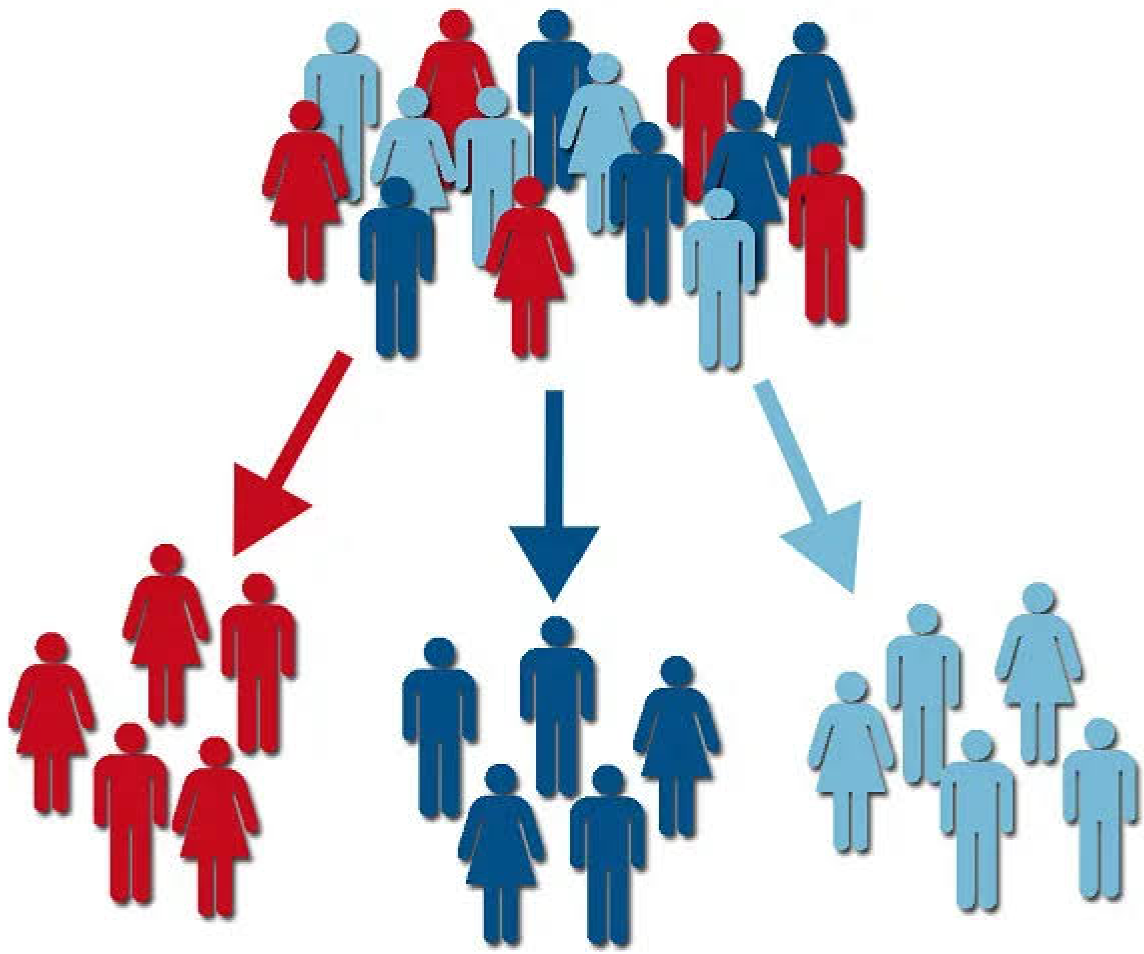


Goal: Customer Segmentation

Customer Segmentation creates information that supports decision making by matching the right customers with the right services and products. With customer segmentation, actions that can address customers' concerns can be taken with greater precision.

In this analysis, K-means and Agglomerative clustering were utilized using the market campaign dataset.

Libraries Used

- Pandas
- Numpy
- Matplotlib
- Seaborn
- Scikit Learn
- Plotly
- Scipy

Importing Libraries

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from matplotlib import colors
from matplotlib.colors import ListedColormap
import seaborn as sns
import plotly as py
import plotly.graph_objs as go
from sklearn.cluster import KMeans
from sklearn.cluster import AgglomerativeClustering
import scipy.cluster.hierarchy as sch
from  sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import LabelEncoder
from sklearn.decomposition import PCA
import plotly.express as px
```

In [2]:

```
import warnings
import sys
if not sys.warnoptions:
    import warnings
    warnings.simplefilter("ignore")
py.offline.init_notebook_mode()
import plotly.offline as py
py.init_notebook_mode()
import plotly.graph_objs as go
import plotly.tools as tls
import plotly.figure_factory as ff
```

Importing the Dataset

In [3]:

```
df = pd.read_csv('marketing_campaign.csv', sep=';')
```

In [4]:

```
pd.set_option('display.max_columns', None)
```

- **Let's get some info from the data**

In [5]:

```
df.head()
```

Out[5]:

	ID	Year_Birth	Education	Marital_Status	Income	Kidhome	Teenhome	Dt_Customer	Recency	M
0	5524	1957	Graduation	Single	58138.0	0	0	2012-09-04	58	
1	2174	1954	Graduation	Single	46344.0	1	1	2014-03-08	38	
2	4141	1965	Graduation	Together	71613.0	0	0	2013-08-21	26	
3	6182	1984	Graduation	Together	26646.0	1	0	2014-02-10	26	
4	5324	1981	PhD	Married	58293.0	1	0	2014-01-19	94	

In [6]:
```
df.describe()
```

Out[6]:

	ID	Year_Birth	Income	Kidhome	Teenhome	Recency	MntWines
count	2240.000000	2240.000000	2216.000000	2240.000000	2240.000000	2240.000000	2240.000000
mean	5592.159821	1968.805804	52247.251354	0.444196	0.506250	49.109375	303.935714
std	3246.662198	11.984069	25173.076661	0.538398	0.544538	28.962453	336.597393
min	0.000000	1893.000000	1730.000000	0.000000	0.000000	0.000000	0.000000
25%	2828.250000	1959.000000	35303.000000	0.000000	0.000000	24.000000	23.750000
50%	5458.500000	1970.000000	51381.500000	0.000000	0.000000	49.000000	173.500000
75%	8427.750000	1977.000000	68522.000000	1.000000	1.000000	74.000000	504.250000
max	11191.000000	1996.000000	666666.000000	2.000000	2.000000	99.000000	1493.000000

Data Cleaning

- **Inspecting the data types.**

In [7]:
```
df.info()
```

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

```
 26  Z_CostContact        2240 non-null   int64
 27  Z_Revenue            2240 non-null   int64
 28  Response             2240 non-null   int64
dtypes: float64(1), int64(25), object(3)
memory usage: 507.6+ KB
```

- **Checking for null values**

In [8]:

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

Out[8]:

```
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
```

- **There are some missing values at the income column**
- **Dt_Customer column needs to be processed to its proper format**
- **There are 3 categorical (non_numerical) columns.**

- **Let's fill up the missing values first**

In [11]:

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

df['Income'].fillna(value=mean_value, inplace=True)
```

- **Let's confirm that there are no more missing values.**

In [13]:

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

Out[13]:
```
ID                     0
Year_Birth             0
Education              0
Marital_Status         0
Income                 0
Kidhome                0
Teenhome               0
Dt_Customer            0
Recency                0
MntWines               0
MntFruits              0
MntMeatProducts        0
MntFishProducts        0
MntSweetProducts       0
MntGoldProds           0
NumDealsPurchases      0
NumWebPurchases        0
NumCatalogPurchases    0
NumStorePurchases      0
NumWebVisitsMonth      0
AcceptedCmp3           0
AcceptedCmp4           0
AcceptedCmp5           0
AcceptedCmp1           0
AcceptedCmp2           0
Complain               0
Z_CostContact          0
Z_Revenue              0
Response               0
dtype: int64
```

- **Let's create a column that shows how many days customers have been registered with the company.**

> - We need to show the oldest customer and newest customer.

In [14]:
```
df["Dt_Customer"] = pd.to_datetime(df["Dt_Customer"])
dates = []
for t in df["Dt_Customer"]:
    t = t.date()
    dates.append(t)

print("Registration date of the newest customer on record is:",max(dates))
print("Registration date of the oldest customer on record is:",min(dates))
```

```
Registration date of the newest customer on record is: 2014-06-29
Registration date of the oldest customer on record is: 2012-07-30
```

- **We look for unique values in columns that are categorical.**

In [16]:
```
print("Unique value in Martial Status column: \n ", df["Marital_Status"].value_counts()
print("Unique value in Education column: \n ", df["Education"].value_counts())
```

```
Unique value in Martial Status column:
```

```
  Married     864
Together    580
Single      480
Divorced    232
Widow        77
Alone         3
Absurd        2
YOLO          2
Name: Marital_Status, dtype: int64

Unique value in Education column:
  Graduation    1127
PhD           486
Master        370
2n Cycle      203
Basic          54
Name: Education, dtype: int64
```

We'll perform label encoding operation by changing the labels of unique values because there are many columns.

