FDS

[1]:

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

#NAME : SYED ASLAM  S
#ROLL NO : 230701522
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - B
```

[2]:

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

[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()
```

[5]:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 ent
```

ries, 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

```
data.describe()
```

[5] :

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm

[6]:

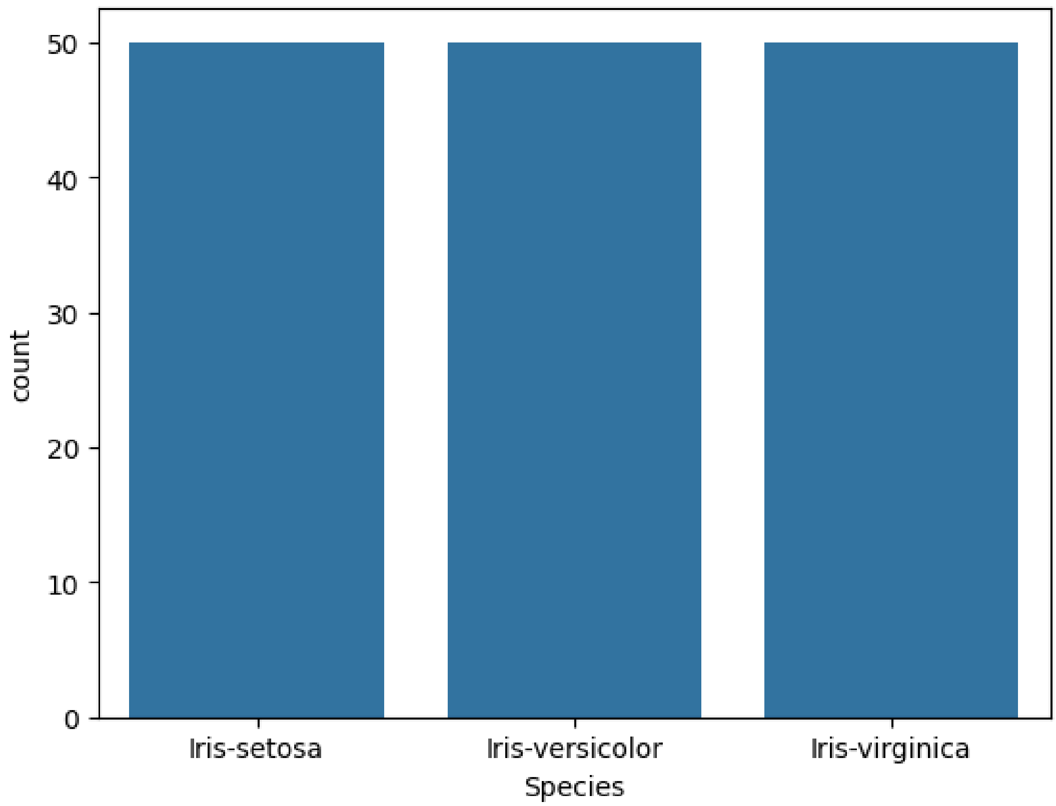
```
data.value_counts('Species')
```

[6] :

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

[7]:

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



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

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

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

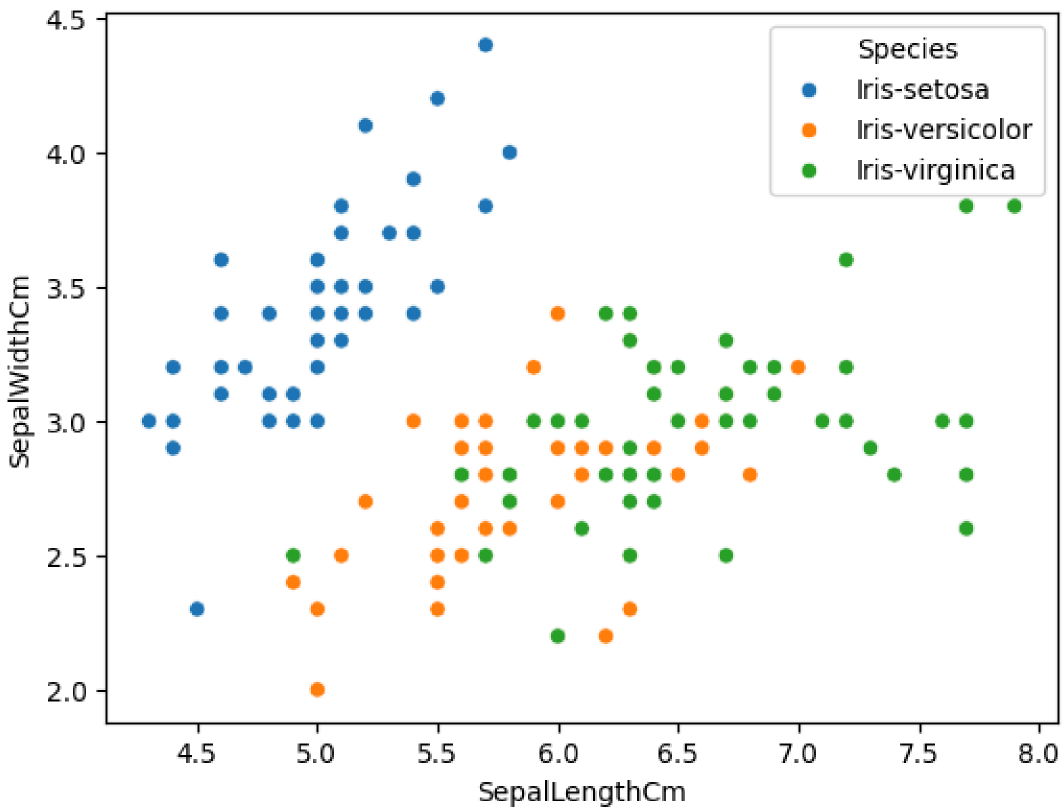
[10]:
```
FinalDataset.head()
```

[10]:
```
   Iris-setosa   Iris-versicolor   Iris-virginica   Id   SepalLengthCm \
```

[11]:

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

[11] : <Axes: xlabel='SepalLengthCm', ylabel='SepalWidthCm'>



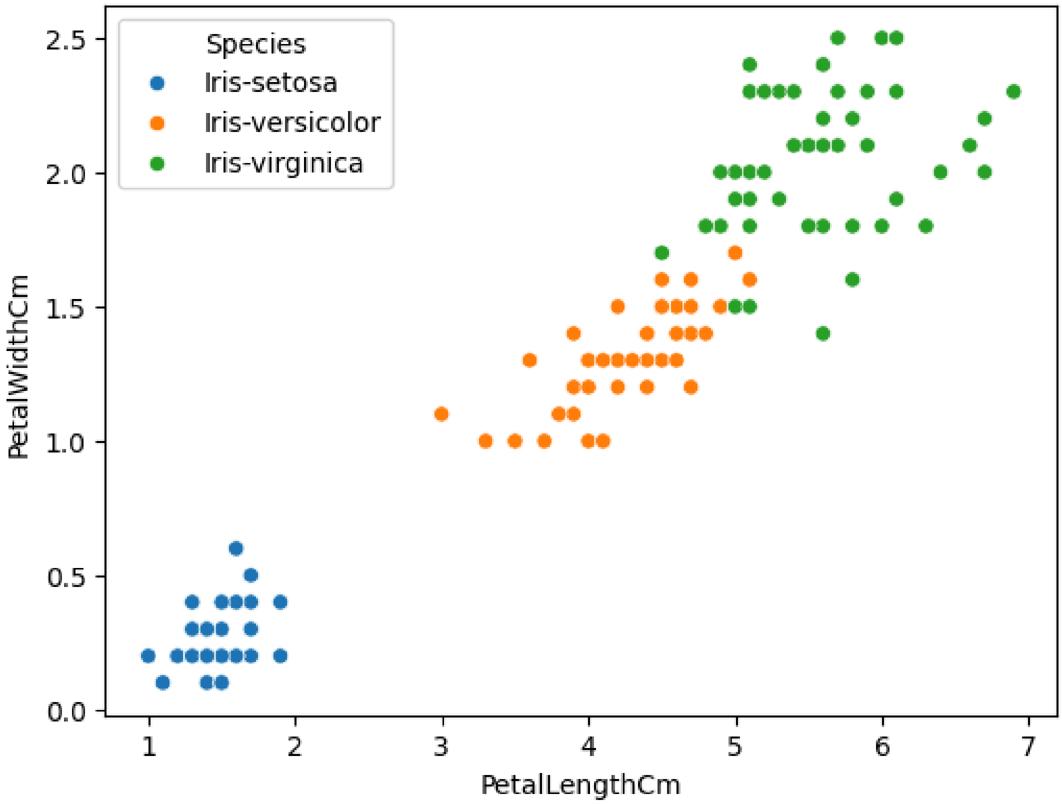
0	True	False	False	1	5.1
1	True	False	False	2	4.9
2	True	False	False	3	4.7
3	True	False	False	4	4.6
4	True	False	False	5	5.0

	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

[12]:

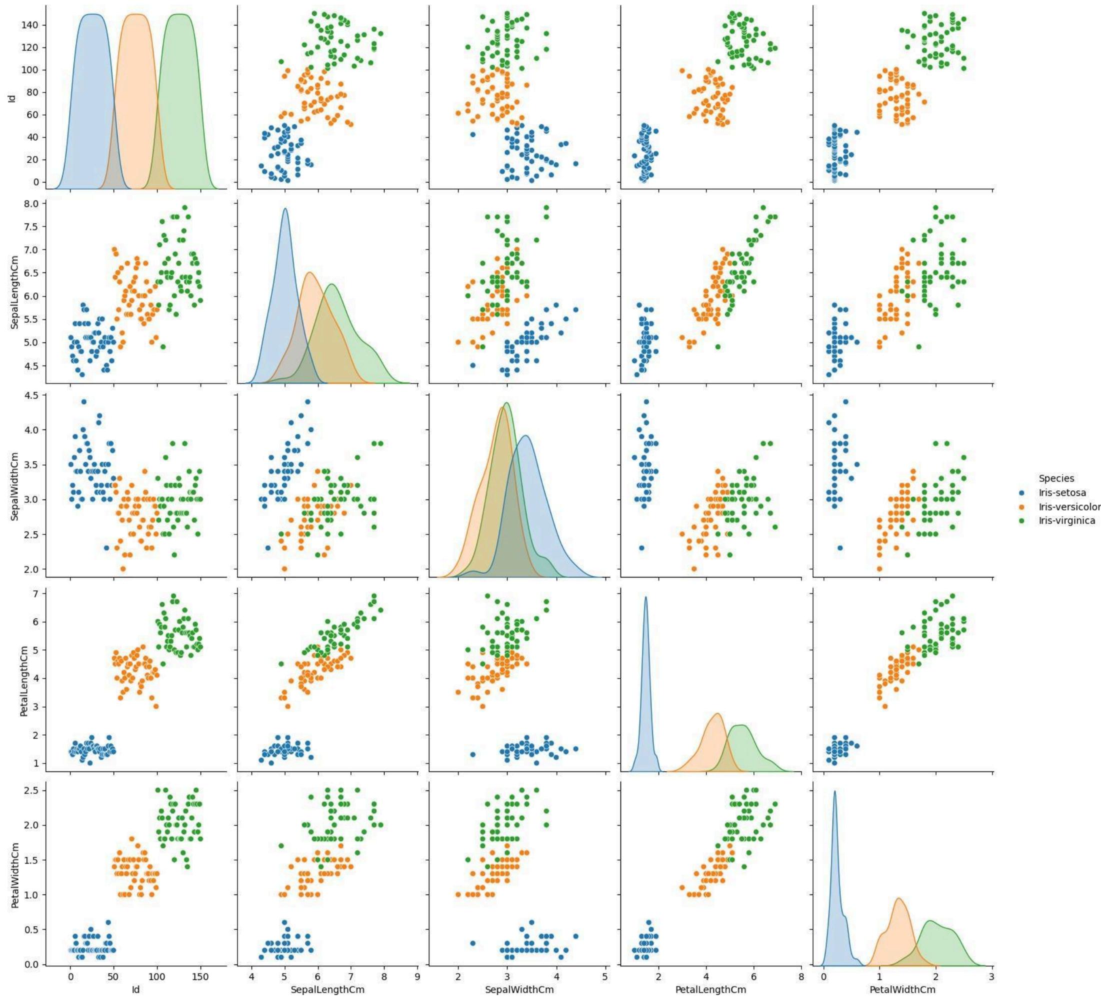
```
sns.scatterplot(x='PetalLengthCm',y='PetalWidthCm',hue='Species',data=data,)
```

[12] : <Axes: xlabel='PetalLengthCm', ylabel='PetalWidthCm'>



[13]:

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

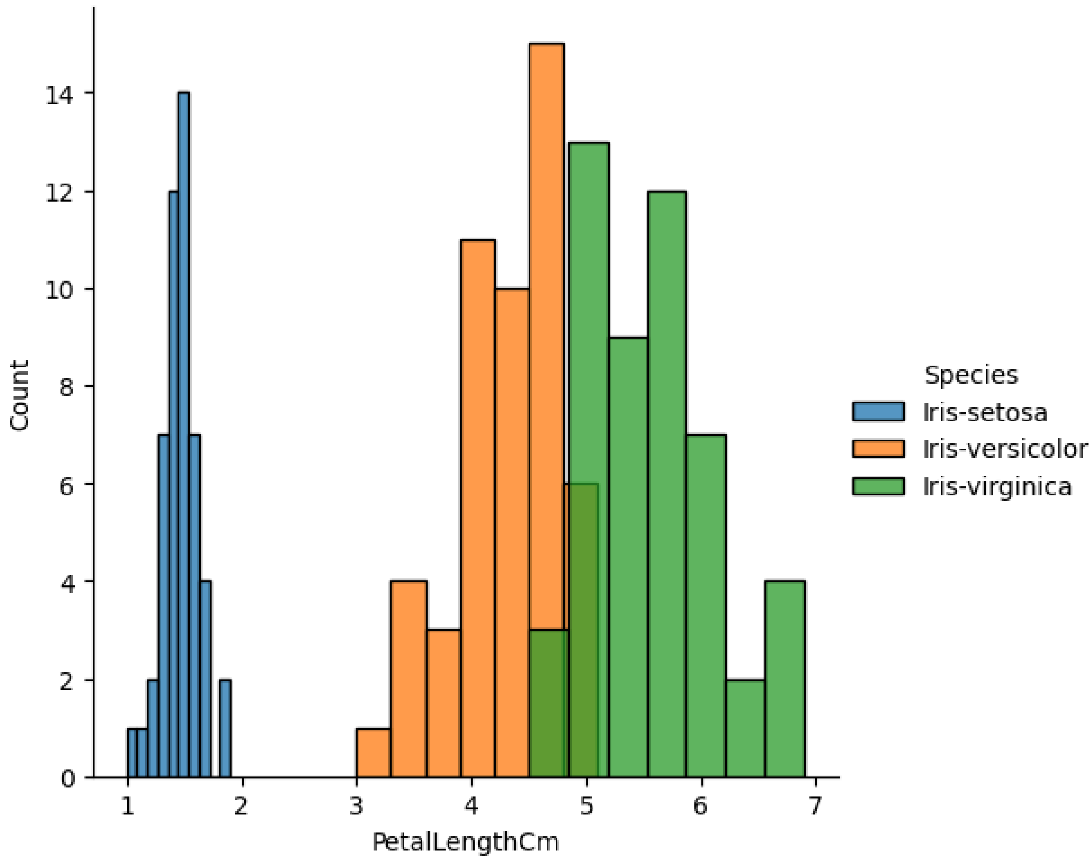


[14]:

```
plt.show()
```

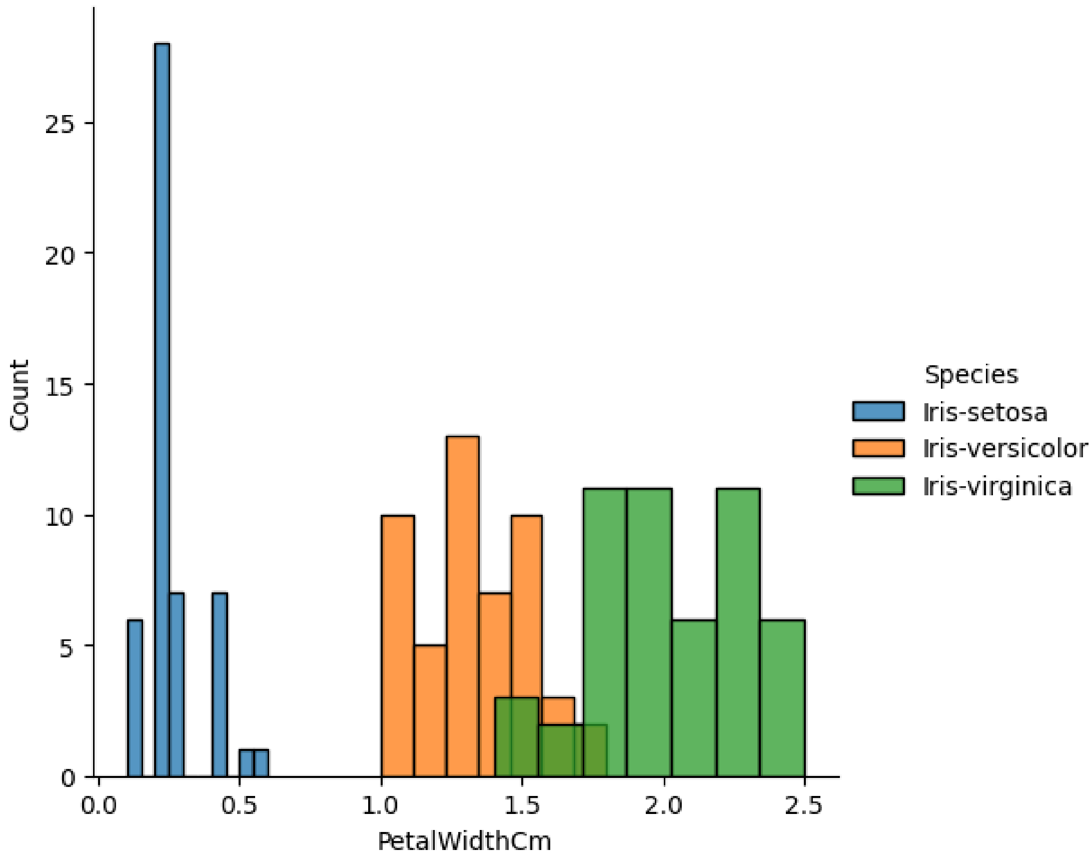
[15]:

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



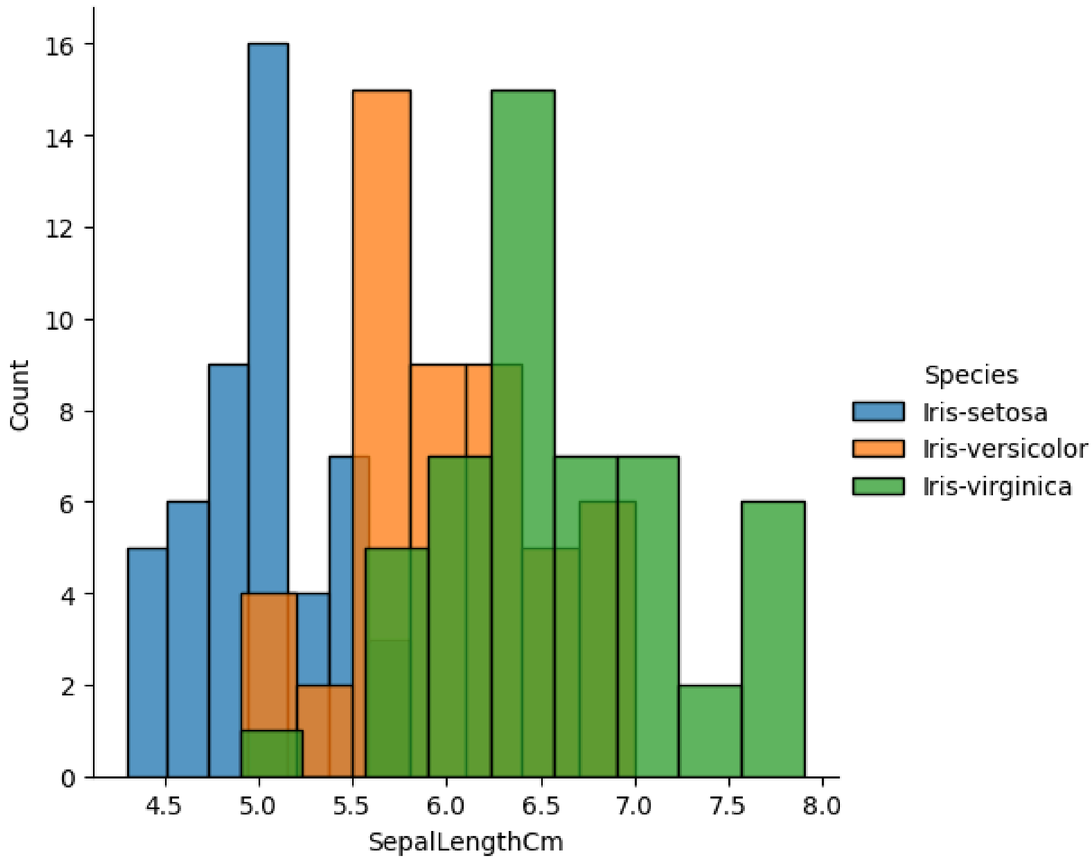
[16]:

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



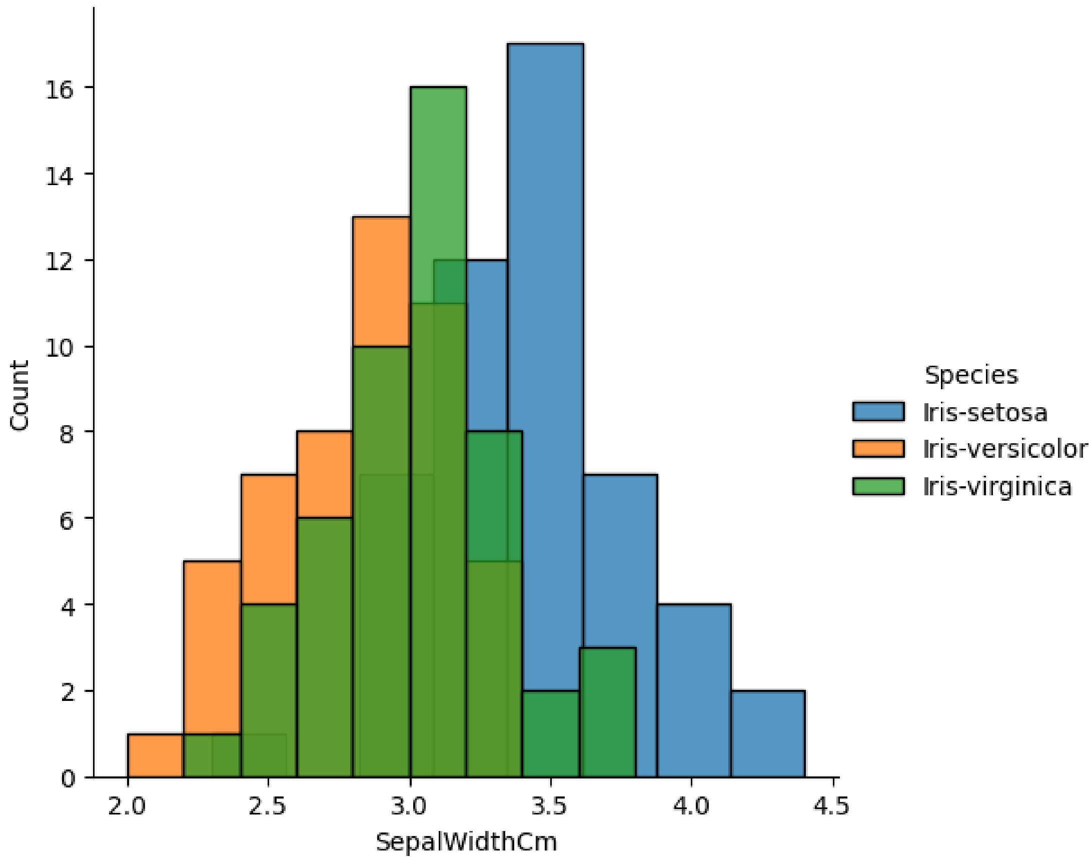
[17]:

```
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();
```



[ ]:

[19]:
```
#EX.NO :1.b Pandas Buit in function. Numpy Buit in fuction- Array slicing,
↪Ravel,Reshape,ndim
                                                            #DATA   :
            06.08.2024

#NAME : SYED ASLAM
```

[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]])

[33]:

```
#EX.NO :2 Outlier detection
#DATA :          13.08.2024

#NAME : SYED ASLAM
S#ROLL NO : 230701522
```

[34]:

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

[34]: ar

[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]:

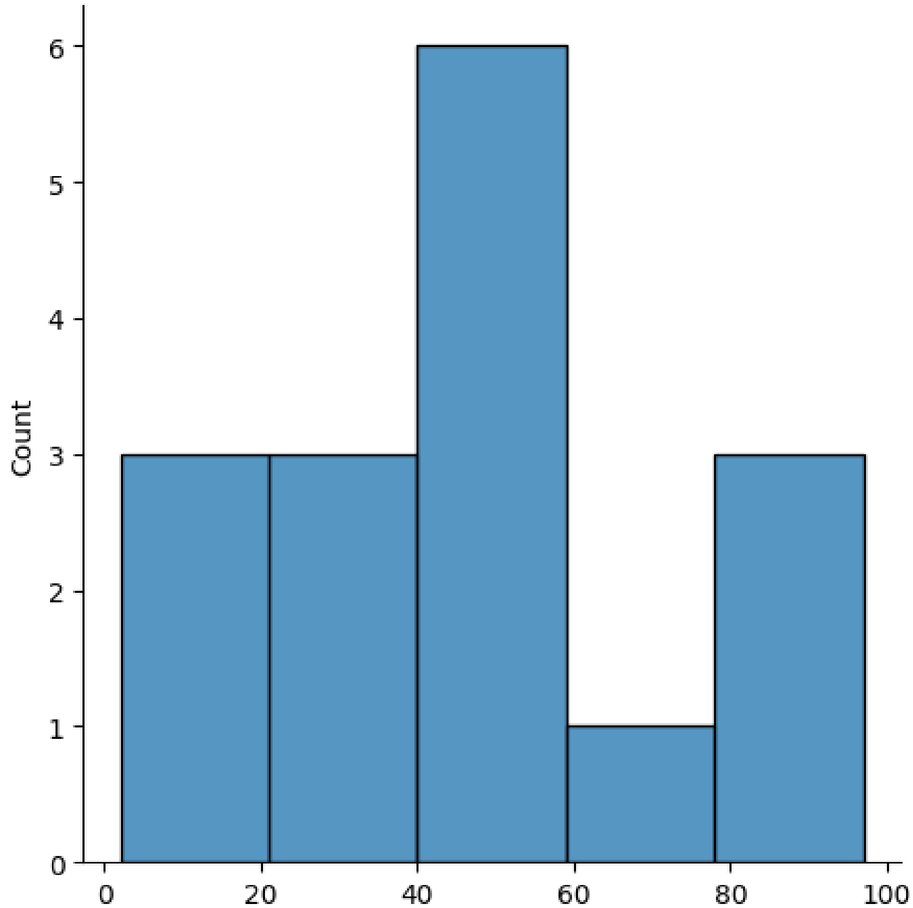
```
#outliers detection
def outDetection(array):
        sorted(array)
Q1,Q3=np.percentile(array,[25,75])
IQR=Q3-Q1
lr=Q1-(1.5*IQR)
        ur=Q3+(1.5*I
        QR)
        return lr,ur
lr,ur=outDetection(array)
lr,ur
```

[40]: (-1

[41]:

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

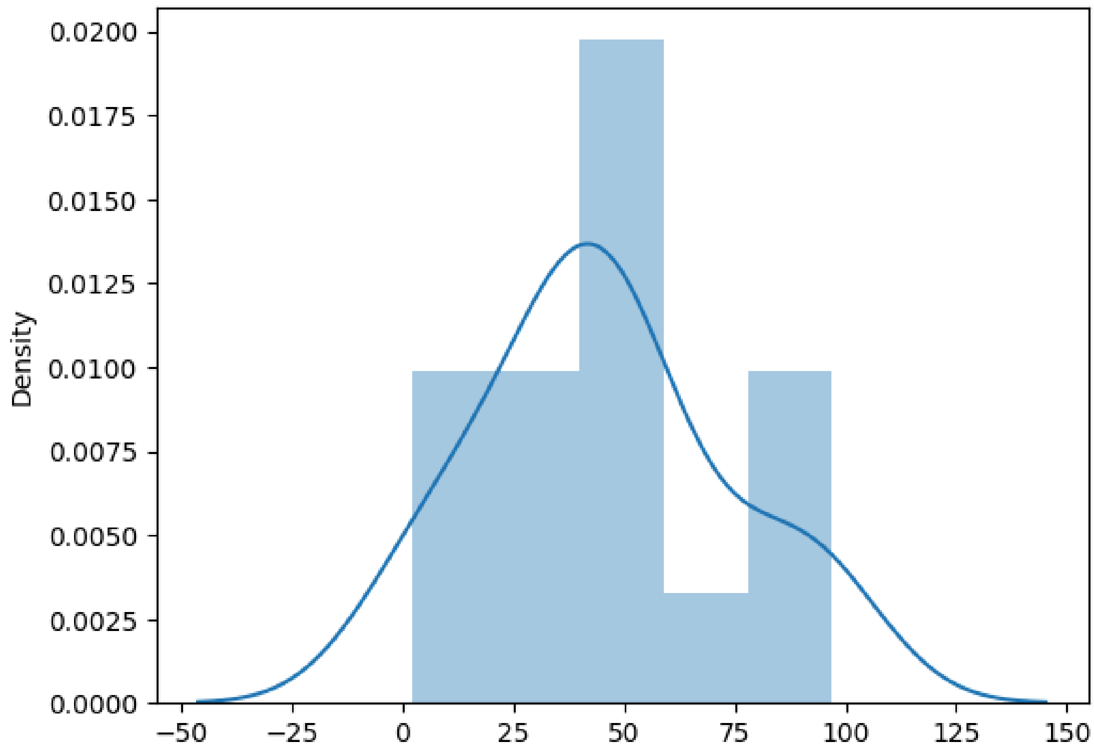
[41] : <seaborn.axisgrid.FacetGrid at 0x20d7cda3b50>



[42]:

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

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

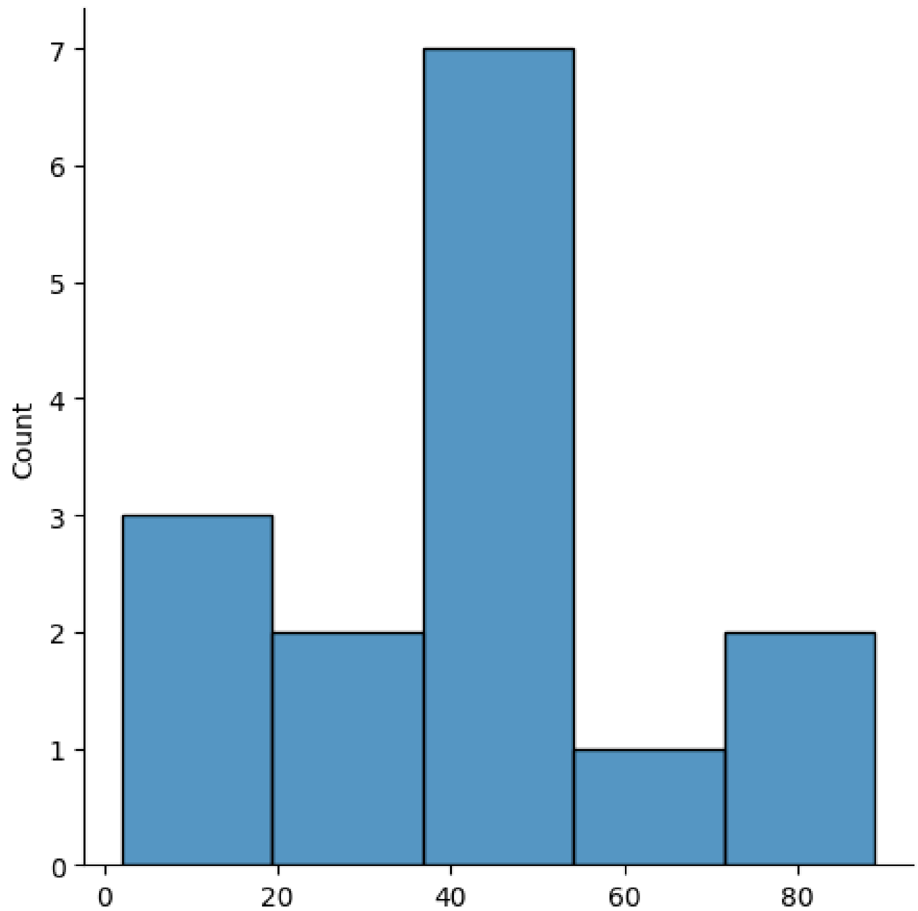


[43]:
```
new_array=array[(array>lr) & (array<ur)]
new_array
```

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

[44]:
```
sns.displot(new_array)
```

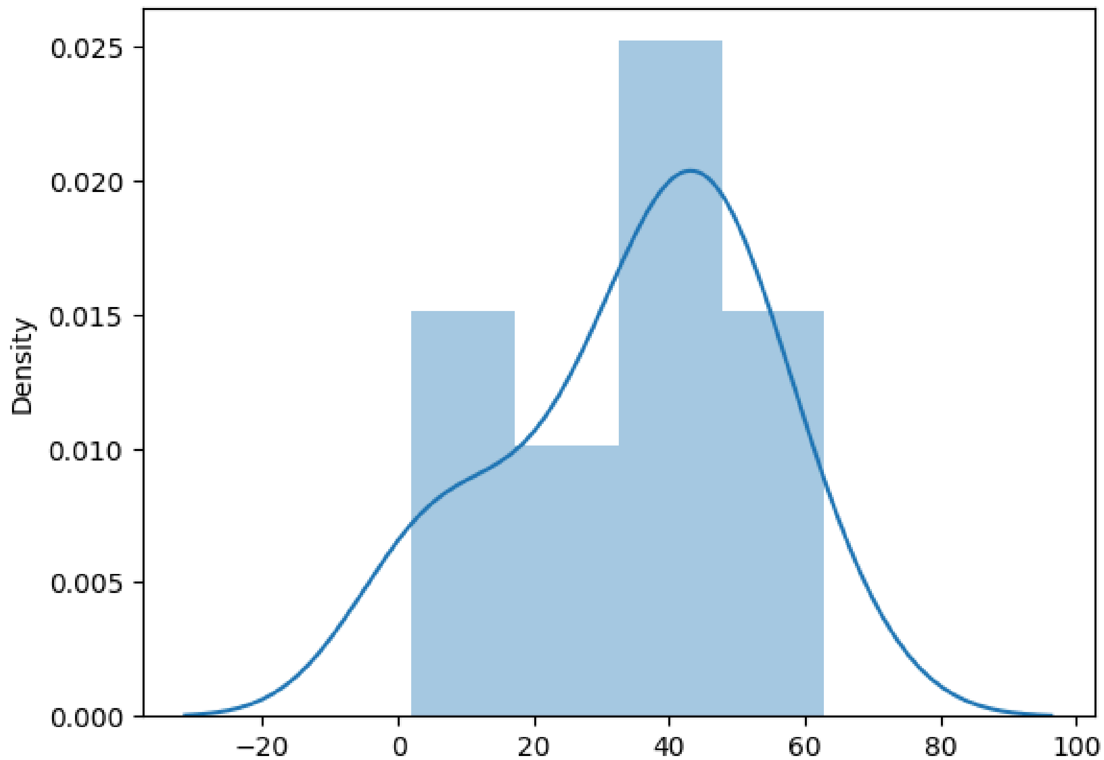
[44]: <seaborn.axisgrid.FacetGrid at 0x20d7d02d950>



[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'>



[48]:

```
#EX.NO :3                  Missing and inappropriate
data #DATA       :         20.08.2024

#NAME : SYED ASLAM
S#ROLL NO : 230701522
```

[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_GroupRating(1-5)   Hotel FoodPreference   Bill   (

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' pa

ndas.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		
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

EstimatedSa...ry

Age_Group.1

0

[53]:

```
len(df)
```

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

[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_GroupRating(1-5) Hotel FoodPreference Bill NoOfPax \

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.na
n 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 (

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

[64]:

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

#NAME : SYED ASLAM S#ROLL
NO : [illegible]
```

[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'>

[67]:

```
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   Purch
```

ased 10 non-null object dtyp

es: float64(2), object(2)
memory usage: 452.0+ bytes

```
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

[72]:

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

[73]:

```
df.info()
```

<class' pandas

[74]:

[75]:

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

#NAME : SYED ASLAM S #ROLL
NO : 230701522
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - B
```

ame.DataFrame' >RangeIndex:1

0 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

```
updated_dataset.Purchased.replace(['No','Yes'],[0
```

[76]:

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

[78]:

```
<class 'pandas.core.frame.DataFrame'>RangeIndex: 10 en
```

tries, 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()
```

[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()
```

<
c
l

```
ass'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

[86]:
```
#EX.NO :5        EDA-Quantitative and Qualitative plots #DATA
: 03.09.2024

