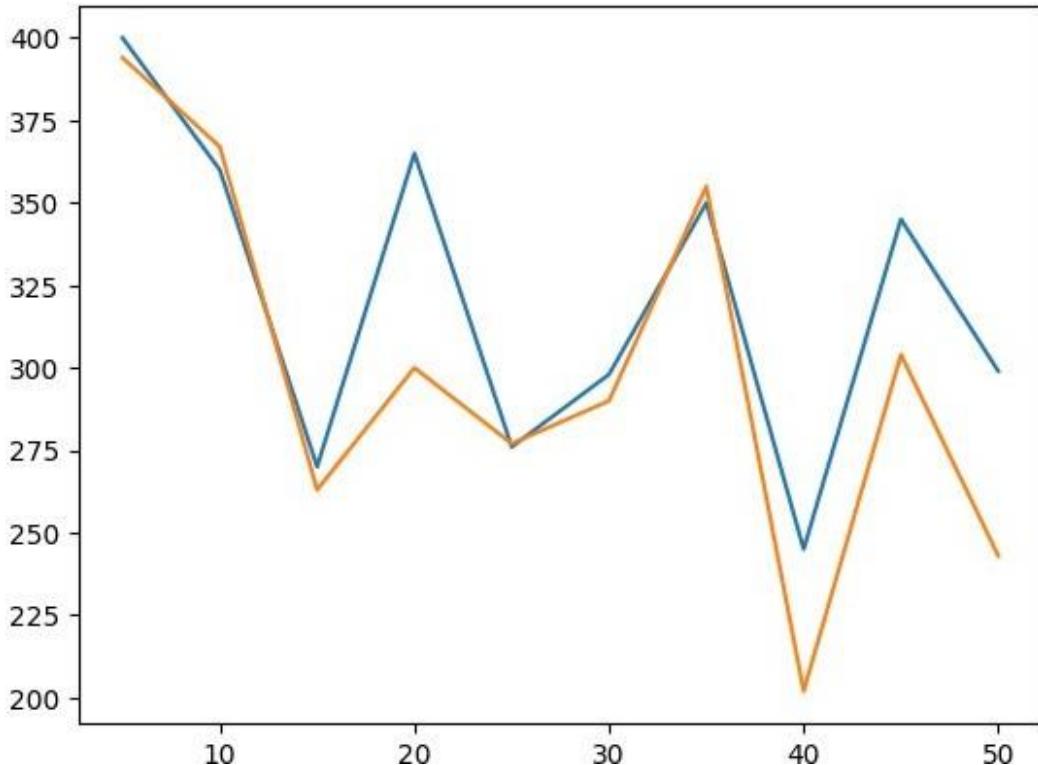


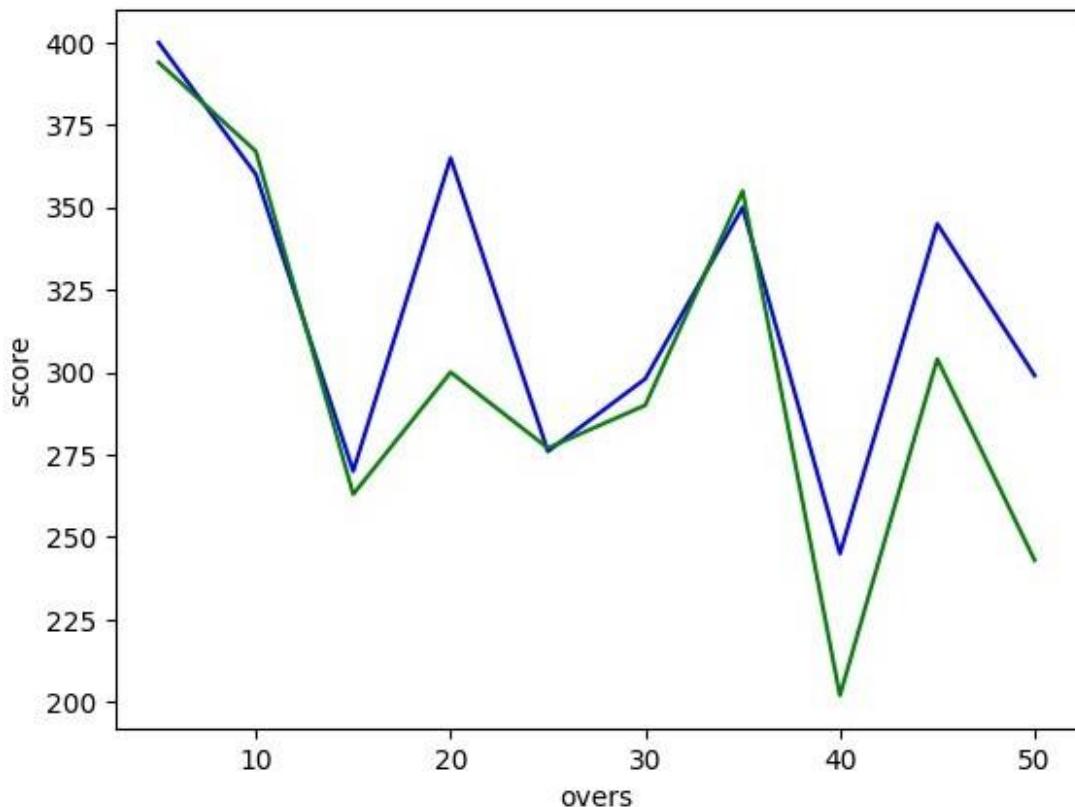
```
#240701542  
#Dhanush  
Kumar.G  
#17-07-25
```

```
import matplotlib.pyplot as plt  
overs=list(range(5,51,5))  
India_Score=[400, 360, 270, 365, 276, 298, 350, 245, 345, 299]  
Srilanka_Score=[394, 367, 263, 300, 277, 290, 355, 202, 304, 243]  
plt.plot(overs,India_Score)  
plt.plot(overs,Srilanka_Score)  
plt.show()  
plt.title("India Vs Srilanka")  
plt.xlabel("overs")  
plt.ylabel("score")  
plt.plot(overs,India_Score,color="blue",label="India")  
plt.plot(overs,Srilanka_Score,color="green",label="Srilanga")
```



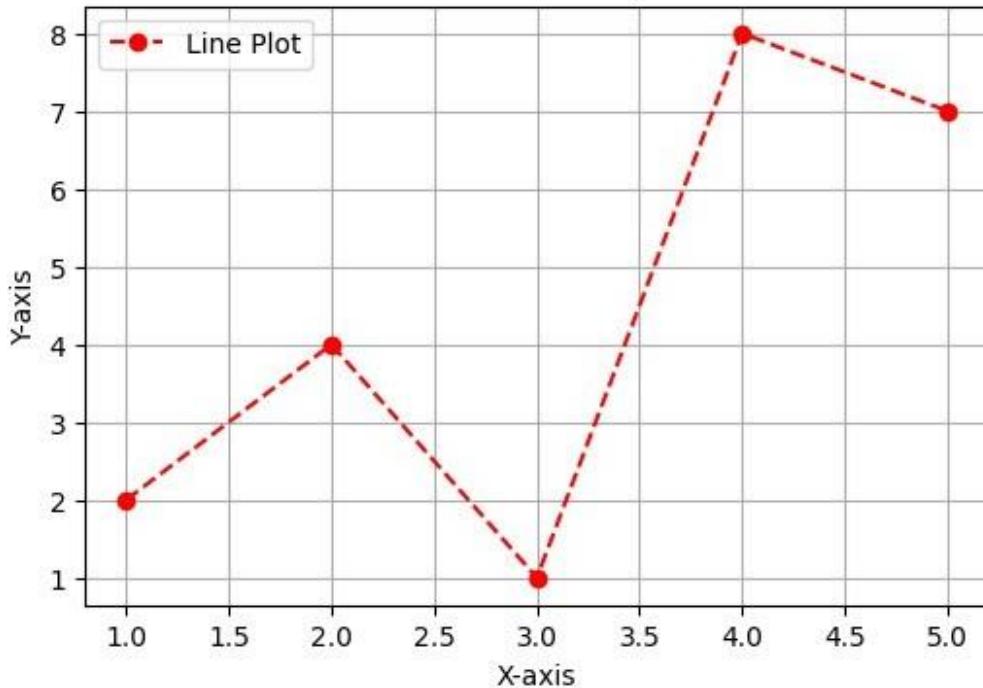
```
[<matplotlib.lines.Line2D at 0x191bd6fd720>]
```

India Vs Srilanka



```
import matplotlib.pyplot as plt
x = [1, 2, 3, 4, 5]
y = [2, 4, 1, 8, 7]
plt.figure(figsize=(6, 4))
plt.plot(x, y, color='red', marker='o', linestyle='--', label='Line Plot')
plt.title("Line Plot Example")
plt.xlabel("X-axis")
plt.ylabel("Y-axis")
plt.legend()
plt.grid(True)
plt.show()
```