- Married : Partner
- Together : Partner
- Absurd : Alone
- Widow : Alone
- YOLO : Alone
- Single : Alone

-

- Basic : Undergraduate

- 2n Cycle : Undergraduate
- Graduatition : Graduate
- Master : Graduate
- PhD : Graduate

Let's carry out some feature engineering

- **Let's open a new column called Customer_For and age of Customer.**

In [17]:

```
days = []
d1 = max(dates)
for i in dates:
    alpha = d1 - i
    days.append(alpha)
df["Customer_For"] = days
df["Customer_For"] = pd.to_numeric(df["Customer_For"], errors="coerce")
```

In [18]:

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

- **Miscellaneous expenses**

In [19]:
```
df["Spent"] = df["MntWines"]+ df["MntFruits"]+ df["MntMeatProducts"]+ df["MntFishProduc
```

- **Determine the client's marital status.**

In [20]:
```
df["Living_With"] = df["Marital_Status"].replace({"Married":"Partner", "Together":"Part
```

- **Total number of children living at home**

In [21]:
```
df["Children"] = df["Kidhome"] + df["Teenhome"]
```

Total size of the family

In [22]:
```
df["Family_Size"] = df["Living_With"].replace({"Alone": 1, "Partner":2}) + df["Children
df["Family_Size"]
```

Out[22]:
```
0       1
1       3
2       2
3       3
4       3
       ..
2235    3
2236    5
2237    1
2238    3
2239    4
Name: Family_Size, Length: 2240, dtype: int64
```

- **Parent status**

In [23]:
```
df["Is_Parent"] = np.where(df.Children > 0, 1, 0)
```

- **Division of education status**

In [24]:
```
df["Education"] = df["Education"].replace({"Basic":"Undergraduate","2n Cycle":"Undergra
```

- **Editing some column names**

In [25]:
```
df = df.rename(columns={"MntWines": "Wines", "MntFruits":"Fruits", "MntMeatProducts":"M
```

- `Z_CostContact` and `Z_Revenue` have fixed values.
- We drop them from the dataset because they are unnecessary.

In [26]:
```
df.Z_CostContact.describe()
```

```
count     2240.0
```

Out[26]:
```
mean         3.0
std          0.0
min          3.0
25%          3.0
50%          3.0
75%          3.0
max          3.0
Name: Z_CostContact, dtype: float64
```

In [27]:
```
df.Z_Revenue.describe()
```

Out[27]:
```
count    2240.0
mean       11.0
std         0.0
min        11.0
25%        11.0
50%        11.0
75%        11.0
max        11.0
Name: Z_Revenue, dtype: float64
```

In [28]:
```
to_drop = ["Marital_Status", "Dt_Customer", "Z_CostContact", "Z_Revenue", "Year_Birth",
df = df.drop(to_drop, axis=1)
```

- **Converting categorical values to numerical value**

In [29]:
```
le = LabelEncoder()
df['Education'] = df[['Education']].apply(le.fit_transform)
df['Living_With'] = df[['Living_With']].apply(le.fit_transform)
```

In [30]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2240 entries, 0 to 2239
Data columns (total 30 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   Education            2240 non-null   int32  
 1   Income               2240 non-null   float64
 2   Kidhome              2240 non-null   int64  
 3   Teenhome             2240 non-null   int64  
 4   Recency              2240 non-null   int64  
 5   Wines                2240 non-null   int64  
 6   Fruits               2240 non-null   int64  
 7   Meat                 2240 non-null   int64  
 8   Fish                 2240 non-null   int64  
 9   Sweets               2240 non-null   int64  
 10  Gold                 2240 non-null   int64  
 11  NumDealsPurchases    2240 non-null   int64  
 12  NumWebPurchases      2240 non-null   int64  
 13  NumCatalogPurchases  2240 non-null   int64  
 14  NumStorePurchases    2240 non-null   int64  
 15  NumWebVisitsMonth    2240 non-null   int64  
 16  AcceptedCmp3         2240 non-null   int64  
```

```
 17  AcceptedCmp4         2240 non-null   int64
 18  AcceptedCmp5         2240 non-null   int64
 19  AcceptedCmp1         2240 non-null   int64
 20  AcceptedCmp2         2240 non-null   int64
 21  Complain             2240 non-null   int64
 22  Response             2240 non-null   int64
 23  Customer_For         2240 non-null   int64
 24  Age                  2240 non-null   int64
 25  Spent                2240 non-null   int64
 26  Living_With          2240 non-null   int32
 27  Children             2240 non-null   int64
 28  Family_Size          2240 non-null   int64
 29  Is_Parent            2240 non-null   int32
dtypes: float64(1), int32(3), int64(26)
memory usage: 498.9 KB
```

Now we can see what our new dataframe looks like.

In [31]:

```
df
```

Out[31]:

	Education	Income	Kidhome	Teenhome	Recency	Wines	Fruits	Meat	Fish	Sweets	Gold	Nu
0	0	58138.0	0	0	58	635	88	546	172	88	88	
1	0	46344.0	1	1	38	11	1	6	2	1	6	
2	0	71613.0	0	0	26	426	49	127	111	21	42	
3	0	26646.0	1	0	26	11	4	20	10	3	5	
4	0	58293.0	1	0	94	173	43	118	46	27	15	
...	...	...	...	...	...	...	...	...	...	...	...	
2235	0	61223.0	0	1	46	709	43	182	42	118	247	
2236	0	64014.0	2	1	56	406	0	30	0	0	8	
2237	0	56981.0	0	0	91	908	48	217	32	12	24	
2238	0	69245.0	0	1	8	428	30	214	80	30	61	
2239	0	52869.0	1	1	40	84	3	61	2	1	21	

2240 rows × 30 columns

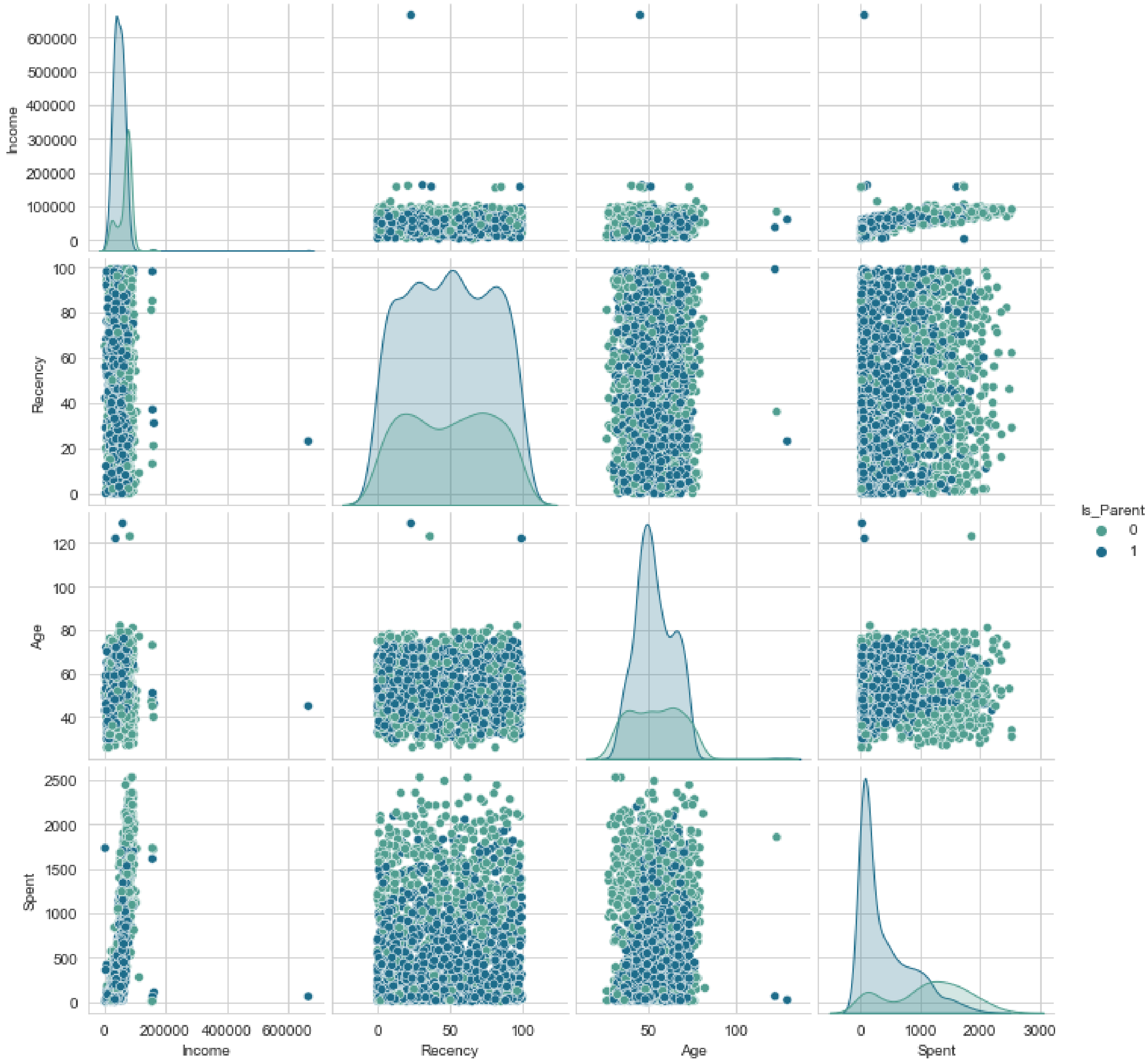
- **PairPlot**

Pairplot plots helps us to see the pairwise relationships in a dataset. It creates a grid of Axes such that each variable in the data is shared along the y-axis along a single row and on the x-axis along a single column.

In [32]:

```
sns.set_style("whitegrid")
plt.figure()
sns.pairplot(df[["Income", "Recency", "Age", "Spent", "Is_Parent"]], hue='Is_Parent', p
plt.show()
```

<Figure size 432x288 with 0 Axes>



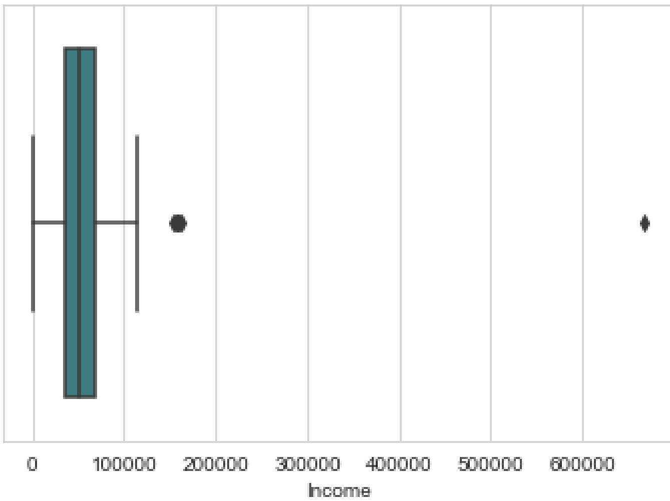
In [33]:
```
df.describe()
```

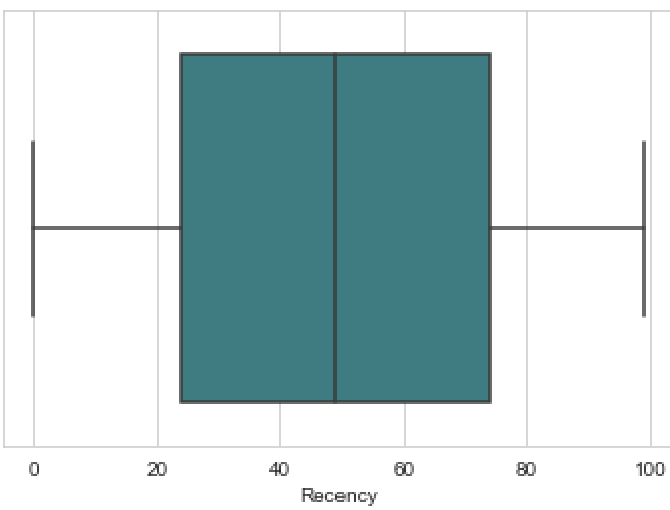
Out[33]:

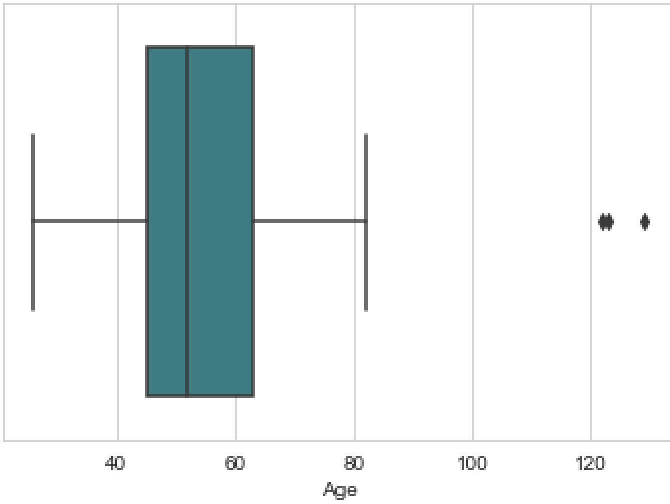
	Education	Income	Kidhome	Teenhome	Recency	Wines	Fruits	
count	2240.000000	2240.000000	2240.000000	2240.000000	2240.000000	2240.000000	2240.000000	22
mean	0.114732	52247.251354	0.444196	0.506250	49.109375	303.935714	26.302232	
std	0.318770	25037.797168	0.538398	0.544538	28.962453	336.597393	39.773434	
min	0.000000	1730.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	35538.750000	0.000000	0.000000	24.000000	23.750000	1.000000	
50%	0.000000	51741.500000	0.000000	0.000000	49.000000	173.500000	8.000000	
75%	0.000000	68289.750000	1.000000	1.000000	74.000000	504.250000	33.000000	
max	1.000000	666666.000000	2.000000	2.000000	99.000000	1493.000000	199.000000	17

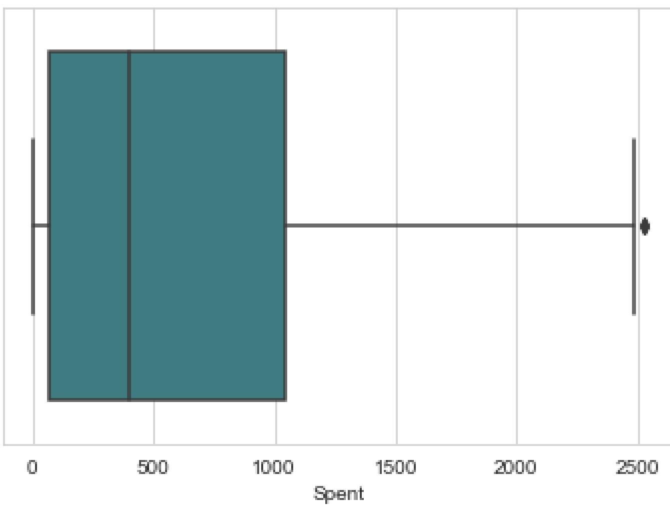
Outlier Detection

In [34]:
```
personal = ["Income", "Recency", "Age", "Spent"]


for i in personal:
    plt.figure()
    sns.boxplot(x=df[i], palette='crest')
    plt.show()
```



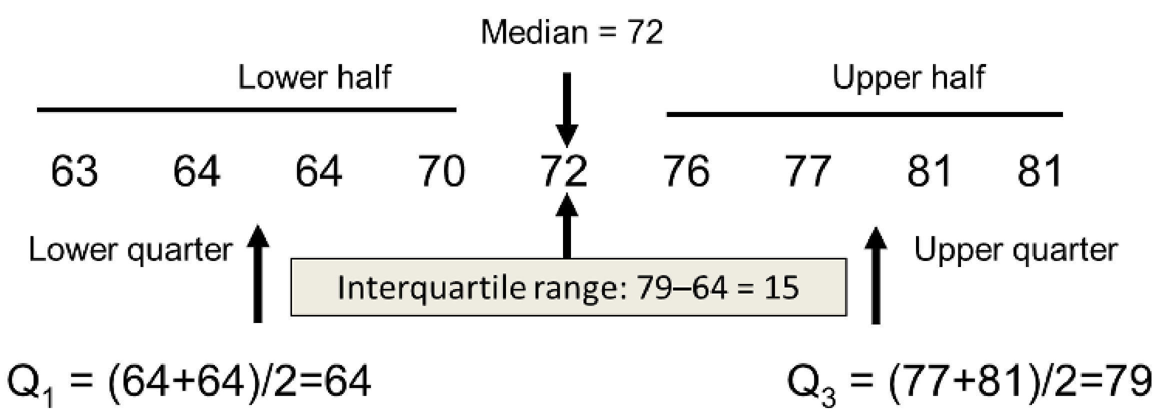






Inter Quantile Range

- We will use the IQR method to detect outlier data.
- First of all, it is necessary to find the distance between the quartiles in the data. (IQR = Q3 - Q1)



In [36]:
```
df['Age'].quantile(0.25)
```
Out[36]:
```
45.0
```

In [37]:
```
df['Age'].quantile(0.75)
```
Out[37]:
```
63.0
```

- **Then IQR limits are determined.**

In [38]:
```
Q1 = df['Age'].quantile(0.25)
Q3 = df['Age'].quantile(0.75)
IQR = Q3 - Q1
```

In [39]:
```
IQR
```
Out[39]:
```
18.0
```

In [40]:
```
lower_lim = Q1 - 1.5 * IQR
upper_lim = Q3 + 1.5 * IQR

#The fixed value used during the determination of the limits changes according to the s
```

In [41]:
```
lower_lim
```
Out[41]:
```
18.0
```

In [42]:
```
upper_lim
```
Out[42]:
```
90.0
```

- **We'll extract the outlier data from our dataset.**

In [43]:
```
outliers_low = (df['Age'] < lower_lim)

outliers_up = (df['Age'] > upper_lim)

