Customer Analysis

Problem Statement: A well known company with numerous products needs to analyze their customer behaviour and classify them to know whether they will accept the campaigns held by the company.

In this project I will be doing an unsupervised clustering of data on customer records from the company's database. Customer clustering/segmentation is the practice of separating customers into groups that reflect similarities among customers in each cluster. It helps to modify products according to distinct needs and behaviours of the customers.

Importing libraries

In [66]:
```
import numpy as np
import pandas as pd
import datetime
import matplotlib
import matplotlib.pyplot as plt
from matplotlib import colors
import seaborn as sns
```

In [67]:
```
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans
from sklearn.cluster import AgglomerativeClustering
from sklearn import metrics
from sklearn.metrics import silhouette_score
import warnings
warnings.filterwarnings('ignore')
```

Loading data

In [187]:
```
data = pd.read_csv("market_train.csv")
data.head()
```

Out[187]:

	Unnamed: 0.1	Unnamed: 0	ID	Year_Birth	Education	Marital_Status	Income	Kidhome
0	0	0	5524	1957	S1	Lajang	58138000.0	0
1	1	1	2174	1954	S1	Lajang	46344000.0	1
2	2	2	4141	1965	S1	Bertunangan	71613000.0	0
3	3	3	6182	1984	S1	Bertunangan	26646000.0	1
4	4	4	5324	1981	S3	Menikah	58293000.0	1

5 rows × 31 columns

In [188]:

```
test = pd.read_csv("market_test.csv")
test.shape
```

Out[188]:

```
(559, 31)
```

In [189]:

```
data.shape
```

Out[189]:

```
(1680, 31)
```

The data is provided as two parts - one for training and the other for testing. The columns can be categorized in to 4 types - customer information, Products, Promotion, Places(details about purchase),

Exploratory Analysis and Data Cleaning

In [190]:

```
# information about the data and features

data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1680 entries, 0 to 1679
Data columns (total 31 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   Unnamed: 0.1         1680 non-null   int64  
 1   Unnamed: 0           1680 non-null   int64  
 2   ID                   1680 non-null   int64  
 3   Year_Birth           1680 non-null   int64  
 4   Education            1680 non-null   object 
 5   Marital_Status       1680 non-null   object 
 6   Income               1663 non-null   float64
 7   Kidhome              1680 non-null   int64  
 8   Teenhome             1680 non-null   int64  
 9   Dt_Customer          1680 non-null   object 
 10  Recency              1680 non-null   int64  
 11  MntCoke              1680 non-null   int64  
 12  MntFruits            1680 non-null   int64  
 13  MntMeatProducts      1680 non-null   int64  
 14  MntFishProducts      1680 non-null   int64  
 15  MntSweetProducts     1680 non-null   int64  
 16  MntGoldProds         1680 non-null   int64  
 17  NumDealsPurchases    1680 non-null   int64  
 18  NumWebPurchases      1680 non-null   int64  
 19  NumCatalogPurchases  1680 non-null   int64  
 20  NumStorePurchases    1680 non-null   int64  
 21  NumWebVisitsMonth    1680 non-null   int64  
 22  AcceptedCmp3         1680 non-null   int64  
 23  AcceptedCmp4         1680 non-null   int64  
 24  AcceptedCmp5         1680 non-null   int64  
 25  AcceptedCmp1         1680 non-null   int64  
 26  AcceptedCmp2         1680 non-null   int64  
 27  Complain             1680 non-null   int64  
 28  Z_CostContact        1680 non-null   int64  
 29  Z_Revenue            1680 non-null   int64  
 30  Response             1680 non-null   int64  
dtypes: float64(1), int64(27), object(3)
memory usage: 407.0+ KB
```

In [191]:
```
test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 559 entries, 0 to 558
Data columns (total 31 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   Unnamed: 0.1         559 non-null    int64  
 1   Unnamed: 0           559 non-null    int64  
 2   ID                   559 non-null    int64  
 3   Year_Birth           559 non-null    int64  
 4   Education            559 non-null    object 
 5   Marital_Status       559 non-null    object 
 6   Income               552 non-null    float64
 7   Kidhome              559 non-null    int64  
 8   Teenhome             559 non-null    int64  
 9   Dt_Customer          559 non-null    object 
 10  Recency              559 non-null    int64  
 11  MntCoke              559 non-null    int64  
 12  MntFruits            559 non-null    int64  
 13  MntMeatProducts      559 non-null    int64  
 14  MntFishProducts      559 non-null    int64  
 15  MntSweetProducts     559 non-null    int64  
 16  MntGoldProds         559 non-null    int64  
 17  NumDealsPurchases    559 non-null    int64  
 18  NumWebPurchases      559 non-null    int64  
 19  NumCatalogPurchases  559 non-null    int64  
 20  NumStorePurchases    559 non-null    int64  
 21  NumWebVisitsMonth    559 non-null    int64  
 22  AcceptedCmp3         559 non-null    int64  
 23  AcceptedCmp4         559 non-null    int64  
 24  AcceptedCmp5         559 non-null    int64  
 25  AcceptedCmp1         559 non-null    int64  
 26  AcceptedCmp2         559 non-null    int64  
 27  Complain             559 non-null    int64  
 28  Z_CostContact        559 non-null    int64  
 29  Z_Revenue            559 non-null    int64  
 30  Response             559 non-null    int64  
dtypes: float64(1), int64(27), object(3)
memory usage: 135.5+ KB
```

There are unwanted coulmns, missing values, values that are objects. These need to be addressed

In [192]:
```
# dropping 2 unwanted columns
data = data.drop(["Unnamed: 0.1","Unnamed: 0"], axis='columns')
```

In [193]:
```
test = test.drop(["Unnamed: 0.1","Unnamed: 0"], axis='columns')
```

In [194]:
```
# replacing null values
income_mean = data['Income'].mean()
data['Income'].fillna(value=income_mean, inplace = True)
```

In [195]:
```
income_mean = test['Income'].mean()
test['Income'].fillna(value=income_mean, inplace = True)
```

In [196]:
```
# converting Dt_Customer to datetime
data["Dt_Customer"] = pd.to_datetime(data["Dt_Customer"])
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1680 entries, 0 to 1679
Data columns (total 29 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   ID                   1680 non-null   int64
 1   Year_Birth           1680 non-null   int64
 2   Education            1680 non-null   object
 3   Marital_Status       1680 non-null   object
 4   Income               1680 non-null   float64
 5   Kidhome              1680 non-null   int64
 6   Teenhome             1680 non-null   int64
 7   Dt_Customer          1680 non-null   datetime64[ns]
 8   Recency              1680 non-null   int64
 9   MntCoke              1680 non-null   int64
 10  MntFruits            1680 non-null   int64
 11  MntMeatProducts      1680 non-null   int64
 12  MntFishProducts      1680 non-null   int64
 13  MntSweetProducts     1680 non-null   int64
 14  MntGoldProds         1680 non-null   int64
 15  NumDealsPurchases    1680 non-null   int64
 16  NumWebPurchases      1680 non-null   int64
 17  NumCatalogPurchases  1680 non-null   int64
 18  NumStorePurchases    1680 non-null   int64
 19  NumWebVisitsMonth    1680 non-null   int64
 20  AcceptedCmp3         1680 non-null   int64
 21  AcceptedCmp4         1680 non-null   int64
 22  AcceptedCmp5         1680 non-null   int64
 23  AcceptedCmp1         1680 non-null   int64
 24  AcceptedCmp2         1680 non-null   int64
 25  Complain             1680 non-null   int64
 26  Z_CostContact        1680 non-null   int64
 27  Z_Revenue            1680 non-null   int64
 28  Response             1680 non-null   int64
dtypes: datetime64[ns](1), float64(1), int64(25), object(2)
memory usage: 380.8+ KB
```

In [197]:
```
test["Dt_Customer"] = pd.to_datetime(test["Dt_Customer"])
```

In [198]:
```
# handling categorical variables
print("Total categories in the feature Marital_Status:\n", data["Marital_St
print("Total categories in the feature Education:\n", data["Education"].val
```

```
Total categories in the feature Marital_Status:
 Menikah        650
Bertunangan    438
Lajang         360
Cerai          177
Janda           52
Duda             3
Name: Marital_Status, dtype: int64

Total categories in the feature Education:
 S1     834
S3     373
S2     279
D3     159
SMA     35
Name: Education, dtype: int64
```

In [199]:
```
# Replacing marital status with english synonyms
data["Marital_Status"] = data['Marital_Status'].replace('Menikah','Married'
data["Marital_Status"] = data['Marital_Status'].replace('Bertunangan','Enga
data["Marital_Status"] = data['Marital_Status'].replace('Lajang','Bachelor'
data["Marital_Status"] = data['Marital_Status'].replace('Cerai','Divorced')

test["Marital_Status"] = test['Marital_Status'].replace('Menikah','Married'
test["Marital_Status"] = test['Marital_Status'].replace('Bertunangan','Enga
test["Marital_Status"] = test['Marital_Status'].replace('Lajang','Bachelor'
test["Marital_Status"] = test['Marital_Status'].replace('Cerai','Divorced')

data["Marital_Status"].value_counts()
```

Out[199]:
```
Married     650
Engaged     438
Bachelor    360
Divorced    177
Janda        52
Duda          3
Name: Marital_Status, dtype: int64
```

Feature Engineering

In [200]:

```
#Creating some new features for grouping

#Age of customer today
data["Age"] = 2023-data["Year_Birth"]
test["Age"] = 2023-test["Year_Birth"]

#Total spendings on various items
data["Spent"] = data["MntCoke"]+ data["MntFruits"]+ data["MntMeatProducts"]
test["Spent"] = test["MntCoke"]+ test["MntFruits"]+ test["MntMeatProducts"]

#Feature indicating total children living in the household
data["Children"]=data["Kidhome"]+data["Teenhome"]
test["Children"]=test["Kidhome"]+test["Teenhome"]

#Feature pertaining parenthood
data["Is_Parent"] = np.where(data.Children> 0, 1, 0)
test["Is_Parent"] = np.where(test.Children> 0, 1, 0)

#Segmenting education levels in three groups
data["Education"]=data["Education"].replace({"SMA":"Undergraduate","S1":"Gr
test["Education"]=test["Education"].replace({"SMA":"Undergraduate","S1":"Gr
```

