## MMAI869\_Assign\_Q1\_FrancisBello

November 8, 2019

- 0.1 MMAI869 Dr. Stephen Thomas
- 0.1.1 Individual Assignment, Question 1
- 0.1.2 Francis Bello
- 0.1.3 20141658

## 1 How Lovely!

```
[1]: import datetime
print(datetime.datetime.now())
```

2019-11-08 19:36:35.183610

#### Import libraries

```
import pandas as pd
import numpy as np
import matplotlib as mpl
import matplotlib.pyplot as plt
import pandas_profiling
import seaborn as sns
from pandas.plotting import scatter_matrix
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import silhouette_score, silhouette_samples
from yellowbrick.cluster import

→SilhouetteVisualizer,KElbowVisualizer,InterclusterDistance
```

[3]: %matplotlib inline

#### Read data

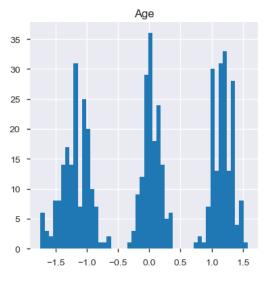
```
[4]: jewelry_cust = pd.read_csv('jewelry_customers.csv')
```

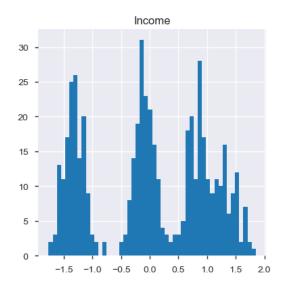
#### Inspect data

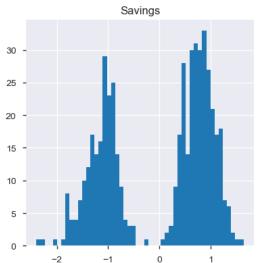
```
[5]: features = list(jewelry_cust) #check features features
```

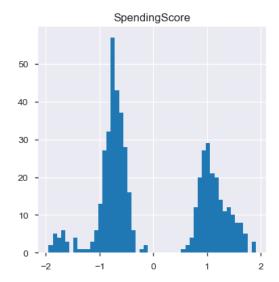
```
[5]: ['Age', 'Income', 'SpendingScore', 'Savings']
     jewelry_cust.shape #check dimension size
 [6]: (505, 4)
 [7]: jewelry_cust.head(5) #check top 5
 [7]:
         Age
              Income
                      SpendingScore
                                            Savings
                            0.791329
      0
          58
               77769
                                        6559.829923
      1
          59
               81799
                            0.791082
                                        5417.661426
      2
          62
               74751
                            0.702657
                                        9258.992965
      3
          59
                            0.765680
                                       7346.334504
               74373
      4
          87
               17760
                            0.348778
                                      16869.507130
 [8]: jewelry_cust.tail(5) #check bottom 5
 [8]:
           Age
                Income
                         SpendingScore
                                              Savings
      500
            28
                101206
                              0.387441
                                        14936.775389
      501
            93
                 19934
                              0.203140
                                        17969.693769
      502
            90
                 35297
                              0.355149
                                        16091.401954
      503
                                        18401.088445
            91
                 20681
                              0.354679
      504
                 30267
            89
                              0.289310
                                        14386.351880
      jewelry_cust.info() #check data types and record count per feature
     <class 'pandas.core.frame.DataFrame'>
     RangeIndex: 505 entries, 0 to 504
     Data columns (total 4 columns):
     Age
                       505 non-null int64
     Income
                       505 non-null int64
     SpendingScore
                       505 non-null float64
     Savings
                       505 non-null float64
     dtypes: float64(2), int64(2)
     memory usage: 15.9 KB
[10]: jewelry_cust.describe() #check statistics values
[10]:
                                 Income
                                          SpendingScore
                                                               Savings
                     Age
             505.000000
                             505.000000
                                             505.000000
                                                           505.000000
      count
      mean
              59.019802
                           75513.291089
                                               0.505083
                                                         11862.455867
      std
              24.140043
                           35992.922184
                                               0.259634
                                                          4949.229253
      min
              17.000000
                           12000.000000
                                               0.000000
                                                              0.000000
      25%
              34.000000
                           34529.000000
                                               0.304792
                                                          6828.709702
      50%
              59.000000
                           75078.000000
                                               0.368215
                                                         14209.932802
              85.000000
                          107100.000000
      75%
                                               0.768279
                                                         16047.268331
              97.000000
                          142000.000000
                                               1.000000
                                                         20000.000000
      max
```

```
[11]: #normalize the dataset
     scaler = StandardScaler()
     jewelry_cust_standard = jewelry_cust
     jewelry_cust_standard[features] = scaler.fit_transform(jewelry_cust[features])
[12]: jewelry_cust_standard.describe() #check normalized statistics values
[12]:
                                Income SpendingScore
                                                            Savings
                     Age
     count 5.050000e+02 5.050000e+02
                                        5.050000e+02 5.050000e+02
     mean
            5.672031e-17 -2.638154e-17 -1.954432e-16 -4.058360e-16
            1.000992e+00 1.000992e+00
                                         1.000992e+00 1.000992e+00
     std
          -1.742394e+00 -1.766355e+00 -1.947295e+00 -2.399206e+00
     min
     25%
           -1.037472e+00 -1.139805e+00 -7.722011e-01 -1.018085e+00
     50%
          -8.211094e-04 -1.210579e-02 -5.276784e-01 4.747819e-01
     75%
            1.077295e+00 8.784513e-01
                                         1.014725e+00 8.463867e-01
     max
            1.574888e+00 1.849048e+00
                                         1.908103e+00 1.645835e+00
[13]: pandas_profiling.ProfileReport(jewelry_cust_standard, check_correlation=False)
      →#check profile of each feature
[13]: <pandas_profiling.ProfileReport at 0x27b6a5edba8>
[14]: | jewelry_cust_standard.hist(bins=50,figsize=(10,10)) #check histogram
     plt.show()
```