len(df['Age'] - (len(df['Age'][outliers_low] + len(df['Age'][outliers_up]))))
```

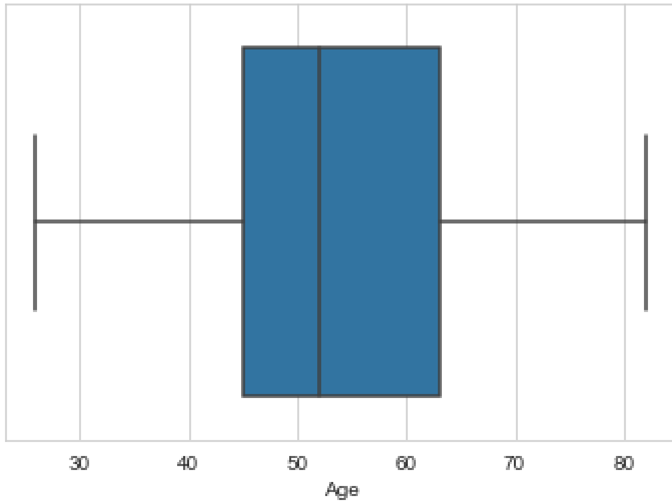
In [44]:
```
df['Age'][(outliers_low | outliers_up)]
```

In [45]:
```
df['Age'][~(outliers_low | outliers_up)]
```
Out[45]:
```
2240
```

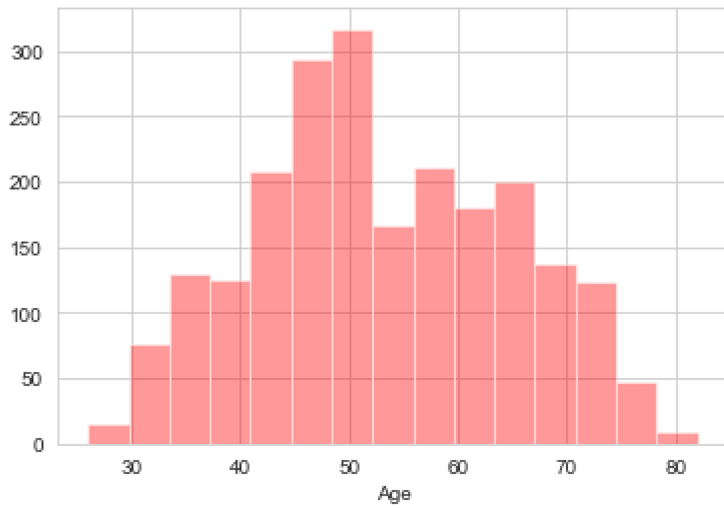
In [48]:
```
df = df[~(outliers_low | outliers_up)]
```

In [50]:
```
sns.boxplot(df.Age)
```

Out[50]: <AxesSubplot:xlabel='Age'>



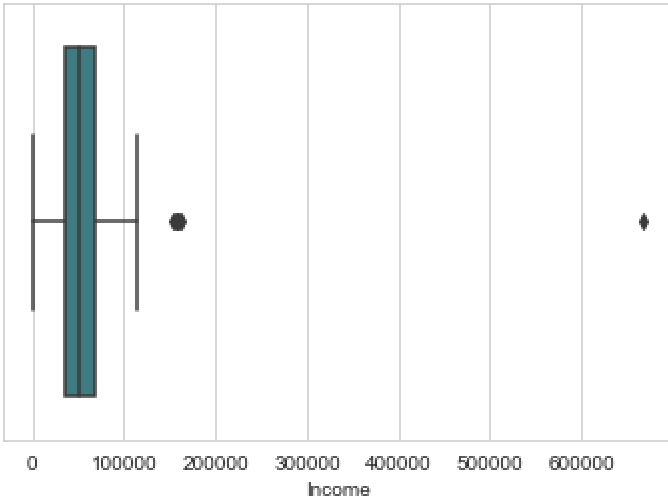
In [52]:
```
sns.distplot(df['Age'], bins = 15, kde = False, color = 'r')
plt.show()
```



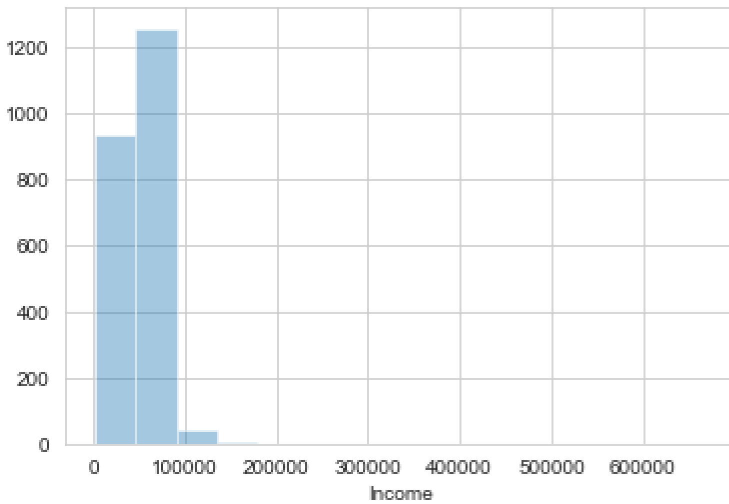
As you can see, there are no more outliers in the data.

In [53]:
```
sns.boxplot(df.Income, palette='crest')
```

Out[53]: <AxesSubplot:xlabel='Income'>



In [54]:
```
sns.distplot(df['Income'], bins = 15, kde = False)
plt.show()
```



This isn't how we want it to be.

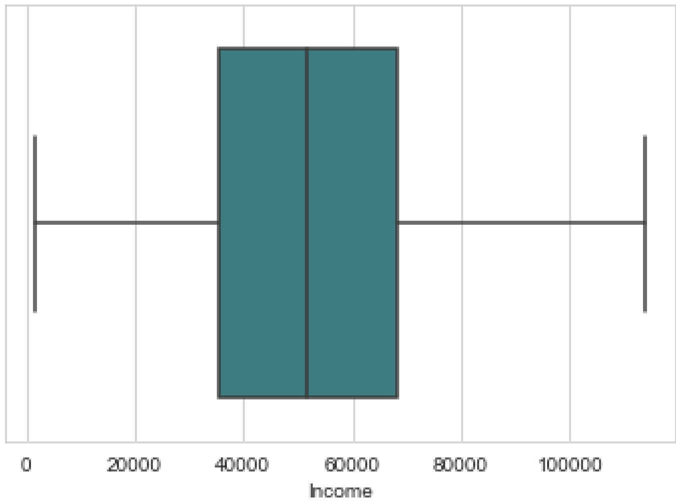
- **Let's handle the income column**

In [58]:
```
Q1 = df['Income'].quantile(0.25)
Q3 = df['Income'].quantile(0.75)
IQR = Q3 - Q1

lower_lim = Q1 - 1.5 * IQR
upper_lim = Q3 + 1.5 * IQR

outliers_low = (df['Income'] < lower_lim)
outliers_up = (df['Income'] > upper_lim)
len(df['Income'] - (len(df['Income'][outliers_low] + len(df['Income'][outliers_up]))))
df['Income'][(outliers_low | outliers_up)]
df['Income'][~(outliers_low | outliers_up)]
df = df[~(outliers_low | outliers_up)]
```

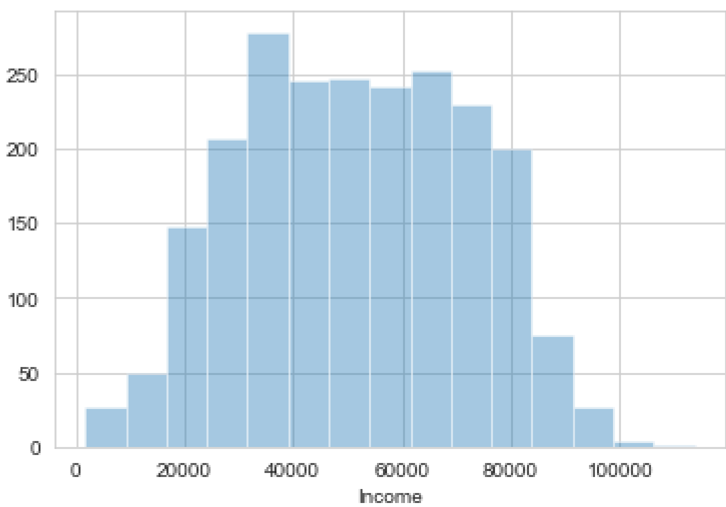
Now let's check the income column again.

In [59]:
```
sns.boxplot(df.Income, palette='crest')
```

Out[59]: <AxesSubplot:xlabel='Income'>



In [60]:
```
sns.distplot(df['Income'], bins = 15, kde = False)
plt.show()
```

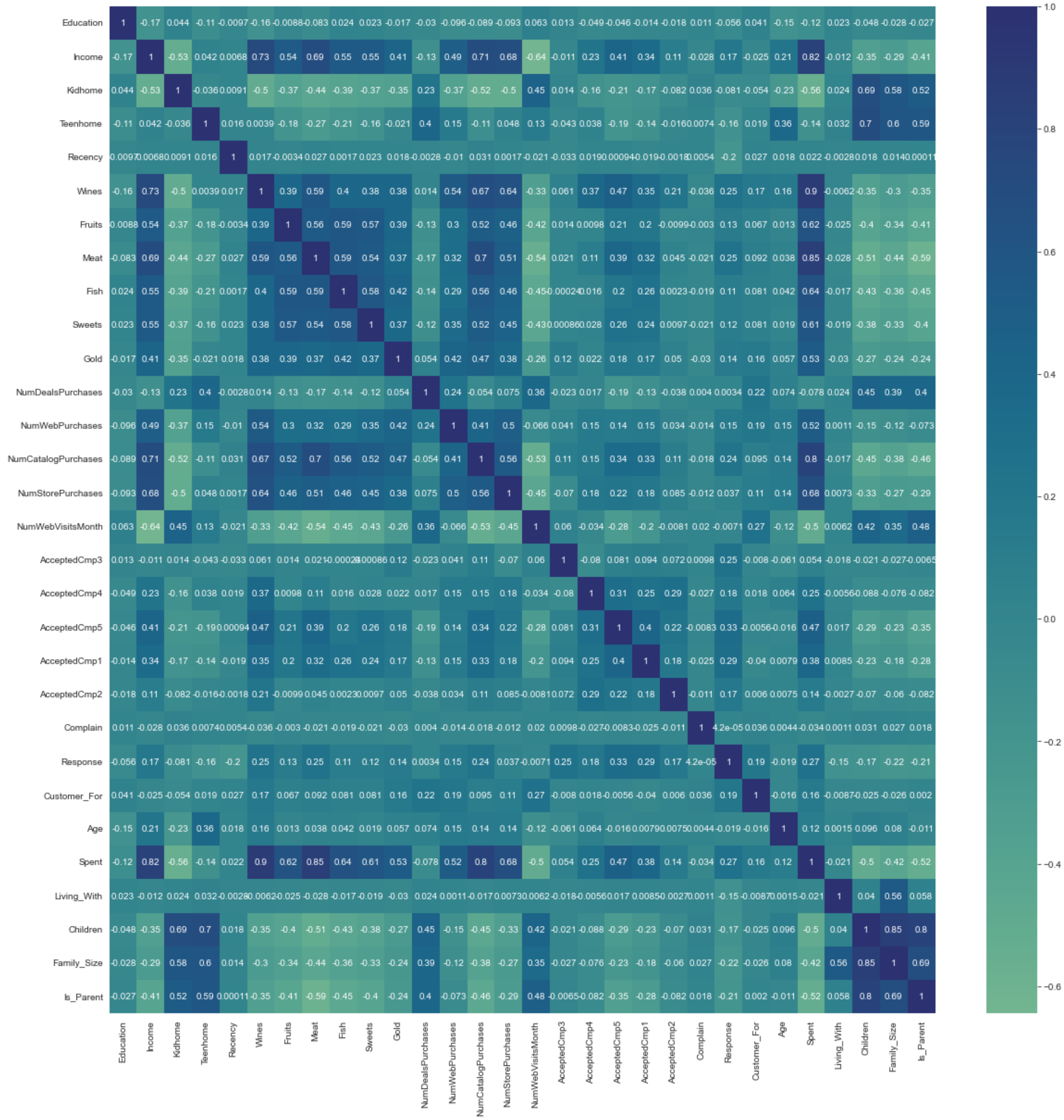


Correlation

- **It is a statistical method used to determine whether there is a linear relationship between two numerical values, and hence, the direction and severity of this relationship.**

In [61]:
```
corrmat = df.corr()
plt.figure(figsize = (20,20))
sns.heatmap(corrmat,annot=True, center=0, cmap='crest')
```

Out[61]: <AxesSubplot:>



Data preprocessing

- **We are removing columns related to deals and promotions from the dataset as they cause semantic confusion.**

In [62]:
```
new_df = df.copy()
cols_del = ['AcceptedCmp3', 'AcceptedCmp4', 'AcceptedCmp5', 'AcceptedCmp1','AcceptedCmp
new_df = new_df.drop(cols_del, axis=1)
```

- **Scaling the data**

In [63]:
```
sc = StandardScaler()
sc.fit(new_df)
```

