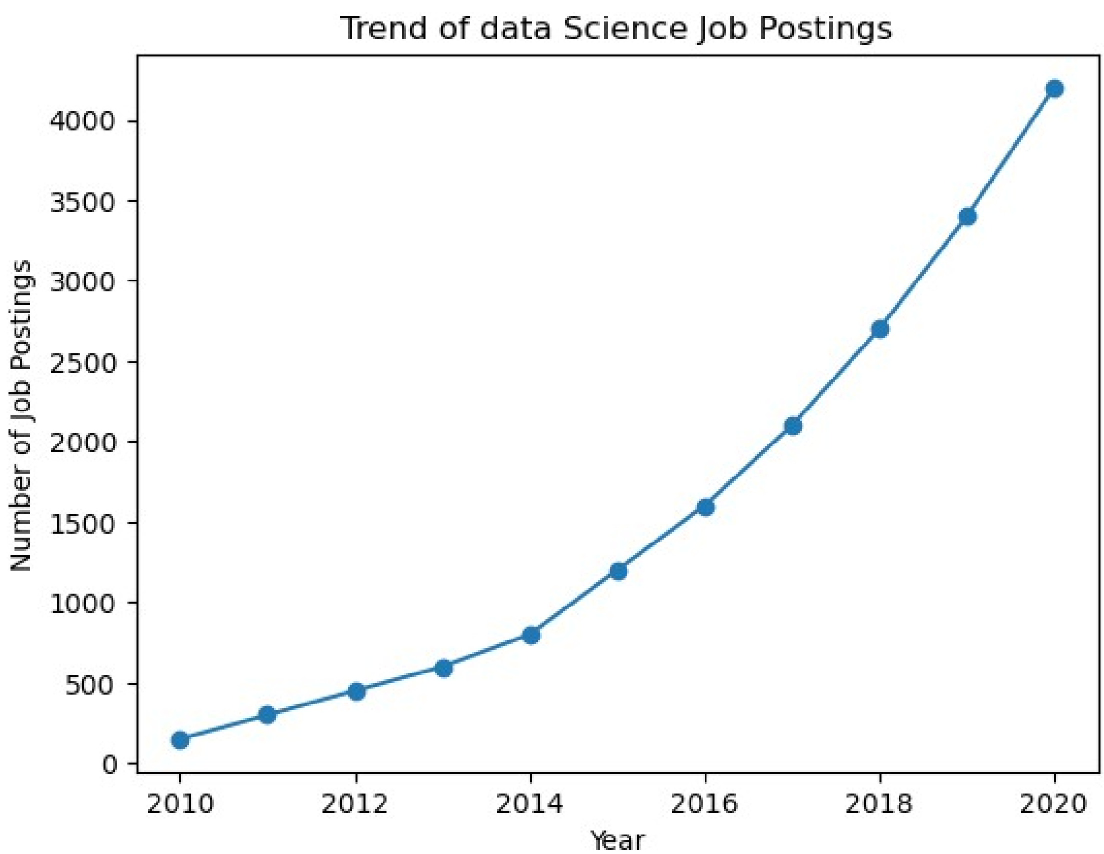
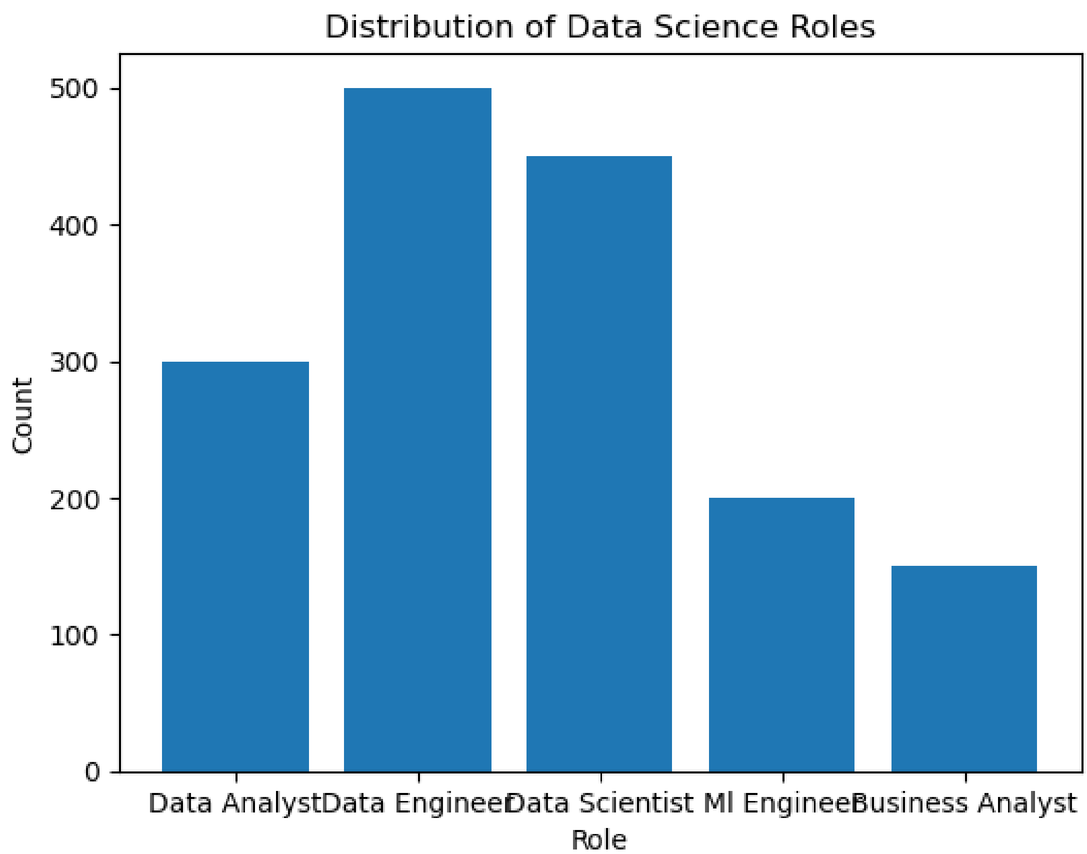
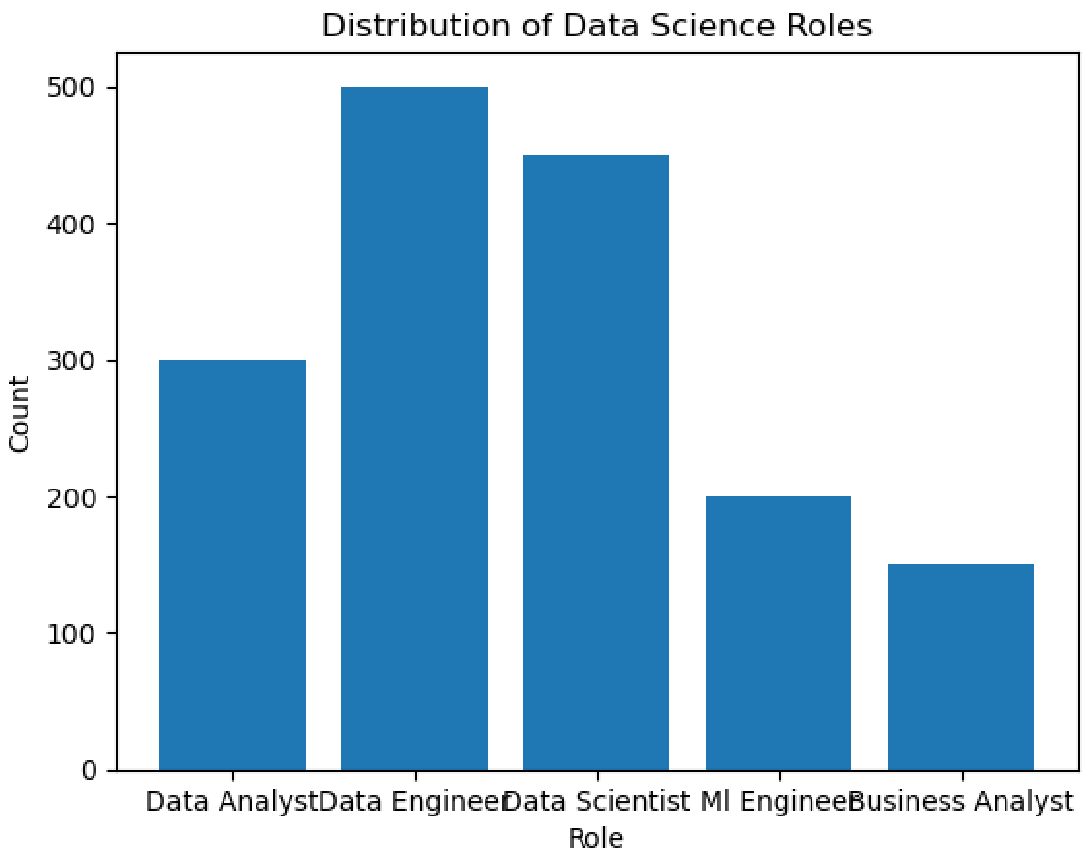
```
import pandas as pd
import matplotlib.pyplot as plt


data={'Year':(range(2010,2021)),
              'Job Postings':
[150,300,450,600,800,1200,1600,2100,2700,3400,4200]}
df=pd.DataFrame(data)
plt.plot(df['Year'],df['Job Postings'],marker='o')
plt.title('Trend of data Science Job Postings')
plt.xlabel('Year')
plt.ylabel('Number of Job Postings')
plt.show()
```