#NAME : SYED ASLAM S
#ROLL NO : 230701522
```

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

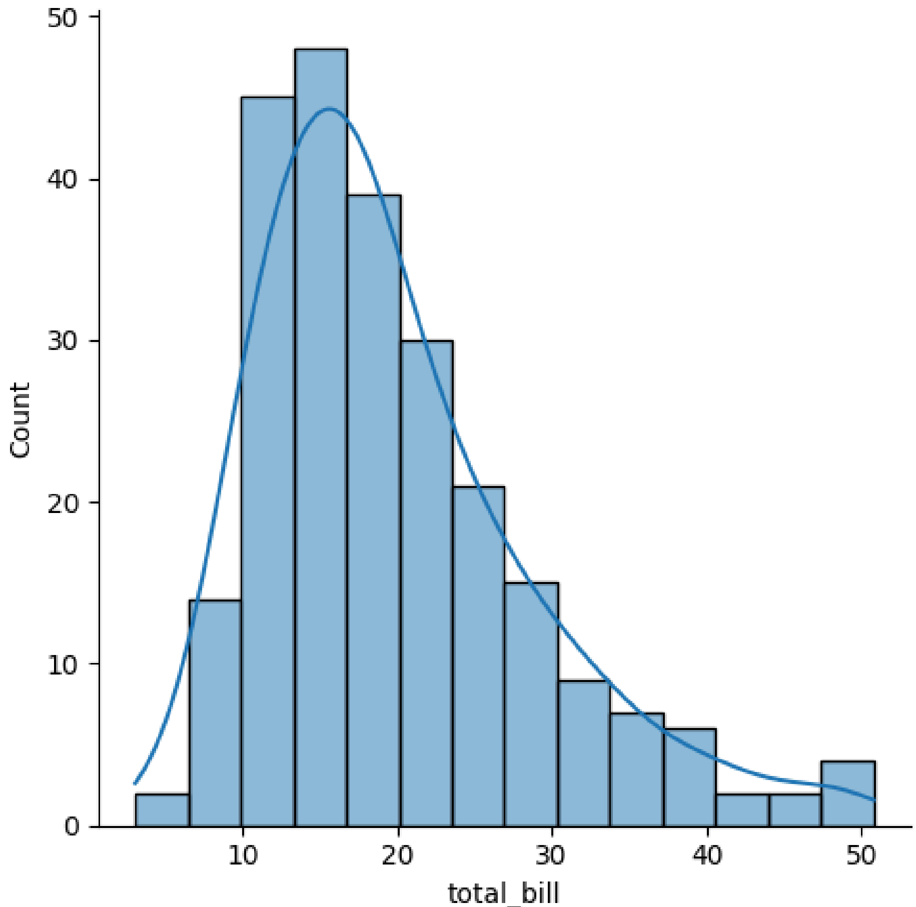
[88]:
```
tips=sns.load_dataset('tips')
tips.head()
```

[88] :

total_bill	tip	sex	smoker	day	time	size

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

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



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

0	1	20-25	4	Ibis	veg 1300	2
1	2	30-35	5	LemonTree	Non-Veg 2000	3

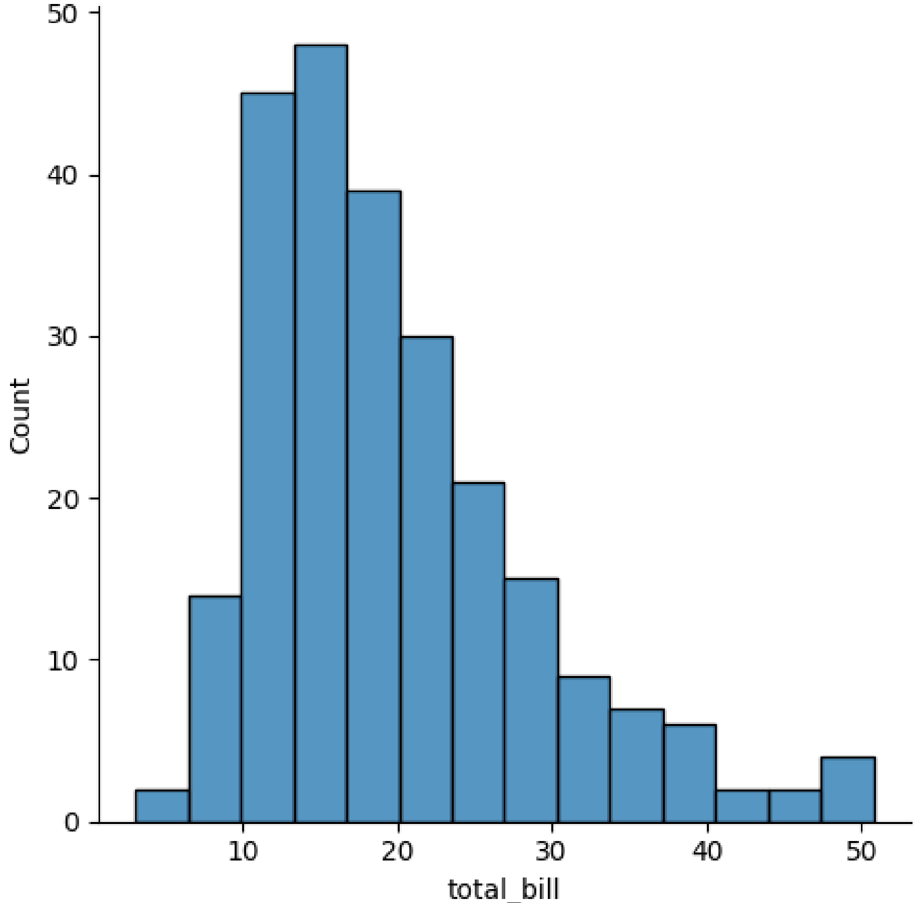
0	1.0	20-25	4	Ibis	Veg	1300.0
1	2.0	30-35	5	LemonTree	Non-Veg	2000.0
2	3.0	25-30	6	RedFox	Veg	1322.0
3	4.0	20-25	-1	LemonTree	Veg	1234.0
4	5.0	35+	3	Ibis	Veg	989.

							0
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

[90]:

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

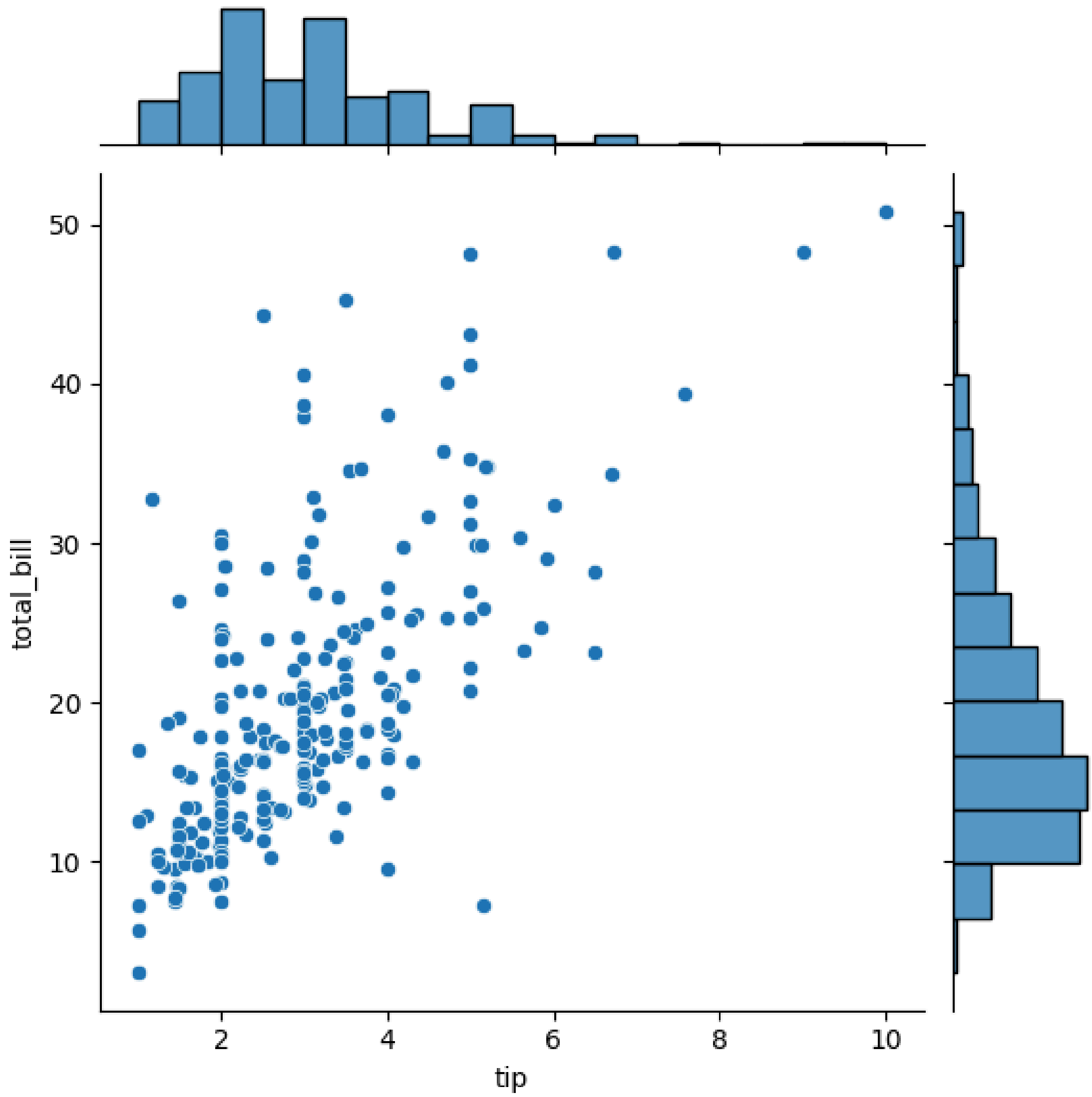
[90] : <seaborn.axisgrid.FacetGrid at 0x20d7dc22790>



[91]:

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

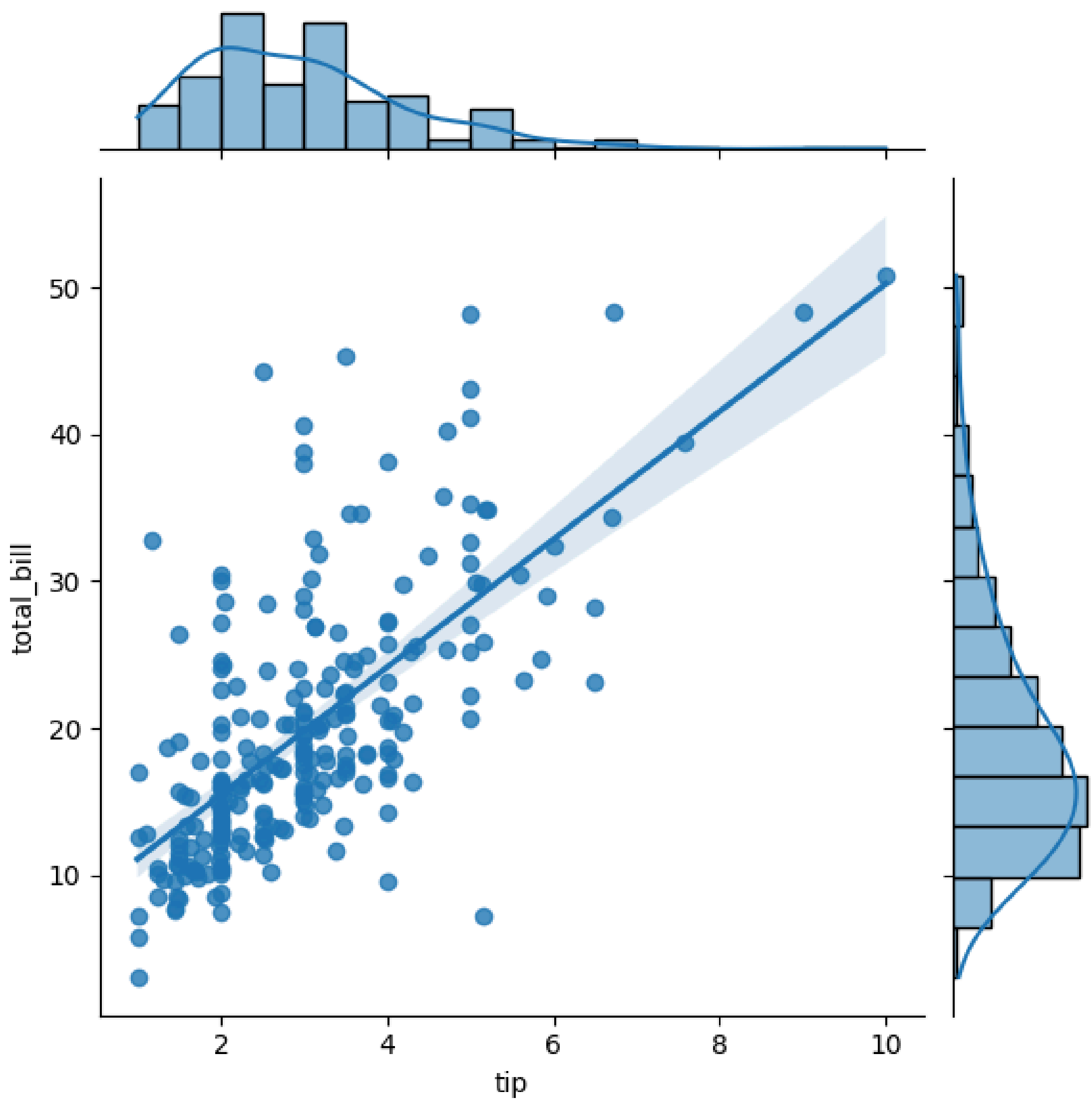
[91] : <seaborn.axisgrid.JointGrid at 0x20d7dc2f2d0>



[92]:

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

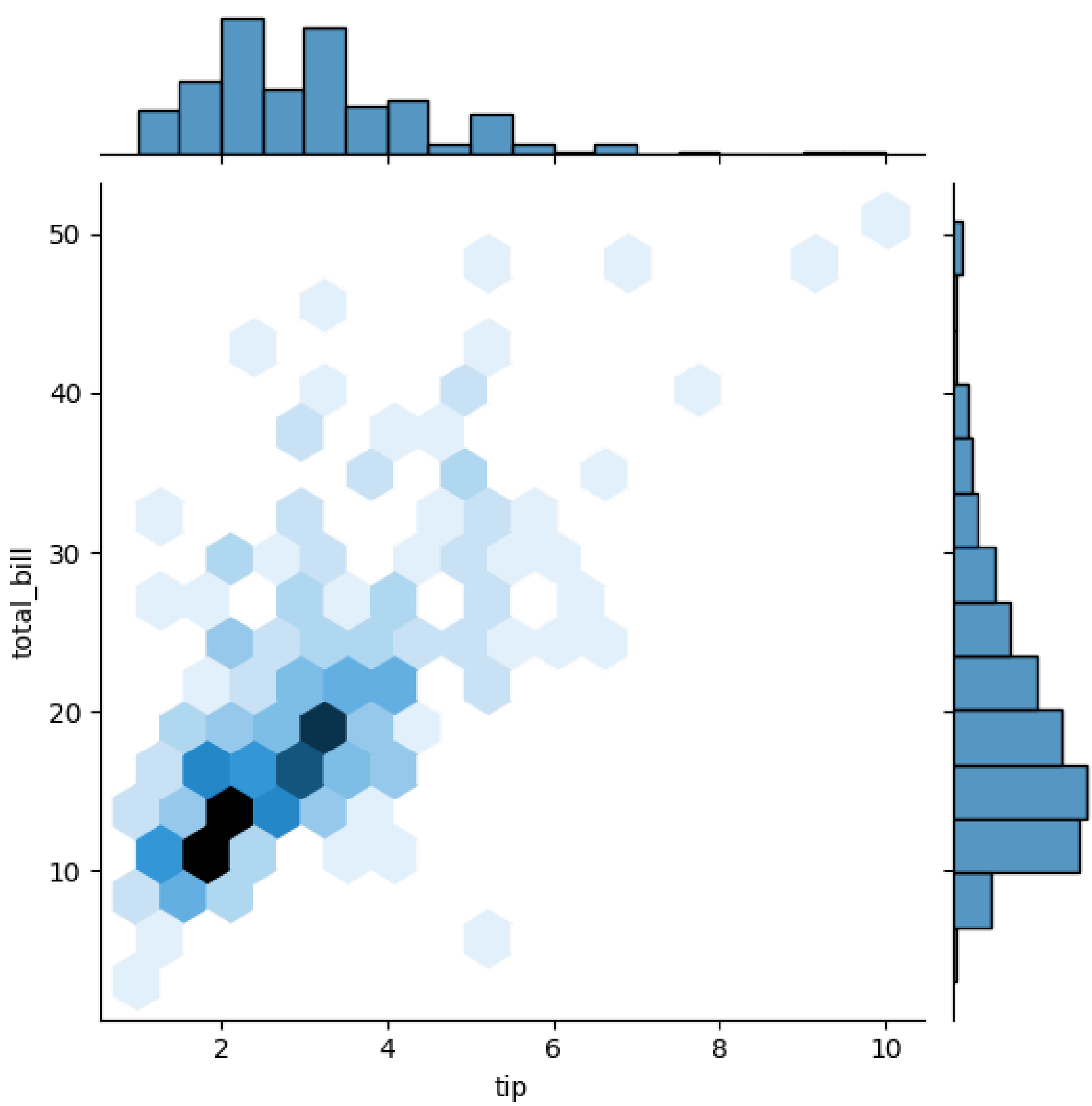
[92] : <seaborn.axisgrid.JointGrid at 0x20d7ed32450>



[93]:

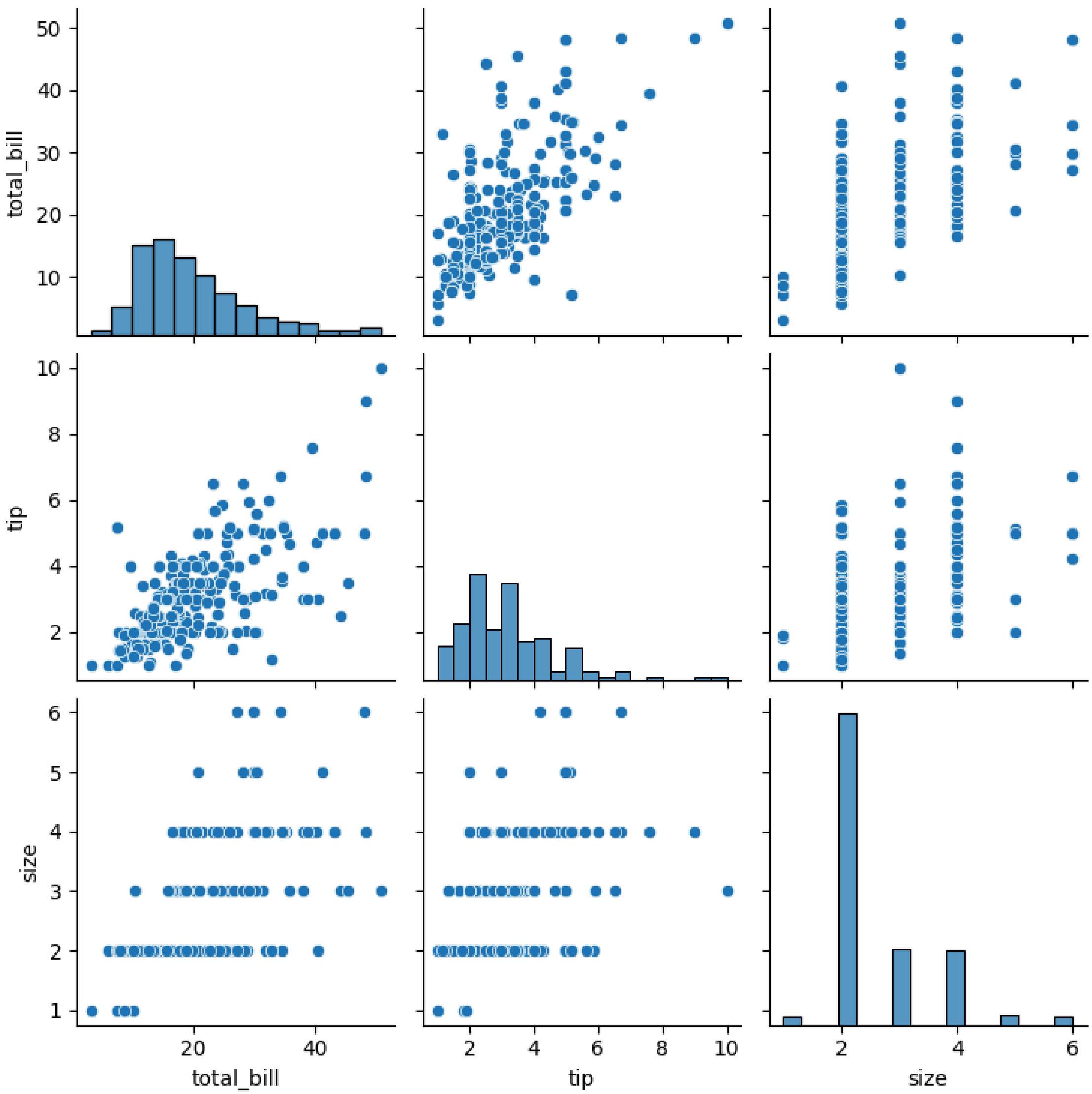
```
sns.jointplot(x=tips.tip,y=tips.total_bill,kind="hex")
```

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



[94]: `sns.pairplot(tips)`

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

