Clustering

March 16, 2022

1 Unsupervised learning

1.1 Dataset Introduction - The dataset used here Mall Customer Segmentation Data from kaggle. This dataset is used for an example of clustering

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Features

CustomerID - ID of the customer

Gender - Gender of the customer

Age - Age of the customer

Annual Income (k$) -Annual Income of the customer

Spending Score (1-100) - Spending Score of the customer

Problem Statement - Segemnt the customer to understand customers better

[154]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import MinMaxScaler, StandardScaler, RobustScaler

from sklearn.metrics import accuracy_score
from sklearn.metrics import silhouette_score

from sklearn.decomposition import PCA
from sklearn.cluster import KMeans, DBSCAN,␣
↪AgglomerativeClustering,MeanShift,estimate_bandwidth
from scipy.cluster import hierarchy
from sklearn.metrics import silhouette_score
from sklearn.pipeline import Pipeline
from sklearn.model_selection import StratifiedShuffleSplit
```

```
[ ]: data = pd.read_csv('/content/drive/MyDrive/ibm/Projects/unsupervisedLearning/
     ↪Mall_Customers(Unsupervised).csv')
     print(data.columns.tolist())
     print(data.describe())
```

```
['CustomerID', 'Gender', 'Age', 'Annual Income (k$)', 'Spending Score (1-100)']
       CustomerID         Age  Annual Income (k$)  Spending Score (1-100)
count  200.000000  200.000000          200.000000              200.000000
mean   100.500000   38.850000           60.560000               50.200000
std     57.879185   13.969007           26.264721               25.823522
min      1.000000   18.000000           15.000000                1.000000
25%     50.750000   28.750000           41.500000               34.750000
50%    100.500000   36.000000           61.500000               50.000000
75%    150.250000   49.000000           78.000000               73.000000
max    200.000000   70.000000          137.000000               99.000000
```

```
[ ]: display(data.head())
     print(data.shape)
```

```
   CustomerID  Gender  Age  Annual Income (k$)  Spending Score (1-100)
0           1    Male   19                  15                      39
1           2    Male   21                  15                      81
2           3  Female   20                  16                       6
3           4  Female   23                  16                      77
4           5  Female   31                  17                      40
```

```
(200, 5)
```

2 Feature deletion

```
[ ]: columnname = data.columns.to_list()
     observation_length = data.shape[0]
     dummies = []
     for x in columnname:
       if len(data[x].unique()) == observation_length:
         dummies.append(x)
     print(dummies)
```

```
['CustomerID']
```

As customer id is basically unique for every observation we shall drop it

```
[ ]: data1 = data.copy()
     data1.drop(dummies, axis = 1, inplace = True)
     data1.shape
```

[ ]: (200, 4)

3 exploratory data analysis

3.1 Numerical Column analysis

[ ]:
```
numerical_cols = data1.select_dtypes('number').columns.tolist()
print(numerical_cols)
```

