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

#NAME : KESHAVALLU B
#ROLL NO : 230701515
#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
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 non-null    float64
 2   SepalWidthCm   150 non-null    float64
 3   PetalLengthCm  150 non-null    float64
 4   PetalWidthCm   150 non-null    float64
 5   Species        150 non-null    object
dtypes: float64(4), int64(1), object(1)
memory usage: 7.2+ KB
```

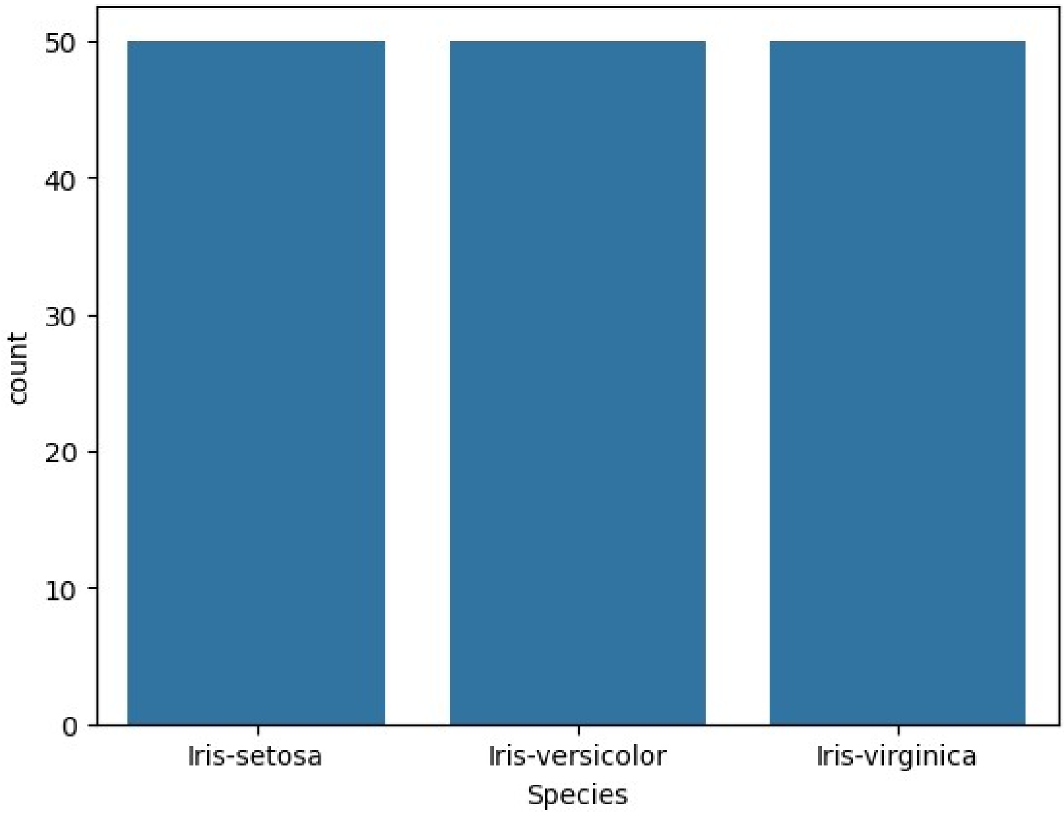
```
data.describe()
```

```
               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
```

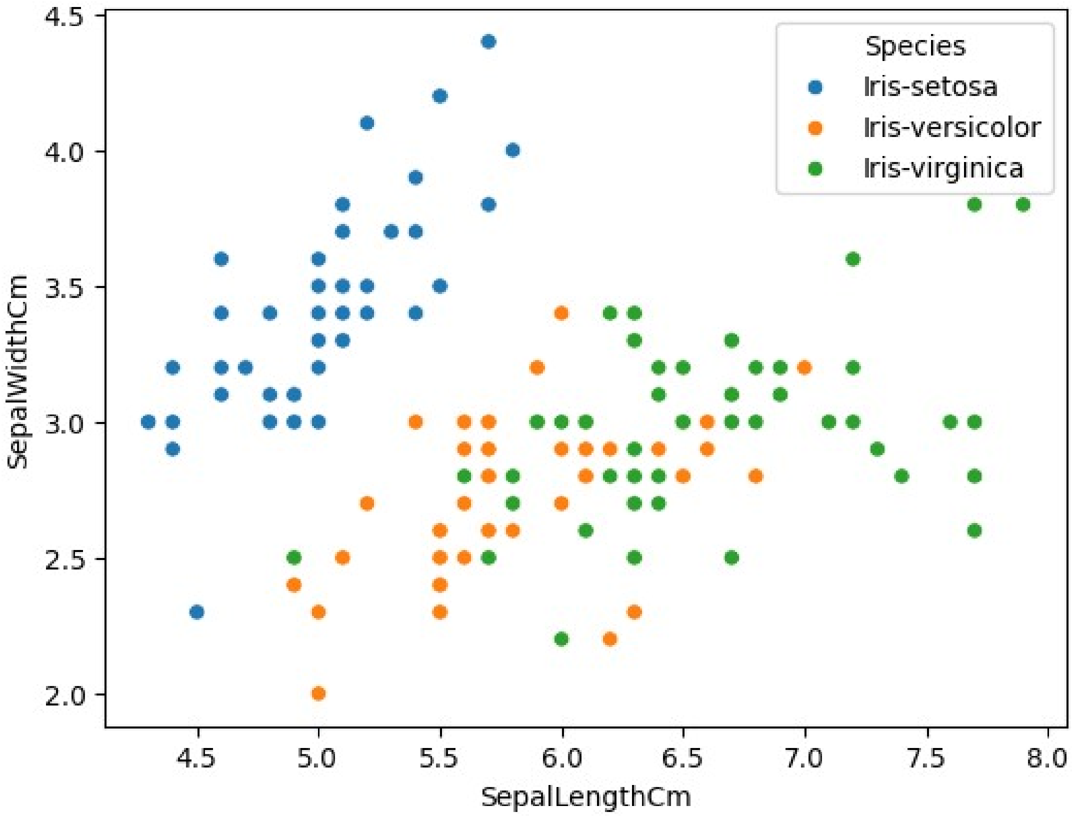
```
data.value_counts('Species')
```

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

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

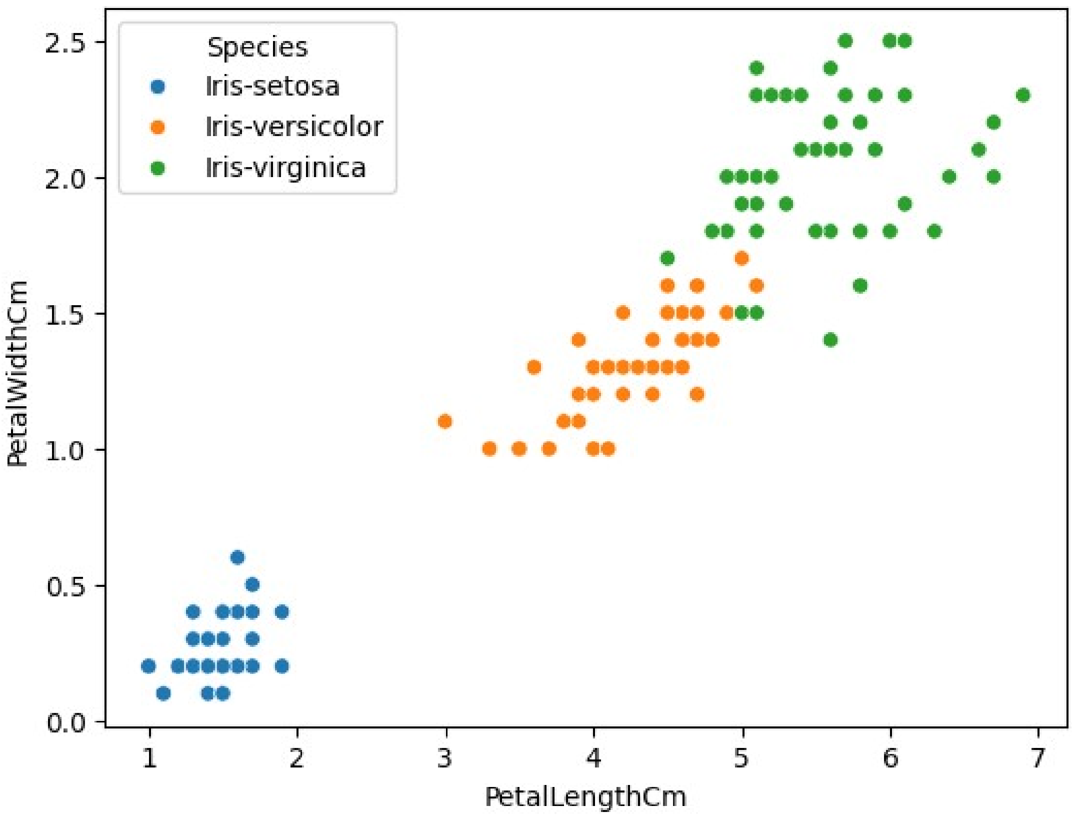



```
dummies=pd.get_dummies(data.Species)

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

FinalDataset.head()

   Iris-setosa  Iris-versicolor  Iris-virginica  Id  SepalLengthCm  \
0         True            False           False   1            5.1
1         True            False           False   2            4.9
2         True            False           False   3            4.7
3         True            False           False   4            4.6
4         True            False           False   5            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'>
```

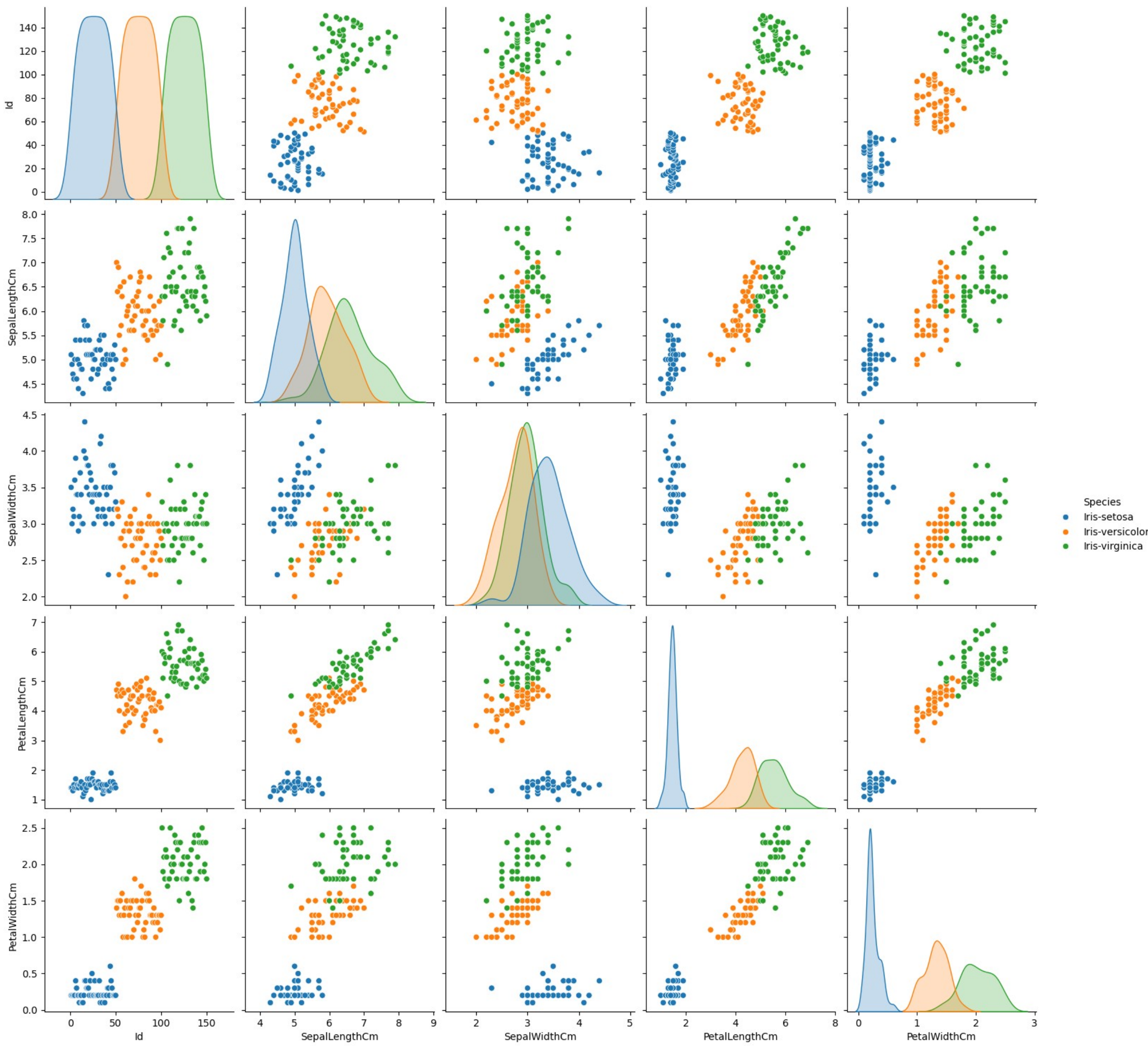



