# Customer Segmentation Analysis

The dataset contains information from 2,000 individuals across various regions. It is derived from the purchasing behavior of these individuals when shopping in a physical FMCG store. The data has been collected through the loyalty cards they used during checkout.

Let's Begin!!

### Import all the necessary libraries

In [100…

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import scipy
import pickle

# Ignore the warnings
import warnings
warnings.filterwarnings("ignore")
```

### Import the dataset

In [101…

```
df = pd.read_csv('segmentation data.csv', index_col = 0)
df.head()
```

Out[101…

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

### Shape of the dataset

In [102…

```
df.shape
```

Out[102…

```
(2000, 7)
```

### Information of the dataset

In [103…
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 2000 entries, 100000001 to 100002000
Data columns (total 7 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   Sex              2000 non-null   int64
 1   Marital status   2000 non-null   int64
 2   Age              2000 non-null   int64
 3   Education        2000 non-null   int64
 4   Income           2000 non-null   int64
 5   Occupation       2000 non-null   int64
 6   Settlement size  2000 non-null   int64
dtypes: int64(7)
memory usage: 125.0 KB
```

## Statistical Description of the dataset

In [104…
```
df.describe()
```

Out[104…

| | Sex | Marital status | Age | Education | Income | Occ |
|---|---|---|---|---|---|---|
| **count** | 2000.000000 | 2000.000000 | 2000.000000 | 2000.00000 | 2000.000000 | 200( |
| **mean** | 0.457000 | 0.496500 | 35.909000 | 1.03800 | 120954.419000 | ( |
| **std** | 0.498272 | 0.500113 | 11.719402 | 0.59978 | 38108.824679 | ( |
| **min** | 0.000000 | 0.000000 | 18.000000 | 0.00000 | 35832.000000 | ( |
| **25%** | 0.000000 | 0.000000 | 27.000000 | 1.00000 | 97663.250000 | ( |
| **50%** | 0.000000 | 0.000000 | 33.000000 | 1.00000 | 115548.500000 | 1 |
| **75%** | 1.000000 | 1.000000 | 42.000000 | 1.00000 | 138072.250000 | 1 |
| **max** | 1.000000 | 1.000000 | 76.000000 | 3.00000 | 309364.000000 | 2 |

## Checking for Null Values

In [105…
```
df.isnull().sum()
```

Out[105…
```
Sex                0
Marital status     0
Age                0
Education          0
Income             0
Occupation         0
Settlement size    0
dtype: int64
```

## Checking for Duplicated Records

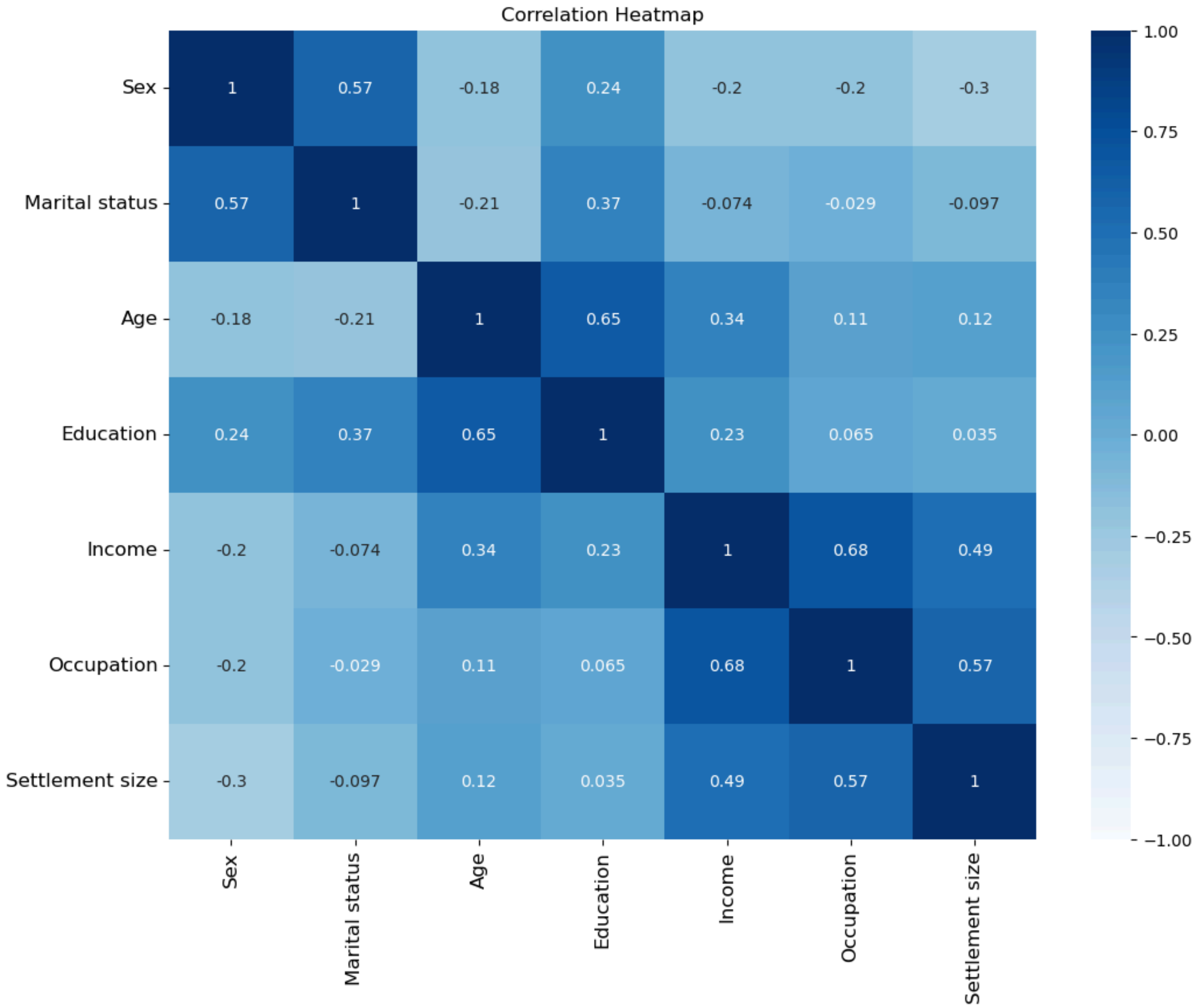
In [106…
```
df.duplicated().sum()
```
Out[106… 0

# Data Visualization

## Correlation Estimate

In [107…
```
# Pearson Correlation
correlation_matrix = df.corr()
print(correlation_matrix)
```
```
                      Sex  Marital status       Age  Education    Income  \
Sex              1.000000        0.566511 -0.182885   0.244838 -0.195146
Marital status   0.566511        1.000000 -0.213178   0.374017 -0.073528
Age             -0.182885       -0.213178  1.000000   0.654605  0.340610
Education        0.244838        0.374017  0.654605   1.000000  0.233459
Income          -0.195146       -0.073528  0.340610   0.233459  1.000000
Occupation      -0.202491       -0.029490  0.108388   0.064524  0.680357
Settlement size -0.300803       -0.097041  0.119751   0.034732  0.490881

                 Occupation  Settlement size
Sex               -0.202491        -0.300803
Marital status    -0.029490        -0.097041
Age                0.108388         0.119751
Education          0.064524         0.034732
Income             0.680357         0.490881
Occupation         1.000000         0.571795
Settlement size    0.571795         1.000000
```