In [201]:

```
#Dropping some of the redundant features
to_drop = ["Z_CostContact", "Z_Revenue", "Year_Birth", "ID"]
data = data.drop(to_drop, axis=1)
test = test.drop(to_drop, axis=1)
```

In [202]:

```
# converting income to thousands
data["Income"] = data["Income"]/1000
test["Income"] = test["Income"]/1000

data.describe()
```

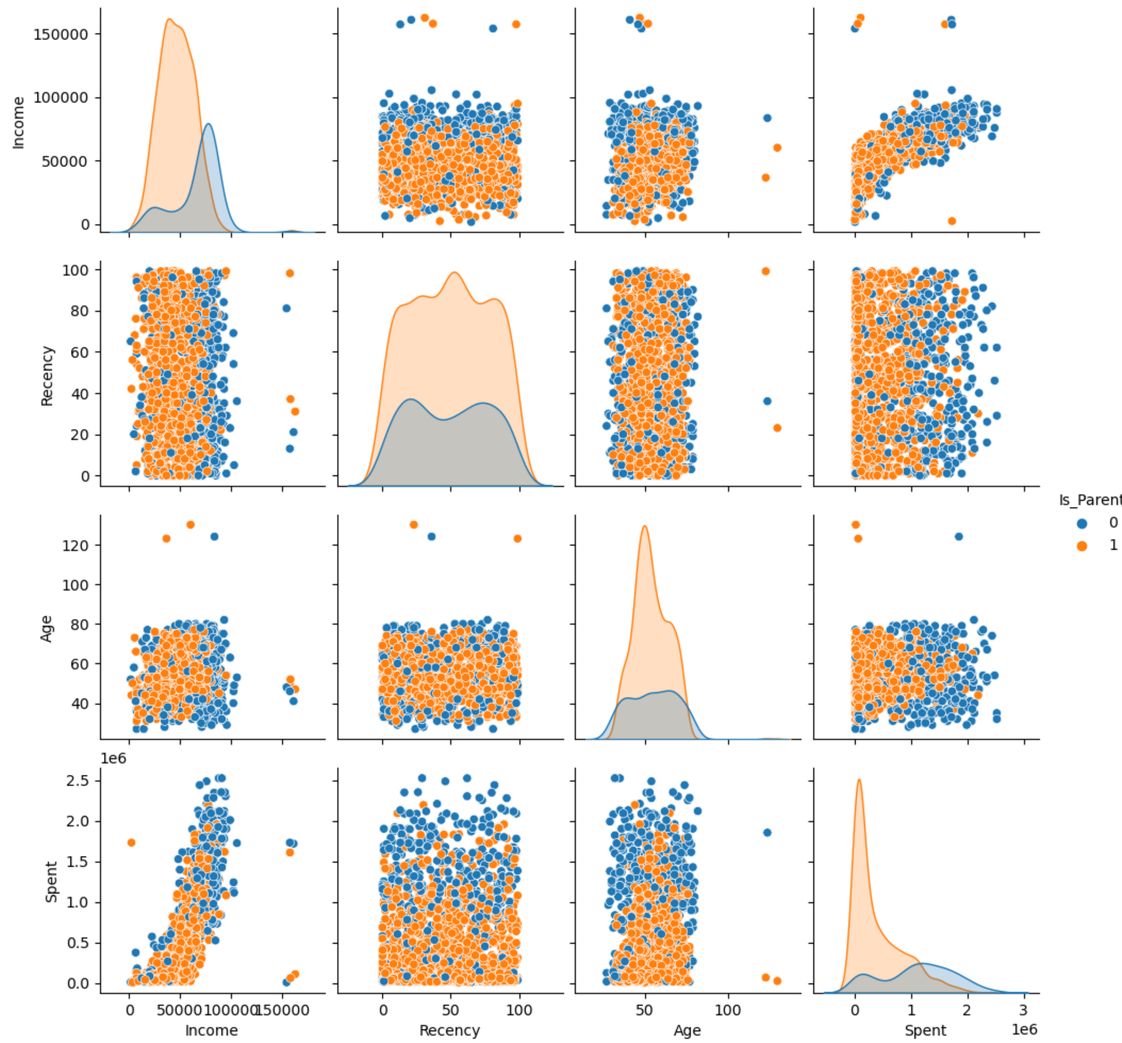
Out[202]:

	Income	Kidhome	Teenhome	Recency	MntCoke	MntFruits
count	1680.000000	1680.000000	1680.000000	1680.000000	1.680000e+03	1680.000000
mean	52014.343355	0.452381	0.500000	49.083333	3.048994e+05	25918.452381
std	21373.445420	0.546901	0.550055	28.930637	3.387051e+05	39532.059109
min	1730.000000	0.000000	0.000000	0.000000	0.000000e+00	0.000000
25%	35790.750000	0.000000	0.000000	24.000000	2.400000e+04	1000.000000
50%	51445.500000	0.000000	0.000000	50.000000	1.730000e+05	8000.000000
75%	67897.500000	1.000000	1.000000	74.000000	4.942500e+05	32000.000000
max	162397.000000	2.000000	2.000000	99.000000	1.492000e+06	199000.000000

8 rows × 26 columns

In [203]:
```
#To plot some selected features
To_Plot = [ "Income", "Recency", "Age", "Spent", "Is_Parent"]
print("Reletiving Plot Of Some Selected Features")
plt.figure()
sns.pairplot(data[To_Plot], hue= "Is_Parent")
#Taking hue
plt.show()
```

```
Reletiving Plot Of Some Selected Features

<Figure size 640x480 with 0 Axes>
```

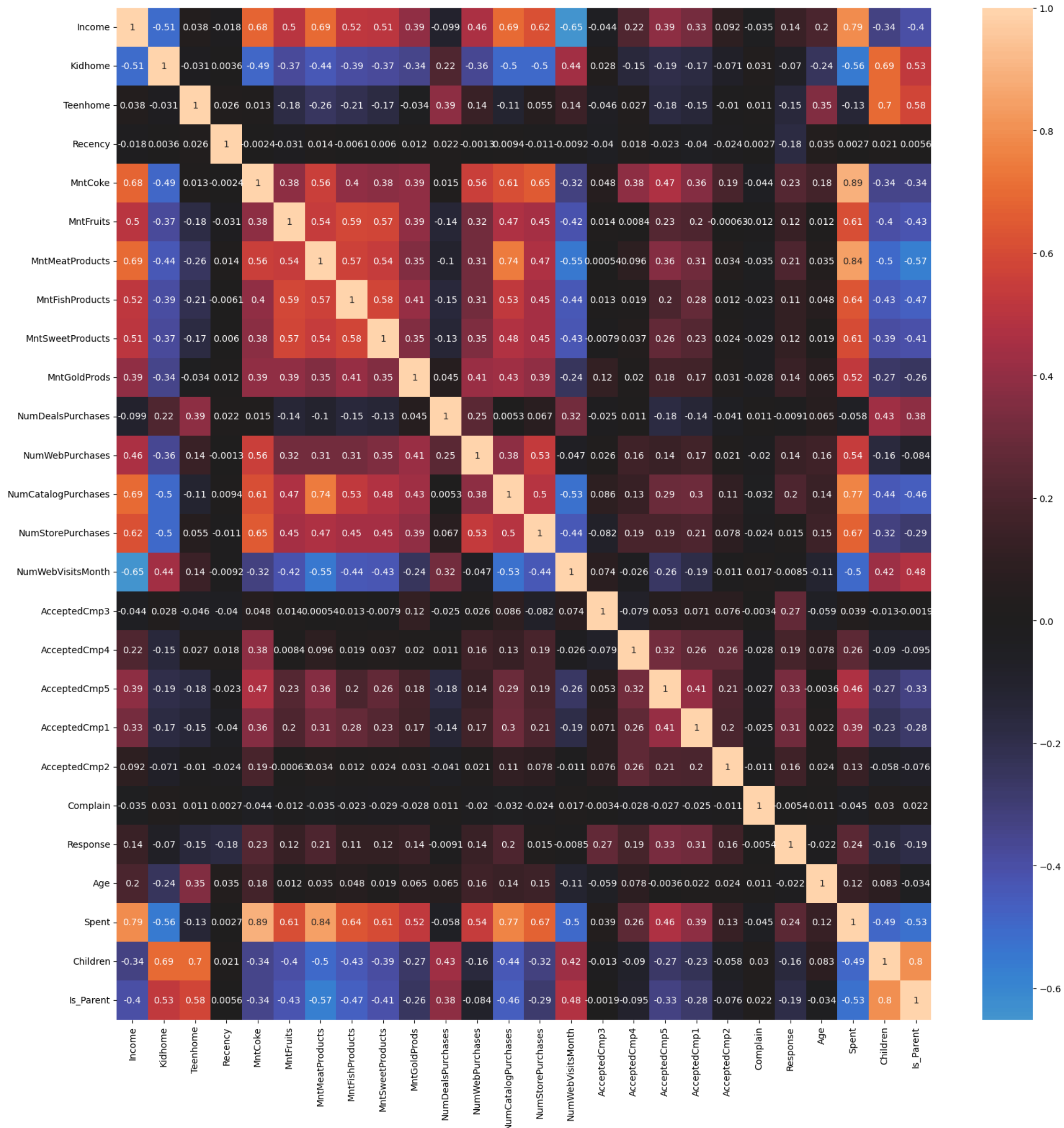


In [204]:
```
#Dropping the outliers on Age and income.
data = data[(data["Age"]<90)]
data = data[(data["Income"]<600000)]

test = test[(test["Age"]<90)]
test = test[(test["Income"]<60000)]

len(data), len(test)
```

Out[204]:
```
(1677, 343)
```

In [205]:
```
#correlation matrix
corrmat= data.corr()
plt.figure(figsize=(20,20))
sns.heatmap(corrmat,annot=True, center=0)
```

Out[205]: <AxesSubplot:>



Data Preprocessing

In [206]:
```
#Get list of categorical variables
s = (data.dtypes == 'object')
object_cols = list(s[s].index)

print("Categorical variables in the dataset:", object_cols)
```

```
Categorical variables in the dataset: ['Education', 'Marital_Status']
```

In [207]:
```
#Label Encoding the object dtypes.
LE=LabelEncoder()
for i in object_cols:
    data[i]=data[[i]].apply(LE.fit_transform)

print("All features are now numerical")
```

