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

#NAME : AKSHAY . N

#ROLL NO : 230701023
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - A

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
1.      Iris-setosa
2.      Iris-setosa
3.      Iris-setosa
4.      Iris-setosa
5.      Iris-setosa
..              ...
145. Iris-virginica
146. Iris-virginica
147. Iris-virginica  ---------------  ------
148. Iris-virginica
149. Iris-virginica
```

```
[150 rows x 6

columns]data.info()

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

```
 0   Id             150 non-null    int64
 1.  SepalLengthCm  150 non-null    float6
 2.  SepalWidthCm   150 non-null    4
 3.  PetalLengthCm  150 non-null    float6
 4.  PetalWidthCm   150 non-null    4
 5   Species        150 non-null
objectdtypes: float64(4), int64(1),
object(1) memory usage: 7.2+ KB
```

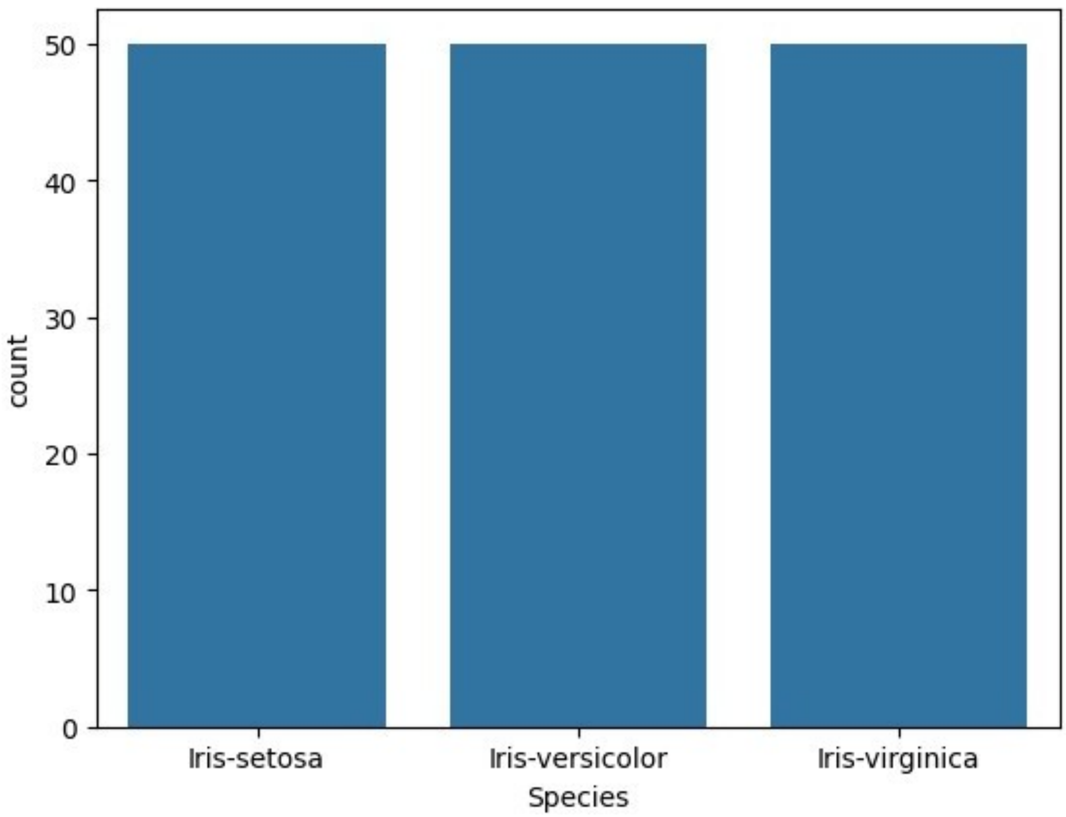
```
data.describe()
```

```
               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
 1.1986
 67
 std      43.4453       0.828066       0.433594      1.764420
              68
 0.7631
 61
 min      1.00000       4.300000       2.000000      1.000000
               0
 0.1000
 00
 25%      38.2500       5.100000       2.800000      1.600000
              00
 0.300000
 50%     75.500000       5.800000      3.000000
 4.350000
 1.300000
 75%    112.750000       6.400000      3.300000
 5.100000
 1.800000
 max    150.000000       7.900000      4.400000
 6.900000
2.500000
```

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

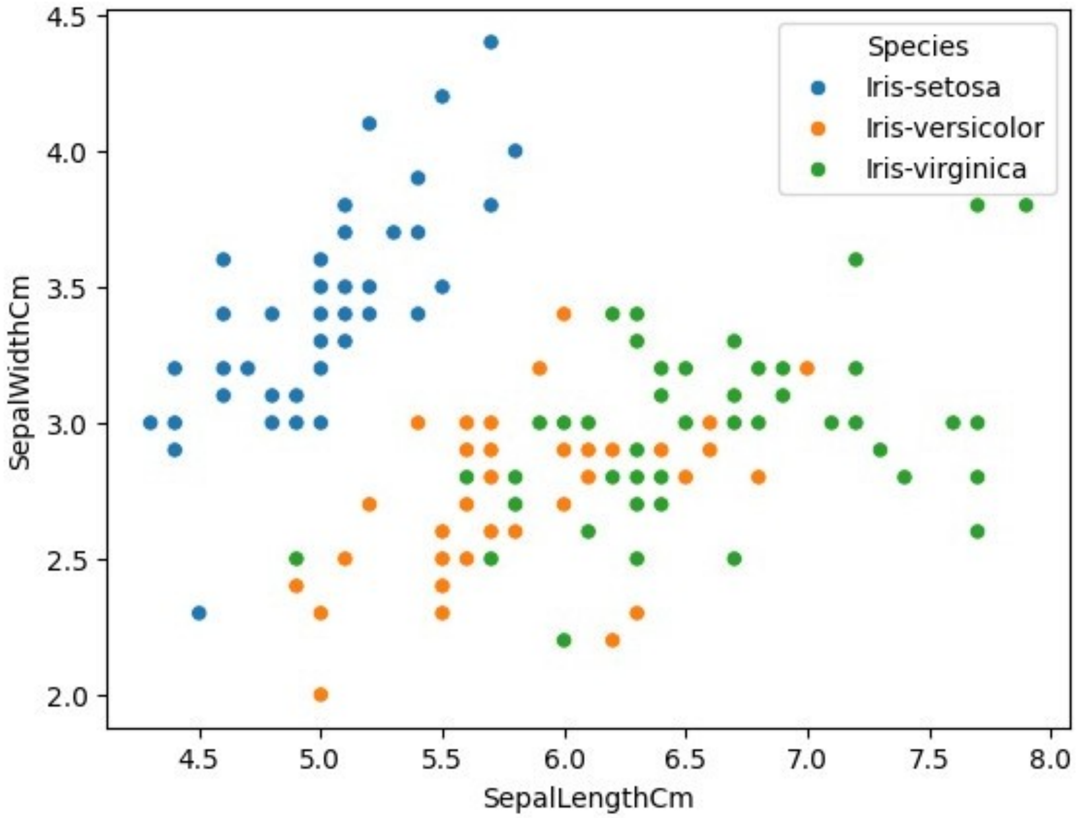
```
)Species

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

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



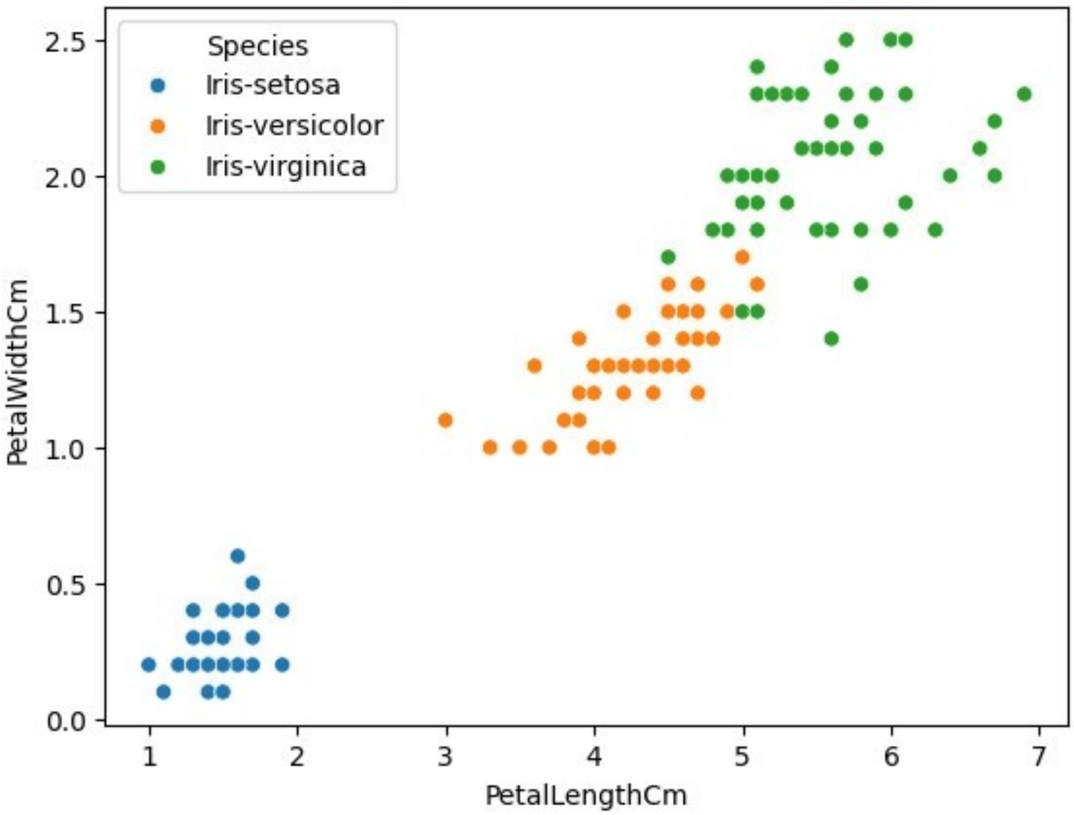

```
dummies=pd.get_dummies(data.Species)

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

FinalDataset.head()
```

```
   SepalWidthCm
PetalLengthCm0              3.5
1.4
1            3.0            1.4
2            3.2            1.3
3            3.1            1.5
```

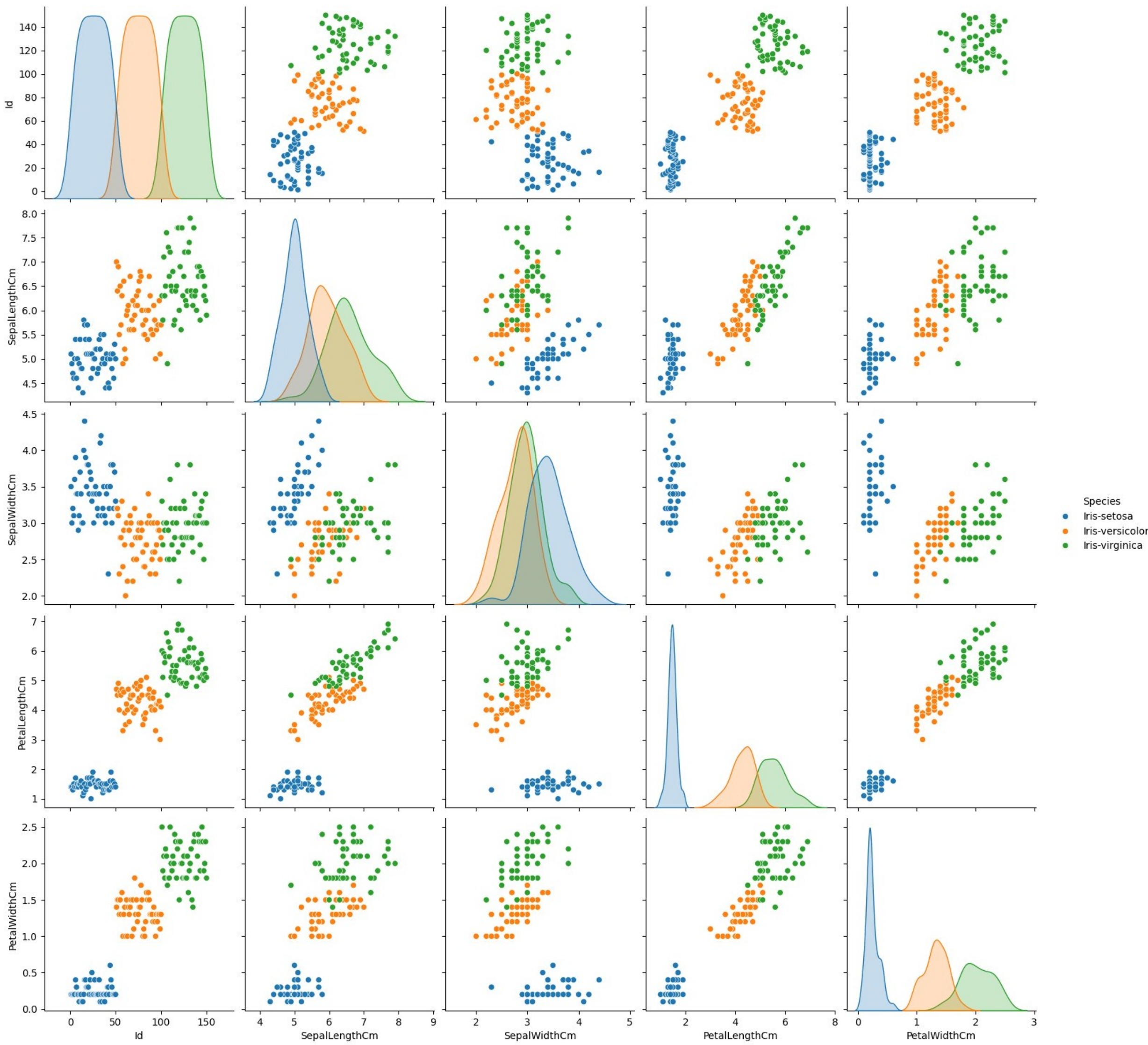



