```
#EX.NO:1.a        BasicPracticeExperiments(1to4)
#DATA : 30.07.2024

#NAME : GAYATHRI V R

#ROLL NO : 230701090
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - B
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
  Iris-setosa
  Iris-setosa
  Iris-setosa
  Iris-setosa
  Iris-setosa
 ..    ...
  Iris-virginica
  Iris-virginica
  Iris-virginica
  Iris-virginica
  Iris-virginica

[150 rows x 6 columns]
```

```
data.info()
```

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

```
0     Id    150 non-null    int64
·  SepalLengthCm 150 non-null    float64
·  SepalWidthCm   150 non-null   float64
·  PetalLengthCm 150 non-null    float64
·  PetalWidthCm   150 non-null   float64
·5    Species          150  non-null
object dtypes: float64(4), int64(1),
object(1) memory usage: 7.2+ KB
```

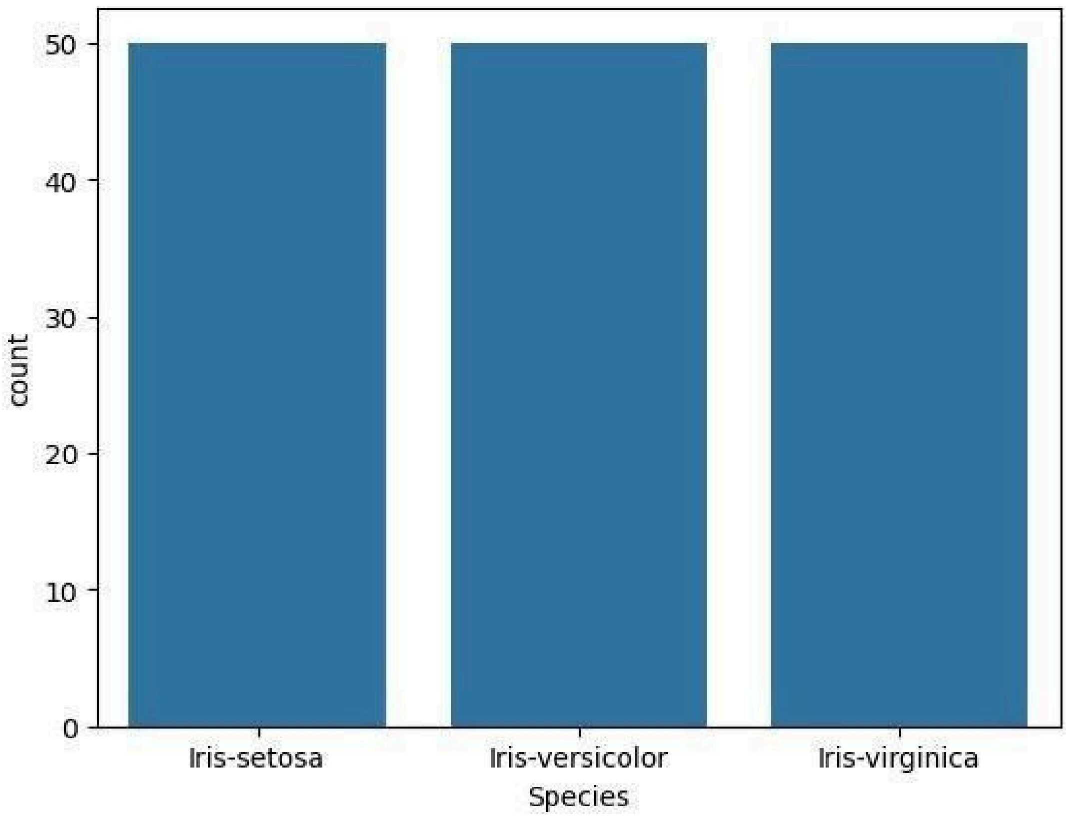
```
data.describe()
```

	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

Name: count, dtype: int64
```

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

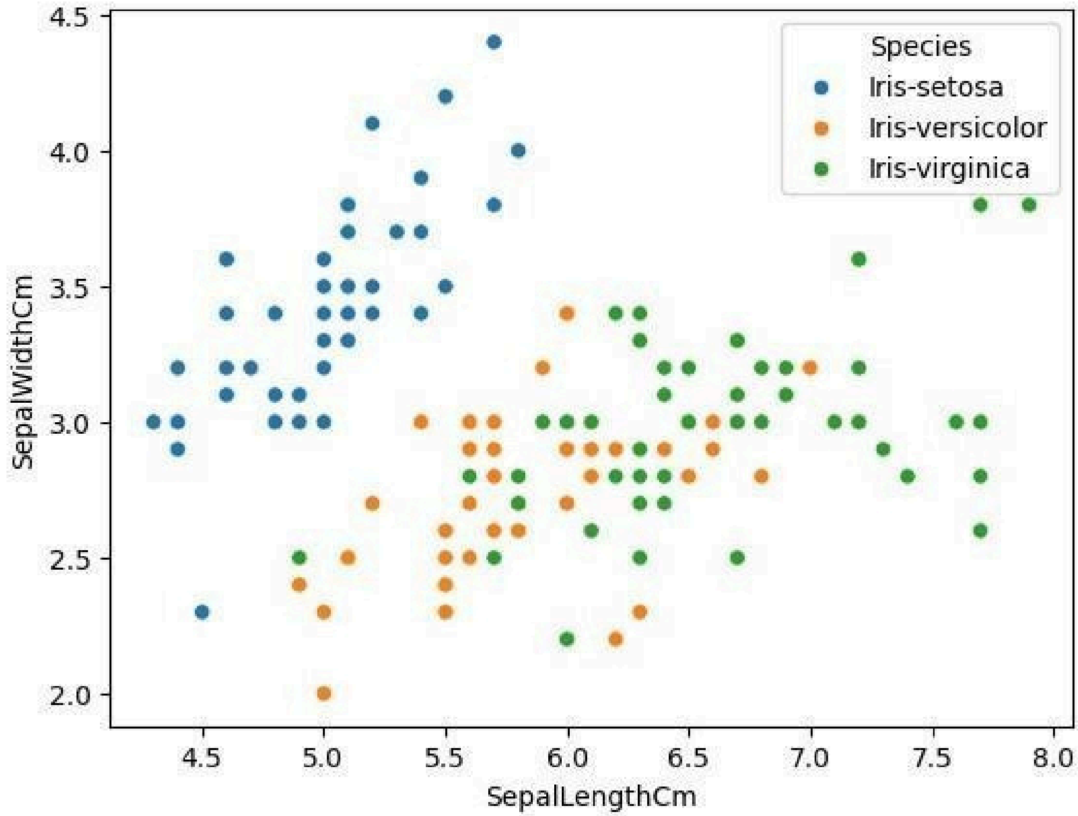



```
dummies=pd.get_dummies(data.Species)

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

FinalDataset.head()
```

```
   Iris-setosa Iris-versicolor Iris-virginica Id     SepalLengthC  \
                                                                m
 True      False False 1                                       5.1
 True      False False 2                                       4.9
 True      False False 3                                       4.7
 True      False False 4                                       4.6
                                                               5.0
   SepalWidthCm PetalLengthCm
0     3.5   1.4
1     3.0   1.4
2     3.2   1.3
3     3.1   1.5
4     3.6   1.4
```

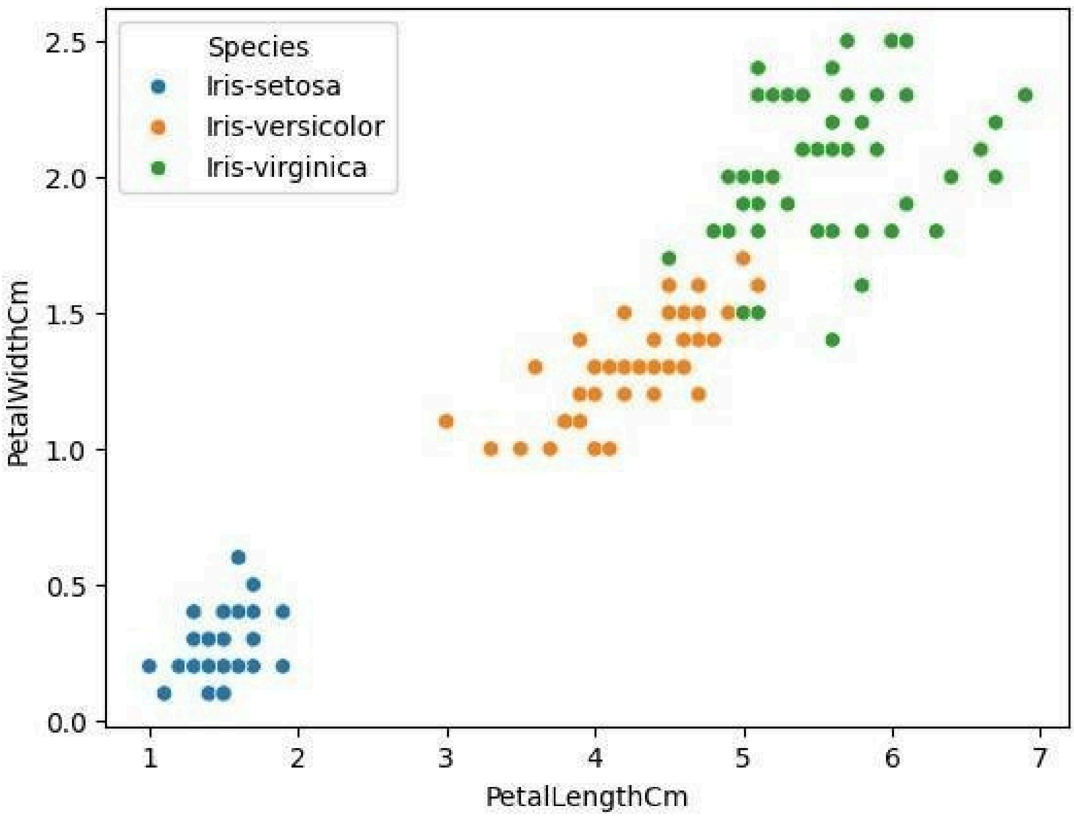
```
sns.scatterplot(x='SepalLengthCm',y='SepalWidthCm',hue='Species',data=
data,)
```

```
<Axes: xlabel='SepalLengthCm', ylabel='SepalWidthCm'>
```

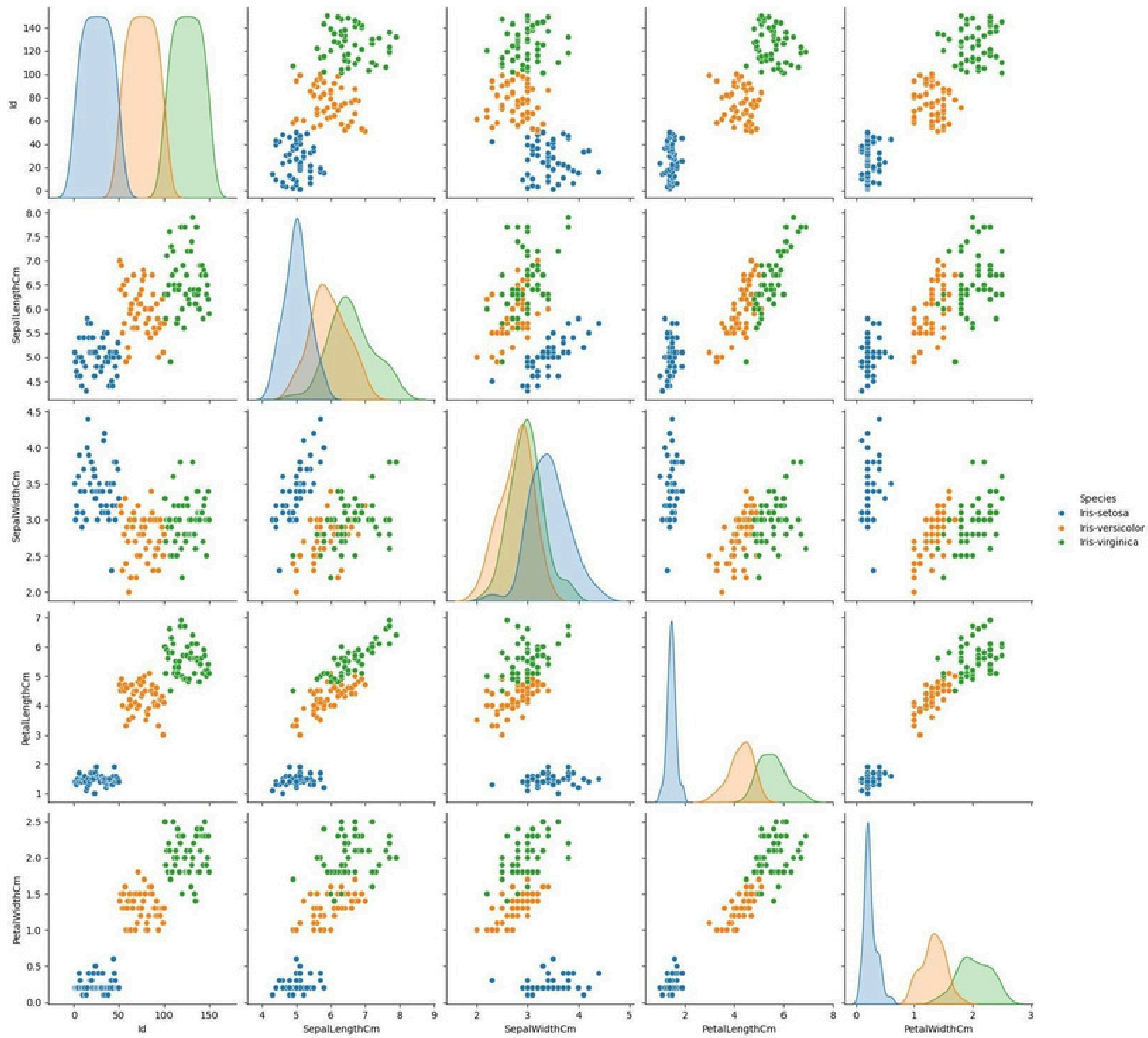



