FUNDAMENTAL OF DATA SCIENCE
Lab experiments

Ex no:01
Roll no: 230701042
Name: Ashna V
Class: CSE-A II
Subject: Fundamentals of data science (CS23334)

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

data=pd.read_csv('/content/Iris_Dataset.csv')
data
```

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	variety
0	1	5.1	3.5	1.4	0.2	Iris-setosa
1	2	4.9	3.0	1.4	0.2	Iris-setosa
2	3	4.7	3.2	1.3	0.2	Iris-setosa
3	4	4.6	3.1	1.5	0.2	Iris-setosa
4	5	5.0	3.6	1.4	0.2	Iris-setosa
...	...	...	...	...	...	...
145	146	6.7	3.0	5.2	2.3	Iris-virginica
146	147	6.3	2.5	5.0	1.9	Iris-virginica
147	148	6.5	3.0	5.2	2.0	Iris-virginica
148	149	6.2	3.4	5.4	2.3	Iris-virginica
149	150	5.9	3.0	5.1	1.8	Iris-virginica

150 rows × 6 columns

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 6 columns):
 # Column Non-Null Count Dtype
--- ---------- ----------------------- ---------
 0 Id 150 non-null int64
 1 SepalLengthCm 150 non-null float64
 2 SepalWidthCm 150 non-null float64
 3 PetalLengthCm 150 non-null float64
 4 PetalWidthCm 150 non-null float64
```

```
 5 variety 150 non-null object
dtypes: float64(4), int64(1), object(1)
memory usage: 7.2+ KB
```

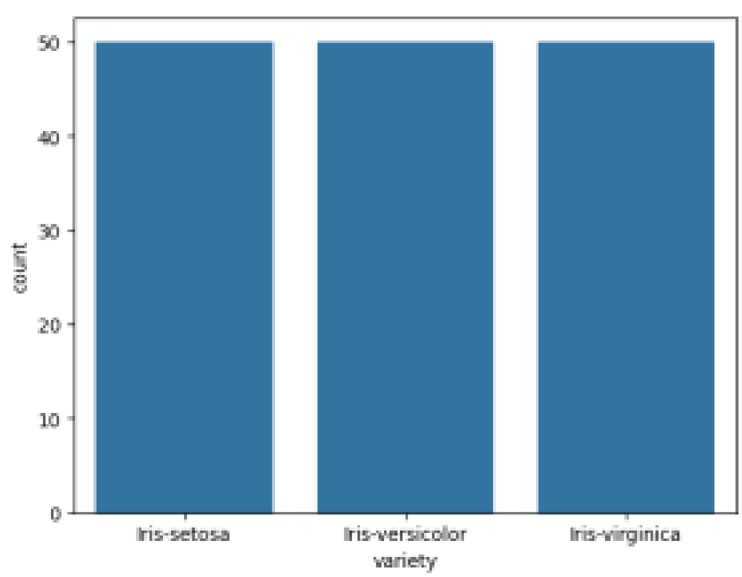
```
data.describe()
```

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
count	150.000000	150.000000	150.000000	150.000000	150.000000
mean	75.500000	5.843333	3.054000	3.758667	1.198667
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

```
data.value_counts('variety')
```

	count
variety	
Iris-setosa	50
Iris-versicolor	50
Iris-virginica	50

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




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

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

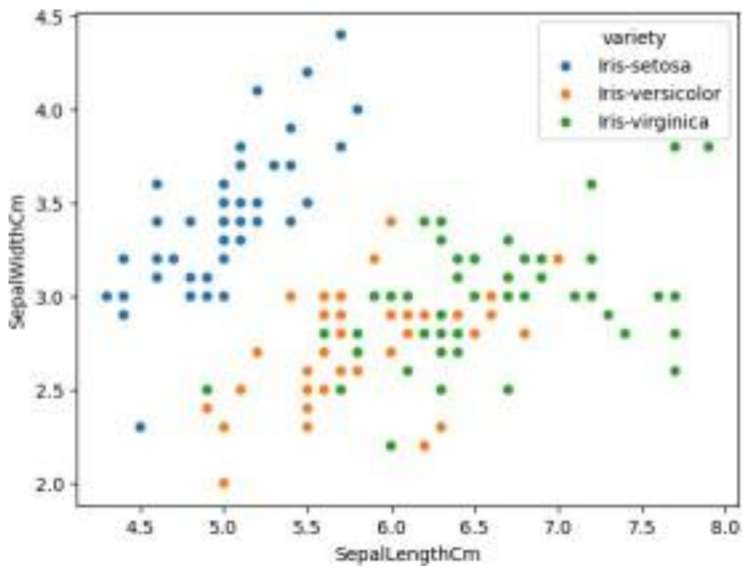
```
FinalDataset.head()
```

Iris-setosa Iris-versicolor Iris-virginica Id

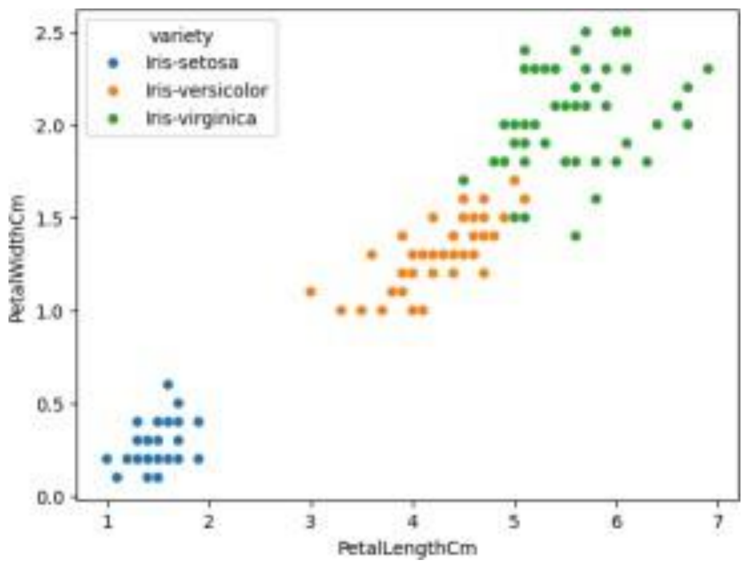
SepalLengthCm SepalWidthCm PetalLengthCm 0 True False False 1 5.1 3.5 1.4 **1** True False False 2 4.9 3.0 1.4 **2** True False False 3 4.7 3.2 1.3 **3** True False False 4 4.6 3.1 1.5 **4** True False False 5 5 0 3 6 1 4

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

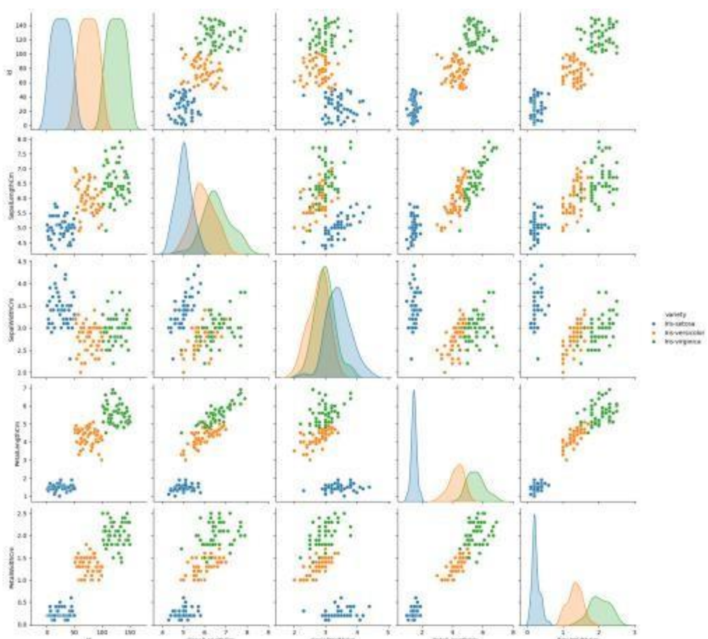
```
<Axes: xlabel='SepalLengthCm', ylabel='SepalWidthCm'>
```



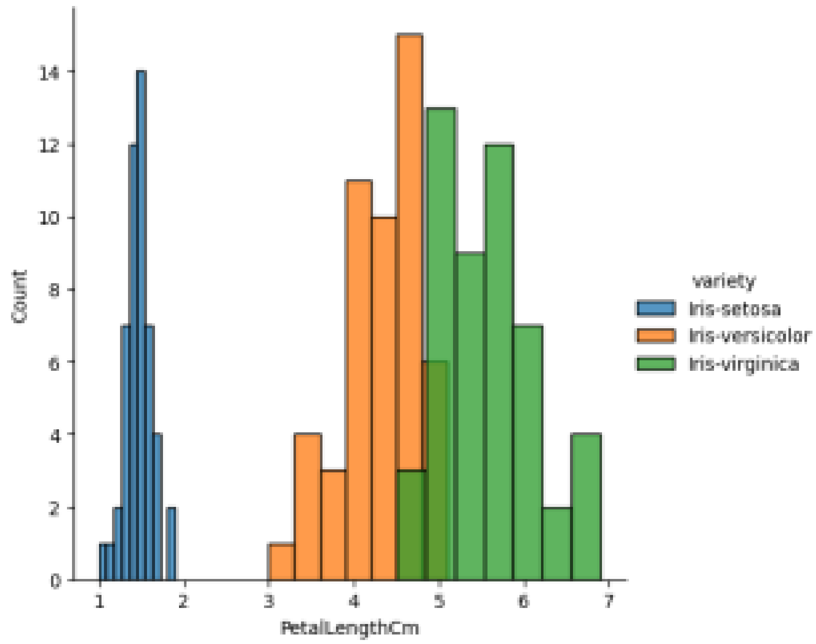

```
sns.scatterplot(x='PetalLengthCm',y='PetalWidthCm',hue='variety',data=data,)
```



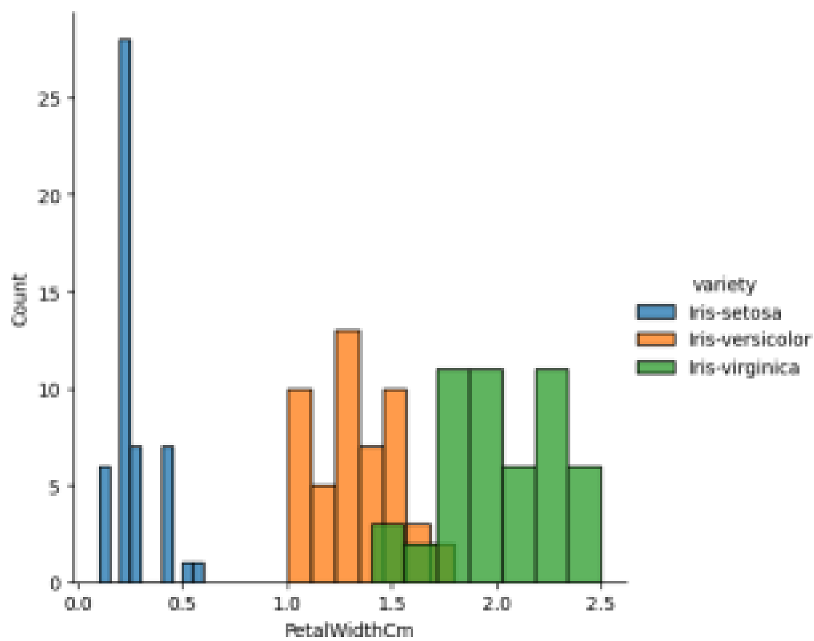

```
sns.pairplot(data,hue='variety',height=3);
```