```
sns.scatterplot(x='PetalLengthCm',y='PetalWidthCm',hue='Species',data=
data,)
```

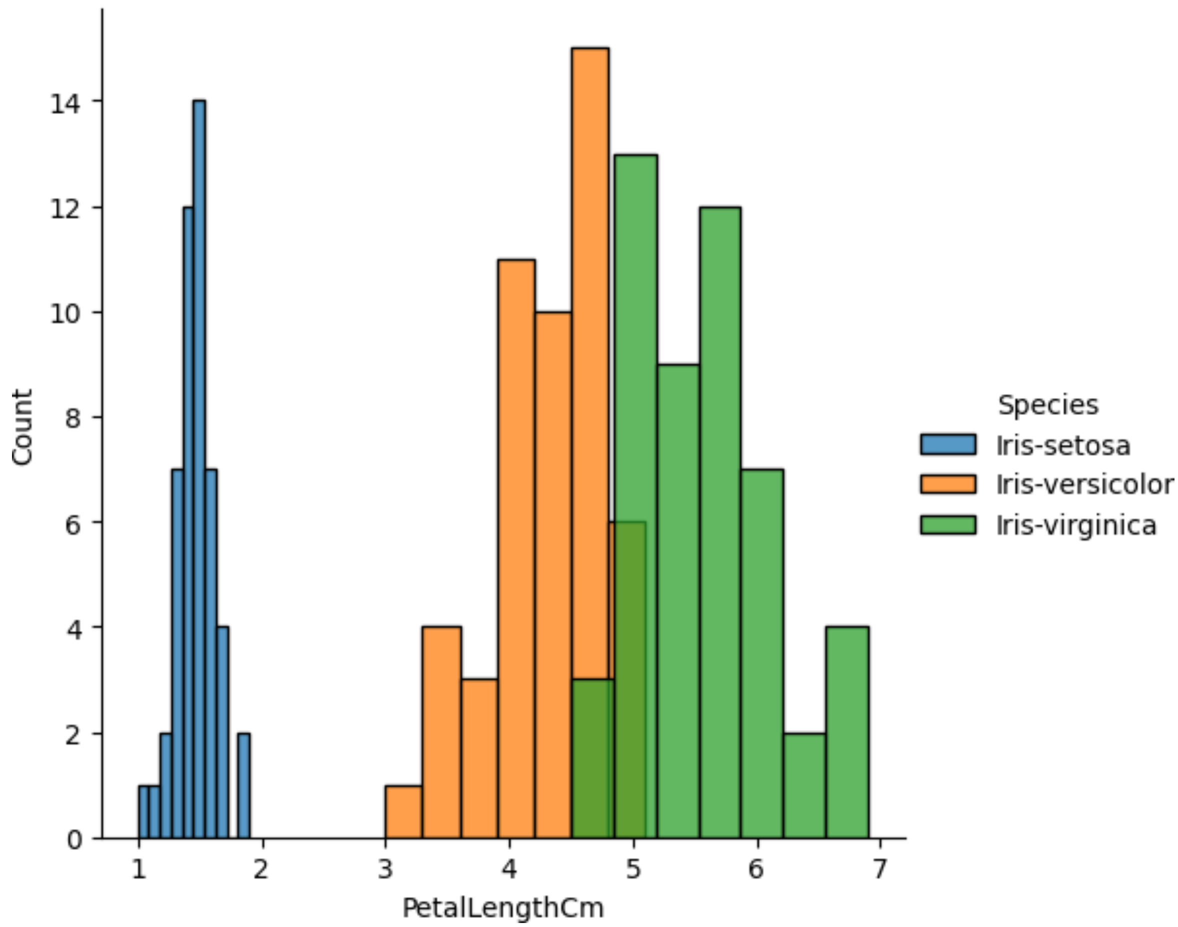
```
<Axes: xlabel='PetalLengthCm', ylabel='PetalWidthCm'>
```



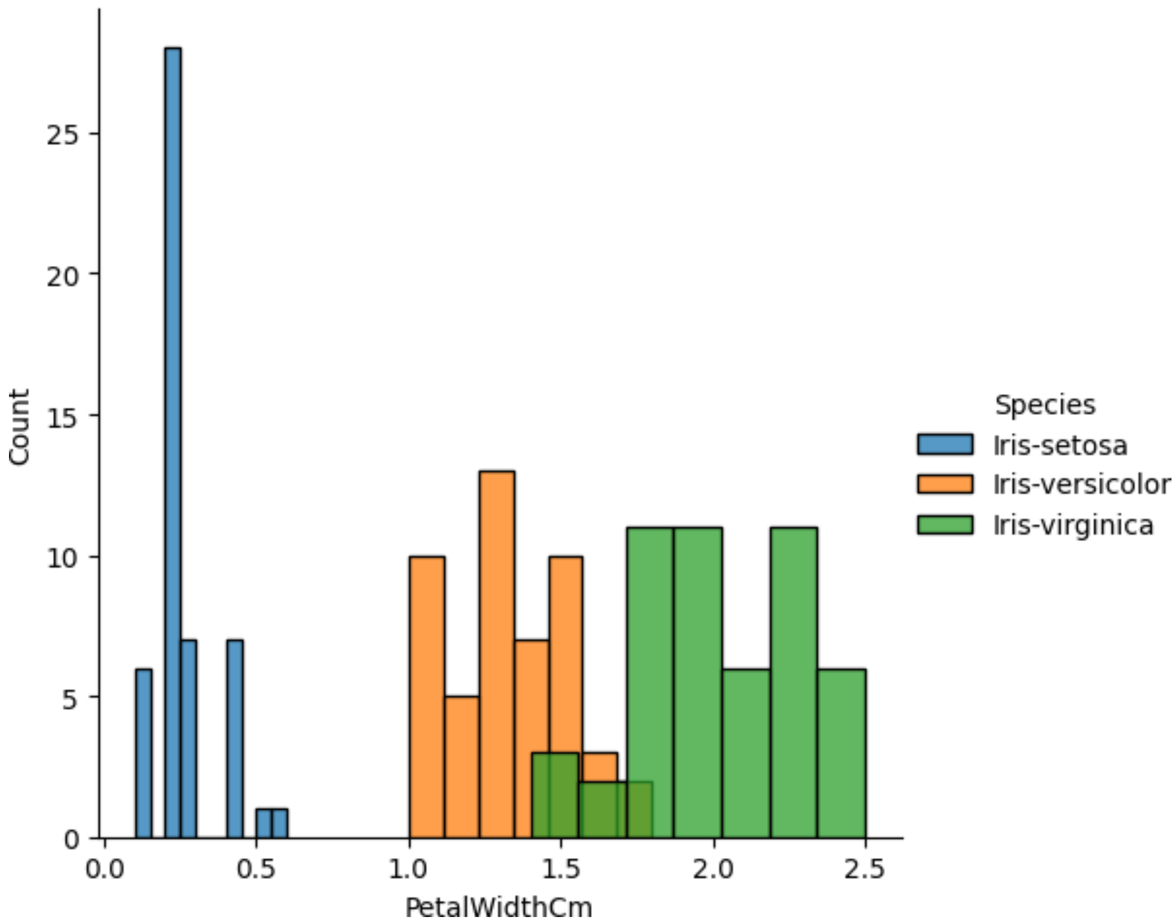

```
sns.pairplot(data,hue='Species',height=3);
```



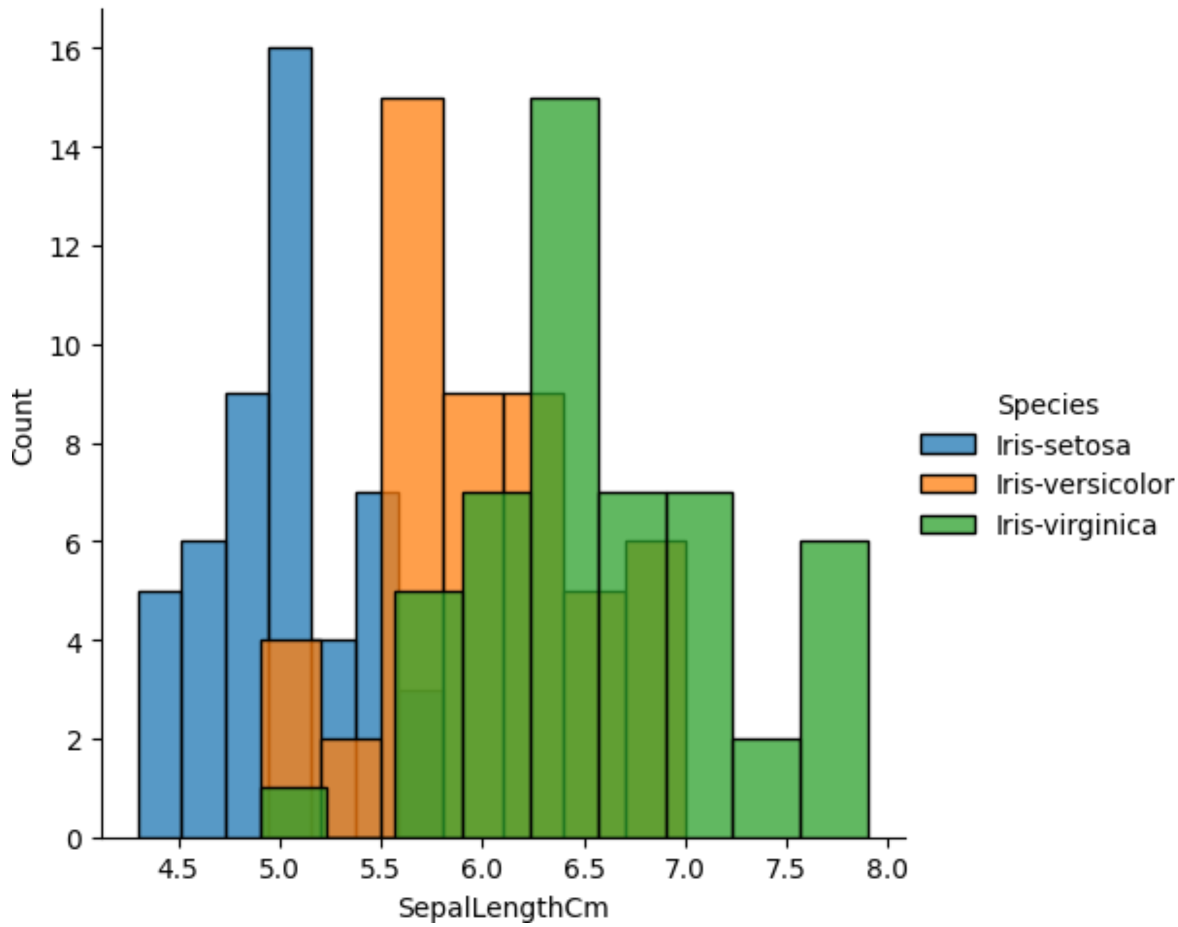

```
plt.show()

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



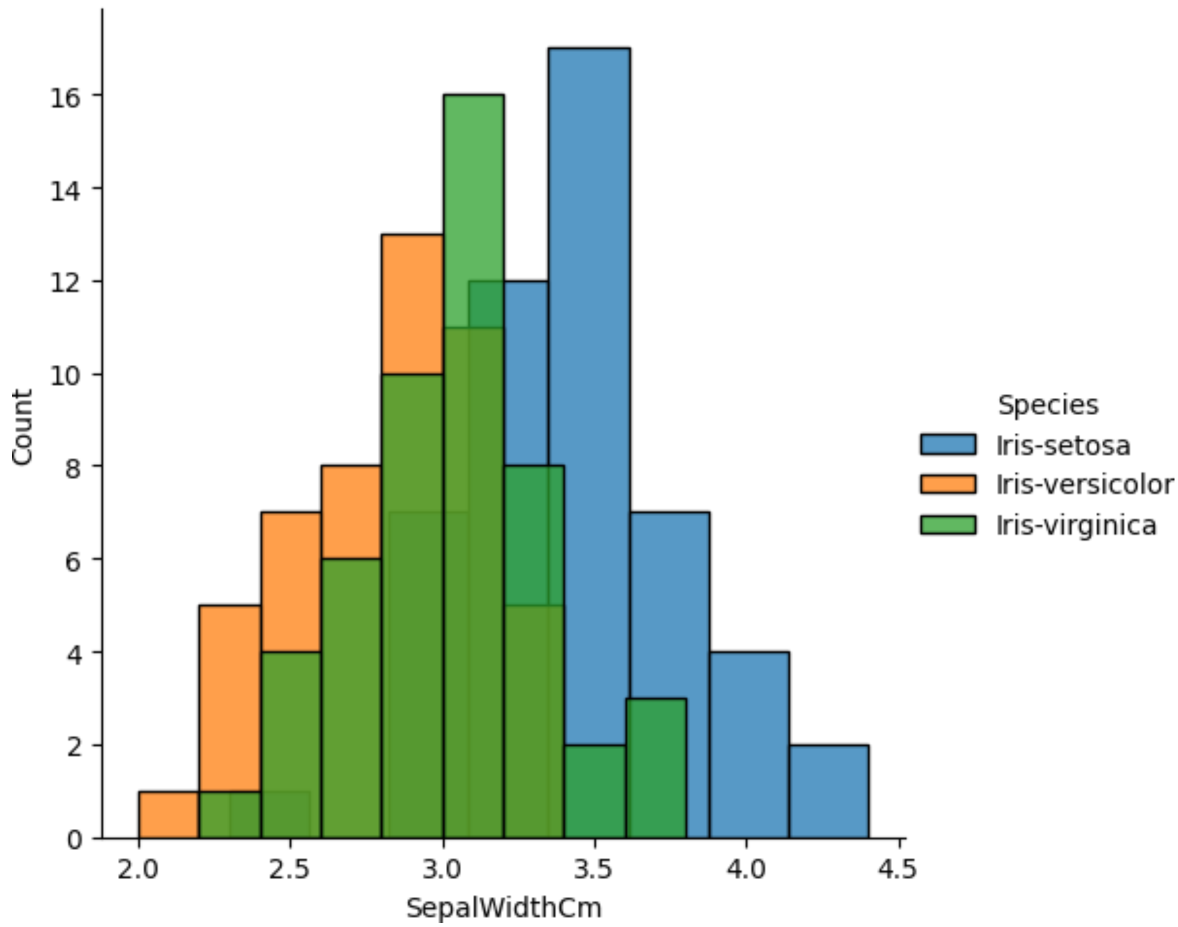

```
sns.FacetGrid(data,hue='Species',height=5).map(sns.histplot,'PetalWidthCm').add_legend();
plt.show();
```




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



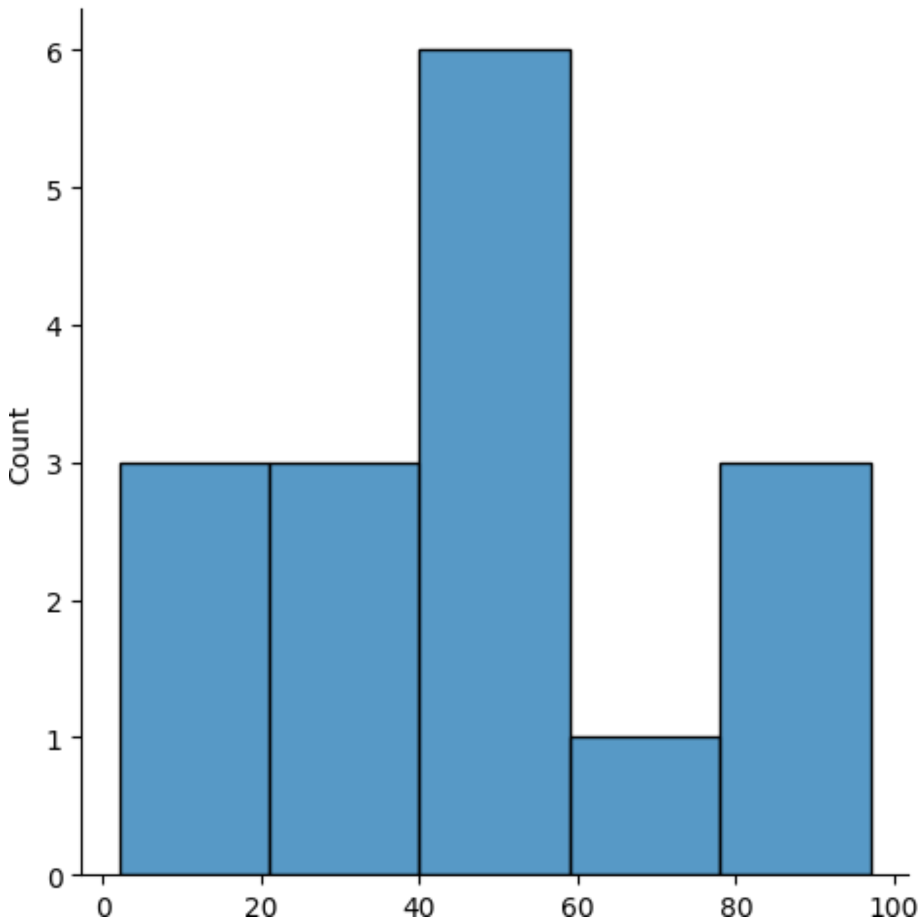

```
sns.FacetGrid(data,hue='Species',height=5).map(sns.histplot,'SepalWidt
hCm').add_legend();
plt.show();
```