```
sns.scatterplot(x='PetalLengthCm',y='PetalWidthCm',hue='Species',data=
 data,)
```

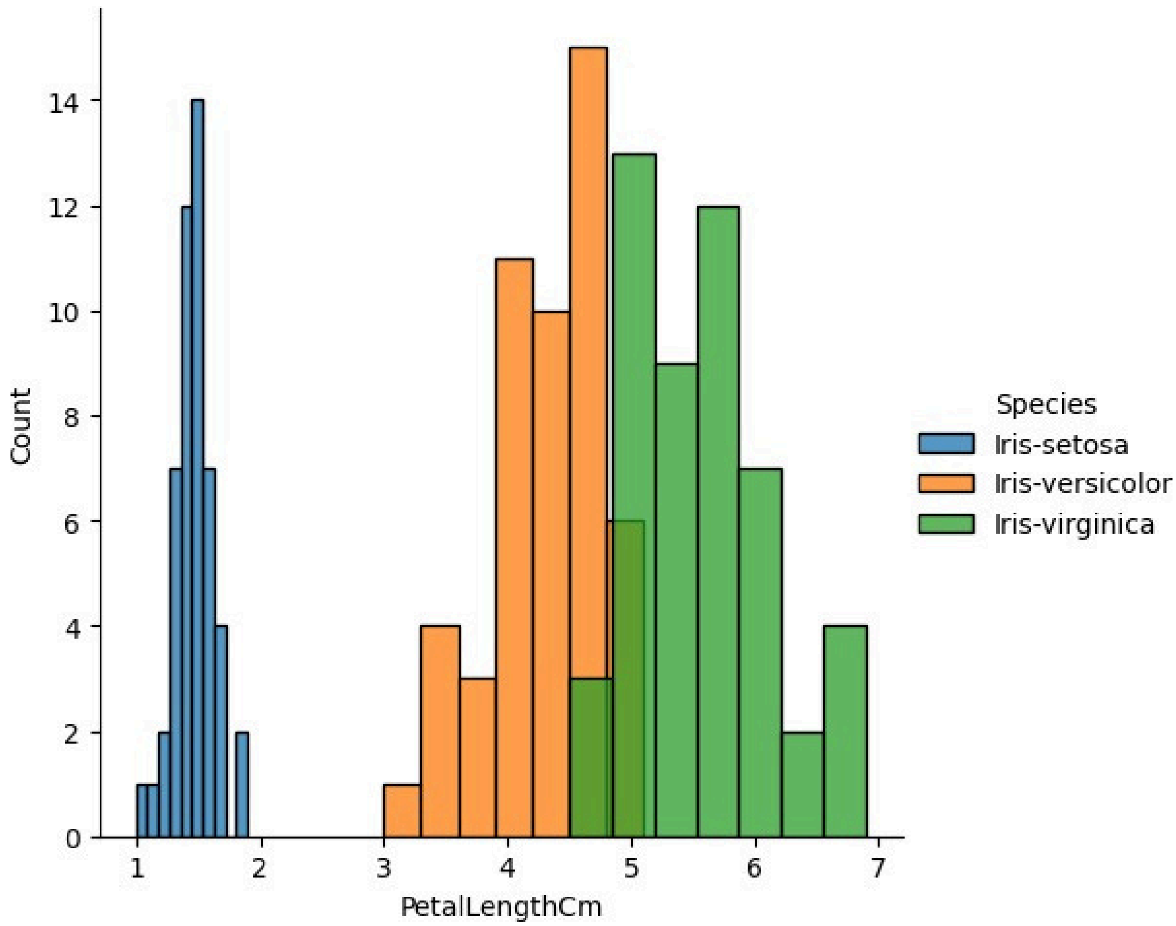
```
<Axes: xlabel='PetalLengthCm', ylabel='PetalWidthCm'>
```



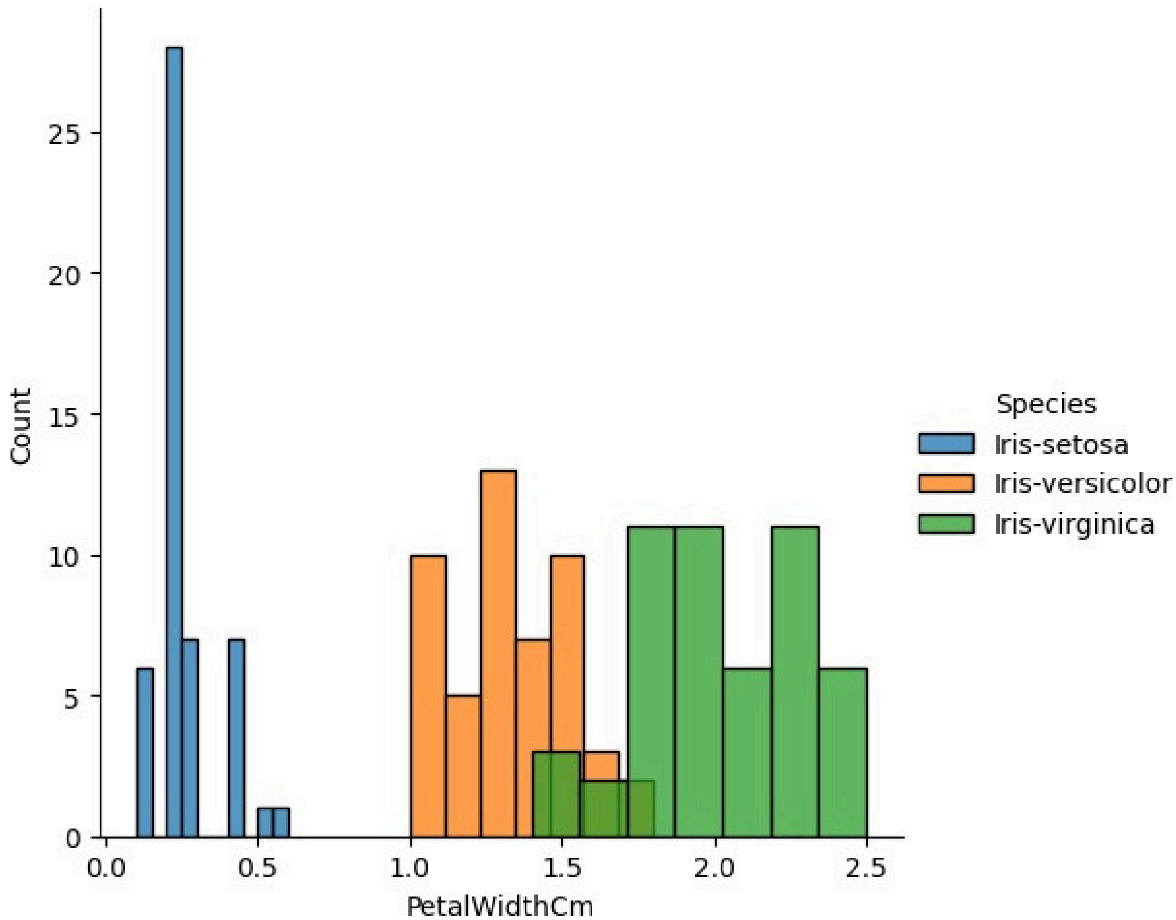

```
sns.pairplot(data,hue='Species',height=3);
```



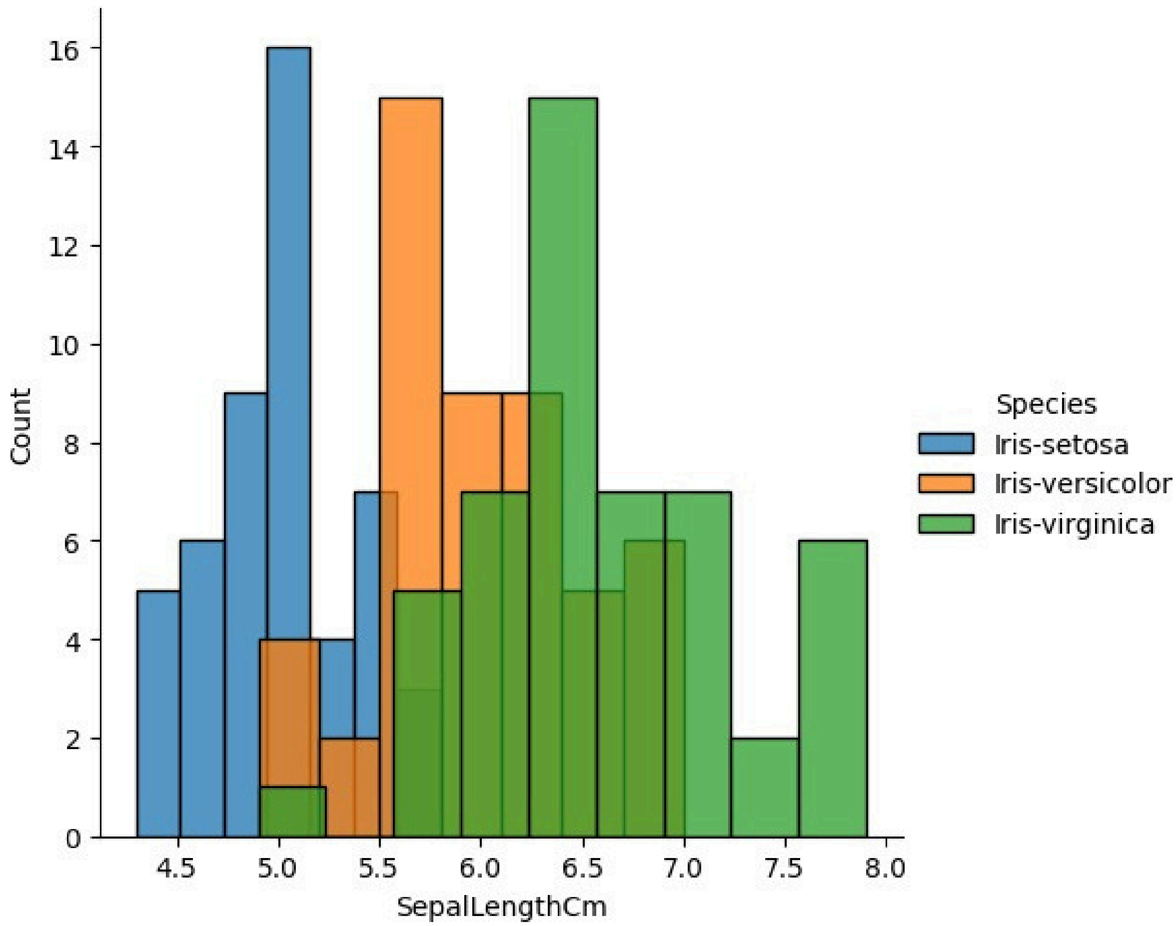

