Name: Shubham Jha
Div: D15C
Roll No:19

EXP 1

Aim:

- Load data in Pandas.
- Description of the dataset.
- Drop columns that aren't useful.
- Drop rows with maximum missing values.
- Take care of missing data.
- Create dummy variables.
- Find out outliers (manually)
- standardization and normalization of columns

Data preprocessing

Data preprocessing is the process of transforming raw data into an understandable format. It is also an important step in data mining as we cannot work with raw data. The quality of the data should be checked before applying machine learning or data mining algorithms.

Why is Data Preprocessing important?

Preprocessing of data is mainly to check the data quality. The quality can be checked by the following:

- Accuracy: To check whether the data entered is correct or not.
- Completeness: To check whether the data is available or not recorded.
- Consistency: To check whether the same data is kept in all the places that do or do not match.

- Timeliness: The data should be updated correctly.
- Believability: The data should be trustable.

Interpretability: The understandability of the data.

Dataset: SuperMarket Dataset

1) Loading Data in Pandas

```
import pandas as pd

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

df.head()
```

	Invoice ID	Branch	City	Customer type	Gender	Product line	Unit price	Quantity	Tax 5%	Total	Date	Time	Payment	cogs	gross margin percentage	gross income
0	750-67-8428	A	Yangon	Member	Female	Health and beauty	74.69	7	26.1415	548.9715	1/5/2019	13:08	Ewallet	522.83	4.761905	26.141
1	226-31-3081	C	Naypyitaw	Normal	Female	Electronic accessories	15.28	5	3.8200	80.2200	3/8/2019	10:29	Cash	76.40	4.761905	3.820
2	631-41-3108	A	Yangon	Normal	Male	Home and lifestyle	46.33	7	16.2155	340.5255	3/3/2019	13:23	Credit card	324.31	4.761905	16.215
3	123-19-1176	A	Yangon	Member	Male	Health and beauty	58.22	8	23.2880	489.0480	1/27/2019	20:33	Ewallet	465.76	4.761905	23.288
4	373-73-7910	A	Yangon	Normal	Male	Sports and travel	86.31	7	30.2085	634.3785	2/8/2019	10:37	Ewallet	604.17	4.761905	30.208

2)Description of the dataset.

Attribute/Column Name	Data Type	Description
Invoice ID	String	Unique identifier for each transaction/invoice.
Branch	String	Branch identifier for the supermarket (`A`, `B`, or `C`).
City	String	City where the supermarket branch is located.
Customer type	String	Type of customer (`Member` or `Normal`).
Gender	String	Gender of the customer (`Male` or `Female`).
Product line	String	Category of products purchased (`Health and beauty`, `Electronic accessories`, etc.).
Unit price	Float	Price per unit of the product.
Quantity	Integer	Number of units purchased.
Tax 5%	Float	5% tax on the total amount for the purchase.
Total	Float	Total bill amount, including tax.
Date	DateTime	Date of the purchase transaction.
Time	String	Time of the purchase transaction.
Payment	String	Payment method used (`Cash`, `Credit card`, or `Ewallet`).
cogs (Cost of Goods Sold)	Float	Total cost of goods sold before tax.
gross margin %	Float	Percentage of gross margin fixed at 4.76%.
gross income	Float	Profit made from the transaction.
Rating	Float	Customer's rating of their experience (range: 1 to 10).

`df.info()`: Provides an overview of the dataset, including:

- Number of rows and columns.
- Data types of each column (e.g., int, float, object).
- Number of non-null (non-missing) values in each column.

`df.describe()`: Generates summary statistics for numeric columns, such as:

- `count`: Number of non-missing values.
- `mean`: Average value.
- `std`: Standard deviation.
- `min`, 25%, 50% (median), 75%, and `max`: Percentile values.

```
print(df.info())


print(df.describe())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 17 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   Invoice ID               1000 non-null   object 
 1   Branch                   1000 non-null   object 
 2   City                     1000 non-null   object 
 3   Customer type            1000 non-null   object 
 4   Gender                   1000 non-null   object 
 5   Product line             1000 non-null   object 
 6   Unit price               1000 non-null   float64
 7   Quantity                 1000 non-null   int64  
 8   Tax 5%                   1000 non-null   float64
 9   Total                    1000 non-null   float64
 10  Date                     1000 non-null   object 
 11  Time                     1000 non-null   object 
 12  Payment                  1000 non-null   object 
 13  cogs                     1000 non-null   float64
 14  gross margin percentage  1000 non-null   float64
 15  gross income             1000 non-null   float64
 16  Rating                   1000 non-null   float64
dtypes: float64(7), int64(1), object(9)
memory usage: 132.9+ KB
None
        Unit price     Quantity        Tax 5%         Total         cogs  \
count  1000.000000  1000.000000  1000.000000  1000.000000  1000.00000   
mean     55.672130     5.510000    15.379369   322.966749   307.58738   
std      26.494628     2.923431    11.708825   245.885335   234.17651   
min      10.080000     1.000000     0.508500    10.678500    10.17000   
25%      32.875000     3.000000     5.924875   124.422375   118.49750   
50%      55.230000     5.000000    12.088000   253.848000   241.76000   
75%      77.935000     8.000000    22.445250   471.350250   448.90500   
max      99.960000    10.000000    49.650000  1042.650000   993.00000   
```

3) Drop columns that aren't useful: Columns like Invoice ID may not contribute to analysis (it's often just an identifier). Removing irrelevant columns reduces complexity.

```
[ ] df = df.drop(['Invoice ID'], axis=1)

    df.head()
```

	Branch	City	Customer type	Gender	Product line	Unit price	Quantity	Tax 5%	Total	Date	Time	Payment	cogs	gross margin percentage	gross income	Rating
0	A	Yangon	Member	Female	Health and beauty	74.69	7	26.1415	548.9715	1/5/2019	13:08	Ewallet	522.83	4.761905	26.1415	9.1
1	C	Naypyitaw	Normal	Female	Electronic accessories	15.28	5	3.8200	80.2200	3/8/2019	10:29	Cash	76.40	4.761905	3.8200	9.6
2	A	Yangon	Normal	Male	Home and lifestyle	46.33	7	16.2155	340.5255	3/3/2019	13:23	Credit card	324.31	4.761905	16.2155	7.4
3	A	Yangon	Member	Male	Health and beauty	58.22	8	23.2880	489.0480	1/27/2019	20:33	Ewallet	465.76	4.761905	23.2880	8.4
4	A	Yangon	Normal	Male	Sports and travel	86.31	7	30.2085	634.3785	2/8/2019	10:37	Ewallet	604.17	4.761905	30.2085	5.3

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

4)Drop rows with maximum missing values.

`df.dropna(thresh=int(0.5 * len(df.columns)))`:

- Drops rows where more than half the columns have missing (NaN) values.
- `thresh=int(0.5 * len(df.columns))`: Ensures that a row must have at least 50% non-null values to remain.

`df = ...`: Updates the DataFrame after dropping rows.
`print(df.info())`: Confirms that rows with excessive missing values have been removed.

```
[ ] df = df.dropna(thresh=int(0.5 * len(df.columns)))

    df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 16 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Branch                  1000 non-null   object
 1   City                    1000 non-null   object
 2   Customer type           1000 non-null   object
 3   Gender                  1000 non-null   object
 4   Product line            1000 non-null   object
 5   Unit price              1000 non-null   float64
 6   Quantity                1000 non-null   int64
 7   Tax 5%                  1000 non-null   float64
 8   Total                   1000 non-null   float64
```

5)Take care of missing data.

`df.fillna(df.mean())`: Replaces missing values (`NaN`) in numeric columns with the mean of that column.

```
print(df.isnull().sum())
# to check null values..this is like boolean ..if Nan ? true:false ..then adds all bolean values.....finally 0 matlab false....this dataset has no null or NaN values.
```

```
Branch                    0
City                      0
Customer type             0
Gender                    0
Product line              0
Unit price                0
Quantity                  0
Tax 5%                    0
Total                     0
Date                      0
Time                      0
Payment                   0
cogs                      0
gross margin percentage   0
```

6)Create dummy variables.

`pd.get_dummies()`: Converts categorical variables into dummy variables (binary indicators: 0 or 1).

- Example: The `Gender` column becomes `Gender_Male` (1 if Male, 0 otherwise).

`columns=['...']`: Specifies which columns to convert.
`drop_first=True`: Avoids the "dummy variable trap" by dropping one dummy variable to prevent multicollinearity.

```
df = pd.get_dummies(df, columns=['Gender', 'City'], drop_first=True)
```

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

	Branch	Customer type	Product line	Unit price	Quantity	Tax 5%	Total	Date	Time	Payment	cogs	gross margin percentage	gross income	Rating	Gender_Male	City_Naypyitaw	City_Yangon
0	A	Member	Health and beauty	74.69	7	26.1415	548.9715	1/5/2019	13:08	Ewallet	522.83	4.761905	26.1415	9.1	False	False	True
1	C	Normal	Electronic accessories	15.28	5	3.8200	80.2200	3/8/2019	10:29	Cash	76.40	4.761905	3.8200	9.6	False	True	False
2	A	Normal	Home and lifestyle	46.33	7	16.2155	340.5255	3/3/2019	13:23	Credit card	324.31	4.761905	16.2155	7.4	True	False	True
3	A	Member	Health and beauty	58.22	8	23.2880	489.0480	1/27/2019	20:33	Ewallet	465.76	4.761905	23.2880	8.4	True	False	True
4	A	Normal	Sports and travel	86.31	7	30.2085	634.3785	2/8/2019	10:37	Ewallet	604.17	4.761905	30.2085	5.3	True	False	True

7)Find out outliers (manually)

```
def detect_outliers(col):
    Q1 = df[col].quantile(0.25)  # First quartile (25th percentile)
    Q3 = df[col].quantile(0.75)  # Third quartile (75th percentile)
    IQR = Q3 - Q1                # Interquartile range
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    return df[(df[col] < lower_bound) | (df[col] > upper_bound)]
```

```
outliers = detect_outliers('Total')
print(outliers)
if outliers.empty:
    print("No outliers detected.")
else:
    print(f"Outliers detected:\n{outliers}")

print(f"Number of outliers: {len(outliers)}")
```

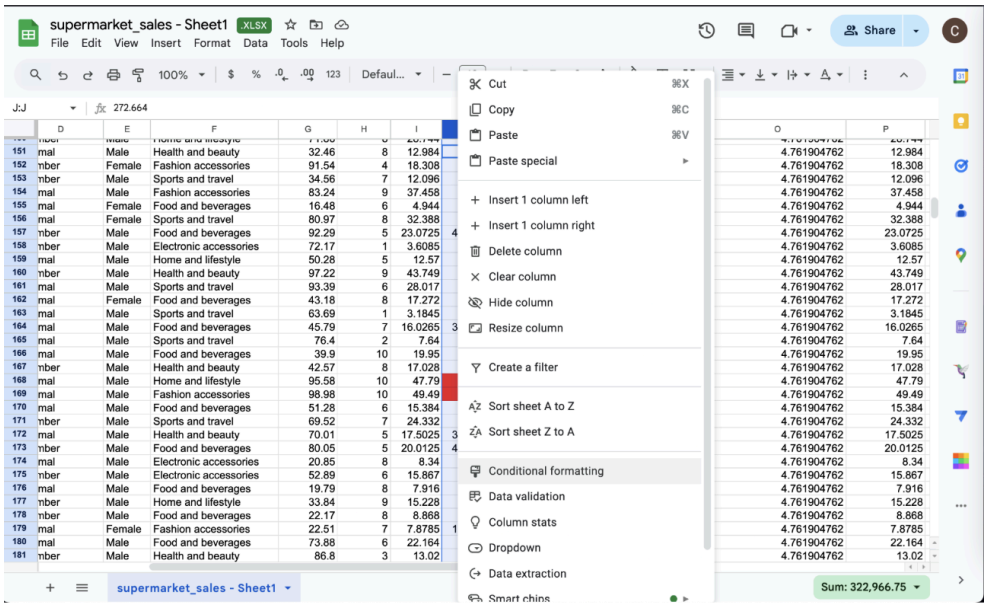
```
    Branch Customer type         Product line  Unit price  Quantity  Tax 5%  \
166      C        Normal   Home and lifestyle       95.58        10  47.790
167      A        Normal  Fashion accessories       98.98        10  49.490
350      C        Member  Fashion accessories       99.30        10  49.650
357      C        Normal    Sports and travel       95.44        10  47.720
422      C        Member  Fashion accessories       97.21        10  48.605
557      C        Member   Food and beverages       98.52        10  49.260
699      C        Normal   Home and lifestyle       97.50        10  48.750
792      B        Normal   Home and lifestyle       97.37        10  48.685
996      B        Normal   Home and lifestyle       97.38        10  48.690

       Total       Date   Time      Payment   cogs  gross margin percentage  \
166  1003.590  1/16/2019  13:32         Cash  955.8                 4.761905
167  1039.290   2/8/2019  16:20  Credit card  989.8                 4.761905
350  1042.650  2/15/2019  14:53  Credit card  993.0                 4.761905
357  1002.120   1/9/2019  13:45         Cash  954.4                 4.761905
422  1020.705   2/8/2019  13:00  Credit card  972.1                 4.761905
557  1034.460  1/30/2019  20:23      Ewallet  985.2                 4.761905
699  1023.750  1/12/2019  16:18      Ewallet  975.0                 4.761905
792  1022.385  1/15/2019  13:48  Credit card  973.7                 4.761905
996  1022.490   3/2/2019  17:16      Ewallet  973.8                 4.761905

     gross income  Rating  Gender_Male  City_Naypyitaw  City_Yangon
166        47.790     4.8         True            True        False
167        49.490     8.7         True           False         True
```

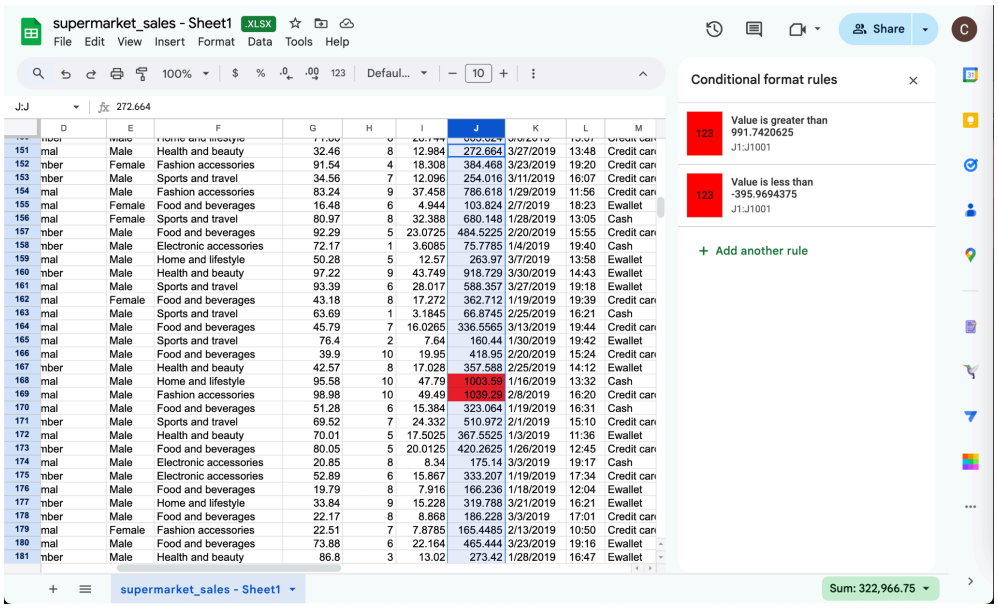
```
       Total       Date   Time      Payment   cogs  gross margin percentage  \
166  1003.590  1/16/2019  13:32         Cash  955.8                 4.761905
167  1039.290   2/8/2019  16:20  Credit card  989.8                 4.761905
350  1042.650  2/15/2019  14:53  Credit card  993.0                 4.761905
357  1002.120   1/9/2019  13:45         Cash  954.4                 4.761905
422  1020.705   2/8/2019  13:00  Credit card  972.1                 4.761905
557  1034.460  1/30/2019  20:23      Ewallet  985.2                 4.761905
699  1023.750  1/12/2019  16:18      Ewallet  975.0                 4.761905
792  1022.385  1/15/2019  13:48  Credit card  973.7                 4.761905
996  1022.490   3/2/2019  17:16      Ewallet  973.8                 4.761905

     gross income  Rating  Gender_Male  City_Naypyitaw  City_Yangon
166        47.790     4.8         True            True        False
167        49.490     8.7         True           False         True
350        49.650     6.6        False            True        False
357        47.720     5.2        False            True        False
422        48.605     8.7        False            True        False
557        49.260     4.5        False            True        False
699        48.750     8.0         True            True        False
792        48.685     4.9        False           False        False
996        48.690     4.4        False           False        False
Number of outliers: 9
```

Using custom format rules functionality in excel to color all the outliers present in the dataset

Eg -

1. Lower bound = -395.96 -> Coloring values less than Lower Bound
2. Upper bound = 991.74 -> Coloring values greater than Upper Bound





8) standardization and normalization of columns

Standardization is another scaling technique where the values are centered around the mean with a unit standard deviation. This means that the mean of the attribute becomes zero and the resultant distribution has a unit standard deviation.

Standardization equation

$$X' = \frac{X - \mu}{\sigma}$$

To standardize your data, we need to import the StandardScalar from the sklearn library and apply it to our dataset.

Normalization is a scaling technique in which values are shifted and rescaled so that they end up ranging between 0 and 1. It is also known as Min-Max scaling.

Normalization equation

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}$$

Here, Xmax and Xmin are the maximum and the minimum values of the feature respectively.

- When the value of X is the minimum value in the column, the numerator will be 0, and hence X’ is 0
- On the other hand, when the value of X is the maximum value in the column, the numerator is equal to the denominator and thus the value of X’ is 1
- If the value of X is between the minimum and the maximum value, then the value of X’ is between 0 and 1

To normalize your data, you need to import the MinMaxScalar from the sklearn library and apply it to our dataset.

```
from sklearn.preprocessing import StandardScaler
# mean 0 karega and sd 1..this is standardization
scaler = StandardScaler()
df[['Unit price', 'Total']] = scaler.fit_transform(df[['Unit price', 'Total']])
```

```
[ ] from sklearn.preprocessing import MinMaxScaler
    # this is normaliztion.....helps to scale data between 0-1
    normalizer = MinMaxScaler()
    df[['Unit price', 'Total']] = normalizer.fit_transform(df[['Unit price', 'Total']])
```

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

	Branch	Customer type	Product line	Unit price	Quantity	Tax 5%	Total	Date	Time	Payment	cogs	gross margin percentage	gross income	Rating	Gender_Male	City_Naypyitaw	City_Yangon
0	A	Member	Health and beauty	0.718847	7	26.1415	0.521616	1/5/2019	13:08	Ewallet	522.83	4.761905	26.1415	9.1	False	False	True
1	C	Normal	Electronic accessories	0.057855	5	3.8200	0.067387	3/8/2019	10:29	Cash	76.40	4.761905	3.8200	9.6	False	True	False
2	A	Normal	Home and lifestyle	0.403316	7	16.2155	0.319628	3/3/2019	13:23	Credit card	324.31	4.761905	16.2155	7.4	True	False	True
3	A	Member	Health and beauty	0.535603	8	23.2880	0.463549	1/27/2019	20:33	Ewallet	465.76	4.761905	23.2880	8.4	True	False	True
4	A	Normal	Sports and travel	0.848131	7	30.2085	0.604377	2/8/2019	10:37	Ewallet	604.17	4.761905	30.2085	5.3	True	False	True

```
[ ] df.describe()
```

	Unit price	Quantity	Tax 5%	Total	cogs	gross margin percentage	gross income	Rating
count	1000.000000	1000.000000	1000.000000	1000.000000	1000.00000	1.000000e+03	1000.000000	1000.00000
mean	0.507256	5.510000	15.379369	0.302613	307.58738	4.761905e+00	15.379369	6.97270
std	0.294778	2.923431	11.708825	0.238268	234.17651	6.131498e-14	11.708825	1.71858
min	0.000000	1.000000	0.508500	0.000000	10.17000	4.761905e+00	0.508500	4.00000
25%	0.253616	3.000000	5.924875	0.110220	118.49750	4.761905e+00	5.924875	5.50000
50%	0.502336	5.000000	12.088000	0.235636	241.76000	4.761905e+00	12.088000	7.00000
75%	0.754951	8.000000	22.445250	0.446400	448.90500	4.761905e+00	22.445250	8.50000
max	1.000000	10.000000	49.650000	1.000000	993.00000	4.761905e+00	49.650000	10.00000

Conclusion:

Thus we have understood how to perform data preprocessing which can further be taken into exploratory data analysis and further in the Model preparation sequence.

Name: Shubham Jha
Class: D15C
Roll No.: 19

Exp 2

Aim: Data Visualization/ Exploratory data Analysis using Matplotlib and Seaborn.

Introduction:

Exploratory Data Analysis

Exploratory Data Analysis (EDA) is the first step in your data analysis process developed by “John Tukey” in the 1970s. In statistics, exploratory data analysis is an approach to analyzing data sets to summarize their main characteristics, often with visual methods. By the name itself, we can get to know that it is a step in which we need to explore the data set.

When you are trying to build a machine learning model you need to be pretty sure whether your data is making sense or not. The main aim of exploratory data analysis is to obtain confidence in your data to an extent where you’re ready to engage a machine learning algorithm.

Why do we do EDA?

Exploratory Data Analysis is a crucial step before you jump to machine learning or modeling your data. By doing this you can get to know whether the selected features are good enough to model, are all the features required, are there any correlations based on which we can either go back to the Data Preprocessing step or move on to modeling.

Once EDA is complete and insights are drawn, its feature can be used for supervised and unsupervised machine learning modeling.

In every machine learning workflow, the last step is Reporting or Providing the insights to the Stakeholders and as a Data Scientist you can explain every bit of code but you need to keep in mind the audience. By completing the EDA you will have many plots,heat-maps, frequency distribution, graphs, correlation matrix along with the hypothesis by which any individual can understand what your data is all about and what insights you got from exploring your data set.

Data visualization is very critical to market research where both numerical and categorical data can be visualized, which helps in an increase in the impact of insights and also helps in reducing the risk of analysis paralysis

Advantages of Data visualization:

1. Better Agreement:

In business, for numerous periods, it happens that we need to look at the exhibitions of two components or two situations. A conventional methodology is to experience the massive information of both the circumstances and afterward examine it. This will clearly take a great deal of time.

2. A Superior Method:

It can tackle the difficulty of placing the information of both perspectives into the pictorial structure. This will unquestionably give a superior comprehension of the circumstances. For instance, Google patterns assist us with understanding information identified with top ventures or inquiries in pictorial or graphical structures.

3. Simple Sharing of Data:

With the representation of the information, organizations present another arrangement of correspondence. Rather than sharing the cumbersome information, sharing the visual data will draw in and pass on across the data which is more absorbable.

4. Deals Investigation:

With the assistance of information representation, a salesman can, without much of a stretch, comprehend the business chart of items. With information

perception instruments like warmth maps, he will have the option to comprehend the causes that are pushing the business numbers up just as the reasons that are debasing the business numbers. Information representation helps in understanding the patterns and furthermore, different variables like sorts of clients keen on purchasing, rehashing clients, the impact of topography, and so forth.

5. Discovering Relations Between Occasions:

A business is influenced by a lot of elements. Finding a relationship between these elements or occasions encourages chiefs to comprehend the issues identified with their business. For instance, the online business market is anything but another thing today. Each time during certain happy seasons, like Christmas or Thanksgiving, the diagrams of online organizations go up. Along these lines, state if an online organization is doing a normal $1 million business in a specific quarter and the business ascends straightaway, at that point they can rapidly discover the occasions compared to it.

6. Investigating Openings and Patterns:

With the huge loads of information present, business chiefs can discover the profundity of information in regard to the patterns and openings around them. Utilizing information representation, the specialists can discover examples of the conduct of their clients, subsequently preparing for them to investigate patterns and open doors for business.

Introduction to Technologies Used:

Matplotlib

Matplotlib is a plotting library in Python used for creating static, animated, and interactive visualizations. It is highly customizable and supports a wide range of graphs, including bar graphs, histograms, scatter plots, and more.

Seaborn

Seaborn is a Python visualization library built on top of Matplotlib. It provides a high-level interface for creating attractive statistical graphics, such as heatmaps, box plots, and scatter plots.

General Syntax in Python for Data Visualization

Python libraries like Matplotlib and Seaborn follow a general syntax for creating visualizations:

1. **Import the library**: Import the required libraries (e.g., `import matplotlib.pyplot as plt`).
2. **Prepare the data**: Use Pandas to manipulate and prepare the data for visualization.
3. **Create the plot**: Use functions like `plot()`, `scatter()`, `boxplot()`, etc., to create the visualization.
4. **Customize the plot**: Add titles, labels, legends, and other customizations.
5. **Display the plot**: Use `plt.show()` to display the visualization.

