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

#NAME : Gokula Sarathy P S

#ROLL NO : 230701095
#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()


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

```
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()
```

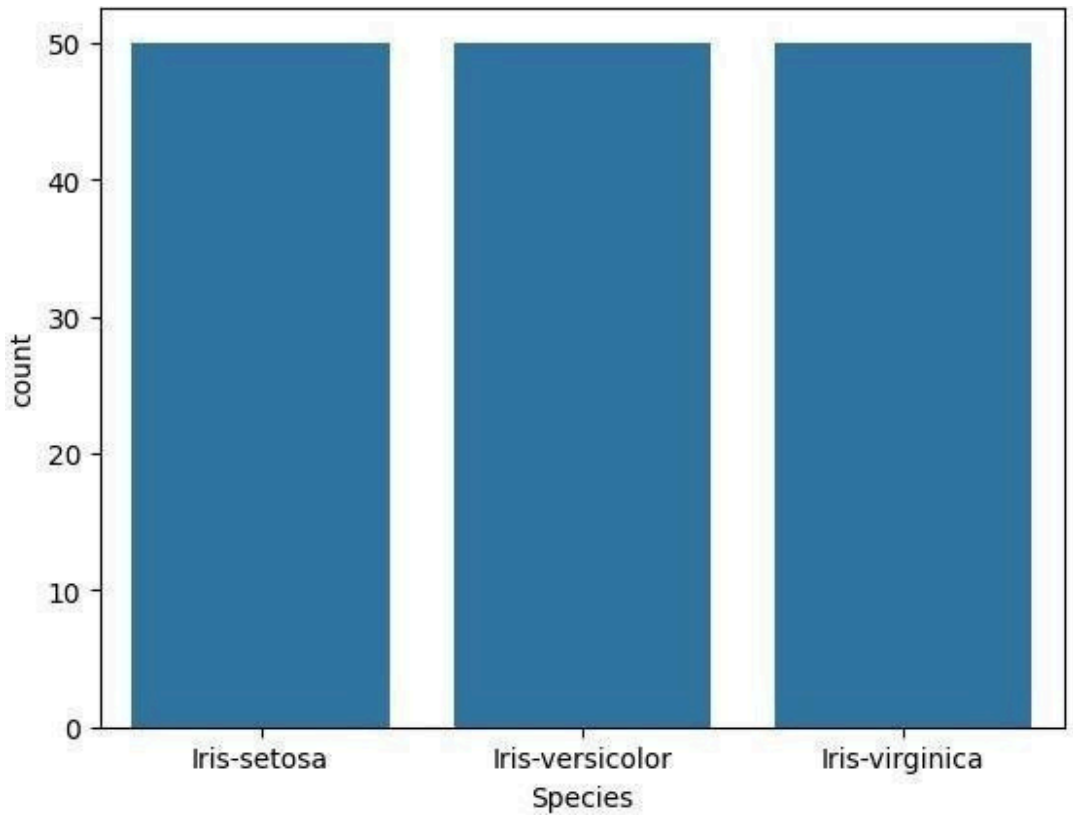
	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
count	150.000000	150.000000	150.000000	150.000000	150.000000
mean	75.500000	5.843333	3.054000	3.758667	1.198667
std	43.445368	0.828066	0.433594	1.764420	0.763161
min	1.000000	4.300000	2.000000	1.000000	0.100000
025.3%0000					
0	38.250000	5.100000	2.800000	1.600000	
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	

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

```
Species
```

```
Name: count, dtype: int64
```

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

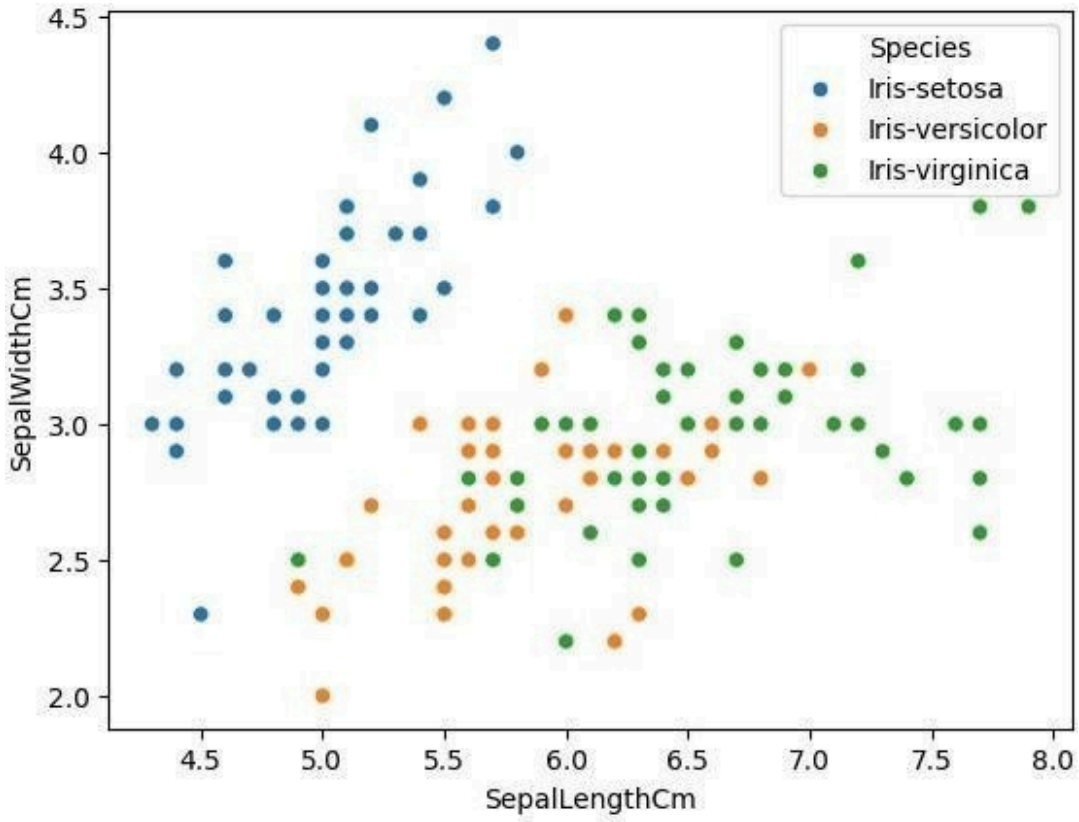



```
dummies=pd.get_dummies(data.Species)

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	SepalWidthCm	PetalLengthCm
0	True	False	False	1	5.1	3.5	1.4
1	True	False	False	2	4.9	3.0	1.4
2	True	False	False	3	4.7	3.2	1.3
3	True	False	False	4	4.6	3.1	1.5
4	True	False	False	5	5.0	3.6	1.4

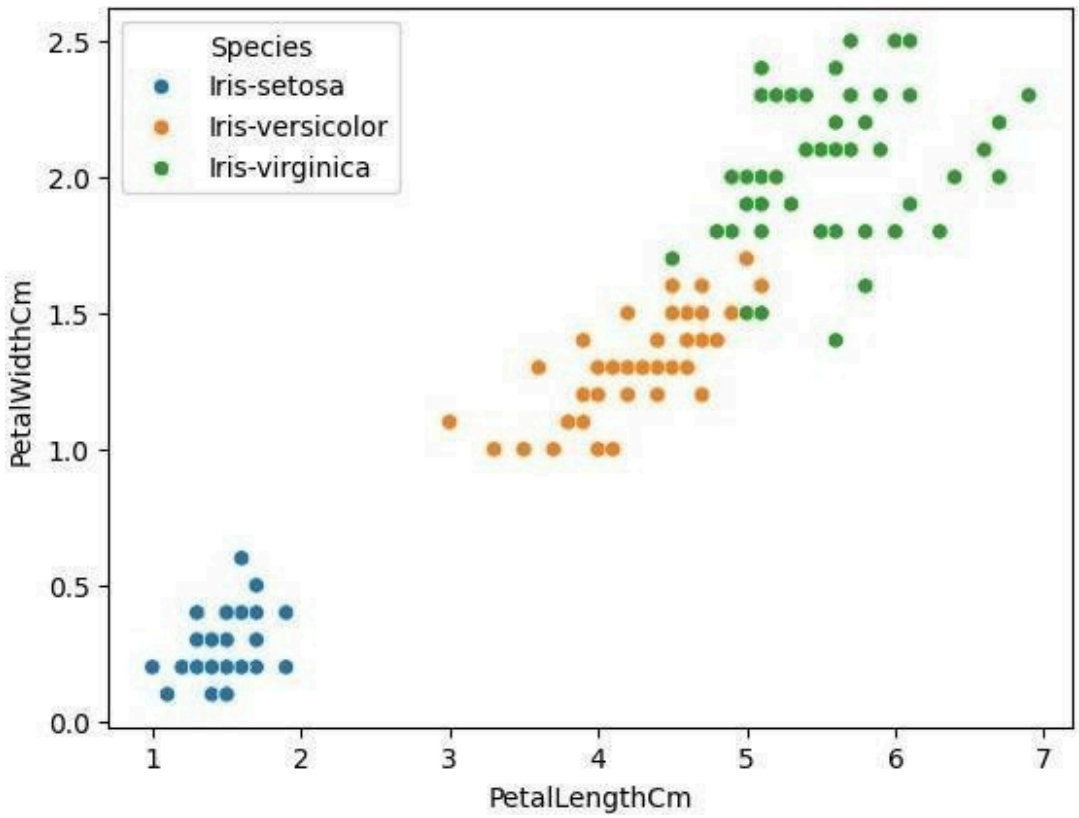
```
sns.scatterplot(x='SepalLengthCm',y='SepalWidthCm',hue='Species',data=
data,)
```

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

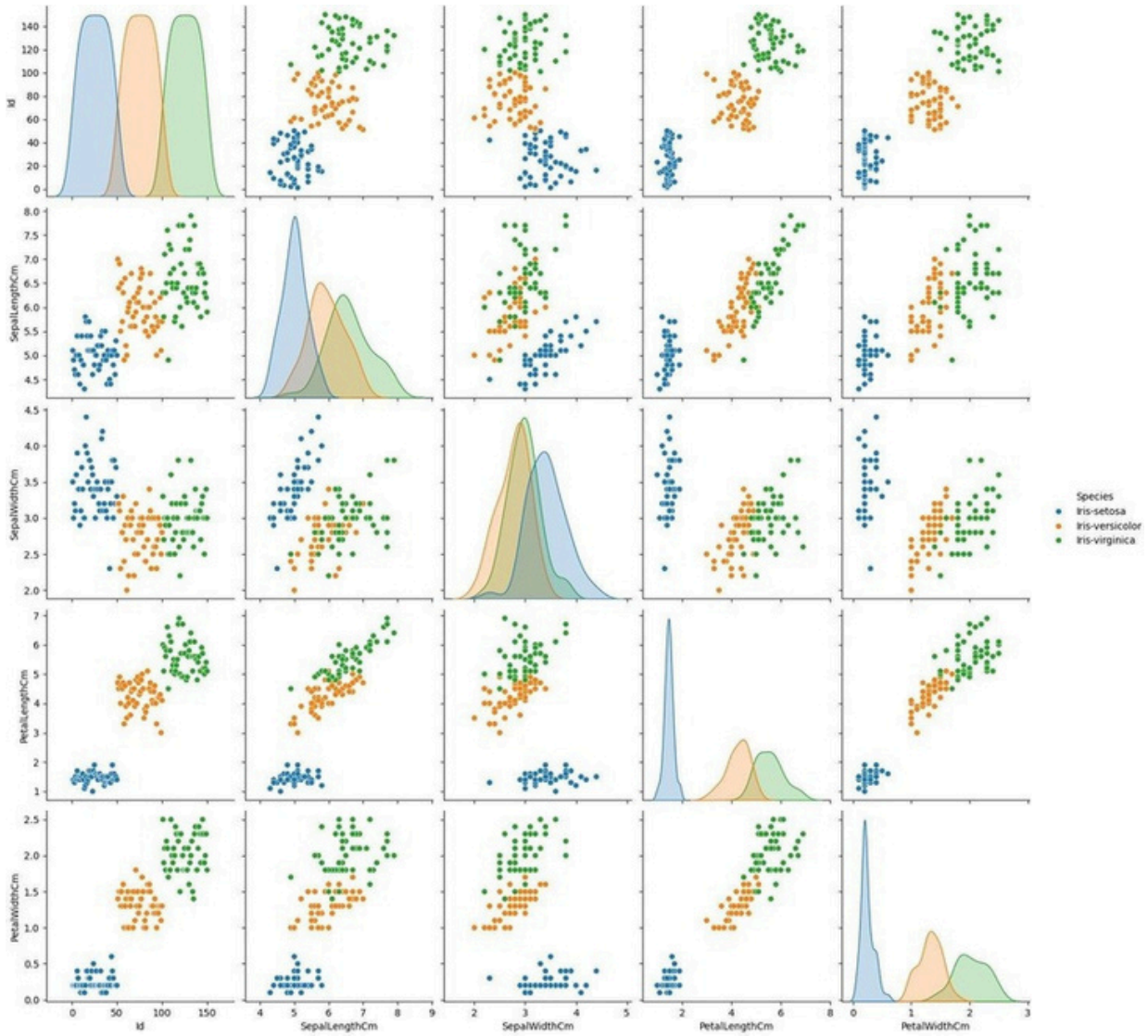



