

FUNDAMENTALS OF DATA SCIENCE

Lab experiments

Ex no:01

Roll no: 230701327

Name: SOWBARNIGAA

SRIDHARAN

Class: CSE-E 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 x 6 columns
```

```
data.info()
```

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

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

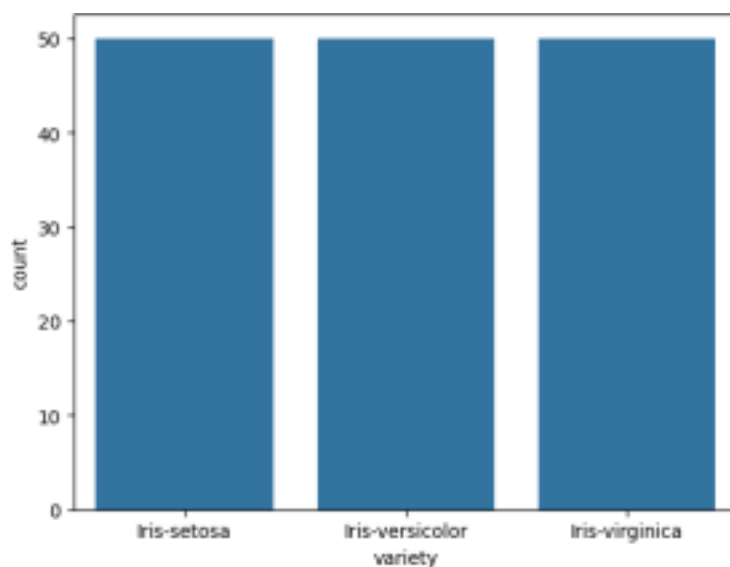
```
data.describe()
```

	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)
```

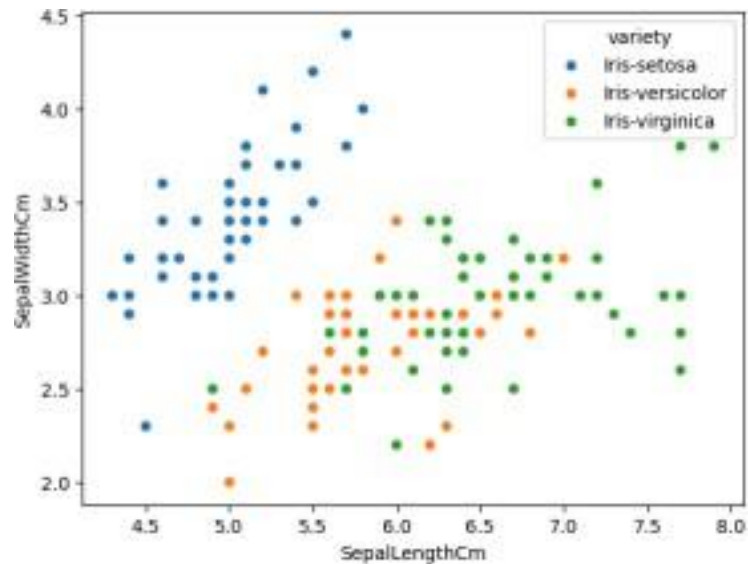
```
FinalDataset=pd.concat([pd.get_dummies(data.variety),data.iloc[:,[0,1,2,3]]],
axis=1)
```

```
FinalDataset.head()
```

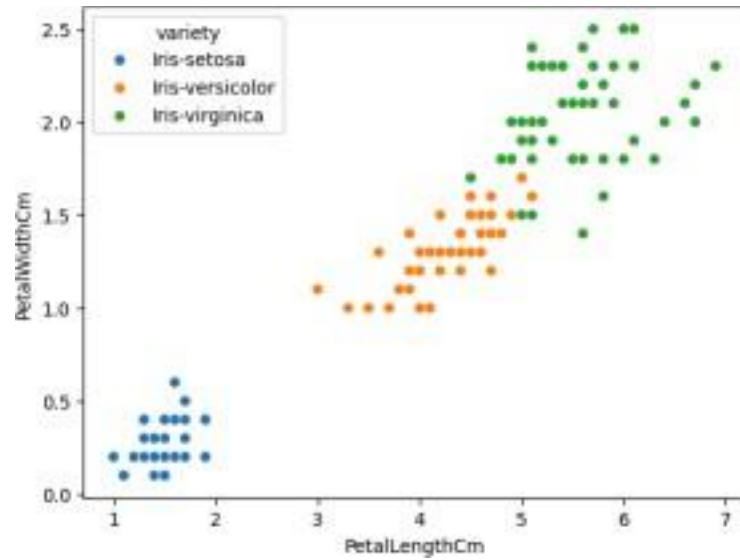
	Iris-setosa	Iris-versicolor	Iris-virginica	Id										
SepalLengthCm	SepalWidthCm	PetalLengthCm	0	True	False									
False	1	5.1	3.5	1.4	1	True	False	False	2	4.9	3.0	1.4	2	True
False	False	3	4.7	3.2	1.3	3	True	False	False	4	4.6	3.1	1.5	4
True	False	False	5	5	0	3	6	1	4					

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

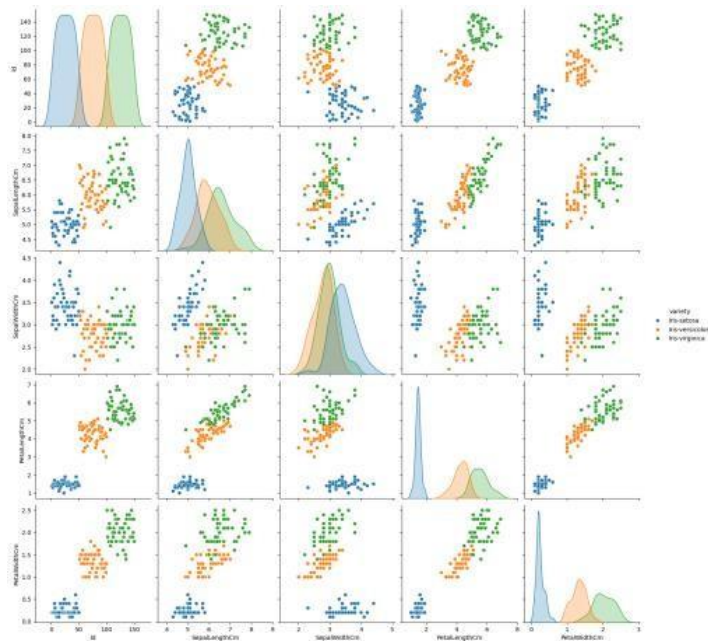
```
<Axes: xlabel='SepalLengthCm', ylabel='SepalWidthCm'>
```