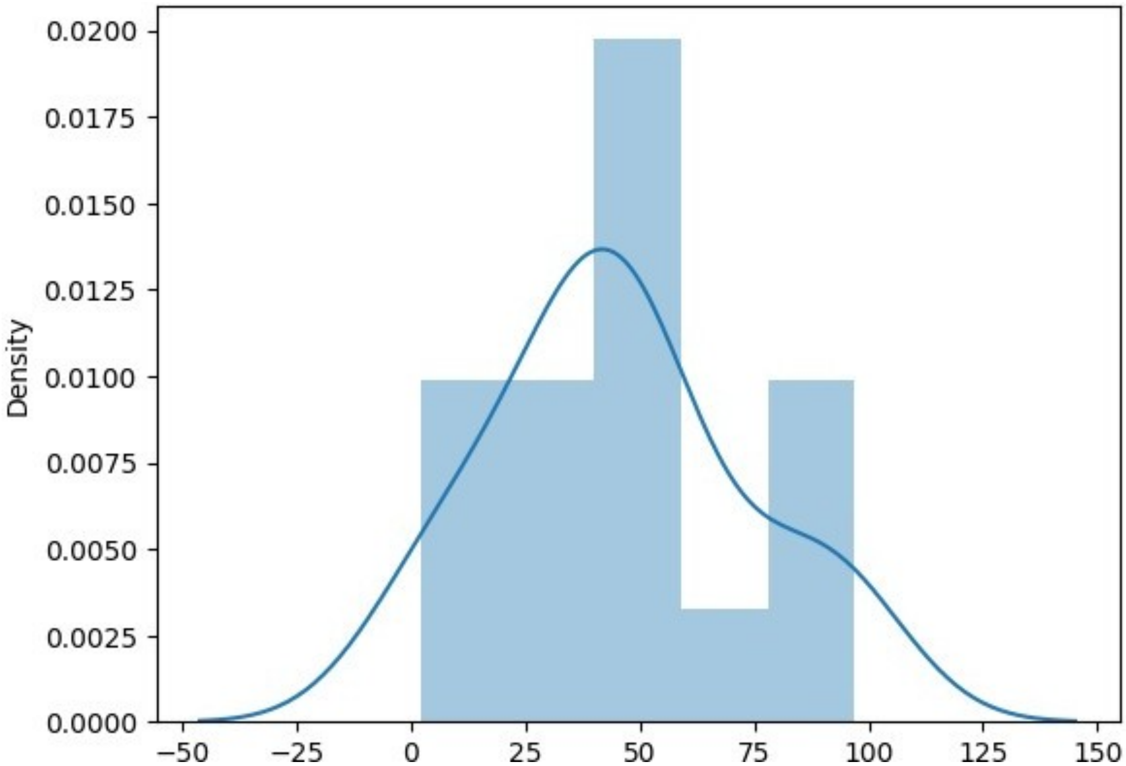

```
#EX.NO :1.b Pandas Buit in function. Numpy Buit in fuction- Array
slicing, Ravel,Reshape,ndim
#DATA  :  06.08.2024

#NAME : AKSHAY . N
#ROLL NO :
230701023
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - A

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])
```

```
1

new_array=array.reshape(3,3

)new_array

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

new_array.ndi

m2

new_array.ravel()

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



newm=new_array.reshape(3,3

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 : GANESHAN M
#ROLL NO : 230701514
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - A

import numpy as
npimport 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
```




```
sns.distplot(array)

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

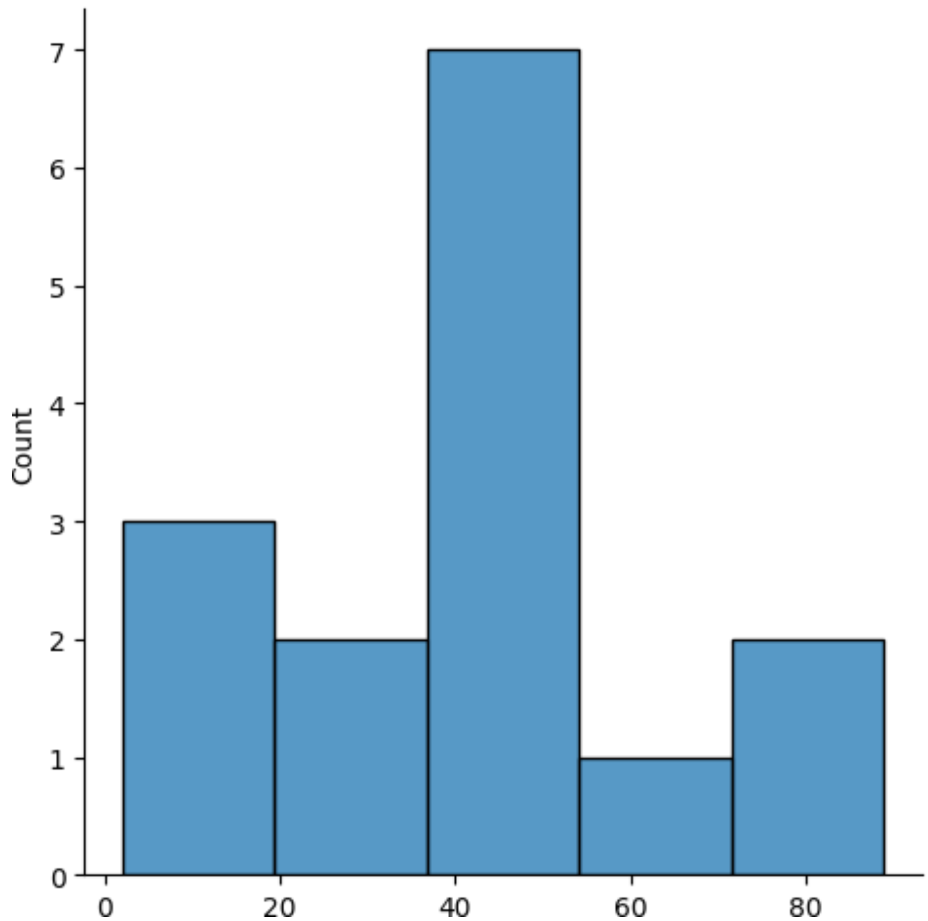



```
new_array=array[(array>lr) & (array<ur)]
new_array
```

```
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
```

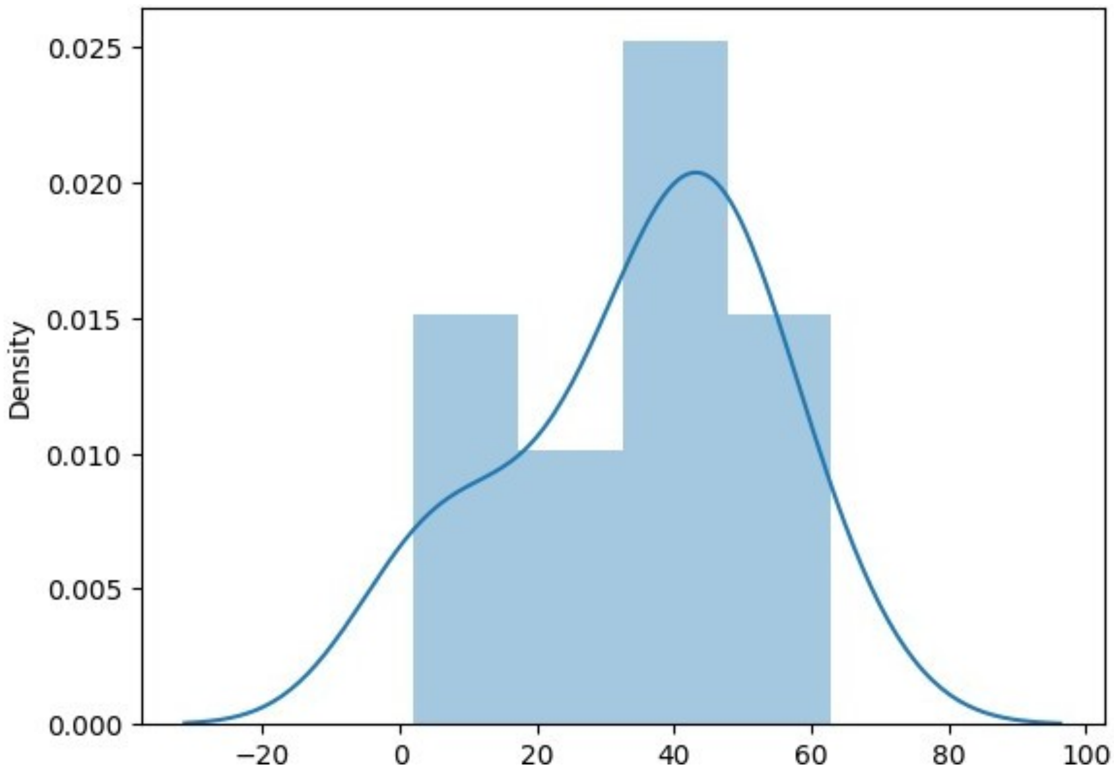
```
(-5.25, 84.75)
```

```
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 : AKSHAY . N
#ROLL NO : 230701023
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - A

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

	CustomerID	Age_Group	Rating(1-5)	Hotel	FoodPreference	Bill
\						
0	1	20-25	4	Ibis	veg	1300
1	2	30-35	5	LemonTree	Non-Veg	2000
2	3	25-30	6	RedFox	Veg	1322

3	4	20-25	-1	LemonTree	Veg	1234
4	5	35+	3	Ibis	Vegetarian	989

5	6	35+	3	Ibys	Non-Veg	1909
6	7	35+	4	RedFox	Vegetarian	1000
7	8	20-25	7	LemonTree	Veg	2999
8	9	25-30	2	Ibis	Non-Veg	3456
9	9	25-30	2	Ibis	Non-Veg	3456
10	10	30-35	5	RedFox	non-Veg	-6755

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

```
df.duplicated()
```

```
df.info()
```

```
<class
'pandas.core.frame.DataFrame'>
RangeIndex: 11 entries, 0 to 10
Data columns (total 9 columns):
 #    Column           Non-Null         Dty
                       Count             pe
--   -----------------  ---
 0    CustomerID       11 non-null      int
                                         64
 1   Age_Group        11 non-null     object
 2   Rating(1-5)      11 non-null     int64
```

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

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

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

	NoOfPax	EstimatedSalary	Age_Group.1
0	2	40000	20-25
1	3	59000	30-35

```
2        2        30000    25-30
3        2       120000    20-25
4        2        45000      35+
5        2       122220      35+
6       -1        21122      35+
7      -10       345673    20-25
8        3       -99999    25-30
10       4        87777    30-35
```

```
len(df)
```

```
10
```

```python
index=np.array(list(range(0,len(df))))
df.set_index(index,inplace=True)
index
```

```
array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
```

```python
df
```

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

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

```
2
```

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

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

```
1            2     30-35            5    LemonTre        Non-Veg  2000
                                                e
3
2            3     25-30            6      RedFox            Veg  1322
2
3            4     20-25           -1    LemonTre            Veg  1234
                                                e
2
4            5       35+            3       Ibis      Vegetarian   989
2
5            6       35+            3       Ibys         Non-Veg  1909
2
6            7       35+            4      RedFox     Vegetarian  1000
-1
7            8     20-25            7    LemonTre            Veg  2999
                                                e
-10
8            9     25-30            2       Ibis         Non-Veg  3456
3
9           10     30-35            5      RedFox        non-Veg  -675
                                                                     5
4
```

```
   EstimatedSalar
y0          40000
1           59000
2           30000
3          120000
4           45000
5          122220
6           21122
7          345673
8          -99999
9           87777
```

```
df.CustomerID.loc[df.CustomerID<0]=np.nan
df.Bill.loc[df.Bill<0]=np.nan
df.EstimatedSalary.loc[df.EstimatedSalary<0]=np.nan
df
```

```
   CustomerI  Age_Grou  Rating(1-5     Hotel  FoodPreferenc    Bill
           D         p           )                        e
\
```

0	1.0	20-25	4	Ibis	veg	1300.0
1	2.0	30-35	5	LemonTree	Non-Veg	2000.0
2	3.0	25-30	6	RedFox	Veg	1322.0
3	4.0	20-25	-1	LemonTree	Veg	1234.0
4	5.0	35+	3	Ibis	Vegetarian	989.0
5	6.0	35+	3	Ibys	Non-Veg	1909.0

6	7.0	35+	4	RedFox	Vegetarian	1000.0
7	8.0	20-25	7	LemonTree	Veg	2999.0
8	9.0	25-30	2	Ibis	Non-Veg	3456.0
9	10.0	30-35	5	RedFox	non-Veg	NaN

	NoOfPax	EstimatedSalary
0	2	40000.0
1	3	59000.0
2	2	30000.0
3	2	120000.0
4	2	45000.0
5	2	122220.0
6	-1	21122.0
7	-10	345673.0
8	3	NaN
9	4	87777.0

```
df['NoOfPax'].loc[(df['NoOfPax']<1) | (df['NoOfPax']>20)]=np.nan
df
```

	CustomerID	Age_Group	Rating(1-5)	Hotel	FoodPreference	Bill
\						
0	1.0	20-25	4	Ibis	veg	1300.0
1	2.0	30-35	5	LemonTree	Non-Veg	2000.0
2	3.0	25-30	6	RedFox	Veg	1322.0
3	4.0	20-25	-1	LemonTree	Veg	1234.0

4	5.0	35+	3	Ibis	Vegetarian	989.0
5	6.0	35+	3	Ibys	Non-Veg	1909.0
6	7.0	35+	4	RedFox	Vegetarian	1000.0
7	8.0	20-25	7	LemonTree	Veg	2999.0
8	9.0	25-30	2	Ibis	Non-Veg	3456.0
9	10.0	30-35	5	RedFox	non-Veg	NaN

	NoOfPax	EstimatedSalary
0	2.0	40000.0
1	3.0	59000.0
2	2.0	30000.0

3	2.0	120000.0
4	2.0	45000.0
5	2.0	122220.0
6	NaN	21122.0
7	NaN	345673.0
8	3.0	NaN
9	4.0	87777.0

```
df.Age_Group.unique()
```

```
array(['20-25', '30-35', '25-30', '35+'], dtype=object)
```

```
df.Hotel.unique()
```

```
array(['Ibis', 'LemonTree', 'RedFox', 'Ibys'], dtype=object)
```

```
df.Hotel.replace(['Ibys'],'Ibis',inplace=True)
df.FoodPreference.unique
```

```
<bound method Series.unique of 0          veg
1.      Non-Veg
2.          Veg
3.          Veg
4.   Vegetarian
5.      Non-Veg
6.   Vegetarian
7.          Veg
8.      Non-Veg
9.      non-Veg
Name: FoodPreference, dtype: object>
```

