CUSTOMER CLUSTERIZATION

HIERARCHICAL CLUSTERING

In [1]:
```
# Importing Libraries & Data
```

In [2]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from scipy.cluster.hierarchy import linkage, dendrogram
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
```

In [3]:
```
df = pd.read_csv('segmentationdata.csv')
```

In [4]:
```
# Exploratory Data Anaysis
```

In [5]:
```
df.head()
```

Out[5]:

	ID	Sex	Marital status	Age	Education	Income	Occupation	Settlement size
0	100000001	0	0	67	2	124670	1	2
1	100000002	1	1	22	1	150773	1	2
2	100000003	0	0	49	1	89210	0	0
3	100000004	0	0	45	1	171565	1	1
4	100000005	0	0	53	1	149031	1	1

In [6]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2000 entries, 0 to 1999
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   ID               2000 non-null   int64
 1   Sex              2000 non-null   int64
 2   Marital status   2000 non-null   int64
 3   Age              2000 non-null   int64
 4   Education        2000 non-null   int64
 5   Income           2000 non-null   int64
 6   Occupation       2000 non-null   int64
 7   Settlement size  2000 non-null   int64
dtypes: int64(8)
memory usage: 125.1 KB
```

In [7]:

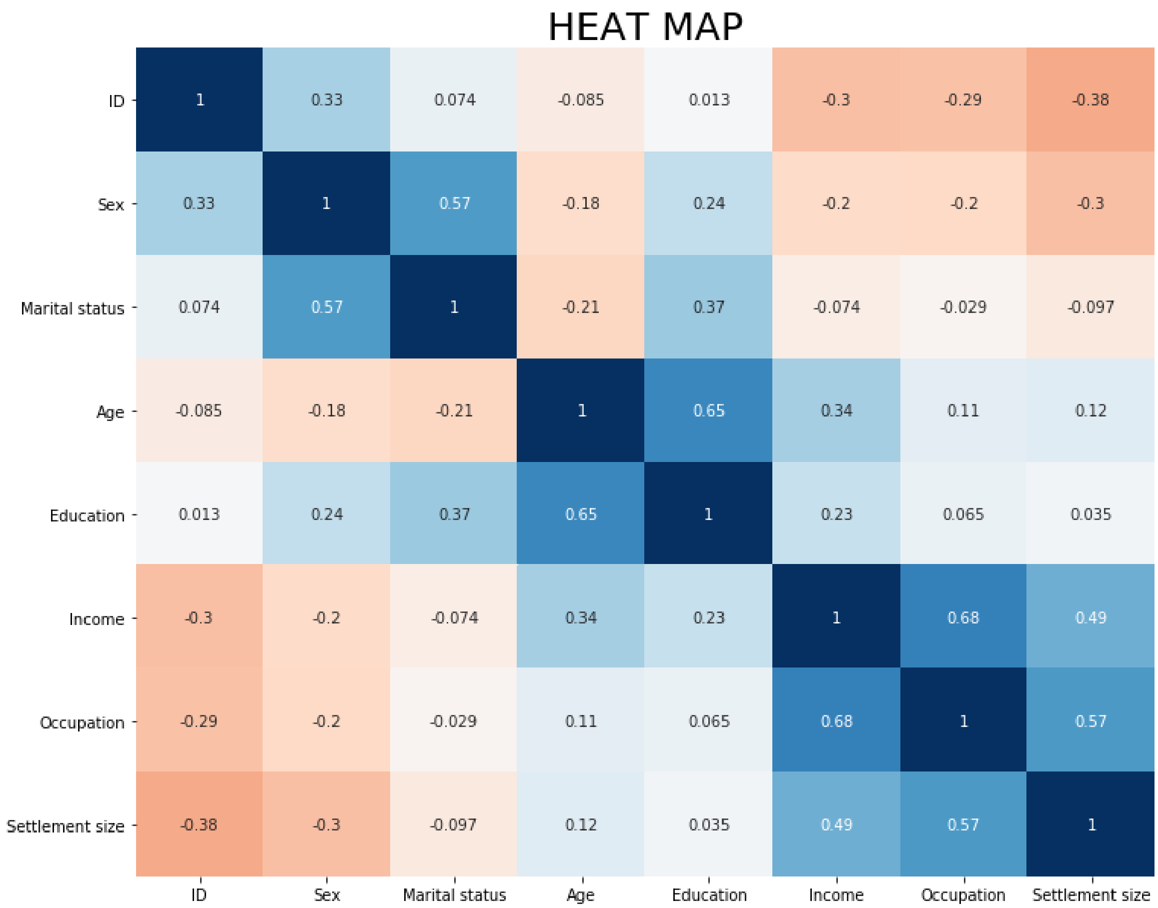
```
df.describe()
```

Out[7]:

	ID	Sex	Marital status	Age	Education	Income	Occ
count	2.000000e+03	2000.000000	2000.000000	2000.000000	2000.00000	2000.000000	2000
mean	1.000010e+08	0.457000	0.496500	35.909000	1.03800	120954.419000	0
std	5.774946e+02	0.498272	0.500113	11.719402	0.59978	38108.824679	0
min	1.000000e+08	0.000000	0.000000	18.000000	0.00000	35832.000000	0
25%	1.000005e+08	0.000000	0.000000	27.000000	1.00000	97663.250000	0
50%	1.000010e+08	0.000000	0.000000	33.000000	1.00000	115548.500000	1
75%	1.000015e+08	1.000000	1.000000	42.000000	1.00000	138072.250000	1
max	1.000020e+08	1.000000	1.000000	76.000000	3.00000	309364.000000	2

In [8]:
```
plt.figure(figsize=(12,10))
plt.title('HEAT MAP', fontdict = {'fontsize' : 25})
sns.heatmap(df.corr(), annot=True, cbar=False, cmap='RdBu', vmin=-1, vmax=1)
```

Out[8]: <matplotlib.axes._subplots.AxesSubplot at 0x188ab9b8488>



In [9]:
```
# Feature Engineering
```

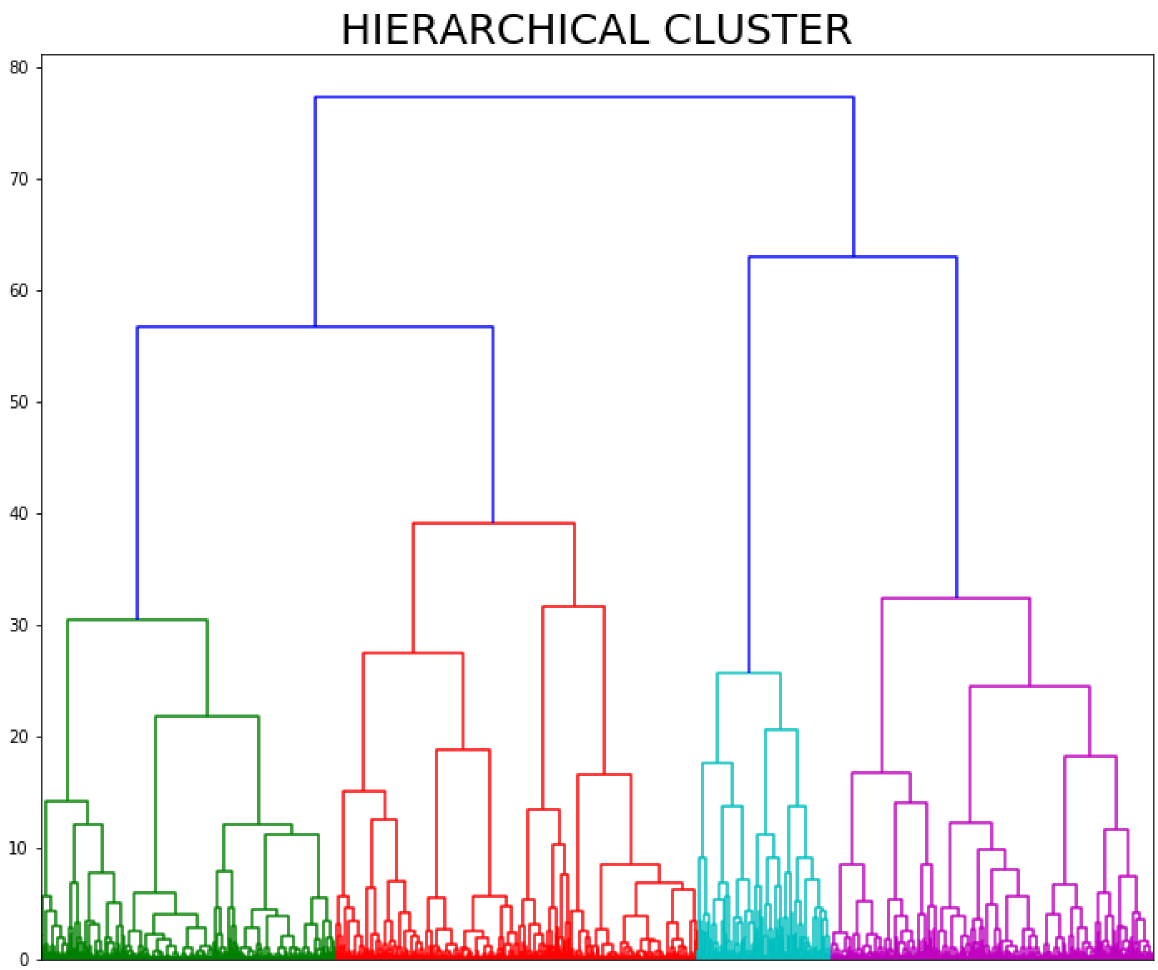
In [10]:
```
df.drop('ID', axis=1, inplace=True)
```

In [11]:
```
scale = StandardScaler()
```

In [12]:
```
df_std = scale.fit_transform(df)
```

In [13]:
```
model = linkage(df_std, method='ward')
```

In [14]:
```
plt.figure(figsize=(12,10))
dendrogram(model, no_labels=True)
plt.title('HIERARCHICAL CLUSTER', fontdict = {'fontsize' : 25})
plt.show()
```



