Comparing Clustering methods in Customer Segementation

In [ ]:
```
# # Mount drive to have access to the data This can be removed in the final
# # version of the notebook this is only needed for colab
# from google.colab import drive
# drive.mount('/content/drive')
# !pip install matplotlib==3.4.3
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
Requirement already satisfied: matplotlib==3.4.3 in /usr/local/lib/python3.7/dist-packages (3.4.3)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.7/dist-packages (from matplotlib==3.4.3) (7.1.2)
Requirement already satisfied: numpy>=1.16 in /usr/local/lib/python3.7/dist-packages (from matplotlib==3.4.3) (1.21.5)
Requirement already satisfied: pyparsing>=2.2.1 in /usr/local/lib/python3.7/dist-packages (from matplotlib==3.4.3) (3.0.7)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.7/dist-packages (from matplotlib==3.4.3) (1.4.0)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.7/dist-packages (from matplotlib==3.4.3) (0.11.0)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.7/dist-packages (from matplotlib==3.4.3) (2.8.2)
Requirement already satisfied: typing-extensions in /usr/local/lib/python3.7/dist-packages (from kiwisolver>=1.0.1->matplotlib==3.4.3) (3.10.0.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/dist-packages (from python-dateutil>=2.7->matplotlib==3.4.3) (1.15.0)
```

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

from matplotlib import colors

from sklearn import metrics
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans, AgglomerativeClustering, SpectralClustering

from yellowbrick.cluster import KElbowVisualizer

from mpl_toolkits.mplot3d import Axes3D

import warnings
warnings.filterwarnings('ignore')
np.random.seed(120)
```

In [ ]:
```
data = pd.read_csv("/content/drive/MyDrive/marketing_campaign.csv", sep="\t")
data.head()
```

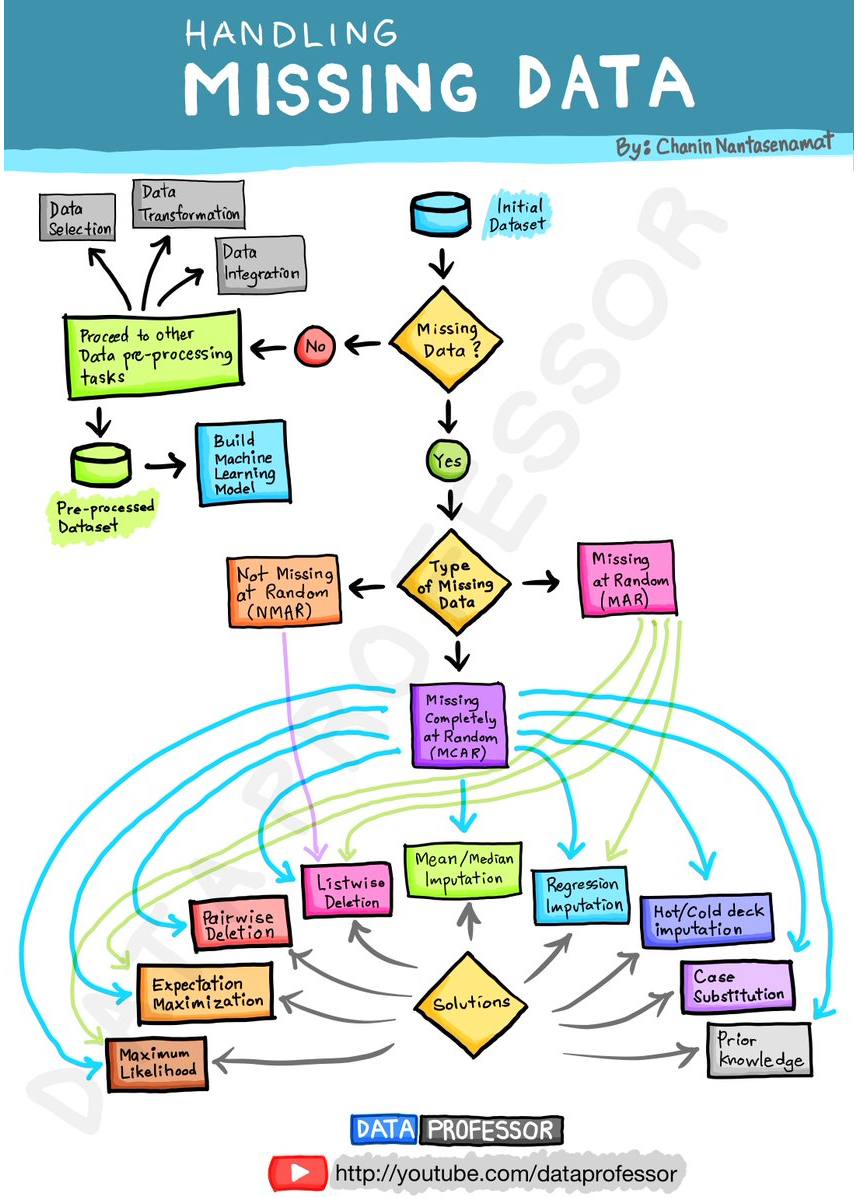
Out[ ]:

	ID	Year_Birth	Education	Marital_Status	Income	Kidhome	Teenhome	Dt_Customer	Recency	MntWines	...	NumWebVisitsMonth	AcceptedCmp3	AcceptedCmp4	AcceptedCmp5	AcceptedCmp1	AcceptedCmp2	Complain	Z_C
0	5524	1957	Graduation	Single	58138.0	0	0	04-09-2012	58	635	...	7	0	0	0	0	0	0	
1	2174	1954	Graduation	Single	46344.0	1	1	08-03-2014	38	11	...	5	0	0	0	0	0	0	
2	4141	1965	Graduation	Together	71613.0	0	0	21-08-2013	26	426	...	4	0	0	0	0	0	0	
3	6182	1984	Graduation	Together	26646.0	1	0	10-02-2014	26	11	...	6	0	0	0	0	0	0	
4	5324	1981	PhD	Married	58293.0	1	0	19-01-2014	94	173	...	5	0	0	0	0	0	0	

5 rows × 29 columns

Handling Missing Data And Preprocessing

We need to first in order to do any data preprocessing, deal with missing data. Included is a helpful graphic created by youtuber data professor



The first thing, which should be looked at is the columns, according to the descriptions available from the source of the dataset, here. The two columns **Z_Revenue**, **Z_CostContact** have the same data in each record and do not add any informaiton and can be dropped. This we can confirm by checking for unique values in those rows before dropping them, we are dropping them to prior to modifying the dataset further so they do not get in the way.

In [ ]:
```
print('Column: Unique Values')
for col in data:
  print(f'{col}: {len(data[col].unique())}')

# since those 2 columns only have 1 unqiue value we can drop them

data = data.drop(columns=['Z_Revenue', 'Z_CostContact', 'ID'])
```

```
Column: Unique Values
ID: 2240
Year_Birth: 59
Education: 5
Marital_Status: 8
Income: 1975
Kidhome: 3
Teenhome: 3
Dt_Customer: 663
Recency: 100
MntWines: 776
MntFruits: 158
MntMeatProducts: 558
MntFishProducts: 182
MntSweetProducts: 177
MntGoldProds: 213
NumDealsPurchases: 15
NumWebPurchases: 15
NumCatalogPurchases: 14
NumStorePurchases: 14
NumWebVisitsMonth: 16
AcceptedCmp3: 2
AcceptedCmp4: 2
AcceptedCmp5: 2
AcceptedCmp1: 2
AcceptedCmp2: 2
Complain: 2
Z_CostContact: 1
Z_Revenue: 1
Response: 2
```

Lets first look at the information of the dataset, this can give us a better look into the data we are working with. For this we will just preform a simple listwise deletion for any data which is missing.

In [ ]:
```
data.info()
data = data.dropna() # This is the listwise deletion
print('\n After performing listwise deletion. \n')
print(f"Records after listwise deletion {len(data)}")
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2240 entries, 0 to 2239
Data columns (total 26 columns):
 #   Column               Non-Null Count  Dtype
```

```
 0   Year_Birth           2240 non-null   int64
 1   Education            2240 non-null   object
 2   Marital_Status       2240 non-null   object
 3   Income               2216 non-null   float64
 4   Kidhome              2240 non-null   int64
 5   Teenhome             2240 non-null   int64
 6   Dt_Customer          2240 non-null   object
 7   Recency              2240 non-null   int64
 8   MntWines             2240 non-null   int64
 9   MntFruits            2240 non-null   int64
 10  MntMeatProducts      2240 non-null   int64
 11  MntFishProducts      2240 non-null   int64
 12  MntSweetProducts     2240 non-null   int64
 13  MntGoldProds         2240 non-null   int64
 14  NumDealsPurchases    2240 non-null   int64
 15  NumWebPurchases      2240 non-null   int64
 16  NumCatalogPurchases  2240 non-null   int64
 17  NumStorePurchases    2240 non-null   int64
 18  NumWebVisitsMonth    2240 non-null   int64
 19  AcceptedCmp3         2240 non-null   int64
 20  AcceptedCmp4         2240 non-null   int64
 21  AcceptedCmp5         2240 non-null   int64
 22  AcceptedCmp1         2240 non-null   int64
 23  AcceptedCmp2         2240 non-null   int64
 24  Complain             2240 non-null   int64
 25  Response             2240 non-null   int64
dtypes: float64(1), int64(22), object(3)
memory usage: 455.1+ KB

 After performing listwise deletion.

