**NAME:**ARUL JOTHI P
**ROLL NO**:230701034
**SUBJECT NAME:**CS23332-FUNDAMENTALS OF DATA SCIENCE

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```
import pandas as pd  import numpy as np  import
seaborn as sns  import matplotlib.pyplot as plt
%matplotlib inline
data=pd.read_csv('/content/Iris_Dataset.csv')
```

```
data
```

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

**150** rows × 6 columns

```
data.info()
```

```
<class
'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 6 columns):
 # Column Non-Null Count Dtype
--- ------ -------------- ----- 0
         Id 150 non-null int64
        1         SepalLengthCm 150 non-null float64
        2         SepalWidthCm 150 non-null float64
        3         PetalLengthCm 150 non-null float64
        4         PetalWidthCm 150 non-null float64
        5         variety 150 non-null object dtypes: float64(4), int64(1), object(1)
 memory usage: 7.2+ KB data.describe()
```

| | Id | SepalLengthCm | SepalWidthCm | PetalLengthCm | PetalWidthCm |
|---|---|---|---|---|---|
| **count** | 150.000000 | 150.000000 | 150.000000 | 150.000000 | |
| 150.000000 **mean** | 75.500000 | 5.843333 | 3.054000 | 3.758667 | |
| 1.198667 **std** | 43.445368 | 0.828066 | 0.433594 | 1.764420 | 0.763161 **min** |
| 1.000000 | 4.300000 | 2.000000 | 1.000000 | 0.100000 | |
| **25%** | 38.250000 | 5.100000 | 2.800000 | 1.600000 | 0.300000 |
| **50%** | 75.500000 | 5.800000 | 3.000000 | 4.350000 | 1.300000 **75%** |
| 112.750000 | 6.400000 | 3.300000 | 5.100000 | 1.800000 **max** | |

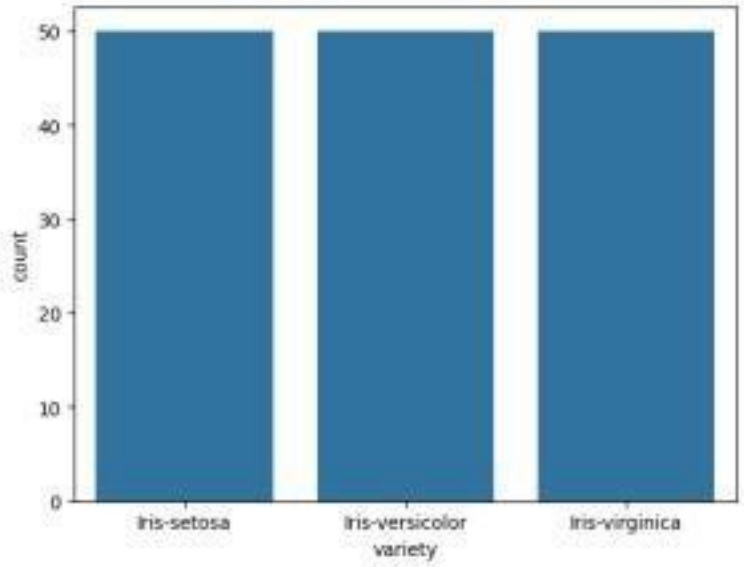
150 000000 7 900000 4 400000 6 900000 2 500000

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

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



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

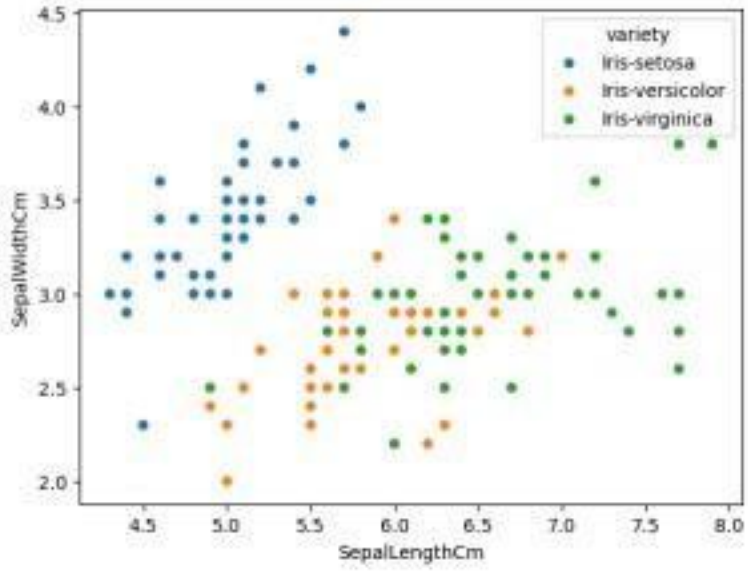



```
dummies=pd.get_dummies(data.variety)

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 |

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

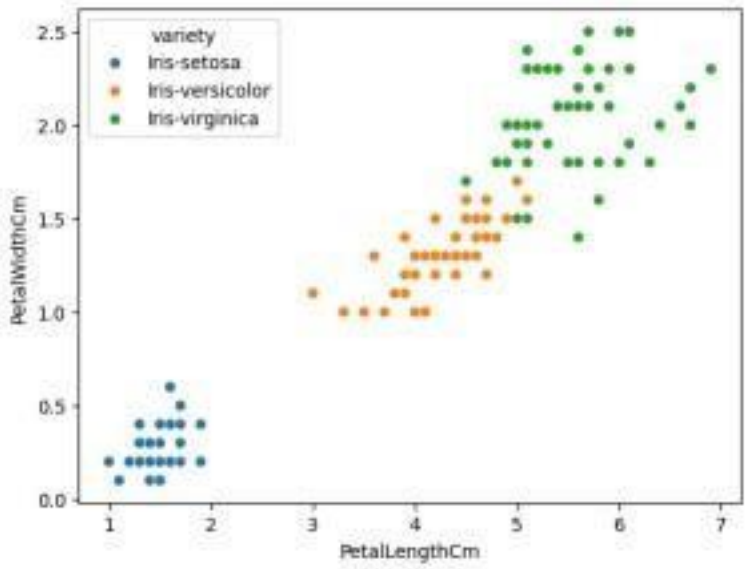
```
<Axes: xlabel='SepalLengthCm', ylabel='SepalWidthCm'>
```



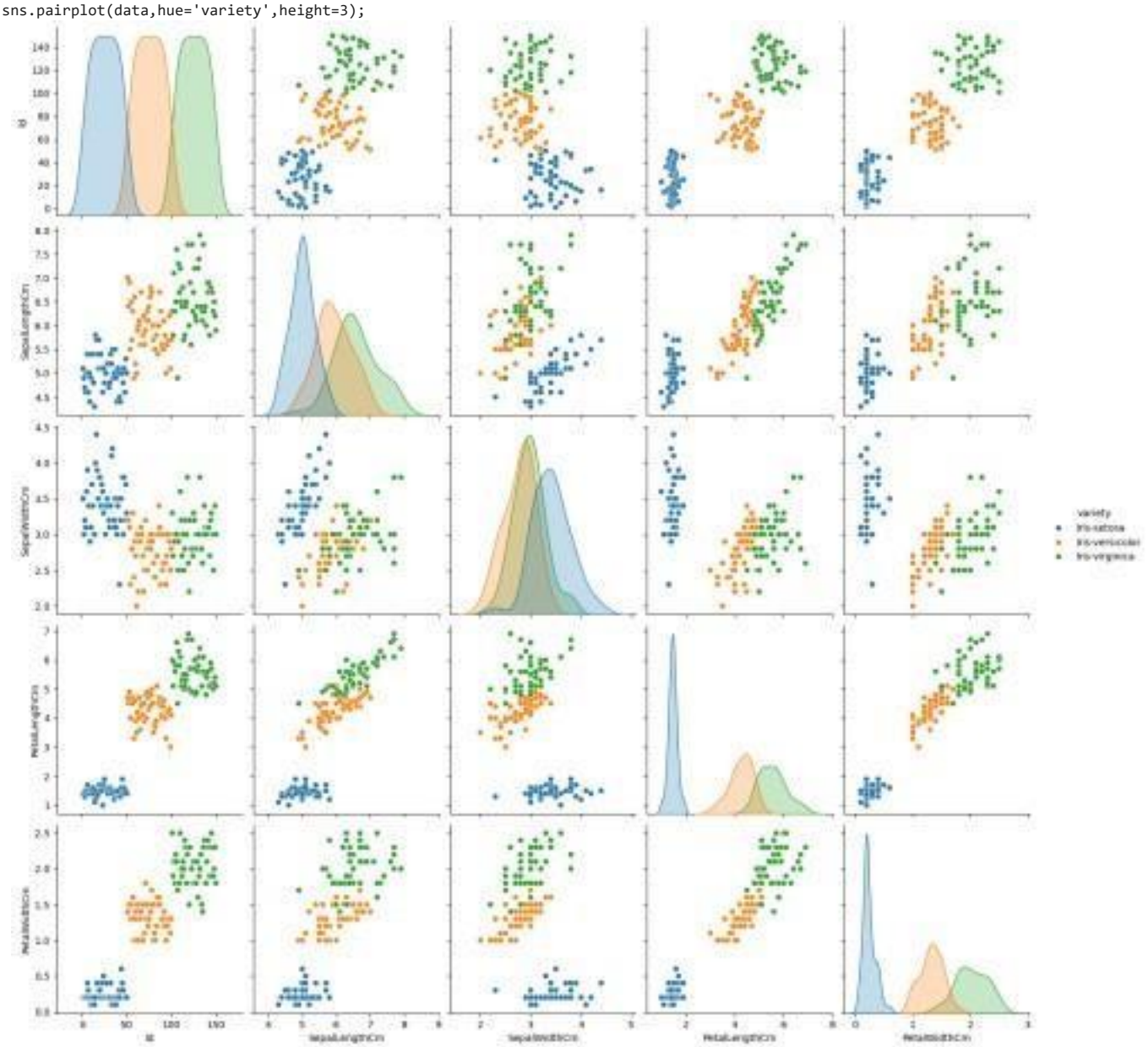

```
sns.scatterplot(x='PetalLengthCm',y='PetalWidthCm',hue='variety',data=data,)
```



```
<Axes: xlabel='PetalLengthCm', ylabel='PetalWidthCm'>
```



