Fundamentals of Data science Record

EX.NO :1.a *Basic experiments 1 to 4*
DATE : 30.07.2024

Name: AKILESH PRASAD I.K

Roll no: 230701020 Department:CSE 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
0       Iris-setosa
1       Iris-setosa
2       Iris-setosa
3       Iris-setosa
4       Iris-setosa
..              ...
145  Iris-virginica
146  Iris-virginica
147  Iris-virginica
148  Iris-virginica
149  Iris-virginica

[150 rows x 6 columns]
```

```
data.info()
```

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

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

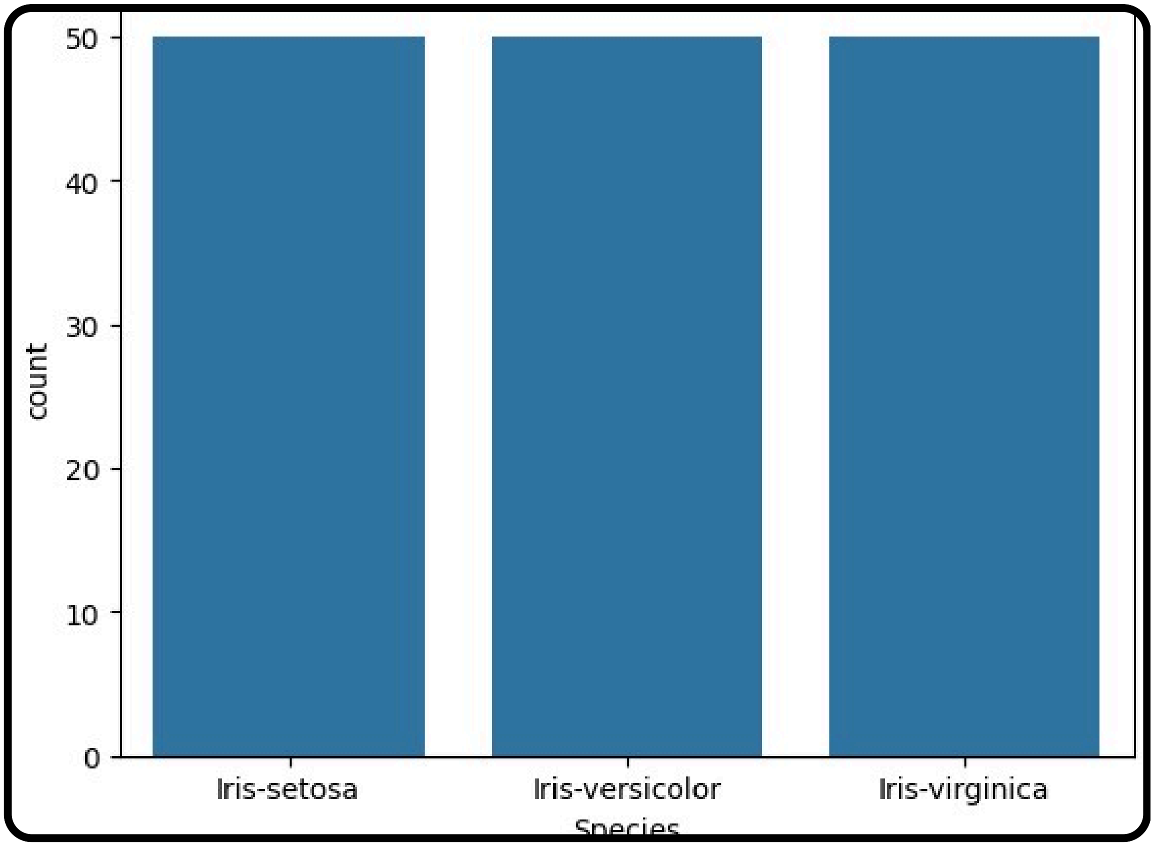
```python
data.describe()
```

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
count	150.000000	150.000000	150.000000	150.000000	150.000000
mean	75.500000	5.843333	3.054000	3.758667	1.198667
std	43.445368	0.828066	0.433594	1.764420	0.763161
min	1.000000	4.300000	2.000000	1.000000	0.100000
25%	38.250000	5.100000	2.800000	1.600000	0.300000
50%	75.500000	5.800000	3.000000	4.350000	1.300000
75%	112.750000	6.400000	3.300000	5.100000	1.800000
max	150.000000	7.900000	4.400000	6.900000	2.500000

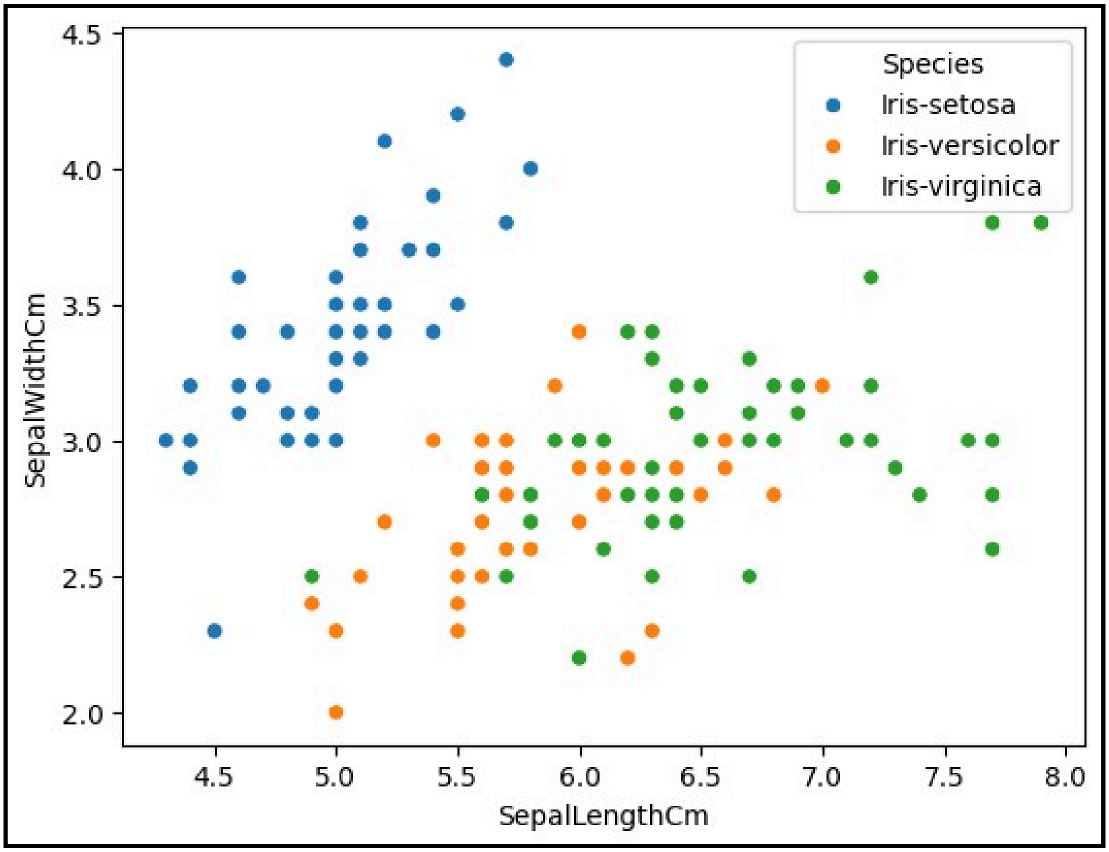
```python
data.value_counts('Species')
```

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

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

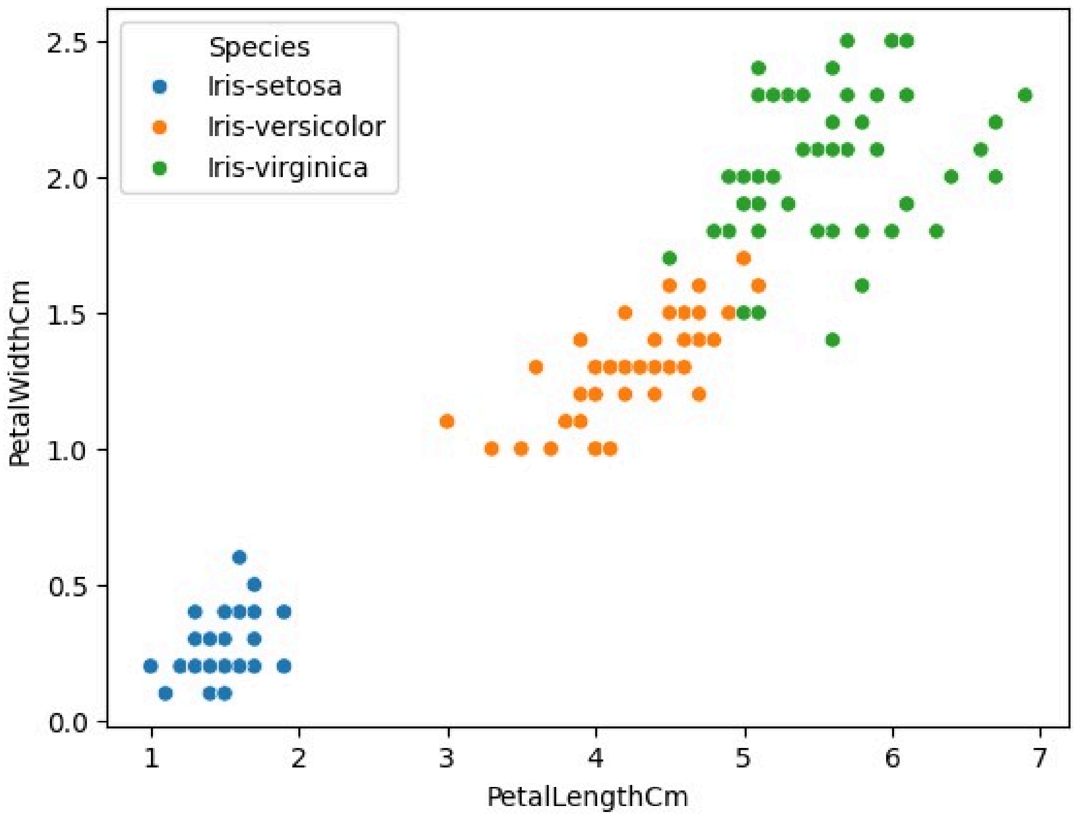



```
dummies=pd.get_dummies(data.Species)

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

  Iris-setosa Iris-versicolor  Iris-virginica  Id  SepalLengthCm \
0        True           False           False   1            5.1
1        True           False           False   2            4.9
2        True           False           False   3            4.7
3        True           False           False   4            4.6
4        True           False           False   5            5.0

   SepalWidthCm PetalLengthCm
0           3.5            1.4
1           3.0            1.4
2           3.2            1.3
3           3.1            1.5
4           3.6            1.4

sns.scatterplot(x='SepalLengthCm',y='SepalWidthCm',hue='Species',data=
data,)
<Axes: xlabel='SepalLengthCm', ylabel='SepalWidthCm'>
```

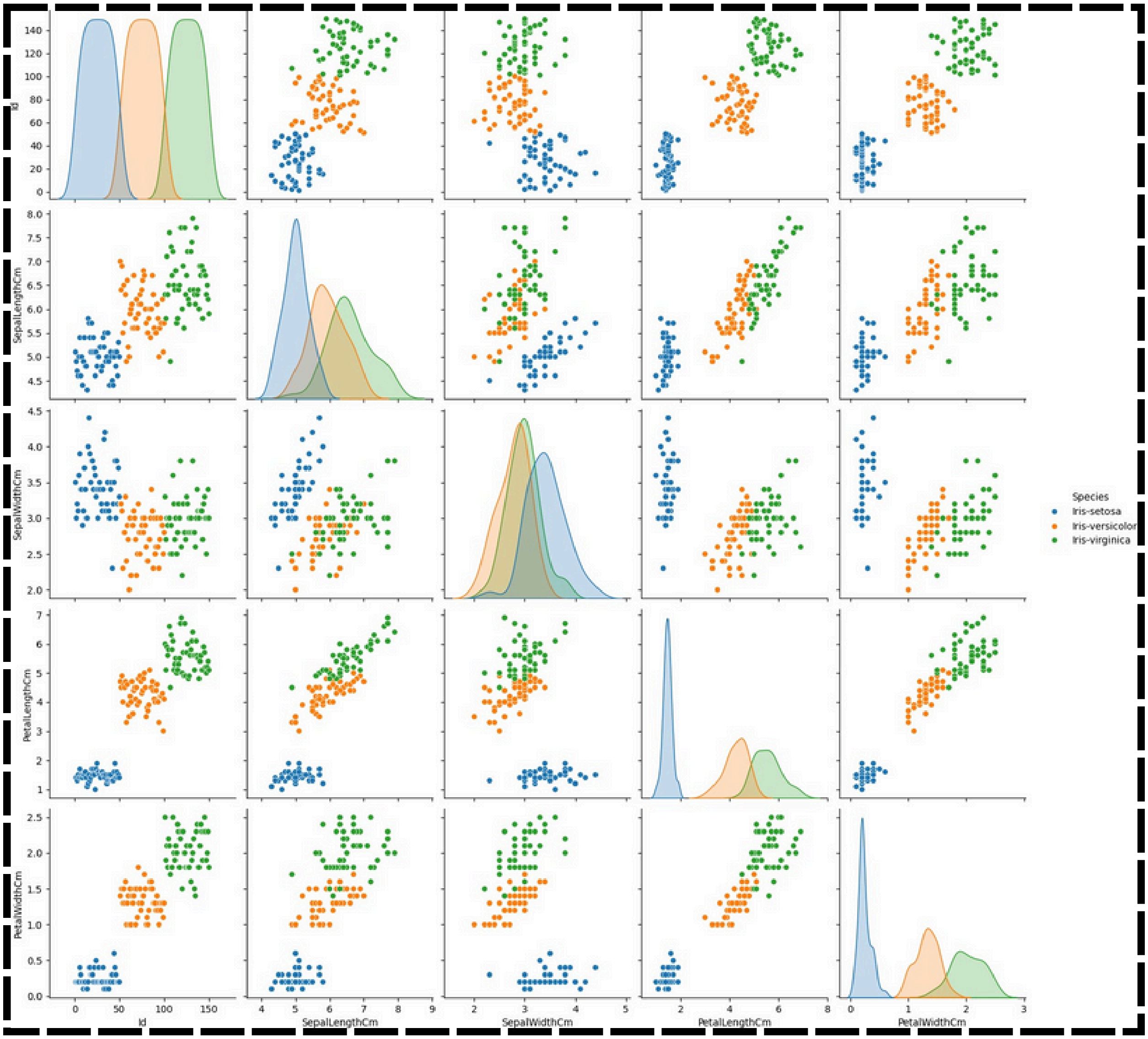