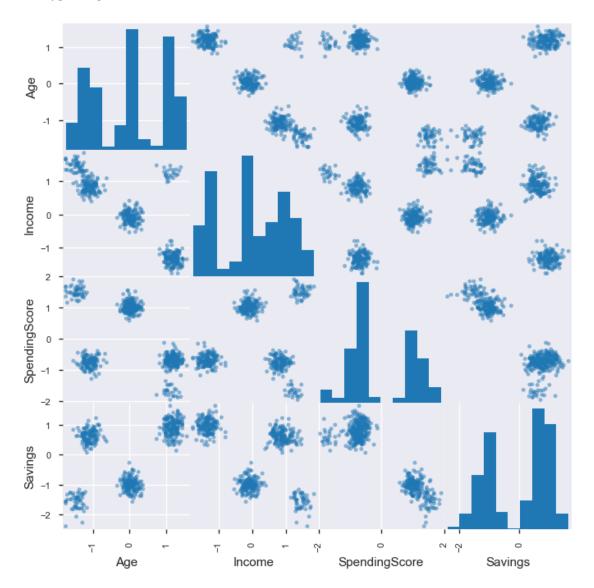




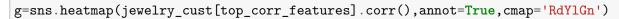


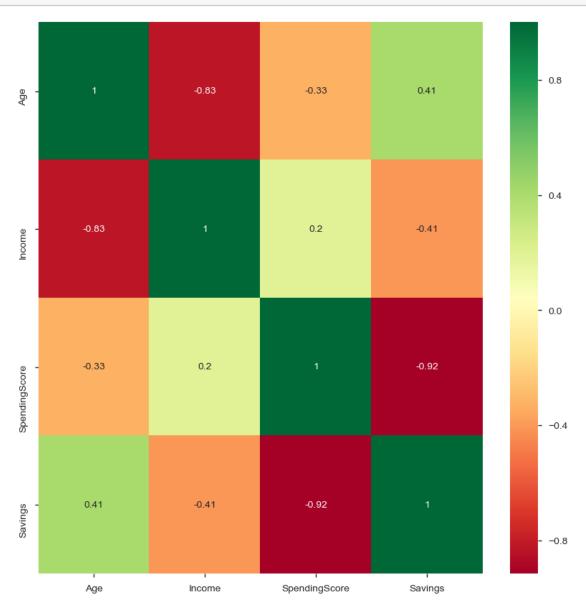


```
[15]: #check scatter matrix
attributes = list(jewelry_cust_standard)
scatter_matrix(jewelry_cust_standard[attributes], figsize=(8,8))
```



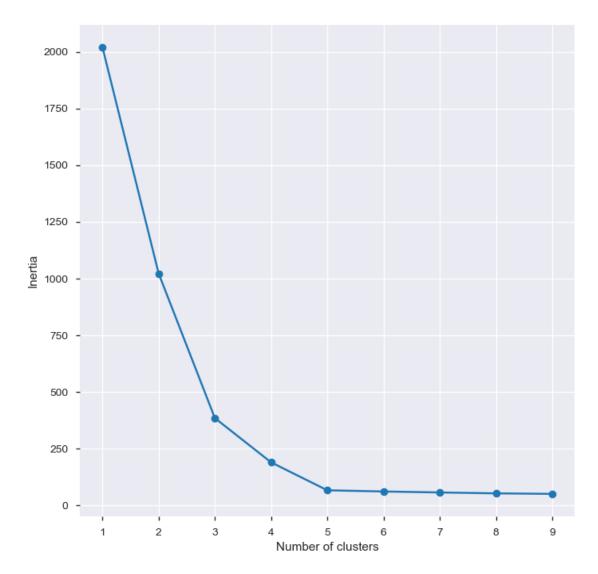
```
[16]: #show different view of correlation
    corrmat = jewelry_cust.corr()
    top_corr_features = corrmat.index
    plt.figure(figsize=(10,10))
```





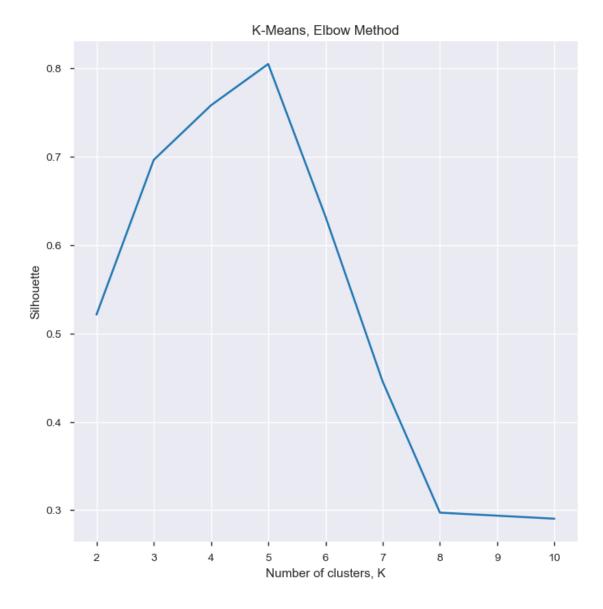
```
frame = pd.DataFrame({'Cluster':range(1,10), 'SSE':inertia_arr})
plt.figure(figsize=(8,8))
plt.grid(True);
plt.plot(frame['Cluster'], frame['SSE'], marker='o')
plt.xlabel('Number of clusters')
plt.ylabel('Inertia')
```

## [17]: Text(0, 0.5, 'Inertia')



```
[18]: #plot different elbow graph to determine optimal value for K
inertias = {}
silhouettes = {}
for k in range(2, 11):
```