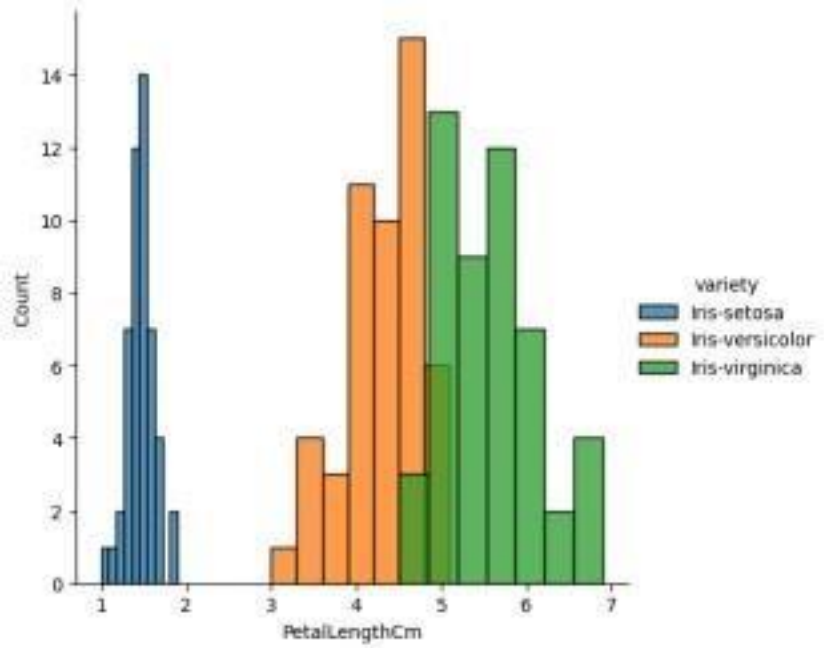

```
sns.pairplot(data,hue='variety',height=3);
```



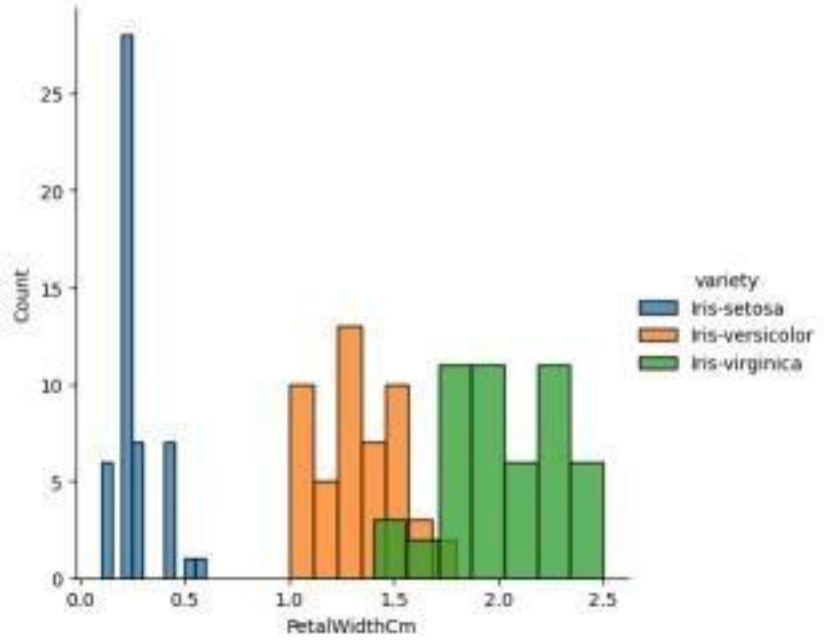



 `plt.show()`

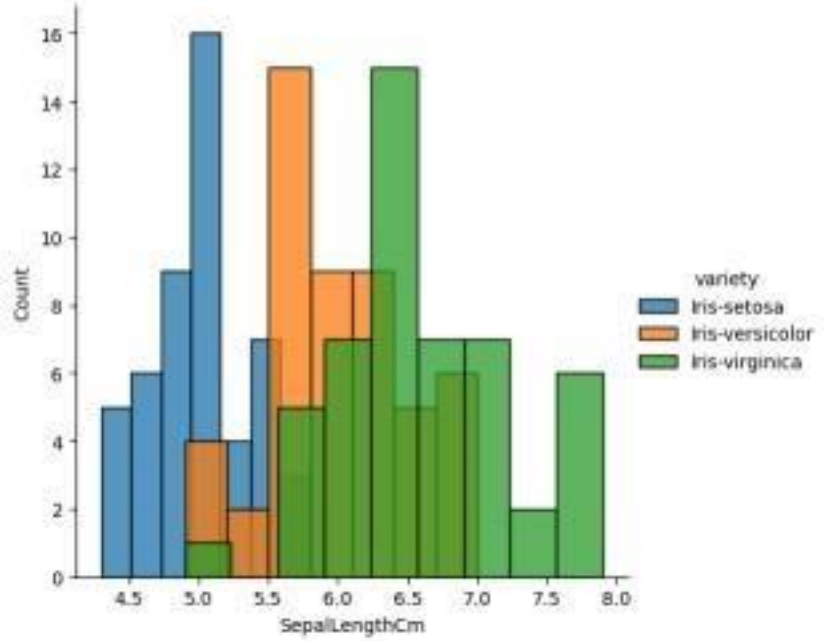
```
sns.FacetGrid(data,hue='variety',height=5).map(sns.histplot,'PetalLengthCm').add_legend();
plt.show();
```




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




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




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

```
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]])
```

```
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 | SREE VARSSINI K S | 5000 |
| **1** | 2 | SREEMATHI B | 6000 |
| **2** | 3 | SREYA G | 7000 |
| **3** | 4 | SREYASKARI MULLAPUDI | 5000 |
| **4** | 5 | SRI AKASH U G | 8000 |

```
df.tail()
```

| | emp id | name | salary |
|---|---|---|---|
| **2** | 3 | SREYA G | 7000 |
| **3** | 4 | SREYASKARI MULLAPUDI | 5000 |
| **4** | 5 | SRI AKASH U G | 8000 |
| **5** | 6 | SRI HARSHAVARDHANAN R | 3000 |
| **6** | 7 | SRI HARSHAVARDHANAN R | 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 | |
| **top** | NaN | SRI HARSHAVARDHANAN R | |
| **freq** | NaN | 2 | NaN |
| **mean** | 4.000000 | NaN | |
| **std** | 2.160247 | NaN | |
| **min** | 1.000000 | NaN | |
| **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, 'SREE VARSSINI K S', 5000],
 [2, 'SREEMATHI B', 6000],
 [3, 'SREYA G', 7000],
 [4, 'SREYASKARI MULLAPUDI', 5000],
 [5,     'SRI     AKASH     U     G',     8000],
 [6, 'SRI HARSHAVARDHANAN R', 3000],
 [7, 'SRI HARSHAVARDHANAN R', 6000]], dtype=object)
```



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

```
employee_DF
```

| | emp id | name | salary |
|---|---|---|---|
| **0** | 1 | SREE VARSSINI K S | 5000 |
| **1** | 2 | SREEMATHI B | 6000 |
| **2** | 3 | SREYA G | 7000 |
| **3** | 4 | SREYASKARI MULLAPUDI | 5000 |
| **4** | 5 | SRI AKASH U G | 8000 |
| **5** | 6 | SRI HARSHAVARDHANAN R | 3000 |
| **6** | 7 | SRI HARSHAVARDHANAN R | 6000 |

```
#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)
```