Distribution of Data Science Roles
Count
500
400
300
200
100
0
Data Analyst
Data Engineer
Data Scientist
Ml Engineer
Business Analyst
Role

```
import pandas as pd
import matplotlib.pyplot as plt
roles=['Data Analyst','Data Engineer','Data Scientist','Ml
Engineer','Business Analyst']
counts=[300,500,450,200,150]
plt.bar(roles,counts)
plt.title('Distribution of Data Science Roles')
plt.xlabel('Role')
plt.ylabel('Count')
plt.show()
```



```python
import pandas as pd
structured_data=pd.DataFrame({'ID':[1,2,3],'name':
['Alice','Bob','Charlie'],'age':[25,30,23]})
print("structured data:\n",structured_data)
```

```
structured data:
    ID     name  age
0   1    Alice   25
1   2      Bob   30
2   3  Charlie   23
```

```python
unstructured_data="This is an example of unstructured data.It can be a
piece of text"
print("Unstructured data:\n",unstructured_data)
```

```
Unstructured data:
 This is an example of unstructured data.It can be a piece of text
```

```python
semistructured_data={'ID':[1,2,3],'name':
['Alice','Bob','Charlie'],'age':[25,30,23]}
print("semistructured_data:\n",semistructured_data)
```

```
semistructured_data:
 {'ID': [1, 2, 3], 'name': ['Alice', 'Bob', 'Charlie'], 'age': [25,
30, 23]}
```

```python
file=open('data.txt','w')
file.writelines(["hello\n","this is file handling using python\n"])
file.close()
```

```python
#unstructured data
f=open("data.txt",'r')
unstruct_data=f.readline()
print("unstructured data:\n",unstruct_data)
```

```
unstructured data:
 he
```

```
from cryptography.fernet import Fernet
key= Fernet.generate_key()
f=Fernet(key)
token=f.encrypt(b"This is plain text.")
")
f.decrypt(token)
key=Fernet.generate_key()
cipher_suite=Fernet(key)
plain_text=b"This is plain text."
cipher_text=cipher_suite.encrypt(plain_text)

decrypted_text=cipher_suite.decrypt(cipher_text)
print("original data: ",plain_text)
print("encrypted data: ",cipher_text)
print("decrypted data: ", decrypted_text)
```

```
original data:  b'This is plain text.'
encrypted data:
b'gAAAAABmtEPcNs087rNAdIGFtE78RR2iTR1t9NDsbKZ2iP_p4uXZDtE3bVcl0MzV-
Cqu2you0EY4-jSd7zQLp0sYj7W1uaVGl2SZt_bkVWE5c6uLk4WLqTQ='
decrypted data:  b'This is plain text.'
```

```
print("hello world")
```

```
hello world
```

```
import pandas as pd
db=pd.read_csv("C:\Users\DELL\Desktop\diabetes.csv
```

```
  Cell In[4], line 2
    db=pd.read_csv("C:\Users\DELL\Desktop\diabetes.csv")
                                                       ^
SyntaxError: (unicode error) 'unicodeescape' codec can't decode bytes
in position 2-3: truncated \UXXXXXXXX escape
```

```
import pandas as pd
db=pd.read_csv("diabetes.csv")
print(db.head())
```

```
   Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin
BMI  \
0            6      148             72             35        0  33.6

1            1       85             66             29        0  26.6

2            8      183             64              0        0  23.3

3            1       89             66             23       94  28.1

4            0      137             40             35      168  43.1


   DiabetesPedigreeFunction  Age  Outcome
0                     0.627   50        1
1                     0.351   31        0
2                     0.672   32        1
3                     0.167   21        0
4                     2.288   33        1
```

```
print(db.info())
```

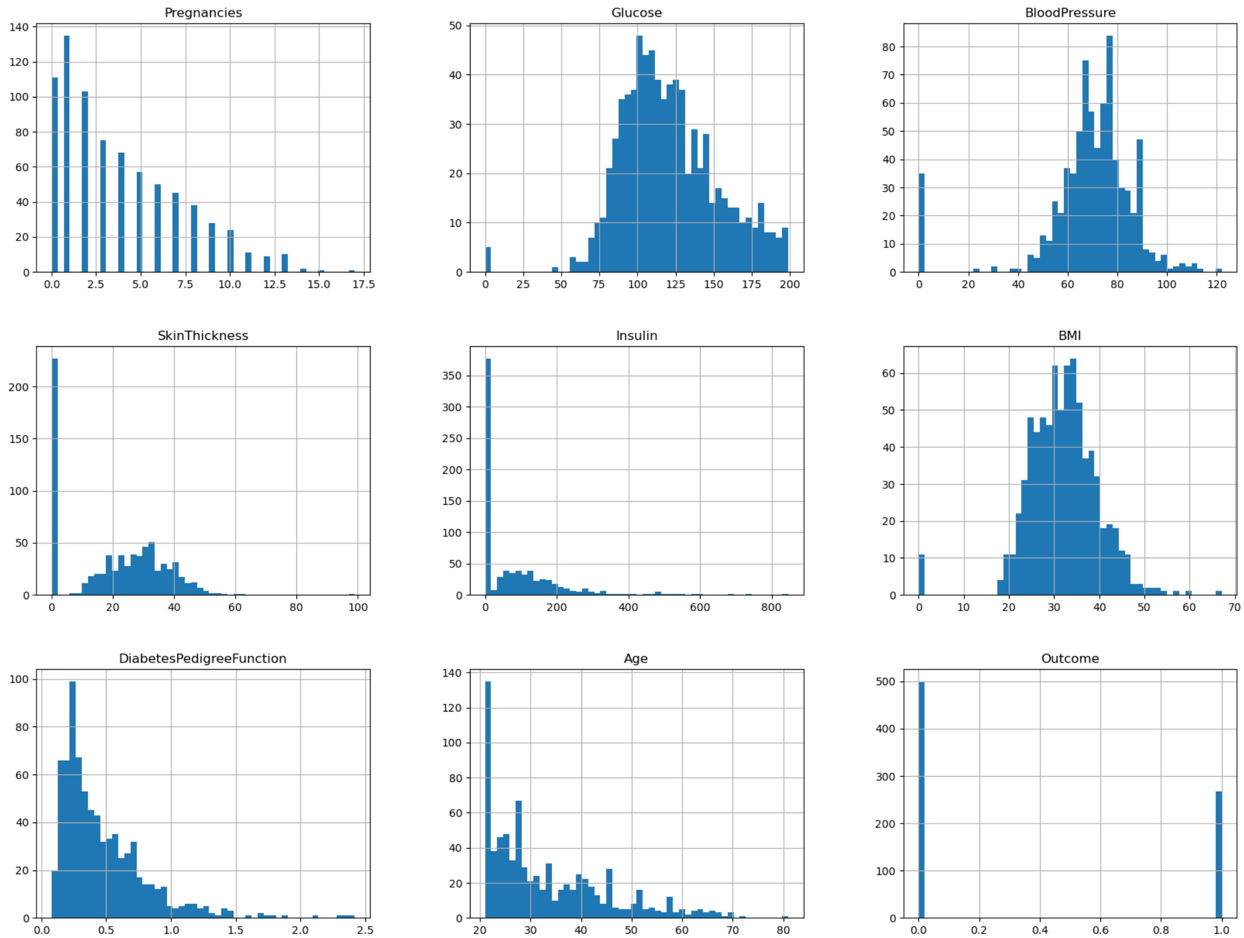
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Pregnancies               768 non-null    int64
 1   Glucose                   768 non-null    int64
 2   BloodPressure             768 non-null    int64
 3   SkinThickness             768 non-null    int64
 4   Insulin                   768 non-null    int64
 5   BMI                       768 non-null    float64
 6   DiabetesPedigreeFunction  768 non-null    float64
 7   Age                       768 non-null    int64
 8   Outcome                   768 non-null    int64
dtypes: float64(2), int64(7)
```

```
memory usage: 54.1 KB
None
```

```python
print(db.describe())
```

```
       Pregnancies     Glucose  BloodPressure  SkinThickness
Insulin  \
count   768.000000  768.000000     768.000000     768.000000
768.000000
mean      3.845052  120.894531      69.105469      20.536458
79.799479
std       3.369578   31.972618      19.355807      15.952218
115.244002
min       0.000000    0.000000       0.000000       0.000000
0.000000
25%       1.000000   99.000000      62.000000       0.000000
0.000000
50%       3.000000  117.000000      72.000000      23.000000
30.500000
75%       6.000000  140.250000      80.000000      32.000000
127.250000
max      17.000000  199.000000     122.000000      99.000000
846.000000

              BMI  DiabetesPedigreeFunction         Age     Outcome
count  768.000000                768.000000  768.000000  768.000000
mean    31.992578                  0.471876   33.240885    0.348958
std      7.884160                  0.331329   11.760232    0.476951
min      0.000000                  0.078000   21.000000    0.000000
25%     27.300000                  0.243750   24.000000    0.000000
50%     32.000000                  0.372500   29.000000    0.000000
75%     36.600000                  0.626250   41.000000    1.000000
max     67.100000                  2.420000   81.000000    1.000000
```

```python
import matplotlib.pyplot as plt
import seaborn as sns
db.hist(bins=50,figsize=(20,15))
plt.show()
```