```
sns.scatterplot(x='PetalLengthCm',y='PetalWidthCm',hue='Species',data=
 data,)
```

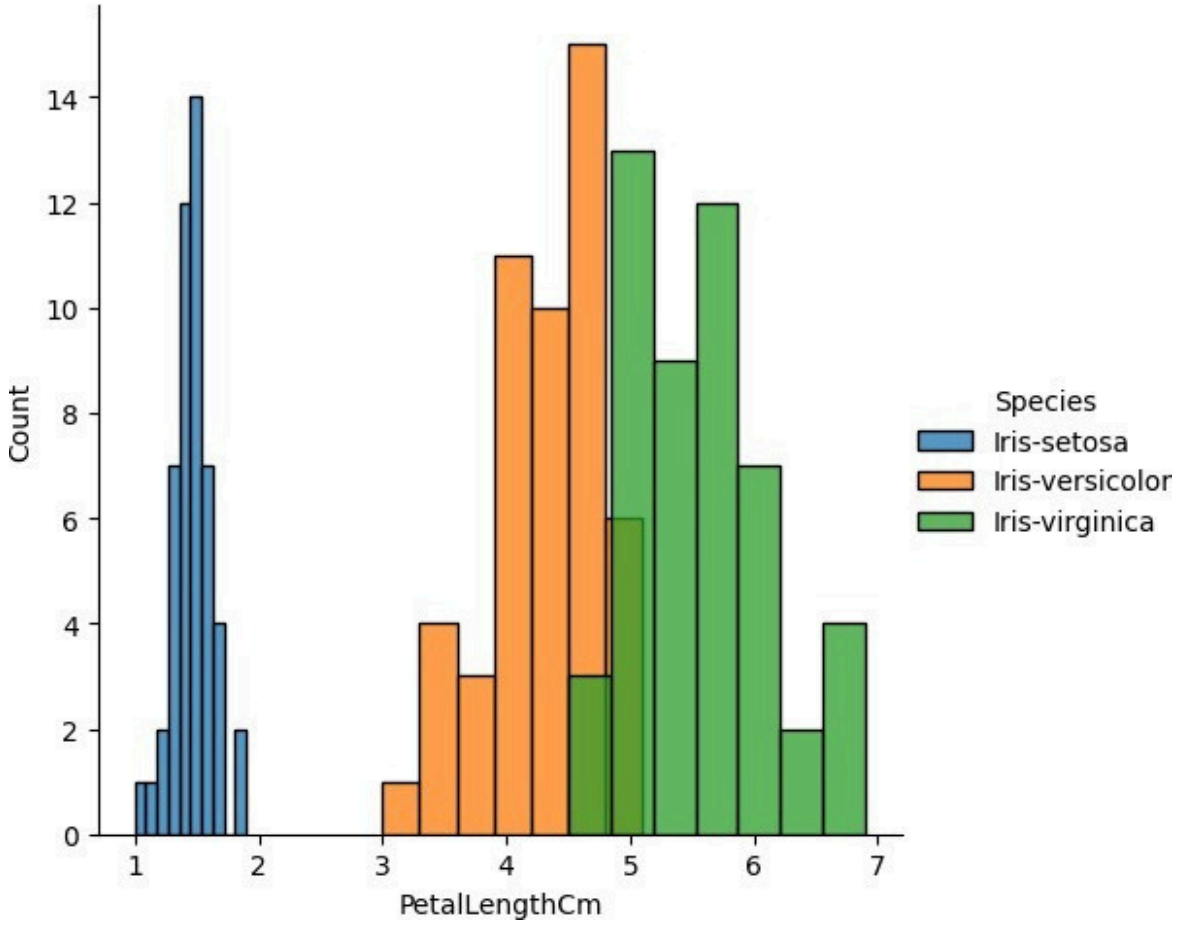
```
<Axes: xlabel='PetalLengthCm', ylabel='PetalWidthCm'>
```



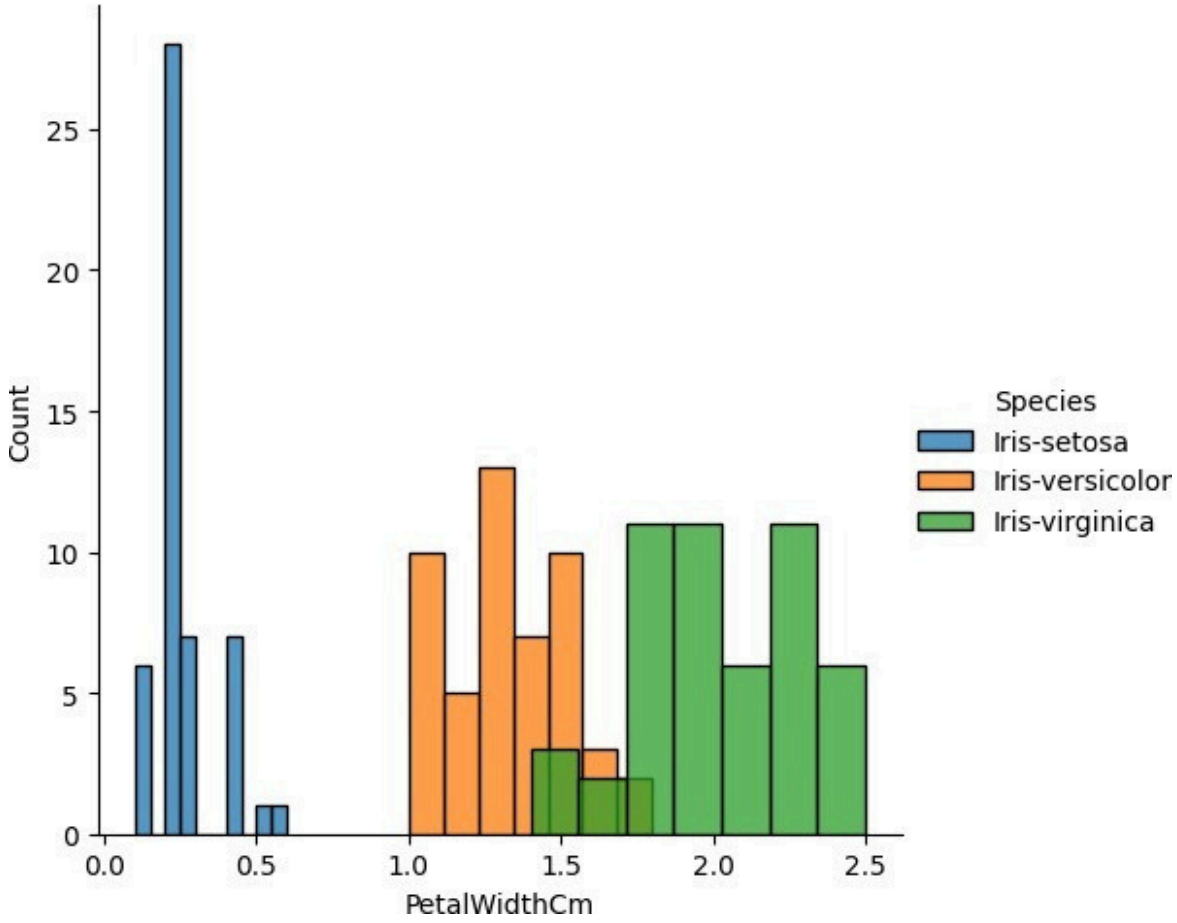

```
sns.pairplot(data,hue='Species',height=3);
```



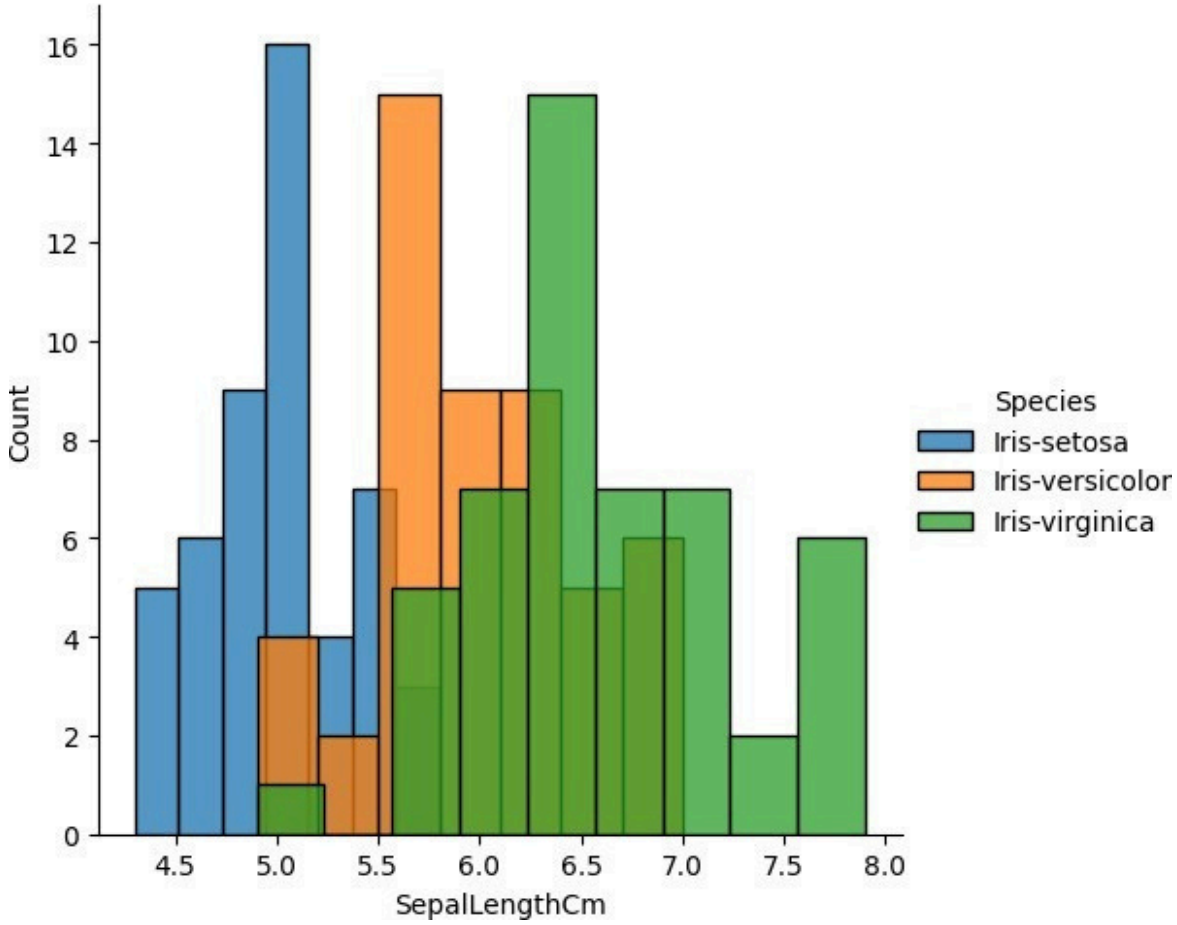

```
plt.show()