Records after listwise deletion 2216
```

Lets look at the summary statistics of the data we will be using during the dimensionality reduction.

In [ ]:
```
pd.set_option('display.float_format', lambda x: '%.2f' % x)
data.drop(['AcceptedCmp3', 'AcceptedCmp4', 'AcceptedCmp5', 'AcceptedCmp1','AcceptedCmp2', 'Complain', 'Response'], axis=1).describe()
```

Out[ ]:

	Year_Birth	Income	Kidhome	Teenhome	Recency	MntWines	MntFruits	MntMeatProducts	MntFishProducts	MntSweetProducts	MntGoldProds	NumDealsPurchases	NumWebPurchases	NumCatalogPurchases	NumStorePurcha
count	2216.00	2216.00	2216.00	2216.00	2216.00	2216.00	2216.00	2216.00	2216.00	2216.00	2216.00	2216.00	2216.00	2216.00	221
mean	1968.82	52247.25	0.44	0.51	49.01	305.09	26.36	167.00	37.64	27.03	43.97	2.32	4.09	2.67	
std	11.99	25173.08	0.54	0.54	28.95	337.33	39.79	224.28	54.75	41.07	51.82	1.92	2.74	2.93	
min	1893.00	1730.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
25%	1959.00	35303.00	0.00	0.00	24.00	24.00	2.00	16.00	3.00	1.00	9.00	1.00	2.00	0.00	
50%	1970.00	51381.50	0.00	0.00	49.00	174.50	8.00	68.00	12.00	8.00	24.50	2.00	4.00	2.00	
75%	1977.00	68522.00	1.00	1.00	74.00	505.00	33.00	232.25	50.00	33.00	56.00	3.00	6.00	4.00	
max	1996.00	666666.00	2.00	2.00	99.00	1493.00	199.00	1725.00	259.00	262.00	321.00	15.00	27.00	28.00	1

Now that we have removed data which is not necessary for analysis we can continue to do some preprocessing, turning categorical data into numerical values which can be used. First we will take the dt_customer and turn it into a integer of how long they have been a customer with a 0 for the newest customer and days from that date as the others.

In [ ]:
```
data["Dt_Customer"] = pd.to_datetime(data["Dt_Customer"])
max_date = max(data["Dt_Customer"])
data["Customer_For"] = data["Dt_Customer"].apply(lambda x: max_date.date() - x.date())
data["Customer_For"] = pd.to_numeric(data["Customer_For"], errors="coerce")
```

In [ ]:
```
# join martial status and make it a categoritcal column
data["Marital_Status"] = data["Marital_Status"].replace({"Together":"Married", "Absurd":"Single", "YOLO":"Single", "Alone": "Single", "Maried": "Married"})
data["Marital_Status"] = pd.Categorical(data["Marital_Status"])

# adding the number of teens and kids home to create a total number of children in the house hold
data["Children"] = data["Kidhome"] + data["Teenhome"]

# setting the age of the custer based on when the dataset was created (max date of custeromer membership)
data["Age"] = max_date.year-data["Year_Birth"]

# Thte total  spend at the grocery store based on everything spent at the store
data["Spent"] = data["MntWines"] + data["MntFruits"] + data["MntMeatProducts"] + data["MntFishProducts"] + data["MntSweetProducts"] + data["MntGoldProds"]

# a temp to count for marital status and then the total size of the family of the customer
data["Living_With"] = data["Marital_Status"].replace({"Married": 2,  "Widow": 1, "Divorced": 1, "Single": 1})
data["Family_Size"] = data["Living_With"] + data["Children"]

# a true false for parent status
data["Is_Parent"] = np.where(data.Children> 0, 1, 0)

# simplify the Education category and turn it into a categoritcal column
data["Education"] = data["Education"].replace({"Basic":"Undergraduate","2n Cycle":"Undergraduate", "Graduation":"Graduate", "Master":"Postgraduate", "PhD":"Postgraduate"})
data["Education"] = pd.Categorical(data["Education"])

# rename columns to make it more simple to understand
data = data.rename(columns={"MntWines": "SpentOnWines","MntFruits":"SpentOnFruits","MntMeatProducts":"SpentOnMeat","MntFishProducts":"SpentOnFish","MntSweetProducts":"SpentOnSweets","MntGoldProd

# drop unnecessary columns
data = data.drop(columns=["Dt_Customer", "Living_With", "Year_Birth"])
```

Lets see the summary statisitics of the data, this will allow us to see any unusual data such as outliers

In [ ]:
```
data.describe()
```

Out[ ]:

	Income	Kidhome	Teenhome	Recency	SpentOnWines	SpentOnFruits	SpentOnMeat	SpentOnFish	SpentOnSweets	SpentOnGold	...	AcceptedCmp1	AcceptedCmp2	Complain	Response	Customer_For	Children	22
count	2216.00	2216.00	2216.00	2216.00	2216.00	2216.00	2216.00	2216.00	2216.00	2216.00	...	2216.00	2216.00	2216.00	2216.00	2216.00	2216.00	22
mean	52247.25	0.44	0.51	49.01	305.09	26.36	167.00	37.64	27.03	43.97	...	0.06	0.01	0.01	0.15	4423734584837544 8.00	0.95	
std	25173.08	0.54	0.54	28.95	337.33	39.79	224.28	54.75	41.07	51.82	...	0.24	0.12	0.10	0.36	2008532455802497 6.00	0.75	
min	1730.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	...	0.00	0.00	0.00	0.00	0.00	0.00	
25%	35303.00	0.00	0.00	24.00	24.00	2.00	16.00	3.00	1.00	9.00	...	0.00	0.00	0.00	0.00	2937600000000000 0.00	0.00	
50%	51381.50	0.00	0.00	49.00	174.50	8.00	68.00	12.00	8.00	24.50	...	0.00	0.00	0.00	0.00	4423230000000000 0.00	1.00	
75%	68522.00	1.00	1.00	74.00	505.00	33.00	232.25	50.00	33.00	56.00	...	0.00	0.00	0.00	0.00	5927040000000000 0.00	1.00	
max	666666.00	2.00	2.00	99.00	1493.00	199.00	1725.00	259.00	262.00	321.00	...	1.00	1.00	1.00	1.00	9184320000000000 0.00	3.00	1

8 rows × 28 columns

We can also look at graphing the data to see if there are any other outliers.

In [ ]:
```
# Color settings for graphing
sns.set(rc={"axes.facecolor":"#ffd4c3","figure.facecolor":"#ffd4c3"})
pallet = ["#131B23", "#d41b2c", "#e05143", "#ea755e", "#f3967c", "#fab59e"]
cmap = colors.ListedColormap(["#131B23", "#d41b2c", "#e05143", "#ea755e", "#f3967c", "#fab59e"])
```

In [ ]:
```
# Lets plot some of the columns
To_Plot = [ "Income", "Recency", "Customer_For", "Age", "Spent", "Is_Parent"]
plt.figure()
sns.pairplot(data[To_Plot], hue= "Is_Parent",palette= (["#131B23","#ED474A"]))
plt.show()
```

```
<Figure size 576x396 with 0 Axes>
```

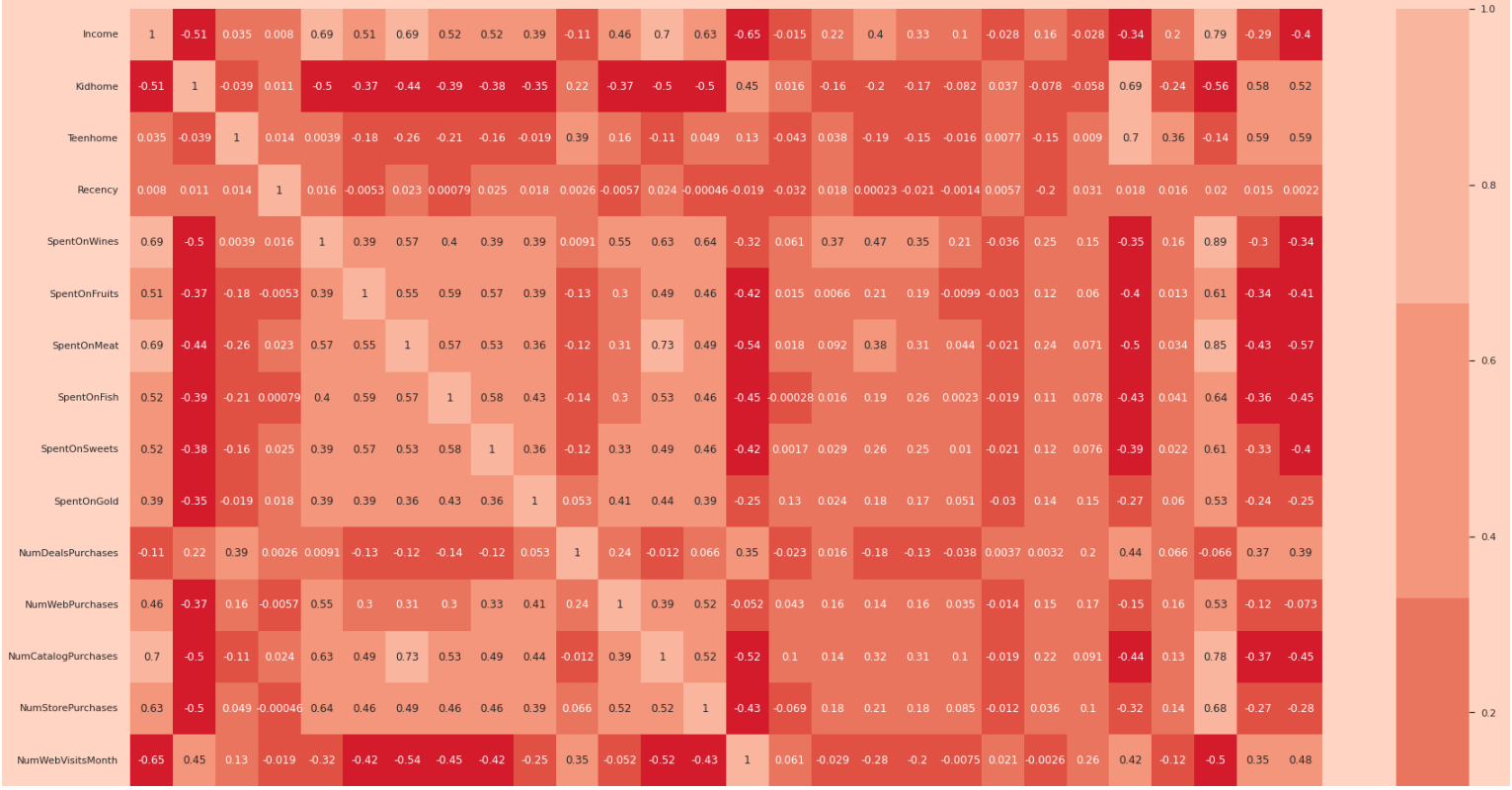
We can see there are outliers in Income and Age so we can remove them thorugh listwise deletion.

In [ ]:
```
# Preform listwise deletion on the outlier data.
data = data[(data["Age"]<90)]
data = data[(data["Income"]<600000)]
print(f"Number of entries after listwise deletion: {len(data)}" )
```

