Assignment - 4

Python Programming

TEAM ID : PNT2022TMID04216

Problem Statement: Customer Segmentation Analysis

Importing Modules

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

1. Download the dataset
2. Look the dataset into the tool

In [2]:
```
data=pd.read_csv("Mall_Customers.csv")
```

3. Perform Below Visualizations

· Univariate Analysis

· Bi-Variate Analysis

· Multi-Variate Analysis

In [3]:
```
data.head()
```

Out[3]:

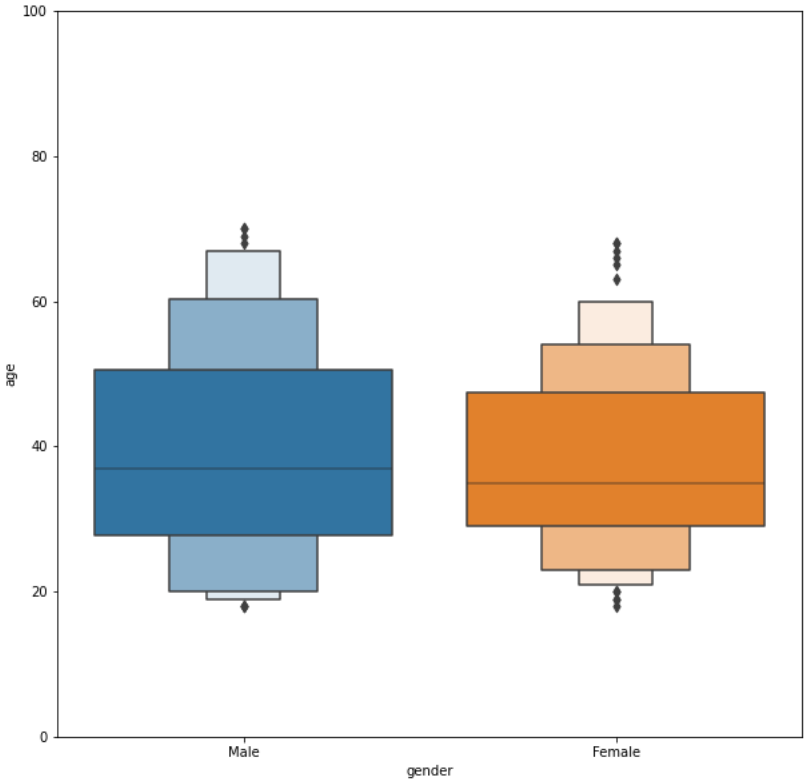
	CustomerID	Genre	Age	Annual Income (k$)	Spending Score (1-100)
0	1	Male	19	15	39
1	2	Male	21	15	81
2	3	Female	20	16	6
3	4	Female	23	16	77
4	5	Female	31	17	40

In [8]:
```
data.rename(columns={"CustomerID":"customer_id","Genre":"gender","Age":"age","Annual Income (k$)":"annual_income",
                     "Spending Score (1-100)":"spending_scores"},inplace=True)
```

In [9]:

```
temp = pd.concat([data['age'], data['gender']], axis=1)

f, ax = plt.subplots(figsize=(10,10))
fig = sns.boxenplot(x='gender', y="age", data=data)
fig.axis(ymin=0, ymax=100);
```



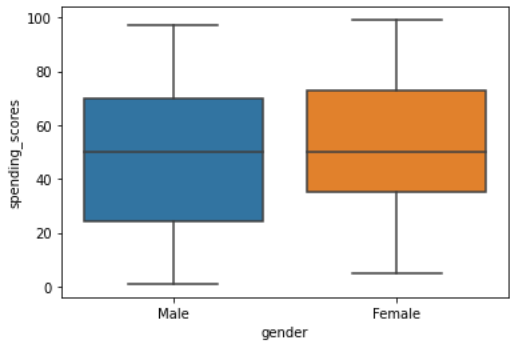
ANALYSIS

There is no difference in age of rings for male and female (18-70).