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



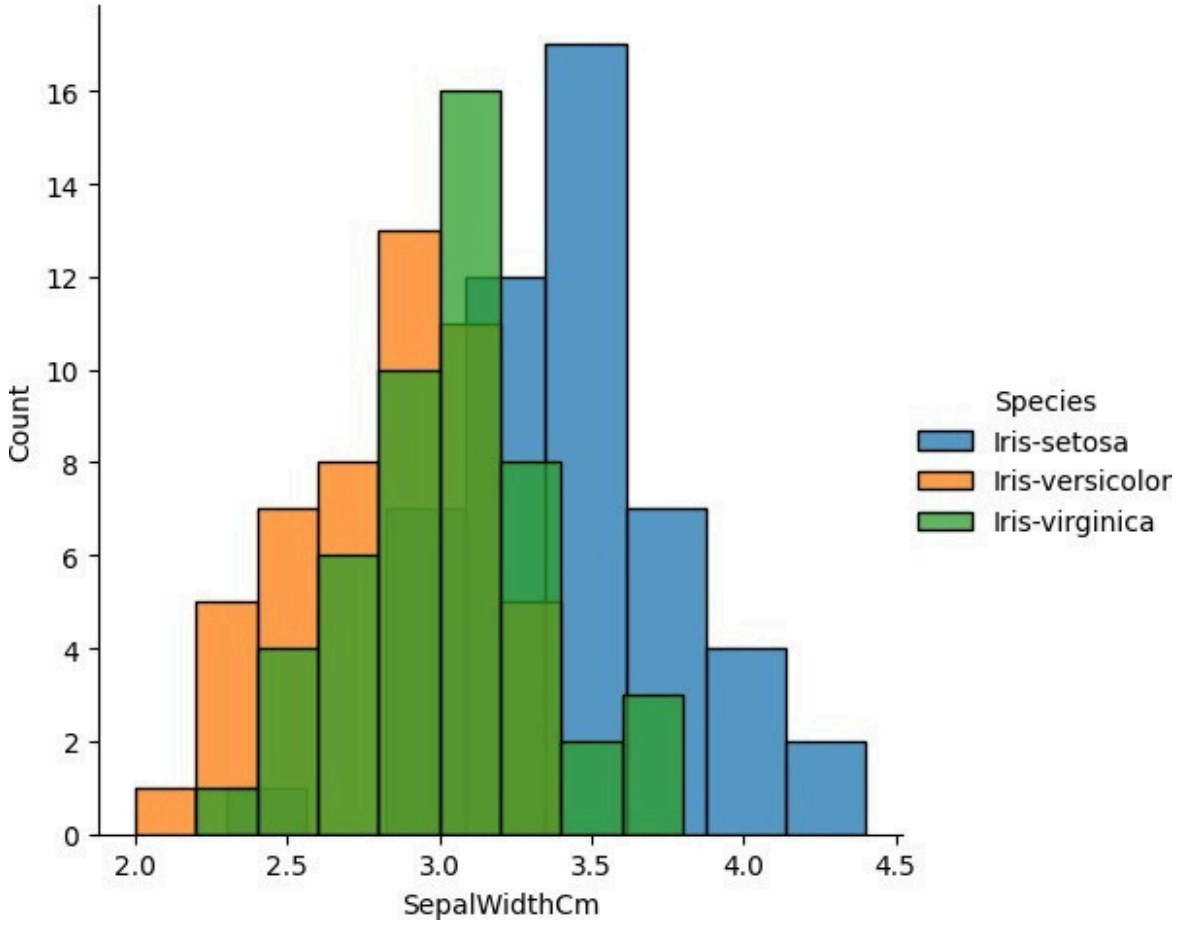

```
sns.FacetGrid(data,hue='Species',height=5).map(sns.histplot,'PetalWidt
 hCm').add_legend();
plt.show();
```




```
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 :Gokulakrishnan.K
#ROLL NO : 230701094
 #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 : GOKULAKRISHNAN.K
#ROLL NO : 230701094
#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)
```

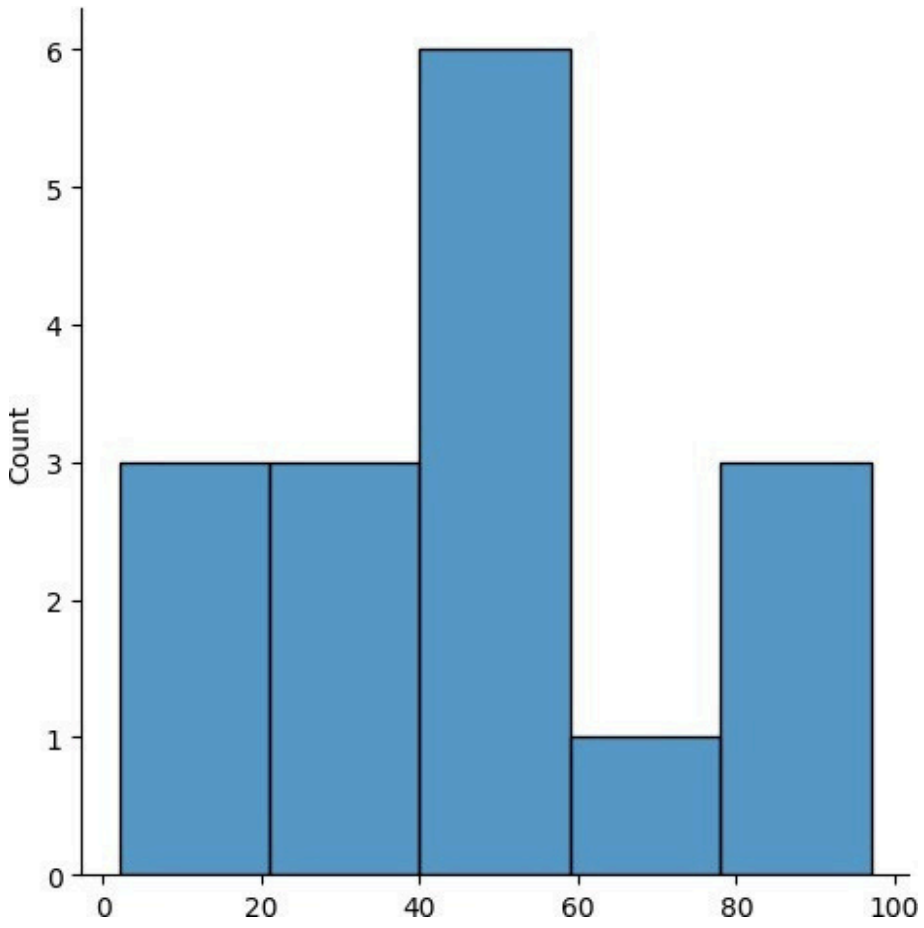
```
 97.0
```

```
 #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)
```

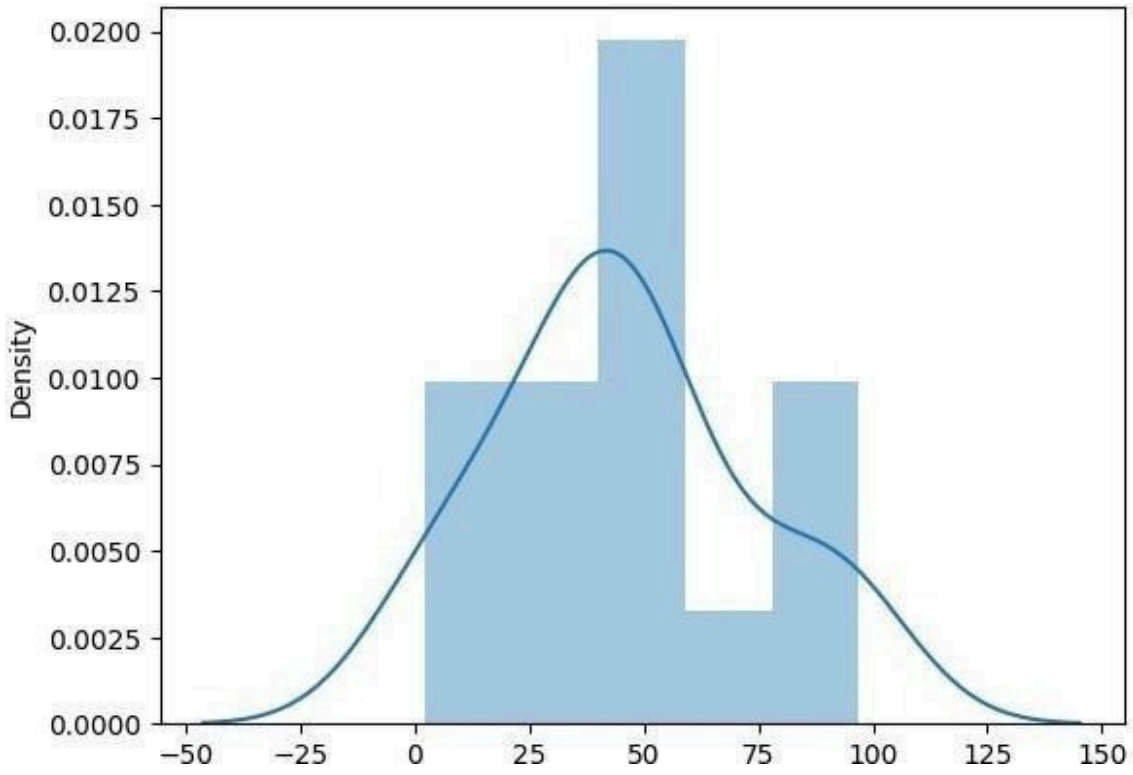
```
import seaborn as sns
%matplotlib inline
 sns.displot(array)
```

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




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

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

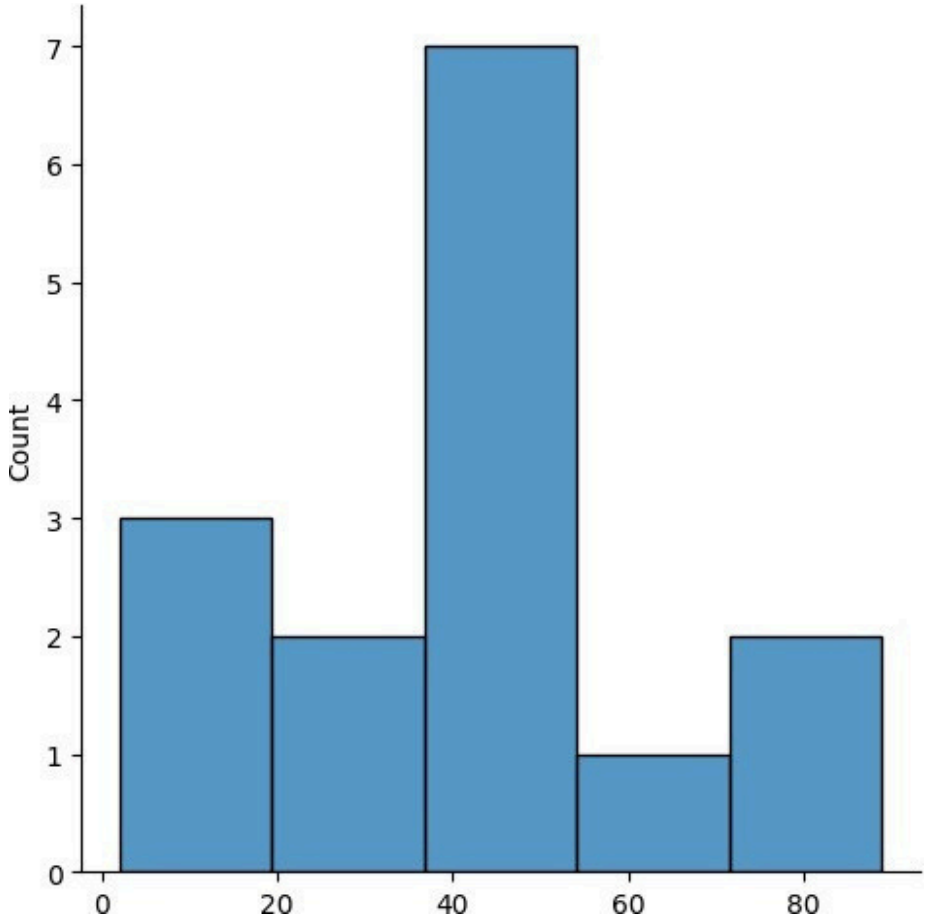



```
new_array=array[(array>lr) & (array<ur)]
 new_array
```

```
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
```

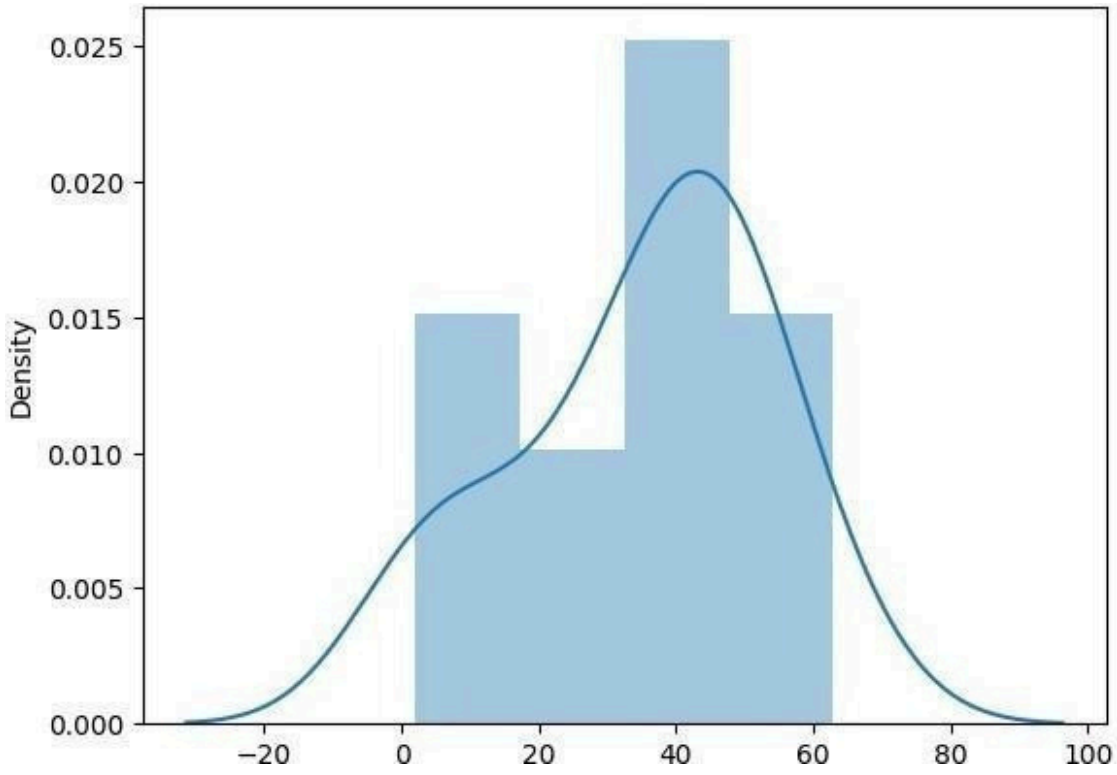
```
(-5.25, 84.75)
```

```
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 : GOKULAKRISHNAN.K
#ROLL NO : 230701094
#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 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-NullCount	Dtype
0	CustomerID	11non-null	int64
1	Age_Group	11 non-null	object
2	Rating(1-5)	11 non-null	int64

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

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

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

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

