```
#EX.NO :1.a   Basic Practice Experiments(1 to 4)
#DATA  :  30.07.2024

#NAME :BOOTHALINGESH
N #ROLL NO :
230701056
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - A

import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

data=pd.read_csv('Iris.csv')
data
```

```
      Id  SepalLengthCm  SepalWidthCm  PetalLengthCm  PetalWidthCm  \
0      1            5.1           3.5            1.4           0.2
1      2            4.9           3.0            1.4           0.2
2      3            4.7           3.2            1.3           0.2
3      4            4.6           3.1            1.5           0.2
4      5            5.0           3.6            1.4           0.2
..   ...            ...           ...            ...           ...
145  146            6.7           3.0            5.2           2.3
146  147            6.3           2.5            5.0           1.9
147  148            6.5           3.0            5.2           2.0
148  149            6.2           3.4            5.4           2.3
149  150            5.9           3.0            5.1           1.8

            Species
0       Iris-setosa
1       Iris-setosa
2       Iris-setosa
3       Iris-setosa
4       Iris-setosa
..              ...
145  Iris-virginica
146  Iris-virginica
147  Iris-virginica
148  Iris-virginica
149  Iris-virginica

[150 rows x 6 columns]
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 6 columns):
 #   Column         Non-Null Count  Dtype
```

```
 0   Id             150 non-null    int64
 1   SepalLengthCm  150   float
     non-null             64
 2   SepalWidthCm   150   float

 5   Species        150 non-null    object
dtypes: float64(4), int64(1), object(1)
memory usage: 7.2+ KB
```

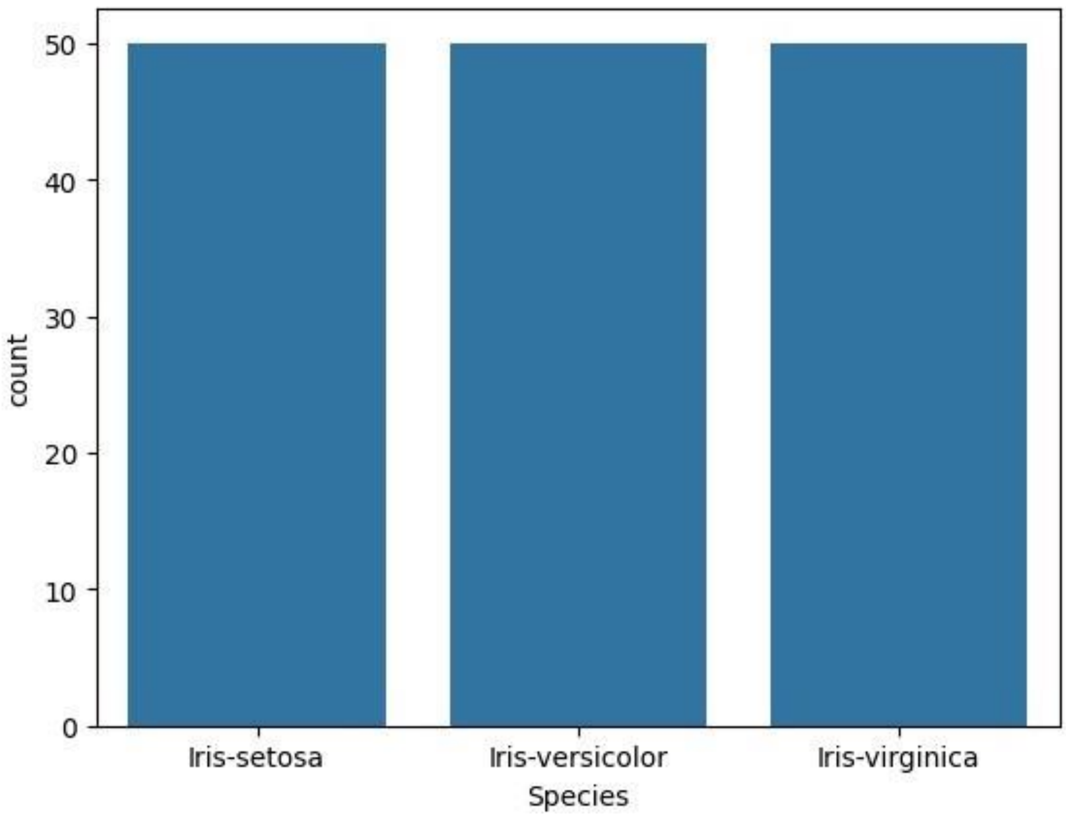
```
data.describe()
```

```
                 Id SepalLengthCm SepalWidthCm PetalLengthCm
PetalWidthCm
count  150.000000     150.000000    150.000000     150.000000
150.000000
mean    75.500000       5.843333      3.054000       3.758667
1.198667
std     43.445368       0.828066      0.433594       1.764420
0.763161
min      1.000000       4.300000      2.000000       1.000000
0.100000
25%     38.250000       5.100000      2.800000       1.600000
0.300000
50%     75.500000       5.800000      3.000000       4.350000
1.300000
75%    112.750000       6.400000      3.300000       5.100000
1.800000
max    150.000000       7.900000      4.400000       6.900000
2.500000
```

```
data.value_counts('Species')
```

```
Species
Iris-setosa        50
Iris-versicolor    50
Iris-virginica     50
Name: count, dtype: int64
```

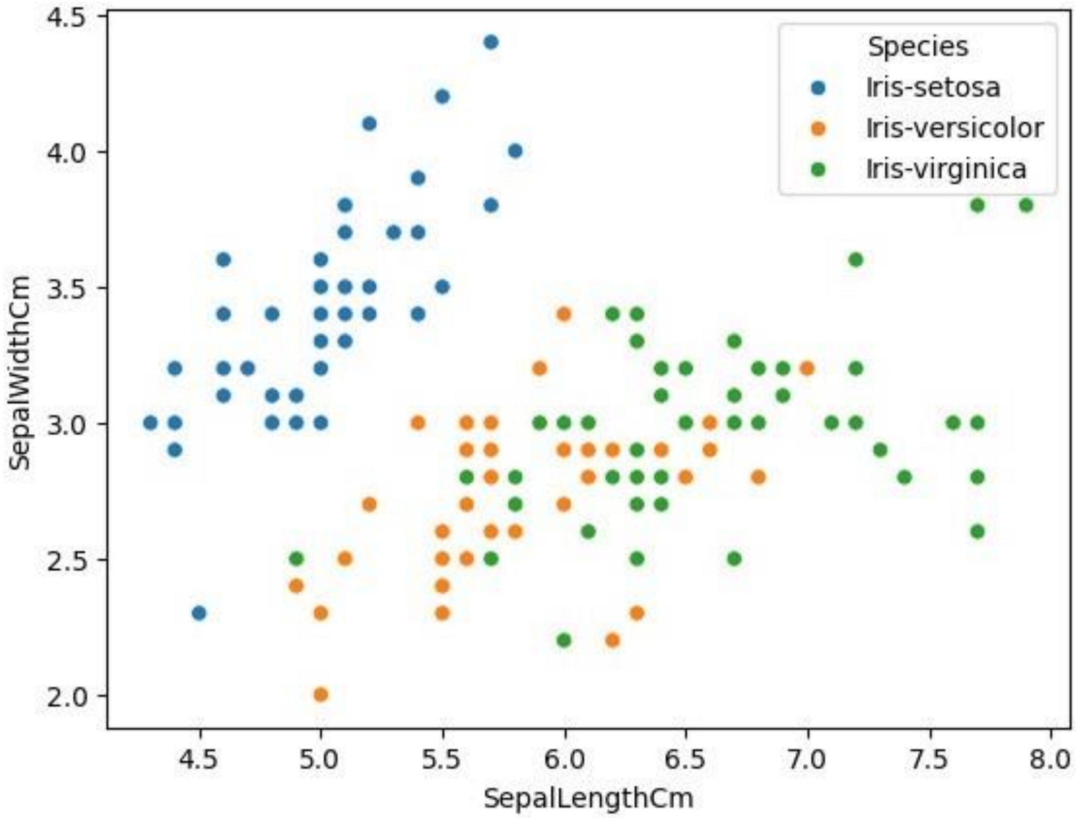
```
sns.countplot(x='Species',data=data,)
plt.show()
```



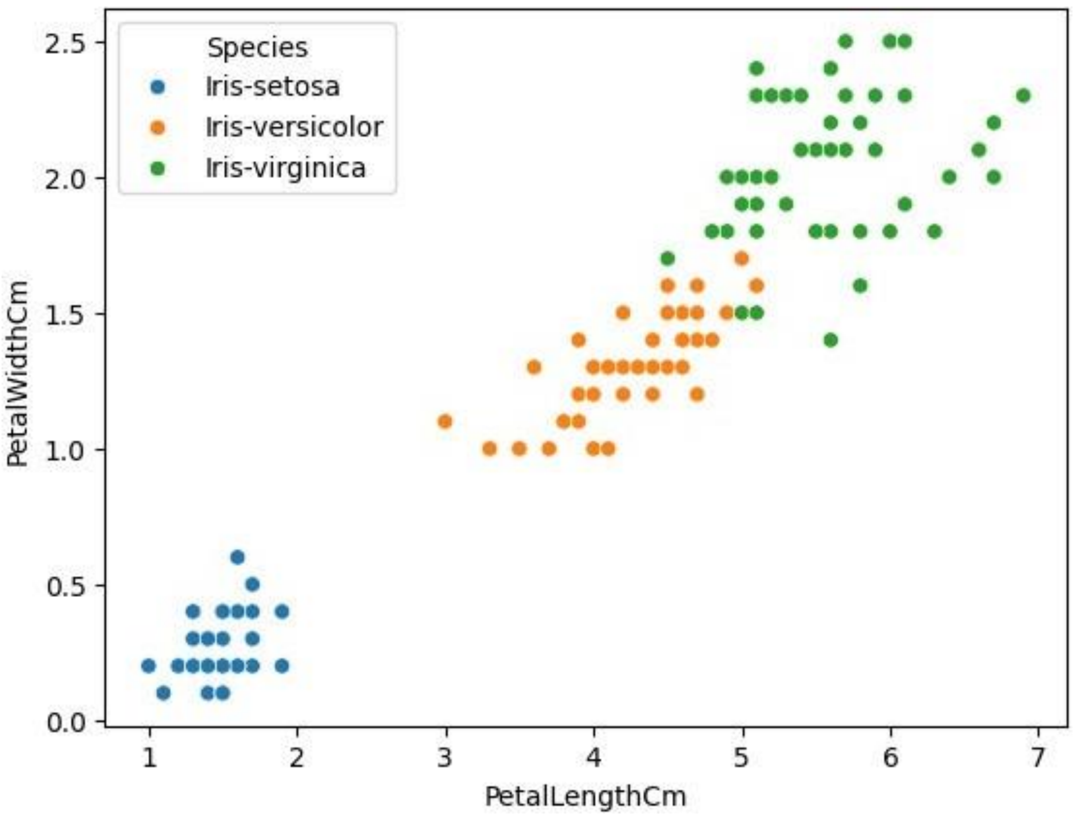

```
dummies=pd.get_dummies(data.Species)

FinalDataset=pd.concat([pd.get_dummies(data.Species
),data.iloc[:,[0,1,2,3]]],axis=1)

FinalDataset.head()
```

```
   Iris-setosa  Iris-versicolor        SepalLeng  \
   Iris-virginica  Id                       thCm
0          True             False              5.1
           False            1                  4.9
```

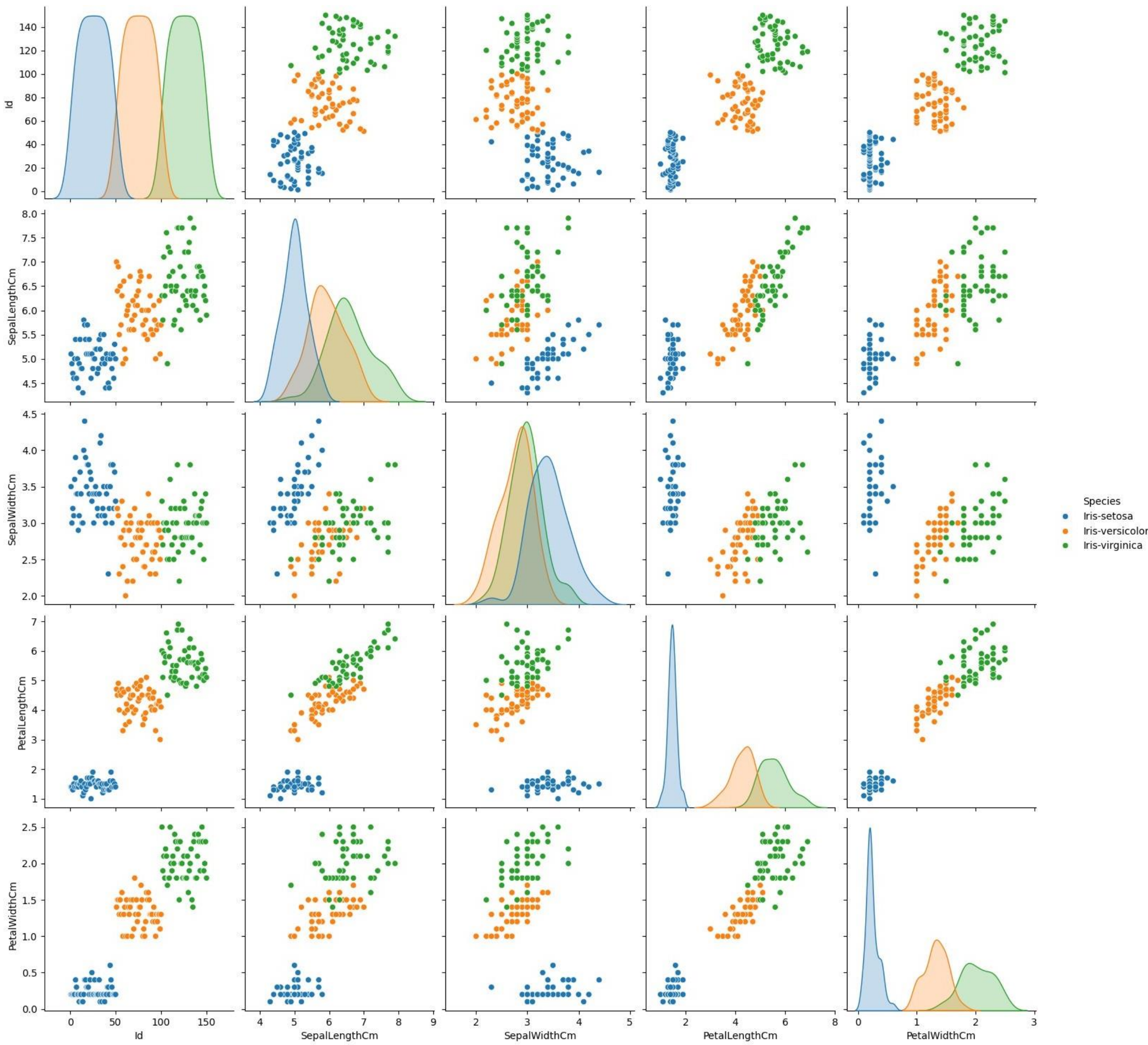
```
   SepalWidthCm
PetalLengthCm0
            3.5    1.4
1           3.0
```



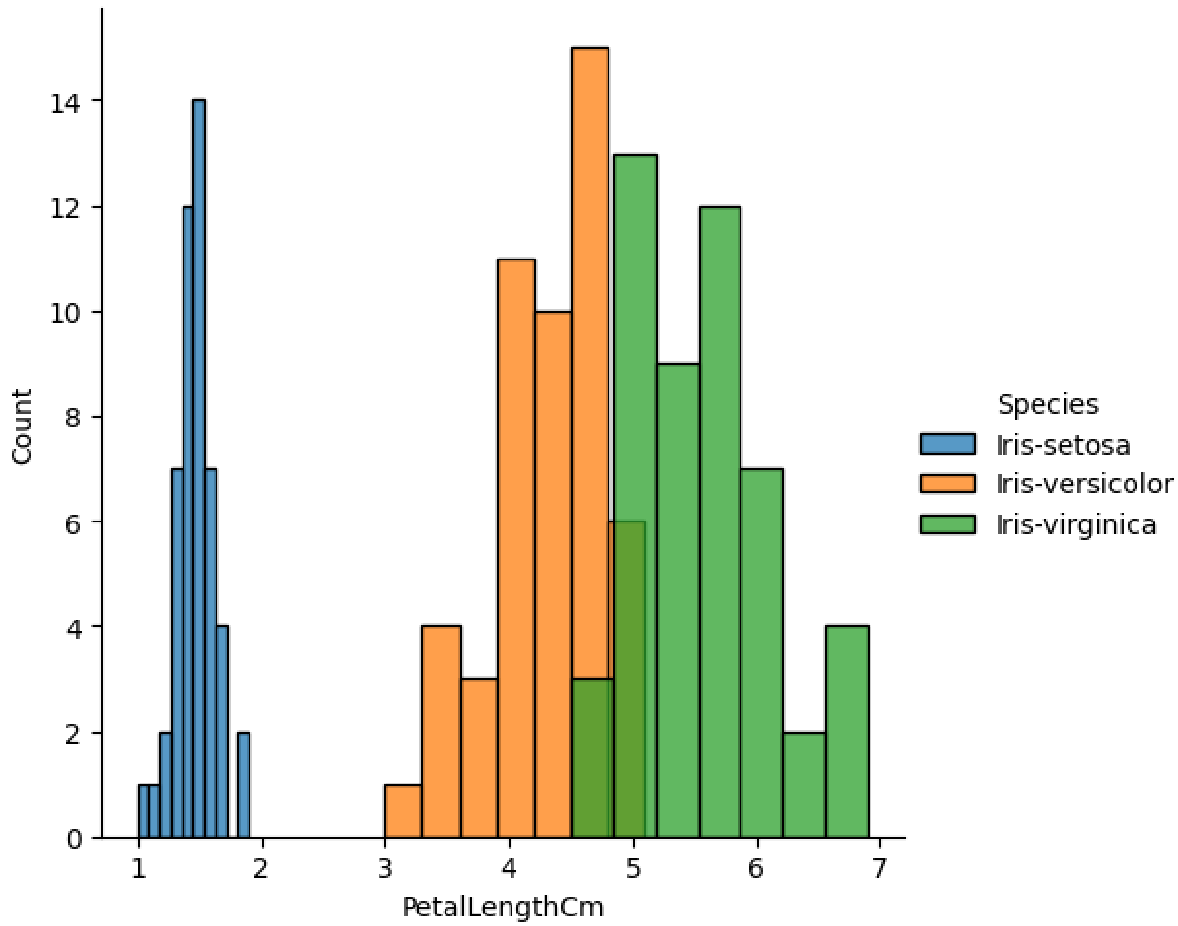

```
sns.scatterplot(x='PetalLengthCm',y='PetalWidthCm',
hue='Species',data=data,)
```