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

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

	CustomerID	Age_Group	Rating(1-5)	Hotel	FoodPreference	Bill
\						
0	1.0	20-25	4	Ibis	Veg	1300.0
1	2.0	30-35	5	LemonTree	Non-Veg	2000.0

2	3.0	25-30	6	RedFox	Veg	1322.0
3	4.0	20-25	-1	LemonTree	Veg	1234.0

4	5.0	35+	3	Ibis	Veg	989.0
5	6.0	35+	3	Ibis	Non-Veg	1909.0
6	7.0	35+	4	RedFox	Veg	1000.0
7	8.0	20-25	7	LemonTree	Veg	2999.0
8	9.0	25-30	2	Ibis	Non-Veg	3456.0
9	10.0	30-35	5	RedFox	Non-Veg	1801.0

	NoOfPax	EstimatedSalary
0	2.0	40000.0
1	3.0	59000.0
2	2.0	30000.0
3	2.0	120000.0
4	2.0	45000.0
5	2.0	122220.0
6	2.0	21122.0
7	2.0	345673.0
8	3.0	96755.0
9	4.0	87777.0

```
#EX.NO :4 Data Preprocessing
#DATA  :  27.08.2024

#NAME : AKSHAY . N
#ROLL NO : 230701023
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - A

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

```
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      float6
 2.  Salary     9 non-null      4

 3   Purchased  10 non-null
objectdtypes: float64(2), object(2)
memory usage: 452.0+

bytesdf.Country.mode()

0    France
Name: Country, dtype:

objectdf.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
```

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

```
   France  Germany  Spain
1.   True    False  False
2.  False    False   True
3.  False     True  False
4.  False    False   True
5.  False     True  False
```

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

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

```
df.info()
```

```
<class
'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 4 columns):
 #   Column     Non-Null Count  Dtype
 0   Country    10 non-null     object
 1   Age        10 non-null     float64
 2   Salary     10 non-null     float64
 3   Purchased  10 non-null
objectdtypes: 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 : GANESHAN M
#ROLL NO : 230701514
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - A

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

```
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      float6
 2.  Salary     9 non-null      4

 3   Purchased  10 non-null
objectdtypes: float64(2), object(2)
memory usage: 452.0+

bytesdf.Country.mode()

0    France
Name: Country, dtype:

objectdf.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
```

```
pd.get_dummies(df.Country)

   France  Germany  Spain
1.   True    False  False
2.  False    False   True
3.  False     True  False
4.  False    False   True
5.  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    Ag    Salary Purchased
0     True    False False  e     72000.0        N
1       False    False      44.0  48000.0        o
2   TrueFalse         True  27.0  54000.0       Ye
3        FalseFalse         30.0  61000.0       sNo
4  se   TrueFalse           38.0  63778.0        No
5              True  False  40.0  58000.0       Ye
6    True    False False    35.0  52000.0        s
7       False    False      38.0  79000.0       Ye
8   TrueTrueFalse  False    48.0  83000.0       sNo
9   False      True  False  50.0  67000.0       Ye
```

```
df.info()
```

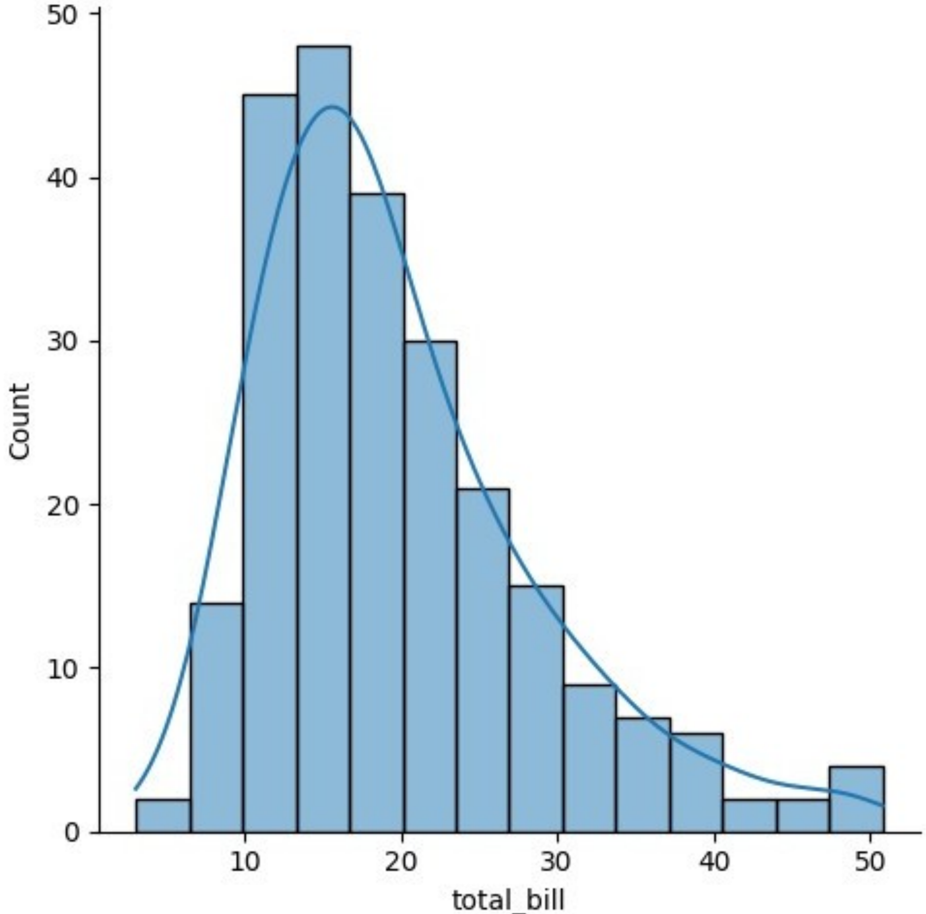
```
<class
'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 4 columns):
 #   Column     Non-Null Count  Dtype
 0   Country    10 non-null     object
 1   Age        10 non-null     float64
 2   Salary     10 non-null     float64
 3   Purchased  10 non-null
objectdtypes: float64(2), object(2)
memory usage: 452.0+
bytesupdated_dataset
```

```
France Germany Spain    Ag    Salary Purchased
```

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

#NAME : AKSHAY . N
#ROLL NO :
230701023
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - A

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

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

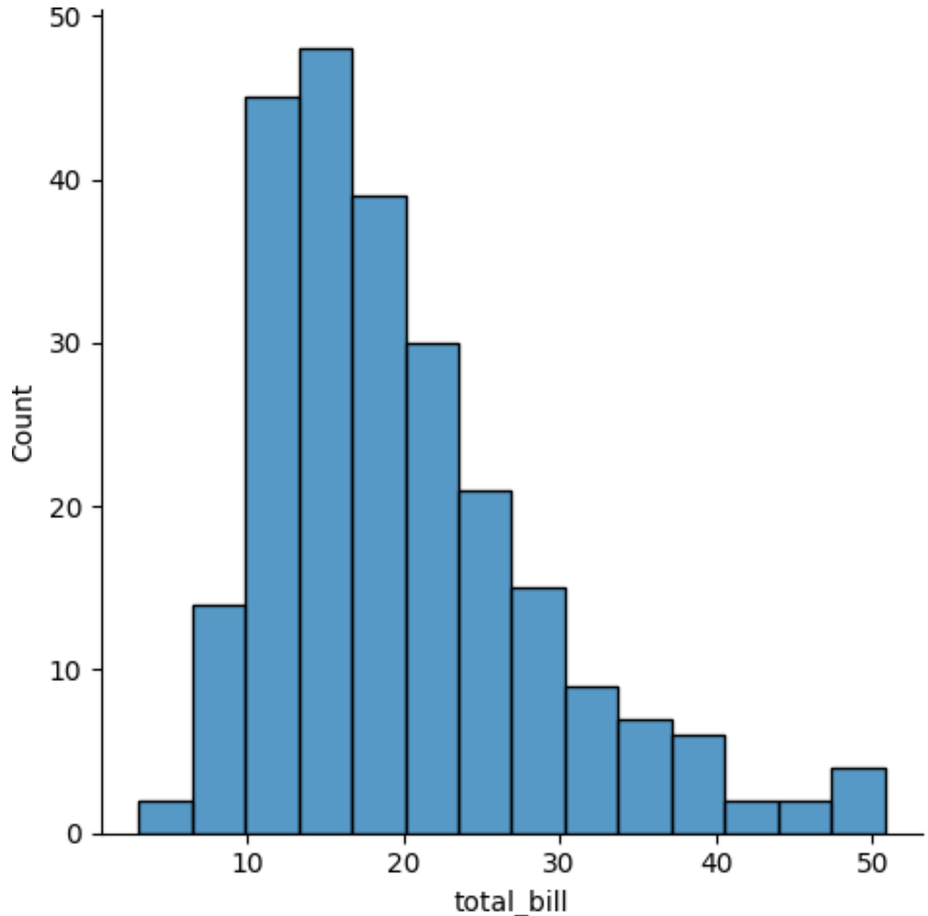
	total_bill	ti	sex		day	time	size
0	16.99	p	smokerFemale	N	Sun	Dinner	2
1	10.34	1.01	Mal	o	Sun	Dinner	3
2	21.01	1.66	eMale	N	Sun	Dinner	3
3	23.68	3.50	Male	o	Sun	Dinner	2
4	24.59	3.31	Female	N	Sun	Dinner	4

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

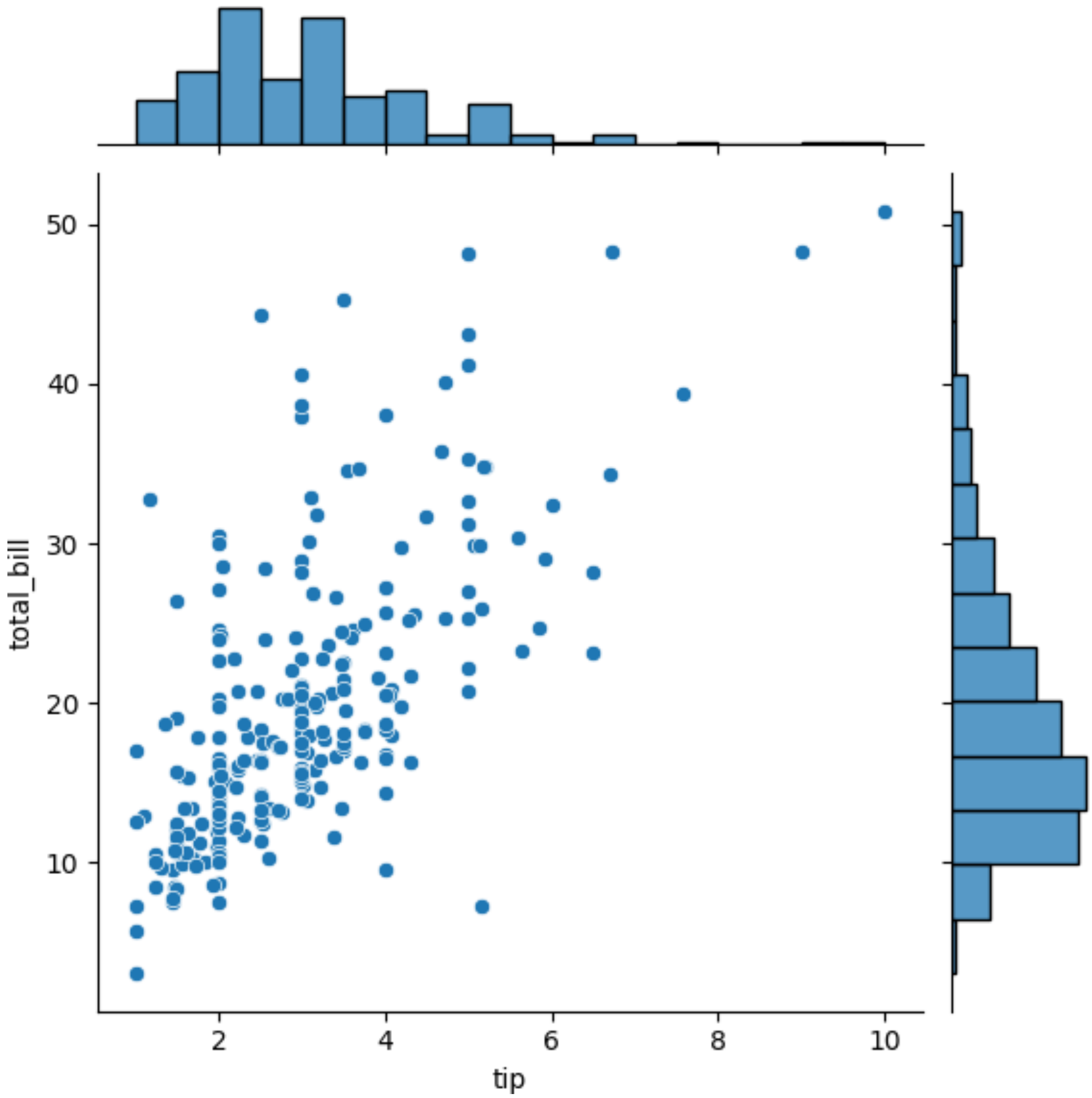



```
sns.displot(tips.total_bill,kde=False)
```