```
len(df)
```

```
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
2
2            3     25-30            6      RedFox             Veg   1322
23
3            4     20-25           -1    LemonTree             Veg   1234
5
4            5       35+            3         Ibis      Vegetarian    989
-1
5            6       35+            3
7
6            7       35+            4         Ibys        Non-Veg  1909
-10
7            8                      7      RedFox      Vegetarian  1000
8
8            9     20-25                 LemonTree             Veg  2999
4
9           10     30-35            5      RedFox        non-Veg-6755

   EstimatedSalary Age_Group.1
0 1 2 3         40000     20-25
4               59000     30-35
5               30000     25-30
6              120000     20-25
7               45000       35+
8              122220       35+
9               21122       35+
               345673     20-25
               99999      25-30
               87777      30-35
df.drop(['Age_Group.1'],axis=1,inplace=True
```

```
)  df
```

```
0            1     20-25            4         Ibis             veg  130
                                                                      0
```

2

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

1	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	+	3	Ibys	Non-Veg	1909
9 4						
	7	35	4	RedFox	Vegetarian	1000
	8	20+25	7	LemonTree	Veg	2999
	9	2535	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
ndf
```

	CustomerID	Age_Group	Rating(1-5)	HotelFoodPreference	Bill
\					
0	1.0	20-25	4	Ibis veg	1300.0
1	2.0	30-35	5	LemonTree Non-Veg	2000.
2	3.0	25-30	6	RedFox Veg	0
3	4.0	20-25	-1	LemonTree Veg	1232342..0

4	5.0	35	3	Ibis	Vegetarian	989.0
5	6.	+	3	Ibys	Non-Veg	1909.0
	0	35				
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)	HotelFoodPreference	Bill
\					
0	1.0	20-25	4	Ibis	veg 1300.0
1	2.0	30-35	5	LemonTree	Non-Veg2000.0
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-Veg3456.0

```
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 of0                veg
9        g
         Non-Ve
         g
         non-Ve
         g


Name:                FoodPreference,              dtype:                object>
```

```
df.FoodPreference.replace(['Vegetarian','veg'],'Veg',inplace=Tru
e) df.FoodPreference.replace(['non-Veg'],'Non-Veg',inplace=True)
df.EstimatedSalary.fillna(round(df.EstimatedSalary.mean()),inplace=T

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

	CustomerID	Age_Group	Rating(1-5)	Hotel	FoodPreference	Bill
0	1.0	20-25	4	Ibis	Veg	1300.0
1	2.0	30-35	5	LemonTree	Non-Veg	2000.0
2	3.0	25-30	6	RedFox	Veg	1322.0
3	4.0	20-25	-1	LemonTree	Veg	1234.0
4	5.0	35	3	Ibi	Veg	989.0
5	6.0	+ 35+	3	s	Non-Veg	1909.0
6	7.0	20+-2	4	RedFox	Veg	1000.0
7	8.	5	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 : GOKULAKRISHNAN K
#ROLL NO : 230701094
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - B

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

	Countr	Age	Salary	
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

```
df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 4 columns):
 #   Column     Non-NullCount Dtype
---  ------     -------------- -----
 0   Country    10 non-null   object
 1   Age        9 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

df.Country.mode()

0    France
Name: Country, dtype:
object df.Country.mode()[0]

'France'

type(df.Country.mode())

pandas.core.series.Series

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

   Countr   Age   Salary  Purchased
0       y  44.   72000.0          N
1  France  0     48000.0          o
2   Spain  27.0  54000.0         Ye
3  German  30.0  61000.0          s
4       y  38.0  63778.0         No
5   Spain  40.0  58000.0         No
6  German  35.0  52000.0         Ye
7       y  38.0  79000.0          s
8  France  48.0  83000.0         Ye
9   Spain  50.0  67000.0          s
pd.get_dummies(df.Country)
   France  37.0                  No
                                 Ye
   France Germany Spain           s
0   True   False  False         No
1   False  False  True          Ye
2   False  True   False          s
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-NullCount Dtype
---  ------     --------------  -----
 0   Country    10  non-null    object
 1   Age        10  non-null    float64
 2   Salary     10  non-null    float64
 3   Purchased10  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 : GOKULAKRISHNAN
#ROLL NO : 230701094
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - B
```

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

)  df
```

```
    Countr   Age   Salary
0        y  44.   72000.0  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       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-NullCount Dtype
---  ------     -------------- -----
 0   Country    10 non-null   object
 1   Age        9 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

df.Country.mode()

0    France
Name: Country, dtype:
object df.Country.mode()[0]

'France'

type(df.Country.mode())

pandas.core.series.Series

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

   Countr   Age   Salary  Purchased
0       y  44.   72000.0          N
1  France  0     48000.0          o
2   Spain  27.0  54000.0         Ye
3  German  30.0  61000.0          s
4       y  38.0  63778.0         No
5   Spain  40.0  58000.0         No
6  German  35.0  52000.0         Ye
7       y  38.0  79000.0          s
8  France  48.0  83000.0         Ye
9   Spain  50.0  67000.0          s
pd.get_dummies(df.Country)
   France  37.0                  No
                                 Ye
   France Germany Spain           s
0   True   False  False         No
1   False  False  True          Ye
2   False  True   False          s
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.  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-NullCount Dtyp
                              e
---  ------     --------------  -----
 0   Country    10  non-null    object
 1   Age        10  non-null    float64
 2   Salary     10  non-null    float64
 3   Purchased10  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 : GOKULAKRISHNAN.K

#ROLL NO : 230701094

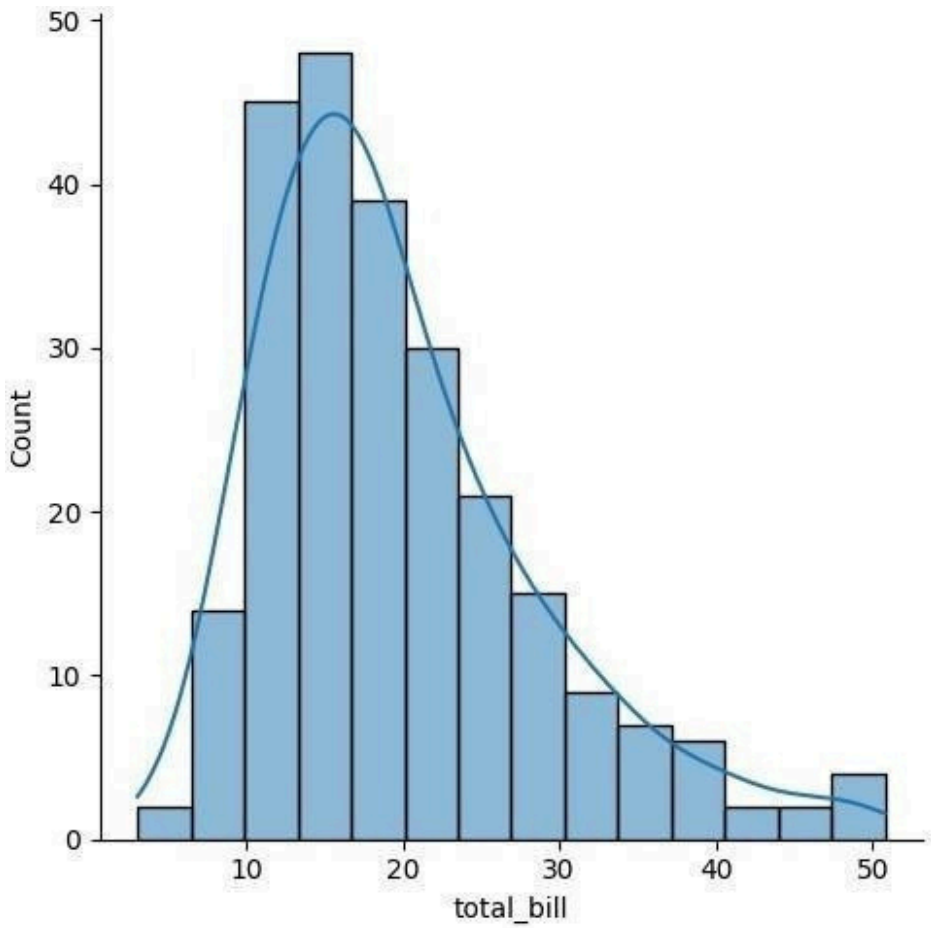
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - B

```
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 l	tip	sex	smoker	day	time	size
0	16.99	1.0	Female	No	Sun	Dinner	2
1	10.34	1	Male	No	Sun	Dinner	3
2	21.01	1.66	Male	No	Sun	Dinner	3
3	23.68	3.50	Male	No	Sun	Dinner	2
4	24.59	3.31	Female	No	Sun	Dinner	4
		3.61					

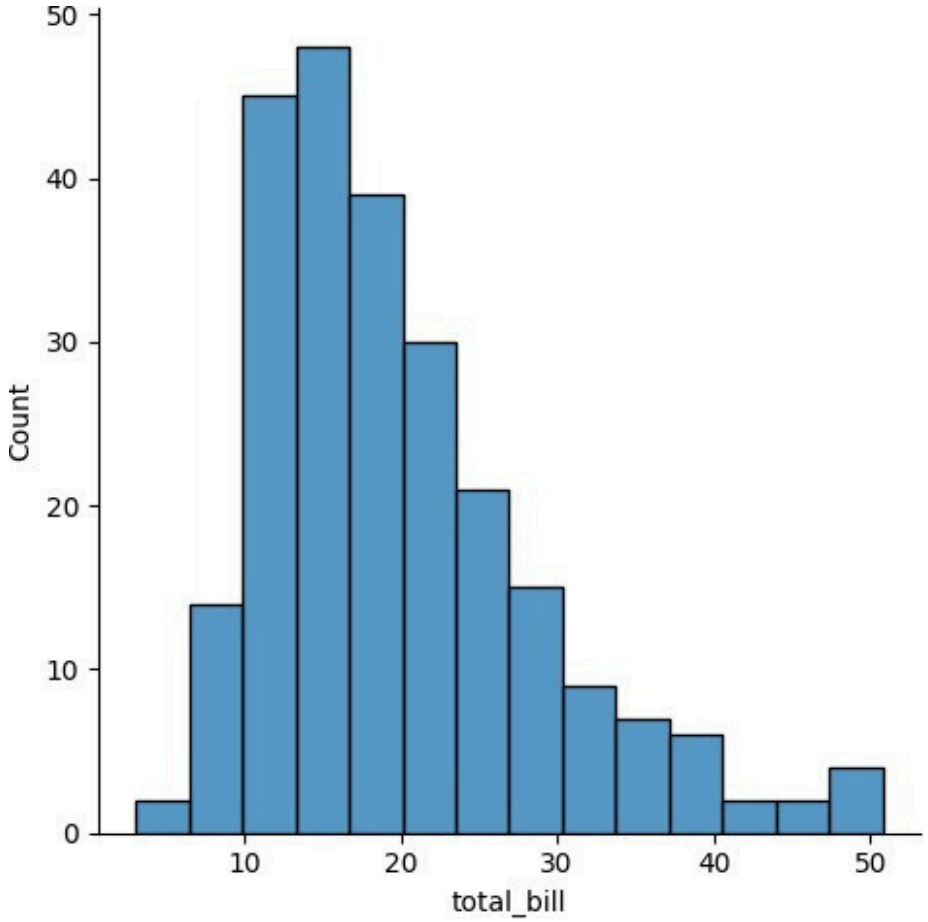
```
sns.displot(tips.total_bill,kde=True)
```