```
Number of entries after listwise deletion: 2212
```

In [ ]:
```
corrmat= data.corr()
plt.figure(figsize=(30,30))
sns.heatmap(corrmat, annot=True, cmap=cmap, center=0)
```

Out[ ]:
```
<AxesSubplot:>
```



In [ ]:
```
# Lets turn each of the categorical columns into numerical data
s = (data.dtypes == 'category')
object_cols = list(s[s].index)

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

In [ ]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2212 entries, 0 to 2239
Data columns (total 30 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   Education            2212 non-null   int64
 1   Marital_Status       2212 non-null   int64
 2   Income               2212 non-null   float64
 3   Kidhome              2212 non-null   int64
 4   Teenhome             2212 non-null   int64
 5   Recency              2212 non-null   int64
 6   SpentOnWines         2212 non-null   int64
 7   SpentOnFruits        2212 non-null   int64
 8   SpentOnMeat          2212 non-null   int64
 9   SpentOnFish          2212 non-null   int64
 10  SpentOnSweets        2212 non-null   int64
 11  SpentOnGold          2212 non-null   int64
 12  NumDealsPurchases    2212 non-null   int64
 13  NumWebPurchases      2212 non-null   int64
 14  NumCatalogPurchases  2212 non-null   int64
 15  NumStorePurchases    2212 non-null   int64
 16  NumWebVisitsMonth    2212 non-null   int64
 17  AcceptedCmp3         2212 non-null   int64
 18  AcceptedCmp4         2212 non-null   int64
 19  AcceptedCmp5         2212 non-null   int64
 20  AcceptedCmp1         2212 non-null   int64
 21  AcceptedCmp2         2212 non-null   int64
 22  Complain             2212 non-null   int64
 23  Response             2212 non-null   int64
 24  Customer_For         2212 non-null   int64
 25  Children             2212 non-null   int64
 26  Age                  2212 non-null   int64
 27  Spent                2212 non-null   int64
 28  Family_Size          2212 non-null   int64
 29  Is_Parent            2212 non-null   int64
dtypes: float64(1), int64(29)
memory usage: 535.7 KB
```

We can then scale the data to make clustering easier for the algorithm.

In [ ]:
```
#Creating a copy of data
ds = data.copy()
# creating a subset of dataframe by dropping the features on deals accepted and promotions
cols_del = ['AcceptedCmp3', 'AcceptedCmp4', 'AcceptedCmp5', 'AcceptedCmp1','AcceptedCmp2', 'Complain', 'Response']
ds = ds.drop(cols_del, axis=1)
#Scaling
scaler = StandardScaler()
scaler.fit(ds)
scaled_ds = pd.DataFrame(scaler.transform(ds),columns= ds.columns )
```

In [ ]:
```
#Scaled data to be used for reducing the dimensionality
scaled_ds.head()
```

Out[ ]:

	Education	Marital_Status	Income	Kidhome	Teenhome	Recency	SpentOnWines	SpentOnFruits	SpentOnMeat	SpentOnFish	...	NumWebPurchases	NumCatalogPurchases	NumStorePurchases	NumWebVisitsMonth	Customer_For	C
0	-0.89	1.26	0.29	-0.82	-0.93	0.31	0.98	1.55	1.69	2.45	...	1.43	2.50	-0.56	0.69	1.97	
1	-0.89	1.26	-0.26	1.04	0.91	-0.38	-0.87	-0.64	-0.72	-0.65	...	-1.13	-0.57	-1.17	-0.13	-1.67	
2	-0.89	-0.28	0.91	-0.82	-0.93	-0.80	0.36	0.57	-0.18	1.34	...	1.43	-0.23	1.29	-0.54	-0.17	
3	-0.89	-0.28	-1.18	1.04	-0.93	-0.80	-0.87	-0.56	-0.66	-0.50	...	-0.76	-0.91	-0.56	0.28	-1.92	
4	0.57	-0.28	0.29	1.04	-0.93	1.55	-0.39	0.42	-0.22	0.15	...	0.33	0.11	0.06	-0.13	-0.82	

5 rows × 23 columns

Dimesntionality Reduction

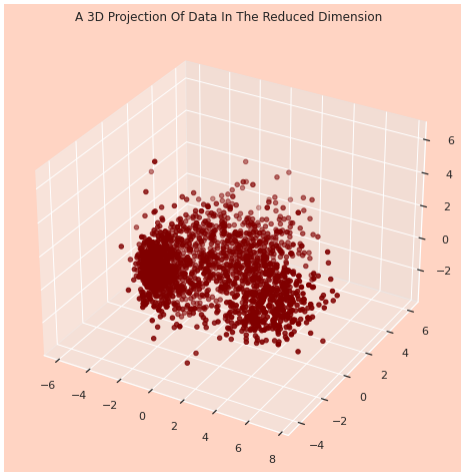
Preform PCA to do dimensionality reduction to 3 columns.

In [ ]:
```
pca = PCA(n_components=3)
pca.fit(scaled_ds)
PCA_ds = pd.DataFrame(pca.transform(scaled_ds), columns=(["col1","col2", "col3"]))
PCA_ds.describe().T
```

Out[ ]:

	count	mean	std	min	25%	50%	75%	max
col1	2212.00	-0.00	2.88	-5.96	-2.54	-0.78	2.37	7.46
col2	2212.00	0.00	1.70	-4.26	-1.33	-0.17	1.25	6.09
col3	2212.00	0.00	1.21	-3.33	-0.87	-0.00	0.81	6.35

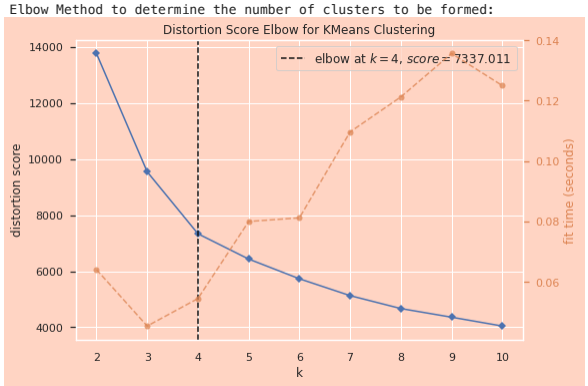
In [ ]:
```
#A 3D Projection Of Data In The Reduced Dimension
x =PCA_ds["col1"]
y =PCA_ds["col2"]
z =PCA_ds["col3"]
#To plot
fig = plt.figure(figsize=(10,8))
ax = fig.add_subplot(111, projection="3d")
ax.scatter(x,y,z, c="maroon", marker="o" )
ax.set_title("A 3D Projection Of Data In The Reduced Dimension")
plt.show()
```



Lets use the elbow method (knee point detection) to decide how many cluster we should have.

In [ ]:
```
print('Elbow Method to determine the number of clusters to be formed:')
Elbow_M = KElbowVisualizer(KMeans(), k=10)
Elbow_M.fit(PCA_ds)
Elbow_M.show()
```

```
Elbow Method to determine the number of clusters to be formed:
```



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

Lets create the clusters and evaluate the clusters creared by different methods agglomatic, kmeans through minibatch, and spectral clustering.

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

In [ ]:
```
#Initiating the KMeans Clustering model
KM = KMeans(n_clusters=4)
# fit model and predict clusters
yhat_KM = KM.fit_predict(PCA_ds)
PCA_ds["KM_Clusters"] = yhat_KM
#Adding the Clusters feature to the orignal dataframe.
data["KM_Clusters"]= yhat_KM
```

In [ ]:
```
#Initiating the Spectral Clustering model
SC = SpectralClustering(n_clusters=4)
# fit model and predict clusters
yhat_SC = SC.fit_predict(PCA_ds)
PCA_ds["SC_Clusters"] = yhat_SC
#Adding the Clusters feature to the orignal dataframe.
data["SC_Clusters"]= yhat_SC
```

In [ ]:
```
cluster_labels = ["SC_Clusters", "KM_Clusters", "AC_Clusters"]
```

Compare Clusters to see if there is a meaningful difference

In [ ]:
```
# lets do the count first
for label in cluster_labels:
  print(data[label].value_counts())
```