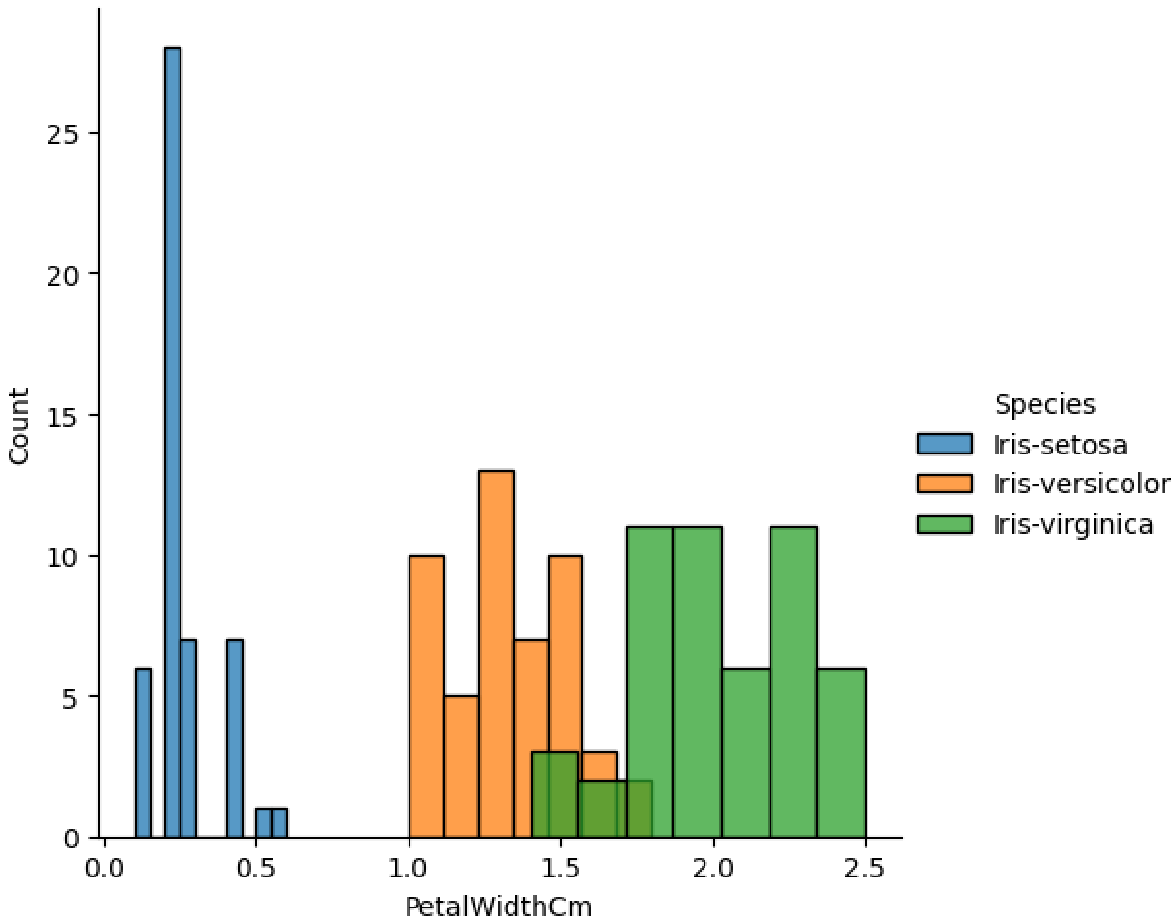

```
sns.pairplot(data,hue='Species',height=3);
```



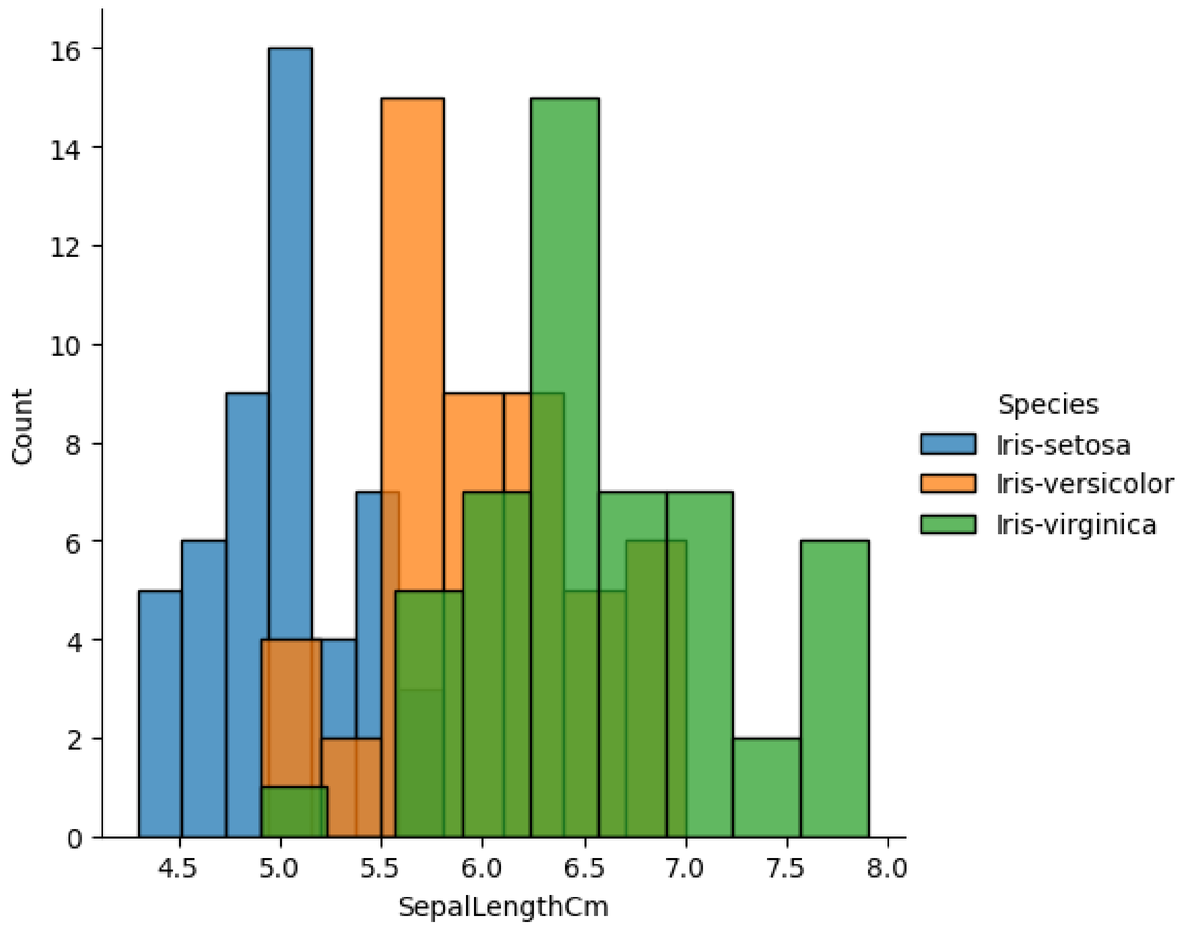

```
plt.show()

sns.FacetGrid(data,hue='Species',height=5).map(sns.
histplot,'PetalLengthCm').add_legend();
```



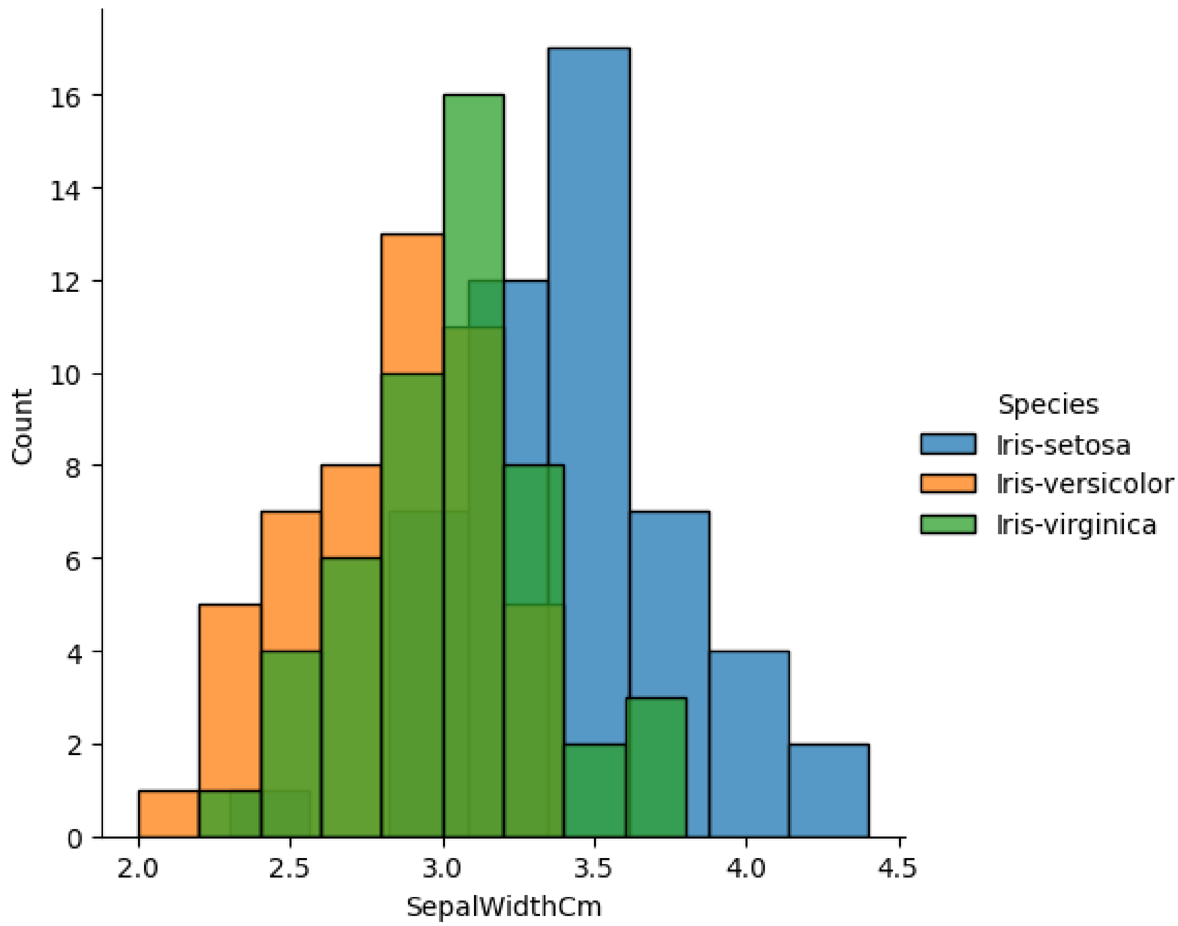

```
sns.FacetGrid(data,hue='Species',height=5).map(sns.
histplot,'PetalWidthCm').add_legend();
```




```
sns.FacetGrid(data,hue='Species',height=5).map(sns.
histplot,'SepalLengthCm').add_legend();
```




```
sns.FacetGrid(data,hue='Species',height=5).map(sns.
histplot,'SepalWidthCm').add_legend();
```




```
#EX.NO :1.b Pandas Buit in function. Numpy Buit in
fuction- Arrayslicing, Ravel,Reshape,ndim
#DATA  :  06.08.2024

#
N
A
M
E
:
B
O
O
```

```
1
```

```
new_array=array.reshape(3,3)
```

```
new_array
```

```
array([[39, 97, 88],
       [58, 29, 87],
       [27, 88, 91]])
```

```
new_array.ndim
```

```
2
```

```
new_array.ravel()
```

```
array([39, 97, 88, 58, 29, 87, 27, 88, 91])
```

```
newm=new_array.reshape(3,3)
```

```
newm
```

```
array([[39, 97, 88],
       [58, 29, 87],
       [27, 88, 91]])
```

```
newm[2,1:3]
```

```
array([88, 91])
```

```
newm[1:2,1:3]
```

```
array([[29, 87]])
```

```
new_array[0:3,0:0]
```

```
array([], shape=(3, 0), dtype=int32)
```

```
new_array[1:3]
```

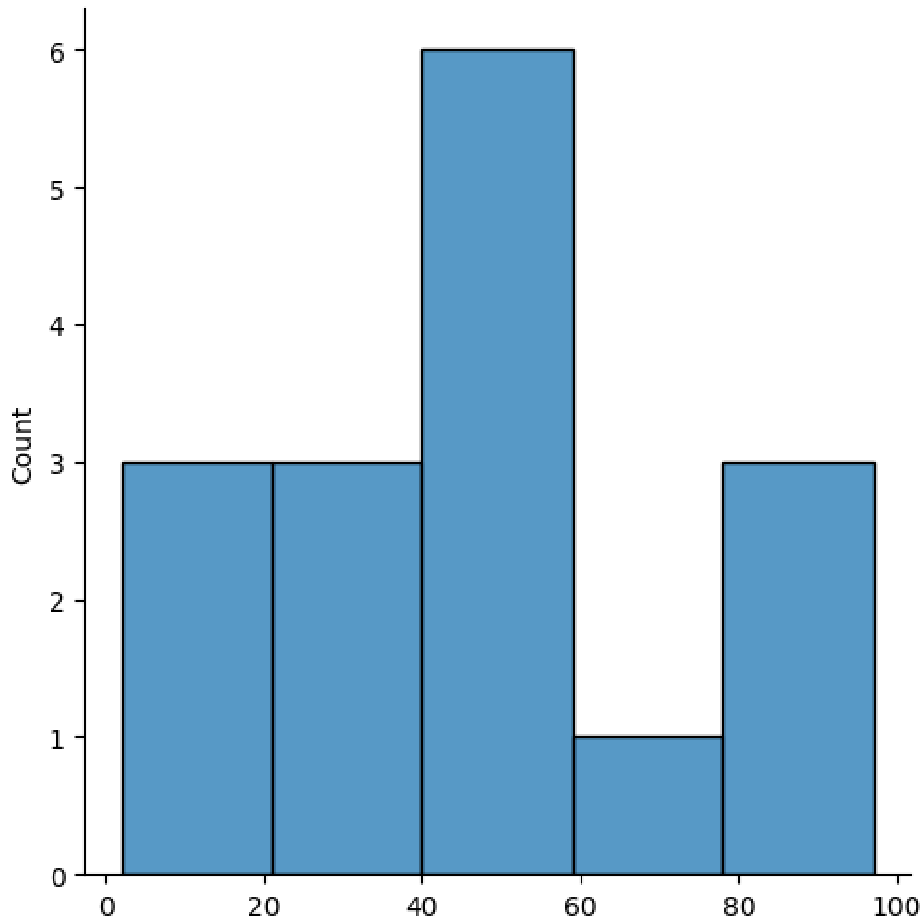
```
array([[58, 29, 87],
       [27, 88, 91]])
```

```
#EX.NO :2 Outlier detection
#DATA  :  13.08.2024

#NAME :
BOOTHALINGESH N
#ROLL NO : 230701056
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - A

import numpy as np
import warnings
warnings.filterwarnings('ignore')
```

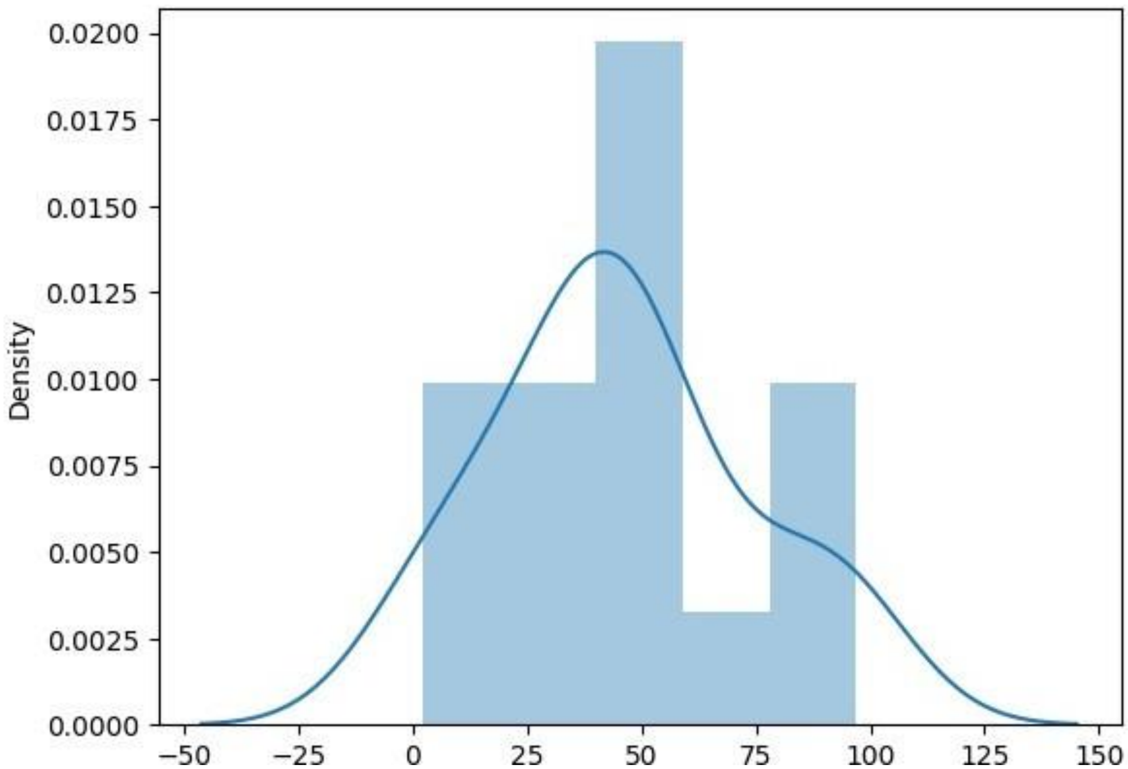
```
array=np.random.
randint(1,100,16
)array
```

```
array([37, 15, 49, 89, 30, 47,  2, 86, 53, 63, 41,
46, 42, 27,  5,
97])
```

```
a

r

r

a

y

.

m

e

a

n

(

)

4
```