### Line Plot Example

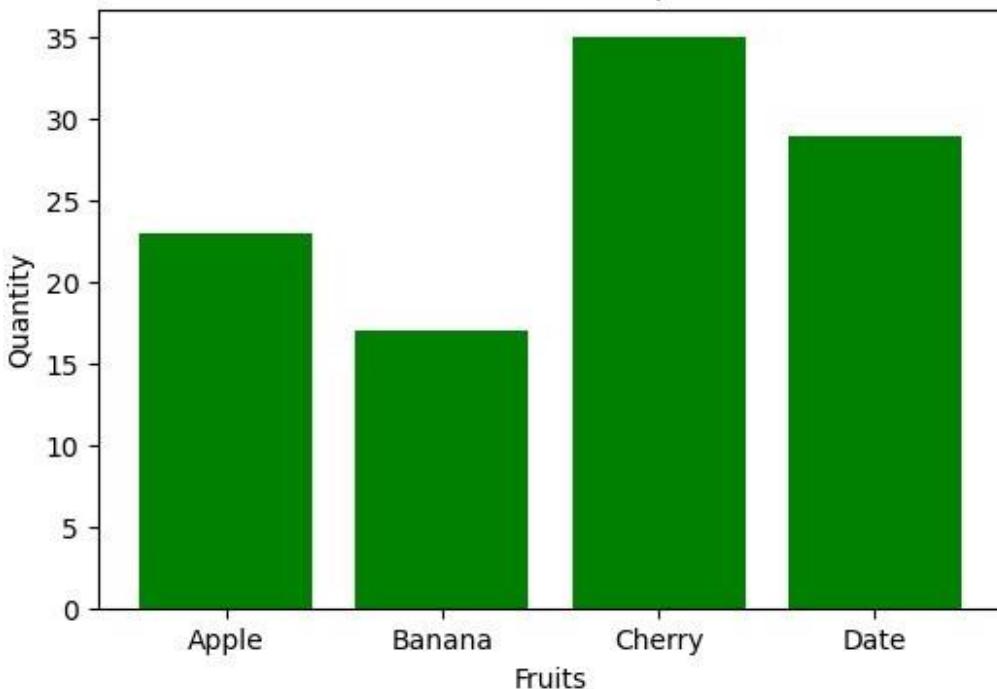


```
categories = ['Apple', 'Banana', 'Cherry', 'Date']

values = [23, 17, 35, 29]

plt.figure(figsize=(6, 4))
plt.bar(categories, values, color='green')
plt.title("Bar Chart Example")
plt.xlabel("Fruits")
plt.ylabel("Quantity")
plt.show()
```

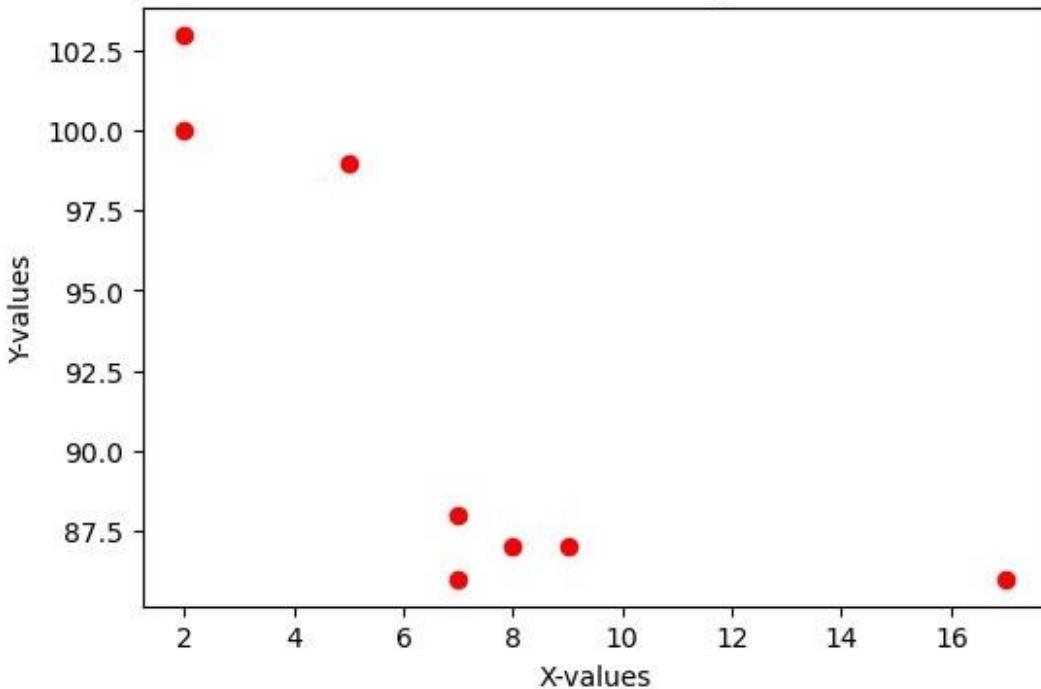
Bar Chart Example



```
x_scatter = [5, 7, 8, 7, 2, 17, 2, 9]
y_scatter = [99, 86, 87, 88, 100, 86, 103, 87]
plt.figure(figsize=(6, 4))
plt.scatter(x_scatter, y_scatter, color='red')
plt.title("Scatter Plot Example")
plt.xlabel("X-values")
plt.ylabel("Y-values")

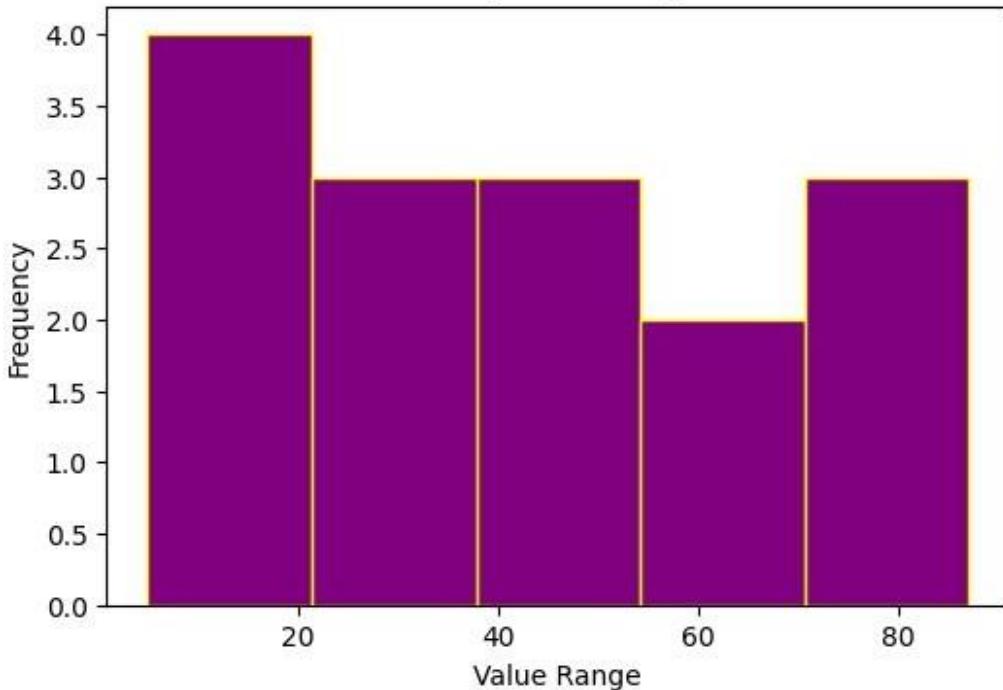
plt.show()
```

