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

#NAME  :Dharaneeish bk

#ROLL NO : 230701072
#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()

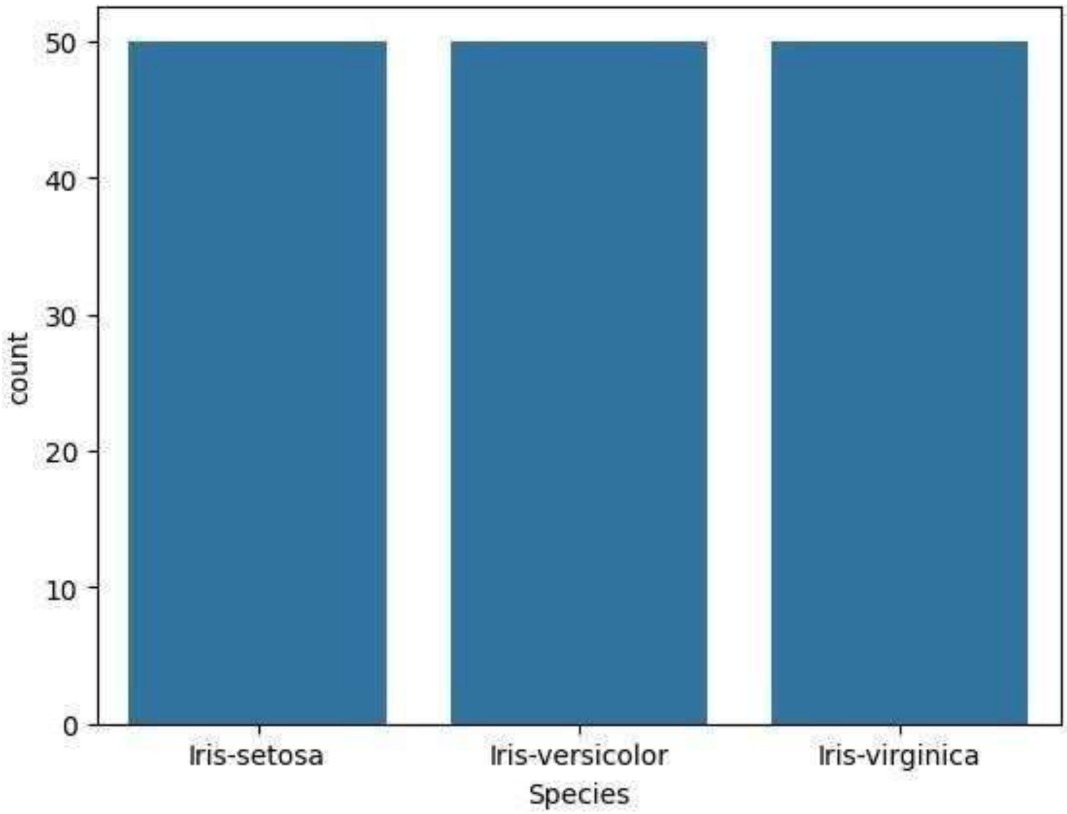
```
                          Id SepalLengthCm SepalWidthCm
PetalLengthCm PetalWidthCm
count  150.000000        150.000000     150.000000       150.000000
150.000000
mean        75.50000          5.843333        3.054000          3.758667
                    0
1.19866
7
std
            43.44536          0.828066        0.433594          1.764420
0.76316             8
1
min
0.10000   1.000000          4.300000         2.000000          1.000000
0
25%
0.30000
            38.25000          5.100000         2.800000          1.600000
0                   0
50%

            75.50000          5.800000         3.000000          4.350000
                    0

1.300000
75%      112.750000          6.400000         3.300000
5.100000
1.800000
max      150.000000          7.900000         4.400000
6.900000
```

data.value_counts('Species')

Species

Name: count, dtype: int64

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

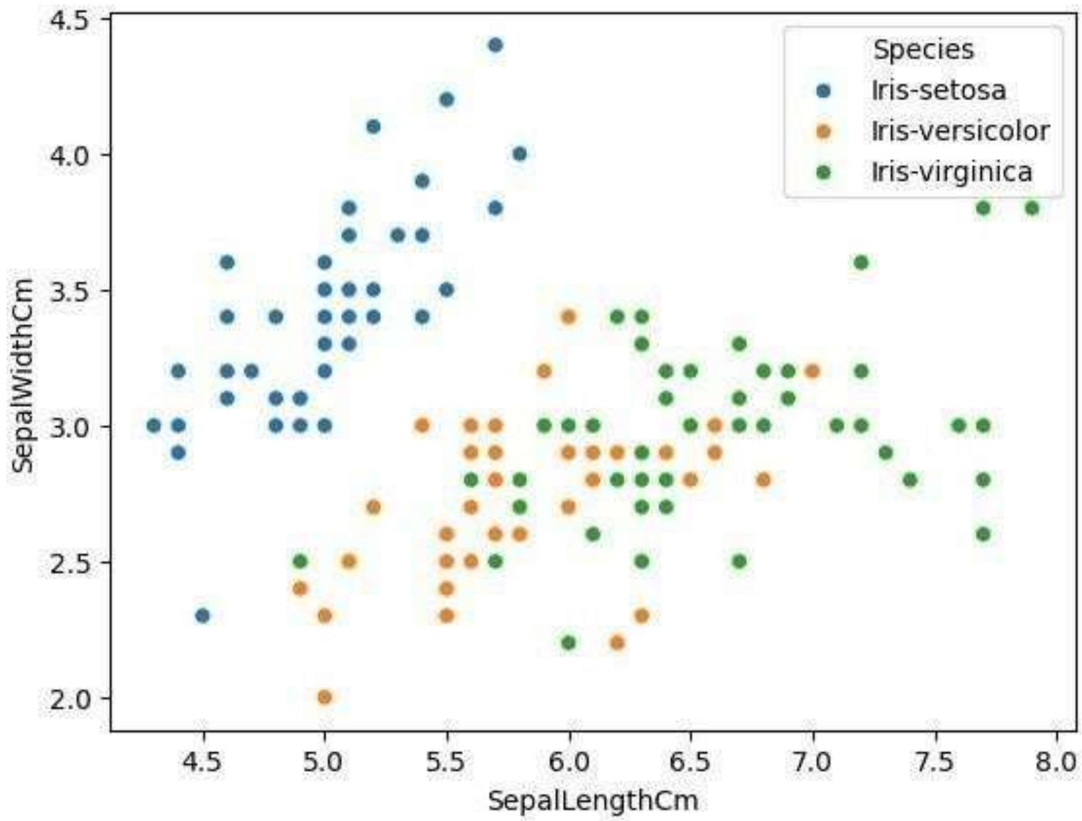



```
dummies=pd.get_dummies(data.Species)

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
```

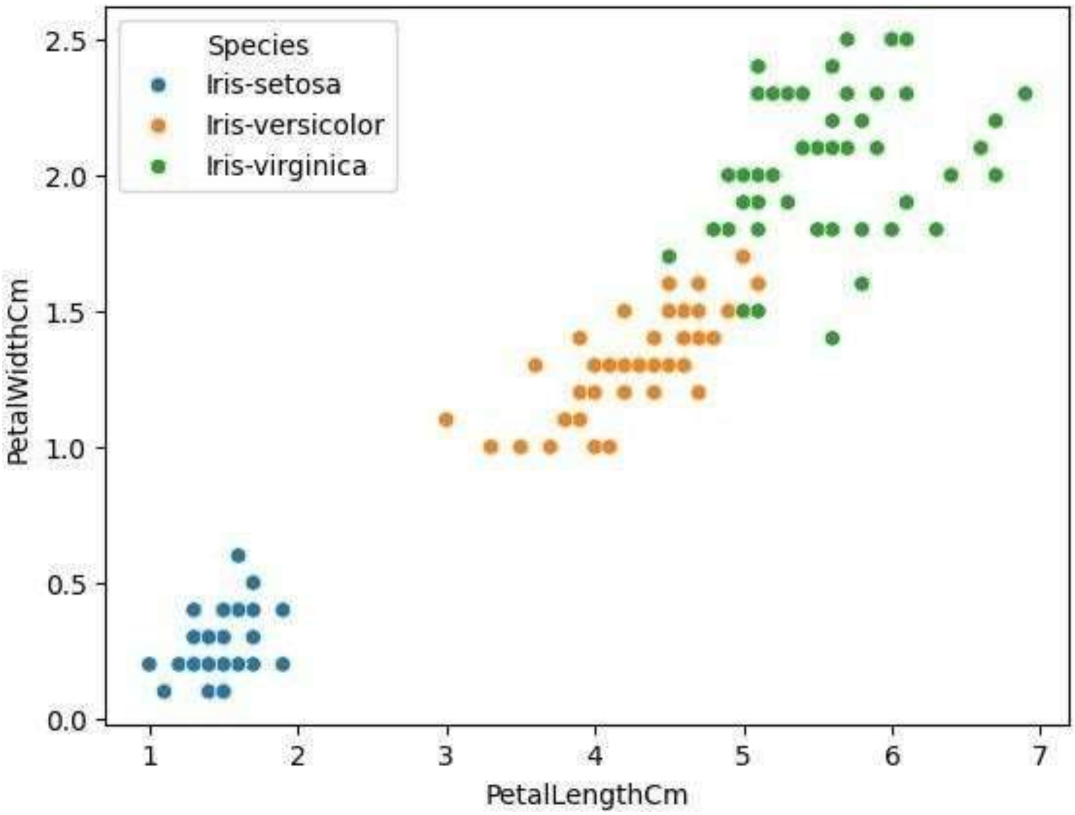
```
sns.scatterplot(x='SepalLengthCm',y='SepalWidthCm',hue='Species',data=
data,)
```

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

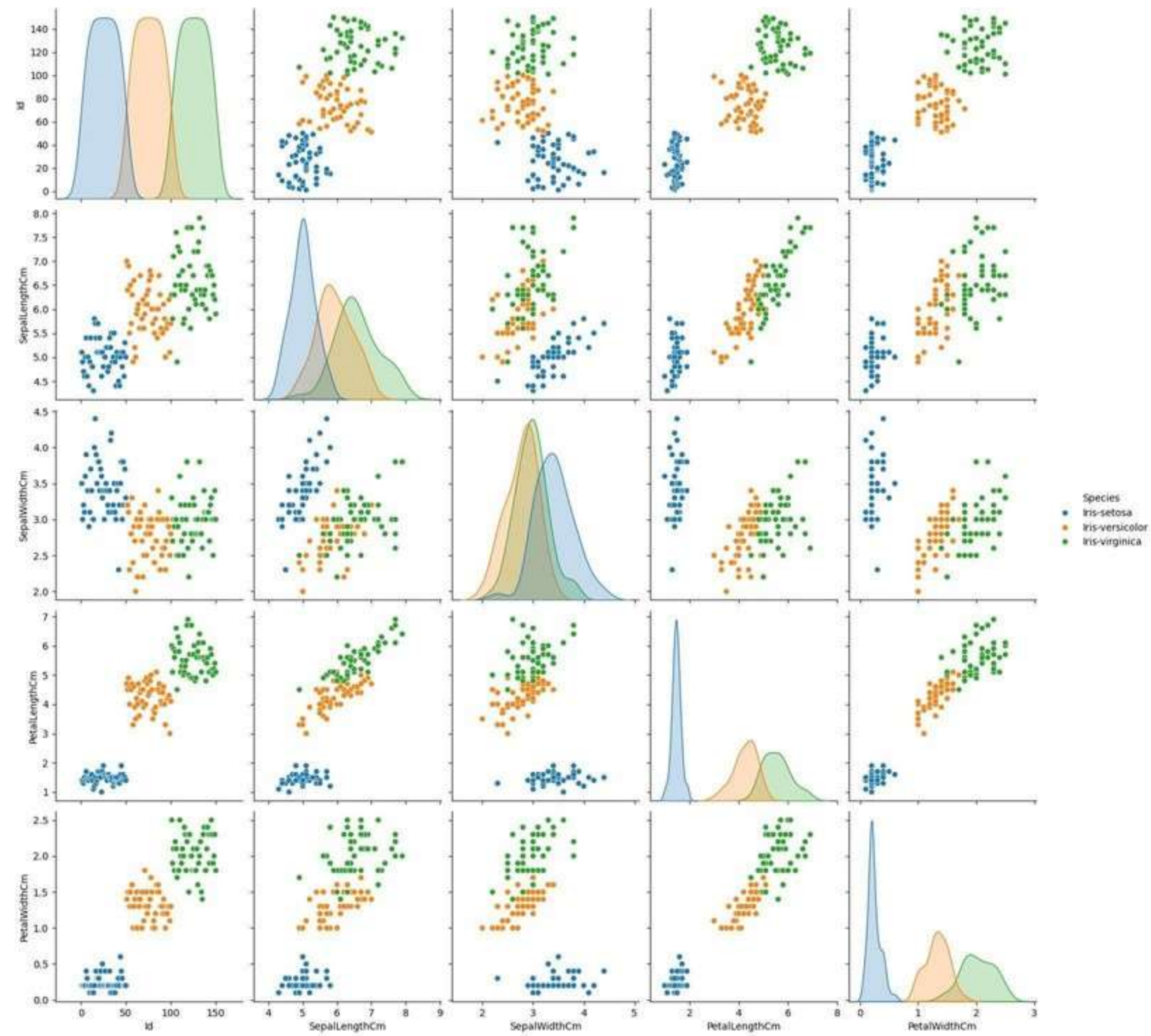



```
sns.scatterplot(x='PetalLengthCm',y='PetalWidthCm',hue='Species',data=
 data,)
```