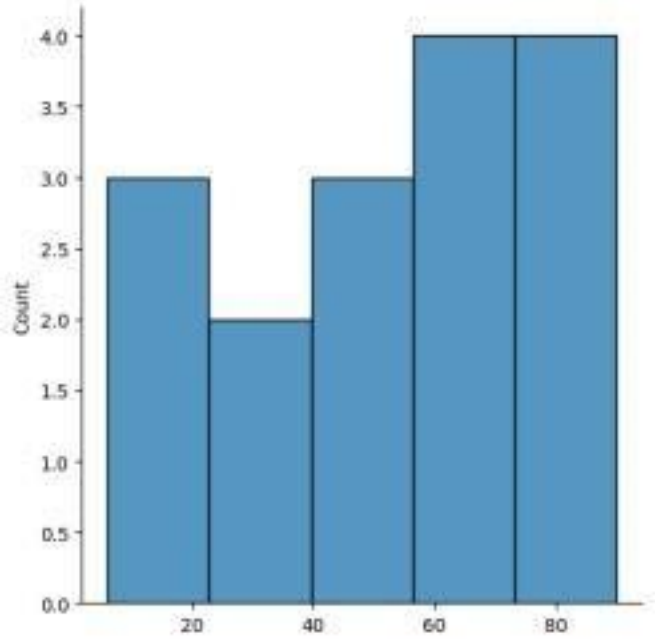
```
90.0
```

```
#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)
```

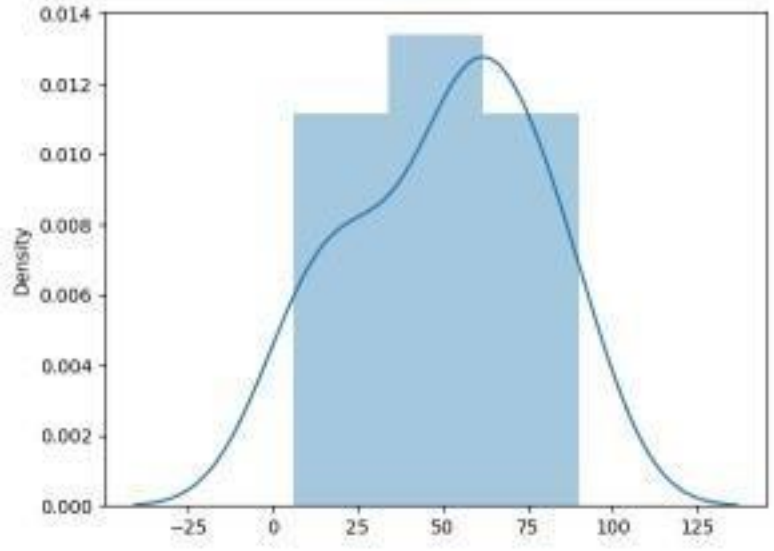
```
<seaborn.axisgrid.FacetGrid at 0x78f3291c2710>
```




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

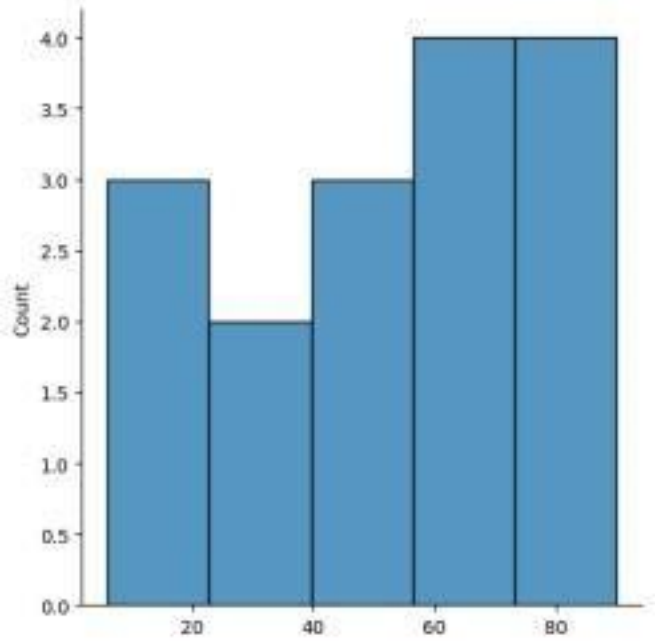
```
`distplot` is a deprecated function and will be removed in seaborn v0.14.0.
Please adapt your code to use either `displot`
```

```
 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>
```

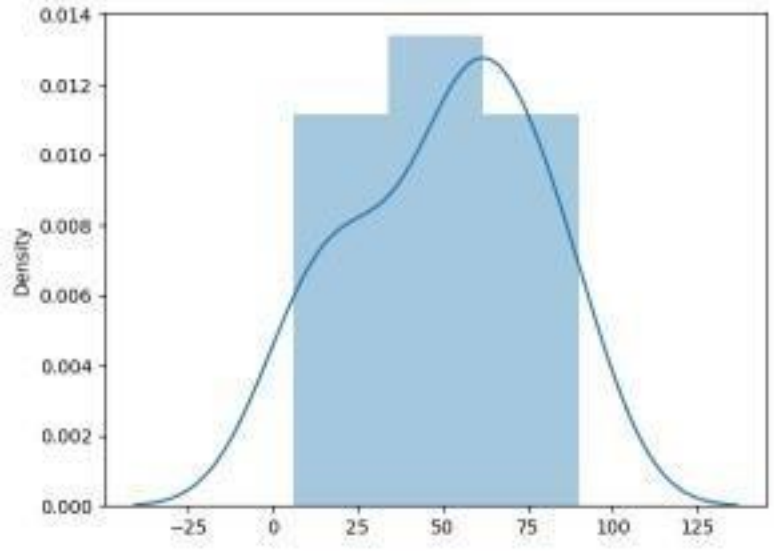



```
lr1,ur1=outDetection(new_array)
lr1,ur1
```

```
(-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)
```

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



**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 |

#From the dataframe identify the duplicate row(i.e row 9)

# The duplicated() method returns a Series with True and False values that describe which rows in the DataFrame are duplicated and not. **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
```

# The info() method prints information about the DataFrame. The information contains the number of columns, column labels, column data types, memory usage, range index, and the number of cells in each column (non-null values).

**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
```

# The drop_duplicates() method removes duplicate rows.

**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 |

#While removing duplicate record row index also removed

# The len() function to return the length of an object. With a dataframe, the function returns the number of rows.

**len(df)**

10

#Reset the index

**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 |

# Axis refers to the dimensions of a DataFrame (index and columns) or Series (index only) Use axis=0 to apply functions row-wise along the index. Use axis=1 to apply functions column-wise across columns.

**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 |

# The function . loc is typically used for label indexing and can access multiple columns.

**df.CustomerID.loc[df.CustomerID<0]=np.nan**

**df.Bill.loc[df.Bill<0]=np.nan**

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

**df**

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

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

**df**

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

**df.Age_Group.unique()**

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

**df.Hotel.unique()**

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

# Using the inplace=True keyword in a pandas method changes the default behaviour such that the operation on the dataframe doesn't return anything, it instead 'modifies the underlying data

**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 |

```
import numpy as np
import pandas as pd
df=pd.read_csv('/content/preprocess_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[col].method(value, inplace=True)', try using 'df.method({col: value}, inpla
```

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

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

Start coding or generate with AI.

```
from sklearn.impute import SimpleImputer

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

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

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

▾ SimpleImputer i? SimpleImputer()

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

▾ SimpleImputer i? SimpleImputer()

SimpleImputer()

▾ SimpleImputer i?

SimpleImputer()

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

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

) features array([['France', 44.0, 72000.0],

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

from sklearn.preprocessing import OneHotEncoder

oh = OneHotEncoder(sparse_output=False)

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


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


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

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

final_set array([[1.0, 0.0, 0.0, 44.0, 72000.0],

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


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

feat_standard_scaler
```

```
array([[ 1.00000000e+00, -5.00000000e-01, -6.54653671e01,
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]])
```

```
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 |

Double-click (or enter) to edit

```
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())
```

```
pandas.core.series.Series
def __init__(data=None, index=None, dtype: Dtype | None=None, name=None, copy: bool | None=None,
fastpath: bool=False) -> None
 index is not None, the resulting Series is reindexed with the index
values. dtype : str, numpy.dtype, or ExtensionDtype, optional Data type for
the output Series. If not specified, this will be inferred from `data`.
 See the :ref:`user guide <basics.dtypes>` for more usages.
name : Hashable, default None
    The name to give to the 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
```

| | 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()
```

```
<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
```

