

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

```
#DATE : 30.07.2024
```

```
#NAME : HARI SANKAR S
```

```
#ROLL NO : 230701100
```

```
#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-NullCountDtype
-----
<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
• Species        150 non-null      float64
object dtypes: float64(4), int64(1),
object(1) memory usage: 7.2+ KB
data.describe()

```

```

              Id SepalLengthCm SepalWidthCm
PetalLengthCm PetalWidthCm
count150.000000      150.000000      150.000000      150.000000
150.000000
mean      75.500000      5.843333      3.054000      3.758667
1.19866
7
std      43.44536      0.828066      0.433594      1.764420
0.76316
1
min      0.100000      1.000000      4.300000      2.000000      1.000000
0
025.3%0000
0      38.25000      5.100000      2.800000      1.600000
50%      0
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')

```

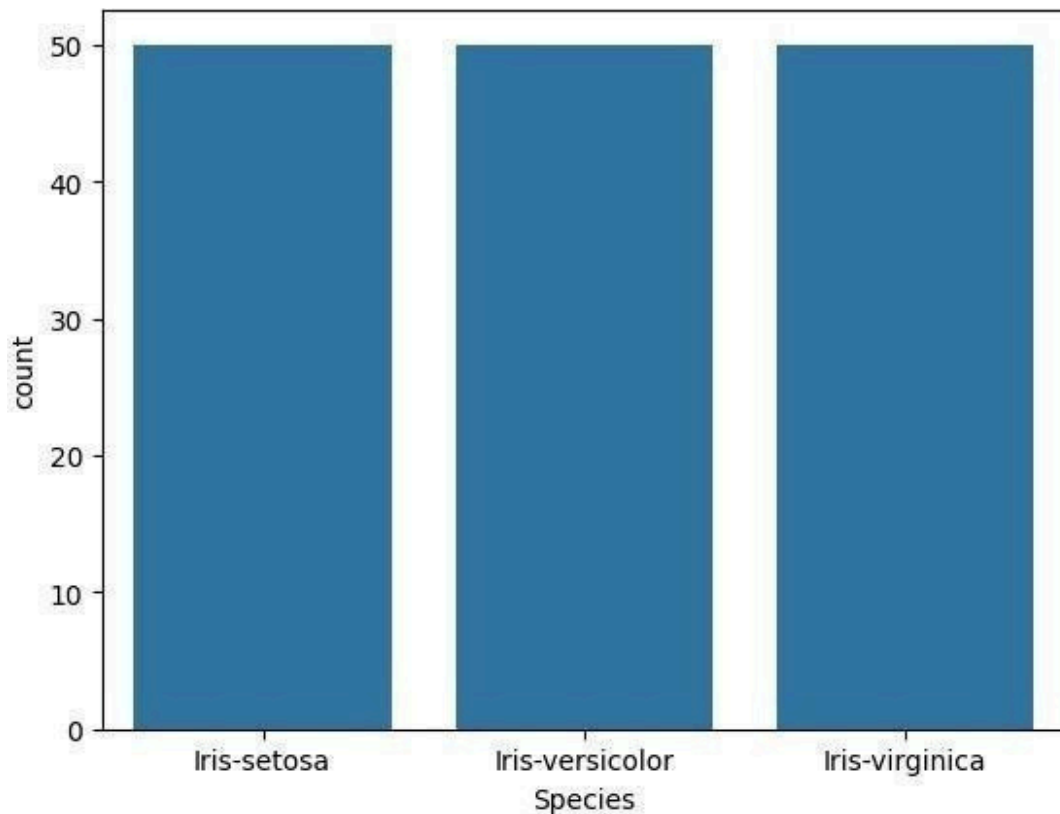
Species

Name: count, dtype: int64

```

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

```



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

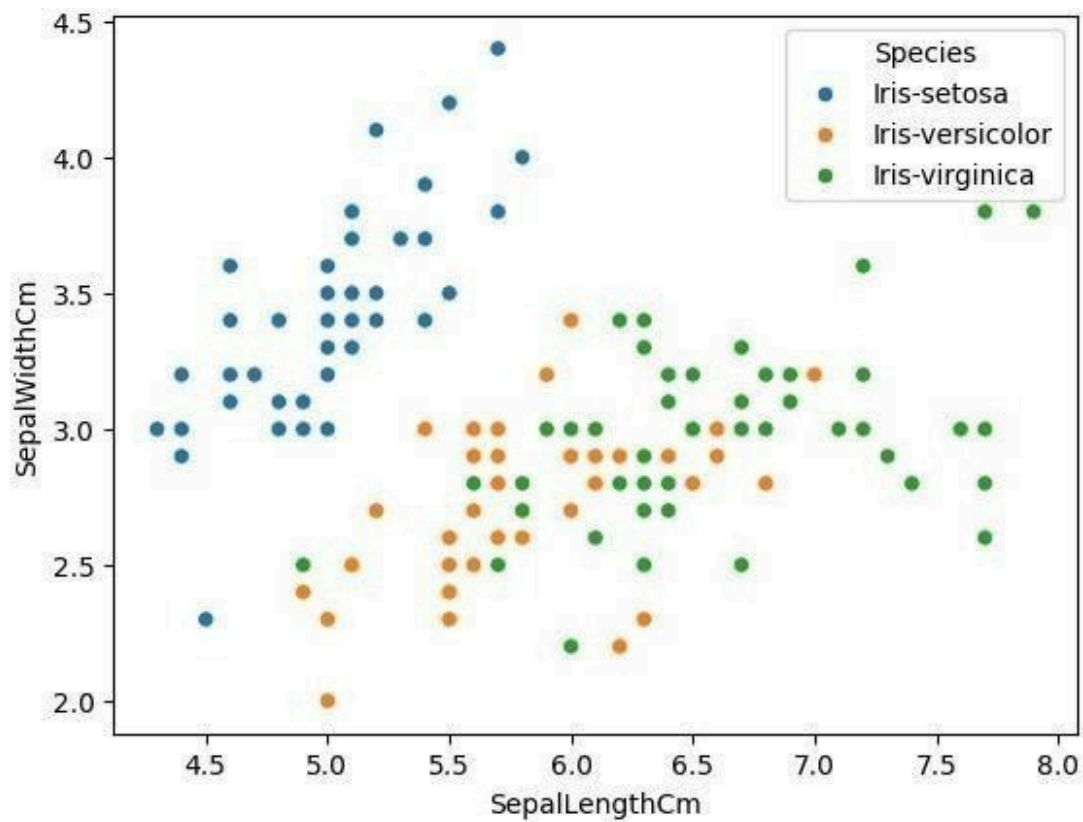
```
FinalDataset=pd.concat([pd.get_dummies(data.Species),data.iloc[:,
[0,1,2,3]]],axis=1)
```

```
FinalDataset.head()
```

	Iris-setosa	Iris-versicolor	Iris-virginica	Id	SepalLengthCm	\
•	True	False	False	1		m
•	True	False	False	2	5.1	
•	True	False	False	3	4.9	
•	True	False	False	4	4.7	
•	True	False	False	4	4.6	
•	True	False	False	4	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				

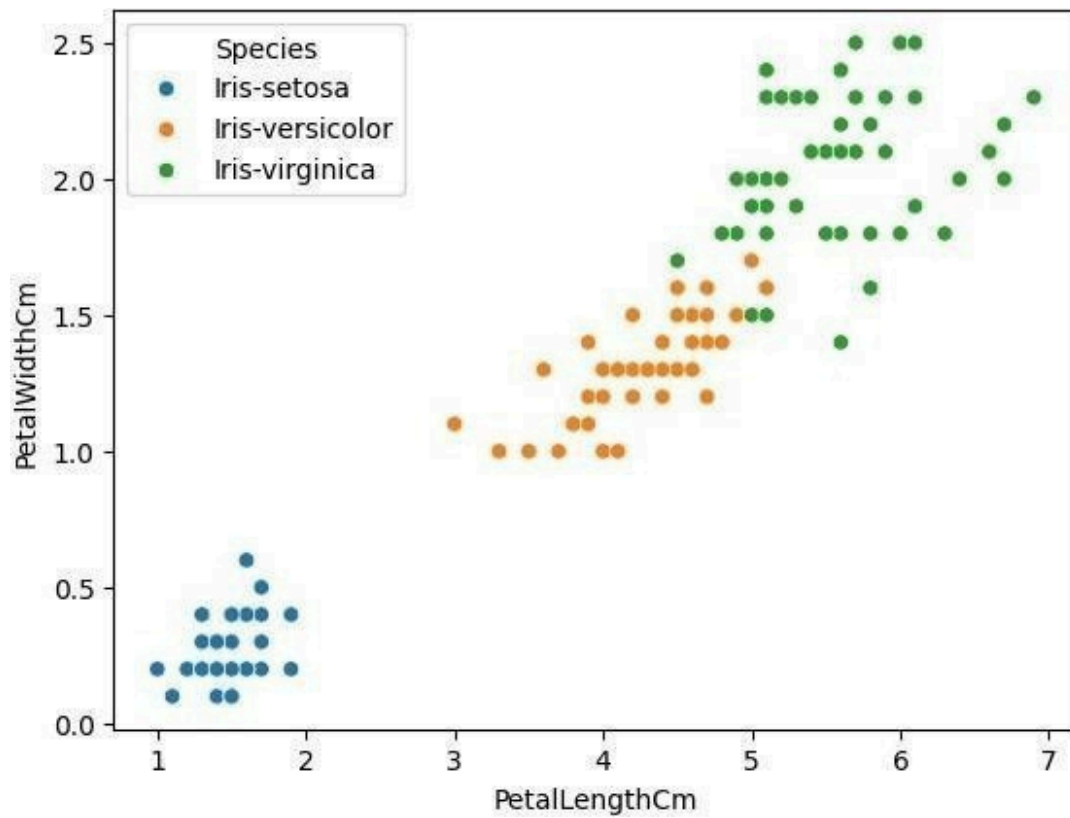
```
sns.scatterplot(x='SepalLengthCm',y='SepalWidthCm',hue='Species',data=
data,)
```

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

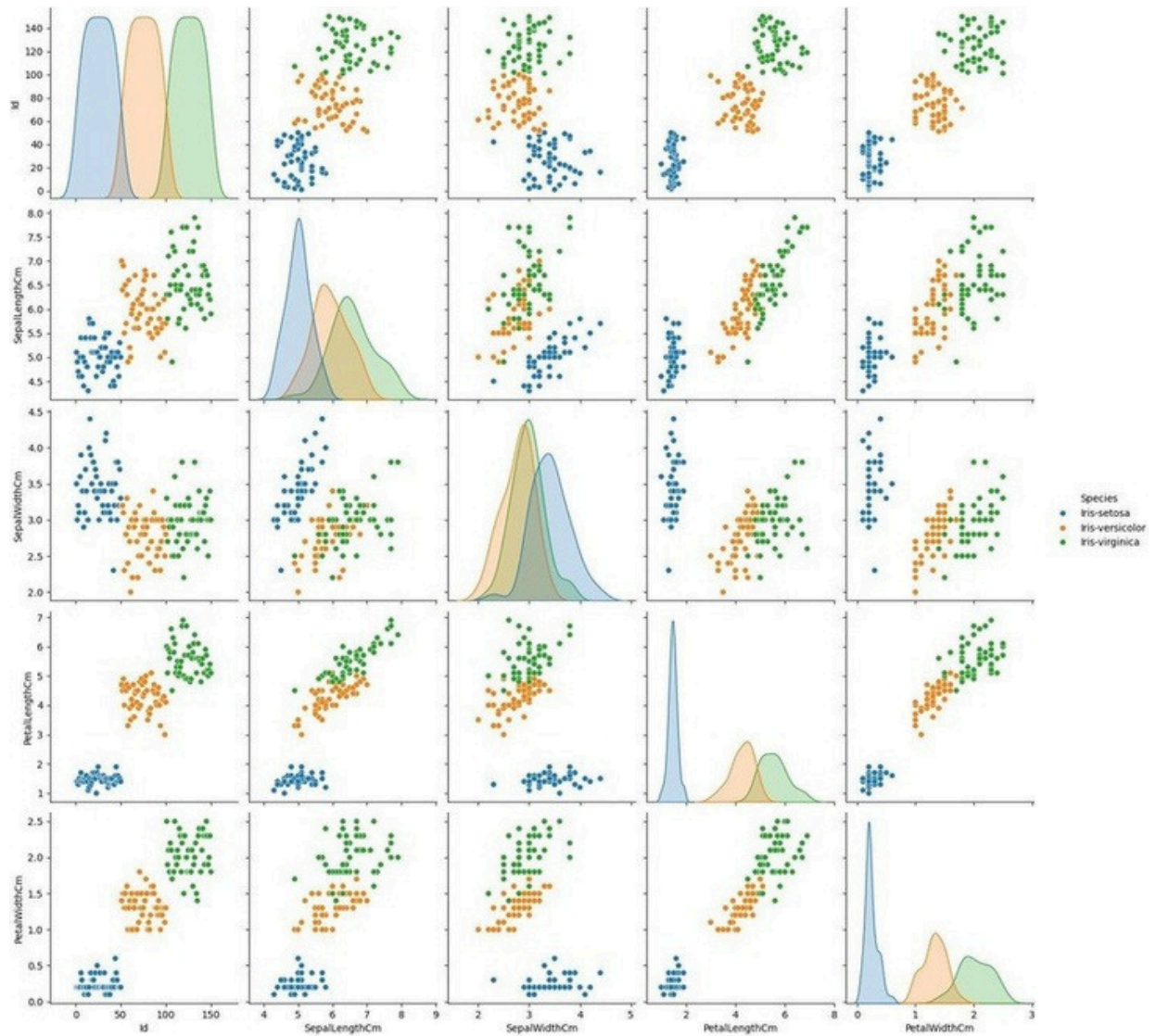


```
sns.scatterplot(x='PetalLengthCm',y='PetalWidthCm',hue='Species',data=
data,)
```