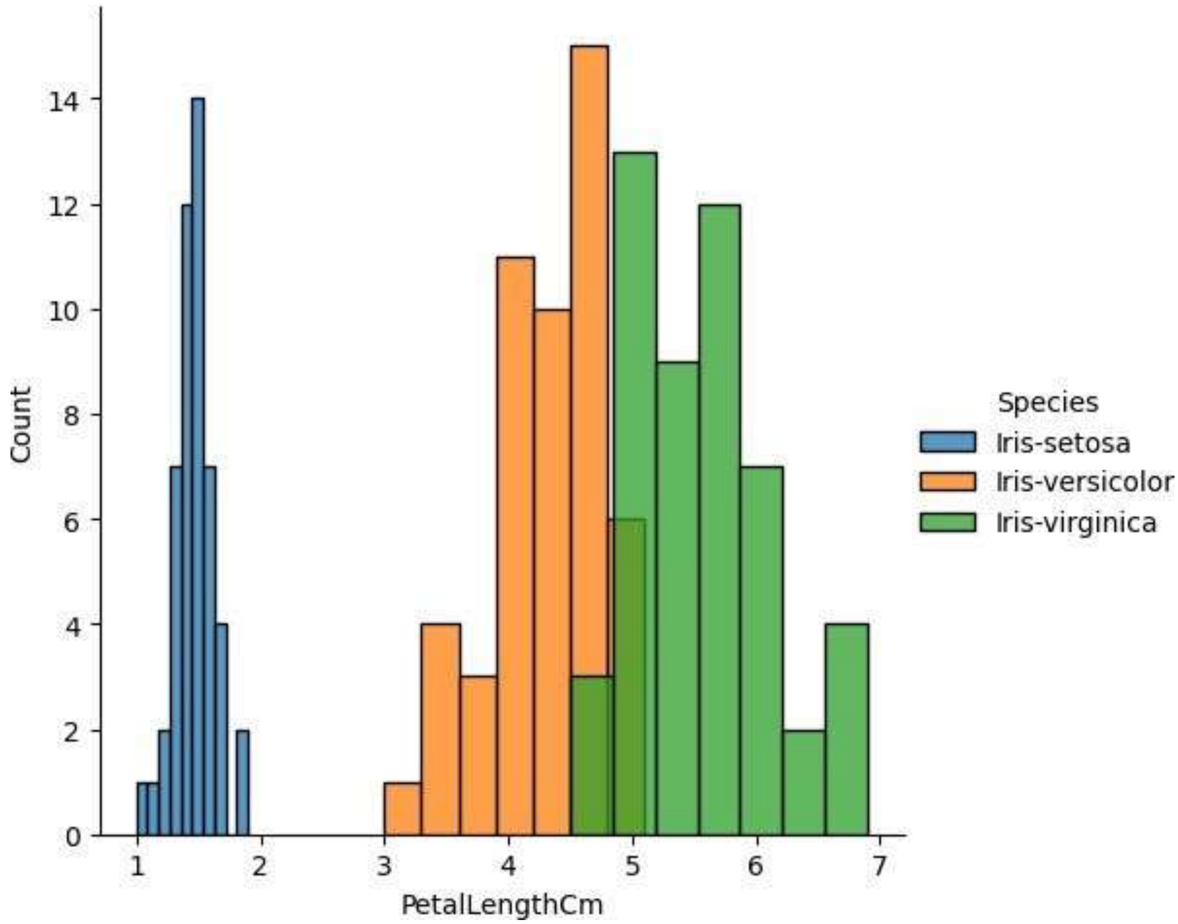
```
<Axes: xlabel='PetalLengthCm', ylabel='PetalWidthCm'>
```



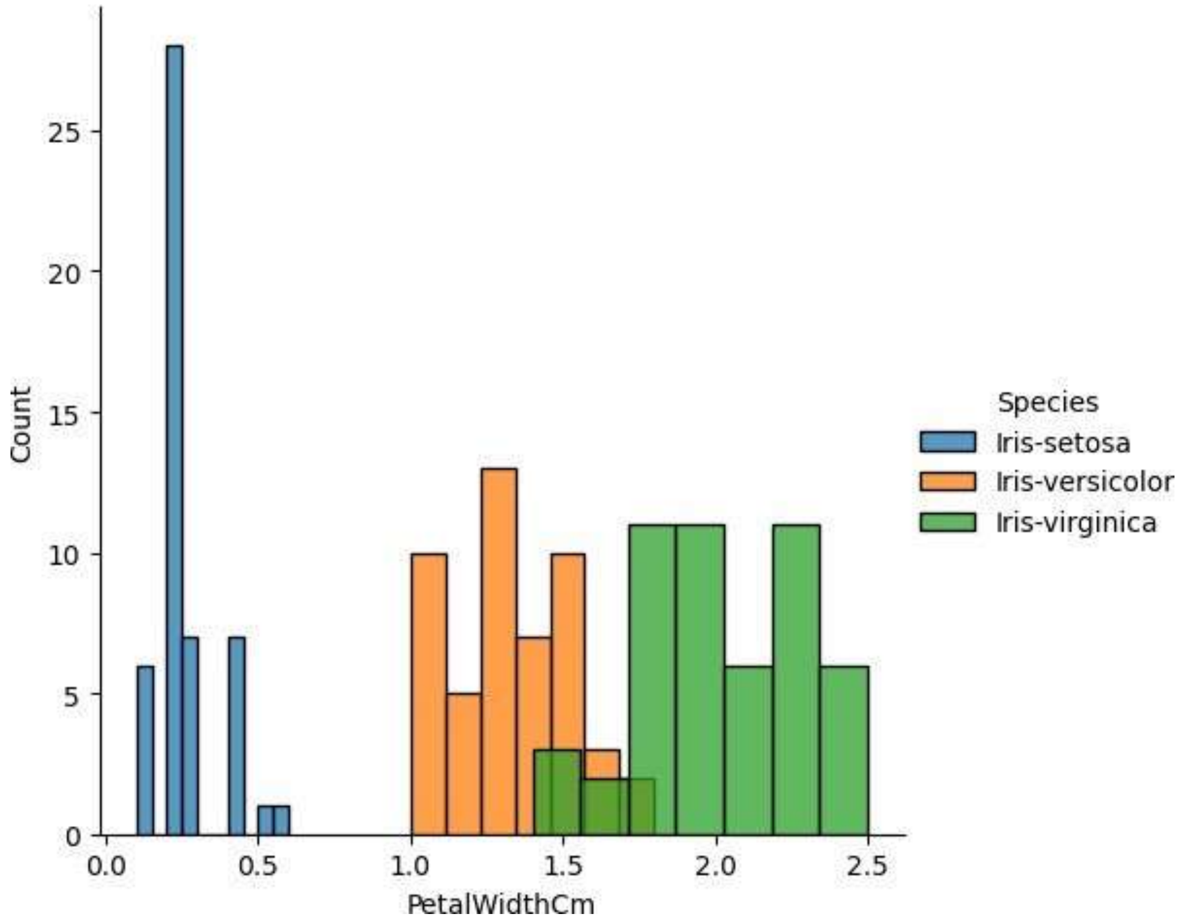

```
sns.pairplot(data,hue='Species',height=3);
```