```
db.duplicated().any()
```

```
False
```

```
db.isnull().sum()
```

```
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

```
import pandas as pd
sales_df=pd.read_csv("Downloads/Sales_Transactions_Dataset_Weekly.csv"
)
sales_df.head()
```

```
  Product_Code  W0  W1  W2  W3  W4  W5  W6  W7  W8  ...  Normalized 42
\
0           P1  11  12  10   8  13  12  14  21   6  ...           0.06

1           P2   7   6   3   2   7   1   6   3   3  ...           0.20

2           P3   7  11   8   9  10   8   7  13  12  ...           0.27

3           P4  12   8  13   5   9   6   9  13  13  ...           0.41

4           P5   8   5  13  11   6   7   9  14   9  ...           0.27


   Normalized 43  Normalized 44  Normalized 45  Normalized 46
Normalized 47  \
0           0.22           0.28           0.39           0.50
0.00
1           0.40           0.50           0.10           0.10
0.40
2           1.00           0.18           0.18           0.36
0.45
3           0.47           0.06           0.12           0.24
0.35
4           0.53           0.27           0.60           0.20
0.20

   Normalized 48  Normalized 49  Normalized 50  Normalized 51
0           0.22           0.17           0.11           0.39
1           0.50           0.10           0.60           0.00
2           1.00           0.45           0.45           0.36
3           0.71           0.35           0.29           0.35
4           0.13           0.53           0.33           0.40

[5 rows x 107 columns]
```

```
import numpy as np
import matplotlib.pyplot as plt
file_path="Downloads/Sales_Transactions_Dataset_Weekly.csv"
sales_df.isnull().sum()
```

```
Product_Code     0
W0               0
W1               0
W2               0
W3               0
                ..
```

```
Normalized 47    0
Normalized 48    0
Normalized 49    0
Normalized 50    0
Normalized 51    0
Length: 107, dtype: int64
```

```
sales_df.describe()
```

```
                W0          W1          W2          W3          W4
W5  \
count  811.000000  811.000000  811.000000  811.000000  811.000000
811.000000
mean     8.902589    9.129470    9.389642    9.717633    9.574599
9.466091
std     12.067163   12.564766   13.045073   13.553294   13.095765
12.823195
min      0.000000    0.000000    0.000000    0.000000    0.000000
0.000000
25%      0.000000    0.000000    0.000000    0.000000    0.000000
0.000000
50%      3.000000    3.000000    3.000000    4.000000    4.000000
3.000000
75%     12.000000   12.000000   12.000000   13.000000   13.000000
12.500000
max     54.000000   53.000000   56.000000   59.000000   61.000000
52.000000

                W6          W7          W8          W9  ...  Normalized
42  \
count  811.000000  811.000000  811.000000  811.000000  ...
811.000000
mean     9.720099    9.585697    9.784217    9.681874  ...
0.299149
std     13.347375   13.049138   13.550237   13.137916  ...
0.266993
min      0.000000    0.000000    0.000000    0.000000  ...
0.000000
25%      0.000000    0.000000    0.000000    0.000000  ...
0.000000
50%      4.000000    4.000000    4.000000    4.000000  ...
0.280000
75%     13.000000   12.500000   13.000000   13.000000  ...
0.490000
max     56.000000   62.000000   63.000000   52.000000  ...
1.000000

       Normalized 43  Normalized 44  Normalized 45  Normalized 46  \
count     811.000000     811.000000     811.000000     811.000000
mean        0.287571       0.304846       0.316017       0.334760
```

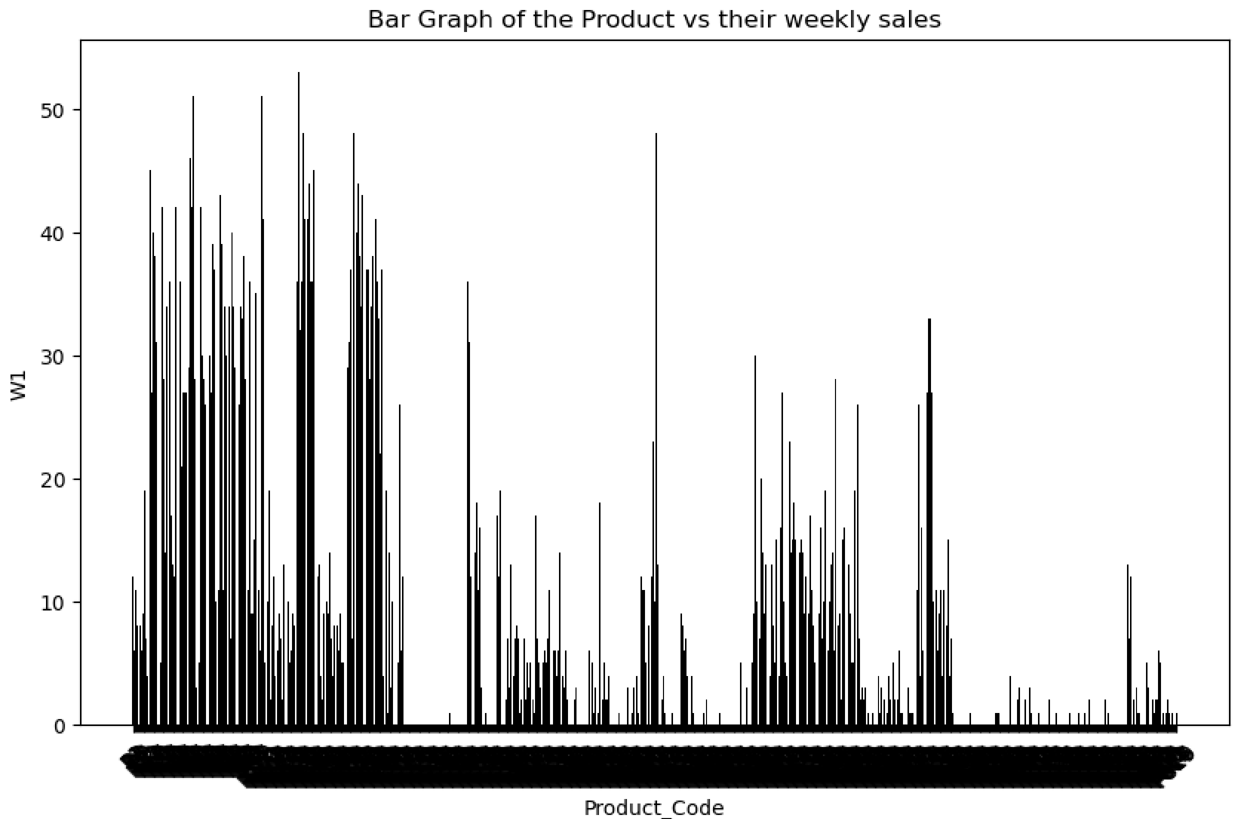
```
std          0.256630       0.263396       0.262226       0.275203
min          0.000000       0.000000       0.000000       0.000000
25%          0.000000       0.000000       0.020000       0.085000
50%          0.270000       0.300000       0.310000       0.330000
75%          0.450000       0.500000       0.500000       0.500000
max          1.000000       1.000000       1.000000       1.000000

       Normalized 47  Normalized 48  Normalized 49  Normalized 50  \
count     811.000000      811.00000     811.000000     811.000000
mean        0.314636        0.33815       0.358903       0.373009
std         0.266029        0.27569       0.286665       0.295197
min         0.000000        0.00000       0.000000       0.000000
25%         0.000000        0.10500       0.100000       0.110000
50%         0.310000        0.33000       0.330000       0.350000
75%         0.500000        0.50000       0.550000       0.560000
max         1.000000        1.00000       1.000000       1.000000

       Normalized 51
count     811.000000
mean        0.427941
std         0.342360
min         0.000000
25%         0.090000
50%         0.430000
75%         0.670000
max         1.000000

[8 rows x 106 columns]
```

```
sales_df['Sales'].fillna(sales_df['Sales'].mean(),inplace=True)
sales_df.dropna(subset=['Product','Quantity','Region'],inplace=True)
```

```
----------------------------------------------------------------------
-----
KeyError                                  Traceback (most recent call
last)
File ~\anaconda3\lib\site-packages\pandas\core\indexes\base.py:3802,
in Index.get_loc(self, key, method, tolerance)
   3801 try:
-> 3802     return self._engine.get_loc(casted_key)
   3803 except KeyError as err:

File ~\anaconda3\lib\site-packages\pandas\_libs\index.pyx:138, in
pandas._libs.index.IndexEngine.get_loc()

File ~\anaconda3\lib\site-packages\pandas\_libs\index.pyx:165, in
pandas._libs.index.IndexEngine.get_loc()

File pandas\_libs\hashtable_class_helper.pxi:5745, in
pandas._libs.hashtable.PyObjectHashTable.get_item()
```

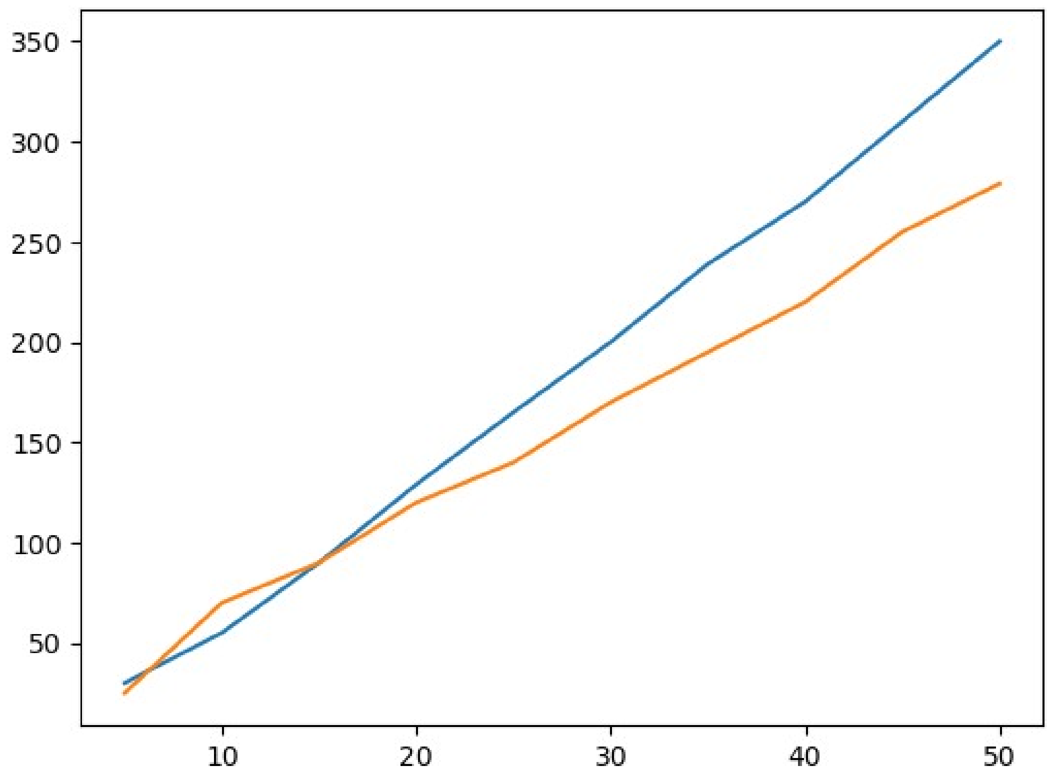
```
File pandas\_libs\hashtable_class_helper.pxi:5753, in
pandas._libs.hashtable.PyObjectHashTable.get_item()

KeyError: 'Sales'

The above exception was the direct cause of the following exception:

KeyError                                  Traceback (most recent call
last)
Cell In[7], line 1
----> 1
sales_df['Sales'].fillna(sales_df['Sales'].mean(),inplace=True)
      2
sales_df.dropna(subset=['Product','Quantity','Region'],inplace=True)

File ~\anaconda3\lib\site-packages\pandas\core\frame.py:3807, in
DataFrame.__getitem__(self, key)
   3805 if self.columns.nlevels > 1:
   3806     return self._getitem_multilevel(key)
-> 3807 indexer = self.columns.get_loc(key)
   3808 if is_integer(indexer):
   3809     indexer = [indexer]

File ~\anaconda3\lib\site-packages\pandas\core\indexes\base.py:3804,
in Index.get_loc(self, key, method, tolerance)
   3802     return self._engine.get_loc(casted_key)
   3803 except KeyError as err:
-> 3804     raise KeyError(key) from err
   3805 except TypeError:
   3806     # If we have a listlike key, _check_indexing_error will
raise
   3807     #  InvalidIndexError. Otherwise we fall through and re-
raise
   3808     #  the TypeError.
   3809     self._check_indexing_error(key)

KeyError: 'Sales'
```

```
plt.figure(figsize=(10, 6))
plt.bar(sales_df['Product_Code'],sales_df['W1'],color='black')
plt.xlabel('Product_Code')
plt.ylabel('W1')
plt.title('Bar Graph of the Product vs their weekly sales')
plt.xticks(rotation=45)
plt.show()
```