[18]: Text(0, 0.5, 'Silhouette')



```
[19]: #plot more elbow graphs to determine optimal value for K

model = KMeans(init='k-means++', n_init=10, max_iter=1000, random_state=42)

KElbowVisualizer(model, k=(2,11), metric='silhouette', timings=False).

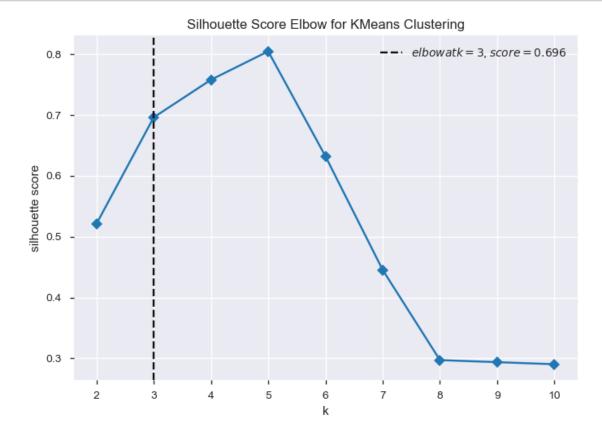
→fit(jewelry_cust_standard).poof()

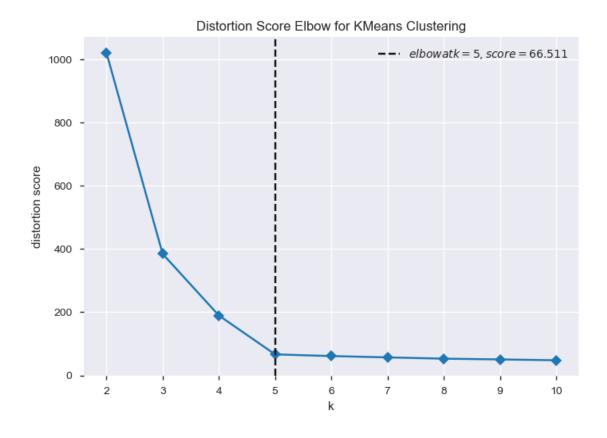
KElbowVisualizer(model, k=(2,11), metric='distortion', timings=False).

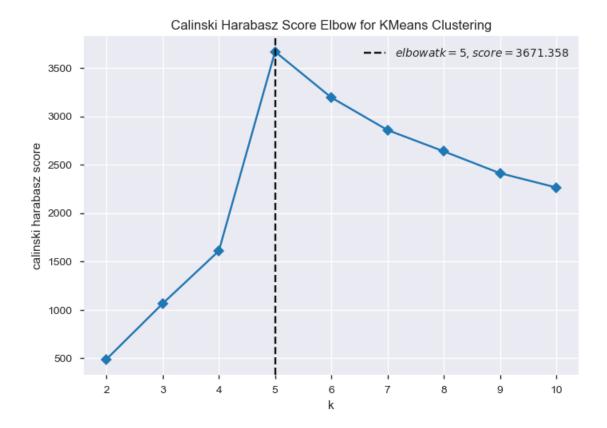
→fit(jewelry_cust_standard).poof()

KElbowVisualizer(model, k=(2,11), metric='calinski_harabasz', timings=False).

→fit(jewelry_cust_standard).poof();
```







```
[20]: #assign to another object to preserve orig dataframe kmeans_arr = jewelry_cust_standard
```

```
[21]: #iterate through different K values (2 to 9) to find optimal value (visual aid_
      \rightarrow as well)
      #display the centers/inertia/silhouette score/mapping of each instance tou
      →cluster/silhouette graph for each cluster iteration,
      for cluster_ctr in range(2,10):
          kmeans = KMeans(n_clusters=cluster_ctr,n_init=10,random_state=42)
          cluster = kmeans.fit(kmeans_arr)
          print("Cluster count:", cluster_ctr)
          print ("Centers")
          print(kmeans.cluster_centers_)
          print("Inertia: {0}".format(str(kmeans.inertia_)))
          #print(kmeans.inertia_)
          print("Silhouette score: {0}".
       →format(str(silhouette_score(jewelry_cust_standard, kmeans.labels_))))
          print("Cluster Assignments:")
          print(kmeans.labels_)
          visualizer = SilhouetteVisualizer(kmeans)
          visualizer.fit(jewelry_cust_standard)
```

## visualizer.poof() print("")

Cluster count: 2

Centers

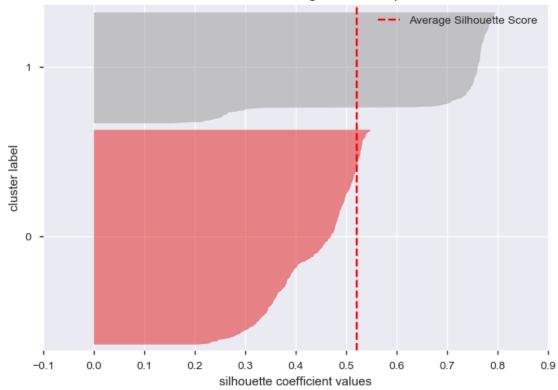
[[-0.61035919 0.49218984 0.42642224 -0.47300618] [1.18168379 -0.95290242 -0.82557329 0.91576197]]

Inertia: 1022.3905044613807

Silhouette score: 0.5212589967674504

Cluster Assignments:





Cluster count: 3

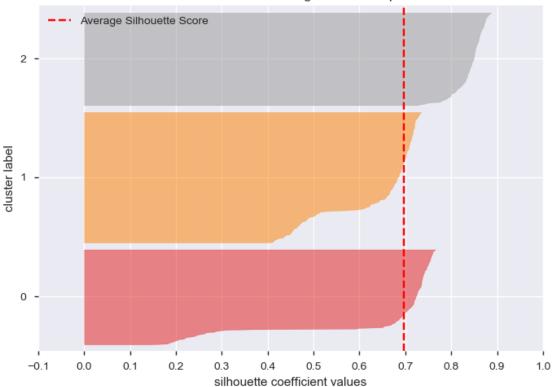
Centers

Inertia: 384.8111859304379

Silhouette score: 0.6963481945884472

Cluster Assignments:





Cluster count: 4

Centers

[[-0.72276928 0.89502598 -0.90658925 0.62188649]

[ 0.03879611 -0.08524639 1.02721559 -1.00569483]

[ 1.19238486 -1.32510593 -0.67963841 0.97016358]