```
['Age', 'Annual Income (k$)', 'Spending Score (1-100)']
```

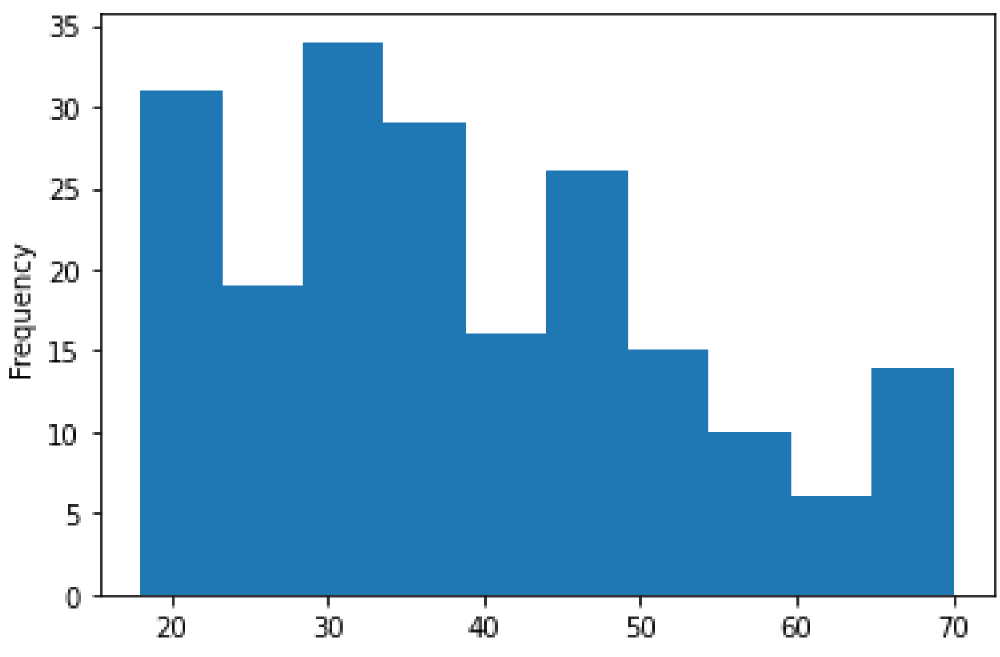
3.1.1 Age

[ ]:
```
data1['Age'].isnull().sum()
```

[ ]: 0

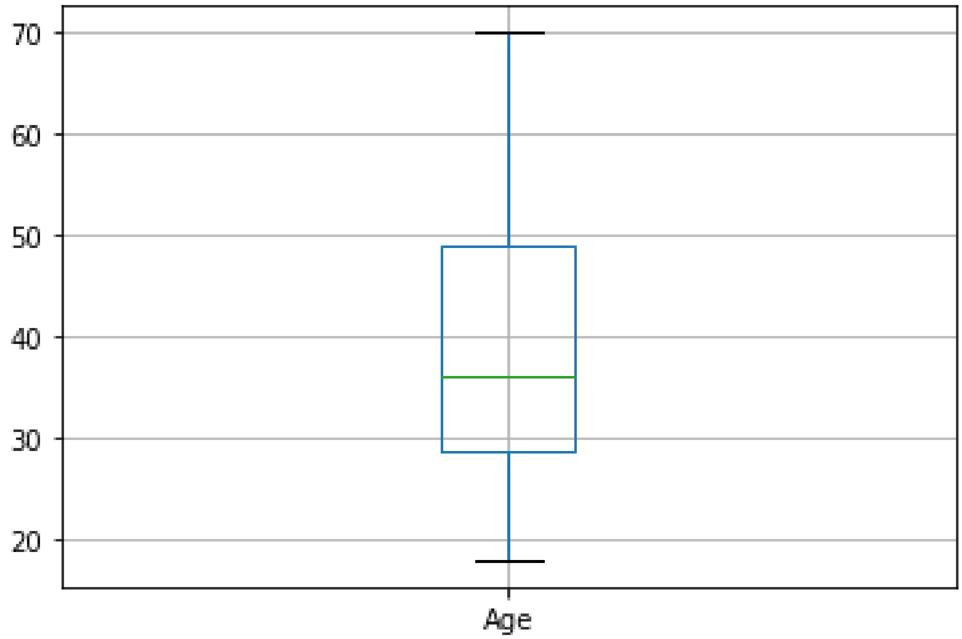
[ ]:
```
data1['Age'].plot(kind = 'hist')
```

[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f6aa81e4fd0>



[ ]:
```
data1.boxplot(column = 'Age')
```

[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f6aa7bfeb90>



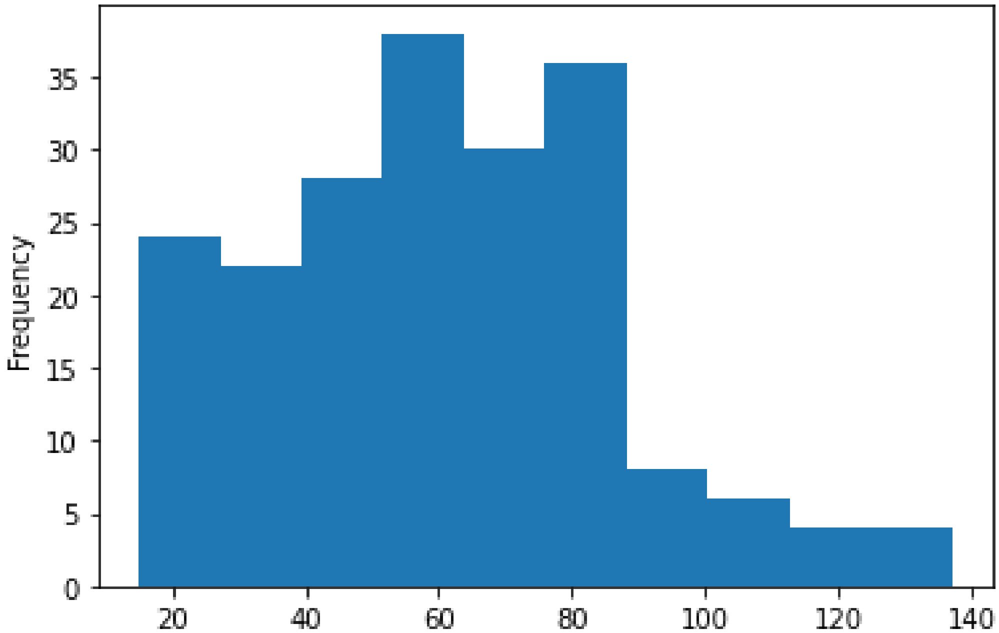
3.1.2 annual Income

[ ]:
```
data1['Annual Income (k$)'].isnull().sum()
```

[ ]: 0

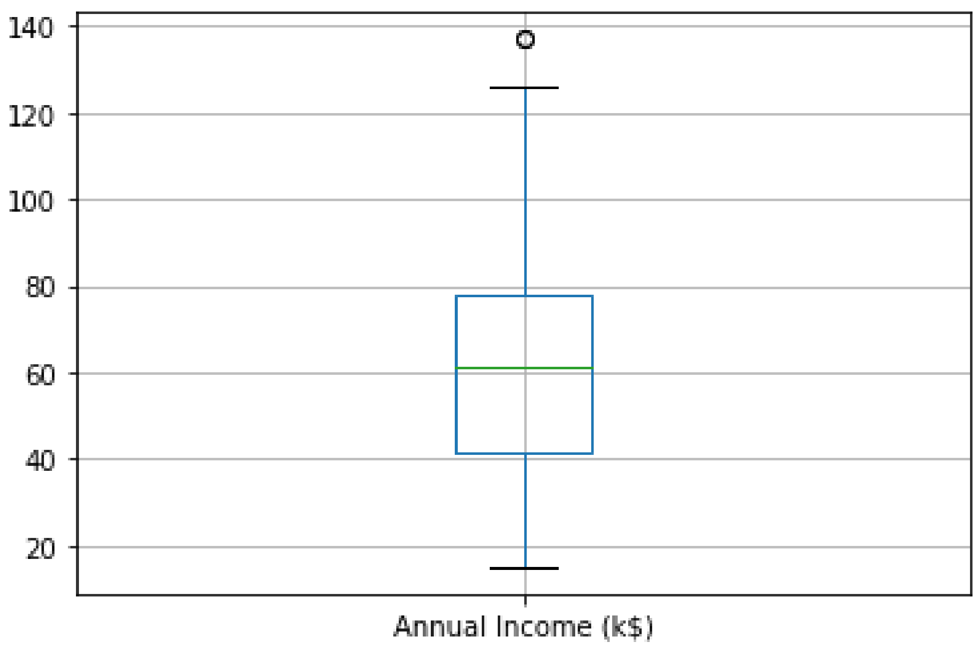
[ ]:
```
data1['Annual Income (k$)'].plot(kind = 'hist')
```

[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f6aa80dacd0>