```
plt.show()

sns.FacetGrid(data,hue='Species',height=5).map(sns.histplot,'PetalLeng
 thCm').add_legend();
plt.show();
```



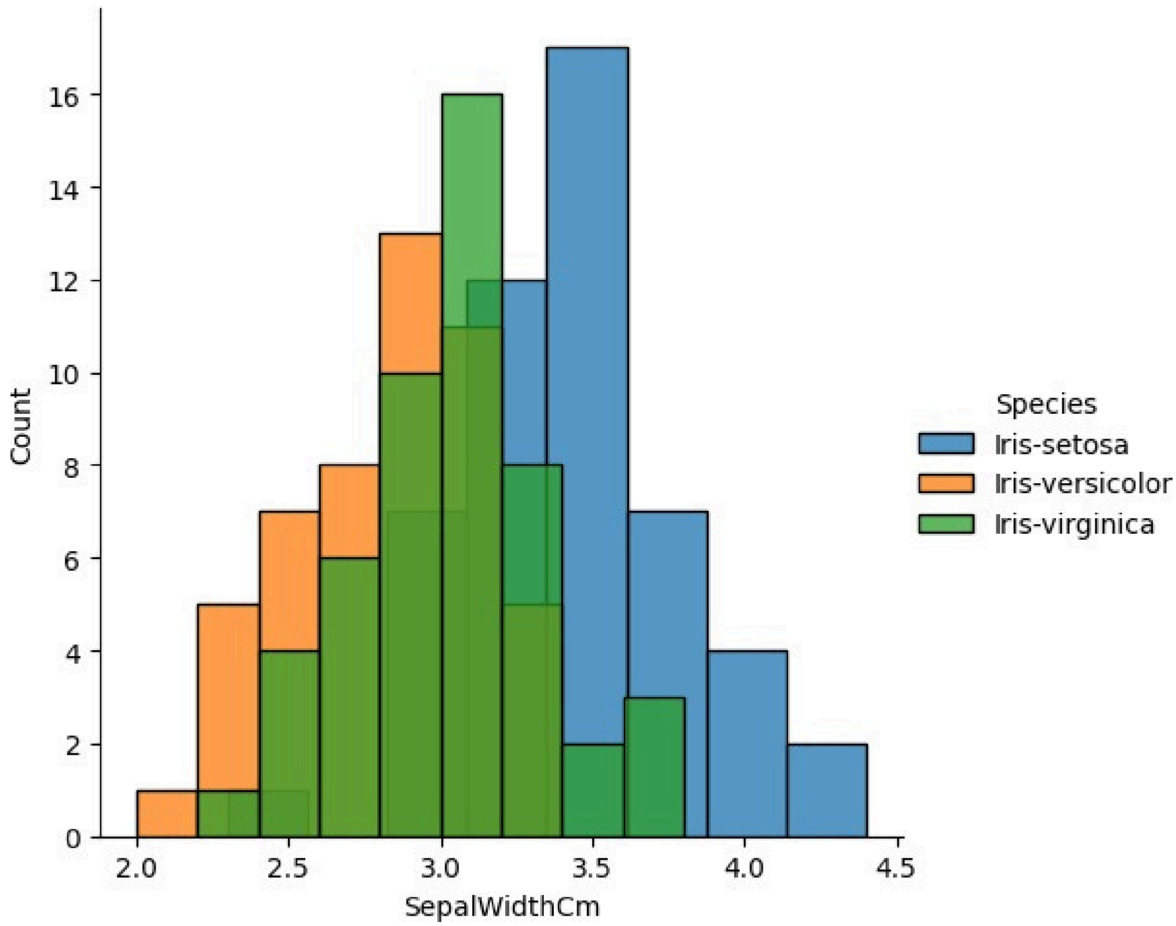

```
sns.FacetGrid(data,hue='Species',height=5).map(sns.histplot,'PetalWidt
 hCm').add_legend();
plt.show();
```




```
sns.FacetGrid(data,hue='Species',height=5).map(sns.histplot,'SepalLeng
thCm').add_legend();
plt.show();
```




```
sns.FacetGrid(data,hue='Species',height=5).map(sns.histplot,'SepalWidt
 hCm').add_legend();
plt.show();
```




```
#EX.NO :1.b Pandas Buit in function. Numpy Buit in fuction- Array
slicing, Ravel,Reshape,ndim
#DATA : 06.08.2024
#NAME : GAYATHRI V R
#ROLL NO : 230701090
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - B

import numpy as np
array=np.random.randint(1,100,9)
array
```

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

```
np.sqrt(array)
```

```
array([6.244998 , 9.8488578 , 9.38083152, 7.61577311, 5.38516481,
 9.32737905, 5.19615242, 9.38083152, 9.53939201])
```

```
array.ndim
```

```
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 : GAYATHRI V R
#ROLL NO : 230701090
#DEPARTMENT : B.E COMPUTER SCIENCE AND
ENGINEERING - B

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])
```

```
array.mean()
```

```
 45.5625
```

```
np.percentile(array,25)
```

```
 29.25
```

```
np.percentile(array,50)
```

```
 44.0
```

```
np.percentile(array,75)
```

```
 55.5
```

```
np.percentile(array,100)
```

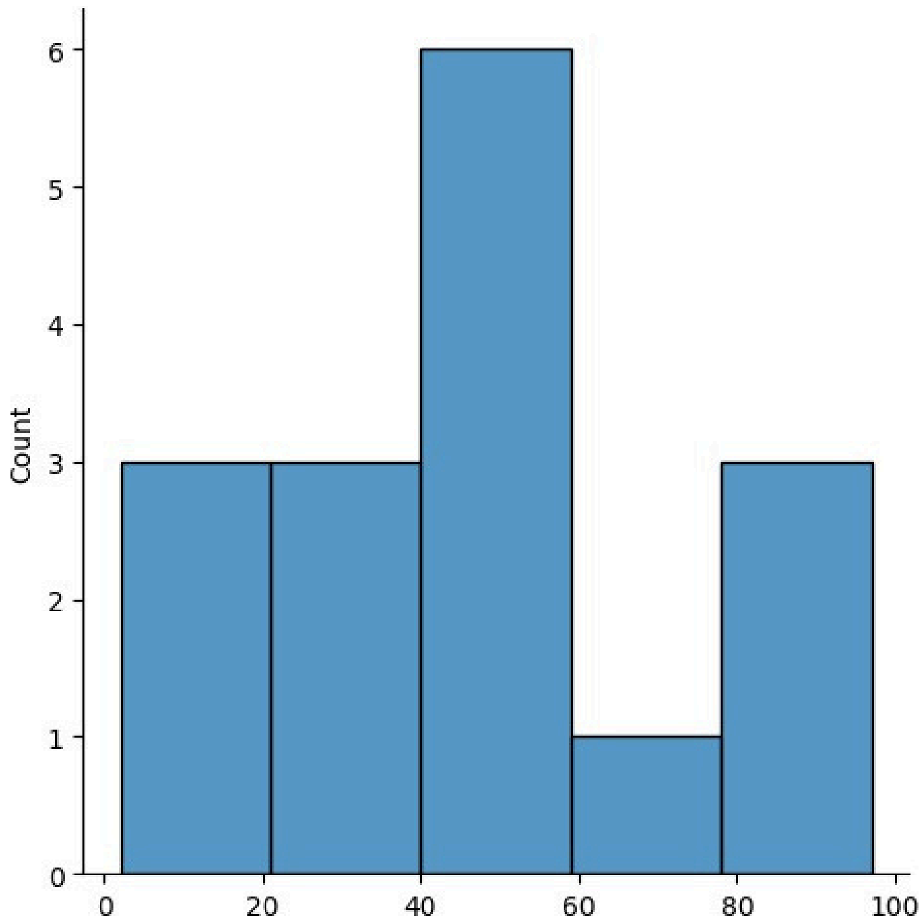
```
 97.0
```

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

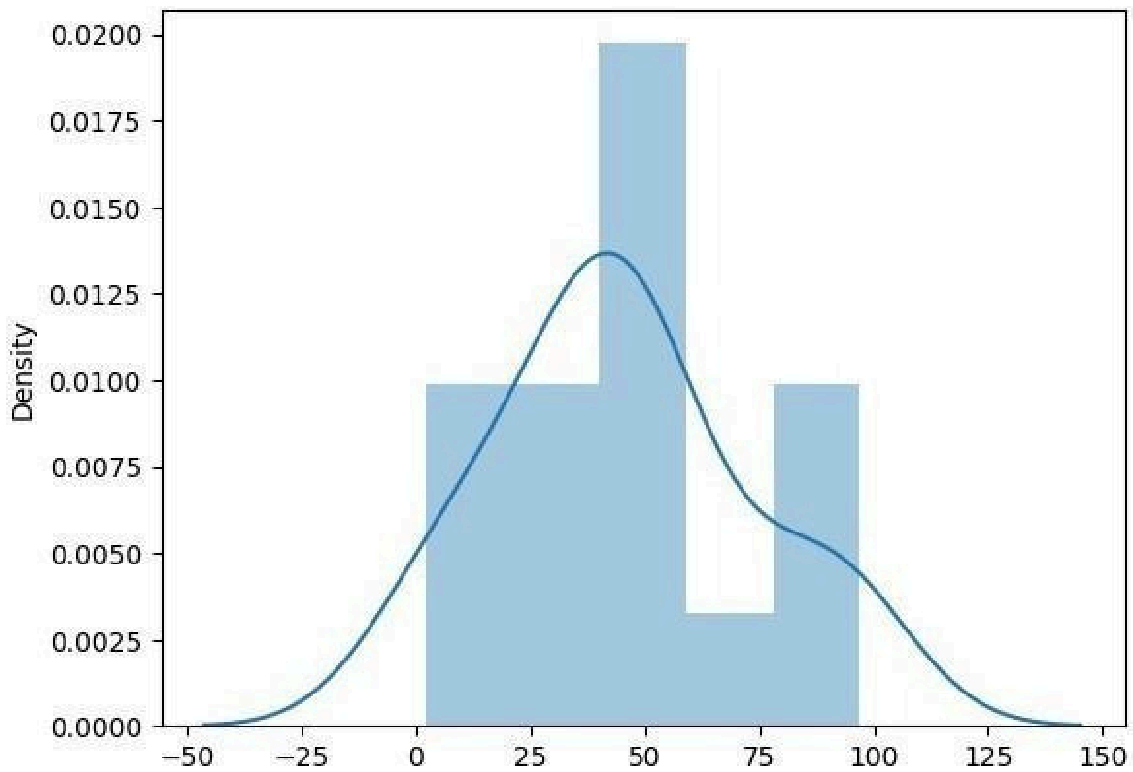
```
(-10.125, 94.875)
```

```
import seaborn as sns
%matplotlib inline
 sns.displot(array)
```

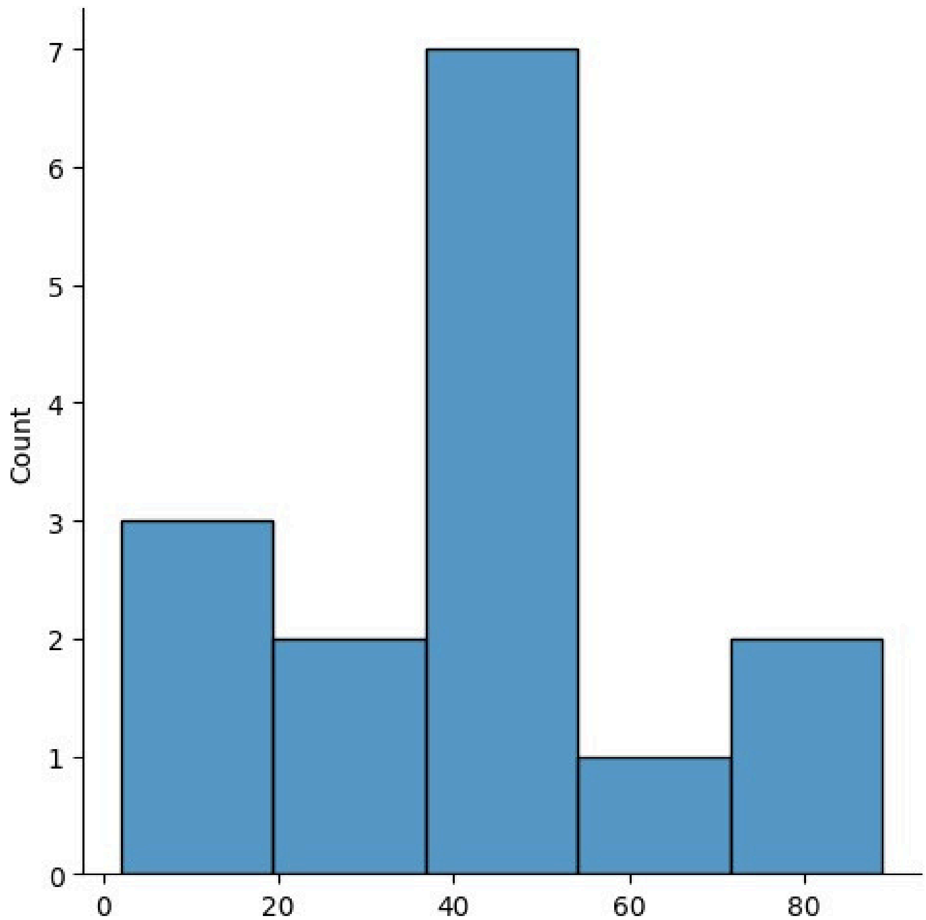
```
<seaborn.axisgrid.FacetGrid at 0x20d7cda3b50>
```




```
sns.distplot(array)

<Axes: ylabel='Density'>
```




```
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])

sns.displot(new_array)