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

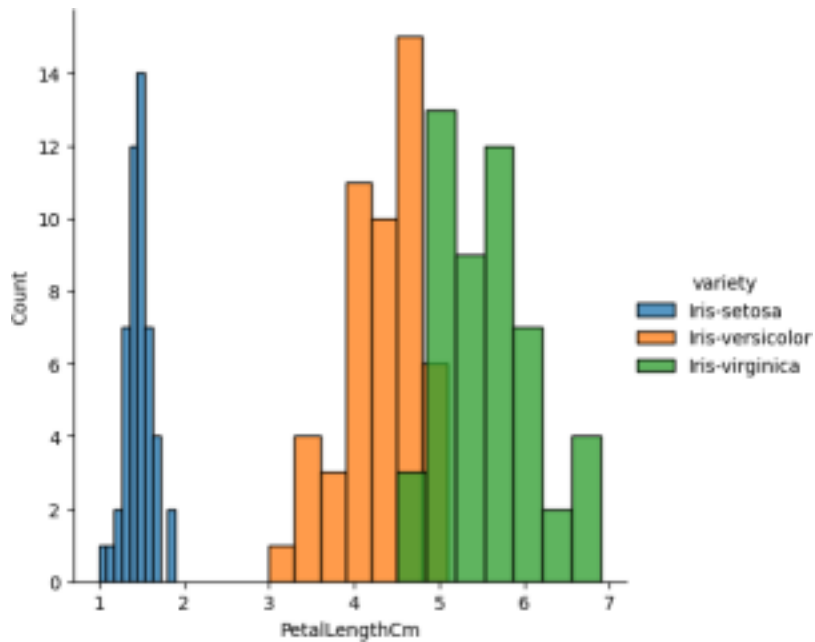


```
sns.pairplot(data,hue='variety',height=3);
```