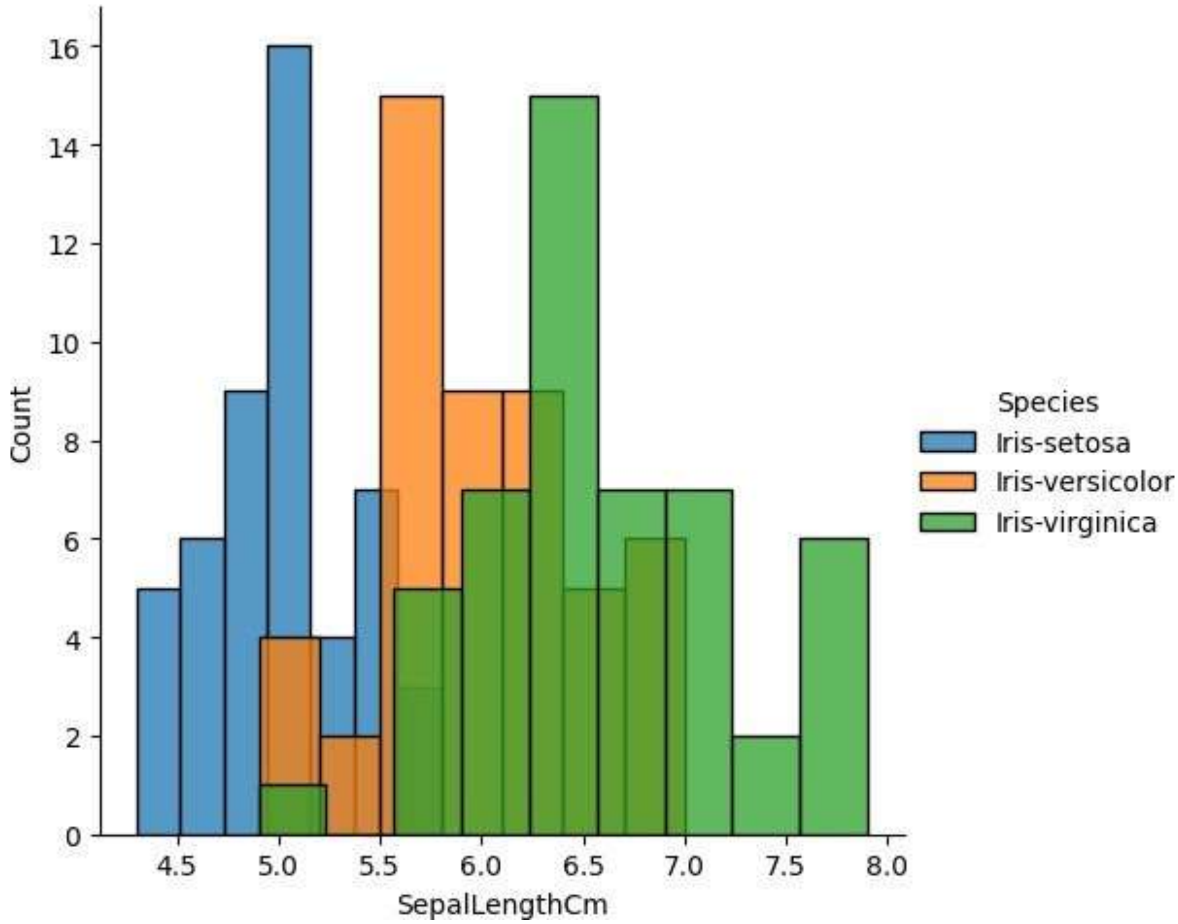

```
plt.show()

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



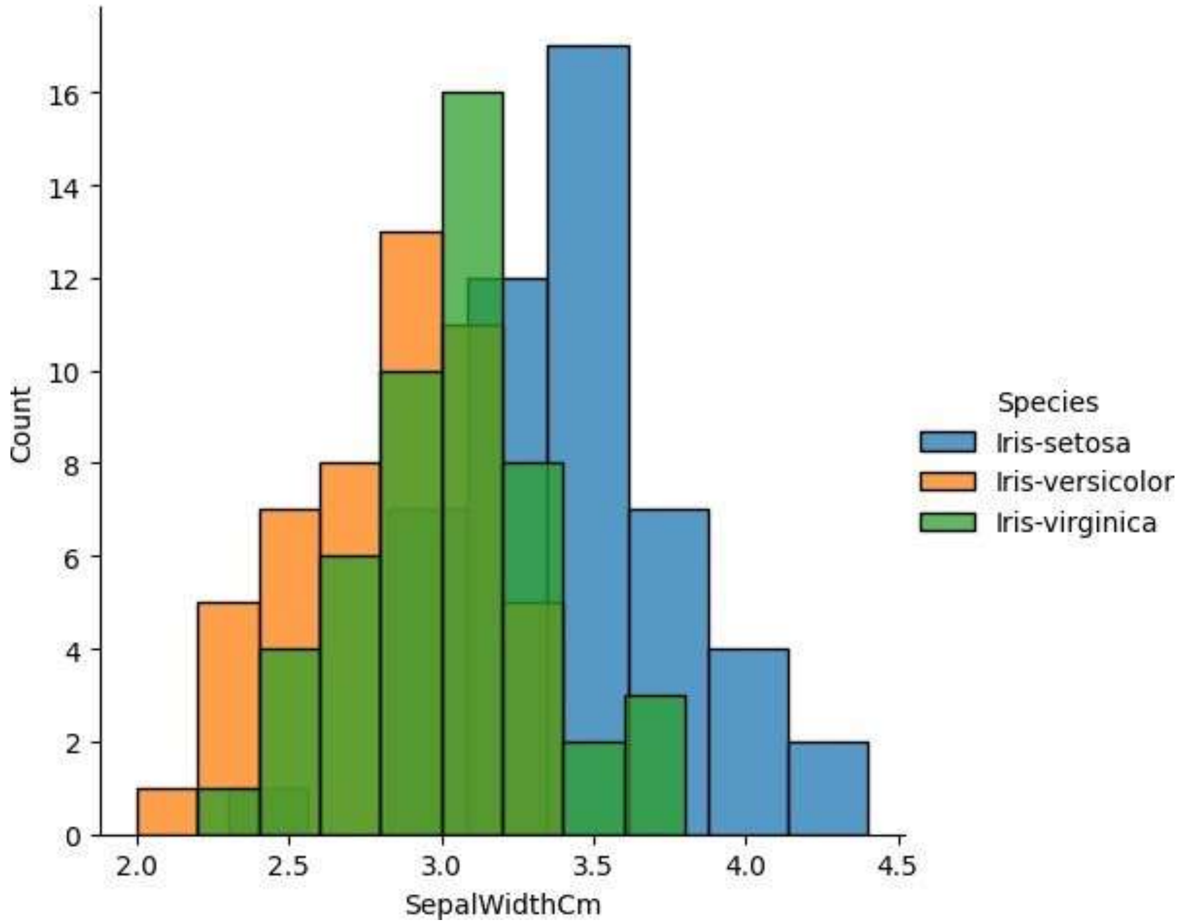

```
sns.FacetGrid(data,hue='Species',height=5).map(sns.histplot,'PetalWidt
hCm').add_legend();
plt.show();
```




```
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 :Dharaneeish bk

#ROLL NO : 230701072

#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]
```

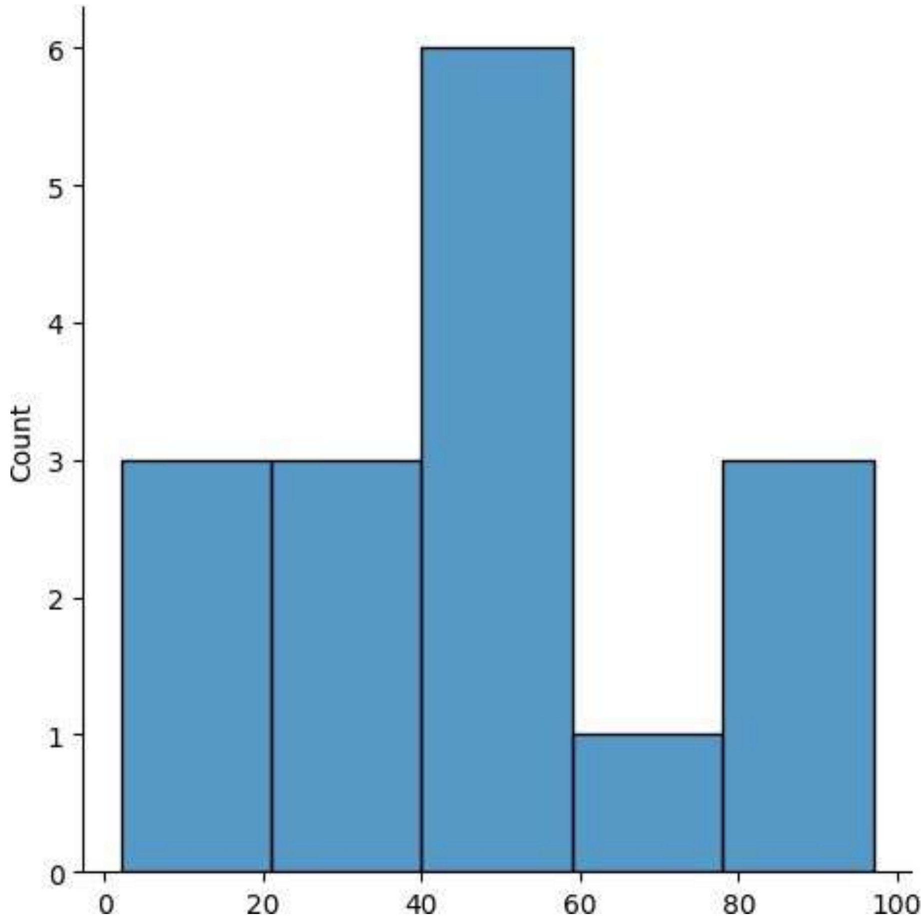
```
array([], shape=(3, 0), dtype=int32)
```

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

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

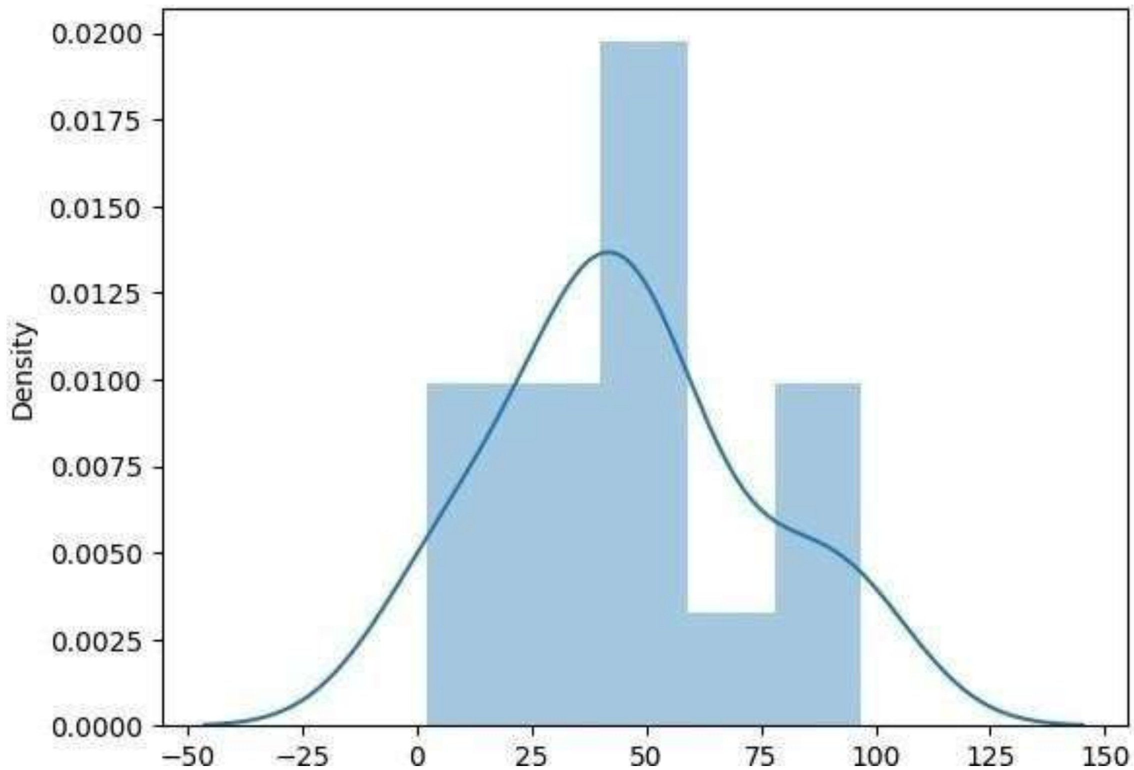
```
#EX.NO :2 Outlier detection #DATA : 13.08.2024
#NAME : Dharaneeish bk
#ROLL NO : 230701072
#DEPARTMENT : B.E COMPUTER SCIENCE AND
ENGINEERING - B
import numpy as np
import warnings
warnings.filterwarnings('ignore')
```

```
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'>
```

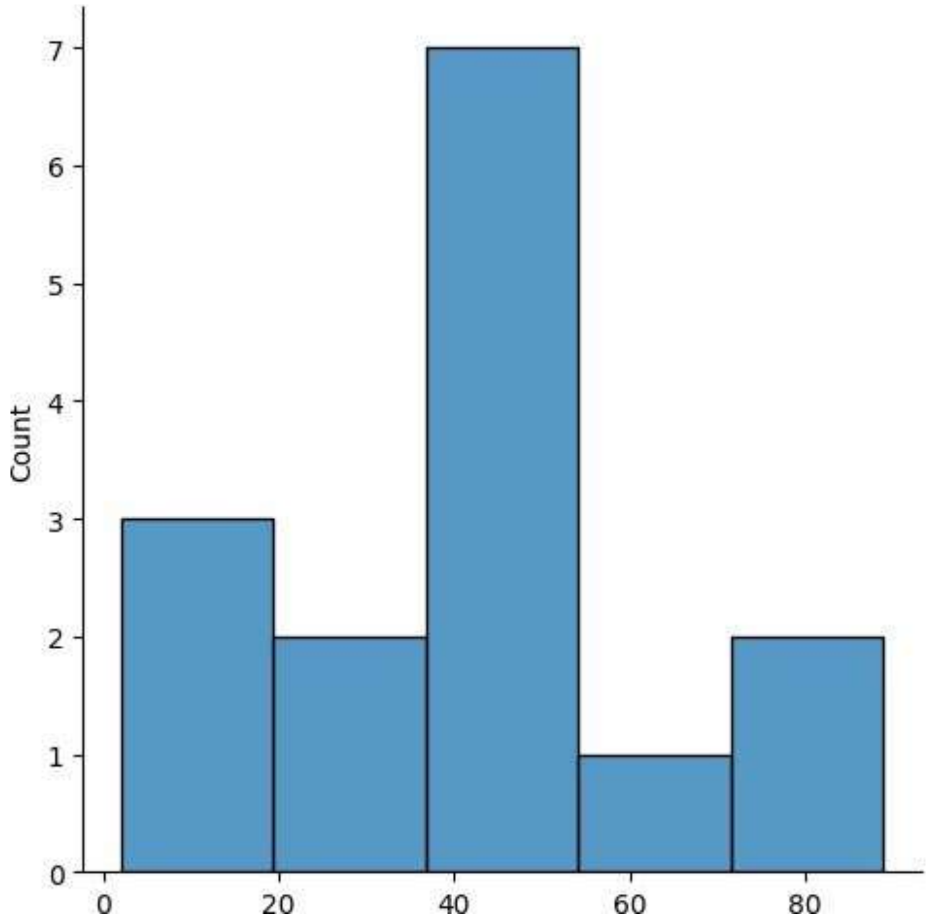



