RAJALAKSHMI ENGINEERING COLLEGE

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Department of Computer Science and Engineering

CS23334 Fundamentals of Data Science Lab

III semester II Year (2023R)

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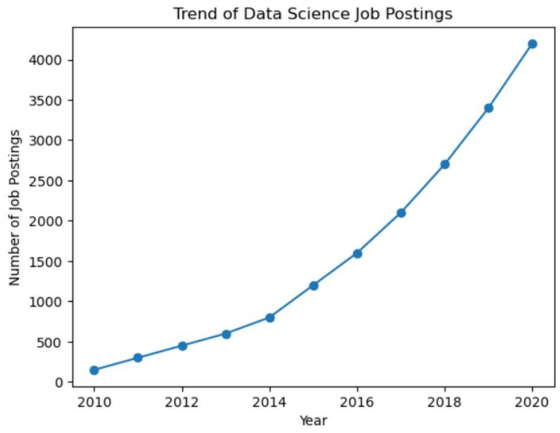
Exp No:1. a Analyze the trend of data science job postings over the last decade

Description: Use web scraping (e.g., BeautifulSoup) or APIs (e.g., LinkedIn API) to gather data on the number of data science job postings each year. Use pandas for data manipulation and matplotlib/seaborn for visualization.

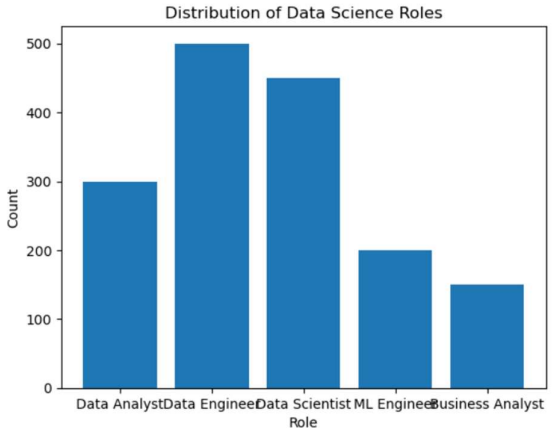
```
[ ]: #1.a
import pandas as pd
import matplotlib.pyplot as plt
data = {'Year': list(range(2010, 2021)), 'Job Postings': [150, 300, 450, 600, 800, 1200, 1600, 2100, 2700, 3400, 4200]}

df = pd.DataFrame(data)
plt.plot(df['Year'], df['Job Postings'], marker='o')
plt.title('Trend of Data Science Job Postings')
plt.xlabel('Year')
plt.ylabel('Number of Job Postings')
plt.show()
```



Exp No:1. b Analyze and visualize the distribution of various data science roles (Data Analyst, Data Engineer, Data Scientist, etc.) from a dataset.

Description: Use a dataset of job postings and categorize them into different roles. Visualize the distribution using pie charts or bar plots.

```
[ ]: #1.b
import matplotlib.pyplot as plt
roles = ['Data Analyst', 'Data Engineer', 'Data Scientist', 'ML Engineer', 'Business Analyst']
counts = [300, 500, 450, 200, 150]
plt.bar(roles, counts)
plt.title('Distribution of Data Science Roles')
plt.xlabel('Role')
plt.ylabel('Count')
plt.show()
```



Exp No:1. c Conduct an Experiment to differentiate Structured, Un-structured and Semi-structured data based on data sets given.

Description: Create small datasets for each type and Explain their characteristics.

```
[ ]: #1.c
structured_data = pd.DataFrame({
'ID': [1, 2, 3],
'Name': ['Alice', 'Bob', 'Charlie'],
'Age': [25, 30, 35] })
print("Structured Data:\n", structured_data)

unstructured_data = "This is an example of unstructured data. It can be a piece of text, an image, or a video file."
print("\nUnstructured Data:\n", unstructured_data)

semi_structured_data = {'ID': 1, 'Name': 'Alice', 'Attributes': {'Height': 165, 'Weight': 68}}
print("\nSemi-structured Data:\n", semi_structured_data)
```

```
Structured Data:
    ID     Name  Age
0   1    Alice   25
1   2      Bob   30
2   3  Charlie   35

Unstructured Data:
 This is an example of unstructured data. It can be a piece of text, an image, or a video file.

Semi-structured Data:
 {'ID': 1, 'Name': 'Alice', 'Attributes': {'Height': 165, 'Weight': 68}}
```

Exp No:1. d Conduct an Experiment to encrypt and decrypt given sensitive data.

Description: Use the cryptography library to encrypt and decrypt a piece of data.

```
[ ]: #1.d
from cryptography.fernet import Fernet
key = Fernet.generate_key()
f = Fernet(key)
token = f.encrypt(b"Rajalakshmi Engineering College")
token
b'...'
f.decrypt(token)
b'Rajalakshmi Engineering College'
key = Fernet.generate_key()
cipher_suite = Fernet(key)
plain_text = b"Rajalakshmi Engineering College."
cipher_text = cipher_suite.encrypt(plain_text)
decrypted_text = cipher_suite.decrypt(cipher_text)
print("Original Data:", plain_text)
print("Encrypted Data:", cipher_text)
print("Decrypted Data:", decrypted_text)
```

```
Original Data: b'Rajalakshmi Engineering College.'
Encrypted Data: b'gAAAAABpAtWBc11w79rOH2yoV5NrWJ3GM9Jy_iQWre9kOcexM-NXLCRYLGz9_z4STpP8HW6bWRkgyxVp1vJ8TKAORCwERgFKkQGff23WaMAqp3BYDe808NSsNS3xLs62KOyYIDH
7dr8a'
Decrypted Data: b'Rajalakshmi Engineering College.'
```

Exp No:2 Upload and Analyze the data set given in csv format and perform data preprocessing and visualization.

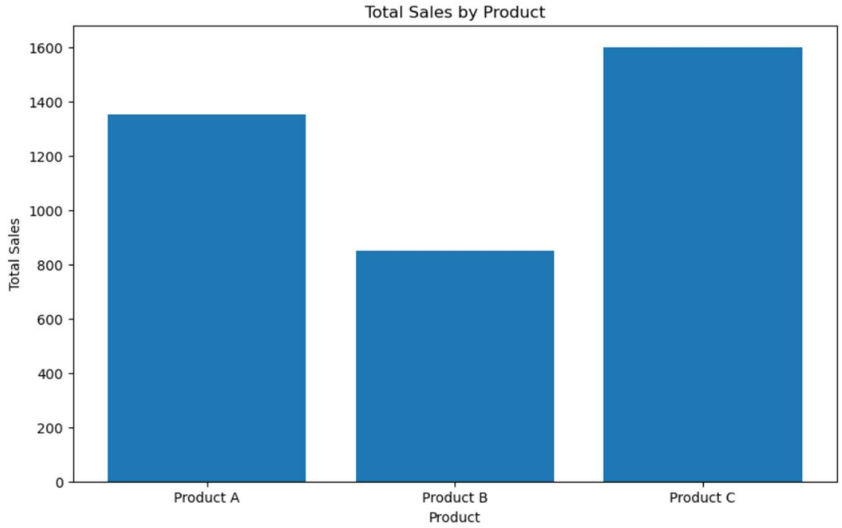
Description: Use sample data set sales-data. csv.

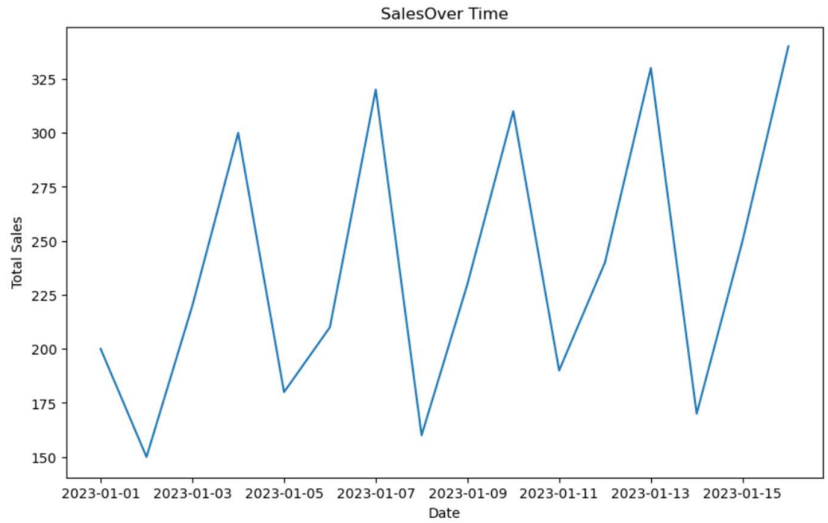
```
[ ]: #2
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

file_path="sales_data.csv"
df = pd.read_csv(file_path)

print(df.head())

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

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

print(df.describe())

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

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['Date'] = pd.to_datetime(df['Date'],dayfirst=True)
sales_over_time = df.groupby('Date').agg({'Sales': 'sum'}).reset_index()
plt.figure(figsize=(10, 6))
plt.plot(sales_over_time['Date'],sales_over_time['Sales'])
plt.xlabel('Date')
plt.ylabel('Total Sales')
plt.title('Sales Over Time')
plt.show()
```

```
df['Date'] = pd.to_datetime(df['Date'],dayfirst=True)
sales_over_time = df.groupby('Date').agg({'Sales': 'sum'}).reset_index()
plt.figure(figsize=(10, 6))
plt.plot(sales_over_time['Date'],sales_over_time['Sales'])
plt.xlabel('Date')
plt.ylabel('Total Sales')
plt.title('Sales Over Time')
plt.show()

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

correlation_matrix = df.corr(numeric_only=True)
print(correlation_matrix)

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

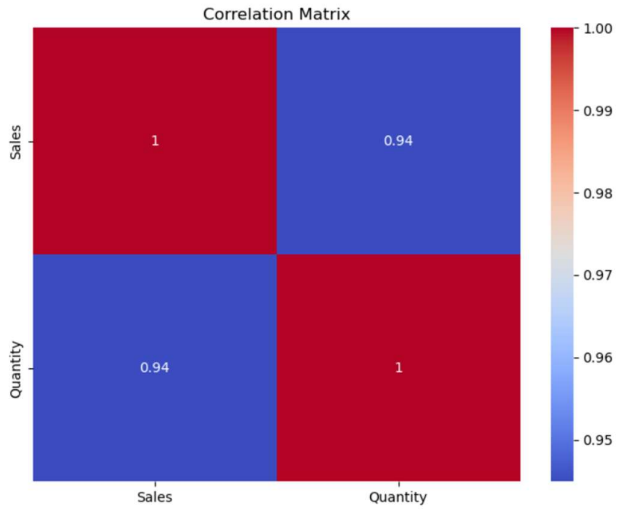
```
         Date    Product  Sales  Quantity Region
0  01-01-2023  Product A    200         4  North
1  02-01-2023  Product B    150         3  South
2  03-01-2023  Product A    220         5  North
3  04-01-2023  Product C    300         6   East
4  05-01-2023  Product B    180         4   West
Date        0
Product     0
Sales       0
Quantity    0
Region      0
dtype: int64
            Sales   Quantity
count   16.000000  16.000000
mean   237.500000   5.375000
std     64.031242   1.746425
min    150.000000   3.000000
25%    187.500000   4.000000
50%    225.000000   5.500000
75%    302.500000   7.000000
```

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





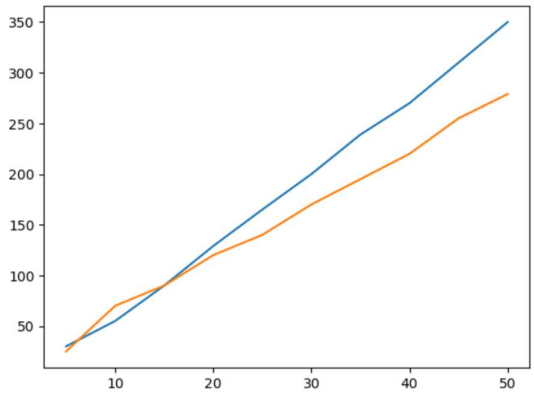

```
Product  Product A  Product B  Product C
Region
East             0          0       1600
North         1350          0          0
South            0        480          0
West             0        370          0
              Sales  Quantity
Sales      1.000000  0.944922
Quantity   0.944922  1.000000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


Correlation Matrix
Sales
Quantity
1
0.94
0.94
1
Sales
Quantity
1.00
0.99
0.98
0.97
0.96
0.95

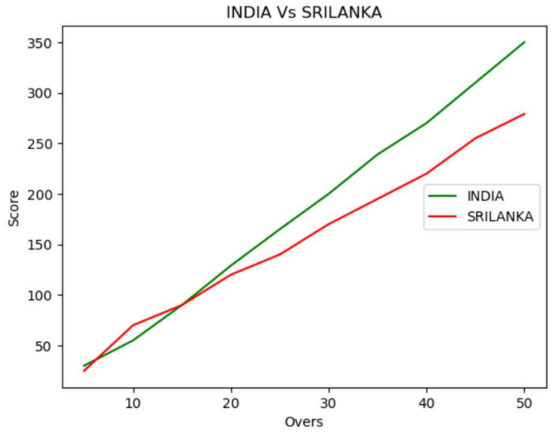
Exp No:3. a Conduct an Experiment to show data visualization using line plot

Description: Take any sample data either through csv file or data fetched directly through code.

```
[ ]: import matplotlib.pyplot as cricket
Overs=list(range(5,51,5))
Indian_Score=[30,55,90,129,165,200,239,270,310,350]
Srilankan_Score=[25,70,90,120,140,170,195,220,255,279]
cricket.plot(Overs,Indian_Score)
cricket.plot(Overs,Srilankan_Score)
cricket.show()
cricket.title("INDIA Vs SRILANKA")
cricket.xlabel("Overs")
cricket.ylabel("Score")
cricket.legend()
cricket.plot(Overs,Indian_Score,color="green",label="INDIA")
cricket.plot(Overs,Srilankan_Score,color="red",label="SRILANKA")
cricket.legend(loc="center right")
```



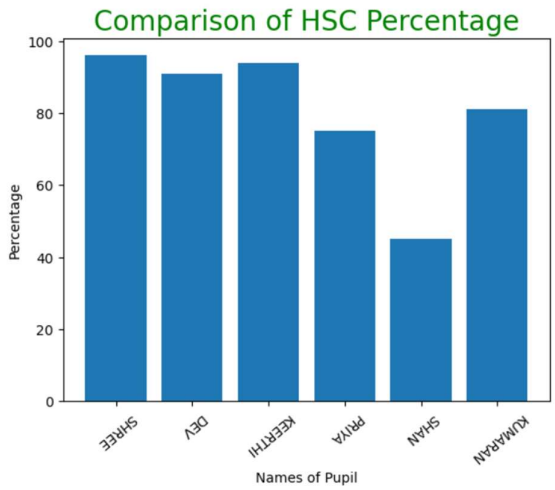

```
[19]: <matplotlib.legend.Legend at 0x1ee61a97dc0>
```



Exp No:3. b Conduct an Experiment to show data visualization using bar chart.

Description: Take any sample data either through csv file or data fetched directly through code.

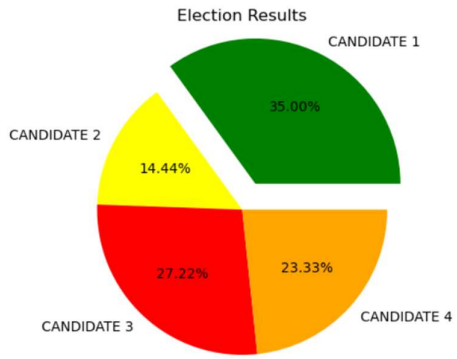
```
[5]: import matplotlib.pyplot as hscmark
import numpy as np
Names = ['SHREE', 'DEV', 'KEERTHI', 'PRIYA', 'SHAN', 'KUMARAN']
xaxis = np.arange(len(Names))
Percentage_hsc = [96, 91, 94, 75, 45, 81]
hscmark.bar(Names, Percentage_hsc)
hscmark.xticks(xaxis, Names, rotation=220)
hscmark.xlabel("Names of Pupil")
hscmark.ylabel("Percentage")
hscmark.title("Comparison of HSC Percentage", fontsize=20, color="green")
hscmark.show()
```



Exp No:3. c Conduct an Experiment to show data visualization using pie chart.

Description: Take any sample data either through csv file or data fetched directly through code.

```
[3]: import matplotlib.pyplot as election
labels = ['CANDIDATE 1', 'CANDIDATE 2', 'CANDIDATE 3', 'CANDIDATE 4']
Votes = [315, 130, 245, 210]
colors = ['green', 'yellow', 'red', 'orange']
explode = (0.2, 0, 0, 0)
election.pie(Votes, labels=labels, colors=colors, explode=explode,autopct="%.2f%%")
election.title('Election Results')
election.show()
```



Exp No:4 To Count the frequency of occurrence of a word in a body of text is often needed during text processing.

Description: Import the word_tokenize function and gutenberg.

[2]:
```
import nltk
from nltk.tokenize import word_tokenize
from nltk.corpus import gutenberg
nltk.download('gutenberg')
nltk.download('punkt')
nltk.download('punkt_tab')
sample = gutenberg.raw("austen-emma.txt")
token = word_tokenize(sample)
wlist = []
for i in range(50):
    wlist.append(token[i])
wordfreq = [wlist.count(w) for w in wlist]
print("Pairs\n" + str(list(zip(wlist, wordfreq))))
```

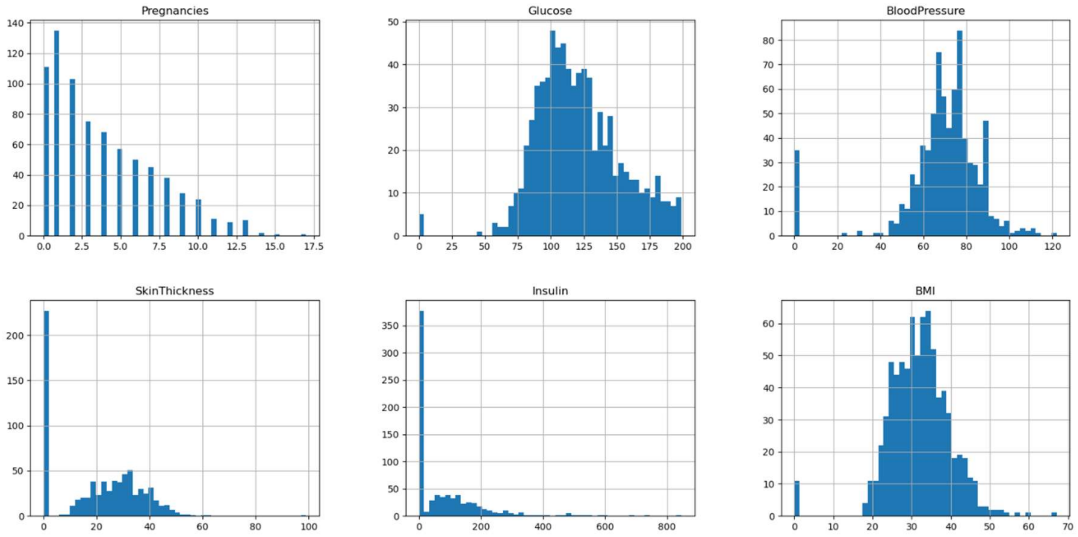
```
[nltk_data] Downloading package gutenberg to
[nltk_data]     C:\Users\merly\AppData\Roaming\nltk_data...
[nltk_data]   Package gutenberg is already up-to-date!
[nltk_data] Downloading package punkt to
[nltk_data]     C:\Users\merly\AppData\Roaming\nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package punkt_tab to
[nltk_data]     C:\Users\merly\AppData\Roaming\nltk_data...
[nltk_data]   Unzipping tokenizers\punkt_tab.zip.
Pairs
[('[', 1), ('Emma', 2), ('by', 1), ('Jane', 1), ('Austen', 1), ('1816', 1), (']', 1), ('VOLUME', 1), ('I', 2), ('CHAPTER', 1), ('I', 2), ('Emma', 2), ('W
oodhouse', 1), (',', 5), ('handsome', 1), (',', 5), ('clever', 1), (',', 5), ('and', 3), ('rich', 1), (',', 5), ('with', 2), ('a', 1), ('comfortable',
1), ('home', 1), ('and', 3), ('happy', 1), ('disposition', 1), (',', 5), ('seemed', 1), ('to', 1), ('unite', 1), ('some', 1), ('of', 2), ('the', 2), ('be
st', 1), ('blessings', 1), ('of', 2), ('existence', 1), (';', 1), ('and', 3), ('had', 1), ('lived', 1), ('nearly', 1), ('twenty-one', 1), ('years', 1),
('in', 1), ('the', 2), ('world', 1), ('with', 2)]
```

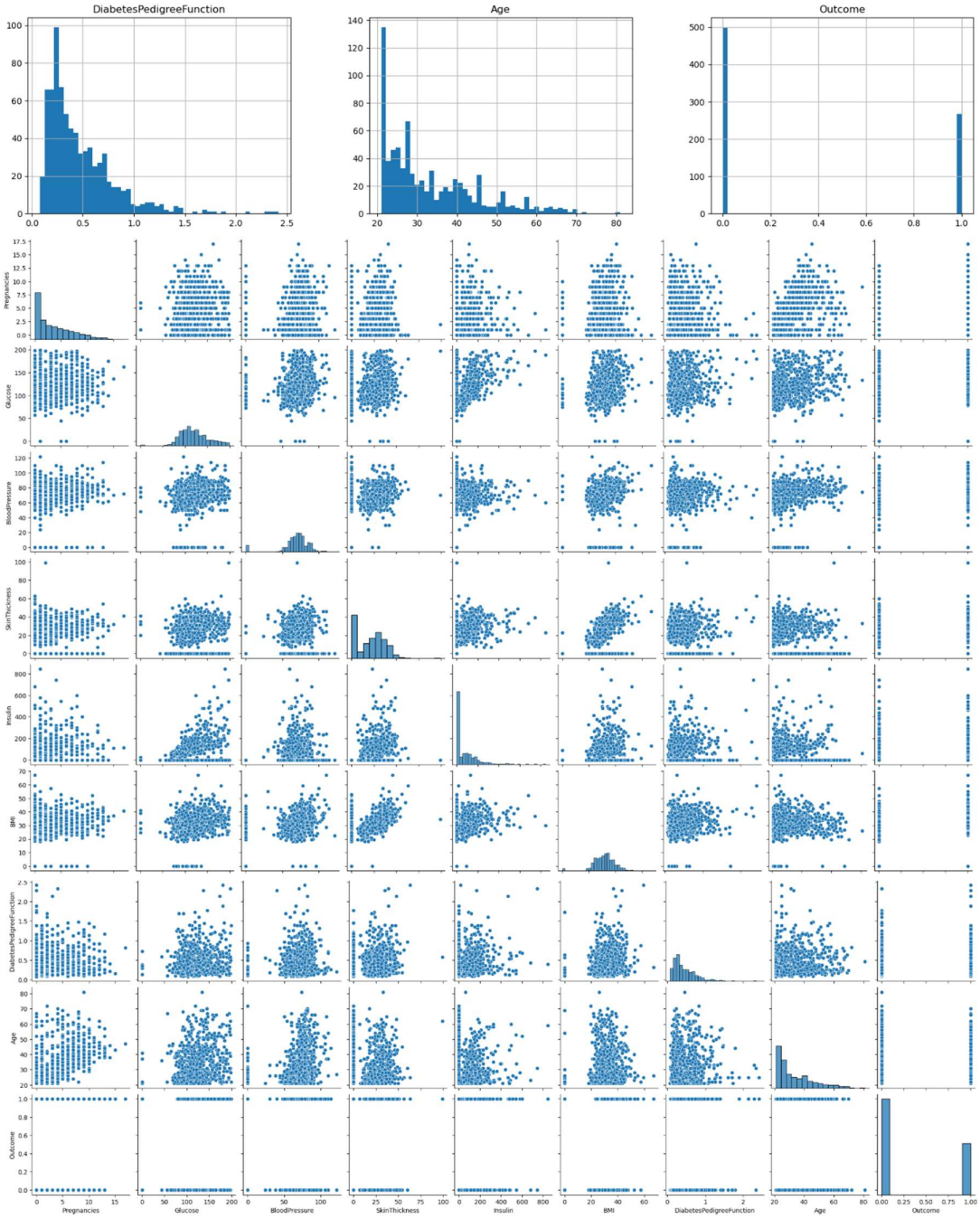
Exp No:5 Data Collection and Initial Exploration

Objective: To collect, load, and perform initial Exploration of the diabetes dataset.

```
[ ]: import pandas as pd
df=pd.read_csv("diabetes.csv")
print(df.info())
print(df.describe())
import matplotlib.pyplot as plt
import seaborn as sns

df.hist(bins=50,figsize=(20,15))
plt.show()

sns.pairplot(df)
plt.show()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Pregnancies               768 non-null    int64
 1   Glucose                   768 non-null    int64
 2   BloodPressure             768 non-null    int64
 3   SkinThickness             768 non-null    int64
 4   Insulin                   768 non-null    int64
 5   BMI                       768 non-null    float64
 6   DiabetesPedigreeFunction  768 non-null    float64
 7   Age                       768 non-null    int64
 8   Outcome                   768 non-null    int64
dtypes: float64(2), int64(7)
memory usage: 54.1 KB
None
       Pregnancies     Glucose  BloodPressure  SkinThickness     Insulin  \
count   768.000000  768.000000     768.000000     768.000000  768.000000
mean      3.845052  120.894531      69.105469      20.536458   79.799479
std       3.369578   31.972618      19.355807      15.952218  115.244002
min       0.000000    0.000000       0.000000       0.000000    0.000000
25%       1.000000   99.000000      62.000000       0.000000    0.000000
50%       3.000000  117.000000      72.000000      23.000000   30.500000
75%       6.000000  140.250000      80.000000      32.000000  127.250000
max      17.000000  199.000000     122.000000      99.000000  846.000000

              BMI  DiabetesPedigreeFunction         Age     Outcome
count  768.000000                768.000000  768.000000  768.000000
mean    31.992578                  0.471876   33.240885    0.348958
std      7.884160                  0.331329   11.760232    0.476951
min      0.000000                  0.078000   21.000000    0.000000
25%     27.300000                  0.243750   24.000000    0.000000
50%     32.000000                  0.372500   29.000000    0.000000
75%     36.600000                  0.626250   41.000000    1.000000
max     67.100000                  2.420000   81.000000    1.000000
```




DiabetesPedigreeFunction
Age
Outcome
Pregnancies
Glucose
BloodPressure
SkinThickness
Insulin
BMI
DiabetesPedigreeFunction
Age
Outcome

Exp:6 Handling Missing and Inappropriate Data in a Dataset

Aim: Demonstrate an Experiment to handle missing data and inappropriate data in a Data set using Python Pandas Library for Data Preprocessing.

[ ]:
```
import numpy as np
import pandas as pd
df=pd.read_csv("Hotel.csv")
df
```

[25]:

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

[ ]:
```
df.duplicated()
```

[26]:
```
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
```

[28]:

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

[ ]:
```
len(df)
```

[29]:
```
10
```

[ ]:
```
index=np.array(list(range(0,len(df))))
df.set_index(index,inplace=True)
index
```

[30]:
```
array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
```

[ ]:
```
df
```

[31]:

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

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

[32]:

	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

[ ]:
```
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
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df.CustomerID.loc[df.CustomerID<0]=np.nan
C:\Users\REC\AppData\Local\Temp\ipykernel_9864\2080958306.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df.Bill.loc[df.Bill<0]=np.nan
C:\Users\REC\AppData\Local\Temp\ipykernel_9864\2080958306.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df.EstimatedSalary.loc[df.EstimatedSalary<0]=np.nan
```

[33]:

	CustomerID	Age_Group	Rating(1-5)	Hotel	FoodPreference	Bill	NoOfPax	EstimatedSalary
0	1.0	20-25	4	Ibis	veg	1300.0	2	40000.0
1	2.0	30-35	5	LemonTree	Non-Veg	2000.0	3	59000.0
2	3.0	25-30	6	RedFox	Veg	1322.0	2	30000.0
3	4.0	20-25	-1	LemonTree	Veg	1234.0	2	120000.0
4	5.0	35+	3	Ibis	Vegetarian	989.0	2	45000.0
5	6.0	35+	3	Ibys	Non-Veg	1909.0	2	122220.0
6	7.0	35+	4	RedFox	Vegetarian	1000.0	-1	21122.0
7	8.0	20-25	7	LemonTree	Veg	2999.0	-10	345673.0
8	9.0	25-30	2	Ibis	Non-Veg	3456.0	3	NaN
9	10.0	30-35	5	RedFox	non-Veg	6755.0	4	87777.0

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

```
C:\Users\REC\AppData\Local\Temp\ipykernel_9864\2129877948.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df['NoOfPax'].loc[(df['NoOfPax']<1) | (df['NoOfPax']>20)]=np.nan
```

[34]:

	CustomerID	Age_Group	Rating(1-5)	Hotel	FoodPreference	Bill	NoOfPax	EstimatedSalary
0	1.0	20-25	4	Ibis	veg	1300.0	2.0	40000.0
1	2.0	30-35	5	LemonTree	Non-Veg	2000.0	3.0	59000.0
2	3.0	25-30	6	RedFox	Veg	1322.0	2.0	30000.0
3	4.0	20-25	-1	LemonTree	Veg	1234.0	2.0	120000.0
4	5.0	35+	3	Ibis	Vegetarian	989.0	2.0	45000.0
5	6.0	35+	3	Ibys	Non-Veg	1909.0	2.0	122220.0
6	7.0	35+	4	RedFox	Vegetarian	1000.0	NaN	21122.0
7	8.0	20-25	7	LemonTree	Veg	2999.0	NaN	345673.0
8	9.0	25-30	2	Ibis	Non-Veg	3456.0	3.0	NaN
9	10.0	30-35	5	RedFox	non-Veg	6755.0	4.0	87777.0

[ ]:
```
df.Age_Group.unique()
```

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

[ ]:
```
df.Hotel.unique()
```

[36]:
```
array(['Ibis', 'LemonTree', 'RedFox', 'Ibys'], dtype=object)
```

[ ]:
```
df.Hotel.replace(['Ibys'],'Ibis',inplace=True)
df.FoodPreference.unique
```

[37]:
```
<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
```

[39]:

	CustomerID	Age_Group	Rating(1-5)	Hotel	FoodPreference	Bill	NoOfPax	EstimatedSalary
0	1.0	20-25	4	Ibis	Veg	1300.0	2.0	40000.0
1	2.0	30-35	5	LemonTree	Non-Veg	2000.0	3.0	59000.0
2	3.0	25-30	6	RedFox	Veg	1322.0	2.0	30000.0
3	4.0	20-25	-1	LemonTree	Veg	1234.0	2.0	120000.0
4	5.0	35+	3	Ibis	Veg	989.0	2.0	45000.0
5	6.0	35+	3	Ibis	Non-Veg	1909.0	2.0	122220.0
6	7.0	35+	4	RedFox	Veg	1000.0	2.0	21122.0
7	8.0	20-25	7	LemonTree	Veg	2999.0	2.0	345673.0
8	9.0	25-30	2	Ibis	Non-Veg	3456.0	3.0	96755.0
9	10.0	30-35	5	RedFox	Non-Veg	6755.0	4.0	87777.0

Exp:7 Experiment to detect outliers in a given data set.

Description: Understand the procedure to identify the outliers in a given dataset

```
[ ]: import numpy as np
     array=np.random.randint(1,100,16)
     array
```

```
[40]: array([38, 16, 55, 79, 35, 60, 47, 78, 18, 42, 89, 91, 43, 70, 38, 64])
```

```
[ ]: array.mean()
```

```
[41]: 53.9375
```

```
[ ]: np.percentile(array,25)
```

```
[42]: 38.0
```

```
[ ]: np.percentile(array,50)
```

```
[43]: 51.0
```

```
[ ]: np.percentile(array,75)
```

```
[44]: 72.0
```

```
[ ]: np.percentile(array,100)
```

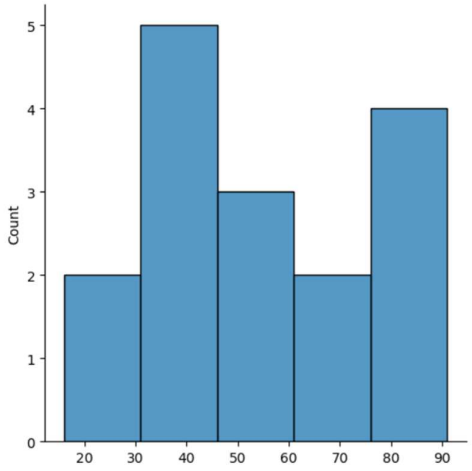
```
[45]: 91.0
```

```
[ ]: 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
```

```
[46]: (-13.0, 123.0)
```

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

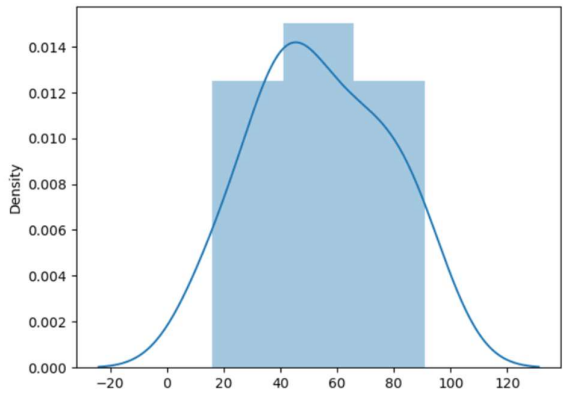
```
[47]: <seaborn.axisgrid.FacetGrid at 0x1ee591f9360>
```



[ ]:
```
sns.distplot(array)
```

```
C:\Users\REC\AppData\Local\Temp\ipykernel_9864\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)
```

[48]:
```
<Axes: ylabel='Density'>
```

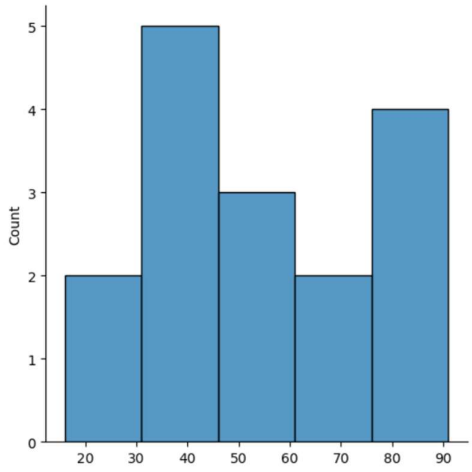


[ ]:
```
new_array=array[(array>lr) & (array<ur)]
new_array
```

[49]:
```
array([38, 16, 55, 79, 35, 60, 47, 78, 18, 42, 89, 91, 43, 70, 38, 64])
```

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

[50]:
```
<seaborn.axisgrid.FacetGrid at 0x1ee66838d00>
```



[ ]:
```
lr1,ur1=outDetection(new_array)
lr1,ur1
```

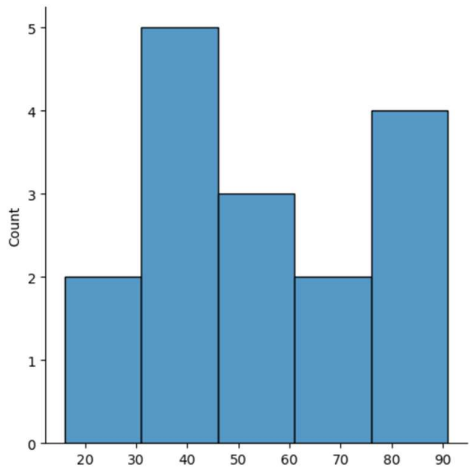
[51]:
```
(-13.0, 123.0)
```

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

[52]:
```
array([38, 16, 55, 79, 35, 60, 47, 78, 18, 42, 89, 91, 43, 70, 38, 64])
```

```
[ ]: sns.displot(final_array)
```

```
[53]: <seaborn.axisgrid.FacetGrid at 0x1ee64e3a9b0>
```



Exp:8. a Experiment to understand feature scaling.

Description: Understand the importance of feature scaling

[ ]:
```
import numpy as np
import pandas as pd
df=pd.read_csv('pre-process_datasample.csv')
df
```

[55]:

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

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

[56]:

	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
```

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

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

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

[60]:
```
SimpleImputer
SimpleImputer()
```

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

[61]:
```
SimpleImputer
SimpleImputer()
```

[ ]:
```
SimpleImputer()
```

[62]:
```
SimpleImputer
SimpleImputer()
```

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

[63]:
```
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
```

[64]:
```
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
```

[65]:
```
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
```

[66]:
```
array([[ 1.00000000e+00, -5.00000000e-01, -6.54653671e-01,
         7.58874362e-01,  7.49473254e-01],
       [-1.00000000e+00, -5.00000000e-01,  1.52752523e+00,
        -1.71150388e+00, -1.43817841e+00],
       [-1.00000000e+00,  2.00000000e+00, -6.54653671e-01,
        -1.27555478e+00, -8.91265492e-01],
       [-1.00000000e+00, -5.00000000e-01,  1.52752523e+00,
        -1.13023841e-01, -2.53200424e-01],
       [-1.00000000e+00,  2.00000000e+00, -6.54653671e-01,
         1.77608893e-01,  6.63219199e-16],
       [ 1.00000000e+00, -5.00000000e-01, -6.54653671e-01,
        -5.48972942e-01, -5.26656882e-01],
       [-1.00000000e+00, -5.00000000e-01,  1.52752523e+00,
         0.00000000e+00, -1.07356980e+00],
       [ 1.00000000e+00, -5.00000000e-01, -6.54653671e-01,
         1.34013983e+00,  1.38753832e+00],
       [ 1.00000000e+00, -5.00000000e-01, -6.54653671e-01,
         1.63077256e+00,  1.75214693e+00],
       [ 1.00000000e+00, -5.00000000e-01, -6.54653671e-01,
        -2.58340208e-01,  2.93712492e-01]])
```

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

[67]:
```
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]])
```

Exp:8. b Experiment to understand the data preprocessing in Data science

Description: Understand the importance of Data preprocessing in data science

[ ]:
```
import numpy as np
import pandas as pd
df=pd.read_csv("pre-process_datasample.csv")
df
```

[69]:

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

[ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 4 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   Country    9 non-null      object 
 1   Age        9 non-null      float64
 2   Salary     9 non-null      float64
 3   Purchased  10 non-null     object 
dtypes: float64(2), object(2)
memory usage: 448.0+ bytes
```

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

[71]:
```
0    France
Name: Country, dtype: object
```

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

[72]:
```
'France'
```

[ ]:
```
type(df.Country.mode())
```

[73]:
```
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
```

[74]:

	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)
```

[75]:

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

[ ]:
```
up=pd.concat([pd.get_dummies(df.Country),df.iloc[:,[]]])
up
```

[76]:

	France	Germany	Spain
0	1.0	0.0	0.0
1	0.0	0.0	1.0
2	0.0	1.0	0.0
3	0.0	0.0	1.0
4	0.0	1.0	0.0
5	1.0	0.0	0.0
6	0.0	0.0	1.0
7	1.0	0.0	0.0
8	1.0	0.0	0.0
9	1.0	0.0	0.0
0	NaN	NaN	NaN
1	NaN	NaN	NaN
2	NaN	NaN	NaN
3	NaN	NaN	NaN
4	NaN	NaN	NaN
5	NaN	NaN	NaN
6	NaN	NaN	NaN
7	NaN	NaN	NaN
8	NaN	NaN	NaN
9	NaN	NaN	NaN

Exp No:9 Experiment to understand EDA-Quantitative and Qualitative analysis.

Description: Understand the importance of EDA-Quantitative and Qualitative analysis.

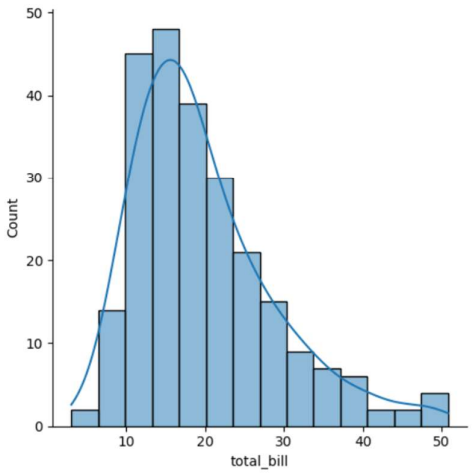
```
[ ]: import seaborn as sns
     import pandas as pd
     import numpy as np
     import matplotlib.pyplot as plt
     %matplotlib inline
     tips=sns.load_dataset('tips')
     tips.head()
```

[78]:

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

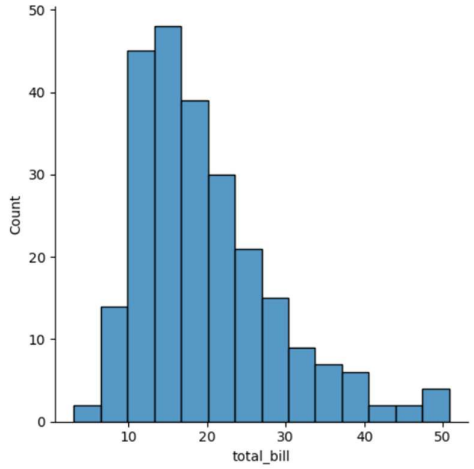
```
[ ]: sns.displot(tips.total_bill,kde=True)
```

```
[79]: <seaborn.axisgrid.FacetGrid at 0x1ee69d7eef0>
```



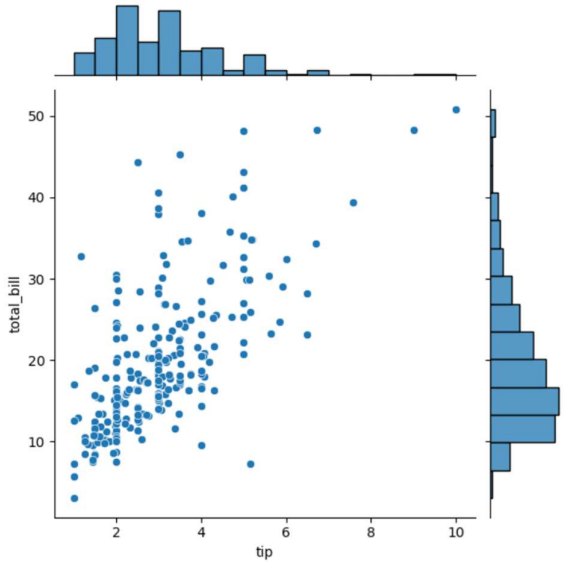
[ ]:
```
sns.displot(tips.total_bill,kde=False)
```

[80]:
```
<seaborn.axisgrid.FacetGrid at 0x1ee6adfbd00>
```



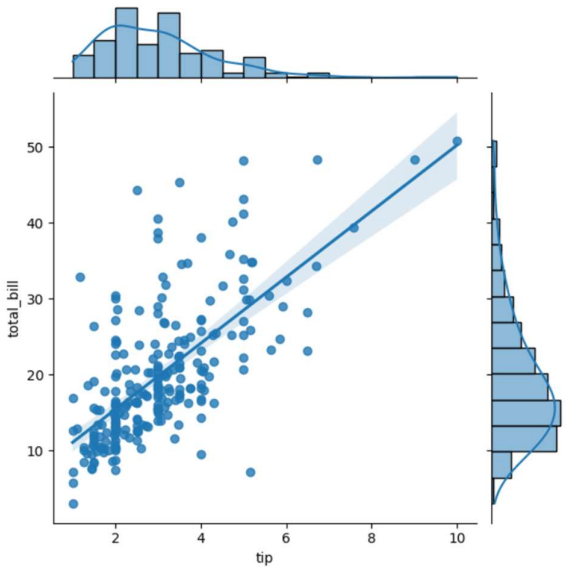
[ ]:
```
sns.jointplot(x=tips.tip,y=tips.total_bill)
```

[81]:
```
<seaborn.axisgrid.JointGrid at 0x1ee6b2ed210>
```



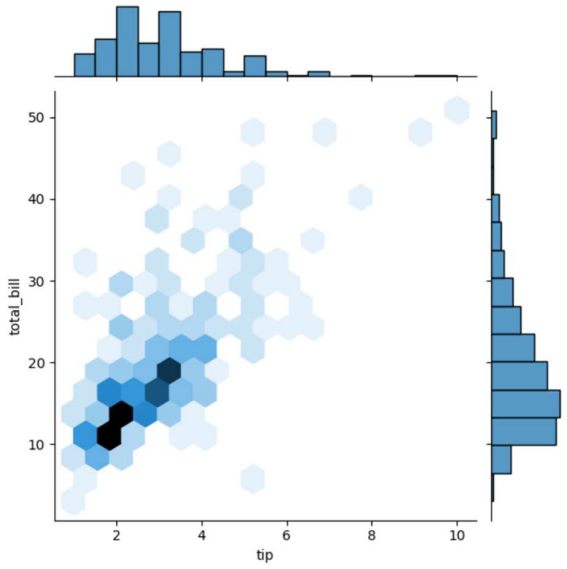
[ ]:
```
sns.jointplot(x=tips.tip,y=tips.total_bill,kind="reg")
```

[82]:
```
<seaborn.axisgrid.JointGrid at 0x1ee6b3f1120>
```



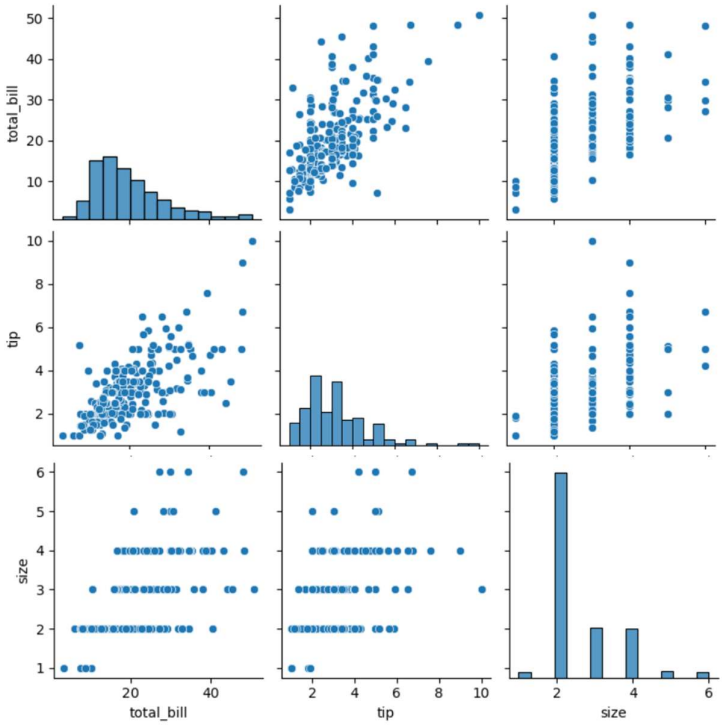
[ ]:
```
sns.jointplot(x=tips.tip,y=tips.total_bill,kind="hex")
```

[83]:
```
<seaborn.axisgrid.JointGrid at 0x1ee6b809600>
```



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

[84]:
```
<seaborn.axisgrid.PairGrid at 0x1ee6b4060e0>
```

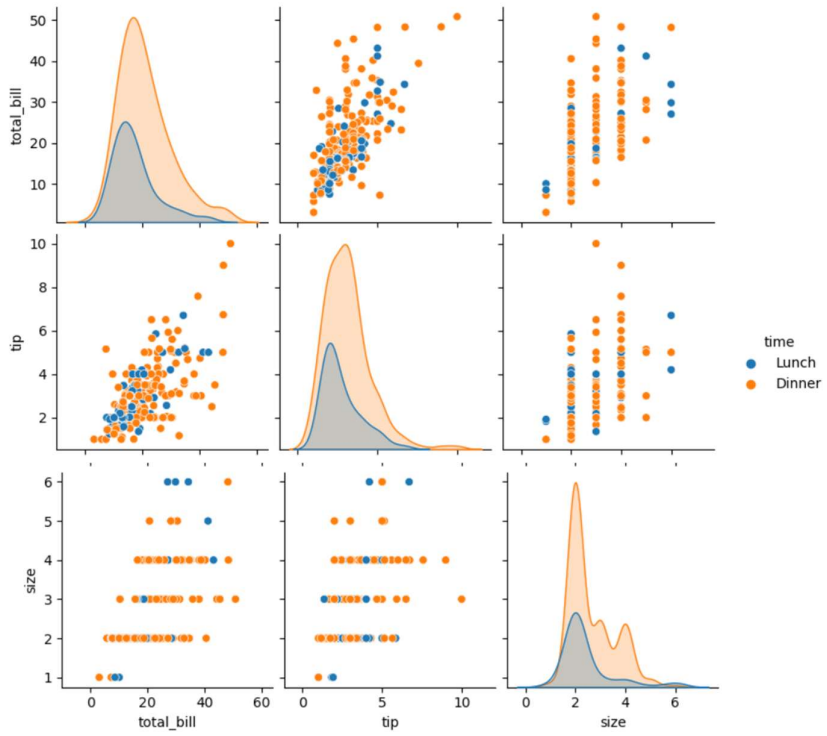


[ ]:
```
tips.time.value_counts()
```

[85]:
```
Dinner    176
Lunch      68
Name: time, dtype: int64
```

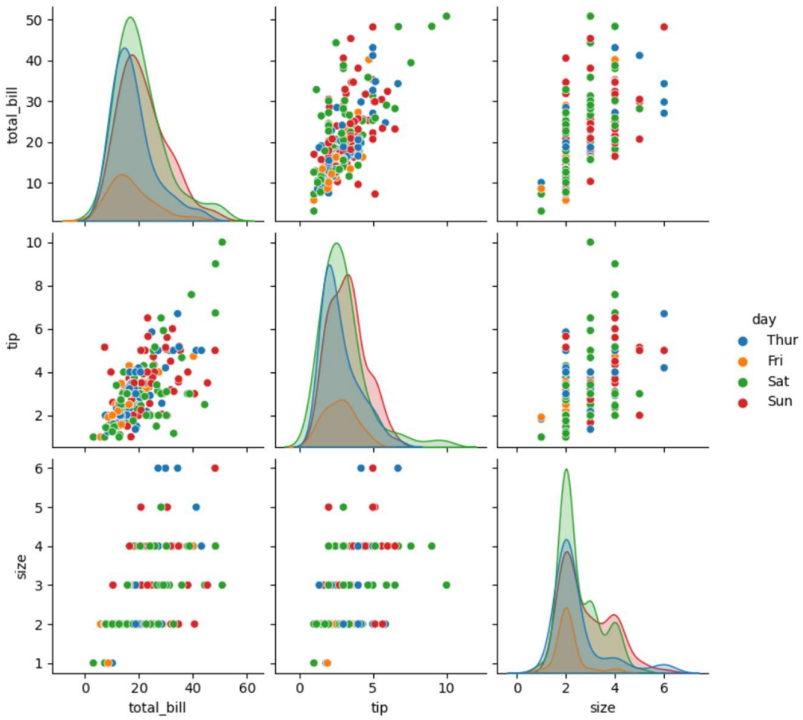
[ ]:
```
sns.pairplot(tips,hue='time')
```

[86]:
```
<seaborn.axisgrid.PairGrid at 0x1ee6c671870>
```



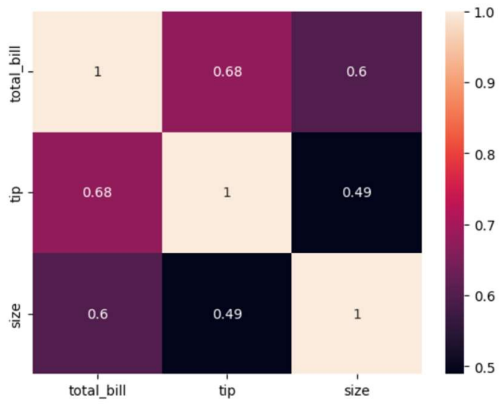
[ ]:
```
sns.pairplot(tips,hue='day')
```

[87]:
```
<seaborn.axisgrid.PairGrid at 0x1ee6cf26ce0>
```

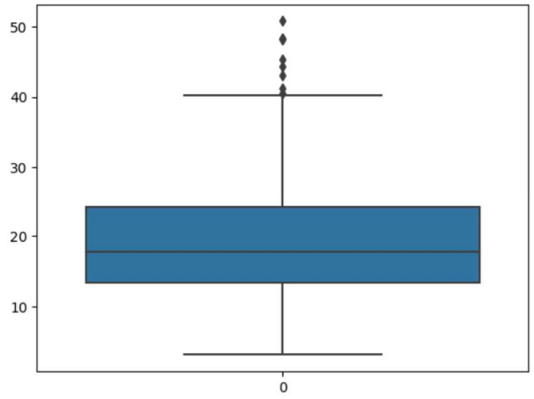


[ ]:
```
sns.heatmap(tips.corr(numeric_only=True),annot=True)
```

[88]:
```
<Axes: >
```

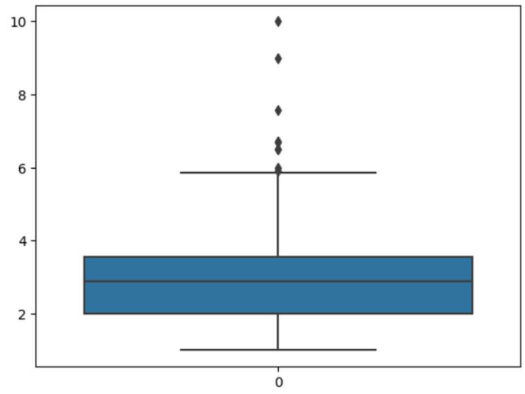


[ ]:
```
sns.boxplot(tips.total_bill)
```



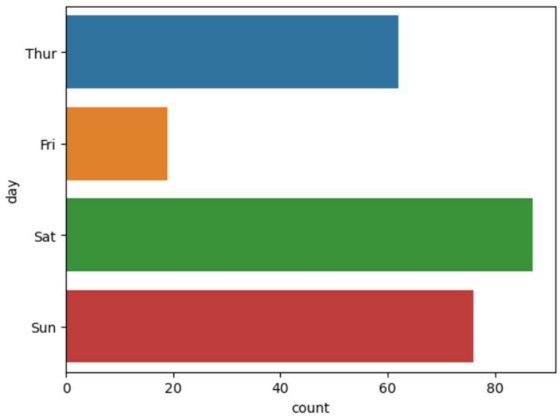
[ ]:
```
sns.boxplot(tips.tip)
```

[90]:
```
<Axes: >
```



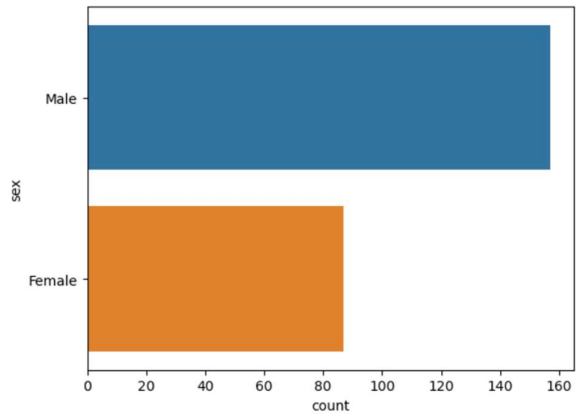
[ ]:
```
sns.countplot(data=tips,y="day")
```

[91]:
```
<Axes: xlabel='count', ylabel='day'>
```



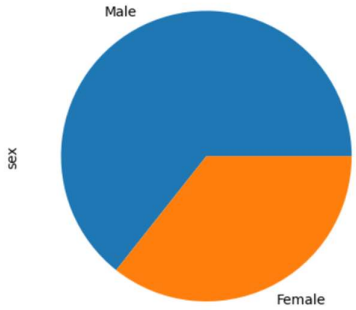
[ ]:
```
sns.countplot(data=tips,y="sex")
```

[92]:
```
<Axes: xlabel='count', ylabel='sex'>
```



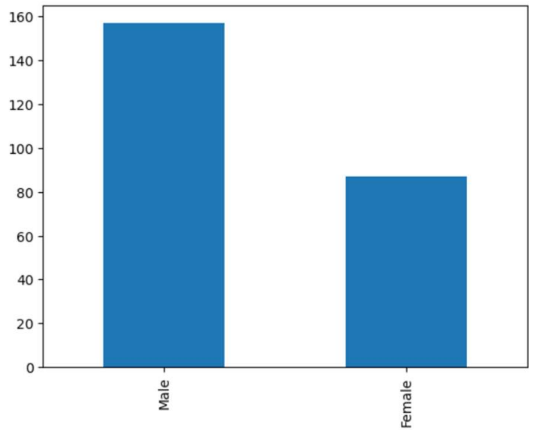
[ ]:
```
tips.sex.value_counts().plot(kind='pie')
```

[93]:
```
<Axes: ylabel='sex'>
```



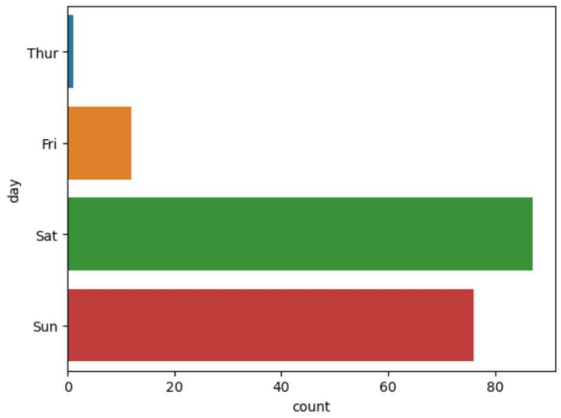
[ ]:
```
tips.sex.value_counts().plot(kind='bar')
```

[94]:
```
<Axes: >
```



[ ]:
```
sns.countplot(data=tips[tips.time == 'Dinner'], y='day')
```

[95]:
```
<Axes: xlabel='count', ylabel='day'>
```



Exp:10 Regression

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

[97]:

	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()
```

[101]:

	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)
```

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

[104]:
```
LinearRegression
LinearRegression()
```

[ ]:
```
model.score(x_train,y_train)
```

[105]:
```
0.9608732656731791
```

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

[106]:
```
0.9387922566107753
```

[ ]:
```
model.coef_
```

[107]:
```
array([[9373.93124487]])
```

[ ]:
```
model.intercept_
```

[108]:
```
array([26116.42617326])
```

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

[ ]:
```
model=pickle.load(open('SalaryPred.model','rb'))
```

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

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

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

```
Estimated Salary for 44.0 years of experience is [[438569.40094767]]:
```

Exp:11 Logistic Regression

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

[114]:

	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

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

[115]:

	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
```

[116]:
```
array([[    19,  19000],
       [    35,  20000],
       [    26,  43000],
       [    27,  57000],
       [    19,  76000],
       [    27,  58000],
       [    27,  84000],
       [    32, 150000],
       [    25,  33000],
       [    35,  65000],
       [    26,  80000],
       [    26,  52000],
       [    20,  86000],
       [    32,  18000],
       [    18,  82000],
       [    29,  80000],
       [    47,  25000],
       [    45,  26000],
       [    46,  28000],
       [    48,  29000],
       [    45,  22000],
       [    47,  49000],
       [    48,  41000],
       [    45,  22000],
       [    46,  23000],
       [    47,  20000],
       [    49,  28000],
       [    47,  30000],
       [    29,  43000],
       [    31,  18000],
       [    31,  74000],
       [    27, 137000],
       [    21,  16000],
       [    28,  44000],
       [    27,  90000],
       [    35,  27000],
       [    33,  28000],
       [    30,  49000],
       [    26,  72000],
       [    27,  31000],
       [    27,  17000],
       [    33,  51000],
```

```
[    35, 108000],
[    30,  15000],
[    28,  84000],
[    23,  20000],
[    25,  79000],
[    27,  54000],
[    30, 135000],
[    31,  89000],
[    24,  32000],
[    18,  44000],
[    29,  83000],
[    35,  23000],
[    27,  58000],
[    24,  55000],
[    23,  48000],
[    28,  79000],
[    22,  18000],
[    32, 117000],
[    27,  20000],
[    25,  87000],
[    23,  66000],
[    32, 120000],
[    59,  83000],
[    24,  58000],
[    24,  19000],
[    23,  82000],
[    22,  63000],
[    31,  68000],
[    25,  80000],
[    24,  27000],
[    20,  23000],
[    33, 113000],
[    32,  18000],
[    34, 112000],
[    18,  52000],
[    22,  27000],
[    28,  87000],
[    26,  17000],
[    30,  80000],
[    39,  42000],
[    20,  49000],
[    35,  88000],
[    30,  62000],
[    31, 118000],
[    24,  55000],
[    28,  85000],
[    26,  81000],
[    35,  50000],
[    22,  81000],
[    30, 116000],
[    26,  15000],
[    29,  28000],
[    29,  83000],
[    35,  44000],
[    35,  25000],
[    28, 123000],
[    35,  73000],
[    28,  37000],
[    27,  88000],
[    28,  59000],
[    32,  86000],
[    33, 149000],
[    19,  21000],
[    21,  72000],
[    26,  35000],
[    27,  89000],
[    26,  86000],
[    38,  80000],
[    39,  71000],
[    37,  71000],
[    38,  61000],
[    37,  55000],
[    42,  80000],
[    40,  57000],
[    35,  75000],
[    36,  52000],
[    40,  59000],
[    41,  59000],
[    36,  75000],
[    37,  72000],
[    40,  75000],
[    35,  53000],
[    41,  51000],
```

```
       [    39,  59000],
       [    46,  41000],
       [    51,  23000],
       [    50,  20000],
       [    36,  33000],
       [    49,  36000]], dtype=int64)
```

[ ]:
```
label
```

[117]:
```
array([0, 0, 0, 0, 0, 0, 0, 1, 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, 1, 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, 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, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 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, 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, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0, 1,
       0, 1, 0, 1, 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)
```

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

[ ]:
```
for i in range(1,401):
    x_train,x_test,y_train,y_test=train_test_split(features,label,test_size=0.1)
    model=LogisticRegression()
    model.fit(x_train,y_train)
    train_score=model.score(x_train,y_train)
    test_score=model.score(x_test,y_test)
    if test_score>train_score:
        print("Test {} Train{} Random State {}".format(test_score,train_score,i))
```

```
Test 0.675 Train0.6388888888888888 Random State 1
Test 0.775 Train0.6277777777777778 Random State 2
Test 0.725 Train0.6333333333333333 Random State 4
Test 0.725 Train0.6333333333333333 Random State 7
Test 0.65 Train0.6416666666666667 Random State 8
Test 0.7 Train0.6361111111111111 Random State 9
Test 0.725 Train0.6333333333333333 Random State 10
Test 0.675 Train0.6388888888888888 Random State 12
Test 0.675 Train0.6388888888888888 Random State 13
Test 0.7 Train0.6361111111111111 Random State 16
Test 0.675 Train0.6388888888888888 Random State 18
Test 0.675 Train0.6388888888888888 Random State 19
Test 0.8 Train0.625 Random State 20
Test 0.675 Train0.6388888888888888 Random State 21
Test 0.65 Train0.6416666666666667 Random State 22
Test 0.675 Train0.6388888888888888 Random State 24
Test 0.65 Train0.6416666666666667 Random State 26
Test 0.65 Train0.6416666666666667 Random State 27
Test 0.7 Train0.6361111111111111 Random State 31
Test 0.725 Train0.6333333333333333 Random State 34
Test 0.725 Train0.6333333333333333 Random State 36
Test 0.75 Train0.6305555555555555 Random State 38
Test 0.65 Train0.6416666666666667 Random State 42
Test 0.75 Train0.6305555555555555 Random State 44
Test 0.675 Train0.6388888888888888 Random State 45
Test 0.65 Train0.6416666666666667 Random State 48
Test 0.725 Train0.6333333333333333 Random State 49
Test 0.775 Train0.6277777777777778 Random State 50
Test 0.8 Train0.625 Random State 51
Test 0.725 Train0.6333333333333333 Random State 56
Test 0.675 Train0.6388888888888888 Random State 57
Test 0.65 Train0.6416666666666667 Random State 58
Test 0.65 Train0.6416666666666667 Random State 59
Test 0.7 Train0.6361111111111111 Random State 64
Test 0.675 Train0.6388888888888888 Random State 67
Test 0.775 Train0.6277777777777778 Random State 68
Test 0.675 Train0.6388888888888888 Random State 71
Test 0.65 Train0.6416666666666667 Random State 72
Test 0.65 Train0.6416666666666667 Random State 76
Test 0.65 Train0.6416666666666667 Random State 77
Test 0.7 Train0.6361111111111111 Random State 82
Test 0.65 Train0.6416666666666667 Random State 83
```

Test 0.775 Train0.6277777777777778 Random State 84
Test 0.675 Train0.6388888888888888 Random State 85
Test 0.7 Train0.6361111111111111 Random State 86
Test 0.65 Train0.6416666666666667 Random State 89
Test 0.65 Train0.6416666666666667 Random State 90
Test 0.675 Train0.6388888888888888 Random State 91
Test 0.675 Train0.6388888888888888 Random State 93
Test 0.7 Train0.6361111111111111 Random State 94
Test 0.7 Train0.6361111111111111 Random State 95
Test 0.725 Train0.6333333333333333 Random State 100
Test 0.75 Train0.6361111111111111 Random State 101
Test 0.65 Train0.6416666666666667 Random State 103
Test 0.675 Train0.6388888888888888 Random State 104
Test 0.725 Train0.6333333333333333 Random State 106
Test 0.65 Train0.6416666666666667 Random State 107
Test 0.65 Train0.6416666666666667 Random State 109
Test 0.7 Train0.6361111111111111 Random State 110
Test 0.7 Train0.6361111111111111 Random State 111
Test 0.75 Train0.6305555555555555 Random State 114
Test 0.7 Train0.6361111111111111 Random State 116
Test 0.65 Train0.6416666666666667 Random State 118
Test 0.675 Train0.6388888888888888 Random State 120
Test 0.725 Train0.6333333333333333 Random State 121
Test 0.85 Train0.8444444444444444 Random State 122
Test 0.7 Train0.6361111111111111 Random State 124
Test 0.65 Train0.6416666666666667 Random State 130
Test 0.65 Train0.6416666666666667 Random State 132
Test 0.65 Train0.6416666666666667 Random State 134
Test 0.65 Train0.6416666666666667 Random State 135
Test 0.675 Train0.6388888888888888 Random State 136
Test 0.675 Train0.6388888888888888 Random State 137
Test 0.725 Train0.6333333333333333 Random State 139
Test 0.7 Train0.6361111111111111 Random State 143
Test 0.7 Train0.6361111111111111 Random State 147
Test 0.7 Train0.6361111111111111 Random State 148
Test 0.7 Train0.6361111111111111 Random State 150
Test 0.675 Train0.6388888888888888 Random State 151
Test 0.675 Train0.6388888888888888 Random State 152
Test 0.65 Train0.6416666666666667 Random State 155
Test 0.75 Train0.6305555555555555 Random State 157
Test 0.7 Train0.6361111111111111 Random State 160
Test 0.65 Train0.6416666666666667 Random State 163
Test 0.65 Train0.6416666666666667 Random State 164
Test 0.65 Train0.6416666666666667 Random State 166
Test 0.675 Train0.6388888888888888 Random State 167
Test 0.7 Train0.6361111111111111 Random State 168
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Test 0.85 Train0.8444444444444444 Random State 171
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Test 0.75 Train0.6305555555555555 Random State 173
Test 0.675 Train0.6388888888888888 Random State 174
Test 0.65 Train0.6416666666666667 Random State 175
Test 0.65 Train0.6416666666666667 Random State 179
Test 0.65 Train0.6416666666666667 Random State 180
Test 0.75 Train0.6305555555555555 Random State 181
Test 0.675 Train0.6388888888888888 Random State 182
Test 0.7 Train0.6361111111111111 Random State 183
Test 0.7 Train0.6361111111111111 Random State 184
Test 0.725 Train0.6333333333333333 Random State 185
Test 0.65 Train0.6416666666666667 Random State 186
Test 0.775 Train0.6277777777777778 Random State 188
Test 0.725 Train0.6333333333333333 Random State 190
Test 0.725 Train0.6333333333333333 Random State 191
Test 0.725 Train0.6333333333333333 Random State 192
Test 0.75 Train0.6305555555555555 Random State 193
Test 0.65 Train0.6416666666666667 Random State 196
Test 0.65 Train0.6416666666666667 Random State 199
Test 0.75 Train0.6305555555555555 Random State 201
Test 0.725 Train0.6333333333333333 Random State 205
Test 0.675 Train0.6388888888888888 Random State 208
Test 0.7 Train0.6361111111111111 Random State 209
Test 0.65 Train0.6416666666666667 Random State 211
Test 0.725 Train0.6333333333333333 Random State 214
Test 0.7 Train0.6361111111111111 Random State 215
Test 0.725 Train0.6333333333333333 Random State 217
Test 0.7 Train0.6361111111111111 Random State 219
Test 0.675 Train0.6388888888888888 Random State 220
Test 0.675 Train0.6388888888888888 Random State 222
Test 0.675 Train0.6388888888888888 Random State 223
Test 0.65 Train0.6416666666666667 Random State 225
Test 0.725 Train0.6333333333333333 Random State 228
Test 0.65 Train0.6416666666666667 Random State 233
Test 0.7 Train0.6361111111111111 Random State 234

```
Test 0.675 Train0.6388888888888888 Random State 373
Test 0.675 Train0.6388888888888888 Random State 377
Test 0.675 Train0.6388888888888888 Random State 378
Test 0.65 Train0.6416666666666667 Random State 382
Test 0.7 Train0.6361111111111111 Random State 383
Test 0.65 Train0.6416666666666667 Random State 384
Test 0.725 Train0.6333333333333333 Random State 386
Test 0.75 Train0.6305555555555555 Random State 388
Test 0.65 Train0.6416666666666667 Random State 390
Test 0.7 Train0.6361111111111111 Random State 391
Test 0.7 Train0.6361111111111111 Random State 394
Test 0.7 Train0.6361111111111111 Random State 397
```

[ ]:
```
x_train,x_test,y_train,y_test=train_test_split(features,label,test_size=0.2)
finalModel=LogisticRegression()
finalModel.fit(x_train,y_train)
```

120]:
```
▾ LogisticRegression
LogisticRegression()
```

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

```
0.628125
0.7
```

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

```
              precision    recall  f1-score   support

           0       0.64      1.00      0.78       257
           1       0.00      0.00      0.00       143

    accuracy                           0.64       400
   macro avg       0.32      0.50      0.39       400
weighted avg       0.41      0.64      0.50       400
```

Exp:13. a KNN

```
[ ]: 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()
```

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

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

```
[126]:
```

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

```
[127]: KNeighborsClassifier
       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))
```

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

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

```
              precision    recall  f1-score   support

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

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

Exp:13. b K-Means

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

```
[ ]: df=pd.read_csv('Mall_Customers.csv')
```

```
[ ]: df.info()
```

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

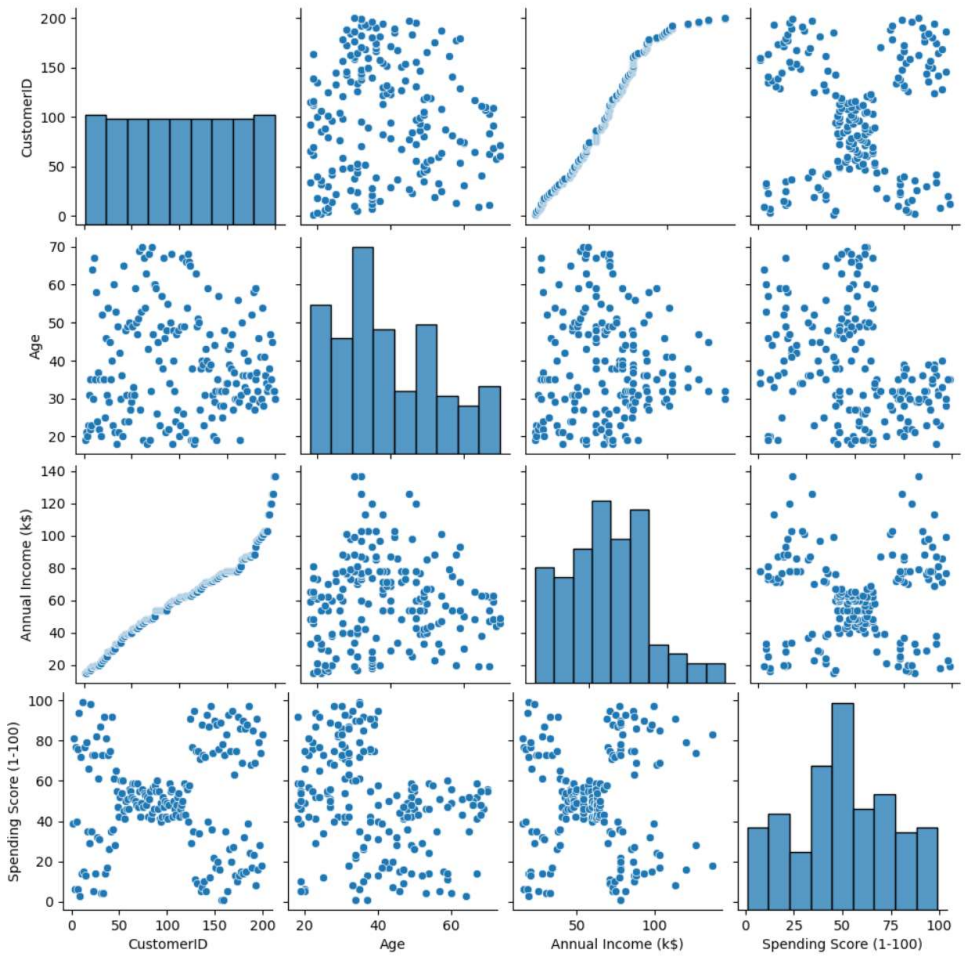
```
[ ]: df.head()
```

135]:

	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)
```

[136]: `<seaborn.axisgrid.PairGrid at 0x1ee6f13f2b0>`



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

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

```
C:\ProgramData\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
C:\ProgramData\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:1382: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP_NUM_THREADS=1.
  warnings.warn(
```

138]:
```
KMeans(n_clusters=5)
```

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

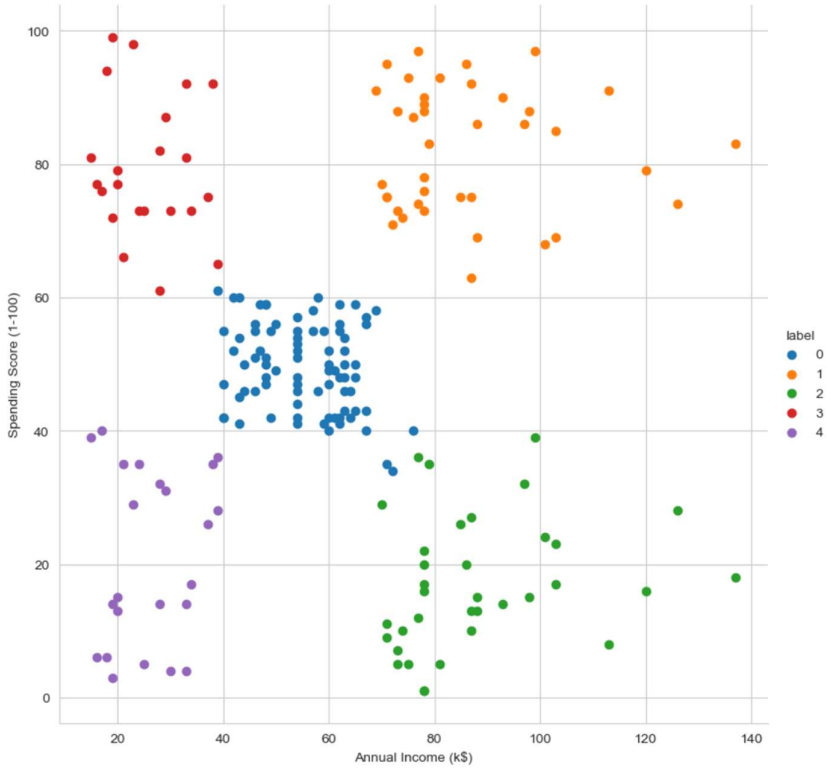
```
C:\Users\REC\AppData\Local\Temp\ipykernel_9864\470183701.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  Final['label']=model.predict(features)
```

[139]:

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

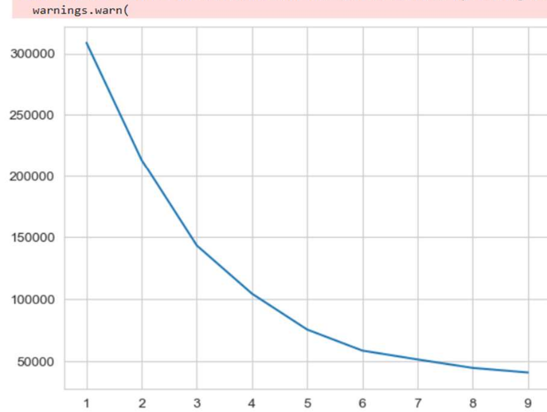
[ ]:
```
sns.set_style("whitegrid")
sns.FacetGrid(Final,hue="label",height=8) \
.map(plt.scatter,"Annual Income (k$)", "Spending Score (1-100)") \
.add_legend();
plt.show()
```



[143]:

```
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, n_init=10)
    model.fit(features_el)
    wcss.append(model.inertia_)
plt.plot(range(1,10),wcss)
plt.show()
```

```
C:\Program Files\Anaconda\Lib\site-packages\sklearn\cluster\_kmeans.py:1429: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP_NUM_THREADS=1.
  warnings.warn(
C:\Program Files\Anaconda\Lib\site-packages\sklearn\cluster\_kmeans.py:1429: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP_NUM_THREADS=1.
  warnings.warn(
C:\Program Files\Anaconda\Lib\site-packages\sklearn\cluster\_kmeans.py:1429: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP_NUM_THREADS=1.
  warnings.warn(
C:\Program Files\Anaconda\Lib\site-packages\sklearn\cluster\_kmeans.py:1429: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP_NUM_THREADS=1.
  warnings.warn(
C:\Program Files\Anaconda\Lib\site-packages\sklearn\cluster\_kmeans.py:1429: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP_NUM_THREADS=1.
  warnings.warn(
C:\Program Files\Anaconda\Lib\site-packages\sklearn\cluster\_kmeans.py:1429: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP_NUM_THREADS=1.
  warnings.warn(
C:\Program Files\Anaconda\Lib\site-packages\sklearn\cluster\_kmeans.py:1429: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP_NUM_THREADS=1.
  warnings.warn(
C:\Program Files\Anaconda\Lib\site-packages\sklearn\cluster\_kmeans.py:1429: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP_NUM_THREADS=1.
  warnings.warn(
C:\Program Files\Anaconda\Lib\site-packages\sklearn\cluster\_kmeans.py:1429: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP_NUM_THREADS=1.
  warnings.warn(
```



Exp:14 Testing

[145]:
```
#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
```

[146]:
```
#Z-TEST
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(f'Z-statistic: {z_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 50 g.')
else:
    print('Fail to Reject Null Hypothesis. No significant difference.')
```

```
Z-statistic: 2.400
P-value: 0.0164
Reject Null Hypothesis. Mean is significantly different from 50 g.
```

[147]:
```
#anova test
```

[148]:
```
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'F-statistic: {f_stat:.3f}')
print(f'P-value: {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.
```