<seaborn.axisgrid.FacetGrid at 0x20d7d02d950>
```




```
lr1,ur1=outDetection(new_array)
 lr1,ur1
```

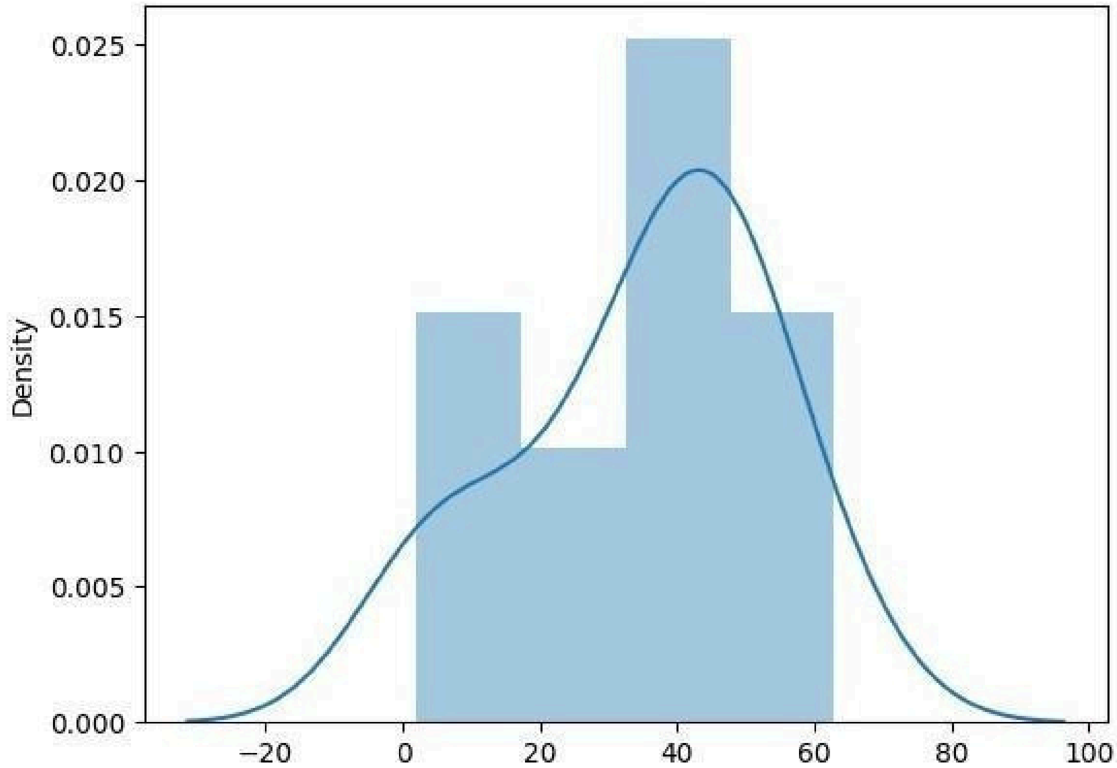
```
(-5.25, 84.75)
```

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

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

```
sns.distplot(final_array)
```

```
<Axes: ylabel='Density'>
```




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

#NAME : GAYATHRI V R
#ROLL NO : 230701090
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - B

```
import numpy as np
import pandas as pd
import warnings
warnings.filterwarnings('ignore')
df=pd.read_csv("Hotel_Dataset.csv")
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
9	9	25-30	2	Ibis	Non-Veg	3456
10	10	30-35	5	RedFox	non-Veg	-6755

```
        NoOfPax EstimatedSalaryAge_Group.1
0  1          2          40000       20-25
2  3          3          59000       30-35
4  5          2          30000       25-30
6  7          2         120000       20-25
8  9          2          45000         35+
10            2         122220         35+
             -1          21122         35+
            -10         345673       20-25
              3         -99999       25-30
              3         -99999       25-30
              4         87777        30-35
```

df.duplicated()

```
5        e
6     Fals
7        e
8     Fals
9        e
10    Fals
dtype:   e
bool  Fals
         e
      Fals
         e
      Fals
         e
      True
      Fals
```

```
df.info()                                  <class
'pandas.core.frame.DataFrame'>
RangeIndex: 11 entries, 0 to 10
Data columns (total 9 columns):
 #     Column              Non-Null  Count    Dtyp
       -------             ---------------      e
-----                                        --------
 0     CustomerID          11   non-null      int6
                                                4
1      Age_Group           11   non-null     object
2      Rating(1-5)         11   non-null     int64
```

```
· Hotel          11 non-null     object
· FoodPreference 11 non-null     int64
· Bill           11 non-null     object
· NoOfPax        11 non-null     int64
· EstimatedSalary 11 non-null    int64
·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	+	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	1	2	40000	20-25
2	3	3	59000	30-35
4	5	2	30000	25-30
6	7	2	120000	20-25
8		2	45000	35+
1	0	2	122220	35+
		-1	21122	35+
len(df)		-10	345673	20-25
		3	-99999	25-30
10		4	87777	30-35

```python
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])

```python
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

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

0	1	20-25	4	Ibis	veg	1300

```
2
```

```
                                        CustomerID Age_Group
Rating(1-5)                             Hotel FoodPreference Bill
NoOfPax \
```

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

          8    20-25    7   LemonTree        Veg 2999

          9    25-30    2   Ibis         Non-Veg 3456

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

```
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.na
n  df
```

```
   CustomerIDAge_Group  Rating(1-5)      HotelFoodPreference     Bill
\
0        1.0    20-25           4     Ibis               veg  1300.0

1        2.0    30-35           5  LemonTree        Non-Veg  2000.

2        3.0    25-30           6     RedFox             Veg  0

3        4.0    20-25          -1  LemonTree             Veg  1322.0 / 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
```

```
   CustomerIDAge_Group Rating(1-5)      HotelFoodPreference       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

```
9         g
          Non-Ve
          g
          non-Ve
          g
```

Name: FoodPreference, dtype: object>

```
df.FoodPreference.replace(['Vegetarian','veg'],'Veg',inplace=Tru
e) df.FoodPreference.replace(['non-Veg'],'Non-Veg',inplace=True)
df.EstimatedSalary.fillna(round(df.EstimatedSalary.mean()),inplace=T
ru 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	+	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 : GAYATHRI V R
#ROLL NO : 230701090
#DEPARTMENT : B.E COMPUTER SCIENCE AND
ENGINEERING - B

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

	Countr y	Age	Salary	Purchased
0		44. 0	72000.0	No
1	France		48000.0	Ye s
2	Spain	27.0	54000.0	No
3	German y	30.0	61000.0	No
4		38.0	NaN	
5	Spain	40.0	58000	No

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 4 columns):
 #     Column      Non-Null  Count Dtyp
                                   e
-----  -------     ----------------  -------
 0     Country     10  non-null      object
 .  Age            9                 float6
                   non-null          4
 .  Salary                           float6
 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
```

```
     Countr   Age    Salary
0         y  44.    72000.0 Purchased    N
1    France  0      48000.0              o
2     Spain  27.0   54000.0             Ye
3    German  30.0   61000.0              s
4         y  38.0   63778.0             No
5     Spain  40.0   58000.0             No
6    German  35.0   52000.0             Ye
7         y  38.0   79000.0              s
8    France  48.0   83000.0             Ye
9     Spain  50.0   67000.0              s
     France  37.0                       No
                                        Ye
                                         s
                                        No
                                        Ye
                                         s
```

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

```
 France Germany Spain
.  True      False False
.  False     False True
.  False     True  False
.  False     False True
.  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)
df.info()
```

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

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

```
#EX.NO :5 EDA-Quantitative and Qualitative plots
#DATA : 27.08.2024
#NAME : GAYATHRI V R
#ROLL NO : 230701090
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - B

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

)  df
```

```
    Countr   Age   Salary
0        y  44.   72000.0Purchased     N
1   France  0     48000.0               o
2    Spain  27.0  54000.0              Ye
3   German  30.0  61000.0               s
4        y  38.0      NaN              No
5    Spain  40.0  58000.               No
6   German  35.0  0                    Ye
7        y   NaN  52000.0               s
8   France  48.   79000.0              Ye
```

```
df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 4 columns):
 #     Column      Non-Null  Count Dtyp
       -------     ---------------   e
-----                               --------
 0     Country     10  non-null       object
 ·  Age            9                  float6
                   non-null           4
 ·  Salary         9                  float6
 3     Purchased 10  non-null         4
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
    Countr   Age    Salary   Purchased
0        y   44.    72000.0          N
1   France   0      48000.0          o
2    Spain   27.0   54000.0         Ye
3   German   30.0   61000.0          s
4        y   38.0   63778.0         No
5    Spain   40.0   58000.0         No
6   German   35.0   52000.0         Ye
7        y   38.0   79000.0          s
8   France   48.0   83000.0         Ye
9    Spain   50.0   67000.0          s
    France   37.0                   No
                                    Ye
                                     s
                                    No
                                    Ye
                                     s
pd.get_dummies(df.Country)

 France Germany Spain
·  True      False False
·  False     False True
·  False     True  False
·  False     False True
·  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 Spain    Age    Salary
0         True False False   44.    72000.0 Purchased      N
1    False          False    0      48000.0                o
2    True  False             27.0   54000.0               Ye
3        True False False    30.0   61000.0                s
4               False True   38.0   63778.0               No
5    False                   40.0   58000.0               No
6     True False TrueFalse   35.0   52000.0               Ye
7    False False             38.0   79000.0                s
8    False     True  True    48.0   83000.0               Ye
9    False False False       50.0   67000.0                s
              True False     37.0                         No
                                                          Ye
                                                           s
                                                          No
                                                          Ye
                                                           s
```

```
df.info()
```

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

```
updated_dataset
```


```
     France Germany Spain    Age    Salary
0         True False False   44.    72000.0 Purchased      N
1    False          False    0      48000.0                o
2    True  False             27.0   54000.0               Ye
3        True False False    30.0   61000.0                s
4               False True   38.0   63778.0               No
5    False                   40.0   58000.0               No
6     True False TrueFalse   35.0   52000.0               Ye
7    False False             38.0   79000.0                s
8    False     True  True    48.0   83000.0               Ye
```

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

#NAME : GAYATHRI V R

#ROLL NO : 230701090

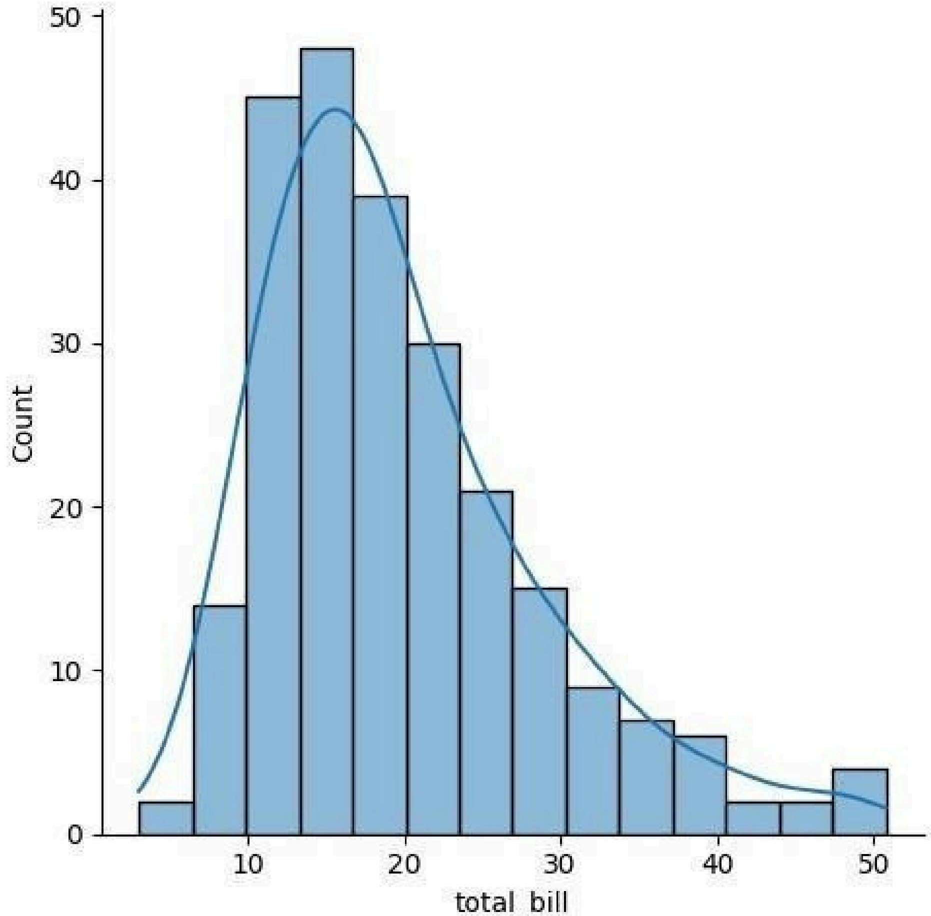
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - B

```
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

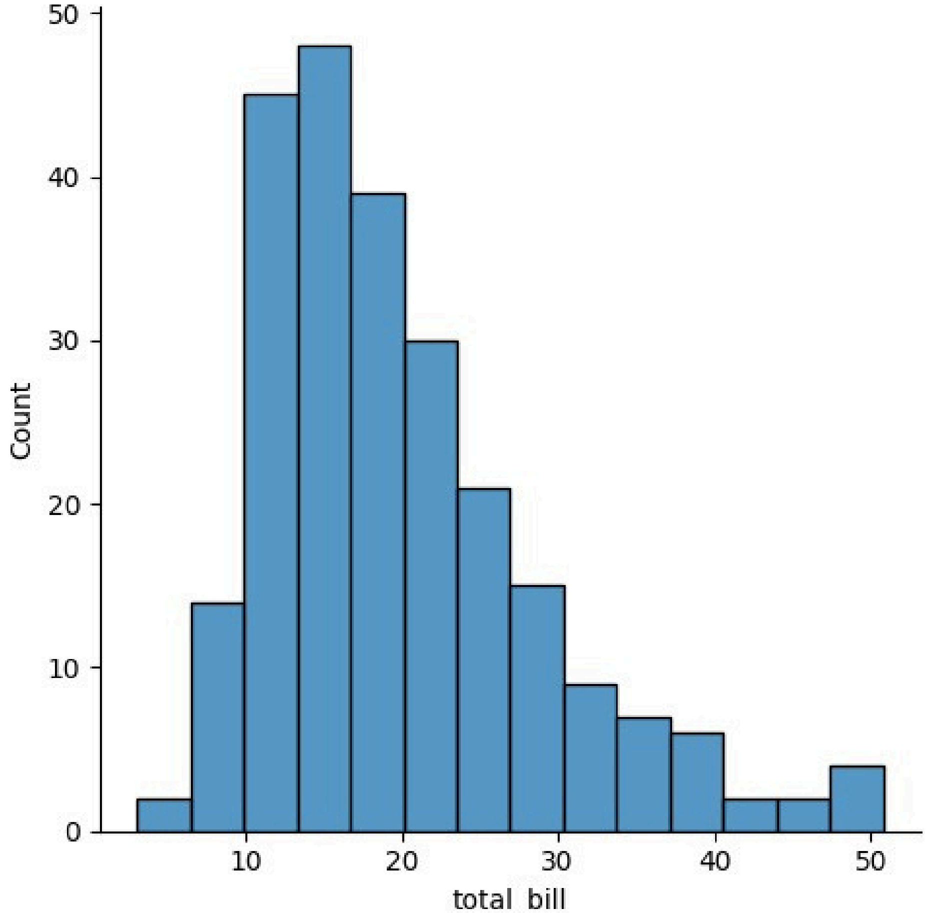
```
sns.displot(tips.total_bill,kde=True)
```