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

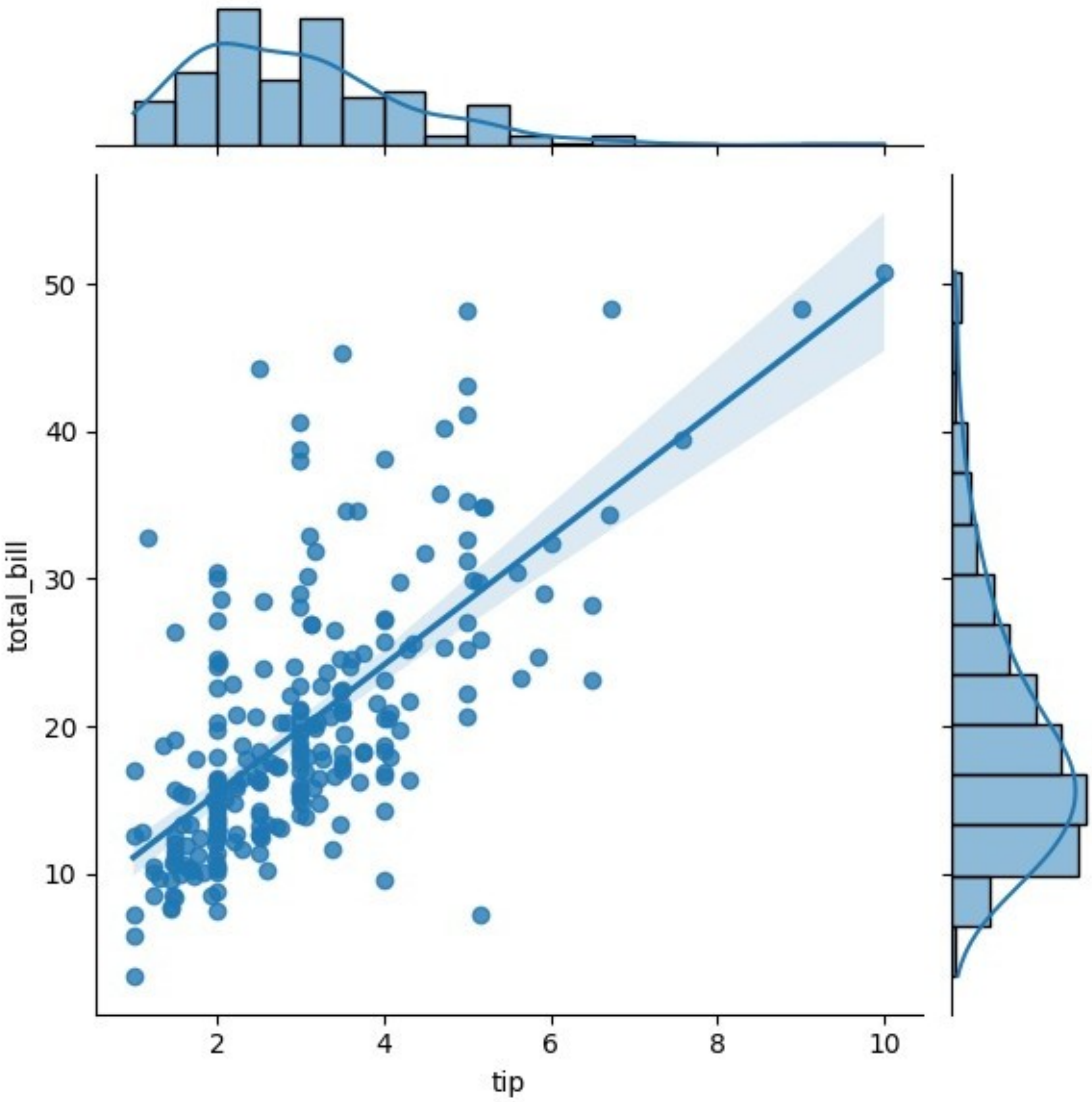



```
sns.jointplot(x=tips.tip,y=tips.total_bill)

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



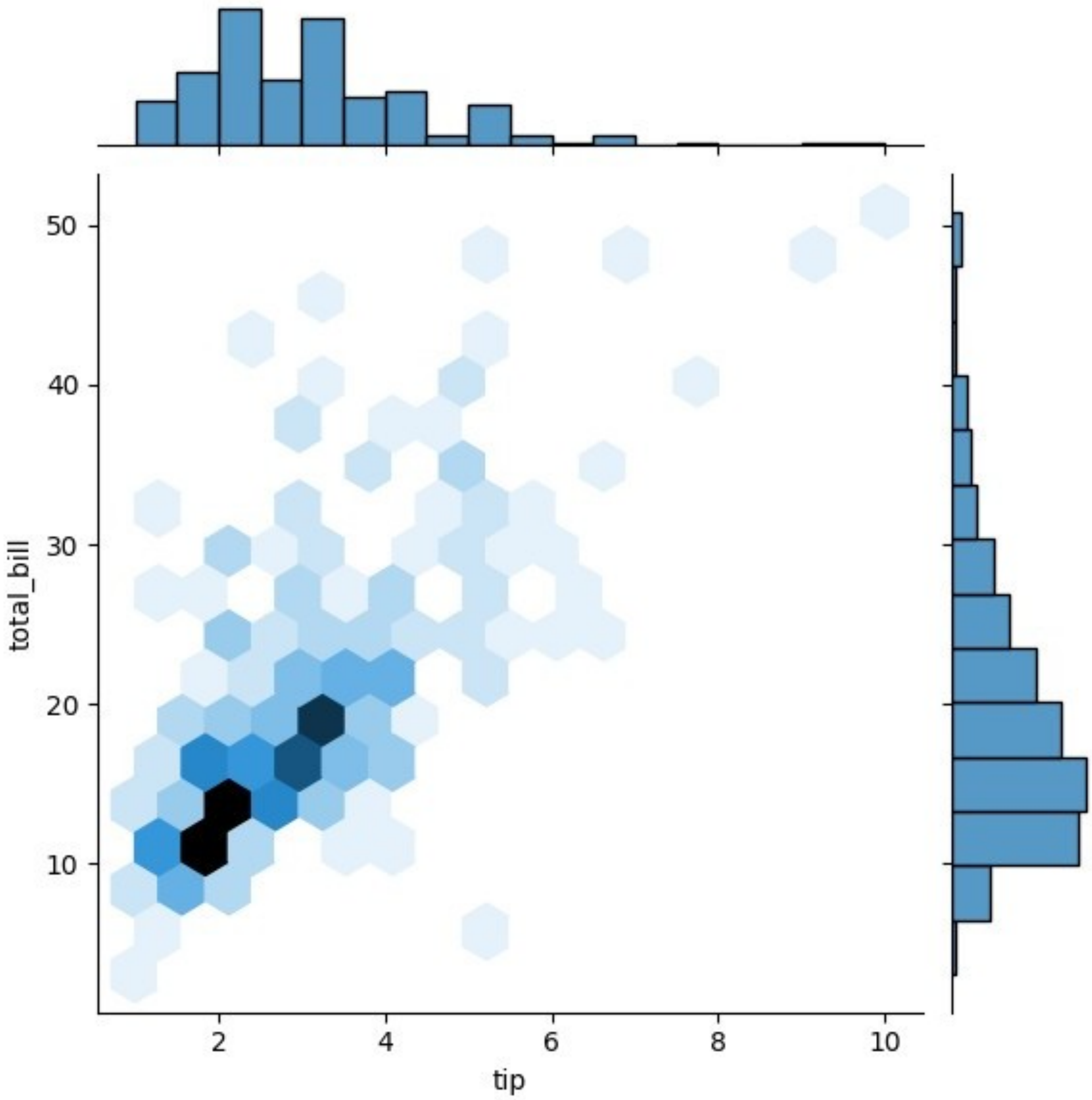

```
sns.jointplot(x=tips.tip,y=tips.total_bill,kind="reg")
```

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



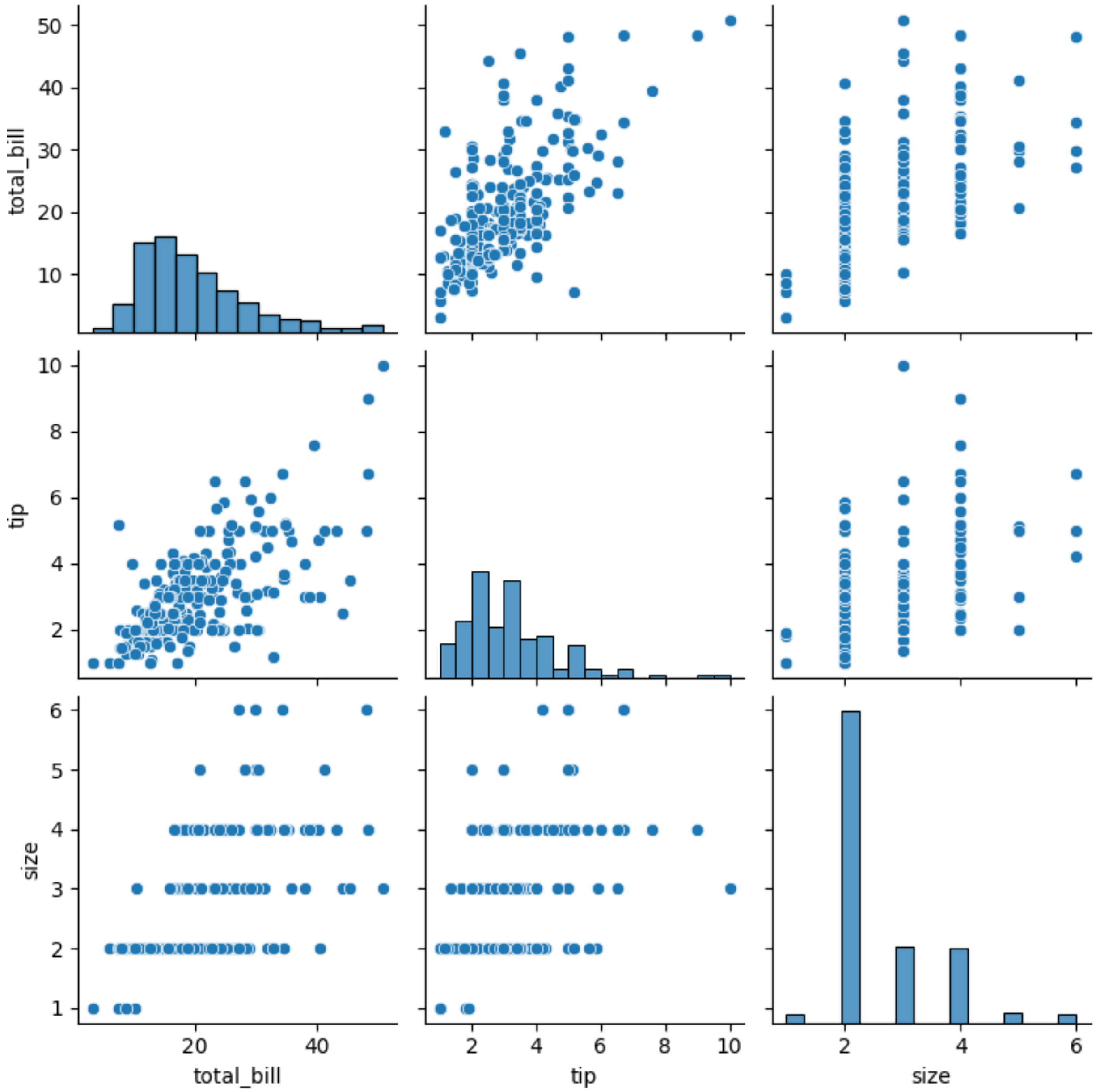

```
sns.jointplot(x=tips.tip,y=tips.total_bill,kind="hex")
```

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




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

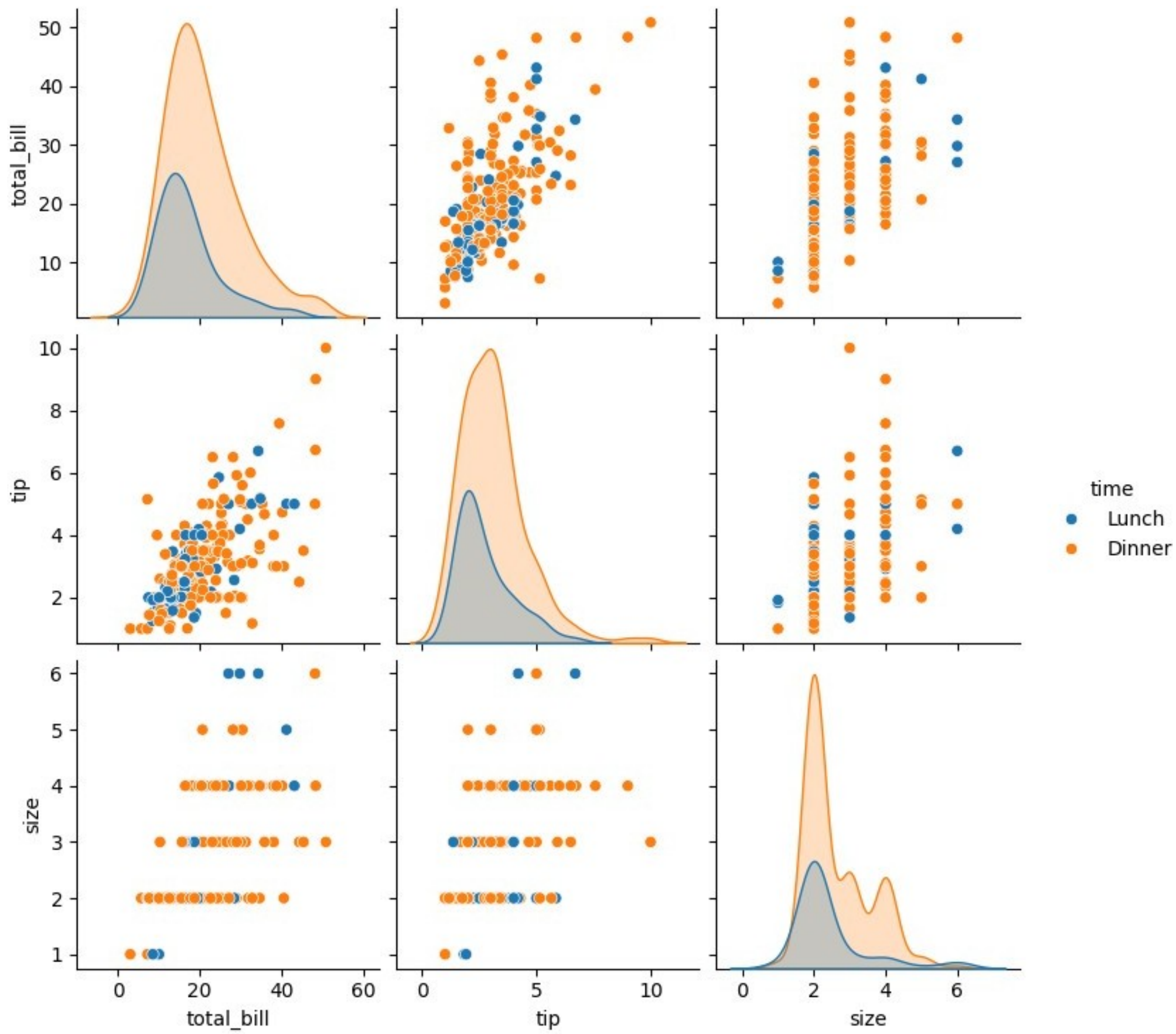
```
<seaborn.axisgrid.PairGrid at 0x20d7f1c9cd0>
```




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

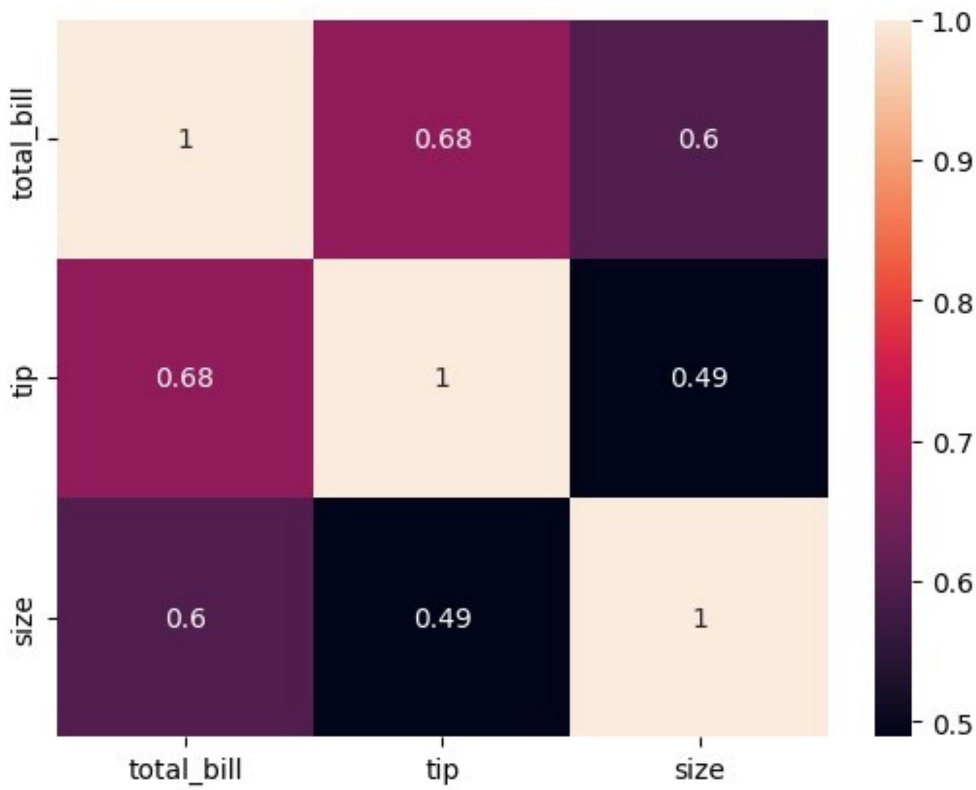
```
time
Dinner    176
Lunch      68
Name: count, dtype: int64
```

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

)
```



