Customer Segmentation and personality analysis

Introduction

Customer personality analysis is a crucial tool that businesses can use to gain a deeper understanding of their target customers. By analyzing customer data, businesses can identify customer segments and their unique preferences, motivations, and behaviors. This information can then be used to modify products and services to better suit the needs of each customer segment.

For instance, instead of launching a product and marketing it to all customers in the company's database, businesses can use customer personality analysis to identify which customer segment is most likely to buy the product. They can then tailor their marketing strategies to target that specific segment, resulting in higher conversion rates and a better return on investment.

Overview

Customer personality analysis involves gathering data on factors such as demographics, psychographics, and past behavior. This data is then analyzed to identify patterns and insights that can help businesses make informed decisions about product development, marketing, and customer engagement. By understanding their customers at a deeper level, businesses can build stronger relationships, increase customer satisfaction, and ultimately drive growth.

About the Dataset

The analysis is based on a dataset called "Customer Personality Analysis" (https://www.kaggle.com/datasets/imakash3011/customer-personality-analysis?datasetId=1546318&sortBy=voteCount) which was sourced from Kaggle and contributed by Dr. Omar Romero-Hernandez . The dataset contains a variety of attributes that help to analyze the factors to segemnt customers. This dataset has 2,240 rows of observations and 28 columns of variables. Among the variables, there are 5-character variables and 23 numerical variables.

Columns

People

ID: Customer's unique identifier Year_Birth: Customer's birth year Education: Customer's education level Marital_Status: Customer's marital status Income: Customer's yearly household income Kidhome: Number of children in customer's household Teenhome: Number of teenagers in customer's household Dt_Customer: Date of customer's enrollment with the company Recency: Number of days since customer's last purchase Complain: 1 if the customer complained in the last 2 years, 0 otherwise

Products

MntWines: Amount spent on wine in last 2 years MntFruits: Amount spent on fruits in last 2 years MntMeatProducts: Amount spent on meat in last 2 years MntFishProducts: Amount spent on fish in last 2 years MntSweetProducts: Amount spent on sweets in last 2 years MntGoldProds: Amount spent on gold in last 2 years

Promotion

NumDealsPurchases: Number of purchases made with a discount AcceptedCmp1: 1 if customer accepted the offer in the 1st campaign, 0 otherwise AcceptedCmp2: 1 if customer accepted the offer in the 2nd campaign, 0 otherwise AcceptedCmp3: 1 if customer accepted the offer in the 3rd campaign, 0 otherwise AcceptedCmp4: 1 if customer accepted the offer in the 4th campaign, 0 otherwise AcceptedCmp5: 1 if customer accepted the offer in the 5th campaign, 0 otherwise Response: 1 if customer accepted the offer in the last campaign, 0 otherwise

Place

NumWebPurchases: Number of purchases made through the company’s website NumCatalogPurchases: Number of purchases made using a catalogue NumStorePurchases: Number of purchases made directly in stores NumWebVisitsMonth: Number of visits to company’s website in the last month

Problem statement and Objective

Our objective is to create a machine learning model that has the ability to categorize customers. To achieve this, we will be working with a dataset that has been collected from a marketing campaign. The goal of the model is to predict the response of various customer segments to a specific product or service.

Solution and Analysis

Prepare the tools

Import the required tools

In [1]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.express as px
import plotly.graph_objects as go
from plotly.subplots import make_subplots
from IPython.display import Markdown
import joblib
import missingno as msno
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
palette = sns.color_palette(['gold','#cc0000', '#ace600','#33cccc'])
from sklearn.pipeline import make_pipeline
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder, OrdinalEncoder, StandardScaler # For handling categorical column and scaling numeric colu
from sklearn.cluster import KMeans
from yellowbrick.cluster import KElbowVisualizer
from sklearn.metrics import silhouette_score
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.ensemble import GradientBoostingClassifier
import joblib
```

Setup plotly

This function is required for plotly to run properly in colab without it sometimes the plots don't render properly.

To avoid code repeatability, enable plotly in cell function is created

In [2]:
```
def enable_plotly_in_cell():
  import IPython
  from plotly.offline import init_notebook_mode
  display(IPython.core.display.HTML('''<script src="/static/components/requirejs/require.js"></script>'''))
  init_notebook_mode(connected=False)
```

Load the data

Read dataset from csv file

In [3]:
```
dataset =  pd.read_csv("marketing_campaign.csv")
```

Understanding the data

Descriptive Analysis

In [4]:
```
dataset.shape
```

Out[4]:
```
(2240, 29)
```

In [5]:
```
print(f'We see the dataset has {dataset.shape[0]} observations and {dataset.shape[1]} features.')
```

```
We see the dataset has 2240 observations and 29 features.
```

Review the data and sample data

In [6]:
```
dataset.head()
```

Out[6]:

	ID	Year_Birth	Education	Marital_Status	Income	Kidhome	Teenhome	Dt_Customer	Recency	MntWines	...	NumWebVisitsMonth	AcceptedCmp3	Accepte
0	5524	1957	Graduation	Single	58138.0	0	0	04-09-2012	58	635	...	7	0	
1	2174	1954	Graduation	Single	46344.0	1	1	08-03-2014	38	11	...	5	0	
2	4141	1965	Graduation	Together	71613.0	0	0	21-08-2013	26	426	...	4	0	
3	6182	1984	Graduation	Together	26646.0	1	0	10-02-2014	26	11	...	6	0	
4	5324	1981	PhD	Married	58293.0	1	0	19-01-2014	94	173	...	5	0	

5 rows × 29 columns

In [7]:
```
dataset.sample(10)
```

Out[7]:

	ID	Year_Birth	Education	Marital_Status	Income	Kidhome	Teenhome	Dt_Customer	Recency	MntWines	...	NumWebVisitsMonth	AcceptedCmp3	Acc
1519	3887	1970	Graduation	Single	27242.0	1	0	11-11-2012	2	3	...	9	0	
1197	6606	1969	Master	Married	70091.0	1	0	31-03-2013	11	964	...	8	0	
1491	7494	1950	PhD	Divorced	42873.0	1	1	21-01-2013	11	209	...	8	0	
537	6931	1967	Graduation	Divorced	76982.0	0	0	15-02-2014	19	464	...	4	0	
481	5154	1972	Master	Divorced	37760.0	1	0	11-08-2013	54	26	...	6	0	
1295	3551	1954	Master	Together	60033.0	0	1	29-03-2014	28	62	...	2	0	
591	7627	1975	Master	Married	92163.0	0	0	12-12-2012	25	817	...	2	0	
1538	1079	1971	PhD	Married	71969.0	0	1	16-10-2012	59	1000	...	8	0	
799	8523	1968	Graduation	Married	19329.0	1	0	14-12-2013	39	24	...	8	0	
383	3310	1973	2n Cycle	Married	35688.0	2	1	22-08-2012	94	73	...	8	0	

10 rows × 29 columns

Check datatype and information regarding all different features

We want to look at the datatypes and check to see if they were interpreted correctly.

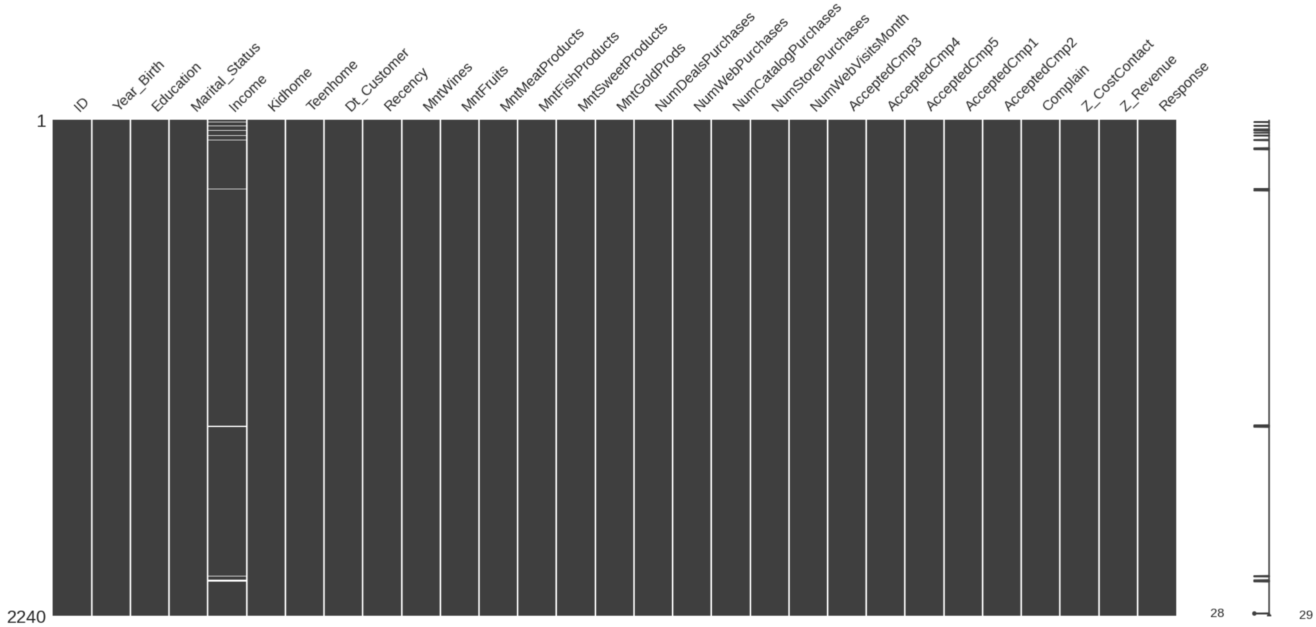
In [8]:

```
dataset.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
```

In [9]:

```
msno.matrix(dataset);
```



Observations

1. There are missing values in income
2. There are some features in the dataset which are of categorical type
3. DT_customer indicates the date when a customer joined however it's not parsed as Date time

Learning the data mathematically

In [10]:
```
dataset.describe(include = 'all')
```

Out[10]:

	ID	Year_Birth	Education	Marital_Status	Income	Kidhome	Teenhome	Dt_Customer	Recency	MntWines	...	NumWebVisitsM
count	2240.000000	2240.000000	2240	2240	2216.000000	2240.000000	2240.000000	2240	2240.000000	2240.000000	...	2240.0
unique	NaN	NaN	5	8	NaN	NaN	NaN	663	NaN	NaN	...	
top	NaN	NaN	Graduation	Married	NaN	NaN	NaN	31-08-2012	NaN	NaN	...	
freq	NaN	NaN	1127	864	NaN	NaN	NaN	12	NaN	NaN	...	
mean	5592.159821	1968.805804	NaN	NaN	52247.251354	0.444196	0.506250	NaN	49.109375	303.935714	...	5.3
std	3246.662198	11.984069	NaN	NaN	25173.076661	0.538398	0.544538	NaN	28.962453	336.597393	...	2.4
min	0.000000	1893.000000	NaN	NaN	1730.000000	0.000000	0.000000	NaN	0.000000	0.000000	...	0.0
25%	2828.250000	1959.000000	NaN	NaN	35303.000000	0.000000	0.000000	NaN	24.000000	23.750000	...	3.0
50%	5458.500000	1970.000000	NaN	NaN	51381.500000	0.000000	0.000000	NaN	49.000000	173.500000	...	6.0
75%	8427.750000	1977.000000	NaN	NaN	68522.000000	1.000000	1.000000	NaN	74.000000	504.250000	...	7.0
max	11191.000000	1996.000000	NaN	NaN	666666.000000	2.000000	2.000000	NaN	99.000000	1493.000000	...	20.0

11 rows × 29 columns

Data Pre-processing

Look for missing values

Even though we have identified missing values for income. Let's check to review to if there are any other missing values which need to be handled

In [11]:
```
dataset.isnull().sum()
```

Out[11]:
```
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
```

We can confirm there are 24 missing values for income feature. There are no missing values for any other feature. We will be handling the missing values for income in an upcoming step

Check for duplicated records

In [12]:
```
print(f'There are {dataset.duplicated().sum()} duplicated rows in the dataset.')
```

```
There are 0 duplicated rows in the dataset.
```

Rename columns of dataset

This is done to make it easier to process the data. At the same time, it helps with the understanding and analysis of the data

In [13]:
```
dataset.rename(columns = {'MntGoldProds':'MntGoldProducts'}, inplace = True)
```

Handling the missing values for Income feature

In [14]:
```
data = dataset.dropna(axis=0)
data.isnull().sum()
```

Out[14]:
```
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
MntGoldProducts        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
```

Check skewness before imputation

In [15]:
```
data['Income'].skew()
```

Out[15]:
```
6.7634873728111184
```

If the skewness is between -0.5 and 0.5, the data are fairly symmetrical. If the skewness is between -1 and – 0.5 or between 0.5 and 1, the data are moderately skewed. If the skewness is less than -1 or greater than 1, the data are highly skewed.

Replacing null values with median cause the data is skewed which means there are outliers in the data

In [16]:
```
data['Income'].fillna(data['Income'].median(), inplace = True)
```

```
<ipython-input-16-fa17dfd754d2>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-cop
y
  data['Income'].fillna(data['Income'].median(), inplace = True)
```

Correcting the datatype

Converting columns to datetime format

In [17]:
```
data['Dt_Customer'] = pd.to_datetime(dataset['Dt_Customer'])
```

```
<ipython-input-17-d25be214e6e9>:1: UserWarning: Parsing dates in DD/MM/YYYY format when dayfirst=False (the default) was specified. This
may lead to inconsistently parsed dates! Specify a format to ensure consistent parsing.
  data['Dt_Customer'] = pd.to_datetime(dataset['Dt_Customer'])
<ipython-input-17-d25be214e6e9>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-cop
y
  data['Dt_Customer'] = pd.to_datetime(dataset['Dt_Customer'])
```

In [18]:
```
data['Year_Birth'] = pd.to_datetime(dataset['Year_Birth'], format ='%Y')
```

```
<ipython-input-18-8d7b170181ac>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-cop
y
  data['Year_Birth'] = pd.to_datetime(dataset['Year_Birth'], format ='%Y')
```

Feature engineering

Examine unique values for various categories

In [19]:
```
data['Education'].value_counts()
```

Out[19]:
```
Graduation    1116
PhD            481
Master         365
2n Cycle       200
Basic           54
Name: Education, dtype: int64
```

In [20]:
```
data['Marital_Status'].value_counts()
```

Out[20]:
```
Married     857
Together    573
Single      471
Divorced    232
Widow        76
Alone         3
Absurd        2
YOLO          2
Name: Marital_Status, dtype: int64
```

In [21]:
```
print("The newest customer's enrolment date in the records:", max(dataset['Dt_Customer']))
print("The oldest customer's enrolment date in the records:", min(dataset['Dt_Customer']))
```

```
The newest customer's enrolment date in the records: 31-12-2013
The oldest customer's enrolment date in the records: 01-01-2013
```

We only have data of three years (2012 to 2014)

Create feature from Dt_Customer that indicates the number of days a customer is registered in the firm's database. To keep it simple, I am taking this value relative to the most recent customer in the record.

In [22]:
```
data['Date_Collected'] = '01-01-2015'
data['Date_Collected'] = pd.to_datetime(data.Date_Collected)
data['Time_Enrolled_Days'] = (data['Date_Collected'] - data['Dt_Customer']).dt.days
```

```
<ipython-input-22-fdcc6b73b1d4>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-cop
y
  data['Date_Collected'] = '01-01-2015'
<ipython-input-22-fdcc6b73b1d4>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-cop
y
  data['Date_Collected'] = pd.to_datetime(data.Date_Collected)
<ipython-input-22-fdcc6b73b1d4>:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-cop
y
  data['Time_Enrolled_Days'] = (data['Date_Collected'] - data['Dt_Customer']).dt.days
```

Create feature to extract "Age" of a customer by the "Year_Birth"

In [23]:
```
data['Age'] = (data["Dt_Customer"].dt.year.max()) - (data['Year_Birth'].dt.year)
```

```
<ipython-input-23-c0c868c06e30>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-cop
y
  data['Age'] = (data["Dt_Customer"].dt.year.max()) - (data['Year_Birth'].dt.year)
```

Create feature to calculate amount of years the person has been a customer

In [24]:
```
data['Years_Customer'] = (data["Dt_Customer"].dt.year.max()) - (data['Dt_Customer'].dt.year)
```

```
<ipython-input-24-876191f4b350>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-cop
y
  data['Years_Customer'] = (data["Dt_Customer"].dt.year.max()) - (data['Dt_Customer'].dt.year)
```

In [25]:
```
data['Month_Customer'] = 12.0 * (2015 - data["Dt_Customer"].dt.year ) + (1 - data["Dt_Customer"].dt.month)
```

```
<ipython-input-25-6c004f147339>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-cop
y
  data['Month_Customer'] = 12.0 * (2015 - data["Dt_Customer"].dt.year ) + (1 - data["Dt_Customer"].dt.month)
```

In [26]:
```
data['Days_Customer'] = (data["Dt_Customer"].max()) - (data['Dt_Customer'])
```

```
<ipython-input-26-4c368547b7e3>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-cop
y
  data['Days_Customer'] = (data["Dt_Customer"].max()) - (data['Dt_Customer'])
```

Create feature Total money spent to indicate the total amount spent by the customer in various categories.

In [27]:
```
data['TotalMoneySpent'] = data['MntWines']+data['MntFruits']+data['MntMeatProducts']+data['MntFishProducts']+data['MntSweetProducts']+data
```

```
<ipython-input-27-02bb39f1e6ad>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-cop
y
  data['TotalMoneySpent'] = data['MntWines']+data['MntFruits']+data['MntMeatProducts']+data['MntFishProducts']+data['MntSweetProducts']+d
ata['MntGoldProducts']
```

Create feature for Total number of purchases made to indicate the total number of purchases made by the customer in various categories.

In [28]:
```
data['TotalNumOfPurchases'] = data['NumWebPurchases'] + data['NumCatalogPurchases'] + data['NumStorePurchases'] + data['NumDealsPurchases
```

```
<ipython-input-28-a5da39dc0871>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-cop
y
  data['TotalNumOfPurchases'] = data['NumWebPurchases'] + data['NumCatalogPurchases'] + data['NumStorePurchases'] + data['NumDealsPurchas
es']
```

Create feature for Total number of accepted campagins to indicate the total accpeted campaigns by the customer in various categories.

In [29]:
```
data['TotalAccCmp'] = data['AcceptedCmp1'] + data['AcceptedCmp2'] + data['AcceptedCmp3'] + data['AcceptedCmp4'] + data['AcceptedCmp5'] + d
```