Count plot

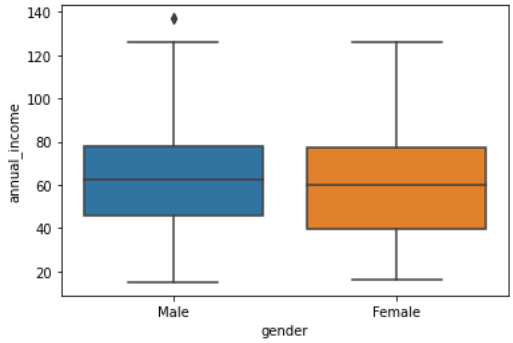
In [10]:
```
sns.boxplot(x=data['gender'],y=data['spending_scores'])
```

Out[10]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4677c22dd0>
```



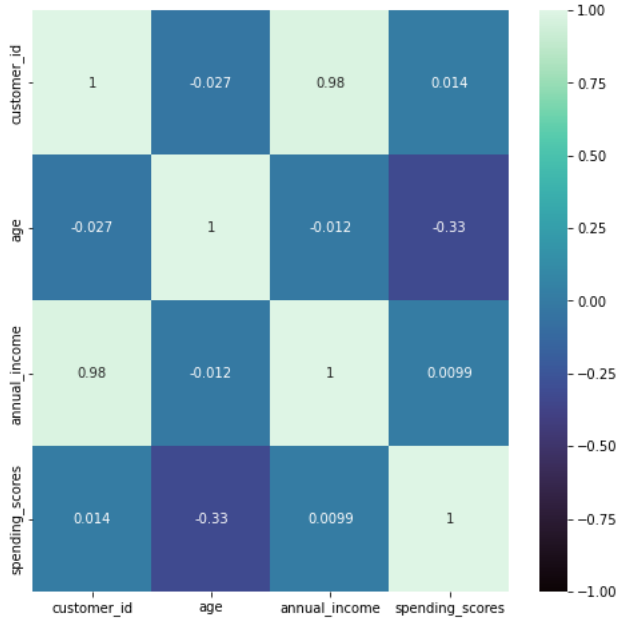
In [11]:
```
sns.boxplot(x=data['gender'],y=data['annual_income'])
```

Out[11]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4674ea2f50>
```



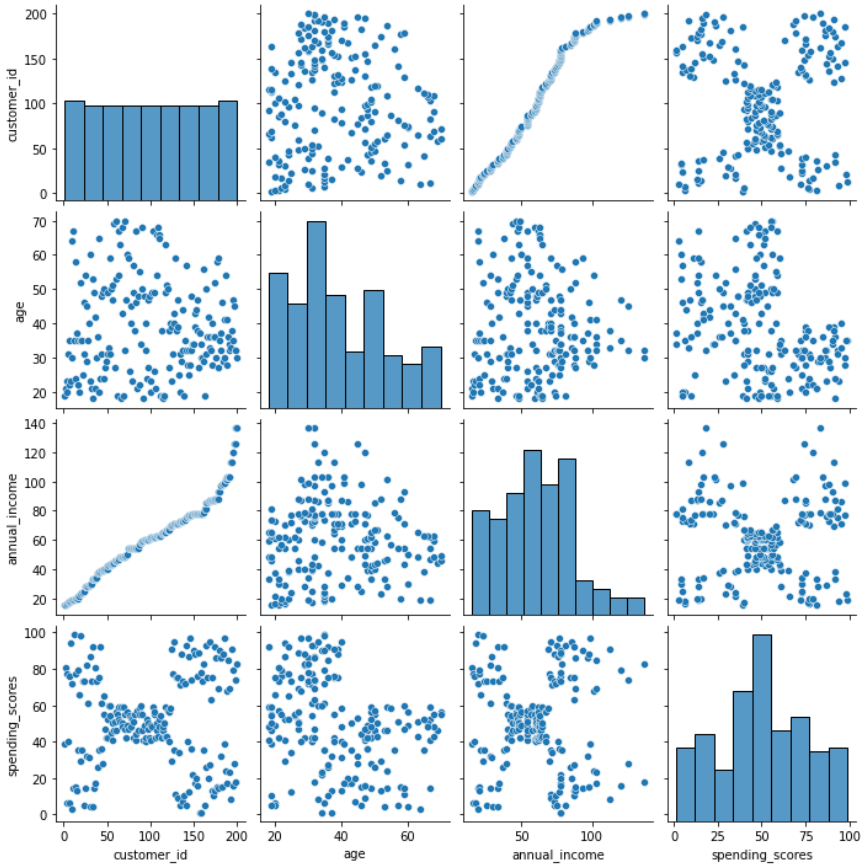
Coorelation Plot

In [12]:
```
corr=data.corr()
plt.figure(figsize=(8,8))
sn=sns.heatmap(corr,vmin=-1,center=0, annot = True, cmap = 'mako')
```