All features are now numerical

In [208]:
```
LE=LabelEncoder()
for i in object_cols:
    test[i]=test[[i]].apply(LE.fit_transform)
```

In [209]:
```
#Creating a copy of data
ds = data.copy()
# creating a subset of dataframe by dropping the features on deals accepted
cols_del = ['AcceptedCmp3', 'AcceptedCmp4', 'AcceptedCmp5', 'AcceptedCmp1',
ds = ds.drop(cols_del, axis=1)
```

In [210]:
```
ts = test.copy()
ts = ts.drop(cols_del, axis=1)
```

In [211]:
```
#Scaling
scaler = StandardScaler()
scaler.fit(ds)
scaled_ds = pd.DataFrame(scaler.transform(ds),columns= ds.columns )
print("All features are now scaled")
```

All features are now scaled

In [212]:
```
scaler = StandardScaler()
scaler.fit(ts)
scaled_ts = pd.DataFrame(scaler.transform(ts),columns= ts.columns )
```

In [213]:
```
#Scaled data to be used for reducing the dimensionality
print("Dataframe to be used for further modelling:")
scaled_ds.head()
```

Dataframe to be used for further modelling:

Out[213]:

	Education	Marital_Status	Income	Kidhome	Teenhome	Recency	MntCoke	MntFruits
0	-0.802765	-1.489737	0.287258	-0.827652	-0.909671	0.308614	0.974724	1.57507
1	-0.802765	-1.489737	-0.264686	1.001034	0.908587	-0.383107	-0.868284	-0.63067
2	-0.802765	0.024072	0.917871	-0.827652	-0.909671	-0.798139	0.357434	0.58629
3	-0.802765	0.024072	-1.186528	1.001034	-0.909671	-0.798139	-0.868284	-0.55461
4	1.064415	1.033277	0.294512	1.001034	-0.909671	1.553710	-0.389811	0.43416

5 rows × 21 columns

Clustering

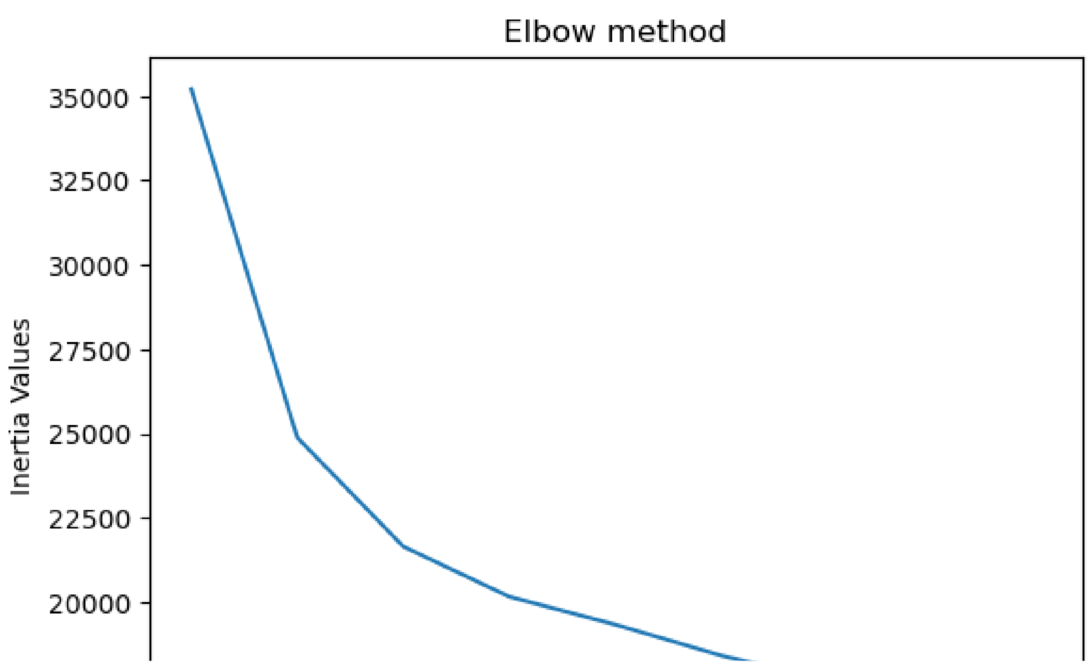
The clustering will be performed by Agglomerative clustering. Agglomerative clustering is a hierarchical clustering method. It involves merging examples until the desired number of clusters is achieved.

Steps involved in the Clustering:

```
Elbow Method to determine the number of clusters to be formed
Clustering via Agglomerative Clustering
Examining the clusters formed via scatter plot
```

In [214]:
```
inertia_values=[]
k = range(1,10)
for i in k:
    model = KMeans(n_clusters=i)
    model.fit(scaled_ds)
    inertia_values.append(model.inertia_)
```

In [215]:
```
plt.plot(k,inertia_values)
plt.title("Elbow method")
plt.xlabel("K Values")
plt.ylabel("Inertia Values")

plt.show()
```



In [216]:
```
score = silhouette_score(scaled_ds, model.labels_, metric='euclidean')
score
```

Out[216]: 0.14616140075079537

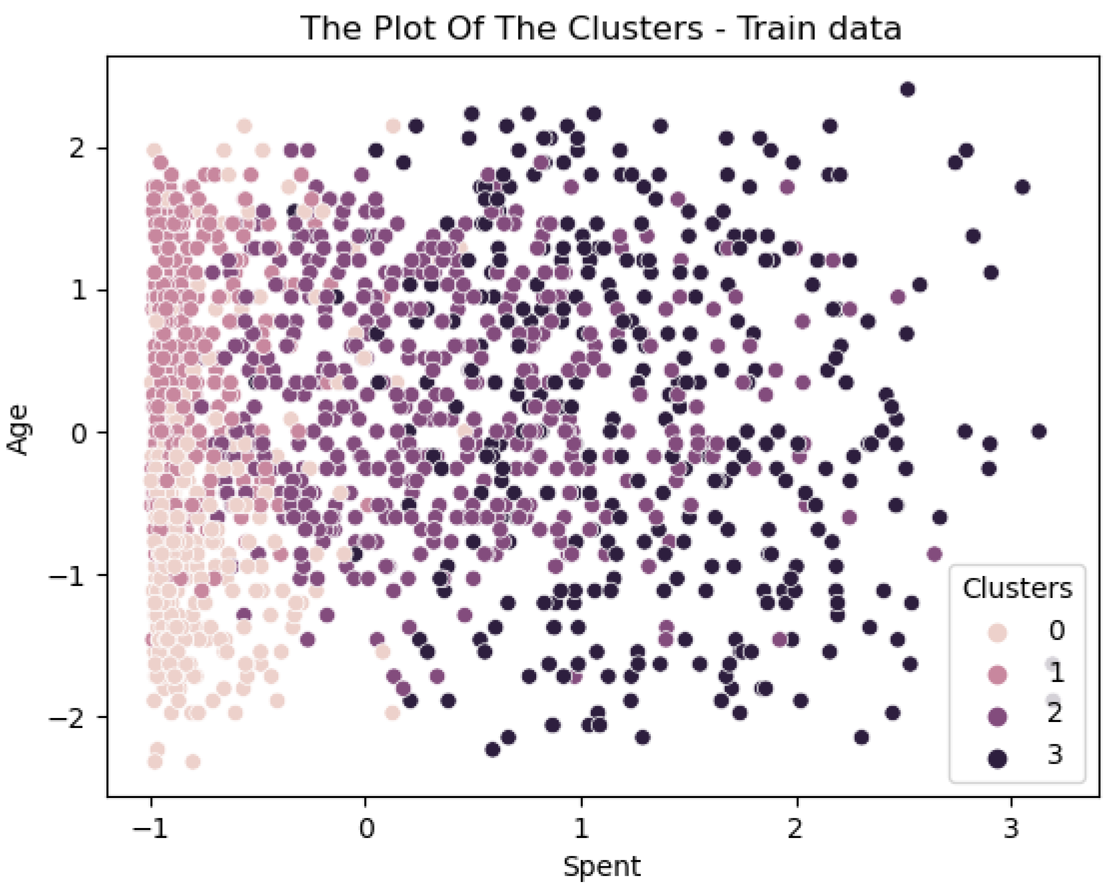
In [217]:
```
#Initiating the Agglomerative Clustering model with k=4
AC = AgglomerativeClustering(n_clusters=4)
# fit model and predict clusters
yhat_AC = AC.fit_predict(scaled_ds)
scaled_ds["Clusters"] = yhat_AC
#Adding the Clusters feature to the orignal dataframe.
data["Clusters"]= yhat_AC
```

In [218]:
```
test_AC = AC.fit_predict(scaled_ts)
scaled_ts["Clusters"] = test_AC
test["Clusters"]= test_AC
```

