CS23334- Fundamentals of data science

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DEPT/SEC:CSE-E

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

#NAME : PRASANNA KUMAR M
#ROLL NO : 230701237
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - D
```

[2]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

[3]:
```
data=pd.read_csv('Iris.csv')
data
```

[3]: 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]

[4]: 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

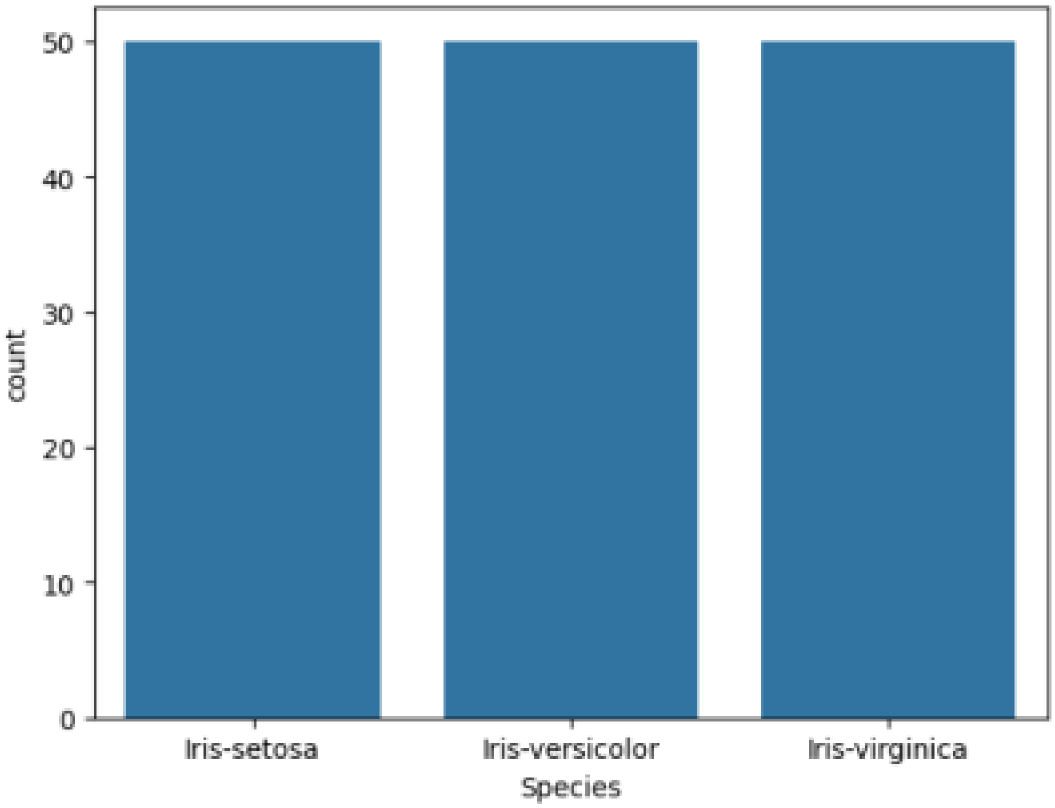
[5]: data.describe()

[5]: 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

[6]: data.value_counts('Species')

[6]: Species
Iris-setosa 50
Iris-versicolor 50
Iris-virginica 50
Name: count, dtype: int64

[7]: sns.countplot(x='Species',data=data,)
plt.show()



[8]: dummies=pd.get_dummies(data.Species)

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

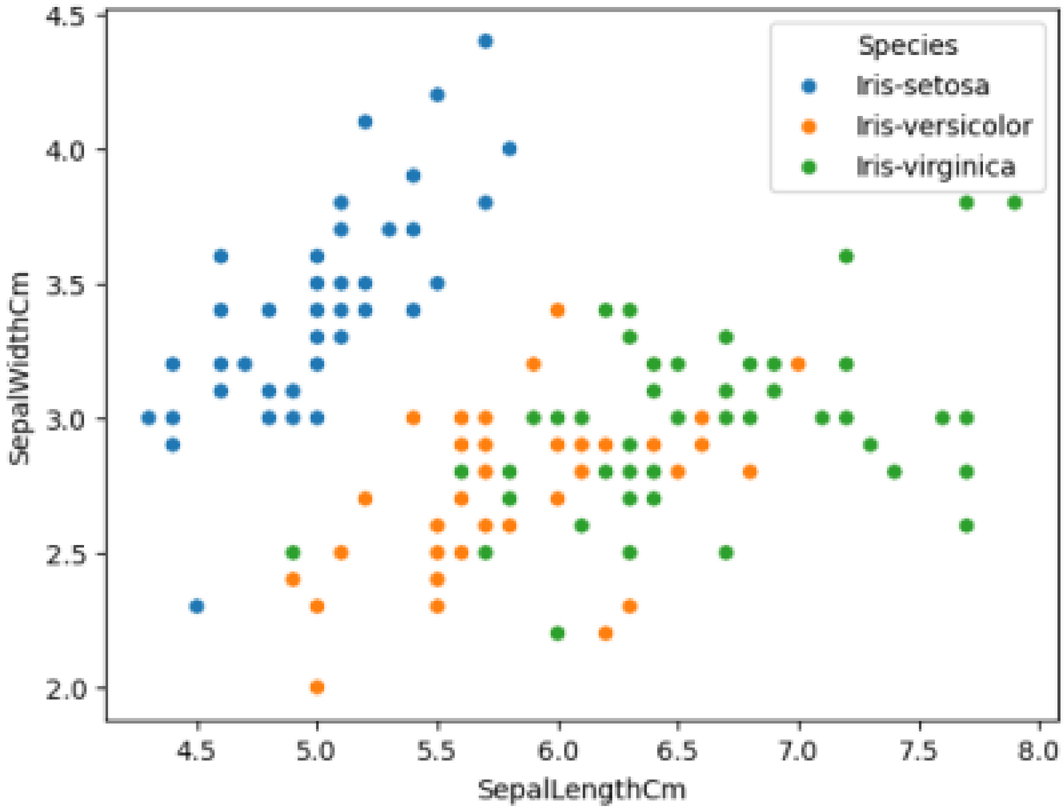
[10]: FinalDataset.head()

[10]: 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

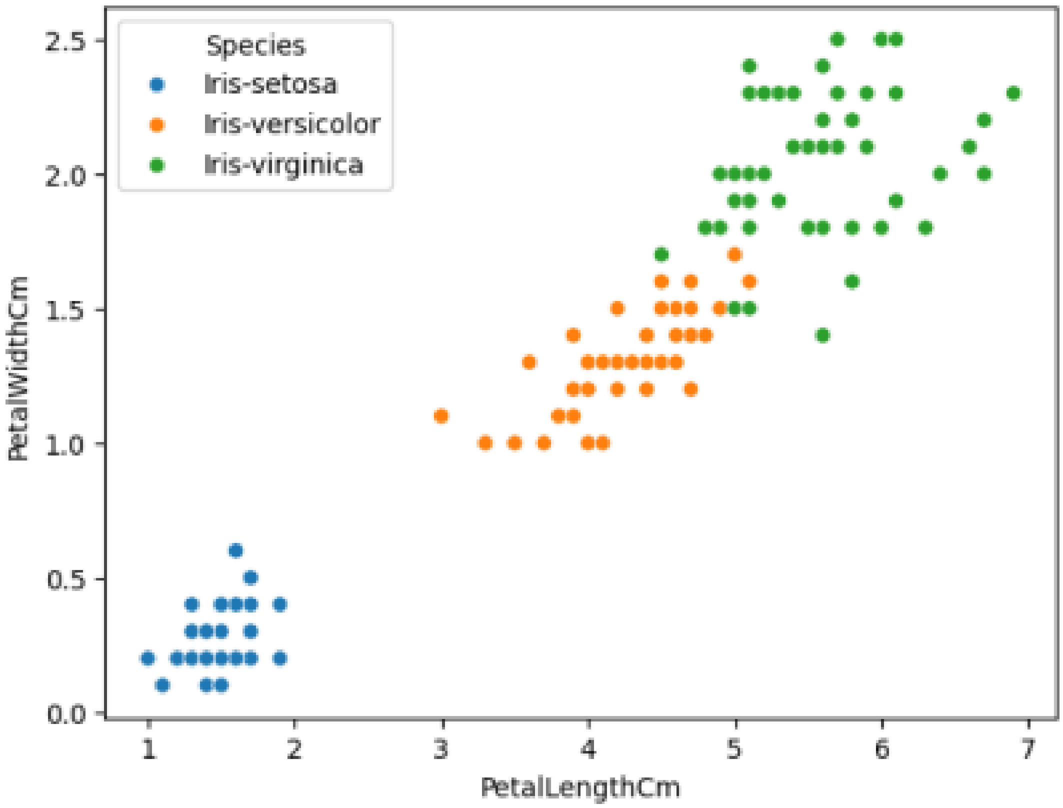
[11]: sns.scatterplot(x='SepalLengthCm',y='SepalWidthCm',hue='Species',data=data,) [11]:

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

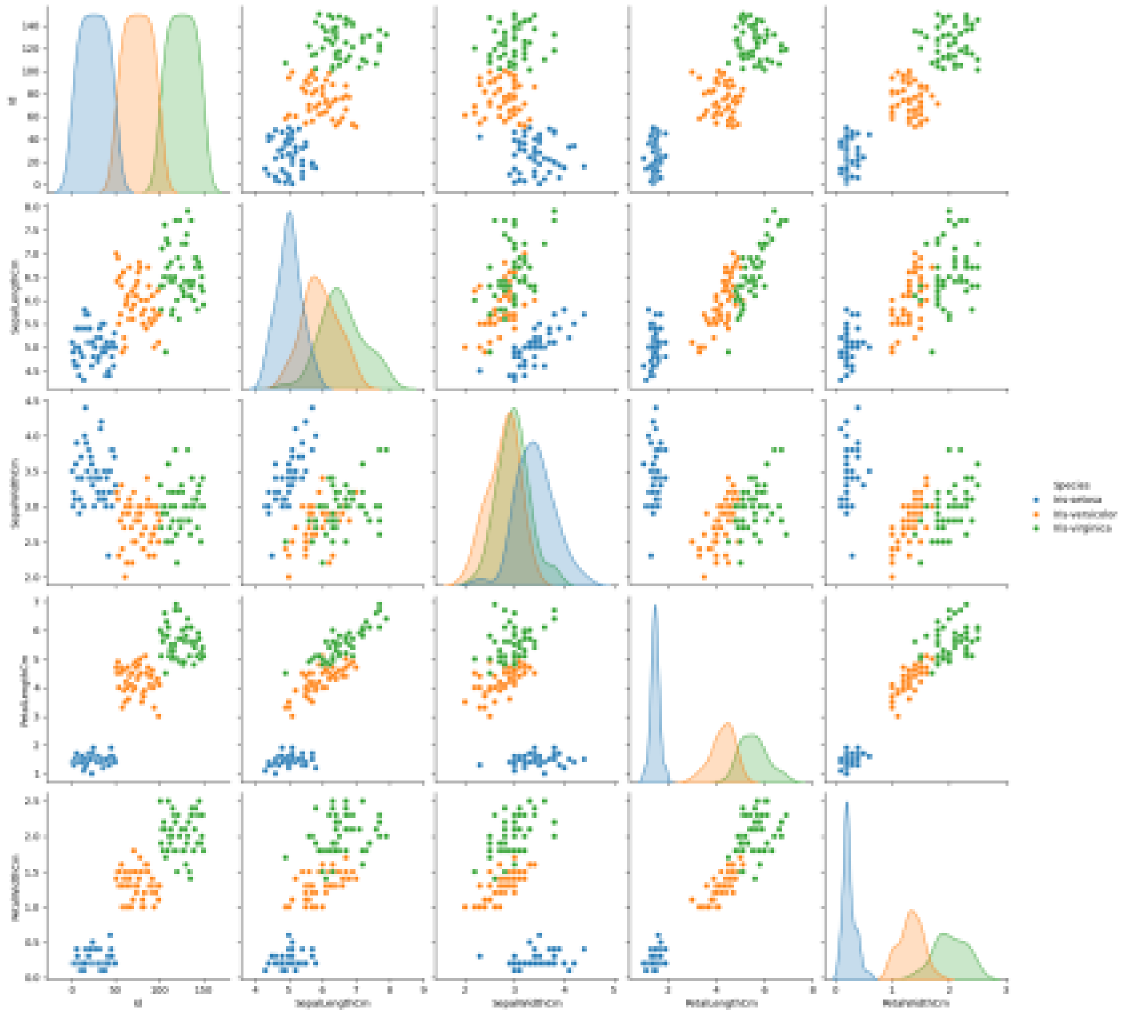


[12]: sns.scatterplot(x='PetalLengthCm',y='PetalWidthCm',hue='Species',data=data,) [12]: <Axes:

xlabel='PetalLengthCm', ylabel='PetalWidthCm'>

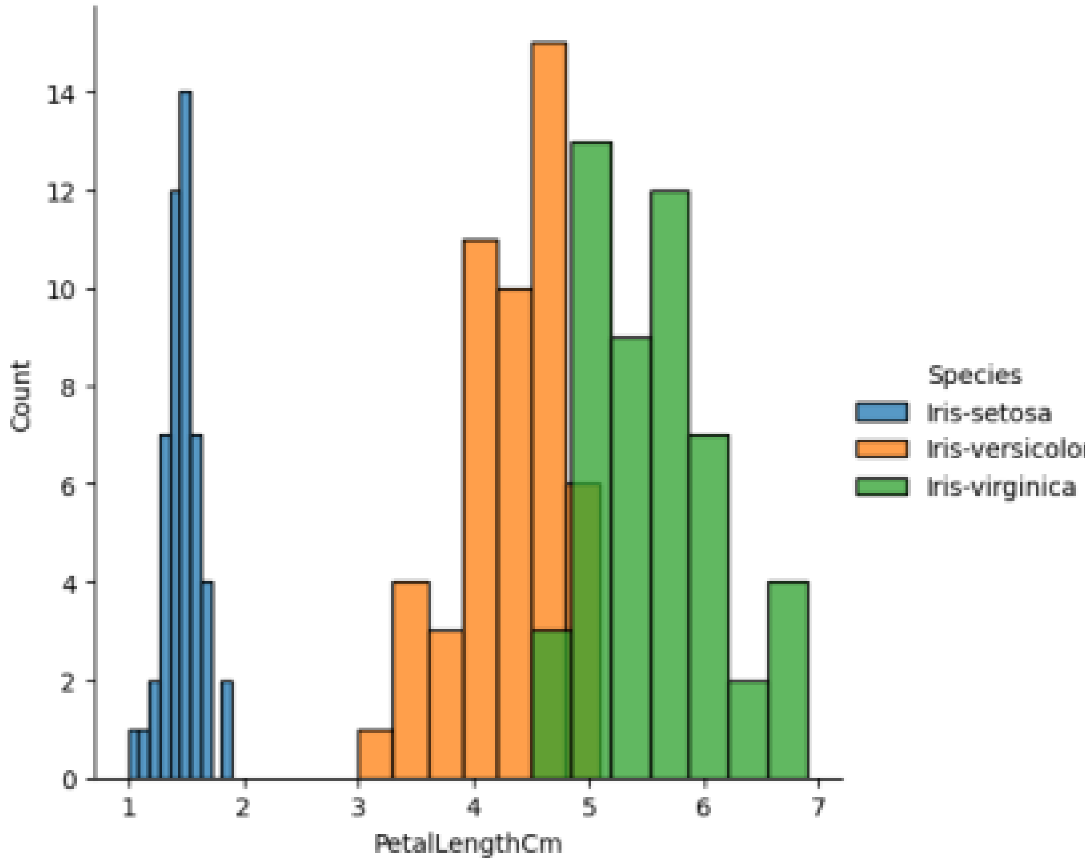