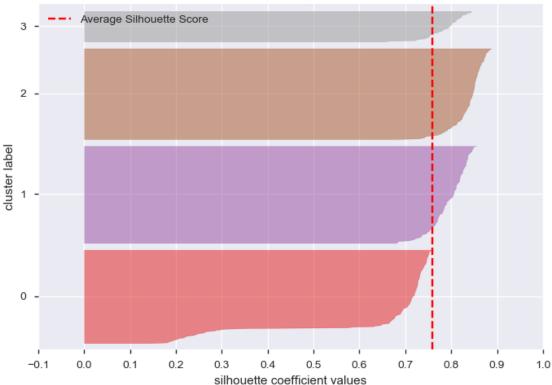
[-1.44466803 1.46050665 1.51057952 -1.57249636]]

Inertia: 189.70178796659562

Silhouette score: 0.7581191889903789

Cluster Assignments:





Cluster count: 5

Centers

[[-1.08815238 0.82744102 -0.75240648 0.6270464 ]

[ 0.03879611 -0.08524639 1.02721559 -1.00569483]

[ 1.19238486 -1.32510593 -0.67963841 0.97016358]

[-1.44466803 1.46050665 1.51057952 -1.57249636]

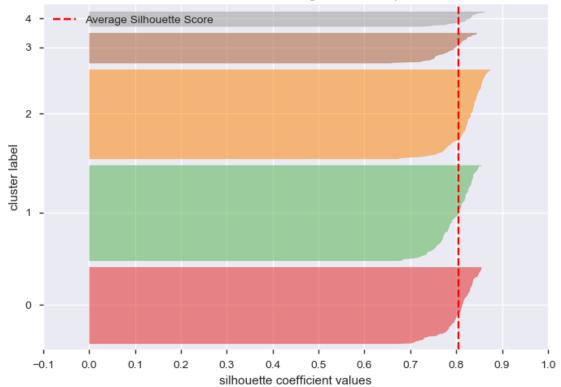
Inertia: 66.5111137485908

Silhouette score: 0.8048976287755765

Cluster Assignments:

 $\begin{bmatrix} 1 & 1 & 1 & 1 & 2 & 3 & 1 & 2 & 2 & 2 & 4 & 0 & 0 & 0 & 1 & 4 & 1 & 2 & 2 & 4 & 0 & 4 & 1 & 2 & 4 & 3 & 3 & 1 & 2 & 1 & 1 & 1 & 2 & 1 & 0 & 1 & 2 \\ 1 & 0 & 0 & 1 & 2 & 3 & 1 & 1 & 3 & 4 & 3 & 0 & 1 & 2 & 0 & 3 & 2 & 1 & 2 & 0 & 2 & 2 & 2 & 2 & 2 & 2 & 1 & 1 & 1 & 2 & 3 & 3 & 1 & 1 & 0 & 2 & 2 \\ 0 & 1 & 0 & 1 & 1 & 3 & 1 & 4 & 1 & 2 & 2 & 0 & 0 & 1 & 1 & 1 & 1 & 1 & 3 & 2 & 1 & 3 & 0 & 1 & 1 & 0 & 0 & 3 & 0 & 3 & 0 & 2 & 2 & 2 & 0 & 0 & 1 & 2 \\ 0 & 1 & 0 & 0 & 0 & 1 & 0 & 3 & 2 & 0 & 2 & 2 & 2 & 0 & 4 & 1 & 2 & 1 & 1 & 0 & 1 & 0 & 1 & 3 & 2 & 4 & 3 & 1 & 0 & 2 & 2 & 1 & 1 & 3 & 1 & 3 & 1 & 4 \\ 1 & 2 & 1 & 0 & 2 & 1 & 2 & 4 & 0 & 1 & 2 & 1 & 0 & 2 & 2 & 0 & 2 & 1 & 0 & 1 & 2 & 1 & 1 & 2 & 2 & 2 & 1 & 1 & 0 & 3 & 3 \\ 2 & 0 & 1 & 1 & 1 & 0 & 2 & 1 & 1 & 1 & 2 & 1 & 1 & 0 & 1 & 0 & 0 & 3 & 1 & 1 & 1 & 4 & 1 & 0 & 2 & 3 & 3 & 3 & 2 & 1 & 0 & 2 & 2 & 0 & 0 & 1 \\ \end{array}$ 





Cluster count: 6

#### Centers

 $\begin{bmatrix} \begin{bmatrix} 0.03879611 & -0.08524639 & 1.02721559 & -1.00569483 \end{bmatrix}$ 

[ 1.15767578 -1.28820856 -0.70159946 0.7628309 ]

[-1.08815238 0.82744102 -0.75240648 0.6270464 ]

[-1.44466803 1.46050665 1.51057952 -1.57249636]

[ 1.21989815 -1.35435385 -0.66223026 1.13451265]]

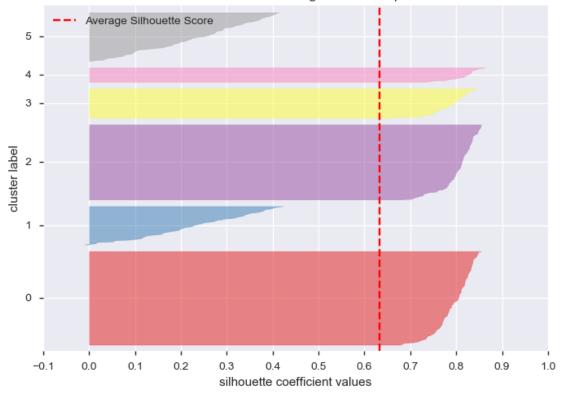
Inertia: 61.14688293497977

Silhouette score: 0.6323567916608213

Cluster Assignments:

 $\begin{bmatrix} 0 & 0 & 0 & 0 & 5 & 3 & 0 & 5 & 1 & 5 & 4 & 2 & 2 & 2 & 0 & 4 & 0 & 1 & 5 & 4 & 2 & 4 & 0 & 1 & 4 & 3 & 3 & 0 & 5 & 0 & 0 & 0 & 5 & 0 & 2 & 0 & 5 \\ 0 & 2 & 2 & 0 & 5 & 3 & 0 & 0 & 3 & 4 & 3 & 2 & 0 & 5 & 2 & 3 & 1 & 0 & 5 & 2 & 5 & 1 & 1 & 1 & 5 & 5 & 0 & 0 & 0 & 5 & 3 & 3 & 0 & 0 & 2 & 1 & 5 \\ \end{array}$ 





