. 10-20,20-30,etc..

[56]:
```
bins = list(range(10, data2["Age"].max() + 10, 10))
age_freq = pd.cut(data2["Age"], bins=bins).value_counts().sort_index()
print(age_freq)
```

```
Age
(10, 20]    16
(20, 30]    32
(30, 40]    39
(40, 50]    40
(50, 60]    33
(60, 70]    30
(70, 80]    10
Name: count, dtype: int64
```

SECOND DRAFT

1. What is a Gender distribution of data?
2. What percent of total population have high cholesterol & high BP?
3. What are the unique values of Drugs given in data? (df["Drug"].unique)
4. How many people have high cholesterol before age of 30?

1. What is a Gender distribution of data?

[58]:
```
g_dist = data2['Sex'].value_counts()
print(g_dist)
```

```
Sex
M    104
F     96
Name: count, dtype: int64
```

2. What percent of total population have high cholesterol & high BP?

[59]:
```
hc_hbp = len(data2[(data2['Cholesterol'] == 'HIGH') & (data2['BP'] == 'HIGH')])
total = len(data2)
pct_hc_hbp = (hc_hbp / total) * 100
print(f"{pct_hc_hbp:.2f}%")
```

```
17.50%
```

3. What are the unique values of Drugs given in data? (df["Drug"].unique)

[61]:
```
d_vals = data2['Drug'].unique()
print(d_vals)
```

```
['drugY' 'drugC' 'drugX' 'drugA' 'drugB']
```

4. How many people have high cholesterol before age of 30?

[62]:
```
hc_under_30 = len(data2[(data2['Cholesterol'] == 'HIGH') & (data2['Age'] < 30)])
print(hc_under_30)
```

```
26
```

[ ]:
```

```

from file: PMRP_3

OM CHOKSI 23AIML010 PMRP CLASSROOM WORK + ASSIGNMENT 3

GOOGLE CLASSROOM WORK

Load 'tips' dataset from seaborn library with .load_dataset('tips') 1) check info about dataset using .info() 2) check statistical measures using .describe(). Write explanation about each value in notebook as comments. 3) Plot histogram for each column, find out kind of skewness. 4) What are the different ways to reduce skewness? Implement any one method and plot histogram 5) Generate covariance matrix, correlation matrix and heatmap for the dataset. Explain all values present in matrix in jupyter notebook. 6) Plot cumulative frequency polygon for 'total bill' column and find out median value from graph 7) Find unique values and their value counts for each column. 8) Find out if there are any null records in data. 9) How to replace null records? 10) Drop unnecessary columns from the data.

[2]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

[3]:
```
# load tips dataset
tips = sns.load_dataset('tips')
tips
```

[3]:
```
     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
..          …     …     …      …     …       …     …
239       29.03  5.92    Male     No   Sat  Dinner     3
240       27.18  2.00  Female    Yes   Sat  Dinner     2
241       22.67  2.00    Male    Yes   Sat  Dinner     2
242       17.82  1.75    Male     No   Sat  Dinner     2
243       18.78  3.00  Female     No  Thur  Dinner     2

[244 rows x 7 columns]
```

Question 1 and Question 2

check info about dataset using .info()

check statistical measures using .describe(). Write explanation about each value in notebook as comments.

[4]:
```
tips.info(),tips.describe()



'''

count: The number of non-missing values for each column.
mean: The average value of each column.
std: The standard deviation, a measure of spread or variability in the data.
min: The smallest value in each column.
25%: The first quartile (25th percentile), a measure of the lower bound of the␣
 ↪interquartile range.
50%: The median (50th percentile) of the column values.
75%: The third quartile (75th percentile), a measure of the upper bound of the␣
 ↪interquartile range.
```

```
max: The largest value in each column.

'''
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 244 entries, 0 to 243
Data columns (total 7 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   total_bill  244 non-null    float64
 1   tip         244 non-null    float64
 2   sex         244 non-null    category
 3   smoker      244 non-null    category
 4   day         244 non-null    category
 5   time        244 non-null    category
 6   size        244 non-null    int64
dtypes: category(4), float64(2), int64(1)
memory usage: 7.4 KB
```

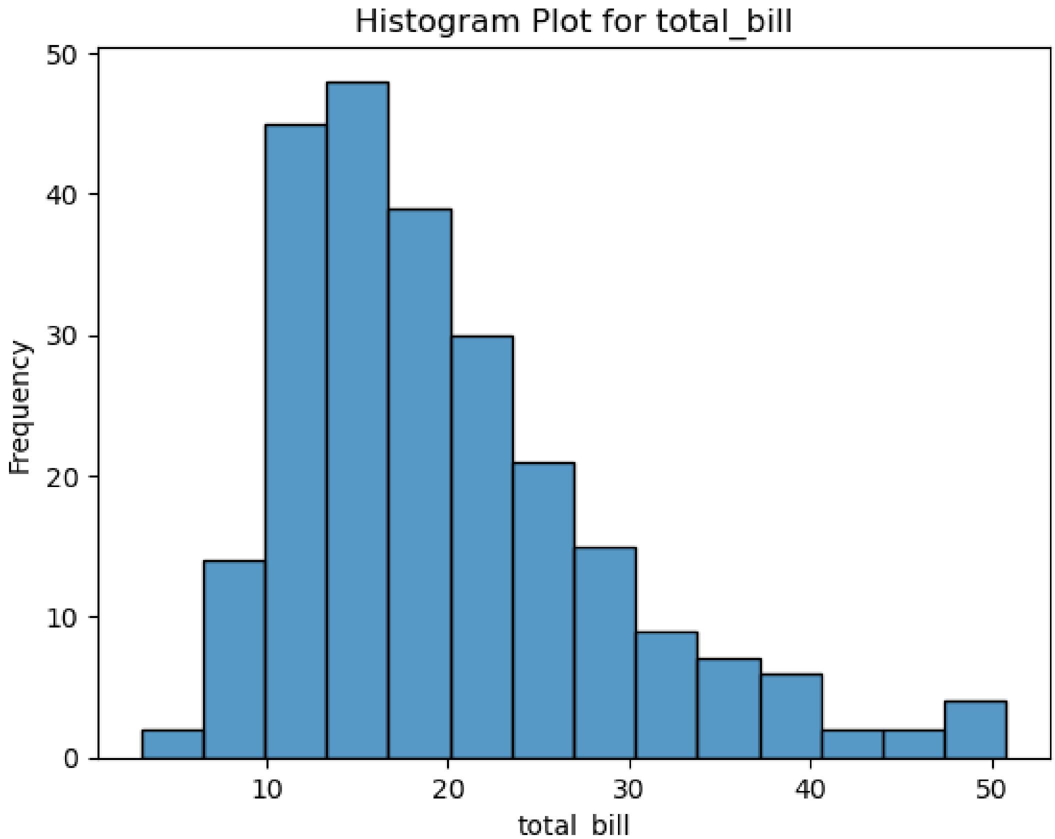
[4]:
```
'\n\ncount: The number of non-missing values for each column.\nmean: The average
value of each column.\nstd: The standard deviation, a measure of spread or
variability in the data.\nmin: The smallest value in each column.\n25%: The
first quartile (25th percentile), a measure of the lower bound of the
interquartile range.\n50%: The median (50th percentile) of the column
values.\n75%: The third quartile (75th percentile), a measure of the upper bound
of the interquartile range.\nmax: The largest value in each column.\n\n'
```

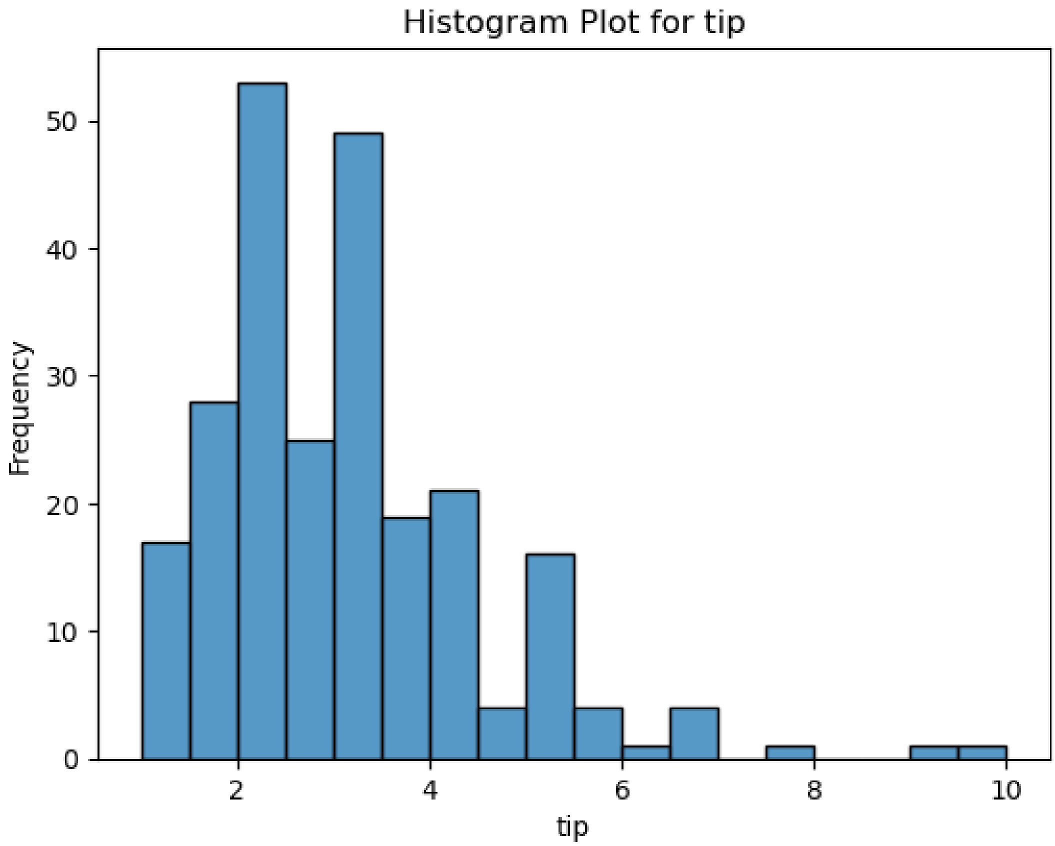
Question 3

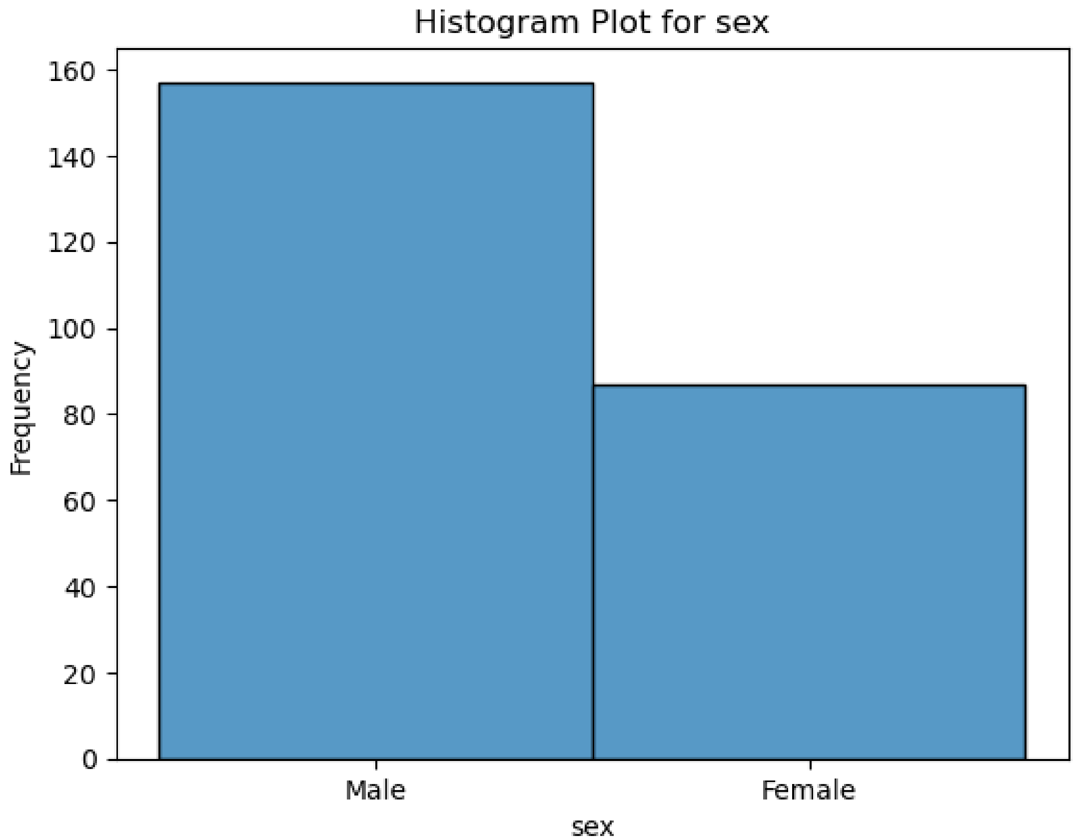
Plot histogram for each column, find out kind of skewness.

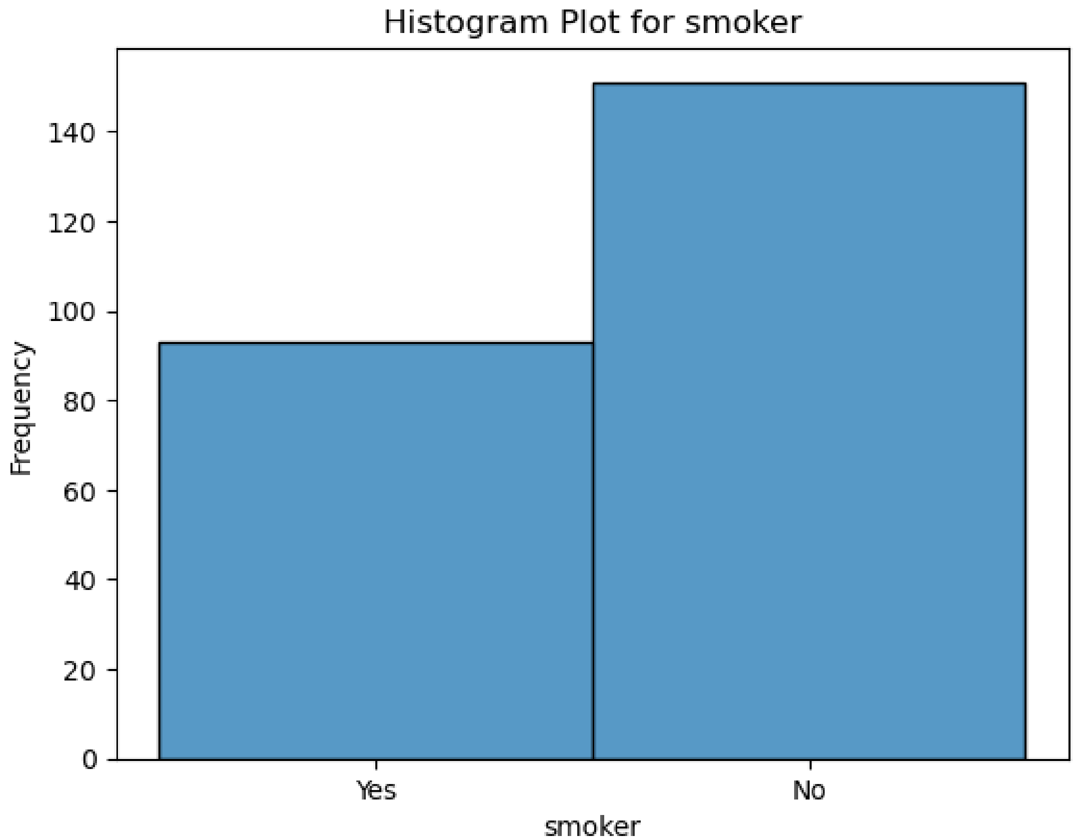
[5]:
```
Column = tips.columns
for column in Column:

    sns.histplot(tips[column])


    plt.title(f'Histogram Plot for {column}')


    plt.xlabel(column)


    plt.ylabel('Frequency')


    plt.show()

```

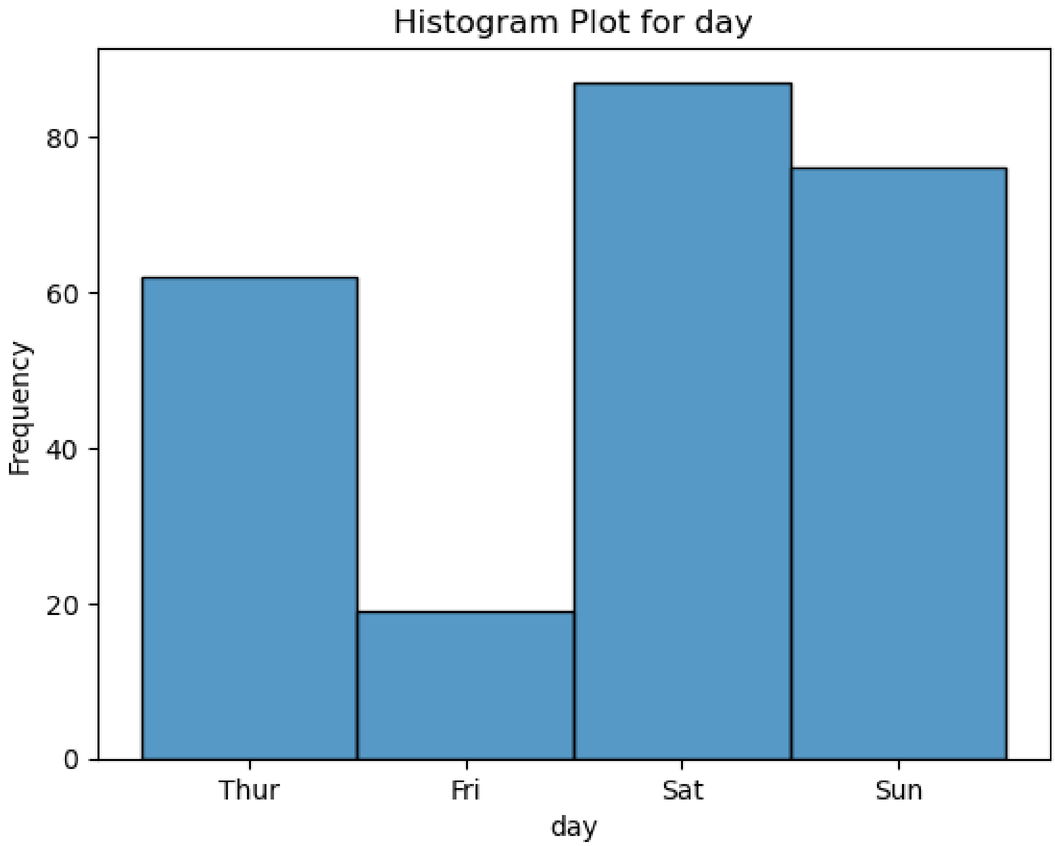
```
tips.hist(bins=15, figsize=(12, 8))
plt.tight_layout()
plt.show()
```

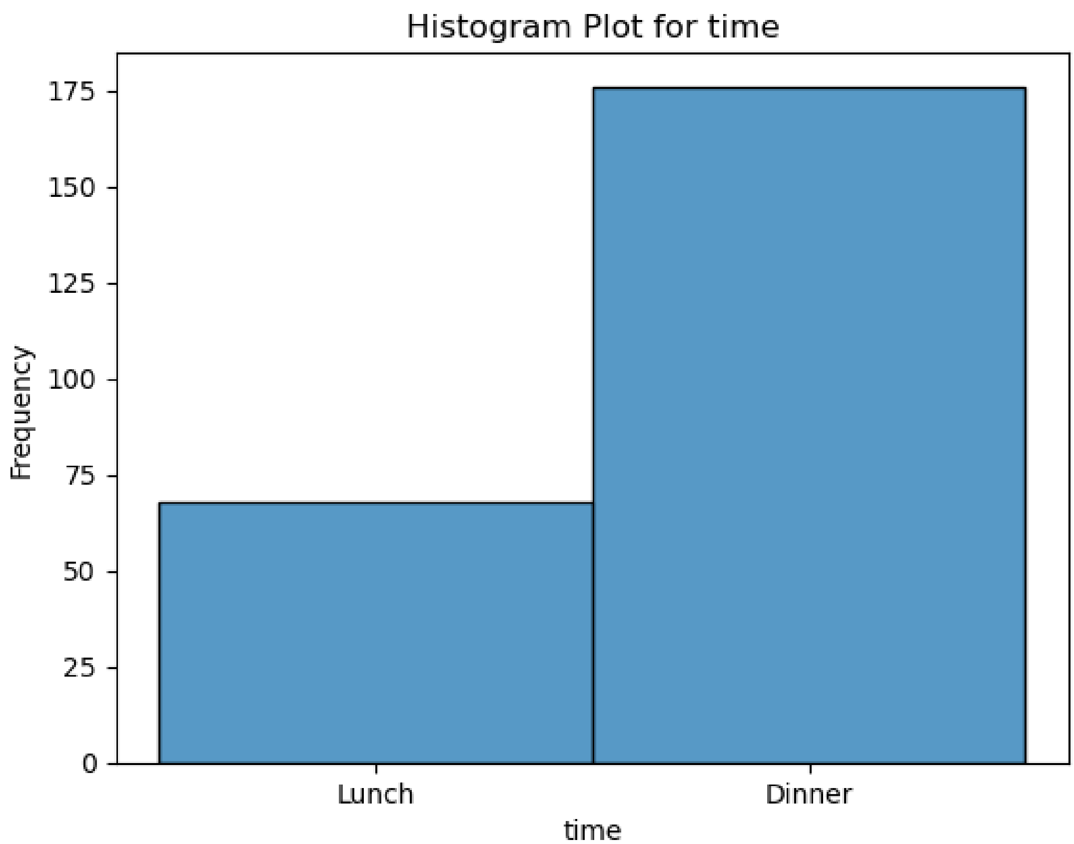



Histogram Plot for tip
Frequency
0
10
20
30
40
50
2
4
6
8
10
tip

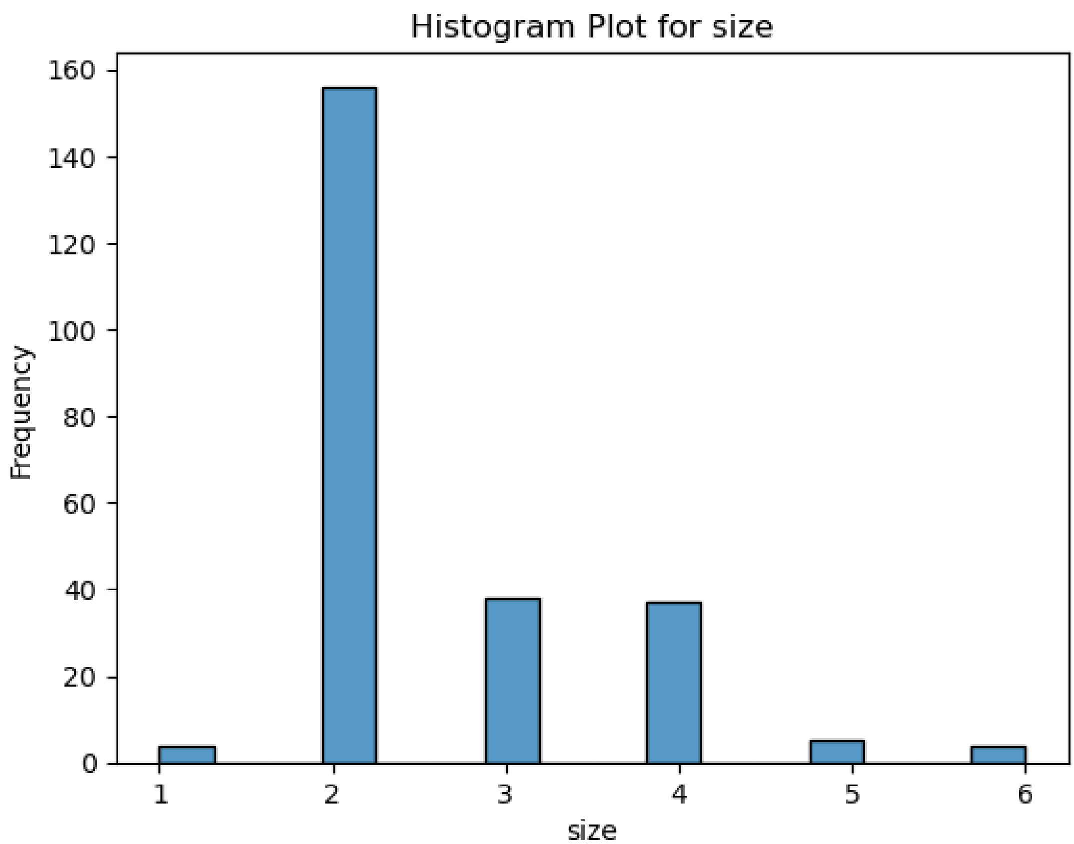

Histogram Plot for sex
Frequency
160
140
120
100
80
60
40
20
0
Male
Female
sex


Histogram Plot for smoker
Frequency
0
20
40
60
80
100
120
140
Yes
No
smoker

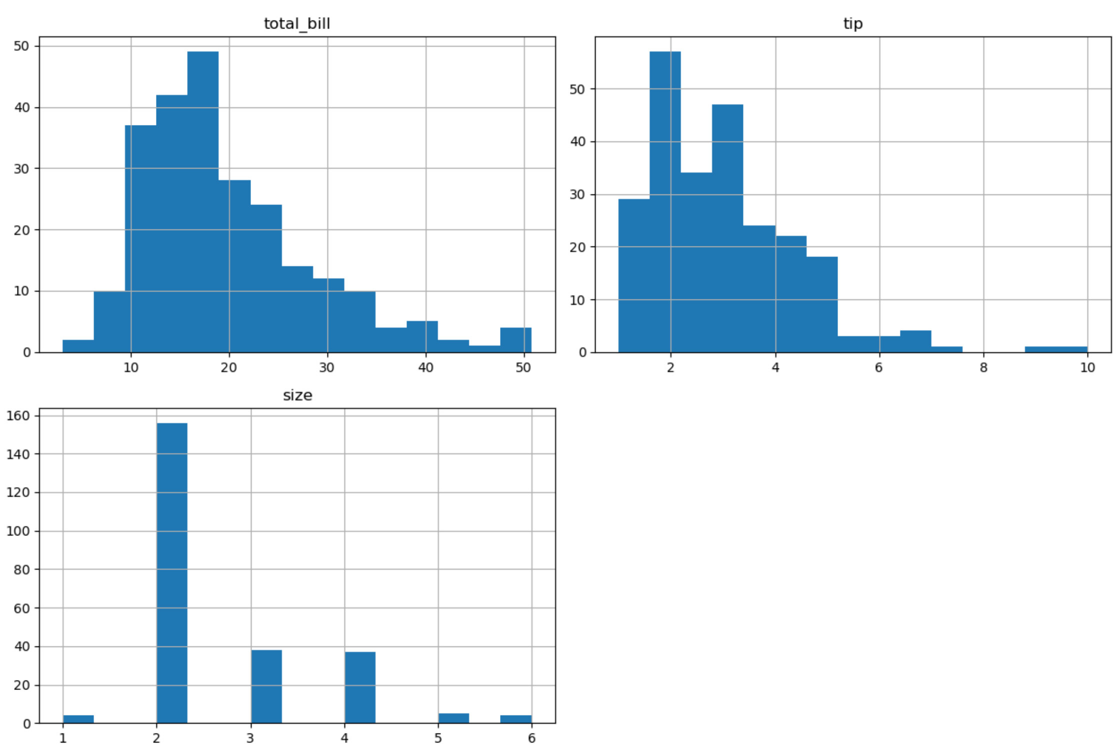

Histogram Plot for day
Frequency
0
20
40
60
80
Thur
Fri
Sat
Sun
day



Histogram Plot for time
Frequency
175
150
125
100
75
50
25
0
Lunch
Dinner
time



Histogram Plot for size
Frequency
size

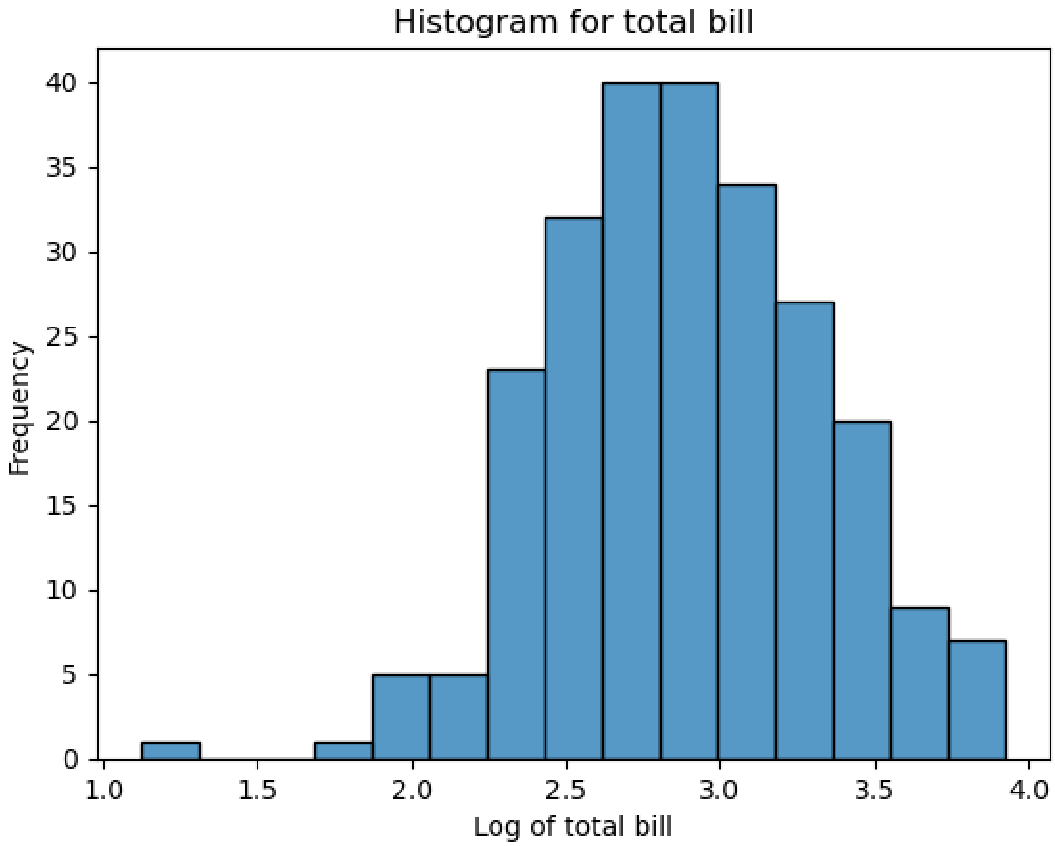


total_bill
tip
size

Question 4

What are the different ways to reduce skewness? Implement any one method and plot histogram

```
[6]: # Q4
tips['total_bill_log'] = np.log(tips['total_bill'])
sns.histplot(tips['total_bill_log'])
plt.title('Histogram for total bill')
plt.xlabel('Log of total bill')
plt.ylabel('Frequency')
plt.show()



'''
Skewness explanation:
 Positive skew: Tail is longer on the right.
 Negative skew: Tail is longer on the left.
 Symmetrical distribution: Balanced tails on both sides.


Methods to reduce skewness
Log Transformation: Reduces positive skewness by compressing large values
Formula: y = log(x)

Square Root Transformation: Compresses larger values, less aggressive than log␣
 ↪transformation
Formula: y = sqrt(x)

Cube Root Transformation: Reduces both positive and negative skewness
Formula: y = x^(1/3)

Box-Cox Transformation: Finds the best power transformation (lambda) for␣
 ↪reducing skewness
Formula: y = (x^lambda - 1) / lambda (for lambda != 0)

Reciprocal Transformation: Dramatically reduces large values, suitable for␣
 ↪highly skewed data
Formula: y = 1/x

Exponential Transformation: Expands small values, useful for negative skewness
Formula: y = x^p, where p > 1


 '''
```



[6]: '\nSkewness explanation:\n Positive skew: Tail is longer on the right.\n Negative skew: Tail is longer on the left.\n Symmetrical distribution: Balanced tails on both sides.\n\n\nMethods to reduce skewness\nLog Transformation: Reduces positive skewness by compressing large values\nFormula: y = log(x)\n\nSquare Root Transformation: Compresses larger values, less aggressive than log transformation\nFormula: y = sqrt(x)\n\nCube Root Transformation: Reduces both positive and negative skewness\nFormula: y = x^(1/3)\n\nBox-Cox Transformation: Finds the best power transformation (lambda) for reducing skewness\nFormula: y = (x^lambda - 1) / lambda (for lambda != 0)\n\nReciprocal Transformation: Dramatically reduces large values, suitable for highly skewed data\nFormula: y = 1/x\n\nExponential Transformation: Expands small values, useful for negative skewness\nFormula: y = x^p, where p > 1\n\n \n '

Question 5

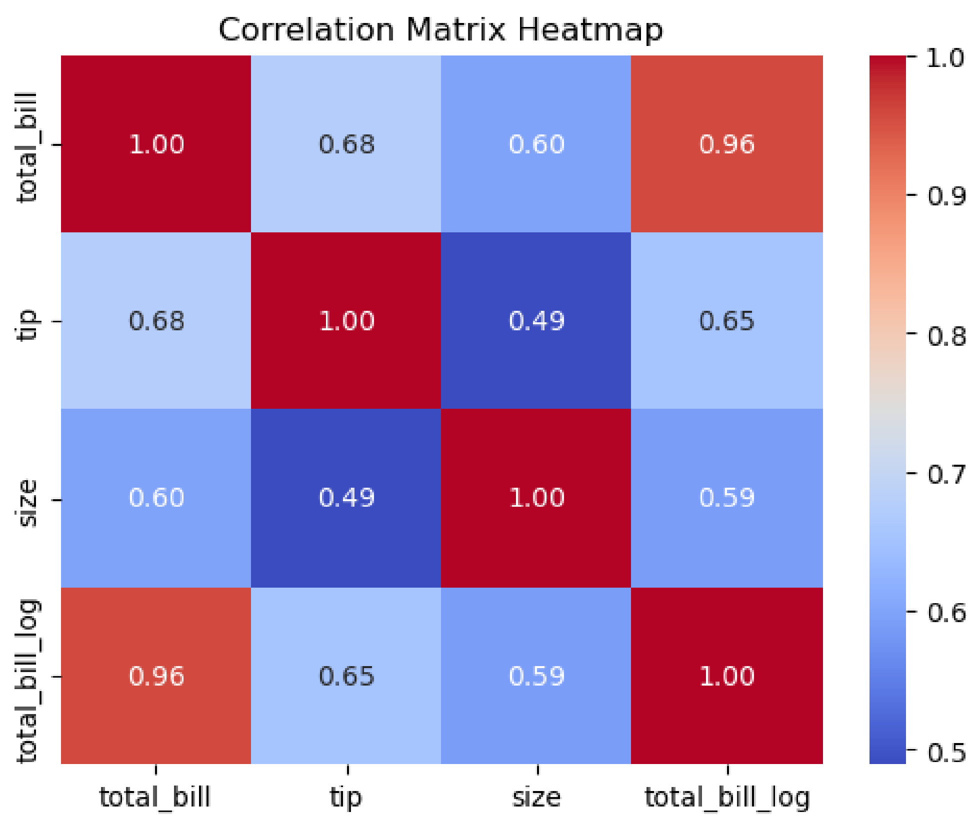
Generate covariance matrix, correlation matrix and heatmap for the dataset.