```
<seaborn.axisgrid.FacetGrid at 0x20d7dc69390>
```



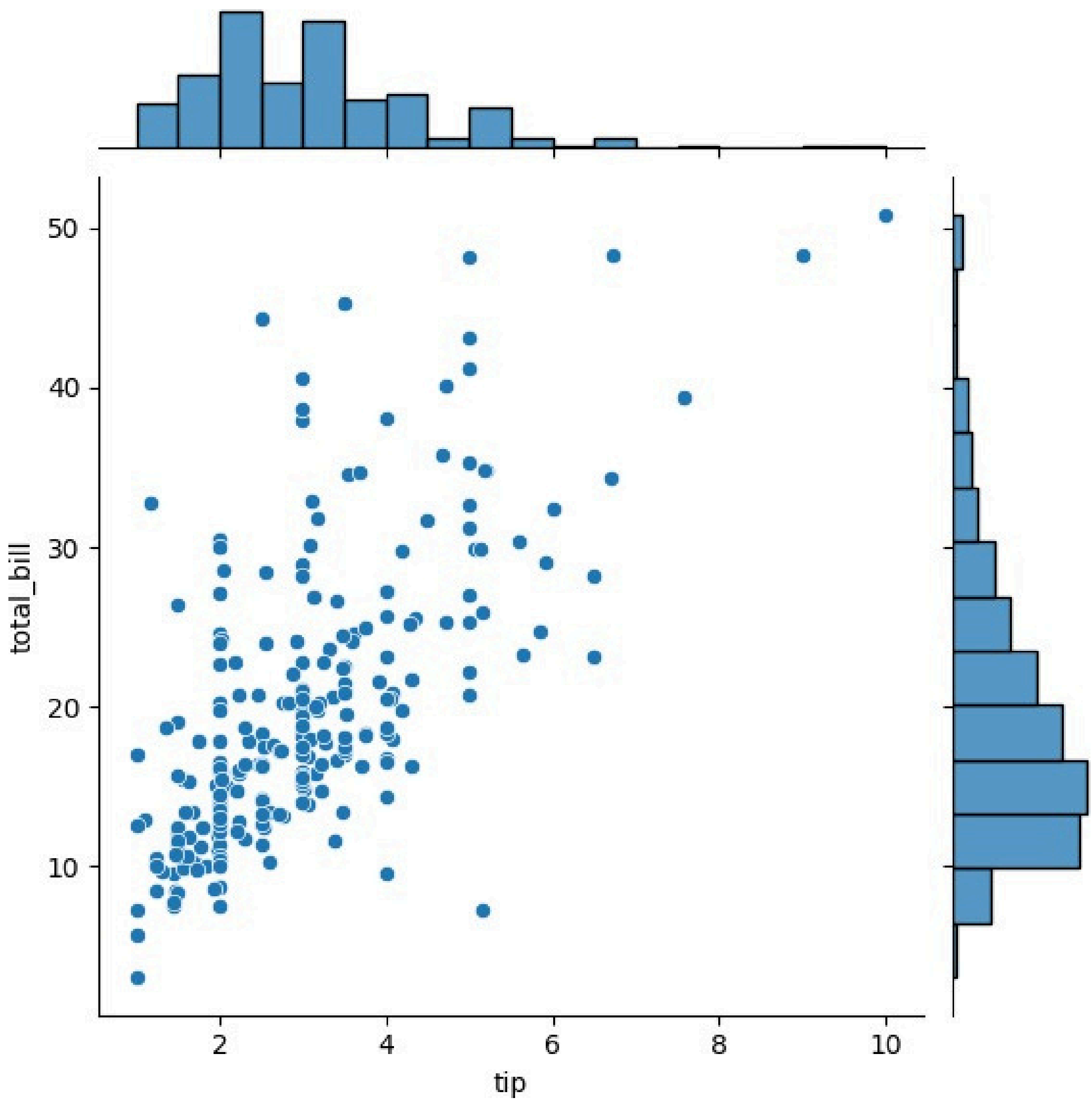

```
sns.displot(tips.total_bill,kde=False)
```

```
<seaborn.axisgrid.FacetGrid at 0x20d7dc22790>
```

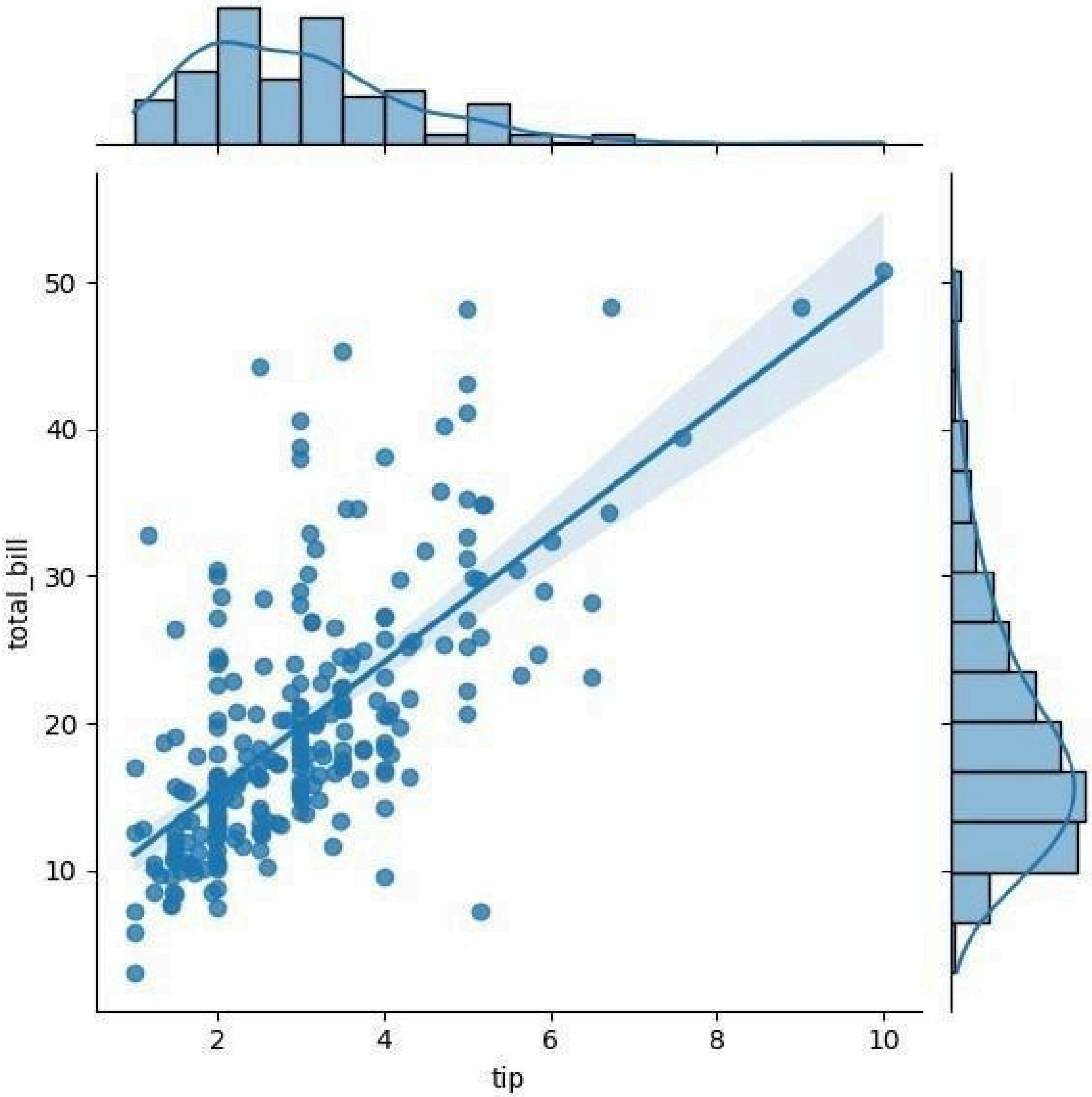