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

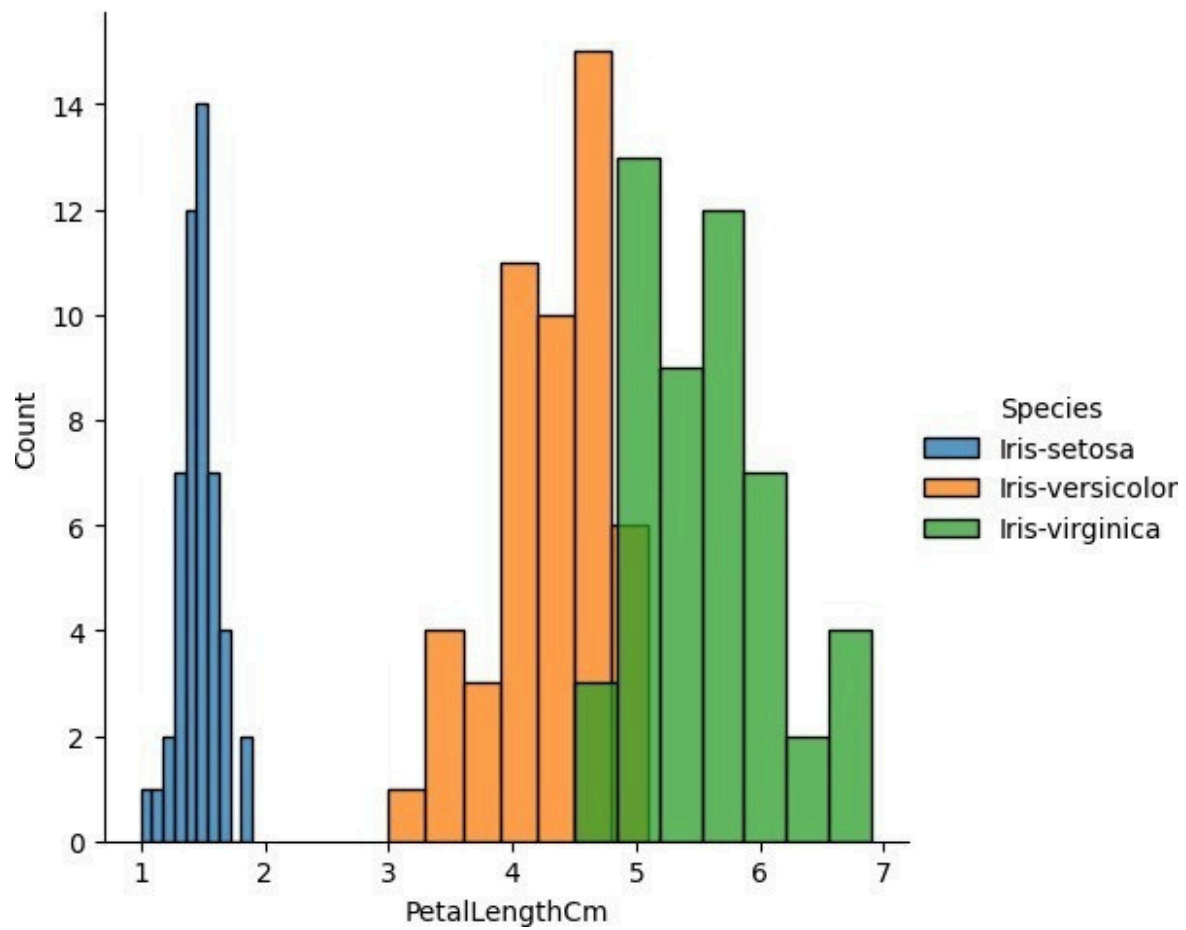


```
sns.pairplot(data,hue='Species',height=3);
```

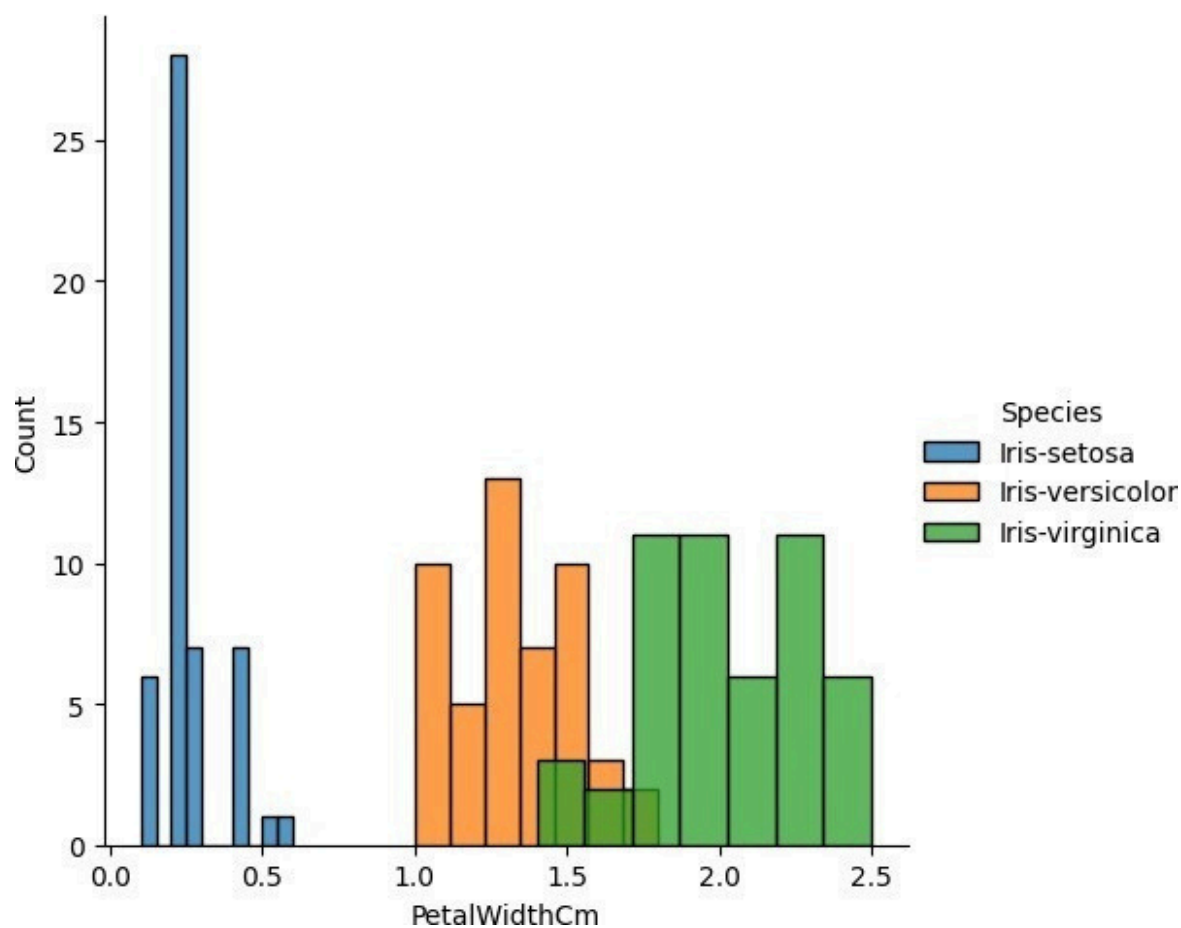


```
plt.show()

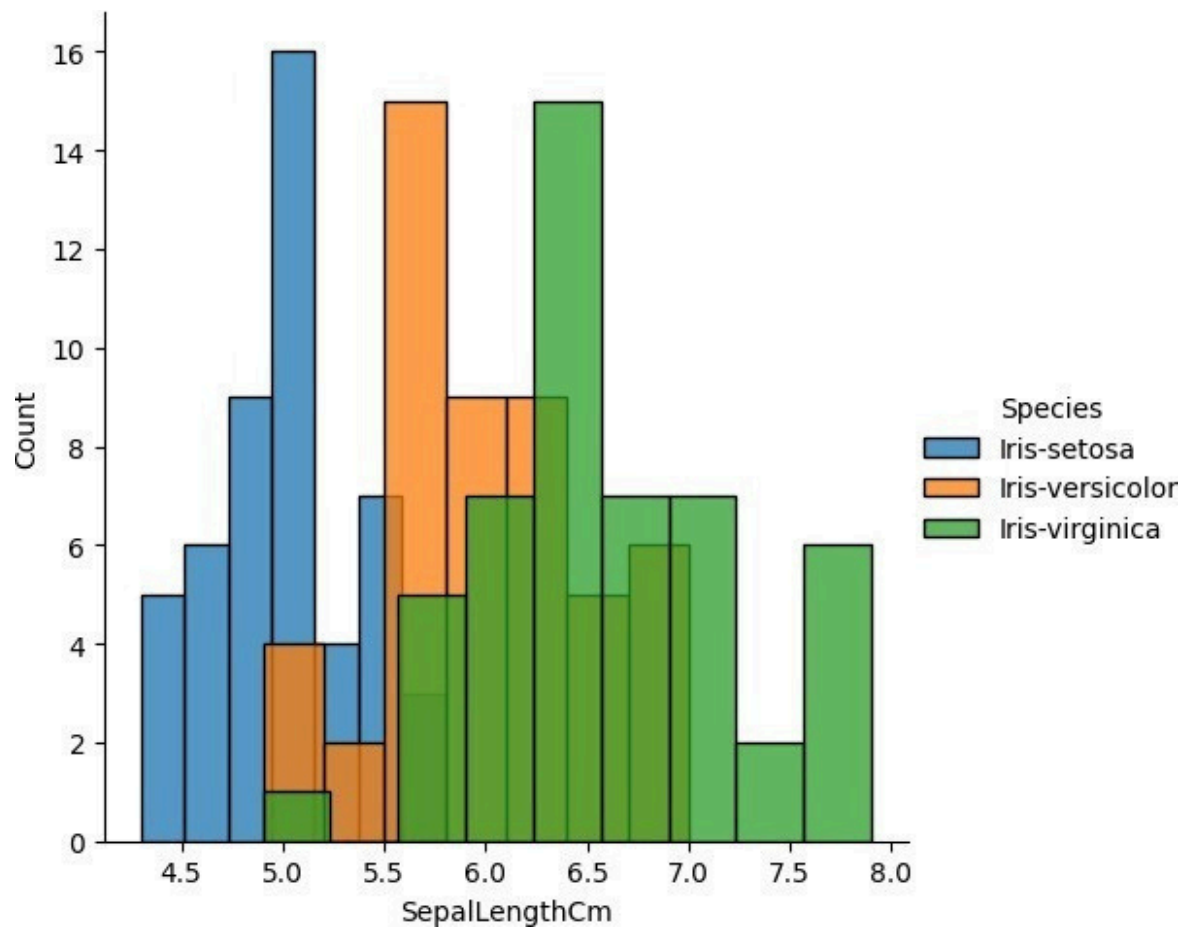
sns.FacetGrid(data, hue='Species', height=5).map(sns.histplot, 'PetalLengthCm', 'PetalWidthCm').add_legend();
plt.show();
```



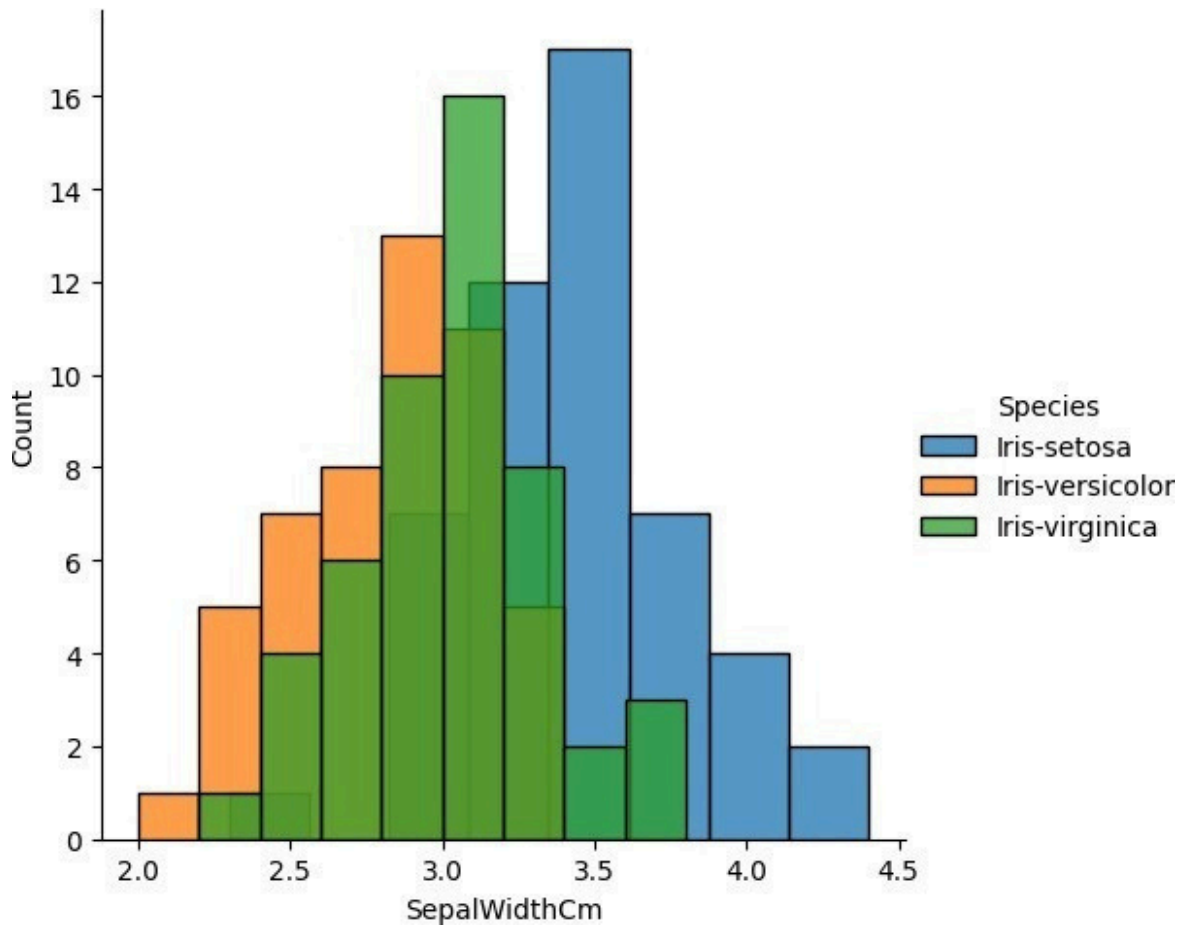
```
sns.FacetGrid(data,hue='Species',height=5).map(sns.histplot,'PetalWidthCm').add_legend();  
plt.show();
```