```
scaled_df = pd.DataFrame(sc.transform(new_df), columns = new_df.columns )
```

In [64]:

```
scaled_df
```

Out[64]:

	Education	Income	Kidhome	Teenhome	Recency	Wines	Fruits	Meat	Fish
0	-0.359415	0.316030	-0.825592	-0.931676	0.307314	0.980166	1.550778	1.736151	2.456789
1	-0.359415	-0.256586	1.031365	0.904492	-0.383771	-0.873191	-0.637618	-0.726371	-0.651738
2	-0.359415	0.970262	-0.825592	-0.931676	-0.798422	0.359410	0.569773	-0.174584	1.341376
3	-0.359415	-1.212954	1.031365	-0.931676	-0.798422	-0.873191	-0.562156	-0.662528	-0.505455
4	-0.359415	0.323556	1.031365	-0.931676	1.551268	-0.392031	0.418849	-0.215626	0.152822
...	...	...	...	...	...	...	...	...	...
2224	-0.359415	0.465812	-0.825592	0.904492	-0.107337	1.199955	0.418849	0.076229	0.079680
2225	-0.359415	0.601319	2.888322	0.904492	0.238206	0.300008	-0.662772	-0.616926	-0.688309
2226	-0.359415	0.259856	-0.825592	-0.931676	1.447605	1.791009	0.544619	0.235837	-0.103175
2227	-0.359415	0.855292	-0.825592	0.904492	-1.420399	0.365350	0.091848	0.222156	0.774527
2228	-0.359415	0.060212	1.031365	0.904492	-0.314662	-0.656372	-0.587310	-0.475559	-0.651738

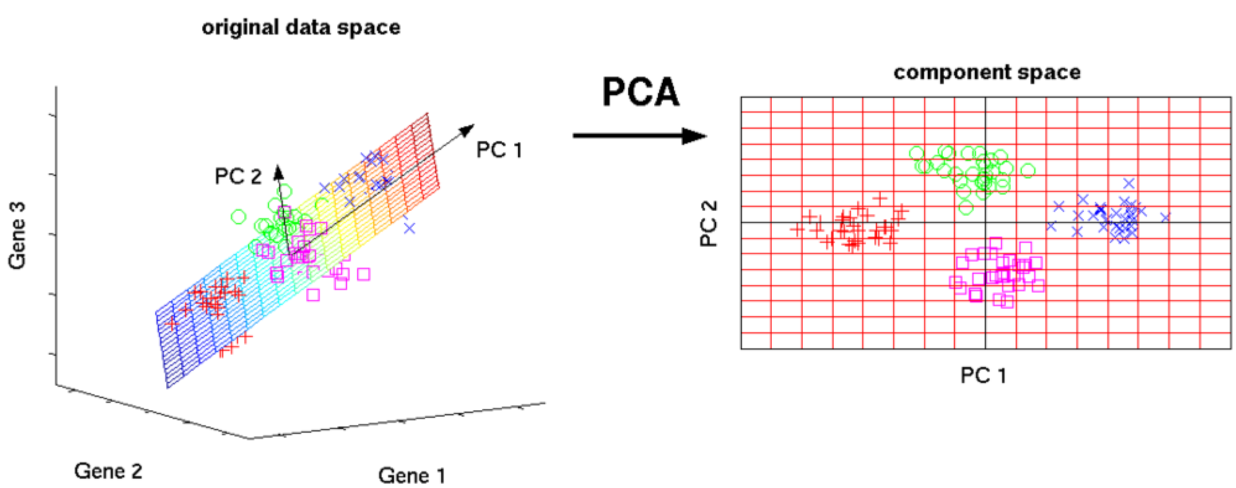
2229 rows × 23 columns

PRINCIPAL COMPONENT ANALYSIS

Dimension Reduction

- **In some cases, dimension reduction is very important.**

> - **For example: improving model performance or enabling visualization.**



By performing this operation, we'll be able to look at the data from a different point of view as new attributes can be extracted.

In [65]:
```
pca = PCA(n_components=3)
pca.fit(scaled_df)
pca_df = pd.DataFrame(pca.transform(scaled_df), columns=(["First_Column","Second_Column
pca_df.describe().T
```

Out[65]:

	count	mean	std	min	25%	50%	75%	max
First_Column	2229.0	2.450560e-17	2.897012	-6.025380	-2.556318	-0.790779	2.435875	7.546411
Second_Column	2229.0	1.280069e-16	1.722300	-4.384414	-1.320616	-0.180058	1.249482	6.204203
Third_Column	2229.0	5.254757e-18	1.238816	-3.385394	-0.827137	-0.041759	0.827515	6.429199

In [66]:
```
pca_df
```

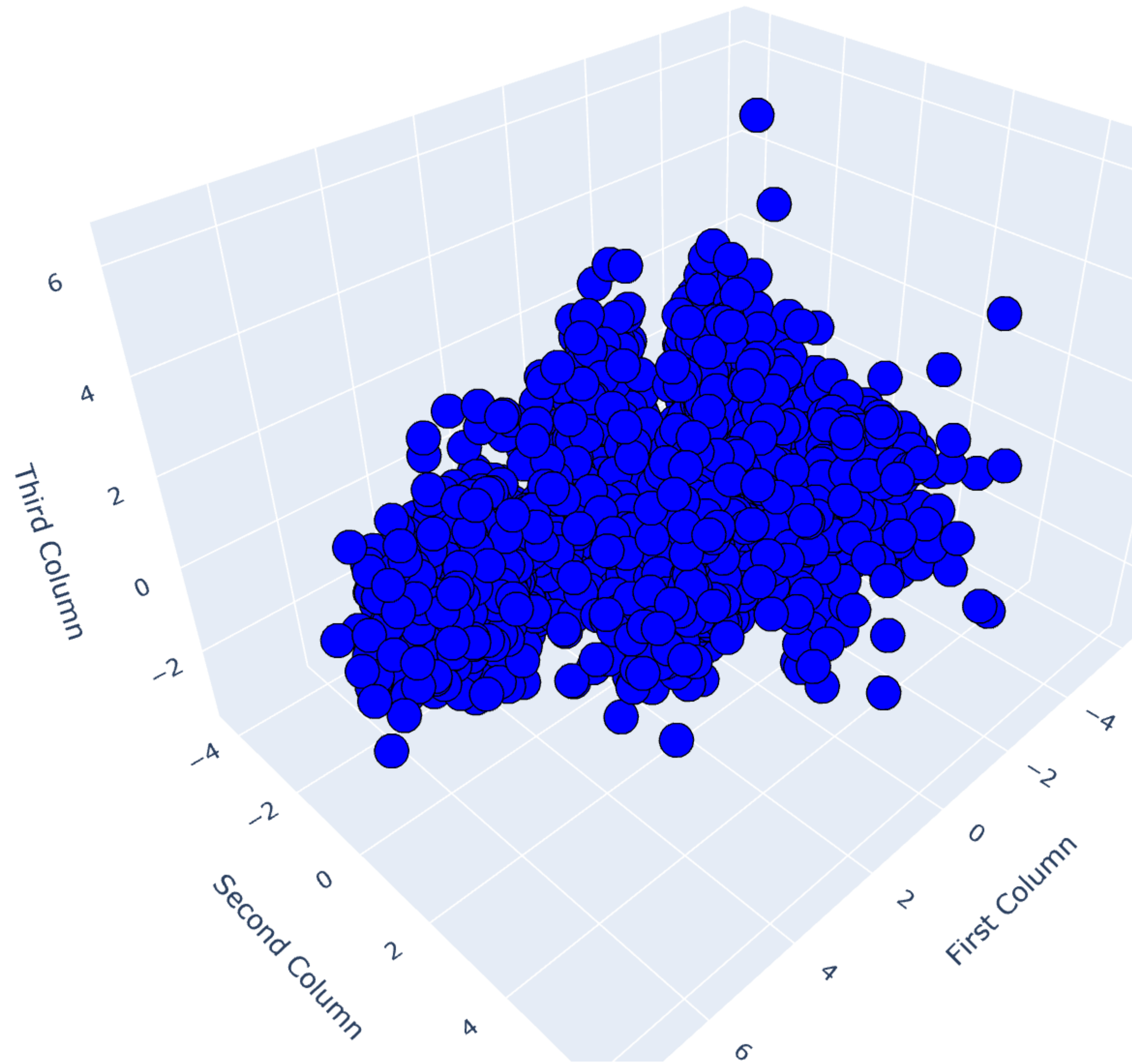
Out[66]:

	First_Column	Second_Column	Third_Column
0	5.013827	-0.201598	2.301202
1	-2.875021	0.069315	-1.782332
2	2.618429	-0.740504	-0.350609
3	-2.687844	-1.457772	-0.335301
4	-0.612702	0.259817	0.023343
...	...	...	...
2224	2.314878	2.363096	0.675740
2225	-3.040796	4.123276	-1.292170
2226	2.672355	-1.872488	0.145840
2227	1.562130	1.729290	-1.784393
2228	-2.691429	1.766236	-0.216543

2229 rows × 3 columns

Image of data reduced to 3D

In [67]:
```
Scene = dict(xaxis = dict(title  = 'First Column'),yaxis = dict(title  = 'Second Column
trace = go.Scatter3d(x=pca_df['First_Column'], y=pca_df['Second_Column'], z=pca_df['Thi
layout = go.Layout(margin=dict(l=0,r=0),scene = Scene,height = 800,width = 800)
data = [trace]
fig = go.Figure(data = data, layout = layout)
fig.show()
```



Modelling

KMeans

K-Means starts by randomly choosing the center point of k clusters, and the data points outside the center are included in the clusters they are similar to, according to their distance from the mean values of the clusters. Then, the average value of each cluster is calculated and new cluster centers are determined. Again, the distances of the objects from the center are examined continuosly until it's over.

In [68]:

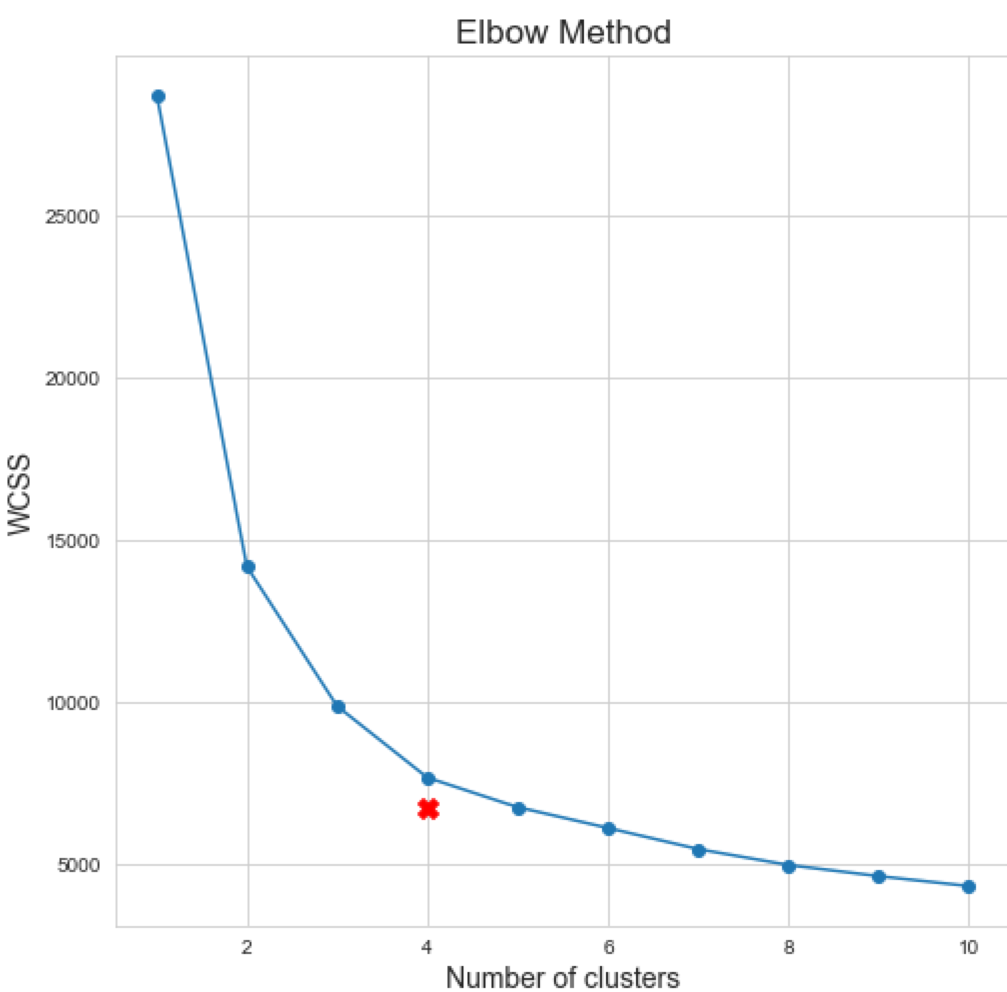
```
plt.rcParams['figure.figsize'] = [8,8]
sns.set_style("whitegrid")
colors = plt.rcParams['axes.prop_cycle'].by_key()['color']