```
0    699
1    616
3    482
2    415
Name: SC_Clusters, dtype: int64
2    674
1    617
3    482
0    439
Name: KM_Clusters, dtype: int64
0    729
1    612
3    468
2    403
Name: AC_Clusters, dtype: int64
```

In [ ]:
```
data.loc[data["KM_Clusters"]== 2].describe()
```

Out[ ]:

	Education	Marital_Status	Income	Kidhome	Teenhome	Recency	SpentOnWines	SpentOnFruits	SpentOnMeat	SpentOnFish	...	Response	Customer_For	Children	Age	Spent	Family_Size	Is_Parent	AC_Cluste
count	674.00	674.00	674.00	674.00	674.00	674.00	674.00	674.00	674.00	674.00	...	674.00	674.00	674.00	674.00	674.00	674.00	674.00	674.0
mean	0.60	1.14	45795.74	0.68	1.01	48.07	138.88	6.29	42.33	8.69	...	0.08	3990064807121661 6.00	1.70	49.30	225.04	3.38	1.00	0.0
std	0.63	0.64	13600.02	0.58	0.31	29.29	144.43	11.36	42.69	13.08	...	0.28	2018995804595 9300.00	0.59	9.08	196.55	0.73	0.00	0.1
min	0.00	0.00	4023.00	0.00	0.00	0.00	1.00	0.00	1.00	0.00	...	0.00	86400000000000.00	1.00	32.00	8.00	2.00	1.00	0.0
25%	0.00	1.00	37296.50	0.00	1.00	24.00	25.25	0.00	11.00	0.00	...	0.00	23306400000000000.00	1.00	42.00	54.00	3.00	1.00	0.0
50%	1.00	1.00	45904.50	1.00	1.00	49.00	81.50	2.00	26.00	4.00	...	0.00	38404800000000000.00	2.00	49.00	160.50	3.00	1.00	0.0
75%	1.00	1.00	54155.75	1.00	1.00	73.00	209.75	7.00	64.00	11.00	...	0.00	54324000000000000.00	2.00	57.00	376.00	4.00	1.00	0.0
max	2.00	3.00	162397.00	2.00	2.00	99.00	734.00	123.00	253.00	82.00	...	1.00	88819200000000000.00	3.00	68.00	1019.00	5.00	1.00	1.0

8 rows × 33 columns

In [ ]:
```
data.loc[data["AC_Clusters"]== 0].describe()
```

Out[ ]:

	Education	Marital_Status	Income	Kidhome	Teenhome	Recency	SpentOnWines	SpentOnFruits	SpentOnMeat	SpentOnFish	...	Response	Customer_For	Children	Age	Spent	Family_Size	Is_Parent	AC_Cluste
count	729.00	729.00	729.00	729.00	729.00	729.00	729.00	729.00	729.00	729.00	...	729.00	729.00	729.00	729.00	729.00	729.00	729.00	729.0
mean	0.60	1.14	46501.37	0.70	0.98	48.47	165.08	7.86	52.43	10.40	...	0.10	41513718518518520.00	1.68	48.58	270.84	3.35	1.00	0.0
std	0.63	0.65	13863.19	0.57	0.39	29.10	185.53	14.16	56.68	15.73	...	0.30	20828640430642868.00	0.59	9.49	254.63	0.75	0.00	0.0
min	0.00	0.00	4023.00	0.00	0.00	0.00	1.00	0.00	1.00	0.00	...	0.00	86400000000000.00	1.00	24.00	8.00	2.00	1.00	0.0
25%	0.00	1.00	37758.00	0.00	1.00	24.00	28.00	0.00	12.00	0.00	...	0.00	25228800000000000.00	1.00	41.00	61.00	3.00	1.00	0.0
50%	1.00	1.00	46098.00	1.00	1.00	49.00	98.00	3.00	32.00	4.00	...	0.00	40867200000000000.00	2.00	48.00	211.00	3.00	1.00	0.0
75%	1.00	1.00	54456.00	1.00	1.00	73.00	238.00	9.00	76.00	13.00	...	0.00	56419200000000000.00	2.00	57.00	417.00	4.00	1.00	0.0
max	2.00	3.00	162397.00	2.00	2.00	99.00	1459.00	123.00	487.00	123.00	...	1.00	91670400000000000.00	3.00	68.00	1750.00	5.00	1.00	0.0

8 rows × 33 columns

In [ ]:
```
data.loc[data["SC_Clusters"]== 0].describe()
```

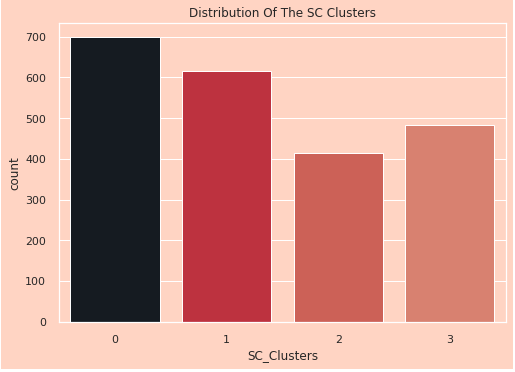
Out[ ]:

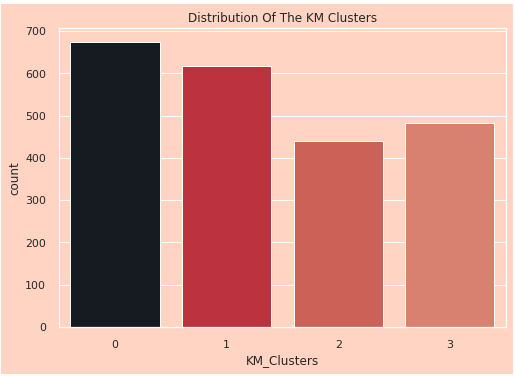
	Education	Marital_Status	Income	Kidhome	Teenhome	Recency	SpentOnWines	SpentOnFruits	SpentOnMeat	SpentOnFish	...	Response	Customer_For	Children	Age	Spent	Family_Size	Is_Parent	AC_Cluste
count	699.00	699.00	699.00	699.00	699.00	699.00	699.00	699.00	699.00	699.00	...	699.00	699.00	699.00	699.00	699.00	699.00	699.00	699.0
mean	0.60	1.14	46010.69	0.69	1.00	48.25	150.69	6.71	45.89	9.23	...	0.09	41031965665236048.00	1.68	48.96	244.07	3.37	1.00	0.0
std	0.63	0.64	13510.36	0.58	0.33	29.21	165.53	12.16	46.97	14.21	...	0.29	20810251147305948.00	0.59	9.33	221.43	0.73	0.00	0.1
min	0.00	0.00	4023.00	0.00	0.00	0.00	1.00	0.00	1.00	0.00	...	0.00	86400000000000.00	1.00	24.00	8.00	2.00	1.00	0.0
25%	0.00	1.00	37737.00	0.00	1.00	24.00	27.00	0.00	11.00	0.00	...	0.00	24408000000000000.00	1.00	41.00	55.00	3.00	1.00	0.0
50%	1.00	1.00	46049.00	1.00	1.00	49.00	87.00	2.00	28.00	4.00	...	0.00	40003200000000000.00	2.00	49.00	177.00	3.00	1.00	0.0
75%	1.00	1.00	54197.50	1.00	1.00	73.00	221.50	7.00	68.00	12.00	...	0.00	56246400000000000.00	2.00	57.00	402.50	4.00	1.00	0.0
max	2.00	3.00	162397.00	2.00	2.00	99.00	1099.00	123.00	253.00	123.00	...	1.00	91670400000000000.00	3.00	68.00	1314.00	5.00	1.00	1.0

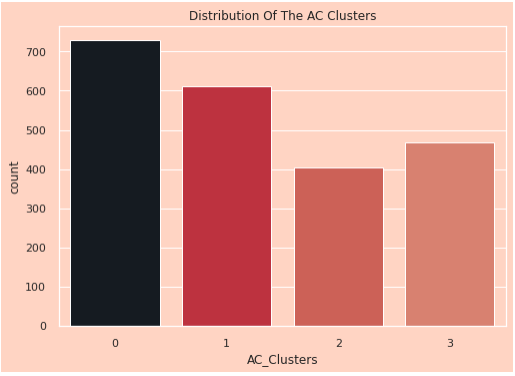
8 rows × 33 columns

In [ ]:
```
# Seems like K means made similar clusters just used different labels we can remedy this by swapping the labels
data.loc[data["KM_Clusters"] == 2, "KM_Clusters"] = 4
data.loc[data["KM_Clusters"] == 0, "KM_Clusters"] = 2
data.loc[data["KM_Clusters"] == 4, "KM_Clusters"] = 0
```

In [ ]:
```
#Plotting countplot of clusters
pal = ["#131B23", "#d41b2c", "#e05143", "#ea755e"]
for label in cluster_labels:
  pl = sns.countplot(x=data[label], palette= pal)
  pl.set_title(f"Distribution Of The {label.replace('_', ' ')}")
  plt.show()
  print(" ")
```





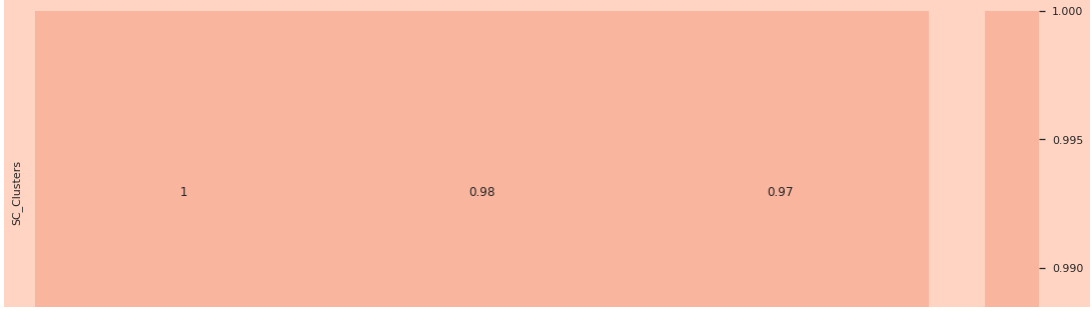


In [ ]:

```
clust_corrmat= data[cluster_labels].corr()
plt.figure(figsize=(20,20))
sns.heatmap(clust_corrmat, annot=True, cmap=cmap, center=0)
```

Out[ ]:

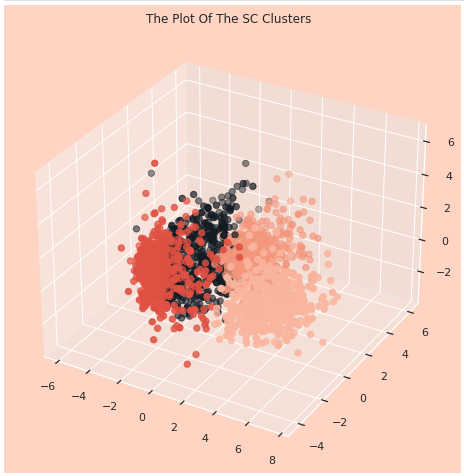
```
<AxesSubplot:>
```

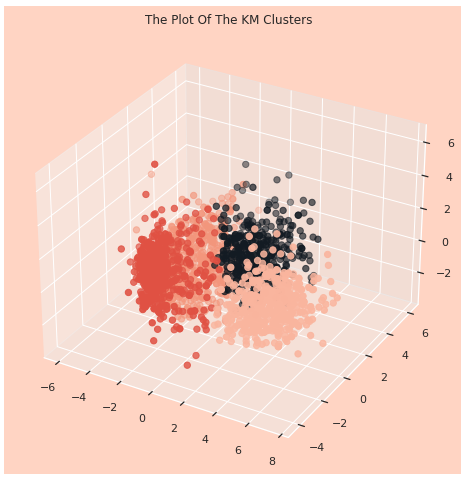


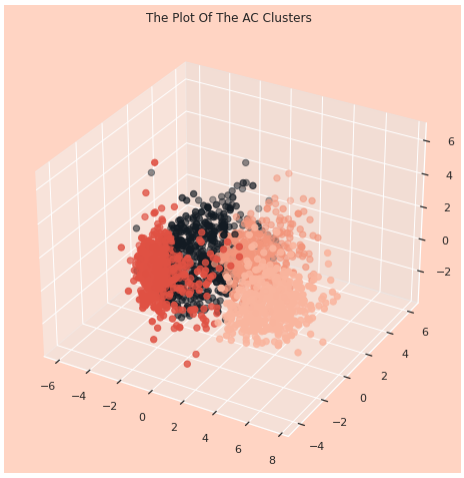
There does not seem to be a meaningful difference between the classification methods, this means that the personas created from any method should be the same for each of the clustering methods which means we only need to create one persona for each cluster we select Agglomerative Clustering to create the customer personas for the segments.

In [ ]:

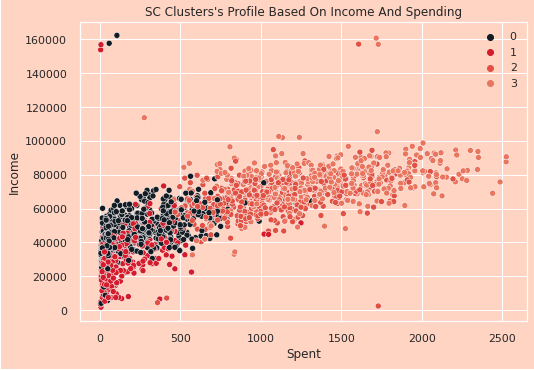
```
#Plotting the clusters
for label in cluster_labels:
  fig = plt.figure(figsize=(10,8))
  ax = plt.subplot(111, projection='3d', label="bla")
  ax.scatter(x, y, z, s=40, c=PCA_ds[label], marker='o', cmap = cmap )
  ax.set_title(f"The Plot Of The {label.replace('_', ' ')}")
  plt.show()
  print(" ")
```

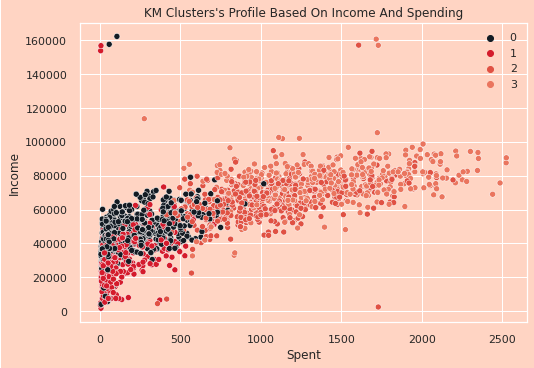


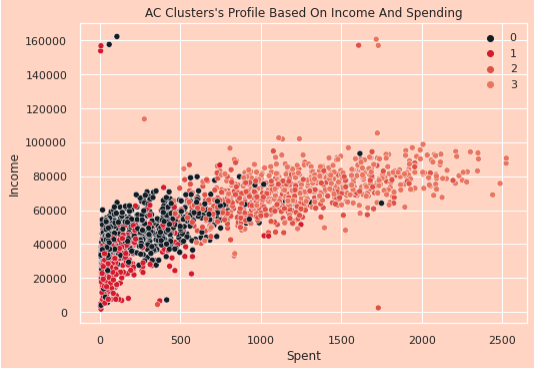




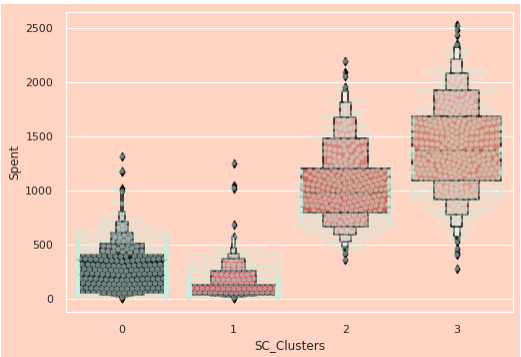
In [ ]:
```
for label in cluster_labels:
  pl = sns.scatterplot(data=data, x=data["Spent"], y=data["Income"],
                       hue=data[label], palette= pal)
  pl.set_title(f"{label.replace('_', ' ')}'s Profile Based On Income And Spending")
  plt.legend()
  plt.show()
  print(" ")
```

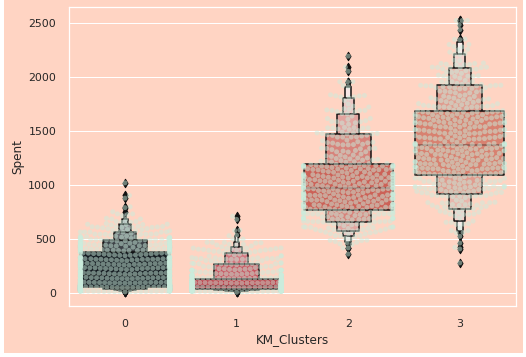






In [ ]:
```
for label in cluster_labels:
  plt.figure()
  pl=sns.swarmplot(x=data[label], y=data["Spent"], color= "#CBEDDD", alpha=0.5 )
  pl=sns.boxenplot(x=data[label], y=data["Spent"], palette=pal)
  plt.show()
  print(" ")
```

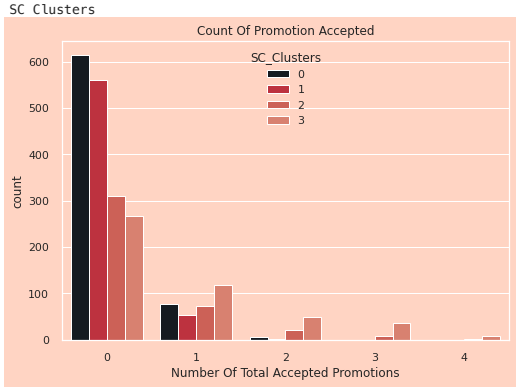




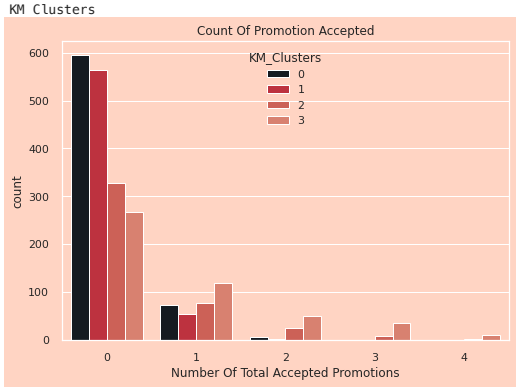
In [ ]:

```
#Creating a feature to get a sum of accepted promotions
data["Total_Promos"] = data["AcceptedCmp1"]+ data["AcceptedCmp2"]+ data["AcceptedCmp3"]+ data["AcceptedCmp4"]+ data["AcceptedCmp5"]
#Plotting count of total campaign accepted.
for label in cluster_labels:
  print(label.replace("_", " "))
  plt.figure()
  pl = sns.countplot(x=data["Total_Promos"],hue=data[label], palette= pal)
  pl.set_title("Count Of Promotion Accepted")
  pl.set_xlabel("Number Of Total Accepted Promotions")
  plt.show()
  print(" ")
```

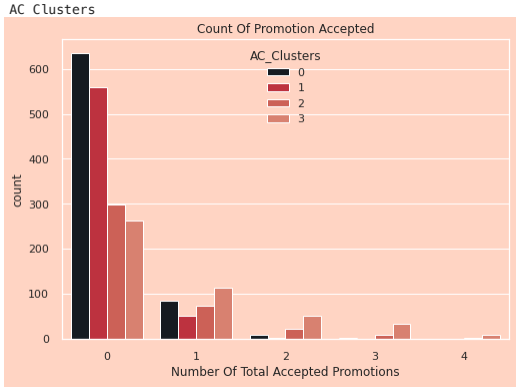
```
SC Clusters
```




```
KM Clusters
```



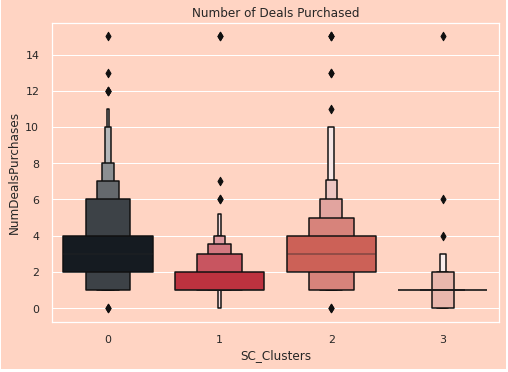

```
AC Clusters
```



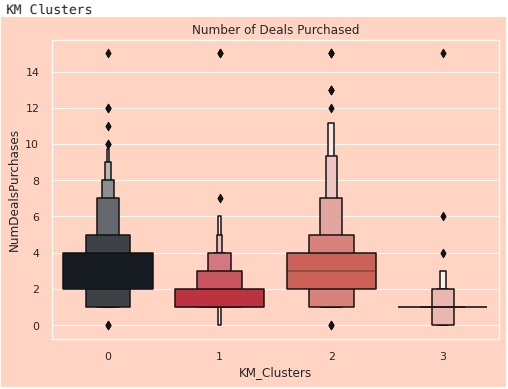
In [ ]:

```
#Plotting the number of deals purchased
for label in cluster_labels:
  print(label.replace("_", " "))
  plt.figure()
  pl=sns.boxenplot(y=data["NumDealsPurchases"],x=data[label], palette= pal)
  pl.set_title("Number of Deals Purchased")
  plt.show()
  print(" ")
```

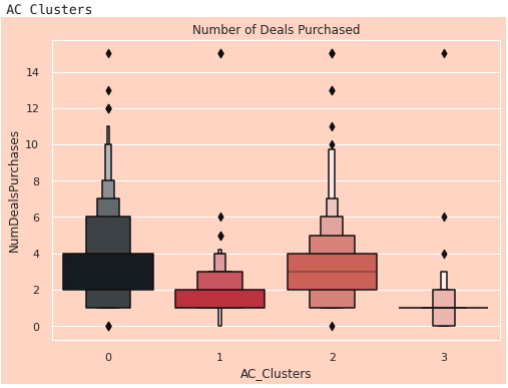
```
SC Clusters
```



KM Clusters



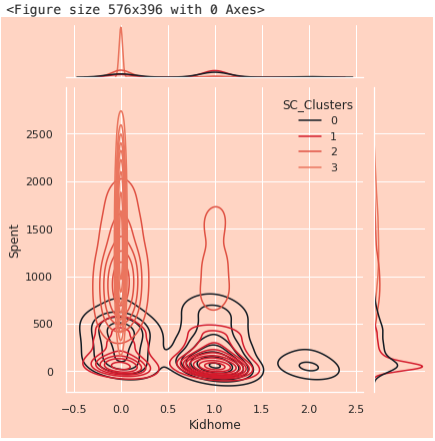
AC Clusters



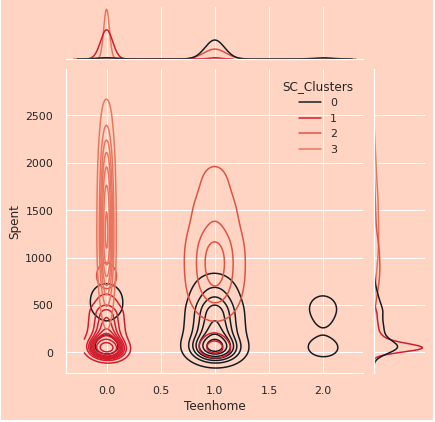
In [ ]:

```
Personal = [ "Kidhome","Teenhome","Customer_For", "Age", "Children", "Family_Size", "Is_Parent", "Education","Marital_Status"]
for label in cluster_labels:
  print(label.replace("_", " "))
  for i in Personal:
    print(i.replace("_", " "))
    plt.figure()
    sns.jointplot(x=data[i], y=data["Spent"], hue=data[label], kind="kde", palette=pal)
    plt.show()
```

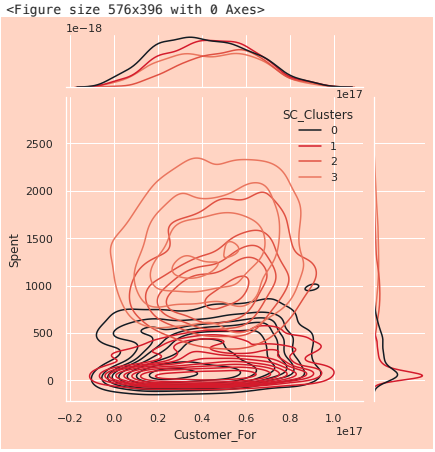
```
SC Clusters
Kidhome
<Figure size 576x396 with 0 Axes>
```



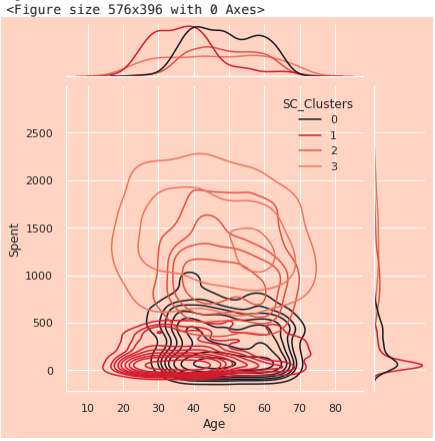

```
Teenhome
<Figure size 576x396 with 0 Axes>
```



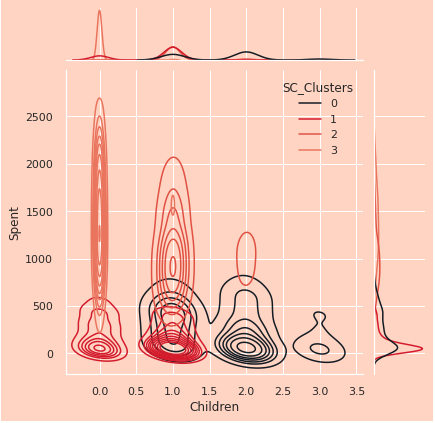

```
Customer For
<Figure size 576x396 with 0 Axes>
```



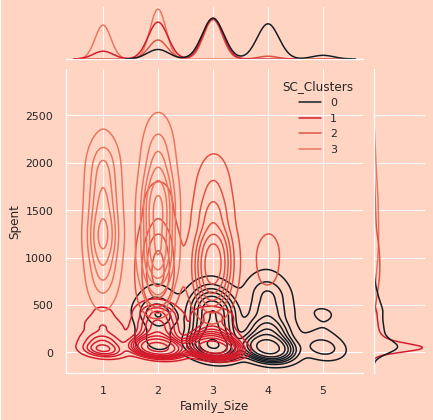

```
Age
<Figure size 576x396 with 0 Axes>
```



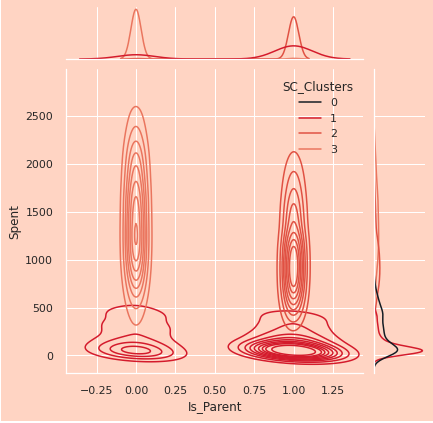

```
Children
<Figure size 576x396 with 0 Axes>
```



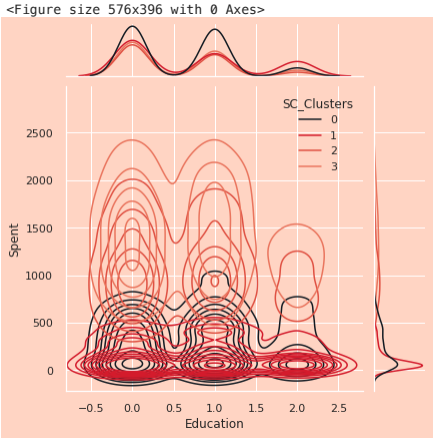