```
sns.jointplot(x=tips.tip,y=tips.total_bill)
```

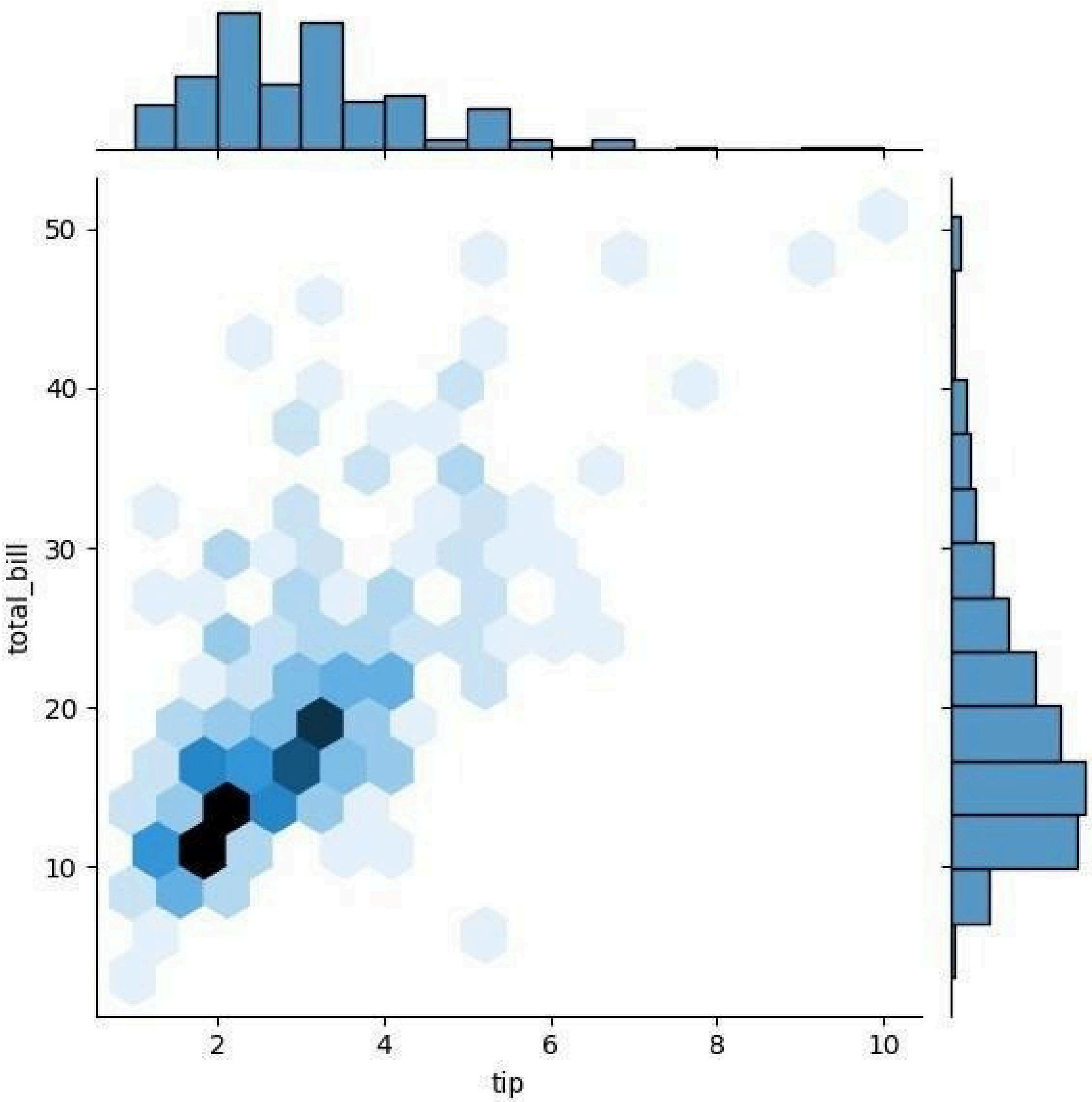
<seaborn.axisgrid.JointGrid at 0x20d7dc2f2d0>



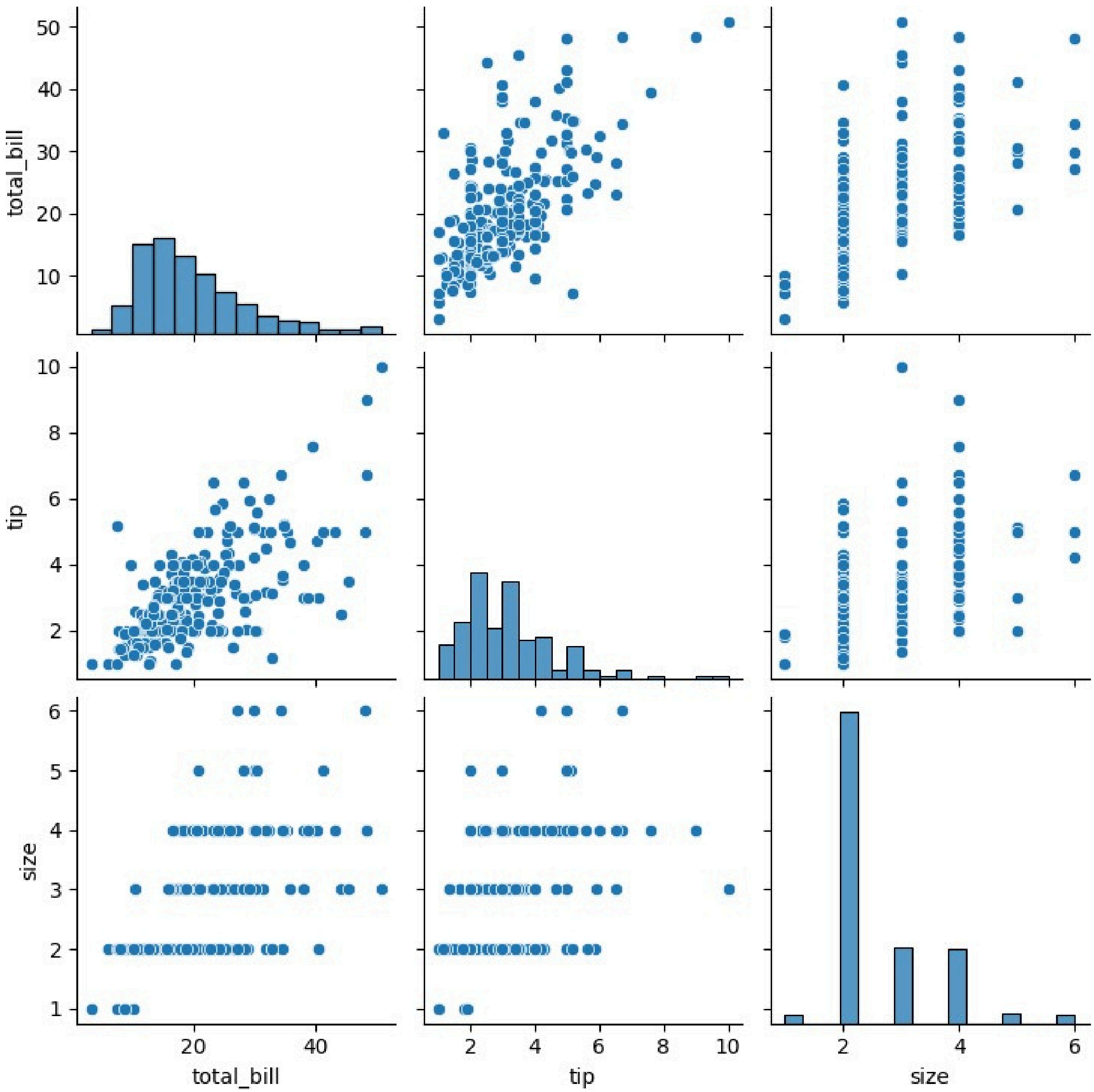

```
sns.jointplot(x=tips.tip,y=tips.total_bill,kind="reg")

<seaborn.axisgrid.JointGrid at 0x20d7ed32450>
```



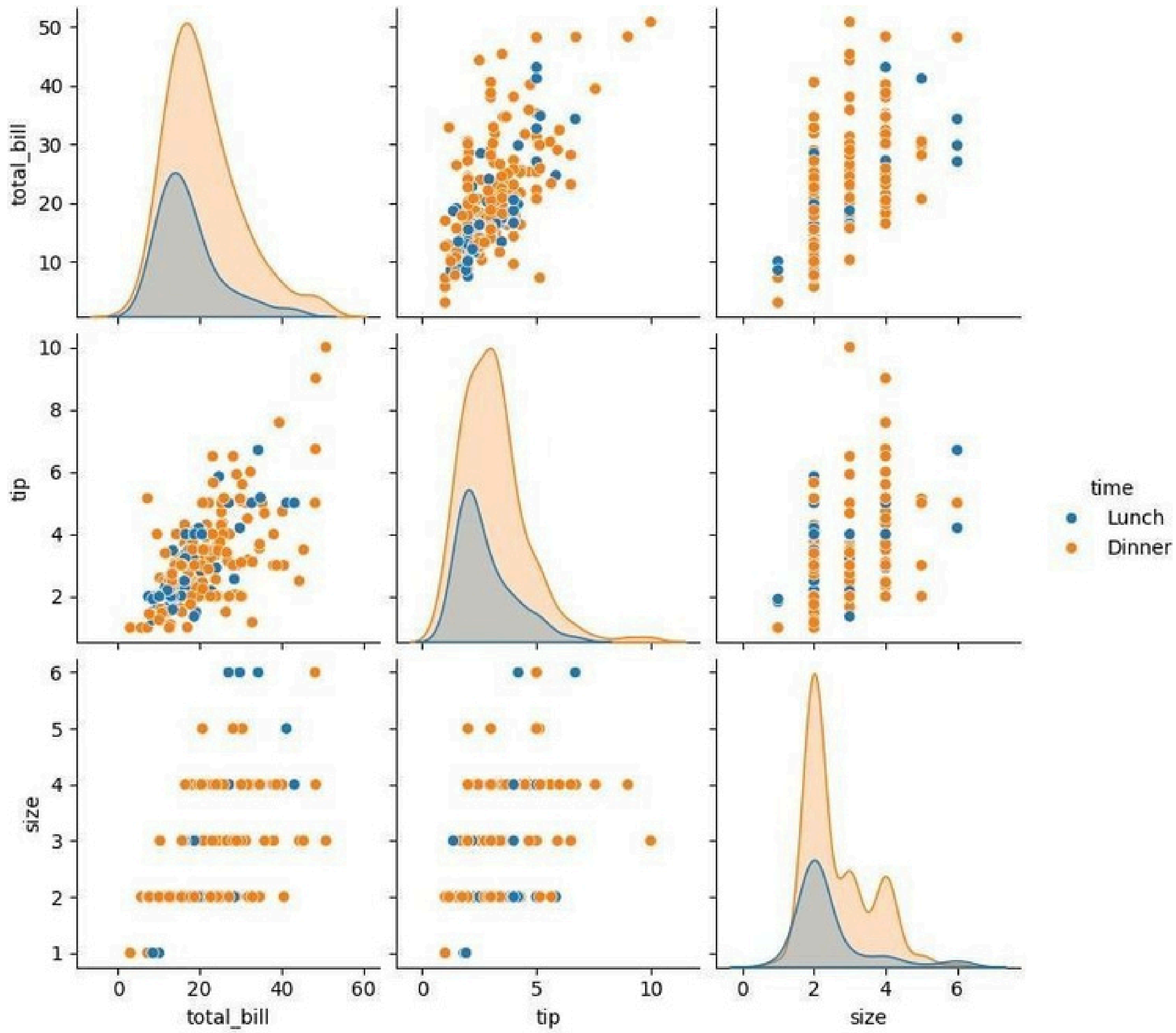

```
sns.jointplot(x=tips.tip,y=tips.total_bill,kind="hex")

<seaborn.axisgrid.JointGrid at 0x20d7ed7d350>
```




```
sns.pairplot(tips)

<seaborn.axisgrid.PairGrid at 0x20d7f1c9cd0>
```

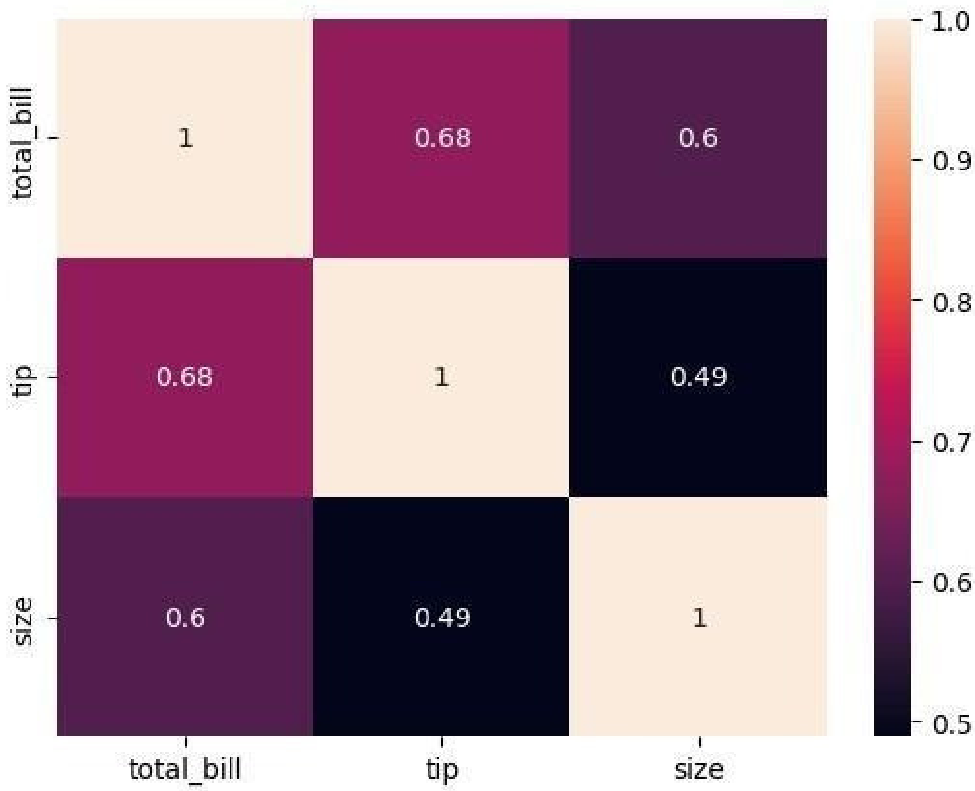



```
tips.time.value_counts()

time
Dinne      17
r           6
Name: count, dtype: int64

sns.pairplot(tips,hue='time')