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

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



```
#EX.NO :1.b Pandas Built in function. Numpy Built in function- Array
slicing, Ravel,Reshape,ndim
#DATA : 06.08.2024
#NAME : HARI SANKAR S
#ROLL NO : 230701100
#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 : HARI SANKAR S

#ROLL NO : 230701100

*#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

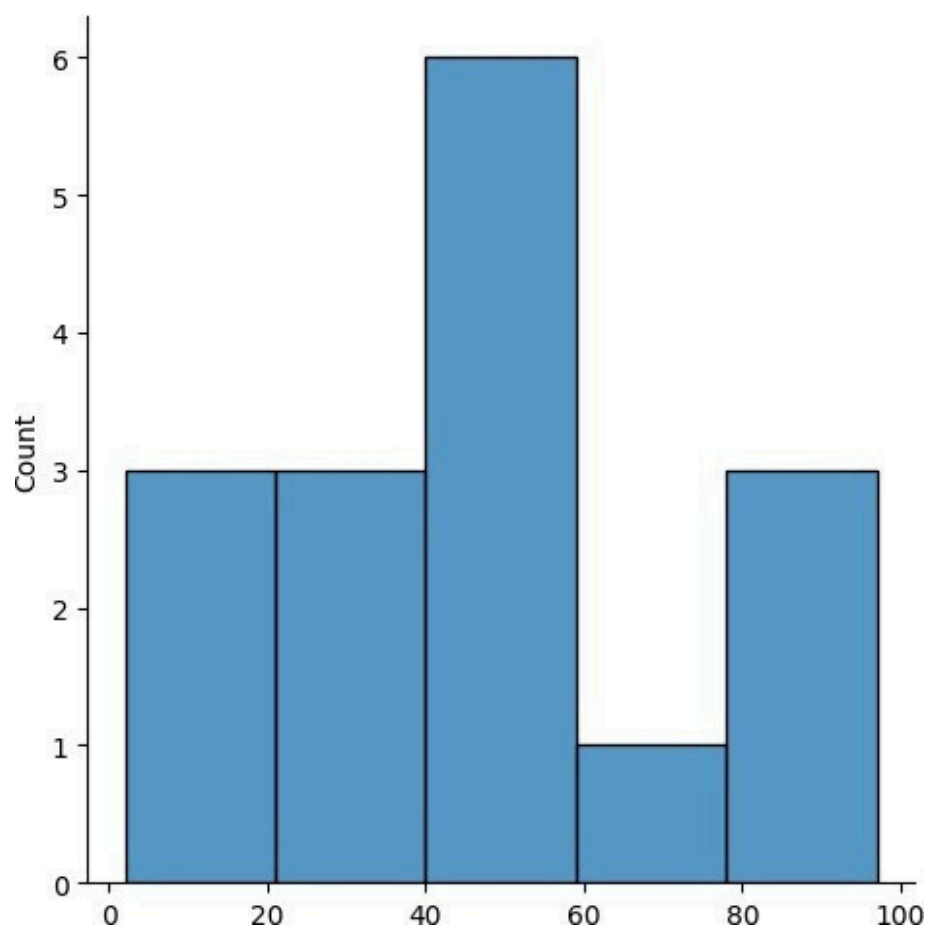
#outliers detection
def outDetection(array):
    sorted(array)
Q1,Q3=np.percentile(array,[25,75])
IQR=Q3-Q1
lr=Q1-(1.5*IQR)
    ur=Q3+(1.5*IQR)
    return lr,ur
lr,ur=outDetection(array)
lr,ur

(-10.125, 94.875)

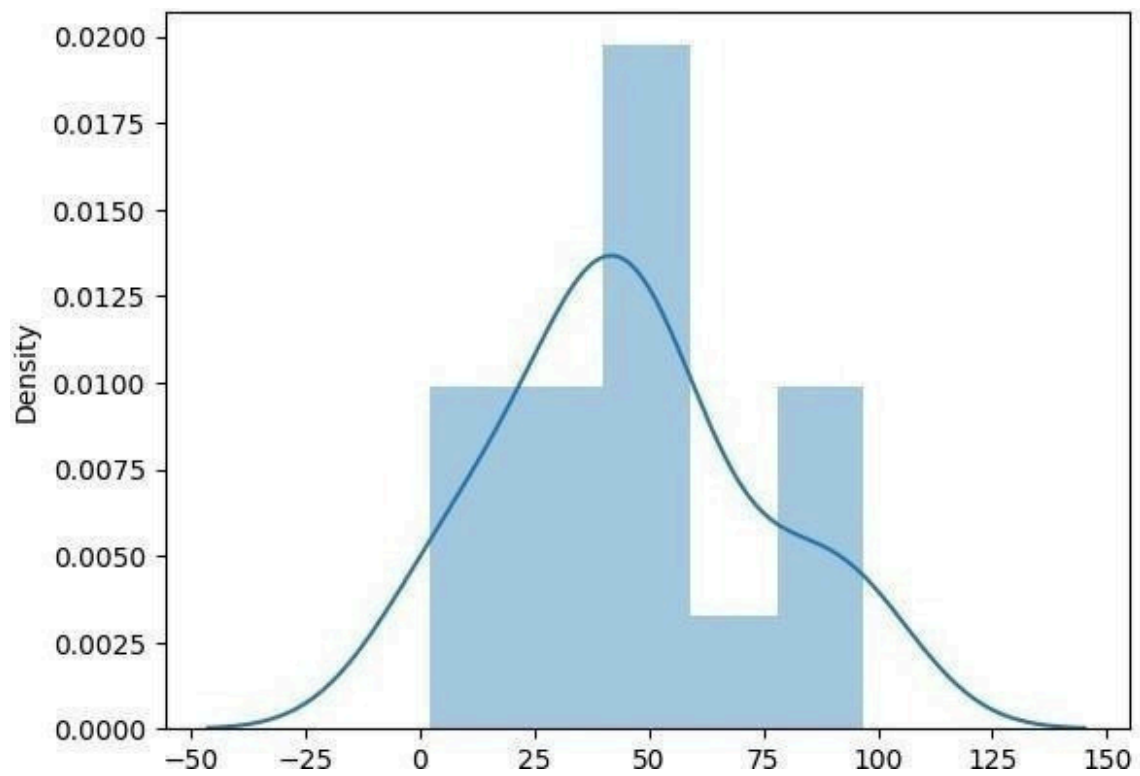
import seaborn as sns
%matplotlib inline
sns.displot(array)

<seaborn.axisgrid.FacetGrid at 0x20d7cda3b50>

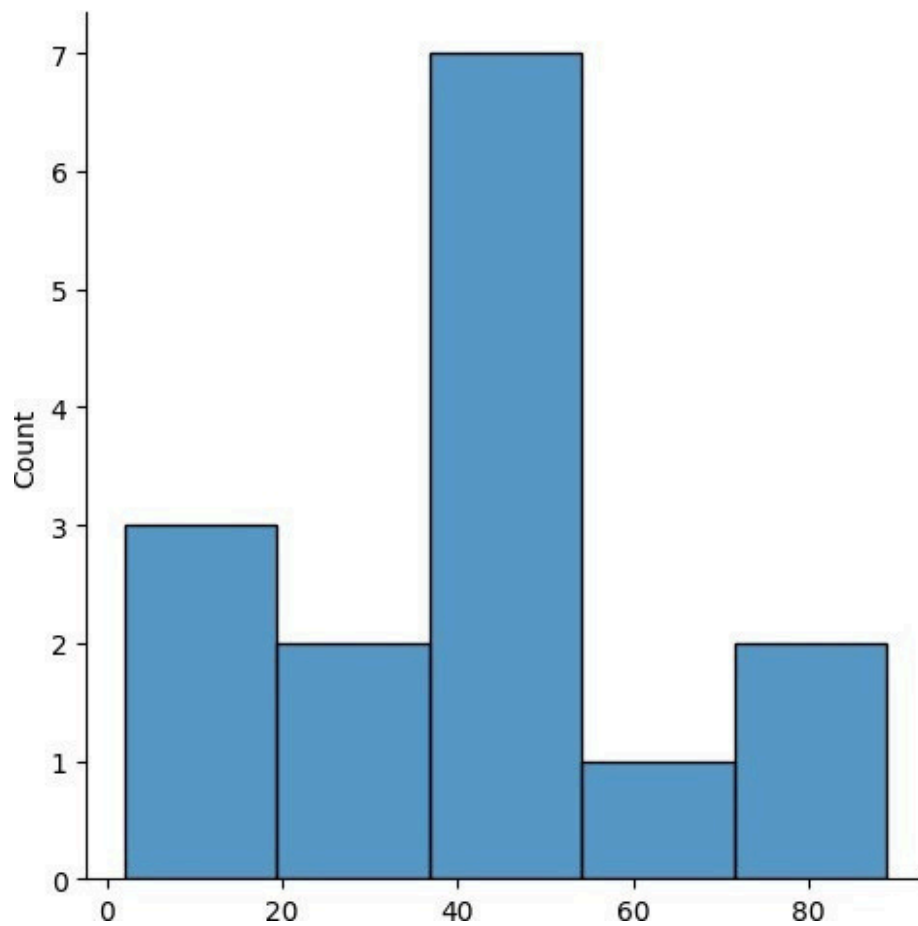
```



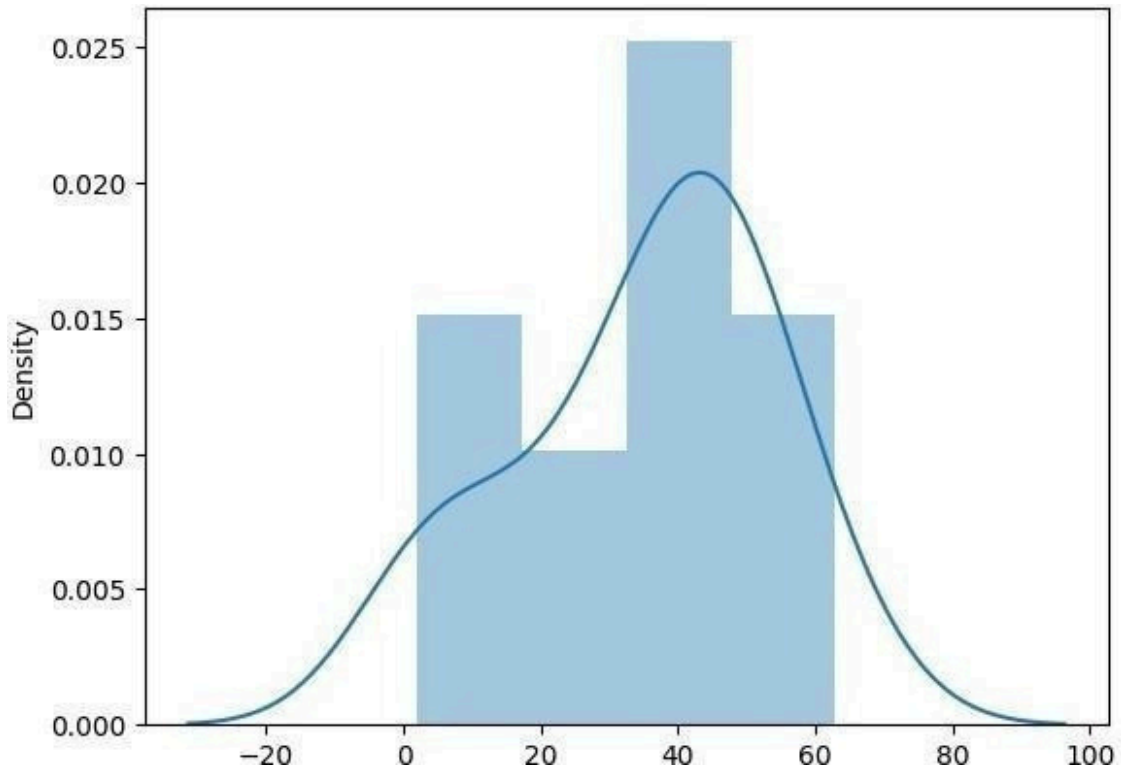
```
sns.distplot(array)
<Axes: ylabel='Density'>
```



```
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>
```



```
lrl,url=outDetection(new_array)
lrl,url
(-5.25, 84.75)
final_array=new_array[(new_array>lrl) & (new_array<url)]
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 : HARI SANKAR S#ROLL NO : 230701100 #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

```

5      e
df.duplicated()
9      e
7      e
8      Fals
9      e
dtype: Fals
10     bool
      e
      Fals
      e
      Fals
      e
      Fals
      e
      True
      Fals

```

```
df.info()
```

```
<class
```

```
'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 11 entries, 0 to 10
```

```
Data columns (total 9 columns):
```

#	Column	Non-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  t
• Bill       11 non-null      int64
• NoOfPax    11 non-null      4
• Age_Group.1 11 non-null     int64
• EstimatedSalary 11 non-null  4
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	-	LemonTree	Veg	1234
4	5	35	1	Ibis	Vegetarian	989
5	6	+	3	Ibys	Non-Veg	1909
6	7	35+	3	RedFox	Vegetarian	1000
7	8	20+-25	4	LemonTree	Veg	2999
8	9	25-30	7	Ibis	Non-Veg	3456
10	10	30-35	2	RedFox	non-Veg	6755
			5			

	NoOfPax	EstimatedSalary	Age_Group.1
0	1	2	40000
2	3	3	59000
4	5	2	30000
6	7	2	120000
8	0	2	45000
1		2	122220
len(df)	-	1	21122
10	-10		345673
	3		-99999
	4		87777

```
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
0	1	20-25	4	Ibis	veg	1300
2						
31	2	30-35	5	LemonTree	Non-Veg	2000
2						
2	3	25-30	6	RedFox	Veg	1322
23						
4	4		-1	LemonTree	Veg	1234
2						
5						
2	5	35+	3	Ibis	Vegetarian	989
6	6	35+	3			
-1	7	35+	4	Ibys	Non-Veg	1909
7	8		7			
-10						
8				RedFox	Vegetarian	1000
9	3					
4		20-25		LemonTree	Veg	2999
	9	25-30	2	Ibis	Non-Veg	3456
	10	30-35	5	RedFox	non-Veg	6755

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

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

```
) df
```

0	1	20-25	4	Ibis	veg	1300
---	---	-------	---	------	-----	------

2

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

31	2	30-35	5	LemonTree	Non-Veg	2000
22						
32	3	25-30	6	RedFox	Veg	1322
42						
52	4	20-25	-1	LemonTree	Veg	1234
6-1						
7	5	35	3	Ibis	Vegetarian	989
-10						
83	6	+	3	Ibys	Non-Veg	1909
94						
	7	35	4	RedFox	Vegetarian	1000
	8	20+-2	7	LemonTree	Veg	2999
	9	5 253-	2	Ibis	Non-Veg	3456
	10	350	5	RedFox	non-Veg	-6755

30+-3

EstimatedSalary		5
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)	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	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)	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	Vegetarian	1234.0
4	5.0	35+	3	Ibis	Vegetarian	1000.0
5	6.0	35+	3	Ibis	Non-Veg	1000.0
6	7.0	20-25	4	RedFox	Non-Veg	3456.0
7	8.0	25-30	2			
8	9.0			LemonTree		
				Ibis		

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
```

```
<boundmethod Series.unique of0 veg
```

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

```
Name: FoodPreference, dtype: object>
```

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

```
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.	+ 35+	3	s	Non-Veg	1909.0
6	0	20+-2	4	RedIbFiox	Veg	1000.0
7	7.	5	7	LemosnTree	Veg	2999.0
8	0.0	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

#DATE : 27.08.2024

#NAME : HARI SANKAR S

#ROLL NO : 230701100

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

```
import numpy as np
import pandas as pd
import warnings
wd)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-Null Count  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	Germany	Spain
0	True	False	False
1	False	False	True
2	False	True	False
3	False	False	True
4	True	False	False
5	False	True	False
6	True	False	False
7	False	True	False
8	True	False	False
9	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      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

```

```

#DATE : 27.08.2024

```

```

#NAME:HARI SANKAR S

```

```

#ROLL NO : 230701100

```

```

#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.  72000.0         No
1  France  0   48000.0         o
2  Spain  27.  54000.0         Ye
3  German 30.  61000.0         s
4      y  38.     NaN         No
5  Spain  40.  58000.         No
6  German 35.  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  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	Germany	Spain
0	True	False	False
1	False	False	True
2	False	True	False
3	False	False	True
4	True	False	False
5	False	True	False
6	True	False	False
7	False	True	False
8	True	False	False
9	False	True	False

