s-customer-segmentation-clustering

April 1, 2024

0.1 Project Name : Customer Segmentation Clustering

0.1.1 Contribution : Individual

The aim of this project is to perform clustering on the data based on the 'Occupation' column to identify group patterns that may exist between different occupations.

0.2 Data Dictionary

Column Name	Description
ID	Shows a unique identificator of a customer
Sex	Gender of a customer. In this dataset there are
Marital Status	Marital status of a customer
Age	The age of a customer
Education	Level education of a customer
Income	Self-reported annual income of the customer
Occupation	Category of occupation of a customer
Settlement Size	The size of the city that the customer lives in

[1]:

```
# import library
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
%matplotlib inline
sns.set(palette='pastel', style='whitegrid')
warnings.filterwarnings('ignore')

from sklearn.cluster import KMeans
from sklearn.metrics import confusion_matrix,classification_report,␣
 ↪silhouette_score
```

[2]:

```
# load dataset
dataset = '/content/segmentation data.csv'

df = pd.read_csv(dataset)
```

```
df.head()
```

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

   Settlement size
0                2
1                2
2                0
3                1
4                1
```

sex : 0 female and 1 male

marital status : 0 single and 1 non single

0.3 Data Preprocessing Part 1

[3]:
```
# drop the ID column because not needed
df.drop('ID', axis=1, inplace=True)
```

[4]:
```
# checking the shape of dataset
df.shape
```

[4]: (2000, 7)

[5]:
```
# checking detail information about dataset
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2000 entries, 0 to 1999
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: 109.5 KB
```

[6]:
```python
# show the descriptive statistics of the dataset
df.describe()
```

[6]:
```
               Sex  Marital status          Age  Education         Income  \
count  2000.000000     2000.000000  2000.000000 2000.00000    2000.000000
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
75%       1.000000        1.000000    42.000000    1.00000  138072.250000
max       1.000000        1.000000    76.000000    3.00000  309364.000000