```
sns.scatterplot(x='PetalLengthCm',y='PetalWidthCm',hue='Species',data=
data,)
```

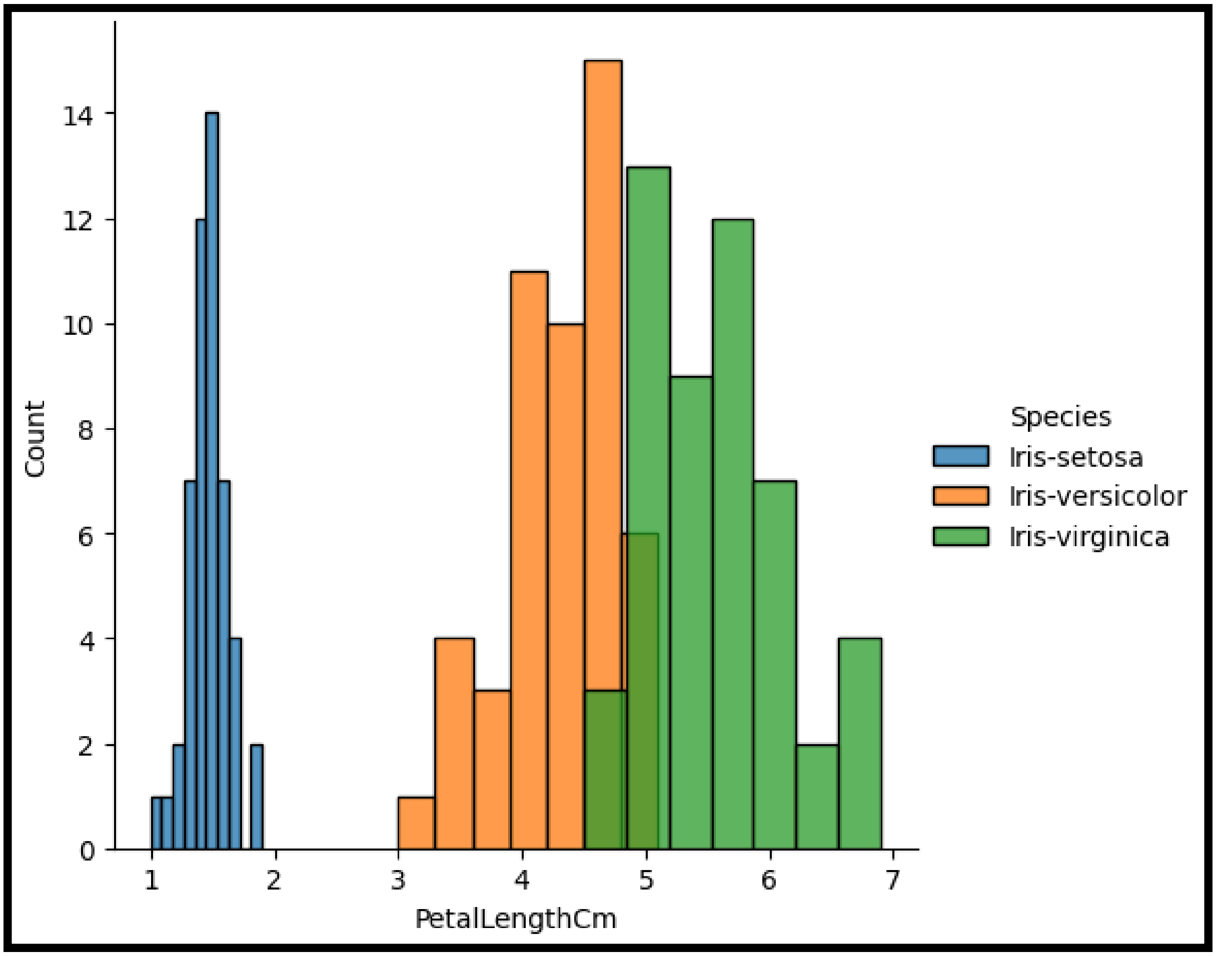
```
<Axes: xlabel='PetalLengthCm', ylabel='PetalWidthCm'>
```



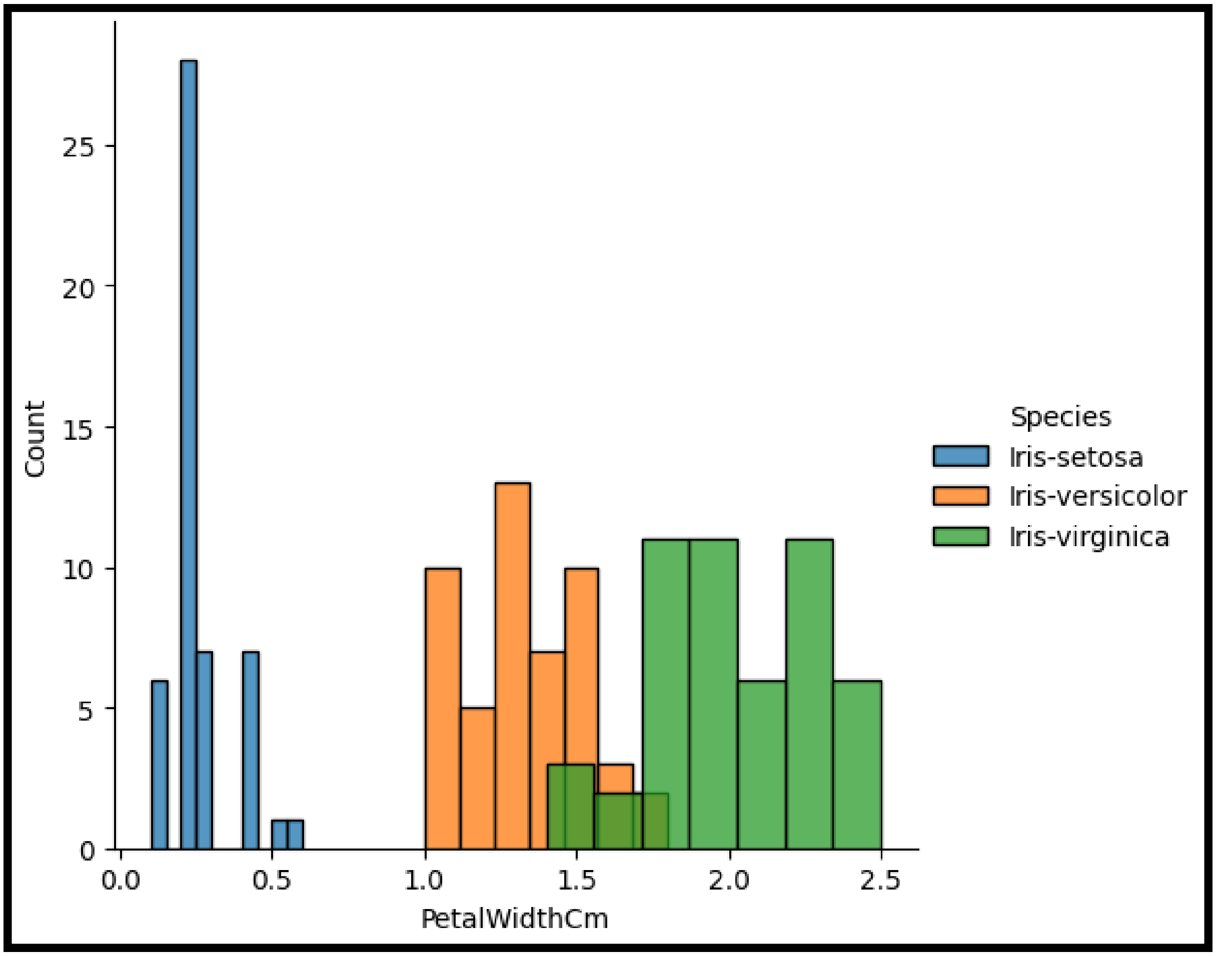

```
sns.pairplot(data,hue='Species',height=3);
```



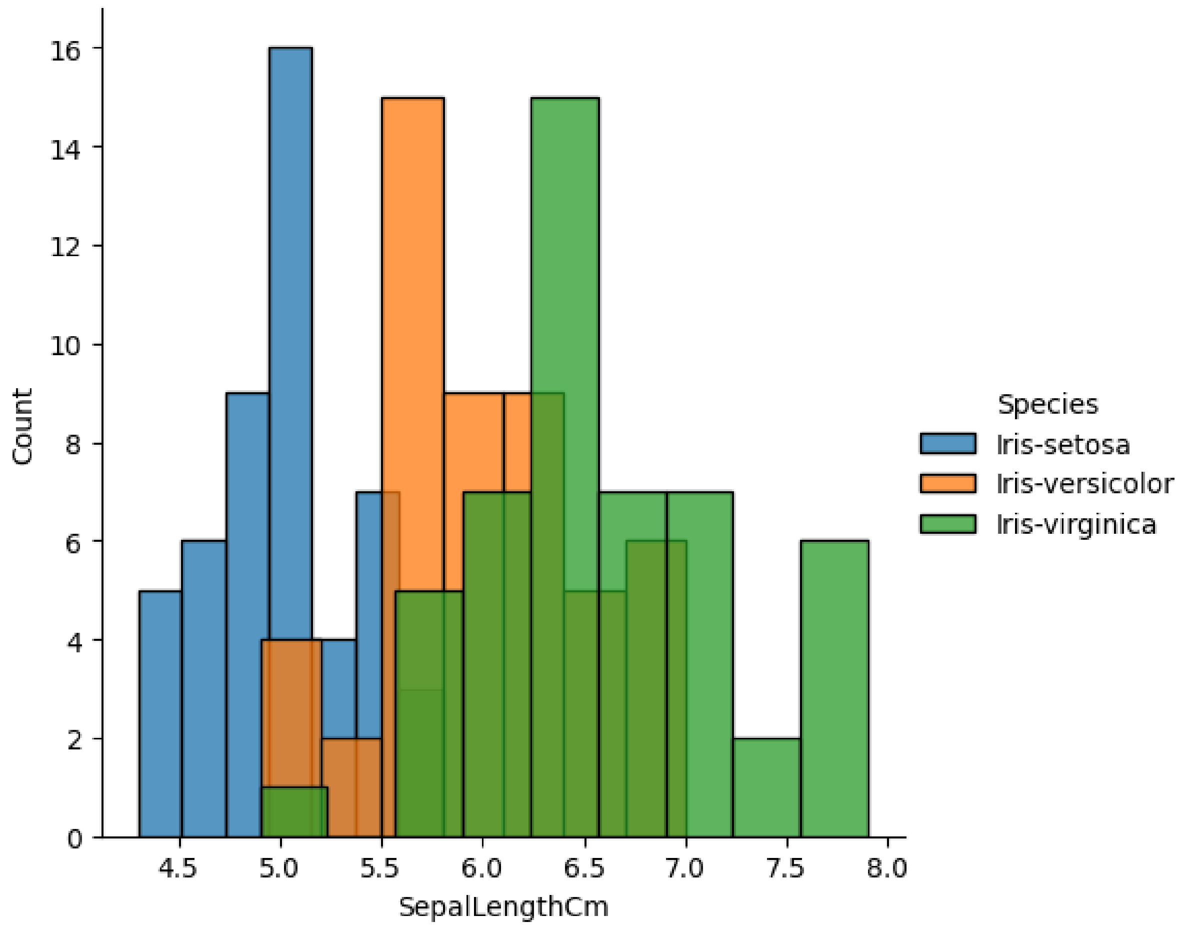

```
plt.show()

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



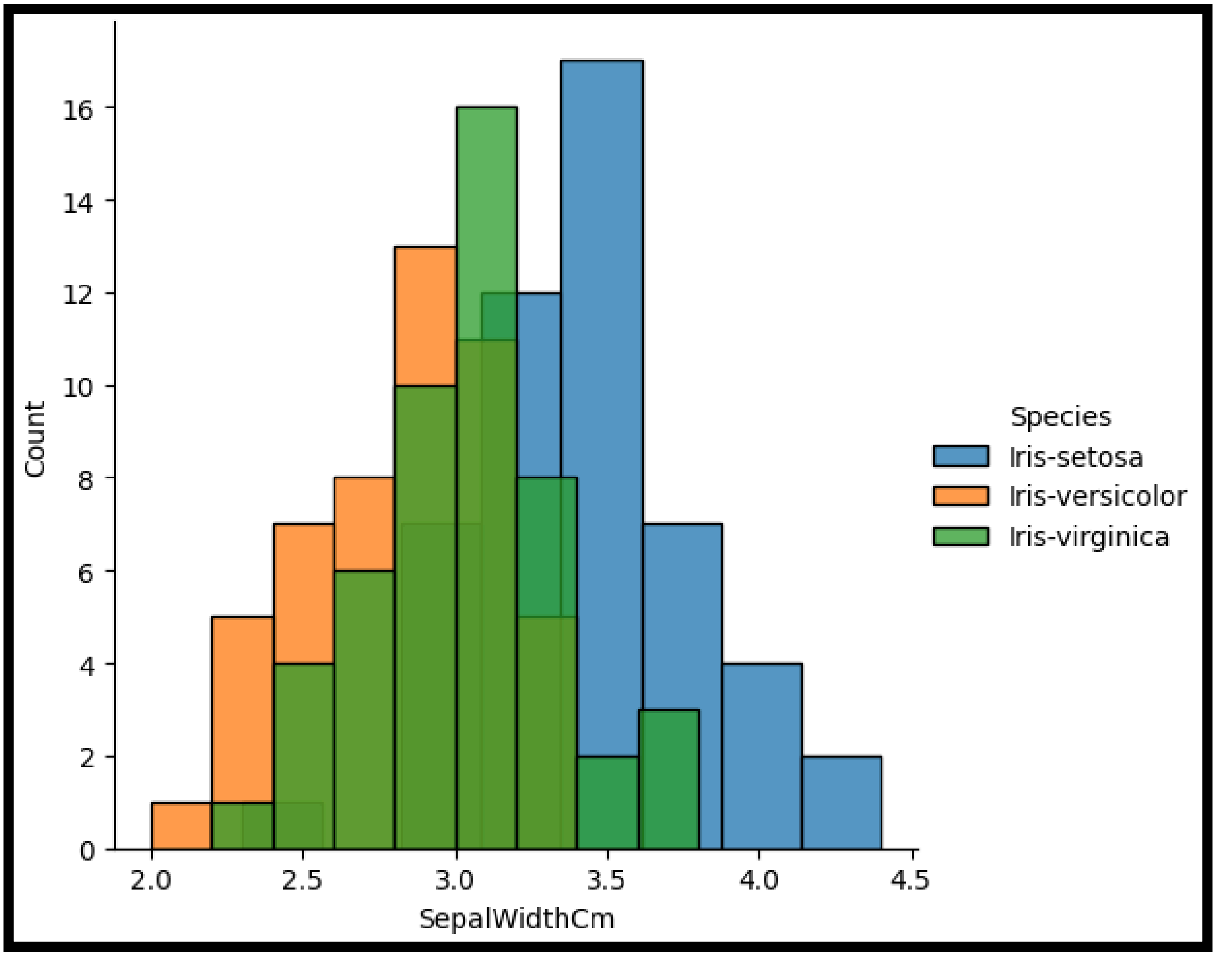

```
sns.FacetGrid(data,hue='Species',height=5).map(sns.histplot,'PetalWidthCm').add_legend(); plt.show();
```




```
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 Buit in function. Numpy Buit in fuction- Array slicing, Ravel,Reshape,ndim
#DATE : 06.08.2024

#NAME : AKILESH PRASAD I.K
#ROLL NO : 230701020
#DEPARTMENT : B.E CSE-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])
```