```
sns.scatterplot(x='PetalLengthCm',y='PetalWidthCm',hue='Species',data=
data,)
```

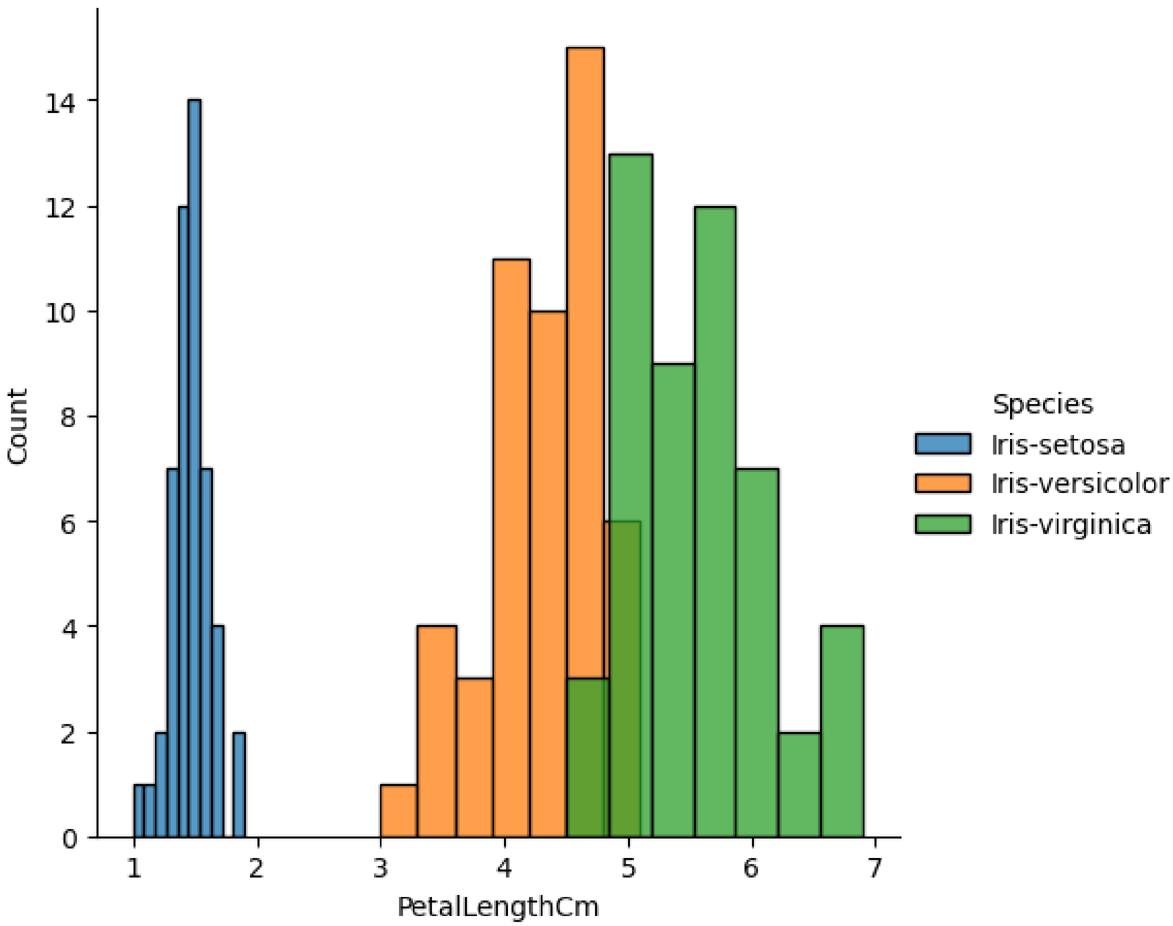
```
<Axes: xlabel='PetalLengthCm', ylabel='PetalWidthCm'>
```



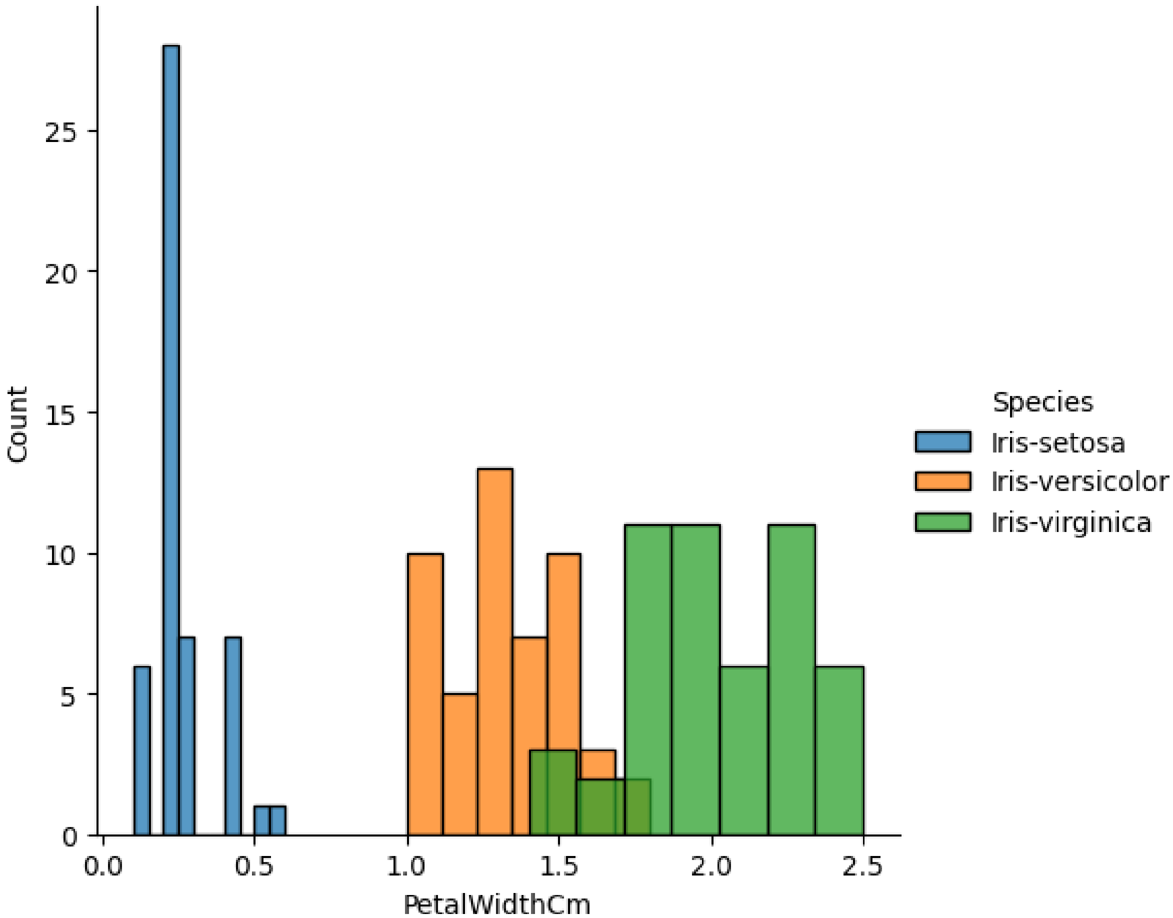

```
sns.pairplot(data,hue='Species',height=3);
```



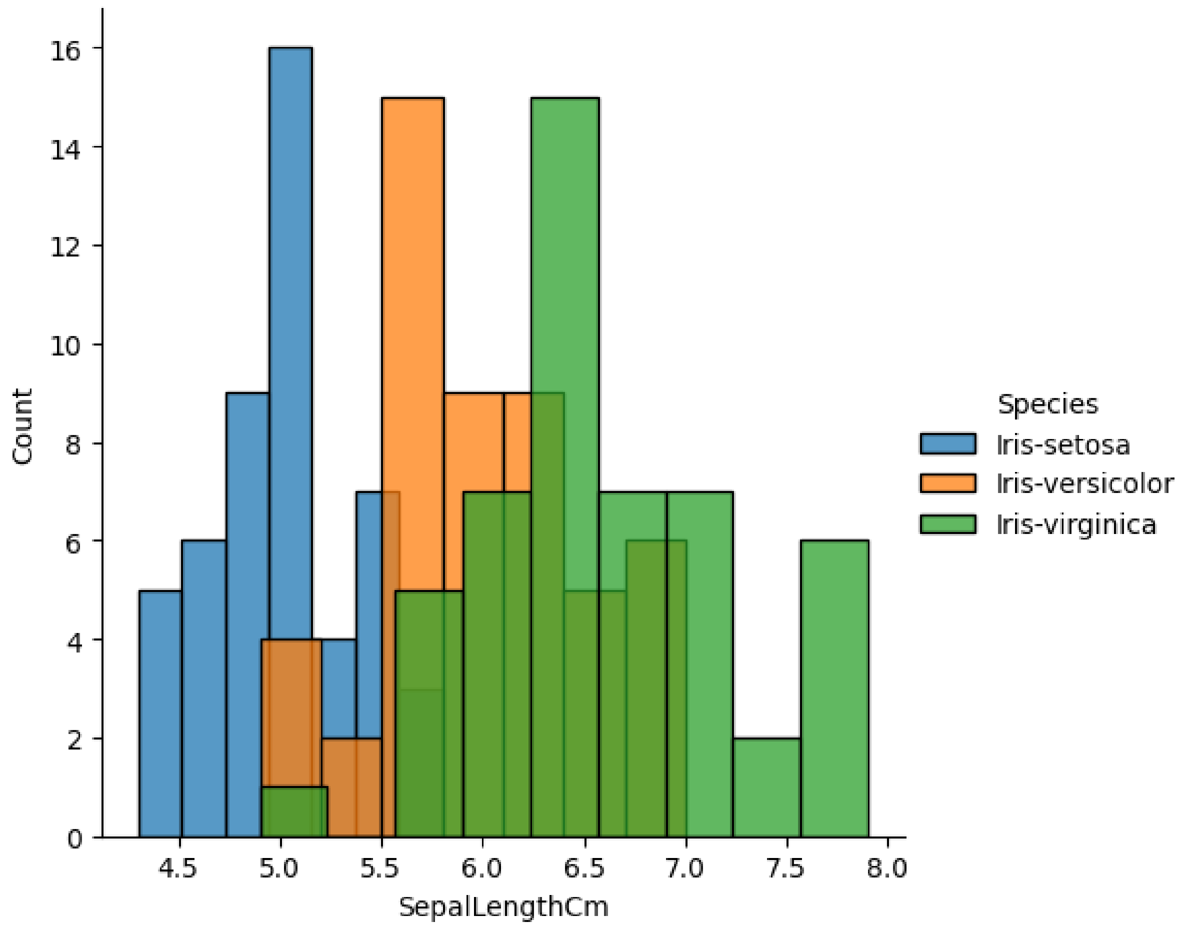