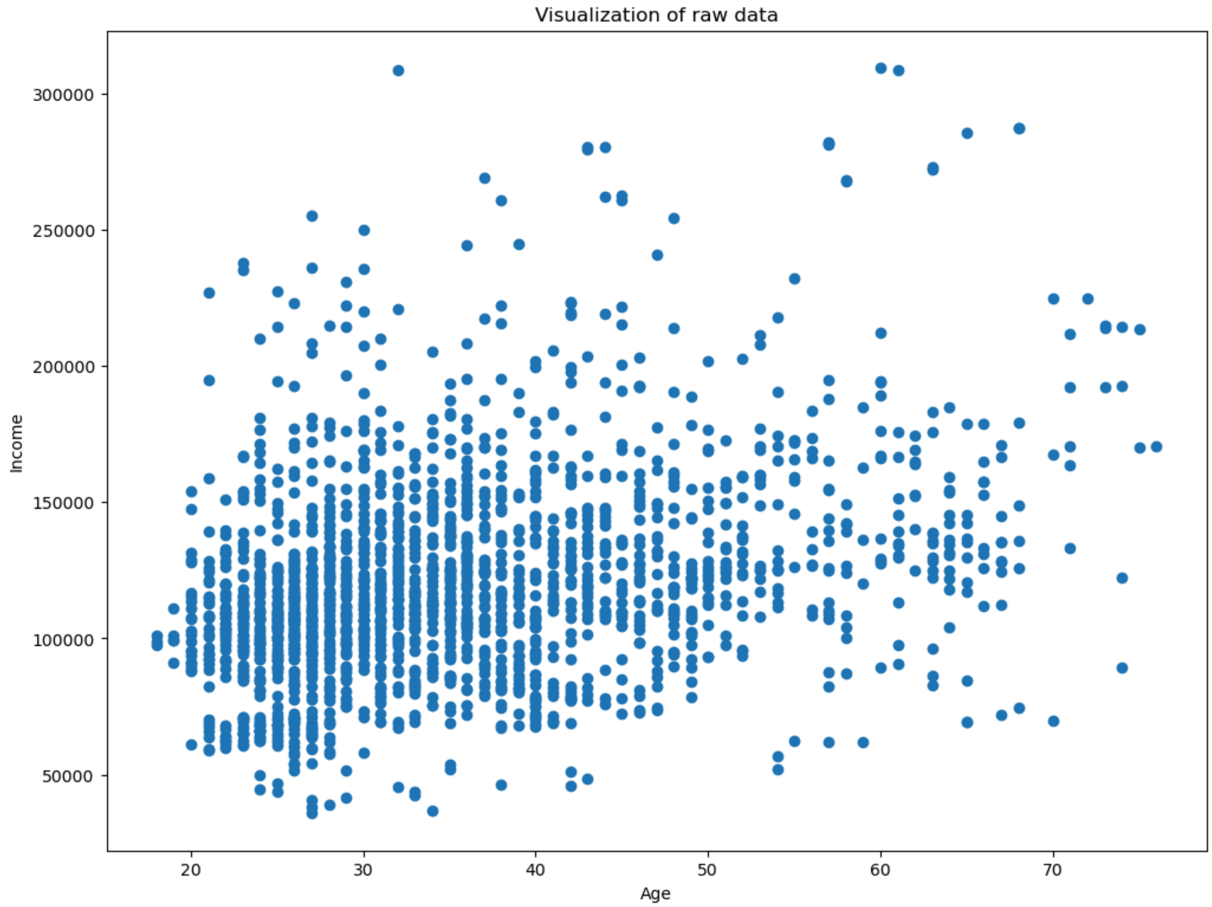
In [108…
```
# Plotting the Correlation Matrix using Heatmap

plt.figure(figsize = (12, 9))
s = sns.heatmap(df.corr(),
               annot = True,
               cmap = 'Blues',
               vmin = -1,
               vmax = 1)
s.set_yticklabels(s.get_yticklabels(), rotation = 0, fontsize = 12)
s.set_xticklabels(s.get_xticklabels(), rotation = 90, fontsize = 12)
plt.title('Correlation Heatmap')
plt.show()
```




## Relationship between Age and Income

In [109…

```
# scatter plot between Age and Income, located on positions 2 and 4 in our c

plt.figure(figsize = (12, 9))
plt.scatter(df.iloc[:, 2], df.iloc[:, 4])
plt.xlabel('Age')
plt.ylabel('Income')
plt.title('Visualization of raw data')
plt.show()
```




### Standardization of the data

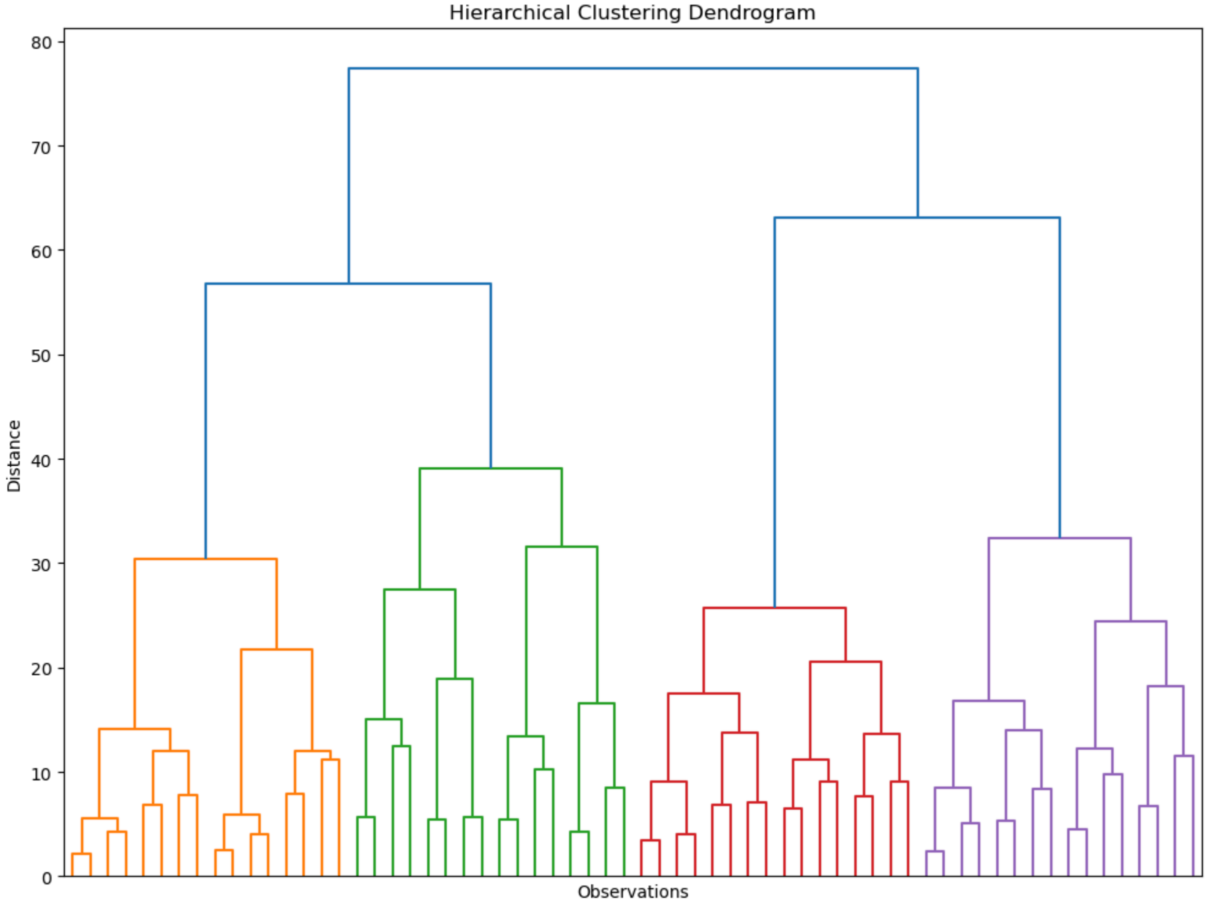
In [110…
```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
segmentation_std = scaler.fit_transform(df)
```