In [13]:
```
sns.pairplot(data)
```

Out[13]:
```
<seaborn.axisgrid.PairGrid at 0x7f4674cafe90>
```



4. Perform descriptive statistics on the dataset.

In [14]:
```
data.head(10)
```

Out[14]:

	customer_id	gender	age	annual_income	spending_scores
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
5	6	Female	22	17	76
6	7	Female	35	18	6
7	8	Female	23	18	94
8	9	Male	64	19	3
9	10	Female	30	19	72

In [15]:
```
data.shape
```

Out[15]:
```
(200, 5)
```

In [16]:
```
data.describe()
```

Out[16]:

	customer_id	age	annual_income	spending_scores
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

In [17]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 5 columns):
 #   Column           Non-Null Count  Dtype 
---  ------           --------------  ----- 
 0   customer_id      200 non-null    int64 
 1   gender           200 non-null    object
 2   age              200 non-null    int64 
 3   annual_income    200 non-null    int64 
 4   spending_scores  200 non-null    int64 
dtypes: int64(4), object(1)
memory usage: 7.9+ KB
```

5. Check for Missing values and deal with them

In [18]:
```
data[data.duplicated()]
```

Out[18]:

customer_id	gender	age	annual_income	spending_scores

there is no missing values and duplicates in dataframe

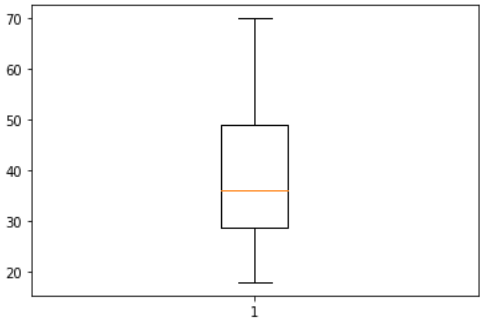
6. Find the outliers and replace them

In [19]:
```
for i in data:
    if data[i].dtype=='int64':
        q1=data[i].quantile(0.25)
        q3=data[i].quantile(0.75)
        iqr=q3-q1
        upper=q3+1.5*iqr
        lower=q1-1.5*iqr
        data[i]=np.where(data[i] >upper, upper, data[i])
        data[i]=np.where(data[i] <lower, lower, data[i])
```

After removing outliers, boxplot will be like

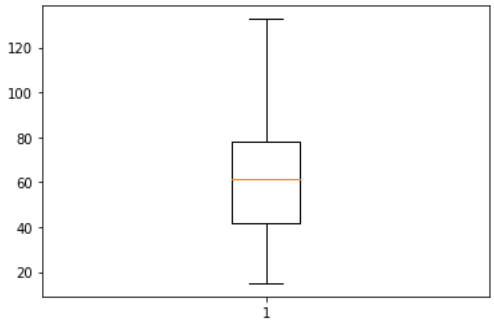
In [20]:
```
plt.boxplot(data['age'])
```

Out[20]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x7f467451fb10>,
  <matplotlib.lines.Line2D at 0x7f4674523090>],
 'caps': [<matplotlib.lines.Line2D at 0x7f46745235d0>,
  <matplotlib.lines.Line2D at 0x7f4674523b10>],
 'boxes': [<matplotlib.lines.Line2D at 0x7f467451f550>],
 'medians': [<matplotlib.lines.Line2D at 0x7f4672ca50d0>],
 'fliers': [<matplotlib.lines.Line2D at 0x7f4672ca5610>],
 'means': []}
```



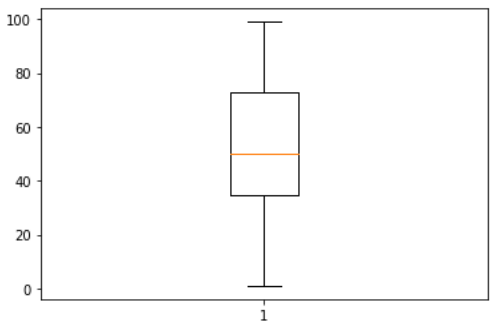
In [21]:
```
plt.boxplot(data['annual_income'])
```

