customer segmentation

March 23, 2022

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import sea
from kneed import KneeLocator
from sklearn.datasets import make_blobs
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from mpl_toolkits.mplot3d import Axes3D
```

Data is obtained from the following site: https://www.kaggle.com/kaushiksuresh147/customer-segmentation

0.0.1 Read Data and Make Sense of It

[2]:
```
auto1 = pd.read_csv("/Users/owner/Desktop/DS_AI_projects/Customer segmentation␣
↪project/Train.csv")
```

[3]:
```
auto2 = pd.read_csv("/Users/owner/Desktop/DS_AI_projects/Customer segmentation␣
↪project/Test.csv")
```

[4]:
```
automobile = pd.concat([auto1, auto2])
automobile.head()
```

[4]:
```
       ID  Gender Ever_Married  Age Graduated     Profession  Work_Experience  \
0  462809    Male           No   22        No     Healthcare              1.0
1  462643  Female          Yes   38       Yes       Engineer              NaN
2  466315  Female          Yes   67       Yes       Engineer              1.0
3  461735    Male          Yes   67       Yes         Lawyer              0.0
4  462669  Female          Yes   40       Yes  Entertainment              NaN

  Spending_Score  Family_Size  Var_1 Segmentation
0            Low          4.0  Cat_4            D
1        Average          3.0  Cat_4            A
2            Low          1.0  Cat_6            B
```

```
3           High          2.0   Cat_6           B
4           High          6.0   Cat_6           A
```

[5]:
```
automobile.describe()
```

[5]:
```
                  ID           Age  Work_Experience   Family_Size
count   10695.000000  10695.000000      9597.000000  10247.000000
mean   463468.088640     43.511828         2.619777      2.844052
std      2600.966411     16.774158         3.390790      1.536427
min    458982.000000     18.000000         0.000000      1.000000
25%    461220.500000     30.000000         0.000000      2.000000
50%    463451.000000     41.000000         1.000000      3.000000
75%    465733.500000     53.000000         4.000000      4.000000
max    467974.000000     89.000000        14.000000      9.000000
```

0.0.2 Imputation, Filling Missing Values, One Hot Encoding

[6]:
```
automobile.columns = ['id', 'gender', 'married', 'age', 'graduated',␣
 ↪'profession',
       'work_experience', 'spending_score', 'family_size', 'var_1',
       'segmentation']
```

[7]:
```
automobile = automobile.drop(columns=["id", "segmentation"])
automobile.head()
```

[7]:
```
   gender married  age graduated     profession  work_experience  \
0    Male      No   22        No     Healthcare              1.0
1  Female     Yes   38       Yes       Engineer              NaN
2  Female     Yes   67       Yes       Engineer              1.0
3    Male     Yes   67       Yes         Lawyer              0.0
4  Female     Yes   40       Yes  Entertainment              NaN

  spending_score  family_size  var_1
0            Low          4.0  Cat_4
1        Average          3.0  Cat_4
2            Low          1.0  Cat_6
3           High          2.0  Cat_6
4           High          6.0  Cat_6
```

[8]:
```
# treating numerical features of null values with mean values
automobile.fillna(automobile[["age", "work_experience", "family_size"]].mean(),␣
 ↪inplace=True)
```

[9]:
```
for c in automobile.columns:
    a = automobile[c].value_counts()
    print(a)
```

```
Male      5841
Female    4854
Name: gender, dtype: int64
Yes    6163
No     4342
Name: married, dtype: int64
35    321
42    320
37    304
43    301
40    300
     …
75     37
78     36
76     36
80     33
85     32
Name: age, Length: 67, dtype: int64
Yes    6570
No     4023
Name: graduated, dtype: int64
Artist           3318
Healthcare       1750
Entertainment    1250
Engineer          935
Doctor            930
Lawyer            844
Executive         775
Marketing         403
Homemaker         328
Name: profession, dtype: int64
1.000000     3127
0.000000     3087
2.619777     1098
9.000000      613
8.000000      612
2.000000      373
4.000000      346
3.000000      337
5.000000      270
6.000000      265
7.000000      256
14.000000      66
10.000000      64
11.000000      64
12.000000      60
13.000000      57
Name: work_experience, dtype: int64
```

```
Low        6494
Average    2599
High       1602
Name: spending_score, dtype: int64
2.000000    3158
1.000000    1965
3.000000    1952
4.000000    1823
5.000000     812
2.844052     448
6.000000     290
7.000000     122
8.000000      65
9.000000      60
Name: family_size, dtype: int64
Cat_6    6910
Cat_4    1475
Cat_3    1089
Cat_2     563
Cat_7     269
Cat_1     167
Cat_5     114
Name: var_1, dtype: int64
```

[10]:
```
automobile.isnull().sum()
```

[10]:
```
gender               0
married            190
age                  0
graduated          102
profession         162
work_experience      0
spending_score       0
family_size          0
var_1              108
dtype: int64
```

[11]:
```
# binary encoding for categorical features with only 2 possible values.

# dict = {# some kind of dictionary with categorical keys mapping to numerical␣
 ↪values}
# df['feature'] = df['feature'].map(dict)
```

[12]:
```
# one-hot encoding for categorical features with 2 or more possible values.
automobiles = pd.get_dummies(automobile, prefix = ['profession'], columns =␣
 ↪['profession'])
```

```python
automobiles = pd.get_dummies(automobiles, prefix = ['gender'], columns =␣
 ↪['gender'])
automobiles = pd.get_dummies(automobiles, prefix = ['married'], columns =␣
 ↪['married'])
automobiles = pd.get_dummies(automobiles, prefix = ['graduated'], columns =␣
 ↪['graduated'])
automobiles = pd.get_dummies(automobiles, prefix = ['var_1'], columns =␣
 ↪['var_1'])
automobiles.head(10)
```

[12]:

```
   age  work_experience spending_score  family_size  profession_Artist  \
0   22         1.000000            Low          4.0                  0
1   38         2.619777        Average          3.0                  0
2   67         1.000000            Low          1.0                  0
3   67         0.000000           High          2.0                  0
4   40         2.619777           High          6.0                  0
5   56         0.000000        Average          2.0                  1
6   32         1.000000            Low          3.0                  0
7   33         1.000000            Low          3.0                  0
8   61         0.000000            Low          3.0                  0
9   55         1.000000        Average          4.0                  1

   profession_Doctor  profession_Engineer  profession_Entertainment  \
0                  0                    0                         0
1                  0                    1                         0
2                  0                    1                         0
3                  0                    0                         0
4                  0                    0                         1
5                  0                    0                         0
6                  0                    0                         0
7                  0                    0                         0
8                  0                    1                         0
9                  0                    0                         0

   profession_Executive  profession_Healthcare  …  married_Yes  \
0                     0                      1  …            0
1                     0                      0  …            1
2                     0                      0  …            1
3                     0                      0  …            1
4                     0                      0  …            1
5                     0                      0  …            1
6                     0                      1  …            0
7                     0                      1  …            0
8                     0                      0  …            1
9                     0                      0  …            1

   graduated_No  graduated_Yes  var_1_Cat_1  var_1_Cat_2  var_1_Cat_3  \
```

```
0          1          0          0          0          0
1          0          1          0          0          0
2          0          1          0          0          0
3          0          1          0          0          0
4          0          1          0          0          0
5          1          0          0          0          0
6          0          1          0          0          0
7          0          1          0          0          0
8          0          1          0          0          0
9          0          1          0          0          0

   var_1_Cat_4  var_1_Cat_5  var_1_Cat_6  var_1_Cat_7
0            1            0            0            0
1            1            0            0            0
2            0            0            1            0
3            0            0            1            0
4            0            0            1            0
5            0            0            1            0
6            0            0            1            0
7            0            0            1            0
8            0            0            0            1
9            0            0            1            0

[10 rows x 26 columns]
```

[13]:
```
automobiles.drop(columns=["gender_Male"], inplace=True)
```

[14]:
```
# Ordincal feature encoding for features that have ordered values
from sklearn.preprocessing import LabelEncoder

#label encoder can't handle missing values
automobiles['spending_score'] = automobiles['spending_score'].fillna('None')
# Label encode ord_1 feature
label_encoder = LabelEncoder()
automobiles['spending_score'] = label_encoder.
 ↪fit_transform(automobiles['spending_score'])
# Print sample of dataset
automobiles.head(10)
```

[14]:
```
   age  work_experience  spending_score  family_size  profession_Artist  \
0   22         1.000000               2          4.0                  0
1   38         2.619777               0          3.0                  0
2   67         1.000000               2          1.0                  0
3   67         0.000000               1          2.0                  0
4   40         2.619777               1          6.0                  0
5   56         0.000000               0          2.0                  1
6   32         1.000000               2          3.0                  0
```

7	33	1.000000	2	3.0	0
8	61	0.000000	2	3.0	0
9	55	1.000000	0	4.0	1

	profession_Doctor	profession_Engineer	profession_Entertainment	\
0	0	0	0	
1	0	1	0	
2	0	1	0	
3	0	0	0	
4	0	0	1	
5	0	0	0	
6	0	0	0	
7	0	0	0	
8	0	1	0	
9	0	0	0	

	profession_Executive	profession_Healthcare	…	married_Yes	\
0	0	1	…	0	
1	0	0	…	1	
2	0	0	…	1	
3	0	0	…	1	
4	0	0	…	1	
5	0	0	…	1	
6	0	1	…	0	
7	0	1	…	0	
8	0	0	…	1	
9	0	0	…	1	

	graduated_No	graduated_Yes	var_1_Cat_1	var_1_Cat_2	var_1_Cat_3	\
0	1	0	0	0	0	
1	0	1	0	0	0	
2	0	1	0	0	0	
3	0	1	0	0	0	
4	0	1	0	0	0	
5	1	0	0	0	0	
6	0	1	0	0	0	
7	0	1	0	0	0	
8	0	1	0	0	0	
9	0	1	0	0	0	

	var_1_Cat_4	var_1_Cat_5	var_1_Cat_6	var_1_Cat_7
0	1	0	0	0
1	1	0	0	0
2	0	0	1	0
3	0	0	1	0
4	0	0	1	0
5	0	0	1	0

```
6             0             0             1             0
7             0             0             1             0
8             0             0             0             1
9             0             0             1             0

[10 rows x 25 columns]
```

[15]:

```python
# feature standardization
scaler = StandardScaler().fit(automobiles)
scaled_features = scaler.transform(automobiles)
scaled_features = pd.DataFrame(scaled_features, columns = automobiles.columns)
scaled_features.head()
```

[15]:

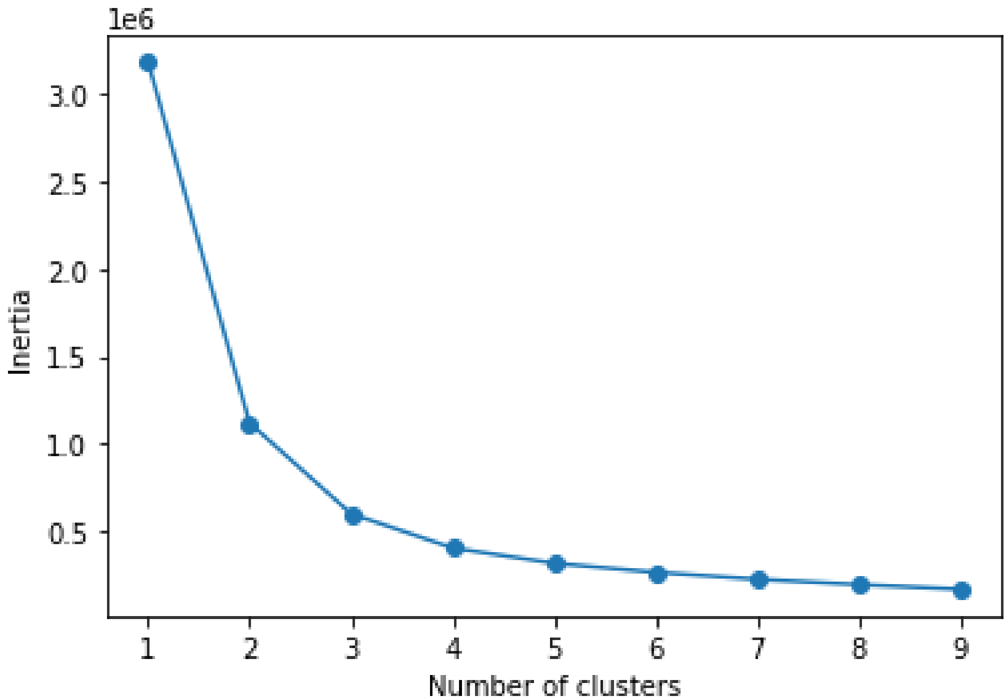
```
        age  work_experience  spending_score  family_size  profession_Artist  \
0 -1.282499        -0.504312        0.750575     0.768669          -0.670654
1 -0.328606         0.000000       -1.610424     0.103701          -0.670654
2  1.400325        -0.504312        0.750575    -1.226237          -0.670654
3  1.400325        -0.815659       -0.429925    -0.561268          -0.670654
4 -0.209369         0.000000       -0.429925     2.098607          -0.670654