```
[ ]: data1.boxplot(column = 'Annual Income (k$)')
```

[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f6aa7b33410>



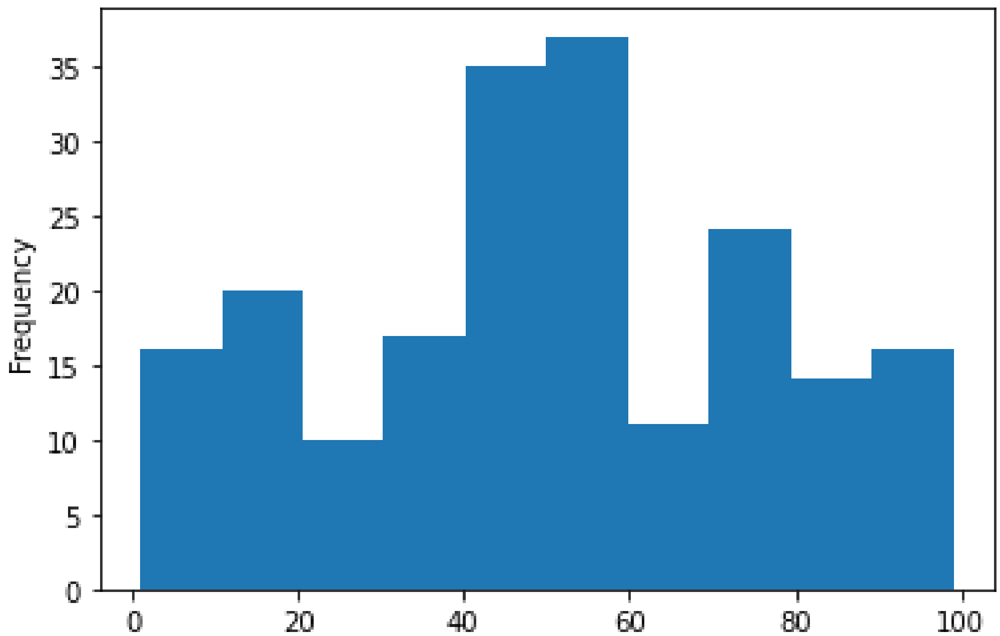
3.1.3 Spending Score (1-100)

[ ]:
```
data1['Spending Score (1-100)'].isnull().sum()
```

[ ]: 0

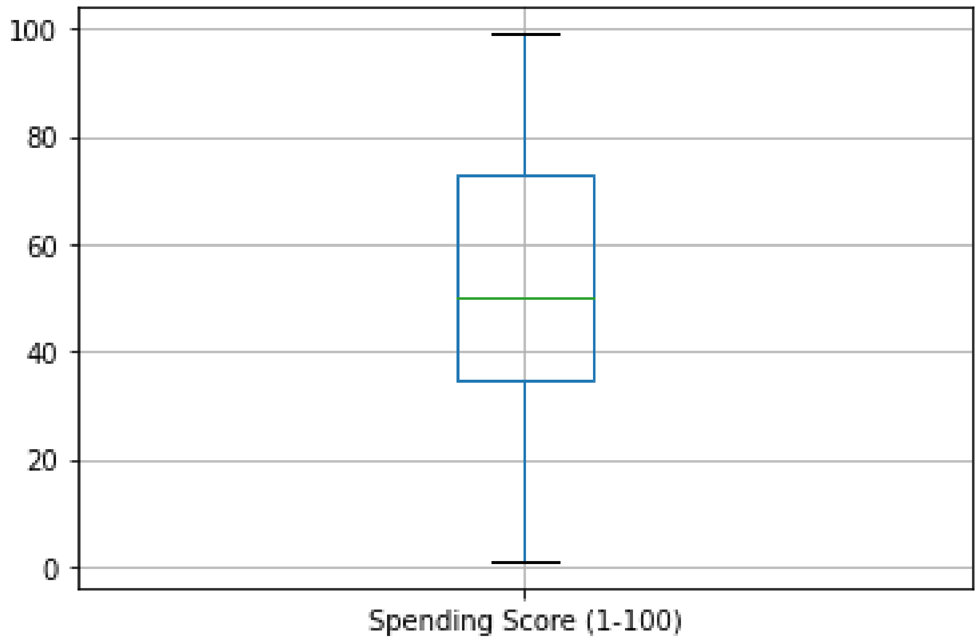
[ ]:
```
data1['Spending Score (1-100)'].plot(kind = 'hist')
```

[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f6aa7b57c10>



[ ]:
```
data1.boxplot(column = 'Spending Score (1-100)')
```

[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f6aa7c1c190>



3.1.4 checking if tranformation is requires

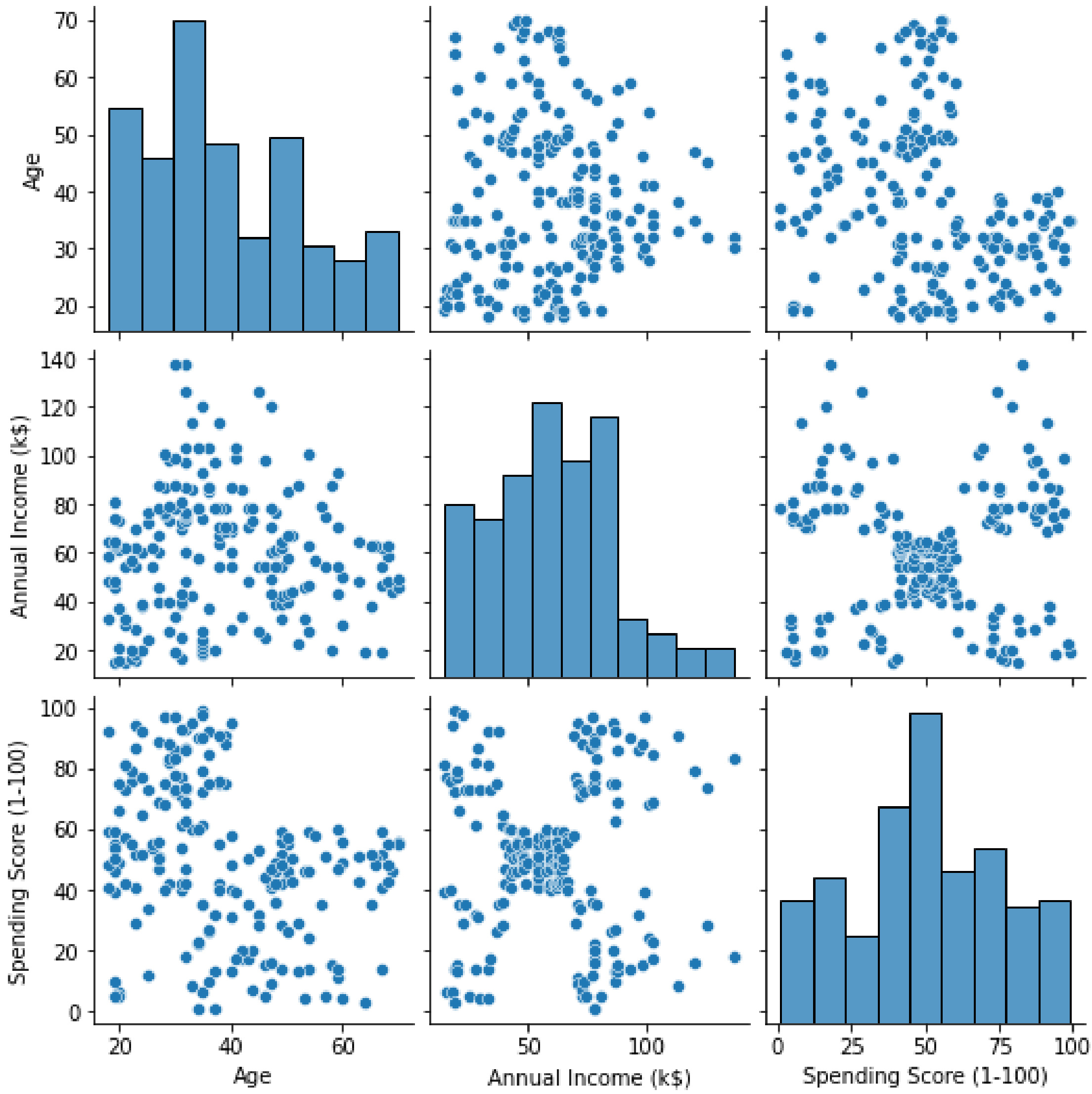
[ ]:
```
log_columns = data1[numerical_cols].skew().sort_values(ascending=False)
log_columns = log_columns.loc[log_columns > 0.75]
log_columns
```

[ ]:
```
Series([], dtype: float64)
```

3.1.5 Pairplot

[ ]:
```
sns.pairplot(data1)
```

[ ]:
```
<seaborn.axisgrid.PairGrid at 0x7f6aa0c0e490>
```



3.2 Categorical column