Out[21]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x7f4672c7f650>,
  <matplotlib.lines.Line2D at 0x7f4672c7fb90>],
 'caps': [<matplotlib.lines.Line2D at 0x7f4672c86110>,
  <matplotlib.lines.Line2D at 0x7f4672c86650>],
 'boxes': [<matplotlib.lines.Line2D at 0x7f4672c7f090>],
 'medians': [<matplotlib.lines.Line2D at 0x7f4672c86bd0>],
 'fliers': [<matplotlib.lines.Line2D at 0x7f4672c8e150>],
 'means': []}
```



In [22]:
```
plt.boxplot(data['spending_scores'])
```

Out[22]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x7f4672bed090>,
  <matplotlib.lines.Line2D at 0x7f4672bed5d0>],
 'caps': [<matplotlib.lines.Line2D at 0x7f4672bedb10>,
  <matplotlib.lines.Line2D at 0x7f4672bf4090>],
 'boxes': [<matplotlib.lines.Line2D at 0x7f4672beaa90>],
 'medians': [<matplotlib.lines.Line2D at 0x7f4672bf4610>],
 'fliers': [<matplotlib.lines.Line2D at 0x7f4672bf4b50>],
 'means': []}
```



7. Check for categorical columns and perform encoding

In [23]:
```
from sklearn.preprocessing import LabelEncoder
encoder=LabelEncoder()
data['gender']=encoder.fit_transform(data['gender'])
```

In [24]:
```
data.head()
```

Out[24]:

	customer_id	gender	age	annual_income	spending_scores
0	1.0	1	19.0	15.0	39.0
1	2.0	1	21.0	15.0	81.0
2	3.0	0	20.0	16.0	6.0
3	4.0	0	23.0	16.0	77.0
4	5.0	0	31.0	17.0	40.0

8. Scaling the data

In [25]:
```
from sklearn.preprocessing import StandardScaler
df=StandardScaler()
data1=df.fit_transform(data)
```