Scatter Plot Example



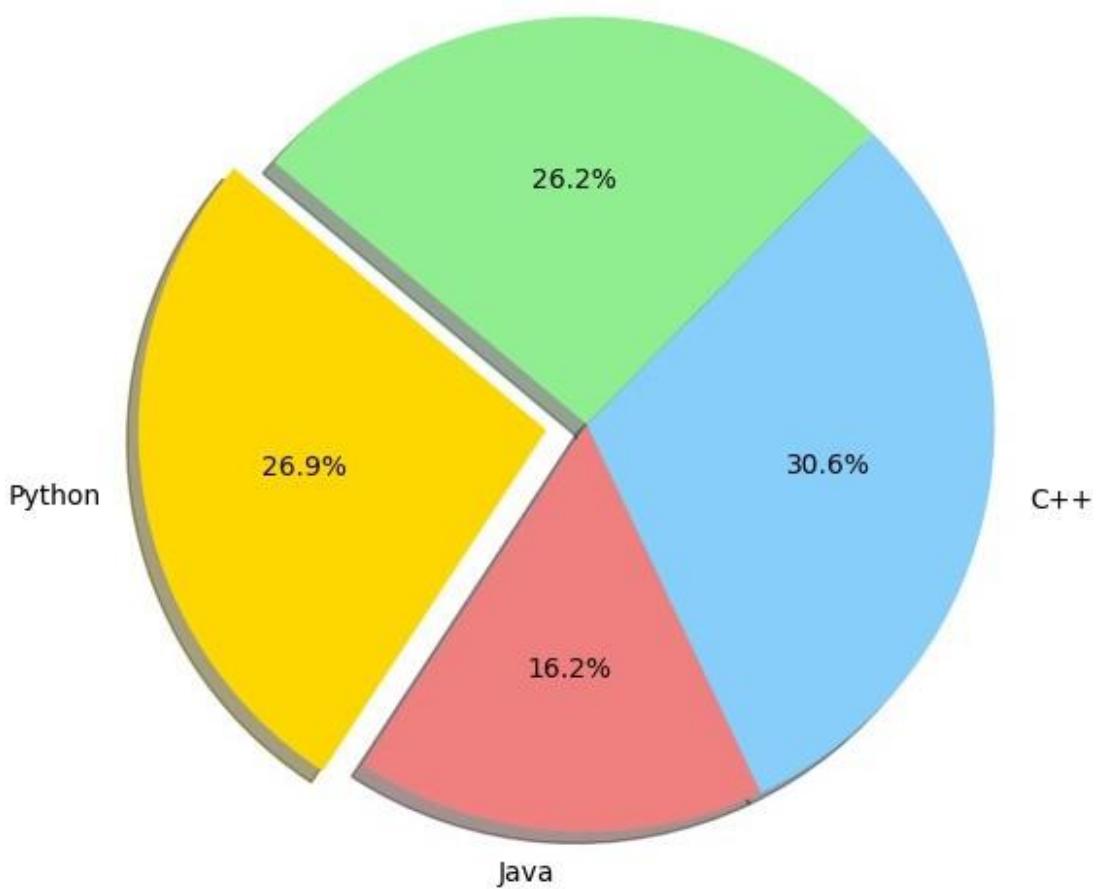
```
data = [22, 87, 5, 43, 56, 73, 55, 54, 11, 20, 51, 5, 79, 31, 27]
plt.figure(figsize=(6, 4))
plt.hist(data, bins=5, color='purple', edgecolor='yellow')
plt.title("Histogram Example")
plt.xlabel("Value Range")
plt.ylabel("Frequency")
plt.show()
```

### Histogram Example



```
labels = ['Python', 'Java', 'C++', 'Ruby']
sizes = [215, 130, 245, 210]
colors = ['gold', 'lightcoral', 'lightskyblue', 'lightgreen']
explode = (0.1, 0, 0, 0)
plt.figure(figsize=(6, 6))
plt.pie(sizes, explode=explode, labels=labels,
colors=colors, autopct='%1.1f%%',
shadow=True, startangle=140)
plt.title("Pie Chart Example")
plt.axis('equal')
plt.show()
```

Pie Chart Example  
Ruby



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

df = pd.read_csv('sales_data.csv')

print(df.head())

print(df.isnull().sum())

df['Sales'] = df['Sales'].fillna(df['Sales'].mean())

df.dropna(subset=['Product', 'Quantity', 'Region'], inplace=True)

df
```

	Date	Product	Sales	Quantity	Region
0	01-01-2023	Product A	200	4	North
1	02-01-2023	Product B	150	3	South
2	03-01-2023	Product A	220	5	North

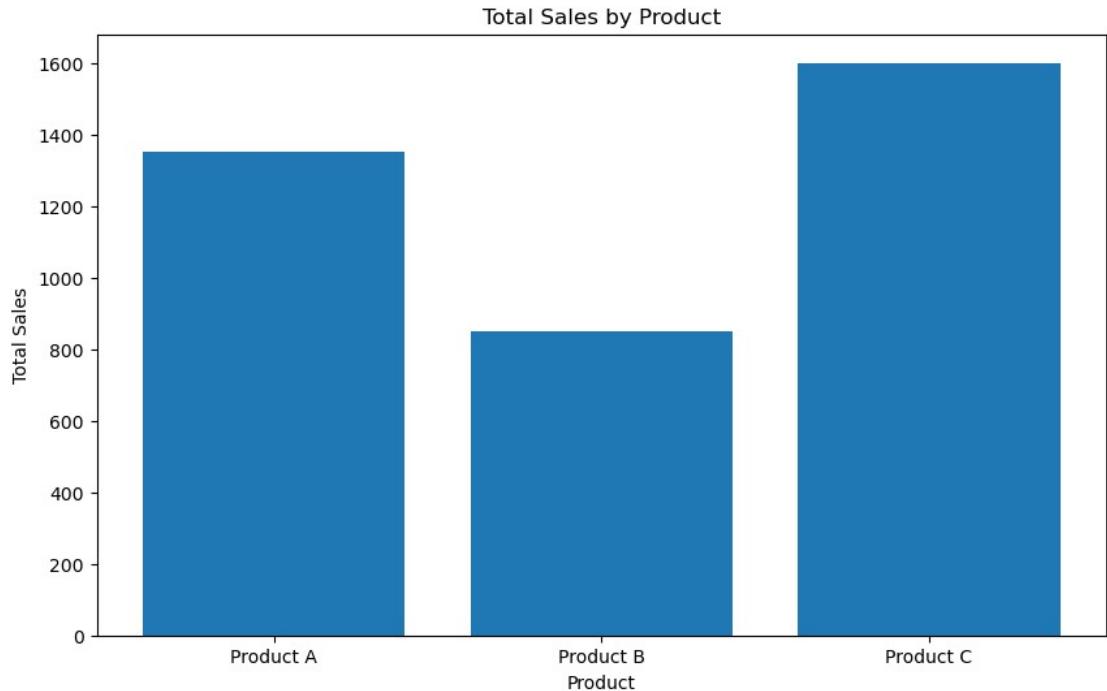
```
3 04-01-2023 Product C    300      6  East
4 05-01-2023 Product B    180      4  West
Date      0
Product    0
Sales      0
Quantity   0
Region     0
dtype: int64
```

	Date	Product	Sales	Quantity	Region
0	01-01-2023	Product A	200	4	North
1	02-01-2023	Product B	150	3	South
2	03-01-2023	Product A	220	5	North
3	04-01-2023	Product C	300	6	East
4	05-01-2023	Product B	180	4	West
5	06-01-2023	Product A	210	5	North
6	07-01-2023	Product C	320	7	East
7	08-01-2023	Product B	160	3	South
8	09-01-2023	Product A	230	6	North
9	10-01-2023	Product C	310	7	East
10	11-01-2023	Product B	190	4	West
11	12-01-2023	Product A	240	6	North
12	13-01-2023	Product C	330	8	East
13	14-01-2023	Product B	170	3	South
14	15-01-2023	Product A	250	7	North
15	16-01-2023	Product C	340	8	East

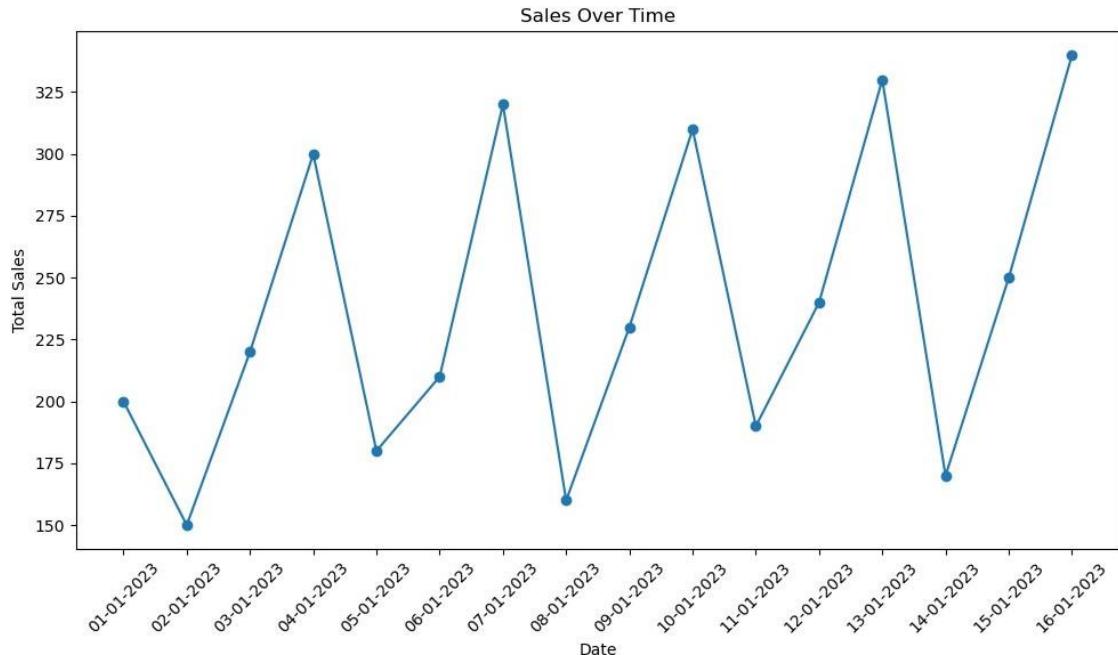
```
product_summary = df.groupby('Product').agg({
    'Sales': 'sum',
    'Quantity': 'sum'
}).reset_index()
print(product_summary)