**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

```
  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

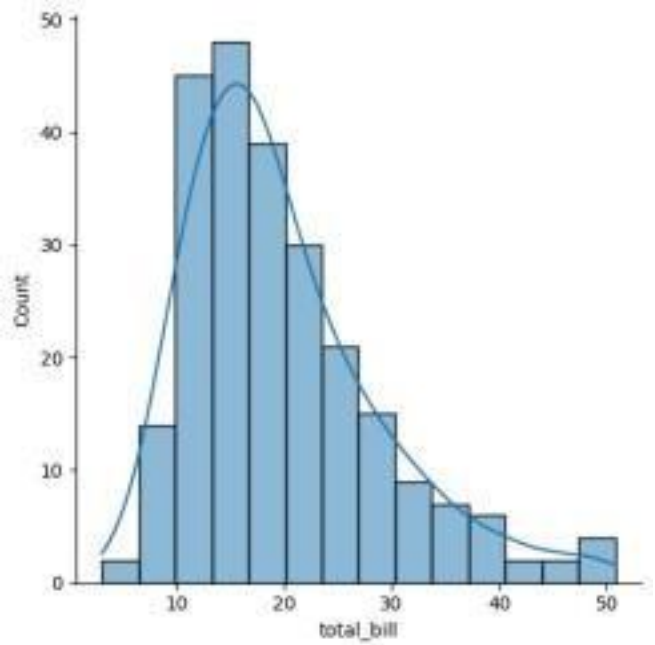
**3** 23.68 3.31 Male No Sun Dinner 2

**4** 24.59 3.61 Female No Sun Dinner 4

Code Text

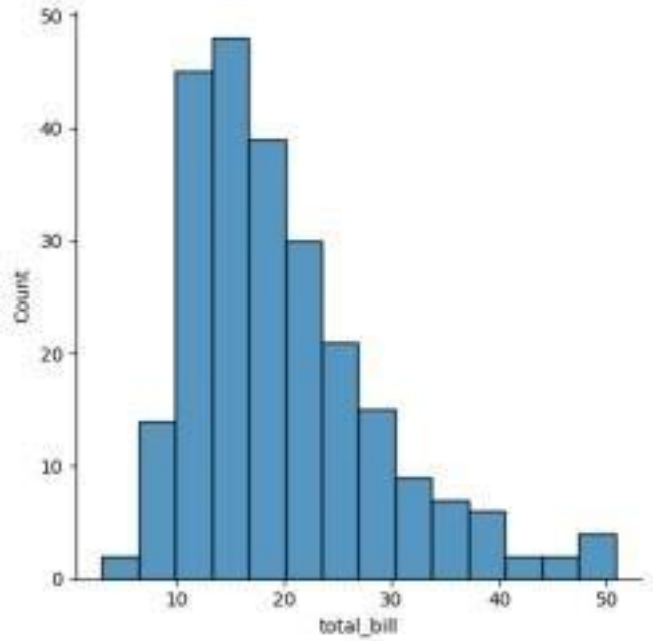
```
sns.displot(tips.total_bill,kde=True)
```

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



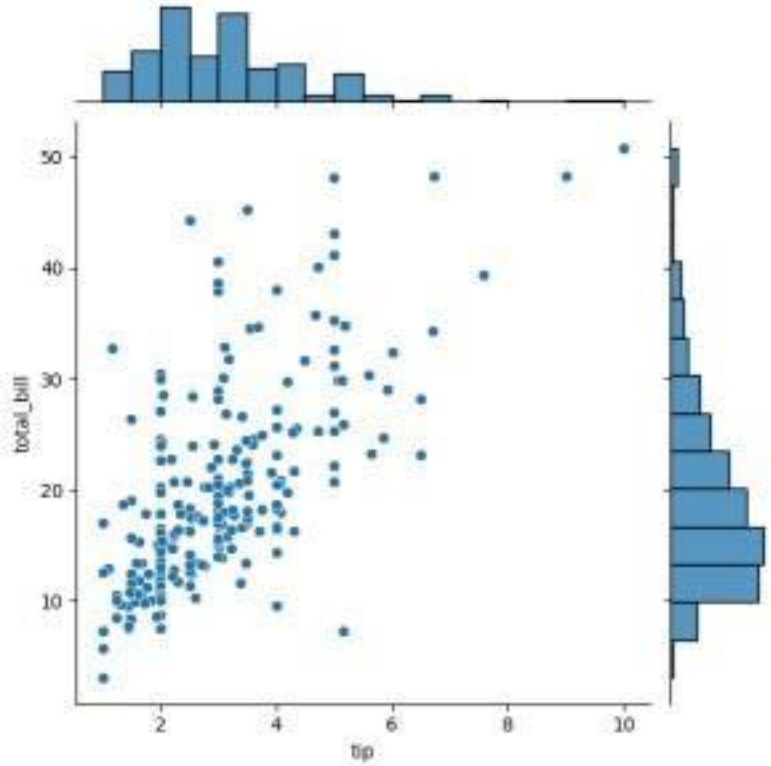

```
sns.displot(tips.total_bill,kde=False)
```

```
<seaborn.axisgrid.FacetGrid at 0x79bb0b0af580>
```



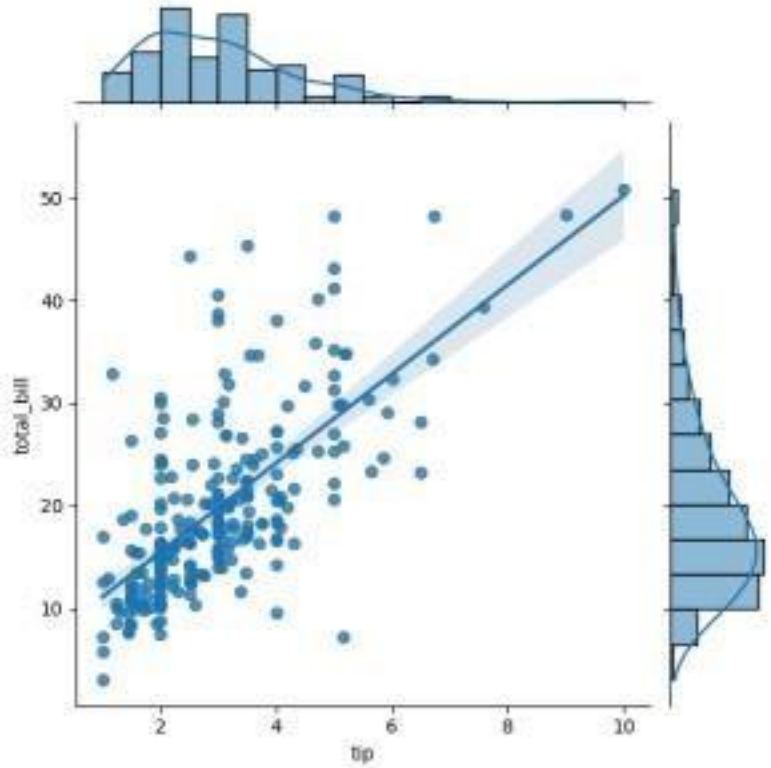

```
sns.jointplot(x=tips.tip,y=tips.total_bill)
```

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



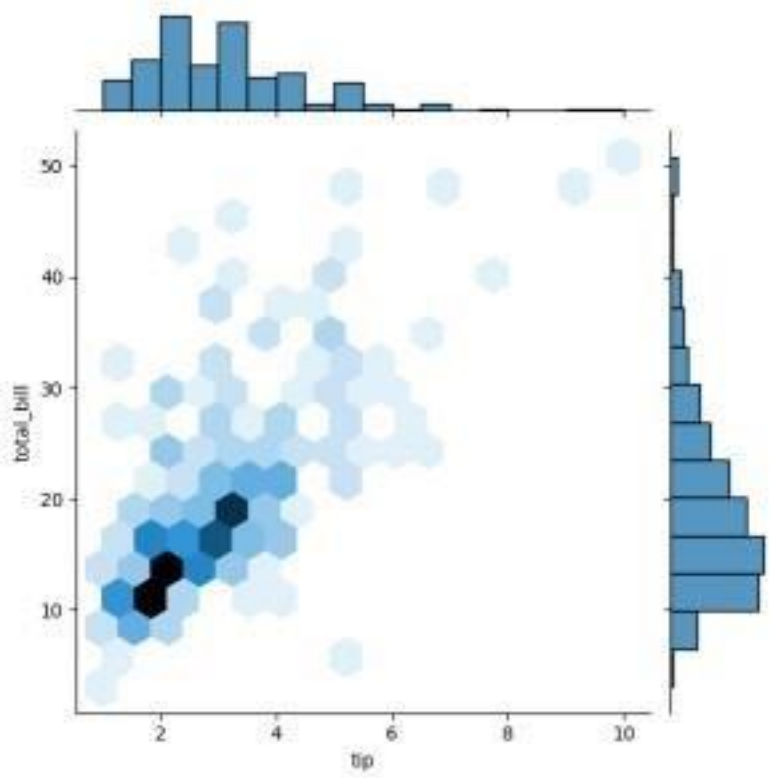

