```
In [57]: #2.3 Missing values
import pandas as pd
df = pd.read_csv(r"C:\Users\vaibh\Downloads\heart (1).csv")
df.head(10)

df_dropped = df.dropna()
df_dropped

#filling with specific value
df_specific = df.fillna(0)
df_specific

df_mean = df.fillna(df.mean())
df_mean
```

_			-	_	_	$\neg$	
	11	+		5	_/	- 1	0
$\cup$	u	_		$\mathcal{L}$	/	- 1	4

•		age	gender	ср	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope
	0	63.000000	1.000000	3	145.0	233	1	0	150	0	2.3	0
	1	54.413333	0.684385	2	130.0	250	0	1	187	0	3.5	0
	2	41.000000	0.000000	1	130.0	204	0	0	172	0	1.4	2
	3	54.413333	1.000000	1	120.0	236	0	1	178	0	0.8	2
	4	57.000000	0.684385	0	120.0	354	0	1	163	1	0.6	2
	•••	•••	•••					•••				
	298	57.000000	0.000000	0	140.0	241	0	1	123	1	0.2	1
	299	45.000000	1.000000	3	110.0	264	0	1	132	0	1.2	1
	300	68.000000	1.000000	0	144.0	193	1	1	141	0	3.4	1
	301	57.000000	1.000000	0	130.0	131	0	1	115	1	1.2	1
	302	57.000000	0.000000	1	130.0	236	0	0	174	0	0.0	1

303 rows × 14 columns

```
In [134... # 2.3 remove outliers
   import pandas as pd
   import numpy as np
   from scipy.stats import zscore

df = pd.read_csv(r"C:\Users\vaibh\Downloads\heart (1).csv")

z_score = zscore(df,nan_policy='omit')
   abs_z_score = np.abs(z_score)
   threshold = 2
   abs_z_score.head(100)
```

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( )	ut.			$\prec$	$\Delta$	
$\sim$	$u  \iota$		_	$\sim$	_	

	age	gender	ср	trestbps	chol	fbs	restecg	thalach	exan
0	0.948186	0.679091	1.973123	0.764565	0.256334	2.394438	1.005832	0.015443	0.69663
1	NaN	NaN	1.002577	0.091038	0.072199	0.417635	0.898962	1.633471	0.69663
2	1.481172	1.472556	0.032031	0.091038	0.816773	0.417635	1.005832	0.977514	0.69663
3	NaN	0.679091	0.032031	0.661440	0.198357	0.417635	0.898962	1.239897	0.69663
4	0.285634	NaN	0.938515	0.661440	2.082050	0.417635	0.898962	0.583939	1.43548
•••		•••							
95	0.156068	0.679091	0.938515	0.593445	0.391612	0.417635	1.005832	1.690047	1.43548
96	0.837760	1.472556	0.938515	0.479364	2.855069	0.417635	1.005832	0.321556	0.69663
97	0.266493	0.679091	0.938515	1.345922	0.256334	2.394438	0.898962	0.115749	0.69663
98	1.260321	0.679091	1.002577	0.091038	1.328356	0.417635	0.898962	0.540209	0.69663
99	0.156068	0.679091	1.002577	0.091038	0.005102	2.394438	1.005832	1.021244	0.69663

100 rows × 14 columns

In [142... df\_cleaned = df.loc[(abs\_z\_score < threshold).all(axis=1)]</pre> df\_cleaned.head(100)

Out[142...

	age	gender	ср	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	1
2	41.0	0.0	1	130.0	204	0	0	172	0	1.4	2	0	
7	44.0	1.0	1	120.0	263	0	1	173	0	0.0	2	0	
9	57.0	1.0	2	150.0	168	0	1	174	0	1.6	2	0	
10	54.0	1.0	0	140.0	239	0	1	160	0	1.2	2	0	
11	48.0	0.0	2	130.0	275	0	1	139	0	0.2	2	0	
•••													
146	44.0	0.0	2	118.0	242	0	1	149	0	0.3	1	1	
147	60.0	0.0	3	150.0	240	0	1	171	0	0.9	2	0	
148	44.0	1.0	2	120.0	226	0	1	169	0	0.0	2	0	
149	42.0	1.0	2	130.0	180	0	1	150	0	0.0	2	0	
151	71.0	0.0	0	112.0	149	0	1	125	0	1.6	1	0	

100 rows × 14 columns

```
In [150... #Api integration
import pandas as pd
import requests

url = "https://api.coingecko.com/api/v3/coins/markets"

params = {
    "vs_currency" : "usd",
    "order" : "market_cap_desc",
    "per_page" : 10,
    "page" : 1,
    "spakLine" : False
}
response = requests.get(url,params=params)

if response.status_code == 200 :
    data = response.json()
```

Data succesfully loaded into dataframe

df = pd.DataFrame(data)

else :

df.head()

print("Data successfully loaded into dataframe")

print(f"Failed to fetch the data : {response.status\_code}")

Data successfully loaded lifto datairally

	id	symbol	name	image	current_price	ma
0	bitcoin	btc	Bitcoin	https://coin- images.coingecko.com/coins/images	92380.000000	182755
1	ethereum	eth	Ethereum	https://coin- images.coingecko.com/coins/images	3113.340000	3748(
2	tether	usdt	Tether	https://coin- images.coingecko.com/coins/images	0.999951	12811
3	solana	sol	Solana	https://coin- images.coingecko.com/coins/images	241.670000	11468
4	binancecoin	bnb	BNB	https://coin-images.coingecko.com/coins/images	615.400000	8991

5 rows × 26 columns

Out[150...

```
Index(['id', 'symbol', 'name', 'image', 'current_price', 'market_cap',
Out[152...
                  'market_cap_rank', 'fully_diluted_valuation', 'total_volume',
                  'high_24h', 'low_24h', 'price_change_24h',
                  'price_change_percentage_24h', 'market_cap_change_24h',
                  'market_cap_change_percentage_24h', 'circulating_supply',
                  'total_supply', 'max_supply', 'ath', 'ath_change_percentage',
                  'ath_date', 'atl', 'atl_change_percentage', 'atl_date', 'roi',
                  'last_updated'],
                 dtype='object')
In [185...
          print("Column names in DataFrame : ")
          print(df.columns)
          df_selected = df[['name','current_price','market_cap']]
          print("\n Selectd Columns : ")
          print(df_selected.head())
          df_sorted = df_selected.sort_values(by='market_cap',ascending = False)
          print("\nTop Cryptocurrencies of by market cap : ")
          print(df_sorted)
          df_selected['price_in_eur'] = df_selected['current_price'] * 0.85
          print("\n Added 'price in eur' column : ")
          print(df_selected.head())
          df_filtered = df_selected[df_selected['market_cap'] > 1e9]
          print("Cryptocurrencies with market cap greter than 1 billion")
          print(df_filtered)
```

```
Column names in DataFrame :
Index(['id', 'symbol', 'name', 'image', 'current_price', 'market_cap',
      'market_cap_rank', 'fully_diluted_valuation', 'total_volume',
      'high_24h', 'low_24h', 'price_change_24h',
      'price_change_percentage_24h', 'market_cap_change_24h',
      'market_cap_change_percentage_24h', 'circulating_supply',
      'total_supply', 'max_supply', 'ath', 'ath_change_percentage',
      'ath_date', 'atl', 'atl_change_percentage', 'atl_date', 'roi',
      'last updated'],
     dtype='object')
Selectd Columns :
      name current price
                            market cap
  Bitcoin 92380.000000 1827556947075
1 Ethereum 3113.340000 374806136312
2
   Tether
              0.999951 128114926302
    Solana 241.670000 114682944570
3
       BNB
              615.400000 89913267776
4
Top Cryptocurrencies of by market cap :
              name current_price
                                    market_cap
           Bitcoin 92380.000000 1827556947075
0
1
          Ethereum
                     3113.340000 374806136312
2
            Tether
                      0.999951 128114926302
3
            Solana 241.670000 114682944570
4
               BNB 615.400000 89913267776
                       1.097000 62439424379
5
               XRP
6
          Dogecoin
                      0.396368 58184329728
7
              USDC
                      0.999439 37239890081
                     3112.840000 30426780421
8 Lido Staked Ether
9
           Cardano 0.733744 26307829353
Added 'price in eur' column :
      name current price
                            market cap price in eur
  Bitcoin 92380.000000 1827556947075 78523.000000
0
1 Ethereum 3113.340000 374806136312 2646.339000
                0.999951 128114926302
2
   Tether
                                          0.849958
3
    Solana
              241.670000 114682944570
                                        205.419500
       BNB
              615.400000 89913267776 523.090000
Cryptocurrencies with market cap greter than 1 billion
              name current_price
                                    market_cap price_in_eur
           Bitcoin 92380.000000 1827556947075 78523.000000
0
1
          Ethereum 3113.340000 374806136312 2646.339000
                        0.999951 128114926302
2
            Tether
                                                  0.849958
3
            Solana
                     241.670000 114682944570 205.419500
4
               BNB
                      615.400000 89913267776 523.090000
5
               XRP
                        1.097000 62439424379 0.932450
6
          Dogecoin
                      0.396368 58184329728
                                                 0.336913
7
                       0.999439 37239890081
              USDC
                                                 0.849523
8 Lido Staked Ether
                     3112.840000 30426780421 2645.914000
           Cardano 0.733744 26307829353
9
                                                  0.623682
```

```
C:\Users\vaibh\AppData\Local\Temp\ipykernel_11488\1469776383.py:12: SettingWithCopyW
arning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/u
ser_guide/indexing.html#returning-a-view-versus-a-copy
   df_selected['price_in_eur'] = df_selected['current_price'] * 0.85
```

```
In [201...
          import sqlite3
          connection = sqlite3.connect("sample_database.db")
          cursor = connection.cursor()
          #create table
          cursor.execute("""
          CREATE TABLE IF NOT EXISTS employees (
              id INTEGER PRIMARY KEY AUTOINCREMENT,
              name TEXT NOT NULL,
              age INTEGER,
              department TEXT,
              salary REAL
          """)
          cursor.executemany("""
          INSERT INTO employees (name, age, department, salary)
          VALUES(?,?,?,?)
          """, [
              ("Allice", 30, "HR", 600000),
              ("Bob",25,"IT",70000),
               ("Charlie", 35, "Finance", 80000),
              ("Diana", 28, "IT", 65000),
              ("Eve", 40, "HR", 72000)
          1)
          connection.commit()
          connection.close()
          print("Data and table setup complete")
```