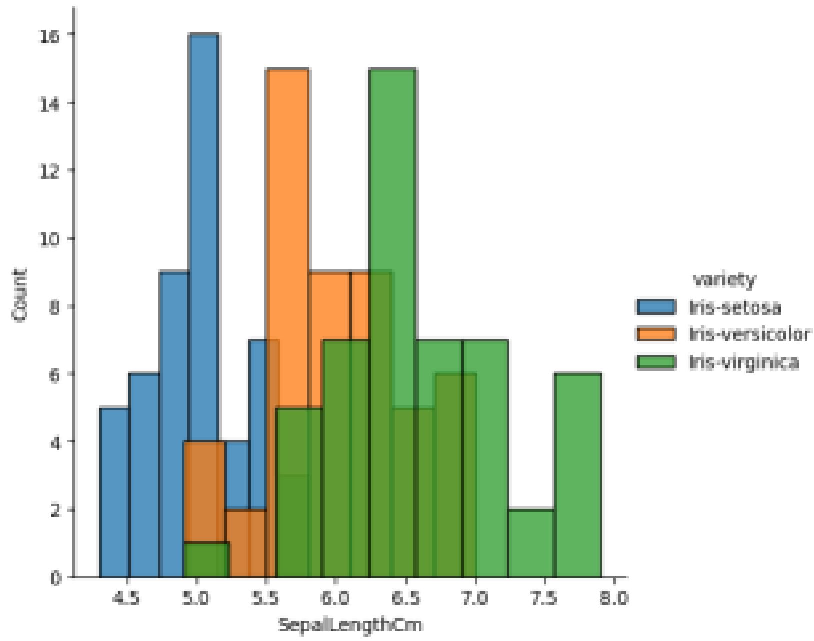
```
    plt.show()
sns.FacetGrid(data,hue='variety',height=5).map(
sns.histplot,'PetalLengthCm').add_legend();
plt.show();
```




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




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




```
sns.FacetGrid(data,hue='variety',height=5).map(sns.histplot,'SepalWidthCm').a
dd_legend();
plt.show();
```

Experiment: 02
Roll no: 230701042
Name: ASHNA V
Class: CSE-A II
Subject: Fundamentals of data science (CS23334)

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

```
array([83, 25, 19, 47, 62, 15, 96, 39, 51])
```

```
np.sqrt(array)
```

```
array([9.11043358, 5.        , 4.35889894, 6.8556546 , 7.87400787,
       3.87298335, 9.79795897, 6.244998  , 7.14142843])
```

```
array.ndim
```

```
1
```

```
new_array=array.reshape(3,3)
```

```
new_array
```

```
array([[83, 25, 19],
 [47, 62, 15],
 [96, 39, 51]])
```

```
new_array.ndim
```

```
2
```

```
new_array.ravel()
```

```
array([83, 25, 19, 47, 62, 15, 96, 39, 51])
```

```
newm=new_array.reshape(3,3)
```

```
newm
```

```
array([[83, 25, 19],
 [47, 62, 15],
 [96, 39, 51]])
```

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

```
array([39, 51])
```

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

```
array([[62, 15]])
```

```
new_array[0:3,0:0]
```

```
array([], shape=(3, 0), dtype=int64)
```

```
new_array[0:2,0:1]
```

```
array([[83],
 [47]])
```

```
new_array[0:3,0:1]
```

```
array([[83],
 [47],
 [96]])
```

```
new_array[1:3]
```

```
array([[47, 62, 15],
 [96, 39, 51]])
```

Experiment: 03
Roll no:230701042
Name: ASHNA V
Class: CSE-A II
Subject: Fundamentals of data science (CS23334)

```
import numpy as np
import pandas as pd
list=[[1,'Smith',50000],[2,'Jones',60000]]
```

```
df=pd.DataFrame(list)
df
```

	0	1	2
0	1	Smith	50000
1	2	Jones	60000

```
df.columns=['Empd','Name','Salary']
df
```

	Empd	Name	Salary
0	1	Smith	50000
1	2	Jones	60000

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2 entries, 0 to 1
Data columns (total 3 columns):
 # Column Non-Null Count Dtype
--- ---------- ----------------------- ---------
 0 Empd 2 non-null int64
 1 Name 2 non-null object
 2 Salary 2 non-null int64
dtypes: int64(2), object(1)
memory usage: 176.0+ bytes
```

```
df=pd.read_csv("/content/50_Startups.csv")
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50 entries, 0 to 49
Data columns (total 5 columns):
 # Column Non-Null Count Dtype
--- ---------- ----------------------- ---------
```

```
 0 R&D Spend 50 non-null float64
 1 Administration 50 non-null float64
 2 Marketing Spend 50 non-null float64
 3 State 50 non-null object
 4 Profit 50 non-null float64
dtypes: float64(4), object(1)
memory usage: 2.1+ KB
```

```
df.head()
```

	R&D Spend	Administration	Marketing Spend	State	Profit
0	165349.20	136897.80	471784.10	New York	192261.83
1	162597.70	151377.59	443898.53	California	191792.06
2	153441.51	101145.55	407934.54	Florida	191050.39
3	144372.41	118671.85	383199.62	New York	182901.99
4	142107 34	91391 77	366168 42	Florida	166187 94

```
df.tail()
```

	R&D Spend	Administration	Marketing Spend	State	Profit
45	1000.23	124153.04	1903.93	New York	64926.08
46	1315.46	115816.21	297114.46	Florida	49490.75
47	0.00	135426.92	0.00	California	42559.73
48	542.05	51743.15	0.00	New York	35673.41
49	0 00	116983 80	45173 06	California	14681 40

```
import numpy as np
import pandas as pd
df=pd.read_csv("/content/employee.csv")
```

```
df.head()
```

	emp id	name	salary
0	1	ASH	5000
1	2	ARON	6000
2	3	SREE	7000
3	4	AAYUSH	5000
4	5	BRAD	8000

```
df.tail()
```

	emp id	name	salary
2	3	SREE	7000
3	4	AAYUSH	5000
4	5	BRAD	8000
5	6	ANU	3000
6	7	AMY	6000

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7 entries, 0 to 6
Data columns (total 3 columns):
 # Column Non-Null Count Dtype
--- ---------- ---------------------- ---------
 0 emp id 7 non-null int64
 1 name 7 non-null object
 2 salary 7 non-null int64
dtypes: int64(2), object(1)
memory usage: 296.0+ bytes
```

```
df.salary
```

	salary
0	5000
1	6000
2	7000
3	5000
4	8000
5	3000
6	6000

```
type(df.salary)
```

pandas.core.series.Series

```
def __init__(data=None, index=None, dtype: Dtype | None=None, name=None,
copy: bool | None=None,
fastpath: bool=False) -> None
```

One-dimensional ndarray with axis labels (including time series).

Labels need not be unique but must be a hashable type. The object supports both integer- and label-based indexing and provides a host of methods for performing operations involving the index. Statistical
 th d f d h b idd t t ti ll l d

```
df.salary.mean()
```

5714.285714285715

```
df.salary.median()
```

6000.0

```
df.salary.mode()
```

	salary
0	5000
1	6000

```
df.salary.var()
```

2571428.5714285714

```
df.salary.std()
```

1603.5674514745463

```
df.describe()
```

	emp id	salary
count	7.000000	7.000000
mean	4.000000	5714.285714
std	2.160247	1603.567451
min	1.000000	3000.000000
25%	2.500000	5000.000000
50%	4.000000	6000.000000
75%	5.500000	6500.000000
max	7 000000	8000 000000

```
df.describe(include='all')
```

	emp id	name	salary
count	7.000000	7	7.000000
unique	NaN	6	NaN
top	NaN	SRI HARSHAVARDHANAN R	NaN
freq	NaN	2	NaN
mean	4.000000	NaN	5714.285714
std	2.160247	NaN	1603.567451
min	1.000000	NaN	3000.000000

25%	2.500000	NaN	5000.000000
50%	4.000000	NaN	6000.000000
75%	5.500000	NaN	6500.000000
max	7 000000	NaN	8000 000000

```
empCol=df.columns
```

```
empCol
```

```
Index(['emp id', 'name ', 'salary'], dtype='object')
```

```
emparray=df.values
```

```
emparray
```

```
array([[1, 'ASH', 5000],
 [2, 'ARON', 6000],
 [3, 'SREE', 7000],
 [4, 'AAYUSH', 5000],
 [5, 'BRAD', 8000],
 [6, 'ANU', 3000],
 [7, 'AMY, 6000]], dtype=object)
```

```
employee_DF=pd.DataFrame(emparray,columns=empCol)
```

```
employee_DF
```

	emp id	name	salary
0	1	ASH	5000
1	2	ARON	6000
2	3	SREE	7000
3	4	AAYUSH	5000
4	5	BRAD	8000
5	6	ANU	3000
6	7	AMY R	6000

Roll no: 230701042
Name: ASHNA V
Class: CSE-A II
Subject: Fundamentals of data science (CS23334)
Experiment: 04

```
#sample calculation for low range(lr) , upper range (ur),percentile
import numpy as np
array=np.random.randint(1,100,16) # randomly generate 16 numbers between 1 to
100
array
```

```
array([27, 50, 44, 6, 58, 61, 23, 86, 67, 20, 75, 7, 79, 61, 90, 54])
```

```
array.mean()
```

```
50.5
```

```
np.percentile(array,25)
```

```
26.0
```

```
np.percentile(array,50)
```

```
56.0
```

```
np.percentile(array,75)
```

```
69.0
```

```
np.percentile(array,100)
```

```
90.0
```