   profession_Doctor  profession_Engineer  profession_Entertainment  \
0          -0.308607            -0.309514                 -0.363793
1          -0.308607             3.230867                 -0.363793
2          -0.308607             3.230867                 -0.363793
3          -0.308607            -0.309514                 -0.363793
4          -0.308607            -0.309514                  2.748818

   profession_Executive  profession_Healthcare  …  married_Yes  \
0             -0.279508               2.260847  …    -1.166141
1             -0.279508              -0.442312  …     0.857529
2             -0.279508              -0.442312  …     0.857529
3             -0.279508              -0.442312  …     0.857529
4             -0.279508              -0.442312  …     0.857529

   graduated_No  graduated_Yes  var_1_Cat_1  var_1_Cat_2  var_1_Cat_3  \
0      1.287814      -1.262033    -0.125946    -0.235726      -0.3367
1     -0.776510       0.792372    -0.125946    -0.235726      -0.3367
2     -0.776510       0.792372    -0.125946    -0.235726      -0.3367
3     -0.776510       0.792372    -0.125946    -0.235726      -0.3367
4     -0.776510       0.792372    -0.125946    -0.235726      -0.3367

   var_1_Cat_4  var_1_Cat_5  var_1_Cat_6  var_1_Cat_7
0     2.500169    -0.103798    -1.351158    -0.160627
1     2.500169    -0.103798    -1.351158    -0.160627
2    -0.399973    -0.103798     0.740106    -0.160627
3    -0.399973    -0.103798     0.740106    -0.160627
4    -0.399973    -0.103798     0.740106    -0.160627
```

```
[5 rows x 25 columns]
```

0.0.3 Make a Plot on the "Elbow Method"

[16]:
```python
# store the squared sum of distances from the mean of each cluster to the data␣
↪points to that mean
sse = []

for cluster in range(1,10):
    kmeans = KMeans(n_clusters = cluster, init='k-means++')
    kmeans.fit(automobiles)
    sse.append(kmeans.inertia_)

# converting the results into a dataframe and plotting them
clustering = pd.DataFrame({'Cluster':range(1,10), 'SSE':sse})
#plt.figure(figsize=(12,6))
plt.plot(clustering['Cluster'], clustering['SSE'], marker='o')
plt.xlabel('Number of clusters')
plt.ylabel('Inertia')
```

[16]:
```
Text(0, 0.5, 'Inertia')
```

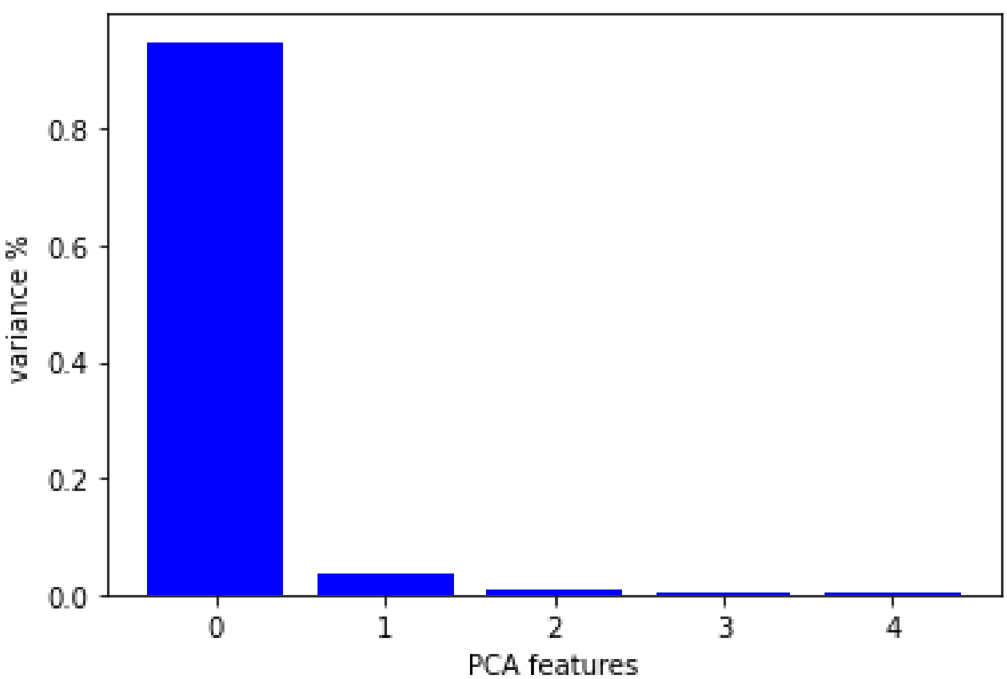


[17]:
```
# based on the elbow method, the best number of clusters to set would be 4,
# since after K=4, the inertia decreases in a linear manner.

# Build a model with 4 clusters
kmeans = KMeans(n_clusters=4, init='k-means++')
kmeans.fit(automobiles)

# Print the silhouette score for the model above
print(silhouette_score(automobiles, kmeans.labels_, metric='euclidean'))
```