```
[ ]: categorical_cols = data1.dtypes[data.dtypes == "object"].index
     print(categorical_cols)
```

```
Index(['Gender'], dtype='object')
```

```
[ ]: data1['Gender'].isnull().sum()
```

```
[ ]: 0
```

```
[ ]: data1['Gender'].unique()
```

[ ]: array(['Male', 'Female'], dtype=object)

[ ]:
```
ct = pd.crosstab(index = data1['Gender'], columns = 'count')
ct
```

[ ]:
```
col_0   count
Gender
Female    112
Male       88
```

[ ]:
```
genderavg = dict()
dummydata = data1[data1['Gender'] == 'Female']
genderavg['Female'] = dummydata['Spending Score (1-100)'].mean()
dummydata = data1[data1['Gender'] == 'Male']
genderavg['Male'] = dummydata['Spending Score (1-100)'].mean()
print(pd.DataFrame(genderavg.items()))
```

```
        0          1
0  Female  51.526786
1    Male  48.511364
```

On a average woman spend more than men

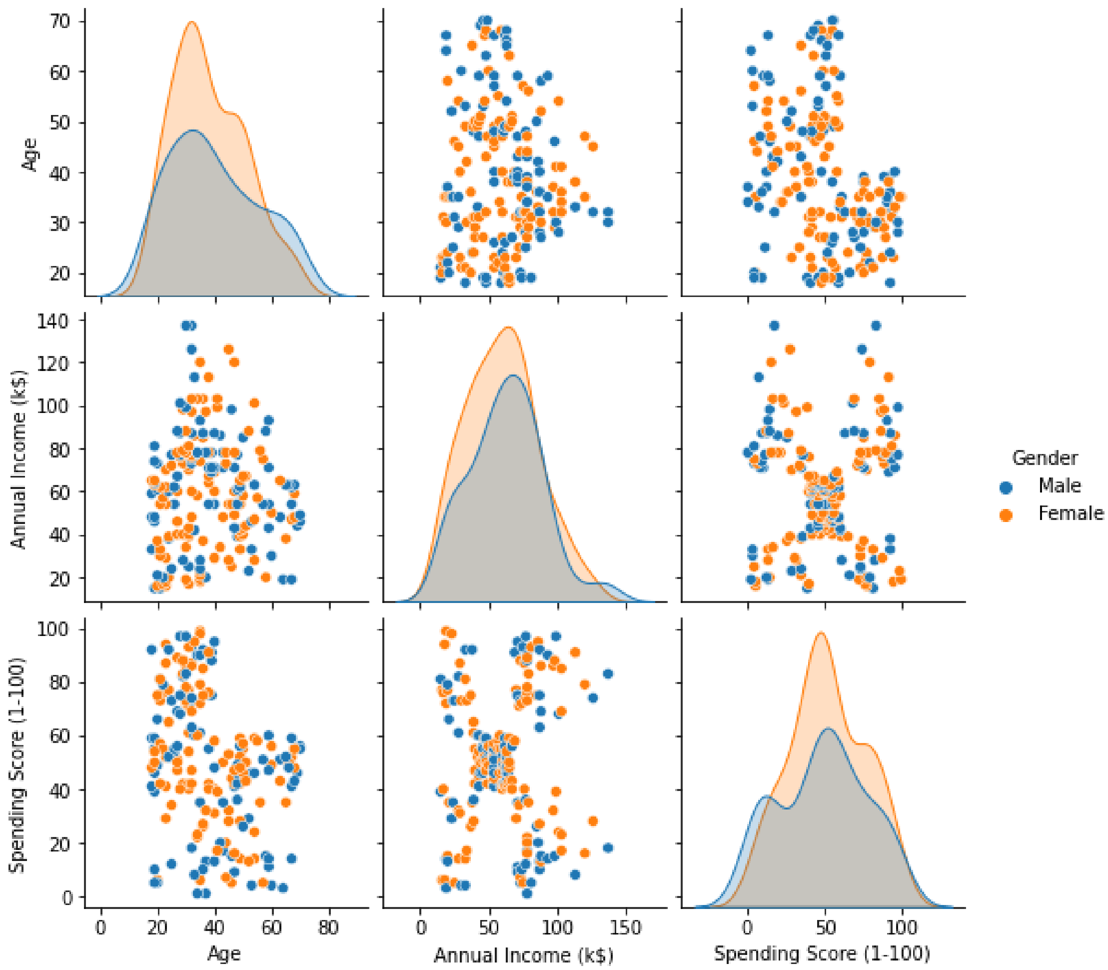
[ ]:
```
genderavg = dict()
dummydata = data1[data1['Gender'] == 'Female']
genderavg['Female'] = dummydata['Annual Income (k$)'].mean()
dummydata = data1[data1['Gender'] == 'Male']
genderavg['Male'] = dummydata['Annual Income (k$)'].mean()
print(pd.DataFrame(genderavg.items()))
```