        Occupation  Settlement size
count  2000.000000      2000.000000
mean      0.810500         0.739000
std       0.638587         0.812533
min       0.000000         0.000000
25%       0.000000         0.000000
50%       1.000000         1.000000
75%       1.000000         1.000000
max       2.000000         2.000000
```

[7]:
```python
df['Education'].value_counts()
```

[7]:
```
1    1386
2     291
0     287
3      36
Name: Education, dtype: int64
```

0 : other

1 : high school

2 : university

3 : graduated school

[8]:
```python
df['Settlement size'].value_counts()
```

[8]:
```
0    989
1    544
2    467
Name: Settlement size, dtype: int64
```

0 : small city

1 : mid city

2 : big city

[9]:
```
df['Occupation'].value_counts()
```

[9]:
```
1    1113
0     633
2     254
Name: Occupation, dtype: int64
```

0 : unemployed / unskilled

1 : skilled employee / official

2 : management / self-employed

[10]:
```
# checking the duplicated value
df.duplicated().sum()
```

[10]:
```
0
```

[11]:
```
# checking the null value
df.isnull().sum() * 100 / len(df)
```

[11]:
```
Sex                0.0
Marital status     0.0
Age                0.0
Education          0.0
Income             0.0
Occupation         0.0
Settlement size    0.0
dtype: float64
```

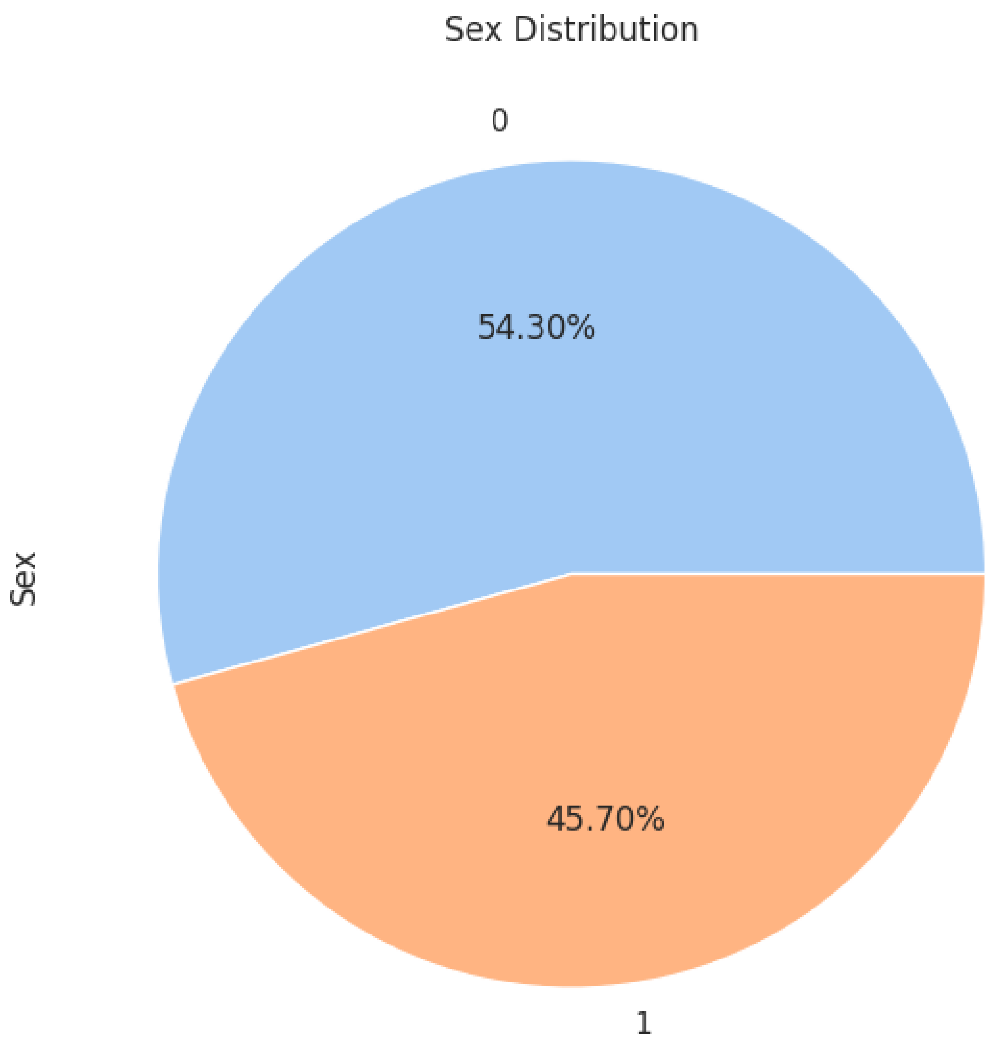
0.4 Eksploratory Data Analysis (EDA)

[12]:
```
df.tail()
```

[12]:

	Sex	Marital status	Age	Education	Income	Occupation	Settlement size