# Hierarchical Clustering

In [111…
```
# We are utilizing a specific type of Agglomerative Clustering known as the
# In Sklearn, the default linkage method is set to "ward.
# The results are returned as a linkage matrix.

from scipy.cluster.hierarchy import dendrogram, linkage

hier_clust = linkage(segmentation_std, method = 'ward')
```

In [112…
```
# We plot the results from the Hierarchical Clustering using a Dendrogram.
# We truncate the dendrogram for better readability. The level p shows only
# We also omit showing the labels for each point.
plt.figure(figsize = (12,9))
plt.title('Hierarchical Clustering Dendrogram')
plt.xlabel('Observations')
plt.ylabel('Distance')
dendrogram(hier_clust,
```

```
            truncate_mode = 'level',
            p = 5,
            show_leaf_counts = False,
            no_labels = True)
plt.show()
```




# K-Means Clustering

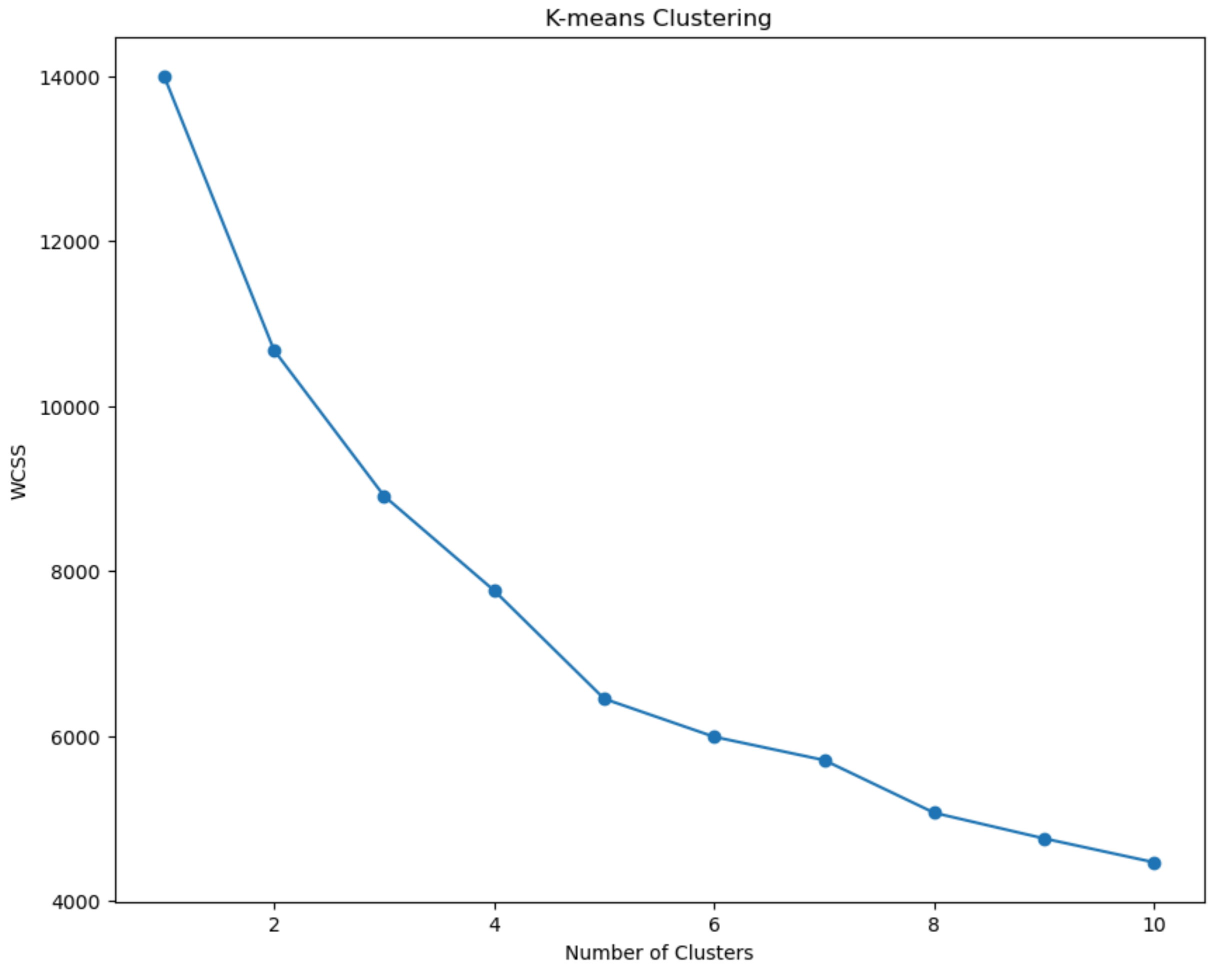
In [113…

```
# Perform K-means clustering. We consider 1 to 10 clusters, so our for loop
# In addition we run the algortihm at many different starting points - k mea
# And we set a random state for reproducibility.

from sklearn.cluster import KMeans

wcss = []
for i in range(1,11):
    kmeans = KMeans(n_clusters = i, init = 'k-means++', random_state = 42)
    kmeans.fit(segmentation_std)
    wcss.append(kmeans.inertia_)
```

In [114…

```
# Plot the Within Cluster Sum of Squares for the different number of cluster
# From this plot we choose the number of clusters.
# We look for a kink in the graphic, after which the descent of wcss isn't a
plt.figure(figsize = (10,8))
plt.plot(range(1, 11), wcss, marker = 'o')
plt.xlabel('Number of Clusters')
```

```
plt.ylabel('WCSS')
plt.title('K-means Clustering')
plt.show()
```




In [115…

```
# We run K-means with a fixed number of clusters. In our case 4.
kmeans = KMeans(n_clusters = 4, init = 'k-means++', random_state = 42)
```

In [116…

```
# We divide our data into the four clusters.
kmeans.fit(segmentation_std)
```

Out[116…

```
KMeans
KMeans(n_clusters=4, random_state=42)
```

## Results

In [117…

```
# We create a new data frame with the original features and add a new colum
df_segm_kmeans = df.copy()
df_segm_kmeans['Segment K-means'] = kmeans.labels_
```

In [118…

```
# Calculate mean values for the clusters
df_segm_analysis = df_segm_kmeans.groupby(['Segment K-means']).mean()
df_segm_analysis
```

Out[118…

| Segment K-means | Sex | Marital status | Age | Education | Income | Occupatior |
|---|---|---|---|---|---|---|
| **0** | 0.066543 | 0.000000 | 33.240296 | 0.489834 | 109932.785582 | 0.639556 |
| **1** | 0.868254 | 0.785714 | 32.928571 | 1.163492 | 98466.955556 | 0.384127 |
| **2** | 0.691099 | 0.979058 | 29.060209 | 1.104712 | 126838.926702 | 1.107330 |
| **3** | 0.149888 | 0.277405 | 49.192394 | 1.467562 | 160958.722595 | 1.364653 |

In [119…

```
# Compute the size and proportions of the four clusters
df_segm_analysis['N Obs'] = df_segm_kmeans[['Segment K-means','Sex']].groupb
df_segm_analysis['Prop Obs'] = df_segm_analysis['N Obs'] / df_segm_analysis[
```

In [120…

```
df_segm_analysis.rename({0:'well-off',
                         1:'fewer-opportunities',
                         2:'standard',
                         3:'career focused'})
```