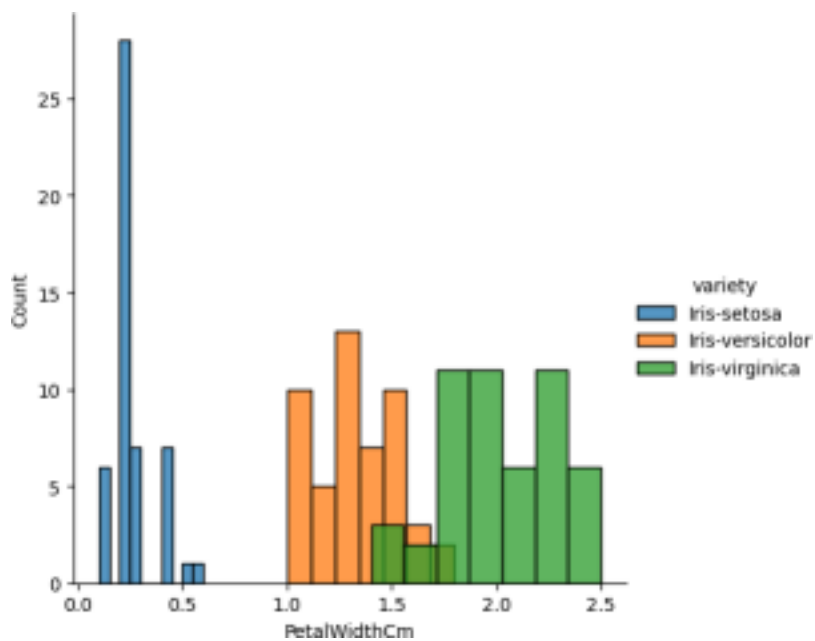


```
plt.show()
```

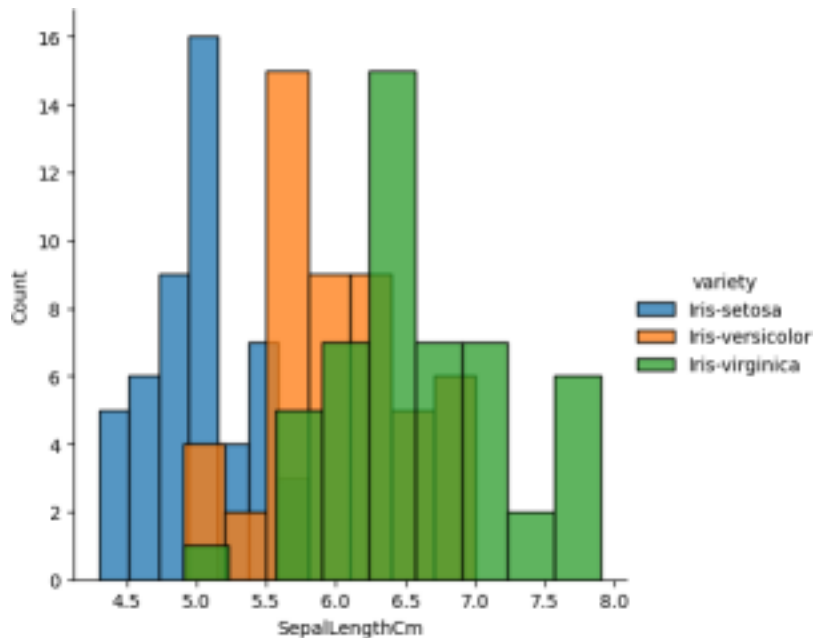
```
sns.FacetGrid(data,hue='variety',height=5).map(
sns.histplot,'Petal.LengthCm').add_legend();
plt.show();
```



```
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: 230701327
Name: SOWBARNIGAA
SRIDHARAN
Class: CSE-E 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: 230701327
Name: SOWBARNIGAA
SRIDHARAN
Class: CSE-E 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: 230701327
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Class: CSE-E II
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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

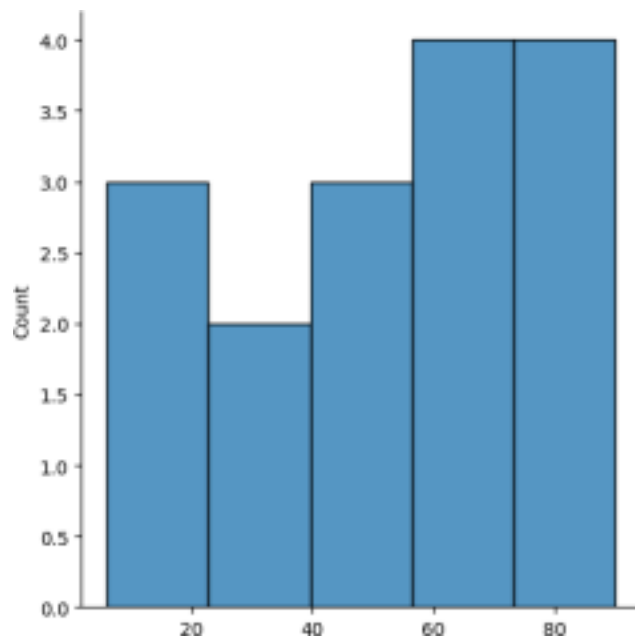
lr,ur=outDetection(array)

lr,ur

(-38.5, 133.5)

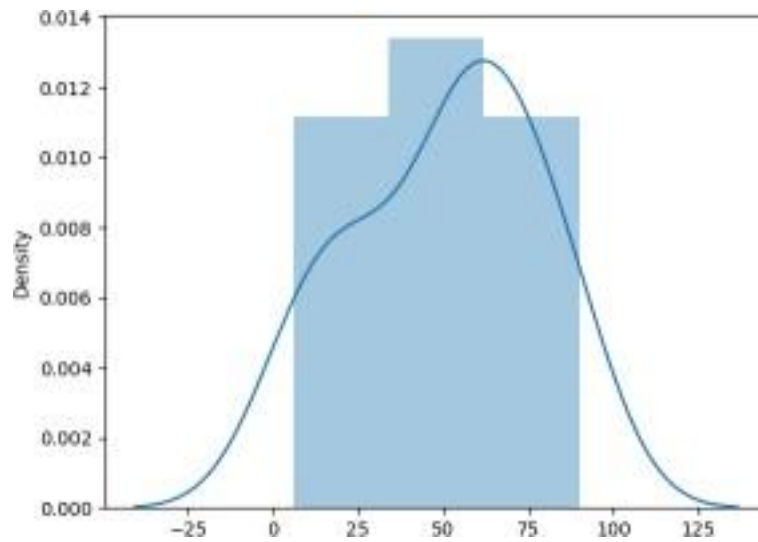
import seaborn as sns
%matplotlib inline
sns.displot(array)

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



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

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



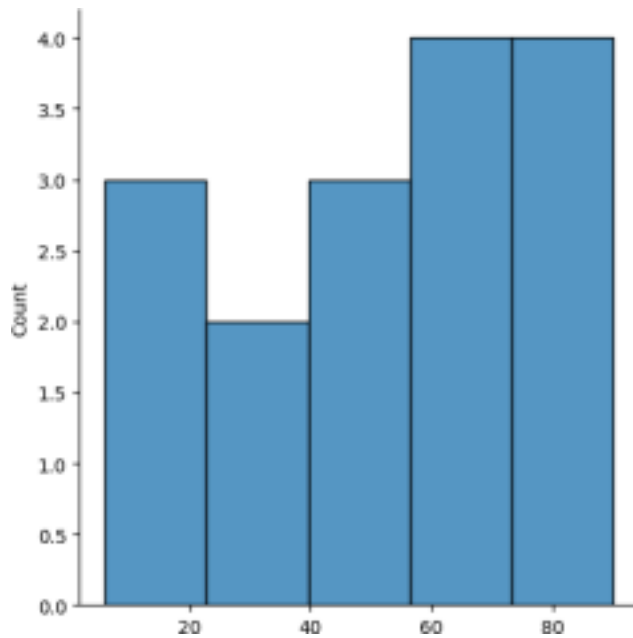
```
new_array=array[(array>lr) & (array<ur)]
```

```
new_array
```

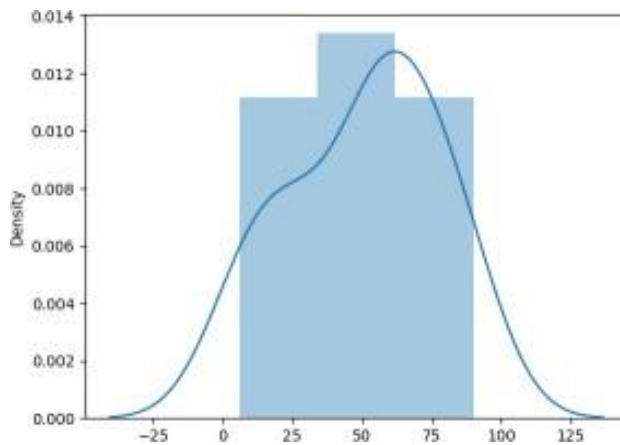
```
array([27, 50, 44, 6, 58, 61, 23, 86, 67, 20, 75, 7, 79, 61, 90, 54])
```

```
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: 230701327
 Name: SOWBARNIGAA SRIDHARAN
 Class: CSE-E 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	Estimated Salary
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: 230701327
 Name: SOWBARNIGAA
 SRIDHARAN
 Class: CSE-E 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 
SimpleImputer()
```

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

```
▼ SimpleImputer 
```

```
SimpleImputer()
```

```
SimpleImputer()
```

```
▼ SimpleImputer ⓘ ⓘ
```

```
SimpleImputer()
```

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

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

```
features
```

```
array([[ 'France', 44.0, 72000.0],  
       [ 'Spain', 27.0, 48000.0],  
       [ 'Germany', 30.0, 54000.0],  
       [ 'Spain', 38.0, 61000.0],  
       [ 'Germany', 40.0, 63777.777777777778],  
       [ '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: 230701327

Name: SOWBARNIGAA

SRIDHARAN

Class: CSE-E 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: 230701327
Name: SOWBARNIGAA
SRIDHARAN
Class: CSE-E 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()
```

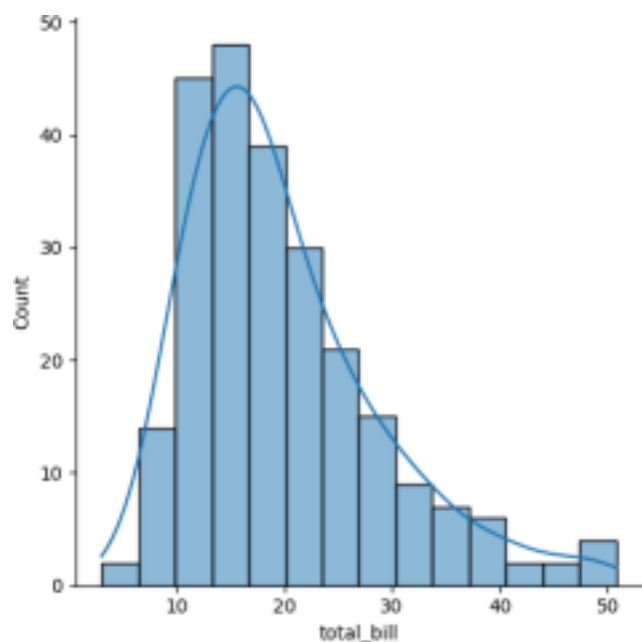
	total_bill	tip	sex	smoker	day	time	size
0	16.99	1.01	Female	No	Sun	Dinner	2
1	10.34	1.66	Male	No	Sun	Dinner	3
2	21.01	3.50	Male	No	Sun	Dinner	3
3	23.68	3.31	Male	No	Sun	Dinner	2
4	24.59	3.61	Female	No	Sun	Dinner	4