```

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

```

```

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

```

```

      France Germany Spain  Age  Salary
0      True False  False  44.  72000.0
1  False          False   0  48000.0
2  True False          27.0  54000.0
3      True False False  30.0  61000.0
4          False True  38.0  63778.0
5  False          40.0  58000.0
6  True False True False  35.0  52000.0
7  False False          38.0  79000.0
8  False    True True  48.0  83000.0
9  False False False  50.0  67000.0
df.info()
      True False  37.0

```

```

<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   Purchased  10 non-null      object

```

```

object dtypes: float64(2), object(2)

```

```

memory usage: 452.0+ bytes

```

```

updated_dataset

```

```

      France Germany Spain  Age  Salary
0      True False  False  44.  72000.0
1  False          False   0  48000.0
2  True False          27.0  54000.0
3      True False False  30.0  61000.0
4          False True  38.0  63778.0
5  False          40.0  58000.0
6  True False True False  35.0  52000.0
7  False False          38.0  79000.0
8  False    True True  48.0  83000.0
9  False False False  50.0  67000.0

```

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

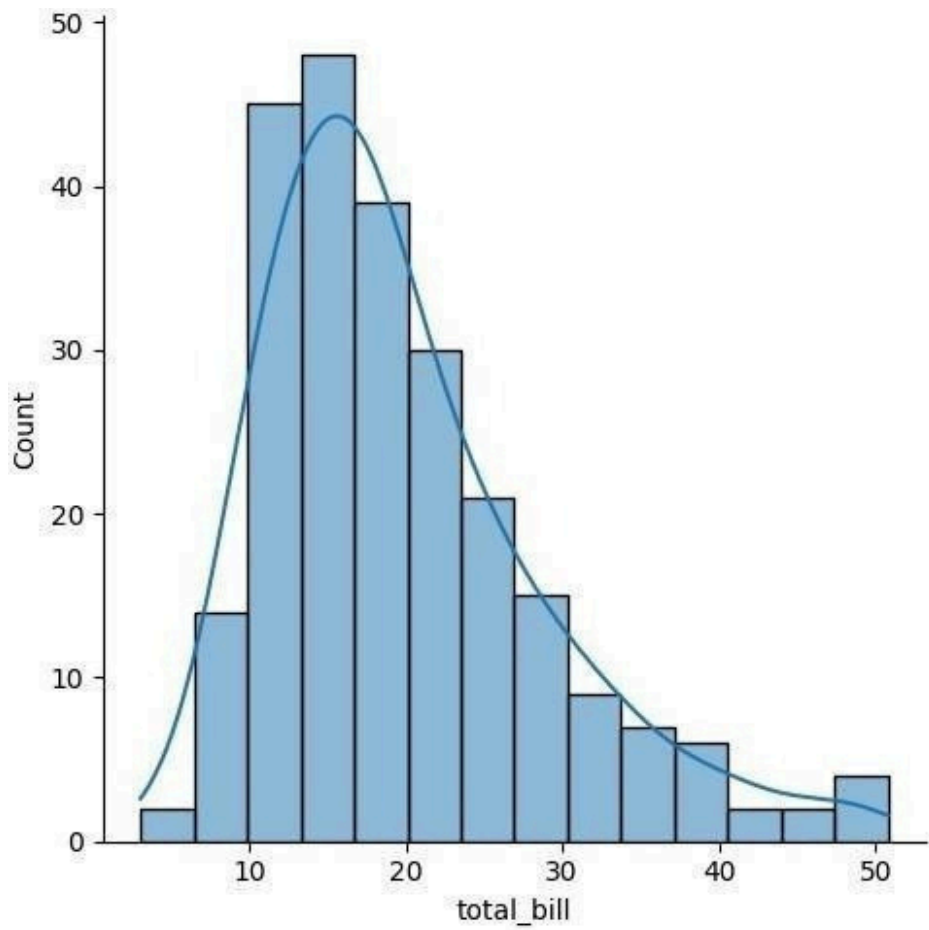
#DATA : 03.09.2024

#NAME : HARI SANKAR S #ROLL NO : 230701100 #DEPARTMENT :

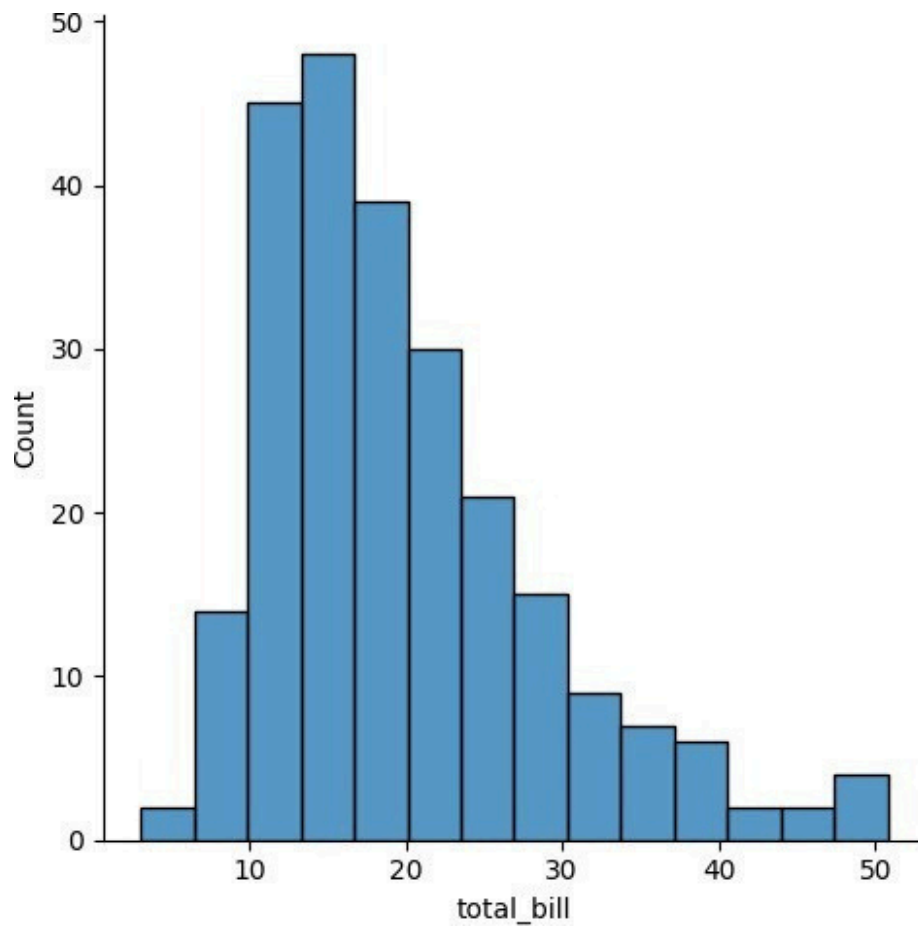
B.E COMPUTER SCIENCE AND ENGINEERING - B

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

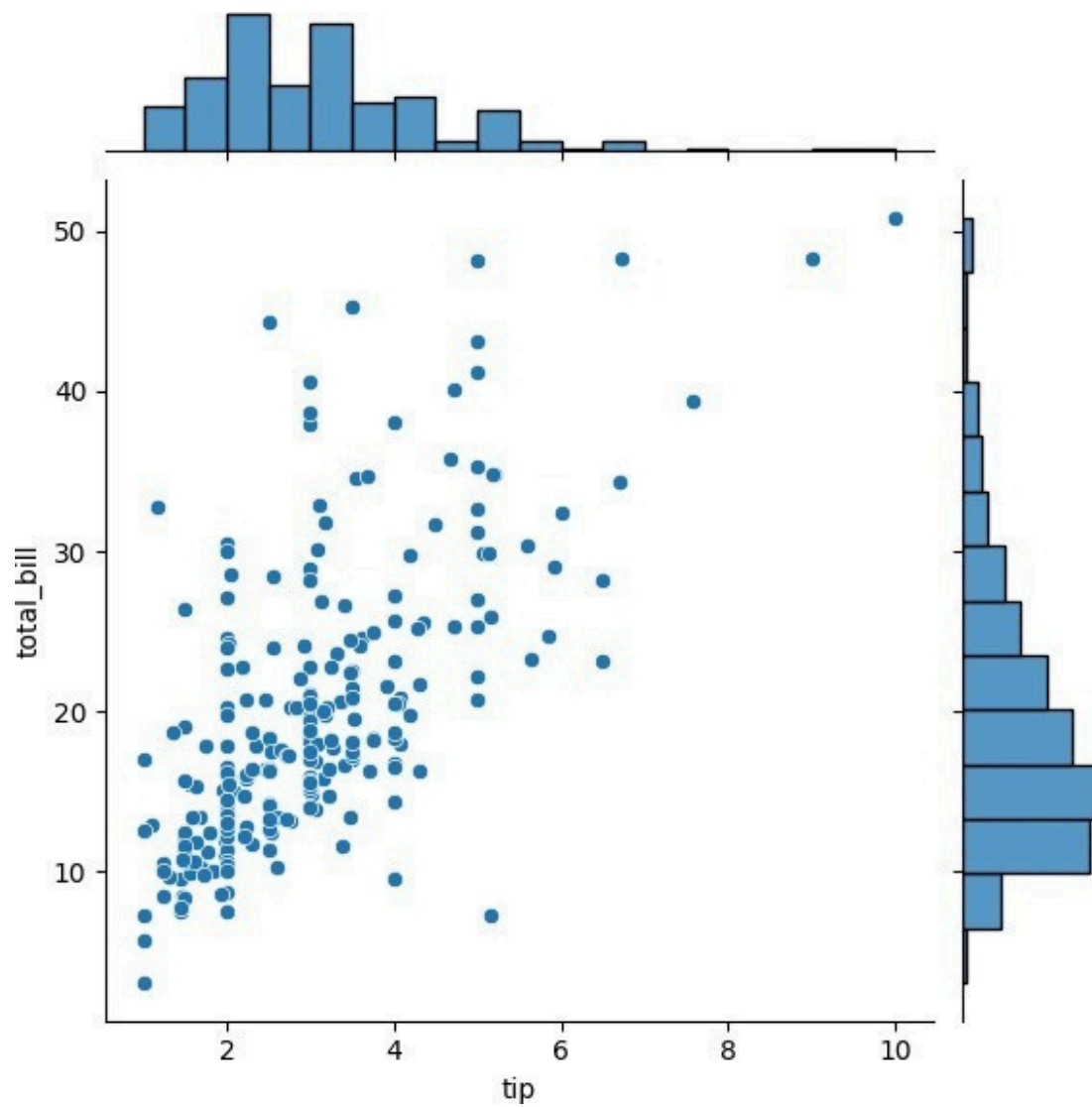
tips=sns.load_dataset('tips')
tips.head()
  total_bill  tip  sex  smoker  day  time  size
0    16.99    1.01  Female  No    Sun  Dinner  2
1    10.34    1.66  Male    No    Sun  Dinner  3
2    21.01    3.50  Female  No    Sun  Dinner  2
3    23.68    3.31  Male    No    Sun  Dinner  4
4    24.59    3.61  Male    No    Sun  Dinner  4
5    25.29    4.71  Female  No    Sun  Dinner  4
6    33.69    3.31  Male    No    Sun  Dinner  4
7    16.99    1.01  Female  No    Sun  Dinner  2
8    10.34    1.66  Male    No    Sun  Dinner  3
9    21.01    3.50  Female  No    Sun  Dinner  2
sns.displot(tips.total_bill, kde=True)
<seaborn.axisgrid.FacetGrid at 0x20d7dc69390>
```



```
sns.displot(tips.total_bill,kde=False)  
<seaborn.axisgrid.FacetGrid at 0x20d7dc22790>
```

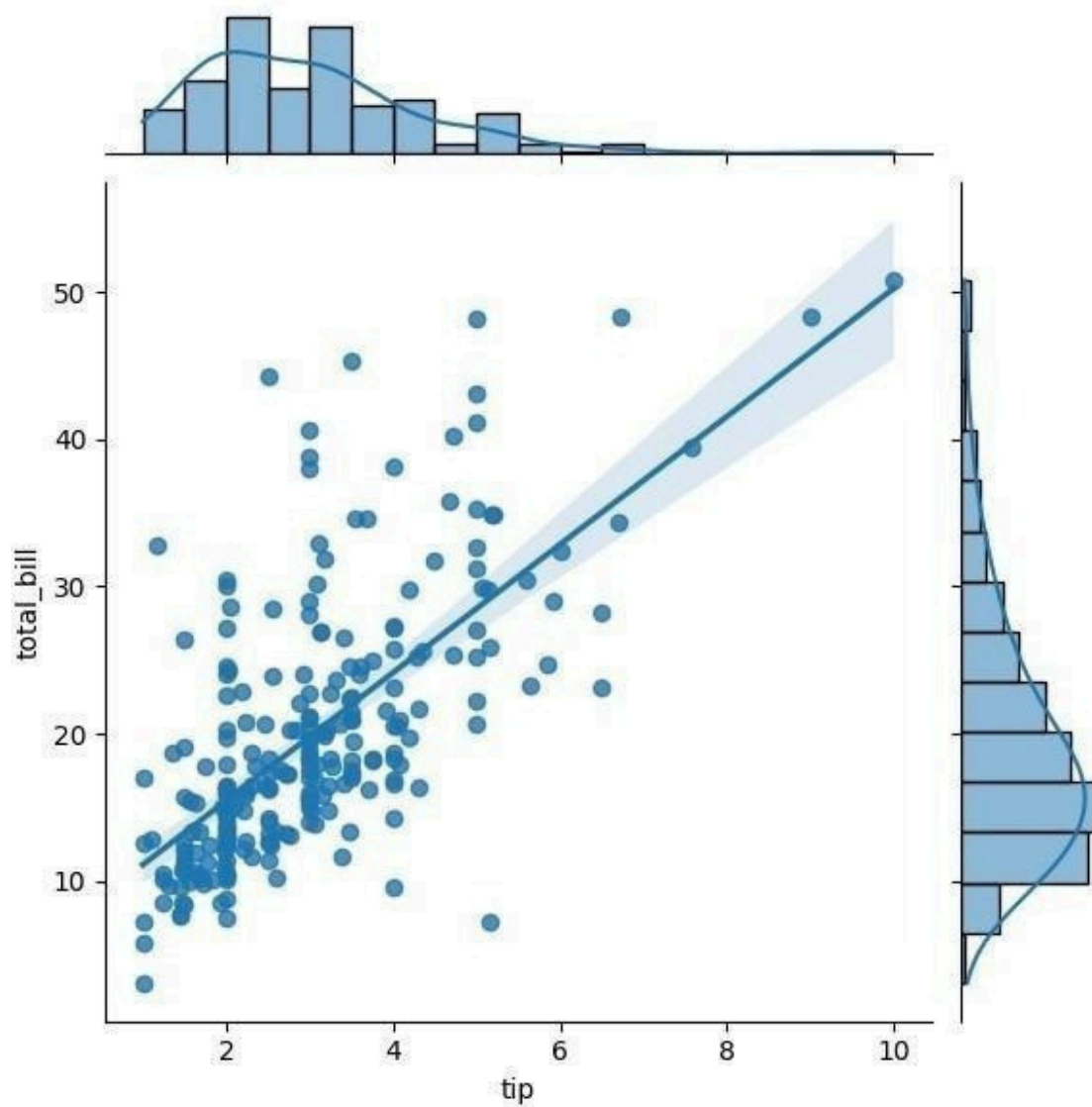


```
sns.jointplot(x=tips.tip,y=tips.total_bill)  
<seaborn.axisgrid.JointGrid at 0x20d7dc2f2d0>
```