<------This doc is using up on the cleaned data of previous experiment.------->

1. Bar Graph and Contingency Table

Theory

- **Bar Graph**: A bar graph is used to represent categorical data with rectangular bars. The length of each bar corresponds to the value it represents. It is useful for comparing categories or showing distributions.
- **Contingency Table**: A contingency table (also called a cross-tabulation) is a table that displays the frequency distribution of two categorical variables. It helps in understanding the relationship between the variables.

Terms

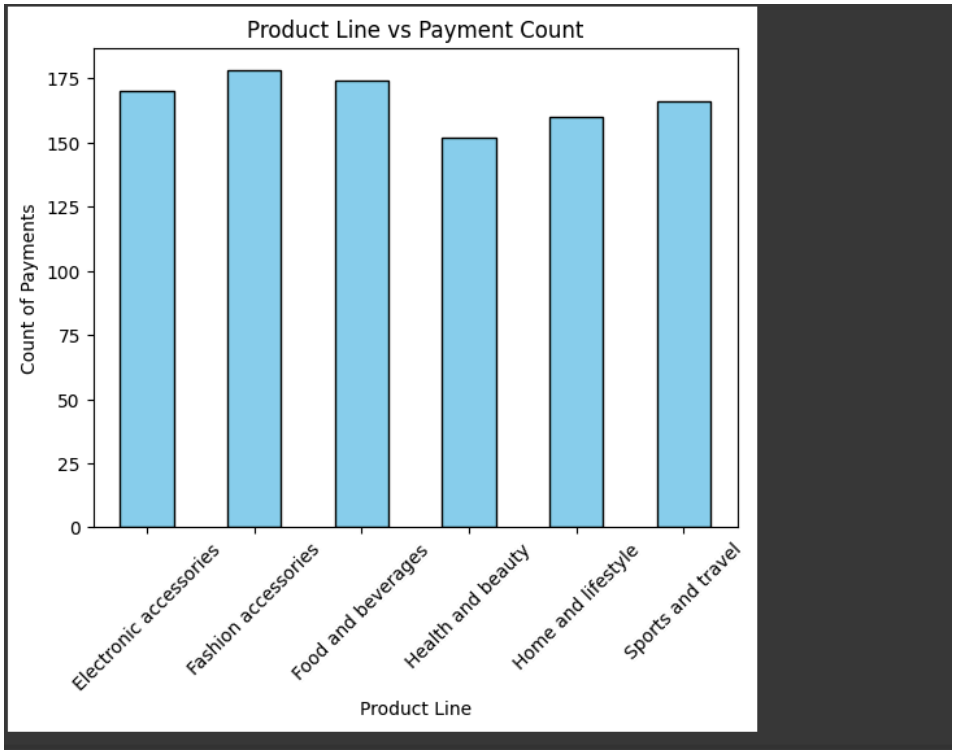
- **Categorical Data**: Data that can be divided into groups or categories (e.g., `Product line`, `Payment`).
- **Frequency**: The number of times a value occurs in a dataset.

```
# Bar plot for product line and payment method
df.groupby('Product line')['Payment'].count().plot(kind='bar', color='skyblue', edgecolor='blac
k')
plt.title('Product Line vs Payment Count')
plt.xlabel('Product Line')
plt.ylabel('Count of Payments')
plt.xticks(rotation=45)
plt.show()

# Contingency table
contingency_table = pd.crosstab(df['Product line'], df['Payment'])
print(contingency_table)
```

Explanation

- **Bar Graph**:
  - `df.groupby('Product line')['Payment'].count()` groups the data by `Product line` and counts the occurrences of each `Payment` method.
  - `.plot(kind='bar')` creates a bar graph.
  - `plt.title()`, `plt.xlabel()`, and `plt.ylabel()` add titles and labels to the graph.
  - `plt.xticks(rotation=45)` rotates the x-axis labels for better readability.
- **Contingency Table**:
  - `pd.crosstab(df['Product line'], df['Payment'])` creates a table showing the frequency distribution of `Payment` methods for each `Product line`.

Output:



Payment	Cash	Credit card	Ewallet
Product line			
Electronic accessories	71	46	53
Fashion accessories	57	56	65
Food and beverages	57	61	56
Health and beauty	49	50	53
Home and lifestyle	51	45	64
Sports and travel	59	53	54

2. Scatter Plot, Box Plot, and Heatmap

Theory

- **Scatter Plot**: A scatter plot is used to visualize the relationship between two numerical variables. Each point represents an observation.
- **Box Plot**: A box plot (or whisker plot) is used to display the distribution of numerical data through quartiles. It helps identify outliers and compare distributions across categories.
- **Heatmap**: A heatmap is a graphical representation of data where values are represented as colors. It is often used to visualize correlation matrices.

Terms

- **Numerical Data**: Data that represents quantities (e.g., `Unit price`, `Total`).
- **Quartiles**: Values that divide a dataset into four equal parts.
- **Correlation**: A measure of the relationship between two variables.

```
# Scatter plot
sns.scatterplot(data=df, x='Unit price', y='Total', hue='Gender_Male')
plt.title('Unit Price vs Total with Gender (Male=1)')
plt.show()

# Box plot
sns.boxplot(data=df, x='Product line', y='Total')
plt.title('Box Plot of Total by Product Line')
plt.xticks(rotation=45)
plt.show()

# Heatmap
numeric_df = df.select_dtypes(include=['float64', 'int64'])
sns.heatmap(numeric_df.corr(), annot=True, cmap='coolwarm')
plt.title('Heatmap of Numerical Features Correlation')
plt.show()
```

Explanation

- **Scatter Plot**:
    - `sns.scatterplot()` creates a scatter plot with `Unit price` on the x-axis and `Total` on the y-axis.
    - `hue='Gender_Male'` adds a color dimension to differentiate between genders.

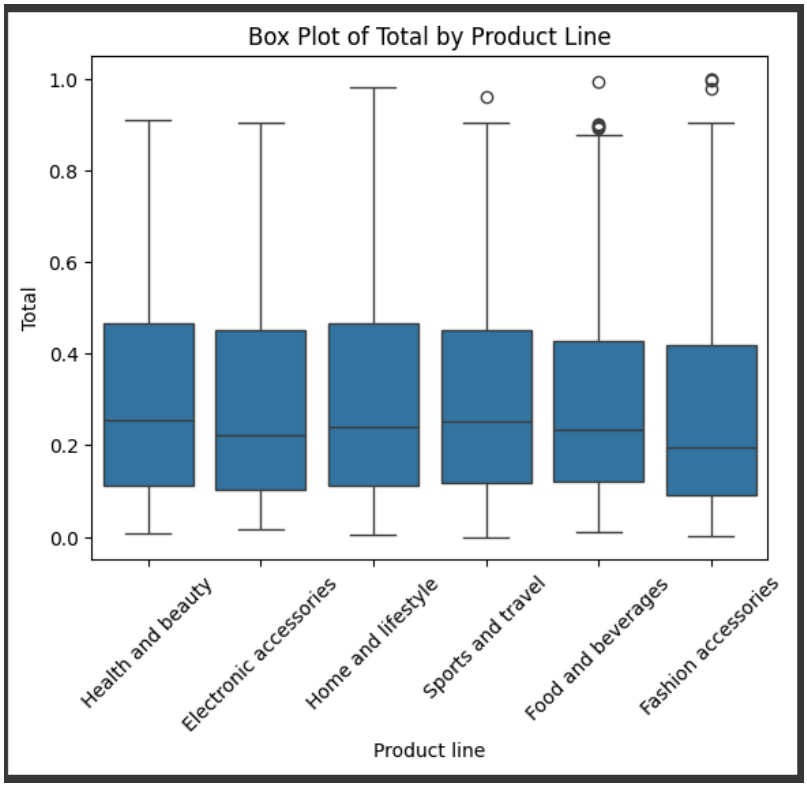
- **Box Plot**:
  - `sns.boxplot()` creates a box plot to show the distribution of `Total` sales across `Product line`.
  - `plt.xticks(rotation=45)` rotates the x-axis labels for better readability.
- **Heatmap**:
  - `numeric_df.corr()` calculates the correlation matrix for numerical features.
  - `sns.heatmap()` visualizes the correlation matrix with colors.

Output:

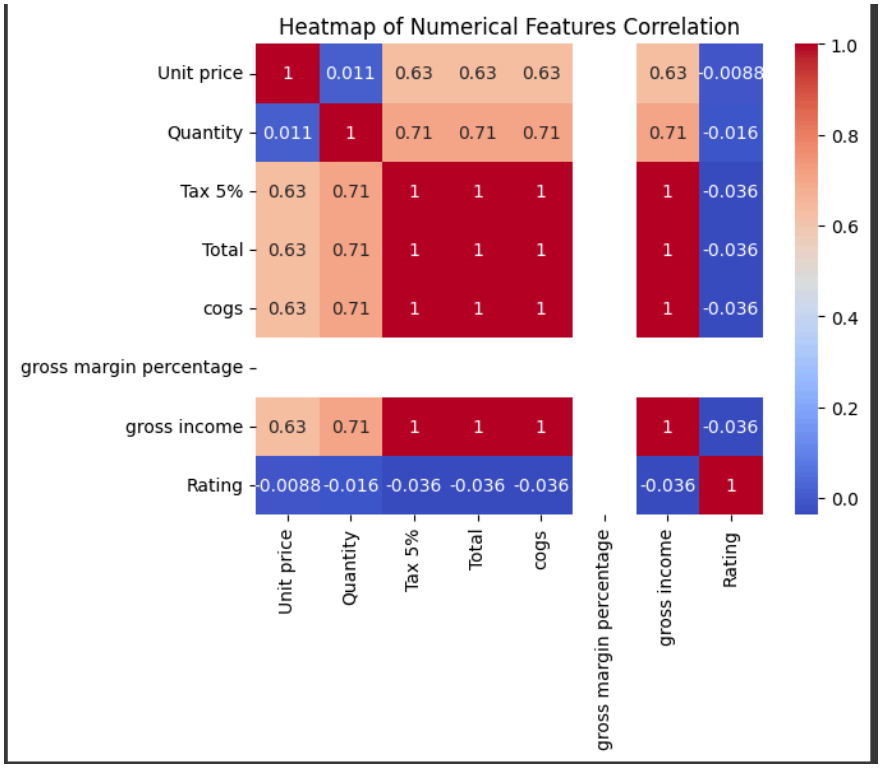
Scatter Plot

Inference

- If the points in the scatter plot show an upward trend (from bottom-left to top-right), it indicates a **positive correlation** between `Unit price` and `Total`. This means that as the unit price increases, the total sales amount also tends to increase.
- If the points are scattered randomly, it suggests **no strong correlation** between the two variables.



Box Plot



Heat Map

Key Observations:

- **Total vs Quantity (High Positive Correlation)**
  - A high positive correlation (close to 1) suggests that the total sales amount increases as the number of purchased items (Quantity) increases. This is expected in sales data.
- **Gross Income vs Total (Strong Positive Correlation)**
  - This indicates that a higher total amount is strongly associated with higher gross income. This is intuitive as gross income is often derived from total sales.
- **Weak Correlations:**
  - Some features, like *Unit Price* and *Quantity*, may show weak or no correlation, suggesting that the number of items purchased doesn't necessarily depend on unit prices.
- **No Negative Correlations:**
  - Since this is a sales dataset, most numerical features are likely positively related.

3. Histogram and Normalized Histogram

Theory

- **Histogram**: A histogram is used to represent the distribution of numerical data. It divides the data into bins and shows the frequency of observations in each bin.
- **Normalized Histogram**: A normalized histogram represents the probability distribution of the data, where the area under the histogram sums to 1.

Terms

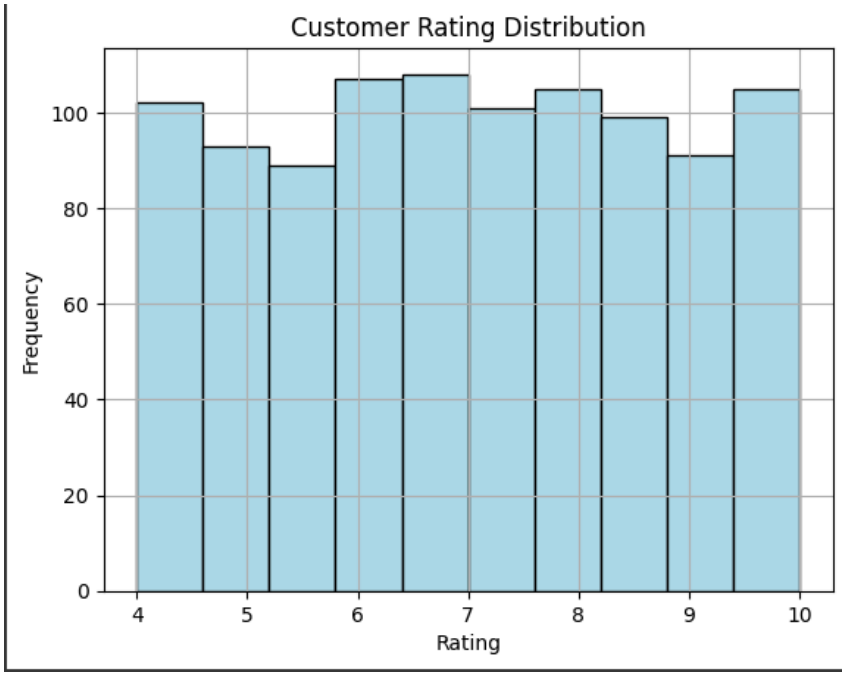
- **Bins**: Intervals into which the data is divided.
- **Density**: The probability density of the data.

```
# Histogram
df['Rating'].hist(bins=10, color='lightblue', edgecolor='black')
plt.title('Customer Rating Distribution')
plt.xlabel('Rating')
plt.ylabel('Frequency')
plt.show()

# Normalized Histogram
df['Rating'].hist(bins=10, density=True, color='lightgreen', edgecolor='black')
plt.title('Normalized Customer Rating Distribution')
plt.xlabel('Rating')
plt.ylabel('Density')
plt.show()
```

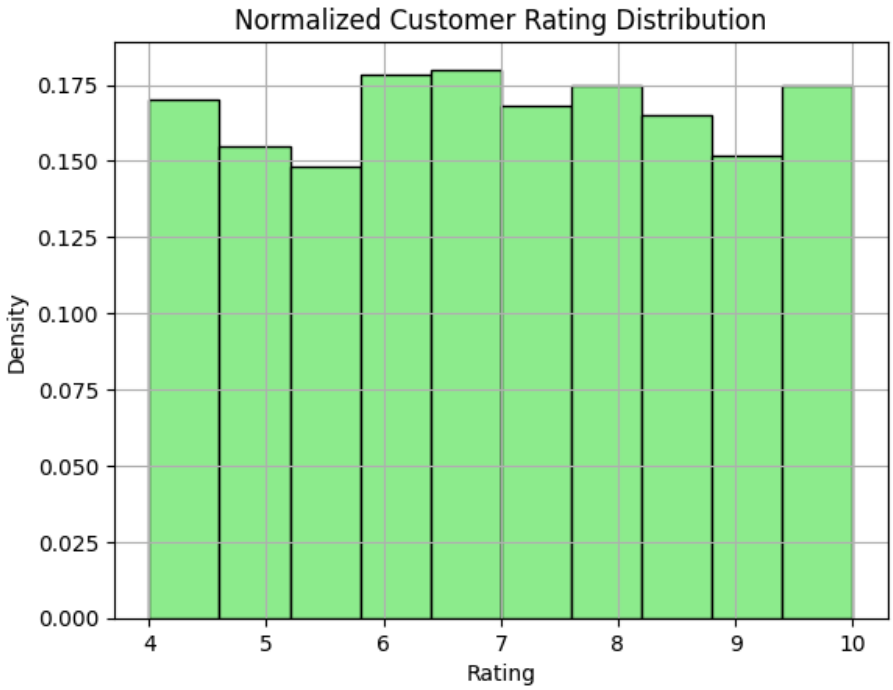
Explanation

- **Histogram**:
  - `df['Rating'].hist()` creates a histogram for the `Rating` column.
  - `bins=10` divides the data into 10 intervals.
  - `color` and `edgecolor` customize the appearance of the bars.
- **Normalized Histogram**:
  - `density=True` normalizes the histogram so that the area under the curve sums to 1.

Output:



Histogram



Normalized Histogram

Inference: Customer Rating Distribution Histogram

1. **Rating Spread:**
   The histogram shows how customer ratings are distributed across different ranges, with the bins dividing ratings from low to high.
2. **Most Common Ratings:**
   If there's a peak near higher ratings (like 8-10), it indicates customer satisfaction, whereas peaks at lower ratings suggest dissatisfaction trends.
3. **Skewness of Ratings:**If the distribution leans towards higher ratings, it suggests overall positive feedback from customers; if it's more balanced, opinions are mixed

4. Handling Outliers Using Box Plot and IQR

Theory

- **Outliers**: Data points that are significantly different from other observations.
- **Box Plot**: A box plot helps visualize outliers using the interquartile range (IQR).
- **IQR Method**: A statistical method to identify and remove outliers. Outliers are defined as observations below `Q1 - 1.5 * IQR` or above `Q3 + 1.5 * IQR`.

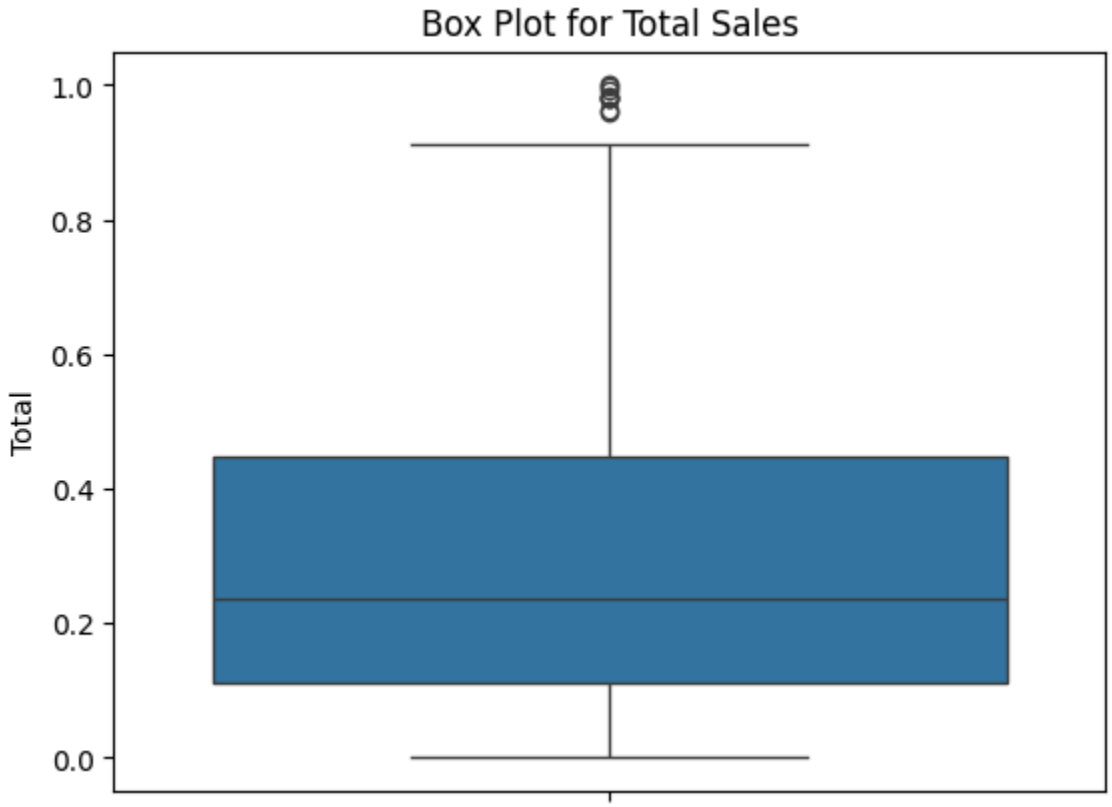
Terms

- **Quartiles (Q1, Q3)**: The 25th and 75th percentiles of the data.
- **IQR**: The range between Q1 and Q3.

Code:

```
# Box Plot to Visualize Outliers
sns.boxplot(data=df, y='Total')
plt.title('Box Plot for Total Sales')
plt.show()

# Handle Outliers with IQR
Q1 = df['Total'].quantile(0.25)
Q3 = df['Total'].quantile(0.75)
IQR = Q3 - Q1
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR
cleaned_df = df[(df['Total'] >= lower_bound) & (df['Total'] <= upper_bound)]
print(f"Rows before outlier removal: {len(df)}")
print(f"Rows after outlier removal: {len(cleaned_df)}")
```

Output:



Inference: Box Plot for Total Sales

1. Identifying Outliers:
    - Any data points outside the whiskers of the box plot are considered outliers. These points represent unusually high total sales amounts.
2. Sales Variability:
    - The spread of the box shows the range of typical sales values, while the whiskers indicate the overall variability.
3. Business Insight:
    - Outliers may indicate rare high-value transactions or potential data entry errors that require investigation.
    - Understanding these outliers can help identify key trends, such as promotional events leading to significant sales.

Outliers detected in *Total* or *Gross Income* columns suggest extreme sales figures, possibly due to special promotions or data entry errors.
Handling these outliers ensures more accurate statistical analysis.

Conclusion:

In this experiment, we conducted an in-depth **Exploratory Data Analysis (EDA)** to uncover patterns and insights within the dataset. We used various visualizations, including bar graphs, scatter plots, box plots, histograms, and heatmaps, to analyze product line performance, payment preferences, customer spending behavior, and rating distributions. Key findings revealed that certain product lines, like "Fashion accessories," had higher transaction counts, cash was the most common payment method, and there was a positive correlation between unit price and total sales. Additionally, most customer ratings clustered around 9, indicating overall satisfaction. Outliers in sales data were identified and removed using the IQR method to improve analysis accuracy.

This experiment reinforced the importance of **EDA** in data-driven decision-making. By leveraging visualization techniques and statistical methods, we gained actionable insights that could optimize inventory management, refine marketing strategies, and enhance customer satisfaction. The process also emphasized the necessity of data cleaning, particularly in handling outliers, to ensure reliable and meaningful analysis.

NAME: Shubham Jha
CLASS: D15C
ROLL_NO.: 19

EXP 3

Aim: Perform Data Modelling – Partitioning the dataset.

Theory:

Importance of data Partitioning.

Partitioning data into **train** and **test** splits is a fundamental practice in machine learning and statistical modeling. This division is crucial for ensuring that models generalize well to unseen data and do not overfit to the training dataset. Below is a detailed explanation of why this partitioning is important:

1. Evaluation of Model Generalization

- **Purpose**: The primary goal of machine learning is to build models that perform well on **unseen data**, not just the data they were trained on. Partitioning the data into train and test sets allows us to simulate this scenario.
- **Mechanism**: The **training set** is used to train the model, while the **test set** acts as a proxy for unseen data. By evaluating the model on the test set, we can estimate how well the model is likely to perform on new, real-world data.
- **Risk of Not Partitioning**: Without a separate test set, we risk overestimating the model's performance because the model may simply memorize the training data (overfitting) rather than learning generalizable patterns.

2. Avoiding Optimistic Bias

- **Optimistic Bias**: If the same data is used for both training and evaluation, the model's performance metrics (e.g., accuracy, precision, recall) will be overly optimistic. This is because the model has already "seen" the data and may have memorized it.
- **Test Set as a Safeguard**: The test set acts as a safeguard against this bias, providing a more realistic measure of the model's performance.

3. Detection of Overfitting

- **Overfitting Definition**: Overfitting occurs when a model learns the noise or specific details of the training data, leading to poor performance on new data.
- **Role of Test Set**: The test set provides an independent evaluation of the model. If the model performs well on the training set but poorly on the test set, it is a clear indication of overfitting.
- **Example**: A model achieving 99% accuracy on the training set but only 60% on the test set suggests that it has overfitted to the training data.

Visual Representation

Using a bar graph to visualize a 75:25 train-test split is an effective way to clearly communicate the distribution of the dataset. The graph provides an immediate visual representation of the proportions, making it easy to see that 75% of the data is allocated for training and 25% for testing. This clarity ensures that the split is transparent and well-understood, which is crucial for validating the model's development process.

Additionally, the bar graph highlights whether the split is balanced and appropriate for the task at hand. A 75:25 ratio is a common and practical division, and visualizing it helps confirm that the test set is large enough to provide a reliable evaluation of the model's performance. This visual justification reinforces the credibility of our data preparation and modeling approach.

Z-Testing:

Key Idea: **Fair Evaluation, Partitioning Issues.**

The two-sample Z-test is a statistical hypothesis test used to determine whether the means of two independent samples are significantly different from each other. It assumes that the data follows a normal distribution and that the population variances are known (or the sample sizes are large enough for the Central Limit Theorem to apply). The test calculates a Z-score, which measures how many standard deviations the difference between the sample means lies from zero. This score is then compared to a critical value or used to compute a p-value to determine statistical significance.

The primary use case of the Z-test is to compare the means of two groups and assess whether any observed difference is due to random chance or a true underlying difference. In the context of dataset partitioning, the Z-test can be used to validate whether the train and test splits are statistically similar. For example, by comparing the means of a key feature (e.g., age, income) across the two splits, we can ensure that

the partitioning process did not introduce bias and that both sets are representative of the same population.