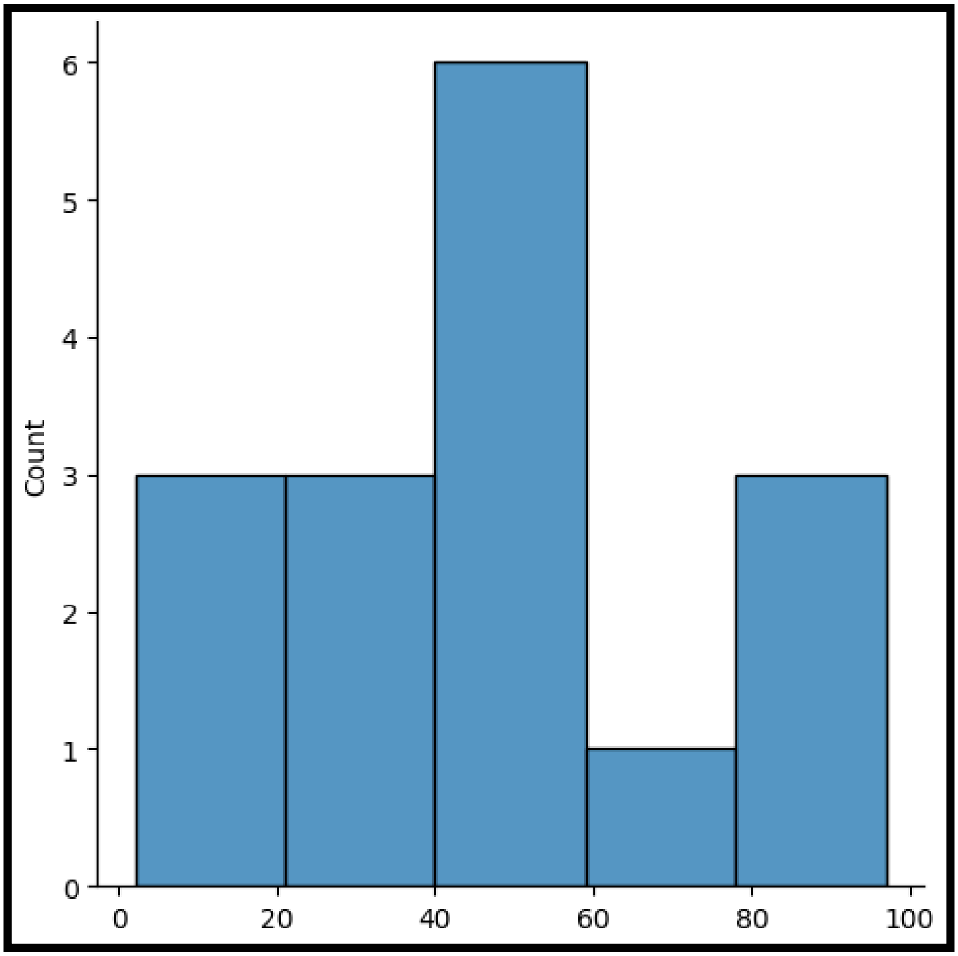
```
array.ndim
```

```
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
#DATE  : 13.08.2024

Name: Akilesh Prasad i.k

Roll no:230701020,Dept: CSE-A

import numpy as np
import warnings
warnings.filterwarnings('ignore')
```

```
ARRAY=NP.RANDOM.RANDINT(1,100,16) ARRAY

ARRAY([37, 15, 49, 89, 30, 47, 97])

ARRAY.MEAN()

45.5625

NP.PERCENTILE(ARRAY,25)

29.25

NP.PERCENTILE(ARRAY,50)

44.0

NP.PERCENTILE(ARRAY,75)

55.5

NP.PERCENTILE(ARRAY,100)

97.0
```

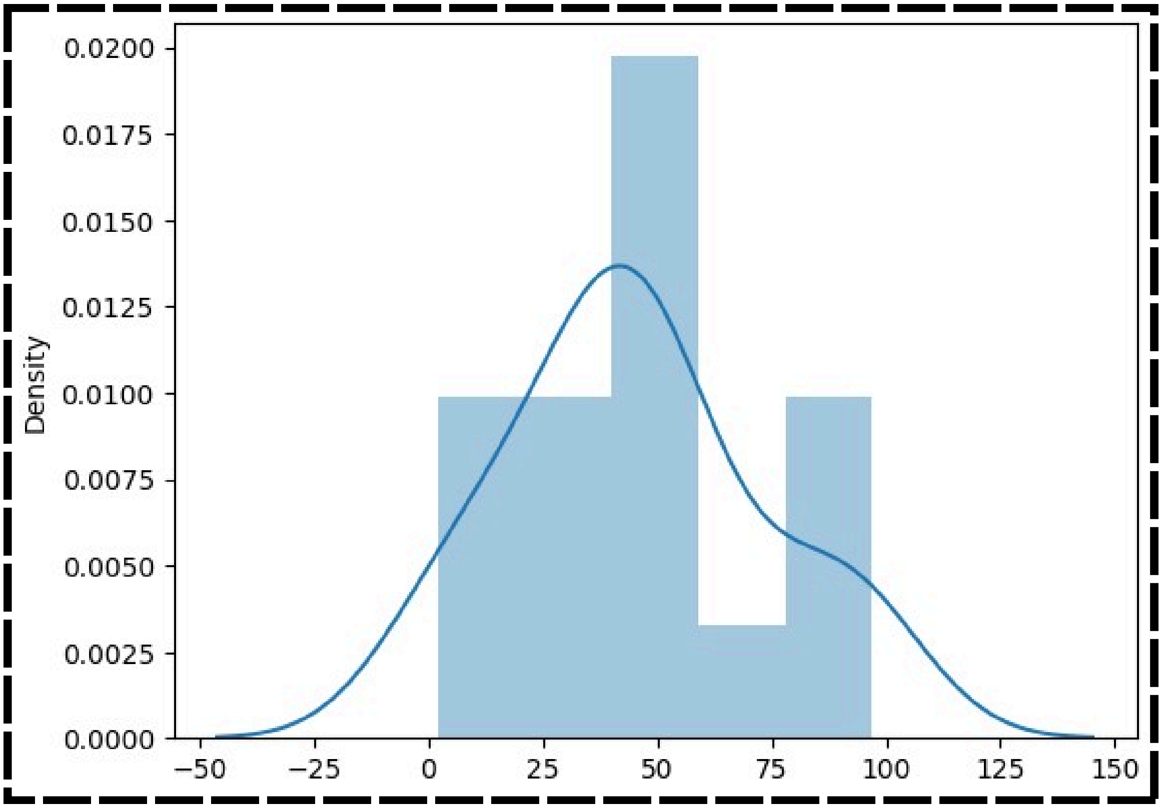
OUTLIERS DETECTION

```
DEF OUTDETECTION(ARRAY):



    sorted(array)
    Q1,Q3=np.percentile(array,[25,75])
    IQR=Q3-Q1
    lr=Q1-(1.5*IQR)
    ur=Q3+(1.5*IQR)
    return lr,ur
LR,UR=OUTDETECTION(ARRAY)
LR,UR

(-10.125, 94.875)

IMPORT SEABORN AS SNS
%MATPLOTLIB INLINE
SNS.DISPLOT(ARRAY)

<SEABORN.AXISGRID.FACETGRID AT

0X20D7CDA3B50>
```




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

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

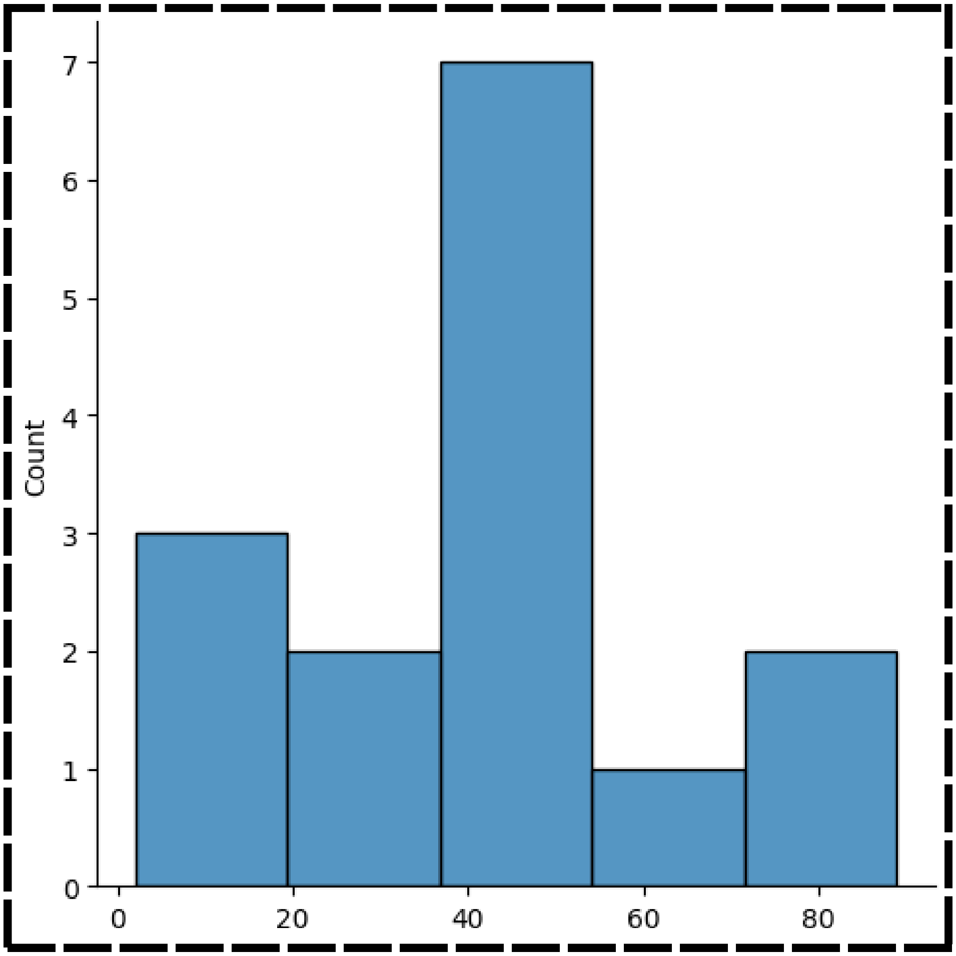



```
new_array=array[(array>lr) & (array<ur)]
new_array
```

```
array([37, 15, 49, 89, 30, 47,              2, 86, 53, 63, 41, 46, 42, 27,              5])
```

```
sns.displot(new_array)
```

```
<seaborn.axisgrid.FacetGrid at 0x20d7d02d950>
```




```
lr1,ur1=outDetection(new_array)
lr1,ur1
```

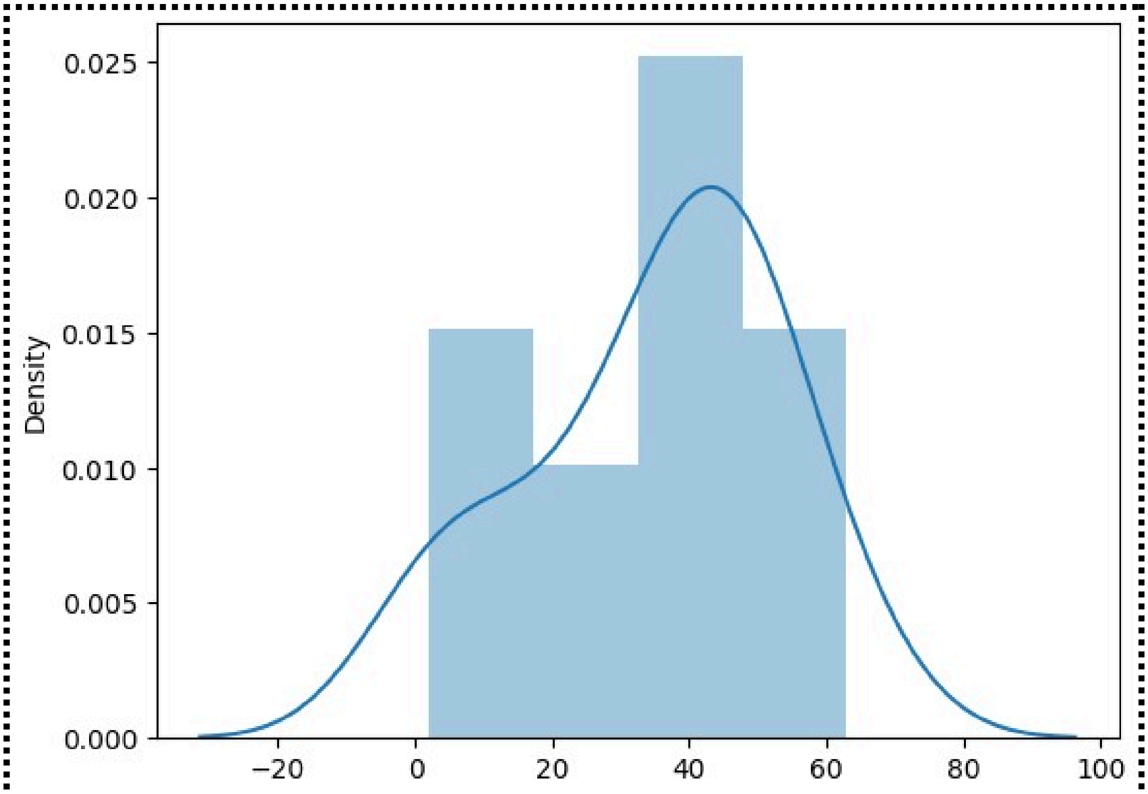
```
(-5.25, 84.75)
```

```
final_array=new_array[(new_array>lr1) & (new_array<ur1)]
final_array
```

```
array([37, 15, 49, 30, 47, 2, 53, 63, 41, 46, 42, 27,
        5])
```

```
sns.distplot(final_array)
```

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



#EX.NO :3 Missing and inappropriate data
#DATE : 20.08.2024

NAME: AKILESH PRASAD I.K

ROLL NO:230701020,DEPT: CSE-A

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

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

```
df.duplicated()
```

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

```
df.info()
```

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

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

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

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

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

```
len(df)
```

```
10
```

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

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

```python
df
```

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

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

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

	CustomerID	Age_Group	Rating(1-5)	Hotel	FoodPreference	Bill	NoOfPax \
0	1	20-25	4	Ibis	veg	1300	2