```
        0          1
0  Female  59.250000
1    Male  62.227273
```

On a average men earn more women

[ ]:
```
sns.pairplot(data1, hue = 'Gender')
```

[ ]: <seaborn.axisgrid.PairGrid at 0x7f6aa302e590>



[ ]:
```
# Do the one hot encoding
data2 = data1.copy()
data2 = pd.get_dummies(data2, columns=['Gender'])
data2.head()
```

[ ]:

	Age	Annual Income (k$)	Spending Score (1-100)	Gender_Female	Gender_Male
0	19	15	39	0	1
1	21	15	81	0	1
2	20	16	6	1	0
3	23	16	77	1	0
4	31	17	40	1	0

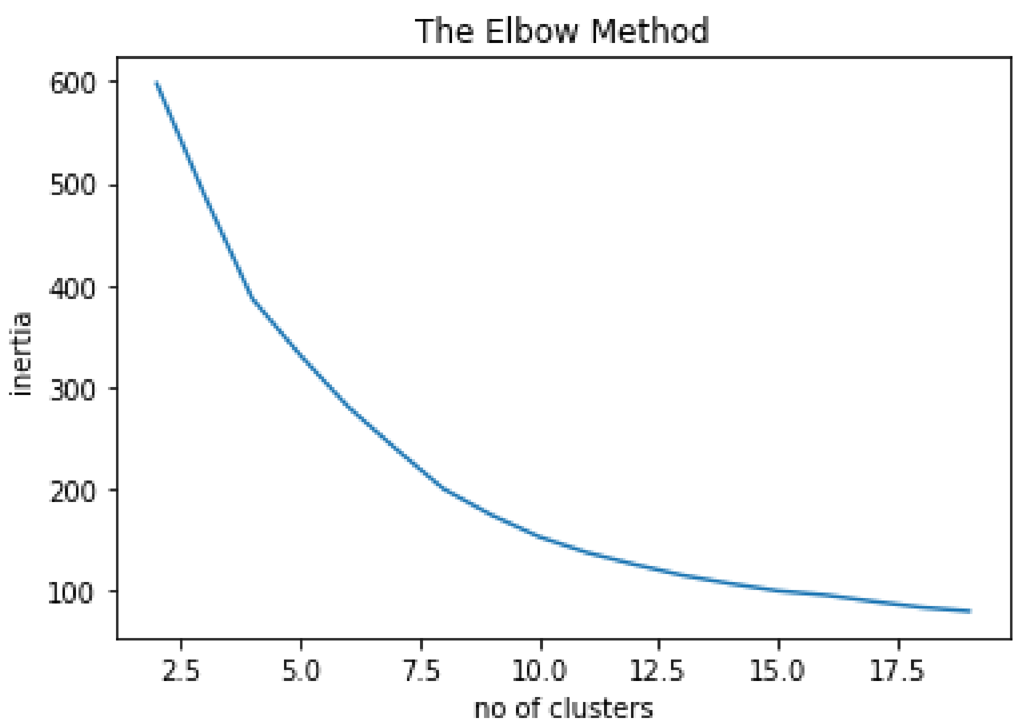
4 SCaling

[116]:
```
sc = StandardScaler()
metrics = dict()
scaled_data = sc.fit_transform(data2)
```

5 K means

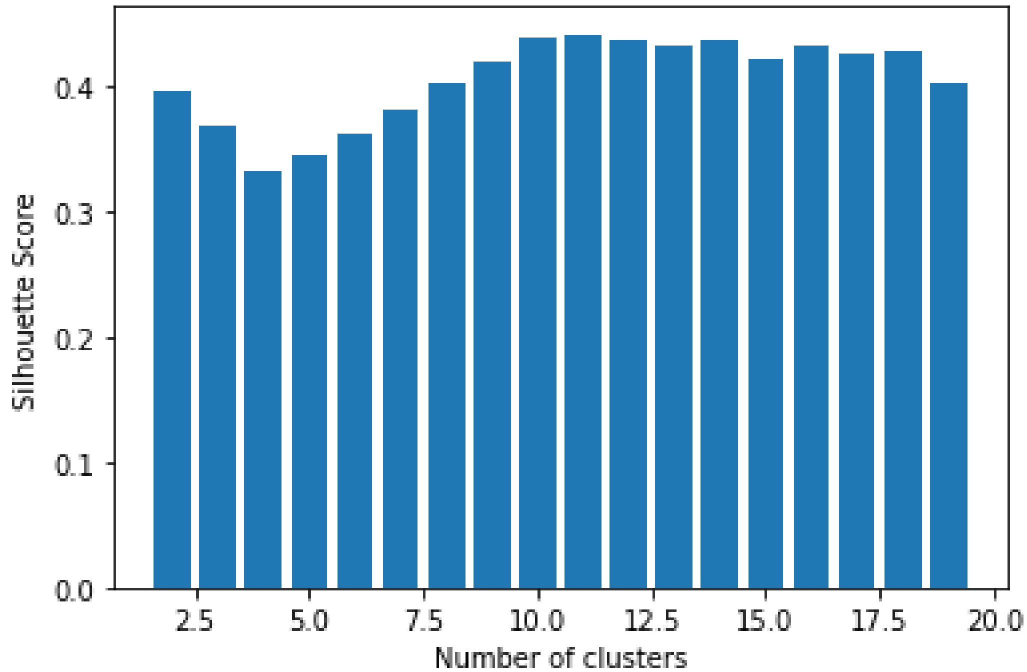
[ ]:
```
scores = []
inertia = []
for i in range(2,20):
    kmeans = KMeans(n_clusters= i, init='k-means++', random_state=0)
    kmeans.fit(scaled_data)
    scores.append(silhouette_score(scaled_data, kmeans.labels_,␣
 ↪metric='euclidean'))
    inertia.append(kmeans.inertia_)
```

[ ]:
```
plt.plot(range(2,20), inertia)
plt.title('The Elbow Method')
plt.xlabel('no of clusters')
plt.ylabel('inertia')
plt.show()
```



[ ]:

```
plt.bar(range(2,20), scores)
plt.xlabel('Number of clusters', fontsize = 10)
plt.ylabel('Silhouette Score', fontsize = 10)
plt.show()
```



[102]:

```
kmeans = KMeans(n_clusters= 11, init='k-means++', random_state=0)
kmeans.fit(scaled_data)
data3 = data2.copy()
data3['kmeans_scaled'] = kmeans.predict(scaled_data)
data3.head()
```

[102]:

```
   Age  Annual Income (k$)  Spending Score (1-100)  Gender_Female  \
0   19                  15                      39              0
1   21                  15                      81              0
2   20                  16                       6              1
3   23                  16                      77              1
4   31                  17                      40              1

   Gender_Male  kmeans_scaled
0            1              3
1            1              3
2            0              8
```