Out[120…

| Segment K-means | Sex | Marital status | Age | Education | Income | Occup |
|---|---|---|---|---|---|---|
| **well-off** | 0.066543 | 0.000000 | 33.240296 | 0.489834 | 109932.785582 | 0.63 |
| **fewer-opportunities** | 0.868254 | 0.785714 | 32.928571 | 1.163492 | 98466.955556 | 0.38 |
| **standard** | 0.691099 | 0.979058 | 29.060209 | 1.104712 | 126838.926702 | 1.10 |
| **career focused** | 0.149888 | 0.277405 | 49.192394 | 1.467562 | 160958.722595 | 1.36 |

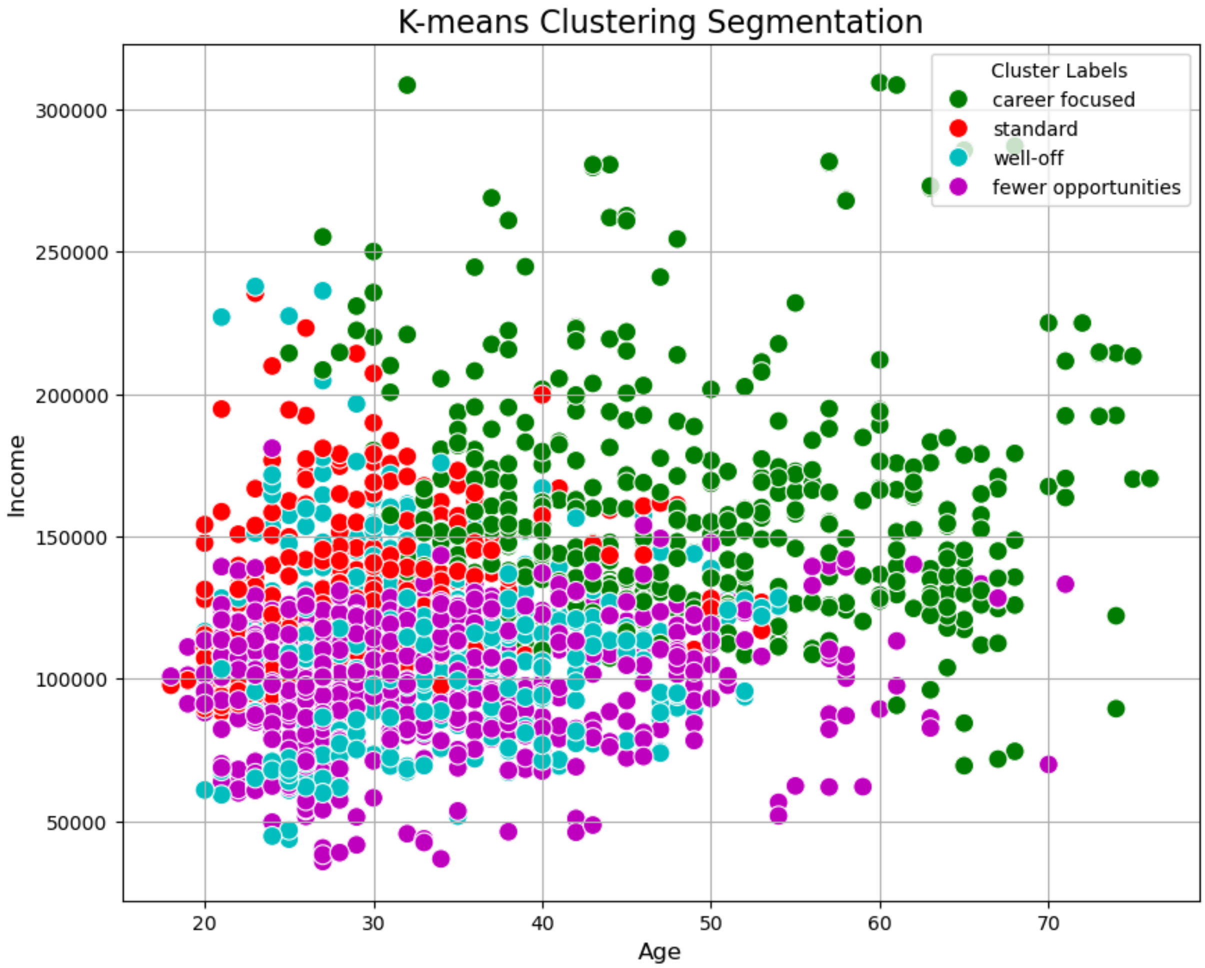
In [121…

```
# Add the segment labels to our table
df_segm_kmeans['Labels'] = df_segm_kmeans['Segment K-means'].map({0:'well-of
                                                                  1:'fewer c
                                                                  2:'standar
                                                                  3:'career
```

In [122…

```
# Plot the results of the K-means algorithm
# Each point in the dataset is plotted and colored according to the cluster
x_axis = df_segm_kmeans['Age']
y_axis = df_segm_kmeans['Income']

plt.figure(figsize=(10, 8))
sns.scatterplot(x=x_axis, y=y_axis, hue=df_segm_kmeans['Labels'], palette=['

plt.title('K-means Clustering Segmentation', fontsize=16)
plt.xlabel('Age', fontsize=12)
plt.ylabel('Income', fontsize=12)
plt.legend(title='Cluster Labels', loc='upper right')
```

```
plt.grid(True)
plt.show()
```




# PCA

In [123…

```
# Employ PCA to find a subset of components, which explain the variance in t

from sklearn.decomposition import PCA

pca = PCA()
```

In [124…

```
# Fit PCA with our standardized data.
pca.fit(segmentation_std)
```

Out[124…

```
PCA
PCA()
```

In [125…

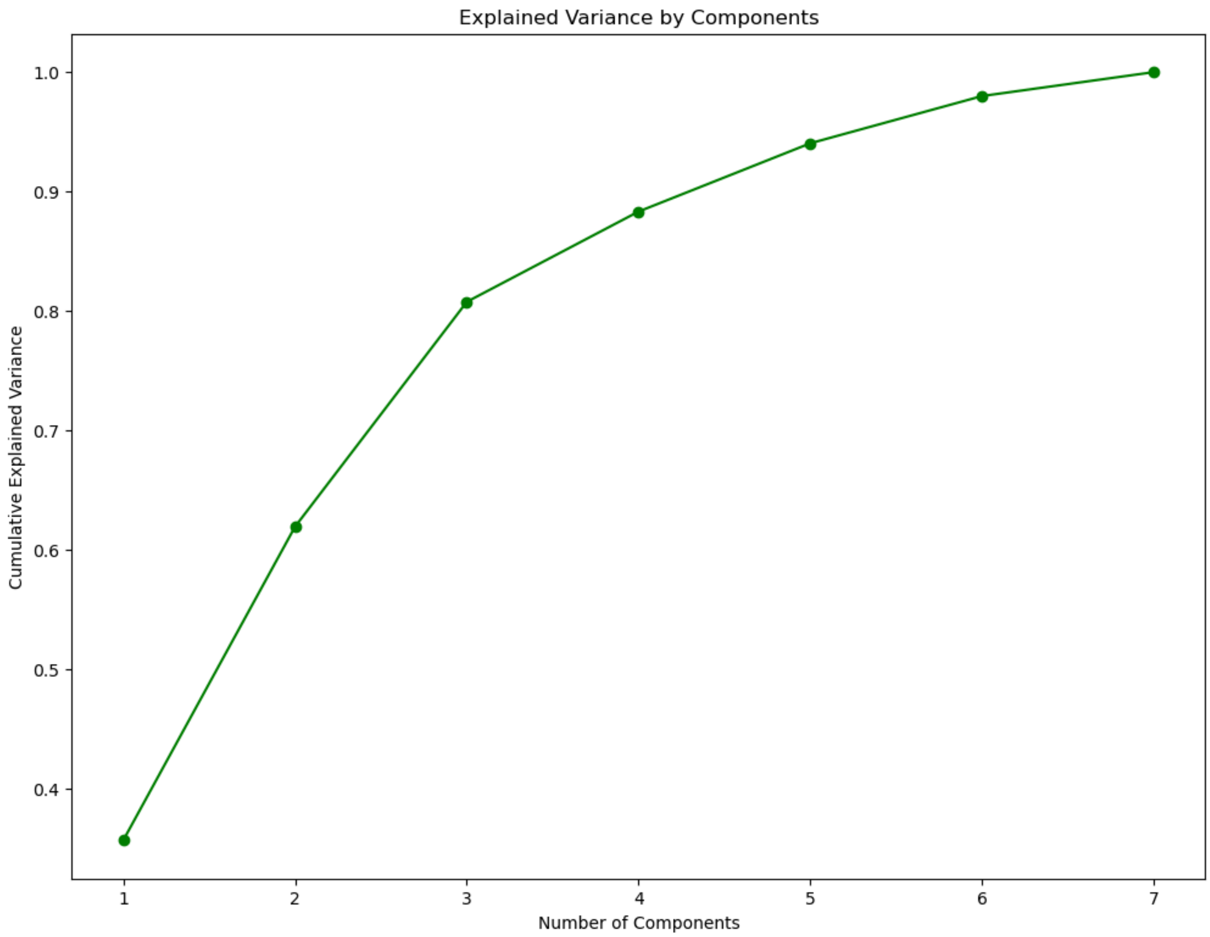
```
# The attribute shows how much variance is explained by each of the seven ir
pca.explained_variance_ratio_
```