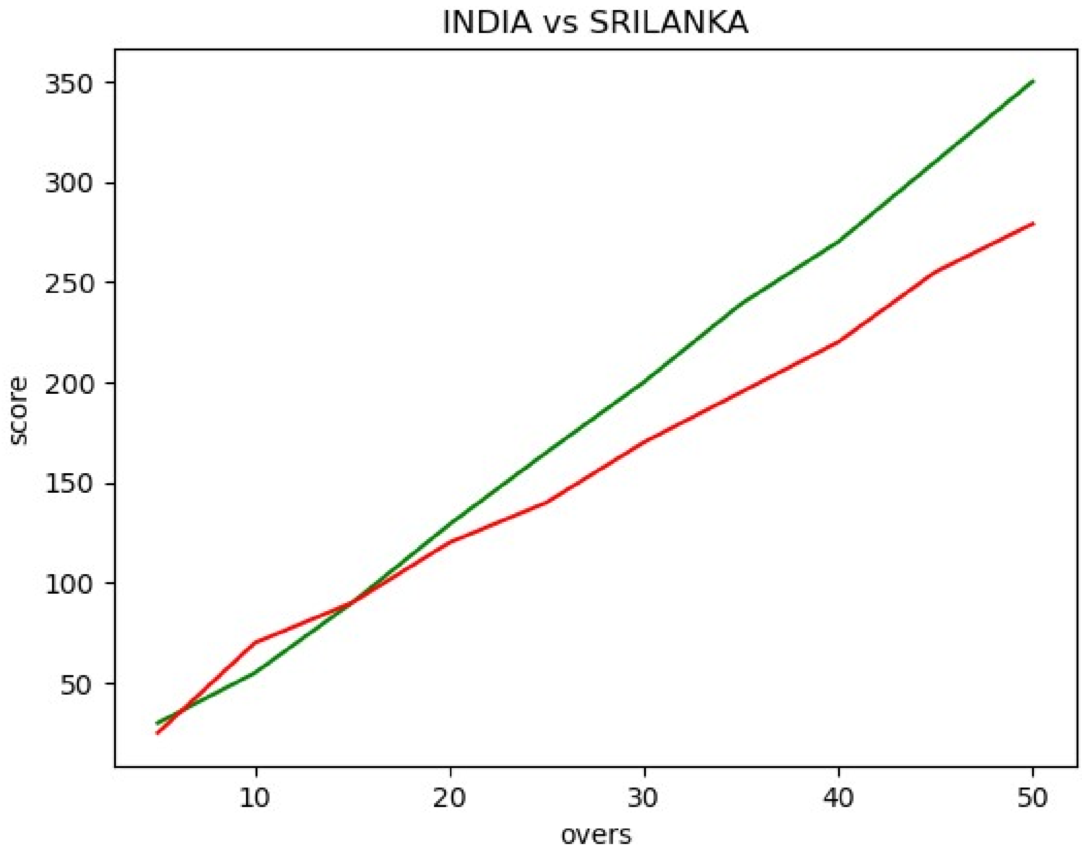


Bar Graph of the Product vs their weekly sales
W1
50
40
30
20
10
0
Product_Code

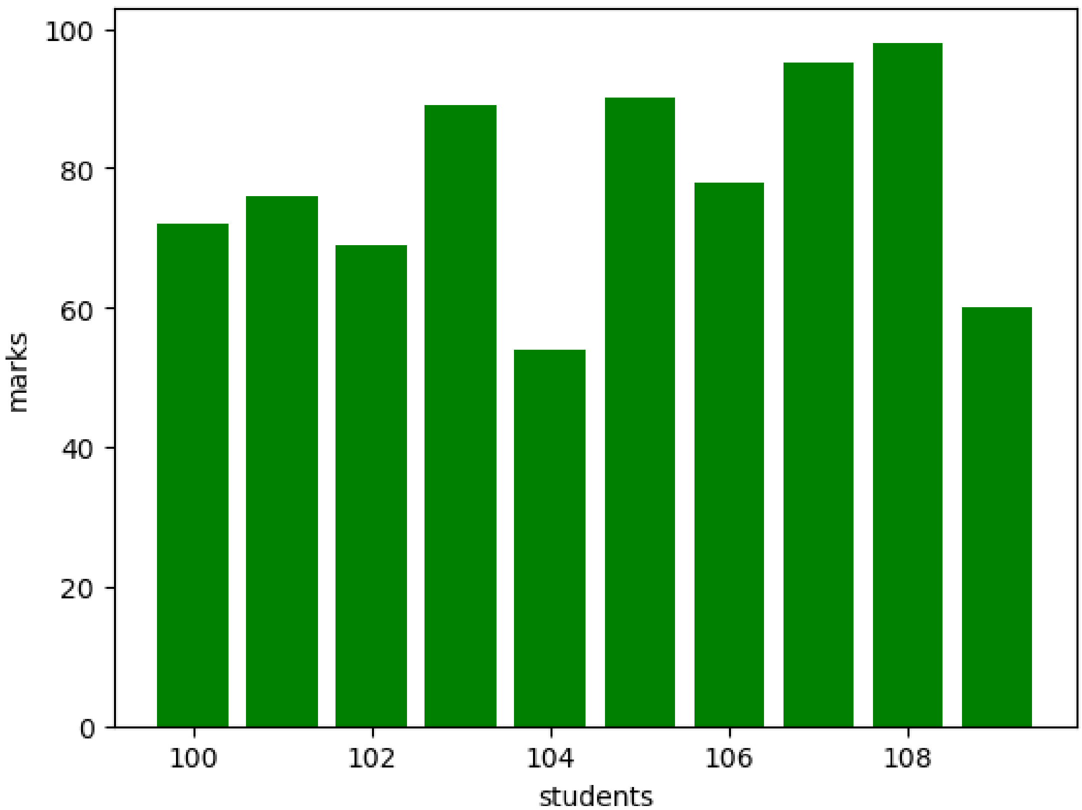
```python
import matplotlib.pyplot as cricket
overs=list(range(5,51,5))
Indian_score=[30,55,90,129,165,200,239,270,310,350]
Srilankan_score=[25,70,90,120,140,170,195,220,255,279]
cricket.plot(overs,Indian_score)
cricket.plot(overs,Srilankan_score)
cricket.show()
cricket.title("INDIA vs SRILANKA")
cricket.xlabel("overs")
cricket.ylabel("score")
cricket.plot(overs,Indian_score,color="green",label="INDIA")
cricket.plot(overs,Srilankan_score,color="red",label="SRILANKA")
```




```
[<matplotlib.lines.Line2D at 0x1f746e08640>]
```




```
import matplotlib.pyplot as plt
student_id=list(range(100,110))
student_marks=[72,76,69,89,54,90,78,95,98,60]
student_remarks=[3,3,2,4,2,5,5,3,5,5,3]
plt.bar(student_id,student_marks,color="green")
plt.xlabel("students")
plt.ylabel("marks")
plt.show()
```




```
election=pd.read_csv("governors.csv")
print(election.head(25))
election.info()
election.describe
```

```
       state                county  current_votes  total_votes  percent
0   Delaware           Kent County          85415        87025      100
1   Delaware     New Castle County         280039       287633      100
2   Delaware         Sussex County         127181       129352      100
3    Indiana          Adams County          14154        14209      100
4    Indiana          Allen County         168312       169082      100
5    Indiana    Bartholomew County          36037        36235      100
6    Indiana         Benton County           4100         4114      100
7    Indiana      Blackford County           5283         5350      100
8    Indiana          Boone County          38492        38520      100
9    Indiana          Brown County           8957         8981      100
10   Indiana        Carroll County           9510         9510      100
11   Indiana           Cass County          15146        15198      100
12   Indiana          Clark County          57426        57869      100
13   Indiana           Clay County          12186        12267      100
14   Indiana        Clinton County          12891        12949      100
15   Indiana       Crawford County           4859         4944      100
16   Indiana        Daviess County          11860        11954      100
17   Indiana       Dearborn County          25295        25383      100
```

```
18   Indiana      Decatur County          12260        12235       95
19   Indiana       DeKalb County          19493        19628      100
20   Indiana     Delaware County          47949        48191      100
21   Indiana       Dubois County          21588        21770      100
22   Indiana      Elkhart County          74425        74425      100
23   Indiana      Fayette County          10054        10136      100
24   Indiana        Floyd County          41589        41802      100
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1025 entries, 0 to 1024
Data columns (total 5 columns):
 #   Column         Non-Null Count  Dtype 
---  ------         --------------  ----- 
 0   state          1025 non-null   object
 1   county         1025 non-null   object
 2   current_votes  1025 non-null   int64 
 3   total_votes    1025 non-null   int64 
 4   percent        1025 non-null   int64 
dtypes: int64(3), object(2)
memory usage: 40.2+ KB

<bound method NDFrame.describe of               state
county  current_votes  total_votes  percent
0          Delaware        Kent County         85415        87025
100
1          Delaware  New Castle County        280039       287633
100
2          Delaware      Sussex County        127181       129352
100
3           Indiana       Adams County         14154        14209
100
4           Indiana       Allen County        168312       169082