1995	1	0	47	1	123525	0	0
1996	1	1	27	1	117744	1	0
1997	0	0	31	0	86400	0	0
1998	1	1	24	1	97968	0	0
1999	0	0	25	0	68416	0	0

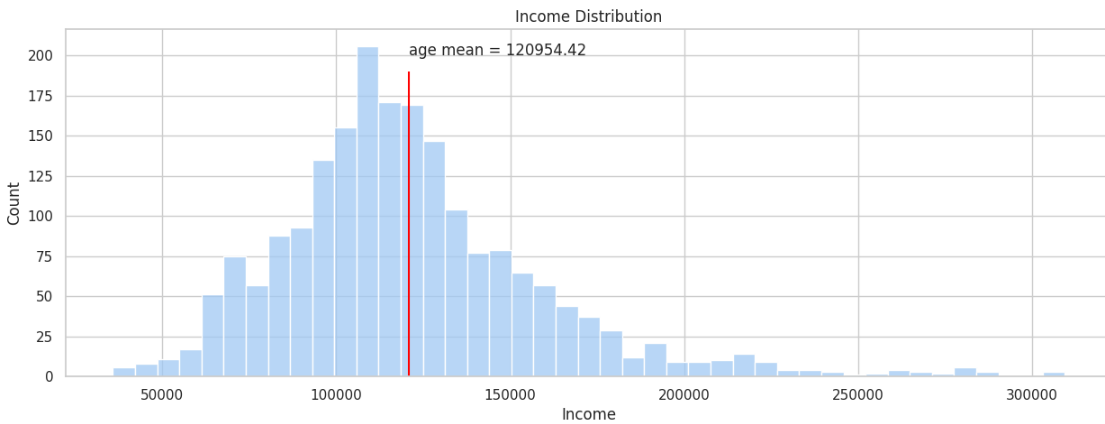
[13]:
```
df['Sex'].value_counts().plot(kind='pie', autopct='%.2f%%', figsize=(7,7))
plt.title('Sex Distribution')
plt.show()
```



Based on the pie plot distribution above, it can be seen that the representation of male sex is greater than that of female sex, with percentages of 54.30% and 45.70% respectively.

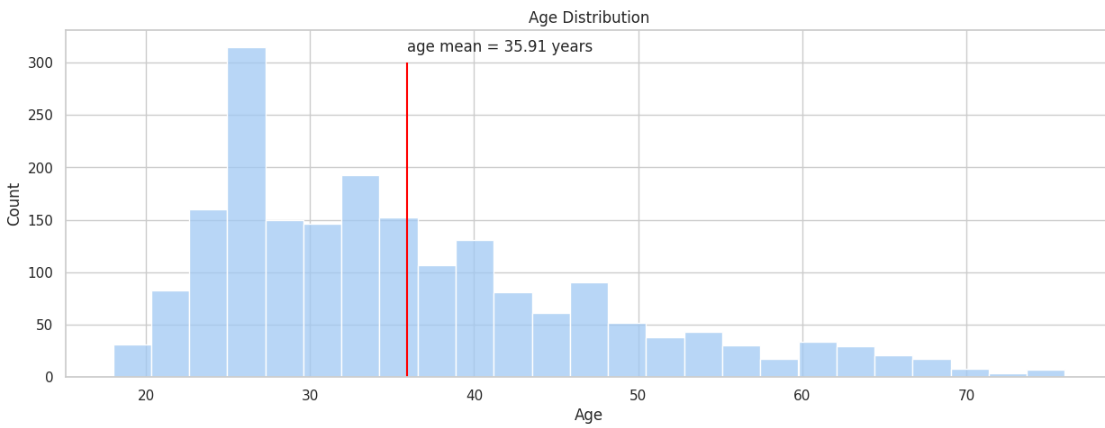
[14]:
```
plt.figure(figsize=(15,5))
ax = sns.histplot(data = df, x = 'Income')
ax.set(title = 'Income Distribution')
plt.vlines(df.Income.mean(),0, 190, color = 'red')
plt.annotate('age mean = %.2f' % df.Income.mean(), (df.Income.mean(), 200))
```

[14]:
```
Text(120954.419, 200, 'age mean = 120954.42')
```



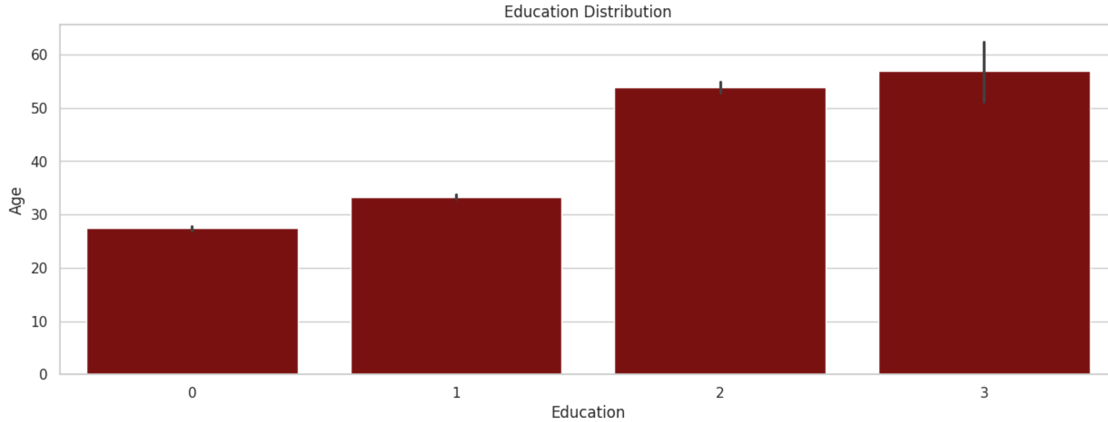
[15]:
```
plt.figure(figsize=(15,5))
ax = sns.histplot(data = df, x = 'Age')
ax.set(title = 'Age Distribution')
plt.vlines(df.Age.mean(),0, 300, color = 'red')
plt.annotate('age mean = %.2f years' % df.Age.mean(), (df.Age.mean(), 310))
```

[15]: Text(35.909, 310, 'age mean = 35.91 years')



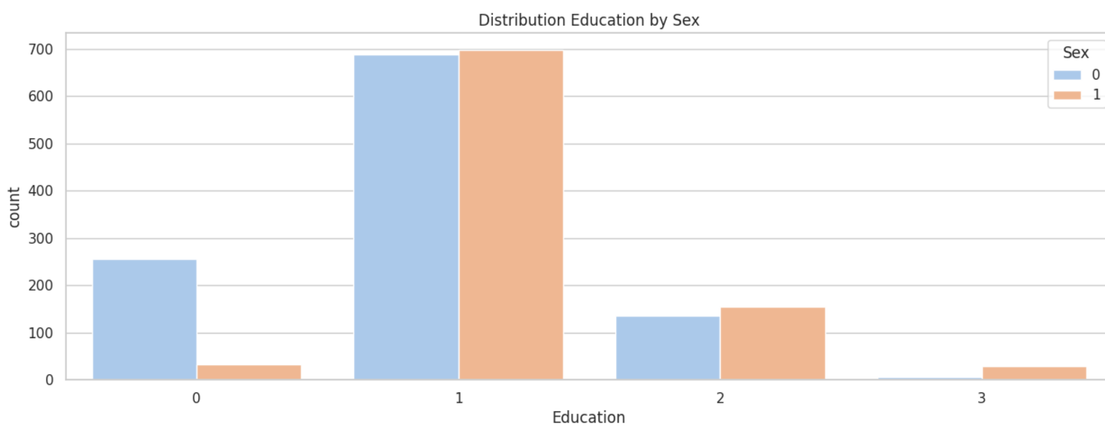
[16]:
```
plt.figure(figsize=(15,5))
sns.barplot(data=df, x='Education', y='Age',color='darkred').
  ↪set_title('Education Distribution')
```

[16]: Text(0.5, 1.0, 'Education Distribution')



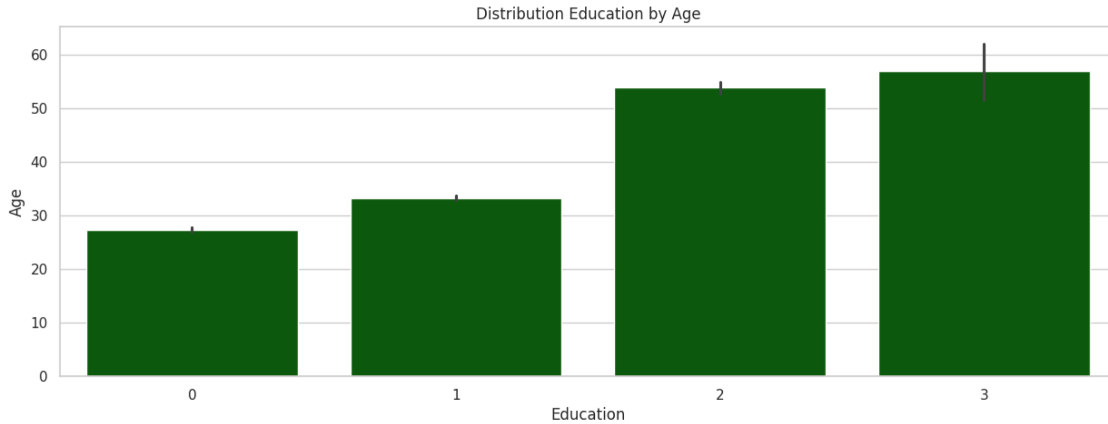