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

```
   EstimatedSalary
0            40000
1            59000
2            30000
3           120000
4            45000
5           122220
6            21122
7           345673
8           -99999
9            87777
```

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

```
   CustomerID Age_Group Rating(1-5)      Hotel FoodPreference     Bill  \
0         1.0     20-25           4       Ibis            veg   1300.0
1         2.0     30-35           5  LemonTree        Non-Veg   2000.0
2         3.0     25-30           6     RedFox            Veg   1322.0
3         4.0     20-25          -1  LemonTree            Veg   1234.0
4         5.0       35+           3       Ibis     Vegetarian    989.0
5         6.0       35+           3       Ibys        Non-Veg   1909.0
```

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

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

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

	CustomerID	Age_Group	Rating(1-5)	Hotel	FoodPreference	Bill \
0	1.0	20-25	4	Ibis	veg	1300.0
1	2.0	30-35	5	LemonTree	Non-Veg	2000.0
2	3.0	25-30	6	RedFox	Veg	1322.0
3	4.0	20-25	-1	LemonTree	Veg	1234.0
4	5.0	35+	3	Ibis	Vegetarian	989.0
5	6.0	35+	3	Ibys	Non-Veg	1909.0
6	7.0	35+	4	RedFox	Vegetarian	1000.0
7	8.0	20-25	7	LemonTree	Veg	2999.0
8	9.0	25-30	2	Ibis	Non-Veg	3456.0
9	10.0	30-35	5	RedFox	non-Veg	NaN

	NoOfPax	EstimatedSalary
0	2.0	40000.0
1	3.0	59000.0
2	2.0	30000.0

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

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

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

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

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

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

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

```
df.FoodPreference.replace(['Vegetarian','veg'],'Veg',inplace=True)
df.FoodPreference.replace(['non-Veg'],'Non-Veg',inplace=True)
df.EstimatedSalary.fillna(round(df.EstimatedSalary.mean()),inplace=Tru
e)
df.NoOfPax.fillna(round(df.NoOfPax.median()),inplace=True)
df['Rating(1-5)'].fillna(round(df['Rating(1-5)'].median()),
inplace=True)
df.Bill.fillna(round(df.Bill.mean()),inplace=True)
df
```

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

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

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

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

NAME: AKILESH PRASAD I.K

ROLL NO:230701020,DEPT:CSE-A

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

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

```
df.info()
```

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

```
df.Country.mode()
```

```
0     France
Name: Country, dtype: object
```

```
df.Country.mode()[0]
```

```
'France'
```

```
type(df.Country.mode())
```

```
pandas.core.series.Series
```

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

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

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

```
     France Germany   Spain
0     True
1     False              True
2     False         True False
3     False   False      True
4     False         True False
```

5 6 7 8 9

```
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):

          Non-Null Count
          --------------
          10 non-null
          10 non-null
          10 non-null
          Purchased 10 non-null

 #   Column     Dtype
                -----
---  ------
0    Country    object
1    Age        float64
 2   Salary     float64
 3              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: AKILESH PRASAD I.K

ROLL NO: 230701020,DEPT:CSE-A

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

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

```
df.info()
```

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

```
df.Country.mode()
```

```
0    France
Name: Country, dtype: object
```

```
df.Country.mode()[0]
```

```
'France'
```

```
type(df.Country.mode())
```

```
pandas.core.series.Series
```

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

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

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

```
    France Germany Spain
0   False False True
1   False False True
2   False True False
3   False False True
4   False True False
```

5 6 7 8 9

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

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

```
df.info()
```

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

```
updated_dataset
```

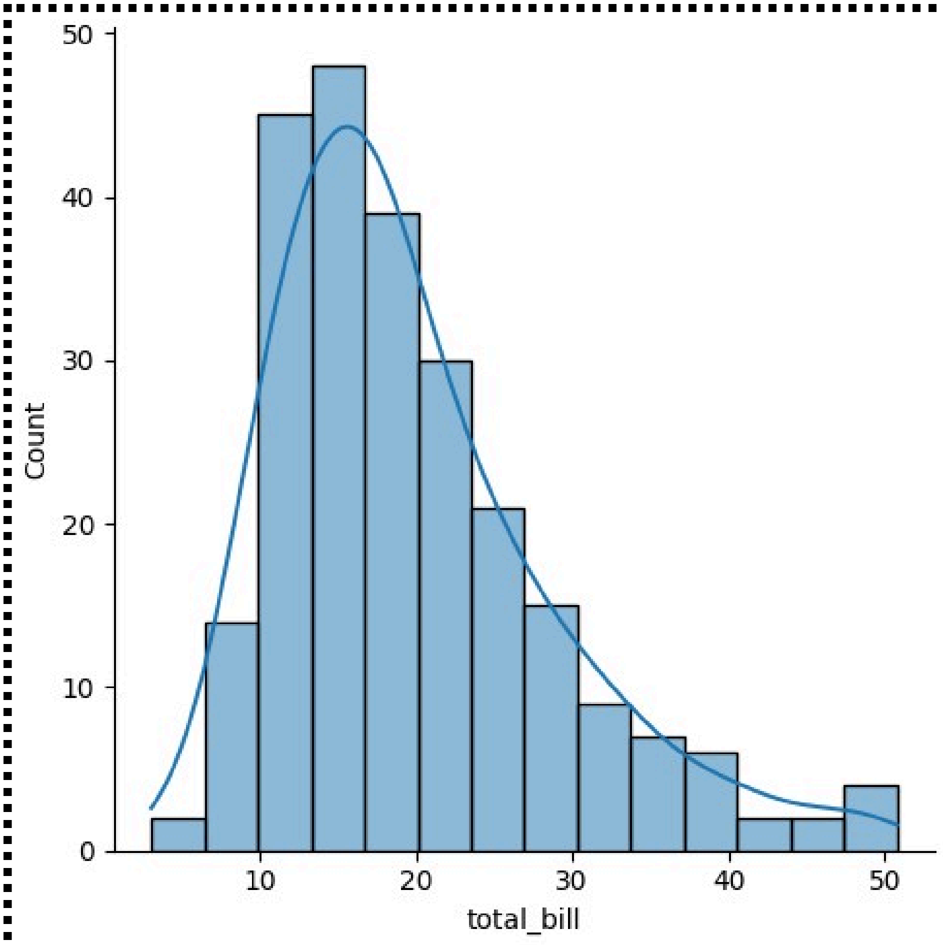
	France	Germany	Spain	Age	Salary	Purchased
0	True	False	False	44.0	72000.0	No
1	False	False	True	27.0	48000.0	Yes
2	False	True	False	30.0	54000.0	No
3	False	False	True	38.0	61000.0	No
4	False	True	False	40.0	63778.0	Yes
5	True	False	False	35.0	58000.0	Yes
6	False	False	True	38.0	52000.0	No
7	True	False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

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

NAME:AKILESH PRASAD I.K

ROLL NO:230701020,DEPT:CSE-A

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

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

	total_bill	tip	sex	smoker	day	time	size
0	16.99	1.01	Female	No	Sun	Dinner	2
1	10.34	1.66	Male	No	Sun	Dinner	3
2	21.01	3.50	Male	No	Sun	Dinner	3
3	23.68	3.31	Male	No	Sun	Dinner	2
4	24.59	3.61	Female	No	Sun	Dinner	4

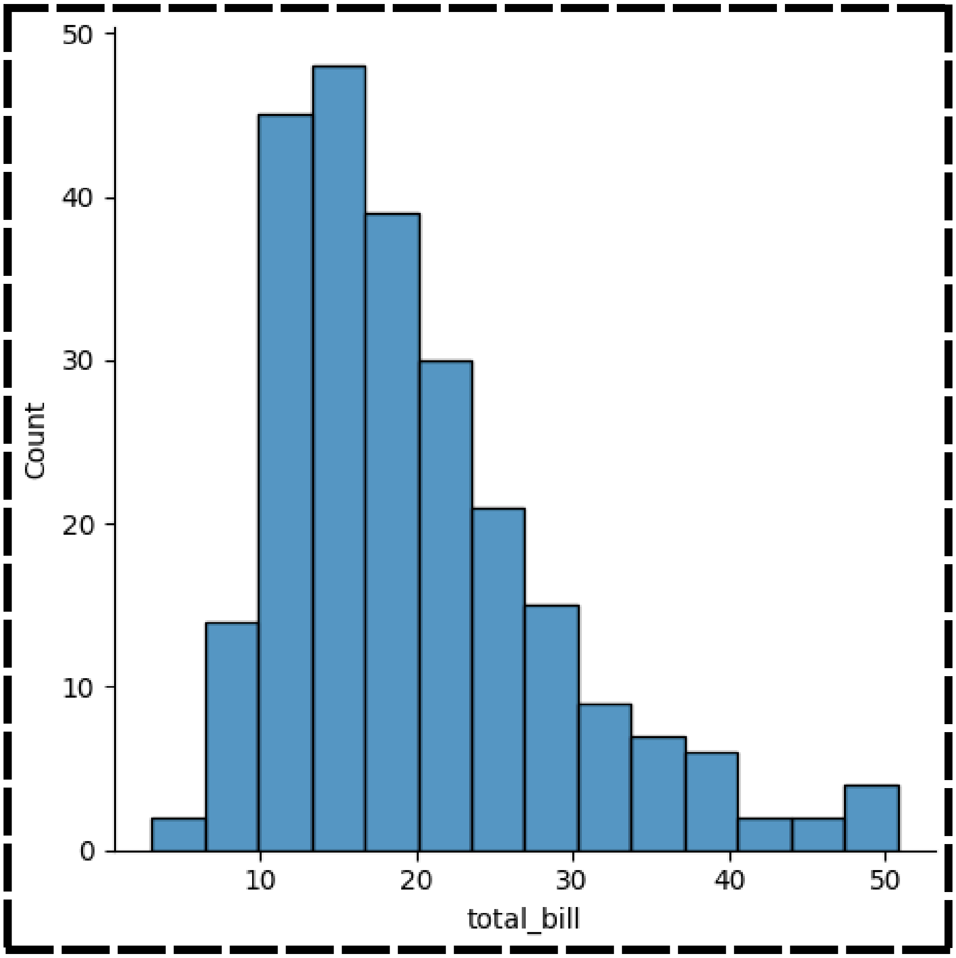
```
sns.displot(tips.total_bill,kde=True)
```

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



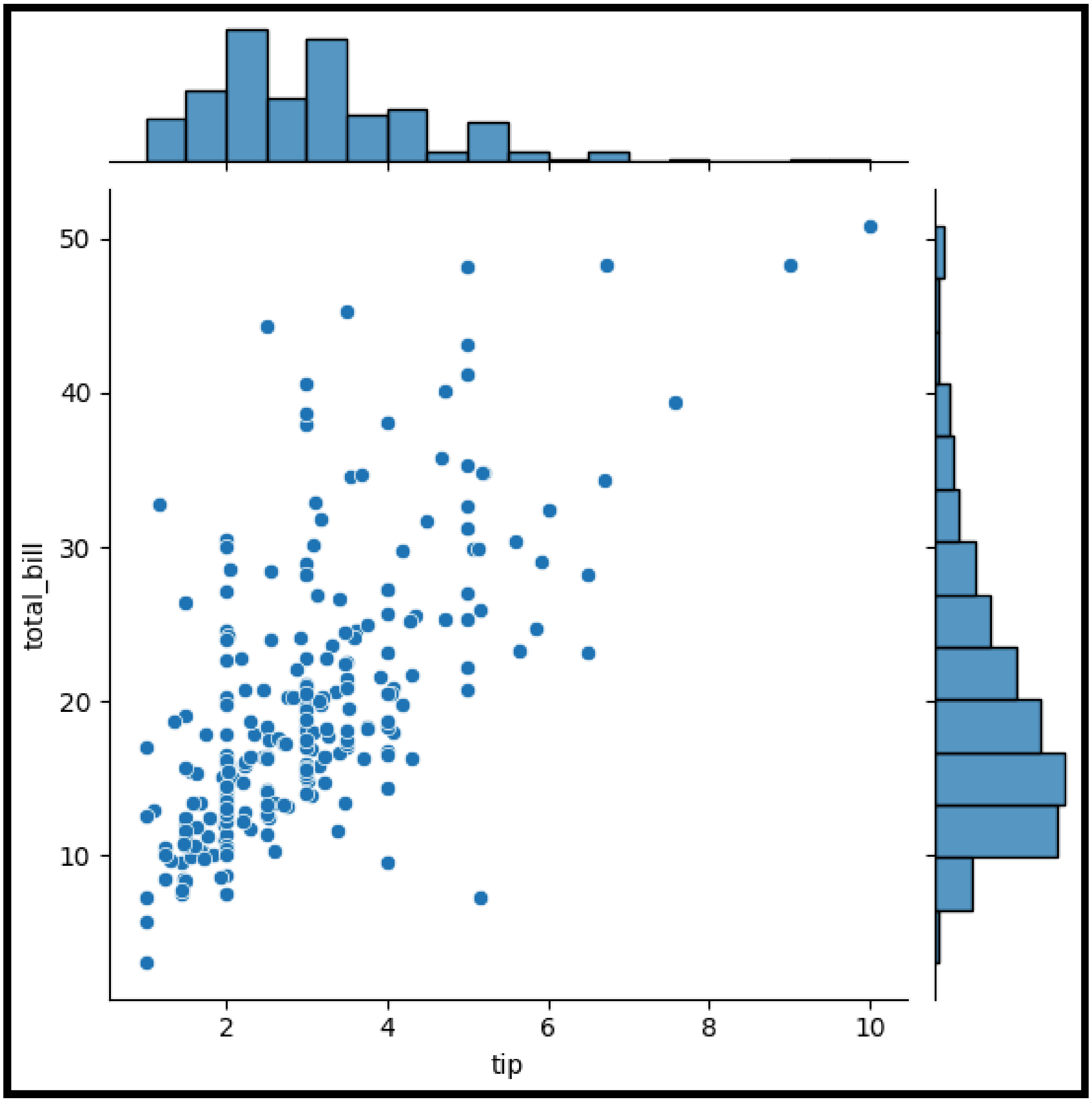