```
new_array=array[(array>lr) & (array<ur)]
 new_array
```

```
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
```

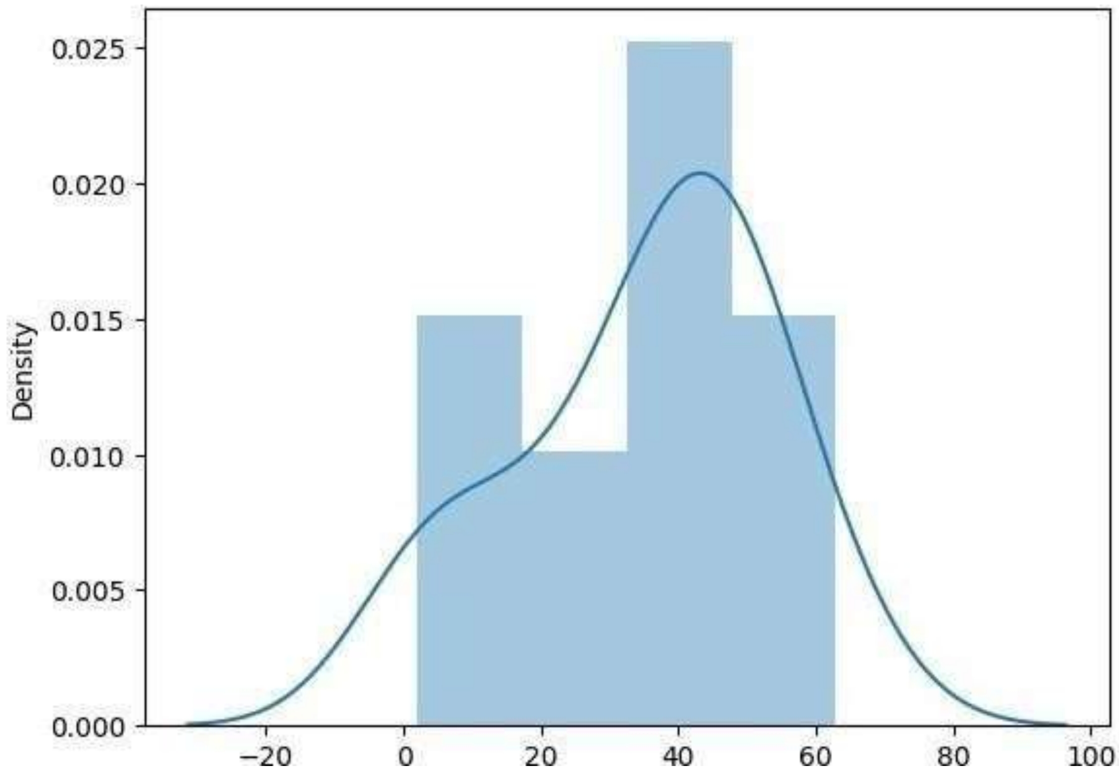
```
(-5.25, 84.75)
```

```
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 : DHARANEEISH BK
#ROLL NO : 230701072
#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
           e
        Fals
           e
        Fals
           e
        Fals
           e
        True
        Fals
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

```
· Hotel     11 non-null                object
                                       t
· FoodPreference 11 non-null           int6
· Bill      11 non-null                objec
                                       4
· NoOfPax   11 non-null                t
                                       int6
·8 EstimatedSalary 11 non-null         4
   Age_Group.1     11 non-null
object dtypes: int64(5), object(4)     int6
memory usage: 924.0+ bytes             4
```

```
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	130 0

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
```

	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.
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
```

	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
```

<boundmethodSeries.unique of 0 veg

1 Non-Veg
2 Ve
3 g veg
4 vegetaria
5 n Non-Veg
6 vegetaria
7 n
8 Ve
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 : DHARANEEISH BK
 #ROLL NO : 230701072
#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 Purchased	
0	y	44.	7[illegible]	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

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
·  Salary        non-null         4
3    Purchased 10  non-null       float6
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 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 : DHARANEEISH BK
#ROLL NO : 230701072
#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	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	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
3    Purchased 10  non-null      float6
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)
updated_dataset
```

```
   France Germany Spain   Age    Salary   Purchased
0        True False False 44.    72000.0          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  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.    72000.0          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 : DHARANEEISH BK

#ROLL NO : 230701072

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

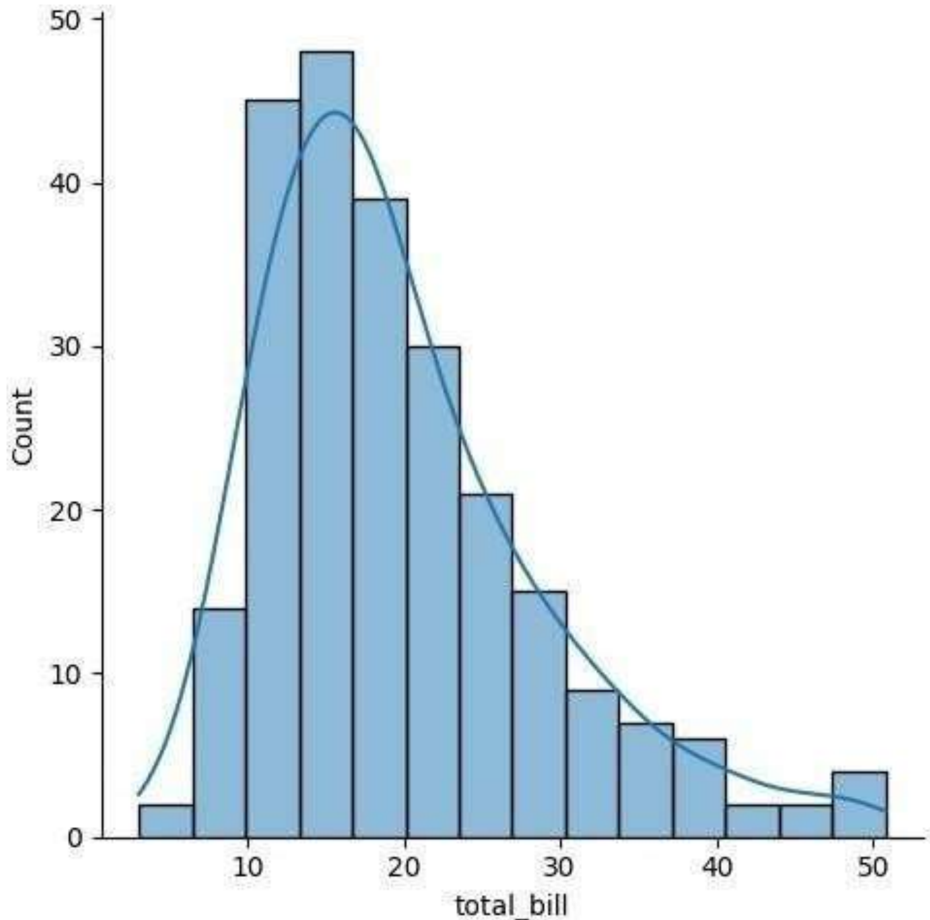
```
import seaborn as sns
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
```

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

```
   total_bil    tip     sex          day   time size
   l            1.0   Femal smoker  N   Sun Dinner 2
0    16.99      1         e         o   Sun Dinner 3
1    10.34      1.66    Mal         N   Sun Dinner 3
2    21.01      3.50      e         o   Sun Dinner 2
3    23.68      3.31   Male         N   Sun Dinner 4
4    24.59      3.61   Male         o
                      Femal         N
                          e         o
                                    N
                                    o
```

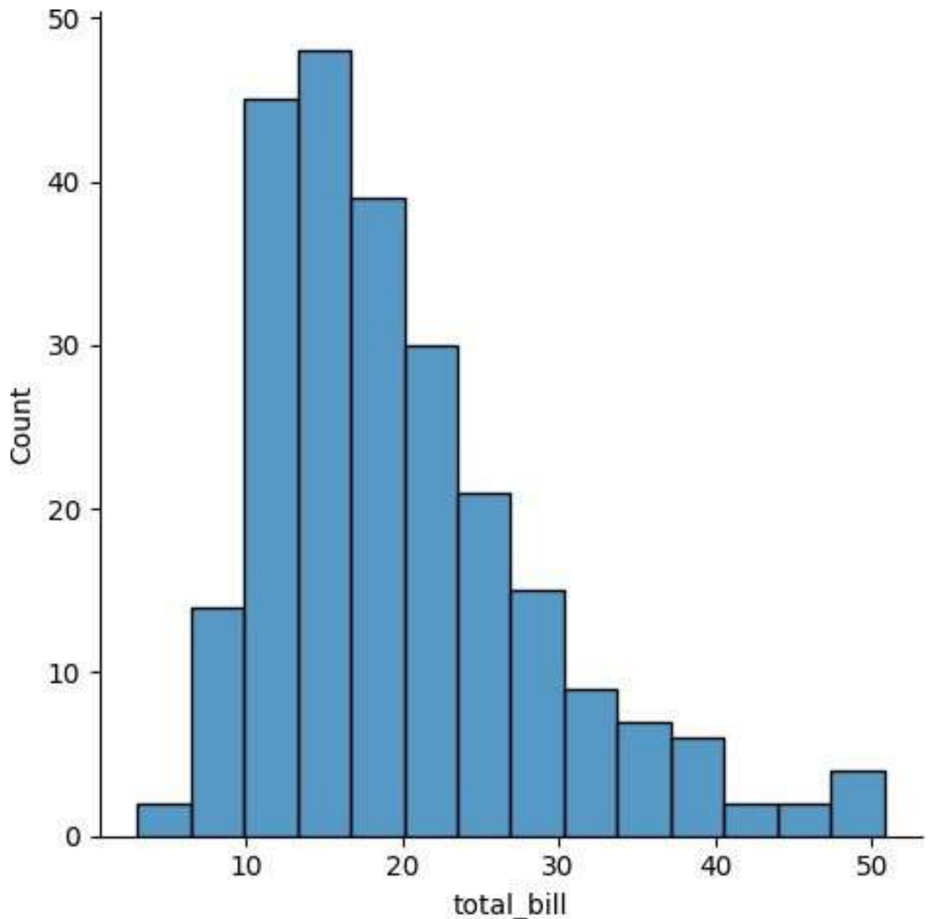
```
sns.displot(tips.total_bill,kde=True)
```