```

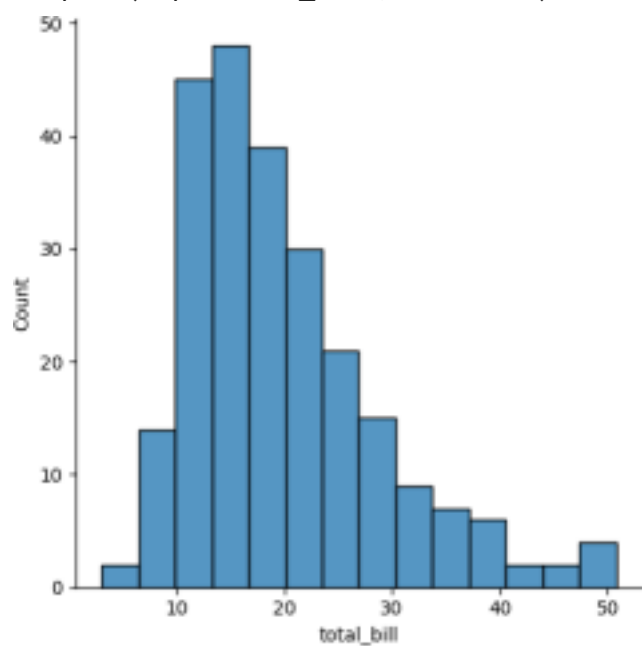
sns.displot(tips.total_bill,kde=True)

<seaborn.axisgrid.FacetGrid at 0x79bb4c7ea680>

```

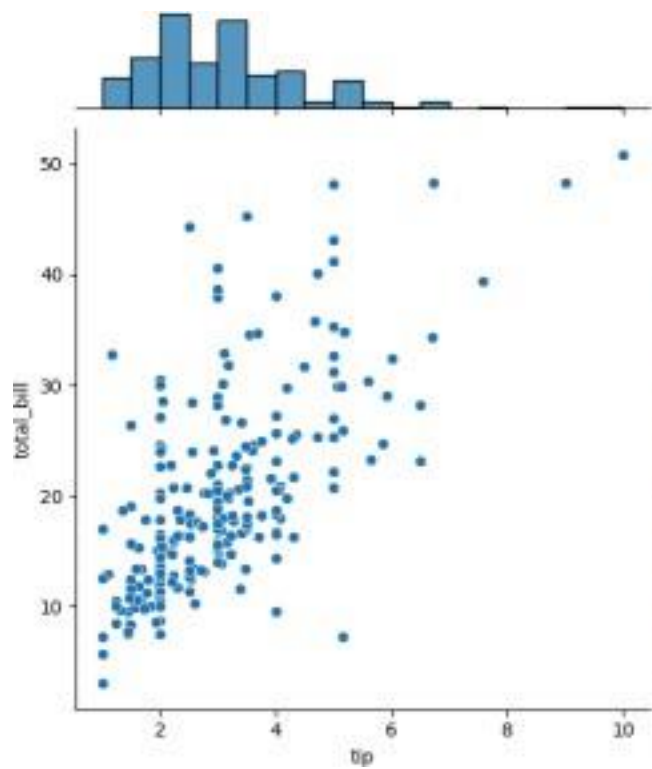


```
sns.displot(tips.total_bill,kde=False)
```

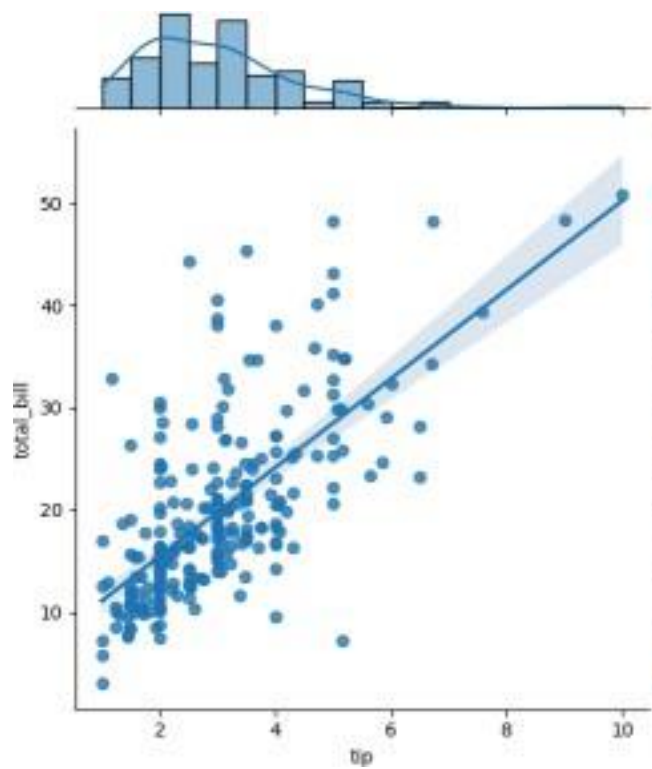


```
sns.jointplot(x=tips.tip,y=tips.total_bill)
```

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

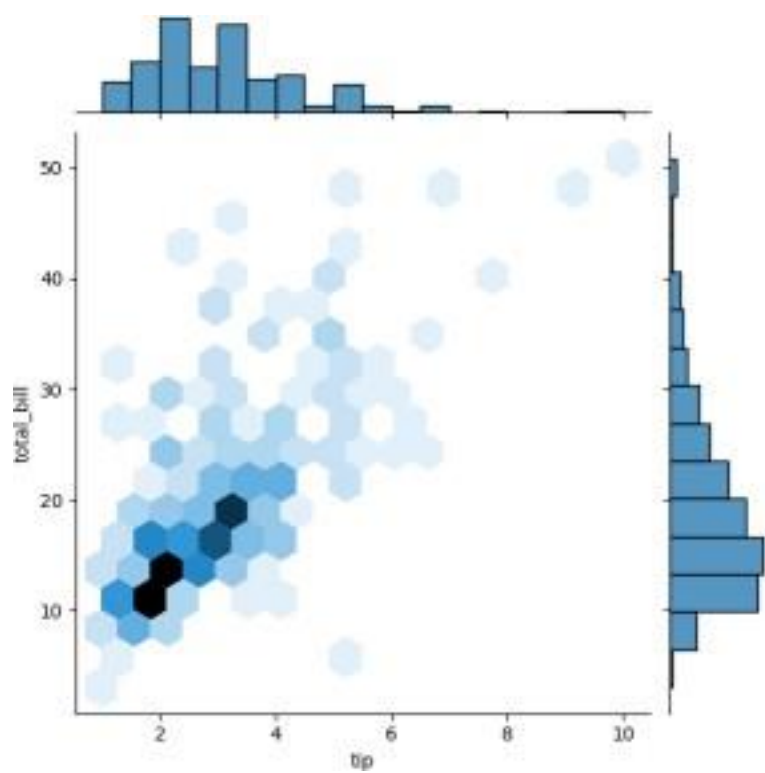