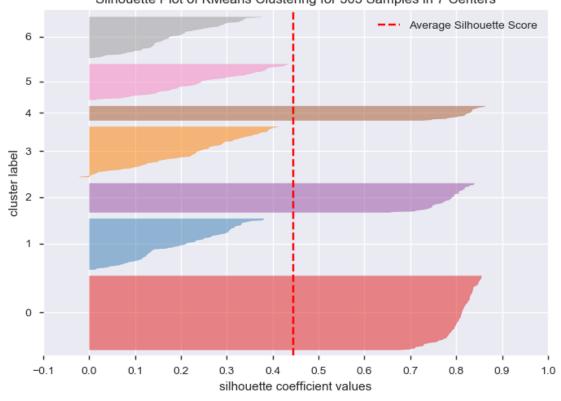
[-0.01326092 -0.00575063 1.10683932 -0.8725227 ]]

Inertia: 56.95698845685121

Silhouette score: 0.44545525411665643

Cluster Assignments:

Silhouette Plot of KMeans Clustering for 505 Samples in 7 Centers



Cluster count: 8

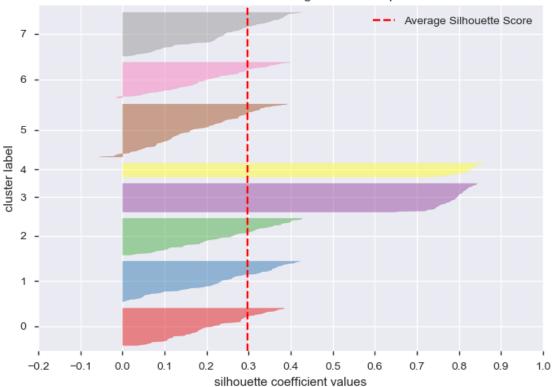
Centers

Inertia: 52.886292892241144

Silhouette score: 0.2971767053193914

#### Cluster Assignments:





Cluster count: 9

#### Centers

[[ 1.20915744 -1.37572663 -0.74282553 1.20588661]

[-0.01326092 -0.00575063 1.10683932 -0.8725227 ]

[-1.08978267 0.77969262 -0.76503963 0.79184312]

[-1.44466803 1.46050665 1.51057952 -1.57249636]

[ 1.19588831 -1.3915265 -0.75094689 0.74802388]

[-1.08641519 0.87832046 -0.73894492 0.45144334]

[ 1.1708146 -1.20059395 -0.53655798 0.95571323]]

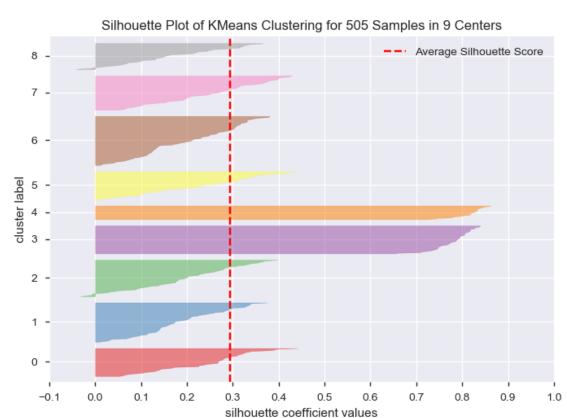
Inertia: 50.56979113010807

Silhouette score: 0.29377143436223707

#### Cluster Assignments:

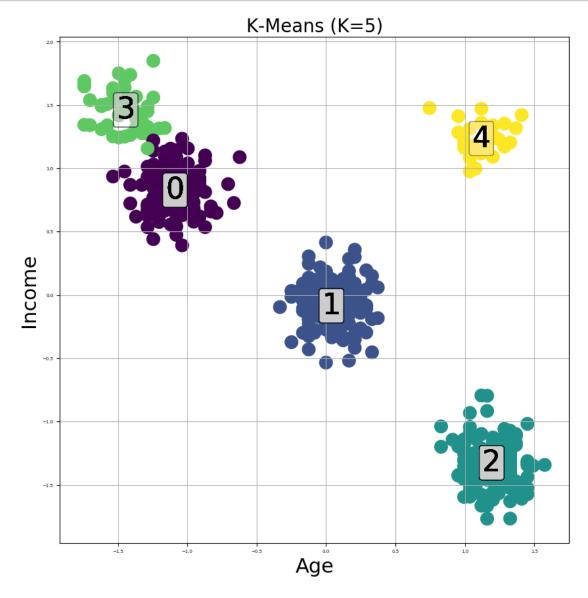
[1 6 1 1 0 3 1 8 5 0 4 2 7 7 1 4 1 8 8 4 7 4 6 5 4 3 3 1 8 1 6 6 0 1 2 6 8 1 2 7 1 0 3 6 1 3 4 3 2 1 0 2 3 5 6 0 2 0 5 5 5 0 0 6 6 6 0 3 3 1 1 7 8 0 7 1 2 6 1 3 1 4 1 8 8 2 7 6 1 1 1 6 3 8 6 3 2 6 6 2 2 3 2 3 2 8 5 7 7 1 8 2 6 2 7 7 6 7 3 0 2 0 8 8 2 4 1 0 6 6 2 1 7 6 3 0 4 3 6 2 8 6 1 3 1 3 6 4 6 5 6 7 8 6 5 4 7 6 0 1 2 8 6 7 8 2 8 6 2 6 0 1 7 1 8 1 6 0 8 0 6 1 7 3 3 5 2 6 1 6 2 0 6 1 1 8 3 7 5 5 0 2 1 2 1 2 1 0 3 6 0 0 8 5 1 5 7 3 7 8 1 6