```
<ipython-input-29-9a83231f3a49>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-cop
y
  data['TotalAccCmp'] = data['AcceptedCmp1'] + data['AcceptedCmp2'] + data['AcceptedCmp3'] + data['AcceptedCmp4'] + data['AcceptedCmp5']
+ data['Response']
```

Deriving living situation by marital status

In [30]:
```
data["Partner"]=data["Marital_Status"].replace({"Married":"Yes", "Together":"Yes", "Absurd":"No", "Widow":"No", "YOLO":"No", "Divorced":"N
```

```
<ipython-input-30-48dbf32217d9>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-cop
y
  data["Partner"]=data["Marital_Status"].replace({"Married":"Yes", "Together":"Yes", "Absurd":"No", "Widow":"No", "YOLO":"No", "Divorce
d":"No", "Single":"No","Alone":"No"})
```

Segmenting education levels in three groups

In [31]:
```
data["Education"]=data["Education"].replace({"Basic":"Undergraduate","2n Cycle":"Undergraduate", "Graduation":"Graduate", "Master":"Postgr
```

```
<ipython-input-31-b03ad7be7d4b>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-cop
y
  data["Education"]=data["Education"].replace({"Basic":"Undergraduate","2n Cycle":"Undergraduate", "Graduation":"Graduate", "Master":"Pos
tgraduate", "PhD":"Postgraduate"})
```

Create feature for Total children living in the house

In [32]:
```
data["Children"] = data["Kidhome"] +  data["Teenhome"]
```

```
<ipython-input-32-d7ffaf6e7085>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-cop
y
  data["Children"] = data["Kidhome"] +  data["Teenhome"]
```

To get further clarity of household, Creating feature indicating Family Size

In [33]:
```
data['Family_Size'] = data['Partner'].replace({'No': 1, 'Yes':2}) + data['Children']
```

```
<ipython-input-33-a2076210534b>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-cop
y
  data['Family_Size'] = data['Partner'].replace({'No': 1, 'Yes':2}) + data['Children']
```

Create a feature Is Parent to indicate parenthood status

In [34]:
```
data['Is_Parent'] = np.where(data.Children > 0, 1, 0)
```

```
<ipython-input-34-2f8420d3ee1c>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-cop
y
  data['Is_Parent'] = np.where(data.Children > 0, 1, 0)
```

Adding columns about the day, month and year cutomer joined

In [35]:
```
data['YearJoined'] = data['Dt_Customer'].dt.year
data['MonthJoined'] = data['Dt_Customer'].dt.strftime("%B")
data['DayJoined'] = data['Dt_Customer'].dt.day_name()
```

```
<ipython-input-35-924ff1fde918>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-cop
y
  data['YearJoined'] = data['Dt_Customer'].dt.year
<ipython-input-35-924ff1fde918>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-cop
y
  data['MonthJoined'] = data['Dt_Customer'].dt.strftime("%B")
<ipython-input-35-924ff1fde918>:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-cop
y
  data['DayJoined'] = data['Dt_Customer'].dt.day_name()
```

Dividing age into groups

In [36]:
```
data['AgeGroup'] = pd.cut(x = data['Age'], bins = [1, 17, 24, 44, 64, 150],
                          labels = ['Under 18','Young adult','Adult','Middel Aged','Senior Citizen'])
```

```
<ipython-input-36-46b6bac01044>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-cop
y
  data['AgeGroup'] = pd.cut(x = data['Age'], bins = [1, 17, 24, 44, 64, 150],
```

Dropping columns which are not required

In [37]:
```
data.drop(['Z_CostContact','Z_Revenue','Year_Birth','Dt_Customer', 'Marital_Status'], axis=1, inplace=True)
```

```
<ipython-input-37-aa143117f976>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-cop
y
  data.drop(['Z_CostContact','Z_Revenue','Year_Birth','Dt_Customer', 'Marital_Status'], axis=1, inplace=True)
```

In [38]:
```
data.head()
```

Out[38]:

	ID	Education	Income	Kidhome	Teenhome	Recency	MntWines	MntFruits	MntMeatProducts	MntFishProducts	...	TotalNumOfPurchases	TotalAccCmp
0	5524	Graduate	58138.0	0	0	58	635	88	546	172	...	25	1
1	2174	Graduate	46344.0	1	1	38	11	1	6	2	...	6	0
2	4141	Graduate	71613.0	0	0	26	426	49	127	111	...	21	0
3	6182	Graduate	26646.0	1	0	26	11	4	20	10	...	8	0
4	5324	Postgraduate	58293.0	1	0	94	173	43	118	46	...	19	0

5 rows × 41 columns

In [39]:
```
data.columns
```

Out[39]:
```
Index(['ID', 'Education', 'Income', 'Kidhome', 'Teenhome', 'Recency',
       'MntWines', 'MntFruits', 'MntMeatProducts', 'MntFishProducts',
       'MntSweetProducts', 'MntGoldProducts', 'NumDealsPurchases',
       'NumWebPurchases', 'NumCatalogPurchases', 'NumStorePurchases',
       'NumWebVisitsMonth', 'AcceptedCmp3', 'AcceptedCmp4', 'AcceptedCmp5',
       'AcceptedCmp1', 'AcceptedCmp2', 'Complain', 'Response',
       'Date_Collected', 'Time_Enrolled_Days', 'Age', 'Years_Customer',
       'Month_Customer', 'Days_Customer', 'TotalMoneySpent',
       'TotalNumOfPurchases', 'TotalAccCmp', 'Partner', 'Children',
       'Family_Size', 'Is_Parent', 'YearJoined', 'MonthJoined', 'DayJoined',
       'AgeGroup'],
      dtype='object')
```

In [40]:
```
data.shape
```

Out[40]:
```
(2216, 41)
```

In [41]:
```
data['Days_Customer'] = data['Days_Customer'].dt.days.astype('int16')
```

```
<ipython-input-41-2427dbb4b435>:1: SettingWithCopyWarning: 
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-cop
y
  data['Days_Customer'] = data['Days_Customer'].dt.days.astype('int16')
```

In [42]:
```
data['Days_Customer']
```

Out[42]:
```
0       971
1       125
2       472
3        65
4       321
       ... 
2235    541
2236     61
2237    315
2238    316
2239    782
Name: Days_Customer, Length: 2216, dtype: int16
```

Exploratory Data Analysis

Examining Unique Values

In [43]:
```
unique_number = []
for i in data.columns:
    x = data[i].value_counts().count()
    unique_number.append(x)

pd.DataFrame(unique_number, index = data.columns, columns = ["Total Unique Values"])
```

Out[43]:

	Total Unique Values
ID	2216
Education	3
Income	1974
Kidhome	3
Teenhome	3
Recency	100
MntWines	776
MntFruits	158
MntMeatProducts	554
MntFishProducts	182
MntSweetProducts	176
MntGoldProducts	212
NumDealsPurchases	15
NumWebPurchases	15
NumCatalogPurchases	14
NumStorePurchases	14
NumWebVisitsMonth	16
AcceptedCmp3	2
AcceptedCmp4	2
AcceptedCmp5	2
AcceptedCmp1	2
AcceptedCmp2	2
Complain	2
Response	2
Date_Collected	1
Time_Enrolled_Days	662
Age	59
Years_Customer	3
Month_Customer	36
Days_Customer	662
TotalMoneySpent	1047
TotalNumOfPurchases	39
TotalAccCmp	6
Partner	2
Children	4
Family_Size	5
Is_Parent	2
YearJoined	3
MonthJoined	12
DayJoined	7
AgeGroup	5

In [44]:

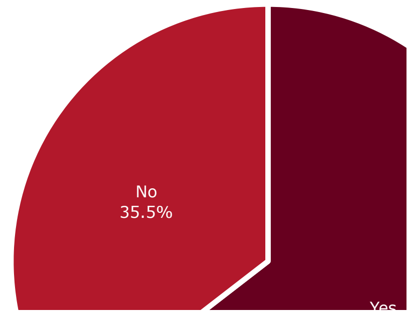
```
data.describe(include=object).T
```

Out[44]:

	count	unique	top	freq
Education	2216	3	Graduate	1116
Partner	2216	2	Yes	1430
MonthJoined	2216	12	August	210
DayJoined	2216	7	Sunday	342

Martial Status

In [45]:
```
enable_plotly_in_cell()

maritalstatus = data['Partner'].value_counts()

fig = px.pie(maritalstatus,
             values = maritalstatus.values,
             names = maritalstatus.index,
             color_discrete_sequence=px.colors.sequential.RdBu)
fig.update_traces(textposition='inside', textinfo='percent+label',
                  marker = dict(line = dict(color = 'white', width = 4)))
fig.show()
```

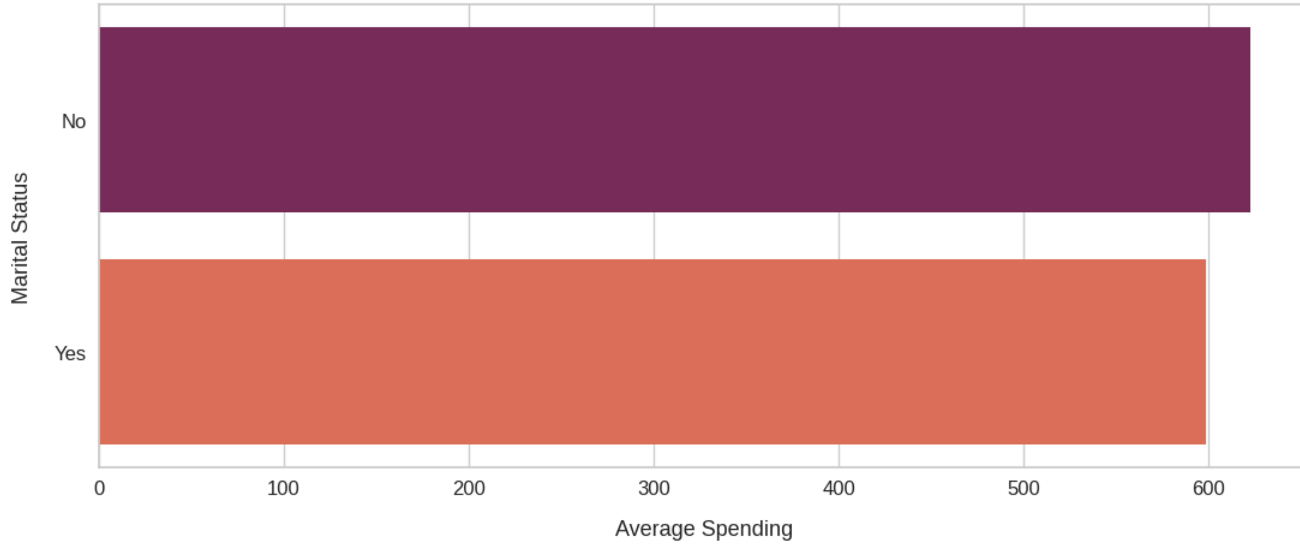


Observation

1. Majority of the customers have partners.
2. Only 1/3rd are singles

Spending by Marital Status

In [46]:
```
enable_plotly_in_cell()
maritalspending = data.groupby('Partner')['TotalMoneySpent'].mean().sort_values(ascending=False)
maritalspending_df = pd.DataFrame(list(maritalspending.items()), columns=['Marital Status', 'Average Spending'])

plt.figure(figsize=(13,5))
sns.barplot(data = maritalspending_df, x="Average Spending", y="Marital Status", palette='rocket');

plt.xticks( fontsize=12)
plt.yticks( fontsize=12)
plt.xlabel('Average Spending', fontsize=13, labelpad=13)
plt.ylabel('Marital Status', fontsize=13, labelpad=13);
```

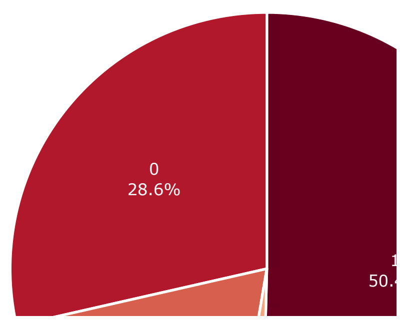


Observation

1. Even though the number of customers who have a partner is considerably higher. THe singles spent more money on the average compared to them

Child Analysis

In [47]:
```
enable_plotly_in_cell()
children = data['Children'].value_counts()

fig = px.pie(children,
             values = children.values,
             names = children.index,
             color_discrete_sequence=px.colors.sequential.RdBu)
fig.update_traces(textposition='inside', textinfo='percent+label',
                  marker = dict(line = dict(color = 'white', width = 2)))
fig.show()
```



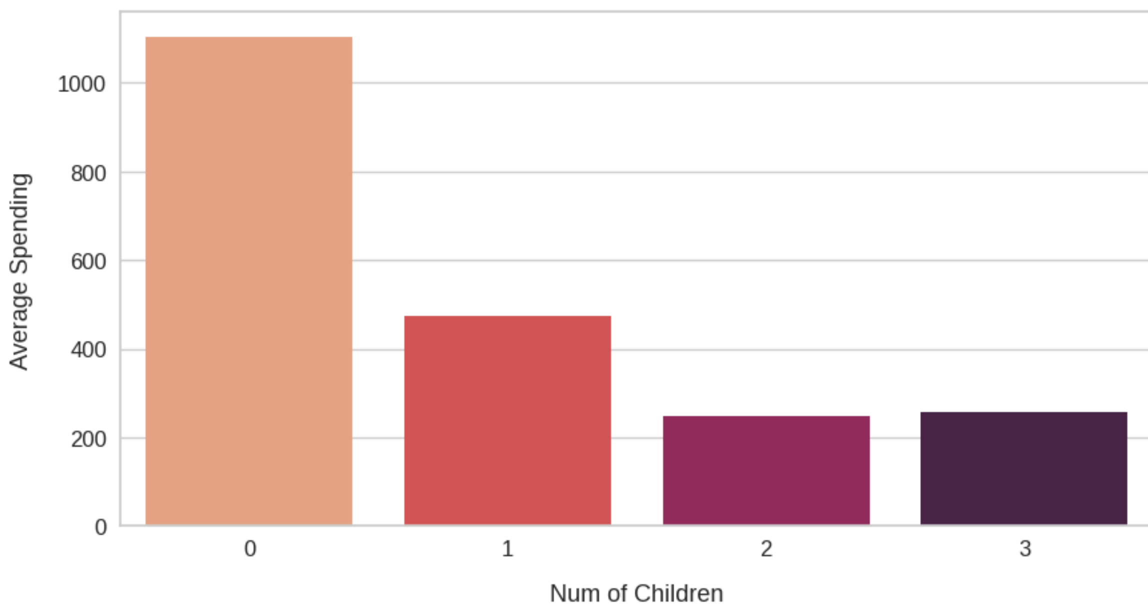
Observation

1. 50% of the customers have 1 child
2. 28% don't have a child and 19% have 2 children

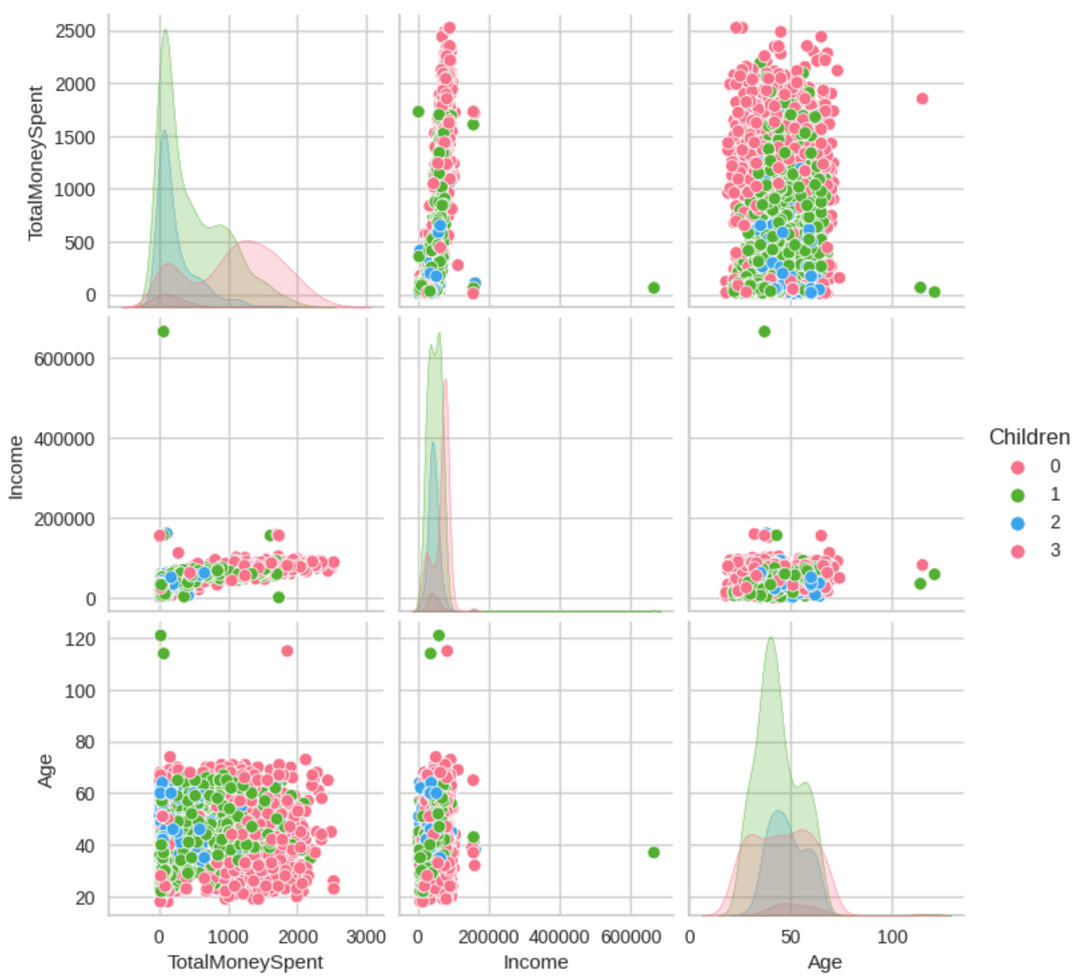
Average Child Wise Spendings

In [48]:
```
enable_plotly_in_cell()
childrenspending = data.groupby('Children')['TotalMoneySpent'].mean().sort_values(ascending=False)
```