```
sns.displot(tips.total_bill,kde=False)
```

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



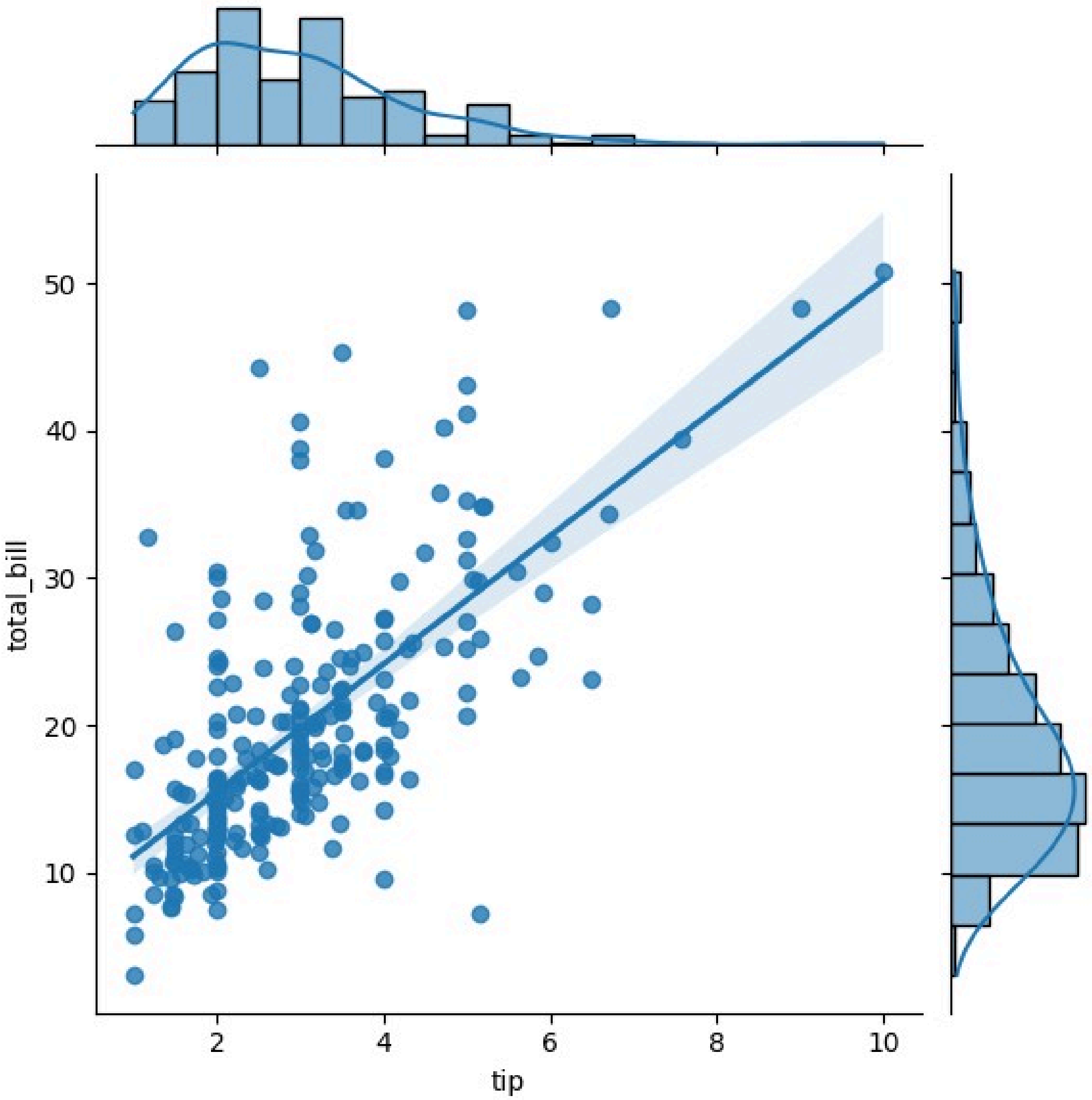

```
sns.jointplot(x=tips.tip,y=tips.total_bill)
```

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



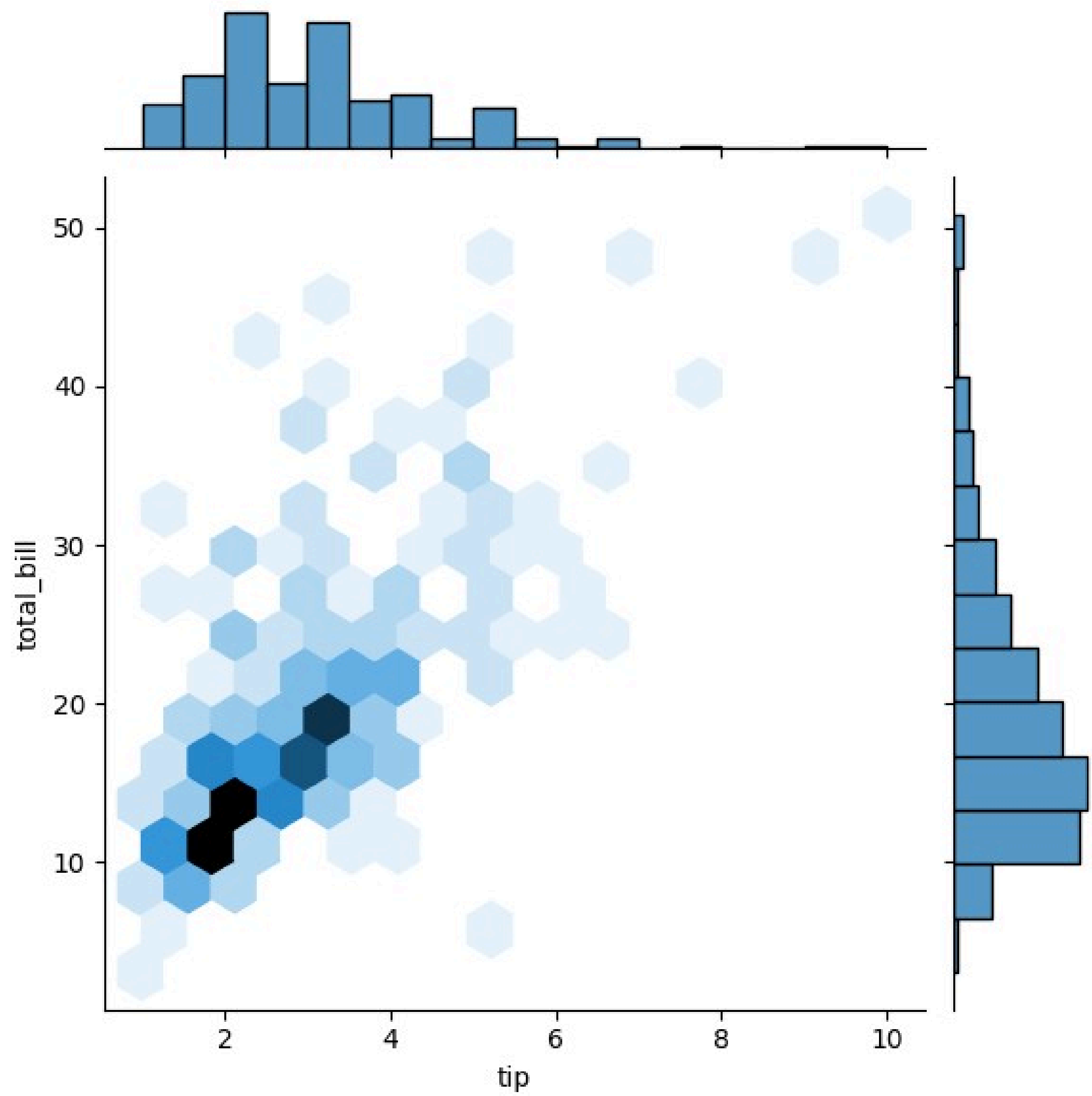

```
sns.jointplot(x=tips.tip,y=tips.total_bill,kind="reg")
```

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

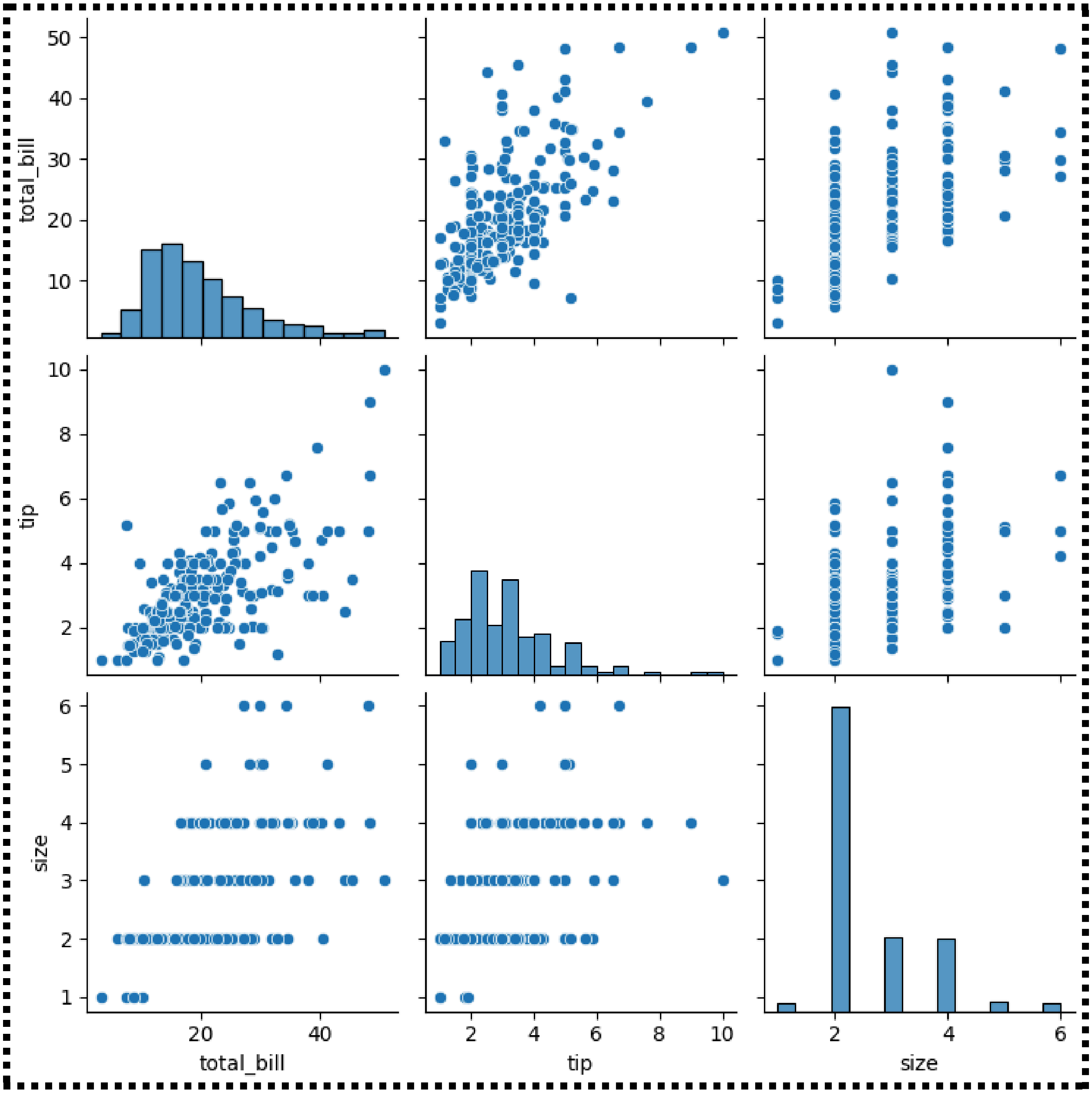



```
sns.jointplot(x=tips.tip,y=tips.total_bill,kind="hex")
```

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




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

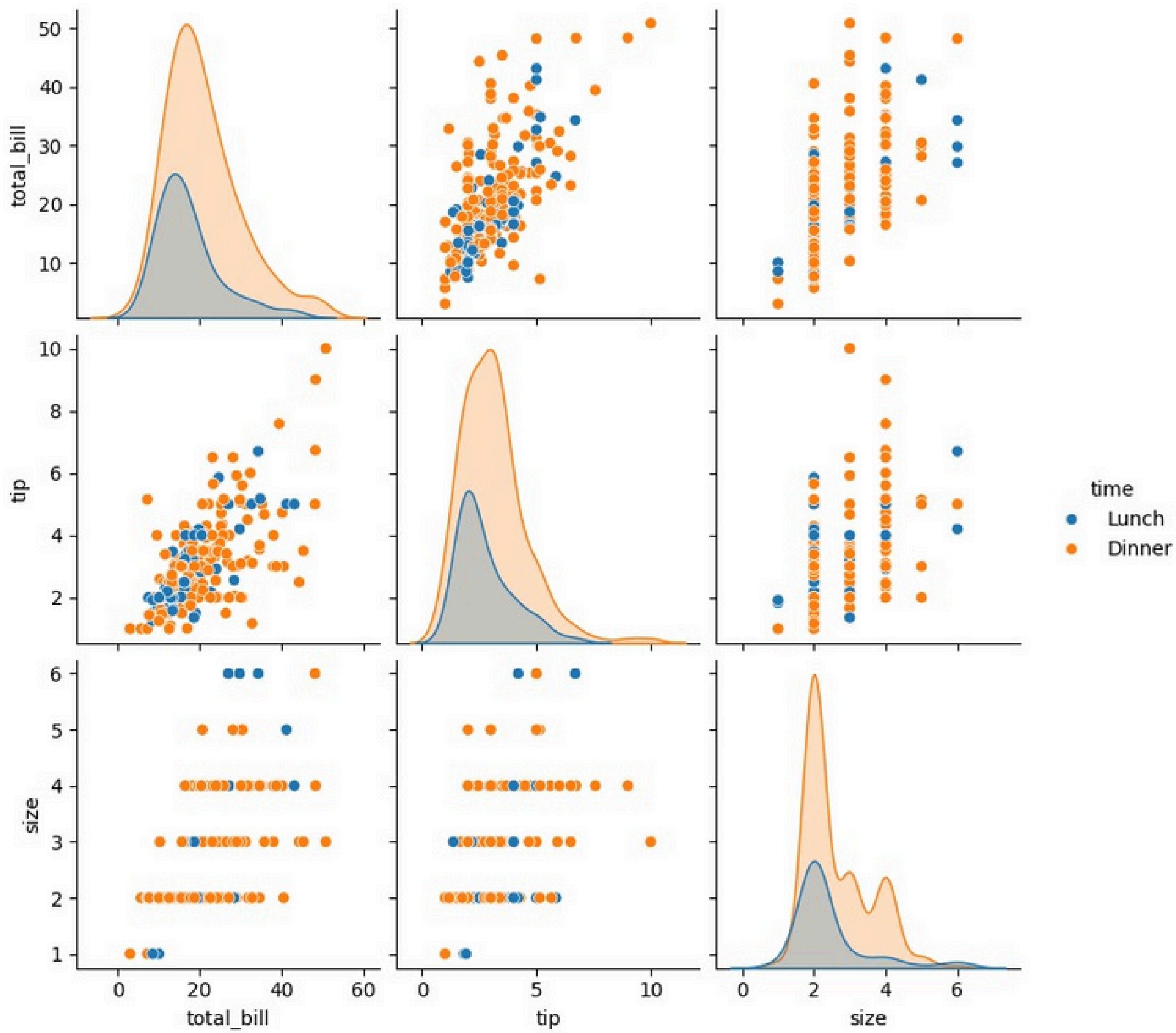