inertia_list = []
for num_clusters in range(1, 11):
    kmeans_model = KMeans(n_clusters=num_clusters, init="k-means++")
    kmeans_model.fit(pca_df)
    inertia_list.append(kmeans_model.inertia_)
```

Plotting the inertia curve using the elbow method

In [69]:

```
plt.plot(range(1,11),inertia_list)
plt.scatter(range(1,11),inertia_list)
plt.scatter(4, inertia_list[4], marker="X", s=100, c="r")
plt.xlabel("Number of clusters", size=14)
plt.ylabel("WCSS", size=14)
plt.title("Elbow Method", size=17)
```

Out[69]: Text(0.5, 1.0, 'Elbow Method')



In [70]:

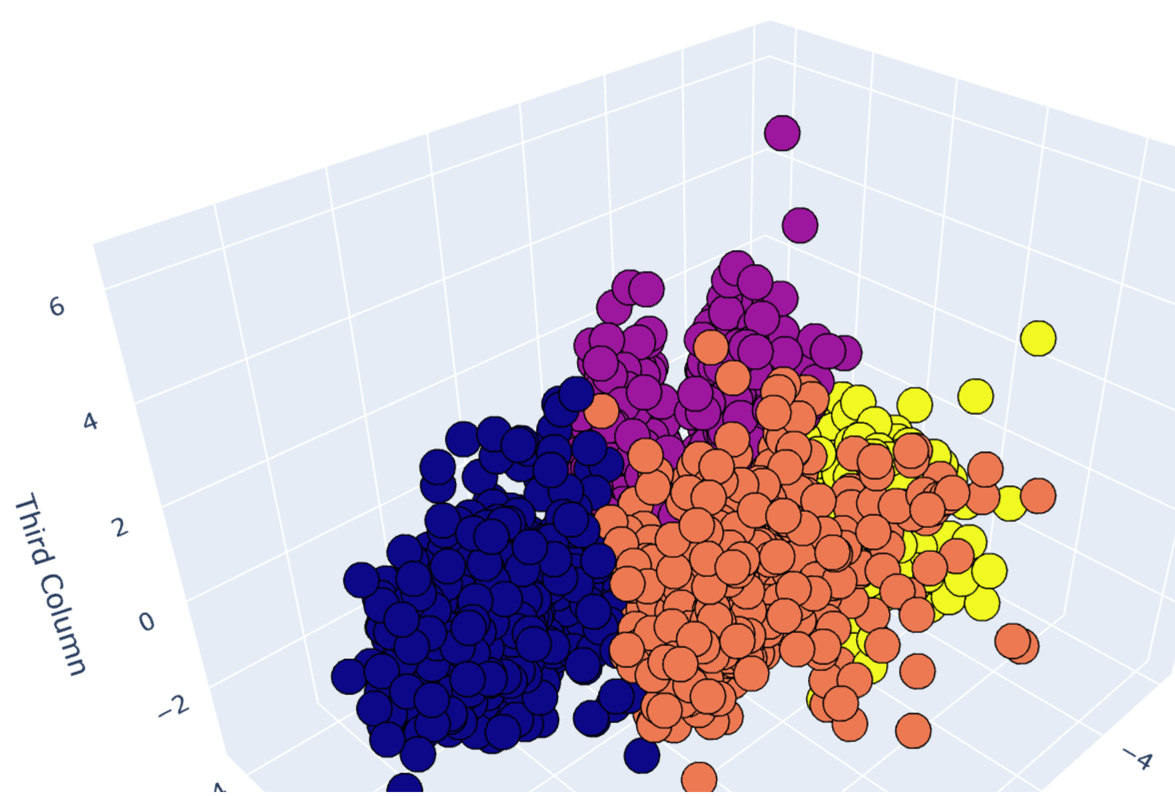
```
print('K-Means')
kMeans = KMeans(n_clusters = 4, init = 'k-means++')
y_pred_kMeans = kMeans.fit_predict(pca_df)
```

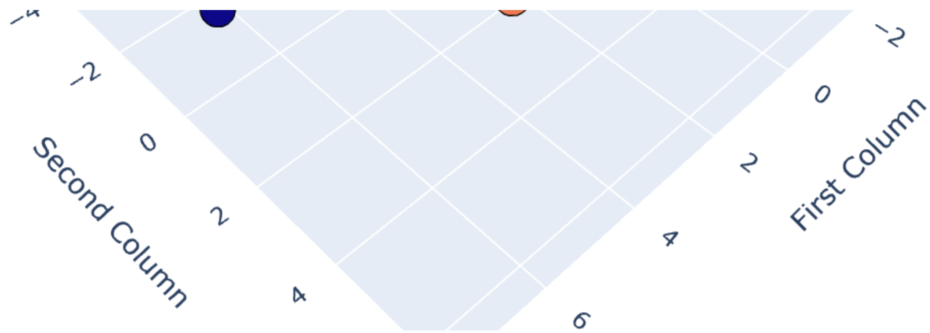
```
pca_df["Clusters_KMeans"] = y_pred_kMeans
df["Clusters_KMeans"]= y_pred_kMeans
print('Pred:\n', y_pred_kMeans)
print('\n\ninertia: ', kMeans.inertia_, '\n\nclusters centers:\n', kMeans.cluster_cente
```