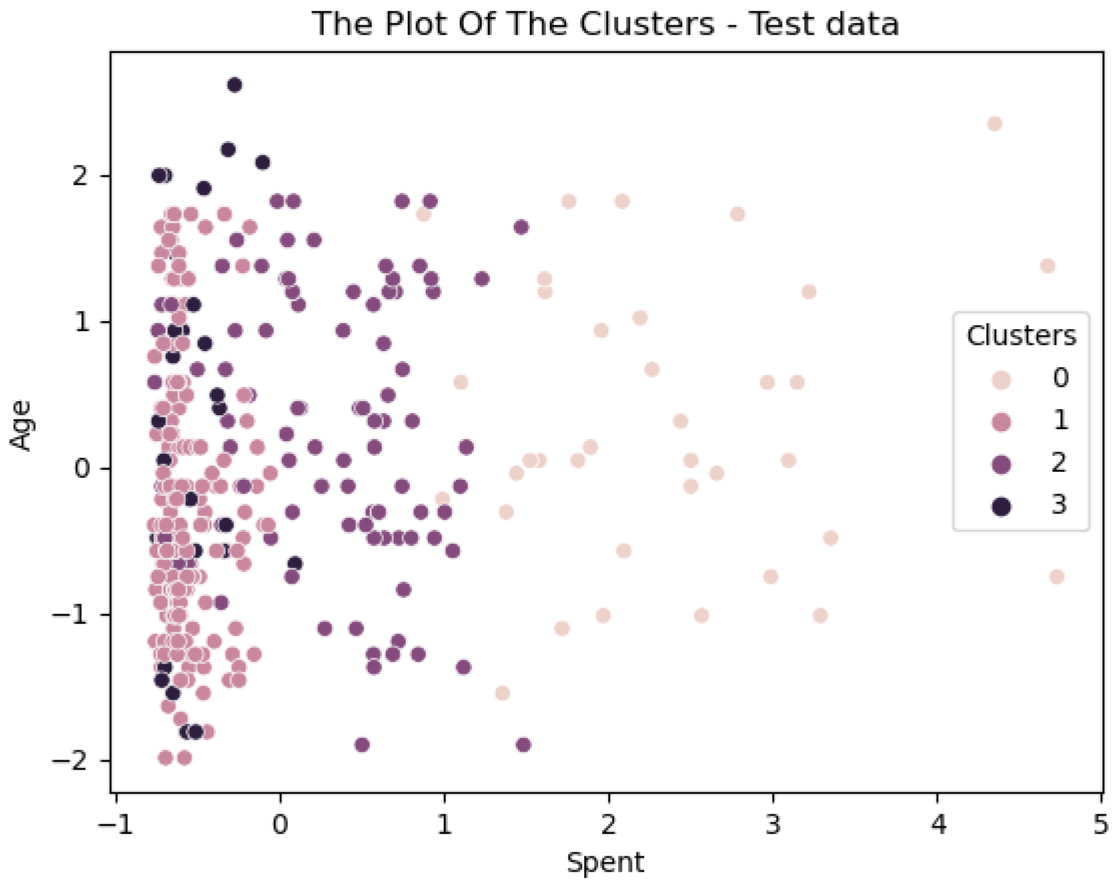
In [219]:
```
score = silhouette_score(scaled_ds, model.labels_, metric='euclidean')
score
```

Out[219]: 0.15411881363017987

In [220]:
```
#Plotting the clusters for train data

sns.scatterplot(data = scaled_ds,x=scaled_ds["Spent"], y=scaled_ds["Age"],h
plt.title("The Plot Of The Clusters - Train data")
plt.show()
```



In [221]:
```
#Plotting the clusters for test data
sns.scatterplot(data = scaled_ts,x=scaled_ts["Spent"], y=scaled_ts["Age"],h
plt.title("The Plot Of The Clusters - Test data")
plt.show()
```



Evaluating Models

The purpose of this section is to study the patterns in the clusters formed and determine the nature of the clusters' patterns.

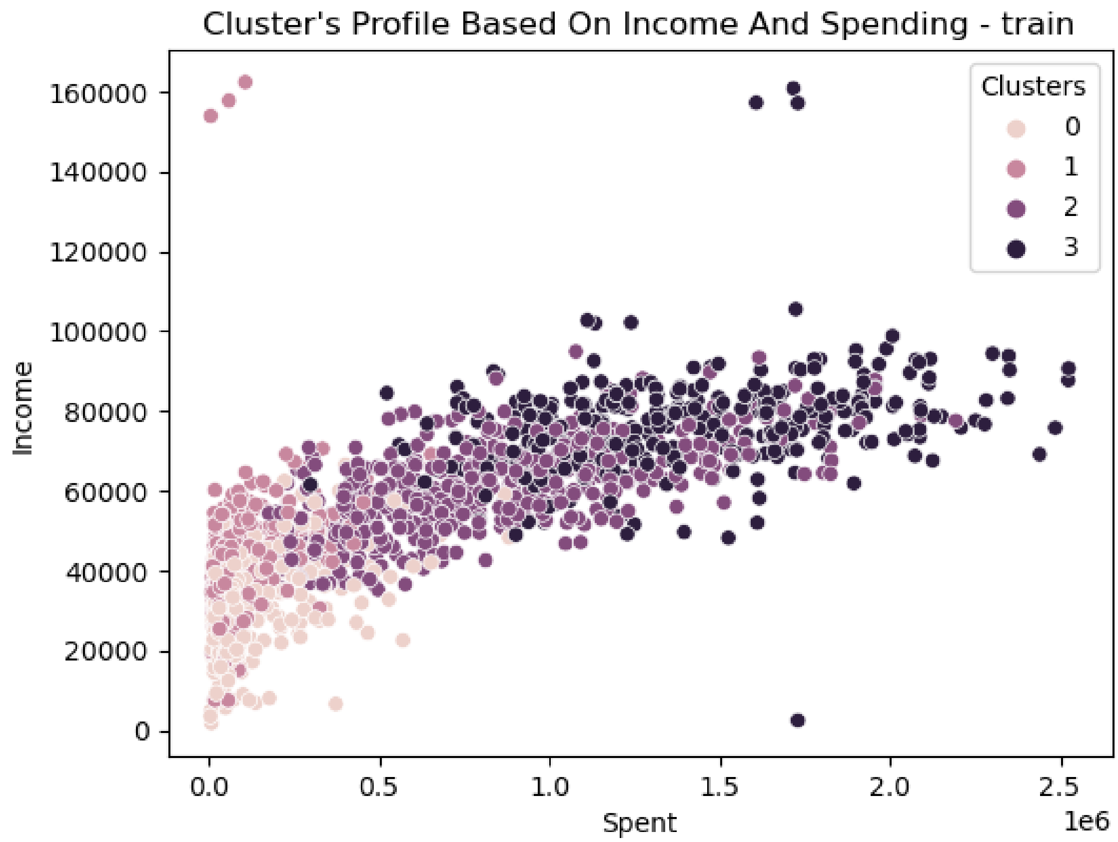
In [222]:
```
pl = sns.countplot(x=test["Clusters"])
pl.set_title("Distribution Of The Clusters for test data")
```

Out[222]:
```
Text(0.5, 1.0, 'Distribution Of The Clusters for test data')
```

The clusters seem to be fairly distributed

In [223]:
```
pl = sns.scatterplot(data = data,x=data["Spent"], y=data["Income"],hue=data
pl.set_title("Cluster's Profile Based On Income And Spending - train")
```

Out[223]:
```
Text(0.5, 1.0, "Cluster's Profile Based On Income And Spending - train")
```

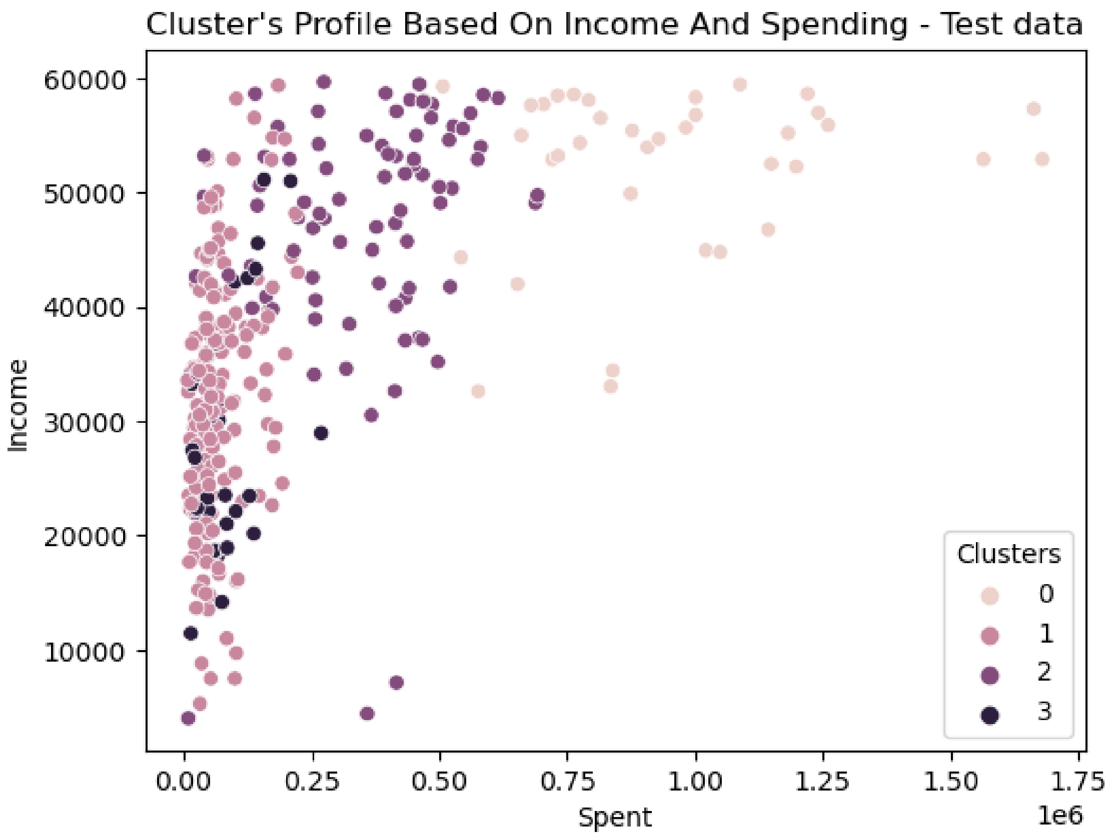


Classification

```
Group 0: Low income and low spending
Group 1: High income and high spending
Group 2: High income and low spending
Group 3: Average income and average spending
```

In [105]:
```
pl = sns.scatterplot(data = test,x=test["Spent"], y=test["Income"],hue=test
pl.set_title("Cluster's Profile Based On Income And Spending - Test data")
```

Out[105]:
```
Text(0.5, 1.0, "Cluster's Profile Based On Income And Spending - Test dat
a")
```