```
sns.jointplot(x=tips.tip,y=tips.total_bill,kind="reg")
```

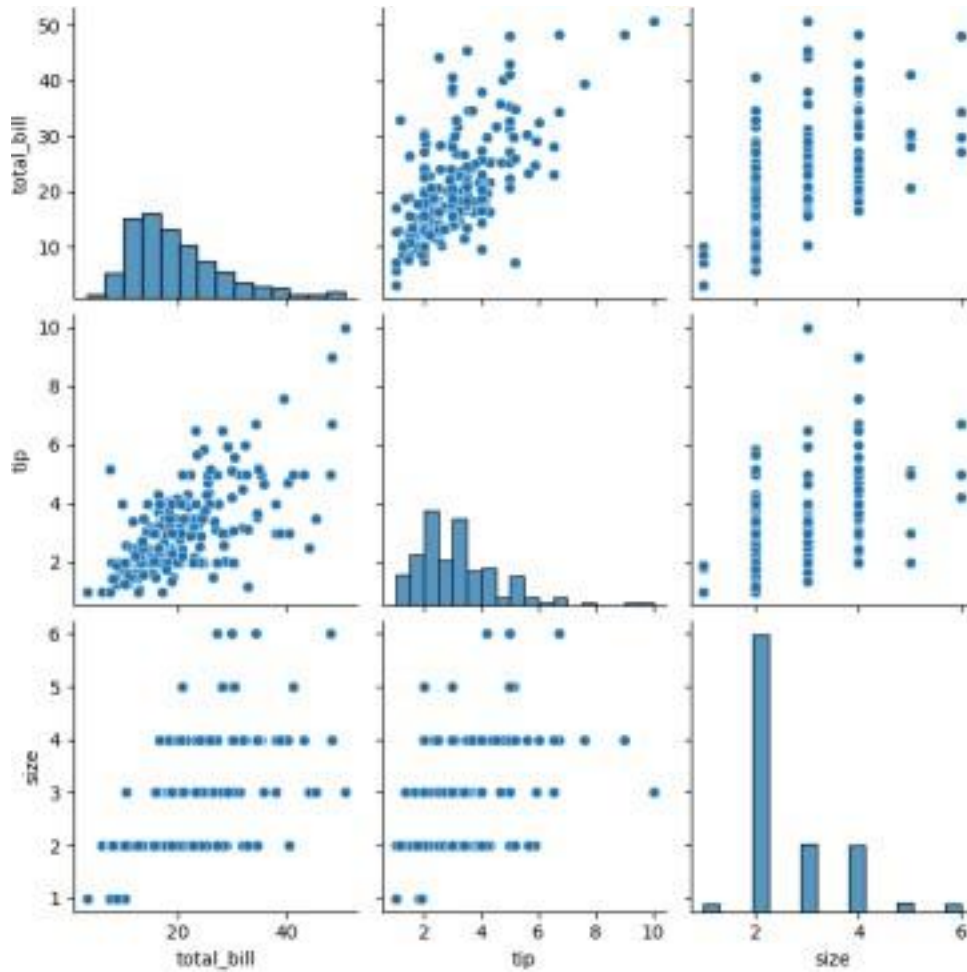


```
sns.jointplot(x=tips.tip,y=tips.total_bill,kind="hex")
```

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



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



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