The Largest vertical line without any horizontal line shows that we can divide our customer group by 4 Clusters

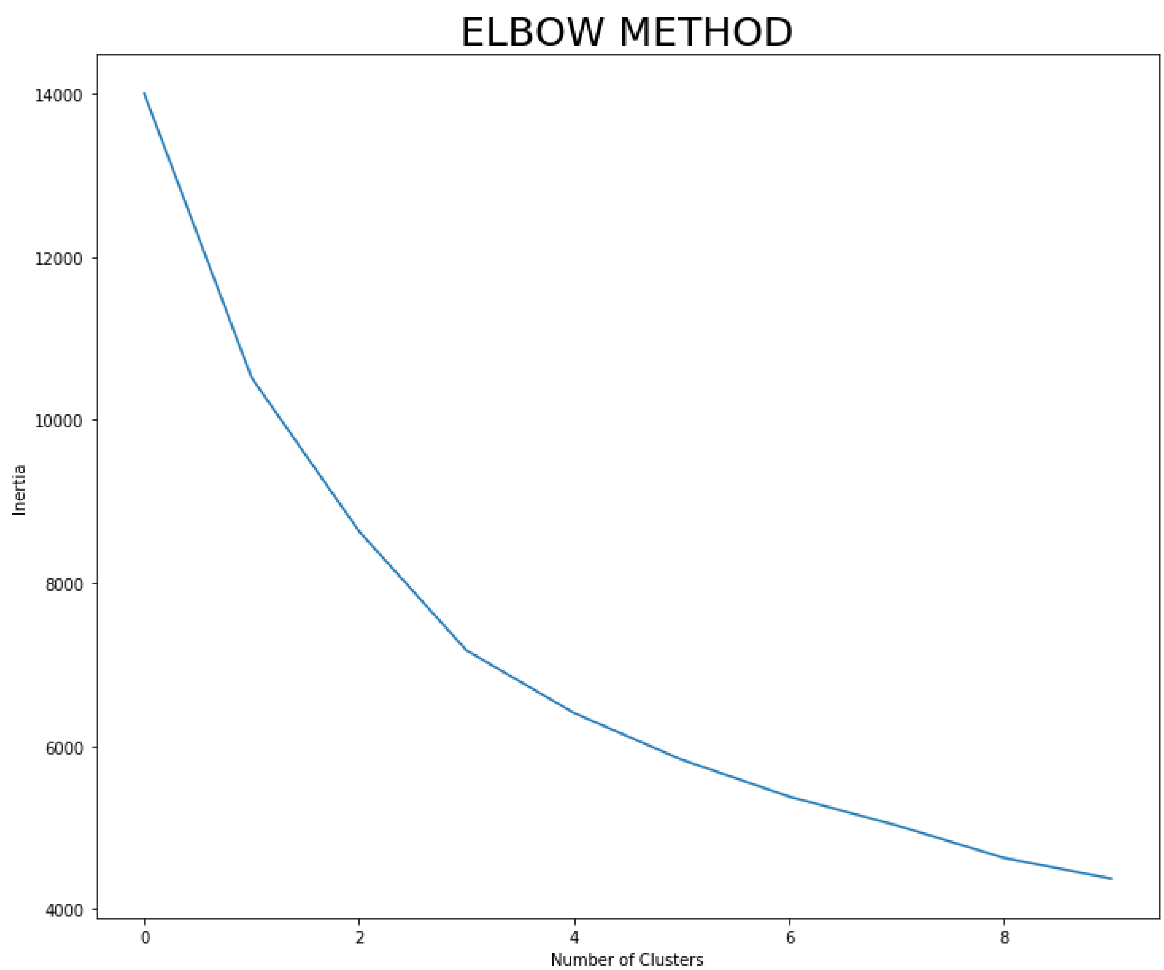
K-MEAN CLUSTERING

In [15]:
```
# Finding the right number of cluster
```

In [16]:
```
wcss = []
for i in range(1,11):
    model = KMeans(n_clusters=i, init='k-means++')
    model.fit(df_std)
    wcss.append(model.inertia_)
```

In [17]:
```
plt.figure(figsize=(12,10))
plt.plot(wcss)
plt.xlabel('Number of Clusters')
plt.ylabel('Inertia')
plt.title('ELBOW METHOD', fontdict = {'fontsize' : 25})
```

Out[17]: Text(0.5, 1.0, 'ELBOW METHOD')



3 or 4 cluster seem to be the best segmentation

In [18]:
```
cluster_model = KMeans(n_clusters=4, init='k-means++')
```

In [19]:
```
cluster_model.fit(df_std)
```

Out[19]:
```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
       n_clusters=4, n_init=10, n_jobs=None, precompute_distances='auto',
       random_state=None, tol=0.0001, verbose=0)
```