      Product  Sales  Quantity
0  Product A    1350       33
1  Product B     850       17
2  Product C    1600       36

plt.figure(figsize=(10, 6))
plt.bar(product_summary['Product'], product_summary['Sales'])
plt.xlabel('Product')
plt.ylabel('Total Sales')
plt.title('Total Sales by Product')
plt.show()
```



```
df = df.dropna(subset=['Date'])
sales_over_time = df.groupby('Date', as_index=False)[['Sales']].sum()
plt.figure(figsize=(10, 6))
plt.plot(sales_over_time['Date'], sales_over_time['Sales'], marker='o')
plt.xlabel('Date')
plt.ylabel('Total Sales')
plt.title('Sales Over Time')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



```

pivot_table = df.pivot_table(values='Sales', index='Region',
                             columns='Product',
                                         aggfunc='sum', fill_value=0)
print(pivot_table)

# Only correlate numeric columns
correlation_matrix = df.select_dtypes(include=[ 'number']).corr()
print(correlation_matrix)

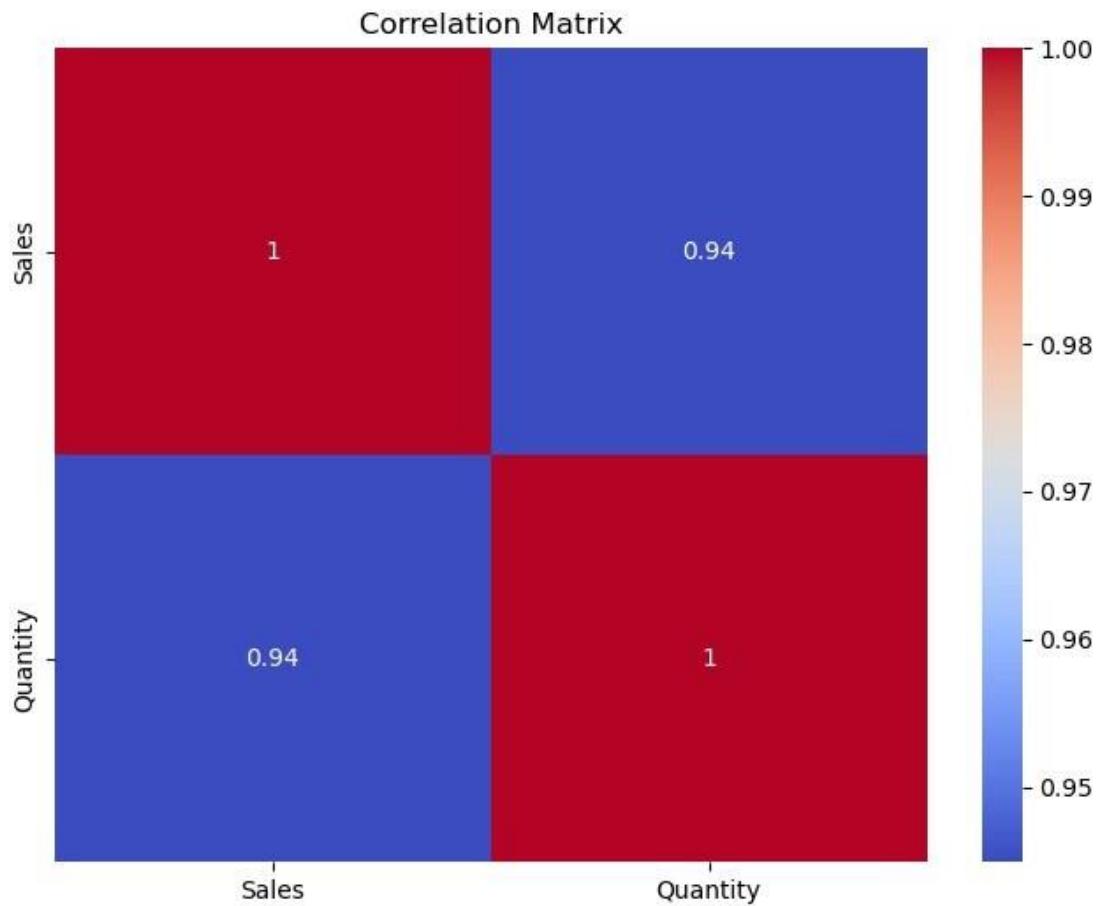
```

Region	Product	Product A	Product B	Product C
East		0	0	1600
North		1350	0	0
South		0	480	0
West		0	370	0
	Sales	Sales	Quantity	
Sales	1.000000	0.944922		
Quantity	0.944922	1.000000		

```

import seaborn as sns
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()

```



```

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

   NoOfPax  EstimatedSalary  Age_Group.1
0          2            40000    20-25

```

```

1      3      59000    30-35
2      2      30000    25-30
3      2     120000   20-25
4      2      45000    35+
5      2    122220    35+
6     -1     21122    35+
7     -10    345673   20-25
8      3     -99999   25-30
9      3     -99999   25-30
10     4      87777   30-35

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: 920.0+ bytes

df.drop_duplicates(inplace=True)
df

  CustomerID  Age_Group  Rating(1-5)  Hotel  FoodPreference  Bill \
0            1      20-25        4       Ibis        veg    1300
1            2      30-35        5  LemonTree  Non-Veg    2000

```

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

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

```
len(df)
```

```
10
```

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

	EstimatedSalary	Age_Group.1
0	40000	20-25
1	59000	30-35
2	30000	25-30
3	120000	20-25

```

4      45000      35+
5      122220      35+
6      21122       35+
7      345673      20-25
8      -99999      25-30
9      87777       30-35

```

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

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

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

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

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

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

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

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

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

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

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

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

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

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

```
df.FoodPreference.unique()
```

```

array(['veg', 'Non-Veg', 'Veg', 'Vegetarian', 'non-Veg'], dtype=object)

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

C:\Users\Dhanush Kumar\AppData\Local\Temp\ipykernel_23860\3377581060.py:1:
FutureWarning: A value is trying to be set on a copy of a DataFrame or Series
through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves
as a copy.

```

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.

```

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

df['EstimatedSalary'] =
df['EstimatedSalary'].fillna(round(df['EstimatedSalary'].mean()))
df['NoOfPax'] = df['NoOfPax'].fillna(round(df['NoOfPax'].median()))
df['Bill'] = df['Bill'].fillna(round(df['Bill'].mean()))
df['Rating(1-5)'] = df['Rating(1-5)'].fillna(round(df['Rating(1-
5)').median()))
df

   CustomerID  Age_Group  Rating(1-5)  Hotel  FoodPreference  Bill \
0          1.0    20-25            4     Ibis        Veg  1300.0
1          2.0    30-35            5  LemonTree    Non-Veg  2000.0
2          3.0    25-30            6    RedFox        Veg  1322.0
3          4.0    20-25           -1  LemonTree        Veg  1234.0
4          5.0      35+            3     Ibis        Veg   989.0
5          6.0      35+            3     Ibis    Non-Veg  1909.0
6          7.0      35+            4    RedFox        Veg  1000.0
7          8.0    20-25            7  LemonTree        Veg  2999.0
8          9.0    25-30            2     Ibis    Non-Veg  3456.0
9         10.0    30-35            5    RedFox    Non-Veg  1801.0

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

```

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

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

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 10 entries, 0 to 9
```

```
Data columns (total 4 columns):
```

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

```
---  ---  -----
```

```
0  Country  10 non-null  object
1  Age      9 non-null  float64
2  Salary   9 non-null  float64
3  Purchased 10 non-null  object
```

```
dtypes: float64(2), object(2)
```

```
memory usage: 448.0+ bytes
```

```
df.Country.mode()
0    France
Name: Country, dtype: object
df.Country.mode()[0]
'France'
type(df.Country.mode())
pandas.core.series.Series
df.Country.fillna(df.Country.mode()[0],inplace=True)
df.Age.fillna(df.Age.median(),inplace=True)
df.Salary.fillna(round(df.Salary.mean()),inplace=True)
df
```

C:\Users\Dhanush Kumar\AppData\Local\Temp\ipykernel\_19496\1020198583.py:1:  
FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through  
chained assignment using an inplace method.

The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.