```
time
```

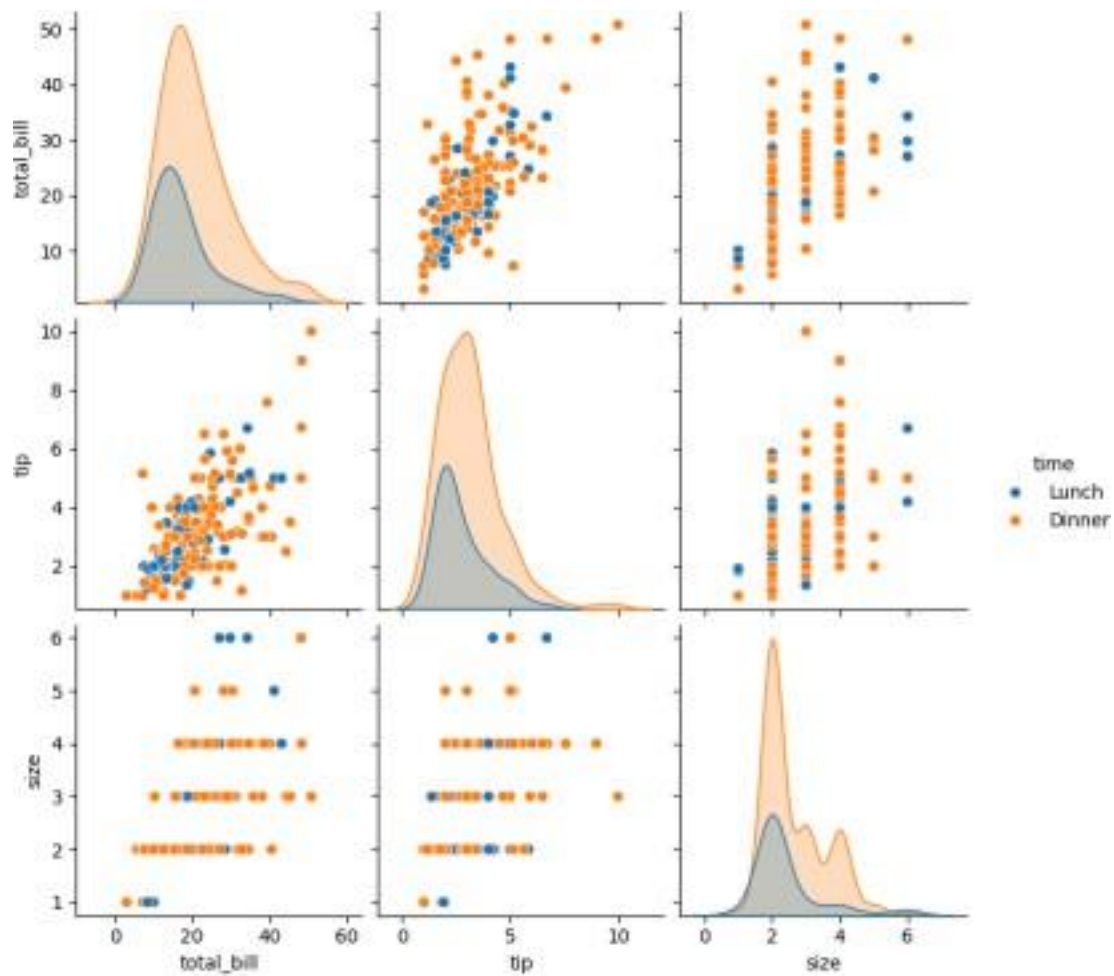
```
Dinner 176
```

```
Lunch 68
```

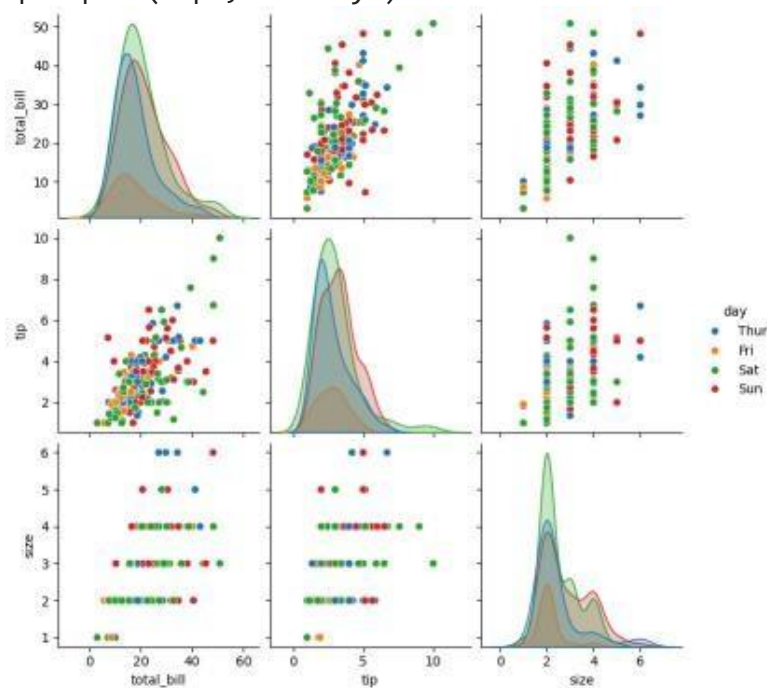
```
dtype: int64
```

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

```
<seaborn.axisgrid.PairGrid at 0x79bb088f4670>
```

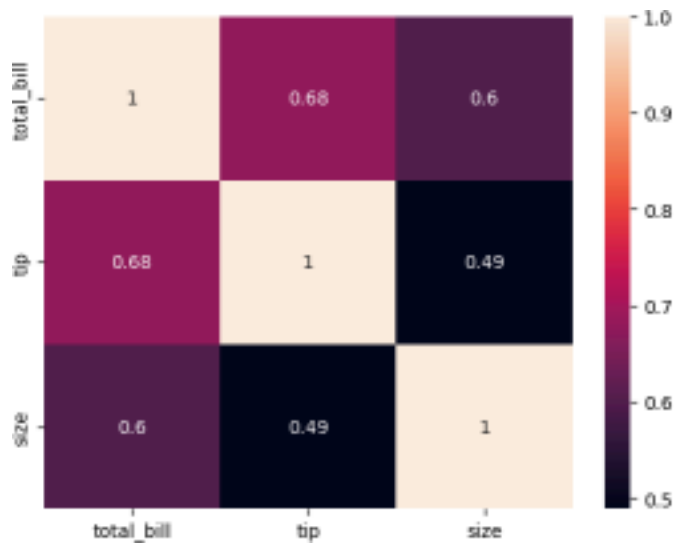