Explain all values present in matrix in jupyter notebook.

[7]:
```
# Q5
numeric_tips = tips.select_dtypes(include=['float64', 'int64'])
```

```
cov = numeric_tips.cov()
corr = numeric_tips.corr()
print(cov)
print(corr)
plt.figure()
sns.heatmap(corr, annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Matrix Heatmap')
plt.show()
```

```
                total_bill       tip      size  total_bill_log
total_bill       79.252939  8.323502  5.065983        3.738577
tip               8.323502  1.914455  0.643906        0.397362
size              5.065983  0.643906  0.904591        0.246124
total_bill_log    3.738577  0.397362  0.246124        0.192612
                total_bill       tip      size  total_bill_log
total_bill        1.000000  0.675734  0.598315        0.956879
tip               0.675734  1.000000  0.489299        0.654368
size              0.598315  0.489299  1.000000        0.589640
total_bill_log    0.956879  0.654368  0.589640        1.000000
```



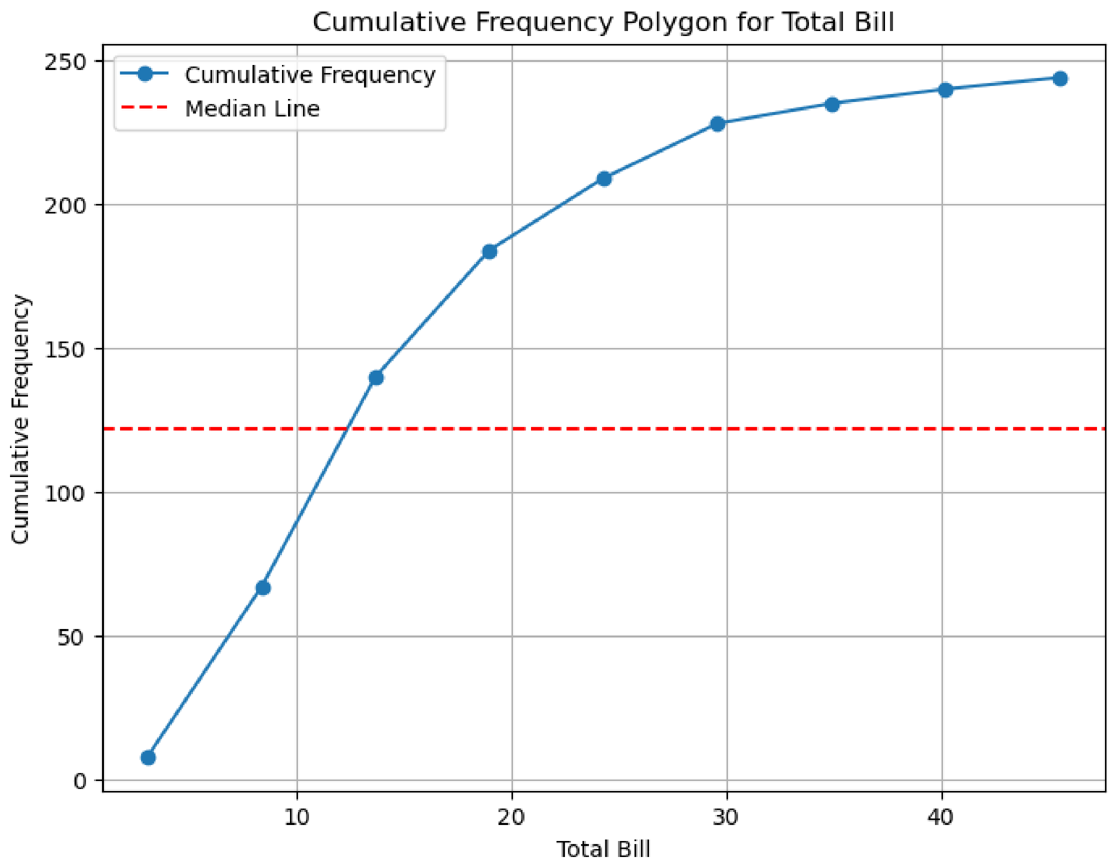
[8]:
```
'''
Explanation :-

Covariance and Correlation Matrices:
Covariance shows how two things change together (uses units).
Correlation makes those values between -1 and 1.
Close to 1/-1 = strong positive/negative link.
Close to 0 = weak or not.

'''
```

[8]:
```
'\nExplanation :-\n\nCovariance and Correlation Matrices:  \nCovariance shows
how two things change together (uses units).  \nCorrelation makes those values
between -1 and 1.  \nClose to 1/-1 = strong positive/negative link.  \nClose to
0 = weak or not.\n\n'
```

Question 6

Plot cumulative frequency polygon for ‘total bill’ column and find out median value from graph

[9]:
```
# Q6
total_bill = tips['total_bill'].sort_values()
bins = np.linspace(total_bill.min(), total_bill.max(), 10)
freq, bin_edges = np.histogram(total_bill, bins=bins)
cumulative_freq = np.cumsum(freq)

plt.figure(figsize=(8, 6))
plt.plot(bin_edges[:-1], cumulative_freq, marker='o', label='Cumulative␣
↪Frequency')
plt.axhline(y=0.5 * cumulative_freq[-1], color='r', linestyle='--',␣
↪label='Median Line')
plt.title('Cumulative Frequency Polygon for Total Bill')
plt.xlabel('Total Bill')
plt.ylabel('Cumulative Frequency')
plt.legend()
plt.grid()
plt.show()

median_bin_index = np.argmax(cumulative_freq >= 0.5 * cumulative_freq[-1])
median_value = bin_edges[median_bin_index]
```



Question 7

Find unique values and their value counts for each column.

[10]:
```
# Q7
for column in tips.columns:
    print(f"Unique values and their counts for {column}:")
    print(tips[column].value_counts())
    print(f"Unique values in {column}: {tips[column].unique()}")
    print("\n")
```

```
Unique values and their counts for total_bill:
total_bill
13.42    3
13.81    2
15.98    2
17.92    2
10.07    2
        ..
24.71    1
21.16    1
```

```
28.97    1
22.49    1
18.78    1
Name: count, Length: 229, dtype: int64
Unique values in total_bill: [16.99 10.34 21.01 23.68 24.59 25.29  8.77 26.88
15.04 14.78 10.27 35.26
 15.42 18.43 14.83 21.58 10.33 16.29 16.97 20.65 17.92 20.29 15.77 39.42
 19.82 17.81 13.37 12.69 21.7  19.65  9.55 18.35 15.06 20.69 17.78 24.06
 16.31 16.93 18.69 31.27 16.04 17.46 13.94  9.68 30.4  18.29 22.23 32.4
 28.55 18.04 12.54 10.29 34.81  9.94 25.56 19.49 38.01 26.41 11.24 48.27
 13.81 11.02 17.59 20.08 16.45  3.07 20.23 15.01 12.02 17.07 26.86 25.28
 14.73 10.51 27.2  22.76 17.29 19.44 16.66 10.07 32.68 15.98 34.83 13.03
 18.28 24.71 21.16 28.97 22.49  5.75 16.32 22.75 40.17 27.28 12.03 12.46
 11.35 15.38 44.3  22.42 20.92 15.36 20.49 25.21 18.24 14.31 14.    7.25
 38.07 23.95 25.71 17.31 29.93 10.65 12.43 24.08 11.69 13.42 14.26 15.95
 12.48 29.8   8.52 14.52 11.38 22.82 19.08 20.27 11.17 12.26 18.26  8.51
 14.15 16.   13.16 17.47 34.3  41.19 27.05 16.43  8.35 18.64 11.87  9.78
  7.51 14.07 13.13 17.26 24.55 19.77 29.85 48.17 25.   13.39 16.49 21.5
 12.66 16.21 17.51 24.52 20.76 31.71 10.59 10.63 50.81 15.81 31.85 16.82
 32.9  17.89 14.48  9.6  34.63 34.65 23.33 45.35 23.17 40.55 20.9  30.46
 18.15 23.1  15.69 19.81 28.44 15.48 16.58  7.56 43.11 13.   13.51 18.71
 12.74 16.4  20.53 16.47 26.59 38.73 24.27 12.76 30.06 25.89 48.33 13.27
 28.17 12.9  28.15 11.59  7.74 30.14 12.16  8.58 16.27 10.09 20.45 13.28
 22.12 24.01 11.61 10.77 15.53 12.6  32.83 35.83 29.03 27.18 22.67 17.82
 18.78]


Unique values and their counts for tip:
tip
2.00    33
3.00    23
4.00    12
5.00    10
2.50    10
        ..
4.34     1
1.56     1
5.20     1
2.60     1
1.75     1
Name: count, Length: 123, dtype: int64
Unique values in tip: [ 1.01  1.66  3.5   3.31  3.61  4.71  2.    3.12  1.96
3.23  1.71  5.
  1.57  3.    3.02  3.92  1.67  3.71  3.35  4.08  2.75  2.23  7.58  3.18
  2.34  4.3   1.45  2.5   2.45  3.27  3.6   3.07  2.31  2.24  2.54  3.06
  1.32  5.6   6.    2.05  2.6   5.2   1.56  4.34  3.51  1.5   1.76  6.73
  3.21  1.98  3.76  2.64  3.15  2.47  1.    2.01  2.09  1.97  3.14  2.2
  1.25  3.08  4.    2.71  3.4   1.83  2.03  5.17  5.85  3.25  4.73  3.48
```

```
  1.64  4.06  4.29  2.55  5.07  1.8   2.92  1.68  2.52  4.2   1.48  2.18
  2.83  6.7   2.3   1.36  1.63  1.73  2.74  5.14  3.75  2.61  4.5   1.61
 10.    3.16  5.15  3.11  3.55  3.68  5.65  6.5   4.19  2.56  2.02  1.44
  3.41  5.16  9.    1.1   3.09  1.92  1.58  2.72  2.88  3.39  1.47  1.17
  4.67  5.92  1.75]


Unique values and their counts for sex:
sex
Male      157
Female     87
Name: count, dtype: int64
Unique values in sex: ['Female', 'Male']
Categories (2, object): ['Male', 'Female']


Unique values and their counts for smoker:
smoker
No     151
Yes     93
Name: count, dtype: int64
Unique values in smoker: ['No', 'Yes']
Categories (2, object): ['Yes', 'No']


Unique values and their counts for day:
day
Sat     87
Sun     76
Thur    62
Fri     19
Name: count, dtype: int64
Unique values in day: ['Sun', 'Sat', 'Thur', 'Fri']
Categories (4, object): ['Thur', 'Fri', 'Sat', 'Sun']


Unique values and their counts for time:
time
Dinner    176
Lunch      68
Name: count, dtype: int64
Unique values in time: ['Dinner', 'Lunch']
Categories (2, object): ['Lunch', 'Dinner']


Unique values and their counts for size:
size
2    156
```

```
3     38
4     37
5      5
1      4
6      4
Name: count, dtype: int64
Unique values in size: [2 3 4 1 6 5]


Unique values and their counts for total_bill_log:
total_bill_log
2.596746    3
2.625393    2
2.771338    2
2.885917    2
2.309561    2
           ..
3.207208    1
3.052113    1
3.366261    1
3.113071    1
2.932792    1
Name: count, Length: 229, dtype: int64
Unique values in total_bill_log: [2.83262494 2.33601987 3.04499851 3.16463081
3.20233986 3.23040906
 2.17133681 3.29138252 2.71071332 2.69327492 2.32922702 3.56274918
 2.73566537 2.91397977 2.69665216 3.07176696 2.33505228 2.79055142
 2.83144708 3.02771532 2.88591741 3.01012815 2.7581094  3.6742733
 2.98669153 2.8797601  2.59301339 2.54081428 3.07731226 2.97807734
 2.25654115 2.90962957 2.71204222 3.02965049 2.87807423 3.18055071
 2.79177842 2.8290872  2.92798862 3.44265917 2.7750856  2.85991255
 2.63476241 2.2700619  3.41444261 2.90635446 3.10144273 3.47815842
 3.35165694 2.89259151 2.52892354 2.33117255 3.5499047  2.29656702
 3.24102863 2.96990151 3.63784928 3.27374273 2.41947884 3.87681025
 2.62539297 2.3997118  2.86733056 2.99972429 2.80032548 1.12167756
 3.00716665 2.70871665 2.48657193 2.83732254 3.29063819 3.23001357
 2.68988623 2.35232718 3.30321697 3.12500461 2.8501283  2.9673328
 2.81301064 2.30956071 3.48676327 2.77133794 3.55047908 2.56725439
 2.90580757 3.20720802 3.05211261 3.36626081 3.11307077 1.74919985
 2.79239135 3.12456515 3.69312045 3.30615383 2.48740353 2.52252351
 2.42921774 2.73306796 3.79098468 3.10995342 3.04070564 2.73176673
 3.01993696 3.22724074 2.90361698 2.66095859 2.63905733 1.98100147
 3.63942657 3.17596832 3.24688002 2.85128437 3.39886132 2.36555989
 2.52011291 3.18138162 2.45873378 2.59674613 2.65745841 2.76945883
 2.52412736 3.39450839 2.14241634 2.67552701 2.43185743 3.12763734
 2.94864067 3.00914196 2.41323161 2.50634193 2.90471288 2.14124194
 2.64971462 2.77258872 2.57718193 2.86048512 3.53514535 3.71819551
 3.29768701 2.79910893 2.12226154 2.92530981 2.47401421 2.28033948
```

```
 2.01623547 2.64404487 2.57489969 2.84839169 3.20071185 2.98416564
 3.39618484 3.87473642 3.21887582 2.59450816 2.80275414 3.06805294
 2.53844742 2.78562834 2.86277215 3.19948911 3.03302806 3.45663209
 2.35991016 2.36368019 3.92809319 2.76064265 3.46103738 2.82256865
 3.49347266 2.8842419  2.67276839 2.2617631  3.54472036 3.54529773
 3.14974009 3.81441018 3.14285834 3.70253578 3.03974916 3.41641435
 2.89867056 3.13983262 2.75302357 2.98618686 3.3477966  2.73954887
 2.80819715 2.02287119 3.76375499 2.56494936 2.60343015 2.92905814
 2.54474665 2.79728133 3.02188723 2.80154054 3.28053521 3.65661449
 3.18924102 2.54631528 3.40319538 3.25385679 3.87805249 2.58550585
 3.33825758 2.55722731 3.33754735 2.45014266 2.04640169 3.40585319
 2.49815188 2.14943391 2.78932292 2.31154483 3.01798288 2.58625914
 3.09648218 3.17847041 2.4518668  2.37676449 2.74277364 2.53369681
 3.49134273 3.57878553 3.36832978 3.30248141 3.12104246 2.88032142
 2.93279247]
```

Question 8

Find out if there are any null records in data.

[11]:
```python
# Q8
null_records = tips.isnull().sum()
print("Null records in each column:")
print(null_records)
```

```
Null records in each column:
total_bill       0
tip              0
sex              0
smoker           0
day              0
time             0
size             0
total_bill_log   0
dtype: int64
```

Question 8

How to replace null records?

[12]:
```python
'''
 Q9. How to replace null records?
Ans: Replace null values in numerical columns with the median

'''
```

[12]:
```
'\n Q9. How to replace null records?\nAns: Replace null values in numerical
columns with the median\n \n'
```

Question 10

Drop unnecessary columns from the data.

[13]:
```
'''
Q10
 Drop unnecessary columns from the dataset (e.g., 'day' and 'time')

'''
tips.drop(columns=['day', 'time'], inplace=True)
tips
```

[13]:
```
     total_bill   tip     sex smoker  size  total_bill_log
0         16.99  1.01  Female     No     2        2.832625
1         10.34  1.66    Male     No     3        2.336020
2         21.01  3.50    Male     No     3        3.044999
3         23.68  3.31    Male     No     2        3.164631
4         24.59  3.61  Female     No     4        3.202340
..          …     …       …      …     …               …
239       29.03  5.92    Male     No     3        3.368330
240       27.18  2.00  Female    Yes     2        3.302481
241       22.67  2.00    Male    Yes     2        3.121042
242       17.82  1.75    Male     No     2        2.880321
243       18.78  3.00  Female     No     2        2.932792

[244 rows x 6 columns]
```

CLASSROOM IS COMPLETED SUCCESSFULLY….

ASSIGNMENT 3 WORK

1) Find out count of unique records in each column.
2) Find if any outliers in data.
3) Plot heatmap of correlation matrix and covariance matrix for the given dataset.
4) Remove unnecessary or empty columns as well as any rows if required from the dataset.
5) Plot histograms for each column and remove any skewness using transformations.
6) Plot Yearly records for numerical columns (e.g. runs, trophies)

QUESTION 1

1) Find out count of unique records in each column.

[18]:
```
df = pd.read_csv("matches.csv")    #we load a dataset
df.head()
unique_counts = df.nunique()
print("Unique counts in each column:\n", unique_counts)
```

```
Unique counts in each column:
 id                  1095
season                17
```

```
city                 36
date                823
match_type            8
player_of_match     291
venue                58
team1                19
team2                19
toss_winner          19
toss_decision         2
winner               19
result                4
result_margin        98
target_runs         170
target_overs         15
super_over            2
method                1
umpire1              62
umpire2              62
dtype: int64
```

QUESTION 2

2) Find if any outliers in data.

[20]:
```
numerical_cols = df.select_dtypes(include=[np.number]).columns
print("Summary statistics for numerical columns:\n", df[numerical_cols].
 ↪describe())
```

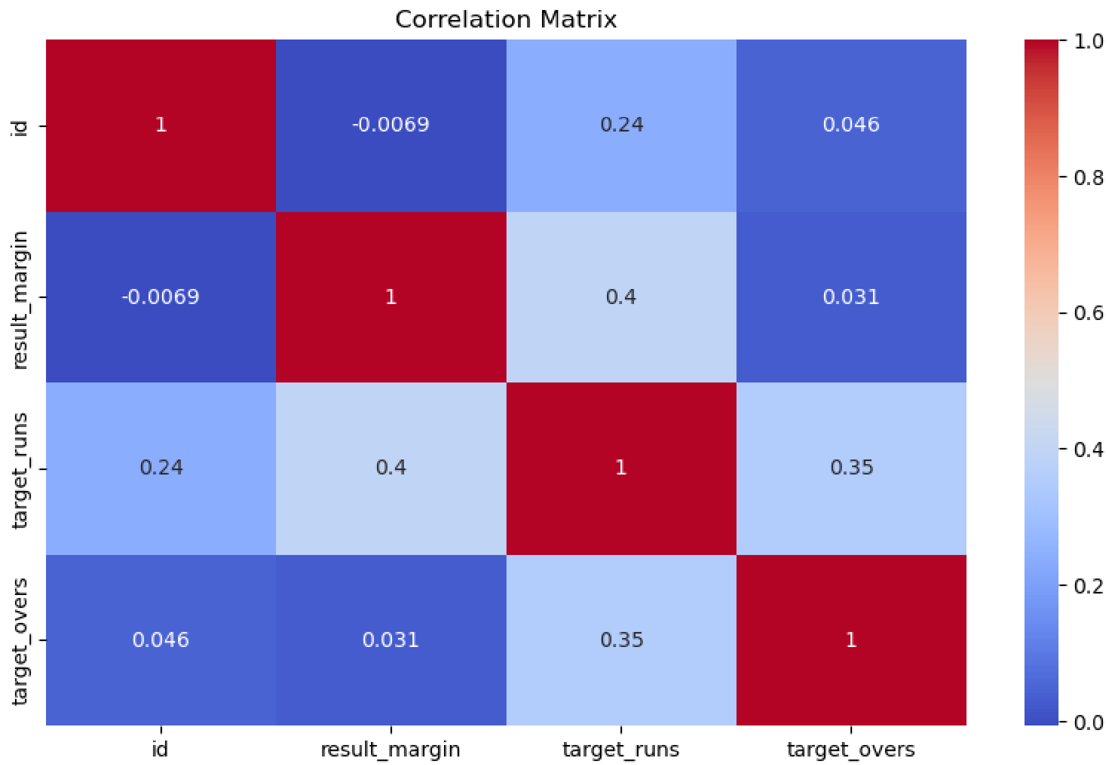
```
Summary statistics for numerical columns:
                  id  result_margin  target_runs  target_overs
count  1.095000e+03    1076.000000  1092.000000   1092.000000
mean   9.048283e+05      17.259294   165.684066     19.759341
std    3.677402e+05      21.787444    33.427048      1.581108
min    3.359820e+05       1.000000    43.000000      5.000000
25%    5.483315e+05       6.000000   146.000000     20.000000
50%    9.809610e+05       8.000000   166.000000     20.000000
75%    1.254062e+06      20.000000   187.000000     20.000000
max    1.426312e+06     146.000000   288.000000     20.000000
```

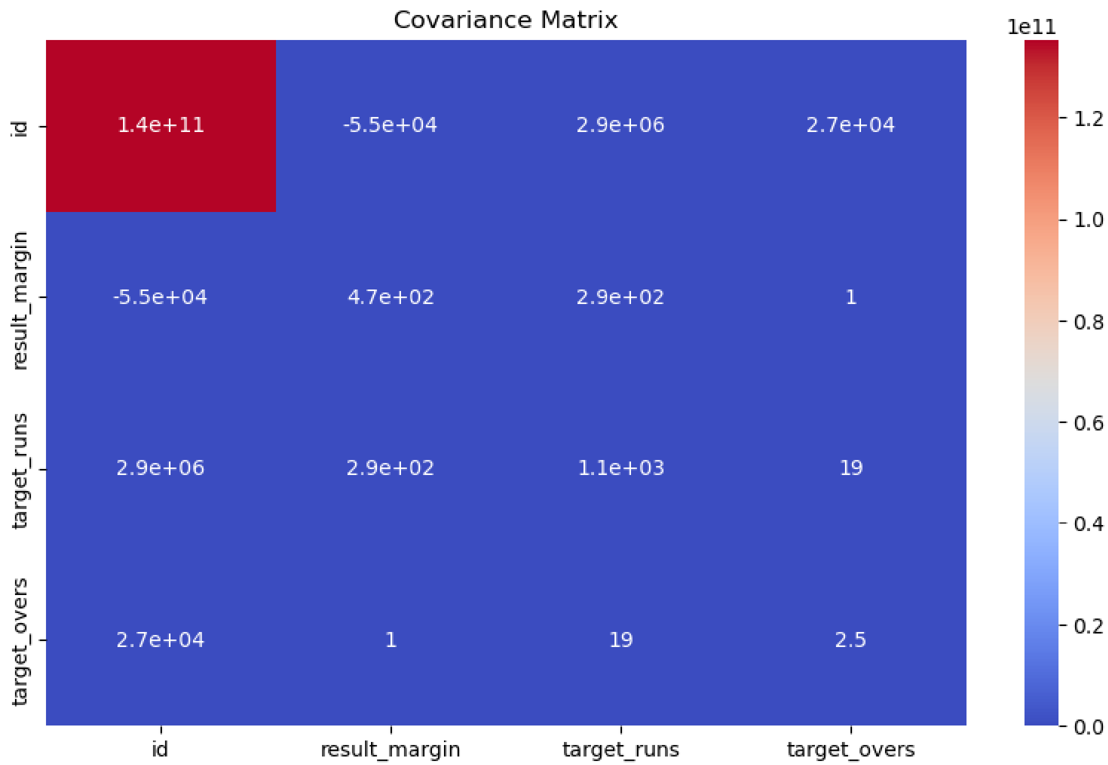
QUESTION 3

3) Plot heatmap of correlation matrix and covariance matrix for the given dataset.

[26]:
```
numerical_cols = df.select_dtypes(include=['float64', 'int64']).columns

correlation_matrix = df[numerical_cols].corr()
covariance_matrix = df[numerical_cols].cov()

plt.figure(figsize=(10, 6))
sns.heatmap(correlation_matrix, annot=True, cmap="coolwarm")
```

```
plt.title("Correlation Matrix")
plt.show()

plt.figure(figsize=(10, 6))
sns.heatmap(covariance_matrix, annot=True, cmap="coolwarm")
plt.title("Covariance Matrix")
plt.show()
```





QUESTION 4

4) Remove unnecessary or empty columns as well as any rows if required from the dataset.