```
df.Country.fillna(df.Country.mode()[0],inplace=True)
C:\Users\Dhanush Kumar\AppData\Local\Temp\ipykernel_19496\1020198583.py:2:  
FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through  
chained assignment using an inplace method.
```

The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.

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

```
C:\Users\Dhanush Kumar\AppData\Local\Temp\ipykernel_19496\1020198583.py:3:  
FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through  
chained assignment using an inplace method.
```

The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.

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

```
Country  Age  Salary Purchased
```

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

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

```
France Germany Spain
```

```
0 True False False
1 False False True
2 False True False
3 False False True
4 False True False
5 True False False
6 False False True
7 True False False
8 False True False
9 True False False
```

```
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 False True False 50.0 83000.0 No
9 True False False 37.0 67000.0 Yes
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 10 entries, 0 to 9
```

Data columns (total 4 columns):

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

```
---
```

0	Country	10	non-null	object
1	Age	10	non-null	float64
2	Salary	10	non-null	float64
3	Purchased	10	non-null	object

dtypes: float64(2), object(2)

memory usage: 448.0+ bytes

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

```
updated_dataset
```

```
C:\Users\Dhanush Kumar\AppData\Local\Temp\ipykernel_19496\3486364662.py:1:  
FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through  
chained assignment using an inplace method.
```

The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.

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

```
C:\Users\Dhanush Kumar\AppData\Local\Temp\ipykernel_19496\3486364662.py:1:  
FutureWarning: Downcasting behavior in `replace` is deprecated and will be removed in a  
future version. To retain the old behavior, explicitly call `result.infer_objects(copy=False)`.  
To opt-in to the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`
```

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

```
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 False True False 50.0 83000.0      0
9 True False False 37.0 67000.0      1

```

```

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

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

df.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'] = df['Country'].fillna(df['Country'].mode()[0])
features = df.iloc[:, :-1].values
label=df.iloc[:, -1].values

features
label

```

```
array(['No', 'Yes', 'No', 'No', 'Yes', 'Yes', 'No', 'Yes', 'No', 'Yes'],
      dtype=object)

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

SimpleImputer()

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

SimpleImputer()

SimpleImputer()

SimpleImputer()

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

array([[['France', 44.0, 72000.0],
       ['Spain', 27.0, 48000.0],
       ['Germany', 30.0, 54000.0],
       ['Spain', 38.0, 61000.0],
       ['Germany', 40.0, 63777.7777777778],
       ['France', 35.0, 58000.0],
       ['Spain', 38.77777777777778, 52000.0],
       ['France', 48.0, 79000.0],
       ['Germany', 50.0, 83000.0],
       ['France', 37.0, 67000.0]], dtype=object)

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

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

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

```

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

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

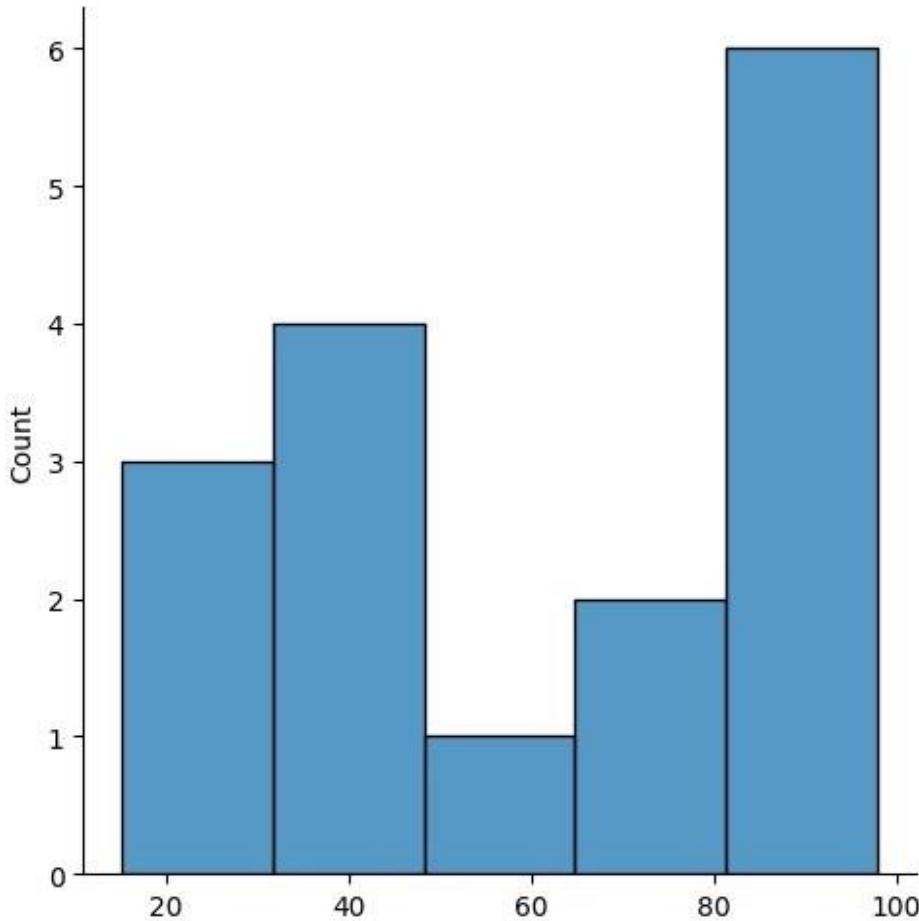
array([[ 1.22474487e+00, -6.54653671e-01, -6.54653671e-01,
       7.58874362e-01,  7.49473254e-01],
      [-8.16496581e-01, -6.54653671e-01,  1.52752523e+00,
       -1.71150388e+00, -1.43817841e+00],
      [-8.16496581e-01,  1.52752523e+00, -6.54653671e-01,
       -1.27555478e+00, -8.91265492e-01],
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

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

array([[1.          , 0.          , 0.          , 0.73913043, 0.68571429],
       [0.          , 0.          , 1.          , 0.          , 0.          ],
       [0.          , 1.          , 0.          , 0.13043478, 0.17142857],
       [0.          , 0.          , 1.          , 0.47826087, 0.37142857],
       [0.          , 1.          , 0.          , 0.56521739, 0.45079365],
       [1.          , 0.          , 0.          , 0.34782609, 0.28571429],
       [0.          , 0.          , 1.          , 0.51207729, 0.11428571],

```

```
[1.          , 0.          , 0.          , 0.91304348, 0.88571429],  
[0.          , 1.          , 0.          , 1.          , 1.          ],  
[1.          , 0.          , 0.          , 0.43478261, 0.54285714]])  
  
import numpy as np  
array=np.random.randint(1,100,16)  
array  
array([78, 82, 16, 15, 41, 27, 40, 37, 52, 83, 69, 93, 98, 90, 94, 33],  
      dtype=int32)  
  
array.mean()  
np.float64(59.25)  
np.percentile(array,25)  
np.float64(36.0)  
np.percentile(array,50)  
np.float64(60.5)  
np.percentile(array,75)  
np.float64(84.75)  
np.percentile(array,100)  
np.float64(98.0)  
  
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  
(np.float64(-37.125), np.float64(157.875))  
  
sns.displot(array)  
<seaborn.axisgrid.FacetGrid at 0x2704bddf7f0>
```



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

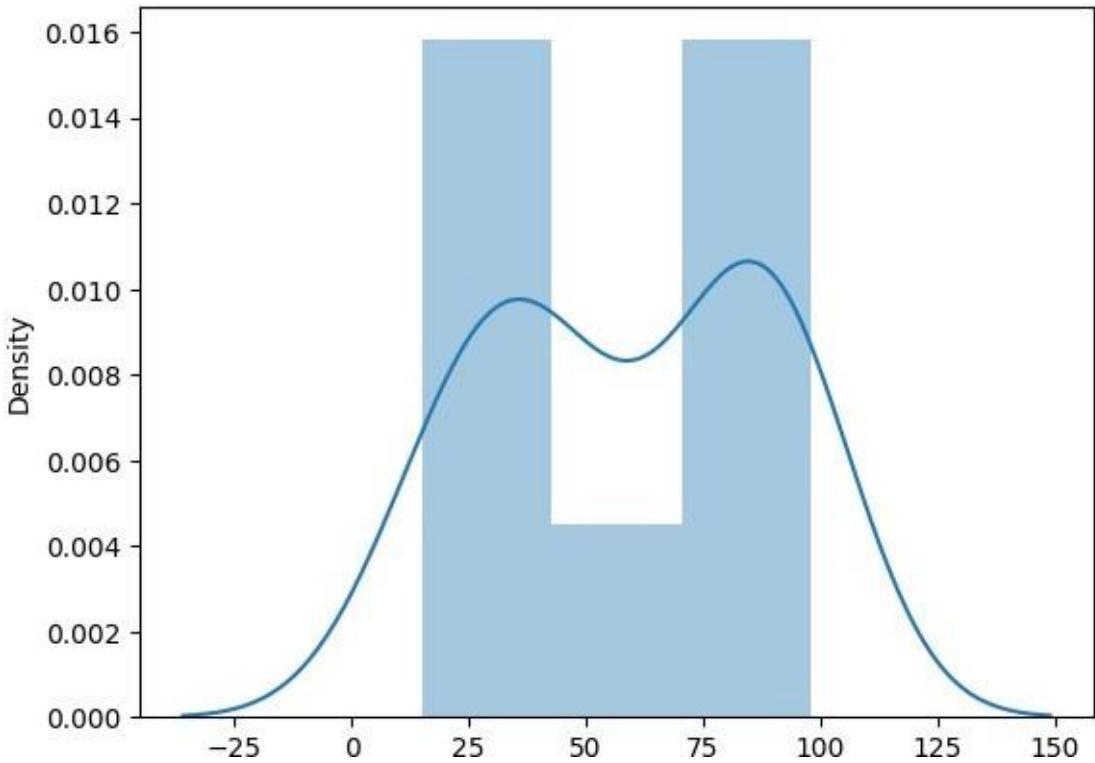
```
C:\Users\Dhanush Kumar\AppData\Local\Temp\ipykernel_24196\1133588802.py:1:  
UserWarning:
```