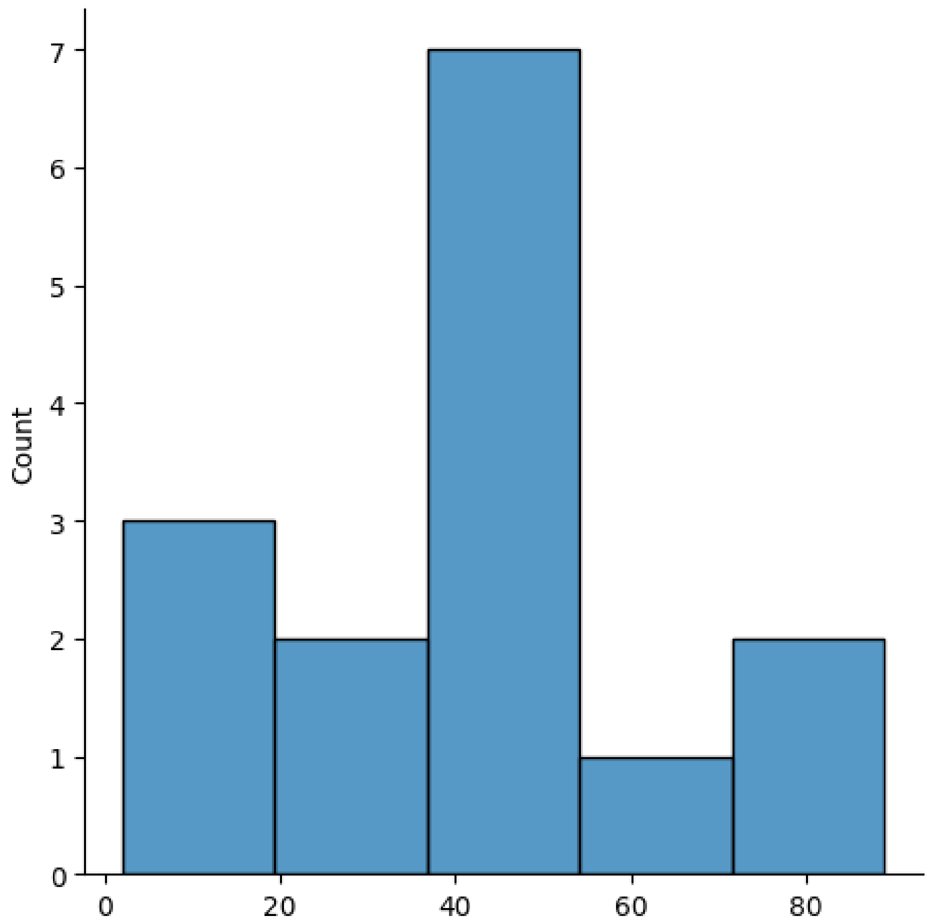



```
sns.distplot(array)
```




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

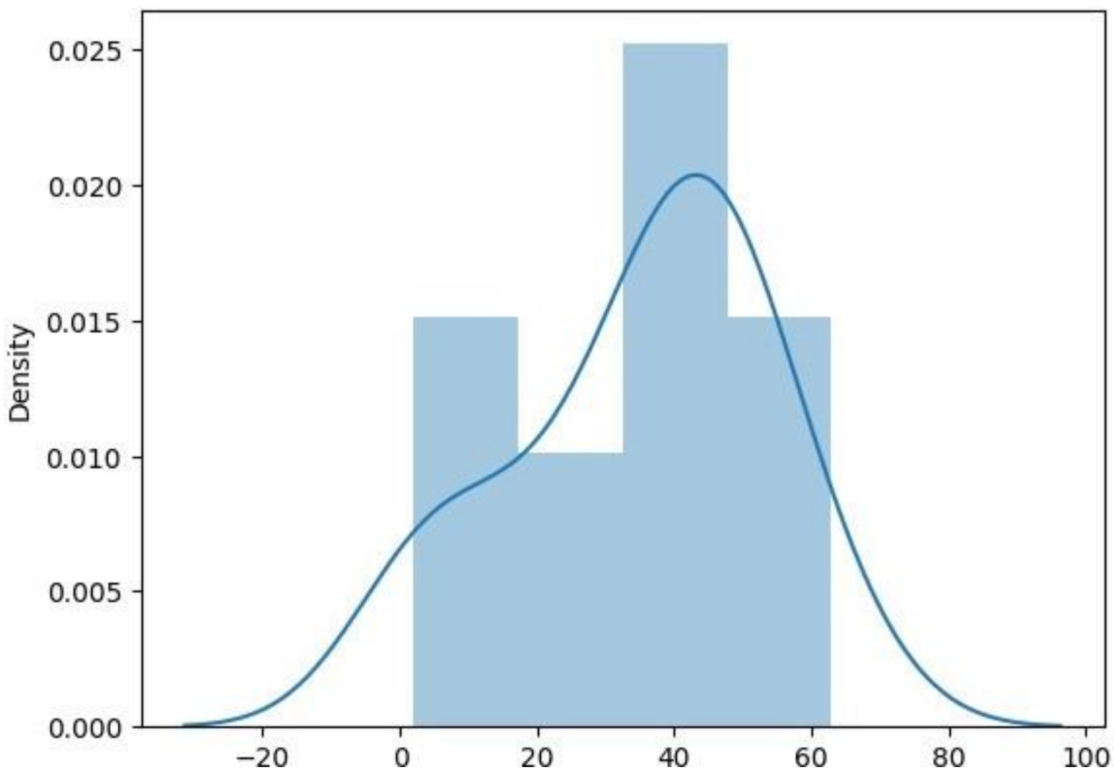
```
array([37, 15, 49, 89, 30, 47,  2, 86, 53, 63, 41,
46, 42, 27,  5])
```




```
lr1,ur1=ou
tDetection
(new_array
)lr1,ur1
```

```
(-5.25, 84.75)
```

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




```
#EX.NO :3 Missing and
inappropriate data#DATA
:  20.08.2024

#
N
A
M
E
:
B
O
O
T
```

```
   CustomerID Age_Group  Rating(1-5)      Hotel FoodPreference  Bill  \
0           1     20-25            4       Ibis            veg  1300
1           2     30-35            5  LemonTree        Non-Veg  2000
2           3     25-30            6     RedFox            Veg  1322
3           4     20-25           -1  LemonTree            Veg  1234
4           5       35+            3       Ibis     Vegetarian   989
```

```
5          6    35+           3       Ibys     Non-Veg  1909
6          7    35+           4     RedFox  Vegetarian  1000
7          8  20-25           7  LemonTree         Veg  2999
8          9  25-30           2       Ibis     Non-Veg  3456
9          9  25-30           2       Ibis     Non-Veg  3456
10        10  30-35           5     RedFox     non-Veg -6755
```

```
    NoOfPax  EstimatedSalary Age_Group.1
0         2            40000       20-25
1         3            59000       30-35
2         2            30000       25-30
3         2           120000       20-25
4         2            45000         35+
5         2           122220         35+
6        -1            21122         35+
7       -10           345673       20-25
8         3           -99999       25-30
9         3           -99999       25-30
10        4            87777       30-35
5     se
df.duplicated()
6    Fal
7     se
dtype:
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11 entries, 0 to 10
Data columns (total 9 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   CustomerID       11 non-null     int64
 1   Age_Group        11 non-null     object
 2   Rating(1-5)      11 non-null     int64
```

```
 3   Hotel              11    obje
     non-null                 ct
 5   Bill               11    int
     non-null                 64

 8   Age_Group.1       11 non-null      object
dtypes: int64(5), object(4)
memory usage: 924.0+ bytes
```

```
df.drop_duplicates(inplace=True)
df
```

```
    CustomerID Age_Group  Rating(1-5)       Hotel FoodPreference  Bill
\
0            1     20-25            4        Ibis            veg  1300

1            2     30-35            5   LemonTree        Non-Veg  2000

2            3     25-30            6      RedFox            Veg  1322

3            4     20-25           -1   LemonTree            Veg  1234

4            5       35+            3        Ibis     Vegetarian   989

5            6       35+            3        Ibys        Non-Veg  1909

6            7       35+            4      RedFox     Vegetarian  1000

7            8     20-25            7   LemonTree            Veg  2999

8            9     25-30            2        Ibis        Non-Veg  3456

10          10     30-35            5      RedFox        non-Veg -6755


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

```
len(df)
```

```
10
```

```
index=np.array(list(range(0,len(df))))
df.set_index(index,inplace=True)
index
```

```
array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
```

```
df
```

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

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

```
df.drop(['Age_Group.1'],axis=1,inplace=True)
df
```

```
   CustomerID Age_Group  Rating(1-5)      Hotel  FoodPreference Bill
NoOfPax  \
0           1     20-25            4       Ibis
2
```

```
1            2      30-35            5  LemonTree        Non-Veg  2000
3
2            3      25-30            6     RedFox            Veg  1322
2
3            4      20-25           -1  LemonTree            Veg  1234
2
4            5        35+            3       Ibis     Vegetarian   989
2
5            6        35+            3       Ibys        Non-Veg  1909
2
6            7        35+            4     RedFox     Vegetarian  1000
-1
7            8      20-25            7  LemonTree            Veg  2999
-10
8            9      25-30            2       Ibis        Non-Veg  3456
3
9           10      30-35            5     RedFox        non-Veg -6755
4

   EstimatedSalary
0            40000
1            59000
2            30000
3           120000
4            45000
5           122220
6            21122
7           345673
8           -99999
9            87777
```

```
df.CustomerID.loc[df.CustomerID<0]=np.nan
df.Bill.loc[df.Bill<0]=np.nan
df.EstimatedSalary.loc[df.EstimatedSalary<0]=np.nan
df
```

```
   CustomerID Age_Group  Rating(1-5)      Hotel FoodPreference     Bill
\
0         1.0     20-25            4       Ibis            veg   1300.0

1         2.0     30-35            5  LemonTree        Non-Veg   2000.0

2         3.0     25-30            6     RedFox            Veg   1322.0

3         4.0     20-25           -1  LemonTree            Veg   1234.0

4         5.0       35+            3       Ibis     Vegetarian    989.0

5         6.0       35+            3       Ibys        Non-Veg   1909.0
```

```
6          7.0        35+              4     RedFox    Vegetarian  1000.0

7          8.0      20-25              7  LemonTree           Veg  2999.0

8          9.0      25-30              2       Ibis       Non-Veg  3456.0

9         10.0      30-35              5     RedFox       non-Veg     NaN


   NoOfPax  EstimatedSalary
0        2          40000.0
1        3          59000.0
2        2          30000.0
3        2         120000.0
4        2          45000.0
5        2         122220.0
6       -1          21122.0
7      -10         345673.0
8        3              NaN
9        4          87777.0
```

```
df['NoOfPax'].loc[(df['NoOfPax']<1) | (df['NoOfPax']>20)]=np.nan
df
```

```
   CustomerID Age_Group  Rating(1-5)      Hotel FoodPreference    Bill  \
0         1.0     20-25            4       Ibis            veg  1300.0

1         2.0     30-35            5  LemonTree        Non-Veg  2000.0

2         3.0     25-30            6     RedFox            Veg  1322.0

3         4.0     20-25           -1  LemonTree            Veg  1234.0

4         5.0       35+            3       Ibis     Vegetarian   989.0

5         6.0       35+            3       Ibys        Non-Veg  1909.0

6         7.0       35+            4     RedFox     Vegetarian  1000.0

7         8.0     20-25            7  LemonTree            Veg  2999.0

8         9.0     25-30            2       Ibis        Non-Veg  3456.0

9        10.0     30-35            5     RedFox        non-Veg     NaN


   NoOfPax  EstimatedSalary
0      2.0          40000.0
1      3.0          59000.0
2      2.0          30000.0
```

```
3       2.0         120000.0
4       2.0          45000.0
5       2.0         122220.0
6       NaN          21122.0
7       NaN         345673.0
8       3.0              NaN
9       4.0          87777.0
```

```
df.Age_Group.unique()
```

```
array(['20-25', '30-35', '25-30', '35+'], dtype=object)
```

```
df.Hotel.unique()
```

```
array(['Ibis', 'LemonTree', 'RedFox', 'Ibys'], dtype=object)
```

```
df.Hotel.replace(['Ibys'],'Ibis',inplace=True)
df.FoodPreference.unique
```

```
<bound method Series.unique of 0           veg
1        Non-Veg
2            Veg
3            Veg
4     Vegetarian
5        Non-Veg
6     Vegetarian
7            Veg
8        Non-Veg
9        non-Veg
Name: FoodPreference, dtype: object>
```

```
df.FoodPreference.replace(['Vegetarian','veg'],'Veg',inplace=True)
df.FoodPreference.replace(['non-Veg'],'Non-Veg',inplace=True)
```

```
df.EstimatedSalary.fillna(round(df.EstimatedSalary.mean()),inplace=Tru
e)
df.NoOfPax.fillna(round(df.NoOfPax.median()),inplace=True)
df['Rating(1-5)'].fillna(round(df['Rating(1-5)'].median()),
inplace=True)
df.Bill.fillna(round(df.Bill.mean()),inplace=True)
df
```

```
   CustomerID Age_Group  Rating(1-5)      Hotel  FoodPreference    Bill
\
0         1.0     20-25            4       Ibis             Veg  1300.0

1         2.0     30-35            5  LemonTree         Non-Veg  2000.0

2         3.0     25-30            6     RedFox             Veg  1322.0

3         4.0     20-25           -1  LemonTree             Veg  1234.0
```

4	5.0	35+	3	Ibis	Veg	989.0
5	6.0	35+	3	Ibis	Non-Veg	1909.0
6	7.0	35+	4	RedFox	Veg	1000.0
7	8.0	20-25	7	LemonTree	Veg	2999.0
8	9.0	25-30	2	Ibis	Non-Veg	3456.0
9	10.0	30-35	5	RedFox	Non-Veg	1801.0

	NoOfPax	EstimatedSalary
0	2.0	40000.0
1	3.0	59000.0
2	2.0	30000.0
3	2.0	120000.0
4	2.0	45000.0
5	2.0	122220.0
6	2.0	21122.0
7	2.0	345673.0
8	3.0	96755.0
9	4.0	87777.0

```
#EX.NO :4 Data Preprocessing
#DATA  :  27.08.2024

#NAME :
BOOTHALINGESH N
#ROLL NO : 230701056
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - A

import numpy as np
import pandas as pd
import warnings
warnings.filterwarnings('ignore')
df=pd.read_csv("pre_process_datasample.csv")
df
```

```
  Count   A    Salary
0    ry  ge    72000       N
1  Franc  44   .0          o
2     e  .0    48000      Ye
3  Spain  27   .0          s
4  Germa  .0   54000      No
5    ny   30   .0         No
6  Spain  .0   61000      Ye
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 4 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Country    10 non-null     object
 3   Purchased  10 non-null     object
dtypes: float64(2), object(2)
memory usage: 452.0+ bytes
```

```
df.Country.mode()
```

```
0    France
Name: Country, dtype: object
```

```
df.Country.mode()[0]
```

```
'France'
```

```
type(df.Country.mode())
```

```
pandas.core.series.Series
```

```
df.Country.fillna(df.Country.mode()[0],inplace=True)
df.Age.fillna(df.Age.median(),inplace=True)
df.Salary.fillna(round(df.Salary.mean()),inplace=True)
df
```

```
pd.get_dummies(df.Country)
```

	France	Germany	Spain
0	True	False	False
1	False	False	True
2	False	True	False
3	False	False	True
4	False	True	False

```
5    True    False  False
6   False    False   True
7    True    False  False
8   False     True  False
9    True    False  False
```

```python
updated_dataset=pd.concat([pd.get_dummies(df.Country),df.iloc[:,
[1,2,3]]],axis=1)
```

```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 4 columns):
 #   Column     Non-Null Count  Dtype

 0   Country    10 non-null     object
 1   Age        10 non-null     float64
 2   Salary     10 non-null     float64
 3   Purchased  10 non-null     object
dtypes: float64(2), object(2)
memory usage: 452.0+ bytes
```

```python
updated_dataset.Purchased.replace(['No','Yes'],[0,1],inplace=True)
```

```python
#EX.NO :5 EDA-Quantitative and Qualitative plots
#DATA  :  27.08.2024

#NAME :
BOOTHALINGESH N
#ROLL NO : 230701056
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - A
import numpy as np
import pandas as pd
import warnings
warnings.filterwarnings('ignore')
df=pd.read_csv("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    .0    61000    No
4                         Ye
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 4 columns):
 #   Column     Non-Null Count  Dtype
 0   Country    10 non-null     object
 3   Purchased  10 non-null     object
dtypes: float64(2), object(2)
memory usage: 452.0+ bytes
```

```
df.Country.mode()
```

```
0    France
Name: Country, dtype: object
```

```
df.Country.mode()[0]
```

```
'France'
```

```
type(df.Country.mode())
```

```
pandas.core.series.Series
```

```
df.Country.fillna(df.Country.mode()[0],inplace=True)
df.Age.fillna(df.Age.median(),inplace=True)
df.Salary.fillna(round(df.Salary.mean()),inplace=True)
df
```

```
  Count  A   Salary
0    ry  ge  72000      N
2     e  .0  48000     Ye
3 Spain  27  .0         s
4 Germa  .0  54000     No
5    ny  30  .0        No
6 Spain  .0  61000     Ye
```