2 8 7 3 7 6 1 8 6 6 8 6 6 6 2 6 7 2 3 6 6 6 4 6 2 0 3 3 3 5 6 7 0 8 7 7 6 6 4 6 6 6 0 1 5 7 3 6 7 5 1 5 0 7 1 0 5 6 6 8 2 7 4 7 5 0 7 4 8 8 3 6 7 2 1 2 0 5 2 1 7 5 1 2 3 6 5 2 2 5 4 4 1 0 7 6 6 8 7 5 2 8 7 5 0 2 5 7 6 7 1 6 2 7 5 0 3 3 7 8 3 0 4 6 6 6 0 0 7 7 4 2 4 6 7 3 5 1 0 3 1 5 5 1 0 2 6 4 7 2 1 4 8 5 0 8 5 2 7 5 1 2 1 4 8 5 6 8 0 6 5 8 2 5 1 2 3 7 1 8 7 1 6 1 5 2 3 7 6 2 1 6 3 2 4 3 7 2 5 1 0 2 5 7 6 6 0 4 2 8 2 1 6 7 6 5 1 2 1 8 1 8 3 2 2 3 7 2 8 5 6 3 1 7 7 4 3 7 3 0 2 7 6 2 0 0 3 6 7 6 1 2 6 6 6 5 7 7 6 1 1 5 2 5 8 5 0 3 5 5 8 1 6 8 0 6 3 5 2 3 2 0 8 0 5]

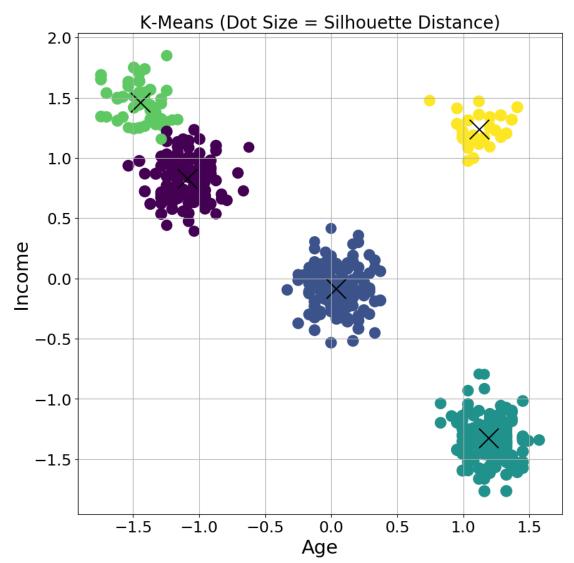


# K=5 resulted as the optimal value, display clusters & centroids, centers, feature-cluster mapping

```
[23]: kmeans.labels_
[23]: array([1, 1, 1, 1, 2, 3, 1, 2, 2, 2, 4, 0, 0, 0, 1, 4, 1, 2, 2, 4, 0, 4,
             1, 2, 4, 3, 3, 1, 2, 1, 1, 1, 2, 1, 0, 1, 2, 1, 0, 0, 1, 2, 3, 1,
             1, 3, 4, 3, 0, 1, 2, 0, 3, 2, 1, 2, 0, 2, 2, 2, 2, 2, 2, 1, 1, 1,
             2, 3, 3, 1, 1, 0, 2, 2, 0, 1, 0, 1, 1, 3, 1, 4, 1, 2, 2, 0, 0, 1,
             1, 1, 1, 1, 3, 2, 1, 3, 0, 1, 1, 0, 0, 3, 0, 3, 0, 2, 2, 0, 0, 1,
             2, 0, 1, 0, 0, 0, 1, 0, 3, 2, 0, 2, 2, 2, 0, 4, 1, 2, 1, 1, 0, 1,
             0, 1, 3, 2, 4, 3, 1, 0, 2, 1, 1, 3, 1, 3, 1, 4, 1, 2, 1, 0, 2, 1,
             2, 4, 0, 1, 2, 1, 0, 2, 1, 0, 2, 0, 2, 1, 0, 1, 2, 1, 0, 1, 2, 1,
             1, 2, 2, 2, 1, 1, 0, 3, 3, 2, 0, 1, 1, 1, 0, 2, 1, 1, 1, 2, 3, 0,
             2, 2, 2, 0, 1, 0, 1, 0, 1, 2, 3, 1, 2, 2, 2, 2, 1, 2, 0, 3, 0, 2,
             1, 1, 0, 2, 0, 3, 0, 1, 1, 2, 1, 1, 2, 1, 1, 1, 0, 1, 0, 0, 3, 1,
             1, 1, 4, 1, 0, 2, 3, 3, 3, 2, 1, 0, 2, 2, 0, 0, 1, 1, 4, 1, 1, 2,
             1, 2, 0, 3, 1, 0, 2, 1, 2, 2, 0, 1, 2, 2, 1, 1, 2, 0, 0, 4, 0, 2,
             2, 0, 4, 2, 2, 3, 1, 0, 0, 1, 0, 2, 2, 0, 1, 0, 2, 1, 0, 3, 1, 2,
             0, 0, 2, 4, 4, 1, 2, 0, 1, 1, 2, 0, 2, 0, 2, 0, 2, 2, 0, 2, 0, 1,
             0, 1, 1, 0, 0, 2, 2, 3, 3, 0, 2, 3, 2, 4, 1, 1, 1, 2, 2, 0, 0, 4,
             0, 4, 1, 0, 3, 2, 1, 2, 3, 1, 2, 2, 1, 2, 0, 1, 4, 0, 0, 1, 2, 2,
             2, 2, 2, 0, 0, 2, 1, 0, 1, 4, 2, 2, 1, 2, 2, 1, 2, 2, 0, 2, 1, 0,
             3, 0, 1, 2, 0, 1, 1, 1, 2, 0, 3, 0, 1, 0, 1, 1, 3, 0, 4, 3, 0, 0,
             2, 1, 2, 0, 2, 0, 1, 1, 2, 4, 0, 2, 0, 1, 1, 0, 1, 2, 1, 0, 1, 2,
             1, 2, 3, 0, 0, 3, 0, 0, 2, 2, 1, 3, 1, 0, 0, 4, 3, 0, 3, 2, 0, 0,
             1, 0, 2, 2, 3, 1, 0, 1, 1, 0, 1, 1, 1, 2, 0, 0, 1, 1, 1, 2, 0, 2,
             2, 2, 2, 3, 2, 2, 2, 1, 1, 2, 2, 1, 3, 2, 0, 3, 0, 2, 2, 2, 2])
[24]: kmeans.cluster_centers_
[24]: array([[-1.08815238, 0.82744102, -0.75240648, 0.6270464],
             [0.03879611, -0.08524639, 1.02721559, -1.00569483],
             [1.19238486, -1.32510593, -0.67963841, 0.97016358],
             [-1.44466803, 1.46050665, 1.51057952, -1.57249636],
             [ 1.11876151, 1.23565419, -1.68367042, 0.59588052]])
[25]: plt.style.use('default');
      plt.figure(figsize=(10, 10));
     plt.grid(True);
      sc = plt.scatter(kmeans_arr.iloc[:, 0], kmeans_arr.iloc[:, 1], s=200, c=kmeans.
      →labels_);
      plt.title("K-Means (K=5)", fontsize=20);
      plt.xlabel('Age', fontsize=22);
      plt.ylabel('Income', fontsize=22);
      plt.xticks(fontsize=5);
      plt.yticks(fontsize=5);
```