Out[125…

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

In [126…

```
# Plot the cumulative variance explained by total number of components.
# On this graph we choose the subset of components we want to keep.
# Generally, we want to keep around 80 % of the explained variance.
plt.figure(figsize = (12,9))
plt.plot(range(1,8), pca.explained_variance_ratio_.cumsum(), marker = 'o', c
plt.title('Explained Variance by Components')
plt.xlabel('Number of Components')
plt.ylabel('Cumulative Explained Variance')
plt.show()
```




In [127…

```
# We choose three components. 3 or 4 seems the right choice according to the
pca = PCA(n_components = 3)
```

In [128…

```
#Fit the model the our data with the selected number of components. In our c
pca.fit(segmentation_std)
```

Out[128…

```
▾ PCA
PCA(n_components=3)
```

## PCA Results

In [129…

```
# The components attribute shows the loadings of each component on each of t
# The loadings are the correlations between the components and the original
```

```
pca.components_
```

Out[129…

```
array([[-0.31469524, -0.19170439,  0.32609979,  0.15684089,  0.52452463,
         0.49205868,  0.46478852],
       [ 0.45800608,  0.51263492,  0.31220793,  0.63980683,  0.12468314,
         0.01465779, -0.06963165],
       [-0.29301261, -0.44197739,  0.60954372,  0.27560461, -0.16566231,
        -0.39550539, -0.29568503]])
```

In [130…

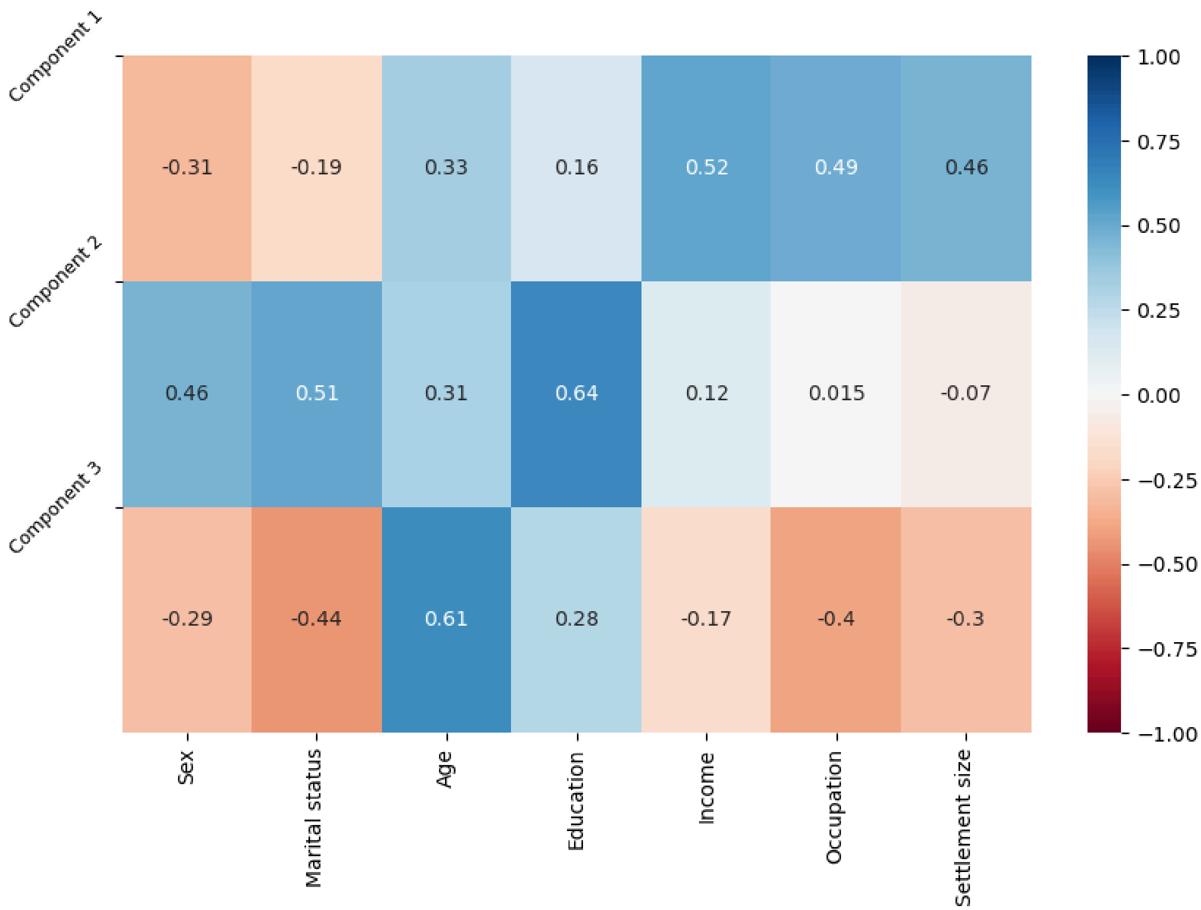
```
df_pca_comp = pd.DataFrame(data = pca.components_,
                           columns = df.columns.values,
                           index = ['Component 1', 'Component 2', 'Component
df_pca_comp
```

Out[130…

| | Sex | Marital status | Age | Education | Income | Occupation |
|---|---|---|---|---|---|---|
| **Component 1** | -0.314695 | -0.191704 | 0.326100 | 0.156841 | 0.524525 | 0.492059 |
| **Component 2** | 0.458006 | 0.512635 | 0.312208 | 0.639807 | 0.124683 | 0.014658 |
| **Component 3** | -0.293013 | -0.441977 | 0.609544 | 0.275605 | -0.165662 | -0.395505 |

In [131…

```
# Heat Map for Principal Components against original features. Again we use
plt.figure(figsize=(10,6))
sns.heatmap(df_pca_comp,
            vmin = -1,
            vmax = 1,
            cmap = 'RdBu',
            annot = True)
plt.yticks([0, 1, 2],
           ['Component 1', 'Component 2', 'Component 3'],
           rotation = 45,
           fontsize = 9)
plt.show()
```