```
tips.time.value_counts()
```

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

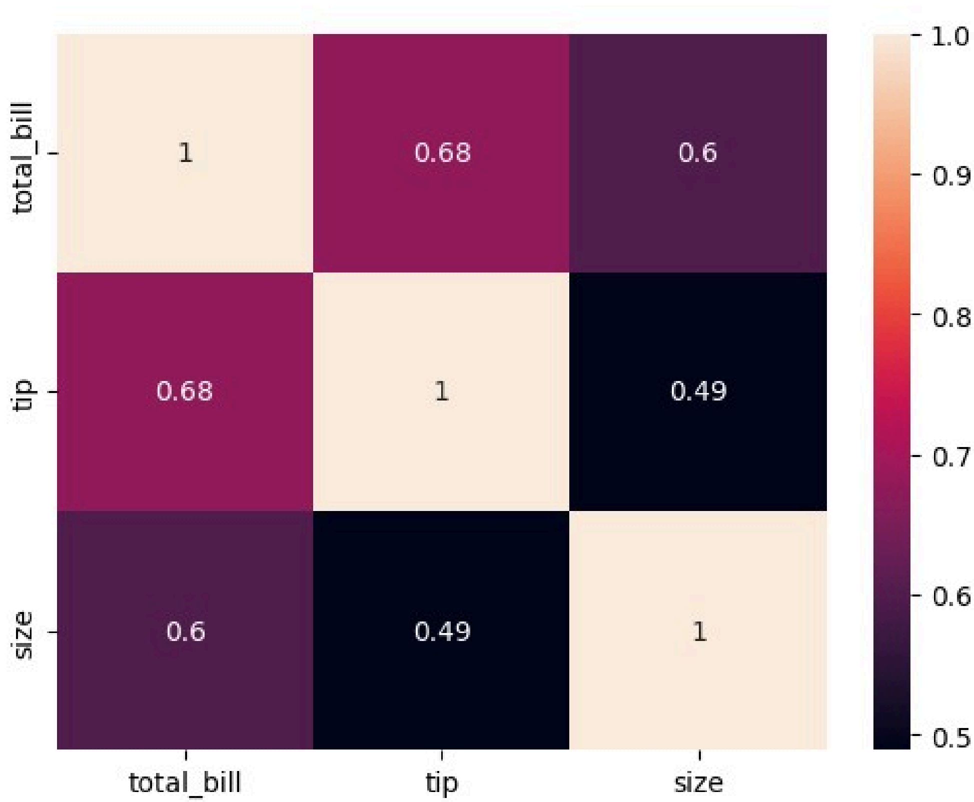
```
sns.pairplot(tips,hue='time')
```

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



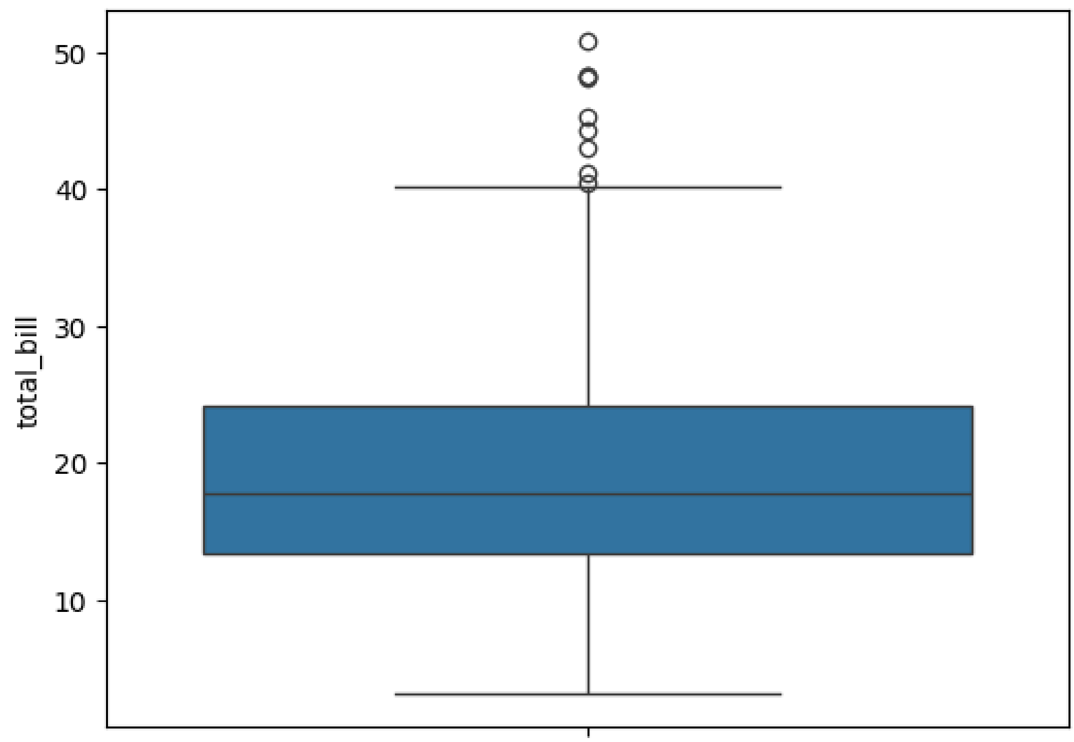

```
sns.heatmap(tips.corr(numeric_only=True),annot=True)
```

```
<Axes: >
```



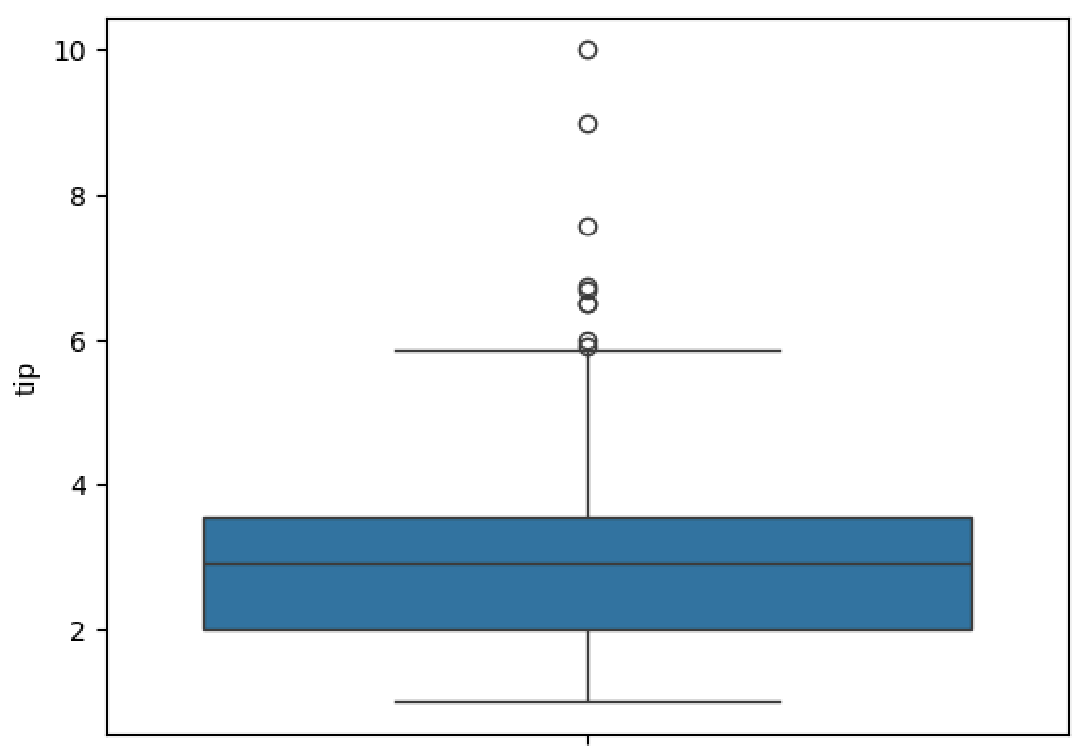

```
sns.boxplot(tips.total_bill)
```

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



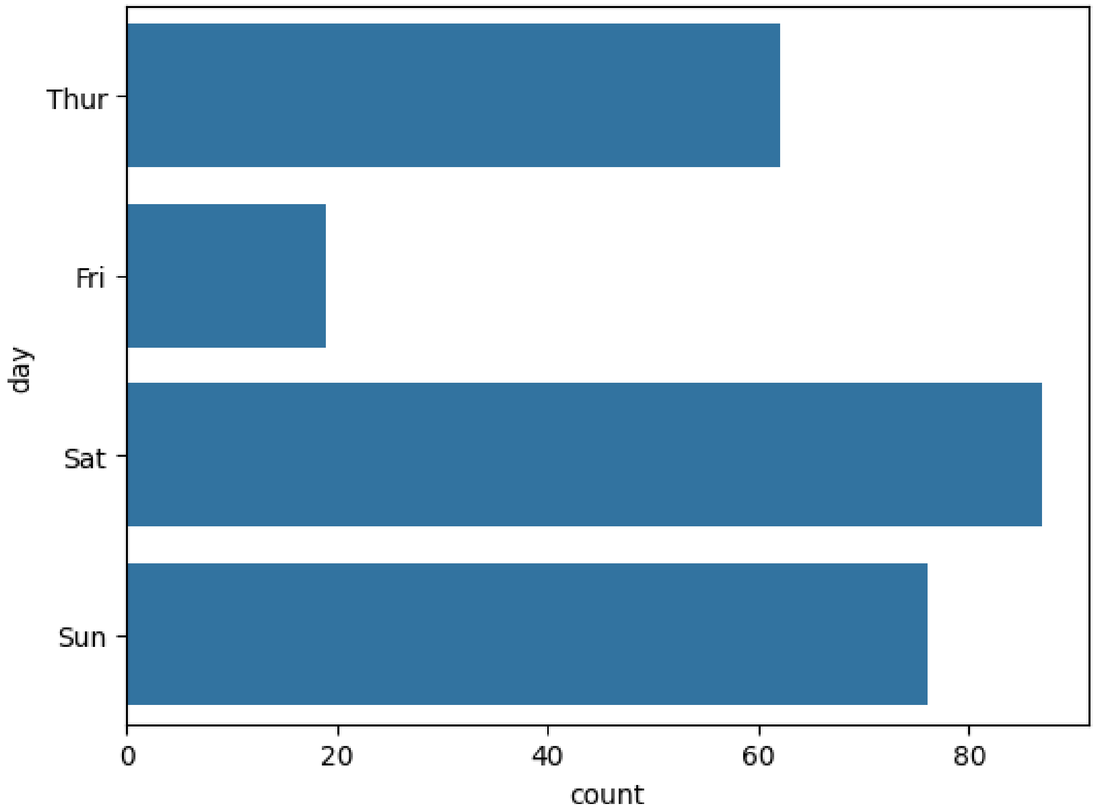

```
sns.boxplot(tips.tip)
```

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



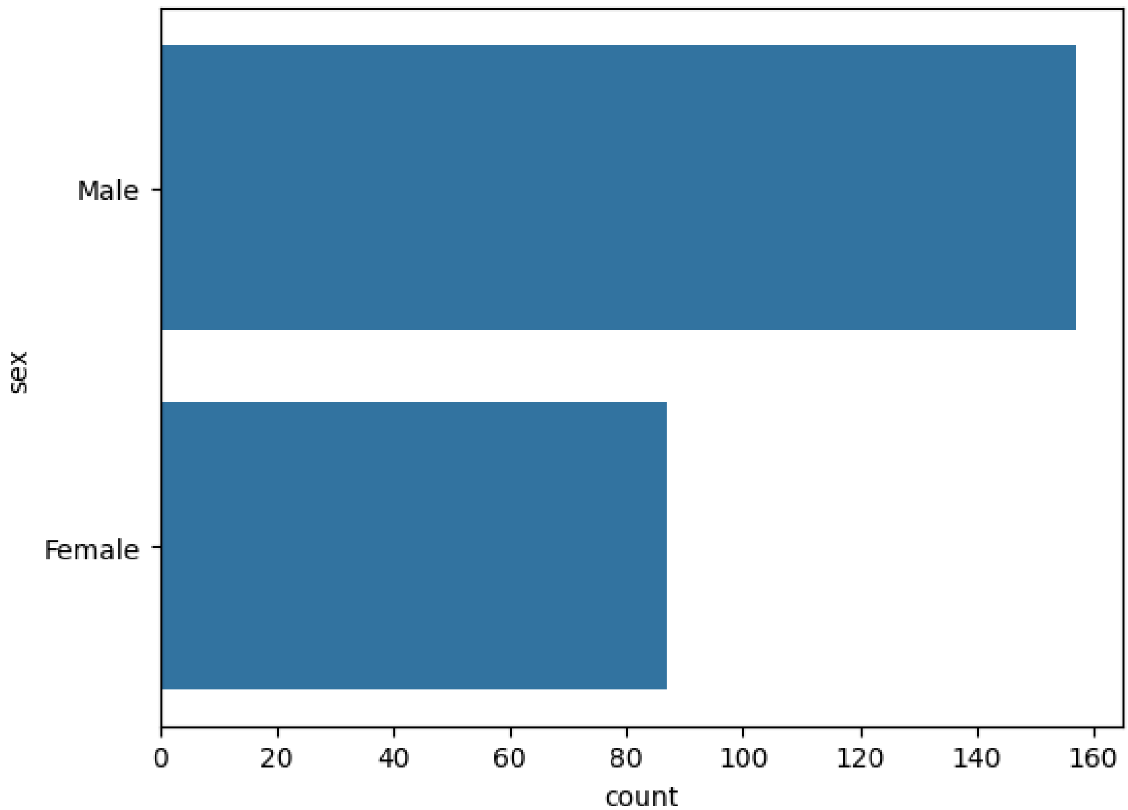
```
sns.countplot(tips.day)
```

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



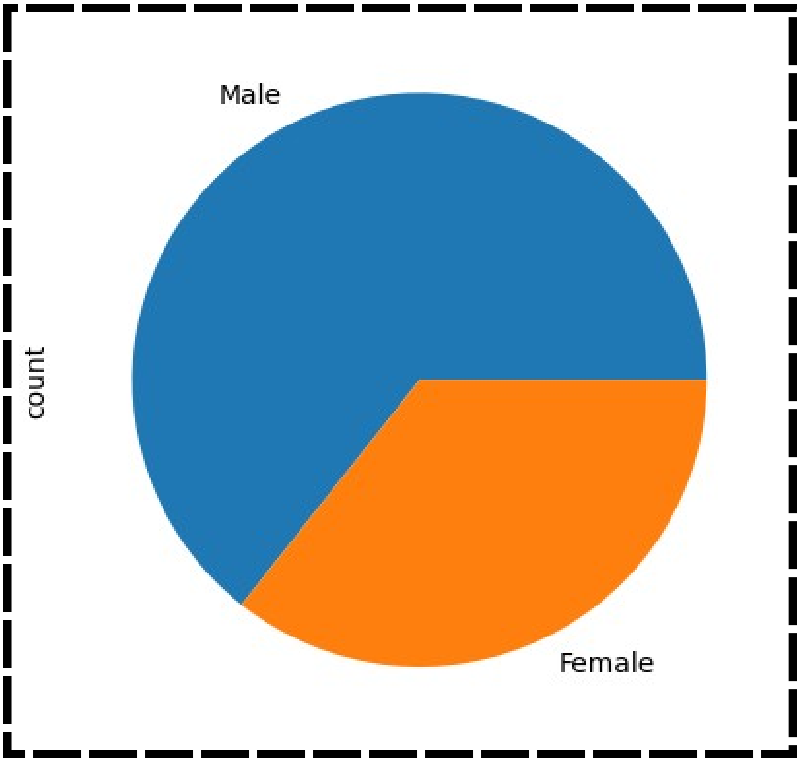