```
[17]: plt.figure(figsize=(15,5))
      sns.countplot(data=df, x='Education', hue='Sex').set_title('Distribution␣
       ↪Education by Sex')
```

```
[17]: Text(0.5, 1.0, 'Distribution Education by Sex')
```



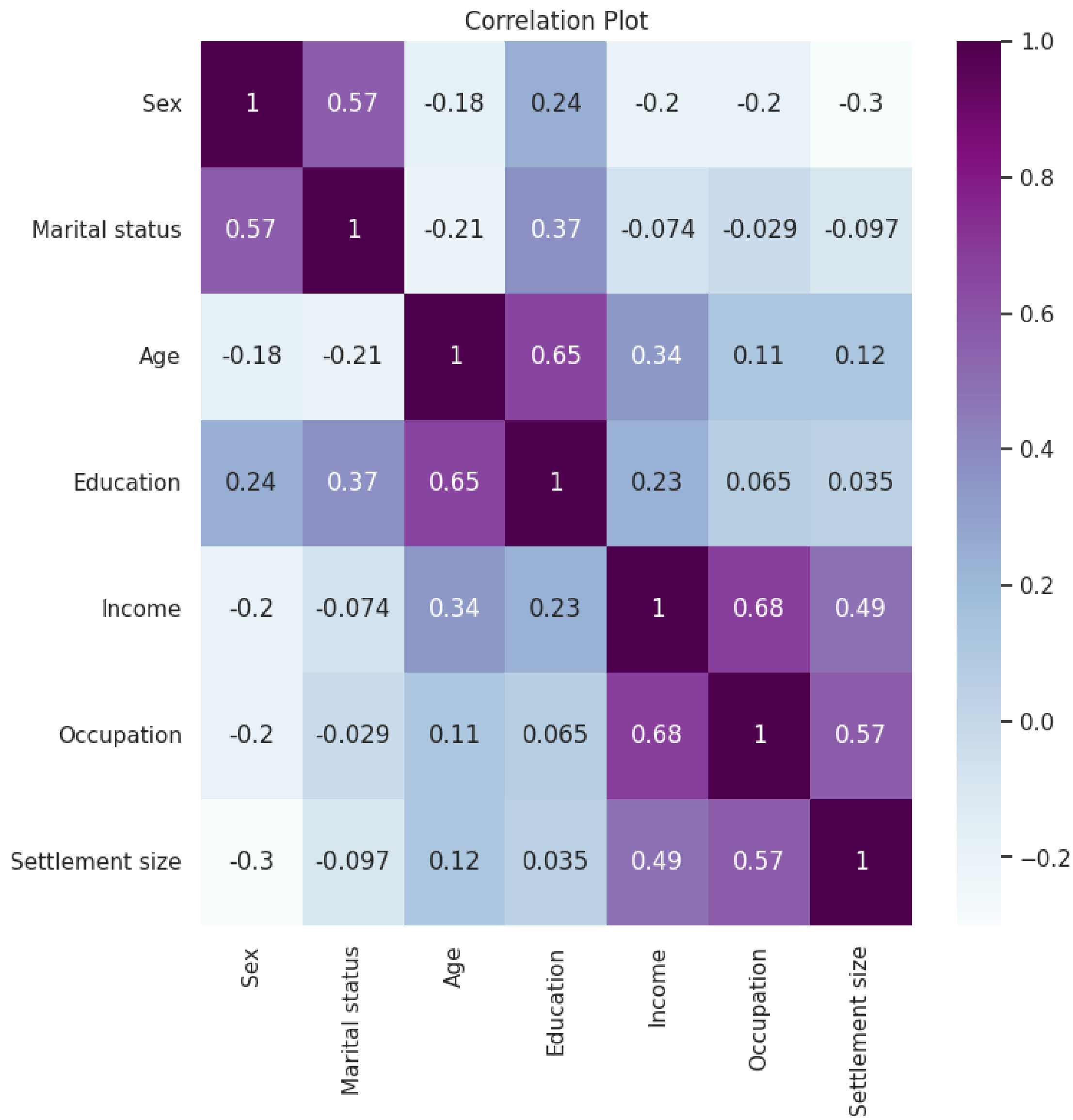