```
plt.show()

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



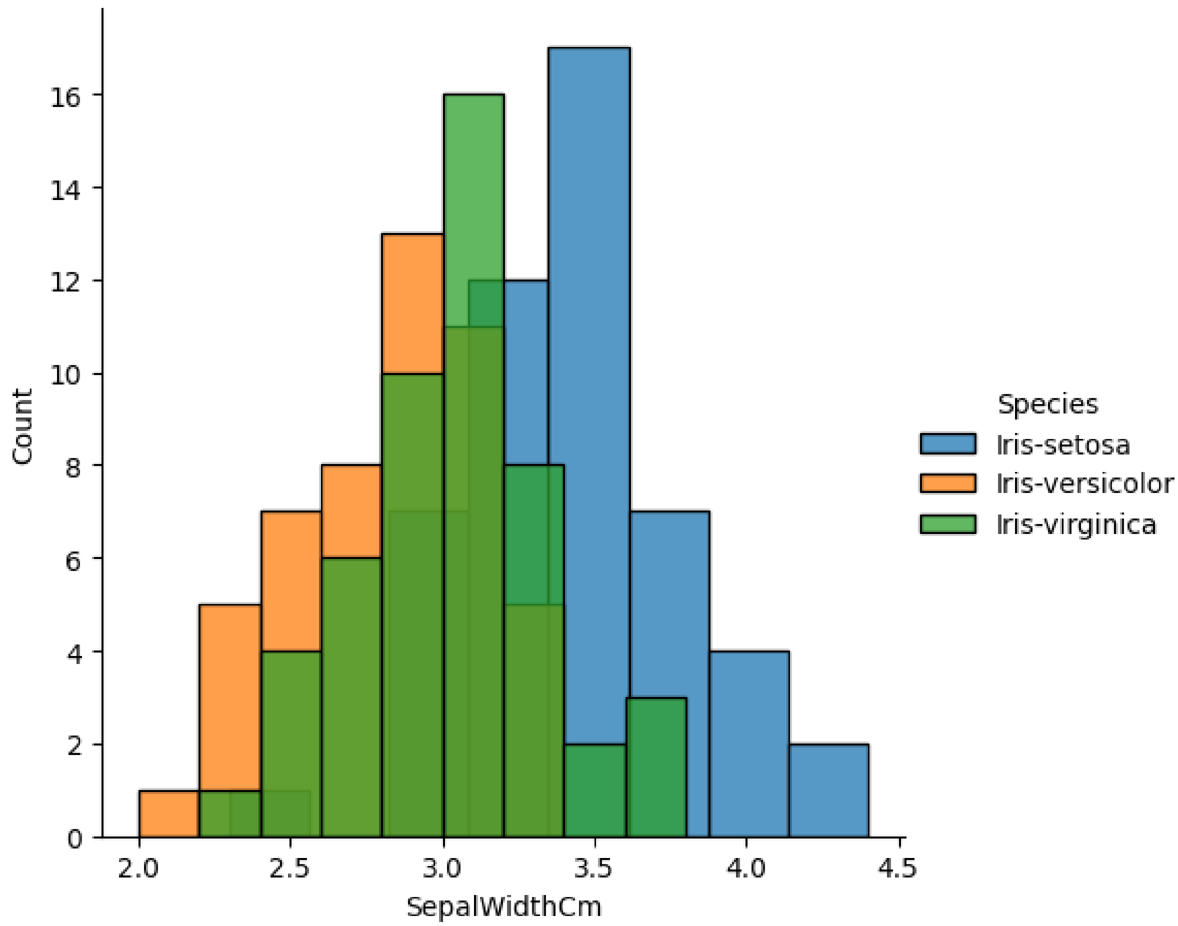

```
sns.FacetGrid(data,hue='Species',height=5).map(sns.histplot,'PetalWidt
hCm').add_legend();
plt.show();
```




```
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,'SepalWidthCm').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 : KESHAVALLU B
#ROLL NO : 230701515
#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 : KESHAVALLU B
#ROLL NO : 230701515
#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)
```

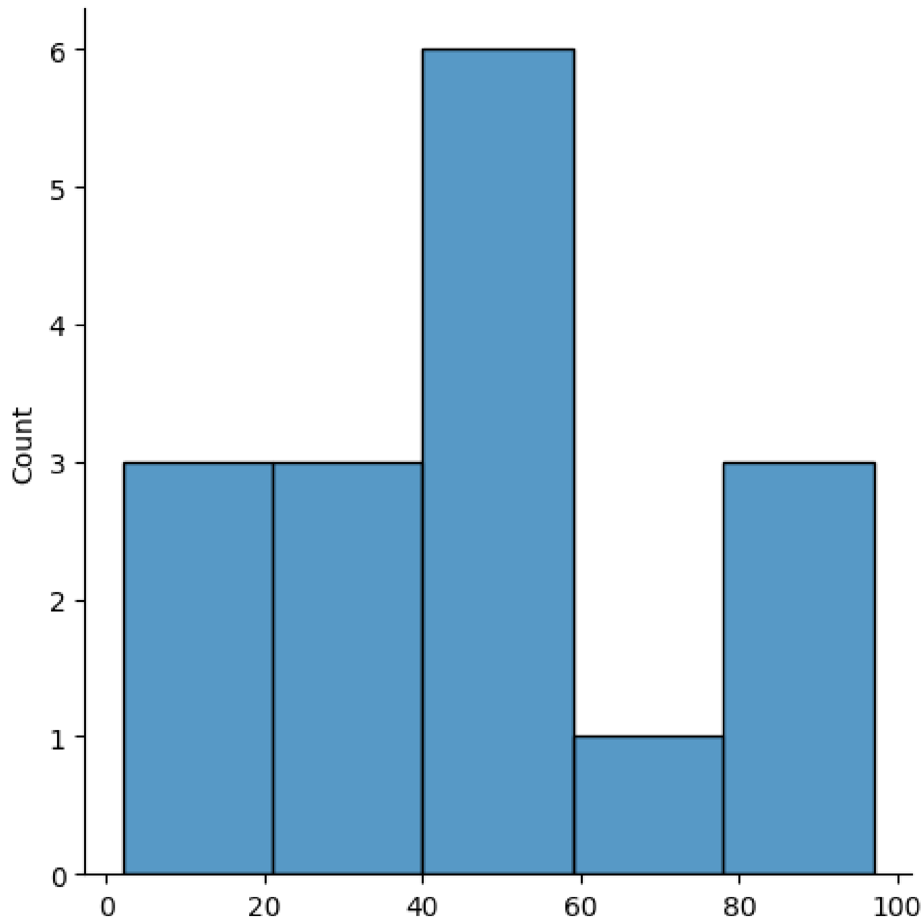
```
97.0
```

```
#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)
```

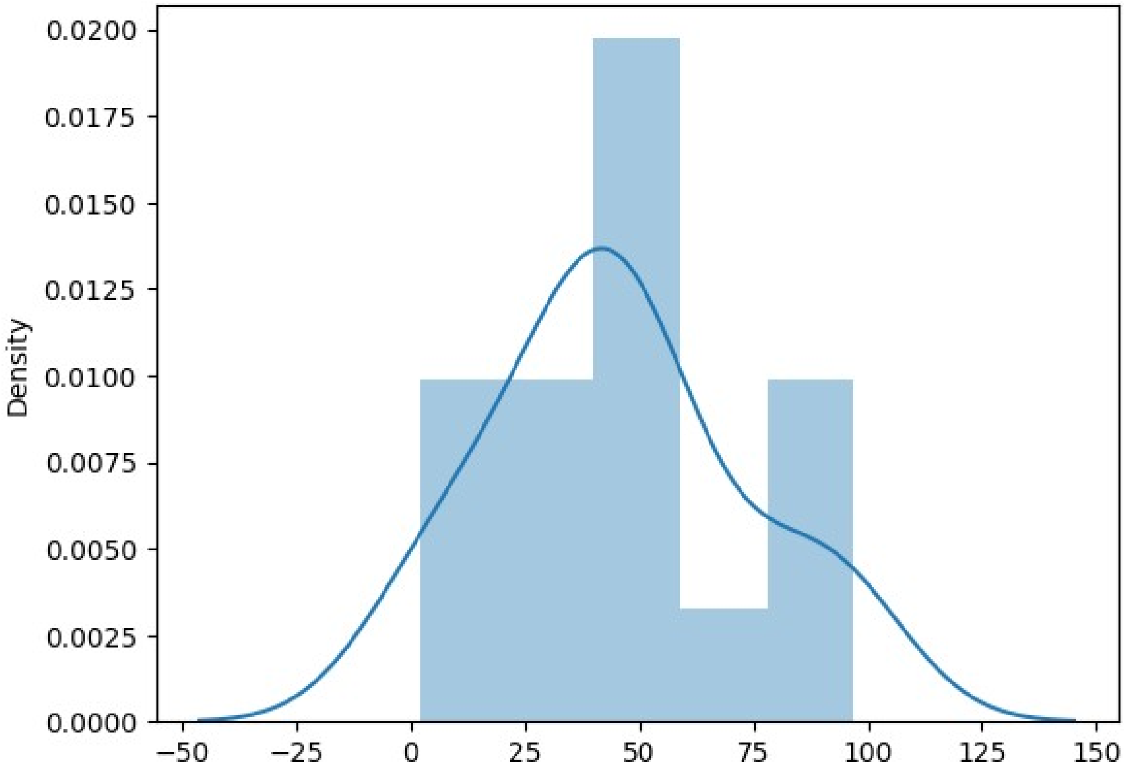
```
import seaborn as sns
%matplotlib inline
sns.displot(array)
```