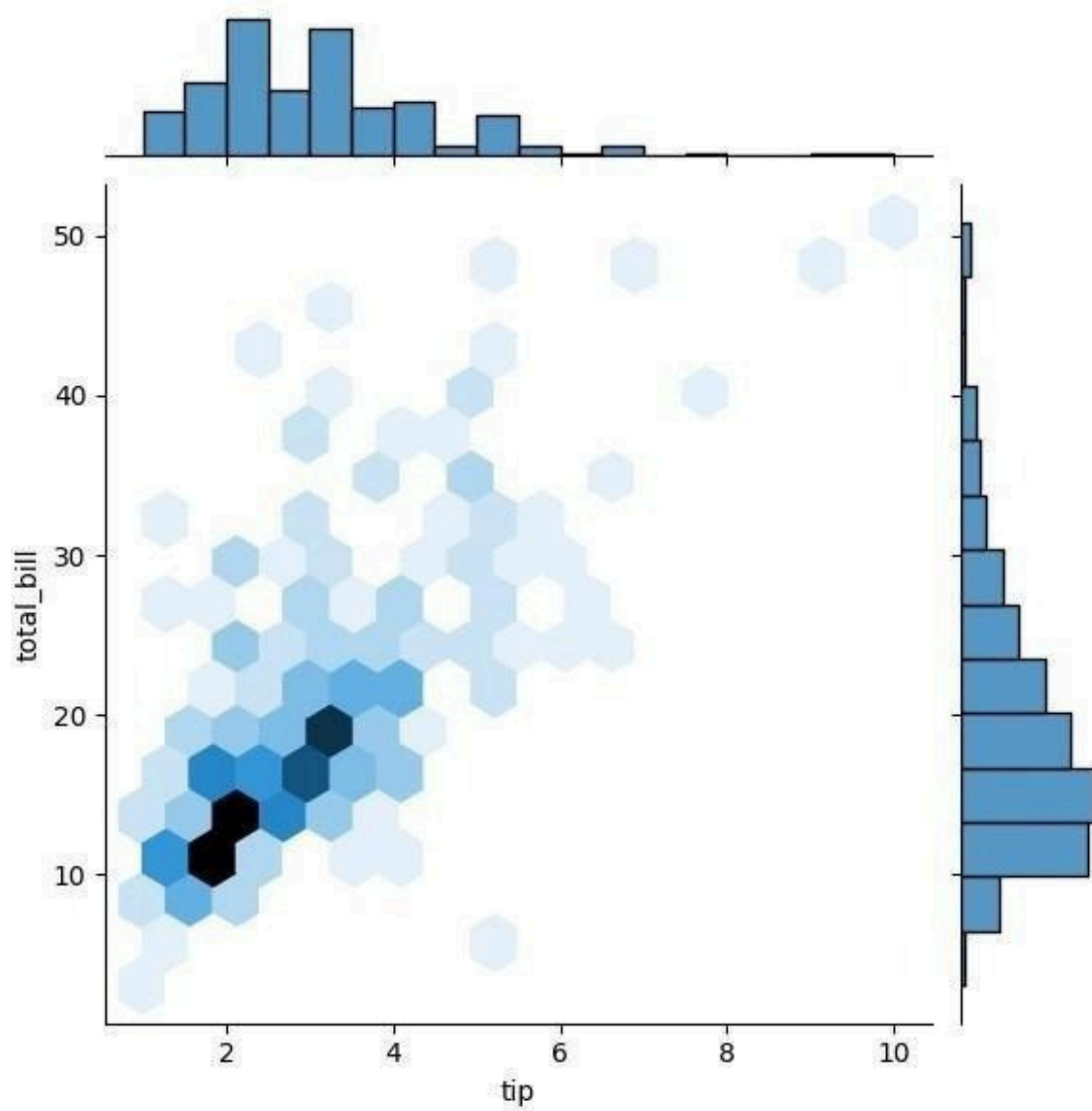
```
sns.jointplot(x=tips.tip,y=tips.total_bill,kind="reg")
```

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



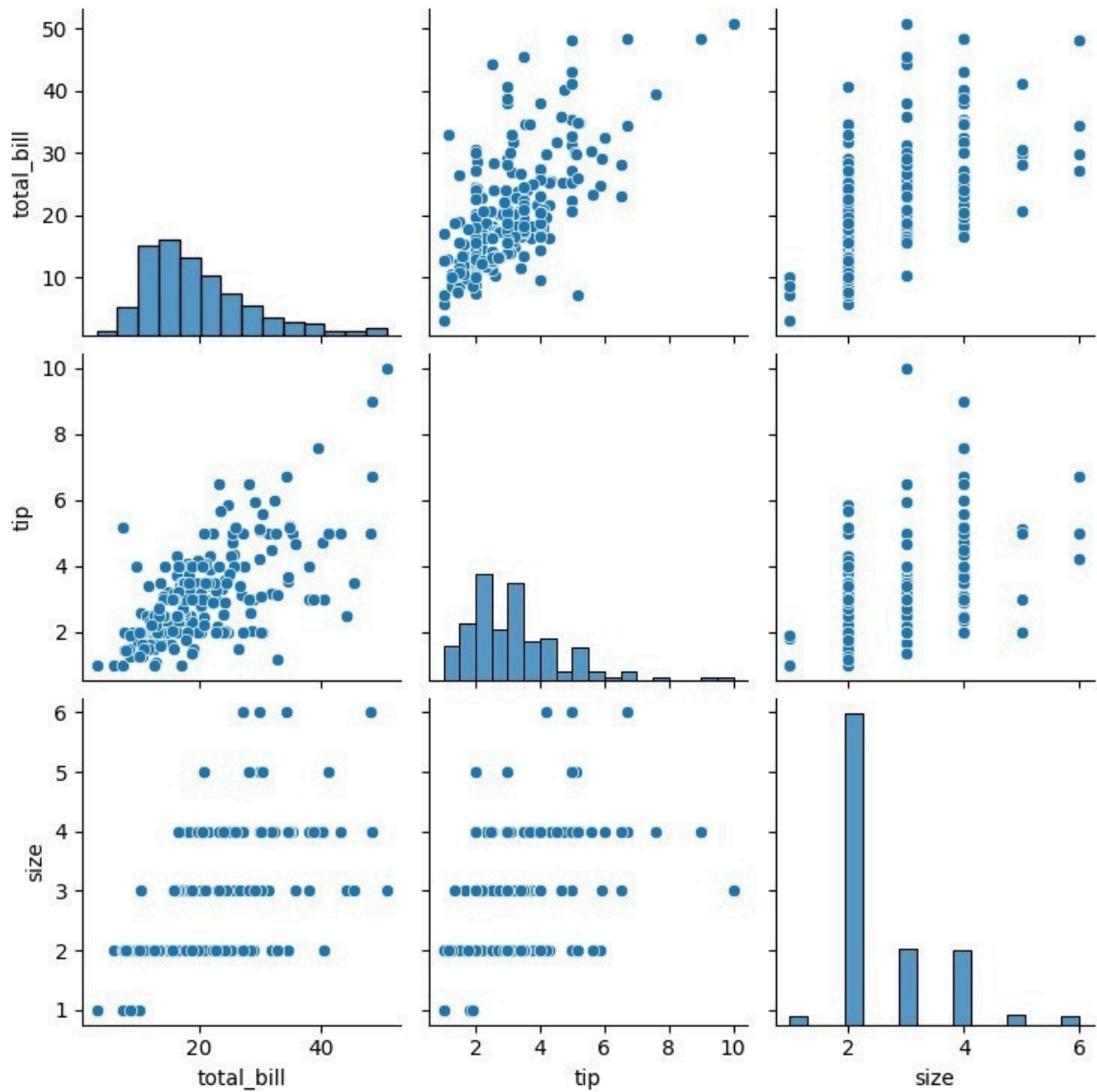
```
sns.jointplot(x=tips.tip,y=tips.total_bill,kind="hex")
```

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



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

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

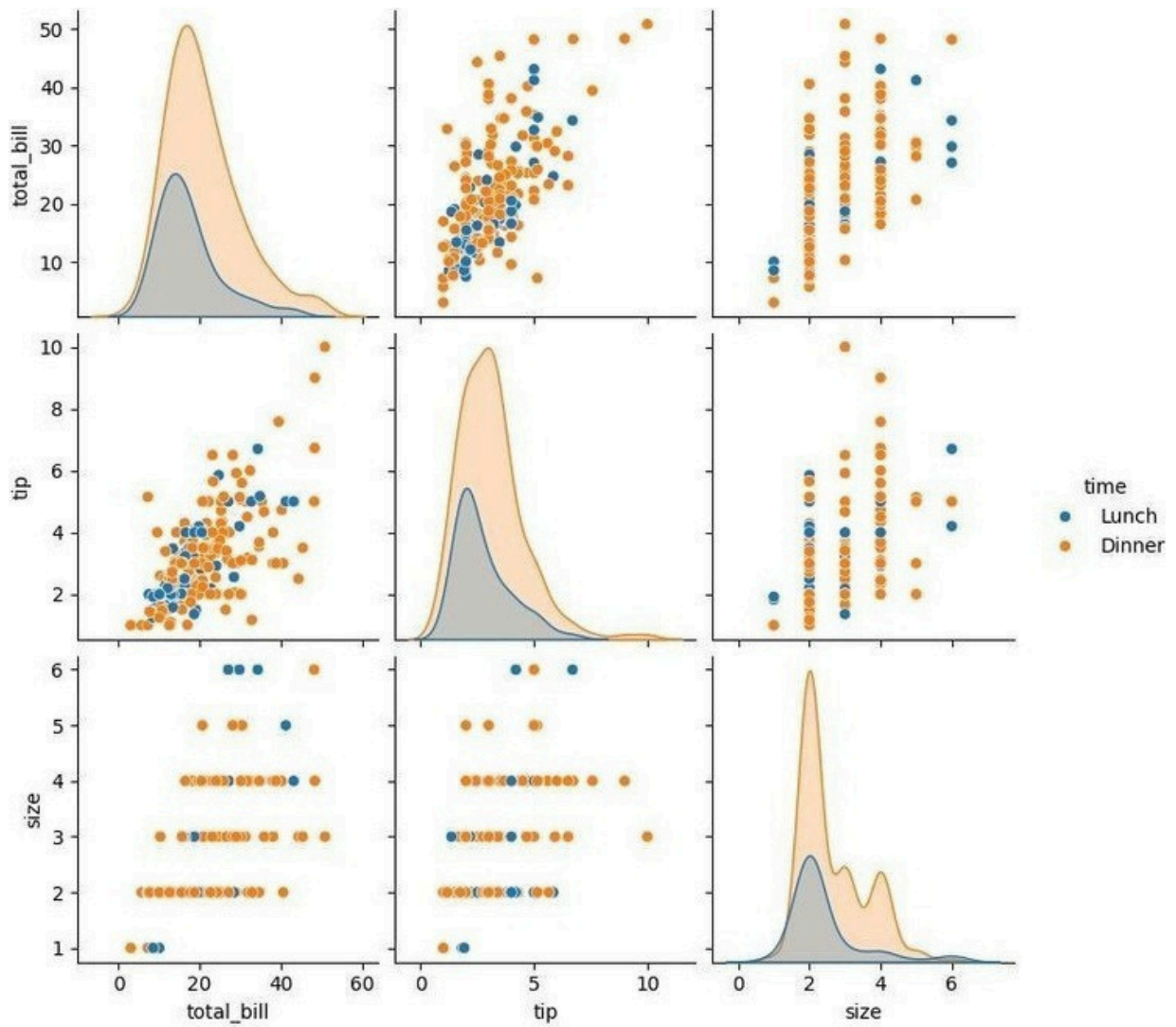


```
tips.time.value_counts()

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

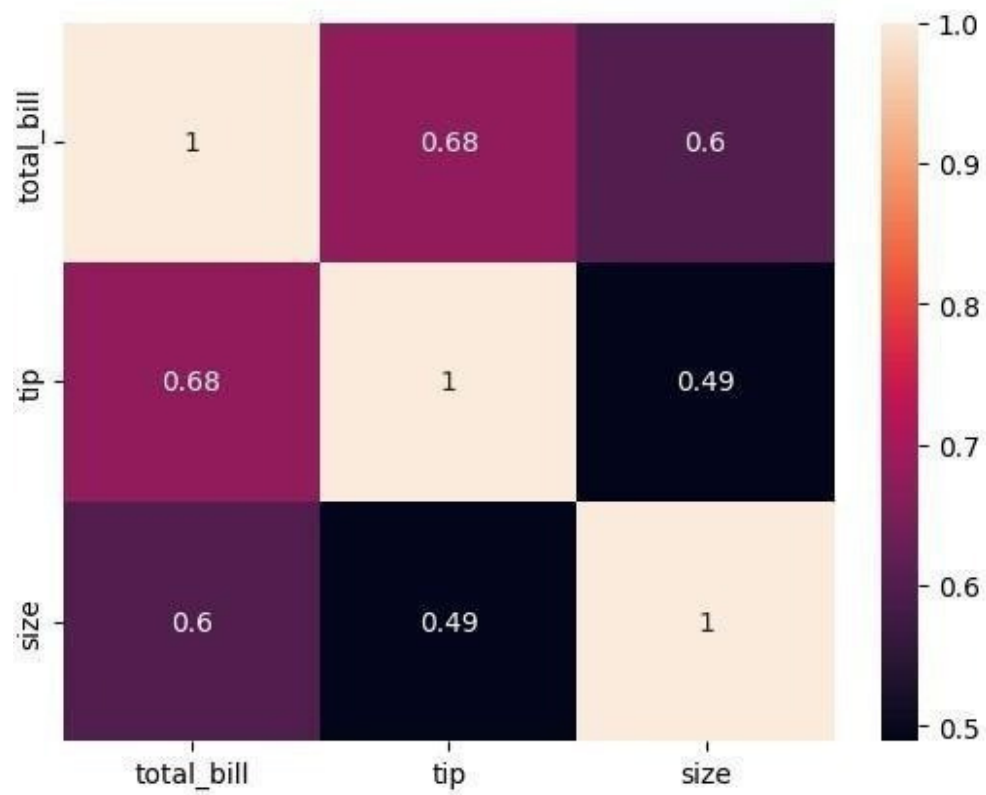
sns.pairplot(tips, hue='time')

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

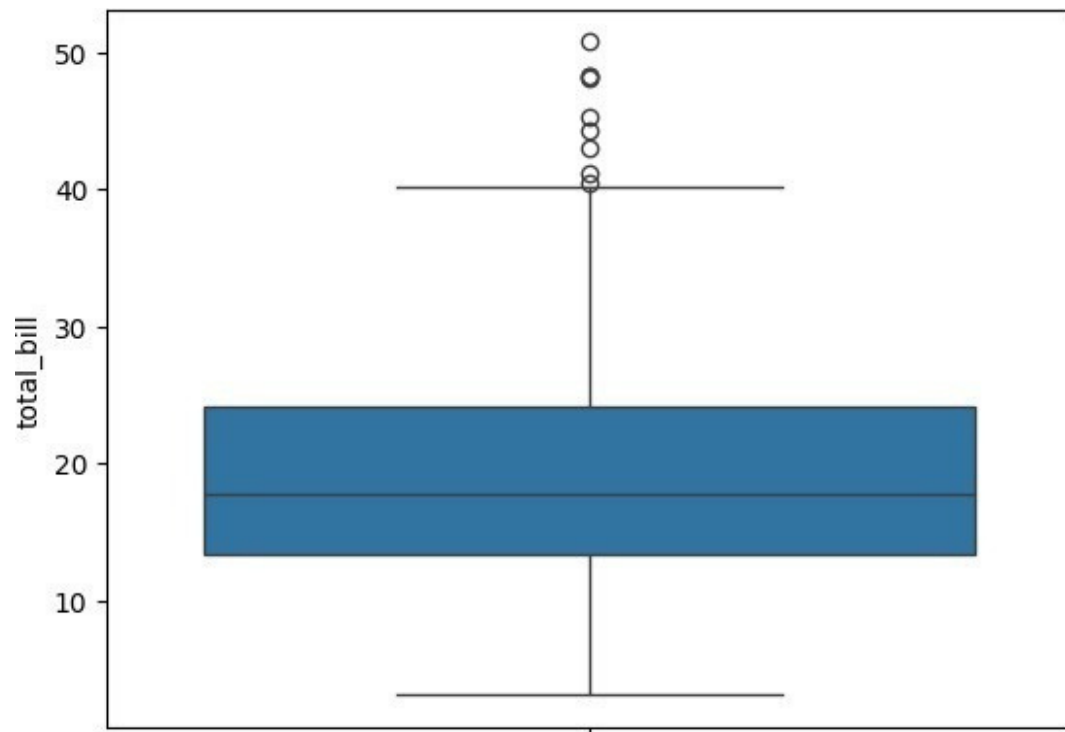


