In [ ]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

Importing the Dataset

In [ ]:

```
data = pd.read_csv('segmentation data.csv')
```

In [ ]:

```
data.shape
```

Out[ ]:

```
(2000, 8)
```

In [ ]:

```
data.drop(['ID'], inplace=True, axis=1)
```

In [ ]:

```
data.head(10)
```

Out[ ]:

	Sex	Marital status	Age	Education	Income	Occupation	Settlement size
0	0	0	67	2	124670	1	2
1	1	1	22	1	150773	1	2
2	0	0	49	1	89210	0	0
3	0	0	45	1	171565	1	1
4	0	0	53	1	149031	1	1
5	0	0	35	1	144848	0	0
6	0	0	53	1	156495	1	1
7	0	0	35	1	193621	2	1
8	0	1	61	2	151591	0	0
9	0	1	28	1	174646	2	0

In [ ]:

```
data.describe()
```

Out[ ]:

	Sex	Marital status	Age	Education	Income	Occupation	Settlement size
count	2000.000000	2000.000000	2000.000000	2000.00000	2000.000000	2000.000000	2000.000000
mean	0.457000	0.496500	35.909000	1.03800	120954.419000	0.810500	0.739000
std	0.498272	0.500113	11.719402	0.59978	38108.824679	0.638587	0.812533
min	0.000000	0.000000	18.000000	0.00000	35832.000000	0.000000	0.000000
25%	0.000000	0.000000	27.000000	1.00000	97663.250000	0.000000	0.000000

	Sex	Marital status	Age	Education	Income	Occupation	Settlement size
50%	0.000000	0.000000	33.000000	1.00000	115548.500000	1.000000	1.000000
75%	1.000000	1.000000	42.000000	1.00000	138072.250000	1.000000	1.000000
max	1.000000	1.000000	76.000000	3.00000	309364.000000	2.000000	2.000000

In [ ]:

```
data.isna().sum()
```

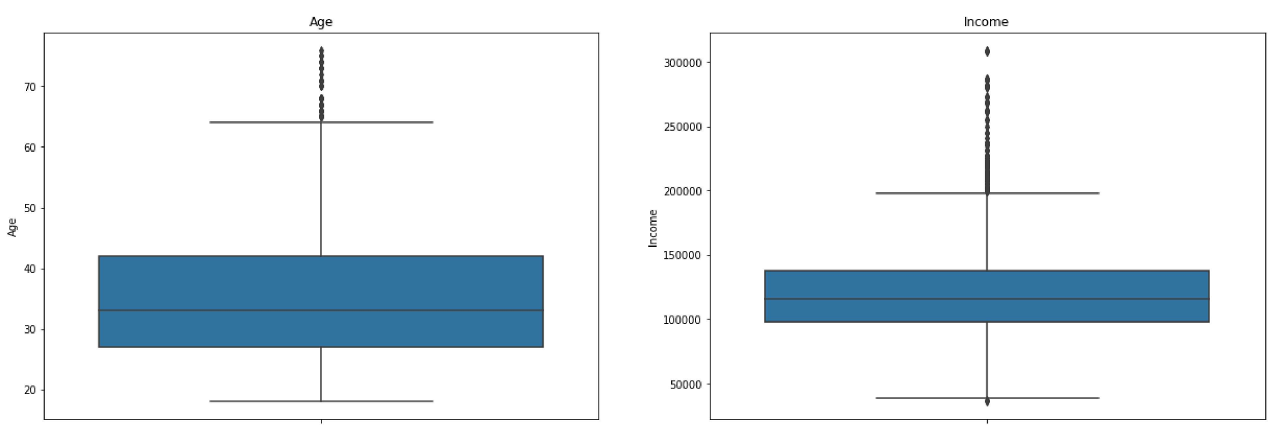
Out[ ]:

```
Sex               0
Marital status    0
Age               0
Education         0
Income            0
Occupation        0
Settlement size   0
dtype: int64
```