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see  
<https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751>

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



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

array([78, 82, 16, 15, 41, 27, 40, 37, 52, 83, 69, 93, 98, 90, 94, 33],
      dtype=int32)

lr1,ur1=outDetection(new_array)
lr1,ur1

(np.float64(-37.125), np.float64(157.875))

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

array([89, 2, 12, 49, 51, 15, 68, 85, 80, 24, 33, 53, 84, 50, 53, 8])

sns.distplot(final_array)

C:\Users\HDC0422095\AppData\Local\Temp\ipykernel_2332\209491988.py:1:
UserWarning:

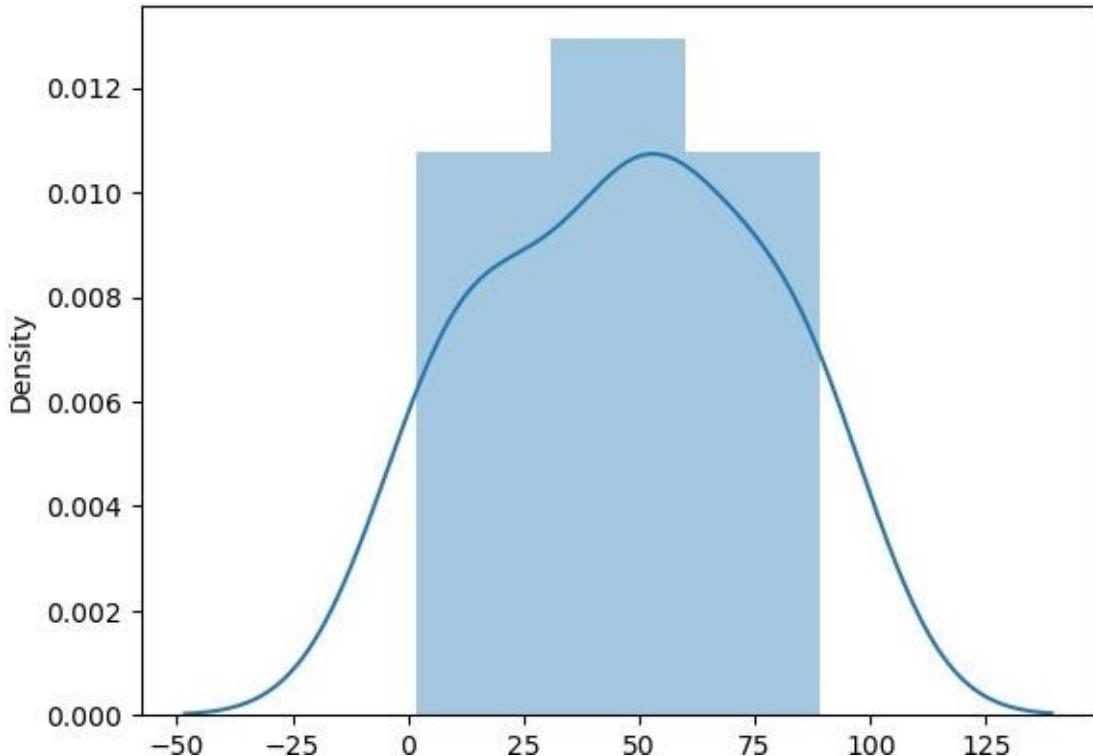
`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
```

<https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751>

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



```
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
tips
      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
...
239   29.03 5.92  Male  No Sat Dinner  3
240   27.18 2.00 Female Yes Sat Dinner  2
241   22.67 2.00  Male Yes Sat Dinner  2
242   17.82 1.75  Male  No Sat Dinner  2
243   18.78 3.00 Female  No Thur Dinner 2
```

[244 rows x 7 columns]

```
sns.displot(tips.total_bill,kde=True)
<seaborn.axisgrid.FacetGrid at 0x1ab9bf48a60>
```

```
sns.displot(tips.total_bill,kde=False)
<seaborn.axisgrid.FacetGrid at 0x294ad6d7d10>
```

```
sns.jointplot(x=tips.tip,y=tips.total_bill)
<seaborn.axisgrid.JointGrid at 0x294ad778a70>
```

```
sns.jointplot(x=tips.tip,y=tips.total_bill,kind="reg")  
<seaborn.axisgrid.JointGrid at 0x294a8ba4740>
```

```
sns.jointplot(x=tips.tip,y=tips.total_bill,kind="hex")  
<seaborn.axisgrid.JointGrid at 0x294ade95220>
```

```
sns.pairplot(tips)  
<seaborn.axisgrid.PairGrid at 0x294a8c7aa20>
```

```
tips.time.value_counts()  
time  
Dinner    176  
Lunch     68  
Name: count, dtype: int64  
sns.pairplot(tips,hue='time')  
<seaborn.axisgrid.PairGrid at 0x294aed013a0>
```

```
sns.pairplot(tips,hue='day')  
<seaborn.axisgrid.PairGrid at 0x294aecf56a0>
```

```
sns.heatmap(tips.corr(numeric_only=True),annot=True)  
<Axes: >
```

```
sns.boxplot(tips.total_bill)  
<Axes: ylabel='total_bill'>
```

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

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

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

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

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

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

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

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

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

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

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

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

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

	YearsExperience	Salary
0	1.1	39343
1	1.3	46205
2	1.5	37731
3	2.0	43525
4	2.2	39891
5	2.9	56642
6	3.0	60150
7	3.2	54445
8	3.2	64445
9	3.7	57189
10	3.9	63218
11	4.0	55794

```

12          4.0    56957
13          4.1    57081
14          4.5    61111
15          4.9    67938
16          5.1    66029
17          5.3    83088
18          5.9    81363
19          6.0    93940
20          6.8    91738
21          7.1    98273
22          7.9    101302
23          8.2    113812
24          8.7    109431
25          9.0    105582
26          9.5    116969
27          9.6    112635
28         10.3   122391
29         10.5   121872

df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30 entries, 0 to 29
Data columns (total 2 columns):
 #   Column           Non-Null Count  Dtype  
--- 
 0   YearsExperience  30 non-null      float64
 1   Salary            30 non-null      int64   
dtypes: float64(1), int64(1)
memory usage: 608.0 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: 608.0 bytes

df.describe()

    YearsExperience      Salary
count      30.000000     30.000000
mean       5.313333     76003.000000
std        2.837888     27414.429785
min        1.100000     37731.000000

```

```
25%           3.200000  56720.750000
50%           4.700000  65237.000000
75%           7.700000  100544.750000
max           10.500000 122391.000000

features=df.iloc[:,[0]].values
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_state=23)

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

LinearRegression()

print(x_train.shape)
print(y_train.shape)

(24, 1)
(24, 1)

model.score(x_train,y_train)

0.9603182547438908

model.score(x_test,y_test)

0.9184170849214232

model.coef_
array([[9281.30847068]])

model.intercept_
array([27166.73682891])

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)

print("Estimated Salary for {} years of experience is: {}".format(yr_of_exp, Salary[0]))