```
sns.heatmap(tips.corr(numeric_only=True),annot=True)
```

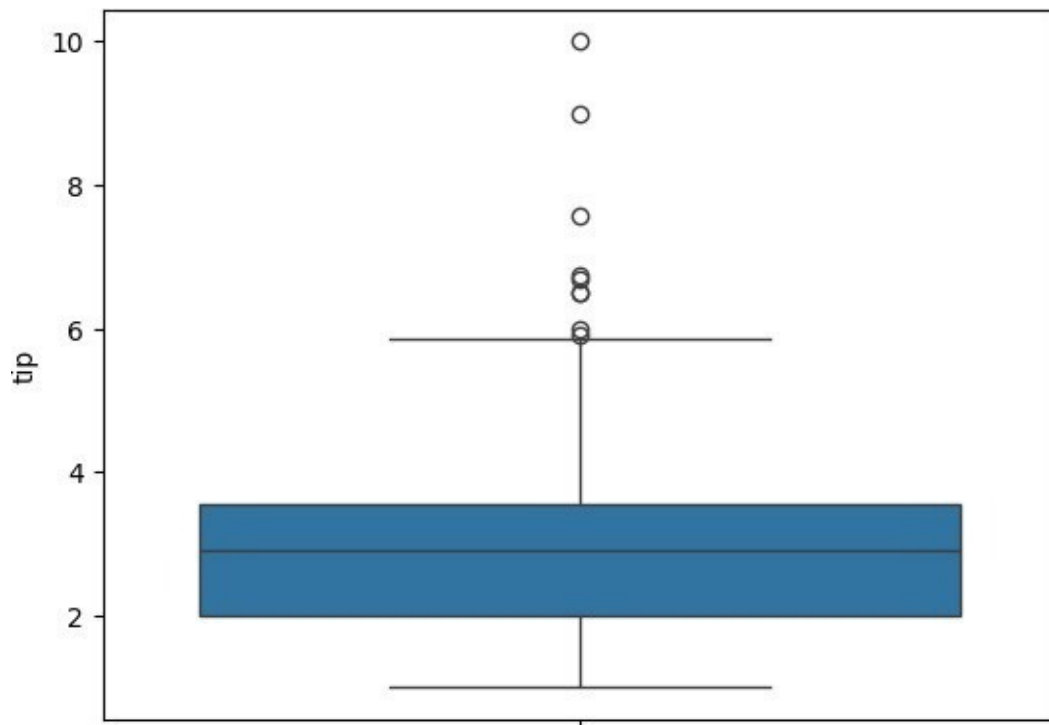
```
<Axes: >
```



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

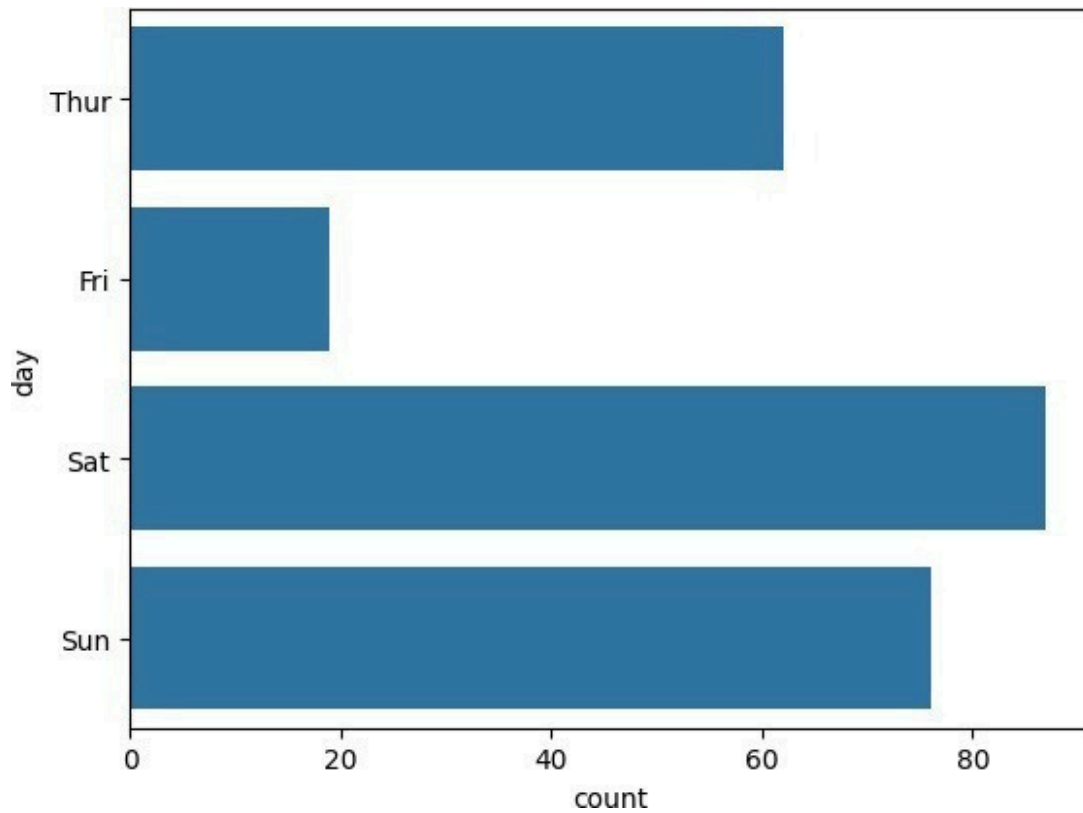


```
sns.boxplot(tips.tip)  
<Axes: ylabel='tip'>
```



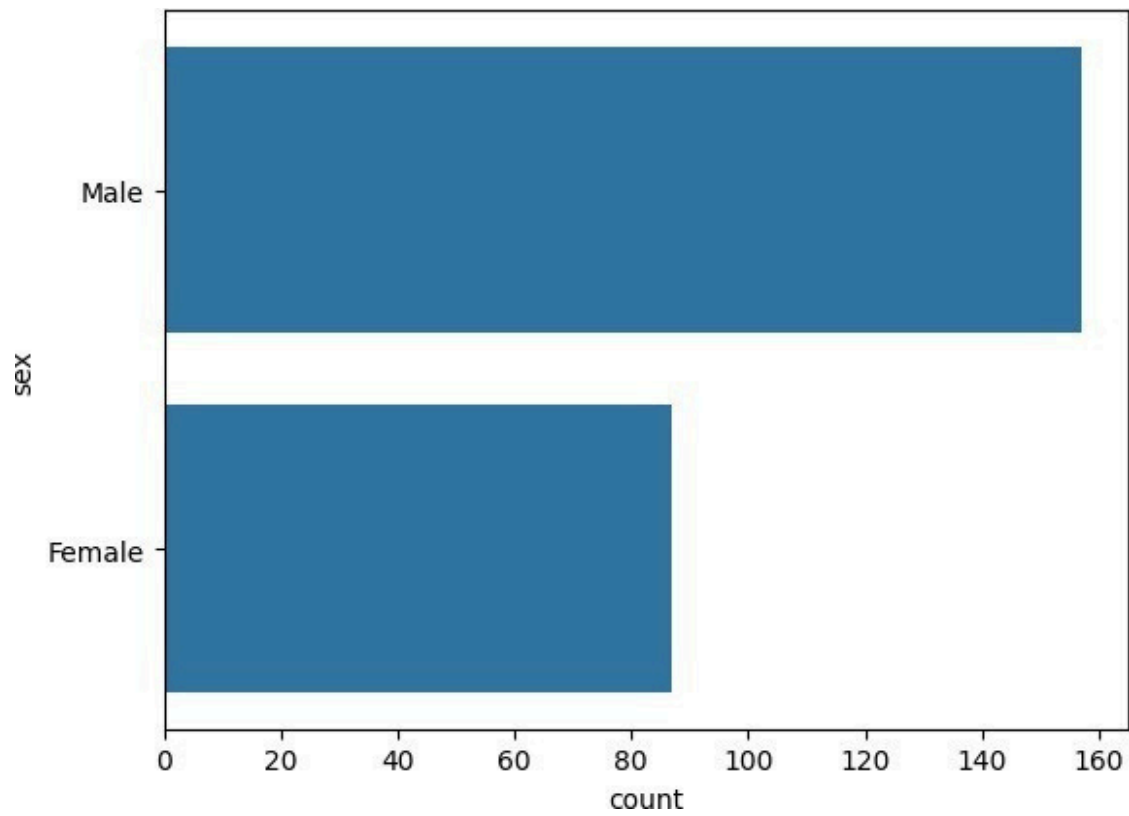
```
sns.countplot(tips.day)
```

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



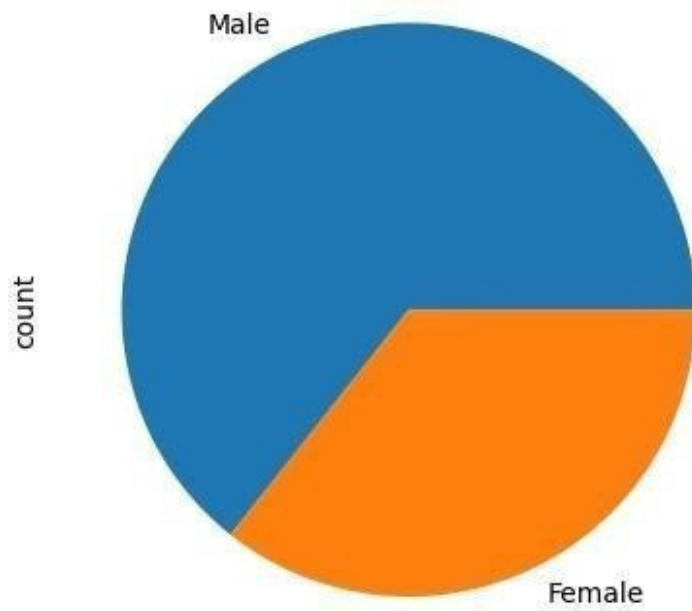
```
sns.countplot(tips.sex)
```

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

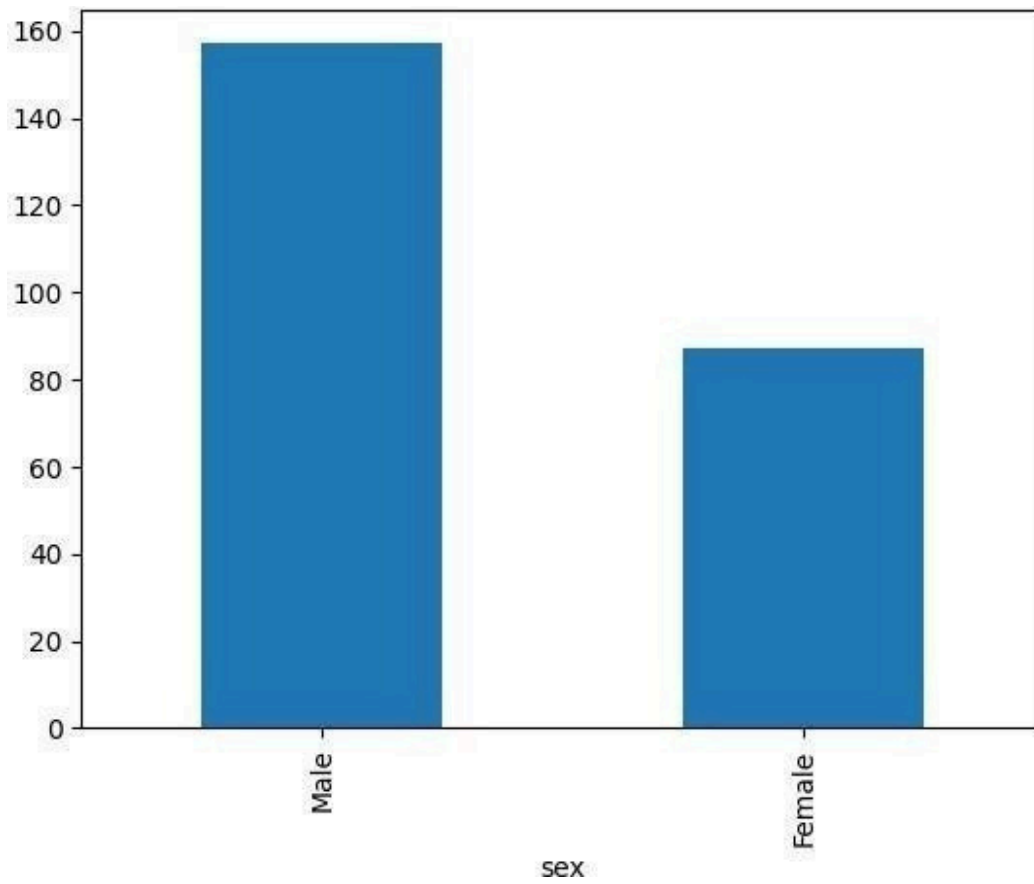