```
Family Size
<Figure size 576x396 with 0 Axes>
```



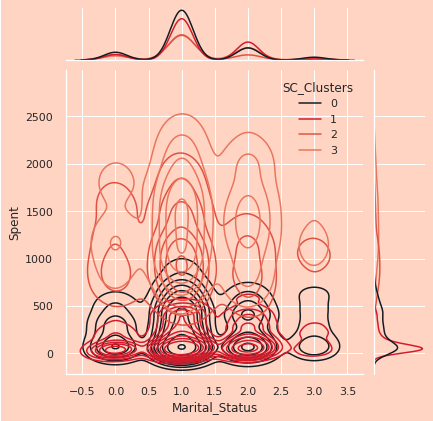
Is Parent
<Figure size 576x396 with 0 Axes>



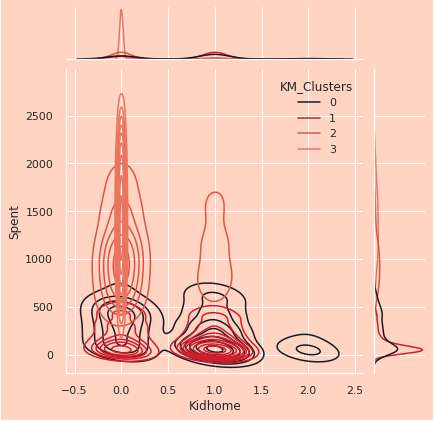
Education
<Figure size 576x396 with 0 Axes>



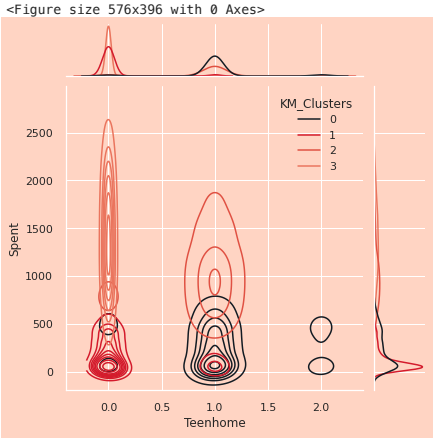
Marital Status
<Figure size 576x396 with 0 Axes>



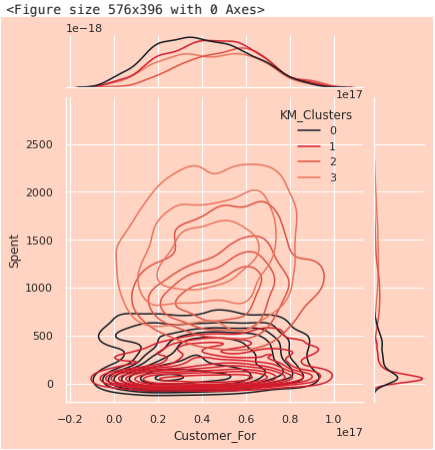
KM Clusters
Kidhome
<Figure size 576x396 with 0 Axes>



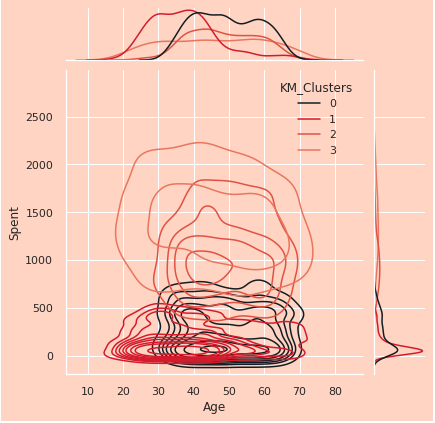
Teenhome
<Figure size 576x396 with 0 Axes>



Customer For
<Figure size 576x396 with 0 Axes>



Age
<Figure size 576x396 with 0 Axes>



Children
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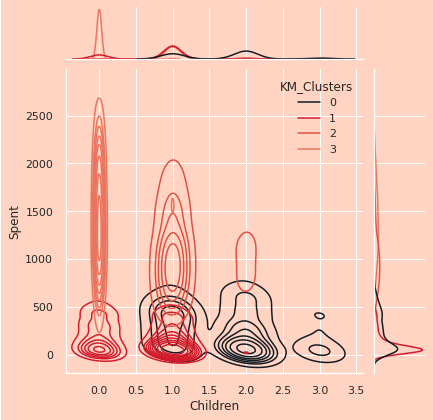
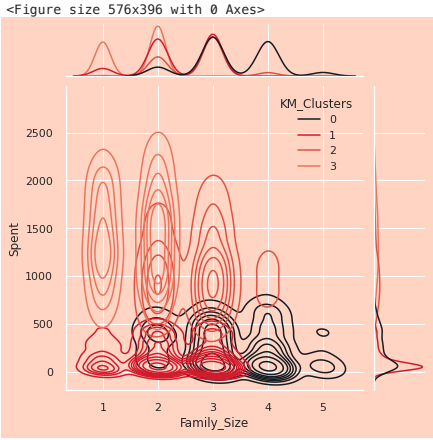


Family Size
<Figure size 576x396 with 0 Axes>



Is Parent
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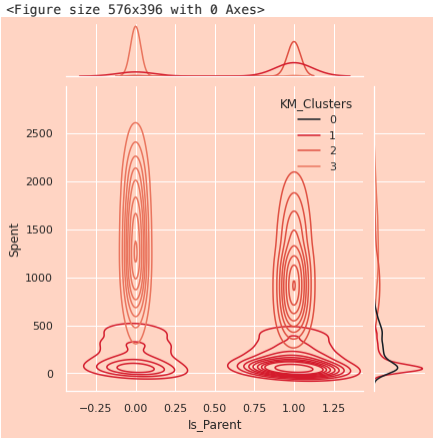

Education
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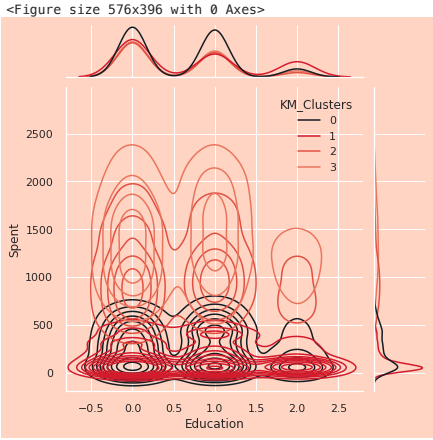

Marital Status
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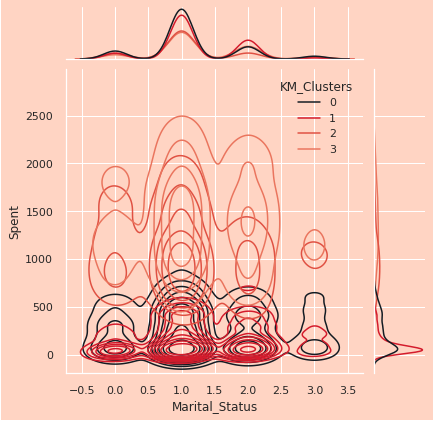
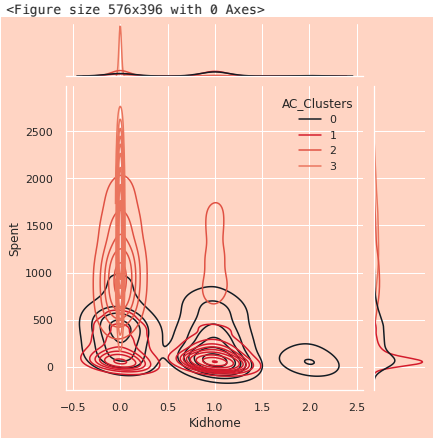



```
AC_Clusters
Kidhome
<Figure size 576x396 with 0 Axes>
```




```
Teenhome
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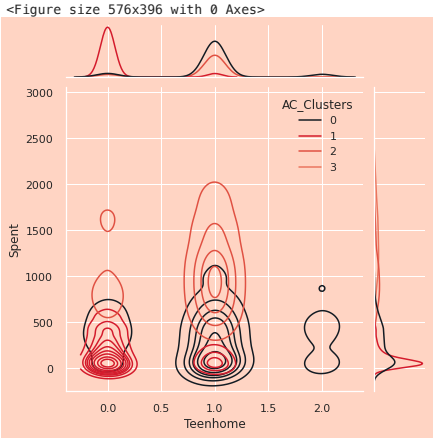


```
Customer_For
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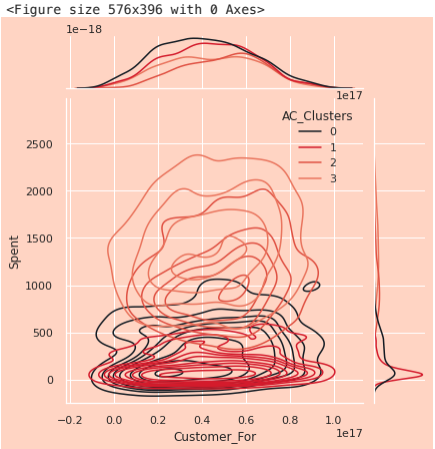
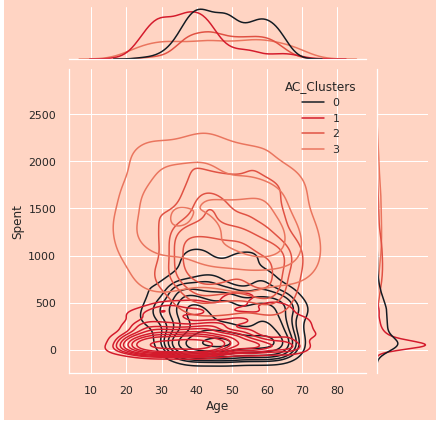