Enter Years of Experience: 41
```

```
Estimated Salary for 41.0 years of experience is: [407700.38412682]
```

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

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

[400 rows x 5 columns]

df.head()

      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

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

array([[ 19,  19000],
       [ 35,  20000],
       [ 26,  43000],
       [ 27,  57000],
       [ 19,  76000],
       [ 27,  58000],
       [ 27,  84000],
       [ 32, 150000],
       [ 25,  33000],
       [ 35,  65000],
       [ 26,  80000],
       [ 26,  52000],
```

```
[ 20, 86000],  
[ 32, 18000],  
[ 18, 82000],  
[ 29, 80000],  
[ 47, 25000],  
[ 45, 26000],  
[ 46, 28000],  
[ 48, 29000],  
[ 45, 22000],  
[ 47, 49000],  
[ 48, 41000],  
[ 45, 22000],  
[ 46, 23000],  
[ 47, 20000],  
[ 49, 28000],  
[ 47, 30000],  
[ 29, 43000],  
[ 31, 18000],  
[ 31, 74000],  
[ 27, 137000],  
[ 21, 16000],  
[ 28, 44000],  
[ 27, 90000],  
[ 35, 27000],  
[ 33, 28000],  
[ 30, 49000],  
[ 26, 72000],  
[ 27, 31000],  
[ 27, 17000],  
[ 33, 51000],  
[ 35, 108000],  
[ 30, 15000],  
[ 28, 84000],  
[ 23, 20000],  
[ 25, 79000],  
[ 27, 54000],  
[ 30, 135000],  
[ 31, 89000],  
[ 24, 32000],  
[ 18, 44000],  
[ 29, 83000],  
[ 35, 23000],  
[ 27, 58000],  
[ 24, 55000],  
[ 23, 48000],  
[ 28, 79000],  
[ 22, 18000],  
[ 32, 117000],  
[ 27, 20000],  
[ 25, 87000],
```

```
[ 23, 66000],  
[ 32, 120000],  
[ 59, 83000],  
[ 24, 58000],  
[ 24, 19000],  
[ 23, 82000],  
[ 22, 63000],  
[ 31, 68000],  
[ 25, 80000],  
[ 24, 27000],  
[ 20, 23000],  
[ 33, 113000],  
[ 32, 18000],  
[ 34, 112000],  
[ 18, 52000],  
[ 22, 27000],  
[ 28, 87000],  
[ 26, 17000],  
[ 30, 80000],  
[ 39, 42000],  
[ 20, 49000],  
[ 35, 88000],  
[ 30, 62000],  
[ 31, 118000],  
[ 24, 55000],  
[ 28, 85000],  
[ 26, 81000],  
[ 35, 50000],  
[ 22, 81000],  
[ 30, 116000],  
[ 26, 15000],  
[ 29, 28000],  
[ 29, 83000],  
[ 35, 44000],  
[ 35, 25000],  
[ 28, 123000],  
[ 35, 73000],  
[ 28, 37000],  
[ 27, 88000],  
[ 28, 59000],  
[ 32, 86000],  
[ 33, 149000],  
[ 19, 21000],  
[ 21, 72000],  
[ 26, 35000],  
[ 27, 89000],  
[ 26, 86000],  
[ 38, 80000],  
[ 39, 71000],  
[ 37, 71000],
```

```
[ 38, 61000],  
[ 37, 55000],  
[ 42, 80000],  
[ 40, 57000],  
[ 35, 75000],  
[ 36, 52000],  
[ 40, 59000],  
[ 41, 59000],  
[ 36, 75000],  
[ 37, 72000],  
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Test 0.855 Train0.83 Random State 394
Test 0.89 Train0.84 Random State 399

x_train,x_test,y_train,y_test=train_test_split(features,label,test_size=0.2,random_state=3)
finalModel=LogisticRegression()
finalModel.fit(x_train,y_train)

LogisticRegression()

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

```
0.85625  
0.8375
```

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

	precision	recall	f1-score	support
0	0.86	0.91	0.89	257
1	0.83	0.74	0.78	143
accuracy			0.85	400
macro avg	0.85	0.83	0.84	400
weighted avg	0.85	0.85	0.85	400

```
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
```

	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
..	...	...	...	...	...
195	196	Female	35	120	79
196	197	Female	45	126	28
197	198	Male	32	126	74
198	199	Male	32	137	18
199	200	Male	30	137	83

```
[200 rows x 5 columns]
```

```
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
```

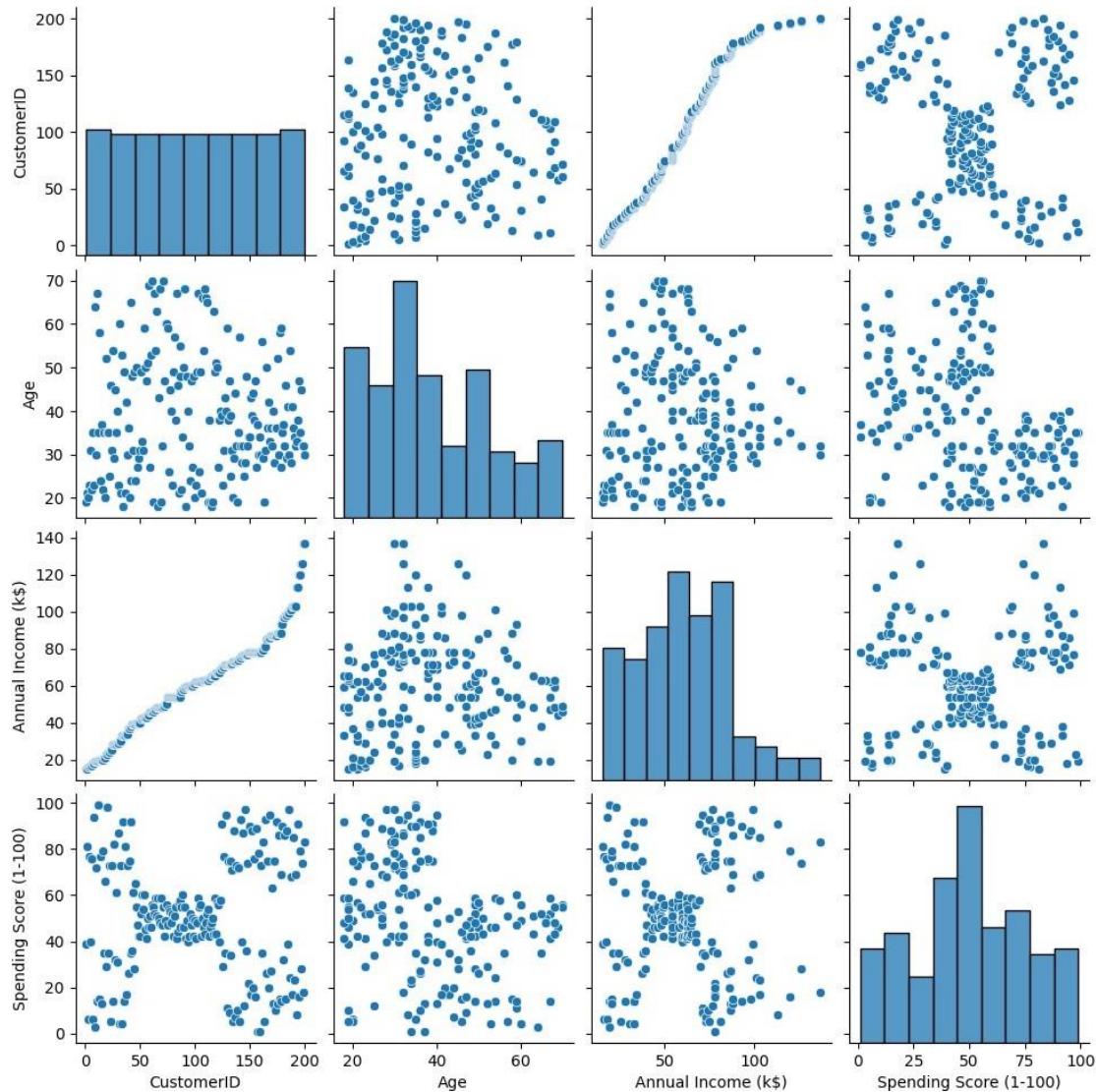
```
2   Age           200 non-null    int64
3   Annual Income (k$)  200 non-null    int64
4   Spending Score (1-100) 200 non-null    int64
dtypes: int64(4), object(1)
memory usage: 7.9+ KB
```

```
df.head()
```

	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)
```

```
<seaborn.axisgrid.PairGrid at 0x179eb0db0a0>
```



```

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

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

KMeans(n_clusters=5)

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