```
0.42861278447347173
```

0.0.4 Try Improve the Quality of Clusters by Selecting Useful Features

[18]:
```
# attempt to improve the model using PCA to reduce dimensionality.
pca = PCA(n_components=5)
pca_fit = pca.fit_transform(automobiles)
n_comp = range(pca.n_components_)
plt.bar(n_comp, pca.explained_variance_ratio_, color='blue')
plt.xlabel('PCA features')
plt.ylabel('variance %')

pca_components = pd.DataFrame(pca_fit)
```



[19]:
```
pca_components.head()
```

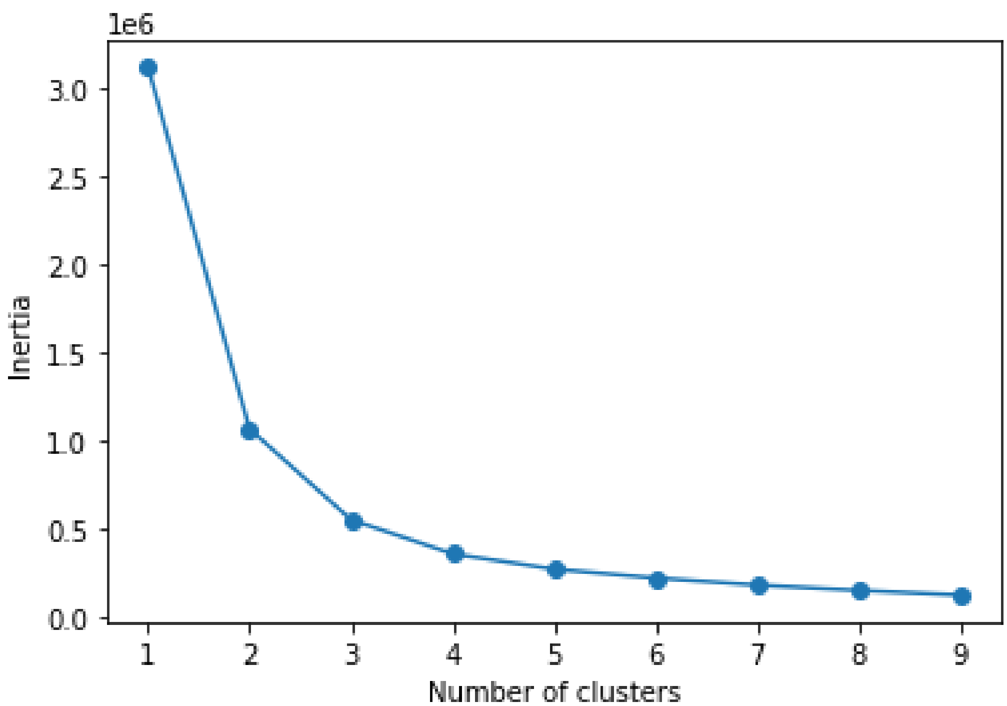
[19]:

	0	1	2	3	4
0	-21.502903	-2.450373	0.521449	0.782306	-0.633519
1	-5.476260	-0.192459	0.297044	-1.566620	-0.290469
2	23.568221	-0.689226	-1.477698	0.566654	0.225764
3	23.602871	-1.765042	-0.394367	-0.085947	0.124108
4	-3.558898	-0.310606	2.998802	-0.374295	0.823571

[20]:

```
# building a new model after PCA.

inertia = []

for cluster in range(1,10):
    kmeans = KMeans(n_clusters = cluster)
    kmeans.fit(pca_components.iloc[:,:2])
    inertia.append(kmeans.inertia_)

# converting the results into a dataframe and plotting them
clusters = pd.DataFrame({'Cluster':range(1,10), 'Inertia':inertia})
# plt.figure(figsize=(12,6))
plt.plot(clusters['Cluster'], clusters['Inertia'], marker='o')
plt.xlabel('Number of clusters')
plt.ylabel('Inertia')
```

[20]: Text(0, 0.5, 'Inertia')

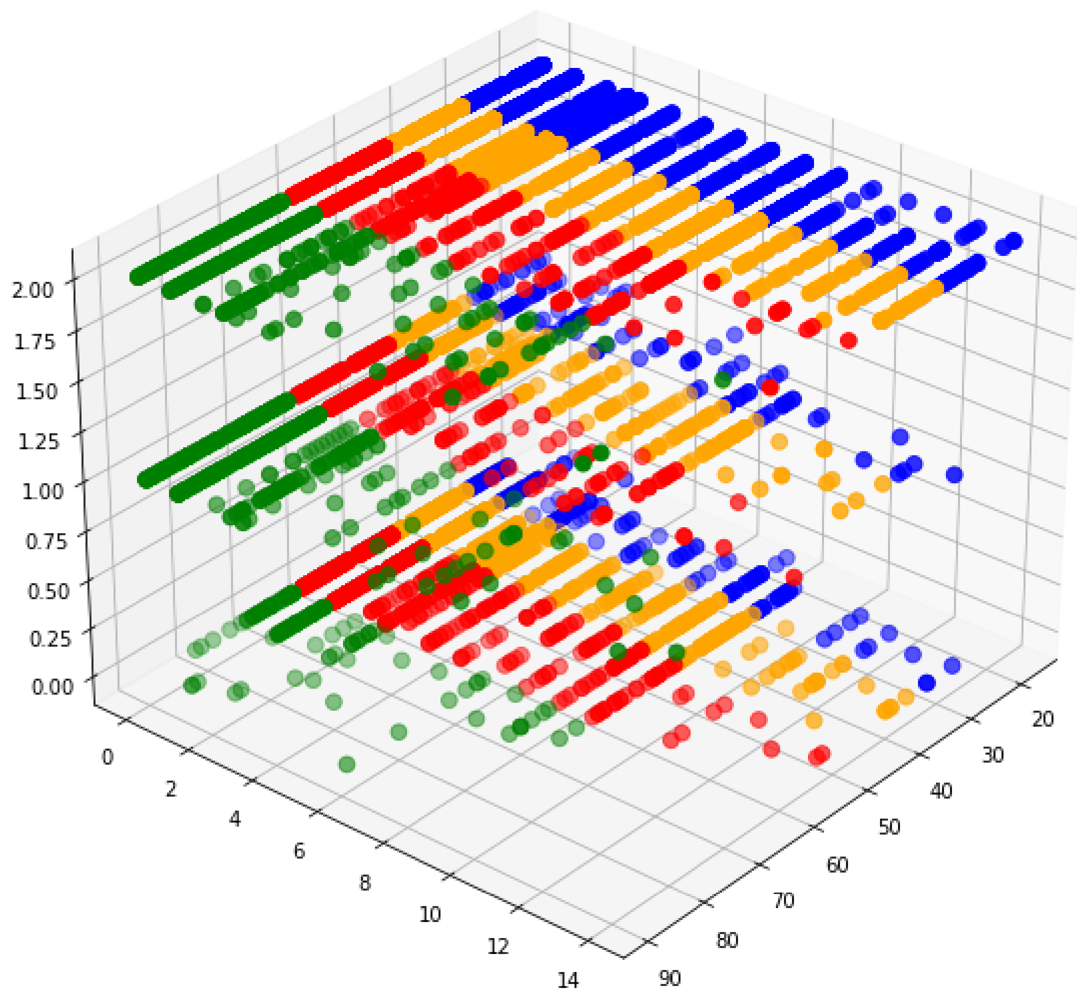


[21]:
```
# still, K=4 seems like the best approach.
kmeans_new = KMeans(n_clusters=4)
kmeans_new.fit(pca_components.iloc[:,:2])