```
3            0              9
4            0              8
```

[165]:
```python
Gender_kmean = pd.crosstab(index=data["Gender"],
                           columns=data3['kmeans_scaled'], margins = True)
Gender_kmean
```

[165]:

kmeans_scaled	0	1	2	3	4	5	6	7	8	9	10	All
Gender												
Female	0	25	0	0	14	26	0	21	13	13	0	112
Male	18	0	20	23	0	0	21	0	0	0	6	88
All	18	25	20	23	14	26	21	21	13	13	6	200

[ ]:
```python
ct = pd.crosstab(index = data3['kmeans_scaled'], columns = 'count')
ct
```

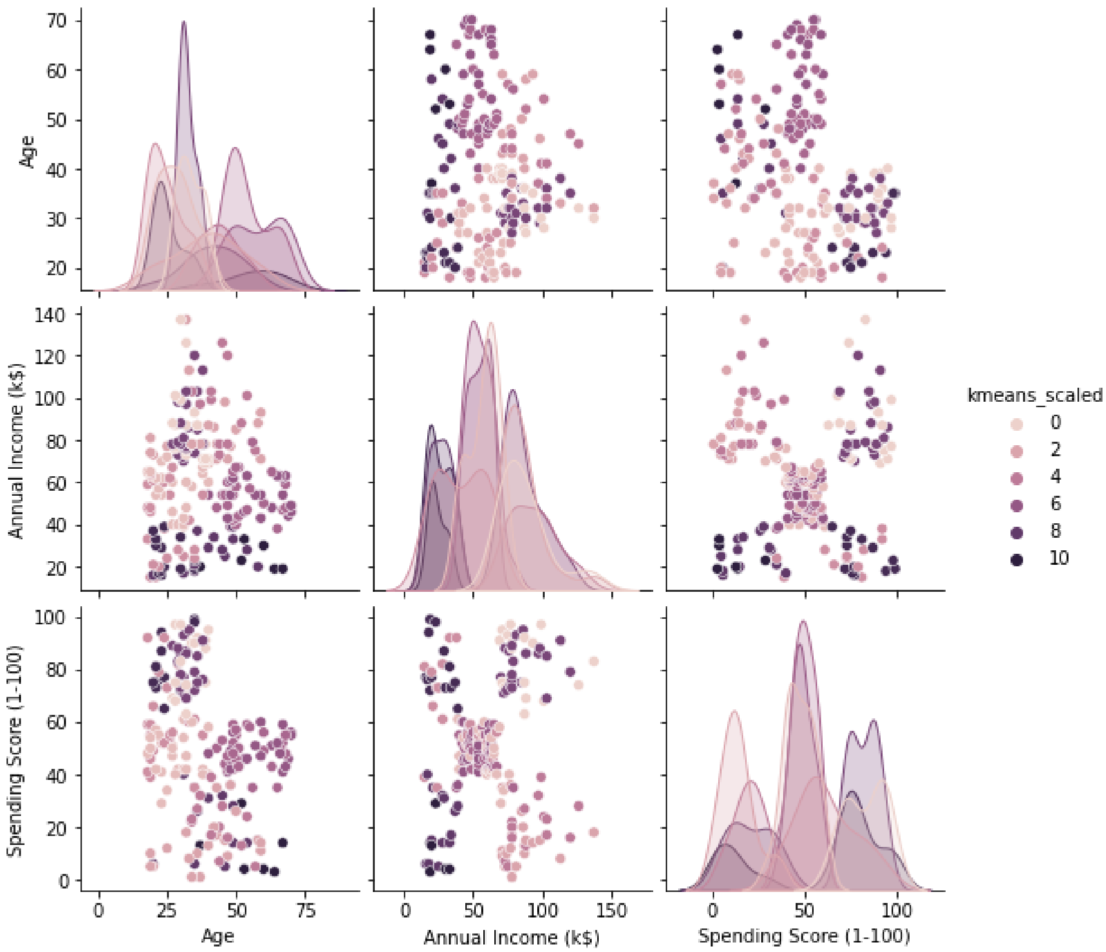
[ ]:

col_0	count
kmeans_scaled	
0	18
1	25
2	20
3	23
4	14
5	26
6	21
7	21
8	13
9	13
10	6

[ ]:
```python
cols = ['Age', 'Annual Income (k$)', 'Spending Score (1-100)','kmeans_scaled']

sns.pairplot(data3[cols], hue = 'kmeans_scaled')
```

[ ]: <seaborn.axisgrid.PairGrid at 0x7f6a9cc02610>




```
[117]: kmeans_clust_scaled = kmeans.predict(scaled_data)

       metrics['kmeans'] = silhouette_score(scaled_data,kmeans_clust_scaled)
       metrics['kmeans']
```

```
[117]: 0.4419137813527599
```

6 Agglomerative Clustering

```
[ ]: scores = dict()
     for linkage in ['ward', 'complete', 'average', 'single']:
         ag = AgglomerativeClustering(n_clusters=11, linkage=linkage,␣
      ↪compute_full_tree=True)
         ag.fit(scaled_data)
```

```
    scores[str('agglom_'+linkage)] = silhouette_score(scaled_data, ag.
↪fit_predict(scaled_data))
```

[ ]:
```
scores
```

[ ]:
```
{'agglom_average': 0.38449330178743374,
 'agglom_complete': 0.4020137460961655,
 'agglom_single': 0.009976340809937402,
 'agglom_ward': 0.4355066737947972}
```

[100]:
```
scores = dict()
for n in range(2,20):
    ag = AgglomerativeClustering(n_clusters=n, linkage='ward',␣
↪compute_full_tree=True)
    ag.fit(scaled_data)