```
sns.jointplot(x=tips.tip,y=tips.total_bill,kind="reg")
```

```
<seaborn.axisgrid.JointGrid at 0x79bb08fc9cf0>
```



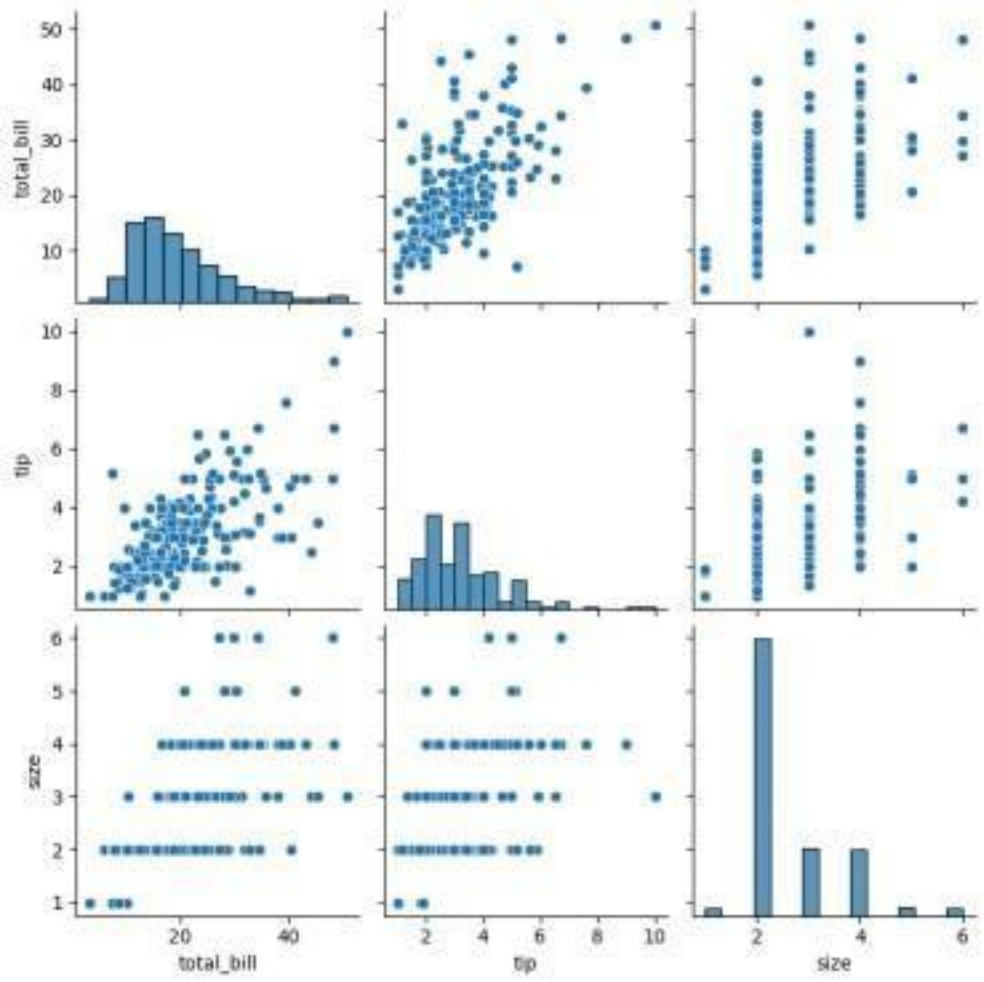

```
sns.jointplot(x=tips.tip,y=tips.total_bill,kind="hex")
```

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




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

```
<seaborn.axisgrid.PairGrid at 0x79bb06fc3d30>
```




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

| | count |
|---|---|

time

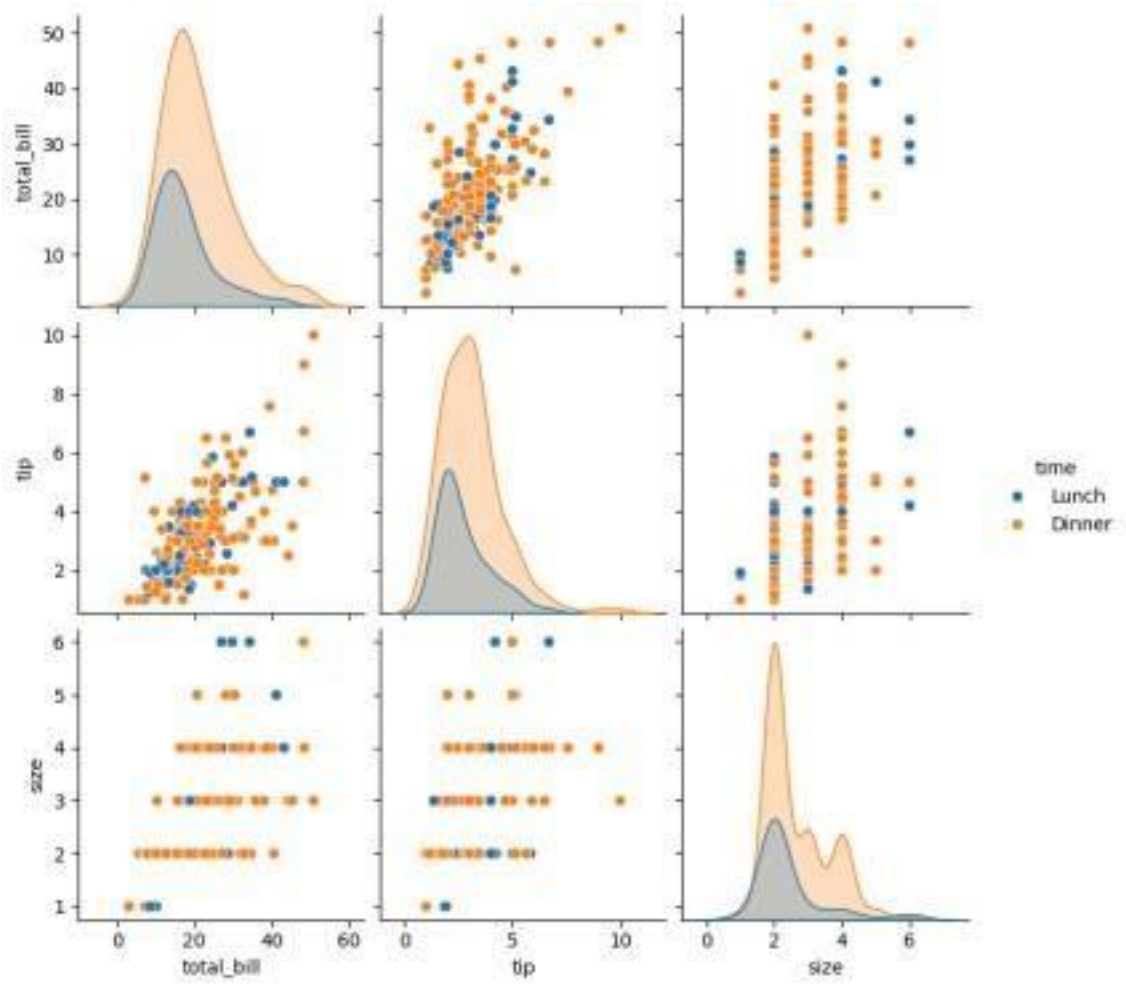
**Dinner** 176

**Lunch** 68

**dtype:** int64

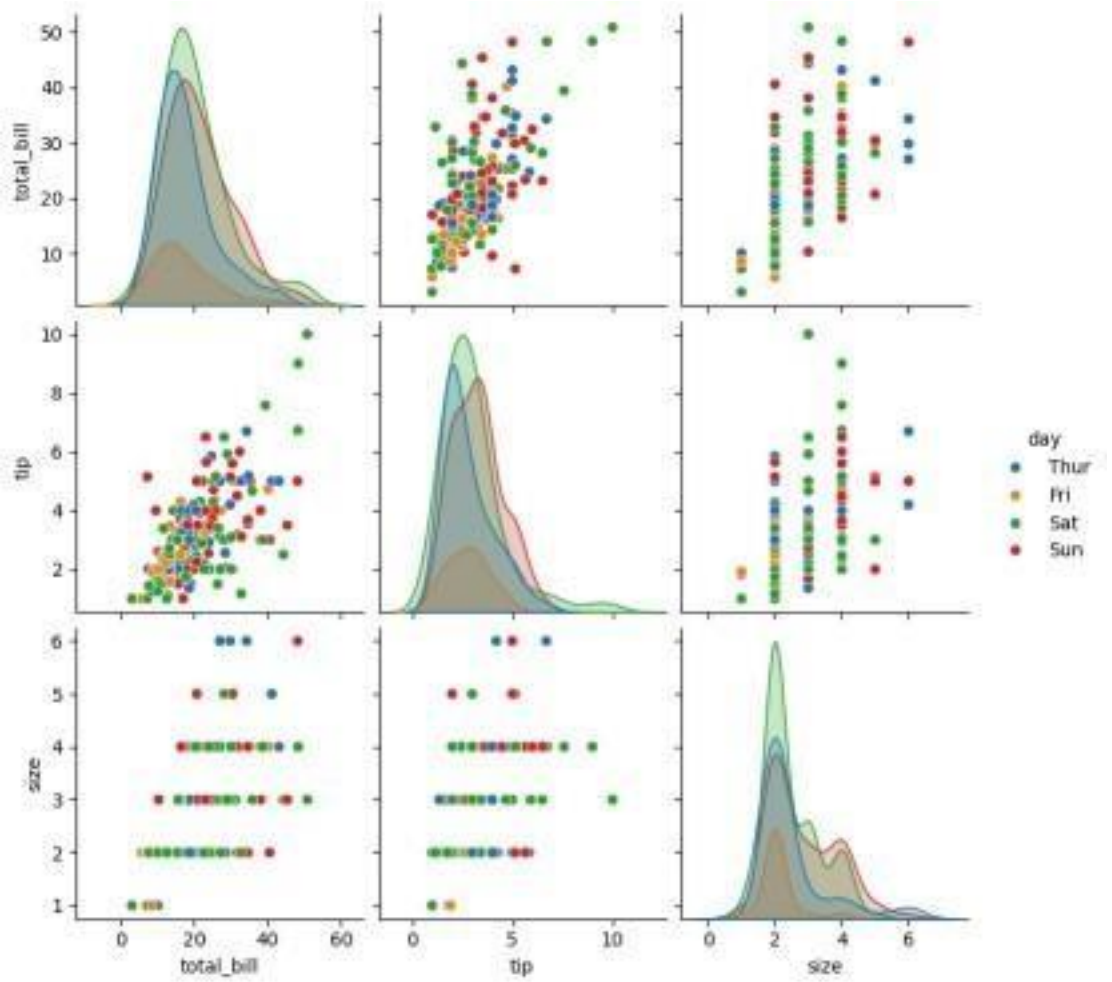
```
sns.pairplot(tips,hue='time')
```

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



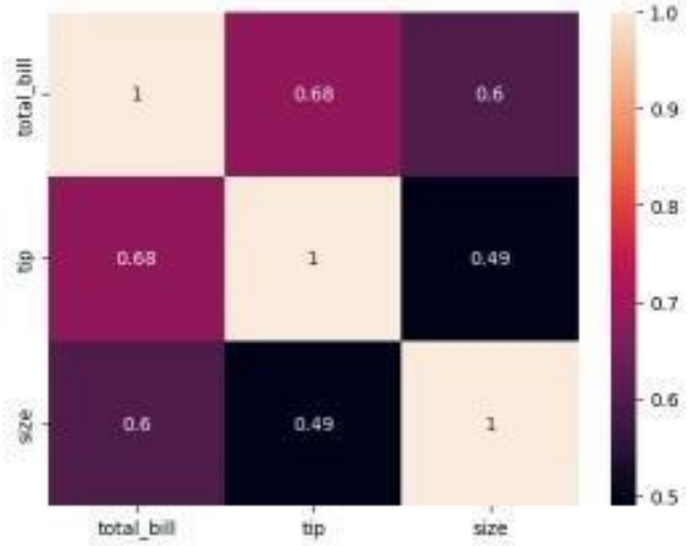