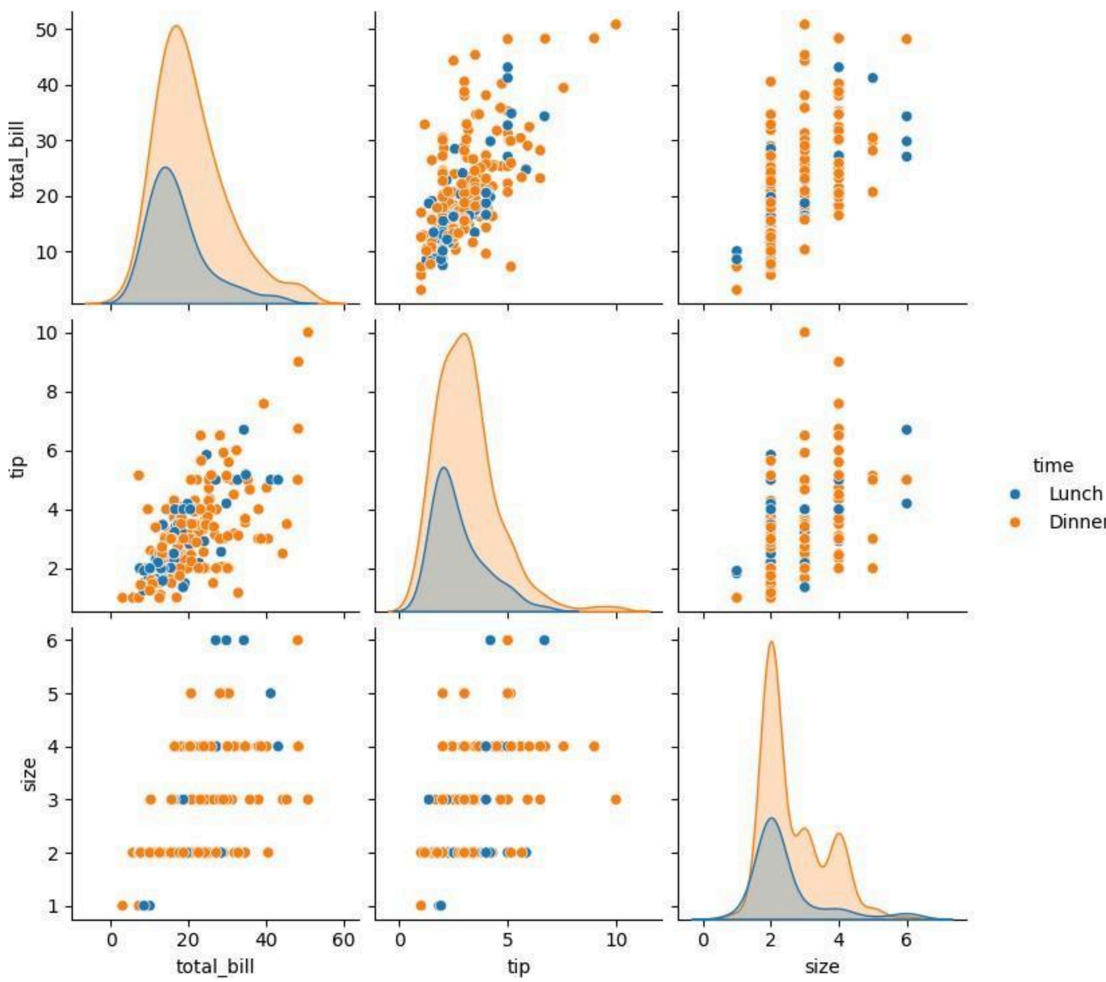


[95]:
```
tips.time.value_counts()
```

[95] :
```
time
Dinner    176
Lunch      68
Name: count, dtype: int64
```

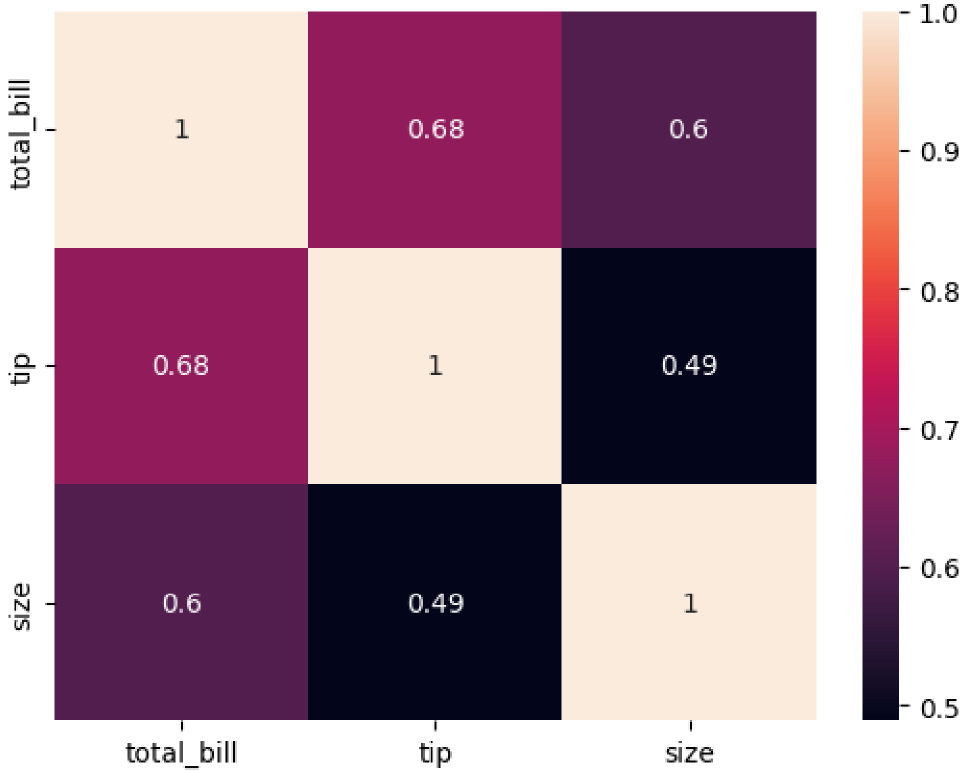
[96]:
```
sns.pairplot(tips,hue='time')
```

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



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

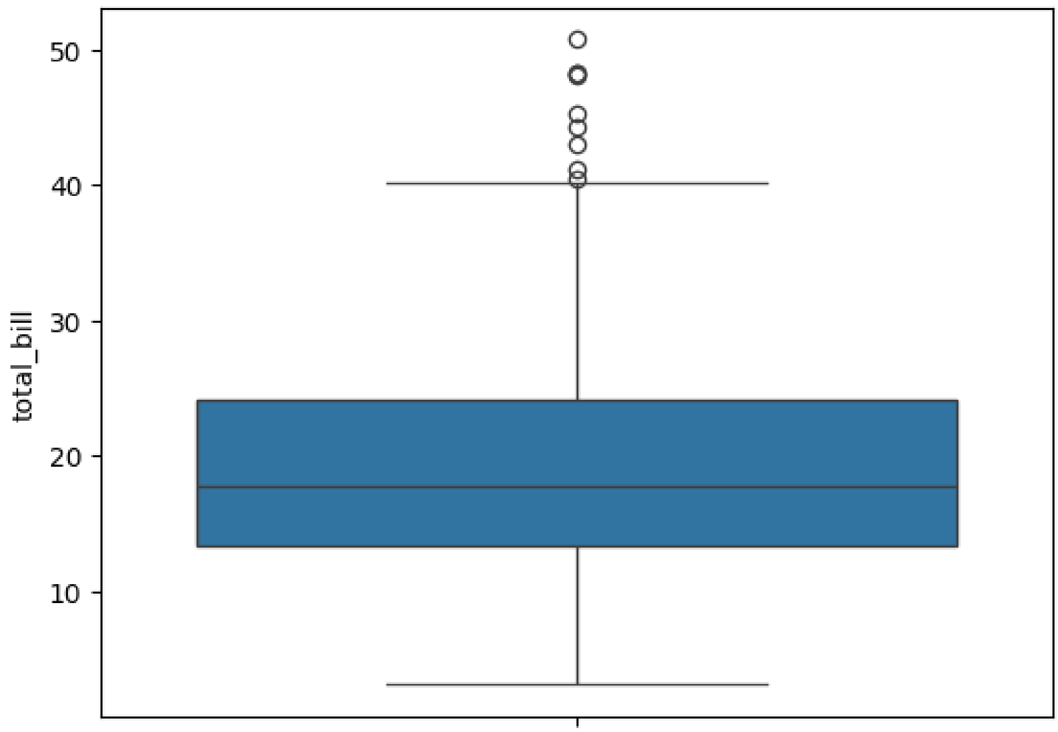
[97] : <Axes: >



[98]:

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

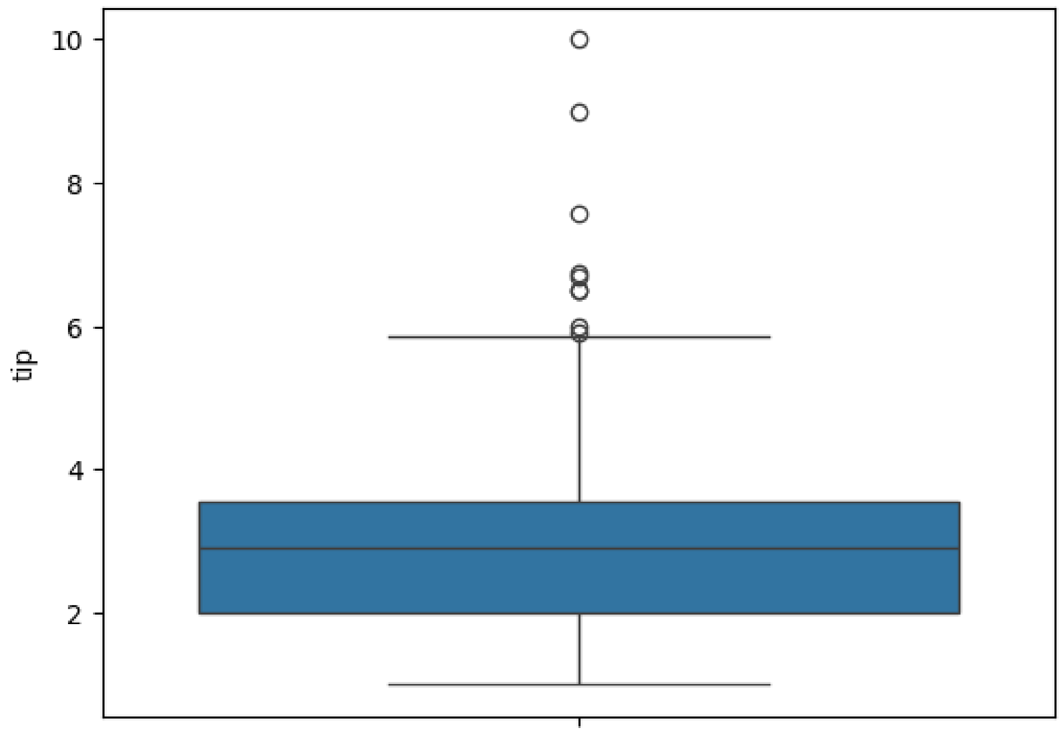
[98] : <Axes: ylabel='total_bill'>



[99]:

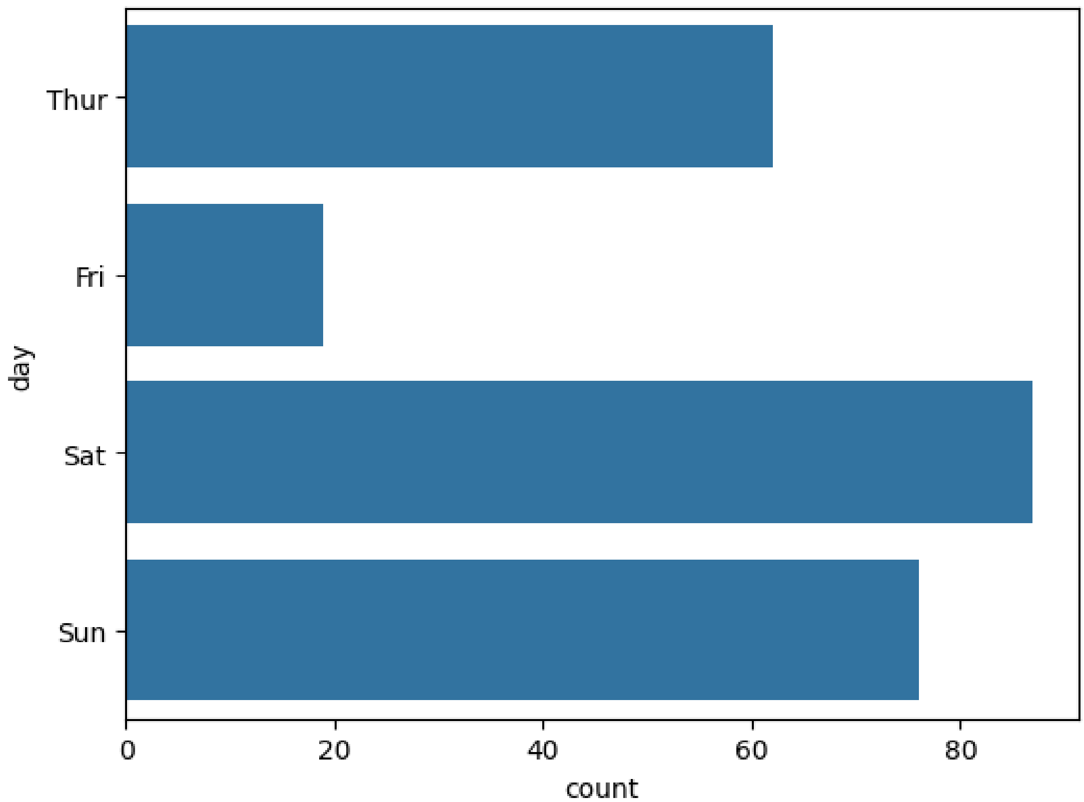
```
sns.boxplot(tips.tip)
```

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



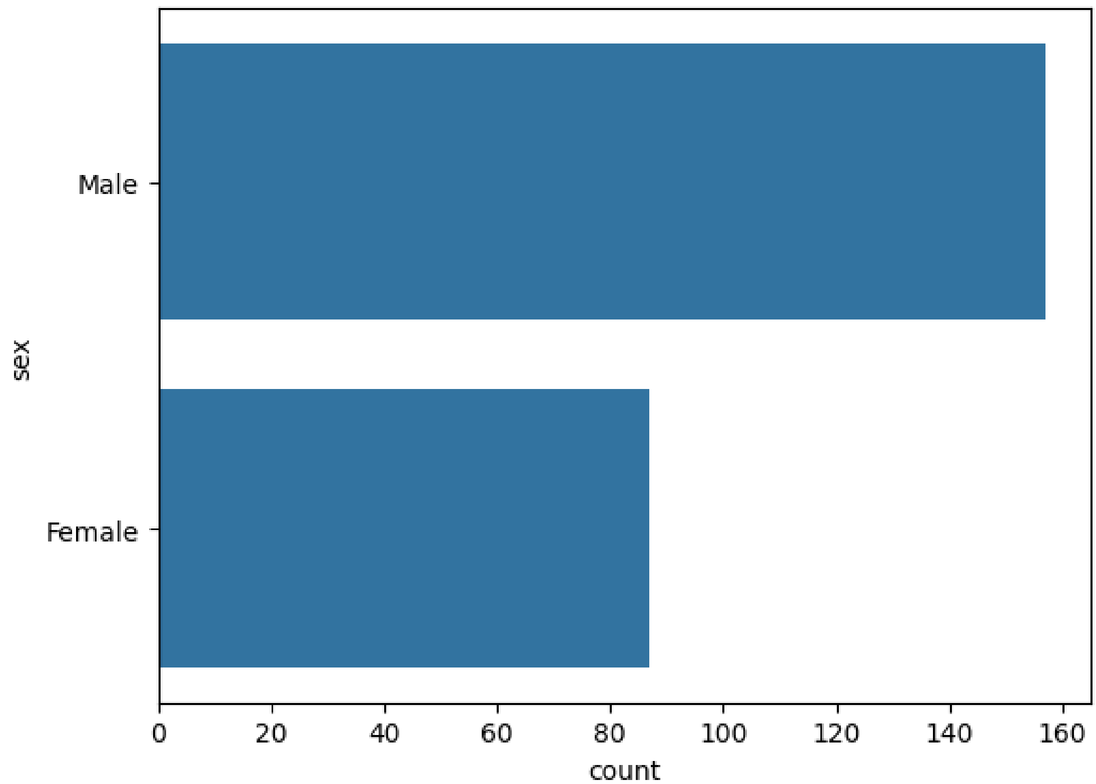
[100]: `sns.countplot(tips.day)`

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



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

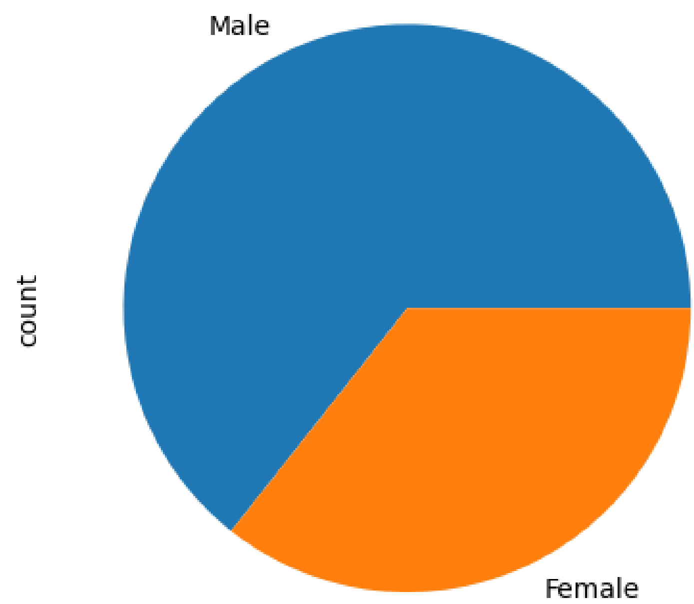
[101] : <Axes: xlabel='count', ylabel='sex'>



[102]:

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

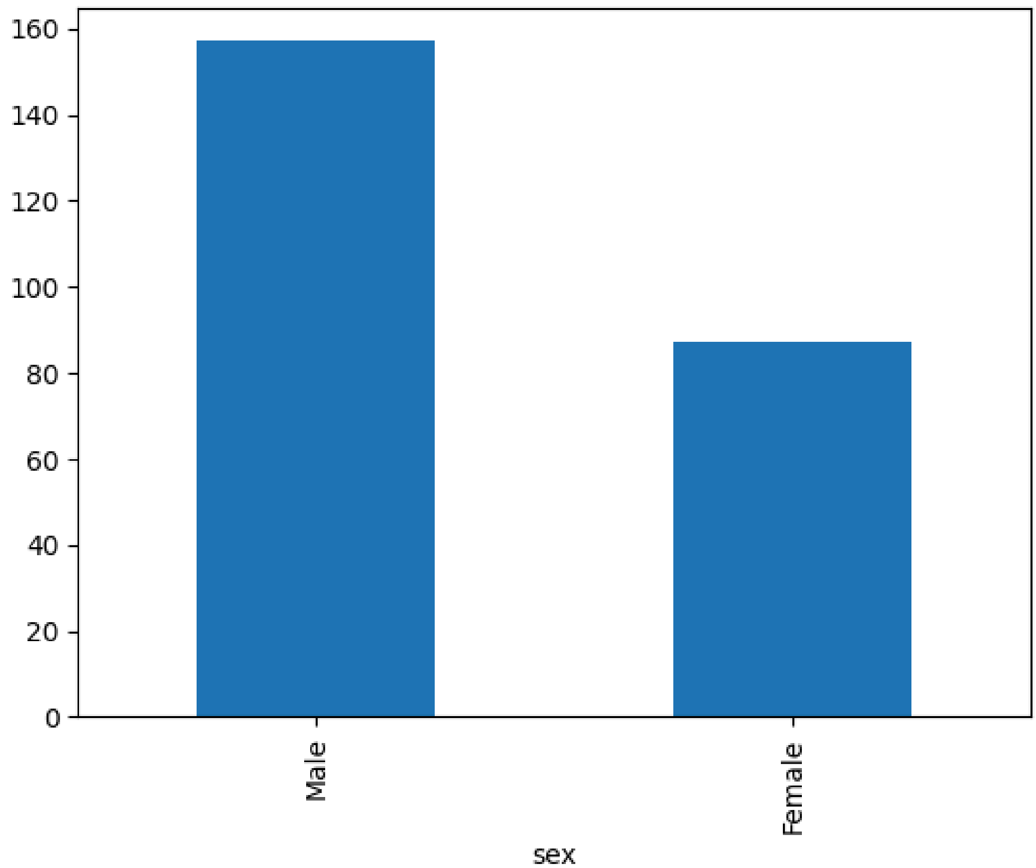
[102] : <Axes: ylabel='count'>



[103]:

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

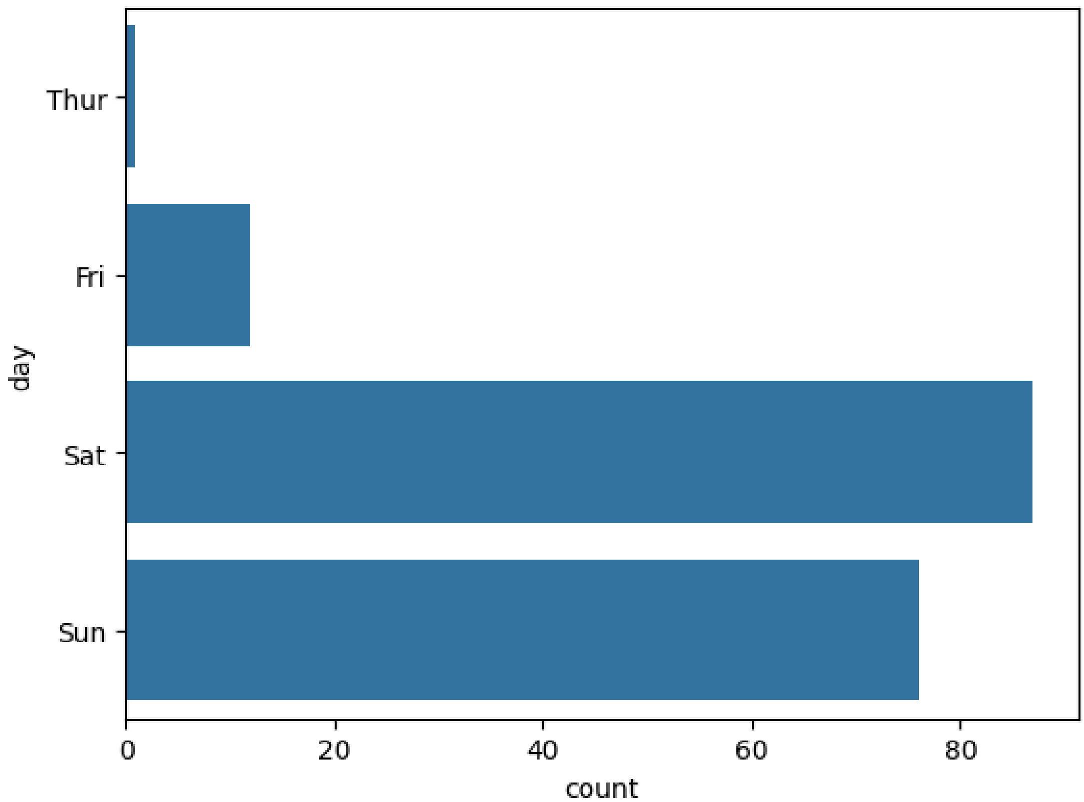
[103] : <Axes: xlabel='sex'>



[104]:

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

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



[105]:
```
#EX.NO :6        Random Sampling and Sampling Distribution #DATA
: 10.09.2024