Data and table setup complete

```
import pandas as pd
connection = sqlite3.connect("sample_database.db")

query = "SELECT * FROM employees"
    df = pd.read_sql_query(query,connection)

print("Data loaded into Dataframe : ")
    print(df)

connection.close()
```

```
Data loaded into Dataframe :
               name age department salary
        0 1 Allice 30
                                 HR 600000.0
          2
                  Bob 25
                                 IT 70000.0
        1
                                HR 600000.0
        2 3 Allice 30
        3 4
                  Bob 25
                                 IT 70000.0
        4 5 Charlie 35 Finance 80000.0
        5 6 Diana 28 IT 65000.0
6 7 Eve 40 HR 72000.0
In [215... print("\n Summary Statistics")
         print(df.describe())
         df["tax"] = df["salary"]*0.10
         print("\n DataFrame with Tax column : ")
         print(df)
         high_earners = df[df["salary"]>65000]
         print("\n Employees with salary > 65000")
         print(high_earners)
         avg_sal_by_dept = df.groupby("department")["salary"].mean()
         print("\nAverage salary by the department : ")
         print(avg_sal_by_dept)
         sorted_by_age = df.sort_values(by="age",ascending = False)
         print("\nEmployees Sorted Age : ")
         print(sorted_by_age)
```

```
Summary Statistics
                    id
                             age
                                         salary
                                                         tax
       count 7.000000
                        7.000000
                                       7.000000
                                                    7.000000
       mean
              4.000000 30.428571 222428.571429 22242.857143
       std
              2.160247
                        5.442338
                                 257968.898088 25796.889809
       min
              1.000000 25.000000
                                   65000.000000
                                                 6500.000000
       25%
              2.500000 26.500000
                                   70000.000000
                                                 7000.000000
       50%
              4.000000 30.000000
                                   72000.000000
                                                 7200.000000
       75%
              5.500000 32.500000 340000.000000 34000.000000
              7.000000 40.000000 600000.000000 60000.000000
       max
        DataFrame with Tax column :
          id
                name age department
                                       salary
                                                   tax
          1
              Allice
                       30
                                 HR 600000.0 60000.0
           2
                  Bob
                       25
                                  ΙT
                                      70000.0
                                                7000.0
       1
           3
       2
              Allice
                       30
                                  HR 600000.0 60000.0
       3
           4
                  Bob
                       25
                                  ΙT
                                      70000.0
                                                7000.0
       4
          5 Charlie
                       35
                           Finance 80000.0
                                                8000.0
       5
           6
                Diana 28
                                IT 65000.0
                                                6500.0
       6
           7
                  Eve
                       40
                                  HR
                                     72000.0 7200.0
        Employees with salary > 65000
          id
                 name
                      age department
                                       salary
                                                   tax
       0
           1
              Allice
                       30
                                 HR 600000.0 60000.0
       1
           2
                  Bob
                       25
                                  ΙT
                                      70000.0
                                                7000.0
       2
           3
              Allice
                       30
                                  HR 600000.0 60000.0
       3
           4
                  Bob
                       25
                                  ΙT
                                      70000.0
                                                7000.0
       4
           5 Charlie
                       35
                                      80000.0 8000.0
                             Finance
           7
                  Eve 40
                                 HR 72000.0 7200.0
       6
       Average salary by the department :
       department
       Finance
                  80000.000000
                  424000.000000
       HR
       IT
                  68333.333333
       Name: salary, dtype: float64
       Employees Sorted Age :
          id
                 name age department
                                                   tax
                                       salary
           7
                  Eve 40
                                 HR
                                      72000.0
                                                7200.0
       6
       4
           5 Charlie 35
                             Finance
                                      80000.0
                                                8000.0
       0
           1
              Allice 30
                                  HR 600000.0 60000.0
       2
          3 Allice 30
                                  HR 600000.0 60000.0
              Diana
       5
           6
                       28
                                  IT
                                      65000.0
                                                6500.0
       1
           2
                  Bob
                       25
                                  ΙT
                                      70000.0
                                               7000.0
       3
           4
                  Bob
                                      70000.0
                       25
                                  IT
                                                7000.0
        import pandas as pd
In [77]:
         import requests
         from bs4 import BeautifulSoup
         from io import StringIO
         url = "https://en.wikipedia.org/wiki/Agriculture_in_India"
         response = requests.get(url)
```

```
soup = BeautifulSoup(response.text,"html.parser")
table = soup.find("table",{"class" : "wikitable"})

df = pd.read_html(StringIO(str(table)))[0]

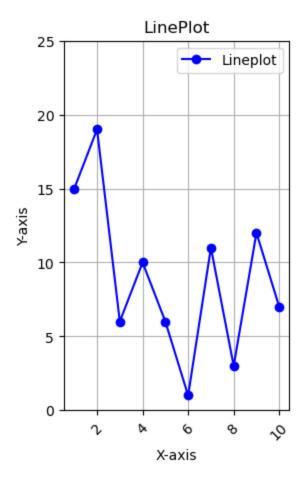
print("Extracted Data : ")
df.head()
```

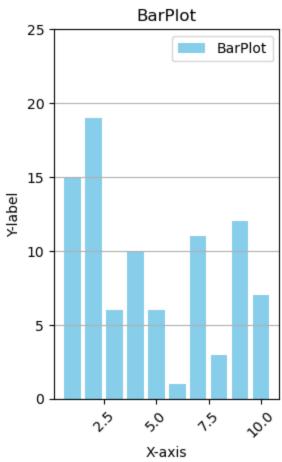
#### Extracted Data:

Out[77]:

	Rank	Commodity	Value (US\$, 2016)	Unit price (US\$ / kilogram, 2009)	Average yield (tonnes per hectare, 2017)	Most productive country (tonnes per hectare, 2017)	Most productive country (tonnes per hectare, 2017).1
0	1	Rice	\$70.18 billion	0.27	3.85	9.82	Australia
1	2	Buffalo milk	\$43.09 billion	0.40	2.00[78]	2.00[78]	India
2	3	Cow milk	\$32.55 billion	0.31	1.2[78]	10.3[78]	Israel
3	4	Wheat	\$26.06 billion	0.15	2.8	8.9	Netherlands
4	5	Cotton (Lint + Seeds)	\$23.30 billion	1.43	1.6	4.6	Israel

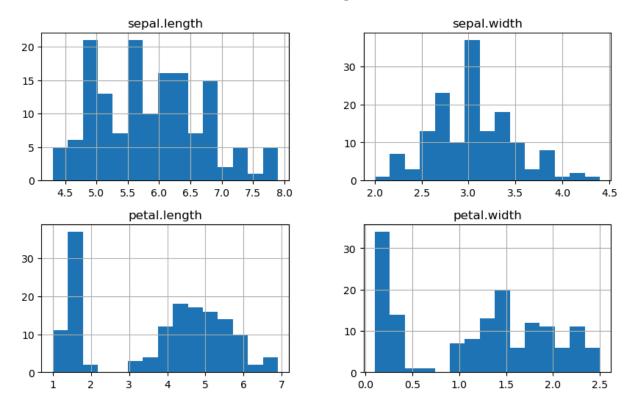
```
name Age rank score
       0 Vaibhav 12 1
                               99
             Riya 14
                         3
                               67
       1
       2 Taniya 16
                          2
                               87
       3 Tanmay 17
                          5
                               12
       4 Yashraj
                  18
                         4
                               34
       Index(['name', 'Age', 'rank', 'score'], dtype='object')
             name Age rank score
       2 Taniya
                          2
                  16
                               87
       3 Tanmay
                  17
                          5
                               12
                  18
       4 Yashraj
                         4
                               34
             name Age rank score
                  17
       3
         Tanmay
                       5
                               12
       4 Yashraj
                  18
                        4
                               34
       1
             Riya 14
                          3
                               67
       2 Taniya 16 2
                               87
       0 Vaibhav 12 1 99
       name
       Riya
                 67.0
       Taniya
                 87.0
       Tanmay
                 12.0
               99.0
       Vaibhav
       Yashraj
                 34.0
       Name: score, dtype: float64
In [87]: import numpy as np
        import matplotlib.pyplot as plt
        A = np.arange(1,11)
        B = np.random.randint(1,20,size = 10)
        plt.subplot(1, 2, 1) # 1 row, 2 columns, first subplot
        plt.plot(A,B,label="Lineplot",marker = "o",linestyle = "-",color = "blue")
         plt.xlabel("X-axis")
        plt.ylabel("Y-axis")
         plt.legend()
        plt.title("LinePlot")
         plt.grid(True)
         plt.ylim(0, 25) # Set y-axis limits
        plt.xticks(rotation=45) # Rotate x-axis labels
        plt.show()
         plt.subplot(1, 2, 1) # 1 row, 2 columns, first subplot
         plt.bar(A,B,label = "BarPlot",color = "skyblue")
         plt.xlabel("X-axis")
        plt.ylabel("Y-label")
         plt.legend()
         plt.title("BarPlot")
         plt.grid(axis="y") # Grid only on the y-axis
         plt.ylim(0, 25) # Set y-axis limits
        plt.xticks(rotation=45) # Rotate x-axis labels
         plt.show()
```