<seaborn.axisgrid.PairGrid at 0x20d7cc27990>
```

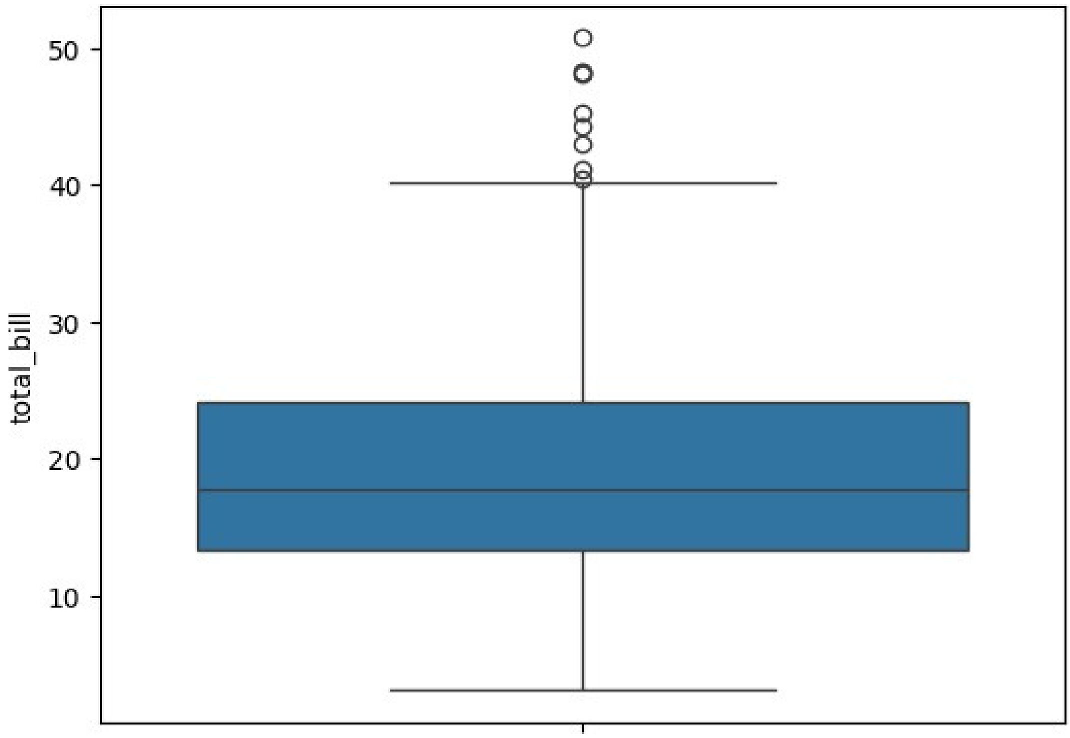



```
sns.heatmap(tips.corr(numeric_only=True),annot=True)
```

```
<Axes: >
```

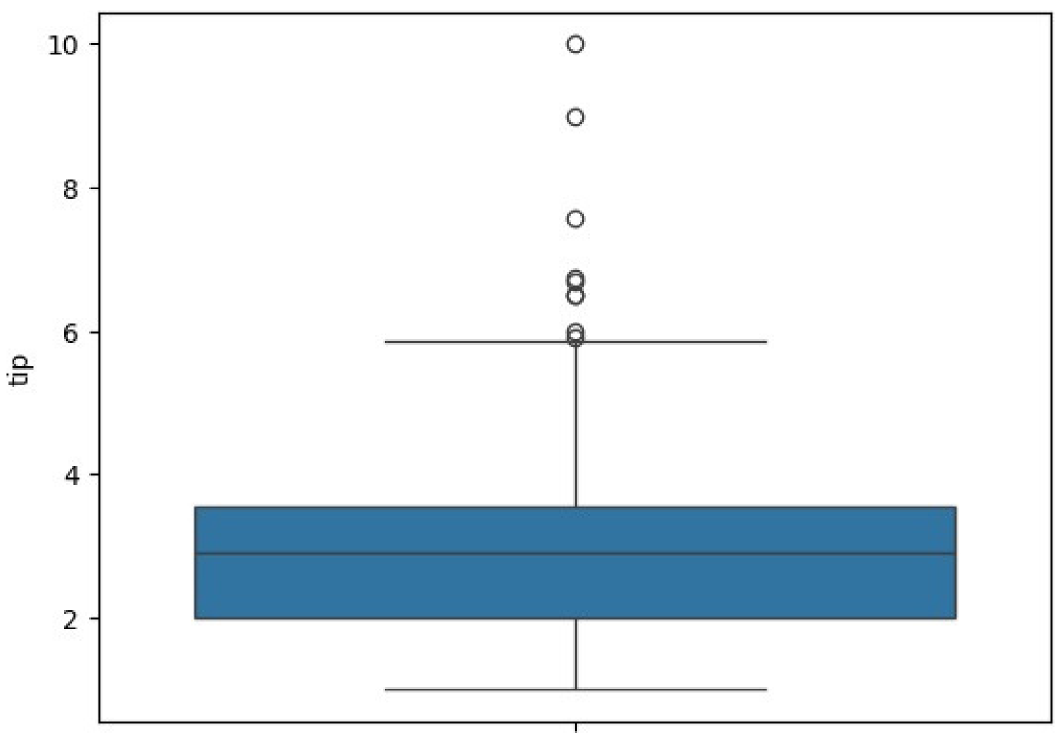



```
sns.boxplot(tips.total_bill)

<Axes: ylabel='total_bill'>
```



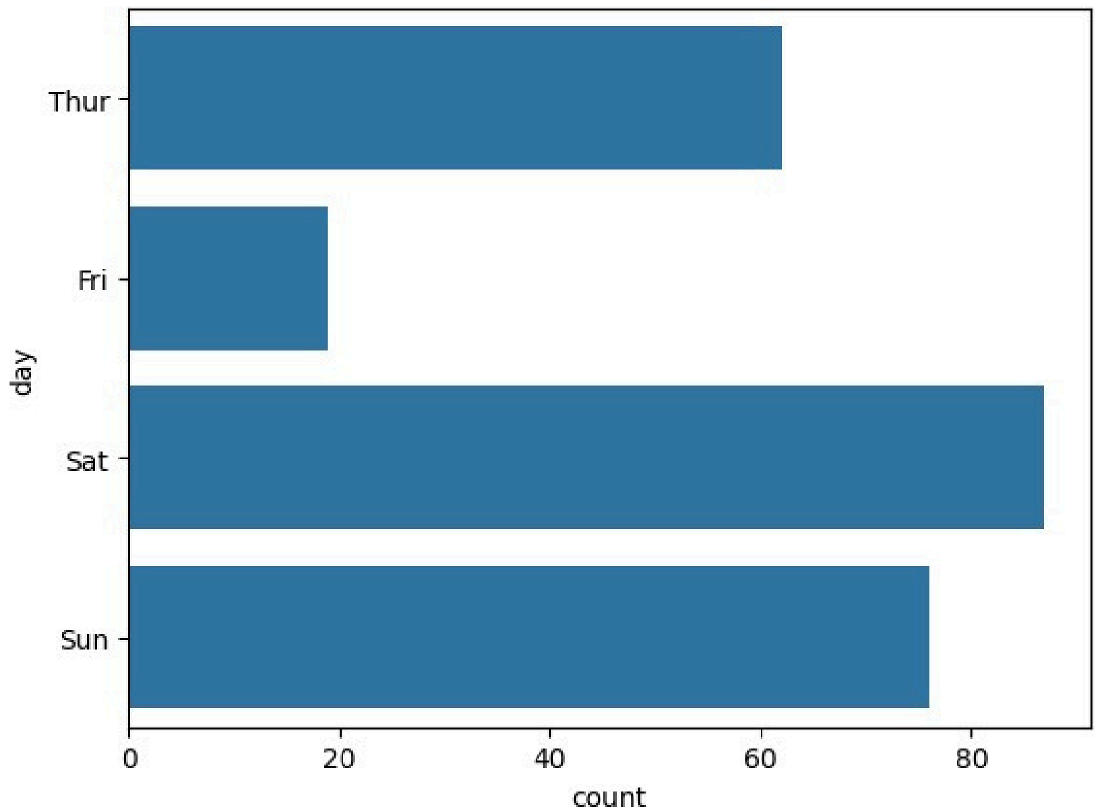

```
sns.boxplot(tips.tip)
```

```
<Axes: ylabel='tip'>
```



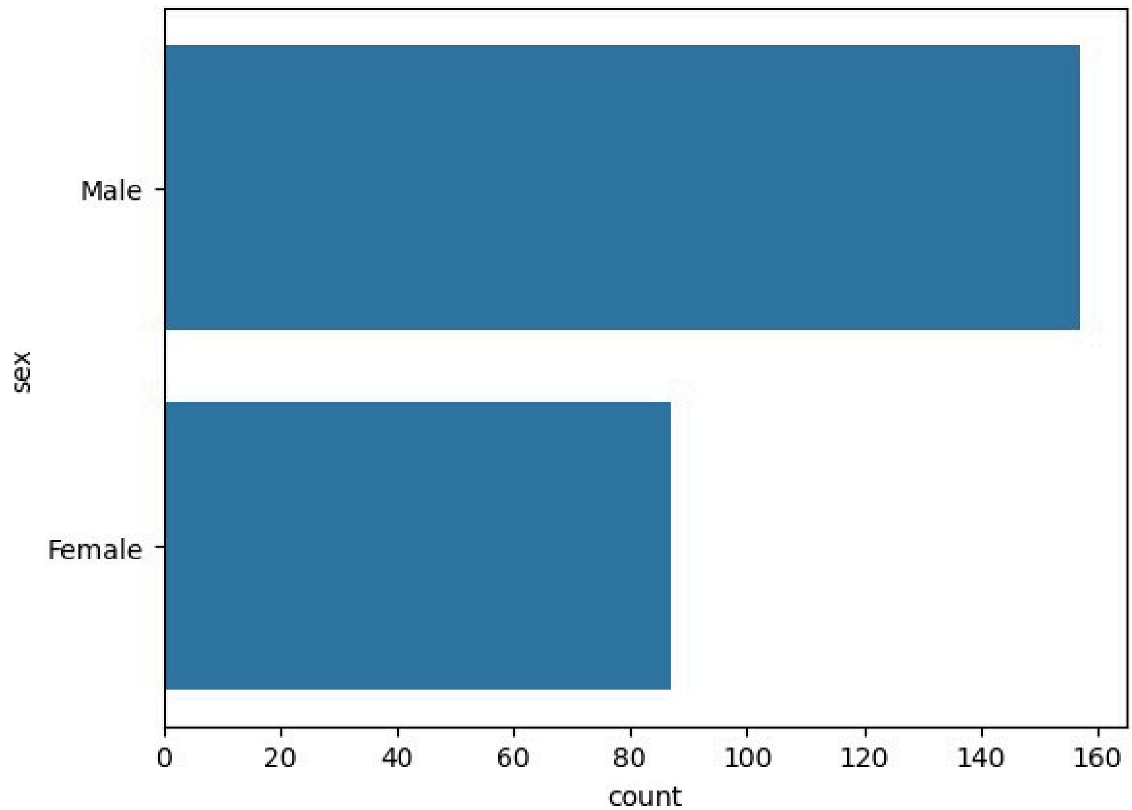
```
sns.countplot(tips.day)
```

```
<Axes: xlabel='count', ylabel='day'>
```



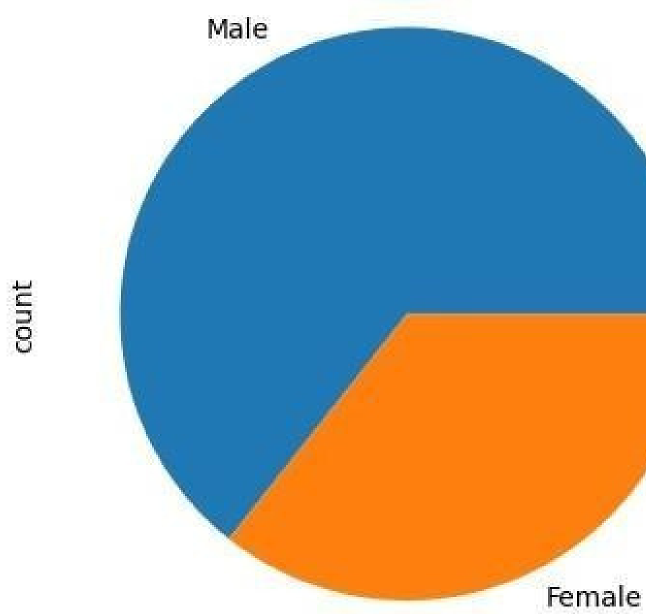