In [132…
```
pca.transform(segmentation_std)
```

Out[132…
```
array([[ 2.51474593,  0.83412239,  2.1748059 ],
       [ 0.34493528,  0.59814564, -2.21160279],
       [-0.65106267, -0.68009318,  2.2804186 ],
       ...,
       [-1.45229829, -2.23593665,  0.89657125],
       [-2.24145254,  0.62710847, -0.53045631],
       [-1.86688505, -2.45467234,  0.66262172]])
```

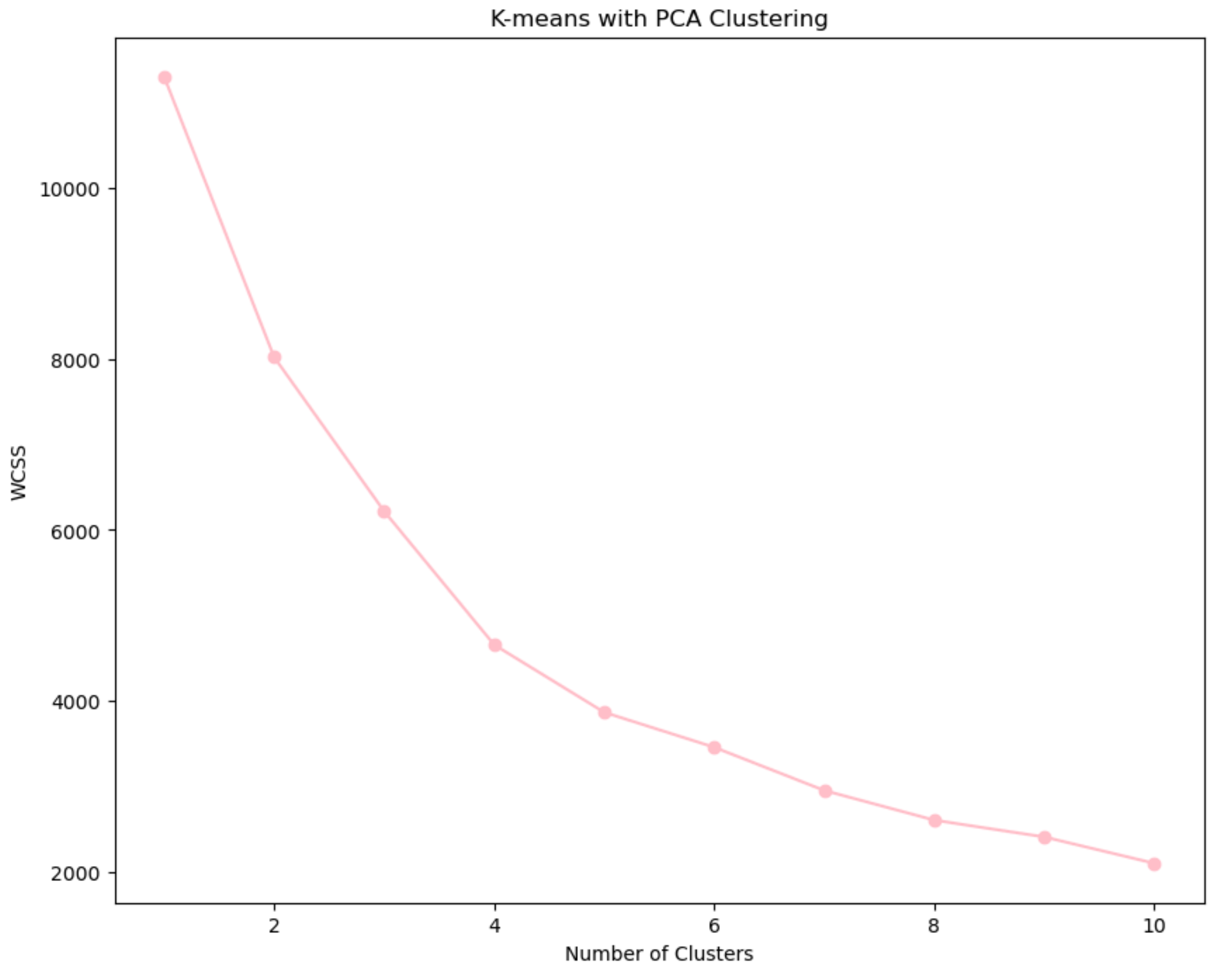
In [133…
```
scores_pca = pca.transform(segmentation_std)
```

# K-Means Clustering with PCA

In [134…
```
# We fit K means using the transformed data from the PCA.
wcss = []
for i in range(1,11):
    kmeans_pca = KMeans(n_clusters = i, init = 'k-means++', random_state = 4
    kmeans_pca.fit(scores_pca)
    wcss.append(kmeans_pca.inertia_)
```

In [135…
```
# Plot the Within Cluster Sum of Squares for the K-means PCA model. Here we
# Again it looks like four is the best option.
plt.figure(figsize = (10,8))
plt.plot(range(1, 11), wcss, marker = 'o', color="pink")
```

```
plt.xlabel('Number of Clusters')
plt.ylabel('WCSS')
plt.title('K-means with PCA Clustering')
plt.show()
```




In [136…

```
# We have chosen four clusters, so we run K-means with number of clusters eq
# Same initializer and random state as before.
kmeans_pca = KMeans(n_clusters = 4, init = 'k-means++', random_state = 42)
```

In [137…

```
# We fit our data with the k-means pca model
kmeans_pca.fit(scores_pca)
```

Out[137…

```
KMeans
KMeans(n_clusters=4, random_state=42)
```

## K-Means Clustering with PCA results

In [138…

```
# We create a new data frame with the original features and add the PCA scor
df_segm_pca_kmeans = pd.concat([df.reset_index(drop = True), pd.DataFrame(sc
df_segm_pca_kmeans.columns.values[-3: ] = ['Component 1', 'Component 2', 'Co
# The last column we add contains the pca k-means clustering labels.
df_segm_pca_kmeans['Segment K-means PCA'] = kmeans_pca.labels_
```

In [139…

```
df_segm_pca_kmeans.head()
```

Out[139…

| | Sex | Marital status | Age | Education | Income | Occupation | Settlement size | Component 1 |
|---|---|---|---|---|---|---|---|---|
| **0** | 0 | 0 | 67 | 2 | 124670 | 1 | 2 | 2.514746 |
| **1** | 1 | 1 | 22 | 1 | 150773 | 1 | 2 | 0.344935 |
| **2** | 0 | 0 | 49 | 1 | 89210 | 0 | 0 | -0.651063 |
| **3** | 0 | 0 | 45 | 1 | 171565 | 1 | 1 | 1.714316 |
| **4** | 0 | 0 | 53 | 1 | 149031 | 1 | 1 | 1.626745 |

In [140…

```
# We calculate the means by segments.
df_segm_pca_kmeans_freq = df_segm_pca_kmeans.groupby(['Segment K-means PCA']
df_segm_pca_kmeans_freq
```

Out[140…

| Segment K-means PCA | Sex | Marital status | Age | Education | Income | Occupation |
|---|---|---|---|---|---|---|
| **0** | 0.001661 | 0.041528 | 36.674419 | 0.684385 | 138482.186047 | 1.20099 |
| **1** | 0.627869 | 0.454098 | 33.473770 | 0.944262 | 88824.154098 | 0.07868 |
| **2** | 0.762357 | 0.973384 | 27.889734 | 1.007605 | 119503.418251 | 1.05513 |
| **3** | 0.492366 | 0.683206 | 55.919847 | 2.129771 | 158400.877863 | 1.12595 |