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

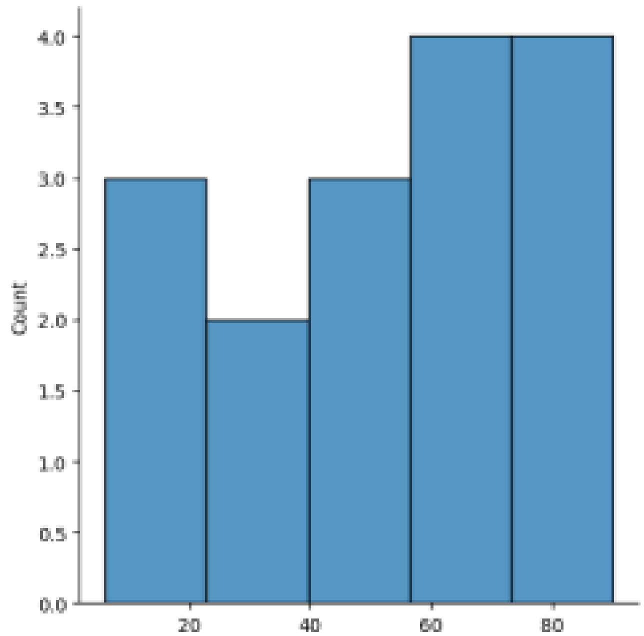
```
lr,ur=outDetection(array)
```

```
lr,ur
```

```
(-38.5, 133.5)
```

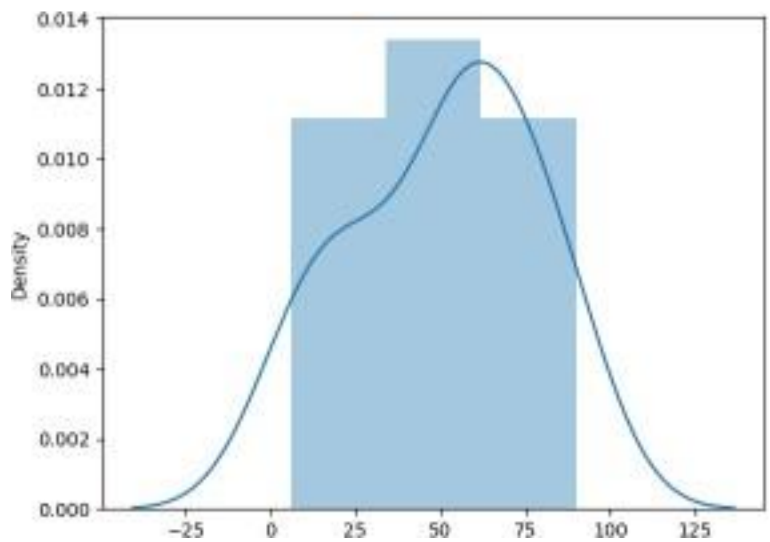
```
import seaborn as sns
%matplotlib inline
sns.displot(array)
```

```
<seaborn.axisgrid.FacetGrid at 0x78f3291c2710>
```




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

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

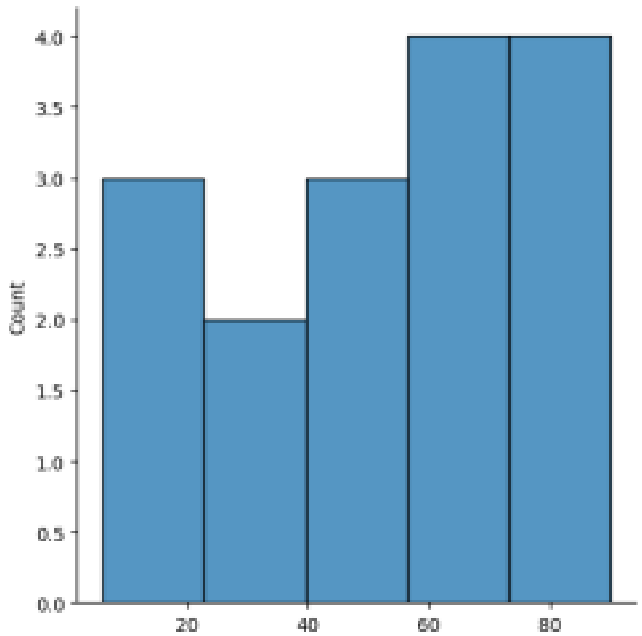



```
new_array=array[(array>lr) & (array<ur)]
new_array
```

```
array([27, 50, 44, 6, 58, 61, 23, 86, 67, 20, 75, 7, 79, 61, 90, 54])
```

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

```
<seaborn.axisgrid.FacetGrid at 0x78f2e09bb580>
```



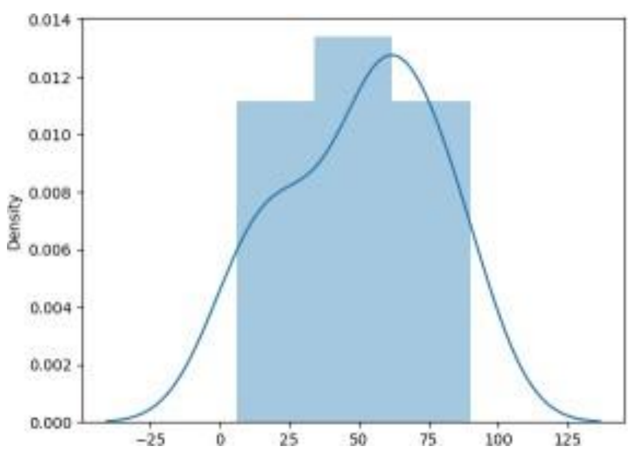

```
lr1,ur1=outDetection(new_array)
lr1,ur1
```

```
(-38.5, 133.5)
```

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

```
array([27, 50, 44, 6, 58, 61, 23, 86, 67, 20, 75, 7, 79, 61, 90, 54])
```

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



Experiment: 05
Roll no: 230701042
Name: ASHNA V
Class: CSE-A II
Subject: Fundamentals of data science (CS23334)

import numpy as np

import pandas as pd

df=pd.read_csv("Hotel_Dataset.csv")

df

	CustomerID	Age_Group	Rating(1-5)	Hotel	FoodPreference	Bill	NoOfPax	EstimatedSalary	Age_Group.1
0	1	20-25	4	Ibis	veg	1300	2	40000	20-25
1	2	30-35	5	LemonTree	Non-Veg	2000	3	59000	30-35
2	3	25-30	6	RedFox	Veg	1322	2	30000	25-30
3	4	20-25	-1	LemonTree	Veg	1234	2	120000	20-25
4	5	35+	3	Ibis	Vegetarian	989	2	45000	35+
5	6	35+	3	Ibys	Non-Veg	1909	2	122220	35+
6	7	35+	4	RedFox	Vegetarian	1000	-1	21122	35+
7	8	20-25	7	LemonTree	Veg	2999	-10	345673	20-25
8	9	25-30	2	Ibis	Non-Veg	3456	3	-99999	25-30
9	9	25-30	2	Ibis	Non-Veg	3456	3	-99999	25-30
10	10	30-35	5	RedFox	non-Veg	-6755	4	87777	30-35

df.duplicated()

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

---

df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11 entries, 0 to 10
Data columns (total 9 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   CustomerID       11 non-null     int64
 1   Age_Group        11 non-null     object
 2   Rating(1-5)      11 non-null     int64
 3   Hotel            11 non-null     object
 4   FoodPreference   11 non-null     object
 5   Bill             11 non-null     int64
 6   NoOfPax          11 non-null     int64
 7   EstimatedSalary  11 non-null     int64
 8   Age_Group.1      11 non-null     object
dtypes: int64(5), object(4)
memory usage: 924.0+ bytes
```

df.drop_duplicates(inplace=True)

df

	CustomerID	Age_Group	Rating(1-5)	Hotel	FoodPreference	Bill	NoOfPax	EstimatedSalary	Age_Group.1
0	1	20-25	4	Ibis	veg	1300	2	40000	20-25
1	2	30-35	5	LemonTree	Non-Veg	2000	3	59000	30-35
2	3	25-30	6	RedFox	Veg	1322	2	30000	25-30
3	4	20-25	-1	LemonTree	Veg	1234	2	120000	20-25
4	5	35+	3	Ibis	Vegetarian	989	2	45000	35+
5	6	35+	3	Ibys	Non-Veg	1909	2	122220	35+
6	7	35+	4	RedFox	Vegetarian	1000	-1	21122	35+
7	8	20-25	7	LemonTree	Veg	2999	-10	345673	20-25
8	9	25-30	2	Ibis	Non-Veg	3456	3	-99999	25-30
10	10	30-35	5	RedFox	non-Veg	-6755	4	87777	30-35

len(df)

10

index=np.array(list(range(0,len(df))))

df.set_index(index,inplace=True)

index

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

df

	CustomerID	Age_Group	Rating(1-5)	Hotel	FoodPreference	Bill	NoOfPax	EstimatedSalary	Age_Group.1
0	1	20-25	4	Ibis	veg	1300	2	40000	20-25
1	2	30-35	5	LemonTree	Non-Veg	2000	3	59000	30-35
2	3	25-30	6	RedFox	Veg	1322	2	30000	25-30
3	4	20-25	-1	LemonTree	Veg	1234	2	120000	20-25
4	5	35+	3	Ibis	Vegetarian	989	2	45000	35+
5	6	35+	3	Ibys	Non-Veg	1909	2	122220	35+
6	7	35+	4	RedFox	Vegetarian	1000	-1	21122	35+
7	8	20-25	7	LemonTree	Veg	2999	-10	345673	20-25
8	9	25-30	2	Ibis	Non-Veg	3456	3	-99999	25-30
9	10	30-35	5	RedFox	non-Veg	-6755	4	87777	30-35

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

df

	CustomerID	Age_Group	Rating(1-5)	Hotel	FoodPreference	Bill	NoOfPax	EstimatedSalary
0	1	20-25	4	Ibis	veg	1300	2	40000
1	2	30-35	5	LemonTree	Non-Veg	2000	3	59000
2	3	25-30	6	RedFox	Veg	1322	2	30000
3	4	20-25	-1	LemonTree	Veg	1234	2	120000
4	5	35+	3	Ibis	Vegetarian	989	2	45000
5	6	35+	3	Ibys	Non-Veg	1909	2	122220
6	7	35+	4	RedFox	Vegetarian	1000	-1	21122
7	8	20-25	7	LemonTree	Veg	2999	-10	345673
8	9	25-30	2	Ibis	Non-Veg	3456	3	-99999
9	10	30-35	5	RedFox	non-Veg	-6755	4	87777

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

df.EstimatedSalary.loc[df.EstimatedSalary<0]=np.nan

df
```

	CustomerID	Age_Group	Rating(1-5)	Hotel	FoodPreference	Bill	NoOfPax	EstimatedSalary
0	1.0	20-25	4.0	Ibis	veg	1300.0	2	40000.0
1	2.0	30-35	5.0	LemonTree	Non-Veg	2000.0	3	59000.0
2	3.0	25-30	NaN	RedFox	Veg	1322.0	2	30000.0
3	4.0	20-25	NaN	LemonTree	Veg	1234.0	2	120000.0
4	5.0	35+	3.0	Ibis	Vegetarian	989.0	2	45000.0
5	6.0	35+	3.0	Ibys	Non-Veg	1909.0	2	122220.0
6	7.0	35+	4.0	RedFox	Vegetarian	1000.0	-1	21122.0
7	8.0	20-25	NaN	LemonTree	Veg	2999.0	-10	345673.0
8	9.0	25-30	2.0	Ibis	Non-Veg	3456.0	3	NaN
9	10.0	30-35	5.0	RedFox	non-Veg	NaN	4	87777.0