```
sns.countplot(tips.sex)
```

```
<Axes: xlabel='count', ylabel='sex'>
```



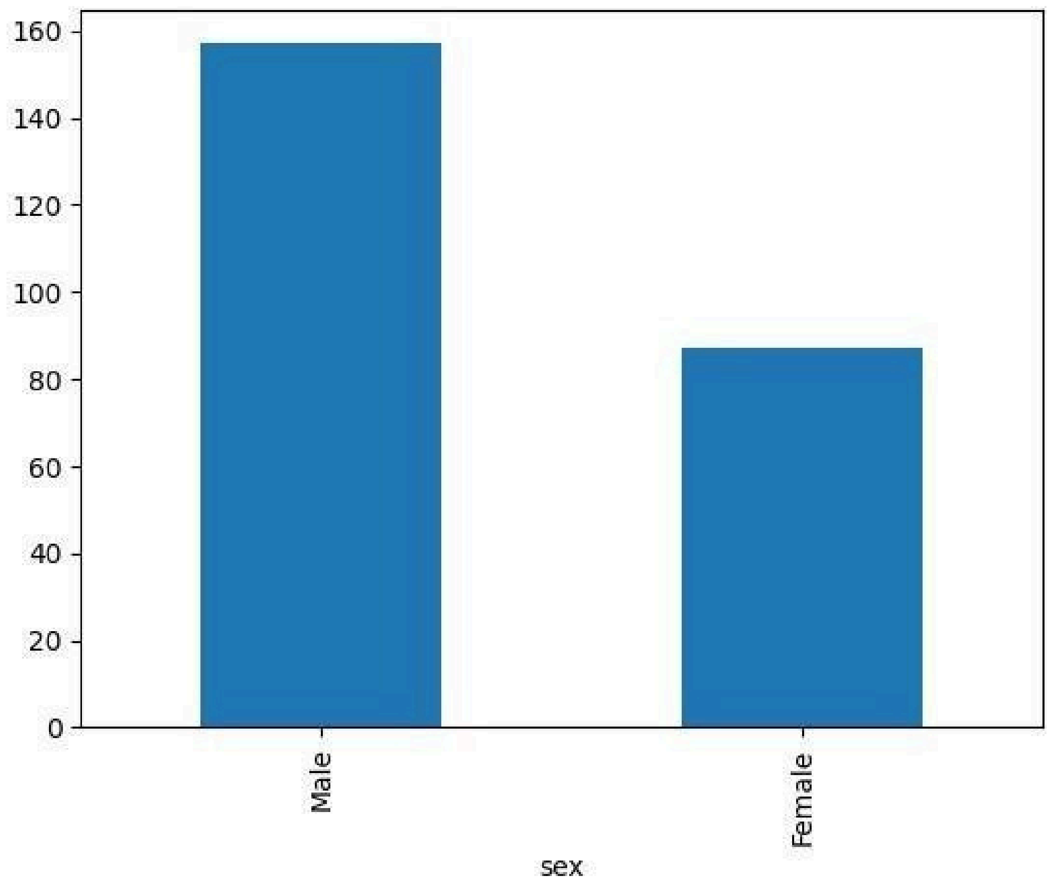

```
tips.sex.value_counts().plot(kind='pie')
```

```
<Axes: ylabel='count'>
```



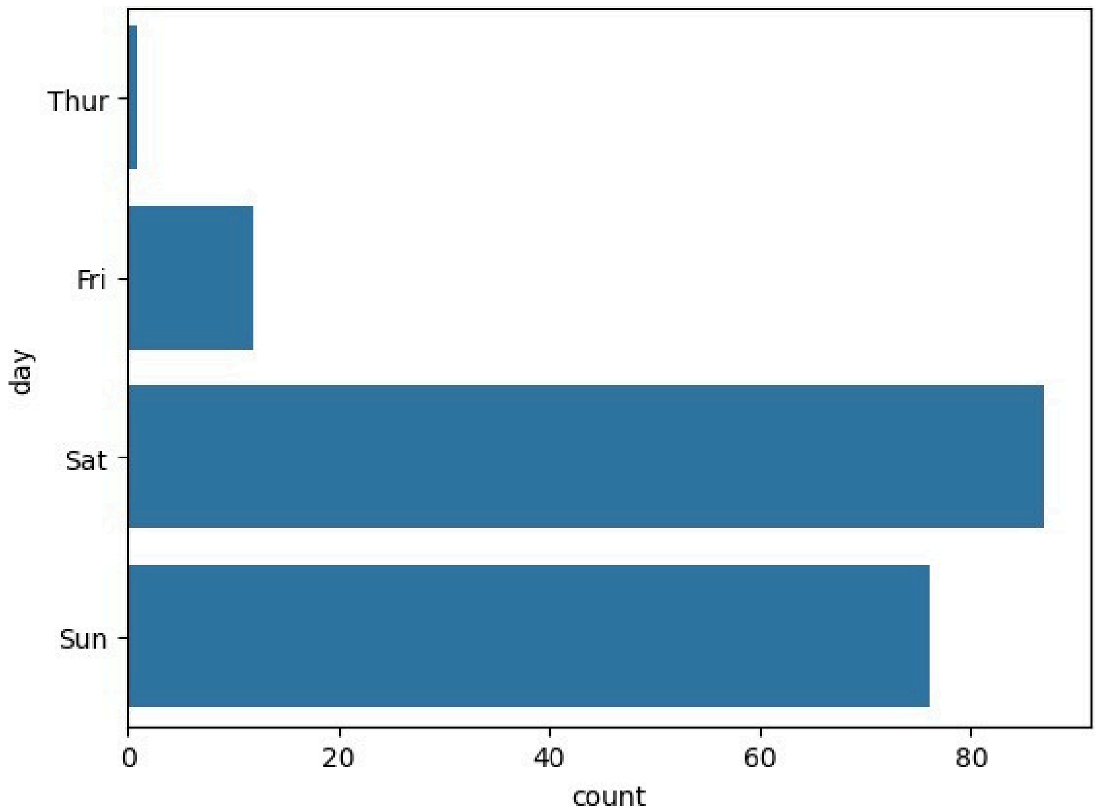

```
tips.sex.value_counts().plot(kind='bar')
```

```
<Axes: xlabel='sex'>
```




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

```
<Axes: xlabel='count', ylabel='day'>
```



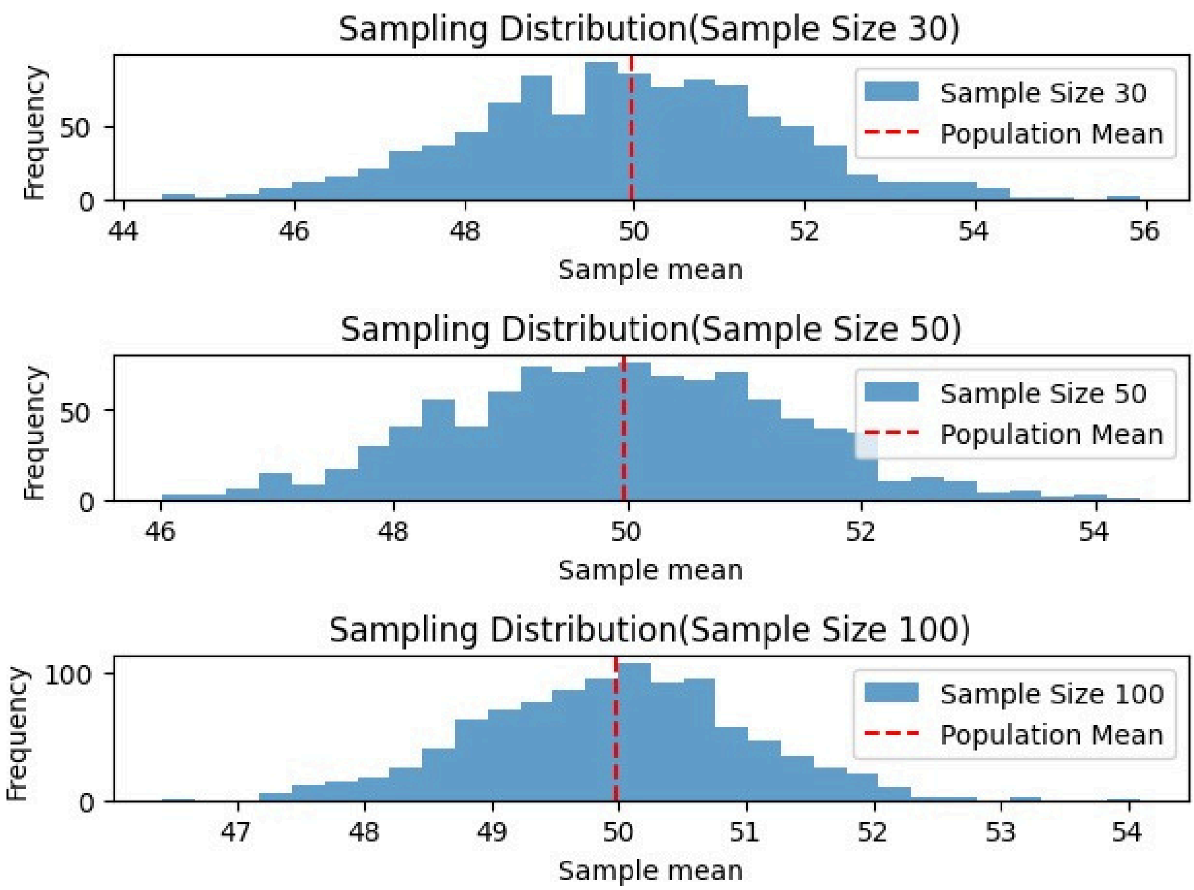

```
#EX.NO :6 Random Sampling and Sampling Distribution
#DATA : 10.09.2024

#NAME : GAYATHRI V R
#ROLL NO : 230701090
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - B

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')
plt.title(f'Sampling Distribution(Sample Size {size})')
    plt.xlabel('Sample mean')
plt.ylabel('Frequency') plt.legend()
plt.tight_layout()
 plt.show()
```




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

```
#NAME : GAYATHRI V R
#ROLL NO : 230701090
 #DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - B
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.
```

```
#EX.NO :8 T-Test
#DATA : 08.10.2024
#NAME : GAYATHRI V R
```

```
#ROLL NO : 230701090
 #DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - B

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 : GAYATHRI V R
#ROLL NO : 230701090
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - B

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:
a     print("Reject the null hypothesis: There is
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   1.46470.0877   -0.16833.0977     False
     A      C   5.5923        0.0  3.95937.2252     True
     B      C   4.1276        0.0  2.49465.7605     True
-----------------------------------------------------------
```

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

#NAME : GAYATHRI V R
#ROLL NO : 230701090
#DEPARTMENT : B.E COMPUTER SCIENCE AND

ENGINEERING - B

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

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

```
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) 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)
```

```python
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,
        [illegible],1.52752523e+00, -6.54653671e-01,
         -1.27555478e+00,
        [illegible],-6.54653671e-01, 1.52752523e+00,
         -1.13023841e-01,
        [illegible],1.52752523e+00, -6.54653671e-01,
          1.77608893e-01, 6.63219199e-16],
        [ 1.22474487e+00, -6.54653671e-01,
        [illegible],
        [illegible],-6.54653671e-01, 1.52752523e+00,
          0.00000000e+00,
        [ [illegible]-6.54653671e-01,
        [illegible], 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]])
```

```python
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 : GAYATHRI V R
 #ROLL NO : 230701090
#DEPARTMENT : B.E COMPUTER SCIENCE AND
ENGINEERING - B

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  Dtyp
      -------             ---------------  e
-----                                      --------
```

```
 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
```

```python
df.describe() #descripte statical report
# find out IYER 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

```python
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=2
3) # 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'
```

```
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'

model.score(x_train,y_train)
'''
accuracy calculating
96%
'''
'\naccuracy calculating\n96 %\n'

model.score(x_test,y_test)

'''
accuracy calculating
91%
'''
'\naccuracy calculating\n91

%\n' model.coef_

array([[9281.30847068]])

model.intercept_

array([27166.73682891])

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




) '''
pickle momory obj to file

'''

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

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

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]] .
```

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

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

```python
#EX.NO:12       LogisticRegression
#DATA : 05.11.2024

#NAME : GAYATHRI V R
#ROLL NO : 230701090
#DEPARTMENT : B.E COMPUTER SCIENCE AND

ENGINEERING - B

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

```
        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]
```

```python
df.tail(20)
```

```
User ID Gender Age EstimatedSalary Purchased
380 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
387 15627220    Male  39    71000 0
```

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	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
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
13	15704987	Male	32	18000	0
14	15628972	Male	18	82000	0
15	15697686	Male	29	80000	0
16	15733883	Male	47	25000	1
17	15617482	Male	45	26000	1
18	15704583	Male	46	28000	1
19	15621083	Female	48	29000	1
20	15649487	Male	45	22000	1
21	15736760	Female	47	49000	1
22	15714658	Male	48	41000	1
23	15599081	Female	45	22000	1
24	15705113	Male	46	23000	1

```
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],
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[25, 33000],
[35, 65000],
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[32, 18000],
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[29, 80000],
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[47, 30000]
```

```
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```

```
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[32, 117000]
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[25, 87000]
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```

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```

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```

```
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```
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```
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       35,
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       40,
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       42,
[               54000],
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       42,
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```
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```
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[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, 1, 0
,
0,
                   0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 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, 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,
                   0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 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, 1, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0
,
1,
0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1, 0, 0, 0, 1, 1
,
0,
1, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 1, 0, 1, 0, 0, 1, 1, 0, 1, 1
,
0,
1, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0
,
1,
0, 1, 0, 1, 1, 1, 1, 0, 0, 0, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 0
,
1,
1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0, 1, 1, 0, 1, 1, 0, 0, 0, 1
,
1,
0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1
,
0,
1, 0, 1, 1, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0
,
1,
0, 1, 0, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0
,
1,
       1, 1, 0, 1], dtype=int64)
```

```python
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
```

```
el,test_siz
```

```
LogisticRegression()
```

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

```
0.85
0.85
```

```python
from sklearn.metrics import classification_report
print(classification_report(label,finalModel.predict(features)))
```

	precision	recall	f1-score	support
0	0.86	0.91	0.89	25
1	0.83	0.73	0.77	7
				143
accuracy			0.85	400
macro avg	0.84	0.82	0.83	400
weighted avg	0.85	0.85	0.85	400