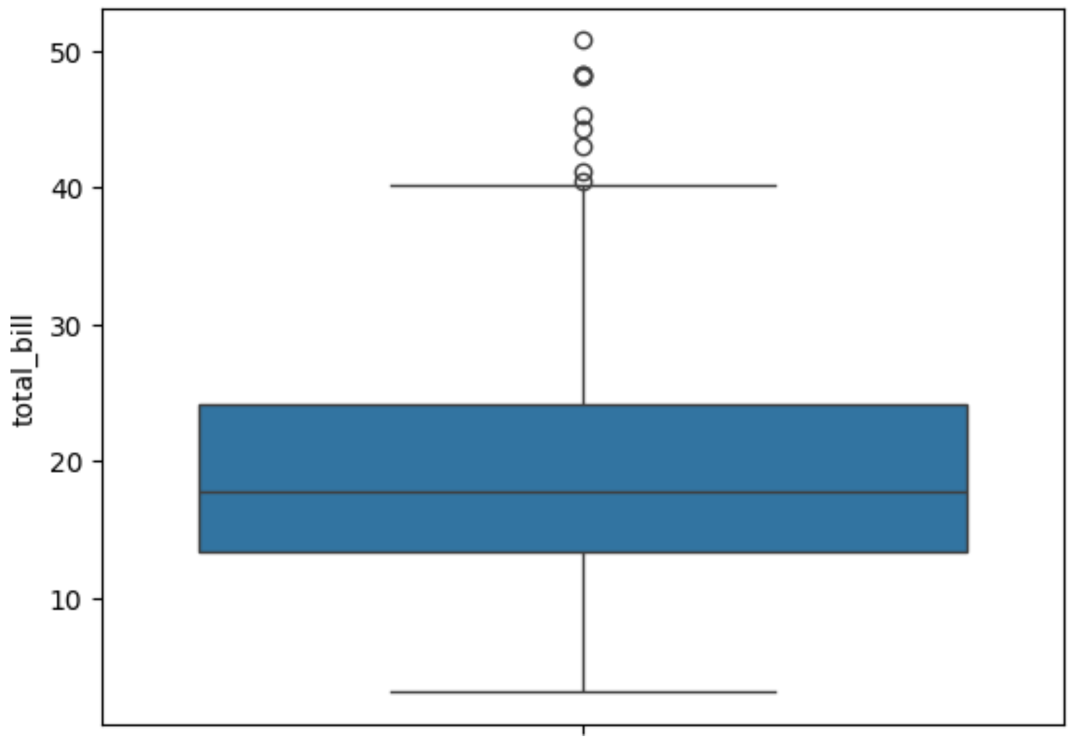

```
sns.heatmap(tips.corr(numeric_only=True),annot=True)
```

```
<Axes: >
```



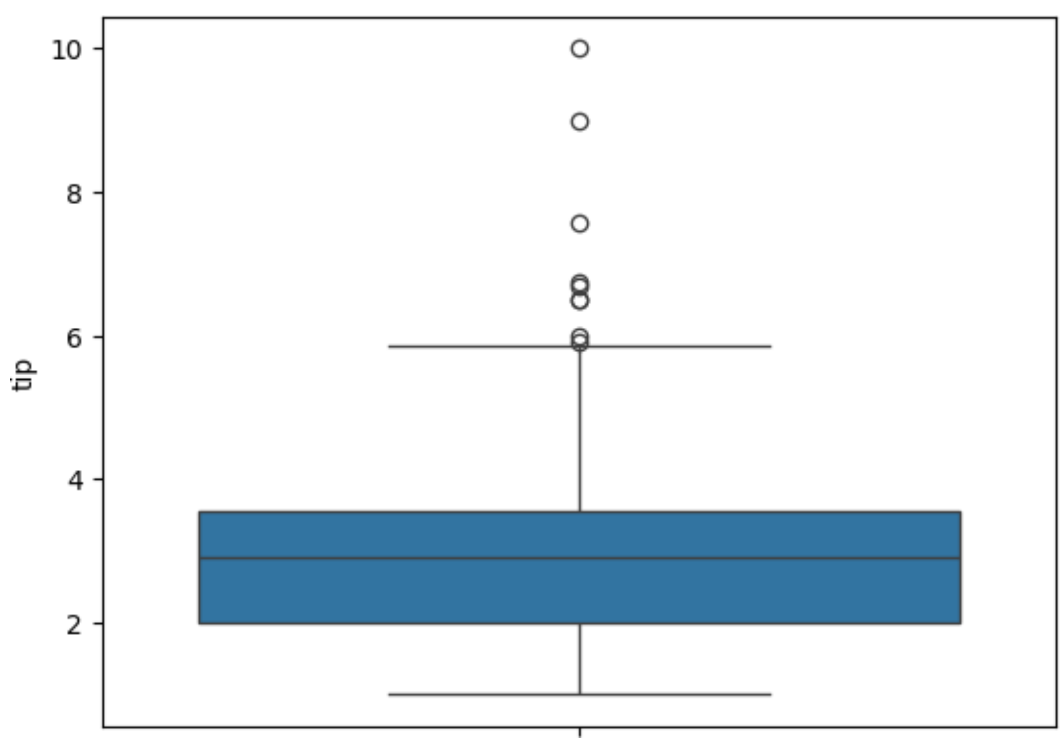

```
sns.boxplot(tips.total_bill)
```

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



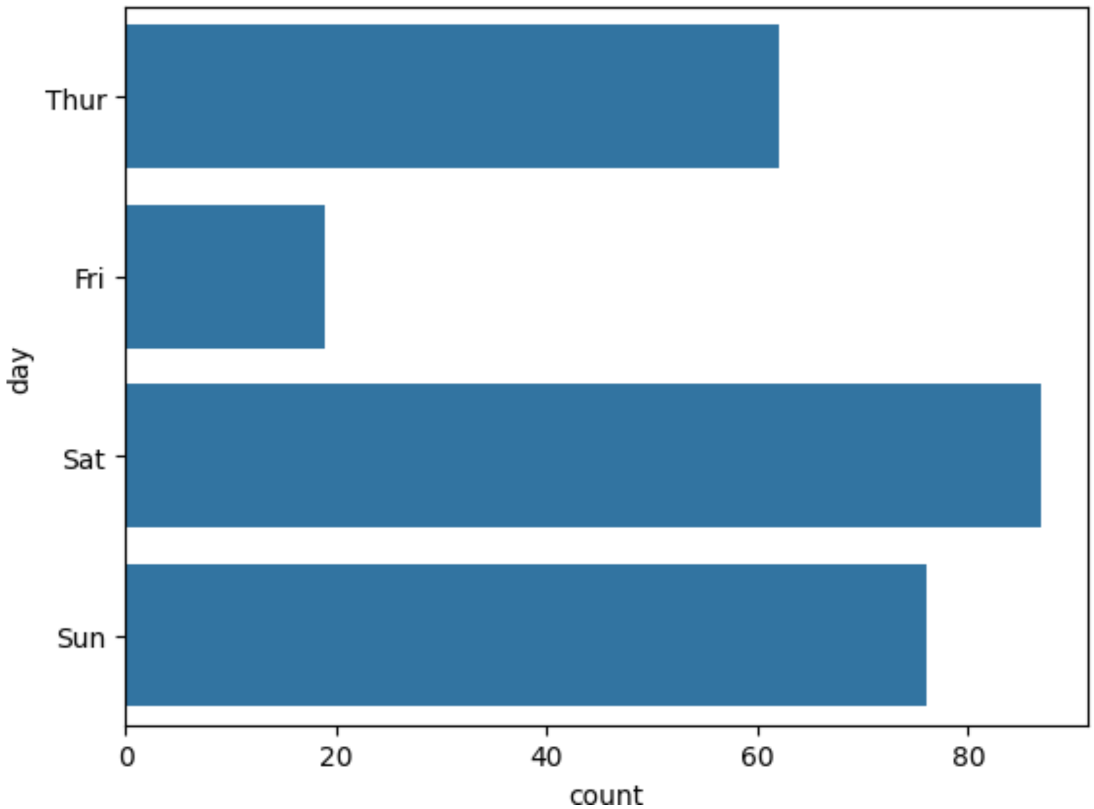

```
sns.boxplot(tips.tip)
```

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



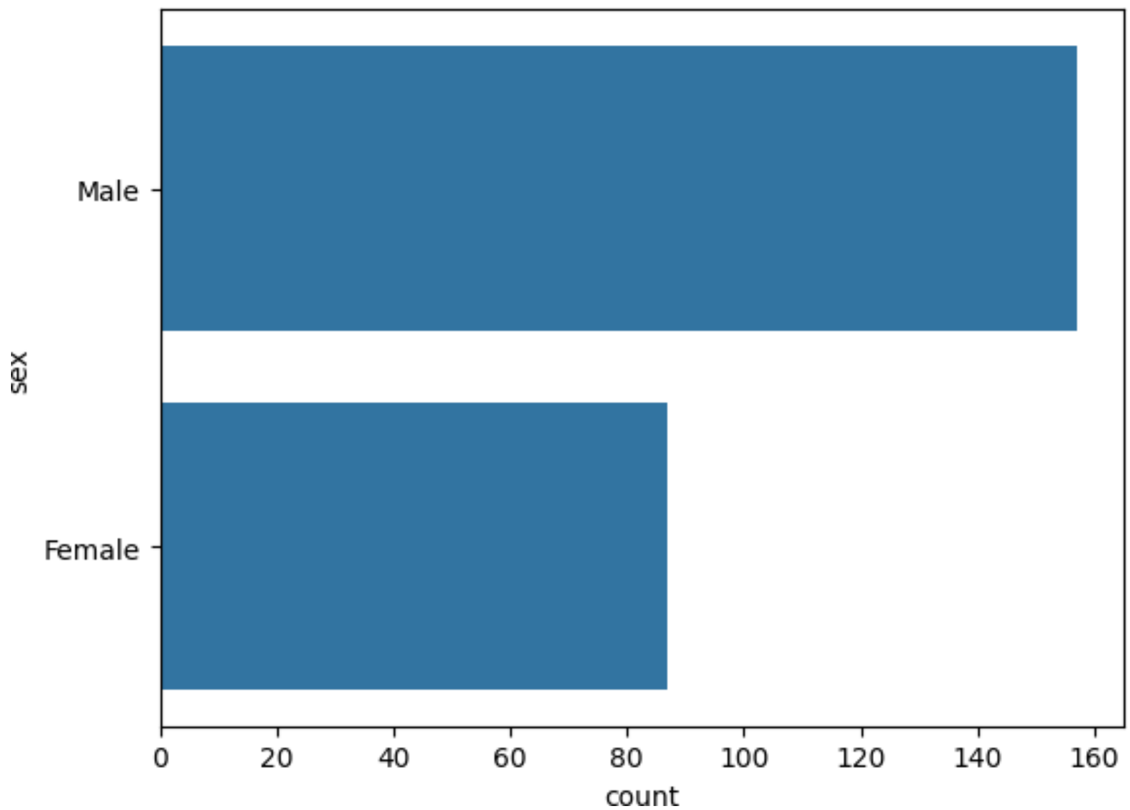
```
sns.countplot(tips.day)
```

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



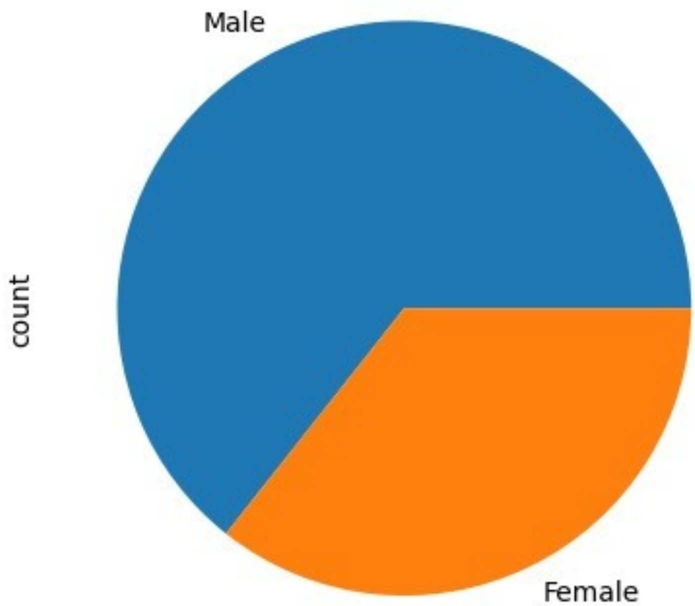

```
sns.countplot(tips.sex)
```

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



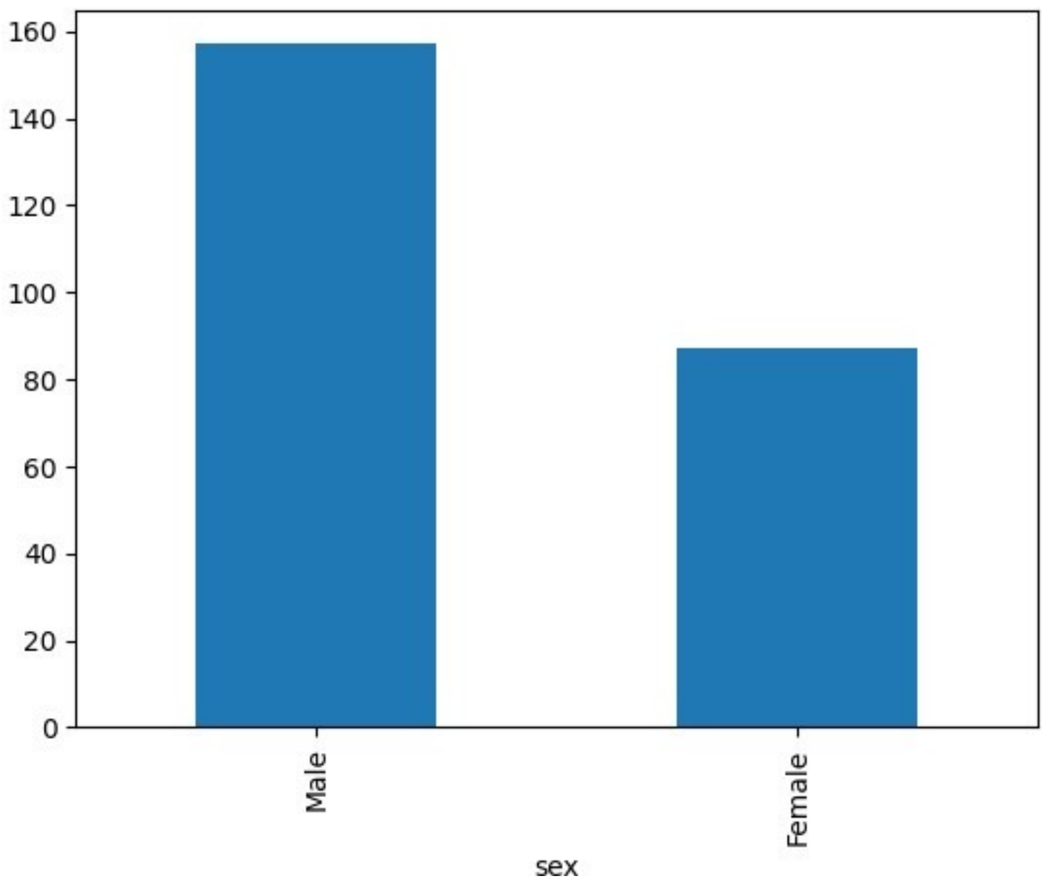

```
tips.sex.value_counts().plot(kind='pie')
```