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



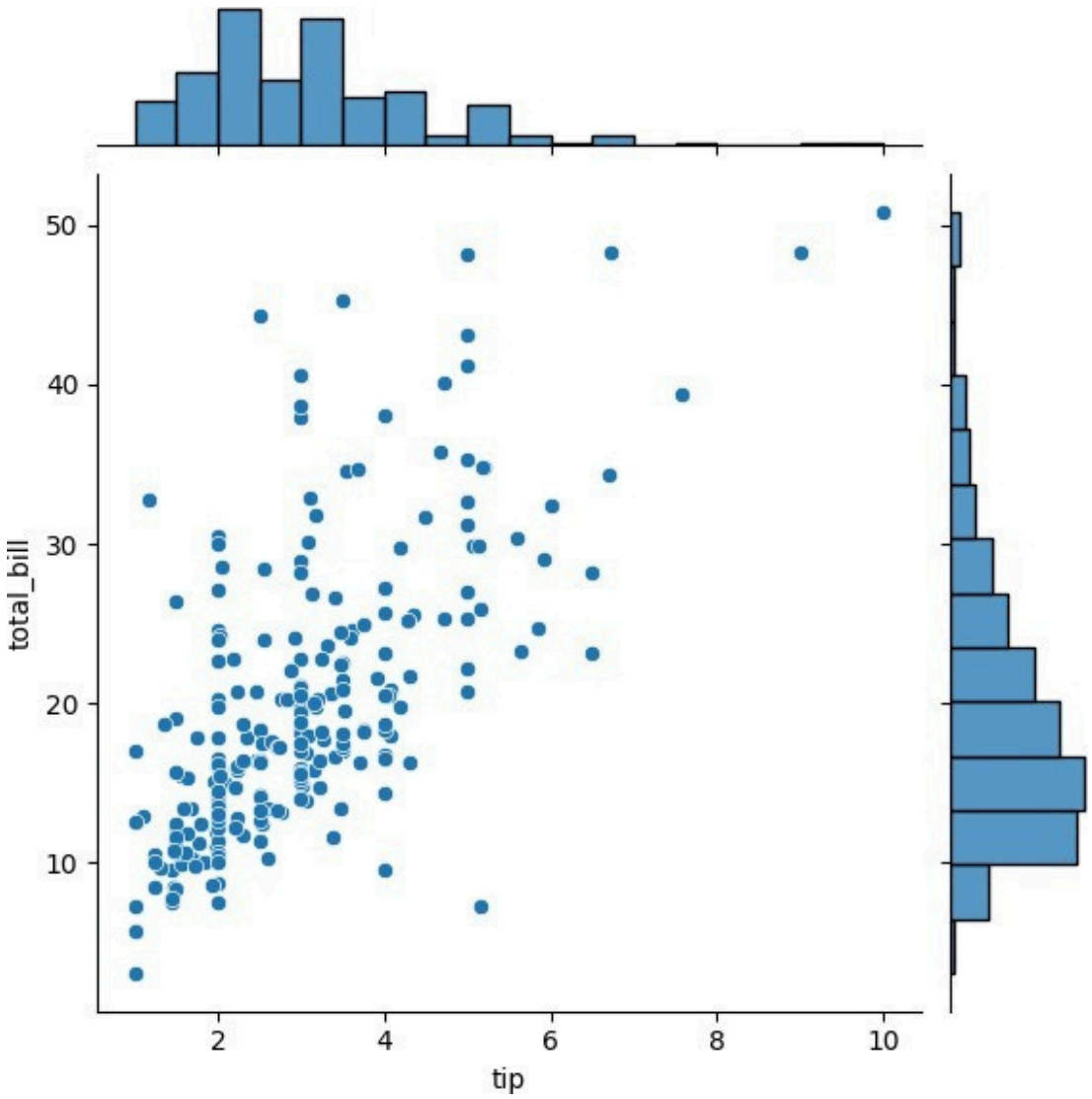

```
sns.displot(tips.total_bill,kde=False)
```

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



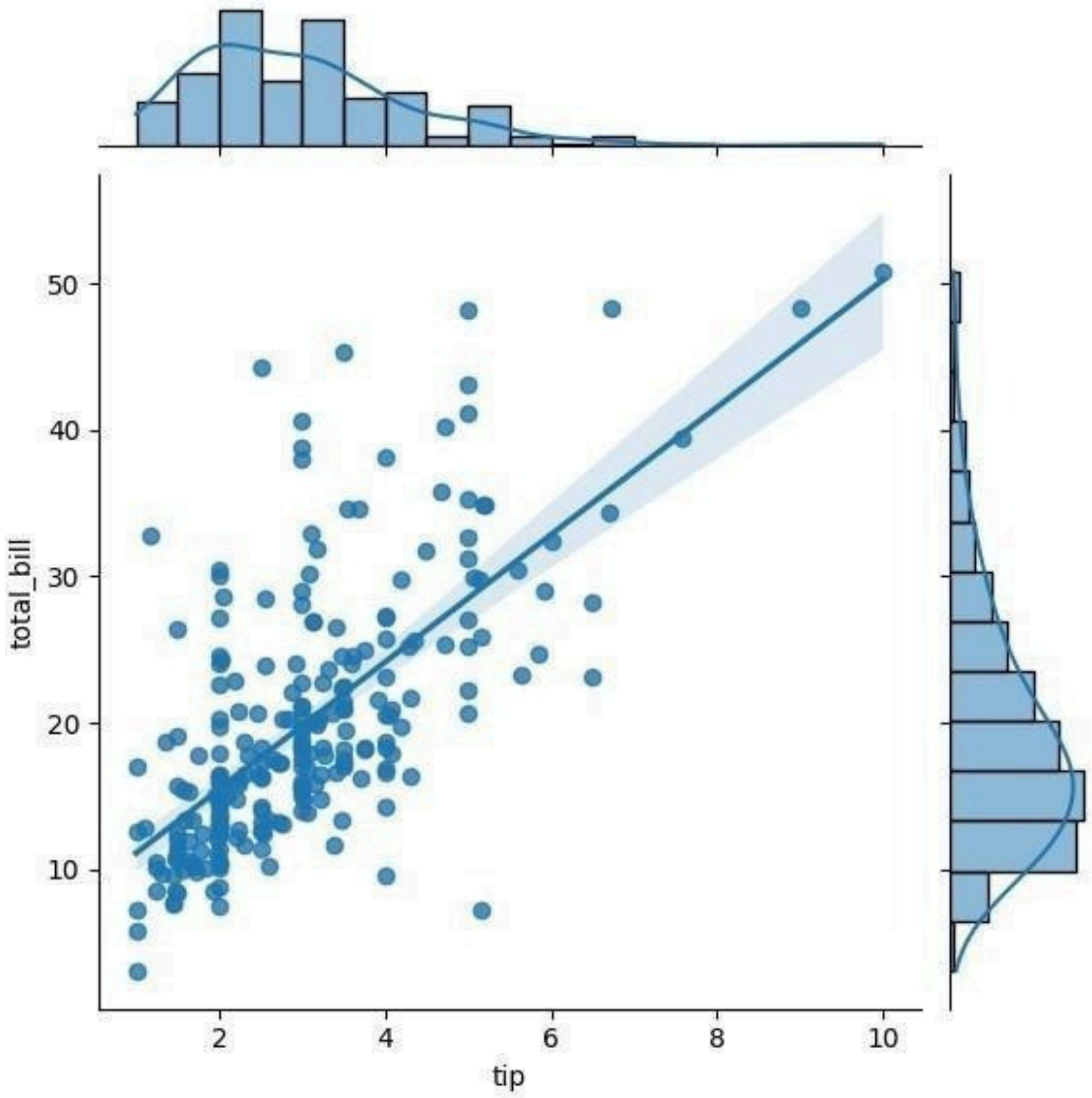

```
sns.jointplot(x=tips.tip,y=tips.total_bill)
```

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



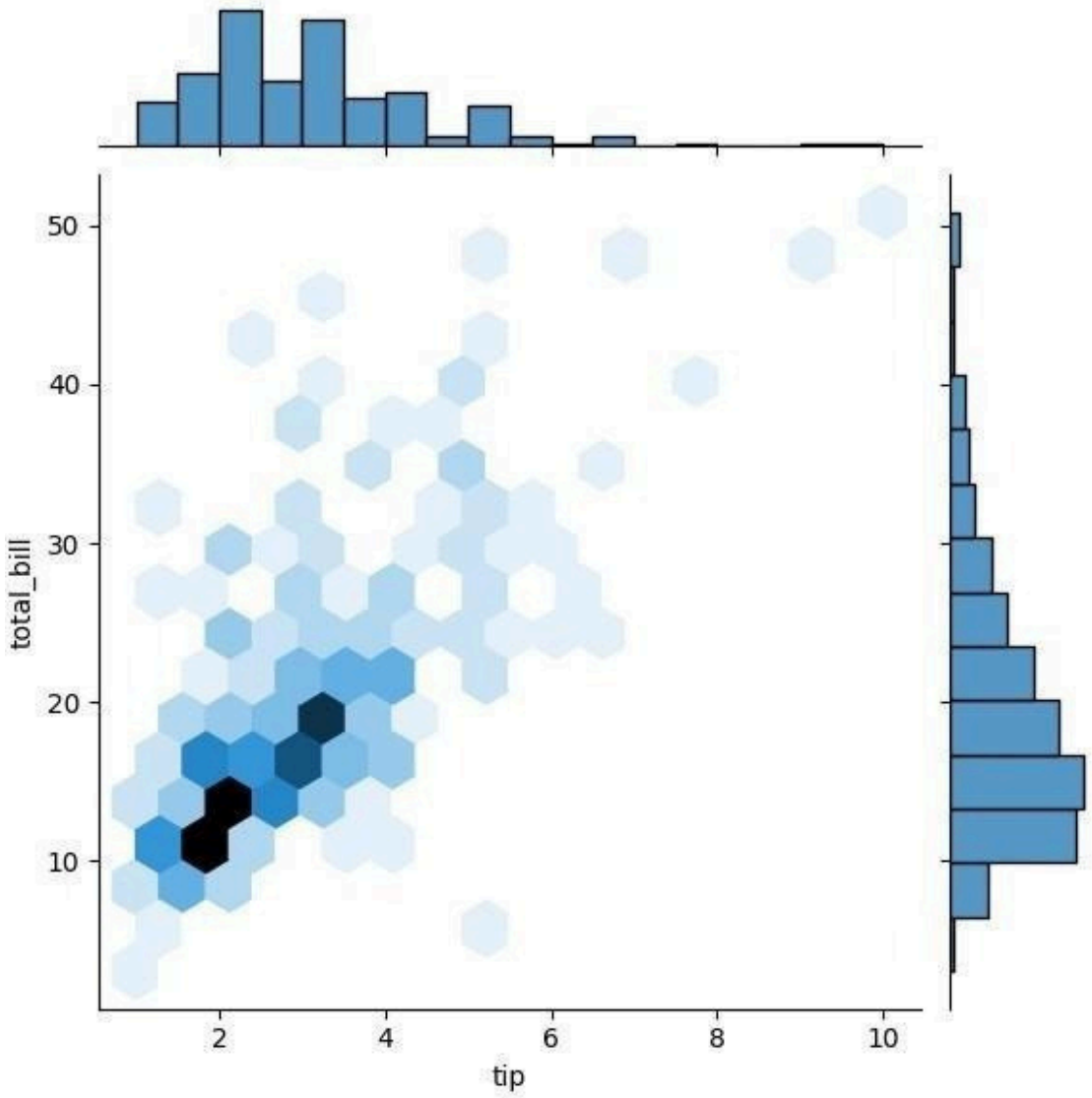

```
sns.jointplot(x=tips.tip,y=tips.total_bill,kind="reg")
```