In [141…

```
# Calculate the size of each cluster and its proportion to the entire data s
df_segm_pca_kmeans_freq['N Obs'] = df_segm_pca_kmeans[['Segment K-means PCA'
df_segm_pca_kmeans_freq['Prop Obs'] = df_segm_pca_kmeans_freq['N Obs'] / df_
df_segm_pca_kmeans_freq = df_segm_pca_kmeans_freq.rename({0:'standard',
                                                          1:'career focused'
                                                          2:'fewer opportuni
                                                          3:'well-off'})
df_segm_pca_kmeans_freq
```

Out[141…

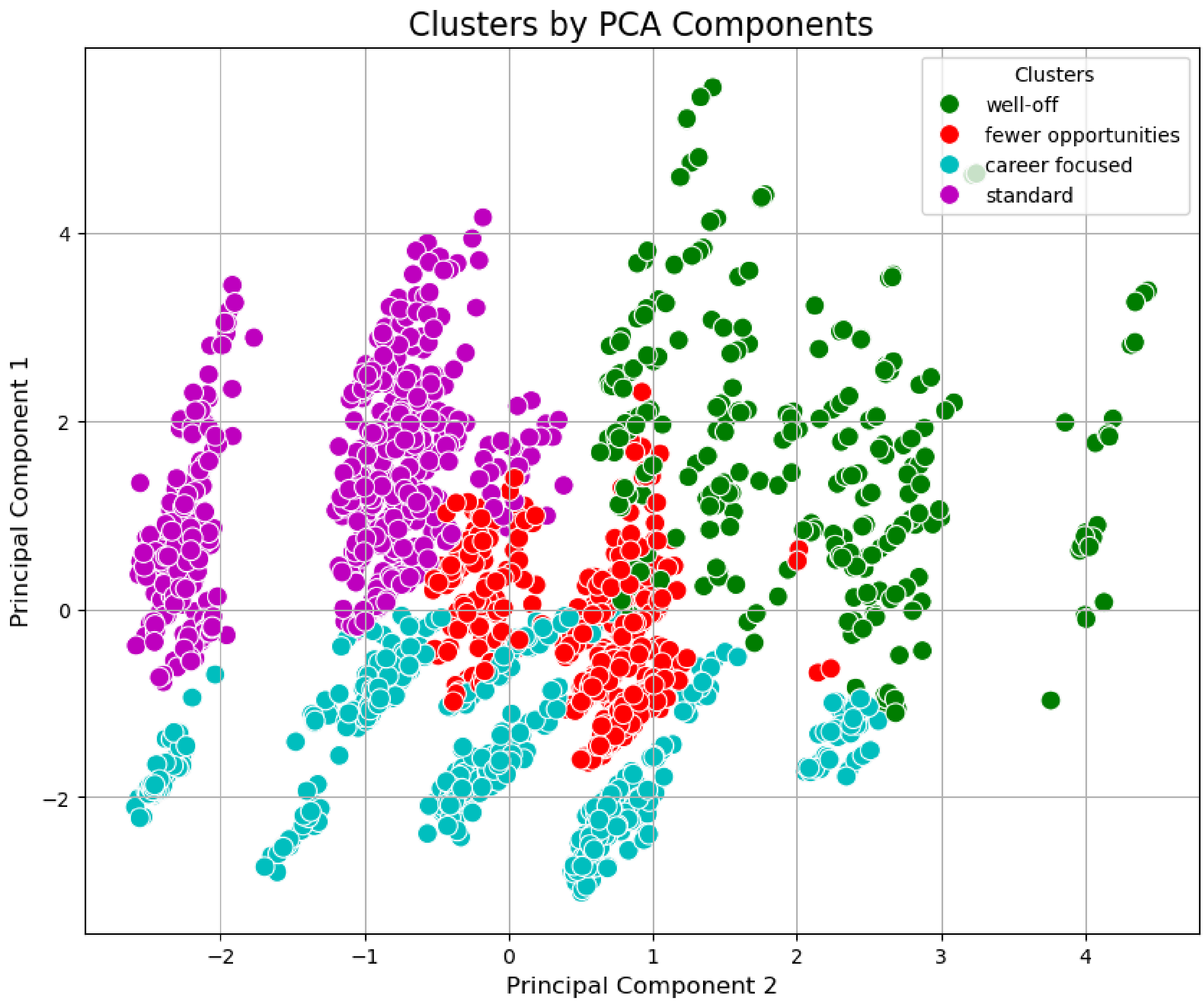
| Segment K-means PCA | Sex | Marital status | Age | Education | Income | Occup |
|---|---|---|---|---|---|---|
| **standard** | 0.001661 | 0.041528 | 36.674419 | 0.684385 | 138482.186047 | 1.2( |
| **career focused** | 0.627869 | 0.454098 | 33.473770 | 0.944262 | 88824.154098 | 0.0 |
| **fewer opportunities** | 0.762357 | 0.973384 | 27.889734 | 1.007605 | 119503.418251 | 1.0! |
| **well-off** | 0.492366 | 0.683206 | 55.919847 | 2.129771 | 158400.877863 | 1.1: |

In [142…

```
df_segm_pca_kmeans['Legend'] = df_segm_pca_kmeans['Segment K-means PCA'].map
                                                          1:'career focused'
                                                          2:'fewer opportuni
                                                          3:'well-off'})
```

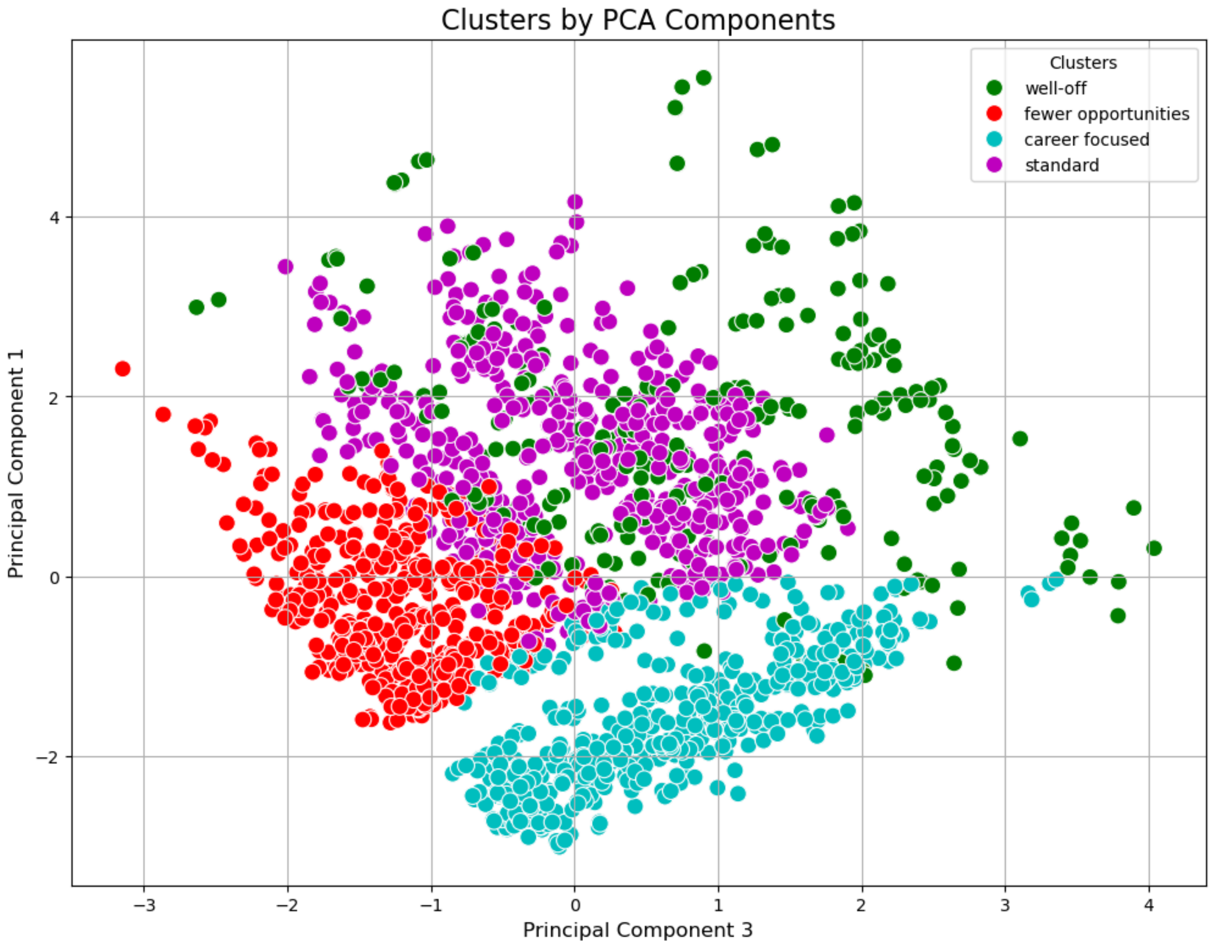
In [143…

```
# Plot data using PCA components
# The Y-axis represents the first principal component, and the X-axis repres
x_axis = df_segm_pca_kmeans['Component 2']
y_axis = df_segm_pca_kmeans['Component 1']

plt.figure(figsize=(10, 8))
sns.scatterplot(x=x_axis, y=y_axis, hue=df_segm_pca_kmeans['Legend'], palett

plt.title('Clusters by PCA Components', fontsize=16)
plt.xlabel('Principal Component 2', fontsize=12)
plt.ylabel('Principal Component 1', fontsize=12)
plt.legend(title='Clusters', loc='upper right')
plt.grid(True)
plt.show()
```