```
[13]: sns.pairplot(data,hue='Species',height=3);
```

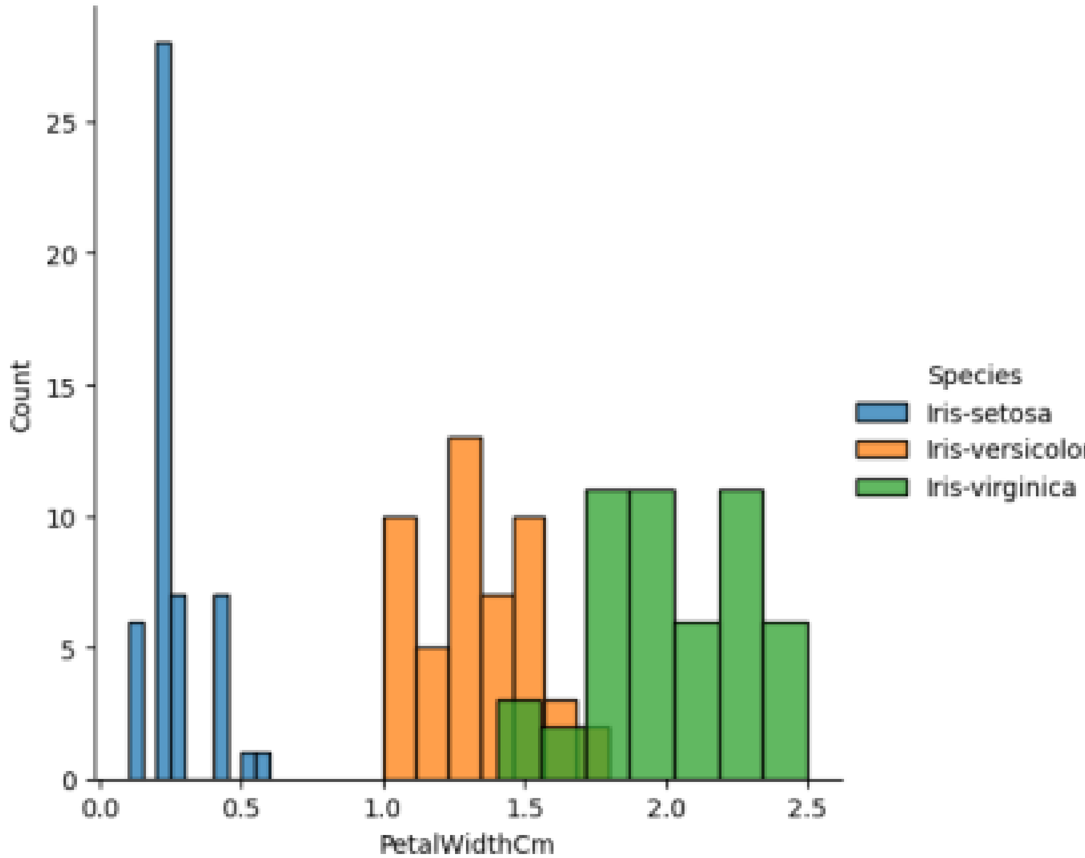


[14]:
```
plt.show()
```

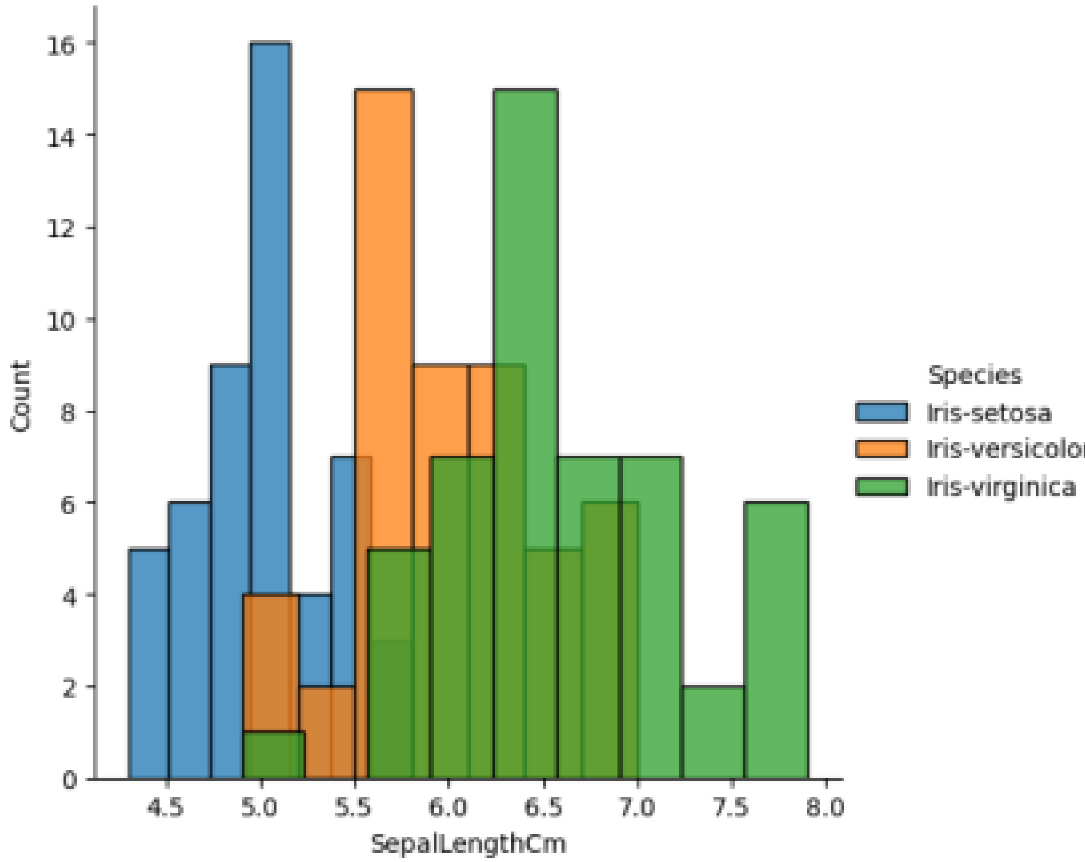
[15]:
```
sns.FacetGrid(data,hue='Species',height=5).map(sns.histplot,'PetalLengthCm').
    ↪add_legend();
plt.show();
```



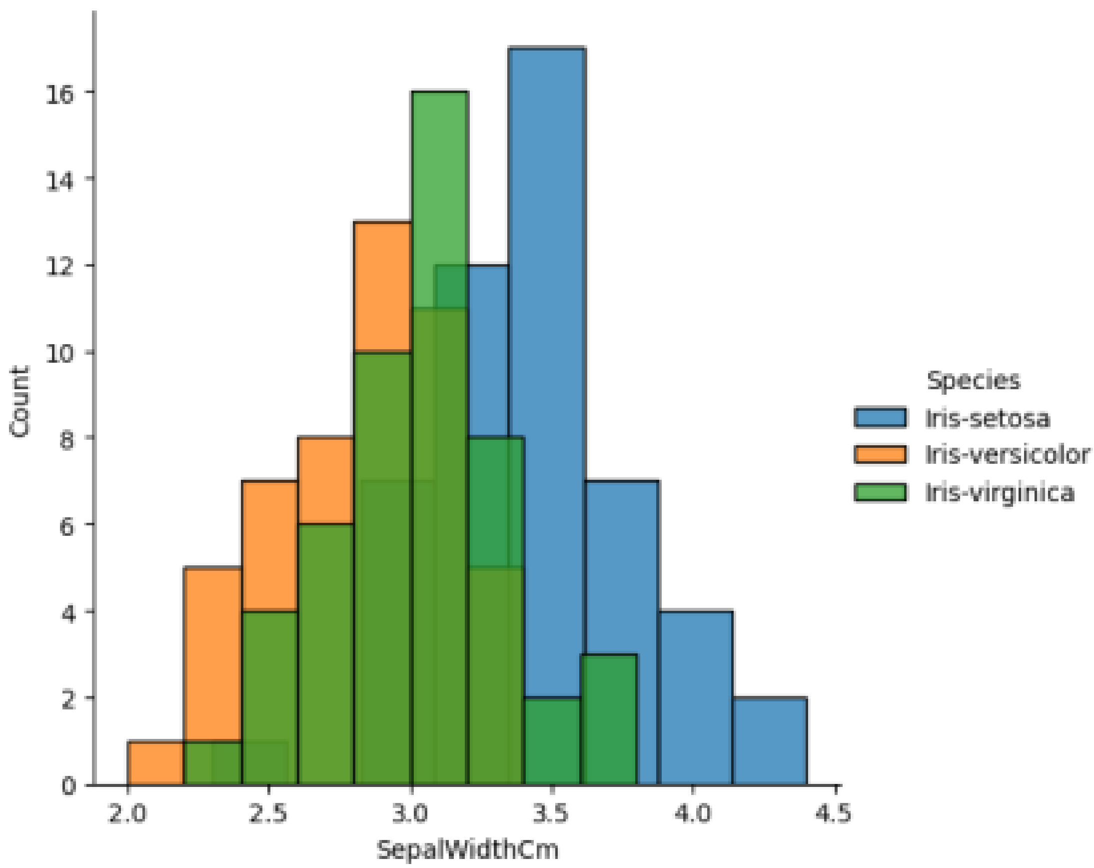
[16]:
```
sns.FacetGrid(data,hue='Species',height=5).map(sns.histplot,'PetalWidthCm').
    ↪add_legend();
plt.show();
```



[17]:
```
sns.FacetGrid(data,hue='Species',height=5).map(sns.histplot,'SepalLengthCm').
↪add_legend();
plt.show();
```




```
[18]: 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
#DATA : 06.08.2024

#NAME : PRASANNA KUMAR M
#ROLL NO : 230701237
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - D
```

[20]:
```
import numpy as np
array=np.random.randint(1,100,9)
array
```

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

[21]:
```
np.sqrt(array)
```


[21]:
```
array([6.244998 , 9.8488578 , 9.38083152, 7.61577311, 5.38516481,
       9.32737905, 5.19615242, 9.38083152, 9.53939201])
```

```
[22]: array.ndim

[22]: 1

[23]: new_array=array.reshape(3,3)

[24]: new_array

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

[25]: new_array.ndim

[25]: 2

[26]: new_array.ravel()

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

[27]: newm=new_array.reshape(3,3)

[28]: newm

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

[29]: newm[2,1:3]

[29]: array([88, 91])

[30]: newm[1:2,1:3]

[30]: array([[29, 87]])

[31]: new_array[0:3,0:0]

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

[32]: new_array[1:3]

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



```
[ ]: #EX.NO :2 Outlier detection
```

```
#DATA : 13.08.2024

#NAME : PRASANNA KUMAR M
#ROLL NO : 230701237
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - D
```

[34]:
```
import numpy as np
import warnings
warnings.filterwarnings('ignore')
array=np.random.randint(1,100,16)
array
```

[34]: array([37, 15, 49, 89, 30, 47, 2, 86, 53, 63, 41, 46, 42, 27, 5, 97]) [35]: array.mean()

[35]: 45.5625

[36]: np.percentile(array,25)

[36]: 29.25

[37]: np.percentile(array,50)

[37]: 44.0

[38]: np.percentile(array,75)

[38]: 55.5

[39]: np.percentile(array,100)

[39]: 97.0

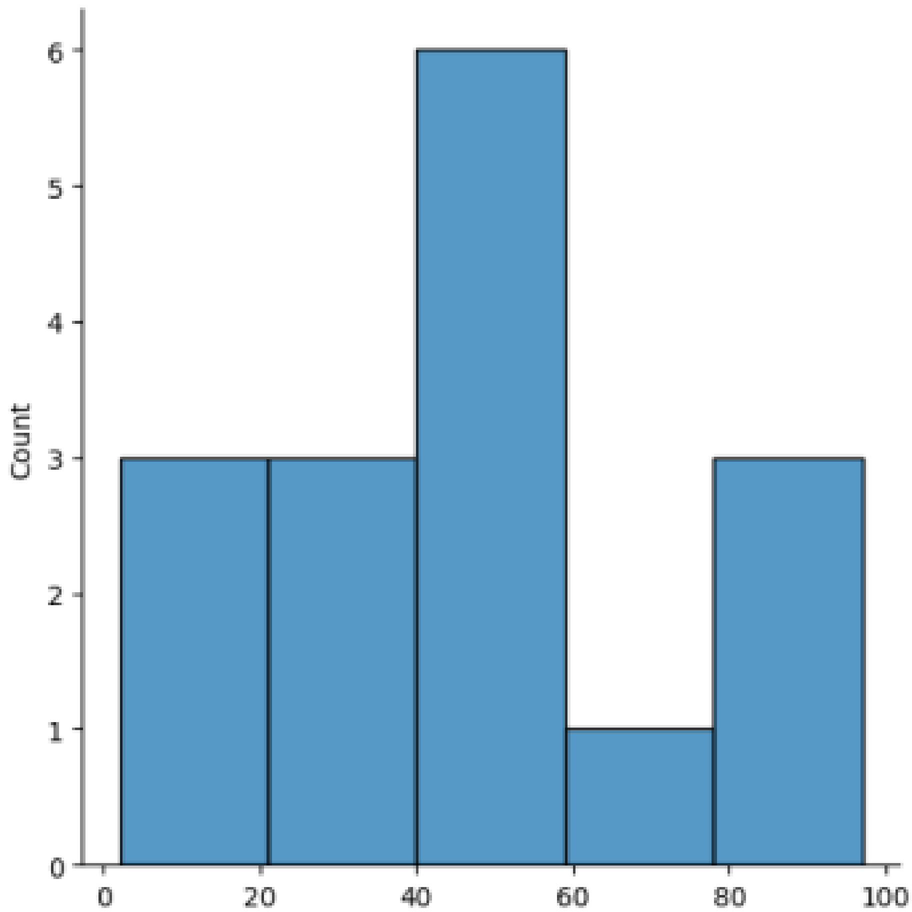
[40]:
```
#outliers detection
def outDetection(array):
    sorted(array)
    Q1,Q3=np.percentile(array,[25,75])
    IQR=Q3-Q1
    lr=Q1-(1.5*IQR)
    ur=Q3+(1.5*IQR)
    return lr,ur
lr,ur=outDetection(array)
lr,ur
```