```
Age
<Figure size 576x396 with 0 Axes>
```



Children
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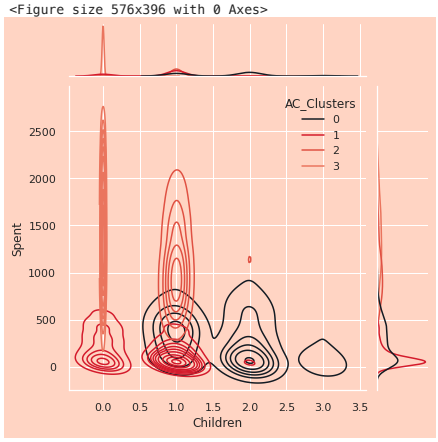
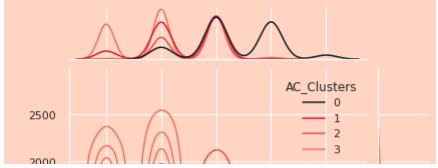


Family Size
<Figure size 576x396 with 0 Axes>



In [ ]:
```
data.loc[data["AC_Clusters"]== 0].describe()
```

Out[ ]:

	Education	Marital_Status	Income	Kidhome	Teenhome	Recency	SpentOnWines	SpentOnFruits	SpentOnMeat	SpentOnFish	...	Customer_For	Children	Age	Spent	Family_Size	Is_Parent	AC_Clusters	KM_Clus
count	729.00	729.00	729.00	729.00	729.00	729.00	729.00	729.00	729.00	729.00	...	729.00	729.00	729.00	729.00	729.00	729.00	729.00	72
mean	0.60	1.14	46501.37	0.70	0.98	48.47	165.08	7.86	52.43	10.40	...	41513718518518520.00	1.68	48.58	270.84	3.35	1.00	0.00	
std	0.63	0.65	13863.19	0.57	0.39	29.10	185.53	14.16	56.68	15.73	...	20828640430642868.00	0.59	9.49	254.63	0.75	0.00	0.00	
min	0.00	0.00	4023.00	0.00	0.00	0.00	1.00	0.00	1.00	0.00	...	86400000000000.00	1.00	24.00	8.00	2.00	1.00	0.00	
25%	0.00	1.00	37758.00	0.00	1.00	24.00	28.00	0.00	12.00	0.00	...	25228800000000000.00	1.00	41.00	61.00	3.00	1.00	0.00	
50%	1.00	1.00	46098.00	1.00	1.00	49.00	98.00	3.00	32.00	4.00	...	40867200000000000.00	2.00	48.00	211.00	3.00	1.00	0.00	
75%	1.00	1.00	54456.00	1.00	1.00	73.00	238.00	9.00	76.00	13.00	...	56419200000000000.00	2.00	57.00	417.00	4.00	1.00	0.00	
max	2.00	3.00	162397.00	2.00	2.00	99.00	1459.00	123.00	487.00	123.00	...	91670400000000000.00	3.00	68.00	1750.00	5.00	1.00	0.00	

8 rows × 34 columns

In [ ]:
```
data.loc[data["AC_Clusters"]== 1].describe()
```

Out[ ]:

	Education	Marital_Status	Income	Kidhome	Teenhome	Recency	SpentOnWines	SpentOnFruits	SpentOnMeat	SpentOnFish	...	Customer_For	Children	Age	Spent	Family_Size	Is_Parent	AC_Clusters	KM_Clus
count	612.00	612.00	612.00	612.00	612.00	612.00	612.00	612.00	612.00	612.00	...	612.00	612.00	612.00	612.00	612.00	612.00	612.00	6
mean	0.72	1.21	30721.14	0.69	0.07	48.46	39.94	7.06	25.90	10.58	...	43930447058823528.00	0.75	38.07	107.76	2.40	0.75	1.00	
std	0.78	0.60	13539.35	0.47	0.25	28.68	89.56	12.00	31.93	19.42	...	19587608521829800.00	0.45	10.16	134.38	0.65	0.44	0.00	
min	0.00	0.00	1730.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	...	0.00	0.00	18.00	5.00	1.00	0.00	1.00	
25%	0.00	1.00	22492.25	0.00	0.00	24.00	5.00	1.00	8.00	2.00	...	29721600000000000.00	0.00	30.00	37.00	2.00	0.00	1.00	
50%	1.00	1.00	30007.00	1.00	0.00	48.00	14.00	3.00	15.00	4.00	...	44193600000000000.00	1.00	37.00	62.00	2.00	1.00	1.00	
75%	1.00	2.00	37702.00	1.00	0.00	74.00	37.00	8.00	28.00	12.00	...	58168800000000000.00	1.00	43.00	122.00	3.00	1.00	1.00	
max	2.00	3.00	156924.00	2.00	1.00	99.00	1166.00	151.00	226.00	179.00	...	91843200000000000.00	2.00	74.00	1250.00	4.00	1.00	1.00	

8 rows × 34 columns

In [ ]:
```
data.loc[data["AC_Clusters"]== 2].describe()
```

Out[ ]:

	Education	Marital_Status	Income	Kidhome	Teenhome	Recency	SpentOnWines	SpentOnFruits	SpentOnMeat	SpentOnFish	...	Customer_For	Children	Age	Spent	Family_Size	Is_Parent	AC_Clusters	KM_Clu
count	403.00	403.00	403.00	403.00	403.00	403.00	403.00	403.00	403.00	403.00	...	403.00	403.00	403.00	403.00	403.00	403.00	403.00	4
mean	0.51	1.09	65504.54	0.11	0.91	51.05	593.74	42.86	221.39	59.77	...	50159809429280400.00	1.01	48.57	1041.11	2.68	0.98	2.00	
std	0.63	0.68	11365.19	0.32	0.32	28.69	301.81	42.43	162.47	60.16	...	18158858361166488.00	0.26	9.47	347.94	0.53	0.16	0.00	
min	0.00	0.00	2447.00	0.00	0.00	0.00	1.00	0.00	12.00	0.00	...	86400000000000.00	0.00	25.00	359.00	1.00	0.00	2.00	
25%	0.00	1.00	58631.50	0.00	1.00	27.00	371.00	12.00	124.00	13.00	...	36892800000000000.00	1.00	41.00	793.50	2.00	1.00	2.00	
50%	0.00	1.00	64866.00	0.00	1.00	51.00	543.00	30.00	186.00	42.00	...	51753600000000000.00	1.00	48.00	982.00	3.00	1.00	2.00	
75%	1.00	1.00	71909.00	0.00	1.00	77.00	782.00	62.00	279.00	85.50	...	63244800000000000.00	1.00	56.00	1218.50	3.00	1.00	2.00	
max	2.00	3.00	157243.00	2.00	2.00	99.00	1492.00	199.00	1725.00	259.00	...	91843200000000000.00	3.00	70.00	2194.00	4.00	1.00	2.00	

8 rows × 34 columns

In [ ]:
```
data.loc[data["AC_Clusters"]== 3].describe()
```

Out[ ]:

	Education	Marital_Status	Income	Kidhome	Teenhome	Recency	SpentOnWines	SpentOnFruits	SpentOnMeat	SpentOnFish	...	Customer_For	Children	Age	Spent	Family_Size	Is_Parent	AC_Clusters	KM_Clu
count	468.00	468.00	468.00	468.00	468.00	468.00	468.00	468.00	468.00	468.00	...	468.00	468.00	468.00	468.00	468.00	468.00	468.00	4
mean	0.56	1.28	76567.78	0.00	0.00	48.85	622.29	66.06	483.29	96.44	...	43837661538461536.00	0.00	45.83	1410.92	1.59	0.00	3.00	
std	0.65	0.69	11858.59	0.05	0.00	29.28	317.31	50.91	244.23	64.83	...	20176279157405988.00	0.05	14.17	420.10	0.49	0.05	0.00	
min	0.00	0.00	33051.00	0.00	0.00	0.00	1.00	0.00	3.00	0.00	...	86400000000000.00	0.00	19.00	277.00	1.00	0.00	3.00	
25%	0.00	1.00	70038.00	0.00	0.00	23.00	375.00	25.00	304.75	42.00	...	28231200000000000.00	0.00	33.00	1101.75	1.00	0.00	3.00	
50%	0.00	1.00	76912.00	0.00	0.00	51.50	580.00	51.00	447.00	84.00	...	43848000000000000.00	0.00	45.00	1375.50	2.00	0.00	3.00	
75%	1.00	2.00	82577.50	0.00	0.00	73.00	847.25	101.25	658.75	145.00	...	59551200000000000.00	0.00	58.00	1686.50	2.00	0.00	3.00	
max	2.00	3.00	160803.00	1.00	0.00	99.00	1493.00	197.00	1725.00	254.00	...	91843200000000000.00	1.00	73.00	2525.00	2.00	1.00	3.00	

8 rows × 34 columns