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



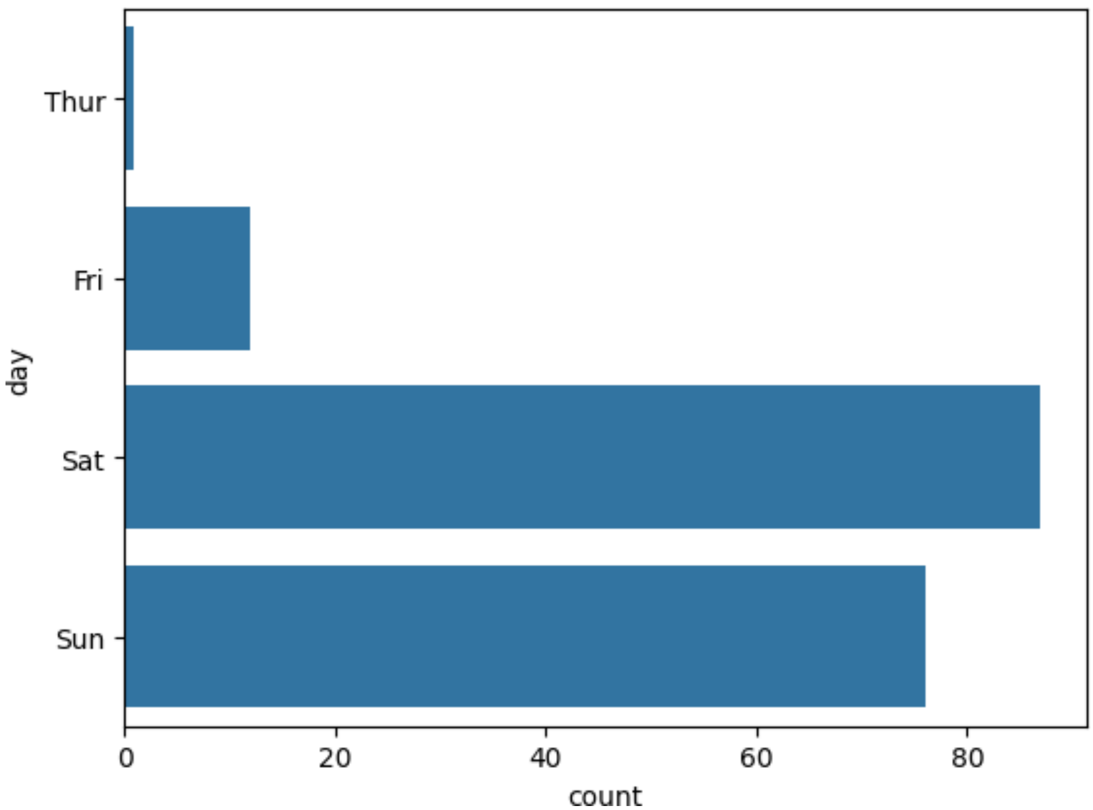

```
tips.sex.value_counts().plot(kind='bar')
```

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



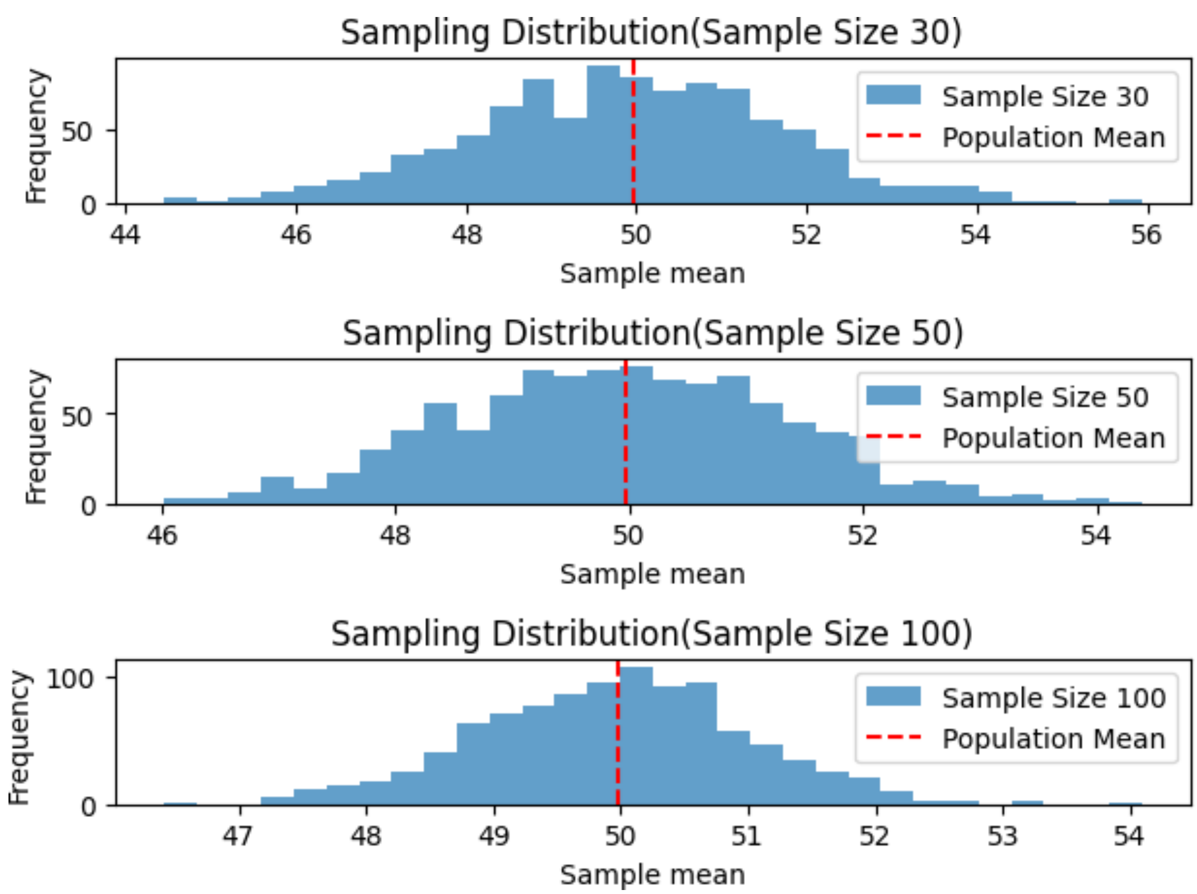

```
sns.countplot(tips[tips.time=='Dinner']['day'])
```

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




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

#NAME : AKSHAY . N
#ROLL NO : 230701023
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - A

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 : AKSHAY . N
#ROLL NO : 230701023
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - A

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
beencalculated:
print(f"Sample Mean: {sample_mean:.2f}
\n")print(f"Z-Statistic: {z_statistic:.4f}
\n")print(f"P-Value: {p_value:.4f}\n")

# Significance level
alpha = 0.05

# Decision based on p-value
if p_value < alpha:
    print("Reject the null hypothesis: The average weight is
significantly different from 150 grams.")
else:
    print("Fail to reject the null hypothesis: There is no significant
difference in average weight from 150 grams.")
```

```
Sample Mean: 150.20

Z-Statistic: 0.6406

P-Value: 0.5218

Fail to reject the null hypothesis: There is no significant difference
in average weight from 150 grams.
```

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

#NAME : AKSHAY . N
```

```
#ROLL NO : 230701002
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - A

import numpy as np
import scipy.stats as
statsnp.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
beencalculated:
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 : AKSHAY . N
#ROLL NO : 230701002
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - A

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

```
from statsmodels.stats.multicomp import pairwise_tukeyhsd

np.random.seed(42
)n_plants = 25

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

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

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

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

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


if p_value < alpha:

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

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

```
Treatment A Mean Growth: 9.6730
Treatment B Mean Growth:
11.1377Treatment C Mean Growth:
15.2652F-Statistic: 36.1214
P-Value: 0.0000
Reject the null hypothesis: There is a significant difference in mean
growth rates among the three treatments.

Tukey's HSD Post-hoc Test:
Multiple Comparison of Means - Tukey HSD, FWER=0.05
```

```
==================================================
==
group1 group2 meandiff p-adj   lower  upper
reject
--------------------------------------------------
    A      B   1.4647  0.087  -0.168  3.097   Fals
                           7       3  7          e

    A      C   5.5923    0.0  3.9593  7.225   True
                                      2

    B      C   4.1276    0.0  2.4946  5.760   True
                                      5
--------------------------------------------------
```

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

#NAME : AKSHAY . N
#ROLL NO : 230701023
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - A

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

df.head()
```

```
   Countr    Ag    Salary Purchased
0  yFrance   e    72000.0         N
1    Spain  44.0  48000.0         o
2  German   27.0  54000.0        Ye
3    ySpain 30.0  61000.0       sNo
4  Germany  38.0      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, -1.43817841e+00],
       [-8.16496581e-01,  1.52752523e+00, -6.54653671e-01,
        -1.27555478e+00, -8.91265492e-01],
       [-8.16496581e-01, -6.54653671e-01,  1.52752523e+00,
        -1.13023841e-01, -2.53200424e-01],
       [-8.16496581e-01,  1.52752523e+00, -6.54653671e-01,
         1.77608893e-01,  6.63219199e-16],
       [ 1.22474487e+00, -6.54653671e-01, -6.54653671e-01,
        -5.48972942e-01, -5.26656882e-01],
       [-8.16496581e-01, -6.54653671e-01,  1.52752523e+00,
         0.00000000e+00, -1.07356980e+00],
       [ 1.22474487e+00, -6.54653671e-01, -6.54653671e-01,
         1.34013983e+00,  1.38753832e+00],
       [-8.16496581e-01,  1.52752523e+00, -6.54653671e-01,
         1.63077256e+00,  1.75214693e+00],
       [ 1.22474487e+00, -6.54653671e-01, -6.54653671e-01,
        -2.58340208e-01,  2.93712492e-01]])
```

```
from sklearn.preprocessing import MinMaxScaler
mms=MinMaxScaler(feature_range=(0,1))
mms.fit(final_set)
feat_minmax_scaler=mms.transform(final_set)
feat_minmax_scaler
```

```
array([[1.        , 0.        , 0.        , 0.73913043, 0.68571429],
       [0.        , 0.        , 1.        , 0.        , 0.        ],
       [0.        , 1.        , 0.        , 0.13043478, 0.17142857],
       [0.        , 0.        , 1.        , 0.47826087, 0.37142857],
       [0.        , 1.        , 0.        , 0.56521739, 0.45079365],
       [1.        , 0.        , 0.        , 0.34782609, 0.28571429],
```

```
       [0.        ,  0.        ,  1.        ,  0.51207729  0.11428571]
                                                   ,          ,
       [1.        ,  0.        ,  0.        ,  0.91304348  0.88571429]
                                                   ,          ,
       [0.        ,  1.        ,  0.        ,  1.          1.        ]
                                                   ,          ,
       [1.        ,  0.        ,  0.        ,  0.43478261  0.54285714]
                                                   ,          ])
```

```
#EX.NO :11 Linear
Regression#DATA  :
29.10.2024
```

```
#NAME : AKSHAY . N
#ROLL NO : 230701023
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - A


import numpy as np
import pandas as pd
df = pd.read_csv('Salary_data.csv')
df
```

```
    YearsExperience
Salary0          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
```

```
 1.  YearsExperience  30 non-null      float64
 2.  Salary           30 non-null
  int64dtypes: float64(1), int64(1)
memory usage: 612.0 bytes
```

```
df.dropna(inplace=True)
;df
```

```
    YearsExperience
Salary0          1.1   39343
1                1.3   46205
2                1.5   37731
3                2.0   43525
4                2.2   39891
5                2.9   56642
6                3.0   60150
7                3.2   54445
8                3.2   64445
9                3.7   57189
10               3.9   63218
11               4.0   55794
12               4.0   56957
13               4.1   57081
14               4.5   61111
15               4.9   67938
16               5.1   66029
17               5.3   83088
18               5.9   81363
19               6.0   93940
20               6.8   91738
21               7.1   98273
22               7.9  101302
23               8.2  113812
24               8.7  109431
25               9.0  105582
26               9.5  116969
27               9.6  112635
28              10.3  122391
29              10.5  121872
```

```
df.info()
```

```
<class
'pandas.core.frame.DataFrame'>
RangeIndex: 30 entries, 0 to 29
Data columns (total 2 columns):
 #   Column           Non-Null Count  Dtype

 0   YearsExperience  30 non-null      float64
 1   Salary           30 non-null      int64
```

```
dtypes: float64(1),
int64(1)memory usage: 612.0
bytes
```

```
df.describe()  #descripte statical
report# find out lYER FOR BELOW META DATA
```

	YearsExperience	Salary
count	30.000000	30.000000
mean	5.313333	76003.000000
std	2.837888	27414.429785
min	1.100000	37731.000000
25%	3.200000	56720.750000
50%	4.700000	65237.000000
75%	7.700000	100544.750000
max	10.500000	122391.000000

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

#iloc index based selection loc location based sentence

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

features
```

```
array([[ 1.1],
       [ 1.3],
       [ 1.5],
       [ 2. ],
       [ 2.2],
       [ 2.9],
       [ 3. ],
       [ 3.2],
       [ 3.2],
```

```
[  3.7]
      ,
[  3.9]
      ,
[  4. ]
      ,
[  4. ]
      ,
[  4.1]
      ,
[  4.5]
      ,
[  4.9]
      ,
[  5.1]
      ,
[  5.3]
      ,
[  5.9]
      ,
[  6. ]
      ,
[  6.8]
      ,
[  7.1]
      ,
[  7.9]
      ,
[  8.2]
      ,
[  8.7]
      ,
[  9. ]
      ,
```

```
       [ 9.5],
       [ 9.6],
       [10.3],
       [10.5]])
```

label

```
array([[ 39343],
       [ 46205],
       [ 37731],
       [ 43525],
       [ 39891],
       [ 56642],
       [ 60150],
       [ 54445],
       [ 64445],
       [ 57189],
       [ 63218],
       [ 55794],
       [ 56957],
       [ 57081],
       [ 61111],
       [ 67938],
       [ 66029],
       [ 83088],
       [ 81363],
       [ 93940],
```

```
       [  91738]
              ,
       [  98273]
              ,
       [101302],
       [113812],
       [109431],
       [105582],
       [116969],
       [112635],
       [122391],
       [121872]], dtype=int64)
```

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test =
train_test_split(features,label,test_size=0.2,random_state=23
)# x independent input  train 80 % test 20 %
'''
y is depenent ouput
0.2 allocate test for 20 % automatically train for 80
%'''
```

```
'\ny is depenent ouput\n0.2 allocate test for 20 % automatically train
for 80 %\n'
```