    scores[str('agglom_'+ str(n))] = silhouette_score(scaled_data, ag.
↪fit_predict(scaled_data))
```

[101]:
```
scores
```

[101]:
```
{'agglom_10': 0.43560596392122847,
 'agglom_11': 0.4355066737947972,
 'agglom_12': 0.4300976960875954,
 'agglom_13': 0.42587063067148523,
 'agglom_14': 0.43083305900124713,
 'agglom_15': 0.4388635672710250 5,
 'agglom_16': 0.44344534774949396,
 'agglom_17': 0.4231040453677005,
 'agglom_18': 0.43083120416847664,
 'agglom_19': 0.42667122533364904,
 'agglom_2': 0.39644160577705434,
 'agglom_3': 0.36282121580109944,
 'agglom_4': 0.3201778121643018,
 'agglom_5': 0.33339195354757967,
 'agglom_6': 0.35445606368360066,
 'agglom_7': 0.36050917293397844,
 'agglom_8': 0.392162082518261,
 'agglom_9': 0.4069804703665158}
```

[118]:
```
ag = AgglomerativeClustering(n_clusters=16, linkage='ward',␣
↪compute_full_tree=True)
ag = ag.fit(scaled_data)
data3['agg'] = ag.fit_predict(scaled_data)
ag_score =  silhouette_score(scaled_data, ag.fit_predict(scaled_data))
metrics['AGG'] = ag_score
metrics['AGG']
```

[118]: 0.44344534774949396

[164]:
```
Gender_agg = pd.crosstab(index=data["Gender"],
                         columns=data3['agg'], margins = True)
Gender_agg
```

[164]:

agg	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	All
Gender																	
Female	25	0	21	15	13	0	0	25	13	0	0	0	0	0	0	0	112
Male	0	6	0	0	0	10	12	0	0	12	4	3	13	16	10	2	88
All	25	6	21	15	13	10	12	25	13	12	4	3	13	16	10	2	200

[109]:
```
ct = pd.crosstab(index = data3['agg'], columns = 'count')
ct
```

[109]:

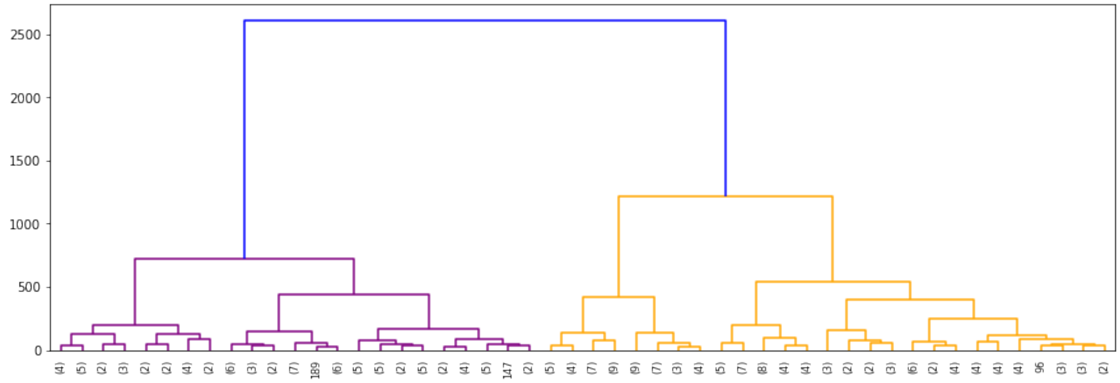
col_0	count
agg	
0	25
1	6
2	21
3	15
4	13
5	10
6	12
7	25
8	13
9	12
10	4
11	3
12	13
13	16
14	10
15	2

[115]:
```
Z = hierarchy.linkage(ag.children_, method='ward')