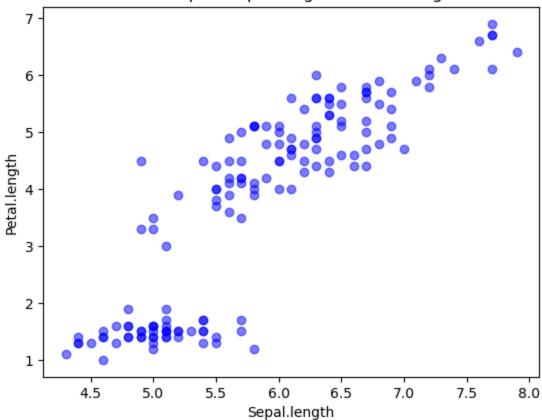
```
import numpy as np
In [106...
          import pandas as pd
          import matplotlib.pyplot as plt
          df = pd.read_csv(r"C:\Users\vaibh\Downloads\iris.csv")
          print(df.describe())
          print()
          print(df.info())
          print(df.isnull().sum())
                sepal.length sepal.width petal.length petal.width
                               150.000000
        count
                 150.000000
                                             150.000000
                                                        150.000000
                   5.843333
                                 3.057333
                                               3.758000
                                                            1.199333
        mean
        std
                   0.828066
                                 0.435866
                                               1.765298
                                                            0.762238
        min
                   4.300000
                                 2.000000
                                               1.000000
                                                            0.100000
        25%
                   5.100000
                                 2.800000
                                               1.600000
                                                            0.300000
        50%
                   5.800000
                                 3.000000
                                               4.350000
                                                            1.300000
        75%
                   6.400000
                                 3.300000
                                               5.100000
                                                            1.800000
                                                            2.500000
                   7.900000
                                 4.400000
                                               6.900000
        max
        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 150 entries, 0 to 149
        Data columns (total 5 columns):
         # Column
                           Non-Null Count Dtype
         --- -----
         0
             sepal.length 150 non-null
                                            float64
         1
             sepal.width 150 non-null
                                           float64
              petal.length 150 non-null
                                            float64
          3
             petal.width 150 non-null
                                            float64
             species
                           150 non-null
                                            object
        dtypes: float64(4), object(1)
        memory usage: 6.0+ KB
        None
        sepal.length
        sepal.width
                         0
        petal.length
                         0
        petal.width
                         0
        species
                         0
        dtype: int64
          df[['sepal.length','sepal.width','petal.length','petal.width']].hist(bins = 15,figs
In [114...
          plt.suptitle("Features Histigram")
          plt.show()
```

#### Features Histigram

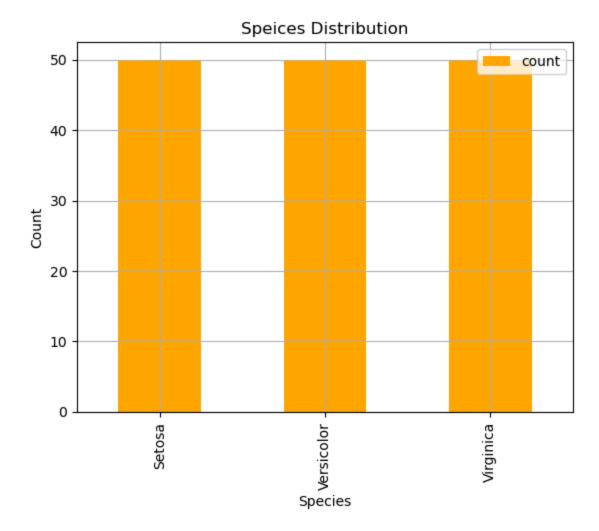


```
In [122... plt.scatter(df['sepal.length'],df['petal.length'],color = 'blue',alpha = 0.5)
    plt.title("Scatter plot Sepal.length vs Petal.length")
    plt.xlabel("Sepal.length")
    plt.ylabel("Petal.length")
    plt.show()
```

# Scatter plot Sepal.length vs Petal.length



```
In [132... df['species'].value_counts().plot(kind = 'bar',color = 'orange')
    plt.title("Species Distribution")
    plt.xlabel("Species")
    plt.ylabel("Count")
    plt.grid(True)
    plt.legend()
    plt.show()
```



```
import seaborn as sns
corelation_matrix = df.select_dtypes(include = 'number').corr()
plt.figure(figsize = (10,6))
sns.heatmap(corelation_matrix,annot = True,cmap = 'coolwarm',fmt='0.2f',cbar = True
plt.show()
```



import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
df = pd.read\_csv(r"C:\Users\vaibh\Downloads\Orange\_Telecom\_Churn\_Data.csv")
df.head(5)

#### Out[3]: state account\_length area\_code phone\_number intl\_plan voice\_mail\_plan number\_vm 0 KS 128 415 382-4657 no yes 1 ОН 107 415 371-7191 no yes 2 NJ 137 415 358-1921 no no 3 OH 84 408 375-9999 yes no 4 OK 75 415 330-6626 yes no

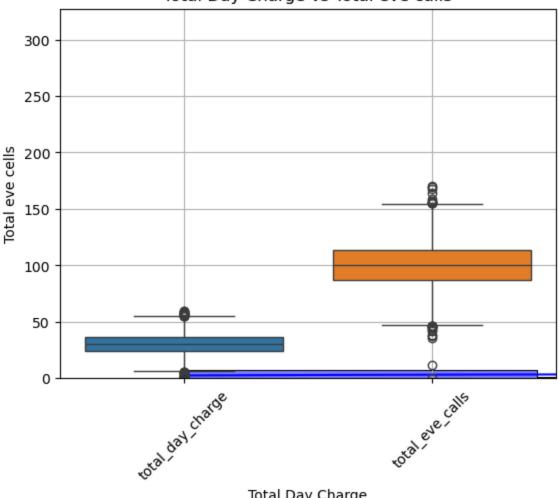
5 rows × 21 columns

```
In [9]: sns.histplot(df['total_day_charge'],kde = True,color = 'blue')
  plt.title("Histogram of total day charge")
  plt.xlabel("Total Day Charge")
  plt.ylabel("Frequency")
  plt.grid(True)
  plt.show()

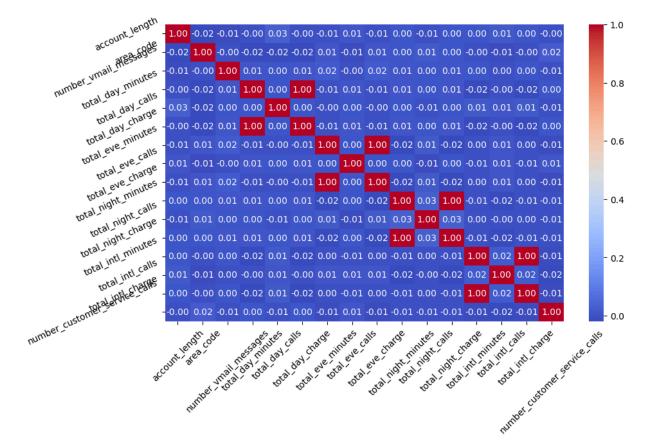
sns.boxplot(data = df[['total_day_charge','total_eve_calls']])
  plt.title("Total Day Charge vs Total eve calls")
  plt.xlabel("Total Day Charge")
```

```
plt.ylabel("Total eve cells")
plt.xticks(rotation = 45)
plt.grid(True)
plt.show()
correlation_matrix = df.select_dtypes(include = 'number').corr()
plt.figure(figsize = (10,6))
sns.heatmap(correlation_matrix,annot= True,cmap = 'coolwarm',fmt = '0.2f',cbar = Tr
plt.xticks(rotation = 45)
plt.yticks(rotation = 25)
plt.show()
```

## Total Day Charge vs Total eve calls

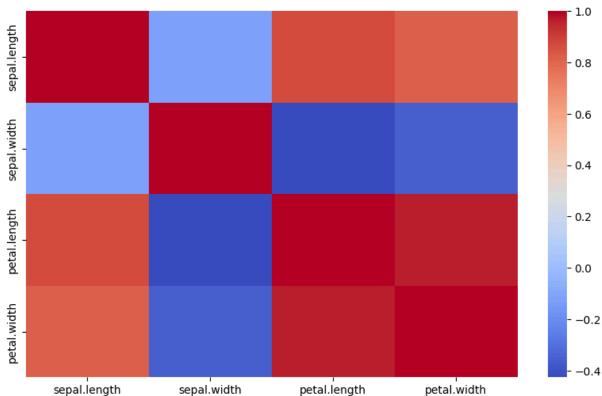


Total Day Charge



```
In [129...
          import pandas as pd
          import seaborn as sns
          import matplotlib.pyplot as plt
          df = pd.read csv(r"C:\Users\vaibh\Downloads\iris.csv")
          print("Data frame with missing values : ")
          print(df.isnull().sum())
          df.dropna(inplace = True)
          print("\n Number of Duplicates rows : ")
          print(df.duplicated().sum())
          df.drop duplicates(inplace = True)
          correalation_matrix = df.select_dtypes(include = 'number').corr()
          print("\n Data set after Cleaning ")
          print(df.info())
          plt.figure(figsize =(10,6))
          sns.heatmap(correalation_matrix,annot =False,cmap='coolwarm',fmt ='0.2f',cbar = Tru
          plt.show()
```

```
Data frame with missing values :
sepal.length
sepal.width
petal.length
               0
petal.width
               0
species
               0
dtype: int64
Number of Duplicates rows :
1
Data set after Cleaning
<class 'pandas.core.frame.DataFrame'>
Index: 149 entries, 0 to 149
Data columns (total 5 columns):
# Column
                 Non-Null Count Dtype
---
                 -----
0
    sepal.length 149 non-null
                                 float64
1
    sepal.width 149 non-null
                                float64
    petal.length 149 non-null
                                 float64
3
    petal.width 149 non-null
                                 float64
    species
                 149 non-null
                                 object
dtypes: float64(4), object(1)
memory usage: 7.0+ KB
None
```