In [26]:
```
data1
```

Out[26]:
```
array([[-1.7234121 ,  1.12815215, -1.42456879, -1.74542941, -0.43480148],
       [-1.70609137,  1.12815215, -1.28103541, -1.74542941,  1.19570407],
       [-1.68877065, -0.88640526, -1.3528021 , -1.70708307, -1.71591298],
       [-1.67144992, -0.88640526, -1.13750203, -1.70708307,  1.04041783],
       [-1.6541292 , -0.88640526, -0.56336851, -1.66873673, -0.39597992],
       [-1.63680847, -0.88640526, -1.20926872, -1.66873673,  1.00159627],
       [-1.61948775, -0.88640526, -0.27630176, -1.6303904 , -1.71591298],
       [-1.60216702, -0.88640526, -1.13750203, -1.6303904 ,  1.70038436],
       [-1.5848463 ,  1.12815215,  1.80493225, -1.59204406, -1.83237767],
       [-1.56752558, -0.88640526, -0.6351352 , -1.59204406,  0.84631002],
       [-1.55020485,  1.12815215,  2.02023231, -1.59204406, -1.4053405 ],
       [-1.53288413, -0.88640526, -0.27630176, -1.59204406,  1.89449216],
       [-1.5155634 , -0.88640526,  1.37433211, -1.55369772, -1.36651894],
       [-1.49824268, -0.88640526, -1.06573534, -1.55369772,  1.04041783],
       [-1.48092195,  1.12815215, -0.13276838, -1.55369772, -1.44416206],
       [-1.46360123,  1.12815215, -1.20926872, -1.55369772,  1.11806095],
       [-1.4462805 , -0.88640526, -0.27630176, -1.51535138, -0.59008772],
       [-1.42895978,  1.12815215, -1.3528021 , -1.51535138,  0.61338066],
       [-1.41163905,  1.12815215,  0.94373197, -1.43865871, -0.82301709],
       [-1.39431833, -0.88640526, -0.27630176, -1.43865871,  1.8556706 ],
       [-1.3769976 ,  1.12815215, -0.27630176, -1.40031237, -0.59008772],
       [-1.35967688,  1.12815215, -0.99396865, -1.40031237,  0.88513158],
       [-1.34235616, -0.88640526,  0.51313183, -1.36196603, -1.75473454],
       [-1.32503543,  1.12815215, -0.56336851, -1.36196603,  0.88513158],
       [-1.30771471, -0.88640526,  1.08726535, -1.24692702, -1.4053405 ],
       [-1.29039398,  1.12815215, -0.70690189, -1.24692702,  1.23452563],
       [-1.27307326, -0.88640526,  0.44136514, -1.24692702, -0.7065524 ],
       [-1.25575253,  1.12815215, -0.27630176, -1.24692702,  0.41927286],
       [-1.23843181, -0.88640526,  0.08253169, -1.20858069, -0.74537397],
       [-1.22111108, -0.88640526, -1.13750203, -1.20858069,  1.42863343],
       [-1.20379036,  1.12815215,  1.51786549, -1.17023435, -1.7935561 ],
       [-1.18646963, -0.88640526, -1.28103541, -1.17023435,  0.88513158],
       [-1.16914891,  1.12815215,  1.01549866, -1.05519534, -1.7935561 ],
       [-1.15182818,  1.12815215, -1.49633548, -1.05519534,  1.62274124],
       [-1.13450746, -0.88640526,  0.7284319 , -1.05519534, -1.4053405 ],
       [-1.11718674, -0.88640526, -1.28103541, -1.05519534,  1.19570407],
       [-1.09986601, -0.88640526,  0.22606507, -1.016849  , -1.28887582],
       [-1.08254529, -0.88640526, -0.6351352 , -1.016849  ,  0.88513158],
       [-1.06522456, -0.88640526, -0.20453507, -0.90180999, -0.93948177],
       [-1.04790384, -0.88640526, -1.3528021 , -0.90180999,  0.96277471],
       [-1.03058311, -0.88640526,  1.87669894, -0.86346365, -0.59008772],
       [-1.01326239,  1.12815215, -1.06573534, -0.86346365,  1.62274124],
       [-0.99594166,  1.12815215,  0.65666521, -0.82511731, -0.55126616],
       [-0.97862094, -0.88640526, -0.56336851, -0.82511731,  0.41927286],
       [-0.96130021, -0.88640526,  0.7284319 , -0.82511731, -0.86183865],
```

```
[ 1.5155634 ,  1.12815215, -0.7786858,  1.5523556 ,  0.6910237 ],
[ 1.53288413, -0.88640526,  0.15429838,  1.62904827, -1.28887582],
[ 1.55020485, -0.88640526, -0.20453507,  1.62904827,  1.35099031],
[ 1.56752558, -0.88640526, -0.34806844,  1.62904827, -1.05594645],
[ 1.5848463 , -0.88640526, -0.49160182,  1.62904827,  0.72984534],
[ 1.60216702,  1.12815215, -0.41983513,  2.01251165, -1.63826986],
[ 1.61948775, -0.88640526, -0.06100169,  2.01251165,  1.58391968],
[ 1.63680847, -0.88640526,  0.58489852,  2.28093601, -1.32769738],
[ 1.6541292 , -0.88640526, -0.27630176,  2.28093601,  1.11806095],
[ 1.67144992, -0.88640526,  0.44136514,  2.51101403, -0.86183865],
[ 1.68877065,  1.12815215, -0.49160182,  2.51101403,  0.92395314],
[ 1.70609137,  1.12815215, -0.49160182,  2.76985181, -1.25005425],
[ 1.7234121 ,  1.12815215, -0.6351352 ,  2.76985181,  1.27334719]])
```

9. Perform any of the clustering algorithms

In [27]:
```
from sklearn.cluster import KMeans
```

In [28]:
```
data.drop('customer_id',axis=1,inplace=True)
```

In [29]:
```
km = KMeans(n_clusters=3, random_state=0)
```

In [30]:
```
data['Group or Cluster'] = km.fit_predict(data)
```

In [31]:
```
data.head()
```

Out[31]:

	gender	age	annual_income	spending_scores	Group or Cluster
0	1	19.0	15.0	39.0	2
1	1	21.0	15.0	81.0	2
2	0	20.0	16.0	6.0	2
3	0	23.0	16.0	77.0	2
4	0	31.0	17.0	40.0	2