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

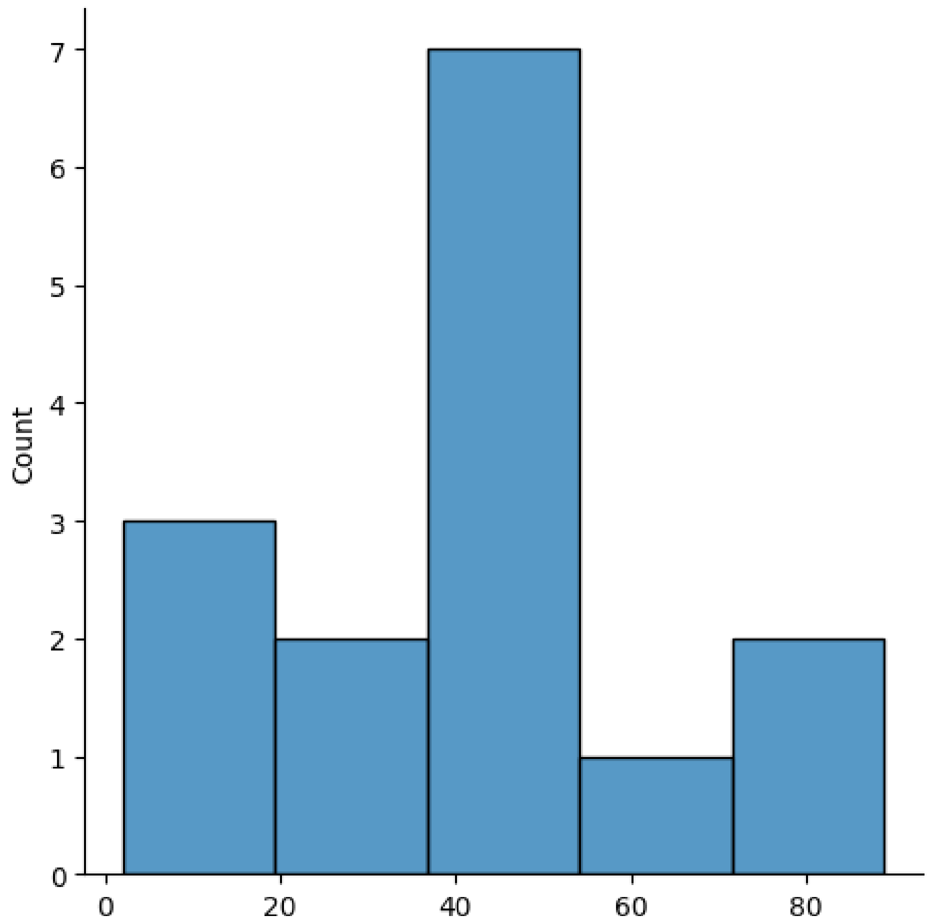



```
sns.distplot(array)
```

```
<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
```

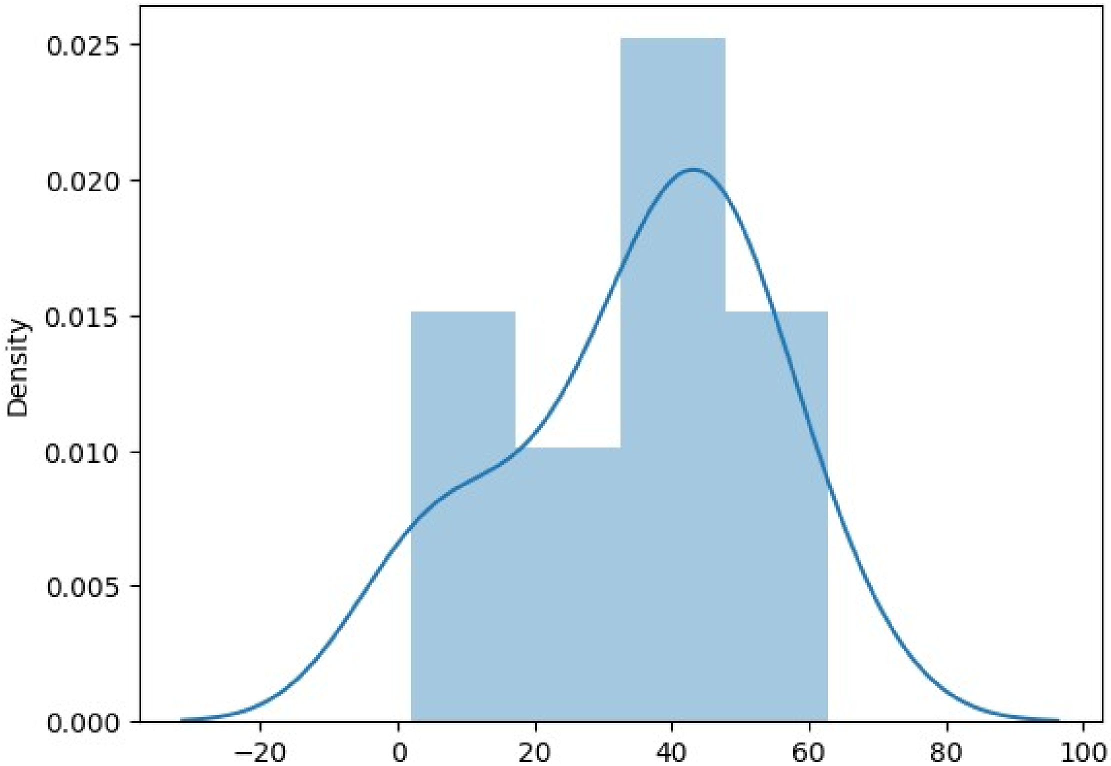
```
(-5.25, 84.75)
```

```
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 : KESHAVALLU B
#ROLL NO : 230701515
#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  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
```

```
df.duplicated()
```

```
0     False
1     False
2     False
3     False
4     False
5     False
6     False
7     False
8     False
9      True
10    False
dtype: bool
```

```
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 non-null     object
 4   FoodPreference   11 non-null     object
 5   Bill             11 non-null     int64
 6   NoOfPax          11 non-null     int64
 7   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       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            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
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 : KESHAVALLU B
#ROLL NO : 230701515
#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
```

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

```
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        9 non-null      float64
 2   Salary     9 non-null      float64
 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
```

```
   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  63778.0       Yes
5   France  35.0  58000.0       Yes
6    Spain  38.0  52000.0        No
7   France  48.0  79000.0       Yes
8  Germany  50.0  83000.0        No
9   France  37.0  67000.0       Yes
```

```
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)
```

```
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
```

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

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

#NAME : KESHAVALLU B
#ROLL NO : 230701515
#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
```

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

```
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        9 non-null      float64
 2   Salary     9 non-null      float64
 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
```

	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	63778.0	Yes
5	France	35.0	58000.0	Yes
6	Spain	38.0	52000.0	No
7	France	48.0	79000.0	Yes
8	Germany	50.0	83000.0	No
9	France	37.0	67000.0	Yes

```
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  Spain   Age   Salary Purchased
0    True    False  False  44.0  72000.0        No
1   False    False   True  27.0  48000.0       Yes
2   False     True  False  30.0  54000.0        No
3   False    False   True  38.0  61000.0        No
4   False     True  False  40.0  63778.0       Yes
5    True    False  False  35.0  58000.0       Yes
6   False    False   True  38.0  52000.0        No
7    True    False  False  48.0  79000.0       Yes
8   False     True  False  50.0  83000.0        No
9    True    False  False  37.0  67000.0       Yes
```

```
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
```

```
updated_dataset
```

```
   France  Germany  Spain   Age   Salary Purchased
0    True    False  False  44.0  72000.0        No
1   False    False   True  27.0  48000.0       Yes
2   False     True  False  30.0  54000.0        No
3   False    False   True  38.0  61000.0        No
4   False     True  False  40.0  63778.0       Yes
5    True    False  False  35.0  58000.0       Yes
6   False    False   True  38.0  52000.0        No
7    True    False  False  48.0  79000.0       Yes
8   False     True  False  50.0  83000.0        No
9    True    False  False  37.0  67000.0       Yes
```

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

#NAME : KESHAVALLU B
#ROLL NO : 230701515
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - B
```