```
pd.get_dummies(df.Country)
```

	France	Germany	Spain
0	True	False	False
1	False	False	True
2	False	True	False
3	False	False	True
4	False	True	False

```
5    True    False  False
6   False    False   True
7    True    False  False
8   False     True  False
9    True    False  False
```

```
updated_dataset=pd.concat([pd.get_dummies(df.Country),df.iloc[:,
[1,2,3]]],axis=1)
updated_dataset
```

```
   France Germany   A    Salary
0   Spain True False  ge  72000       N
1       False False  44  .0           o
2            False  .0   48000       Ye
3             True  27   .0           s
4   False     True  .0   54000       No
5      FalseFalse   30   .0          No
6            False  .0   61000       Ye
```

```
--- -----   ---------- ----
```

```
df.info()
```

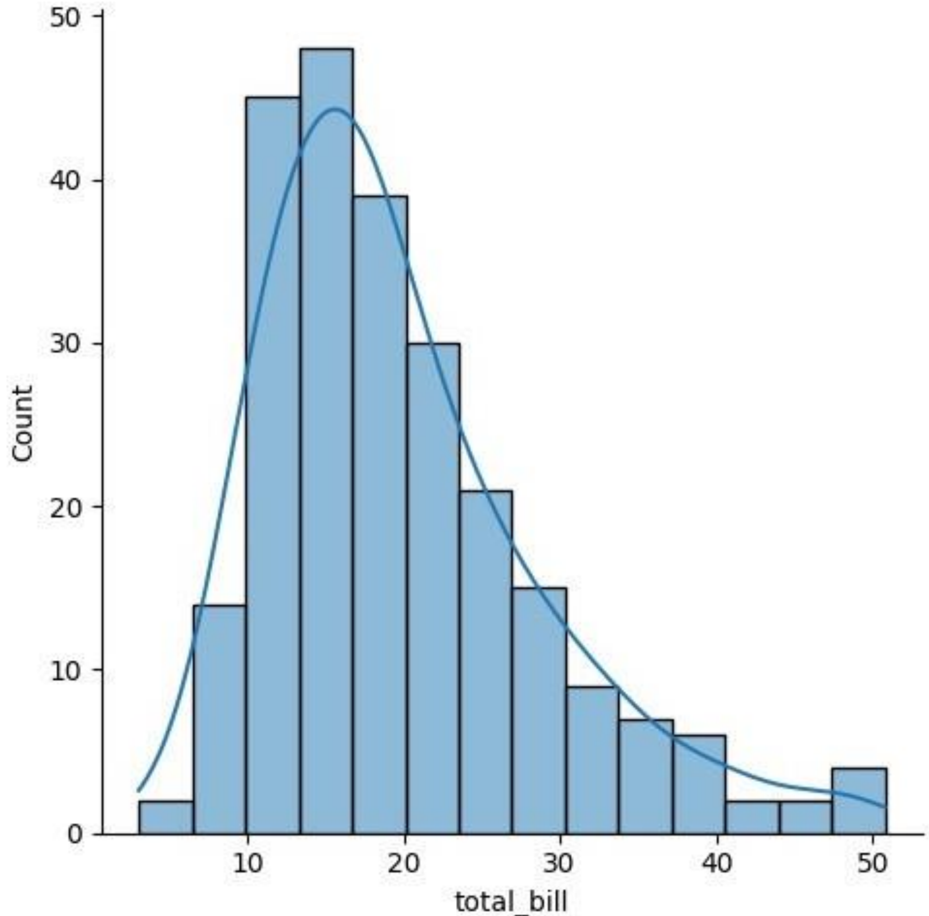
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 4 columns):
 #   Column     Non-Null Count  Dtype
 0   Country    10 non-null     object
 1   Age        10 non-null     float64
 2   Salary     10 non-null     float64
 3   Purchased  10 non-null     object
dtypes: float64(2), object(2)        No
memory usage: 452.0+ bytes    )00     Ye
```

```
updated_dataset
```

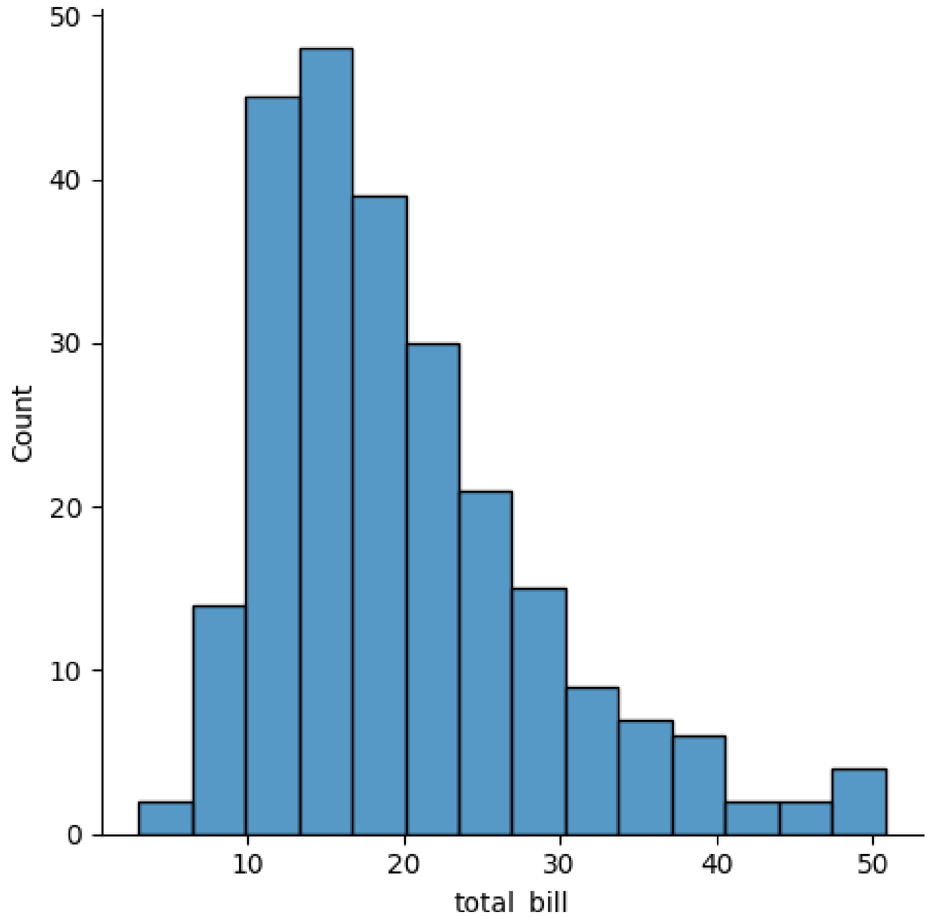
```
#EX.NO :5 EDA-Quantitative and Qualitative plots
#DATA  : 03.09.2024

#NAME :
BOOTHALINGESH N
#ROLL NO :
BOOTHALINGESH N
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - A

import seaborn as sns
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline

tips=sns.load_dataset('tips')
tips.head()
```

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

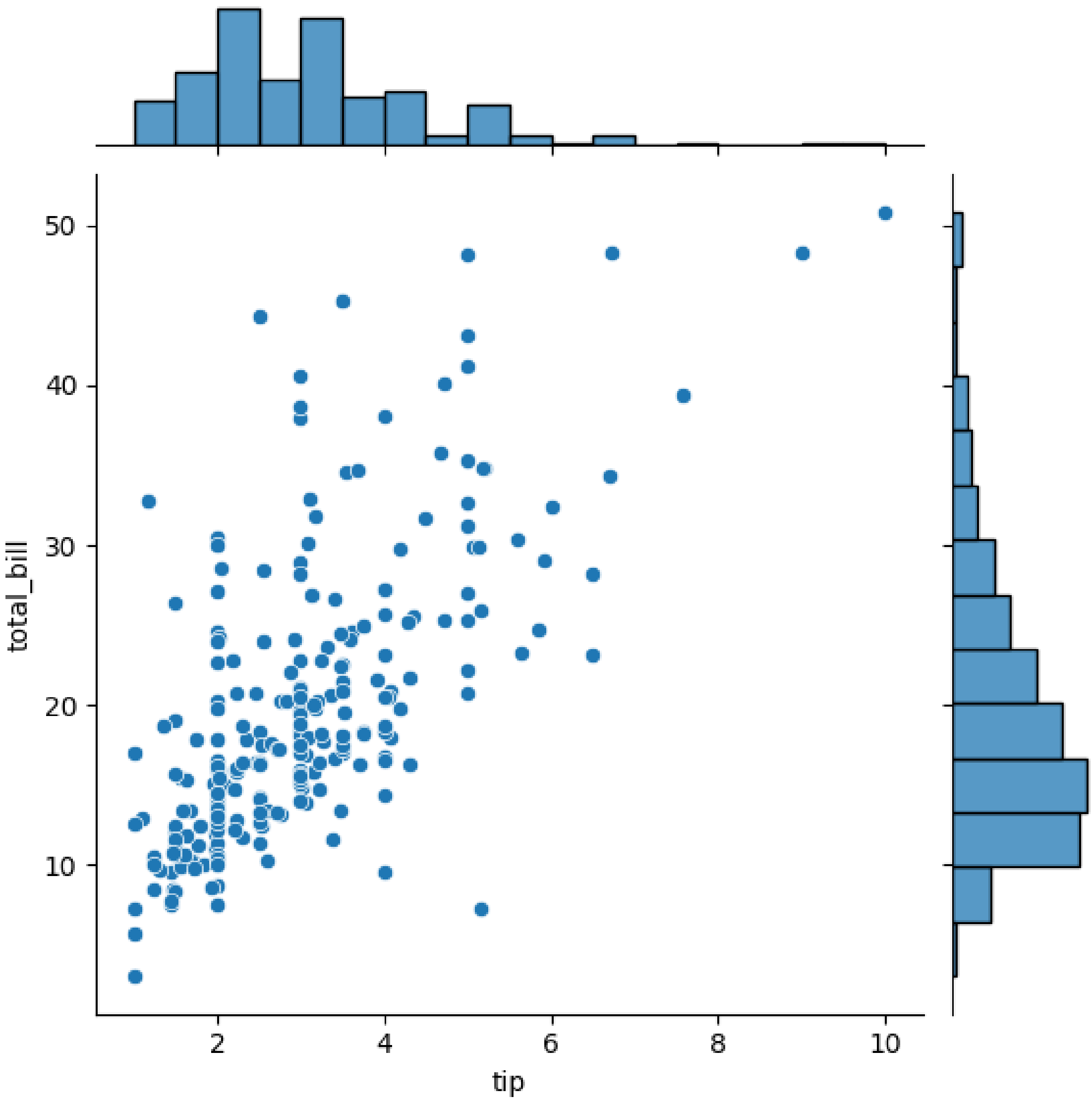
```
sns.displot(tips.total_bill,kde=True)
```



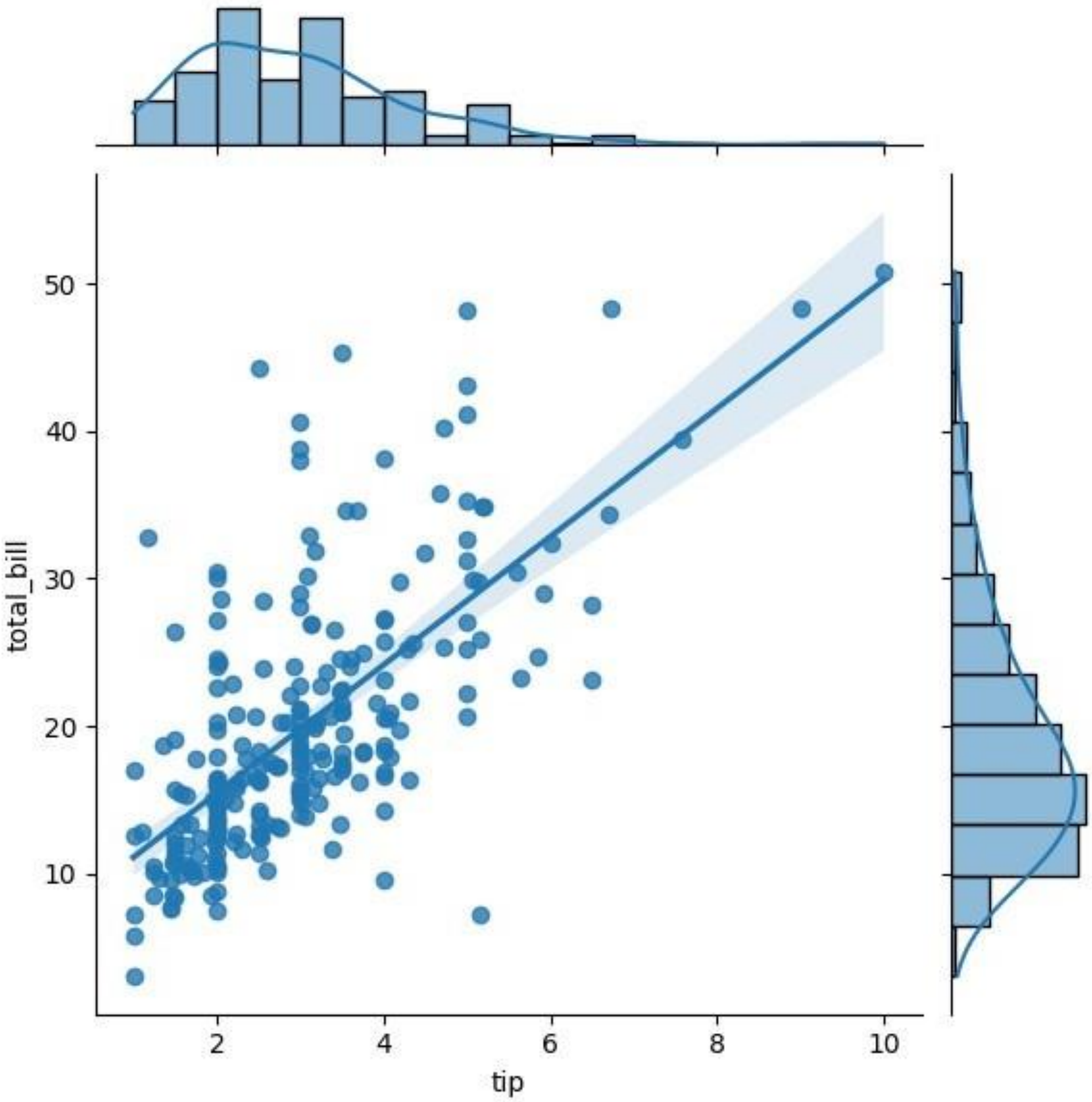

```
sns.displot(tips.total_bill,kde=False)
```



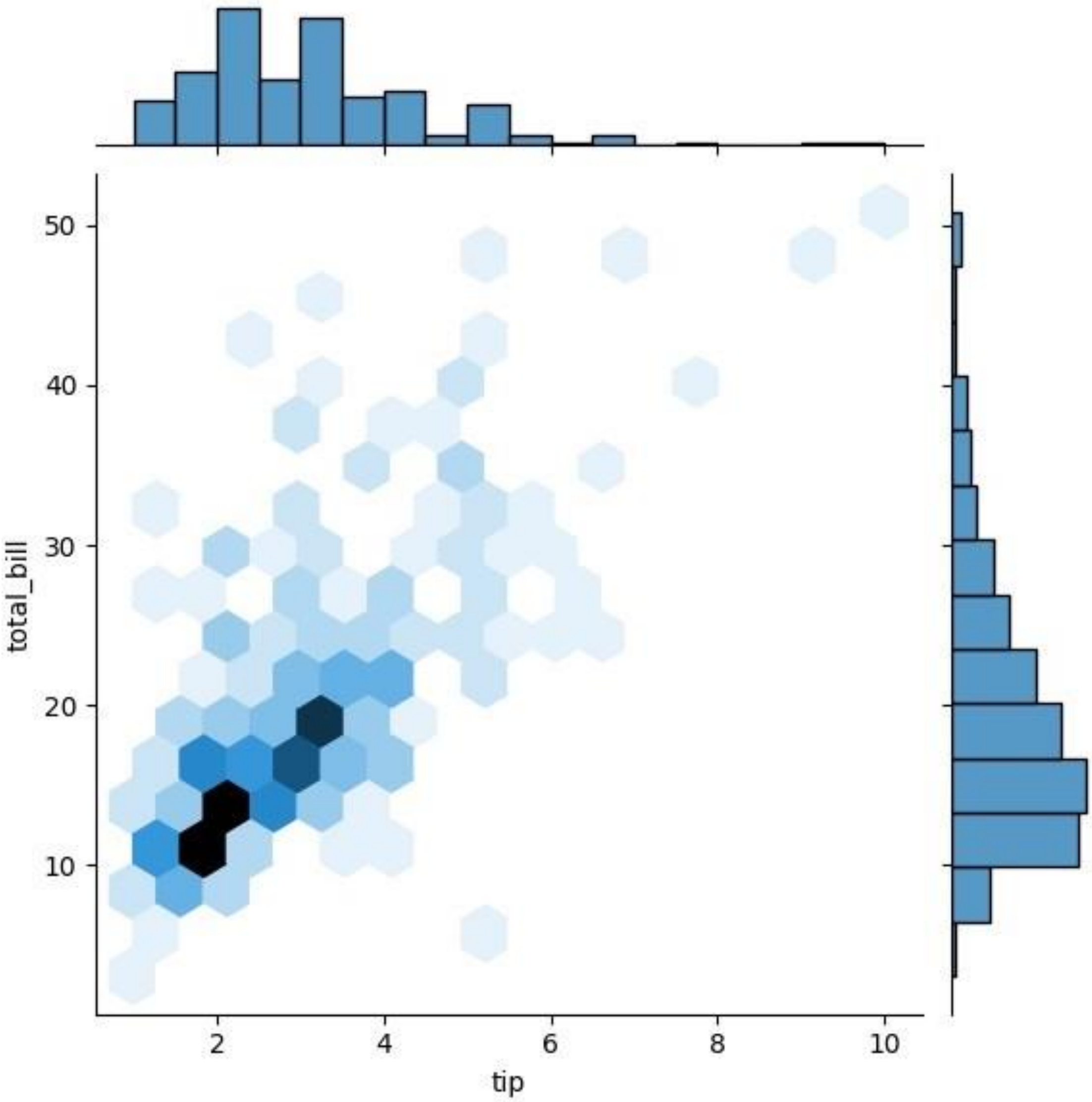

```
sns.jointplot(x=tips.tip,y=tips.total_bill)
```