[28]:
```
df_cleaned = df.dropna(axis=1, how='all')

df_cleaned = df_cleaned.dropna()

print("Cleaned Dataset Info:")
print(df_cleaned.info())
df
```

```
Cleaned Dataset Info:
<class 'pandas.core.frame.DataFrame'>
Index: 21 entries, 38 to 1023
Data columns (total 20 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   id               21 non-null     int64
 1   season           21 non-null     object
 2   city             21 non-null     object
 3   date             21 non-null     object
 4   match_type       21 non-null     object
```

```
 5   player_of_match  21 non-null     object
 6   venue            21 non-null     object
 7   team1            21 non-null     object
 8   team2            21 non-null     object
 9   toss_winner      21 non-null     object
 10  toss_decision    21 non-null     object
 11  winner           21 non-null     object
 12  result           21 non-null     object
 13  result_margin    21 non-null     float64
 14  target_runs      21 non-null     float64
 15  target_overs     21 non-null     float64
 16  super_over       21 non-null     object
 17  method           21 non-null     object
 18  umpire1          21 non-null     object
 19  umpire2          21 non-null     object
dtypes: float64(3), int64(1), object(16)
memory usage: 3.4+ KB
None
```

[28]:

```
           id   season        city        date   match_type  player_of_match  \
0      335982  2007/08   Bangalore  2008-04-18       League      BB McCullum
1      335983  2007/08  Chandigarh  2008-04-19       League       MEK Hussey
2      335984  2007/08       Delhi  2008-04-19       League      MF Maharoof
3      335985  2007/08      Mumbai  2008-04-20       League       MV Boucher
4      335986  2007/08     Kolkata  2008-04-20       League        DJ Hussey
…         …       …           …          …            …                 …
1090  1426307     2024   Hyderabad  2024-05-19       League  Abhishek Sharma
1091  1426309     2024   Ahmedabad  2024-05-21  Qualifier 1         MA Starc
1092  1426310     2024   Ahmedabad  2024-05-22   Eliminator         R Ashwin
1093  1426311     2024     Chennai  2024-05-24  Qualifier 2    Shahbaz Ahmed
1094  1426312     2024     Chennai  2024-05-26        Final         MA Starc

                                                  venue  \
0                                 M Chinnaswamy Stadium
1            Punjab Cricket Association Stadium, Mohali
2                                      Feroz Shah Kotla
3                                      Wankhede Stadium
4                                         Eden Gardens
…                                                   …
1090  Rajiv Gandhi International Stadium, Uppal, Hyd…
1091                   Narendra Modi Stadium, Ahmedabad
1092                   Narendra Modi Stadium, Ahmedabad
1093           MA Chidambaram Stadium, Chepauk, Chennai
1094           MA Chidambaram Stadium, Chepauk, Chennai

                            team1                        team2  \
0     Royal Challengers Bangalore        Kolkata Knight Riders
```

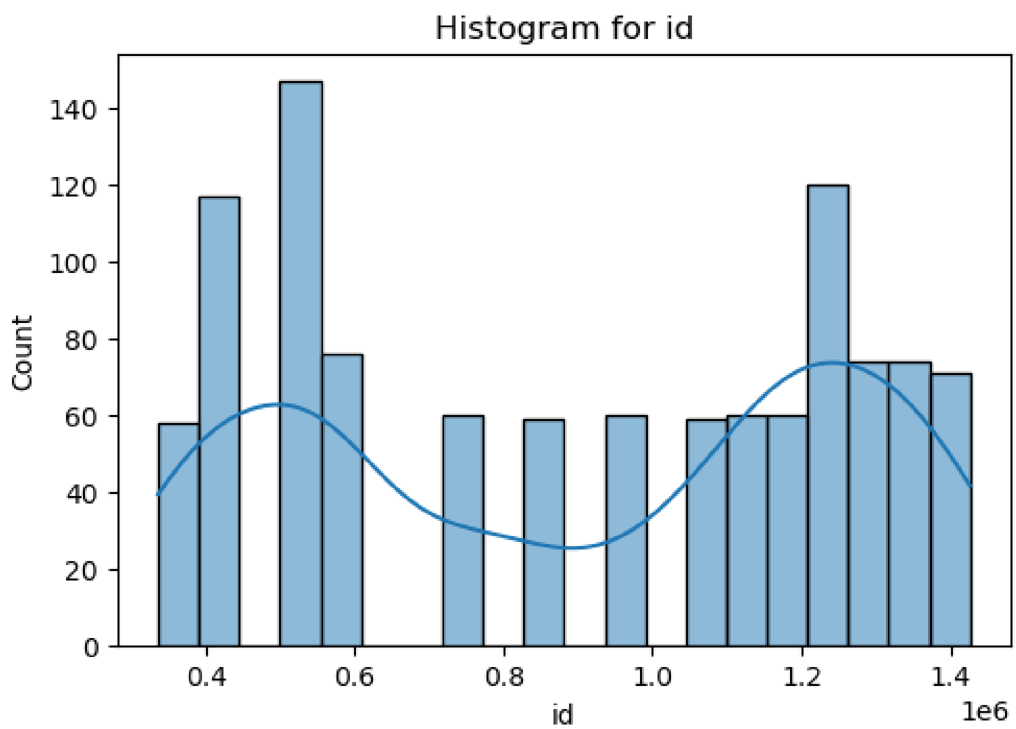
```
1                 Kings XI Punjab         Chennai Super Kings
2               Delhi Daredevils            Rajasthan Royals
3                 Mumbai Indians  Royal Challengers Bangalore
4          Kolkata Knight Riders             Deccan Chargers
…                            …                           …
1090               Punjab Kings         Sunrisers Hyderabad
1091        Sunrisers Hyderabad       Kolkata Knight Riders
1092  Royal Challengers Bengaluru            Rajasthan Royals
1093        Sunrisers Hyderabad            Rajasthan Royals
1094        Sunrisers Hyderabad       Kolkata Knight Riders

                      toss_winner toss_decision                       winner  \
0     Royal Challengers Bangalore         field        Kolkata Knight Riders
1             Chennai Super Kings           bat          Chennai Super Kings
2                Rajasthan Royals           bat             Delhi Daredevils
3                  Mumbai Indians           bat  Royal Challengers Bangalore
4                 Deccan Chargers           bat        Kolkata Knight Riders
…                            …            …                          …
1090                 Punjab Kings           bat          Sunrisers Hyderabad
1091          Sunrisers Hyderabad           bat        Kolkata Knight Riders
1092             Rajasthan Royals         field             Rajasthan Royals
1093             Rajasthan Royals         field          Sunrisers Hyderabad
1094          Sunrisers Hyderabad           bat        Kolkata Knight Riders

       result  result_margin  target_runs  target_overs super_over method  \
0        runs          140.0        223.0          20.0          N    NaN
1        runs           33.0        241.0          20.0          N    NaN
2     wickets            9.0        130.0          20.0          N    NaN
3     wickets            5.0        166.0          20.0          N    NaN
4     wickets            5.0        111.0          20.0          N    NaN
…       …            …          …            …         …    …
1090  wickets            4.0        215.0          20.0          N    NaN
1091  wickets            8.0        160.0          20.0          N    NaN
1092  wickets            4.0        173.0          20.0          N    NaN
1093     runs           36.0        176.0          20.0          N    NaN
1094  wickets            8.0        114.0          20.0          N    NaN

                    umpire1               umpire2
0                 Asad Rauf           RE Koertzen
1                 MR Benson            SL Shastri
2                 Aleem Dar        GA Pratapkumar
3                  SJ Davis             DJ Harper
4                 BF Bowden           K Hariharan
…                       …                   …
1090            Nitin Menon             VK Sharma
1091           AK Chaudhary              R Pandit
1092  KN Ananthapadmanabhan  MV Saidharshan Kumar
```

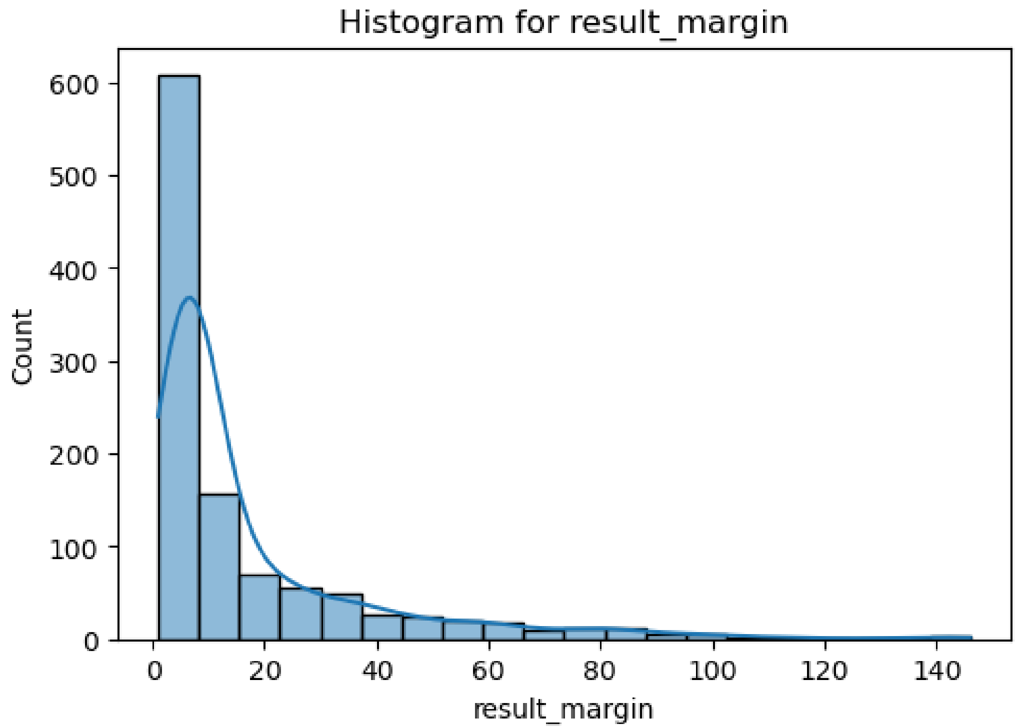
```
1093             Nitin Menon             VK Sharma
1094           J Madanagopal           Nitin Menon

[1095 rows x 20 columns]
```

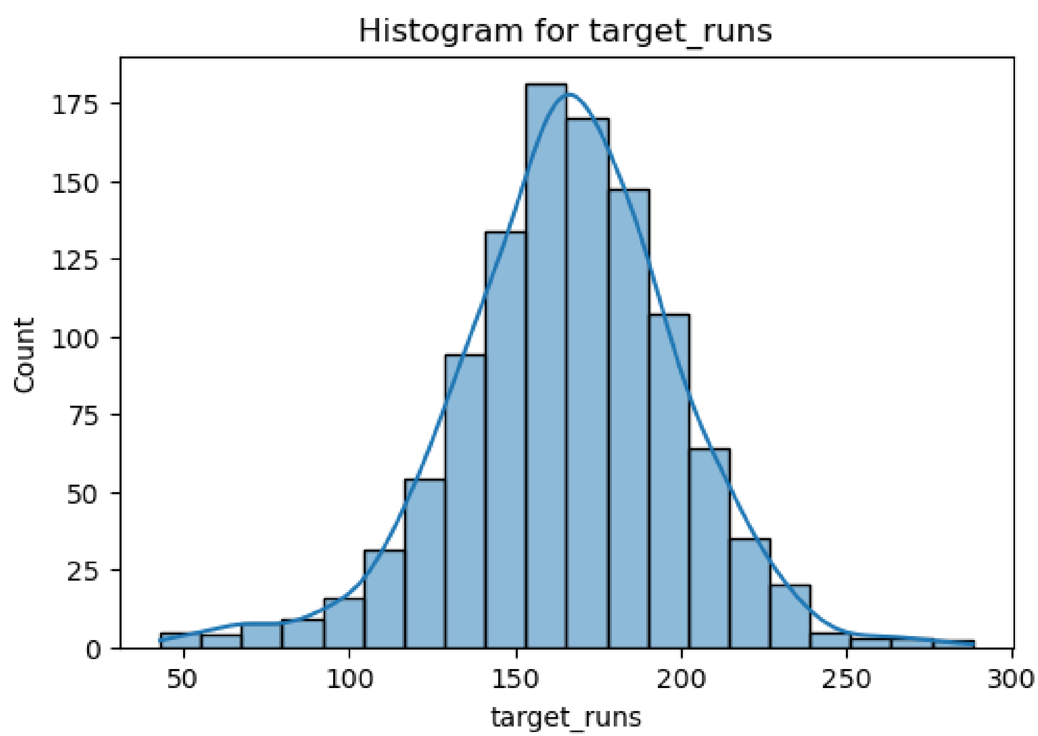
QUESTION 5

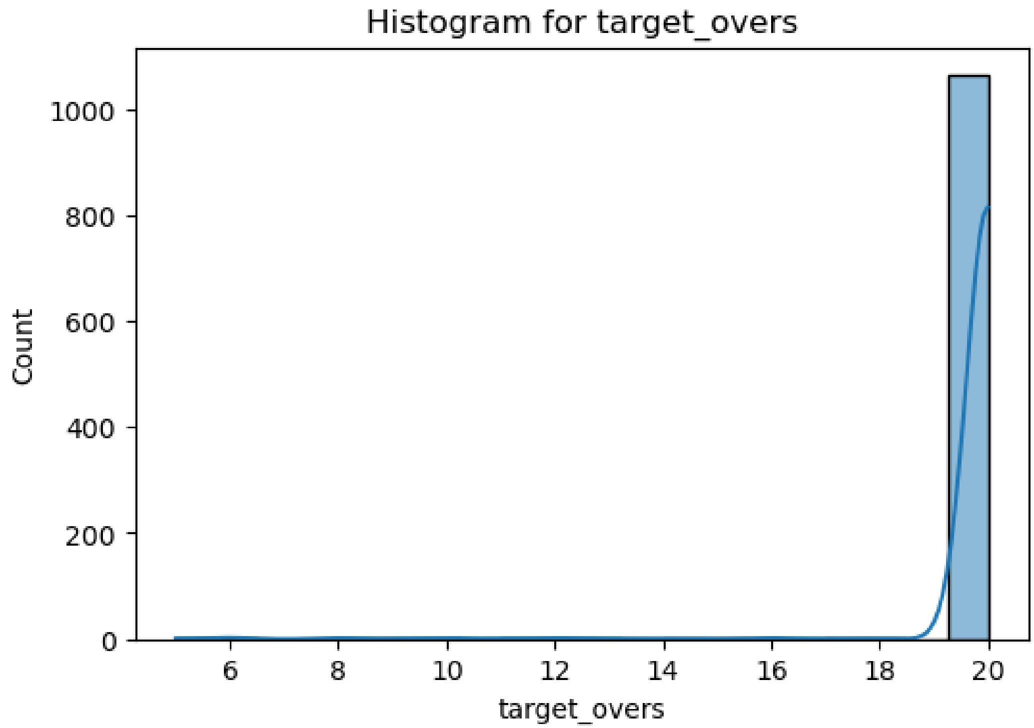
5) Plot histograms for each column and remove any skewness using transformations.

[29]:
```
for col in numerical_cols:
    plt.figure(figsize=(6, 4))
    sns.histplot(df[col], kde=True, bins=20)
    plt.title(f"Histogram for {col}")
    plt.show()


# Example: Log Transformation
df['log_result_margin'] = np.log1p(df['result_margin'])  # Log transformation␣
 ↪for skewed column
```




Histogram for result_margin
Count
0
100
200
300
400
500
600
0
20
40
60
80
100
120
140
result_margin


Histogram for target_runs
Count
0
25
50
75
100
125
150
175
50
100
150
200
250
300
target_runs

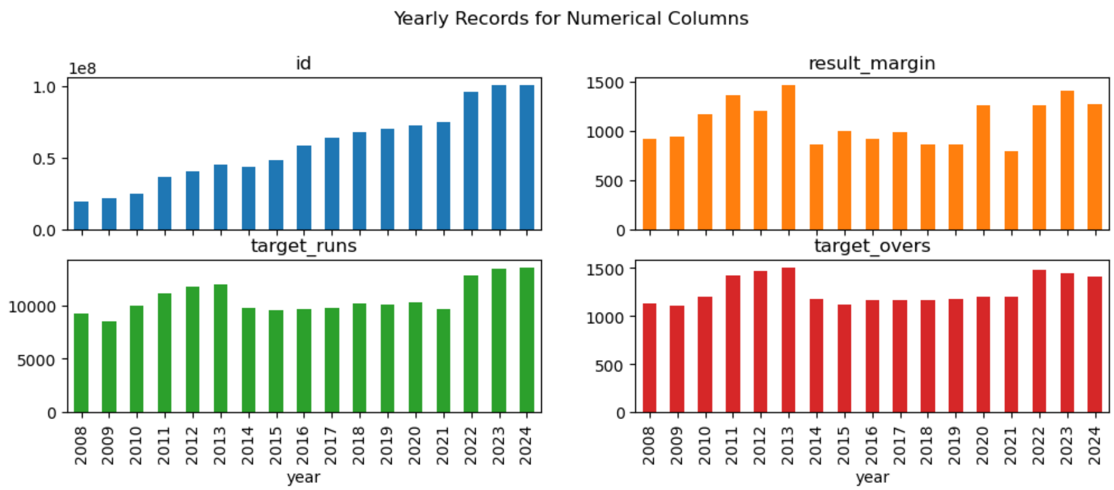


QUESTION 6

6) Plot Yearly records for numerical columns (e.g. runs, trophies)

[30]:

```
df['year'] = pd.to_datetime(df['date']).dt.year


yearly_data = df.groupby('year')[numerical_cols].sum()


yearly_data.plot(kind='bar', figsize=(12, 6), subplots=True, layout=(3, 2),
 ↪legend=False)
plt.suptitle("Yearly Records for Numerical Columns")
plt.show()
```



ASSIGNMENT 3 WORK COMPELTED

---

from file: PMRP_4

OM CHOKSI 23AIML010 CLASSROOM ASSIGNMENT 4 TASK

CLASS TASK TWO EXAMPLES

1) A factory produces light bulbs, and 5% of the bulbs produced are defective. There is a test that is used to check the bulbs:

- It correctly identifies defective bulbs 98% of the time (True Positive Rate).
- It incorrectly identifies non-defective bulbs as defective 3% of the time (False Positive Rate).

If a bulb tests positive for being defective, what is the probability that it is actually defective?

2) Consider an email spam filter that classifies emails as either "spam" or "not spam." The filter is trained on a dataset where:

- 10% of emails are spam.
- The filter correctly identifies spam emails 90% of the time (True Positive Rate).
- The filter incorrectly identifies non-spam emails as spam 5% of the time (False Positive Rate).

If an email is flagged as spam, what is the probability that it is actually spam?

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

Question 1

[2]:
```
'''
```

```
1) A factory produces light bulbs, and 5% of the bulbs produced are defective.␣
 ↪There is a test that is used to check the bulbs:
- It correctly identifies defective bulbs 98% of the time (True Positive Rate).
- It incorrectly identifies non-defective bulbs as defective 3% of the time␣
 ↪(False Positive Rate).

'''



P_D = 0.05
P_not_D = 0.95
P_T_D = 0.98
P_T_not_D = 0.03


P_T = (P_T_D * P_D) + (P_T_not_D * P_not_D)


P_D_T = (P_T_D * P_D) / P_T

print(f"The probability that the bulb is actually defective given it tests␣
 ↪positive is: {P_D_T:.4f}")
```

```
The probability that the bulb is actually defective given it tests positive is:
0.6323
```

Question 2

[ ]:
```
'''
2) Consider an email spam filter that classifies emails as either "spam" or␣
 ↪"not spam." The filter is trained on a dataset where:
- 10% of emails are spam.
- The filter correctly identifies spam emails 90% of the time (True Positive␣
 ↪Rate).
- The filter incorrectly identifies non-spam emails as spam 5% of the time␣
 ↪(False Positive Rate).

If an email is flagged as spam, what is the probability that it is actually␣
 ↪spam?

'''



P_S = 0.1
P_not_S = 0.9
P_F_given_S = 0.9
P_F_given_not_S = 0.05
```

```
P_F = (P_F_given_S * P_S) + (P_F_given_not_S * P_not_S)


P_S_given_F = (P_F_given_S * P_S) / P_F


print(f"The probability that the email is actually spam given it is flagged as␣
↪spam is: {P_S_given_F:.4f}")
```

```
The probability that the email is actually spam given it is flagged as spam is:
0.6667
```

CLASSWORK ASSIGNMENT 4

Use this dataset: https://www.kaggle.com/datasets/mlg-ulb/creditcardfraud

Apply Bayes theorem on the dataset to calculate probability of fraudulent transaction if there is high amount transaction. Threshold for higher amount is 100. Calculate all the required probabilities from dataset. Perform necessary data cleaning part (V1 to V8 columns are not required) and perform all calculations in .py or .ipynb file.

[ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

[ ]:
```
file_path = '/content/my-drive/creditcard.csv'
df = pd.read_csv(file_path)
df
```

[ ]:
```
      Time        V1        V2        V3        V4        V5        V6  \
0        0 -1.359807 -0.072781  2.536347  1.378155 -0.338321  0.462388
1        0  1.191857  0.266151  0.166480  0.448154  0.060018 -0.082361
2        1 -1.358354 -1.340163  1.773209  0.379780 -0.503198  1.800499
3        1 -0.966272 -0.185226  1.792993 -0.863291 -0.010309  1.247203
4        2 -1.158233  0.877737  1.548718  0.403034 -0.407193  0.095921
…      …         …         …         …         …         …         …
5969  6634 -1.611463  0.190648  0.901715  1.531254 -1.535865  0.799245
5970  6635 -1.420272  1.449354  1.320110 -1.894320  0.913695  0.454601
5971  6637 -1.206696  0.284728  2.152053 -2.850437 -0.437285 -0.238376
5972  6644  1.067611  0.091006 -0.153917  0.704233  0.113894 -0.826866
5973  6645 -0.535272 -0.132299  2.180041  1.018303 -1.498819  0.529570

            V7        V8        V9  …       V21       V22       V23  \
0     0.239599  0.098698  0.363787  … -0.018307  0.277838 -0.110474
1    -0.078803  0.085102 -0.255425  … -0.225775 -0.638672  0.101288
```

```
2     0.791461  0.247676 -1.514654  …  0.247998  0.771679  0.909412
3     0.237609  0.377436 -1.387024  … -0.108300  0.005274 -0.190321
4     0.592941 -0.270533  0.817739  … -0.009431  0.798278 -0.137458
…          …         …        …   …        …         …        …
5969  1.513786  0.495829  0.200390  …  0.211223  0.007477  1.026272
5970  0.894179 -0.385450  2.433841  … -0.529027 -0.368394 -0.247773
5971 -0.333341  0.334679  2.870542  …  0.039460  0.464476 -0.457193
5972  0.567690 -0.464181  0.957295  … -0.476723 -1.410090 -0.037550
5973  0.420147  0.045445  1.543919  …        NaN       NaN       NaN

           V24       V25       V26       V27       V28  Amount  Class
0     0.066928  0.128539 -0.189115  0.133558 -0.021053  149.62    0.0
1    -0.339846  0.167170  0.125895 -0.008983  0.014724    2.69    0.0
2    -0.689281 -0.327642 -0.139097 -0.055353 -0.059752  378.66    0.0
3    -1.175575  0.647376 -0.221929  0.062723  0.061458  123.50    0.0
4     0.141267 -0.206010  0.502292  0.219422  0.215153   69.99    0.0
…          …         …        …        …         …       …      …
5969  0.057628 -0.024955 -0.368263  0.081684  0.140669  458.92    0.0
5970 -1.189156 -0.126040  0.701487  0.277333 -0.222694    0.77    0.0
5971 -0.556105  0.517579  0.008006  0.366054  0.185008   14.00    0.0
5972 -0.177773  0.321810  0.114930 -0.109640  0.023205  139.90    0.0
5973       NaN       NaN       NaN       NaN       NaN     NaN    NaN

[5974 rows x 31 columns]
```

[ ]:
```
df.head(),df.tail(),df.describe()
```

[ ]:
```
(   Time        V1        V2        V3        V4        V5        V6        V7
\
 0     0 -1.359807 -0.072781  2.536347  1.378155 -0.338321  0.462388  0.239599
 1     0  1.191857  0.266151  0.166480  0.448154  0.060018 -0.082361 -0.078803
 2     1 -1.358354 -1.340163  1.773209  0.379780 -0.503198  1.800499  0.791461
 3     1 -0.966272 -0.185226  1.792993 -0.863291 -0.010309  1.247203  0.237609
 4     2 -1.158233  0.877737  1.548718  0.403034 -0.407193  0.095921  0.592941

         V8        V9  …       V21       V22       V23       V24       V25  \
 0  0.098698  0.363787  … -0.018307  0.277838 -0.110474  0.066928  0.128539
 1  0.085102 -0.255425  … -0.225775 -0.638672  0.101288 -0.339846  0.167170
 2  0.247676 -1.514654  …  0.247998  0.771679  0.909412 -0.689281 -0.327642
 3  0.377436 -1.387024  … -0.108300  0.005274 -0.190321 -1.175575  0.647376
 4 -0.270533  0.817739  … -0.009431  0.798278 -0.137458  0.141267 -0.206010

         V26       V27       V28  Amount  Class
 0 -0.189115  0.133558 -0.021053  149.62    0.0
 1  0.125895 -0.008983  0.014724    2.69    0.0
 2 -0.139097 -0.055353 -0.059752  378.66    0.0
 3 -0.221929  0.062723  0.061458  123.50    0.0
```

```
4  0.502292  0.219422  0.215153   69.99    0.0

[5 rows x 31 columns],
      Time        V1        V2        V3        V4        V5        V6  \
5969  6634 -1.611463  0.190648  0.901715  1.531254 -1.535865  0.799245
5970  6635 -1.420272  1.449354  1.320110 -1.894320  0.913695  0.454601
5971  6637 -1.206696  0.284728  2.152053 -2.850437 -0.437285 -0.238376
5972  6644  1.067611  0.091006 -0.153917  0.704233  0.113894 -0.826866
5973  6645 -0.535272 -0.132299  2.180041  1.018303 -1.498819  0.529570

            V7        V8        V9  …       V21       V22       V23  \
5969  1.513786  0.495829  0.200390  …  0.211223  0.007477  1.026272
5970  0.894179 -0.385450  2.433841  … -0.529027 -0.368394 -0.247773
5971 -0.333341  0.334679  2.870542  …  0.039460  0.464476 -0.457193
5972  0.567690 -0.464181  0.957295  … -0.476723 -1.410090 -0.037550
5973  0.420147  0.045445  1.543919  …       NaN       NaN       NaN

           V24       V25       V26       V27       V28  Amount  Class
5969  0.057628 -0.024955 -0.368263  0.081684  0.140669  458.92    0.0
5970 -1.189156 -0.126040  0.701487  0.277333 -0.222694    0.77    0.0
5971 -0.556105  0.517579  0.008006  0.366054  0.185008   14.00    0.0
5972 -0.177773  0.321810  0.114930 -0.109640  0.023205  139.90    0.0
5973       NaN       NaN       NaN       NaN       NaN     NaN    NaN

[5 rows x 31 columns],
              Time           V1           V2           V3           V4  \
count  5974.000000  5974.000000  5974.000000  5974.000000  5974.000000
mean   2677.615501    -0.266159     0.285505     0.844231     0.104200
std    1765.025532     1.395405     1.208867     1.031448     1.442339
min       0.000000   -12.168192   -15.732974   -12.389545    -4.657545
25%    1162.250000    -1.015749    -0.280054     0.295701    -0.839417
50%    2537.000000    -0.420703     0.346083     0.882882     0.161767
75%    3781.750000     1.115402     0.941548     1.504158     1.071412
max    6645.000000     1.685314     7.467017     4.101716     6.013346

                V5           V6           V7           V8           V9  …  \
count  5974.000000  5974.000000  5974.000000  5974.000000  5974.000000  …
mean      0.000709     0.194948     0.018324    -0.039006     0.396916  …
std       1.185900     1.365525     1.059870     1.304005     1.047749  …
min     -32.092129    -7.465603   -12.968670   -23.632502    -3.336805  …
25%      -0.609206    -0.677720    -0.492968    -0.189736    -0.264280  …
50%      -0.083983    -0.142606     0.041761     0.037831     0.360826  …
75%       0.441406     0.605784     0.566306     0.343067     0.961662  …
max      10.658654    21.393069    34.303177     3.877662     9.272376  …

               V21          V22          V23          V24          V25  \
count  5973.000000  5973.000000  5973.000000  5973.000000  5973.000000
```

```
mean     -0.043098   -0.161548   -0.036483    0.028960    0.089873
std       0.883330    0.646380    0.373210    0.619810    0.407680
min     -11.468435   -8.454599   -7.996811   -2.512377   -2.322906
25%      -0.260507   -0.594625   -0.187108   -0.350226   -0.152744
50%      -0.111701   -0.177197   -0.046772    0.094946    0.106290
75%       0.059809    0.273148    0.088154    0.435670    0.355157
max      22.580675    4.393846    4.095021    3.200201    1.972515

                V26          V27          V28       Amount        Class
count  5973.000000  5973.000000  5973.000000  5973.000000  5973.000000
mean     -0.040197     0.025234     0.006116    65.061811     0.000502
std       0.488284     0.364482     0.265131   192.490314     0.022407
min      -1.338556    -7.976100    -2.909294     0.000000     0.000000
25%      -0.399334    -0.049681    -0.017776     4.450000     0.000000
50%      -0.079583     0.015976     0.019417    15.620000     0.000000
75%       0.245560     0.155281     0.082701    56.660000     0.000000
max       3.463246     3.852046     4.860769  7712.430000     1.000000

[8 rows x 31 columns])
```

[ ]:
```python
df = df.drop(columns=[f"V{i}" for i in range(1, 9)])
```

[ ]:
```python
df = df.dropna()
```

[ ]:
```python
threshold = 100


total_transactions = len(df)
fraud_transactions = df[df['Class'] == 1]
high_amount_transactions = df[df['Amount'] > threshold]
```

[ ]:
```python
p_fraud = len(fraud_transactions) / total_transactions

p_high_amount = len(high_amount_transactions) / total_transactions

print("Probability Of Fraud : ",p_fraud)
print("Probability Of high Amount  : ",p_high_amount)
```

```
Probability Of Fraud :  0.0005022601707684581
Probability Of high Amount  :  0.1523522517997656
```

[ ]:
```python
# P(High Amount | Fraud)
high_amount_fraud = fraud_transactions[fraud_transactions['Amount'] > threshold]
p_high_amount_given_fraud = len(high_amount_fraud) / len(fraud_transactions)
print(f"P(High Amount | Fraud): {p_high_amount_given_fraud:.4f}")
```

```
P(High Amount | Fraud): 0.6667
```

[ ]:
```python
# P(Fraud | High Amount)
if p_high_amount > 0:
    p_fraud_given_high_amount = (p_high_amount_given_fraud * p_fraud) /
 ↪p_high_amount
else:
    p_fraud_given_high_amount = 0

print(f"P(Fraud | High Amount): {p_fraud_given_high_amount:.4f}")
```

```
P(Fraud | High Amount): 0.0022
```

ANOTHER LAB TASK CODE

Generate 15 random numbers from 1 to 50 and plot Q-Q plot for the points.

Plot Q-Q plot for earning column of this dataset and notedown your inference

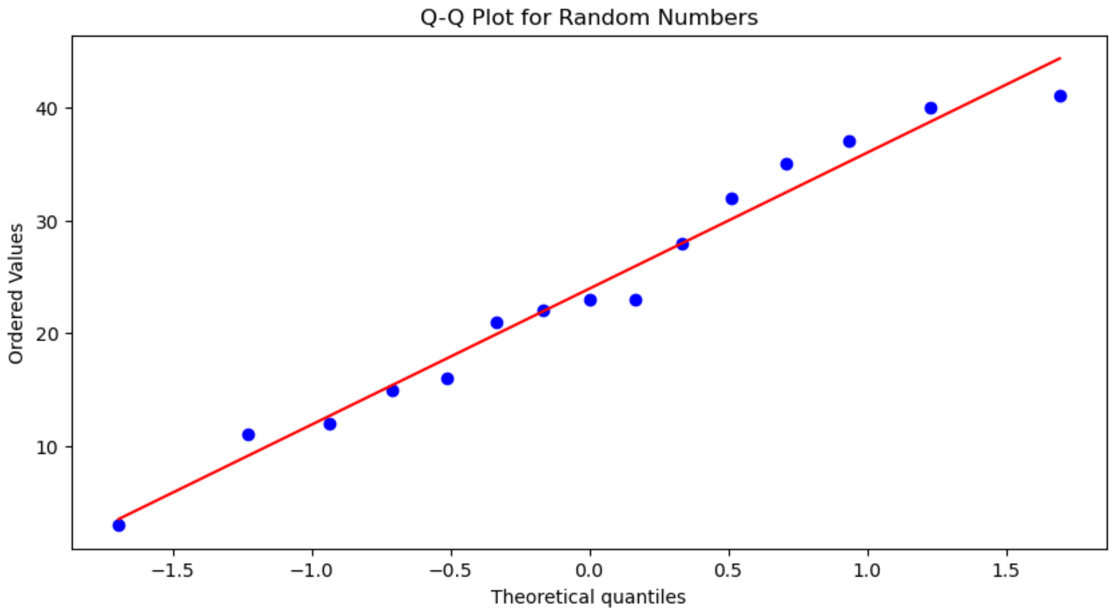
[4]:
```python
data2=pd.read_csv("G:\SEM 4\PMRP\RAW_CODE\PMRP_DAY_10\Forbes Richest Atheletes
 ↪(Forbes Richest Athletes 1990-2020).csv")
data2
```

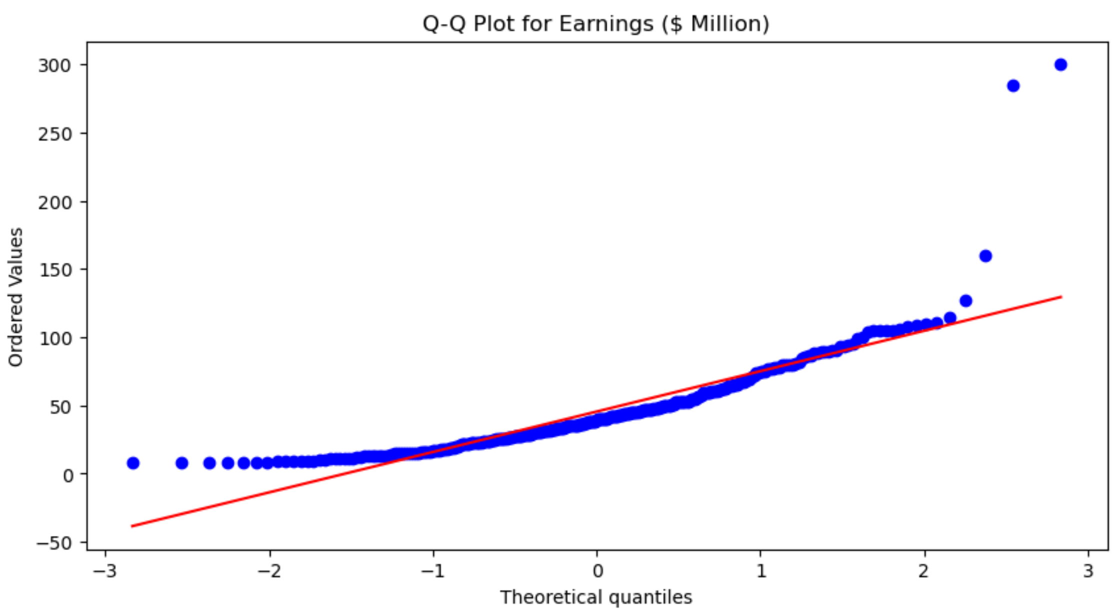
```
<>:1: SyntaxWarning: invalid escape sequence '\S'
<>:1: SyntaxWarning: invalid escape sequence '\S'
C:\Users\omcho\AppData\Local\Temp\ipykernel_14844\3117694017.py:1:
SyntaxWarning: invalid escape sequence '\S'
  data2=pd.read_csv("G:\SEM 4\PMRP\RAW_CODE\PMRP_DAY_10\Forbes Richest Atheletes
(Forbes Richest Athletes 1990-2020).csv")
```

[4]:
```
     S.NO              Name Nationality  Current Rank Previous Year Rank  \
0       1        Mike Tyson         USA             1                NaN
1       2    Buster Douglas         USA             2                NaN
2       3  Sugar Ray Leonard        USA             3                NaN
3       4      Ayrton Senna      Brazil             4                NaN
4       5       Alain Prost      France             5                NaN
..    …                 …         …             …                  …
296   297     Stephen Curry         USA             6                  9
297   298      Kevin Durant         USA             7                 10
298   299       Tiger Woods         USA             8                 11
299   300      Kirk Cousins         USA             9               >100
300   301      Carson Wentz         USA            10               >100

            Sport  Year  earnings ($ million)
0          boxing  1990                  28.6
1          boxing  1990                  26.0
2          boxing  1990                  13.0
3     auto racing  1990                  10.0
4     auto racing  1990                   9.0
..              …     …                     …
296    Basketball  2020                  74.4
```

```
297          Basketball  2020                    63.9
298                Golf  2020                    62.3
299   American Football  2020                    60.5
300   American Football  2020                    59.1

[301 rows x 8 columns]
```