100
...             ...                ...           ...          ...
...
1020  West Virginia     Webster County          3339         3402
100
1021  West Virginia      Wetzel County          6553         6667
100
1022  West Virginia        Wirt County          2544         2653
100
1023  West Virginia        Wood County         38435        38762
100
1024  West Virginia     Wyoming County          8320         8592
100

[1025 rows x 5 columns]>
```

```python
election['county'].unique().any()
```

```
'Kent County'
```

```python
l=list(election.current_votes)
l.sort()
print(l)
```

```
[5, 20, 22, 43, 43, 50, 55, 62, 65, 76, 106, 112, 115, 127, 129, 129,
135, 136, 137, 139, 140, 150, 164, 171, 171, 176, 180, 184, 190, 191,
191, 210, 216, 222, 229, 233, 233, 233, 244, 248, 249, 258, 259, 272,
272, 279, 292, 293, 295, 296, 305, 326, 328, 329, 330, 334, 340, 343,
349, 350, 351, 351, 357, 361, 364, 368, 368, 371, 375, 379, 385, 386,
389, 393, 397, 408, 411, 416, 417, 421, 421, 431, 432, 437, 439, 439,
445, 447, 447, 451, 454, 460, 471, 475, 476, 476, 476, 477, 482, 483,
488, 488, 491, 503, 504, 505, 509, 516, 517, 519, 521, 524, 527, 534,
535, 536, 536, 537, 540, 541, 547, 551, 552, 562, 562, 574, 577, 579,
585, 588, 591, 593, 601, 604, 607, 612, 613, 618, 619, 621, 622, 627,
629, 633, 635, 638, 638, 643, 643, 644, 657, 659, 660, 664, 665, 667,
669, 678, 678, 696, 700, 700, 707, 708, 709, 722, 724, 726, 730, 730,
738, 739, 742, 747, 748, 748, 748, 756, 763, 763, 768, 776, 778, 780,
780, 783, 785, 788, 790, 792, 794, 796, 806, 806, 813, 818, 820, 821,
822, 823, 825, 830, 834, 836, 844, 844, 847, 848, 852, 857, 858, 862,
874, 876, 877, 880, 893, 902, 907, 908, 908, 909, 918, 919, 919, 919,
924, 926, 943, 943, 945, 946, 949, 950, 950, 954, 954, 957, 993, 1001,
1009, 1020, 1032, 1032, 1043, 1051, 1056, 1060, 1061, 1068, 1069,
1071, 1078, 1080, 1083, 1084, 1089, 1095, 1097, 1106, 1111, 1112,
1117, 1117, 1122, 1125, 1129, 1129, 1130, 1132, 1133, 1134, 1136,
1141, 1141, 1144, 1154, 1158, 1164, 1178, 1188, 1191, 1193, 1195,
1203, 1204, 1206, 1214, 1218, 1228, 1230, 1243, 1248, 1249, 1250,
1252, 1270, 1270, 1273, 1275, 1276, 1279, 1288, 1298, 1302, 1304,
1306, 1320, 1328, 1334, 1346, 1351, 1374, 1391, 1400, 1400, 1401,
1413, 1448, 1458, 1462, 1466, 1474, 1475, 1478, 1478, 1481, 1487,
1527, 1536, 1541, 1555, 1564, 1567, 1569, 1581, 1587, 1629, 1639,
1647, 1654, 1662, 1662, 1665, 1683, 1689, 1690, 1698, 1711, 1716,
1717, 1718, 1719, 1726, 1727, 1736, 1741, 1742, 1742, 1756, 1762,
1765, 1770, 1786, 1802, 1805, 1815, 1833, 1834, 1846, 1850, 1851,
1859, 1867, 1888, 1890, 1931, 1949, 1955, 1956, 1965, 1976, 2015,
2016, 2016, 2019, 2023, 2038, 2056, 2060, 2079, 2087, 2090, 2094,
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```
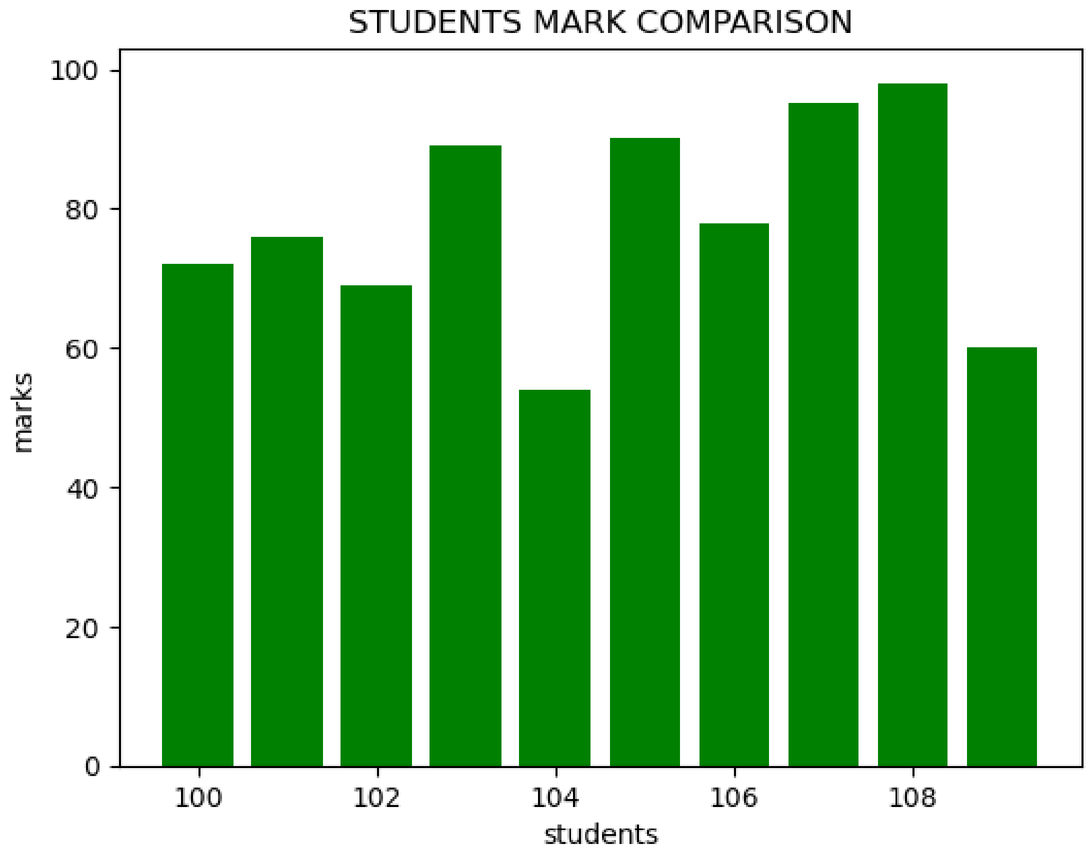
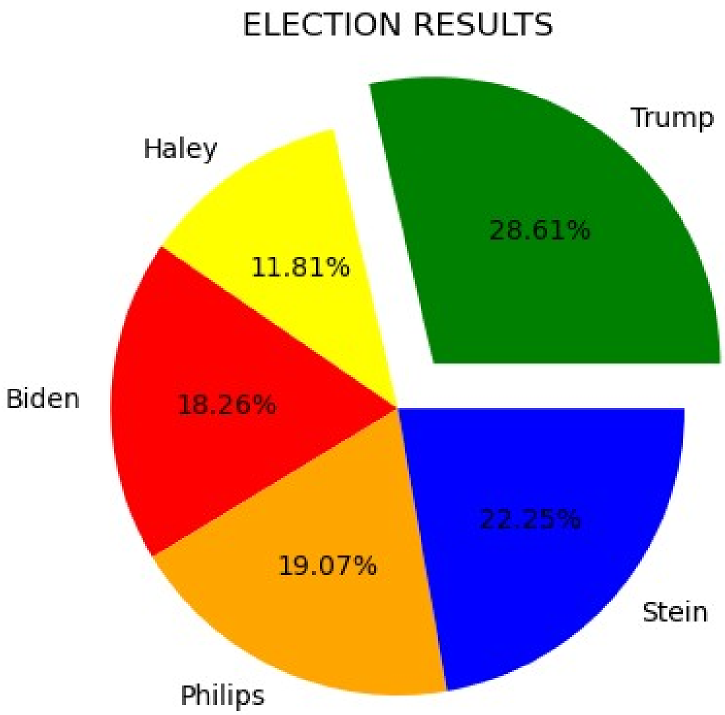

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
df=pd.read_csv("diabetes.csv")
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Pregnancies               768 non-null    int64
 1   Glucose                   768 non-null    int64
 2   BloodPressure             768 non-null    int64
 3   SkinThickness             768 non-null    int64
 4   Insulin                   768 non-null    int64
 5   BMI                       768 non-null    float64
 6   DiabetesPedigreeFunction  768 non-null    float64
 7   Age                       768 non-null    int64
 8   Outcome                   768 non-null    int64
dtypes: float64(2), int64(7)
memory usage: 54.1 KB
```

```
import matplotlib.pyplot as plt
student_id=list(range(100,110))
student_marks=[72,76,69,89,54,90,78,95,98,60]
student_remarks=[3,3,2,4,2,5,5,3,5,5,3]
plt.bar(student_id,student_marks,color="green")
plt.title("STUDENTS MARK COMPARISON")
plt.xlabel("students")
plt.ylabel("marks")
plt.show()
```