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



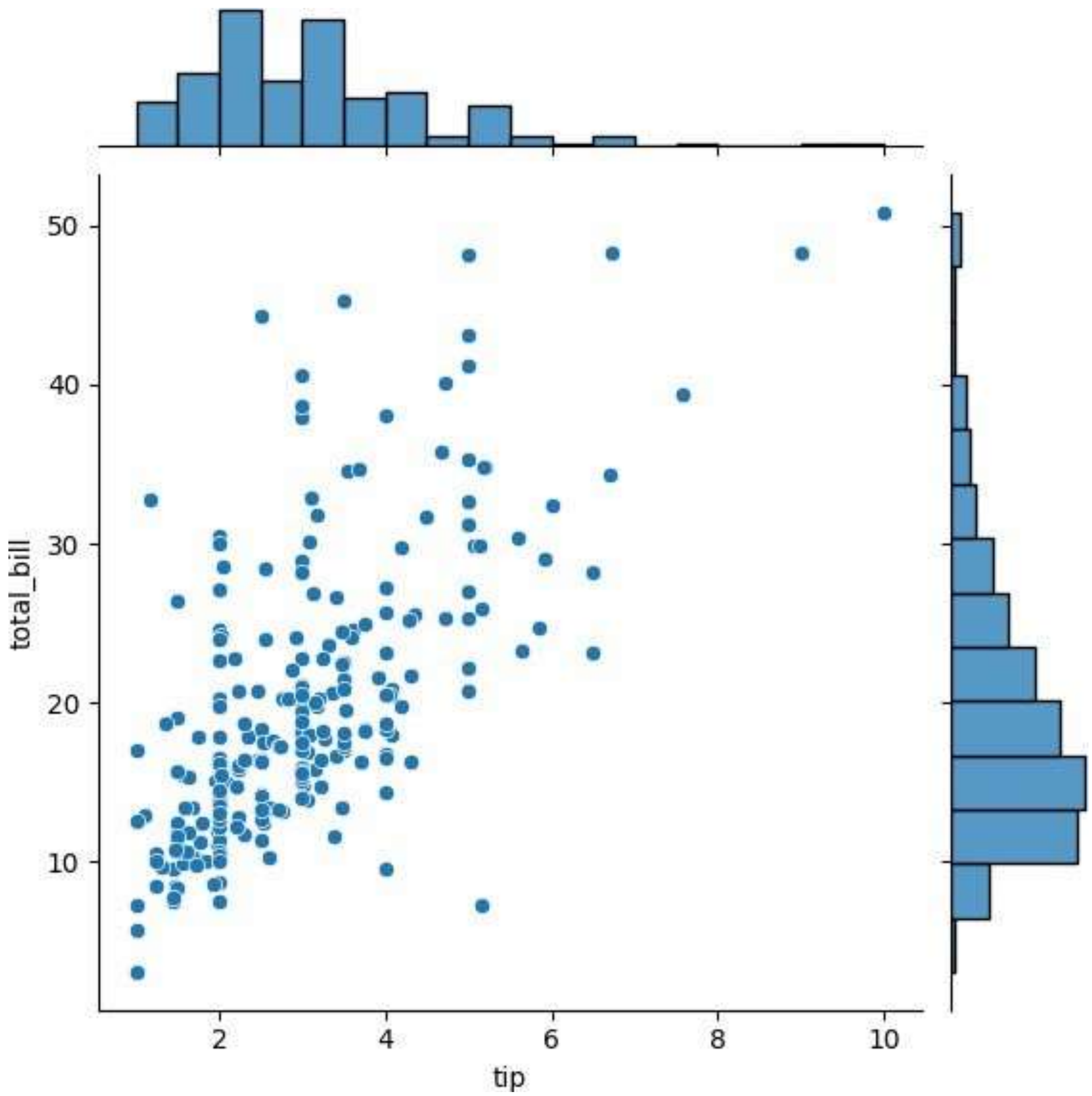

```
sns.displot(tips.total_bill,kde=False)
```

<seaborn.axisgrid.FacetGrid at 0x20d7dc22790>



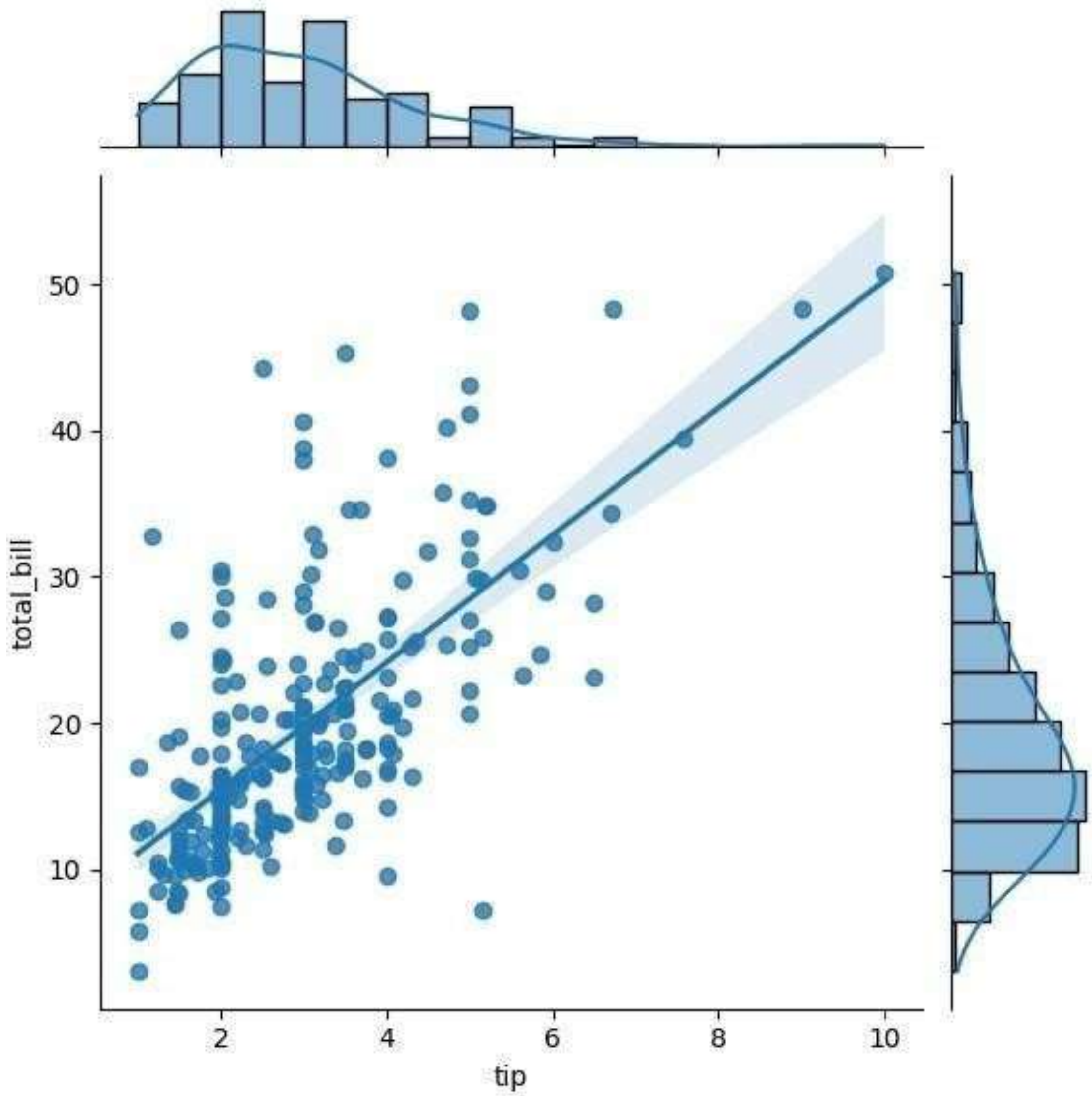

```
sns.jointplot(x=tips.tip,y=tips.total_bill)
```

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



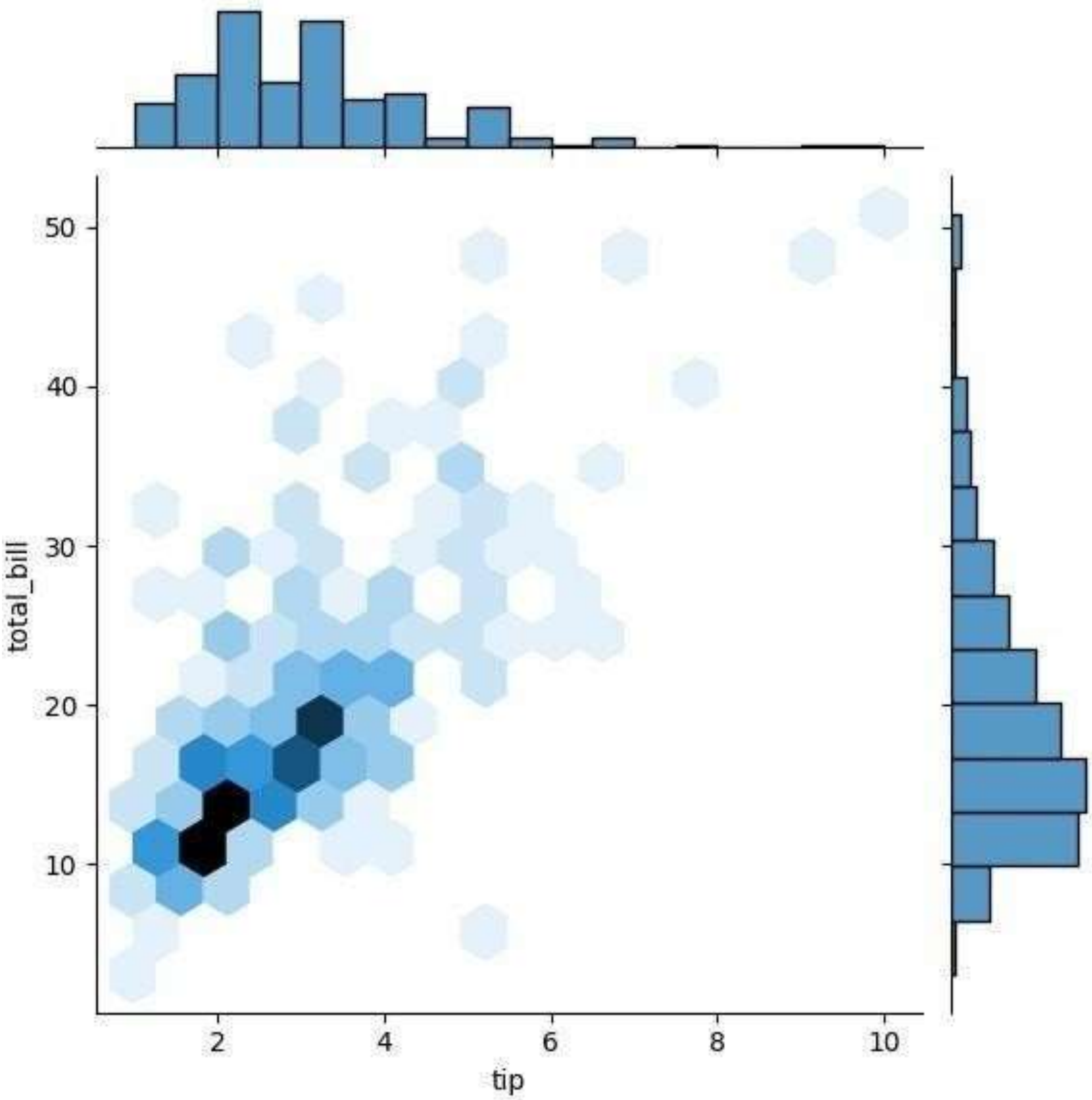

```
sns.jointplot(x=tips.tip,y=tips.total_bill,kind="reg")
```