```
sns.pairplot(tips,hue='day')
```

```
<seaborn.axisgrid.PairGrid at 0x79bb08f1f6a0>
```



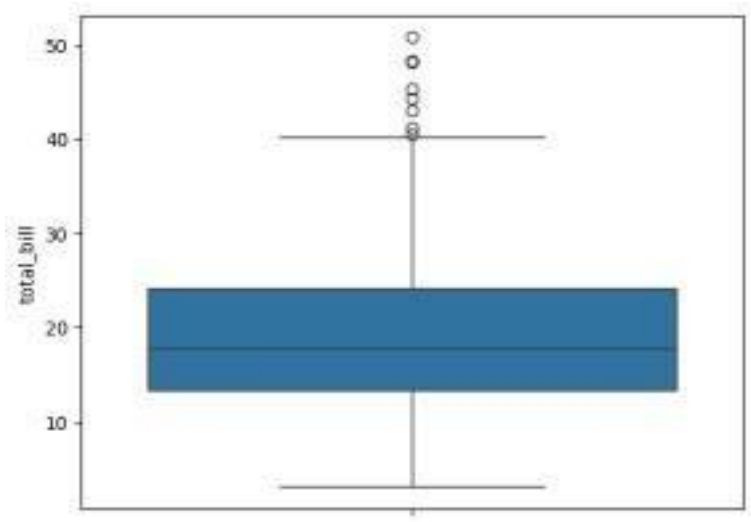

```
sns.heatmap(tips.corr(numeric_only=True),annot=True)
```

```
<Axes: >
```



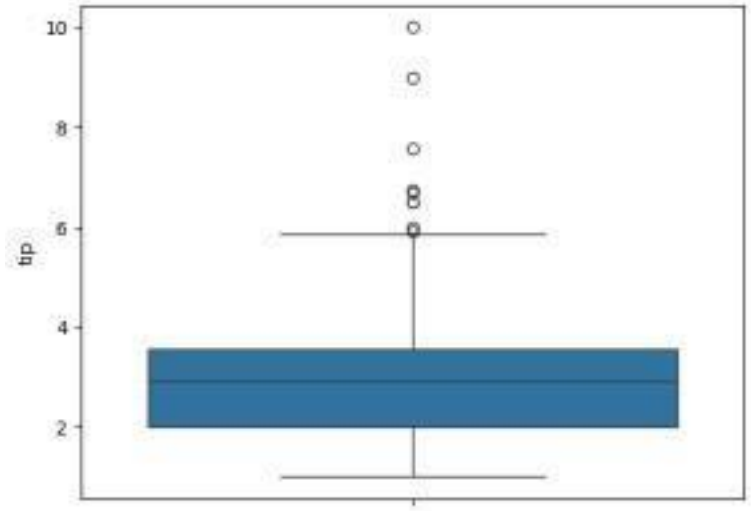

```
sns.boxplot(tips.total_bill)
```

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



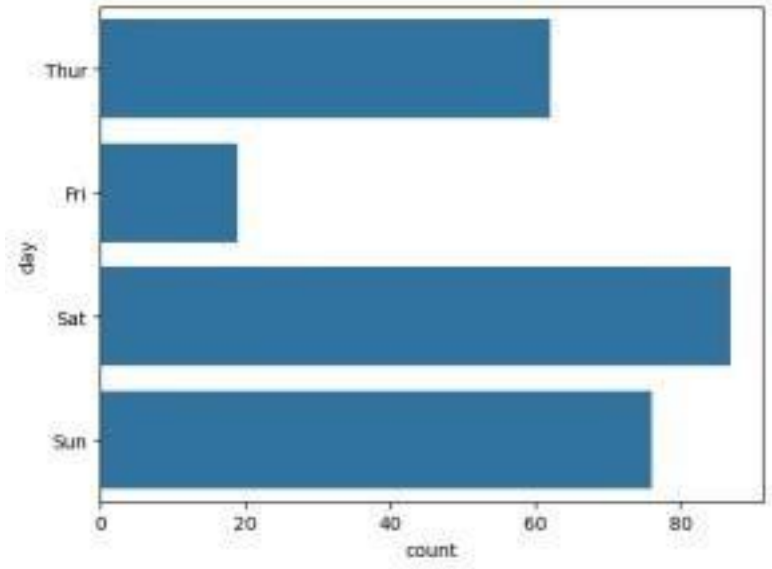

```
sns.boxplot(tips.tip)
```

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



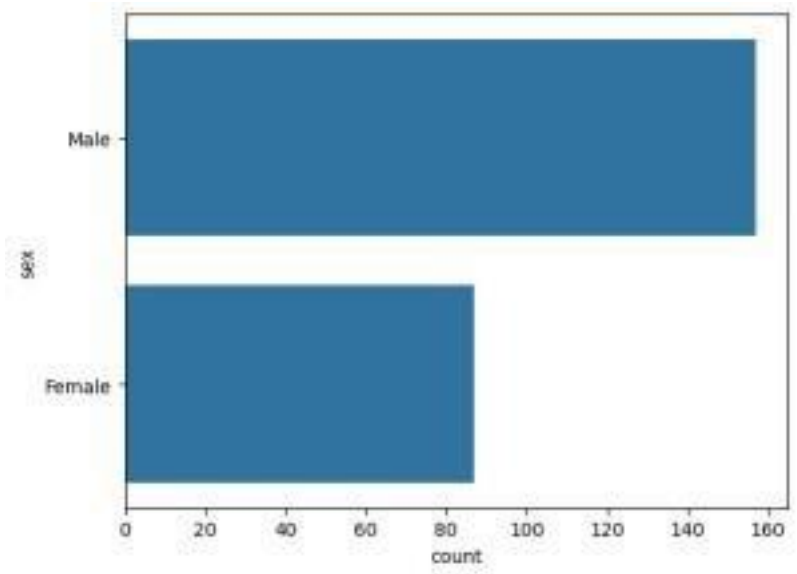

```
sns.countplot(tips.day)
```

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



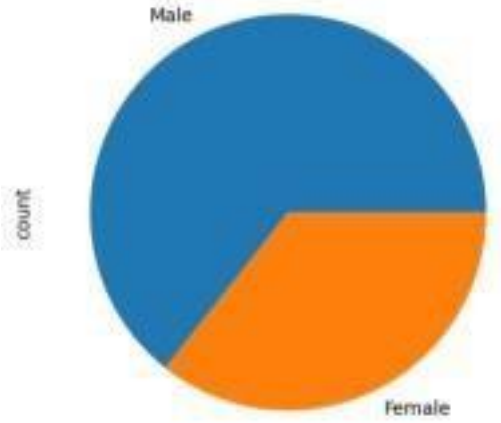