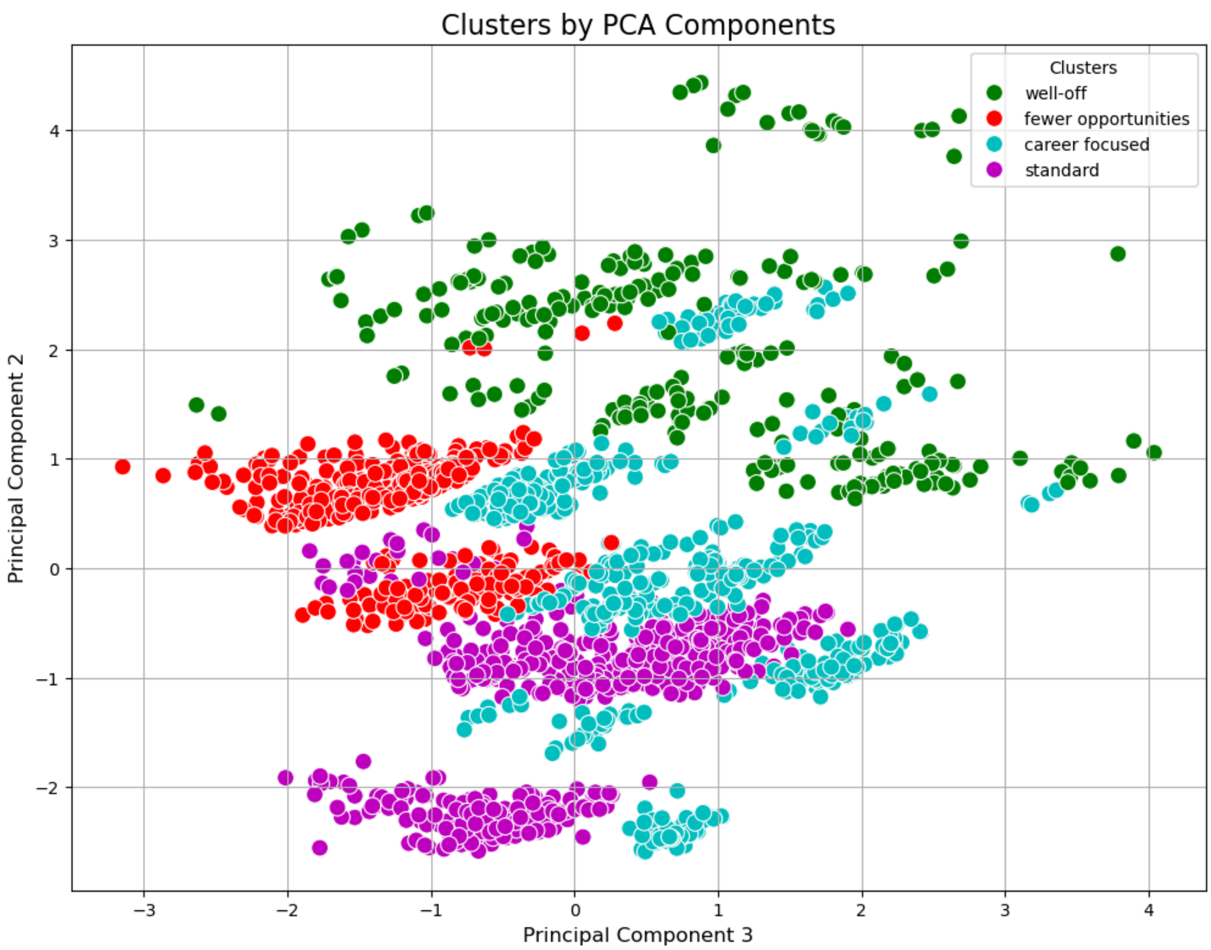

In [144…

```
# The next two plots depict our data by the remaining components. The first
# We can see there is a more significant overlap between the purple and gree
# and well-off respectively.
# The second plot shows the data by Components 2 and 3.
# We can observe there is significant overlap between the purple and blue se
# In general, it does not appear that we can separate he clusters easily on
# The reason is that the second and third components contain less of the var
# which is why PCA returns the components in order of importance.
# Plot data using PCA components
# The Y-axis represents the first principal component, and the X-axis repres
x_axis_1 = df_segm_pca_kmeans['Component 3']
y_axis_1 = df_segm_pca_kmeans['Component 1']

plt.figure(figsize=(12, 9))
sns.scatterplot(x=x_axis_1, y=y_axis_1, hue=df_segm_pca_kmeans['Legend'], pa

plt.title('Clusters by PCA Components', fontsize=16)
plt.xlabel('Principal Component 3', fontsize=12)
plt.ylabel('Principal Component 1', fontsize=12)
plt.legend(title='Clusters', loc='upper right')
plt.grid(True)
plt.show()
```




In [145…

```
# Plot data using PCA components
# The Y-axis represents the second principal component, and the X-axis repre
x_axis_1 = df_segm_pca_kmeans['Component 3']
y_axis_1 = df_segm_pca_kmeans['Component 2']

plt.figure(figsize=(12, 9))
sns.scatterplot(x=x_axis_1, y=y_axis_1, hue=df_segm_pca_kmeans['Legend'], pa

plt.title('Clusters by PCA Components', fontsize=16)
plt.xlabel('Principal Component 3', fontsize=12)
plt.ylabel('Principal Component 2', fontsize=12)
plt.legend(title='Clusters', loc='upper right')
plt.grid(True)
plt.show()
```




## Export Data

In [147…
```
pickle.dump(scaler, open('scaler.pickle', 'wb'))
```

In [148…
```
pickle.dump(pca, open('pca.pickle', 'wb'))
```

In [149…
```
pickle.dump(kmeans_pca, open('kmeans_pca.pickle', 'wb'))
```

In [ ]:

This notebook was converted with convert.ploomber.io