<seaborn.axisgrid.JointGrid at 0x20d7ed32450>

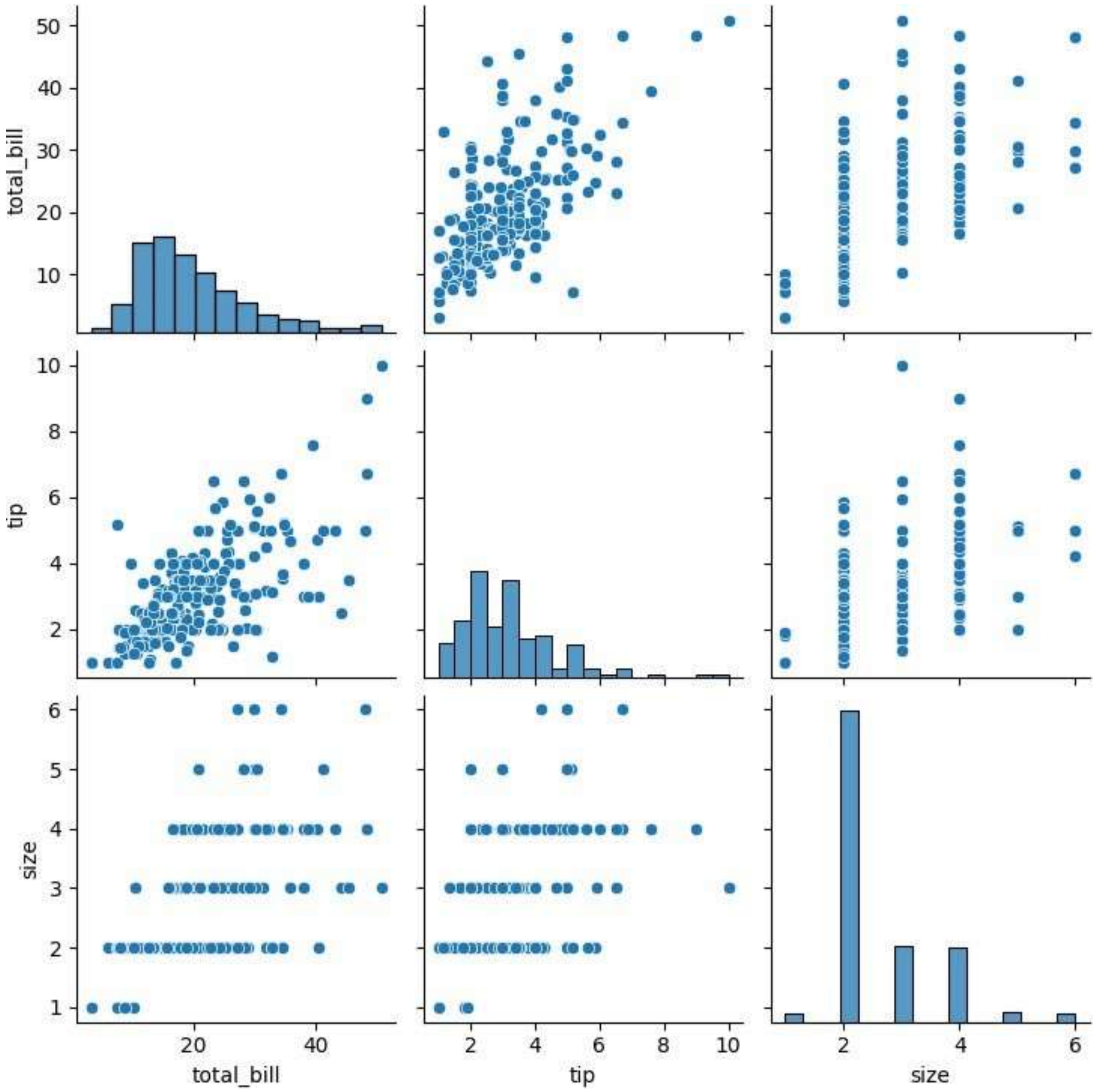



```
sns.jointplot(x=tips.tip,y=tips.total_bill,kind="hex")
```

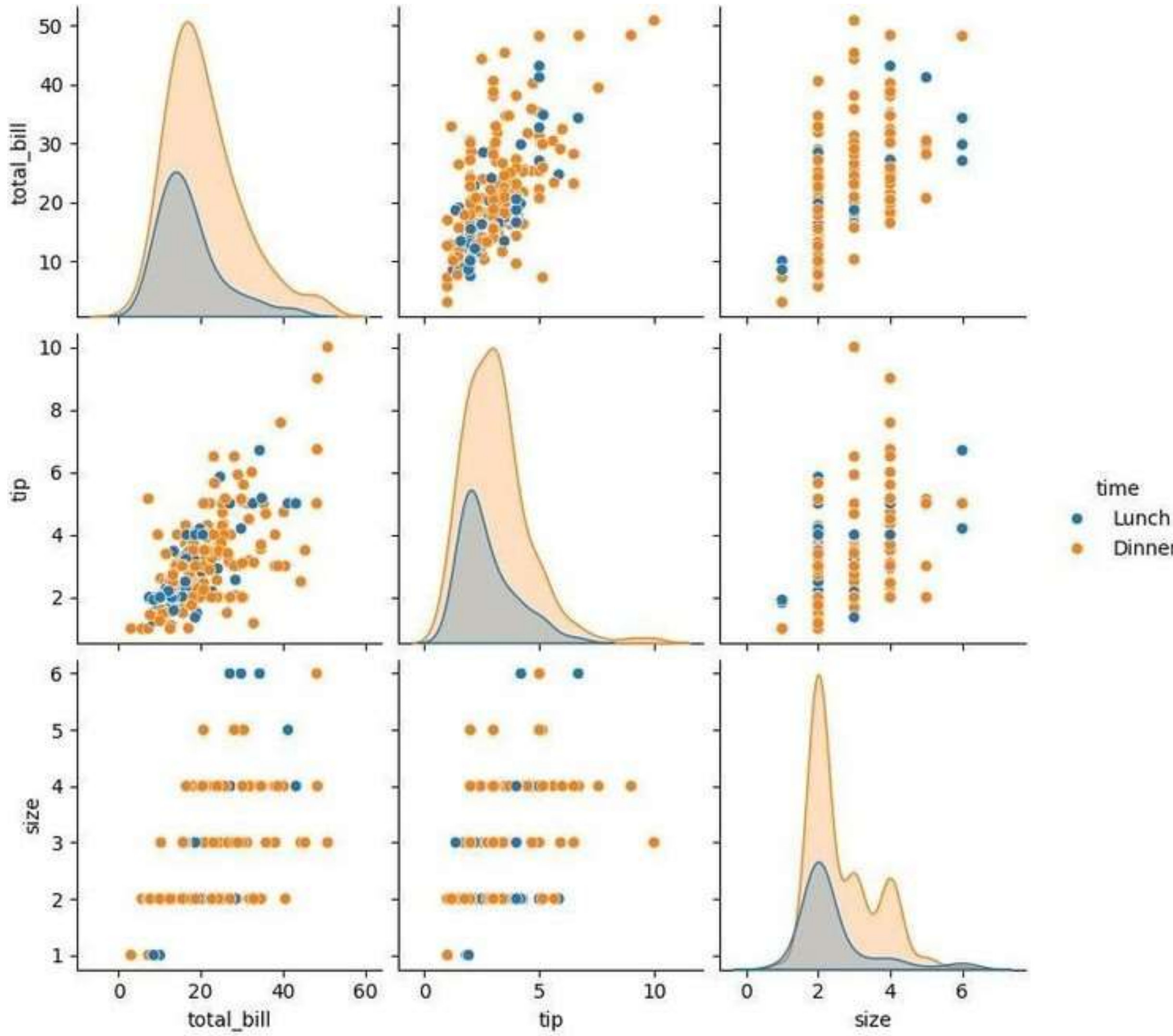
```
<seaborn.axisgrid.JointGrid at 0x20d7ed7d350>
```




```
sns.pairplot(tips)
<seaborn.axisgrid.PairGrid at 0x20d7f1c9cd0>
```

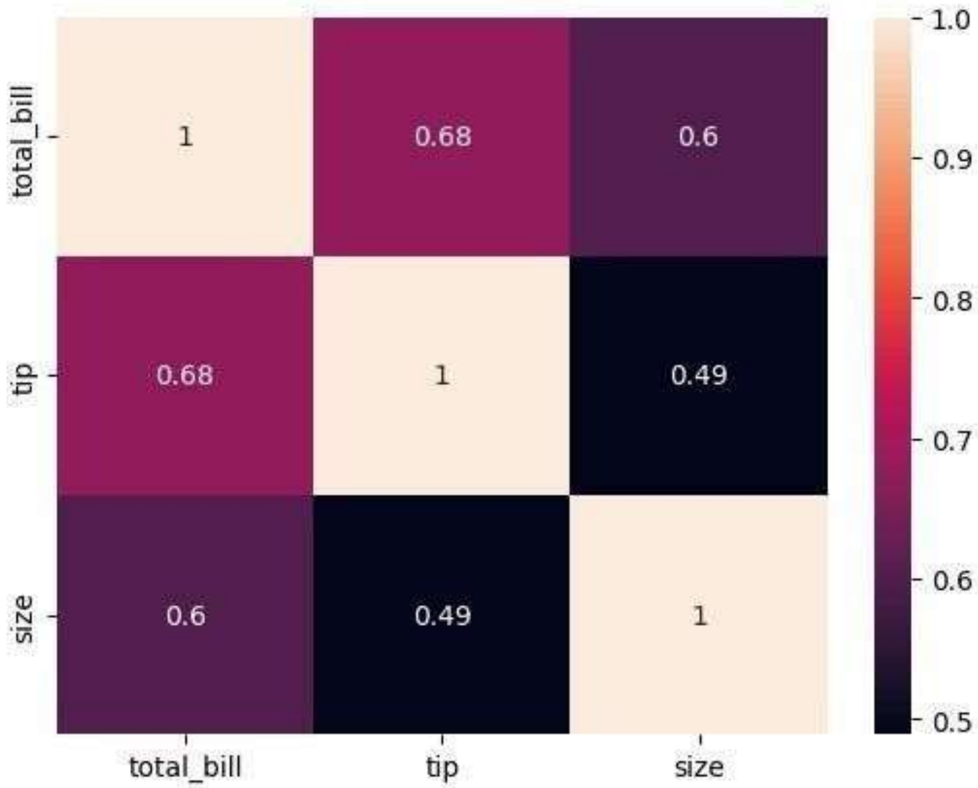



```
tips.time.value_counts()

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

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

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



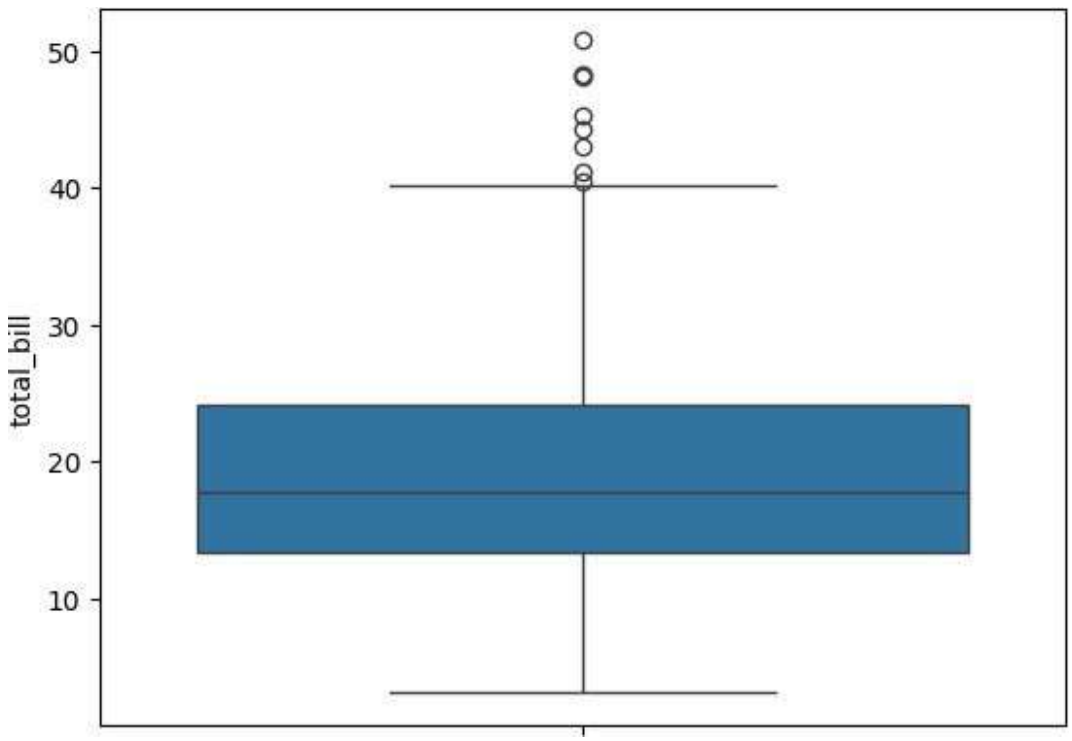