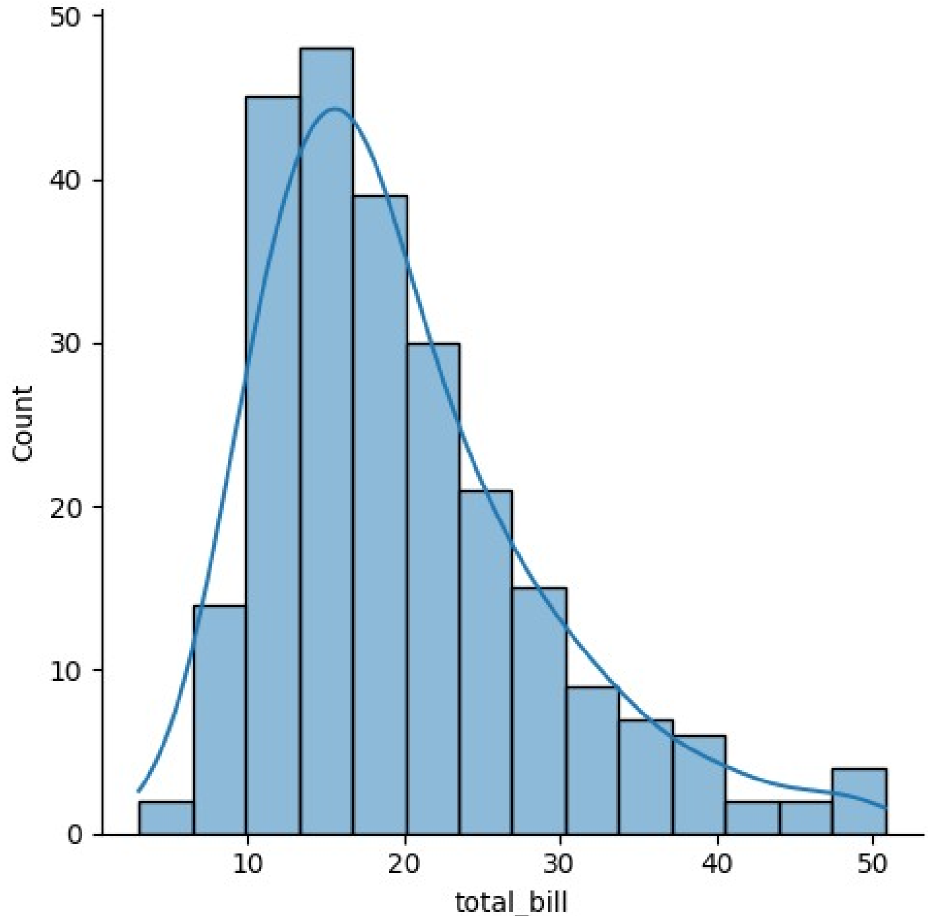
```
import seaborn as sns
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
```

```
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

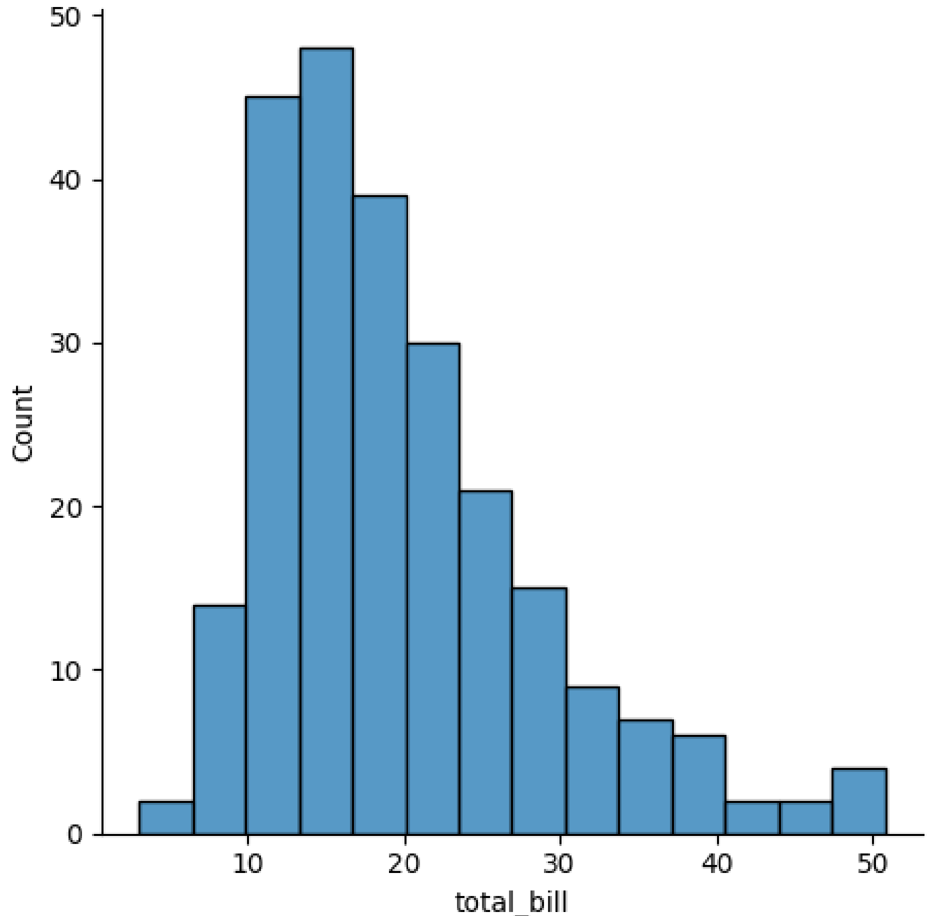
```
sns.displot(tips.total_bill,kde=True)
```

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

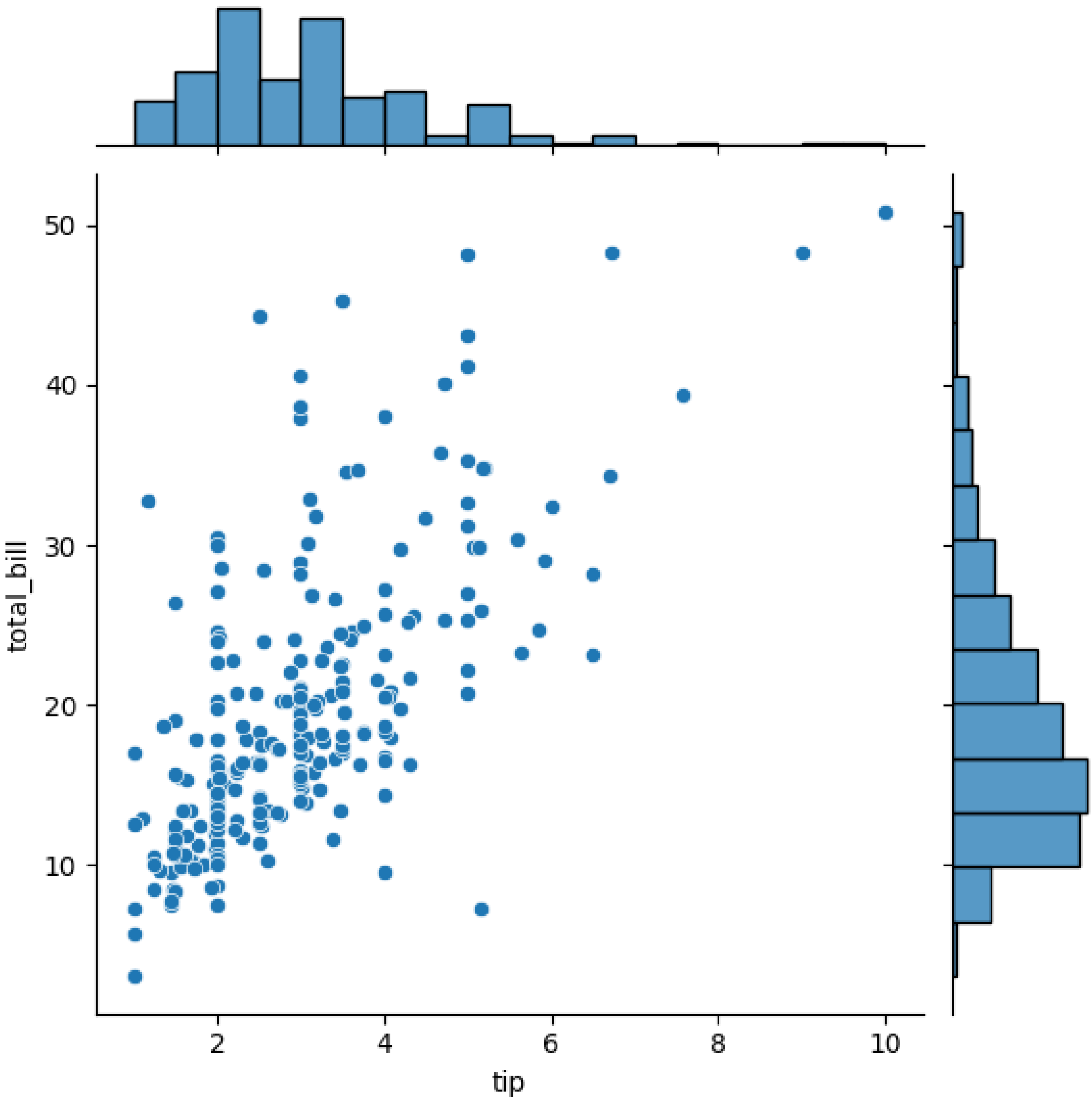



```
sns.displot(tips.total_bill,kde=False)
```

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

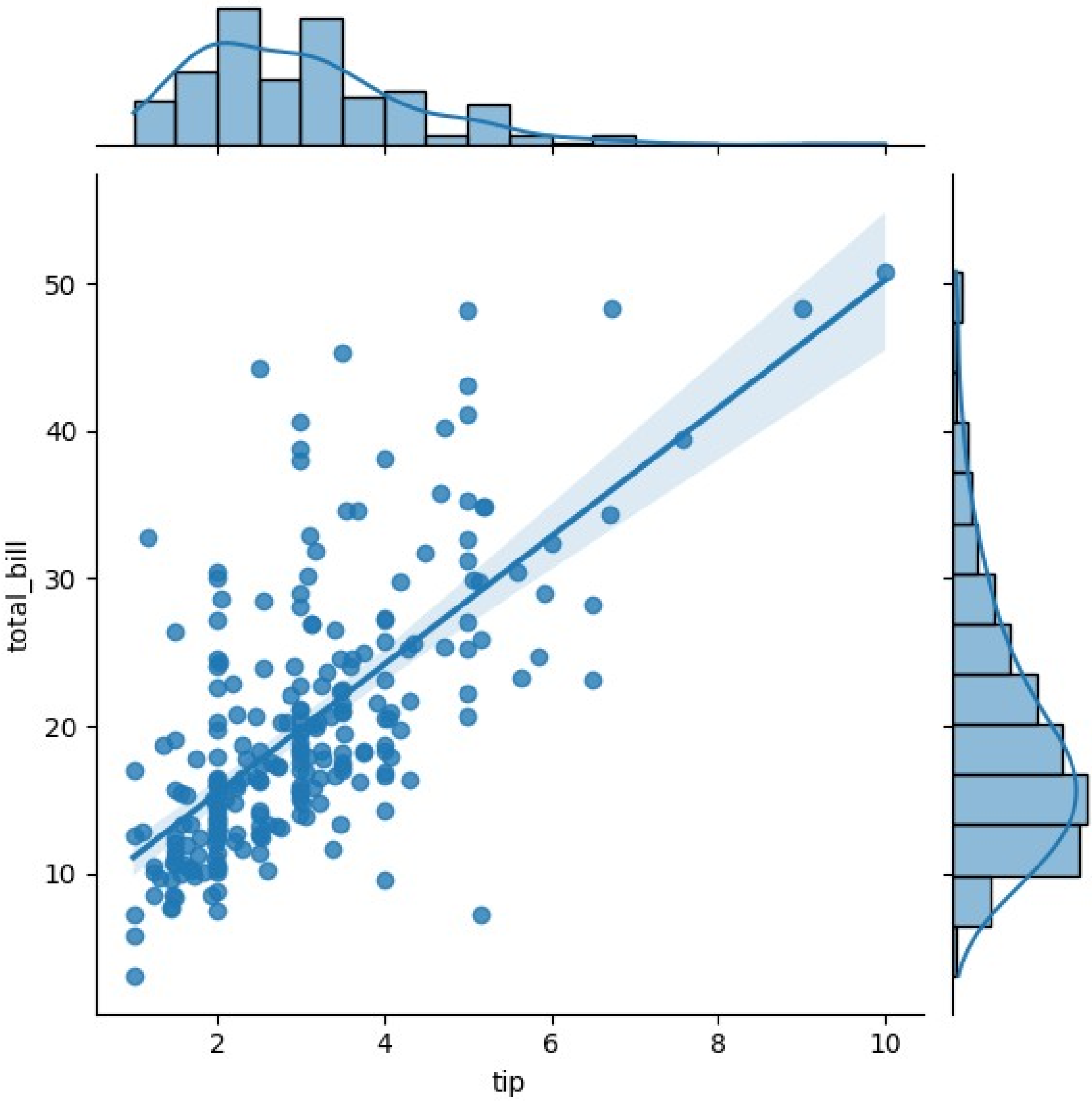



```
sns.jointplot(x=tips.tip,y=tips.total_bill)

<seaborn.axisgrid.JointGrid at 0x20d7dc2f2d0>
```



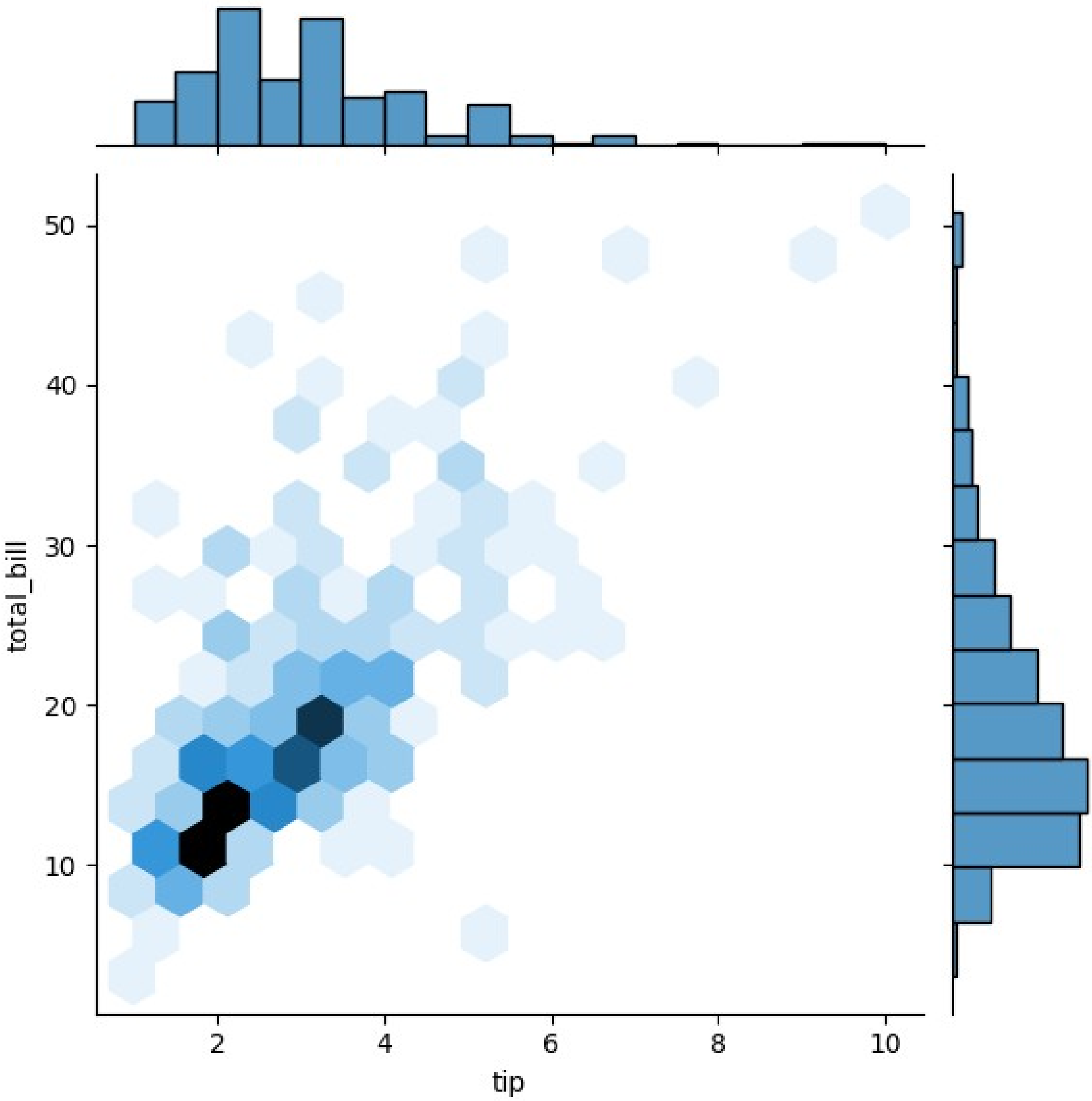