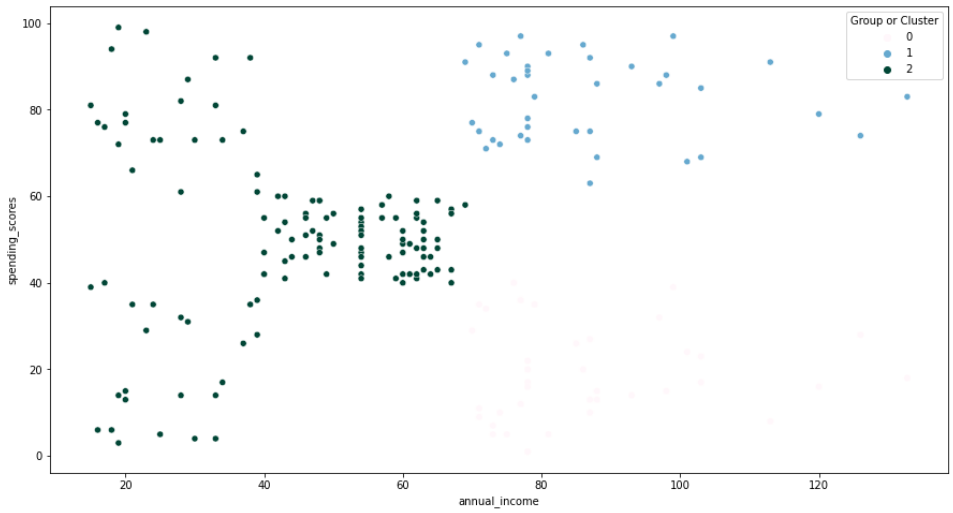
In [32]:
```
data['Group or Cluster'].value_counts()
```

Out[32]:
```
2    123
1     39
0     38
Name: Group or Cluster, dtype: int64
```

In [33]:

```
import matplotlib.pyplot as plt

fig,ax = plt.subplots(figsize=(15,8))
sns.scatterplot(x=data['annual_income'],
                y=data['spending_scores'],
                hue=data['Group or Cluster'],
                palette='PuBuGn')
plt.show()
```



In [34]:

```
from sklearn.metrics import silhouette_score, silhouette_samples
score = silhouette_score(data,
                         km.labels_,
                         metric='euclidean')
score
```