Exploratory Data Analysis

In [ ]:

```
plt.figure(figsize=(21,15))

plt.subplot2grid((2,2), (0,0))
box1 = sns.boxplot(y=data.Age)
plt.title("Age")

plt.subplot2grid((2,2), (0,1))
box2 = sns.boxplot(y=data.Income)
plt.title("Income")

plt.show()
```



In [ ]:

```
data.Age.describe()
```

Out[ ]:

```
count    2000.000000
mean       35.909000
std        11.719402
min        18.000000
25%        27.000000
50%        33.000000
```

```
75%        42.000000
max        76.000000
Name: Age, dtype: float64
```

In [ ]:

```
data.Income.describe()
```

Out[ ]:

```
count       2000.000000
mean      120954.419000
std        38108.824679
min        35832.000000
25%        97663.250000
50%       115548.500000
75%       138072.250000
max       309364.000000
Name: Income, dtype: float64
```

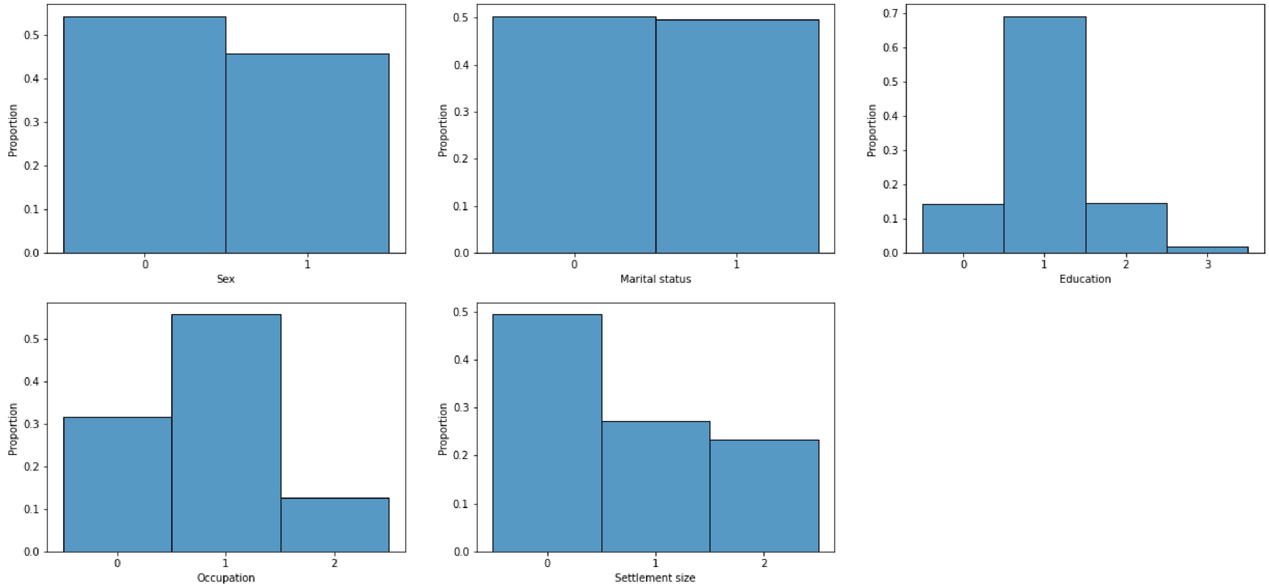
Inferences

- Mean age is approximately 36 years. Max is 76 meanwhile Min is 18
- Mean income is 121k. Max is 310k meanwhile Min is 36k

Proportion of data values in each feature

In [ ]:

```
plt.figure(figsize=(21,15))

plt.subplot2grid((3,3), (0,0))
sns.histplot(data.Sex.astype(str), stat='proportion')

plt.subplot2grid((3,3), (0,1))
sns.histplot(data['Marital status'].astype(str), stat='proportion')

plt.subplot2grid((3,3), (0,2))
sns.histplot(data.Education.astype(str).sort_values(), stat='proportion')

plt.subplot2grid((3,3), (1,0))
sns.histplot(data.Occupation.astype(str).sort_values(), stat='proportion')

plt.subplot2grid((3,3), (1,1))
sns.histplot(data['Settlement size'].astype(str).sort_values(), stat='proportion')

plt.show()
```