```
sns.jointplot(x=tips.tip,y=tips.total_bill,kind="reg")
```

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



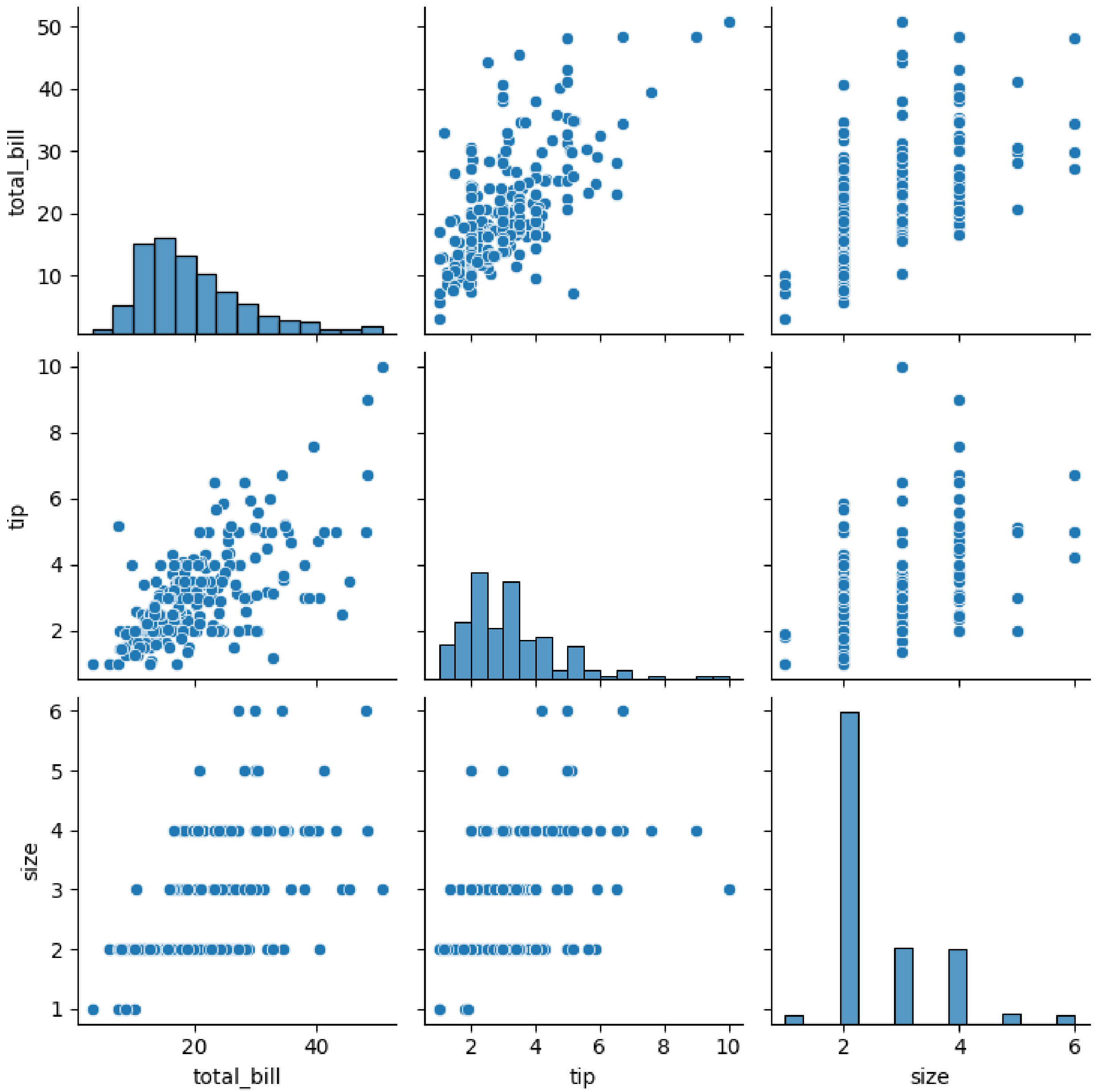

```
sns.jointplot(x=tips.tip,y=tips.total_bill,kind="hex")
```

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




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

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

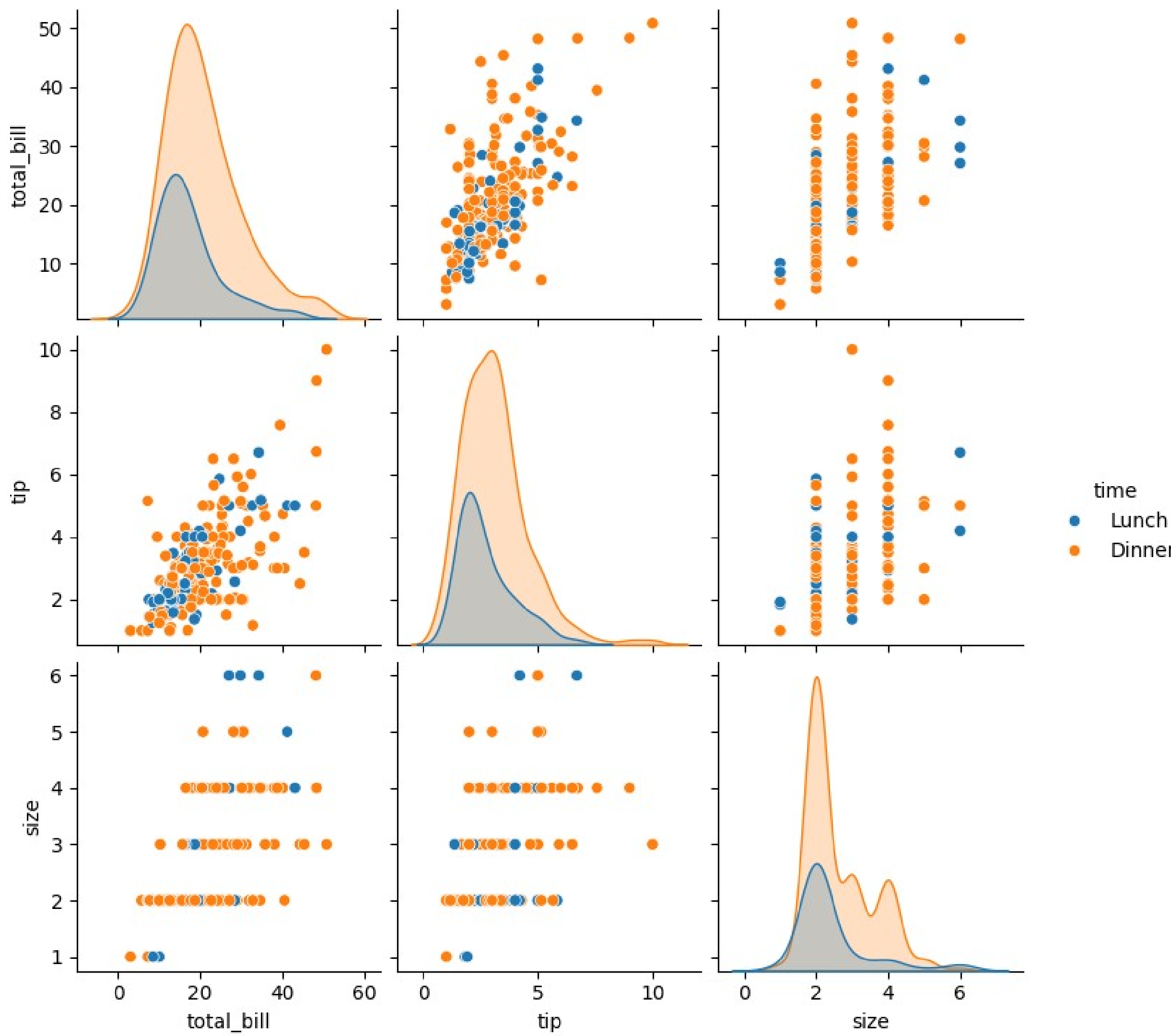



```
tips.time.value_counts()
```

```
time
Dinner    176
Lunch      68
Name: count, dtype: int64
```

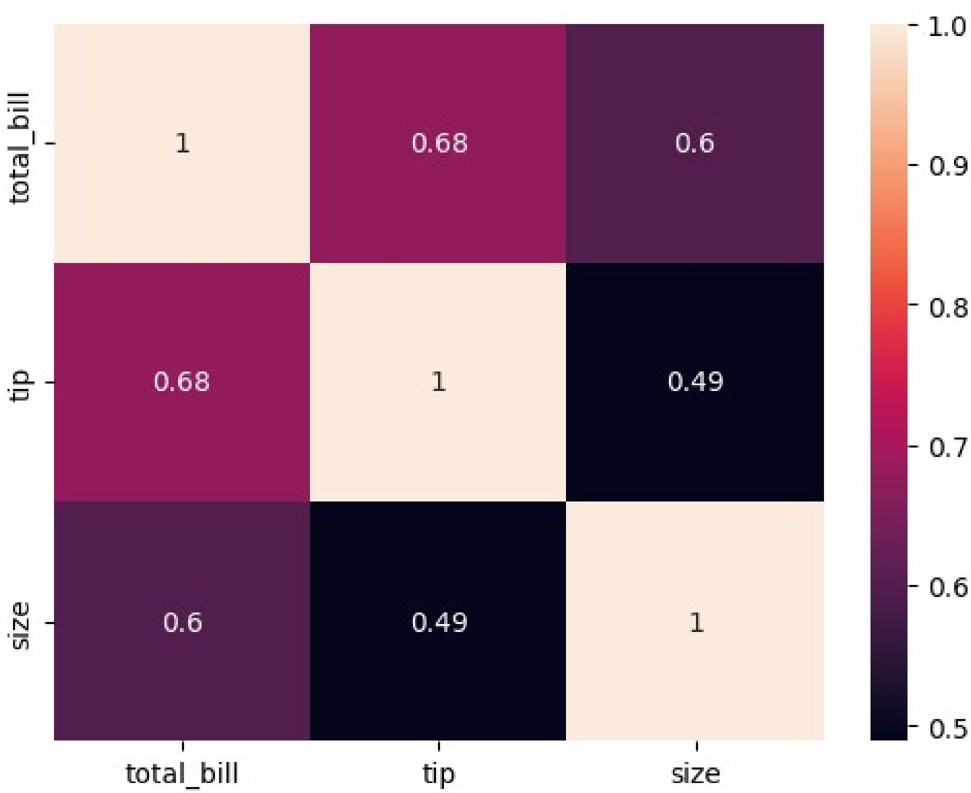
```
sns.pairplot(tips,hue='time')
```

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



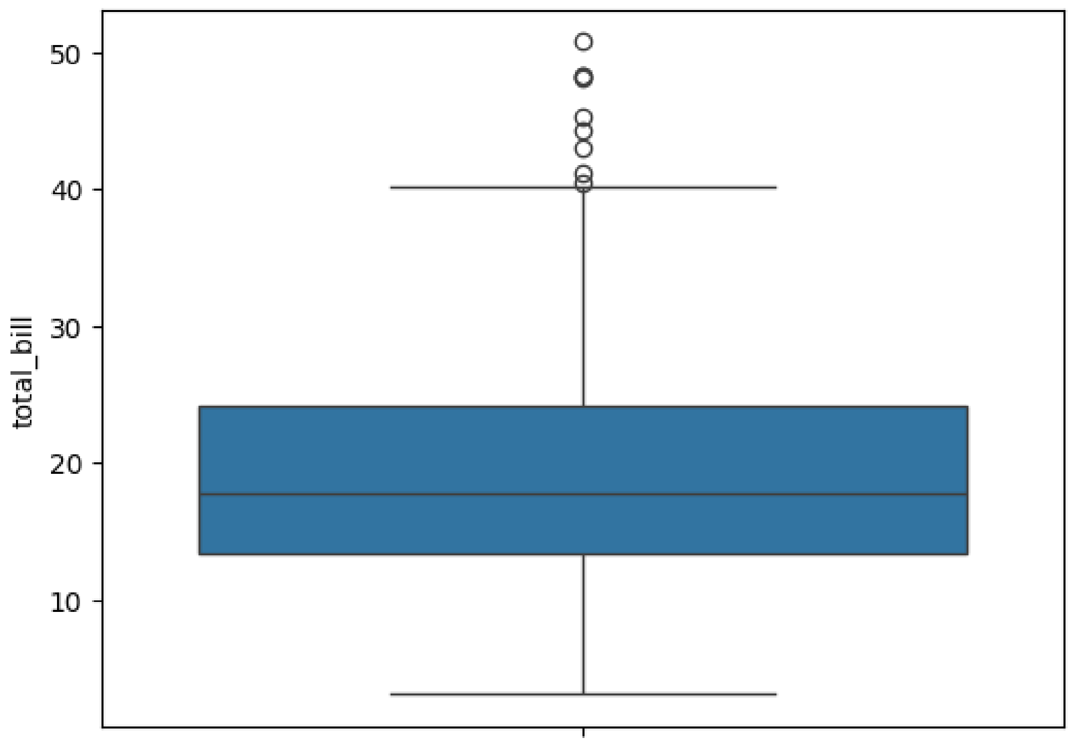