[5]:
```python
import scipy.stats as stats

random_numbers = np.random.randint(1, 51, 15)


plt.figure(figsize=(10, 5))
stats.probplot(random_numbers, dist="norm", plot=plt)
plt.title("Q-Q Plot for Random Numbers")
plt.show()


data2['earnings ($ million)'] = pd.to_numeric(data2['earnings ($ million)'],␣
 ↪errors='coerce')
earnings = data2['earnings ($ million)'].dropna()

plt.figure(figsize=(10, 5))
stats.probplot(earnings, dist="norm", plot=plt)
plt.title("Q-Q Plot for Earnings ($ Million)")
plt.show()


print("Inference:")
print("- The Q-Q plot for random numbers will show whether they follow a normal␣
 ↪distribution.")
print("- The Q-Q plot for earnings will indicate whether the earnings data␣
 ↪aligns with a normal distribution.")
```






```
Inference:
- The Q-Q plot for random numbers will show whether they follow a normal
distribution.
- The Q-Q plot for earnings will indicate whether the earnings data aligns with
a normal distribution.
```

[ ]:

from file: PMRP_5

23AIML010 OM CHOKSI PMRP ASSIGNMENT 5 + CLASSWORK

CLASSWORK QUESTIONS

IPL DATA ANALYTICS

1. Calculate the total number of matches played in each season
2. Find the most successful team (team with the most wins)
3. Find the average margin of victory by wickets and by runs
4. Which player won the most 'Player of the Match awards?
5. Find the number of matches where the toss winner won the match
6. Calculate the total number of runs scored in all matches for each team
7. Determine the average number of wickets taken by the winning team in each match
8. How many matches were decided by a Super Over?
9. Find the distribution of match results (runs vs wickets)
10. Find the top 5 venues with the most matches played
11. Find the match with the highest margin of victory (by wickets or runs)
12. Calculate the win percentage for each team
13. Find the average number of overs played in all matches
14. Find the most common match outcome (runs, wickets, or no result)
15. Find the total number of matches played at each venue by year
16. Analyze the win margin distribution by year
17. Calculate the total number of 'no result' matches and their impact on the tournament
18. How many matches were won by teams batting first vs. batting second?
19. Find out the average number of runs scored by the winning team
20. Identify the most successful captain (team with the most wins under a captain)

[77]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

df=pd.read_csv('D:/SEM4/PMRP/RAW_CODE/PMRP_DAY_13/matches.csv')
df.head,df.tail,df.describe,df.info
```

[77]:
```
(<bound method NDFrame.head of             id   season      city       date
match_type  player_of_match  \
 0      335982  2007/08   Bangalore  2008-04-18       League      BB McCullum
```

```
1      335983  2007/08  Chandigarh  2008-04-19        League        MEK Hussey
2      335984  2007/08       Delhi  2008-04-19        League      MF Maharoof
3      335985  2007/08      Mumbai  2008-04-20        League       MV Boucher
4      335986  2007/08     Kolkata  2008-04-20        League        DJ Hussey
…         …        …          …          …             …               …
1090  1426307     2024   Hyderabad  2024-05-19        League  Abhishek Sharma
1091  1426309     2024   Ahmedabad  2024-05-21  Qualifier 1         MA Starc
1092  1426310     2024   Ahmedabad  2024-05-22    Eliminator        R Ashwin
1093  1426311     2024     Chennai  2024-05-24  Qualifier 2    Shahbaz Ahmed
1094  1426312     2024     Chennai  2024-05-26         Final         MA Starc

                                                  venue  \
0                                 M Chinnaswamy Stadium
1            Punjab Cricket Association Stadium, Mohali
2                                      Feroz Shah Kotla
3                                      Wankhede Stadium
4                                          Eden Gardens
…                                                   …
1090  Rajiv Gandhi International Stadium, Uppal, Hyd…
1091                   Narendra Modi Stadium, Ahmedabad
1092                   Narendra Modi Stadium, Ahmedabad
1093             MA Chidambaram Stadium, Chepauk, Chennai
1094             MA Chidambaram Stadium, Chepauk, Chennai

                            team1                        team2  \
0     Royal Challengers Bangalore        Kolkata Knight Riders
1                 Kings XI Punjab          Chennai Super Kings
2                Delhi Daredevils             Rajasthan Royals
3                  Mumbai Indians  Royal Challengers Bangalore
4           Kolkata Knight Riders              Deccan Chargers
…                             …                          …
1090                 Punjab Kings          Sunrisers Hyderabad
1091          Sunrisers Hyderabad        Kolkata Knight Riders
1092  Royal Challengers Bengaluru             Rajasthan Royals
1093          Sunrisers Hyderabad             Rajasthan Royals
1094          Sunrisers Hyderabad        Kolkata Knight Riders

                      toss_winner toss_decision                       winner  \
0     Royal Challengers Bangalore         field        Kolkata Knight Riders
1             Chennai Super Kings           bat          Chennai Super Kings
2                Rajasthan Royals           bat             Delhi Daredevils
3                  Mumbai Indians           bat  Royal Challengers Bangalore
4                 Deccan Chargers           bat        Kolkata Knight Riders
…                             …            …                          …
1090                 Punjab Kings           bat          Sunrisers Hyderabad
1091          Sunrisers Hyderabad           bat        Kolkata Knight Riders
1092             Rajasthan Royals         field             Rajasthan Royals
```

```
1093           Rajasthan Royals        field         Sunrisers Hyderabad
1094         Sunrisers Hyderabad         bat       Kolkata Knight Riders

       result  result_margin  target_runs  target_overs super_over method  \
0        runs          140.0        223.0          20.0          N    NaN
1        runs           33.0        241.0          20.0          N    NaN
2     wickets            9.0        130.0          20.0          N    NaN
3     wickets            5.0        166.0          20.0          N    NaN
4     wickets            5.0        111.0          20.0          N    NaN
…       …             …          …            …          …    …
1090  wickets            4.0        215.0          20.0          N    NaN
1091  wickets            8.0        160.0          20.0          N    NaN
1092  wickets            4.0        173.0          20.0          N    NaN
1093     runs           36.0        176.0          20.0          N    NaN
1094  wickets            8.0        114.0          20.0          N    NaN

                   umpire1                umpire2
0                Asad Rauf            RE Koertzen
1                MR Benson            SL Shastri
2                Aleem Dar        GA Pratapkumar
3                 SJ Davis             DJ Harper
4                BF Bowden            K Hariharan
…                    …                    …
1090           Nitin Menon             VK Sharma
1091          AK Chaudhary              R Pandit
1092  KN Ananthapadmanabhan  MV Saidharshan Kumar
1093           Nitin Menon             VK Sharma
1094         J Madanagopal           Nitin Menon

[1095 rows x 20 columns]>,
 <bound method NDFrame.tail of            id   season        city        date
match_type  player_of_match  \
0      335982  2007/08   Bangalore  2008-04-18       League      BB McCullum
1      335983  2007/08  Chandigarh  2008-04-19       League      MEK Hussey
2      335984  2007/08       Delhi  2008-04-19       League      MF Maharoof
3      335985  2007/08      Mumbai  2008-04-20       League      MV Boucher
4      335986  2007/08     Kolkata  2008-04-20       League       DJ Hussey
…       …       …         …          …          …              …
1090  1426307     2024   Hyderabad  2024-05-19       League  Abhishek Sharma
1091  1426309     2024   Ahmedabad  2024-05-21  Qualifier 1         MA Starc
1092  1426310     2024   Ahmedabad  2024-05-22   Eliminator         R Ashwin
1093  1426311     2024     Chennai  2024-05-24  Qualifier 2    Shahbaz Ahmed
1094  1426312     2024     Chennai  2024-05-26        Final         MA Starc

                                              venue  \
0                             M Chinnaswamy Stadium
1           Punjab Cricket Association Stadium, Mohali
```

```
2                                          Feroz Shah Kotla
3                                          Wankhede Stadium
4                                              Eden Gardens
…                                                       …
1090  Rajiv Gandhi International Stadium, Uppal, Hyd…
1091                    Narendra Modi Stadium, Ahmedabad
1092                    Narendra Modi Stadium, Ahmedabad
1093             MA Chidambaram Stadium, Chepauk, Chennai
1094             MA Chidambaram Stadium, Chepauk, Chennai

                            team1                        team2  \
0     Royal Challengers Bangalore        Kolkata Knight Riders
1                 Kings XI Punjab          Chennai Super Kings
2                Delhi Daredevils             Rajasthan Royals
3                  Mumbai Indians  Royal Challengers Bangalore
4           Kolkata Knight Riders              Deccan Chargers
…                             …                            …
1090                 Punjab Kings          Sunrisers Hyderabad
1091          Sunrisers Hyderabad        Kolkata Knight Riders
1092  Royal Challengers Bengaluru             Rajasthan Royals
1093          Sunrisers Hyderabad             Rajasthan Royals
1094          Sunrisers Hyderabad        Kolkata Knight Riders

                      toss_winner toss_decision                       winner  \
0     Royal Challengers Bangalore         field        Kolkata Knight Riders
1             Chennai Super Kings           bat          Chennai Super Kings
2                Rajasthan Royals           bat             Delhi Daredevils
3                  Mumbai Indians           bat  Royal Challengers Bangalore
4                 Deccan Chargers           bat        Kolkata Knight Riders
…                             …           …                          …
1090                 Punjab Kings           bat          Sunrisers Hyderabad
1091          Sunrisers Hyderabad           bat        Kolkata Knight Riders
1092             Rajasthan Royals         field             Rajasthan Royals
1093             Rajasthan Royals         field          Sunrisers Hyderabad
1094          Sunrisers Hyderabad           bat        Kolkata Knight Riders

       result  result_margin  target_runs  target_overs super_over method  \
0        runs          140.0        223.0          20.0          N    NaN
1        runs           33.0        241.0          20.0          N    NaN
2     wickets            9.0        130.0          20.0          N    NaN
3     wickets            5.0        166.0          20.0          N    NaN
4     wickets            5.0        111.0          20.0          N    NaN
…        …              …            …             …          …    …
1090  wickets            4.0        215.0          20.0          N    NaN
1091  wickets            8.0        160.0          20.0          N    NaN
1092  wickets            4.0        173.0          20.0          N    NaN
1093     runs           36.0        176.0          20.0          N    NaN
```

```
1094  wickets             8.0        114.0          20.0          N    NaN

                   umpire1               umpire2
0                Asad Rauf          RE Koertzen
1                MR Benson           SL Shastri
2                Aleem Dar       GA Pratapkumar
3                 SJ Davis            DJ Harper
4                BF Bowden          K Hariharan
…                       …                    …
1090           Nitin Menon            VK Sharma
1091          AK Chaudhary             R Pandit
1092  KN Ananthapadmanabhan  MV Saidharshan Kumar
1093           Nitin Menon            VK Sharma
1094         J Madanagopal          Nitin Menon

[1095 rows x 20 columns]>,
<bound method NDFrame.describe of            id   season        city
date   match_type  player_of_match  \
0      335982  2007/08   Bangalore  2008-04-18       League      BB McCullum
1      335983  2007/08  Chandigarh  2008-04-19       League      MEK Hussey
2      335984  2007/08       Delhi  2008-04-19       League      MF Maharoof
3      335985  2007/08      Mumbai  2008-04-20       League      MV Boucher
4      335986  2007/08     Kolkata  2008-04-20       League       DJ Hussey
…         …       …          …          …           …               …
1090  1426307     2024   Hyderabad  2024-05-19       League  Abhishek Sharma
1091  1426309     2024   Ahmedabad  2024-05-21  Qualifier 1         MA Starc
1092  1426310     2024   Ahmedabad  2024-05-22   Eliminator         R Ashwin
1093  1426311     2024     Chennai  2024-05-24  Qualifier 2    Shahbaz Ahmed
1094  1426312     2024     Chennai  2024-05-26        Final         MA Starc

                                              venue  \
0                             M Chinnaswamy Stadium
1        Punjab Cricket Association Stadium, Mohali
2                                  Feroz Shah Kotla
3                                  Wankhede Stadium
4                                      Eden Gardens
…                                               …
1090  Rajiv Gandhi International Stadium, Uppal, Hyd…
1091                 Narendra Modi Stadium, Ahmedabad
1092                 Narendra Modi Stadium, Ahmedabad
1093          MA Chidambaram Stadium, Chepauk, Chennai
1094          MA Chidambaram Stadium, Chepauk, Chennai

                             team1                        team2  \
0     Royal Challengers Bangalore        Kolkata Knight Riders
1                 Kings XI Punjab          Chennai Super Kings
2                Delhi Daredevils             Rajasthan Royals
```

```
3                  Mumbai Indians  Royal Challengers Bangalore
4          Kolkata Knight Riders              Deccan Chargers
…                             …                           …
1090                 Punjab Kings          Sunrisers Hyderabad
1091          Sunrisers Hyderabad        Kolkata Knight Riders
1092  Royal Challengers Bengaluru             Rajasthan Royals
1093          Sunrisers Hyderabad             Rajasthan Royals
1094          Sunrisers Hyderabad        Kolkata Knight Riders

                      toss_winner toss_decision                       winner  \
0     Royal Challengers Bangalore         field        Kolkata Knight Riders
1             Chennai Super Kings           bat          Chennai Super Kings
2                Rajasthan Royals           bat             Delhi Daredevils
3                  Mumbai Indians           bat  Royal Challengers Bangalore
4                 Deccan Chargers           bat        Kolkata Knight Riders
…                             …             …                           …
1090                 Punjab Kings           bat          Sunrisers Hyderabad
1091          Sunrisers Hyderabad           bat        Kolkata Knight Riders
1092             Rajasthan Royals         field             Rajasthan Royals
1093             Rajasthan Royals         field          Sunrisers Hyderabad
1094          Sunrisers Hyderabad           bat        Kolkata Knight Riders

       result  result_margin  target_runs  target_overs super_over method  \
0        runs          140.0        223.0          20.0          N    NaN
1        runs           33.0        241.0          20.0          N    NaN
2     wickets            9.0        130.0          20.0          N    NaN
3     wickets            5.0        166.0          20.0          N    NaN
4     wickets            5.0        111.0          20.0          N    NaN
…       …             …          …            …          …    …
1090  wickets            4.0        215.0          20.0          N    NaN
1091  wickets            8.0        160.0          20.0          N    NaN
1092  wickets            4.0        173.0          20.0          N    NaN
1093     runs           36.0        176.0          20.0          N    NaN
1094  wickets            8.0        114.0          20.0          N    NaN

                    umpire1               umpire2
0                 Asad Rauf          RE Koertzen
1                 MR Benson           SL Shastri
2                 Aleem Dar       GA Pratapkumar
3                  SJ Davis            DJ Harper
4                 BF Bowden          K Hariharan
…                       …                   …
1090            Nitin Menon            VK Sharma
1091           AK Chaudhary             R Pandit
1092  KN Ananthapadmanabhan  MV Saidharshan Kumar
1093            Nitin Menon            VK Sharma
1094          J Madanagopal          Nitin Menon
```

```
[1095 rows x 20 columns]>,
 <bound method DataFrame.info of             id   season        city        date
match_type  player_of_match  \
0      335982  2007/08   Bangalore  2008-04-18       League      BB McCullum
1      335983  2007/08  Chandigarh  2008-04-19       League       MEK Hussey
2      335984  2007/08       Delhi  2008-04-19       League      MF Maharoof
3      335985  2007/08      Mumbai  2008-04-20       League       MV Boucher
4      335986  2007/08     Kolkata  2008-04-20       League        DJ Hussey
…         …        …         …         …            …              …
1090  1426307     2024   Hyderabad  2024-05-19       League  Abhishek Sharma
1091  1426309     2024   Ahmedabad  2024-05-21  Qualifier 1         MA Starc
1092  1426310     2024   Ahmedabad  2024-05-22   Eliminator         R Ashwin
1093  1426311     2024     Chennai  2024-05-24  Qualifier 2    Shahbaz Ahmed
1094  1426312     2024     Chennai  2024-05-26        Final         MA Starc

                                                  venue  \
0                                 M Chinnaswamy Stadium
1            Punjab Cricket Association Stadium, Mohali
2                                      Feroz Shah Kotla
3                                      Wankhede Stadium
4                                          Eden Gardens
…                                                   …
1090  Rajiv Gandhi International Stadium, Uppal, Hyd…
1091                  Narendra Modi Stadium, Ahmedabad
1092                  Narendra Modi Stadium, Ahmedabad
1093          MA Chidambaram Stadium, Chepauk, Chennai
1094          MA Chidambaram Stadium, Chepauk, Chennai

                            team1                        team2  \
0     Royal Challengers Bangalore        Kolkata Knight Riders
1                 Kings XI Punjab          Chennai Super Kings
2                Delhi Daredevils             Rajasthan Royals
3                  Mumbai Indians  Royal Challengers Bangalore
4           Kolkata Knight Riders              Deccan Chargers
…                             …                            …
1090                 Punjab Kings          Sunrisers Hyderabad
1091          Sunrisers Hyderabad        Kolkata Knight Riders
1092  Royal Challengers Bengaluru             Rajasthan Royals
1093          Sunrisers Hyderabad             Rajasthan Royals
1094          Sunrisers Hyderabad        Kolkata Knight Riders

                      toss_winner toss_decision                       winner  \
0     Royal Challengers Bangalore         field        Kolkata Knight Riders
1             Chennai Super Kings           bat          Chennai Super Kings
2                Rajasthan Royals           bat             Delhi Daredevils
3                  Mumbai Indians           bat  Royal Challengers Bangalore
```

```
4               Deccan Chargers          bat       Kolkata Knight Riders
...                         ...          ...                         ...
1090               Punjab Kings          bat         Sunrisers Hyderabad
1091        Sunrisers Hyderabad          bat       Kolkata Knight Riders
1092           Rajasthan Royals        field            Rajasthan Royals
1093           Rajasthan Royals        field         Sunrisers Hyderabad
1094        Sunrisers Hyderabad          bat       Kolkata Knight Riders

       result  result_margin  target_runs  target_overs super_over method  \
0        runs          140.0        223.0          20.0          N    NaN
1        runs           33.0        241.0          20.0          N    NaN
2     wickets            9.0        130.0          20.0          N    NaN
3     wickets            5.0        166.0          20.0          N    NaN
4     wickets            5.0        111.0          20.0          N    NaN
...       ...            ...          ...           ...        ...    ...
1090  wickets            4.0        215.0          20.0          N    NaN
1091  wickets            8.0        160.0          20.0          N    NaN
1092  wickets            4.0        173.0          20.0          N    NaN
1093     runs           36.0        176.0          20.0          N    NaN
1094  wickets            8.0        114.0          20.0          N    NaN

                     umpire1               umpire2
0                  Asad Rauf           RE Koertzen
1                  MR Benson            SL Shastri
2                  Aleem Dar        GA Pratapkumar
3                   SJ Davis             DJ Harper
4                  BF Bowden           K Hariharan
...                      ...                   ...
1090             Nitin Menon             VK Sharma
1091            AK Chaudhary              R Pandit
1092  KN Ananthapadmanabhan  MV Saidharshan Kumar
1093             Nitin Menon             VK Sharma
1094           J Madanagopal           Nitin Menon

[1095 rows x 20 columns]>)
```

1.Calculate the total number of Matches Played in Each Session

[78]:
```
matches_per_season = df['season'].value_counts().sort_index()
print(matches_per_season)
```

```
season
2007/08    58
2009       57
2009/10    60
2011       73
2012       74
2013       76
```

```
2014       60
2015       59
2016       60
2017       59
2018       60
2019       60
2020/21    60
2021       60
2022       74
2023       74
2024       71
Name: count, dtype: int64
```

2. Find the Most Successfull team (team with most runs)

[79]:
```python
# runs_df = df[df['result'] == 'runs']


# most_successful_team = runs_df.groupby('winner')['result_margin'].sum().
↪idxmax()
# print(f"The most successful team (team with most runs) is:␣
↪{most_successful_team}")

df["winner"].value_counts()
```

[79]:
```
winner
Mumbai Indians                 144
Chennai Super Kings            138
Kolkata Knight Riders          131
Royal Challengers Bangalore    116
Rajasthan Royals               112
Kings XI Punjab                 88
Sunrisers Hyderabad             88
Delhi Daredevils                67
Delhi Capitals                  48
Deccan Chargers                 29
Gujarat Titans                  28
Lucknow Super Giants            24
Punjab Kings                    24
Gujarat Lions                   13
Pune Warriors                   12
Rising Pune Supergiant          10
Royal Challengers Bengaluru      7
Kochi Tuskers Kerala             6
Rising Pune Supergiants          5
Name: count, dtype: int64
```

3. Find the average margin of victory by wickets and runs

[80]:
```
average_runs_margin = df[df['result'] == 'runs']['result_margin'].mean()
average_wickets_margin = df[df['result'] == 'wickets']['result_margin'].mean()
print(f'Average margin of victory by runs: {average_runs_margin}')
print(f'Average margin of victory by wickets: {average_wickets_margin}')
```

```
Average margin of victory by runs: 30.104417670682732
Average margin of victory by wickets: 6.192041522491349
```

4. Which player won the most 'Player of the Match awards?

[81]:
```
most_player_of_match = df['player_of_match'].value_counts().idxmax()
print(f"The player who won the most 'Player of the Match' awards is:␣
↪{most_player_of_match}")
```

```
The player who won the most 'Player of the Match' awards is: AB de Villiers
```

5. Find the number of matches where the toss winner won the match

[82]:
```
toss_winner_matches = df[df['toss_winner'] == df['winner']].shape[0]
print(f"The number of matches where the toss winner won the match:␣
↪{toss_winner_matches}")
```

```
The number of matches where the toss winner won the match: 554
```

6. Calculate the total number of runs scored in all matches for each team

[83]:
```
total_runs_per_team = df.groupby('team1')['target_runs'].sum() + df.
↪groupby('team2')['target_runs'].sum()
print(total_runs_per_team)
```

```
team1
Chennai Super Kings            39503.0
Deccan Chargers                12047.0
Delhi Capitals                 15930.0
Delhi Daredevils               25492.0
Gujarat Lions                   5077.0
Gujarat Titans                  7865.0
Kings XI Punjab                31391.0
Kochi Tuskers Kerala            2014.0
Kolkata Knight Riders          40557.0
Lucknow Super Giants            7835.0
Mumbai Indians                 43728.0
Pune Warriors                   6950.0
Punjab Kings                    9787.0
Rajasthan Royals               36250.0
Rising Pune Supergiant          2571.0
Rising Pune Supergiants         1993.0
Royal Challengers Bangalore    39807.0
Royal Challengers Bengaluru     2986.0
Sunrisers Hyderabad            30071.0
Name: target_runs, dtype: float64
```

7. Determine the average number of wickets taken by the winning team in each match

[84]:
```python
average_wickets_taken = df[df['result'] == 'wickets']['result_margin'].mean()
print(f'The average number of wickets taken by the winning team in each match␣
↪is: {average_wickets_taken}')
```

```
The average number of wickets taken by the winning team in each match is:
6.192041522491349
```

8. How many matches were decided by a Super Over?

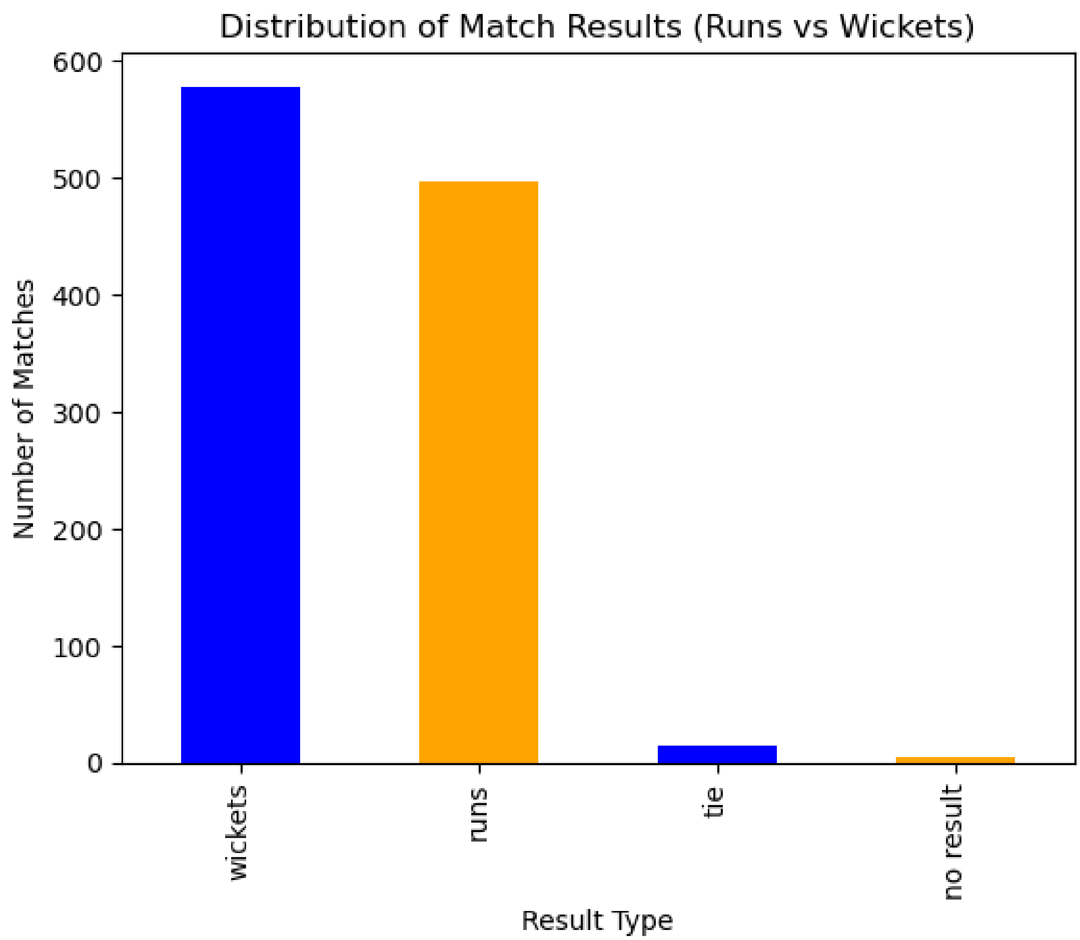
[85]:
```python
super_over_matches = df[df['super_over'] == 'Y'].shape[0]
print(f"The number of matches decided by a Super Over: {super_over_matches}")
```

```
The number of matches decided by a Super Over: 14
```

9. Find the distribution of match results (runs vs wickets)

[86]:
```python
result_distribution = df['result'].value_counts()
print(result_distribution)

# Plotting the distribution
result_distribution.plot(kind='bar', color=['blue', 'orange'])
plt.title('Distribution of Match Results (Runs vs Wickets)')
plt.xlabel('Result Type')
plt.ylabel('Number of Matches')
plt.show()
```

```
result
wickets      578
runs         498
tie           14
no result      5
Name: count, dtype: int64
```



10. Find the top 5 venues with the most matches played

[87]:
```
top_venues = df['venue'].value_counts().head(5)
print(top_venues)

# # Plotting the top 5 venues
# top_venues.plot(kind='bar', color='green')
# plt.title('Top 5 Venues with the Most Matches Played')
# plt.xlabel('Venue')
# plt.ylabel('Number of Matches')
# plt.show()
```

```
venue
Eden Gardens                               77
Wankhede Stadium                           73
M Chinnaswamy Stadium                      65
Feroz Shah Kotla                           60
Rajiv Gandhi International Stadium, Uppal    49
```

```
Name: count, dtype: int64
```

11. Find the match with the highest margin of victory (by wickets or runs)

[88]:
```
df[df['result_margin']==df['result_margin'].max()]
```

[88]:
```
          id season   city        date match_type player_of_match  \
620  1082635   2017  Delhi  2017-05-06     League     LMP Simmons

                venue            team1           team2       toss_winner  \
620  Feroz Shah Kotla  Delhi Daredevils  Mumbai Indians  Delhi Daredevils

    toss_decision          winner result  result_margin  target_runs  \
620         field  Mumbai Indians   runs          146.0        213.0

     target_overs super_over method      umpire1    umpire2
620          20.0          N    NaN  Nitin Menon  CK Nandan
```

[89]:
```
# Find the match with the highest margin of victory (by wickets or runs)
df_wickets=df[df['result']=='wickets']
df_runs=df[df['result']=='runs']

max_margin_wicket=df_wickets.loc[df_wickets['result_margin'].idxmax()]

max_margin_run=df_runs.loc[df_runs['result_margin'].idxmax()]

max_margin_run,max_margin_wicket
```

[89]:
```
(id                          1082635
 season                         2017
 city                          Delhi
 date                     2017-05-06
 match_type                   League
 player_of_match         LMP Simmons
 venue              Feroz Shah Kotla
 team1              Delhi Daredevils
 team2                Mumbai Indians
 toss_winner        Delhi Daredevils
 toss_decision                 field
 winner               Mumbai Indians
 result                         runs
 result_margin                 146.0
 target_runs                   213.0
 target_overs                   20.0
 super_over                        N
 method                          NaN
 umpire1                 Nitin Menon
 umpire2                   CK Nandan
```

```
Name: 620, dtype: object,
id                                     335994
season                                2007/08
city                                   Mumbai
date                               2008-04-27
match_type                             League
player_of_match                  AC Gilchrist
venue              Dr DY Patil Sports Academy
team1                          Mumbai Indians
team2                         Deccan Chargers
toss_winner                   Deccan Chargers
toss_decision                           field
winner                        Deccan Chargers
result                                wickets
result_margin                            10.0
target_runs                             155.0
target_overs                             20.0
super_over                                  N
method                                    NaN
umpire1                             Asad Rauf
umpire2                            SL Shastri
Name: 12, dtype: object)
```

12. Calculate the win percentage for each team

[90]:
```python
matches_played = df['team1'].value_counts() + df['team2'].value_counts()

matches_won = df['winner'].value_counts()
win_percentage = (matches_won / matches_played) * 100

print(win_percentage)
```

```
Chennai Super Kings            57.983193
Deccan Chargers                38.666667
Delhi Capitals                 52.747253
Delhi Daredevils               41.614907
Gujarat Lions                  43.333333
Gujarat Titans                 62.222222
Kings XI Punjab                46.315789
Kochi Tuskers Kerala           42.857143
Kolkata Knight Riders          52.191235
Lucknow Super Giants           54.545455
Mumbai Indians                 55.172414
Pune Warriors                  26.086957
Punjab Kings                   42.857143
Rajasthan Royals               50.678733
Rising Pune Supergiant         62.500000
Rising Pune Supergiants        35.714286
```

```
Royal Challengers Bangalore    48.333333
Royal Challengers Bengaluru    46.666667
Sunrisers Hyderabad            48.351648
Name: count, dtype: float64
```

13. Find the average number of overs played in all matches

[91]:
```
average_overs_played = df['target_overs'].mean()

print(f'The average number of overs played in all matches is:␣
↪{average_overs_played}')
```

```
The average number of overs played in all matches is: 19.75934065934066
```

14. Find the most common match outcome (runs, wickets, or no result)

[92]:
```
most_common_outcome = result_distribution.idxmax()
print(f'The most common match outcome is: {most_common_outcome}')
```

```
The most common match outcome is: wickets
```

15. Find the total number of matches played at each venue by year

[93]:
```
matches_per_venue_year = df.groupby(['season','venue']).size()
print(matches_per_venue_year)
```