#NAME : SYED ASLAM S
#ROLL NO : 230701522
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - B
```

[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]:

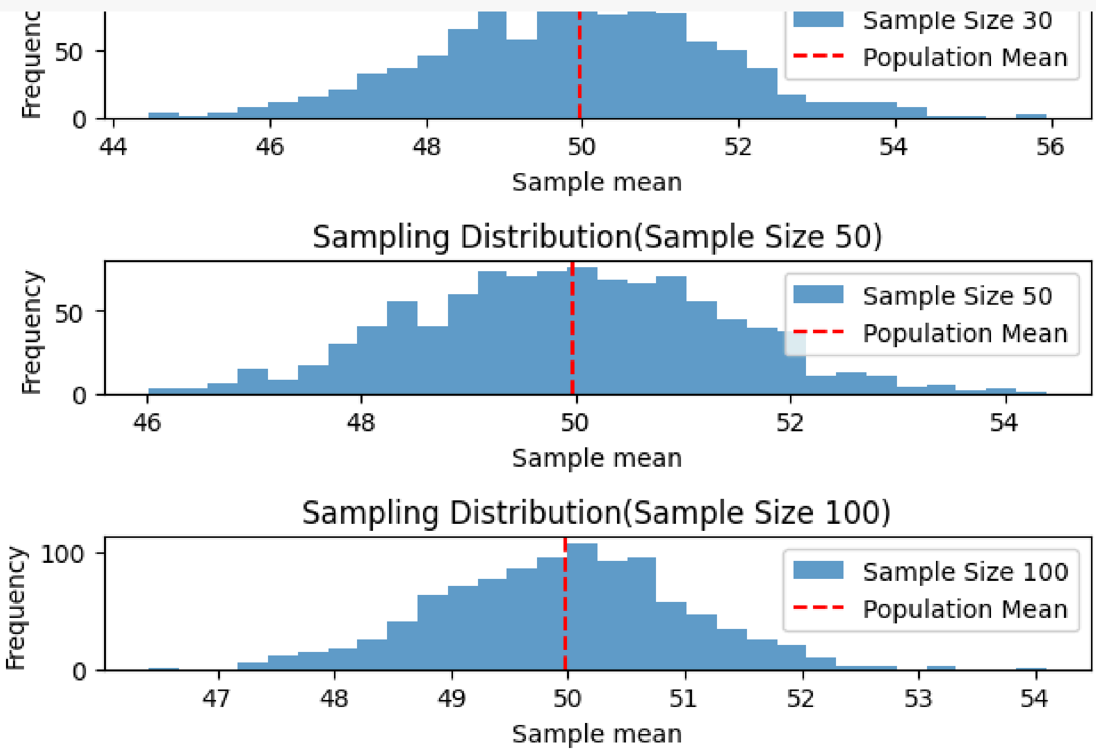
```
plt.figure(figsize=(12, 8))
```

[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()
```