```
[18]: plt.figure(figsize=(15,5))
      sns.barplot(data=df, x='Education', y='Age', color='darkgreen').
       ↪set_title('Distribution Education by Age')
```

```
[18]: Text(0.5, 1.0, 'Distribution Education by Age')
```



[19]:
```
plt.figure(figsize=(8,8))
sns.heatmap(df.corr(), annot=True, cmap='BuPu').set_title('Correlation Plot')
```

[19]: Text(0.5, 1.0, 'Correlation Plot')

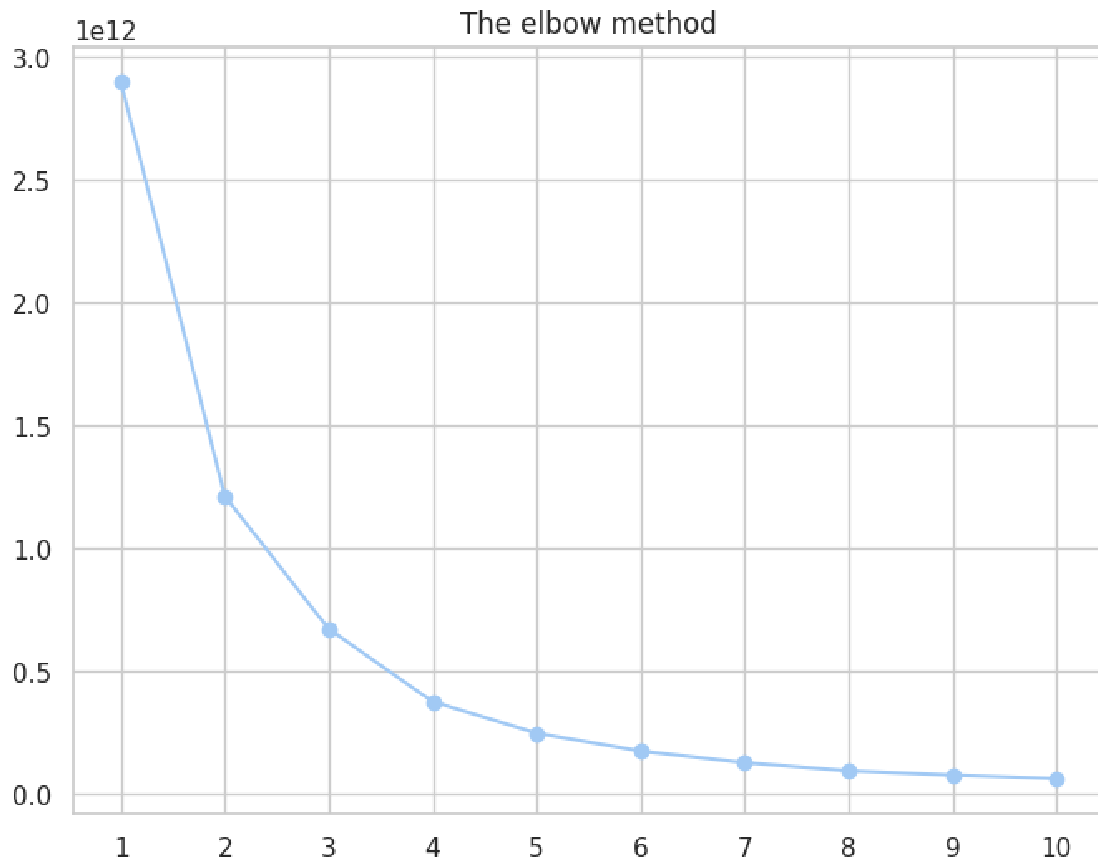


0.5 Data Preprocessing Part 2

[20]:
```
num_clusters = range(1, 11)
inertia = []
for k in num_clusters:
    kmeans = KMeans(n_clusters=k)
    kmeans.fit(df)
    inertia.append(kmeans.inertia_)
```

[21]:
```
plt.figure(figsize=(8, 6))
plt.plot(num_clusters, inertia, marker='o')
```