```
season   venue
2007/08  Dr DY Patil Sports Academy                                     4
         Eden Gardens                                                   7
         Feroz Shah Kotla                                               6
         M Chinnaswamy Stadium                                          7
         MA Chidambaram Stadium, Chepauk                                7
                                                                       ..
2024     Maharaja Yadavindra Singh International Cricket Stadium, Mullanpur    5
         Narendra Modi Stadium, Ahmedabad                               8
         Rajiv Gandhi International Stadium, Uppal, Hyderabad           6
         Sawai Mansingh Stadium, Jaipur                                 5
         Wankhede Stadium, Mumbai                                       7
Length: 175, dtype: int64
```

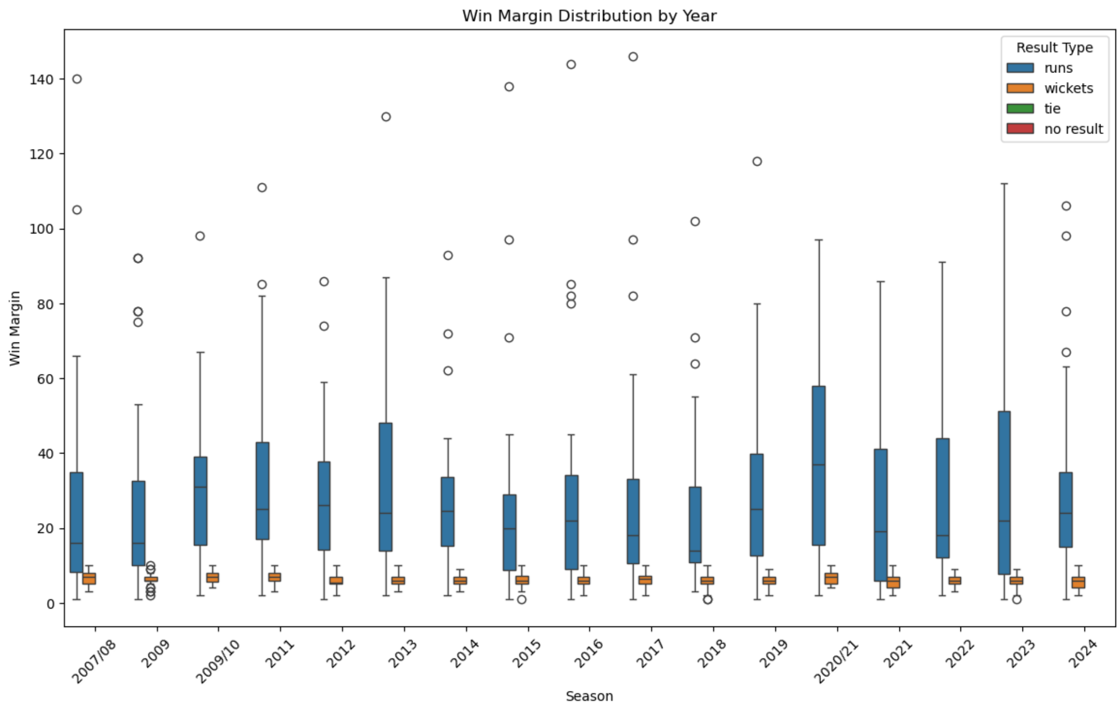
16. Analyze the win margin distribution by year

[94]:
```
# Grouping the data by season and result type
win_margin_by_year = df.groupby(['season', 'result'])['result_margin'].
↪describe()
print(win_margin_by_year)
# Plotting the win margin distribution by year
plt.figure(figsize=(14, 8))
sns.boxplot(x='season', y='result_margin', hue='result', data=df)
plt.title('Win Margin Distribution by Year')
plt.xlabel('Season')
```

```python
plt.ylabel('Win Margin')
plt.xticks(rotation=45)
plt.legend(title='Result Type')
plt.show()
```

```
                   count       mean        std  min    25%   50%    75%    max
season  result
2007/08 runs        24.0  29.375000  34.291351  1.0   8.25  16.0  35.00  140.0
        wickets     34.0   6.500000   2.078024  3.0   5.00   7.0   8.00   10.0
2009    runs        27.0  28.296296  28.894789  1.0  10.00  16.0  32.50   92.0
        tie          0.0        NaN        NaN  NaN    NaN   NaN    NaN    NaN
        wickets     29.0   6.206897   1.820112  2.0   6.00   6.0   7.00   10.0
2009/10 runs        31.0  31.483871  20.990269  2.0  15.50  31.0  39.00   98.0
        tie          0.0        NaN        NaN  NaN    NaN   NaN    NaN    NaN
        wickets     28.0   6.785714   1.571909  4.0   5.75   7.0   8.00   10.0
2011    no result    0.0        NaN        NaN  NaN    NaN   NaN    NaN    NaN
        runs        33.0  33.272727  26.081929  2.0  17.00  25.0  43.00  111.0
        wickets     39.0   6.794872   1.794428  3.0   6.00   7.0   8.00   10.0
2012    runs        34.0  28.235294  19.645431  1.0  14.25  26.0  37.75   86.0
        wickets     40.0   6.025000   1.716996  2.0   5.00   5.5   7.00   10.0
2013    runs        37.0  33.540541  28.657551  2.0  14.00  24.0  48.00  130.0
        tie          0.0        NaN        NaN  NaN    NaN   NaN    NaN    NaN
        wickets     37.0   6.135135   1.669367  3.0   5.00   6.0   7.00   10.0
2014    runs        22.0  29.272727  22.416367  2.0  15.25  24.5  33.50   93.0
        tie          0.0        NaN        NaN  NaN    NaN   NaN    NaN    NaN
        wickets     37.0   6.081081   1.516179  3.0   5.00   6.0   7.00    9.0
2015    no result    0.0        NaN        NaN  NaN    NaN   NaN    NaN    NaN
        runs        32.0  26.562500  28.598373  1.0   8.75  20.0  29.00  138.0
        tie          0.0        NaN        NaN  NaN    NaN   NaN    NaN    NaN
        wickets     24.0   6.166667   2.219805  1.0   5.00   6.0   7.25   10.0
2016    runs        21.0  32.190476  36.347791  1.0   9.00  22.0  34.00  144.0
        wickets     39.0   6.256410   1.772865  2.0   5.00   6.0   7.00   10.0
2017    runs        26.0  30.307692  33.638988  1.0  10.50  18.0  33.00  146.0
        tie          0.0        NaN        NaN  NaN    NaN   NaN    NaN    NaN
        wickets     32.0   6.375000   1.896516  2.0   5.00   6.5   7.25   10.0
2018    runs        28.0  24.107143  23.850366  3.0  10.75  14.0  31.00  102.0
        wickets     32.0   5.812500   2.206113  1.0   5.00   6.0   7.00   10.0
2019    no result    0.0        NaN        NaN  NaN    NaN   NaN    NaN    NaN
        runs        22.0  30.227273  27.194068  1.0  12.50  25.0  39.75  118.0
        tie          0.0        NaN        NaN  NaN    NaN   NaN    NaN    NaN
        wickets     35.0   5.771429   1.646488  2.0   5.00   6.0   7.00    9.0
2020/21 runs        27.0  39.370370  26.716673  2.0  15.50  37.0  58.00   97.0
        tie          0.0        NaN        NaN  NaN    NaN   NaN    NaN    NaN
        wickets     29.0   6.965517   1.762360  4.0   5.00   7.0   8.00   10.0
2021    runs        22.0  26.454545  24.039110  1.0   6.00  19.0  41.00   86.0
        tie          0.0        NaN        NaN  NaN    NaN   NaN    NaN    NaN
        wickets     37.0   5.918919   2.019053  2.0   4.00   6.0   7.00   10.0
2022    runs        37.0  27.945946  23.085525  2.0  12.00  18.0  44.00   91.0
```

```
            wickets     37.0    6.000000    1.615893  3.0    5.00   6.0    7.00     9.0
2023        no result    0.0         NaN         NaN  NaN     NaN   NaN     NaN     NaN
            runs        40.0   30.400000   27.554887  1.0    7.75  22.0   51.25   112.0
            wickets     33.0    5.727273    1.908414  1.0    5.00   6.0    7.00     9.0
2024        runs        35.0   30.142857   25.994505  1.0   15.00  24.0   35.00   106.0
            wickets     36.0    5.944444    1.999206  2.0    4.00   6.0    7.00    10.0
```



17. Calculate the total number of ‘no result’ matches and their impact on the tournament

[95]:
```python
# Calculate the total number of 'no result' matches
no_result_matches = df[df['result'] == 'no result'].shape[0]
print(f"The total number of 'no result' matches: {no_result_matches}")

# Analyze the distribution of 'no result' matches by season
no_result_by_season = df[df['result'] == 'no result']['season'].value_counts().
↪sort_index()
print("Distribution of 'no result' matches by season:")
print(no_result_by_season)

# Analyze the distribution of 'no result' matches by team
no_result_by_team = df[df['result'] == 'no result']['team1'].value_counts() +␣
↪df[df['result'] == 'no result']['team2'].value_counts()
print("Distribution of 'no result' matches by team:")
print(no_result_by_team)
```

```
The total number of 'no result' matches: 5
Distribution of 'no result' matches by season:
season
2011    1
2015    2
2019    1
2023    1
Name: count, dtype: int64
Distribution of 'no result' matches by team:
Chennai Super Kings            NaN
Delhi Daredevils               2.0
Lucknow Super Giants           NaN
Pune Warriors                  NaN
Rajasthan Royals               NaN
Royal Challengers Bangalore    NaN
Name: count, dtype: float64
```

18. How many matches were won by teams batting first vs. batting second?

[96]:
```
# Matches won by teams batting first
batting_first_wins = df[(df['toss_decision'] == 'bat') & (df['toss_winner'] ==␣
 ↪df['winner'])].shape[0] + \
                     df[(df['toss_decision'] == 'field') & (df['toss_winner'] !
 ↪= df['winner'])].shape[0]

# Matches won by teams batting second
batting_second_wins = df[(df['toss_decision'] == 'field') & (df['toss_winner']␣
 ↪== df['winner'])].shape[0] + \
                      df[(df['toss_decision'] == 'bat') & (df['toss_winner'] !=␣
 ↪df['winner'])].shape[0]

print(f"Matches won by teams batting first: {batting_first_wins}")
print(f"Matches won by teams batting second: {batting_second_wins}")
```

```
Matches won by teams batting first: 504
Matches won by teams batting second: 591
```

19. Find out the average number of runs scored by the winning team

[97]:
```
average_runs_scored_by_winning_team = df[df['result'] == 'runs']['target_runs'].
 ↪mean()
print(f'The average number of runs scored by the winning team is:␣
 ↪{average_runs_scored_by_winning_team}')
```

```
The average number of runs scored by the winning team is: 179.69678714859438
```

20. Identify the most unsuccessful team (team with lowest wins)

[98]:
```
most_unsuccessful_team = matches_won.idxmin()
print(f"The most unsuccessful team (team with the lowest wins) is:␣
↪{most_unsuccessful_team}")
```

```
The most unsuccessful team (team with the lowest wins) is: Rising Pune
Supergiants
```

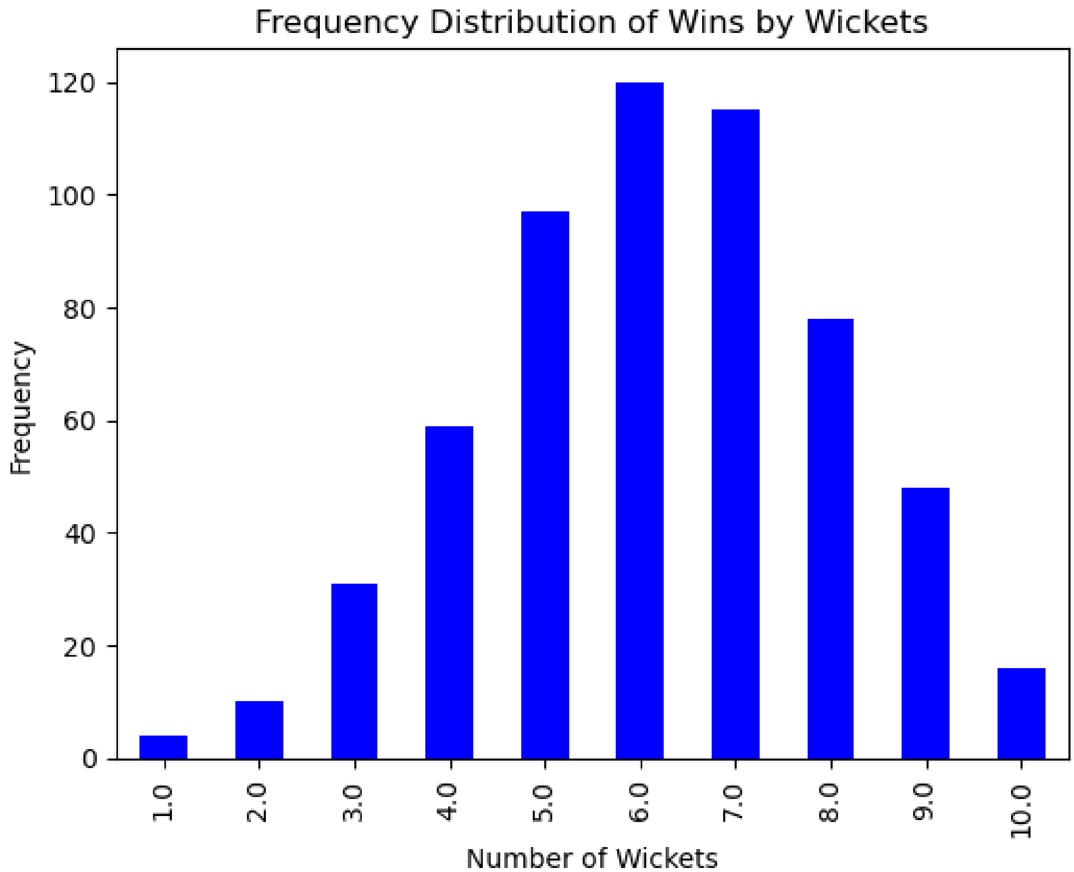
ASSIGNMENT QUESTIONS

Explore following for given dataset and also perform EDA. 1. Frequency Distribution of Wins by Wickets 2. Relative Frequency Distribution 3. Cumulative Relative Frequency Graph 4. Probability of Winning by 6 Wickets or Less 5. Normal Distribution of Wins by Wickets 6. Mean, Standard Deviation, and Percentile Calculation 7. Find out outliers for the selective columns for lower range outliers will be lower than mu - 2sigma, similarly for upper range outliers will be greater than mu+2sigma.

1. Frequency Distribution of Wins by Wickets

[107]:
```
# Frequency distribution of wins by wickets
wins_by_wickets = df_wickets['result_margin'].value_counts().sort_index()
print(wins_by_wickets)

# Plotting the frequency distribution
wins_by_wickets.plot(kind='bar', color='blue')
plt.title('Frequency Distribution of Wins by Wickets')
plt.xlabel('Number of Wickets')
plt.ylabel('Frequency')
plt.show()
```

```
result_margin
1.0      4
2.0     10
3.0     31
4.0     59
5.0     97
6.0    120
7.0    115
8.0     78
9.0     48
10.0    16
Name: count, dtype: int64
```

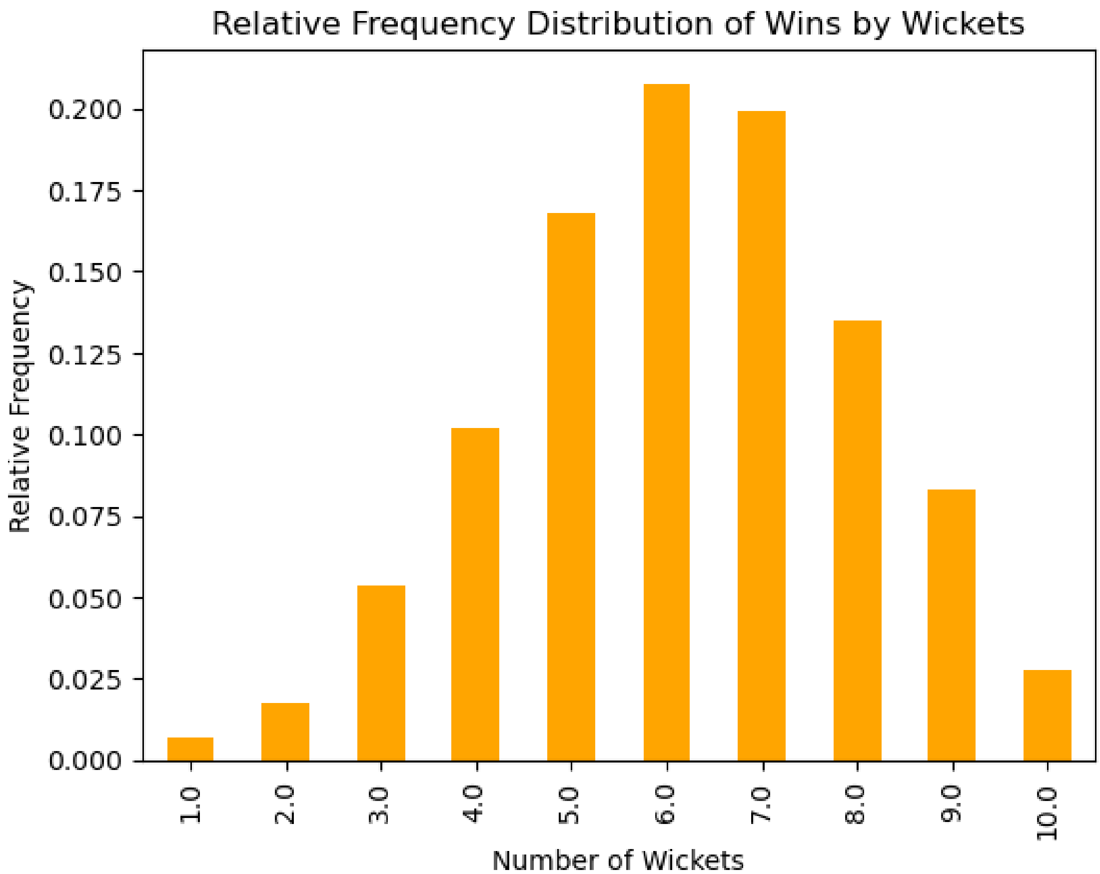


2. Relative Frequency Distribution

[109]:
```
relative_frequency_wins_by_wickets = wins_by_wickets / wins_by_wickets.sum()
print(relative_frequency_wins_by_wickets)

# Plotting the relative frequency distribution
relative_frequency_wins_by_wickets.plot(kind='bar', color='orange')
plt.title('Relative Frequency Distribution of Wins by Wickets')
plt.xlabel('Number of Wickets')
plt.ylabel('Relative Frequency')
plt.show()
```

```
result_margin
1.0     0.006920
2.0     0.017301
3.0     0.053633
4.0     0.102076
5.0     0.167820
6.0     0.207612
7.0     0.198962
```

```
8.0     0.134948
9.0     0.083045
10.0    0.027682
Name: count, dtype: float64
```



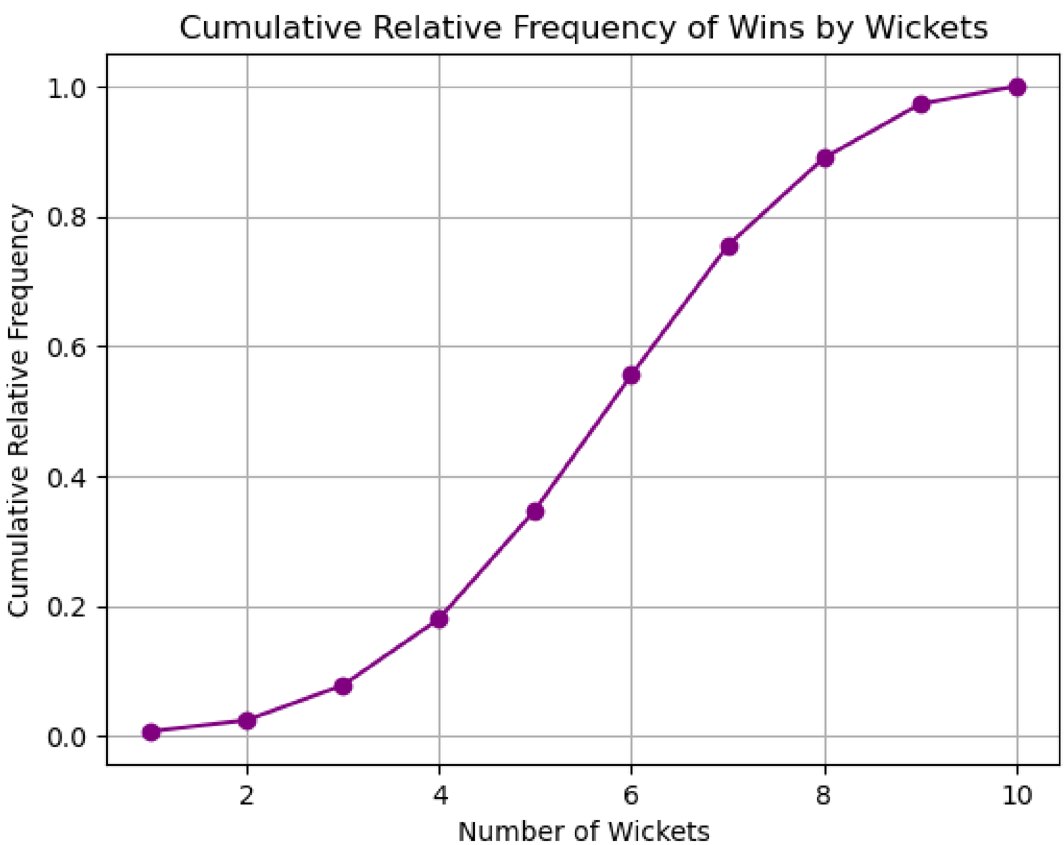
3. Cumulative Relative Frequency Graph

[110]:

```python
# Calculate the cumulative relative frequency
cumulative_relative_frequency = relative_frequency_wins_by_wickets.cumsum()
print(cumulative_relative_frequency)

# Plotting the cumulative relative frequency graph
cumulative_relative_frequency.plot(kind='line', marker='o', color='purple')
plt.title('Cumulative Relative Frequency of Wins by Wickets')
plt.xlabel('Number of Wickets')
plt.ylabel('Cumulative Relative Frequency')
plt.grid(True)
plt.show()
```

```
result_margin
```

```
1.0     0.006920
2.0     0.024221
3.0     0.077855
4.0     0.179931
5.0     0.347751
6.0     0.555363
7.0     0.754325
8.0     0.889273
9.0     0.972318
10.0    1.000000
Name: count, dtype: float64
```



4. Probability of Winning by 6 Wickets or Less

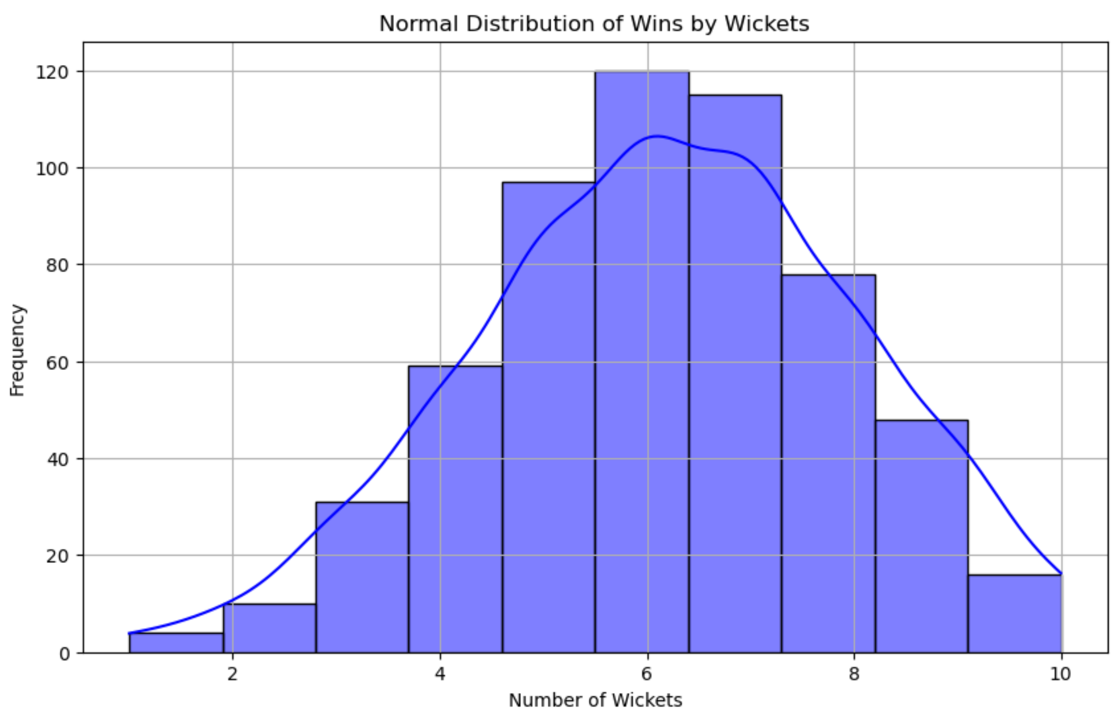
[111]:
```python
# Calculate the total number of wins by wickets
total_wins_by_wickets = wins_by_wickets.sum()

# Calculate the number of wins by 6 wickets or less
wins_by_6_or_less = wins_by_wickets[wins_by_wickets.index <= 6].sum()
```

```
# Calculate the probability
probability_wins_by_6_or_less = wins_by_6_or_less / total_wins_by_wickets
print(f'The probability of winning by 6 wickets or less is:␣
↪{probability_wins_by_6_or_less}')
```

```
The probability of winning by 6 wickets or less is: 0.5553633217993079
```

5. Normal Distribution of Wins by Wickets

[112]:
```
# Plotting the normal distribution of wins by wickets
plt.figure(figsize=(10, 6))
sns.histplot(df_wickets['result_margin'], kde=True, bins=10, color='blue')
plt.title('Normal Distribution of Wins by Wickets')
plt.xlabel('Number of Wickets')
plt.ylabel('Frequency')
plt.grid(True)
plt.show()
```



6. Mean, Standard Deviation, and Percentile Calculation

[116]:
```
print(df.describe())
```

```
                 id  result_margin  target_runs  target_overs
count  1.095000e+03    1076.000000  1092.000000   1092.000000
mean   9.048283e+05      17.259294   165.684066     19.759341
std    3.677402e+05      21.787444    33.427048      1.581108
```

```
min    3.359820e+05      1.000000    43.000000     5.000000
25%    5.483315e+05      6.000000   146.000000    20.000000
50%    9.809610e+05      8.000000   166.000000    20.000000
75%    1.254062e+06     20.000000   187.000000    20.000000
max    1.426312e+06    146.000000   288.000000    20.000000
```

7. Find out outliers for the selective columns for lower range outliers will be lower than mu - 2sigma, similarly for upper range outliers will be greater than mu+2sigma.

[118]:
```
# Calculate the mean and standard deviation for the result_margin column
mu = df['result_margin'].mean()
sigma = df['result_margin'].std()

# Calculate the lower and upper bounds for outliers
lower_bound = mu - 2 * sigma
upper_bound = mu + 2 * sigma

# Find the outliers
outliers = df[(df['result_margin'] < lower_bound) | (df['result_margin'] >␣
↪upper_bound)]
print(outliers)
```

```
           id   season          city        date  match_type player_of_match  \
0      335982  2007/08     Bangalore  2008-04-18      League     BB McCullum
9      335991  2007/08    Chandigarh  2008-04-25      League    KC Sangakkara
39     336023  2007/08        Jaipur  2008-05-17      League        GC Smith
55     336038  2007/08        Mumbai  2008-05-30  Semi Final       SR Watson
59     392182     2009     Cape Town  2009-04-18      League        R Dravid
…         …       …            …          …          …             …
1030  1422125     2024       Chennai  2024-03-26      League          S Dube
1039  1422134     2024  Visakhapatnam  2024-04-03     League       SP Narine
1058  1426273     2024         Delhi  2024-04-20      League         TM Head
1069  1426284     2024       Chennai  2024-04-28      League      RD Gaikwad
1077  1426292     2024       Lucknow  2024-05-05      League       SP Narine

                                                  venue  \
0                                 M Chinnaswamy Stadium
9              Punjab Cricket Association Stadium, Mohali
39                               Sawai Mansingh Stadium
55                                     Wankhede Stadium
59                                             Newlands
…                                                     …
1030              MA Chidambaram Stadium, Chepauk, Chennai
1039  Dr. Y.S. Rajasekhara Reddy ACA-VDCA Cricket St…
1058                          Arun Jaitley Stadium, Delhi
1069              MA Chidambaram Stadium, Chepauk, Chennai
1077  Bharat Ratna Shri Atal Bihari Vajpayee Ekana C…
```

```
                         team1                        team2  \
0     Royal Challengers Bangalore        Kolkata Knight Riders
9                 Kings XI Punjab               Mumbai Indians
39              Rajasthan Royals  Royal Challengers Bangalore
55               Delhi Daredevils            Rajasthan Royals
59    Royal Challengers Bangalore            Rajasthan Royals
…                           …                           …
1030          Chennai Super Kings              Gujarat Titans
1039        Kolkata Knight Riders             Delhi Capitals
1058          Sunrisers Hyderabad             Delhi Capitals
1069          Chennai Super Kings         Sunrisers Hyderabad
1077        Kolkata Knight Riders         Lucknow Super Giants

                    toss_winner toss_decision                       winner  \
0     Royal Challengers Bangalore         field        Kolkata Knight Riders
9                  Mumbai Indians         field              Kings XI Punjab
39    Royal Challengers Bangalore         field             Rajasthan Royals
55               Delhi Daredevils         field             Rajasthan Royals
59    Royal Challengers Bangalore           bat  Royal Challengers Bangalore
…                           …           …                           …
1030               Gujarat Titans         field          Chennai Super Kings
1039        Kolkata Knight Riders           bat        Kolkata Knight Riders
1058               Delhi Capitals         field          Sunrisers Hyderabad
1069          Sunrisers Hyderabad         field          Chennai Super Kings
1077         Lucknow Super Giants         field        Kolkata Knight Riders

     result  result_margin  target_runs  target_overs super_over method  \
0      runs          140.0        223.0          20.0          N    NaN
9      runs           66.0        183.0          20.0          N    NaN
39     runs           65.0        198.0          20.0          N    NaN
55     runs          105.0        193.0          20.0          N    NaN
59     runs           75.0        134.0          20.0          N    NaN
…      …            …          …            …        …      …
1030   runs           63.0        207.0          20.0          N    NaN
1039   runs          106.0        273.0          20.0          N    NaN
1058   runs           67.0        267.0          20.0          N    NaN
1069   runs           78.0        213.0          20.0          N    NaN
1077   runs           98.0        236.0          20.0          N    NaN

                 umpire1            umpire2
0              Asad Rauf        RE Koertzen
9              Aleem Dar          AM Saheba
39             BF Bowden         SL Shastri
55             BF Bowden        RE Koertzen
59           BR Doctrove          RB Tiffin
…                    …                  …
1030            AG Wharf       Tapan Sharma
1039             A Totre          UV Gandhe
```

```
1058         J Madanagopal         Navdeep Singh
1069              R Pandit  MV Saidharshan Kumar
1077  MV Saidharshan Kumar               YC Barde

[65 rows x 20 columns]
```

from file: PMRP_6

OM CHOKSI 23AIML010 PMRP ASSIGNMENT 6 WITH CONCLUSION

CLASSWORK

QUESTIONS:- ->General Population and Gender Distribution

What is the total population in each county, and how does it vary by state? What is the gender distribution (Men vs. Women) across different counties? What is the average population size for census tracts in each state? How does the population of each race (White, Black, Hispanic, etc.) differ across states? What is the proportion of the male population compared to the female population in each census tract?

->Ethnicity and Race

What is the distribution of Hispanic population across various counties and states? How do different racial groups (White, Black, Native, etc.) vary in terms of percentage of total population in different counties? Which states have the highest percentage of Black or Hispanic populations?

->Employment and Work Type

What is the employment rate (Employed vs. Unemployed) for each census tract? How does the rate of self-employed individuals compare to those working in private/public sectors across different states? What percentage of the population works from home, and how does it vary by county and state? How does the unemployment rate vary across different states and counties? What is the distribution of employed individuals working in private vs. public sectors?

->Commuting and Transportation

What is the average commuting time across counties and states, and how does it differ for employed individuals? What modes of transportation are most commonly used for commuting in different states (e.g., car, public transportation, walking)? How does the percentage of people commuting via walking or public transportation vary between urban and rural areas?

->Income and Housing

What is the average income (or median household income) in each state and county? How does the distribution of housing type (e.g., owner-occupied vs. renter-occupied) vary across different counties? How does the cost of living compare across different states based on average income and housing costs?

-> Social Characteristics

What is the relationship between education levels (e.g., percentage with a high school diploma, bachelorâ€™s degree) and employment types across different states?

3 General Population and Gender Distribution

What is the total population in each county, and how does it vary by state?

What is the gender distribution (Men vs. Women) across different counties?

What is the average population size for census tracts in each state?

How does the population of each race (White, Black, Hispanic, etc.) differ across states?

What is the proportion of the male population compared to the female population in each census tract?

[2]:
```python
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np

df=pd.read_csv('acs2017_census_tract_data.csv')
df,df.head(),df.tail(),df.describe(),df.info(),df.columns
```