```
sns.countplot(tips.sex)
```

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



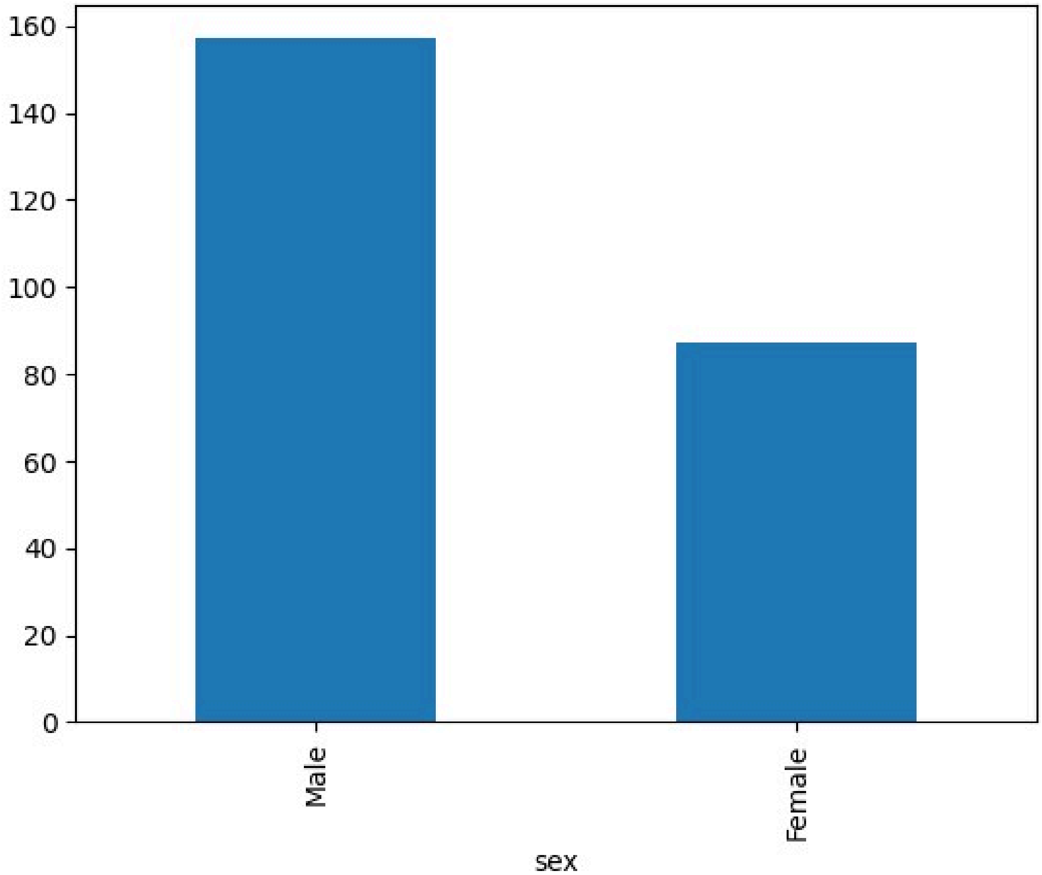

```
tips.sex.value_counts().plot(kind='pie')
```

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



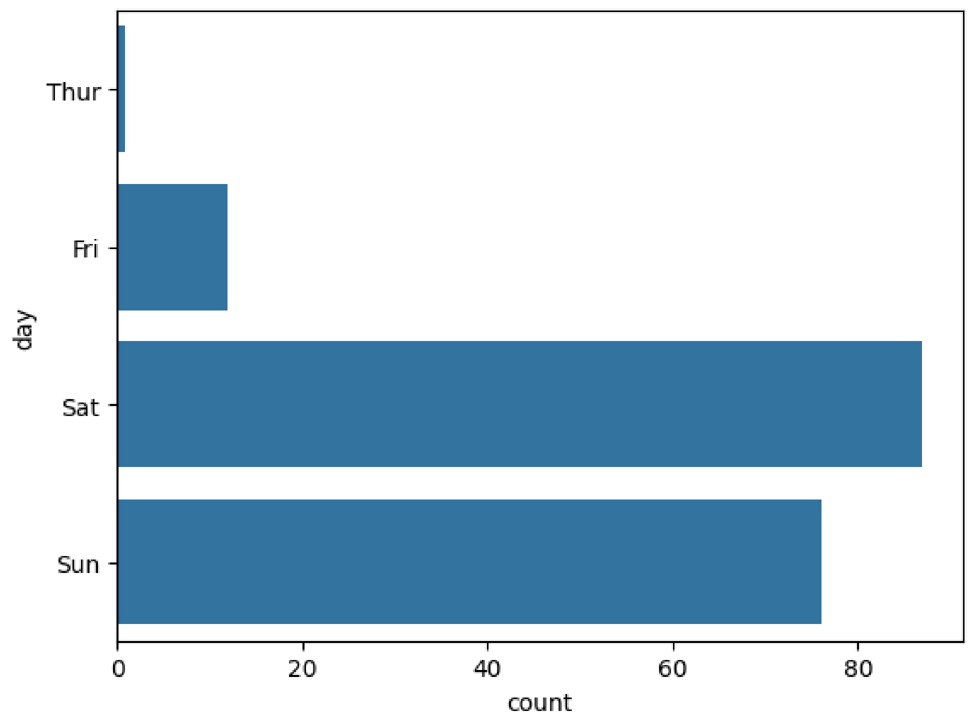

```
tips.sex.value_counts().plot(kind='bar')
```

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



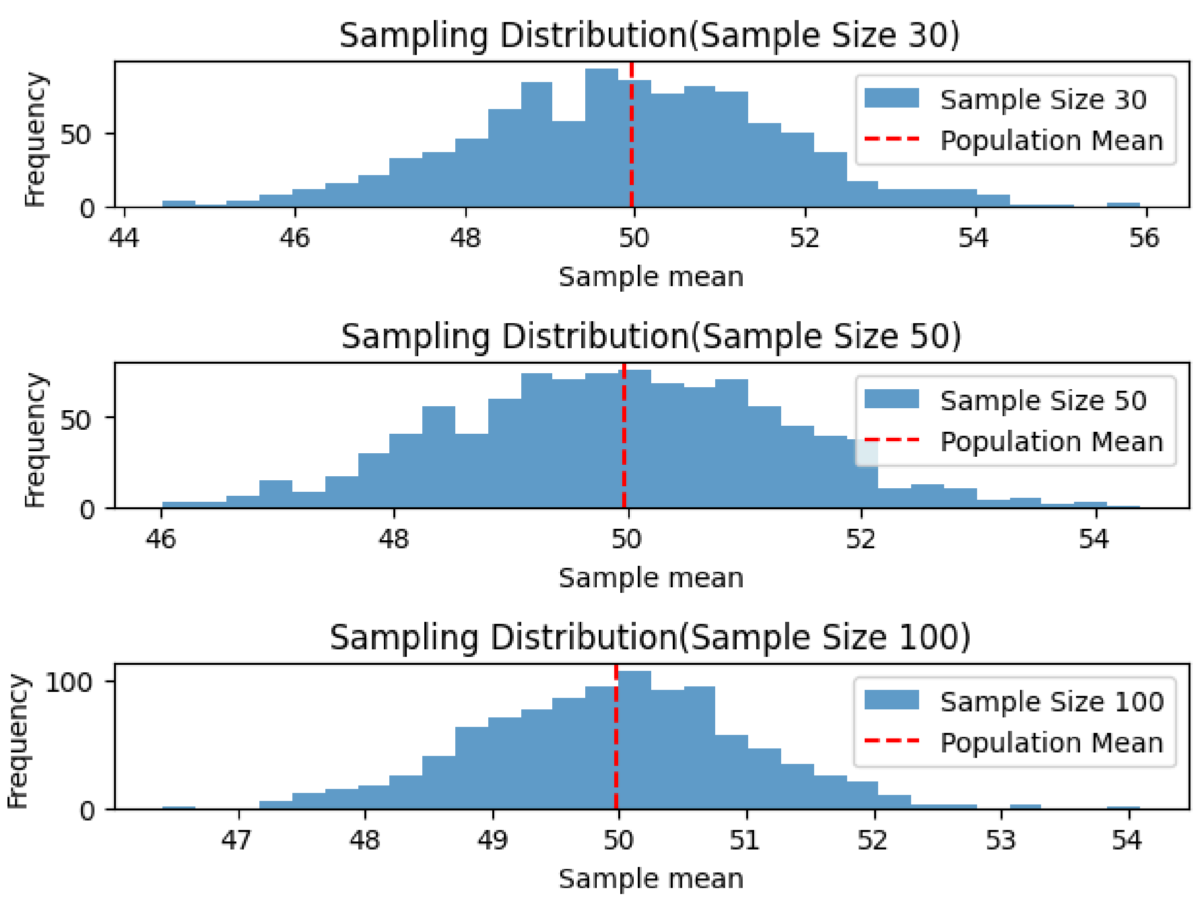

```
sns.countplot(tips[tips.time=='Dinner']['day'])
```

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




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

NAME:AKILESH PRASAD I.K

ROLL NO:230701020,DEPT:CSE-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
#DATe  : 10.09.2024
```

NAME:AKILESH PRASAD I.K
ROLL NO:230701020,DEPT:CSE-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 been
calculated:
print(f"Sample Mean: {sample_mean:.2f}\n")
print(f"Z-Statistic: {z_statistic:.4f}\n")
print(f"P-Value: {p_value:.4f}\n")

# Significance level
alpha = 0.05
# Decision based on p-value
if p_value < alpha:
    print("Reject the null hypothesis: The average weight is
significantly different from 150 grams.")
else:
    print("Fail to reject the null hypothesis: There is no significant
difference in average weight from 150 grams.")
```

Sample Mean: 150.20 Z-Statistic: 0.6406 P-Value: 0.5218 Fail to reject the null

hypothesis: There is no significant difference
in average weight from 150 grams.

#EX.NO :8 T-Test

#DATE : 08.10.2024
#NAME : AKILESH PRASAD

I.K

```
#ROLL NO : 230701020 #DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - A

import numpy as np
import scipy.stats as stats
np.random.seed(42)
sample_size = 25
sample_data = np.random.normal(loc=102, scale=15, size=sample_size)

population_mean = 100
sample_mean = np.mean(sample_data)
sample_std = np.std(sample_data, ddof=1)

n = len(sample_data)
t_statistic, p_value = stats.ttest_1samp(sample_data,population_mean)
# Assuming sample_mean, t_statistic, and p_value have already been
calculated:
print(f"Sample Mean: {sample_mean:.2f}\n")
print(f"T-Statistic: {t_statistic:.4f}\n")
print(f"P-Value: {p_value:.4f}\n")

# Significance level
alpha = 0.05
# Decision based on p-value
if p_value < alpha:
    print("Reject the null hypothesis: The average IQ score is
significantly different from 100.")
else:
    print("Fail to reject the null hypothesis: There is no significant
difference in average IQ score from 100.")
```

Sample Mean: 99.55 T-Statistic: -0.1577 P-Value: 0.8760 Fail to reject the null

hypothesis: There is no significant difference
in average IQ score from 100.

#EX.NO :9 Annova TEST

#DATE : 08.10.2024

NAME:AKILESH PRASAD I.K

ROLL NO:230701020,DEPT:CSE-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: 11.1377
Treatment C Mean Growth: 15.2652
F-Statistic: 36.1214
P-Value: 0.0000
Reject the null hypothesis: There is a significant difference in mean
growth rates among the three treatments.

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

```
==================================================
group1 group2 meandiff p-adj   lower   upper  reject
--------------------------------------------------
     A      B   1.4647 0.0877 -0.1683 3.0977  False
     A      C   5.5923    0.0  3.9593 7.2252   True
     B      C   4.1276    0.0  2.4946 5.7605   True
--------------------------------------------------
```

#EX.NO :10 Feature Scaling

#DATE : 22.10.2024

NAME:AKILESH PRASAD I.K

ROLL NO:230701020,DEPT:CSE-A

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

```
df.head()
```

	Country	Age	Salary	Purchased
0	France	44.0	72000.0	No
1	Spain	27.0	48000.0	Yes
2	Germany	30.0	54000.0	No
3	Spain	38.0	61000.0	No
4	Germany	40.0	NaN	Yes

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

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

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

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

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

SimpleImputer()    SimpleImputer()    SimpleImputer()

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

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

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

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

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

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

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

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

```
array([[ 1.22474487e+00, -6.54653671e-01, -6.54653671e-01,
         7.58874362e-01, 7.49473254e-01],
       [-8.16496581e-01, -6.54653671e-01, 1.52752523e+00,
        -1.71150388e+00, -1.43817841e+00],
       [-8.16496581e-01, 1.52752523e+00, -6.54653671e-01,
        -1.27555478e+00, -8.91265492e-01],
       [-8.16496581e-01, -6.54653671e-01, 1.52752523e+00,
        -1.13023841e-01, -2.53200424e-01],
       [-8.16496581e-01, 1.52752523e+00, -6.54653671e-01,
         1.77608893e-01, 6.63219199e-16],
       [ 1.22474487e+00, -6.54653671e-01, -6.54653671e-01,
        -5.48972942e-01, -5.26656882e-01],
       [-8.16496581e-01, -6.54653671e-01, 1.52752523e+00,
         0.00000000e+00, -1.07356980e+00],
       [ 1.22474487e+00, -6.54653671e-01, -6.54653671e-01,
         1.34013983e+00, 1.38753832e+00],
       [-8.16496581e-01, 1.52752523e+00, -6.54653671e-01,
         1.63077256e+00, 1.75214693e+00],
       [ 1.22474487e+00, -6.54653671e-01, -6.54653671e-01,
        -2.58340208e-01, 2.93712492e-01]])
```

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

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

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

Name:Akilesh Prasad i.k
Roll no:230701020
Dept:CSE-A

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

	YearsExperience	Salary
0	1.1	39343
1	1.3	46205
2	1.5	37731
3	2.0	43525
4	2.2	39891
5	2.9	56642
6	3.0	60150
7	3.2	54445
8	3.2	64445
9	3.7	57189
10	3.9	63218
11	4.0	55794
12	4.0	56957
13	4.1	57081
14	4.5	61111
15	4.9	67938
16	5.1	66029
17	5.3	83088
18	5.9	81363
19	6.0	93940
20	6.8	91738
21	7.1	98273
22	7.9	101302
23	8.2	113812
24	8.7	109431
25	9.0	105582
26	9.5	116969
27	9.6	112635
28	10.3	122391
29	10.5	121872

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30 entries, 0 to 29
Data columns (total 2 columns):

 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
```

```
 0   YearsExperience 30 non-null   float64
1    Salary          30 non-null   int64
dtypes: float64(1), int64(1) memory usage:
612.0 bytes
```