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



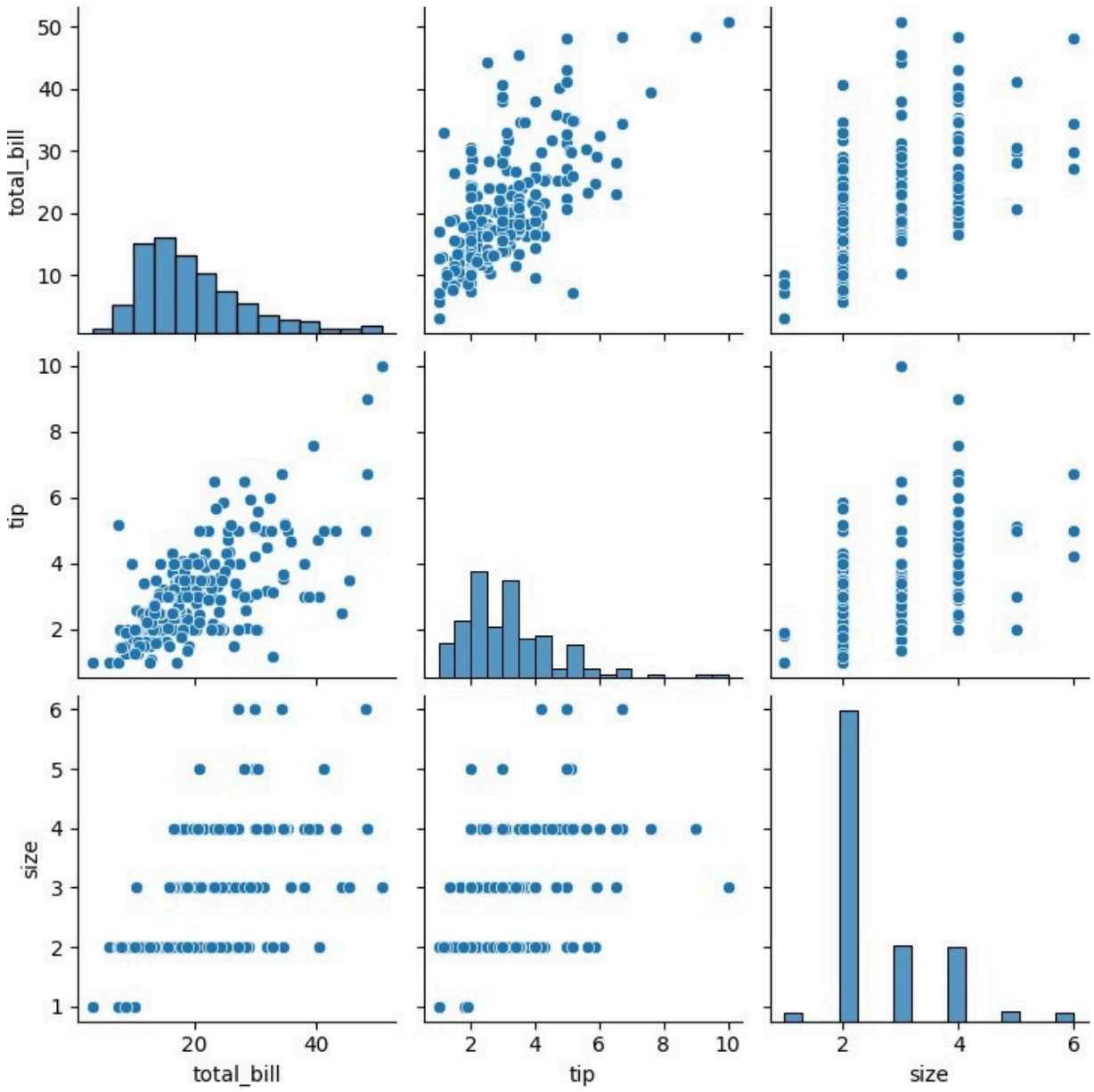

```
sns.jointplot(x=tips.tip,y=tips.total_bill,kind="hex")
```

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

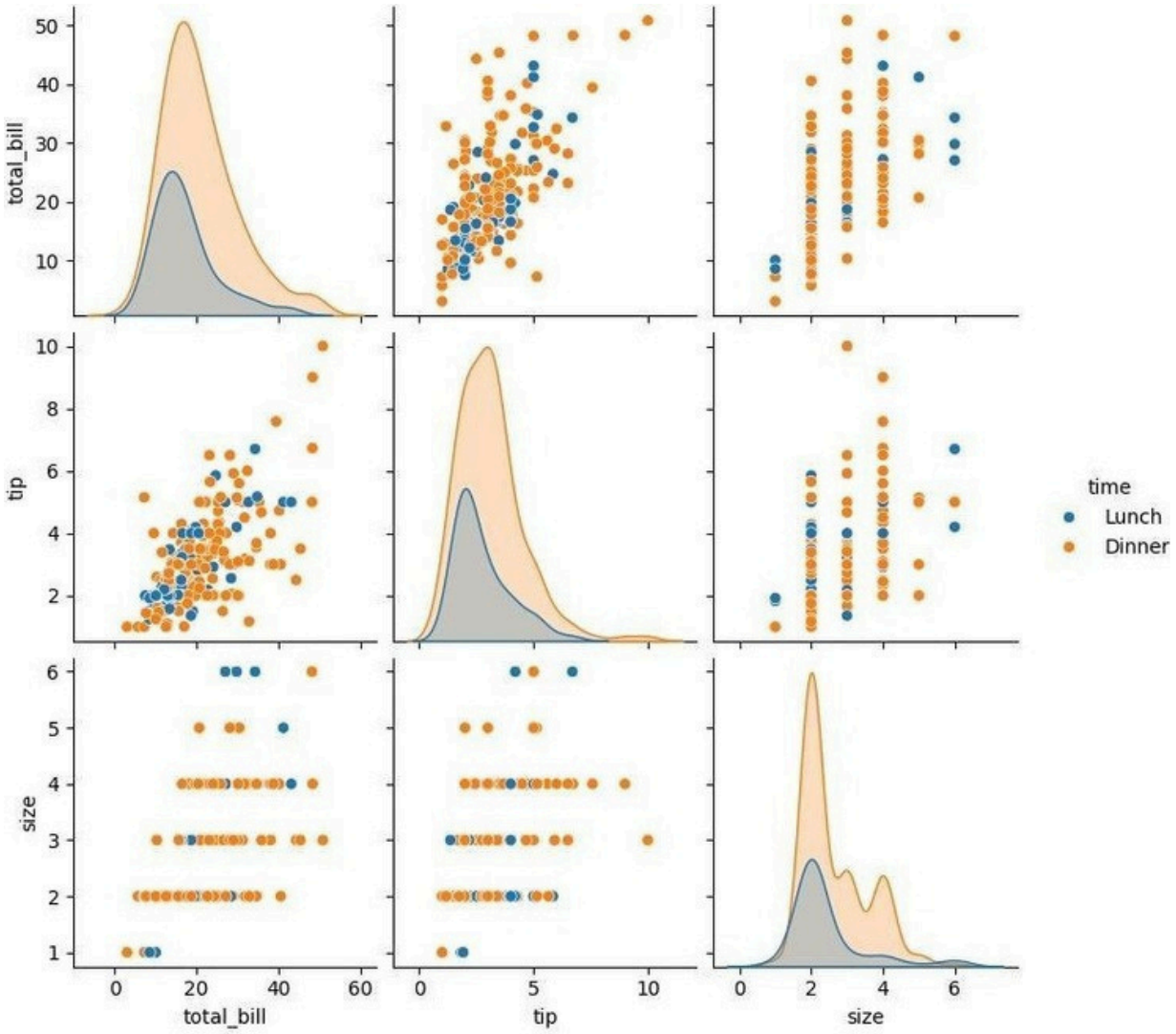



```
sns.pairplot(tips)
```

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

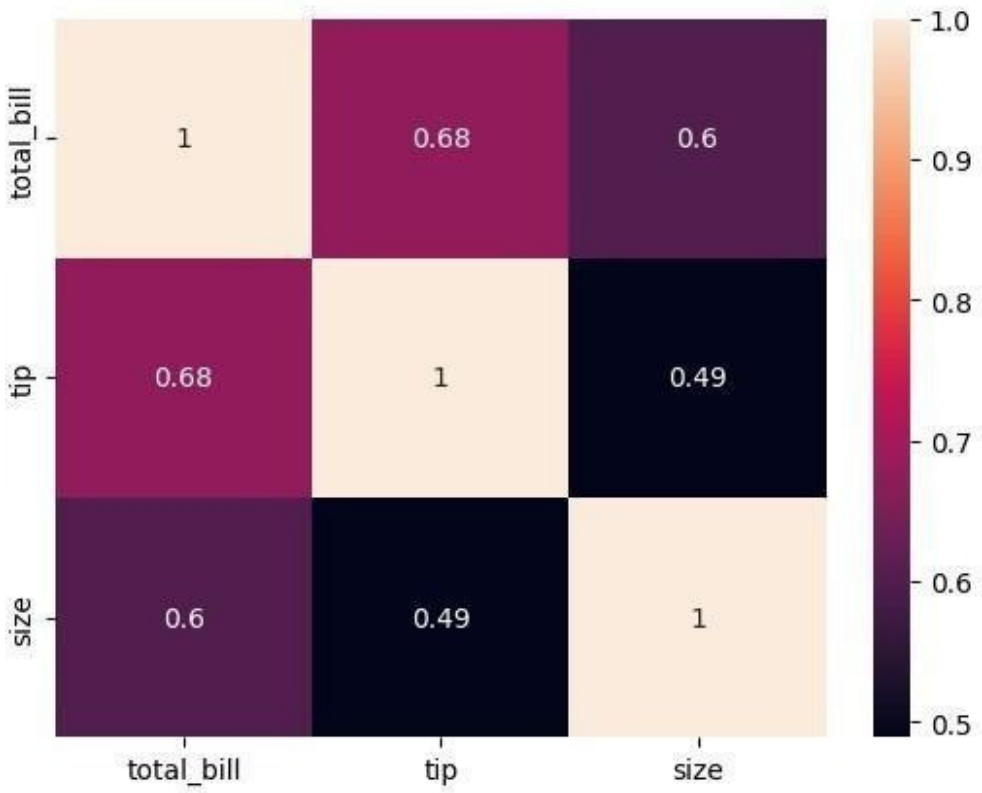



```
tips.time.value_counts()

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

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

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



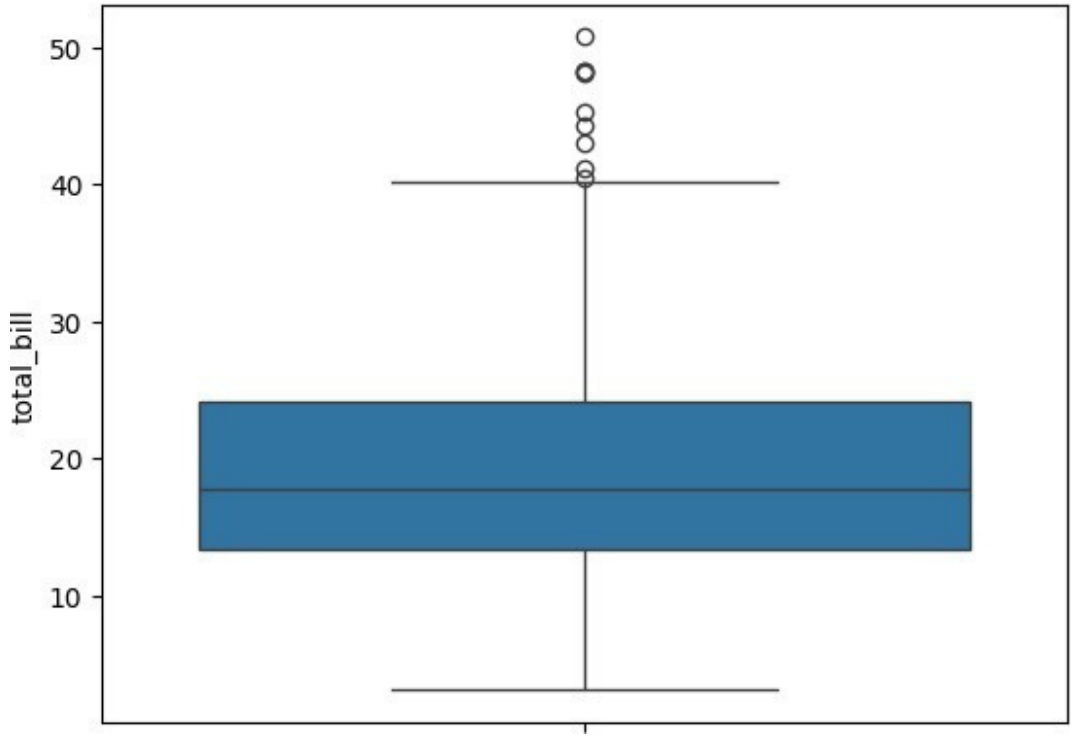