```
K-Means
Pred:
 [0 3 0 ... 0 2 3]


inertia:  7678.734659289398

clusters centers:
 [[ 4.23410141 -0.91933676 -0.19733263]
 [-2.06654234 -1.70838114  0.5575856 ]
 [ 0.92546531  1.93282707  0.35625703]
 [-2.53899992  0.79702106 -0.79298866]]
```

In [72]:

```
Scene = dict(xaxis = dict(title  = 'First Column'),yaxis = dict(title  = 'Second Column
trace = go.Scatter3d(x=pca_df['First_Column'], y=pca_df['Second_Column'], z=pca_df['Thi
layout = go.Layout(margin=dict(l=0,r=0),scene = Scene,height = 800,width = 800)
data = [trace]
fig = go.Figure(data = data, layout = layout)
fig.show()
```



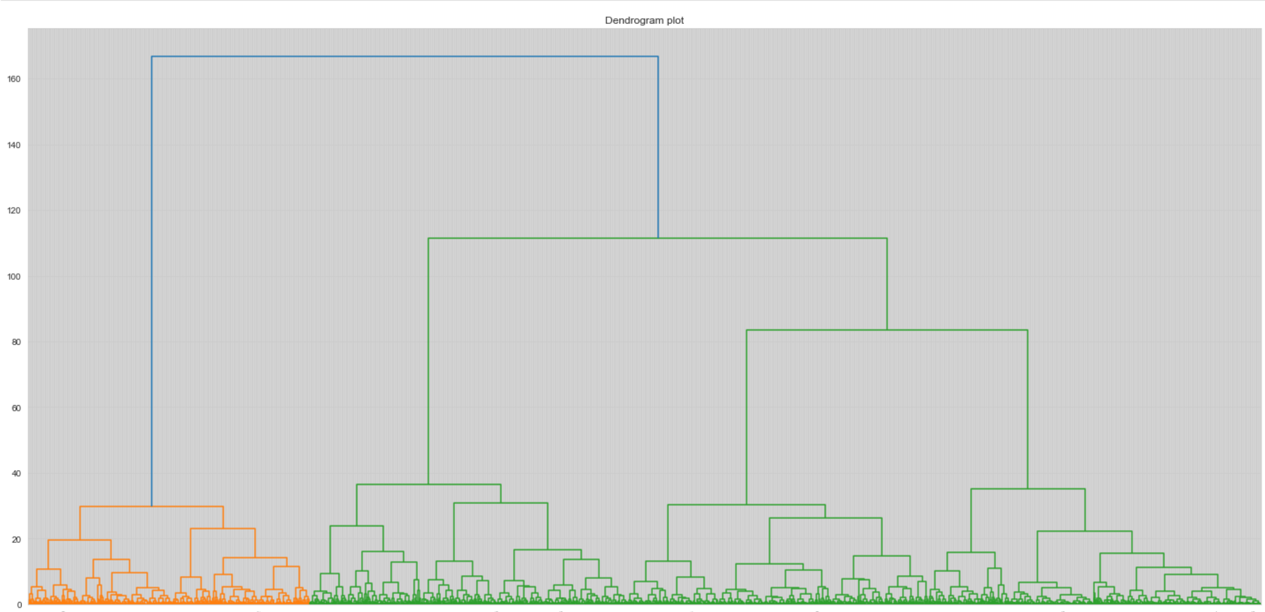


Hierarchical Clustering

Hierarchical clustering typically works by sequentially combining similar clusters.

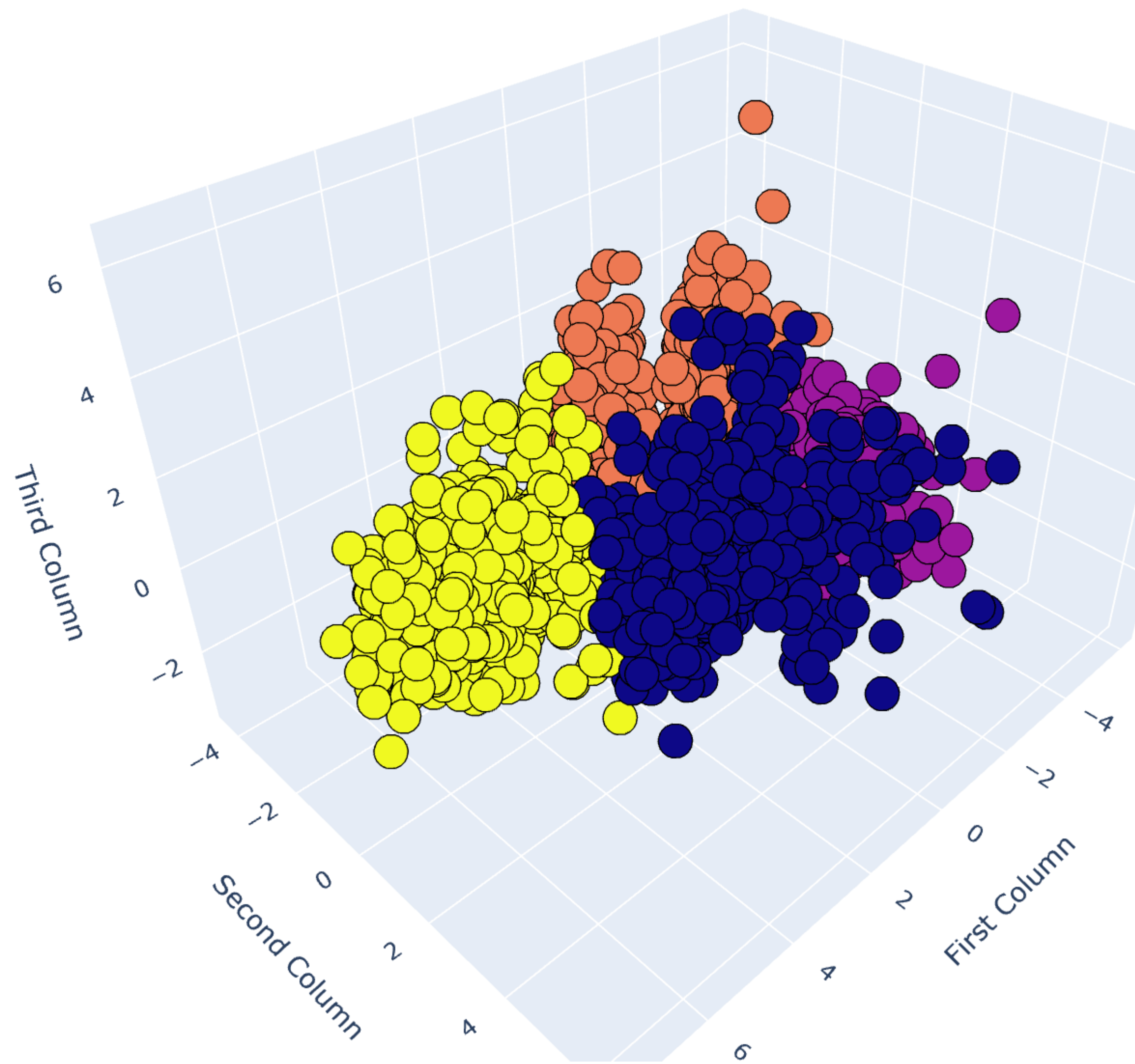
Let's create a dendogram

In [74]:
```
%matplotlib inline
import scipy.cluster.hierarchy as sch
plt.figure(figsize=(25,12))
dendrogram=sch.dendrogram(sch.linkage(pca_df,method = 'ward'))
plt.title('Dendrogram plot')
plt.show()
```



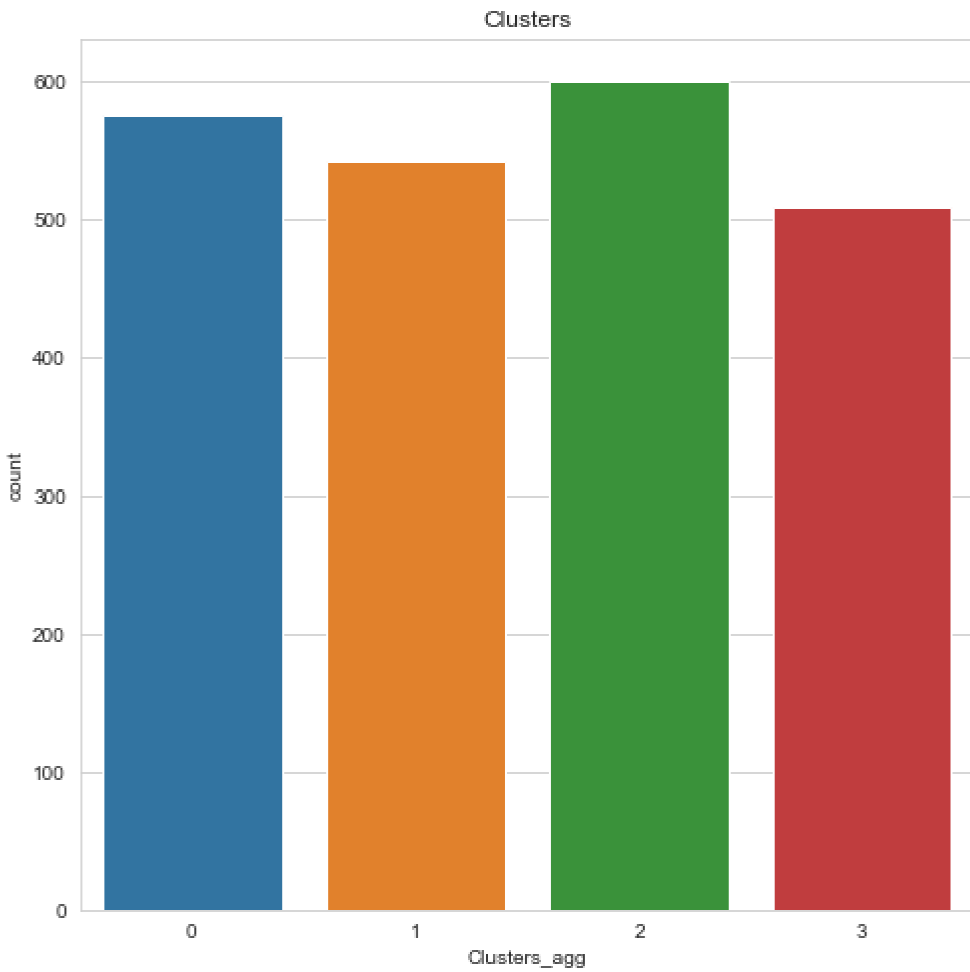
In [75]:
```
agg = AgglomerativeClustering(n_clusters=4)
y_pred_agg = agg.fit_predict(pca_df)
pca_df["Clusters_agg"] = y_pred_agg
df["Clusters_agg"]= y_pred_agg
```

In [77]:
```
Scene = dict(xaxis = dict(title  = 'First Column'),yaxis = dict(title  = 'Second Column