K Means Model

In [ ]:

```
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
```

In [ ]:

```
wcss = {'wcss_score':[], 'no_of_clusters':[]}
for i in range(1,11):
    kmeans = KMeans(i, random_state=0)
    kmeans.fit(data)
    wcss['wcss_score'].append(kmeans.inertia_)
    wcss['no_of_clusters'].append(i)
wcss_df = pd.DataFrame(wcss)
```

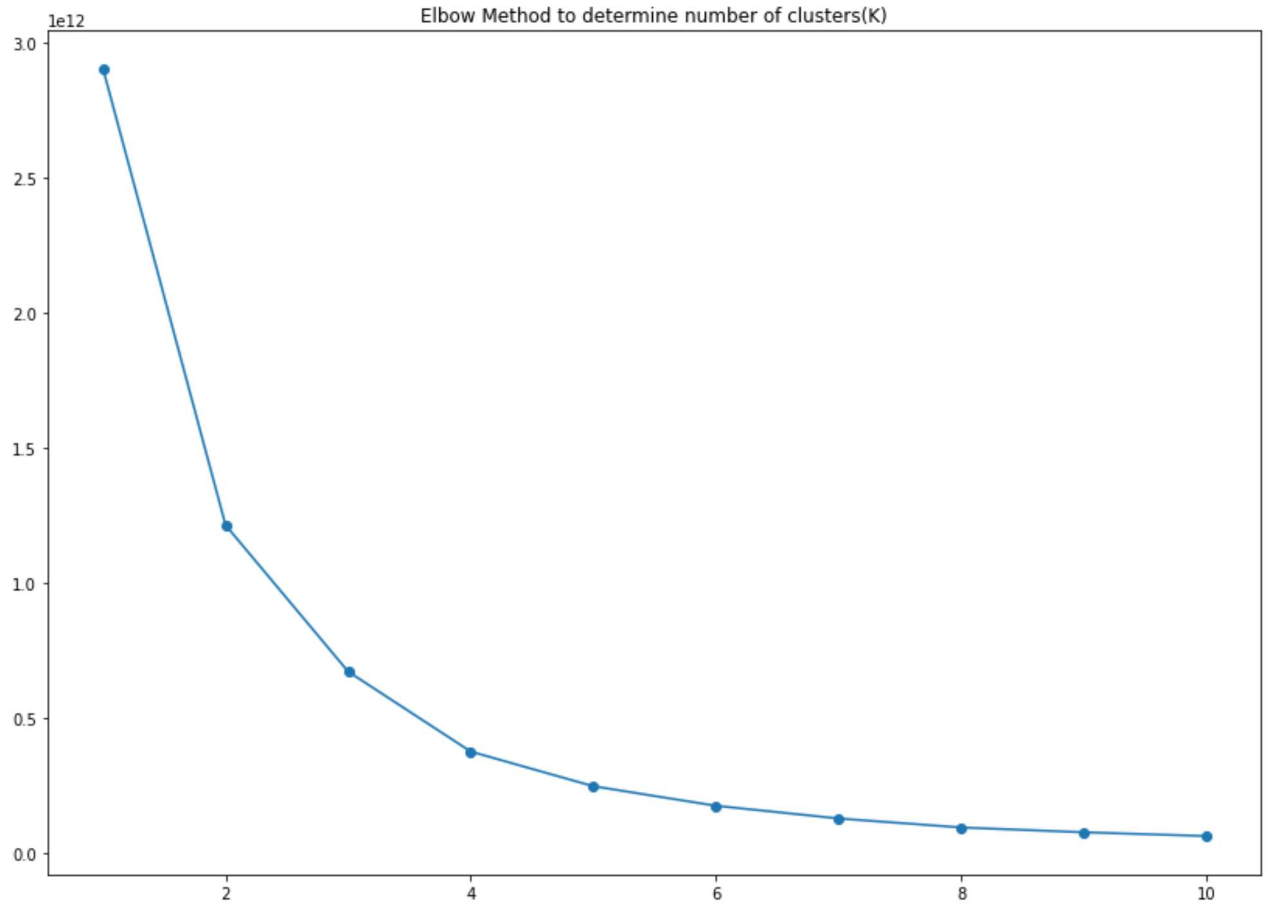
In [ ]:

```
wcss_df.head(10)
```

Out[ ]:

	wcss_score	no_of_clusters
0	2.903113e+12	1
1	1.214580e+12	2
2	6.730437e+11	3
3	3.771293e+11	4
4	2.489869e+11	5
5	1.766212e+11	6
6	1.296322e+11	7
7	9.631701e+10	8
8	7.855599e+10	9
9	6.450587e+10	10

In [ ]:
```
plt.figure(figsize=(14,10))
plt.plot(wcss_df.no_of_clusters, wcss_df.wcss_score, marker='o')
plt.title("Elbow Method to determine number of clusters(K)")
plt.show()
```



Inference

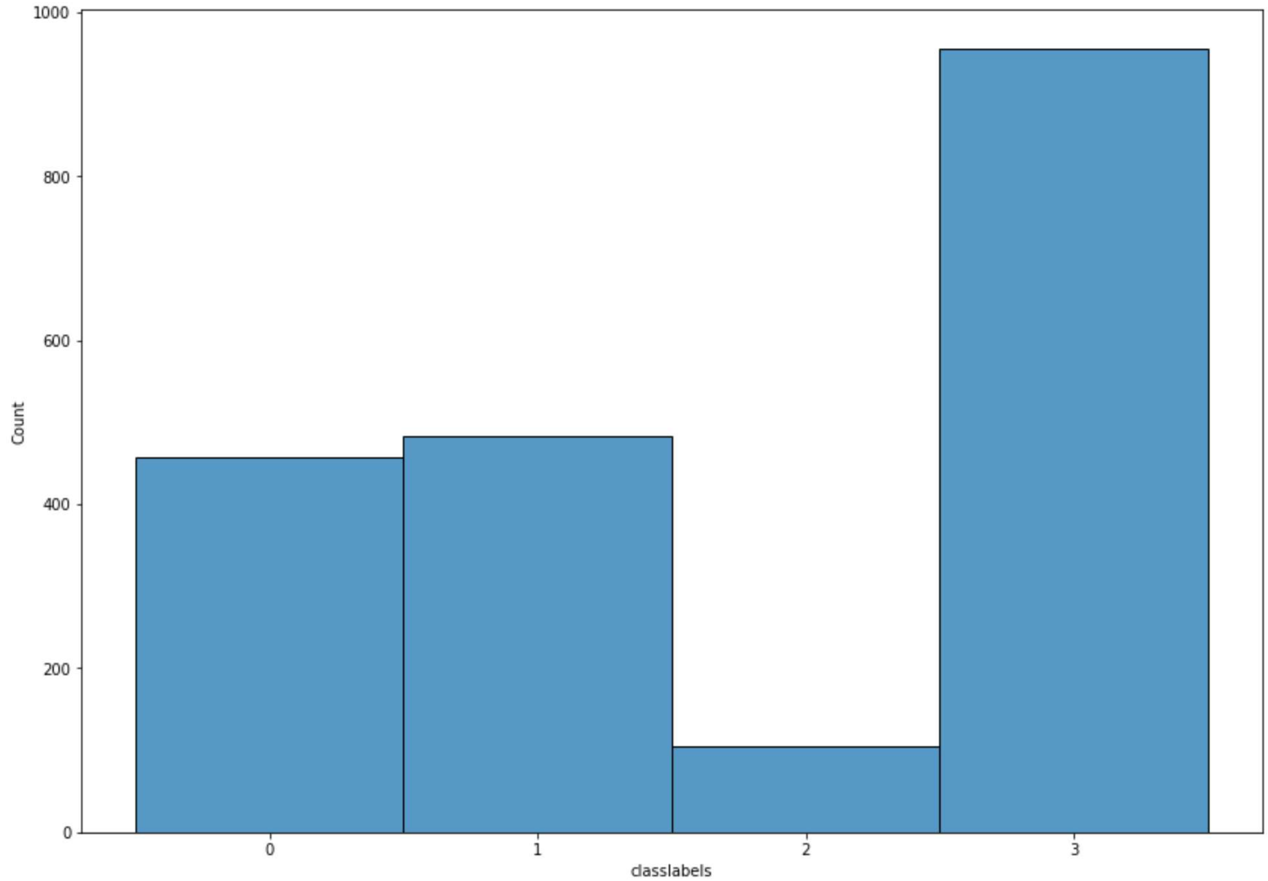
Number of clusters in this dataset are 4