```
from sklearn.linear_model import LinearRegression
model = LinearRegression()
model.fit(x_train,y_train)
'''
sk - size kit
linear means using linear
regressionfit means add data
'''

'\nsk - size kit \nlinear means using linear regression \nfit means
add data \n'

model.score(x_train,y_train)
'''
accuracy
calculating96 %
'''
'\naccuracy calculating\n96 %

\n'model.score(x_test,y_test)

'''
accuracy
calculating91 %
'''

'\naccuracy calculating\n91 %

\n'model.coef_

array([[9281.30847068]])

model.intercept_

array([27166.73682891])

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

file'''

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

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

yr_of_exp = float(input("Enter years of expreience: "))
yr_of_exp_NP = np.array([[yr_of_exp]])
salary = model.predict(yr_of_exp_NP)
print("Estimated salary for {} years of expreience is {} .
".format(yr_of_exp,salary))
```

```
Enter years of expreience:  24
Estimated salary for 24.0 years of expreience is [[249918.14012525]] .
```

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

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

```
#EX.NO :12   Logistic
Regression#DATA  : 05.11.2024

#NAME : AKSHAY . N
#ROLL NO : 230701023
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - A

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

	User ID	Gender	Age	EstimatedSalary	Purchased
0	15624510	Male	19	19000	0
1	15810944	Male	35	20000	0
2	15668575	Female	26	43000	0
3	15603246	Female	27	57000	0
4	15804002	Male	19	76000	0
..	...	...	...	...	...
395	15691863	Female	46	41000	1
396	15706071	Male	51	23000	1
397	15654296	Female	50	20000	1
398	15755018	Male	36	33000	0
399	15594041	Female	49	36000	1

[400 rows x 5

	User ID	Gender	Age	EstimatedSalary	Purchased
380	15683758	Male	42	64000	0
381	15670615	Male	48	33000	1
382	15715622	Female	44	139000	1
383	15707634	Male	49	28000	1
384	15806901	Female	57	33000	1
385	15775335	Male	56	60000	1
386	15724150	Female	49	39000	1
387	15627220	Male	39	71000	0

388	15672330	Male	47	34000	1
389	15668521	Female	48	35000	1
390	15807837	Male	48	33000	1
391	15592570	Male	47	23000	1
392	15748589	Female	45	45000	1
393	15635893	Male	60	42000	1
394	15757632	Female	39	59000	0
395	15691863	Female	46	41000	1
396	15706071	Male	51	23000	1
397	15654296	Female	50	20000	1
398	15755018	Male	36	33000	0
399	15594041	Female	49	36000	1

```
df.head(25)
```

```
features = df.iloc[:,
[2,3]].valueslabel =
df.iloc[:,4].values features
```

```
array([[   19,   19000],
       [   35,   20000],
       [   26,   43000],
       [   27,   57000],
```

```
       [    19,  76000],
       [    27,  58000],
       [    27,  84000],
       [    32,  150000]
                      ,
       [    25,  33000],
       [    35,  65000],
       [    26,  80000],
       [    26,  52000],
       [    20,  86000],
       [    32,  18000],
       [    18,  82000],
       [    29,  80000],
       [    47,  25000],
       [    45,  26000],
       [    46,  28000],
       [    48,  29000],
       [    45,  22000],
       [    47,  49000],
       [    48,  41000],
       [    45,  22000],
       [    46,  23000],
       [    47,  20000],
       [    49,  28000],
       [    47,  30000],
       [    29,  43000],
       [    31,  18000],
       [    31,  74000],
       [    27,  137000]
                      ,
       [    21,  16000],
       [    28,  44000],
       [    27,  90000],
       [    35,  27000],
       [    33,  28000],
```

```
       [    30,  49000],
       [    26,  72000],
       [    27,  31000],
       [    27,  17000],
       [    33,  51000],
       [    35,  108000]
                      ,
       [    30,  15000],
       [    28,  84000],
       [    23,  20000],
       [    25,  79000],
       [    27,  54000],
       [    30,  135000]
                      ,
       [    31,  89000],
       [    24,  32000],
       [    18,  44000],
       [    29,  83000],
```

```
     User ID  Gender  Age  EstimatedSalary
Purchased0      15624510             Male
19  19000       0
1   15810944    Male   35            20000          0
2   15668575  Female   26            43000          0
3   15603246  Female   27            57000          0
4   15804002    Male   19            76000          0
5   15728773    Male   27            58000          0
6   15598044  Female   27            84000          0
7   15694829  Female   32           150000          1
8   15600575    Male   25            33000          0
9   15727311  Female   35            65000          0
10  15570769  Female   26            80000          0
11  15606274  Female   26            52000          0
12  15746139    Male   20            86000          0
13  15704987    Male   32            18000          0
14  15628972    Male   18            82000          0
15  15697686    Male   29            80000          0
16  15733883    Male   47            25000          1
17  15617482    Male   45            26000          1
18  15704583    Male   46            28000          1
19  15621083  Female   48            29000          1
20  15649487    Male   45            22000          1
21  15736760  Female   47            49000          1
22  15714658    Male   48            41000          1
```

```
       [    35,  23000],
       [    27,  58000],
       [    24,  55000],
       [    23,  48000],
       [    28,  79000],
       [    22,  18000],
       [    32,  117000]
                       ,
       [    27,  20000],
       [    25,  87000],
       [    23,  66000],
       [    32,  120000]
                       ,
       [    59,  83000],
       [    24,  58000],
       [    24,  19000],
       [    23,  82000],
       [    22,  63000],
       [    31,  68000],
       [    25,  80000],
       [    24,  27000],
       [    20,  23000],
       [    33,  113000]
                       ,
       [    32,  18000],
       [    34,  112000]
                       ,
       [    18,  52000],
       [    22,  27000],
       [    28,  87000],
       [    26,  17000],
       [    30,  80000],
       [    39,  42000],
       [    20,  49000],
       [    35,  88000],
       [    30,  62000],
```

```
       [    31,  118000],
       [    24,  55000],
       [    28,  85000],
       [    26,  81000],
       [    35,  50000],
       [    22,  81000],
       [    30,  116000],
       [    26,  15000],
       [    29,  28000],
       [    29,  83000],
       [    35,  44000],
       [    35,  25000],
       [    28,  123000],
       [    35,  73000],
       [    28,  37000],
       [    27,  88000],
       [    28,  59000],
```

```
        [    32,  86000],
        [    33,  149000]
                       ,
        [    19,  21000],
        [    21,  72000],
        [    26,  35000],
        [    27,  89000],
        [    26,  86000],
        [    38,  80000],
        [    39,  71000],
        [    37,  71000],
        [    38,  61000],
        [    37,  55000],
        [    42,  80000],
        [    40,  57000],
        [    35,  75000],
        [    36,  52000],
        [    40,  59000],
        [    41,  59000],
        [    36,  75000],
        [    37,  72000],
        [    40,  75000],
        [    35,  53000],
        [    41,  51000],
        [    39,  61000],
        [    42,  65000],
        [    26,  32000],
        [    30,  17000],
        [    26,  84000],
        [    31,  58000],
        [    33,  31000],
        [    30,  87000],
        [    21,  68000],
        [    28,  55000],
        [    23,  63000],
```

```
       [    20,  82000],
       [    30,  107000]
                      ,
       [    28,  59000],
       [    19,  25000],
       [    19,  85000],
       [    18,  68000],
       [    35,  59000],
       [    30,  89000],
       [    34,  25000],
       [    24,  89000],
       [    27,  96000],
       [    41,  30000],
       [    29,  61000],
       [    20,  74000],
       [    26,  15000],
```

```
       [    41,  45000],
       [    31,  76000],
       [    36,  50000],
       [    40,  47000],
       [    31,  15000],
       [    46,  59000],
       [    29,  75000],
       [    26,  30000],
       [    32,  135000]
                      ,
       [    32,  100000]
                      ,
       [    25,  90000],
       [    37,  33000],
       [    35,  38000],
       [    33,  69000],
       [    18,  86000],
       [    22,  55000],
       [    35,  71000],
       [    29,  148000]
                      ,
       [    29,  47000],
       [    21,  88000],
       [    34,  115000]
                      ,
       [    26,  118000]
                      ,
       [    34,  43000],
       [    34,  72000],
       [    23,  28000],
       [    35,  47000],
       [    25,  22000],
       [    24,  23000],
       [    31,  34000],
       [    26,  16000],
       [    31,  71000],
```

```
       [    32,  117000]
                       ,
       [    33,  43000],
       [    33,  60000],
       [    31,  66000],
       [    20,  82000],
       [    33,  41000],
       [    35,  72000],
       [    28,  32000],
       [    24,  84000],
       [    19,  26000],
       [    29,  43000],
       [    19,  70000],
       [    28,  89000],
       [    34,  43000],
       [    30,  79000],
       [    20,  36000],
       [    26,  80000],
       [    35,  22000],
```

```
       [    35,  39000],
       [    49,  74000],
       [    39,  134000]
                      ,
       [    41,  71000],
       [    58,  101000]
                      ,
       [    47,  47000],
       [    55,  130000]
                      ,
       [    52,  114000]
                      ,
       [    40,  142000]
                      ,
       [    46,  22000],
       [    48,  96000],
       [    52,  150000]
                      ,
       [    59,  42000],
       [    35,  58000],
       [    47,  43000],
       [    60,  108000]
                      ,
       [    49,  65000],
       [    40,  78000],
       [    46,  96000],
       [    59,  143000]
                      ,
       [    41,  80000],
       [    35,  91000],
       [    37,  144000]
                      ,
       [    60,  102000]
                      ,
       [    35,  60000],
       [    37,  53000],
       [    36,  126000]
                      ,
       [    56,  133000]
                      ,
```

```
       [    40,  72000],
       [    42,  80000],
       [    35,  147000]
                      ,
       [    39,  42000],
       [    40,  107000]
                      ,
       [    49,  86000],
       [    38,  112000]
                      ,
       [    46,  79000],
       [    40,  57000],
       [    37,  80000],
       [    46,  82000],
       [    53,  143000]
                      ,
       [    42,  149000]
                      ,
       [    38,  59000],
       [    50,  88000],
       [    56,  104000]
                      ,
       [    41,  72000],
       [    51,  146000]
                      ,
       [    35,  50000],
       [    57,  122000]
                      ,
       [    41,  52000],
```

```
       [    35,  97000],
       [    44,  39000],
       [    37,  52000],
       [    48, 134000],
       [    37, 146000],
       [    50,  44000],
       [    52,  90000],
       [    41,  72000],
       [    40,  57000],
       [    58,  95000],
       [    45, 131000],
       [    35,  77000],
       [    36, 144000],
       [    55, 125000],
       [    35,  72000],
       [    48,  90000],
       [    42, 108000],
       [    40,  75000],
       [    37,  74000],
       [    47, 144000],
       [    40,  61000],
       [    43, 133000],
       [    59,  76000],
       [    60,  42000],
       [    39, 106000],
       [    57,  26000],
       [    57,  74000],
       [    38,  71000],
       [    49,  88000],
       [    52,  38000],
```

```
       [    50,  36000],
       [    59,  88000],
       [    35,  61000],
       [    37,  70000],
       [    52,  21000],
       [    48,  141000]
                    ,
       [    37,  93000],
       [    37,  62000],
       [    48,  138000]
                    ,
       [    41,  79000],
       [    37,  78000],
       [    39,  134000]
                    ,
       [    49,  89000],
       [    55,  39000],
       [    37,  77000],
       [    35,  57000],
       [    36,  63000],
       [    42,  73000],
       [    43,  112000]
                    ,
```

```
       [    45,  79000],
       [    46,  117000]
                       ,
       [    58,  38000],
       [    48,  74000],
       [    37,  137000]
                       ,
       [    37,  79000],
       [    40,  60000],
       [    42,  54000],
       [    51,  134000]
                       ,
       [    47,  113000]
                       ,
       [    36,  125000]
                       ,
       [    38,  50000],
       [    42,  70000],
       [    39,  96000],
       [    38,  50000],
       [    49,  141000]
                       ,
       [    39,  79000],
       [    39,  75000],
       [    54,  104000]
                       ,
       [    35,  55000],
       [    45,  32000],
       [    36,  60000],
       [    52,  138000]
                       ,
       [    53,  82000],
       [    41,  52000],
       [    48,  30000],
       [    48,  131000]
                       ,
       [    41,  60000],
       [    41,  72000],
       [    42,  75000],
```

```
       [    36,  118000]
                       ,
       [    47,  107000]
                       ,
       [    38,  51000],
       [    48,  119000]
                       ,
       [    42,  65000],
       [    40,  65000],
       [    57,  60000],
       [    36,  54000],
       [    58,  144000]
                       ,
       [    35,  79000],
       [    38,  55000],
       [    39,  122000]
                       ,
       [    53,  104000]
                       ,
       [    35,  75000],
       [    38,  65000],
       [    47,  51000],
       [    47,  105000]
                       ,
       [    41,  63000],
       [    53,  72000],
```

```
[    54, 108000 ],
[    39,  77000 ],
[    38,  61000 ],
[    38, 113000 ],
[    37,  75000 ],
[    42,  90000 ],
[    37,  57000 ],
[    36,  99000 ],
[    60,  34000 ],
[    54,  70000 ],
[    41,  72000 ],
[    40,  71000 ],
[    42,  54000 ],
[    43, 129000 ],
[    53,  34000 ],
[    47,  50000 ],
[    42,  79000 ],
[    42, 104000 ],
[    59,  29000 ],
[    58,  47000 ],
[    46,  88000 ],
[    38,  71000 ],
```

```
[    54,   26000
           ],
[    60,   46000
           ],
[    60,   83000
           ],
[    39,   73000
           ],
[    59,  130000
          ],
[    37,   80000
           ],
[    46,   32000
           ],
[    46,   74000
           ],
[    42,   53000
           ],
[    41,   87000
           ],
[    58,   23000
           ],
[    42,   64000
           ],
[    48,   33000
           ],
[    44,  139000
          ],
[    49,   28000
           ],
[    57,   33000
           ],
[    56,   60000
           ],
[    49,   39000
           ],
[    39,   71000
           ],
[    47,   34000
           ],
[    48,   35000
           ],
[    48,   33000
           ],
[    47,   23000
           ],
```

```
        [     45,   45000
                    ],
        [     60,   42000
                    ],
        [     39,   59000
                    ],
        [     46,   41000
                    ],
        [     51,   23000
                    ],
```

```
       [    50,  20000],
       [    36,  33000],
       [    49,  36000]], dtype=int64)
```

label

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

    0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,

    0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 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, 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, 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, 1, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0,

    0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1, 0, 0, 0, 1, 1,

    1, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 1, 0, 1, 0, 0, 1, 1, 0, 1, 1,
```

```
       1, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0,

       0, 1, 0, 1, 1, 1, 1, 0, 0, 0, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 0,

       1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0, 1, 1, 0, 1, 1, 0, 0, 0, 1,

       0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1,

       1, 0, 1, 1, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0,

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

```
from sklearn.model_selection import
train_test_splitfrom sklearn.linear_model import
LogisticRegression

# Assuming `features` and `label` are already defined

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

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

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

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

'''


'''
```

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

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
```

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

	precision	recall	f1-score	support
0	0.86	0.91	0.89	257
1	0.83	0.73	0.77	143
accuracy			0.85	400
macro avg	0.84	0.82	0.83	400

```
   weighted        0.8      0.85      0.85     400
        avg          5
```