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

	YearsExperience	Salary
0	1.1	39343
1	1.3	46205
2	1.5	37731
3	2.0	43525
4	2.2	39891
5	2.9	56642
6	3.0	60150
7	3.2	54445
8	3.2	64445
9	3.7	57189
10	3.9	63218
11	4.0	55794
12	4.0	56957
13	4.1	57081
14	4.5	61111
15	4.9	67938
16	5.1	66029
17	5.3	83088
18	5.9	81363
19	6.0	93940
20	6.8	91738
21	7.1	98273
22	7.9	101302
23	8.2	113812
24	8.7	109431
25	9.0	105582
26	9.5	116969
27	9.6	112635
28	10.3	122391
29	10.5	121872

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30 entries, 0 to 29
Data columns (total 2 columns):

 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
0    YearsExperience 30 non-null      float64
 1   Salary          30 non-null      int64
```

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

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

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

```
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)
```

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

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

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

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

```
model.score(x_train,y_train)
'''
accuracy calculating
96 %
'''
```

'\naccuracy calculating\n96 %\n'

```
model.score(x_test,y_test)
'''
accuracy calculating
91 %
'''
```

'\naccuracy calculating\n91 %\n'

```
model.coef_
```

array([[9281.30847068]])

```
model.intercept_
```

array([27166.73682891])

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

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

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

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

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

```python
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*

DATE : 05.11.2024

NAME:AKILESH PRASAD I.K

ROLL NO:230701020,CSE-A

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

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

[400 rows x 5 columns]

```python
df.tail(20)
```

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

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

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

	User ID	Gender	Age	EstimatedSalary	Purchased
0	15624510	Male	19	19000	0
1	15810944	Male	35	20000	0
2	15668575	Female	26	43000	0
3	15603246	Female	27	57000	0
4	15804002	Male	19	76000	0
5	15728773	Male	27	58000	0
6	15598044	Female	27	84000	0
7	15694829	Female	32	150000	1
8	15600575	Male	25	33000	0
9	15727311	Female	35	65000	0
10	15570769	Female	26	80000	0
11	15606274	Female	26	52000	0
12	15746139	Male	20	86000	0
13	15704987	Male	32	18000	0
14	15628972	Male	18	82000	0
15	15697686	Male	29	80000	0
16	15733883	Male	47	25000	1
17	15617482	Male	45	26000	1
18	15704583	Male	46	28000	1
19	15621083	Female	48	29000	1
20	15649487	Male	45	22000	1
21	15736760	Female	47	49000	1
22	15714658	Male	48	41000	1
23	15599081	Female	45	22000	1
24	15705113	Male	46	23000	1

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

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

```
 [ 19, 76000],  [ 27, 58000],  [
27, 84000],  [ 32, 150000],  [
25, 33000],  [ 35, 65000],  [
26, 80000],  [ 26, 52000],  [
20, 86000],  [ 32, 18000],  [
18, 82000],  [ 29, 80000],  [
47, 25000],  [ 45, 26000],  [
46, 28000],  [ 48, 29000],  [
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48, 41000],  [ 45, 22000],  [
46, 23000],  [ 47, 20000],  [
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31, 74000],  [ 27, 137000],  [
21, 16000],  [ 28, 44000],  [
27, 90000],  [ 35, 27000],  [
33, 28000],  [ 30, 49000],  [
26, 72000],  [ 27, 31000],  [
27, 17000],  [ 33, 51000],  [
35, 108000],  [ 30, 15000],  [
28, 84000],  [ 23, 20000],  [
25, 79000],  [ 27, 54000],  [
30, 135000],  [ 31, 89000],  [
24, 32000],  [ 18, 44000],  [
29, 83000],
```

```
 [ 35, 23000],  [ 27, 58000],  [
24, 55000],   [ 23, 48000],   [
28, 79000],   [ 22, 18000],   [
32, 117000],   [ 27, 20000],   [
25, 87000],   [ 23, 66000],   [
32, 120000],   [ 59, 83000],   [
24, 58000],   [ 24, 19000],   [
23, 82000],   [ 22, 63000],   [
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24, 27000],   [ 20, 23000],   [
33, 113000],   [ 32, 18000],   [
34, 112000],   [ 18, 52000],   [
22, 27000],   [ 28, 87000],   [
26, 17000],   [ 30, 80000],   [
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35, 44000],   [ 35, 25000],   [
28, 123000],   [ 35, 73000],   [
28, 37000],   [ 27, 88000],   [
28, 59000],
```

[32, 86000],   [33, 149000],
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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],   [
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28, 59000],   [19, 25000],   [
19, 85000],   [18, 68000],   [
35, 59000],   [30, 89000],   [
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26, 15000],

```
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18, 86000],   [ 22, 55000],   [
35, 71000],   [ 29, 148000],  [
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20, 36000],   [ 26, 80000],   [
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```

```
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[ 35, 60000],  [ 37, 53000],  [
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40, 72000],  [ 42, 80000],  [
35, 147000],  [ 39, 42000],  [
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40, 57000],  [ 37, 80000],  [
46, 82000],  [ 53, 143000],  [
42, 149000],  [ 38, 59000],  [
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41, 72000],  [ 51, 146000],  [
35, 50000],  [ 57, 122000],  [
41, 52000],
```

```
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[ 37, 146000],   [ 50, 44000],
[ 52, 90000],   [ 41, 72000],   [
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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],   [
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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],   [
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53, 104000],   [ 35, 75000],   [
38, 65000],   [ 47, 51000],   [
47, 105000],   [ 41, 63000],   [
53, 72000],
```

[54, 108000], [39, 77000],
[38, 61000], [38, 113000], [
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37, 57000], [36, 99000], [
60, 34000], [54, 70000], [
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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, 1, 0, 0, 0, 0, 0, 0, 0,
0,
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        1, 0, 0, 1, 0, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1], dtype=int64)
0,
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```

```
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:

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





'''
```

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

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

Test Score: 0.8500 | Train Score: 0.8375 | Random State: 163 Test Score: 0.8750 | Train Score: 0.8313 | Random State: 164 Test Score: 0.8625 | Train Score: 0.8500 | Random State: 169 Test Score: 0.8750 | Train Score: 0.8406 | Random State: 171 Test Score: 0.8500 | Train Score: 0.8406 | Random State: 172 Test Score: 0.9000 | Train Score: 0.8250 | Random State: 180 Test Score: 0.8500 | Train Score: 0.8344 | Random State: 184 Test Score: 0.9250 | Train Score: 0.8219 | Random State: 186 Test Score: 0.9000 | Train Score: 0.8313 | Random State: 193 Test Score: 0.8625 | Train Score: 0.8500 | Random State: 195 Test Score: 0.8625 | Train Score: 0.8406 | Random State: 196 Test Score: 0.8625 | Train Score: 0.8375 | Random State: 197 Test Score: 0.8750 | Train Score: 0.8406 | Random State: 198 Test Score: 0.8875 | Train Score: 0.8375 | Random State: 199 Test Score: 0.8875 | Train Score: 0.8438 | Random State: 200 Test Score: 0.8625 | Train Score: 0.8375 | Random State: 202 Test Score: 0.8625 | Train Score: 0.8406 | Random State: 203 Test Score: 0.8875 | Train Score: 0.8313 | Random State: 206 Test Score: 0.8625 | Train Score: 0.8344 | Random State: 211 Test Score: 0.8500 | Train Score: 0.8438 | Random State: 212 Test Score: 0.8625 | Train Score: 0.8344 | Random State: 214 Test Score: 0.8750 | Train Score: 0.8313 | Random State: 217 Test Score: 0.9625 | Train Score: 0.8187 | Random State: 220 Test Score: 0.8750 | Train Score: 0.8438 | Random State: 221 Test Score: 0.8500 | Train Score: 0.8406 | Random State: 222 Test Score: 0.9000 | Train Score: 0.8438 | Random State: 223 Test Score: 0.8625 | Train Score: 0.8531 | Random State: 227 Test Score: 0.8625 | Train Score: 0.8344 | Random State: 228 Test Score: 0.9000 | Train Score: 0.8406 | Random State: 229 Test Score: 0.8500 | Train Score: 0.8438 | Random State: 232 Test Score: 0.8750 | Train Score: 0.8469 | Random State: 233 Test Score: 0.9125 | Train Score: 0.8406 | Random State: 234 Test Score: 0.8625 | Train Score: 0.8406 | Random State: 235 Test Score: 0.8500 | Train Score: 0.8469 | Random State: 236 Test Score: 0.8750 | Train Score: 0.8469 | Random State: 239 Test Score: 0.8500 | Train Score: 0.8438 | Random State: 241 Test Score: 0.8875 | Train Score: 0.8500 | Random State: 242 Test Score: 0.8875 | Train Score: 0.8250 | Random State: 243 Test Score: 0.8750 | Train Score: 0.8469 | Random State: 244 Test Score: 0.8750 | Train Score: 0.8406 | Random State: 245 Test Score: 0.8750 | Train Score: 0.8469 | Random State: 246 Test Score: 0.8625 | Train Score: 0.8594 | Random State: 247 Test Score: 0.8875 | Train Score: 0.8438 | Random State: 248 Test Score: 0.8625 | Train Score: 0.8500 | Random State: 250 Test Score: 0.8750 | Train Score: 0.8313 | Random State: 251 Test Score: 0.8875 | Train Score: 0.8438 | Random State: 252 Test Score: 0.8625 | Train Score: 0.8469 | Random State: 255 Test Score: 0.9000 | Train Score: 0.8406 | Random State: 257 Test Score: 0.8625 | Train Score: 0.8562 | Random State: 260

Test Score: 0.8625 | Train Score: 0.8406 | Random State: 266 Test Score: 0.8625 | Train Score: 0.8375 | Random State: 268 Test Score: 0.8750 | Train Score: 0.8406 | Random State: 275 Test Score: 0.8625 | Train Score: 0.8500 | Random State: 276 Test Score: 0.9250 | Train Score: 0.8375 | Random State: 277 Test Score: 0.8750 | Train Score: 0.8469 | Random State: 282 Test Score: 0.8500 | Train Score: 0.8469 | Random State: 283 Test Score: 0.8500 | Train Score: 0.8438 | Random State: 285 Test Score: 0.9125 | Train Score: 0.8344 | Random State: 286 Test Score: 0.8500 | Train Score: 0.8406 | Random State: 290 Test Score: 0.8500 | Train Score: 0.8406 | Random State: 291 Test Score: 0.8500 | Train Score: 0.8469 | Random State: 292 Test Score: 0.8625 | Train Score: 0.8375 | Random State: 294 Test Score: 0.8875 | Train Score: 0.8281 | Random State: 297 Test Score: 0.8625 | Train Score: 0.8344 | Random State: 300 Test Score: 0.8625 | Train Score: 0.8500 | Random State: 301 Test Score: 0.8875 | Train Score: 0.8500 | Random State: 302 Test Score: 0.8750 | Train Score: 0.8469 | Random State: 303 Test Score: 0.8625 | Train Score: 0.8344 | Random State: 305 Test Score: 0.9125 | Train Score: 0.8375 | Random State: 306 Test Score: 0.8750 | Train Score: 0.8469 | Random State: 308 Test Score: 0.9000 | Train Score: 0.8438 | Random State: 311 Test Score: 0.8625 | Train Score: 0.8344 | Random State: 313 Test Score: 0.9125 | Train Score: 0.8344 | Random State: 314 Test Score: 0.8750 | Train Score: 0.8375 | Random State: 315 Test Score: 0.9000 | Train Score: 0.8469 | Random State: 317 Test Score: 0.9125 | Train Score: 0.8219 | Random State: 319 Test Score: 0.8625 | Train Score: 0.8500 | Random State: 321 Test Score: 0.9125 | Train Score: 0.8281 | Random State: 322 Test Score: 0.8500 | Train Score: 0.8469 | Random State: 328 Test Score: 0.8500 | Train Score: 0.8375 | Random State: 332 Test Score: 0.8875 | Train Score: 0.8531 | Random State: 336 Test Score: 0.8500 | Train Score: 0.8375 | Random State: 337 Test Score: 0.8750 | Train Score: 0.8406 | Random State: 343 Test Score: 0.8625 | Train Score: 0.8438 | Random State: 346 Test Score: 0.8875 | Train Score: 0.8313 | Random State: 351 Test Score: 0.8625 | Train Score: 0.8500 | Random State: 352 Test Score: 0.9500 | Train Score: 0.8187 | Random State: 354 Test Score: 0.8625 | Train Score: 0.8500 | Random State: 356 Test Score: 0.9125 | Train Score: 0.8406 | Random State: 357 Test Score: 0.8625 | Train Score: 0.8375 | Random State: 358 Test Score: 0.8500 | Train Score: 0.8406 | Random State: 362 Test Score: 0.9000 | Train Score: 0.8438 | Random State: 363 Test Score: 0.8625 | Train Score: 0.8531 | Random State: 364 Test Score: 0.9375 | Train Score: 0.8219 | Random State: 366 Test Score: 0.9125 | Train Score: 0.8406 | Random State: 369 Test Score: 0.8625 | Train Score: 0.8531 | Random State: 371 Test Score: 0.9250 | Train Score: 0.8344 | Random State: 376 Test Score: 0.9125 | Train Score: 0.8281 | Random State: 377

```
Test Score: 0.8875 | Train Score: 0.8500 | Random State: 378 Test Score: 0.8875 |
Train Score: 0.8500 | Random State: 379 Test Score: 0.8625 | Train Score: 0.8406 |
Random State: 382 Test Score: 0.8625 | Train Score: 0.8594 | Random State: 386
Test Score: 0.8500 | Train Score: 0.8375 | Random State: 387 Test Score: 0.8750 |
Train Score: 0.8281 | Random State: 388 Test Score: 0.8500 | Train Score: 0.8438 |
Random State: 394 Test Score: 0.8625 | Train Score: 0.8375 | Random State: 395
Test Score: 0.9000 | Train Score: 0.8438 | Random State: 397 Test Score: 0.8625 |
Train Score: 0.8438 | Random State: 400

'\n\n\n'
```

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

```
LogisticRegression()
```

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

```
0.85
0.85
```

```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 avg	0.85	0.85	0.85	400