STUDENTS MARK COMPARISON
marks
students
0
20
40
60
80
100
100
102
104
106
108

```python
import matplotlib.pyplot as plt
labels=['Trump','Haley','Biden','Philips','Stein']
votes=[315,130,201,210,245]
colors=['green','yellow','red','orange','blue']
explode=(0.2,0,0,0,0)
plt.pie(votes, labels=labels, colors=colors,
explode=explode,autopct='%0.2f%%')
plt.title('ELECTION RESULTS')
plt.show()
```




```

```

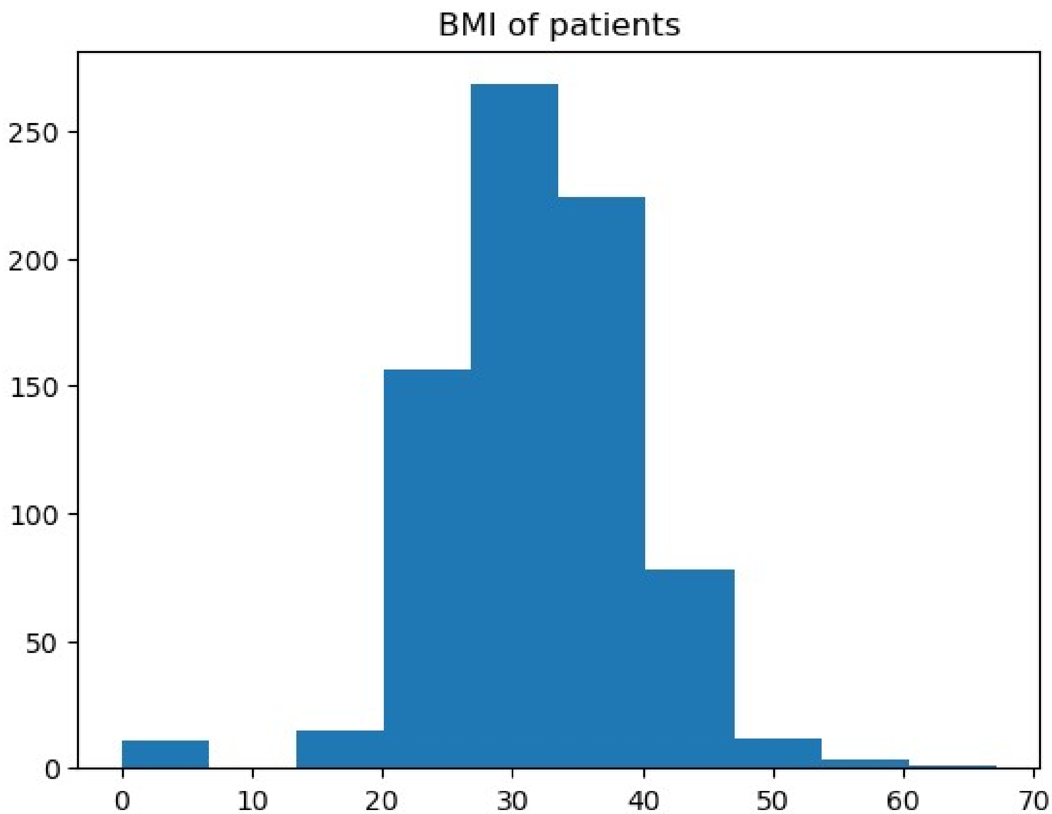
```python
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
df=pd.read_csv("diabetes.csv")

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   Pregnancies               768 non-null    int64  
 1   Glucose                   768 non-null    int64  
 2   BloodPressure             768 non-null    int64  
 3   SkinThickness             768 non-null    int64  
 4   Insulin                   768 non-null    int64  
 5   BMI                       768 non-null    float64
 6   DiabetesPedigreeFunction  768 non-null    float64
 7   Age                       768 non-null    int64  
 8   Outcome                   768 non-null    int64  
dtypes: float64(2), int64(7)
memory usage: 54.1 KB
```

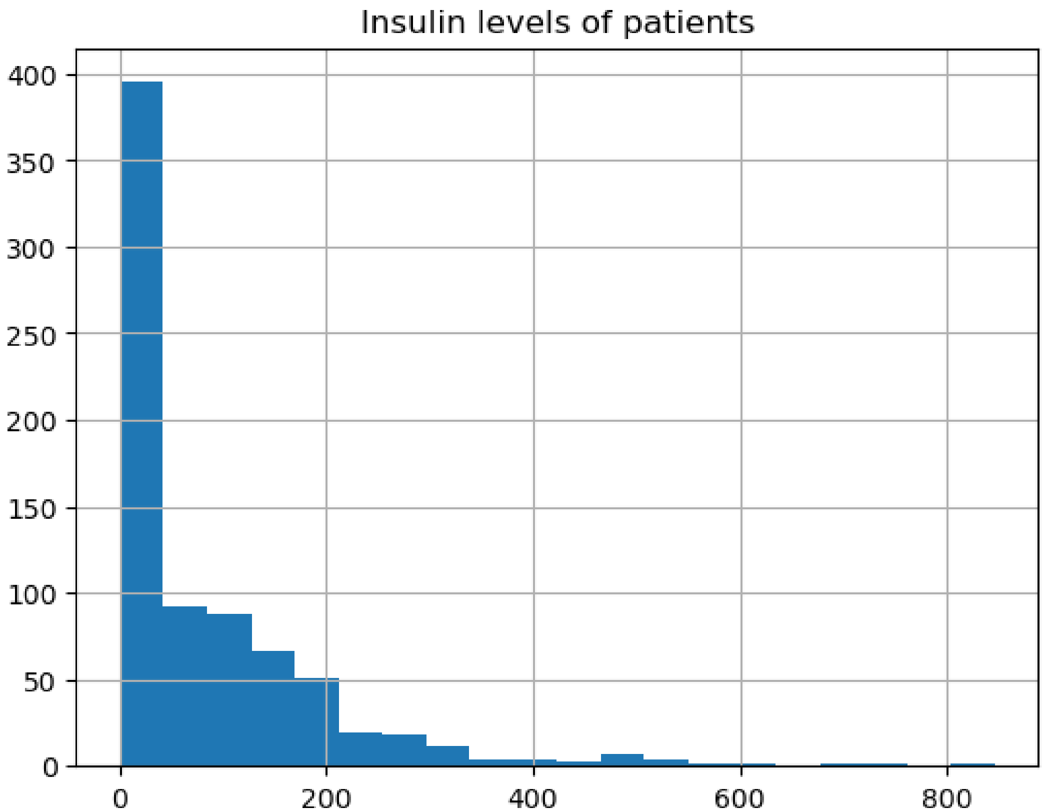
```python
df.describe()
```

```
       Pregnancies     Glucose  BloodPressure  SkinThickness
Insulin  \
count   768.000000  768.000000     768.000000     768.000000
768.000000
mean      3.845052  120.894531      69.105469      20.536458
79.799479
std       3.369578   31.972618      19.355807      15.952218
115.244002
min       0.000000    0.000000       0.000000       0.000000
0.000000
25%       1.000000   99.000000      62.000000       0.000000
0.000000
50%       3.000000  117.000000      72.000000      23.000000
30.500000
75%       6.000000  140.250000      80.000000      32.000000
127.250000
max      17.000000  199.000000     122.000000      99.000000
846.000000

              BMI  DiabetesPedigreeFunction         Age     Outcome
count  768.000000                768.000000  768.000000  768.000000
mean    31.992578                  0.471876   33.240885    0.348958
std      7.884160                  0.331329   11.760232    0.476951
```

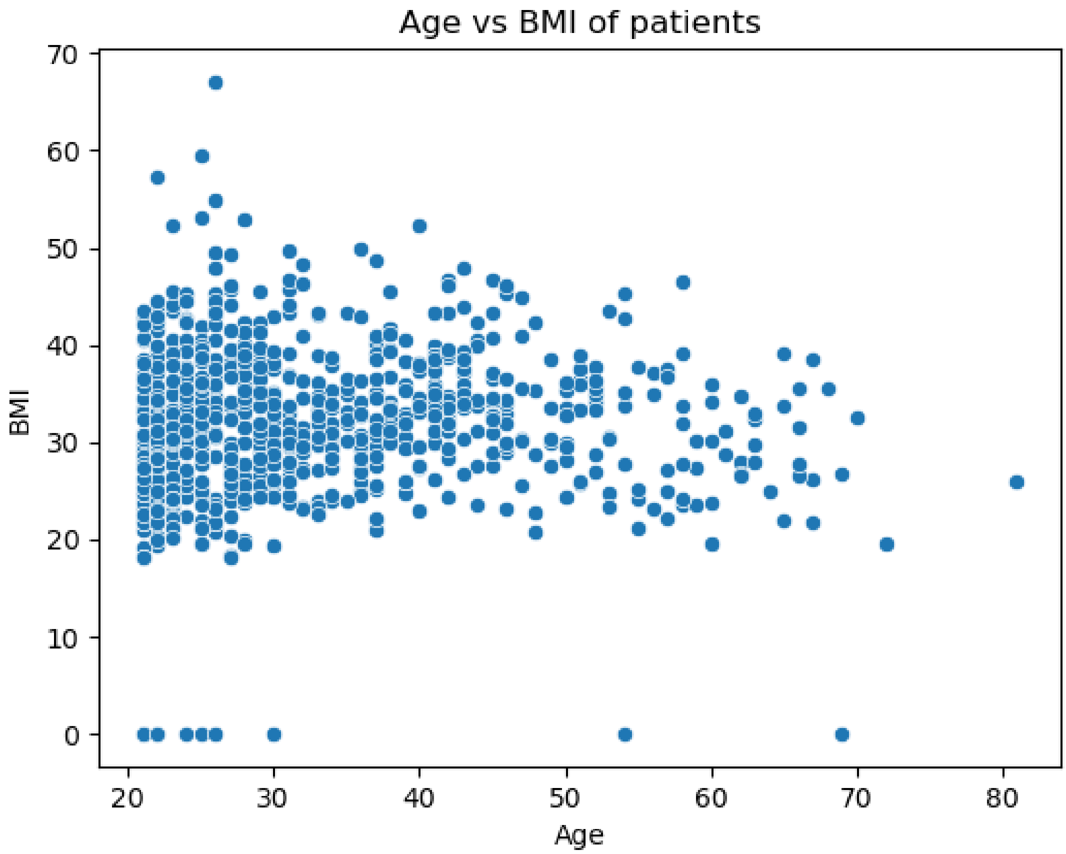
```
min      0.000000                    0.078000   21.000000    0.000000
25%     27.300000                    0.243750   24.000000    0.000000
50%     32.000000                    0.372500   29.000000    0.000000
75%     36.600000                    0.626250   41.000000    1.000000
max     67.100000                    2.420000   81.000000    1.000000

#univariate analysis

plt.hist(df['BMI'])
plt.title("BMI of patients")
plt.show()
```