```
sns.heatmap(tips.corr(numeric_only=True),annot=True)
```

```
<Axes: >
```



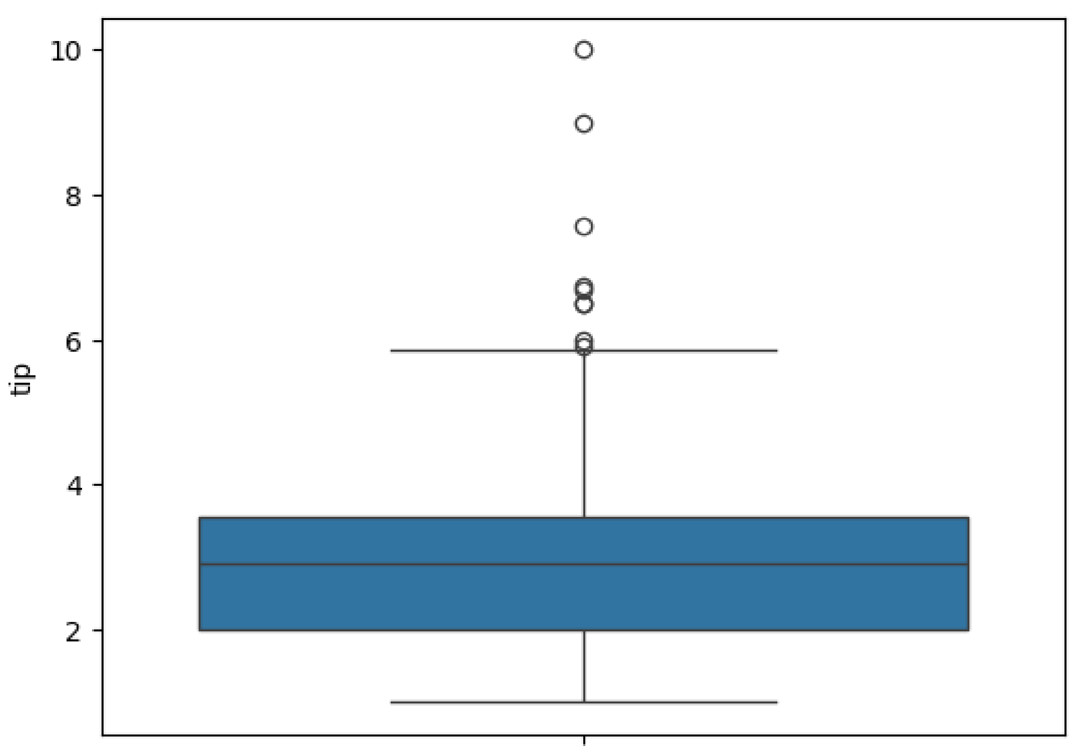

```
sns.boxplot(tips.total_bill)
```

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



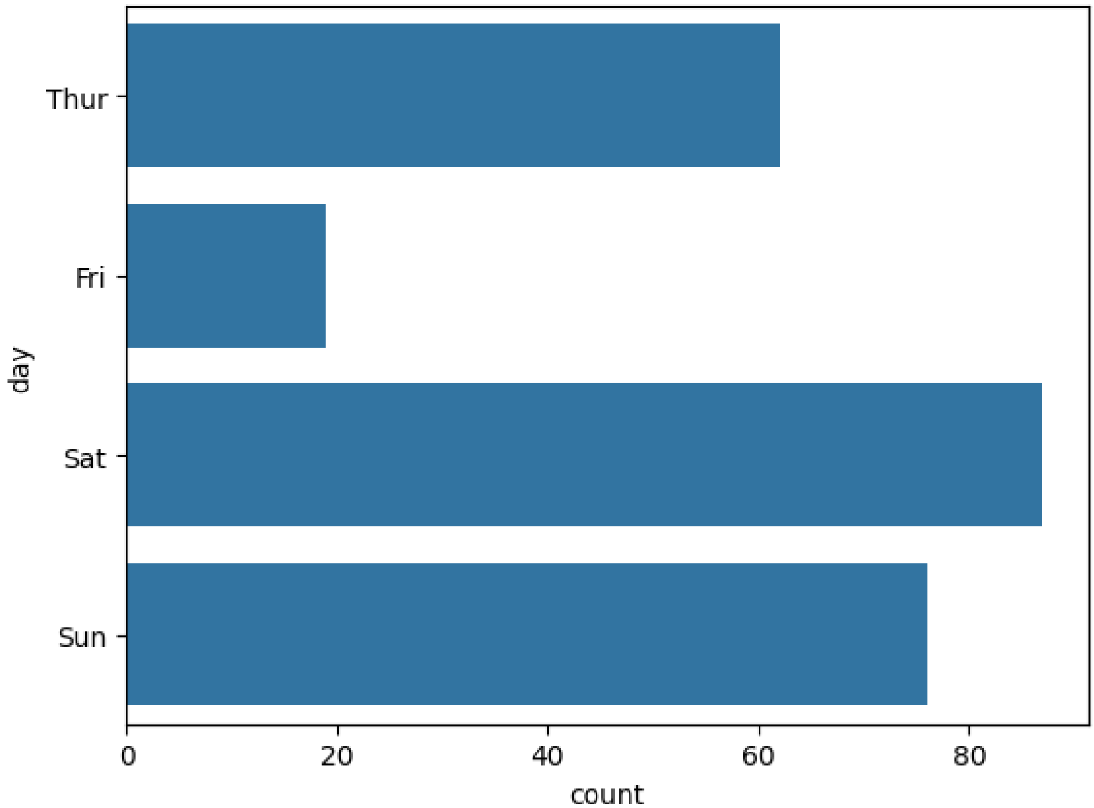

```
sns.boxplot(tips.tip)
```

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



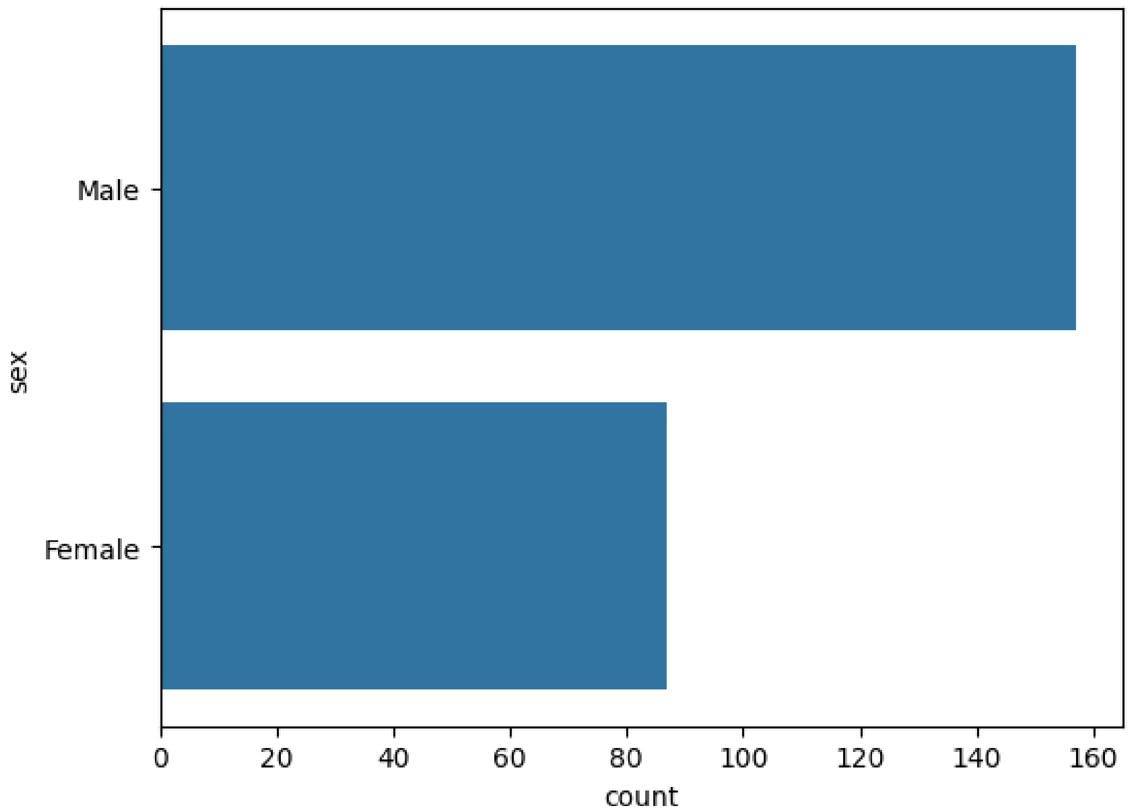
```
sns.countplot(tips.day)
```

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



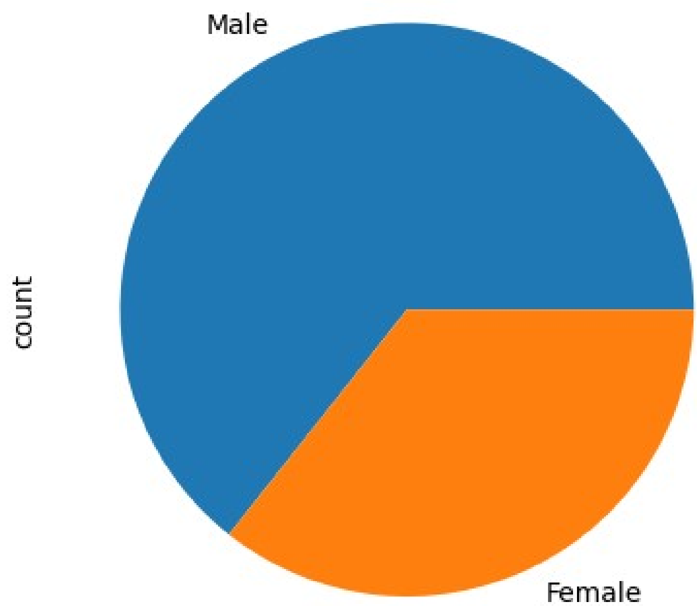