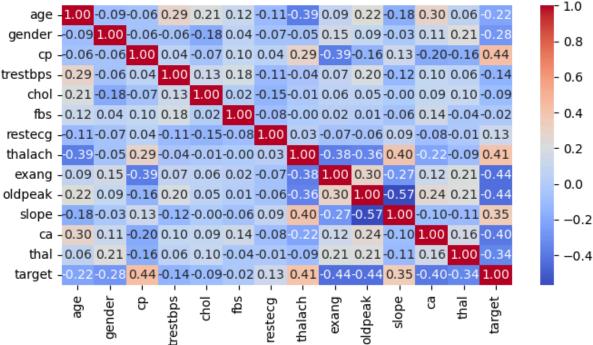
```
import numpy as np
from scipy.stats import ttest_1samp

sample = [23, 27, 26, 30, 29, 22, 24, 28, 25, 31]
population_mean = 25
```

```
t_stat,p_value = ttest_1samp(sample,population_mean)
          alpha = 0.05
          print("T-statics : ",t_stat)
          print("p_value : ",p_value)
          if p value < alpha :</pre>
              print("Reject the null hypothesis : The sample mean is completly diffrent from p
          else :
              print("Failed to reject the null hupothesis : there is no significant diffrence
         T-statics : 1.5666989036012806
         p value : 0.1516274744876827
         Failed to reject the null hupothesis : there is no significant diffrence between sam
         ple mean and population mean
In [232... | from sklearn.model_selection import train_test_split
          from sklearn.linear_model import LogisticRegression
          from sklearn.metrics import accuracy_score,classification_report,confusion_matrix
          import pandas as pd
          df = pd.read_csv(r"C:\Users\vaibh\Downloads\heart (1).csv")
          print("Missing values : ")
          print(df.isnull().sum())
          df.dropna(inplace = True)
          print("\n Duplicated items : ")
          print(df.duplicated().sum())
          df.drop_duplicates(inplace = True)
          X = df.iloc[:,0:13]
          y = df['target']
          print(X)
          print(y)
          X_train,X_test,y_train,y_test = train_test_split(X,y,test_size = 0.3,random_state =
          model = LogisticRegression(max iter=1000)
          model.fit(X_train,y_train)
          y_pred = model.predict(X_test)
          confusion = confusion_matrix(y_test,y_pred)
          print("Confusion matrix ")
          print(confusion)
          acuuracy = accuracy_score(y_test,y_pred)
          print("\nAccuracy Score : ")
          print(acuuracy)
          classification = classification_report(y_test,y_pred)
          print("Classification Report : ")
          print(classification)
          plt.figure(figsize = (8,4))
          sns.heatmap(df.corr(),annot = True,cmap = 'coolwarm',fmt = '0.2f',cbar = True)
          plt.title("Corelation Matrix")
          plt.show()
```

```
Missing values :
age
gender
           2
           0
ср
trestbps
           1
chol
           0
fbs
           0
restecg
           0
thalach
           0
exang
           0
oldpeak
           0
slope
           0
ca
           0
thal
           0
           0
target
dtype: int64
Duplicated items :
     age gender cp trestbps chol fbs
                                          restecg thalach exang oldpeak \
                         145.0
                                                                       2.3
0
    63.0
             1.0
                  3
                                 233
                                       1
                                                0
                                                       150
                                                                0
    41.0
                                                0
2
             0.0
                         130.0
                                 204
                                       0
                                                       172
                                                                0
                                                                       1.4
                   1
5
    57.0
             1.0
                   0
                         140.0 192
                                       0
                                                1
                                                       148
                                                                0
                                                                       0.4
7
    44.0
             1.0
                   1
                         120.0
                                 263
                                       0
                                                1
                                                       173
                                                                0
                                                                       0.0
8
    52.0
             1.0
                   2
                         172.0
                                199
                                       1
                                                1
                                                       162
                                                                0
                                                                       0.5
. .
     . . .
             . . .
                          . . .
                                 . . .
                                                       . . .
                                                                       . . .
                  . .
                                                              . . .
298 57.0
             0.0
                         140.0
                                 241
                                       0
                                                1
                                                       123
                                                                       0.2
                   0
                                                                1
299 45.0
             1.0
                   3
                         110.0
                                 264
                                       0
                                                1
                                                       132
                                                                0
                                                                       1.2
300 68.0
             1.0
                         144.0
                                 193
                                       1
                                                1
                                                       141
                                                                0
                                                                       3.4
                   0
                                                                       1.2
301 57.0
             1.0
                   0
                         130.0
                                 131
                                       0
                                                1
                                                       115
                                                                1
302 57.0
             0.0
                         130.0
                                 236
                                       0
                                                0
                                                       174
                                                                0
                                                                       0.0
                   1
    slope
           ca thal
0
        0
            0
                  1
2
        2
            0
                  2
5
        1
            0
                  1
7
        2
            0
                  3
8
        2
            0
                  3
. .
                . . .
      . . .
298
        1
            0
                  3
299
        1
            0
                  3
            2
                  3
300
        1
301
        1
            1
                  3
                  2
302
        1
            1
[298 rows x 13 columns]
0
      1
2
      1
5
      1
7
      1
8
      1
      . .
298
      0
299
      0
300
      0
301
      0
```

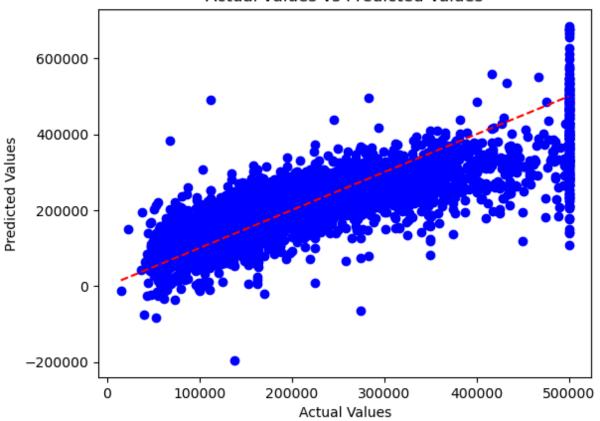
```
302
Name: target, Length: 298, dtype: int64
Confusion matrix
[[27 9]
[ 6 48]]
Accuracy Score :
0.8333333333333334
Classification Report :
              precision recall f1-score
                                              support
           0
                   0.82
                             0.75
                                       0.78
                                                    36
           1
                   0.84
                             0.89
                                       0.86
                                                    54
                                       0.83
                                                    90
    accuracy
                             0.82
                                       0.82
                                                    90
   macro avg
                   0.83
weighted avg
                             0.83
                                       0.83
                   0.83
                                                   90
                               Corelation Matrix
```



```
X = df.drop(columns=['median_house_value'])
y = df['median_house_value']
print(y)
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size = 0.2,random_state =
#scaler = StandardScaler()
#X_train_scaled = scaler.fit_transform(X_train)
#X_test_scaled = scaler.fit_transform(X_test)
model = LinearRegression()
model.fit(X_train,y_train)
y_pred = model.predict(X_test)
mse = mean_squared_error(y_test,y_pred)
print("\nMean Squared Error : ",mse)
mae = mean_absolute_error(y_test,y_pred)
print("Mean absolute square : ",mae)
r2 = r2_score(y_test,y_pred)
print("R2 score : ",r2)
```

```
Missing values :
         longitude
         latitude
         housing_median_age
         total_rooms
                                 0
         total_bedrooms
                               207
         population
                                 0
         households
                                 0
         median income
         median_house_value
         ocean_proximity
         dtype: int64
          Duplicate Values :
         <class 'pandas.core.frame.DataFrame'>
         Index: 20433 entries, 0 to 20639
         Data columns (total 10 columns):
          # Column
                                 Non-Null Count Dtype
         ---
                                  -----
          0 longitude
                                 20433 non-null float64
                                 20433 non-null float64
          1
             latitude
          2 housing_median_age 20433 non-null float64
            total_rooms 20433 non-null float64
total_bedrooms 20433 non-null float64
population 20433 non-null float64
          3
          5
              households 20433 non-null float64 median_income 20433 non-null float64
          6
             households
          7
          8
             median_house_value 20433 non-null float64
              ocean_proximity
                                  20433 non-null object
         dtypes: float64(9), object(1)
         memory usage: 1.7+ MB
         None
         0
                  452600.0
         1
                  358500.0
         2
                 352100.0
         3
                 341300.0
                 342200.0
                    . . .
         20635 78100.0
         20636 77100.0
20637 92300.0
         20638 84700.0
         20639
                   89400.0
         Name: median_house_value, Length: 20433, dtype: float64
         Mean Squared Error: 4927778339.313827
         Mean absolute square : 51434.3984174052
         R2 score: 0.6396553423014997
In [290... plt.scatter(y_test,y_pred,color = "blue")
          plt.title("Actual values vs Predicted Values")
          plt.xlabel("Actual Values")
          plt.ylabel("Predicted Values")
          plt.plot([y_test.min(),y_test.max()],[y_test.min(),y_test.max()],color = "red",line
          plt.show()
```

#### Actual values vs Predicted Values



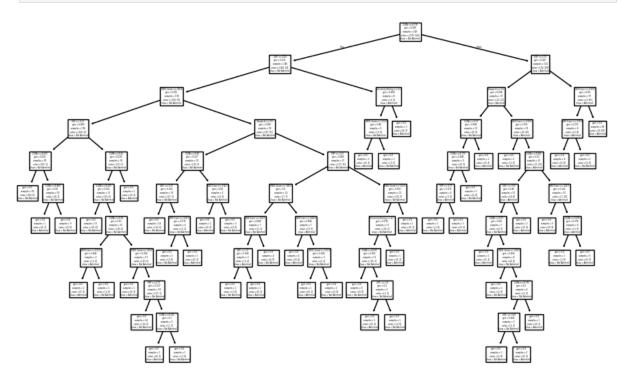
```
In [63]: import pandas as pd
         import numpy as np
         from sklearn.model_selection import train_test_split
         from sklearn.tree import DecisionTreeClassifier,plot_tree
         from sklearn.metrics import accuracy_score,classification_report
         df = pd.read_csv(r"C:\Users\vaibh\Downloads\Admission_Predict.csv")
         df.head()
         df = df.drop(columns = ['Serial No.'])
         df['Admit'] = (df['Chance of Admit ']>= 0.75).astype(int)
         df = df.drop(columns = ['Chance of Admit '])
         X = df.drop(columns = 'Admit')
         y= df['Admit']
         X_train,X_test,y_train,y_test = train_test_split(X,y,test_size = 0.2,random_state
         clf = DecisionTreeClassifier()
         clf.fit(X_train,y_train)
         y_pred = clf.predict(X_test)
         print("Acucuracy score : ",end = " ")
         print(accuracy_score(y_test,y_pred))
```

```
print("Classification Report : ")
print(classification_report(y_test,y_pred))
```