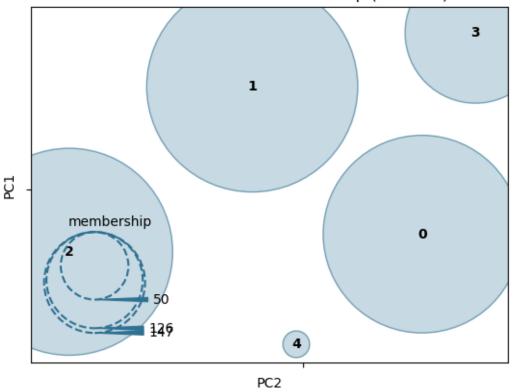


```
[26]: plt.style.use('default');
sample_silhouette_values = silhouette_samples(kmeans_arr, kmeans.labels_)
sizes = 200*sample_silhouette_values
```



```
[27]: visualizer = InterclusterDistance(kmeans)
    visualizer.fit(kmeans_arr)
    visualizer.poof()
```

### KMeans Intercluster Distance Map (via MDS)

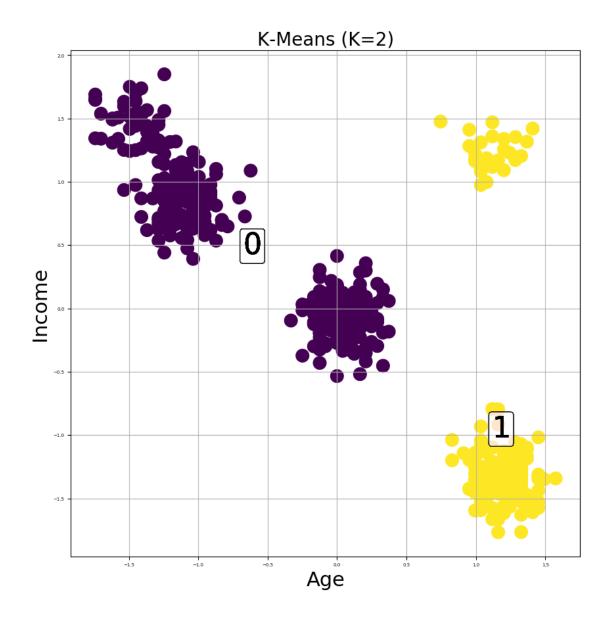


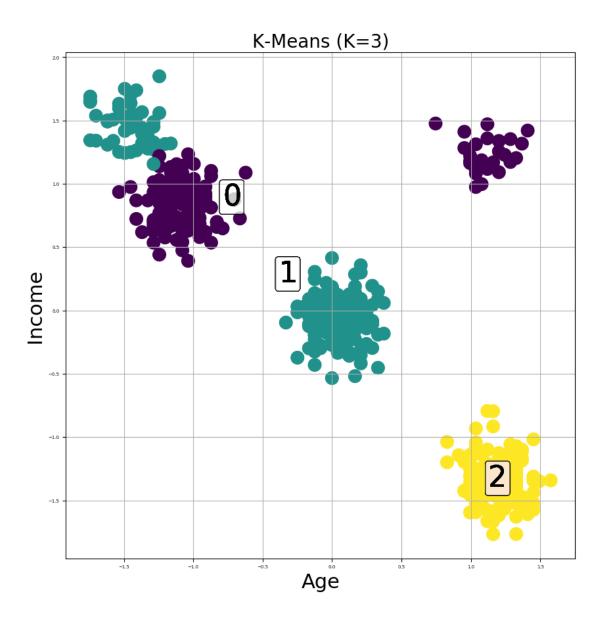
[27]: <matplotlib.axes.\_subplots.AxesSubplot at 0x27b6d967e48>

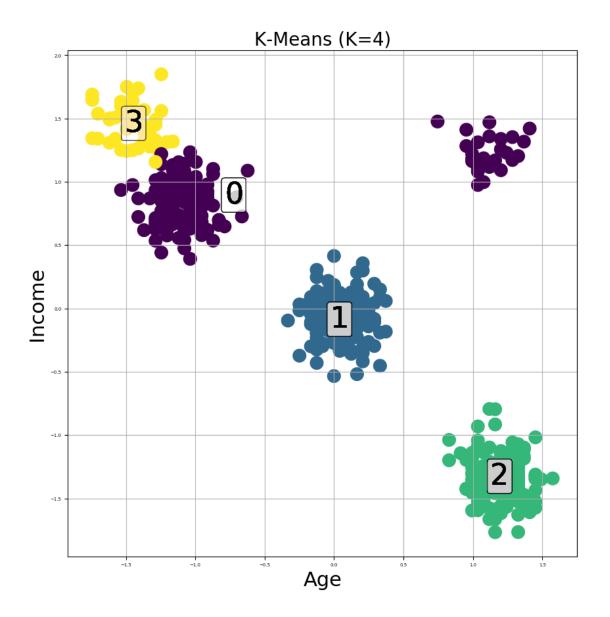
### Visually check all clusters one at a time (cluster count from 2 to 9)