```
---------------------------------------------------------------------------
FileNotFoundError                         Traceback (most recent call last)
Cell In[2], line 5
      2 import pandas as pd
      3 import numpy as np
----> 5 df=pd.read_csv('acs2017_census_tract_data.csv')
      6 df,df.head(),df.tail(),df.describe(),df.info(),df.columns

File ~\AppData\Roaming\Python\Python313\site-packages\pandas\io\parsers\readers
↪py:1026, in read_csv(filepath_or_buffer, sep, delimiter, header, names,
↪index_col, usecols, dtype, engine, converters, true_values, false_values,
↪skipinitialspace, skiprows, skipfooter, nrows, na_values, keep_default_na,
↪na_filter, verbose, skip_blank_lines, parse_dates, infer_datetime_format,
↪keep_date_col, date_parser, date_format, dayfirst, cache_dates, iterator,
↪chunksize, compression, thousands, decimal, lineterminator, quotechar,
↪quoting, doublequote, escapechar, comment, encoding, encoding_errors, dialect,
↪on_bad_lines, delim_whitespace, low_memory, memory_map, float_precision,
↪storage_options, dtype_backend)
   1013 kwds_defaults = _refine_defaults_read(
   1014     dialect,
   1015     delimiter,
   (...)
   1022     dtype_backend=dtype_backend,
   1023 )
   1024 kwds.update(kwds_defaults)
-> 1026 return _read(filepath_or_buffer, kwds)

File ~\AppData\Roaming\Python\Python313\site-packages\pandas\io\parsers\readers
↪py:620, in _read(filepath_or_buffer, kwds)
    617 _validate_names(kwds.get("names", None))
    619 # Create the parser.
--> 620 parser = TextFileReader(filepath_or_buffer, **kwds)
```

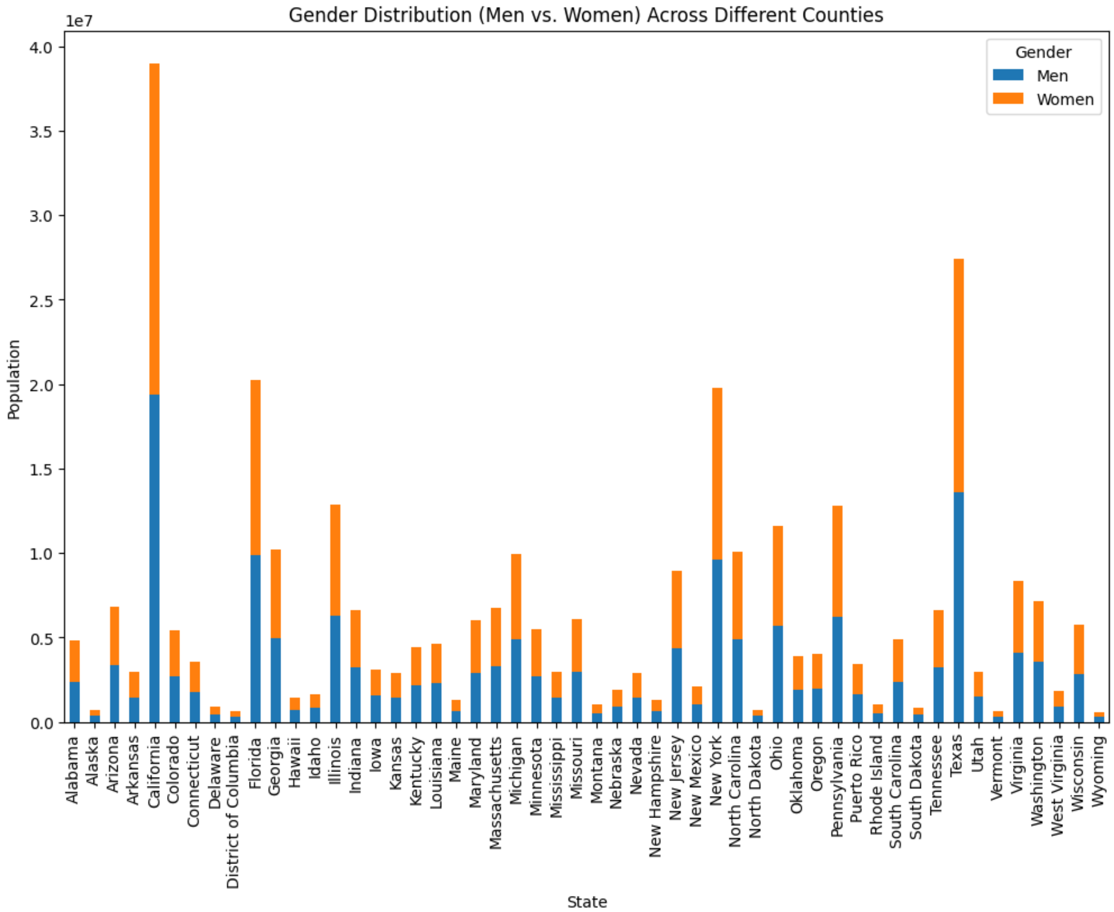
```
    622 if chunksize or iterator:
    623     return parser

File ~\AppData\Roaming\Python\Python313\site-packages\pandas\io\parsers\readers.py:1620, in TextFileReader.__init__(self, f, engine, **kwds)
   1617     self.options["has_index_names"] = kwds["has_index_names"]
   1619 self.handles: IOHandles | None = None
-> 1620 self._engine = self._make_engine(f, self.engine)

File ~\AppData\Roaming\Python\Python313\site-packages\pandas\io\parsers\readers.py:1880, in TextFileReader._make_engine(self, f, engine)
   1878     if "b" not in mode:
   1879         mode += "b"
-> 1880 self.handles = get_handle(
   1881     f,
   1882     mode,
   1883     encoding=self.options.get("encoding", None),
   1884     compression=self.options.get("compression", None),
   1885     memory_map=self.options.get("memory_map", False),
   1886     is_text=is_text,
   1887     errors=self.options.get("encoding_errors", "strict"),
   1888     storage_options=self.options.get("storage_options", None),
   1889 )
   1890 assert self.handles is not None
   1891 f = self.handles.handle

File ~\AppData\Roaming\Python\Python313\site-packages\pandas\io\common.py:873, in get_handle(path_or_buf, mode, encoding, compression, memory_map, is_text, errors, storage_options)
    868 elif isinstance(handle, str):
    869     # Check whether the filename is to be opened in binary mode.
    870     # Binary mode does not support 'encoding' and 'newline'.
    871     if ioargs.encoding and "b" not in ioargs.mode:
    872         # Encoding
--> 873         handle = open(
    874             handle,
    875             ioargs.mode,
    876             encoding=ioargs.encoding,
    877             errors=errors,
    878             newline="",
    879         )
    880     else:
    881         # Binary mode
    882         handle = open(handle, ioargs.mode)

FileNotFoundError: [Errno 2] No such file or directory: 'acs2017_census_tract_data.csv'
```

[ ]:
```python
#What is the total population in each county, and how does it vary by state?
total_population_by_county = df.groupby(['State', 'County'])['TotalPop'].sum().
    ↪reset_index()
print(total_population_by_county)

total_population_by_state = df.groupby('State')['TotalPop'].sum().reset_index()
print(total_population_by_state)
```

```
        State              County  TotalPop
0     Alabama      Autauga County     55036
1     Alabama      Baldwin County    203360
2     Alabama      Barbour County     26201
3     Alabama         Bibb County     22580
4     Alabama       Blount County     57667
…         …                 …         …
3215  Wyoming   Sweetwater County     44527
3216  Wyoming        Teton County     22923
3217  Wyoming        Uinta County     20758
3218  Wyoming     Washakie County      8253
3219  Wyoming       Weston County      7117

[3220 rows x 3 columns]
                   State  TotalPop
0                Alabama   4850771
1                 Alaska    738565
2                Arizona   6809946
3               Arkansas   2977944
4             California  38982847
5               Colorado   5436519
6            Connecticut   3594478
7               Delaware    943732
8   District of Columbia    672391
9                Florida  20278447
10               Georgia  10201635
11                Hawaii   1421658
12                 Idaho   1657375
13              Illinois  12854526
14               Indiana   6614418
15                  Iowa   3118102
16                Kansas   2903820
17              Kentucky   4424376
18             Louisiana   4663461
19                 Maine   1330158
20              Maryland   5996079
21         Massachusetts   6789319
22              Michigan   9925568
23             Minnesota   5490726
24           Mississippi   2986220
```

```
25              Missouri   6075300
26               Montana   1029862
27              Nebraska   1893921
28                Nevada   2887725
29         New Hampshire   1331848
30            New Jersey   8960161
31            New Mexico   2084828
32              New York  19798228
33        North Carolina  10052564
34          North Dakota    745475
35                  Ohio  11609756
36              Oklahoma   3896251
37                Oregon   4025127
38          Pennsylvania  12790505
39           Puerto Rico   3468963
40          Rhode Island   1056138
41        South Carolina   4893444
42          South Dakota    855444
43             Tennessee   6597381
44                 Texas  27419612
45                  Utah   2993941
46               Vermont    624636
47              Virginia   8365952
48            Washington   7169967
49         West Virginia   1836843
50             Wisconsin   5763217
51               Wyoming    583200
```

[ ]:
```
#What is the gender distribution (Men vs. Women) across different counties?

gender_distribution_by_county = df.groupby(['State', 'County'])[['Men',␣
 ↪'Women']].sum().reset_index()


fig, ax = plt.subplots(figsize=(12, 8))
gender_distribution_by_county.groupby('State')[['Men', 'Women']].sum().
 ↪plot(kind='bar', stacked=True, ax=ax)
ax.set_title('Gender Distribution (Men vs. Women) Across Different Counties')
ax.set_xlabel('State')
ax.set_ylabel('Population')
plt.legend(title='Gender')
plt.show()
```



[ ]:
```
#What is the average population size for census tracts in each state?

average_population_by_state = df.groupby('State')['TotalPop'].mean().
 ↪reset_index()
# print(average_population_by_state)
average_population_by_state.head()
```

[ ]:

	State	TotalPop
0	Alabama	4107.342083
1	Alaska	4422.544910
2	Arizona	4462.612058
3	Arkansas	4341.026239
4	California	4838.382400

[3]:
```
#How does the population of each race (White, Black, Hispanic, etc.) differ␣
 ↪across states?
```

```
# race_population_by_state = df.groupby('State')[['Hispanic', 'White', 'Black',␣
↪'Native', 'Asian', 'Pacific']].sum().reset_index()
# # print(race_population_by_state)
# race_population_by_state

# # Plot the population of each race across states
# race_population_by_state.set_index('State').plot(kind='bar', stacked=True,␣
↪figsize=(15, 10))
# plt.title('Population of Each Race Across States')
# plt.xlabel('State')
# plt.ylabel('Population')
# plt.legend(title='Race')
# plt.show()

white = df.groupby('State').apply(lambda x: x['White'] / 100 * x['TotalPop']).
↪sum()
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Cell In[3], line 15
      1 #How does the population of each race (White, Black, Hispanic, etc.)␣
↪differ across states?
      2
      3 # race_population_by_state = df.groupby('State')[['Hispanic', 'White',␣
↪'Black', 'Native', 'Asian', 'Pacific']].sum().reset_index()
   (…)
     12 # plt.legend(title='Race')
     13 # plt.show()
---> 15 white = df.groupby('State').apply(lambda x: x['White'] / 100 *␣
↪x['TotalPop']).sum()

NameError: name 'df' is not defined
```

[ ]:
```
#What is the proportion of the male population compared to the female␣
↪population in each census tract?

df['MaleToFemaleRatio'] = df['Men'] / df['Women']

# Display the first few rows to verify the calculation
df[['State', 'County', 'TractId', 'Men', 'Women', 'MaleToFemaleRatio']].head()
```

[ ]:

	State	County	TractId	Men	Women	MaleToFemaleRatio
0	Alabama	Autauga County	1001020100	899	946	0.950317
1	Alabama	Autauga County	1001020200	1167	1005	1.161194
2	Alabama	Autauga County	1001020300	1533	1852	0.827754
3	Alabama	Autauga County	1001020400	2001	2266	0.883054

```
4  Alabama  Autauga County  1001020500  5054   4911           1.029118
```

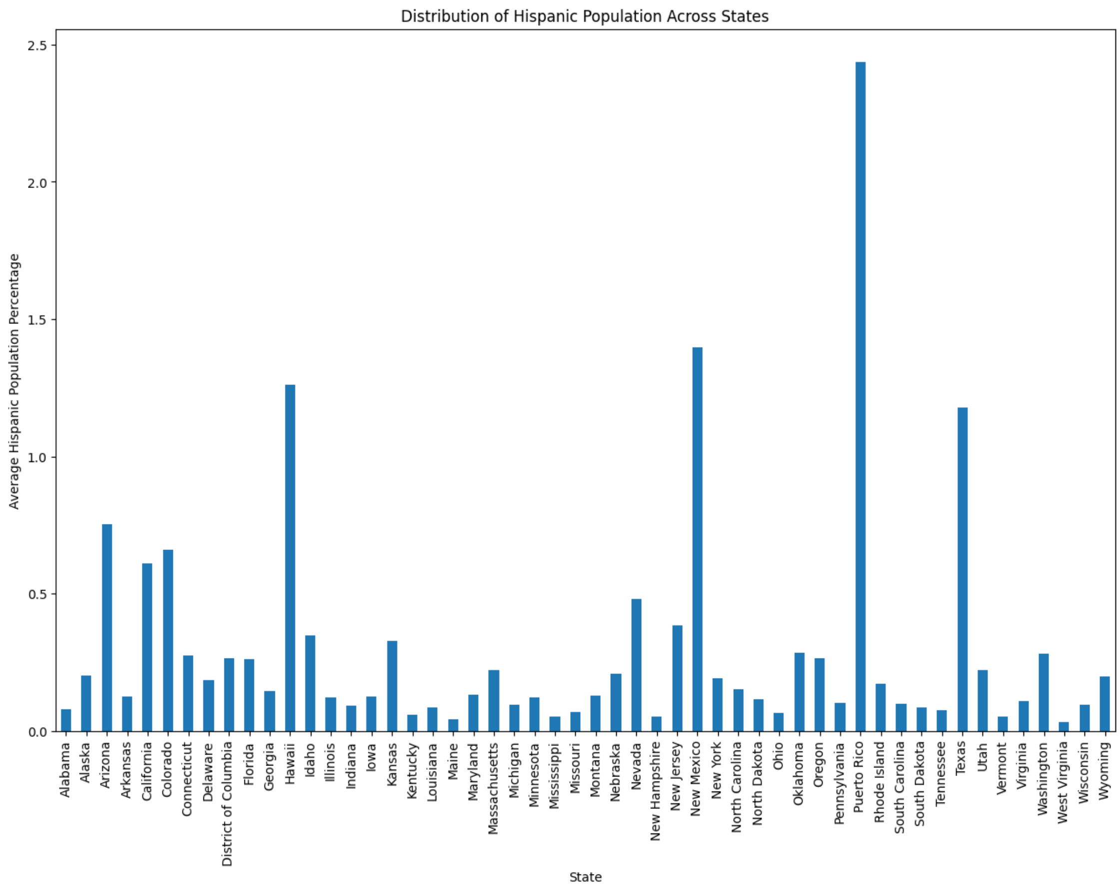
4 Ethnicity and Race

What is the distribution of Hispanic population across various counties and states?

How do different racial groups (White, Black, Native, etc.) vary in terms of percentage of total population in different counties?

Which states have the highest percentage of Black or Hispanic populations?

```
[ ]: #What is the distribution of Hispanic population across various counties and␣
     ↪states?

     df['Hispanic_Percentage'] = (df['Hispanic'] / df['TotalPop']) * 100


     hispanic_by_county = df.groupby(['State', 'County'])[['Hispanic', 'TotalPop']].
     ↪sum().reset_index()
     hispanic_by_county['Hispanic_Percentage'] = (hispanic_by_county['Hispanic'] /␣
     ↪hispanic_by_county['TotalPop']) * 100


     hispanic_state_data = hispanic_by_county.
     ↪groupby('State')['Hispanic_Percentage'].mean()

     hispanic_state_data.plot(kind='bar', figsize=(15, 10))
     plt.title('Distribution of Hispanic Population Across States')
     plt.xlabel('State')
     plt.ylabel('Average Hispanic Population Percentage')
     plt.show()
```



[ ]:
```
#How do different racial groups (White, Black, Native, etc.) vary in terms of␣
↪percentage of total population in different counties?
# Calculate the percentage of each racial group in each county
df['White_Percentage'] = (df['White'] / df['TotalPop']) * 100
df['Black_Percentage'] = (df['Black'] / df['TotalPop']) * 100
df['Native_Percentage'] = (df['Native'] / df['TotalPop']) * 100
df['Asian_Percentage'] = (df['Asian'] / df['TotalPop']) * 100
df['Pacific_Percentage'] = (df['Pacific'] / df['TotalPop']) * 100

racial_percentage_by_county = df.groupby(['State',␣
↪'County'])[['White_Percentage', 'Black_Percentage', 'Native_Percentage',␣
↪'Asian_Percentage', 'Pacific_Percentage']].mean().reset_index()

racial_percentage_by_county
```

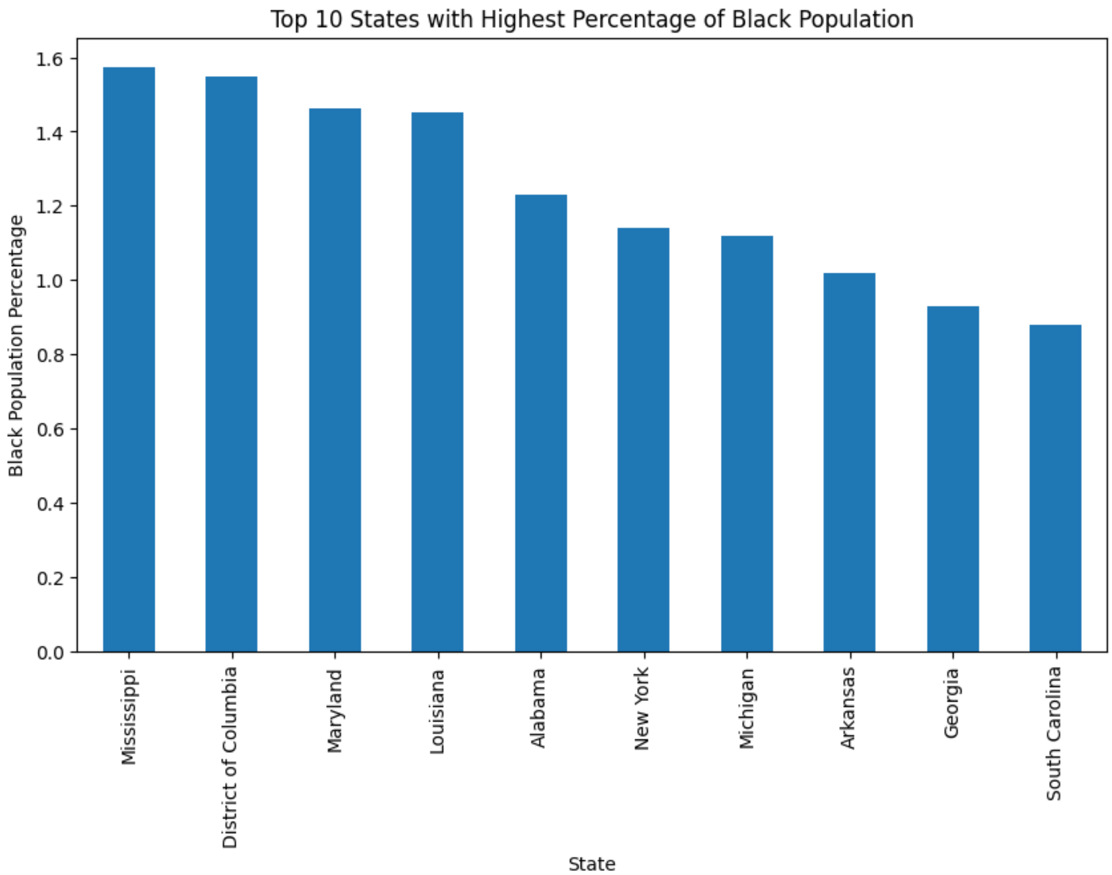
[ ]:
```
       State            County  White_Percentage  Black_Percentage  \
0     Alabama     Autauga County          2.033985          0.677915
1     Alabama     Baldwin County          1.837739          0.193102
2     Alabama     Barbour County          1.749863          1.845252
```

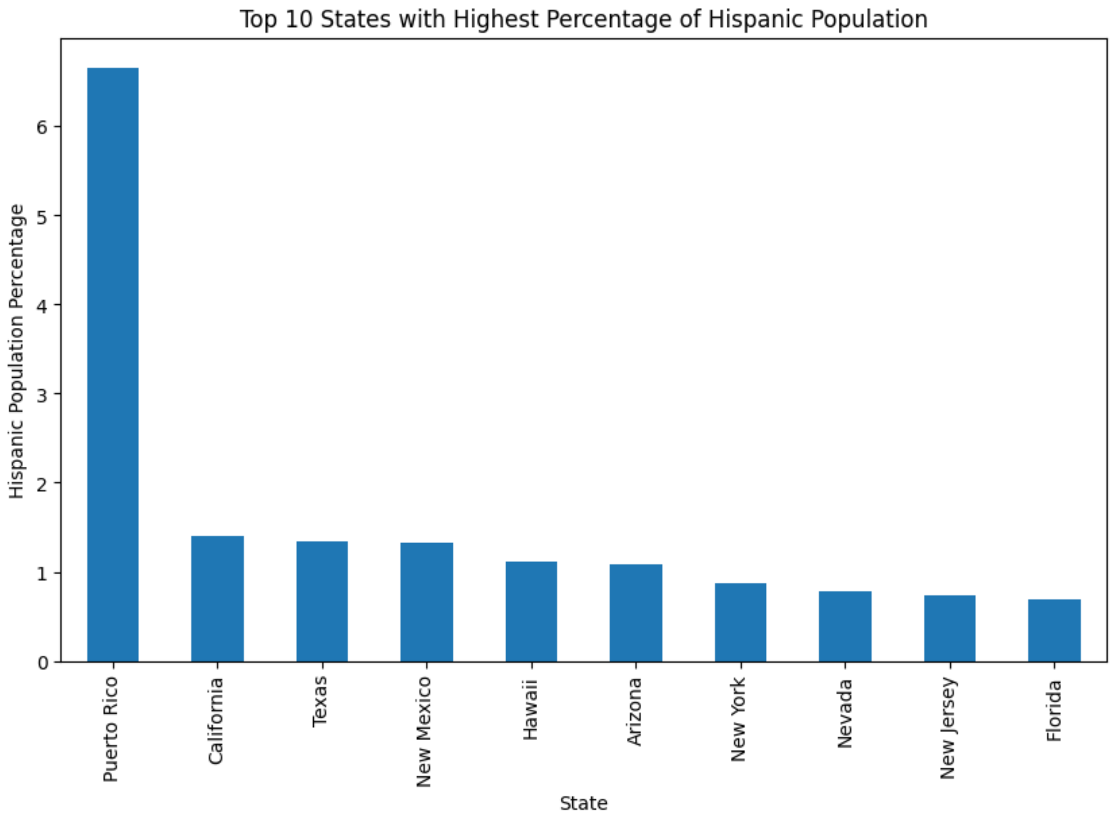
```
3     Alabama        Bibb County          1.787693          0.285017
4     Alabama      Blount County          1.496798          0.018945
…        …                …                  …                 …
3215  Wyoming  Sweetwater County          2.699432          0.017665
3216  Wyoming       Teton County          1.701364          0.008142
3217  Wyoming       Uinta County          1.283898          0.001929
3218  Wyoming    Washakie County          2.996604          0.008328
3219  Wyoming      Weston County          2.578226          0.015020

      Native_Percentage  Asian_Percentage  Pacific_Percentage
0              0.011672          0.015104            0.000985
1              0.017746          0.007720            0.000000
2              0.004166          0.014984            0.000000
3              0.006752          0.000000            0.000000
4              0.006233          0.002023            0.000000
…                   …                 …                  …
3215           0.018119          0.021793            0.009755
3216           0.005138          0.037086            0.000000
3217           0.011570          0.001302            0.000000
3218           0.013837          0.005118            0.000000
3219           0.002822          0.116336            0.000000

[3220 rows x 7 columns]
```

[ ]:
```python
#Which states have the highest percentage of Black or Hispanic populations?

# Calculate the average percentage of Black and Hispanic populations in each␣
↪state
black_hispanic_percentage_by_state = df.groupby('State')[['Black_Percentage',␣
↪'Hispanic_Percentage']].mean().reset_index()

# the highest percentage of Black population
highest_black_percentage_states = black_hispanic_percentage_by_state.
↪sort_values(by='Black_Percentage', ascending=False).head(10)
print("States with the highest percentage of Black population:")
print(highest_black_percentage_states)

# the highest percentage of Hispanic population
highest_hispanic_percentage_states = black_hispanic_percentage_by_state.
↪sort_values(by='Hispanic_Percentage', ascending=False).head(10)
print("States with the highest percentage of Hispanic population:")
print(highest_hispanic_percentage_states)

# Plot Black population
highest_black_percentage_states.plot(x='State', y='Black_Percentage',␣
↪kind='bar', figsize=(10, 6), legend=False)
plt.title('Top 10 States with Highest Percentage of Black Population')
```

```
plt.xlabel('State')
plt.ylabel('Black Population Percentage')
plt.show()

# Plot Hispanic population
highest_hispanic_percentage_states.plot(x='State', y='Hispanic_Percentage',␣
↪kind='bar', figsize=(10, 6), legend=False)
plt.title('Top 10 States with Highest Percentage of Hispanic Population')
plt.xlabel('State')
plt.ylabel('Hispanic Population Percentage')
plt.show()
```

```
States with the highest percentage of Black population:
                   State  Black_Percentage  Hispanic_Percentage
24           Mississippi          1.574405             0.113420
8   District of Columbia          1.548670             0.280445
20              Maryland          1.462464             0.235107
18             Louisiana          1.452869             0.165938
0                Alabama          1.229608             0.114788
32              New York          1.139241             0.865029
22              Michigan          1.118413             0.183960
3               Arkansas          1.020047             0.162479
10               Georgia          0.930425             0.196465
41        South Carolina          0.878945             0.145437
States with the highest percentage of Hispanic population:
          State  Black_Percentage  Hispanic_Percentage
39  Puerto Rico          0.003747             6.660837
4    California          0.249553             1.394659
44        Texas          0.325855             1.339024
31   New Mexico          0.050507             1.325957
11       Hawaii          0.077773             1.115713
2       Arizona          0.103129             1.080010
32     New York          1.139241             0.865029
28       Nevada          0.223116             0.787030
30   New Jersey          0.459594             0.731697
9       Florida          0.757573             0.685121
```


Top 10 States with Highest Percentage of Black Population
Black Population Percentage
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
1.6
Mississippi
District of Columbia
Maryland
Louisiana
Alabama
New York
Michigan
Arkansas
Georgia
South Carolina
State



5 Employment and Work Type

What is the employment rate (Employed vs. Unemployed) for each census tract?

How does the rate of self-employed individuals compare to those working in private/public sectors across different states?

What percentage of the population works from home, and how does it vary by county and state?

How does the unemployment rate vary across different states and counties?

What is the distribution of employed individuals working in private vs. public sectors?

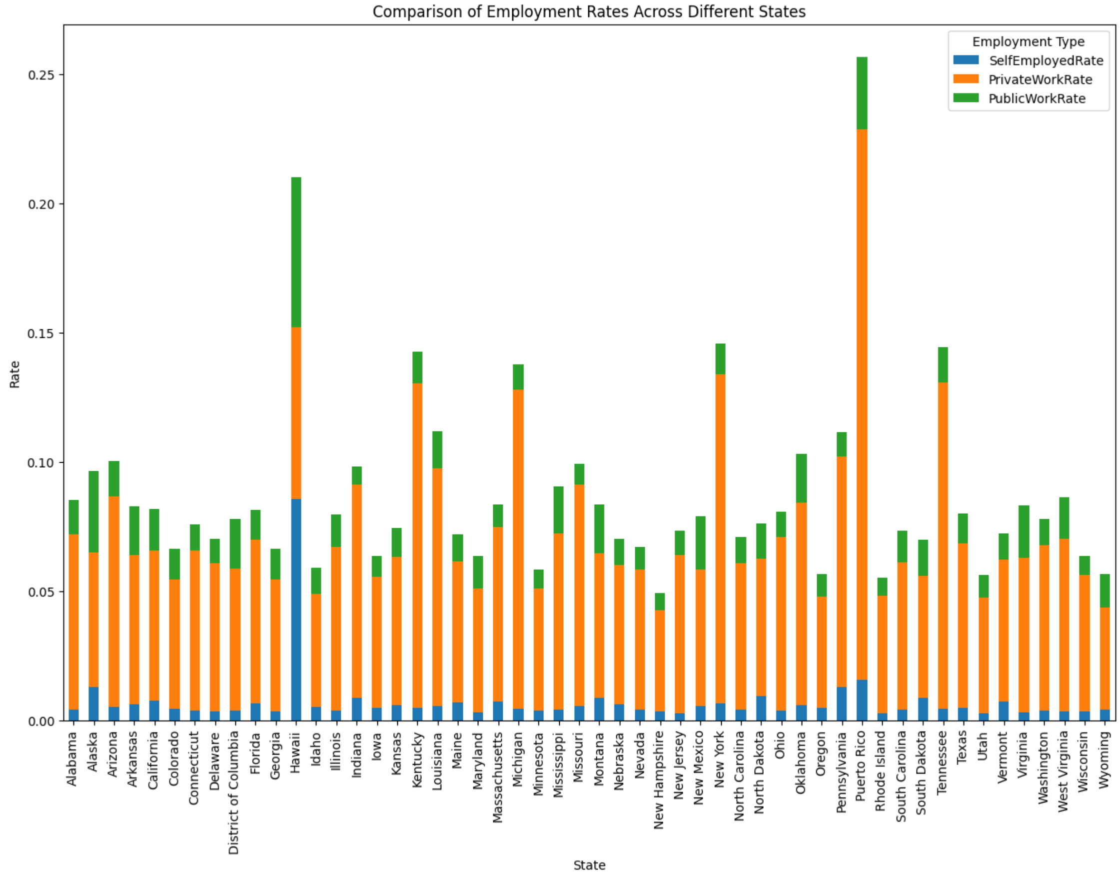
[ ]:
```
#What is the employment rate (Employed vs. Unemployed) for each census tract?
df['EmploymentRate'] = df['Employed'] / df['TotalPop']
df['UnemploymentRate'] = df['Unemployment'] / df['TotalPop']
df[['State', 'County', 'TractId', 'Employed', 'Unemployment', 'EmploymentRate',␣
↪'UnemploymentRate']]
```

[ ]:
```
             State            County     TractId  Employed  Unemployment  \
0          Alabama    Autauga County  1001020100       881           4.6
1          Alabama    Autauga County  1001020200       852           3.4
```

```
2          Alabama   Autauga County   1001020300      1482            4.7
3          Alabama   Autauga County   1001020400      1849            6.1
4          Alabama   Autauga County   1001020500      4787            2.3
…             …            …             …        …            …
73996  Puerto Rico  Yauco Municipio  72153750501      1576           20.8
73997  Puerto Rico  Yauco Municipio  72153750502       666           26.3
73998  Puerto Rico  Yauco Municipio  72153750503       560           23.0
73999  Puerto Rico  Yauco Municipio  72153750601      1062           29.5
74000  Puerto Rico  Yauco Municipio  72153750602       759           17.9