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

	CustomerID	Age_Group	Rating(1-5)	Hotel	FoodPreference	Bill	NoOfPax	EstimatedSalary
0	1.0	20-25	4.0	Ibis	veg	1300.0	2.0	40000.0
1	2.0	30-35	5.0	LemonTree	Non-Veg	2000.0	3.0	59000.0
2	3.0	25-30	NaN	RedFox	Veg	1322.0	2.0	30000.0
3	4.0	20-25	NaN	LemonTree	Veg	1234.0	2.0	120000.0
4	5.0	35+	3.0	Ibis	Vegetarian	989.0	2.0	45000.0
5	6.0	35+	3.0	Ibys	Non-Veg	1909.0	2.0	122220.0
6	7.0	35+	4.0	RedFox	Vegetarian	1000.0	NaN	21122.0
7	8.0	20-25	NaN	LemonTree	Veg	2999.0	NaN	345673.0
8	9.0	25-30	2.0	Ibis	Non-Veg	3456.0	3.0	NaN
9	10.0	30-35	5.0	RedFox	non-Veg	NaN	4.0	87777.0

df.Age_Group.unique()

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

df.Hotel.unique()

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

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

df.FoodPreference.unique

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

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

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

df.EstimatedSalary.fillna(round(df.EstimatedSalary.mean()),inplace=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

	CustomerID	Age_Group	Rating(1-5)	Hotel	FoodPreference	Bill	NoOfPax	EstimatedSalary
0	1.0	20-25	4.0	Ibis	Veg	1300.0	2.0	40000.0
1	2.0	30-35	5.0	LemonTree	Non-Veg	2000.0	3.0	59000.0
2	3.0	25-30	4.0	RedFox	Veg	1322.0	2.0	30000.0
3	4.0	20-25	4.0	LemonTree	Veg	1234.0	2.0	120000.0
4	5.0	35+	3.0	Ibis	Veg	989.0	2.0	45000.0
5	6.0	35+	3.0	Ibis	Non-Veg	1909.0	2.0	122220.0
6	7.0	35+	4.0	RedFox	Veg	1000.0	2.0	21122.0
7	8.0	20-25	4.0	LemonTree	Veg	2999.0	2.0	345673.0
8	9.0	25-30	2.0	Ibis	Non-Veg	3456.0	3.0	96755.0
9	10.0	30-35	5.0	RedFox	Non-Veg	1801.0	4.0	87777.0

Experiment: 06
Rollno:230701042
Name: Ashna v
Class: CSE-A II
Subject: Fundamentals of data science (CS23334)

```
import numpy as np
import pandas as pd
df=pd.read_csv('/content/pre-process_datasample.csv')
```

```
df
```

	Country	Age	Salary	Purchased
0	France	44.0	72000.0	No
1	Spain	27.0	48000.0	Yes
2	Germany	30.0	54000.0	No
3	Spain	38.0	61000.0	No
4	Germany	40.0	NaN	Yes
5	France	35.0	58000.0	Yes
6	Spain	NaN	52000.0	No

7 France 48.0 79000.0 Yes

8 NaN 50.0 83000.0 No

9 France 37.0 67000.0 Yes

Next steps: `df.head()`

Country Age Salary Purchased

0 France 44.0 72000.0 No **1** Spain 27.0

48000.0 Yes **2** Germany 30.0 54000.0

No **3** Spain 38.0 61000.0 No **4**

Germany 40 0 NaN Yes

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



```
df.Country.fillna(df.Country.mode()[0],inplace=True)
```



```
label=df.iloc[:,-1].values
from sklearn.impute import SimpleImputer

age=SimpleImputer(strategy="mean",missing_values=np.nan)

Salary=SimpleImputer(strategy="mean",missing_values=np.nan)

age.fit(features[:,[1]])
```

▾ SimpleImputer i ?

SimpleImputer()

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

▾ SimpleImputer i ?

```
SimpleImputer()
```

```
SimpleImputer()
```

▾ SimpleImputer i ?

```
SimpleImputer()
```

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

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

```
features
```

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

```
from sklearn.preprocessing import OneHotEncoder
```

```
oh = OneHotEncoder(sparse_output=False)
```

```
Country=oh.fit_transform(features[:,[0]])
```

```
Country
```

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

 [1., 0., 0.],
```

```
 [1., 0., 0.]])
```

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

```
final_set
```

```
array([[1.0, 0.0, 0.0, 44.0, 72000.0],
 [0.0, 0.0, 1.0, 27.0, 48000.0],
 [0.0, 1.0, 0.0, 30.0, 54000.0],
 [0.0, 0.0, 1.0, 38.0, 61000.0],
 [0.0, 1.0, 0.0, 40.0, 63777.77777777778],
 [1.0, 0.0, 0.0, 35.0, 58000.0],
 [0.0, 0.0, 1.0, 38.77777777777778, 52000.0],
 [1.0, 0.0, 0.0, 48.0, 79000.0],
 [1.0, 0.0, 0.0, 50.0, 83000.0],
 [1.0, 0.0, 0.0, 37.0, 67000.0]], dtype=object)
```

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

```
feat_standard_scaler
```

```
array([[ 1.00000000e+00, -5.00000000e-01, -6.54653671e-01,
 7.58874362e-01, 7.49473254e-01],
 [-1.00000000e+00, -5.00000000e-01, 1.52752523e+00,
 -1.71150388e+00, -1.43817841e+00],
 [-1.00000000e+00, 2.00000000e+00, -6.54653671e-01,
 -1.27555478e+00, -8.91265492e-01],
 [-1.00000000e+00, -5.00000000e-01, 1.52752523e+00,
 -1.13023841e-01, -2.53200424e-01],
 [-1.00000000e+00, 2.00000000e+00, -6.54653671e-01,
 1.77608893e-01, 6.63219199e-16],
 [ 1.00000000e+00, -5.00000000e-01, -6.54653671e-01,
 -5.48972942e-01, -5.26656882e-01],
 [-1.00000000e+00, -5.00000000e-01, 1.52752523e+00,
 0.00000000e+00, -1.07356980e+00],
 [ 1.00000000e+00, -5.00000000e-01, -6.54653671e-01,
 1.34013983e+00, 1.38753832e+00],
 [ 1.00000000e+00, -5.00000000e-01, -6.54653671e-01,
 1.63077256e+00, 1.75214693e+00],
 [ 1.00000000e+00, -5.00000000e-01, -6.54653671e-01,
 -2.58340208e-01, 2.93712492e-01]])
```

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

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

Experiment: 07
Roll no: 230701042
Name: Ashna v
Class: CSE-A II
Subject: Fundamentals of data science (CS23334)

```
import numpy as np
import pandas as pd
df=pd.read_csv("/content/pre-process_datasample.csv")
df
```

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

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 4 columns):
 # Column Non-Null Count Dtype
--- ---------- ----------------------- ---------
 0 Country 9 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: 448.0+ bytes
```

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

	Country
0	France

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

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

```
df.Country.fillna(df.Country.mode()[0],inplace=True)

df.Age.fillna(df.Age.median(),inplace=True)

df.Salary.fillna(round(df.Salary.mean()),inplace=True)

df
```

	Country	**Age**	**Salary**	**Purchased**
0	France	44.0	72000.0	No
1	Spain	27.0	48000.0	Yes
2	Germany	30.0	54000.0	No
3	Spain	38.0	61000.0	No
4	Germany	40.0	63778.0	Yes
5	France	35.0	58000.0	Yes
6	Spain	38.0	52000.0	No

7	France	48.0	79000.0	Yes
8	France	50.0	83000.0	No
9	France	37 0	67000 0	Yes

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

	France	Germany	Spain
0	True	False	False
1	False	False	True
2	False	True	False
3	False	False	True
4	False	True	False
5	True	False	False
6	False	False	True
7	True	False	False
8	True	False	False
9	True	False	False

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

```
updated_dataset
```

	France	Germany	Spain	Age	Salary	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	True	False	False	50.0	83000.0	No
9	True	False	False	37 0	67000 0	Yes

```
df.info()
```

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

```
updated_dataset
```

	France	Germany	Spain	Age	Salary	Purchased
0	True	False	False	44.0	72000.0	0
1	False	False	True	27.0	48000.0	1
2	False	True	False	30.0	54000.0	0
3	False	False	True	38.0	61000.0	0
4	False	True	False	40.0	63778.0	1
5	True	False	False	35.0	58000.0	1
6	False	False	True	38.0	52000.0	0
7	True	False	False	48.0	79000.0	1
8	True	False	False	50.0	83000.0	0
9	True	False	False	37 0	67000 0	1

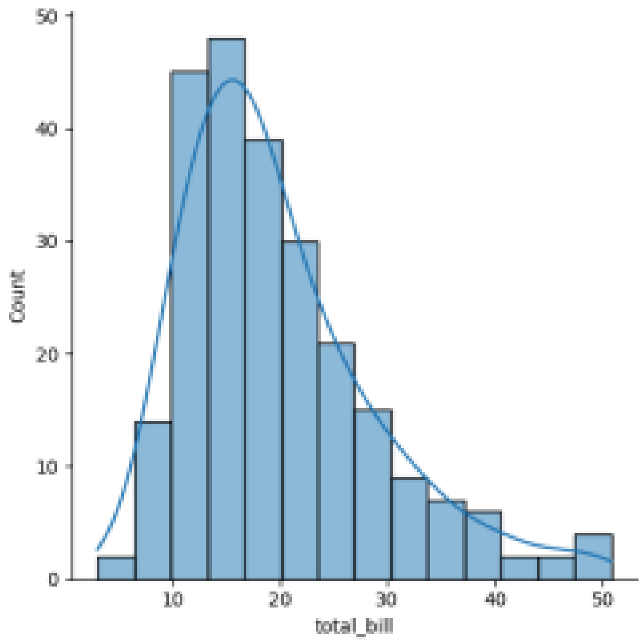
Experiment: 08
Roll no: 230701042
Name: Ashna v
Class: CSE-A II
Subject: Fundamentals of data science (CS23334)