trace = go.Scatter3d(x=pca_df['First_Column'], y=pca_df['Second_Column'], z=pca_df['Thi
                     mode='markers',marker=dict(color = pca_df["Clusters_agg"], size= 1
                        line=dict(color= 'black',width = 10)))
layout = go.Layout(margin=dict(l=0,r=0),scene = Scene,height = 800,width = 800)
data = [trace]
fig = go.Figure(data = data, layout = layout)
fig.show()
```



Quantities of samples in each cluster.

In [83]:
```
pl = sns.countplot(x=df["Clusters_agg"], palette= 'tab10')
pl.set_title("Clusters")
plt.show()
```



Cluster profile based on income and spent.

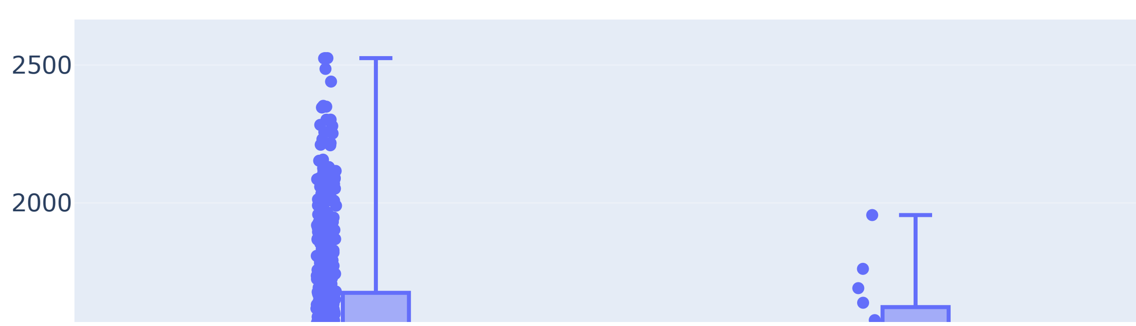
In [84]:
```
pal = ["#b0282f","#9E00FF", "#30832c","#286090"]
plt.rcParams['figure.figsize'] = [8,8]
pl = sns.scatterplot(data = df,x=df["Spent"], y=df["Income"],hue=df["Clusters_agg"], pa
pl.set_title("Cluster profile based on income and spent.")
plt.legend()
plt.show()
```

- **Grup 0:** Average income, high spending
- **Grup 1:** Average income, low spending
- **Grup 2:** Low income, low spending.
- **Grup 3:** High income, high spending

PROFILING

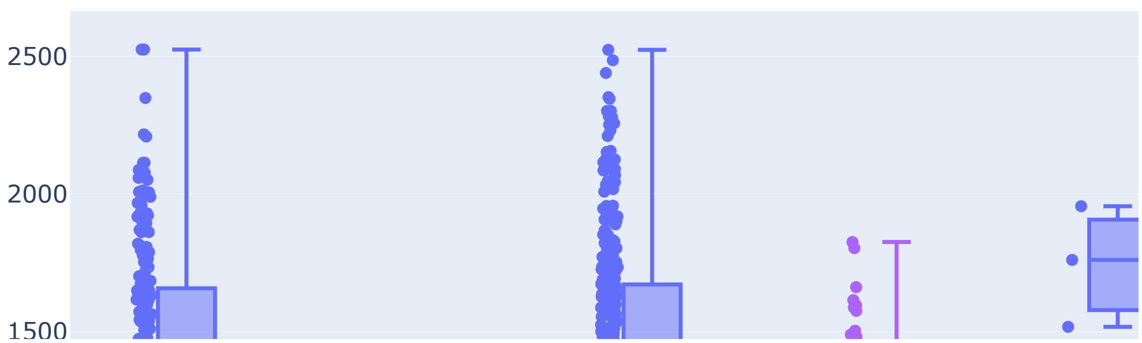
- **Qualifications of customers belonging to different clusters.**

In [85]:
```
fig = px.box(df, x=df['Children'], y=df['Spent'], points="all", color="Clusters_agg")
fig.show()
```



In [86]:

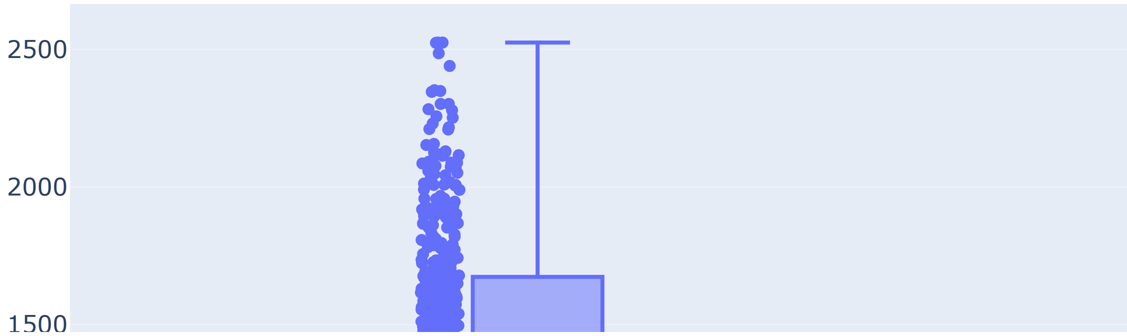
```
fig = px.box(df, x=df['Family_Size'], y=df['Spent'], points="all", color="Clusters_agg"
fig.show()
```



In [87]:

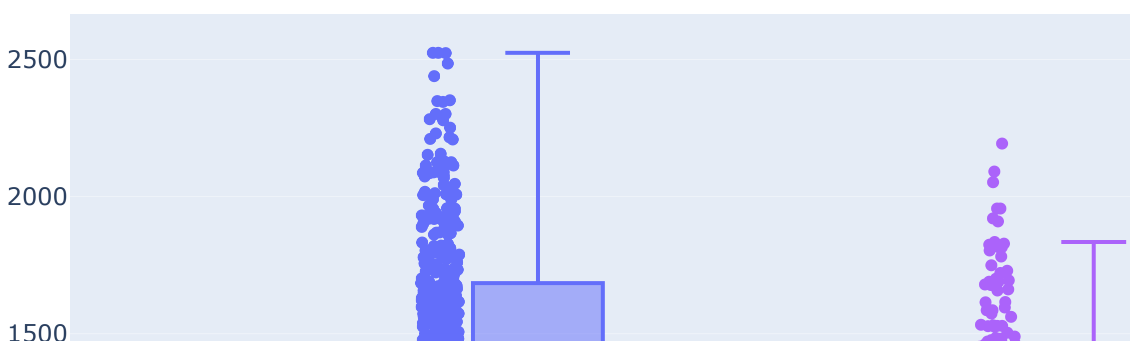
```
fig = px.box(df, x=df['Is_Parent'], y=df['Spent'], points="all", color="Clusters_agg")
```

```
fig.show()
```



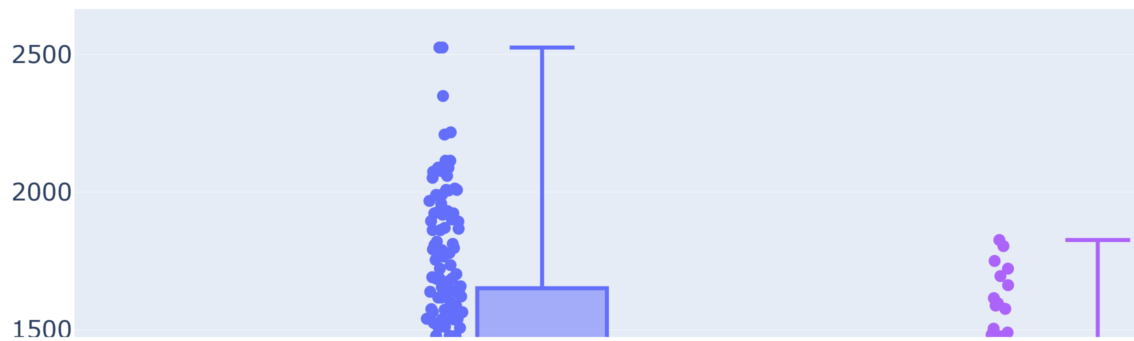
In [88]:

```
fig = px.box(df, x=df['Education'], y=df['Spent'], points="all", color="Clusters_agg")
fig.show()
```



In [89]:

```
fig = px.box(df, x=df['Living_With'], y=df['Spent'], points="all", color="Clusters_agg"
fig.show()
```



In [ ]:

```
```