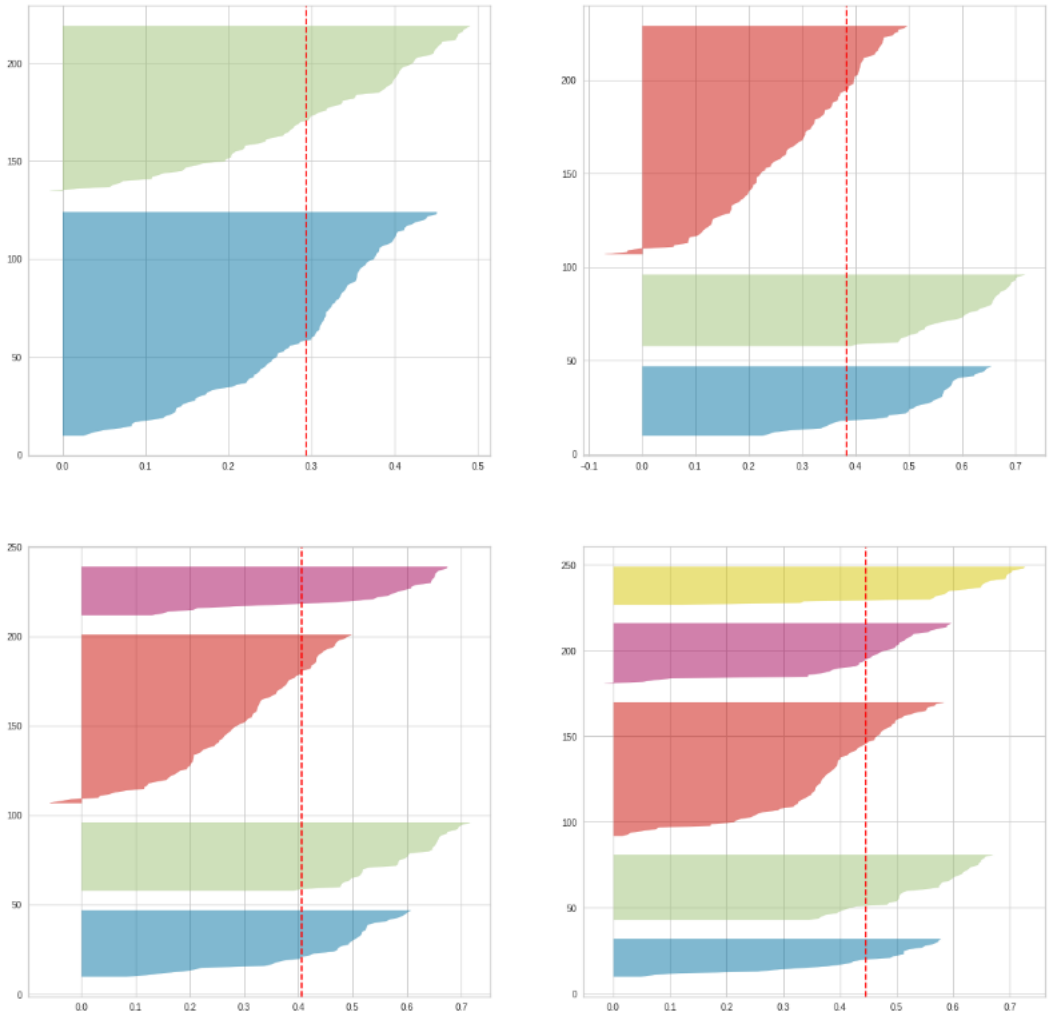
Out[34]:

```
0.3842057644019546
```

In [35]:

```
import matplotlib.pyplot as plt
from yellowbrick.cluster import SilhouetteVisualizer

fig, ax = plt.subplots(2, 2, figsize=(20,20))
for i in [2, 3, 4, 5]:
    '''
    Create KMeans instance for different number of clusters
    '''
    km = KMeans(n_clusters=i,
                init='k-means++',
                n_init=10,
                max_iter=100,
                random_state=0)
    q, mod = divmod(i, 2)
    '''
    Create SilhouetteVisualizer instance with KMeans instance
    Fit the visualizer
    '''
    visualizer = SilhouetteVisualizer(km,
                                      colors='yellowbrick',
                                      ax=ax[q-1][mod])
    visualizer.fit(data)
```



10. Add the cluster to the primary dataset

```
df_transformed = df_initial
```

```
[ ] df_transformed['class'] = y_predicted
```

```
df_transformed
```

	Gender	Age	Annual Income (k$)	Spending Score (1-100)	class
0	1	19.0	15.0	39	4
1	1	21.0	15.0	81	3
2	0	20.0	16.0	6	4
3	0	32.0	16.0	77	3
4	0	31.0	17.0	40	4
...	...	...	...	...	...
195	0	35.0	120.0	79	0
196	0	45.0	126.0	28	2
197	1	32.0	126.0	74	0
198	1	32.0	137.0	18	2
199	1	30.0	137.0	83	0

200 rows × 5 columns

11. Split Dataset into Predictors and Target

```
[ ] feature =pd.DataFrame(df_transformed.drop(['class'], axis = 1))
    label = pd.DataFrame(df_transformed['class'])
```

```
feature.head()
```

	Gender	Age	Annual Income (k$)	Spending Score (1-100)
0	1	19.0	15.0	39
1	1	21.0	15.0	81
2	0	20.0	16.0	6
3	0	32.0	16.0	77
4	0	31.0	17.0	40

+ Code + Text

```
[ ] label.head()
```

	class
0	4
1	3
2	4
3	3
4	4

12. Splitting into Training and Test Datasets

```
[ ] X_train, X_test, y_train, y_test = train_test_split(feature, label, test_size = 0.2, random_state = 0)

    print('X_train : ')
    print(X_train)
    print(X_train.shape)

    print('')
    print('X_test : ')
    print(X_test)
    print(X_test.shape)

    print('')
    print('y_train : ')
    print(y_train)
    print(y_train.shape)

    print('')
    print('y_test : ')
    print(y_test)
    print(y_test.shape)
```

```
X_train :
     Gender   Age  Annual Income (k$)  Spending Score (1-100)
134       1  20.0                73.0                       5
66        0  43.0                48.0                      50
26        0  45.0                28.0                      32
113       1  19.0                64.0                      46
168       0  36.0                87.0                      27
..      ...   ...                 ...                     ...
67        0  68.0                48.0                      48
192       1  33.0               113.0                       8
117       0  49.0                65.0                      59
47        0  27.0                40.0                      47
172       1  36.0                87.0                      10

[160 rows x 4 columns]
(160, 4)

X_test :
     Gender   Age  Annual Income (k$)  Spending Score (1-100)
18        1  52.0           60.641026                      29
170       1  40.0           87.000000                      13
107       1  54.0           63.000000                      46
98        1  48.0           61.000000                      42
177       1  27.0           88.000000                      69
182       1  46.0           98.000000                      15
5         0  22.0           17.000000                      76
146       1  48.0           77.000000                      36
12        0  58.0           20.000000                      15
152       0  44.0           78.000000                      20
61        1  19.0           46.000000                      55
125       0  31.0           70.000000                      77
180       0  37.0           97.000000                      32
154       0  47.0           78.000000                      16
80        1  57.0           54.000000                      51
7         0  23.0           18.000000                      94
33        1  18.0           33.000000                      92
130       1  47.0           71.000000                       9
37        0  30.0           34.000000                      73
74        1  59.0           54.000000                      47
183       0  29.0           98.000000                      88
```

```
y_train :
     class
134      2
66       1
26       4
113      1
168      2
..     ...
67       1
192      2
117      1
47       1
172      2

[160 rows x 1 columns]
(160, 1)

y_test :
     class
18       1
170      2
107      1
98       1
177      0
182      2
5        3
146      2
12       4
152      2
61       1
125      0
180      2
154      2
80       1
7        3
33       3
130      2
37       3
```