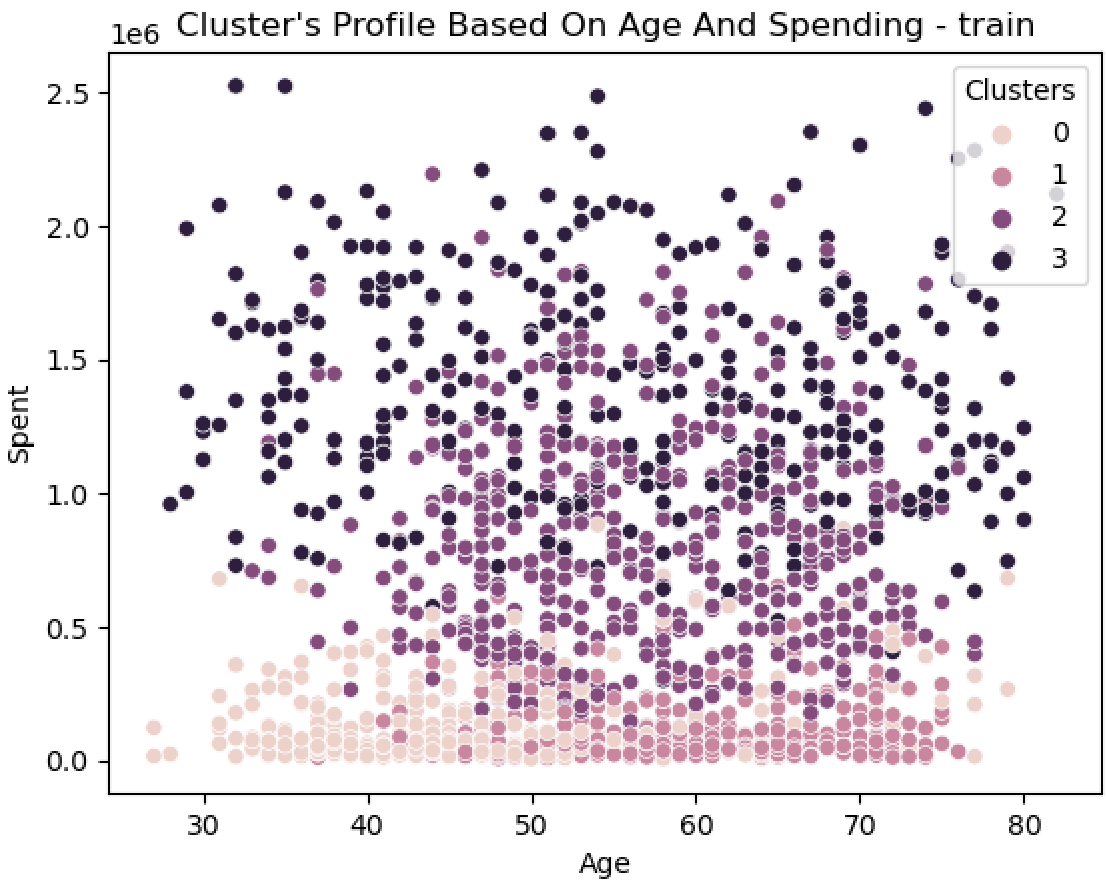


Classification

```
Group 0: High income and average spending
Group 1: Low income and low spending
Group 2: Low income high spending
Group 3: Average income and low spending
```

In [106]:
```
pl = sns.scatterplot(data = data,x=data["Age"], y=data["Spent"],hue=data["C
pl.set_title("Cluster's Profile Based On Age And Spending - train")
```

Out[106]: Text(0.5, 1.0, "Cluster's Profile Based On Age And Spending - train")



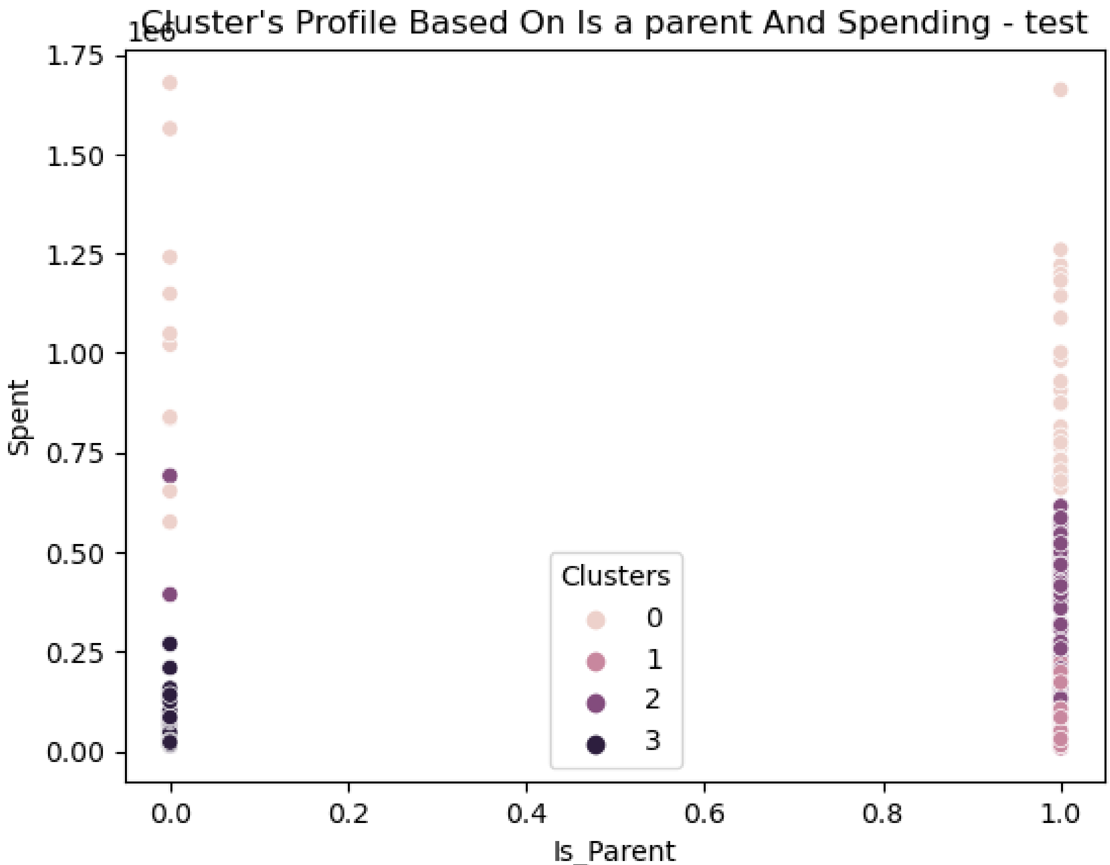
In [107]:
```
pl = sns.scatterplot(data = test,x=test["Age"], y=test["Spent"],hue=test["C
pl.set_title("Cluster's Profile Based On Age And Spending - test")
```

Out[107]:
```
Text(0.5, 1.0, "Cluster's Profile Based On Age And Spending - test")
```

Group 0: Age between 40 & 80 with average to high spending Group 1: Age between 30 & 80 with average spending Group 2: Age between 25 & 80 with high spending Group 3: Age between 40 & 70 low spending

In [108]:
```
pl = sns.scatterplot(data = test,x=test["Is_Parent"], y=test["Spent"],hue=t
pl.set_title("Cluster's Profile Based On Is a parent And Spending - test")
```

Out[108]:
```
Text(0.5, 1.0, "Cluster's Profile Based On Is a parent And Spending - tes
t")
```

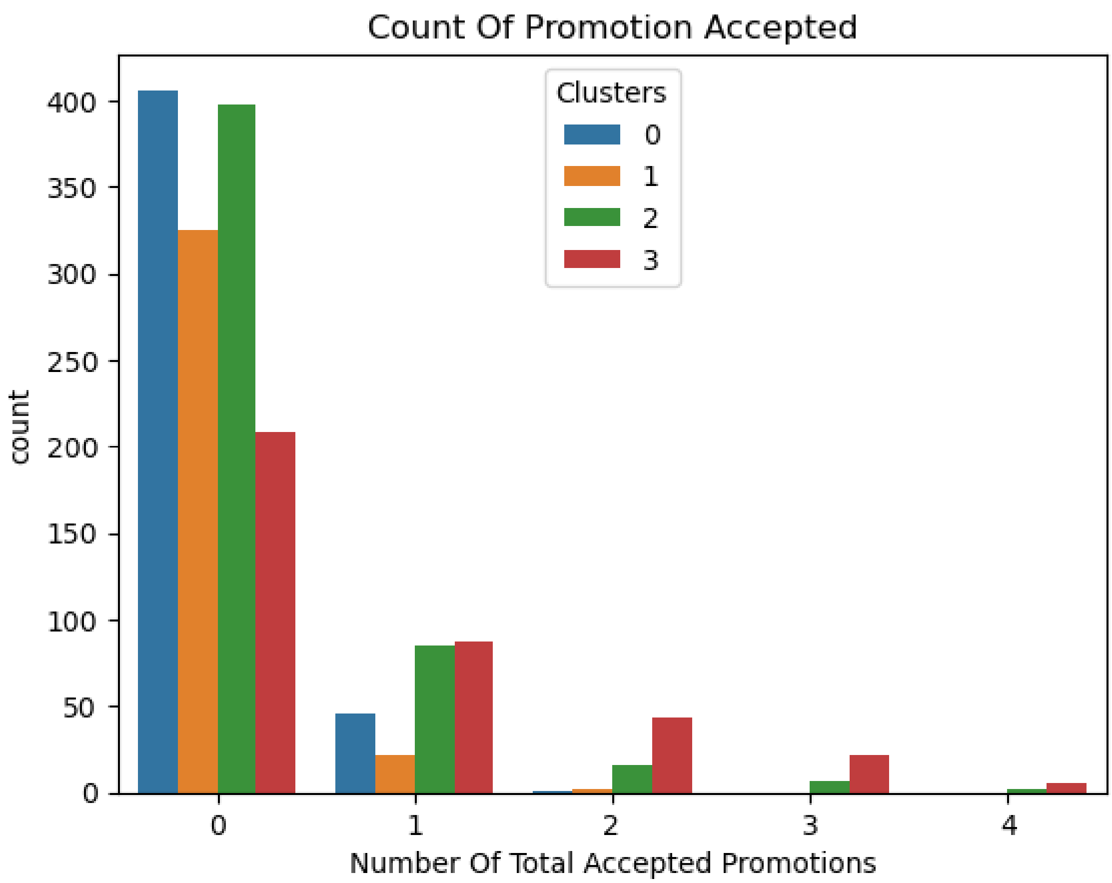


Most spending comes from customers who are not parents

In [109]:

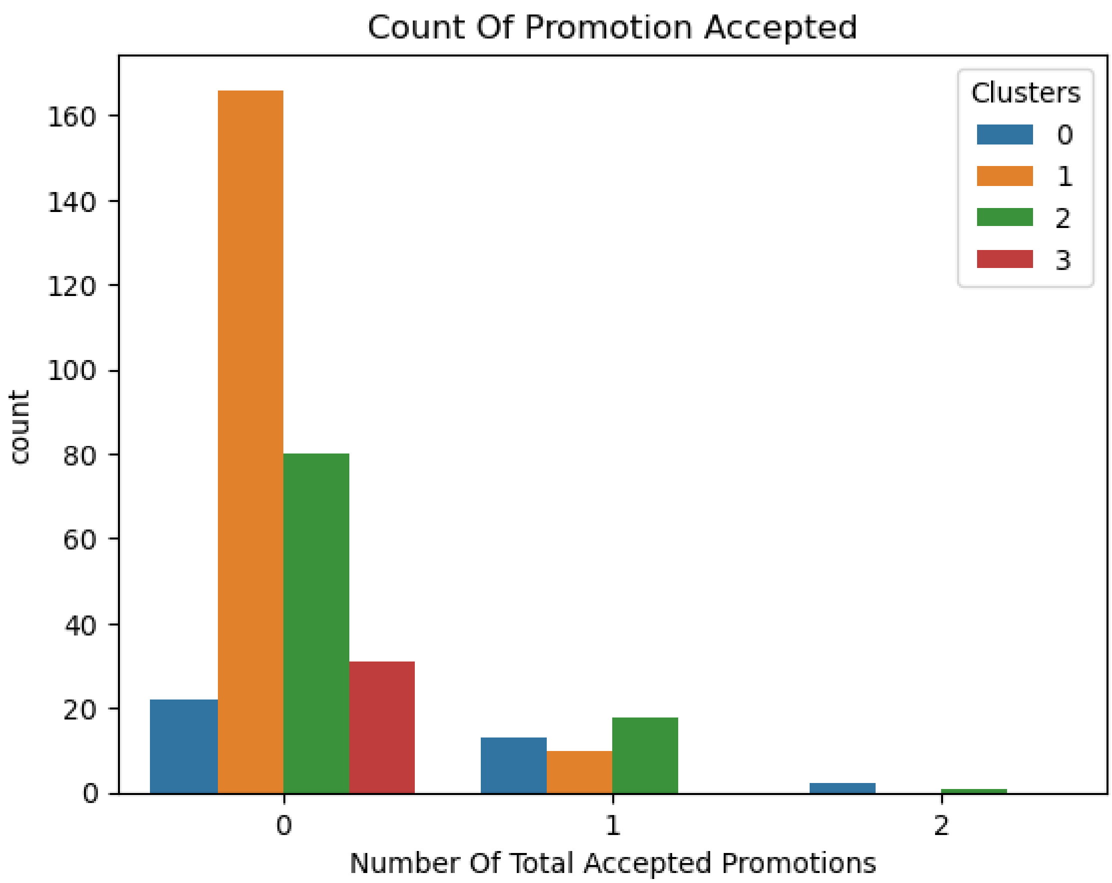
```
#Creating a feature to get a sum of accepted promotions for train data
data["Total_Promos"] = data["AcceptedCmp1"]+ data["AcceptedCmp2"]+ data["Ac
#Plotting count of total campaign accepted.
pl = sns.countplot(x=data["Total_Promos"],hue=data["Clusters"])
pl.set_title("Count Of Promotion Accepted")
pl.set_xlabel("Number Of Total Accepted Promotions")
```

Out[109]: Text(0.5, 0, 'Number Of Total Accepted Promotions')



In [110]:
```
#Creating a feature to get a sum of accepted promotions for test data
test["Total_Promos"] = test["AcceptedCmp1"]+ test["AcceptedCmp2"]+ test["Ac
#Plotting count of total campaign accepted.
pl = sns.countplot(x=test["Total_Promos"],hue=test["Clusters"])
pl.set_title("Count Of Promotion Accepted")
pl.set_xlabel("Number Of Total Accepted Promotions")
```

Out[110]:
```
Text(0.5, 0, 'Number Of Total Accepted Promotions')
```



There isnt any overwhelming response to the campaigns so far. There are only a few participants overall. Moreover, no one has taken part in all 5 of them. Perhaps better-targeted and well-planned campaigns are required to boost sales.

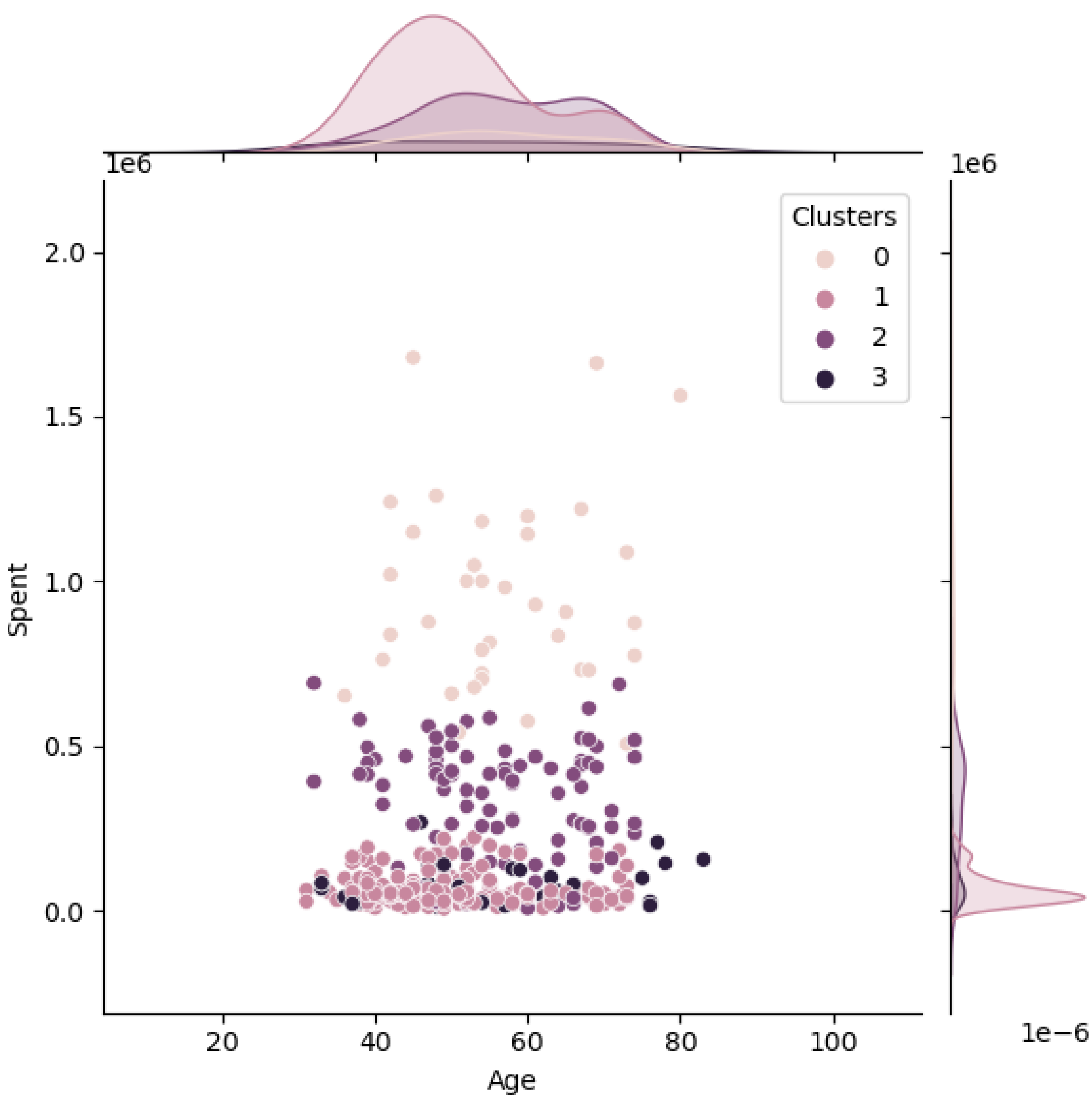
Profiling the clusters

This is done to get an idea about who are valuable customer and who needs more attention from the retail store's marketing team. Plotting some of the features that indicates customer's personal traits based on the cluster they are in.

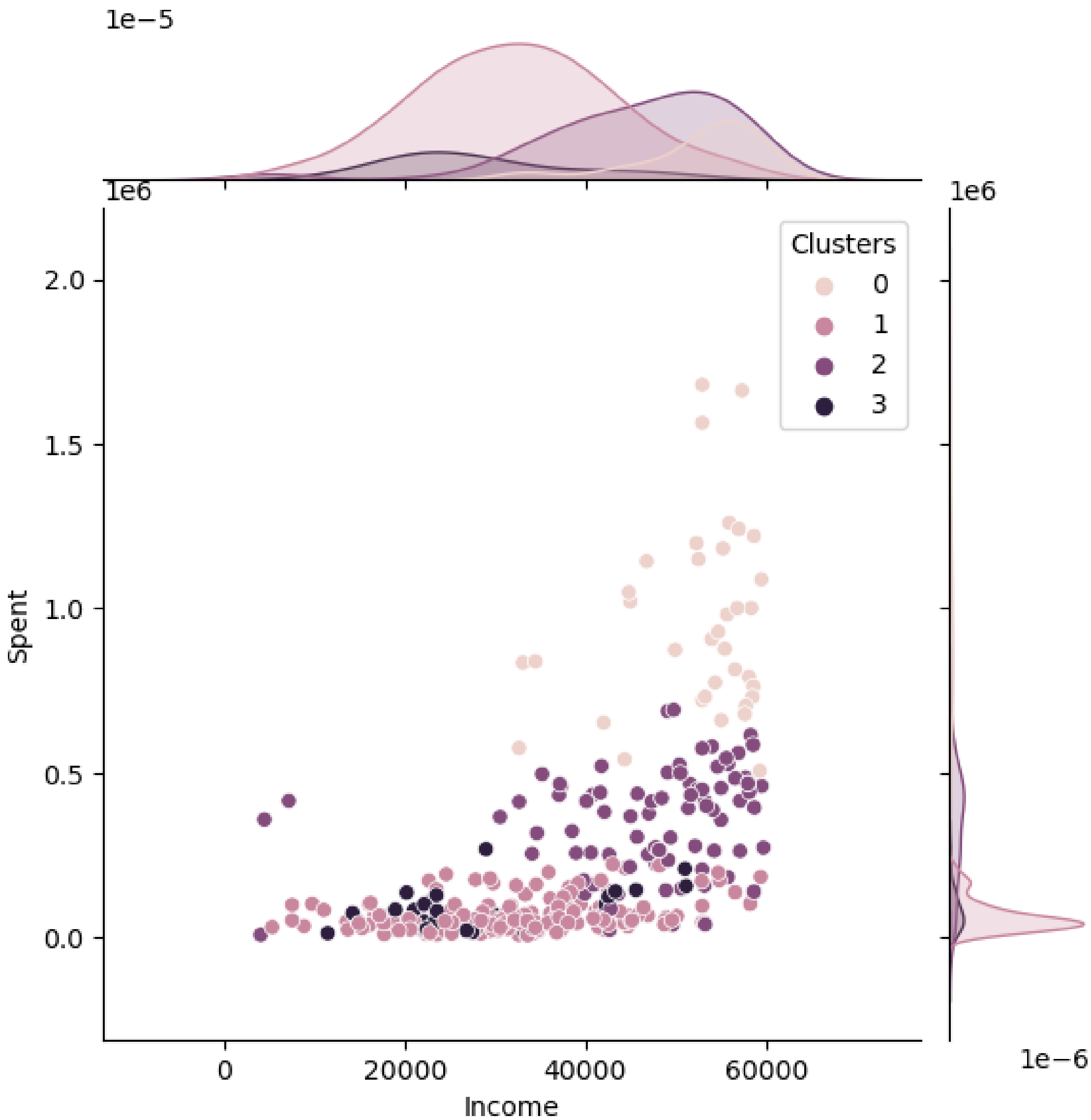
In [111]:

```
Features = ["Age","Income", "Marital_Status", "Teenhome", "Is_Parent", "Edu

for i in Features:
    plt.figure()
    sns.jointplot(x=test[i], y=test["Spent"], hue =test["Clusters"], kind="
    plt.show()
```