# silhouette score
print(silhouette_score(pca_components.iloc[:,:2], kmeans_new.labels_,␣
↪metric='euclidean'))
```

```
0.47313464575183084
```

We see roughly 4.5% increase in the Silhouette score!

[22]:
```
model = KMeans(n_clusters=4)

clusters = model.fit_predict(pca_components.iloc[:,:2])
automobiles["label"] = clusters

fig = plt.figure(figsize=(21,10))
ax = fig.add_subplot(111, projection='3d')
ax.scatter(automobiles.age[automobiles.label == 0],␣
↪automobiles["work_experience"][automobiles.label == 0],␣
↪automobiles["spending_score"][automobiles.label == 0], c='blue', s=60)
ax.scatter(automobiles.age[automobiles.label == 1],␣
↪automobiles["work_experience"][automobiles.label == 1],␣
↪automobiles["spending_score"][automobiles.label == 1], c='red', s=60)
ax.scatter(automobiles.age[automobiles.label == 2],␣
↪automobiles["work_experience"][automobiles.label == 2],␣
↪automobiles["spending_score"][automobiles.label == 2], c='green', s=60)
ax.scatter(automobiles.age[automobiles.label == 3],␣
↪automobiles["work_experience"][automobiles.label == 3],␣
↪automobiles["spending_score"][automobiles.label == 3], c='orange', s=60)