[112]:

```
#EX.NO :7        Z-Test
#DATA  : 10.09.2024

#NAME : SYED ASLAM S
#ROLL NO : 230701522
```

[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.")
```

Sa

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.

[118]:

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

#NAME : SYED ASLAM S
#ROLL NO : 230701522
```

[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.")
```

P-Value: 0.8760

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

[123]:

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

```
#NAME : SYED ASLAM S
#ROLL NO : 230701522
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - B
```

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

np.random.seed
(42) n_plants =
```

[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(gr
```

```
owth_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
```

TreatmentBMeanGro

[129]:

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

#NAME : SYED ASLAM S
#ROLL NO : 230701522
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - B
```

77TreatmentCMeanGrowth:15.2652F-Statis

t
i
c
:
3
6
.
1
2
1
4
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
--------------------------------------------------------------
```

[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],

[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.n
an) 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.],
```

[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]:

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

[141]:

```
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,

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

[143]:
```
#EX.NO :11 Linear Regression
#DATA : 29.10.2024

#NAME : SYED ASLAM S
#ROLL NO : 230701522
```

[144]:
```
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]:

```
df.info()
```

```
<class 'pandas.core.frame.Da
```

[146]:

taFrame'> RangeIndex: 30 entrie
s, 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
```

[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()
```

[148]:

```
<class 'pandas.core.frame.Da
```

```
taFrame'>
RangeIndex:30entrie
s, 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
```

```python
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]:

```python
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]
```

[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] : ''

```
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]: '\r

[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))
```

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

[160]:

```
print(f" Estimated salary for {yr_of_exp} years of
```

Estimated salary for 24.0 years of expreience

[161]:

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

```
#NAME : SYED ASLAM S
#ROLL NO : 230701522
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - B
```

[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	Female	49	39000	1
15724150				
387	Male	39	71000	0
15627220				
388	Male	47	34000	1
15672330				
389	Female	48	35000	1
15668521				
390	Male	48	33000	1
15807837				
391	Male	47	23000	1
15592570				
392	Female	45	45000	1
15748589				
393	Male	60	42000	1
15635893				
394	Female	39	59000	0
15757632				
395	Female	46	41000	1
15691863				
396	Male	51	23000	1
15706071				
397	Female	50	20000	1
15654296				

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      Male   45          22000         1
15649487
        21    Female   47          49000         1
15736760
        22      Male   48          41000         1
15714658
        23    Female   45          22000         1
15599081
        24      Male   46          23000         1
15705113
```

[165]:

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

[165]:

```
array([[     19,   19000],
       [     35,   20000],
       [     26,   43000],
       [     27,   57000],
       [     19,   76000],
       [     27,   58000],
       [     27,   84000],
       [     32, 150000],
       [     25,   33000],
       [     35,   65000],
       [     26,   80000],
```

```
[      26,  52000],
[      20,  86000],
[      32,  18000],
[      18,  82000],
[      29,  80000],
[      47,  25000],
[      45,  26000],
[      46,  28000],
[      48,  29000],
[      45,  22000],
[      47,  49000],
[      48,  41000],
[      45,  22000],
[      46,  23000],
[      47,  20000],
[      49,  28000],
[      47,  30000],
[      29,  43000],
[      31,  18000],
[      31,  74000],
[      27, 137000],
[      21,  16000],
[      28,  44000],
[      27,  90000],
[      35,  27000],
[      33,  28000],
[      30,  49000],
[      26,  72000],
[      27,  31000],
[      27,  17000],
[      33,  51000],
[      35, 108000],
[      30,  15000],
[      28,  84000],
[      23,  20000],
[      25,  79000],
[      27,  54000],
[      30, 135000],
[      31,  89000],
[      24,  32000],
[      18,  44000],
[      29,  83000],
[      35,  23000],
[      27,  58000],
[      24,  55000],
[      23,  48000],
[      28,  79000],
```

```
[      22,   18000],
[      32, 117000],
[      27,   20000],
[      25,   87000],
[      23,   66000],
[      32, 120000],
[      59,   83000],
[      24,   58000],
[      24,   19000],
[      23,   82000],
[      22,   63000],
[      31,   68000],
[      25,   80000],
[      24,   27000],
[      20,   23000],
[      33, 113000],
[      32,   18000],
[      34, 112000],
[      18,   52000],
[      22,   27000],
[      28,   87000],
[      26,   17000],
[      30,   80000],
[      39,   42000],
[      20,   49000],
[      35,   88000],
[      30,   62000],
[      31, 118000],
[      24,   55000],
[      28,   85000],
[      26,   81000],
[      35,   50000],
[      22,   81000],
[      30, 116000],
[      26,   15000],
[      29,   28000],
[      29,   83000],
[      35,   44000],
[      35,   25000],
[      28, 123000],
[      35,   73000],
[      28,   37000],
[      27,   88000],
[      28,   59000],
[      32,   86000],
[      33, 149000],
[      19,   21000],
```

```
[       21,   72000],
[       26,   35000],
[       27,   89000],
[       26,   86000],
[       38,   80000],
[       39,   71000],
[       37,   71000],
[       38,   61000],
[       37,   55000],
[       42,   80000],
[       40,   57000],
[       35,   75000],
[       36,   52000],
[       40,   59000],
[       41,   59000],
[       36,   75000],
[       37,   72000],
[       40,   75000],
[       35,   53000],
[       41,   51000],
[       39,   61000],
[       42,   65000],
[       26,   32000],
[       30,   17000],
[       26,   84000],
[       31,   58000],
[       33,   31000],
[       30,   87000],
[       21,   68000],
[       28,   55000],
[       23,   63000],
[       20,   82000],
[       30,  107000],
[       28,   59000],
[       19,   25000],
[       19,   85000],
[       18,   68000],
[       35,   59000],
[       30,   89000],
[       34,   25000],
[       24,   89000],
[       27,   96000],
[       41,   30000],
[       29,   61000],
[       20,   74000],
[       26,   15000],
[       41,   45000],
```

```
[        31,   76000],
[        36,   50000],
[        40,   47000],
[        31,   15000],
[        46,   59000],
[        29,   75000],
[        26,   30000],
[        32, 135000],
[        32, 100000],
[        25,   90000],
[        37,   33000],
[        35,   38000],
[        33,   69000],
[        18,   86000],
[        22,   55000],
[        35,   71000],
[        29, 148000],
[        29,   47000],
[        21,   88000],
[        34, 115000],
[        26, 118000],
[        34,   43000],
[        34,   72000],
[        23,   28000],
[        35,   47000],
[        25,   22000],
[        24,   23000],
[        31,   34000],
[        26,   16000],
[        31,   71000],
[        32, 117000],
[        33,   43000],
[        33,   60000],
[        31,   66000],
[        20,   82000],
[        33,   41000],
[        35,   72000],
[        28,   32000],
[        24,   84000],
[        19,   26000],
[        29,   43000],
[        19,   70000],
[        28,   89000],
[        34,   43000],
[        30,   79000],
[        20,   36000],
[        26,   80000],
```

```
[       35,  22000],
[       35,  39000],
[       49,  74000],
[       39, 134000],
[       41,  71000],
[       58, 101000],
[       47,  47000],
[       55, 130000],
[       52, 114000],
[       40, 142000],
[       46,  22000],
[       48,  96000],
[       52, 150000],
[       59,  42000],
[       35,  58000],
[       47,  43000],
[       60, 108000],
[       49,  65000],
[       40,  78000],
[       46,  96000],
[       59, 143000],
[       41,  80000],
[       35,  91000],
[       37, 144000],
[       60, 102000],
[       35,  60000],
[       37,  53000],
[       36, 126000],
[       56, 133000],
[       40,  72000],
[       42,  80000],
[       35, 147000],
[       39,  42000],
[       40, 107000],
[       49,  86000],
[       38, 112000],
[       46,  79000],
[       40,  57000],
[       37,  80000],
[       46,  82000],
[       53, 143000],
[       42, 149000],
[       38,  59000],
[       50,  88000],
[       56, 104000],
[       41,  72000],
[       51, 146000],
```

```
[       35,   50000],
[       57, 122000],
[       41,   52000],
[       35,   97000],
[       44,   39000],
[       37,   52000],
[       48, 134000],
[       37, 146000],
[       50,   44000],
[       52,   90000],
[       41,   72000],
[       40,   57000],
[       58,   95000],
[       45, 131000],
[       35,   77000],
[       36, 144000],
[       55, 125000],
[       35,   72000],
[       48,   90000],
[       42, 108000],
[       40,   75000],
[       37,   74000],
[       47, 144000],
[       40,   61000],
[       43, 133000],
[       59,   76000],
[       60,   42000],
[       39, 106000],
[       57,   26000],
[       57,   74000],
[       38,   71000],
[       49,   88000],
[       52,   38000],
[       50,   36000],
[       59,   88000],
[       35,   61000],
[       37,   70000],
[       52,   21000],
[       48, 141000],
[       37,   93000],
[       37,   62000],
[       48, 138000],
[       41,   79000],
[       37,   78000],
[       39, 134000],
[       49,   89000],
[       55,   39000],
```

```
[      37,  77000],
[      35,  57000],
[      36,  63000],
[      42,  73000],
[      43, 112000],
[      45,  79000],
[      46, 117000],
[      58,  38000],
[      48,  74000],
[      37, 137000],
[      37,  79000],
[      40,  60000],
[      42,  54000],
[      51, 134000],
[      47, 113000],
[      36, 125000],
[      38,  50000],
[      42,  70000],
[      39,  96000],
[      38,  50000],
[      49, 141000],
[      39,  79000],
[      39,  75000],
[      54, 104000],
[      35,  55000],
[      45,  32000],
[      36,  60000],
[      52, 138000],
[      53,  82000],
[      41,  52000],
[      48,  30000],
[      48, 131000],
[      41,  60000],
[      41,  72000],
[      42,  75000],
[      36, 118000],
[      47, 107000],
[      38,  51000],
[      48, 119000],
[      42,  65000],
[      40,  65000],
[      57,  60000],
[      36,  54000],
[      58, 144000],
[      35,  79000],
[      38,  55000],
[      39, 122000],
```

```
[      53, 104000],
[      35,  75000],
[      38,  65000],
[      47,  51000],
[      47, 105000],
[      41,  63000],
[      53,  72000],
[      54, 108000],
[      39,  77000],
[      38,  61000],
[      38, 113000],
[      37,  75000],
[      42,  90000],
[      37,  57000],
[      36,  99000],
[      60,  34000],
[      54,  70000],
[      41,  72000],
[      40,  71000],
[      42,  54000],
[      43, 129000],
[      53,  34000],
[      47,  50000],
[      42,  79000],
[      42, 104000],
[      59,  29000],
[      58,  47000],
[      46,  88000],
[      38,  71000],
[      54,  26000],
[      60,  46000],
[      60,  83000],
[      39,  73000],
[      59, 130000],
[      37,  80000],
[      46,  32000],
[      46,  74000],
[      42,  53000],
[      41,  87000],
[      58,  23000],
[      42,  64000],
[      48,  33000],
[      44, 139000],
[      49,  28000],
[      57,  33000],
[      56,  60000],
[      49,  39000],
```

```
[      39,   71000],
[      47,   34000],
[      48,   35000],
[      48,   33000],
[      47,   23000],
[      45,   45000],
[      60,   42000],
[      39,   59000],
[      46,   41000],
[      51,   23000],
[      50,   20000],
[      36,   33000],
[      49,   36000]], dtype=int64)
```

[166]:

```
label
```

[166]:

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

[167]:

```python
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
```

[168]:

```python
# 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: 0.862 | Train Score: 0.8344 | Random State: 30
```

5 m

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: 0.875 | Train Score: 0.8344 | Rando State: 119

0 m
Test Score: 0.912 | Train Score: 0.8281 | Rando State: 120
5 m
Test Score: 0.862 | Train Score: 0.8594 | Rando State: 125
5 m
Test Score: 0.850 | Train Score: 0.8469 | Rando State: 128
0 m
Test Score: 0.875 | Train Score: 0.8500 | Rando State: 130
0 m
Test Score: 0.900 | Train Score: 0.8438 | Rando State: 133
0 m
Test Score: 0.925 | Train Score: 0.8344 | Rando State: 134
0 m
Test Score: 0.862 | Train Score: 0.8500 | Rando State: 135
5 m
Test Score: 0.875 | Train Score: 0.8313 | Rando State: 138
0 m
Test Score: 0.862 | Train Score: 0.8500 | Rando State: 141
5 m
Test Score: 0.850 | Train Score: 0.8469 | Rando State: 143
0 m
Test Score: 0.850 | Train Score: 0.8469 | Rando State: 146
0 m
Test Score: 0.850 | Train Score: 0.8438 | Rando State: 147
0 m
Test Score: 0.862 | Train Score: 0.8500 | Rando State: 148
5 m
Test Score: 0.875 | Train Score: 0.8375 | Rando State: 150
0 m
Test Score: 0.887 | Train Score: 0.8313 | Rando State: 151
5 m
Test Score: 0.925 | Train Score: 0.8438 | Rando State: 152
0 m
Test Score: 0.850 | Train Score: 0.8406 | Rando State: 153
0 m
Test Score: 0.900 | Train Score: 0.8438 | Rando State: 154
0 m
Test Score: 0.900 | Train Score: 0.8406 | Rando State: 155
0 m
Test Score: 0.887 | Train Score: 0.8469 | Rando State: 156
5 m
Test Score: 0.887 | Train Score: 0.8344 | Rando State: 158
5 m
Test Score: 0.875 | Train Score: 0.8281 | Rando State: 159
0 m
Test Score: 0.900 | Train Score: 0.8313 | Rando State: 161
0 m
Test Score: 0.850 | Train Score: 0.8375 | Rando State: 163
0 m

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: 0.850 | Train Score: 0.8406 | Rando State: 222

0 m

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: 0.912 | Train Score: 0.8344 | Rando State: 314

5 m
Test Score: 0.875 | Train Score: 0.8375 | Rando State: 315
0 m
Test Score: 0.900 | Train Score: 0.8469 | Rando State: 317
0 m
Test Score: 0.912 | Train Score: 0.8219 | Rando State: 319
5 m
Test Score: 0.862 | Train Score: 0.8500 | Rando State: 321
5 m
Test Score: 0.912 | Train Score: 0.8281 | Rando State: 322
5 m
Test Score: 0.850 | Train Score: 0.8469 | Rando State: 328
0 m
Test Score: 0.850 | Train Score: 0.8375 | Rando State: 332
0 m
Test Score: 0.887 | Train Score: 0.8531 | Rando State: 336
5 m
Test Score: 0.850 | Train Score: 0.8375 | Rando State: 337
0 m
Test Score: 0.875 | Train Score: 0.8406 | Rando State: 343
0 m
Test Score: 0.862 | Train Score: 0.8438 | Rando State: 346
5 m
Test Score: 0.887 | Train Score: 0.8313 | Rando State: 351
5 m
Test Score: 0.862 | Train Score: 0.8500 | Rando State: 352
5 m
Test Score: 0.950 | Train Score: 0.8187 | Rando State: 354
0 m
Test Score: 0.862 | Train Score: 0.8500 | Rando State: 356
5 m
Test Score: 0.912 | Train Score: 0.8406 | Rando State: 357
5 m
Test Score: 0.862 | Train Score: 0.8375 | Rando State: 358
5 m
Test Score: 0.850 | Train Score: 0.8406 | Rando State: 362
0 m
Test Score: 0.900 | Train Score: 0.8438 | Rando State: 363
0 m
Test Score: 0.862 | Train Score: 0.8531 | Rando State: 364
5 m
Test Score: 0.937 | Train Score: 0.8219 | Rando State: 366
5 m
Test Score: 0.912 | Train Score: 0.8406 | Rando State: 369
5 m
Test Score: 0.862 | Train Score: 0.8531 | Rando State: 371
5 m
Test Score: 0.925 | Train Score: 0.8344 | Rando State: 376
0 m

```
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.predic
```

	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