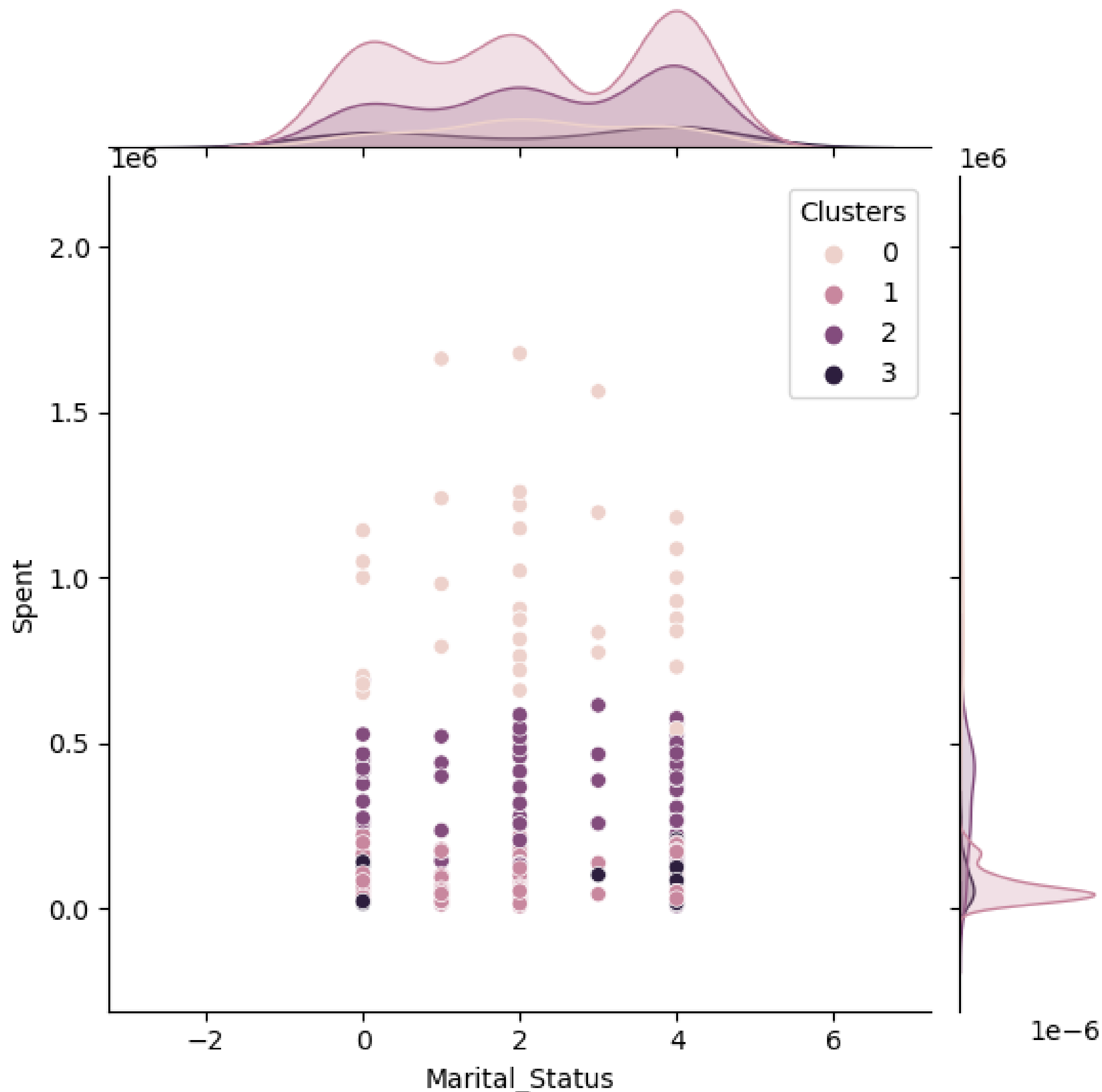
```
<Figure size 640x480 with 0 Axes>
```



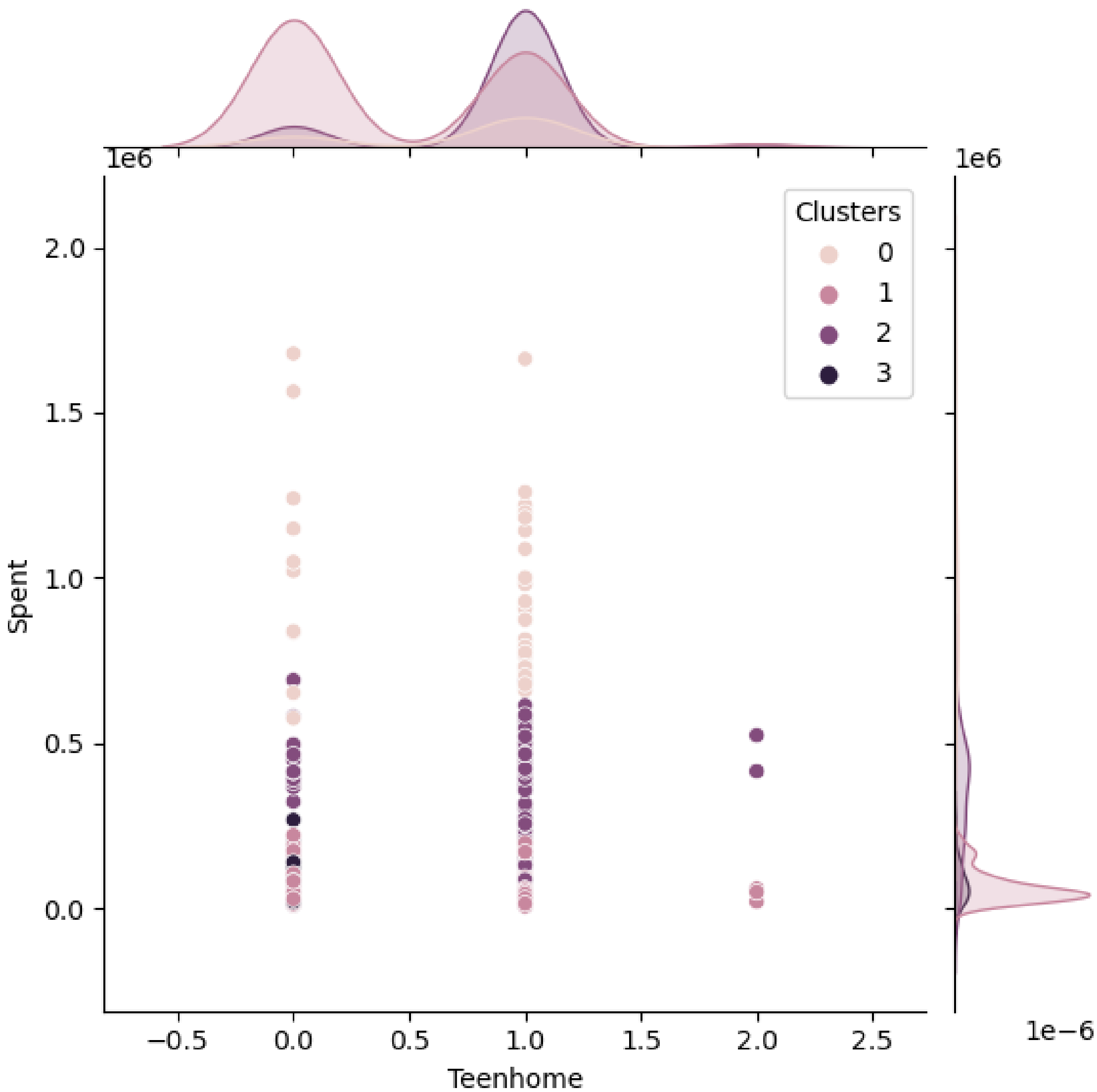

```
<Figure size 640x480 with 0 Axes>
```