```
tips.sex.value_counts().plot(kind='pie')
```

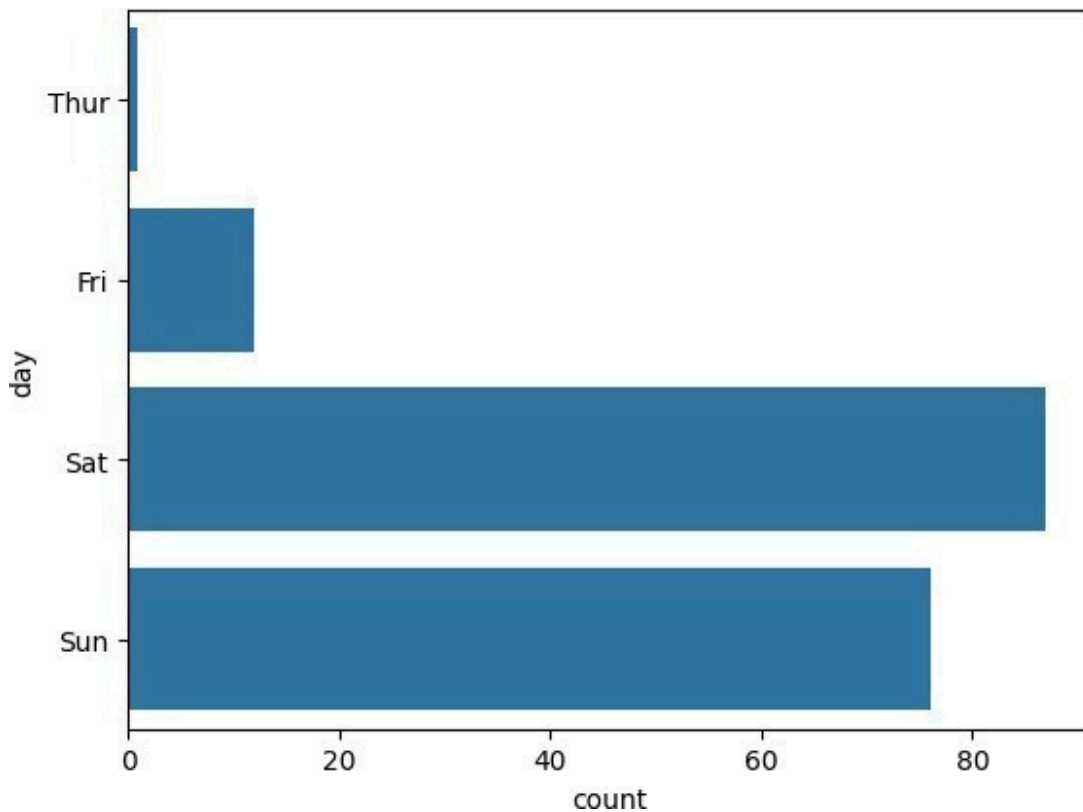
```
<Axes: ylabel='count'>
```



```
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 #DATE : 10.09.2024

#NAME : HARI SANKAR S

#ROLL NO : 230701100

#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:

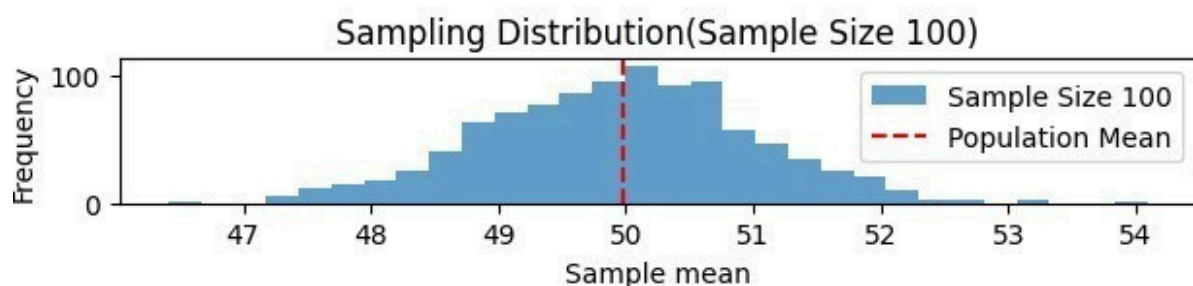
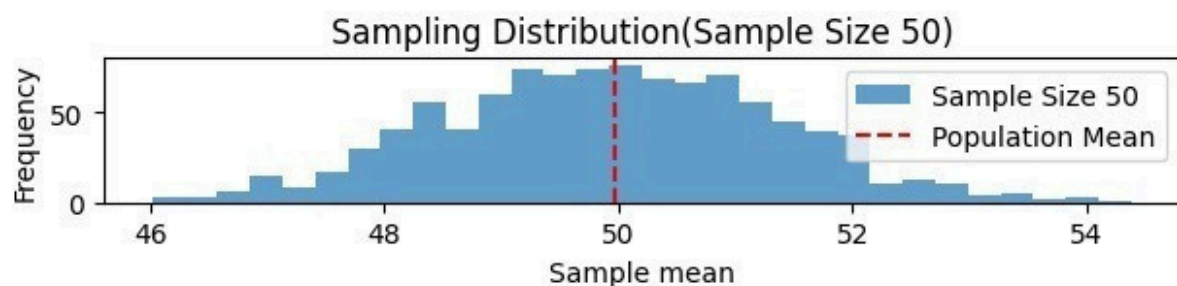
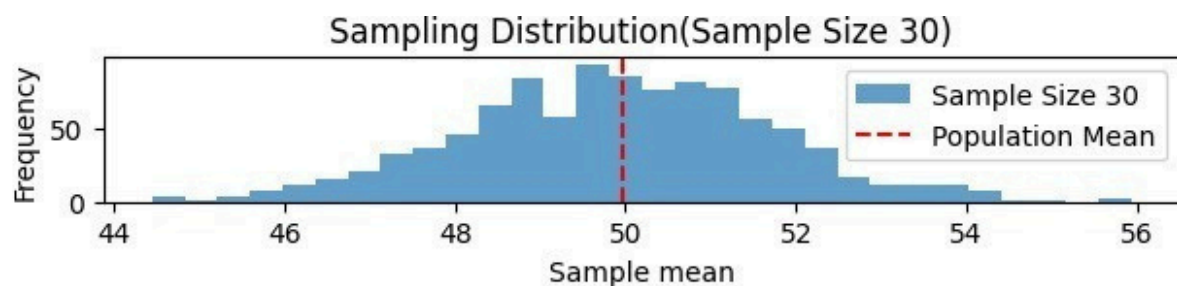
    sample_means[size] = []
    for _ in range(num_samples):
        sample = np.random.choice(population, size=size, replace=False)
        sample_means[size].append(np.mean(sample))
```

```
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 : HARI SANKAR S
#ROLL NO : 230701100
#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
{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
#DATE : 08.10.2024
#NAME : HARI SANKAR S

```

#ROLL NO : 230701100 #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"
      f"T-Statistic: {t_statistic:.4f}\n"
      f"P-Value: {p_value:.4f}")
# 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 :Jayasudhan.V

#ROLL NO : 230701131

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

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

```

from statsmodels.stats.multicomp import pairwise_tukeyhsd

np.random.seed(42)
n_plants = 25
growth_A = np.random.normal(loc=10, scale=2, size=n_plants)
growth_B = np.random.normal(loc=12, scale=3, size=n_plants)
growth_C = np.random.normal(loc=15, scale=2.5, size=n_plants)
all_data = np.concatenate([growth_A, growth_B, growth_C])
treatment_labels = ['A'] * n_plants + ['B'] * n_plants + ['C'] *
n_plants
f_statistic, p_value = stats.f_oneway(growth_A, growth_B, growth_C)

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

alpha = 0.05
if p_value < alpha:
    print("Reject the null hypothesis: There is 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 .0877B                -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 #DATE : 22.10.2024

#NAME : HARI SANKAR S

#ROLL NO : 230701100

*#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_data/sample.csv')
```

```
df.head()
```

```
   Countr  Age  Salary  Purchased  No
0        y  44.0  72000.0         N
1  France  40.0  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     NaN         No
```

```
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,
        -8.45893881e+00], 1.52752523e+00, -6.54653671e-01,
        -1.27555478e+00,
        -8.95205392e-01], -6.54653671e-01,  1.52752523e+00,
        -1.13023841e-01,
        -2.55206522e-01], 1.52752523e+00, -6.54653671e-01,
        1.77608893e-01,  6.63219199e-16],
       [ 1.22474487e+00, -6.54653671e-01,
        -6.55489329e+00],
       [-8.26696882e-01], -6.54653671e-01,  1.52752523e+00,
        0.00000000e+00,
       [ 1.22474487e+00], -6.54653671e-01,
       -6.15346938e+00,  1.38753832e+00],
       [-8.16496581e-01,  1.52752523e+00, -6.54653671e-01,
        1.63077256e+00,  1.75214693e+00],
       [ 1.22474487e+00, -6.54653671e-01,
        -6.54653671e-01,
        -2.58340208e-01,  2.93712492e-01]])
```

```
from sklearn.preprocessing import MinMaxScaler
```

```
mms=MinMaxScaler(feature_range=(0,1))
```

```
mms.fit(final_set)
```

```
feat_minmax_scaler=mms.transform(final_set)
```

```
feat_minmax_scaler
```

```
array([[1.          , 0.          , 0.          , 0.73913043, 0.68571429],
       [0.          , 0.          , 1.          , 0.          , 0.          ],
       [0.          , 1.          , 0.          , 0.13043478, 0.17142857],
       [0.          , 0.          , 1.          , 0.47826087, 0.37142857],
       [0.          , 1.          , 0.          , 0.56521739, 0.45079365],
       [1.          , 0.          , 0.          , 0.34782609, 0.28571429],
       [0.          , 0.          , 1.          , 0.51207729, 0.11428571],
       [1.          , 0.          , 0.          , 0.91304348, 0.88571429],
       [0.          , 1.          , 0.          , 1.          , 1.          ],
       [1.          , 0.          , 0.          , 0.43478261, 0.54285714]])
```

#EX.NO :11 Linear Regression

#DATE : 29.10.2024

```
#NAME : HARI SANKAR S #ROLL NO : 230701100  
#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-NullCount	Dtype
.....	-----	-----	-----
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 IYER FOR BELOW META DATA
```

	YearsExperience	Salary
count	30.000000	30.000000
mean	5.313333	76003.000000
std	2.837888	27414.629785
min	1.100000	26730.980000
25%	3.200000	32121.000000
50%	7.700000	100544.750000
75%		
max	10.500000	122391.000000

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

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

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

```
features
```

```
array([ 1.],
[ 1.3],
[ 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 depernent ouput
```

```
0.2 allocate test for 20 % automatically train for 80 %
```

```
'''
```

```
'\ny is depernent 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 experience: 24

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

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

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

#EX.NO:12 LogisticRegression

#DATE : 05.11.2024

#NAME : HARI SANKAR S

#ROLL NO : 230701100

*#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')
```

	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
..	46	...	0
395	15691863	Female	51	41000	1
315	97606071	Male	50	23000	1
397	15654296	Female	36	20000	0
398	15755018	Male	49	33000	1
399	15594041	Female		36000	

[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 158972390 Male 4 3400 1
1580783768521 Female 7 0 1
15592570 Male 4 3500 1
391 e 8 0 1
392 15748589 Female 4 3300 1
393 15635893 15776312 8 0 1
394 Female 15691863 4 2300 0
395 Female 15706071 7 0 1
396 Male 4 4500 1
397 15654296 Female 5 0 1
398 15755018 Male 6 4200 0
399 15594041 Female 0 0 1