```
childrenspending_df = pd.DataFrame(list(childrenspending.items()), columns=['Num of Children', 'Average Spending'])

plt.figure(figsize=(10,5))

sns.barplot(data=childrenspending_df,  x="Num of Children", y="Average Spending", palette='rocket_r');
plt.xticks( fontsize=12)
plt.yticks( fontsize=12)
plt.xlabel('Num of Children', fontsize=13, labelpad=13)
plt.ylabel('Average Spending', fontsize=13, labelpad=13);
```



In [49]:
```
sns.pairplot(data , vars=['TotalMoneySpent','Income','Age'] , hue='Children', palette='husl');
```

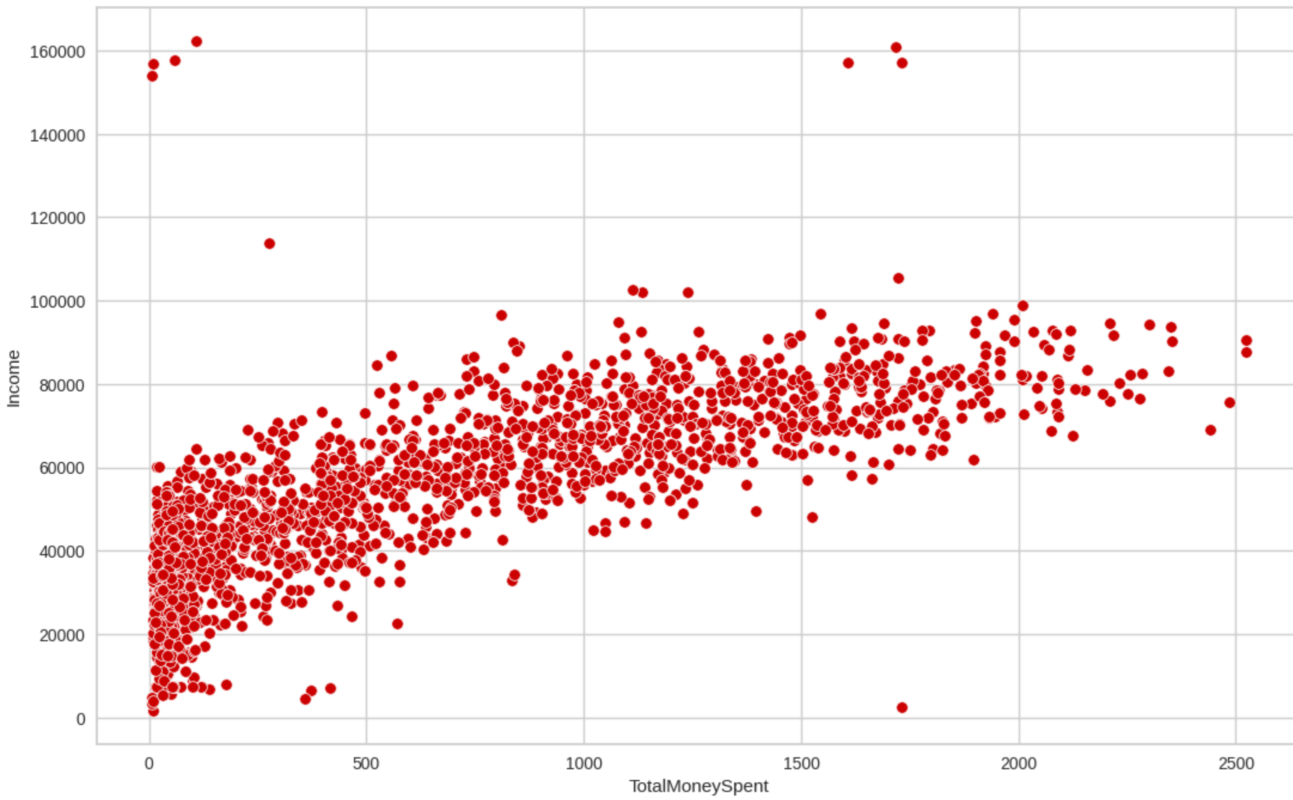


Observation

1. Customers who don't have any children at home spent higher than the customers having 1 children. The customers having 1 children are spending higher than the customers havin 2 and 3 children.

Income distribution

In [50]:
```
plt.figure(figsize=(13,8))
sns.scatterplot(x=data[data['Income']<600000]['TotalMoneySpent'], y=data[data['Income']<600000]['Income'], color='#cc0000');
```

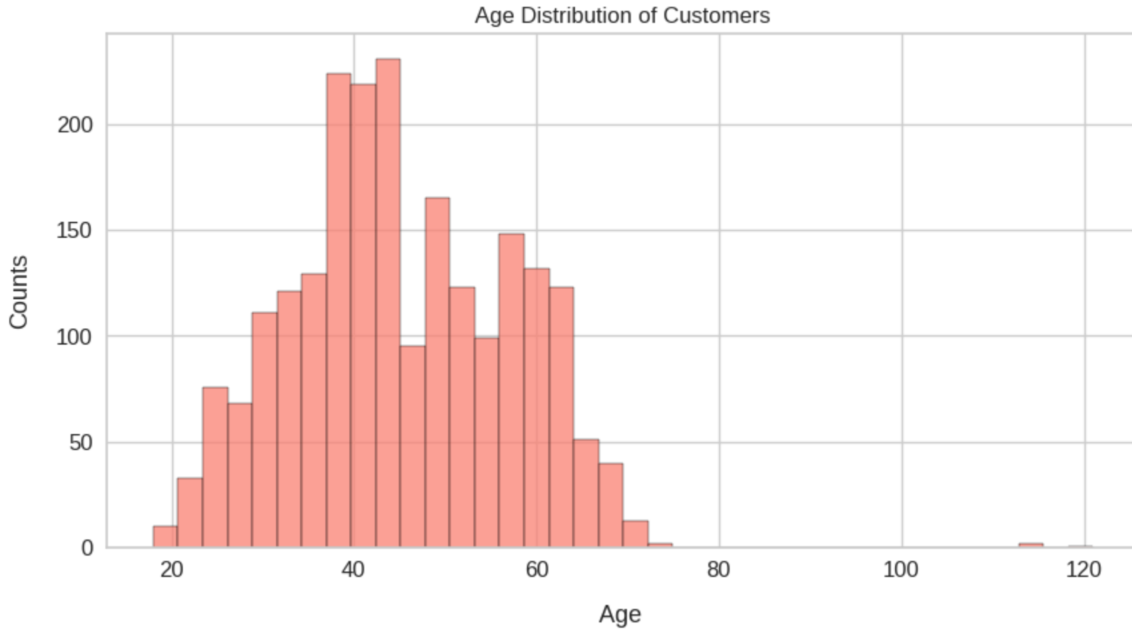


Observation

1. The salaries of the customers have normal distribution with most of the customers earning between 25000 and 85000.

Age Distribution

In [51]:
```
enable_plotly_in_cell()
plt.figure(figsize=(10,5))
ax = sns.histplot(data = data['Age'], color='salmon')
ax.set(title = "Age Distribution of Customers");
plt.xticks( fontsize=12)
plt.yticks( fontsize=12)
plt.xlabel('Age ', fontsize=13, labelpad=13)
plt.ylabel('Counts', fontsize=13, labelpad=13);
```

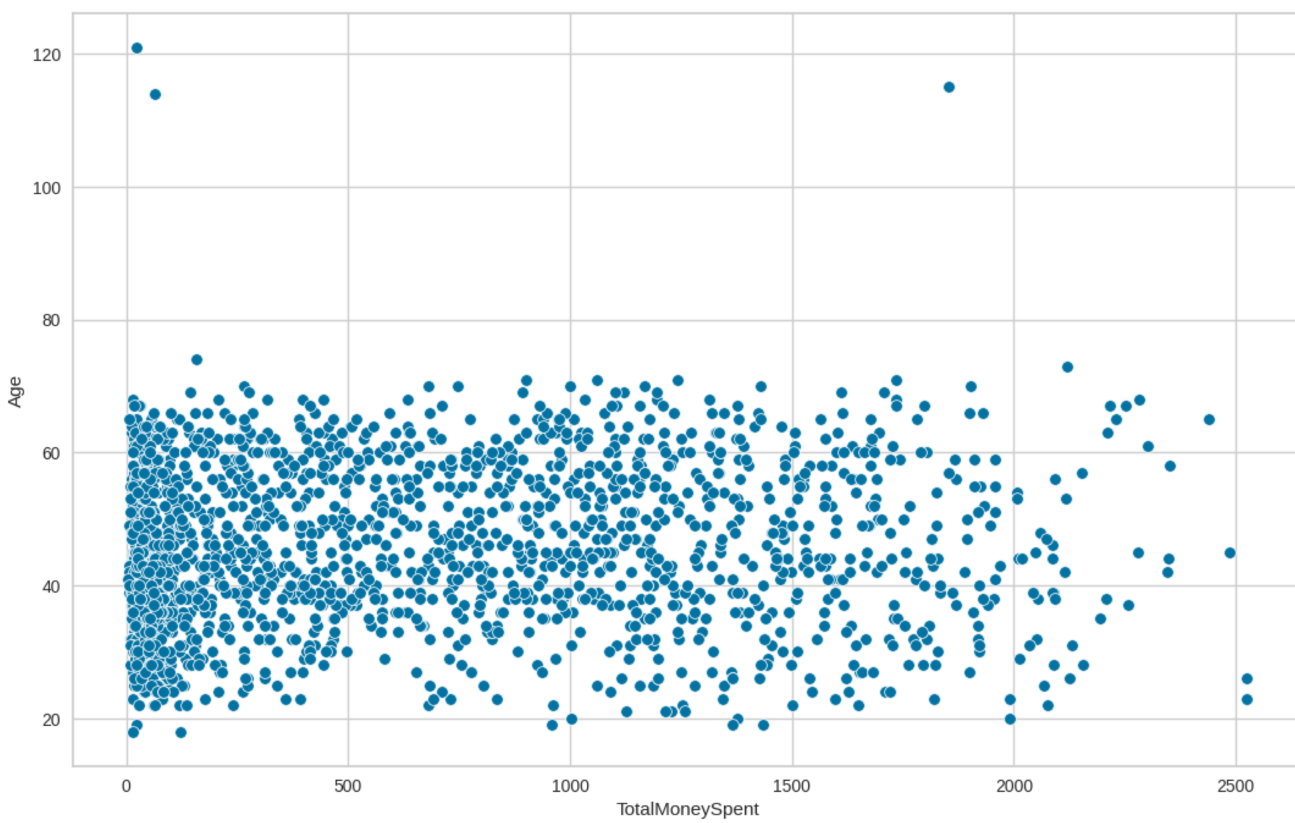


Observation

1. Age of the customers is nearly normally distributed, with most of the customers aged between 40 and 60.

Age analysis with spending

In [52]:
```
plt.figure(figsize=(13,8))
sns.scatterplot(x=data['TotalMoneySpent'], y=data['Age']);
```



Observation

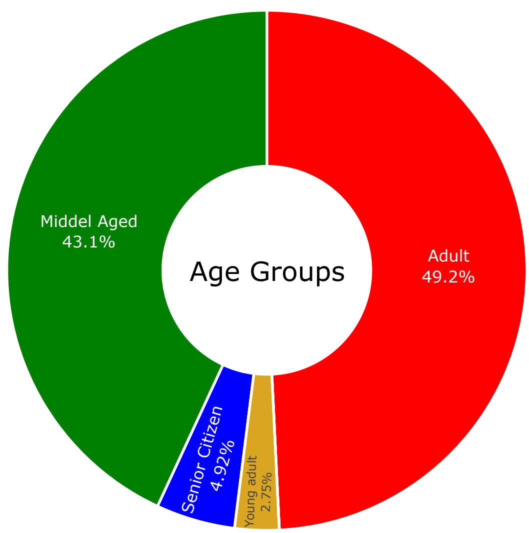
1.There doesn't seem to be any clear relationship between age of customers and their spending habits.

Age group analysis

In [53]:
```
enable_plotly_in_cell()
agegroup = data['AgeGroup'].value_counts()
```

```
fig = px.pie(labels = agegroup.index, values = agegroup.values, names = agegroup.index, width = 550, height = 550)

fig.update_traces(textposition = 'inside',
                  textinfo = 'percent + label',
                  hole = 0.4,
                  marker = dict(colors = ["red", "green", "blue", "goldenrod", "magenta"],
                                line = dict(color = 'white', width = 2)))

fig.update_layout(annotations = [dict(text = 'Age Groups',
                                      x = 0.5, y = 0.5, font_size = 20, showarrow = False,
                                      font_color = 'black')],
                  showlegend = False)

fig.show()
```

```
/usr/local/lib/python3.10/dist-packages/plotly/express/_core.py:137: FutureWarning:

Support for multi-dimensional indexing (e.g. `obj[:, None]`) is deprecated and will be removed in a future version.  Convert to a numpy a
rray before indexing instead.
```

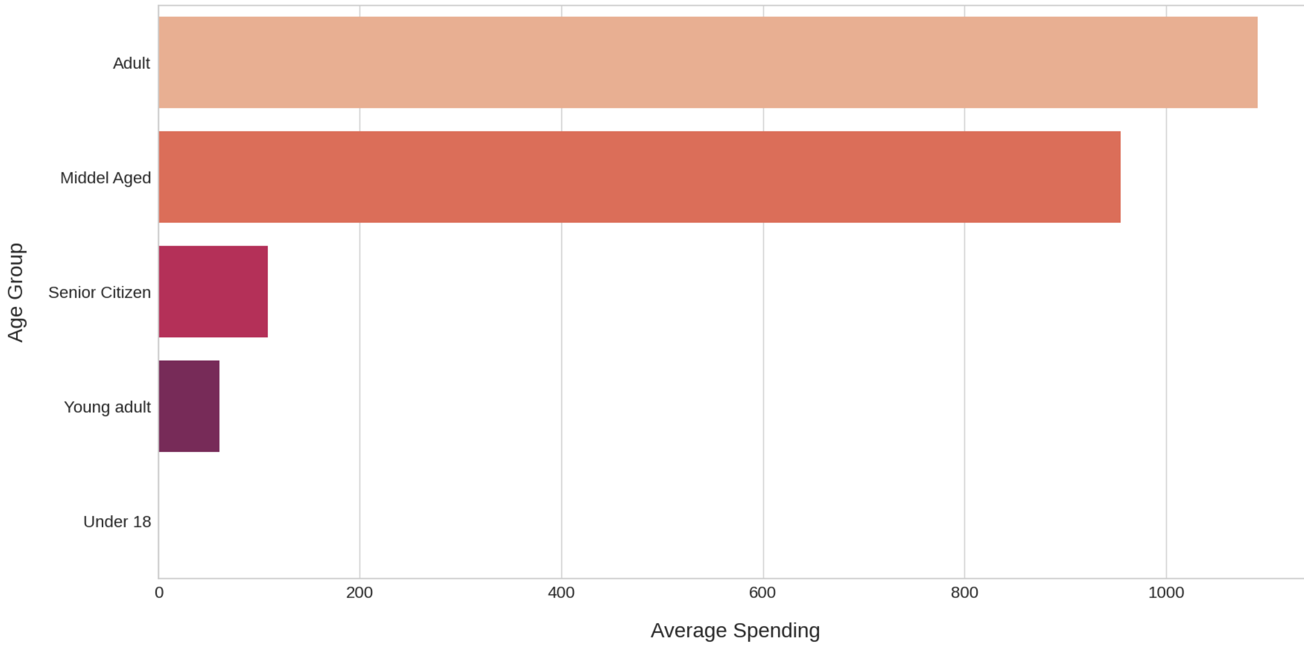


Observation

1. Almost 50% of the customers are adults
2. The second most popular category is middel aged

Age group analysis with spending

In [54]:
```
agegroupspending = data.groupby('AgeGroup')['TotalMoneySpent'].mean().sort_values(ascending=False)
agegroupspending_df = pd.DataFrame(list(agegroup.items()), columns=['Age Group', 'Average Spending'])

plt.figure(figsize=(20,10))