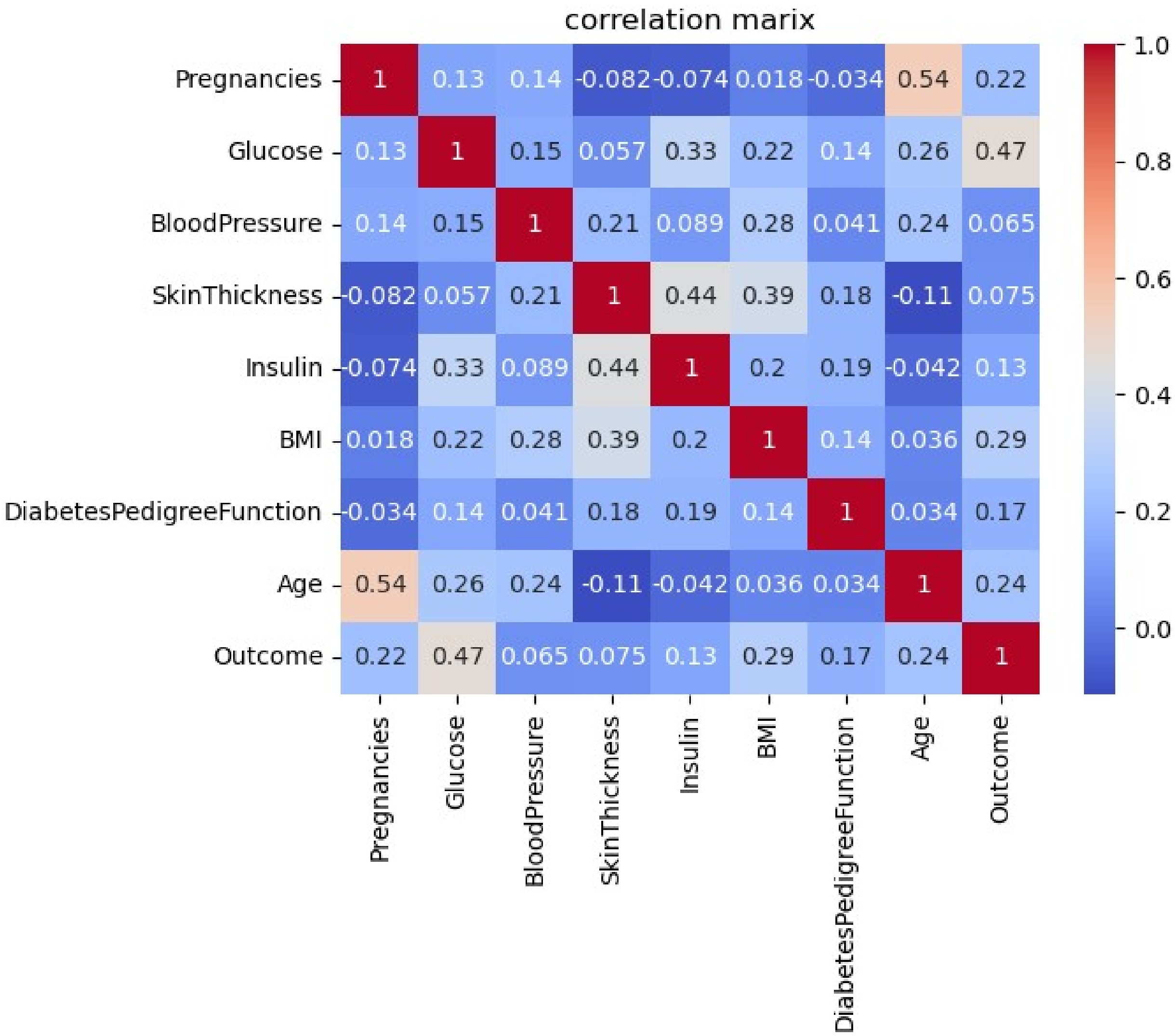

```
df['Insulin'].hist(bins=20)
plt.title("Insulin levels of patients")
plt.show()
```




```
#bivariate analysis

sns.scatterplot(x="Age",y="BMI",data=df)
plt.title("Age vs BMI of patients")
plt.show()
```




```
sns.heatmap(df.corr(), annot=True, cmap='coolwarm')
plt.title('correlation marix')
plt.show()
```




```
df["Insulin"].corr(df['BloodPressure'])
```

```
0.08893337837319315
```

```
#it is weak positively correlted
```

```python
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt

df=pd.read_csv("Salary_data.csv")
df.describe()
```

```
       YearsExperience         Salary
count        30.000000      30.000000
mean          5.313333   76003.000000
std           2.837888   27414.429785
min           1.100000   37731.000000
25%           3.200000   56720.750000
50%           4.700000   65237.000000
75%           7.700000  100544.750000
max          10.500000  122391.000000
```

```python
df.duplicated().sum()
```

```
0
```

```python
df.isnull().sum()
```

```
YearsExperience    0
Salary             0
dtype: int64
```

```python
features=df.iloc[:,[0]].values
label=df.iloc[:,[1]].values

features
```

```
array([[ 1.1],
       [ 1.3],
       [ 1.5],
       [ 2. ],
       [ 2.2],
       [ 2.9],
       [ 3. ],
       [ 3.2],
       [ 3.2],
       [ 3.7],
       [ 3.9],
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       [ 4. ],
       [ 4.1],
       [ 4.5],
       [ 4.9],
       [ 5.1],
       [ 5.3],
```

```
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       [ 6. ],
       [ 6.8],
       [ 7.1],
       [ 7.9],
       [ 8.2],
       [ 8.7],
       [ 9. ],
       [ 9.5],
       [ 9.6],
       [10.3],
       [10.5]])
```

```
label
```

```
array([[ 39343],
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       [ 43525],
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       [101302],
       [113812],
       [109431],
       [105582],
       [116969],
       [112635],
       [122391],
       [121872]], dtype=int64)
```

```
x_train,x_test,y_train,y_test=train_test_split(features,label,test_siz
e=0.2,random_state=42)
```

```
from sklearn.linear_model import LinearRegression
model=LinearRegression()
model.fit(x_train,y_train)

LinearRegression()

model.score(x_train,y_train)

0.9645401573418146

model.score(x_test,y_test)

0.9024461774180497

#further applying linear regression for training data set
x_train2, x_test2, y_train2,
y_test2=train_test_split(x_train,y_train,test_size=0.2,random_state=42
)



new_model=LinearRegression()
new_model.fit(x_train2,y_train2)

LinearRegression()

new_model.score(x_train2,y_train2)

0.9581077653380569

new_model.score(x_test2,y_test2)

0.9836657383524982

model.coef_

array([[9423.81532303]])

model.intercept_

array([25321.58301178])

new_model.coef_

array([[9306.04618233]])

new_model.intercept_

array([26241.34560505])

import pickle
pickle.dump(model,open('SalaryPred.model','wb'))

model=pickle.load(open('SalaryPred.model','rb'))
```

```
yr_of_exp=float(input("Enter Years of Experience: "))
yr_of_exp_NP=np.array([[yr_of_exp]])
Salary=model.predict(yr_of_exp_NP)
```

```
Enter Years of Experience: 25
```

```
print("estimated salary for {} years is {}".format(yr_of_exp,Salary))
```

```
estimated salary for 25.0 years is [[260916.96608755]]
```

```
new_Salary=new_model.predict(yr_of_exp_NP)
print("estimated salary for {} years is
{}".format(yr_of_exp,new_Salary))
```

```
estimated salary for 25.0 years is [[258892.50016338]]
```

```python
#logistic regression

import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression

df=pd.read_csv("Social_Network_Ads.csv")
df.head()
```

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

```python
df.describe()
```

	User ID	Age	EstimatedSalary	Purchased
count	4.000000e+02	400.000000	400.000000	400.000000
mean	1.569154e+07	37.655000	69742.500000	0.357500
std	7.165832e+04	10.482877	34096.960282	0.479864
min	1.556669e+07	18.000000	15000.000000	0.000000
25%	1.562676e+07	29.750000	43000.000000	0.000000
50%	1.569434e+07	37.000000	70000.000000	0.000000
75%	1.575036e+07	46.000000	88000.000000	1.000000
max	1.581524e+07	60.000000	150000.000000	1.000000

```python
features=df.iloc[:,[2,3]].values
features
```

```
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```

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label=df.iloc[:,-1].values
label

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       1, 1, 0, 1])
```

```python
for i in range(1,401):

x_train,x_test,y_train,y_test=train_test_split(features,label,test_siz
e=0.2,random_state=42)
    model=LogisticRegression()
    model.fit(x_train,y_train)
    train_score=model.score(x_train,y_train)
    test_score=model.score(x_test,y_test)
    if test_score > train_score:
        print("test {} train {} random state
{}".format(test_score,train_score,i))
```