```

```

df.head(25)
3 5900
9 0
4 4100
6 0

```

```

User ID Gender Age EstimatedSalary Purchased
0 15624510 Male 19 19000 0
1 15810944 Male 35 20000 0
2 15668575 Female 26 43000 2000
3 15603246 Female 27 57000 0
4 15804002 Male 19 76000 3300
5 15728773 Male 27 58000 0
6 15598044 Female 27 84000 3600
7 15694829 Female 32 15000 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]
[,	570'00]
		,

27

['	76000]
	19,	
[27,	58000]
	27,	
[840'00]
		,
[32,	150000]
[25,	33000]
[35,	
	26,	650'00]
		,
[26,	
	20,	8000]
		52000]
[
	32,	
[18,	86000]
[29,	
		18000]
[47,	
		,
	45,	82000]
[
	46,	
	48,	800'00]
		250,00]
[
	45,	
[47,	26000]
[48,	
		,
[45,	28000]
[46,	290'00]
[47,	
	49,	220'00]
[47,	
		49000]
[
		41000]
[
		220,00]
[
		230'00]
[
		200'00]
[
		280'00]
[
		300'00]

[29, 43000]

[31, ,

[31, 18000]

[74000]

[27, 137000]

[21, 16000]

[28, ,

[27, 44000]

[35, 9000]

[33, 27000]

[30, ,

[26, 28000]

[27, ,

[27, 49000]

[27, ,

[33, 72000]

[,

[31000]

[,

[17000]

[,

[35, 1080501,00]0]

[30, 15000]

[28, ,

[23, 84000]

[25, 2000]

[27, 79000]

[,

[54000]

[30, 135000,]

[31, 89000]

[24, ,

[18, 32000]

[29, 440,00]

[83000]

[,

[35, 23000]

[27,	58000]
	24,	,
[23,	55000]
	28,	,
[22,	79000]
		18000]
[,
[32,	117000]
	27,	20000]
	25,	,
[23,	87000]
		66000]
[32,	120000,]
	59,	83000]
	24,	,
[24,	58000]
	23,	,00]
	22,	190
[82000]
	31,	
[25,	,
	24,	63000]
		,
[20,	68000]
		,
[80000]
		27000]
[33,	113020300,]00]
		,
[32,	18000]
	34,	112000]
	18,	52000]
	22,	,
	28,	27000]
	26,	,
[30,	87000]
		17000]
[,
		80000]

[39,	42000]
	20,	,
[35,	49000]
	30,	88000]
[62000]
[31,	118000]
	24,	55000]
[28,	,
	26,	85000]
[35,	50000]
	22,	81000]
[
[30,	116000,]
	26,	15000]
[29,	,
	29,	28000]
[35,	,
	35,	83000]
[44000]
		25000]
[28,	123000,]
	35,	73000]
[28,	,
	27,	37000]
[28,	88000]
		59000]
		,
		86000]
[32,	,
[33,	149000]
	19,	21000]
[21,	,
	26,	72000]
[35000]

[27,	890'000]
[26,	860'000]
[38,	800'000]
[39,	710'000]
[37,	710'000]
[38,	610'000]
[37,	550'000]
[42,	800'000]
[40,	570'000]
[35,	750'000]
[36,	520'000]
[40,	590'000]
[41,	590'000]
[36,	750'000]
[37,	720'000]
[40,	750'000]
[35,	530'000]
[41,	510'000]
[39,	610'000]
[42,	650'000]
[26,	320'000]
[30,	170'000]
[26,	840'000]
[31,	580'000]
[33,	310'000]
[30,	870'000]
[21,	680'000]

[28,	55000]
	23,	,
[20,	63000]
[82000]
[30,	107000]
[28,	59000]
	19,	
[19,	25000]
		,
[18,	8500]
	35,	88000]
[
	30,	,
[34,	59000]
[24,	,
		89000]
[27,	,
	41,	25000]
[29,	89000]
	20,	960,00]
[26,	,
		30000]
[
		61000]
[
		74000]
[
		15000]
		45000]
		76000]
		500,00]
[41,	
	31,	47000]
[36,	
	40,	,
[31,	15000]
[46,	59000]
	29,	
[75000]
	26,	
[30000]
[
[
[32,	135000,]

[32,	100000]
[25,	90000]
[37,	,
[35,	33000]
[33,	38000]
[18,	69000]
[22,	86000]
[35,	55000]
[71000]
[
[29,	148000,]
[29,	47000]
[21,	,
[88000]
[34,	115000,]
[26,	118000]
[34,	43000]
[34,	,
[23,	72000]
[35,	,
[25,	2800]
[47000]
[24,	,
[31,	22000]
[26,	,
[31,	23000]
[,
[34000]
[16000]
[70100,]00]
[32,	1170
[33,	43000]
[33,	,
[31,	60000]
[20,	660
[,00]
[82000]

[33,	410'00]
	35,	
[28,	720'00]
[24,	320'00]
[19,	840'00]
[29,	260'00]
[19,	430'00]
	28,	
[34,	700'00]
[30,	890'00]
[20,	430'00]
	26,	
[35,	790'00]
[360'00]
		800,00]
[
		220'00]
[,

[35,	39000]
	49,	
[740'00]
[39,	134000']
[41,	710'00]
[58,	101000']
[47,	470'00]
[55,	130000']
[52,	114000']
[40,	142000']
[46,	220'00]
[48,	
		960'00]
[52,	150000,]
[59,	420'00]

[35,	58'000]
[47,	430'000]
[60,	108'000]
[49,	65'000]
[40,	'
[46,	78'000]
[96'000]
[59,	143'000,]
[41,	80'000]
[35,	'
[91'000]
[37,	144'000,]
[60,	102'000]
[35,	60'000]
[37,	'
[53'000]
[36,	126'000,]
[56,	133'000]
[40,	72'000]
[42,	'
[80'000]
[35,	147'000,]
[39,	42'000]
[40,	107'000]
[49,	86'000]
[38,	112'000]
[46,	79'000]
[40,	'
[37,	57'000]
[46,	'
[800'00]
[82'000]
[53,	143'000,]

[42,149000]
[38, 59000]
[50, 88000]
[56,104000]
[41, 72000]
[51,146000]
[35, 50000]
[57,122000]
[41, 52000]
,

[35, 97000]
[44, ,]
[37, 39000]
[52000]
[48,134000,]
[37,146000]
[50, 44000]
[52, 90000]
[41, ,]
[40, 72000]
[58, 57000]
[,]
[95000]
[45,131000,]
[35, 77000]
[36,144000]
[55,125000]
[35, 72000]
[48, 90000]
[42,108000,]

[40,	75'000]
[37,	74'000]
[47,	144'000]
[40,	61'000]
[43,	133'000]
[59,	76'000]
[60,	42'000]
[39,	106'000,]
[57,	26'000]
[57,	,
[38,	74'000]
[49,	,00]
[52,	710
[50,	88'000]
[59,	,
[35,	38'000]
[37,	,
[52,	36'000]
[,
[88'000]
[61'000]
[70'000]
[48,141020,	100,0]0]
[37,	93'000]
[37,	,
[62'000]
[48,	138'000,]
[41,	79'000]
[37,	,
[78'000]
[39,	134'000,]
[49,	89'000]
[55,	,
		39'000]

[37, 77000]
35, ,
[36, 57000]
[42, 63000]
[73000]
[43, 112000]
,

[45, 79000]
[46, 117000]
[58, 38000]
48, ,
[74000]
[37, 137000]
[37, 79000]
40, ,
[42, 60000]
[54000]
[51, 134000,]
[47, 113000]
[36, 125000]
[38, 50000]
[42, ,
39, 70000]
[38, ,
960,00]
[50000]
[49, 141000,]
[39, 79000]
[39, ,
75000]
[54, 10400,0]
[35, 55000]
[45, ,
32000]

[36, 60'000]

[52, 138'000]

[53, 82'000]

[41, 52'000]

[48, 30'000]

[48, 131'000,]

[41, 60'000]

[41, ,

[42, 72'000]

[, 75'000]

[36, 118'000,]

[47, 107'000]

[38, 51'000]

[48, 119'000]

[42, 65'000]

[40, ,

[57, 65'000]

[36, 60'000]

[, 54'000]

[58, 144'000,]

[35, 79'000]

[38, ,

[55'000]

[39, 122'000,]

[53, 104'000]

[35, 75'000]

[38, ,

[47, 65'000]

[, 51'000]

[47, 105'000,]

[41, 63'000]

[53, 72000]
,

[54, 108000]
,

[39, 77000]
 [38, 61000]
 [38, 113000]
 [37, 75000]
 [42, 90000]
 [36, 57000]
 [60, 99000]
 [54, 34000]
 [41, 70000]
 [40, 72000]
 [42, 71000]
 [43, 12905040,]00]
 [53, 34000]
 [47, 50000]
 [42, 79000]
 [42, 10400,0]
 [59, 29000]
 [58, 47000]
 [46, 38, 88000]
 [54, 71000]
 [60, 60, 26000]
 [39, 46000]
 [83000]
 [59, 13007030,0]0]
 [37, 80000]
 [46, 32000]
 [42, 74000]
 [53000]
 ,

[41,	87000]
	58,	,
[42,	23000]
	48,	640,00]
[,
		33000]
[,
	44,	139000]
		,
[49,	28000]
	57,	,
[56,	33000]
		,
[49,	6000]
	39,	39000]
[,
	47,	71000]
[48,	
		,
[48,	34000]
	47,	,
[45,	35000]
	60,	33000]
[39,	230,00]
	46,	,
[51,	45000]
		,
[42000]
		,
[59000]
		,
[41000]
		,
[23000]
		,

```
[ [ 50 20000],  
 [ , 33000],  
 4369,, 36000]], dtype=int64)
```

label

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

1,

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

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
# Assuming `features` and `label` are already defined

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

```

x_train, x_test, y_train, y_test = train_test_split(features,
label, test_size=0.2, random_state=i)
model = LogisticRegression()
model.fit(x_train, y_train)

train_score = model.score(x_train, y_train)
test_score = model.score(x_test, y_test)

if test_score > train_score:
    print(f"Test Score: {test_score:.4f} | Train Score:
{train_score:.4f} | Random State: {i}")

```

```
'''
```

```

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

```

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

Test Score: 0.8500 | Train Score: 0.8375 | Random State:
163
Test Score: 0.8750 | Train Score: 0.8313 | Random State:
164
Test Score: 0.8625 | Train Score: 0.8500 | Random State:
169
Test Score: 0.8750 | Train Score: 0.8406 | Random State:
171
Test Score: 0.8500 | Train Score: 0.8406 | Random State:
172
Test Score: 0.9000 | Train Score: 0.8250 | Random State:
180
Test Score: 0.8500 | Train Score: 0.8344 | Random State:
184
Test Score: 0.9250 | Train Score: 0.8219 | Random State:
186
Test Score: 0.9000 | Train Score: 0.8313 | Random State:
193
Test Score: 0.8625 | Train Score: 0.8500 | Random State:
195
Test Score: 0.8625 | Train Score: 0.8406 | Random State:
196
Test Score: 0.8625 | Train Score: 0.8375 | Random State:
197
Test Score: 0.8750 | Train Score: 0.8406 | Random State:
198
Test Score: 0.8875 | Train Score: 0.8375 | Random State:
199
Test Score: 0.8875 | Train Score: 0.8438 | Random State:
200
Test Score: 0.8625 | Train Score: 0.8375 | Random State:
202
Test Score: 0.8625 | Train Score: 0.8406 | Random State:
203
Test Score: 0.8875 | Train Score: 0.8313 | Random State:
206
Test Score: 0.8625 | Train Score: 0.8344 | Random State:
211
Test Score: 0.8500 | Train Score: 0.8438 | Random State:
212
Test Score: 0.8625 | Train Score: 0.8344 | Random State:
214
Test Score: 0.8750 | Train Score: 0.8313 | Random State:
217
Test Score: 0.9625 | Train Score: 0.8187 | Random State:
220
Test Score: 0.8750 | Train Score: 0.8438 | Random State:
221
Test Score: 0.8500 | Train Score: 0.8406 | Random State:
222
Test Score: 0.9000 | Train Score: 0.8438 | Random State:
223
Test Score: 0.8625 | Train Score: 0.8531 | Random State:
227
Test Score: 0.8625 | Train Score: 0.8344 | Random State:
228
Test Score: 0.9000 | Train Score: 0.8406 | Random State:
229
Test Score: 0.8500 | Train Score: 0.8438 | Random State:

232
Test Score: 0.8750 | Train Score: 0.8469 | Random State:
233
Test Score: 0.9125 | Train Score: 0.8406 | Random State:
234
Test Score: 0.8625 | Train Score: 0.8406 | Random State:
235
Test Score: 0.8500 | Train Score: 0.8469 | Random State:
236
Test Score: 0.8750 | Train Score: 0.8469 | Random State:
239
Test Score: 0.8500 | Train Score: 0.8438 | Random State:
241
Test Score: 0.8875 | Train Score: 0.8500 | Random State:
242
Test Score: 0.8875 | Train Score: 0.8250 | Random State:
243
Test Score: 0.8750 | Train Score: 0.8469 | Random State:
244
Test Score: 0.8750 | Train Score: 0.8406 | Random State:
245
Test Score: 0.8750 | Train Score: 0.8469 | Random State:
246
Test Score: 0.8625 | Train Score: 0.8594 | Random State:
247
Test Score: 0.8875 | Train Score: 0.8438 | Random State:
248
Test Score: 0.8625 | Train Score: 0.8500 | Random State:
250
Test Score: 0.8750 | Train Score: 0.8313 | Random State:
251
Test Score: 0.8875 | Train Score: 0.8438 | Random State:
252
Test Score: 0.8625 | Train Score: 0.8469 | Random State:
255
Test Score: 0.9000 | Train Score: 0.8406 | Random State:
257
Test Score: 0.8625 | Train Score: 0.8562 | Random State:
260

Test Score: 0.8625 | Train Score: 0.8406 | Random State:
266
Test Score: 0.8625 | Train Score: 0.8375 | Random State:
268
Test Score: 0.8750 | Train Score: 0.8406 | Random State:
275
Test Score: 0.8625 | Train Score: 0.8500 | Random State:
276
Test Score: 0.9250 | Train Score: 0.8375 | Random State:
277
Test Score: 0.8750 | Train Score: 0.8469 | Random State:
282
Test Score: 0.8500 | Train Score: 0.8469 | Random State:
283
Test Score: 0.8500 | Train Score: 0.8438 | Random State:
285
Test Score: 0.9125 | Train Score: 0.8344 | Random State:
286
Test Score: 0.8500 | Train Score: 0.8406 | Random State:
290
Test Score: 0.8500 | Train Score: 0.8406 | Random State:
291
Test Score: 0.8500 | Train Score: 0.8469 | Random State:
292
Test Score: 0.8625 | Train Score: 0.8375 | Random State:
294
Test Score: 0.8875 | Train Score: 0.8281 | Random State:
297
Test Score: 0.8625 | Train Score: 0.8344 | Random State:
300
Test Score: 0.8625 | Train Score: 0.8500 | Random State:
301
Test Score: 0.8875 | Train Score: 0.8500 | Random State:
302
Test Score: 0.8750 | Train Score: 0.8469 | Random State:
303
Test Score: 0.8625 | Train Score: 0.8344 | Random State:
305
Test Score: 0.9125 | Train Score: 0.8375 | Random State:
306
Test Score: 0.8750 | Train Score: 0.8469 | Random State:
308
Test Score: 0.9000 | Train Score: 0.8438 | Random State:
311
Test Score: 0.8625 | Train Score: 0.8344 | Random State:
313
Test Score: 0.9125 | Train Score: 0.8344 | Random State:
314
Test Score: 0.8750 | Train Score: 0.8375 | Random State:
315
Test Score: 0.9000 | Train Score: 0.8469 | Random State:
317
Test Score: 0.9125 | Train Score: 0.8219 | Random State:
319
Test Score: 0.8625 | Train Score: 0.8500 | Random State:
321
Test Score: 0.9125 | Train Score: 0.8281 | Random State:
322
Test Score: 0.8500 | Train Score: 0.8469 | Random State:

328
Test Score: 0.8500 | Train Score: 0.8375 | Random State:
332
Test Score: 0.8875 | Train Score: 0.8531 | Random State:
336
Test Score: 0.8500 | Train Score: 0.8375 | Random State:
337
Test Score: 0.8750 | Train Score: 0.8406 | Random State:
343
Test Score: 0.8625 | Train Score: 0.8438 | Random State:
346
Test Score: 0.8875 | Train Score: 0.8313 | Random State:
351
Test Score: 0.8625 | Train Score: 0.8500 | Random State:
352
Test Score: 0.9500 | Train Score: 0.8187 | Random State:
354
Test Score: 0.8625 | Train Score: 0.8500 | Random State:
356
Test Score: 0.9125 | Train Score: 0.8406 | Random State:
357
Test Score: 0.8625 | Train Score: 0.8375 | Random State:
358
Test Score: 0.8500 | Train Score: 0.8406 | Random State:
362
Test Score: 0.9000 | Train Score: 0.8438 | Random State:
363
Test Score: 0.8625 | Train Score: 0.8531 | Random State:
364
Test Score: 0.9375 | Train Score: 0.8219 | Random State:
366
Test Score: 0.9125 | Train Score: 0.8406 | Random State:
369
Test Score: 0.8625 | Train Score: 0.8531 | Random State:
371
Test Score: 0.9250 | Train Score: 0.8344 | Random State:
376
Test Score: 0.9125 | Train Score: 0.8281 | Random State:
377

```

Test Score: 0.8875 | Train Score: 0.8500 | Random State:
378
Test Score: 0.8875 | Train Score: 0.8500 | Random State:
379
Test Score: 0.8625 | Train Score: 0.8406 | Random State:
382
Test Score: 0.8625 | Train Score: 0.8594 | Random State:
386
Test Score: 0.8500 | Train Score: 0.8375 | Random State:
387
Test Score: 0.8750 | Train Score: 0.8281 | Random State:
388
Test Score: 0.8500 | Train Score: 0.8438 | Random State:
394
'\n\n\n'
Test Score: 0.8625 | Train Score: 0.8375 | Random State:
395
x_train,x_test,y_train,y_test=train_test_split(features,label,test_size=0.2,random_state=0)
Test Score: 0.9000 | Train Score: 0.8438 | Random State:
397
finalModel=LogisticRegression()
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	0.8	0.91	0.8	25
	1	6	0.73	9	7
		0.83		0.77	143
accuracy		0.8		0.8	40
macro avg		4	0.8		0
weighted		0.85	2	5	40
avg			0.8	3	0
			5	0.8	40
				5	0