[40]: (-10.125, 94.875)

[41]:
```
import seaborn as sns
```

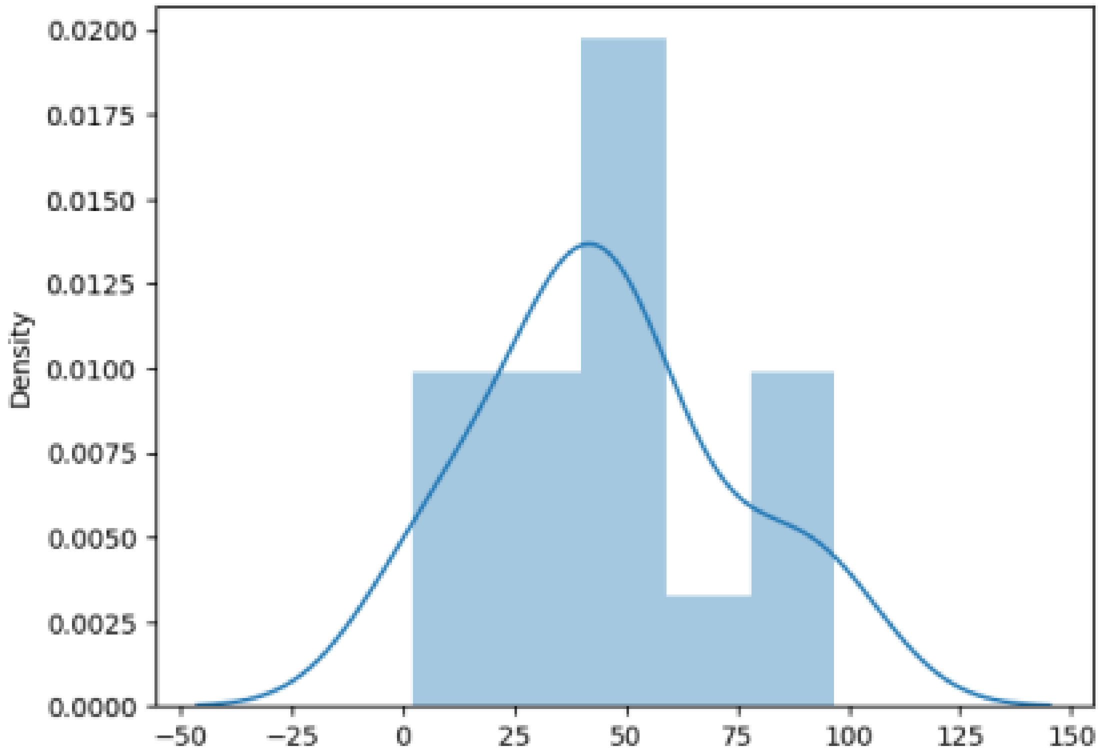
```
%matplotlib inline
sns.displot(array)
```

[41]: <seaborn.axisgrid.FacetGrid at 0x20d7cda3b50>



[42]: sns.distplot(array)

[42]: <Axes: ylabel='Density'>

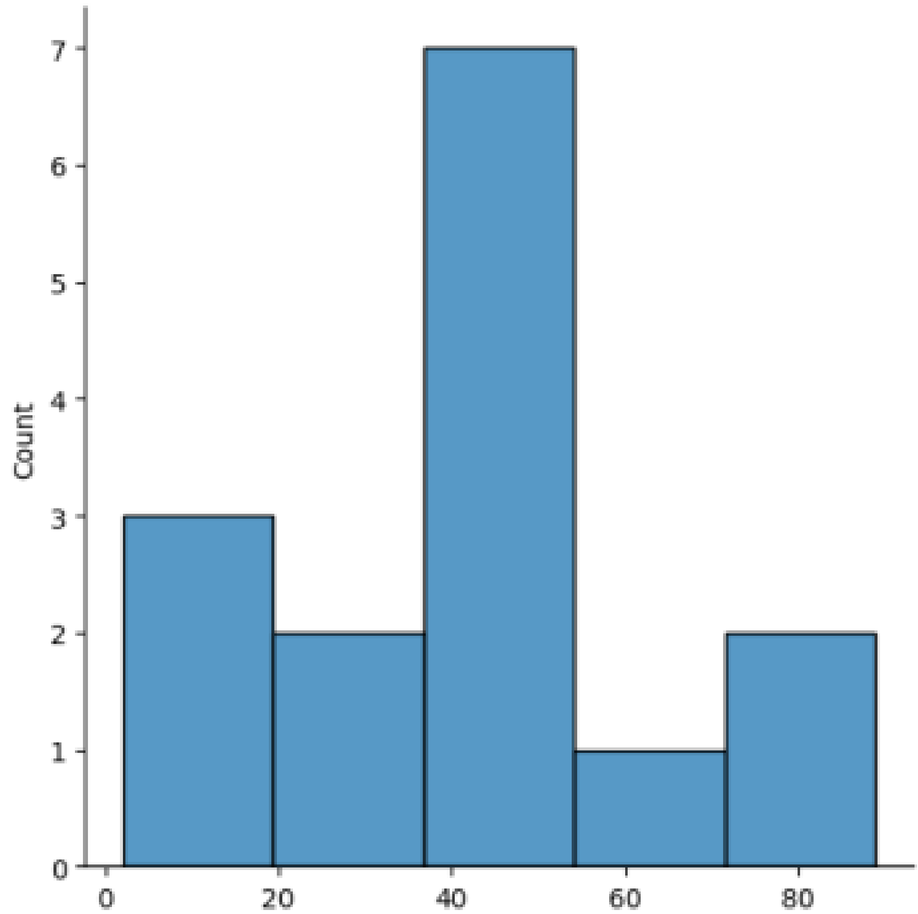


[43]:
```
new_array=array[(array>lr) & (array<ur)]
new_array
```

[43]: array([37, 15, 49, 89, 30, 47, 2, 86, 53, 63, 41, 46, 42, 27, 5]) [44]:

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

[44]: <seaborn.axisgrid.FacetGrid at 0x20d7d02d950>




```
[45]: lr1,ur1=outDetection(new_array)
      lr1,ur1
```

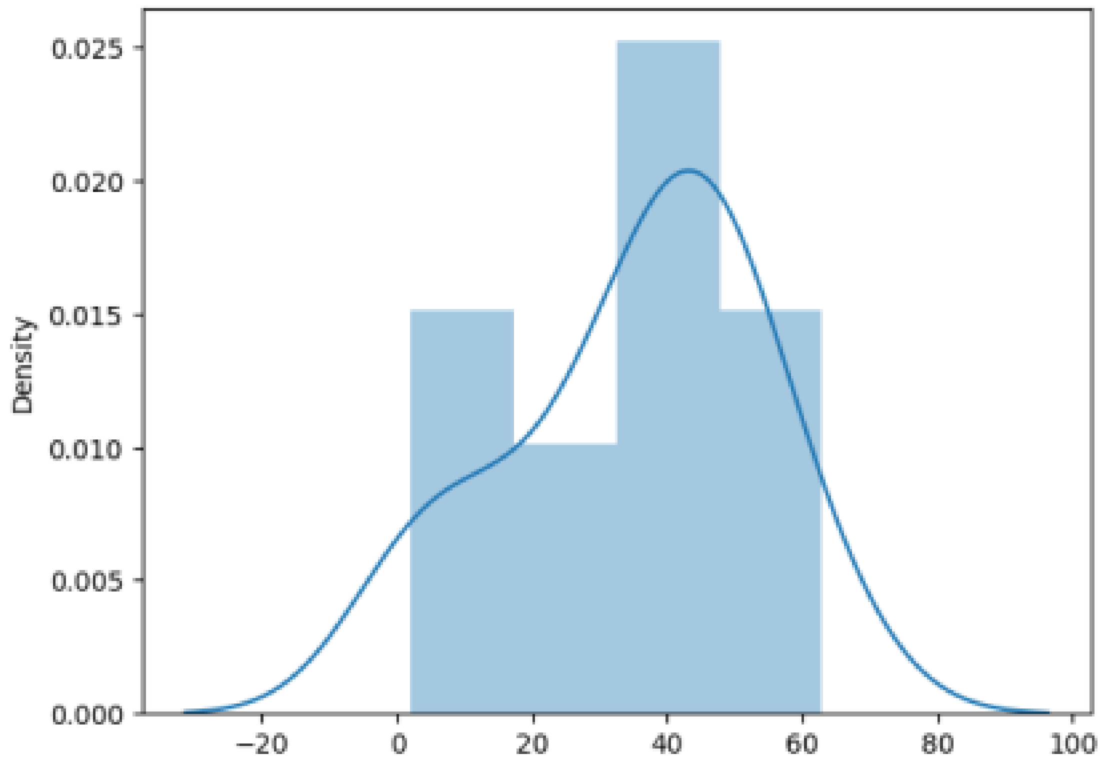
```
[45]: (-5.25, 84.75)
```

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

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

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

```
[47]: <Axes: ylabel='Density'>
```



[ ]: *#EX.NO :3 Missing and inappropriate data*
#DATA : 20.08.2024

#NAME : PRASANNA KUMAR M
#ROLL NO : 230701237
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - D

[49]:
```
import numpy as np
import pandas as pd
import warnings
warnings.filterwarnings('ignore')
df=pd.read_csv("Hotel_Dataset.csv")
df
```

[49]: 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
```

[50]: df.duplicated()

[50]:
```
0 False
1 False
2 False
3 False
4 False
5 False
6 False
7 False
8 False
9 True
10 False
dtype: bool
```

[51]: 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
```

[52]: df.drop_duplicates(inplace=True)

df

[52]: 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

[53]: len(df)

[53]: 10

[54]:
```
index=np.array(list(range(0,len(df))))
df.set_index(index,inplace=True)
index
```

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

[55]: df

[55]: 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

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

[56]: 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
0 40000
1 59000
2 30000
3 120000
4 45000
5 122220
6 21122
7 345673
8 -99999
9 87777


```
[57]: 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
```

[57]: 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

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

[58]: 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

[59]: df.Age_Group.unique()

[59]: array(['20-25', '30-35', '25-30', '35+'], dtype=object) [60]:

df.Hotel.unique()

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

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

[61]: <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>

[62]:
```
df.FoodPreference.replace(['Vegetarian','veg'],'Veg',inplace=True)
df.FoodPreference.replace(['non-Veg'],'Non-Veg',inplace=True)
```

[63]:
```
df.EstimatedSalary.fillna(round(df.EstimatedSalary.mean()),inplace=True)
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
```

[63]: 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 : PRASANNA KUMAR M
#ROLL NO : 230701237
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - D
```

[65]:
```
import numpy as np
import pandas as pd
import warnings
warnings.filterwarnings('ignore')
df=pd.read_csv("pre_process_datasample.csv")
df
```

[65]: 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

[66]: 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

[67]: df.Country.mode()

[67]: 0 France
Name: Country, dtype: object

[68]: df.Country.mode()[0]

[68]: 'France'

[69]: type(df.Country.mode())

[69]: pandas.core.series.Series

[70]: 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

[70]: 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
```

[71]:
```
pd.get_dummies(df.Country)
```

[71]:
```
France Germany Spain
0 True False False
1 False False True
2 False True False
```



```
3 False False True
4 False True False
5 True False False
6 False False True
7 True False False
8 False True False
9 True False False
```

[72]:
```
updated_dataset=pd.concat([pd.get_dummies(df.Country),df.iloc[:
↪,[1,2,3]]],axis=1)
```

[73]:
```
df.info()
```

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

[74]:
```
updated_dataset.Purchased.replace(['No','Yes'],[0,1],inplace=True)
```

[ ]:
```
#EX.NO :5 EDA-Quantitative and Qualitative plots
#DATA : 27.08.2024
```

```
#NAME : PRASANNA KUMAR M
#ROLL NO : 230701237
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - D
```

[76]:
```
import numpy as np
import pandas as pd
import warnings
warnings.filterwarnings('ignore')
df=pd.read_csv("pre_process_datasample.csv")
df
```

[76]:
```
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
```

[77]:
```
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
```

[78]:
```
df.Country.mode()
```

[78]:
```
0 France
Name: Country, dtype: object
```

[79]:
```
df.Country.mode()[0]
```

[79]: 'France'

[80]: type(df.Country.mode())

[80]: pandas.core.series.Series

```
[81]: 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
```

[81]: 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

[82]: pd.get_dummies(df.Country)

[82]: France Germany Spain
0 True False False
1 False False True
2 False True False
3 False False True
4 False True False
5 True False False
6 False False True
7 True False False
8 False True False
9 True False False

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

[83]: 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

[84]: df.info()

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


[85]: updated_dataset

[85]: 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 #DATA : 03.09.2024*

#NAME : PRASANNA KUMAR M
#ROLL NO : 230701237
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - D