```
plt.title('The elbow method')
plt.xticks(num_clusters)
plt.show()
```

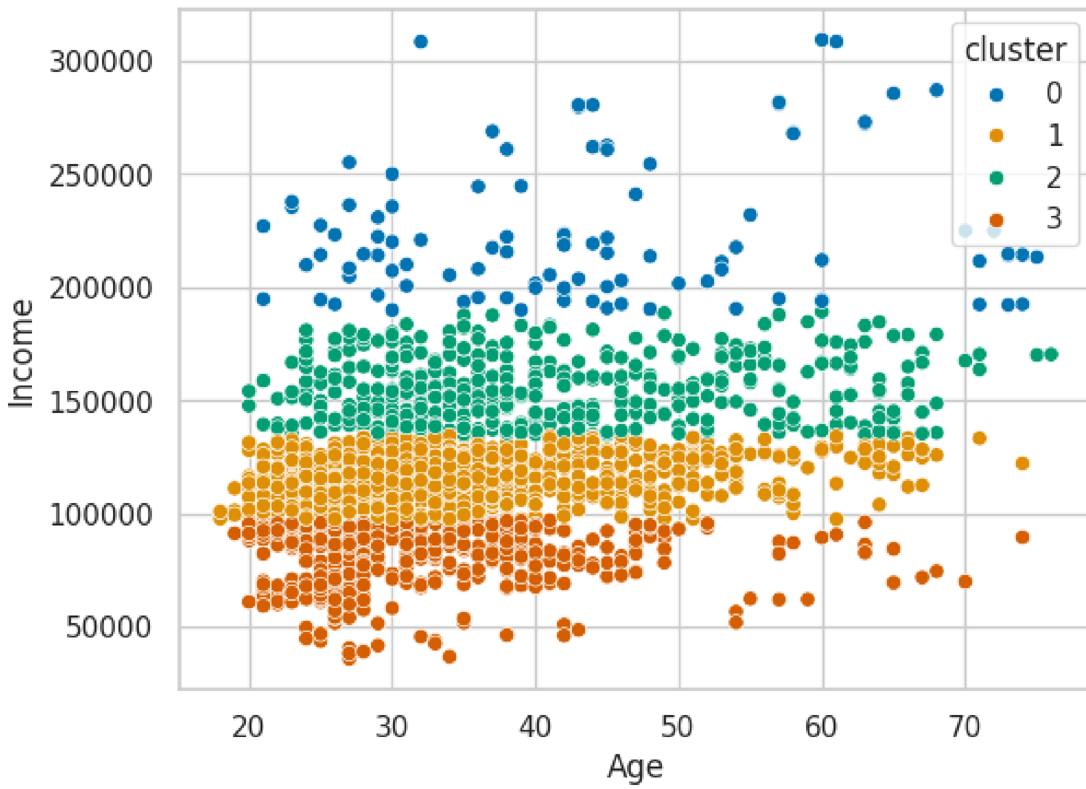


ccording to the elbow method we can assume 3 clusters for our data

[22]:
```
SEED = np.random.seed(300)
kmeans = KMeans(n_clusters=4, random_state=SEED)
labels = kmeans.fit_predict(df)
df['cluster'] = labels
```

[23]:
```
sns.scatterplot(data = df, x = 'Age', y = 'Income', hue = 'cluster',␣
↪palette='colorblind')
```

[23]: <Axes: xlabel='Age', ylabel='Income'>



[24]:
```
silhouette_avg = silhouette_score(df, df.cluster)

print(f"Silhouette Score: {silhouette_avg}")
```

```
Silhouette Score: 0.5428478923817803
```

The silhouette score ranges from -1 to 1.

A higher silhouette score indicates better-defined clusters. Evaluate the score based on the following guidelines:

0.71 - 1.0: Excellent clustering.

0.51 - 0.70: Reasonable clustering.

0.26 - 0.50: Poor clustering.

Less than 0.25: Very poor clustering

Let's try different numbers of clusters, i will choose 3 and 5 cluster therefore it is closest to 4

[25]:
```
# cluster 3
SEED = np.random.seed(300)
df.drop(columns = 'cluster')
kmeans = KMeans(n_clusters = 3, random_state = SEED)
```

```
labels = kmeans.fit_predict(df)
df['cluster'] = labels
silhouette_avg = silhouette_score(df, df.cluster)
print(f"Silhouette Score: {silhouette_avg}")
```

```
Silhouette Score: 0.5124711688681454
```

[26]:
```
# cluster 5
SEED = np.random.seed(300)
df.drop(columns = 'cluster')
kmeans = KMeans(n_clusters = 5, random_state = SEED)
labels = kmeans.fit_predict(df)
df['cluster'] = labels
silhouette_avg = silhouette_score(df, df.cluster)
print(f"Silhouette Score: {silhouette_avg}")
```