sns.barplot(data = agegroupspending_df, x="Average Spending", y='Age Group', palette='rocket_r');
plt.xticks( fontsize=16)
plt.yticks( fontsize=16)
plt.xlabel('Average Spending', fontsize=20, labelpad=20)
plt.ylabel('Age Group', fontsize=20, labelpad=20);
```

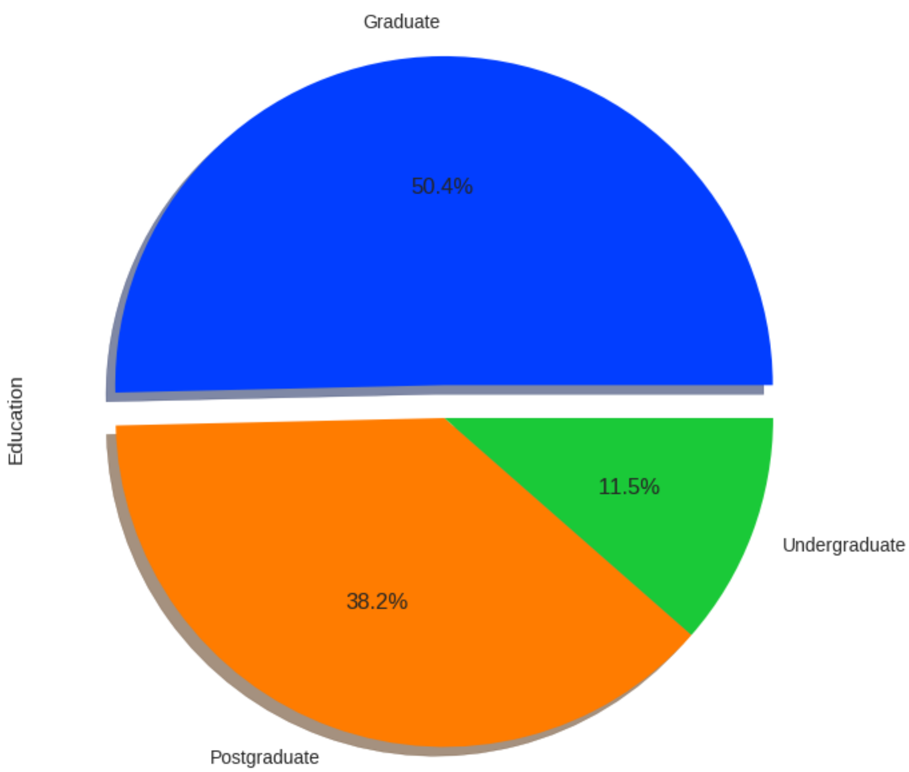


Observations

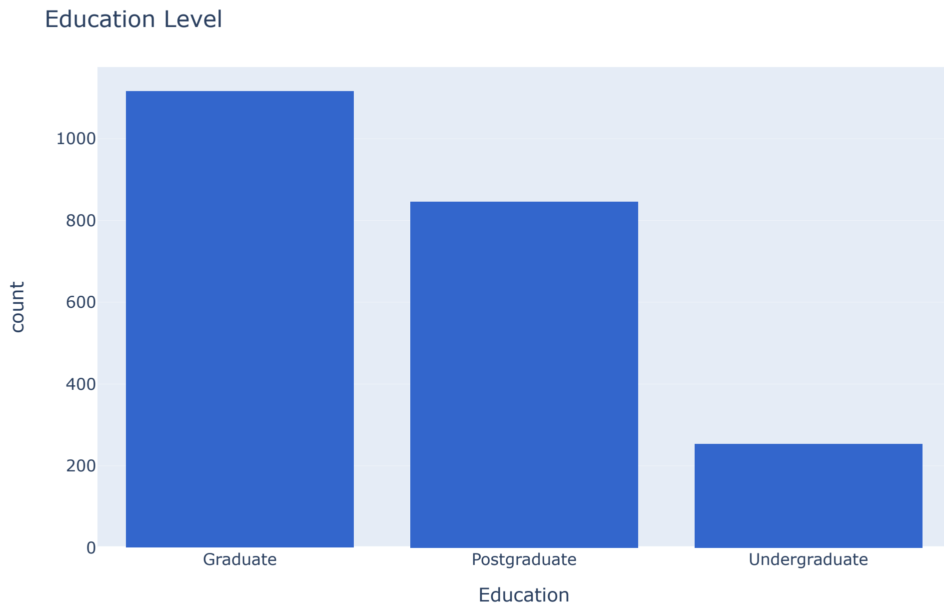
1. Adults spend more than other age groups

Education analysis

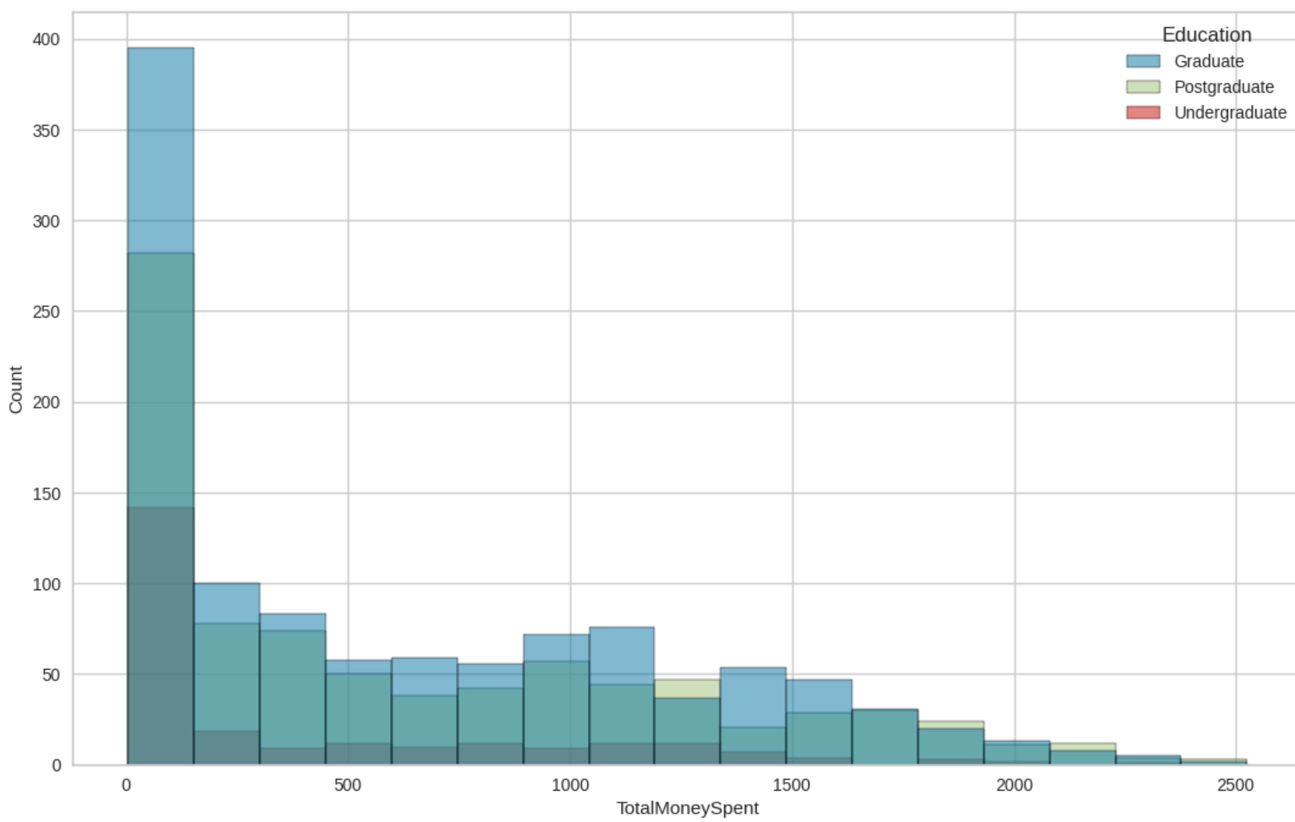
In [55]:
```
data['Education'].value_counts().plot.pie(explode=[0.1,0,0], autopct='%1.1f%%', shadow=True, figsize=(8,8), colors=sns.color_palette("brig
```



In [56]:
```
enable_plotly_in_cell()

fig = px.histogram(data, x = 'Education',
                   opacity = 1, barmode = 'overlay',
                   width = 800, height = 500,
                  color_discrete_sequence=px.colors.qualitative.G10)

fig.update_layout(title='Education Level')
fig.show()
```



In [57]:
```
plt.figure(figsize=(13,8))
sns.histplot(x=data['TotalMoneySpent'], hue=data['Education']);
```



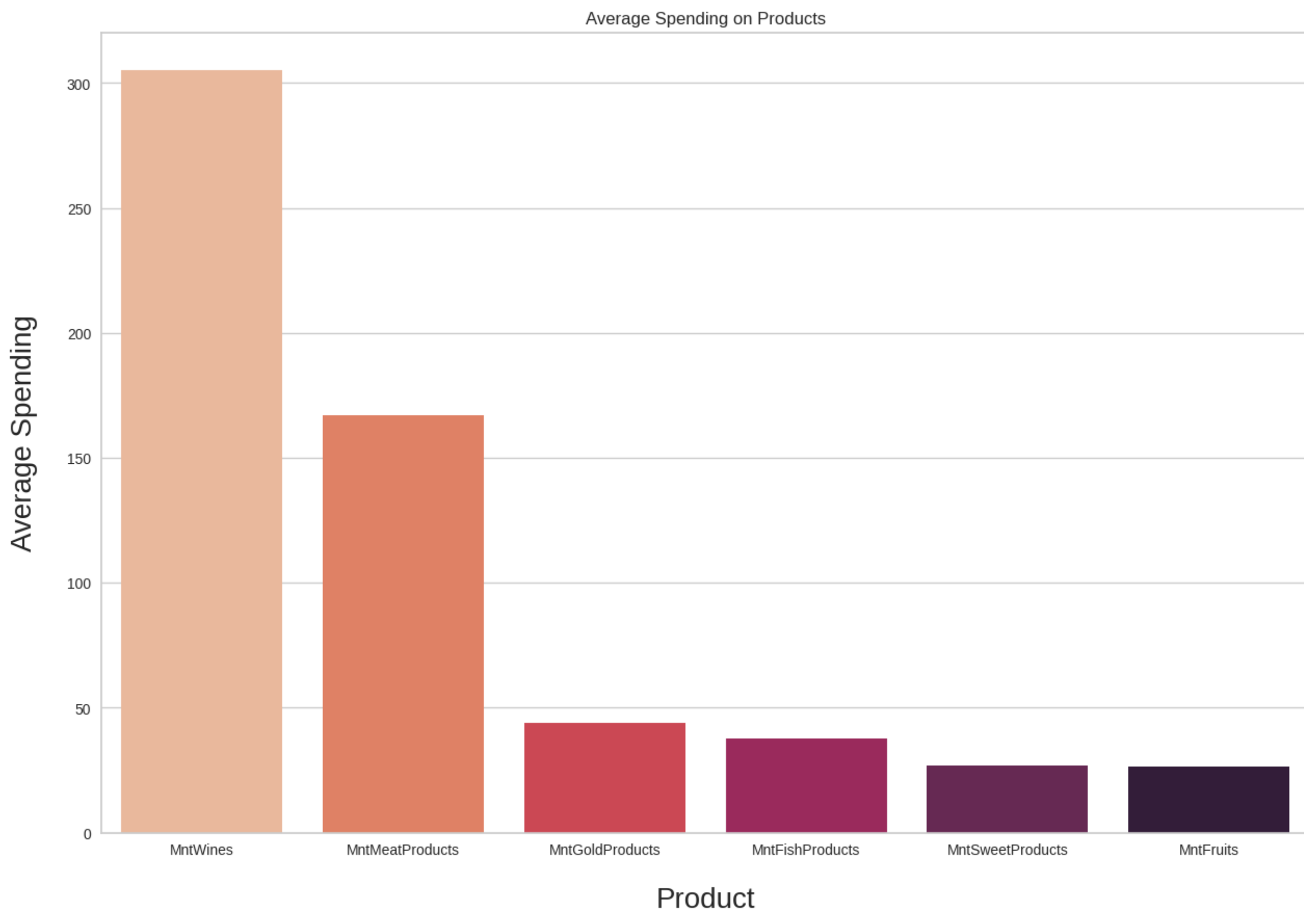
Observation

1. 50% of caustomers are graduates and only 11% of customers are undergraduates, remaining are postgraduates
2. Majority are well educated

Most Bought Products

In [58]:
```
products = data[['MntWines', 'MntFruits', 'MntMeatProducts', 'MntFishProducts', 'MntSweetProducts', 'MntGoldProducts']]
product_means = products.mean(axis=0).sort_values(ascending=False)
product_means_df = pd.DataFrame(list(product_means.items()), columns=['Product', 'Average Spending'])

plt.figure(figsize=(15,10))
plt.title('Average Spending on Products')
```

```
sns.barplot(data=product_means_df, x='Product', y='Average Spending', palette='rocket_r');
plt.xlabel('Product', fontsize=20, labelpad=20)
plt.ylabel('Average Spending', fontsize=20, labelpad=20);
```



Observation

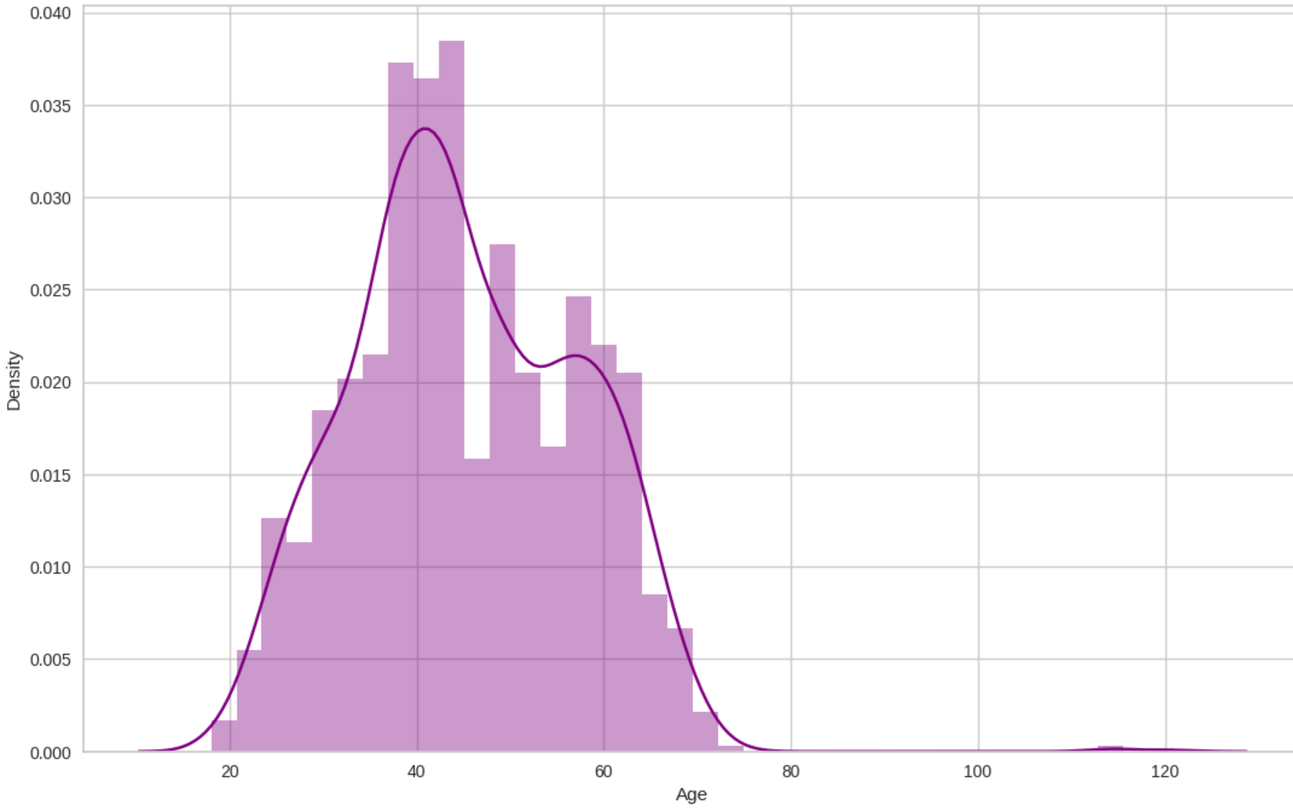
1. Wine and Meats products are the most famous products among the customers.
2. Sweets and Fruits are not being purchased often.

Outlier Detection

The presence of outliers in a classification or regression dataset can result in a poor fit and lower predictive modeling performance, therefore we should see there are ouliers in the data

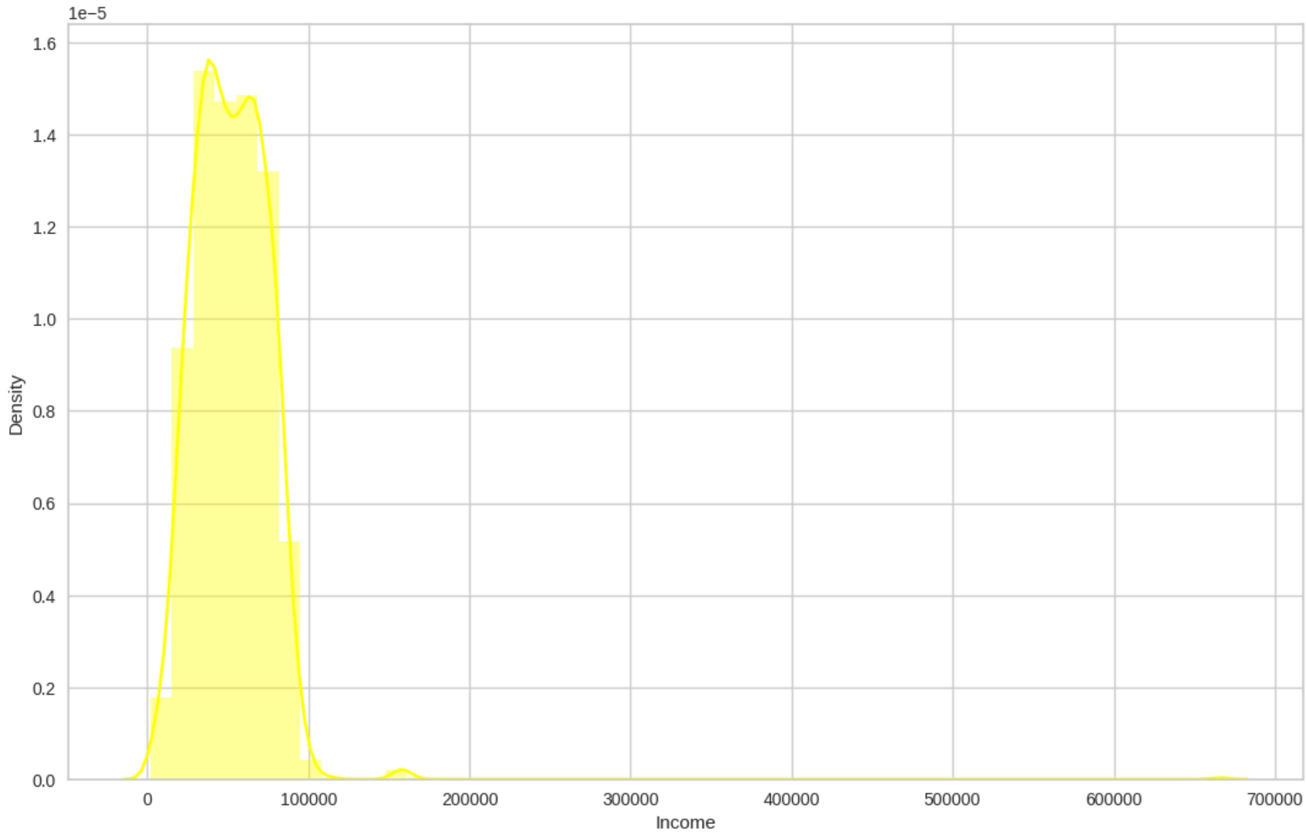
In [59]:
```
plt.figure(figsize=(13,8))
sns.distplot(data.Age, color='purple');
```

```
<ipython-input-59-0e7ab541b29d>:2: UserWarning:



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

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

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



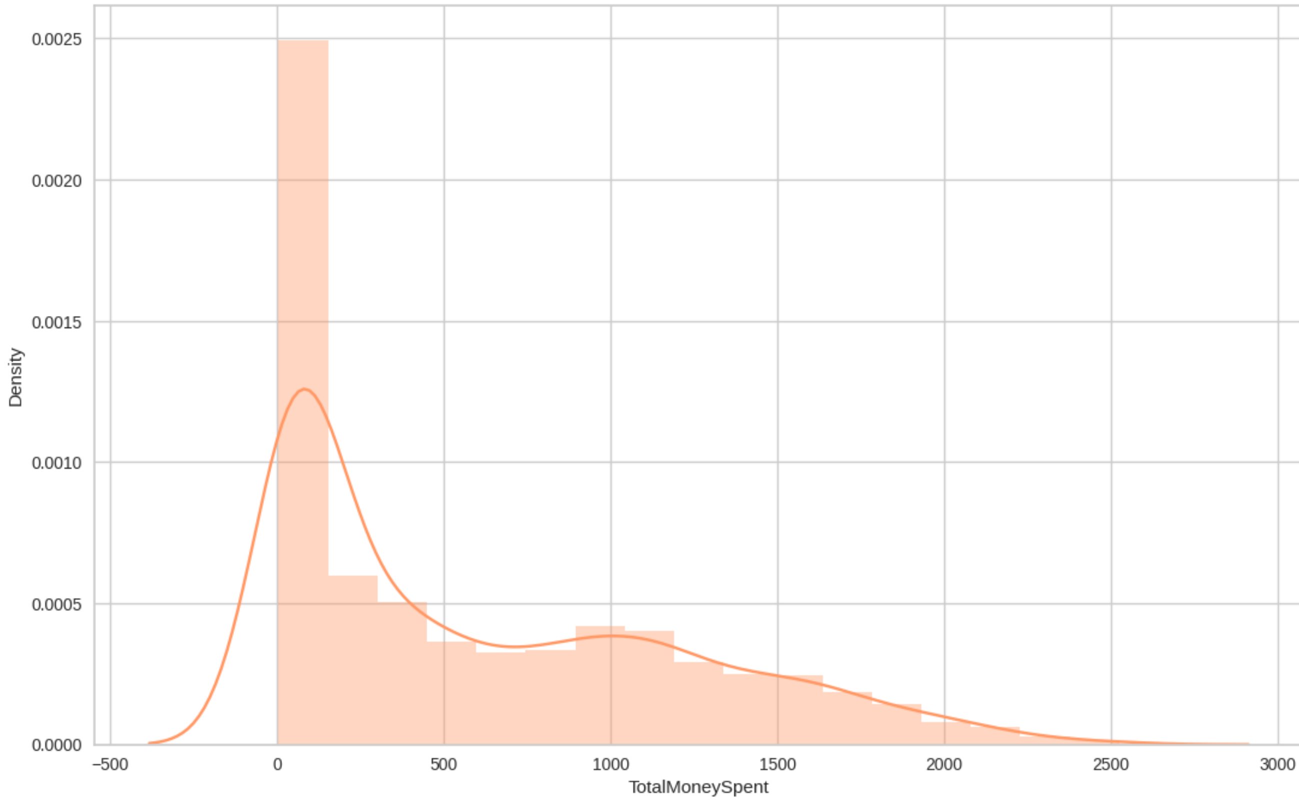
In [60]:
```
plt.figure(figsize=(13,8))
sns.distplot(data.Income, color='Yellow');
```

```
<ipython-input-60-16cfc341aea8>:2: UserWarning:



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

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

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

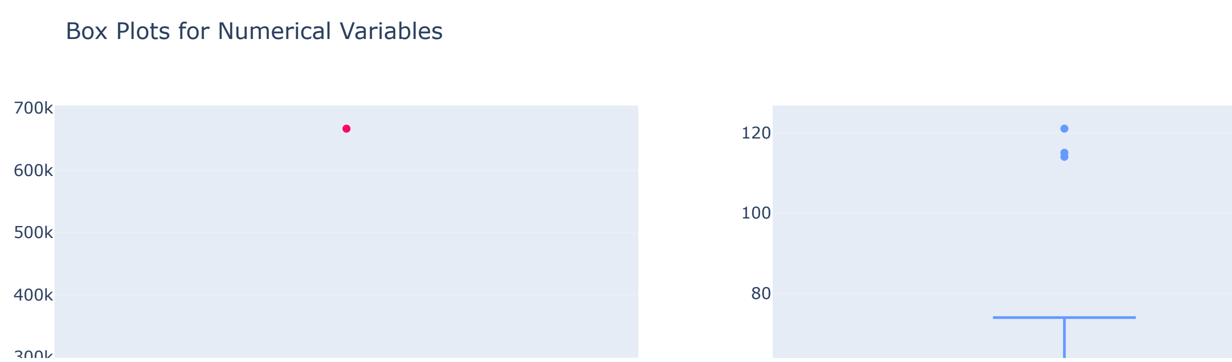


In [61]:
```
plt.figure(figsize=(13,8))
sns.distplot(data.TotalMoneySpent, color='#ff9966');
```

```
<ipython-input-61-20f604d0b302>:2: UserWarning:



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

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

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



In [62]:
```
enable_plotly_in_cell()

fig = make_subplots(rows=1, cols=3)

fig.add_trace(go.Box(y=data['Age'], notched=True, name='Age', marker_color = '#6699ff',
                     boxmean=True, boxpoints='suspectedoutliers'), 1, 2)

fig.add_trace(go.Box(y=data['Income'], notched=True, name='Income', marker_color = '#ff0066',
                     boxmean=True, boxpoints='suspectedoutliers'), 1, 1)

fig.add_trace(go.Box(y=data['TotalMoneySpent'], notched=True, name='Money Spent', marker_color = 'lightseagreen',
                     boxmean=True, boxpoints='suspectedoutliers'), 1, 3)

fig.update_layout(title_text='Box Plots for Numerical Variables')

fig.show()
```



In [63]:
```
data.head(1)
```

Out[63]:

	ID	Education	Income	Kidhome	Teenhome	Recency	MntWines	MntFruits	MntMeatProducts	MntFishProducts	...	TotalNumOfPurchases	TotalAccCmp	Pa
0	5524	Graduate	58138.0	0	0	58	635	88	546	172	...	25	1	

1 rows × 41 columns

In [64]:
```
numerical = ['Income', 'Recency', 'Age', 'TotalMoneySpent']
```

In [65]:
```
def detect_outliers(d):
  for i in d:
    Q3, Q1 = np.percentile(data[i], [75 ,25])
    IQR = Q3 - Q1

    ul = Q3+1.5*IQR
    ll = Q1-1.5*IQR

    outliers = data[i][(data[i] > ul) | (data[i] < ll)]
    print(f'*** {i} outlier points***', '\n', outliers, '\n')
```

In [66]:
```
detect_outliers(numerical)
```

```
*** Income outlier points***
 164     157243.0
617     162397.0
655     153924.0
687     160803.0
1300    157733.0
1653    157146.0
2132    156924.0
2233    666666.0
Name: Income, dtype: float64

*** Recency outlier points***
 Series([], Name: Recency, dtype: int64)

*** Age outlier points***
 192    114
239    121
339    115
Name: Age, dtype: int64

*** TotalMoneySpent outlier points***
 1179    2525
1492    2524
1572    2525
Name: TotalMoneySpent, dtype: int64
```

Observation

There are some customers aged above 100. This is unlikely to happen. Let's drop those customers from data.

There are some customers who are earning more than 120,000 and some of them even more than 600,000. They are clearly the outliers in the data, so we will leave them out.

Delete the outlier points

In [67]:
```
data = data[(data['Age']<100)]
data = data[(data['Income']<600000)]
```

In [68]:
```
data.shape
```

Out[68]:
```
(2212, 41)
```

Check for Rare Categories

Some categories may appear a lot in the dataset, whereas some other categories appear only in a few number of observations.

Rare values in categorical variables tend to cause over-fitting, particularly in tree based methods. Rare labels may be present in training set, but not in test set, therefore causing over-fitting to the train set. Rare labels may appear in the test set, and not in the train set. Thus, the machine learning model will not know how to evaluate it.

In [69]:
```
categorical = [var for var in data.columns if data[var].dtype=='O']
```

In [70]:
```
# check the number of different labels
for var in categorical:
    print(data[var].value_counts() / np.float(len(data)))
```

```
    print()
    print()
```

```
Graduate         0.504069
Postgraduate     0.382007
Undergraduate    0.113924
Name: Education, dtype: float64


Yes    0.64557
No     0.35443
Name: Partner, dtype: float64


August       0.094937
October      0.093580
December     0.090416
March        0.089964
January      0.085443
May          0.084539
April        0.083183
February     0.083183
November     0.081374
June         0.075949
September    0.073689
July         0.063743
Name: MonthJoined, dtype: float64


Sunday       0.154611
Wednesday    0.148734
Thursday     0.141953
Tuesday      0.141953
Monday       0.139693
Friday       0.137884
Saturday     0.135172
Name: DayJoined, dtype: float64
```

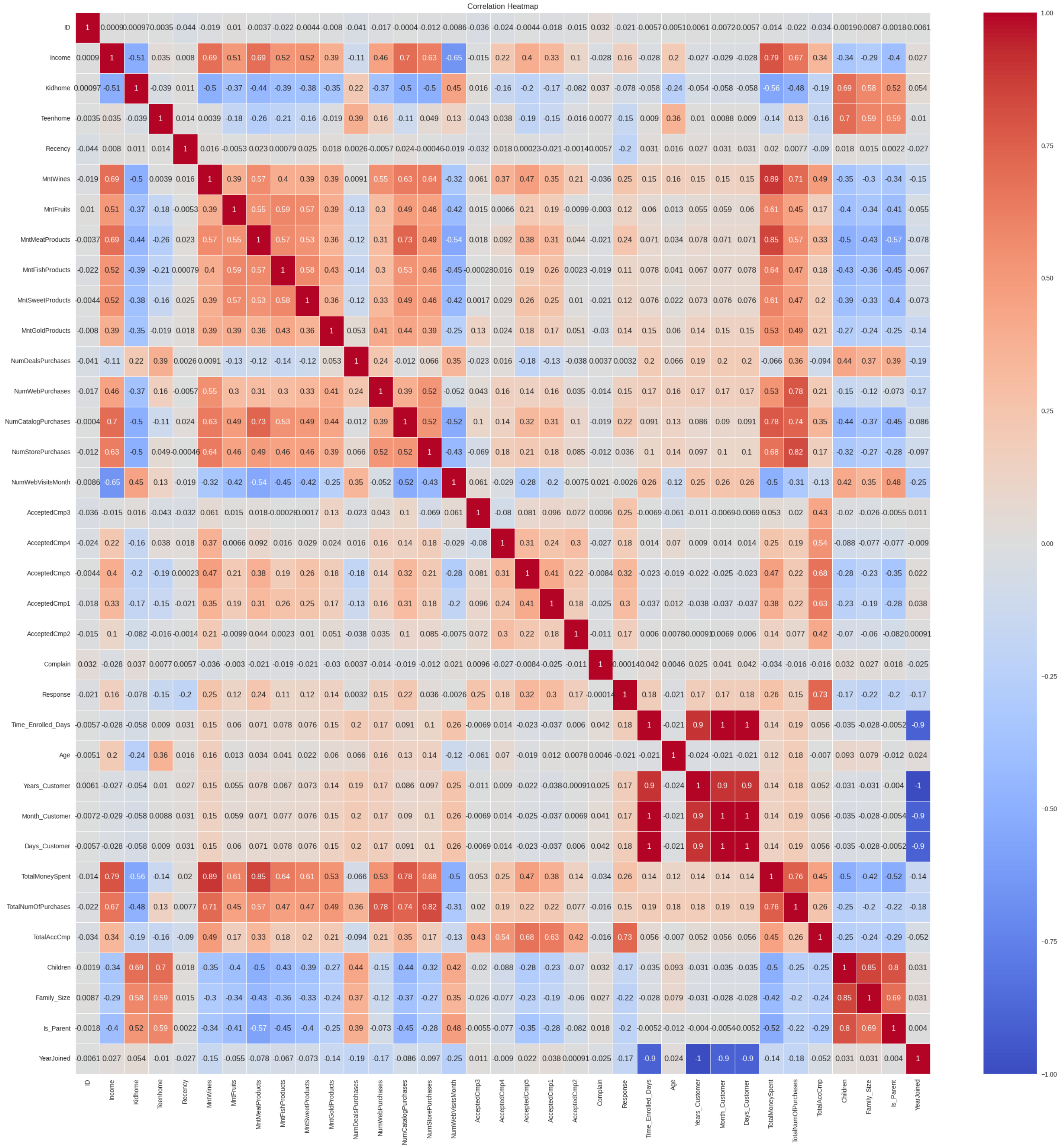
```
<ipython-input-70-685aeeb43f44>:3: DeprecationWarning:

`np.float` is a deprecated alias for the builtin `float`. To silence this warning, use `float` by itself. Doing this will not modify any
behavior and is safe. If you specifically wanted the numpy scalar type, use `np.float64` here.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdocs/release/1.20.0-notes.html#deprecations

<ipython-input-70-685aeeb43f44>:3: DeprecationWarning:

`np.float` is a deprecated alias for the builtin `float`. To silence this warning, use `float` by itself. Doing this will not modify any
behavior and is safe. If you specifically wanted the numpy scalar type, use `np.float64` here.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdocs/release/1.20.0-notes.html#deprecations

<ipython-input-70-685aeeb43f44>:3: DeprecationWarning:

`np.float` is a deprecated alias for the builtin `float`. To silence this warning, use `float` by itself. Doing this will not modify any
behavior and is safe. If you specifically wanted the numpy scalar type, use `np.float64` here.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdocs/release/1.20.0-notes.html#deprecations

<ipython-input-70-685aeeb43f44>:3: DeprecationWarning:

`np.float` is a deprecated alias for the builtin `float`. To silence this warning, use `float` by itself. Doing this will not modify any
behavior and is safe. If you specifically wanted the numpy scalar type, use `np.float64` here.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdocs/release/1.20.0-notes.html#deprecations
```

As shown above, there is no rare category in the categorical variables.

In [71]:

```
plt.figure(figsize=(30, 30))
sns.heatmap(data.corr() , annot=True, cmap='coolwarm', linewidths=0.5)
plt.title('Correlation Heatmap')
plt.show()
```

```
<ipython-input-71-be08efe55ea6>:2: FutureWarning:

The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid colum
ns or specify the value of numeric_only to silence this warning.
```



Observation

1. There are no features which are highly correlated

Feature Transformation

Choosing the features we we will be reporting by removing unnecessary features

In [72]:
```
subset = data[['Income','Kidhome','Teenhome','Age','Partner','Education']]
print('This is the data we will use for clustering:')
subset.head()
```

```
This is the data we will use for clustering:
```

Out[72]:

	Income	Kidhome	Teenhome	Age	Partner	Education
0	58138.0	0	0	57	No	Graduate
1	46344.0	1	1	60	No	Graduate
2	71613.0	0	0	49	Yes	Graduate
3	26646.0	1	0	30	Yes	Graduate
4	58293.0	1	0	33	Yes	Postgraduate

In [73]:

```
subset.describe()
```

Out[73]:

	Income	Kidhome	Teenhome	Age
count	2212.000000	2212.000000	2212.000000	2212.000000
mean	51958.810579	0.441682	0.505877	45.086347
std	21527.278844	0.536955	0.544253	11.701599
min	1730.000000	0.000000	0.000000	18.000000
25%	35233.500000	0.000000	0.000000	37.000000
50%	51371.000000	0.000000	0.000000	44.000000
75%	68487.000000	1.000000	1.000000	55.000000
max	162397.000000	2.000000	2.000000	74.000000

We aren not scaling the kidhome, teenhome cols, cause their min, max lies between 0 & 2

In [74]:

```
num_cols = ['Income','Age']
numeric_pipeline = make_pipeline(StandardScaler())
```

In [75]:

```
ord_cols = ['Education']
ordinal_pipeline = make_pipeline(OrdinalEncoder(categories=[['Undergraduate','Graduate','Postgraduate']]))
```

In [76]:

```
nom_cols = ['Partner']
nominal_pipeline = make_pipeline(OneHotEncoder())
```

Transform pipelines

In [77]:

```
transformer = ColumnTransformer(transformers=[('num',numeric_pipeline,num_cols),
                                           ('ordinal', ordinal_pipeline,ord_cols),
                                              ('nominal' ,nominal_pipeline,nom_cols)
                                             ])
```

In [78]:

```
transformer
```

Out[78]:

```
ColumnTransformer
num              ordinal           nominal
StandardScaler   OrdinalEncoder    OneHotEncoder
```

Fit the transformed data

In [79]:

```
transformed = transformer.fit_transform(subset)
print('Data has been Transformed')
```

```
Data has been Transformed
```

In [80]:

```
# subset = data[['Income','Age','Month_Customer','TotalMoneySpent','Children']]
# print('This is the data we will use for clustering:')
# subset.head()
```

Machine Learning Model

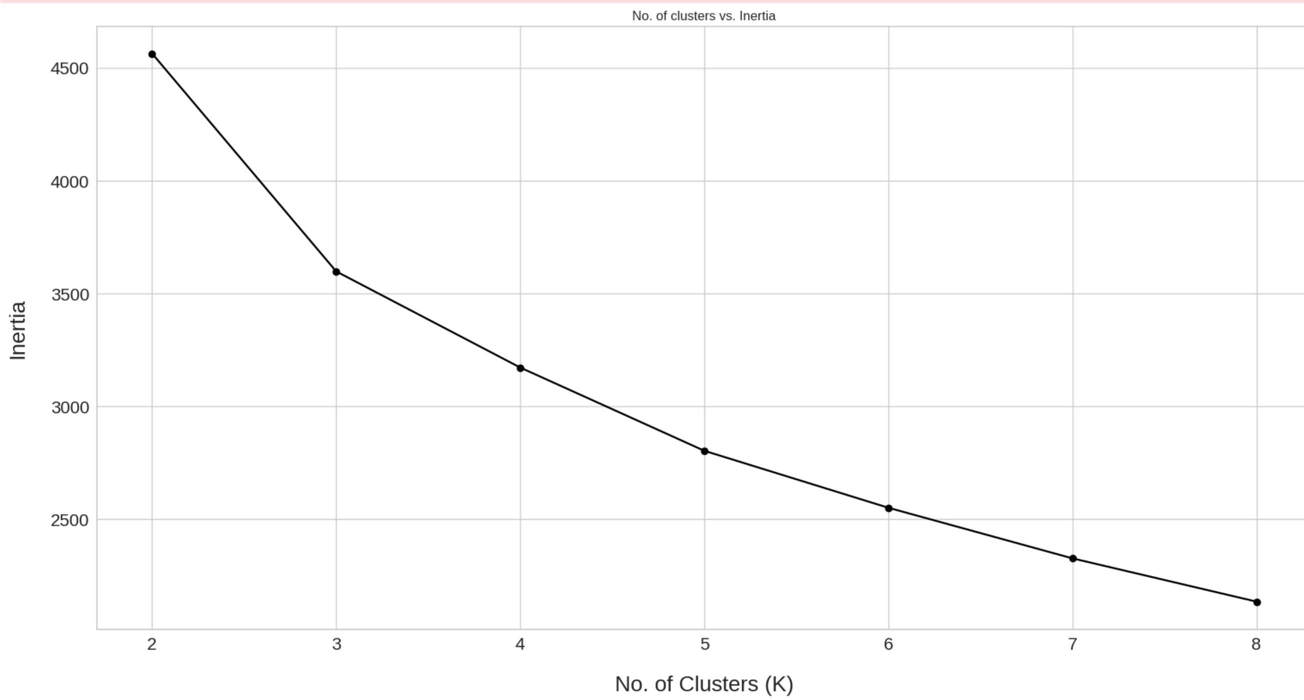
We wii use the Elbow method to identify the optimum clusters

In [81]:

```
from sklearn.cluster import KMeans

options = range(2,9)
inertias = []

for n_clusters in options:
    model = KMeans(n_clusters, random_state=42).fit(transformed)
    inertias.append(model.inertia_)

plt.figure(figsize=(20,10))
```

```
plt.title("No. of clusters vs. Inertia")
plt.plot(options, inertias, '-o', color = 'black')
plt.xticks( fontsize=16)
plt.yticks( fontsize=16)
plt.xlabel('No. of Clusters (K)', fontsize=20, labelpad=20)
plt.ylabel('Inertia', fontsize=20, labelpad=20);
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning:

The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning

/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning:

The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning

/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning:

The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning

/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning:

The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning

/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning:

The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning

/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning:

The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning

/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning:

The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
```



Observation

1. Based on the plot above we will group customers into 4 clusters, because the inertia value does not decrease much after 4 clusters.