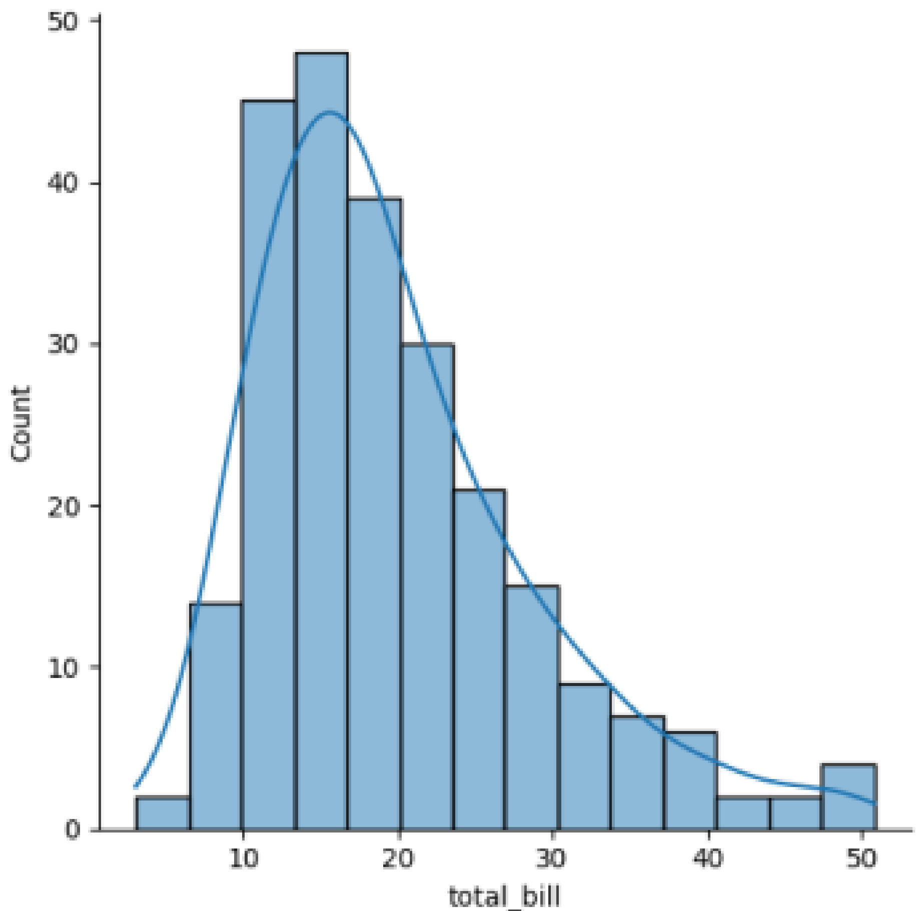
[87]:
```
import seaborn as sns
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
```

[88]:
```
tips=sns.load_dataset('tips')
tips.head()
```

[88]: 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

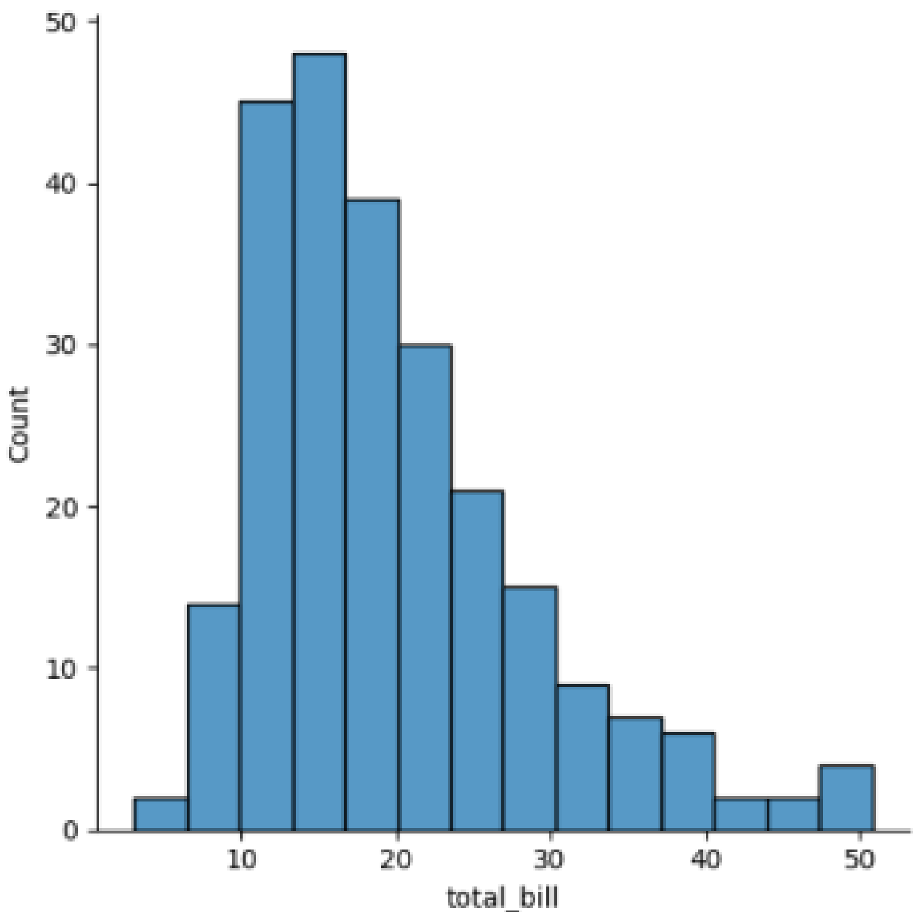
[89]: sns.displot(tips.total_bill,kde=**True**)

[89]: <seaborn.axisgrid.FacetGrid at 0x20d7dc69390> 27



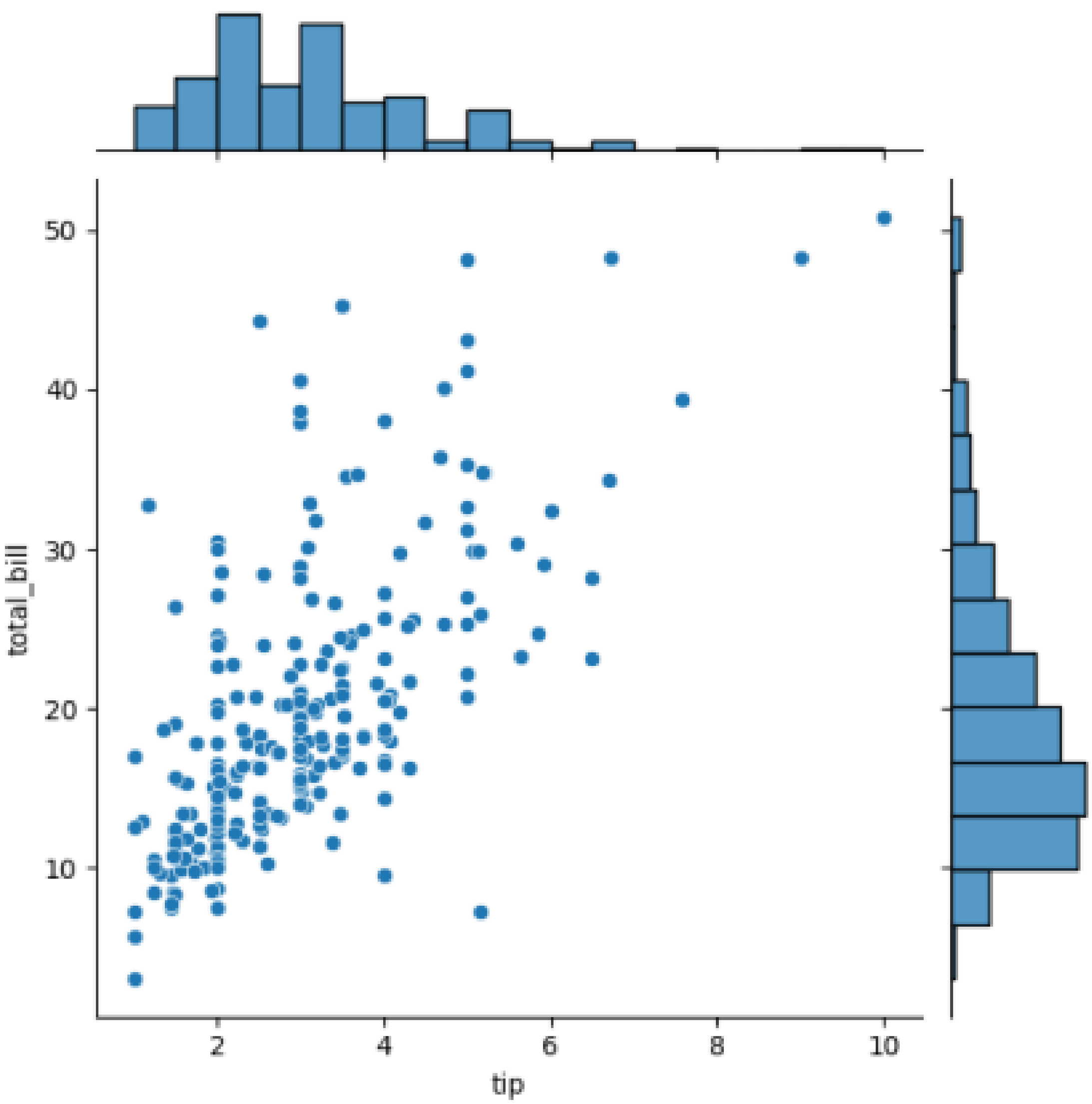
[90]: sns.displot(tips.total_bill,kde=**False**)

[90]: <seaborn.axisgrid.FacetGrid at 0x20d7dc22790>



[91]: sns.jointplot(x=tips.tip,y=tips.total_bill)

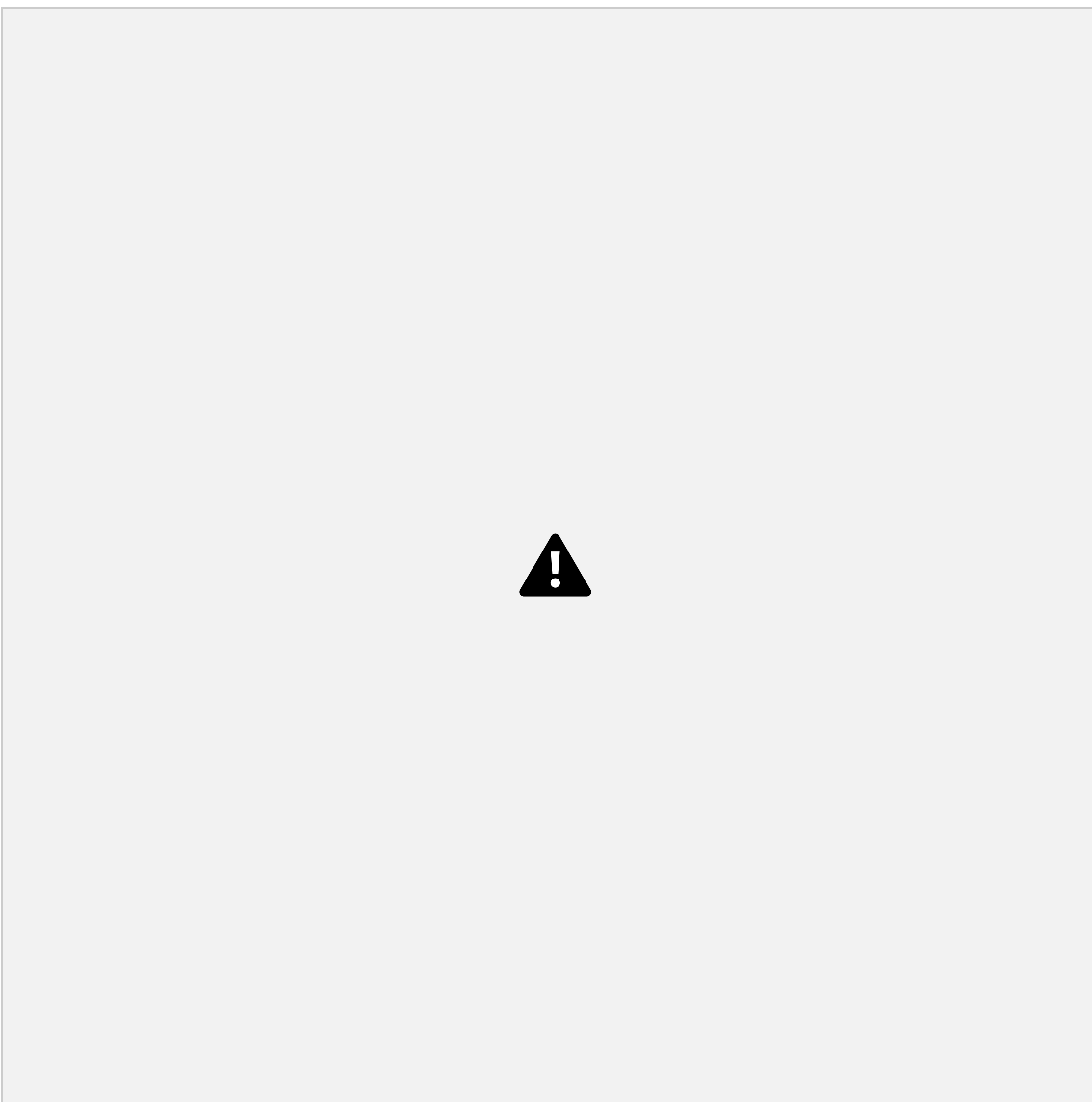
[91]: <seaborn.axisgrid.JointGrid at 0x20d7dc2f2d0>