Acucuracy score : 0.8375 Classification Report :

	precision	recall	f1-score	support
0	0.79	0.95	0.87	44
1	0.93	0.69	0.79	36
accuracy			0.84	80
macro avg	0.86	0.82	0.83	80
weighted avg	0.85	0.84	0.83	80

```
In [85]: plt.figure(figsize = (10,6))
  plot_tree(clf,feature_names=X.columns,class_names= ["Not Adimted","Admitted"])
  plt.show()
```



```
In []: #sample code
   import sqlite3
   import pandas as pd
   connection = sqlite3.connect("sample_database.db")
   cursor = connection.cursor()

#create table
   cursor.execute("""
   CREATE TABLE IF NOT EXISTS employees (
      id INTEGER PRIMARY KEY AUTOINCREMENT,
      name TEXT NOT NULL,
      age INTEGER,
      department TEXT,
      salary REAL
```

```
""")
cursor.executemany("""
INSERT INTO employees (name,age,department,salary)
VALUES(?,?,?,?)
""", [
    ("Allice", 30, "HR", 600000),
    ("Bob", 25, "IT", 70000),
    ("Charlie", 35, "Finance", 80000),
    ("Diana", 28, "IT", 65000),
    ("Eve", 40, "HR", 72000)
])
connection.commit()
connection.close()
print("Data and table setup complete")
connection = sqlite3.connect("sample_database.db")
query = "SELECT * FROM employees"
df = pd.read_sql_query(query,connection)
print("Data loaded into Dataframe : ")
print(df)
connection.close()
print("\n Summary Statistics")
print(df.describe())
df["tax"] = df["salary"]*0.10
print("\n DataFrame with Tax column : ")
print(df)
high_earners = df[df["salary"]>65000]
print("\n Employees with salary > 65000")
print(high_earners)
avg_sal_by_dept = df.groupby("department")["salary"].mean()
print("\nAverage salary by the department : ")
print(avg_sal_by_dept)
sorted_by_age = df.sort_values(by="age",ascending = False)
print("\nEmployees Sorted Age : ")
print(sorted_by_age)
connection = sqlite3.connect("samp.db")
cursor = connection.cursor()
```

```
import sqlite3
connection = sqlite3.connect("samp.db")
cursor = connection.cursor()

cursor.execute ("""
CREATE TABLE IF NOT EXISTS employees(
   id INTEGER PRIMARY KEY AUTOINCREMENT,
   name TEXT NOT NULL,
   age INTEGER,
```

```
department TEXT,
    salary REAL
""")
cursor.executemany("""
INSERT INTO employees(name,age,department,salary)
VALUES(?,?,?,?)
],""
    ("Allice",23,"HR",60000),
    ("BOB",34,"IT",70000),
    ("Charlie", 25, "Finance", 80000),
    ("Dianna", 45, "HR", 56000),
    ("EVE",40,"HR",72000)
)
connection.commit()
connection.close()
print("Data loaded succesfully")
```

Data loaded succesfully

```
import pandas as pd
connection = sqlite3.connect("samp.db")
query ="SELECT * FROM employees"
df = pd.read_sql_query(query,connection)
print("data loaded into dataframe")
df.head()
```

data loaded into dataframe

```
Out[47]:
                name age department
                                         salary
                 Allice
                                    HR 60000.0
         0
            1
                        23
                        34
                  BOB
                                     IT 70000.0
             2
         1
         2
            3 Charlie
                        25
                                Finance 80000.0
         3
            4 Dianna
                        45
                                    HR 56000.0
         4 5
                  EVE
                        40
                                    HR 72000.0
```

```
In [59]: df['tax'] = (df['salary']*0.05)
    print(df.head())
    high_earners = df[df['salary']>65000]
    print("\n Empoyees with salry greter than 65000")
    print(high_earners)
    avg_sal_by_dept = df.groupby("department").salary.mean()
    print("\n Average salary by department")
    print(avg_sal_by_dept)
    sort_by_age = df.sort_values(by="age",ascending = False)
    print("\nsort by age")
    print(sort_by_age)
```

```
1 Allice 23 HR 60000.0 3000.0 2 BOB 34 IT 70000.0 3500.0
         2
       1
       2 3 Charlie 25 Finance 80000.0 4000.0
       3 4 Dianna 45 HR 56000.0 2800.0
4 5 EVE 40 HR 72000.0 3600.0
        Empoyees with salry greter than 65000
                name age department salary
          id
                                                tax
       1 2
                 BOB 34
                            IT 70000.0 3500.0
       2 3 Charlie 25 Finance 80000.0 4000.0
                 EVE 40 HR 72000.0 3600.0
        Average salary by department
       department
                 80000.000000
       Finance
       HR
                 62666.666667
       IT
                 70000.000000
       Name: salary, dtype: float64
       sort by age
               name age department salary
          id
                                              tax
       3
          4 Dianna 45 HR 56000.0 2800.0
       4 5 EVE 40
                               HR 72000.0 3600.0
       1
         2
                 BOB 34 IT 70000.0 3500.0
       2 3 Charlie 25 Finance 80000.0 4000.0
       0 1 Allice 23 HR 60000.0 3000.0
In [67]: import pandas as pd
        import requests
        from bs4 import BeautifulSoup
        # Fetch the webpage content
        url = "https://en.wikipedia.org/wiki/Agriculture_in_India"
        response = requests.get(url)
        # Parse the HTML using BeautifulSoup
        soup = BeautifulSoup(response.text, "html.parser")
        # Extract all tables using pandas
        tables = pd.read_html(response.text)
        # Print all tables
        print(f"Number of tables found: {len(tables)}")
        for i, table in enumerate(tables):
            print(f"\nTable {i + 1}:")
            print(table.head()) # Display the first few rows of each table
```

tax

id

name age department salary

```
Country or Territory Population(1 July 2022) Population(1 July 2023) \
                        World
                                      8,021,407,192
                                                       8,091,734,930
                                                            1,438,069,596
1,422,584,933
                        India
                                      1,425,423,212
        1
        2
                     China[a]
                                      1,425,179,569
        3
                United States
                                        341,534,046
                                                               343,477,335
                    Indonesia
                                        278,830,529
                                                               281,190,067
           Change UN Continental Region UN Statistical Subregion
        0 +0.88%
                                               Southern Asia
        1 +0.89%
                                  Asia
        2 -0.18%
                                 Asia
                                                 Eastern Asia
                                            Northern America
        3 +0.57%
                            Americas
        4 +0.85%
                                Asia
                                            South-eastern Asia
In [153... import pandas as pd
         import requests
         from bs4 import BeautifulSoup
         from io import StringIO
         url = "https://en.wikipedia.org/wiki/Agriculture_in_India"
         response = requests.get(url)
         soup = BeautifulSoup(response.text, "html.parser")
         table = soup.find("table",{"class" : "wikitable"})
         df = pd.read_html(StringIO(str(table)))[0]
         print("Extracted Data : ")
         df.head()
        Extracted Data :
```

Out[153...

	Rank	Commodity	Value (US\$, 2016)	Unit price (US\$ / kilogram, 2009)	Average yield (tonnes per hectare, 2017)	Most productive country (tonnes per hectare, 2017)	Most productive country (tonnes per hectare, 2017).1
0	1	Rice	\$70.18 billion	0.27	3.85	9.82	Australia
1	2	Buffalo milk	\$43.09 billion	0.40	2.00[78]	2.00[78]	India
2	3	Cow milk	\$32.55 billion	0.31	1.2[78]	10.3[78]	Israel
3	4	Wheat	\$26.06 billion	0.15	2.8	8.9	Netherlands
4	5	Cotton (Lint + Seeds)	\$23.30 billion	1.43	1.6	4.6	Israel

```
In [123...
          # import pandas as pd
          # from bs4 import BeautifulSoup
          # import requests
          # from io import StringIO
          # url = "https://en.wikipedia.org/wiki/Agriculture_in_India"
          # response = requests.get(url)
          # soup = BeautifulSoup(response.text, "html.parser")
          # table =soup.find("table",{"class" : "wikitable"})
          # df = pd.read_html(StringIO(str(table)))[0]
          # rows = table.find_all("tr")
          # data = []
          # for row in rows:
                cells = row.find_all(["th", "td"]) # Include both headers and data cells
                data.append([cell.text.strip() for cell in cells])
          # # Convert to DataFrame
          # df = pd.DataFrame(data)
          # print("Extracted Table Data:")
          # print(df.head())
          # tables = pd.read_html(response.text)
          # for i, table in enumerate(tables):
                print(f"\nTable {i + 1}:\n", table.head())
In [107...
          df.describe()
                                                 3
                                                                                    5
                                                                                          6
```

Out[107...

count 21 21 21 21 21 21 20 unique 21 21 21 19 20 21 16 Value (US\$, Most productive country(tonnes 0.4 1.1 top Rank Commodity Israel 2016) per hectare, 2017) 1 1 2 2 1 3 freq

```
In [117...
          #Api integration
           import pandas as pd
           import requests
          url = "https://api.coingecko.com/api/v3/coins/markets"
           params = {
               "vs_currency" : "usd",
               "order" : "market_cap_desc",
               "per_page" : 10,
               "page" : 1,
               "spakLine" : False
```

```
response = requests.get(url,params=params)

if response.status_code == 200 :
    data = response.json()
    df = pd.DataFrame(data)
    print("Data succesfully loaded into dataframe")

else :
    print(f"Failed to fetch the data : {response.status_code}")

df.head()
```