```
Silhouette Score: 0.5401417577104871
```

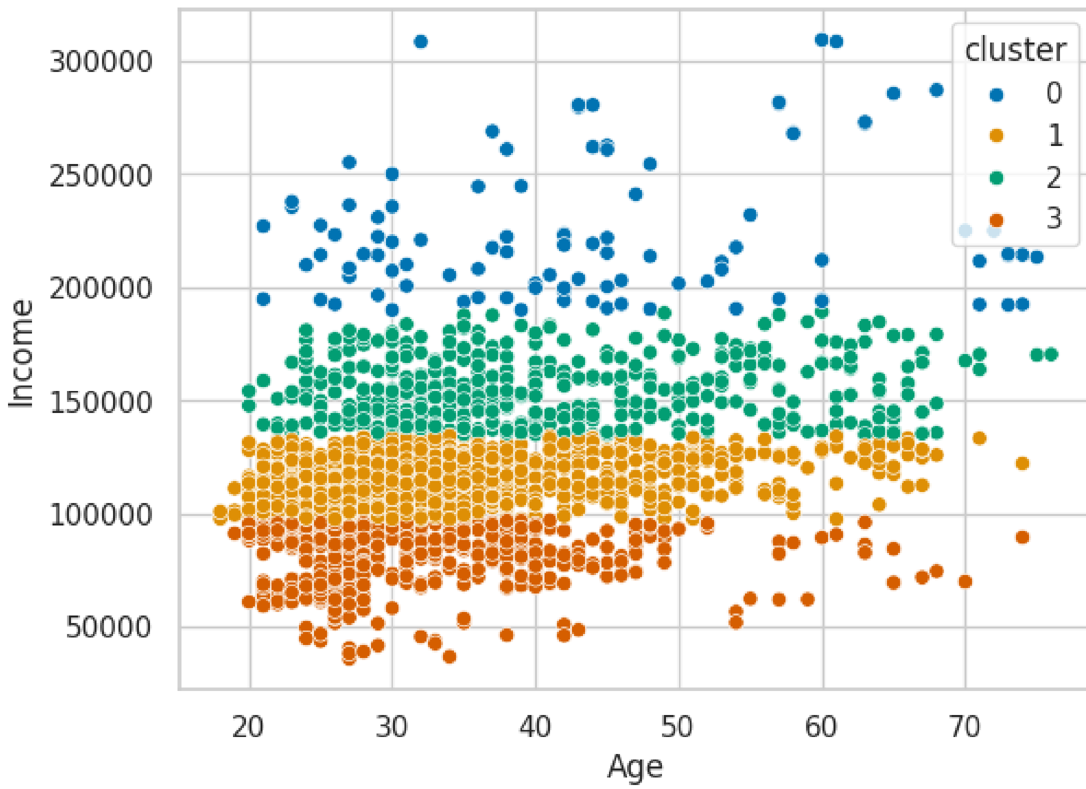
We can conclude that the best number of clusters was 4 according to silhouette score.

[27]:
```
# Getting data with 4 clusters
SEED = np.random.seed(300)
df.drop(columns = 'cluster')
kmeans = KMeans(n_clusters = 4, random_state = SEED)
labels = kmeans.fit_predict(df)
df['cluster'] = labels
silhouette_avg = silhouette_score(df, df.cluster)
print(f"Silhouette Score: {silhouette_avg}")
```