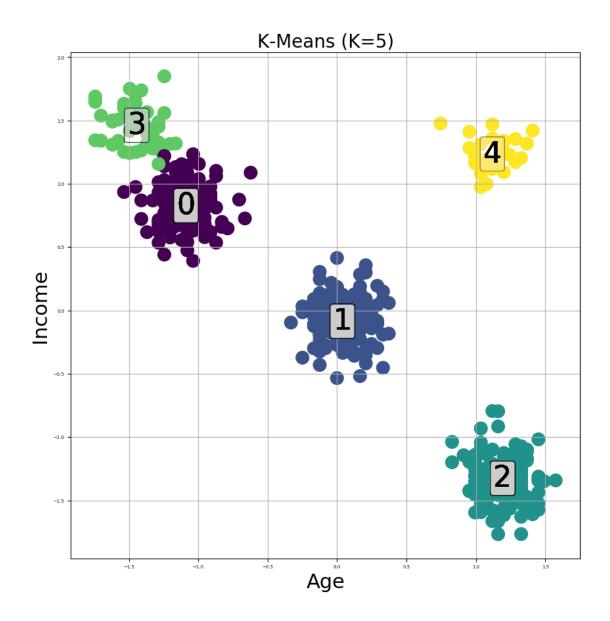
```
plt.figure(figsize=(10, 10));
   plt.grid(True);
   sc = plt.scatter(kmeans_arr.iloc[:, 0], kmeans_arr.iloc[:, 1], s=200,__
\hookrightarrow c=kmeans.labels_);
   plt.title("K-Means (K=" + str(cluster_count) + ")", fontsize=20);
   plt.xlabel('Age', fontsize=22);
   plt.ylabel('Income', fontsize=22);
   plt.xticks(fontsize=5);
   plt.yticks(fontsize=5);
   for label in kmeans.labels_:
       plt.text(x=kmeans.cluster_centers_[label, 0], y=kmeans.

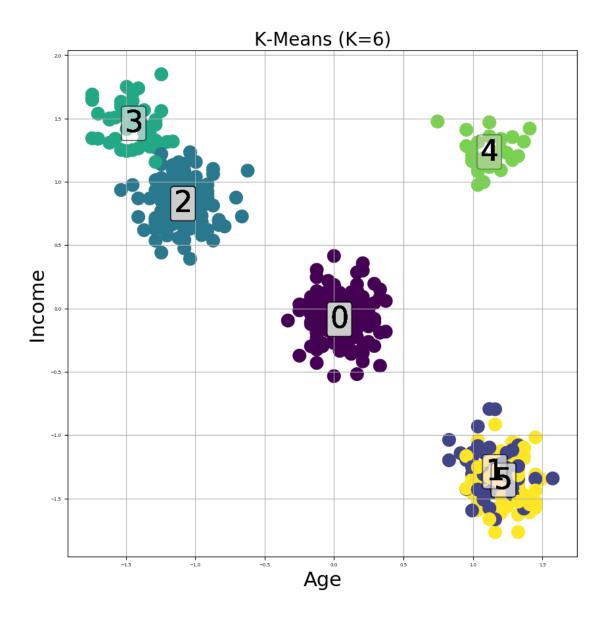
cluster_centers_[label, 1], s=label, fontsize=32,
            horizontalalignment='center', verticalalignment='center', u
bbox=dict(facecolor='white', edgecolor='black',__
⇒boxstyle='round,pad=0.1', alpha=0.02));
```

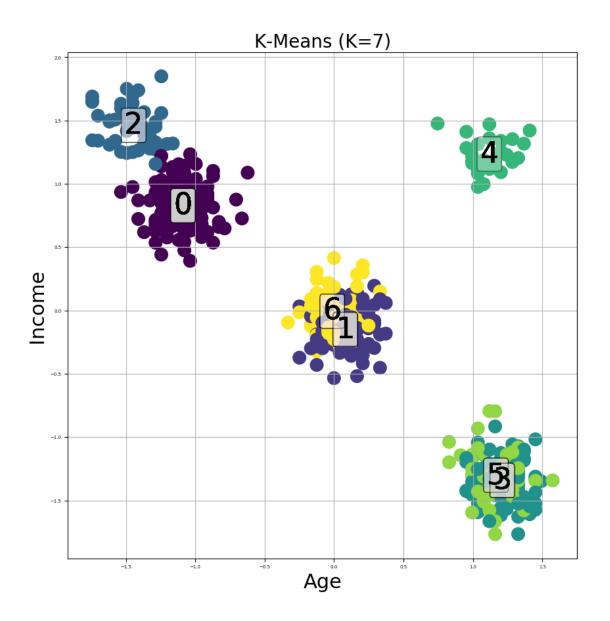


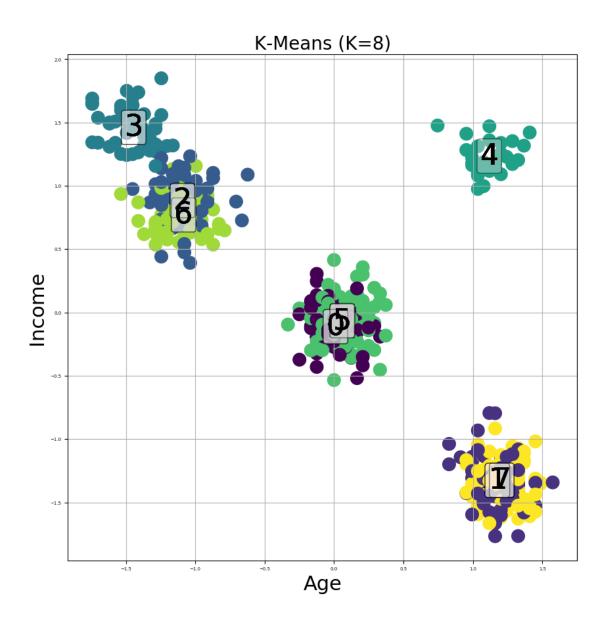












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