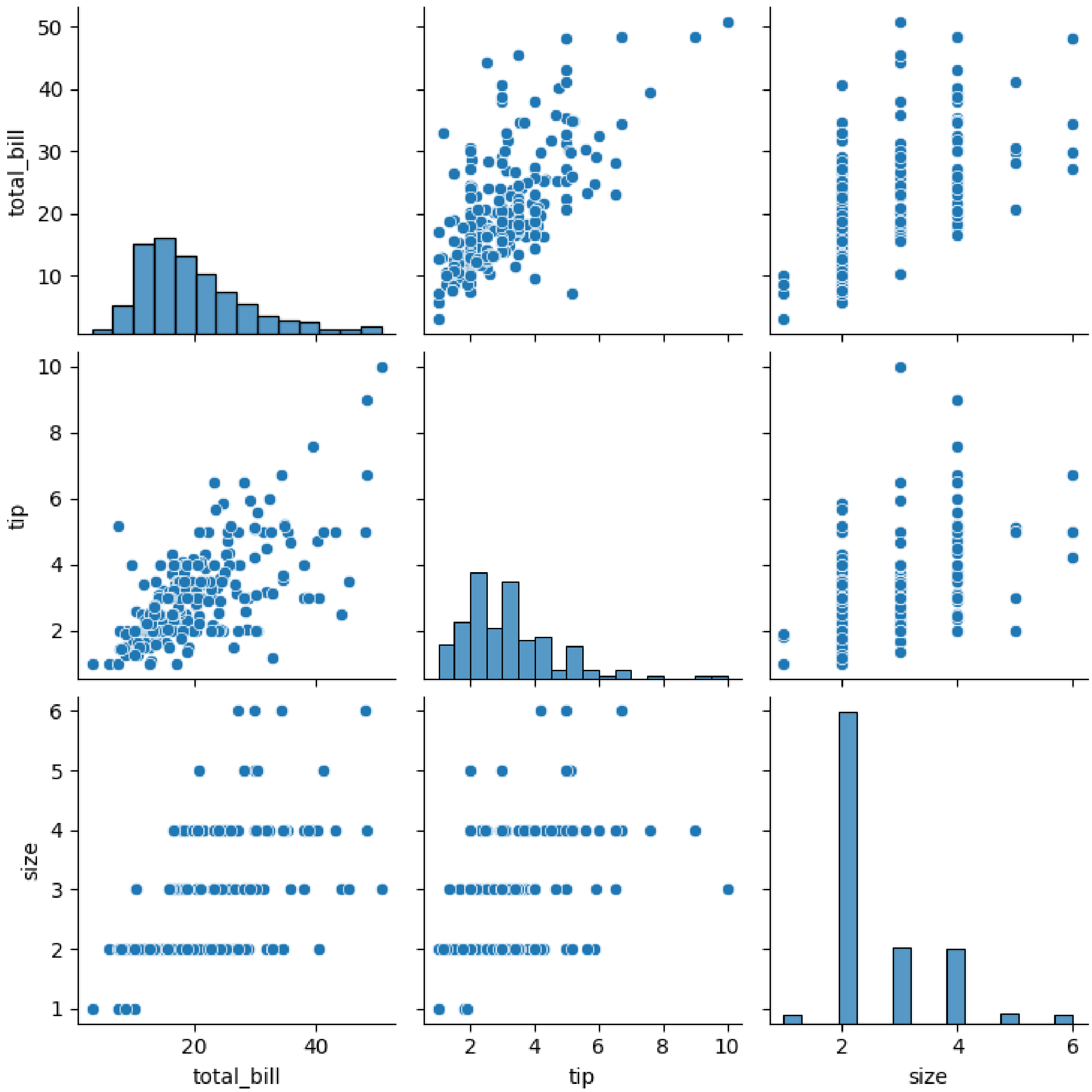

```
sns.jointplot(x=tips.tip,y=tips.total_bill,kind="re
g")
```



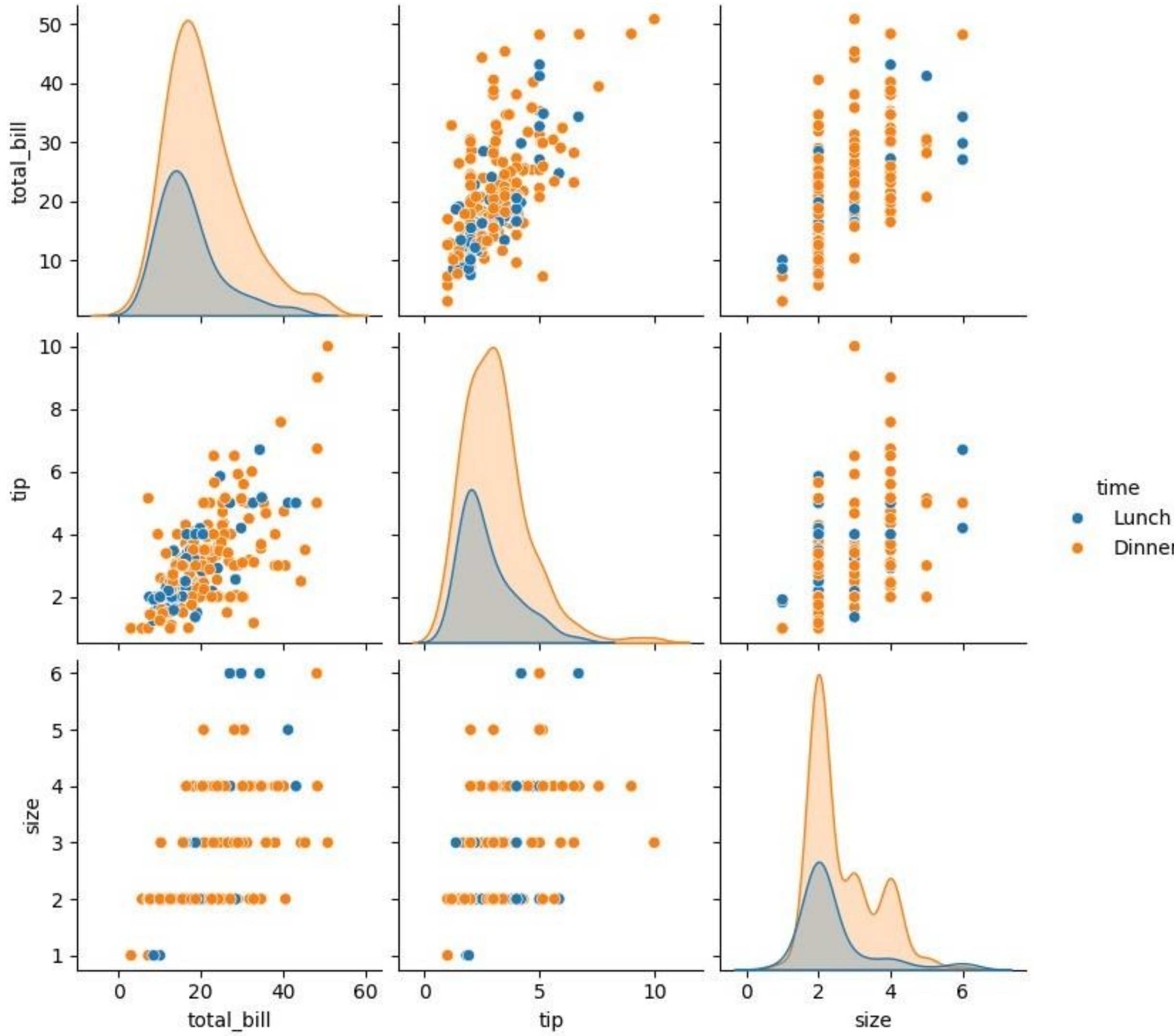

```
sns.jointplot(x=tips.tip,y=tips.total_bill,kind="he
x")
```



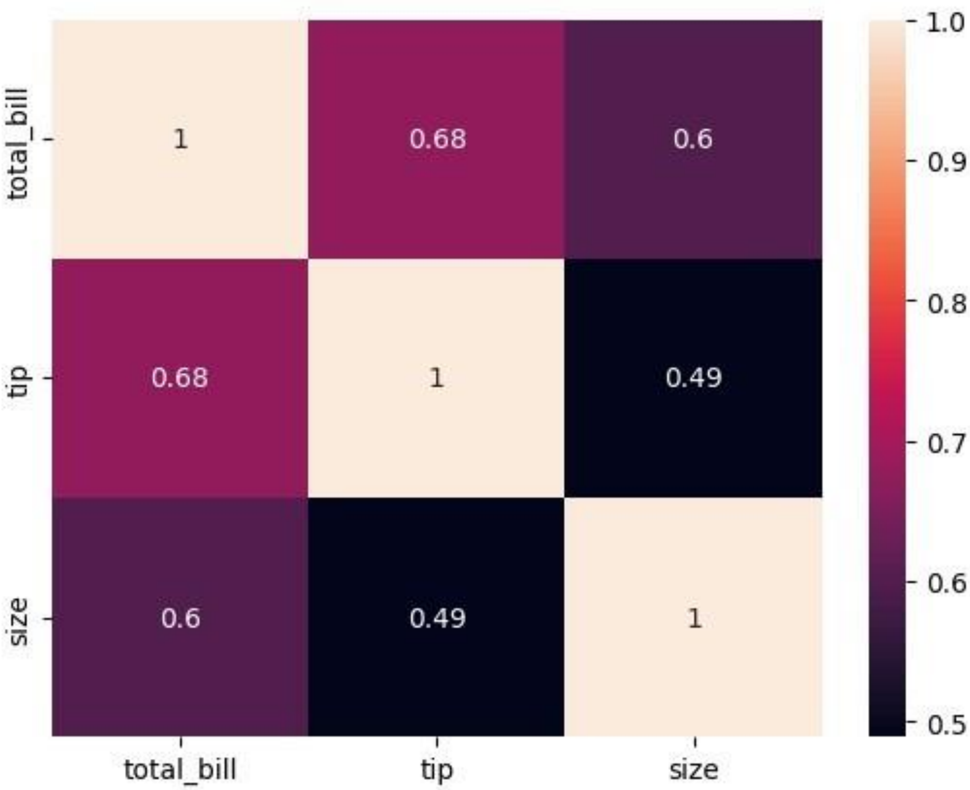

```
sns.pairplot(tips)
```



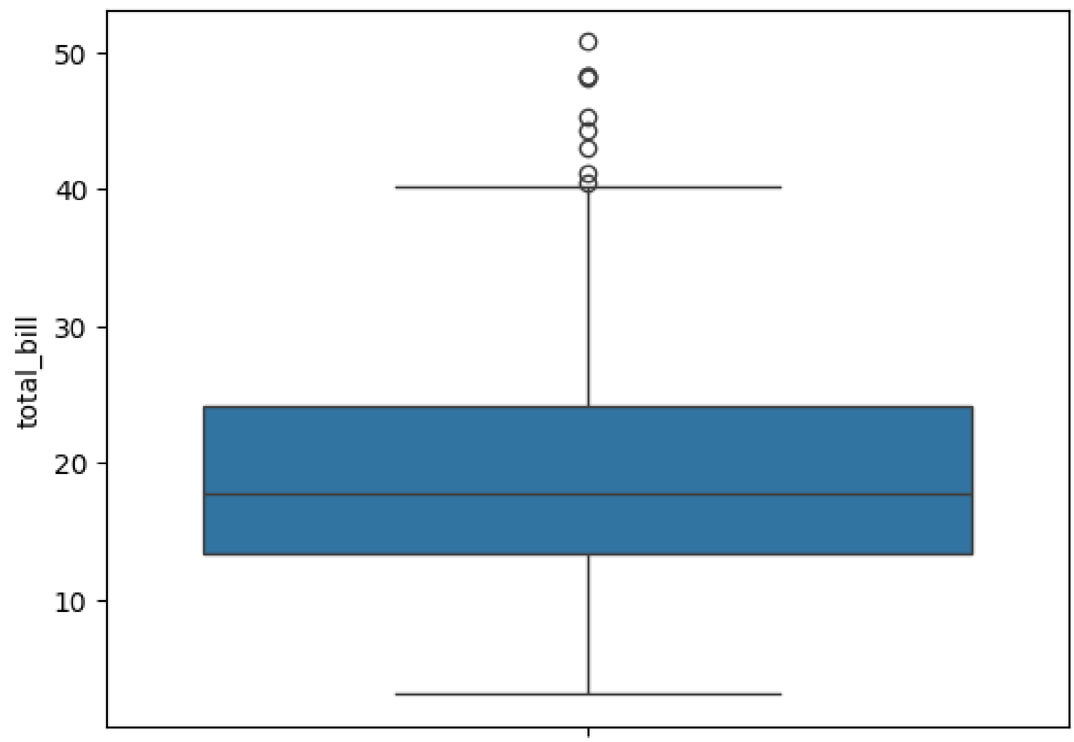

```
tips.time.value_counts()

time
Dinner    176
Lunch      68
Name:
```



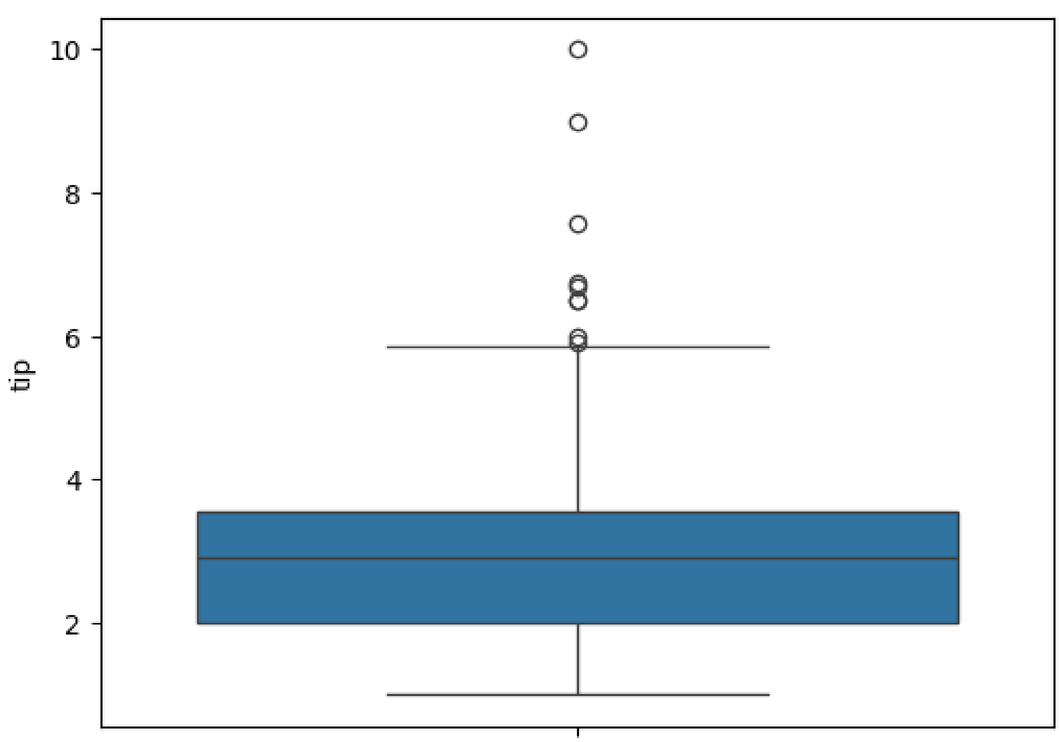

```
sns.heatmap(tips.corr(numeric_only=True),annot=True
)
```