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

tips=sns.load_dataset('tips')

tips.head()
```

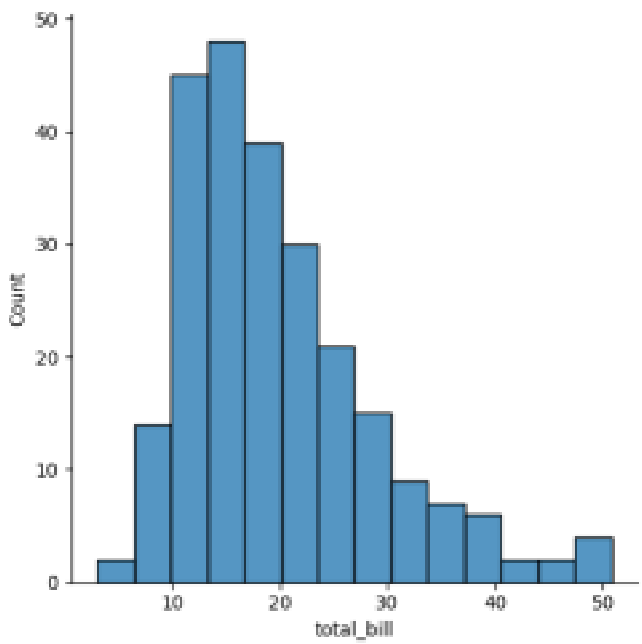
	total_bill	tip	sex	smoker	day	time	size
0	16.99	1.01	Female	No	Sun	Dinner	2
1	10.34	1.66	Male	No	Sun	Dinner	3
2	21.01	3.50	Male	No	Sun	Dinner	3
3	23.68	3.31	Male	No	Sun	Dinner	2
4	24.59	3.61	Female	No	Sun	Dinner	4

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

```
<seaborn.axisgrid.FacetGrid at 0x79bb4c7ea680>
```

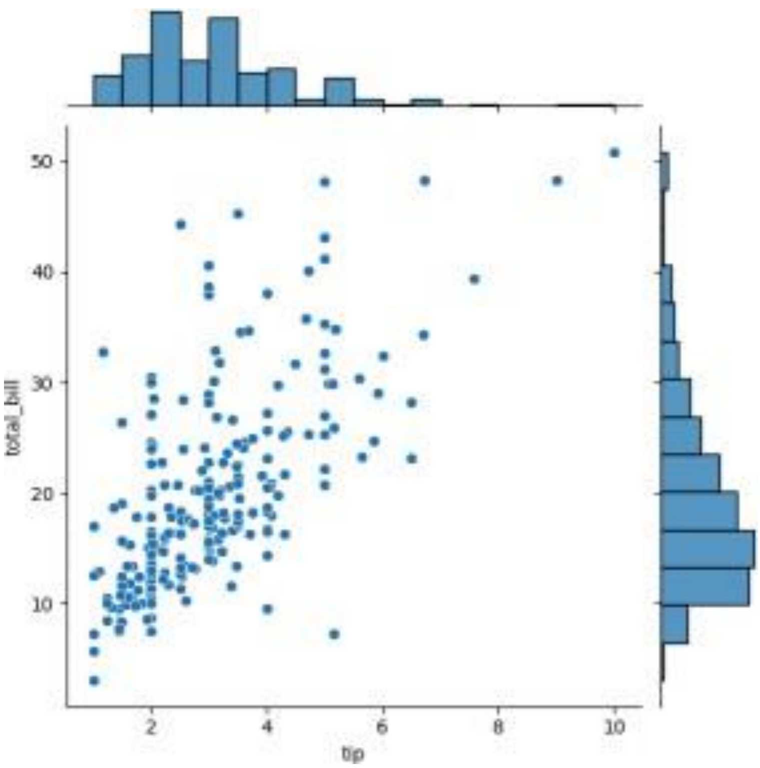



```
sns.displot(tips.total_bill,kde=False)
```

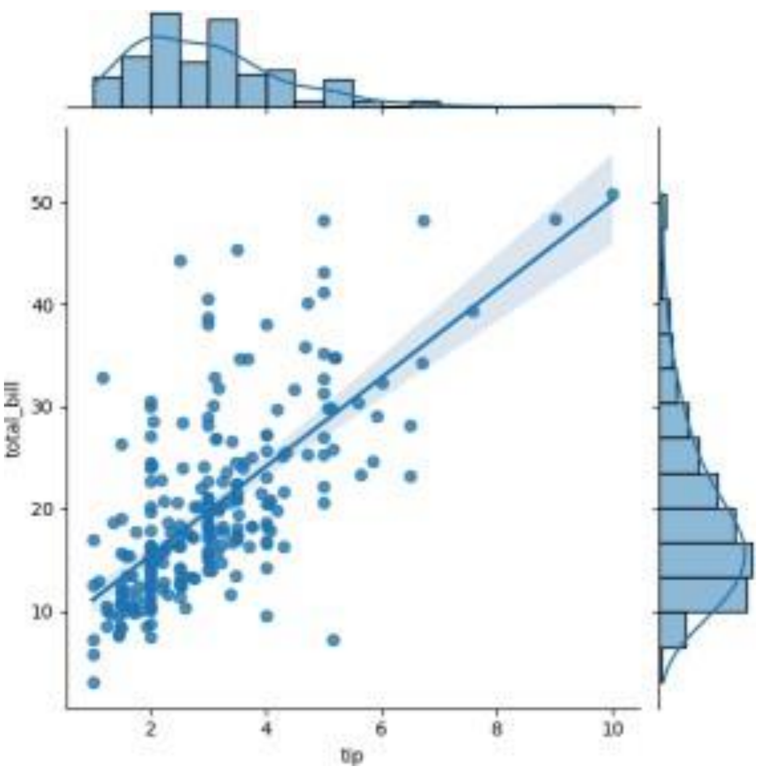



```
sns.jointplot(x=tips.tip,y=tips.total_bill)
```

```
<seaborn.axisgrid.JointGrid at 0x79bb08fc96c0>
```

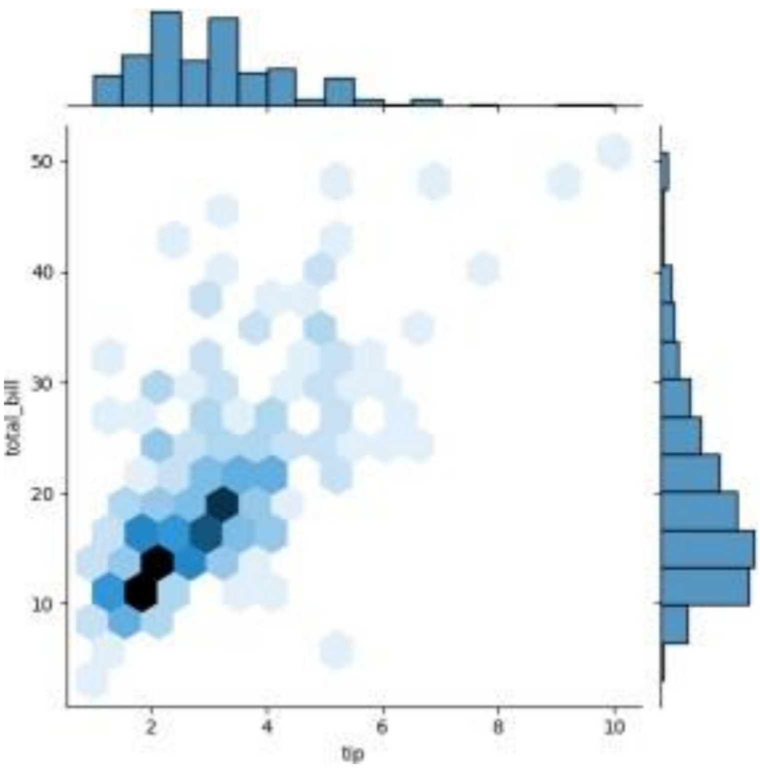


sns.jointplot(x=tips.tip,y=tips.total_bill,kind="reg")

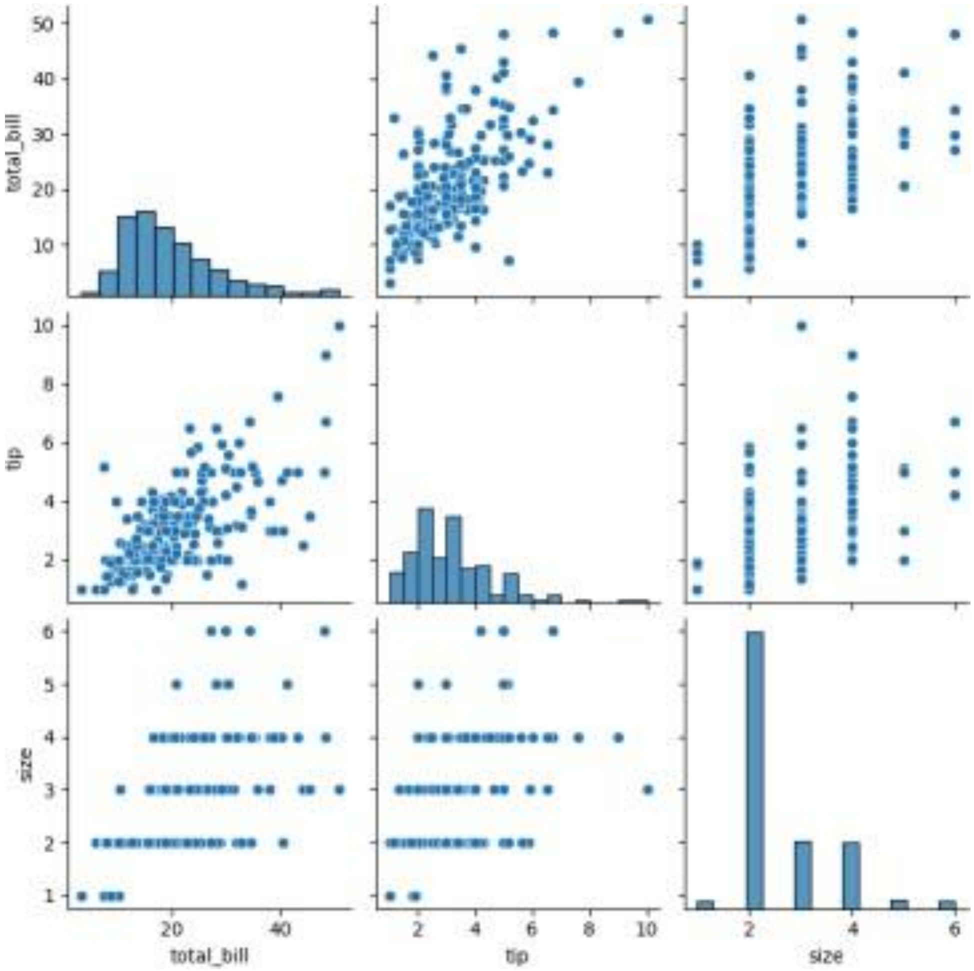


sns.jointplot(x=tips.tip,y=tips.total_bill,kind="hex")