total_bill
50
40
30
20
10
2
4
6
8
10
tip

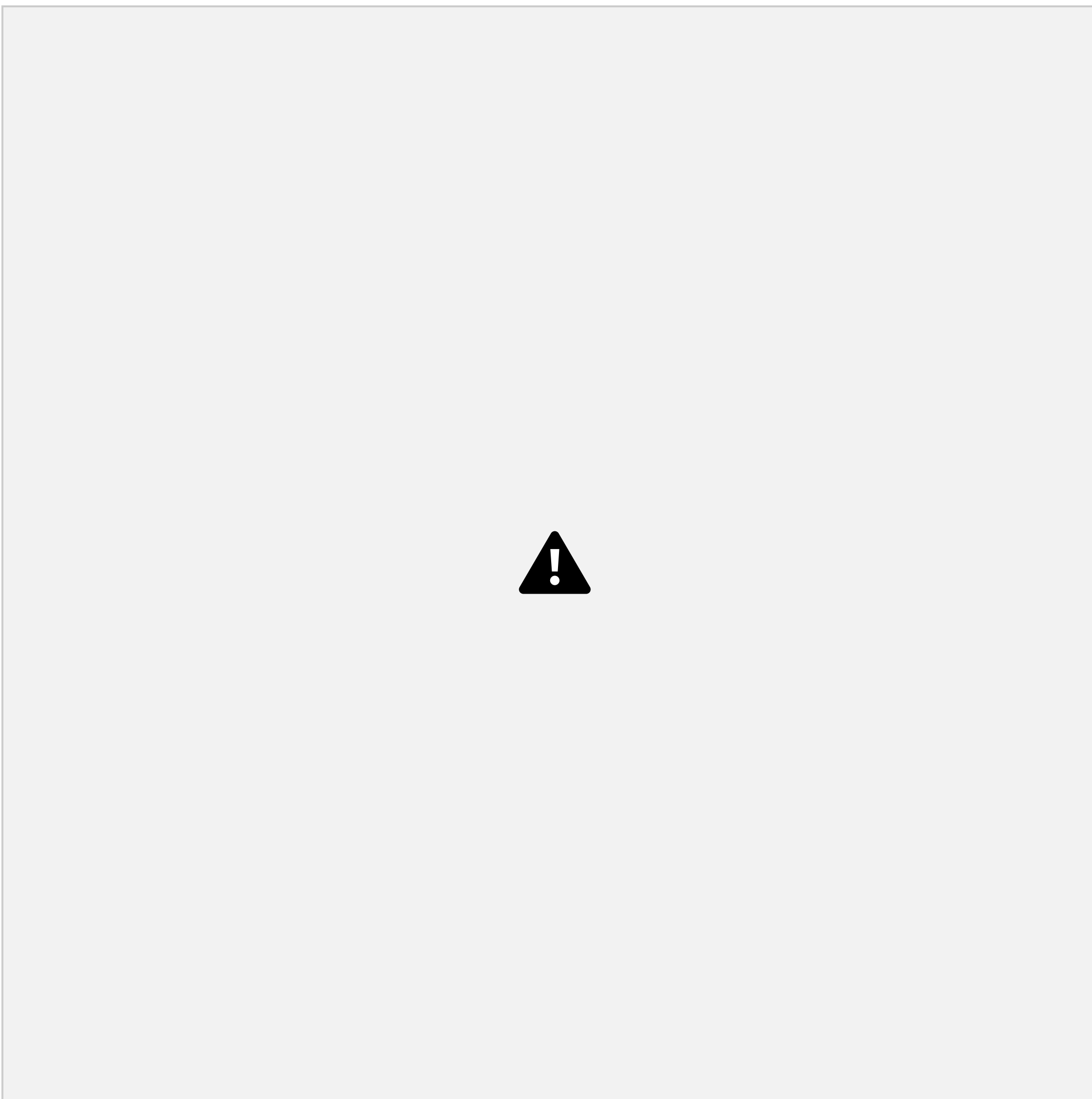
[92]:
```
sns.jointplot(x=tips.tip,y=tips.total_bill,kind="reg")
```

[92]: <seaborn.axisgrid.JointGrid at 0x20d7ed32450>



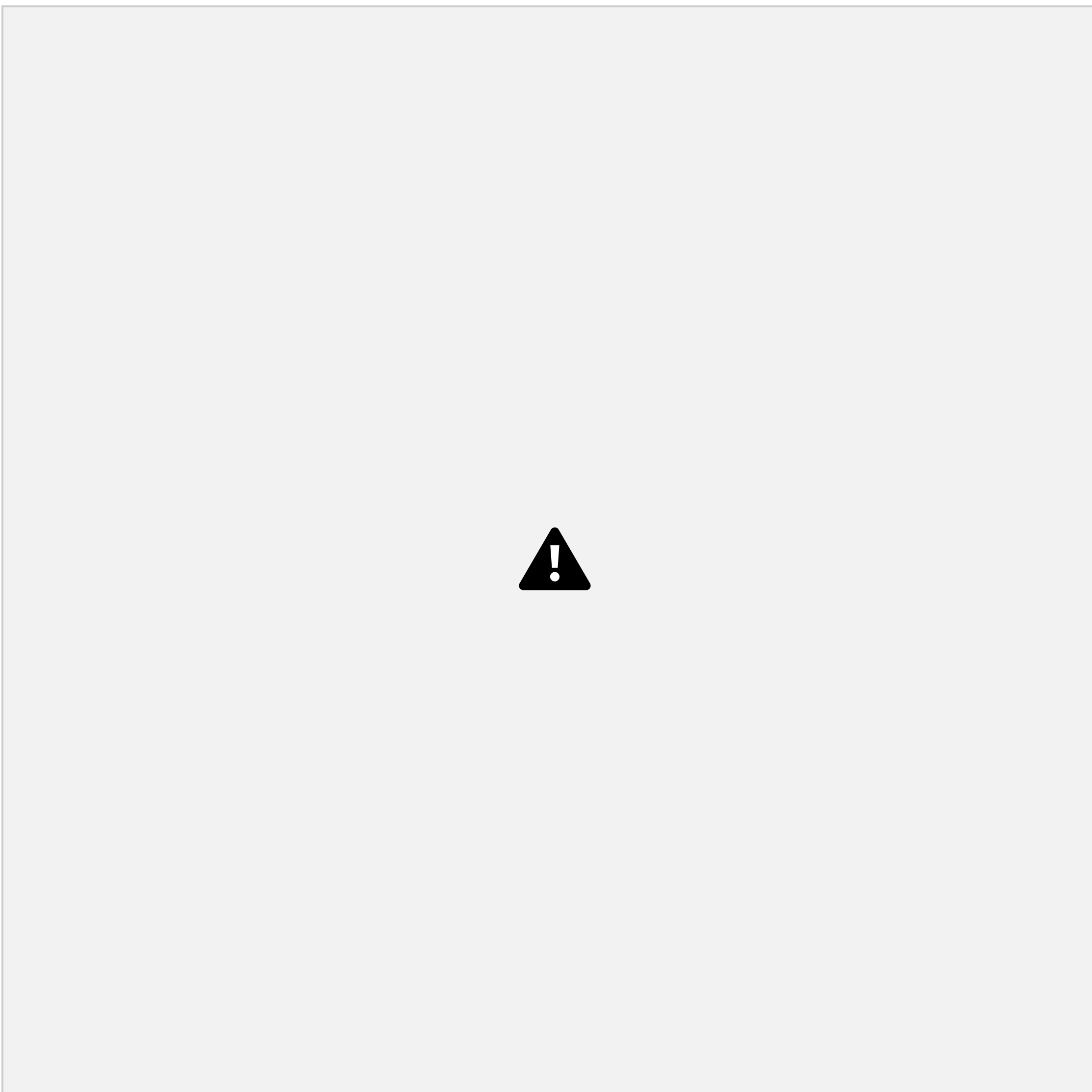
[93]:
```
sns.jointplot(x=tips.tip,y=tips.total_bill,kind="hex")
```

[93]: <seaborn.axisgrid.JointGrid at 0x20d7ed7d350>



[94]: sns.pairplot(tips)

[94]: <seaborn.axisgrid.PairGrid at 0x20d7f1c9cd0>



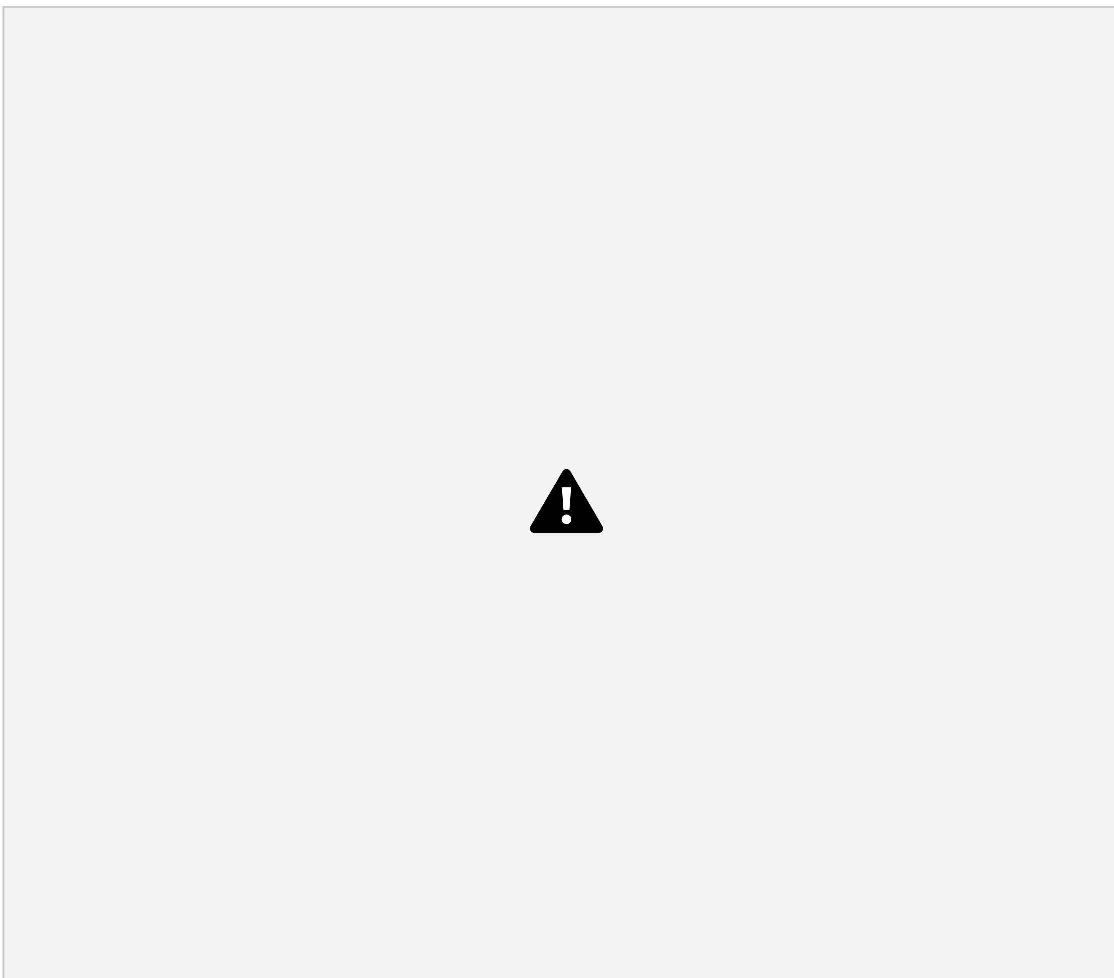
[95]:
```
tips.time.value_counts()
```

[95]:
```
time
Dinner 176
Lunch 68
```

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

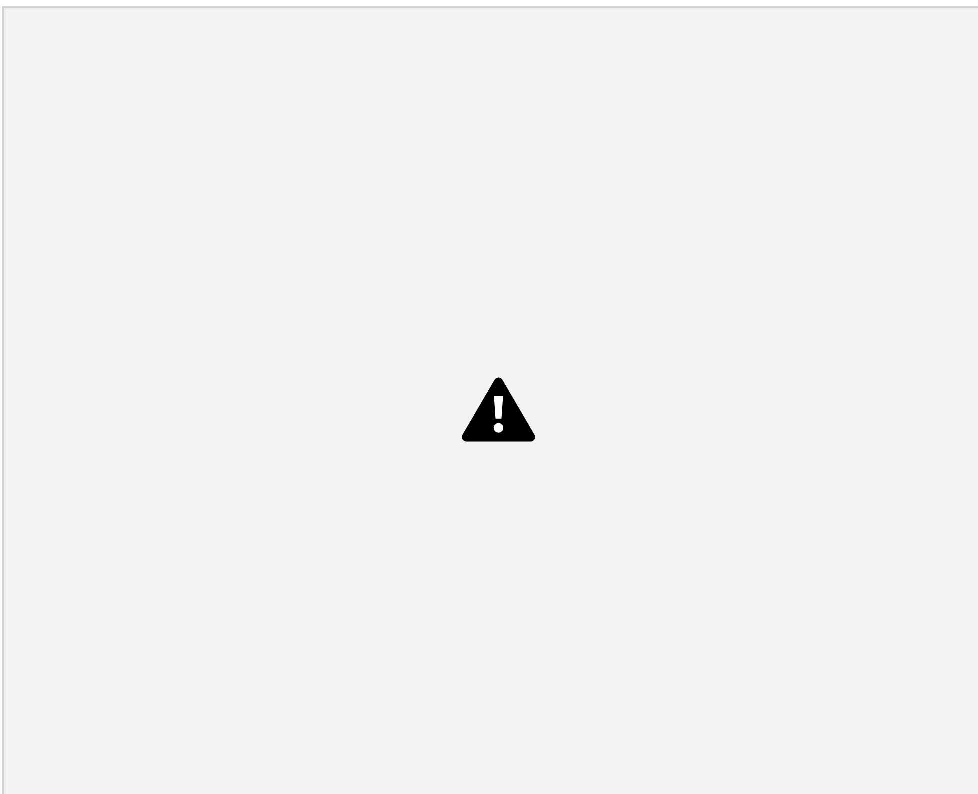
[96]:
```
sns.pairplot(tips,hue='time')
```

[96]:
```
<seaborn.axisgrid.PairGrid at 0x20d7cc27990>
```

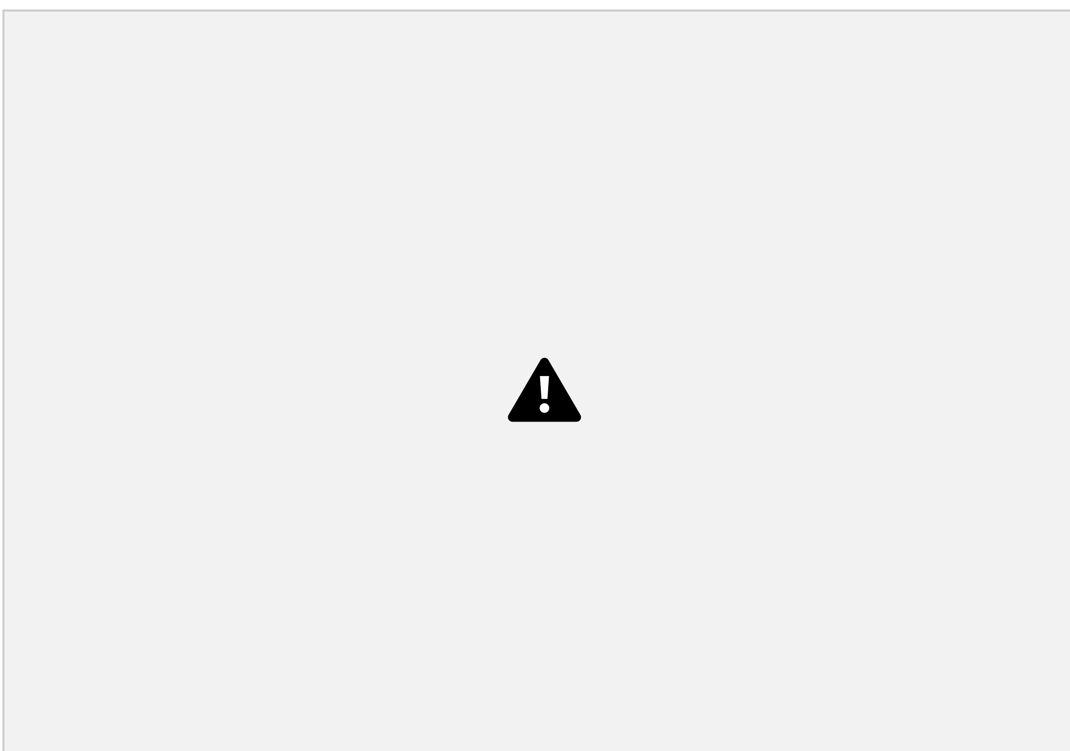
[97]:
```
sns.heatmap(tips.corr(numeric_only=True),annot=True)
```