```
sns.pairplot(tips,hue='day')
```



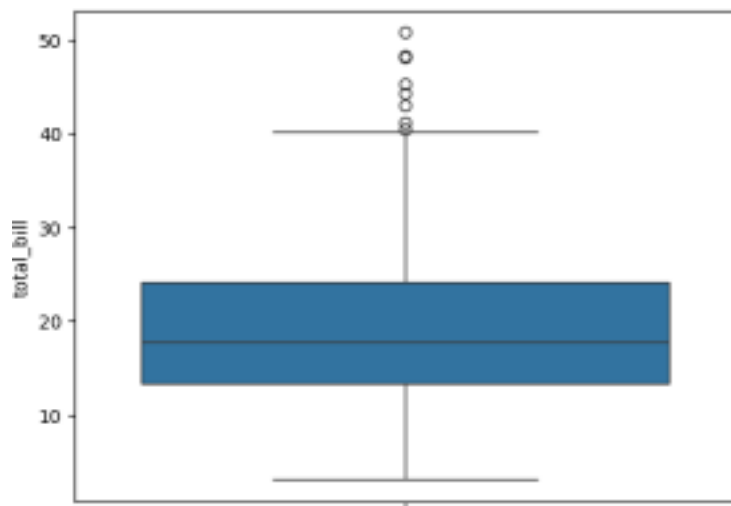

```
sns.heatmap(tips.corr(numeric_only=True),annot=True)
```

<Axes: >



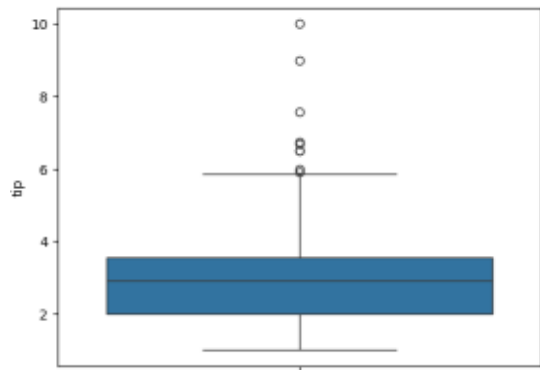
```
sns.boxplot(tips.total_bill)
```

<Axes: ylabel='total_bill'>



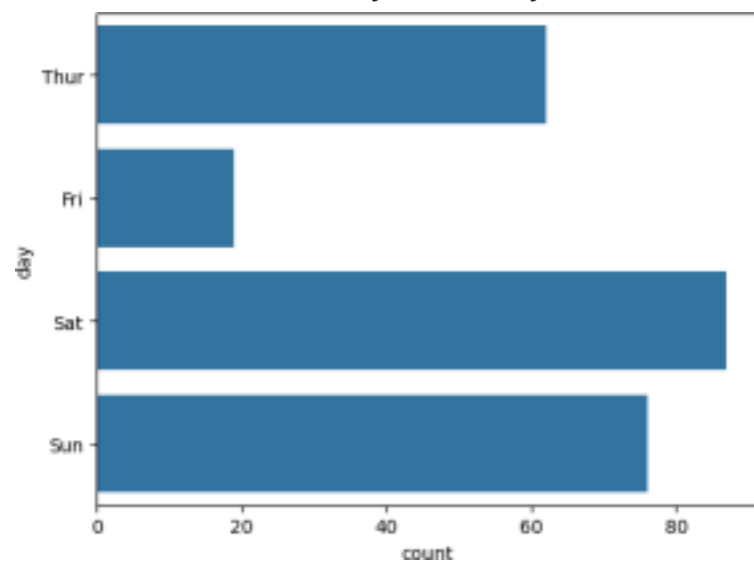
```
sns.boxplot(tips.tip)
```

<Axes: ylabel='tip'>



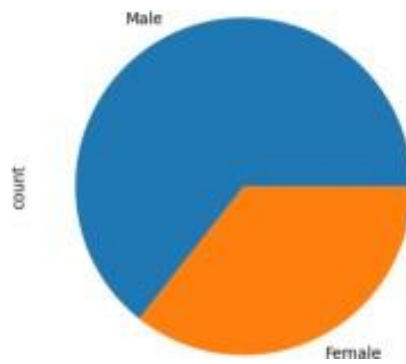
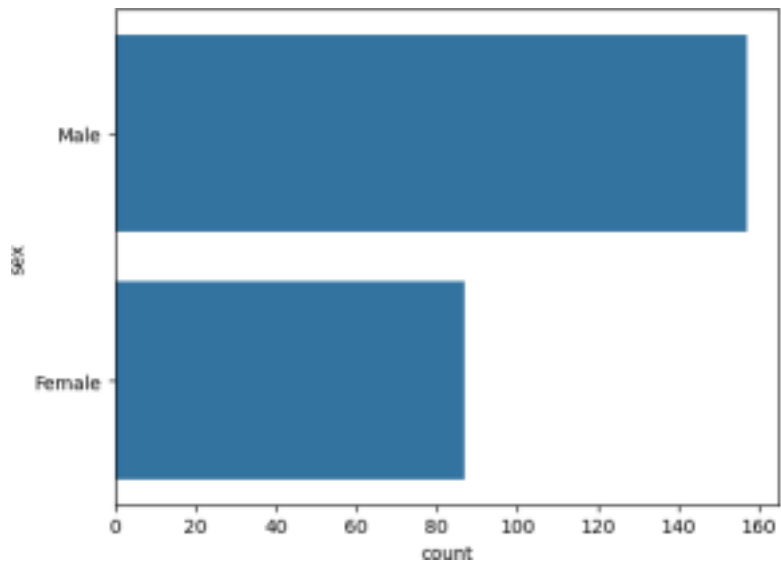
```
sns.countplot(tips.day)
```

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



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

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

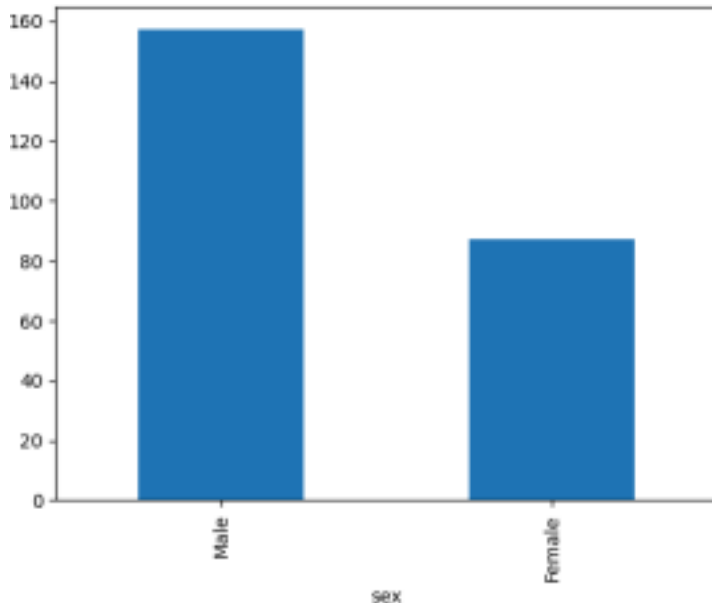


```
tips.sex.value_counts().plot(kind='pie')
```

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

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

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



Experiment: 09
 Roll no: 230701327
 Name: SOWBARNIGAA
 SRIDHARAN
 Class: CSE-E 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_train,y_train)
```

```
Out[21]: 0.9603182547438908
          model.score(x_test,y_test)
```

In [23]:

```
Out[23]: 0.9184170849214232
          model.coef_
```

In [24]:

```
Out[24]: array([[9281.30847068]])
          model.intercept_
```

In [25]:

```
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: 230701327
Name: SOWBARNIGAA
SRIDHARAN
Class: CSE-E 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,random_state=0)
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: 230701327
Name: SOWBARNIGAA
SRIDHARAN
Class: CSE-E 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 x 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, 1, 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, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,  
0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 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, 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, 0, 1, 1, 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, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 0, 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, 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, 1, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0, 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, 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, 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,  
0, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 0, 1, 0, 0, 1, 1, 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,label,  
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  
{},i).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 S t t 37
```

```
x_train,x_test,y_train,y_test=train_test_split(features,label,
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: 230701327
Name: SOWBARNIGAA
SRIDHARAN
Class: CSE-E 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
```