ax.view_init(30, 40)
plt.show()
```



[23]:
```
automobiles.columns
```

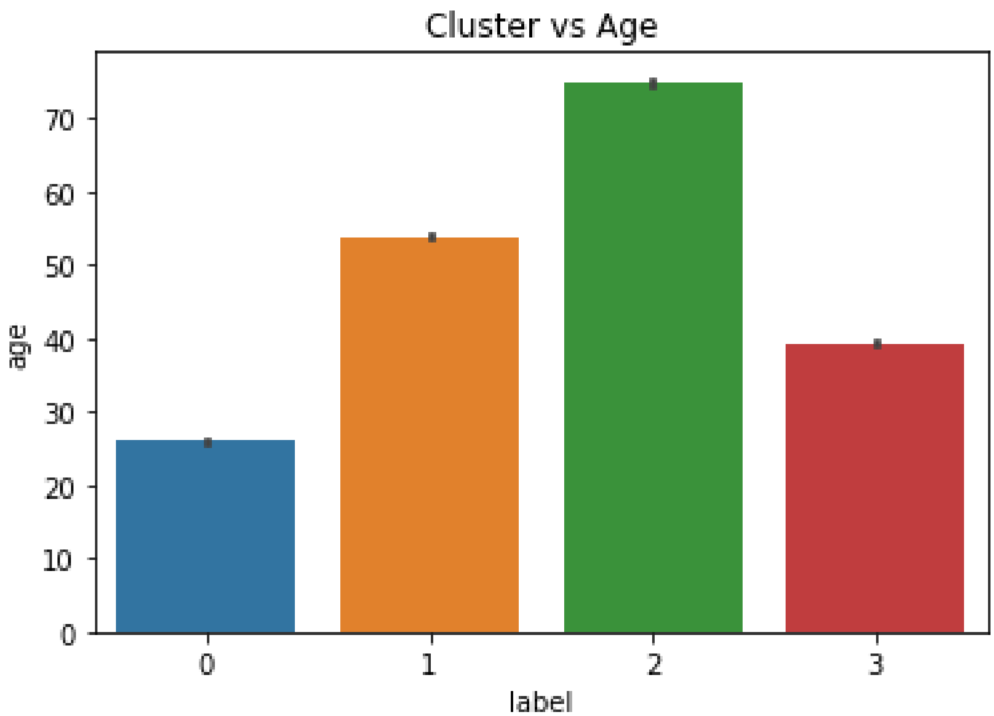
[23]:
```
Index(['age', 'work_experience', 'spending_score', 'family_size',
       'profession_Artist', 'profession_Doctor', 'profession_Engineer',
       'profession_Entertainment', 'profession_Executive',
       'profession_Healthcare', 'profession_Homemaker', 'profession_Lawyer',
       'profession_Marketing', 'gender_Female', 'married_No', 'married_Yes',
       'graduated_No', 'graduated_Yes', 'var_1_Cat_1', 'var_1_Cat_2',
       'var_1_Cat_3', 'var_1_Cat_4', 'var_1_Cat_5', 'var_1_Cat_6',
       'var_1_Cat_7', 'label'],
      dtype='object')
```

As you can see, the clusters look like they can be separated quite easily, except a few spots where different colors overlap a bit. As far as the results go, I'm satisfied with the clusters!

0.0.5 Take a Look at the Demographics

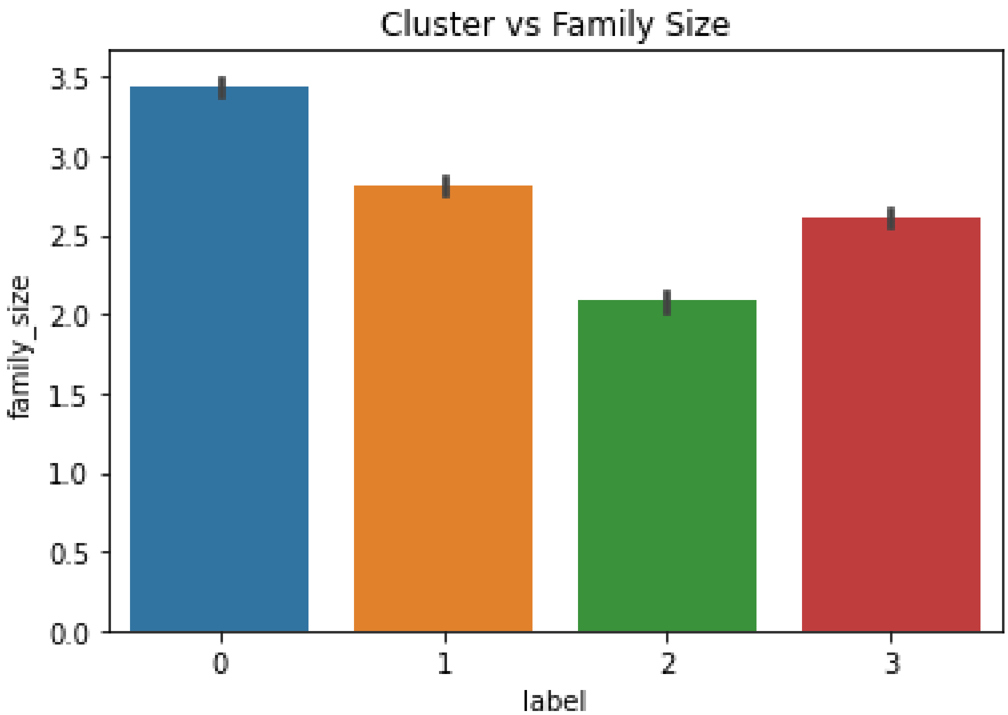
[24]:
```
sns.barplot(x='label', y='age', data=automobiles).set(title='Cluster vs Age')
```

[24]: [Text(0.5, 1.0, 'Cluster vs Age')]



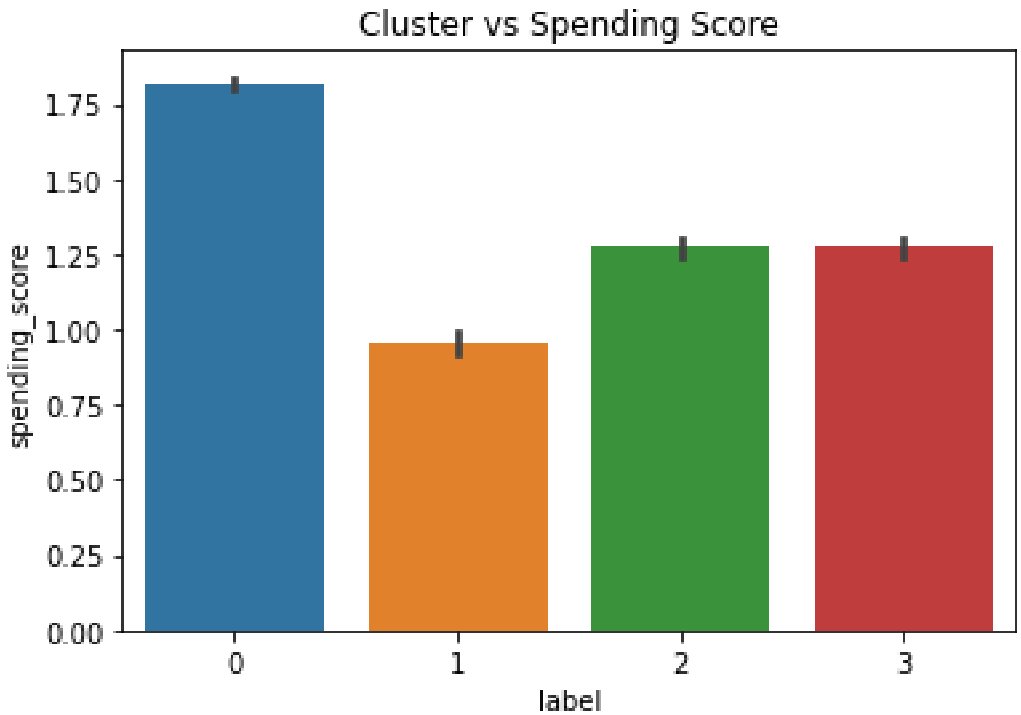