[97]:
```
<Axes: >
```



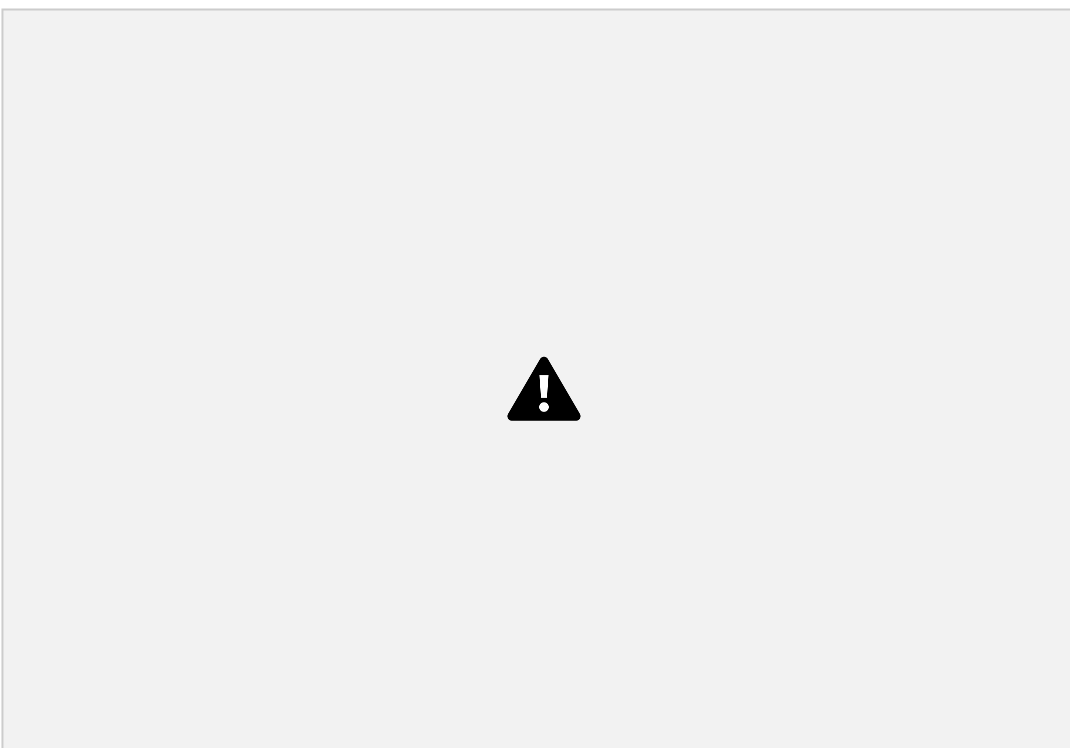
[98]:
```
sns.boxplot(tips.total_bill)
```

[98]:
```
<Axes: ylabel='total_bill'>
```



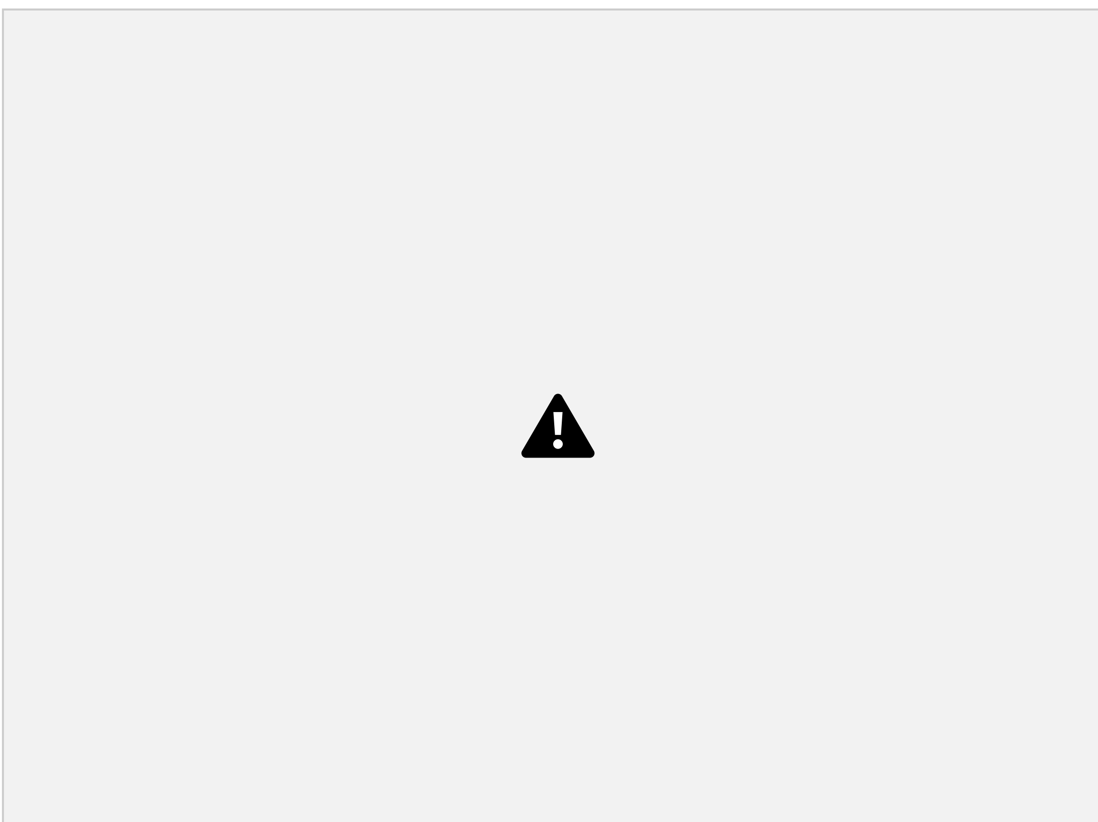
```
[99]: sns.boxplot(tips.tip)
```

```
[99]: <Axes: ylabel='tip'>
```



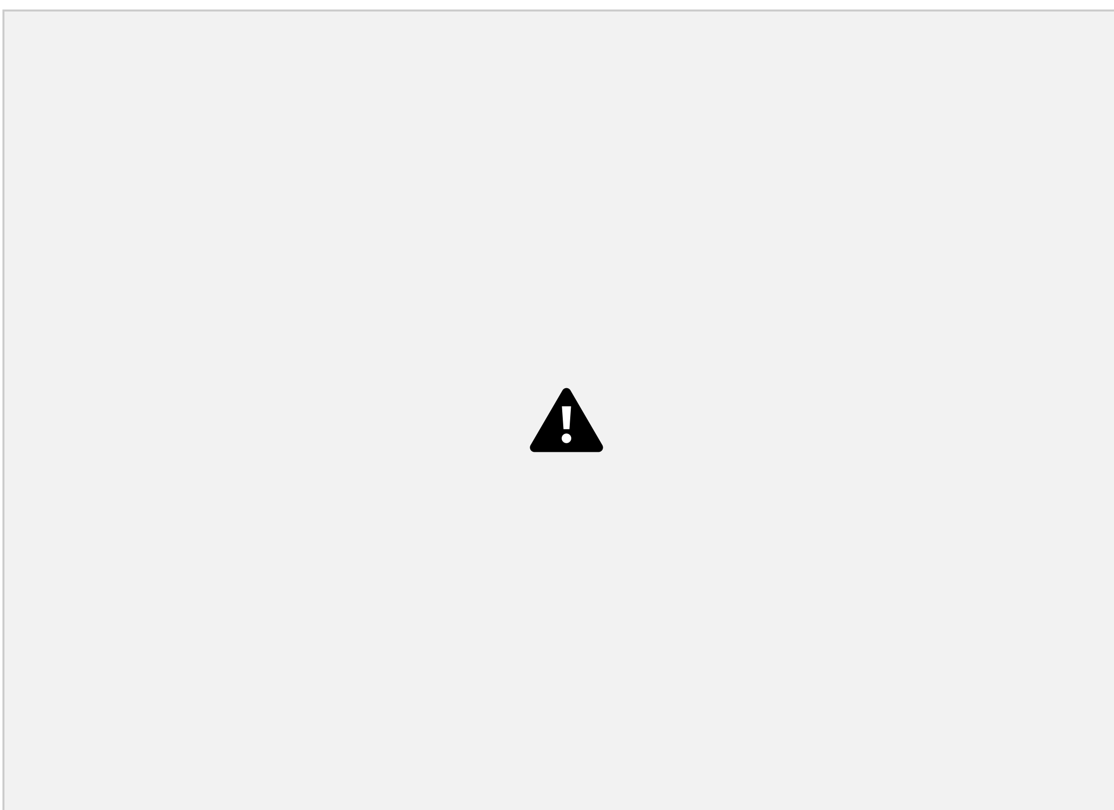
[100]: sns.countplot(tips.day)

[100]: <Axes: xlabel='count', ylabel='day'>



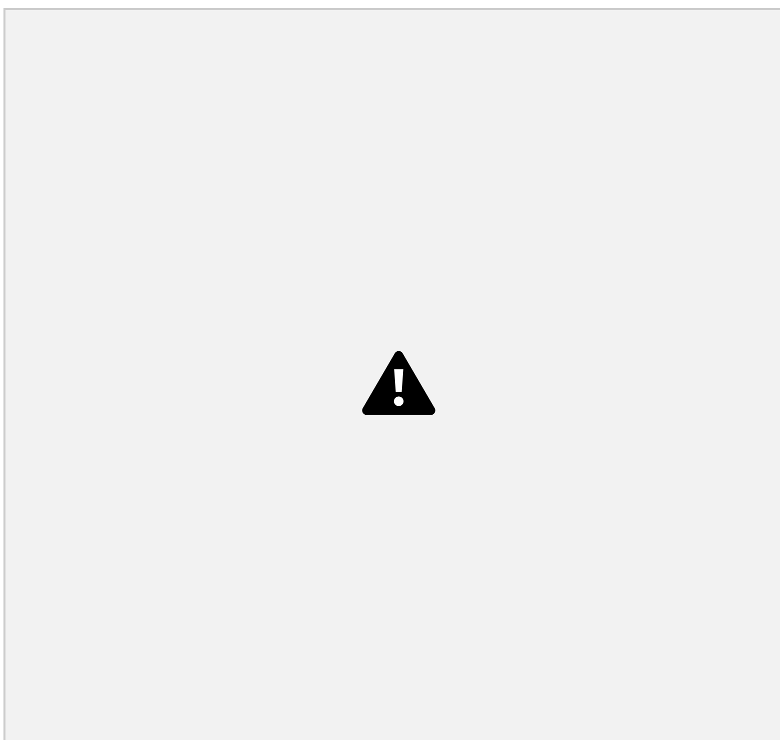
[101]:
```python
sns.countplot(tips.sex)
```

[101]:
```
<Axes: xlabel='count', ylabel='sex'>
```



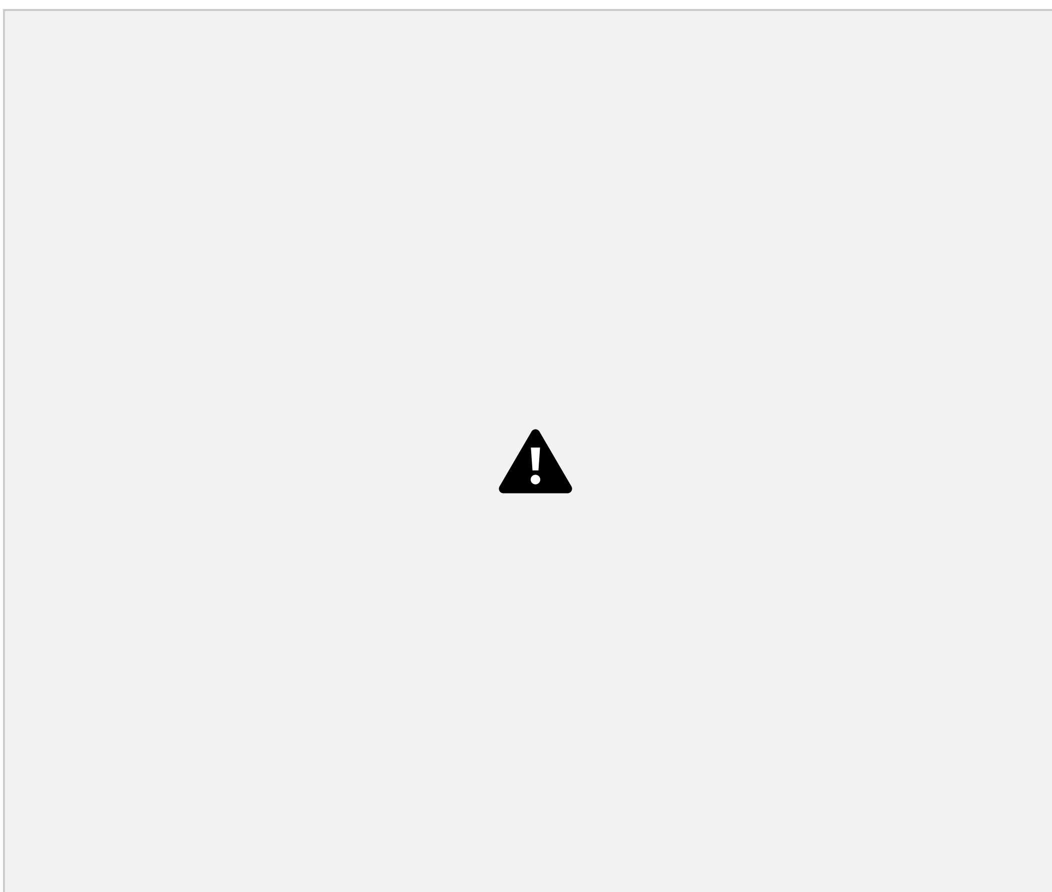
```
[102]: tips.sex.value_counts().plot(kind='pie')
```

```
[102]: <Axes: ylabel='count'>
```



```
[103]: tips.sex.value_counts().plot(kind='bar')
```