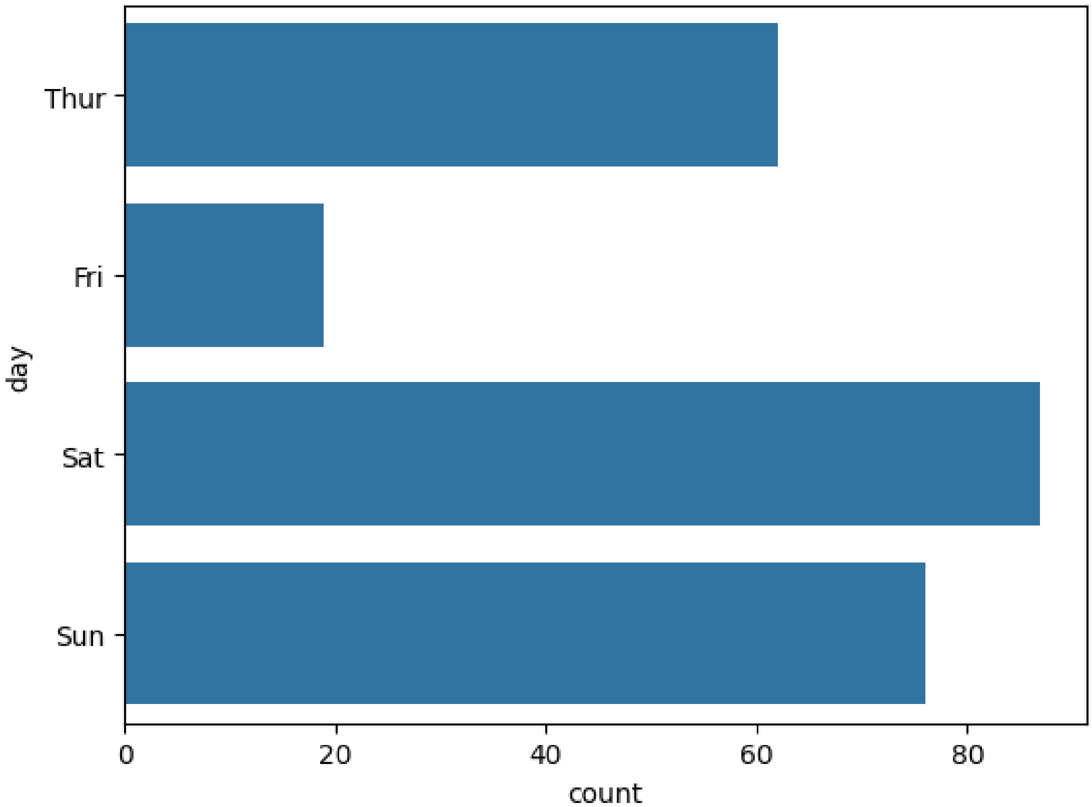

```
sns.boxplot(tips.total_bill)
```



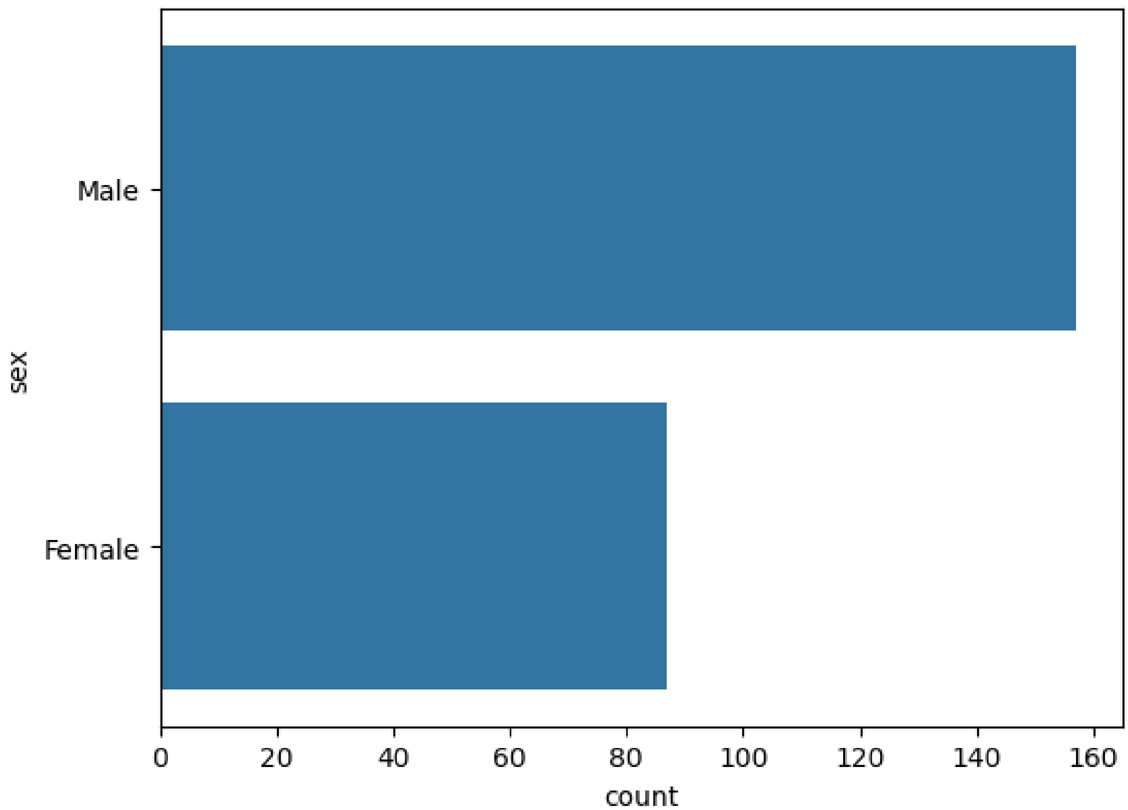

```
sns.boxplot(tips.tip)
```



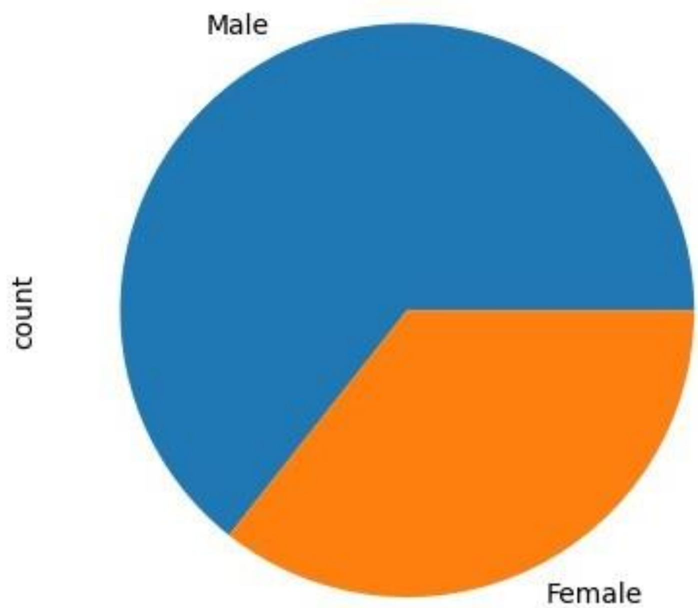
```
sns.countplot(tips.day)
```



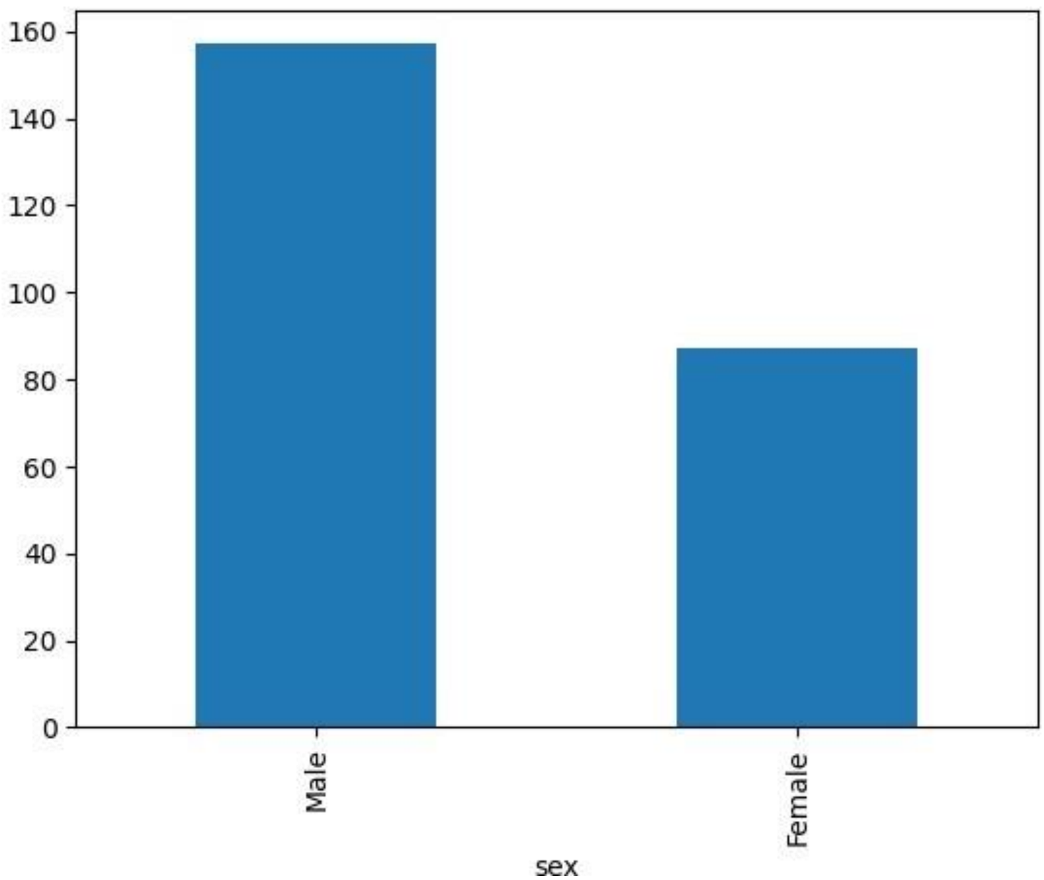

```
sns.countplot(tips.sex)
```



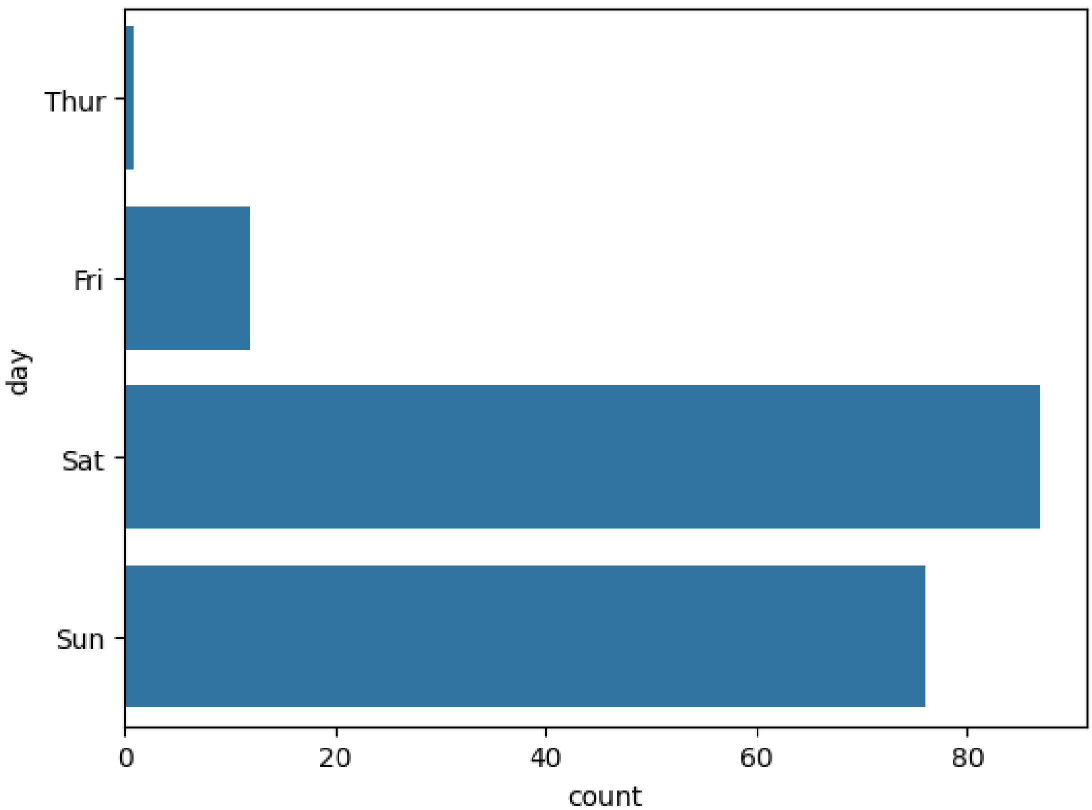

```
tips.sex.value_counts().plot(kind='pie')
```




```
tips.sex.value_counts().plot(kind='bar')
```

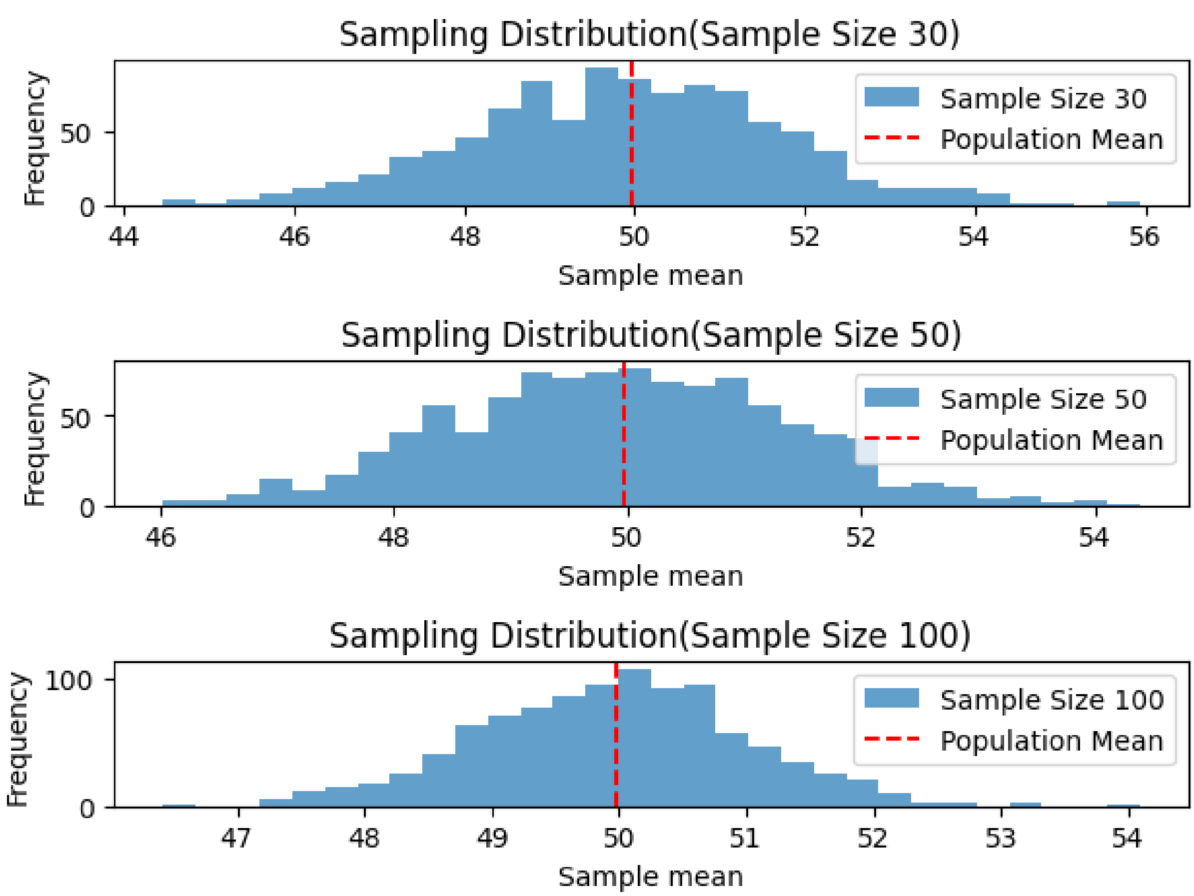



```
sns.countplot(tips[tips.time=='Dinner']['day'])
```




```
#EX.NO :6 Random Sampling and Sampling Distribution
#DATA  : 10.09.2024

#NAME :
BOOTHALINGESH N
#ROLL NO : 230701056
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - A

import numpy as np
import matplotlib.pyplot as plt

population_mean = 50
population_std = 10
population_size = 100000
population = np.random.normal(population_mean, population_std,
population_size)

sample_sizes = [30, 50, 100]
num_samples = 1000

sample_means = {}
for size in sample_sizes:
   sample_means[size] = []
   for _ in range(num_samples):
      sample = np.random.choice(population, size=size, replace=False)
      sample_means[size].append(np.mean(sample))
```

```
plt.figure(figsize=(12, 8))

<Figure size 1200x800 with 0 Axes>

<Figure size 1200x800 with 0 Axes>

for i, size in enumerate(sample_sizes):
   plt.subplot(len(sample_sizes), 1, i+1)
   plt.hist(sample_means[size], bins=30,
   alpha=0.7, label=f'Sample
Size {size}')
   plt.axvline(np.mean(population), color='red',
linestyle= 'dashed',linewidth=1.5,
label= 'Population Mean')
```




```
#EX.NO :7  Z-Test
#DATA  : 10.09.2024
```

```python
#NAME :
BOOTHALINGESH N
#ROLL NO : 230701056
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - A

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
sample_mean = np.mean(sample_data)
sample_std = np.std(sample_data, ddof=1)

n = len(sample_data)
z_statistic = (sample_mean - population_mean) / (sample_std /
np.sqrt(n))
p_value = 2 * (1 - stats.norm.cdf(np.abs(z_statistic)))

# Assuming sample_mean, z_statistic, and p_value have already been
calculated:
print(f"Sample Mean: {sample_mean:.2f}\n")
print(f"Z-Statistic: {z_statistic:.4f}\n")
print(f"P-Value: {p_value:.4f}\n")

# Significance level
alpha = 0.05

# Decision based on p-value
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.")
```

```
Sample Mean: 150.20

Z-Statistic: 0.6406

P-Value: 0.5218

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

```python
#EX.NO :8  T-Test
#DATA : 08.10.2024

#NAME :

BOOTHALINGESH N
```

```
#ROLL NO : 230701056
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - A

import numpy as np
import scipy.stats as stats
np.random.seed(42)
sample_size = 25
sample_data = np.random.normal(loc=102, scale=15, size=sample_size)

population_mean = 100
sample_mean = np.mean(sample_data)
sample_std = np.std(sample_data, ddof=1)

n = len(sample_data)
t_statistic, p_value = stats.ttest_1samp(sample_data,population_mean)

# Assuming sample_mean, t_statistic, and p_value have already been
calculated:
print(f"Sample Mean: {sample_mean:.2f}\n")
print(f"T-Statistic: {t_statistic:.4f}\n")
print(f"P-Value: {p_value:.4f}\n")

# Significance level
alpha = 0.05

# Decision based on p-value
if p_value < alpha:
    print("Reject the null hypothesis: The average IQ score is
significantly different from 100.")
else:
    print("Fail to reject the null hypothesis: There is no significant
difference in average IQ score from 100.")
```

```
Sample Mean: 99.55

T-Statistic: -0.1577

P-Value: 0.8760

Fail to reject the null hypothesis: There is no significant difference
in average IQ score from 100.
```

```
#EX.NO :9  Annova TEST
#DATA  : 08.10.2024

#NAME :
BOOTHALINGESH N
#ROLL NO : 230701056
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - A