```
sns.heatmap(tips.corr(numeric_only=True),annot=True)
```

```
<Axes: >
```



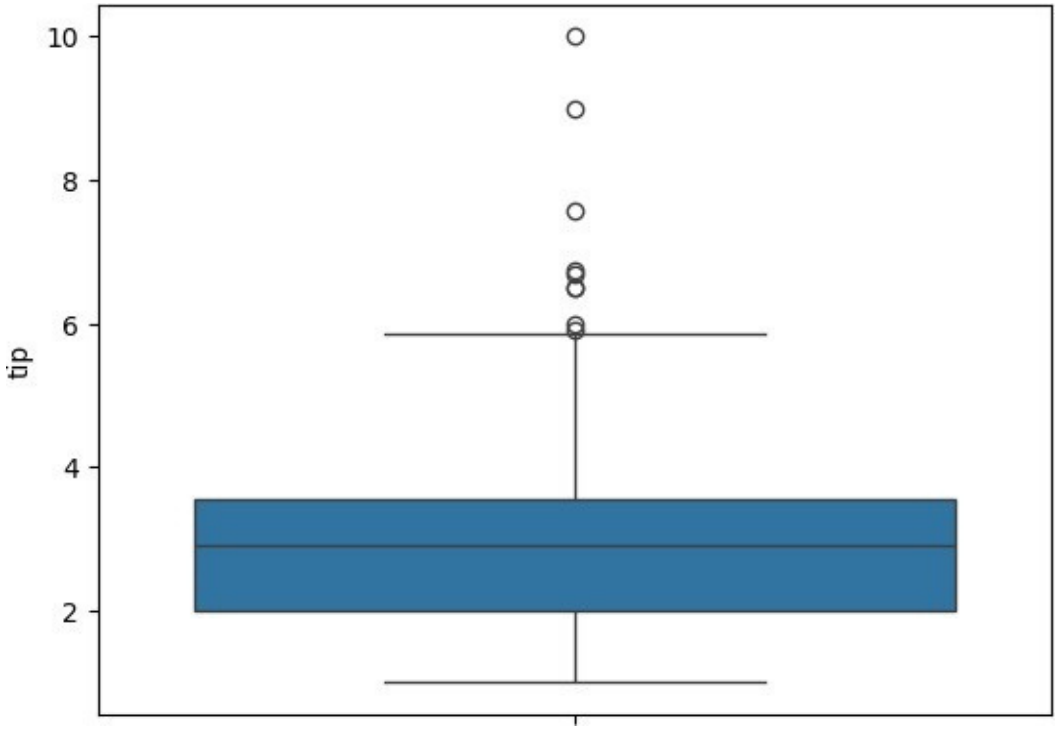

```
sns.boxplot(tips.total_bill)
```

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



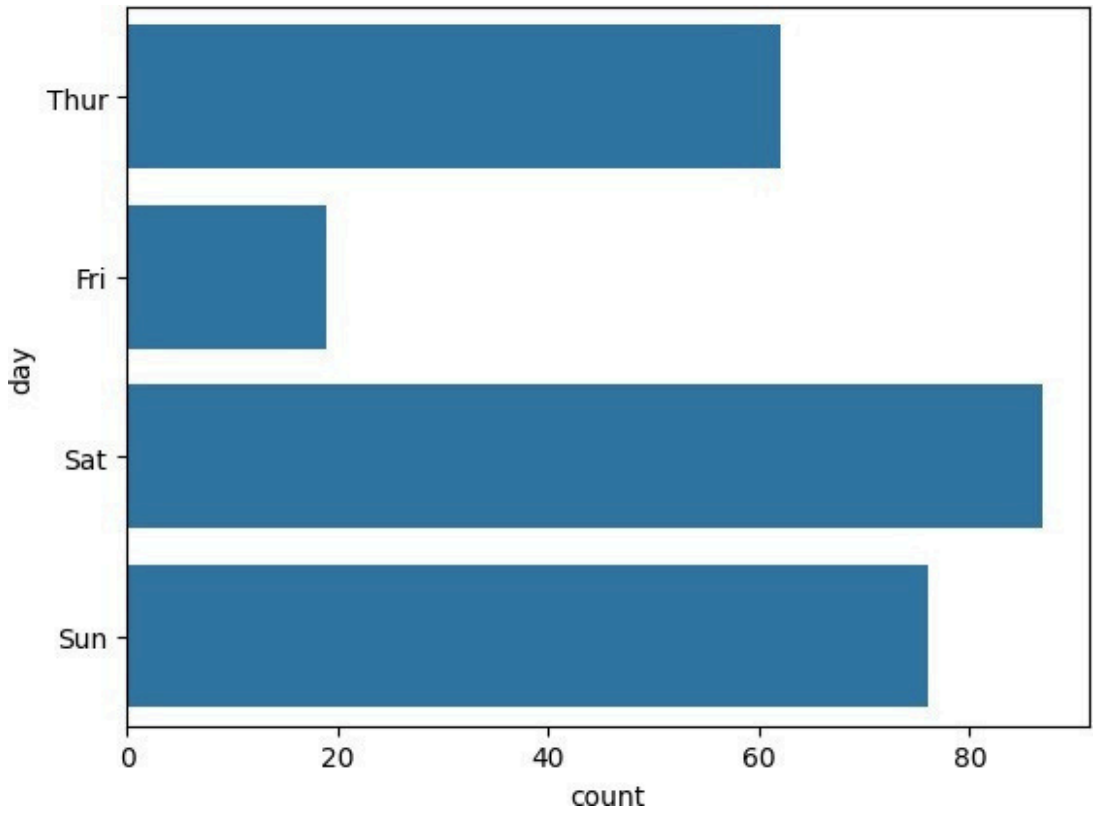

```
sns.boxplot(tips.tip)
```

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



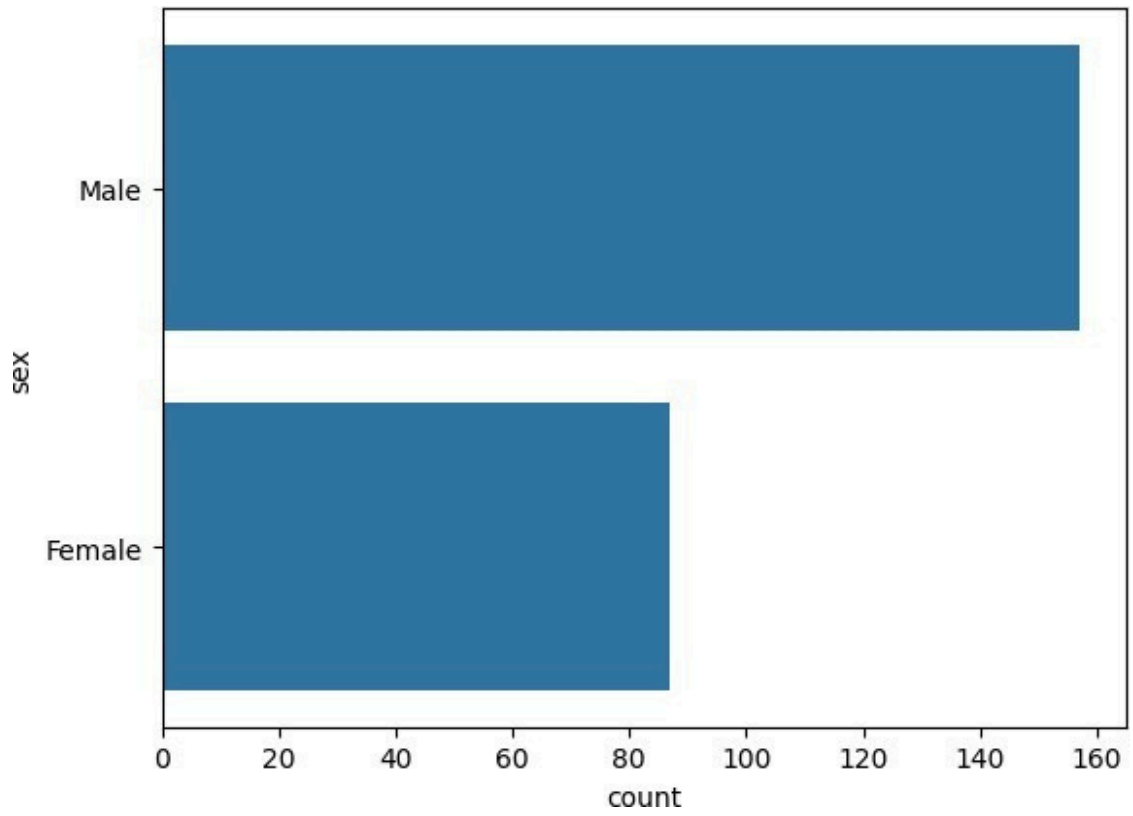
```
sns.countplot(tips.day)
```

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



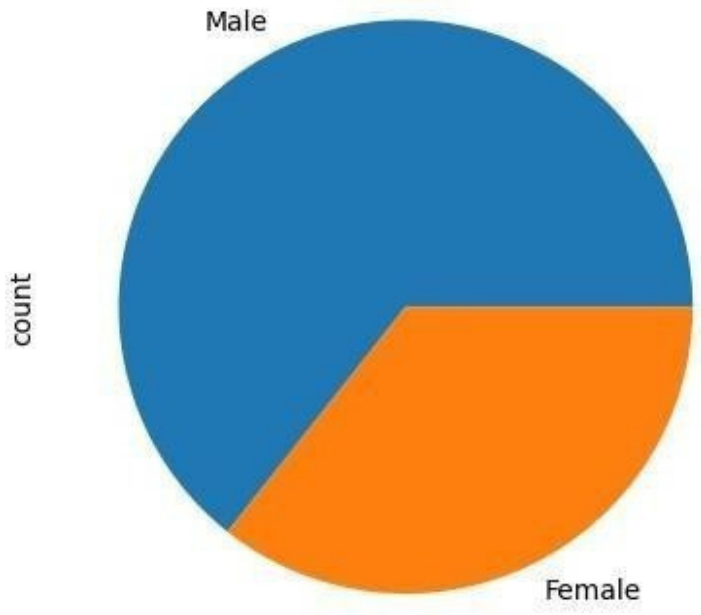

```
sns.countplot(tips.sex)
```

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



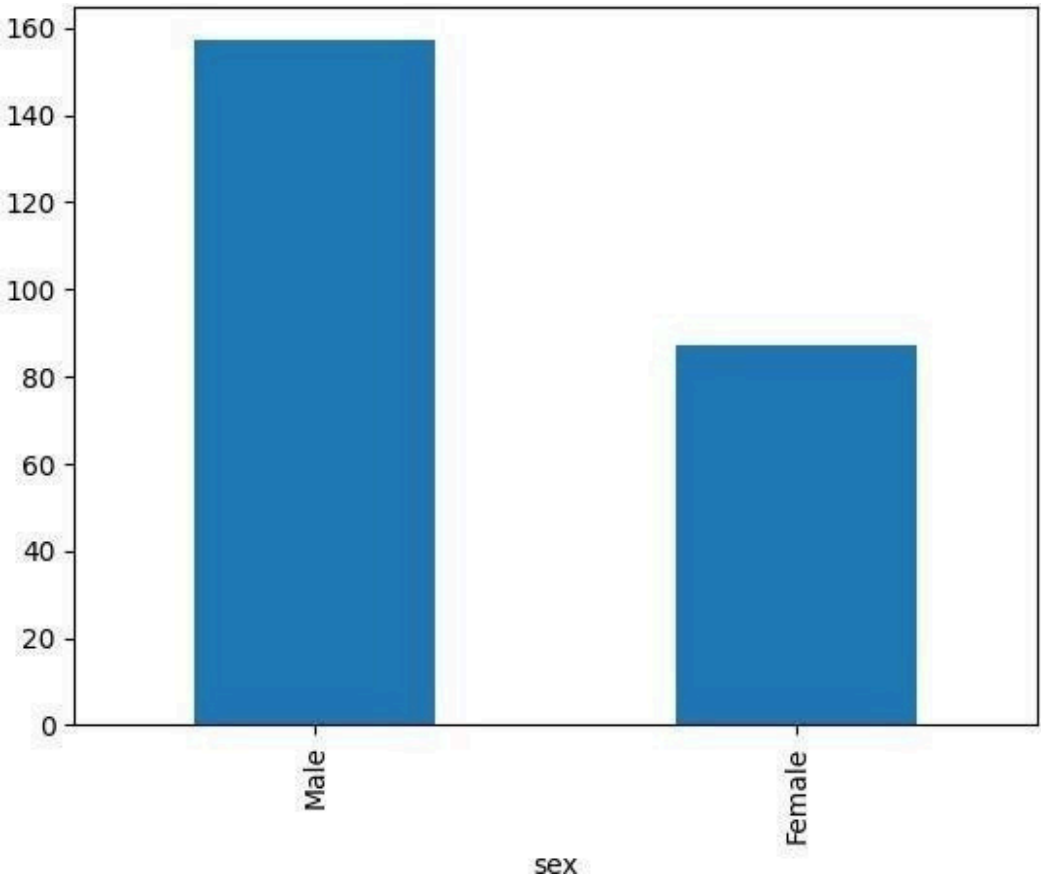