[25]:
```
sns.barplot(x='label', y='family_size', data=automobiles).set(title='Cluster vs␣
↪Family Size')
```

[25]: [Text(0.5, 1.0, 'Cluster vs Family Size')]



[26]:
```
sns.barplot(x='label', y='spending_score', data=automobiles).set(title='Cluster␣
↪vs Spending Score')
```

[26]: [Text(0.5, 1.0, 'Cluster vs Spending Score')]



[27]:
```
sns.barplot(x='label', y='work_experience', data=automobiles).
 ↪set(title='Cluster vs Work Experience')
```

[27]:
```
[Text(0.5, 1.0, 'Cluster vs Work Experience')]
```

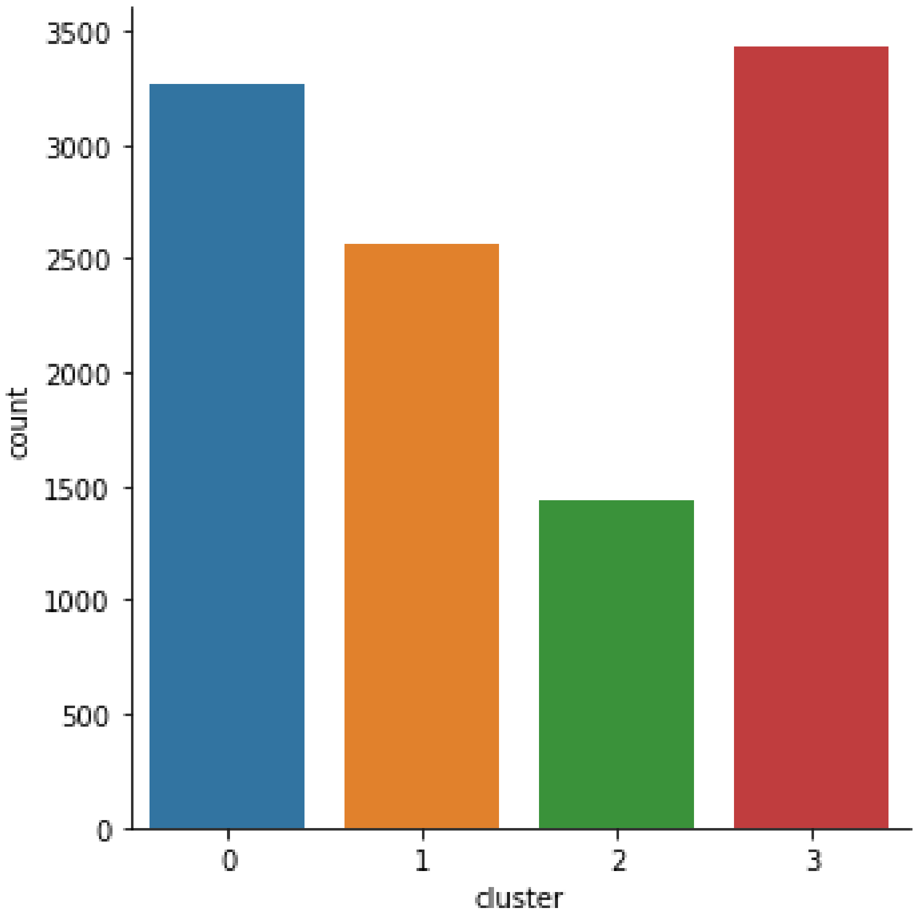
0.0.6 Now take a look at the count of each cluster

[28]:
```
automobile = automobile.fillna('Unknown')
automobile["cluster"] = clusters
automobile.head()
```

[28]:
```
   gender married  age graduated     profession  work_experience  \
0    Male      No   22        No     Healthcare         1.000000
1  Female     Yes   38       Yes       Engineer         2.619777
2  Female     Yes   67       Yes       Engineer         1.000000
3    Male     Yes   67       Yes         Lawyer         0.000000
4  Female     Yes   40       Yes  Entertainment         2.619777