```

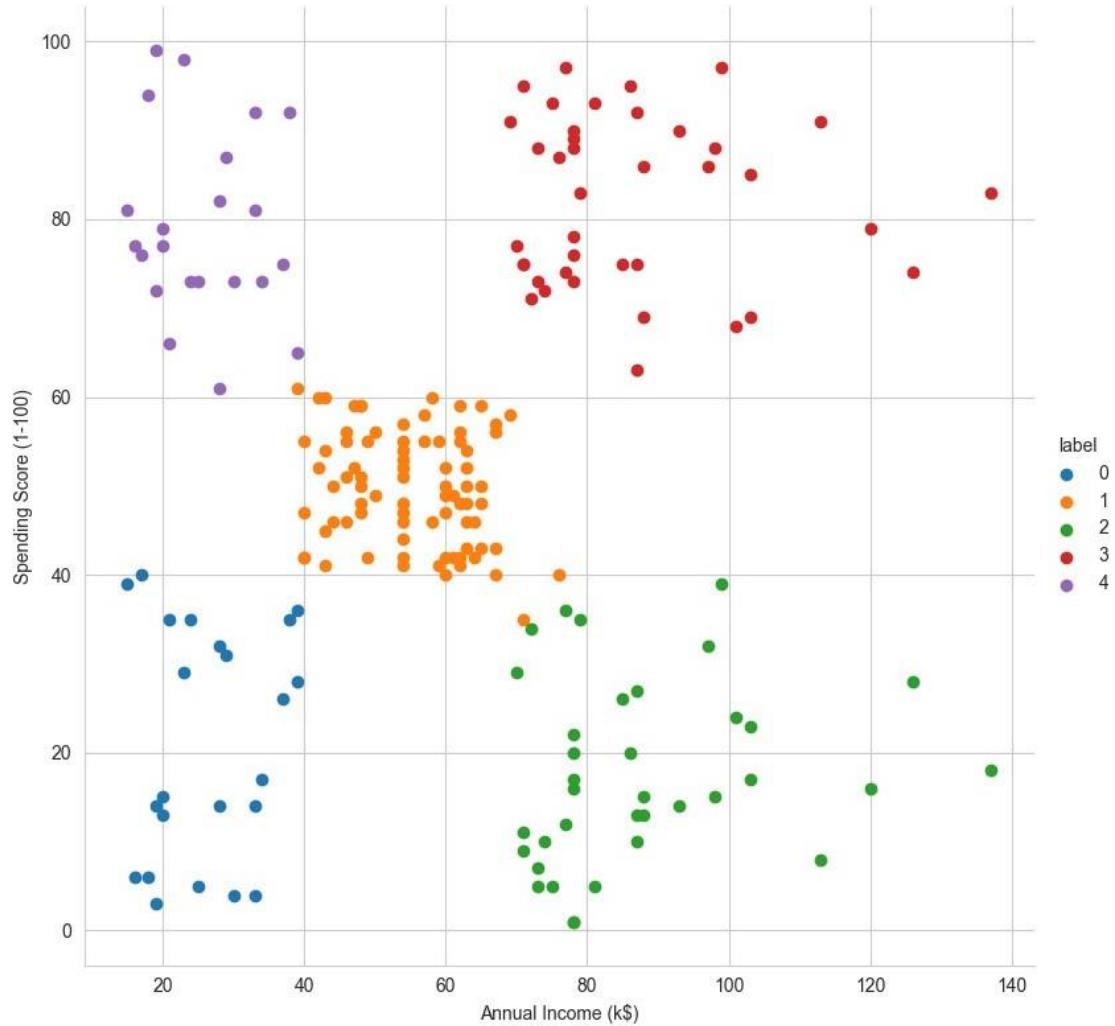
	Annual Income (k\$)	Spending Score (1-100)	label
0	15	39	0
1	15	81	4
2	16	6	0

3	16	77	4
4	17	40	0

```

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()

```



```

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, random_state=42)
    model.fit(features_el)
    wcss.append(model.inertia_)

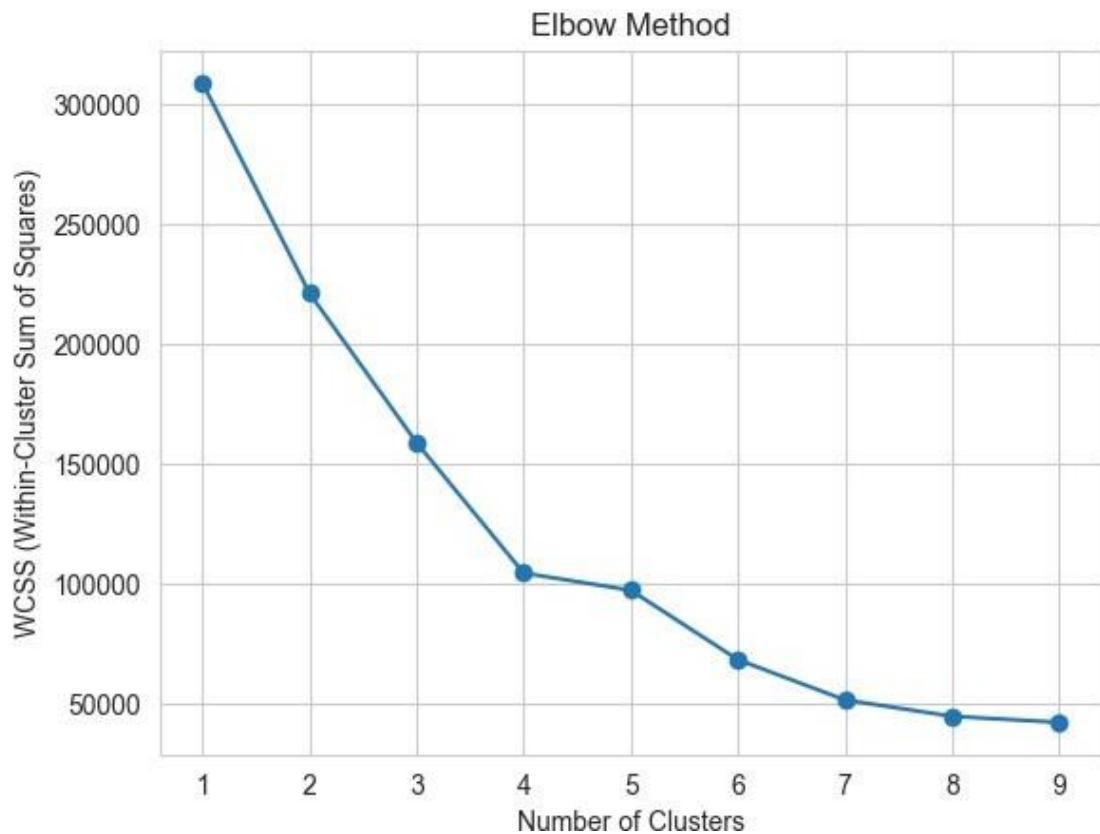
plt.plot(range(1, 10), wcss, marker='o')
plt.title("Elbow Method")

```

```

plt.xlabel("Number of Clusters")
plt.ylabel("WCSS (Within-Cluster Sum of Squares)")
plt.show()

```



```

import numpy as np
import pandas as pd
df=pd.read_csv('Iris.csv')
df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
 #   Column            Non-Null Count  Dtype  
--- 
 0   sepal.length      150 non-null    float64
 1   sepal.width       150 non-null    float64
 2   petal.length      150 non-null    float64
 3   petal.width       150 non-null    float64
 4   variety          150 non-null    object  
dtypes: float64(4), object(1)
memory usage: 6.0+ KB

df.variety.value_counts()

```

```

variety
Setosa      50
Versicolor  50
Virginica   50
Name: count, dtype: int64

df.head()

   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

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=3)
model_KNN=KNeighborsClassifier(n_neighbors=5)
model_KNN.fit(xtrain,ytrain)

KNeighborsClassifier()

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

0.9666666666666667
0.9666666666666667

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

array([[50,  0,  0],
       [ 0, 46,  4],
       [ 0,  1, 49]], 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   0.98      0.92      0.95       50
 Virginica   0.92      0.98      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
--	--------------	------	------	------	-----

### #T-Test

```
import numpy as np
from scipy import stats

marks = np.array([72, 68, 75, 70, 74, 69, 71, 73, 70, 72])
mu_0 = 70
t_stat, p_value = stats.ttest_1samp(marks, mu_0)
print(f"T-statistic: {t_stat:.3f}")
print(f"P-value: {p_value:.4f}")
alpha = 0.05
if p_value < alpha:
    print("Reject Null Hypothesis → Mean is significantly different from 70.")
else:
    print("Fail to Reject Null Hypothesis → No significant difference.")

T-statistic: 1.993
P-value: 0.0774
Fail to Reject Null Hypothesis → No significant difference.
```

```
import numpy as np
from math import sqrt
from scipy.stats import norm
x_bar = 51.2
mu_0 = 50
sigma = 3
n = 36
z_stat = (x_bar - mu_0) / (sigma / sqrt(n))
p_value = 2 * (1 - norm.cdf(abs(z_stat)))
print("Z-statistic: {z_stat:.3f}")
print("P-value: {p_value:.4f}")
alpha = 0.05
if p_value<alpha:
    print("Reject Null Hypothesis → Mean is significantly different from 50 g.")
else:
    print("Fail to Reject Null Hypothesis → No significant difference")

Z-statistic: {z_stat:.3f}
P-value: {p_value:.4f}
Reject Null Hypothesis → Mean is significantly different from 50 g.
```

```
#Anova test

import numpy as np
from scipy import stats

A = [20, 22, 23]
B = [19, 20, 18]
C = [25, 27, 26]

f_stat, p_value = stats.f_oneway(A, B, C)

print("F-statistic: {:.3f}")
print("P-value: {:.4f}")

alpha = 0.05
if p_value < alpha:
    print("Reject Null Hypothesis → Means are significantly different.")
else:
    print("Fail to Reject Null Hypothesis → No significant difference.")

F-statistic: 25.923
P-value: 0.0011
Reject Null Hypothesis → Means are significantly different.
```