```
tips.sex.value_counts().plot(kind='pie')
```

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



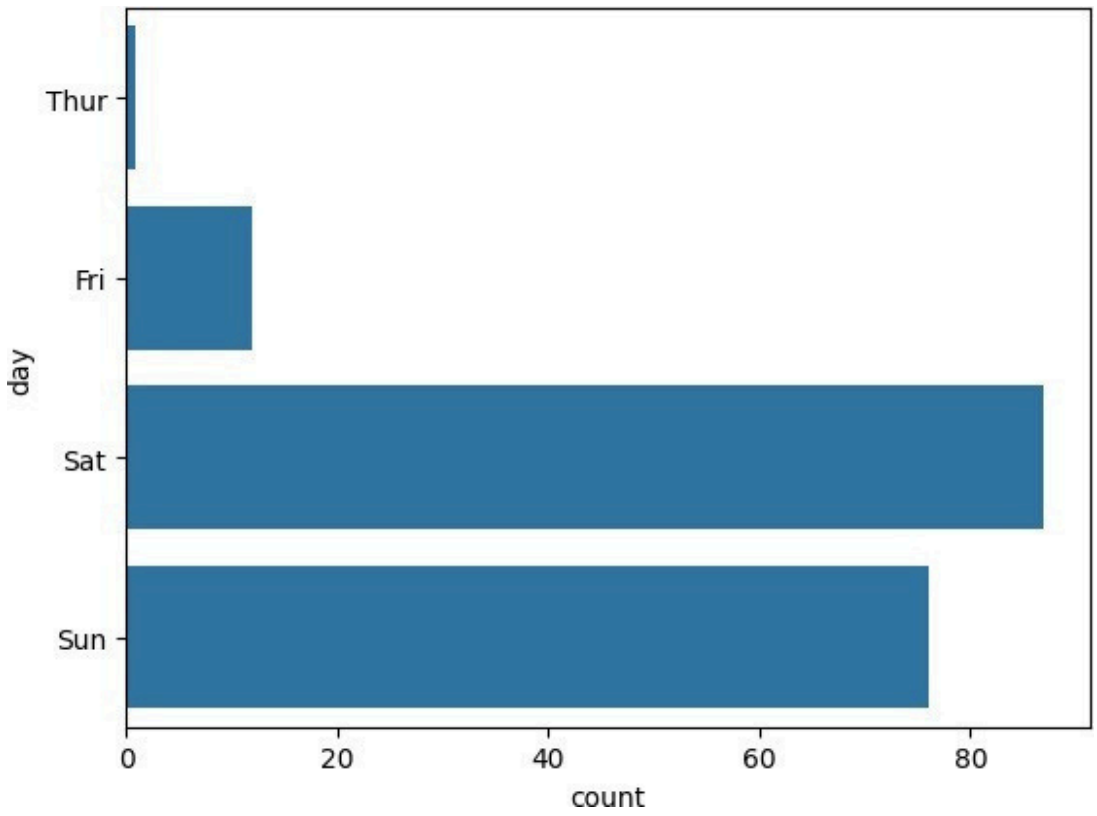

```
tips.sex.value_counts().plot(kind='bar')
```

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




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

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



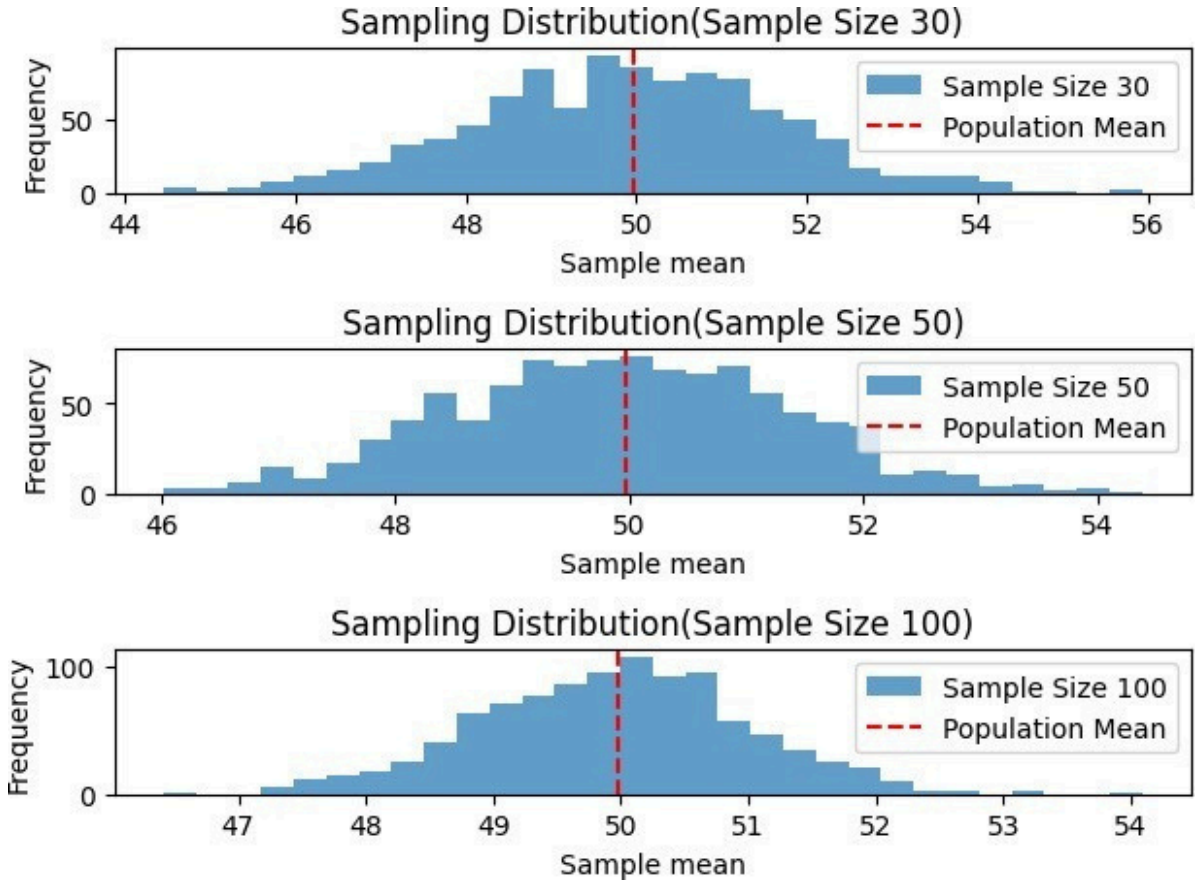

```
#EX.NO :6 Random Sampling and Sampling Distribution
#DATA : 10.09.2024

#NAME : GOKULAKRISHNAN.K
#ROLL NO : 230701094
#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 : GOKULAKRISHNAN
#ROLL NO : 230701094
 #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")
{p_value:.4f}\n")                  print(f"P-Value:

# 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 : GOKULAKRISHNAN K
```

```
#ROLL NO : 230701094   #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 : GOKULAKRISHNNAN K
#ROLL NO : 230701094
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - B

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

```
from statsmodels.stats.multicomp import pairwise_tukeyhsd

np.random.seed(42)
n_plants = 25
growth_A = np.random.normal(loc=10, scale=2, size=n_plants)
growth_B = np.random.normal(loc=12, scale=3, size=n_plants)
growth_C = np.random.normal(loc=15, scale=2.5, size=n_plants)

all_data = np.concatenate([growth_A, growth_B, growth_C])

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

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

alpha = 0.05
if p_value < alpha:
a print("Reject the null hypothesis: There is
significant difference in mean growth rates among the three
treatments.") else:
    print("Fail to reject the null hypothesis: There is no
significant difference in mean growth rates among the three
treatments.")


if p_value < alpha:

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

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

```
Treatment A Mean Growth: 9.6730
Treatment B Mean Growth:
11.1377 Treatment C Mean
Growth: 15.2652 F-Statistic:
36.1214
P-Value: 0.0000
Reject the null hypothesis: There is a significant difference in mean
growth rates among the three treatments.
Tukey's HSD Post-hoc Test:
Multiple Comparison of Means - Tukey HSD, FWER=0.05
```

```
==================================================
=
group1 group2 meandiff p-adj     lower upper reject
--------------------------------------------------
1.4647A0.0877 B                       -0.16833.0977       False
      A       C   5.5923     0.0  3.95937.2252        True
      B       C   4.1276     0.0  2.49465.7605        True
--------------------------------------------------
```

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

#NAME : GOKULAKRISHNAN K

#ROLL NO : 230701094

#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()
```

	Countr	Age	Salary	
0	y	44.	72000.0	N
			Purchased	
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
	Spain	40.0		No
	German			Ye
	y			s

```
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,
       [-8.16496581e-01,  1.52752523e+00, -6.54653671e-01,
        -1.27555478e+00,
       [-8.16496581e-01, -6.54653671e-01,  1.52752523e+00,
        -1.13023841e-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,
       [-8.16496581e-01, -6.54653671e-01,  1.52752523e+00,
         0.00000000e+00,
       [ 1.22474487e+00, -6.54653671e-01,
       -6.54653671e-01,  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 : GOKULAKRISHNAN K
#ROLL NO : 230701094
#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          30non-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-NullCountDtyp
                                 e
-----
 0   YearsExperience  30non-null     float64
 1   Salary           30non-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	5.31333376	003.000000
std	2.837888	27414.429785
min	1.10000037	731.000000
25%	3.20000056	720.750000
50%	4.70000065	237.000000
75%	7.700000100	544.750000
max	10.500000122	391.000000

```
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=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 : GOKULAKRISHNAN K
#ROLL NO : 230701094
#DEPARTMENT : B.E COMPUTER SCIENCE AND

ENGINEERING - B

import numpy as np
import pandas as pd
import warnings
w)adrfnings.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    Mal    4              3500           1
391  15592570    e      8              0              1
392  15748589  Female   Mal 4          3300           1
393  15635893    e      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
df.head(25)              9              0
                         4              4100
User ID Gender Age EstimatedSalary Purchased
                         6              0
0     15624510   Male  19 51  19000 0    2300
1     15810944   Male  35 5   20000 0    0
2     15668575 Female 26 0   43000 0    2000
3     15603246 Female 27 3   57000 0    0
4     15804002   Male  19 6   76000 0    3300
5     15728773   Male  27 4   58000 0    0
6     15598044 Female 27 9   84000 0    3600
7     15694829 Female 32     150000     0
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],
[ 20, 52000],
[ 32, 86000],
[ 18, 29000],
[ 47, 82000],
[ 45, 80000],
[ 46, 25000],
[ 48, 26000],
[ 45, 28000],
[ 46, 29000],
[ 47, 22000],
[ 49, 49000],
[ 47, 41000],
[ 22000],
[ 23000],
[ 20000],
[ 28000],
 30000]
```

```
        [    29,  43000],
        [    31,  18000],
        [    31,  74000],
        [    27, 137000],
        [    21,  16000],
        [    28,  44000],
        [    27,  90000],
        [    33,  27000],
        [    30,  28000],
        [    26,  49000],
        [    27,  72000],
        [    33,  31000],
        [    35, 108000],
        [    30,  15000],
        [    28,  84000],
        [    23,  20000],
        [    27,  79000],
        [    30, 135000],
        [    31,  89000],
        [    24,  32000],
        [    18,  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]
```

```
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        43000],
        [
        60,
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        [
        49,
        65000],
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        78000],
        [
        46,
        96000],
        [
        59,
        143000],
        [
        41,
        80000],
        [
        35,
        91000],
        [
        37,
        144000],
        [
        60,
        102000],
        [
        35,
        60000],
        [
        37,
        53000],
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        36,
        126000],
        [
        56,
        133000],
        [
        40,
        72000],
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        42,
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        42000],
        [
        40,
        107000],
        [
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        86000],
        [
        38,
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        [
        46,
        79000],
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        [
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        [
        46,
        82000],
        [
        53,
        143000]
```

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        [    51, 146000],
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        [    41,  52000],

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        [    36, 144000],
        [    55, 125000],
        [    35,  72000],
        [    48,  90000],
        [    42, 108000]
```

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        [    47, 144000],
        [    40,  61000],
        [    43, 133000],
        [    59,  76000],
        [    60,  42000],
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        [    57,  74000],
        [    38,  71000],
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        [    52,  38000],
        [    50,  36000],
        [    59,  88000],
        [    35,  61000],
        [    37,  70000],
        [    52, 141000],
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        [    37,  62000],
        [    48, 138000],
        [    41,  79000],
        [    37,  78000],
        [    39, 134000],
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        [    55,  39000]
```

```
,
[ 37, 77000]
 35, ,
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[ 42, 63000]
,
[ 73000]
[ 43, 112000]
,

[ 45, 79000]
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,
[ 58, 38000]
[ 48, 74000]
[ 37, 137000]
,
[ 37, 79000]
[ 40, ,
60000]
[ 42, ,
54000]
[ 51, 134000]
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[ 47, 113000]
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[ 36, 125000]
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[ 42, ,
70000]
[ 39, ,
 38, 96000]
[ ,
50000]
[ 49, 141000]
,
[ 39, 79000]
[ 39, ,
75000]
[ 54, 104000]
,
[ 35, 55000]
[ 45, ,
32000]
```

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        [    48,  30000],
        [    48, 131000],
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        [    41,  72000],
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        [    38,  51000],
        [    48, 119000],
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        [    57,  60000],
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        [    58, 144000],
        [    35,  79000],
        [    38,  55000],
        [    39, 122000],
        [    53, 104000],
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        [    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]
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[ 47, 50000]
[ 42, 79000]
[ 42, 104000]
[ 59, 29000]
[ 58, 47000]
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[ 38, 71000]
[ 54, 26000]
[ 60, 46000]
[ 60, 83000]
[ 39, 73000]
[ 59, 130000]
[ 37, 80000]
[ 46, 32000]
[ 46, 74000]
[ 42, 53000]
```

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[ 41, 87000],
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[ 48, 64000],
[ 33000],
[ 44, 139000],
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[ 57, 33000],
[ 56, 49, 60000],
[ 39, 39000],
[ 47, 71000],
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[ 47, 35000],
[ 45, 60, 33000],
[ 39, 23000],
[ 46, 51, 45000],
[ 42000],
[ 59000],
[ 41000],
[ 23000],
```

```
        [ [    50   20000],
        [      ,     33000],
               30,   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, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 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, 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, 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, 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
```

```
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       0.73      0.83      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
```