```
<seaborn.axisgrid.JointGrid at 0x79bb088f4730>
```




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



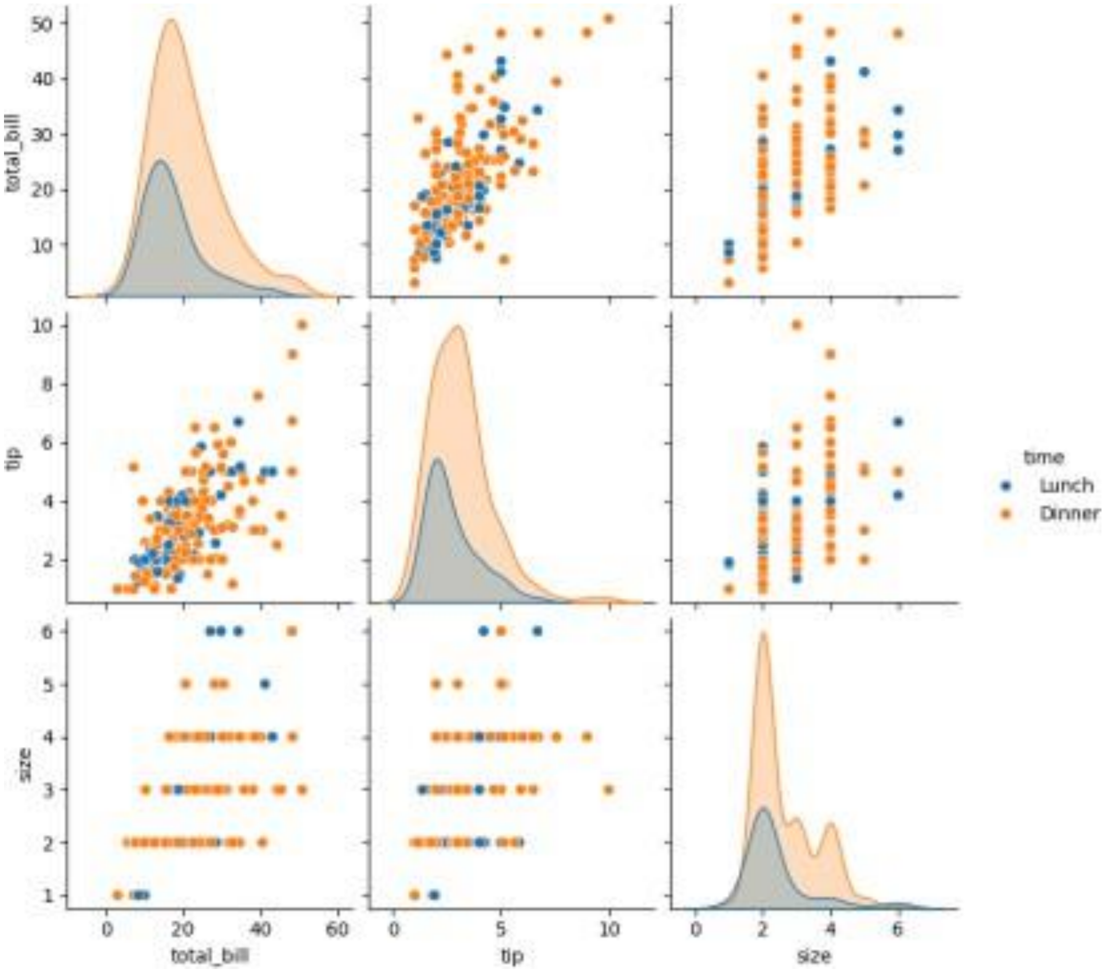

```
tips.time.value_counts()
```

	count
time	
Dinner	176
Lunch	68

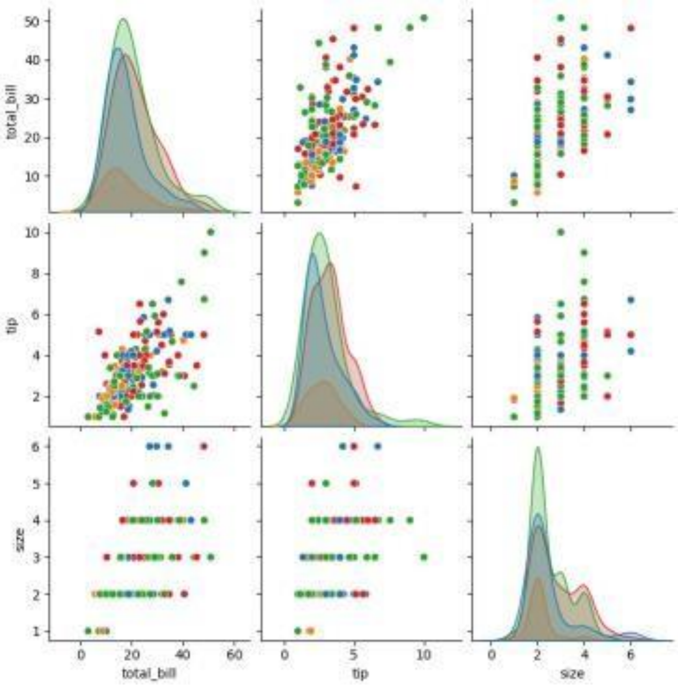
dtype: int64

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

<seaborn.axisgrid.PairGrid at 0x79bb088f4670>

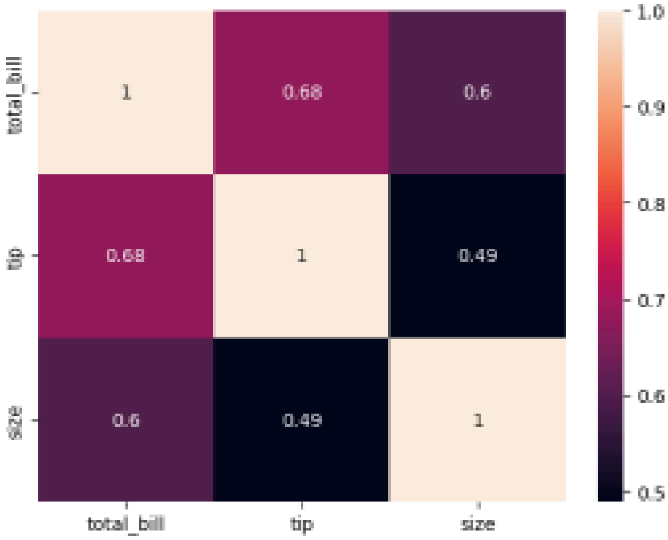



```
sns.pairplot(tips,hue='day')
```



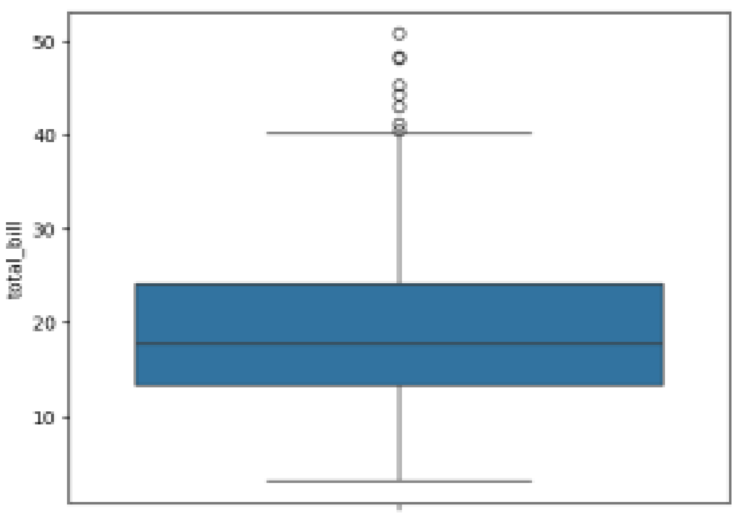
```
sns.heatmap(tips.corr(numeric_only=True),annot=True)
```

```
<Axes: >
```



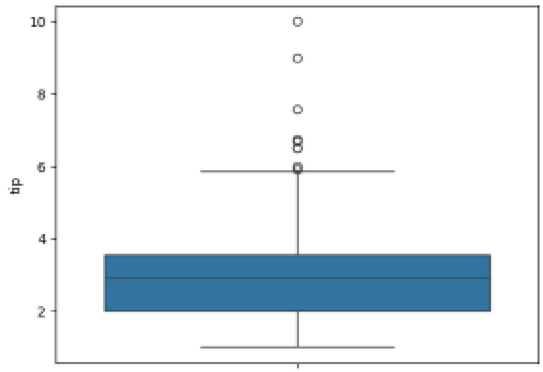

```
sns.boxplot(tips.total_bill)
```

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



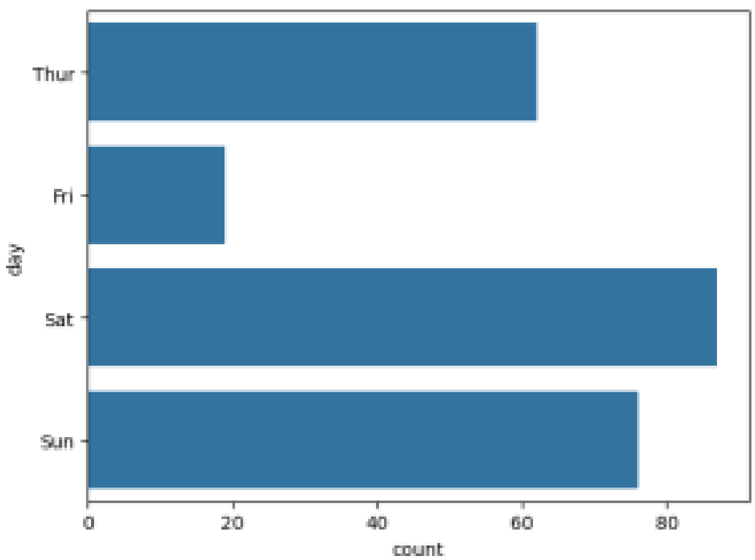

```
sns.boxplot(tips.tip)
```

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



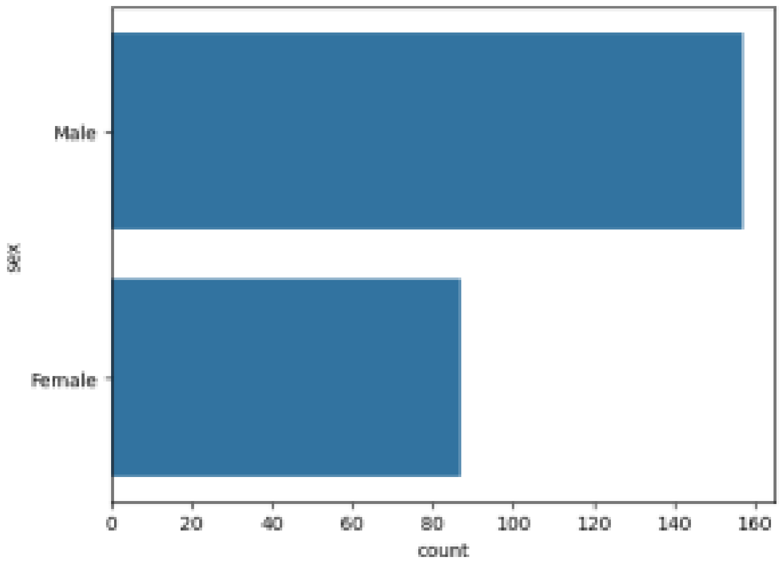