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

```
from statsmodels.stats.multicomp import pairwise_tukeyhsd

np.random.seed(42)
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=2.5, 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_statistic, p_value = stats.f_oneway(growth_A, growth_B, growth_C)

mean_A = np.mean(growth_A)
mean_B = np.mean(growth_B)
mean_C = np.mean(growth_C)
print(f"Treatment A Mean Growth: {mean_A:.4f}")
print(f"Treatment B Mean Growth: {mean_B:.4f}")
print(f"Treatment C Mean Growth: {mean_C:.4f}")
print(f"F-Statistic: {f_statistic:.4f}")
print(f"P-Value: {p_value:.4f}")

alpha = 0.05
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.")


if p_value < alpha:

    tukey_results = pairwise_tukeyhsd(all_data, treatment_labels,
alpha=0.05)

    print("\nTukey's HSD Post-hoc Test:")
    print(tukey_results)
```

```
Treatment A Mean Growth: 9.6730
Treatment B Mean Growth: 11.1377
Treatment C Mean Growth: 15.2652
F-Statistic: 36.1214
P-Value: 0.0000
Reject the null hypothesis: There is a significant difference in mean
growth rates among the three treatments.

Tukey's HSD Post-hoc Test:
Multiple Comparison of Means - Tukey HSD, FWER=0.05
```

```
====================================================
group1 group2 meandiff p-adj   lower  upper  reject
----------------------------------------------------
     A      B   1.4647 0.0877 -0.1683 3.0977  False
     A      C   5.5923    0.0  3.9593 7.2252   True
     B      C   4.1276    0.0  2.4946 5.7605   True
----------------------------------------------------
```

```python
#EX.NO :10 Feature Scaling
#DATA  : 22.10.2024

#NAME :
BOOTHALINGESH N
#ROLL NO : 230701056
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - A

import numpy as np
import pandas as pd
import warnings
warnings.filterwarnings('ignore')
df=pd.read_csv('pre_process_datasample.csv')

df.head()
```

```
  Count  A   Salary
0   ry ge   72000      N
1  Franc 44     0      o
2    e .0   48000      Y
3               0      e
```

```python
df.Country.fillna(df.Country.mode()[0],inplace=True)
features=df.iloc[:,:-1].values
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, nan],
       ['France', 35.0, 58000.0],
       ['Spain', nan, 52000.0],
       ['France', 48.0, 79000.0],
       ['Germany', 50.0, 83000.0],
       ['France', 37.0, 67000.0]], dtype=object)
```

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

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()

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

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],
       ['Germany', 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.],
       [0., 1., 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],
       [0.0, 1.0, 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([[ 1.22474487e+00, -6.54653671e-01, -6.54653671e-01,
         7.58874362e-01,  7.49473254e-01],
       [-8.16496581e-01, -6.54653671e-01,  1.52752523e+00,
        -1.71150388e+00, -1.43817841e+00],
       [-8.16496581e-01,  1.52752523e+00, -6.54653671e-01,
        -1.27555478e+00, -8.91265492e-01],
       [-8.16496581e-01, -6.54653671e-01,  1.52752523e+00,
        -1.13023841e-01, -2.53200424e-01],
       [-8.16496581e-01,  1.52752523e+00, -6.54653671e-01,
         1.77608893e-01,  6.63219199e-16],
       [ 1.22474487e+00, -6.54653671e-01, -6.54653671e-01,
        -5.48972942e-01, -5.26656882e-01],
       [-8.16496581e-01, -6.54653671e-01,  1.52752523e+00,
         0.00000000e+00, -1.07356980e+00],
       [ 1.22474487e+00, -6.54653671e-01, -6.54653671e-01,
         1.34013983e+00,  1.38753832e+00],
       [-8.16496581e-01,  1.52752523e+00, -6.54653671e-01,
         1.63077256e+00,  1.75214693e+00],
       [ 1.22474487e+00, -6.54653671e-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],
       [0.        , 1.        , 0.        , 1.        , 1.        ],
       [1.        , 0.        , 0.        , 0.43478261, 0.54285714]])
```

```
#EX.NO :11 Linear Regression
#DATA  : 29.10.2024
```

```
#NAME :
BOOTHALINGESH N
#ROLL NO : 230701056
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - A

import numpy as np
import pandas as pd
df = pd.read_csv('Salary_data.csv')
df
```

```
    YearsExperience  Salary
0               1.1   39343
1               1.3   46205
2               1.5   37731
3               2.0   43525
4               2.2   39891
5               2.9   56642
6               3.0   60150
7               3.2   54445
8               3.2   64445
9               3.7   57189
10              3.9   63218
11              4.0   55794
12              4.0   56957
13              4.1   57081
14              4.5   61111
15              4.9   67938
16              5.1   66029
17              5.3   83088
18              5.9   81363
19              6.0   93940
20              6.8   91738
21              7.1   98273
22              7.9  101302
23              8.2  113812
24              8.7  109431
25              9.0  105582
26              9.5  116969
27              9.6  112635
28             10.3  122391
29             10.5  121872
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30 entries, 0 to 29
Data columns (total 2 columns):
 #   Column           Non-Null Count  Dtype
```

```
 0   YearsExperience  30 non-null     float64
 1   Salary           30 non-null     int64
dtypes: float64(1), int64(1)
memory usage: 612.0 bytes
```

```
df.dropna(inplace=True);
df
```

	YearsExperience	Salary
0	1.1	39343
1	1.3	46205
2	1.5	37731
3	2.0	43525
4	2.2	39891
5	2.9	56642
6	3.0	60150
7	3.2	54445
8	3.2	64445
9	3.7	57189
10	3.9	63218
11	4.0	55794
12	4.0	56957
13	4.1	57081
14	4.5	61111
15	4.9	67938
16	5.1	66029
17	5.3	83088
18	5.9	81363
19	6.0	93940
20	6.8	91738
21	7.1	98273
22	7.9	101302
23	8.2	113812
24	8.7	109431
25	9.0	105582
26	9.5	116969
27	9.6	112635
28	10.3	122391
29	10.5	121872

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30 entries, 0 to 29
Data columns (total 2 columns):
 #   Column           Non-Null Count  Dtype

 0   YearsExperience  30 non-null     float64
 1   Salary           30 non-null     int64
```

```
dtypes: float64(1), int64(1)
memory usage: 612.0 bytes

df.describe()  #descripte statical report
# find out lYER FOR BELOW META DATA

       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

features = df.iloc[:,[0]].values # : - > all row , 0 -> first column

#iloc index based selection loc location based sentence

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],
       [ 4. ],
       [ 4. ],
       [ 4.1],
       [ 4.5],
       [ 4.9],
       [ 5.1],
       [ 5.3],
       [ 5.9],
       [ 6. ],
       [ 6.8],
       [ 7.1],
       [ 7.9],
       [ 8.2],
       [ 8.7],
       [ 9. ],
```

```
       [ 9.5],
       [ 9.6],
       [10.3],
       [10.5]])
```

```
label
```

```
array([[ 39343],
       [ 46205],
       [ 37731],
       [ 43525],
       [ 39891],
       [ 56642],
       [ 60150],
       [ 54445],
       [ 64445],
       [ 57189],
       [ 63218],
       [ 55794],
       [ 56957],
       [ 57081],
       [ 61111],
       [ 67938],
       [ 66029],
       [ 83088],
       [ 81363],
       [ 93940],
       [ 91738],
       [ 98273],
       [101302],
       [113812],
       [109431],
       [105582],
       [116969],
       [112635],
       [122391],
       [121872]], dtype=int64)
```

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test =
train_test_split(features,label,test_size=0.2,random_state=23)
# x independent input  train 80 % test 20 %
'''
y is depenent ouput
0.2 allocate test for 20 % automatically train for 80 %
'''
```

```
'\ny is depenent ouput\n0.2 allocate test for 20 % automatically train
for 80 %\n'
```

```python
from sklearn.linear_model import LinearRegression
model = LinearRegression()
model.fit(x_train,y_train)
'''
sk - size kit
linear means using linear regression
fit means add data
'''
```

```
'\nsk - size kit \nlinear means using linear regression \nfit means add data \n'
```

```python
model.score(x_train,y_train)
'''
accuracy calculating
96 %
'''
```

```
'\naccuracy calculating\n96 %\n'
```

```python
model.score(x_test,y_test)
'''
accuracy calculating
91 %
'''
```

```
'\naccuracy calculating\n91 %\n'
```

```python
model.coef_
```

```
array([[9281.30847068]])
```

```python
model.intercept_
```

```
array([27166.73682891])
```

```python
import pickle
pickle.dump(model,open('SalaryPred.model','wb'))
'''
pickle momory obj to file

'''
```

```
'\npickle momory obj to file\n\n'
```

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

```python
yr_of_exp = float(input("Enter years of expreience: "))
yr_of_exp_NP = np.array([[yr_of_exp]])
salary = model.predict(yr_of_exp_NP)
print("Estimated salary for {} years of expreience is {} .
".format(yr_of_exp,salary))
```

```
Enter years of expreience:  24

Estimated salary for 24.0 years of expreience is [[249918.14012525]] .


print(f" Estimated salary for {yr_of_exp} years of expreience is
{salary} . ")

 Estimated salary for 24.0 years of expreience is
[[249918.14012525]] .

#EX.NO :12   Logistic Regression
#DATA  : 05.11.2024

#NAME :
BOOTHALINGESH N
#ROLL NO : 230701056
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - A

import numpy as np
import pandas as pd
import warnings
warnings.filterwarnings('ignore')
df=pd.read_csv('Social_Network_Ads.csv.csv')
df

      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
..        ...     ...  ...              ...        ...
395  15691863  Female   46            41000          1
396  15706071    Male   51            23000          1
397  15654296  Female   50            20000          1
398  15755018    Male   36            33000          0
399  15594041  Female   49            36000          1

[400 rows x 5 columns]

df.tail(20)

      User ID Gender Age  EstimatedSalary
Purchased380  15683758  Male          42
                 64000  0
381  15670615    Male   48            33000         1
382  15715622  Female   44           139000         1
383  15707634    Male   49            28000         1
384  15806901  Female   57            33000         1
385  15775335    Male   56            60000         1
386  15724150  Female   49            39000         1
```

```
388  15672330    Male   47            34000          1
389  15668521  Female   48            35000          1
390  15807837    Male   48            33000          1
391  15592570    Male   47            23000          1
392  15748589  Female   45            45000          1
393  15635893    Male   60            42000          1
394  15757632  Female   39            59000          0
395  15691863  Female   46            41000          1
396  15706071    Male   51            23000          1
397  15654296  Female   50            20000          1
398  15755018    Male   36            33000          0
399  15594041  Female   49            36000          1
```

```
df.head(25)
```

```
     User ID  Gender  Age  EstimatedSalary
Purchased0       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
5   15728773    Male   27             58000
    0
6   15598044  Female   27             84000
    0
7   15694829  Female   32            150000         1
8   15600575    Male   25             33000
    0
9   15727311  Female   35             65000
    0
10  15570769  Female   26             80000
                       0
11  15606274  Female   26             52000
                       0
12  15746139    Male   20             86000
                 0
```

```
features = df.iloc[:,[2,3]].values
label = df.iloc[:,4].values
features
```

```
array([[    19,  19000],
       [    35,  20000],
       [    26,  43000],
       [    27,  57000],
```

```
       [    19,  76000],
       [    27,  58000],
       [    27,  84000],
       [    32, 150000],
       [    25,  33000],
       [    35,  65000],
       [    26,  80000],
       [    26,  52000],
       [    20,  86000],
       [    32,  18000],
       [    18,  82000],
       [    29,  80000],
       [    47,  25000],
       [    45,  26000],
       [    46,  28000],
       [    48,  29000],
       [    45,  22000],
       [    47,  49000],
       [    48,  41000],
       [    45,  22000],
       [    46,  23000],
       [    47,  20000],
       [    49,  28000],
       [    47,  30000],
       [    29,  43000],
       [    31,  18000],
       [    31,  74000],
       [    27, 137000],
       [    21,  16000],
       [    28,  44000],
       [    27,  90000],
       [    35,  27000],
       [    33,  28000],
       [    30,  49000],
       [    26,  72000],
       [    27,  31000],
       [    27,  17000],
       [    33,  51000],
       [    35, 108000],
       [    30,  15000],
       [    28,  84000],
       [    23,  20000],
       [    25,  79000],
       [    27,  54000],
       [    30, 135000],
       [    31,  89000],
       [    24,  32000],
       [    18,  44000],
       [    29,  83000],
```

```
       [    35,  23000],
       [    27,  58000],
       [    24,  55000],
       [    23,  48000],
       [    28,  79000],
       [    22,  18000],
       [    32, 117000],
       [    27,  20000],
       [    25,  87000],
       [    23,  66000],
       [    32, 120000],
       [    59,  83000],
       [    24,  58000],
       [    24,  19000],
       [    23,  82000],
       [    22,  63000],
       [    31,  68000],
       [    25,  80000],
       [    24,  27000],
       [    20,  23000],
       [    33, 113000],
       [    32,  18000],
       [    34, 112000],
       [    18,  52000],
       [    22,  27000],
       [    28,  87000],
       [    26,  17000],
       [    30,  80000],
       [    39,  42000],
       [    20,  49000],
       [    35,  88000],
       [    30,  62000],
       [    31, 118000],
       [    24,  55000],
       [    28,  85000],
       [    26,  81000],
       [    35,  50000],
       [    22,  81000],
       [    30, 116000],
       [    26,  15000],
       [    29,  28000],
       [    29,  83000],
       [    35,  44000],
       [    35,  25000],
       [    28, 123000],
       [    35,  73000],
       [    28,  37000],
       [    27,  88000],
       [    28,  59000],
```

```
       [    32,  86000],
       [    33, 149000],
       [    19,  21000],
       [    21,  72000],
       [    26,  35000],
       [    27,  89000],
       [    26,  86000],
       [    38,  80000],
       [    39,  71000],
       [    37,  71000],
       [    38,  61000],
       [    37,  55000],
       [    42,  80000],
       [    40,  57000],
       [    35,  75000],
       [    36,  52000],
       [    40,  59000],
       [    41,  59000],
       [    36,  75000],
       [    37,  72000],
       [    40,  75000],
       [    35,  53000],
       [    41,  51000],
       [    39,  61000],
       [    42,  65000],
       [    26,  32000],
       [    30,  17000],
       [    26,  84000],
       [    31,  58000],
       [    33,  31000],
       [    30,  87000],
       [    21,  68000],
       [    28,  55000],
       [    23,  63000],
       [    20,  82000],
       [    30, 107000],
       [    28,  59000],
       [    19,  25000],
       [    19,  85000],
       [    18,  68000],
       [    35,  59000],
       [    30,  89000],
       [    34,  25000],
       [    24,  89000],
       [    27,  96000],
       [    41,  30000],
       [    29,  61000],
       [    20,  74000],
       [    26,  15000],
```

```
       [    41,  45000],
       [    31,  76000],
       [    36,  50000],
       [    40,  47000],
       [    31,  15000],
       [    46,  59000],
       [    29,  75000],
       [    26,  30000],
       [    32, 135000],
       [    32, 100000],
       [    25,  90000],
       [    37,  33000],
       [    35,  38000],
       [    33,  69000],
       [    18,  86000],
       [    22,  55000],
       [    35,  71000],
       [    29, 148000],
       [    29,  47000],
       [    21,  88000],
       [    34, 115000],
       [    26, 118000],
       [    34,  43000],
       [    34,  72000],
       [    23,  28000],
       [    35,  47000],
       [    25,  22000],
       [    24,  23000],
       [    31,  34000],
       [    26,  16000],
       [    31,  71000],
       [    32, 117000],
       [    33,  43000],
       [    33,  60000],
       [    31,  66000],
       [    20,  82000],
       [    33,  41000],
       [    35,  72000],
       [    28,  32000],
       [    24,  84000],
       [    19,  26000],
       [    29,  43000],
       [    19,  70000],
       [    28,  89000],
       [    34,  43000],
       [    30,  79000],
       [    20,  36000],
       [    26,  80000],
       [    35,  22000],
```

```
       [    35,  39000],
       [    49,  74000],
       [    39, 134000],
       [    41,  71000],
       [    58, 101000],
       [    47,  47000],
       [    55, 130000],
       [    52, 114000],
       [    40, 142000],
       [    46,  22000],
       [    48,  96000],
       [    52, 150000],
       [    59,  42000],
       [    35,  58000],
       [    47,  43000],
       [    60, 108000],
       [    49,  65000],
       [    40,  78000],
       [    46,  96000],
       [    59, 143000],
       [    41,  80000],
       [    35,  91000],
       [    37, 144000],
       [    60, 102000],
       [    35,  60000],
       [    37,  53000],
       [    36, 126000],
       [    56, 133000],
       [    40,  72000],
       [    42,  80000],
       [    35, 147000],
       [    39,  42000],
       [    40, 107000],
       [    49,  86000],
       [    38, 112000],
       [    46,  79000],
       [    40,  57000],
       [    37,  80000],
       [    46,  82000],
       [    53, 143000],
       [    42, 149000],
       [    38,  59000],
       [    50,  88000],
       [    56, 104000],
       [    41,  72000],
       [    51, 146000],
       [    35,  50000],
       [    57, 122000],
       [    41,  52000],
```

```
       [    35,  97000],
       [    44,  39000],
       [    37,  52000],
       [    48, 134000],
       [    37, 146000],
       [    50,  44000],
       [    52,  90000],
       [    41,  72000],
       [    40,  57000],
       [    58,  95000],
       [    45, 131000],
       [    35,  77000],
       [    36, 144000],
       [    55, 125000],
       [    35,  72000],
       [    48,  90000],
       [    42, 108000],
       [    40,  75000],
       [    37,  74000],
       [    47, 144000],
       [    40,  61000],
       [    43, 133000],
       [    59,  76000],
       [    60,  42000],
       [    39, 106000],
       [    57,  26000],
       [    57,  74000],
       [    38,  71000],
       [    49,  88000],
       [    52,  38000],
       [    50,  36000],
       [    59,  88000],
       [    35,  61000],
       [    37,  70000],
       [    52,  21000],
       [    48, 141000],
       [    37,  93000],
       [    37,  62000],
       [    48, 138000],
       [    41,  79000],
       [    37,  78000],
       [    39, 134000],
       [    49,  89000],
       [    55,  39000],
       [    37,  77000],
       [    35,  57000],
       [    36,  63000],
       [    42,  73000],
       [    43, 112000],
```