       EmploymentRate  UnemploymentRate
0            0.477507          0.002493
1            0.392265          0.001565
2            0.437814          0.001388
3            0.433326          0.001430
4            0.480381          0.000231
…                 …                 …
73996        0.262186          0.003460
73997        0.284372          0.011230
73998        0.252480          0.010370
73999        0.242466          0.006735
74000        0.252916          0.005965

[74001 rows x 7 columns]
```

[ ]:

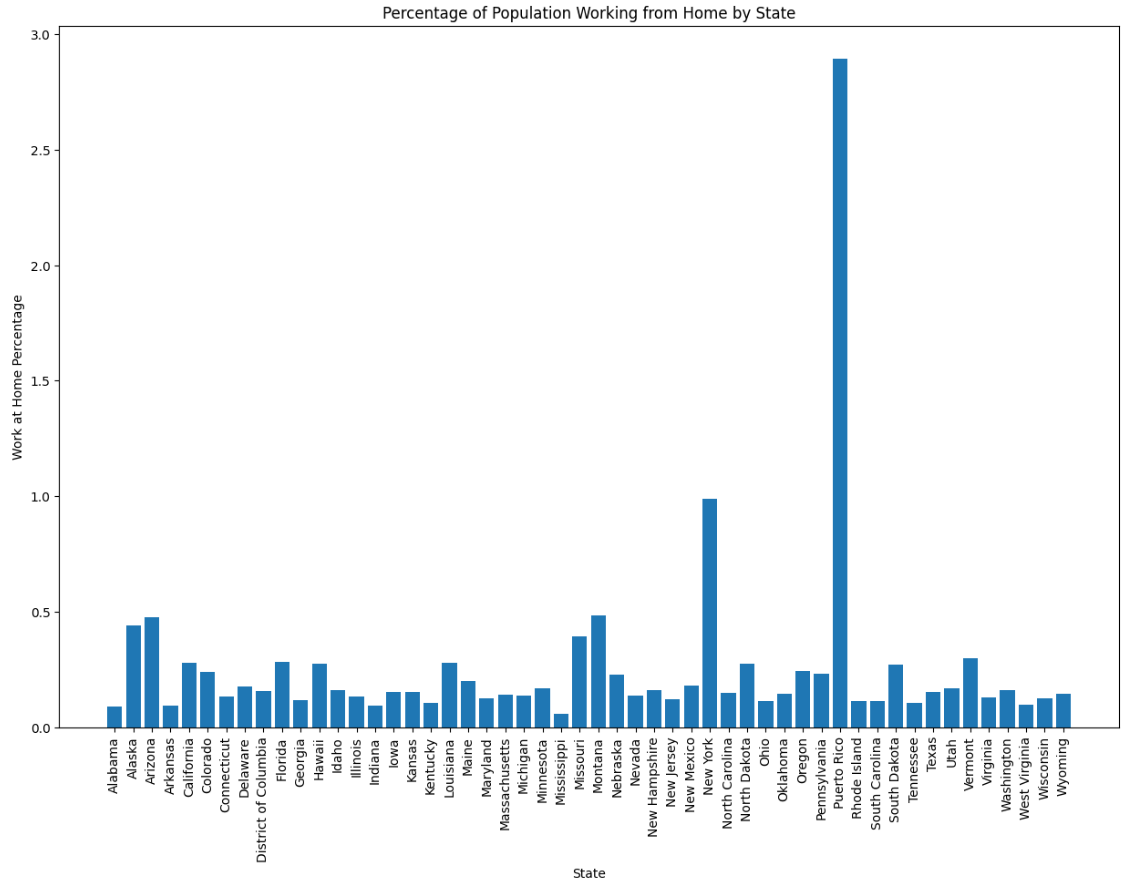
```
#How does the rate of self-employed individuals compare to those working in␣
↪private/public sectors across different states?
df['SelfEmployedRate'] = df['SelfEmployed'] / df['Employed']
df['PrivateWorkRate'] = df['PrivateWork'] / df['Employed']
df['PublicWorkRate'] = df['PublicWork'] / df['Employed']


employment_rates_by_state = df.groupby('State')[['SelfEmployedRate',␣
↪'PrivateWorkRate', 'PublicWorkRate']].mean().reset_index()

employment_rates_by_state.head()


employment_rates_by_state.set_index('State').plot(kind='bar', stacked=True,␣
↪figsize=(15, 10))
plt.title('Comparison of Employment Rates Across Different States')
plt.xlabel('State')
plt.ylabel('Rate')
plt.legend(title='Employment Type')
plt.show()
```



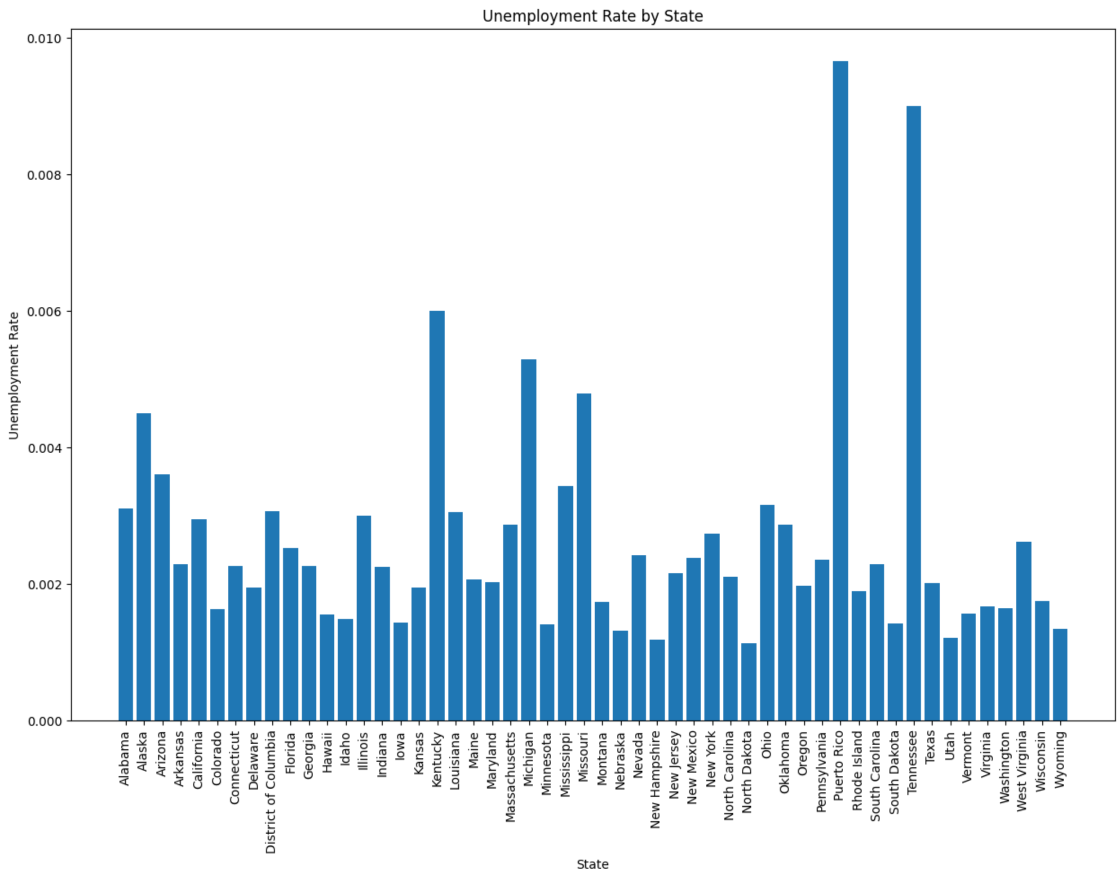
[ ]:

```
#What percentage of the population works from home, and how does it vary by county and state?

df['WorkAtHomePercentage'] = (df['WorkAtHome'] / df['TotalPop']) * 100


work_at_home_by_county = df.groupby(['State', 'County'])['WorkAtHomePercentage'].mean().reset_index()
work_at_home_by_state = df.groupby('State')['WorkAtHomePercentage'].mean().reset_index()


plt.figure(figsize=(15, 10))
plt.bar(work_at_home_by_state['State'], work_at_home_by_state['WorkAtHomePercentage'])
plt.title('Percentage of Population Working from Home by State')
plt.xlabel('State')
plt.ylabel('Work at Home Percentage')
plt.xticks(rotation=90)
```

```
plt.show()
```



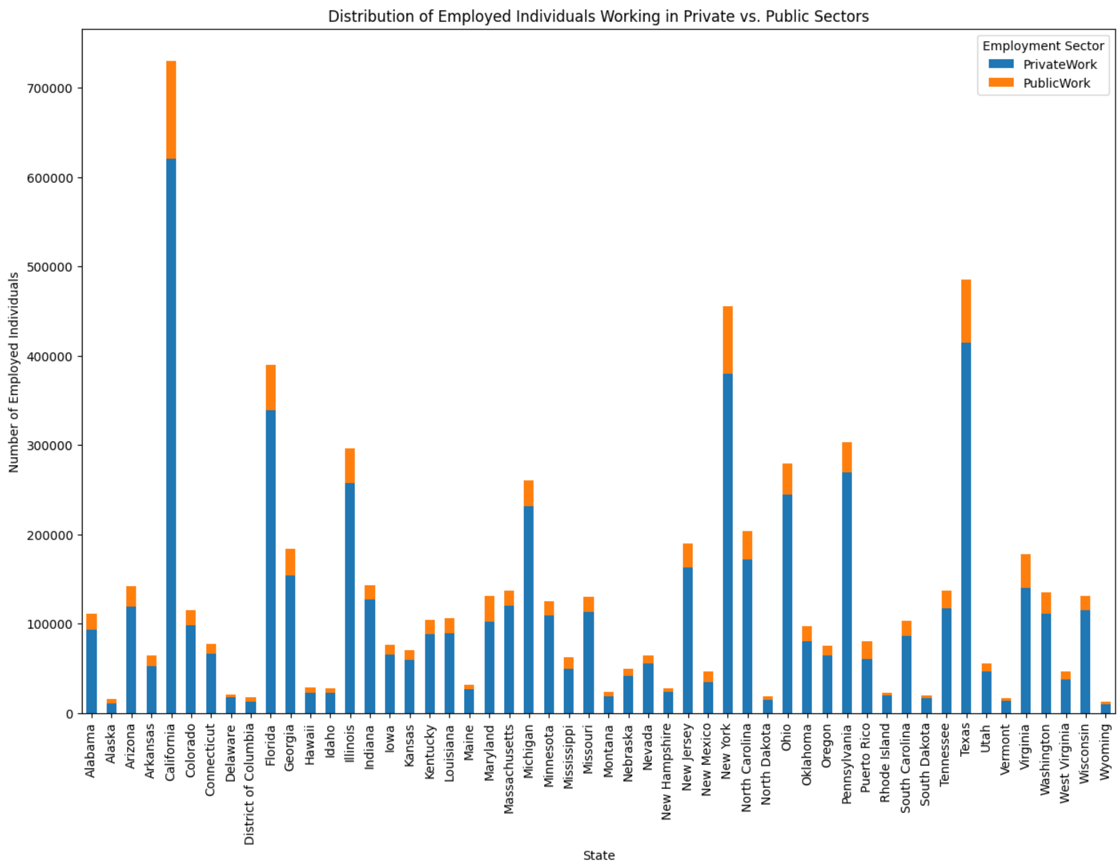
[ ]:
```
#How does the unemployment rate vary across different states and counties?

unemployment_rate_by_county = df.groupby(['State',␣
↪'County'])['UnemploymentRate'].mean().reset_index()
unemployment_rate_by_state = df.groupby('State')['UnemploymentRate'].mean().
↪reset_index()


plt.figure(figsize=(15, 10))
plt.bar(unemployment_rate_by_state['State'],␣
↪unemployment_rate_by_state['UnemploymentRate'])
plt.title('Unemployment Rate by State')
plt.xlabel('State')
plt.ylabel('Unemployment Rate')
plt.xticks(rotation=90)
plt.show()
```



[ ]:
```
#What is the distribution of employed individuals working in private vs. public␣
↪sectors?
employment_distribution_by_sector = df.groupby('State')[['PrivateWork',␣
↪'PublicWork']].sum().reset_index()
print(employment_distribution_by_sector)

employment_distribution_by_sector.set_index('State').plot(kind='bar',␣
↪stacked=True, figsize=(15, 10))
plt.title('Distribution of Employed Individuals Working in Private vs. Public␣
↪Sectors')
plt.xlabel('State')
plt.ylabel('Number of Employed Individuals')
plt.legend(title='Employment Sector')
plt.show()
```

```
                   State  PrivateWork  PublicWork
0                Alabama      93013.8     18161.0
1                 Alaska      10828.5      4559.1
2                Arizona     119351.9     22220.5
3               Arkansas      52857.1     11189.5
```

4	California	620398.1	109397.2
5	Colorado	97844.1	17353.8
6	Connecticut	66745.7	10529.6
7	Delaware	17486.0	3008.6
8	District of Columbia	12648.6	4495.2
9	Florida	339459.8	50039.8
10	Georgia	154053.7	30032.9
11	Hawaii	22185.5	6871.9
12	Idaho	22544.6	4713.8
13	Illinois	257640.6	38630.2
14	Indiana	127561.2	15807.4
15	Iowa	65720.6	10575.5
16	Kansas	59007.9	11671.1
17	Kentucky	87831.4	16510.3
18	Louisiana	88930.0	17008.1
19	Maine	26940.6	4891.5
20	Maryland	101853.0	29729.1
21	Massachusetts	119845.6	17640.1
22	Michigan	231237.5	29144.3
23	Minnesota	109311.0	15853.7
24	Mississippi	49870.3	12135.6
25	Missouri	113203.8	17254.2
26	Montana	18926.0	5122.4
27	Nebraska	41686.2	7305.3
28	Nevada	55822.1	8199.3
29	New Hampshire	23277.0	3879.4
30	New Jersey	162630.5	27280.9
31	New Mexico	34674.1	11583.9
32	New York	379901.5	75897.8
33	North Carolina	172143.5	31173.4
34	North Dakota	14928.3	3435.3
35	Ohio	244297.7	34850.6
36	Oklahoma	80218.8	17329.3
37	Oregon	64121.0	11690.7
38	Pennsylvania	269785.3	33345.0
39	Puerto Rico	60283.9	19938.7
40	Rhode Island	19867.9	2902.2
41	South Carolina	86280.9	16694.5
42	South Dakota	16150.8	3726.8
43	Tennessee	116793.3	20576.8
44	Texas	414609.8	70444.0
45	Utah	46872.6	8617.6
46	Vermont	13926.9	2583.8
47	Virginia	140180.9	37739.8
48	Washington	111172.3	24186.2
49	West Virginia	37205.6	9021.3
50	Wisconsin	114720.4	16816.3
51	Wyoming	9333.9	2849.7



6 Commuting and Transportation

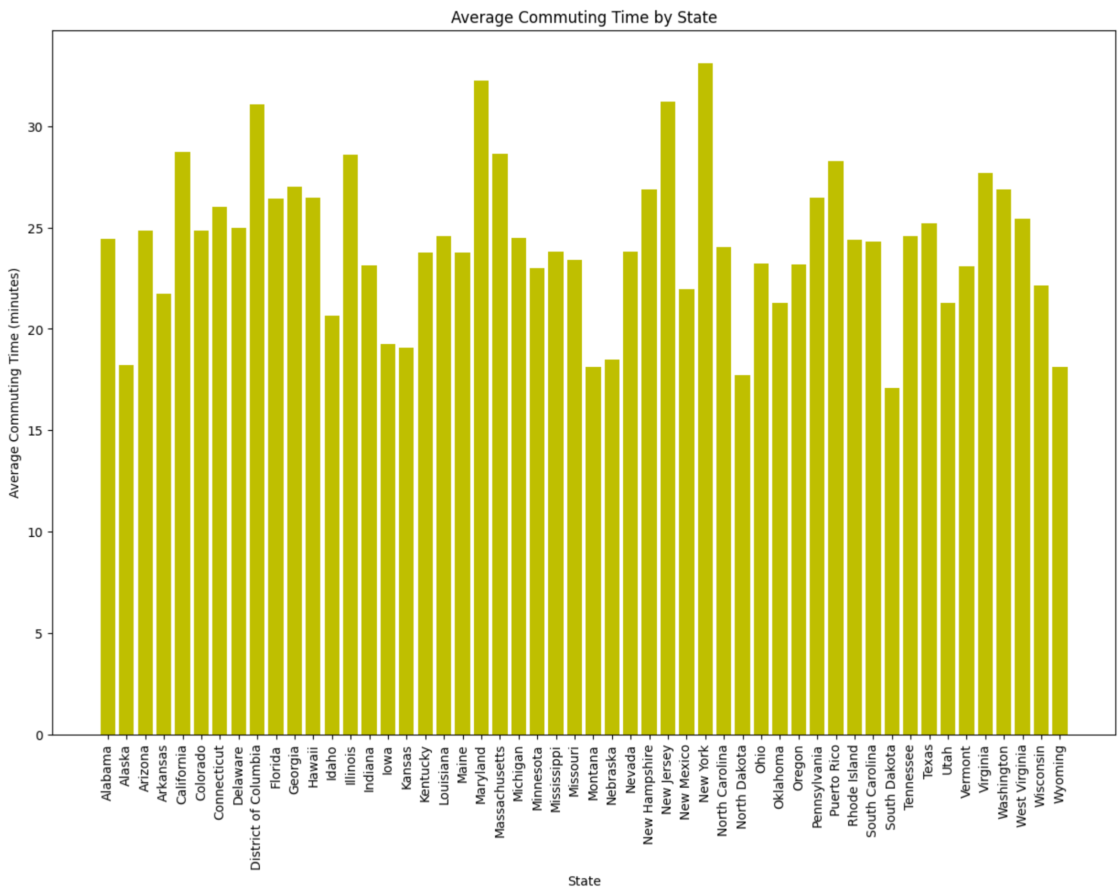
What is the average commuting time across counties and states, and how does it differ for employed individuals?

What modes of transportation are most commonly used for commuting in different states (e.g., car, public transportation, walking)?

How does the percentage of people commuting via walking or public transportation vary between urban and rural areas?

[ ]:
```
#What is the average commuting time across counties and states, and how does it
↪differ for employed individuals?

average_commute_by_county = df.groupby(['State', 'County'])['MeanCommute'].
↪mean().reset_index()
average_commute_by_state = df.groupby('State')['MeanCommute'].mean().
↪reset_index()

#see how differ
```

```
plt.figure(figsize=(15, 10))
plt.bar(average_commute_by_state['State'],
    average_commute_by_state['MeanCommute'],color='y')
plt.title('Average Commuting Time by State')
plt.xlabel('State')
plt.ylabel('Average Commuting Time (minutes)')
plt.xticks(rotation=90)
plt.show()


print(average_commute_by_county)
print(average_commute_by_state)
```

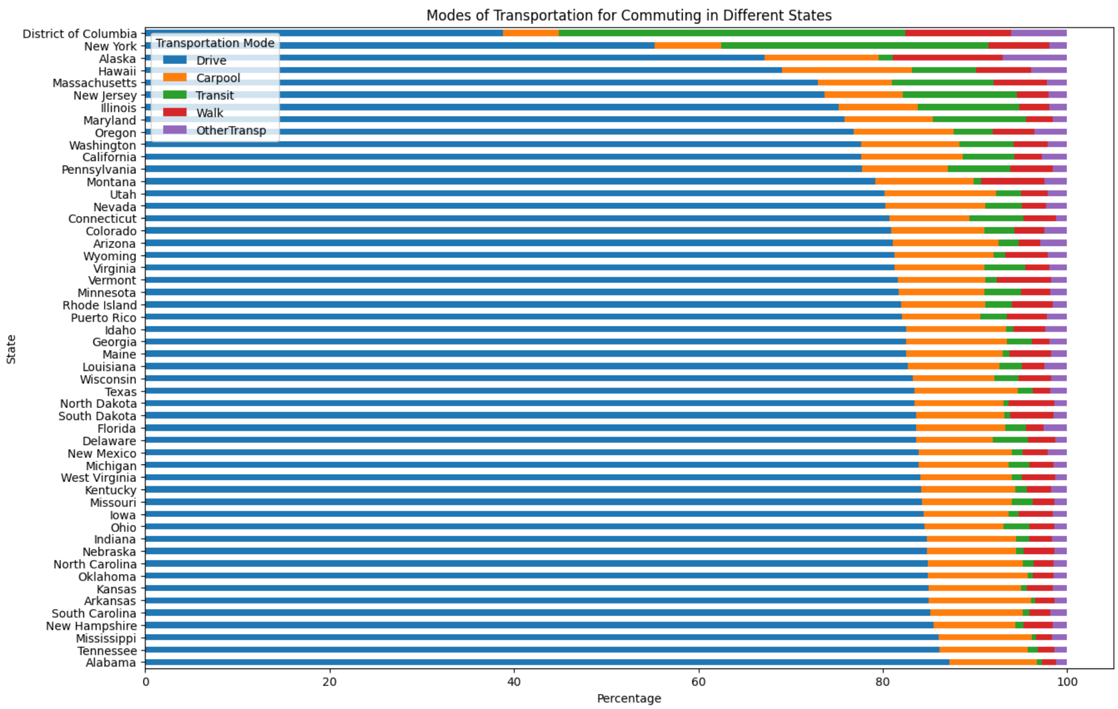



```
      State           County  MeanCommute
0   Alabama   Autauga County    25.766667
1   Alabama   Baldwin County    27.054839
2   Alabama   Barbour County    22.744444
3   Alabama      Bibb County    31.200000
4   Alabama    Blount County    35.011111
```

```
…       …                …           …
3215  Wyoming  Sweetwater County    20.708333
3216  Wyoming       Teton County    14.450000
3217  Wyoming       Uinta County    20.233333
3218  Wyoming    Washakie County    14.533333
3219  Wyoming      Weston County    26.000000

[3220 rows x 3 columns]
                   State  MeanCommute
0                Alabama    24.458638
1                 Alaska    18.209639
2                Arizona    24.833444
3               Arkansas    21.739824
4             California    28.720396
5               Colorado    24.836812
6            Connecticut    26.018909
7               Delaware    24.965421
8   District of Columbia    31.087640
9                Florida    26.436147
10               Georgia    27.015984
11                Hawaii    26.475641
12                 Idaho    20.638721
13              Illinois    28.584158
14               Indiana    23.149035
15                  Iowa    19.248967
16                Kansas    19.061133
17              Kentucky    23.754430
18             Louisiana    24.555298
19                 Maine    23.745584
20              Maryland    32.228974
21         Massachusetts    28.636557
22              Michigan    24.467458
23             Minnesota    22.994670
24           Mississippi    23.791450
25              Missouri    23.416955
26               Montana    18.123792
27              Nebraska    18.464839
28                Nevada    23.829056
29         New Hampshire    26.895890
30            New Jersey    31.191014
31            New Mexico    21.963454
32              New York    33.084997
33        North Carolina    24.020849
34          North Dakota    17.738537
35                  Ohio    23.213692
36              Oklahoma    21.298177
37                Oregon    23.183981
38          Pennsylvania    26.470801
```

```
39           Puerto Rico   28.281087
40          Rhode Island   24.409167
41        South Carolina   24.292173
42          South Dakota   17.077477
43             Tennessee   24.576626
44                 Texas   25.205923
45                  Utah   21.286770
46               Vermont   23.095082
47              Virginia   27.695833
48            Washington   26.888989
49         West Virginia   25.428306
50             Wisconsin   22.135396
51               Wyoming   18.145802
```

[ ]:
```
#What modes of transportation are most commonly used for commuting in different␣
↪states (e.g., car, public transportation, walking)?

#Calcultions
transportation_modes_by_state = df.groupby('State')[['Drive', 'Carpool',␣
↪'Transit', 'Walk', 'OtherTransp']].sum().reset_index()

# Normalize the data to get percentages
transportation_modes_by_state[['Drive', 'Carpool', 'Transit', 'Walk',␣
↪'OtherTransp']] = transportation_modes_by_state[['Drive', 'Carpool',␣
↪'Transit', 'Walk', 'OtherTransp']].
↪div(transportation_modes_by_state[['Drive', 'Carpool', 'Transit', 'Walk',␣
↪'OtherTransp']].sum(axis=1), axis=0) * 100

# Sort the data by the 'Drive' column in descending order
transportation_modes_by_state = transportation_modes_by_state.
↪sort_values(by='Drive', ascending=False)

# HoriZontal Plot of the data
transportation_modes_by_state.set_index('State').plot(kind='barh',␣
↪stacked=True, figsize=(15, 10))
plt.title('Modes of Transportation for Commuting in Different States')
plt.xlabel('Percentage')
plt.ylabel('State')
plt.legend(title='Transportation Mode')
plt.show()


print(transportation_modes_by_state)
```



	State	Drive	Carpool	Transit	Walk	\
0	Alabama	87.237800	9.464023	0.586360	1.483553	
43	Tennessee	86.129360	9.594789	1.083404	1.773425	
24	Mississippi	86.086598	10.119360	0.424133	1.671821	
29	New Hampshire	85.520991	8.814976	0.895838	3.211881	
41	South Carolina	85.126841	10.013474	0.761312	2.265327	
3	Arkansas	85.009745	11.042141	0.500057	2.015314	
16	Kansas	84.992725	10.007144	0.596194	2.837533	
36	Oklahoma	84.907412	10.795471	0.583061	2.210284	
33	North Carolina	84.901295	10.254153	1.212449	2.128705	
27	Nebraska	84.767305	9.650356	0.817301	3.337992	
14	Indiana	84.761873	9.662309	1.482523	2.462258	
35	Ohio	84.513781	8.589462	2.775086	2.761280	
15	Iowa	84.454221	9.198036	1.067967	3.695741	
25	Missouri	84.286308	9.674766	2.303347	2.313148	
17	Kentucky	84.152657	10.172520	1.336560	2.625019	
49	West Virginia	84.103448	9.925722	1.045823	3.613250	
22	Michigan	83.925573	9.733940	2.229668	2.609457	
31	New Mexico	83.907252	10.063634	1.180954	2.694058	
7	Delaware	83.632857	8.266754	3.799419	2.954340	
9	Florida	83.585773	9.656995	2.252973	1.895705	
42	South Dakota	83.578985	9.608715	0.613847	4.691166	
34	North Dakota	83.455019	9.613547	0.561868	5.015786	
44	Texas	83.448608	11.148666	1.682065	1.891720	
50	Wisconsin	83.272902	8.829600	2.647031	3.519228	

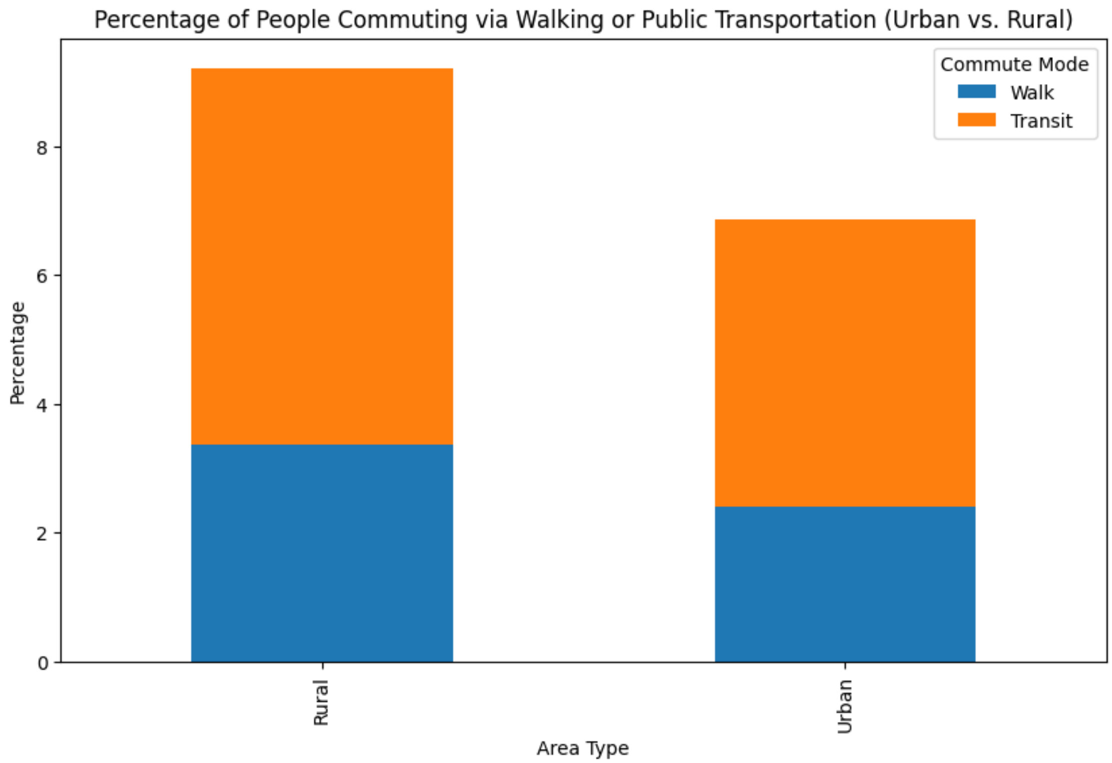
```
18             Louisiana  82.752882   9.928719   2.361261   2.474868
19                 Maine  82.560276  10.427820   0.708804   4.577618
10               Georgia  82.553645  10.903683   2.667940   1.965389
12                 Idaho  82.548234  10.779917   0.809219   3.478675
39           Puerto Rico  82.061982   8.496652   2.871417   4.380004
40          Rhode Island  81.987316   9.117606   2.908490   4.454913
23             Minnesota  81.692781   9.298336   3.999825   3.195506
46               Vermont  81.644848   9.479608   1.221118   5.917226
47              Virginia  81.290401   9.740763   4.383332   2.682129
51               Wyoming  81.222942  10.773234   1.309205   4.608724
2                Arizona  81.052286  11.526215   2.146066   2.364155
5               Colorado  80.907299  10.085541   3.281061   3.280014
6            Connecticut  80.681142   8.678442   5.921638   3.466852
28                Nevada  80.267411  10.829486   3.976415   2.597373
45                  Utah  80.194172  12.128832   2.663132   2.935868
26               Montana  79.196714  10.630047   0.787306   6.936447
38          Pennsylvania  77.786649   9.225055   6.836267   4.608836
4             California  77.665634  11.035172   5.574819   2.972786
48            Washington  77.643134  10.693114   5.855954   3.677865
37                Oregon  76.806406  10.869483   4.276663   4.449932
20              Maryland  75.852719   9.589507  10.078988   2.900839
13              Illinois  75.248824   8.560149  11.003480   3.269925
30            New Jersey  73.641468   8.522955  12.381831   3.447695
21         Massachusetts  72.916093   8.115665  10.971217   5.811922
11                Hawaii  69.115348  14.034894   6.945447   5.954481
1                 Alaska  67.163846  12.427795   1.499818  11.904292
32              New York  55.260617   7.185068  29.055900   6.596035
8   District of Columbia  38.846324   6.042644  37.586481  11.469521

    OtherTransp
0      1.228263
43     1.419022
24     1.698087
29     1.556314
41     1.833046
3      1.432743
16     1.566404
36     1.503772
33     1.503398
27     1.427046
14     1.631036
35     1.360391
15     1.584035
25     1.422432
17     1.713244
49     1.311757
22     1.501362
31     2.154102
```

```
7      1.346630
9      2.608554
42     1.507287
34     1.353779
44     1.828942
50     1.731240
18     2.482271
19     1.725482
10     1.909344
12     2.383955
39     2.189944
40     1.531675
23     1.813552
46     1.737200
47     1.903376
51     2.085894
2      2.911277
5      2.446085
6      1.251926
28     2.329315
45     2.077996
26     2.449487
38     1.543194
4      2.751590
48     2.129932
37     3.597516
20     1.577947
13     1.917621
30     2.006051
21     2.185103
11     3.949830
1      7.004248
32     1.902380
8      6.055030
```

[ ]:

```
#How does the percentage of people commuting via walking or public␣
↪transportation vary between urban and rural areas?