In [20]:
```
cluster_model.labels_
```

Out[20]:
```
array([2, 1, 3, ..., 3, 1, 3])
```

In [21]:
```
df['Kmean_label'] = cluster_model.labels_
```

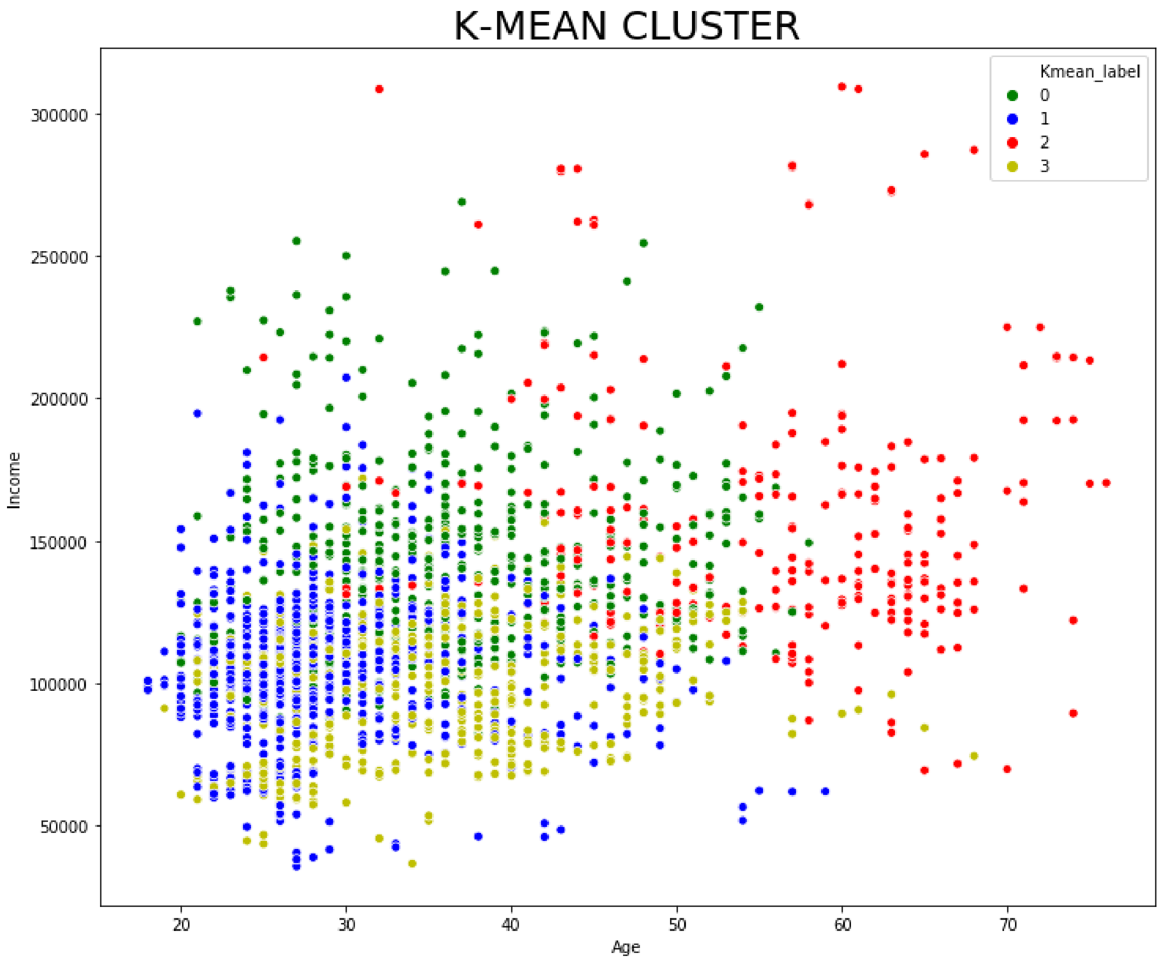
In [22]:
```
df.groupby('Kmean_label').mean()
```

Out[22]:

Kmean_label	Sex	Marital status	Age	Education	Income	Occupation	Settlemen siz
0	0.029825	0.173684	35.635088	0.733333	141218.249123	1.271930	1.52280
1	0.853901	0.997163	28.963121	1.068085	105759.119149	0.634043	0.42269
2	0.501901	0.692015	55.703422	2.129278	158338.422053	1.129278	1.11026
3	0.352814	0.019481	35.577922	0.746753	97859.852814	0.329004	0.04329

In [23]:
```
plt.figure(figsize=(12,10))
plt.title('K-MEAN CLUSTER', fontdict = {'fontsize' : 25})
sns.scatterplot(x=df['Age'], y=df['Income'], hue=df['Kmean_label'], palette=[
```

Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x188ac1aadc8>



PCA & K-MEAN CLUSTERING

In [24]:
```
# PCA model
```

In [25]:
```
model_pca = PCA()
```

In [26]:
```
model_pca.fit(df_std)
```

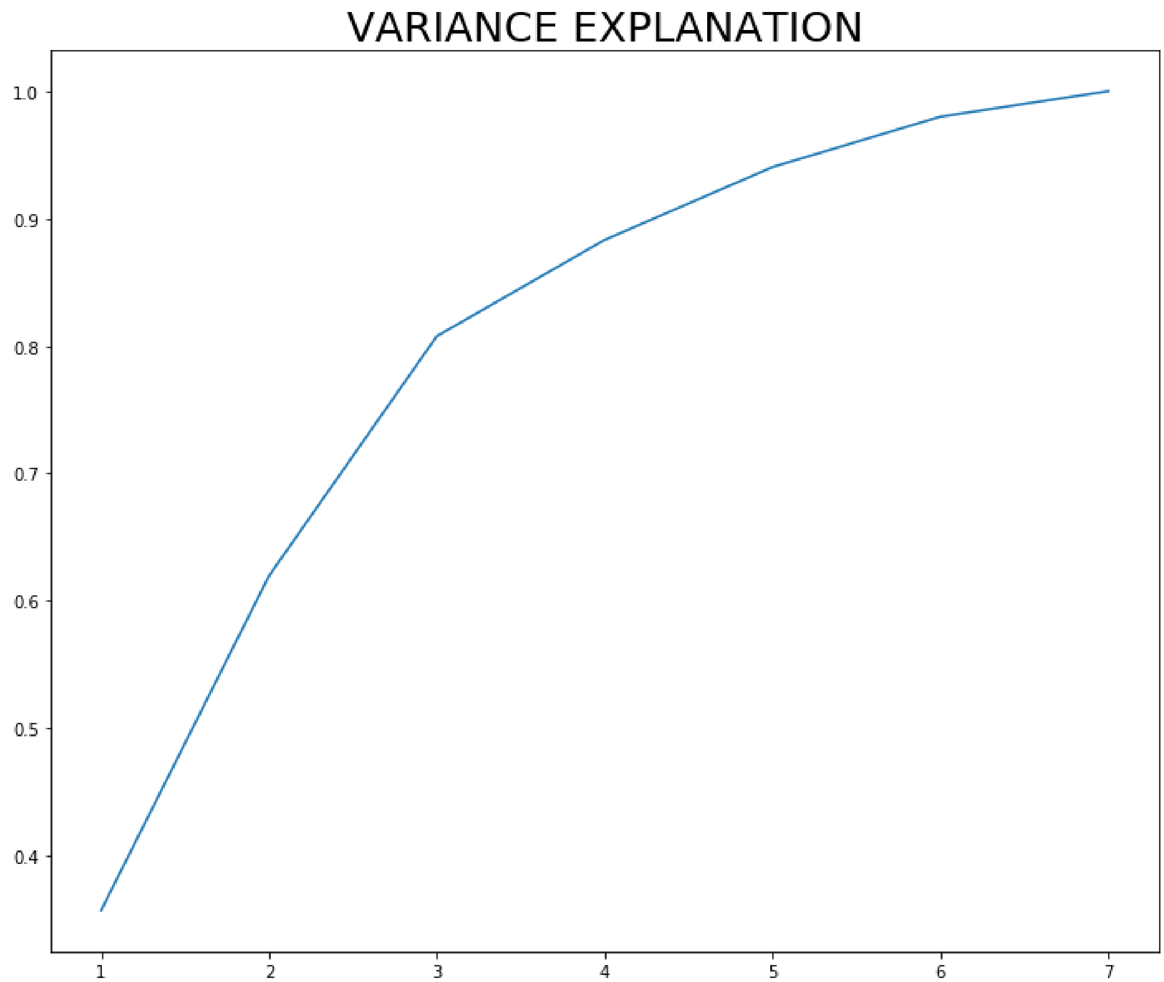
Out[26]:
```
PCA(copy=True, iterated_power='auto', n_components=None, random_state=None,
    svd_solver='auto', tol=0.0, whiten=False)
```

In [27]:
```
model_pca.explained_variance_ratio_
```

Out[27]:
```
array([0.35696328, 0.26250923, 0.18821114, 0.0755775 , 0.05716512,
       0.03954794, 0.02002579])
```

In [28]:
```
plt.figure(figsize=(12,10))
plt.title('VARIANCE EXPLANATION', fontdict = {'fontsize' : 25})
sns.lineplot(range(1,8), model_pca.explained_variance_ratio_.cumsum(), )
```

Out[28]: <matplotlib.axes._subplots.AxesSubplot at 0x188ac2c1748>



In [29]:
```
# PCA with 4 components
```

In [30]:
```
model_pca = PCA(n_components=4)
model_pca.fit(df_std)
```

Out[30]:
```
PCA(copy=True, iterated_power='auto', n_components=4, random_state=None,
    svd_solver='auto', tol=0.0, whiten=False)
```