Data succesfully loaded into dataframe

#### Out[117...

	id	symbol	name	image	current_price	ma
0	bitcoin	btc	Bitcoin	https://coin- images.coingecko.com/coins/images	97041.000000	191756
1	ethereum	eth	Ethereum	https://coin- images.coingecko.com/coins/images	3107.370000	37371
2	tether	usdt	Tether	https://coin- images.coingecko.com/coins/images	0.998863	1298€
3	solana	sol	Solana	https://coin- images.coingecko.com/coins/images	239.550000	11355
4	binancecoin	bnb	BNB	https://coin-images.coingecko.com/coins/images	609.310000	8873

5 rows × 26 columns



In [121...

```
import requests
import pandas as pd

url = "https://api.coingecko.com/api/v3/coins/markets"
params = {
    "vs_currency" : "usd",
    "order" : "market_cap_desc",
    "per_page" : 10,
    "page" : 1,
    "spakLine" : False
}

response = requests.get(url,params = params)
if response.status_code == 200 :
    data = response.json()
    df = pd.DataFrame(data)
    print("Data succesfully loaded")
else :
    print(f"Failed to load the data {response.status_code}")
```

```
df.head()
```

#### Data succesfully loaded

#### Out[121...

	id	symbol	name	image	current_price	ma
0	bitcoin	btc	Bitcoin	https://coin- images.coingecko.com/coins/images	97041.000000	19175(
1	ethereum	eth	Ethereum	https://coin- images.coingecko.com/coins/images	3107.370000	37371
2	tether	usdt	Tether	https://coin-images.coingecko.com/coins/images	0.998863	12986
3	solana	sol	Solana	https://coin-images.coingecko.com/coins/images	239.550000	11355
4	binancecoin	bnb	BNB	https://coin- images.coingecko.com/coins/images	609.310000	8873

5 rows × 26 columns

4

In [139...

```
import pandas as pd

df = pd.read_csv(r"C:\Users\vaibh\Downloads\heart (1).csv")
print(df)
print("\nMissing values : ")
print(df.isnull().sum())

df_dropped = df.dropna()
print("\n Data after droping Missing values : ")
print(df_dropped)

df_specific_value = df.fillna(0)
print("\nFilling with Specific Value(0) ")
print(df_specific_value)

df_fill_mean = df.fillna(df.mean())
print("Filling missing values with mean: ")
print(df_fill_mean)
```

	age	gender	ср	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	\
0	63.0	1.0	3	145.0	233	1	0	150	0	2.3	
1	NaN	NaN	2	130.0	250	0	1	187	0	3.5	
2	41.0	0.0	1	130.0	204	0	0	172	0	1.4	
3	NaN	1.0	1	120.0	236	0	1	178	0	0.8	
4	57.0	NaN	0	120.0	354	0	1	163	1	0.6	
298	57.0	0.0	0	140.0	241	0	1	123	1	0.2	
299	45.0	1.0	3	110.0	264	0	1	132	0	1.2	
300	68.0	1.0	0	144.0	193	1	1	141	0	3.4	
301	57.0	1.0	0	130.0	131	0	1	115	1	1.2	
302	57.0	0.0	1	130.0	236	0	0	174	0	0.0	
	slope	ca th	al	target							
_	٠.		_	· ·							

	slope	ca	thal	target
0	0	0	1	1
1	0	0	2	1
2	2	0	2	1
3	2	0	2	1
4	2	0	2	1
298	1	0	3	0
299	1	0	3	0
300	1	2	3	0
301	1	1	3	0
302	1	1	2	0

[303 rows x 14 columns]

### Missing values :

3 age gender 2 ср trestbps 1 chol 0 0 fbs restecg 0 thalach exang 0 oldpeak 0 slope 0 0 ca thal target dtype: int64

## Data after droping Missing values :

			_	0							
	age	gender	ср	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	١
0	63.0	1.0	3	145.0	233	1	0	150	0	2.3	
2	41.0	0.0	1	130.0	204	0	0	172	0	1.4	
5	57.0	1.0	0	140.0	192	0	1	148	0	0.4	
7	44.0	1.0	1	120.0	263	0	1	173	0	0.0	
8	52.0	1.0	2	172.0	199	1	1	162	0	0.5	
		• • •									
298	57.0	0.0	0	140.0	241	0	1	123	1	0.2	
299	45.0	1.0	3	110.0	264	0	1	132	0	1.2	
300	68.0	1.0	0	144.0	193	1	1	141	0	3.4	

301 302	57.0 57.0		.0 0 .0 1	130.0 130.0		0 0		1 11 0 17		1.2 0.0	
	slope	ca		target							
0	0	0	1	1							
2	2	0	2	1							
5	1	0	1	1							
7	2	0	3	1							
8	2	0	3	1							
• •	• • •	• •	• • •	• • •							
298	1	0	3	0							
299	1	0	3	0							
300	1	2	3	0							
301	1 1	1	3 2	0							
302	1	1	2	0							
[299	rows x	14	columns	5]							
Fill	ing wit	h Sp	ecific	Value(0)							
	_	gend		trestbp	s chol	fbs	restec	g thalac	h exang	oldpeak	\
0	63.0	1	.0 3	145.0	233	1		0 15	0 0	2.3	
1	0.0	0	.0 2	130.0	250	0		1 18	7 0	3.5	
2	41.0	0	.0 1	130.0	204	0		0 17	2 0	1.4	
3	0.0	1	.0 1	120.0	236	0		1 17	8 0	0.8	
4	57.0	0	.0 0	120.0	354	0		1 16	3 1	0.6	
• •											
298	57.0	0	.0 0	140.0	241	0		1 12	3 1	0.2	
299	45.0	1	.0 3	110.0	264	0		1 13	2 0	1.2	
300	68.0	1	.0 0	144.0	ð 193	1		1 14	1 0	3.4	
301	57.0	1	.0 0	130.0	ð 131	0		1 11	5 1	1.2	
302	57.0	0	.0 1	130.0	236	0		0 17	4 0	0.0	
•	slope	ca		target							
0	0	0	1	1							
1	0	0	2	1							
2	2	0	2	1							
3	2	0	2	1							
4	2	0	2	1							
200		• •	• • •	• • • •							
298 299	1 1	0 0	3	0 0							
300	1	2	3 3	0							
301	1	1	3	0							
302	1	1	2	0							
[303	rows x	14	columns		an:						
	_	age	gend		trestbps	chol	fbs	restecg	thalach	exang	\
0	63.000		1.0000		145.0	233		0	150	0	`
1	54.413		0.6843		130.0	250		1	187	0	
2	41.000		0.0000		130.0	204		0	172	0	
3	54.413		1.0000		120.0	236		1	178	0	
4	57.000		0.6843		120.0	354		1	163	1	
• •					•••			• • •	•••	• • •	
298	57.000	000	0.0000		140.0	241		1	123	1	
299	45.000	000	1.0000		110.0	264		1	132	0	

```
300 68.000000 1.000000 0
                                     1
                         144.0
                                193
                                            1
                                                  141
                                                         0
301 57.000000 1.000000 0 130.0
                                131
                                           1
                                                  115
                                                         1
302 57.000000 0.000000 1
                         130.0
                                236 0
                                           0
                                                  174
                                                         0
   oldpeak slope ca thal target
          0 0
      2.3
0
                    1
                            1
                     2
1
      3.5
             0 0
                            1
            2 0
2
      1.4
                     2
                            1
            2 0
                     2
3
      0.8
                            1
4
      0.6
            2 0
                     2
                            1
       ... ... ..
      0.2 1 0 3
1.2 1 0 3
3.4 1 2 3
1.2 1 1 3
0.0 1 1 2
298
                            0
299
                            0
300
                          0
301
                            0
302
                            0
```

[303 rows x 14 columns]

```
import pandas as pd
from scipy.stats import zscore
import numpy as np
df = pd.read_csv(r"C:\Users\vaibh\Downloads\heart (1).csv")
z_score = zscore(df,nan_policy = "omit")
print(abs_z_score)
abs_z_score = np.abs(z_score)
threshold = 2

df_cleaned = df.loc[(abs_z_score < threshold).all(axis = 1)]
print("\nData cleaned : ")
print(df_cleaned)</pre>
```