Using k-means to form clusters

In [82]:
```
kmeans = KMeans(n_clusters=4, init='k-means++', random_state=42).fit(transformed)
subset['Clusters'] = kmeans.fit_predict(transformed) #fit the data and adding back clusters to the data in clusters column
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning:

The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning

/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning:

The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning

<ipython-input-82-6a59e3753c42>:2: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-cop
y
```

In [83]:

```
subset.head()
```

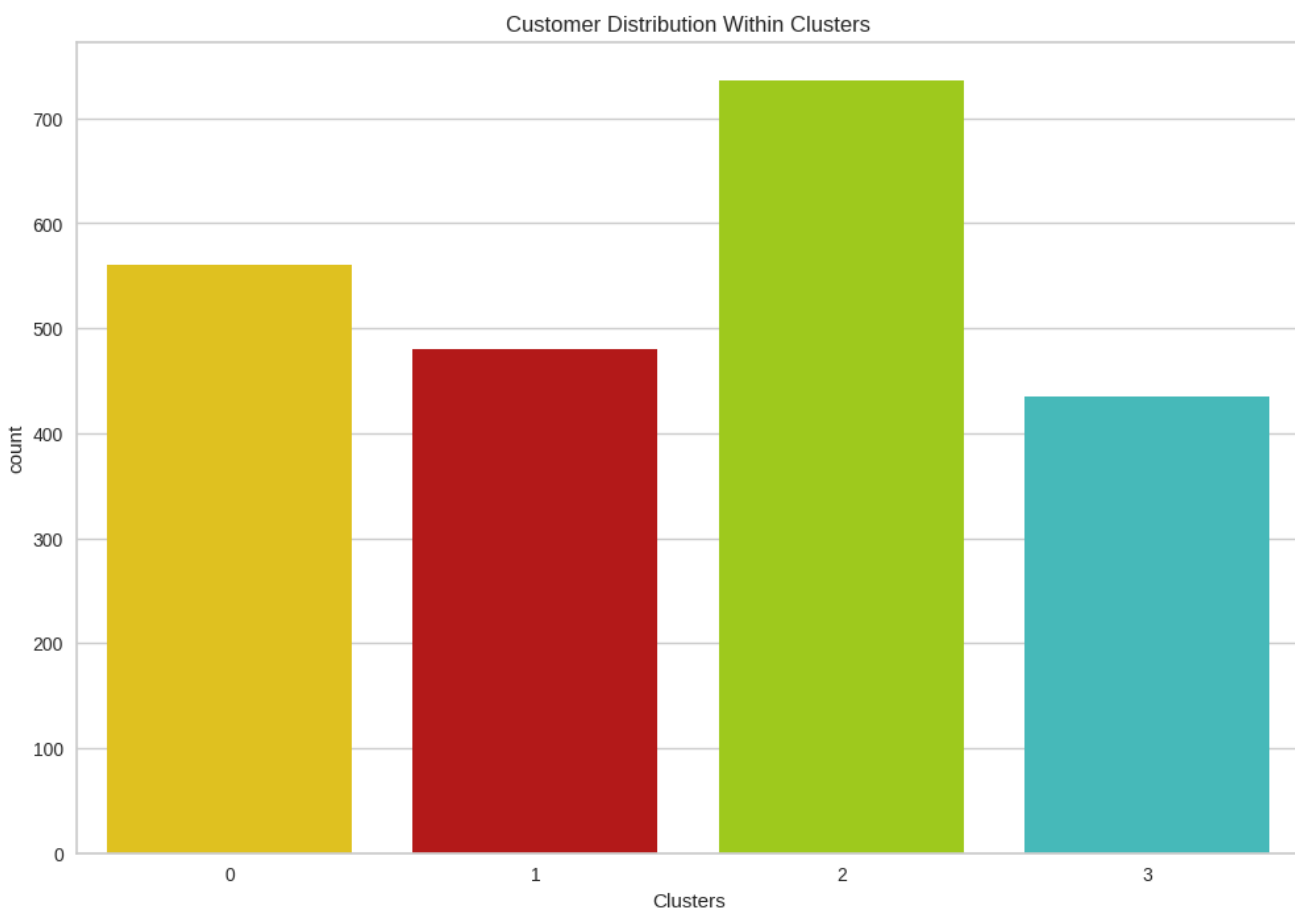
Out[83]:

	Income	Kidhome	Teenhome	Age	Partner	Education	Clusters
0	58138.0	0	0	57	No	Graduate	3
1	46344.0	1	1	60	No	Graduate	3
2	71613.0	0	0	49	Yes	Graduate	0
3	26646.0	1	0	30	Yes	Graduate	2
4	58293.0	1	0	33	Yes	Postgraduate	1

Count plot to see number of customers in each cluster

In [84]:

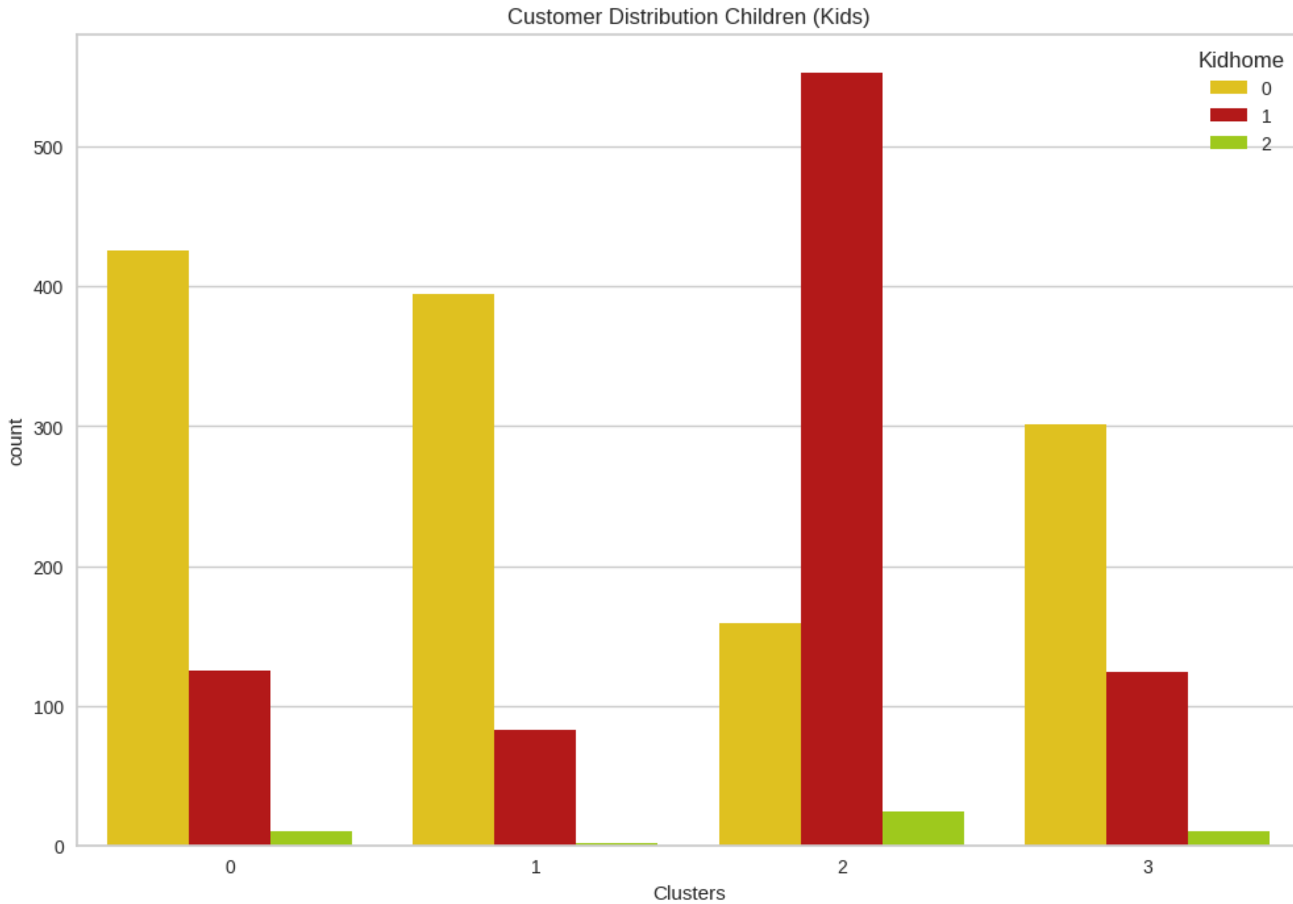
```
plt.figure(figsize=(12, 8))
sns.countplot(x='Clusters', data=subset, palette=palette)
plt.title('Customer Distribution Within Clusters')
plt.show()
```



Observations

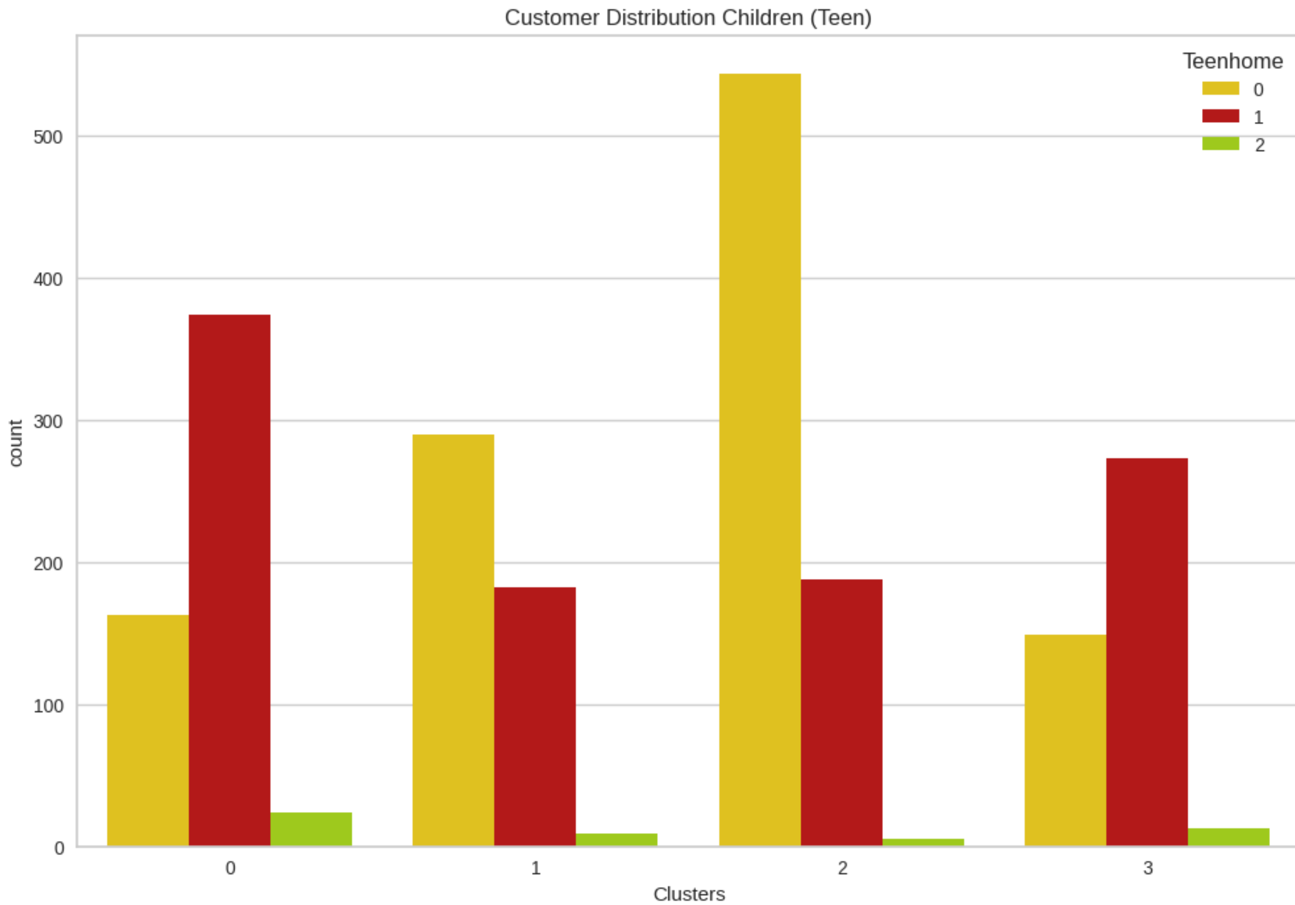
1. Cluster 2 has highest number of customers
2. Cluster 3 has least number of customers

In [85]:
```
plt.figure(figsize=(12, 8))
sns.countplot(x='Clusters', data=subset, hue='Kidhome', palette=palette)
plt.title('Customer Distribution Children (Kids)')
plt.show()
```