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test 0.8875 train 0.8375 random state 1
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test 0.8875 train 0.8375 random state 3
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```

```
x_train,x_test,y_train,y_test=train_test_split(features,label,test_siz
e=0.2,random_state=42)
finalmodel=LogisticRegression()
finalmodel.fit(x_train,y_train)

finalmodel.score(x_train,y_train)

0.8375

finalmodel.score(x_test,y_test)

0.8875
```

```python
#z-test
import numpy as np
import scipy.stats as stats

sample_data=np.array([152, 148, 151, 149, 147, 153, 150, 148, 152,
149,151, 150, 149, 152, 151, 148, 150, 152, 149, 150,148, 153, 151,
150, 149, 152, 148, 151, 150, 153])
population_mean=150 #given
sample_mean=np.mean(sample_data)
sample_std=np.std(sample_data, ddof=1)
n=len(sample_data)

z_stats=(sample_mean - population_mean)/(sample_std / np.sqrt(n))
p_value=2 * (1 - stats.norm.cdf(np.abs(z_stats))) #since it is a two
tailed test

print(f"Sample Mean: {sample_mean:.2f}")
print(f"Z-Statistic: {z_stats:.4f}")
print(f"P-Value: {p_value:.4f}")
```

```
Sample Mean: 150.20
Z-Statistic: 0.6406
P-Value: 0.5218
```

```python
alpha = 0.05
if p_value < alpha:
    print("Reject the null hypothesis: The average weight is
significantly different from 150 grams.")
else:
    print("Fail to reject the null hypothesis: There is no significant
difference in average weight from 150 grams.")
```

```
Fail to reject the null hypothesis: There is no significant difference
in average weight from 150 grams.
```

```python
#t-test

np.random.seed(42)
sample_size=25
sample_data=np.random.normal(loc=102, scale=15, size=sample_size)
population_mean=150
sample_mean=np.mean(sample_data)
sample_std=np.std(sample_data, ddof=1)
n=len(sample_data)
t_stats,p_value=stats.ttest_1samp(sample_data,population_mean)

print(f"Sample Mean: {sample_mean:.2f}")
print(f"T-Statistic: {t_stats:.4f}")
print(f"P-Value: {p_value:.4f}")
```

```
Sample Mean: 99.55
T-Statistic: -17.5814
P-Value: 0.0000
```

```
alpha = 0.05
if p_value < alpha:
    print("Reject the null hypothesis: The average IQ score is
significantly different from 100.")
else:
    print("Fail to reject the null hypothesis: There is no significant
difference in average IQ score from 100.")
```

```
Reject the null hypothesis: The average IQ score is significantly
different from 100.
```

```
#ANOVA test
#To compare the growth rates of plants under three different
fertilizer treatments
#(Treatment A, B, and C) to determine if there is a significant
difference in their mean growth.
n_plants=25
growth_A=np.random.normal(loc=10, scale=2, size=n_plants)
growth_B=np.random.normal(loc=12, scale=3, size=n_plants)
growth_C=np.random.normal(loc=15, scale=2, size=n_plants)

all_data=np.concatenate([growth_A, growth_B, growth_C])
treatment_labels = ['A'] * n_plants + ['B'] * n_plants + ['C'] *
n_plants
f_stats, p_value = stats.f_oneway(growth_A, growth_B, growth_C)

print("Treatment A Mean Growth:", np.mean(growth_A))
print("Treatment B Mean Growth:", np.mean(growth_B))
print("Treatment C Mean Growth:", np.mean(growth_C))
print()
print(f"F-Statistic: {f_stats:.4f}")
print(f"P-Value: {p_value:.4f}")
```

```
Treatment A Mean Growth: 9.425120496291623
Treatment B Mean Growth: 12.318281885794768
Treatment C Mean Growth: 14.858935558008634

F-Statistic: 38.2963
P-Value: 0.0000
```

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

```
Reject the null hypothesis: There is a significant difference in mean
growth rates among the three treatments.
```

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

```
---------------------------------------------------------------------------
-----
NameError                                 Traceback (most recent call
last)
Cell In[15], line 2
      1 # Additional: Post-hoc analysis (Tukey's HSD) if ANOVA is
----> 2 significant
      3 if p_value < alpha:
      4     from statsmodels.stats.multicomp import pairwise_tukeyhsd

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

```
import numpy as np
import pandas as pd
df=pd.read_csv('/content/pre-process_datasample.csv')
```

```
df
```

	Country	Age	Salary	Purchased
0	France	44.0	72000.0	No
1	Spain	27.0	48000.0	Yes
2	Germany	30.0	54000.0	No
3	Spain	38.0	61000.0	No
4	Germany	40.0	NaN	Yes
5	France	35.0	58000.0	Yes
6	Spain	NaN	52000.0	No
7	France	48.0	79000.0	Yes
8	NaN	50.0	83000.0	No
9	France	37.0	67000.0	Yes

Next steps: Generate code with df View recommended plots New interactive sheet

```
df.head()
```

	Country	Age	Salary	Purchased
0	France	44.0	72000.0	No
1	Spain	27.0	48000.0	Yes
2	Germany	30.0	54000.0	No
3	Spain	38.0	61000.0	No
4	Germany	40.0	NaN	Yes

Next steps: Generate code with df View recommended plots New interactive sheet

```
df.Country.fillna(df.Country.mode()[0],inplace=True)
features=df.iloc[:,:-1].values
```

```
<ipython-input-5-20665a0bbaa1>:1: FutureWarning: A value is trying to be set on a copy of a DataFrame c
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate ob

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inpla


  df.Country.fillna(df.Country.mode()[0],inplace=True)
```

```
label=df.iloc[:,-1].values
```

Start coding or generate with AI.

```
from sklearn.impute import SimpleImputer
```

```
age=SimpleImputer(strategy="mean",missing_values=np.nan)
```

```
Salary=SimpleImputer(strategy="mean",missing_values=np.nan)
```

```
age.fit(features[:,[1]])
```

```
▾ SimpleImputer
SimpleImputer()
```

```
Salary.fit(features[:,[2]])
```

```
▾ SimpleImputer
SimpleImputer()
```

```
SimpleImputer()
```

```
▾ SimpleImputer
SimpleImputer()
```

```
features[:,[1]]=age.transform(features[:,[1]])
```

```
features[:,[2]]=Salary.transform(features[:,[2]])
```

```
features
```

```
array([['France', 44.0, 72000.0],
       ['Spain', 27.0, 48000.0],
       ['Germany', 30.0, 54000.0],
       ['Spain', 38.0, 61000.0],
       ['Germany', 40.0, 63777.77777777778],
       ['France', 35.0, 58000.0],
       ['Spain', 38.77777777777778, 52000.0],
       ['France', 48.0, 79000.0],
       ['France', 50.0, 83000.0],
       ['France', 37.0, 67000.0]], dtype=object)
```

```
from sklearn.preprocessing import OneHotEncoder
```

```
oh = OneHotEncoder(sparse_output=False)
```

```
Country=oh.fit_transform(features[:,[0]])
```

```
Country
```

```
array([[1., 0., 0.],
       [0., 0., 1.],
       [0., 1., 0.],
       [0., 0., 1.],
       [0., 1., 0.],
       [1., 0., 0.],
       [0., 0., 1.],
       [1., 0., 0.],
```

```
       [1., 0., 0.],
       [1., 0., 0.]])
```

```
final_set=np.concatenate((Country,features[:,[1,2]]),axis=1)
```

```
final_set
```

```
array([[1.0, 0.0, 0.0, 44.0, 72000.0],
       [0.0, 0.0, 1.0, 27.0, 48000.0],
       [0.0, 1.0, 0.0, 30.0, 54000.0],
       [0.0, 0.0, 1.0, 38.0, 61000.0],
       [0.0, 1.0, 0.0, 40.0, 63777.77777777778],
       [1.0, 0.0, 0.0, 35.0, 58000.0],
       [0.0, 0.0, 1.0, 38.77777777777778, 52000.0],
       [1.0, 0.0, 0.0, 48.0, 79000.0],
       [1.0, 0.0, 0.0, 50.0, 83000.0],
       [1.0, 0.0, 0.0, 37.0, 67000.0]], dtype=object)
```

```
from sklearn.preprocessing import StandardScaler
sc=StandardScaler()
sc.fit(final_set)
feat_standard_scaler=sc.transform(final_set)
```

```
feat_standard_scaler
```

```
array([[ 1.00000000e+00, -5.00000000e-01, -6.54653671e-01,
         7.58874362e-01,  7.49473254e-01],
       [-1.00000000e+00, -5.00000000e-01,  1.52752523e+00,
        -1.71150388e+00, -1.43817841e+00],
       [-1.00000000e+00,  2.00000000e+00, -6.54653671e-01,
        -1.27555478e+00, -8.91265492e-01],
       [-1.00000000e+00, -5.00000000e-01,  1.52752523e+00,
        -1.13023841e-01, -2.53200424e-01],
       [-1.00000000e+00,  2.00000000e+00, -6.54653671e-01,
         1.77608893e-01,  6.63219199e-16],
       [ 1.00000000e+00, -5.00000000e-01, -6.54653671e-01,
        -5.48972942e-01, -5.26656882e-01],
       [-1.00000000e+00, -5.00000000e-01,  1.52752523e+00,
         0.00000000e+00, -1.07356980e+00],
       [ 1.00000000e+00, -5.00000000e-01, -6.54653671e-01,
         1.34013983e+00,  1.38753832e+00],
       [ 1.00000000e+00, -5.00000000e-01, -6.54653671e-01,
         1.63077256e+00,  1.75214693e+00],
       [ 1.00000000e+00, -5.00000000e-01, -6.54653671e-01,
        -2.58340208e-01,  2.93712492e-01]])
```

```
from sklearn.preprocessing import MinMaxScaler
mms=MinMaxScaler(feature_range=(0,1))
mms.fit(final_set)
feat_minmax_scaler=mms.transform(final_set)
feat_minmax_scaler
```

```
array([[1.        , 0.        , 0.        , 0.73913043, 0.68571429],
       [0.        , 0.        , 1.        , 0.        , 0.        ],
       [0.        , 1.        , 0.        , 0.13043478, 0.17142857],
       [0.        , 0.        , 1.        , 0.47826087, 0.37142857],
       [0.        , 1.        , 0.        , 0.56521739, 0.45079365],
       [1.        , 0.        , 0.        , 0.34782609, 0.28571429],
       [0.        , 0.        , 1.        , 0.51207729, 0.11428571],
       [1.        , 0.        , 0.        , 0.91304348, 0.88571429],
       [1.        , 0.        , 0.        , 1.        , 1.        ],
       [1.        , 0.        , 0.        , 0.43478261, 0.54285714]])
```

Start coding or generate with AI.