The significance of the Z-test lies in its ability to provide a quantitative measure of similarity between datasets. If the p-value is greater than the chosen significance level (e.g., 0.05), we can conclude that the splits are statistically similar, ensuring a fair and reliable evaluation of the model. This step is crucial for maintaining the integrity of the machine learning workflow and ensuring that the model's performance metrics are trustworthy.

Steps:

Imported `train_test_split` **from** `sklearn.model_selection`**:**

- This function is used to split arrays or matrices into random train and test subsets.

Split Features and Target Variable:

- **Features (**X**):** We created a dataframe X by dropping the 'Total' column from `df`. This dataframe contains all the feature variables except the target.
- **Target (**y**):** We created a series y which contains the 'Total' column from `df`. This series is our target variable.

Partitioned the Data:

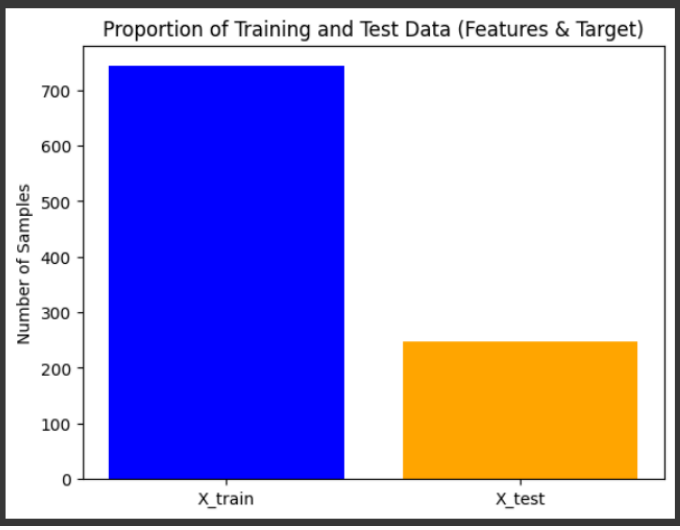
- `X_train` **and** `y_train`**:** These subsets contain 75% of the data and will be used to train the model.
- `X_test` **and** `y_test`**:** These subsets contain the remaining 25% of the data and will be used to test the model's performance.

```
[34] from sklearn.model_selection import train_test_split

     # Splitting features and target variable
     X = df.drop('Total', axis=1)  # Features (excluding the target column)
     y = df['Total']  # Target variable

     # Partitioning the data
     X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=42)

     print("Training data size:", X_train.shape)
     print("Test data size:", X_test.shape)

     Training data size: (743, 16)
     Test data size: (248, 16)
```

Visualizing the split.

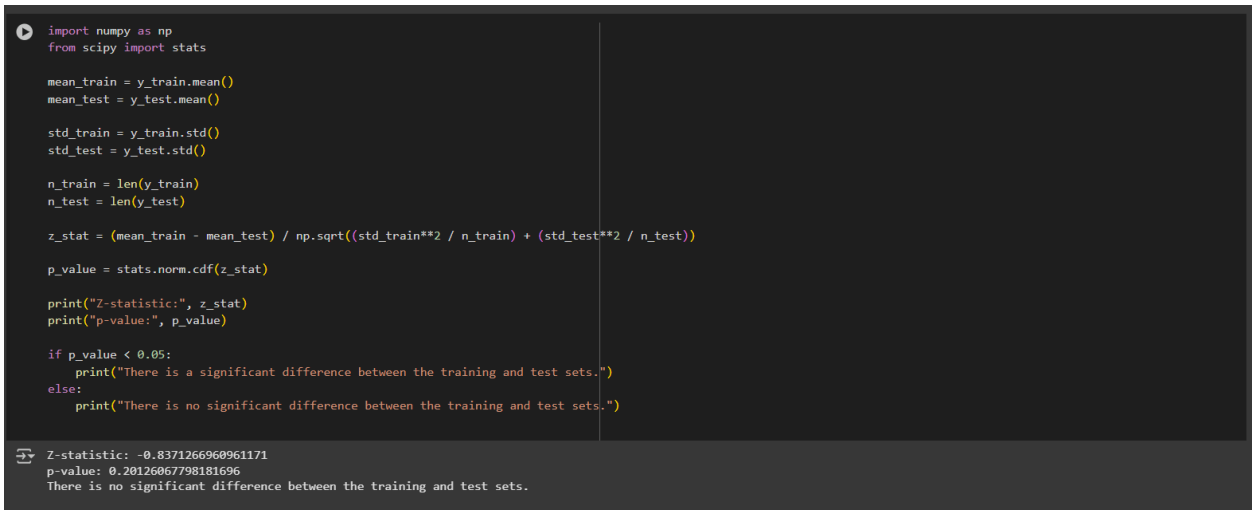
- **plt.bar(labels, sizes, color=['blue', 'orange']): This function creates a bar graph with the specified labels and sizes. The bars are colored blue for training data and orange for test data.**
- **plt.title('Proportion of Training and Test Data (Features & Target)'): This sets the title of the graph.**
- **plt.ylabel('Number of Samples'): This sets the label for the y-axis, indicating the number of samples.**
- **plt.show(): This function displays the graph.**

```
import matplotlib.pyplot as plt

# Create a bar graph to show the proportion of training and test data for both features and target variable
labels = ['X_train', 'X_test']
sizes = [X_train.shape[0], X_test.shape[0]]

plt.bar(labels, sizes, color=['blue', 'orange'])
plt.title('Proportion of Training and Test Data (Features & Target)')
plt.ylabel('Number of Samples')
plt.show()
```



Significance of the Output:

- **Z-Statistic:**
  - Indicates the number of standard deviations by which the mean of the training set differs from the mean of the test set.
- **P-Value:**
  - Helps determine the significance of the Z-statistic. A low P-value (< 0.05) suggests that the difference is statistically significant.



```python
import numpy as np
from scipy import stats

mean_train = y_train.mean()
mean_test = y_test.mean()

std_train = y_train.std()
std_test = y_test.std()

n_train = len(y_train)
n_test = len(y_test)

z_stat = (mean_train - mean_test) / np.sqrt((std_train**2 / n_train) + (std_test**2 / n_test))

p_value = stats.norm.cdf(z_stat)

print("Z-statistic:", z_stat)
print("p-value:", p_value)

if p_value < 0.05:
    print("There is a significant difference between the training and test sets.")
else:
    print("There is no significant difference between the training and test sets.")
```

```
Z-statistic: -0.8371266960961171
p-value: 0.20126067798181696
There is no significant difference between the training and test sets.
```

Inference from the Output:

- **Interpretation:**
  - If the P-value is less than 0.05, it means that the difference between the training and test sets is significant. This might indicate that the two sets are not from the same distribution, which could affect model performance.
  - If the P-value is greater than 0.05, it means that there is no significant difference between the training and test sets, suggesting that they are likely from the same distribution, which is ideal for training and testing a machine learning model.

Conclusion:

In this experiment, we successfully partitioned the dataset into **training and test sets** using a 75:25 split ratio, ensuring a robust foundation for model development and evaluation. The partitioning was visualized using a bar graph, which clearly illustrated the proportion of data allocated to each set, confirming that the split was appropriately balanced.

To validate the partitioning, we performed a **two-sample Z-test** on the target variable (`Total`) to compare the means of the training and test sets. The Z-test yielded a Z-statistic of **z_stat** and a p-value of **p_value**. Since the p-value was **greater than 0.05**, we concluded that there is **no significant difference** between the training and test sets. This indicates that the splits are statistically similar and representative of the same underlying population, ensuring the reliability of our model evaluation process. Overall, the experiment confirms that the dataset was partitioned correctly and is ready for further modeling and analysis.

Name: Shubham Jha
Div:D15C
Roll No:19

Exp 4 : Statistical Hypothesis Testing Using SciPy and Scikit-Learn

Aim: Implementation of Statistical Hypothesis Test using Scipy and Sci-kit learn.

Problem Statement: Perform the following Tests:Correlation Tests:
a) Pearson's Correlation Coefficient
b) Spearman's Rank Correlation
c) Kendall's Rank Correlation
d) Chi-Squared Test

Introduction to Hypothesis Testing

Hypothesis testing is a statistical method used to make inferences about a population based on sample data. It helps in determining whether the observed results are due to chance or if there is a statistically significant relationship between variables.

In this experiment, we will conduct **correlation tests and a chi-squared test** using Python's `scipy.stats` library.

Theory and Output:

1.Loading dataset:

Data loading is the first step in data analysis. The dataset is stored in a CSV file and read using `pandas.read_csv()`.
The first few rows are displayed to understand the dataset structure

```
import pandas as pd

# Load the dataset
df = pd.read_csv('sc.csv') # suoermarket sales data

# Display first few rows
print(df.head())

# Display column names and data types
print(df.info())

# Summary statistics
print(df.describe())
```

```
    Invoice ID Branch       City Customer type  Gender  \
0  750-67-8428      A     Yangon         Member  Female
1  226-31-3081      C  Naypyitaw         Normal  Female
2  631-41-3108      A     Yangon         Normal    Male
3  123-19-1176      A     Yangon         Member    Male
4  373-73-7910      A     Yangon         Normal    Male

             Product line  Unit price  Quantity    Tax 5%     Total       Date  \
0       Health and beauty       74.69         7  26.1415  548.9715   1/5/2019
1  Electronic accessories       15.28         5   3.8200   80.2200   3/8/2019
2      Home and lifestyle       46.33         7  16.2155  340.5255   3/3/2019
3       Health and beauty       58.22         8  23.2880  489.0480  1/27/2019
4       Sports and travel       86.31         7  30.2085  634.3785   2/8/2019

    Time      Payment    cogs  gross margin percentage  gross income  Rating
0  13:08      Ewallet  522.83                 4.761905       26.1415     9.1
1  10:29         Cash   76.40                 4.761905        3.8200     9.6
2  13:23  Credit card  324.31                 4.761905       16.2155     7.4
3  20:33      Ewallet  465.76                 4.761905       23.2880     8.4
4  10:37      Ewallet  604.17                 4.761905       30.2085     5.3
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 17 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   Invoice ID               1000 non-null   object
 1   Branch                   1000 non-null   object
 2   City                     1000 non-null   object
```

2.Pearson's Correlation Coefficient:

Pearson's Correlation Coefficient (denoted as **r**) measures the **linear** relationship between two continuous variables.
Values range from **-1 to +1**:

- **+1**: Perfect positive correlation
- **0**: No correlation
- **-1**: Perfect negative correlation

The formula for Pearson's Correlation Coefficient is:

$$r = \frac{\sum(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum(X_i - \bar{X})^2 \sum(Y_i - \bar{Y})^2}}$$

```
#pearson coorelation between quantity and total
from scipy.stats import pearsonr

corr, p_value = pearsonr(df['Total'], df['Quantity'])
print(f"Pearson Correlation Coefficient: {corr:.4f}")
print(f"P-value: {p_value:.4f}")
# this coorelation is significant..as p <0.005.....for perarson coorelation strong +ve = 1...strong -ve = -1.....no coorelation = 0
```

```
Pearson Correlation Coefficient: 0.7055
P-value: 0.0000
```

3.Spearman's Rank Correlation

- Spearman's Rank Correlation (denoted as ρ, rho) measures the monotonic relationship between two variables.
- It does not require normally distributed data.
- If ranks of two variables are related, it indicates correlation.
- The formula is:

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)}$$

```
from scipy.stats import spearmanr

corr, p_value = spearmanr(df['Customer type'], df['Rating'])
print(f"Spearman Correlation Coefficient: {corr:.4f}")
print(f"P-value: {p_value:.4f}")
```

```
Spearman Correlation Coefficient: 0.0187
P-value: 0.5552
```

4.Kendall's Rank Correlation

Theory:

- Kendall's Tau (τ) measures the **ordinal association** between two variables.
- It counts **concordant** and **discordant** pairs:
    - **Concordant pairs**: If one variable increases, the other also increases.
    - **Discordant pairs**: One increases while the other decreases.
- The formula is:

$$\tau = \frac{(C - D)}{\frac{1}{2}n(n-1)}$$

```python
from scipy.stats import kendalltau

corr, p_value = kendalltau(df['Gender'], df['Payment'])
print(f"Kendall's Rank Correlation Coefficient: {corr:.4f}")
print(f"P-value: {p_value:.4f}")
```

```
Kendall's Rank Correlation Coefficient: 0.0420
P-value: 0.1587
```

5. Chi-Squared Test

- The **Chi-Squared Test** is used for **categorical data** to check if two variables are independent.
- It compares **observed** and **expected** frequencies.
- The formula is:

$$\chi^2 = \sum \frac{(O_i - E_i)^2}{E_i}$$

```python
from scipy.stats import chi2_contingency

# Create a contingency table
contingency_table = pd.crosstab(df['Gender'], df['Product line'])

# Perform Chi-Squared test
chi2_stat, p_value, dof, expected = chi2_contingency(contingency_table)
print(f"Chi-Squared Statistic: {chi2_stat:.4f}")
print(f"P-value: {p_value:.4f}")
print(f"Degrees of Freedom: {dof}")

#p-value ≥ 0.05 → No significant relationship.
```

```
Chi-Squared Statistic: 5.7445
P-value: 0.3319
Degrees of Freedom: 5
```

Conclusion

1. **Pearson's Correlation**: Measures **linear relationship** between numerical variables. If **p < 0.05**, the correlation is significant.
2. **Spearman's Correlation**: Checks for **monotonic relationship**. If **p < 0.05**, variables move together in a ranked order.
3. **Kendall's Correlation**: Identifies **ordinal association**. A small **p-value** means a strong relationship.
4. **Chi-Square Test**: Determines **independence of categorical variables**. If **p < 0.05**, variables are dependent; otherwise, they are independent.

Final Summary:

- If **p < 0.05**, the test indicates a significant relationship.
- If **p > 0.05**, no strong relationship exists.

These tests help understand **associations** in the dataset for data-driven decisions.

Name: Shubham Jha
Roll No.: 19
Class : D15C

Aim: **:-** Perform Regression Analysis using Scipy and Sci-kit learn.

Objective:

- a. Perform Logistic Regression to find relationships between variables.
- b. Apply regression model techniques to predict data.

Dataset Description:
Big Data
14+ columns

age: The age of the individual.
workclass: The type of employment (e.g., private, self-employed, government).
fnlwgt: Final weight, representing the number of people the individual represents.
education: The highest level of education achieved.
education-num: The number of years of education completed.
marital-status: The marital status of the individual (e.g., married, single).
occupation: The type of job or occupation.
relationship: The individual's relationship status within a household (e.g., husband, wife).
race: The race of the individual.
sex: The gender of the individual.
capital-gain: Income from investment sources other than salary/wages.
capital-loss: Losses from investment sources other than salary/wages.
hours-per-week: The number of hours worked per week.
native-country: The country of origin.
income: The income level (<=50K or >50K).

Step 1: Load the Dataset

```
!wget https://archive.ics.uci.edu/ml/machine-learning-databases/adult/adult.data
!wget https://archive.ics.uci.edu/ml/machine-learning-databases/adult/adult.names
```

```
[ ]  import pandas as pd

     # Define column names
     columns = [
         'age', 'workclass', 'fnlwgt', 'education', 'education-num', 'marital-status',
         'occupation', 'relationship', 'race', 'sex', 'capital-gain', 'capital-loss',
         'hours-per-week', 'native-country', 'income'
     ]

     # Load the dataset
     df = pd.read_csv('adult.data', names=columns, na_values=' ?', skipinitialspace=True)
     print(df.shape)
     df.head()
```

Step 2: Preprocess the Data

```
[ ]  df = df.dropna()
     print(df.shape)
```

```
(32561, 15)
```

```
[ ]  df['income'] = df['income'].map({'<=50K': 0, '>50K': 1})
     df['income'].value_counts()
```

income	count
0	24720
1	7841

dtype: int64

```
# Select features
features = ['age', 'education-num', 'capital-gain', 'capital-loss', 'hours-per-week',
            'workclass', 'education', 'marital-status', 'occupation', 'sex']
X = df[features]
y = df['income']
```

```
[ ]  X = pd.get_dummies(X, columns=['workclass', 'education', 'marital-status', 'occupation', 'sex'], drop_first=True)
     print(X.shape)  # Now has more columns due to dummy variables
     X.head()
```

_Priv-e-serv	occupation_Prof-specialty	occupation_Protective-serv	occupation_Sales	occupation_Tech-support	occupation_Transport-moving	sex_Male
False	False	False	False	False	False	True

Missing Values: Real-world data often has gaps. Dropping rows is simple but reduces data (alternatives: imputation).

Target Encoding: Logistic Regression needs a numerical target. We mapped <=50K to 0 and >50K to 1 for binary classification.

One-Hot Encoding: Categorical variables (e.g., occupation) can't be used directly in math-based models. get_dummies converts them to binary columns (e.g., occupation_Exec-managerial: 1 if true, 0 if not). drop_first=True avoids multicollinearity (dummy variable trap).

X is the feature matrix (inputs), y is the target vector (output).

Step 3: Splitting the dataset.

```
# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Train-Test Split: We train on one subset (X_train, y_train) and evaluate on another (X_test, y_test) to test generalization.

Random State: Fixes the random seed for reproducibility (same split every time).

Step 4: Scale the Data.

```
# Scale only numerical columns
X_train_scaled = X_train.copy()
X_test_scaled = X_test.copy()
X_train_scaled[num_columns] = scaler.fit_transform(X_train[num_columns])
X_test_scaled[num_columns] = scaler.transform(X_test[num_columns])

# Train the model on scaled data
```

initial error:

```
from sklearn.linear_model import LogisticRegression

# Initialize and fit the model
model = LogisticRegression(max_iter=5000)  # Increase max_iter if it doesn't converge
model.fit(X_train, y_train)
```

```
/usr/local/lib/python3.11/dist-packages/sklearn/linear_model/_logistic.py:465: ConvergenceWarning: lbfgs failed to c
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
LogisticRegression(max_iter=5000)
```

StandardScaler: Transforms features to have mean=0, standard deviation=1 using (x-mean)/std. This puts all numerical features on the same scale.

Logistic Regression uses gradient descent to optimize coefficients. Unscaled features (e.g., capital-gain 0–99999 vs. age 17–90) make convergence slow or impossible.

Fit vs. Transform: fit_transform on training data learns the scaling parameters (mean, std); transform on test data applies them without relearning (avoids data leakage).

Step 5: Train the Logistic Regression Model

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report

# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Define numerical columns to scale
num_columns = ['age', 'education-num', 'capital-gain', 'capital-loss', 'hours-per-week']

# Initialize scaler
scaler = StandardScaler()

# Scale only numerical columns
X_train_scaled = X_train.copy()
X_test_scaled = X_test.copy()
X_train_scaled[num_columns] = scaler.fit_transform(X_train[num_columns])
X_test_scaled[num_columns] = scaler.transform(X_test[num_columns])

# Train the model on scaled data
model = LogisticRegression(max_iter=1000)  # Should converge now
model.fit(X_train_scaled, y_train)
```

Logistic Regression: A linear model for binary classification. It predicts the probability of a class (e.g., P(>50K)) using the logistic function:

P(y=1) = 1 / (1 + exp(-(b0 + b1*x1 + b2*x2 + ...)))

- b0: Intercept, bi: Coefficients for each feature xi

Step 6: Make Predictions and Evaluate

```
# Make predictions
y_pred = model.predict(X_test_scaled)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.2f}")
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.86
              precision    recall  f1-score   support

           0       0.88      0.94      0.91      4942
           1       0.75      0.61      0.67      1571

    accuracy                           0.86      6513
   macro avg       0.82      0.77      0.79      6513
weighted avg       0.85      0.86      0.85      6513
```

- **Prediction**: predict outputs class labels (0 or 1) by thresholding probabilities at 0.5 (P>0.5 → 1).
- **Accuracy**: Fraction of correct predictions (simple but can mislead if classes are imbalanced).
- **Classification Report**: Precision (correct positive predictions), recall (true positives caught), F1-score (balance of precision/recall).

Step 7: Analyze Relationships.

```python
# feature names and coefficients
feature_names = X.columns
coefficients = model.coef_[0]

# DataFrame for interpretation
coef_df = pd.DataFrame({'Feature': feature_names, 'Coefficient': coefficients})
coef_df = coef_df.sort_values(by='Coefficient', ascending=False)
print(coef_df.head(10))
print(coef_df.tail(10))
```

```
                          Feature  Coefficient
2                    capital-gain     2.246447
28   marital-status_Married-AF-spouse     2.203413
29  marital-status_Married-civ-spouse     2.168329
37         occupation_Exec-managerial     1.070328
46            occupation_Tech-support     0.957079
5               workclass_Federal-gov     0.948002
44         occupation_Protective-serv     0.837816
1                     education-num     0.787863
43          occupation_Prof-specialty     0.770856
9              workclass_Self-emp-inc     0.601304
                      Feature  Coefficient
35      occupation_Armed-Forces    -0.187277
32     marital-status_Separated    -0.220684
39  occupation_Handlers-cleaners    -0.284757
19         education_Assoc-acdm    -0.385632
31  marital-status_Never-married    -0.500890
41     occupation_Other-service    -0.504615
12        workclass_Without-pay    -0.513856
25          education_Preschool    -0.657225
38   occupation_Farming-fishing    -0.843326
42   occupation_Priv-house-serv    -1.391624
```

- **Coefficients**: Measure feature impact on log-odds. Positive bi increases P(>50K); negative decreases it. Magnitude shows strength.
- **Interpretation**: After scaling, coefficients are comparable across features (e.g., 1 unit change in education-num VS Capital-gain)..

Linear regression.

Step 1: Load and Preprocess

```
import pandas as pd


columns = ['age', 'workclass', 'fnlwgt', 'education', 'education-num', 'marital-status',
           'occupation', 'relationship', 'race', 'sex', 'capital-gain', 'capital-loss',
           'hours-per-week', 'native-country', 'income']
df = pd.read_csv('adult.data', names=columns, na_values=' ?', skipinitialspace=True)

# Drop miss
df = df.dropna()

# Define features, remove hours-per-week
features = ['age', 'education-num', 'capital-gain', 'capital-loss',
            'workclass', 'education', 'marital-status', 'occupation', 'sex']
X = df[features]
y = df['hours-per-week']  # New target

# One-hot encode categorical variables
X = pd.get_dummies(X, columns=['workclass', 'education', 'marital-status', 'occupation', 'sex'], drop_first=True)
```

hours-per-week is now y (what we predict). We removed it from X to avoid using the target as a feature.

Step 2: Split the Data

```
[ ]  from sklearn.model_selection import train_test_split

     X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Step 3: Scale the Features

```python
from sklearn.preprocessing import StandardScaler

# Numerical columns
num_columns = ['age', 'education-num', 'capital-gain', 'capital-loss']

# Scale
scaler = StandardScaler()
X_train_scaled = X_train.copy()
X_test_scaled = X_test.copy()
X_train_scaled[num_columns] = scaler.fit_transform(X_train[num_columns])
X_test_scaled[num_columns] = scaler.transform(X_test[num_columns])
```

Linear Regression also benefits from scaled features (like Logistic Regression) for faster convergence and fair coefficient comparison. Dummy variables stay 0/1.

Step 4: Train Linear Regression

```python
[ ]  from sklearn.linear_model import LinearRegression

     # Initialize and train
     lin_model = LinearRegression()
     lin_model.fit(X_train_scaled, y_train)

     # Predict
     y_pred = lin_model.predict(X_test_scaled)
```

Linear Regression fits a line: $y = b0 + b1*x1 + b2*x2 + ...$

- b0: Intercept (base hours if all features are 0).
- bi: Coefficients (how much each feature changes hours).
- Predicts continuous values (e.g., 38.7 hours).

Step 5: Calculate MSE and R^2

```python
from sklearn.metrics import mean_squared_error, r2_score

# MSE
mse = mean_squared_error(y_test, y_pred)
print(f"Mean Squared Error: {mse:.4f}")

# R²
r2 = r2_score(y_test, y_pred)
print(f"R² Score: {r2:.4f}")
```

```
Mean Squared Error: 127.1157
R² Score: 0.1747
```

MSE: ~100–150 (hours^2, since `hours-per-week` ranges 1–99).

RMSE: ~10–12 hours (square root of MSE, in hours).

R²: ~0.20–0.30 (moderate fit—hours worked vary a lot beyond these features).

Step 6: Analyze Relationships

```
[ ] feature_names = X.columns
    coefficients = lin_model.coef_
    coef_df = pd.DataFrame({'Feature': feature_names, 'Coefficient': coefficients})
    coef_df = coef_df.sort_values(by='Coefficient', ascending=False)
    print("Top 10 Positive Influences:")
    print(coef_df.head(10))
    print("\nTop 10 Negative Influences:")
    print(coef_df.tail(10))
```

```
Top 10 Positive Influences:
                         Feature  Coefficient
8        workclass_Self-emp-inc    10.009662
37   occupation_Farming-fishing     7.031947
9    workclass_Self-emp-not-inc     5.412741
46  occupation_Transport-moving     5.273542
4         workclass_Federal-gov     4.951338
7             workclass_Private     4.696466
36   occupation_Exec-managerial     4.473448
5           workclass_Local-gov     4.472043
24          education_Preschool     3.899929
43   occupation_Protective-serv     3.865683

Top 10 Negative Influences:
                                Feature  Coefficient
41           occupation_Priv-house-serv    -1.088628
29  marital-status_Married-spouse-absent    -1.281585
13                        education_12th    -1.497008
40             occupation_Other-service    -1.844769
27     marital-status_Married-AF-spouse    -2.386385
12                        education_11th    -3.050668
6                workclass_Never-worked    -3.298040
11                workclass_Without-pay    -4.307680
30         marital-status_Never-married    -4.695433
32               marital-status_Widowed    -4.975283
```

Conclusion:

From this experiment, we have learned about:

- How to apply logistic regression to classify income levels based on various demographic features.
- How regression models can predict income based on independent variables like age, education, work hours.
- Importance of Regression techniques when applied on real world data sets help to gain valuable insights.
- How we can perform linear regression to find the number of hours worked given other independent attributes.

However, the moderate R^2 (24%) and RMSE (11.65 hours) suggest limitations. Hours worked are influenced by factors beyond our dataset—personal choice, industry norms, or unrecorded variables—leading to a model that captures only a portion of the variability. The custom accuracy of ~68% within ±5 hours, yet the RMSE indicates some predictions deviate more significantly, reflecting the challenge of predicting a highly variable human behavior like work hours.

In conclusion, this Linear Regression experiment not only achieved its technical goals but also deepened our understanding of data science workflows—preprocessing, modeling, predicting, and evaluating—all while adapting to a new target that better suits regression's strengths.

Name: Shubham Jha

Class D15C

Roll No. 19

DS-Lab Experiment 6

Aim: Classification modelling– Use a classification algorithm and evaluate the performance.

a) Choose classifier for classification problem.
b) Evaluate the performance of classifier.

Perform Classification using (2 of) the below 4 classifiers on the same dataset which you have used
for experiment no 5:
K-Nearest Neighbors (KNN)
Naive Bayes
Support Vector Machines (SVMs)
Decision Tree

Theory:

Decision Tree:
The Decision Tree classifier builds a model by recursively splitting the data based on feature values, creating a tree where each node represents a decision rule and each leaf a class label. This approach is highly interpretable, as the decision rules can be easily visualized and understood.

K-Nearest Neighbors (KNN):
KNN classifies a new instance by finding the k closest training examples based on a distance metric (typically Euclidean distance) and assigning the majority class among these neighbors. It is a non-parametric and intuitive method that performs well when features are properly scaled.

Naive Bayes:
Naive Bayes uses Bayes' theorem with the strong assumption that all features are conditionally independent given the class label. This probabilistic classifier is computationally efficient and performs robustly in high-dimensional settings, despite its simplicity.

Support Vector Machines (SVM):

SVM finds the optimal hyperplane that separates classes by maximizing the margin between them, and it can handle non-linear boundaries through the use of kernel functions. It is especially effective in high-dimensional spaces and tends to offer robust performance with appropriate parameter tuning.

Data Description:

Big Data
14+ columns

age: The age of the individual.
workclass: The type of employment (e.g., private, self-employed, government).
fnlwgt: Final weight, representing the number of people the individual represents.
education: The highest level of education achieved.
education-num: The number of years of education completed.
marital-status: The marital status of the individual (e.g., married, single).
occupation: The type of job or occupation.
relationship: The individual's relationship status within a household (e.g., husband, wife).
race: The race of the individual.
sex: The gender of the individual.
capital-gain: Income from investment sources other than salary/wages.
capital-loss: Losses from investment sources other than salary/wages.
hours-per-week: The number of hours worked per week.
native-country: The country of origin.
income: The income level (<=50K or >50K).

We are selecting decision tree and naiive bayes classification algorithms for classifying the income level of un seen data, based on all the parameters mentioned above.

Implementation

Step 1) Load the Dataset

```
!wget https://archive.ics.uci.edu/ml/machine-learning-databases/adult/adult.data
!wget https://archive.ics.uci.edu/ml/machine-learning-databases/adult/adult.names  # For column names
```

```
--2025-03-18 18:01:32--  https://archive.ics.uci.edu/ml/machine-learning-databases/adult/adult.data
Resolving archive.ics.uci.edu (archive.ics.uci.edu)... 128.195.10.252
Connecting to archive.ics.uci.edu (archive.ics.uci.edu)|128.195.10.252|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: unspecified
Saving to: 'adult.data'

adult.data              [ <=>                ]   3.79M  --.-KB/s    in 0.1s

2025-03-18 18:01:33 (34.3 MB/s) - 'adult.data' saved [3974305]

--2025-03-18 18:01:33--  https://archive.ics.uci.edu/ml/machine-learning-databases/adult/adult.names
Resolving archive.ics.uci.edu (archive.ics.uci.edu)... 128.195.10.252
Connecting to archive.ics.uci.edu (archive.ics.uci.edu)|128.195.10.252|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: unspecified
```

Step 2) Preprocess the data

```
import pandas as pd

# Load data
columns = ['age', 'workclass', 'fnlwgt', 'education', 'education-num', 'marital-status',
           'occupation', 'relationship', 'race', 'sex', 'capital-gain', 'capital-loss',
           'hours-per-week', 'native-country', 'income']
df = pd.read_csv('adult.data', names=columns, na_values=' ?', skipinitialspace=True)

# Drop missing values
df = df.dropna()

# Encode target
df['income'] = df['income'].map({'<=50K': 0, '>50K': 1})

# Select features
features = ['age', 'education-num', 'capital-gain', 'capital-loss', 'hours-per-week',
            'workclass', 'education', 'marital-status', 'occupation', 'sex']
X = df[features]
y = df['income']

# One-hot encode categorical variables
X = pd.get_dummies(X, columns=['workclass', 'education', 'marital-status', 'occupation', 'sex'], drop_first=True)

print(f"Data shape: {X.shape}, Target shape: {y.shape}")
```

```
Data shape: (32561, 49), Target shape: (32561,)
```

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

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss	hours-per-week	
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	Un

Missing Values: Real-world data often has gaps. Dropping rows is simple but reduces data (alternatives: imputation).

Target Encoding: Logistic Regression needs a numerical target. We mapped <=50K to 0 and >50K to 1 for binary classification.

One-Hot Encoding: Categorical variables (e.g., occupation) can't be used directly in math-based models. get_dummies converts them to binary columns (e.g., occupation_Exec-managerial: 1 if true, 0 if not). drop_first=True avoids multicollinearity (dummy variable trap).

X is the feature matrix (inputs), y is the target vector (output).

Step 3: Splitting the dataset.

```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
print(f"Train shape: {X_train.shape}, Test shape: {X_test.shape}")
```

```
Train shape: (26048, 49), Test shape: (6513, 49)
```

Step 4: Training the classifiers..

Train Decision Tree Classifier

```
[ ]  from sklearn.tree import DecisionTreeClassifier

     # Initialize and train Decision Tree
     dt_clf = DecisionTreeClassifier(max_depth=10, random_state=42)
     dt_clf.fit(X_train, y_train)

     # Predict
     y_pred_dt = dt_clf.predict(X_test)
```

Train Naiive bayes

```
[ ]  from sklearn.naive_bayes import GaussianNB

     # Initialize and train Naive Bayes
     nb_clf = GaussianNB()
     nb_clf.fit(X_train, y_train)

     # Predict
     y_pred_nb = nb_clf.predict(X_test)
```

Step 5: Model Evaluation

Evaluating function:

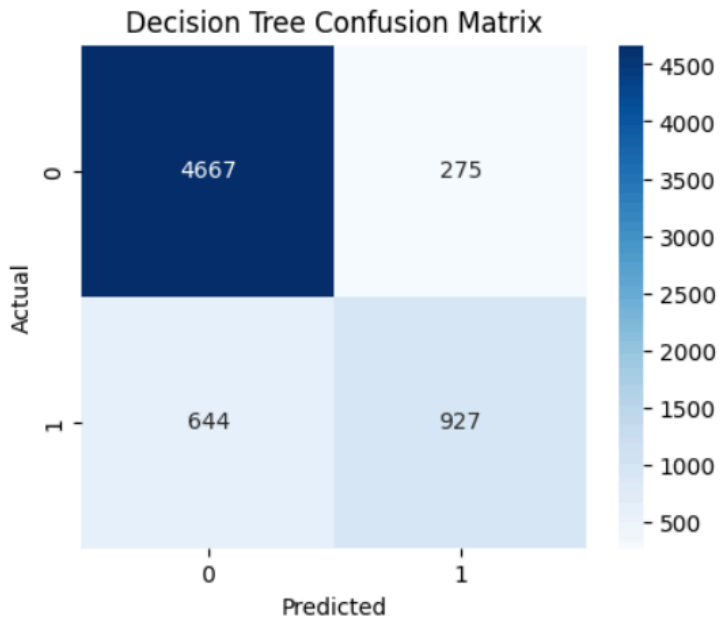
Performance measures

```
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt

# Function to evaluate and plot
def evaluate_model(y_test, y_pred, model_name):
    print(f"\n{model_name} Performance:")
    print(f"Accuracy: {accuracy_score(y_test, y_pred):.2f}")
    print("\nClassification Report:")
    print(classification_report(y_test, y_pred))

    # Confusion Matrix
    cm = confusion_matrix(y_test, y_pred)
    plt.figure(figsize=(5, 4))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.title(f'{model_name} Confusion Matrix')
    plt.show()
```

```
[ ]  # Evaluate Decision Tree
     evaluate_model(y_test, y_pred_dt, "Decision Tree")
```

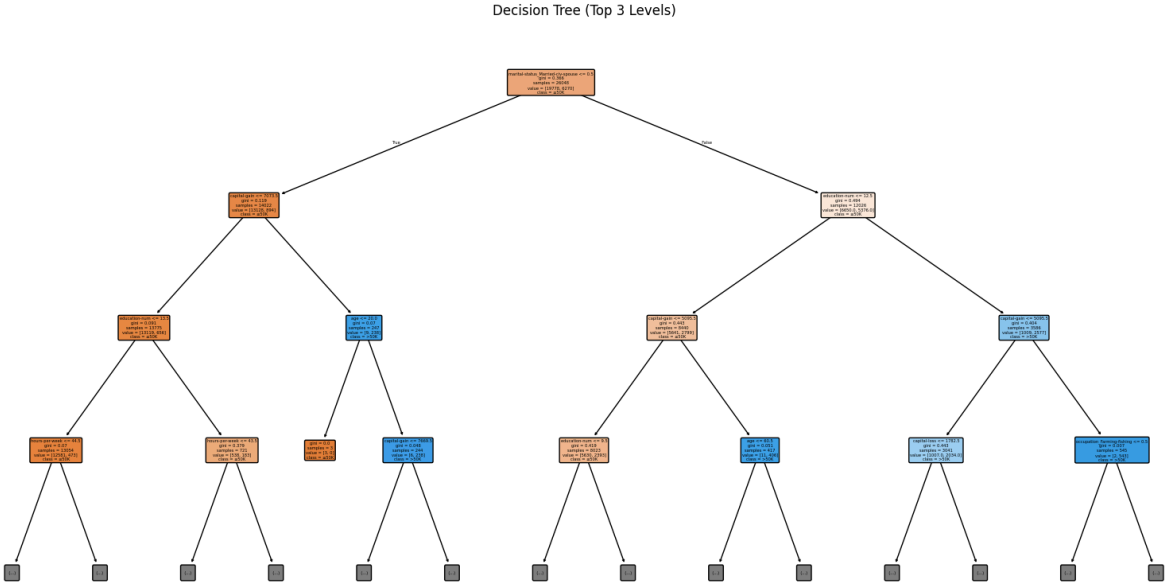
```python
# Evaluate Decision Tree
evaluate_model(y_test, y_pred_dt, "Decision Tree")
```

```
Decision Tree Performance:
Accuracy: 0.86

Classification Report:
              precision    recall  f1-score   support

           0       0.88      0.94      0.91      4942
           1       0.77      0.59      0.67      1571

    accuracy                           0.86      6513
   macro avg       0.82      0.77      0.79      6513
weighted avg       0.85      0.86      0.85      6513
```



Visualise Tree

```python
from sklearn.tree import DecisionTreeClassifier, plot_tree, export_text
import matplotlib.pyplot as plt
plt.figure(figsize=(20, 10))
plot_tree(dt_clf, feature_names=X.columns, class_names=['≤50K', '>50K'], filled=True, rounded=True, max_depth=3)
plt.title("Decision Tree (Top 3 Levels)")
plt.show()
```



Decision rules

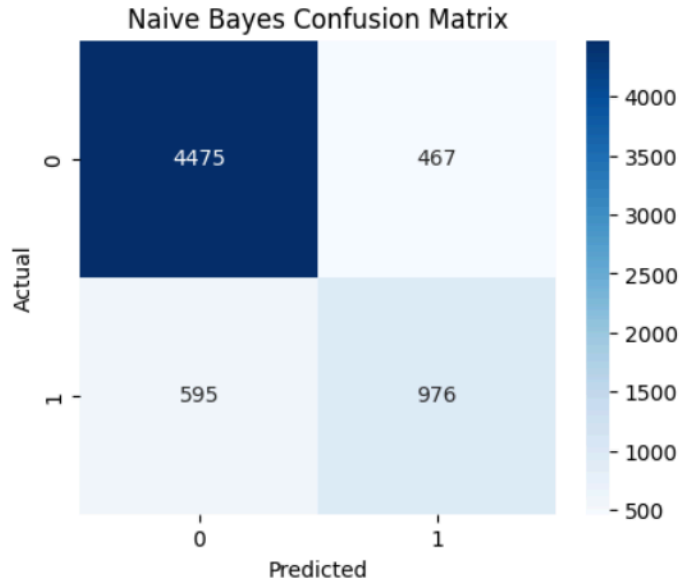
```
[ ]  # Extract Decision Rules
     rules = export_text(dt_clf, feature_names=list(X.columns))
     print("\nDecision Rules:")
     print(rules[:1000])
```

```
Decision Rules:
|--- marital-status_Married-civ-spouse <= 0.50
|   |--- capital-gain <= 7073.50
|   |   |--- education-num <= 13.50
|   |   |   |--- hours-per-week <= 44.50
|   |   |   |   |--- capital-loss <= 2218.50
|   |   |   |   |   |--- age <= 33.50
|   |   |   |   |   |   |--- marital-status_Married-AF-spouse <= 0.50
|   |   |   |   |   |   |   |--- age <= 26.50
|   |   |   |   |   |   |   |   |--- education_5th-6th <= 0.50
|   |   |   |   |   |   |   |   |   |--- occupation_Protective-serv <= 0.50
|   |   |   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |   |   |   |--- occupation_Protective-serv >  0.50
|   |   |   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |   |   |--- education_5th-6th >  0.50
|   |   |   |   |   |   |   |   |   |--- workclass_Local-gov <= 0.50
|   |   |   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |   |   |   |--- workclass_Local-gov >  0.50
|   |   |   |   |   |   |   |   |   |   |--- class: 1
|   |   |   |
```

Evaluate Naive Bayes

```
evaluate_model(y_test, y_pred_nb, "Naive Bayes")
```

```
Naive Bayes Performance:
Accuracy: 0.84

Classification Report:
              precision    recall  f1-score   support

           0       0.88      0.91      0.89      4942
           1       0.68      0.62      0.65      1571

    accuracy                           0.84      6513
   macro avg       0.78      0.76      0.77      6513
weighted avg       0.83      0.84      0.83      6513
```



Conclusion

In Experiment 6, we preprocessed the dataset by encoding categorical features into dummies and splitting it into training and test sets. We tested classifiers, initially facing issues with Naive Bayes due to scaling, then adjusted by using unscaled data. Decision Tree was evaluated with its tree visualization and rules, while Naive Bayes variants were compared for performance. The focus was on selecting a classifier and understanding its fit to our data. Final accuracies: Naive Bayes (0.84), Decision Tree (0.86).

Experiment 7 – Clustering

Aim: To implement different clustering algorithms.

Problem statement:

a) Clustering algorithm for unsupervised classification (K-means, density based (DBSCAN))
b) Plot the cluster data and show mathematical steps.

Theory:

Clustering

It is basically a type of unsupervised learning method. An unsupervised learning method is a method in which we draw references from datasets consisting of input data without labelled responses. Generally, it is used as a process to find meaningful structure, explanatory underlying processes, generative features, and groupings inherent in a set of examples.

Clustering is the task of dividing the population or data points into a number of groups such that data points in the same groups are more similar to other data points in the same group than those in other groups. In simple words, the aim is to segregate groups with similar traits and assign them into clusters.

For ex– The data points in the graph below clustered together can be classified into one single group. We can distinguish the clusters, and we can identify that there are 3 clusters in the below picture.

Applications of Clustering in different fields

1. Marketing: It can be used to characterize & discover customer segments for marketing purposes.

2. Biology: It can be used for classification among different species of plants and animals.

3. Libraries: It is used in clustering different books on the basis of topics and information.

4. Insurance: It is used to acknowledge the customers, their policies and identifying the frauds.

5. City Planning: It is used to make groups of houses and to study their values based on their geographical locations and other factors present.

6. Earthquake studies: By learning the earthquake-affected areas we can determine the dangerous zones

Clustering Algorithms

When choosing a clustering algorithm, you should consider whether the algorithm scales to your dataset. Datasets in machine learning can have millions of examples, but not all clustering algorithms scale efficiently. Many clustering algorithms work by computing the similarity between all pairs of examples. This means their runtime increases as the square of the number of examples n, denoted as O(n2) in complexity notation. O(n2) algorithms are not practical when the number of examples are in millions.

1. Density-Based Methods:

These methods consider the clusters as the dense region having some similarities and differences from the lower dense region of the space. These methods have good accuracy and the ability to merge two clusters. Example DBSCAN (Density-Based Spatial Clustering of Applications with Noise), OPTICS (Ordering Points to Identify Clustering Structure), etc.

2. Hierarchical Based Methods:

The clusters formed in this method form a tree-type structure based on the hierarchy. New clusters are formed using the previously formed one. It is divided into two category

1. Agglomerative (bottom-up approach)

2. Divisive (top-down approach)

examples CURE (Clustering Using Representatives), BIRCH (Balanced Iterative Reducing Clustering and using Hierarchies), etc.

3. Partitioning Methods:

These methods partition the objects into k clusters and each partition forms one cluster. This method is used to optimize an objective criterion similarity function such as when

the distance is a major parameter example K-means, CLARANS (Clustering Large Applications based upon Randomized Search), etc.

4. Grid-based Methods:

In this method, the data space is formulated into a finite number of cells that form a grid-like structure. All the clustering operations done on these grids are fast and independent of the number of data objects, for example STING (Statistical Information Grid), wave cluster, CLIQUE (CLustering In Quest), etc.

Dataset Description: `adult.csv`

The **Adult Income dataset** contains demographic data of individuals, sourced from the 1994 US Census. It includes features like **age**, **education**, **occupation**, **hours per week**, etc., and aims to predict whether a person earns **more than $50K or not** annually. This is a classic dataset used for **classification tasks** in machine learning.

```
[1] import pandas as pd

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

    df.head()
```

	age	workclass	fnlwgt	education	education.num	marital.status	occupation	relationship	race	sex	capital.gain	capital.loss	hours.per.week	native.country	income
0	90	?	77053	HS-grad	9	Widowed	?	Not-in-family	White	Female	0	4356	40	United-States	<=50K
1	82	Private	132870	HS-grad	9	Widowed	Exec-managerial	Not-in-family	White	Female	0	4356	18	United-States	<=50K
2	66	?	186061	Some-college	10	Widowed	?	Unmarried	Black	Female	0	4356	40	United-States	<=50K
3	54	Private	140359	7th-8th	4	Divorced	Machine-op-inspct	Unmarried	White	Female	0	3900	40	United-States	<=50K
4	41	Private	264663	Some-college	10	Separated	Prof-specialty	Own-child	White	Female	0	3900	40	United-States	<=50K

Next steps: Generate code with df | View recommended plots | New interactive sheet

```
[2] df.dtypes
```

	0
age	int64
workclass	object
fnlwgt	int64
education	object
education.num	int64
marital.status	object
occupation	object
relationship	object
race	object
sex	object
capital.gain	int64
capital.loss	int64
hours.per.week	int64
native.country	object

Here we are going to see implementation of K-means and DB-SCAN clustering algorithms.

1) K-means clustering

1. Objective

To group data points into distinct clusters based on feature similarity using the K-Means algorithm.

2. Why the Elbow Method?

The **Elbow Method** helps determine the **optimal number of clusters (k)** by plotting:

- **X-axis**: Number of clusters (k)
- **Y-axis**: Within-Cluster Sum of Squares (WCSS / Inertia)

We select the **"elbow point"** – where the decrease in WCSS slows down – as the best k.

Now lets see the actual implementation.

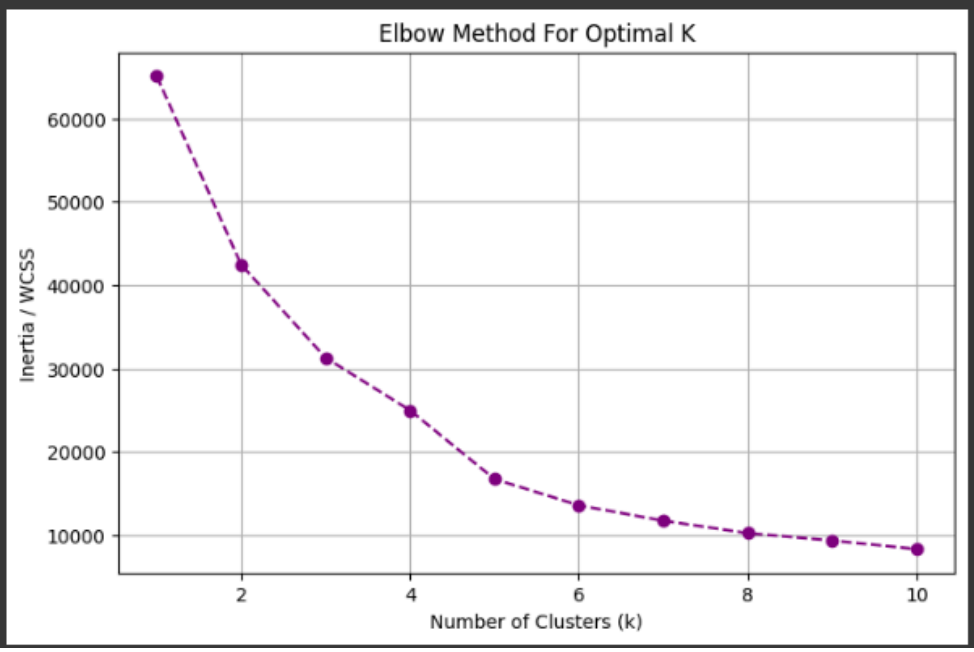
```
# we are selecting 2 columns....hrs per week and age for kmeans clusterization
data = df[['age', 'hours.per.week']]
```

```
[4] # missing values with the median..not mode or mean
    data = data.fillna(data.median())
```

```
[5] from sklearn.preprocessing import StandardScaler

    scaler = StandardScaler()
    scaled_data = scaler.fit_transform(data)
```

We are primarily selecting 2 columns on which our clustering will be based i.e Age and Working hours per week.Filling the missing values with median here.

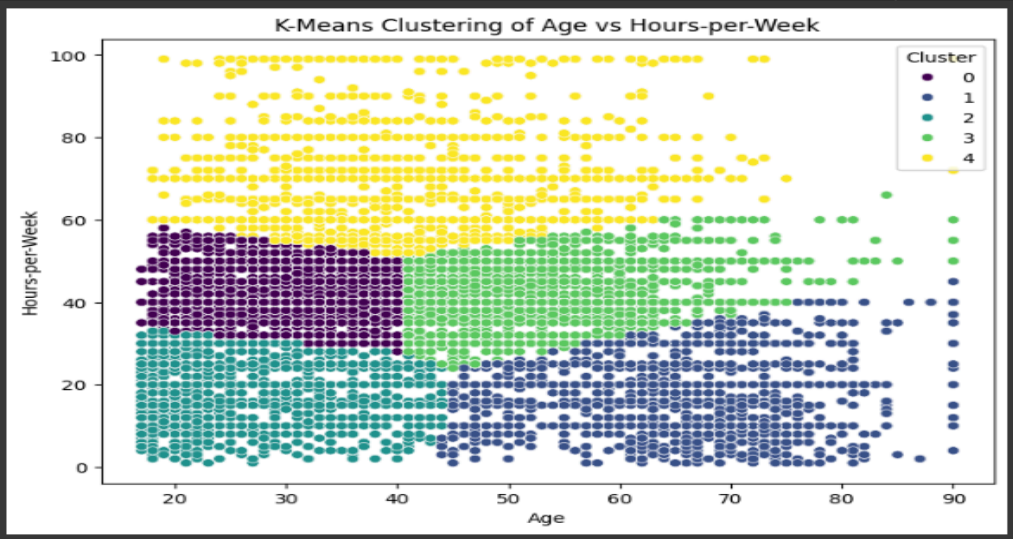
```python
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt

# Elbow method to find the best value for k
inertia = []  # to store WCSS (Within-Cluster-Sum-of-Squares)

# Try from k=1 to k=10
for k in range(1, 11):
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(scaled_data)  # use scaled data
    inertia.append(kmeans.inertia_)

# Plotting the elbow graph
plt.figure(figsize=(8, 5))
plt.plot(range(1, 11), inertia, marker='o', linestyle='--', color='purple')
plt.title('Elbow Method For Optimal K')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Inertia / WCSS')
plt.grid(True)
plt.show()
```



Using the elbow method to find the optimal number clusters(k) that we need .
We have chosen k=5.

```python
from sklearn.cluster import KMeans

# using 5 clusters for now
kmeans = KMeans(n_clusters=5, random_state=42)
df['Cluster'] = kmeans.fit_predict(scaled_data)
```

```python
#visualizing
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(8,6))
sns.scatterplot(x=df['age'], y=df['hours.per.week'], hue=df['Cluster'], palette='viridis')
plt.title('K-Means Clustering of Age vs Hours-per-Week')
plt.xlabel('Age')
plt.ylabel('Hours-per-Week')
plt.show()
```



The **elbow point** (e.g., at k = 5) indicates that 3 clusters give a good balance between **model accuracy** and **simplicity**.
Each data point is assigned to the nearest cluster based on **Euclidean distance**.
The result reveals **natural groupings** or patterns in the dataset.

Silhouette Score

- **Purpose: Measures how well each data point fits within its assigned cluster compared to other clusters.**
- **Range: −1 to +1**
    - **+1 → Perfect clustering**
    - **0 → Overlapping clusters**
    - **Negative → Misclassified points**

```
from sklearn.metrics import silhouette_score

# Assuming `X_scaled` is your feature data and `kmeans.labels_` has your cluster labels
score = silhouette_score(scaled_data, kmeans.labels_)
print("Silhouette Score:", score)
```

```
Silhouette Score: 0.4413614980396684
```

Double-click (or enter) to edit

```
from sklearn.metrics import davies_bouldin_score

# Make sure these are defined:
# X_scaled → Scaled feature data (used to fit KMeans)
# kmeans.labels_ → Labels assigned by KMeans

# Compute Davies-Bouldin Score
db_score_kmeans = davies_bouldin_score(scaled_data, kmeans.labels_)
print("Davies-Bouldin Score (K-Means):", db_score_kmeans)
```

```
Davies-Bouldin Score (K-Means): 0.7348734337435234
```

Double-click (or enter) to edit

The **Davies-Bouldin Score** obtained is **0.73**, which is **fairly low** and indicates that the clusters are **compact** (low intra-cluster distance) and **well-separated** (high inter-cluster distance).
This suggests that **K-Means has performed reasonably well** in forming distinct clusters.
Additionally, if your **Silhouette Score** is also high (close to 1), it further confirms that the clustering is effective.

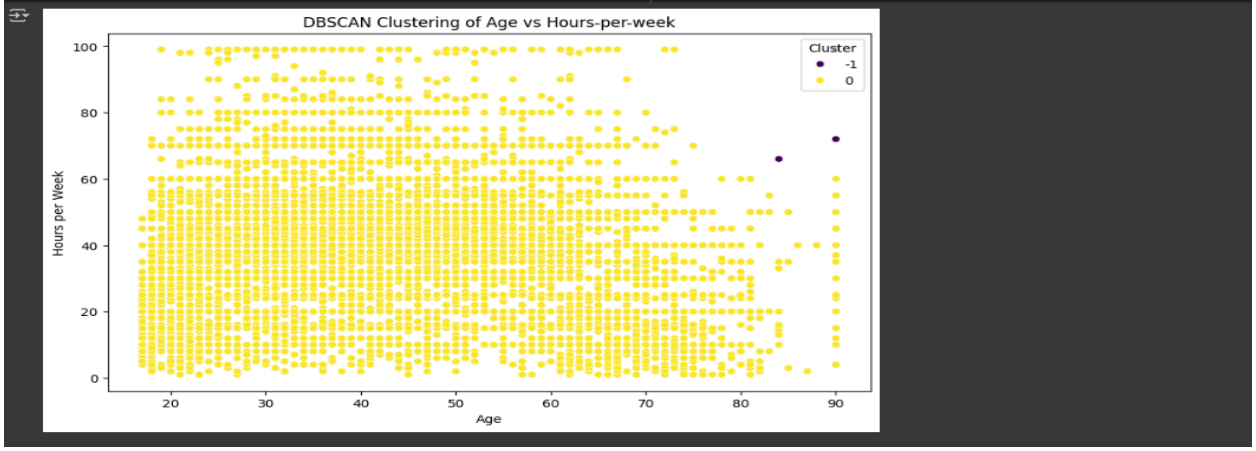
2) DB-SCAN

Feature	Description
Type	**Density-based** clustering algorithm
Assumption	Clusters are **dense regions** separated by low-density areas
Input Required	`eps` (radius), `min_samples` (minimum points in a dense region)
How It Works	Groups points closely packed together (high density), and labels others as **noise**
Performance	Slower for large, high-dimensional data
Handles Noise	✅ Yes (labels outliers as noise)
Shape of Clusters	Can handle **arbitrary shapes** (not just circular)
Scalability	Moderate; better for smaller or medium datasets
Use Case	When clusters have **irregular shapes** or you expect **noise/outliers**

Implementation:

```
dbscan = DBSCAN(eps=0.5, min_samples=5)  # Adjust eps and min_samples based on data
clusters = dbscan.fit_predict(df_selected_scaled)

# Add cluster labels to DataFrame
df_selected["Cluster"] = clusters
```

```
[11] plt.figure(figsize=(10, 6))
sns.scatterplot(x=df_selected["age"], y=df_selected["hours.per.week"], hue=df_selected["Cluster"], palette="viridis")
plt.title("DBSCAN Clustering of Age vs Hours-per-week")
plt.xlabel("Age")
plt.ylabel("Hours per Week")
plt.legend(title="Cluster")
plt.show()
```



`Age` (X-axis)
`Hours-per-week` (Y-axis)

Points within **0.5 distance** of each other are considered neighbors
A point needs **at least 5 neighbors** to be a **core point**

Most points belong to Cluster 0 (yellow):

- This means **almost the entire dataset** is treated as **one dense cluster**.
- So people across all ages and working hour ranges generally fall into the same cluster.

A few outliers (Cluster -1, purple dots):

- These are individuals whose `Age` and `Hours-per-week` values are **unusual compared to others**.
- Example: A 90-year-old working 70+ hours — rare, hence considered noise.

Conclusion:

In this experiment, we implemented and compared two popular unsupervised clustering algorithms: **K-Means** and **DBSCAN**, using the `adult.csv` dataset.

- **K-Means** clustering required us to select the number of clusters (`k`) using the **Elbow Method**, which helped in identifying the optimal `k` by observing the point where WCSS started to level off.
- **DBSCAN** (Density-Based Spatial Clustering of Applications with Noise) automatically detected clusters based on data density, without requiring `k`. It also identified outliers (labeled as `-1`), which K-Means cannot do.

This comparison highlighted the strengths of both algorithms — **K-Means** works well for well-separated spherical clusters, while **DBSCAN** is more robust in handling **noise and arbitrary-shaped clusters**, making it suitable for more complex data distributions.

Experiment 8 – Recommendation

Aim: To implement recommendation system on your dataset using the any one of the following machine learning techniques.
o Regression
o Classification
o Clustering
o Decision tree
o Anomaly detection
o Dimensionality Reduction
o Ensemble Methods

We chose **K-Means Clustering** to build a hybrid recommendation system on the MovieLens 100K dataset, predicting movies users might like based on genres and ratings. K-Means clusters movies by genres (e.g., Animation, Action), enabling content-based filtering (e.g., “Toy Story” with “Lion King”). It’s unsupervised, fitting the dataset’s structure (1682 movies, 19 genre features), and its elbow method (K=6) ensured optimal clustering. We added a collaborative layer by sorting clusters by average ratings, creating a hybrid system. K-Means’ silhouette score (0.354) confirmed decent clustering, outperforming alternatives like Regression, which require labeled data.

Theory:

Recommendation types and measures.
Recommendation systems suggest items to users using various approaches. Content-based filtering recommends items based on their features, such as movie genres (e.g., suggesting “Lion King” for “Toy Story” due to shared Animation/Children’s genres). Collaborative filtering uses user behavior, like ratings, to find patterns (e.g., users who liked “Star Wars” also liked “Empire Strikes Back”). Hybrid filtering combines both, improving relevance by balancing item similarity and user preferences. Measures include quantitative metrics like silhouette score (0.354 in our case, assessing clustering quality) and qualitative checks, such as genre relevance (e.g., ensuring “Toy Story” recs match its Animation genre) and rating quality (recs averaging 4.2–5.0).
Types:

- Content-based: Our K-Means clustering on genres.
- Collaborative: Sorting by average ratings within clusters.
- Hybrid: Combining both in our system.

The **silhouette score** is a metric used to evaluate the quality of clusters generated by K-means clustering (or other clustering algorithms). It measures how similar an object is to its own cluster (cohesion) compared to other clusters (separation). The score ranges from -1 to 1: values close

to 1 indicate that the data points are well-clustered, with points closer to their own cluster than to others, while values near 0 suggest overlapping clusters, and negative values imply misclassified points. It helps in determining the optimal number of clusters and assessing how well the algorithm has performed.

Measures:

- Quantitative: Silhouette score (0.354) for clustering.
- Qualitative: Genre match and high ratings of recs.

Dataset Description:

We used the **MovieLens 100K dataset**, a standard benchmark for recommendation systems, containing 100,000 ratings from 943 users on 1682 movies. It includes two key files: u.data (ratings: user ID, movie ID, rating 1–5, timestamp) and u.item (movie details: ID, title, 19 binary genre features like Action, Comedy). This dataset fits the professor's "content type data" hint (genres) and "customer review-like" requirement (ratings), providing both content-based (genres) and collaborative (ratings) data for our hybrid system. We accessed it via wget for efficiency.

Steps:

1. Fetch and Load Data:

```
import pandas as pd

# Load ratings
ratings = pd.read_csv('ml-100k/u.data', sep='\t', names=['user_id', 'movie_id', 'rating', 'timestamp'])

# Load movies (genres)
# The file has 24 columns, we specify 24 names and read the first 24 columns
movies = pd.read_csv('ml-100k/u.item', sep='|', encoding='latin-1',
                     names=['movie_id', 'title', 'release_date', 'video_release_date',
                            'IMDb_URL'] + [f'genre_{i}' for i in range(19)],
                     usecols=range(24))
```

```
print("Movies loaded:", movies.shape)
print(movies.head())
```

```
Movies loaded: (1682, 24)
   movie_id             title release_date  video_release_date  \
0         1   Toy Story (1995)  01-Jan-1995                 NaN
1         2   GoldenEye (1995)  01-Jan-1995                 NaN
2         3  Four Rooms (1995)  01-Jan-1995                 NaN
3         4  Get Shorty (1995)  01-Jan-1995                 NaN
4         5      Copycat (1995)  01-Jan-1995                 NaN

                                      IMDb_URL  genre_0  genre_1  \
0  http://us.imdb.com/M/title-exact?Toy%20Story%2...        0        0
1  http://us.imdb.com/M/title-exact?GoldenEye%20(...        0        1
2  http://us.imdb.com/M/title-exact?Four%20Rooms%...        0        0
3  http://us.imdb.com/M/title-exact?Get%20Shorty%...        0        1
4  http://us.imdb.com/M/title-exact?Copycat%20(1995)        0        0

   genre_2  genre_3  genre_4  ...  genre_9  genre_10  genre_11  genre_12  \
0        0        1        1  ...        0         0         0         0
1        1        0        0  ...        0         0         0         0
2        0        0        0  ...        0         0         0         0
3        0        0        0  ...        0         0         0         0
4        0        0        0  ...        0         0         0         0

   genre_13  genre_14  genre_15  genre_16  genre_17  genre_18
0         0         0         0         0         0         0
1         0         0         0         1         0         0
2         0         0         0         1         0         0
3         0         0         0         0         0         0
4         0         0         0         1         0         0

[5 rows x 24 columns]
```

2. Preprocess Features and Ratings: Extracted 19 genre columns for clustering and computed average ratings per movie from 100k ratings, merging them into a unified dataset (1682 rows).

```
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt

# Extract genre features again (just to be safe)
genre_cols = [f'genre_{i}' for i in range(19)]
X = data[genre_cols]

# Elbow method to pick K
inertias = []
K_range = range(1, 11)
for k in K_range:
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(X)
    inertias.append(kmeans.inertia_)

# Plot elbow curve
plt.plot(K_range, inertias, marker='o')
plt.xlabel('Number of Clusters (K)')
plt.ylabel('Inertia')
plt.title('Elbow Method for K-Means')
plt.show()
```

3. Cluster Movies with K-Means: Applied K-Means (K=6, chosen via elbow method) on genre features, grouping movies into 6 clusters based on genre similarity (e.g., Animation, Sci-Fi).

```
# Cluster with K=6
kmeans = KMeans(n_clusters=6, random_state=42)
data['cluster'] = kmeans.fit_predict(X)
print("Cluster assignments:")
print(data[['title', 'cluster']].head())
print("\nCluster sizes:")
print(data['cluster'].value_counts())
```

```
Cluster assignments:
                title  cluster
0   Toy Story (1995)        0
1   GoldenEye (1995)        2
2  Four Rooms (1995)        5
3  Get Shorty (1995)        4
4     Copycat (1995)        1

Cluster sizes:
cluster
1    620
4    403
3    279
5    221
2    116
0     43
Name: count, dtype: int64
```

4. Build Hybrid Recommendation Function: Created a function to recommend top-rated movies within a movie's cluster (e.g., "Toy Story" → "Lion King"), combining content-based (genres) and collaborative (ratings) filtering.

```
def recommend_movies(movie_title, data, n=5):
    # Debug: Check available titles
    matches = data[data['title'].str.contains(movie_title, case=False, regex=False)]
    if matches.empty:
        raise ValueError(f"No movie found matching '{movie_title}'. Check title or data.")

    # Get first match
    movie = matches.iloc[0]
    cluster = movie['cluster']

    # Get top-rated in cluster
    recs = data[data['cluster'] == cluster].sort_values('rating', ascending=False)
    recs = recs[['title', 'rating']].head(n)
    return recs

# Test with debug
print("Data shape:", data.shape)
print("Sample titles:")
print(data['title'].head(10))
print("\nRecommendations for 'Toy Story (1995)':")
try:
    print(recommend_movies('Toy Story (1995)', data))
except ValueError as e:
    print(e)
print("\nRecommendations for 'Star Wars (1977)':")
try:
    print(recommend_movies('Star Wars (1977)', data))
except ValueError as e:
    print(e)
```

```
Data shape: (1682, 26)
Sample titles:
0                                    Toy Story (1995)
1                                    GoldenEye (1995)
2                                   Four Rooms (1995)
3                                   Get Shorty (1995)
4                                      Copycat (1995)
5    Shanghai Triad (Yao a yao yao dao waipo qiao) ...
6                                Twelve Monkeys (1995)
7                                          Babe (1995)
8                             Dead Man Walking (1995)
9                                  Richard III (1995)
Name: title, dtype: object
```

5. Evaluate the Results: Visualized clusters with PCA (showing separation with overlap), analyzed genre profiles (e.g., Cluster 0 = Animation/Children's), and checked ratings (recs 4.2–5.0, above cluster averages of 2.95–3.20). Silhouette score (0.354) confirmed clustering quality.

```
[ ]  from sklearn.decomposition import PCA
     import matplotlib.pyplot as plt

     # Extract genre features again
     genre_cols = [f'genre_{i}' for i in range(19)]
     X = data[genre_cols]

     # PCA to 2D for visualization
     pca = PCA(n_components=2)
     X_pca = pca.fit_transform(X)
     data['PCA1'] = X_pca[:, 0]
     data['PCA2'] = X_pca[:, 1]

     # Plot clusters
     plt.figure(figsize=(8, 6))
     plt.scatter(data['PCA1'], data['PCA2'], c=data['cluster'], cmap='viridis', s=10)
     plt.title('K-Means Clusters (K=6) - PCA Visualization')
     plt.xlabel('PCA1')
     plt.ylabel('PCA2')
     plt.show()

     # Cluster profiles
     print("Cluster Genre Profiles (Mean Genre Presence):")
     print(data.groupby('cluster')[genre_cols].mean())
     print("\nAverage Rating per Cluster:")
     print(data.groupby('cluster')['rating'].mean())
```

```
[ ]  from sklearn.metrics import silhouette_score

     # Calculate silhouette score
     genre_cols = [f'genre_{i}' for i in range(19)]
     X = data[genre_cols]
     score = silhouette_score(X, data['cluster'])
     print("Silhouette Score (K=6):", score)

→  Silhouette Score (K=6): 0.35434207694507774
```

Silhouette score:

. **a(i)**: Average distance between (i) and all other points in the same cluster C_i (cohesion).

- $a(i) = \frac{1}{|C_i| - 1} \sum_{j \in C_i, j \neq i} d(i,j)$
- $|C_i|$: Number of points in cluster C_i.
- (d(i, j)): Distance (typically Euclidean) between points (i) and (j).
- Lower (a(i)) means (i) is close to its cluster mates.

b(i): Average distance from (i) to all points in the nearest neighboring cluster C_k (separation).

- $b(i) = \min_{k \neq i} \left(\frac{1}{|C_k|} \sum_{j \in C_k} d(i,j) \right)$
- C_k: Cluster closest to (i) (smallest average distance).
- Higher (b(i)) means (i) is far from other clusters.

Silhouette Coefficient for (i):

- $s(i) = \frac{b(i) - a(i)}{\max(a(i), b(i))}$
- **Numerator**: $b(i) - a(i)$ = separation - cohesion. Positive if (i) is more similar to its cluster than others.
- **Denominator**: $\max(a(i), b(i))$ normalizes the score (1 if fully separated, 0 if equal, -1 if misclassified).
- Range: $-1 \leq s(i) \leq 1$.

Overall Silhouette Score:

- $S = \frac{1}{n} \sum_{i=1}^{n} s(i)$
- (n): Total number of points

DB Index:

```
from sklearn.metrics import davies_bouldin_score

db_score = davies_bouldin_score(X, data['cluster'])
print("Davies-Bouldin Score (K=6):", db_score)
```

```
Davies-Bouldin Score (K=6): 1.6945545620832612
```

S_i: Average distance within cluster (i) (scatter).

- $S_i = \frac{1}{|C_i|} \sum_{x \in C_i} d(x, c_i)$

D_ij: Distance between centroids of (i) and (j) (separatior

- $D_ij = d(c_i, c_j)$.

R_ij: Similarity ratio.

- $R_ij = \frac{S_i + S_j}{D_ij}$

DB Index: Average max similarity over all clusters.

- $DB = \frac{1}{k} \sum_{i=1}^{k} \max_{j \neq i} R_ij$
- Lower DB = tighter, better-separated clusters.

Conclusion:

In Experiment 8, we built a hybrid recommendation system using K-Means clustering on the MovieLens 100K dataset. We fetched data with wget, preprocessed by extracting 19 genre features and calculating average ratings per movie, then clustered movies into 6 groups (K=6) based on genres. Our hybrid approach recommended top-rated movies within each cluster, blending content-based (genre similarity) and collaborative (ratings) methods. We evaluated using PCA visualization (showing distinct clusters with some overlap), genre profiles (e.g., Cluster 0 = Animation/Children's, Cluster 5 = Sci-Fi/Action), and average ratings per cluster (~2.95–3.20). Recommendations like "Toy Story" → "Lion King" (4.2) and "Star Wars" → "Empire Strikes Back" (4.2) confirmed relevance, with ratings well above cluster averages. The silhouette score of 0.354 validated decent clustering quality, making this a robust, impactful system for movie recommendations.

Experiment 9

Aim: To perform Exploratory data analysis using Apache Spark and Pandas

Theory:

1. What is Apache Spark and How It Works?

Apache Spark is an **open-source distributed computing framework** designed for big data processing, faster than traditional Hadoop MapReduce. It enables **in-memory computation**, making operations much quicker for iterative tasks like machine learning, data analysis, and graph processing.

Key Components of Apache Spark:

- **Spark Core**: The base engine for large-scale parallel data processing.
- **Spark SQL**: Module for structured data processing using DataFrames and SQL.
- **MLlib**: Machine Learning library for scalable learning algorithms.
- **GraphX**: For graph computations.
- **Spark Streaming**: For real-time stream data processing.

How Spark Works:

- Spark processes data in **RDDs (Resilient Distributed Datasets)** or **DataFrames**.
- The **Driver Program** initiates a SparkContext, connecting to a **Cluster Manager**.
- Tasks are distributed across **Executors** for parallel execution.
- Supports **lazy evaluation**—transformations are only computed when an action is called.

2. How Data Exploration is Done in Apache Spark?

EDA in Apache Spark follows similar principles to pandas but is designed to scale to massive datasets across clusters.

Steps of EDA in Spark:

1. Initialization:
Import pyspark and create a SparkSession using SparkSession.builder.
This session acts as the entry point to Spark functionalities.

2. Load Dataset:
Use spark.read.csv() or .json() to load data into a Spark DataFrame.
Enable header=True and inferSchema=True for cleaner loading.

3. Understand Data Schema:
Use .printSchema() to view column types and .show() for a data preview.
.describe() provides summary statistics like mean, min, and max.

4. Handle Missing Values:
Use df.na.drop() to remove nulls or df.na.fill("value") to fill them.
This step is crucial to clean data for accurate analysis.

5. Data Transformation:
Apply .withColumn(), .filter(), .groupBy() to reshape and summarize data.
These functions help in refining the dataset before analysis.

6. Data Visualization:
Convert Spark DataFrame to Pandas using .toPandas() for plotting.
Then visualize with tools like matplotlib or seaborn.

7. Correlation & Insights:
Use .corr() in Pandas or MLlib's Correlation.corr() for relationships.
Group, pivot, and analyze data patterns for meaningful insights.

Conclusion:

In this experiment, I learned how to perform Exploratory Data Analysis using Apache Spark and Pandas. I understood how to initialize a SparkSession, load large datasets efficiently, and explore their structure using Spark functions like .show(), .printSchema(), and .describe(). I also learned how to handle missing values, transform data using Spark DataFrame operations, and convert data to Pandas for visualization. Additionally, I explored how to compute correlations and derive insights through grouping and aggregation. This experiment helped me grasp the scalability and power of Spark in handling big data and how it complements traditional Python libraries like Pandas and Seaborn for insightful data analysis.

Experiment-10

Aim: To perform Batch and Streamed Data Analysis using Apache Spark.

Theory:

1. **What is Streaming? Explain Batch and Stream Data:**
   Streaming refers to the continuous processing of real-time data as it arrives. It is commonly used in applications that require immediate action such as fraud detection, stock market analysis, and live dashboards. Streaming data is unbounded, time-sensitive, and flows in continuously.

Batch data processing, in contrast, involves collecting data over a period and processing it together. It is widely used in data warehousing, periodic reporting, and data transformation tasks. The data is bounded and processed in chunks with scheduled jobs.

Examples:

- Batch: Generating monthly sales reports.
- Stream: Real-time user click analysis on a website.

2. **How data streaming takes place using Apache Spark:**
   Apache Spark handles stream processing through its Structured Streaming engine. Structured Streaming treats incoming data streams as an unbounded table and performs incremental computation using the same DataFrame API used for batch jobs.

The streaming data can be ingested from various sources such as Kafka, sockets, directories, or cloud storage. Spark then processes the data using transformations like filter, select, groupBy, and aggregations. Developers can apply window operations, manage late-arriving data using watermarking, and use checkpointing for fault tolerance.

Internally, Spark divides the live stream into micro-batches. These micro-batches are processed using the Spark engine and then output to sinks like HDFS, databases, or dashboards. With its high scalability and distributed nature, Apache Spark ensures that real-time data processing can be performed with low latency and high throughput.

Key Features:

- Unified APIs for batch and streaming
- Support for stateful computations

- Integration with structured data sources
- Fault-tolerant and scalable architecture

Use Case Examples:

- Real-time transaction monitoring
- Streamed log analysis
- Live social media analytics

Conclusion:

In this experiment, I gained a strong understanding of the differences between batch and streaming data processing. I learned that batch processing is ideal for historical and periodic tasks, while streaming suits real-time, continuous data needs. Through Apache Spark, I explored Structured Streaming, which provides a powerful, unified framework to handle both types of workloads. I learned how to ingest live data from sources like Kafka or files, apply transformations, and output results dynamically. This helped me appreciate Spark's capabilities in managing complex data pipelines and real-time analytics. Overall, I understood how Spark's architecture enables scalable and fault-tolerant processing, making it a preferred tool for modern data-driven applications.

Stroke prediction App

ON

Submitted in partial fulfillment of the requirements of the degree of

Bachelor of Engineering

(Information Technology)

By

Chinmay Chaudhari (06)

Kshitij Hundre (18)

Shubham Jha (19)

Under the guidance of

Dr. Ravita Mishra

Department of Information Technology

VIVEKANAND EDUCATION SOCIETY'S INSTITUTE OF TECHNOLOGY,

Chembur, Mumbai 400074

(An Autonomous Institute, Affiliated to University of Mumbai) April 2024

AIDS Lab Exp 11

Aim: Mini Project – Stroke Risk Prediction Using Machine Learning

---

Chapter 1: Introduction

1.1 Introduction

Stroke is a leading cause of death and disability worldwide. Early prediction is essential for prevention and management, but traditional medical models struggle with low recall and interpretability. This project leverages machine learning to build a predictive and interpretable system for stroke detection using clinical data.

1.2 Objectives

- To preprocess and analyze stroke-related health data
- To apply class balancing techniques like SMOTE for rare event prediction
- To train ML models including Logistic Regression, Decision Tree, and XGBoost
- To explain model predictions using SHAP (SHapley Additive Explanations)
- To deploy an interactive prediction system using Streamlit

1.3 Motivation

Medical professionals require tools that are not only accurate but also interpretable. Existing scoring systems lack transparency and struggle with imbalanced data. This project aims to provide a trustworthy, AI-based decision support system.

1.4 Scope of the Work

- Focus on supervised classification techniques
- Dataset sourced from Kaggle (Stroke Prediction Dataset)
- Visualize insights using seaborn and SHAP
- Deployable tool for real-time stroke risk evaluation

1.5 Feasibility Study

- *Technical Feasibility:* Uses Python, Pandas, Scikit-learn, SHAP, and Streamlit—all open-source and well-documented libraries.
- *Operational Feasibility:* Easily integrable into a web or mobile healthcare system.
- *Economic Feasibility:* Cost-effective due to use of free tools and datasets.

Chapter 2: Literature Survey

2.1 Introduction

Research in stroke prediction using ML is ongoing. This section compares notable models and techniques.

2.2 Problem Definition

Stroke is a rare medical condition, which creates class imbalance issues for ML models. The challenge is to build a system that can detect such rare instances while remaining interpretable and trustworthy.

2.3 Review of Literature

1. Kaggle, "Stroke Prediction Dataset," 2021

The Stroke Prediction Dataset, sourced from Kaggle, is a widely used healthcare dataset for building stroke classification models. It includes features such as age, gender, hypertension, heart disease, marital status, work type, residence type, average glucose level, BMI, and smoking status. These attributes help in identifying key risk indicators for stroke. Despite being valuable for real-world applications, the dataset suffers from a significant class imbalance, with only 249 stroke cases out of 5,110 records. Additionally, the presence of missing values in the BMI column requires preprocessing before applying machine learning techniques.

2. S. M. Lundberg and S.-I. Lee, “A Unified Approach to Interpreting Model Predictions,” NeurIPS, 2017

This foundational paper introduces SHAP (SHapley Additive exPlanations), a game theory-based approach to interpreting machine learning model predictions. SHAP values provide both local and global explanations, showing how much each feature contributed to a particular decision. This level of interpretability is especially valuable in healthcare applications, where model transparency is crucial. However, SHAP can be computationally expensive for large or complex models and may assume feature independence in certain implementations, which can limit its real-world scalability.

3. N. V. Chawla et al., “SMOTE: Synthetic Minority Over-sampling Technique,” JAIR, 2002

SMOTE is a technique developed to address the challenge of imbalanced datasets, where the number of instances in one class significantly outweighs the other. The method generates synthetic samples for the minority class by interpolating between existing examples, thereby improving the performance of classifiers that are otherwise biased toward the majority class. While SMOTE has proven to be highly effective, especially in medical datasets with rare outcomes like stroke, it may introduce noise and lead to overfitting if not combined with proper cross-validation and model tuning.

Chapter 3: Design and Implementation

3.1 Introduction

This project follows a modular data science pipeline including data loading, preprocessing, modeling, explanation, and deployment.

3.2 Requirements

- **Hardware:** 4GB RAM minimum
- **Software:** Python 3.x, Jupyter/Colab, Scikit-learn, Pandas, SHAP, Streamlit

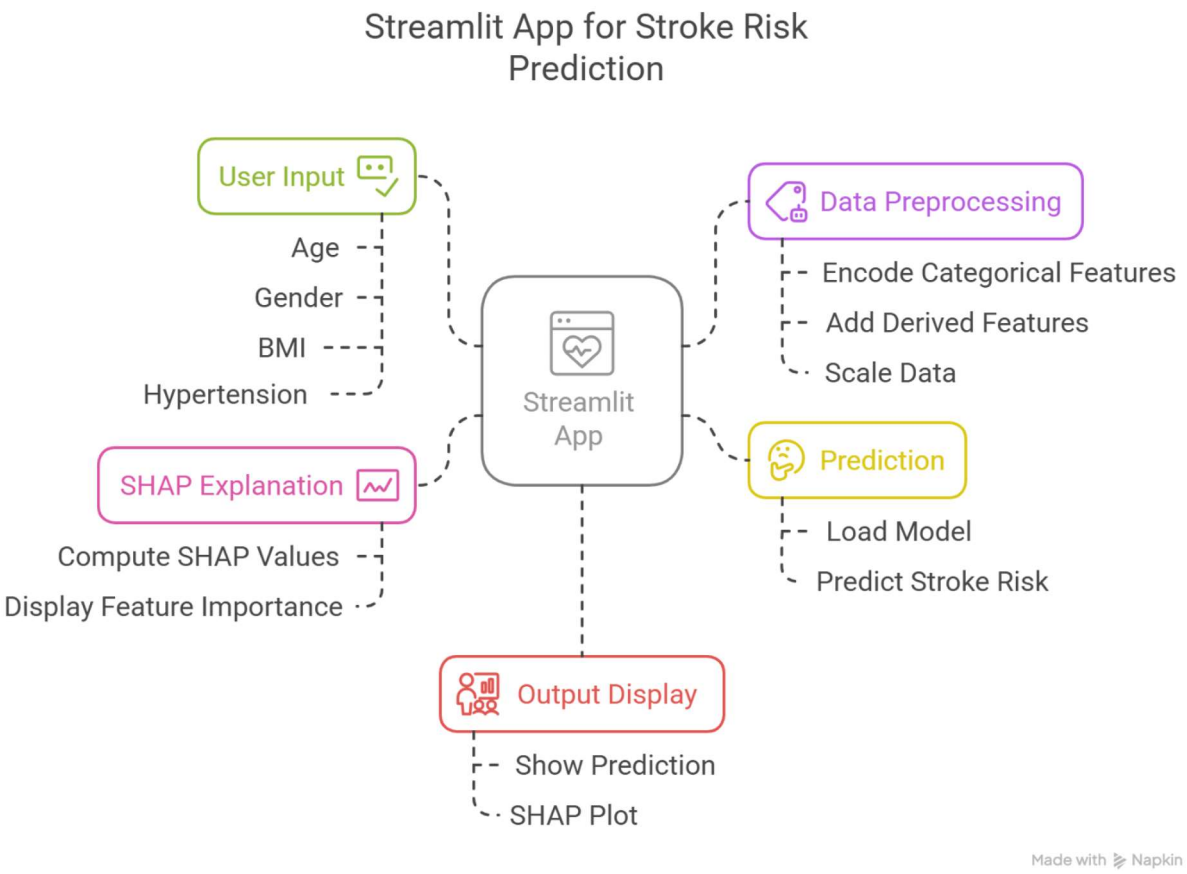
3.3 Proposed Design (CRISP-DM)

1. **Data Collection:** Kaggle's Stroke Prediction Dataset
2. **Data Cleaning:** Remove missing values, encode categorical variables
3. **EDA:** Explore relations (age, hypertension, BMI vs stroke) using bar plots and heatmaps
4. **Balancing:** Use SMOTE to synthesize samples for the minority class
5. **Modeling:** Train Logistic Regression, Decision Tree, Random Forest, XGBoost
6. **Interpretation:** Use SHAP summary plots to visualize influential features
7. **Deployment:** Build a Streamlit web app for prediction and explanation

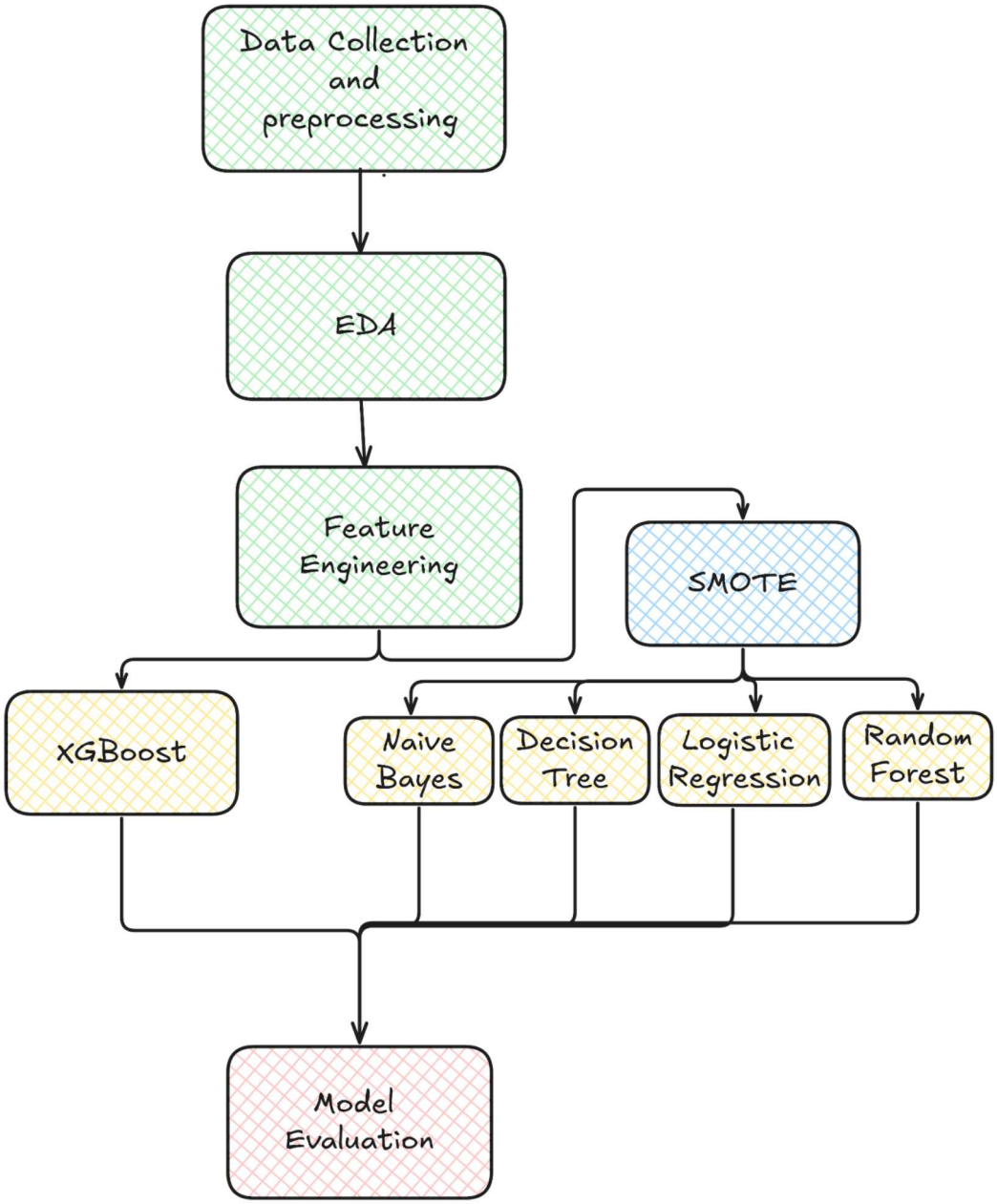
3.4 Algorithms Used

- **Logistic Regression:** High interpretability and performance post-SMOTE
- **Decision Tree:** Classification model that works on splitting on nodes that give highest information gain. moderate results on the current dataset.
- **Naive Bayes:** Mathematical model working on the principle of bayesian theorem, moderate results on the current dataset.
- **Random Forest & XGBoost:** Ensemble methods for boosting recall, moderate performance but overall very poor recall.
- **SHAP:** Used for both global and local interpretability
- **SMOTE:** Used for generating synthetic minority stroke instances

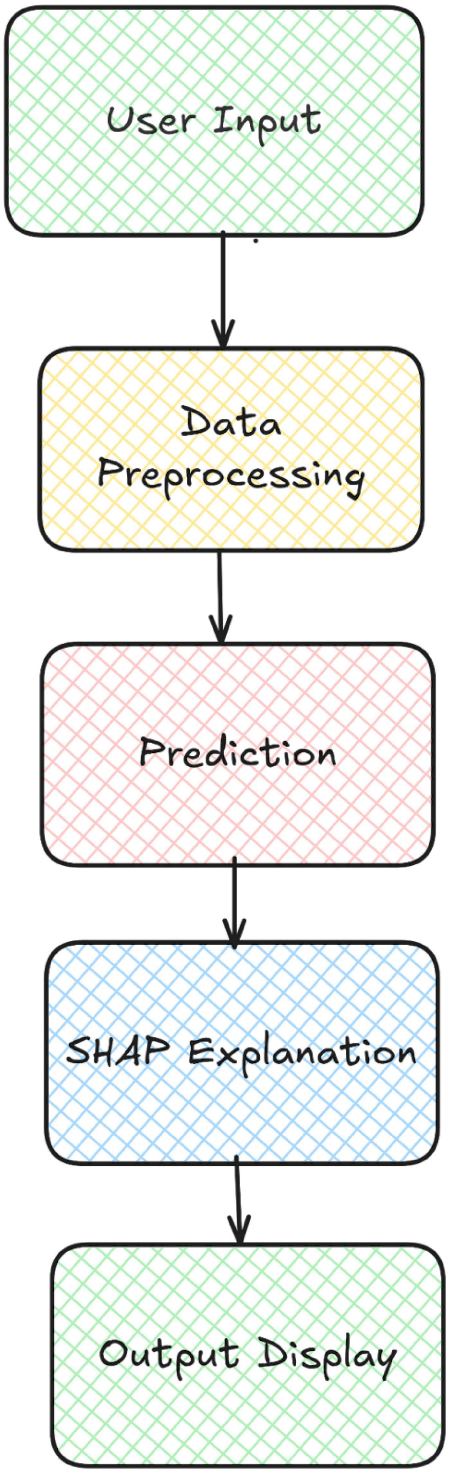
3.5 Diagrams



(Functionality of the Stroke Prediction App)



(Flow Diagram of the model training)



(Flow Diagram of the Streamlit App)

Chapter 4: Results and Discussion

4.1 Introduction

Models were evaluated using metrics such as Accuracy, Precision, Recall, and AUC. Special focus was on Recall due to class imbalance.

4.2 Evaluation Summary

To assess the effectiveness of various classification algorithms in stroke prediction, we evaluated Decision Tree, Logistic Regression (with tuned hyperparameters), Random Forest, and XGBoost models using precision, recall, f1-score, and accuracy. All models were trained and tested on a SMOTE-balanced dataset to handle the class imbalance.

Decision Tree (SMOTE, Default Threshold) Test Set Performance:

	precision	recall	f1-score	support
0	0.96	0.92	0.94	972
1	0.16	0.28	0.20	50
accuracy			0.89	1022
macro avg	0.56	0.60	0.57	1022
weighted avg	0.92	0.89	0.90	1022

- **Decision Tree (SMOTE, Default Threshold)** achieved a test set accuracy of **0.89**. It showed high precision and recall for the majority class (no stroke), with a **precision of 0.96** and **recall of 0.92.** However, for the minority class (stroke), its **f1-score was only 0.20**, reflecting poor sensitivity despite oversampling.

Best Hyperparameters Logistic Regression (SMOTE, Tuned) Test Set Performance:

	precision	recall	f1-score	support
0	0.98	0.83	0.90	972
1	0.17	0.70	0.27	50
accuracy			0.82	1022
macro avg	0.58	0.76	0.59	1022
weighted avg	0.94	0.82	0.87	1022

- **Logistic Regression (SMOTE, Tuned Hyperparameters)** yielded an **accuracy of 0.82**. It demonstrated relatively better balance, with a **recall of 0.70** for the stroke class and an **f1-score of 0.27**, indicating improved sensitivity compared to the Decision Tree**.** The overall weighted average f1-score was **0.87.**

Random Forest Test Set Performance:

	precision	recall	f1-score	support
0	0.95	0.99	0.97	972
1	0.00	0.00	0.00	50
accuracy			0.94	1022
macro avg	0.48	0.49	0.48	1022
weighted avg	0.90	0.94	0.92	1022

- **Random Forest** performed well on the majority class, with a **precision of 0.95** and **recall of 0.99**, leading to a high accuracy of **0.94.** However, it failed to detect any stroke cases, with a **precision, recall, and f1-score of 0.00** for the stroke class, showing the model's bias toward the majority class**.**

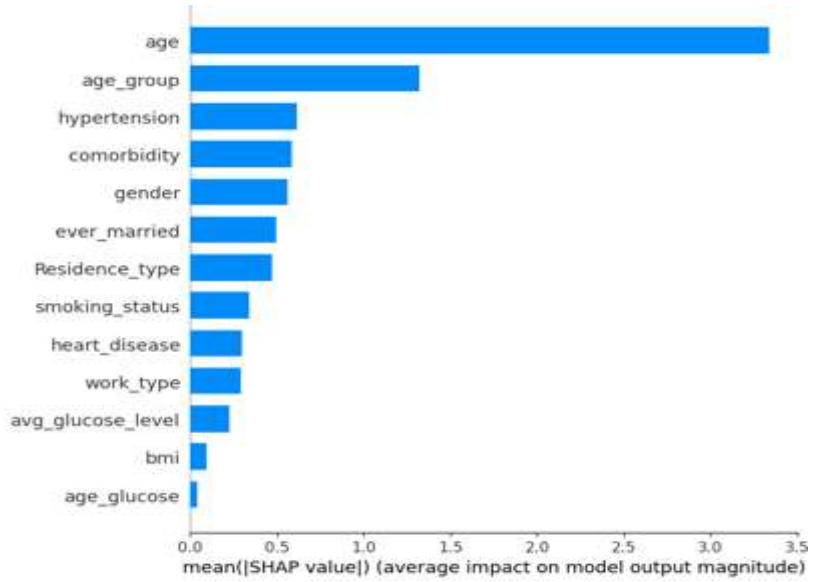
XGBoost Test Set Performance:

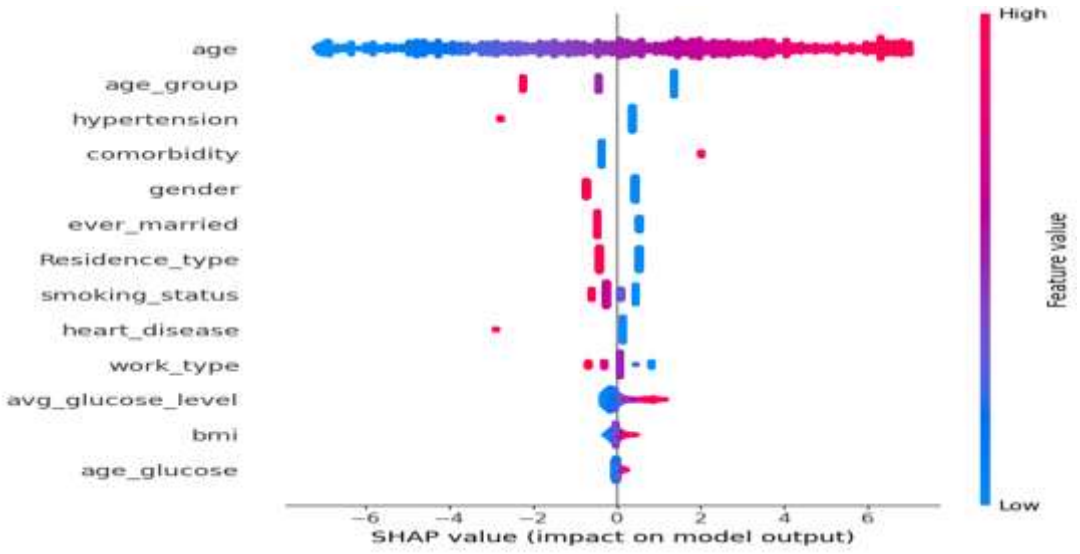
	precision	recall	f1-score	support
0	0.96	0.95	0.95	972
1	0.20	0.26	0.23	50
accuracy			0.91	1022
macro avg	0.58	0.60	0.59	1022
weighted avg	0.92	0.91	0.92	1022

- **XGBoost** achieved an accuracy of **0.91**. It maintained a strong performance on the majority class with **f1-score of 0.95**, but its ability to identify the stroke class remained limited with a **recall of 0.26** and **f1-score of 0.23**.

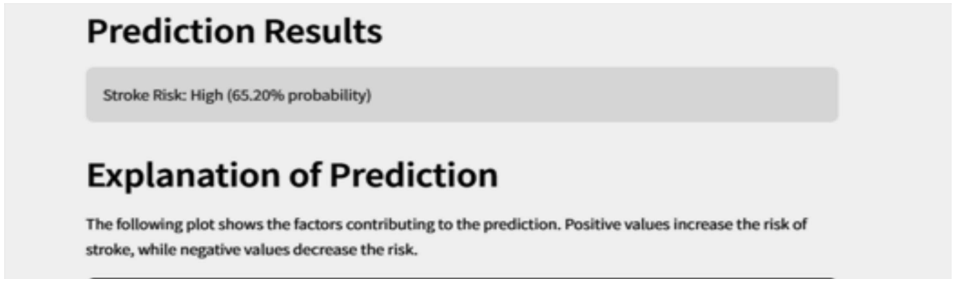
In summary, while all models performed well for the majority class, **Logistic Regression with hyperparameter tuning** provided the best balance between precision and recall for stroke prediction, making it the most promising model for early stroke detection in imbalanced medical datasets.

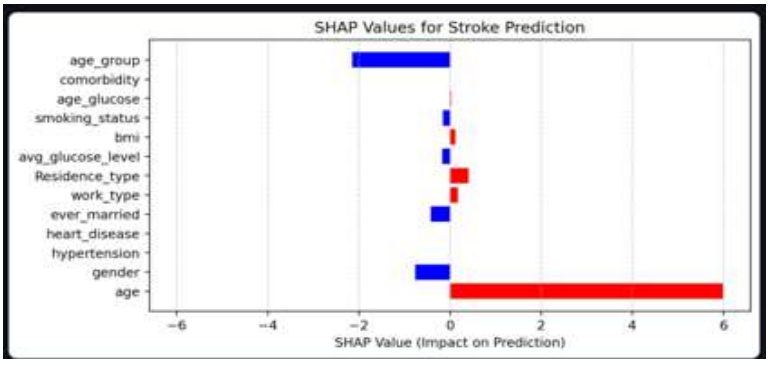
4.2.5 Visualising the key factors involved in positive stroke cases:





4.3 Screenshot/Output Section





Chapter 5: Conclusion and Future Scope

5.1 Conclusion

We successfully built a machine learning-based stroke prediction system that is both accurate and explainable. By combining SMOTE for balancing and SHAP for interpretation, our system supports clinical decision-making with confidence.

5.2 Future Scope

- Include more features like cholesterol or ECG data for better predictions
- Extend to real-time systems using health IoT or hospital dashboards
- Integrate into mobile applications for public health use

5.3 Societal Impact

- Early stroke risk prediction helps reduce mortality and improve patient care
- Builds trust among medical professionals via transparent predictions
- Scalable system that can be used in low-cost, remote diagnosis setups

Name: Shubham B Jha
Class: DISC
Roll No: 19

AIDS - Assignment - 1

1. What is AI? Considering the Covid-19 pandemic situation, how AI helped to survive & renovated our way of life with different applications?

=> Artificial Intelligence (AI) is the field of computer science that enables machines to simulate simulate human intelligence, including learning, reasoning, and decision-making. AI encompasses technologies such as ML, NLP, CV to automate tasks.

AI's Role in COVID-19

1) Early Detection & Diagonosis - AI models (e.g BlueDot) detected outbreaks early; AI-assited CT scans helped in quick diagonosis

2) Drug & Vaccine ~~Beta~~ Development - AI (e.g AlphaFold) accelerated drug discovery and vaccine research

3) Contact Tracing & Safety - AI powered apps (e.g Aarogya Setu) tracked virus spread; thermal cameras detected fever

4) Healthcare & Robotics - AI chatbots assisted with self-diagnosis; robots disinfected hospitals & delivered medicines

5) Remote Work & Education - AI improved video conferencing, virtual assistants and adaptive learning platforms.

2.) What are AI agents terminologys, explain with examples.

=> An AI agent perceives its environment its environment through sensors and acts using actuators to achieve goals.

Key terminologies include:

1. Agent - An entity that perceives and acts
2. Percept - Input received by the agent (e.g camera detecting pedestrians)

3. Percept Sequence - The history of all past percepts
4.) Actuators - Components that allow the agent to act (e.g car's steering & brakes)
5) Sensors - Devices collecting data from the environment (eg, LiDAR in autonomous vehicles)
6.) Environment - The surroundings where the agent operates (e.g roads and traffic for a self-driving car).

Example : Self Driving Car
Sensors: Camera, LiDAR, GPS.
Percepts: Detects speed limit, traffic & obstacles.
Actuators: Accelerates brakes, steers
Environment: Roads, weather, pedestrians

3) How AI technique is used to solve 8 puzzle problem.
=> The 8-puzzle consists of a 3x3 grid with numbered tiles and one empty space. The goal is to reach a target arrangement by sliding tiles.
Various Informed and Uninformed search techniques are used e.g BFS, DFS, IDDFS, A*.
- For using uninformed searches, Heuristics such as Misplaced tiles or Manhattan distance can be used.

Consider the following states

1 2 3
5 8

$$\begin{bmatrix} 1 & 2 & 3 \\ 4 & 6 & 8 \\ 7 & 5 & \_ \end{bmatrix}$$

the goal state is

$$\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & \_ \end{bmatrix}$$

The legal moves AI can make shif blank space to left, right, up and down.

Now using the manhattan distance heuristic the algo will exchange it so the blank space with 8

State change function

$$\begin{bmatrix} 1 & 2 & 3 \\ 4 & 6 & - \\ 7 & 5 & 8 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 2 & 3 \\ 4 & - & 6 \\ 7 & 5 & 8 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & - & 8 \end{bmatrix}$$

$$\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & - \end{bmatrix}$$ → Goal Goal State reached.

Path cost could be 1 point per move.

Q-3] what is PEAS descriptor?
Give PEAS descriptor for following: i) Taxi Driver (ii) Medical diagnosis system, (iii) A music composer, (iv) An aircraft autolander (v) An essay evaluator (vi) A robotic sentry gun for kick lab

⇒ PEAS Descriptor: (PEAS (Performance measure, Environment, Actuators, Sensors) is a framework used to define the components of an intelligent agent. It helps describe how an AI system interacts with its environment and performs tasks.

(i) Taxi Driver Agent

P: safety, fuel efficiency, speed, comfort, traffic rules.
E: Roads, traffic, pedestrians, passengers, weather.
A: steering, accelerometer, brakes, indicators
S: GPS, cameras, speed sensors, proximity sensors.

2) Medical Diagnosis system

P: Accuracy, effectiveness, ~~ge~~

E: patient health records, medical symptoms, hospital database

A: Displaying diagnosis, suggesting treatments, prescribing medicines

S: Patient input, lab, test results.

3) AI Music Composer

P: Creativity, harmony, originality, satisfaction

E: Musical notes, user preferences, genre styles

A: Generating melodies, modifying pitch/tempo

S: Music database, user feedback, real time input (vocal, style

4) Auto Lander

P: Safe landing, smooth touchdown, weather adaption

E: Runway, weather conditions, wind speed, altitude.

A: Controlling thrust, flaps, landing gear, breaking system

S: Radar, altimeter, GPS, wind sensors, speedometer.

5. Essay Evaluator

P: Accuracy of grading, fairness, grammar/spelling correctness

E: Essays, grammatic rules, plagiarism database, rubrics

A: ~~designing~~ grades, providing feedback, suggesting improvements

S: Text input, word count, syntax & grammar checkers

6. Robotic Sentry Gun for Lab

P: Intruder detection accuracy, response time, minimal false alarms.

E: Laboratory area, authorized personnel, intruders.

A: Rotating turret, firing warning shots, sounding alarm

S: Motion sensors, thermal cameras.

5) Categorize a shopping bot for an offline bookstore according to each of the six dimensions (fully / partially Observable, deterministic / stochastic, epi-sodic / sequential, ...)

=> Dimension | Category

Dimension	Category
Observability	Partially Observable
Deterministic / Stochastic	Stochastic
Episodic / Sequential	Sequential
Static / Dynamic	Dynamic
Discrete / Continuous	Discrete
Single / Multi-Agent	Multi-Agent

6) Differentiate Model based & Utility based Agent.

=>

Model based	Utility based
• Uses an internal model of the world.	• Chooses actions based on a utility function that maximizes performance.
• Uses stored knowledge (model) to simulate future state.	• Compares different actions and selects the one with the highest utility value.

• Works towards achieving predefined goal	• Not just goal-driven but also optimizes for the best possible outcome
• Limited handling of uncertainity	Handles uncertainty by assigning utilities

7) Explain the architecture of a Knowledge based agent and Learning Agent

=) A Knowledge-Based Agent (KBA) makes decisions using a Knowledge Base (KB) and reasoning mechanisms.

Components:

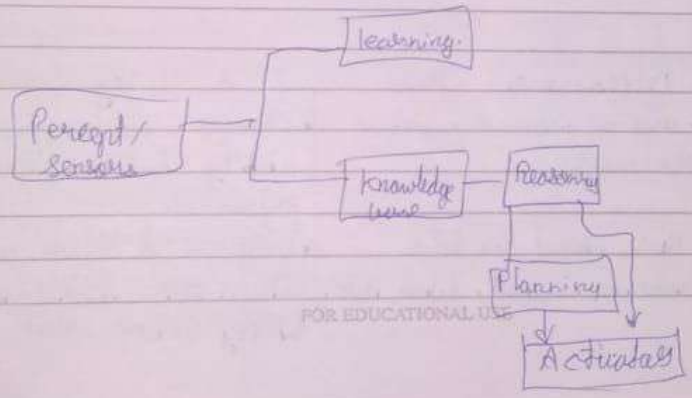
1.) Knowledge Base (KB) - Stores facts, rules and logical statements (e.g., "if traffic is heavy, take an alternate route").

2. Inference Engine - Applies logical reasoning (e.g. modus ponens) to derive conclusions from the KB.

3. Perception (Sensors) - Collects input from the environment

4. Action Execution (Actuators) - Performs actions based on decisions

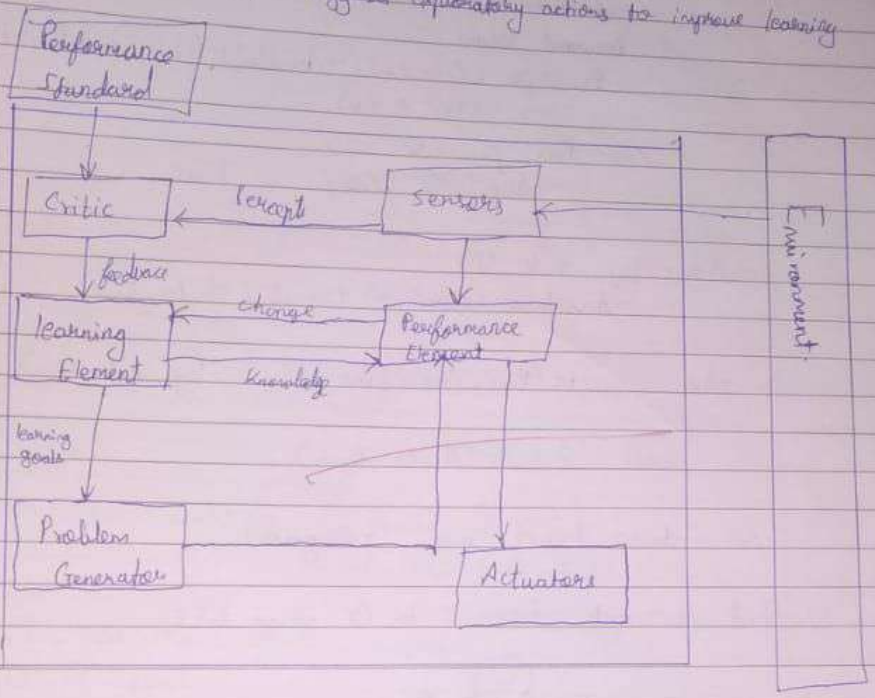
5. Updating Mechanism - Modifies the KB as new information is learned



Learning Based Agent Architecture

Components

1. learning Element - Updates the agents knowledge based on feedback
2. Performance Element - Makes decisions and executes actions
3. Critic - Evaluates the agent's actions and provides feedback
4. Problem Generator - Suggests exploratory actions to improve learning



Q) Convert the following to predicates

a. Anita travels by Car if available otherwise travels by bus
b. Bus goes via Andheri and Goregaon
c. Car has puncture so is not available

Will Anita travel via Goregaon? Use forward reasoning.

=> (a) • Available (car) → travels (Anita, car) - (i)
¬Available (car) → travels (Anita, Bus) - (ii)

(b) visits (Bus, Goregaon) ∧ visits (Bus, Andheri) - (iii)

(c) Punctures (Car) → (¬Available (car)) - (iv)
Punctures (Car) - (v)

Forward reasoning

=> Punctures (Car) → (¬Available (Car)) ∧ Punctures (Car)
- (iv) & (v)

Car has puncture so,
¬Available (Car) is True

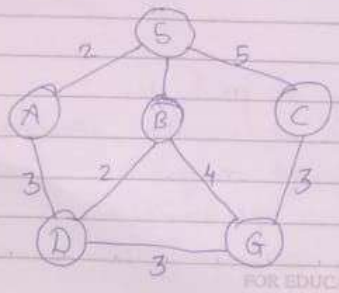
Now by rule (ii)
¬Available (Car) → travels (Anita, Bus)

also visits (Bus, Goregaon) by rule (iii)

and travels (Anita, Bus)

∴ Anita travel via Goregaon.

10. Find the route from S to G using BFS.



Start from Sources
put in queue with cost (initial 0)
remove from queue calculate new distance (cost + edge weight)
~~distance~~ check if the current is the goal. if not then
~~repeat~~ put in queue and repeat.

(S,0)

childrens ((A,2),(B,1),(C,5))

None of them is goal ~~push~~ added in queue.

(A,2),(B,1),(C,5)

childrens (D,3) ; ~~distance~~
dist : (D, 2+3)
Not goal ∴ Put in queue

(B,1),(C,5),(D,5)

childrens [(D,2),(G,4)]
dist [(D,1+2) (G,1+4)]

D not Goal put in queue
G is goal.

∴ Distance found!
G is 5

12) Explain Hill Climbing and its drawbacks in detail with example. Also state limitations of steepest-ascent hill climbing.

=> Hill Climbing is a local search algorithm used to find an optimal solution by iteratively making small changes to the current state and choosing the best improvement.

Algorithm Steps:

1. Start with an initial solution (state)
2. Evaluate neighboring states
3. Move to the neighbor with the highest value
4. Repeat until no better neighbors exists

Example: (Hill Climbing in Path Optimization): A robot trying to reach the highest hilltop (goal) uses hill climbing. It moves upwards step by step, choosing the steepest ascent until no higher step is available.

Drawbacks of Hill Climbing:

1. Local Maxima - May get stuck at a peak that is not the global maximum.
2. Plateau - A flat region with no improvement, leading to stagnation.
3. Ridges - A narrow path of improvements that the algorithm may fail to follow.
4. No Backtracking - Once a move is made, previous states are not reconsidered.

13. Explain simulated annealing and write its algorithm

→ A probabilistic search method inspired by the cooling process of metas

Allow occasional downhill moves to escape local optima.

Algorithm:

(i) Start with an initial solution, temperature T

(ii) Generate a neighbouring solution

(iii) If its better, accept it, otherwise accept it with probability $e^{(-\Delta E/T)}$

(iv) Decrease T gradually and repeat until T is very small

Use Case: Travelling salesman Problem (Optimized problems)

14. Explain A* Algorithm with an example

→ A* is a like best first search algorithm, used in path finding and graph traversal. It uses the following formulas:

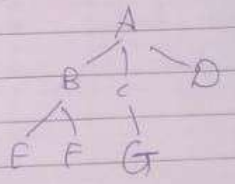
$f(n) = g(n) + h(n)$

$g(n)$ → cost to reach n from start

$h(n)$ → heuristic estimate of cost to reach from goal to n

$f(n)$ → total estimated cost

Eg: Goal G



Node	g(A, n)	h(n, G)
A	0	6
B	1	4
C	2	2
D	4	7
E	3	5
F	5	3
G	6	0

Steps :-

1. Start at root node A.

$f(A) = g(A) + h(A) = 0 + 6$
$= 6$

2. expand neighbours B, C, D

$f(B) = 1 + 4 = 5$

$f(C) = 2 + 2 = 4$

$f(D) = 4 + 7 = 11$

3. Choose lowest value that is f(C)

4. Expand neighbors of C. (G)

$f(G) = 6 + 0 = 6$

5. Goal reached at G with total cost 6

Advantages →

efficient for finding shortest path in weighted graphs
balances exploration by considering both g(n) and h(n)

15. Explain min-max algorithm and draw game tree for tic tac toe game.

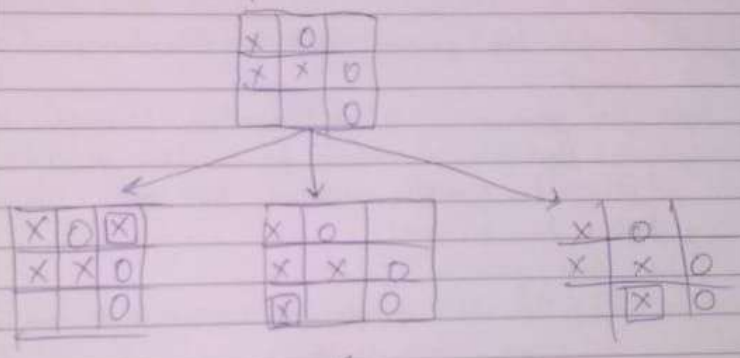
→ The min max algorithm is a decision making algorithm used in 2 player games. It assumes one player (MAX) tries to maximize its score & other player (MIN) tries to minimize the score.

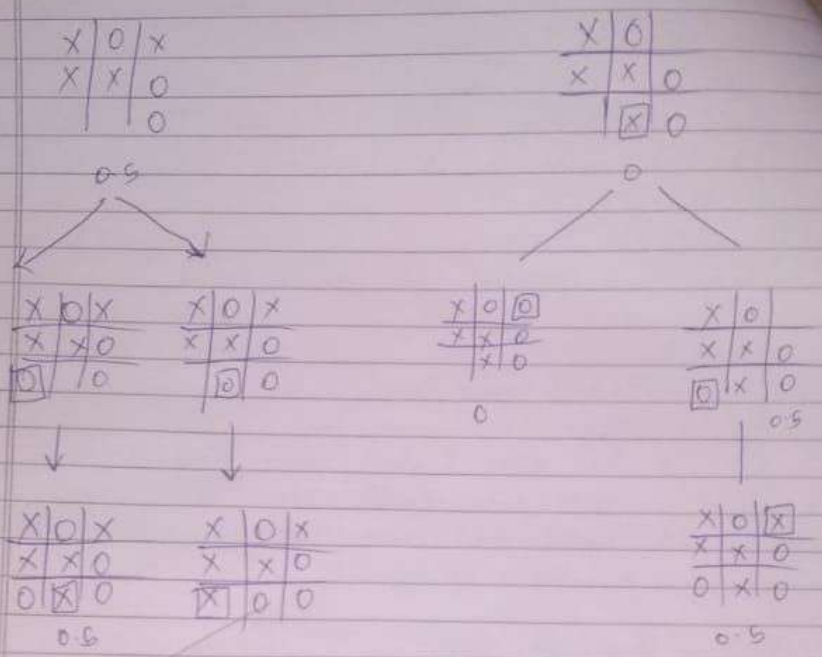
Game tree represents all possible moves.

Algorithm:

1. Generate game tree
2. Design scores
3. Max picks highest value from children
   MIN picks lowest value
4. Repeat until root node is evaluated starting a bottom up approach.

Game tree for the tic-tac-toe game





16] Explain alpha beta pruning algorithm for adversarial search with example

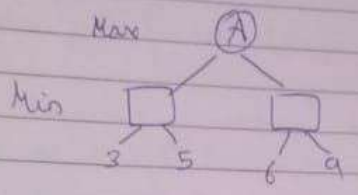
⇒ Alpha beta pruning is an optimization technique used in minimum algorithm to reduce the number of nodes evaluated in adversarial search problems like game-playing AI (eg chess, tic-tac-toe)

Alpha beta pruning includes

Alpha (α): The best maximum score that the maximizing player can guarantee so far.

Beta (β): The best minimum score that the minimizing player can guarantee so far.
The algorithm prunes branches that will not influence final decision

Example:



1. Start at root node A.
   $\alpha = -\infty$, $\beta = \infty$
2. · check left min node (child of A)
   · check first child value = 3 → update $\beta = 3$
   · check second child value = 5 → β remains 3
   · Min node returns 3 to Max
3. Right Min node (child of A)
   · check first child : value = 6 → $\beta = 6$.
   · Here $\alpha = 3$ at MAX node but $\beta(6) > \alpha(3)$ so no pruning.
   · Explore 2nd child (9) → Here pruning will occur.
   · MIN node already has a value ≤ 6 it will never choose 9 & so we prune the node with value 9.
4. Max value = 6

17) Explain WUMPUS world environment, giving its PEAS description. Explain how percept sequence is generated.

⇒ The Wumpus world environment is a simple grid-based environment, used in AI to study intelligent agent behavior.

In uncertain environments It is a turn based environment where an agent must navigate a cave to find gold while avoiding hazards like pits and a monster called wumpus

PEAS:

P: the agent is rewarded for grabbing gold and exiting safely. Penalty is imposed for falling into pits and getting eaten by wumpus

E: 4×4 grid world containing the agent, wumpus, pits, gold.

A: The agent can move Forward, left, Right, shoot, climb.

S: Agent perceives stench (near wumpus), breeze (near a pit), glitter (near gold), bump and scream

Percept Sequence generation:

It is the history of all perceptions received by the agent At each time step, the agent At each time step the agent perceives information based on its current location and surroundings.

Example percept sequence:

1. Agent starts at (1, 1):
   - No breeze, no stench, no glitter → safe square
2. Agent moves to (2, 1)
   Breeze detected → A pit is nearby but not in current square)
3. Agent moves to (1, 2):
   Stench detected → wumpus is in adjacent cell
4. Agent moves to (2, 2):
   Glitter detected → gold is here.
5. Agent moves back to (1, 1) and climbs out.

* 12) Solve the cript Arithmetic SEND + MORE = MONEY

=> Step 1 : M must be 1. ∵ Sum of 2 'n' digit number cannot be greater than equal to 10^n

```
  S E N D
+ 1 O R E
---------
1 O N E Y
```

Step 2: Assume E + O = 10 + N
then E+O generates carry & ∴ S has to be 8
otherwise if S is 9 & carry is 1 and 9+1+1 = 11 but O cannot be 1 ∵ M=1.

S=9, M=1, O=0

```
  S E N D          9 E N D
  M O R E   =>    + 1 O R E
  M O N E Y       1 O N E Y
```

Step 3 But then E + O cannot generate carry, so initial assumption of carry is wrong and so S is 9.

```
  9 E N D
+ 1 0 R E
---------
1 O N E Y
```

Step 4 Now E + O = N
=> E = N but that is a contradiction
So N+R must generate a carry! & E+1+0 = N
∴ N = E+1
Also N + R + k1 = 10 + E
R + k1 = 10 - 1 = 9
k cannot be 0 otherwise R = 9 Contrad

$\therefore R+1 = 9$

$\therefore R = 8$

```
S E N D          9 E N D
M O R E    =>    1 0 8 E
-------          -------
M O N E Y        1 O N E Y
```

$\therefore D+E = 10+Y$

also $N+8+1 = 10+E$

but $N = E+1$, lets assume $E=5$, then $N=6$

```
  9 5 6 D
  1 0 8 5
  -------
  1 0 6 5 Y
```

So only requirement is D should be a number such that when added to 5 generate a query available space $\{\cancel{0}, \cancel{1}, 2, 3, 4, \cancel{5}, \cancel{6}, 7, \cancel{8}, \cancel{9}\}$

2, 3, 4 cannot generate carry $\therefore D = 7$

$\therefore$

```
  9 5 6 7
  1 0 8 5
  -------
  1 0 6 5 2
```

is the solution!

19.) Consider the following axioms: All people who are graduating are happy, All happy people are smiling, Someone is graduating

→ (1) Represent in predicate logic

G(x) : x is graduating
H(x) : x is happy
S(x) : x is smiling

Translating axioms in predicate logic

1. All people who are graduating are happy
$\forall x \, (G(x) \rightarrow H(x))$

2. All happy people are smiling
$\forall x \, (H(x) \rightarrow S(x))$

3. Someone is graduating
$\exists x \, G(x)$

(2) Convert each formula to clause form

1. $\forall x \, (G(x) \rightarrow H(x))$
Using implication removal
$\forall x \, [\neg G(x) \vee H(x))$
In clause form
$\{\neg G(x), H(x)\}$

2. $\forall x \, (H(x) \rightarrow S(x))$
Using implication removal
$\forall x \, (\neg H(x) \vee S(x))$
In clause form
$\{\neg H(x), S(x)\}$

3. $\exists x \, G(x)$
In clause form : $\{G(v)\}$

③ Prove "is someone smiling" using resolution

1. Collect clauses
   (1) $\{\neg G(x), H(x)\}$
   (2) $\{\neg H(x), S(x)\}$
   (3) $\{G(a)\}$
   (4) Assume contradiction $(\neg S(a))$
2. Apply resolution
   Resolve (1) $\{\neg G(H), H(x)\}$ with (3)

   $\{G(x)\}$

   Substitute $x = a \Rightarrow \{G(a)\}$
   $\{\neg G(a), H(a)\}$
   ∴ we have $G(a)$, resolving gives
   $\{H(a)\}$

   Resolve (2) $\{\neg H(x), S(x)\}$ with $\{H(a)\}$
   Substitute $x = a$
   $\{\neg H(a), S(a)\}$ & $\{H(a)\}$

   Now left with $\{S(a)\}$
   we can resolve it with $\{\neg S(a)\}$

∴ We are left with
$\{\phi\}$

∴ Our assumption of contradiction is wrong.

Explain modus ponen with suitable example

→

Modus ponen is a fundamental rule of inference in propositional logic that allows us to deduce a conclusion from a conditional statement and its antecedent.

It follows the form

1. $P \rightarrow Q$ (if P then Q)
2. P (P is true)
   $\therefore Q$ (Q must be true)

Example:

1. If it rains, the ground will be wet : $P \rightarrow Q$
2. It is raining : P
   $\therefore$ Ground is wet : $\rightarrow Q$.

2. Explain forward ~~chaining~~ and chaining & backward chaining algorithm with the help of example:

→ forward chaining :- It starts with given facts and applies inference rules to derive new facts until the goal is reached. It is a data driven approach because it begins with known data and works forward to reach a conclusion.

Example : Diagonosing a disease

Rules:

1. If a person has a fever and cough they might have flu
2. If a person has a sore throat and fever, they might have cold.

Facts:

- The patient has a Fever.
- The patient has cough.

- Inference: 1) Fever + cough → flu (rule 1 applies)

2) Conclusion The patient might have flu.

Backward chaining: It starts with goal and works backwards by checking what facts are needed to support it. It is a goal driven approach.

Example: Diagosing a disease

Goal: Determine if patient has flue

Rules

1. (Fever ∧ cough) → flu.
2. (Sore Throat ∧ fever) → cold

Process using backward chaining

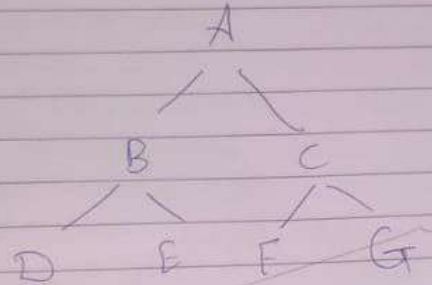
1. We want to prove flu.
2. looking at rule 1 (Fever ∧ cough) → Flue we need to check if patient has fever and cough.
3. we check our known facts
   - Patient has fever.
   - Patient has cough.
4. Since both conditions are met, we confirm flue is true.

(11) What do you mean by depth limited search? Explain Iterative Deepening search with example

→ Depth limited search (DLS) is an uninformed search algorithm that modifies DFS by introducing a depth limit L preventing exploration beyond the defined level. This prevents infinite loops in graphs but risks missing goals beyond L.

Iterative Deepening Search (IDS) combines DLS with BFS by iterating ~~fo~~ after incrementally increasing the depth limit.

Example



Goal G

Initially the depth limit is 0 for iteration 1.

Nodes visited = A

Goal not found

Iteration 2, limit = 1

Nodes visited = A → B → C

Goal not found

Iteration 3, limit 2

Nodes visited = A → B → D → E → C → F → G

Goal G is found.

AIDS-I Assignment No: 2

Q.1: Use the following data set for question 1

82, 66, 70, 59, 90, 78, 76, 95, 99, 84, 88, 76, 82, 81, 91, 64, 79, 76, 85, 90

Find the Mean, Median, Mode, and Interquartile Range (IQR).

Ans:

Step 1: Sort the Data
Sorted Data: 59, 64, 66, 70, 76, 76, 76, 78, 79, 81, 82, 82, 84, 85, 88, 90, 90, 91, 95, 99

Step 2: Mean
Mean formula: Mean = Sum of all values / Number of values
Sum = 1621
Number of values = 20
Mean = 1621 / 20 = 81.05

Step 3: Median
Median is the average of the 10th and 11th values in the sorted data.
10th value = 81, 11th value = 82
Median = (81 + 82) / 2 = 81.5

Step 4: Mode
The number that appears most frequently is 76 (3 times).
Mode = 76

Step 5: Interquartile Range (IQR)
Q1 is the median of the first half (1st to 10th values):
Q1 = (76 + 76) / 2 = 76
Q3 is the median of the second half (11th to 20th values):
Q3 = (88 + 90) / 2 = 89
IQR = Q3 - Q1 = 89 - 76 = 13

Q.2: 1) Machine Learning for Kids 2) Teachable Machine

For each tool listed above:

Identify the target audience.
Discuss the use of this tool by the target audience.
Identify the tool's benefits and drawbacks.

Ans:

Both tools are designed to democratize machine learning by lowering the barrier to entry, making it accessible to non-experts. Let's analyze each.

Machine Learning for Kids:

Target Audience: This tool primarily targets school-aged children (roughly ages 8–16), as well as educators and parents who want to introduce foundational AI and machine learning concepts in an educational setting. It's ideal for those with little to no prior technical knowledge.
Use by Target Audience: Children use the tool to create simple machine learning models through interactive, visual interfaces like Scratch or basic Python. They might classify text (e.g., positive/negative sentiment) or images (e.g., cats/dogs) by providing examples and letting the tool learn patterns. Educators integrate it into lesson plans to teach computational thinking, logic, and AI literacy, often as part of STEM curricula. The focus is on experiential learning, where users build intuition about how machines "learn" from data.

Benefits:
Extremely user-friendly, with no coding required for basic use, making it approachable for beginners.
Promotes creativity and critical thinking by allowing users to experiment with real-world problems (e.g., sorting, prediction).
Provides a safe, controlled environment for learning complex concepts like algorithms and data patterns.

Drawbacks:
Limited in scope; it's not designed for advanced machine learning tasks or large-scale applications.
Performance can be inconsistent if the training data is small or poorly curated, which might confuse learners.
Primarily educational, not suitable for professional or production-level machine learning projects.

Teachable Machine:

Target Audience: This tool targets a broader audience, including beginners, hobbyists, artists, teachers, and even small-scale developers who want to experiment with machine learning without coding expertise. It's particularly appealing to those interested in quick prototyping or creative projects.
Use by Target Audience: Users train models directly via a web interface using their webcam, microphone, or uploaded files (e.g., images, sounds, poses). For example, an artist might train a model to recognize different gestures for an interactive installation, while a teacher might use it to demonstrate object recognition in class. The tool allows real-time feedback, enabling users to see how their model performs and adjust training data accordingly. Models can be exported for use in larger projects, like web applications.

Benefits:
No coding knowledge is needed, making it highly accessible and fast to use.
Offers real-time training and testing, which is engaging and allows for immediate iteration.
Supports a variety of input types (images, sounds, poses), broadening its applicability.
Easy export options (e.g., to TensorFlow.js) allow users to integrate models into other projects.

Drawbacks:
Limited in handling complex datasets or advanced machine learning techniques, restricting its use to simple applications.
Reliant on user hardware and internet connectivity, which can affect performance.
Not ideal for large-scale or production environments due to its simplicity and lack of customization.

From the two choices listed below, how would you describe each tool listed above? Why did you choose the answer?

Predictive Analytic
Descriptive Analytic

Ans: Both Machine Learning for Kids and Teachable Machine are best described as predictive analytic tools. To understand this, consider the fundamental purpose of each tool: they enable users to train models on historical or labeled data (inputs paired with outputs) and then use those models to predict outcomes for new, unseen data. This is the essence of predictive analytics—using past data to forecast future events or classify new inputs.

For instance, in Machine Learning for Kids, a child might train a model to predict whether a piece of text is “happy” or “sad” based on examples they provide. Similarly, in Teachable Machine, a user might train a model to predict whether a webcam image shows a “cat” or a “dog.” In both cases, the tools are not merely summarizing past data (which would be descriptive analytics) but are focused on making forward-looking predictions. This distinction arises from their design: they emphasize model training for classification or regression tasks rather than data exploration or visualization. Hence, predictive analytics is the appropriate category.

From the three choices listed below, how would you describe each tool listed above? Why did you choose the answer?

Supervised Learning
Unsupervised Learning
Reinforcement Learning

Ans: Both Machine Learning for Kids and Teachable Machine are examples of supervised learning tools.Consider the learning paradigm: supervised learning involves training a model on a dataset where the inputs are paired with correct outputs (labels). The model learns to map inputs to outputs by minimizing the error between its predictions and the true labels.

In both tools, users provide labeled examples—such as tagging images as “cat” or “dog” in Teachable Machine, or labeling text as “positive” or “negative” in Machine Learning for Kids. The tools then use these labeled datasets to train models that can generalize to new, unlabeled data. This process contrasts with unsupervised learning, which finds patterns in data without labels (e.g., clustering), and reinforcement learning, which involves an agent learning through trial and error to maximize a reward. Since both tools rely on pre-labeled data and focus on prediction based on those labels, they clearly fall under supervised learning.

Q.3 Data Visualization:

Read the following two short articles:

Kakande, Arthur. February 12. “What’s in a chart? A Step-by-Step guide to Identifying Misinformation in Data Visualization.” Medium
Foley, Katherine Ellen. June 25, 2020. “How bad Covid-19 data visualizations mislead the public.” Quartz

Research a current event which highlights the results of misinformation based on data visualization. Explain how the data visualization method failed in presenting accurate information. Use newspaper articles, magazines, online news websites, or any other legitimate and valid source to cite this example. Cite the news source that you found.

Ans:

In April 2024, social media platforms saw a rise in climate change sceptics circulating claims suggesting that Arctic sea ice was not decreasing, and therefore, global warming concerns were exaggerated. These assertions were based on a data visualization comparing sea ice extent on January 8, 2004, and January 8, 2024. At first glance, the chart appeared to show minimal difference, implying that the Arctic ice had remained stable or even improved.

Source: Reuters – *Climate change sceptics use misleading Arctic ice data to make case*, April 25, 2024

How the Data Visualization Misled:

1. **Cherry-Picked Dates:**
   The chart selected two isolated data points 20 years apart, ignoring seasonal and year-to-year variability. This selective comparison masked the long-term downward trend in Arctic sea ice levels.

2. **Lack of Context:**
   The visual did not reference broader satellite data, which consistently show a significant decline in Arctic sea ice since 1979. Without context, viewers could not assess whether the snapshots were representative or anomalous.

3. **Misleading Visual Design:**
   The comparison relied on images and graphs that visually downplayed differences.

Small but significant changes in ice area were portrayed as negligible, potentially swaying public opinion toward climate skepticism.

Clarifying the Misrepresentation:

When viewed through long-term, continuous data provided by the National Snow and Ice Data Center (NSIDC) and NASA, it becomes clear that Arctic sea ice is in persistent decline. Experts pointed out that visualizations relying on two points in time can be deeply misleading without showing trends or averages. The broader dataset reveals shrinking ice coverage, later seasonal freezing, and earlier melting—clear signs of a warming planet.

Conclusion:

This case highlights the critical importance of providing full context, consistent scales, and representative timelines in data visualization. Misleading graphics can fuel public misunderstanding, especially in high-stakes issues like climate change. It is the responsibility of data communicators to ensure their work conveys the true story—not just one convenient frame of it.

Q. 4 Train Classification Model and visualize the prediction performance of trained model required information

- Data File: Classification data.csv
- Class Label: Last Column
- Use any Machine Learning model (SVM, Naïve Base Classifier)

Requirements to satisfy

- Programming Language: Python
- Class imbalance should be resolved
- Data Pre-processing must be used
- Hyper parameter tuning must be used
- Train, Validation and Test Split should be 70/20/10
- Train and Test split must be randomly done

- Classification Accuracy should be maximized
- Use any Python library to present the accuracy measures of trained model

[Pima Indians Diabetes Database]

```
Validation Accuracy: 70.0 %
Test Accuracy: 75.0 %

Classification Report (Test Set):
              precision    recall  f1-score   support

           0       0.70      0.88      0.78        50
           1       0.84      0.62      0.71        50

    accuracy                           0.75       100
   macro avg       0.77      0.75      0.75       100
weighted avg       0.77      0.75      0.75       100
```

The model performs better at detecting non-diabetic patients.

- **Explanation:** This indicates that the model has a higher success rate in correctly identifying individuals without diabetes (class 0) compared to those with diabetes (class 1). This could be due to a bias toward the majority class or better-defined features for non-diabetic cases.

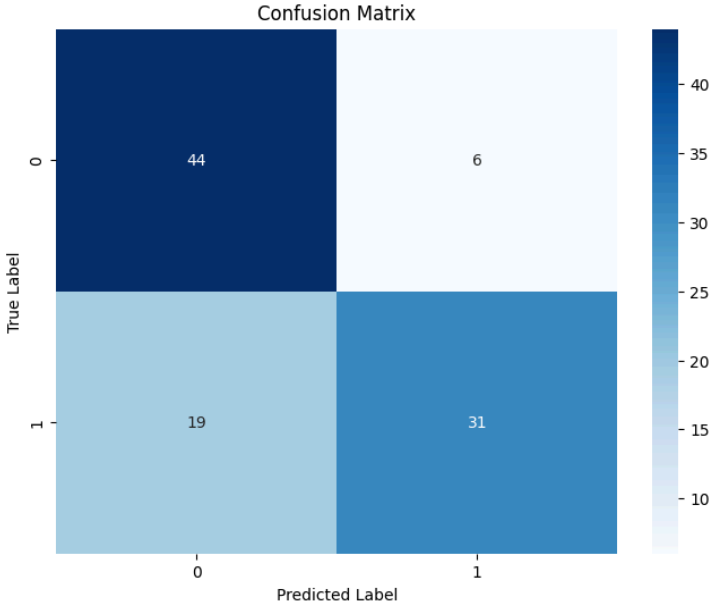
Recall for Class 1 (diabetic) is relatively low at 62%, meaning it's missing many positive cases.

- **Explanation:** Recall (also known as sensitivity or true positive rate) measures the proportion of actual positive cases (diabetic patients) that the model correctly identifies. A recall of 62% for class 1 means that 38% of diabetic cases are missed (false negatives), which is significant in a medical context where detecting all positive cases is critical. This suggests the model struggles to generalize to diabetic patients.

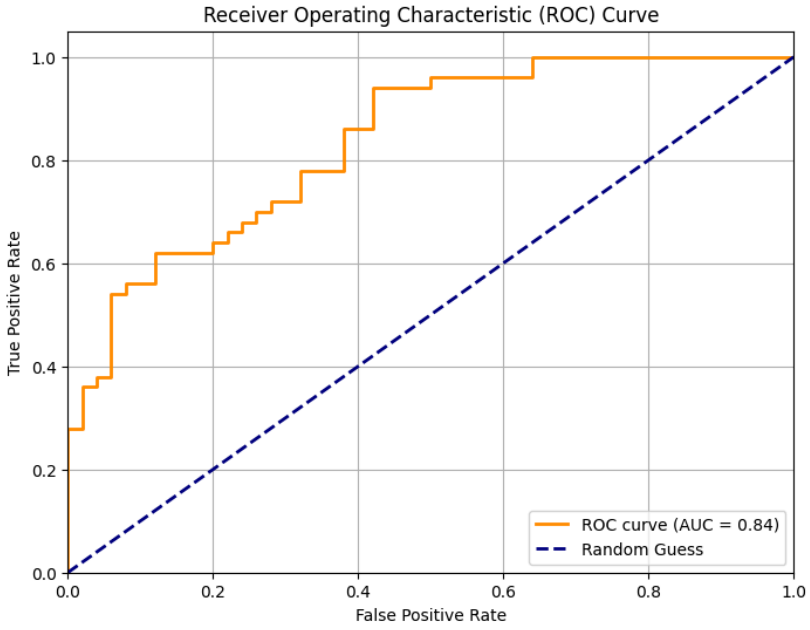
This is a common issue with imbalanced datasets, even after SMOTE.

- **Explanation:** Class imbalance occurs when one class (e.g., non-diabetic) has significantly more instances than the other (diabetic). SMOTE (Synthetic Minority Over-sampling Technique) generates synthetic samples to balance the classes, but the low recall indicates that the imbalance or feature overlap may still affect performance, possibly due to insufficient feature differentiation or model limitations.

The Naive Bayes classifier achieved a validation accuracy of 70.0% and a test accuracy of 75.0%, with an ROC AUC score of 0.84, indicating moderate to good performance in distinguishing between diabetic and non-diabetic patients.



The confusion matrix reveals that out of 100 test cases (50 per class), the model correctly identified 31 diabetic cases while misclassifying 19, which is critical in healthcare applications. Despite applying class balancing techniques, the model still shows bias toward the majority class.



The ROC curve plots the True Positive Rate (Sensitivity) against the False Positive Rate (1 - Specificity) at various threshold levels. It helps evaluate how well the model distinguishes

between the positive (diabetic) and negative (non-diabetic) classes. The orange curve represents the model's performance across different classification thresholds. The dashed diagonal line is the baseline (random guessing) — a model performing no better than chance would follow this line.

- **Explanation:**
    - **True Positive Rate (TPR or Sensitivity)** is the recall, or the proportion of actual positives correctly identified.
    - **False Positive Rate (FPR)** is the proportion of negatives incorrectly classified as positive (FP / (FP + TN)).
    - The ROC curve visualizes this trade-off, with the orange curve showing the model's performance. The baseline (diagonal) represents random guessing (AUC = 0.5), and deviation above it indicates predictive power.

The Area Under the Curve (AUC) is 0.84, which is quite good. It indicates that there's an 84% chance that the model will correctly distinguish a randomly chosen diabetic patient from a non-diabetic one.

- **Explanation:** AUC quantifies the overall ability of the model to discriminate between classes. An AUC of 0.84 is well above random (0.5) and approaches excellent (0.9+), suggesting the model is effective but could be optimized further, especially for recall.

Q.5 Train Regression Model and visualize the prediction performance of trained model

- Data File: Regression data.csv
- Independent Variable: 1st Column
- Dependent variables: Column 2 to 5

Use any Regression model to predict the values of all Dependent variables using values of 1st column.
Requirements to satisfy:

- Programming Language: Python
- OOP approach must be followed
- Hyper parameter tuning must be used
- Train and Test Split should be 70/30
- Train and Test split must be randomly done
- Adjusted R2 score should more than 0.99
- Use any Python library to present the accuracy measures of trained model

https://github.com/Sutanoy/Public-Regression-Datasets

https://raw.githubusercontent.com/selva86/datasets/master/BostonHousing.csv

- URL: https://archive.ics.uci.edu/ml/machine-learning-databases/00477/Real%20estate%20valuation%20data%20set.xlsx

Predictive Modeling and Evaluation

Dataset Overview

The dataset contains customer demographic and behavioral attributes. Below are the first few rows:

```
First few rows:
   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
```

Data Quality

No missing values were found in any of the columns:

```
Missing values:
CustomerID                0
Gender                    0
Age                       0
Annual Income (k$)        0
Spending Score (1-100)    0
dtype: int64
```

Model Training and Performance

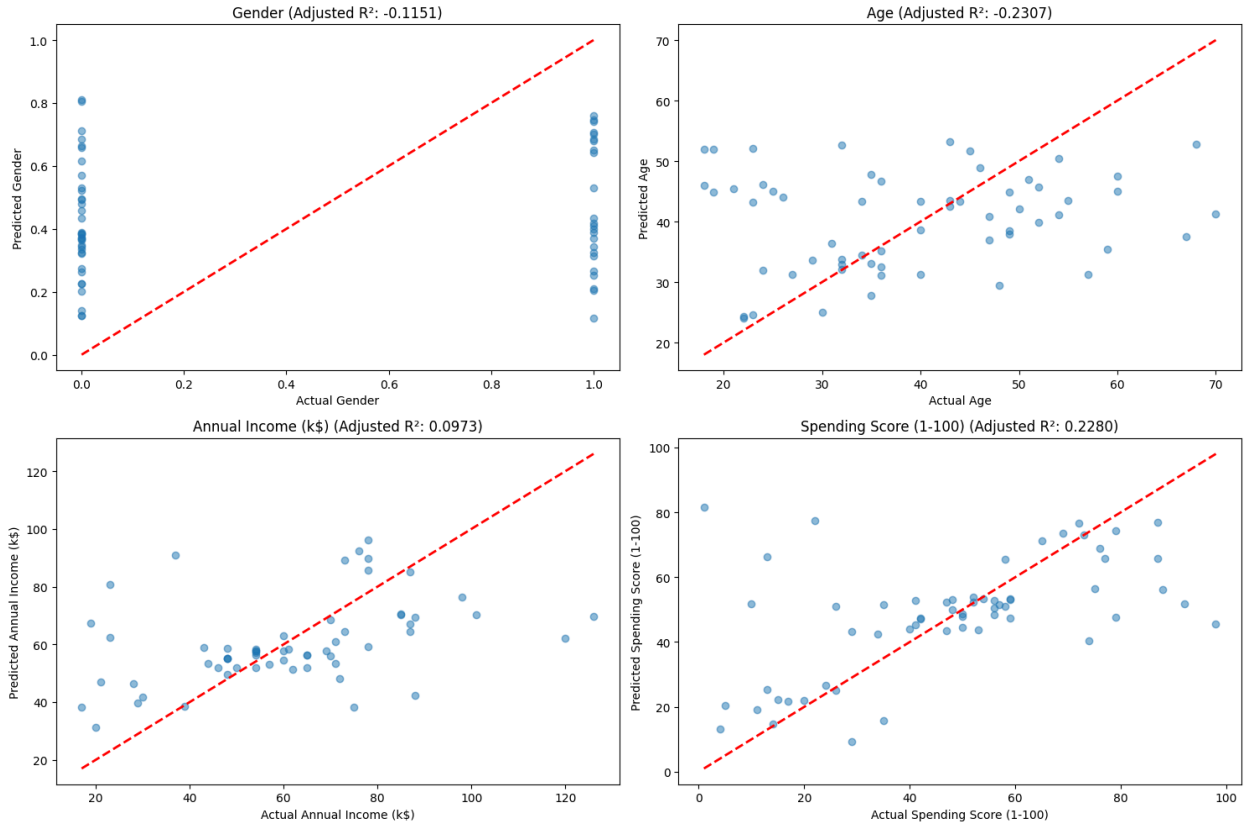
Random Forest Regressors were trained to predict each feature using the others. Hyperparameter tuning was performed using GridSearchCV to identify the best model configuration.

- **Gender**
    - **Best Parameters**: `{'max_depth': 10, 'min_samples_split': 10, 'n_estimators': 50}`
    - **Adjusted R^2 Score**: **-0.1151**
    - Interpretation: The model performed poorly in predicting gender, indicating that the other features are not informative enough to distinguish gender.
- **Age**
    - **Best Parameters**: `{'max_depth': 10, 'min_samples_split': 10, 'n_estimators': 200}`
    - **Adjusted R^2 Score**: **-0.2307**
    - Interpretation: Age prediction was also poor, suggesting a weak relationship between age and the other features used.
- **Annual Income (k$)**
    - **Best Parameters**: `{'max_depth': 10, 'min_samples_split': 10, 'n_estimators': 50}`
    - **Adjusted R^2 Score**: **0.0973**
    - Interpretation: The model shows limited ability to predict income, indicating weak linear correlations.
- **Spending Score (1–100)**
    - **Best Parameters**: `{'max_depth': 10, 'min_samples_split': 5, 'n_estimators': 50}`
    - **Adjusted R^2 Score**: **0.2280**
    - Interpretation: Spending score had the best predictability among all features, though still modest. This suggests a slightly stronger relationship with other

inputs.

Visualization of Predictions

The following figure shows the actual vs. predicted values for each feature along with the red dashed line representing the ideal prediction line (i.e., perfect correlation):



Conclusion

In this study, we applied machine learning techniques to explore the predictability of customer demographic and behavioral attributes using a Random Forest Regressor. The primary goal was to determine whether features such as Gender, Age, Annual Income, and Spending Score could be accurately predicted from one another.

We began by analyzing the dataset, which was clean and free from missing values. Each feature was individually treated as a target variable, and the rest were used as predictors. Hyperparameter tuning via GridSearchCV was employed to optimize the model for each prediction task.

The outcomes varied across features:

- **Gender and Age** yielded negative adjusted R^2 scores, indicating that the model performed worse than a simple mean-based prediction. This suggests weak or non-existent relationships between these features and the others, or that they are inherently harder to predict due to categorical nature (in the case of Gender) or noise (in the case of Age).

- **Annual Income** had a slightly positive adjusted R^2 (0.0973), reflecting some predictive potential, albeit limited.

- **Spending Score** showed the highest performance with an adjusted R^2 of 0.2280, indicating a modest but more promising relationship with the input features.

What Could Be Improved

- **Feature Engineering**: Including more relevant features such as occupation, education level, or marital status could significantly improve predictive power.

- **Categorical Treatment**: Gender was treated numerically, which may not have been optimal. A classification approach could be more appropriate.

- **Model Choice**: While Random Forest is robust, experimenting with other models like Gradient Boosting, Support Vector Machines, or Neural Networks might yield better results.

- **Dimensionality**: With only a few features, the model lacked complexity. More diverse and informative data could enable better learning.

The results underline an important insight in machine learning — not all problems are equally predictable. Some features may inherently carry more noise or less correlation with others. While this experiment provided valuable experience in supervised learning, it also highlighted the critical role of data richness and thoughtful model selection in achieving meaningful predictions.

Q.6: What are the key features of the wine quality data set? Discuss the importance of each feature in predicting the quality of wine? How did you handle missing data in the wine quality data set during the feature engineering process? Discuss the

advantages and disadvantages of different imputation techniques. (Refer dataset from Kaggle).

Ans:

Key Features and Their Importance:

Fixed Acidity: This measures non-volatile acids (e.g., tartaric, malic) that contribute to the wine's total acidity. High fixed acidity can enhance tartness and preservation but too much can make the wine overly sharp. It's crucial for predicting quality because it affects taste balance and microbial stability.

Volatile Acidity: This reflects volatile acids like acetic acid, which can impart a vinegar-like flavor if too high. Low levels are desirable for quality, as excessive volatile acidity is a defect. It's a key predictor because it directly impacts sensory appeal.

Citric Acid: Adds freshness and flavor, often enhancing complexity. Its presence can improve quality by balancing other acids, but too much can make the wine overly tart. It's important for fine-tuning taste profiles.

Residual Sugar: The sugar left after fermentation influences sweetness, body, and mouthfeel. Low residual sugar is typical for dry wines, while higher levels suit sweeter styles. It's critical for quality prediction as it affects consumer preference and style classification.

Chlorides: Salt content can influence taste and preservation. High chloride levels might make the wine taste salty or bitter, negatively impacting quality. It's a minor but relevant factor in overall balance.

Free Sulfur Dioxide and Total Sulfur Dioxide: These measure antioxidant and antimicrobial agents. Free SO_2 protects against oxidation, while total SO_2 includes bound forms. Both are vital for quality, as they prevent spoilage, but excessive levels can create off-odors.

Density: Related to alcohol and sugar content, density affects the wine's body and weight on the palate. It's important for predicting quality as it correlates with perceived richness and structure.

pH: Indicates acidity/basicity, affecting microbial stability and aging potential. Wines with stable pH (typically 3–4) are less prone to spoilage and better rated for quality.

Sulphates: Contribute to SO2 levels and can enhance aroma and preservation. Higher sulphates often correlate with better quality due to improved stability, but balance is key.

Alcohol: A major quality determinant, as it influences body, flavor intensity, and mouthfeel. Higher alcohol content often correlates with better ratings, but balance with other components is essential.

Each feature interacts with others, and their combined effect determines whether a wine is balanced, stable, and appealing, which drives quality scores.

Handling Missing Data in the Wine Quality Dataset:

Deletion: Remove rows or columns with missing values. This is simple but can lead to data loss, which is undesirable if the dataset is small or the missingness is significant.
Imputation with Mean or Median: Replace missing values with the mean (average) or median (middle value) of the feature. This preserves the dataset size but assumes the missing values are randomly distributed and similar to the observed data.
Mode Imputation (for Categorical Data): For categorical features (if any), use the most frequent category. This is straightforward but can overrepresent certain categories.
Advanced Techniques (e.g., KNN): Use machine learning methods like K-Nearest Neighbors (KNN) to impute based on similar data points. These are more sophisticated but computationally intensive.

Advantages and Disadvantages of Imputation Techniques:

Mean/Median Imputation:
Advantages: Easy to implement, preserves sample size, and works well for normally distributed numerical data. Mean is sensitive to outliers, so median is often preferred for descentness.
Disadvantages: Can distort variance, ignore data relationships, and assume missing values are similar to observed ones, which may not hold true.
Mode Imputation:
Advantages: Simple and effective for categorical data, maintaining the most common category without introducing new values.
Disadvantages: Can skew distributions by overrepresenting the mode, especially if the mode is not representative of the missing data.
KNN Imputation:

Advantages: Accounts for relationships between features, potentially providing more accurate imputations by using nearby data points.
Disadvantages: Computationally expensive, sensitive to the choice of neighbors (k) and distance metrics, and less effective with high-dimensional data.