13. Build the Model

```
[ ] rfc = RandomForestClassifier()

    forest_params = [{'max_depth': list(range(10, 15)), 'max_features': list(range(0,14))}]

    clf = GridSearchCV(rfc, forest_params, cv = 10, scoring='accuracy')
```

```
clf.fit(X_train, y_train)

print(clf.best_params_)

print(clf.best_score_)
```

```
c:\python\python39\lib\site-packages\sklearn\model_selection\_validation.py:598: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples,), f
  estimator.fit(X_train, y_train, **fit_params)
c:\python\python39\lib\site-packages\sklearn\model_selection\_validation.py:615: FitFailedWarning: Estimator fit failed. The score on this train-test partition for these parameters will be set to nan. Details:
Traceback (most recent call last):
  File "c:\python\python39\lib\site-packages\sklearn\model_selection\_validation.py", line 598, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "c:\python\python39\lib\site-packages\sklearn\ensemble\_forest.py", line 387, in fit
    trees = Parallel(n_jobs=self.n_jobs, verbose=self.verbose,
  File "c:\python\python39\lib\site-packages\joblib\parallel.py", line 1041, in __call__
    if self.dispatch_one_batch(iterator):
  File "c:\python\python39\lib\site-packages\joblib\parallel.py", line 859, in dispatch_one_batch
    self._dispatch(tasks)
  File "c:\python\python39\lib\site-packages\joblib\parallel.py", line 777, in _dispatch
    job = self._backend.apply_async(batch, callback=cb)
  File "c:\python\python39\lib\site-packages\joblib\_parallel_backends.py", line 208, in apply_async
    result = ImmediateResult(func)
  File "c:\python\python39\lib\site-packages\joblib\_parallel_backends.py", line 572, in __init__
    self.results = batch()
  File "c:\python\python39\lib\site-packages\joblib\parallel.py", line 262, in __call__
    return [func(*args, **kwargs)
  File "c:\python\python39\lib\site-packages\joblib\parallel.py", line 262, in <listcomp>
    return [func(*args, **kwargs)
  File "c:\python\python39\lib\site-packages\sklearn\utils\fixes.py", line 222, in __call__
    return self.function(*args, **kwargs)
```

14. Train the Model

```
[ ] model = RandomForestClassifier(max_depth=12, max_features=1).fit(X_train,y_train)
```

15. Test the Model

```
[ ] y_pred = model.predict(X_test)
```

```
[ ] y_pred
```

```
array([1, 2, 1, 1, 0, 2, 3, 1, 4, 2, 1, 0, 2, 2, 1, 3, 3, 2, 3, 1, 0, 0,
       1, 0, 1, 0, 0, 0, 1, 4, 4, 1, 2, 1, 4, 0, 0, 1, 1, 1])
```

16. Evaluation Metrics

```
[ ] from sklearn.metrics import confusion_matrix,classification_report,accuracy_score
```

```
cm = confusion_matrix(y_test,y_pred)
sns.heatmap(cm,annot=True,cmap='viridis')
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        10
           1       0.80      1.00      0.89        12
           2       1.00      0.88      0.93         8
           3       1.00      0.80      0.89         5
           4       1.00      0.80      0.89         5

    accuracy                           0.93        40
   macro avg       0.96      0.89      0.92        40
weighted avg       0.94      0.93      0.93        40
```