```
       [    45,  79000],
       [    46, 117000],
       [    58,  38000],
       [    48,  74000],
       [    37, 137000],
       [    37,  79000],
       [    40,  60000],
       [    42,  54000],
       [    51, 134000],
       [    47, 113000],
       [    36, 125000],
       [    38,  50000],
       [    42,  70000],
       [    39,  96000],
       [    38,  50000],
       [    49, 141000],
       [    39,  79000],
       [    39,  75000],
       [    54, 104000],
       [    35,  55000],
       [    45,  32000],
       [    36,  60000],
       [    52, 138000],
       [    53,  82000],
       [    41,  52000],
       [    48,  30000],
       [    48, 131000],
       [    41,  60000],
       [    41,  72000],
       [    42,  75000],
       [    36, 118000],
       [    47, 107000],
       [    38,  51000],
       [    48, 119000],
       [    42,  65000],
       [    40,  65000],
       [    57,  60000],
       [    36,  54000],
       [    58, 144000],
       [    35,  79000],
       [    38,  55000],
       [    39, 122000],
       [    53, 104000],
       [    35,  75000],
       [    38,  65000],
       [    47,  51000],
       [    47, 105000],
       [    41,  63000],
       [    53,  72000],
```

```
       [     54, 108000],
       [     39,  77000],
       [     38,  61000],
       [     38, 113000],
       [     37,  75000],
       [     42,  90000],
       [     37,  57000],
       [     36,  99000],
       [     60,  34000],
       [     54,  70000],
       [     41,  72000],
       [     40,  71000],
       [     42,  54000],
       [     43, 129000],
       [     53,  34000],
       [     47,  50000],
       [     42,  79000],
       [     42, 104000],
       [     59,  29000],
       [     58,  47000],
       [     46,  88000],
       [     38,  71000],
       [     54,  26000],
       [     60,  46000],
       [     60,  83000],
       [     39,  73000],
       [     59, 130000],
       [     37,  80000],
       [     46,  32000],
       [     46,  74000],
       [     42,  53000],
       [     41,  87000],
       [     58,  23000],
       [     42,  64000],
       [     48,  33000],
       [     44, 139000],
       [     49,  28000],
       [     57,  33000],
       [     56,  60000],
       [     49,  39000],
       [     39,  71000],
       [     47,  34000],
       [     48,  35000],
       [     48,  33000],
       [     47,  23000],
       [     45,  45000],
       [     60,  42000],
       [     39,  59000],
       [     46,  41000],
       [     51,  23000],
```

```
       [    50,  20000],
       [    36,  33000],
       [    49,  36000]], dtype=int64)
```

```
label
```

```
array([0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1,
1,
       1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,
0,
       0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0,
0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0,
1,
       0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1,
0,
       1, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 1, 0, 1, 0, 0,
0,
       1, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1,
1,
       0, 1, 0, 1, 1, 1, 1, 0, 0, 0, 1, 1, 0, 1, 1, 1,
1,

1,

0,

1,

1,
       1, 1, 0, 1], dtype=int64)
```

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression

# Assuming `features` and `label` are already defined

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

```
    x_train, x_test, y_train, y_test = train_test_split(features,
label, test_size=0.2, random_state=i)
    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(f"Test Score: {test_score:.4f} | Train Score:
{train_score:.4f} | Random State: {i}")

'''


'''

Test Score: 0.9000 | Train Score: 0.8406 | Random State: 4
Test Score: 0.8625 | Train Score: 0.8500 | Random State: 5
Test Score: 0.8625 | Train Score: 0.8594 | Random State: 6
Test Score: 0.8875 | Train Score: 0.8375 | Random State: 7
Test Score: 0.8625 | Train Score: 0.8375 | Random State: 9
Test Score: 0.9000 | Train Score: 0.8406 | Random State: 10
Test Score: 0.8625 | Train Score: 0.8562 | Random State: 14
Test Score: 0.8500 | Train Score: 0.8438 | Random State: 15
Test Score: 0.8625 | Train Score: 0.8562 | Random State: 16
Test Score: 0.8750 | Train Score: 0.8344 | Random State: 18
Test Score: 0.8500 | Train Score: 0.8438 | Random State: 19
Test Score: 0.8750 | Train Score: 0.8438 | Random State: 20
Test Score: 0.8625 | Train Score: 0.8344 | Random State: 21
Test Score: 0.8750 | Train Score: 0.8406 | Random State: 22
Test Score: 0.8750 | Train Score: 0.8406 | Random State: 24
Test Score: 0.8500 | Train Score: 0.8344 | Random State: 26
Test Score: 0.8500 | Train Score: 0.8406 | Random State: 27
Test Score: 0.8625 | Train Score: 0.8344 | Random State: 30
Test Score: 0.8625 | Train Score: 0.8562 | Random State: 31
Test Score: 0.8750 | Train Score: 0.8531 | Random State: 32
Test Score: 0.8625 | Train Score: 0.8438 | Random State: 33
Test Score: 0.8750 | Train Score: 0.8313 | Random State: 35
Test Score: 0.8625 | Train Score: 0.8531 | Random State: 36
Test Score: 0.8875 | Train Score: 0.8406 | Random State: 38
Test Score: 0.8750 | Train Score: 0.8375 | Random State: 39
Test Score: 0.8875 | Train Score: 0.8375 | Random State: 42
Test Score: 0.8750 | Train Score: 0.8469 | Random State: 46
Test Score: 0.9125 | Train Score: 0.8313 | Random State: 47
Test Score: 0.8750 | Train Score: 0.8313 | Random State: 51
Test Score: 0.9000 | Train Score: 0.8438 | Random State: 54
Test Score: 0.8500 | Train Score: 0.8438 | Random State: 57
Test Score: 0.8750 | Train Score: 0.8438 | Random State: 58
Test Score: 0.9250 | Train Score: 0.8375 | Random State: 61
```

```
Test Score: 0.8875 | Train Score: 0.8344 | Random State: 65
Test Score: 0.8875 | Train Score: 0.8406 | Random State: 68
Test Score: 0.9000 | Train Score: 0.8313 | Random State: 72
Test Score: 0.8875 | Train Score: 0.8375 | Random State: 75
Test Score: 0.9250 | Train Score: 0.8250 | Random State: 76
Test Score: 0.8625 | Train Score: 0.8406 | Random State: 77
Test Score: 0.8625 | Train Score: 0.8594 | Random State: 81
Test Score: 0.8750 | Train Score: 0.8375 | Random State: 82
Test Score: 0.8875 | Train Score: 0.8375 | Random State: 83
Test Score: 0.8625 | Train Score: 0.8531 | Random State: 84
Test Score: 0.8625 | Train Score: 0.8406 | Random State: 85
Test Score: 0.8625 | Train Score: 0.8406 | Random State: 87
Test Score: 0.8750 | Train Score: 0.8469 | Random State: 88
Test Score: 0.9125 | Train Score: 0.8375 | Random State: 90
Test Score: 0.8625 | Train Score: 0.8500 | Random State: 95
Test Score: 0.8750 | Train Score: 0.8500 | Random State: 99
Test Score: 0.8500 | Train Score: 0.8406 | Random State: 101
Test Score: 0.8500 | Train Score: 0.8406 | Random State: 102
Test Score: 0.9000 | Train Score: 0.8250 | Random State: 106
Test Score: 0.8625 | Train Score: 0.8406 | Random State: 107
Test Score: 0.8500 | Train Score: 0.8344 | Random State: 109
Test Score: 0.8500 | Train Score: 0.8406 | Random State: 111
Test Score: 0.9125 | Train Score: 0.8406 | Random State: 112
Test Score: 0.8625 | Train Score: 0.8500 | Random State: 115
Test Score: 0.8625 | Train Score: 0.8406 | Random State: 116
Test Score: 0.8750 | Train Score: 0.8344 | Random State: 119
Test Score: 0.9125 | Train Score: 0.8281 | Random State: 120
Test Score: 0.8625 | Train Score: 0.8594 | Random State: 125
Test Score: 0.8500 | Train Score: 0.8469 | Random State: 128
Test Score: 0.8750 | Train Score: 0.8500 | Random State: 130
Test Score: 0.9000 | Train Score: 0.8438 | Random State: 133
Test Score: 0.9250 | Train Score: 0.8344 | Random State: 134
Test Score: 0.8625 | Train Score: 0.8500 | Random State: 135
Test Score: 0.8750 | Train Score: 0.8313 | Random State: 138
Test Score: 0.8625 | Train Score: 0.8500 | Random State: 141
Test Score: 0.8500 | Train Score: 0.8469 | Random State: 143
Test Score: 0.8500 | Train Score: 0.8469 | Random State: 146
Test Score: 0.8500 | Train Score: 0.8438 | Random State: 147
Test Score: 0.8625 | Train Score: 0.8500 | Random State: 148
Test Score: 0.8750 | Train Score: 0.8375 | Random State: 150
Test Score: 0.8875 | Train Score: 0.8313 | Random State: 151
Test Score: 0.9250 | Train Score: 0.8438 | Random State: 152
Test Score: 0.8500 | Train Score: 0.8406 | Random State: 153
Test Score: 0.9000 | Train Score: 0.8438 | Random State: 154
Test Score: 0.9000 | Train Score: 0.8406 | Random State: 155
Test Score: 0.8875 | Train Score: 0.8469 | Random State: 156
Test Score: 0.8875 | Train Score: 0.8344 | Random State: 158
Test Score: 0.8750 | Train Score: 0.8281 | Random State: 159
Test Score: 0.9000 | Train Score: 0.8313 | Random State: 161
```

```
Test Score: 0.8500 | Train Score: 0.8375 | Random State: 163
Test Score: 0.8750 | Train Score: 0.8313 | Random State: 164
Test Score: 0.8625 | Train Score: 0.8500 | Random State: 169
Test Score: 0.8750 | Train Score: 0.8406 | Random State: 171
Test Score: 0.8500 | Train Score: 0.8406 | Random State: 172
Test Score: 0.9000 | Train Score: 0.8250 | Random State: 180
Test Score: 0.8500 | Train Score: 0.8344 | Random State: 184
Test Score: 0.9250 | Train Score: 0.8219 | Random State: 186
Test Score: 0.9000 | Train Score: 0.8313 | Random State: 193
Test Score: 0.8625 | Train Score: 0.8500 | Random State: 195
Test Score: 0.8625 | Train Score: 0.8406 | Random State: 196
Test Score: 0.8625 | Train Score: 0.8375 | Random State: 197
Test Score: 0.8750 | Train Score: 0.8406 | Random State: 198
Test Score: 0.8875 | Train Score: 0.8375 | Random State: 199
Test Score: 0.8875 | Train Score: 0.8438 | Random State: 200
Test Score: 0.8625 | Train Score: 0.8375 | Random State: 202
Test Score: 0.8625 | Train Score: 0.8406 | Random State: 203
Test Score: 0.8875 | Train Score: 0.8313 | Random State: 206
Test Score: 0.8625 | Train Score: 0.8344 | Random State: 211
Test Score: 0.8500 | Train Score: 0.8438 | Random State: 212
Test Score: 0.8625 | Train Score: 0.8344 | Random State: 214
Test Score: 0.8750 | Train Score: 0.8313 | Random State: 217
Test Score: 0.9625 | Train Score: 0.8187 | Random State: 220
Test Score: 0.8750 | Train Score: 0.8438 | Random State: 221
Test Score: 0.8500 | Train Score: 0.8406 | Random State: 222
Test Score: 0.9000 | Train Score: 0.8438 | Random State: 223
Test Score: 0.8625 | Train Score: 0.8531 | Random State: 227
Test Score: 0.8625 | Train Score: 0.8344 | Random State: 228
Test Score: 0.9000 | Train Score: 0.8406 | Random State: 229
Test Score: 0.8500 | Train Score: 0.8438 | Random State: 232
Test Score: 0.8750 | Train Score: 0.8469 | Random State: 233
Test Score: 0.9125 | Train Score: 0.8406 | Random State: 234
Test Score: 0.8625 | Train Score: 0.8406 | Random State: 235
Test Score: 0.8500 | Train Score: 0.8469 | Random State: 236
Test Score: 0.8750 | Train Score: 0.8469 | Random State: 239
Test Score: 0.8500 | Train Score: 0.8438 | Random State: 241
Test Score: 0.8875 | Train Score: 0.8500 | Random State: 242
Test Score: 0.8875 | Train Score: 0.8250 | Random State: 243
Test Score: 0.8750 | Train Score: 0.8469 | Random State: 244
Test Score: 0.8750 | Train Score: 0.8406 | Random State: 245
Test Score: 0.8750 | Train Score: 0.8469 | Random State: 246
Test Score: 0.8625 | Train Score: 0.8594 | Random State: 247
Test Score: 0.8875 | Train Score: 0.8438 | Random State: 248
Test Score: 0.8625 | Train Score: 0.8500 | Random State: 250
Test Score: 0.8750 | Train Score: 0.8313 | Random State: 251
Test Score: 0.8875 | Train Score: 0.8438 | Random State: 252
Test Score: 0.8625 | Train Score: 0.8469 | Random State: 255
Test Score: 0.9000 | Train Score: 0.8406 | Random State: 257
Test Score: 0.8625 | Train Score: 0.8562 | Random State: 260
```

```
Test Score: 0.8625 | Train Score: 0.8406 | Random State: 266
Test Score: 0.8625 | Train Score: 0.8375 | Random State: 268
Test Score: 0.8750 | Train Score: 0.8406 | Random State: 275
Test Score: 0.8625 | Train Score: 0.8500 | Random State: 276
Test Score: 0.9250 | Train Score: 0.8375 | Random State: 277
Test Score: 0.8750 | Train Score: 0.8469 | Random State: 282
Test Score: 0.8500 | Train Score: 0.8469 | Random State: 283
Test Score: 0.8500 | Train Score: 0.8438 | Random State: 285
Test Score: 0.9125 | Train Score: 0.8344 | Random State: 286
Test Score: 0.8500 | Train Score: 0.8406 | Random State: 290
Test Score: 0.8500 | Train Score: 0.8406 | Random State: 291
Test Score: 0.8500 | Train Score: 0.8469 | Random State: 292
Test Score: 0.8625 | Train Score: 0.8375 | Random State: 294
Test Score: 0.8875 | Train Score: 0.8281 | Random State: 297
Test Score: 0.8625 | Train Score: 0.8344 | Random State: 300
Test Score: 0.8625 | Train Score: 0.8500 | Random State: 301
Test Score: 0.8875 | Train Score: 0.8500 | Random State: 302
Test Score: 0.8750 | Train Score: 0.8469 | Random State: 303
Test Score: 0.8625 | Train Score: 0.8344 | Random State: 305
Test Score: 0.9125 | Train Score: 0.8375 | Random State: 306
Test Score: 0.8750 | Train Score: 0.8469 | Random State: 308
Test Score: 0.9000 | Train Score: 0.8438 | Random State: 311
Test Score: 0.8625 | Train Score: 0.8344 | Random State: 313
Test Score: 0.9125 | Train Score: 0.8344 | Random State: 314
Test Score: 0.8750 | Train Score: 0.8375 | Random State: 315
Test Score: 0.9000 | Train Score: 0.8469 | Random State: 317
Test Score: 0.9125 | Train Score: 0.8219 | Random State: 319
Test Score: 0.8625 | Train Score: 0.8500 | Random State: 321
Test Score: 0.9125 | Train Score: 0.8281 | Random State: 322
Test Score: 0.8500 | Train Score: 0.8469 | Random State: 328
Test Score: 0.8500 | Train Score: 0.8375 | Random State: 332
Test Score: 0.8875 | Train Score: 0.8531 | Random State: 336
Test Score: 0.8500 | Train Score: 0.8375 | Random State: 337
Test Score: 0.8750 | Train Score: 0.8406 | Random State: 343
Test Score: 0.8625 | Train Score: 0.8438 | Random State: 346
Test Score: 0.8875 | Train Score: 0.8313 | Random State: 351
Test Score: 0.8625 | Train Score: 0.8500 | Random State: 352
Test Score: 0.9500 | Train Score: 0.8187 | Random State: 354
Test Score: 0.8625 | Train Score: 0.8500 | Random State: 356
Test Score: 0.9125 | Train Score: 0.8406 | Random State: 357
Test Score: 0.8625 | Train Score: 0.8375 | Random State: 358
Test Score: 0.8500 | Train Score: 0.8406 | Random State: 362
Test Score: 0.9000 | Train Score: 0.8438 | Random State: 363
Test Score: 0.8625 | Train Score: 0.8531 | Random State: 364
Test Score: 0.9375 | Train Score: 0.8219 | Random State: 366
Test Score: 0.9125 | Train Score: 0.8406 | Random State: 369
Test Score: 0.8625 | Train Score: 0.8531 | Random State: 371
Test Score: 0.9250 | Train Score: 0.8344 | Random State: 376
Test Score: 0.9125 | Train Score: 0.8281 | Random State: 377
```

```
Test Score: 0.8875 | Train Score: 0.8500 | Random State: 378
Test Score: 0.8875 | Train Score: 0.8500 | Random State: 379
Test Score: 0.8625 | Train Score: 0.8406 | Random State: 382
Test Score: 0.8625 | Train Score: 0.8594 | Random State: 386
Test Score: 0.8500 | Train Score: 0.8375 | Random State: 387
Test Score: 0.8750 | Train Score: 0.8281 | Random State: 388
Test Score: 0.8500 | Train Score: 0.8438 | Random State: 394
Test Score: 0.8625 | Train Score: 0.8375 | Random State: 395
Test Score: 0.9000 | Train Score: 0.8438 | Random State: 397
Test Score: 0.8625 | Train Score: 0.8438 | Random State: 400
```

```
'\n\n\n'
```

```
x_train,x_test,y_train,y_test=train_test_split(feat
ures,label,test_size=0.2,random_state=209)
finalModel
=LogisticR
egression(
)
finalModel
.fit(x_tra
in,y_train
)
```

```
LogisticRegression()
```

```
print(finalModel.score(x_train,y_train))
```

```
           0       0.86      0.91      0.89       257
           1       0.83      0.73      0.77       143

    accuracy                           0.85       400
   macro avg       0.84      0.82      0.83       400
weighted avg       0.85      0.85      0.85       400
```