- K = 4

In [ ]:
```
kmeans_final = KMeans(n_clusters=4, random_state=0, init='k-means++')
classlabels = kmeans_final.fit_predict(data)
```

In [ ]:
```
data['classlabels'] = classlabels
data.classlabels = data.classlabels.astype(str)
data = data.sort_values('classlabels')
```

In [ ]:
```
plt.figure(figsize=(14,10))
sns.histplot(data.classlabels)
plt.show()
```



In [ ]:

```
score = silhouette_score(data, kmeans_final.labels_, random_state=0)
print(f"Silhouette score: {score:0.3f} ~ 0")
```

```
Silhouette score: -0.070 ~ 0
```

Silhouette score of 0 means our model did not work very well. The worse could be -1, but the best can go upto 1.

Hierarchical clustering - Agglomerative

To improve the clustering model, we move to hierarchical clustering

In [ ]:

```
new_data = data.drop(['classlabels'], axis=1)
```

In [ ]:

```
from sklearn.cluster import AgglomerativeClustering
```

Distances and Linkages

With multiple computation options for both distance and linkage in clusters, we calculate the silhouette score for all permutations

In [ ]:

```
## function to compute scores for all permutations
def s_score(distance, linkage):
    agc = AgglomerativeClustering(n_clusters=4, affinity=distance, linkage=linkage)
    agc.fit_predict(new_data)
```

```
    score = silhouette_score(new_data, agc.labels_, random_state=0)
    return score
```

In [ ]:

```
distances = ['euclidean', 'l1', 'l2', 'manhattan', 'cosine']
linkages = ['ward', 'complete', 'average', 'single']
```

In [ ]:

```
scoring = {'dist':[], 'link':[], 'sScore':[]}
for i in distances:
    for j in linkages:
        try:
            score = s_score(i, j)
            scoring['dist'].append(i)
            scoring['link'].append(j)
            scoring['sScore'].append(score)
        except:
            scoring['dist'].append(i)
            scoring['link'].append(j)
            scoring['sScore'].append(np.nan)
scoringDf = pd.DataFrame(scoring)
```

We put this process in try-except block since 'ward' only works with 'euclidean' distance. We can now find the best permutation.

In [ ]:

```
scoringDf.dropna(axis=0, inplace=True)
```

In [ ]:

```
scoringDf.head(20)
```

Out[ ]:

	dist	link	sScore
0	euclidean	ward	0.531762
1	euclidean	complete	0.528703
2	euclidean	average	0.514481
3	euclidean	single	0.703858
5	l1	complete	0.524776
6	l1	average	0.533594
7	l1	single	0.703858
9	l2	complete	0.528703
10	l2	average	0.514481
11	l2	single	0.703858
13	manhattan	complete	0.524776
14	manhattan	average	0.533594
15	manhattan	single	0.703858
17	cosine	complete	-0.095663

	dist	link	sScore
18	cosine	average	-0.013463
19	cosine	single	0.228778

In [ ]:

```
final_result = scoringDf[scoringDf['sScore'] == max(scoringDf['sScore'])]
final_result
```

Out[ ]:

	dist	link	sScore
3	euclidean	single	0.703858
7	l1	single	0.703858
11	l2	single	0.703858
15	manhattan	single	0.703858

Finally

- ‘single’ uses the minimum of the distances between all observations of the sets. This linkage produces the best result with all distance methods.
- We produce a silhouette score of 0.704, which is a decent score.
- This dataset containing information about 2000 customers has been classified into 4 clusters or segments.