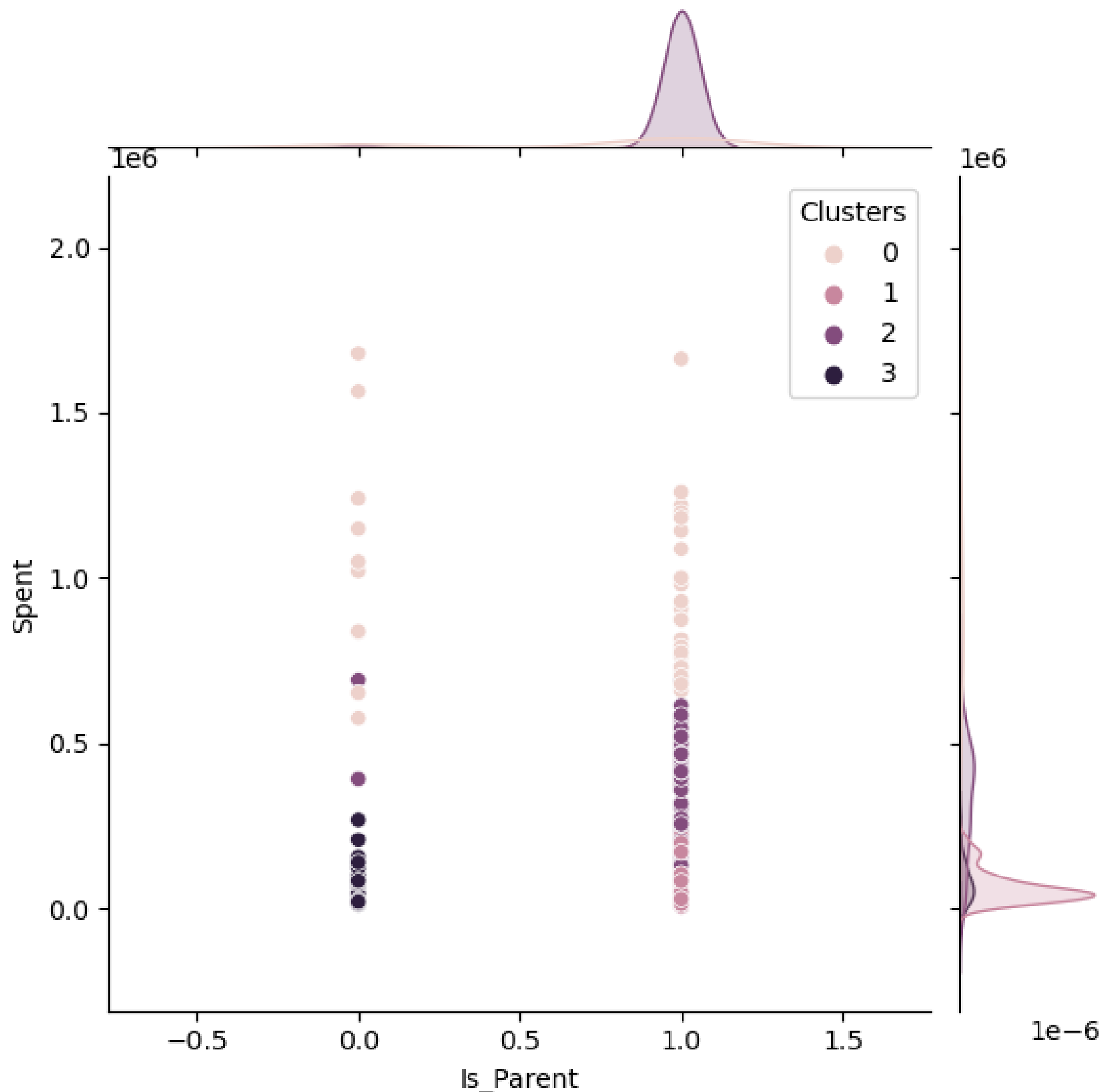

```
<Figure size 640x480 with 0 Axes>
```



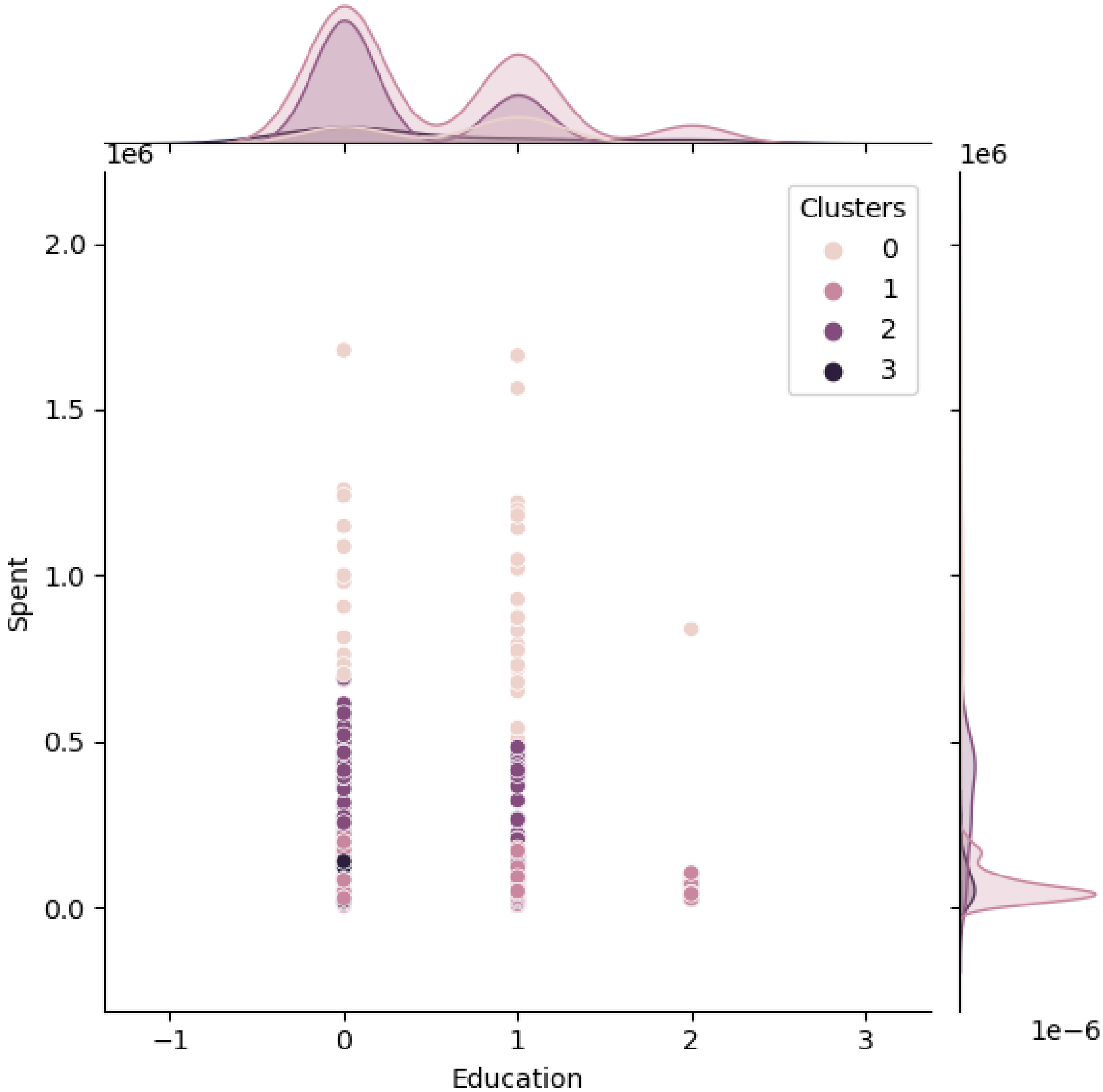

```
<Figure size 640x480 with 0 Axes>
```



<Figure size 640x480 with 0 Axes>




```
<Figure size 640x480 with 0 Axes>
```



The following inferences are obtained from the analysis:

Cluster 0:

```
Between age 40 & 80 with average spending with high income. Mostly par
ents with teens at home. Mostly graduates
```

Cluster 1:

```
Between age 20 & 90 with low spending and low-average income. Mostly p
arents with all education types
```

Cluster 2:

```
Between age 40 & 80 with high spending and average to high income. Inc
ludes people in all marital status and all education types
```

Cluster 3:

```
Between age 40 & 80 low spending and mostly high income. There are mos
tly parents with teens.
```

Classification

Trying the classification using Random Forest Classifier

In [224]:
```
data.head()
data.shape
```
Out[224]:
```
(1677, 30)
```

In [225]:
```
scaled_ds.shape
```
Out[225]:
```
(1677, 22)
```

In [226]:
```
scaled_ds["Response"] = data["Response"]
scaled_ds["Response"].unique()
```
Out[226]:
```
array([ 1.,  0., nan])
```

In [227]:
```
scaled_ds = scaled_ds.dropna()
```

In [236]:
```
# Classifying based on response for promotion

scaled_ts["Response"] = test["Response"]
scaled_ts = scaled_ts.dropna()
```

In [230]:
```
target = ["Response"]
x_train = scaled_ds.drop(target, axis=1)
y_train = scaled_ds[target]
```

In [237]:
```
x_test = scaled_ts.drop(target,axis=1)
y_test = scaled_ts[target]
```

In [231]:
```
from sklearn.ensemble import RandomForestClassifier
model = RandomForestClassifier()
model.fit(x_train, y_train)
```
Out[231]:
```
RandomForestClassifier()
```

In [232]:
```
model.score(x_train,y_train)
```
Out[232]:
```
0.983273596176822
```

In [238]:
```
model.score(x_test,y_test)
```
Out[238]:
```
0.8640776699029126
```

In [165]:
```
#Classifying based on clusters

target = ["Clusters"]
x_train = scaled_ds.drop(target, axis=1)
y_train = scaled_ds[target]
```

In [166]:
```
x_test = scaled_ts.drop(target,axis=1)
y_test = scaled_ts["Clusters"]
```

In [167]:
```
model = RandomForestClassifier()
model.fit(x_train, y_train)
```

Out[167]:
```
RandomForestClassifier()
```

In [168]:
```
model.score(x_train,y_train)
```

Out[168]:
```
1.0
```

In [169]:
```
model.score(x_test,y_test)
```

Out[169]:
```
0.41690962099125367
```

In [170]:
```
model.predict([[-0.768549,-0.138043,0.025063,0.764156,0.823622,1.271718,-0.
```

Out[170]:
```
array([2], dtype=int64)
```

In [171]:
```
y_test.values[2]
```

Out[171]:
```
1
```

In [172]:
```
y_test.iloc[0]
```

Out[172]:
```
1
```

The cluster is predicted correctly for the given input and the accuracy score for test data is 0.42

Conclusion

The dataset is analysed and segmented using unsupervised clustering. The whole customers are categorized in to 4 clusters based on their income, age and family background. This can be made use by the company to plan their products and promotions.

Thank you!!

In [ ]:
```

```