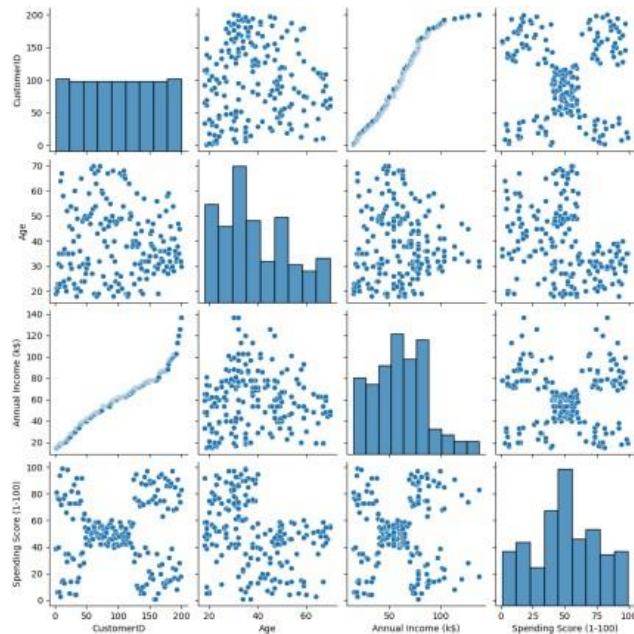
```
sns.pairplot(df)
```

```
In [5]:
```

```
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

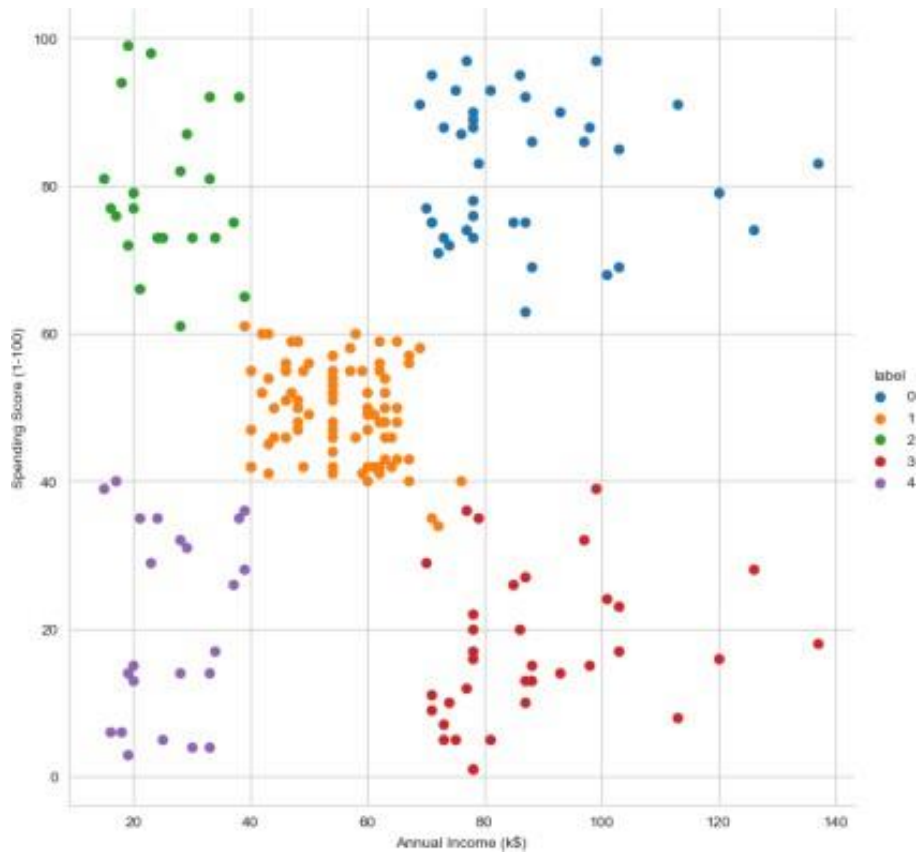
1 15 81 2

2 16 6 4

3 16 77 2

4 17 40 4

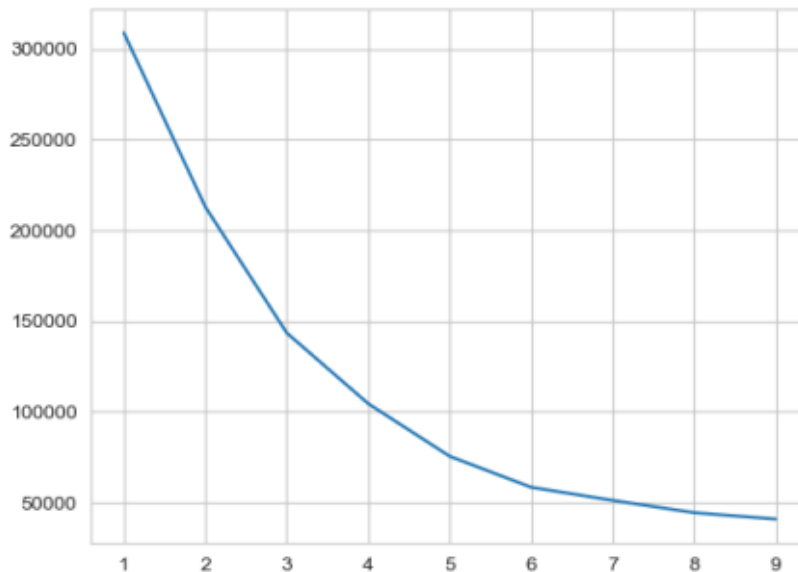
```
In [9]: sns.set_style("whitegrid")
sns.FacetGrid(Final, hue="label", height=8) \
.map(plt.scatter, "Annual Income (k$)", "Spending Score (1-100)") \
.add_legend();
plt.show()
```



```
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: 230701327
Name: SOWBARNIGAA
SRIDHARAN
Class: CSE-E 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))

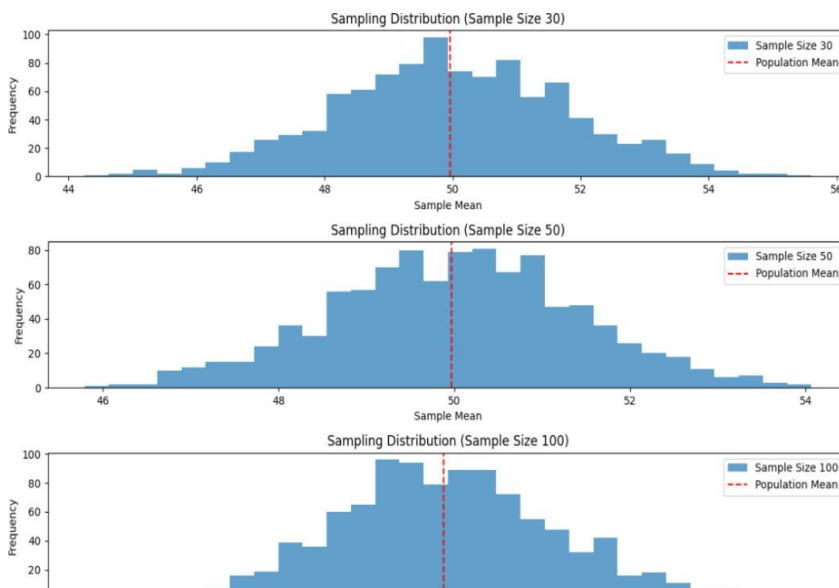
# Step 3: Plotting sampling distributions
plt.figure(figsize=(12, 8))

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: 230701327

Name: SOWBARNIGAA

SRIDHARAN

Class: CSE-E 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: 230701327

Name: SOWBARNIGAA

SRIDHARAN

Class: CSE-E 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: 230701327

**Name: SOWBARNIGAA
SRIDHARAN**

Class: CSE-E 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.