```
sns.countplot(tips.day)
```

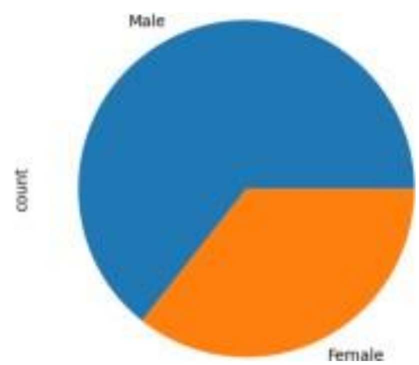
<Axes: xlabel='count', ylabel='day'>




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

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



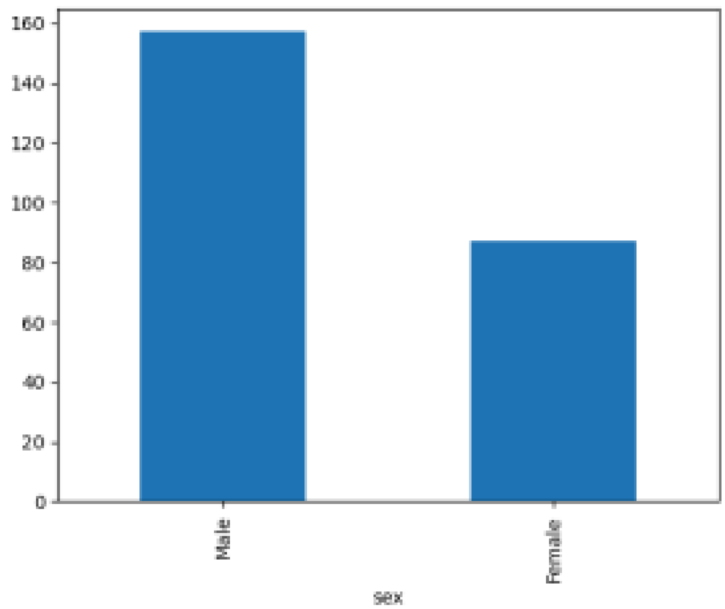



```
tips.sex.value_counts().plot(kind='pie')
```

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

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

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



Experiment: 09
Roll no: 230701042
Name: Ashna V
Class: CSE-A II
Subject: Fundamentals of data science (CS23334)

```
# 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.info()
```

```
<class 'pandas.core.frame.DataFrame'> RangeIndex: 30 entries, 0 to 29
Data columns (total 2 columns):
# Column Non-Null Count Dtype  --- ------ -------------- -----  0 YearsExperience 30
non-null float64 1 Salary 30 non-null int64  dtypes: float64(1), int64(1)
memory usage: 612.0 bytes
```

```
df.describe()
```

Out[5]: **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

In [6]:

```
features=df.iloc[:,[0]].values
label=df.iloc[:,[1]].values

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_
st

from sklearn.linear_model import LinearRegression
model=LinearRegression()
model.fit(x_train,y_train)
```

Out[20]: ▾ LinearRegression

LinearRegression()

In [21]:

```
model.score(x_tr
ain,y_train)
```

Out[21]: 0.9603182547438908

In [23]:

```
model.score(x_t
est,y_test)
```

Out[23]: 0.9184170849214232

In [24]:

```
model.coe
f_
```

Out[24]: array([[9281.30847068]])

In [25]:

```
model.inter
cept_
```

Out[25]: array([27166.73682891])

In [26]:

```
import pickle
pickle.dump(model,open('SalaryPred.model','wb'))

model=pickle.load(open('SalaryPred.model','rb'))  yr_of_exp=float(input("Enter  Years
```

```
of Experience: "))
yr_of_exp_NP=np.array([[yr_of_exp]])
Salary=model.predict(yr_of_exp_NP)
```

```
Enter Years of Experience: 44
```

```
print("Estimated Salary for {} years of experience is {}: "
```

```
.format(yr_of_exp,Salary) Estimated Salary for 44.0 years of experience is
```

```
[[435544.30953887]]:
```

Experiment: 10
Roll no: 230701042
Name: ASHNA V
Class: CSE-A II
Subject: Fundamentals of data science (CS23334)

```
import numpy as np
import pandas as pd
```

```
df=pd.read_csv('Iris.csv')
df.info()
```

```
df.variety.value_counts()
```

```
Out[3]: Setosa 50
        Versicolor 50
        Virginica 50
        Name: variety, dtype: int64
```

```
In [4]:
df.head()
```

Out[4]: sepal.length sepal.width petal.length petal.width variety **0** 5.1 3.5 1.4 0.2 Setosa

1 4.9 3.0 1.4 0.2 Setosa **2** 4.7 3.2 1.3 0.2 Setosa **3** 4.6 3.1 1.5

0.2 Setosa **4** 5.0 3.6 1.4 0.2 Setosa

```
In [5]: In [6]: In [8]:
```

```
features=df.iloc[:,:-1].values
label=df.iloc[:,4].values

from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier

xtrain,xtest,ytrain,ytest=train_test_split(features,label,test_size=.2,rando
model_KNN=KNeighborsClassifier(n_neighbors=5)
model_KNN.fit(xtrain,ytrain)
```

Out[8]: KNeighborsClassifier()

```
print(model_KNN.score(xtrain,ytrain))
print(model_KNN.score(xtest,ytest))
```

0.9583333333333334
1.0

```
from sklearn.metrics import confusion_matrix
confusion_matrix(label,model_KNN.predict(features))
```

```
Out[10]: array([[50, 0, 0],
       [ 0, 47, 3],
       [ 0, 2, 48]], dtype=int64)
```

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

precision recall f1-score support

Setosa 1.00 1.00 1.00 50 Versicolor 0.96 0.94 0.95 50 Virginica 0.94 0.96 0.95 50

accuracy 0.97 150 macro avg 0.97 0.97 0.97 150 weighted avg 0.97 0.97 0.97 150

Experiment: 11
Roll no: 230701042
Name: ASHNA V
Class: CSE-A II
Subject: Fundamentals of data science (CS23334)

In [1]:

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

Out[1]: **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 × 5 columns

In [2]:
```
df.head()
```

Out[2]: **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

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

Out[4]:
```
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]
```

In [5]:
```
label
```

Out[5]:
```
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)
```

In [6]:
```
from sklearn.model_selection import train_test_split from
sklearn.linear_model import LogisticRegression

for i in range(1,401):

x_train,x_test,y_train,y_test=train_test_split(features,labe
l,test_size=0.  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("Test {} Train{} Random State
{}".format(test_score,train_score,i)
```

```
Test 0.6875 Train0.63125 Random State 3
Test 0.7375 Train0.61875 Random State 4
Test 0.6625 Train0.6375 Random State 5
Test 0.65 Train0.640625 Random State 6
Test 0.675 Train0.634375 Random State 7
Test 0.675 Train0.634375 Random State 8
Test 0.65 Train0.640625 Random State 10
Test 0.6625 Train0.6375 Random State 11
Test 0.7125 Train0.625 Random State 13
Test 0.675 Train0.634375 Random State 16
Test 0.7 Train0.628125 Random State 17
```

```
Test 0.7 Train0.628125 Random State 21
Test 0.65 Train0.640625 Random State 24
Test 0.6625 Train0.6375 Random State 25
Test 0.75 Train0.615625 Random State 26
Test 0.675 Train0.634375 Random State 27
Test 0.7 Train0.628125 Random State 28
Test 0.6875 Train0.63125 Random State 29
Test 0.6875 Train0.63125 Random State 31
T t 0 6625 T i 0 6375 R d St t 37
```

```
x_train,x_test,y_train,y_test=train_test_split(features,labe
l,test_size=0.2, finalModel=LogisticRegression()
finalModel.fit(x_train,y_train)
```

Out[8]: LogisticRegression()

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

```
print(finalModel.score(x_test,y_test))
```

```
0.834375
0.9125
```

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

```
precision recall f1-score support

0 0.85 0.93 0.89 257  1 0.84 0.71 0.77 143

accuracy 0.85 400  macro avg 0.85 0.82 0.83 400 weighted avg 0.85 0.85
0.85 400
```

Experiment: 12
Roll no: 230701042
Name: ASHNA V
Class: CSE-A II
Subject: Fundamentals of data science (CS23334)

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

```
df=pd.read_csv('Mall_Customers.csv')
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 5 columns):
# Column Non-Null Count Dtype  --- ------ --------------
-----  0 CustomerID 200 non-null int64  1 Gender 200 non-
null object 2 Age 200 non-null int64   3 Annual Income
(k$) 200 non-null int64  4 Spending Score (1-100) 200
non-null int64  dtypes: int64(4), object(1)
memory usage: 7.9+ KB
```

```
df.head()
```

Out[4]:

	CustomerID	Gender	Age	Annual Income (k$)	Spending Score (1-100)
0	1	Male	19	15	39
1	2	Male	21	15	81
2	3	Female	20	16	6
3	4	Female	23	16	77
4	5	Female	31	17	40

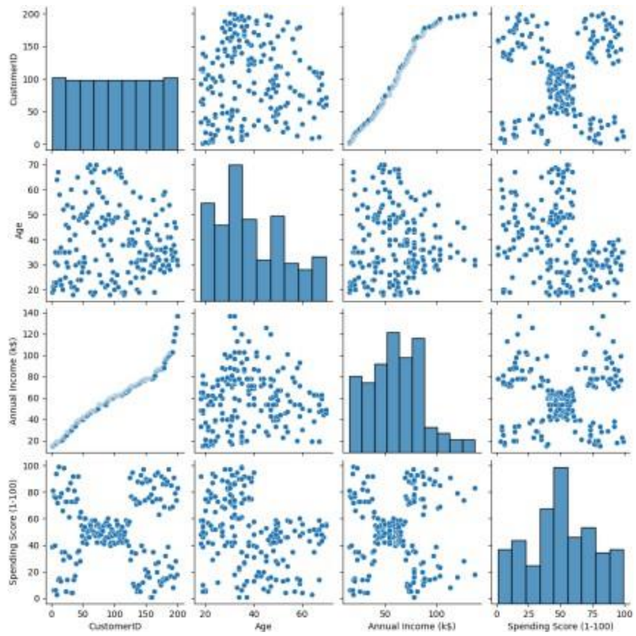
In [5]:

```
sns.pairplot(df)
```

Out[5]: <seaborn.axisgrid.PairGrid at 0x170e8e47850>

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

In [6]:



In [7]:

```
from sklearn.cluster import KMeans
model=KMeans(n_clusters=5)
model.fit(features)
KMeans(n_clusters=5)
```

Out[7]: KMeans(n_clusters=5)

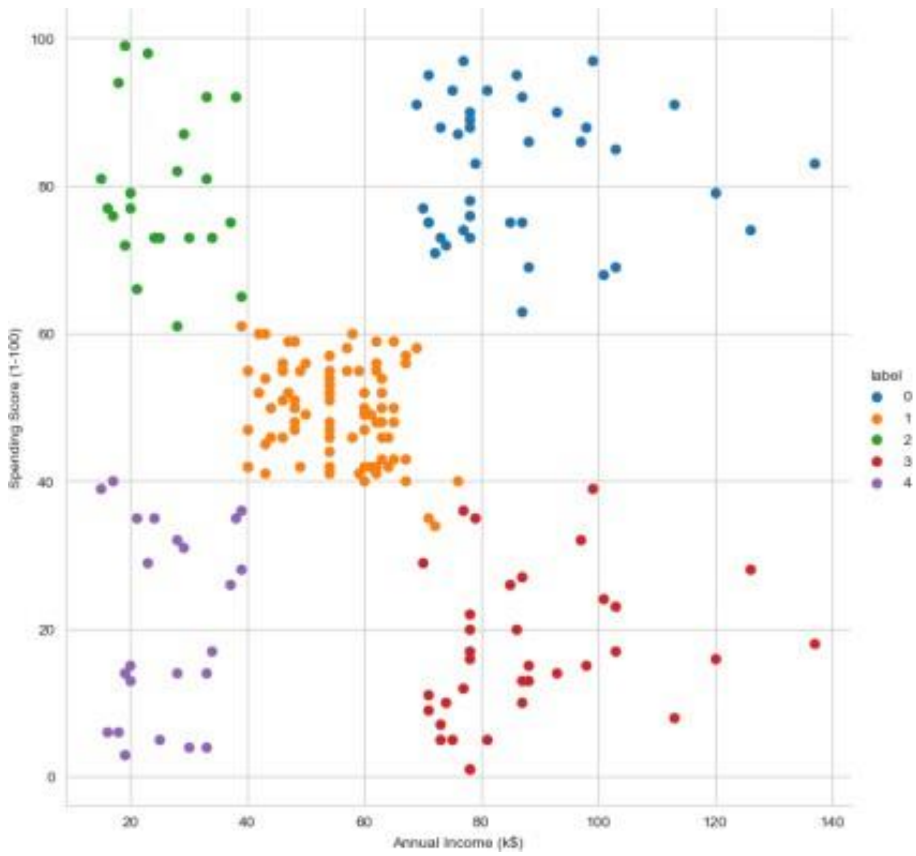
In [8]:

```
Final=df.iloc[:,[3,4]]
Final['label']=model.predict(features)
Final.head()
Final['label']=model.predict(features)
```

Out[8]:

	Annual Income (k$)	Spending Score (1-100)	label
0	15	39	4
1	15	81	2
2	16	6	4
3	16	77	2
4	17	40	4

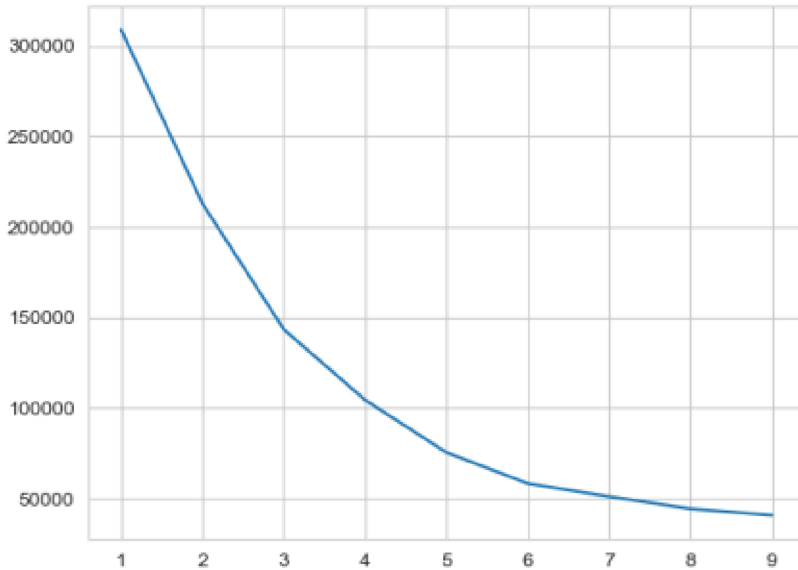
```
In [9]: sns.set_style("whitegrid")
sns.FacetGrid(Final,hue="label",height=8) \
.map(plt.scatter,"Annual Income (k$)", "Spending Score (1-100)") \
.add_legend();
plt.show()
```




```
In [10]: features_el=df.iloc[:,[2,3,4]].values
         from sklearn.cluster import KMeans
         wcss=[]
         for i in range(1,10):
          model=KMeans(n_clusters=i)
          model.fit(features_el)
          wcss.append(model.inertia_)
```

```
plt.plot(range(1,10),wcss)
```

Out[10]: [<matplotlib.lines.Line2D at 0x170e99f3550>]

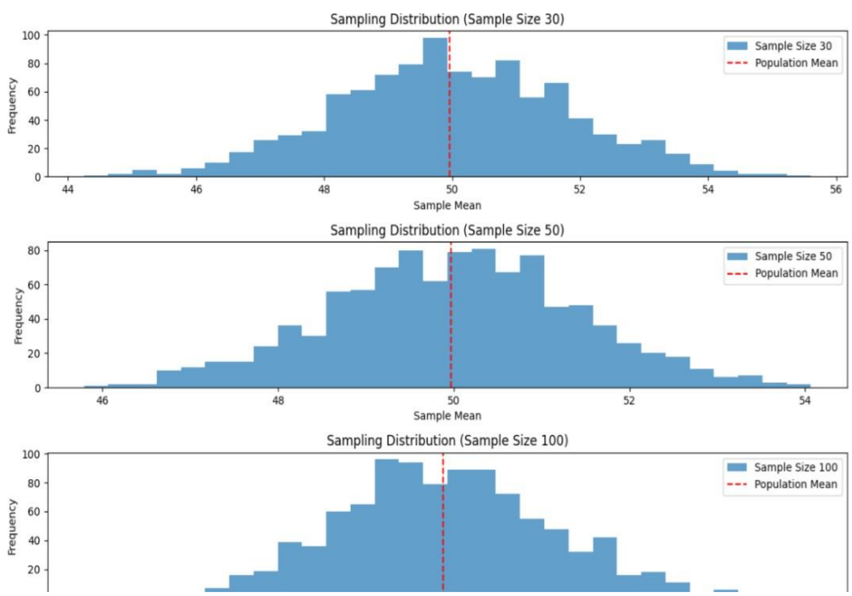


Experiment: 13
Roll no: 230701042
Name: ASHNA V
Class: CSE-A II
Subject: Fundamentals of data science (CS23334)

```
import numpy as np
import matplotlib.pyplot as plt

# Step 1: Generate a population (e.g., normal distribution)
population_mean = 50
population_std = 10
population_size = 100000
population = np.random.normal(population_mean, population_std, population_size)

# Step 2: Random sampling
sample_sizes = [30, 50, 100]  # different sample sizes to consider
num_samples = 1000  # number of samples for each sample size

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))

# Step 3: Plotting sampling distributions
plt.figure(figsize=(12, 8))

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()
```

OUTPUT:



Experiment: 14

Roll no: 230701042
Name: ASHNA V
Class: CSE-A II
Subject: Fundamentals of data science (CS23334)

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

sample_data = np.array([152, 148, 151, 149, 147, 153, 150, 148, 152,
                        149, 151, 150, 149, 152, 151, 148, 150, 152,
                        149, 150, 148, 153, 151, 150, 149, 152,
                        148, 151, 150, 153])

population_mean = 150
sample_mean = np.mean(sample_data)
sample_std = np.std(sample_data, ddof=1)
n = len(sample_data)

z_statistic = (sample_mean - population_mean) / (sample_std / np.sqrt(n))
p_value = 2 * (1 - stats.norm.cdf(np.abs(z_statistic)))

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

alpha = 0.05
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.")
```

OUTPUT:

```
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.
```

Experiment: 15
Roll no: 230701042
Name: ASHNA V
Class: CSE-A II
Subject: Fundamentals of data science (CS23334)

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

```
# Set a random seed for reproducibility
np.random.seed(42)

# Generate hypothetical sample data (IQ scores)
sample_size = 25
sample_data = np.random.normal(loc=102, scale=15, size=sample_size)  # Mean IQ of
102, SD of 15

# Population mean under the null hypothesis
population_mean = 100

# Calculate sample statistics
sample_mean = np.mean(sample_data)
sample_std = np.std(sample_data, ddof=1)  # Using sample standard deviation

# Number of observations
n = len(sample_data)

# Calculate the T-statistic and p-value
t_statistic, p_value = stats.ttest_1samp(sample_data, population_mean)

# Print results
print(f"Sample Mean: {sample_mean:.2f}")
print(f"T-Statistic: {t_statistic:.4f}")
print(f"P-Value: {p_value:.4f}")

# Decision based on the significance level
alpha = 0.05
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.")
```

OUTPUT:

```
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.
```

Experiment: 16

Roll no: 230701042
Name: ASHNA V
Class: CSE-A II
Subject: Fundamentals of data science (CS23334)

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

# Set a random seed for reproducibility
np.random.seed(42)

# Generate hypothetical growth data for three treatments (A, B, C)
n_plants = 25

# Growth data (in cm) for Treatment A, B, and C
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)

# Combine all data into one array
all_data = np.concatenate([growth_A, growth_B, growth_C])

# Treatment labels for each group
treatment_labels = ['A'] * n_plants + ['B'] * n_plants + ['C'] * n_plants

# Perform one-way ANOVA
f_statistic, p_value = stats.f_oneway(growth_A, growth_B, growth_C)

# Print results
print("Treatment A Mean Growth:", np.mean(growth_A))
print("Treatment B Mean Growth:", np.mean(growth_B))
print("Treatment C Mean Growth:", np.mean(growth_C))
print()
print(f"F-Statistic: {f_statistic:.4f}")
print(f"P-Value: {p_value:.4f}")

# Decision based on the significance level
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.")

# Additional: Post-hoc analysis (Tukey's HSD) if ANOVA is significant
```

```
if p_value < alpha:
    from statsmodels.stats.multicomp import pairwise_tukeyhsd

    tukey_results = pairwise_tukeyhsd(all_data, treatment_labels, alpha=0.05)
    print("\nTukey's HSD Post-hoc Test:")
    print(tukey_results)
```

```
OUTPUT:
Treatment A Mean Growth: 9.672983882683818
Treatment B Mean Growth: 11.137680744437432
Treatment C Mean Growth: 15.265234904828972

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.
```