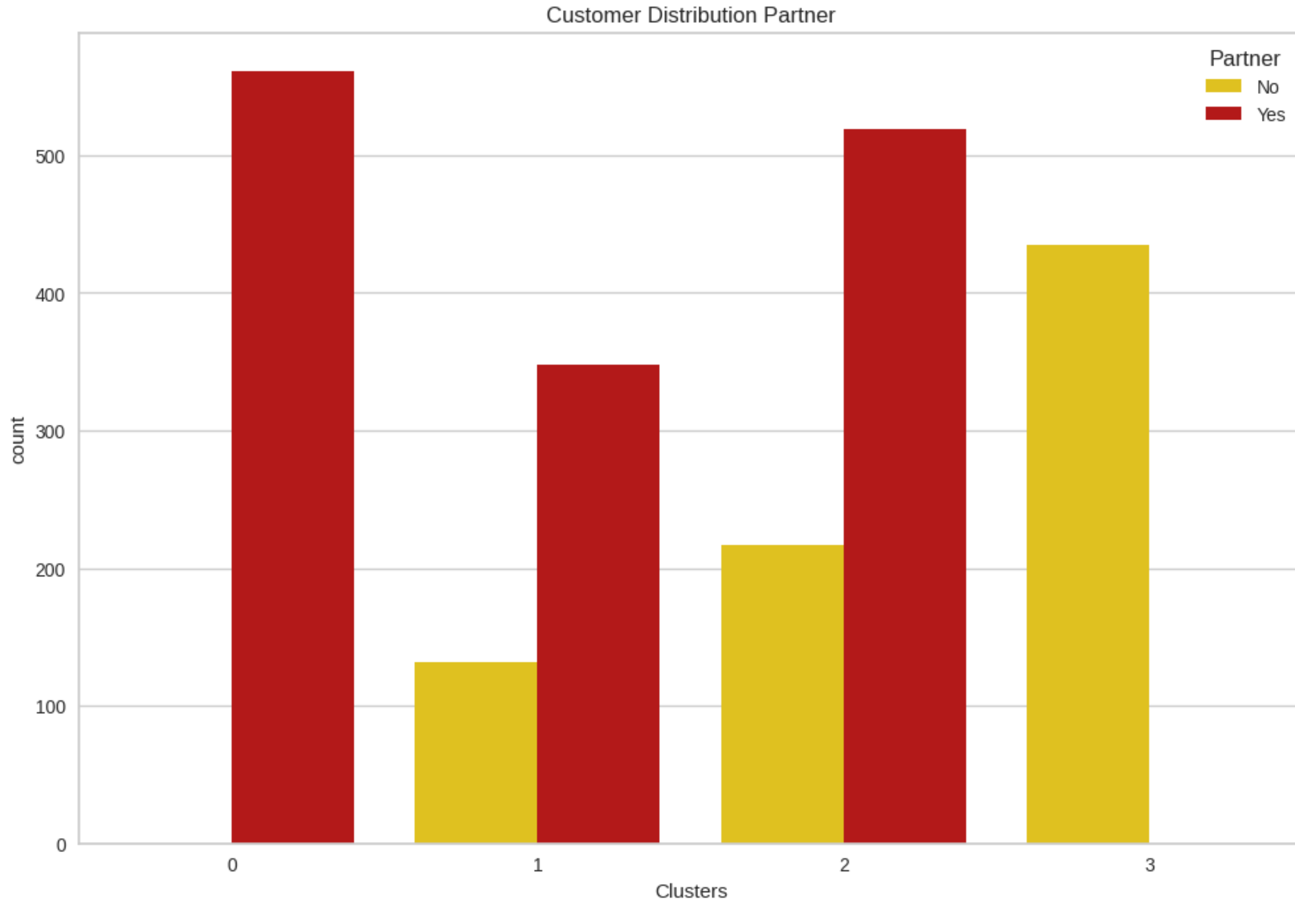


Clusters Identification

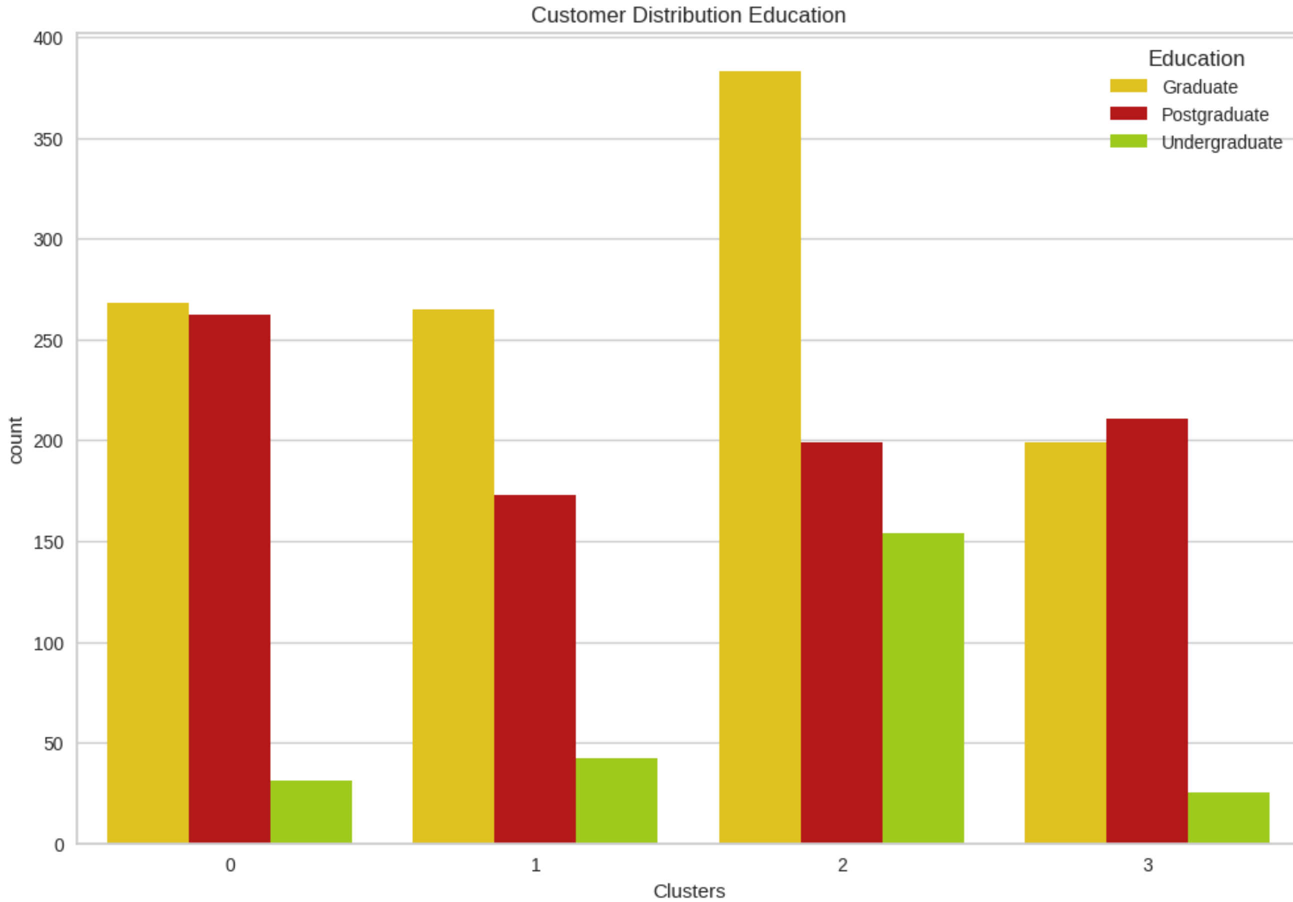
In [86]:
```
plt.figure(figsize=(12, 8))
sns.countplot(x='Clusters', data=subset, hue='Teenhome', palette=palette)
plt.title('Customer Distribution Children (Teen)')
plt.show()
```



In [87]:
```
plt.figure(figsize=(12, 8))
sns.countplot(x='Clusters', data=subset, hue='Partner', palette=palette)
plt.title('Customer Distribution Partner')
plt.show()
```



In [88]:
```
plt.figure(figsize=(12, 8))
sns.countplot(x='Clusters', data=subset, hue='Education', palette=palette)
plt.title('Customer Distribution Education')
plt.show()
```



Observation

1. Kidhome

- Cluster 0 mostly has customers with 1 kid in household
- Cluster 1 has customers with no kids in household
- Cluster 2 also has large number of customers with no kids in household
- Cluster 3 has customers with 0 and 1 kids in household

1. Teenhome:

- Cluster 0 consist of customers with no teen in household & few of them have 1 Teen in household
- Same goes for the cluster 1 & 3
- Cluster 2 has customers with 1 Teen in household

1. Partner

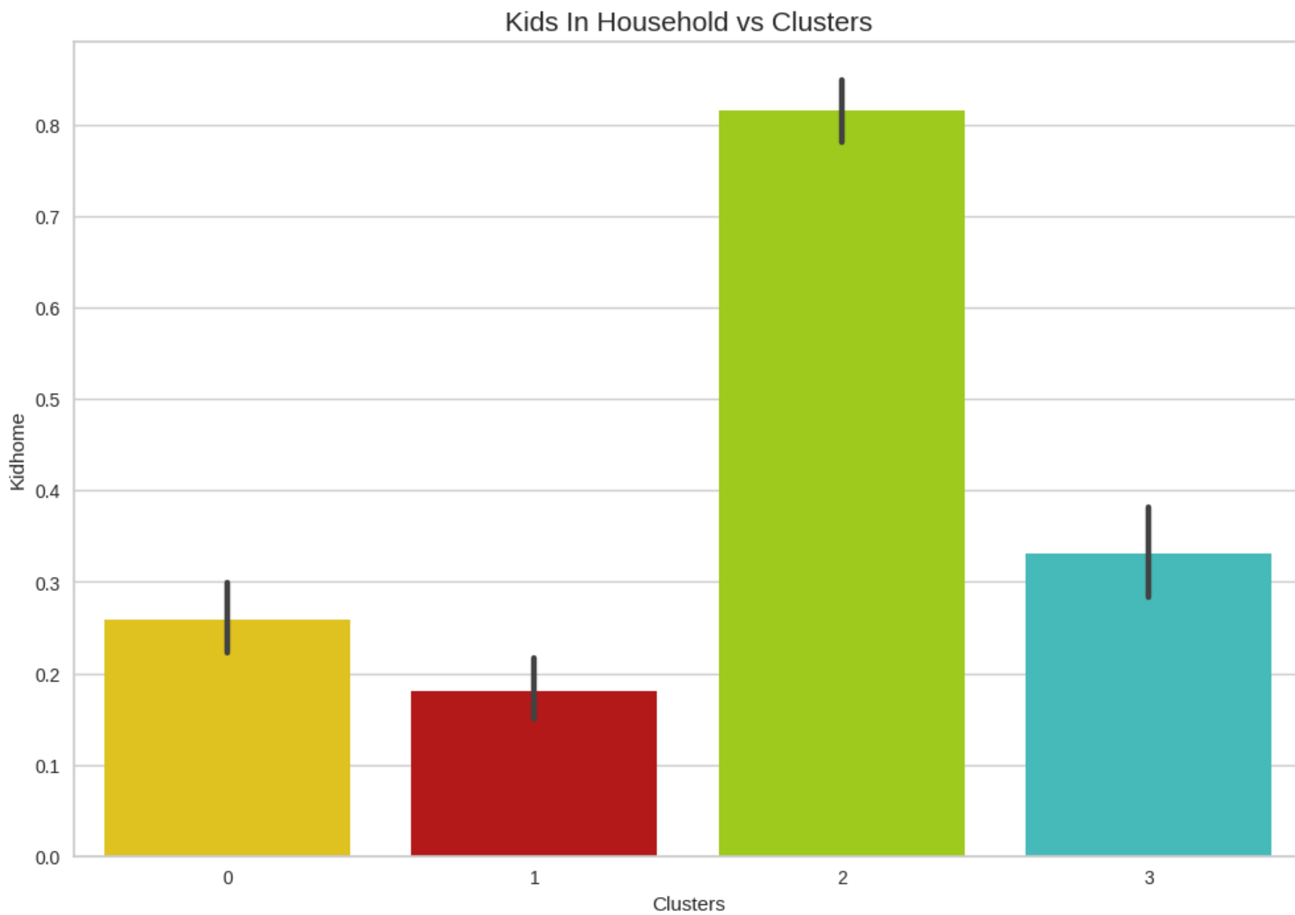
- All the customers in cluster 0 have partner
- All The customers in cluster 3 have no partner
- Cluster 1 & 2 has customers with and without partner, but most of them have partner

1. Education:

- All clusters have customers with graduate, postgraduate and undergraduate background
- All clusters have less number of customers with undergraduate background
- Cluster 2 has highest number of postgraduates and graduates

Find out the customers which have kids in different clusters

In [89]:
```
plt.figure(figsize=(12, 8))
sns.barplot(x=subset["Clusters"], y=subset["Kidhome"],palette=palette)
plt.title("Kids In Household vs Clusters", size=15)
plt.show()
```

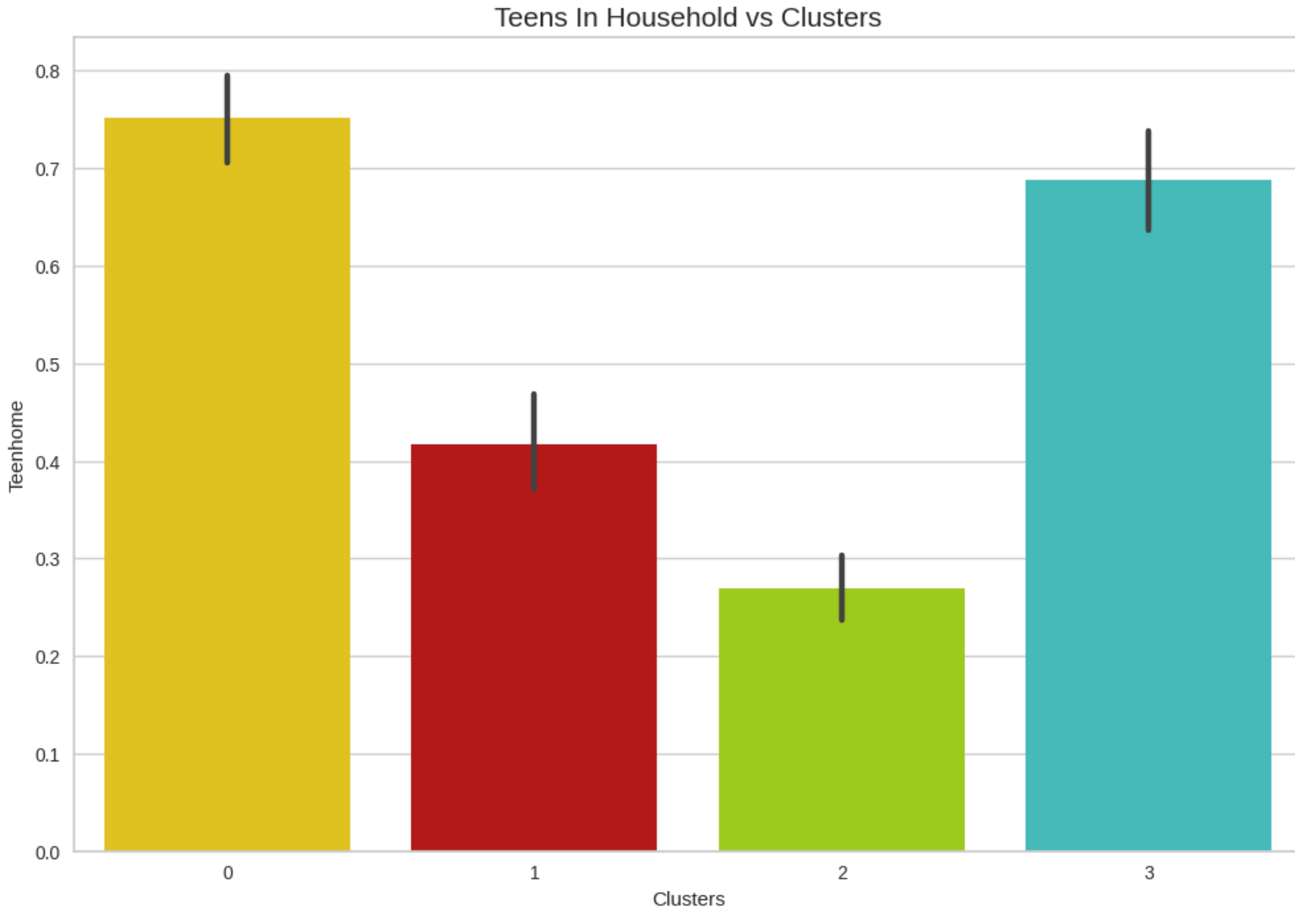


Observation

1. Cluster 0 and 3 has the maximum number of customers with kids in household
2. Cluster 1 and 2 has the least number of customers with kids in household

Find out the customers which have kids in different clusters

In [90]:
```
plt.figure(figsize=(12, 8))
sns.barplot(x=subset["Clusters"], y=subset["Teenhome"],palette=palette)
plt.title("Teens In Household vs Clusters", size=15)
plt.show()
```

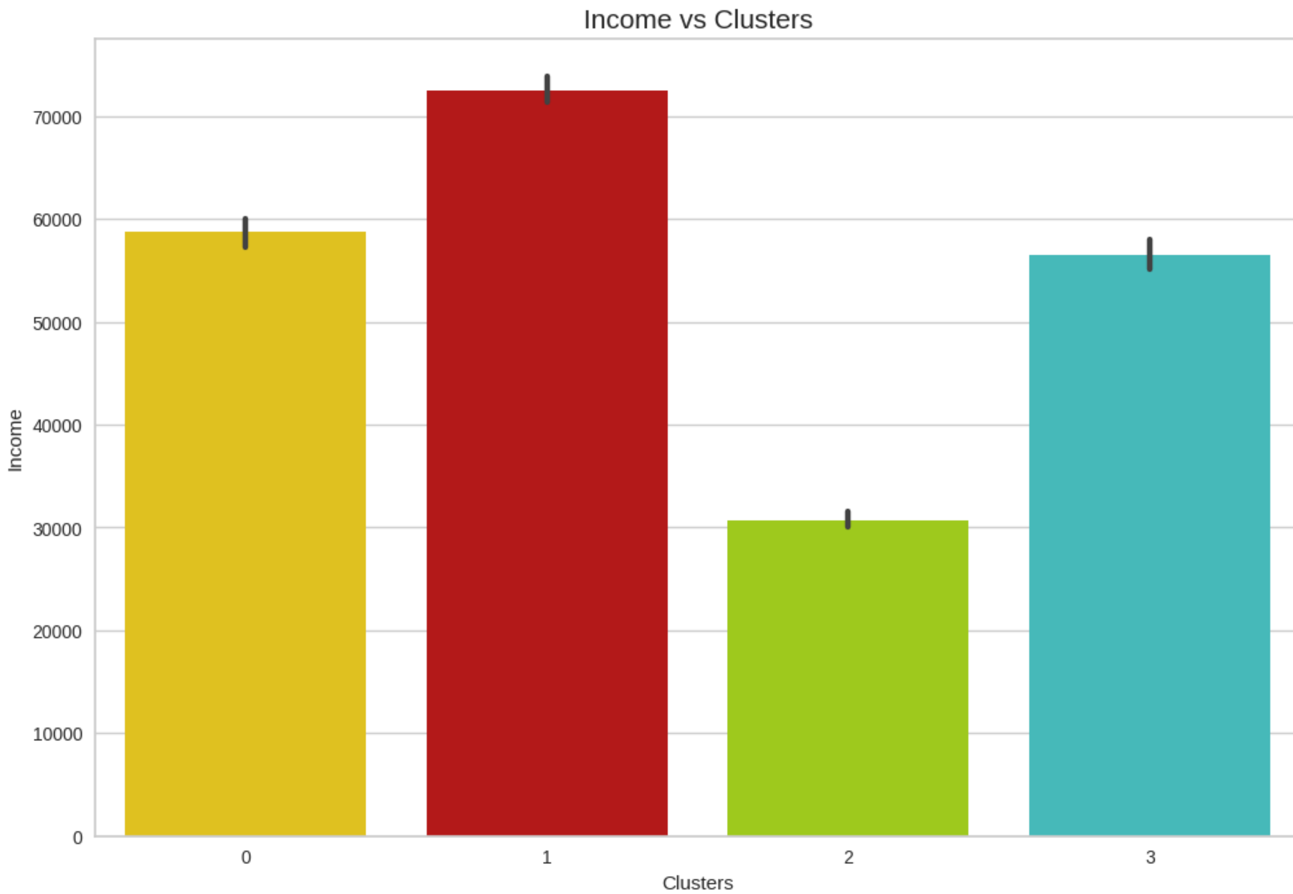


Observation

1. Cluster 2 has maximum number of customers having Teens in household
2. Remaining Clusters also have customers with Teens in household but they are less as compared to cluster 2

Findout income of customers with in clusters

In [91]:
```
plt.figure(figsize=(12, 8))
sns.barplot(x=subset["Clusters"], y=subset["Income"],palette=palette)
plt.title("Income vs Clusters", size=15)
plt.show()
```