0 1 2 3 4  298 299 300 301 302	ag 0.94818 Na 1.48117 Na 0.28563  0.28563 1.03947 1.50031 0.28563 0.28563	66 0.6 N 12 1.4 N 0.6 4 1.4 1 0.6 3 0.6 4 0.6 4 1.4	gender 79093 Nat 72556 79093 72556 79093 779093 772556 exang	1.973123 1.002577 0.032031 0.032031 0.938515 0.938515 1.973123 0.938515 0.938515 0.032031	0.7 0.0 0.0 0.6 0.6 0.6 0.4 1.2 0.7 0.0	stbps 64565 91038 91038 61440 61440  79364 31842 07525 91038 91038	0.256334 0.072199 0.816773 0.198357 2.082050  0.101730 0.342756 1.029353 2.227533 0.198357	2.3944 0.4176 0.4176 0.4176 0.4176 0.4176 2.3944 0.4176	38 1.0 35 0.8 35 1.0 35 0.8 35 0.8 35 0.8 35 0.8 35 0.8 35 0.8 35 1.0	stecg \ 95832 98962 98962 98962 98962 98962 98962 98962 98962 98962	
0	0.01544		96632			74579				14529	
1	1.63347		96632			74579				14529	
2	0.97751		96632			76352	0.714429			14529	
3	1.23989		96631			76352				14529	
4	0.58393		135482			76352	0.714429			14529	
 298	1.16528		 135481			49113	0.714429		 29 1.0	93459	
299	0.77170		96632			49113	0.714429			93459	
300	0.37813		96632			49113	1.244593			93459	
301	1.51512		35481			49113	0.265082			93459	
302	1.06497	5 0.6	96632	0.896862	0.6	49113	0.265082	0.5129	22 1.0	93459	
[303	rows x	14 col	.umns	I							
Data	cleaned	· :									
Data	age g	gender	ср	trestbps	chol	fbs	restecg ·	thalach	exang	oldpeak	\
2	age g 41.0	ender 0.0	1	130.0	204	0	0	172	0	1.4	\
2 7	age g 41.0 44.0	ender 0.0 1.0	1	130.0 120.0	204 263	0 0	0	172 173	0	1.4	\
2 7 9	age g 41.0 44.0 57.0	gender 0.0 1.0 1.0	1 1 2	130.0 120.0 150.0	204 263 168	0 0 0	0 1 1	172 173 174	0 0 0	1.4 0.0 1.6	\
2 7 9 10	age g 41.0 44.0 57.0 54.0	ender 0.0 1.0 1.0	1 1 2 0	130.0 120.0 150.0 140.0	204 263 168 239	0 0 0 0	0 1 1 1	172 173 174 160	0 0 0	1.4 0.0 1.6 1.2	\
2 7 9 10 11	age g 41.0 44.0 57.0 54.0 48.0	ender 0.0 1.0 1.0 1.0 0.0	1 1 2 0 2	130.0 120.0 150.0 140.0 130.0	204 263 168 239 275	0 0 0	0 1 1	172 173 174 160 139	0 0 0	1.4 0.0 1.6 1.2 0.2	\
2 7 9 10 11	age g 41.0 44.0 57.0 54.0 48.0	ender 0.0 1.0 1.0 1.0 0.0	1 1 2 0 2	130.0 120.0 150.0 140.0 130.0	204 263 168 239 275	0 0 0 0	0 1 1 1 1	172 173 174 160 139	0 0 0 0 0	1.4 0.0 1.6 1.2 0.2	\
2 7 9 10 11 	age g 41.0 44.0 57.0 54.0 48.0 	gender 0.0 1.0 1.0 0.0 	1 1 2 0 2	130.0 120.0 150.0 140.0 130.0 	204 263 168 239 275  212	0 0 0 0 0 0 0	0 1 1 1 1 	172 173 174 160 139 	0 0 0 0 	1.4 0.0 1.6 1.2 0.2	\
2 7 9 10 11  293 296	age g 41.0 44.0 57.0 54.0 48.0  67.0 63.0	gender 0.0 1.0 1.0 0.0  1.0 0.0	1 1 2 0 2  2	130.0 120.0 150.0 140.0 130.0  152.0 124.0	204 263 168 239 275  212 197	0 0 0 0	0 1 1 1 1 	172 173 174 160 139  150 136	0 0 0 0 0 	1.4 0.0 1.6 1.2 0.2  0.8 0.0	\
2 7 9 10 11 	age g 41.0 44.0 57.0 54.0 48.0 	gender 0.0 1.0 1.0 0.0 	1 1 2 0 2	130.0 120.0 150.0 140.0 130.0 	204 263 168 239 275  212	0 0 0 0 0 0	0 1 1 1 1 	172 173 174 160 139 	0 0 0 0 	1.4 0.0 1.6 1.2 0.2	\
2 7 9 10 11  293 296 298	age 841.0 44.0 57.0 54.0 48.0 67.0 63.0 57.0	gender 0.0 1.0 1.0 0.0  1.0 0.0	1 1 2 0 2  2 0	130.0 120.0 150.0 140.0 130.0  152.0 124.0 140.0	204 263 168 239 275  212 197 241	0 0 0 0 0  0	0 1 1 1 1  0 1	172 173 174 160 139  150 136 123	0 0 0 0 0  0 1	1.4 0.0 1.6 1.2 0.2  0.8 0.0 0.2	\
2 7 9 10 11  293 296 298 299 302	age 841.0 44.0 57.0 54.0 48.0 67.0 63.0 57.0 45.0 57.0 slope	gender 0.0 1.0 1.0 0.0  1.0 0.0 0.0	1 1 2 0 2  2 0 0 3 1	130.0 120.0 150.0 140.0 130.0  152.0 124.0 140.0 110.0	204 263 168 239 275  212 197 241 264	0 0 0 0 0 0 0	0 1 1 1 1  0 1 1	172 173 174 160 139  150 136 123 132	0 0 0 0 0  0 1 1	1.4 0.0 1.6 1.2 0.2  0.8 0.0 0.2 1.2	\
2 7 9 10 11  293 296 298 299 302	age 41.0 44.0 57.0 54.0 48.0 67.0 63.0 57.0 45.0 57.0 slope	gender 0.0 1.0 1.0 0.0  1.0 0.0 0.0	1 1 2 0 2  2 0 0 3 1	130.0 120.0 150.0 140.0 130.0  152.0 124.0 140.0 110.0 130.0	204 263 168 239 275  212 197 241 264	0 0 0 0 0 0 0	0 1 1 1 1  0 1 1	172 173 174 160 139  150 136 123 132	0 0 0 0 0  0 1 1	1.4 0.0 1.6 1.2 0.2  0.8 0.0 0.2 1.2	\
2 7 9 10 11  293 296 298 299 302	age 841.0 44.0 57.0 54.0 48.0 57.0 63.0 57.0 45.0 57.0 slope 2 2	ender 0.0 1.0 1.0 0.0 0.0 0.0 1.0 0.0 ca th	1 1 2 0 2  2 0 3 1	130.0 120.0 150.0 140.0 130.0  152.0 124.0 140.0 110.0 130.0	204 263 168 239 275  212 197 241 264	0 0 0 0 0 0 0	0 1 1 1 1  0 1 1	172 173 174 160 139  150 136 123 132	0 0 0 0 0  0 1 1	1.4 0.0 1.6 1.2 0.2  0.8 0.0 0.2 1.2	\
2 7 9 10 11  293 296 298 299 302	age 8 41.0 44.0 57.0 54.0 48.0 67.0 63.0 57.0 45.0 57.0 slope 2 2 2	gender 0.0 1.0 1.0 0.0  1.0 0.0 0.0	1 1 2 0 2  2 0 3 1	130.0 120.0 150.0 140.0 130.0 152.0 124.0 140.0 130.0  carget  1 1 1	204 263 168 239 275  212 197 241 264	0 0 0 0 0 0 0	0 1 1 1 1  0 1 1	172 173 174 160 139  150 136 123 132	0 0 0 0 0  0 1 1	1.4 0.0 1.6 1.2 0.2  0.8 0.0 0.2 1.2	\
2 7 9 10 11  293 296 298 299 302 2 7 9	age 41.0 44.0 57.0 54.0 48.0 67.0 63.0 57.0 45.0 57.0 slope 2 2 2 2	gender 0.0 1.0 1.0 0.0 0.0 0.0 0.0 0.0	1 1 2 0 2  2 0 3 1	130.0 120.0 150.0 140.0 130.0 152.0 124.0 140.0 130.0  carget  1 1 1	204 263 168 239 275  212 197 241 264	0 0 0 0 0 0 0	0 1 1 1 1  0 1 1	172 173 174 160 139  150 136 123 132	0 0 0 0 0  0 1 1	1.4 0.0 1.6 1.2 0.2  0.8 0.0 0.2 1.2	\
2 7 9 10 11  293 296 298 299 302	age 41.0 44.0 57.0 54.0 48.0 67.0 63.0 57.0 45.0 57.0 slope 2 2 2 2 2	gender 0.0 1.0 1.0 0.0 0.0 1.0 0.0 0.0	1 1 2 0 2  2 0 3 1	130.0 120.0 150.0 140.0 130.0 152.0 124.0 140.0 130.0  carget  1 1 1	204 263 168 239 275  212 197 241 264	0 0 0 0 0 0 0	0 1 1 1 1  0 1 1	172 173 174 160 139  150 136 123 132	0 0 0 0 0  0 1 1	1.4 0.0 1.6 1.2 0.2  0.8 0.0 0.2 1.2	\
2 7 9 10 11  293 296 298 299 302 2 7 9 10 11	age 41.0 44.0 57.0 54.0 48.0 67.0 63.0 57.0 45.0 57.0 slope 2 2 2 2	gender 0.0 1.0 1.0 0.0 0.0 1.0 0.0 0.0	1 1 2 0 2  2 0 3 1	130.0 120.0 150.0 140.0 130.0 152.0 124.0 140.0 130.0  carget  1 1 1 1 1 1	204 263 168 239 275  212 197 241 264	0 0 0 0 0 0 0	0 1 1 1 1  0 1 1	172 173 174 160 139  150 136 123 132	0 0 0 0 0  0 1 1	1.4 0.0 1.6 1.2 0.2  0.8 0.0 0.2 1.2	
2 7 9 10 11  293 296 298 299 302 2 7 9 10 11 	age 41.0 44.0 57.0 54.0 48.0 67.0 63.0 57.0 45.0 57.0 slope 2 2 2 2 1	render 0.0 1.0 1.0 0.0 0.0 0.0 ca th 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	1 1 2 0 2  2 0 3 1	130.0 120.0 150.0 140.0 130.0 152.0 124.0 140.0 130.0  carget  1 1 1 1 1 0	204 263 168 239 275  212 197 241 264	0 0 0 0 0 0 0	0 1 1 1 1  0 1 1	172 173 174 160 139  150 136 123 132	0 0 0 0 0  0 1 1	1.4 0.0 1.6 1.2 0.2  0.8 0.0 0.2 1.2	\
2 7 9 10 11  293 296 298 299 302 2 7 9 10 11  293 296	age 41.0 44.0 57.0 54.0 48.0 67.0 63.0 57.0 45.0 57.0 slope 2 2 2 2 1 1 1	render 0.0 1.0 1.0 0.0 0.0 0.0 0.0 ca th 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	1 1 2 0 2  2 0 0 3 1 2 2 2 2 2 2 2  3 2	130.0 120.0 150.0 140.0 130.0 152.0 124.0 140.0 130.0  carget  1 1 1 1 0 0	204 263 168 239 275  212 197 241 264	0 0 0 0 0 0 0	0 1 1 1 1  0 1 1	172 173 174 160 139  150 136 123 132	0 0 0 0 0  0 1 1	1.4 0.0 1.6 1.2 0.2  0.8 0.0 0.2 1.2	
2 7 9 10 11  293 296 298 299 302 2 7 9 10 11 	age 41.0 44.0 57.0 54.0 48.0 67.0 63.0 57.0 45.0 57.0 slope 2 2 2 2 1	render 0.0 1.0 1.0 0.0 0.0 0.0 ca th 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	1 1 2 0 2  2 0 3 1	130.0 120.0 150.0 140.0 130.0 152.0 124.0 140.0 130.0  carget  1 1 1 1 1 0	204 263 168 239 275  212 197 241 264	0 0 0 0 0 0 0	0 1 1 1 1  0 1 1	172 173 174 160 139  150 136 123 132	0 0 0 0 0  0 1 1	1.4 0.0 1.6 1.2 0.2  0.8 0.0 0.2 1.2	