```
Silhouette Score: 0.5428478923817803
```

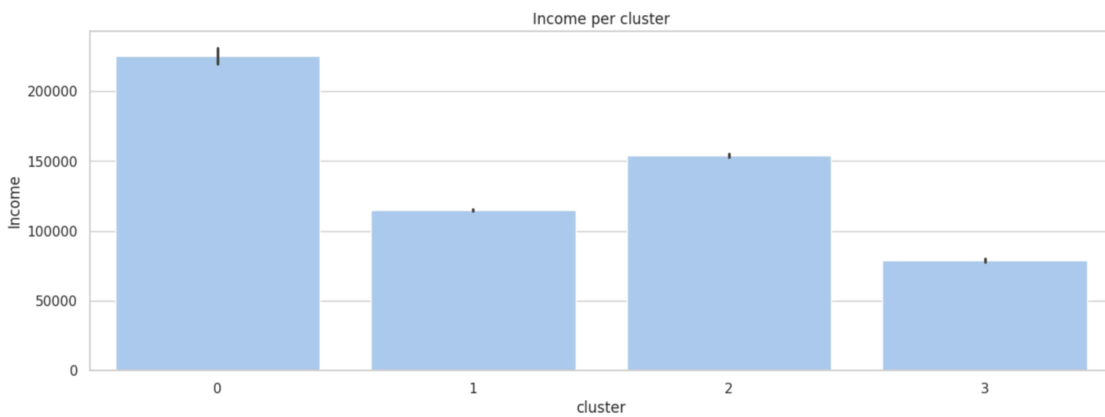
[28]:
```
sns.scatterplot(data = df, x = 'Age', y = 'Income', hue = 'cluster',␣
↪palette='colorblind')
```

[28]:
```
<Axes: xlabel='Age', ylabel='Income'>
```



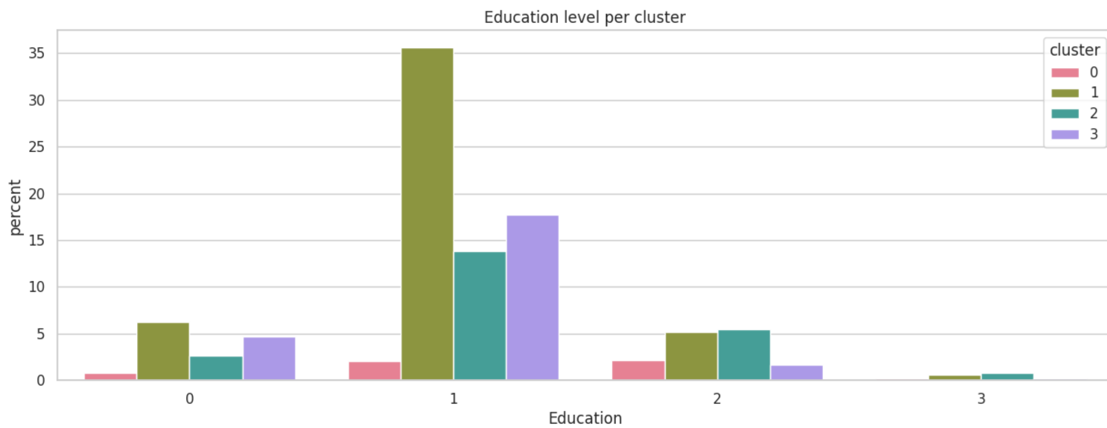
[29]:
```
# Which Cluster has the best income?
plt.figure(figsize=(15,5))
sns.barplot(df, x = 'cluster', y = 'Income').set_title('Income per cluster')
```

[29]: Text(0.5, 1.0, 'Income per cluster')



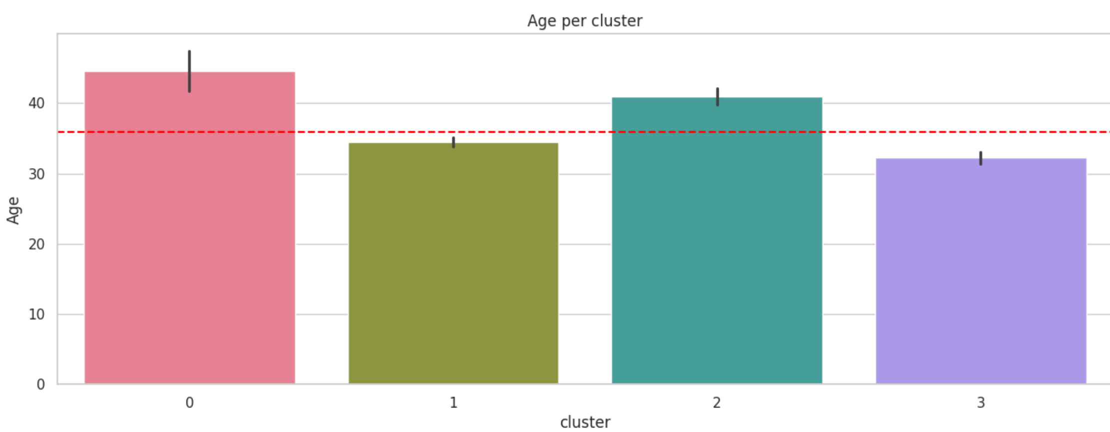
[30]:
```
# Which cluster has the best education level?
plt.figure(figsize=(15,5))
sns.countplot(df, x = 'Education', hue = 'cluster',stat='percent', palette =␣
↪sns.color_palette('husl', 4)).set_title('Education level per cluster')
```

[30]: Text(0.5, 1.0, 'Education level per cluster')



[31]:
```
# What is the average age per cluster?
plt.figure(figsize=(15,5))
sns.barplot(df, x = 'cluster', y = 'Age', palette = sns.color_palette('husl',␣
↪4)).set_title('Age per cluster')
plt.axhline(df['Age'].mean(), 0,4, linestyle = '--', color = 'red')
```

[31]: <matplotlib.lines.Line2D at 0x7c5679a8ac80>



[32]:
```
# Is Salary correlated with Age?
plt.figure(figsize=(15,5))
```

```
sns.regplot(df, x = 'Income', y= 'Age',scatter_kws={'alpha':0.0},␣
 ↪line_kws={'color':'red'})
sns.scatterplot(df, x='Income',y='Age',hue='cluster', palette = sns.
 ↪color_palette('husl', 4))
plt.title('Income per Age clustered')
```

[32]:
```
Text(0.5, 1.0, 'Income per Age clustered')
```

We can see that elder people earns more money than yonger people and we have it clusterized

0.5.1 Conclusion

From the results of the k means clustering that we have done, it can be concluded that there are 4 clusters for customer segmentation, starting from income analysis per cluster, education per cluster and there are still many analyzes that can be done from these 4 clusters to get a better analysis.