  spending_score  family_size  var_1  cluster
0            Low          4.0  Cat_4        0
1        Average          3.0  Cat_4        3
2            Low          1.0  Cat_6        2
3           High          2.0  Cat_6        2
4           High          6.0  Cat_6        3
```

[29]:
```
sns.catplot(x="cluster", kind="count", data=automobile)
```

[29]: <seaborn.axisgrid.FacetGrid at 0x7ffb588fad30>



The above barplots show the following insights: 1. Cluster 1: The averge or typical customer in this cluster is middle-aged (around 40) with an average family size of 2.5 and a moderate ~ moderately high spending score. This customer group has the longest years of work_experience on average. This is the largest customer group. My recommendation to this company is to focus on utility —— advertise versatile models that cater to a variety of driving consitions and preferences to maximize the reach to the largest pool of potential buyers.

2. Cluster 2: The typical customer in this cluster is a senior (over 70) with an average family size of 2 and a moderate ~ moderately high spending score. This is the smallest group and its members should be mostly retired.

3. Cluster 3: The typical customer is a slightly older middle-aged person with an average family size of 2.8 and the lowest spending score out of all groups with a less than 1.0 average. This group won't be able to afford expensive vehicles, probably because it has more family members to spend money on or this group as a whole do not spend beyond their needs. The company's strategy should be to advertise less expensive, mid-to-low tier vehicles.

4. Cluster 4: The typical customer is a young adult aged around 25 who has the highest spending score of all groups and the largest average family size! This is surprising because we normally assume older customers to have more spending power and larger family size, but for this

automobile company, this is simply not the case. This cluster is likely a group of young working professionals with high pay and/or heritage. The company should promote the most top-of-the-line car models to this group as their primary target consumer base because this group is most likely able to afford more expensive cars.

[30]:
```
automobiles.columns
```

[30]:
```
Index(['age', 'work_experience', 'spending_score', 'family_size',
       'profession_Artist', 'profession_Doctor', 'profession_Engineer',
       'profession_Entertainment', 'profession_Executive',
       'profession_Healthcare', 'profession_Homemaker', 'profession_Lawyer',
       'profession_Marketing', 'gender_Female', 'married_No', 'married_Yes',
       'graduated_No', 'graduated_Yes', 'var_1_Cat_1', 'var_1_Cat_2',
       'var_1_Cat_3', 'var_1_Cat_4', 'var_1_Cat_5', 'var_1_Cat_6',
       'var_1_Cat_7', 'label'],
      dtype='object')
```

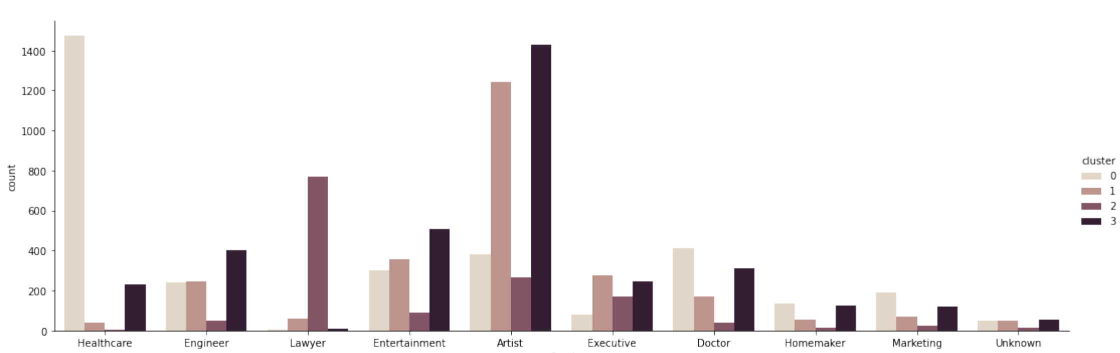
[31]:
```
automobiles.groupby("label")["graduated_Yes"].mean()
```

[31]:
```
label
0    0.357340
1    0.771875
2    0.616933
3    0.740017
Name: graduated_Yes, dtype: float64
```

[32]:
```
plt.figure(figsize=(20,5))
sns.catplot(x="profession", kind="count", hue='cluster', data=automobile,␣
 ↪palette="ch:.25",
            height=5, aspect=3)
```

[32]:
```
<seaborn.axisgrid.FacetGrid at 0x7ffb68ae3550>
```

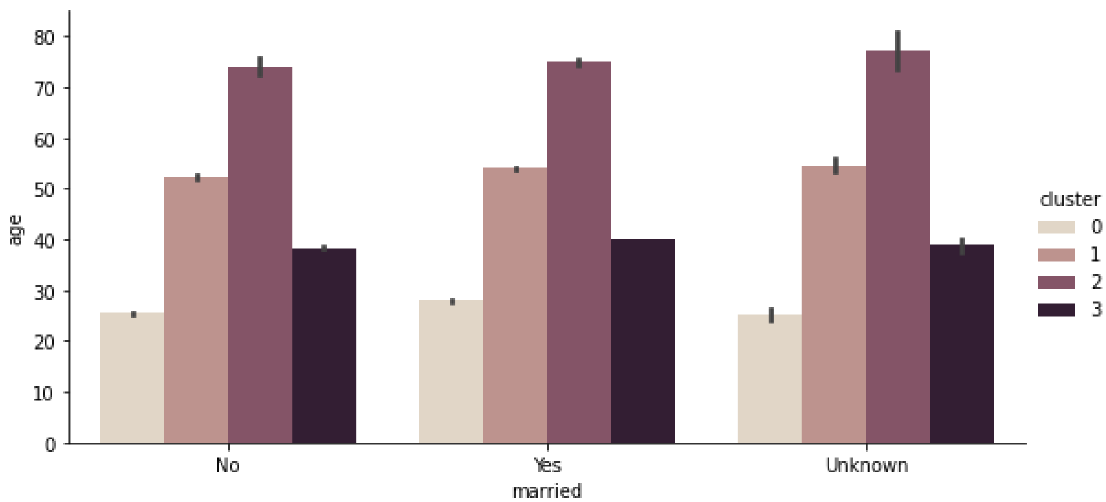
```
<Figure size 1440x360 with 0 Axes>
```



We can see the following trends: 1. Artists, entertainment workers, and engineers are most represented in the 1st cluster. 2. Lawyers, artists, and executives are most represented in the 2nd cluster. 3. Artists, entertainment workers, and executives are most represented in the 3rd cluster. 4. Healthcare professionals, doctors, and artists are most represented in the 4th cluster.

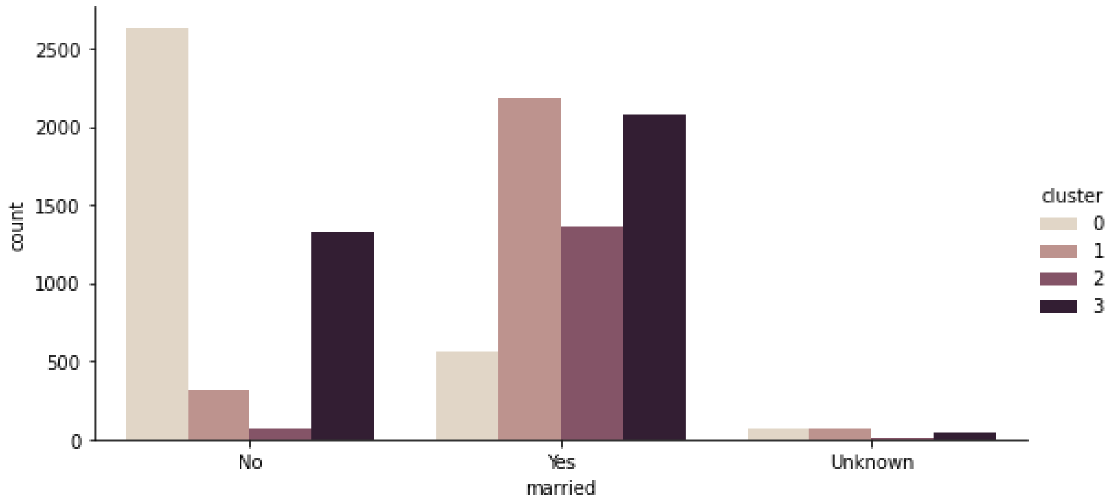
[33]:
```
sns.catplot(x="married", y="age", kind="bar", hue='cluster', data=automobile,␣
↪palette="ch:.25",
            height=4, aspect=2)
```

[33]: <seaborn.axisgrid.FacetGrid at 0x7ffb8b9f3490>



[34]:
```
sns.catplot(x="married", kind="count", hue='cluster', data=automobile,␣
↪palette="ch:.25",
            height=4, aspect=2)
```

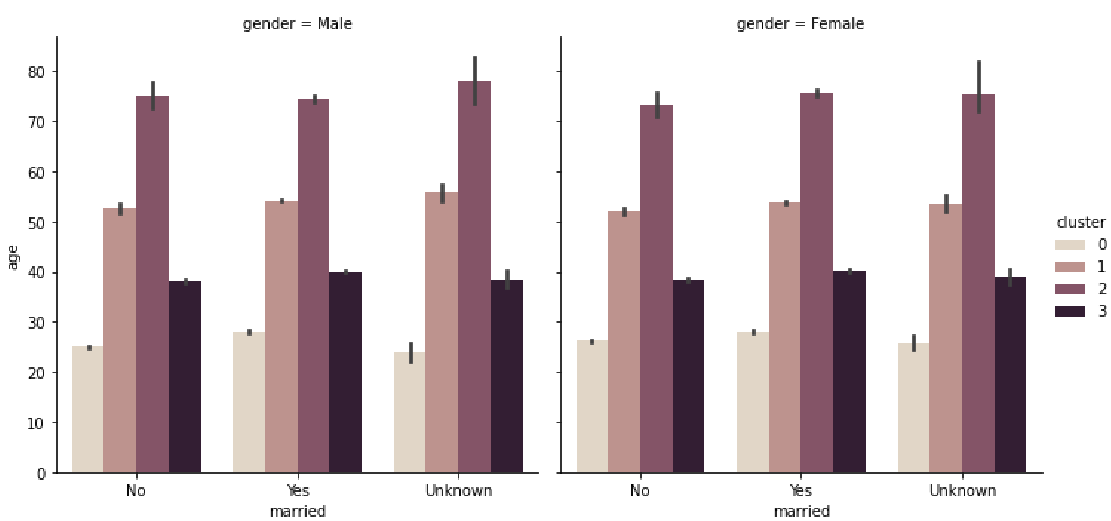
[34]: <seaborn.axisgrid.FacetGrid at 0x7ffb79c89370>



For all clusters except cluster 3 (actually the cluster 4 because python starts counting from 0), there are more married people than unmarried. The last cluster (represented by black) is the young professional group. It's understandable that most of them are unmarried.

[35]:
```
sns.catplot(x="married", y="age", col="gender", kind="bar", hue='cluster',␣
↪data=automobile, palette="ch:.25")
```

[35]: <seaborn.axisgrid.FacetGrid at 0x7ffb79c89340>



The charts show that the age for each cluster for unmarried and married people is roughly equivalent. Age for female customers in each cluster is lower than the male counterparts.

[36]:
```
automobile["gender"].value_counts()
```

[36]:
```
Male      5841
Female    4854
Name: gender, dtype: int64
```

[37]:
```
print(f"Male to Female Ratio is: {5841/4854}")
```

```
Male to Female Ratio is: 1.2033374536464772
```

0.0.7 This is the end of the analysis!