```
sns.countplot(tips.sex)
```

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



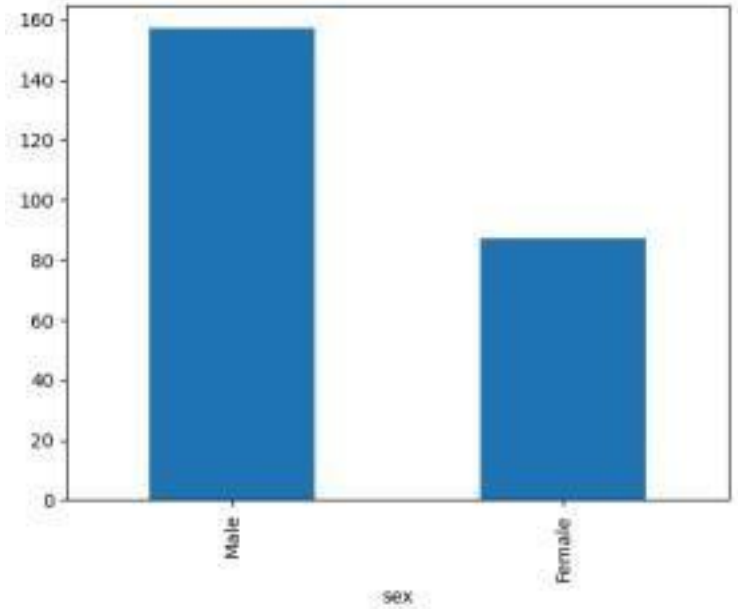

```
tips.sex.value_counts().plot(kind='pie')
```

```
<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'>
```

In [ ]: In [19]:

In [3]: In [4]:

In [5]: import numpy as np import pandas as pd
df=pd.read_csv('Salary_data .csv') df

df.info() <class

'pandas.core.frame.DataFram e'>

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.dropna(inpl ace=True) df.info()

<class
'pandas.core .frame.DataF ram e'>
RangeIndex:
30 entries,
0 to 29
Data columns
(total 2 columns): # Column Non-Null Count
Dtype ---
---
---
--- ----- 0 YearsExpe
rience 30 non-null float64 1
Salary 30

non-null int64 dtypes:
float64(1 ), int64(1) memory
usage: 612.0 bytes

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 |

df.describe()

**50%** 4.700000 65237.000000 **75%** 7.700000 100544.750000 **max**

10.500000 122391.000000 train_test_split

In [6]:
```
features=df.iloc[:,[0]].values
label=df.iloc[:,[1]].values
```

In [7]:
```
from sklearn.model_selection import
```

Out[20]:

▾ LinearRegression LinearRegression()

In [20]:
```
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)
```





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

In [27]:
```
print("Estimated Salary for {} years of experience is {}: " .format(yr_of_exp,Salary)
```

Estimated Salary for 44.0 years of experience is [[435544.30953887]]:

In [28]:

In [ ]:

In [29]:
```
df.info()
<class
```

In [1]:
```
'pandas.core.frame.DataFr
ame'> 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
nonnull  object  dtypes:
float64(4),     object(1)
memory usage: 6.0+ KB
```

In [3]:
```
import
numpy as np import
pandas as pd

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

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

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

```
df.head(
) In
```

[4]:

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

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

In [8]:
```
from sklearn.neighbors import
KNeighborsClassifier
xtrain,xtest,ytrain,ytest=train_test_split
(features,label,test_size=.2,rando
model_KNN=KNeighborsClassifier(n_neighbors
=5)
model_KNN.fit(xtrain,ytrain)
```

Out[8]:
```
KNeighborsClassifier()
```



In [9]:
```
print(model_KNN.score(xtrain,yconfusion_matrix(label,model_K
train))
print(model_KNN.score(xtest,yt
est))
```

In [10]:
```
0.9583333333333334 1.0

from sklearn.metrics import confusion_matrix
NN.predict(features))
```

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

In [11]:
```
In [ ]:
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
```



In [1]:
```
import pandas as pd
df=pd.read_csv('Social_Network_Ads.csv')
df
import numpy as np
```

Out[1]:

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

400 rows × 5 columns

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

Out[2]:

| | User ID | Gender | Age | EstimatedSalary | Purchased |
|---|---|---|---|---|---|
| **0** | 15624510 | Male | 19 | 19000 | 0 |
| **1** | 15810944 | Male | 35 | 20000 | 0 |
| **2** | 15668575 | Female | 26 | 43000 | 0 |
| **3** | 15603246 | Female | 27 | 57000 | 0 |
| **4** | 15804002 | Male | 19 | 76000 | 0 |

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

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

```
Out[5]: array([0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1,
          1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
          0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,
          0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0,
          0, 0, 0, 0, 0, 0, 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,
          1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1,
          1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 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, 1, 0, 1, 0,
          1, 0, 1, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 1, 1, 0, 0, 1, 1, 0,
          1, 1, 0, 1, 1, 0, 1, 0, 0, 0, 1, 1, 0, 1, 1, 0, 1, 0, 1, 0, 1, 0, 0,
          1, 1, 0, 1, 0, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1,
          1, 0, 1, 1, 1, 1, 0, 1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 1, 0, 0, 0, 1, 1,
          0, 1, 1, 1, 1, 1, 0, 0, 0, 1, 1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0, 1,
          1, 0, 1, 1, 0, 0, 0, 1, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1, 0, 0, 1,
          1, 0, 1, 1, 0, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 1,
          1, 0, 1, 1, 1, 0, 1, 0, 1, 0, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1,
1,  1,  1,  0,  1,  1,  1,  0,  1], dtype=int64)  import  train_test_split  from
sklearn.linear_model import In [6]:
                            LogisticRegression
```

```
features=df.iloc[:,[alues features
```

```
from sklearn.model_selection
```

In [7]:
```
in range(1,401):
```

In [8]:
```
for i
    x_train,x_test,y_train,y_test=train_test_
    s
    LogisticRegression()
    plit(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
{}".format(test_score,train_score,i)
```

Out[8]:
```
Test 0.6875 Train0.63125 Random State 3
Test 0.7375 Train0.61875 Random State 4
Test 0.6625 Train0.6375 Random State 5
Test 0.65 Train0.640625 Random State 6
Test 0.675 Train0.634375 Random State 7
Test 0.675 Train0.634375 Random State 8
Test 0.65 Train0.640625 Random State 10
Test 0.6625 Train0.6375 Random State 11
Test 0.7125 Train0.625 Random State 13
Test 0.675 Train0.634375 Random State 16
Test 0.7 Train0.628125 Random State 17
Test 0.7 Train0.628125 Random State 21
Test 0.65 Train0.640625 Random State 24
Test 0.6625 Train0.6375 Random State 25
Test 0.75 Train0.615625 Random State 26
Test 0.675 Train0.634375 Random State 27
Test 0.7 Train0.628125 Random State 28
Test 0.6875 Train0.63125 Random State 29
Test 0.6875 Train0.63125 Random State 31
T t 0 6625 T i 0 6375 R d St t 37
```

```
x_train,x_test,y_train,y_test=train_test_
s plit(features,label,test_size=0.2,
finalModel=LogisticRegression()
finalModel.fit(x_train,y_train)
```

In [9]:

In [10]:
```
from sklearn.metrics import
```

```
print(finalModel.score(x_train,y_tra
in))

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

```
0.834375
0.9125
```

```
classification_report
print(classification_report(label,fi
nalModel.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
```

```
import seaborn as sns
%matplotlib inline

df=pd.read_csv('Mall_Customer s.csv')
```

In [1]:

```
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 nonnull
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
```

In [2]: In [3]:

In [4]:

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

usage: 7.9+ KB

```
df.head()
```

```
matplotlib.pyplot plt
```

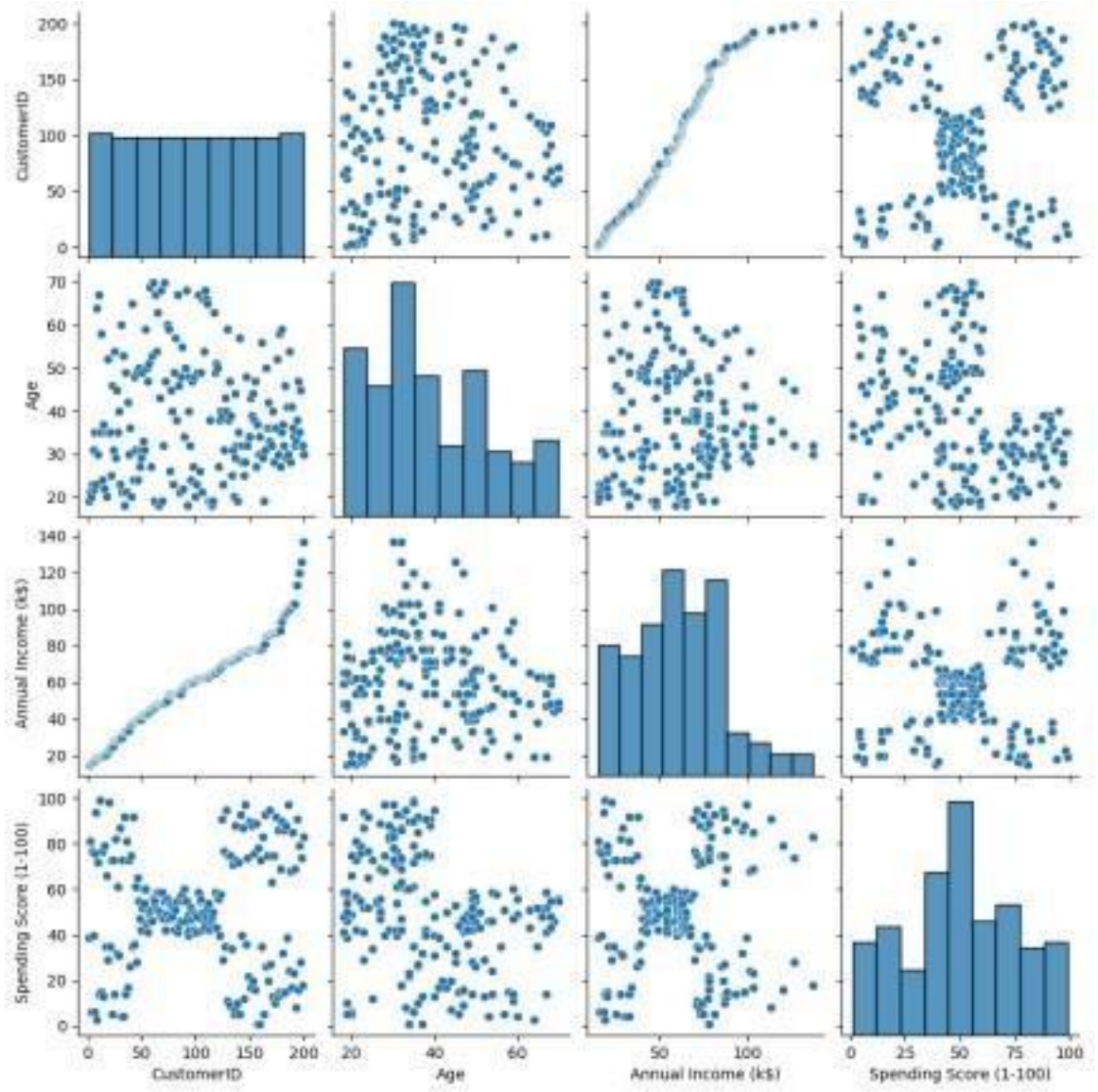
Out[4]:

| | 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]:
```