fig, ax = plt.subplots(figsize=(15,5))


hierarchy.set_link_color_palette(['purple', 'orange'])

den = hierarchy.dendrogram(Z, orientation='top',
                           p=50, truncate_mode='lastp',
                           show_leaf_counts=True, ax=ax,
                           above_threshold_color='blue')
```



7 DBSCAN

[148]:
```python
dbscan = DBSCAN(eps=2, min_samples=20)
dbscan.fit(scaled_data)
data3['dbscan'] = dbscan.fit_predict(scaled_data)
dbscan_score =  silhouette_score(scaled_data, dbscan.fit_predict(scaled_data))
metrics['dbscan'] = dbscan_score
metrics['dbscan']
```

[148]:
```
0.39644160577705434
```

[162]:
```python
Gender_dbscan = pd.crosstab(index=data["Gender"],
                            columns=data3['dbscan'], margins = True)
Gender_dbscan
```

[162]:
```
dbscan   0    1  All
Gender
Female   0  112  112
Male    88    0   88
All     88  112  200
```

[146]:
```python
ct = pd.crosstab(index = data3['dbscan'], columns = 'count')
ct
```

[146]:
```
col_0   count
dbscan
0          88
1         112
```

8 Mean Shift

[158]:
```
bandwidth = estimate_bandwidth(scaled_data,quantile=0.20)
meanshift = MeanShift(bandwidth=bandwidth,bin_seeding=True)
meanshift.fit(scaled_data)

data3['meanshift'] = meanshift.fit_predict(scaled_data)
ms_score =  silhouette_score(scaled_data, meanshift.fit_predict(scaled_data))
metrics['meanshift'] = ms_score
metrics['meanshift']
```

[158]: 0.39644160577705434

[160]:
```
ct = pd.crosstab(index = data3['meanshift'], columns = 'count')
ct
```

[160]:

col_0	count
meanshift	
0	112
1	88

[163]:
```
Gender_meanshift = pd.crosstab(index=data["Gender"],
                           columns=data3['meanshift'], margins = True)
Gender_meanshift
```

[163]:

meanshift	0	1	All
Gender			
Female	112	0	112
Male	0	88	88
All	112	88	200

9 Model selection

[159]:
```
pd.DataFrame(metrics.items())
```

[159]:

	0	1
0	kmeans	0.441914
1	AGG	0.443445
2	dbscan	0.396442
3	meanshift	0.396442

[167]:
```
display(Gender_kmean)
display(Gender_agg)
display(Gender_dbscan)
display(Gender_meanshift)
```

```
kmeans_scaled   0   1   2   3   4   5   6   7   8   9  10  All
Gender
Female          0  25   0   0  14  26   0  21  13  13   0  112
Male           18   0  20  23   0   0  21   0   0   0   6   88
All            18  25  20  23  14  26  21  21  13  13   6  200
```

```
agg      0  1   2   3   4   5   6   7   8   9  10  11  12  13  14  15  All
Gender
Female  25  0  21  15  13   0   0  25  13   0   0   0   0   0   0   0  112
Male     0  6   0   0   0  10  12   0   0  12   4   3  13  16  10   2   88
All     25  6  21  15  13  10  12  25  13  12   4   3  13  16  10   2  200
```

```
dbscan   0    1  All
Gender
Female   0  112  112
Male    88    0   88
All     88  112  200
```

```
meanshift    0   1  All
Gender
Female     112   0  112
Male         0  88   88
All        112  88  200
```

10 Conclusion

Comparing both results we get to know that Ward-link Agglomerative Clustering was better with silhouette_score of 0.443445 Even though DBscan and meanShift were able to cluster the genders perfectly

11 Next steps

- Use pca to reduce and repeat the all alogrithm to see any better customer segmentation
- Hyperparameter tuning for meanshift and dbscan