```
sns.heatmap(tips.corr(numeric_only=True),annot=True)
```

```
<Axes: >
```

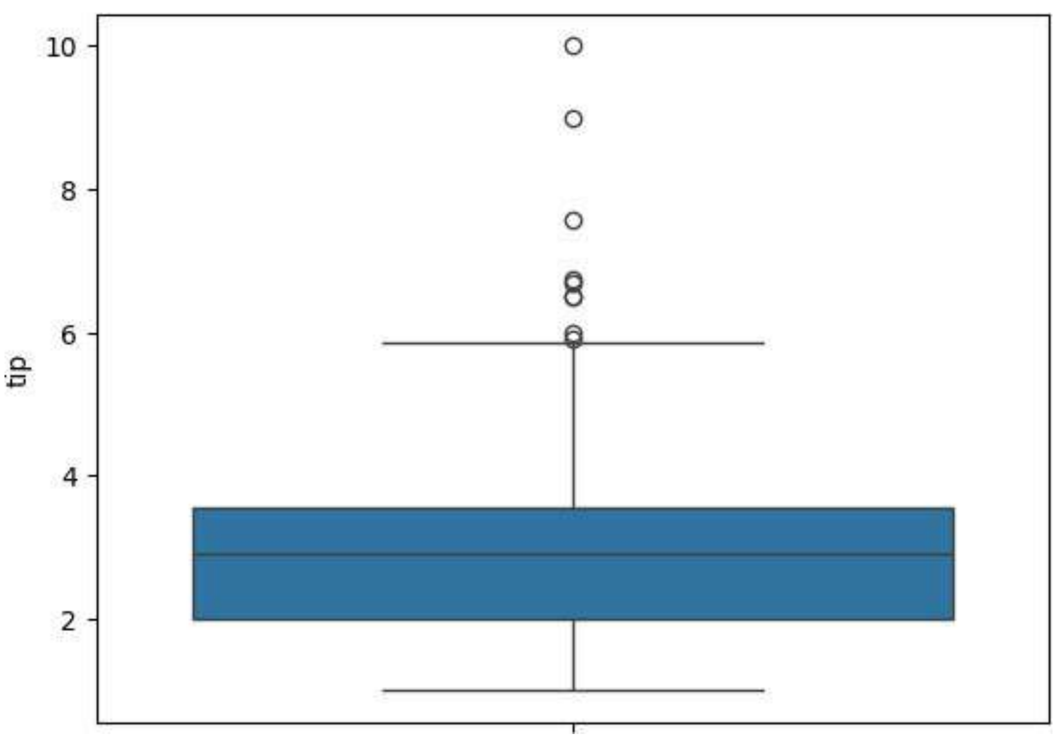



```
sns.boxplot(tips.total_bill)
```

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

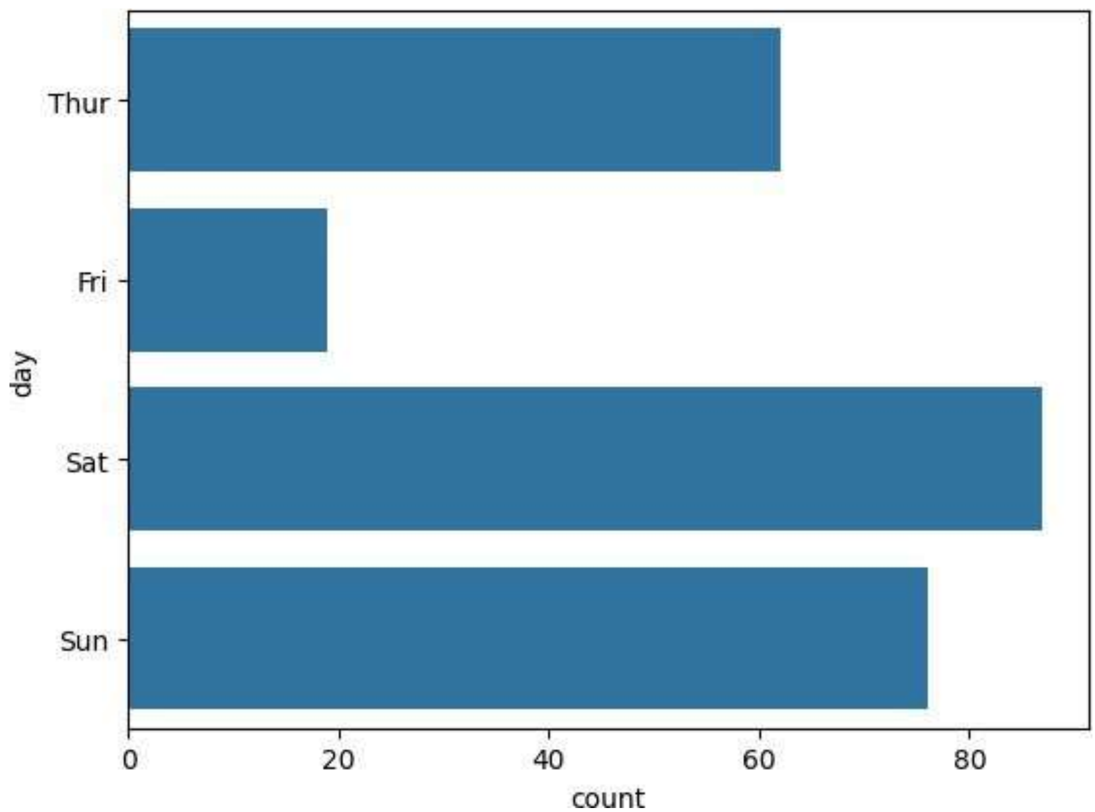



```
sns.boxplot(tips.tip)
<Axes: ylabel='tip'>
```



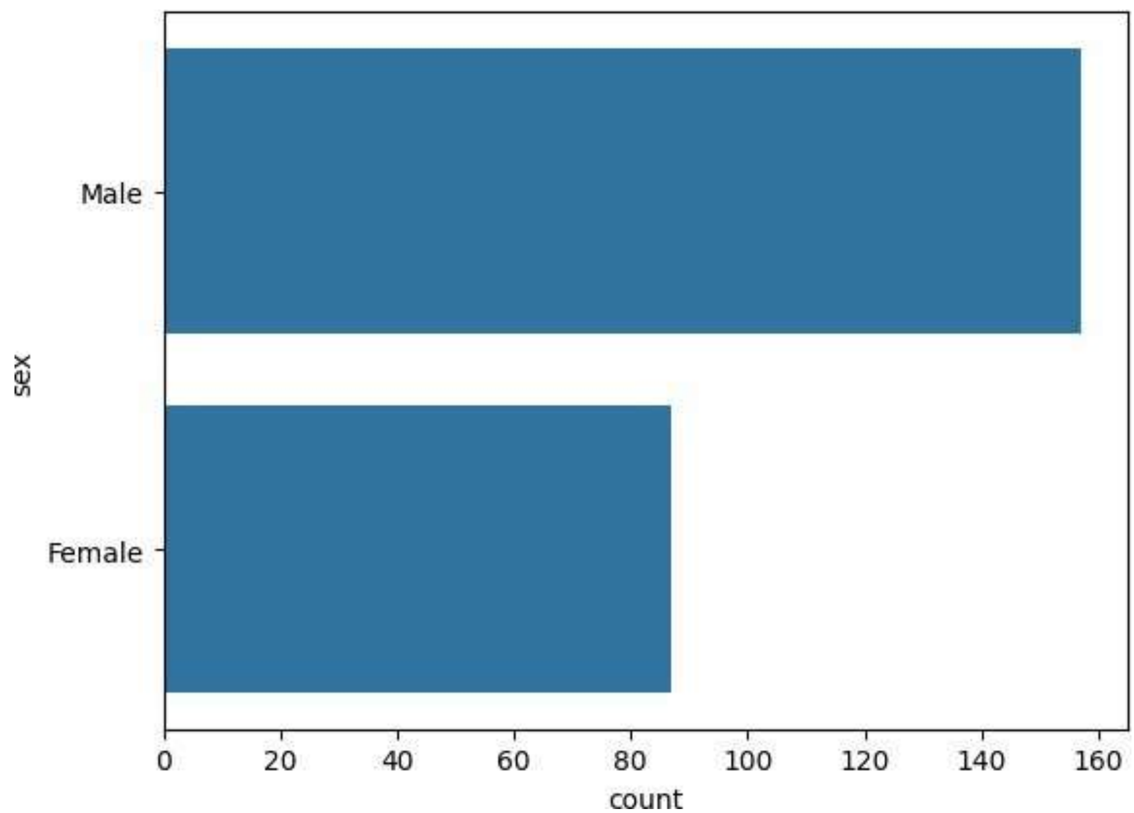
```
sns.countplot(tips.day)
```

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



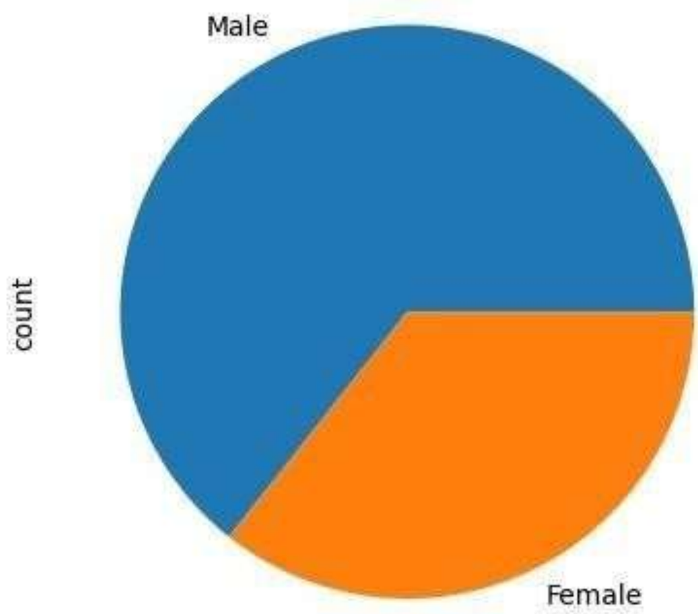

```
sns.countplot(tips.sex)
```

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



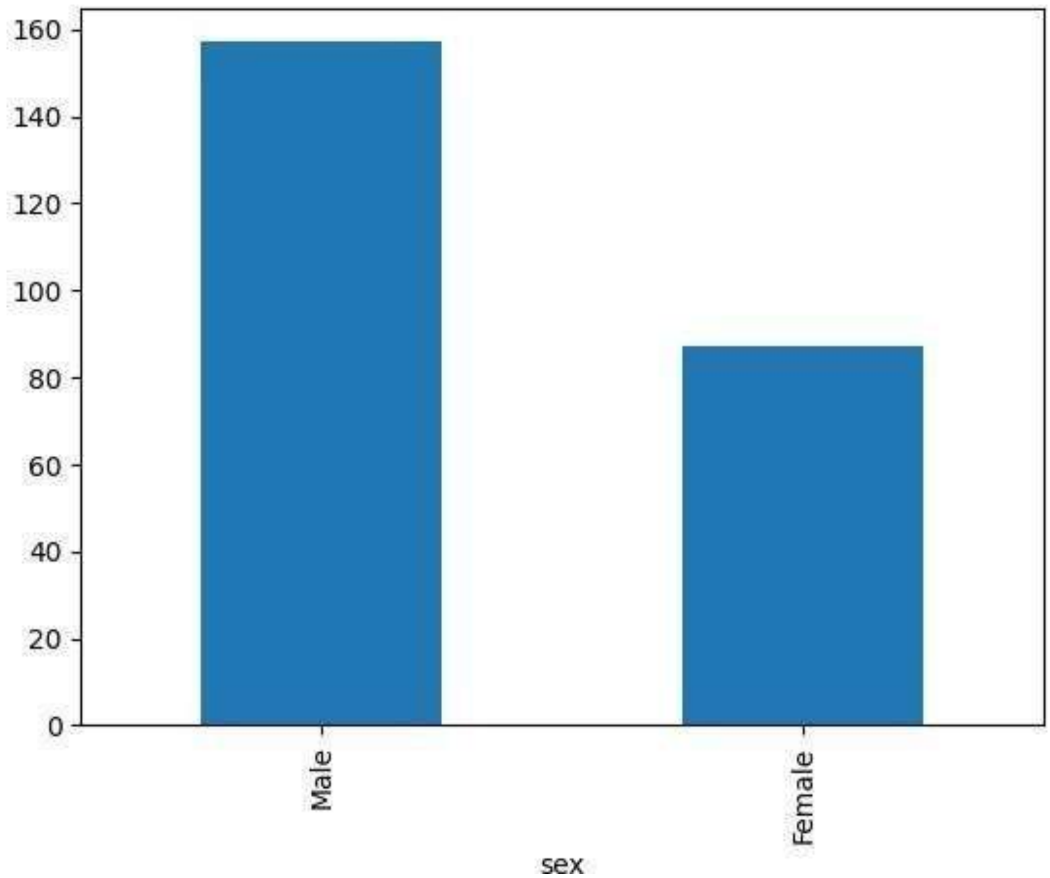