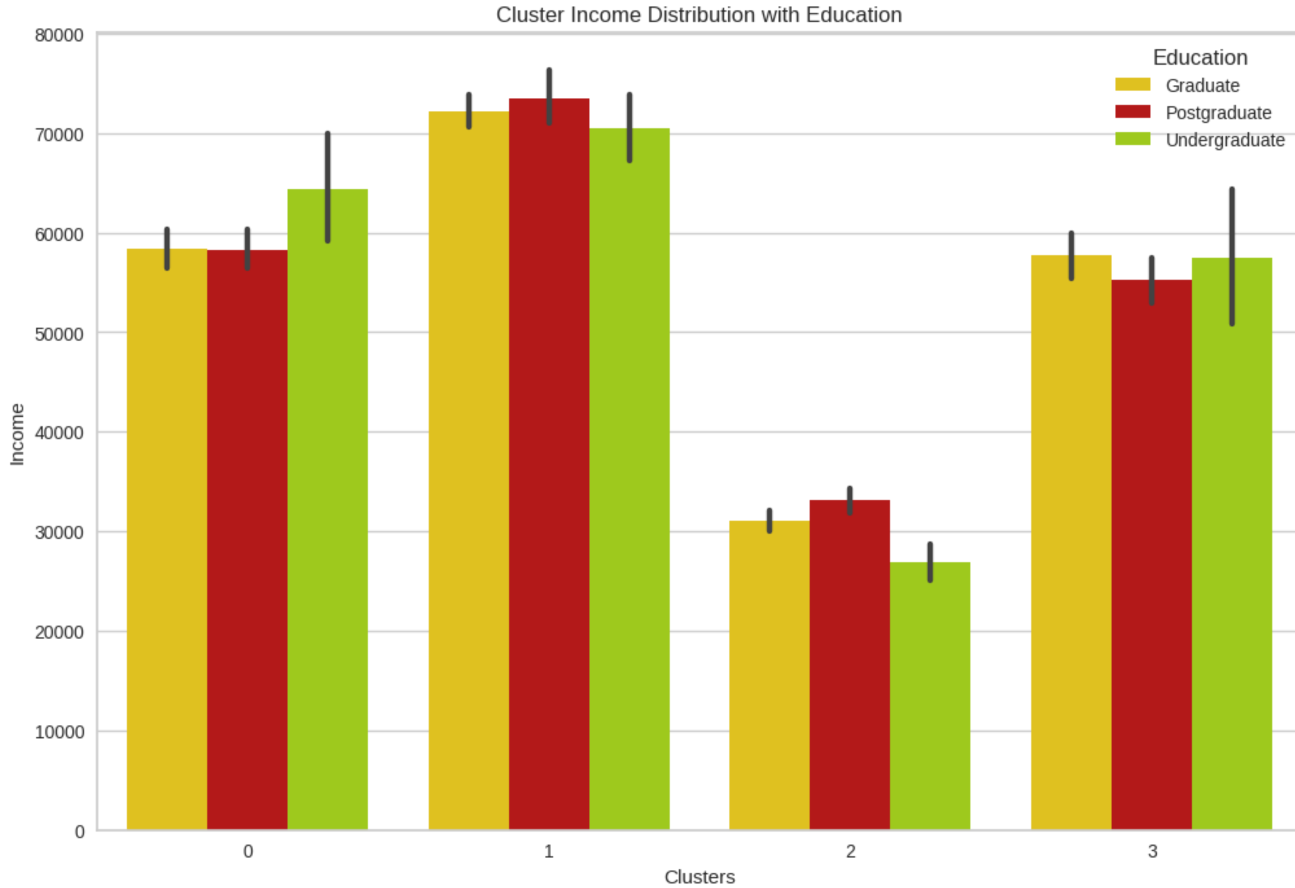


Observations

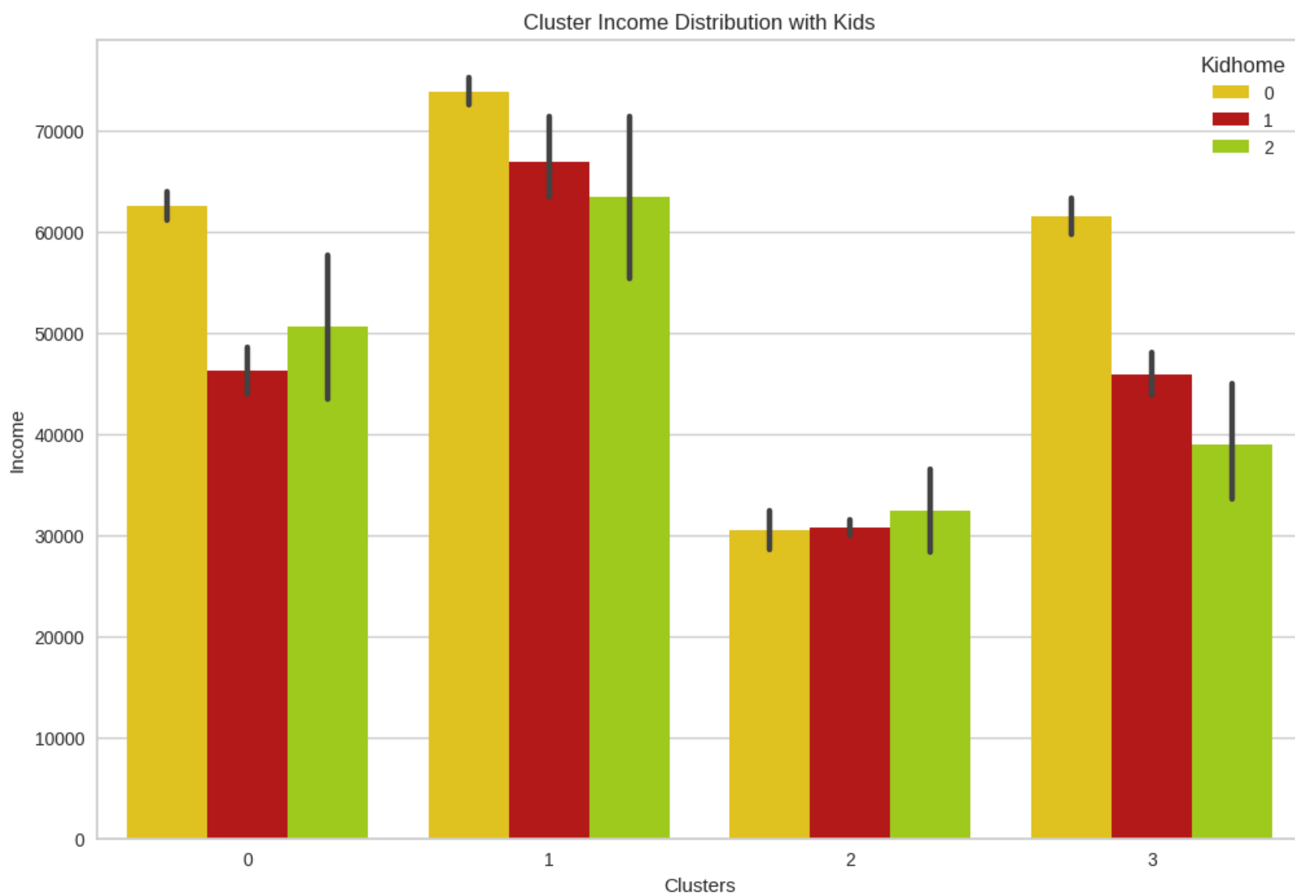
1. Cluster 1 has high Income followed by cluster 2 even though cluster 2 has highest number of customers and most number of post graduates & graduates as compared to cluster 1
2. Cluster 0 and 3 have least income

Contributing factor to income

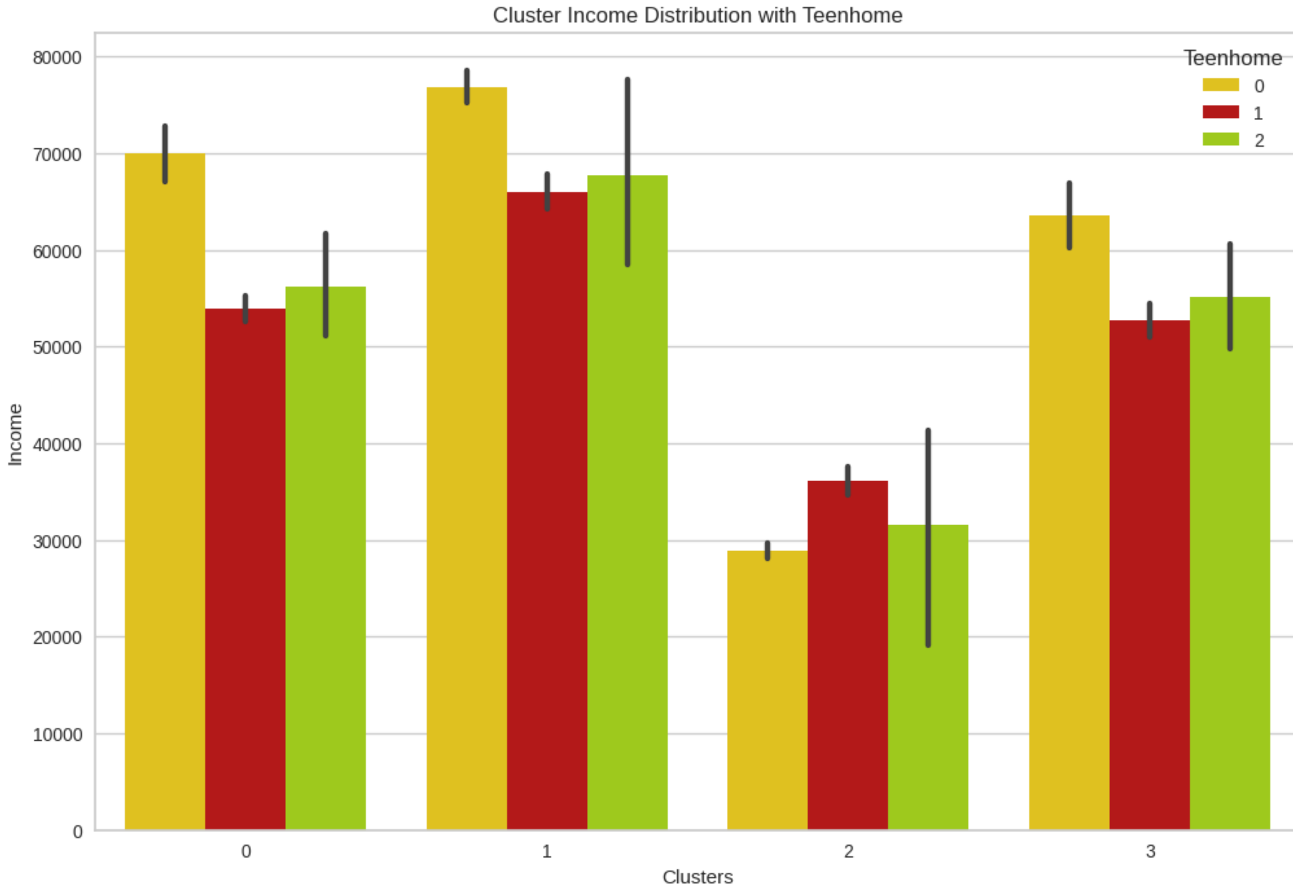
In [92]:
```
plt.figure(figsize=(12, 8))
sns.barplot(x='Clusters', y='Income', data=subset, hue='Education', palette=palette)
plt.title('Cluster Income Distribution with Education')
plt.show()
```



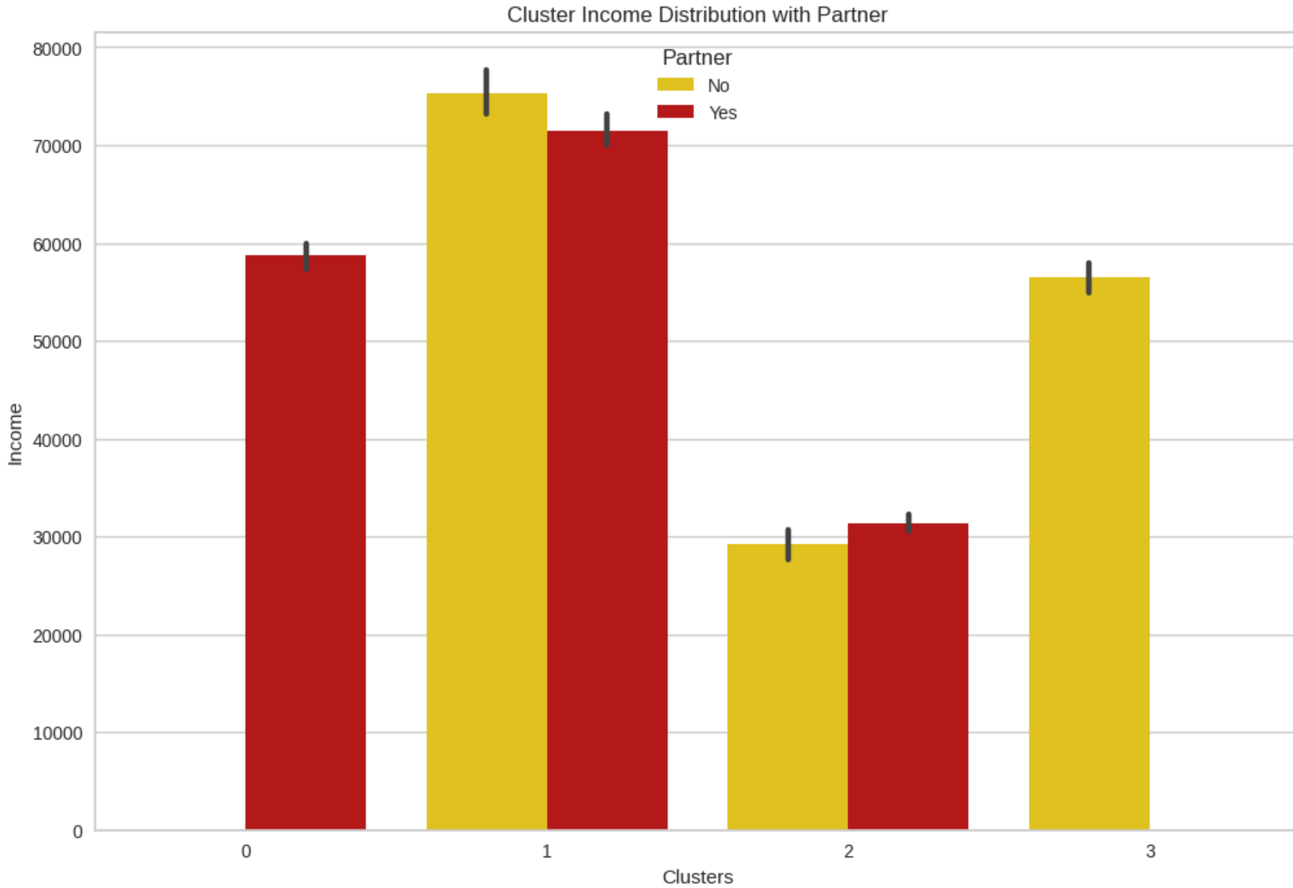
In [93]:
```python
plt.figure(figsize=(12, 8))
sns.barplot(x='Clusters', y='Income', data=subset, hue='Kidhome', palette=palette)
plt.title('Cluster Income Distribution with Kids')
plt.show()
```



In [94]:
```
plt.figure(figsize=(12, 8))
sns.barplot(x='Clusters', y='Income', data=subset, hue='Teenhome', palette=palette)
plt.title('Cluster Income Distribution with Teenhome')
plt.show()
```



In [95]:
```
plt.figure(figsize=(12, 8))
sns.barplot(x='Clusters', y='Income', data=subset, hue='Partner', palette=palette)
plt.title('Cluster Income Distribution with Partner')
plt.show()
```



Observations

1. Interesting thing to note is that the number of customers with 2 kids or teens is very very less still their income is similar to the customers which have no kids or teens or have 1 kid & teen. So I conclude that the customers with more than 1 kid or teen in houehold has high household income 1
2. From the plots for Education and partner, I can conclude it has nothing to do with income. Infact undergraduates are earniing equal or more than graduates and postgraduates within each cluster.

Customer Profiling

1. Cluster 1

- Fewer customers but with the highest income
- No kids, few have 1 teen
- Graduates and Post Graduates
- Most of them have partners

1. Cluster 2

- Max number of customers and high income
- No kids, few have 1 or 2 teens
- High number of post graduates and graduates
- Most of them have partners

1. Cluster 0

They have the least income

- 1 kid and few have teen
- Graduates and post graudates but also has most graduates
- All have partners

1. Cluster 3 Few customers and less income

- 1 kid and few have teen
- Graduates and Post graduates
- All have no partner

Model Building

Separate features and target column

In [96]:
```
x = subset.drop('Clusters', axis=1)
y = subset['Clusters']
```

Create train and test data

In [97]:
```
x_train, x_test, y_train, y_test = train_test_split(x,y, test_size=0.3, random_state=42)
```

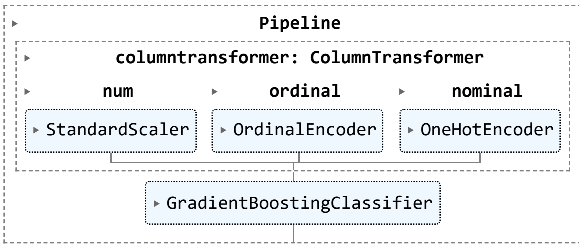
Adding GradientBoostingClassifier to transformer pipeline

In [98]:
```
final_pipeline = make_pipeline(transformer, GradientBoostingClassifier())
```

Fit the data to new pipeline & model

In [99]:
```
final_pipeline.fit(x_train, y_train)
```

Out[99]:



Check the accuracy of our model

In [100…
```
final_pipeline.score(x_test, y_test)
```

Out[100]:
```
0.9864457831325302
```

In [101…
```
joblib.dump(final_pipeline, 'customer_segmentation_cluster.pkl')
```

Out[101]:
```
['customer_segmentation_cluster.pkl']
```

Bibliography

- Mehreen Saeed, Modeling Pipeline Optimization With scikit-learn URL - https://machinelearningmastery.com/modeling-pipeline-optimization-with-scikit-learn/
- Pratik Parmar, Enable plotfly in a cell in colab URL - https://stackoverflow.com/a/54771665
- Gilbert Tanner, Building web app with streamlit and deploying wit Heroku - URL - https://gilberttanner.com/blog/deploying-your-streamlit-dashboard-with-heroku/

Note from the Author

This file was generated using The NBConvert, additional information on how to prepare articles for submission is here.

The article itself is an executable colab Markdown file that could be downloaded from Github with all the necessary artifacts.

Link to the web application - Student Dropout Predictor

Kunwar Rajdeep Singh - York University School of Continuing Studies