df['AreaType'] = np.where(df['TotalPop'] > 5000, 'Urban', 'Rural')


commute_modes_by_area = df.groupby('AreaType')[['Walk', 'Transit']].mean().
↪reset_index()

# Plot the data
```

```
commute_modes_by_area.set_index('AreaType').plot(kind='bar', stacked=True,␣
 ↪figsize=(10, 6))
plt.title('Percentage of People Commuting via Walking or Public Transportation␣
 ↪(Urban vs. Rural)')
plt.xlabel('Area Type')
plt.ylabel('Percentage')
plt.legend(title='Commute Mode')
plt.show()

commute_modes_by_area
```



[ ]:

	AreaType	Walk	Transit
0	Rural	3.36198	5.855194
1	Urban	2.39732	4.464799

7 Income and Housing

What is the average income (or median household income) in each state and county?

How does the distribution of housing type (e.g., owner-occupied vs. renter-occupied) vary across different counties?

How does the cost of living compare across different states based on average income and housing costs?

[ ]:
```
#What is the average income (or median household income) in each state and␣
↪county?
average_income_by_county = df.groupby(['State', 'County'])['Income'].mean().
↪reset_index()
average_income_by_state = df.groupby('State')['Income'].mean().reset_index()

print(average_income_by_county.head())
print(average_income_by_state.head())
```

```
     State           County        Income
0  Alabama  Autauga County  53567.500000
1  Alabama  Baldwin County  52732.225806
2  Alabama  Barbour County  32717.777778
3  Alabama     Bibb County  44677.000000
4  Alabama   Blount County  46325.555556
        State        Income
0     Alabama  45938.212947
1      Alaska  73796.757576
2     Arizona  57815.571807
3    Arkansas  44245.267936
4  California  73070.965821
```

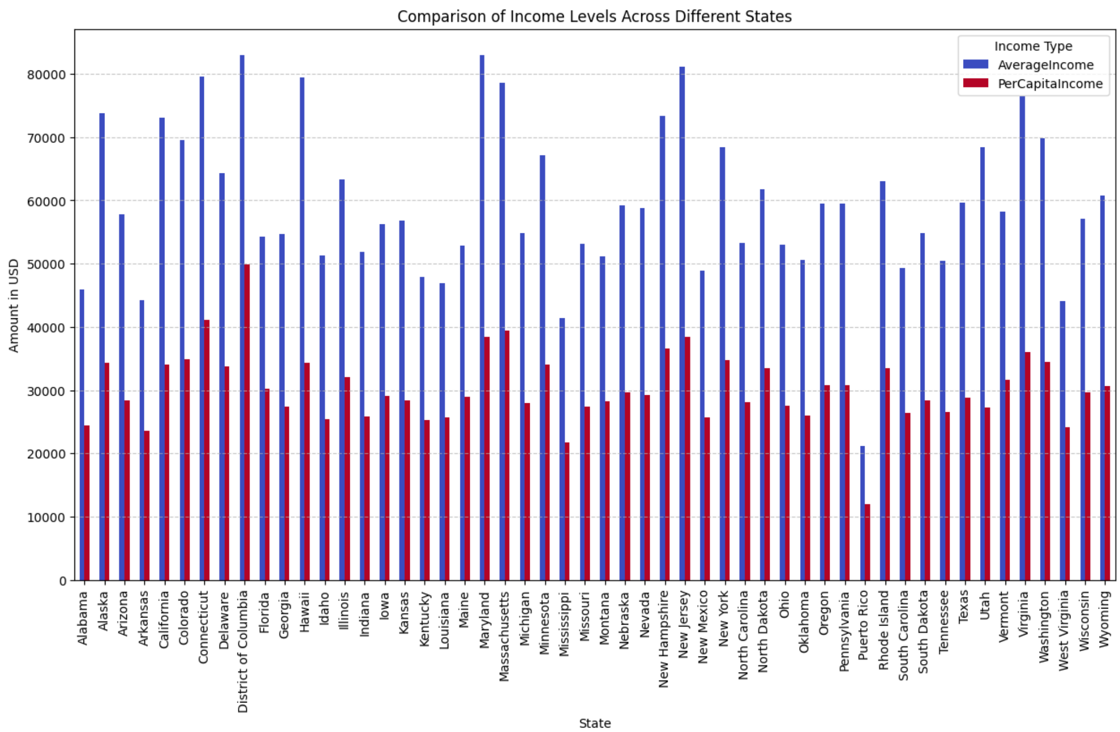
[ ]:
```
# Calculate the total number of owner-occupied and renter-occupied housing␣
↪units in each county
# housing_distribution_by_county = df.groupby(['State',␣
↪'County'])[['OwnerOccupied', 'RenterOccupied']].sum().reset_index()

# # Plot the distribution
# fig, ax = plt.subplots(figsize=(15, 10))
# housing_distribution_by_county.set_index(['State', 'County']).
↪plot(kind='bar', stacked=True, ax=ax)
# ax.set_title('Distribution of Housing Type (Owner-Occupied vs.␣
↪Renter-Occupied) Across Different Counties')
# ax.set_xlabel('County')
# ax.set_ylabel('Number of Housing Units')
# plt.legend(title='Housing Type')
# plt.show()
'''

(Current dataset does not include owner/renter data, so this needs additional␣
↪information.)
'''
print(df.columns)
```

```
Index(['TractId', 'State', 'County', 'TotalPop', 'Men', 'Women', 'Hispanic',
       'White', 'Black', 'Native', 'Asian', 'Pacific', 'VotingAgeCitizen',
```

```
       'Income', 'IncomeErr', 'IncomePerCap', 'IncomePerCapErr', 'Poverty',
       'ChildPoverty', 'Professional', 'Service', 'Office', 'Construction',
       'Production', 'Drive', 'Carpool', 'Transit', 'Walk', 'OtherTransp',
       'WorkAtHome', 'MeanCommute', 'Employed', 'PrivateWork', 'PublicWork',
       'SelfEmployed', 'FamilyWork', 'Unemployment', 'MaleToFemaleRatio',
       'Hispanic_Percentage', 'White_Percentage', 'Black_Percentage',
       'Native_Percentage', 'Asian_Percentage', 'Pacific_Percentage',
       'EmploymentRate', 'UnemploymentRate', 'SelfEmployedRate',
       'PrivateWorkRate', 'PublicWorkRate', 'WorkAtHomePercentage',
       'AreaType'],
      dtype='object')
```

[ ]:

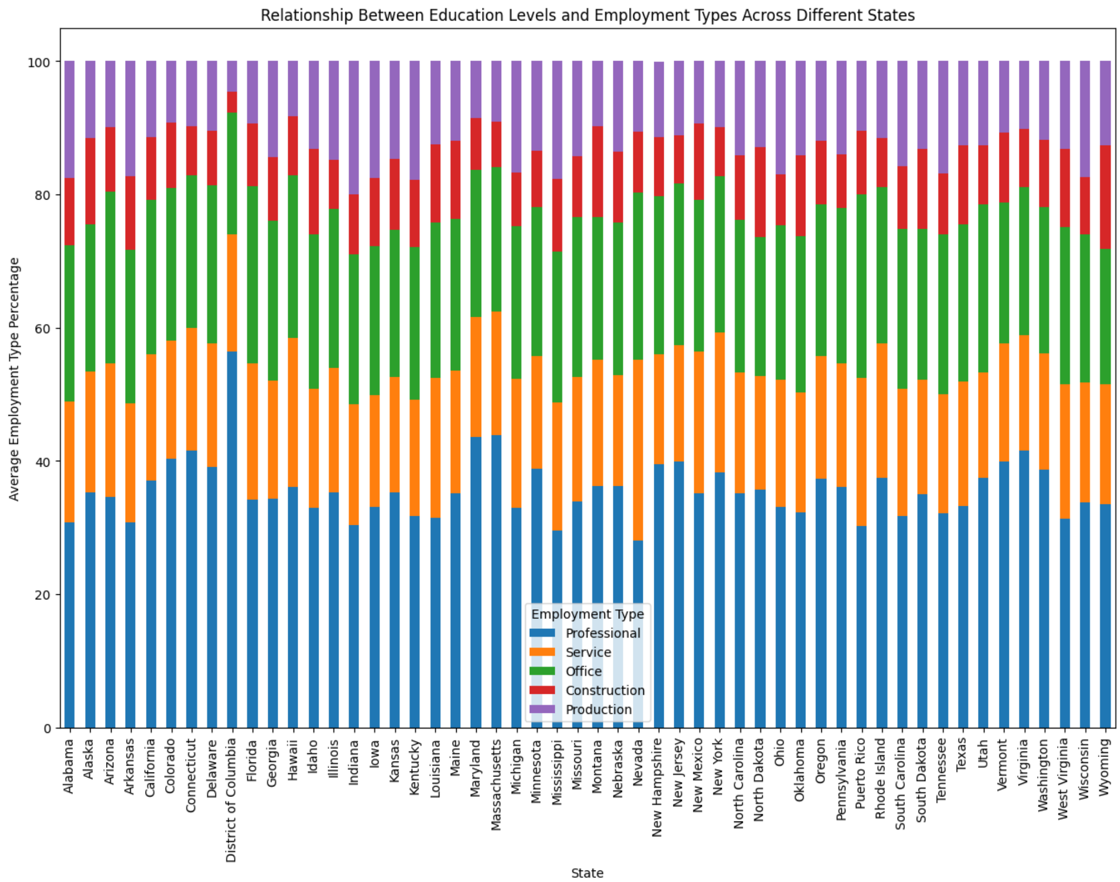
```
#How does the cost of living compare across different states based on average␣
↪income and housing costs?



average_income_by_state = df.groupby('State')['Income'].mean().reset_index()
average_per_capita_income_by_state = df.groupby('State')['IncomePerCap'].mean().
↪reset_index()

cost_of_living_by_state = pd.merge(average_income_by_state,␣
↪average_per_capita_income_by_state, on='State')
cost_of_living_by_state.columns = ['State', 'AverageIncome', 'PerCapitaIncome']␣
↪ # Better naming

cost_of_living_by_state.set_index('State').plot(kind='bar', figsize=(15, 8),␣
↪colormap='coolwarm')
plt.title('Comparison of Income Levels Across Different States')
plt.xlabel('State')
plt.ylabel('Amount in USD')
plt.legend(title='Income Type')
plt.xticks(rotation=90)
plt.grid(axis='y', linestyle='--', alpha=0.7)

plt.show()
```



8 Social Characteristics

What is the relationship between education levels (e.g., percentage with a high school diploma, bachelorâ€™s degree) and employment types across different states?

[ ]:
```
#What is the relationship between education levels (e.g., percentage with a␣
↪high school diploma, bachelorâ€ s degree) and employment types
# across different states?

'''
(Current dataset does not include direct education data, but employment types␣
↪are available.)

'''

education_employment.plot(kind='bar', stacked=True, figsize=(15, 10))
plt.title('Relationship Between Education Levels and Employment Types Across␣
↪Different States')
plt.xlabel('State')
plt.ylabel('Average Employment Type Percentage')
plt.legend(title='Employment Type')
plt.show()
```



9 Conclusion

The analysis of the dataset provides valuable insights into various demographic, social, and economic characteristics across different states and counties in the United States. Here are the key conclusions drawn from the tasks performed:

1. **General Population and Gender Distribution**:
   - The total population varies significantly across states and counties, with California having the highest population.
   - Gender distribution shows a relatively balanced ratio of men to women across most counties, with some variations.
2. **Ethnicity and Race**:
   - The Hispanic population is predominantly concentrated in states like California, Texas, and New Mexico.
   - States like Mississippi and the District of Columbia have the highest percentages of Black

populations.
    - The racial composition varies widely, with some states having higher percentages of specific racial groups.
3. **Employment and Work Type**:
    - Employment rates and types of employment (private, public, self-employed) vary across states.
    - States like Puerto Rico have higher self-employment rates, while others like Hawaii have significant public sector employment.
    - The percentage of people working from home is higher in states like Puerto Rico and Montana.
4. **Commuting and Transportation**:
    - Average commuting times differ across states, with some states having longer average commutes.
    - Driving is the most common mode of transportation, but states like New York and the District of Columbia have higher percentages of public transit users.
5. **Income and Housing**:
    - Average income levels vary across states, with states like California and New York having higher average incomes.
    - The cost of living, based on average income and housing costs, also varies, impacting the overall economic well-being of residents.
6. **Social Characteristics**:
    - The relationship between education levels and employment types indicates that higher education levels are associated with higher employment rates in professional sectors.

Overall, the dataset provides a comprehensive view of the demographic, social, and economic landscape of the United States, highlighting the diversity and disparities across different regions. This analysis can be useful for policymakers, researchers, and organizations aiming to address social and economic issues at the state and county levels.

[ ]:
```

```

from file: PMRP_7

9.1 23AIML010 OM CHOKSI PMRP ASSIGNMENT 7 + CLASSWORK

10 PART 1:

11 Statistical Concepts Applied to Iris Dataset

This dataset contains 150 samples of iris flowers, with four features (sepal length, sepal width, petal length, and petal width), and the target variable is the species of the flower. Let's begin by loading and exploring the dataset. 1. Calculate basic descriptive statistics such as the mean, median, standard deviation, and more for each of the numeric columns. 2. Normal Distribution (Check for Normality) check whether the `sepal_length` follows a normal distribution using a histogram and a Q-Q plot. 3. Hypothesis Testing (One-Sample t-Test) perform a one-sample t-test to check if the average `sepal_length` is different from 5.0. 4. Correlation Analysis calculate the Pearson correlation coefficient between `sepal_length` and `petal_length` to see if they are related. 5. Simple Linear Regression perform a simple linear regression to predict `petal_length` based on `sepal_length`. 6. ANOVA (One-Way Analysis of Variance) We will perform an ANOVA test to check if there is a significant difference in the `sepal_length` between different species. PART 2 1. Calculate the 95% confidence interval for the `petal_length` for each species. Use the `petal_length` column and apply the `groupby()` function to compute the confidence interval by species.

2. Find the correlation between `petal_length` and `petal_width`. Is it a strong positive, weak positive, or negative correlation? Provide the correlation coefficient and p-value.

3. Conduct a Chi-Square test to see if there is an association between the `season` and `species`. You will need to categorize the `season` column (Spring, Summer, Fall, Winter) and check if the distribution of species varies by season.

4. Calculate the Z-scores for `sepal_length` and identify if any values are outliers (with a

threshold of Â±3). How many outliers do you find? 5. Create a pair plot to visualize the relationships between `sepal_length`, `sepal_width`, `petal_length`, and `petal_width`. Based on the plot, describe any patterns or correlations you observe.

This dataset contains 150 samples of iris flowers, with four features (sepal length, sepal width, petal length, and petal width), and the target variable is the species of the flower. Let's begin by loading and exploring the dataset.

[28]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import scipy.stats as stats
from sklearn.datasets import load_iris

# Load Iris dataset
iris = load_iris()
df = pd.DataFrame(iris.data, columns=iris.feature_names)
df['species'] = pd.Categorical.from_codes(iris.target, iris.target_names)

print(df.describe, df.head(), df.shape, df.describe(), df.tail())
```

```
<bound method NDFrame.describe of      sepal length (cm)  sepal width (cm)
petal length (cm)  petal width (cm)  \
0                  5.1               3.5                1.4               0.2
1                  4.9               3.0                1.4               0.2
2                  4.7               3.2                1.3               0.2
3                  4.6               3.1                1.5               0.2
4                  5.0               3.6                1.4               0.2
..                 …                …                 …                …
145                6.7               3.0                5.2               2.3
146                6.3               2.5                5.0               1.9
147                6.5               3.0                5.2               2.0
148                6.2               3.4                5.4               2.3
149                5.9               3.0                5.1               1.8

       species
0       setosa
```

```
1       setosa
2       setosa
3       setosa
4       setosa
..         …
145  virginica
146  virginica
147  virginica
148  virginica
149  virginica

[150 rows x 5 columns]>    sepal length (cm)  sepal width (cm)  petal length
(cm)  petal width (cm)  \
0                5.1               3.5                1.4               0.2
1                4.9               3.0                1.4               0.2
2                4.7               3.2                1.3               0.2
3                4.6               3.1                1.5               0.2
4                5.0               3.6                1.4               0.2

  species
0  setosa
1  setosa
2  setosa
3  setosa
4  setosa   (150, 5)        sepal length (cm)  sepal width (cm)  petal length
(cm)  \
count         150.000000        150.000000         150.000000
mean            5.843333          3.057333           3.758000
std             0.828066          0.435866           1.765298
min             4.300000          2.000000           1.000000
25%             5.100000          2.800000           1.600000
50%             5.800000          3.000000           4.350000
75%             6.400000          3.300000           5.100000
max             7.900000          4.400000           6.900000

       petal width (cm)
count        150.000000
mean           1.199333
std            0.762238
min            0.100000
25%            0.300000
50%            1.300000
75%            1.800000
max            2.500000        sepal length (cm)  sepal width (cm)  petal length
(cm)  petal width (cm)  \
145                6.7               3.0                5.2               2.3
146                6.3               2.5                5.0               1.9
147                6.5               3.0                5.2               2.0
```

```
148                6.2                3.4                5.4                2.3
149                5.9                3.0                5.1                1.8

       species
145  virginica
146  virginica
147  virginica
148  virginica
149  virginica
```

1. Calculate basic descriptive statistics such as the mean, median, standard deviation, and more for each of the numeric columns. Calculate basic descriptive statistics

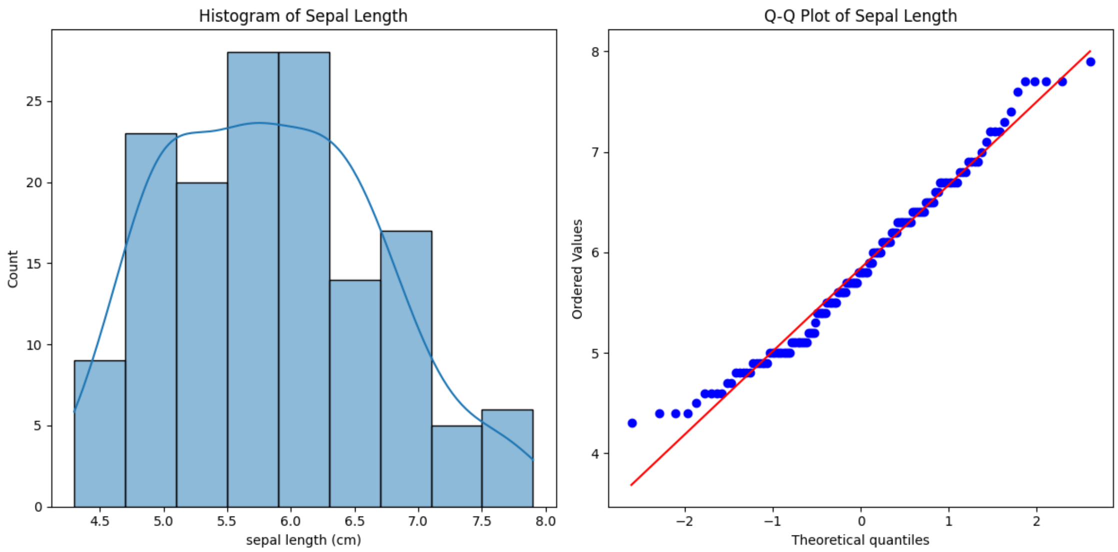
[29]:
```
print("Descriptive Statistics:")
print(df.describe())
```

```
Descriptive Statistics:
       sepal length (cm)  sepal width (cm)  petal length (cm)  \
count         150.000000        150.000000         150.000000
mean            5.843333          3.057333           3.758000
std             0.828066          0.435866           1.765298
min             4.300000          2.000000           1.000000
25%             5.100000          2.800000           1.600000
50%             5.800000          3.000000           4.350000
75%             6.400000          3.300000           5.100000
max             7.900000          4.400000           6.900000

       petal width (cm)
count        150.000000
mean           1.199333
std            0.762238
min            0.100000
25%            0.300000
50%            1.300000
75%            1.800000
max            2.500000
```

2. Normal Distribution (Check for Normality) check whether the `sepal_length` follows a normal distribution using a histogram and a Q-Q plot.

[30]:
```
fig, axs = plt.subplots(1, 2, figsize=(12, 6))

# Histogram
sns.histplot(df['sepal length (cm)'], kde=True, ax=axs[0])
axs[0].set_title("Histogram of Sepal Length")

# Q-Q Plot
stats.probplot(df['sepal length (cm)'], dist="norm", plot=axs[1])
axs[1].set_title("Q-Q Plot of Sepal Length")
```

```
plt.tight_layout()
```



3. Hypothesis Testing (One-Sample t-Test) perform a one-sample t-test to check if the average `sepal_length` is different from 5.0.

[31]:
```
t_stat, p_value = stats.ttest_1samp(df['sepal length (cm)'], 5.0)
print(f"One-Sample t-Test: t-statistic={t_stat:.3f}, p-value={p_value:.3f}")
```

```
One-Sample t-Test: t-statistic=12.473, p-value=0.000
```

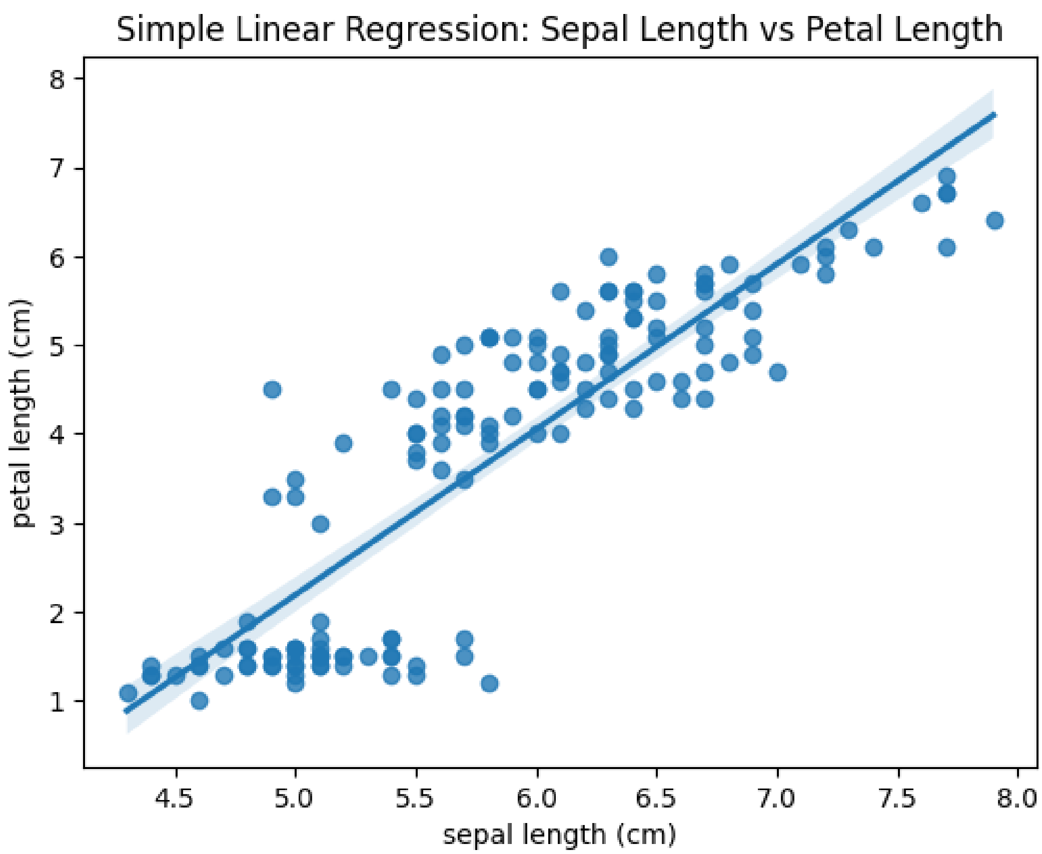
4. Correlation Analysis calculate the Pearson correlation coefficient between `sepal_length` and `petal_length` to see if they are related.

[32]:
```
corr, p_val = stats.pearsonr(df['sepal length (cm)'], df['petal length (cm)'])
print(f"Pearson Correlation: r={corr:.3f}, p-value={p_val:.3f}")
```

```
Pearson Correlation: r=0.872, p-value=0.000
```

5. Simple Linear Regression perform a simple linear regression to predict `petal_length` based on `sepal_length`.

[33]:
```
sns.regplot(x=df['sepal length (cm)'], y=df['petal length (cm)'])
plt.title("Simple Linear Regression: Sepal Length vs Petal Length")
plt.show()
```



6. ANOVA (One-Way Analysis of Variance) We will perform an ANOVA test to check if there is a significant difference in the `sepal_length` between different species.

[34]:
```
groups = [df[df['species'] == species]['sepal length (cm)'] for species in␣
↪df['species'].unique()]
anova_result = stats.f_oneway(*groups)
print(f"ANOVA Results: F-statistic={anova_result.statistic:.3f},␣
↪p-value={anova_result.pvalue:.3f}")
```

```
ANOVA Results: F-statistic=119.265, p-value=0.000
```

12 PART 2

1. Calculate the 95% confidence interval for the `petal_length` for each species. Use the `petal_length` column and apply the `groupby()` function to compute the confidence interval by species.
2. Find the correlation between `petal_length` and `petal_width`. Is it a strong positive, weak positive, or negative correlation? Provide the correlation coefficient and p-value.
3. Conduct a Chi-Square test to see if there is an association between the `season` and `species`.

You will need to categorize the **season** column (Spring, Summer, Fall, Winter) and check if the distribution of species varies by season.

4. Calculate the Z-scores for `sepal_length` and identify if any values are outliers (with a threshold of Â±3). How many outliers do you find?

5. Create a pair plot to visualize the relationships between `sepal_length`, `sepal_width`, `petal_length`, and `petal_width`. Based on the plot, describe any patterns or correlations you observe.

1. Calculate the 95% confidence interval for the `petal_length` for each species. Use the `petal_length` column and apply the `groupby()` function to compute the confidence interval by species.

[35]:
```
def confidence_interval(data):
    mean = np.mean(data)
    sem = stats.sem(data)
    return stats.t.interval(0.95, len(data)-1, loc=mean, scale=sem)

ci_by_species = df.groupby('species')['petal length (cm)'].
 ↪apply(confidence_interval)
print("95% Confidence Intervals for Petal Length by Species:")
print(ci_by_species)
```

```
95% Confidence Intervals for Petal Length by Species:
species
setosa        (1.4126452382875103, 1.51135476171249)
versicolor    (4.126452777905478, 4.393547222094521)
virginica     (5.395153262927524, 5.708846737072477)
Name: petal length (cm), dtype: object
```

```
C:\Users\omcho\AppData\Local\Temp\ipykernel_22464\2906686433.py:6:
FutureWarning: The default of observed=False is deprecated and will be changed
to True in a future version of pandas. Pass observed=False to retain current
behavior or observed=True to adopt the future default and silence this warning.
  ci_by_species = df.groupby('species')['petal length
(cm)'].apply(confidence_interval)
```

2. Find the correlation between `petal_length` and `petal_width`. Is it a strong positive, weak positive, or negative correlation? Provide the correlation coefficient and p-value.

[36]:
```
corr_pw, p_val_pw = stats.pearsonr(df['petal length (cm)'], df['petal width␣
 ↪(cm)'])
print(f"Correlation between Petal Length and Petal Width: r={corr_pw:.3f},␣
 ↪p-value={p_val_pw:.3f}")
```

```
Correlation between Petal Length and Petal Width: r=0.963, p-value=0.000
```

3. Conduct a Chi-Square test to see if there is an association between the `season` and `species`. You will need to categorize the `season` column (Spring, Summer, Fall, Winter) and check if the distribution of species varies by season.

[37]:
```
df['season'] = np.random.choice(['Spring', 'Summer', 'Fall', 'Winter'],␣
↪size=len(df))
contingency_table = pd.crosstab(df['season'], df['species'])
chi2, p, _, _ = stats.chi2_contingency(contingency_table)
print(f"Chi-Square Test: chi2={chi2:.3f}, p-value={p:.3f}")
```

```
Chi-Square Test: chi2=7.376, p-value=0.288
```

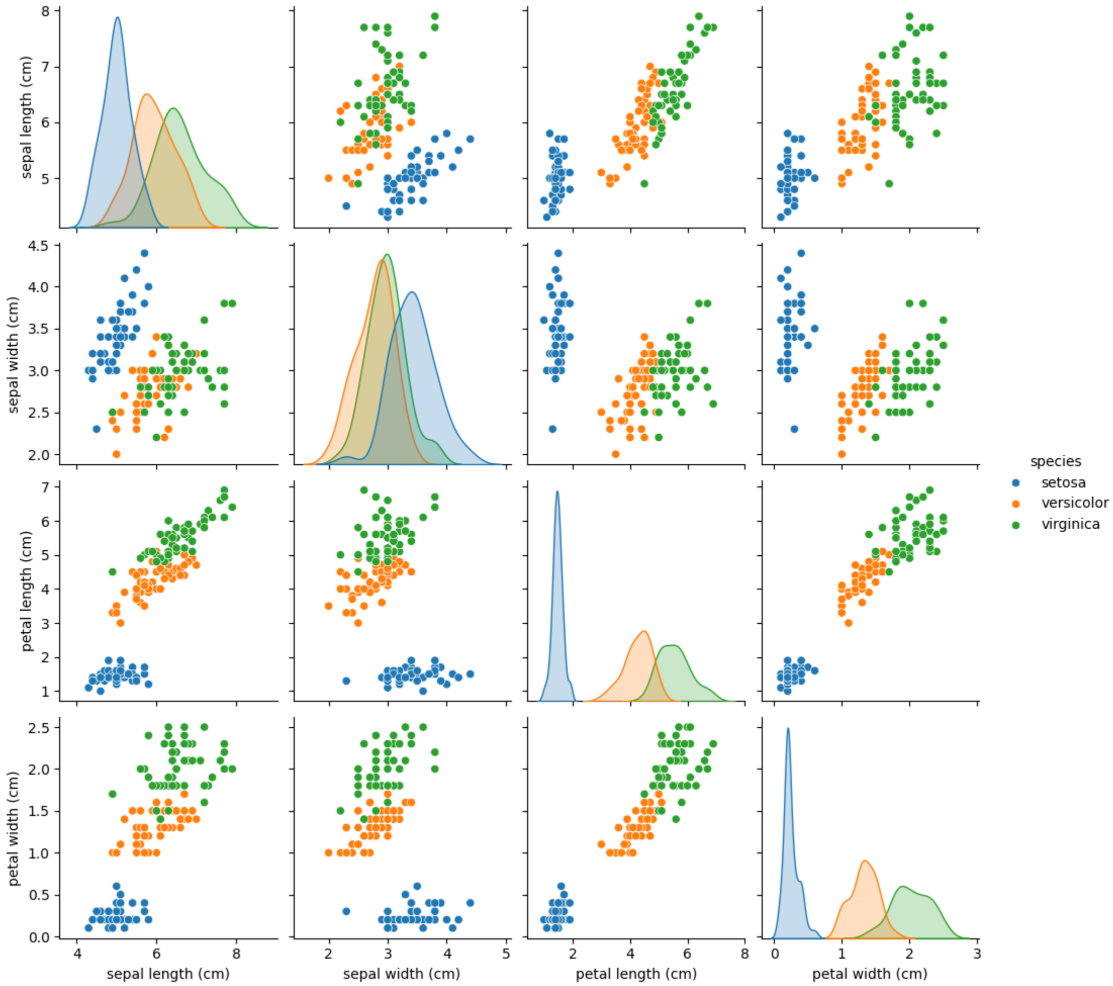
4. Calculate the Z-scores for `sepal_length` and identify if any values are outliers (with a threshold of Â±3). How many outliers do you find?

[38]:
```
z_scores = stats.zscore(df['sepal length (cm)'])
outliers = np.where(np.abs(z_scores) > 3)[0]
print(f"Number of Outliers in Sepal Length: {len(outliers)}")
```

```
Number of Outliers in Sepal Length: 0
```

5. Create a pair plot to visualize the relationships between `sepal_length`, `sepal_width`, `petal_length`, and `petal_width`. Based on the plot, describe any patterns or correlations you observe.

[40]:
```
sns.pairplot(df, vars=['sepal length (cm)', 'sepal width (cm)', 'petal length␣
↪(cm)', 'petal width (cm)'], hue='species')
plt.show()
```




```
[ ]:
```

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