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

```
In [7]:
model.fit(features)
```

```
.loc[row_indexer,col_indexer] = value
```

```
In [8]:
```

instead

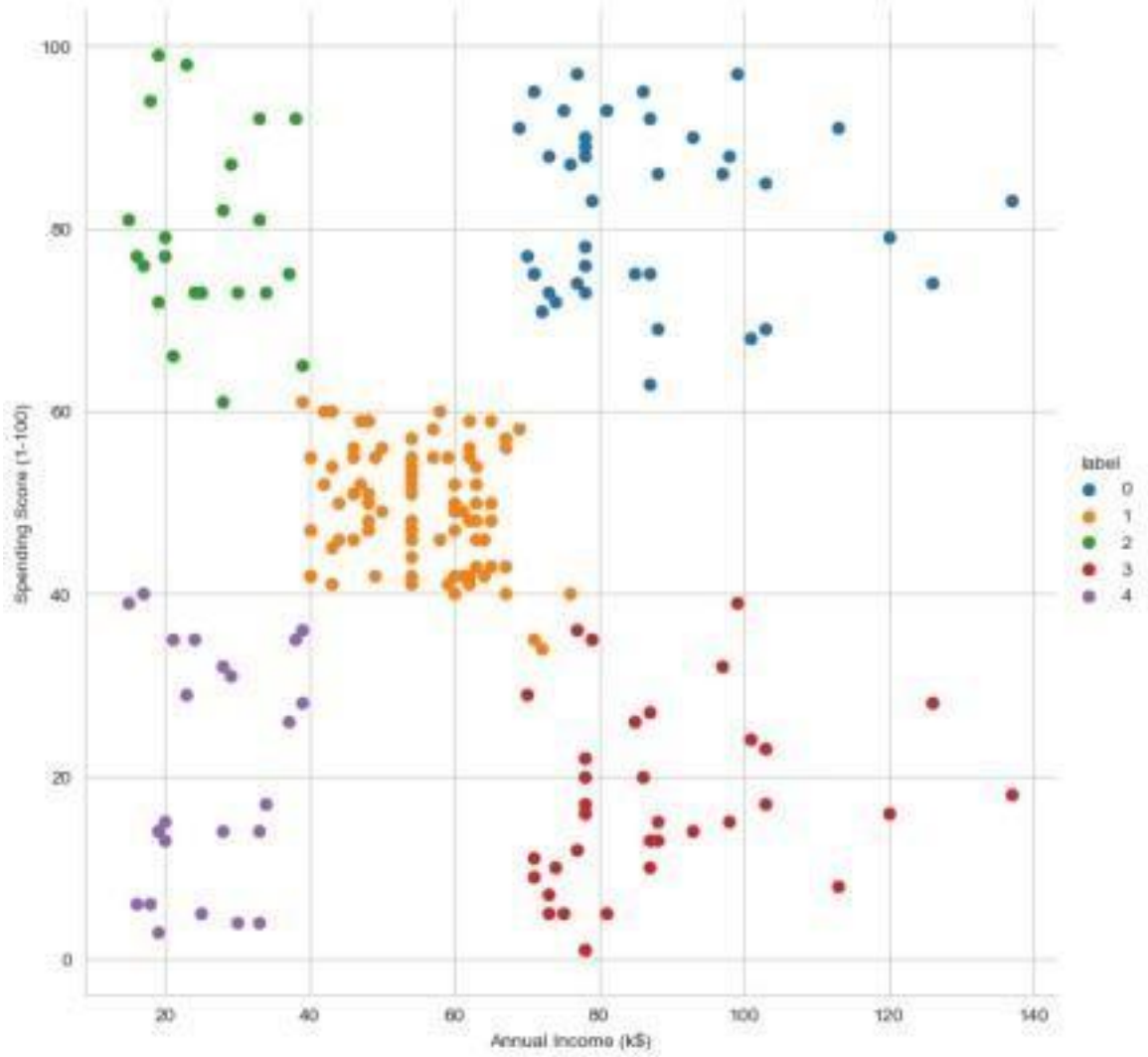
```
Final=df.iloc[:,[3,4]]
Final['label']=model.predict(features)
```

```
     Final['label']=model.predict(features)
```

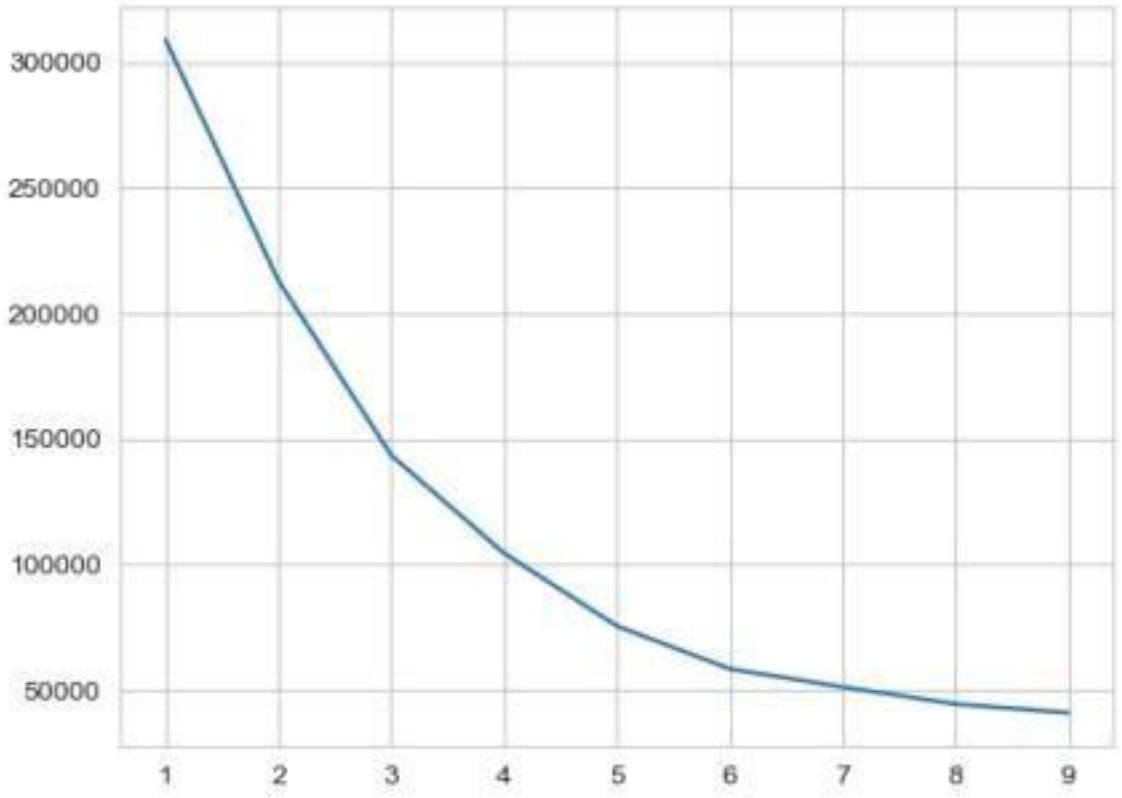
Out[8]:

| | 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>]
```


300000
250000
200000
150000
100000
50000
1
2
3
4
5
6
7
8
9