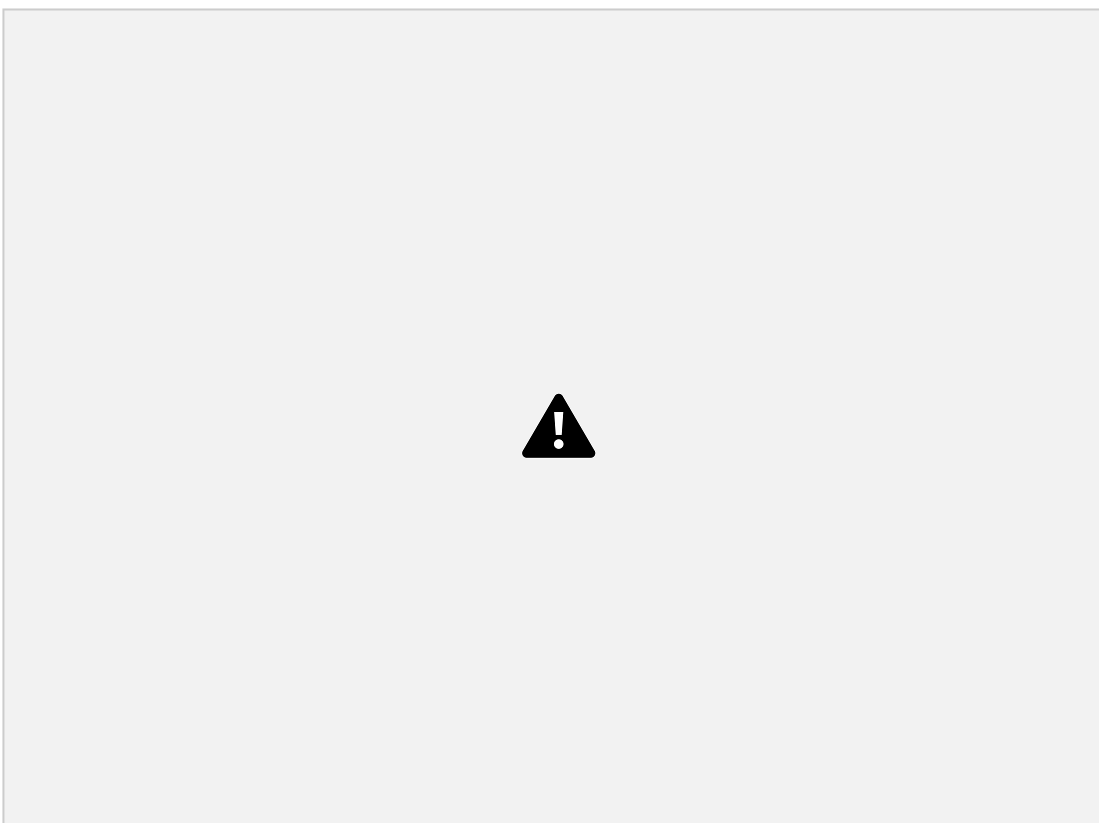
```
[103]: <Axes: xlabel='sex'>
```



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

[104]:

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

[ ]:

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

#NAME : PRASANNA KUMAR M
#ROLL NO : 230701237
```

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

[106]:
```
import numpy as np
import matplotlib.pyplot as plt
```

[107]:
```
population_mean = 50
population_std = 10
population_size = 100000
        population = np.random.normal(population_mean, population_std, population_size)
```

[108]:
```
sample_sizes = [30, 50, 100]
num_samples = 1000
```

[109]:
```
sample_means = {}
for size in sample_sizes:
    sample_means[size] = []
```



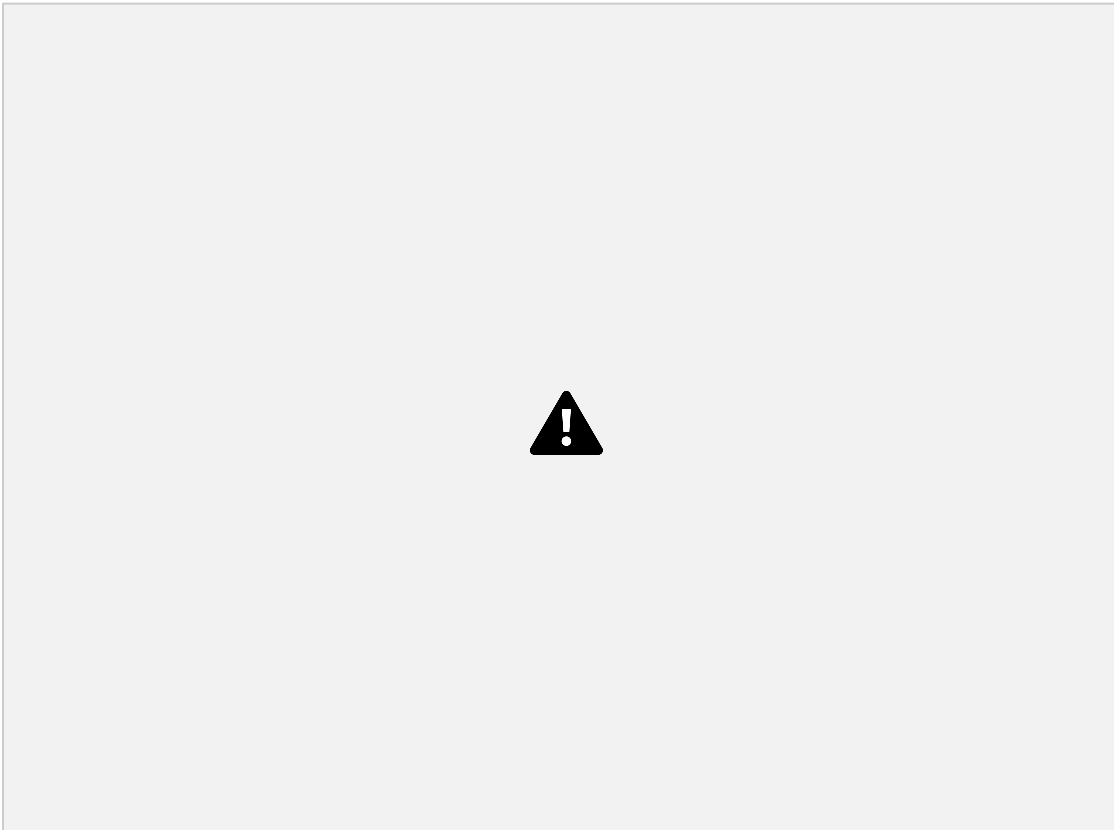
```
    for _ in range(num_samples):
            sample = np.random.choice(population, size=size, replace=False)
        sample_means[size].append(np.mean(sample))
```

[110]:
```
plt.figure(figsize=(12, 8))
```

[110]:
```
<Figure size 1200x800 with 0 Axes>
```

```
<Figure size 1200x800 with 0 Axes>
```

[111]:
```
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 : PRASANNA KUMAR M
     #ROLL NO : 230701237
     #DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - D

[113]: import numpy as np
       import scipy.stats as stats

[114]: 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])

[115]: population_mean = 150
       sample_mean = np.mean(sample_data)
       sample_std = np.std(sample_data, ddof=1)

[116]: 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)))

[117]: # Assuming sample_mean, z_statistic, and p_value have already been calculated:
       print(f"Sample Mean: {sample_mean:.2f}\n")
```

```
print(f"Z-Statistic: {z_statistic:.4f}\n")
print(f"P-Value: {p_value:.4f}\n")

# Significance level
alpha = 0.05

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

Sample Mean: 150.20

Z-Statistic: 0.6406

P-Value: 0.5218

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


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

     #NAME : PRASANNA KUMAR M
     #ROLL NO : 230701237
     #DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - D
```

```
[119]: 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)
```

```
[120]: population_mean = 100
       sample_mean = np.mean(sample_data)
       sample_std = np.std(sample_data, ddof=1)
```

```
[121]: n = len(sample_data)
       t_statistic, p_value = stats.ttest_1samp(sample_data,population_mean)
```

```
[122]: # Assuming sample_mean, t_statistic, and p_value have already been calculated:
       print(f"Sample Mean: {sample_mean:.2f}\n")
       print(f"T-Statistic: {t_statistic:.4f}\n")
       print(f"P-Value: {p_value:.4f}\n")
```

```
# Significance level
alpha = 0.05

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

Sample Mean: 99.55

T-Statistic: -0.1577

P-Value: 0.8760

Fail to reject the null hypothesis: There is no significant difference in average IQ score from 100.

```
[ ]: #EX.NO :9 Annova TEST
     #DATA : 08.10.2024
```



```
     #NAME : PRASANNA KUMAR M
     #ROLL NO : 230701237
     #DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - D
```

```
[124]: import numpy as np
       import scipy.stats as stats
       from statsmodels.stats.multicomp import pairwise_tukeyhsd

       np.random.seed(42)
       n_plants = 25

[125]: 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)

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

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

[128]: 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
     #DATA : 22.10.2024

     #NAME : PRASANNA KUMAR M
```

```
#ROLL NO : 230701237
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - D
```

[130]:
```
import numpy as np
import pandas as pd
import warnings
warnings.filterwarnings('ignore')
df=pd.read_csv('pre_process_datasample.csv')
```

[131]:
```
df.head()
```

[131]:
```
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
```

[132]:
```
df.Country.fillna(df.Country.mode()[0],inplace=True)
features=df.iloc[:,:-1].values
features
```

[132]:
```
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)
```

[133]:
```
label=df.iloc[:,-1].values
```

[134]:
```
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]])
```

[134]:
```
SimpleImputer()
```

[135]:
```
Salary.fit(features[:,[2]])
```

[135]:
```
SimpleImputer()
```

[136]: SimpleImputer()

[136]: SimpleImputer()

[137]:
```
features[:,[1]]=age.transform(features[:,[1]])
features[:,[2]]=Salary.transform(features[:,[2]])
features
```

[137]:
```
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)
```

[138]:
```
from sklearn.preprocessing import OneHotEncoder oh
    = OneHotEncoder(sparse_output=False)
Country=oh.fit_transform(features[:,[0]])
Country
```

[138]:
```
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.]])
```

[139]:
```
final_set=np.concatenate((Country,features[:,[1,2]]),axis=1) final_set
```

[139]:
```
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)
```

[140]:
```python
from sklearn.preprocessing import StandardScaler
sc=StandardScaler()
sc.fit(final_set)
feat_standard_scaler=sc.transform(final_set)
```

[141]:
```python
feat_standard_scaler
```

[141]:
```
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]])
```

[142]:
```python
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
```

[142]:
```
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]])
```

[ ]:
```python
#EX.NO :11 Linear Regression
```

```
#DATA : 29.10.2024

#NAME : PRASANNA KUMAR M
#ROLL NO : 230701237
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - D
```

[144]:
```python
import numpy as np
import pandas as pd
df = pd.read_csv('Salary_data.csv')
df
```

[144]:
```
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
```

[145]:
```python
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

[146]: df.dropna(inplace=True);
 df

[146]: 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

[147]: 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

[148]: df.describe() #descripte statical report
 # find out IYER FOR BELOW META DATA

[148]: 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

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

selection loc location based sentence

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

features

[149]: 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]])
```

[150]: label

```
[150]: 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)
```

```
[151]: 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 %
       '''
```

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

```
[152]: 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
       '''
```

```
[152]: '\nsk - size kit \nlinear means using linear regression \nfit means add data \n'
```

```
[153]: model.score(x_train,y_train)
       '''
       accuracy calculating
       96 %
```



```
       '''
```

```
[153]: '\naccuracy calculating\n96 %\n'
```

```
[154]: model.score(x_test,y_test)
       '''
       accuracy calculating
       91 %
       '''
```

```
[154]: '\naccuracy calculating\n91 %\n'
```

```
[155]: model.coef_
```

[155]: array([[9281.30847068]])

[156]: model.intercept_

[156]: array([27166.73682891])

[157]:
```
import pickle
pickle.dump(model,open('SalaryPred.model','wb'))
'''
pickle momory obj to file

'''
```

[157]: '\npickle momory obj to file\n\n'

[158]:
```
model = pickle.load(open('SalaryPred.model','rb'))
```

[159]:
```
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]] .

[160]:
```
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 : PRASANNA KUMAR M
#ROLL NO : 230701237
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - D
```

[162]:
```
import numpy as np
import pandas as pd
import warnings
warnings.filterwarnings('ignore')
df=pd.read_csv('Social_Network_Ads.csv.csv')
df
```

[162]: 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]

[163]:
```
df.tail(20)
```

[163]: 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

[164]:
```
df.head(25)
```

[164]: 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

[165]:
```
features = df.iloc[:,[2,3]].values
label = df.iloc[:,4].values
```

features

```
[165]: array([[ 19, 19000],
       [ 35, 20000],
       [ 26, 43000],
       [ 27, 57000],
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       [ 27, 84000],
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       [ 25, 33000],
       [ 35, 65000],
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```



```
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```

```
[ 35, 108000],
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```



```
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```
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```
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```



```
[ 39, 71000],
[ 47, 34000],
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[ 48, 33000],
[ 47, 23000],
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```

```
                [ 39, 59000],
                [ 46, 41000],
                [ 51, 23000],
                [ 50, 20000],
                [ 36, 33000],
                [ 49, 36000]], dtype=int64)
```

[166]:
```
label
```

[166]:
```
array([0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0,
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       0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1, 0, 0, 0, 1, 1, 0,
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       0, 0, 1, 0, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 0, 1, 1,
       1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 0, 1, 0, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1,
       1, 1, 0, 1, 1, 1, 0, 1], dtype=int64)
```

[167]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
```

[168]:
```
# Assuming `features` and `label` are already defined

for i in range(1, 401):
    x_train, x_test, y_train, y_test = train_test_split(features, label,␣
 ↪test_size=0.2, random_state=i)
    model = LogisticRegression()
    model.fit(x_train, y_train)
```



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

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

'''


'''
```