[176 rows x 14 columns]

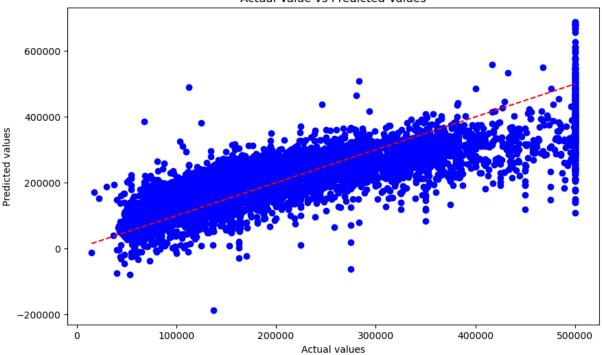
```
In [49]: from sklearn.model_selection import train_test_split
         from sklearn.linear_model import LinearRegression
         from sklearn.metrics import mean_squared_error,mean_absolute_error,r2_score
         import pandas as pd
         import matplotlib.pyplot as plt
         df = pd.read_csv(r"C:\Users\vaibh\Downloads\housing.csv")
         print("Missing values : ")
         print(df.isnull().sum())
         df.dropna(inplace = True)
         print("Duplicate values : ")
         print(df.duplicated().sum())
         df.drop_duplicates(inplace = True)
         df = df.select_dtypes(include = "number")
         X = df.drop(columns = ['median_house_value'])
         y = df['median_house_value']
         X_train,X_test,y_train,y_test = train_test_split(X,y,test_size = 0.3,random_state =
         model = LinearRegression()
         model.fit(X_train,y_train)
         y_pred = model.predict(X_test)
         mse = mean_squared_error(y_test,y_pred)
         print("\nMean squared Error",end = " ")
         print(mse)
         print("Mean absolute square : ",mean_absolute_error(y_test,y_pred))
         print("r2 score : ",r2_score(y_test,y_pred))
         plt.figure(figsize = (10,6))
         plt.scatter(y_test,y_pred,color = "blue")
         plt.title("Actual Value vs Predicted Values")
         plt.xlabel("Actual values")
         plt.ylabel("Predicted values")
         plt.plot([y_test.min(),y_test.max()],[y_test.min(),y_test.max()],color = "red",line
         plt.show()
```

Missing values:
longitude 0
latitude 0
housing\_median\_age 0
total\_rooms 0
total\_bedrooms 207
population 0
households 0
median\_income 0
median\_house\_value 0
ocean\_proximity 0
dtype: int64
Duplicate values:

Mean squared Error 4738972791.400478 Mean absolute square : 50704.919692847856

r2 score: 0.6445130291082346

#### Actual Value vs Predicted Values



```
In [45]:
    from sklearn.model_selection import train_test_split
    from sklearn.linear_model import LogisticRegression
    from sklearn.metrics import classification_report,confusion_matrix,accuracy_score
    import pandas as pd

    df = pd.read_csv(r"C:\Users\vaibh\Downloads\heart (1).csv")
    print("Missing values : ")
    print(df.isnull().sum())
    df.dropna(inplace = True)
    print("\nDuplicate values : ")
    print(df.duplicated().sum())
    df.drop_duplicates(inplace = True)

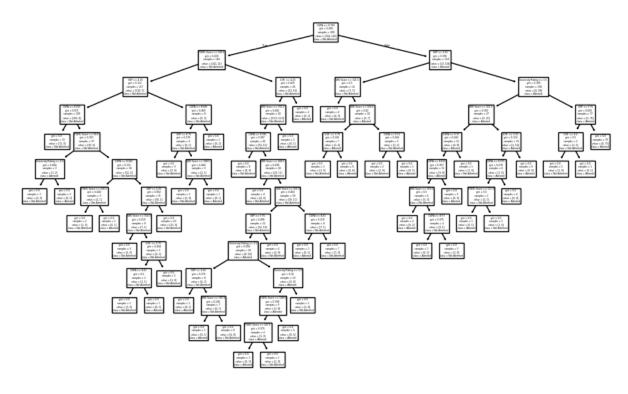
X = df.iloc[:,0:13]
y = df['target']
```

```
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size = 0.3,random_state =
 model = LogisticRegression(max_iter = 1000)
 model.fit(X_train,y_train)
 y_pred = model.predict(X_test)
 classification = classification_report(y_test,y_pred)
 confusion = confusion_matrix(y_test,y_pred)
 accuracy = accuracy_score(y_test,y_pred)
 print("\nAccuracy Score : ")
 print(accuracy)
 print("\nClassification Report : ")
 print(classification)
 print("\nconfusion Matrix : ")
 print(confusion)
Missing values :
age
gender
           2
ср
trestbps
           1
chol
           0
fbs
           0
restecg
           0
thalach
           0
exang
oldpeak
           0
slope
           0
ca
thal
           0
target
dtype: int64
Duplicate values :
Accuracy Score :
0.8333333333333334
Classification Report :
             precision recall f1-score support
          0
                  0.82
                            0.75
                                      0.78
                                                  36
                            0.89
          1
                  0.84
                                      0.86
                                                  54
                                      0.83
                                                  90
   accuracy
  macro avg
                 0.83
                            0.82
                                      0.82
                                                  90
                 0.83
                            0.83
                                      0.83
                                                  90
weighted avg
confusion Matrix :
[[27 9]
[ 6 48]]
```

```
In [92]: import pandas as pd
         from sklearn.tree import DecisionTreeClassifier,plot_tree
         from sklearn.model_selection import train_test_split
         from sklearn.metrics import classification report,confusion matrix
         import matplotlib.pyplot as plt
         df = pd.read_csv(r"C:\Users\vaibh\Downloads\Admission_Predict.csv")
         df.dropna(inplace = True)
         df.drop_duplicates(inplace = True)
         df = df.select_dtypes(include = "number")
         df = df.drop(columns = ['Serial No.'])
         df['Admit'] = (df['Chance of Admit '] >= 0.75).astype(int)
         df = df.drop(columns = ['Chance of Admit '])
         X = df.drop(columns = ['Admit'])
         y = df['Admit']
         X_train,X_test,y_train,y_test = train_test_split(X,y,test_size = 0.3,random_state =
         clf = DecisionTreeClassifier()
         clf.fit(X_train,y_train)
         y_pred = clf.predict(X_test)
         classification = classification_report(y_test,y_pred)
         confusion = confusion_matrix(y_test,y_pred)
         print("\nConfusion Matrix")
         print(confusion)
         print("\nClssification Report")
         print(classification)
        Confusion Matrix
        [[59 7]
        [13 41]]
        Clssification Report
                      precision recall f1-score support
                   0
                           0.82
                                     0.89
                                               0.86
                                                           66
                   1
                           0.85
                                     0.76
                                                           54
                                               0.80
                                               0.83
                                                          120
            accuracy
                          0.84
                                     0.83
                                               0.83
                                                          120
           macro avg
        weighted avg
                          0.84
                                     0.83
                                               0.83
                                                          120
In [98]: plt.figure(figsize = (10,6))
```

plot\_tree(clf,feature\_names = X.columns,class\_names = ['Not Adimited','Admited'])

plt.show()



```
In [7]: from scipy.stats import ttest_1samp

sample = [23,24,25,26,27,28]
population_mean = 25

t_stat,p_value = ttest_1samp(sample,population_mean)
print(t_stat)
print(p_value)
alpha = 0.05
if p_value < alpha :
    print("Reject the null1 hypothes : there is significant diiffrence bettween population_mean)
else :
    print("Fail to reject the null hypothesis : There is no ignificant diffrence between population_mean)</pre>
```

#### 0.6546536707079772

#### 0.5416045607931204

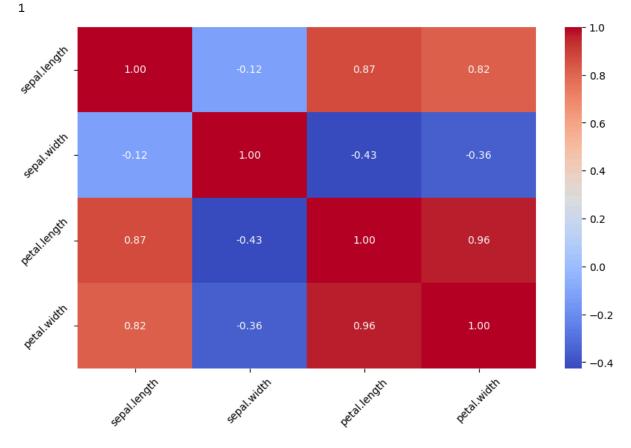
Fail to reject the null hypothesis : There is nos ignificaant diffrence between samp le mean and population mean

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

df = pd.read_csv(r"C:\Users\vaibh\Downloads\iris.csv")
print("missing values : ")
print(df.isnull().sum())
print("Duplicates : ")
print(df.duplicated().sum())
df.dropna(inplace = True)
df.drop_duplicates(inplace =True)
corelation_matrix = df.select_dtypes(include = "number").corr()
plt.figure(figsize=(10,6))
```

```
sns.heatmap(corelation_matrix,annot = True,cmap = 'coolwarm',fmt = '0.2f',cbar = Tr
plt.xticks(rotation = 45)
plt.yticks(rotation = 45)
plt.show()
```

missing values :
sepal.length 0
sepal.width 0
petal.length 0
petal.width 0
species 0
dtype: int64
Duplicates :



In [ ]: