Project Name : PREDICTIVE CUSTOMER BEHAVIOUR MODELLING USING AI

Predictive Customer Behavior Modelling Using AI is an in-depth analysis of a company's ideal customers. This approach enables businesses to gain a clearer understanding of their audience, making it easier to adapt products to meet the unique needs, preferences, and concerns of various customer groups. By leveraging predictive behavior modelling, organizations can tailor their offerings based on distinct customer segments. For example, instead of investing resources to promote a new product to every individual in the company's database, the business can identify which segment is most likely to purchase the product and focus its marketing efforts on that specific group.

Time Line of the project :

- Importing Libraries
- Data Analysis
- Data Cleaning and Feature Engineering
- Performing Clustering

Importing Libraries

```
import pandas as pd ## analysis
import numpy as np ## comptutational ability
import seaborn as sns
```

```
import matplotlib.pyplot as plt  ## visualization
%matplotlib inline

df= pd.read_csv("Customer_Analytics_DB.csv",sep='\t')

df
```

```
         ID  Year_Birth   Education Marital_Status   Income
Kidhome  \
0      5524        1957  Graduation         Single  58138.0        0

1      2174        1954  Graduation         Single  46344.0        1

2      4141        1965  Graduation       Together  71613.0        0

3      6182        1984  Graduation       Together  26646.0        1

4      5324        1981         PhD        Married  58293.0        1

...     ...         ...         ...            ...      ...      ...

2235  10870        1967  Graduation        Married  61223.0        0

2236   4001        1946         PhD       Together  64014.0        2

2237   7270        1981  Graduation       Divorced  56981.0        0

2238   8235        1956      Master       Together  69245.0        0

2239   9405        1954         PhD        Married  52869.0        1


      Teenhome Dt_Customer  Recency  MntWines  ...  NumWebVisitsMonth
\
0            0  04-09-2012       58       635  ...                  7

1            1  08-03-2014       38        11  ...                  5

2            0  21-08-2013       26       426  ...                  4

3            0  10-02-2014       26        11  ...                  6

4            0  19-01-2014       94       173  ...                  5

...        ...         ...      ...       ...  ...                ...

2235         1  13-06-2013       46       709  ...                  5

2236         1  10-06-2014       56       406  ...                  7

2237         0  25-01-2014       91       908  ...                  6
```

```
2238         1  24-01-2014        8       428  ...                     3

2239         1  15-10-2012       40        84  ...                     7


      AcceptedCmp3  AcceptedCmp4  AcceptedCmp5  AcceptedCmp1
AcceptedCmp2  \
0                0             0             0             0
0
1                0             0             0             0
0
2                0             0             0             0
0
3                0             0             0             0
0
4                0             0             0             0
0
...            ...           ...           ...           ...
...
2235             0             0             0             0
0
2236             0             0             0             1
0
2237             0             1             0             0
0
2238             0             0             0             0
0
2239             0             0             0             0
0

      Complain  Z_CostContact  Z_Revenue  Response
0            0              3         11         1
1            0              3         11         0
2            0              3         11         0
3            0              3         11         0
4            0              3         11         0
...        ...            ...        ...       ...
2235         0              3         11         0
2236         0              3         11         0
2237         0              3         11         0
2238         0              3         11         0
2239         0              3         11         1

[2240 rows x 29 columns]
```

```
df.shape
```

```
(2240, 29)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2240 entries, 0 to 2239
Data columns (total 29 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   ID                   2240 non-null   int64  
 1   Year_Birth           2240 non-null   int64  
 2   Education            2240 non-null   object 
 3   Marital_Status       2240 non-null   object 
 4   Income               2216 non-null   float64
 5   Kidhome              2240 non-null   int64  
 6   Teenhome             2240 non-null   int64  
 7   Dt_Customer          2240 non-null   object 
 8   Recency              2240 non-null   int64  
 9   MntWines             2240 non-null   int64  
 10  MntFruits            2240 non-null   int64  
 11  MntMeatProducts      2240 non-null   int64  
 12  MntFishProducts      2240 non-null   int64  
 13  MntSweetProducts     2240 non-null   int64  
 14  MntGoldProds         2240 non-null   int64  
 15  NumDealsPurchases    2240 non-null   int64  
 16  NumWebPurchases      2240 non-null   int64  
 17  NumCatalogPurchases  2240 non-null   int64  
 18  NumStorePurchases    2240 non-null   int64  
 19  NumWebVisitsMonth    2240 non-null   int64  
 20  AcceptedCmp3         2240 non-null   int64  
 21  AcceptedCmp4         2240 non-null   int64  
 22  AcceptedCmp5         2240 non-null   int64  
 23  AcceptedCmp1         2240 non-null   int64  
 24  AcceptedCmp2         2240 non-null   int64  
 25  Complain             2240 non-null   int64  
 26  Z_CostContact        2240 non-null   int64  
 27  Z_Revenue            2240 non-null   int64  
 28  Response             2240 non-null   int64  
dtypes: float64(1), int64(25), object(3)
memory usage: 507.6+ KB
```

```
df.dtypes
```

```
ID                       int64
Year_Birth               int64
Education               object
Marital_Status          object
Income                 float64
Kidhome                  int64
Teenhome                 int64
Dt_Customer             object
Recency                  int64
MntWines                 int64
MntFruits                int64
```

```
MntMeatProducts            int64
MntFishProducts            int64
MntSweetProducts           int64
MntGoldProds               int64
NumDealsPurchases          int64
NumWebPurchases            int64
NumCatalogPurchases        int64
NumStorePurchases          int64
NumWebVisitsMonth          int64
AcceptedCmp3               int64
AcceptedCmp4               int64
AcceptedCmp5               int64
AcceptedCmp1               int64
AcceptedCmp2               int64
Complain                   int64
Z_CostContact              int64
Z_Revenue                  int64
Response                   int64
dtype: object
```

Data Analysis

Null Values

```
df.isnull().sum()
```

```
ID                      0
Year_Birth              0
Education               0
Marital_Status          0
Income                 24
Kidhome                 0
Teenhome                0
Dt_Customer             0
Recency                 0
MntWines                0
MntFruits               0
MntMeatProducts         0
MntFishProducts         0
MntSweetProducts        0
MntGoldProds            0
NumDealsPurchases       0
NumWebPurchases         0
NumCatalogPurchases     0
NumStorePurchases       0
NumWebVisitsMonth       0
AcceptedCmp3            0
AcceptedCmp4            0
AcceptedCmp5            0
```

```
AcceptedCmp1            0
AcceptedCmp2            0
Complain                0
Z_CostContact           0
Z_Revenue               0
Response                0
dtype: int64
```

```
mean= df['Income'].mean()
df['Income']= df['Income'].fillna(mean)
```

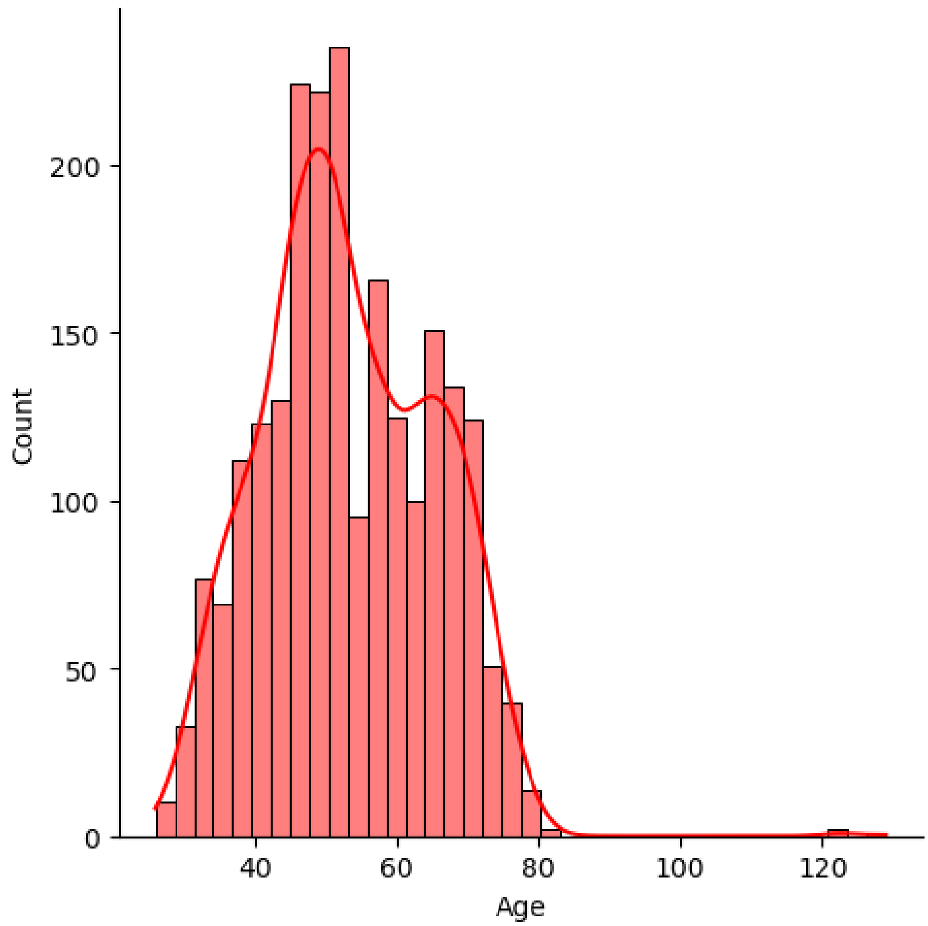
Let us create a new column Age by using year of birth

```
df['Age']= 2022-df['Year_Birth']
```

```
df['Age']
```

```
0       65
1       68
2       57
3       38
4       41
        ..
2235    55
2236    76
2237    41
2238    66
2239    68
Name: Age, Length: 2240, dtype: int64
```

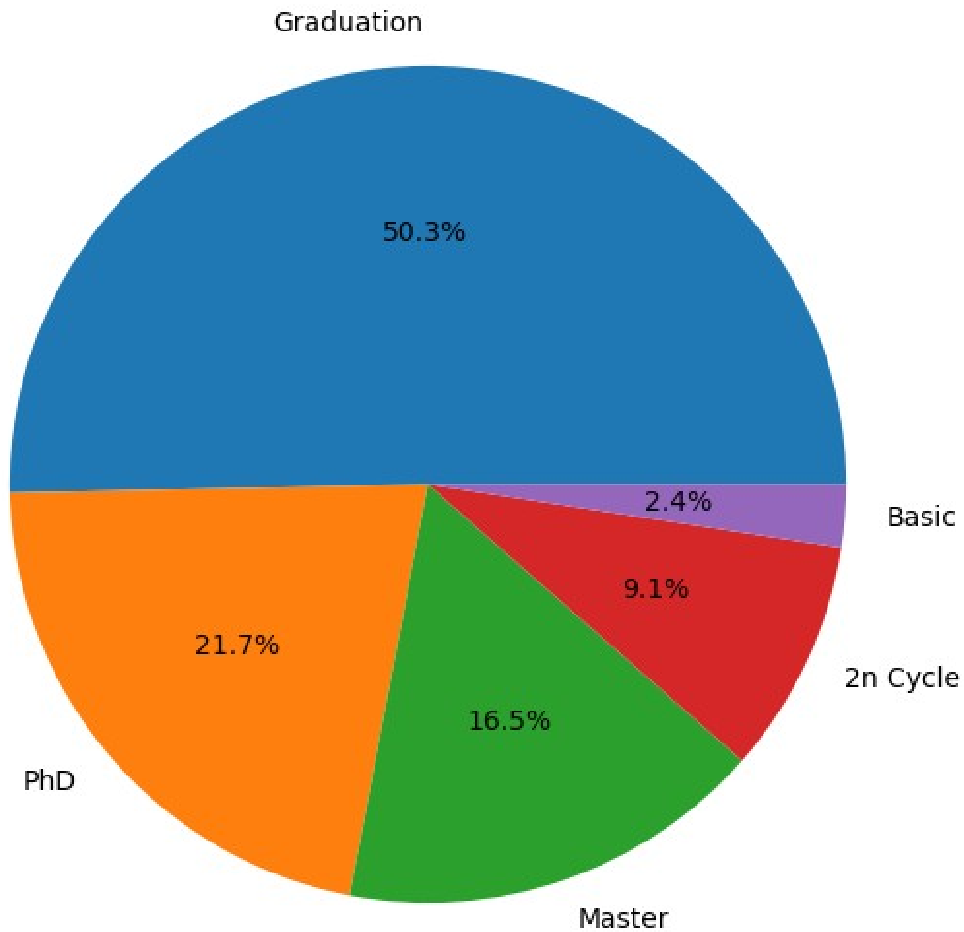
```
sns.displot(df['Age'], color='red', kde=True)
plt.show()
```



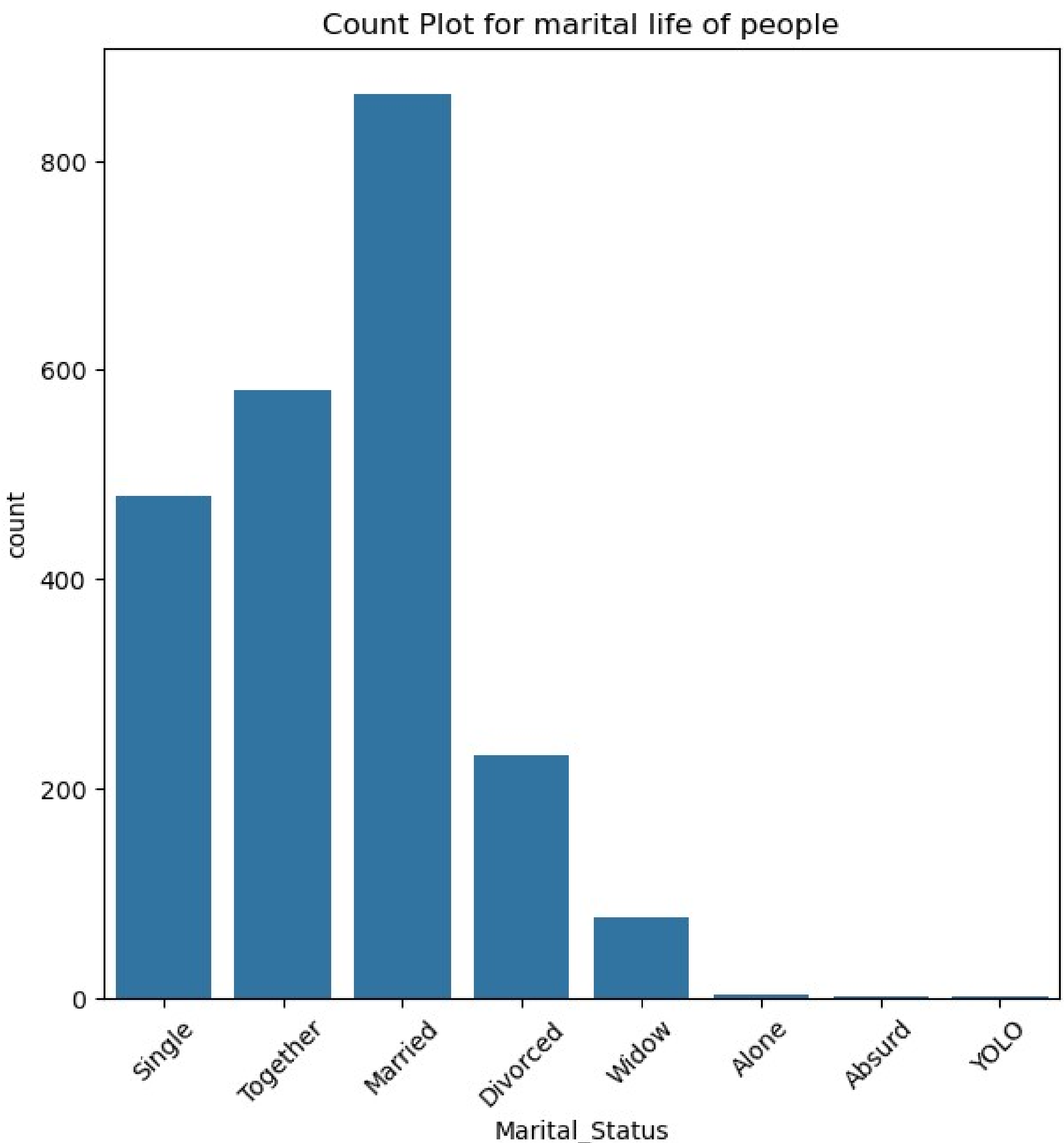

```
df['Education'].value_counts()
```

```
Education
Graduation    1127
PhD            486
Master         370
2n Cycle       203
Basic           54
Name: count, dtype: int64
```

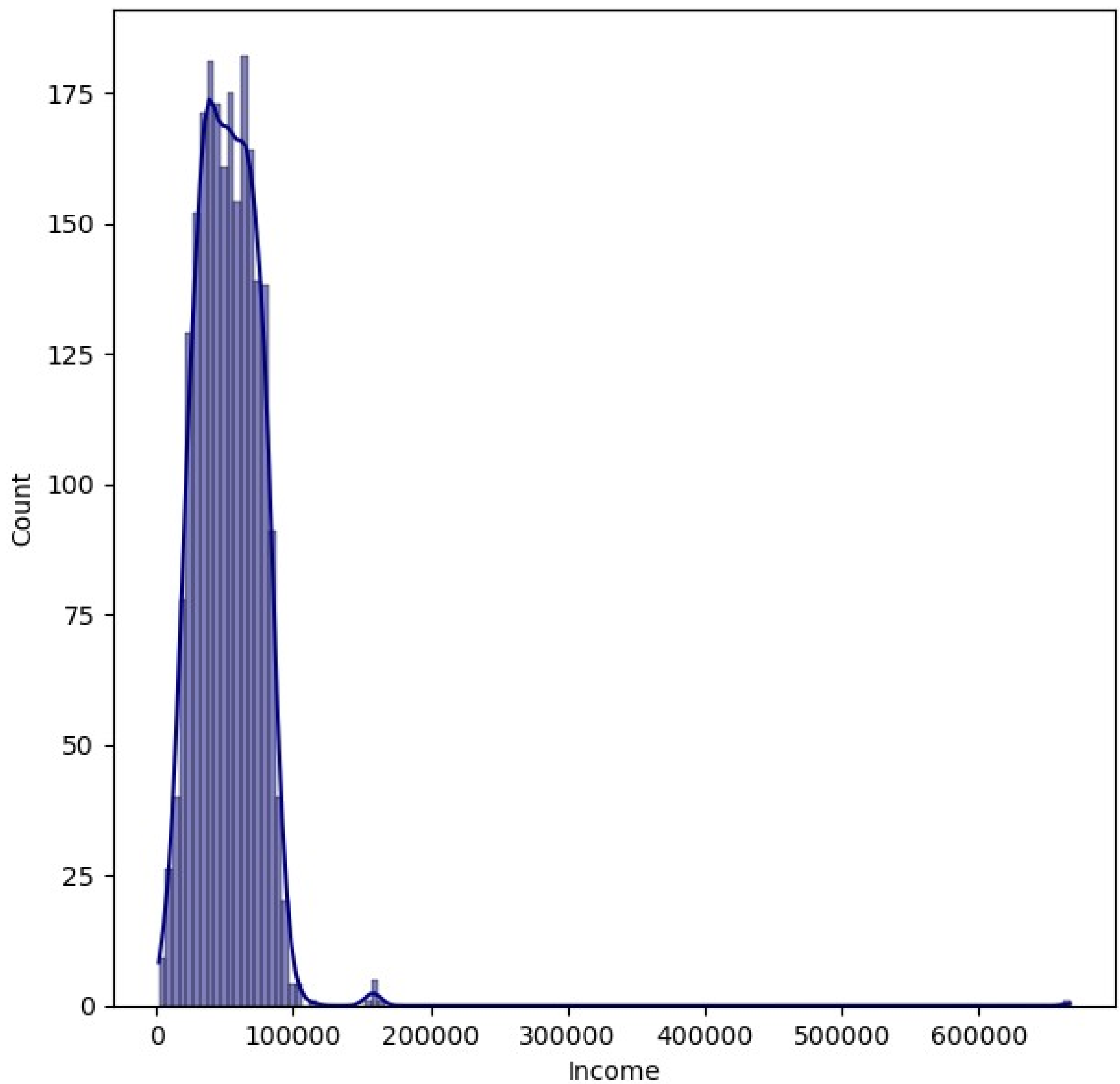
```
plt.figure(figsize=(7,7))
ed = df['Education'].value_counts()
plt.pie(ed,autopct='%.1f%
%',labels=[ed.index[0],ed.index[1],ed.index[2],ed.index[3],ed.index[4]
])
plt.show()
```



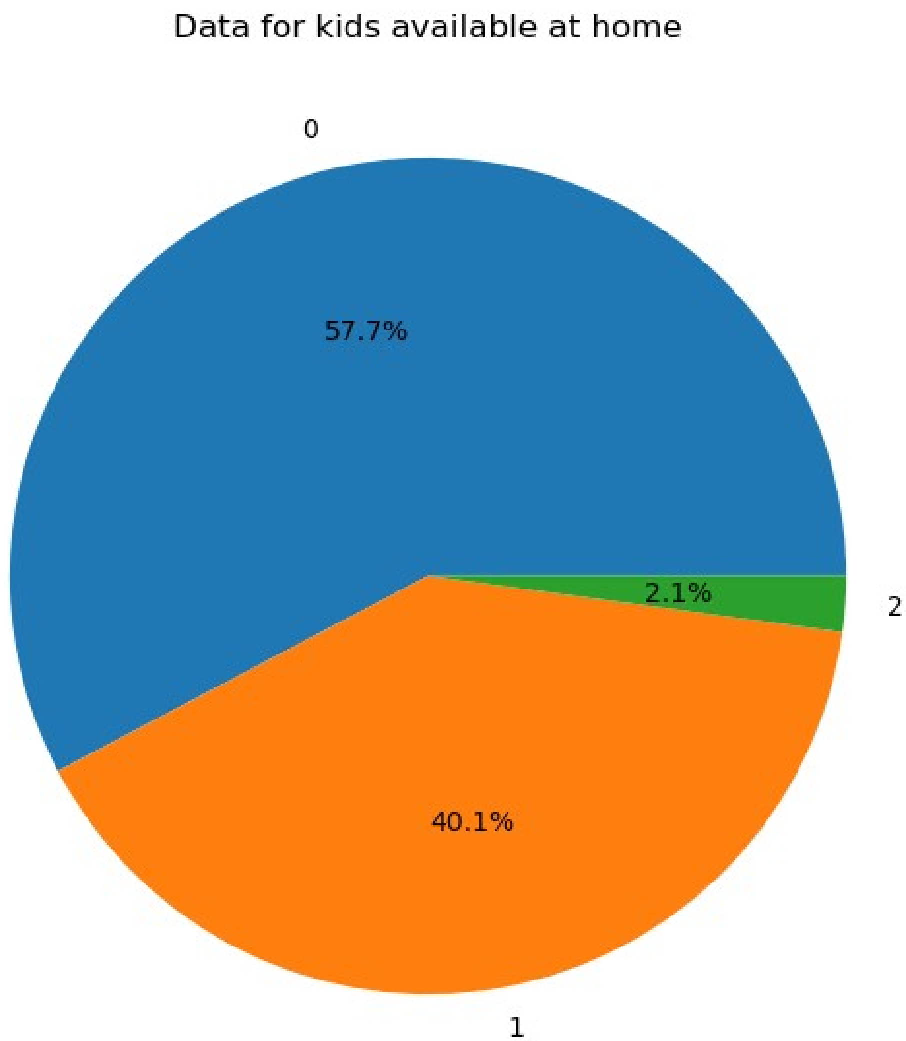

```
# Create a figure with specified size
plt.figure(figsize=(7, 7))

# Create the count plot
ms = sns.countplot(x='Marital_Status', data=df)

# Modify the x-tick labels
ms.tick_params(axis='x', rotation=45)

# Set the title of the plot
plt.title("Count Plot for marital life of people")

# Display the plot
plt.show()
```



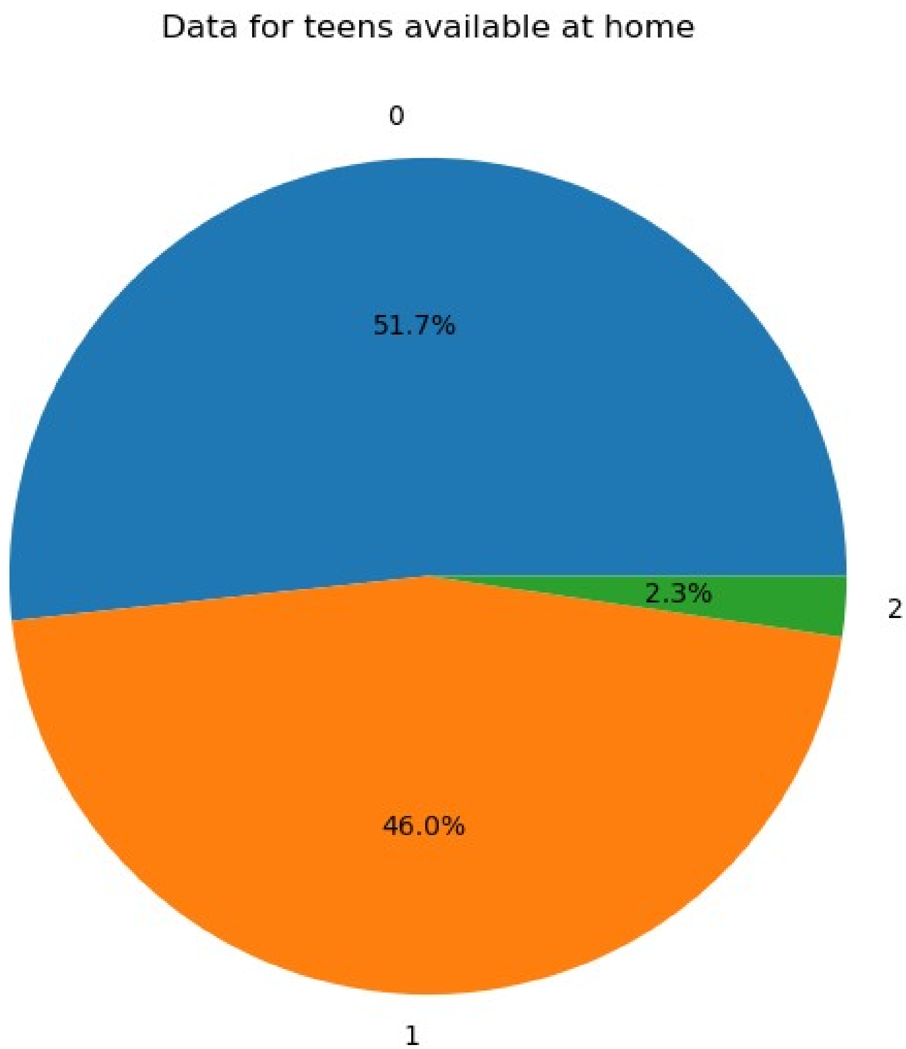

```
# Create a figure with specified size
plt.figure(figsize=(7, 7))

# Create the histogram plot using histplot
sns.histplot(df['Income'], color='navy', kde=True)

# Display the plot
plt.show()
```



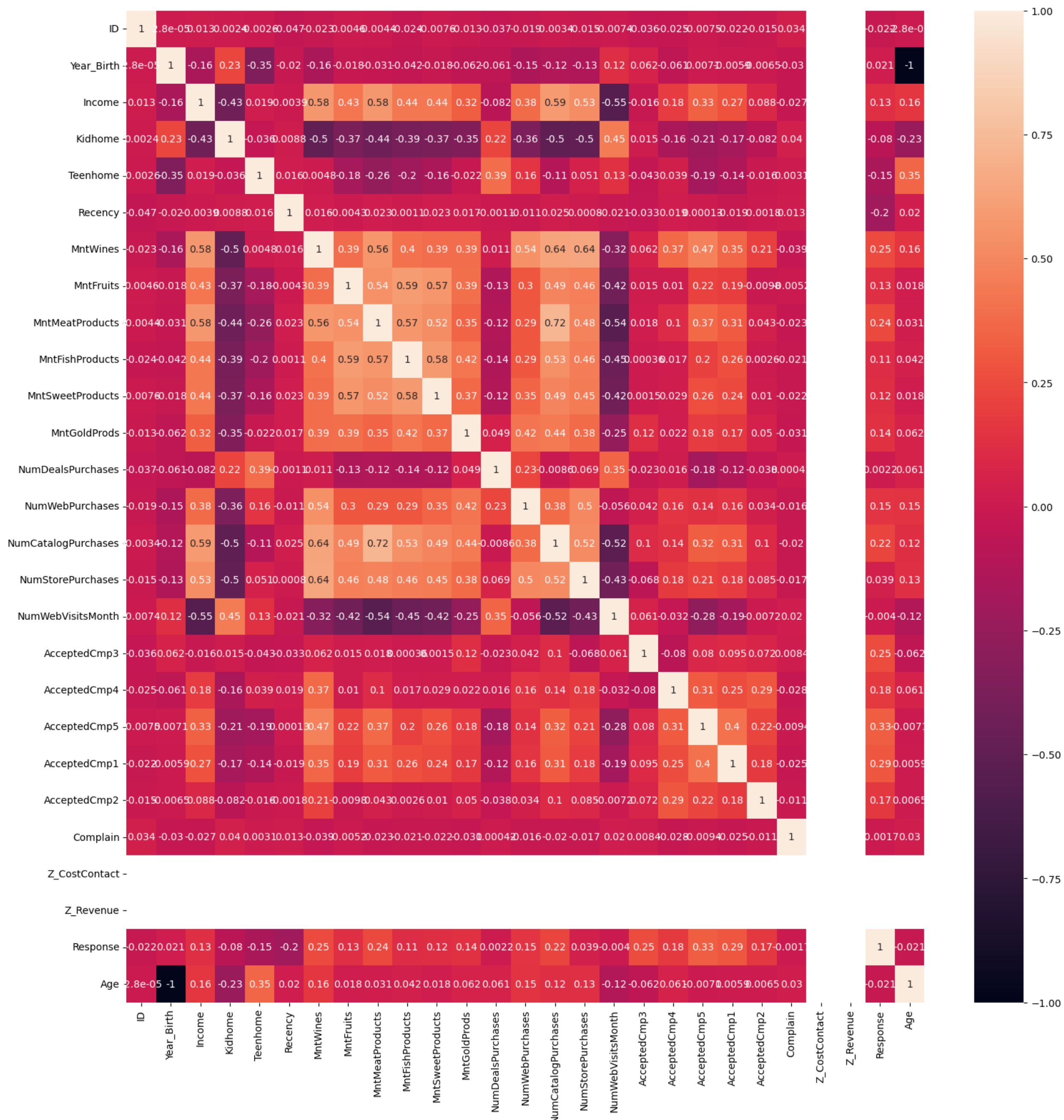

```
plt.figure(figsize=(7,7))
kid = df['Kidhome'].value_counts()
plt.pie(kid,autopct='%.1f%
%',labels=[kid.index[0],kid.index[1],kid.index[2]])
plt.title("Data for kids available at home")
plt.show()
```



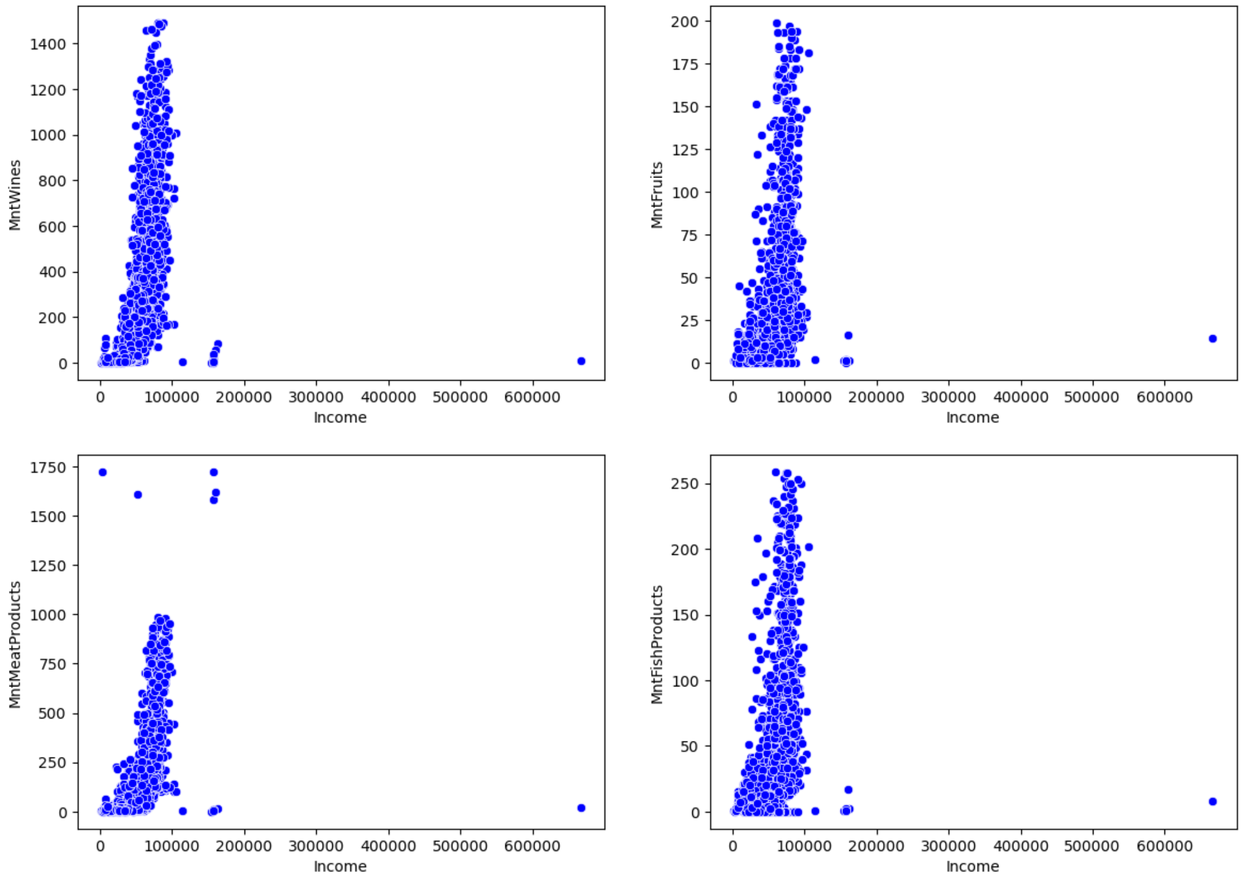

```
plt.figure(figsize=(7,7))
teen= df['Teenhome'].value_counts()
plt.pie(teen,autopct='%.1f%
%',labels=[teen.index[0],teen.index[1],teen.index[2]])
plt.title("Data for teens available at home")
plt.show()
```



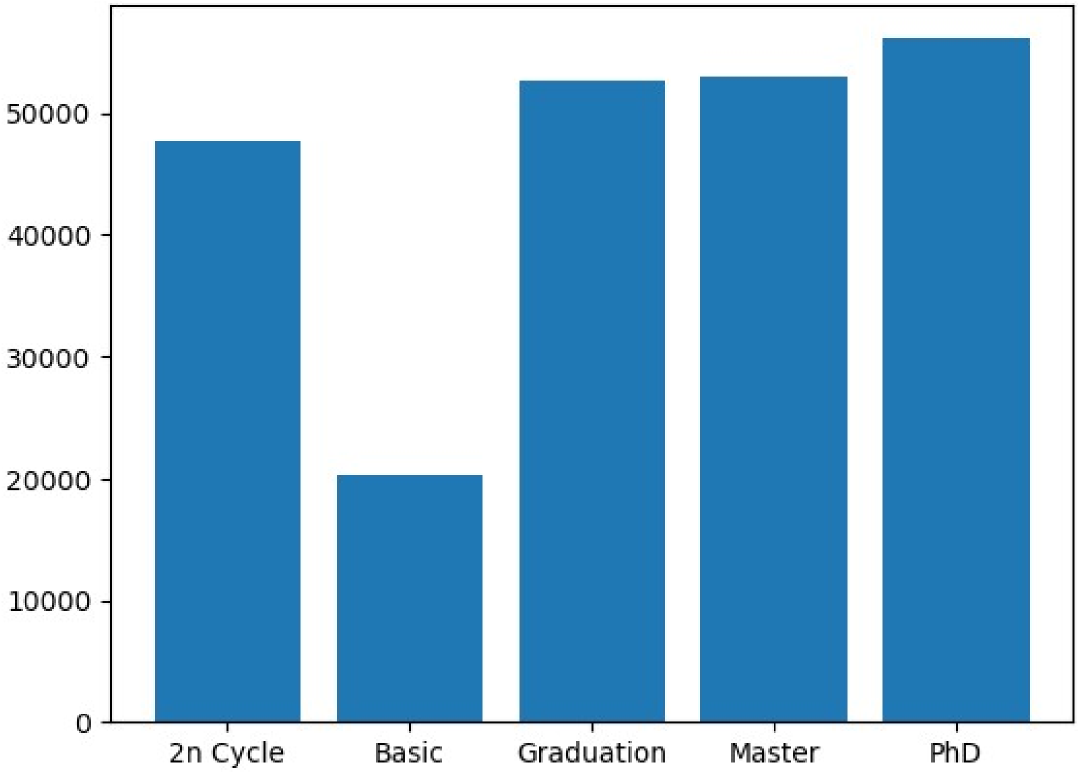

```
# Select only numeric columns for correlation calculation
numeric_df = df.select_dtypes(include='number')

# Plot the heatmap
plt.figure(figsize=(18, 18))
sns.heatmap(numeric_df.corr(), annot=True)

plt.show()
```



```
plt.figure(figsize=(14,10))
plt.subplot(2,2,1)
sns.scatterplot(data=df,x='Income',y='MntWines',color='blue')
plt.subplot(2,2,2)
sns.scatterplot(data=df,x='Income',y='MntFruits',color='blue')
plt.subplot(2,2,3)
sns.scatterplot(data=df,x='Income',y='MntMeatProducts',color='blue')
plt.subplot(2,2,4)
sns.scatterplot(data=df,x='Income',y='MntFishProducts',color='blue')
plt.show()
```




```
education_income= df.groupby('Education')['Income'].mean()

plt.bar(education_income.index,height=round(education_income,2))
plt.show()
```



Data Cleaning and Feature Engineering

```
mean

52247.25135379061

df= df.dropna()  ## we replaced the income null values with avg or mean of income

df.isnull().sum()

ID                     0
Year_Birth             0
Education              0
Marital_Status         0
Income                 0
Kidhome                0
Teenhome               0
Dt_Customer            0
Recency                0
MntWines               0
MntFruits              0
MntMeatProducts        0
MntFishProducts        0
MntSweetProducts       0
MntGoldProds           0
```

```
NumDealsPurchases       0
NumWebPurchases         0
NumCatalogPurchases     0
NumStorePurchases       0
NumWebVisitsMonth       0
AcceptedCmp3            0
AcceptedCmp4            0
AcceptedCmp5            0
AcceptedCmp1            0
AcceptedCmp2            0
Complain                0
Z_CostContact           0
Z_Revenue               0
Response                0
Age                     0
dtype: int64
```

Creating extra features like total money spent, family size

```
df["Total_Spent"] = df["MntWines"]+ df["MntFruits"]+
df["MntMeatProducts"]+ df["MntFishProducts"]+ df["MntSweetProducts"]+
df["MntGoldProds"]


# Replace values in "Marital_Status" column and create "Relation"
column
df["Relation"] = df["Marital_Status"].replace({"Married": 2,
"Together": 2, "Absurd": 1, "Widow": 1, "YOLO": 1, "Divorced": 1,
"Single": 1, "Alone": 1}).astype(int)

# Create "Children" column by summing "Kidhome" and "Teenhome"
df["Children"] = df["Kidhome"] + df["Teenhome"]

# Create "Family_Size" column by summing "Relation" and "Children"
df["Family_Size"] = df["Relation"] + df["Children"]

print(df)

         ID  Year_Birth   Education Marital_Status   Income
Kidhome  \
0      5524        1957  Graduation         Single  58138.0        0

1      2174        1954  Graduation         Single  46344.0        1

2      4141        1965  Graduation       Together  71613.0        0

3      6182        1984  Graduation       Together  26646.0        1

4      5324        1981         PhD        Married  58293.0        1
```

```
...     ...         ...         ...             ...      ...      ...
2235  10870        1967  Graduation        Married  61223.0        0
2236   4001        1946         PhD       Together  64014.0        2
2237   7270        1981  Graduation       Divorced  56981.0        0
2238   8235        1956      Master       Together  69245.0        0
2239   9405        1954         PhD        Married  52869.0        1

      Teenhome Dt_Customer  Recency  MntWines  ...  AcceptedCmp2
Complain  \
0            0  04-09-2012       58       635  ...             0
0
1            1  08-03-2014       38        11  ...             0
0
2            0  21-08-2013       26       426  ...             0
0
3            0  10-02-2014       26        11  ...             0
0
4            0  19-01-2014       94       173  ...             0
0
...        ...         ...      ...       ...  ...           ...
...
2235         1  13-06-2013       46       709  ...             0
0
2236         1  10-06-2014       56       406  ...             0
0
2237         0  25-01-2014       91       908  ...             0
0
2238         1  24-01-2014        8       428  ...             0
0
2239         1  15-10-2012       40        84  ...             0
0

      Z_CostContact  Z_Revenue  Response  Age  Total_Spent
Relation  \
0                 3         11         1   65         1617         1
1                 3         11         0   68           27         1
2                 3         11         0   57          776         2
3                 3         11         0   38           53         2
4                 3         11         0   41          422         2
```

```
...              ...        ...       ...  ...           ...        ...
2235               3         11         0   55          1341          2
2236               3         11         0   76           444          2
2237               3         11         0   41          1241          1
2238               3         11         0   66           843          2
2239               3         11         1   68           172          2

      Children  Family_Size
0            0            1
1            2            3
2            0            2
3            1            3
4            1            3
...        ...          ...
2235         1            3
2236         3            5
2237         0            1
2238         1            3
2239         2            4

[2240 rows x 34 columns]

C:\Users\ChatterjeeSo\AppData\Local\Temp\
ipykernel_28452\3846774764.py:2: FutureWarning: Downcasting behavior
in `replace` is deprecated and will be removed in a future version. To
retain the old behavior, explicitly call
`result.infer_objects(copy=False)`. To opt-in to the future behavior,
set `pd.set_option('future.no_silent_downcasting', True)`
  df["Relation"] = df["Marital_Status"].replace({"Married": 2,
"Together": 2, "Absurd": 1, "Widow": 1, "YOLO": 1, "Divorced": 1,
"Single": 1, "Alone": 1}).astype(int)
```

```
df= df.drop(['Relation','Children'],axis=1)

df.columns
```

```
Index(['ID', 'Year_Birth', 'Education', 'Marital_Status', 'Income',
'Kidhome',
       'Teenhome', 'Dt_Customer', 'Recency', 'MntWines', 'MntFruits',
       'MntMeatProducts', 'MntFishProducts', 'MntSweetProducts',
       'MntGoldProds', 'NumDealsPurchases', 'NumWebPurchases',
       'NumCatalogPurchases', 'NumStorePurchases',
'NumWebVisitsMonth',
       'AcceptedCmp3', 'AcceptedCmp4', 'AcceptedCmp5', 'AcceptedCmp1',
       'AcceptedCmp2', 'Complain', 'Z_CostContact', 'Z_Revenue',
```

```
'Response',
       'Age', 'Total_Spent', 'Family_Size'],
      dtype='object')
```

Label Encoding categorical data i.e. Education data

```python
from sklearn.preprocessing import LabelEncoder ## one hot encoding
from sklearn.preprocessing import StandardScaler  ## scale the values
based on mean of the data

df['Education']
```

```
0       Graduation
1       Graduation
2       Graduation
3       Graduation
4              PhD
           ...
2235    Graduation
2236           PhD
2237    Graduation
2238        Master
2239           PhD
Name: Education, Length: 2240, dtype: object
```

```python
lb = LabelEncoder()
df['Education']= lb.fit_transform(df['Education'])

df['Response']
```

```
0       1
1       0
2       0
3       0
4       0
       ..
2235    0
2236    0
2237    0
2238    0
2239    1
Name: Response, Length: 2240, dtype: int64
```

Scaling Data

```python
df1 = df.copy()
to_drop = ["AcceptedCmp3", "AcceptedCmp4", "AcceptedCmp5",
"AcceptedCmp1","AcceptedCmp2", "Complain", "Response", ]
df1 = df1.drop(to_drop, axis=1)
```

```
df1

         ID  Year_Birth  Education Marital_Status   Income  Kidhome
Teenhome  \
0      5524        1957          2         Single  58138.0        0
0
1      2174        1954          2         Single  46344.0        1
1
2      4141        1965          2       Together  71613.0        0
0
3      6182        1984          2       Together  26646.0        1
0
4      5324        1981          4        Married  58293.0        1
0
...     ...         ...        ...            ...      ...      ...
...
2235  10870        1967          2        Married  61223.0        0
1
2236   4001        1946          4       Together  64014.0        2
1
2237   7270        1981          2       Divorced  56981.0        0
0
2238   8235        1956          3       Together  69245.0        0
1
2239   9405        1954          4        Married  52869.0        1
1

     Dt_Customer  Recency  MntWines  ...  NumDealsPurchases
NumWebPurchases  \
0     04-09-2012       58       635  ...                  3
8
1     08-03-2014       38        11  ...                  2
1
2     21-08-2013       26       426  ...                  1
8
3     10-02-2014       26        11  ...                  2
2
4     19-01-2014       94       173  ...                  5
5
...          ...      ...       ...  ...                ...
...
2235  13-06-2013       46       709  ...                  2
9
2236  10-06-2014       56       406  ...                  7
8
2237  25-01-2014       91       908  ...                  1
2
2238  24-01-2014        8       428  ...                  2
6
2239  15-10-2012       40        84  ...                  3
```

```
3

      NumCatalogPurchases  NumStorePurchases  NumWebVisitsMonth  \
0                      10                  4                  7
1                       1                  2                  5
2                       2                 10                  4
3                       0                  4                  6
4                       3                  6                  5
...                   ...                ...                ...
2235                    3                  4                  5
2236                    2                  5                  7
2237                    3                 13                  6
2238                    5                 10                  3
2239                    1                  4                  7

      Z_CostContact  Z_Revenue  Age  Total_Spent  Family_Size
0                 3         11   65         1617            1
1                 3         11   68           27            3
2                 3         11   57          776            2
3                 3         11   38           53            3
4                 3         11   41          422            3
...             ...        ...  ...          ...          ...
2235              3         11   55         1341            3
2236              3         11   76          444            5
2237              3         11   41         1241            1
2238              3         11   66          843            3
2239              3         11   68          172            4

[2240 rows x 25 columns]

scaler = StandardScaler()
#scaled_feature = scaler.fit_transform(df.values)
#scaled_df = pd.DataFrame(scaled_feature, index=df.index,
columns=df.columns)

df['Response']

0       1
1       0
2       0
3       0
4       0
       ..
2235    0
2236    0
2237    0
2238    0
2239    1
Name: Response, Length: 2240, dtype: int64
```

Aproach 1: Unsupervised Learning

Perform Clustering

We will use the Elbob method to find the optimum number of clusters

```
!pip install yellowbrick
#

Requirement already satisfied: yellowbrick in c:\users\chatterjeeso\
appdata\local\anaconda3\lib\site-packages (1.5)
Requirement already satisfied: matplotlib!=3.0.0,>=2.0.2 in c:\users\
chatterjeeso\appdata\local\anaconda3\lib\site-packages (from
yellowbrick) (3.9.2)
Requirement already satisfied: scipy>=1.0.0 in c:\users\chatterjeeso\
appdata\local\anaconda3\lib\site-packages (from yellowbrick) (1.13.1)
Requirement already satisfied: scikit-learn>=1.0.0 in c:\users\
chatterjeeso\appdata\local\anaconda3\lib\site-packages (from
yellowbrick) (1.5.1)
Requirement already satisfied: numpy>=1.16.0 in c:\users\chatterjeeso\
appdata\local\anaconda3\lib\site-packages (from yellowbrick) (1.26.4)
Requirement already satisfied: cycler>=0.10.0 in c:\users\
chatterjeeso\appdata\local\anaconda3\lib\site-packages (from
yellowbrick) (0.11.0)
Requirement already satisfied: contourpy>=1.0.1 in c:\users\
chatterjeeso\appdata\local\anaconda3\lib\site-packages (from
matplotlib!=3.0.0,>=2.0.2->yellowbrick) (1.2.0)
Requirement already satisfied: fonttools>=4.22.0 in c:\users\
chatterjeeso\appdata\local\anaconda3\lib\site-packages (from
matplotlib!=3.0.0,>=2.0.2->yellowbrick) (4.51.0)
Requirement already satisfied: kiwisolver>=1.3.1 in c:\users\
chatterjeeso\appdata\local\anaconda3\lib\site-packages (from
matplotlib!=3.0.0,>=2.0.2->yellowbrick) (1.4.4)
Requirement already satisfied: packaging>=20.0 in c:\users\
chatterjeeso\appdata\local\anaconda3\lib\site-packages (from
matplotlib!=3.0.0,>=2.0.2->yellowbrick) (24.1)
Requirement already satisfied: pillow>=8 in c:\users\chatterjeeso\
appdata\local\anaconda3\lib\site-packages (from matplotlib!
=3.0.0,>=2.0.2->yellowbrick) (10.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in c:\users\
chatterjeeso\appdata\local\anaconda3\lib\site-packages (from
matplotlib!=3.0.0,>=2.0.2->yellowbrick) (3.1.2)
Requirement already satisfied: python-dateutil>=2.7 in c:\users\
chatterjeeso\appdata\local\anaconda3\lib\site-packages (from
matplotlib!=3.0.0,>=2.0.2->yellowbrick) (2.9.0.post0)
Requirement already satisfied: joblib>=1.2.0 in c:\users\chatterjeeso\
appdata\local\anaconda3\lib\site-packages (from scikit-learn>=1.0.0-
>yellowbrick) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in c:\users\
```

```
chatterjeeso\appdata\local\anaconda3\lib\site-packages (from scikit-learn>=1.0.0->yellowbrick) (3.5.0)
Requirement already satisfied: six>=1.5 in c:\users\chatterjeeso\appdata\local\anaconda3\lib\site-packages (from python-dateutil>=2.7->matplotlib!=3.0.0,>=2.0.2->yellowbrick) (1.16.0)
```

```
import os
from sklearn.cluster import KMeans
from sklearn import metrics
from sklearn.cluster import AgglomerativeClustering
from yellowbrick.cluster import KElbowVisualizer
```

```
df= df.drop(['Marital_Status','Dt_Customer'],axis=1)


# Set the environment variables to avoid the warnings
os.environ["LOKY_MAX_CPU_COUNT"] = "4"
os.environ["OMP_NUM_THREADS"] = "9"

em = KElbowVisualizer(KMeans(), k=10)
em.fit(df)
em.show()
```

```
C:\Users\ChatterjeeSo\AppData\Local\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1429: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP_NUM_THREADS=9.
  warnings.warn(
C:\Users\ChatterjeeSo\AppData\Local\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1429: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP_NUM_THREADS=9.
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C:\Users\ChatterjeeSo\AppData\Local\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1429: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP_NUM_THREADS=9.
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C:\Users\ChatterjeeSo\AppData\Local\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1429: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP_NUM_THREADS=9.
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C:\Users\ChatterjeeSo\AppData\Local\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1429: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than
```

```
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  warnings.warn(
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C:\Users\ChatterjeeSo\AppData\Local\anaconda3\Lib\site-packages\
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C:\Users\ChatterjeeSo\AppData\Local\anaconda3\Lib\site-packages\
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  warnings.warn(
C:\Users\ChatterjeeSo\AppData\Local\anaconda3\Lib\site-packages\
sklearn\cluster\_kmeans.py:1429: UserWarning: KMeans is known to have
a memory leak on Windows with MKL, when there are less chunks than
available threads. You can avoid it by setting the environment
variable OMP_NUM_THREADS=9.
  warnings.warn(
```
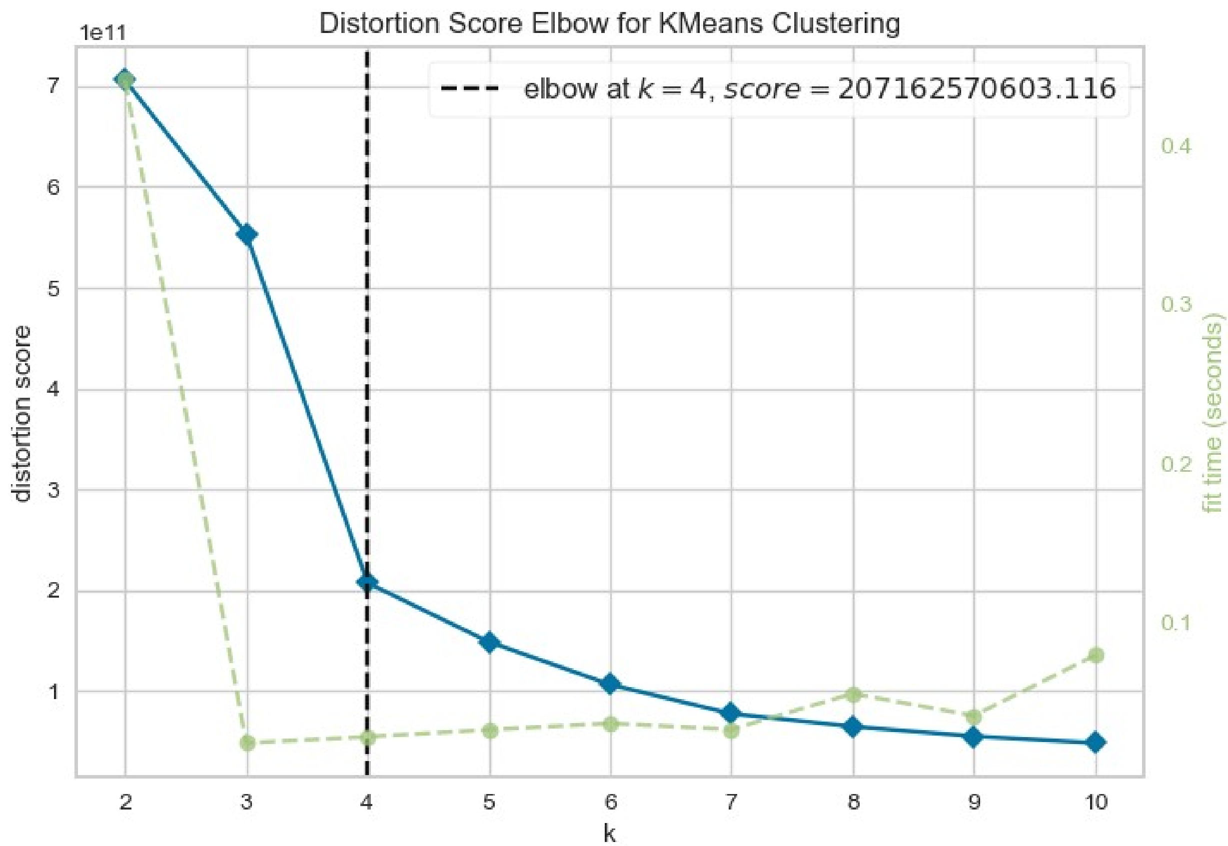




```
<Axes: title={'center': 'Distortion Score Elbow for KMeans
Clustering'}, xlabel='k', ylabel='distortion score'>
```

We see that the optimum number of clusters that should be used is k=4

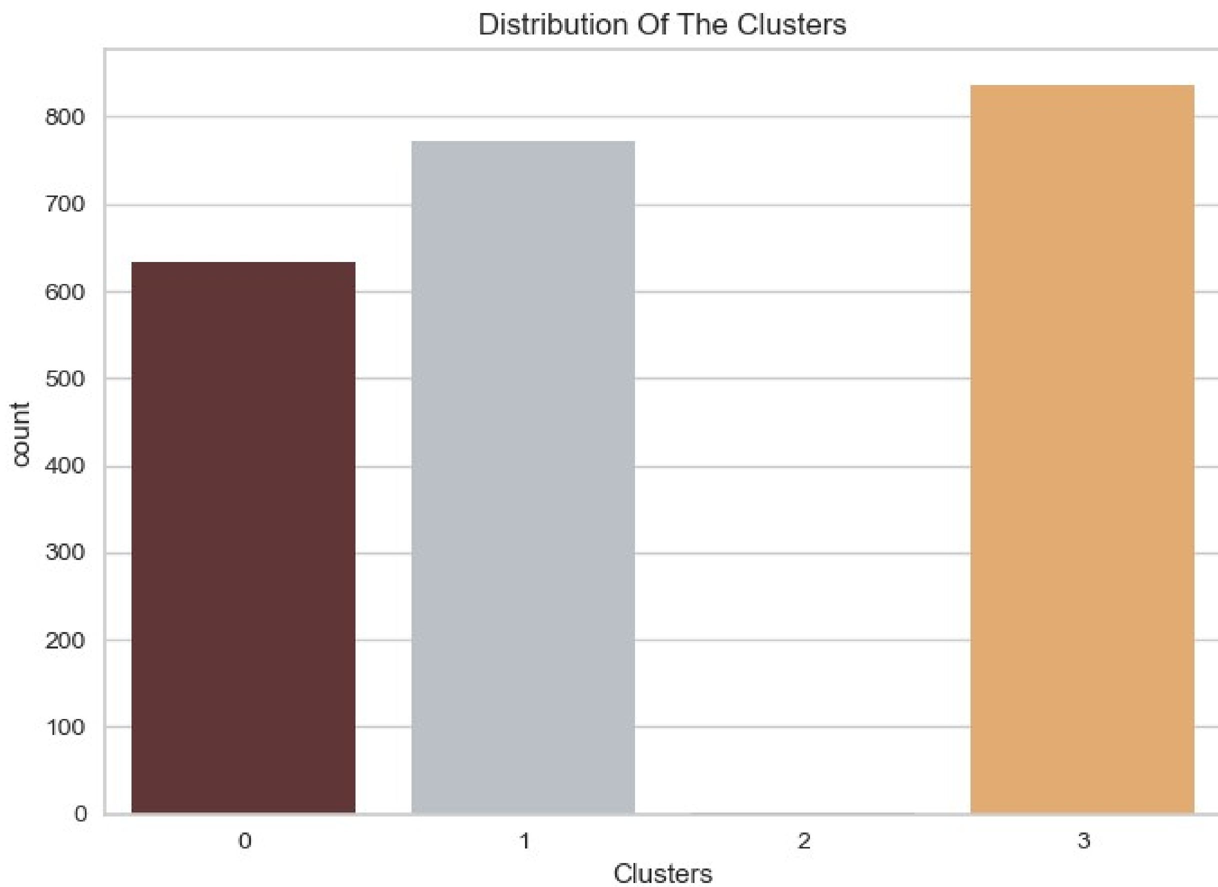
We will use K Means Clutering for the operation

```
from sklearn.cluster import KMeans

os.environ["OMP_NUM_THREADS"] = "9"
kmc = KMeans(n_clusters=4)
# fit model and predict clusters
pred = kmc.fit_predict(df)
df["Clusters"] = pred

C:\Users\ChatterjeeSo\AppData\Local\anaconda3\Lib\site-packages\
sklearn\cluster\_kmeans.py:1429: UserWarning: KMeans is known to have
a memory leak on Windows with MKL, when there are less chunks than
available threads. You can avoid it by setting the environment
variable OMP_NUM_THREADS=9.
  warnings.warn(

df['Clusters']
```

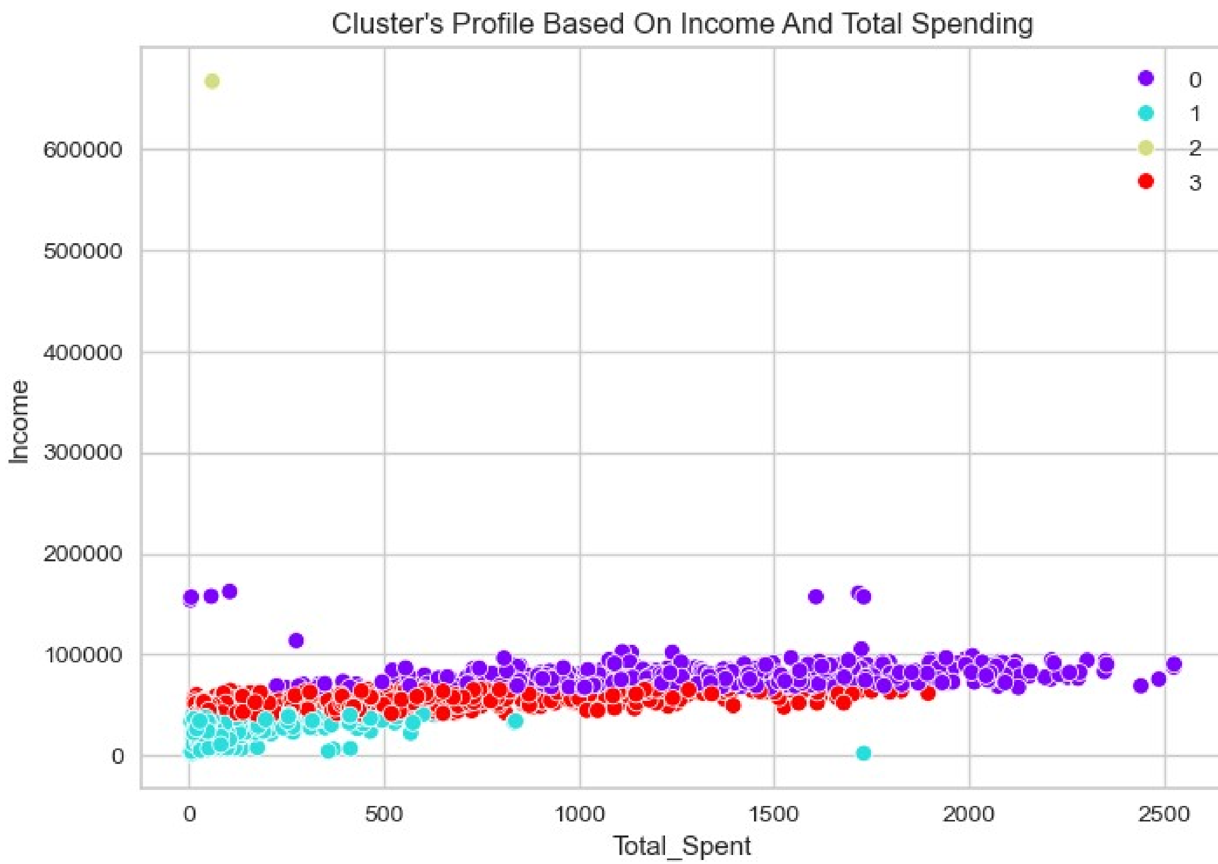
```
0       3
1       3
2       0
3       1
4       3
       ..
2235    3
2236    3
2237    3
2238    0
2239    3
Name: Clusters, Length: 2240, dtype: int32
```

Let us visualize our Clusters

```
# Define the palette
pal = ["#682F2F", "#B9C0C9", "#9F8A78", "#F3AB60"]

# Plot the countplot with hue set to the same variable as x and legend
set to False
fig = sns.countplot(x="Clusters", hue="Clusters", palette=pal,
data=df, legend=False)
fig.set_title("Distribution Of The Clusters")
plt.show()
```




```
fig = sns.scatterplot(data = df,x=df["Total_Spent"],
y=df["Income"],hue=df["Clusters"], palette="rainbow")
fig.set_title("Cluster's Profile Based On Income And Total Spending")
plt.legend()
plt.show()
```



Approach 2 : Supervised Learning

```
y=df['Response'] ## dependent var
X_new=df.drop(['Response','Education'],axis=1) ## independent var

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X_new,y,
test_size=0.2, random_state=51)

print('Shape of X_train = ', X_train.shape)
print('Shape of y_train = ', y_train.shape)
print('Shape of X_test = ', X_test.shape)
print('Shape of y_test = ', y_test.shape)

Shape of X_train =  (1792, 29)
Shape of y_train =  (1792,)
Shape of X_test =  (448, 29)
Shape of y_test =  (448,)
```

Decision Tree

```
from sklearn.tree import DecisionTreeClassifier
classifier = DecisionTreeClassifier(criterion='gini')
classifier.fit(X_train, y_train)
```

```
DecisionTreeClassifier()

classifier.score(X_test, y_test)

0.84375
```

KNN

```
from sklearn.neighbors import KNeighborsClassifier
classifier = KNeighborsClassifier(n_neighbors=5)
classifier.fit(X_train, y_train)
classifier.score(X_test, y_test)

0.8504464285714286
```

Random Forest

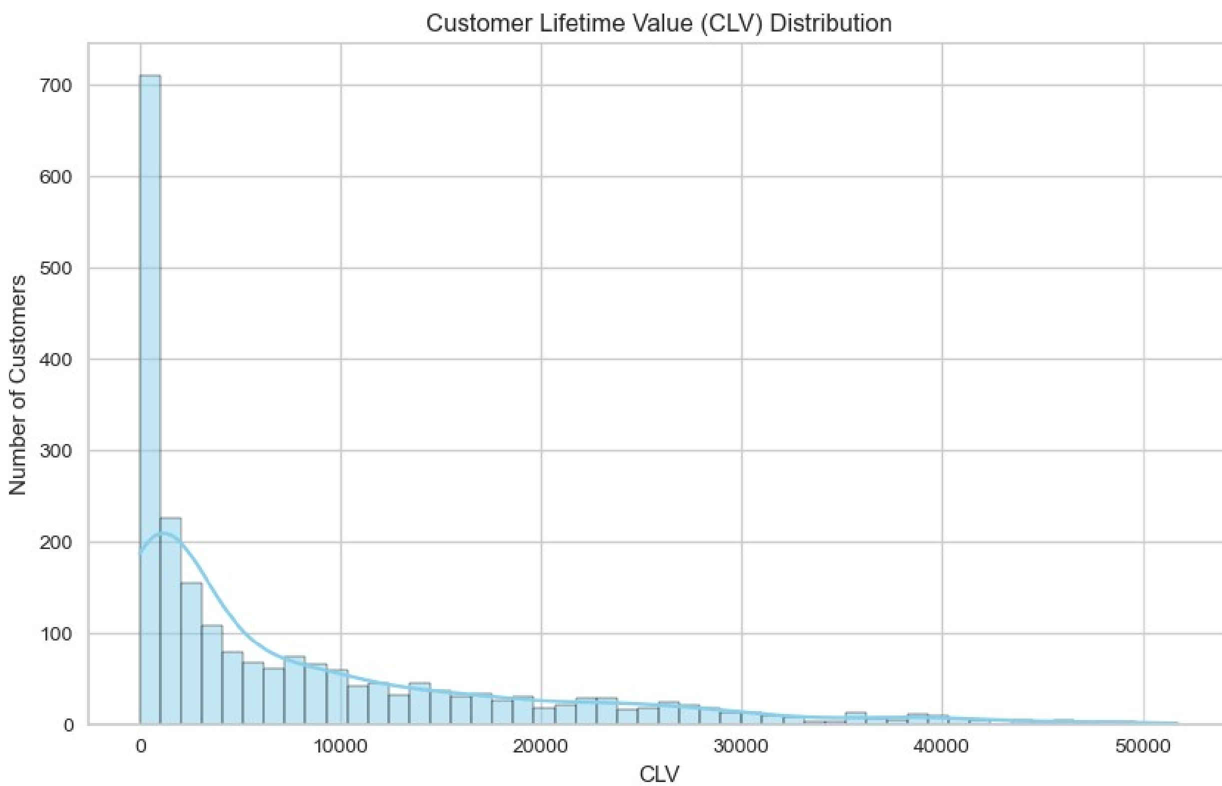
```
from sklearn.ensemble import RandomForestClassifier

rf= RandomForestClassifier()

rf.fit(X_train,y_train)

RandomForestClassifier()

rf.score(X_test,y_test)

0.8973214285714286
```

Customer Lifetime Value (CLV) Prediction Module

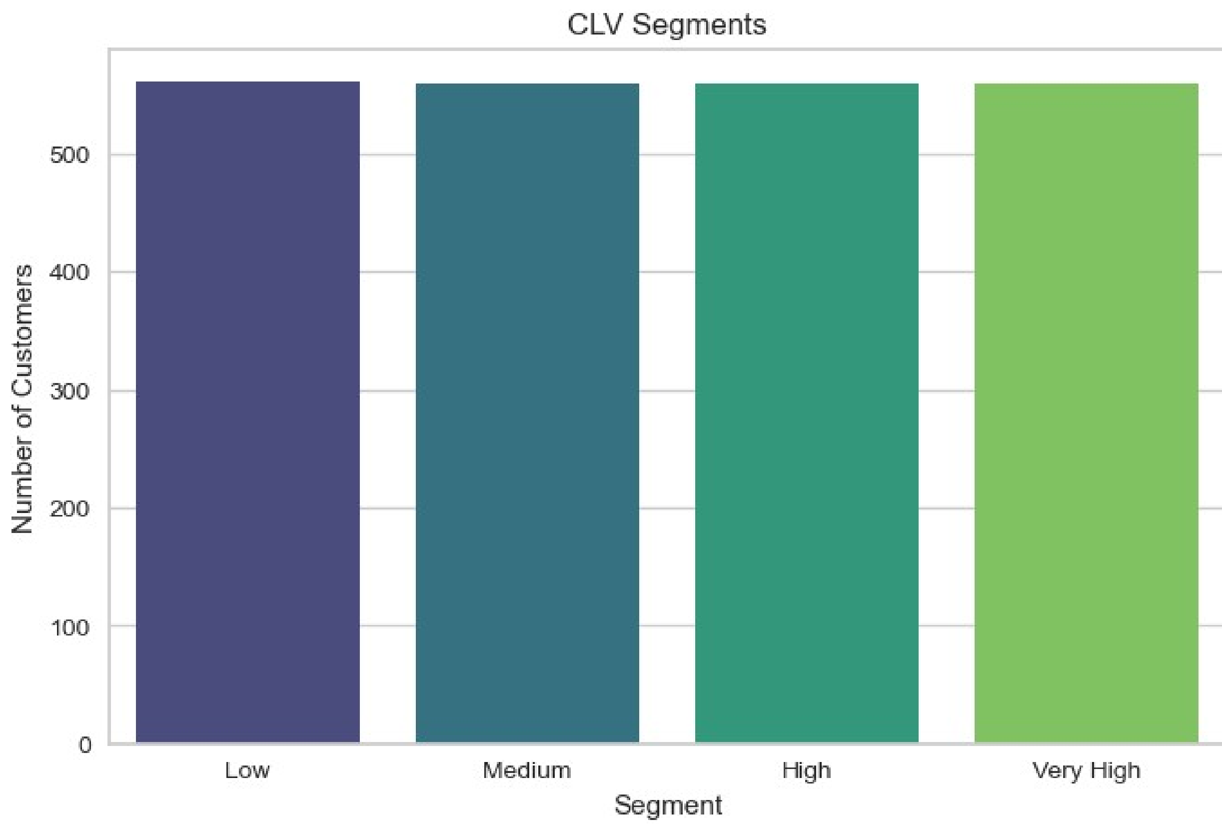
```
# --- Customer Lifetime Value (CLV) Prediction Module ---

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Load your data (adjust the path if needed)
df = pd.read_csv('Customer_Analytics_DB.csv', sep='\t')

# --- Feature Engineering ---

# Fill missing income values with mean (if not already done)
df['Income'] = df['Income'].fillna(df['Income'].mean())

# Calculate Total_Spent per customer
product_cols = ['MntWines', 'MntFruits', 'MntMeatProducts',
```

```
'MntFishProducts', 'MntSweetProducts', 'MntGoldProds']
df['Total_Spent'] = df[product_cols].sum(axis=1)

# Calculate Purchase Frequency (total purchases across all channels)
purchase_cols = ['NumWebPurchases', 'NumCatalogPurchases',
'NumStorePurchases']
df['Total_Purchases'] = df[purchase_cols].sum(axis=1)

# Estimate Customer Lifespan (in months) using Dt_Customer and Recency
df['Dt_Customer'] = pd.to_datetime(df['Dt_Customer'], dayfirst=True,
errors='coerce')
max_date = df['Dt_Customer'].max()
df['Customer_Lifespan_Months'] = ((max_date -
df['Dt_Customer']).dt.days // 30) + 1

# --- CLV Calculation ---
# Simple CLV formula: Average Purchase Value × Purchase Frequency ×
Lifespan
df['Avg_Purchase_Value'] = df['Total_Spent'] /
(df['Total_Purchases'].replace(0, np.nan))
df['CLV'] = df['Avg_Purchase_Value'] * df['Total_Purchases'] *
df['Customer_Lifespan_Months']
df['CLV'] = df['CLV'].fillna(0)

# --- CLV Segmentation ---
# Segment customers into quartiles based on CLV
df['CLV_Segment'] = pd.qcut(df['CLV'], 4, labels=['Low', 'Medium',
'High', 'Very High'])

# --- Visualization ---

plt.figure(figsize=(10, 6))
sns.histplot(df['CLV'], bins=50, kde=True, color='skyblue')
plt.title('Customer Lifetime Value (CLV) Distribution')
plt.xlabel('CLV')
plt.ylabel('Number of Customers')
plt.show()

plt.figure(figsize=(8, 5))
sns.countplot(x='CLV_Segment', data=df, palette='viridis')
plt.title('CLV Segments')
plt.xlabel('Segment')
plt.ylabel('Number of Customers')
plt.show()

# --- Segment Profile Table ---
segment_profile = df.groupby('CLV_Segment')[['Total_Spent',
'Total_Purchases', 'Income', 'CLV']].mean().round(2)
print("CLV Segment Profiles:\n", segment_profile)
```

```
# --- Insights ---
print("\nTop 5 High-CLV Customers:")
print(df[['ID', 'CLV', 'CLV_Segment', 'Total_Spent',
'Total_Purchases', 'Income']].sort_values('CLV',
ascending=False).head())

# --- Optional: Save results ---
# df.to_csv('customer_clv_results.csv', index=False)
```




```
C:\Users\ChatterjeeSo\AppData\Local\Temp\
ipykernel_28452\1656866214.py:49: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.countplot(x='CLV_Segment', data=df, palette='viridis')
```




```
CLV Segment Profiles:
             Total_Spent  Total_Purchases    Income       CLV
CLV_Segment
Low                57.87             4.87  34231.68    298.60
Medium            293.33             9.24  45454.45   1716.93
High              728.90            16.07  58703.37   7183.52
Very High        1343.52            19.97  70619.55  23216.69

Top 5 High-CLV Customers:
        ID      CLV CLV_Segment  Total_Spent  Total_Purchases   Income
1601  5453  51744.0   Very High         2352               23  90226.0
1010  5236  50462.0   Very High         2194               20  77568.0
1280  3698  48990.0   Very High         2130               18  78687.0
248   8867  48898.0   Very High         2126               19  67546.0
1890  2747  48898.0   Very High         2126               19  67546.0

C:\Users\ChatterjeeSo\AppData\Local\Temp\
ipykernel_28452\1656866214.py:56: FutureWarning: The default of
observed=False is deprecated and will be changed to True in a future
version of pandas. Pass observed=False to retain current behavior or
observed=True to adopt the future default and silence this warning.
  segment_profile = df.groupby('CLV_Segment')[['Total_Spent',
'Total_Purchases', 'Income', 'CLV']].mean().round(2)
```