```
sns.countplot(tips.sex)
```

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



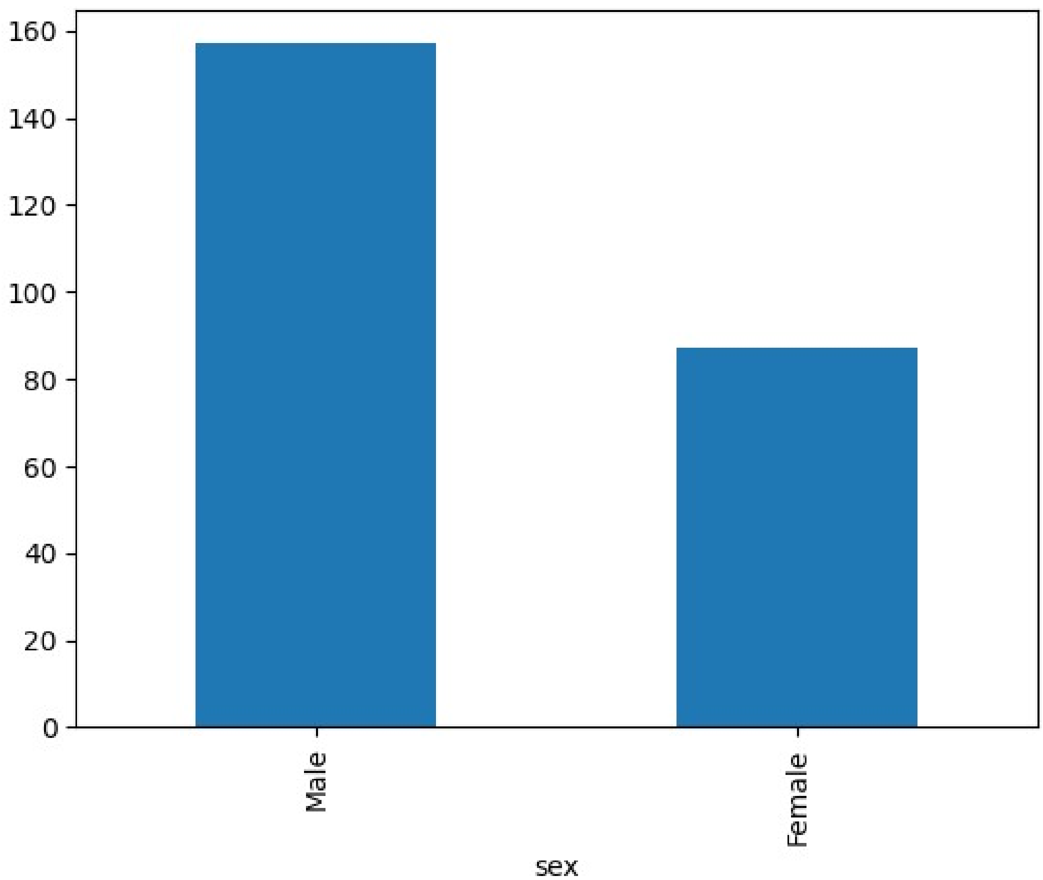

```python
tips.sex.value_counts().plot(kind='pie')
```

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



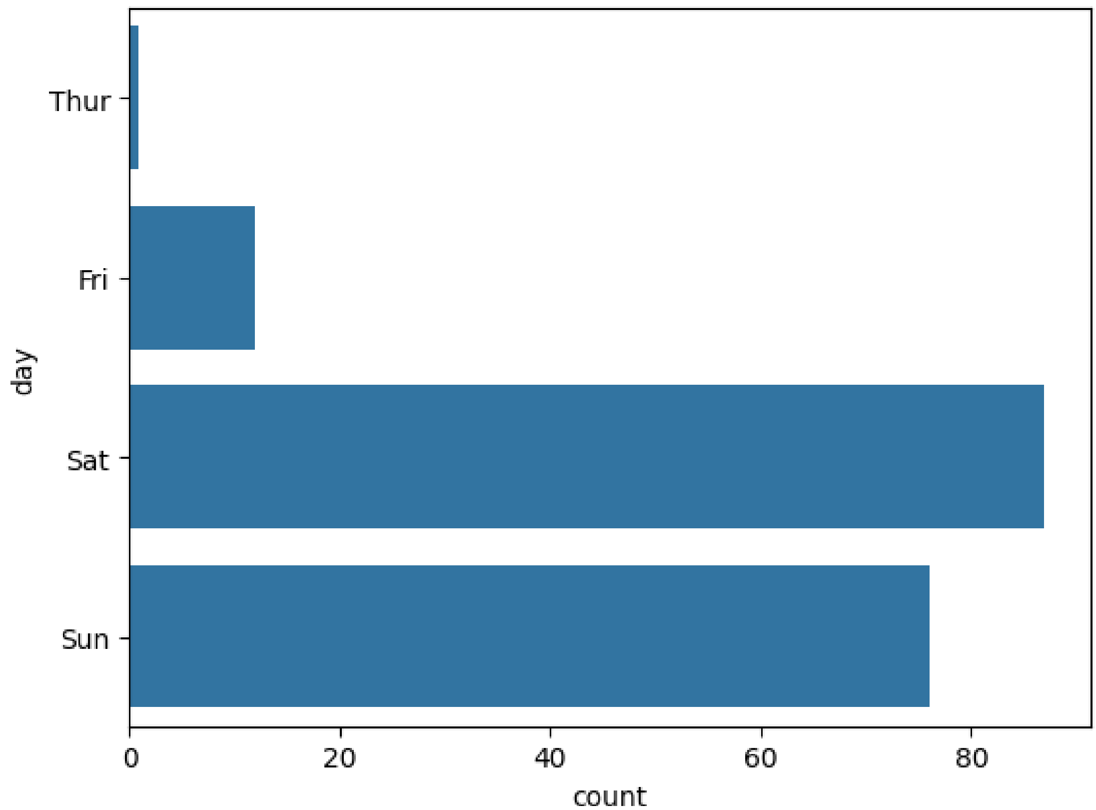

```
tips.sex.value_counts().plot(kind='bar')
```

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




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

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



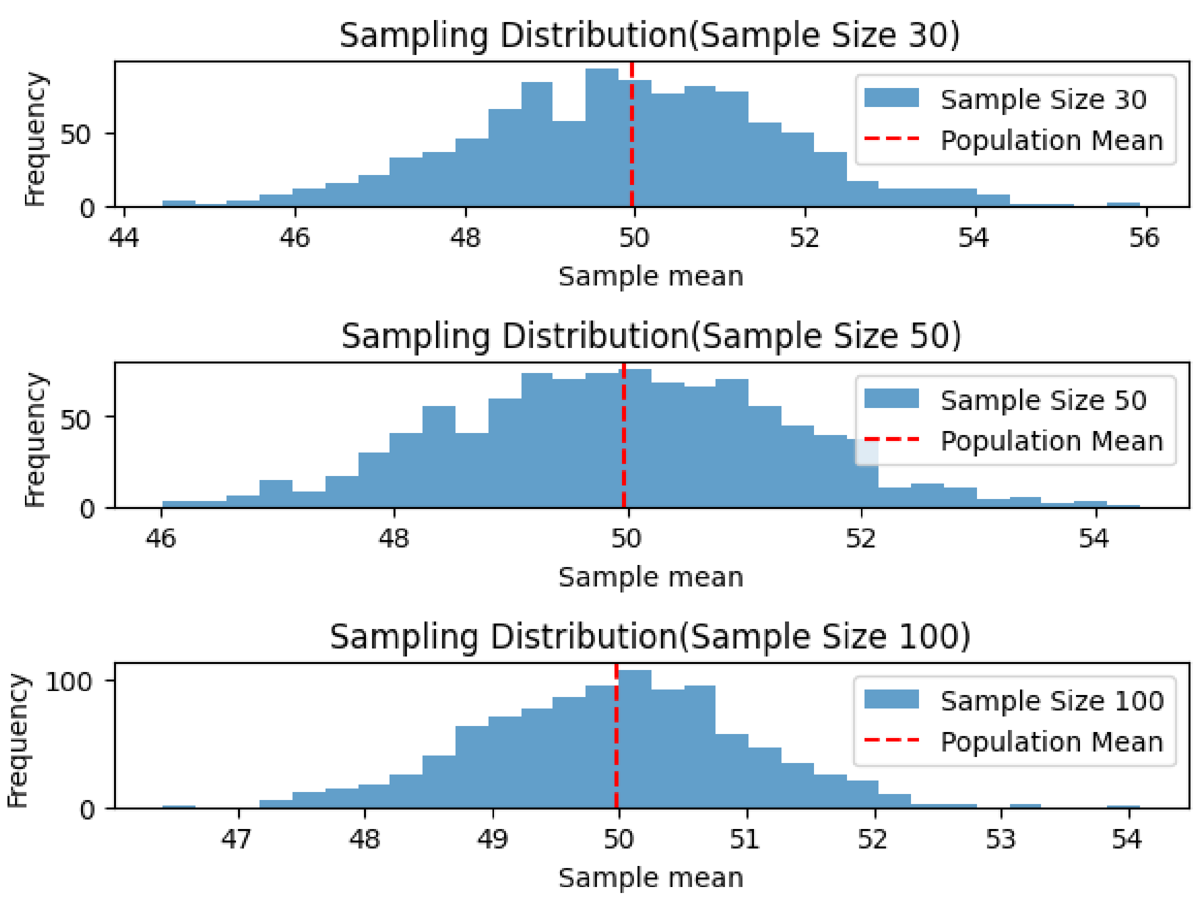

```
#EX.NO :6  Random Sampling and Sampling Distribution
#DATA  : 10.09.2024

#NAME : KESHAVALLU B
#ROLL NO : 230701515
#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
```

```python
#NAME : KESHAVALLU B
#ROLL NO : 230701515
#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.
```

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

#NAME : KESHAVALLU B
```

```python
#ROLL NO : 230701515
#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.
```

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

#NAME : KESHAVALLU B
#ROLL NO : 230701515
#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:
    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
----------------------------------------------------
```

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

#NAME : KESHAVALLU B
#ROLL NO : 230701515
#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)
```

```
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
```

```python
#NAME : KESHAVALLU B
#ROLL NO : 230701515
#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

```python
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'
```

```
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]] .
```

```
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 : KESHAVALLU B
#ROLL NO : 230701515
#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('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  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],
       [    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, 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):
```

```python
    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(features,label,test_siz
e=0.2,random_state=209)
finalModel=LogisticRegression()
finalModel.fit(x_train,y_train)
```

```
LogisticRegression()
```

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

```
0.85
0.85
```

```
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       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
```