Test Score: 0.9000 | Train Score: 0.8406 | Random State: 4
Test Score: 0.8625 | Train Score: 0.8500 | Random State: 5
Test Score: 0.8625 | Train Score: 0.8594 | Random State: 6
Test Score: 0.8875 | Train Score: 0.8375 | Random State: 7
Test Score: 0.8625 | Train Score: 0.8375 | Random State: 9
Test Score: 0.9000 | Train Score: 0.8406 | Random State: 10
Test Score: 0.8625 | Train Score: 0.8562 | Random State: 14
Test Score: 0.8500 | Train Score: 0.8438 | Random State: 15
Test Score: 0.8625 | Train Score: 0.8562 | Random State: 16
Test Score: 0.8750 | Train Score: 0.8344 | Random State: 18
Test Score: 0.8500 | Train Score: 0.8438 | Random State: 19
Test Score: 0.8750 | Train Score: 0.8438 | Random State: 20
Test Score: 0.8625 | Train Score: 0.8344 | Random State: 21
Test Score: 0.8750 | Train Score: 0.8406 | Random State: 22
Test Score: 0.8750 | Train Score: 0.8406 | Random State: 24
Test Score: 0.8500 | Train Score: 0.8344 | Random State: 26
Test Score: 0.8500 | Train Score: 0.8406 | Random State: 27
Test Score: 0.8625 | Train Score: 0.8344 | Random State: 30
Test Score: 0.8625 | Train Score: 0.8562 | Random State: 31
Test Score: 0.8750 | Train Score: 0.8531 | Random State: 32
Test Score: 0.8625 | Train Score: 0.8438 | Random State: 33
Test Score: 0.8750 | Train Score: 0.8313 | Random State: 35
Test Score: 0.8625 | Train Score: 0.8531 | Random State: 36
Test Score: 0.8875 | Train Score: 0.8406 | Random State: 38
Test Score: 0.8750 | Train Score: 0.8375 | Random State: 39
Test Score: 0.8875 | Train Score: 0.8375 | Random State: 42
Test Score: 0.8750 | Train Score: 0.8469 | Random State: 46
Test Score: 0.9125 | Train Score: 0.8313 | Random State: 47
Test Score: 0.8750 | Train Score: 0.8313 | Random State: 51
Test Score: 0.9000 | Train Score: 0.8438 | Random State: 54
Test Score: 0.8500 | Train Score: 0.8438 | Random State: 57
Test Score: 0.8750 | Train Score: 0.8438 | Random State: 58
Test Score: 0.9250 | Train Score: 0.8375 | Random State: 61
Test Score: 0.8875 | Train Score: 0.8344 | Random State: 65
Test Score: 0.8875 | Train Score: 0.8406 | Random State: 68

Test Score: 0.9000 | Train Score: 0.8313 | Random State: 72 Test Score: 0.8875 | Train Score: 0.8375 | Random State: 75 Test Score: 0.9250 | Train Score: 0.8250 | Random State: 76 Test Score: 0.8625 | Train Score: 0.8406 | Random State: 77 Test Score: 0.8625 | Train Score: 0.8594 | Random State: 81 Test Score: 0.8750 | Train Score: 0.8375 | Random State: 82 Test Score: 0.8875 | Train Score: 0.8375 | Random State: 83 Test Score: 0.8625 | Train Score: 0.8531 | Random State: 84 Test Score: 0.8625 | Train Score: 0.8406 | Random State: 85 Test Score: 0.8625 | Train Score: 0.8406 | Random State: 87 Test

Score: 0.8750 | Train Score: 0.8469 | Random State: 88 Test Score: 0.9125 | Train Score: 0.8375 | Random State: 90 Test Score: 0.8625 | Train Score: 0.8500 | Random State: 95 Test Score: 0.8750 | Train Score: 0.8500 | Random State: 99 Test Score: 0.8500 | Train Score: 0.8406 | Random State: 101
Test Score: 0.8500 | Train Score: 0.8406 | Random State: 102 Test Score: 0.9000 | Train Score: 0.8250 | Random State: 106 Test Score: 0.8625 | Train Score: 0.8406 | Random State: 107 Test Score: 0.8500 | Train Score: 0.8344 | Random State: 109 Test Score: 0.8500 | Train Score: 0.8406 | Random State: 111 Test Score: 0.9125 | Train Score: 0.8406 | Random State: 112 Test Score: 0.8625 | Train Score: 0.8500 | Random State: 115 Test Score: 0.8625 | Train Score: 0.8406 | Random State: 116 Test Score: 0.8750 | Train Score: 0.8344 | Random State: 119 Test Score: 0.9125 | Train Score: 0.8281 | Random State: 120 Test Score: 0.8625 | Train Score: 0.8594 | Random State: 125 Test Score: 0.8500 | Train Score: 0.8469 | Random State: 128 Test Score: 0.8750 | Train Score: 0.8500 | Random State: 130 Test Score: 0.9000 | Train Score: 0.8438 | Random State: 133 Test Score: 0.9250 | Train Score: 0.8344 | Random State: 134 Test Score: 0.8625 | Train Score: 0.8500 | Random State: 135 Test Score: 0.8750 | Train Score: 0.8313 | Random State: 138 Test Score: 0.8625 | Train Score: 0.8500 | Random State: 141 Test Score: 0.8500 | Train Score: 0.8469 | Random State: 143 Test Score: 0.8500 | Train Score: 0.8469 | Random State: 146 Test Score: 0.8500 | Train Score: 0.8438 | Random State: 147 Test Score: 0.8625 | Train Score: 0.8500 | Random State: 148 Test Score: 0.8750 | Train Score: 0.8375 | Random State: 150 Test Score: 0.8875 | Train Score: 0.8313 | Random State: 151 Test Score: 0.9250 | Train Score: 0.8438 | Random State: 152 Test Score: 0.8500 | Train Score: 0.8406 | Random State: 153 Test Score: 0.9000 | Train Score: 0.8438 | Random State: 154 Test Score: 0.9000 | Train Score: 0.8406 | Random State: 155 Test Score: 0.8875 | Train Score: 0.8469 | Random State: 156 Test Score: 0.8875 | Train Score: 0.8344 | Random State: 158 Test Score: 0.8750 | Train Score: 0.8281 | Random State: 159 Test Score: 0.9000 | Train Score: 0.8313 | Random State: 161 Test Score: 0.8500 | Train Score: 0.8375 | Random State: 163

Test Score: 0.8750 | Train Score: 0.8313 | Random State: 164 Test Score: 0.8625 | Train Score: 0.8500 | Random State: 169 Test Score: 0.8750 | Train Score: 0.8406 | Random State: 171 Test Score: 0.8500 | Train Score: 0.8406 | Random State: 172 Test Score: 0.9000 | Train Score: 0.8250 | Random State: 180 Test Score: 0.8500 | Train Score: 0.8344 | Random State: 184 Test Score: 0.9250 | Train Score: 0.8219 | Random State: 186 Test Score: 0.9000 | Train Score: 0.8313 | Random State: 193 Test Score: 0.8625 | Train Score: 0.8500 | Random State: 195 Test Score: 0.8625 | Train Score: 0.8406 | Random State: 196 Test Score: 0.8625 | Train Score: 0.8375 | Random State: 197 Test Score: 0.8750 | Train Score: 0.8406 | Random State: 198 Test Score: 0.8875 | Train Score: 0.8375 | Random State: 199 Test Score: 0.8875 | Train

Score: 0.8438 | Random State: 200 Test Score: 0.8625 | Train Score: 0.8375 | Random State: 202 Test Score: 0.8625 | Train Score: 0.8406 | Random State: 203 Test Score: 0.8875 | Train Score: 0.8313 | Random State: 206 Test Score: 0.8625 | Train Score: 0.8344 | Random State: 211 Test Score: 0.8500 | Train Score: 0.8438 | Random State: 212 Test Score: 0.8625 | Train Score: 0.8344 | Random State: 214 Test Score: 0.8750 | Train Score: 0.8313 | Random State: 217 Test Score: 0.9625 | Train Score: 0.8187 | Random State: 220 Test Score: 0.8750 | Train Score: 0.8438 | Random State: 221 Test Score: 0.8500 | Train Score: 0.8406 | Random State: 222 Test Score: 0.9000 | Train Score: 0.8438 | Random State: 223 Test Score: 0.8625 | Train Score: 0.8531 | Random State: 227 Test Score: 0.8625 | Train Score: 0.8344 | Random State: 228 Test Score: 0.9000 | Train Score: 0.8406 | Random State: 229 Test Score: 0.8500 | Train Score: 0.8438 | Random State: 232 Test Score: 0.8750 | Train Score: 0.8469 | Random State: 233 Test Score: 0.9125 | Train Score: 0.8406 | Random State: 234 Test Score: 0.8625 | Train Score: 0.8406 | Random State: 235 Test Score: 0.8500 | Train Score: 0.8469 | Random State: 236 Test Score: 0.8750 | Train Score: 0.8469 | Random State: 239 Test Score: 0.8500 | Train Score: 0.8438 | Random State: 241 Test Score: 0.8875 | Train Score: 0.8500 | Random State: 242 Test Score: 0.8875 | Train Score: 0.8250 | Random State: 243 Test Score: 0.8750 | Train Score: 0.8469 | Random State: 244 Test Score: 0.8750 | Train Score: 0.8406 | Random State: 245 Test Score: 0.8750 | Train Score: 0.8469 | Random State: 246 Test Score: 0.8625 | Train Score: 0.8594 | Random State: 247 Test Score: 0.8875 | Train Score: 0.8438 | Random State: 248 Test Score: 0.8625 | Train Score: 0.8500 | Random State: 250 Test Score: 0.8750 | Train Score: 0.8313 | Random State: 251 Test Score: 0.8875 | Train Score: 0.8438 | Random State: 252 Test Score: 0.8625 | Train Score: 0.8469 | Random State: 255 Test Score: 0.9000 | Train Score: 0.8406 | Random State: 257 Test Score: 0.8625 | Train Score: 0.8562 | Random State: 260

Test Score: 0.8625 | Train Score: 0.8406 | Random State: 266 Test Score: 0.8625 | Train Score: 0.8375 | Random State: 268 Test Score: 0.8750 | Train Score: 0.8406 | Random State: 275 Test Score: 0.8625 | Train Score: 0.8500 | Random State: 276 Test Score: 0.9250 | Train Score: 0.8375 | Random State: 277 Test Score: 0.8750 | Train Score: 0.8469 | Random State: 282 Test Score: 0.8500 | Train Score: 0.8469 | Random State: 283 Test Score: 0.8500 | Train Score: 0.8438 | Random State: 285 Test Score: 0.9125 | Train Score: 0.8344 | Random State: 286 Test Score: 0.8500 | Train Score: 0.8406 | Random State: 290 Test Score: 0.8500 | Train Score: 0.8406 | Random State: 291 Test Score: 0.8500 | Train Score: 0.8469 | Random State: 292 Test Score: 0.8625 | Train Score: 0.8375 | Random State: 294 Test Score: 0.8875 | Train Score: 0.8281 | Random State: 297 Test Score: 0.8625 | Train Score: 0.8344 | Random State: 300 Test Score: 0.8625 | Train Score: 0.8500 | Random State: 301 Test Score: 0.8875 | Train Score: 0.8500 | Random State: 302 Test Score: 0.8750 | Train Score: 0.8469 | Random State:

303 Test Score: 0.8625 | Train Score: 0.8344 | Random State: 305 Test Score: 0.9125 | Train Score: 0.8375 | Random State: 306 Test Score: 0.8750 | Train Score: 0.8469 | Random State: 308 Test Score: 0.9000 | Train Score: 0.8438 | Random State: 311 Test Score: 0.8625 | Train Score: 0.8344 | Random State: 313 Test Score: 0.9125 | Train Score: 0.8344 | Random State: 314 Test Score: 0.8750 | Train Score: 0.8375 | Random State: 315 Test Score: 0.9000 | Train Score: 0.8469 | Random State: 317 Test Score: 0.9125 | Train Score: 0.8219 | Random State: 319 Test Score: 0.8625 | Train Score: 0.8500 | Random State: 321 Test Score: 0.9125 | Train Score: 0.8281 | Random State: 322 Test Score: 0.8500 | Train Score: 0.8469 | Random State: 328 Test Score: 0.8500 | Train Score: 0.8375 | Random State: 332 Test Score: 0.8875 | Train Score: 0.8531 | Random State: 336 Test Score: 0.8500 | Train Score: 0.8375 | Random State: 337 Test Score: 0.8750 | Train Score: 0.8406 | Random State: 343 Test Score: 0.8625 | Train Score: 0.8438 | Random State: 346 Test Score: 0.8875 | Train Score: 0.8313 | Random State: 351 Test Score: 0.8625 | Train Score: 0.8500 | Random State: 352 Test Score: 0.9500 | Train Score: 0.8187 | Random State: 354 Test Score: 0.8625 | Train Score: 0.8500 | Random State: 356 Test Score: 0.9125 | Train Score: 0.8406 | Random State: 357 Test Score: 0.8625 | Train Score: 0.8375 | Random State: 358 Test Score: 0.8500 | Train Score: 0.8406 | Random State: 362 Test Score: 0.9000 | Train Score: 0.8438 | Random State: 363 Test Score: 0.8625 | Train Score: 0.8531 | Random State: 364 Test Score: 0.9375 | Train Score: 0.8219 | Random State: 366 Test Score: 0.9125 | Train Score: 0.8406 | Random State: 369 Test Score: 0.8625 | Train Score: 0.8531 | Random State: 371 Test Score: 0.9250 | Train Score: 0.8344 | Random State: 376


```
Test Score: 0.9125 | Train Score: 0.8281 | Random State: 377
Test Score: 0.8875 | Train Score: 0.8500 | Random State: 378
Test Score: 0.8875 | Train Score: 0.8500 | Random State: 379
Test Score: 0.8625 | Train Score: 0.8406 | Random State: 382
Test Score: 0.8625 | Train Score: 0.8594 | Random State: 386
Test Score: 0.8500 | Train Score: 0.8375 | Random State: 387
Test Score: 0.8750 | Train Score: 0.8281 | Random State: 388
Test Score: 0.8500 | Train Score: 0.8438 | Random State: 394
Test Score: 0.8625 | Train Score: 0.8375 | Random State: 395
Test Score: 0.9000 | Train Score: 0.8438 | Random State: 397
Test Score: 0.8625 | Train Score: 0.8438 | Random State: 400
```

[168]: '\n\n\n'

[169]:
```
x_train,x_test,y_train,y_test=train_test_split(features,label,test_size=0.
↪2,random_state=209)
finalModel=LogisticRegression()
finalModel.fit(x_train,y_train)
```

[169]: LogisticRegression()

```
[170]: print(finalModel.score(x_train,y_train))
       print(finalModel.score(x_train,y_train))
```

0.85
0.85

```
[171]: 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