In [31]:
```
df_pca = model_pca.transform(df_std)
```

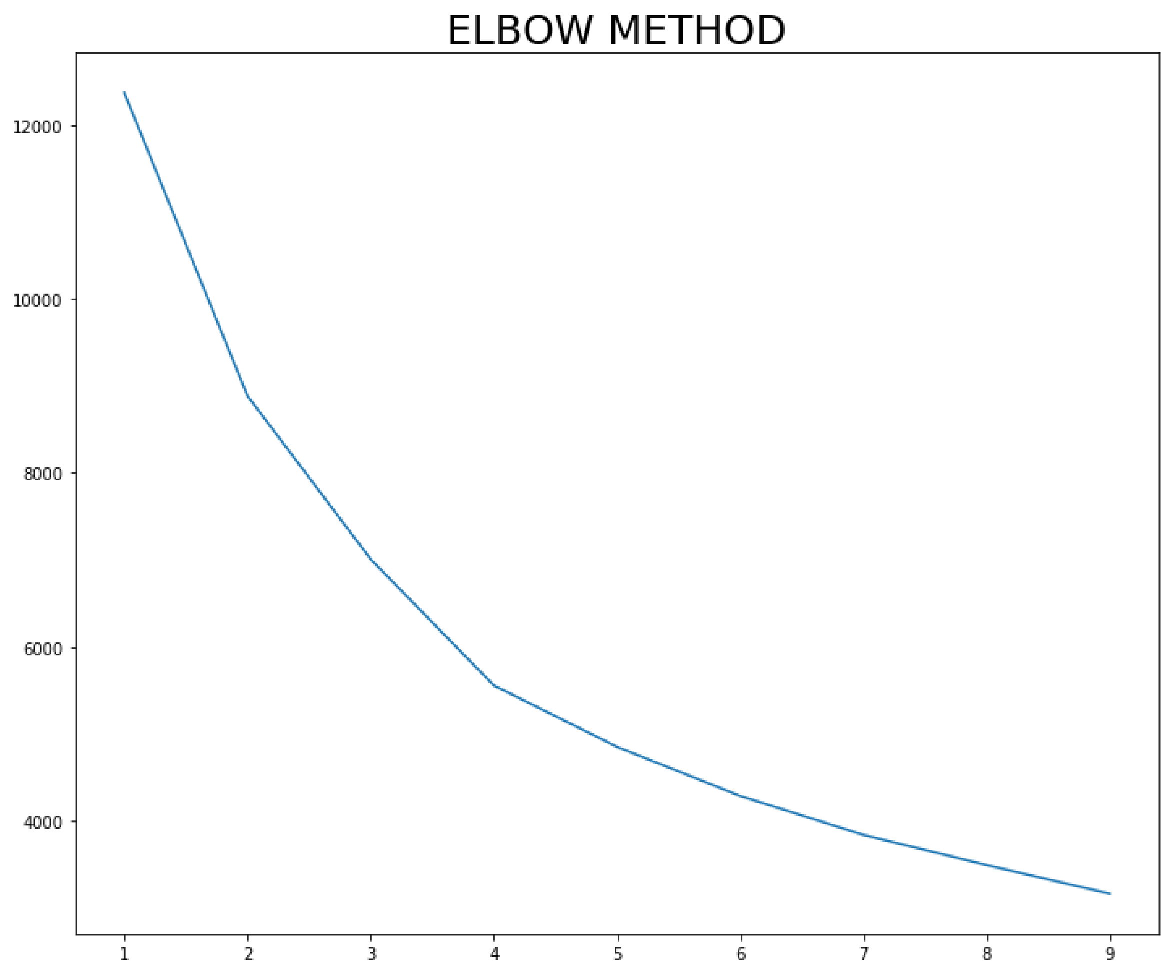
In [32]:
```
df_pca.shape
```

Out[32]: (2000, 4)

In [33]:
```
wcss = []
for i in range(1,10):
    model_pca_kmean = KMeans(n_clusters=i, init='k-means++')
    model_pca_kmean.fit(df_pca)
    wcss.append(model_pca_kmean.inertia_)
```

In [34]:
```
plt.figure(figsize=(12,10))
plt.title('ELBOW METHOD', fontdict = {'fontsize' : 25})
sns.lineplot(range(1,10),wcss)
```

Out[34]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x188ac297388>
```



In [35]:
```
model_pca_kmean = KMeans(n_clusters=4, init='k-means++')
model_pca_kmean.fit(df_pca)
```

Out[35]:
```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
       n_clusters=4, n_init=10, n_jobs=None, precompute_distances='auto',
       random_state=None, tol=0.0001, verbose=0)
```

In [36]:
```
df['pca_kmean_label'] = model_pca_kmean.labels_
```

In [37]:

```
df
```

Out[37]:

	Sex	Marital status	Age	Education	Income	Occupation	Settlement size	Kmean_label	pca_kmea
0	0	0	67	2	124670	1	2	2	
1	1	1	22	1	150773	1	2	1	
2	0	0	49	1	89210	0	0	3	
3	0	0	45	1	171565	1	1	0	
4	0	0	53	1	149031	1	1	0	
...	...	...	...	...	...	...	...	...	
1995	1	0	47	1	123525	0	0	3	
1996	1	1	27	1	117744	1	0	1	
1997	0	0	31	0	86400	0	0	3	
1998	1	1	24	1	97968	0	0	1	
1999	0	0	25	0	68416	0	0	3	

2000 rows × 9 columns

In [38]:

```
df.groupby('Kmean_label')['Age', 'Income', 'Settlement size', 'Sex', 'Marital
```

```
C:\Users\15516\anaconda3\lib\site-packages\ipykernel_launcher.py:1: FutureW
arning: Indexing with multiple keys (implicitly converted to a tuple of key
s) will be deprecated, use a list instead.
  """Entry point for launching an IPython kernel.
```

Out[38]:

Kmean_label	Age	Income	Settlement size	Sex	Marital status	Education	Occupatio
0	35.635088	141218.249123	1.522807	0.029825	0.173684	0.733333	1.27193
1	28.963121	105759.119149	0.422695	0.853901	0.997163	1.068085	0.63404
2	55.703422	158338.422053	1.110266	0.501901	0.692015	2.129278	1.12927
3	35.577922	97859.852814	0.043290	0.352814	0.019481	0.746753	0.32900

In [39]:

```
df.groupby('pca_kmean_label')['Age', 'Income', 'Settlement size', 'Sex', 'Mar
```

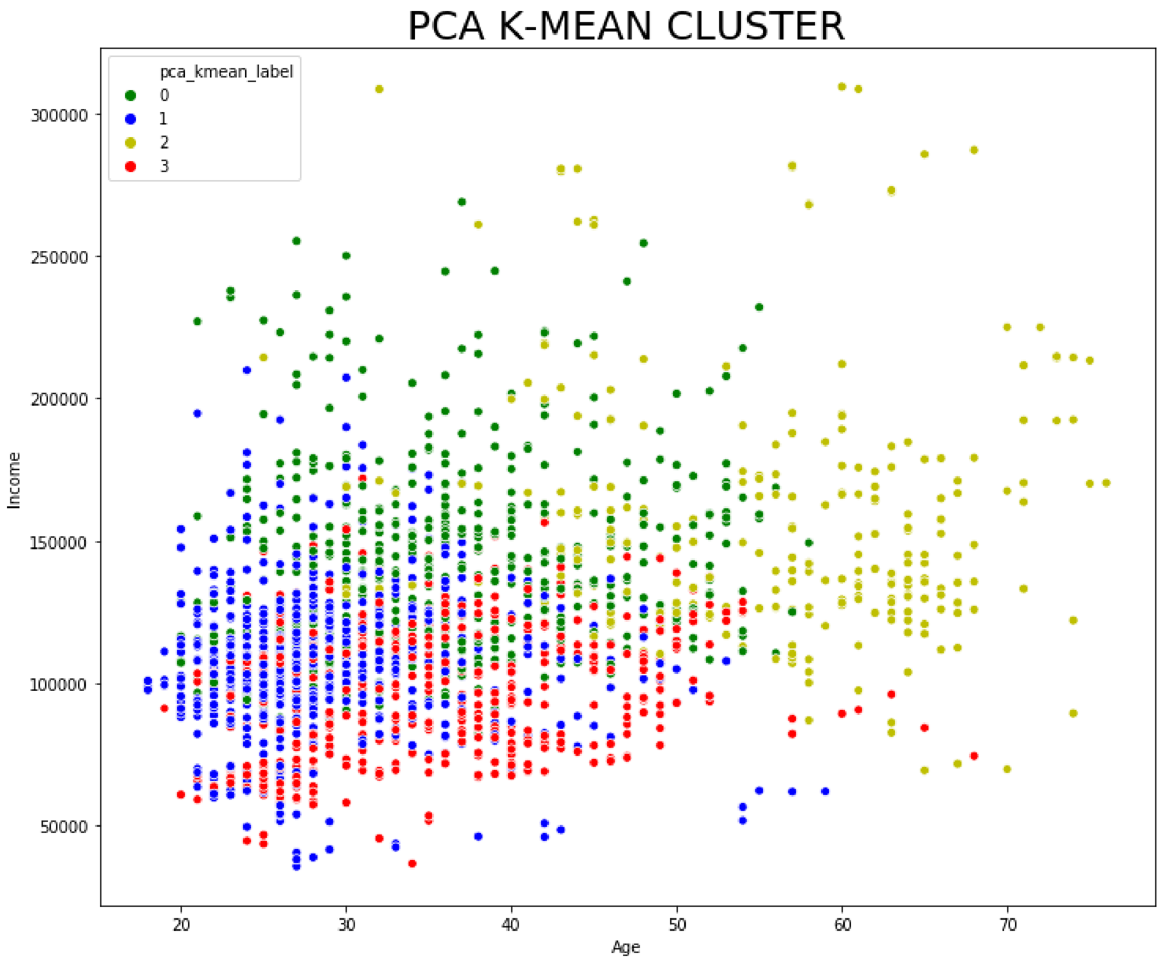
```
C:\Users\15516\anaconda3\lib\site-packages\ipykernel_launcher.py:1: FutureW
arning: Indexing with multiple keys (implicitly converted to a tuple of key