```
tips.sex.value_counts().plot(kind='pie')
```

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



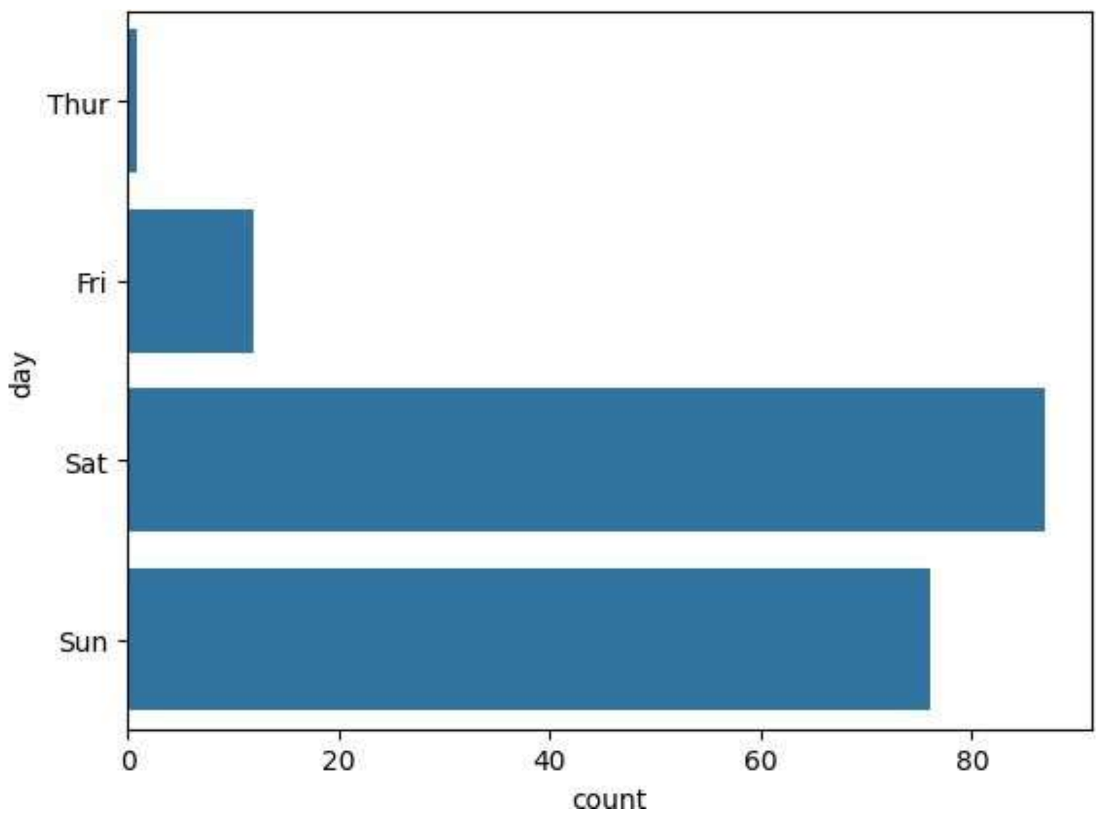

```
tips.sex.value_counts().plot(kind='bar')
```

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




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

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



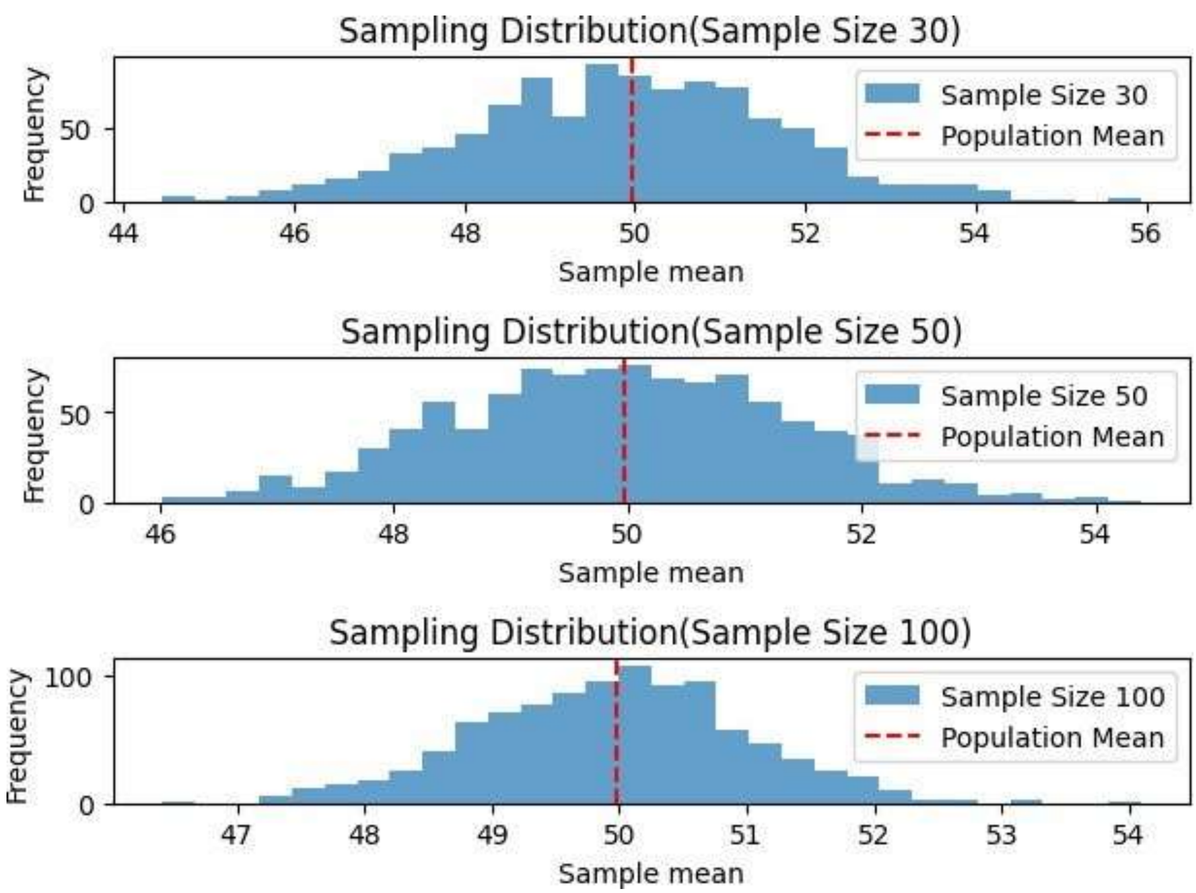

```
#EX.NO :6 Random Sampling and Sampling Distribution
#DATA : 10.09.2024

#NAME : DHARANEEISH BK


 #ROLL NO : 230701072
#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 : DHARANEEISH BK
#ROLL NO : 230701072
 #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 : DHARANEEISH BK
```

```
#ROLL NO : 230701072
 #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 : DHARANEEISH BK
```

```
#ROLL NO : 230701072
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - B

import numpy as np
```

```python
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   1.4647 0.087 7  -0.1683 3.0977   False
     A      C   5.5923     0.0   3.9593 7.2252    True
     B      C   4.1276     0.0   2.4946 5.7605    True
-------------------------------------------------------------
```

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

#NAME : DHARANEEISH BK
#ROLL NO : 230701072
#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

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

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

dtype=object)
```

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

from sklearn.impute import SimpleImputer
age=SimpleImputer(strategy="mean",missing_values=np.nan)
Salary=SimpleImputer(strategy="mean",missing_values=np.nan)
age.fit(features[:,[1]])
```

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

SimpleImputer()     SimpleImputer()     SimpleImputer()

features[:,[1]]=age.transform(features[:,[1]])
features[:,[2]]=Salary.transform(features[:,[2]])
features
```

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

```
from sklearn.preprocessing import OneHotEncoder
oh = OneHotEncoder(sparse_output=False)
Country=oh.fit_transform(features[:,[0]])
Country
```

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

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

```
array([[1.0, 0.0, 0.0, 44.0,
        72000.0],
       [0.0, 0.0, 1.0, 27.0, 48000.0],
       [0.0, 1.0, 0.0, 30.0, 54000.0],
       [0.0, 0.0, 1.0, 38.0, 61000.0],
       [0.0, 1.0, 0.0, 40.0, 63777.77777777778],
       [1.0, 0.0, 0.0, 35.0, 58000.0],
       [0.0, 0.0, 1.0, 38.77777777777778, 52000.0],
```

```
       [1.0,   0.0,   0.0,   48.0,   79000.0],   [0.0,   1.0,   0.0,   50.0,
       83000.0], [1.0, 0.0, 0.0, 37.0, 67000.0]], dtype=object)
```

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

```
array([[  1.22474487e+00,  -6.54653671e-01,  -6.54653671e-01,
          7.58874362e-01, 7.49473254e-01],
        [-8.16496581e-01, -6.54653671e-01, 1.52752523e+00,
         -1.71150388e+00,
        [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]])
```

```
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 : DHARANEEISH BK
#ROLL NO : 230701072
#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  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
```

```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
```

```python
#iloc index based selection loc location based sentence
```

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

```python
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)
```

```python
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]] .


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      LogisticRegression
#DATA : 05.11.2024

#NAME : DHARANEEISH BK

#ROLL NO : 230701072
#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'
```

	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	4	3400	1
389	15668521	Female	7	0	1
390	15807837	Male	4	3500	1
391	15592570	Male	8	0	1
392	15748589	Female	4	3300	1
393	15635893	Male	8	0	1
394	15757632	Female	4	2300	0
395	15691863	Female	7	0	1
396	15706071	Male	4	4500	1
397	15654296	Female	5	0	1
398	15755018	Male	6	4200	0
399	15594041	Female	0	0	1
			3	5900	
			9	0	
			4	4100	
			6	0	
			51	2300	
			5	0	
			0	2000	
			3	0	
			6	3300	
			4	0	
			9	3600	
				0	

```
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	
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]
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[32, 18000]
[34, 112000]
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[22, 27000]
[28, 87000]
[26, 17000]
[30, 80000]
```

```
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 [ 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]
```

```
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[30, 17000],
[26, 84000],
[31, 58000],
[33, 31000],
[30, 87000],
[21, 68000]
```

```
[28, 55000],
[23, 63000],
[20, 82000],
[30, 107000],
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[26, 30000],
[32, 135000]
```

```
[32, 100000]
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```

```
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[ 29, 43000],
[ 19, 70000],
[ 28, 89000],
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[ 30, 79000],
[ 20, 36000],
[ 26, 80000],
[ 35, 22000],
[ 35, 39000],
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[ 39, 134000],
[ 41, 71000],
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```

```
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[ 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],
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[57, 122000],
[41, 52000],
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[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],
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[36, 63000],
[42, 73000],
[43, 112000],
[45, 79000],
[46, 117000],
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```

```
[ 36,  60000]
[ 52, 138000]
[ 53,  82000]
[ 41,  52000]
[ 48,  30000]
[ 48, 131000]
[ 41,  60000]
[ 41,  72000]
[ 42,  75000]
[ 36, 118000]
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[ 38,  51000]
[ 48, 119000]
[ 42,  65000]
[ 40,  65000]
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[ 36,  54000]
[ 58, 144000]
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[ 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)
```

```
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()

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	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