s) will be deprecated, use a list instead.
  """Entry point for launching an IPython kernel.
```

Out[39]:

	Age	Income	Settlement size	Sex	Marital status	Education	Occup
pca_kmean_label							
0	35.550173	140737.435986	1.517301	0.025952	0.185121	0.737024	1.26
1	28.887892	107510.721973	0.433483	0.911809	0.986547	1.064275	0.67
2	55.689394	158209.094697	1.106061	0.503788	0.689394	2.128788	1.12
3	35.259714	95850.155419	0.038855	0.319018	0.089980	0.768916	0.29

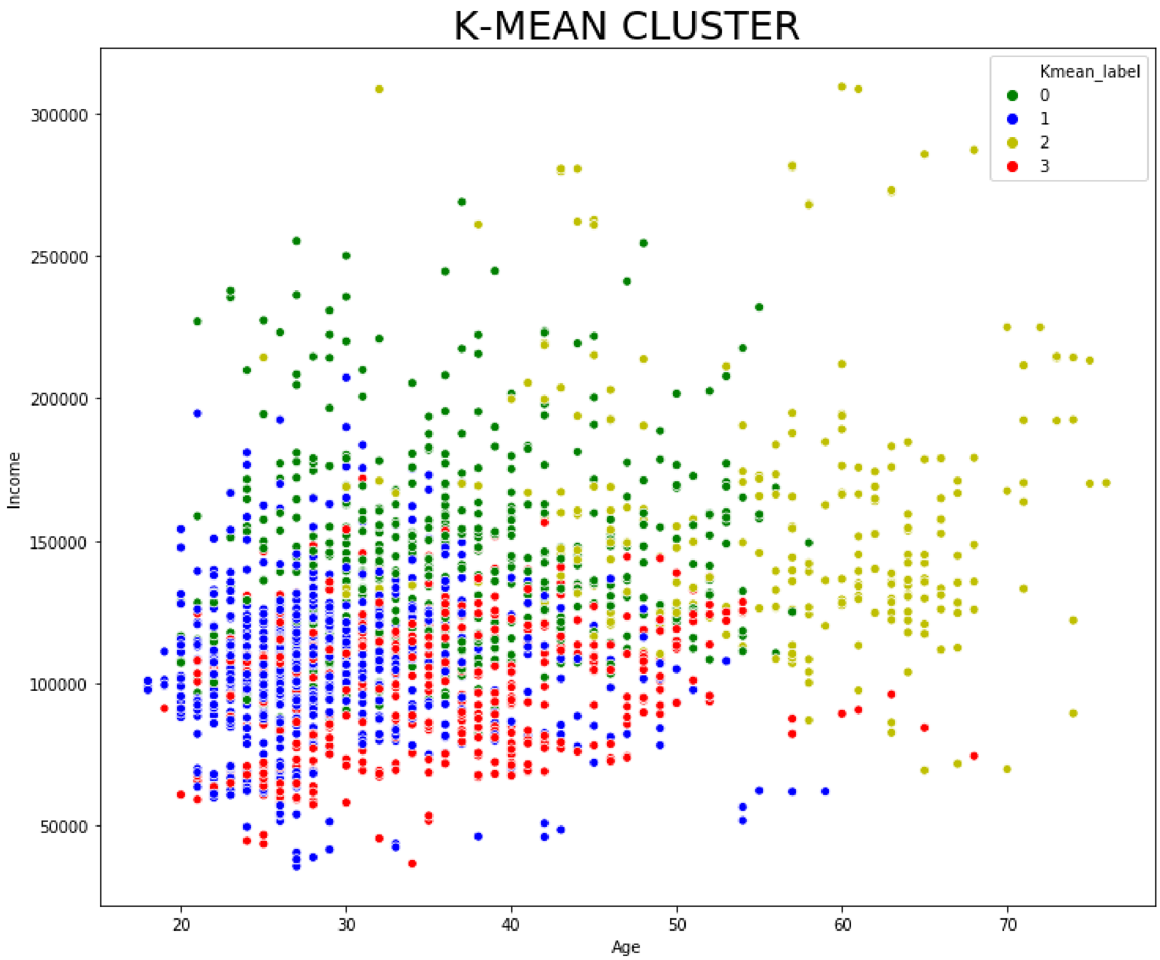
In [40]:
```
plt.figure(figsize=(12,10))
sns.scatterplot(x=df['Age'], y=df['Income'], hue=df['pca_kmean_label'], palet
plt.title('PCA K-MEAN CLUSTER', fontdict = {'fontsize' : 25})
```

Out[40]: `Text(0.5, 1.0, 'PCA K-MEAN CLUSTER')`



In [41]:
```
plt.figure(figsize=(12,10))
sns.scatterplot(x=df['Age'], y=df['Income'], hue=df['Kmean_label'], palette=[
plt.title('K-MEAN CLUSTER', fontdict = {'fontsize' : 25})
```

Out[41]: Text(0.5, 1.0, 'K-MEAN CLUSTER')



Both K-Mean, PCA-K-Mean has almost similar cluster pattern